

Role vs relational similarity in analogical processing

Vencislav Popov (vencislav.popov@gmail.com)

Department of Psychology, Carnegie Mellon University, Pittsburgh, PA

Margarita Pavlova (margarita.velinova@gmail.com)

Department of Psychology, University of Kansas, Lawrence, KA

Penka Hristova (phristova@cogs.nbu.bg)

Department of Cognitive Science and Psychology, New Bulgarian University, Montevideo Str. 21, Sofia, Bulgaria

Abstract

We tested whether relational knowledge is represented as a set of relations among entities or as a set of relational roles to which entities are bound. Participants performed four relational processing tasks with the same set of word-pair stimuli: relational exemplar generation; similarity ranking; analogical verification; and a paired-associate learning task. In the similarity ranking task, we gathered separate rankings for relational, role and semantic similarity between word pairs. Relational similarity predicted exemplar generation frequencies, analogical verification accuracy and RTs, and relational luring in associative memory. Role similarity predicted exemplar generation frequency, and, weakly, analogical verification RTs. Semantic similarity did not predict any of the tasks, after controlling for the other two factors. Contrary to current theories which posit that semantic similarity is more important for retrieving relevant analogues, and that analogical mapping is based on role-filler bindings, relational similarity was the strongest predictor across all tasks.

Keyword semantic relations; analogical reasoning; similarity; memory

Semantic relations between concepts (e.g. the “*is made of*” relation between the concepts *glass* and *window*) are a key aspect of human knowledge and reasoning. Researchers have argued that in order to support higher-level cognition, relational representations should be explicit, i.e. to be independent of their arguments (Doumas & Hummel, 2005; Popov, Hristova, & Anders, 2017).

Two major approaches have been proposed for representing relations explicitly and they are a matter of a prominent debate in the field (Doumas & Hummel, 2005; Halford, Wilson, & Phillips, 2010). Relations can be represented by predicate-like entities, in which the arguments to the relation are specified by their spatial/order positions. For example, to represent the fact that a handle is part of a cup, one could posit three representational entities – R, x and y, where R stands for the part-of relation, and x and y stand for the part and whole arguments respectively. Thus xRy or R(x,y) represents the relational exemplar and one determines which object is the part and which the whole by their order in the representation. These types of relation-based representations can be isomorphically implemented as predicates, *part-of(handle, cup)* (e.g. Gentner, 1983), localist nodes in a network with separate entities representing the relation and its arguments (e.g. Anderson, 1983), or conjunctions of distributed vectors, where each vector stands for either the relation or its arguments (e.g. tensor products, Halford et al, 1998).

Alternatively, relations can be represented as a set of relational roles to which entities are bound. For example, rather than explicitly representing the part-of relation as a separate symbol, the relational information can be represented as two roles, *whole* and *part*, to which each of the objects is bound (e.g., *whole&cup + part&handle*). In distributed models, this is achieved when two vectors representing each role of a diadic relation are bound either by multiplication or by addition or synchrony of firing/activation to vectors representing the entities that fill those roles (e.g. Hummel & Holyoak, 1997).

Whether relational representations are based on a relational symbol or role-filler bindings has implications for understanding relational mapping and retrieval. There is considerable variability in the accuracy and speed of analogical reasoning, and, as we show in the current paper, this variability can be partially explained by the fact that both retrieval and mapping are influenced by the similarity between a base analogue and a target scenario. The question is, what aspects of the representation are responsible for these effects. For example, some theorists have proposed that retrieval is influenced more by semantic similarity between the concepts, rather than by the similarity of the relations that connect them. Furthermore, if relational information is based on role-filler bindings rather than on relational symbols, the similarity between the roles concepts play should be a stronger predictor of relational processing than the similarity between the relations between those concepts.

In the current study, we had two aims: 1) to systematically show how different aspects of relational processing are affected by how typical the exemplars are of the semantic relation; 2) to determine whether each of these aspects of relational processing is mostly driven by the semantic similarity between the concepts, the similarity between the roles each concept plays, or the similarity between the relations in each exemplar.

Overview of experiments

We performed four experiments that tested different aspects of relational processing – 1) a relational exemplar generation task, 2) a semantic/role/relational similarity ranking task, 3) an analogical verification task and 4) a continuous paired-associate learning task. In Task 1, participants saw two word pairs that were representative of a semantic relation, and they had to generate three additional word pairs that had the same relation. A subset of the generated exemplars served as stimuli for the other three tasks. In Task 2, participants saw one pair as a base, and they had to rank three additional pairs according to their semantic, role or relational similarity to the base. In Task 3,

participants saw a base and a target word pair and they had to respond as quickly as possible whether the two word pairs were analogical or not. In Task 4, participants studied pairs of words and had to discriminate between studied, recombined and new pairs of words. Each task was completed by a different sample of participants, and those included both convenience samples of undergraduate students, as well as more heterogeneous samples recruited on social media.

Methods

Task 1: Relational exemplar generation

Participants Seventy-nine people (58 female) participated. Participants were native Bulgarian speakers that were recruited on social media and were asked in turn to share the study link with their contacts. Their age ranged from 18 to 67 years ($M = 38$, $SD = 12$); Participants had heterogeneous education backgrounds - 80% had a bachelor's degree or higher, 16% had a high-school diploma and 4% had not graduated from high school. They were offered a chance to win a gift card for finishing the full study and for giving very typical exemplars of a relation.

Materials, procedure and design We selected 2 exemplars for each of 58 relations, which we had already determined to be good exemplars of their relation in a previous pretesting study (for details, see Popov & Hristova, 2015). Materials were administered through an online survey platform (<http://esurv.org>). For each relation the two exemplars were presented together and we asked participants to generate up to 3 novel exemplars for each relation. For example, participants were given the following two word pairs:

NURSE HOSPITAL
WAITER RESTAURANT

They were told that the two word pairs are analogical, because they share the same relation. Namely, a “nurse” works in a “hospital”, just as a “waiter” works in a “restaurant”. They were told that this is not a creativity test and that they should attempt to write down the first analogical word pair that comes to mind. The whole procedure took between 30 and 120 minutes, and participants were told that if they are having trouble with some examples, it is better to move on to the next and that even partial responses will be of use. Relations were presented in random order for each participant, thus even if participants gave up before completing the task, responses were equally spread among all relations.

Stimuli selection All responses were subsequently spell-checked and manually inspected before analysis, to remove differences between singular and plural forms, alternative spellings, etc. For each relation we counted the proportion of participants who gave each exemplar in each position (first, second or third response). Each of the 58 relations was given at least one answer from 47 to 67 participants. Each relation received between 117 and 186 separate responses. For each relation group, we first identified the 8 most dominant responses. Going from the least to the most dominant response across relations, we manually and iteratively removed exemplars that

shared one or two of their words with exemplars to other relations, until only responses with unique words remained. Only 35 of the initial 58 relations had more than 1 generated exemplar left, and for each we selected the 3 most dominant responses. Combined with the original two exemplars, this resulted in 35 relations with 5 exemplars each.

For each relational group we calculated the proportion of people that generated it in first place. This measure reflects how typical the exemplar is of the relation (more typical exemplars are generated more frequently) and it was used in all correlation and regression analyses presented later.

Task 2: Ranking relational/role/semantic similarity

Participants Fifty-two people (37 female) volunteered to participate. Participants were native Bulgarian speakers that were recruited through personal contact and social media. Their age ranged from 21 to 65 years ($M = 35.0$, $SD = 9.6$). 82% held a bachelor's degree or higher.

Materials, procedure and design The 35 groups of word pairs selected in the *Relational exemplar generation* task were split into 5 groups. Each of the five groups was assigned to be ranked by one of the following conditions using a latin-square design: 1) relational similarity, 2) role similarity of the first words in each pair, 3) role similarity of the second words in each pair, 4) semantic similarity of the first words in each pair, 5) semantic similarity of the second words in each pair

Each participant rated each group in only one of the 5 conditions and the conditions were randomized across participants such that each group was tested equally often in each condition. Half of the participants ranked the target pairs in response to the first base pair, and the other half ranked them in response to the second base pair. Thus, participants ranked 35 trials, which took them between 15 and 45 minutes. The task was administered through an online survey platform (Qualtrics.com).

On each trial, one of the base pairs in the group was presented on top (e.g. NURSE HOSPITAL). Below it were shown the three target pairs (WAITER RESTAURANT, LAWYER LAWYER, MECHANIC WORKSHOP) and participants had to rank how similar they are to the base according to one of the 5 criteria given above (semantic, role of relational similarity). Trials were presented in blocks of 7 where all the trials in a block required the same criterion for ranking. The order of the blocks, the order of the trials within a block and the default order of the target pairs on each trial were randomized across participants.

After participants completed all trials, they had to answer how difficult they found on average each ranking, and also about how difficult it was to distinguish between every pair of criteria. The debriefing questionnaire contained 4 questions 1) Which of the three comparisons (semantic/relational/role) was most difficult to you? Rank them in decreasing order of difficulty. 2) How confident are you about the rankings you gave for each criteria (on a scale from 1 = completely unconfident to 5 = completely confident)? 3) Which two criteria did you have most difficulty distinguishing from one another? Rank them in decreasing order of difficulty (semantic from relational; relational from role; role from semantic). 4) On a scale from 1 (Completely indistinguishable) to 5 (Completely distinguishable), how difficult was it for you to distinguish the different criteria? Give a separate rating for each pair of criteria.

Instructions Before each block, participants were instructed in detail as to how to rank the exemplars in each trial. The full instructions and examples are available at <https://git.io/vNHMe>

Task 3: Analogical verification

Participants Twenty-eight undergraduate students (7 males) at New Bulgarian University participated in the lab for partial fulfillment for course credit. All were native Bulgarian speakers, whose age ranged from 19 to 54 years ($M = 32.4$, $SD = 11$). One participant was excluded from all analyses due to low overall accuracy in the task (59%).

Materials The final set of stimuli consisted of 444 unique word pairs. Half of the pairs were taken from the 6 exemplars of each of the 37 relations selected in the exemplar generation task. The other half of the pairs were fillers used on non-analogical trials, and they were not examples of any of the relations we previously used. For each relation, two of the pairs were always used as bases in the analogical judgement task, and the remaining four were always used as targets. For example, the relation “lives in” was represented by two bases [CHEETAH SAVANNAH] and [DOLPHIN SEA] and four targets [MONKEY JUNGLE], [CAMEL DESERT], [GOAT MOUNTAIN] and [MOUSE FIELD]. An analogical trial consisted of one base and one target from the same relational group (e.g. CHEETAH SAVANNAH :: MONKEY JUNGLE). Non-analogical trials consisted of an existing base pair, and a filler target pair, in which the words were either unrelated, or not related in the same ways as the words in the base (e.g. DOLPHIN SEA :: ZEBRA STRIPES).

Procedure We used a verbal analogy judgement task in which analogical trials were intermixed with the same number of non-analogical trials. Each trial began with a fixation cross for 500 ms. The fixation was followed by two words that appeared one above the other in the middle of the screen for 3.5 s. Next, a question mark appeared for 500 ms, indicating that the participants will be asked to provide an answer for the following word pair. Next, two words appeared one above the other until a response was given, followed by a blank screen for 500 ms. For each second word pair, the participants had to indicate whether the words in it were semantically related in the same way as the words in the preceding pair. We will use the response times for analogical verification as a marker of the accessibility of the shared relation.

Design The design was within-subject with the type of the target pair (analogical or non-analogical to the base) as a single factor. Stimuli were counterbalanced with a latin-square across participants so that each participant rated two trials with different bases and targets from each relational group (for a total of 4 pairs from each relation), and each possible pairing of a base and target from each relational group was rated by a quarter of all participants. Participants completed 148 trials within ~ 20 min.

Task 4: Relational luring in associative recognition

The data for relational luring comes from Popov et al. (2017). In that paper we performed a continuous associative recognition task, in which people had to respond on each trial whether a pair of words was seen previously in the experiment (i.e. “old pairs”),

whether the words were seen, but in different pairs (i.e., “recombined pairs”), or whether they were new. The old and recombined pairs were selected from the 35 relational groups identified in the relational exemplar generation task described above. People studied and responded to 4 or 5 different exemplars of each relation. The relational luring effect (RLE) stands for the false recognition of an exemplar (FLOOR CARPET), which is relationally similar to a previously studied word pair (TABLE CLOTH). We found that false alarms and response times (RTs) to relational lures as well as hits for previously seen exemplars in a continuous associative recognition task increased linearly with the number of *different* instances of the same relation that were studied beforehand.

For our current goals, we needed to quantify the strength of the RLE for each relational group (e.g. how strong is the RLE for the “X works in Y” relation and its five exemplars). To do that, in our mixed-effects regression analysis of RTs, we fitted separate slopes for each relational group for the effect of “number of previously studied exemplars of the relation”. This estimates for each relational group, how strongly participants were lured by seeing previous relational exemplars.

Results and discussion

From the four different tasks we have gathered seven different measures for the same stimuli: 1) exemplar generation frequency, 2) analogical verification RTs, 3) relational similarity ratings, 4) role similarity ratings, 5) semantic similarity ratings, 6) relational luring effect, and 7) associative recognition RTs. First, we will review how difficult it was to discriminate between semantic, role and relational similarity in ranking the pairs, and then we will test which of those measures best predicts performance in the remaining task. Finally, we will look at how performance in each of the other tasks predict performance in the others.

Difficulty/discriminability of similarity rankings

Since participants gave separate rankings for the role and semantic similarities of each word within a pair, we averaged the ranks over the two words into composite scores for overall role and semantic similarity rankings of each base-target pair. The rankings were centered and reversed to created similarity scores that ranged from -1 (least similar) to 1 (most similar).

The three ranking criteria were equally difficult – Wilcoxon signed rank tests revealed that there were no significant differences in how difficult participants ranked the relational ($M = 2.16$, $SD = 0.79$), role ($M = 1.94$, $SD = 0.82$) and semantic criteria ($M = 1.90$, $SD = 0.81$), all $ps > .168$. Confidence scores for the three criteria were also similar ($M = 3.37$, $SD = 1.06$; $M = 3.39$, $SD = 0.85$; $M = 3.39$, $SD = 0.80$; respectively for the relational, role and semantic criteria). We had also asked participants to rank how difficult it was to discriminate each criterion from the other two (e.g., relational from role, role from semantic, and semantic from relational). Participants found it more difficult to discriminate the role from the other two criteria ($M = 1.69$, $SD = 0.76$, against the relational criterion, $M = 1.82$, $SD = 0.8$, against the semantic criterion, $p = .47$), compared to discriminating the relational from the semantic ($M = 2.49$, $SD = 0.64$, both p 's $< .001$).

The three types of similarity for each base-target pair correlated moderately with each other, which suggests that

participants were able to distinguish among them. Table 1 shows the Kendal tau rank correlation, calculated separately for each base-target group and averaged over groups. In summary, all ranking were equally difficult participants were able to evaluate separately the semantic, role and relational similarities between word pairs.

Relational and role similarity independently predict generation frequencies

All similarity measures correlated positively with exemplar generation frequency. The correlation was greatest for relational similarity, $r(195) = 0.44$, $p < .001$, medium for role similarity, $r(195) = 0.41$, $p < .001$, and smallest for semantic similarity $r(195) = 0.35$, $p < .001$.

Since the three similarity measures correlated with each other as well, we compared all three as predictors in a mixed-effects logistic regression model of the generation frequency proportions. We used a mixed effects regression model, rather than just partial correlation, because the observations for each pair of word pairs are not independent, but are nested within each relational group. The mixed effects regression had random intercepts for each relational group, and random slopes for the three similarity measures within each relational group as well. After controlling for the other two factors, relational similarity significantly predicted generation frequencies, $\Delta AIC = -15$, $\chi^2(1) = 16.87$, $p < .001$. The effect of role similarity was also significant, but to a lesser degree, $\Delta AIC = -2$, $\chi^2(1) = 4.06$, $p = .044$. Semantic similarity had no effect, after controlling for the other two factors, $\Delta AIC = -0.9$, $\chi^2(1) = 2.84$, $p = .092$. The results for each measure after controlling for the other two are shown in Figure 1. In summary, when participants generated novel relational exemplars in response to a base pair, their memory search was guided mostly by the relation present in the base, and less by the roles that each word played in the pair.

Relational and role similarity independently predict analogical verification RTs

The results were similar for analogical verification RTs and accuracy – all three similarity measures correlated significantly with analogical performance. For analogical RTs, the correlation was strongest for relational similarity, $r(210) = -0.38$, $p < .001$, followed by role similarity, $r(210) = -0.35$, $p < .001$, and weakest for semantic similarity, $r(210) = -0.31$, $p < .001$.

To contrast the three different measures, we used all three as predictors in a linear mixed-effects regression of analogical RTs, which included random intercepts for each relational group and for each subject, and random slopes for each of the three similarity measures within each relational group and within each subject. Relational similarity was the only significant predictor of analogical RTs, $\Delta AIC = -2$, $\chi^2(1) = 4.69$, $p = .03$. Neither role similarity, nor semantic similarity significantly predicted RTs after controlling for the other two measures ($\Delta AIC = -1$, $\chi^2(1) = 3.006$, $p = .083$ and $\Delta AIC = 1.9$, $\chi^2(1) = 0.023$, $p = 0.879$, respectively). Since semantic similarity was not a significant predictor, and the significance for role similarity was close to the $p = 0.05$ threshold, we rerun the model without the semantic similarity predictor. In this model, both relational and role similarity predicted analogical RTs (both p 's $< .05$). The results for each measure after controlling for the other two are shown in Figure 2. In summary, greater relational and role similarity both

Table 1 Correlations among average rankings for each base-target pair for all criteria in Task 2.

| | rel | role | sem | role1 | role2 | sem1 |
|-------|------|------|------|-------|-------|------|
| role | 0.62 | | | | | |
| sem | 0.6 | 0.65 | | | | |
| role1 | 0.57 | 0.85 | 0.6 | | | |
| role2 | 0.55 | 0.83 | 0.6 | 0.68 | | |
| sem1 | 0.59 | 0.64 | 0.77 | 0.62 | 0.56 | |
| sem2 | 0.6 | 0.62 | 0.77 | 0.53 | 0.62 | 0.53 |

* Rel = relational rankings; Role and Sem are composite rankings, averaged over the two words in each pair; role1, role2, sem1 and sem2 are the rankings based on the first and the second word in each pair, respectively

lead to faster analogical decisions, although the evidence is stronger for the relational similarity contribution.

Only relational similarity predicts relational luring

Relational luring represents the degree to which participants are influenced to falsely recognize a novel stimulus as previously seen because it implements the same relation as some of the studied stimuli. Only relational similarity correlated significantly with the strength of relational luring, $r(142) = 0.20$, $p = .02$; the correlation with role and semantic similarity was not significant, both $r(142) = 0.11$, $p = .18$. Once again, we also fit a linear mixed-effects regression model with random intercepts and slopes for each relational group, in which we could estimate the unique contribution of each similarity type. Confirming the correlation analyses, only relational similarity predicted relational luring, $\Delta AIC = 3.2$, $\chi^2(1) = 5.35$, $p = .021$. The results are shown on Figure 3. It is worth noting that the predicted RLE size from the model for relational similarity of -1 is ~ 0 – there is no luring if the pairs are very dissimilar relationally. In contrast, luring occurs regardless of whether the words in the pairs are semantically dissimilar or whether they play dissimilar roles.

Exemplar generation frequencies predict verbal analogy RTs and relational luring strength

The exemplar generation frequency in Task 1 predicted the speed and accuracy of verbal analogy judgements in Task 3 (Figure 4b) – the greater proportion of people generate that exemplar when cued with other exemplars of the relation, the more accessible the relation is during verbal analogies, $r(210) = -0.49$, $p < .001$ for RTs and $r(210) = 0.25$, $p < .001$ for accuracy. Similarly, the RLE was stronger for pairs that were generated by more people, $r(210) = 0.31$, $p < .001$ (Figure 4a). Combined with the finding that relational similarity drives performance in all of these tasks, these findings suggest that the more relationally similar two items are, the easier it is to retrieve items from memory, both intentionally, during exemplar generation, and unintentionally, influenced during associative recognition

Verbal analogy RTs predict associative recognition

Prior research has demonstrated that semantically related word pairs are remembered more easily than non-related pairs and that this effect is modulated by the association strength of the two

words in a pair. Popov et al. (2017) suggested that association strength reflects the strength of the underlying semantic relation. If that is the case, we should expect that the accessibility of the relation as measured by verbal analogy RTs to be predictive of overall associative recognition performance. We reanalyzed the associative recognition RTs in task 4 by including the average verbal analogy RT estimates for each relation as predictors in our existing mixed-effect regression of associative recognition times (for more details, see Popov et al., 2017). Indeed, related word pairs were recognized more quickly, when the average

analogical verification RTs for all exemplars of that relation were faster, $\Delta \text{AIC} = -3$, $\chi^2(1) = 4.83$, $p = .028$. For example, when it is easier to confirm that exemplars of the “X works in Y” relation are analogical to one another, it is also easier to remember that one has recently seen an exemplar of that relation (Figure 4d). This suggests that the availability of the relational representation affects episodic memory retrieval.

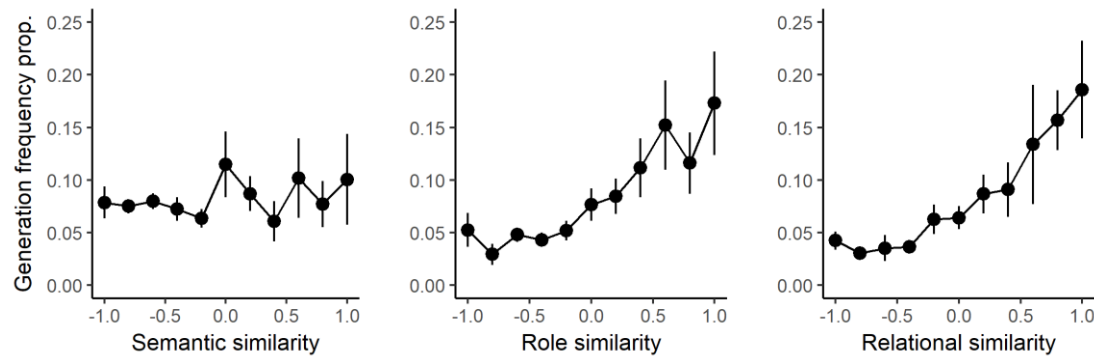


Figure 1. The effects of semantic, role and relational similarity on the frequency of generating relational exemplars. The results are shown after accounting for the effects of the other two factors. Each point represents the average generation frequency across pairs that received the same similarity score.

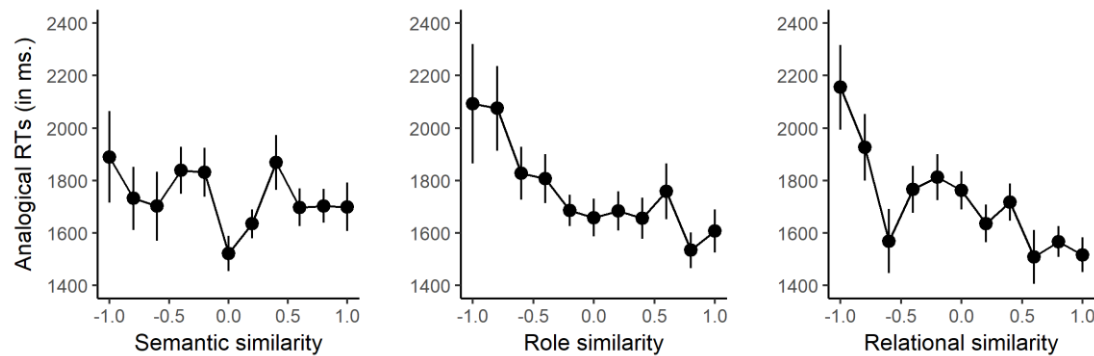


Figure 2. The effects of semantic, role and relational similarity on response times for analogical decisions. The results are shown after accounting for the effects of the other two factors. Each point represents the average analogical RTs across pairs that received the same similarity score.

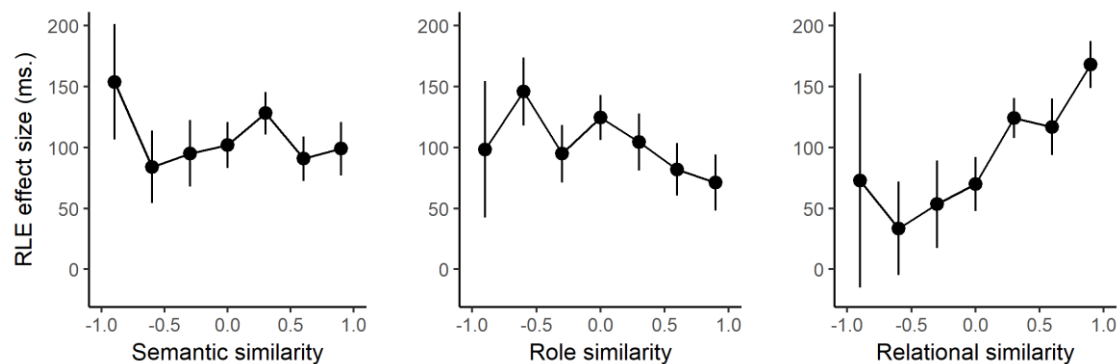


Figure 3. The effects of semantic, role and relational similarity on the strength of the relational luring effect (RLE). The results are shown after accounting for the effects of the other two factors. Each point represents the average relational luring across pairs that received the same similarity score.

Verbal analogy RTs predict relational luring strength

Given that the results so far suggested that both generation frequencies and verbal analogy RTs tap the same accessibility aspect of the relational representation, we should expect that verbal analogy RTs to also predict the strength of the RLE. The RLE was stronger for pairs that were more accessible during the verbal analogy task (Figure 4c). There was a significant interaction between the number of previously studied exemplars of the relation and the verbal analogy RT estimate for the relational group, $\Delta \text{AIC} = -4$, $\chi^2(1) = 6.34$, $p = 0.012$. That is, when target word pairs were identified faster as exemplars of a given relation in the verbal analogy task, they were also more difficult to identify it as lures in the associative recognition task. This result suggests that whether relational luring will occur, and how strong it will be, depends on the accessibility of the relational representation.

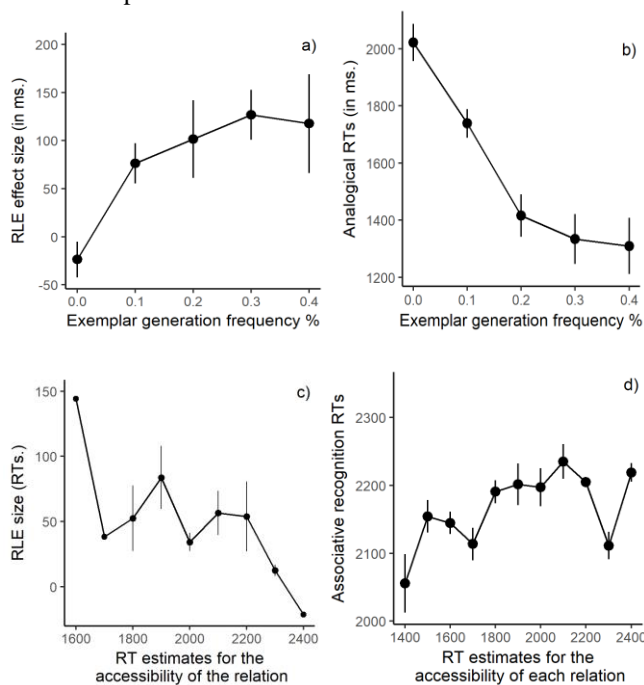


Figure 4. The effect of exemplar generation frequency on: a) the size of the RLE (i.e., the increase in RTs in ms. due to the number of previously studied exemplars of the relation; b) verbal analogy verification RTs. The effect of average analogical RTs for each relational group on the c) relational luring effect size and the d) overall associative recognition RTs

General discussion

The current findings suggest three conclusions. First, semantic relations exhibit typicality effects similar to those shown for entity concepts (Rosch et al, 1976) – the frequency of generating a novel word pair exemplar of a semantic relation, the subjective relational similarity between exemplars, the speed of making analogical judgements, associative memory for relational exemplars and relational luring are all correlated with one another. These interdependencies suggest a common factor that determines variance in relational processing.

Second, we found no evidence for the claim that semantic similarity is a stronger driver of relational retrieval than

relational similarity. Both explicit (exemplar generation) and implicit (relational luring) relational retrieval was better predicted by relational rather than semantic similarity, and only the former was significant after controlling for the latter, but not vice versa. This result sheds doubt on the existence of a relational retrieval gap, and suggests that failures in relational retrieval might be due to differences in the initial encoding of relations across exemplars (i.e., it is more an encoding gap; for a detailed argument, see Popov et al, 2017).

Finally, across all tasks, relational similarity accounted for a greater amount of the variance in relational processing than role similarity. At the extreme, there was no evidence that role-based information contributes to implicit relational luring from long-term memory, an effect that has been used as a support that relational information is explicitly represented in semantic memory (Popov et al, 2017). These findings are at odds with some current prominent theories of analogical reasoning that assume relational information is represented exclusively as role-filler bindings (Doumas et al, 2008; Hummel & Holyoak, 1997), and sheds light on an important debate concerning the representation of relational information (Doumas & Hummel, 2005; Halford et al, 2010). The current dataset could be an important benchmark against which to test competing models of relational processing.

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