VNIVERSITAT DE VALÈNCIA

***DEPARTAMENTO DE INFORMATICA***

***(COMPUTER SCIENCES DEPARTMENT)***

***Doctoral Programme:***

INFORMATION TECHNOLOGY, COMMUNICATIONS
AND COMPUTATIONAL MATHEMATICS

# *SEMANTICALLY-ENHANCED ADVERTISEMENT RECOMMENDER SYSTEMS IN SOCIAL NETWORKS*

**Doctoral Thesis by**

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**Valencia, May 2017**

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**CERTIFICAN** QUE:

La presente Tesis Doctoral original de D. Ali Pazahr titulada "**SEMANTICALLY-ENHANCED ADVERTISEMENT RECOMMENDER SYSTEMS IN SOCIAL NETWORKS**", ha sido realizada bajo nuestra dirección y supervisión y, a nuestro juicio, reúne los requisitos para su lectura y obtención del grado de Doctor.

Y para que así conste a los efectos oportunos, firmamos el presente certificado en Valencia, a 16 de mayo de 2017.

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# ACKNOWLEDGEMENTS

*This thesis is dedicated to my family particularly my parents and my wife, Nasim, for their infinite LoVe, support and encouragements.*

*Furthermore, I would like to thank and appreciate my supervisors, Dr. J. Javier Samper Zapater and Dr. Francisco García Sánchez for their great advices and support for this study.*

*I wish all the best for these dear people.*

*This Thesis is included in the Spanish MINECO project "Radio Access Technologies for Heterogeneous Wireless Networks" (RACHEL TEC2013-47141-C4-4-R).*

# OVERVIEW

Giving recommendations on Social systems has been famous and fruitful in different urban practical applications, for example, internet sharing, items suggestion and shopping administrations. These applications permit clients to shape a few certain social networks through their day by day social cooperative communications. The clients in such informal communities can rate some intriguing things and represent their interests about the things. Most of the current studies have explored the rating expectation and suggestion of things taking into account established procedures of proposal frameworks while in this study, the exertion is to consolidate some of those traditional methods in type of one way to deal with scope to a more quality arrangement and fulfillment about the outcome. Albeit, classical hybrid techniques for recommendation frameworks can beat the constraints, yet at the same time they endure some different issues.

In our regular life, we depend vigorously on suggestions from our family, associates, articles and news to pick among the accessible books, music, motion pictures, eateries, items, administrations et cetera. Online recommender frameworks are increasing expanding prevalence step by step where the objective is to create significant recommendations to clients for administration or items that may intrigue them. Some genuine cases of recommendation frameworks incorporate Amazon's book recommendations, Netflix's motion picture recommendations, Pandora's music recommendations and YouTube's video suggestions. In the meantime, today's online experience depends progressively on social association. Social figuring applications, for example, Facebook, MySpace, and LinkedIn enhance clients' social availability through joint effort and coordination by empowering convincing and powerful on-line social communications. There have been frameworks utilizing informal community to empower customized recommendations. For instance, Facebook cannot just prescribe about new associations in which the client may be intrigued additionally recommend ways of life, pages and numerous different stuffs.

One of the main concerns in social network is establishing a successful business plan to make more profit from the social network. Doing a business on every platform needs a good business plan with some important solutions such as advertise the products or services of other companies which would be a kind of marketing for those external businesses. There are lots of advertising which are annoying for the users of social network because they are not relevant or interesting for the users. Therefore, it is very important for the success of the social network to design a plan containing advertisements which are interesting for its users, because in case of showing irrelevant ads to the users, they will probably give up using or even membership of the social network and the less the number of users are in the social network, the less success the social network will have to make a good business. So, choosing a correct strategy in this matter is very important.

One of the specifications of old systems of social network was that they were sending all advertisement for all of users without considering their preferences. In this case users once again face to annoying advertisements. So for more efficiency in the advertisement system, it is necessary to send advertisements only based on the particular group of users whom we know their interests whereas those ads are interesting for the users. This kind of advertising is famous as targeted advertising.

Another characteristic of old social networks was that the procedure of choosing, preparing and sending of advertisements were manual while nowadays for the new level of facilities in social networks with new related technologies, it is not possible to do it in the previous traditional form. So it is important to select a solution to generate suggestion of the products for the users based on an automatic mechanism. This methodology can be named as recommendation system. Accordingly, we have to establish advertisement recommendation system in our social networks.

There has been tremendous efforts and progresses about recommendation systems so far because of their incredible role in the business. But, still there are some problems from which the recommendation systems suffer. The most important aspect of these problems is that they are not flexible and intelligent in detecting the best suggestions. So, if it is possible to incorporate an intelligence solution with the current available recommender systems, we can observe incredible results from the recommender systems through assess the users' opinions. Such solution can be semantic technology as the best way to make intelligent recommender systems.

The main drawbacks of current state-of-the-art solutions are mentioned as below:

1- They have kept the problems of each including components. As hybrid recommender systems are considered, they are comprising standard recommender techniques which have limitations.

2- Usually they do not use artificial intelligence techniques to enrich the performance of the overall method. As a result, their outcome has limited benefits in a few specific areas.

3- They usually do not have an acceptable flexibility in changing the components of the integrated system. It means that for modifying one part of the system, probably a considerable cost should be paid to change the complete system and finally adjust it with the preliminary rules and structure.

4- They do not speak about the security of their framework whereas in every software system, the security is one the most important part of the system which the lack of attention to this part would lead to irreparable damages even to the other available related systems which are contributing to the system.

5- Their prototype applications are not usually quick and easy to use. As many of the current solutions have been checked, mostly they needed to be setup with specific configurations and in many cases, they were not quick to run and show how system works.

But, how the current study can overcome the mentioned limitations? The suggested framework in this study have overcome to these problems as follows: The proposed system tries to collect some standard techniques and use the benefits of each of them along with choosing specific rates which show the amount of impact for each technique. Furthermore, by using semantic technology, it has been tried to overcome the limitations of the composed recommender techniques during putting the standard methods together. Some artificial intelligence technologies have been used in the suggested framework such as K Nearest Neighborhood (kNN) for finding the closest neighbors to the user for whom the system wants to find recommendations. One of the positive points of the suggested framework is that its components have independent operations to each other, so every change can be applied to specific component without any side effect to another component. This flexibility can be led to comfortability for the application developer when any change is needed. The current framework fulfils the essential level of security and complies minimum considerations for user privileges in different parts of the framework. Because of the web based platform of the used prototype, the software application works quickly, everywhere and every time, with user friendly interface and easy to use environment.

Semantic recommendation frameworks are portrayed by the joining of semantic learning in their procedures with a specific end goal to enhance suggestion's quality. The vast majority of them utilize an idea based way to deal with enhance the user profile representation. Other recommender frameworks concentrate on misusing semantics to enhance their suggestion procedures (content adjustment stage). The greater part of them make utilization of semantic likeness strategies to upgrade the execution of content based (CB) approaches, despite the fact that there are additionally recommenders utilizing semantics to improve the user profile coordinating of collaborative filtering approaches.

The current research is composed of five sections. In section I, including the Chapter 1, Introduction: approach to the problem will be spoken. In this chapter, some elementary comments about the current research will be stated and the main problems of available and previous works are mentioned so that the primary motivations to solve those problems will be formed. In section II of this study with the title theoretical foundations, technologies and state of the art, including the Chapter 2 with the title definitions, a philosophy of a system speaking to of a comprehensive structure of advertisement recommender system for social networks along with the all used concepts will be defined and presented so that these concepts would be familiar to the reader during reading the consequent parts of the study. In section III, with the title proposals and contributions, including the Chapter 3, expressing the Methodology of the suggested framework, the structure of the framework along with how it is developed including frontend and backend will be discussed. Furthermore, the main contributions of the solution in the current research will be illustrated along with comprehensive detailed explanations. In section IV which is evaluation and results section of the study, including Chapter 4 with the title of Evaluation, the validation of the framework will be accomplished so as to assess the utilized estimations in the suggested framework as the main solution. The framework uses a semantic logic to provide the recommended products and this capability can differentiate the recommender part of the framework from classical recommender methods. Generally speaking, the used framework in this study has been designed in a form that can generate advertisement recommendations in a simplified and effectiveness way for social network users. Then in section V of the study, including the subjects results, discussions, conclusions and future work, the result of the study will be mentioned and discussed in Chapter 5 and finally, a conclusion about the research will be demonstrated, along with mentioning the future research works which will be expressed in Chapter 6.

# SECTION I: Introduction

# CHAPTER 1

# 1. INTRODUCTION: APPROACH TO THE PROBLEM

Promoting on the social communities is a multibillion dollar market and has turned great income into the popular social networks for their business [1][2][3]. To get ready advertisements and convey them to conceivably intrigued clients, these social media platforms take in a divination model for all users according to the users' interests and activities [4][5][6]. Notwithstanding, as client interests frequently advance gradually, the client may wind up accepting tedious promotions. So it is essential for the organizations of social networks to upgrade the logic of their framework's software to provide qualified advertisement based on the users' feedback [7][8]. In this study, a framework of semantically-enhanced advertising recommender system in social networks is introduced that takes into account the relatively static personal interests by their rates to the products as well as the dynamic retrieving user interests through their activities such as search for specific products and browse and see the details of the products. To meet the real-time requirement, an online recommender system strategy as the form of a web application tool is proposed that considers users' preferences and activities, finds the most relevant products accordingly and recommends them as ads to the users. To make a superiority of the framework than the other research works, not only a particular compose of classical recommendation methods as a hybrid model has been considered, but also a semantic technique to find the recommendations has been added to the framework so as to more efficiency and robustness in this research.

## 1.1 IDENTIFICATION OF THE PROBLEM

The composition of Semantic Web advances [9][10] with Web 2.0 [11] application [12][13] plan designs has risen to the social semantic Web [14], additionally introduced as Web 3.0 [15]. In accordance with this thought, a software platform will be displayed that effectively joins both Web 2.0 ideas [16] and Semantic Web advancements. The structure of this study joins a progression of semantic-based application modules in a completely fledged social application with the goal of catching semantics in the purpose of information retrieval. Once the establishments and principle ideas of the alluded framework are brought up and its architecture was explained, a comprehensive model of the system will be demonstrated. Finally, the result of a case study will be validated using the standard metrics. It will be spoken to how the system can help in obtaining semantically-improved financially related data from the clients of the social applications and giving valuable proposals to advertisement recommender.

The ability of knowledge contribution nowadays is unmatched ever. At no other time have such a large number of inventive and proficient individuals been associated by such a productive, all-inclusive system. The expenses of social occasion and registering over their commitments have come down to the point where new organizations with extremely humble spending plans give imaginative new administrations to a great number of online members.

Collective intelligence is an amazing insight which can have numerous constructive outcomes on social networks. The outcome nowadays is amazing broadness of data and variety of point of view, and a society of mass investment that supports a wellspring of freely accessible substance [17].

The Social Web (containing services, for example, MySpace, Flickr, last.fm, and WordPress) has caught the consideration of a large number of clients and in addition billions of dollars in venture and procurement. Social sites, advancing around the associations amongst individuals and their entities of interest, are experiencing limits in the territories of information integration, dispersal, reuse, compactness, searchability, automation and requesting undertakings like questioning. The Semantic Web is a perfect tool for interlinking and performing operations on various individual and item related information accessible from the Social Web, and has delivered an assortment of ways to deal with beat the limits being knowledgeable about Social Web application ranges.

Recommendation is a compelling approach to diminish the expense for discovering data furthermore a capable approach to draw in clients. It has been broadly utilized as a part of numerous e-commerce applications, e.g., Amazon.com, CDNOW.com, eBay.com, Reel.com, et cetera. As of late, numerous techniques have been proposed for suggestion, for instance, Content-based Filtering, Collaborative Filtering, Clustering Model, Classification Model, Graph Model, and Association Rule approach. The proposed approaches have been connected to the conventional Web applications, which as a rule need suggest one and only sort of data (e.g., Amazon prescribes books, news.baidu.com prescribes news, and movielens.com prescribes films).

So as to defeat data over-burden, recommender frameworks have turned into a key apparatus for giving clients customized suggestions on things, for example, films, music, books, news, and web pages. Captivated by numerous viable applications, analysts have created calculations and frameworks in the course of the most recent decade. Some of them have been popularized by online merchants, for example, Amazon.com, Netflix.com, and IMDb.com. These frameworks foresee user preferences (frequently spoke to as numeric evaluations) for new items in light of the client's past appraisals on different items. There are regularly two sorts of calculations for recommender frameworks - content-based techniques and collaborative filtering. Content-based techniques measure the likeness of the prescribed item (target item) to the ones that an objective user (i.e., user who gets recommendations) likes or aversions in light of item properties. Then again, collaborative filtering discovers users with tastes that are like the objective users depends on their ratings in the past. Collaborative filtering will then make recommendations to the objective user in light of the feelings of those comparative users.

In spite of these endeavors, recommender frameworks still face numerous testing issues [18]. These problems will make many limitations on the operation of recommendation systems. To start with, there are requests for further upgrades on the forecast precision of recommender frameworks. In October 2006, Netflix reported an open rivalry with the terrific prize of $1,000,000 for the best calculation that predicts client evaluations for movies (http://www.netflixprize.com). The change in the expectation precision can build client fulfillment, which thusly prompts higher benefits for those e-trade sites. Second, calculations for recommender frameworks experience the side effects of numerous problems. For instance, keeping in mind the end goal to gauge thing closeness, Content-based strategies depend with respect to express thing depictions. Be that as it may, such depictions might be hard to acquire for things like thoughts or feelings.

Collaborative filtering has the Data Sparsity issue, Scalability, and the Cold-start issue. These three problems are explained in more details.

For the Cold-start issue, the frameworks regularly require a lot of existing information on a client so as to make precise recommendations.

For the Sparsity issue, the quantity of items sold on real e-trade sites is to a great degree extensive. The most dynamic clients will just have rated a little subset of the general database. Along these lines, even the most famous items have not many ratings.

Another issue from which the collaborative filtering methodologies are endured is Scalability. In a considerable lot of the situations in which these frameworks make recommendations, there are a large number of clients and items. Therefore, a lot of calculation force is frequently important to figure suggestions.

As opposed to the tremendous number of things in recommender frameworks, every client regularly just rates a couple. In this way, the user/thing rating grid is commonly extremely scanty. It is troublesome for recommender frameworks to precisely quantify client likenesses from those predetermined number of audits. A related issue is the Cold-start issue. Notwithstanding for a framework that is not especially meager, when a client at first joins, the framework has none or maybe just a couple audits from this client. In this manner, the framework can't precisely translate this current client's inclination.

To handle those issues, two methodologies have been proposed. The main methodology is to gather the user/item rating lattice through dimensionality lessening systems, for example, Singular Value Decomposition (SVD). By grouping clients or things as per their idle structure, unrepresentative clients or things can be disposed of, and in this way the user/item grid gets to be denser. Nonetheless, these strategies don't essentially enhance the execution of recommender frameworks, and now and again aggravate the execution even.

For using this approach, a methodology of kNN has been utilized for the framework to cluster users to two groups of neighbors and the other. So, the framework considers only those neighbor users which have more relative and similar data to the current user.

The second approach is to "improve" the user/item rating matrix by 1) presenting default evaluations or verifiable client ratings, e.g., the time spent on perusing articles; 2) utilizing silly evaluating expectations from content-based techniques; or 3) abusing transitive relationship among clients through their past exchanges and feedback.

For using this approach, the default values of rating 5 for just searched products and 4 for browse or visit the product details without needing any user rating are considered which the relevant explanation will be discussed in the methodology chapter. In both of these conditions, without showing any rating by the users or their direct expression, these rating of 4 or 5 will be assigned to the users' interest by the framework.

These techniques enhance the execution of recommender frameworks to some degree. Specifically, another worldview of recommender frameworks is proposed by using data in social networks, particularly that of social impact.

Customary recommender frameworks do not think about unequivocal social relations among clients, yet the significance of social impact in item advertising has for quite some time been perceived. Instinctively, when we need to purchase an item that is not commonplace, we frequently counsel with our companions who have as of now had involvement with the item, since they are those that we can go after quick exhortation. At the point when companions prescribe an item to us, we additionally have a tendency to acknowledge the suggestion in light of the fact that their inputs are dependable. This is one reason that collaborative filtering has been used as one of the components of the recommender system. Numerous promoting methodologies that have utilized this part of human instinct have made extraordinary progress. One exemplary case is the Hotmail's free email administration. The showcasing technique of Hotmail is to append an advancement message at the base of each friendly email: "Get your private, free email at http://www.hotmail.com." People who get the email will join and afterward advance proliferate this advancement message. Thus, the quantity of Hotmail client accounts developed from zero to 12 million in year and a half on just a $500,000 promoting spending plan—consequently beating numerous ordinary advertising systems. Accordingly, social impacts assume a key part when individuals are settling on choices of embracing items.

Furthermore, the combination of social networks can hypothetically enhance the execution of current recommender frameworks. To start with, as far as the forecast precision, the extra data about clients and their companions acquired from social networks enhances the comprehension of client practices and appraisals. In this manner, we can demonstrate and translate client inclinations all the more absolutely, and accordingly enhance the forecast precision. Second, with companion data in social networks, it is no more important to discover comparable clients by measuring their rating comparability, in light of the fact that the way that two individuals are companions as of now demonstrates that they have things in like manner. In this manner, the information Sparsity issue can be reduced. At long last, for the Cold-start issue, regardless of the possibility that a client has no past audits, recommender framework still can make proposals to the client in view of the inclinations of his/her companions on the off chance that it coordinates with social networks. These instincts and perceptions rouse us to plan another worldview of recommender frameworks that can exploit data in social networks.

The late rise of online social networks (OSNs) gives us a chance to examine the part of social impact in recommender frameworks. With the expanding ubiquity of Web 2.0, numerous OSNs, for example, Myspace.com, Facebook.com, and Linkedin.com have risen. Individuals in those systems have their own customized space where they not just distribute their life stories, leisure activities, interests, online journals, and so forth., additionally list their companions. Companions or guests can visit these individual spaces and leave remarks. OSNs give stages where individuals can put themselves on show and keep up associations with companions. As OSNs keep on gaining more fame, the phenomenal measure of individual data and social relations enhance sociology research where it was once constrained by an absence of information.

As an exploration, the part of unequivocal social relations in recommender frameworks is as an important part of the research, for example, how client inclinations or evaluations are connected with those of neighbors, and how to utilize such relationships to outline a superior recommender framework. Specifically, a calculation structure is planned which makes suggestions taking into account client's own particular inclinations, the general acknowledgment of the objective thing, and the assessments from social networks. A genuine online social network data from last.fm has been crawled as a contextual investigation, and perform broad examination on this dataset.

Additionally, the dataset is utilized, accumulated from the social network, to assess the execution of the proposed framework on the forecast precision, information sparsity, and cool begin. The exploratory aftereffects of our framework show critical change against customary community oriented sifting in those perspectives. For instance, the computed precision in the wake of running the contextual analysis has enhanced by 0.7498 contrasted with conventional shared separating. Moreover, it is proposed to utilize the semantics of client connections by their similitudes and better grained client appraisals to enhance the expectation exactness.

## 1.2 MOTIVATION

Recommendation systems assist clients search and choose things (for example books, motion pictures, clubs) from the gigantic number accessible on the web or in other electronic data sources [19][20][21]. Specified a huge arrangement of things and a depiction of the client's needs, they present to the client a little arrangement of the things that are appropriate to the portrayal. Late work in suggestion frameworks incorporates insightful helpers for sifting and picking sites [22], news narratives [23], TV postings [24], and other data. The clients of such frameworks regularly have assorted, clashing necessities. Contrasts in individual inclinations, social and instructive foundations, and private or expert interests are inescapable. Subsequently, it appears to be attractive to have customized wise frameworks that procedure, channel, and show accessible data in a way that suits every individual utilizing them. The requirement for personalization has prompted the improvement of frameworks that adjust by changing their conduct taking into account the deduced attributes of the client communicating with them [25][26][27]. The capacity of PCs to speak with clients in regular dialect would apparently expand their helpfulness and adaptability much further. Research in useful exchange frameworks, while still in its early stages, has developed enormously lately [28][29][30]. Recent discourse frameworks normally concentrate on assisting clients to finish a particular work, for example, arranging, data seek, occasion administration, or conclusion.

The main motivation for doing this research was that there were several similar related works in which there were some problems and limitations whether on base of design or operation and it was a good start point to analyze the similar works, check their functionality and propose a more comprehensive framework which can overcome those problems and limitations and my previous research in this area was about analyzing some recommendation systems in social networks like Last.fm, Facebook and Instagram whose recommendation engines were working based on the specific standard recommendation algorithms, as I could check their outcomes, witnesses and how they work. These thoughts proved that many of famous social networks are only using the benefits of available standard techniques, instead of utilizing innovative methods for their system, and a gap was felt for designing the recommendation systems, particularly those which are used in business. This motivation could help design and develop a framework for advertisement recommender systems in social networks, considering how much a good design of a recommendation system can affect the success of a business. Moreover, the current research can demonstrate a suitable solution for the available systems and enhance them to operate better than before. The novelties which are used in this study’s framework can make evolutions in the future recommender system which work on the social media platform.

According to the established researches related to the security before starting the current studies, the other motivation for starting the thesis was that new security mechanisms could be proposed for the other platforms such as social networks and consequently more studies in form of the papers were accomplished. Afterwards for taking the advantages of the other experiences in the other research groups with the similar subjects, two visiting researches were carried out, first one in the Data and Web Science research group at the University of Mannheim and the second one in Multimedia Information System group at the University of Vienna. These research stays had very useful outcomes for enriching the quality of the thesis and they could trigger the work in the right way.

## 1.3 RESEARCH QUESTIONS

In all researches usually there are some key questions about which the researchers think. A number of the main questions in the current study are:

1- Is possible to overcome the current problems of recommender systems in social networks?

2- How much is the role of semantic in shaping an efficient recommender system?

3- How much are the users satisfied by the recommended products?

4- Is possible to collect a comprehensive database with a high quantity of data to increase the level of reliability?

These queries later will be solved in the section 6.1.

Answer to these questions can help to have a better sight for solving the main problems to which the researchers of similar works are facing.

## 1.4 OBJECTIVES

The main objective of the research is to study and design of a framework for advertisement recommender system in social networks which can be enriched by semantic technologies. Although there are many applications and solutions about recommender systems, but in this study it is important to design a robust framework with a suitable performance which can be implemented on every social network to extend the business purposes.

The secondary objectives in this study can be listed as follows:

1- To overcome to the primary constraints of classical methods.

2- To increase the quality of recommendations and the performance of recommender system

3- To use the suggested methodology conveniently

4- To establish the suggested framework on a real software platform

5- To consider portability as one of the important issues in software systems for the solution

6- To consider reliability for the framework

7- To have an acceptable level of security for the framework

First, it is necessary to overcome the constraints of classical methods. This goal in the current study will be reached by composing four basic recommendation methods as a form of hybrid method which has all benefits of each one. As explained in the previous part, collaborative filtering methods suffer from three problems, although it was needed to utilize the benefits of collaborative technique. So not only bypassing these limitations in the collaborative element of the framework is necessary, but also it is valuable to use collaborative approach while the framework overcomes its problems. Furthermore, by adding semantic techniques during the process of calculating the advertisement recommendations, the quality of recommendations will be increased. The used semantic technology in the framework has enhanced the performance of the system and in point of novelty, the solution is very interesting rather than the similar researches. Truth be told, to enhance the exactness of the anticipated recommendation settings, the semantics of information items and client profiles into thought have been taken. Bringing semantics into forecast gives extra insights about the basic explanations behind which a client could possibly permit access for specific products (something that is understood and covered up to customary strategies without semantics mindfulness). The used semantic in this study is meant in the form of relations between concepts. As a result, it is possible to extract incredible knowledge from the available items.

The other goal is convenience of the methodology. It is necessary for the research to get acceptable results by implementing easy to use algorithms and convenient approach. To reach this goal, a case study is designed, then a web application is implemented to discover the recommendation for the users. Developing such web application although has its own difficulties and complexities, but the application is user friendly and very convenient to use. The users can easily browse the online website and work with the provided facilities on the website.

The other important objective for the research is to be able to establish the framework on a real software platform to test the framework and observe the performance of it. This goal is very important because if there is not the possibility of establishing a prototype to implement the idea of the research, it is not possible to get an appropriate conclusion and reach the objectives of the study. So, before developing the idea of the research, it was checked whether it was possible to find a software solution for making real outcomes on the implemented framework and after observing suitable result, there could be sure that the claims of the research in the form of final results can be proved.

One other goal in the study is portability. It means that it can be possible to implement the framework on every possible or available platform including hardware, software, type of social network and advertisement. The type of designing and introducing of the framework is in the form that is not depended to any particular platform. The framework has been proposed in a general format and it is very easy to adjust it based on the available software and hardware systems. Even it is possible to establish the framework on different operating systems and also there is no limitation on the number of installation instances.

Reliability is one of the other goals in this study. Reliability, similar to validity, is a method for evaluating the nature of the estimation strategy used to gather information in a study. All together for the outcomes from a study to be viewed as substantial, the estimation system should first be solid. The thought behind Reliability is that any critical results must be more than an irregular finding and be characteristically repeatable. Different scientists must have the capacity to perform the very same investigation, under the same conditions and produce the same results. This will fortify the discoveries and guarantee that the more extensive academic group will acknowledge the theory. Without this replication of measurably noteworthy results, the investigation and exploration have not satisfied the greater part of the prerequisites of testability. This essential will be vital to a theory building up itself as an acknowledged experimental truth. As the repetitions of working with the web application by the users are shown, the system of the framework presents a good level of reliability because the number of 73 experiments are performed without any difficulty in execution and therefore, it is possible to conclude that the framework is inherently in a good condition of reliability.

The security of the framework is another goals of this study. Security is one the main concerns of all software applications and implementing the framework on a secure platform is very important to reach. For this purpose, a security component as one of the framework elements was considered which is composed of different levels of establishment. A single sign on mechanism is considered to authenticate the users who try to login to the software system. In the other side, a session checking of the validated user is performed so that in case of trying to access a web page from outside of the authority, the system prevents this kinds of invalid access.

## 1.5 METHODOLOGY OF RESEARCH, WORK PLAN

In this study there are various parts to demonstrate a solution for the problems of recommender systems in social networks by introducing a novel framework. The structure of the current study is devoted to the following steps in a glimpse with the most prominent parts as shown in Figure 1-1.

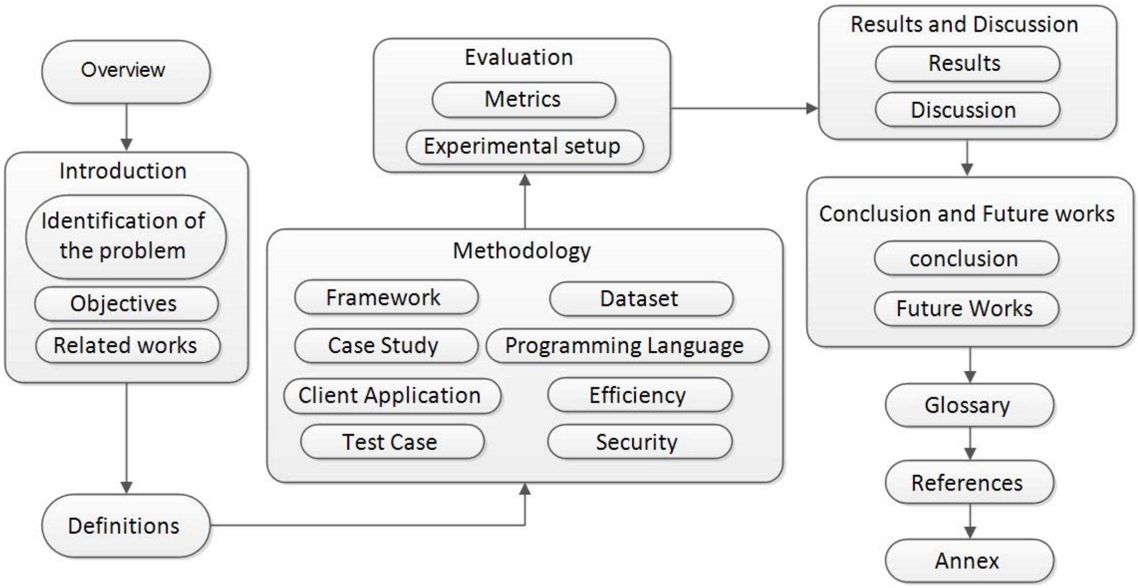



*Figure 1-1 Structure of the study*

First of all, an overview of the research is expressed to make the readers familiar with the scope and general idea of the study. In the overview of the study a brief introduction of the research is demonstrated while the details are discussed in the latter chapters. The subject of this study is about advertisement recommender systems in social network which is enriched with semantic technology to surpass the other methodologies.

After that, it is necessary to explain what is the problem in the current systems related to the study. So the content of this part is related to identification of the problem. In fact, the problems and deficiencies of the current and similar systems is desired to be exposed. Consequently, it is necessary to express why this research is wanted to be done, because there are problems with the mentioned systems and it is needed for the market to find solutions for these problems. So a part with the content of objectives is brought to speak about the goals of the study. Meantime it is necessary to look at the other related works to see what are the progresses and how many researches have been published in this matter. This issue can help to understand about where we are and how we have to make advancements by proposing innovative frameworks in the field of the research.

After knowing the current conditions and developments, learning about the necessary definitions of the study is a prominent part of the study because according to this information, it is easier to propose a simpler framework with more performance as the solution of this study. After getting the necessary knowledge about the research, it is the time to propose the methodology of the solution. In this part, first the framework of the study is explained in details along with its preliminary conditions of users' activities and semantic recommendation engine which has a positive role in the current framework.

Usually, beside suggesting a general framework, as it is explained in the other similar works, at least a case study about that framework is exposed to implement the framework in a real platform. The case study in the current work is a sample social network with sufficient number of training data including users and music tracks so that the result will have more validity. Furthermore, this social network has a very flexible API which is a good choice for the developers who want to extend their frameworks. After choosing the case study for this research, it is necessary to develop a client application presenting a website which uses the data from the selected case study and make a platform for the users to have their activity on the application and express their interests and feed their data to complement the content of the application.

In this way, a test case containing sample data entry for experiment is provided for a test user to visit and check the application. The used data of this application is gathered from the case study in the form of offline so that working with the application will be convenient and fast with the lowest probability of faults, whereas the system of client application has been developed according to the framework of the study with the lowest bugs in the heart of application development.

In the other part of the study, the programming language and the IDE for development are introduced and the reasons for these choices are presented. Afterwards, some comments are mentioned about the efficiency of the proposed framework to make it more clear how much efforts have been considered for designing this framework to be valuable and efficient as much as possible.

In the last part of this chapter, one of the main concerns about the structure of software systems has been taken into account: security. For the security of the framework, before completion of designing of the framework, it was preferred to utilize the proposed security architecture which was introduced in the master thesis, but later, it was decided to establish the security for the framework in the level of authentication and session securing. It will be postponed the old decision for the future works as mentioned in the relevant section of this study.

In the evaluation chapter, after demonstrating the significance of the evaluation for this study, some evaluation metrics are introduced along with mentioning some types of metrics which can be used for validation of the current work. By using this information, it would be more convenient to get the results and represent the appropriate discussion for this research. In the result part, the data gathered from the application of case study is prepared and collected. Then, in the next part, it is necessary to discuss how much this information is valid and can satisfy the main preliminary objectives. The motivation behind the examination is to decipher and depict the essentialness of the discoveries in light of what was at that point thought about the exploration issue being explored, and to clarify any new understanding or crisp experiences about the issue after the specialist has contemplated the discoveries. The dialog will dependably associate with the presentation by method for the exploration inquiries or speculations which the agent postured.

After discussion, it is the time to finish the discussion at the final stage of the research by a conclusion part. In this part, the result and the other comments in discussion part was spoken and made a deduction about what was earned in this research. Then, the future works will be explained. Future works are the tasks which could not be accomplished within the research but the investigator is interested in following and doing them in the close future using the available information provided in the current research.

a list of acronyms is provided in the glossary part, including the term and an equal explanation for it. This part can help the reader to understand the used abbreviations in the text of the study better with more convenience. Every time which the user does not realize the meaning of the acronym inside the text, it is possible to refer to this part.

A complete list of references, with a standard format has been provided in the part of references, including the name of study work, the authors' names, the name of publication place, the year of publishing and some extra information. This part can be useful for the other researchers who are interested in follow some of discussed topics in this study and learn more about them.

For more information about this study, some other related publications have been written by me which are issued from this thesis and they are brought in the publications section. With this part, it is possible to be informed about similar researches which have been performed by me during the time of doing the current study.

At the end, a part comprising of some parts of the codes related to the phase of development has been exposed for more information. This part shows that the web application has been really able to demonstrate and implement the framework of the study. Furthermore, this part helps the readers to recognize how each part of the web application woks as described in the methodology section. The related web application is flexible and it is possible to enrich some parts of the framework by adding more developing codes to the appropriate places.

## 1.6 SUMMARY

The structure of Semantic Web propels with Web 2.0 application arrangement outlines has ascended to the social semantic Web, moreover presented as Web 3.0. As per this idea, a product stage will be shown that successfully joins both Web 2.0 thoughts and Semantic Web progressions. The structure in this study, joins a movement of semantic-based application modules in a totally fledged social application with the objective of getting semantics in the reason for data recovery.

The capacity of learning commitment these days is unmatched ever. At no other time have such countless and capable people been related by such a beneficial, comprehensive framework. The costs of social event and enrolling over their responsibilities have come down to the point where new associations with amazingly humble spending arranges give creative new organizations to an incredible number of online individuals.

Collaborative filtering has the Data Sparsity issue, Scalability, and the Cold-start issue. For the Cold-start issue, the structures routinely require a considerable measure of existing data on a customer to make exact proposals. For the Sparsity issue, the amount of things sold on genuine e-exchange destinations is to an awesome degree broad. The most element customers will simply have evaluated a little subset of the general database. Thusly, even the most acclaimed things have relatively few evaluations. Another issue from which the Collaborative filtering techniques are persisted is Scalability. In an impressive parcel of the circumstances in which these structures make proposals, there are an expansive number of customers and things. Along these lines, a great deal of count power is as often as possible critical to figure recommendations.

In this chapter, some key questions have been asked that it is necessary to find their answers in the conclusion part of the research. The principle goal of the research is to study and outline of a structure for advertisement recommender framework in social networks which can be advanced by semantic advances. In spite of the fact that there are numerous applications and arrangements about recommender frameworks, however in this study it is critical to outline a hearty structure with a reasonable execution which can be actualized on each social networks to augment the business purposes.

Then some of the important considered objectives of the research have been exposed which in the discussion part, it will be checked whether these objectives are reached or not?

Then several related works have revealed which can make a better sense about what the other similar established researches are.

# SECTION II: Theoretical foundations, technologies and state of the art

# CHAPTER 2

# 2. DEFINITIONS (LITERATURE STUDY)

## 2.1 INTRODUCTION

The innovation of the Semantic Web has been spoken to as the incremental advancement of the present Web in which the Web substance is improved with express meaning of its semantics along these lines empowering computer frameworks to improve utilization of that substance to help and improve our everyday exercises [31][32]. The most valuable productive components of the Semantic Web are ontologies [33][34]. Ontologies are formally characterized, shared conceptualizations of a particular information area [35][36]. They are introduced along with the other standard concepts (for example, RDF [37] and OWL [38]), which permit them to be consolidated, shared, effortlessly stretched out and used to semantically explain various types of assets, for example, Web pages, archives, and interactive media content.

By utilizing such ontological foundation, different distinctive smart administrations can be assembled, for example, semantic search engines [39][40][41] which give more significant and particular results than conventional search engines connecting Web content as indicated by the accessible semantic annotations, and consequently deciphering its importance concerning the fundamental ontologies.

In spite of the numerous promising angles that we have portrayed, the Semantic Web is still not broadly matched [42]. This is primarily because of the troubles in ontology making and keeping, and the procedure of semantic annotation. The advancement of ontologies is troublesome and severe for space specialists who normally do not have the required learning engineering skills [43]. Regardless of current endeavors to build the accessibility and reusability of ontologies, through the advancement of online ontology libraries (e.g., Swoogle or Schemapedia) or (semi-)spontaneous ontology expansion tools, the utilization of these libraries and tools still requires a high value of specialized information [44].

A late surge of alleged social applications has showed up as a peak of innovation and collaboration procedures, and has been announced the Social Web or Web 2.0. [45]. While much buildup has encompassed these late advancements, the uptake and patterns of the software has been noteworthy. The Social Web changes the "old" model of the Web – a compartment of data got to inactively by clients - into a platform for social and cooperative substitution; in which clients face, team up, connect and in particular make substance and collaborate information to each other. Famous social sites, for example, Facebook, Flickr and YouTube, empower individuals to stay in contact with companions and share contents. Different administrations, for example, sites, wikis, video and photograph sharing that together empower what as of late has been characterized as "lifestreaming" permit amateur clients to effectively make, distribute and share their own particular substance.

Moreover, clients can without much of a stretch annotate and extend Web content utilizing social bookmarking and labeling, hence making metadata for Web content regularly alluded to as "folksonomies". Be that as it may, Social Web advancements generally, and cooperative tagging specifically, experience the side effects of the issues of uncertainty of implications. For example, cooperative tags are frequently questionable because of their absence of semantics (e.g., synonymous implications for a tag). In addition, they do not have a lucid classification conspire, and require noteworthy time and a considerable group to be utilized viably [46].

In spite of the underlying recognition that the Social Web and the Semantic Web contradict each other, the two endeavors are mutually being utilized to make a typical space of semantic innovations. Truth be told, the Semantic Web cannot work lonely. It needs society-scale tools (e.g., progressed community oriented applications that make utilization of shared information and annotations) [47]. Furthermore, the worldview of learning creation got from the Social Web can be adequately used to improve/overhaul ontologies produced by Semantic Web Technologies and best-rehearses. In the meantime, the Social Web can profit by the worldview of organized learning, announced by standard dialects received in the Semantic Web insight. Such principles will make it less demanding for aggregate information to be imparted and to collaborate to some kind of application.

Merging the best of both universes has focalized in the idea of the Social Semantic Web, in which in a social form made and contributed new information on the Web prompts the making of unequivocal and semantically-enhanced information demonstrations. The Social Semantic Web may be considered as a Web of aggregate information frameworks, which can give helpful data that depends on man-made commitments, and that enhances as more individuals partake [48].

Particular case of the Social Semantic Web is being attempted in a large number of activities. For example, DBpedia is a vast scale semantic learning base, which structures socially made information on the Wikipedia, a wiki-based reference book. DBpedia exploits the basic examples and layouts utilized by Wikipedia creators to assemble organized data into an information base of socially made organized information. The outcome is an immense database of shared information which permits "intelligent" inquiries, for example, "catalog the nineteenth century writers from England" [49]. Using its capacity of noting certain inquiries, DBpedia is able to minister as an exceptionally convenient learning instrument and is a brilliant case of the preferences that Social Semantic Web worldview conveys to the instructive area. All through the accompanying segments we give a considerable measure of extra case of the advantages that the Social Semantic Web conveys to training section.

## 2.2 SEMANTIC WEB

In this research, semantic web has been used to increase the performance of the suggested framework. The Semantic Web is a shared development drove by the World Wide Web Consortium (W3C which advances basic configurations for information on the World Wide Web) [50]. By empowering the consideration of semantic substance in website pages, the Semantic Web goes for changing over the present web of unstructured reports into a "web of data". It expands on the W3C's Resource Description Framework (RDF) [51].

Conforming to the W3C, "The Semantic Web gives a typical system that permits information to be shared and reused crosswise over application, finance, and group limits."

The vocabulary was authored by Tim Berners-Lee, the designer of the World Wide Web and executive of the World Wide Web Consortium ("W3C"), which supervises the advancement of proposed Semantic Web measures [52]. He characterizes the Semantic Web as "a web of data which can be handled specifically and in a roundabout way by computers."

Whereas its faultfinders have scrutinized its plausibility, advocates contend that applications in industry, science and human sciences research have effectively demonstrated the legitimacy of the first idea. Researchers have investigated the social capability of the semantic web in the business and wellbeing divisions, and for person to person communication [53]. The first 2001 methodical US paper by Berners-Lee portrayed a normal advancement of the current Web to a Semantic Web, however this has yet to occur [54]. In the year 2006, Berners-Lee and associates expressed that: "This straightforward thought... stays to a great extent hidden." [55]

### 2.2.1 Purpose

The real motivation behind the Semantic Web is taking without end the advancement of the present Web by empowering clients to find, contribute, and consolidate data all the more effortlessly. People are fit for utilizing the Web to complete assignments, for example, finding the Irish word for "folder", saving a library book, and looking at the most minimal cost for a DVD. In any case, computers are not capable of performing these jobs without human heading, since site pages are intended to be perused by individuals, not computers. The semantic web is a dream of data that is able to be promptly deciphered by computers, so computers can run a greater amount of the repetitive work required in discovering, joining, and following up on data on the web.

The Semantic Web, as initially imagined, is a framework that empowers computers to "understand" and react to complex human solicitations in light of their significance. Such an "understanding" needs that the significant data sources be semantically organized.

Tim Berners-Lee initially represented the insight of the Semantic Web as takes below [56]:

“I have a fantasy for the Web [in which machines] get to be equipped for breaking down every one of the information on the Web – the substance, connections, and exchanges amongst individuals and machines”. A "Semantic Web", which ought to make this conceivable, has yet to develop, however when it does, the everyday instruments of commerce, administration and our day by day existences will be taken care of by computers conversing with computers. The "intelligent agents" populations have accosted for a long time will at last emerge.

The Semantic Web is viewed as an integrator crosswise over various substance, data applications and frameworks. It has applications in distributed, blogging, and numerous different sections.

Frequently the expressions "semantics", "metadata", "ontologies" and "Semantic Web" are utilized conflictingly. Specifically, these vocabularies are utilized as ordinary phrasing by scientists and experts, spreading over an inconceivable scene of various fields, advances, ideas and application regions. Besides, there is perplexity with respect to the present status of the empowering advancements imagined to understand the Semantic Web. In a paper expressed by Gerber, Barnard and Van der Merwe, the Semantic Web scene is graphed and a concise rundown of related words and empowering innovations is displayed [57]. The structural pattern proposed by Tim Berners-Lee is utilized as premise to introduce a status pattern that represents present and rising advancements [58].

#### *2.2.1.1 Limitations of HTML*

Numerous records on a common computer can be inexactly isolated into intelligible reports and machine meaningful information. Archives such as mail messages, reports, and handouts are perused by people. Information, similar to logbooks, address books, playlists, and spreadsheets are introduced utilizing an application system that gives them a chance to be seen, looked and consolidated in various paths.

Presently, the World Wide Web is construct primarily in light of archives written in Hypertext Markup Language (HTML), a markup tradition that is utilized for programming a collection of content sprinkled with multimedia contents, for example, pictures and intelligent structures. Metadata labels give a technique by that computers can classify the substance of site pages, for instance:

```
<meta name="keywords" content="Semantic, Advertisement, Recommendation, Social" />
```

<meta name="description" content="Recommended Products for advertising" />

<meta name="author" content="Ali Pazahr" />

Using HTML and an apparatus to generate it (maybe web navigator application, maybe another client agent), one can make and show a page that rundowns things available to be purchased. The HTML of this list page can create straightforward, record level declarations, for example, "this present report's title is 'Gadget Superstore'", yet there is no capacity inside the HTML itself to affirm unambiguously that, for instance, thing number X586172 is an Acme Gizmo with a retail cost of €199, or that it is a customer item. Or maybe, HTML can just say that the range of content "X586172" is something that ought to be situated close "Top Gizmo" and "€199", and so on. There is no real way to say "this is a list" or even to build up that "Zenith Gizmo" is a sort of title or that "€199" is a cost. There is additionally no real way to express that these bits of data are related together in explaining a discrete thing, unmistakable from different things maybe recorded on the page [59].

Semantic HTML alludes to the conventional HTML routine of markup taking after goal, as opposed to determining format subtle elements straightforwardly. For instance, the utilization of <em> meaning "emphasis" instead of <i>, which indicates italics. Design points of interest are surrendered over to the navigator, in composition with Cascading Style Sheets. Yet, this practice misses the mark concerning indicating the semantics of articles, for example, things at deal or costs.

Microformats speak to informal endeavors to stretch out HTML language structure to make machine-comprehensible semantic markup about articles, for example, retail shops and things available to be purchased.

#### 2.2.1.2 Semantic Web solutions

The Semantic Web demonstrates more insights about the arrangement. It incorporates distributed in dialects particularly intended for information: Resource Description Framework (RDF), Web Ontology Language (OWL), and Extensible Markup Language (XML). HTML depicts records and the connections between them. RDF, OWL, and XML, by difference, can depict self-assertive things, for example, individuals, gatherings, or plane parts.

These advancements are joined keeping in mind the end goal to give portrayals that complement or supplant the substance of Web reports. In this way, substance may show itself as expressive information put away in Web-open databases, or as markup inside records (especially, in Extensible HTML (XHTML) scattered with XML, or, all the more regularly, absolutely in XML, with design or generating signs put away independently) [60]. The details which can be read by machines empower content supervisors to add intending to the substance, i.e., to portray the structure of the learning we have about that substance. Along these lines, a machine can handle learning itself, rather than content, utilizing forms like human deductive thinking and induction, in this way acquiring more important results and helping PCs to perform robotized data assembling and research.

A case of a tag which could be utilized as a part of a non-semantic page:

<item>dog</item>

Encoding equivalent data in a semantic website page may appear as though below:

<item rdf:about="http://dbpedia.org/resource/Dog">dog</item>

Tim Berners-Lee calls the subsequent system of Linked Data the Giant Global Graph, as opposed to the HTML-based World Wide Web. Berners-Lee sets that if the past was archive sharing, what's to come is information sharing. His response to the topic of "how" gives three purposes of direction. First, a URL ought to indicate the information. Second, anybody getting to the URL ought to get information back. Third, connections in the information ought to indicate extra URLs with information.

### 2.2.2 Standards

Institutionalization for Semantic Web with regards to Web 3.0 is under the consideration of W3C [61].

#### *2.2.2.1 Components*

The vocabulary "Semantic Web" is usually utilized more particularly to refer to the concepts and technologies that drive it in the applications. The collection, structuring and recovery of linked data are enabled by technologies that provide a formal description of concepts, terms, and relationships within a given knowledge domain. These technologies are specified as W3C standards and include:

- Resource Description Framework (RDF), a general method for describing information
- RDF Schema (RDFS)
- Simple Knowledge Organization System (SKOS)
- SPARQL, an RDF query language
- Notation3 (N3), designed with human-readability in mind
- N-Triples, a format for storing and transmitting data
- Turtle (Terse RDF Triple Language)
- Web Ontology Language (OWL), a family of knowledge representation languages

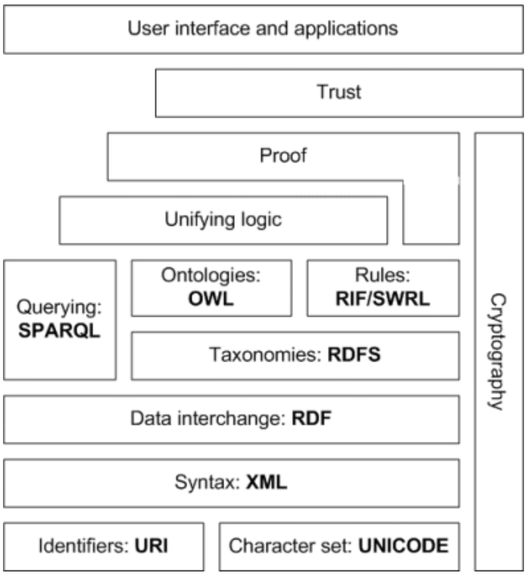



*Figure 2-1 The Semantic Web Stack*

The Semantic Web Stack shows the design of the Semantic Web, delineated in Figure 2-1 [62]. The capacities and connections of the parts can be outlined as takes after [63]:

- XML gives an essential language structure to substance structure inside reports, yet relates no semantics with the significance of the substance included inside. XML is not already an essential part of Semantic Web advances usually, as another option syntactics exists, for example, Turtle. Turtle is a true standard, however has not been through a formal institutionalization procedure.
- XML Schema is a dialect for giving and limiting the structure and substance of components contained inside XML archives.
- RDF is a straightforward dialect for communicating information models, which allude to items ("resources") and their connections. A RDF-based model can be spoken to in an assortment of sentence structures, e.g., RDF/XML, N3, Turtle, and RDFa. RDF is a central standard of the Semantic Web [64][65][66][67].
- RDF Schema amplifies RDF and is a term for depicting properties and classes of RDF-based assets, with semantics for summed up orders of such properties and classes.
- OWL includes more terms for depicting properties and classes: among others, relations between classes (e.g. disjointness), cardinality (e.g. "precisely one"), balance, wealthier writing of properties, attributes of properties (e.g. symmetry), and listed classes.
- SPARQL is a convention and inquiry dialect for semantic web information resources.

#### *2.2.2.2 Current state of standardization*

In the field of semantic web some standards, including format and logic have been introduced. These standards can help to demonstrate information in the form of more usable format.

Progressing institutionalization:

- Rule Interchange Format (RIF) as the Rule Layer of the Semantic Web Stack

Not yet fully realized:

- Unifying Logic and Proof layers

The aim is to improve the ease of use and value of the Web and its interconnected assets through:

- Servers which uncover existing information frameworks utilizing the RDF and SPARQL principles. Numerous converters to RDF exist from various applications. Social databases are an essential source. The semantic web server joins to the current framework without influencing its operation.
- Archives "set apart up" with semantic data (an augmentation of the HTML <meta> labels utilized as a part of today's Web pages to supply data for web indexes utilizing web crawlers). This could be machine-justifiable data about the human-reasonable substance of the archive, (for example, the designer, title, depiction, and so on.) or it could be absolutely metadata speaking to an arrangement of truths, (for example, assets and administrations somewhere else on the site). Note that anything that can be related to a Uniform Resource Identifier (URI) can be depicted, so the semantic web can reason about creatures, individuals, places, thoughts, and so on. Semantic markup is frequently produced naturally, instead of physically.
- Basic metadata vocabularies (ontologies) and maps between vocabularies that permit record makers to know how to stamp up their archives so operators can utilize the data in the supplied metadata (so that Author in the feeling of 'the Author of the page' won't be mistaken for Author in the feeling of a book that is the subject of a book survey)
- Computerized specialists to perform undertakings for users of the semantic web utilizing this information
- Electronic administrations (frequently with operators of their own) to supply data particularly to specialists, for instance, a Trust administration that an operator could inquire as to whether some online store has a past filled with poor administration or spamming

### 2.2.3 Projects

This area records a portion of the numerous activities and devices that exist to make Semantic Web arrangements [68].

#### 2.2.3.1 DBpedia

DBpedia is an endeavor to uncover organized information assembled from Wikipedia: the information is discharged in RDF and made accessible on the Web for use under the GNU Free Documentation License, subsequently permitting Semantic Web specialists to give inferencing and progressed questioning over the Wikipedia-inferred dataset and encouraging interlinking, re-use and expansion in other information sources.

#### 2.2.3.2 FOAF

A well-known idea on the semantic web is Friend of a Friend (FOAF), that utilizations RDF to portray the connections individuals need to other individuals and the "things" about them. FOAF permits canny specialists to comprehend a huge number of associations individuals have with each other, their occupations and the things imperative to their lives; associations that might possibly be counted in quests utilizing conventional web crawlers. Since the associations are so incomprehensible in number, human elucidation of the data may not be the most ideal method for investigating them. FOAF is a case of how the Semantic Web endeavors to make utilization of the connections inside a social setting.

#### 2.2.3.3 SIOC

The Semantically-Interlinked Online Communities venture (SIOC, affirmed "stun") gives a vocabulary of terms and connections that model web information spaces. Case of such information spaces incorporate, among others: examination gatherings, web journals, blogrolls/sustain memberships, mailing records, shared bookmarks and picture exhibitions.

#### 2.2.3.4 NextBio

A database solidifying high-throughput life sciences trial information labeled and associated by means of biomedical ontologies. Nextbio is open by means of a web crawler interface. Analysts can contribute their discoveries for fuse to the database. The database as of now backings quality or protein expression information and succession driven information and is relentlessly growing to bolster other natural information sorts.

### 2.2.4 Common Semantic Web technologies and terms

The Semantic Web permits interfacing information as opposed to archives by including structure and formalisms [69][70]. Resource Description Format (RDF) is the dialect for information trade, which can be serialized a few ways, including Turtle (Table 2-1), RDFa (inserted in HTML) (Table 2-2), and RDF/XML (Table 2-3) [71]. Using RDF Schema (RDFS), confinements, for example, space and range, and connections, for example, rdfs:subClassOf, can be announced [72].

OWL, the Web Ontology Language, can be utilized to express cardinality, correspondence (owl:sameAs), and different ideas. SPARQL (Table 2-4) is the standard question dialect for RDF, which permits questioning on the Semantic Web [73]. Linked

Data is the way to go that HTTP URIs ought to be utilized as identifiers, with significant comprehensible data, and in addition connections to other related representations and information [74].

```
@prefix dcterms : <http :// purl . org /dc/ elements /1.1/ > .
@prefix foaf : <http :// xmlns .com / foaf /0.1/ > .
@prefix rdf : <http :// www .w3.org /1999/02/22 - rdf - syntax -ns#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
:registeredTo a rdf:Property;
rdfs:domain :MotorVehicle;
rdfs:range :Person.
:rearSeatLegRoom a rdf:Property;
rdfs:domain :PassengerVehicle;
rdfs:range xsd:integer.
:Person a rdfs:Class.
xsd:integer a rdfs:Datatype.
```

*Table 2-1 Sample RDF in Turtle*

```
<? xml version ="1.0" encoding =" UTF -8"? >
<! DOCTYPE html PUBLIC " -// W3C // DTD XHTML + RDFa 1.0// EN"
" http :// www.w3. org / MarkUp / DTD/xhtml -rdfa -1. dtd ">
<html xmlns =" http :// www .w3. org /1999/ xhtml "
xmlns : dcterms =" http :// purl . org /dc/ elements /1.1/"
xmlns : foaf =" http :// xmlns . com / foaf /0.1/"
version =" XHTML + RDFa 1.0" xml : lang =" en">
<head >
<title > Ali Pazahr 's Home Page </ title >
<base href =" http :// www.Pazahr.ir /" />
<meta property =" dcterms : title " content =" Ali Pazahr 's homepage " />
<meta property =" dcterms : creator " content =" Ali Pazahr " />
</head >
<body about =" http :// www . Pazahr . ir /# me">
<div typeof =" foaf : Person ">
<h1 property =" foaf : name "> Ali Pazahr  </h1 >
<p> Email : <a rel =" foaf : mbox " href =" mailto : Pazahr@Alumni.uv.es ">
Pazahr@Alumni.uv.es </a ></p>
</div >
</body >
</html >
```

*Table 2-2 An example presented in XHTML+RDFa 1.0*

The Linked Data standards are:

1. Use URIs as names for things.
2. Use HTTP URIs with the goal that individuals can search for those names.
3. When somebody searches for a URI, give valuable data, utilizing the technologies (RDF, SPARQL).

```
<? xml version ="1.0" encoding =" utf -8"? >
<rdf : RDF
xmlns : dcterms =" http :// purl . org /dc/ elements /1.1/"
xmlns : foaf =" http :// xmlns . com / foaf /0.1/"
xmlns :rdf =" http :// www .w3. org /1999/02/22 - rdf - syntax -ns #">
<rdf : Description rdf : about =" http ://www. Pazahr.ir . com /">
<dcterms : title xml : lang =" en"> Ali Pazahr 's homepage </ dcterms :
title >
<dcterms : creator xml : lang =" en"> Ali Pazahr </ dcterms : creator >
</ rdf : Description >
<foaf : Person >
<foaf : name xml : lang =" en"> Ali Pazahr </ foaf :name >
<foaf : mbox rdf : resource =" mailto : Pazahr@Alumni.uv.es "/>
</ foaf : Person >
</ rdf :RDF >
```

*Table 2-3 The same example, presented in XML/RDF*

```
PREFIX foaf : <http :// xmlns . com / foaf /0.1/ >
SELECT ? email
WHERE
{
? person a foaf : Person
? person foaf : mbox ? email
}
```

*Table 2-4 Using SPARQL to retrieve all email addresses*

4. Incorporate connections to different URIs, with the goal that they can find more things.

In actuality, this way to utilize identifiers which can be dereferenced to give "helpful" data and connections. The thought of what is helpful is a social, instead of an innovative, matter, bringing on a few intricacies in the establishment of a Web of Linked Data.

### 2.2.5 Other aspect to the Semantic Web

Consistently, the greater part of data we get from the web drops by calculations that chiefly take a gander at content. This is on the grounds that the lion's share of pages is made up by intelligible terms [75][76]. In other words, semantic technology can be utilized in the recommendation systems to enhance the intelligence of their structure and consequently, we can see great results as the outcome of the recommendation systems.

The main guideline of the semantic web is to give metadata to giving content a significance. One methodology is utilizing clarified advancements, for example, principles specified in 2.2.2.1, however another is considering to the Semantic Relation between ideas. This issue can be set up by a few sorts of metadata like labels or different apparatuses which uncover the similitude amongst ideas and can be encouraged to interface ideas. Relatedly, we have to mine ideas and select coveted information taking into account the other information utilizing specified apparatuses which are characterized and carried alongside the information as metadata. Some scrutinizes are only case for this part of the semantic web [18][77][78][79][80].

For this research, this aspect is considered to implement a software application which proves the research's framework. Further details about the framework will be explained in the section 3.2.

### 2.2.6 Ontology

In software engineering and data science, an ontology formally speaks to learning as an arrangement of ideas inside a space, and the connections between those ideas [81]. It can be utilized to reason about the substances inside that space and might be utilized to depict the area.

In principle, a ontology is a "formal, unequivocal determination of a common conceptualization" [82]. A ontology renders shared vocabulary and scientific categorization which models an area with the meaning of items and/or ideas and their properties and relations [83].

Ontologies are the basic structures for sorting out data and are utilized as a part of counterfeit consciousness, the Semantic Web, frameworks building, programming designing, biomedical informatics, library science, undertaking bookmarking, and data engineering as a type of learning representation about the world or some a player in it. The production of space ontologies is additionally major to the definition and utilization of an endeavor engineering system.

#### *2.2.6.1 Ontology components*

Contemporary ontologies offer numerous basic likenesses, paying little respect to the dialect in which they are communicated. As said above, most ontologies depict concepts (occurrences), classes (ideas), characteristics, and relations. In this area each of these segments is examined thus.

Popular ingredients of ontologies comprise:

- Individuals: occasions or questions (the essential or "ground level" items)
- Classes: sets, accumulations, ideas, classes in programming, sorts of items, or sorts of things
- Attributes: angles, properties, elements, qualities, or parameters that items (and classes) can have
- Relations: routes in which classes and people can be identified with each other
- Function terms: complex structures shaped from specific relations that can be utilized as a part of spot of an individual term in an announcement
- Restrictions: formally expressed depictions of what must be valid all together for some declaration to be acknowledged as information
- Rules: explanations as an assuming then (predecessor ensuing) sentence that portray the sensible deductions that can be drawn from a declaration in a specific structure

- Axioms: attestations (counting rules) in a sensible structure that together include the general hypothesis that the ontology depicts in its area of use. This definition contrasts from that of "axioms" in generative language structure and formal rationale. In those orders, aphorisms incorporate just explanations attested as from the earlier learning. As utilized here, "axioms" additionally incorporate the hypothesis got from proverbial proclamations
- Events: the changing of traits or relations

Ontologies are normally encoded utilizing ontology dialects.

#### 2.2.6.2 Domain ontologies and upper ontologies

A domain ontology (or area particular ontology) models a particular area, which speaks to part of the world. Specific implications of terms connected to that space are given by area ontology. For instance, the word card has a wide range of implications. An ontology about the space of poker would show the "playing card" which means of the word, while an ontology about the area of PC equipment would demonstrate the "punched card" and "video card" implications.

An upper ontology (or establishment ontology) is a model of the regular questions that are by and large pertinent over an extensive variety of area ontologies. It utilizes a center glossary that contains the terms and related article portrayals as they are utilized as a part of different important area sets. There are a few institutionalized upper ontologies accessible for use, including Dublin Core, GFO, OpenCyc/ResearchCyc, SUMO, and DOLCE [84]. WordNet, while considered an upper ontology by a few, is not entirely an ontology. Be that as it may, it has been utilized as an etymological device for learning space ontologies [85]. The Gellish ontology is a case of a mix of an upper and an area ontology.

Since space ontologies speak to ideas in certain and regularly varied ways, they are frequently inconsistent. As frameworks that depend on area ontologies extend, they frequently need to consolidation space ontologies into a broader representation. This introduces a test to the cosmology fashioner. Diverse ontologies in the same area can likewise emerge because of various impression of the space in light of social foundation, training, belief system, or on the grounds that an alternate representation dialect was picked.

Already, combining ontologies that are not created from a typical establishment ontology is a to a great extent manual procedure and in this way tedious and costly. Space ontologies that utilization the same establishment ontology to give an arrangement of essential components with which to determine the implications of the area ontology components can be combined consequently. There are studies on summed up systems for consolidating ontologies, yet this territory of examination is still to a great extent hypothetical.

#### 2.2.6.3 Ontology engineering

Ontology designing (or metaphysics building) is a subfield of learning designing that studies the strategies and systems for building ontologies. It concentrates on the Ontology advancement prepare, the Ontology life cycle, the strategies and systems for building ontologies, and the apparatus suites and dialects that help them [86][87].

Ontology building expects to make express the learning contained inside programming applications, and inside undertakings and business methods for a specific space. Ontology designing offers a bearing towards taking care of the interoperability issues achieved by semantic obstructions, for example, the hindrances identified with the meanings of business terms and programming classes. Ontology building is an arrangement of assignments identified with the improvement of ontologies for a specific area [88].

#### 2.2.6.4 Ontology languages

An ontology language is an official dialect used to encode the ontology. There are various such dialects for ontologies, both exclusive and classical based:

- Usual Algebraic Description Language is a general rationale based determination dialect created inside the IFIP working gathering 1.3 "Foundations of System Specifications" and capacities as a true standard in the range of programming details. It is presently being connected to ontology determinations with a specific end goal to give measured quality and organizing instruments.
- Common rationale is ISO standard 24707, a particular for a group of ontology dialects which can be precisely interpreted into each other.
- The Cyc venture has its own ontology dialect called CycL, taking into account first-arrange predicate analytics with some higher-request augmentations.
- DOGMA (Developing Ontology-Grounded Methods and Applications) receives the actuality arranged demonstrating way to deal with give a more elevated amount of semantic steadiness.
- The Gellish dialect incorporates rules for its own particular augmentation and along these lines coordinates an ontology with a ontology dialect.
- IDEF5 is a product designing strategy to create and keep up usable, exact, space ontologies.
- KIF is a punctuation for first-arrange rationale that depends on S-expressions.
- Rule Interchange Format (RIF) and F-Logic consolidate ontologies and guidelines.
- OWL is a dialect for putting forth ontological expressions, created as a take after on from RDF and RDFS, and in addition prior ontology dialect ventures including OIL, DAML, and DAML+OIL. OWL is proposed to be utilized over the World Wide Web, and every one of its components (classes, properties and people) are characterized as RDF assets, and distinguished by URIs.

- Semantic Application Design Language (SADL) catches a subset of the expressiveness of OWL, utilizing an English-like dialect entered through an Eclipse Plug-in [89].
- SBVR (Semantics of Business Vocabularies and Rules) is an OMG standard received in industry to manufacture ontologies.
- OBO, a dialect utilized for natural and biomedical ontologies.
- (E)MOF and UML are norms of the OMG

#### *2.2.6.5 Ontology libraries*

The improvement of ontologies for the Web has prompted the development of administrations giving records or indexes of ontologies with look up capability. Such indexes have been named ontology libraries.

The following are static libraries of human-selected ontologies:

- COLORE [90] is an open repository of first-order ontologies in Common Logic with official links connecting ontologies in the reservoir.
- DAML Ontology Library [91] keeps a patrimony of ontologies in DAML.
- Protégé Ontology Library [92] includes a set of OWL, Frame-based and other format ontologies.
- SchemaWeb is a space of RDF schema expressed in RDFS, OWL and DAML+OIL.

The next concepts are both directories and search engines. They contain crawlers searching the Web for well-formed ontologies.

- OBO Foundry / Bioportal [93] (ontology repository of NCBO) is a sequence of compatible reference ontologies in biology and biomedicine.
- OntoSelect [94] Ontology Library suggests likewise services for RDF/S, DAML and OWL ontologies.
- Ontaria [95] is a "searchable and browsable directory of semantic web data" with a focus on RDF vocabularies with OWL ontologies. (NB Project "on hold" since 2004).
- Swoogle is a directory and search engine for all RDF resources available on the Web, comprises ontologies.

## 2.3 SOCIAL WEB

In this study, social web is the platform which has been used to implement the suggested framework. The Social Web is one name for the present era of sites, which advance coordinated effort, discourse, and sharing of individual data [96]. Different names are used to refer to the Social Web, including web2.0 and read-write web, social media [97], social software, social networks, and social platforms.

The Social Web includes blogs [98][99], wikis [100], photo and video sharing [101], tagging, and microblogging [102][103][104], among others.

Emerging Social Web genres include life streaming, aggregation, and `internetworking' services [105] and location-based social networking [106][107].

The Social Web has many antecedents on the pre-Web Internet, as well as in the early Web, including email and listservs [108][109], Usenet [110], and Bulletin Boards [111]. The Social Web builds on groupware [112] and collaborative software [113], meeting Lessig's 2004 call for 21st century media to be "both read and write" [114]. Social Websites are often object-centred [115], and individual items (e.g. a Twitter post) may have their own URI or family of URIs (e.g. a Flickr image).

These URIs capacity as identifiers, encouraging connections both between various social items on a site and over the more extensive Web. In any case, all in all, over the Web, diverse URIs might be utilized to allude to the same protest; this absence of extraordinary identifiers balkanizes the Web.

Different characterizations of the groupware, cooperative programming, and the Social Web have been offered, for example, whether a medium is synchronous or not synchronous, what imperatives are given to messages, (for example, size, gathering of people, and so forth.), what sorts of articles are examined and shared, and whether things are cooperatively altered.

The social Web is an arrangement of social relations that connection individuals through the World Wide Web [116]. The Social web envelops how sites and programming are planned and created to backing and encourage social collaboration [117]. These online social collaborations frame the premise of much online action including internet shopping, instruction, gaming and interpersonal interaction sites [118]. The social part of Web 2.0 correspondence has been to encourage collaboration between individuals with comparative tastes [119]. These tastes fluctuate contingent upon who the intended interest group is, and what they are searching for. For people working in the general population connection office, the occupation is reliably changing and the effect is originating from the social web [120]. The impact, held by the informal community is expansive and perpetually evolving. As individuals' exercises on the Web and correspondence build, data about their social connections turn out to be more accessible Social systems administration locales, for example, MySpace and Facebook, and additionally the future Dataweb empower individuals and associations to get in touch with each other with tireless human-accommodating names [121]. Today a huge number of Internet clients are utilizing a huge number of social sites to stay associated with their companions, find new ''friends,''and to share client made substance, for example, photographs, recordings, social bookmarks, and web journals, despite the fact that versatile stage support for mobile phones By the end quarter in 2008, Facebook reported 67 million individuals, MySpace possessed 100 million clients, and YouTube had more than 100 million recordings and 2.9 million client channels, and these numbers are reliably developing [122][123]. The social Web is rapidly reexamining itself, moving past straightforward web applications that associate people to end up a completely better approach forever.

### 2.3.1 The Evolving Social Web

The social Web is rapidly turning into a lifestyle: numerous individuals visit person to person communication locales at any rate once every day, and in 2008 the normal measure of time per visit to MySpace drifted around twenty-six minutes (the length of a sitcom). Besides, the astoundingly quick development of the social Web subsequent to the '90s is not anticipated to back off at any point in the near future: with under 20% of the world's populace utilizing the Internet, the social Web is felt by some to in any case be in its outset. The line between long range informal communication and online networking is turning out to be progressively obscured as destinations, for example, Facebook and Twitter further join photograph, video, and different functionalities common of social networking locales into clients' open profiles, pretty much as online networking destinations have been incorporating highlights normal for person to person communication locales into their own particular online systems. One outstanding change that has been achieved by the converging of long range interpersonal communication/media is the change of social web applications into egocentric programming that put individuals at the focal point of utilizations. In spite of the fact that there had been talk around a feeling of group on the web preceding these advancements, present day social web programming makes a more extensive arrangement of social associations accessible to the client, for example, "friending" and "taking after" people, notwithstanding sending them virtual endowments or kisses. Social Web applications are regularly manufactured utilizing object arranged programming, using mixes of a few programming dialects, for example, Ruby, PHP, Python, and/or Java Often APIs are used to attach non-social sites to social sites, one case being Campusfood.com [124][125].

#### *2.3.1.1 Social features that are added to non-social web sites*

Sites that are not worked around social association by the by include highlights that empower examination and coordinated effort out of an enthusiasm for growing their client bases—a pattern that is anticipated to proceed in the coming years. As ahead of schedule as 1995 electronic retailer Amazon had executed such components, particularly the client audit, to incredible achievement; Joshua Porter, writer of Designing for the Social Web, composes [126]:

“ At Amazon, customer reviews act like a magnet, pulling people down the page. That's the content people want...They keep scrolling until they hit the reviews, which in some cases are up to 6000 pixels down from the top of the page! Nobody seems to mind...Customer reviews allow people to learn about a product from the experience of others without any potentially biased seller information. No wonder everyone wanted to shop at Amazon. They had information that no other site had: they had the Truth. And that truth, interestingly enough, arose from simply aggregating the conversation of normal people. “

These client audits contribute significant data that people search out, and are composed by clients for nothing basically out of a longing to impart their encounters to an item or administration with others; the quality and estimation of every survey is further dictated by different clients, who rate them based upon regardless of whether they found the criticism accommodating, "getting rid of the terrible (by pushing them to the base of the page)."

Non-retailer, uncommon interest sites have likewise executed social web components to expand their allure: one illustration is Allrecipes.com, a group of 10 million cooks that offer thoughts and formulas with each other [127]. Notwithstanding trading formulas with others through the site, clients can rate and post audits of formulas they have attempted, and to give recommendations in the matter of how to enhance or change them [128]; as per the site, "The evaluations/reviews...are an important asset to our group since they demonstrate how the individuals and their families feel around a formula. Does the formula get raves—or does it never get made again? Your conclusion numbers". This criticism is utilized to assess and order formulas based upon how effectively they went through the site's "publication prepare" and to what degree they were endorsed by site individuals, possibly bringing about accepting "Kitchen affirmed" status that is tantamount to Wikipedia's "great article" assignment process. The website has likewise increased its administrations by including social components, for example, client writes and associating with other person to person communication/media destinations like Facebook to extend its nearness on the social Web [129]. The formulas seen on this site turn out to be a piece of the social web as different individuals rank them, remark and give input in the matter of why the formula was great or awful, or to share courses in which they would transform it.

The coordination of "social" components has likewise started to reach out into non-Web media shapes including print and show. Progressively predominant cell phones have offered a stage for media organizations to make hybridized media frames which draw upon the social web, for example, the Fango versatile application offered by Australian Partnership Yahoo! which joins customary TV programming with live online discourses and existing long range informal communication channels.

#### *2.3.1.2 Collaborative Efforts Facilitated by the Social Web*

##### 2.3.1.2.1 Crowdsourcing

Crowdsourcing has gotten to be one of the courses in which the social Web can be utilized cooperative endeavors, especially in the most recent couple of years, with the beginning of the semantic web and Web 2.0. Current web applications have the abilities for crowdsourcing systems, and thusly the term is presently utilized only for electronic movement. Illustrations incorporate locales, for example, SurveyMonkey.com and SurveyU.com; for instance, SurveyMonkey empowers clients to direct overviews to a rundown of contacts they oversee, then gather and examine reaction information utilizing essential instruments gave on the site itself lastly send out these outcomes once they are done [130].

Crowdsourcing is utilized by analysts as a part of request to imitate a customary center gathering, however in a less costly and less personal climate. Because of the way of the social Web, individuals feel more open to express what their contemplations are on the point of dialog without feeling as if they will be as substantial examined by whatever remains of the gathering when contrasted with a conventional setting. The Internet serves as a screen, bringing out the purest input from the members in the gathering, as it evacuates a lot of a swarm mindset [131].

Facebook has likewise been a mode in which crowdsourcing can happen, as clients ordinarily pose a question in their status message trusting those that see it on his or her news food will answer the inquiry, or clients may select to utilize the survey choice now accessible to acquire data from those inside their companions system [132].

##### 2.3.1.2.2 Community-based software projects

Using the social Web, numerous product designers pick to take an interest in group based open-source programming ventures, and in addition hacking ventures for exclusive programming, piece (processing) adjustments, and freeware ports of recreations and programming. Linux cycles are immaculate case of how viable and effective this kind of joint effort can be. Google's Android working framework is another case, the same number of coders work on changing existing equipment portions and ROMs to make tweaked types of a discharged Android rendition. These communitarian endeavors for Android occur regularly through xda-engineers and androidforums.com.

#### *2.3.1.3 Mobile Application Development*

The majority of the present day versatile applications, and for sure considerably program applications, originate from discharged Software Development Kits to engineers. The engineers make their applications and offer them with clients by means of "application markets." Users can remark on their encounters with the applications, permitting all clients to see the remarks of others, and subsequently have a more noteworthy comprehension of what is not out of the ordinary from the application. Commonly, there is additionally a rating a framework notwithstanding remarks.

Portable social Web applications are constructed utilizing different APIs. These APIs take into consideration the cooperation and interconnection of information on one social database, be it Facebook, Twitter, or Google Account, consequently making an exacting web of information associations. These applications then add to the client experience particular to the application itself. Cases incorporate TweetDeck and Blogger (administration).

### 2.3.2 From the Social Web to Real Life

The way individuals do ordinary things has been changed by the social Web; today's workforce is driven by an era that was raised utilizing this system [133]. The path in which people offer cozy subtle elements, and perform undertakings, for example, dating, shopping, and applying for employments is vastly different than in past eras. Presently, one's inclinations, feelings, and exercises are routinely imparted to a gathering of companions with whom they might possibly ever meet were it not for the social Web [134].

Numerous social sites use online social communication to make a scaffold to genuine cooperation. Connections are shaped between people by means of the web and after that turn out to be more individual through different types of correspondence. A case of this sort of connection is found on eBay: with more than 94 million dynamic clients universally, eBay is the world's biggest online commercial center, where anybody can purchase and offer for all intents and purposes anything [135]. This site permits people to offer things and other to offer on these things. Toward the end of the sale, the purchaser pays the merchant; the purchaser then sends the acquired item to the champ of the sale. The relationship starts on the web, yet stretches out into genuine connection. Routes in eBay encourages this cooperation incorporate Skype, a main online interchanges benefit that empowers individuals to impart through voice or video online without paying [136]. eBay Inc. gained Skype in 2005 and fundamentally extended its client base to more than 480 million enlisted clients in almost every nation on earth. The deciding consequence of all eBay exchanges is a dealer furnishing the purchaser with an item, most ordinarily by means of mail: web communication finishing in a certifiable trade.

The relationship that is shaped with eBay clients is like the clients of craigslist. Clients place things that they need to offer on the site, and different clients that are hoping to buy these things contact the merchant. Craigslist is accustomed to unite people and associations and interface them to the assets, instruments, innovation and thoughts they have to successfully take part in group building and see the effect of their activities [137]. This is done by means of email or via phone. The purchaser and the merchant shape a meeting in which products are traded for cash. Without this sort of site, the purchaser would not realize that the item was accessible by the vender. This kind of site permits individuals from a physical group to connect with alternate individuals from their group to trade merchandise and administrations [138].

The exchange from web to genuine is seen on a full scale most as of late on dating sites, which are utilized to pursuit and match different clients [139]. These sites permit individuals with a typical enthusiasm, to discover others with this same interest. Scholastics who have examined the business trust that it and different types of electronic correspondence, for example, email and informal communities are beginning to significantly affect the routes in which individuals discover love [140] Clients can interface with each other and find in the event that they have regular interests. Numerous destinations have been produced that objective various vested parties, and connections shape and create utilizing the web. On the off chance that the clients conclude that they share a common bond, they can cooperate by means of the phone, and in the end in individual. The relationship starts on the web, yet can prompt genuine dating and inevitably even marriage.

### 2.3.3 Social Networks

An informal community is a social structure made up of an arrangement of performing artists, (for example, people or associations) and the dyadic ties between these on-screen characters [141]. The informal organization point of view gives a reasonable method for breaking down the structure of entire social elements The investigation of these structures utilizes interpersonal organization examination to recognize nearby and worldwide examples, find compelling elements, and inspect system elements [142].

Interpersonal organizations and the examination of them is an intrinsically interdisciplinary scholarly field which rose up out of social brain research, human science, measurements, and chart hypothesis. Georg Simmel composed early auxiliary speculations in human science stressing the progression of triads and "web of gathering affiliations."[143] Jacob Moreno is credited with building up the principal sociograms in the 1930s to concentrate on interpersonal connections. These methodologies were scientifically formalized in the 1950s and speculations and strategies for interpersonal organizations got to be pervasive in the social and behavioral sciences by the 1980s Social system examination is presently one of the real ideal models in contemporary humanism, and is likewise utilized in various other social and formal sciences [144]. simultaneously with the other compound systems, it shapes part of the beginning field of system science [145][146].

A social network is a hypothetical develop valuable in the sociologies to study connections between people, gatherings, associations, or even whole social orders (social units, see separation). The term is utilized to depict a social structure dictated by such cooperations. The ties through which any given social unit interfaces speak to the joining of the different social contacts of that unit. This hypothetical methodology is, essentially, social. A saying of the informal community way to deal with comprehension social communication is that social wonders ought to be essentially considered and researched through the properties of relations between and inside units, rather than the properties of these units themselves. Therefore, one normal feedback of informal community hypothesis is that individual organization is regularly disregarded, in spite of the fact that this may not be the situation by and by (see specialist based demonstrating) [147]. Exactly in light of the fact that various sorts of relations, particular or in mix, shape these system designs, system examination are valuable to a wide scope of exploration endeavors. In sociology, these fields of study incorporate, however are not restricted to human studies, science, correspondence ponders, financial matters, geology, data science, authoritative studies, social brain research, humanism, and sociolinguistics.

#### 2.3.3.1 Social Network Analysis

Social network analysis (SNA) is the theoretical analysis of social network [148]. Social network analysis sees social connections regarding system hypothesis, comprising of nodes (speaking to individual performing artists inside the system) and ties (which speak to connections between the people, for example, companionship, family relationship, hierarchical position, sexual connections, and so on.) [149][150]. These systems are regularly portrayed in a social network graph, where hubs are spoken to as focuses and ties are spoken to as lines.

Social network analysis has risen as a key method in present day humanism. It has likewise picked up a noteworthy following in human studies, science, correspondence ponders, information science, biology, hierarchical studies, financial matters, social psychology, and sociolinguistics.

Individuals have utilized the possibility of "informal community" freely for over a century to suggest complex arrangements of connections between individuals from social frameworks at all scales, from interpersonal to global. In 1954, J. A. Barnes began utilizing the term deliberately to signify examples of ties, enveloping ideas generally utilized by people in general and those utilized by social researchers: limited gatherings (e.g., tribes, families) and social classifications (e.g., sex, ethnicity).

##### 2.3.3.1.1 Connections

Homophily: The degree to which performing artists structure ties with comparable versus unique others. Similitude can be characterized by sex, race, age, occupation, instructive accomplishment, status, values or whatever other notable trademark [151].

Multiplexity: The quantity of substance structures contained in a tie [152]. For instance, two individuals who are companions furthermore cooperate would have a multiplexity of 2 [153]. Multiplexity has been connected with relationship quality.

Commonality/Reciprocity: The degree to which two on-screen characters respond each other's fellowship or other connection [154].

System Closure is a measure of the fulfillment of social triads. An individual's suspicion of system conclusion (i.e. that their companions are additionally companions) is called transitivity. Transitivity is a result of the individual or situational characteristic of Need for Cognitive Closure [155].

Propinquity: The propensity for performing artists to have more ties with topographically close others.

##### 2.3.3.1.2 Segmentation

Gatherings are recognized as "cliques" if each individual is specifically attached to each other individual, 'social circles' if there is less stringency of direct contact, which is uncertain, or as fundamentally firm pieces if exactness is needed.

Grouping coefficient: A measure of the probability that two partners of a hub are partners. A higher bunching coefficient shows a more noteworthy "cliquishness"[156].

Cohesion: The extent to which on-screen characters are associated specifically to each other by firm bonds. Basic attachment alludes to the base number of individuals who, if expelled from a gathering, would separate the gathering [157][158].

#### 2.3.3.1.3 Modeling and visualization of networks

Visual representation of interpersonal organizations is vital to comprehend the system information and pass on the aftereffect of the investigation. Large portions of the systematic programming have modules for system representation. Investigation of the information is done through showing hubs and ties in different designs, and ascribing hues, size and other propelled properties to hubs. Visual representations of systems might be a capable strategy for passing on complex data, however care ought to be taken in translating hub and chart properties from visual shows alone, as they may distort basic properties better caught through quantitative examinations [159].

Coordinated effort diagrams can be utilized to represent great and terrible connections between people. A positive edge between two hubs means a positive relationship (fellowship, union, dating) and a negative edge between two hubs indicates a negative relationship (contempt, outrage). Marked informal organization diagrams can be utilized to anticipate the future advancement of the chart. In marked informal communities, there is the idea of "adjusted" and "uneven" cycles. An adjusted cycle is characterized as a cycle where the result of the considerable number of signs are certain. Adjusted charts speak to a gathering of individuals who are unrealistic to change their conclusions of the other individuals in the gathering. Uneven diagrams speak to a gathering of individuals who are prone to change their conclusions of the general population in their gathering. For instance, a gathering of 3 individuals (A, B, and C) where A and B have a positive relationship, B and C have a positive relationship, yet C and A have a negative relationship is a lopsided cycle. This gathering is liable to transform into an adjusted cycle, for example, one where B just has a decent association with A and both A and B have a negative association with C. By utilizing the idea of parities and lopsided cycles, the development of marked informal organization diagrams can be anticipated.

Particularly when utilizing informal community examination as an apparatus for encouraging change, distinctive methodologies of participatory system mapping have demonstrated helpful. Here members / questioners give system information by really mapping out the system (with pen and paper or digitally) amid the information gathering session. One advantage of this methodology is that it permits scientists to gather subjective information and ask clearing up inquiries while the system information is gathered [160].

The primary representations of informal community were sociograms where individuals are spoken to by focuses and connections by lines associating them [161][162]. Much research has been led on SNA taking into account this diagram based perspective utilizing chart hypothesis [163][164].

Among vital results is the ID of sociometric elements that describe a system. The thickness demonstrates the union of the system. The centrality highlights the most critical on-screen characters of the system and three definitions have been proposed [165]. The degree centrality considers hubs with the higher degrees (number of contiguous edges). The closeness centrality depends on the normal length of the ways (number of edges) connecting a hub to others and uncovers the limit of a hub to be come to. The betweenness centrality concentrates on the limit of a hub to be a go between any two different hubs. A system is exceptionally subject to on-screen characters with high betweenness centrality and these performing artists have a key favorable position because of their position as delegates and intermediaries [166][167][168]. Its accurate calculation is tedious; a few calculations handle this issue with a base time unpredictability of O (n.m) - n is the quantity of vertices and m the quantity of edges [169][170][171][172]. To manage extensive systems, approximating calculations [173][174][175][176] and parallel calculations have been proposed [177][178]. Society finding helps understanding the worldwide structure of a system and the conveyance of performing artists and exercises. Additionally, the group structure impacts the way data is shared and the way performers carry on [179].

Scott gives three diagram designs that compare to firm subgroups of performing artists assuming an essential part in group identification: segments (secluded associated subgraphs), clubs (complete subgraphs), and cycles (ways coming back to their purpose of flight). Elective definitions have additionally been proposed, for example, n-faction, n-tribe and k-plex that augment these underlying ideas. Group recognition calculations are deteriorated into two classifications, either various leveled or in view of heuristics [180][181][182]. Two procedures are utilized as a part of various leveled calculations: the divisive calculations consider the entire system and separation it iteratively into sub group [173][183][184][185] furthermore, the agglomerative calculations bunch hubs into bigger and bigger groups [186][187]. Different calculations depend on heuristics, for example, irregular walk, analogies to electrical systems or recipe improvement [188][189][190].

Social network diagrams hold particular examples that can be utilized to describe them and quicken calculations [191]. Regarding to the little world impact [192], the request of the briefest way between two performing artists in an interpersonal organization of size n is log(n). Interpersonal organizations have an imperative grouping inclination and a group structure, moreover, the degree dispersion takes after a force law.

These diagram based representations are just worried with linguistic structure – they all need semantics, and have a particularly poor abuse of the sorts of relations. We will now perceive how as of late online interpersonal organizations began to be spoken to with rich organized information consolidating semantics.

#### 2.3.3.2 Semantic Web Representation of Online Social Networks

Semantic web structures give a diagram model (RDF), an inquiry dialect (SPARQL) and sort and definition frameworks (RDFS and OWL) to speak to and trade information on the web. These systems give a radical better approach for catching interpersonal organizations in much wealthier structures than crude charts.

A few ontologies can be utilized to speak to informal communities. The most prevalent is FOAF, utilized for portraying individuals, their connections and their action. An extensive arrangement of properties is committed to the meaning of a client profile: "family name", "nick", "interest", and so on. The "knows" property is utilized to interface individuals and to construct an informal community. Different properties are accessible to portray web uses: online record, weblog, enrollments, and so on. The properties characterized in the RELATIONSHIP ontology practice the "knows" property of FOAF to sort connections in an informal organization all the more absolutely (familial, companionship or expert connections). For example, the connection "livesWith" practices the connection "knows". The primitives of the SIOC ontology practice "OnlineAccount" and "HasOnlineAccount" from FOAF with a specific end goal to show the collaborations and assets controlled by social web applications; SIOC characterizes ideas, for example, posts in discussions, sites, and so on. Specialists have demonstrated that SIOC and alternate ontologies introduced can be utilized and stretched out for connecting reuse situations and information from web 2.0 group locales [193].

In parallel, web 2.0 applications made social labeling mainstream: clients label assets of the web (pictures, video, blog entries and so on.) The arrangement of labels structures a folksonomy that can be seen as a mutual vocabulary that is both started by, and commonplace to, its essential clients [194]. Ontologies have been intended to catch and adventure the exercises of social labeling while analysts have endeavored to connect folksonomies and ontologies to influence the semantics of labels [195][196][197] (see overview in [198]).

When they are written and organized, the relations between the labels and between the labels and the clients are additionally another wellspring of informal communities.

An easier approach to add semantics to the representation of persons and utilizations of the web is to utilize microformats [199][200]. Some microformats may be utilized for portraying client profiles, including assets and informal organizations. For instance, hCard and hResume microformats portray a man (name, email, address, individual resume and so forth.) and XFN (XTML Friends Network) is valuable for depicting connections.

A large number of FOAF profiles are presently distributed on the web, because of the appropriation of this cosmology by web 2.0 stages with expansive groups of onlookers (www.livejournal.net, www.tribe.net) [201]. The colleague and experienced socials individually shaped by the properties "foaf:knows" and "foaf:interest" show genuine social networks [202]. As an outcome, analysts have connected established SNA techniques to FOAF [203][204]. As it has been up to now, there is one kind and only group of email clients (anybody can mail anybody), the selection of institutionalized ontologies for non-expert online informal organizations will prompt expanding interoperability amongst them and to the requirement for uniform apparatuses to investigate and oversee them.

#### 2.3.3.3 Toward a Semantic Social Network Analysis

The online accessibility of social network information in various arrangements, the accessibility of related semantic models and the diagram structure of the RDF dialect are prompting another method for investigating social networks. Current calculations that are connected to SNA depend on chart design location and utilize almost no semantics. The semantics of sociometric examples that are measured are never considered because of the absence of semantics of the representation of the investigated systems. As an illustration, group recognition calculations depend on diagram structure qualities of social networks yet none depends on a sociological meaning of group and sorts of relations are under-abused [205]. Ontologies were intended to portray specific groups and can be a fascinating approach to broaden group identification among semantically depicted social networks [206].

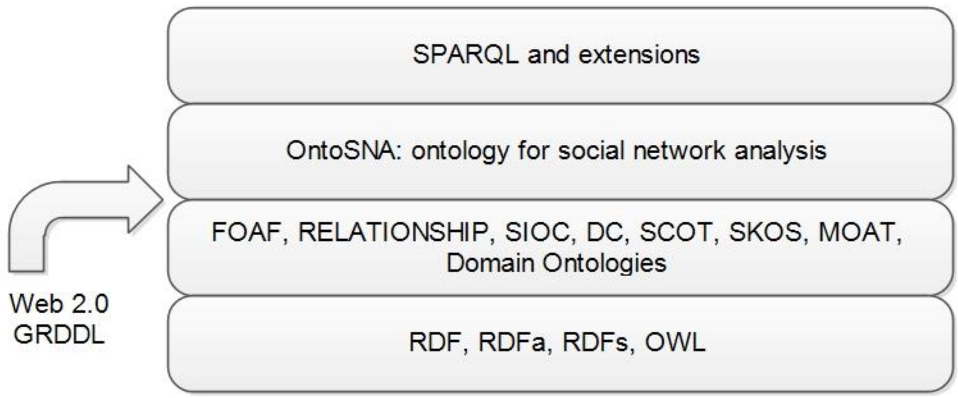



*Figure 2-2 A semantic social network analysis architecture*

A design has been designed as appeared in Figure 2-2 for another apparatus to examine online social networks [207]. This facility investigates RDF-based comments depicting profiles and communications of clients through social applications, utilizing the theoretical vocabulary of already said ontologies and space particular ontologies. A philosophy, called OntoSNA (Ontology of Social Network Analysis), depicts general sociometric highlights and their connections to social RDF information. As of late, SPARQL expansions have been proposed for improving the RDF diagram questions and have been executed in the internet searcher CORESE [208][209][210][211]. These expansions empower us to concentrate ways in RDF diagrams by indicating numerous criteria, for example, the sort of the properties required in the way with normal expressions, or edge bearings or imperatives on the vertices that ways experience. We reuse these expansions and propose new ones devoted to SNA keeping in mind the end goal to make less demanding the examination of RDF-based representations of informal communities. With such a device, we can center or parameterize the investigation determining sorts of assets or properties to be considered, and broaden established calculations with semantic components communicated in SPARQL and in light of sociological definitions. See Table 2-5.

| | |
|---|---|
| select count(?y) as ?cdegree<br>{<br>{?y foaf:knows ?x}<br>UNION<br>{?x foaf:knows ?y}<br>}<br>group by ?x | select count(?y) as ?cdegree<br>{<br>{?y relationship:worksWith ?x}<br>UNION<br>{?x relationship:worksWith ?y}<br>}<br>group by ?x |

*Table 2-5 SPARQL queries that concentrate the degree centrality of performing artists*

## 2.4 SOCIAL SEMANTIC WEB

In this research in order to combine the benefits of social web as the platform of the work and semantic web as the technology which enrich the efficiency of the work, social semantic web has been used. The Social Semantic Web (SSW) remains for another worldview for making, overseeing and sharing data through joining the innovations and methodologies from the Semantic Web and the Social Web (Web 2.0) [212]. The previous goes for giving data an "all around characterized significance, better empowering PCs and individuals to work in collaboration" through the meaning of ontologies [213][214]. The last is a stage for social and community trade where clients meet, team up, collaborate and in particular make substance and offer information through, e.g., wikis, websites, photograph and video sharing administrations. SSW has risen by blending the best of these two universes, through consolidating the basic organizations for characterizing and organizing data with the social instruments for making and sharing information [215]. On SSW, socially made and shared information prompts the formation of unequivocal and semantically-rich learning representations.

With a developing volume of information on the web, it has turned out to be more hard to comprehend, understand, and get a complete perspective of what we know. Besides, the simplicity of production and correspondence imply that customary quality controls and expected classes are changing, making sifting of the boundless volume of information important.

Unstructured information is characteristically constrained: for case, it may not be promptly clear whether a date is indicated as month/day/year or day/month/year, and catchphrases can have a few implications: a "crown" implies diverse things to a royalist, a plant scholar, and a dental specialist, and Paris, Texas is not Paris, France.

Nonetheless, connection can lessen vagueness, permitting us to construe implications and include structure.

The possibility of the Social Semantic Web is that we can arrange the world's information while utilizing online networking, by utilizing Semantic Web advancements to make cooperative energy between intelligible and machine-justifiable information.

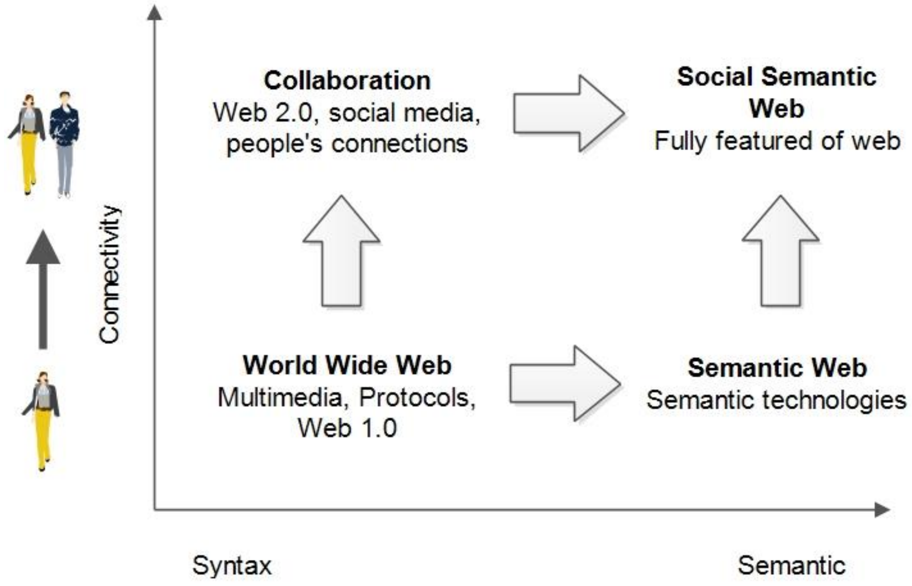



*Figure 2-3 Social Semantic Information Spaces*

As appeared in Figure 2-3, the Social Semantic Web influences the linguistic structure of the World Wide Web, the additional semantic structure of the Semantic Web, and the social network of the Social Web, to convey the Web to its maximum capacity. Tom Gruber communicates the vision of the Social Semantic Web as a move from the gathered knowledge of web2.0 to an aggregate insight [216]. As Gruber clarifies, Semantic Web advances can "empower information sharing and calculation crosswise over free, heterogeneous Social Web applications. By joining organized and unstructured information, drawn from numerous destinations over the Internet, Semantic Web innovation could give a substrate to the disclosure of new learning that is not contained in any one source, and the arrangement of issues that were not foreseen by the designers of individual sites". Such total and sifting would not require noteworthy overhead as extra exertion by end-clients; rather, lightweight curation would be a reaction of existing social discussions. Further, the Social Semantic Web may be bootstrapped from existing media [217].

Two case of bootstrapping methodologies are surmising understood structures and consolidating ontologies with folksonomies. By gathering understood structures, with human investigation of webpage structures or machine-based information mining, we can lift pages from a Social Website into the Social Semantic Web. Case in point, Wikipedia layouts don't have express semantics proclaimed, yet they are adequately surely knew to be deciphered into semantically improved renditions for DBpedia [218]. By joining ontologies with folksonomies, we can have better recovery while keeping up adaptability in information passage. Joining chains of command of unstructured information, we could, for occasion grow a quest for "Ireland" to incorporate parts of Ireland (e.g. \Dublin", \West of Ireland", \County Galway"), or permit closeness seeking, i.e. to incorporate Limerick in a quest for \places close Shannon airplane terminal". The Social Semantic Web has been further examined and has as of late gotten book-length and proposition medications [17][219][220].

The Social Semantic Web can be seen as a Web of aggregate learning frameworks, which can give helpful data in light of human commitments and which improve as more individuals partake [221]. The Social Semantic Web can be seen as a Web of aggregate learning frameworks, which can give helpful data in view of human commitments and which show signs of improvement as more individuals take an interest [222]. The Social Semantic Web joins advancements, systems and strategies from the Semantic Web, social programming and the Web 2.0 [223].

The social-semantic web (s2w) intends to supplement the formal Semantic Web vision by including a down to business approach depending portrayal dialects for semantic perusing utilizing heuristic grouping and semiotic ontologies. A socio-semantic framework has a persistent procedure of inspiring significant learning of a space through semi-formal ontologies, scientific classifications or folksonomies. S2w accentuate the significance of humanly made free semantics as intends to satisfy the vision of the semantic web. Rather than depending totally on computerized semantics with formal ontology handling and inferencing, people are cooperatively assembling semantics supported by socio-semantic data frameworks. While the semantic web empowers reconciliation of business preparing with exact programmed rationale derivation processing crosswise over spaces, the socio-semantic web opens up for a more social interface to the semantics of organizations, permitting interoperability between business items, activities and their clients.

Socio-semantic web was instituted by Manuel Zacklad and Jean-Pierre Cahier in 2003 and utilized as a part of the field of Computer Supported Cooperative Work (CSCW). It as of late increased more extensive request after the arrival of Peter Morville's book Ambient Findability [224]. He characterizes the socio-semantic web as depending on "the pace-layering of ontologies, scientific categorizations, and folksonomies to learn and adjust and in addition instruct and recollect that." We are seeing an expanding utilization of folksonomies on the web, and a relating diminish in the utilization of various leveled scientific categorizations. Morville, the perceived curator and data designer keeps in touch with; "I'll take the antiquated tree of information over the transient leaves of prevalence quickly". There is without a doubt wariness towards the across the board and bushfire like appropriation of folksonomies. The socio-semantic web might be seen as a center route between the top-down solid scientific categorization approach like the Yahoo! Catalog and the later community oriented labeling (folksonomy) approaches.

The socio-semantic web contrasts from the semantic web in that the semantic web frequently is viewed as a framework that will tackle the epistemic interoperability issues we need to day. While the semantic web will give approaches to organizations to interoperate crosswise over areas the socio-semantic web will empower clients to share information.

Morville is dubious in his meaning of the socio-semantic web and does not lay out any proposed models. We have recognized three conceivable social methodologies for tackling the issues of client driven ontology advancement for the semantic web. To start with, clients could make a folksonomy (level scientific classification). With Social Network Analysis (SNA) in conjunction with computerized parsers, the ontology could be removed from the labels and this ontology could be gone into a Topic Map/TMCL or RDF/OWL ontology store [225]. Also an arrangement of cosmology architects or philosophers could physically break down the labels made by the clients and by utilizing this information, make a more stable philosophy. The third approach is to make a framework for self-administration where the clients themselves make the ontology after some time in a natural style. These methodologies could begin with a vacant ontology or be seeded physically or with a current ontology, for instance the WordNet ontology [226]. Social Networks Ontology is the most essential idea in social web.

Examples:

- DBpedia is a group push to remove organized data from Wikipedia and to make this data accessible on the Web. DBpedia permits you to ask modern questions against Wikipedia and to connect different datasets on the Web to Wikipedia information.
- SIOC gives techniques to interconnecting dialog strategies, for example, online journals, gatherings and mailing records to each other. It comprises of the SIOC metaphysics, an open-standard machine meaningful configuration for communicating the data contained both expressly and verifiably in web dialog techniques, of SIOC metadata makers for various well known blogging stages and substance administration frameworks, and of capacity and skimming/looking frameworks for utilizing this SIOC information.
- OPO gives an approach to portray the information with respect to client's nearness in online social frameworks, for the motivations behind information mix and trade among heterogeneous frameworks. The nearness data, scattered and conveyed everywhere throughout the Web can be combined utilizing OPO-based apparatuses.
- Stumpedia is a social undertaking and group exertion that depends on human investment and folksonomies to list, sort out, and audit the internet. The point is to construct Natural Language Processing and the Semantic Web.
- Semandeks is a base up methodology for building the semantic web. Its quality is the UI it employments.
- Twine consolidates elements of discussions, wikis, online databases and newsgroups and utilizes shrewd programming to consequently mine and store information connections communicated utilizing RDF articulations.

- Faviki and Tagnauts are social bookmarking groups which confine their clients to labels to which Wikipedia articles exist.

## 2.4.1 Users Semantic Profiles

A semantic user profile is a portrayal of a client's advantages and boredoms which is appeared in Figure 2-4 [227]:

$$
\begin{aligned}
Profile \equiv\ & \textstyle\prod_i \exists hasInterest.Interest_i \\
& \textstyle\prod_j \forall hasInterest.(\neg Disinterest_j)
\end{aligned}
$$

*Figure 2-4 A semantic user profile*

This definition expresses that the client is keen on all ideas secured by the Interesting ideas without the ideas secured by Disinteresting. This profile depiction is entirely like the one found in, yet we manage without encoding numeric levels of interest [228]. Despite the fact that a client profile may contain extra data about his personality and belonging or capacities, we will concentrate exclusively on a mysterious semantic depiction of her long haul interests.

For the semantic administrations and profiles to cooperate, it is imperative that the Things offered in the administration definition utilize the same metaphysics (or vocabulary) as the interests from the profile definition.

The semantic data for clients is given by client profiles. Every client in the framework has profile portrayed by method for a scientific classification. The scientific classification speaks to the client intrigues utilizing a semantic chain of importance representation, e.g. on the off chance that a client is keen on Java then this present client's profile is {Computerscience => Programminglanguages => Objectorientedlanguages => Java} [229].

## 2.4.2 Frameworks for Social Networks

### *2.4.2.1 Six paths to gage Social Network Results*

#### 2.4.2.1.1 Begin with the strategic aims

Entrepreneurs who see incredible online networking achievement attach their innovation decisions to their vital objectives [230]. The Table 2-6 demonstrates the significance of an attentive procedure when planning an online networking arrangement.

| Strategy | Metrics | Organization | Technology |
|---|---|---|---|
| - Define business objectives<br><br>- Identify required insights | - Define success<br><br>- Recommend actions | - Identify required resources<br><br>- Identify required training<br><br>- Identify barriers | - Identify tools based on strategy, metrics, and organization |

*Table 2-6 The significance of an attentive procedure*

Pay attention to a point to begin with your business objectives while picking your instruments and measures.

Etlinger exhorts all organizations tail this procedure, however especially little organizations that have restricted assets and less resilience for slips.

Invest sufficient energy thoroughly considering your vision of accomplishment so you can choose the right measurements. This implies getting particular about your business destinations and methodologies before thoroughly considering social goals. At that point you can compose your staff (or your own time in case you're a solopreneur) around those measurements. At exactly that point is you prepared to choose the best advancements (counting which social stages and estimation instruments to utilize).

Once you've set up your objectives, then you're prepared to consider Altimeter's Social Media Measurement Compass. The purposes of this compass recognize six noteworthy business objectives that online networking can impact.

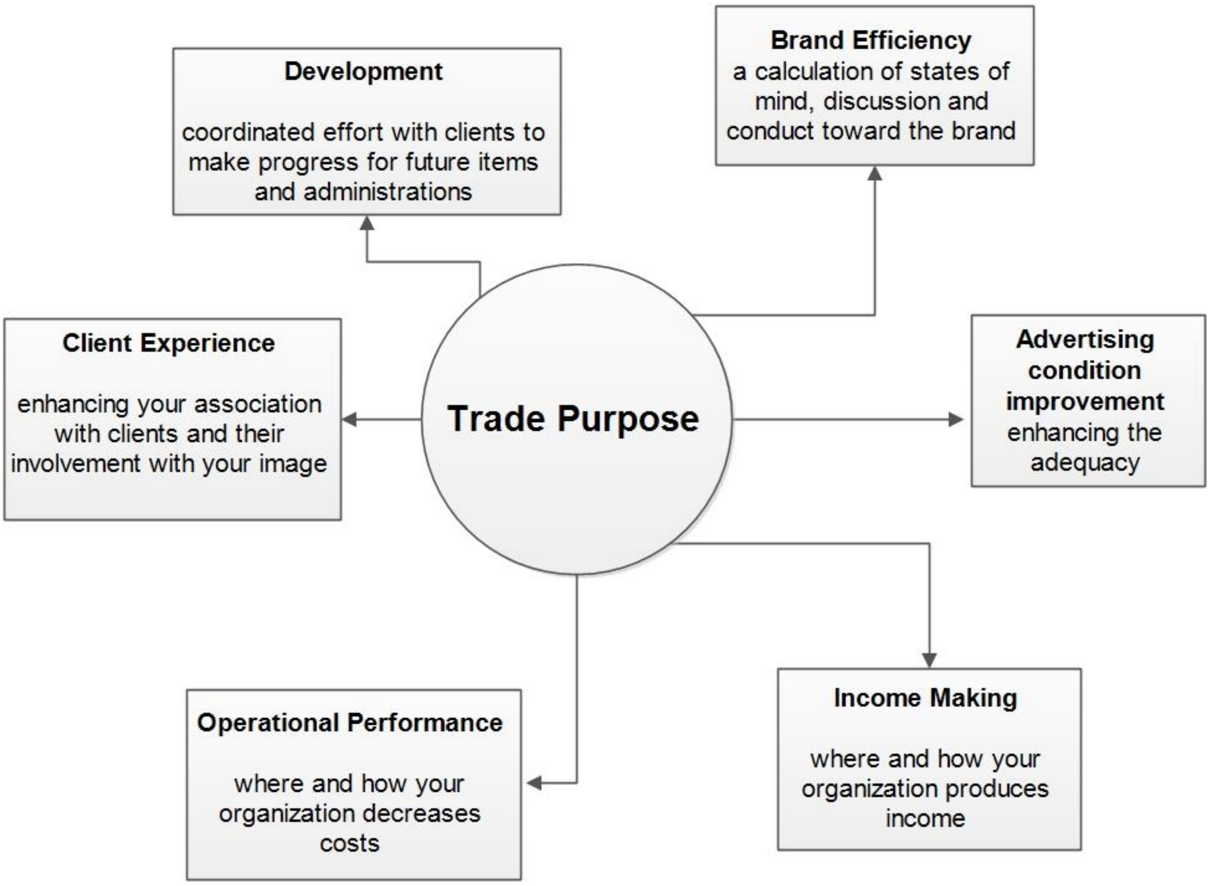



*Figure 2-5 The six classes of the social media estimation*

The six classes which are appeared in Figure 2-5 will help you thoroughly consider the business goals of your estimations.

##### 2.4.2.1.2 The Six Points of the Compass

#1: Brand Efficiency

Do you identify how individuals are discussing your administration, your items or client experience? Enormous brands spend heaps of cash dealing with their image picture, however little organizations additionally should know about clients' observations.

How are individuals discussing your administration, items and choices?

Etlinger noticed that individuals have no issue grumbling specifically to huge brands, however may feel more held about condemning a little entrepreneur to his or her face.

Online networking observing can help you hear what individuals are telling their companions, however won't not will to let you know specifically.

Be careful that you can never hear the entire online networking discussion about your image. There are no less than two reasons: 1) Twitter is catching such extensive volumes that you can just find out about 5% of the discussion; 2) Privacy settings on Facebook restrict non-companions from listening to numerous discussions.

These two elements make it basic to discover approaches to accept what individuals are stating. Little entrepreneurs may think that its testing to hear evaluates, yet put on your intense skin and ask a few clients (in individual and online).

To uncover how online networking listening can help you comprehend your image wellbeing, Etlinger's examination found the accompanying subjects in the Table 2-7 [231] as basic for your social networking tuning in.

| Themes | Insights | Metrics | Actions |
|---|---|---|---|
| Conversation and sentiment drivers | How people feel about your brand<br>What words or qualities they associate with it<br>Where conversations occur<br>Conversation drivers<br>Frequently shared topics | Sentiment over time<br>Source of positive, negative and neutral sentiment<br>Highest-performing topics, brands, regions<br>Number of fans/followers, brand mentions<br>Top keywords<br>Top shared liked | **Research**<br>Conduct real-time market research<br>**Planning**<br>Conduct scenario Planning, crisis planning<br>**Decision Support**<br>Use as support for marketing service, product or other business decisions.<br>**Competitive Intelligence**<br>Inform competitive moves<br>**Advocacy**<br>Identify and develop relationships with advocates, detractors. |
| Location, time and impact of conversations | Top channels<br>Sentiment variation by channel<br>Location of conversations about your brand/products<br>How far your conversations reaches<br>Content speed/resonance | Where people talk about your brand or products<br>Sentiment by social media channel<br>Time-parting analysis by conversation topic | |
| Competitive implications | How people talk about your competitors<br>Competitive position in industry/product area/topic<br>Competitive opportunities, threats | Sentiment by company/competitor<br>Share of total conversation by industry, product, topic | |
| Issues identifications | Emerging issues<br>Issue sentiment<br>Sentiment drivers | Accelerating keywords, volume, sentiment | |
| Influence | Influencer, whether advocates or detractors | Influencer by topic (by followers and/or reach)<br>Sentiment by influencer | |

*Table 2-7 brand health insights, metrics and actions*

Notice the bits of knowledge to be picked up and how to gauge your listening results to discover these markers of wellbeing. Allow these questions and thoughts to force you deeper into your measurement practices.

#2: Advertising condition improvement

Online networking listening can help you calibrate your showcasing endeavors to better discover your intended interest group. For some organizations, Google Analytics may be the best apparatus.

You will probably figure out what terms individuals are seeking and from what destinations they are going to your site. A portion of the things to upgrade are battles, content, channels, timing and influencers.

Realize that individuals share diversely on various social channels. While not entirely an online networking stage, Yelp gives a decent case. Individuals needing to position themselves as sustenance faultfinders are prone to be much more basic on Yelp than they may be on Twitter or Facebook.

#3: Income making

This estimation might be less pertinent on the off chance that you don't have an online store; be that as it may, all organizations need to know whether online networking is driving deals.

By and large, online networking shouldn't be relied upon to straightforwardly prompt expanded deals. Rather, it can create leads and transformations. On the off chance that you consider income as a relationship and not only an exchange, as recommended by Richard Binhammer of Dell, then you'll see that online networking can impact the long haul relationship.

Some critical things to comprehend are the effect of online networking on: 1) buy conduct, 2) query items and 3) client faithfulness.

In the event that you have a physical store, ensure you have following frameworks set up for every channel.

You may attempt crusades on Facebook, Twitter and Groupon and see what drives rehash business the best. Groupon is prone to draw in arrangement seekers who may turn out to be new clients, while your fans on Facebook and Twitter may get themselves all the more profoundly associated subsequent to encountering one of your "Facebook just" arrangements. Test the theory and run your own particular numbers. Results will differ broadly in view of your business sort and fan base.

#4: Operational Performance

Social media may facilitate chances for hard and soft savings to your business. As customers become brand advocates, your brand reach will extend without significant expenses.

Furthermore, social stages can get to be far less costly places for taking care of client administration. That relies on upon whether you have somebody who can be committed to listening to online discussions continuously.

One keen exercise is to manufacture associations with fans who have solid online networking impact. These individuals can turn into your promoters and even help with client administration. In the event that they've as of now demonstrated an eagerness to talk for your sake, discover approaches to encourage them data.

#5: Client Experience

Etlinger's examination found an immediate connection between's online networking and client encounter that deciphered into enhanced brand wellbeing, expanded income and cost funds.

A case not refered to in the report originates from Kraft Foods. The online networking listening group found a pattern on words like "cut," "blood" and "plate of mixed greens dressing." Those aren't words you need connected with nourishment, so the group burrowed further to find that clients were cutting themselves when opening a recently composed serving of mixed greens dressing bottle.

The issue was effortlessly explained, however wouldn't have been found without online networking. The wounds weren't not kidding enough to require crisis room treatment. It was only a bother, so clients didn't call the 1-800 number. Rather they told their companions on online networking and disregarded it. Since you don't as a rule purchase plate of mixed greens dressing frequently, this issue could've gone undetected for a considerable length of time.

#6: Development

As mentioned by Etlinger, Starbucks and Proctor and Gamble have discovered approaches to crowdsource thoughts through their inventive locales MyStarbucksIdeas.com and pgconnect.com. Not everybody can asset their own online networking advancement webpage, yet all organizations can discover approaches to listen to their clients for bits of knowledge into item and administration changes.

For instance, Twitter can give you bits of knowledge into what individuals need. Take after articulations, for example, "I like," "I wish" or "I detest." If you listened, "I wish Charlie's hadn't suspended the chicken cordon bleu," you would have some extraordinary insight.

On the other hand, you could even begin a discussion on Facebook approaching your clients for thoughts on new items, administrations or advancements. Perhaps you could even host a "Thought Wednesday" where you spend an hour on your Facebook page searching for imaginative thoughts.

###### 2.4.2.1.3 Finding the Right Tools

There are numerous estimation apparatuses accessible, and many are free or exceptionally reasonable. Notwithstanding Google Analytics, here are some worth looking at:

Basically Measured has made two apparatuses that function admirably together.

- Export.ly assists you investigate your Facebook fan page, Twitter crowd and more through downloading adjustable Excel spreadsheets.

With Export.ly, you can trade information from Twitter, Facebook and email into an Excel spreadsheet or CSV record.

- RowFeeder was a modest approach to screen what individuals are saying in regards to your image. See Figure 2-6 [230].


*Figure 2-6 RowFeeder: a social network monitoring and analyzing application*

With RowFeeder, you could follow your brand name; Twitter handle; the hashtag for a particular group, event or advertisement; or public issues which are interesting. The project has been completed and closed after March 2016. Insteadly, on the website of the company, Simply Measured, there are new features and tools available to use for users as shown in Figure 2-7 [232].

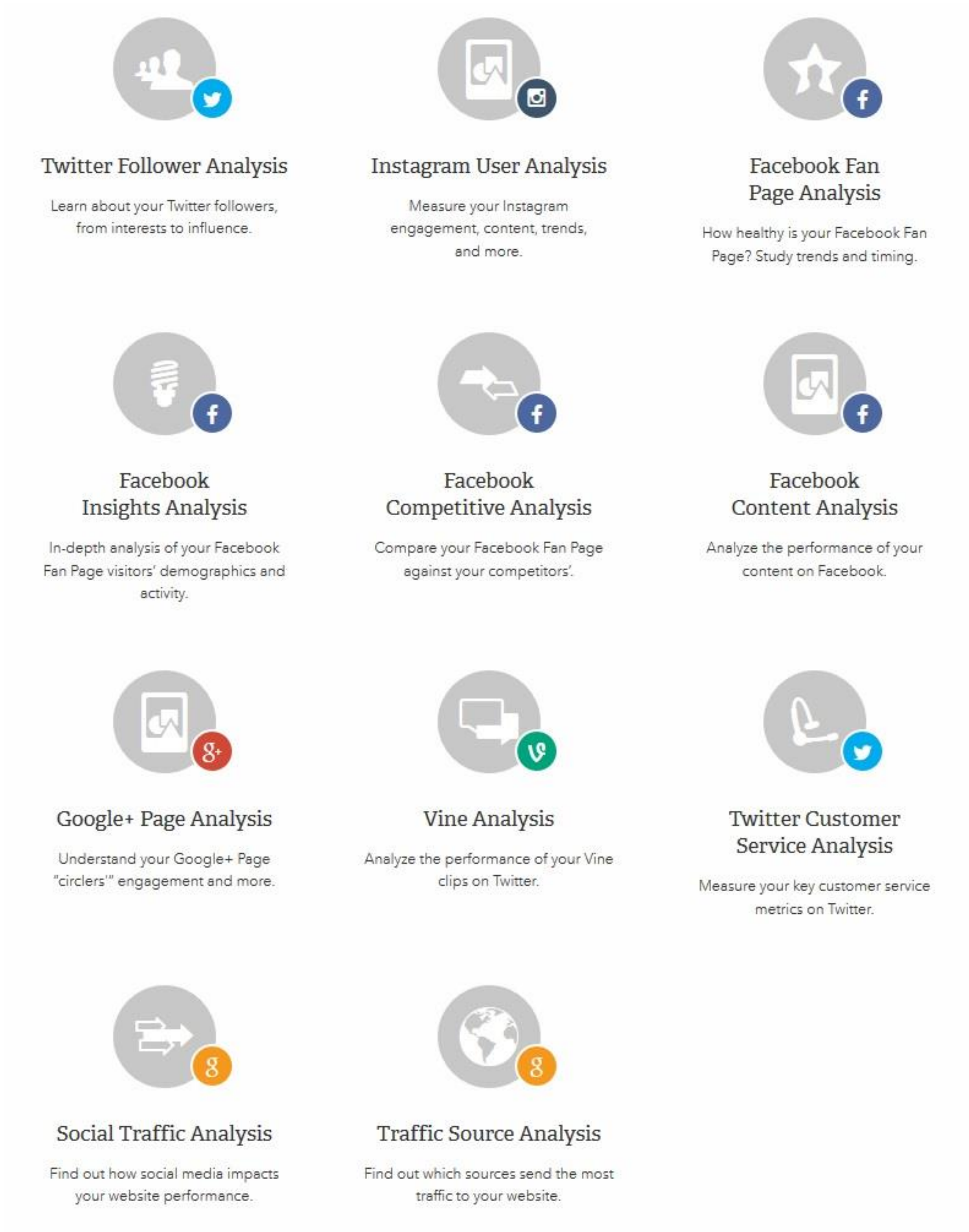



*Figure 2-7 List of free available tools of Simply Measured*

TweetReach investigates the tweets that match your inquiry.

Edelman has created two devices called TweetLevel which is appeared in Figure 2-8 [233] and BlogLevel that measure the level of impact, notoriety, engagement and trust on your Twitter record and blog. These can be great markers of the soundness of your online networking endeavors. Edelman additionally gives accommodating tips on the best way to enhance in each of these zones.

The New TweetLevel

*Your GPS for Navigating Twitter Influence*

BY JONNY BENTWOOD PUBLISHED NOVEMBER 26, 2012

Welcome to the new TweetLevel! – In our biggest update since the first version of the product was launched four years ago, we have focused on delivering you unprecedented Twitter intelligence in a more visual and user-friendly way, at no cost that gives you the real time, actionable insight you need to engage in Twitter most effectively.



With just one click, you can analyse who are the most influential tweeters on any topic, or take a deeper dive into what makes those influentials tick.

WHAT'S DIFFERENT ABOUT TWEETLEVEL

This tool was created by PR professionals at Edelman for PR and marketing professionals. This means that we know what information is

*Figure 2-8 TweetLevel*

You are able to utilize TweetLevel to discover "essential" individuals inside a particular connection and begin discussions with them.

TweetLevel and BlogLevel: A GPS for Navigating Influence

July 14, 2011

Share This Story

Like 14 people like this. Be the first of your friends.

G+1 Pin it

Posted by Jonny Bentwood
Edelman Technology, London
Follow on Twitter @JonnyBentwood

*Originally posted on Technobabble 2.0.*

Today, we're excited to share with you two of Edelman's latest innovations: BlogLevel, and the "2.0 version" of TweetLevel, originally launched in 2009. Both tools are designed to identify who is influential on a particular topic, in any language, on a designated platform. TweetLevel finds the influentials on Twitter, and BlogLevel does the same in the blogosphere.

www.tweetlevel.com • www.bloglevel.com

*Figure 2-9 BlogLevel*

BlogLevel is a reason constructed apparatus for PR and advertising to guarantee brands use writes successfully. See Figure 2-9 [234].

For more understanding:
Susan Etlinger has revealed nittier gritty data about the report in the accompanying online class made for CoreMetrics.

Key takeaways:
1. Attach your estimation system to key business destinations.
2. Comprehend the key terms to take after for your business.
3. Discover apparatuses that will give you the outcomes you look for without breaking your financial plan.
4. Comprehend that income is not an exchange, but rather a relationship. Treat your clients like individuals and see how your online activities are influencing those connections.

5. Discover approaches to get your clients required through client administration, brand promotion and thought era.

### *2.4.2.2 Modeling Social Networks using semantic web technologies*

As of late, semantic web advances, for example, Resource Description Framework (RDF) and the Web Ontology Language (OWL) have been utilized for social network community information [235][236]. In spite of the fact that the objective in these papers is not to propose new semantic methodologies for demonstrating online social network information, it has been taken into account to give a brief review of current methodologies for culmination by indicating out additionally other social network data that could be displayed by semantic innovations. In the dialog, Facebook as a running illustration will be utilized. In the meantime, it is possible to push that the examination could be effectively stretched out to other long range social network systems. By and large, five classes of social network information are recognized that could be displayed by semantic innovations. These are: (1) individual data; (2) individual connections; (3) social network assets; (4) connections amongst clients and assets; (5) activities that can be performed in a social network. In the accompanying, it is talked about how this social network information can be spoken to.

#### 2.4.2.2.1 Modeling Personal Information

A portion of the individual data gave on OSNs, for example, Facebook can be displayed by utilizing the Friend-of-a-Friend ontology(FOAF) [237]. FOAF is an OWL-based configuration for speaking to individual data and an individual's social network. FOAF gives different classes and properties to depict social network information, for example, essential individual data, online record, ventures, gatherings, archives and pictures. Be that as it may, these fundamental systems are insufficient to catch all the accessible data. For instance, there is no FOAF develop to catch the significance for searching for (e.g., John Smith is searching for kinship). On account of the extensibility of the RDF/OWL dialect, this is effectively reasonable. For instance, consider the accompanying situation where we catch the data identified with a person with Facebook Profile Id 7777777 utilizing another Facebook cosmology written in the RDF/OWL language.2 In this case, we expect that "fb" metaphysics has a property name lookingFor to catch the required data.

```
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns>.
@prefix foaf: <http://xmlns.com/foaf/0.1/>.
@prefix fbw: <http://example.org/facebook>.
<http://www.facebook.com/profile.php?id=7777777>
foaf:name ”Ali Pazahr”.
<http://www.facebook.com/profile.php?id=7777777>
fbw:lookingFor ”Friendship”.
```

As the case proposes, existing ontologies, for example, FOAF could be effectively reached out to catch individual data accessible on online social networks.

#### 2.4.2.2.2 Modeling Personal Relationships

As of now, online social networks don't bolster fine-grained meanings of connections. Case in point, Facebook permits you to indicate whether you went to class or work with a companion, yet offers no real way to express what that genuinely implies, that is, the quality of the relationship. It is this finegrained structure that we wish to catch. Mika proposes a reification based model for catching relationship quality. Rather, to agree to W3C determinations, we embrace the utilization of the n-ary connection design as opposed to utilize straightforward articulation reification, which is an infringement of the characteristics [238][239]. If we somehow managed to abuse the detail, then connections would be demonstrated utilizing a progression of four RDF articulations to make an identifier for the relationship.

Tragically, as a consequence of that, SWRL would be not able comprehend these connections. We trust that utilizing a detail prescribed example and holding the capacity to utilize SWRL to do surmising on connections is the best arrangement. For the reasons expressed above, we demonstrate individual connections utilizing n-ary connection design. To follow n-ary connection particular, we characterize a FriendshipRelation class which has subclasses that signify a general quality of kinship. The root FriendshipRelation class suggests an unspecific fellowship while the three subclasses, Family, CloseFriend, and DistantFriend, give a pointer of the closeness between individuals. The CloseFriend subclass has a further expansion: BestFriend.

This fundamental structure permits us to effortlessly copy the current structure of Facebook relationship sorts. In any case, as said already, these relationship sorts have no predefined implications. Keeping in mind the end goal to start to measure the significance of relationship assignments, every case of FriendshipRelation has an information property TrustValue. This speaks to the level of trust that the initiator has with the companion.

As an illustration assume that an individual (e.g., John Smith) characterizes an association with a partner (e.g., Jane Doe). This makes a case of the FriendshipRelation class with the TrustValue information property, which speaks to the level of trust between the initiator and his companion. The case likewise has an article property that connections it to the occurrence of the companion. This occurrence of the FriendshipRelation class is then attached back to John Smith using the Friendship object property.

Note that any (uni-directional) relationship in the informal community is a solitary occurrence of the FriendshipRelation class. In this manner, to show the standard bidirectional nature of informal community relations, we require two cases of this class. In any case, the basic intelligent induction that if B is a companion of A, then A will be a companion of B can't be actualized by SWRL, in this would suggest to make another case of the Friendship class. Lamentably, this is outside the domain of SWRL's ability. So this must be dealt with outside of the SWRL system by an outer application. It is additionally essential to note that the TrustValue property of connections is a worth that is figured naturally outside the OWL/SWRL part of the interpersonal organization. This quality is utilized to do different surmising undertakings further in the system. At the most fundamental level, where the TrustValue is a static number in light of the companionship sort, this is an unimportant segment. We expect that there will be a more confused recipe utilized as a part of figuring the TrustValue that might be past the limits of the inherent numerical administrators of SWRL.

We encounter a comparable trouble with backhanded connections. To characterize a construed relationship, we would by and by need to make another case of FriendshipRelation. We can, in any case, make these backhanded connections like how we keep up symmetry of connections, nitty gritty above. The main contrast in the roundabout relationship is that as opposed to making an occasion of the class FriendshipRelation, we make a case of a different class, InferredRelation, which has no nitty gritty subclasses, yet is generally indistinguishable to the FriendshipRelation base class.

#### 2.4.2.2.3 Modeling Resources

A run of the mill OSN gives a few assets, for example, Albums or Walls to share data among people. Obviously RDF/OWL could be utilized to catch the way that Albums are made out of pictures and every photo may have various individuals in it. In our system, we show assets as a class, starting with a nonexclusive Resource class. As subclasses to this, we can have, for instance, PhotoAlbum, Photo, and Message. Each of these has particular, extraordinary properties and connections. Case in point, PhotoAlbum has a name and a depiction as information properties and has an article property called containsPhoto that connections it to occasions of Photo.

These have a name, an inscription, and a way to the put away area of the record. Messages have a sender, a recipient, a subject, a message, and a period stamp. We can likewise make a subclass of Messages called WallMessage which is like Messages in that it has the same information properties, however it has extra confinements, for example, that a WallMessage may just be sent to a solitary person.

#### 2.4.2.2.4 Modeling User/Resource Relationships

Available applications, for example, Facebook expect that the main relationship amongst clients and assets is the possession.

In any case, from an entrance control perspective this is insufficient. Give us a chance to consider, for instance, a photo that contains both John Smith and Jane Doe. Jane took the photo and posted it on the informal community. Customarily, Jane would be the sole chairman of that asset. Since the photograph contains the picture of John (we say that John is labeled to the photograph), in our model John may have some determination as to which people can see the photograph.

To show something like a photograph collection, we can utilize two classes. The first is a basic Photo class that basically has a discretionary name and inscription of the photograph and an obliged way to the area of the record. A photograph is then connected to every individual that is recorded as being in the photograph. A PhotoAlbum has a name and a depiction. PhotoAlbum and Photo are connected utilizing the containsPhoto relationship. The individual proprietor – the individual who transferred the photographs – is demonstrated by the ownsAlbum relationship. Essentially, we can speak to different connections amongst clients and assets.

##### 2.4.2.2.5 Modeling Actions

In a social network, activities are the premise of client interest. As indicated by the proposed representation an activity is characterized as item property that relates clients, assets, and activities. In addition, we display chains of importance for activities by method for subproperty. Take, for case, three bland activities:

Perused, Write, Delete. We characterize a chain of importance in which Delete is a subtype of Write which is, itself, a subtype of Read. In a non-various leveled model, if John Smith could read, compose, and erase a photograph, then we would require three approvals to speak to this property. Be that as it may, as we have characterized the pecking order, with just the approvals of <"John Smith", Delete, Photo1>, John Smith has every one of the three properties permitted.

We can likewise stretch out conventional access confinements to exploit social network augmentations. Case in point, the activity Post can be characterized as a subtype of Write. Thus, let us say that we characterize the activities Write to imply that an individual can send a private message to another individual, and that the activity Post implies that an individual can present a message on another's Wall so that any of their companions can see it. At that point permitting a client the Post activity would permit them to see the companions' divider, send them a private message, and compose on their divider, yet she couldn't erase anything.

#### *2.4.2.3 Spring Social*

Spring Social is an augmentation of the Spring Framework that permits you to interface your applications with Software-as-a-Service (SaaS) suppliers, for example, Facebook and Twitter. [240].

##### 2.4.2.3.1 capabilities

- An extendable administration supplier structure that significantly improves the way toward associating nearby client records to facilitated supplier accounts.
- An interface controller that handles the approval stream between your Java/Spring web application, an administration supplier, and your clients.
- Java ties to well-known administration supplier APIs, for example, Facebook, Twitter, LinkedIn, TripIt, and GitHub.
- A signin controller that empowers clients to verify with your application by marking in through an administration supplier.

## 2.5 ONLINE PROMOTING

One of the other elements of this research is advertising which can be facilitated as online promoting. Web promoting is a type of advancement that uses the Internet and World Wide Web to convey promoting messages to pull in clients. Case of web promoting incorporate relevant advertisements on web index results pages, flag promotions, web journals, Rich Media Ads, Social system promotion, interstitial promotions, online arranged publicizing, promoting systems and email showcasing, including email spam. A hefty portion of these sorts of promotions are conveyed by an Ad server.

### 2.5.1 Online advertisement

The web has turned into a continuous developing source that has a tendency to extend increasingly. The development of this specific medium draws in the consideration of promoters as a more profitable source to get purchasers.

A reasonable favorable position customers have with online commercial is the control they have over the item, picking whether to look at it or not [241].

Online ads may likewise offer different types of movement. In its most basic utilize, the expression "internet promoting" contains a wide range of pennant, email, in-amusement, and watchword publicizing, including on stages, for example, Facebook, Twitter, and MySpace. Web-related promoting has an assortment of approaches to broadcast and achieve a specialty crowd to center its consideration regarding a particular gathering. Research has demonstrated that web promoting has given results and is a developing business income. [242]. For the year 2012, Jupiter Research anticipated $34.5 billion in US web promoting spending.

### 2.5.2 Competitive benefit over Customary Promoting

One noteworthy advantage of web promoting is the quick distributed of data and substance that is not constrained by topography or time. To that end, the developing region of intuitive promoting presents crisp difficulties for publicists who have until now embraced an interruptive procedure.

Another advantage is the productivity of the sponsor's speculation. Web publicizing takes into account the customization of ads, including content and posted sites. For instance, AdWords, Yahoo! Look Marketing and Google AdSense empower promotions to be appeared on pertinent website pages or nearby indexed lists.

### 2.5.3 Semantic advertising

Semantic advertising applies semantic examination strategies to website pages. The procedure is intended to precisely translate and arrange the importance and/or principle subject of the page and after that populate it with focused promoting spots. By nearly connecting substance to promoting, it is expected that the viewer will probably demonstrate an interest (i.e., through engagement) in the advertised item or administration.

### 2.5.4 Social Network Advertising

Social network advertising is a concept that is utilized to depict a type of Online promoting that spotlights on long range social networking locales [243]. One of the significant advantages of promoting on a long range social networking site is that publicists can exploit the clients' demographic data and focus on their advertisements properly.

## 2.6 RECOMMENDER SYSTEMS

The premise of a suggestion framework is to make expectations utilizing existing client profiles and the profile of a given client [244]. Its goal is to prescribe a given client with data that he may discover significant yet might not have known utilizing the current client profiles.

These profiles can be developed in an understood path by monitoring client activities, or by expressly requesting that he rate data.

With the expanding data of client propensities on the web, proposal frameworks are always present in our regular online life. Case of these suggesting frameworks are Last.fm, Amazon, Netflix, Epinions, and so on.

Building a suggestion framework has a few difficulties, it is important to have a broad dataset to make exact expectations and it is expected to pick what qualities depict for clients the best for the examination's destinations. In spite of the fact that the framework can make forecasts it can just make these utilizing measurements in view of our dataset, which implies that the suggestion may not be impeccable and from time to time is most certainly not.

### 2.6.1 About recommendation systems

There are several definitions of recommender systems [245]. One of the first was exhibited by Paul Resnick and Hal R. Varian in 1997. They guarantee that "in an ordinary recommender framework, individuals give suggestions as inputs, which the framework then totals and coordinates to fitting beneficiaries". These frameworks are generally characterized as far as their usefulness as the frameworks or operators that propose the items to the clients who buy items on e–commerce locales. The recommender frameworks help the customer to settle on the choice what to purchase.

Recommender frameworks can now be found in numerous present day applications that open the client to an enormous accumulations of things [246]. Such frameworks normally give the client a rundown of prescribed things they may incline toward, or foresee the amount they may lean toward everything. These frameworks help clients to choose proper things, and facilitate the errand of discovering favored things in the gathering. For instance, the DVD rental supplier Netflix shows anticipated appraisals for each showed film with a specific end goal to help the client choose which motion picture to lease. The online book retailer Amazon gives normal client evaluations to showed books, and a rundown of different books that are purchased by clients who purchase a particular book. Microsoft gives numerous free downloads to clients, for example, bug fixes, items et cetera. At the point when a client downloads some product, the framework introduces a rundown of extra things that are downloaded together. The Epinions site contains audits made by clients on things. Things are any item or administration. They have names and have a place with one of a kind classification. In a given classification, things may demonstrate a typical depiction structure. Classes are organized in a tree and may contain any number of things or subcategories [247]. The evaluations are in the scope of 1(min) to 5(max). Clients additionally dole out trust values (i.e. an estimation of 1) to different clients whose surveys and/or appraisals they discover profitable [248]. Every one of these frameworks are ordinarily ordered as recommender frameworks, despite the fact that they give assorted administrations.

In the previous decade, there has been an immeasurable measure of examination in the field of recommender frameworks, for the most part concentrating on planning new calculations for suggestions. An application creator who wishes to add a proposal framework to her application has an extensive assortment of calculations available to her, and must settle on a choice about the most proper calculation for her objectives. Regularly, such choices depend on examinations, contrasting the execution of various hopeful recommenders. The creator can then choose the best performing calculation, given auxiliary imperatives. Moreover, most scientists who propose new suggestion calculations additionally think about the execution of their new calculation to an arrangement of existing methodologies. Such assessments are commonly performed by applying some assessment metric that gives a positioning of the hopeful calculations (for the most part utilizing numeric scores).

At first most recommenders have been assessed and positioned on their forecast power and their capacity to precisely anticipate the client's decisions. Notwithstanding, it is presently broadly concurred that precise expectations are significant however deficient to send a decent suggestion motor. In numerous applications individuals utilize a proposal framework for more than a definite expectation of their tastes. Clients may likewise be keen on finding new things, in quickly investigating various things, in protecting their security, in the quick reactions of the framework, and numerous more properties of the communication with the proposal motor. We should consequently recognize the arrangement of properties that may impact the accomplishment of a recommender framework with regards to a particular application.

### 2.6.2 Five Problems of Recommender Systems

Underneath, five issues which exist in proposal frameworks, are clarified [249]:

**1. Absence of Information**

Maybe the greatest issue confronting recommender frameworks is that they require a considerable measure of information to adequately make proposals. It's no fortuitous event that the organizations most related to having fantastic proposals are those with a considerable measure of customer client information: Google, Amazon, Netflix, and Last.fm.

**2. Modifying Information**

Paul Edmunds, CEO of 'clever proposals' organization remarked that frameworks are normally "one-sided towards the old and experience issues demonstrating new". A case of this was blogged by David Reinke an asset and group for design aficionados. David noticed that "past conduct [of users] is not a decent instrument in light of the fact that the patterns are continually evolving". Obviously an algorithmic methodology will think that its troublesome if not difficult to stay aware of design patterns. Most mold tested individuals - for that classification - depend on trusted style cognizant loved ones to prescribe new garments to them. David Reinke went ahead to say that "thing suggestions don't work in light of the fact that there are just an excessive number of item properties in design and every trait (think fit, value, shading, style, fabric, brand, and so forth) has an alternate level of significance at various times for the same customer." He pointed out however that social recommenders might have the capacity to "fathom" this issue.

**3. Modifying User priorities**

Again proposed by Paul Edmunds, the issue here is that while today I have a specific expectation when scanning e.g. Amazon - tomorrow I may have an alternate expectation. An exemplary case is that one day I will skim Amazon for new books for myself, yet the following day I'll be on Amazon looking for a birthday present for my sister (really I got her a present card, yet that is unimportant).

**4. Casual things**

About the $1 Million prize offered by Netflix for an outsider to convey a cooperative separating calculation that will enhance Netflix's own particular proposals calculation by 10%, it is noticed that there was an issue with flighty motion pictures. The kind of motion picture that individuals either love or detest, for example, Napoleon Dynamite. These kind of things are hard to make proposals on, on the grounds that the client response to them has a tendency to be differing and flighty.

**5. This matter is Complicated**

It takes a great deal of variables to do even the most straightforward proposals and it is envisioned the variables just begin to expose what's underneath. So far just a modest bunch of organizations have truly gotten suggestions to an abnormal state of client fulfillment - Amazon, Netflix (despite the fact that obviously they are searching for a 10% change on their calculation), Google are a few names that spring to mind. However, for those chosen few examples of overcoming adversity, there are many different sites and applications that are as yet attempting to locate the enchantment equation for prescribing new items or substance to their clients.

### 2.6.3 Role of Social Networks in recommendation systems

The late rise of online social networks (OSNs) gives us a chance to examine the part of social impact in recommender frameworks [18]. With the expanding notoriety of Web 2.0, numerous OSNs, for example, Myspace.com, Facebook.com, and Linkedin.com have risen. Individuals in those systems have their own particular customized space where they not just distribute their memoirs, pastimes, interests, online journals, and so on., additionally list their companions. Companions or guests can visit these individual spaces and leave remarks. Companions can be characterized as any two clients who are associated by an unequivocal social connection. We characterize quick companions as those companions who are only one bounce far from each other in a social network diagram, and far off companions as companions who are numerous jumps away.

OSNs give stages where individuals can put themselves on display and keep up associations with companions. As OSNs keep on gaining more prominence, the phenomenal measure of individual data and social relations enhance sociology research where it was once restricted by an absence of information.

### 2.6.4 Aim of Recommender Systems

Recommender frameworks turned into an essential and practically basic piece of websites [245] Besides, the inconceivable number of them is connected to e–commerce. Jeff Bezos, CEO of Amazon.com, said: "On the off chance that I had 3 million clients on the Web, I ought to have 3 million stores on the Web". Why do individuals trust that personalization and suggestions are a vital piece of e–commerce? The point of these frameworks is to help the potential purchasers to pick the fitting item to purchase, with the goal that they can be seen as choice emotionally supportive networks. Then again, they serve as the advertising help for the e–commerce stores since they build the engaging quality of the offer.

The principle objectives of the recommender frameworks are:

- To adapt to data over-burden
- To help all clients (new, successive, and rare) to settle on choices what items to purchase, which news to peruse next, which film merits viewing, and so on.
- To change over onlookers to purchasers

- To assemble believability through group and keep up the unwaveringness of the clients
- To welcoming clients to return
- To upgrade e–commerce deals and cross–sell

The initial two things show why the RS are critical from the purchaser perspective. As a matter of first importance, they are extremely valuable instrument that adapt to the data over-burden. The recommender frameworks empower to choose a little subset of things, from a huge number of items, that appears to fit the clients' needs and inclinations. In spite of the fact that it is verging on difficult to foresee absolutely the clients' needs, such arrangement of recommendations constrains the quantity of decisions. Moreover, by confining the quantity of recommended items, these sorts of frameworks individuals to decide, what things to purchase, which news to peruse next or which motion picture merits watching, much speedier than by the consistent look through.

Whatever is left of the specified above things demonstrate that RS can be seen as the promoting instruments since they improve e–commerce deals. As it was said some time recently, these frameworks can individuals to discover the items that they need to have. Subsequently, this encourages to change over the general population who just watch to the purchasers. At the point when buyers purchase things that are prescribed by the framework, the extra things can be proposed keeping in mind the end goal to expand the cross–sell. This prompts constructing and keeping up the faithfulness of the clients, besides, it urges the client to return what's to come. In the Internet and e–commerce where the quantity of contenders is high, this element is an urgent favorable position of the recommender frameworks.

The point of the considerable number of objectives that were pinpointed above is to fulfill the client. The reason is straightforward. The inquires about demonstrate that it is significantly less costly to keep a present client than to locate another one. In addition, the disappointed client has a tendency to grumble about item or administration to twice the same number of individuals as fulfilled clients will educate positive things regarding the administration or item. Furthermore, RS should be as high effectiveness as could be expected under the circumstances so as to expand their ROI (Return on Investment). In any case, the proposals ought to exist as well as should be applicable. The issue that can show up is too high number of false–positive proposals, which are characterized as recommendations that were made for the clients, despite the fact that they sometimes fall short for them. Taking everything into account, the objectives of the proposals can be accomplished just if the created recommendations are pertinent.

The fundamental point of a recommender framework is to furnish its clients with an arrangement of customized, appropriate suggestions for things [78]. As contribution for such a recommender framework, three principle sources can be misused: (i) the arrangement of clients of the framework and their profile portraying their inclinations and attributes, (ii) the arrangement of things accessible for suggestion and their individual elements and metadata and (iii) the arrangement of client thing relations derived from the two past sources. With a specific end goal to evaluate a client's inclinations, either express or understood input of this specific client might be utilized to make a client profile her inclinations. Unequivocal input is assembled from client appraisals for things, similar to the 5-star rating framework for books and different things on Amazon which are a decent marker for whether a specific client loved a specific thing or not. Certain input depends on more unpretentious, for the most part behavioral data as the client does not need to enter criticism expressly. The way that a client e.g. bought or bookmarked a specific thing or essentially tapped the depiction of a specific thing can be gathered and utilized as verifiable input.

A suggestion assignment can formally be characterized as takes after [250]:

Give U a chance to be an arrangement of all clients of a framework and let I be the arrangement of all things inside the framework (each of these things might be prescribed). The utility capacity s (u, i) can then be utilized to gauge how helpful and appropriate a specific thing i ϵ I may be for a specific client u ϵ U. The capacity is characterized as s: U × I → R where R is a non-negative whole number or genuine number (generally inside a given extent) speaking to a utility worth. It is critical to note that s (u, i) is not accessible for every last combine (u, i) (e.g., because of data sparsity on account of another client who has not indicated any inclinations yet). Subsequently, just a subset of the U × I space is indicated. The missing utility qualities for things the client has not effectively or inactively evaluated yet must be anticipated.

Taking into account these definitions, Mobasher determines the profile of a specific client u ϵ U as a n-dimensional vector of requested sets (n being the quantity of things in I), where the utility capacity s doles out an utility worth to things i ϵ I for every client u (see Equation 2-1) [251].

$$u(m) = ((i_1, s(u, i_1)), (i_2, s(u, i_2)), \ldots, (i_m, s(u, i_m)))$$

*Equation 2-1 Calculation of vector u*

On account of a framework with express evaluations, the capacity s (u, i) can be seen as a rating capacity, as indicated by Mobasher. I.e. all things the client has effectively appraised highlight the thing's evaluating as the utility worth for the comparing thing. In this way, the client is described by her inclinations.

Mobasher portrays the arrangement of all client profiles as UP, the arrangement of n-dimensional client profile vectors (which might be vacant in the dispatch period of the framework).

The assignment of a recommender framework can then be characterized as a mapping of clients U to an arrangement of suggested things P(I) which are processed in view of a subset of other client profiles P(UP). The suggestion capacity REC is accordingly of the structure REC: P(UP) × U → P(I).

The arrangement of all client profiles frames a client thing lattice [s (uk, ij)] m×n, where the sections of the m × n network are the utility qualities for the separate things, as can be found in Figure 2-10. This network demonstrates a client thing lattice for unequivocal client criticism in a 0 to 5 stars rating framework. Interestingly, a client thing lattice beginning from verifiable criticism which highlights just boolean qualities (e.g., for a client having gone by a specific item depiction page or not) can be found in Figure 2-11. As can be seen, such networks are ordinarily exceptionally meager as it is not really feasible for a client on Amazon to visit or rate all things accessible.

$$\begin{array}{cc} & \begin{matrix} i_1 & i_2 & \dots & \dots & i_{n-1} & i_n \end{matrix} \\ \begin{matrix} u_1 \\ u_2 \\ \vdots \\ \vdots \\ u_{m-1} \\ u_m \end{matrix} & \begin{pmatrix} 1 & & & 4 & & \\ & & 2 & 3 & & \\ & 3 & & & & 2 \\ 0 & & & 5 & & \\ 0 & & & 5 & & 1 \\ & & & 2 & 0 & \end{pmatrix} \end{array}$$

*Figure 2-10 User-item Matrix for Explicit User Feedback*

$$\begin{array}{cc} & \begin{matrix} i_1 & i_2 & \dots & \dots & i_{n-1} & i_n \end{matrix} \\ \begin{matrix} u_1 \\ u_2 \\ \vdots \\ \vdots \\ u_{m-1} \\ u_m \end{matrix} & \begin{pmatrix} 1 & & & 1 & & \\ & & 1 & 1 & & \\ & 1 & & & & 1 \\ 1 & & & 1 & & \\ 1 & & & 1 & & 1 \\ & & & 1 & 1 & \end{pmatrix} \end{array}$$

*Figure 2-11 User-item Matrix for Implicit User Feedback*

In view of these definitions, the suggestion assignment for a specific client uk can be formalized as appeared in Equation 2-2, where up is a subset of client profiles significant for the proposal errand.

REC (up, uk) = { i | s(uk, i) = arg maxi є I s(uk, i) }

*Equation 2-2 the suggestion assignment for a specific client uk*

From this condition it turns out to be clear that the undertaking is to discover things which this specific client has not already evaluated going for amplifying the utility worth for these things as indicated by some utility capacity s. The capacity arg max is utilized to decide the most extreme utility worth for the given things.

Henceforth, the suggestion undertaking goes for discovering things which achieve a most extreme utility quality, i.e. to locate the most reasonable and valuable things for a specific client which have not been evaluated yet by the agreeing client. For the most part, the top-x most valuable things are at last prescribed to the client.

### 2.6.5 Recommendation Techniques

With a specific end goal to satisfy the already depicted proposal errand, different methodologies for the suggestion of things have been created all through the most recent two decades. The calculations and methodologies hidden run of the mill recommender frameworks are arranged into the accompanying classes (as in [252][253]) and depicted in Table 2-8:

- Collaborative filtering
- Content-based recommender systems
- Demographic recommender systems
- Knowledge-based recommender systems
- Hybrid recommender systems

| Technique | Background data | Input data | Technique |
|---|---|---|---|
| **Collaborative** | Ratings from *C*[1] of items in *S*[2] | Ratings from *c*[3] of items in *S* | Identify users in *C* similar to *c* and extrapolate from their ratings of *s*[4] |
| **Content–based** | Features of items in *S* | Ratings of user *c* of items in *S* | Generate a classifier that fits user's *c* rating behaviour and use it on *s* |
| **Demographic** | Demographic information about *C* and their ratings of items in *S* | Demographic information about *c* | Identify users that are demographically similar to *c* and extrapolate from their ratings of *s* |
| **Knowledge–based** | Features of items in *S*. Knowledge of how these items meet user's needs | A description of user's *c* needs or interests | Infer match between *s* and user's *c* needs |
| **Hybrid** | Combination of two methods of RS | Both from collaborative and content-based | Implement both methods separately and combine the outputs of these methods |

*Table 2-8 The division of recommendation techniques*

1 C in the table alludes to set of all clients in the particular store whose inclinations are known
2 S shows to all things over which proposal can be made
3 c alludes to the client for whom the suggestion is made

4 s is the single thing for which client's u inclinations ought to be anticipated

Adomavicius et al. propose three classifications of recommender frameworks, to be specific community sifting, content-based and half and half methodologies. Jannach et al. preclude the demographic methodology [250][254]. Nonetheless, keeping in mind the end goal to give a complete review about the diverse proposal strategies, we recognize five distinctive suggestion approaches as recorded previously.

In the accompanying segments, these diverse methodologies going for prescribing things to a particular client are presented. As shared sifting is by a long shot the most prominent methodology, it is talked about in more detail.

#### *2.6.5.1 Demographic Recommender Systems*

Demographic recommender frameworks make utilization of demographic information about its clients, similar to age, sex, conjugal status and so on. Such demographic data can be abused to make classes of clients for which proposals can be registered.

The work by Pazzani portrays a structure which goes for prescribing sites to clients. Other than both substance and synergistic suggestion approaches, additionally a demographic recommender framework is introduced in this work [255]. This recommender framework endeavors to concentrate demographic elements (for this situation age, sex and zone code) from the client's sites and influence this data for making relations between things (sites) and classes of clients, which are shaped in view of their demographic elements. In view of these relations, suggestions are registered. Be that as it may, demographic recommender frameworks have not been exceptionally famous in exploration as demographic classes just can give a harsh personalization of proposals.

#### *2.6.5.2 Context-aware Recommender Systems*

Numerous past methodologies have been trailed by expecting the presence of certain relevant components, for example, time, area, and the acquiring reason, that distinguish the setting in which suggestions are given [256]. We accept that each of these logical elements can have a structure; the Time variable, for instance, can be characterized regarding seconds, minutes, hours, days, months, and years. The arrangement of connection that we propose in this article depends on the accompanying two parts of logical components: what a recommender framework may think about these relevant elements, and how context oriented elements change after some time.

A recommender framework can have diverse sorts of information, which may incorporate the accurate rundown of all the significant variables, their structure, and their qualities, about the relevant components. Connection mindful recommender frameworks (CARS) create more applicable proposals by adjusting them to the particular relevant circumstance of the client.

#### 2.6.5.3 Content-based filtering

Content-based recommender frameworks are engaged with respect to suggesting comparative and likewise things [78][250][253][254][257]. A substance based recommender framework processes suggestions by discovering things which are like the thing inclinations of the client (customarily the inclinations are displayed in a client profile). Schafer et al. call this thing to-thing relationship [258]. With respect to the profile of the client, the things a client beforehand enjoyed or evaluated are utilized to manufacture a profile for the client which speaks to her interests and inclinations. The genuine proposals are construct exclusively in light of the components of the things and the concurring similitude of things (rather than thing based community oriented separating where client profiles are utilized to decide the likeness of things). For a book recommender framework, such components might be the class, the writer or the subject of the book. For the calculation of closeness, distinctive methodologies have been encouraged previously. An extremely straightforward methodology is to utilize the catchphrases of the components related to specific things and process a set-based closeness coefficient of the sets (e.g. the Dice coefficient) of watchwords for things with a specific end goal to register the likeness of two things. A famous methodology for substance based recommender framework is displaying the elements of two things as vectors where the segments of the vector speak to the thing's elements (the segments of the parts may likewise be weighted to speak to the significance of specific components).

The comparability of two things is registered by deciding the cosine of the edge between these two component vectors. One illustration is the Fab framework, which goes for prescribing sites to clients [259]. It utilizes the most imperative words speaking to the agreeing sites as highlight vectors which are utilized to register the similitude of the concurring sites.

The fundamental preferred standpoint of substance based recommender frameworks is that these methodologies don't need to adapt to the cool begin issue as the components of the recommendable things are surely understood. In any case, evaluations and inclinations of different clients inside the framework shape an important wellspring of pertinent data which is not misused at all in substance based recommender frameworks.

#### 2.6.5.4 Collaborative filtering

Collaborative filtering (CF) goes for prescribing things to a specific client in light of her past activities (buy of a specific item, utilization of certain music tracks, unequivocal rating of specific things, and so on.) and past activities of other, comparable clients. The term community oriented sifting was initially presented in 1992 by Goldberg et al. for Tapestry, which was utilized to cooperatively channel connections of corporate messages [260].

Shardanand and Maes state that a cooperative separating framework is a mechanization of the verbal standard [261]. This rule fundamentally depicts that suggestions are registered in view of things which were appraised by different clients who have indicated comparative inclinations. Subsequently, CF methods go for prescribing things taking into account the client profiles of different clients as clients having indicated comparable interests in the past might be a decent hotspot for suggestions.

CF calculation depends on a lattice comprising of all clients, things and the clients' appraisals for things. Proposals grids are alluded to as client thing frameworks throughout this proposition. Such a network may contain either express or understood rating data. Case for client thing frameworks have been appeared in Figure 2-10 respectably Figure 2-11.

On a basic level, two methodologies for synergistic sifting can be recognized: memory-based and demonstrate based methodologies. Both of these methodologies are portrayed in the following segments.

#### 2.6.5.4.1 Memory-Based CF

Memory-based methodologies for CF make utilization of the whole client thing framework and proposals are figured specifically in light of the data accessible from this grid. By and large, two sorts of suggestion undertakings can be processed: client based sifting and thing based separating. Client based sifting goes for coordinating the present client to different clients in the lattice, whose inclinations are utilized to make forecasts about the conceivable inclinations of the present client. By extricating every new thing from the most comparable clients, an arrangement of proposals is made which is then positioned and exhibited to the client. [250] characterizes the errand of memory-based strategies as foreseeing the rating for a specific item by accumulating the appraisals of the top-k most comparative clients inside the framework of kNN. For the most part, a weighted collection capacity (e.g., the normal of all evaluations weighted by the similitude of the two clients) is connected for the calculation of the rating forecasts. In this way, the things with the most astounding anticipated appraisals are prescribed. Concerning the comparability of clients, [262] and [263] state that for the most part either a relationship based likeness (e.g., Pearson connection coefficient) or a cosine-similitude measure in view of client profile vectors is connected. With respect to thing based sifting, the objective is to locate the most comparable things taking into account the client profiles of the clients who appraised these things [264]. The most comparable things are positioned and in this way given to the client. Two things are comparative if the same clients have appraised these things comparably or verifiably indicated enthusiasm for these two things. Once more, the similitudes are figured by either Pearson relationship coefficient or the cosine closeness of the concurring vectors.

#### 2.6.5.4.2 Model-Based CF

As opposed to memory-based CF, show based CF goes for taking in an anticipating model for a specific client in light of a client thing grid. This learning of a model in view of preparing information is done disconnected. At the season of calculation of suggestions, the precomputed model is connected. Concerning the models basic the calculation, Breese et al. propose two distinctive probabilistic models: group models and Bayesian systems [263]. The bunch model goes for processing a likelihood esteem evaluating how likely it is that a client has a place with a specific group or class of clients. Taking into account this probabilistic attribution to a specific class (highlighting certain basic inclinations), suggestions are figured. The Bayesian system approach models the CF issue as a Bayesian system where every hub speaks to a thing and the concurring inclinations. Taking into account this system, a Bayesian system is found out keeping in mind the end goal to have the capacity to anticipate inclinations for specific things.

Memory-based CF is a computationally exceptionally concentrated errand as this methodology registers proposals in light of the entire grid. The versatility of such methodologies is to some degree restricted as the span of the fundamental network develops with the quantity of clients and things inside the framework. Interestingly, demonstrate based CF are better ready to adapt to adaptability issues as models are prepared once and after that, these models can be connected. Notwithstanding, these models require a preparation stage ex bet which is not the situation for memory-based CF.

The principle issue with which both CF approaches need to adapt to is sparsity of information. As most clients customarily just have appraised a little part of every single accessible thing, the client thing grid is generally tremendously scanty.

Particularly amid the underlying period of a framework where barely any client appraisals are accessible, the nature of the proposals because of the absence of accessible data for the calculation of suggestions is not fulfilling. This is likewise the case for new things which have not been appraised at all and clients who have not (certainly or expressly) expressed any inclinations yet. This issue is likewise alluded to as the cold-start issue [254].

### *2.6.5.5 Knowledge-based Recommender Systems*

Knowledge-based recommender systems are engaged with respect to complex client requires and how to discover things coordinating these client requirements [252][254][253]. The more perplexing a client need is, the more outlandish it is to discover other similar clients keeping in mind the end goal to figure suggestions in view of their past inclinations and activities.

In this way, information based recommender frameworks don't depend on other client's encounters and activities, they are fairly in view of a thinking and surmising errand taking into account requirements, examples and tenets. Additionally, practical learning with respect to how certain things meet the client's prerequisites is utilized. Guidelines and examples are characterized ahead of time by a space master and accordingly abused for suggestions [258]. Knowledge-based recommender frameworks are for the most part specifically identified with conversationally inspiring the client's needs and inclinations.

This considers narrowing down the quantity of things comparing to the client's inclinations like feature based inquiry. This can likewise be accomplished by effectively approaching the client for his inclinations as to specific elements of the coveted thing. Consider an auto recommender framework. Individuals don't purchase autos frequently and henceforth, data about the need of a specific client is meager and in this manner, cooperation to evoke her inclinations is required. In light of this picked up learning, tenets, examples and imperatives are connected to process appropriate proposals.

Knowledge-based recommender frameworks are for the most part used to supplement the deficiencies of another kind of a recommender framework. E.g., for a substance based recommender framework or CF a learning based recommender framework may manage the icy begin issue as no past client activities must be available in the framework with a specific end goal to have the capacity to figure proposals.

In any case, the creation and definition of the principles, examples and imperatives hidden such a recommender framework is exceptionally costly and the learning of an area master is required. Moreover, such frameworks are fairly resolute and static as changes with respect to recommendable things require a past (re)definition of principles, examples and limitations.

#### *2.6.5.6 Hybrid recommender systems*

Taking into account the recommender framework approaches presented in Sections 2.6.5.1 - 2.6.5.5, hybrid recommender frameworks encourage different diverse recommender methodologies and join these to one single, mixture methodology. The fundamental objective of such a blend is to misuse the benefits of the distinctive methodologies while in the meantime keeping away from the burdens of a specific methodology by the upsides of another. In the event that e.g., no profile data around a specific client is available in a recommender framework in light of communitarian separating, demographic methodologies can be utilized to give a fundamental profile to the client until the client gave the required data by e.g. rating certain things. In [265], a cross breed methodology of collective sifting and substance based separating is utilized to give customized hypermedia content (interlinked content, pictures, sounds or recordings) to the clients of the framework. In this framework, the utility estimation of things is characterized by the crossing point of the Gaussian bends showing the client's inclinations and the qualities of a specific thing. A broad study about half breed recommender frameworks is given by Burke [252].

The fundamental objective of hybrid techniques is to maintain a strategic distance from the deficiencies of the two identified strategies content-based and collaborative filtering [245]. There are various approaches to join the content–based and collaborative filtering. The best known are:

- Implement both techniques independently and consolidate the yields of these strategies
- Add a portion of the content–based qualities to the collective separating
- Add a portion of the community attributes to the content–based separating
- Develop one model that applies both content–based and community attributes

These two methodologies supplement each other and add to alternate's viability.

### 2.6.6 Role of recommender systems in E-commerce

Recommender frameworks upgrade E-trade deals in three approaches [266]:

**Changing over Browsers into Buyers:**

Guests to a Web website frequently look over the webpage without buying anything. Recommender frameworks can help buyers discover items they wish to buy.

**Incremental Cross-sell:** Recommender frameworks enhance cross-offer by proposing extra items for the client to buy. On the off chance that the proposals are great, the normal request size ought to increment. Case in point, a site may prescribe extra items in the checkout procedure, in light of those items as of now in the shopping basket.

**Making fidelity:** In reality as we know it where a site's rivals are just a tick or two away, picking up purchaser unwaveringness is a crucial business methodology. Recommender frameworks enhance dedication by making a worth included relationship between the site and the client. Locales put resources into finding out about their clients, use recommender frameworks to operationalize that learning, and present custom interfaces that match purchaser needs. Customers reimburse these locales by coming back to the ones that best match their necessities.

The more a client uses the proposal framework – showing it what he needs – the more steadfast he is to the site. "Regardless of the possibility that a contender has to assemble precisely the same, a client ... would need to invest an excessive measure of time and vitality educating the contender what the organization definitely knows". Making connections between buyers can likewise build faithfulness, for customers will come back to the site that suggests individuals with whom they will get a kick out of the chance to communicate.

### 2.6.7 Limitations of classical approaches

**Rating data is very sparse**

A rating matrix is a space for keeping the rates which are acquired by client conclusions. Typically, the rating framework is excessively meager, making it impossible to discover adequately numerous co-evaluated things, in this manner prompting incorrect expectations.

**Cold start problem**

The cold start issue is most predominant in recommender frameworks. In particular, it concerns the issue that the framework can't draw any derivations for clients or things about which it has not yet accumulated adequate data. Commonly, a recommender framework looks at the client's profile to some reference qualities. These qualities might be from the data thing (the substance based methodology) or the client's social surroundings (the cooperative separating approach).
The cold start issue would suggest that the client needs to commit a measure of exertion utilizing the framework as a part of its "moronic" state – adding to the development of their client profile – before the framework can begin giving any insightful proposals.
The cold start issue is additionally displayed by interface specialists. Since such a specialist regularly take in the client's inclinations certainly by watching designs in the client's conduct – "viewing over the shoulder" – it would require significant investment before the operator may play out any adjustments customized to the client. And still, after all that, its help would be restricted to exercises which it has once watched the client taking part in.

**Generality bias**

This constraint is the inclination for prominent things to be prescribed all the more habitually. Conventional suggestion framework procedures experience the ill effects of the issue of ubiquity predisposition as a consequence of which the things prescribed need curiosity in them. The need today is, to fuse novel things in the prescribed rundown of things, as well known things are evident and need curiosity.

## 2.7 RELATED WORKS

In the following international journal, conference papers and theses, the descriptions, results and conclusions related to this thesis are presented:

In [77] the authors have proposed the architecture of a social recommendation system based on the data from microblogs. The social recommendation system is conducted according to the messages and social structure of target users. The similarity of the discovered features of users and products has been calculated as the essence of the recommendation engine. A case study has included to present how the recommendation system works based on real data that collected from Plurk.

In [78] the authors have proposed to facilitate recommender systems to create and maintain a common structure within collaborative social media platforms aiming at improving search performance. For this purpose, two different recommender systems for two showcase platforms are presented. The first recommender system provides recommendations for structuring information within a semistructured information system whereas the second recommender systems is a hashtag recommender system for microblogging services.

In [267] the authors have supposed that new book has been published and the publishers would like to recommend this new book to a group of users. In order to save time and money of publishers and users and instead of sending recommendations everywhere and to everyone, it proposes a semantic social recommendation algorithm which sends recommendations about this book to the only interested users. The proposal connects the users via collaborative social network in order to use semantic representation of users and products. It combines the social network analysis measures with the semantics of users and products in one semantic social recommendation algorithm.

In this thesis [268] the authors have proposed a framework to address an important challenge in the context of the ongoing adoption of the “Web 2.0” in science and research, often referred to as “Research 2.0”. A growing number of people are connected via online social networks and thus get indirect access to a huge amount of new ideas. To enrich and verify social data, the research links such content in social networks to existing open data provided by the online community. It has used semantic technologies (RDF, SPARQL), common ontologies and Linked Data (like DBpedia) to extract the data about scientific conferences out of context of microblogs. It has identified users related to each other based on entities such as topics (tags), events, time, locations and persons (mentions). The application, Researcher Affinity Browser, introduces the concept “affinity” that exposes the implicit proximity between entities and users based on the content users produced.

In this paper [79] the main target is having an advertisement according to user favorites and interests by mining his/her interactions in digital social networks semantically. Briefly, in this method, social network users are categorized based on the topic exchanges by them in the network, these topics discovered by mining of flowing data in that environment, considering that these topics shows the user willing, finally relevant advertisements will be represented to them. In fact, by finding people that have more chance to accept the desired advertisement, system will have more success over traditional method at lowered cost.

In this thesis [269] the authors have utilized data mining and machine learning techniques to address the problems of finding interesting information. In particular, the researcher designs and develops recommender systems to aid the user in contributing to the Social Semantic Web. A framework has been proposed that maps domain properties to recommendation technologies. This framework provides a systematic approach to find the appropriate recommendation technology for addressing a given problem in a specific domain. Second, the existing graph-based approaches have been improved for personalized tag recommendation in folksonomies. Third, some machine learning algorithms have been developed for recommendation of semantic relations to support continuous ontology development in a social semantic web environment. Finally, a framework has been introduced to analyze different types of potential attacks against social tagging systems and evaluate their impact on those systems.

In [80] the authors have proposed to annotate learning resources with folksonomy-derived description metadata for personalization to context profiles of users. A semantic model for folksonomy was formulated to integrate controlled vocabularies in folksonomy. It not only reduces reliance on domain experts in annotating learning resources but also opens new avenues for more comprehensive resource description, compared to numerical ratings in resource recommendation algorithm. The working principle of the resource annotation and recommendation mechanism is demonstrated via a prototype system implemented in a social network environment. A pilot user study shows that learners are positive about the system in terms of aspects apart from accuracy.

In this work [270] a hybrid recommender system based on knowledge and social networks is presented. Its evaluation in the cinematographic domain yields very promising results compared to state-of-the-art solutions.

In this paper [18] the authors have presented a new paradigm of recommender systems which can utilize information in social networks, including user preferences, item's general acceptance, and influence from social friends. A probabilistic model is developed to make personalized recommendations from such information. Data are extracted from a real online social network, and the analysis of this large dataset reveals that friends have a tendency to select the same items and give similar ratings. An improvement of the performance of the system is proposed by applying semantic filtering of social networks, and validated its improvement via a class project experiment. In this experiment it is demonstrated how relevant friends can be selected for inference based on the semantics of friend relationships and finer-grained user ratings. Such technologies can be deployed by most content providers.

In this paper [271] a model as OCSO was characterized as semantic web diagram to depict finely social articles and their afferent social action. At that point the utilization of spreading initiation calculations to reenact client intrigue and perform complex suggestion in multidimensional informal communities has been characterized.

In the study [272] a novel semantic-based friend recommendation system for social networks was presented, which recommends friends to users based on their life styles instead of social graphs. By taking advantage of sensor-rich smartphones, Friendbook discovers life styles of users from user-centric sensor data, measures the similarity of life styles between users, and recommends friends to users if their life styles have high similarity. Inspired by text mining, a user’s daily life as life documents was modeled, from which his/her life styles are extracted by using the Latent Dirichlet Allocation algorithm. Furthermore, a similarity metric to measure the similarity of life styles between users, and calculate users’ impact in terms of life styles with a friend-matching graph was proposed. Upon receiving a request, Friendbook returns a list of people with highest recommendation scores to the query user. Finally, Friendbook integrates a feedback mechanism to further improve the recommendation accuracy. The Friendbook has implemented on the Android-based smartphones, and evaluated its performance on both small-scale experiments and large-scale simulations. The results show that the recommendations accurately reflect the preferences of users in choosing friends. Both evaluation of Friendbook and the web application of the proposed framework (SARSIS) are compared, then with more precision and lower recall in SARSIS, it was concluded that the current framework has a better efficiency.

In the study [273] the researchers proposed a recommendation system which utilizes semantic web technology and healthcare social networking to provide personalized recommendation to speed patient recovery and improve healthcare outcomes. Extensive experiments have been performed to evaluate the performance of the system. The results demonstrated the effectiveness of the proposed strategy. With a comparison of MAE in this work and MAE earned in SARSIS, it is realized that with lower MAE in SARSIS, the current study's framework has a better efficiency.

In the paper [274] an intelligent semantics-based privacy configuration system was proposed, named SPAC, to automatically recommend privacy settings for SNS users. SPAC learns users' privacy configuration patterns and make predictions by utilizing machine learning techniques on users' profiles and privacy setting history. To increase the accuracy of the predicted privacy settings, especially in the context of heterogeneous user profiles, they enhanced privacy configuration predictor by integrating it with structured semantic knowledge in the SNS. This, in turn, allows SPAC to make inferences based on additional source of knowledge, resulting in improved accuracy of privacy recommendation. their experimental results have proven the effectiveness of our approach. By a comparison between the accuracy of SPAC and SARSIS, on average, SPAC showed a better accuracy.

In this work [275] a Movie Recommendations system as FilmTrust for Semantic Web-based Social Networks was introduced. FilmTrust is a website that integrates social networks with movie ratings and reviews. Using FOAF-based social networks augmented with trust ratings, the site computes predictive movie ratings based on the ratings of trusted people in the network. Preliminary results show these results to be significantly more accurate than other predictive ratings in certain situations. This demo will show the FilmTrust website, demonstrate cases where the predictive movie ratings are successful, and illustrate its RDF and OWL output for those interested in the backend.

In this paper [276] the authors concerns the members recommendation in social networks. The proposed approach is based on the semantic and social collaborative filtering technique (SSCF). In this approach, the formation of communities of users is based on the calculation of similarities between them and includes semantic and social dimensions. These two dimensions are respectively related to the calculation of similarity between the user and (1) his close friends and (2) those he trusts. A recommender system based on this approach has been developed. The preliminary experiments results show the importance of integrating the semantic and social dimensions in the recommendation process.

In the work [277] two recommendation algorithms, called Node-Edge-Based and Node-Based recommendation algorithms are presented. These algorithms are designed to recommend items to users connected via a social network. The algorithms are based on three main features: a social network analysis measure (degree centrality), the graph searching algorithm (Depth First Search algorithm), and the semantic similarity measure (which measures the closeness between an input item and users). The researchers apply these algorithms to a real dataset (Amazon dataset) and they compare them with item-based collaborative filtering and hybrid recommendation algorithms. their results show good precision as well as good performance in terms of runtime. Moreover, Node-Edge-Based and Node-Based algorithms search a small part of the dataset, compared to item-based and hybrid algorithms.

In the article [278] social network analysis and semantic user profile are combined to provide a new semantic-social recommendation, featuring a two-stage process that relies on a simple formalization of semantic user preferences that contains the user's main interests, and heuristically explores the social graph. Given a recommendation request concerning a product, the semantic-social recommendation algorithm compares the user preferences, which are found in the exploration path, with the product preferences by referencing them to domain ontology. Experiments on real-world data from Amazon, examine the quality of our recommendation method as well as the efficiency of our recommendation algorithms.

In this paper [279] the SITIO approach is presented, discussed its forthcomings and introduce BLISS, its proof-of-concept implementation, a biological literature social ranking system used in the bioinformatics field.

In this paper [280] exploiting the possibilities that Web 2.0 offers, a recommender system that goes one step further to increase coupon redemptions is proposed, by utilizing social networks as tools to add extra information to the system and reach new consumers.

In [281] the authors have proposed a system that provides users with a service for recommending categories by utilizing social folksonomy with clustered data. Further, a method to reduce the dimension of vectors by removing meaningless words in the contents is introduced.

In this paper [282] a context-aware advertising framework is proposed that takes into account the relatively static personal interests as well as the dynamic news feed from friends to drive growth in the ad click-through rate. To meet the real-time requirement, they first propose an online retrieval strategy that finds k most relevant ads matching the dynamic context when a read operation is triggered. To avoid frequent retrieval when the context varies little, they propose a safe region method to quickly determine whether the top-k ads of a user are changed. Finally, they propose a hybrid model to combine the merits of both methods by analyzing the dynamism of news feed to determine an appropriate retrieval strategy. Extensive experiments conducted on multiple real social networks and ad datasets verified the efficiency and robustness of our hybrid model.

The authors in [283] have proposed spatial social union (SSU), an approach of similarity measurement between two users that integrates the interconnection among users, items and locations. The SSU-aware location sensitive recommendation algorithm is then devised. The researchers evaluate and compare the proposed approach with the existing rating prediction and item recommendation algorithms subject to a real-life data set. Experimental results show that the proposed SSU-aware recommendation algorithm is more effective in recommending items with the better consideration of user’s preference and location.

In [284] the authors have presented a recommendation approach based on quantified social tie strength. They propose an unsupervised method to estimate tie strength from user similarity and online social interactions. Then the approach improves the social recommendation with quantified social tie strength. Experiments are made on a large book rating dataset from Douban.com. The experimental results show that this approach can effectively improve the recommendation accuracy.

In this work [285] in order to make it possible to employ social recommendation methods in those non-social information websites, a general framework to construct a homophilybased implicit social network is proposed by utilizing both the rating and comments of items given by the users. Their scalable framework can be easily extended to enhance the performance of any recommender systems without social network by replacing the homophily-based implicit social relation definition. They propose four methods to extract and analyze the implicit social links between users, and then conduct the experiments on Amazon dataset. Experimental results show that our proposed methods work better than traditional recommendation methods without social information.

In this paper [286] a joint social-content recommendation framework is designed to suggest users which videos to import or re-share in the online social network. In this framework, they first propose a user-content matrix update approach which updates and fills in cold user-video entries to provide the foundations for the recommendation. Then, based on the updated user-content matrix, they construct a joint social-content space to measure the relevance between users and videos, which can provide a high accuracy for video importing and re-sharing recommendation. They conduct experiments using real traces from Tencent Weibo and Youku to verify their algorithm and evaluate its performance. The results demonstrate the effectiveness of their approach and show that their approach can substantially improve the recommendation accuracy.

In this paper [287] the social recommendation problem on the basis of psychology and sociology studies is investigated, which exhibit two important factors:

individual preference and interpersonal influence. they first present the particular importance of these two factors in online behavior prediction. Then they propose a novel probabilistic matrix factorization method to fuse them in latent space. They further provide a scalable algorithm which can incrementally process the large scale data. They conduct experiments on both Facebook style bidirectional and Twitter style unidirectional social network data sets. The empirical results and analysis on these two large data sets demonstrate that their method significantly outperforms the existing approaches.

In this paper [288] a recommendation framework AOPUT contributed to recommend both content and friend list for sharing to users leveraging content and social information in SNSs. It consists of two recommendation components: Recder and ShareAider. Recder generates content recommendations by connecting users with common interests. An improved Jaccard similarity is proposed to improve the Collaborative Filtering (CF) recommendation quality. ShareAider recommends a friend list to users when they want to share content with their friends. CF method and a social-based method are compared and the combination of them are explored to achieve better results. AOPUT is evaluated on a real world social network. The experimental results show that (1) Recder can provide better recommendation quality than the traditional CF method thanks to the improved Jaccard similarity; (2) social-based method performs better than CF since the sharing behavior in SNSs are highly dominated by users' social preferences, and the combination of these two methods performs better than each of them individually.

In this study [289] a social recommendation algorithm for top-N recommendation using only implicit user preference data is proposed. In particular, they model users' consumption behavior in the social network with Bayesian networks, using which it is possible to infer the probabilities for items to be selected by each user. They develop an Expectation Propagation (EP) message-passing algorithm to perform approximate inference efficiently in the constructed Bayesian network. The original proposed algorithm is a central scheme, in which the user data are collected and processed by a central authority. However, it can be easily adapted for a distributed implementation, where users only exchange messages with their directly connected friends in the social network. This helps further protect user privacy, as users do not release any data to the public. They evaluate the proposed algorithm on the Epinions dataset, and compare it with other existing social recommendation algorithms. The results show its superior top-N recommendation performance in terms of recall.

In the study [290] a research model and tested it in an online experiment using Facebook data is developed for the use case of online news with 193 participants. The structural equation model results show that a strong tie relationship has positive influence on the value of a recommendation. The credibility of the recommending person and the recommendation's media source affect the value of a recommendation as well.

In this work [291] it is highlighted how iSoNTRE (the intelligent Social Network Transformer into Recommendation Engine) addresses this challenge by transforming the GPSN into useful information for recommendation based on middle layer of domain concepts. iSoNTRE overcomes the cold start problem on new users and items. It has been evaluated over Twitter, on new users, recommending offers as a kind of SLiR, results showed that iSoNTRE succeeded in recommending good offers with 14% of click on recommended offers, which is high compared to general open rate in social media, especially when we have nothing about users and we are recommending SLiR resources.

In this paper [292] the social-based recommendation algorithms on heterogeneous social networks is investigated and proposed Hete-CF, a social collaborative filtering algorithm using heterogeneous relations. Distinct from the exiting methods, Hete-CF can effectively utilise multiple types of relations in a heterogeneous social network. More importantly, Hete-CF is a general approach and can be used in arbitrary social networks, including event based social networks, location based social networks, and any other types of heterogeneous information networks associated with social information. The experimental results on a real-world dataset DBLP (a typical heterogeneous information network) demonstrate the effectiveness of our algorithm.

In [293] the authors have proposed a social recommendation algorithm for use in a research social network environment. The social recommendation algorithm proposed combines the concepts of a relationship ontology and item-based collaborative filtering (CF). While the network setup in social networking sites can accurately reflect the social landscape of its users, it is much harder to detect the importance or strength of any one link. They therefore propose an extension to their recommendation algorithm which makes use of the idea of co-presence communities to increase the relevance of the recommendations. A co-presence community can be detected from with data collected from Bluetooth-enabled mobiles. Detection of a co-presence community can help determine the nature and importance of the social links between participating members.

In this paper [294] a novel solution for cross-site cold-start product recommendation proposed, which aims to recommend products from e-commerce websites to users at social networking sites in "cold-start" situations, a problem which has rarely been explored before. A major challenge is how to leverage knowledge extracted from social networking sites for cross-site cold-start product recommendation. They propose to use the linked users across social networking sites and e-commerce websites (users who have social networking accounts and have made purchases on e-commerce websites) as a bridge to map users' social networking features to another feature representation for product recommendation. In specific, they propose learning both users' and products' feature representations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websites using recurrent neural networks and then apply a modified gradient boosting trees method to transform users' social networking features into user embeddings. They then develop a feature-based matrix factorization approach which can leverage the learnt user embeddings for cold-start product recommendation. Experimental results on a large dataset constructed from the largest Chinese microblogging service SINA WEIBO and the largest Chinese B2C e-commerce website JINGDONG have shown the effectiveness of their proposed framework.

In this study [295] a case study of recommending YouTube videos to Facebook users based on their social interactions is conducted. They first measure social interactions related to YouTube videos among Facebook users. They observe that the attention a video attracts on Facebook is not always well-aligned with its popularity on YouTube. Unpopular videos on YouTube can become popular on Facebook, while popular videos on YouTube often do not attract proportionally high attentions on Facebook. This finding motivates them to develop a simple top-k video recommendation algorithm that exploits user social interaction information to improve the recommendation accuracy for niche videos, that are globally unpopular, but highly relevant to a specific user or user group. Through experiments on the collected Facebook traces, they demonstrate that their recommendation algorithm significantly outperforms the YouTube popularity based video recommendation algorithm as well as a collaborative filtering algorithm based on user similarities.

In this paper [296] a new group recommendation method is proposed, which combines topic identification and social networks for group recommendation. In detail, they firstly identify different topical sub-groups by topics in social networks. Secondly, different user factors are used to calculate the user influence (including individual and social) on the topical sub-groups, which can depict the topical subgroup characteristics in different points of view. Experimental results demonstrate that the proposed method can improve the prediction accuracy of the group recommendation.

In this paper [297] a social recommendation method based on interest propagation is proposed, which focuses on the interest influence by other user interest in social networks. Their method combines the user-item click information, social relationship, as well as social action information between users in social networks for recommendations. The effectiveness of the proposed method is evaluated on Sina Weibo, one of the most popular social network sites in China. The experimental results show that the proposed method outperforms the traditional collaborative filtering based method.

In this paper [298] a new framework of online social recommendation from the viewpoint of online graph regularized user preference learning (OGRPL) is presented, which incorporates both collaborative user-item relationship as well as item content features into an unified preference learning process. They further develop an efficient iterative procedure, OGRPL-FW which utilizes the Frank-Wolfe algorithm, to solve the proposed online optimization problem. They conduct extensive experiments on several large-scale datasets, in which the encouraging results demonstrate that the proposed algorithms obtain significantly lower errors (in terms of both RMSE and MAE) than the state-of the-art online recommendation methods when receiving the same amount of training data in the online learning process.

## 2.8 SUMMARY

The development of the Semantic Web has been addressed as the incremental progression of the present Web in which the Web substance is enhanced with express importance of its semantics thusly engaging PC systems to enhance use of that substance to help and enhance our regular activities. The most significant gainful parts of the Semantic Web are ontologies. Ontologies are formally portrayed, shared conceptualizations of a specific data range. They are presented alongside the other standard ideas, which license them to be combined, shared, easily extended and used to semantically clarify different sorts of benefits, for instance, Web pages, documents, and intelligent media content.

By using such ontological establishment, diverse unmistakable savvy organizations can be gathered, for instance, semantic web crawlers which give more critical and specific results than traditional internet searchers interfacing Web content as showed by the available semantic comments, and thus unraveling its significance concerning the essential ontologies.

The Social Semantic Web (SSW) stays for another perspective for making, managing and sharing information through joining the advancements and approachs from the Semantic Web and the Social (Web 2.0). The past goes for giving information an "inside and out portrayed hugeness, better enabling PCs and people to work in joint effort" through the importance of ontologies. The latter is a phase for social and group exchange where customers meet, group up, work together and specifically make substance and offer data through, e.g., wikis, sites, photo and video sharing organizations. SSW has ascended by mixing the best of these two universes, through combining the essential associations for portraying and sorting out information with the social instruments for making and sharing data. On SSW, socially made and shared data prompts the development of unequivocal and semantically-rich learning representations.

The web has transformed into a nonstop creating source that tends to augment progressively. The improvement of this particular medium attracts the thought of promoters as a more beneficial source to get buyers.

There are a few meanings of recommender frameworks. One of the first was shown by Paul Resnick and Hal R. Varian in 1997. They promise that "in a standard recommender system, people give recommendations as inputs, which the structure then sums and arranges to fitting recipients". These systems are by and large described similarly as their helpfulness as the structures or administrators that propose the things to the customers who purchase things on e–commerce regions. The recommender systems help the client to settle on the decision what to buy.

With a particular final objective to fulfill the effectively portrayed proposition errand, diverse techniques for the recommendation of things have been made all through the latest two decades. The estimations and techniques concealed ordinary recommender structures are orchestrated into the going with classes:

- Content-based recommender systems
- Collaborative filtering
- Knowledge-based recommender systems
- Demographic recommender systems
- Hybrid recommender systems

# SECTION III: Proposals and contributions

# CHAPTER 3

# 3. METHODOLOGY

## 3.1 INTRODUCTION

A thorough analysis of the state-of-the-art in recommendation systems revealed that existing recommendation frameworks have been designed based on the composition of previous approaches. In most cases, some elementary techniques have been used to build enhanced recommenders which, indeed, boosted the precision results. Even though recommendation standard methods have evolved over time, the gathered experience during the recent years proves that by composing some standard methods into one integrated method, it is possible to overcome some of the past limitations and problems. However, there are still many challenges that need to be addressed in this area. One of the most obvious problems which the users of social networks are dealing with is that the results of the recommendation engine of those systems are not actually aligned with their interests and so the recommended products or services are usually irrelevant. Furthermore, no feedback is taken into consideration in order to enrich the quality and precision of the recommendations.

In this chapter, a detailed description of the main characteristics of the proposed framework, along with relevant technical aspects, calculations and formulas, is put forward. The provided rates and coefficients have been used in the formulas based on the previous works and also the impact amount of each element of the method. It means, the more an element has influence in producing the recommendations, the more value each coefficient has. Usually different methods have used various algorithms to implement the logic of their specific logic that each of them have their own particular specifications and policy to demonstrate their structure.

At first, the operational mechanism of the framework will be illustrated by demonstrating a visualized solution, including of the main components of the methodology. Later, each component of the method will be explained in details along with their own specifications and their role in the framework.

As it will be discussed in the next parts, the advantage of the current framework will be explained by introducing a novel solution which will be added to the composed solution. To prove the validity of the suggested method, the framework has been implemented on the real platforms. An available social network has been selected as the case study, a web software system as a client application has been developed to implement the methodology, a comprehensive DBMS has been chosen as a dataset for storing the needed data, an efficient programming language has been considered to deploy the software system and an instance has been provided as an example to prove the efficiency of the framework. Later, the security of the model will be considered which will be implemented in two levels.

In total, a more precise vision of the purpose in this study has been developed which can help achieve more information about the provided solution. It was important that the suggested methodology would be comprehensive and efficient as much as possible. For this purpose, even some techniques of artificial intelligence have been used to enrich the performance of the framework.

## 3.2 THE FRAMEWORK

The most of recommendation systems are using one or mix of two techniques as a hybrid technique, while the suggested framework in this research utilizes the benefits of four techniques. Furthermore, some technical novelties totally empowered this framework. In the proposed model, main components of the framework have been illustrated. The framework contains of entities and the relations between them. This model shows how a user starts working with the software platform. This procedure will continue with the users' activities and finally with observing the recommended products by the software platform. The complete process can repeat again later so as to enrich the results of the proposed model by making some feedbacks through the users' activities. According to the given information, the platform works as a knowledge based recommendation system, since it works on the users' information and extracts knowledge from this information in the form of recommendations to present to the users.

The suggested framework of recommendation system includes some components as Figure 3-1:

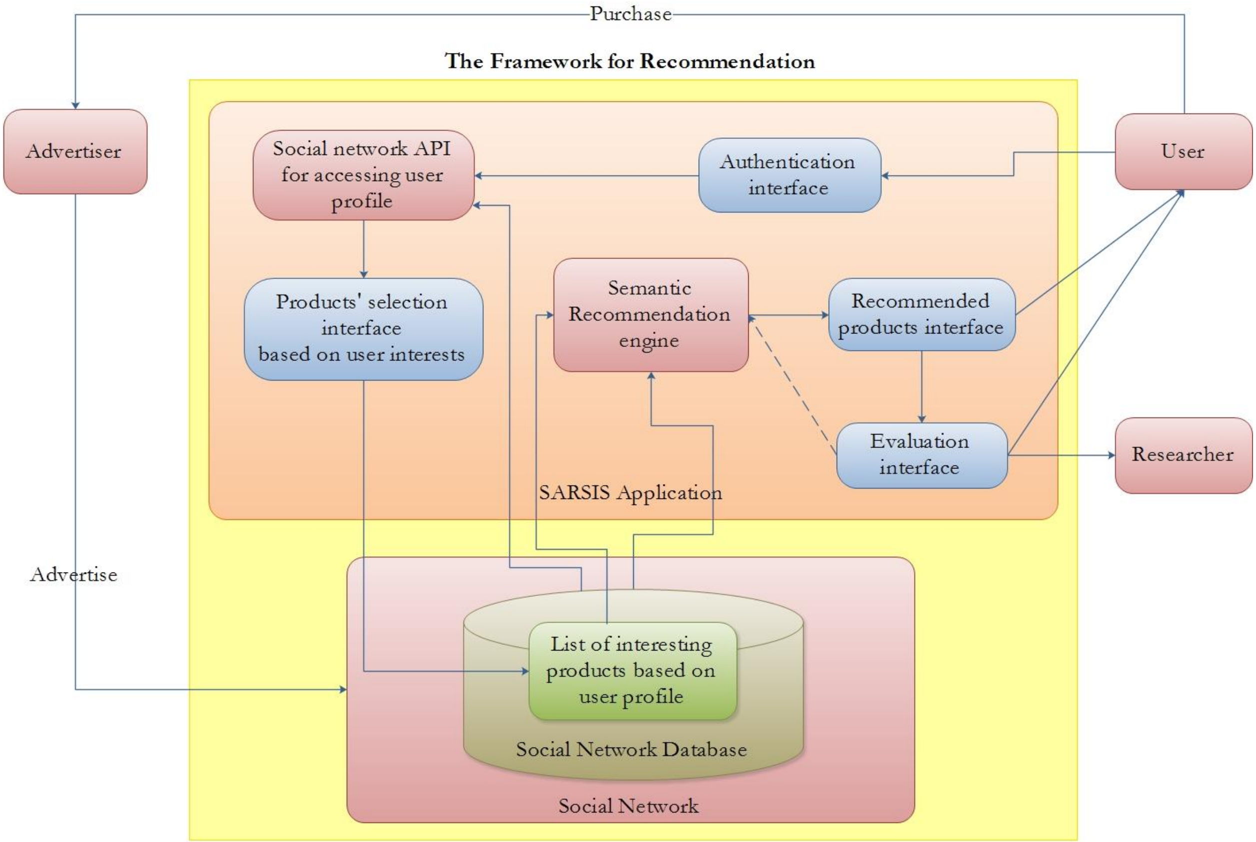



*Figure 3-1 suggested framework for recommendation*

To represent the structure of utilized system in this study, the fundamental parts of the system alongside their operability are clarified as a rule. As appeared in Figure 3-1, first of all the **user** tries to enter the space of the application through the user **authentication interface**. This element of the framework in the illustrated structure can be executed by a login page.

One of the most popular mechanisms which can be used in web applications is single sign on (SSO) system. In the beginning of the user activity, first the user is requested to login to the software system. On the client application, the authentication interface is shown along with requesting a username and password from the user. After a successful operation of SSO, the user is qualified to enter the framework. At that moment, utilizing an API gave by the social network, the user can access to the required information of the social network, including the data of products and the producers.

In this progression, it is feasible for the user by an interface to choose the interesting items which are fascinating for this user. In fact, a **product's selection interface** is used in this step which works based on the user interest. In this step, it is possible for the user to select a producer from a list of producers which can be retrieved from the API, then based on the selected producer, the user can pick a product from a list of products whose producer was chosen in the previous step. By client's movement, **a list of interesting items is arranged and stored in the dataset** of the framework. **The**

**semantic recommender framework engine** which is mindful to produce the recommendations for the clients, plans suggestions taking into account the client's inclinations which can be extricated by client's exercises.

The **recommended items** are given to the client by a particular interface. At that point clients can choose about the recommended items and buy their coveted items from the sponsor corporation, whether they are coordinated to clients' inclinations or not. Then again, the data which are set up after suggestion procedure is given to the **researcher** to assess the framework's execution using an **evaluation interface**. Besides, there is the likelihood of utilizing suggested items as a part of instance of fulfillment affirmation by the client, and inject them to the framework to build the precision of the system for the future use. In this condition, we can watch extraordinary results by the framework's preparation.

The **social network** component of the framework is containing of a **database** which has all necessary data for being used in the presented framework. The mentioned data is including the user account information, products, producers and some other important details. Later, a list of interesting products based on the users' profile and their activities will be calculated, generated and stored in the appropriate dataset. Consequently, this important information will be used for providing recommendations to the current user.

On the other hand, **advertisers** give the information of their advertisements to the social network so that in case of presenting advertisements, this information will be shown to the users through the framework and particularly by the software system of the proposed model. Furthermore, by users' activities, it is possible for the users to see the recommended advertisements, then users can select their desired products based on their preferences. The logic of the framework has been designed with considerations of users' interests in order to provide accurate recommendations as much as possible.

Finally, the users can purchase the selected products based on their interests from the company which has provided the advertisements. This proposed model can help users to have their best choices for purchasing because during their activities on the social network, the framework can detect the users' preferences based on the users' activities. As a result, the recommended products will be more attractive for the users according to this fascinating model. The other important outcome of this benefit is that when the advertisements are enough interesting for the client, they will be more motivated to buy the products from the company which has promoted their products on the social network. As a result, the business of the company would be more successful by choosing appropriate advertisements which have been recommended by the proposed model.

### 3.2.1 Preliminary User Activity

The web application of the framework should be ready to use. The users try to login using an authentication interface by entering their username and password. It is necessary to predict of joining to the social network by using the capability of registering. After a successful checking, they have access to social network and their profile. It is possible for the users to search the products, see and select the products, and rate them to express their interest about the specific products. A list of interesting products is saved to the social network's database.

### 3.2.2 Semantic Recommendation Engine

In the next step, based on the users' interests, the recommendation engine uses a hybrid recommendation method to find the products which can be best suited to users' preferences. This compound method overcomes the classical approaches with limitations mentioned in the section 2.6.7. The hybrid recommendation method is composed of four recommendation techniques mentioned in 2.6.5.1 – 2.6.5.5 as described here: The users with the similar demographic attributes, probably have similar expectations, taste and interests [299]. Therefore, as one part of the framework, a demographic filtering method has been considered to select users' probable interests. Hence first, for the current logged in user, the engine calculates the similarity of other registered users to the current user based on users' demographic information. The rate of similarity is counted by the number of equal demographic related information which is saved in each user profile during the registration process. For example, considering demographic related fields in the table of Users, including "`demolocation`", "`demoage`", "`demolooking`", "`demorelig`" and "`demoedu`", if two fields out of these five fields have the same values between two users, the rate of similarity of these users is 0.4. A variable as "`demorate`" and consequently an array of users' similarities as "`arrSimilarUsersDemo`" is considered for this calculation. The more `demorate` is, the more similarity between the current user and the other user to be kept in each element of `arrSimilarUsersDemo`. Thus, the meaningful similarities between users are computed. Likewise, the engine uses the other variables as "`ctxrate`" and "`arrSimilarUsersCtx`" for the Context-aware section of the recommendations. The table "Interests" is used for maintaining of users' interests. According to the gathered information in 3.2.1. by the user as their interests, the engine is prepared to do several calculations and then find the recommendations.

To demonstrate how the rates, indicating users' activities, are stored in a Rates' matrix, the Figure 3-2 is depicted as below:

| Rates | | | | | | | |
|---|---|---|---|---|---|---|---|
| Products / Users | Produtct 1 | Produtct 2 | Produtct 3 | Produtct 4 | Produtct 6 | . . . | Produtct n |
| User 1 | | 2 | | | 4 | 1 | 5 |
| User 2 | 5 | | 1 | 3 | | 2 | |
| ... | | | | | | | |
| User m | | 3 | | 4 | 1 | | 3 |

*Figure 3-2 Example of Rates' matrix*

There is a question that how the rates of Rates' matrix are calculated? For answering this question, we consider that there are five levels of interests to the products which for each level of the users' activity, we assign a number to a level and each level of interest is determined by the users' activity. The variable "`irank`" meaning interest rank is assigned for the user interest level.

If the product is searched by the user, "`irank`" is set to 5. In this research, searching can be used as a level of interest. If the product is shown and browsed for the user along with its details, "`irank`" is set to 4. It means that the user pays more attention to the product rather than just searching. Next, if the user interested in the product, there is a possibility to rate the product from 1 to 3 which can set "`irank`" from 3 to 1 respectively.

There is another variable as "`trank`" meaning product rank which refers to the rank of the advertised product in social network related to a specific producer. This rank is populated from users' activities on social networks and indicates the popularity of the product among users of social network. Two linear formulas are used to calculate the final rate as "`itrate`" for each product which is qualified to be recommended to the current user. These formulas are shown in Equation 3-1 for the Demographic part and Equation 3-2 for the Context-aware part of recommendations [300].

```
itrate = arrSimilarUsersDemo[i, 1] / (5 * irank * trank)
```

*Equation 3-1 Calculation of itrate for the Demographic part of recommendations*

```
itrate = arrSimilarUsersCtx[i, 1] / (6 * irank * trank)
```

*Equation 3-2 Calculation of itrate for the Context-aware part of recommendations*

The value of `itrate` operates as a score for the product to show the strength of interest for the user. It is calculated using `irank`, `trank`, users' similarity, and a fixed ratio depending to the recommendation techniques which is 5 for demographic and 6 for context-aware recommender method. The labels "`demo`" and "`ctx`" are assigned to recommendations by demographic and context-aware methods and this information along with the username of the current user are added to the table as "`Recs`". To prevent saving repetitive recommendation in these two methods, before entering the recommendation to database, all of previous recommendations which have been made before by these two methods, are replaced by the new recommendations.

Up to now, the engine has provided a list of products to be recommended as advertisements by two techniques. But there are still two recommendation techniques remained to be considered. For content-based filtering, the mentioned aspect of semantic in 2.2.5. is used to generate appropriate recommendations which mines semantic relation between concepts in the domain of products.

For the first part of the recommendations with content-based filtering, a list of the current user's interesting products whose irate from table "Interests" is between 1 and 3 was prepared. The tags brought from social network and were set for the products in this list, were extracted. Thus these tags which were related to the interesting products for the current user were found. It means that the current user prefers the products containing these tags. Then the tags were sorted in descending order based on their frequency in the recent list. So the more tags preceded, the more current user interested in. for each tag, three products from the table "products" for which the user has not visited and the products which have the most "`trank`" value earned from social network and contain the tag, were selected.

For the second part of the recommendations with content-based filtering, the music tracks which were rated by the current user were considered. Then, the top three of the most popular other music tracks distinguished by "rank" of tracks with the same artist were found.

The product details along with the label "`cb`" indicating content-based recommended products, username of current user and "`itrate`" which was calculated using Equation 3-3 were added to the table "Recs":

```
itrate = 1 / (6 * trank)
```

*Equation 3-3 Calculation of itrate for Content-based Filtering part of recommendations*

For the collaborative filtering recommendations, the method of kNN was used to find the most similar users. First, registered users along with their interesting products were considered. This information was used from the table "`Interests`". Accordingly, the matrix "`rates`" as `rates [userid, productid]` was defined and the rate values given to the products by the users were entered to this matrix based on users' interests or their activities. The reason for choosing the table "`Interests`" as the dataset for filling matrix rates' values is that the rates computable by recommendation engine, could not be calculated by the products for which no user had rated before. Therefore, the products without any rate value by any user were not taken into consideration [301]. The set of items rated by each both users in the matrix rates should be considered. The matrix of "w" containing all weights or the amounts of closeness of users together as $w_{a,u}$ was prepared according to the Equation 3-4 [301]:

$$w_{a,u} = \frac{\sum_{i \in I} (r_{a,i} - \overline{r}_a)(r_{u,i} - \overline{r}_u)}{\sqrt{\sum_{i \in I} (r_{a,i} - \overline{r}_a)^2 \sum_{i \in I} (r_{u,i} - \overline{r}_u)^2}}$$

*Equation 3-4 Calculation of $w_{a,u}$*

where I is the set of products rated by each both users, $r_{u,i}$ is the rating given to product i by user u, and $\overline{r}_a$ is the mean rating given by user u. Each of unrated elements of the matrix "w" was calculated by the Equation 3-5 [301]:

$$p_{a,i} = \overline{r}_a + \frac{\sum_{u \in K} (r_{u,i} - \overline{r}_u) \times w_{a,u}}{\sum_{u \in K} w_{a,u}}$$

*Equation 3-5 Calculation of $p_{a,i}$*

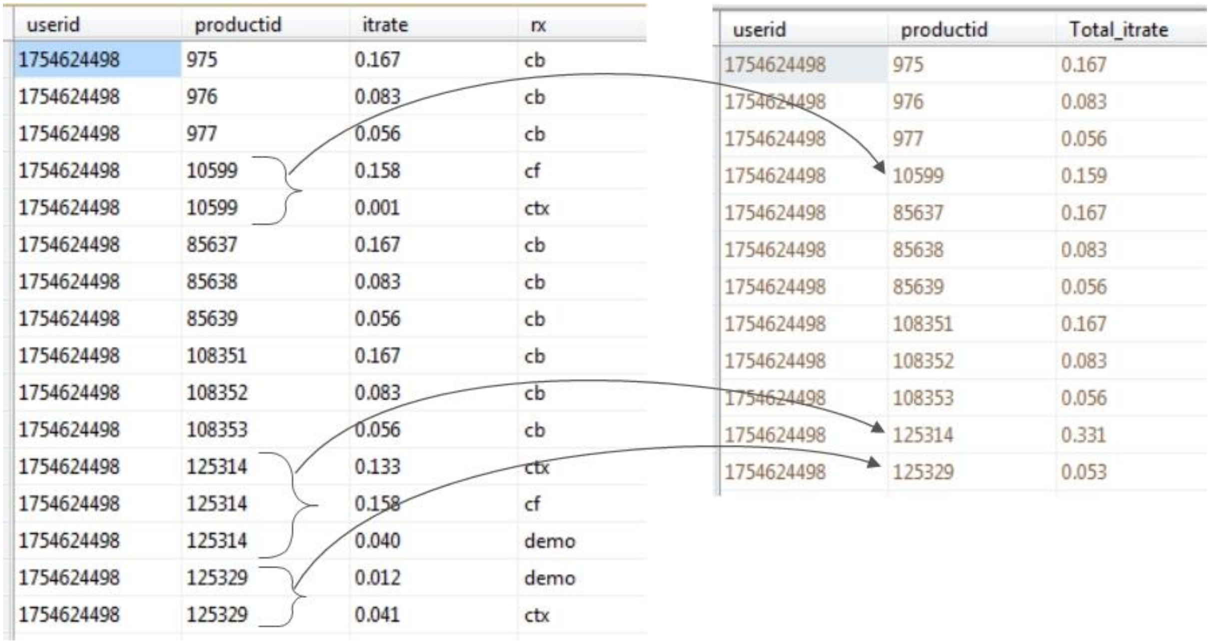
where $p_{a,i}$ is the prediction for the active user a for product i, $w_{a,u}$ is the similarity between users a and u, and K is the neighborhood or set of most similar users. If the collaborative filtering recommendations had been previously saved to the table "Recs", they were replaced by these up-to-date recommended products. For each user, the highest element values, which were calculated by the last equation, were added to the table "Recs" along with the other details containing username, product id, the label "cf" indicating the recommendation technique and "`itrate`" which was computed by the Equation 3-6:

```
Itrate = rates[useridindex, productidindex] / 10
```

*Equation 3-6 Calculation of itrate for Collaborative Filtering part of recommendations*

Finally, among total prepared recommendations through four techniques from the table "`Recs`", a list of top ten products with highest "`itrate`" values, is shown to the current user.

One interesting novelty in this recommendation engine is that a group of calculated recommended products for the current user which even could be found repeatedly but estimated by different techniques with different "`itrate`" values, are aggregated based on "`itrate`" values. For this purpose, a SQL operation of "Group by" `userid` and `productid` is done along with considering a total "`itrate`" of recommendations using four techniques as `Total_itrate`. As a result, the earned records of the recent dataset potentially show the probable interest rates of the user about the products. Finally, these records should be sorted by `Total_itrate` in order to find the best recommendations. In other words, the method of recommendation is ranking-based. See Figure 3-3. The top most records of the recent dataset will be shown to the user as the recommendations.



| userid | productid | itrate | rx |
|---|---|---|---|
| 1754624498 | 975 | 0.167 | cb |
| 1754624498 | 976 | 0.083 | cb |
| 1754624498 | 977 | 0.056 | cb |
| 1754624498 | 10599 | 0.158 | cf |
| 1754624498 | 10599 | 0.001 | ctx |
| 1754624498 | 85637 | 0.167 | cb |
| 1754624498 | 85638 | 0.083 | cb |
| 1754624498 | 85639 | 0.056 | cb |
| 1754624498 | 108351 | 0.167 | cb |
| 1754624498 | 108352 | 0.083 | cb |
| 1754624498 | 108353 | 0.056 | cb |
| 1754624498 | 125314 | 0.133 | ctx |
| 1754624498 | 125314 | 0.158 | cf |
| 1754624498 | 125314 | 0.040 | demo |
| 1754624498 | 125329 | 0.012 | demo |
| 1754624498 | 125329 | 0.041 | ctx |

| userid | productid | Total_itrate |
|---|---|---|
| 1754624498 | 975 | 0.167 |
| 1754624498 | 976 | 0.083 |
| 1754624498 | 977 | 0.056 |
| 1754624498 | 10599 | 0.159 |
| 1754624498 | 85637 | 0.167 |
| 1754624498 | 85638 | 0.083 |
| 1754624498 | 85639 | 0.056 |
| 1754624498 | 108351 | 0.167 |
| 1754624498 | 108352 | 0.083 |
| 1754624498 | 108353 | 0.056 |
| 1754624498 | 125314 | 0.331 |
| 1754624498 | 125329 | 0.053 |

*Figure 3-3 a sample of table Recs and data aggregations*

So for each distinct product, its "`itrate`" is calculated using Equation 3-7:

$$\texttt{Total\_itrate} = \sum_{i=1}^{n}(itrate(i))$$

*Equation 3-7 Calculation of Total_itrate*

Where "n" at most can be 4, equal to the four used techniques and depends on count of calculated recommendations and "i" is referring to the number of each used technique.

Through recommended products interface, the users have the choice to make decision about the recommended products and rate them based on how far they are matched to the users' taste. With this feature, it is possible to arrange an evaluation for the framework.

## 3.3 CASE STUDY

The presented framework in the previous section is in general so that it can be applied for all social networks working for even other media like video or image. But for illustrating the framework and make it more clear, it is better to specialize and implement it over a social network to observe how the methodology works in a real platform and how is the quality of the framework for assessing its performance.

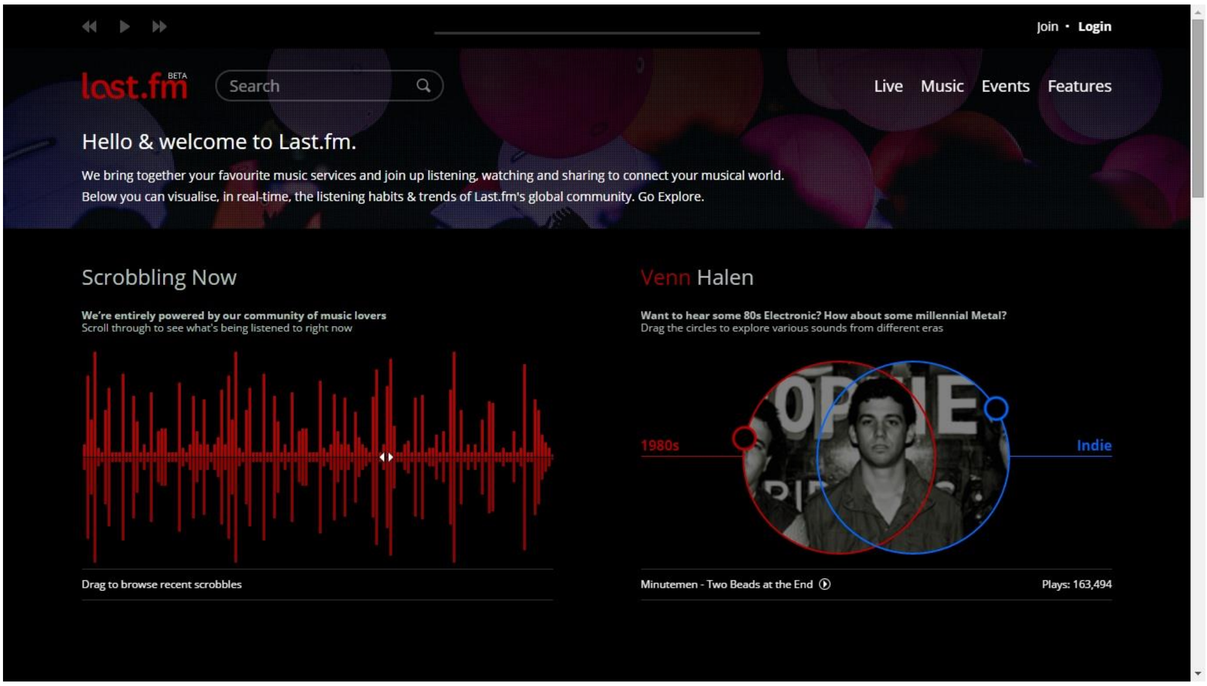



*Figure 3-4 Main page of Last.fm*

The social network Last.fm is selected for this section as a suitable case study. Last.fm is a music website, founded in the United Kingdom in 2002. See Figure 3-4 [302]. The site offers numerous social networking features and can recommend and play artists similar to the user's favorites. It also features a wiki system analogous to Wikipedia, wherein registered users can collaborate on hyperlinked information about tracks, releases (albums, etc.), artists, bands, tags, and record labels.

The reasons for choosing this social network as the case study of the framework are:

1) It is very famous and usual for people and it has numerous active users
2) There are tremendous amount of music track information enriched by semantic facilities
3) An easy to use and strong RESTful API to retrieve music track information

To make more clear about the API of Last.fm in terms of developing, its methods are taken in Table 3-1 [302]:

| | | |
|---|---|---|
| **Album** | **Chart** | Track.getTopTags |
| Album.addTags | Chart.getTopArtists | Track.love |
| Album.getInfo | Chart.getTopTags | Track.removeTag |
| Album.getTags | Chart.getTopTracks | Track.scrobble |
| Album.getTopTags | **Geo** | Track.search |
| Album.removeTag | Geo.getTopArtists | Track.unlove |
| Album.search | Geo.getTopTracks | Track.updateNowPlaying |
| **Artist** | **Library** | **User** |
| Artist.addTags | Library.getArtists | User.getArtistTracks |
| Artist.getCorrection | **Tag** | User.getFriends |
| Artist.getInfo | Tag.getInfo | User.getInfo |
| Artist.getSimilar | Tag.getSimilar | User.getLovedTracks |
| Artist.getTags | Tag.getTopAlbums | User.getPersonalTags |
| Artist.getTopAlbums | Tag.getTopArtists | User.getRecentTracks |
| Artist.getTopTags | Tag.getTopTags | User.getTopAlbums |
| Artist.getTopTracks | Tag.getTopTracks | User.getTopArtists |
| Artist.removeTag | Tag.getWeeklyChartList | User.getTopTags |
| Artist.search | **Track** | User.getTopTracks |
| **Auth** | Track.addTags | |
| Auth.getMobileSession | Track.getCorrection | User.getWeeklyAlbumChart |
| Auth.getSession | Track.getInfo | |
| Auth.getToken | Track.getSimilar | User.getWeeklyArtistChart |
| | Track.getTags | User.getWeeklyChartList |
| | | |
| | | User.getWeeklyTrackChart |

*Table 3-1 List of REST API methods in Last.fm*

In this case study, the methods "`tag.gettopartists`", "`artist.getinfo`", "`artist.gettoptracks`", "`tag.getsimilar`" and "track.gettoptags" have been used to retrieve needed information from Last.fm. These methods could help to get the information from the social network and design recommendation system properly. By the method "`gettopartists`" related to the object "`tag`", it was possible to get the top artists tagged by a specific tag, ordered by tag count, where Persian tags were considered as the domain of work for this framework. Using "`getinfo`" which works on the object "`artist`" it was possible to get the metadata for an artist including biography or photos of artists. The method "`artist.gettoptracks`" was used to get the top tracks by an artist on Last.fm, ordered by popularity. Using "`tag.getsimilar`" it is possible to search for tags similar to specific one which returns tags ranked by similarity, based on listening data. The method "`gettoptags`" which can be called on the object "`track`", was used to get the top tags for a specific track on Last.fm, ordered by tag count [303].

# 3.4 CLIENT APPLICATION

A web application for running the framework was developed. Regarding to the subject of the thesis, Semantically-enhanced Advertisement Recommender Systems in Social network, the name of SARSIS was chosen for the web application implementing the framework which is available online [304]. In this case the web application was developed in MS Visual Studio .NET and with the technology ASP.NET. The interface of the application has been designed in two languages: English and Persian which appropriate codes in all pages handle this facility.

On the page “Default.aspx”, the user tries to login as shown in Figure 3-5.

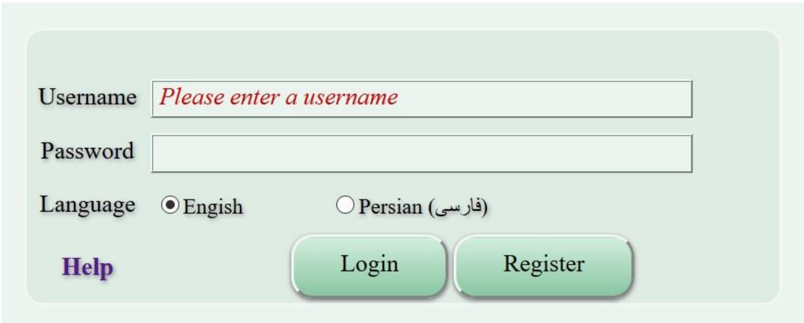



*Figure 3-5 Login Form on the Default.aspx*

If it is the first time that users try to login, it is necessary to register by pressing the “Register” button. Then, users enter their specifications and preferences by means of the page “Register.aspx” which is depicted in Figure 3-6.

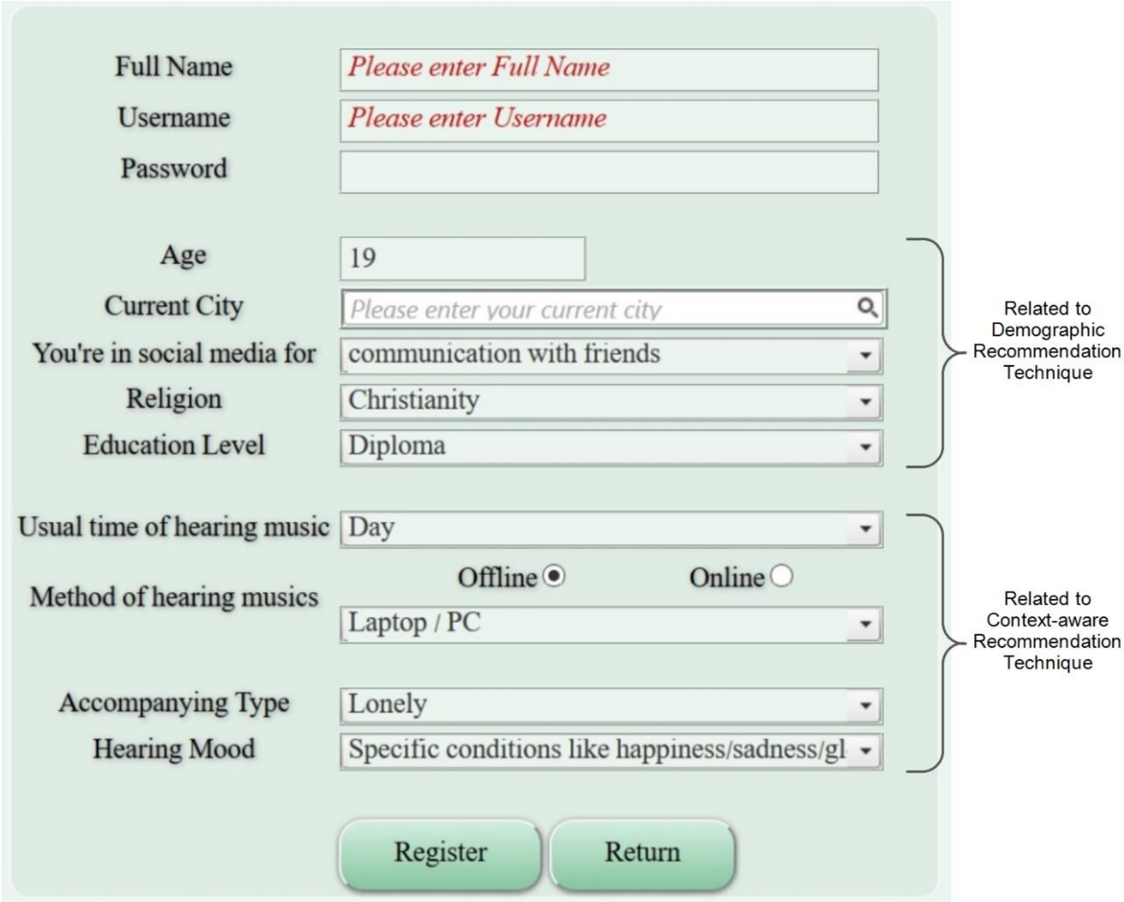



*Figure 3-6 Registration Form on the Register.aspx*

Users are redirected from “Register.aspx” to “Default.aspx” after a successful registration.

If users succeeded to be logged in, they visit the page “Main.aspx” as the principal place for their activities. See Figure 3-7.

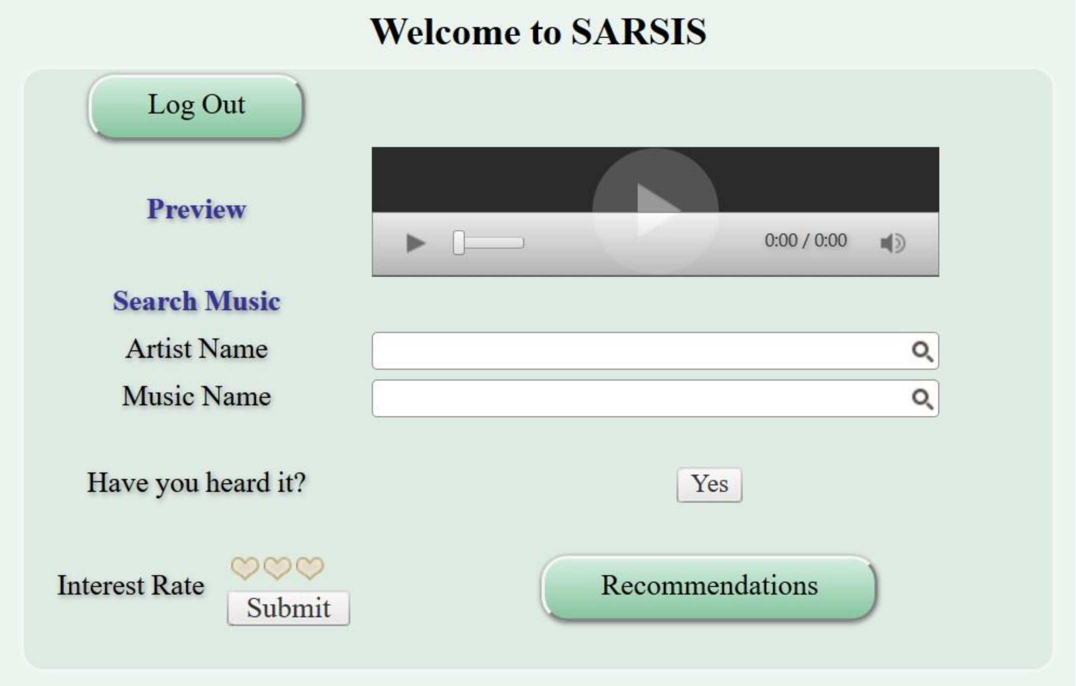



*Figure 3-7 Main Form on the Main.aspx*

On this page, users look for an artist and after selecting an artist from the list, they are able to select one of the music tracks performed by the selected artist. The "`irate`" of 5 is assigned to the interesting track of users once they select that track. If there is the possibility of listening to the selected track through the preview player or even users heard it before, they can express a positive answer to the question "Have you heard it?" and then the "`itrate`" of 4 is assigned to the track for users. Many websites including online music databases were reviewed, but among all of them, Spotify was selected as the best one to retrieve the source of music track previews, whereas Last.fm itself is using Spotify to preview tracks in its own website. In fact, not only Spotify contains the more comprehensive database of track previews rather than the other websites as checked, but also it is possible to get the link of track source easily. To get the source of tracks from Spotify a specific code was developed and appropriate hyperlinks of tracks were set as the "`source`" property of the player. Finally, users can rate the track from 1 to 3 based on their personal idea and after pressing submit button, the "`itrate`" of correspondingly 3 to 1 is assigned to the track. It is possible for the users to repeat this procedure and rate more tracks to express their opinion about the tracks.

Finally, it is the time to view the recommended tracks by pressing the related button. At this moment, users are redirected to the page "ShowRecs.aspx" which is shown in Figure 3-8.

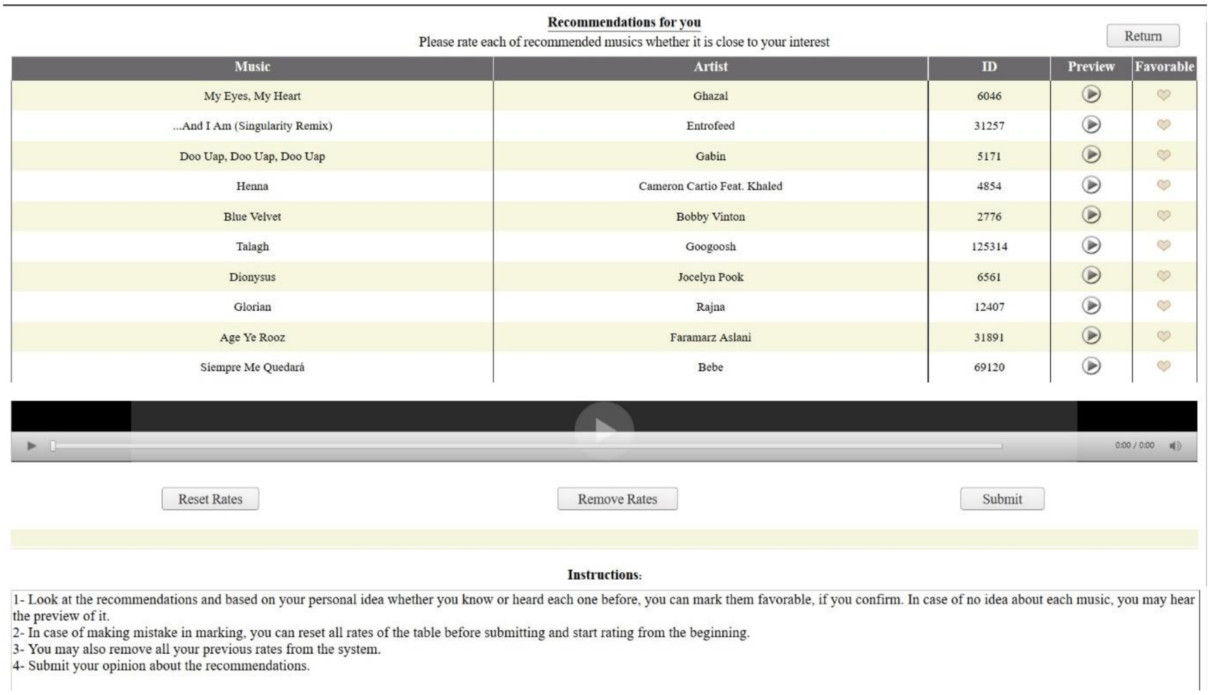



*Figure 3-8 Recommendations on the ShowRecs.aspx*

On this page, a list of recommendations is shown to the users. There is the possibility of playing the preview of each track. Moreover, users can like the recommended tracks.

There is an instruction for users as a guide how they can interact with the system. When users finish doing their likes to the recommendations, they have to submit their opinions by pressing "`Submit`" button. In case of making mistake in giving likes, it is possible to reset rates by pressing the button "`Reset Rates`" so that all of liked recommended tracks will be reset. If users had previously rated the tracks, they can press "`Remove Rates`" to eliminate them from the database.

As explained, a schematic of page navigation for this web application is shown in Figure 3-9:

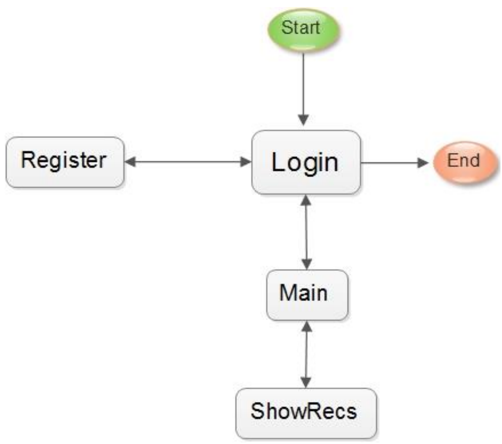



*Figure 3-9 Page Navigation of the Web Application*

## 3.5 A TEST CASE

For testing SARSIS, a tester person was asked to work with SARSIS as the next steps and the related information:

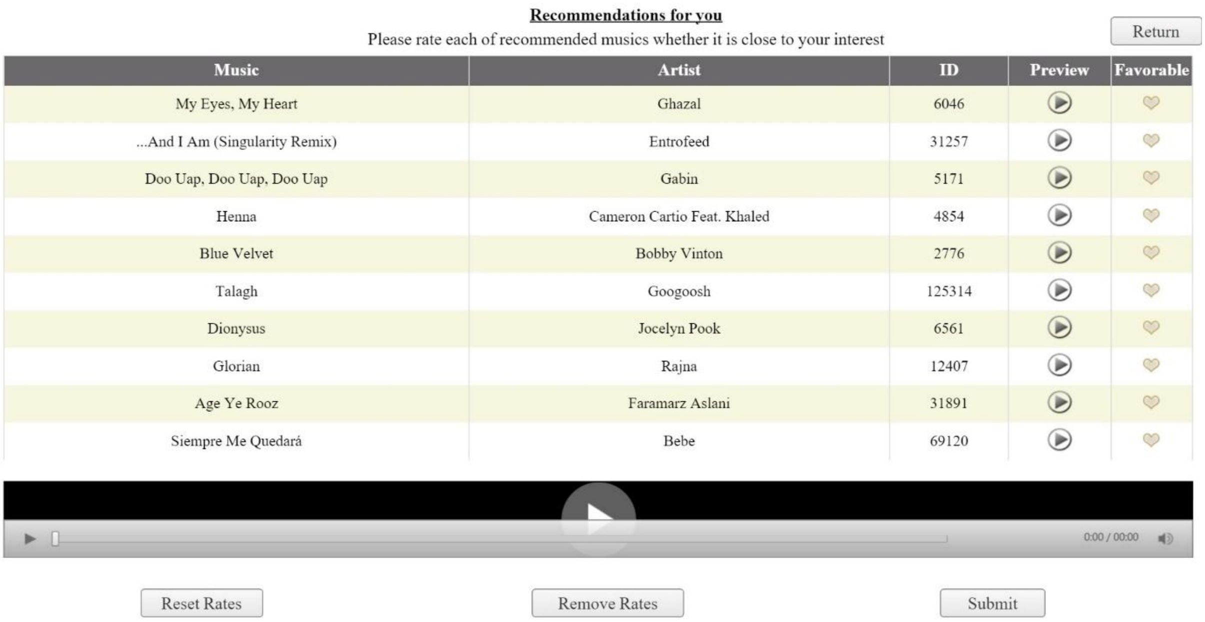
1- On the Default page, the tester could login with this credential:
Username: 1754624499
Password: 2165

2- On the Main page, the tester searched for the first below artist name and music name (A) with the related operation after them, then repeated this job for the following information of music tracks B and C:

A) Artist Name = Googoosh Music Name = Do Panjereh Have you heard it? = yes
B) Artist Name = Shadmehr Aghili Music Name = Zolmat interest rate = 3
C) Artist Name = Siavash Ghomayshi Music Name = Navazesh interest rate = 2

3- The tester clicked on the Recommendations button

4- On the `ShowRecs` page, a list of 10 recommended music tracks generated by SARSIS is shown and depicted in Figure 3-10.




| Music | Artist | ID | Preview | Favorable |
|---|---|---|---|---|
| My Eyes, My Heart | Ghazal | 6046 | | |
| ...And I Am (Singularity Remix) | Entrofeed | 31257 | | |
| Doo Uap, Doo Uap, Doo Uap | Gabin | 5171 | | |
| Henna | Cameron Cartio Feat. Khaled | 4854 | | |
| Blue Velvet | Bobby Vinton | 2776 | | |
| Talagh | Googoosh | 125314 | | |
| Dionysus | Jocelyn Pook | 6561 | | |
| Glorian | Rajna | 12407 | | |
| Age Ye Rooz | Faramarz Aslani | 31891 | | |
| Siempre Me Quedará | Bebe | 69120 | | |

*Figure 3-10 The recommendations by SARSIS according to the test case data*

As of being familiar with the recommended music tracks, the tester tried to play all the preview of the list. All music tracks could be played except 4th and 10th tracks. The tester liked all recommended tracks as Favorable and then clicked on the submit button.

5- On the `ShowRecs` page, the tester clicked on the Return button.

6- On the Main page, the tester clicked on the Log Out button and exited SARSIS.

## 3.6 DATASET

In this section the dataset that was used in the experimental part of the thesis is presented. Since no suitable dataset matched to the framework, could be found, it was better to collect real data from the social network directly. The DBMS MS SQL Server was used for saving the dataset. This reasons for this choice were:

1) Good handling of large number of tracks records
2) Suitable performance and speed
3) Compatible with MS Visual studio .Net as the IDE for developing the framework
4) Having knowledge and experience of working with it

The information of this database comprises the tables tracks, artists, users, user interests, recommendations, user rates and so on. For initiating the tables of tracks and artists, a C# code was developed to retrieve music information from social network last.fm. The data was collected within three weeks including 137685 tracks and 2125 artists after filtration of some invalid data in the collected dataset. For both tables of tracks and artists by RESTful requests, the information was acquired and in response, an XML stream of data containing of the specifications of tracks and artists was received. The research domain was limited to Persian music tracks and artists because the users who were considered to work with the system were Iranian people, therefore only those music tracks which were performed by Iranian artists and familiar for the users, were collected so that they could have meaningful activity. The strategy for collecting Persian music tracks was that first a list of popular Persian related tags in Last.fm were found using the method “`tag.getsimilar`”. The process was started from one tag and followed by finding other similar tags where all of these tags were used for Persian music tracks on the social network. All of popular used Persian tags were found by this method as much as possible. Then for each tag, a REST query including the method “`tag.gettopartists`” was executed to get a list of Persian artists along with their details and saved to the table “artists”.

The structure of table artists is shown in Figure 3-11.

| id | name | url | img |
|---|---|---|---|
| 254 | Sima Mafiha | http://www.last.fm/music/Sima+Mafiha | http://userser... |
| 255 | Simin Agha Razi | http://www.last.fm/music/Simin+Agha+Razi | http://userser... |
| 256 | Steve Shehan, with R... | http://www.last.fm/music/Steve+Shehan,+with+Re... | http://userser... |
| 257 | Strunz & Farah | http://www.last.fm/music/Strunz+&+Farah | http://userser... |
| 258 | The Boyz | http://www.last.fm/music/The+Boyz | http://userser... |
| 298 | Rana Farhan | http://www.last.fm/music/Rana+Farhan | http://userser... |
| 299 | Rapknot | http://www.last.fm/music/Rapknot | http://userser... |
| 300 | Rastaak | http://www.last.fm/music/Rastaak | http://userser... |
| 301 | Rastak | http://www.last.fm/music/Rastak | http://userser... |
| 302 | Rastak Ensemble | http://www.last.fm/music/Rastak+Ensemble | http://userser... |
| 303 | Rastin | http://www.last.fm/music/Rastin | http://userser... |
| 304 | Ravaanbakhsh | http://www.last.fm/music/Ravaanbakhsh | |
| 305 | Raven Mind | http://www.last.fm/music/Raven+Mind | http://userser... |
| 306 | Razavi Sarvestani | http://www.last.fm/music/Razavi+Sarvestani | http://userser... |
| 307 | ReBeat | http://www.last.fm/music/ReBeat | http://userser... |

*Figure 3-11 Table Artists*

So it was possible to conclude that these artists were performing music with the genre indicated by that tag. After completing this process for all tags, the iterative and incomplete information was eliminated from the table “artists” considering integrity rule in a DBMS and without data loss. Later, for each artist, a list of performed tracks by that performer artist were retrieved using REST requests including the method “`artist.gettoptracks`”. Then for each track, a list of tags assigned by Last.fm users were collected by the method “`track.gettoptags`” and joined to the corresponding track in the table “Tracks”.

The data gathered from last.fm was in English format, no change was considered for it. For example, the music track “`Negaran`” with a Persian performance by the artist “`Benyamin`” was saved to the table tracks.

The structure of table tracks is shown in Figure 3-12.

| id | name | artist | tags | rank |
|---|---|---|---|---|
| 2097 | Echo Of The East (Tanine Shargh) | Bijan Mortazavi | Persian | 92 |
| 2125 | Fire On Ice (violin) | Bijan Mortazavi | Persian | 120 |
| 2127 | Ghebleh | Bijan Mortazavi | a | 122 |
| 2135 | Storm (Toofan) | Bijan Mortazavi | Persian | 130 |
| 2141 | Utopia | Bijan Mortazavi | pop,world,iran,Middle Eastern,Persian,toop | 136 |
| 2248 | Heal | Bijan Mortazavi | pop,Bijan Mortazavi,iran,toop,romantic violin,Bija... | 243 |
| 2336 | Yeki Bood Yeki Nabood | Black Cats | black cats,Persian,persian music,dimbology,Yeki ... | 1 |
| 2337 | Jooneh Khodet | Black Cats | mmrs,cool,Persian,toop,black cats | 2 |
| 2338 | Aftab | Black Cats | Persian | 3 |
| 2342 | Ey Daad | Black Cats | Persian | 7 |
| 2343 | Mano Del | Black Cats | Dambil | 8 |
| 2344 | Khanoom | Black Cats | Persian | 9 |
| 2345 | Begoo | Black Cats | Persian,Oriental,begoo,beautiful,Iranian | 10 |
| 2346 | Popfather | Black Cats | rock n roll,middle east,Persian,kashayer | 11 |
| 2347 | Ahange Man | Black Cats | Persian,world,pop,synthpop,Disco,00s,middle eas... | 12 |
| 2348 | Boro | Black Cats | Persian,boro,toop,blackcats,dimbology | 13 |
| 2351 | Cheghad Asheghetam | Black Cats | Persian | 16 |
| 2355 | Mamanieh | Black Cats | Persian,black cats,toop | 20 |
| 2359 | Doost Dashtani | Black Cats | Persian | 24 |
| 2360 | Atash | Black Cats | Persian,Iranian,persian pop,Black Cats - Atash,roc... | 25 |

*Figure 3-12 Table Tracks*

# 3.7 PROGRAMMING LANGUAGE

Choosing a right language for programming always has been one of the challenges for developing of applications. The reasons of considering C# language for developing the web application are below:

1) Good capabilities including object oriented programming
2) Integrity in Visual Studio .NET as a powerful IDE for developing
3) Good error handling and support by Microsoft and other references
4) Having knowledge and experience about it

# 3.8 EFFICIENCY

By many test cases, the web application presented with an acceptable efficiency and speed. One of the reasons was that the dataset including the tables Artists and Tracks, was prepared in the form of offline as explained in 3.6. In fact, a separate time was dedicated to collect needed data from the social network and make them more available and as a result it will be more secure. So, each time instead of running REST requests which could be time consuming with high memory overheads when connecting to the social network and retrieving desired data, hopefully the application was connecting to the database faster and there was a higher level of reliability for implementing the framework which led to more efficient outcomes. Furthermore, as explained in 1.1 the framework can overcome three recommendation problems including cold-start, sparsity and scalability, and increase the efficiency of the system.

## 3.9 THE SECURITY OF THE FRAMEWORK

Information security is the practice of defending information from unauthorized access, use, disclosure, disruption, modification, perusal, inspection, recording or destruction [305].

The act of providing trust of the information, that the Confidentiality, Integrity and Availability (CIA) of the information are not violated. E.g., ensuring that data is not lost when critical issues arise. These issues include, but are not limited to: natural disasters, computer/server malfunction, physical theft, or any other instance where data has the potential of being lost. Since most information is stored on computers in our modern era, information assurance is typically dealt with by IT security specialists. A common method of providing information assurance is to have an off-site backup of the data in case one of the mentioned issues arise. In this framework, the database administrator makes regularly database backups to consider information assurance.

The security evaluation of the framework is based on the Information Security Attributes:

1- Availability: Availability models keep data and resources available for authorized use, especially during emergencies or disasters [306].

As mentioned in 3.8, the data is available as needed. The up time of Database Server considered for maintaining the data is almost 100%.

2- Integrity: In information security, data integrity means maintaining and assuring the accuracy and completeness of data over its entire life-cycle. This means that data cannot be modified in an unauthorized or undetected manner [305].

The access to the main data, containing two tables Artists and Tracks is read only, without any way to change data by code. So it is not possible to modify the data in an unauthorized or undetected manner.

3- Confidentiality: It means that the network security engineer or group needs ensure that information is known only by those who need to know. In Other words, information must be shared in a need-to-know basis [307].

By authentication of the users, using a single sign on mechanism in application development.

4- Audit: Audit refers to the examination and confirmation of controls around data and the IT infrastructure. This is perhaps the most complex aspect of the CIAA concept, as it can be difficult to navigate a maze of emerging regulatory standard, some of which have conflicting clauses [308].

This attribute of security is established by controlling the session validation for the users in all web pages of corresponding application, manual checking of data and web application for unauthorized access.

Furthermore, it is possible to evaluate the security of the framework based on the level of user placement on the application:

### 3.9.1 On the level of user entry

#### 3.9.1.1 Authentication

As it can be seen in Figure 3-1, in the framework an authentication interface has been considered for the users. With this possibility, invalid or unauthorized users cannot enter to the system as much as possible so that unpermitted users are not able to access to the social network easily.

### 3.9.2 On the level of user activity

#### 3.9.2.1 Access control for Online Social Networks

Users of social networks deal with their profile, interface with different users, and self-sort out into various groups [309]. Users' profiles normally comprise data, for example, the user's name, contact data, birthdate, messages, address, instruction, interests, music, photographs, recordings, websites and numerous different properties.

Checking access to the data posted on users' profile is an important job undertaking as it requires normal Internet users to go about as framework executives to determine and design access control strategies for their profiles. To check associations between users, the client's reality is isolated into a trusted and a non-trusted group of users, ordinarily alluded to as companions and outsiders separately. Moreover, some social networks enable clients to further part the arrangement of companions by geological area, social gathering, association, or by how well they know them. Clients are furnished with gathering based access control instruments that apply get to rules on the distinctive gatherings of companions and outsiders.

Facebook, a standout amongst the most well-known social websites, empowers clients to make companion records and to make profile arrangements in view of these companion records [310]. Notwithstanding the difficulties required with empowering fine grain access control for client profiles to control which information qualities distinguishable by different clients, a yet unexplored issue is identified with clients' profile access from substances not quite the same as other social network users.

With the advancement of Web 2.0 innovations, online social networks can give open stages to empower the consistent sharing of profile information to empower general engineers to interface and expand the social network benefits as applications (or APIs). For instance, Facebook enables anybody to make programming modules which can be added to client profiles to give administrations in view of profile information.

Despite the fact that these open stages empower such propelled highlights, they likewise posture genuine protection dangers. Clients' profiles in actuality have an awesome business incentive to showcasing organizations, contending organizing locales, and personality criminals. Social networks stages have concentrated on client to-client fine grain access control, for instance, the Facebook Privacy Policy enables clients to indicate fine grain strategies controlling which profile traits can be gotten to by their companions and companions of companions. When introducing social network applications clients need to give the applications all the asked for permission with a specific end goal to effectively make entire the establishment procedure.

Fundamentally, the received application access control model is a win big or bust approach, where the application ought to be allowed all the asked for consents keeping in mind the end goal to introduce it effectively. Furthermore, API engineers approach clients' information paying little mind to the genuine applications' needs, prompting possibly genuine security ruptures. Such security risk is regularly covered up or not clear to social network clients, who are frequently not mindful of the measure of information that is really being unveiled, since they don't generally recognize social network clients and designers outside the social network limits. In November 2011, Facebook's security practices were the subject of grumblings recorded with the Federal Trade Commission (FTC). The dissensions were identified with the Facebook's security hones that hoodwinked clients and neglected to keep protection guarantees. One of the fundamental grievances was identified with Facebook's claim that outsider applications that clients' introduced would approach just to client data that they expected to work, where truth be told, the applications could get to almost the greater part of clients' close to home information. Also, Facebook guaranteed that it confirmed the security of applications taking an interest in its "Checked Apps" program, where in certainty they didn't.

We accept, keeping in mind the end goal to advance solid improvement of social network conditions and to ensure people's protection rights, clients ought to have the capacity to exploit the accessible applications while as yet having a more grounded control on their information. The issue is not paltry, in that it requires planning new get to control models for APIs in social network, and also broadening social network applications. Applications ought to be planned and redone with the clients' profile inclinations, and clients ought to be able to indicate the information that they will uncover. Moreover, clients ought to have the capacity to utilize information protection systems, for example, speculation to appreciate the administrations given through APIs without disclosing recognizing or private data.

It is possible to define different levels of accessing to the system with specific privileges for the users. In this case, users’ activity could be limited to below:

1- The authenticated users can only access to their profile when their session is not timed out.

2- The other membered users, rather than the current authenticated user, cannot access to the profile of the user.

3- All users are permitted to access just to the specific area of the system, not more and only the administrator can have full permission privileges.

According to the above mentioned, a systematic mechanism for implementing of access control has been considered for the suggested framework.

#### *3.9.2.2 Risk-Aware Recommender Systems*

##### 3.9.2.2.1 Risk Aware Decision

The dominant part of existing ways to deal with RS concentrate on prescribing the most pertinent reports to the clients utilizing the logical data and don't consider the danger of aggravating the client in particular circumstances [311]. Nonetheless, in numerous applications, for example, prescribing a customized content, it is additionally vital to fuse the danger of annoying the client into the recommendation procedure all together not to prescribe archives to clients in specific circumstances, for case, amid an expert meeting, early morning, late-night. In this way, the execution of the RS relies on upon the extent to which it has consolidated the danger into the recommendation procedure.

##### 3.9.2.2.2 The Variance of the Cost

The fluctuation of the cost methodology is identified with the defective information of the issue parameters. For example, with regards to Markovien Decision Process (MDPs) and tending to natural vulnerability, Howard and Matheson have proposed to utilize an exponential utility capacity, where the parameter of the type controls the danger affectability [312].

##### 3.9.2.2.3 The Expected Environment Cost

The normal environment cost methodology is identified with the stochastic way of the framework. For instance, Geibel and Wysotzki have considered a MDPs model where a few states have been mistake states [313]. They characterize the danger as the likelihood of entering such a state when every strategy is taken after. At that point, they attempt to discover great strategies with a danger littler than some edge predefined by the client. This issue is formalized as a compelled MDPs with a danger capacity taking into account a total return. The creators exhibit a support learning calculation that goes for discovering great deterministic arrangements.

##### 3.9.2.2.4 Hybrid Approach

The hybrid methodology is a mix of both the normal environment cost and the difference of the expense [314].

According to [314], the creators build up an approach angle calculation for criteria that include both the normal expense and the difference of the expense. The creators demonstrate the merging of these calculations to nearby minima and show their appropriateness in a portfolio arranging issue.

## 3.10 SUMMARY

The greater part of recommendation frameworks is utilizing one or blend of two procedures as a half and half system, while the recommended structure in this exploration uses the advantages of four methods. Besides, some specialized oddities completely enabled this system.

In this section, the rationale of the structure has been presented and clarified what segments it has and how they function. Every part of the structure was shown in points of interest furthermore the relations between the segments have been spoken to. Moreover, a few key variables which are utilized as a part of the system have been presented alongside their usefulness.

For the collaborative filtering recommendations, the technique for kNN was utilized to locate the most comparative clients. Initially, enrolled clients alongside their intriguing items were considered. This data was utilized from the table "Interests". Likewise, the lattice "rates" as rates [userid, productid] was characterized and the rate values given to the items by the clients were entered to this framework taking into account clients' interests or their exercises. The arrangement of things evaluated by each both clients in the framework rates ought to be considered.

The displayed structure is by and large so that can be connected for every informal organization working for even other media like video or picture. In any case, for delineating the system and make it all the clearer, it is ideal to practice and execute it over an informal organization to watch how the strategy functions in a genuine stage and how is the nature of the structure for evaluating its execution. The interpersonal organization Last.fm is chosen for this area as an appropriate contextual analysis.

A web application for performing the structure was produced. As to the subject of the research, Semantically-enhanced Advertisement Recommender Systems in Social networks, the name of SARSIS which stands for this subject, was decided for the web application actualizing the structure which is accessible on the web. For this situation the web application was produced in MS Visual Studio .NET and with the innovation ASP.NET.

For testing the web application, the needed information for working is provided so that it is possible to work with the system and watch how it works in practical.

The dataset that was utilized as a part of the exploratory part of the proposition was displayed. Since no appropriate dataset coordinated to the structure, could be discovered, it was ideal to gather genuine information from the interpersonal organization straightforwardly. The DBMS MS SQL Server was utilized for sparing the dataset. The data of this database includes the tables tracks, artists, users, user interests, recommendations, user rates et cetera. For starting the tables of tracks and specialists, a C# code was developed to recover music data from social network last.fm. The information was gathered inside three weeks including 137685 tracks and 2125 artists after filtration of some invalid information in the gathered dataset. For both tables of tracks and artists by RESTful queries, the data was procured and accordingly, a XML stream of information containing of the details of tracks and artists was gotten. The exploration space was restricted to Persian music tracks and specialists in light of the fact that the users who were considered to work with the framework were Iranian individuals, in this way just those music tracks which were performed by Iranian artists and well known for the users, were gathered so they could have important action.

The demonstration of giving trust of the data, that the Confidentiality, Integrity and Availability (CIA) of the data are not damaged. For example, guaranteeing that information is not lost when basic issues emerge. These issues incorporate, however are not restricted to: regular debacles, PC/server glitch, physical burglary, or whatever other case where information has the capability of being lost. Since most data is put away on PCs in our advanced period, data confirmation is regularly managed by IT security authorities. A typical technique for giving data affirmation is to have an off-site reinforcement of the information in the event that one of the said issues emerge.

The proposed model has his specific strength points which differs to the other similar frameworks. These differences make the proposed framework better rather than the other approaches. The points are described as below:

1- In many recommendation systems, a suitable mechanism of security controlling is not considered, although this issue is one of the main concerns of every software system and it is necessary to implement a security solution for the recommender system frameworks. Thereby, an appropriate level of security has been considered for the proposed model. If a minimum level of security is not considered for the model, for example an SSO solution, the software system can be accessed by all people without any user authentication, and it is probable to observe irreparable disasters by invalid users or hackers. Therefore, the existence of an SSO mechanism which is used in the current study's model would be sensed mandatory and helps the framework to work appropriately.

2- As the other similar approaches were studied, most of them had not utilized artificial intelligence (AI) techniques to enrich the outcomes of the recommender systems. Using a semantic logic in the proposed model to calculate the recommendations based on the well-known methods has been special strength point in the current study and a kind of robustness in designing recommender systems rather than the similar works. The approaches without AI benefits had not been able to present any particular difference in the quality of the recommended results. But, the semantic engine of the current framework has helped users to observe incredible accurate product recommendations whereas the semantic technology which has been used in the framework finds the relations between main concepts (including products, producers and so on) and anticipates the users' needs based on the users' preferences. The semantic logic of the framework helps the results to be more realistic and accurate rather than the other approaches.

3- The similar studied researches are often utilizing a simple linear formula for blending limited number of the standard techniques as a hybrid method which there is no specific innovation in their presented solution. But in the current study, a suitable composition of four classical recommender techniques as a hybrid method has been chosen along with selecting of promising formulas for estimating each of the particular methods. Choosing the particular rates in the used formulas of the current methodology provides better recommended products with more user satisfaction from the provided products. The rates are considered in the formulas based on their role and importance so that they can influence on the proximity of the user expectation and the outcome of the model for the user.

4- One of the limitations in the previous studied works was that they could generate the recommendations only in one step without using a memory of the past calculations. The weak point of such methods is that they cannot apply users' opinions and as a consequence, in many cases the outcome of the recommender system did not have accurate results. But in the proposed model, a feedback of users' opinions is used as finding more users' interests and adding them to the dataset of users' interests for estimating the future recommendations so that the provided recommendations would be more accurate. In the current framework, after calculating of the recommended products, the information which is stored in the related dataset, is kept so that in the next turns of providing the recommendations this information is used to generate more updated and efficient recommended products.

5- In the reviewed related works, a limited number of users were working on the related software systems which could not have a promising and convincible results of recommended products. But in the current study's framework, an adequate number of online users has been considered to have activity on the framework. Using more number of active users of social network can help the system to reduce the calculation error and act as a strength point.

# SECTION IV: Evaluation

# CHAPTER 4

# 4. EVALUATION

## 4.1 INTRODUCTION

The different aspects of the framework have been explained in the previous sections. Moreover, the structure of the framework was demonstrated in details in the section of methodology. In this part of dissertation, the outcome of the web application as a case study for the suggested framework is validated. Therefore, it is possible to conclude that the framework has an appropriate efficiency and the results of the evaluation have been able to prove the previous assertions along with an improved framework rather than the previous established works with a novelty in its design.

Evaluation refers to a process of gathering data and then analyzing or ordering it in such a way that the resulting information can be used to determine whether the application is effectively carrying out planned framework, and the extent to which it is achieving its stated objectives and anticipated results.

Assessment of the current research can be depicted as a kind of study that utilizes standard examination systems for evaluative purposes, as a particular examination structure, and as an examination procedure that utilizes exceptional methodologies unprecedented to the assessment of the structure. Assessment is a technique that basically looks web application. It joins amassing and isolating data about the site's exercises, properties, and results. Its motivation is to make judgments about the site as a delegate for the endorsed general structure, to update its adequacy, and/or to train programming choices.

Evaluation is an approach to check and observe the efficiency of the suggested methodology and its structure based on the scientific methods. By the evaluation, it is possible to test the system and see how the system works in practical, then measure the quality of the solution for the mentioned problem. There are a lot of ways for expressing the evaluation of a methodology which usually are scientific and based on the popular standards and metrics. In this chapter, after exposing the significance of the evaluation for the current research, the used metrics will be announced along with expressing the types of metrics and their differences. Moreover, based on the standard metrics which will be used for this part of the research, an experimental setup will be discussed to explain how the evaluation will be setup.

Some information about the details and statistics of the evaluation will be provided to determine how the suggested framework has been evaluated.

## 4.2 SIGNIFICANCE OF EVALUATION

Evaluation is a methodical gathering and investigation of information to survey the qualities and shortcomings of the recommended structure to enhance its adequacy. Evaluation of this examination can be characterized as a kind of study that utilizations standard exploration strategies for evaluative purposes, as a particular examination system, and as an appraisal procedure that utilizes exceptional methods special to the assessment of the structure.

Evaluation is a procedure that basically looks at the web application. It includes gathering and breaking down data about the site's exercises, attributes, and results. Its motivation is to make judgments about the site as a delegate for the recommended general structure, to enhance its adequacy, and/or to educate programming choices.

At last, the assessment can give valuable criticism to an assortment of gatherings of people including supports, contributors, customer bunches, executives, staff, and other important bodies electorate. Regularly, criticism is seen as "helpful" on the off chance that it helps in basic leadership. However, the relationship between an Evaluation and its effect is not a straightforward one, thinks about that appear to be basic now and then neglect to impact fleeting choices, and studies that at first appear to have no impact can have a deferred sway when more amicable conditions emerge. Regardless of this, there is wide accord that the real objective of assessment ought to be to impact basic leadership or approach definition through the procurement of exactly determined input.

## 4.3 EVALUATION METRICS

In an open access world, much significance has been given in utilizing open source instruments, open access assets and open answers for connect with creators and scientists in community oriented examination, distributed sharing of insightful data and cooperative assessment of researchers' works [315].

Then again, exponential development of exploratory writing likewise has prompted fast vanishing of created writing before it really gets saw by scientific groups. No single database can catch this over-developed exploratory writing. A few information mining instruments are presumably required to stay up to date with quantum of delivered writing. The social networks, accessible to the scientists' groups notwithstanding whatever other gatherings of subjects, help the specialists in scattering their delivered or contributed information to worldwide groups. The more you are dynamic in online networking, the more you have opportunities to get saw by kindred scientists and conceivable exploration teammates. Numerous customized electronic administrations are currently progressively made accessible focusing on worldwide scientists' groups, helping them to upgrade their online networking nearness and perceivability.

Hence, inquire about assessment of a specialist or an examination establishment or an exploration bunch investigates point by point investigation of numerous parts of this substance. Figure 4-1 delineates four vital measurements of exploration assessment. These viewpoints are amazingly interrelated and associated. Shortcoming in one perspective will prompt bringing esteem down to other viewpoint. Research assessment ought to be completed to decide qualities and shortcomings in efficiency, perceivability, notoriety, and effect of logical scientists or organizations.

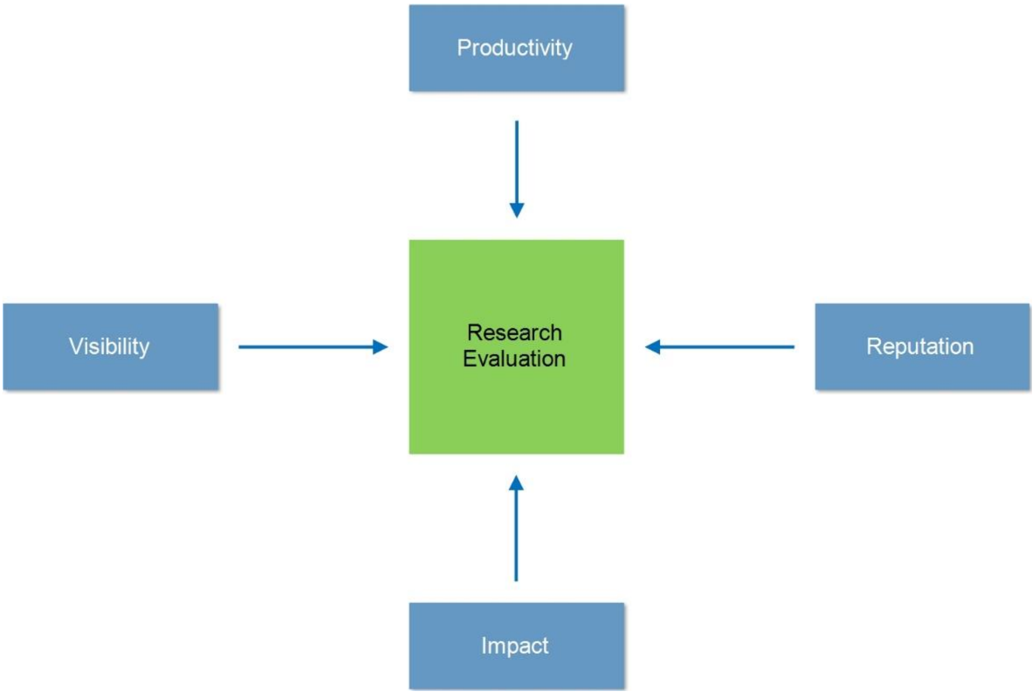



*Figure 4-1 Dimensions of research evaluation*

# 4.4 TYPES OF METRICS

## 4.4.1 Error-based metrics

Recommender frameworks research has utilized a few sorts of measures for assessing the nature of a recommender framework [316]. They can be principally arranged into two classes:

Measurable exactness measurements assess the precision of a framework by looking at the numerical proposal scores against the real client evaluations for the client thing sets in the test dataset. Mean Absolute Error (MAE) amongst appraisals and forecasts is a broadly utilized metric. MAE is a measure of the deviation of suggestions from their actual client determined qualities. For every evaluations forecast pair <pi,qi> this metric treats the outright mistake between them i.e., |pi-qi| similarly. The MAE is processed by first summing these total mistakes of the N relating evaluations expectation sets and afterward figuring the normal. Formally as appeared in Equation 4-1 [301]:

$$MAE = \frac{\sum_{i=1}^{N} |pi - qi|}{\mathrm{N}}$$

*Equation 4-1 Calculation of MAE as the evaluation of the framework*

The lower the MAE, the more accurately the recommendation engine predicts user ratings. Root Mean Squared Error (RMSE), and Correlation are also used as statistical accuracy metric.

### 4.4.2 Information retrieval metrics

A standout amongst the most popular assessment measurements in information and retrieval is precision-recall [317].

Precision is the part of recovered reports that are applicable to the inquiry. The Equation 4-2 demonstrates how Precision is ascertained.

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

*Equation 4-2 Calculation of precision*

Recall in data recovery is the portion of the records that are important to the inquiry that are effectively recovered. The Equation 4-3 demonstrates how Recall is ascertained.

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

*Equation 4-3 Calculation of recall*

Precision and recall are then determined as Equation 4-4 and Equation 4-5 [318]:

$$\text{Precision} = \frac{tp}{tp + fp}$$

*Equation 4-4 Calculation of precision in another way*

$$\text{Recall} = \frac{tp}{tp + fn}$$

*Equation 4-5 Calculation of recall in another way*

Where `tp` (genuine positive) alludes to the prescribed music tracks which have been enjoyed by the clients (the quantity of Likes for every clients, appeared in Table 5-1), `fp` (false positive) alludes to the suggested music tracks which have not been loved by the clients (the quantity of `Unlikes` for every clients, appeared in Table 5-1), and `fn` (false negative) alludes to the music tracks which are not prescribed (have a place with the progression 2 of section 4) however the clients are keen on those music tracks whether via looking, listening or communicating their loan cost.

## 4.5 EXPERIMENTAL SETUP

The users have worked with the web application on the online platform. So the data needed for the evaluation section is located on the database server. To establish the experimental setup, first it was necessary to transfer the online data to the local machine as offline so that working with the desired data would be easy to use and more ready to handle.

For this purpose, a web page was developed using ASP.NET C# that could do the appropriate data movement. After that, it was possible to analyze data easily.

List of experimental information comprising the tables of the prepared database is shown in Table 4-1 after collecting information from the users' activities on the website:

| **Table name** | **Description** | **Number of rows** |
|---|---|---|
| Artists | Details of music artists | 2128 |
| Tracks | Details of music tracks | 137685 |
| Users | Registered users, working on the web application | 73 |
| Interests | Interesting music tracks for the users by their activity | 1096 |
| Recs | Recommended music tracks by the web application (Framework) | 6690 |
| UserRates | User rates about the recommendations In the evaluation page by the users | 625 |

*Table 4-1 Statistics about the database of the web application*

The information related to artists and tracks have been got using a separate C# web application whose source code is available. The 73 users have been selected from the students of Islamic Azad University, computer hardware department. The users feed their preferences as activities into the related table as their interests. The recommendation system provides suggested music tracks for the users and this information are saved into the table Recs. When the users observe the recommendations, they can rate these results which are saved into the table UserRates.

## 4.6 SUMMARY

In this segment of this study, the result of the web application as a contextual investigation for the recommended structure was approved. In this manner, it is conceivable to presume that the system has a fitting proficiency and the aftereffects of the assessment have possessed the capacity to demonstrate the past attestations alongside an enhanced structure as opposed to the past built up works with a curiosity in its configuration.

Assessment alludes to a procedure of social affair information and afterward examining or requesting it in a manner that the subsequent data can be utilized to figure out if the application is viably completing arranged structure, and the degree to which it is accomplishing its expressed targets and expected results.

Assessment of this examination can be portrayed as a sort of study that uses standard investigation methodologies for evaluative purposes, as a specific examination framework, and as an examination methodology that uses outstanding strategies extraordinary to the evaluation of the structure. Evaluation is a method that essentially takes a gander at the web application. It incorporates assembling and separating information about the site's activities, properties, and results. Its inspiration is to make judgments about the site as a representative for the prescribed general structure, to upgrade its sufficiency, and/or to instruct programming decisions.

Consequently, ask about evaluation of an expert or an examination foundation or an investigation bundle explores point by point examination of various parts of this substance. As indicated by four essential estimations of investigation evaluation, Shortcoming in one point of view will provoke conveying regard down to other perspective. Research evaluation should be finished to choose qualities and deficiencies in proficiency, detectable quality, reputation, and impact of sensible researchers or associations.

Quantifiable precision estimations survey the accuracy of a structure by taking a gander at the numerical proposition scores against the genuine customer assessments for the customer thing sets in the test dataset. Mean Absolute Error (MAE) amongst examinations and conjectures is a comprehensively used metric. MAE is a measure of the deviation of proposals from their real customer decided qualities.

Precision is the piece of recouped reports that are appropriate to the request. Review in information recuperation is the segment of the records that are essential to the request that are viably recouped. The clients have worked with the web application on the online system. So the information required for the assessment segment is situated on the database server. To build up the exploratory setup, first it was important to exchange the online information to the nearby machine as disconnected so that working with the coveted information would be anything but difficult to utilize and more prepared to handle. For this reason, a page was produced utilizing ASP.NET C# that could do the proper information development. After that, it was conceivable to examine information effectively.

# SECTION V: Results and conclusions

# CHAPTER 5

# 5. RESULTS AND DISCUSSION

## 5.1 INTRODUCTION

In the previous chapters, the details of methodology along with comprehensive information about the organization of the research have been proposed. Later, the performance of the framework was evaluated using some evaluation metrics and the efficiency of the solution was estimated and provided.

One of the recent developments that might upgrade the efficiency of advancements on social network is semantic technologies. Using every procedure for semantic web in working up the courses of action can incite grow the adequacy of attentions. Nowadays, proposition structures accept a basic part in going on plugs as sorts of things or organizations to the right market which suggests concentrated on business division. Thusly, blueprint of an appropriate structure which sets up these beliefs would energy for the investigation.

In this chapter, the gathered results from the evaluation process will be presented. These results demonstrate the current study's foundations and it is possible to discuss about the results in the consequent part. In the discussion part, the results of this study are compared to the similar works and it will be presented how much the suggested framework has superiority rather than the previous similar accomplished works. The accuracy of the presented claims will be shown using the evaluation metrics.

About such frameworks it is ideal to plan and build up a more perfect recommender framework including the upsides of both gathering of techniques. For this situation, the proposed structure will be more powerful and dependable. Additionally, it is remarkable that it ought to be viewed as that every structure has its own particular confinements and issues. A creative structure was presented which not just has a blend of four recommender systems, additionally it utilizes the advantages of semantic innovation.

## 5.2 RESULTS

In this part of study, the gathered results of the mentioned case study of the framework will be explained. First, the information about the users who have worked with SARSIS is pointed. The age classes of the users are shown in Figure 5-1.

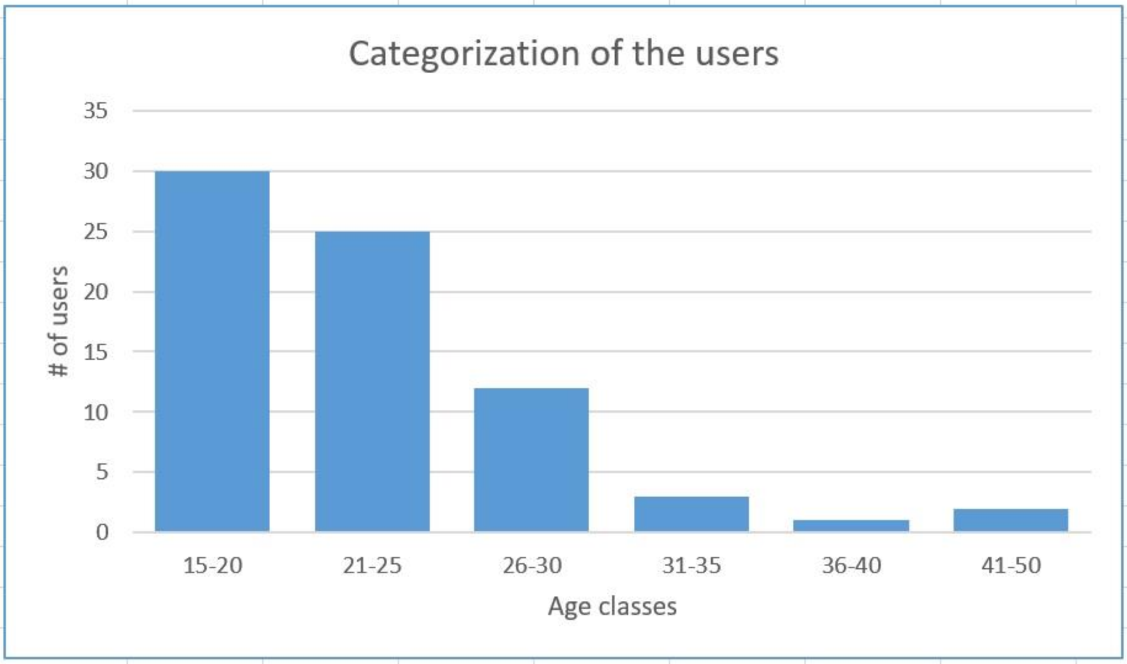



*Figure 5-1 Categorization of the users based on age classes*

As can be seen in this histogram, most of the users who participated in the research work are belong to the ages between 15 and 25.

By analyzing the table UserRates and the number of liked music tracks which each user has submitted, using the Equation 4-1, it is possible to get the result using a SQL query which is executed in MS SQL Server Management Studio. The query shown in the Figure 5-2 depicts how the results can be prepared using a SQL query.

```
SELECT userid AS Userid,
       COUNT(userid) AS Recommendations,
       SUM (userrate) AS Likes,
       COUNT(userrate) - SUM(userrate) AS Unlikes
FROM   UserRates
GROUP BY userid
```

*Figure 5-2 The SQL query used for preparing the result*

The information of the outcome which is produced by the query of the Figure 5-2, is used for calculating Precision and Recall and they are shown in Table 5-1 as the results information.

| User ID | Recommendations | Likes | Unikes | Interesting | Precision per user | Recall per user |
|---|---|---|---|---|---|---|
| 1000000000 | 7 | 5 | 2 | 12 | 0.71428571 | 0.294117647 |
| 1100110011 | 10 | 2 | 8 | 0 | 0.2 | 1 |
| 1111111111 | 10 | 9 | 1 | 7 | 0.9 | 0.5625 |
| 1147567876 | 6 | 2 | 4 | 1 | 0.33333333 | 0.666666667 |
| 1221344356 | 6 | 6 | 0 | 14 | 1 | 0.3 |
| 1234567891 | 10 | 10 | 0 | 37 | 1 | 0.212765957 |
| 1652964028 | 7 | 3 | 4 | 14 | 0.42857143 | 0.176470588 |
| 1740294068 | 8 | 8 | 0 | 21 | 1 | 0.275862069 |
| 1740331941 | 5 | 5 | 0 | 18 | 1 | 0.217391304 |
| 1740364295 | 7 | 6 | 1 | 6 | 0.85714286 | 0.5 |
| 1740476999 | 10 | 6 | 4 | 18 | 0.6 | 0.25 |
| 1740494970 | 10 | 8 | 2 | 42 | 0.8 | 0.16 |
| 1740601920 | 7 | 4 | 3 | 1 | 0.57142857 | 0.8 |
| 1740751698 | 7 | 5 | 2 | 11 | 0.71428571 | 0.3125 |
| 1740763777 | 9 | 8 | 1 | 24 | 0.88888889 | 0.25 |
| 1740841891 | 7 | 3 | 4 | 16 | 0.42857143 | 0.157894737 |
| 1740925823 | 8 | 7 | 1 | 14 | 0.875 | 0.333333333 |
| 1741129206 | 9 | 8 | 1 | 18 | 0.88888889 | 0.307692308 |
| 1741143292 | 7 | 7 | 0 | 17 | 1 | 0.291666667 |
| 1741361461 | 10 | 10 | 0 | 14 | 1 | 0.416666667 |
| 1741375827 | 10 | 5 | 5 | 21 | 0.5 | 0.192307692 |
| 1741422701 | 7 | 6 | 1 | 5 | 0.85714286 | 0.545454545 |
| 1741453690 | 10 | 4 | 6 | 9 | 0.4 | 0.307692308 |
| 1741726591 | 10 | 9 | 1 | 9 | 0.9 | 0.5 |
| 1741805090 | 10 | 8 | 2 | 7 | 0.8 | 0.533333333 |
| 1741873479 | 10 | 6 | 4 | 3 | 0.6 | 0.666666667 |
| 1741873681 | 7 | 5 | 2 | 9 | 0.71428571 | 0.357142857 |
| 1741912891 | 7 | 5 | 2 | 7 | 0.71428571 | 0.416666667 |
| 1741922089 | 10 | 5 | 5 | 16 | 0.5 | 0.238095238 |
| 1741975565 | 10 | 9 | 1 | 11 | 0.9 | 0.45 |
| 1742013937 | 10 | 6 | 4 | 5 | 0.6 | 0.545454545 |
| 1742018246 | 10 | 9 | 1 | 4 | 0.9 | 0.692307692 |
| 1742046509 | 7 | 7 | 0 | 10 | 1 | 0.411764706 |
| 1742059457 | 7 | 6 | 1 | 6 | 0.85714286 | 0.5 |
| 1742113419 | 7 | 6 | 1 | 8 | 0.85714286 | 0.428571429 |
| 1742227341 | 10 | 10 | 0 | 21 | 1 | 0.322580645 |
| 1742302149 | 6 | 5 | 1 | 12 | 0.83333333 | 0.294117647 |
| 1742318770 | 10 | 9 | 1 | 13 | 0.9 | 0.409090909 |
| 1742327273 | 7 | 7 | 0 | 14 | 1 | 0.333333333 |
| 1742328407 | 10 | 9 | 1 | 14 | 0.9 | 0.391304348 |
| 1742335942 | 10 | 5 | 5 | 30 | 0.5 | 0.142857143 |
| 1742351387 | 6 | 3 | 3 | 7 | 0.5 | 0.3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1742380727 | 10 | 9 | 1 | 18 | 0.9 | 0.333333333 |
| 1742386431 | 7 | 4 | 3 | 2 | 0.57142857 | 0.666666667 |
| 1742388991 | 10 | 4 | 6 | 14 | 0.4 | 0.222222222 |
| 1742413080 | 7 | 6 | 1 | 10 | 0.85714286 | 0.375 |
| 1742428819 | 10 | 10 | 0 | 25 | 1 | 0.285714286 |
| 1742449948 | 9 | 7 | 2 | 12 | 0.77777778 | 0.368421053 |
| 1742454216 | 8 | 5 | 3 | 23 | 0.625 | 0.178571429 |
| 1742531407 | 7 | 3 | 4 | 18 | 0.42857143 | 0.142857143 |
| 1750467534 | 6 | 3 | 3 | 3 | 0.5 | 0.5 |
| 1750598353 | 7 | 7 | 0 | 12 | 1 | 0.368421053 |
| 1752428819 | 8 | 7 | 1 | 17 | 0.875 | 0.291666667 |
| 1754624498 | 10 | 10 | 0 | 7 | 1 | 0.588235294 |
| 1754624499 | 10 | 6 | 4 | 45 | 0.6 | 0.117647059 |
| 1756797366 | 10 | 8 | 2 | 13 | 0.8 | 0.380952381 |
| 1756998124 | 10 | 10 | 0 | 15 | 1 | 0.4 |
| 1757037179 | 10 | 6 | 4 | 2 | 0.6 | 0.75 |
| 1757052811 | 10 | 8 | 2 | 18 | 0.8 | 0.307692308 |
| 1757144315 | 10 | 7 | 3 | 35 | 0.7 | 0.166666667 |
| 1757594752 | 10 | 6 | 4 | 3 | 0.6 | 0.666666667 |
| 1757755888 | 9 | 8 | 1 | 17 | 0.88888889 | 0.32 |
| 1810374146 | 10 | 8 | 2 | 10 | 0.8 | 0.444444444 |
| 1810381282 | 8 | 8 | 0 | 14 | 1 | 0.363636364 |
| 1870443888 | 10 | 5 | 5 | 1 | 0.5 | 0.833333333 |
| 1900251485 | 9 | 7 | 2 | 38 | 0.77777778 | 0.155555556 |
| 1911165100 | 7 | 3 | 4 | 28 | 0.42857143 | 0.096774194 |
| 1920332022 | 10 | 8 | 2 | 41 | 0.8 | 0.163265306 |
| 1940524695 | 6 | 6 | 0 | 23 | 1 | 0.206896552 |
| 1940548276 | 7 | 4 | 3 | 3 | 0.57142857 | 0.571428571 |
| 1943149638 | 10 | 4 | 6 | 16 | 0.4 | 0.2 |
| 1960167413 | 9 | 9 | 0 | 36 | 1 | 0.2 |
| 1987835301 | 10 | 6 | 4 | 25 | 0.6 | 0.193548387 |

*Table 5-1 The results information*

According to the Table 5-1, it is possible to see the information based on each user. But as explained before, the information for each user related to user rates, includes some rows. So for a better analysis of MAE based on each user, a graph of calculated values is depicted in Figure 5-3.

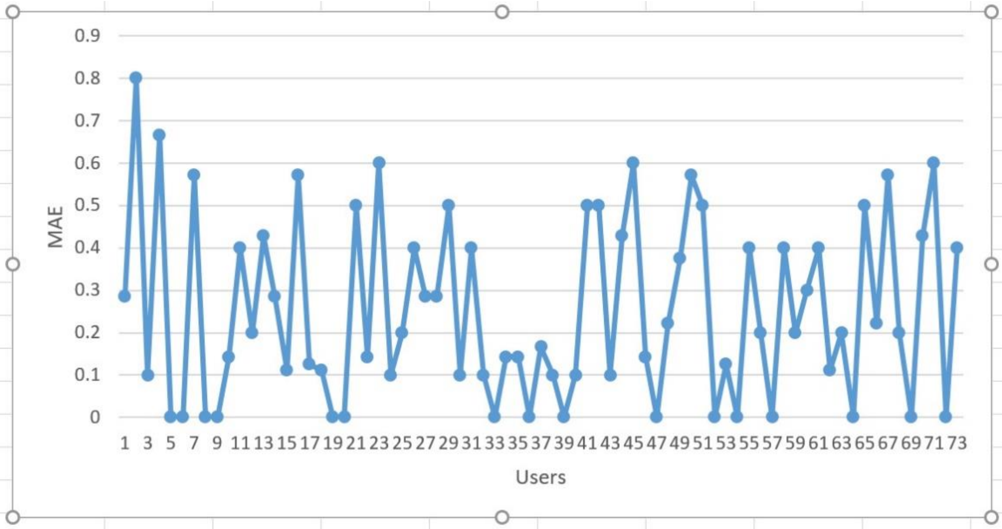



*Figure 5-3 The calculated MAE for each user*

The maximum value, as the top of this graph is 1. The horizontal axis presents the User IDs of the users and the vertical axis shows the values of MAE for each User ID.
Another graph has been depicted the number of unliked recommended music tracks versus the number of recommended music tracks for each user which is shown as Figure 5-4.

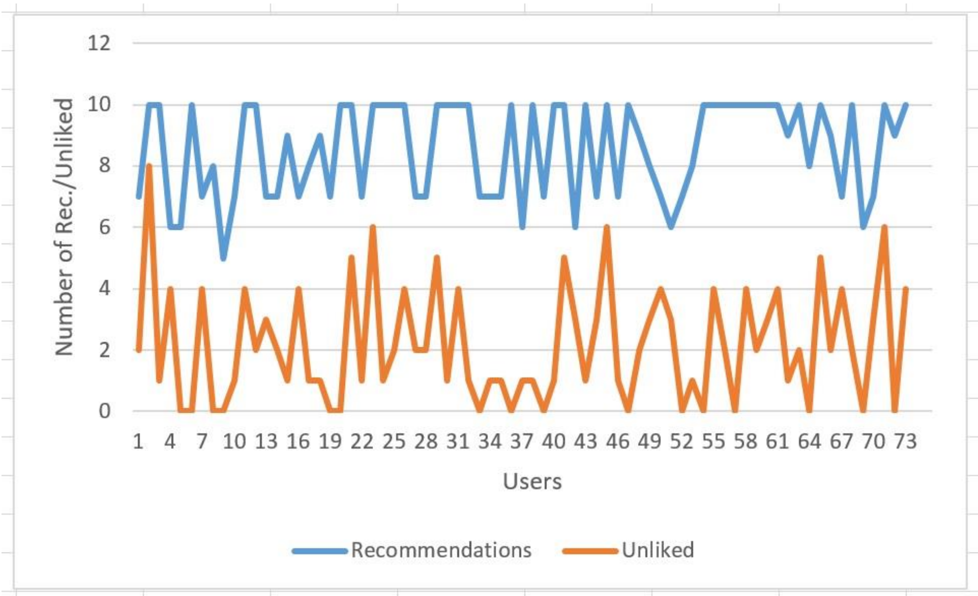



*Figure 5-4 The numbers of unliked recommended music tracks versus the number of recommended music tracks for each user*

The overall MAE for the total users, or on the other word for the whole of the web application, can be estimated as Equation 5-1

$$\text{MAE} = \frac{157}{625} = 0.2512$$

*Equation 5-1 Calculation of total MAE for the whole of web application*

For calculating Precision and Recall, first it is better to make a clearer insight about the concepts in the section 4.4.2 that the result can be shown in Table 5-2 [78][318].

| | **Recommended** | **Not Recommended (Interests)** |
|---|---|---|
| **Liked** | True Positive (Liked recommended music tracks) | False Negative (Interesting music tracks for users in Main page) |
| **Unliked** | False Positive (Unliked recommended music tracks) | True Negative ( - ) |

*Table 5-2 The relations between concepts*

It is still needed to generate a list of False Negative items which would be the music tracks that are interesting for the users. For preparing this list, an appropriate SQL query has been designed which is shown in Figure 5-5.

```
SELECT userid, COUNT(userid) AS fn
FROM   Interests
GROUP BY userid
ORDER BY userid
```

*Figure 5-5 The SQL query used for preparing the False Negative (fn) values*

According to the Table 5-2, the values of precision and recall can be estimated by merging the previous list and the Table 5-1. They are shown in Figure 5-6 as the precision and recall curves separately next to each other and Figure 5-7 as a precision-recall curve.

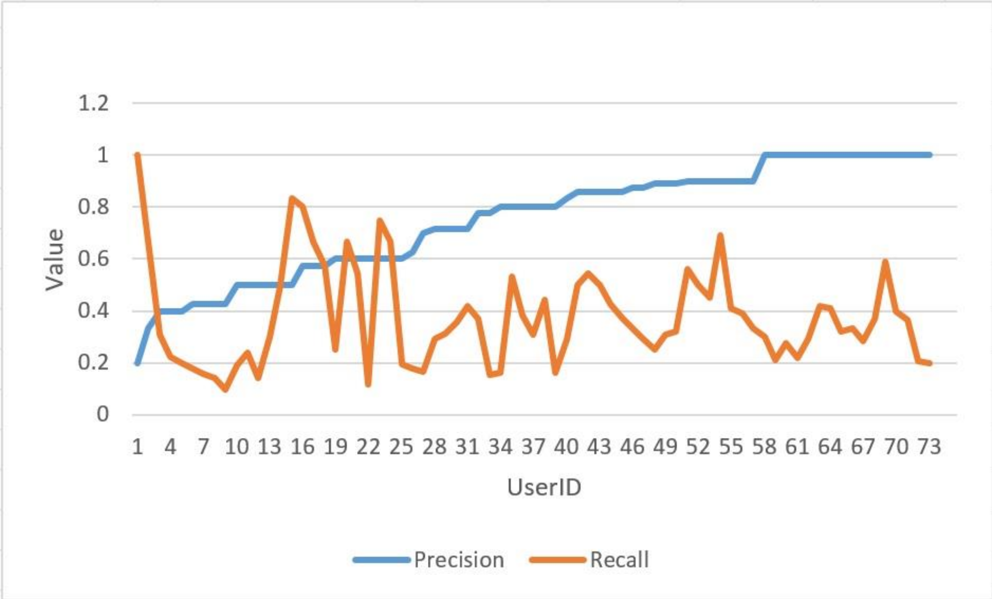



*Figure 5-6 Precision and Recall curves*

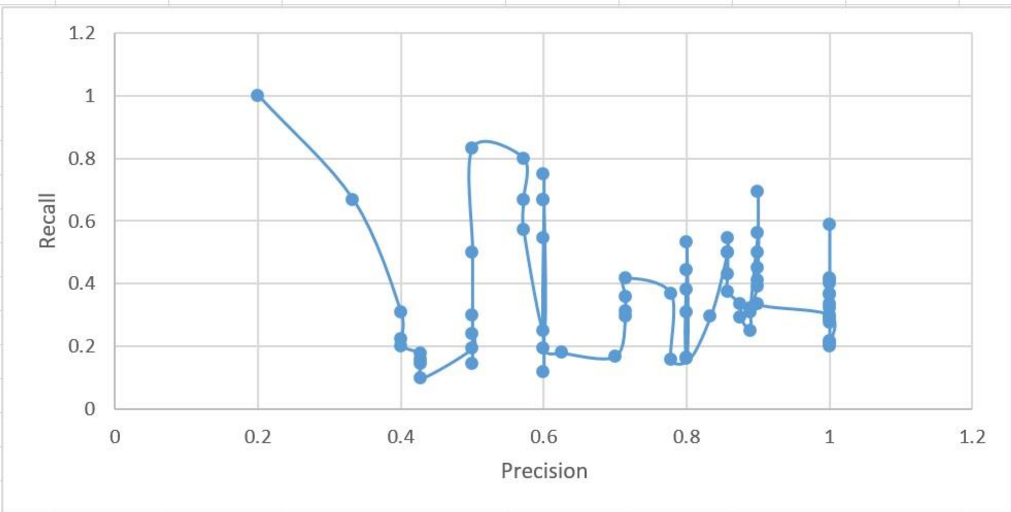



*Figure 5-7 Precision-Recall Curve*

The average accuracy of the whole system as a representative of precisions which is estimated as 0.7498.

## 5.3 DISCUSSION

This section of the Chapter 5 provides a brief overview of the study, including a statement of the problem and the major methods involved. The majority of this section is, however, devoted to a summary and discussion of the implemented framework as the form of a case study. Finally, it is checked how much the main objectives of this research which were mentioned in the section 1.4 have been attained.

The platform of a social network is a good opportunity for businesses to make progress their business by using adequate advertisements for the users of social network. Traditional type of advertisements was using inefficient methods to advertise the message of companies. The disappointing outcome of those approaches were led to avoid paying attention to the advertisements because the advertisements were mostly bothering, boring and irrelevant. One of the recent technologies that could improve the efficiency of advertisements on social network is semantic technologies. Using every method of semantic web in developing the solutions can lead to increase the efficiency of advertisements. Nowadays, recommendation systems play an important role in conveying advertisements as forms of products or services to the right market which means targeted market. Therefore, design of an appropriate framework which establishes these ideas would be interesting for the research.

To illustrate the structure of employed framework in this study, main components of the framework are explained along with their operability in general. As shown in Figure 3-1, firstly user tries to enter the space of the application through the authentication interface. This part of the framework can be implemented by a web page and after a successful operation of SSO, the user is eligible to enter the system. Then, using an API provided by the social network, the user can access to the needed data of the social network, including the information of products and the producers. In this step, it is possible for the user by an interface to select the desired products which are interesting for this user. By user’s activity, a list of interesting products is prepared and saved in the dataset of the platform. The semantic recommender system engine which is responsible to generate the recommendations for the users, prepares recommendations based on the user’s preferences which can be extracted by user’s activities.

The recommended products are provided to the user by a specific interface. Then users can decide about the recommended products and purchase their desired products from the advertiser company, whether they are matched to users’ preferences or not. On the other hand, the information which are prepared after recommendation process is provided to the researcher to evaluate the system’s performance. Furthermore, there is the possibility of using recommended products in case of satisfaction confirmation by the user, and feed them to the system to increase the accuracy of the framework for the future use. In this condition, we can observe great results by the system’s training.

In this study, a comprehensive framework has been introduced so that using its advantages, every business can improve its business model using a semantically-enhanced advertisement recommender system which can be implemented on a platform of a social network for the company. The suggested framework is in a general form. So for evaluating the framework, it was necessary to implement at least one case study to validate the solution. After developing a website with the data gathered from a social network, a number of users browsed the website and had activities, then based on their activities and their interests that they expressed their interests directly and indirectly, it was possible for the users to see some recommendations made by the semantic engine of the framework and at the end of their activity, the users could rate to the recommendations. This recent data was used for the validation of the framework, demonstrated in the Chapter 5.

One significant issue is that for implementing the chosen case study, the website of last.fm has been selected to work. Last.fm as mentioned in [319], uses collaborative filtering as a classical recommendation technique. While the methodology of the framework utilizes a particular kind of hybrid recommender system to suggest advertisements. Therefore, it is possible to observe absolute better results in SARSIS rather than in last.fm, because not only SARSIS uses the benefits of collaborative filtering techniques but also it utilizes many advantages of the other recommender methods as content-based, context-aware and demographic recommendation methods. To sum up, this good tip can be expressed that the performance of SARSIS is better than the recommendation system in last.fm.

The gathered results showed that the efficiency of the designed case study, as a sample for the framework, is adequate. For reaching this aim, an evaluation criterion as the Mean Absolute Error was used and calculated to prove the accuracy of the framework.

Although the value of MAE for whole of the web application was not very low but it was promising and acceptable. One reason about the value of MAE which is a little bit relatively high after interview with some of the users was that there is no possibility of finding and listening a preview for some of the music tracks. As a result, they could not like the music track and as an outcome, the number of liked music tracks was reduced that influenced directly in estimating of MAE. So, if it was possible to select a more comprehensive website of music track resources, absolutely the value of MAE could be decreased accordingly. But the problem was that after doing an investigation and comparing many websites as the resources of music track which could be used for playing the previews, the best choice among distinguished websites was Spotify. Moreover, based on the Figure 5-6 and Figure 5-7, it is possible to see positive values for precision and recall for the users.

In total, the results and the gathered data from user rates which reflects their feedback about the framework, proves that they are generally satisfied about the recommendations. So based on this information we can conclude that if the framework can be implemented on a social network and use semantic methods to provide advertisements, the results will have enough efficiency for the business which consider this framework.

Here, the results of the current research are compared to the other similar researches. As described in the section 2.7 and pointing to these papers [272][273][274], it is possible to see the differences between this study and the other more similar studies. First the work [274] is referred whose application's name is SPAC. A comparison between SARSIS and SPAC has been depicted in Figure 5-8.

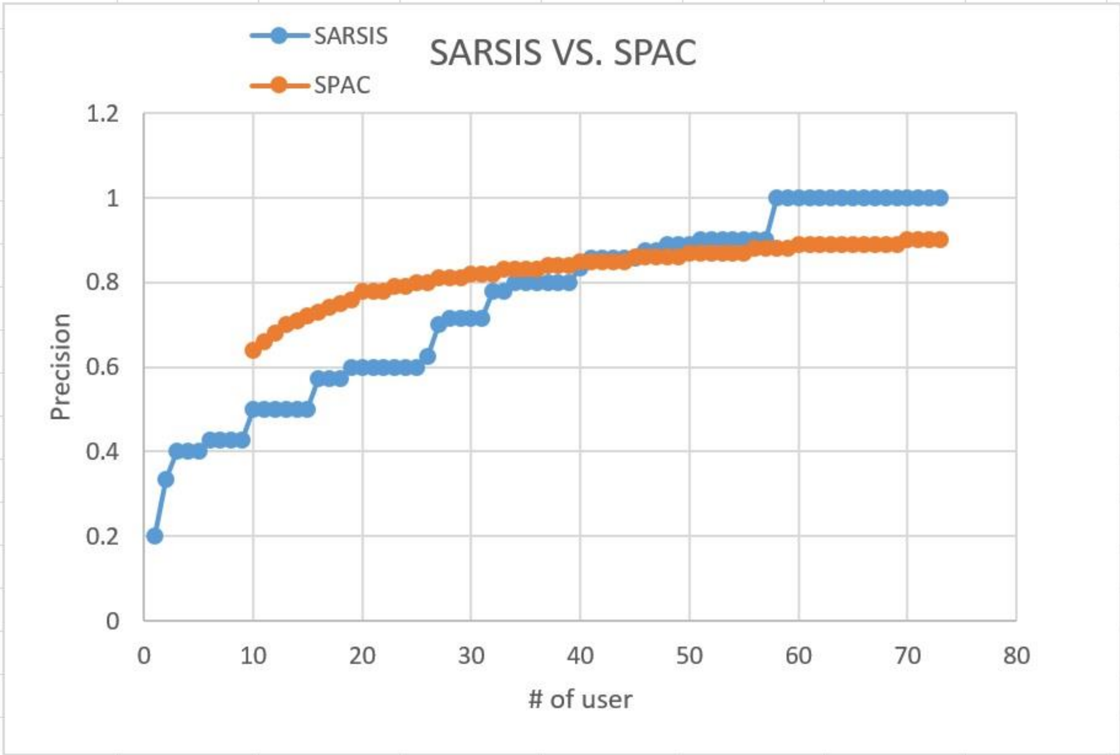



*Figure 5-8 A comparison of accuracy between SARSIS and SPAC*

On average, SPAC showed a better accuracy rather than SARSIS.

Second, the study [273] is pointed. A graph including the MAE in SARSIS and this system has been shown in Figure 5-9.

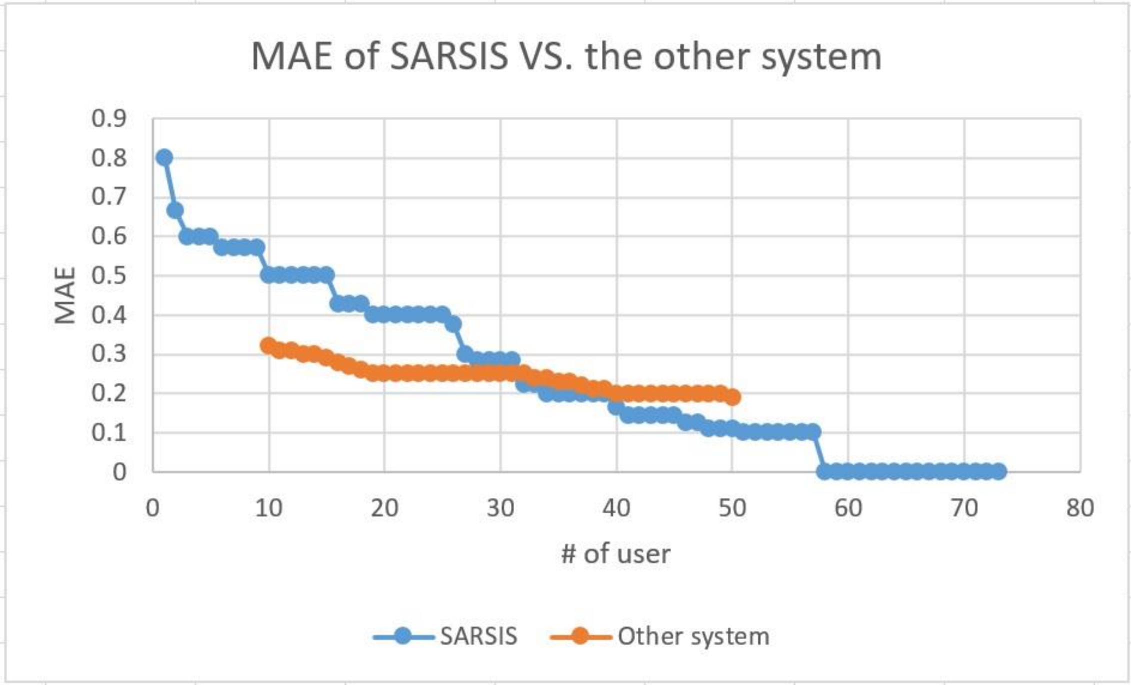



*Figure 5-9 A comparison of MAE between SARSIS and the other system*

According to the graph shown in this paper and depicted in Figure 5-9, indicating the MAE of its application and the MAE of SARSIS, it can be concluded that SARSIS has a better efficiency with lower average MAE.

Third, the study [272] is referred whose application's name is Friendbook. A comparison between Recall of SARSIS and Friendbook has been depicted in Figure 5-10.

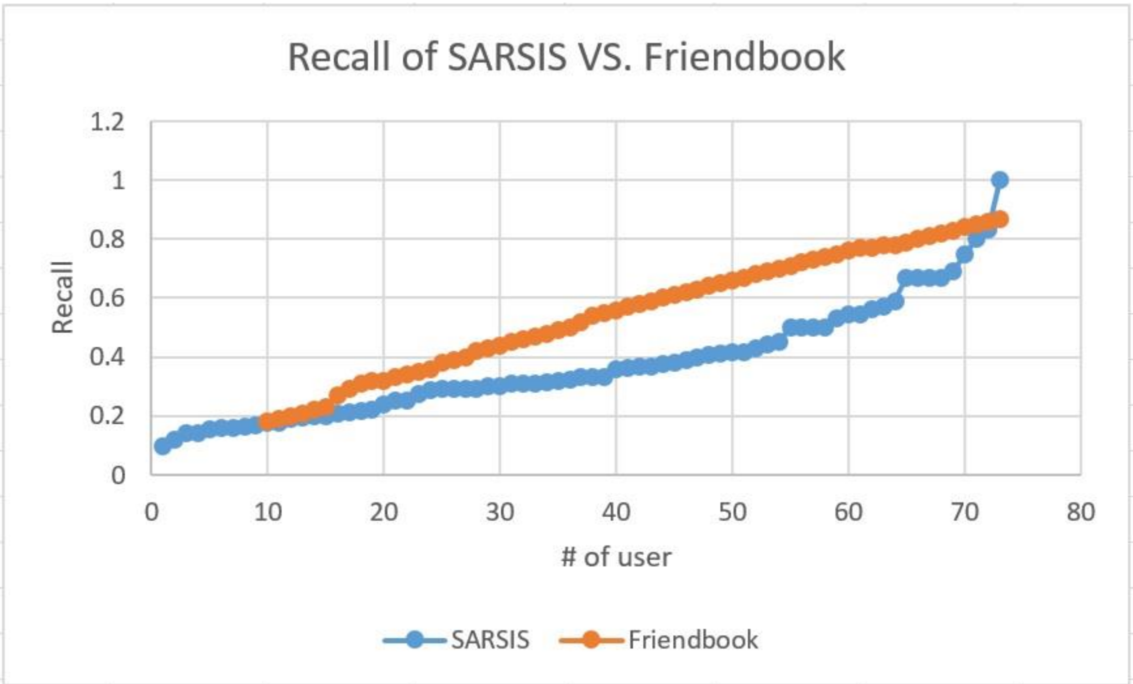



*Figure 5-10 A comparison of Recall between SARSIS and Friendbook*

According to this graph, SARSIS has a lower average recall with a higher average precision rather than Friendbook. So it can be concluded that SARSIS has a better efficiency than Friendbook.

Furthermore, there were some restrictions in this study which did not permit to do the research with more degree of quality. For example, among API functions of the social network, last.fm. as the case study of the social network, there was not a sign up method which a platform for the users of web application could not be prepared to join the last.fm and have activity on its own interface. In this case it could be possible to assess the efficiency of recommender system, which is used in last.fm. Therefore, more comprehensive comparison details between SARSIS and the recommender system of last.fm could not be provided.

One difficulty in doing this research was that there was no suitable prepared dataset to be utilized in the web application. As a result, a customized dataset should be prepared based on the real data of a social network. Then, there was a try to collect data from selected social network, last.fm, including the important data as music tracks with 137685 records and artist people with 2125 records which was crawled from this social network by several REST queries and it took a complete three weeks of time by an intensive hard work.

As described in this section, it is possible to check whether the main goals which were mentioned in the section 1.4 have been attained or not. The primary constraints of classical methods have been overcome since it is possible to see that the recommender system of last.fm utilizes a collaborative filtering technique as a classical method and its performance is lower than the recommender system of SARSIS which utilizes a hybrid method by mixing four standard methods.

Since the recommended products by SARSIS show more satisfactory results than the other similar works, it is possible to say that the quality of the recommendations has been increased.

During designing the methodology of this study, it has been considered that the suggested methodology should be used conveniently so that the implementation of the client application would be easier. As explained in the section 3, all details of the methodology have been utilized and implemented without any complexity.

As described in the section 3, the suggested framework has been established on a real software platform. The selected social network has been the website of last.fm and the client application, SARSIS, has been developed on a web application platform.

Because the client application of SARSIS has been developed on an online platform during the process of initializing of SARSIS and the activities by the online users, the portability as one of the important issues in software systems for the solution of this study has been considered since SARSIS could be accessed everywhere and every time without any limitation.

As it is evaluated in the section 4 and the information provided in the Table 5-1, the results of the recommendation process have had acceptable outcome based on the users' likes, so it is possible to say that the reliability has been considered in the framework of this study. Furthermore, using a feedback system which is designed in the framework proves that the framework has considered the reliability.

As explained in the section 3.9, an acceptable level of security for the framework has been considered as an important part of the software system of the framework. Although it could be possible to design a more complete mechanism of security for the framework, but the same level of security has been satisfied to prevent complexity in the suggested framework.

In conclusion, based on the provided information it is possible to see that the major objectives of the research have been attained. Perhaps the number of main objectives in this study was not too much, but it was preferred to reach to all of them as much as possible which seems to be a better outcome for this study.

## 5.4 SUMMARY

In this chapter, two important parts of the research have been explained, including results and discussion. These two parts, prove that how much the research has new outcomes and how surpasses to the similar works. Furthermore, the advantages and superiorities of the framework in comparison to the other framework have been discussed. In the first part, results, some information about the implemented case study has been provided. Then the data gathered from users of SARSIS has been assessed and analyzed. To this aim, the complete details of how the collected data has been presented was justified, including the SQL queries, contents of users' activities, and finally this data has been evaluated by some scientific approaches like MAE, precision and recall concepts. Although this data is related to different classes of users in term of age, they presented their interests directly or indirectly by their activities.

The efficiency of the framework was compared to four platforms. Three of belongs to the papers mentioned in 2.7 and 5.3 and the one is related to the last.fm social network. In three of them the efficiency of the current study was better and in one study, that application (SPAC) showed a better performance in terms of evaluation metrics.

The stage of a social network is a decent open door for organizations to gain ground their business by utilizing sufficient commercials for the clients of social network. Conventional sort of promotions was utilizing wasteful strategies to publicize the message of organizations. The disillusioning result of those methodologies were directed to abstain from paying consideration on the commercials on the grounds that the ads were for the most part trying, exhausting and unimportant. One of the late innovations that could enhance the productivity of promotions on social network is semantic advancements. Utilizing each strategy for semantic web in building up the arrangements can prompt expand the effectiveness of notices. These days, proposal frameworks assume an imperative part in passing on commercials as types of items or administrations to the right market which implies focused on business sector. Along these lines, outline of a proper structure which sets up these thoughts would enthusiasm for the examination.

Customary recommender frameworks, for example, those taking into account content-based and collaborative filtering, tend to utilize decently basic client models. For instance, client based collaborative filtering by and large models the client as a vector of thing appraisals. As extra perceptions are made about clients' inclinations, the client models are broadened, and the full gathering of client inclinations is utilized to produce suggestions or make forecasts. This methodology, in this manner, disregards the idea of "arranged activities", the way that clients interface with the framework inside a specific "setting" and that inclinations for things inside one setting might be not the same as those in another setting.

For such systems it is better to design and develop a more completed recommender system including the advantages of both group of methods. In this case, the suggested framework will be more effective and reliable. Also, it is notable that it should be considered that each framework has its own limitations and problems. An innovative framework was introduced which not only has a combination of four recommendation techniques, but also it uses the benefits of semantic technology.

The results based on the experiments mentioned in this chapter demonstrate that the proposed framework outflanks many similar strategies.

## CHAPTER 6

# 6. CONCLUSION AND FUTURE WORKS

In this chapter, a summary of whole text will be expressed. Consequently, the research work which will be considered to be established in the future will be mentioned.

In conclusion, the strength points of the framework are summarized as below:

1- An appropriate level of security has been considered for the framework

2- Utilizing a semantic logic to calculate the recommendations which is special and a kind of robustness in designing recommender systems

3- Choosing a suitable composition of classical recommender methods as a hybrid method along with selecting of promising formulas for estimating each of the particular methods.

4- A feedback of users' opinions is used as finding more users' interests and adding them to the users' Interests dataset for the future recommendations and making them more accurate.

5- An adequate number of online users to have activity on the framework.

## 6.1 CONCLUSION

Some questions in the section 1.3 of Chapter 1 were asked which here, it is the time to answer them:

1- Is possible to overcome the current problems of recommender systems in social networks?

Yes, it is. As explained before, there were two approaches to solve the problems of recommender systems for which the mentioned solutions were explained, implementing them. The available problems in recommender system are sparsity, cold-start and scalability. As mentioned in 1.1 in the framework, the possibility of solving three problems has been considered. Therefore, the effort in this study has set to decrease the side effects of the problems in the section of recommender system.

2- How much is the role of semantic in shaping an efficient recommender system?

Most of recommender systems do not use a semantic methodology to enhance the performance of their recommender system but in the current framework, as a semantic approach for generating recommendations was utilized, a more efficient system can be developed according to this framework to recommend the products. Semantic methods can improve the chance of finding recommendation closer to user interests rather than classical methods, because they can extract the real relations between entities which are working in a recommendation system in social network.

3- How much are the users satisfied by the recommended products?

In brief in this framework it is possible to observe a high degree of users' satisfaction by analyzing experimental results. By using semantically enhanced solution, the recommendations are more precise and better express the users' preferences. Moreover, one of the other positive aspects of the framework is that the system feeds the feedbacks to the dataset and utilizes them for the next recommendation generation. As a result, the consequent recommendations will be very accurate and more interesting rather than the previous recommendations.

4- Is possible to collect a comprehensive database with a high quantity of data to increase the level of reliability?

Yes, it is. Because in the framework, the data which are used for the recommendation system are collected from a big social network with a tremendous number of active users, so accordingly by developing an extra software solution, it is possible to gather comprehensive data from the users' activities over the social network. In fact, not only the social network which was used as a prototype for testing of the framework, has suitable amount of data, on base of quality and quantity, but also this social network could help me to gather good volume of data by providing a complete API and this API was integrated within a software application which was developed so as to get needed data. On the other hand, after a hard work to collect desired data, a robust dataset was prepared which was ready to work for the users of the framework. Because of this good dataset, all of the users could work with the prototype software and the results were reliable since the users could always observe logical and consistent outcome.

As a conclusion for this research the next statements are presented as a brief comment about how previous chapters were demonstrated: In Overview an abstract of whole study has been described. An introduction to the complete research was explained in Chapter 1 containing the sections approach to the problem, objectives, related works and methodology of the research. Chapter 2 demonstrates about the definitions of the study including semantic web technology, social web, social semantic web and online promoting. Because the main component of the research is recommender systems, this concept was completely characterized in the section 2.6. In Chapter 3, the methodology of the research, describing the details of the suggested framework was mentioned which comprised the sections revealing the framework, case study, client application, a test case, dataset, used programming language for developing of the case study, efficiency and the security of the framework. The details of the evaluation for the study were illustrated in Chapter 4. In Chapter 5 the results and discussion are explained. Finally, to sum up the study including conclusion and future works is mentioning in Chapter 6.

## 6.2 FUTURE WORKS

Doing every research includes constraints and problems. So usually researchers cannot finish all jobs of their research and normally some of the jobs can be done in the future. Some of the planned future works about the framework are listed as below:
1- To define different levels of accessing or access control for the security part of the framework.
About the security of the framework, it is a good idea to develop its structure by enhancing some part of its security and enriching a multi factor authentication for the user entrance.
2- To run the web application once again with more number of users to see the differences of outcomes and get better results.
In the future, if possible, it is preferred to run some times more to get a more volume of data by users' activities and after that do a comprehensive analysis on the collected data. As a result, the outcome will have more accuracy and consequently the users will be more satisfaction about the framework.
3- To find a more comprehensive resource of products for showing the details in the implementation section of the case studies.
4- If more social network matched to this framework can be emerged in the future, it is preferred to run and test the framework on more social networks. The social network should have flexible API with easy to use syntax for developing.

Using the above considerations, it is possible to have more complete framework with its own structure and details which will absolutely have many productive outcomes for the research.

"To me, it was urging to perceive how best organizations over the world are putting resources into recommenders, as they are appeared to upgrade consumer loyalty and convey genuine quality to both clients and organizations." expresses Mendeley Senior Data Scientist, Maya Hristakeva [320]. "LinkedIn reported that half of the associations made in their interpersonal organization originate from their supporter recommender, while Netflix says that in the event that they can prevent 1% of clients from crossing out their membership then that is worth $500M a year, which obviously legitimizes the certainty they are contributing $150M/year in their substance suggestion group, comprising of 300 individuals."

In any case, one of the upsides of such a half and half strategy is, to the point that it didn't bashful far from tending to the more extensive issues, for example, how to ward against making a "channel bubble" impact, how to save client's protection, and streamlining frameworks for what truly matters (and how this can be viably characterized).

"The best frameworks have been appeared to begin off by giving suggestions that can rapidly be assessed by clients as being valuable before steadily presenting more novel proposals. So on account of helping scientists to discover applicable articles to peruse, it's likely best to begin by prescribing understood however imperative articles in their field, before suggesting some less surely understood yet exceptionally correlated articles to their particular issue area.” Says Kris. “Other imperative elements incorporate reranking (the request in which suggestions ought to be appeared), the UI plan that can best bolster communication with the recommender framework, and the routes in which we can construct connection mindful recommendations.”

# GLOSSARY

| | |
|---|---|
| IMDb.com | Internet Movie Database |
| SVD | Singular Value Decomposition |
| kNN | K Nearest Neighborhood |
| OSN | Online Social Network |
| RDF | Resource Description Framework |
| SPARQL | Simple Protocol And RDF Query Language |
| SARSIS | Semantically-enhanced Advertisement Recommendation System In Social network |
| MAE | Mean Absolute Error |
| SNS | Social Networking Service |
| OWL | Web Ontology Language |
| CF | Collaborative Filtering |
| DVD | Digital Versatile Disc |
| XML | Extensible Markup Language |
| HTML | Hyper Text Markup Language |
| XHTML | Extensible HTML |
| URL | Uniform Resource Locator |
| W3C | World Wide Web Consortium |
| RDFS | Resource Description Framework Schema |
| N3 | Notation3 |
| SKOS | Simple Knowledge Organization System |
| RDFa | Resource Description Framework attributes |
| RIF | Rule Interchange Format |

| | |
|---|---|
| GNU | General Public License |
| FOAF | Friend Of A Friend |
| SIOC | Semantically-Interlinked Online Communities |
| HTTP | HyperText Transfer Protocol |
| URI | Uniform Resource Identifier |
| PC | Personal Computer |
| IFIP | International Federation for Information Processing |
| DOLCE | Descriptive Ontology for Linguistic and Cognitive Engineering |
| ISO | International Organization for Standardization |
| DOGMA | Developing Ontology-Grounded Methods and Applications |
| OIL | Ontology Inference Layer |
| DAML | DARPA Agent Markup Language |
| SADL | Semantic Application Design Language |
| SBVR | Semantics of Business Vocabularies and Rules |
| UML | Unified Modeling Language |
| API | Application Programming Interface |
| SNA | Social Network Analysis |
| XFN | XTML Friends Network |
| OntoSNA | Ontology of Social Network Analysis |
| SSW | Social Semantic Web |
| CSCW | Computer Supported Cooperative Work |
| CSV | Comma Separated Values |
| CEO | Chief Executive Officer |
| RS | Recommender System |

| | |
|---|---|
| ROI | Return Of Investment |
| IDE | Integrated Development Environment |
| CIA | Confidentiality, Integrity and Availability |
| MDP | Markovien Decision Process |
| SSO | Single Sign On |
| AI | Artificial Intelligence |

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# PUBLICATIONS

**PART 1) PUBLICATIONS DERIVED FROM THE THESIS:**

1. Ali Pazahr, J. Javier Samper Zapater, Francisco García Sánchez, Parisa Ganjeh, and Carmen Botella. 2016. A two-layer security model for accessing multimedia content in social networks. In Proceedings of the 14th International Conference on Advances in Mobile Computing and Multi Media (MoMM '16), Bessam Abdulrazak, Eric Pardede, Matthias Steinbauer, Ismail Khalil, and Gabriele Anderst-Kotsis (Eds.). ACM, New York, NY, USA, 269-275. DOI: https://doi.org/10.1145/3007120.3011490

Quality Indicators: Classified B by Conference Ranking -Computing Research and Education (CORE)

In this paper, a semantically-empowered security model for accessing multimedia content in social networks is presented. The application of this model ensures that (1) unauthorized users cannot access to private multimedia data, and (2) the overall level of trust among social networks users who share their private and sensitive data is enhanced. Two questionnaires were developed to select the most characteristic features to consider in our model to differentiate legitimate users and attackers. By using parametric considerations, both security and users' convenience are reached which makes our proposed model more effective.

2. Ali Pazahr, J. Javier Samper Zapater, Francisco García Sánchez, Carmen Botella, and Rafael Martinez. 2016. Semantically-enhanced advertisement recommender systems in social networks. In Proceedings of the 18th International Conference on Information Integration and Web-based Applications and Services (iiWAS '16). ACM, New York, NY, USA, 179-189. DOI: https://doi.org/10.1145/3011141.3011489

Quality Indicators: Classified C by Conference Ranking -Computing Research and Education (CORE)

In this study a philosophy of a system speaking to of a comprehensive structure of advertisement recommender system for social networks will be presented. The framework uses a semantic logic to provide the recommended products and this capability can differentiate the recommender part of the framework from classical recommender methods. Briefly, the framework proposed in this study has been designed in a form that can generate advertisement recommendations in a simplified and effective way for social network users.

3. Ali Pazahr, J. Javier Samper Zapater, Francisco García Sánchez, an access control architecture based on cryptography for social networks, THEOR COMPUT SCI (under evaluation), ISSN 0304-3975, Published by ELSEVIER, 2017.

Quality Indicators: ISI JCR indexed

In this paper, an architecture of access control for a social network has been proposed. This architecture is containing layers and levels along with a software application solution including a cryptographic method. Layers are consisting of some generic methods which can set up a confident framework for social network platforms while levels are different sections in these systems. Finally, the focus of this paper is on proposing a cryptographic solution for authentication on social networks. In fact, the proposed approach is a reliable solution for authentication component, an appropriate way for users to log-in to social networks.

**PART 2) OTHER PUBLICATIONS RELATED TO THE THESIS:**

1. Ali Pazahr, Kambiz Mizanian, Seyyed Mohammad Safi, Shiva Taghipour Eivazi, Mehdi Rezaei, Fault-Tolerant and Information security in Networks using Multi-Level Redundant Residue Number System, Res. J. Recent Sci., E-ISSN: 2277 - 2502, vol. 3, no. 3, pp. 1–111, Indore, India, 2014.

2. Ali Pazahr, an access control architecture for a web information system, in International Journal of Novel Computer Science and Power Solutions (IJNCSPS), ISSN: 2476-7476, Volume 1. No.1, Ahvaz, Iran, 2016.

# ANNEX

The code for event of search related to the textbox in which the user looks for a track
##########################################################################

```
//-------------------- Try Finding Track source for playing ---------------------
        Uri uri = new Uri(@"https://api.spotify.com/v1/search?q=" +
txtartist.Text + "%20" + txttrack.Text + "&type=track");
        WebRequest webRequest = WebRequest.Create(uri);

        rate.Value = 0;
        lblmsgfound.Visible = false;
        lblmsgerrorplay.Visible = false;
        lblmustentertrack.Visible = false;

        try
        {
            WebResponse response = webRequest.GetResponse();
            StreamReader streamReader = new
StreamReader(response.GetResponseStream());
            bool FoundMusic = false;
            do
            {
                string ss = streamReader.ReadLine();
                SearchPlayer.StartTime = 0;
                SearchPlayer.Source = "";

                if (ss.IndexOf("preview_url") != -1)
                {
                    string sss = ss.Substring(23);

                    SearchPlayer.Source = sss.Substring(0, sss.IndexOf('"'));

                    FoundMusic = true;
                    SearchPlayer.AutoPlay = true;
                    break;
                }
            } while (!streamReader.EndOfStream);

            if (!FoundMusic)
            {
                lblmsgfound.Visible = true;
            }

            //--------------------- Add a Record to table Interests & Set its
irank = 5 --------------
            SqlConnection cn = new
SqlConnection(ConfigurationManager.ConnectionStrings["MusicRecCn"].ToString());
            cn.Open();
            SqlCommand cmd = new SqlCommand("Select * from Tracks where (name='"
+ txttrack.Text + "') and (artist='" + txtartist.Text + "')", cn);
            SqlDataAdapter da = new SqlDataAdapter(cmd);
            DataSet ds = new DataSet();
            da.Fill(ds, "Tracks");
            string tid = ds.Tables[0].Rows[0].ItemArray.GetValue(0).ToString();
            string trank = ds.Tables[0].Rows[0].ItemArray.GetValue(4).ToString();
            Session["trackid"] = tid;
            cmd.Dispose();
            ds.Dispose();
            da.Dispose();
```

```
            //--------------- check and insert if not exists -------------
            cmd = new SqlCommand("Select * from Interests where (userid=" +
Session["userid"].ToString() + ") and (musicid=" + tid + ")", cn);
            da = new SqlDataAdapter(cmd);
            ds = new DataSet();
            da.Fill(ds, "Interests");
            if (ds.Tables[0].Rows.Count == 0)
            {
                SqlCommand cmd2 = new SqlCommand("Insert into Interests(userid,
musicid, irank, trank)  Values(" + Session["userid"].ToString() + " , " + tid + "
, 5 , " + trank + ")", cn);
                cmd2.ExecuteNonQuery();
            }

            cn.Close();
            cn.Dispose();
        }
        catch
        {
            lblmsgerrorplay.Visible = true;
        }
```

################################################################################

The code for the event of button click when the user answers to the question about hearing the track

################################################################################

```
   if (Convert.ToString(Session["trackid"]) != "")
        {
            lblmustentertrack.Visible = false;
            SqlConnection cn = new
SqlConnection(ConfigurationManager.ConnectionStrings["MusicRecCn"].ToString());
            cn.Open();
            SqlCommand cmd = new SqlCommand("Update Interests set irank=4 where
(userid=" + Session["userid"].ToString() + ") and (musicid=" +
Session["trackid"].ToString() + ") and (irank > 4)", cn);
            cmd.ExecuteNonQuery();
            cn.Close();
            cn.Dispose();
        }
        else
        {
            lblmustentertrack.Visible = true;
        }
```

################################################################################

The code of event when the user clicks on the rate button for a track

################################################################################

```
if (Convert.ToString(Session["trackid"]) != "")
        {
            lblmustentertrack.Visible = false;
            int x = Convert.ToInt16(rate.Value);
            switch (x)
            {
                case 1: x = 3; break;
                case 2: x = 2; break;
```

```
                case 3: x = 1; break;
                default: x = 4; break;
            }
            SqlConnection cn = new
SqlConnection(ConfigurationManager.ConnectionStrings["MusicRecCn"].ToString());
            cn.Open();
            SqlCommand cmd = new SqlCommand("Update Interests set irank=" +
x.ToString() + " where (userid=" + Session["userid"].ToString() + ") and
(musicid=" + Session["trackid"].ToString() + ")", cn);
            cmd.ExecuteNonQuery();
            cn.Close();
            cn.Dispose();
        }
        else
        {
            lblmustentertrack.Visible = true;
        }
################################################################################

The event for calculating Recommendations
################################################################################

//================================== Find Recommendations Demo & Ctx
===========================================

        //-------------------- find Sorted Similar musics of Demo approach ------
---------------------------
        SqlConnection cn = new
SqlConnection(ConfigurationManager.ConnectionStrings["MusicRecCn"].ToString());
        cn.Open();
        SqlCommand cmd = new SqlCommand("Select * from Users", cn);
        cmd.CommandType = CommandType.Text;
        SqlDataAdapter da = new SqlDataAdapter(cmd);
        DataSet ds = new DataSet();
        da.Fill(ds, "User");
        int nOtherUsers = ds.Tables[0].Rows.Count - 1;
        int[,] arrSimilarUsersDemo = new int[nOtherUsers, 2];
        int[,] arrSimilarUsersCtx = new int[nOtherUsers, 2];
        int iOtherUsers = 0;

        for (int i = 0; i < ds.Tables[0].Rows.Count; i++)
        {
            int demorate = 0;
            int ctxrate = 0;

            if (ds.Tables[0].Rows[i].ItemArray.GetValue(0).ToString() !=
Session["userid"].ToString())
            {
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(9).ToString() ==
Session["demolocation"].ToString())
                {
                    demorate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(10).ToString() ==
Session["demoage"].ToString())
                {
                    demorate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(11).ToString() ==
Session["demolooking"].ToString())
                {
```

```
                    demorate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(12).ToString() ==
Session["demorelig"].ToString())
                {
                    demorate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(13).ToString() ==
Session["demoedu"].ToString())
                {
                    demorate++;
                }
                arrSimilarUsersDemo[iOtherUsers, 0] =
Convert.ToInt32(ds.Tables[0].Rows[i].ItemArray.GetValue(0));
                arrSimilarUsersDemo[iOtherUsers, 1] = demorate;
                for (int j = 0; j < nOtherUsers - 1; j++)
                {
                    for (int k = j + 1; k < nOtherUsers; k++)
                    {
                        if (arrSimilarUsersDemo[j, 1] < arrSimilarUsersDemo[k,
1])

                        {
                            int temp;
                            temp = arrSimilarUsersDemo[j, 1];
                            arrSimilarUsersDemo[j, 1] = arrSimilarUsersDemo[k,
1];

                            arrSimilarUsersDemo[k, 1] = temp;
                            temp = arrSimilarUsersDemo[j, 0];
                            arrSimilarUsersDemo[j, 0] = arrSimilarUsersDemo[k,
0];

                            arrSimilarUsersDemo[k, 0] = temp;
                        }
                    }
                }

                //--------------------------- find Sorted Similar musics of
Context-aware approach ----------------------------
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(3).ToString() ==
Session["ctxheartime"].ToString())
                {
                    ctxrate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(4).ToString() ==
Session["ctxlonewith"].ToString())
                {
                    ctxrate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(5).ToString() ==
Session["ctxmentcond"].ToString())
                {
                    ctxrate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(6).ToString() ==
Session["ctxway"].ToString())
                {
                    ctxrate++;
                }
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(7).ToString() ==
Session["ctxonsite"].ToString())
                {
                    ctxrate++;
                }
```

```
                if (ds.Tables[0].Rows[i].ItemArray.GetValue(8).ToString() ==
Session["ctxoffdev"].ToString())
                {
                    ctxrate++;
                }
                arrSimilarUsersCtx[iOtherUsers, 0] =
Convert.ToInt32(ds.Tables[0].Rows[i].ItemArray.GetValue(0));
                arrSimilarUsersCtx[iOtherUsers, 1] = ctxrate;
                for (int j = 0; j < nOtherUsers - 1; j++)
                {
                    for (int k = j + 1; k < nOtherUsers; k++)
                    {
                        if (arrSimilarUsersCtx[j, 1] < arrSimilarUsersCtx[k, 1])
                        {
                            int temp;
                            temp = arrSimilarUsersCtx[j, 1];
                            arrSimilarUsersCtx[j, 1] = arrSimilarUsersCtx[k, 1];
                            arrSimilarUsersCtx[k, 1] = temp;
                            temp = arrSimilarUsersCtx[j, 0];
                            arrSimilarUsersCtx[j, 0] = arrSimilarUsersCtx[k, 0];
                            arrSimilarUsersCtx[k, 0] = temp;
                        }
                    }
                }
                iOtherUsers++;
            }

        }

        ds.Dispose();
        da.Dispose();
        cmd.Dispose();
        //cn.Close();
        //-------------------------------- Making Recommendations, Demo Approach -
---------------------------

        DataTable table = new DataTable();
        table.Columns.Add(new DataColumn("userid", typeof(int)));
        table.Columns.Add(new DataColumn("musicid", typeof(int)));
        table.Columns.Add(new DataColumn("itrate", typeof(decimal)));
        table.Columns.Add(new DataColumn("rx", typeof(string)));

        for (int i = 0; i < nOtherUsers; i++)
        {

            cmd = new SqlCommand("Select * from interests Where (userid='" +
arrSimilarUsersDemo[i, 0] + "')", cn);
            da = new SqlDataAdapter(cmd);
            ds = new DataSet();
            da.Fill(ds, "interests");

            for (int j = 0; j < ds.Tables["interests"].Rows.Count; j++)
            {
                int musicid =
Convert.ToInt32(ds.Tables["interests"].Rows[j].ItemArray.GetValue(1));
                int irank =
Convert.ToInt32(ds.Tables["interests"].Rows[j].ItemArray.GetValue(2));
                int trank =
Convert.ToInt32(ds.Tables["interests"].Rows[j].ItemArray.GetValue(3));
                decimal itrate = Decimal.Divide(arrSimilarUsersDemo[i, 1], (5 *
irank * trank));
```

```
                DataRow row = table.NewRow();
                row["userid"] = Convert.ToInt32(Session["userid"].ToString());
                row["musicid"] = musicid;
                row["itrate"] = itrate;
                row["rx"] = "demo";
                table.Rows.Add(row);
            }

            ds.Dispose();
            da.Dispose();
            cmd.Dispose();
        }
        //------------------------------- Making Recommendations, Context-Aware
Approach ---------------------------
        for (int i = 0; i < nOtherUsers; i++)
        {

            cmd = new SqlCommand("Select * from interests Where (userid='" +
arrSimilarUsersCtx[i, 0] + "')", cn);
            da = new SqlDataAdapter(cmd);
            ds = new DataSet();
            da.Fill(ds, "interests");

            for (int j = 0; j < ds.Tables["interests"].Rows.Count; j++)
            {
                int musicid =
Convert.ToInt32(ds.Tables["interests"].Rows[j].ItemArray.GetValue(1));
                int irank =
Convert.ToInt32(ds.Tables["interests"].Rows[j].ItemArray.GetValue(2));
                int trank =
Convert.ToInt32(ds.Tables["interests"].Rows[j].ItemArray.GetValue(3));
                decimal itrate = Decimal.Divide(arrSimilarUsersCtx[i, 1], (6 *
irank * trank));

                DataRow row = table.NewRow();
                row["userid"] = Convert.ToInt32(Session["userid"].ToString());
                row["musicid"] = musicid;
                row["itrate"] = itrate;
                row["rx"] = "ctx";
                table.Rows.Add(row);
            }

            ds.Dispose();
            da.Dispose();
            cmd.Dispose();
        }
        //-------------------- End of Finding a list of Recommendation based on
Similar users with demo & ctx --------------

        using (SqlBulkCopy bulk = new SqlBulkCopy(cn))
        {
            bulk.DestinationTableName = "Recs_Temp";
            bulk.WriteToServer(table);
        }

        //---------------------------- Delete old recommendations by two
approaches demo & ctx -------------------

        cmd = new SqlCommand();
        cmd.Connection = cn;
        cmd.CommandText = "DELETE From Recs WHERE ((rx='demo') or (rx='ctx')) and
(userid='" + Session["userid"].ToString() + "')";
```

```
        cmd.ExecuteNonQuery();
        cmd.Dispose();

        //-------------------------------- Transfer from Recs_Temp to Recs Table
----------------------------------

        cmd = new SqlCommand();
        cmd.Connection = cn;
        cmd.CommandText = "INSERT INTO Recs(userid, musicid, itrate, rx) Select
TOP (10) userid, musicid, itrate, rx from Recs_Temp Where (userid='" +
Session["userid"].ToString() + "') ORDER BY itrate DESC";
        cmd.ExecuteNonQuery();
        cmd.Dispose();

        cmd = new SqlCommand();
        cmd.Connection = cn;
        cmd.CommandText = "DELETE from Recs_Temp";
        cmd.ExecuteNonQuery();
        cmd.Dispose();

        cn.Close();
        cn.Dispose();

        //------------------------------ Go to Calculate Content-Based
Recommendations ---------------------------------
        Response.Redirect("AddCBRecs.aspx");

################################################################################
```

Finding recommendations based on content-based method

```
################################################################################

//------------- Find CB recs based on favorite user's tag --------------
        //SqlConnection cn = new SqlConnection("Data Source=PAZAHR-PC;Initial
Catalog=MusicRec;Integrated Security=True");
        SqlConnection cn = new
SqlConnection(ConfigurationManager.ConnectionStrings["MusicRecCn"].ToString());
        cn.Open();
        SqlCommand cmduserlikes = new SqlCommand("Select * from
View_Interests_Tracks where (userid='" + Session["userid"].ToString() + "') and
(irank <= 3)", cn);
        SqlDataAdapter dauserlikes = new SqlDataAdapter(cmduserlikes);
        DataSet dsuserlikes = new DataSet();
        dauserlikes.Fill(dsuserlikes, "View_Interests_Tracks");

        for (int i = 0; i < dsuserlikes.Tables[0].Rows.Count; i++)
        {
            string s =
dsuserlikes.Tables[0].Rows[i].ItemArray.GetValue(3).ToString();
            char[] chr = { ',' };
            string[] arrtags = s.Split(chr);
            for (int j = 0; j < arrtags.Length; j++)
            {
                SqlCommand cmdextracttags = new SqlCommand("Insert Into
CBTags(tag) Values ('" + arrtags[j] + "')", cn);
                cmdextracttags.ExecuteNonQuery();
                cmdextracttags.Dispose();
            }
        }
```

```
        SqlCommand cmdtags = new SqlCommand("Select tag, count(tag) as count from 
CBTags Group By tag Order By count DESC", cn);
        SqlDataAdapter datags = new SqlDataAdapter(cmdtags);
        DataSet dstags = new DataSet();
        datags.Fill(dstags, "CBTags");

        for (int i = 0; i < dstags.Tables[0].Rows.Count; i++)
        {
            string strtag = 
dstags.Tables[0].Rows[i].ItemArray.GetValue(0).ToString();
            if (strtag == "") continue;

            //-------------- Find 3 best tracks whose tags are of interest of the 
user, except the tracks which have been interested by the user ---------- 3 track 
bartar az nazare tag morede alaghe user, gheir az unaei ke like karde, peida 
mishe
            SqlCommand cmdothertracks = new SqlCommand("Select TOP (3) id, name, 
artist, tags, rank From Tracks WHERE (tags LIKE '%" + strtag + "%') AND (id NOT 
IN (SELECT  musicid  FROM    View_Interests_Tracks    WHERE   (userid='" + 
Session["userid"].ToString() + "') and (irank <= 3))) Order BY rank", cn);
            SqlDataAdapter daothertracks = new SqlDataAdapter(cmdothertracks);
            DataSet dsothertracks = new DataSet();
            daothertracks.Fill(dsothertracks, "Tracks");
            for (int j = 0; j < dsothertracks.Tables[0].Rows.Count; j++)
            {
                int trank = 
Convert.ToInt16(dsothertracks.Tables[0].Rows[j].ItemArray.GetValue(4));
                SqlCommand cmdCBRecs = new SqlCommand("Insert Into Recs(userid, 
musicid, itrate, rx) Values (" + Session["userid"].ToString() + ", " + 
dsothertracks.Tables[0].Rows[j].ItemArray.GetValue(0).ToString() + ", " + 
Decimal.Divide(1, 6 * trank).ToString() + ", 'cb')", cn);
                cmdCBRecs.ExecuteNonQuery();
                cmdCBRecs.Dispose();
            }
            cmdothertracks.Dispose();
            daothertracks.Dispose();
            dsothertracks.Dispose();
        }
        //------------ delete all temp data from table CBTags -----------------
        SqlCommand cmdDelTags = new SqlCommand("Delete from CBTags", cn);
        cmdDelTags.ExecuteNonQuery();
        cmdDelTags.Dispose();

        cmduserlikes.Dispose();
        dauserlikes.Dispose();
        dsuserlikes.Dispose();
        cmdtags.Dispose();
        datags.Dispose();
        dstags.Dispose();

        //------------ Find CB recs: consider the musics which the user has 
rated them, find the other musics with the same artist ------------
        SqlCommand cmdUserLikesArtist = new SqlCommand("SELECT Distinct artist 
FROM View_Interests_Tracks WHERE (userid='" + Session["userid"].ToString() + "') 
AND (irank <= 3)", cn);
        SqlDataAdapter daUserLikesArtist = new 
SqlDataAdapter(cmdUserLikesArtist);
        DataSet dsUserLikesArtist = new DataSet();
        daUserLikesArtist.Fill(dsUserLikesArtist, "View_Interests_Tracks");

        for (int i = 0; i < dsUserLikesArtist.Tables[0].Rows.Count; i++)
        {
```

```
            string artist =
dsUserLikesArtist.Tables[0].Rows[i].ItemArray.GetValue(0).ToString();
            SqlCommand cmdOtherTracksByArtist = new SqlCommand("Select TOP (3)
id, name, artist, tags, rank From Tracks WHERE (artist=N'" + artist + "') AND (id
NOT IN (SELECT  musicid  FROM    View_Interests_Tracks    WHERE   (userid='" +
Session["userid"].ToString() + "') and (irank <= 3))) Order BY rank", cn);
            SqlDataAdapter daOtherTracksByArtist = new
SqlDataAdapter(cmdOtherTracksByArtist);
            DataSet dsOtherTracksByArtist = new DataSet();
            daOtherTracksByArtist.Fill(dsOtherTracksByArtist, "Tracks");
            for (int j = 0; j < dsOtherTracksByArtist.Tables[0].Rows.Count; j++)
            {
                int trank =
Convert.ToInt16(dsOtherTracksByArtist.Tables[0].Rows[j].ItemArray.GetValue(4));
                //------------- check if the rec has not been added before then
add the rec ----------
                string strsql = "Select * From Recs Where (userid = " +
Session["userid"].ToString() + ") and (musicid = " +
dsOtherTracksByArtist.Tables[0].Rows[j].ItemArray.GetValue(0).ToString() + ") and
(rx = 'cb')";
                SqlDataAdapter dacheck = new SqlDataAdapter(strsql, cn);
                DataSet dscheck = new DataSet();
                dacheck.Fill(dscheck, "Recs");

                if (dscheck.Tables[0].Rows.Count == 0)
                {
                    SqlCommand cmdCBRecs = new SqlCommand("Insert Into
Recs(userid, musicid, itrate, rx) Values (" + Session["userid"].ToString() + ", "
+ dsOtherTracksByArtist.Tables[0].Rows[j].ItemArray.GetValue(0).ToString() + ", "
+ Decimal.Divide(1, 6 * trank).ToString() + ", 'cb')", cn);
                    cmdCBRecs.ExecuteNonQuery();
                    cmdCBRecs.Dispose();
                }
            }
            cmdOtherTracksByArtist.Dispose();
            daOtherTracksByArtist.Dispose();
            dsOtherTracksByArtist.Dispose();
        }
        cmdUserLikesArtist.Dispose();
        daUserLikesArtist.Dispose();
        dsUserLikesArtist.Dispose();

        //--------------------------- Go to calculate Collaborative Filtering
Recommendations ------------------------
        Response.Redirect("AddCFRecs.aspx");
```

################################################################################

Finding recommendations based on content-based method

################################################################################

```
SqlConnection cn = new
SqlConnection(ConfigurationManager.ConnectionStrings["MusicRecCn"].ToString());
        cn.Open();
        SqlCommand cmdusers = new SqlCommand("Select distinct userid from
interests", cn);
        SqlDataAdapter dausers = new SqlDataAdapter(cmdusers);
        DataSet dsusers = new DataSet();
        dausers.Fill(dsusers, "interests");
        int m = dsusers.Tables[0].Rows.Count;
        int[] RowMap = new int[m];
```

```
        for (int i = 0; i < m; i++)
        {
            RowMap[i] =
Convert.ToInt32(dsusers.Tables[0].Rows[i].ItemArray.GetValue(0));
        }

        SqlCommand cmditems = new SqlCommand("Select distinct musicid from
interests", cn);
        SqlDataAdapter daitems = new SqlDataAdapter(cmditems);
        DataSet dsitems = new DataSet();
        daitems.Fill(dsitems, "interests");
        int n = dsitems.Tables[0].Rows.Count;
        int[] ColMap = new int[n];
        for (int j = 0; j < n; j++)
        {
            ColMap[j] =
Convert.ToInt32(dsitems.Tables[0].Rows[j].ItemArray.GetValue(0));
        }

        decimal[,] rates = new decimal[m + 1, n + 1];
        SqlCommand cmdinterests = new SqlCommand("Select * from interests", cn);
        SqlDataAdapter dainterests = new SqlDataAdapter(cmdinterests);
        DataSet dsinterests = new DataSet();
        dainterests.Fill(dsinterests, "interests");

        int row = 0;
        int col = 0;
        for (int i = 0; i < dsinterests.Tables[0].Rows.Count; i++)
        {
            int userid =
Convert.ToInt32(dsinterests.Tables[0].Rows[i].ItemArray.GetValue(0));
            int musicid =
Convert.ToInt32(dsinterests.Tables[0].Rows[i].ItemArray.GetValue(1));
            int irank =
Convert.ToInt32(dsinterests.Tables[0].Rows[i].ItemArray.GetValue(2));
            for (int j = 0; j < m; j++)
            {
                if (RowMap[j] == userid)
                {
                    row = j + 1;
                    break;
                }
            }
            for (int j = 0; j < n; j++)
            {
                if (ColMap[j] == musicid)
                {
                    col = j + 1;
                    break;
                }
            }
            rates[row, col] = irank;

        }

        cmdusers.Dispose();
        dausers.Dispose();
        dsusers.Dispose();
        cmditems.Dispose();
        daitems.Dispose();
        dsitems.Dispose();
        cmdinterests.Dispose();
```

```
        dainterests.Dispose();
        dsinterests.Dispose();


        //----------------------------- mohasebe W(a,u) -----------------------
------------
        bool[,] SharedInterest = new bool[m+1, m+1];
        for (int i = 0; i <= m; i++)
        {
            for (int j = 0; j <= m; j++)
            {
                SharedInterest[i, j] = false;
            }
        }

        decimal[,] w = new decimal[m, m];
        for (int i = 1; i <= m - 1; i++)
        {
            for (int j = i + 1; j <= m; j++)
            {
                //----------- check whether there are any items rated by both
users for the formula pearson ----------
                int RatedByBothUsers = 0;
                for (int k = 1; k <= n; k++)
                {
                    if (rates[i, k] != 0 && rates[j, k] != 0)
                    {
                        RatedByBothUsers++;
                    }
                }

                if (RatedByBothUsers != 0)
                {
                    SharedInterest[i, j] = true;
                    SharedInterest[j, i] = true;
                }

                if (RatedByBothUsers != 0)  //------------- if there are items
rated by both users, start calculating W(a,u) -----------------
                {
                    decimal ru_ = 0;
                    decimal ra_ = 0;
                    for (int k = 1; k <= n; k++)
                    {
                        ru_ += rates[i, k];
                    }
                    ru_ = ru_ / n;
                    for (int k = 1; k <= n; k++)
                    {
                        ra_ += rates[j, k];
                    }
                    ra_ = ra_ / n;

                    decimal up = 0;                //----- mohasebe surate kasr
w(u,a) ----
                    for (int k = 1; k <= n; k++)
                    {
                        up += (rates[j, k] - ra_) * (rates[i, k] - ru_);
                    }

                    decimal down = 1;                //----- mohasebe makhraje
kasr w(u,a) ----
```

```
                        decimal down1 = 1;
                        decimal down2 = 1;
                        for (int k = 1; k <= n; k++)
                        {
                            down1 += (decimal)Math.Pow((double)(rates[j, k] - ra_),
2);
                            down2 += (decimal)Math.Pow((double)(rates[i, k] - ru_),
2);
                        }
                        down = down1 * down2;            //----- mohasebe w(u,a) ---
-
                        down = (decimal)Math.Sqrt((double)down);
                        w[i - 1, j - 1] = Decimal.Divide(up, down);
                        w[j - 1, i - 1] = w[i - 1, j - 1];

                    } //----------- end of if (RatedByBothUsers != 0) ---------------
-----



                }
            }


            for (int i = 1; i <= m; i++)        //------ mohasebe p(a,i) ha baraye
matrix Rates ke 2bodie (i,j) -----
            {
                //-------- mohasebe ra_ --------------
                decimal ra_ = 0;
                int nra = 0;
                decimal sumra = 0;
                for (int k = 1; k <= n; k++)
                {
                    if (rates[i, k] != 0)
                    {
                        sumra += rates[i, k];
                        nra++;
                    }
                }
                ra_ = decimal.Divide(sumra, nra);
                //-----------------------------------


                for (int j = 1; j <= n; j++)
                {
                    if (rates[i, j] != 0)   //---- agar ghablan ratesh dade shode va
mohasebe nashode nist -----
                    { continue; }

                    decimal up = 0;
                    decimal down = 0;
                    //--------- peida kardane k nearest neighbors --------
                    if (m <= 8) //---- tedade 7 hamsaye ro entekhab kardam. age kolle
userha ta 8ta/7hamsaye bashan ke hamashun, age na (bishtar budan) 7tashuno ke
bishtarin w dashte bashan entekhab mikonim ---
                    {
                        for (int u = 1; u <= m; u++)
                        {
                            //-------- mohasebe ru_ --------------
                            decimal ru_ = 0;
                            int nru = 0;
                            decimal sumru = 0;
```

```
                        if (u == i)
                        { continue; }

                        if (!SharedInterest[i, u])
                        { continue; }

                        for (int k = 1; k <= n; k++)
                        {
                            if (rates[u, k] != 0)
                            {
                                sumru += rates[u, k];
                                nru++;
                            }
                        }
                        ru_ = decimal.Divide(sumru, nru);
                        //-------------------------------------
                        down += w[i - 1, u - 1];

                        up += (rates[u, j] - ru_) * w[i - 1, u - 1];
                    }
                }
                else
                {
                    int[] index_knn = new int[7];
                    decimal[,] wp = new decimal[m, m];  //--- wp ye matrix vazne
moshabehe w, ke index haye khune ha ro ham dare ----
                    for (int u = 0; u <= m - 1; u++)
                    {
                        wp[0, u] = w[i - 1, u];
                        wp[1, u] = u;
                    }
                    for (int u = 0; u < m - 1; u++) //--- sort kardan nozuli wp
baraye peida kardane bishtarin wp ha ---
                    {
                        for (int v = u + 1; v <= m - 1; v++)
                        {
                            if (wp[0, u] < wp[0, v])
                            {
                                decimal temp = wp[0, u];
                                wp[0, u] = wp[0, v];
                                wp[0, v] = temp;
                                temp = wp[1, u];
                                wp[1, u] = wp[1, v];
                                wp[1, v] = temp;
                            }

                        }
                    }
                    for (int u = 0; u <= 6; u++)
                    {
                        index_knn[u] = (int)wp[1, u]; //-- in array, index haye
nazdik tarin hamsaye haye be user i ro dare ---
                    }
                    foreach (int u in index_knn)
                    {
                        //-------- mohasebe ru_ --------------
                        decimal ru_ = 0;
                        int nru = 0;
                        decimal sumru = 0;
                        if (u == i)
                        { continue; }
```

```
                        if (!SharedInterest[i, u])
                        { continue; }

                        for (int k = 1; k <= n; k++)
                        {
                            if (rates[u, k] != 0)
                            {
                                sumru += rates[u, k];
                                nru++;
                            }
                        }
                        ru_ = decimal.Divide(sumru, nru);
                        //-----------------------------------
                        down += w[i - 1, u];

                        up += (rates[u + 1, j] - ru_) * w[i - 1, u];
                    }
                }

                if (down != 0)
                {
                    rates[i, j] = decimal.Round((ra_ + decimal.Divide(up, down)),
2);

                    //------------- check kon age ghablan ezafe nashode, Rec ro
ezafe kon ----------
                    string strsql = "Select * From Recs Where (userid = " +
RowMap[i - 1].ToString() + ") and (musicid = " + ColMap[j - 1].ToString() + ")
and (rx = 'cf')";
                    SqlDataAdapter dacheck = new SqlDataAdapter(strsql, cn);
                    DataSet dscheck = new DataSet();
                    dacheck.Fill(dscheck, "Recs");

                    if (dscheck.Tables[0].Rows.Count == 0)
                    {
                        //------------- code ezafe kardane record CF Recs -------
-------------
                        SqlCommand cmdCFRecs = new SqlCommand("Insert Into
Recs(userid, musicid, itrate, rx) Values (" + RowMap[i - 1].ToString() + ", " +
ColMap[j - 1].ToString() + ", " + Decimal.Divide(rates[i, j], 10).ToString() + ",
'cf')", cn);
                        cmdCFRecs.ExecuteNonQuery();
                        cmdCFRecs.Dispose();
                        //------------- end of code ezafe kardane record CF Recs
--------------------
                    }

                }

            }

        }


        cn.Close();

        //---------------------------- Go to Show Recommendations to the Current
User --------------------------
        Response.Redirect("ShowRecs.aspx");
```