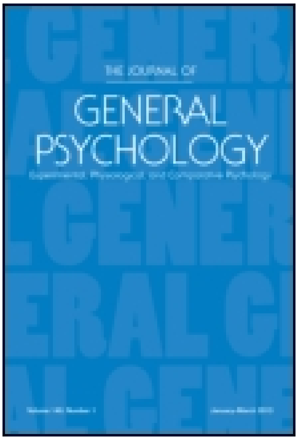

The Journal of General Psychology

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/vgen20

Differences Between Young and Old University Students on a Lexical Decision Task: Evidence Through an Ex-Gaussian Approach

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Published online: 25 Sep 2013.

The Journal of General Psychology, 2013, *140*(4), 251–268

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ABSTRACT. This work compared two common variants of a lexical decision task (LDT) through two different analysis procedures: first, the classical ANOVA method, and second, by fitting the data to an ex-Gaussian distribution function. Two groups of participants (old and young university students) had to perform, blocks of go/no-go and yes/no tasks. Reaction times and error rates were much lower in the go/no-go task than in the yes/no task. Changes in the ex-Gaussian parameter related to attention were found with word frequency but not with the type of LDT tasks. These findings suggest that word frequency shows an attentional cost that is independent of age.

Keywords: age-related differences, ex-Gaussian fit, lexical decision task

TWO OF THE MOST POPULAR TASKS to examine underlying cognitive lexical processes are the lexical decision task (LDT) and the naming task. In a LDT experiment, the participants have to decide whether *stimuli* are words by pressing a key. In the case of the naming task (which is very similar to LDT), the participants have to respond to the *stimuli* by naming it. The LDT is more popular because the naming task might be contaminated by other processes such as pronunciation

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(D'Amico, Devescovi, & Bates, 2001; Paap, McDonald, Schvaneveldt, & Noel, 1987).

At the same time, LDT can be divided into two well-known variants: yes/no and go/no-go tasks. In the yes/no variant, the participants have to decide whether the *stimuli* are words or not by pressing corresponding keys for "yes" or "no" depending on their decision. In the second case, go/no-go variant, there is only one possible key, such that the participants have to press the key when they decide that the *stimulus* is a word and do nothing otherwise. Some studies have examined this methodological issue and shown evidence that the popular yes/no variant leads to a larger number of errors, longer latency responses and more variability for developing readers (Moret-Tatay & Perea, 2011) as well as adults (Perea, Rosa, & Gomez, 2002). These results were similar for old people. In particular, Allen, Madden, Weber, and Groth (1993) examined the influence of age on visual word recognition and confirmed that there was a processing cost when the selection load was increased (employing yes/no vs go/no-go LDT).

The experiments cited above recorded error rates and reaction times (RT) as dependent variables. RT has turned into a star dependent variable on most of cognitive assessment tests due to its sensitivity; however, it has been characterized by positively skewed data distribution that obstructs data analysis.

One option is the trimming technique of extreme data, even though, as Heathcote, Popiel, and Mewhort (1991) claimed, "there is no clear criterion with which to distinguish outliers from valid extreme scores." When some values are discarded, we may lose valuable information, so it is not easy to distinguish noise from valid data. Another option is to perform a distributional analysis of the data. In the case of positively skewed data, an appealing possibility for this distribution is the ex-Gaussian distribution function (Lacouture, & Cousineau, 2008; Luce, 1986; Ratcliff, & Murdock, 1976). Moreover, this option can be a useful tool when dealing with high variability in the data (e.g. data obtained from a sample of old people). The effects of age on a task and how reaction times are affected, is the subject of much discussion in the literature. Many authors have shown that reaction time distributions of old students have longer tails than young students (e.g. Fozard, Thomas, & Waugh, 1976; Smith, Poon, Hale, & Myerson, 1988), which means an enhanced asymmetry in the RT distribution. In the case of the ex-Gaussian distribution, this asymmetry can be cast to one of its parameters: the τ parameter, which will be explained in what follows.

The ex-Gaussian function is the convolution of two processes; a Gaussian (normal) and an exponential distributions. Luce (1986) describes this function as a model for the decision-making inside the temporal space (and therefore, a model which might describe different cognitive processes). The ex-Gaussian distribution is specified through three parameters: μ, τ and σ. The first and second parameters (μ and σ), correspond to the average and standard diversion of the Gaussian component, while the third parameter (τ) is the decay rate of the exponential component. When analyzing the results from an ex-Gaussian fit, one must be careful because μ and σ should not be interpreted as the distribution's average and standard deviation. The average of the ex-Gaussian distribution in terms of its components' parameters is $\bar{M} = \mu + \tau$ and its variance is $S^2 = \sigma^2 + \tau^2$. On the other hand, its skewness can be calculated via $\gamma_1 = 2\tau^3/S^3$. Luce (1986) has argued that the ex-Gaussian function provides a good fit to multiple empirical response time distributions. In addition, many researchers have related these parameters to underlying cognitive processes. Matzke and Wagenmakers (2009) provide a review on the interpretation on the ex-Gaussian parameters in terms of underlying cognitive processes. One of the most relevant works in the subject is the research performed by Leth-Steensen, King Elbaz, and Douglas (2000). These researchers compared groups of children with ADHD to controls and found different tailed distributions, slower response times and, what is more important to the aim of our study, differences on τ parameter for those with ADHD. The findings provide evidence about the role of τ parameter on attention and was supported by other literature (Spieler, Balota, & Faust, 1996; West, 1999; West, Murphy, Armilio, Craik, & Stuss, 2002). Even if the τ parameter is the most studied, some researchers have been also interested in the μ parameter. For example, Balota and Spieler (1999) after a series of 3 word recognition experiments indicated that the μ parameter might reflect a stimulus driven automatic process.

The present work discusses the cost of cognitive processing for old participants when performing a LDT, which usually has a high variability. Thereby, an ex-Gaussian fit analysis was employed as an alternative strategy to the conventional ANOVA analysis. The characterization of the obtained RT distribution allows us to better describe the results and to interpret them through the different parameters or distribution components. Thus, the objective of this work is to analyze two of the most common variants employed on LDT (go/no-go and the yes/no task) in two groups of participants (young and old students), using two different techniques, the classical ANOVA and the data fit to an ex-Gaussian distribution function. The reason that we performed this additional analysis (the ex-Gaussian fit) is because it provides us parameters (such as τ) that might be related to attentional process while the classical ANOVA analysis can only give information on the RT difference for different conditions and/or groups, but provides no information on the underlying cognitive processes. Therefore, the benefit from the ex-Gaussian fit is that it does allow one to associate parameters to different underlying processes.

In order to carry out this work we have employed the same words used in Moret-Tatay and Perea (2011). The frequency of the words was manipulated: high- vs. low-frequency (high-frequency words are recognized faster and more efficiently than low frequency words). The effect of word frequency is a classical effect in cognitive psychology that is characterized by its robustness. The word frequency effect is an essential issue on models of visual word recognition, from the traditional Morton's Logogen Model (1969) to the interactive McClelland and Rumelhart's (1981) activation model or the dual-route coding model (2001).

However, most of these models do not examine the role of attention or the load of task demands.

Method

Participants

Two groups of participants took part voluntarily in our experiment. The first group was composed by a sample of 40 students from the Universidad Católica de Valéncia, San Vicente Mártir (31 women and 9 men with an average age of 20.27 years and $SD = 1.26$). And the second was a sample of 40 students from a program for senior students at the Universidad de Salamanca (29 women and 11 men with an average age of 69.15 years and $SD = 7.13$). Four participants in group 2 were replaced due to an error rate higher than 40%. The classical inclusion criteria were a punctuation of 26 or higher on the Mini-Mental State Examination MMSE (Folstein, Folstein, & McHugh, 1975) and absence of cognitive or neurological problems.

All the participants had normal vision or vision corrected to normality, were native Spanish speakers, and did not report cognitive impairment or neurological disorders. The sample selected for both groups has a female majority, but in any case there is no reason to believe that the variables analyzed here might be gender dependent

Materials

The same words from Moret-Tatay and Perea (2011) materials for developing readers were employed. The *stimuli* consisted of a set of 120 words of five letters from the Spanish database (Davis & Perea, 2005). Half were high frequency (146.7 for million, range: 30.9–675.6) and half were low frequency (10.2 per million, range: 0.7–23.2). Furthermore, 120 non-words were selected in order to carry out a LDT (streams of letters with similar characteristics to Spanish words, but with no meaning).

Althought Moret-Tatay and Perea's material was developed for children, it was chosen specifically because the authors confirmed their frequency in relation to Corral, Goikoetxea, and Ferrero's database (1999). When choosing material for experiments involving old people, it is important to think about the different participant's backgrounds. A way to ensure that all participants will be familiarized with the words presented in the experiment is to employ *stimuli* (words) for children.

Procedure

The participants were tested in a quiet room in groups of three or four people. The presentation of the *stimuli* and recorded response times were controlled by computers through the Windows software DMDX (Forster & Forster, 2003). In each trial, a fixation point (+) was presented for 500 ms in the center of the screen. Then the target *stimulus* was presented until the participant's response, with a maximum of 2500 ms. The stimuli were presented in lowercase 14-pt Times New Roman. For the go/no-go variant, participants were instructed to press a button (marked "yes") if the *stimulus* was an existing word in Spanish, and refrain from responding if the *stimulus* was not a word. For the yes/no variant, participants were instructed to press a button (labeled "yes") if the *stimulus* was an existing word in Spanish, and press another button (labeled "no") otherwise. For the whole experiment, the participants were instructed to respond as fast as possible, maintaining a reasonable level of accuracy. Each participant received a different random order of the *stimuli*. Each session lasted about 15 minutes.

Design and Data Analysis

Word frequency (high vs. low) and LDT tasks (go/no-go vs. yes/no) were manipulated as within group variables. The stimuli were presented in counter-balanced blocks for both old and young groups: twenty participants, selected randomly, performed the go/no-go task in the first block and the yes/no task in the second block, while the other twenty participants did it vice-versa. Each block was preceded by 16 practice trials (with similar characteristics to the experimental blocks).

Two different analysis procedures were carried out: the classical ANOVA procedure and the procedure that fits the data to an ex-Gaussian distribution function. Changes in the ex-Gaussian parameter related to attention were found with word frequency but not with the type of LDT tasks. These findings suggest that word frequency shows an attentional cost that is independent of age. Due to a violation of homogeneity of variance in groups, a mixed ANOVA was performed separately. Thereby, a 2 (Task: go/no-go or yes/no) X 2 (Word Frequency: high or low) X 2 (Order: go/no-go first and yes/no in second place or yes/no first and go/no-go in second place) design was carried out on both old and young university students correct RTs.

An alternative data analysis strategy was also carried out: the characterization of the response time distribution though an ex-Gaussian fit. Data sets were distributed in intervals in order to create a histogram. In total there were 14 data sets to be analyzed. For each group, old and young subjects, one has the data sets corresponding to the go/no-go and yes/no tasks, and for each task we analyzed the whole data set and the data sets for the high and for the low frequency words separately. Additionally, for the yes/no task we also analyzed the pseudo-words data sets separately. Differences between parameters from the ex-Gaussian fit were analyzed regarding their uncertainties (errors) as confidence interval lengths for each parameter.

Results

As in Perea and colleagues (2002), RTs less than 250, greater than 1500 ms and incorrect responses were excluded: a total 1244 for the old and 194 response times for the young were omitted in the data analysis as shown in Table 1. However, due to a high number of RT for non-words for the group of old participants, a second analysis was also performed for this group, employing a different cut-off from 250 to 2500 ms (in this case, 638 data would be trimming, which means a total of 6.64%).

Mean latencies for correct responses and error rates are presented in Table 2. The RT were faster for the go/no-go blocks than in the yes/no ones for both groups. This pattern was not affected by the change in the cut-off for the old group[1].

As expected from Allen and colleagues (1993), mean response times for words on go/no-go blocks were faster than the yes/no blocks, however these differences were not statistically significant: $F(1,76) = 3.71$; $MSE = 2686.48$ $\eta_2 = 0.05$; $p = 0.058$. On the other hand, response times were shorter for high frequency words than low frequency words[2]: $F(1,76) = 178.27$; $MSE = 1532.68$; $\eta_2 = 0.70$; $p < 0.001$. In addition, young students were faster than old ones: $F(1,76) = 53.46$; $MSE = 73848.11$; $\eta_2 = 0.04$; $p < 0.001$. No interactions were found.

As expected by the results of Moret-Tatay and Perea (2011), the analysis on the SDs showed significant age differences. Old university students had more variability in the RTs than young students: $F(1,76) = 4.78$; $MSE = 7518.06$; $\eta_2 = 0.06$; $p < 0.05$. A similar pattern for high frequency versus low frequency words (in terms of variance) was found: $F(1,76) = 30.91$; $MSE = 1520.57$; $\eta_2 = 0.29$; $p < 0.01$. Finally, for go/no-go and yes/no task the variance analysis was $F < 1$. It should be pointed out that the homogeneity of variance assumption is a limitation

TABLE 1. Percentage of Response Times (RT in Terms of Ms) Excluded (Under 250 or Over 1500 Ms) Through the Trimming Technique Employed in Relation to Experimental Blocks for the ANOVA Analysis

	% of RT excluded		
	High frequency	Low frequency	Non-words
go/no-go			
young	0.12	0.20	—
old	3.08	3.38	—
yes/no			
young	1.07	3.08	1.82
old	2.82	5	18.67

TABLE 2. Average Lexical Decision Times (in Terms of Ms), Error Percentages (in Parentheses) and Standard Deviations (SD) for Words (High and Low Frequency) and Non-Words in the Experiment

Task		High frequency	Low frequency	Non-words
go/no-go				
young	RT(error%)	560 (1%)	627 (1%)	–(1%)
	SD	70.32	80.12	—
old	RT(error%)	777 (3%)	836 (3%)	–(3%)
	SD	210.72	223.71	—
yes/no				
young	RT(error%)	608 (2%)	655 (6%)	714 (4%)
	SD	79.31	92.13	257.74
old	RT(error%)	807 (2%)	855 (5%)	1075 (4%)
	SD	203.12	202.52	423.49

of the ANOVA. For this reason we ran the ANOVAs on the SD separately for each of the participants groups.

Lexical decision times difference between the go/no-go blocks and the yes/no blocks for young student were statistical significant: $F(1,38) = 32.26$; $MSE = 2510.38$; $\eta_2 = 0.46$; $p < 0.001$. Nevertheless, this was not the case for the variance analysis, where $F < 1$. On the other hand, response times variance from word frequency showed: $F(1,38) = 103.93$; $MSE = 1299.14$; $\eta_2 = 0.73$; $p < 0.001$.

The old students showed shorter lexical decision times in the go/no-go blocks than in the yes/no blocks. Neither response times differences nor the variance were statistically significant ($F < 1$). Finally, as it happened to young university students, old response times variance for word frequency also reached the statistical significance: $F(1,38) = 38.01$; $MSE = 1766.22$; $\eta_2 = 0.67$; $p < 0.001$.

Given such a high variability for the results for old students and the great number of trimmed data, a characterization of the response time distribution though an ex-Gaussian fit was performed. In order to perform the fits, a python script has been programmed (see Appendix I for Python Script). This script automatically reads a set of data (reaction times), groups this data in intervals in order to create a histogram (employing their relative frequency) and interacts with the Gnuplot software in order to fit an ex-Gaussian function to the data points. Gnuplot is an open-source, freely distributed, command-line graphing utility available for Linux as well as other platforms like Windows or Macintosh. This robust software is wildely used by physicist and mathematicians in order to produce plot and perform fits to experimental data sets. Its fitting utility uses the Levenberg–Marquardt algorithm (Marquardt, 1963), also known as the dumped least-square method, in order to find the optimal parameters that minimize the square of the difference

TABLE 3. Example of Parameters Provided From Different Choices of Nint (Number Of Intervals) for the Histograms and for the Young Sample at the High Frequency Go/No-Go, With the Number χ^2/dof Is Employed To Evaluate the Goodness Of the Fit

Nint	μ	σ	τ	χ^2/dof
30	451.50	50.39	103.30	1.36
50	450.46	45.45	102.45	1.33
70	451.08	44.42	102.46	1.16
90	452.24	46.83	98.70	1.28
110	450.82	43.90	103.72	1.14

dof = degrees of freedom.

between a given data set (x_i and y_i) and a target function that depends on a given set of parameters. The algorithm is an interactive procedure that readjusts the set of parameters in each interaction. The goodness of the obtained fits can be evaluated by the sum of residuals divided by the number of degrees of freedom (χ^2/dof), information provided for each fit by the software.

The full data sets have around 2350 reaction times each, while the low- and high-frequency data sets have half this amount. To perform the fits, one must first choose a reasonable number of intervals for the histograms. A reasonable choice for this number is twice the square root of the total amount of data. Since the majority of the data sets have around 1170 reaction times, we worked with 70 intervals. In any case, we performed tests varying this number in order to assure that the fitting parameters are not very sensible to this choice. In Table 3, we show the resulting parameters for the go/no-go high-frequency words data set for the young group with different choices for the number of intervals in the histograms. One can clearly see that the variation in the parameters for these different choices is very small (less than 1% for the μ parameter, less than 5% for the τ parameter and around 5% for the σ parameter, although in only one case, for very few intervals, it reached 10% variation). The numerical results for the fits of all data sets can be found in Table 4 and Figures I to IV show plots of the histograms together with the fits.

The python script for analyzing the data can be found in the supplementary materials. This script uses two python libraries: the scipy (http://www.scipy.org/) and the gnuplot.py (http://gnuplot-py.sourceforge.net/). It has been run for each one of the 14 data sets analyzed in this work under a linux debian distribution. All graphs and parameters presented in this work have been generated by this script. The Gnuplot fit procedure also returns the variance of residuals (or reduced χ^2/dof) for each fit. This number is a way to quantify the goodness of the fit. This number was close to 1 for every fit.

TABLE 4. μ, σ and τ Parameters With Their Uncertainty in Parentheses (Error), Ratio Between τ/σ, and the Goodness of Fit By χ^2 Test, Dof and the Ratio Between χ^2/dof For Go/No-Go And Yes/No Tasks On Young And Old Students

Task/ Parameters		μ	σ	τ	τ/σ	χ^2	dof	χ^2/dof
go/no-go								
young	words	456.20	48.59	132.99	2.74	62.51	47	1.33
	error	±3.26	±2.60	±4.71	—	—	—	—
	high frequency	451.08	44.42	102.46	2.30	44.08	38	1.16
	error	±3.83	±3.10	±5.15	—	—	—	—
	low frequency	473.94	55.46	147.81	2.67	50.84	41	1.24
	error	±5.27	±4.40	±7.83	—	—	—	—
old	words	523.49	79.14	292.35	3.69	89.49	57	1.57
	error	±6.49	±5.37	±10.14	—	—	—	—
	high frequency	512.34	78.91	263.88	3.34	71.4	51	1.40
	error	±8.62	±7.51	± 13.33	—	—	—	—
	low frequency	535.50	68.64	308.55	4.50	89.04	56	1.59
	error	±8.84	±7.42	±15.68	—	—	—	—
yes/no								
young	words	494.73	55.88	141.00	2.52	49.72	44	1.13
	error	±3.38	±2.52	±4.69	—	—	—	—
	non-words	556.36	60.98	156.70	2.62	55.2	48	1.15
	error	±3.76	±2.79	±5.11	—	—	—	—
	high frequency	490.55	55.08	119.55	2.17	44.28	36	1.23
	error	±4.75	±3.62	±6.46	—	—	—	—
	low frequency	506.68	59.73	148.70	2.49	48.6	45	1.08
	error	±5.32	±4.48	±7.75	—	—	—	—
old	words	566.43	73.09	288.77	3.95	68.5	50	1.37
	error	±5.78	±4.68	±10.12	—	—	—	—
	non-words	746.66	132.09	471.78	3.83	94.62	57	1.66
	error	±12.97	±10.62	±24.15	—	—	—	—
	high frequency	558.60	67.98	263.39	3.87	54.28	46	1.18
	error	±7.12	±5.40	±12.52	—	—	—	—
	low frequency	580.49	76.26	305.21	4.00	42.24	48	0.88
	error	±7.02	±5.64	±12.65	—	—	—	—

dof = degrees of freedom.

In order to analyze the ex-Gaussian parameters from Table 4 for the different conditions, one should regard the uncertainties (errors) as confidence interval lengths for each parameter. For comparing the distribution averages (mean reaction time for each condition) one should remember that the ex-Gaussian average is given by $\bar{M} = \mu + \tau$, and verify whether the average difference (or any other parameter difference) between two groups (or conditions) is bigger than the sum

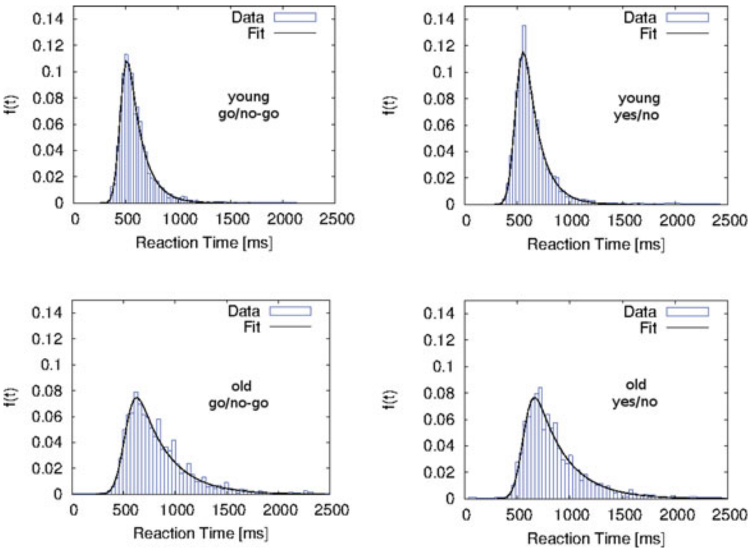

FIGURE 1. Left side: Ex-Gaussian fits for the go/no-go task. Right side: The yes/no task. Graphics on the top come from young University students, and at the bottom for old university students. (Color figure available online).

of their respective uncertainties. If the difference between two parameters is bigger than the combined uncertainties for this parameter, the difference can be considered statistically significant, otherwise it cannot be distinguished from random fluctuations. For example, the average reaction time for the go/no-go condition in the older group, according to the ex-Gaussian fit, was 815.84 $\pm$ 16.49 ms while the average reaction time for the yes/no condition in the same group was 855.20 $\pm$ 15.90 ms. The difference between the two averages (39.36 ms) is slightly higher than the uncertainties sum (32.39 ms), which is indication of a weak effect between the two tasks for this group. On the other hand, it was not possible to determine an attention effect through the τ parameter, since the difference between this parameter in the two conditions (3.58 ms) was much lower than the sum pf the respective uncertainties (20.26 ms). For the young students, the average reaction time in the go/no-go condition, according to the ex-Gaussian fit, was 589.19 $\pm$ 7.97 ms, while the average reaction time for the yes/no condition was 635.73 $\pm$ 8.07 ms, here the difference between the two averages (46.54 ms) is much higher than the sum of the uncertainties (16.04), indicating a clear effect for these conditions. In the case of the τ parameter the difference between the two task conditions (8.01 ms) was much lower than the uncertainties sum (14.85) and therefore one might conclude that there is no difference for this parameter between the two tasks.

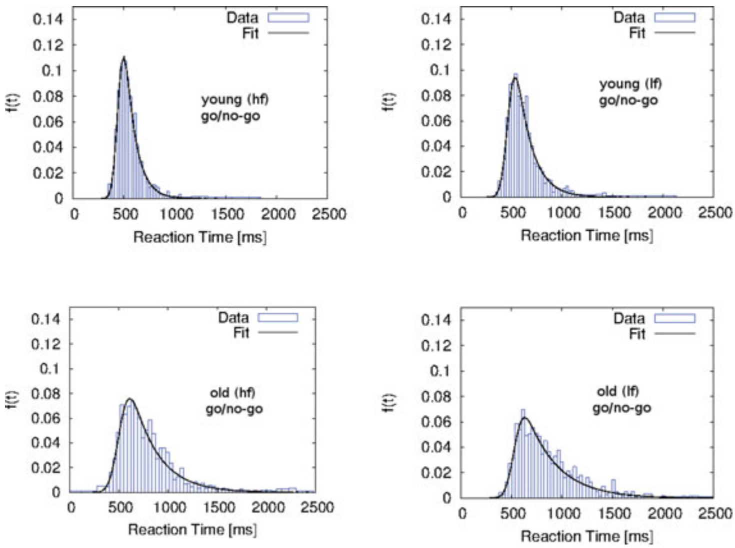

FIGURE 2. Go/no-go task graphics. Left side: Ex-Gaussian fits for high frequency (hf) *stimuli*. Right side: Ex-Gaussian fits for low frequency (lf). Graphics on the top come from young University students, and at the bottom for old university students. (Color figure available online).

Regarding the word-frequency effect, the older students showed, in the go/no-go task, a $\bar{M}$ difference of 67.83 ms, while the uncertainties sum was 46.47 ms. For the same group, in the yes/no task, this difference was 63.71 ms and the correspondent uncertainties sum was 39.31 ms. On the other hand, the τ parameter showed a difference of 44.67 ms and 29.01 ms for the uncertainties respectively in the go/no-go task. This same parameter in the ys/no task showed a difference of 41.82 ms with 25.17 for the uncertainties sum. In the case of the young students, the $\bar{M}$ difference for word frequency effect was 68.22 ms and the uncertainties sum was 22.08 in the go/no-go task. For the yes/no task that difference was 45.28 ms and the uncertainties sum 24.28 ms. Finally, the τ parameter showed a difference average of 45.35 ms with 12.98 ms for the uncertainties sum in the go/no-go task, and a difference average of 29,15 ms and 14,21 for the uncertainties sum in the yes/no task.

Discussion

The main conclusions can be summarized as follows: (1) In the go/no-go task, participants showed shorter reaction times and fewer errors than in the yes/no variant,;however, this difference just reached statistical significance for young

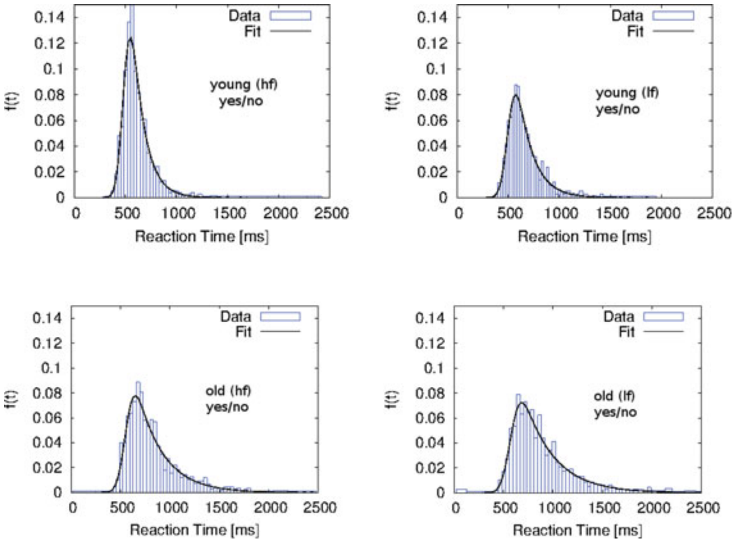

FIGURE 3. Yes/no task graphics. Left side: ex-Gaussian fits for high frequency (hf) *stimuli*. Right side: ex-Gaussian fits for low frequency (lf). Graphics on the top comes from young University students, and at the bottom for old university students. (Color figure available online).

university students; (2) The variants of LDT do not change attentional processes (as it is concluded from the τ parameter); (3) word-frequency effect is involved with attentional processes, as one can see by the high difference in the τ parameter between these two conditions.

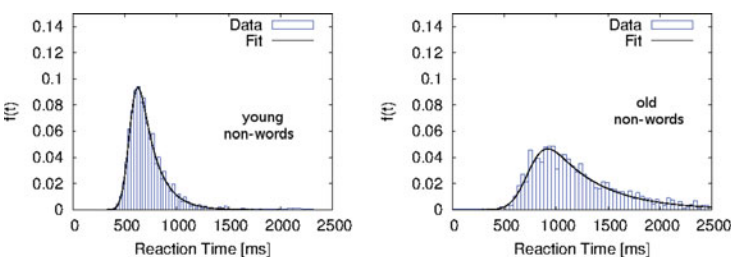

FIGURE 4. Non-words on the yes/no task graphics. Left side: ex-Gaussian fits from young University students. Right side: ex-Gaussian fits from old university students. (Color figure available online).

As one can appreciate in the results section, the classical variance analysis was clear for the university students, but it was not conclusive for the old ones. Nevertheless, during the classical variance analysis a trimming technique is carried out, an action that might result in the loss of valuable information. This work demonstrates the utility of a description with asymmetric distributions through an ex-Gaussian fit, which provides parameters that have been related to cognitive processes (Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004; Leth-Steensen et al., 2000; Spieler et al., 1996; West, 1999; West, Murphy, Armilio, Craik, & Stuss, 2002). Likewise, it is advisable not to restrict the data to classical analyses or techniques such as trimming.

As expected, reaction times were higher and more variable for the old than for young students. The old students showed higher skewed distribution and higher dispersion. Regarding the parameter interpretations, researchers such as Balota and Spieler (1999) claimed that the μ parameter might be related to the automation of processes, while the τ parameter might be related to attentional demands. This last explanation seems to be the most accepted one in the literature. Following this idea, the go/no-go task would be preferable because of its lower distribution average ($\bar{M} = \mu + \tau$). Analogously, it is possible to conclude that differences in the load or demand of the LDT do not change attentional processes, since we do not observed statistically significant differences in the τ parameter between the two tasks. However, the word frequency effect might have an attentional role, as it can be concluded from the significant τ differences observed for these conditions.

On the other hand, Myerson, Robertson, and Hale (2007), argued whether the older participants are more varied because of lapses of attention and concluded that the old subjects can perform a task as reliably as the young ones. They emphasize two aspects: (1) the importance of using big samples (due to the high intravariability); (2) do not to confuse the τ parameter as a skewness measure. At the second point they propose the ratio of $\tau\ /\sigma$. This ratio will follow the same tendency as the ex-Gaussian skewness ($\gamma_1 = 2\tau^3/S^3$). Focusing on the proposed ratio, old and young university students's distributions were slightly more positively skewed on the go/no-go task than the yes/no task.

To summarize, the present work shows that variants of LDT do not change attentional demands, however as expected from Balota and Spieler (1999), word frequency does. Old were slower in terms of processing information than the young university students. This work also shows that the ex-Gaussian fits could be a useful tool for data analysis, especially when dealing with high variability. Hence, researchers should not be exclusively limited to the classic analysis and should take advantage of useful technologies like the one presented in this work. Contrary to other truncating techniques (i.e., trimming), the ex-Gaussian fits employ all observed values, avoiding in this way, errors of interpretation due to extreme data.

NOTES

1. Actually, the old showed a 796.07 ms average for high frequency, and 856.40 in low frequency at the go/no-go block. In the yes/no variant case RT time was higher: 820.21 for high frequency, 879.70 for low frequency and 1179.01 ms for non-words.
2. The case with a different cut-off did not reach statistical significance ($F < 1$) for the old group, either.

ACKNOWLEDGMENTS

We would like to thank the Interdisciplinary modeling group (InterTech, http://www.intertech.upv.es/) which we collaborate with. Specially we would like to thank Professor Pedro Fernández de Córdoba Castellá for his invaluable help.

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Original manuscript received December 23, 2012
Final version accepted June 18, 2013

APPENDIX

PYTHON SCRIPT

```
from random import random as rand
from math import *
import Gnuplot
from Gnuplot import Data as gdata
from scipy.special import erf
### Functions and Routines Definitions
def exgauss(x,mu,sig,tau):
  expo = (1./(2.*tau))*exp((1./(2.*tau))*(2.*mu+(sig**2)/tau-2.*x))
  exg = expo*(1.-erf((mu+(sig**2)/tau-x)/((2.**.5)*sig)))
  return exg
def histogram(lista,ini,fin,Nint):
  fin = float(fin)
  ini = float(ini)
  anch = (fin-ini)/Nint
  hist = [0. for ele in xrange(Nint)]
  for ele in lista:
    if ele > = ini and ele < fin:
      Int = int((ele-ini)/anch)
      hist[Int] + = 1.
  dx = (fin-ini)/Nint
  xxx = [ini+dx*(ii+.5) for ii in xrange(Nint)]
  return [xxx, hist]
def stats(lista):
  N = float(len(lista))
```

```
    xmed = sum(lista)/N
    s2 = [(xmed-ele)**2 for ele in lista]
    s = (sum(s2)/(N-1.))**.5
    return [xmed,s]
# Reading the data
filen = "datas/young_hfgng.dat"
fil = open(filen)
data = fil.readlines()
fil.close()
nums = []
N = 0
for linea in data:
    line = linea.replace("\n","")
    kk = line.split()
    numis = [float(ele) for ele in kk]
    numis = filter(lambda x:(x > 0 and x < = 15000.),numis)
    nums.extend(numis)
    N + = len(numis)
# Creating the histogram
ini = min(nums)−50.
fin = max(nums)+50.
Nint = 70
delt = (fin-ini)/Nint
print ini,fin
[xxx,histo] = histogram(nums,ini,fin,Nint)
fil = open("data.dat","w")
ii = 0
for ii, ele in enumerate(histo):
    poin = xxx[ii]
    print >>fil,poin,ele
fil.close()
## Performing the fit (pipeline with gnuplot)
mu = 500.
sig = 10.
tau = 100
A = N*delt
g = Gnuplot.Gnuplot(persist = 1)
g("f(x) = A*(1./(2.*tau))*exp((1./(2.*tau))*(2.*mu+(sig**2)/tau-2.*x))*(1.-erf((mu+(sig**2)/tau-x)/((2.**.5)*sig)))")
g("mu = %f"%mu)
g("sig = %f"%sig)
g("tau = %f"%tau)
g("A = %f"%A)
```

```
g("fit f(x) './data.dat' u 1:2 via mu,sig,tau, A")
g("plot [0:2500][0:300] f(x) lw 3,'./data.dat' u 1:2 lt 3 pt 3 w boxes t "")
# Making the plots (with gnuplot)
g("set term post eps enh color 'Helvetica' 30")
g('set xlab "Reaction Time [ms]"')
g('set ylab "f(t)"')
kk = filen.replace(".dat",".eps")
kk = kk.replace("datas/","graphs/")
g('set out "%s"'%kk)
kk = filen.replace(".dat","")
#g('se title "%s"'%kk)
g("se xtic 500")
g("plot [0:2500][0:300] f(x),'./data.dat' u 1:2 lt 3 pt 3 t ' ' ")
g.close()
```