An efficient hybrid recommender system framework using semantic technology for social networks

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Abstract.- The first group of companies that have a business on online social networks try to design an efficient plan for making more money on this platform. Advertising can be a solution for introducing and promoting the services or products for the clients and it can be led to more sells. There are a second group of companies intended to use advertisements on social networks, many of these annoy the users since they are not fascinating or matched for the clients. The primary target of the current study is to design and present a model of advertising recommender systems on social networks using innovative techniques. Although there are numerous applications and research works about recommender frameworks, in the proposed model, it is valuable to plan a recommender system which focus more precisely on the user's interests. The framework uses a semantic logic to increase the accuracy of the recommendations along with using a combination of four recommender methods, the particular estimations for each method and the integration of recommendations generated by each method using a rank-based approach which totally can differentiate the proposed recommender framework from the previous similar methods. The accuracy of suggested framework is 0,7498 that was revealed by implementing a web application. The comparison of some similar models with the current work based on various features and aspects shows a significant excellence of this study.

Keywords: recommender systems; social networks; user preferences; semantic technology.

Framework de un sistema de recomendación híbrido eficiente utilizando tecnología semántica para redes sociales

Resumen.- El primer grupo de empresas que tienen un negocio en línea en redes sociales intenta diseñar un plan eficiente para incrementar sus ganancias en esta plataforma. La publicidad puede ser una solución para introducir y promocionar servicios o productos para los clientes, lo cual puede conducir a más ventas. Existe un segundo grupo de empresas destinadas a utilizar anuncios en las redes sociales, muchos de los cuales molestan a los usuarios ya que no son fascinantes o coinciden con los clientes. El objetivo principal del actual estudio es diseñar y presentar un modelo de sistemas de recomendación publicitaria en las redes sociales utilizando técnicas innovadoras. Aunque existen numerosas aplicaciones y trabajos de investigación sobre frameworks de recomendación, en el modelo propuesto, es valioso planificar un sistema de recomendación que se centre en los intereses del usuario. El *framework* utiliza una lógica semántica para aumentar la precisión de las recomendaciones junto con el uso de una combinación de cuatro métodos, las estimaciones particulares para cada método y la integración de las recomendaciones generadas mediante un enfoque basado en posiciones que puede diferenciar totalmente el *framework* de recomendación propuesto con respecto a métodos similares anteriores. La precisión del *framework* sugerido tiene un valor de 0,7498 que se obtuvo mediante la implementación de una aplicación web. La comparación de algunos modelos similares con el trabajo actual basado en diversas características y aspectos, muestra una excelencia significativa en este estudio.

Palabras clave: sistemas de recomendación; redes sociales; preferencias de usuario; tecnología semántica.

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1. Introduction

The platform of social network as a place of communicating users, is a great opportunity to get billions of dollars in venture and procurement using advertisements [1]. The information on social websites is generated by users and to determine their interests, there are several limits and obstacles for acquiring user's information and preferences [2]. The semantic technology can operate as a suitable facility to determine the relationship among products and clients on social networks. This technology has been considered as a utility for developing the web, whereas it expresses the meaning of the contents on the web using different frameworks that resolve the ambiguity of unclear concepts and as a result it upgrades the level of our life [3][4]. One of the most popular elements of semantic web that can be also utilized for recommender systems is ontology [5][6]. The ontologies have simple structures and they can easily present the concept of various information [7]. Besides, the other technologies that can be affiliated are OWL [8] and RDF [9], totally they can semantically describe many kinds of concepts and entities. Using these assets it is possible to define smart web applications such as semantic search engines [10] that represent considerably more acceptable and usable outcomes rather than traditional search engines which is led to more client's satisfaction. As the present research contribution, the current study brings the advantages of four standard techniques altogether, along with using the semantic technology for improving the recommendations, the generation of recommendations using specific estimations, aggregating the same recommendations by different standard methods into one recommendation by the sum of their rates, utilization of both social network user rates and recommender framework user rates, preparing a new dataset required for evaluation of the framework by collecting data from a social network, and comparing some similar related works with several features and factors demonstrating the superiorities of the proposed model.

2. Related works

In spite of the numerous promising provided aspects, the semantic web has not been broadly utilized in software platforms [11]. The reason is that the process of ontology establishment, annotation and its maintenance is relatively difficult. In addition, it is troublesome to not only learn the required skills [12] but also use of necessary libraries for which it is needed to get expertise [13]. The combination of social web and semantic technology [14][15] presents social semantic web or web 3.0 [16]. Proportionate to this definition, a web application can display the benefits of semantic utilities and social web altogether [17][18]. Moreover, the clustering approaches can increase the accuracy of decision making systems [19] such as recommender systems. The methodology explained in [20] utilizes the collaborative tagging aggregated by numerous number of users to enhance the quality of social network recommendation. The solution comprised two phases, in the first step, the tag-item weight pattern was estimated and in the second phase, the user-tag preference pattern was computed. Then the two patterns were considered to seek the appropriate items fit to the users' interests and recommend the items including the maximum rate. Furthermore, the tag rate can be estimated and suggest the tags with the maximum weight to the user considering their interests. By applying the social web properties, it is possible to see the capabilities of recommender systems that are implemented on social networks and observe the wonderful results in attracting the audiences and clients [21]. As mentioned in [22] a new combined method is demonstrated that increases sparse tag shows without presenting content in direct. The provided method coordinates pseudo-tags gained from information into the tag presentation of a track, and a unique weighting plan constrains the quantity of pseudo-tags that are permitted to contribute. Examinations represent that this technique enables tags to stay predominant when they give a solid presentation, and pseudo-tags to assume control over when labels are sparse. The context-aware recommender model in [23] improves the recommendation procedure with context to suit the recommendation outcomes to end users. By utilizing the social tagging, the model estimated the latent interests of users on contexts from other similar contexts, also latent parts of contexts for items from other similar items. By discovering the similarities between the user's contexts, the contexts and items, it is possible to specify the marvelous items using a particular context. Consequently, the method maps the context on the items regarding on that specific user, for recommending the closest item suitable to the users' preferences. The research [24] combines clustering and ranking aggregation methods to find a solution for sparsity, scalability, and cold-start problems. The suggested clustering method utilizes K-means algorithm. The framework is performed based on the dataset of MovieLens, which includes the genre and demographic information. Furthermore, the ranking aggregation method facilitates Borda and Copeland approaches to be evaluated. In [25] it is argued that items are endured from the sparsity problem more seriously than users, because items are normally seen with fewer attributes to help a feature-based or content-based method. To overcome this difficulty, the complicated relation of each item×user×query triple from item's point of view is sufficiently prospected. Using integration of item-based collaborative information for this task, another factorized method was presented that could primarily measure the ranks of the items with sparse data for the provided query-user pair. Moreover, a bayesian personalized ranking (BPR) method was suggested to be utilized to enhance latent collaborative retrieval difficulty from pairwise learning point of view. The accuracy of recommendations can be enriched using a semantic approach and a hybrid recommender technique [26][27]. The solution proves that such composed system can provide more relatively accurate recommendations in comparison with three other models as SPAC, Friendbook and another system. The current research is an extended version of [27], but in this work, the proposed framework is compared with the other similar investigations as Pseudo-tag algorithm [22], CAMRST [23], RABCRS [24], and TIIREC [25] models along with more discussion. An appropriate search through Google Scholar database for the most recent related works based on some excellence of a recommender system [28] were established including item's features, users' feedback, similarity metrics, utilized recommender techniques, considered evaluation metrics, and cold-start overcome and the mentioned works in Table 3 were found. The current proposed method was evaluated using Precision & Recall, MAE, RMSE and discussed to find the improvements and excellences of the proposed model in comparison to the mentioned similar works. Semantic recommender methods are organized through the usage of semantic learning in the procedures of recommendation production along with a particular purpose to increase recommendation's precision [29]. The concepts earned from improving the representation of user profiles is utilized by majority of these methods [30]. Although in the current work there is an attention to use of a particular aspect of semantic technology, the other similar works have usually misused it for enriching the recommendations [31]. The prominent part of similar works has used semantic similarity to increase the accuracy of content-based models [32], however the other recommender systems exist which use semantic technology and try to concentrate on user profile in standard recommender techniques [33].

3. Literature review

The recommender systems are the software applications that check a user profile and try to generate some suggestions for the user based on user's interests and activities. It is possible to update the profiles of users by controlling their activities or direct rating of products. Although these systems anticipate the recommendations with the most possibility of accuracy, but in some cases may not be successful in providing the desirable results. Recently the usage of recommender systems has been rising as an advantageous part of the websites [34]. Furthermore, many of e-commerce websites have been equipped with the recommender systems [35]. The calculations in the proposed model of recommender system are as follows [36]: Considering the set of users u as U where $u \in U$ and the set of items i as I where $i \in I$, a matrix including the given rates by users to the items is named as $s(u,i)$ as a $U \times I$

space. In this matrix, some cells are initiated that means a user has rated the item and the rest of cells are remained blank for which the recommender system will anticipate appropriate values. If a considerable number of the cells are initially blank, the matrix is sparse and the recommender system will suffer from this issue as cold start problem [37]. As indicated in [38], the U_P is an array including all user profiles. The functionality of a recommender system is distinguished using a map of users of U to $P(I)$ as the recommended items which can be considered $P(U_P)$ as a set of user profiles. Accordingly, *REC* as the recommendation set can be defined as REC: $P(U_P) \times U \rightarrow P(I)$. More clearly the rating matrix is utilized as matrix $[s(u_k, i_j)]_{m\times n}$ that can be illustrated in Figure 1. The values in this matrix are in the range of 0 to 5. Moreover, the rating matrix can be normalized to another matrix that is shown in Figure 2.

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

Figure 1: The main rating matrix

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

Figure 2: The rating matrix after normalization

In other words, *REC* as the recommendations can be stated for the user u_k considering up as the user profile in equation (1).

$$REC(u_p, u_k) = \{i \mid s(u_k, i) = \arg\max i \in I\} \quad (1)$$

The most valuable item is assigned as arg max. Therefore, the main part of a recommender system is to detect the unspecified cells of the rating matrix that relate to the items without any opinion from the corresponding user and then, calculate appropriate values for the cells according to the recommender system strategy. Finally, the highest values in form of ranks are recommended to the user.

4. Methodology

In this section an overview of the proposed framework is depicted containing different elements. Consequently, each of the elements are demonstrated including their main characteristics and their task. In this study the effort has been that a complete and accurate system is designed and implemented as much as possible. To reach this aim we used artificial intelligence techniques in the recommender system algorithm. The proposed method uses the advantages and highlights of four standard techniques while the majority of similar research works only utilize one or two techniques. During the user activities, it is possible to use the generated recommendations as the feedbacks for the next rounds of recommendation generation process. Figure 3 displays the proposed model of recommender system along with its elements.

For calculating of the matrix of rates, five degrees for user's interests are considered which can be assigned to the products. These values are determined during their activities on the specific web pages when the users express their opinions about the products. As a variable, i_{rank} (rank of interest) is pointed to the user interest rate. In this research the values of 1 to 5 are assigned to the different levels of tendency related to each product. If the user looks for a product, the value of i_{rank} is set to value 5. In the more interesting condition, i_{rank} is set to 4, if the specific product is browsed or shown along with its details for the user. It can be determined that the user attention to that product in case of browsing or showing has more rank rather than searching. Totally, the

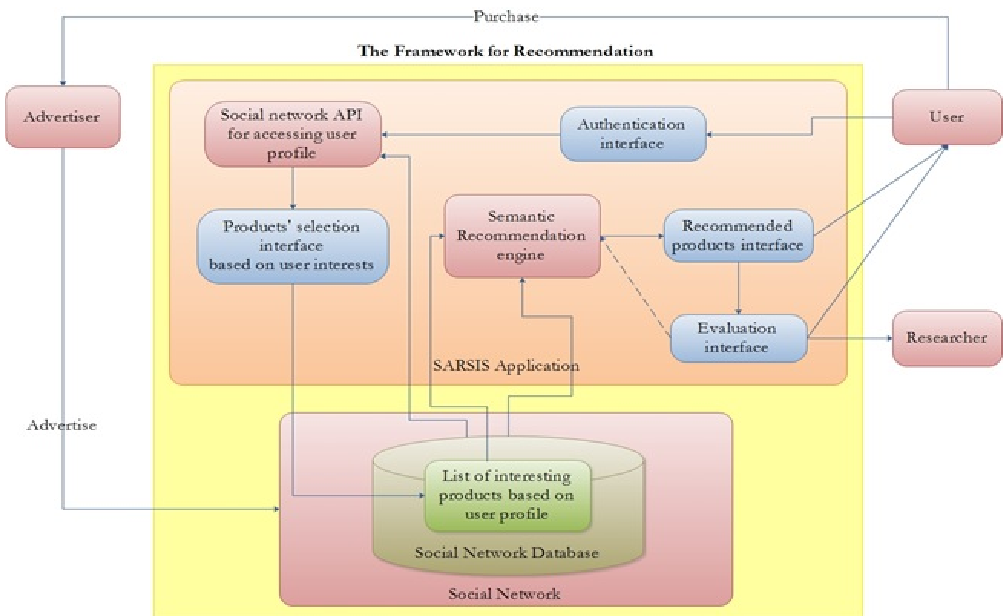

Figure 3: The suggested framework of recommender system

more rank of i_{rank} is, the higher user has interest to the product. Subsequently, if the user has a direct intention to the product by starring it between 1 to 3, the logic of the recommender system sets i_{rank} respectively from 3 to 1. There is another important variable in the current framework as t_{rank} (rank of product) which points to the rank of an advertisement on social network, created by a producer. The t_{rank} value is gathered from the activity of other users on social networks generally and earned previously. It indicates the popularity value of the product among social networks' users. In this study, two equations, one for demographic recommender technique (equation (2)) and another for the context-aware recommender technique (equation (3)) are used to calculate a final rate of it_{rate} separately based on the user's available data on social network for detecting the potential recommendations in the next step [27].

$$it_{rate} = \frac{arrSimilarUsersDemo[i,1]}{(5 \cdot i_{rank} \cdot t_{rank})} \tag{2}$$

$$it_{rate} = \frac{arrSimilarUsersCtx[i,1]}{(6 \cdot i_{rank} \cdot t_{rank})} \tag{3}$$

The value of the variable it_{rate} shows the amount of user's interest about a product. This variable is based on some parameters including i_{rank}, t_{rank}, user's similarity, and a fixed ratio which in this study is set to 5 for demographic and 6 for context-aware recommender parts. For the content-based filtering part of the suggested framework, the details of the products along with the label *cb* which indicates the type of recommender element, current user's username and it_{rate} estimated by equation (4) were added to the table *Recs*:

$$it_{rate} = \frac{1}{(6 \cdot t_{rank})} \tag{4}$$

The final part of the recommender system, collaborative filtering, uses the kNN algorithm to discover the users with the most similarity to the current user. The matrix $w_{a,u}$ was calculated based on the equation (5) [39] including all weights or the values of user's closeness together.

$$w_{a,u} = \frac{\sum_{i\in I}\left(r_{a,i} - \bar{r}_a\right)\left(r_{u,i} - \bar{r}_u\right)}{\sqrt{\sum_{i\in I}\left(r_{a,i} - \bar{r}_a\right)^2 \sum_{i\in I}\left(r_{u,i} - \bar{r}_u\right)^2}} \tag{5}$$

In equation (5) I refers to the set of items (products) which can be rated by the users, the assigned rate to the product i by the user u is $r_{u,I}$, and the mean rate which is given by user u is $\bar{r}_a$. Using equation (6) [39] the unrated cells of the matrix w were estimated:

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u \in K} \left(r_{u,i} - \bar{r}_u\right) \cdot w_{a,u}}{\sum_{u \in K} w_{a,u}} \tag{6}$$

In equation (6), the prediction value of the current user for the product i is considered as $p_{a,i}$, the similarity value between the user a and the user u is assigned as $w_{a,u}$, and the set of most similar users as a kind of neighborhood is considered as K. If the generated recommendations by the collaborative filtering part have been formerly saved to the table *Recs*, their relevant values are replaced by the new recommended items to avoid redundancy. The highest values estimated by the recent equation were appended to the table *Recs* for each user, along with the other necessary details including product *id*, the mark *cf* showing the recommendation method, username, and it_{rate} value which was calculated using the equation (7):

$$It_{rate} = \frac{rates[\text{useridindex, productidindex}]}{10} \tag{7}$$

Consequently, among all out arranged recommendations through four strategies from the table *Recs*, top ten items with most elevated it_{rate} values, is appeared to the current user. One fascinating curiosity with regards to this recommender system is that a gathering of determined prescribed items for the current user which even could be found more than once yet assessed by various methods with various it_{rate} values, are collected dependent on it_{rate} values. For this reason, a SQL task of "Group by" *productid* and *userid* is accomplished alongside considering an all out it_{rate} of suggestions utilizing four methods as $Total\_it_{rate}$. Therefore, the records obtained of the ongoing dataset conceivably demonstrate the expected interest rate of the user about the items. At last, these records ought to be arranged by $Total\_it_{rate}$ so as to locate the best suggestions. Furthermore, the technique of generating the recommendations is based on the ranks. Therefore, for each item, its it_{rate} is estimated by equation (8):

$$Total\_it_{rate} = \sum_{i=1}^{n} \left(it_{rate}\,(i)\right) \tag{8}$$

In equation (8), the maximum value as n is 4 referring to the four standard techniques and i points to the number of each recommendation method. The implementation steps of the proposed model have been depicted in Figure 4 where it shows how the model works.

The proposed model mentioned has been depicted generally and it is possible to use the framework for any social network containing even other types of media. However, to run the model on a real platform and present the operation of the model, the social network of `last.fm` as a suitable case study was chosen to perceive the functionality of the recommender system in practice. The social network `last.fm` was established in the UK in 2002 working on music category [40]. In this case study, several methods are utilized to collect data from the social network such as `tag.gettopartists`, `artist.getinfo`, `artist.gettoptracks`, `tag.getsimilar` and `track.gettoptags`. For running the model, a web application named SARSIS was developed in Microsoft Visual Studio .NET using ASP.NET technology. The frontend of this application was designed based on two languages consist of Persian and English. Figure 5 shows the navigation of web pages in the application.

For testing the framework and monitoring how it really works, it was necessary to use a dataset as the backend of the web application. The software application Microsoft SQL Server was used to maintain and manage the database. The tables in the database include user interests, artists, users, user rates, recommendations, and tracks. To start the web application and initialize the tables tracks and artists, a separate code was developed to crawl music data from `last.fm` as the case study of social network. The collected data was prepared including 13.7685 music tracks and 2.125 artist profiles during three weeks. In this code a number of RESTful queries have been executed on the

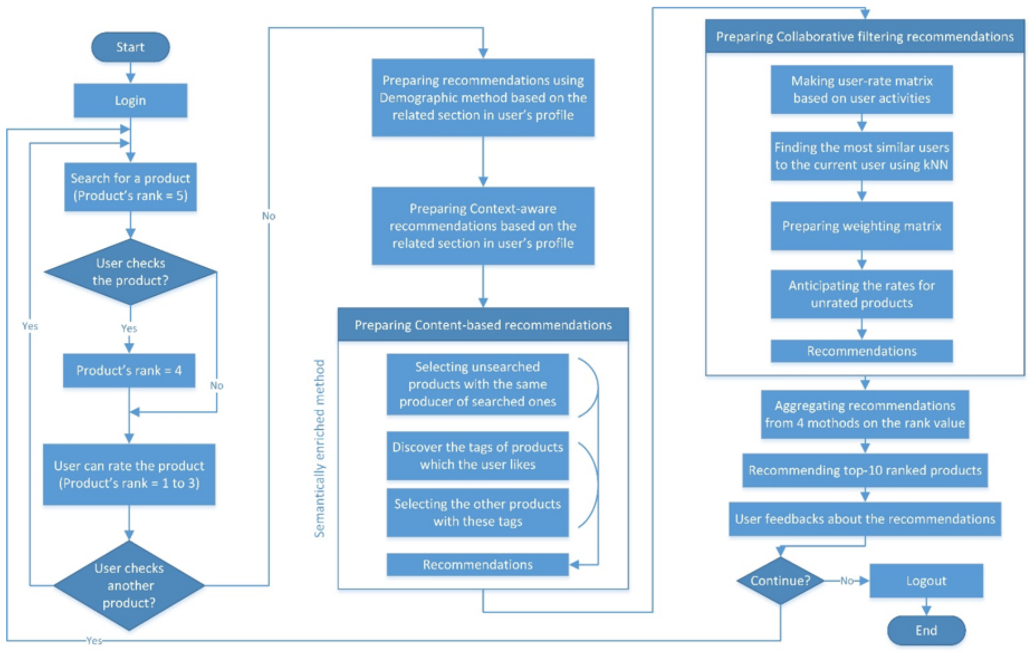

Figure 4: Implementation and work model

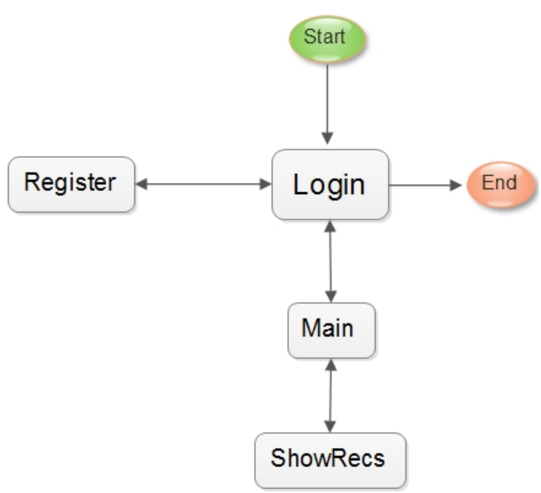

Figure 5: The navigation of web pages in SARSIS

`last.fm`, the streams of responses as the results were obtained in XML format, parsed to enumerate the artist and track data and finally saved into the database as the tables artists and tracks so that they can be utilized for the recommender system.

5. Evaluation

The generated recommendations using SARSIS were assessed using some evaluation metrics and it proved that SARSIS has had an enhanced combination in comparison with the previous similar works. The metric of MAE as the error of the framework could be used to discover the total amount of distance between the recommendations and what the users really preferred. Equation (9) shows how MAE is calculated:

$$MAE = \frac{\sum_{i=1}^{N} |p_i - q_i|}{N} \tag{9}$$

A high value of accuracy is recognized through the lower values of MAE. The precision, recall and F1 metrics can be estimated using equation (10), equation (11) and equation (12) respectively.

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{12}$$

The variable *TP* refers to the previewed tracks that were liked by users (the number of likes in Table 1), the variable *FP* refers to the recommended tracks that were not liked by users (the number of

Unlikes for each user in Table 1), and the variable *FN* refers to the tracks that were not shown to the user via searching, listening or rating and they are not recommended, while they can be potentially interesting for the users as the recommendations.

6. Results and discussions

The ideal results in recommender systems comprise the recommendations with the lowest error and highest accuracy as much as possible. Furthermore, it is important to remember that the design of such frameworks encounters particular limitations and problems. In the proposed model not only the benefits of four standard techniques but also a semantic technology has been totally used. The number of 73 users tested SARSIS and based on the gathered information from running the case study, remarkable results were seen related to the framework. The range of user ages in running the case study is classified to 6 groups as shown in Figure 6.

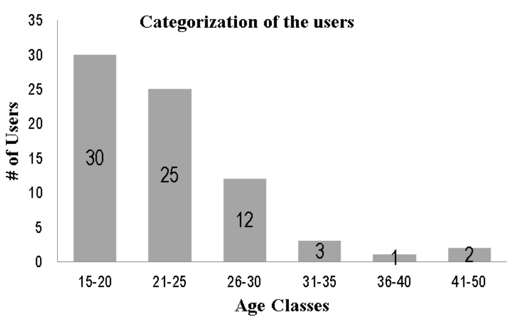

Figure 6: User's age classes

Based on the Figure 6, most of the users have ages in the range of 15 to 25. By assessing the table UserRates (which is a table related to the application, including user rates about the suggestions in the validation page by the users), the quantity of liked music tracks which every user has determined, and also according to the equation (9), the outcome using a SQL query that was executed in Microsoft SQL Server. Figure 7 shows how the results can be obtained utilizing a SQL query.

The results from the Figure 7 are used for estimation of recall and precision which can be presented in Table 1.

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

Figure 7: The SQL query used for preparing the result

As shown in Table 1, the information is based on the users. Accordingly Figure 8 illustrates a graph of MAE values for each user.

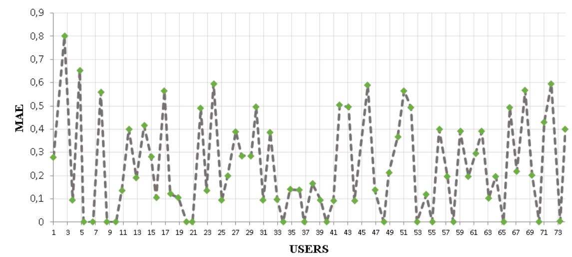

Figure 8: MAE for all users

The Figure 9 shows the number of unliked recommended tracks along with the number of recommended tracks presented to each user.

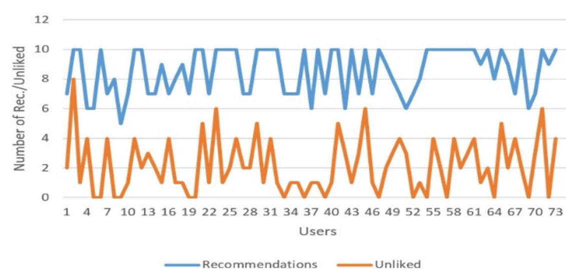

Figure 9: The number of recommended music tracks for each user versus the numbers of unliked recommended music tracks

The total MAE for the all users working with SARSIS can be estimated as equation (13).

$$MAE = \frac{157}{625} = 0{,}2512 \qquad (13)$$

The other metrics for evaluation of the model are recall and precision. Table 2 explains how these two metrics are defined.

Table 1: The information of results.

User ID	Recommendations	Likes	Unlikes	Interesting	Precision per user	Recall per user
1000000000	7	5	2	12	0,714286	0,294118
1100110011	10	2	8	0	0,200000	1,000000
1111111111	10	9	1	7	0,900000	0,562500
1147567876	6	2	4	1	0,333333	0,666667
1221344356	6	6	0	14	1,000000	0,300000
1234567891	10	10	0	37	1,000000	0,212766
1652964028	7	3	4	14	0,428571	0,176471
1740294068	8	8	0	21	1,000000	0,275862
1740331941	5	5	0	18	1,000000	0,217391
1740364295	7	6	1	6	0,857143	0,500000
1740476999	10	6	4	18	0,600000	0,250000
1740494970	10	8	2	42	0,800000	0,160000
1740601920	7	4	3	1	0,571429	0,800000
1740751698	7	5	2	11	0,714286	0,3125
1740763777	9	8	1	24	0,888889	0,250000
1740841891	7	3	4	16	0,428571	0,157895
1740925823	8	7	1	14	0,875000	0,333333
1741361461	10	10	0	14	1,000000	0,416667
1741375827	10	5	5	21	0,500000	0,192308
1741422701	7	6	1	5	0,857143	0,545455
1741453690	10	4	6	9	0,400000	0,307692
1741726591	10	9	1	9	0,900000	0,500000
1741805090	10	8	2	7	0,800000	0,533333
1741912891	7	5	2	7	0,714286	0,416667
1741922089	10	5	5	16	0,500000	0,238095
1741975565	10	9	1	11	0,900000	0,450000
1742013937	10	6	4	5	0,600000	0,545455
1742018246	10	9	1	4	0,900000	0,692308
1742046509	7	7	0	10	1,000000	0,411765
1742059457	7	6	1	6	0,857143	0,500000
1742113419	7	6	1	8	0,857143	0,428571
1742227341	10	10	0	21	1,000000	0,322581
1742328407	10	9	1	14	0,900000	0,391304
1742335942	10	5	5	30	0,500000	0,142857
1742351387	6	3	3	7	0,500000	0,300000
1742380727	10	9	1	18	0,900000	0,333333
1742386431	7	4	3	2	0,571429	0,666667
1742388991	10	4	6	14	0,400000	0,222222
1742413080	7	6	1	10	0,857143	0,375000
1742428819	10	10	0	25	1,000000	0,285714
1742449948	9	7	2	12	0,777778	0,368421
1742454216	8	5	3	23	0,625000	0,178571
1742531407	7	3	4	18	0,428571	0,142857
1750467534	6	3	3	3	0,500000	0,500000
1750598353	7	7	0	12	1,000000	0,368421
1752428819	8	7	1	17	0,875000	0,291667
1754624498	10	10	0	7	1,000000	0,588235
1754624499	10	6	4	45	0,600000	0,117647
1756797366	10	8	2	13	0,800000	0,380952
1756998124	10	10	0	15	1,000000	0,400000
1757037179	10	6	4	2	0,600000	0,750000
1757052811	10	8	2	18	0,800000	0,307692
1757144315	10	7	3	35	0,700000	0,166667
1757594752	10	6	4	3	0,600000	0,666667
1757755888	9	8	1	17	0,888889	0,320000
1810374146	10	8	2	10	0,800000	0,444444
1920332022	10	8	2	41	0,800000	0,163265
1940524695	6	6	0	23	1,000000	0,206897
1940548276	7	4	3	3	0,571429	0,571429
1943149638	10	4	6	16	0,400000	0,200000
1960167413	9	9	0	36	1,000000	0,200000
1987835301	10	6	4	25	0,600000	0,193548

Table 2: The relations between concepts

	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 (-)

To generate a list of false negative items it is necessary to consider the music tracks in which users interest. This list can be prepared using a SQL query which is depicted in Figure 10.

Based on the provided definitions in Table 2 and the data from Table 1 the graphs of recall and precision based on the users are estimated and show in Figure 11 separately, while another graph presents the recall values based on the precision values in Figure 12.

In brief the value of 0,7498 is estimated as a total precision of the accomplished case study using the suggested model.

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

Figure 10: The SQL query used for preparing the False Negative (fn) values

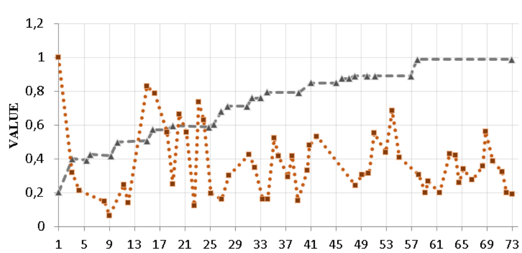

Figure 11: Precision (▲) and Recall (■) curves

7. Discussion

The current research has described a novel framework including special specifications and advantages. The businesses on social network are able to employ the benefits of the proposed model as a part of their e-commerce solutions. Although the proposed methodology was suggested in general, it was necessary to validate the mentioned solution on at least one social network as a case study and observe the efficiency of the model. For this purpose, a web application was developed and a dataset was crawled and saved to implement the idea of the methodology so that the users can browse the web application and have their own activities on the application to express their indirect or direct preferences. A semantic engine was responsible to act as a part of recommendation generation and when the users finished their activity, they could rate the recommended items. One of the challenges in developing the case study was the selection of a proper social network that eventually the social network last.fm was chosen. As indicated in [27] the recommender system employed in `last.fm` only uses a collaborative filtering as a standard recommender technique, whereas the method of suggested framework provides the advertisements using a hybrid recommender system. Hence the more accurate recommendations can be observed with SARSIS rather that with `last.fm` since in SARSIS the features of other recommender techniques as context-aware, demographic and content-based filtering are also used that can make recommendations closer to the users' interests. Simply, it is clear to see the recommendations by SARSIS have more accuracy in comparison with `last.fm`.

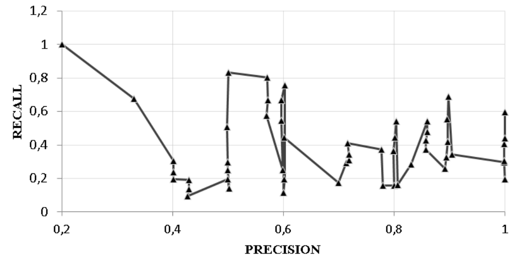

Figure 12: Graph of recall based on precision

As a further study, more similar recommender systems were compared with SARSIS and interesting findings were discovered as the positive

Table 3: Comparison of similar Recommender Systems with SARSIS

RS model	Features					feedback	Similarity Metrics	RS techniques	Evaluation Metrics	Dataset	Cold-start overcome
	genre	tag	social rank	time	location						
SARSIS (Proposed)	✓	✓	✓	✓	✓	User rating	Pearson correlation, kNN	CB, CF, CA, Demo	Precision& Recall, MAE, RMSE	Last.fm (137685 tracks, 2125 artists)	Tag based, content based, ranking aggregation.
Pseudo-tag [22]	✓	✓	✓	χ	✓	χ	kNN	Psedu-tag&tag	Precision & Recall	(3174 track, 764 artist)	Pseudo-tag&tag.
CAMRST [23]	χ	✓	✓	χ	χ	User rating	cosine similarity	CF, CA	Precision & Recall, F1	Last.fm (2747 users, 7805 items)	χ
RABCRS [24]	✓	χ	χ	✓	χ	User rating	Clustering	CF, Demo	Accuracy, Complexity	MovieLens (943 users, 1682 movies)	Clustering, ranking Aggregation
TIIREC [25]	✓	✓	χ	χ	χ	User rating	Bayesian personalized ranking	CF	Recall	Last.fm (1529 users, 8669 items), Yelp (16826 users, 14902 items)	Bayesian personalized ranking

achievements of the current proposed framework.

The quality of recommendations is increased when a recommender algorithm uses both content-based filtering and tag-based system along with acceptable number of tags [22]. According to the summarized information in Table 3, the excellence of proposed model is that SARSIS uses a tag-based system along with a content-based recommender system which totally can equally or more efficiently overcome the cold-start problem than the existing similar models. The more evaluation metrics including precision and recall, MAE and RMSE which were accomplished for SARSIS in comparison with the other models, proves that SARSIS has a better efficiency in terms of recommendation's quality. The mechanism of proposed model benefits the advantages of four standard techniques (content-based, collaborative filtering, context-aware and demographic filtering) and as a result, more accurate recommendations are presented to the users.

Both Pearson correlation and kNN have been used in the proposed model which helps find similarities faster than the other metrics [41]. Furthermore, SARSIS uses user rating which improves the quality of recommendations [17]. In the SARSIS framework, all of studied features, including genre, tag, social rank, time and location, have been utilized, while they have not been considered completely in the other similar models.

The results demonstrated that the effectiveness of the planned case study, as an example for the model, was satisfactory. For achieving this point, an assessment routine as the Mean Absolute Error was utilized and determined to express the exactness of the system. Despite the fact that the estimation of MAE for entire of the web application was not exceptionally low but rather it was promising and tolerable. One reason about the estimation of MAE which was somewhat moderately high after interacting with a portion of the users, was that there is no probability of finding and listening a review for a part of the music tracks.

It means that the there was no music preview for the selected songs and it was a noise for the framework. Thus, they could not probably like those music tracks and as a result, the quantity of liked music tracks was diminished that affected straightforwardly in evaluating of MAE. Thus, if it was conceivable to choose a web service with more complete resources of music tracks, totally the estimation of MAE could be diminished appropriately. However, the issue was that after doing a research and looking at numerous sites as the sources of music tracks which could be utilized for playing the previews, the best decision among recognized sites was Spotify.

Additionally, in view of the Figure 11 and Figure 12, it was conceivable to see positive qualities for precision and recall for the users. Altogether, the outcomes and the accumulated information from user rates which mirrored their opinion about the proposed model, demonstrated that they were significantly satisfied about the quality of the recommendations. Along these lines, and based on the provided information, we can infer that if the model can be actualized on a social network and utilize semantic strategies to give ads, the outcomes will have enough performance for the business which uses the suggested framework.

8. Conclusion

In this study a hybrid recommender system framework was described including novel approaches to reduce the error of calculations. The popular problems in recommender systems comprise cold-start, scalability and sparsity that using tag-based, content-based and ranking aggregation techniques in the suggested recommender model, it was possible to overcome these problems. The main concentration in this study was the increment of accuracy for the recommendations that was possible to be accomplished using a semantic method along with the combination of four standard recommender technique. For increasing the probability of discovering recommendations which could be very similar to the user's exact expectations and interests, a semantically enriched solution was utilized while the classical recommender methods could not cope with such important purpose properly. In this work, the actual relationships between concepts such as clients and products on social network were considered as the pure concept of semantic technology that can declare the user interests. By evaluating the experimental outcomes, a considerable value of user satisfaction was met. As the other strength point of the framework, the recommender system could feed the user opinions about the recommendations using a rating system and these feedbacks update the dataset so that the user's opinions are used in the next rounds of recommendation process for generating more accurate recommendations.

As a limitation of the study, there was not any dataset which can be matched to the framework's specification. Therefore, by developing an application, a new dataset from the social network `last.fm` as a case study was prepared and used for the evaluation of the research.

The last.fm is a popular social network with a high number of users and its data can be a suitable choice to be used for the proposed recommender framework. For implementing the recommender solution, a web application was developed and alongside, an extensive dataset including social network artists, music tracks and their metadata were gathered from last.fm. The social network profits a simple and easy to use RESTful API which could help in developing the web application. The superiority of gaining such robust dataset with huge number of records is that the users of web application can observe stable and logical results. For the future works, it is possible to: Firstly, specify a more complete security solution with different levels of access control for the recommender system, more than the existing single sign on system such as two factor authentication. Secondly, it is better to run the web application more times to obtain a higher volume of information by the user activities and consequently perform a more complete evaluation on the gathered data to get more satisfaction for the users. Thirdly, to represent more complete details of products to be shown for the users that can help users decide about rating the products more conveniently. Fourthly, in case of emerging or finding any new social network in the future which can be suited to the proposed model, it is better to implement the model on more social network. The requirements for considering such social network would be usable API with simple syntax for development. Finally, it is interesting to run the model using other datasets.

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