Hands-on false memories:

A combined study with distributional semantics and mouse-tracking

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Abstract

Despite mouse-tracking has been taken as a real-time window into different aspects of human decision-making processes, currently little is known about how the decision process unfolds in veridical and false memory retrieval. Here, we directly investigated these processes by predicting participants' performance in a mouse-tracking version of a typical Deese–Roediger–McDermott (DRM) task through distributional semantic models, a usage-based approach to meaning. Participants were required to study lists of associated words and then to perform a recognition task with the mouse. Results showed that mouse trajectories were extensively affected by the semantic similarity between the words presented in the recognition phase and the ones previously studied. In particular, the higher the semantic similarity, the larger the conflict driving the choice and the higher the irregularity in the trajectory when correctly rejecting new words (i.e., the false memory items). Conversely, on the temporal evolution of the decision, our results showed that semantic similarity affects more complex temporal measures indexing the online decision processes subserving task performance. Together, these findings demonstrate that semantic similarity can affect human behavior at the level of motor control, testifying its influence on online decision-making processes. More generally, our findings complement previous seminal theories on false memory and provide insights on the impact of the semantic memory structure on different decision-making components.

Keywords: false memory, DRM task, semantic memory, distributional semantic models, mouse-tracking.

Introduction

Human memory is not simply a precise tape recorder, but a system that encodes and ultimately represents knowledge through a process of active reconstruction rather than passive reproduction (Schacter, 2001; Vecchi & Gatti, 2020). This was first testified in Bartlett's pioneering studies on memory (1932) and supported by a large body of subsequent research, in which it was demonstrated that participants would forget the precise features of the stimuli they have memorized, in favor of an extraction of the gist of the information (for a review: Chang & Brainerd, 2021; Brainerd, Reyna & Ceci, 2008). That is, humans would use their semantic memory to encode, store and retrieve information, adapting new information to what has been previously memorized, with systematic errors that may occur during these phases (Brewer & Treyens, 1981; Sulin & Dooling, 1974).

The origins of inaccurate or false memories have therefore gradually become a matter of great scientific interest. Different experimental paradigms have been developed to account for false memories formation, with the Deese–Roediger–McDermott (DRM; Deese, 1959; Roediger & McDermott, 1995) task being one of the most widely used method in the verbal domain. In this task, participants are typically first presented once with several lists of words that have to be memorized (within each list, the words are related to a non-shown target word, named critical lure; e.g., words list: *door, glass, pan, shade, ledge*, etc. – critical lure: *window*) and then, after a brief distracting task, they are asked to perform a recognition task in which they have to indicate whether a given word was part of the memorized lists or not. Interestingly, during this latter phase, participants tend to erroneously report as “old” the critical lures, (i.e., they recognize them as if they were part of the memorized lists, although these words were never presented during the encoding phase; for a review, see Gallo, 2010).

To explain participants' performance in the DRM task, two main theories have been proposed, the activation-monitoring framework (AMF – Gallo & Roediger, 2002; Roediger, Watson, McDermott, & Gallo, 2001) and the fuzzy-trace theory (FTT – Brainerd & Reyna, 2002; Reyna & Brainerd, 1995). According to the AMF, the critical lure would be hyperactivated by the presentation of the studied words related to it, thus leading to high levels of false recognitions (Roediger et al., 2001). Conversely, according to the FTT, while studying the words participants would encode a memory trace – called gist trace – linked to the semantic content of each list, which would be responsible for the production of the false recognitions (Brainerd & Reyna, 2002; Reyna & Brainerd, 1995).

Consistent with these perspectives, previous studies have successfully predicted false memory occurrence on associative (i.e., associative relationships reflect word use, such as “spider-web”) and semantic (i.e., semantic relationships reflect overlap of conceptual features between words, such as

“horse-pony”) bases (Brainerd, Yang, Reyna, Howe, & Mills, 2008; Roediger et al., 2001). In particular, seminal studies have shown that the association strength between the words that compose each list and the critical lure (i.e., the backward associative strength, BAS) is a central factor in determining false memories (Roediger et al., 2001) and that multiple semantic sub-components underlie false memories (Cann, McRae, & Katz, 2011). In addition to this, recent evidence indicates that participants’ memory performance follows a continuous semantic gradient, with higher false recognitions occurring for higher semantic similarity between the new words presented in the recognition phase and the words previously studied (Gatti, Rinaldi, Marelli, Mazzoni, & Vecchi, *in press*).

However, currently little is known about how the decision process unfolds when participants accept or reject words in the DRM task. That is, accuracy and reaction times – the classical dependent variables used in memory research – although informative of some explicit and implicit cognitive components, are associated to the final state of the decision process, and hence cannot provide a direct measure of how this process unfolds or cannot directly quantify potential conflicts in the response (Freeman, 2018; Stillman, Shen, & Ferguson, 2018). These cognitive components are generally measured through other methodological approaches such as mouse-tracking, a paradigm which is particularly reliable in isolating the dynamics of response conflict and indecision, as well as the evolution of the choice (Freeman, 2018). In recent years, mouse-tracking has been indeed successfully used to investigate how participants’ decision unfolds across several cognitive domains such as language (Lins, & Schöner, 2019; Spivey, Grosjean, & Knoblich, 2005), social cognition (Freeman, Dale, & Farmer, 2011; Freeman, Pauker, & Sanchez, 2016), recognition memory (Papesh, & Goldinger, 2012; Papesh, Hicks, & Guevara Pinto, 2019), semantic memory (Gatti, Marelli & Rinaldi, 2021), and also to detect faking-good behavior when responding to personality questionnaires (Mazza et al., 2020).

In mouse-tracking paradigms, participants are required to make decisions by moving their mouse from a starting position (typically placed in the middle-bottom part of the screen) to one of the two options presented (typically placed in the two upper corners of the screen). It is assumed that motor outputs (i.e., hand movements) are executed in parallel with the decision that participants are required to make (Freeman, & Ambady, 2010), thus allowing for the quantification of the conflict of the choice and its evolution, which cannot be directly assessed using only reaction times (Stillman et al., 2018). Through mouse-tracking packages (e.g., Kieslich, Henninger, Wulff, Haslbeck, & Schulte-Mecklenbeck, 2019) it is indeed possible to extract several dependent variables that are informative about decision-making processes. Generally, decision conflict is quantified by computing the maximum deviation from the direct path (MD; i.e., the furthest point on the actual trajectory from the

idealized straight trajectory between the starting point and the selected stimulus), while the decision evolution is quantified by computing the sample entropy, which measures the irregularity and unpredictability degree of the trajectory (for a complete discussion on other possible indexes see, Freeman & Ambady, 2010; Stillman et al., 2018). For both measures the higher the value, the higher the conflict and the level of indecision. Additionally, mouse-tracking paradigms allow for more refined decision time indexes, such as the computation of the time at which the trajectory reaches the maximum distance (the time at which the decision takes place).

Here, building upon this evidence, we take advantage from mouse-tracking paradigms to explore the decisional stages subserving recognition memory in the DRM task. Participants were asked to study several lists of words from a classical DRM task and then, in the recognition phase, to indicate using their mouse if the words showed were “old” (i.e., presented in the encoding phase) or “new” (i.e., not previously presented). Specifically, we applied an already established method to compute the semantic similarity between the new words and the studied words (for a complete discussion see: Gatti et al., *in press*), by employing indexes extracted from distributional semantic models (DSMs). DSMs induce words meanings from large databases of natural language data, representing them as high-dimensional numerical vectors: these models indeed are thought to well capture the structure of semantic memory (Günther, Rinaldi & Marelli, 2019; Jones, Willits, & Dennis, 2015). This method thus allowed us to investigate whether the decision process differs depending on the position of the new (and studied) words in the semantic space (i.e., whether they are more semantically similar or not to the studies words)

Methods

Participants

Seventy-one students participated in the study (28 males, M age = 24.4 years, SD = 3.63, age range = 19 – 35). All participants were native Italian speakers, had normal or corrected to normal vision and were naïve to the purpose of the study. Informed consent was obtained from all participants before the experiment. The protocol was approved by the psychological ethical committee of the University of Pavia and participants were treated in accordance with the Declaration of Helsinki.

Stimuli

We used the DRM task (Deese, 1959; Roediger & McDermott, 1995), a typical false memories paradigm. Participants were first instructed to memorize several lists of words and then to perform a

recognition task. The words that composed each list were associatively related to a non-shown word (called critical lure).

For the encoding phase, we selected 12 lists of words out of 24 from the normative data for the Italian DRM test (Iacullo & Marucci, 2016). Each list was originally composed by 15 words: we selected the first 12 words (144 words in total), while 2 of the 3 remaining words were used as weakly related lures.

The recognition phase was composed of 96 words, 48 of which had been presented in the previous phase (i.e., studied words) and 48 of which had not been previously presented (i.e., new words). The 48 studied words presented in this experimental phase were those in serial positions 1, 4, 7 and 10 in the studied lists. Of the 48 new words, 12 were the critical lures from the studied lists (i.e., the non-shown words mostly associated with the words composing each list), 24 were weakly related lures and 12 were unrelated words. The weakly related lures were 2 of the 3 words of the studied lists that were not presented in the list, specifically those in position 13 and 14. The unrelated words were chosen randomly among the words of the excluded lists; this criterion was established arbitrarily (for a similar method, see: Gatti et al., *in press*).

Procedure

Participants were tested using Psychopy (Pierce, 2007, 2009; Pierce & MacAskill, 2018; Pierce et al., 2019) through the online platform Pavlovia (<https://pavlovia.org/>). Only participants performing the task with an external mouse were included (i.e., those with a trackpad were excluded a priori).

During the first part of the task, participants had to memorize a series of words (i.e., they were required to study 12 lists of words without interruptions). Participants were shown the 12 words that composed each of the 12 lists in descending forward associative strength (FAS; i.e., the association strength from the critical lure to the word that compose the list). The order by which the lists were presented was random, while the order of the words within each list was fixed according to the FAS (see: Iacullo & Marucci, 2016). Each trial started with a central fixation cross (presented for 500 ms) followed by a word (presented for 1500 ms) and a blank screen (presented for 300 ms), then the script moved automatically to the next fixation cross.

At the end of the encoding phase, participants were required perform an attentional task (i.e., a modified version of the go-no go) as a distracting task for 2 minutes.

Then participants were asked to perform the recognition phase. Participants were instructed to make old/new judgments using their mouse: participants had to first click on a square presented below the

“START” label by pressing the left button of the mouse, and next to move to the selected option (old or new), again pressing the left button to make their decision. Each trial began with a fixation cross presented at the center of the screen (500 ms), then “START” appeared at the bottom-center of the screen (Arial red font, white button to be pressed located at: $x = 0$, $y = -.35$); after the participants clicked on it, the word to be recognized appeared just above the starting button (showed for 1500 ms; Arial font, $x = 0$, $y = 0$), while “old” and “new” buttons appeared in the upper right and upper left of the screen (old/new buttons had always the same location within the same participant, locations were counterbalanced across participants, Arial font for the old/new; buttons located at: $x = \pm .50$, $y = .25$; see Figure 1). Participants were asked to initiate their physical movement as fast as possible.

Figure 1. Recognition task. Participants were asked to make old/new judgments using their mouse. After clicking on the START button, they were shown a word and were required to make the memory judgement (i.e., indicate whether the target word was previously presented or not during the encoding phase).

Distributional semantic model

Vector representations for the words used in this study were extracted from a DSM obtained via the application of neural networks, and in particular the Continuous Bag of Words (CBOW) method, an approach originally proposed by Mikolov and colleagues (Mikolov, Chen, Corrado, & Dean, 2013): when using CBOW, the obtained vector dimensions capture the extent to which a target word is reliably predicted by the contexts in which it appears. The model, released by Marelli (2017), was trained on ItWaC, a free Italian text corpus based on web-collected data and consisting of about 1.9 billion tokens (semantic relatedness values are available online via the SNAUT database:

<http://meshugga.ugent.be/snaut-italian/>). The model used is set on the following parameters: *9-word co-occurrence window*, *400-dimension vectors*, negative sampling with $k = 10$, subsampling with $t = 1e^{-5}$. This set of parameters defines the learning procedure used to induce word vectors (Mikolov et al., 2013). Co-occurrence window size indicates how large the considered lexical contexts are; in our case, a *9-word window* indicates that we estimated predictions concerning 4 words on the left and 4 words on the right of the target word.

From this semantic space, we extracted vector-based estimates for the word items of the present study¹. Specifically, for each word pair it is possible to obtain the cosine of the angle formed by the vectors representing the meanings of these words. The higher the cosine the more semantically similar the words will be. A heatmap matrix of the cosine values among the words composing a reference DRM list is represented in Figure 2.

Figure 2. A heatmap matrix of the cosine values among the words composing the list *window* (i.e., critical lure; words list taken from Roediger & McDermott, 1995). Darker blue colors represent higher cosine values (and, hence, account for more semantically related words as predicted by DSMs). Note that in this case we plotted all the words in the list (i.e., including the possible weakly related lures) and that we computed the cosine values through an English DSM, available here: <http://meshugga.ugent.be/snaut-english/> (see also: Mandera, Keuleers, & Brysbaert, 2017).

¹ The relative cosine values used in this Experiment can be reproduced through the freely available user-friendly interface at: <http://meshugga.ugent.be/snaut-italian/>. Note that the produced distance estimates were subtracted from 1 to obtain a proximity scale.

Computation of semantic similarity values

For each new word (12 critical lures, 24 weakly related lures and 12 unrelated words) we computed a semantic similarity index (SSim). That is, SSim was computed as the frequency-weighted average value of the cosines of the angles formed by the vectors representing the meanings of each new word in the recognition phase and each of the 12 words that composed its relative list (for a similar approach see: Gatti et al., *in press*; Marelli & Amenta, 2018). For unrelated words, we computed the index randomly matching each word with a list. The formula used was:

$$SSim(nw) = \frac{\sum_{i=1}^k \cos(\vec{nw}, \vec{sw}_i) \times Fsw_i}{\sum_{i=1}^k Fsw_i}$$

where nw is a new word showed during the recognition task, $\cos$ refers to the cosine of the angle formed by the vectors representing a new word ($\vec{nw}$) and each of the k studied words ($\vec{sw}$) composing its list (e.g., for critical lures, we computed all the cosines between the critical lure and each word of its list), while Fsw_i is the frequency of each studied word as extracted from the Italian SUBTLEX (<http://crr.ugent.be/subtlex-it/>). Following the same rationale, the SSim index for studied words was computed between each studied word presented in the recognition phase and each of the other 11 words that composed its relative list.

Data analysis

All the analyses were performed using R-Studio (RStudio Team, 2015). Data were analyzed through a mixed-effects approach, which incorporates both fixed-effects and random-effects (associated to participants and task stimuli) and allow for the specification of predictors at both participants and/or item level. All the generalized linear mixed models (GLMMs) and linear mixed models (LMMs) were run using the *lme4* R package (Bates, Maechler, Bolker, & Walker, 2015). The graphs reported were obtained using the *effects* R package (Fox, 2003; Fox & Weisberg, 2019).

Besides participants' explicit memory judgements (i.e., “new” responses were scored as 0, whereas “old” responses as 1), our main dependent variables were: maximum deviation from direct path (MD), sample entropy, initiation reaction times (RTs) and maximum deviation from direct path time (MDtime).

MD is defined as the furthest point on the actual trajectory from the idealized straight trajectory and is thought to quantify the conflict in the choice. Sample entropy is defined as the degree of irregularity and unpredictability in movement across the x-axis and is thought to measure the evolution of the choice (i.e., with higher values indicating higher irregularity). Initiation RT is computed as the time elapsed between the click on the START button and the first hand-movement, while MDtime indexes the time at which the trajectory reaches the MD. These two dependent variables are considered to measure two different time windows of decision-making, with the former (initiation RTs) indicating the time at which the decisional process starts and the latter (MDtime) indicating the time at which a decision is finally achieved (see for a complete discussion regarding mouse-tracking variables: Stillman et al., 2018).

All the mouse-tracking related dependent variables were computed using the *mousetrap R* package (Kieslich, et al., 2019). All trajectories were normalized into 101 time-steps and remapped symmetrically in order to allow for direct comparison of trajectories which differed in duration and number of data points. Initiation RTs, MDtime and sample entropy were all log-transformed.

First, we aimed to replicate the significant interaction SSim by type of stimuli (new vs. old) on participants' explicit memory judgements as previously reported (for a complete discussion of this analysis see: Gatti et al., *in press*). Participants' explicit memory judgements were thus analyzed estimating a GLMM with SSim, type of stimuli (new vs. old) and their interaction as predictors; subjects and items were included as random intercepts.

Then, following a similar approach, we included the SSim predictor in the analyses on mouse-tracking dependent variables, estimating four LMMs in which we included SSim, type of stimuli (new vs. old), participant's response (new vs. old; i.e., whether the participant judged each word as showed or not) and their interactions as predictors; subjects and items were included as random intercepts. In case of singularity issues (i.e., for MD, sample entropy and initiation RTs, but not for MDtime), the random model was simplified removing the intercept of the item and then refitted. In particular, in *lme4* syntax, the models tested were:

$$DV \sim SSim * Type * Response + (1|Participant) + (1|Item)$$

Then, to exclude the impact of overly influential outliers, after having fitted the model data points were removed on the basis of a threshold of 2.5 *SD* standardized residual errors (model criticism; Baayen, 2008). Results based on the refitted models are reported.

Results

Trials in which overall reaction times (i.e., the time between the initiation of the movement and the selection of one option) were faster than 300 ms or slower than 5000 ms were excluded from the analysis (.7% of the trials excluded). Aberrant movements were detected in 6% of additional trials and were discarded. Trials in which MD and sample entropy were $\pm 3SD$ from the mean of the participants were removed from the analysis (2% of additional trials excluded).

1. The differential effect of SSim on false and veridical recognitions

In the GLMM including recognition explicit responses (i.e., “new” responses were scored as 0, “old” as 1) as dependent variable, SSim and type of stimuli (studied vs. new words) as predictors, we found significant effects of both variables on recognition (SSim: $z = 9.84$, $p < .001$; type of stimuli: $z = 3.36$, $p < .001$; *Pseudo-R*² (total) = .47). Critically, the interaction SSim by type of stimuli was significant, $z = -3.24$, $p = .001$.

The significant interaction indicates that the effect of SSim was specific for false recognitions, $z = 6.43$, $p < .001$, while it was not significant for veridical recognitions, $z = .90$, $p = .37$ (Figure 3). In particular, for new words, the higher the SSim value, the higher the occurrence of false memories, in line with previous findings (Gatti et al., *in press*).

Figure 3. Results from the GLMM including the interaction between SSim and type of stimuli on participants' proportion of old response (i.e., for new words, the lower the value the higher the occurrence of false memories).

2. Analyses on mouse-tracking dependent variables

2.1 Descriptive statistics

Descriptive statistics for the four variables are reported in Table 1. The correlation matrix between the four dependent variables is reported in Table 2. Overall, the correlations ranged from very low, as the one between MD and MDtime ($r = -.06$), to high, as the one between MD and sample entropy ($r = .59$). Note that the correlations were computed on raw data, hence on a total of 6203 trials.

Table 1. Descriptive statistics for the four dependent variables analyzed. The descriptive statistics of the two variables expressing temporal processes (initiation RTs and MDtime) are reported in milliseconds.

	Initiation RTs	MD	Sample entropy	MDtime
Mean	330	.22	.10	917
SD	197	.12	.03	204
Min – Max	51 – 907	-.01 – .48	.05 – .90	554 – 1402

Table 2. Correlation matrix between the four dependent variables included in the current study. The correlation values ranged from very low to moderate (6201 degrees of freedom, all $ps < .01$).

	Initiation RTs	MD	Sample entropy	MDtime
Initiation RTs	1			
MD	-.20	1		
Sample entropy	-.24	.59	1	
MDtime	.42	-.06	.08	1

2.2 Initiation reaction times

In the LMM including Initiation RTs as dependent variable, SSim, type of stimuli and participant's response as predictors, we found no significant effect, all $ps > .20$.

2.3 Maximum deviation from direct path

In the LMM including MD as dependent variable, SSim, type of stimuli and participant's response as predictors, we found significant effects of SSim, $F(1,6040) = 4.91$, $p = .02$, of participant's response, $F(1,6047) = 10.11$, $p = .001$, of the interaction SSim by participant's response, $F(1,6044) = 13.97$, $p < .001$, of the interaction type of stimuli by participant's response, $F(1,6045) = 7.22$, $p = .007$, and, critically, of the three-way interaction SSim by type of stimuli by participant's response, $F(1,6043) = 4.71$, $p = .02$, $Pseudo-R^2$ (total) = .27 (Figure 4A and Figure 4B).

Figure 4. Results from the LMM on MD including the interaction between SSIm, type of stimuli divided across participant's response = old (A) and participant's response = new (B), showing the positive relationship between SSIm and MD when participants correctly rejected new words. A pictorial representation of how the maximum deviation (in dashed lines) from the direct path (black straight line) varied across two hypothetical levels of SSIm (i.e., low and high SSIm; the two categories were created by selecting the half of words with lower SSIm and the other half with the higher SSIm) of new words when participants correctly rejected them (C).

The significant three-way interaction indicates that, when participants correctly rejected new words (i.e., participant's response = new), SSIm significantly predicted MD, $t(6041) = 6.36, p < .001, \beta = .39$. In particular, the higher the SSIm for new words, the higher participants' degree of indecision when correctly rejecting it (Figure 4C). No effect of SSIm was found when participants reported as old both new, $t(6041) = -1.54, p = .12, \beta = -.12$, and studied words, $t(6040) = -.11, p = .90, \beta = -.008$, or when rejecting studied words, $t(6043) = 1.05, p = .29, \beta = .12$.

2.4 Sample entropy

In the LMM including sample entropy as dependent variable, SSIm, type of stimuli and participant's response as predictors, we found significant effects of participant's response, $F(1,6083) = 4.98, p = .02$, of the interaction type of stimuli by participant's response, $F(1,6082) = 6.80, p = .009$ and, critically, of the three-way interaction SSIm by type of stimuli by participant's response, $F(1,6080) = 4.68, p = .03, Pseudo-R^2 \text{ (total)} = .27$ (Figure 5).

The significant three-way interaction indicates that, when participants correctly rejected new words (i.e., participant's response=new), SSIm significantly predicted sample entropy, $t(6079) = 6.79, p <$

.001, $\beta = .50$. In particular, the higher the SSim between the new words, the higher the participants' degree of indecision when correctly rejecting it. No effect of SSim was found when participants reported as old both new, $t(6079) = -1.26, p = .21, \beta = -.22$, and studied words, $t(6078) = .91, p = .36, \beta = .14$, or when rejecting studied words, $t(6080) = .18, p = .86, \beta = .05$.

Figure 5. Results from the LMM on log-transformed entropy including the interaction between SSim, type of stimuli divided across participant's response = old (A) and participant's response = new (B), showing the positive relationship between SSim and log-transformed entropy when participants correctly rejected new words.

2.5 MDtime

In the LMM including MDtime as dependent variable, SSim, type of stimuli and participant's response as predictors, we found significant effects of participant's response, $F(1,4783) = 6.28, p = .01$, of the interaction type of stimuli by participant's response, $F(1,4783) = 8.05, p = .004$ and of the interaction SSim by participant's response, $F(1,4899) = 10.94, p < .001$, $Pseudo-R^2$ (total) = .39 (Figure 6). On the contrary, the three-way interaction SSim by type of stimuli by participant's response was not significant, $F(1,4912) = 1.29, p = .25$.

The significant interaction SSim by participant's response indicates that, regardless of the type of stimuli, the higher the SSim, the faster participants were in deciding that a word was old, $t(280) = -$

2.10, $p = .04$, $\beta = -.26$; conversely, the higher the SSim, the slower participants were in rejecting a word (i.e., identifying it as new), $t(153) = 2.22$, $p = .03$, $\beta = .22$.

Figure 6. Results from the LMM on log-transformed MDtime including the interaction between SSim, type of stimuli divided across participant's response = old (A) and participant's response = new (B), showing the negative relationship between SSim and MDtime when participants recognized as old both types of stimuli (left) and the positive relationship between SSim and MDtime when participants rejected both types of stimuli (right).

Discussion

In the present study, we explored the decisional stages subserving recognition memory in the DRM task taking advantage from mouse-tracking and from distributional semantic models. Participants were asked to memorize several lists of words in a classical DRM task and then to recognize them among newly words using their mouse. The decision-making processes were indexed through different variables computed from mouse trajectories and predicted using an item-level semantic metrics extracted from distributional semantic models (for a complete discussion see: Gatti et al., *in press*). Overall, our findings indicate that semantic memory can affect human behavior at the level of motor control, testifying its pervasive influence on online decision-making. Specifically, our findings indicate that mouse trajectories are affected by the semantic similarity between each word in the recognition phase and the previously studied words. That is, the higher the semantic similarity, the higher the conflict driving the choice and the irregularity in the trajectory (respectively measured with

the maximum deviation from direct path and with sample entropy) when correctly rejecting new words. Conversely, on the temporal evolution of the decision, our findings indicate that semantic similarity predicts complex temporal measures indexing the online decision processes subserving task performance. More specifically, we found that regardless of the type of stimuli (old or new), when responding that a word was “old”, the higher the semantic similarity, the earlier the stage at which the decision was achieved; on the contrary, when rejecting a word (i.e., when responding that a word was “new”), the higher the semantic similarity, the later the stage at which the decision was achieved.

Previous studies investigating associative and semantic involvement in the DRM task have shown that backward associative strength is a major predictor of false memories (Roediger et al., 2001), that multiple semantic sub-components underlie false memories (Cann, McRae, & Katz, 2011) and that memory performance follows a continuous semantic gradient (Gatti et al., *in press*). This last finding was replicated in this study, by observing that for new words, the higher the SSim value, the higher the occurrence of false memories. Critically, here we extended this evidence by showing that the semantic similarity between the words presented in the recognition phase and those previously studied affects not only the explicit memory judgements (i.e., “yes” and “no” recognition responses), but also more implicit measures extracted from participants’ motor outputs.

These findings well complement the key assumptions of the two main theories accounting for false memory in the DRM task, namely the AMF and the FTT. Indeed, both theories trace back the origin of false recognitions to associative/semantic mechanisms, with adequate episodic and source memory processes that would counter them and enhance the occurrence of veridical recognition (Brainerd, & Reyna, 2002; Gallo & Roediger, 2002; Reyna & Brainerd, 1995; Roediger et al., 2001; and for individual differences evidence see: Gatti, Rinaldi, Mazzoni, & Vecchi, 2021). In interpreting our findings in light of these theories, we first note that the dependent variable used to measure the conflict in the decision (maximum deviation from direct path) quantifies it as a measure of the attractiveness of the unselected option (Freeman, & Ambady, 2010). Thus, the higher the attractiveness of the unselected option, the higher the maximum deviation value, because mouse trajectories would be associated with a larger curvature. Accordingly, our results show that even when participants correctly rejected new words (i.e., by selecting the “new” button), the “old” button exerted high attractivity. Notably, the level of attractiveness varied as a function of the semantic similarity, with greater level of conflict for more semantically similar new words. Hence, while previous studies have shown that semantic memory is involved in the production of false memories (Gatti et al., *in press*), here we demonstrate that in the DRM task semantic processes participate also when correctly rejecting new words (i.e., the false memory items). Such an interpretation holds as

well for the degree of irregularity and unpredictability of mouse movements, as the evolution of the choice was similarly affected by semantic similarity. That is, when correctly rejecting new words, movement irregularity was higher for more semantically similar new words.

The increased conflict in the rejection of new words as a function of their semantic similarity can be interpreted in terms of the alleged conflict emerging when participants are requested to judge if a new word was actually studied or not. In particular, the AMF assumes that the critical lure is associatively hyperactivated in the encoding phase and then, in the recognition phase, such hyperactivation would be responsible of the false recognition (Gallo & Roediger, 2002; Roediger et al., 2001). On the other hand, the FTT assumes that while studying the word lists the participants would encode two memory traces: a semantic one, linked to the semantic content of each list; and an episodic one, linked to the contextual and perceptual features. In the recognition of a new word, these two traces would therefore counter each other (i.e., the semantic trace would increase the likelihood of a false recognition, while the episodic trace would operate in the opposite direction), while for studied words they would both boost veridical recognition (Brainerd, & Reyna, 2002; Reyna & Brainerd, 1995). The enhanced conflict and uncertainty in participants' rejection of new words with increasing semantic similarity observed here documents for the first time the online decision processes underpinning false memories, as maintained by both AMT and FTT. That is, for the new words in which the episodic trace is lacking, the conflict and the uncertainty would increase with increased semantic similarity of the new word.

For the main timing measure (i.e., the time at which the mouse trajectory finally deviates), we found that the semantic similarity affected participants' performance in both veridical and false memories. In particular, the higher the semantic similarity, the faster participants were in deciding that a word was old, and vice versa for "new" judgments. Hence, the time at which the decision occurred was influenced in opposite directions by semantic similarity, indicating that this variable overall impacted on the temporal dynamics subserving task performance. This dissociation could indicate that semantic memory involvement in the DRM task could affect differently temporal vs. spatial measures of decision making, thus dissociating the time needed to decide if a word was old or new from deeper decision-making components, such as the conflict and indecision underlying memory judgements.

Our findings have relevant implications from both theoretical and methodological points of view. On a theoretical level, our results clarify semantic memory involvement in a complex memory task such as the DRM when participants' performance is measured through fine-grained hand movements. In particular, here we provide evidence for a possible differential involvement of semantic memory across time, conflict and uncertainty of participants' decisions. Additionally, by successfully

predicting mouse-tracking measures using a semantic predictor extracted from a distributional semantic model, we provide further support to the idea that these models are extremely efficient in capturing the structure of human semantic memory (Günther et al., 2019). Indeed, while previous studies have predicted participants' performance using distributional semantic models across a wide range of semantic tasks, such as multiple-choice tests (Bullinaria & Levy, 2012), word categorization (Baroni & Lenci, 2010), word relatedness ratings (Bruni, Tran, & Baroni, 2014), word naming and lexical decision (Marelli & Amenta, 2018), semantic priming (Günther et al., 2016), recognition memory (Gatti, et al., *in press*), as well as using mouse-tracking (Gatti et al., 2021), our study is the first to report its effect also on mouse-tracking variables in a complex memory task such as the DRM. Furthermore, on a methodological level, we show that by pairing distributional semantic models with mouse-tracking it is possible to investigate deep decision-making features of human behavior, thus opening new avenues for probing the detailed processes subserving human memory.

In conclusion, using distributional semantic models combined with mouse-tracking, we document the decision-making semantic processes underpinning false memories. Our findings are consistent with previous theories on participants' behavior in the DRM task and provide novel insights on the impact of semantic memory on different decision-making components.

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