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Accumulating Evidence for Myriad Alternatives: Modeling the Generation of Free Association

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Abstract

The associative manner by which thoughts follow one another has intrigued scholars for decades. The process by which an association is generated in response to a cue can be explained by classic models of semantic processing through distinct computational mechanisms. Distributed attractor networks implement rich-get-richer dynamics and assume that stronger associations can be reached with fewer steps. Conversely, spreading activation models assume that a cue distributes its activation, in parallel, to all associations at a constant rate. Despite these models' huge influence, their intractability together with the unconstrained nature of free association have restricted their few previous uses to qualitative predictions. To test these computational mechanisms quantitatively, we conceptualize free association as the product of internal evidence accumulation, and generate predictions concerning the speed and strength of people's associations. To this end, we first develop a novel approach to mapping the personalized space of words from which an individual chooses an association to a given cue. We then use state-of-the-art evidence accumulation models to demonstrate the function of rich-get-richer dynamics on the one hand, and of stochasticity in the rate of spreading activation on the other hand, in preventing an exceedingly slow resolution of the competition among myriad potential associations. Furthermore, whereas our results uniformly indicate that stronger associations require less evidence, only in combination with rich-get-richer dynamics does this explain why weak associations are slow yet prevalent. We discuss implications for models of semantic processing and evidence accumulation, and offer recommendations for practical applications and individual-differences research.

Keywords: Free association; Evidence accumulation; Semantic memory; Attractor networks; Spreading Activation

“Are there any more fascinating data in psychology than tables of associations”?

James Deese (1966)

In real life, thoughts, and memories often spring to mind in a fairly unrestricted fashion in response to internal or external stimuli. For example, when seeing a dog, we might think of one of our countless previous encounters with dogs, one of many related animals (e.g., cats, wolves), or other idiosyncratic associations (e.g., ‘man’s best friend’) – which together comprise the meaning of dogs to us. It has long been thought that examination of such associations can reveal the contents of human memory and the dynamics of spontaneous thought (Andrews-Hanna et al., 2021; Deese, 1966; Flekkøy, 1981; Freud, 2013; Jung, 1910; Laffal, 1955; Nelson et al., 2005). Recent advances in computational modeling led to remarkable progress in understanding the structure and development of associative networks (Cosgrove et al., 2021; Griffiths et al., 2007; Kenett and Faust, 2019; Tenenbaum et al., 2011). However, most models have focused on how associations are represented rather than on the process by which they are produced and reported (Kumar, 2021). Moreover, the few extant process-focused accounts have primarily investigated how people can efficiently retrieve groups of semantically associated words (Abbott et al., 2015; Avery and Jones, 2019; Hills et al., 2012). Conversely, the dynamic process by which a single association is selected, among many, sometimes idiosyncratic competing associations (e.g., in response to the word ‘table’, selecting the association ‘eat’, rather than ‘chair, ‘cloth’, ‘wood’, ‘glass’, ‘operating’, etc.) remains poorly understood.

One promising avenue for understanding this dynamic process is to undertake a detailed analysis not only of what associations people produce but also of how long it takes them to produce each association. Previous examinations of reaction times (RTs) in free association reveal three key determinants (Figure 1). First, associations that are more strongly associated with a given cue are produced and reported more quickly than weaker associations (Flekkøy, 1973; Schlosberg and Heineman, 1950; Snyder and Munakata, 2008). Second, regardless of the strength of the selected association, associations are produced more slowly in response to cues to which there are more, equally-strong associations (Flekkøy, 1973, 1981; Laffal, 1955), suggesting a competitive process (i.e., a process in which the existence of multiple response alternatives interferes with each's progress towards being selected). Third, cues with stronger associations on average tend to elicit faster responses, regardless of the strength of the chosen association (Snyder et al., 2010, 2011). Coherently accounting for these different determinants of the speed with which an association is produced, as for previously investigated determinants of the choice of association (e.g., strong or weak; Laffal, 1955), has the potential to illuminate the process that gives rise to a free association.

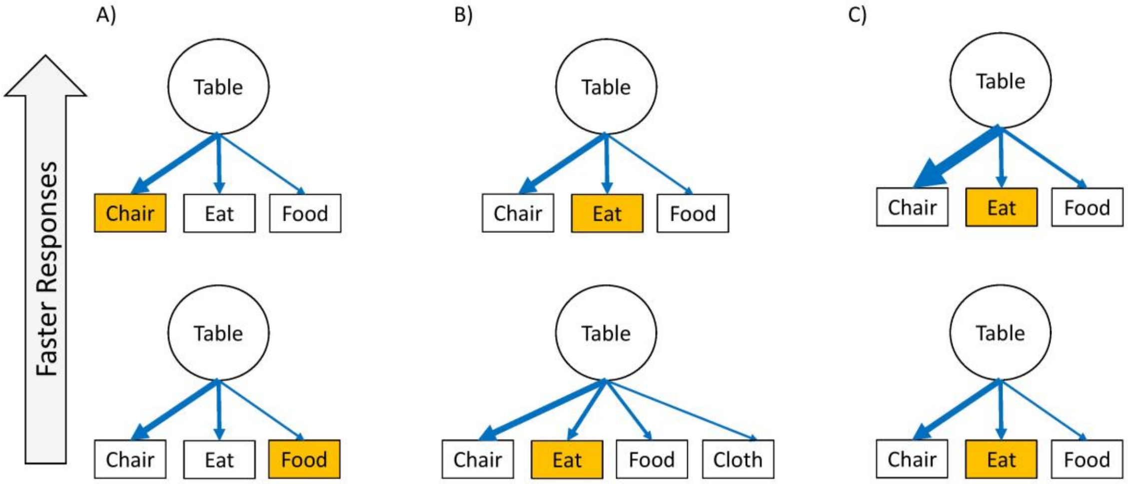

Figure 1 – Key determinants of reaction times in free association. Wider arrows represent stronger connections. A) For a given cue, stronger associations are generated faster; B) Responses are faster when there is less competition between associations. C) Responses are faster when the cue's associations are on average stronger (even if the strength of the chosen association, and the degree of competition are the same).

Previous Process Models of Free Association

Some of these findings can be accounted for by two widespread frameworks of semantic memory activation: attractor models and spreading activation models. Attractor models of semantic activation usually formalize each word as *a pattern of activation* in a network of densely connected nodes. Each activated node is often thought to represent a feature, with different combinations of features comprising different words. Consequently, the degree of overlap between two patterns of activations representing two different words reflects the words' semantic similarity (Cheyette and Plaut, 2017; Lerner et al., 2012b; Masson, 1995; Plaut, 1995). This implementation of semantic similarity is illustrated in Figure 2A where 'Table' is highly similar to 'Chair,' less so to 'Eat' and even less so to 'Food'. Notably, a similar notion of similarity is also used in central models of categorization (Nosofsky, 1986), detection (Ashby and Perrin, 1988), and real-life decision-making (Roe et al., 2001).

This overlap in representation means that the network has to travel a shorter distance (Figure 2B) to reach stronger associations because fewer nodes have to change their states (Figure 2A). Greater representational overlap can thus explain the fact that stronger associations are generated more frequently and faster (Lerner et al., 2012b). The competition between response alternatives is usually assumed to rely on recurrent connections among nodes resulting in 'rich-get-richer' dynamics. These dynamics are illustrated in Figure 2B in that as soon as the network's state of activation (denoted by the black arrow) starts approaching the attractor state 'Eat', the probability that the network will settle into this attractor increases substantially, while the other alternatives become less and less influential. The idea that associations inhibit each other in this way can, in principle, explain the positive relationship between the number of associations and response times (Snyder et al., 2010). Conversely, the fact that the average strength of non-reported associations affects RT has been attributed to mutual facilitation among associations (Snyder et al., 2010).

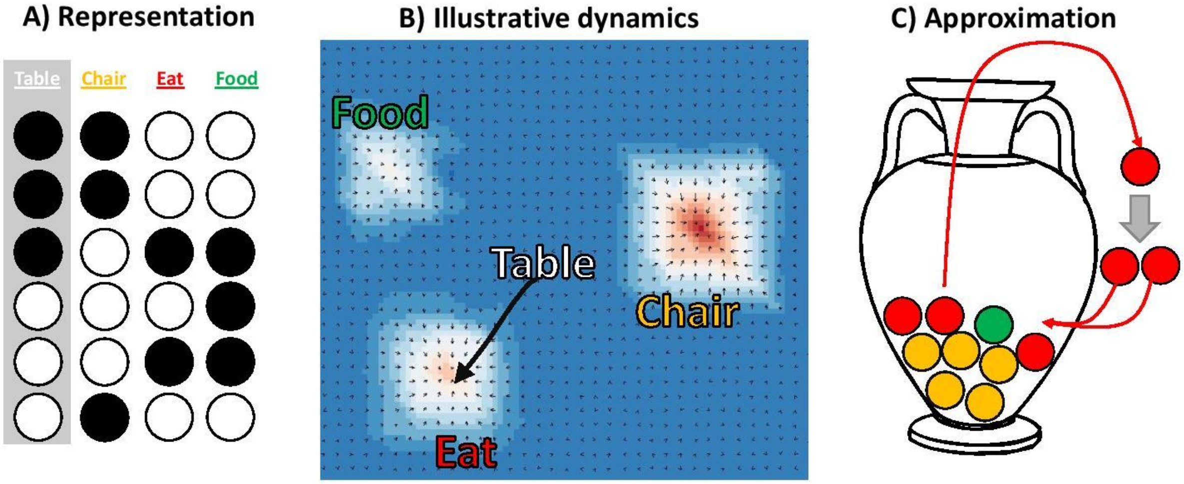

Figure 2 – Illustration of distributed representation of semantic memory (Panel A) and attractor network dynamics (Panel B) in a simple free association task where 'Table' serves as a cue. In Panel B, the evolving state of the network is illustrated by a thick black arrow, drawn within an arbitrary 2-dimensional reduction of the space of possible network states. Attractor states lie at the center of each white-red patch. The redder the color, the stronger the attractor. The small vectors represent the increased tendency of the network to move towards an attractor the closer it gets to it (i.e., rich-get-richer dynamics). Panel C illustrates the approach we take in the current paper to approximate such rich-get-richer dynamics, using a Multivariate Pólya Process (MVP) evidence accumulation model. In this illustration, the association 'Eat' gets sampled by chance in the first few time-steps, and as a result, rich-get-rich dynamics lead it to be chosen even though it is not the strongest association to 'Table.'

Spreading activation models, by contrast, conceptualize semantic knowledge as a network of concepts, where each concept is represented by a single node (i.e., semantic representation is local rather than distributed). Of course, as already noted by Collins and Loftus (1975), representing words in such a localist network does not exclude the distributed representation of attractor models: "any process that can be represented in a feature model is representable in a network model" (p. 410). However, classic spreading activation models (Anderson and Bower, 2013; Collins and Loftus, 1975) assert a computationally distinct process, which does not necessitate rich-get-richer dynamics, and where stronger associations do not require less evidence. In such models, as long as a node (e.g., a cue) is activated, its activation is distributed in parallel to connected concepts (e.g., associations) in proportion to their associative strength. A node is deemed ‘actively processed’ once its activation level reaches a certain threshold (though threshold-crossing is unnecessary for the node to spread activity further). Thus, cues with more associations lead to slower responses because the activation of such cues is distributed across more nodes. Similarly, stronger associations are generated faster because they receive a larger proportion of the cue’s activation and thus reach their threshold faster.

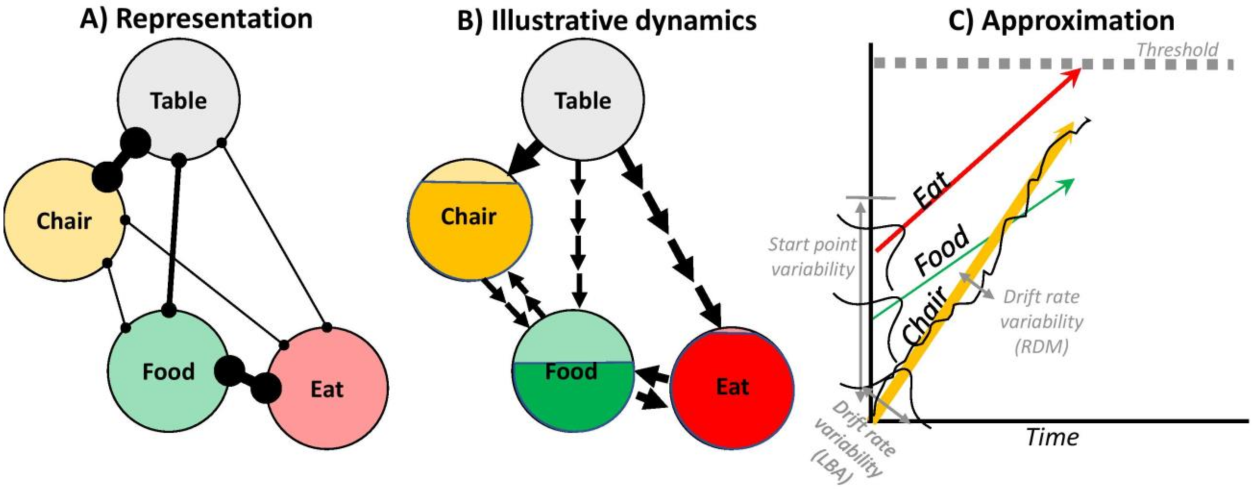

Figure 3 – Illustration of a localist network representation of semantic memory (Panel A) and spreading activation dynamics operating on such a network (Panel B). The activation of the cue is distributed among its associations in accordance with their associative strength, while assuming that a fixed sum of activation spread at each time-point. Panel C illustrates the approach we take in the current paper to approximate spreading activation dynamics using normalized accumulator models. In these models, the average slopes of the different accumulators are computed by normalizing the associative strength of the possible associations such that they sum to 1 (to highlight the difference we also use line width to denote normalized associative strength). Normalized accumulator models include two sources of noise. First, the accumulators start from a random point, ranging from 0 to some upper bound (‘start-point variability’), and race towards a threshold. Second, the rate of evidence accumulation may very either across trials (in the linear ballistic accumulator, LBA; see Gaussian curves at the bases of the accumulators), or within trials (in the racing diffusion model, RDM; see an illustration along with the ‘Chair’ accumulator).

Both frameworks have been highly influential in guiding the conceptualization and research of sematic processing (Cheyette and Plaut, 2017; Lerner et al., 2012b; McNamara, 2005; Plaut, 1995; Rabovsky and McRae, 2014; Rabovsky et al., 2018; Siew et al., 2019). However, previous applications of these models focused mostly on qualitative effects (often in other, constrained tasks such as lexical decision), and thus, we cannot know whether they account for participants` associations and RTs at the trial-level (R Anders et al., 2015; Osth and Farrell, 2019; Ratcliff and Murdock, 1976). In fact, spreading activation models have never been used to formalize the process of generating an association, and attractor models of free association were limited to illustrative scenarios wherein the number of associations is unrealistically small (Lerner et al., 2012b; Snyder et al., 2010). Therefore, the quantitative predictions entailed by the underlying principles of attractor models and spreading activation models concerning realistic choice-RT in free association have never been scrutinized.

As one concrete example consider the mechanism used in spreading activation models to account for effects of competition on increasing RTs: distribution of fixed amount of activation. This mechanism predicts cues with more associations to always produce slower responses, and thus, is unable to account for any natural variability in this effect. Furthermore, one of the most established findings in decision making is that of a log-linear relationship between the number of response alternatives and RTs (Hick, 1952; Proctor and Schneider, 2018), but whether this is also the case in free association is unknown and remains underspecified under existing models. As another example, despite the ubiquity of the assumption that stronger associations require less evidence in attractor models, its computational role in free association remains unknown, given that other mechanisms have been suggested to explain why stronger associations are faster (Plaut, 1995).

Of course, the fact that attractor models and spreading activation models were never fitted to realistic, trial-level data is not coincidental, but rather reflects the natural cost of their typical intractability, algorithmic complexity, and unidentifiability (R Anders et al., 2015). Here we approach the problem of fitting trial-level choice-RT data in the free association task by building upon one of the most resourceful frameworks for joint modeling of choice-RT data: evidence accumulation modeling. We focus on several key evidence accumulation models that incorporate basic mechanisms implemented in attractor models and spreading activation models, yet remain well-suited to fit trial-level choice-RT data, and produce identifiable and recoverable parameter estimates. Inevitably, this integration of semantic processing models and evidence accumulation models is bound to violate some common assumptions of one or the other framework. For instance, whereas in models of semantic processing related associations facilitate one another, this feature cannot be easily accounted for by evidence accumulation models. Despite this limitation, however, we demonstrate how the framework of evidence accumulation can be used to capture and empirically test key features of semantic processing models, and thereby benefit both frameworks while advancing the understanding of free association.

Free Association as Accumulation of Internal Evidence

Evidence accumulation models have been highly successful in explaining the dynamics of perceptual decision making (S. D. Brown and Heathcote, 2008; Heathcote et al., 2019; Heitz, 2014; Ratcliff and McKoon, 2008; Ratcliff et al., 2016; Usher and McClelland, 2001). These models posit that support for different response alternatives is accumulated over time until a threshold in favor of one alternative is reached. Pertinent to the present study, such models have been used to investigate various determinants of RT and choice in the domain of perception that may also apply in the domain of free association. First, evidence accumulation models have been designed to explain why, in some conditions, responses with greater support (e.g., correct responses) tend to be faster (S. D. Brown and Heathcote, 2008; Ratcliff and McKoon, 2008; Tillman et al., 2020). Second, evidence accumulation models offer a variety of distinct mechanisms to account for competition between response alternatives, including rich-get-richer dynamics (or closely-related lateral inhibition), and normalization of evidence (Teodorescu and Usher, 2013). Third, an increasing number of studies have highlighted the role of the absolute level of support (in addition to relative support) for selected and non-selected response alternatives in evidence accumulation (Kirkpatrick et al., 2021; Simen et al., 2016; Teodorescu et al., 2016; van Ravenzwaaij et al., 2020). Thus, evidence accumulation models are, in principle, well-equipped to explain the latent cognitive dynamics giving rise to empirically observed associations and the speed with which they are generated.

Interestingly, some of the earliest applications of evidence accumulation models transcended perceptual decision making, focusing on the accumulation of internal information stored in memory (Ratcliff, 1978; Ratcliff, Gomez, et al., 2004; Ratcliff, Thapar, et al., 2004). More recently, several studies have demonstrated the potential of using evidence accumulation to model how people recall learned lists of words (Osth and Farrell, 2019; Osth et al., 2021; Polyn et al., 2009; Sederberg et al., 2008), where the number of potential responses can be large. Modeling such `free recall`, though, is aided by the fact that the response alternatives are controlled by, and thus known to, the experimenter. Conversely, the space of possible responses in the free association task is not predefined by the experimenter. Thus, it is typically much larger than that of any previous memory task, and is partially unknown.

This unique feature of free association highlights how our work can also contribute to evidence accumulation theory in general. Pushing the limits of different evidence accumulation models (which often show equivalent performance in classical tasks with two alternatives) to a task with an unprecedent number of response alternatives can reveal their distinct strengths and weaknesses. Indeed, choosing one of myriad associations within reasonable time requires that interference between associations is not too extreme. Such excessive interference might appear in models wherein only one accumulator can gain evidence at each time point (Ratcliff et al., 2016; Vickers, 1970), and thus, the probability that one of myriad associations will repeatedly gain evidence so as to reach the threshold within reasonable time is small. This highlights the need to investigate how rich-get-richer dynamics and parallel distribution of evidence may help in preventing bottlenecks in the processing of myriad alternatives.

Free association diverges from typical perceptual decision-making tasks in another important way: the accumulation of evidence is primed by a cue, which may affect not only the strength of evidence accumulated in favor of each association but also where the competition starts. As noted above, distributed representation models suggest that a consequence of starting a trial by processing the cue, is that stronger associations (those with greater overlap with the cue) start the race with greater activation (Figure 2), and thus require less evidence to reach their thresholds. Although introducing a bias towards a certain response is common in evidence accumulation models, such bias is typically assumed to be determined independently from the strength of evidence in favor of different response alternatives. For example, a bias towards a certain response in a categorization task can be modulated by heading each trial with a cue indicating the probability for a certain category (Dunovan et al., 2014; Mulder et al., 2012). Similarly, priming can be used to bias semantic processing in favor of specific words, which both classic distributed representation models and spreading activation models explain by means of an elevated baseline activation of these words, before they are experimentally presented (Collins and Loftus, 1975; Masson, 1995; McNamara, 2005; Plaut, 1995). Conversely, in free association, the associations primed by processing the cue, also accumulate internal evidence in response to the same cue. In the current study, we will thus examine whether allowing stronger associations to require less evidence (henceforth: associative strength modulated bias, or *AS-modulated bias*) is computationally warranted and empirically supported, both under rich-get-richer dynamics and under parallel distribution of evidence. Next, we describe three tractable evidence accumulation models, each implementing a different combination of the mechanisms potentially involved in free association.

A tractable model with rich-get-richer dynamics: the multivariate Pólya urn process model

As noted above, attractor models of semantic memory are usually characterized by rich-get-richer dynamics (but see Rogers and McClelland, 2004) for feed-forward neural networks of semantic memory). This property has been implemented (e.g., via lateral inhibition) in several previous evidence accumulation models of decision making (Blurton et al., 2020; Busemeyer and Townsend, 1993; Deco et al., 2013; Roe et al., 2001; Usher and McClelland, 2001; X.-J. Wang, 2008), but these models cannot be readily and identifiably fit to trial-level choice-RT data (Miletić et al., 2017). Thus, here we extend a recently proposed, tractable evidence accumulation model that implements rich-get-richer dynamics via the Pólya urn process (Blurton et al., 2020). A Pólya urn process can be illustrated by an urn from which drawing a ball of a specific color is followed by returning two balls of the same color to the urn, thus increasing the probability of drawing this color again (Figure 1C). Blurton et al. (2020) have successfully demonstrated the ability of this model to account for trial-level choice-RT distributions in correct and incorrect trials in a speeded categorization task with up to 4 response alternatives. The multivariate Pólya urn process (MVP) we develop here relies on a similar scheme, but with a novel implementation that facilitates analysis of choice among myriad alternatives (for a detailed comparison see Supplemental Material S1).

To apply the MVP to the modeling of free association, we take different colors to represent different possible associations, and the drawing of a ball to represent the activation of a node that shifts the state of the network towards the corresponding association's attractor. The relative strength of different associations is thus naturally represented by the relative number of balls of each color the urn starts with. From an evidence accumulation perspective, each time a ball of a given color is drawn from the urn, the association represented by that color gains more evidence, and the probability that it will gain further evidence in the future increases. The extent to which the model implements such rich-get-richer dynamics depends on the initial total number of balls in the urn, because adding an additional red ball (see Figure 2C) would have a higher impact, for instance, if initially there were 3/9 compared to 30/90 red balls. When the evidence for a certain association (i.e., the number of times its color was drawn) reaches a pre-defined threshold, the process stops, and the association is reported.

Tractable models for parallel distribution of evidence: normalized accumulator models

As noted above, spreading activation models implement a competition among myriad alternatives by distributing among them, in parallel, a fixed amount of evidence (Figure 3B). A similar mechanism is used in two classic evidence accumulation models that often implement competition between alternatives via normalization[1] (henceforth: *normalized accumulator models*; Figure 3C): the linear ballistic accumulator (S. D. Brown and Heathcote, 2008) and the racing diffusion model (RDM; Tillman et al., 2020). In both models, previously shown to successfully account for free recall (Osth and Farrell, 2019; Osth et al., 2021), associations are represented by independent accumulators racing towards a threshold, while the sum of the average accumulation rate is often fixed to 1 (S. D. Brown and Heathcote, 2008; Donkin et al., 2009). Both models can allow the start points of the accumulators to randomly vary in order to account for premature responses (i.e., an accumulator can win even with little evidence if it has started closer to the threshold, by chance). The models differ with regards to whether the rate of evidence accumulation varies between trials (LBA) or within trials (RDM). Both of these types of stochasticity are not considered in classic spreading activation models, yet are required to account for randomness in trial-level choice-RT data, and might affect the ability of the models to account for key determinants of RT (Figure 1).

Tractable models balancing absolute and relative strength: advantage accumulator models

The above models do not naturally account for the effects of absolute, as opposed to relative, associative strength (Figure 1C). Though we explored several ad-hoc solutions for this problem within each model (see Methods), a recent, tractable extension of accumulator models offers a natural way to account for the effects of absolute strength (Miletić et al., 2020; van Ravenzwaaij et al., 2020). In this class of models, each accumulator represents competition between a pair of associations (Figure 4), with the rate of accumulation being a function of both the relative (i.e.,

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[1] We note here that the LBA and RDM are not always normalized, and that other parameters can be constrained to ensure identifiability (Donkin et al., 2009; Osth and Farrell, 2019; Osth et al., 2021). Here we focus on the normalized version to ensure that, similar to spreading activation models, cues with more competition result in slower responses.

difference) and absolute (i.e., sum) strength of the two associations. Such *advantage accumulator models* ensure that RTs are not affected only by the absolute strength of the reported association, but also by the absolute strength of the non-reported associations. Thus, even a weak association can be reported faster when the other associations to that cue are strong.

According to a commonly used decision rule, an alternative is selected once all accumulators in its favor have reached the threshold (see the second row in Figure 4; yet, as described in the methods we also examined two alternative decision rules). Similar to normalized accumulator models, the rate of evidence accumulation can randomly vary either between trials (advantage linear ballistic accumulator; ALBA; Figure 4) or within trials (advantage racing diffusion model; ARDM; (Miletić et al., 2021). These models have exhibited impressive performance in fitting data from tasks with 2-9 response alternatives in both perceptual (van Ravenzwaaij et al., 2020) and value-based decision making (Miletić et al. 2021), but they have yet to be tested on selections between larger numbers of alternatives. The vast numbers of possible associations in the free association task means that a large number of accumulators would have to reach the threshold for an association to be selected, and this can pose a problem in fitting real free association data.

We note here that although the algorithm underlying advantage models does not resemble any established model for semantic processing, advantage models have the additional, unique benefit of being able to account for covariation among associations. Such covariation is a feature of both attractor models and spreading activation models, wherein co-related associations facilitate each other, whereas other models and findings suggest inhibition between co-related associations (Oppenheim et al., 2010; Roe et al., 2001). Advantage accumulator models are well suited to capture positive or negative covariation since they inherently assume stronger mutual inhibition or facilitation between pairs of strong associations. Of course, strong associations to the same cue are not always co-related, but they do tend to be (since associations tend to cluster in local neighborhoods; Steyvers and Tenenbaum, 2005). Moreover, advantage accumulator models could potentially be enhanced by tailoring greater weights to the competition and/or facilitation between co-related associations while maintaining tractability. Although such enhancement lies beyond the scope of the current paper, this possibility is important to highlight as a theoretical argument in favor of the application of advantage models to semantic processing.

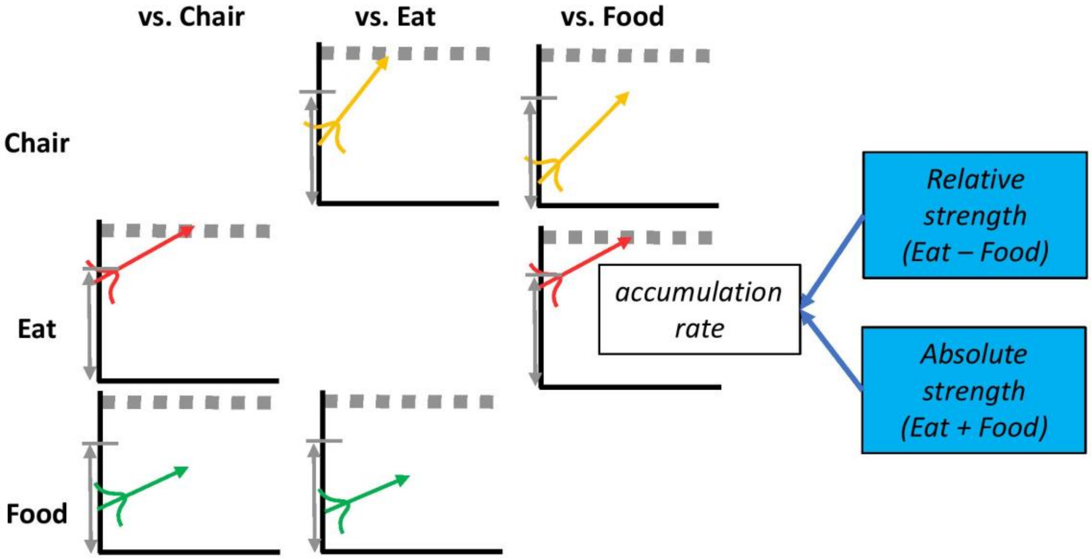

Figure 4 – Modeling free association using an advantage accumulator model (the advantage linear ballistic accumulator in this case), where each accumulator is driven by both the difference between, and the sum of, the associative strengths of two possible associations, corresponding with relative and absolute strength, respectively. Here we depict the common decision rule according to which the race ends when all accumulators representing the relative advantage of one accumulator (here 'Eat') reach the common threshold, but other decision rules are also examined (see methods).

The Importance of Outlining the Space of Possible Associations

Simplifying the principles governing attractor models and spreading activation models using tractable evidence accumulation models provides only part of the solution for fitting trial-level choice-RT data. As mentioned above, a key obstacle for modeling realistic free association data (vs. minimal toy examples as in Lerner et al., 2012b; Snyder et al., 2010) is delineating the space of associations from which a participant chooses their association for a given cue. Previous studies relied for this purpose either on population-wide norms (Nelson et al., 2004) or on corpus-based methods for calculating semantic similarity (Beaty and Johnson, 2021; Olson et al., 2021; Snyder and Munakata, 2008; Snyder et al., 2011). However, both approaches ignore the fact that many cues tend to elicit a significant number of idiosyncratic associations. In one study, for instance, up to 79% of the associations reported in response to some cues were only reported by a single participant and were therefore excluded from the norms reported in that study (Nelson et al., 2004). Cues that elicit a high proportion of idiosyncratic associations may do so because they are strongly associated with different associations in different people or because they are weakly associated with each of a very large set of associations that is shared across participants. This distinction is critical for studying free association because, for example, if an association that looks weak in population-based measures is actually strong for a specific individual, it will be generated more quickly than predicted. Thus, a method for assessing the strength of associations for each given individual is necessary.

The Current Paper

The current paper aims to develop a computational framework for investigating the different mechanisms allowing people to efficiently select one of myriad associations. We focus primarily on the role of three mechanisms: rich-get-richer dynamics, parallel distribution of noisy evidence, and representational overlap allowing stronger associations to require less evidence. Whereas these mechanisms were inspired by classical attractor and spreading activation models of semantic processing, we do not aim to compare these two classes of models against each other but rather to investigate the function of the mechanisms they each implement. To examine the quantitative predictions ensued by these mechanisms we conceptualize free association as evidence accumulation, and in so doing, we extend classic evidence accumulation models to the case of myriad alternatives.

The overall structure of this paper is as follows. We first describe the free association task used in this study, replicate the key determinants of RT presented above, and present a novel result pertaining to the determinants of associative strength. Then, to enable evidence accumulation modeling, and to examine the importance of idiosyncratic associations and subjective associative strength, we develop and validate a novel method for mapping the personalized spaces of possible associations. Next, we examine the ability of the three evidence accumulation models presented above to account for the associations participants report and the speed with which they report them. We compare the models' ability to account for trial-level choice RT data, as well as the key determinants of RT and associative strength. In our analysis of model performance, we focus on the function of the mechanisms which these models share with attractor models and spreading activation models.

To foreshadow, this examination revealed several key insights: First, as predicted, strong associations, and those evoked by cues with fewer or stronger associations, are evoked faster. Conversely, greater competition between many, potentially weak, associations takes longer to resolve and is more likely to produce a weak association. Second, rich-get-richer dynamics in the MVP, and accumulation rate variance in normalized accumulator models offer two different ways of explaining how people avoid becoming excessively slow in producing associations for cues that evoke greater competition. Second, the assumption that stronger associations require less evidence to be selected (i.e., AS-modulated bias) ubiquitously improves model fit, but only in the presence of the rich-get-richer dynamics of the MVP, can it explain why strong associations are faster. Third, fully explaining the finding that cues evoking greater competition produce weaker associations requires a moderate level of stochasticity, and normalized accumulator models perform best in this regard. Fourth, advantage accumulator models perform relatively poorly in accounting for the data, since currently developed decision rules make them overly sensitive to competition among associations when the number of associations is particularly large. Finally, we show strong evidence for the importance of considering personalized association spaces when predicting and modeling realistic choice-RT data.

The Free Association Task and Behavioral Results

In our free association task, we asked participants to report a single association to each of many cues. To quantify the strength of participants' reported associations, after the main task, we presented participants with their own associations in random order and asked them to rate the degree to which each cue word reminds them of the association they gave (i.e., associative strength ratings, or *AS ratings*). This approach is similar, in principle, to how alternative responses are typically characterized in value-based decisions, specifically, by asking participants to subjectively rate the value of each (Bakkour et al., 2018). In this section we focus on establishing the hypothesized effects of the strength of the reported association, and the degree of competition, on RT (to also establish the effect of the overall strength of a cue's associations we first need to develop a way to estimate it, which we do in the next section). In addition, to establish the importance of probing subjective associative strength, as opposed to using only population-based measures (previous norms and corpus-based similarity), we examine the proportion of reported associations not appearing in previous norms, as well as the relative contribution of subjective vs. population-based measures of associative strength to predicting RT.

Method

Participants

Thirty adults were recruited via the Prolific Academic internet platform, with the following inclusion criteria: Adults (age ≥ 18), raised monolingual with English as first language, who report having no language-related disorders, Dyslexia or ADHD, currently residing in an English-speaking country (US, UK, Ireland, Australia or New Zealand), and with a minimum approval rate of 97% from at least 200 previous studies. Participants included 15 women (50%) and were 40.33 (SD = 13.87) years old on average. The highest level of education acquired was high school for twelve participants (41.38), a bachelor's degree for twelve participants (41.38%), and a master's degree or higher for five participants (17.25%). Participants provided informed consent as approved by an ethics committee at the Hebrew University of Jerusalem. Participants received monetary compensation for their participation (£9 for an experiment taking approximately 1.25 hours).

Materials and Procedure

The free association task was administered over the internet using Gorilla Experiment Builder (Anwyl-Irvine et al., 2020). Participants were instructed to "write the first association that comes to mind in response to the presented word". This task included 306 relatively familiar and short cue words (Nelson et al., 2004) divided into six balanced blocks (see Section S2 in the

Supplemental Material for additional details). Each trial consisted of a fixation cross presented for 1000±150ms, followed by a cue word (e.g., table) presented in the center of the screen for 500ms. Participants were asked to press the spacebar as soon as an association comes to mind and then type their association and press enter. If the participant did not press the spacebar within 15 seconds, the trial ended without a response. A stopwatch indicated to participants how much time was left to respond. Participants were instructed to press the spacebar only after having an association in mind and were nudged to do so by limiting the time given for starting to write the association. Thus, if a participant has entered the first letter of the association (either initially or after deleting what they had first typed) more than 1300ms after pressing the spacebar, the trial ended, and a message “Please press the spacebar only after you have a response” appeared in red on the screen for 2000ms.

To estimate the subjective associative strength of reported associations, following the task of generating associations, we asked each participant to rate the extent to which each cue word reminds them of their own association, based on their subjective intuition and knowledge. To account for the finding that associative strength is asymmetric (Griffiths et al., 2007; Plaut, 1995), they were asked “To what extent does the word _ reminds you of the word _”, and the two words were presented sequentially with a 500ms lag. Associative strength (AS) ratings were collected using a visual analog scale from 0 (“not at all”) to 1 (“very much”).

Several measures were taken to monitor and minimize negligent performance. First, the experiment was presented on the participants’ entire screen, and participants were not allowed to navigate away from it. Second, we inspected participants’ responses on the free association task for careless responding (e.g., writing gibberish). Third, attention checks were added to the rating phase, where participants were asked to respond in a specific manner upon seeing the word 'attention' as a cue. Fourth, AS ratings were expected to be positively correlated with the population-based frequency of an association. Based on these criteria, no participants were excluded in the current study.

Statistical analysis

We used generalized linear mixed-effects models (Bates et al., 2014) to succinctly characterize the effects of the different determinants of RT and associative strength. To keep RT in its original scale, all analyses predicting RT assumed an inverse-Gaussian distribution of residuals with an identity link function (Royce Anders et al., 2016; Lo and Andrews, 2015). Since analyses targeted within-participant relationships between RT and different variables, we standardized all variables within participants to eliminate individual differences in averages (L. P. Wang and Maxwell, 2015). Importantly, alongside the predictions of these generalized linear models, in the plots below, we also depict model-free conditional means demonstrating that the generalized linear models adequately capture key patterns in both empirical and model-simulated data. This study was not preregistered. All data and models are available at https://osf.io/qvts4/?view_only=950962c4f5a84d2cb09563cb674ce400.

Basic Results

General performance

On average, participants failed to start writing the association on time in 12.73 (*SD* = 7.82) trials (out of 306) and have provided illegal responses (i.e., empty responses, misspelled words, responses with more than one word) on 8.47 (*SD* = 7.86) trials on average. In addition to such trials, we also excluded trials with overly short RTs (<100ms, three trials overall). Thus, we collected valid data from an average of 284.7 (*SD* = 13.17) trials per participant.

Determinants of response times

As noted above, previous studies have shown that both the strength of the reported association and the degree of competition affect RT. In our study, the strength of the reported association was estimated based on participants' AS ratings. As expected, we found a moderate, negative relationship between AS ratings and RT ($\beta = -0.23$, SE = 0.02, $t = -11.55$, $p < .001$; Figure 5A). The median Pearson correlation within participants was -0.23, and the inter-quartile range [-0.34, -0.15]. The degree of competition was measured here as the entropy of the distribution of associations across participants (following the next section, we will also measure entropy using individualized spaces of associations estimated for a specific participant and a specific cue). A significant linear relationship was found between cue entropy and RT ($\beta = 0.12$, SE = 0.01, $t = 7.97$, $p < .001$; Figure 5B). To verify that the shape of this relationship is indeed linear we examined whether a quadratic or cubic relationship might fit the data better. In accordance with Hick's law, a linear association accounted for the data better than a quadratic (ΔBIC = -34.93) or cubic association (ΔBIC = -73.31). The median Pearson correlation within participants was 0.13, and the inter-quartile range [0.10, 0.15].

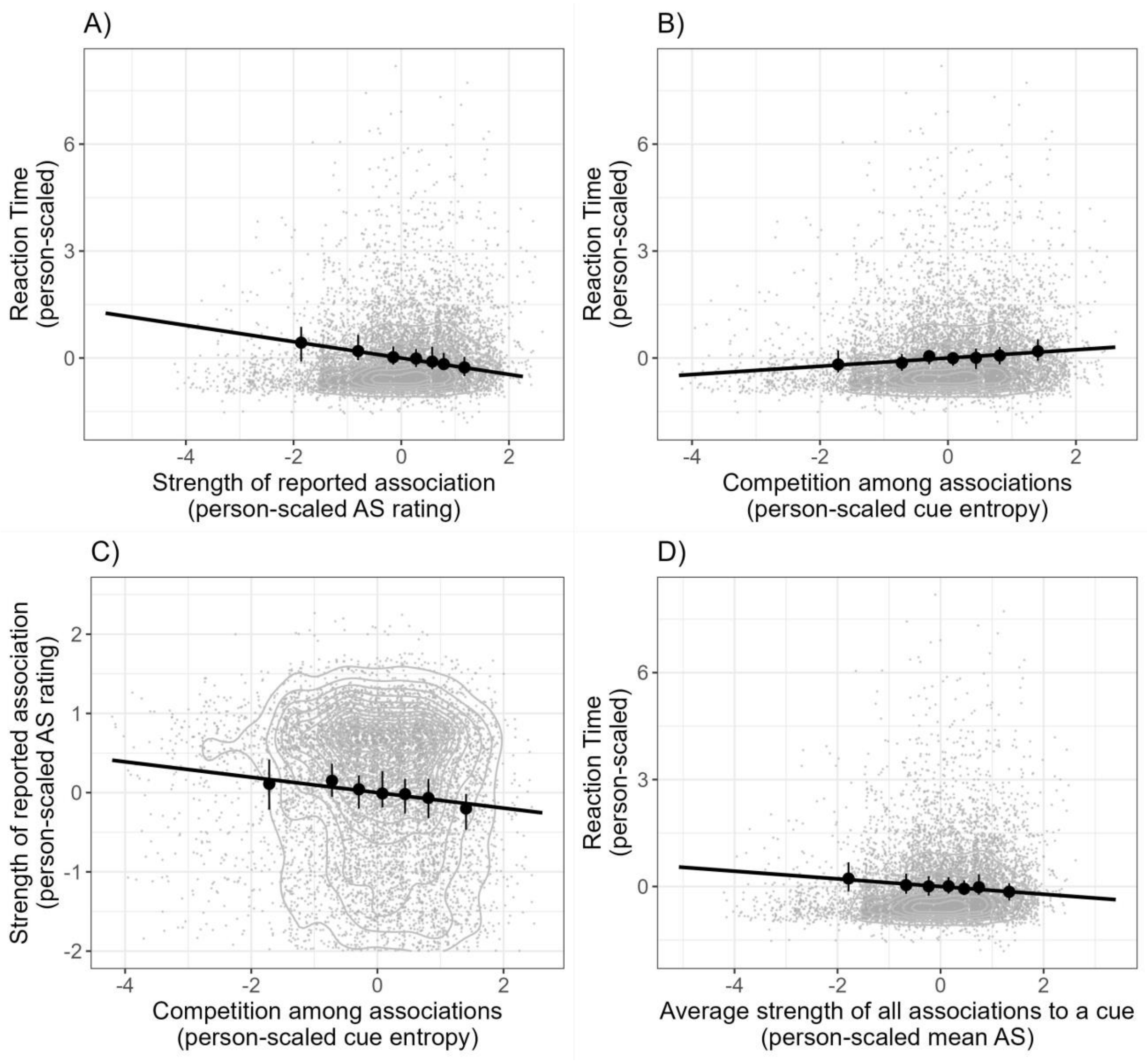

Figure 5 – Empirical results concerning the determinants of reaction time (Panels A,B, D) and associative strength ratings (Panel C). The black lines correspond with the predictions of the generalized linear mixed effects models accounting for the scale and skewness of reaction time. To demonstrate the fit of these regression lines to the raw, empirical data, we also depict the mean RT, for each of 7 bins (with the same number of observations) of the respective independent variables (± 95% confidence intervals).

Importantly, cues with higher entropy also tended to elicit lower ratings (β = -0.12, SE = 0.01, *t* = -8.07, *p* < .001; Figure 5C). However, the negative association between ratings and RTs held even when controlling for entropy (β = -0.21, SE = 0.02, *t* = -11.05, *p* < .001; median partial Pearson correlation = -0.22), as did the positive association between cue entropy and RT (β =

0.09, SE = 0.013, *t* = 6.69, *p* < .001; median partial Pearson correlation = 0.09). Thus, in accordance with previous studies, both the strength of the reported association, and the degree of competition between associations independently determined RT.

Finally, we examined whether probing subjective AS improves the ability to predict RT, over and above what can be achieved using only population-based measures of similarity. The first notable finding in this regard is that nearly half of associations reported in our study did not appear in the Nelson (2006) previous norms (henceforth: *non-normed associations*; M = 45.30%, SD = 9.66%). Furthermore, although non-normed associations were weaker on average (β = - 0.13, SE = 0.01, *t* (29.26) = -10.67, *p* < .001), a non-negligible proportion of these associations obtained higher AS ratings than most normed associations (i.e., 33.54% of AS ratings for non-normed associations were above the median of normed associations). Thus, non-normed associations are common, and may often be strong enough to substantially impact the dynamics of free association even when it is a normed association that is eventually reported.

A common way to estimate associative strength that can be used for any pair of words, and can thus be applied to non-normed associations, is using corpus-based similarity measures (Gray et al., 2019; Olson et al., 2021; Snyder and Munakata, 2008; Snyder et al., 2011). This measure, however, still relies on aggregating population data, and thus, cannot reflect individual-level associative strength. To compare the usefulness of corpus-based cue-association similarity (based on GloVE or LSA; Landauer et al., 1998; Pennington et al., 2014) for present purposes with that of subjective AS rating, we tested how well each of these measures account for RT. We found that associations with high (i.e., above median) subjective AS but low (i.e., below median) corpus-based similarity scores were faster than associations with low subjective AS rating yet high corpus-based similarity (β = -0.12, SE = 0.02, *t* = -4.73, *p* < .001; Figure 4A), regardless of the type of embedding model used (Figure 4B). This effect was similar for normed and non-normed associations (interaction: β = -0.02, SE = 0.02, *t* = -0.99, *p* = .322). Thus, quantifying individual-level AS is paramount for explaining the speed with which associations are generated.

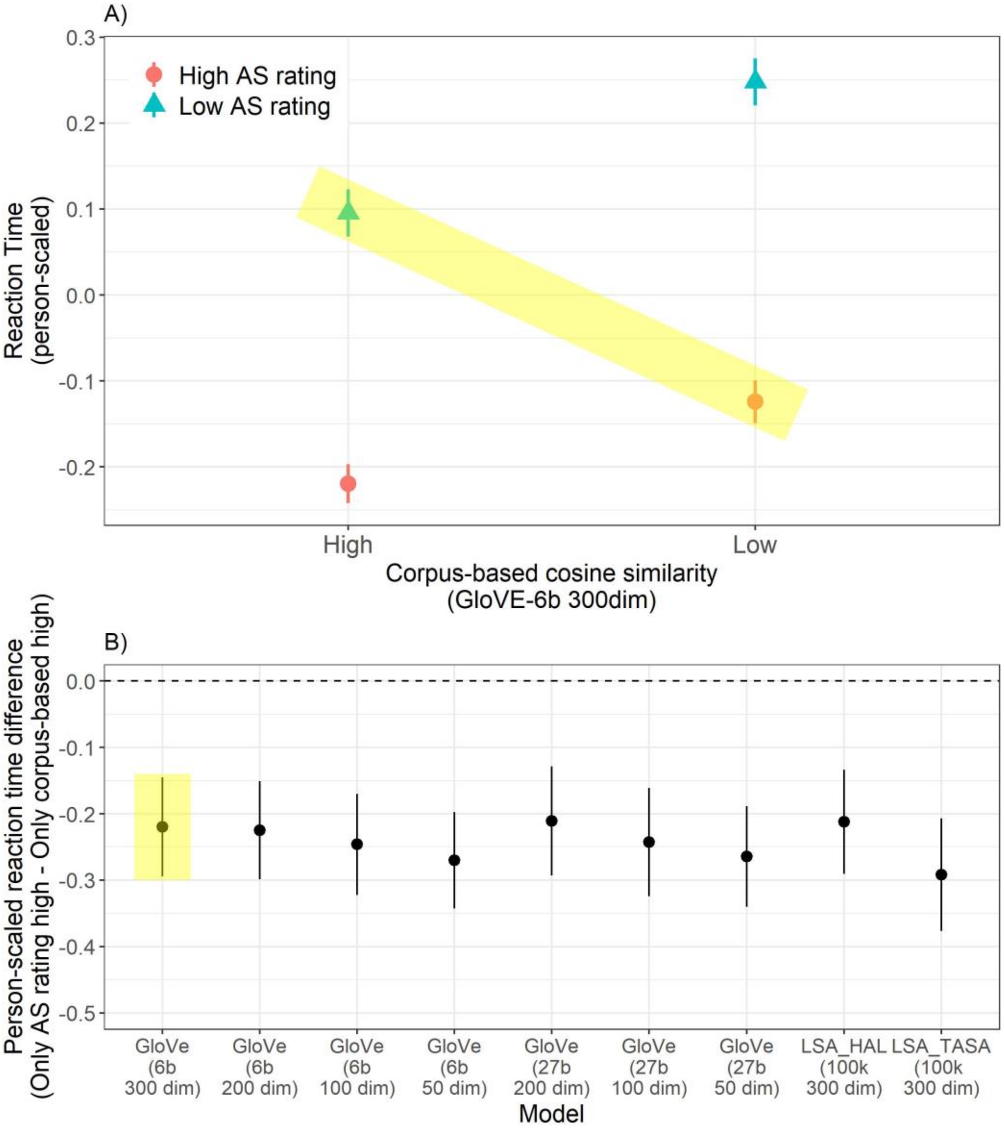

Figure 6 – Comparing the extent to which generation dynamics are better captured by subjective associative strength (AS) ratings vs. corpus-based similarity. The highlighted comparison demonstrates the superiority of subjective AS ratings when the two measures disagree. Panel A focused on the results of a GloVe model with 300 dimensions, whereas Panel B generalizes these results to other models. We used a median split to define high and low similarity/AS rating.

A Novel Method for Outlining the Space of Possible Associations

As noted above, as a precondition for analyzing the process through which associations compete against each other we first need to characterize the number and strengths of the competing associations. To estimate the number of associations, we first assume that any association reported in previous norms (Nelson et al., 2004) could have been reported by each participant in our study. The estimated number of non-normed associations is then tailored to each cue and participant based on the empirical proportions of non-normed associations reported for that cue (by all participants) and by that participant (for all cues). Importantly, since normed associations tend to be stronger ($\beta = 0.13$, $SE = 0.01$, $Z = 10.67$, $p <.001$) the proportion of reported non-normed associations does not reflect that proportion of possible non-normed associations. However, this difficulty can be resolved by estimating the ratio of non-normed to normed associations separately for each level of associative strength.

Motivated by the above findings (Figure 6), the strengths of reported associations are estimated as participants' AS ratings. To estimate the strength of unreported normed associations, we assume it can be derived from their frequency in the population combined with the average AS rating for the relevant cue and participant. The assumption that the frequency of an association in the population explains some variance in AS ratings was justified by a significant relationship in our data ($\beta = 0.18$, SE = 0.02, $t = 10.68$, $p < .001$; note that accounting also for corpus-based similarity did not improve the prediction of AS ratings, $\beta = 0.02$, SE = 0.02, $t = 1.48$, $p = 0.15$). Finally, we estimate associative strength for unreported non-normed associations based on the distribution of normed associations and the empirical proportions of non-normed associations reported for each level of AS.

This method, described in detail in Section S3 in the Supplemental Material, allows us to obtain an estimate of the total number of (normed and non-normed) associations for each participant and cue, as well as the estimated associative strength for each possible association (but note that it does not allow us to know the actual non-reported, non-normed associations). The resulting spaces of associations followed key patterns in the data and agreed with the common assumptions that weaker associations usually go unreported, and that associations reported across many participants (i.e., normed associations) are particularly strong (Figure 7A). Yet, many non-normed associations remained viable competitors (compare the middle two boxplots in Figure 7A), indicating that they cannot be simply disregarded.

The estimated numbers of possible non-normed associations for each cue were expectedly tied to two known quantities of that cue: the proportion of non-normed associations reported, and the number of possible normed associations (Figure 7B). Finally, cues that were predicted by our model to have a larger number of non-normed associations (i.e., high n(U) in Figure 7B), also had a larger number of idiosyncratic associations in an independent study (Nelson et al., 2006; r (304) = 0.44, t = 8.49, p < .001), providing external validation for the results of our method. We note, of course, that in addition to accounting for this population-level criterion, our method allows us to account for individual differences in the number of non-normed associations (with 45.7% of the variance in this estimate explained by the individual differences). An illustrative example for a personalized space of associations for one participant and cue (`Item`) is provided in Figure 7C.

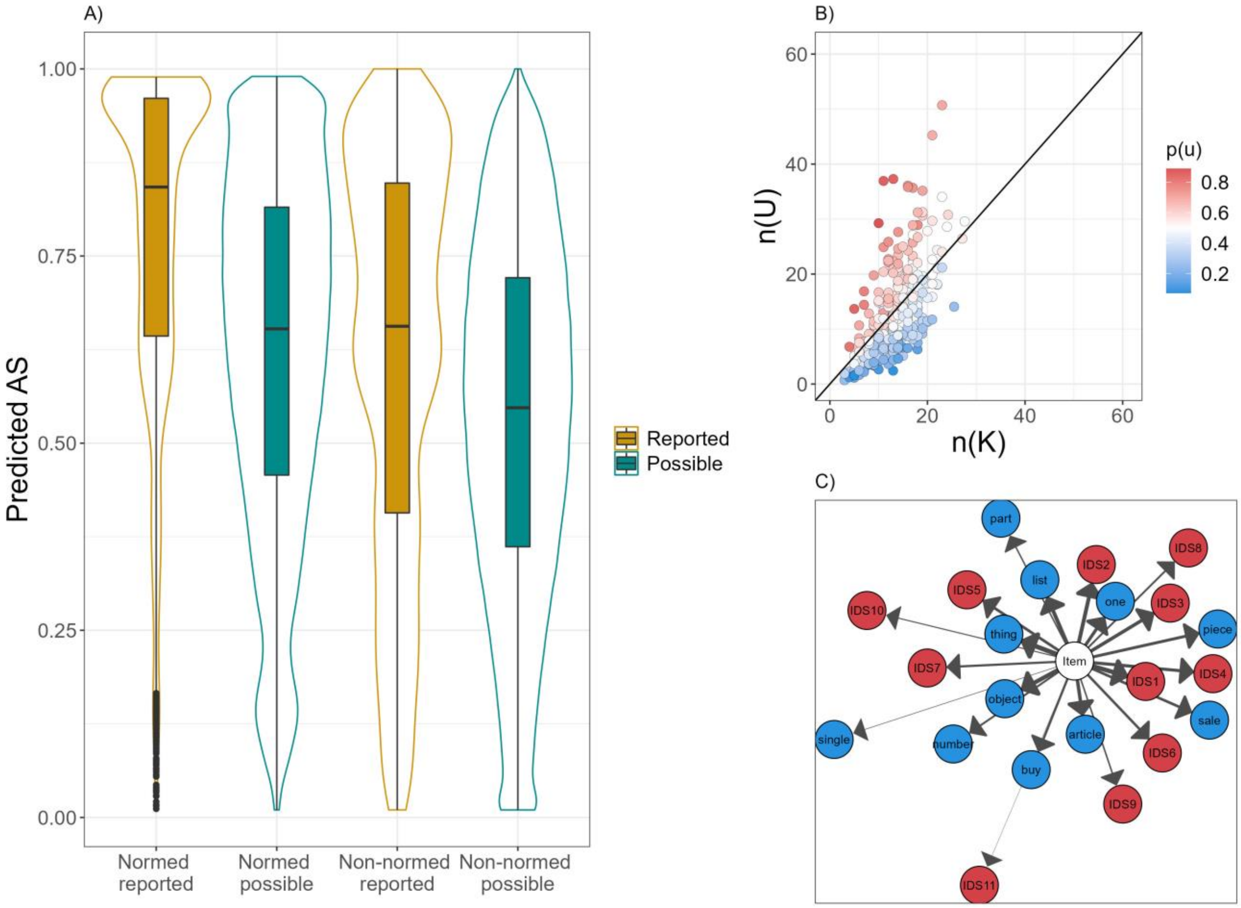

Figure 7 – Inferred cue- and participant-specific spaces of associations. Panel A depicts model predictions regarding the associative strength (AS) of the associations participants have reported and those they could have reported (possible associations) for both normed and non-normed associations. Panel B shows the main two factors affecting the estimated number of non-normed associations (i.e., associations absent from population-wide norms) for each cue, averaged across participants. n(K) – the number of possible normed associations (derived from population norms). p(u) – the empirical probability of reporting a non-normed association for the cue. n(U) – the estimated number of non-normed, additional associations. Panel C illustrates the association space for the cue 'Item' for a single participant, with blue and red nodes corresponding with common and idiosyncratic (denoted by IDS) associations, respectively.

To further test the validity of our method, and the importance of accounting for non-normed associations, we examined whether trials for which our model predicts a larger number of possible non-normed associations are generally slower. As expected, we found a significant effect for the (standardized) number of estimated possible non-normed associations in predicting

RT, after controlling for the number of possible normed associations (β = 1.18, SE = 0.30, *t* = 4.03, *p* < .001). This effect was independent of whether the reported association was normed or non-normed (interaction: β = 0.17, SE = 0.12, *t* = 1.36, *p* = .172). Furthermore, this effect was 2.5 times stronger than the effect of the number of normed associations on RT (β = 0.44, SE = 0.20, *t* = 2.24, *p* = .025). This finding shows that association generation dynamics are affected by the number of potential unreported non-normed associations, and that our estimation procedure provides a valid estimate for this number.

The delineation of the internal space of associations also provides us with the unique opportunity to examine the effect of the absolute associative strength of non-reported associations on RT (Figure 1C). Indeed, we found that cues with stronger possible associations (on average) evoked faster responses (Figure 5D), even after controlling for the strength of the reported association and for the entropy of possible associations (β = -0.05, SE = 0.01, *t* = -3.89, *p* < .001), with an effect size that is similar that of entropy (median Pearson correlation = -0.13).

Most importantly, this delineation of the personal spaces of associations is necessary for fitting evidence accumulation models to trial-level choice-RT data. However, before proceeding to the model fitting, we note two important caveats of this method. First, whereas it provides us with highly elaborated and personalized estimates of the number and strengths of associations for each cue and participant, there is no way of knowing what the actual non-normed associations are (with the exception of reported, non-normed associations, of course). This means that this method cannot be used to estimate how related the different idiosyncratic associations are to each other, nor other linguistic characteristics (e.g., frequency in language of the different competing associations).

Second, our method relies on participants` AS ratings, and thus reflects not only the actual (latent) associative strength but also potential biases, noise, and non-linearity in participants' subjective reports. That being said, these contaminating effects are partially mitigated by the fact that our estimates for the strength of possible associations are not affected only by the actual rating of the association reported in that trial, but also on how common this association is, and on the distribution of ratings across cues (for a given participant) and participants (for a given cue). Nonetheless, in line with previous studies relying on estimates of similarity (Osth et al., 2020) or subjective value (Bakkour et al., 2018), we consider the possibility that an additional transformation might be needed to better capture the latent associative strength affecting evidence accumulation.

Evidence Accumulation in The Free Association Task

To investigate the process through which people generate associations, we compared three classes of tractable multi-alternative evidence accumulation models, which allow for efficient selection among myriad alternatives via either rich-get-richer dynamics (MVP) or parallel evidence accumulation (accumulator models). We next describe each of the three models in detail.

Models

Multivariate Pólya Urn process (MVP)

As briefly described above, the MVP is a discrete sampling scheme that can be thought of as the opposite of sampling without replacement (see Figure 2C). To apply the MVP to free association, we represent different possible associations for a given cue as different colors of balls in an urn. The associative strength (AS) of an association is represented by the initial proportion of balls of the corresponding color. We denote the initial number of balls of color *j* by α_j, and the total number of balls before evidence accumulation begins by $\sum\alpha$:

$$\alpha_j = \sum\alpha \cdot \frac{AS_j}{\sum_j AS_j}. \qquad 1$$

At each time step, a ball is drawn from the urn, its color is noted, and a variable counting the *number of draws* of this color (denoted by b_j) is updated. Then, the ball is returned to the urn together with another ball of the same color, thus increasing the probability that the color will be drawn again in subsequent steps. At the limit of $\Sigma\alpha = \infty$, the process reduces to simple sampling with replacement, since the probability of drawing each color (which is proportional to $a_j + b_j$) remains fixed. Conversely, the lower $\Sigma\alpha$ is, the more the process is characterized by rich-get-richer dynamics. The accumulated evidence for each association is given by b_j, and the process continues until any of the associations reaches a threshold *Bj*.

To use the MVP to explain responses and RTs in the free association task, we derive the joint probability that response *j* has reached its threshold, B_j, at time step *n*, before any other response has reached its threshold. This probability can be obtained by first finding the probability that at time *n*-1 color *j* has been drawn exactly B_{j-1} times whereas each of the other colors has been drawn fewer than B_j times, and then multiplying by the probability of subsequently drawing color *j*. For color *j*=1, and a total of *J*=3 available colors (without a loss of generality), this is[2]:

$$\mathrm{p}(\text{response} = 1, \text{time steps to response} = n)$$
$$= \mathrm{p}(b_1(n) = B_1, b_1(n-1) = B_1 - 1, b_2(n) < B_2, b_3(n) < B_2)$$
$$= \mathrm{p}(b_1(n) = B_1 | b_1(n-1) = B_1 - 1) \cdot$$
$$\mathrm{p}(b_1(n-1) = B_1 - 1, b_2(n-1) < B_2, b_3(n-1) < B_3) \qquad 2$$

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[2] all terms below are conditioned on $\alpha_{1:J}, \sum\alpha, B$, which are not shown for conciseness

Given the basic principles of the Pólya urn process, the term in the third row of Equation 2, which describes the probability of sampling color j = 1 for the B^{th} time on time-step n, is simply:

$$\mathrm{p}(b_1(n) = B_1 | b_1(n-1) = B_1 - 1) = \frac{\alpha_1 + B_1 - 1}{\sum\alpha + n - 1} \qquad 3$$

The remaining challenge is to evaluate the term in the fourth row in Equation 2, which is a cumulative Dirichlet-multinomial distribution with respect to b_2 and b_3. When B and J (the number of associations) are very small, computing this cumulative distribution function can be achieved through enumeration, using the Dirichlet-multinomial probability mass function. However, enumeration is impractical even for modest spaces of associations (e.g., J = 18, and B = 10). Instead, we rely on the solution proposed by Corrado (2010) to efficiently calculate cumulative probabilities for the Dirichlet-multinomial distribution (see Supplemental Material Section S4).

To study the role of allowing stronger associations to require less evidence (AS-modulated bias), we allowed B_j to be determined as a function of AS_j, with the free parameter B_{boost} determining the strength of this relationship. More specifically, we use a formalization wherein for each cue, the threshold for the lowest-AS association was set as the free parameter B_{max}, and the threshold of the highest-AS association was set to:

$$B_{min} = B_{max} - (B_{max} - 1) * B_{boost}. \qquad 4$$

whereas the threshold for all other associations was determined by min-max normalization.

The last step is to convert the discrete distribution of time-steps required to reach a threshold, n, into a continuous distribution of response time t. For this purpose, we follow the approach used in Blurton et al. (2020), wherein each inter-step interval is assumed to be exponentially distributed with a common rate (λ) parameter, such that a sum of exponentials (i.e., an Erlang distribution) can describe the entire process. Because n is a latent variable in the model, we marginalize over n, computing a mixture of Erlang distributions:

$$\mathrm{p}(\text{response} = 1, \text{response time} = t \mid \lambda) = \sum_{n=B_1}^{B_1+\sum_{j=2}^{J}(B_j-1)} \mathrm{p}(\text{response} = 1, \text{time steps to response} = n)\,\mathrm{Erlang}(t-\tau \mid n, \lambda)\,, \qquad 5$$

where τ is a non-decision time parameter, typically used in evidence accumulation models to account for the time it takes to perceive presented stimuli (i.e., the cue) and execute a response. For the summation, we use the fact that *n* can only range from B_1 (if only the winning color, here j=1, was drawn) to $B_1 + \sum_{j=2}^{J}(B_j - 1)$ (if all other colors were drawn B_j-1 times). To reiterate, Equation 5 describes the joint probability that a response (in this case, response 1) has reached its threshold at time t-τ, and that none of the other responses have reached their threshold.

The effect of absolute strength was incorporated in the MVP in two alternative ways. In the first model variant, the initial number of balls representing each association, and the AS-modulated bias were a function of absolute, rather than relative strength. Thus, Equation 1 was multiplied by $\sum_j AS_j$, and Equation 4 determined the threshold for the strongest association *across cues*. Second, instead of assuming that the inter-step interval λ (i.e., time to draw a ball from the urn) is constant, it could correspond with the absolute associative strength of the respective association. However, since using a separate inter-step interval for each association will make the model intractable, we can approximate this feature by setting λ, for a specific cue, to be a function of the mean absolute AS of the associations to that cue (similar to Blurton et al., 2020).

Finally, another variant of the MVP included a transformation of AS which aims to map the estimated AS ratings to estimates of latent AS. Since AS is normalized in the MVP, its linear transformation would not change the output of the model. Thus, we used a non-linear transformation, whereby a free parameter η controls the extent to which associations with higher estimated AS are actually stronger:

$$lAS_j = \frac{AS_j^{e^{\eta}}}{\sum_{j \in J} AS_j^{e^{\eta}}}. \quad (6)$$

where lAS_j is the latent strength of association j, and J includes all associations to the cue.

Normalized accumulator models

As illustrated in Figure 3C, the LBA and RDM involve a race between several accumulators, where each accumulator corresponds with a possible association. The mean slope (v) of each accumulator is defined by the normalized AS of association j (for cue c and participant s), and is thus not a free parameter:

$$v_j = \frac{AS_j}{\sum_j AS_j} \quad (7)$$

Whereas the original purpose of this normalization is to ensure the identifiability of the model's parameters (i.e., to avoid the 'scaling problem'; Donkin et al., 2009), it also has the desirable consequence that accumulators compete for a fixed amount of possible evidence at each time point. Note that, in our case, a model with non-normalized v would be identifiable (because v_j it is not a free parameter) but inconsistent with the data, since this would eliminate competition among associations and thus lead to faster response times to cues with more diverse associations.

In the RDM, the momentary rate of each accumulator at each time point is drawn from a normal distribution with a mean v_j and a standard deviation given by a free parameter s. This within-trial variance is replaced in the LBA by between trial-variance, such that the slope of each linear accumulator is drawn from a normal distribution, truncated at zero, with a mean v_j, and a standard deviation given by a free parameter s. In both models, the accumulators race towards a threshold defined by a free parameter B[3], and the starting point of each accumulator is drawn from a uniform distribution with range $[0, A]$. As in the MVP, the free parameter τ was used to define the non-decision time.

The amount of evidence for a decision is, thus, a sample from a uniform distribution with range $[B - A, B]$. To implement the assumption that stronger associations require less evidence we can either assume that the upper bound of this distribution is lower for stronger associations (assuming that $B – A$ is fixed across associations), or that the lower bound of this distribution is lower for stronger associations (assuming that B is fixed across associations). In other words, stronger associations can either require less maximum evidence or less minimum evidence. Following previous work showing that starting point variability might be unnecessary in the RDM (Tillman et al., 2020), we also examined an RDM where A was constrained to zero, such that AS-modulated bias was formalized simply by allowing B to vary as a function of AS. In either case, the relevant quantity was determined by a min-max function of associative strength, similar to the parameterization used in the MVP.

Whereas normalized accumulator models do not naturally account for absolute associative strength (because of the normalization), we tested several possible ways in which absolute strength can influence evidence accumulation. First, we examined a variant in which v_j`s were either added with, or multiplied by, mean AS (see also Miletić et al., 2020). Second, similar to the MVP, we examined a variant in which absolute, rather than relative AS determined the AS-modulated bias (i.e., with the min-max function calculated across cues). Finally, as in the MVP, we tested a variant of normalized accumulator models including a non-linear transformation to

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[3] Note that the standard notation for the threshold is a lowercase *b* in these models (whereas uppercase B is sometimes used to refer to the difference *b* – *A*). Here we use upper case B for consistency with the MVP notation above.

capture individual differences in the mapping of estimated AS to latent AS, controlled by a free parameter η.

Advantage accumulator models

As illustrated in Figure 4, advantage models share many of their characteristics with the RDM and LBA, with one key difference – accumulators correspond with pairwise comparison between associations. Thus, for instance, a competition between three associations (A_1, A_2 and A_3) would be represented by 6 accumulators corresponding with all possible comparisons (i.e., A_1 - A_2, A_2 – A_1, A_1 – A_3, A_3 – A_1, A_2 – A_3, A_3 – A_2). The mean slope of an accumulator A_j – A_k is given by:

$$v_{j-k} = v_0 + w_d\left(AS_j - AS_k\right) + w_s\left(AS_j + AS_k\right) \tag{8}$$

This calculation involves three free parameters, constrained to be non-negative. w_d controls the extent to which a difference in associative strength between associations affects the slope of the accumulator, whereas w_s controls the contribution of the absolute associative strength of the two associations; v_0 serves as a bias parameter, designed to ensure that mean slopes are non-negative. The threshold and start-point variability are defined as in the LBA and RDM. As in the case of the RDM, we also examined a reduced version of the ARDM with no start-point variability. A non-decision time parameter τ was included in both the ARDM and the ALBA. To ensure identifiability, and in accordance with previous applications (Miletić et al., 2020; van Ravenzwaaij et al., 2020). we fixed the s parameter (corresponding with either within- or between-trial variability in the rate of each accumulator) to 1.

We also examined whether AS-modulated bias improved model fit (assuming that the maximum or minimum evidence required for *all* accumulators representing the advantage of a given association is a function of this association`s strength). Finally, since advantage accumulator models already have considerable flexibility in mapping inputted and latent associative strengths (modulated by the model's *wd* and *ws* parameters), and having an additional non-linear transformation (similar to the models above) made the models unidentifiable, we did not further examine such variants.

In all model variants, the race stops and an association is reported in accordance with some decision rule. The most widely used `Win-All` rule assumes that as soon as all accumulators representing the advantages of association j (e.g., A1-A2, A1-A3 if j=1) reach their threshold this association is reported, as long as no other association has won all its battles before. We also examine two additional rules. First, in the `Lose-All` rule, the association that is the last to lose in all battles is being reported (e.g., A1 is reported if A1-A2, A3-A2, A1-A3, and A2-A3 reached their thresholds, and either A2-A1 or A3-A1 did not reach their thresholds). Second, in the `Lose-One` rule, the association that is the last to lose any battle is being reported (e.g., one scenario in which A1 will be reported, is if A2-A3 and A3-A2 reached their thresholds, and neither A2-A1 nor A3-A1 reached their thresholds).

Dealing with outliers, and parameter fitting details

Evidence accumulation models fitted to trialwise data can be extremely sensitive to outliers (Ratcliff and Tuerlinckx, 2002; Vandekerckhove and Tuerlinckx, 2007). Indeed, the range of RT in the free association task was particularly large ([0.32s, 14.15s]), and we did not have a justification to exclude RTs above a certain threshold. Thus, as explained in detail in Section S5 in the Supplemental Material, we used mixture modelling to minimize the effects of outliers on parameter fitting (Ratcliff and Tuerlinckx, 2002; Vandekerckhove and Tuerlinckx, 2007).

Data were fitted using the Rmalschains R package (Bergmeir et al., 2016), which combines global-optimization (using an evolutionary algorithm), with gold-standard local search algorithms (Solis-Wets algorithm). These procedures helped avoid local minima while obtaining more accurate best-fit parameter values. Thus, each model was fitted separately for each of our 30 participants, based on data from an average of 284.7 (*SD* = 13.17) trials per participant.

Modelling results

Parameter recovery and formal model comparison

Before proceeding to examine how the different types of models account for the principled determinants of RT and AS ratings, we aimed to select, for each model type, only the models showing acceptable parameter recovery (i.e., a correlation of at least 0.6 between the fitted parameters and recovered parameters) and relatively good fit (Table 1; we present here only a subset of the best variants for brevity. Section S6 in the Supplemental material presents all possible combinations of the different variants). The first notable finding is that the MVP and normalized accumulator models outperformed advantage accumulator models, regardless of the type of decision rule used for the latter. Furthermore, normalized accumulator models performed better than the MVP, as long as both were matched with regards to their assumptions (i.e., free parameters). Second, for both the MVP and normalized accumulator models, allowing stronger associations to require less evidence (AS-modulated bias) improved model fits considerably. Third, adding a free parameter (η) controlling the degree to which differences in estimated associative strength reflected differences in latent associative strength improved fit for both the MVP and normalized accumulator models, but resulted in some parameter recovery difficulties.

Next, to clarify the reasons underlying these results, we examine how well the best variants of each model type, compared with informatively reduced versions (e.g., models with no AS-modulated bias), account for the overall distributions and determinants of RT and AS ratings. As noted above, we focus on the models' ability to reproduce the extent to which RTs are slower for weaker associations, and for cues with more competition or lower overall associability, as well as the extent to which greater competition results in weaker associations. These quantitative predictions were derived by simulating 100 samples (of 30 simulated participants, each) from each model, using the best-fitted parameter values. Since the determinants of RTs and AS ratings are continuous, we primarily used GLMMs (as in Figure 5) to examine these quantitative predictions. To validate that these GLMMs capture key patterns in model predictions we also depict model-free conditional means, after discretizing each determinant. Thus, combining both methods allowed us to verify that the results cannot be explained solely by mis-specification in the GLMMs or in the discretization, and to focus on the overall effects of the determinants rather than on isolated misfits that might occur in specific ranges. Finally, although models including the η parameter showed some identifiability problems, we wanted to test whether the addition of this theoretically important mapping between estimated and latent associative strength plays an important role in recovering key quantitative patterns in the data. Thus, we included them in the analyses below, despite their failure to satisfy our recovery criterion.

Table 1 – Relative fit and parameter recovery for the different variants of the three main types of models examined.

Model		AIC	Parameter recovery (Pearson correlations)						
	MVP		log(Σα)	*Bmax*	*Bboost*	λ	τ	η	
2	**λ per mean AS**	**110292.6**	**.92**	**.71**	**.89**	**.80**	**.62**	**-**	
1	**& non-linear transformation of AS**	**109383.6**	**.72**	**.40**	**.78**	**.63**	**.69**	**.14**	
3	**& no AS-modulated bias**	**111979.5**	**.92**	**.67**	**-**	**.74**	**.60**	**-**	
4	**& no rich-get-richer dynamics**	**113413.4**	**-**	**.93**	**.75**	**.79**	**.53**	**-**	
	Σα and threshold per absolute AS	110559.8	.90	.63	.87	.88	.58	-	
	Not accounting for mean AS	110515.3	.80	.40	.87	.78	.74	-	
	Normalized accumulator models	LBA / RDM	*s*	A	*B*	τ	*Bboost*	η	
3	**Standard (no AS-modulated bias)**	**110679.1 / 111032.6**	**.92 / .87**	**.88 / .89**	**.89 / .86**	**.97 / .83**	**-**	**-**	
	High AS - less min. evidence needed	110099.6 / 110045.8	.84 / .86	.98 / 1	.98 / .99	.92 / .72	.91 / .91	-	
2	**Low AS - less max. evidence needed**	**108713.0 / 109105.2**	**.96 / .63**	**.75 / .67**	**.75 / .67**	**.85 / .92**	**.75 / .81**	**-**	
	& per absolute AS	108741.6 / 109108.2	.93 / .52	.78 / .79	.77 / .79	.86 / .87	.49 / .61	-	
	& v × mean AS	108758.8 / 109322.7	.83 / .52	.75 / .58	.75 / .57	.90 / .74	.76 / .95	-	
	& v + mean AS	109467.4 / 109510.2	.91 / .63	.92 / .96	.91 / .96	.78 / .79	.71 / .98	-	
1	**& non-linear transformation of AS**	**108387.6 / 108727.6**	**.73 / .82**	**.83 / .83**	**.83 / .83**	**.84 / .85**	**.68 / .81**	**.44 / .36**	
4	**& no start-point variability**	**- / 111204.7**	**- / .98**	**-**	**- / .98**	**- / .89**	**- / .97**	**-**	
	Advantage accumulator models	ALBA / ARDM	*v0*	*wd*	*ws*	A	B	τ	*Bboost*
1	**Standard (win-all decision rule)**	**115071.1 / 115514.4**	**.68 / .60**	**.93 / .85**	**.52 / .82**	**.50 / -**	**.80 / .54**	**.77 / .75**	**-**
	High AS - less min. evidence	115281.0 / -	.68 / -	.67 / -	.79 / -	.46 / -	.50 / -	.23 / -	.32 / -
	Low AS - less max. evidence	115227.3 / 119361.2	.69 / .48	.93 / .98	.13 / .39	.40 / -	.67 / -.11	.71 / .05	.04 / .25
2	**Lose-all decision rule**	**117400.2 / 119473.9**	**.95 / .96**	**.94 / .78**	**.62 / .54**	**.67 / -**	**.91 / .77**	**.93 / .90**	**-**
3	**Lose-one decision rule**	**118999.5 / 126615.4**	**.44 / -.05**	**.92 / .94**	**.46 / .58**	**.58 / -**	**.58 / .87**	**.75 / .60**	**-**

Note: MVP – multivariate Polya process model; LBA – linear ballistic accumulator; RDM – racing diffusion model; ALBA – advantage linear ballistic accumulator; ARDM – advantage racing diffusion model (with no start point variability). AS – Associative strength. Only models in boldface font are included in subsequent analyses, and are referred to using the numbers appearing to their left.

Multivariate Polya process model

The MVP was largely able to reproduce the empirical RT distribution (with the exception of the 90th percentile; Figure 8A, see also Section S7 in the Supplemental Material for participant-level fit), as well as the extent to which an association is reported faster when it is stronger (Figure 8C) and when it has less competition (Figure 8D). The model also produced an effect of a cue's overall associativity (i.e., mean absolute associative strength) on RT, though this was slightly overestimated (Figure 8F). Finally, the model produced an effect of competition on the strength of the selected association, but this was grossly underestimated (Figure 8E). This also produced an overly shallow distribution of AS ratings (Figure 8B).

Crucially, the results demonstrated the critical role of both rich-get-richer dynamics and AS-modulated bias in the MVP. Thus, rich-get-richer dynamics were necessary to capture the linear effect of competition on RT (the lack thereof predicted an exponential effect in 66.2% of simulations) and on the strength of the selected association (Figure 8E). These results show that, as hypothesized, rich-get-richer dynamics can explain why weak associations are selected in reasonable time even when myriad associations compete.

However, if not coupled with AS-modulated bias, rich-get-richer dynamics lead to scenarios in which weak associations can be reached as quickly as strong associations, because in both cases the process continues along its initial momentum with little interference by other associations. The addition of AS-modulated bias is thus necessary to ensure that strong associations are nevertheless selected faster (Figure 8C). It is also important to note that only in the presence of rich-get-richer dynamics, AS-modulated bias can reduce RTs for strong associations without biasing the model in favor of strong associations. This is because if a weak association was sampled in the first one or two time-steps, rich-get-richer dynamics will continue supporting this association even if its threshold is considerably higher than that of stronger associations.

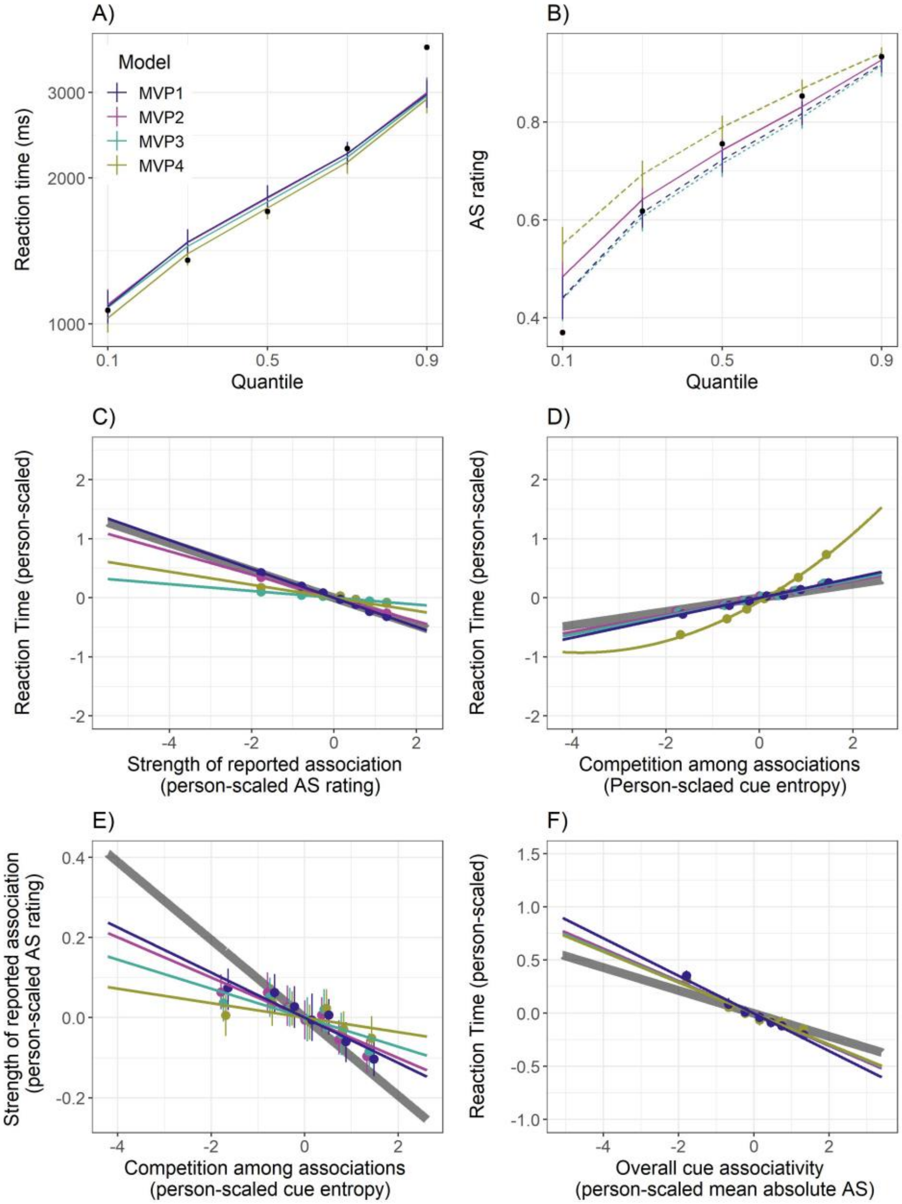

Figure 8 – The ability of the multivariate Polya process model (MVP) to recover key patterns in the data. Panels A and B present QQ plots examining the ability of the MVP models to account for the shapes of the RT (Y-axis is presented in a log scale) and AS ratings distributions. The other panels depict the ability of the models to explain how the strength of the reported association (C), the competition among associations (D), and the overall cue associativity (F), determine RT, and how competition determines the strength of the selected association (E). The thick gray line corresponds with the empirical linear effects also presented in Figure 5. The colored lines correspond with the best-fitted regression line estimated based on simulated datasets from each model. To demonstrate the fit of these regression lines to the raw, simulated

data, we also depict the mean RT/AS rating, for each of 7 bins (with the same number of observations) of the respective independent variable (represented by the points ±95% CI). MVP1 – AS-modulated bias, rich-get-richer dynamics and non-linear transformation of the AS; MVP2 –AS-modulated bias and rich-get-richer dynamics; MVP3 – no AS-modulated bias; MVP4 – no rich-get-richer dynamics

To understand the greatest discrepancy between the model predictions and the data, which concerned the strength of produced associations and how it was affected by competition, we simulated from the model across a wide range of parameter values (Figure 9). The simulations showed that to account for the empirical effect of competition on the strength of the selected association, the model requires a certain, intermediate level of rich-get-richer dynamics, which would overestimate the empirical effect of competition on RT. The reason a certain, intermediate level of rich-get-richer dynamics produces the strongest effect of competition on the strength of the selected association is that such a level is required to produce a differential effect that more strongly impacts which association is selected for cues with many competing associations than for cues with few associations. For example, the effect of rich-get-richer dynamics in an MVP urn with a total of 50 balls will be highly impactful if these 50 balls are distributed among 100 colors (associations), but weak if there are only 5 colors (such that each color starts with a substantial number of balls). Conversely, if the urn only has a total of 2 or 3 balls (which corresponds with the more significant level of rich-get-richer dynamics), rich-get-richer dynamics would more similarly affect cues with any number of colors.

Finally, the effect of the cue's mean absolute associative strength on RT was best captured by the MVP wherein mean absolute associative strength determined the time it takes to sample each ball (Table 1). This result generalizes the solution developed by Blurton et al. (2020) to account for visual processing capacity to the current, considerably different, task. Conversely, setting the initial number of balls and threshold as a function of absolute associative strength produced worse fit (Table 1), and thus was not examined further. This worse fit could be explained by the fact that this model features weaker rich-get-richer dynamics for trials in which the sum of the absolute AS is larger (since the urn starts with a higher total number of balls), and this has the undesirable effect of slowing down responses on such trials.

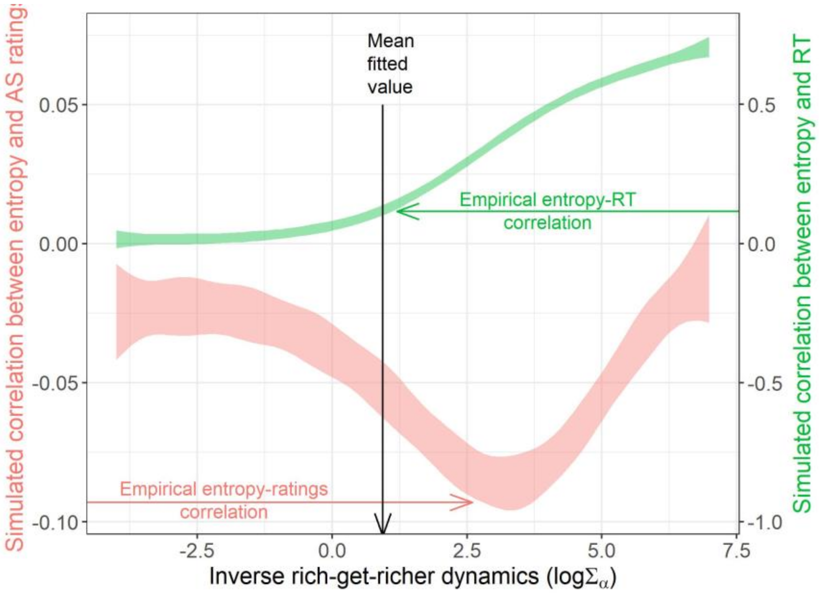

Figure 9 – Demonstrating the impact of rich-get-richer dynamics on the effects of cue entropy on the strength of the selected associations (red curve, left Y axis), and RT (green curve, right Y axis), across a wide range (1000 simulations) of possible parameter values, averaged across all participants.

Normalized accumulator models

Normalized accumulator models were able to recover the shape of the RT distribution with fewer disparities than the MVP (compare Figure 10A to Figure 8A). AS-modulated bias (LBA/RDM1-2 vs. LBA/RDM3) was necessary for these models to select strong enough associations on average (Figure 10B), but this modification compromised the models' ability to account for the effects of competition on RT (Figure 10D). Most strikingly, all normalized accumulator models grossly underestimated the degree to which stronger associations were chosen more quickly (Figure 10C), as well as the degree to which cues with stronger associations overall produce faster responses (Figure 10F).

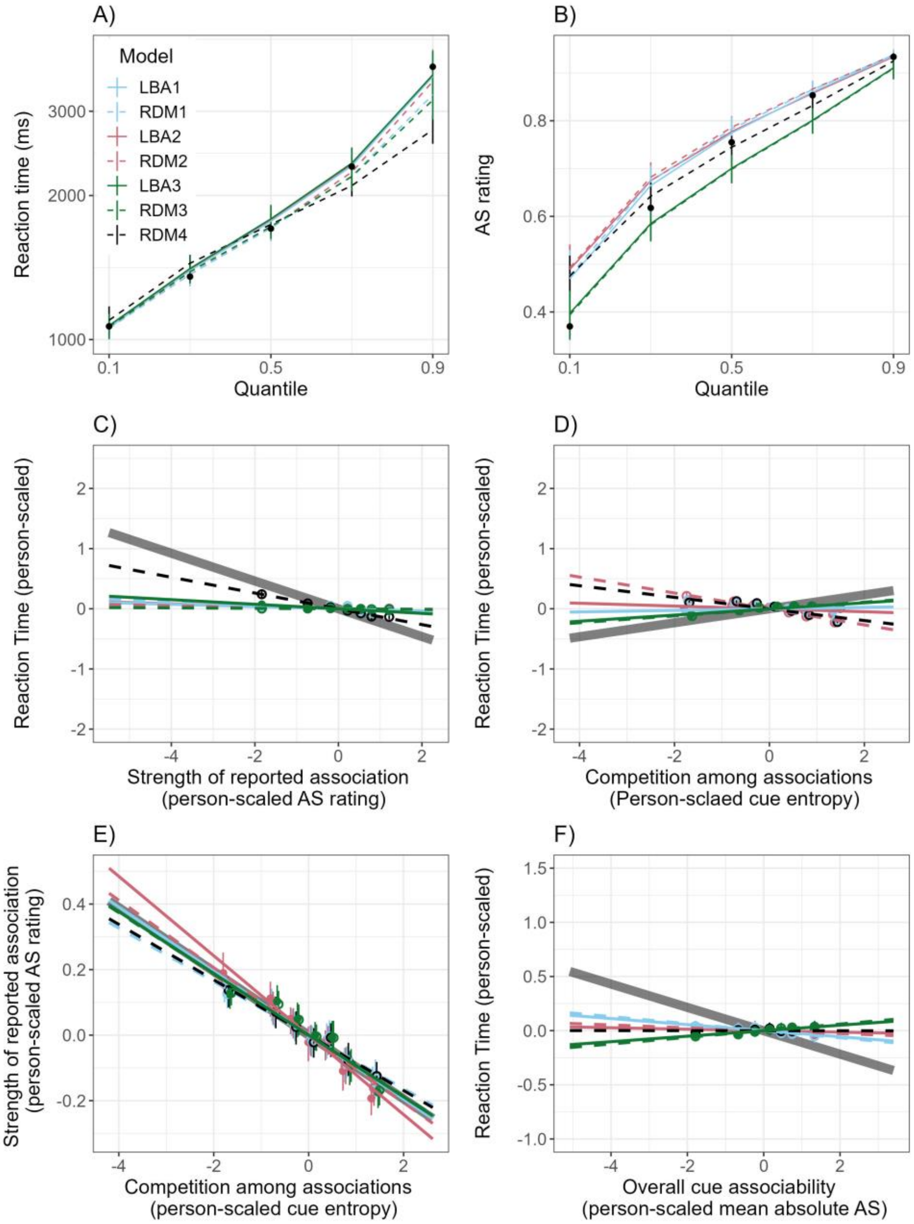

Figure 10 – The ability of normalized accumulator models to recover key patterns in the data. LBA – linear ballistic accumuator. RDM – racing diffusion model. LBA1/RDM1 – AS-modulated bias + non-linear scaling of the AS; LBA2/RDM2 – only AS-modulated bias; LBA3/RDM3 – no AS-modulated bias; RDM4 – AS-modulated bias + no start-point variability. See the caption for Figure 8 for further details.

Similar to the role of rich-get-richer dynamics in the MVP, variability in accumulation rate is necessary to allow normalized accumulator models to avoid being excessively slower under high competition (i.e., high entropy). Figure 11, depicting the influence of key parameters on the effects of interest, illustrates this effect in its middle panel. However, similar to the MVP, this variability also impairs the model`s ability to account for the finding that stronger associations are selected faster. That is, although variability in accumulation rate has been shown to underlie the generation of `slow errors` (S. D. Brown and Heathcote, 2008; Ratcliff and McKoon, 2008), which here manifest in a negative ratings-RT correlation, our simulations show that this effect is not monotonic (Figure 11, top panel). The reason for this is intuitive – if the variability in accumulation rate considerably surpasses the average accumulation rates, the effect of AS on the selection of an association is attenuated.

A clear distinction between normalized accumulator models and the MVP concerns the effect of AS-modulated bias. Similar to the MVP, AS-modulated bias improves the overall fit of normalized accumulator models. However, in the MVP, rich-get-richer dynamics allow AS-modulated bias to speed up strong associations without making them more probable. This is not the case in normalized accumulator models. Indeed, as depicted in the bottom panel of Figure 11, AS-modulated bias increases overall ratings, allowing it to balance the otherwise excessive selection of weak associations caused by the level of accumulation rate variability required to ensure time-efficient competition (see the third quantile of variability in the left middle and bottom panels of Figure 11). This, however, does not allow the model to increase AS-modulated bias sufficiently to reach the empirical ratings-RT correlation (see the left top and bottom panels of Figure 11), without producing excessively strong associations. Indeed, to allow the model to select not only the strongest associations, normalized accumulator models with AS-modulated bias have to considerably increase accumulation rate variance (see Section S8 in the Supplemental Material presenting the best-fitted parameter values), which further compromises the models' ability to produce strong associations faster. This increased variability also results in an additional misfit, in that it emphasizes the natural tendency of models with independent accumulators to respond faster when there are more response alternatives (i.e., statistical facilitation; Figure 9D and Figure 11, middle panel).

An ancillary reason for which AS-modulated bias was unable to allow the model to select strong associations faster is that this effect was attenuated by the additional variability in start-points. Indeed, an RDM with no start-point variability performed better in this regard (Figure 10C) and showed greater effect of AS-modulated bias in general (Figure 11, right panel). Importantly, though, the key reasons underlying the difficulty of other normalized accumulator models to jointly account for this and other findings affected this model as well.

Finally, standard normalized accumulator models were unable to account for the finding that cues with stronger association overall produces faster responses (Figure 10F). Furthermore, in contrast to the MVP, attempts to link average accumulation rates to mean AS, or to have AS-modulated bias account for differences between cues in mean AS performed worse (Table 1). We now turn to examine in detail the results for a class of models, which offers a more natural choice for accounting for the effects of mean AS on RT, namely, advantage accumulator models.

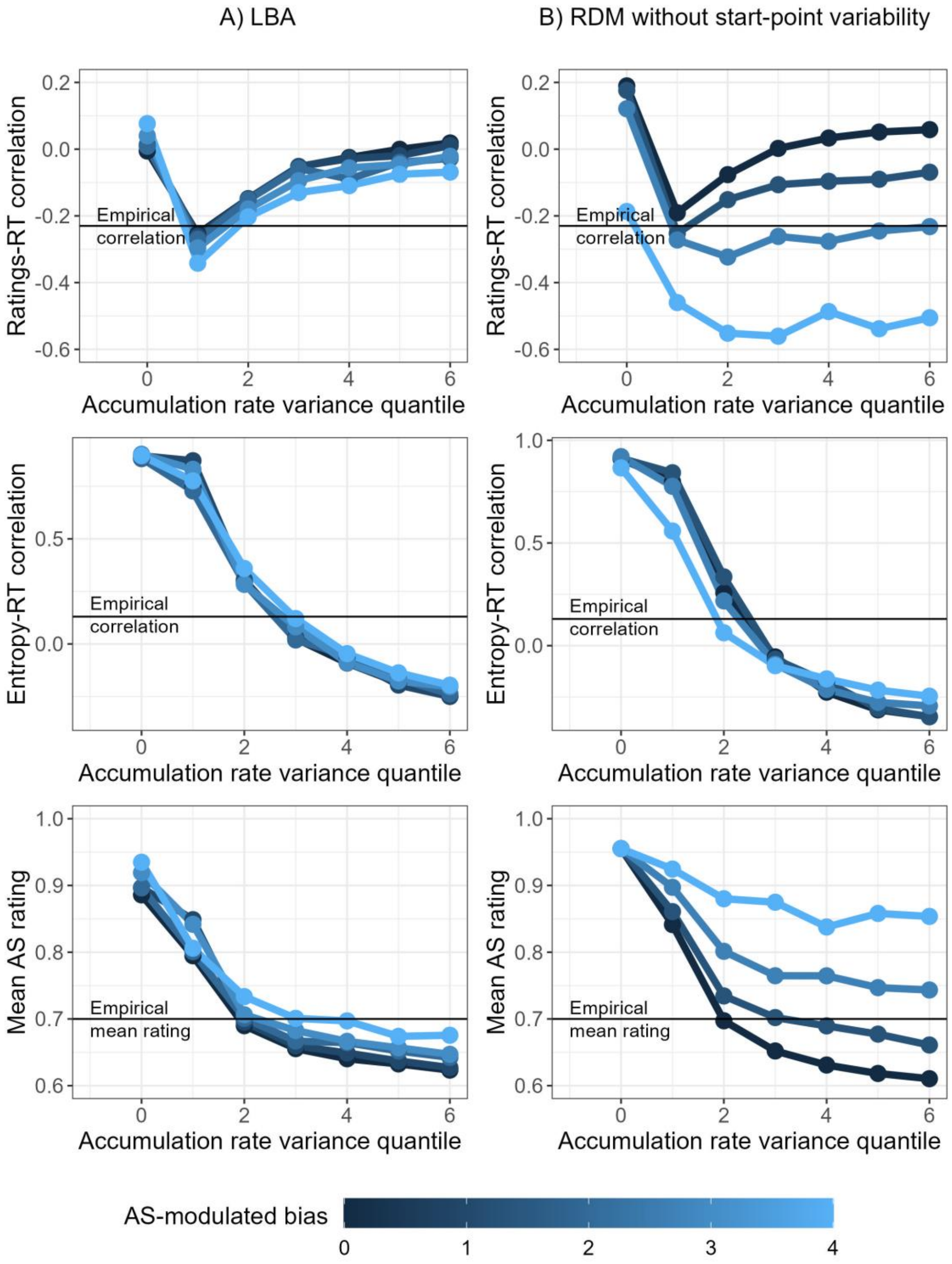

Figure 11 – Demonstrating the impact of accumulation rate variability and AS-modulated bias on how RTs are influenced by the strength of the selected association (top plots), and the competition between associations (middle plots). The bottom plots show the effects of these parameters on the average strength of reported associations. These plots were derived from 5000 simulations across a wide range of possible parameter values for an artificial participant.

Advantage accumulator models

As shown in Figure 12 and consistent with the AIC results in Table 1, advantage accumulator models could not fully account for the shape of the RT distribution (Figure 12A) or the determinants of RT and AS ratings (Figure 12C-F). We focus here on two key misfits that can explain the inability of these models to recover the data. First, advantage models in which a decision is made after an association either prevails over all other (WA) or does not lose to all other associations (LA) grossly overestimated the entropy-RT correlation (Figure 12D), and tended to produce an exponential relationship (ALBA_{WA} = 61.6% of simulations across participants supported a polynomial regression; ARDM_{WA} = 70.20%, ALBA_{LA} = 85.47%, ARDM_{LA} = 73.33%). Conversely, advantage models in which a decision is made as soon as all but one association have lost *at least one* pairwise competition (LO) wrongfully predicted faster responses for cues with more competing associations (Figure 12D). Second, all advantage models tended to produce a positive rather than negative relationship between entropy and ratings (Figure 12E). In other words, greater competition increased (or at least did not decrease) the prospects of strong associations.

To understand these findings, consider a chess tournament in which either three or ten players, with varying abilities, play against each other. For obvious reasons, although the weakest player might, occasionally, win a match, it is much less likely to do so for nine than for three straight matches. Furthermore, this difference will be less pronounced if instead of the requirement to win all matches (WA), a weak player can win the tournament if all other players have lost one (LO) or all (LA) their matches. Now imagine that all matches occur simultaneously (thus, each player plays all her matches at the same time). If the tournament ends as soon as all players but one have lost *at least a single* match (LO), then adding more players (and thus having each player play more matches) will make this happen faster. Indeed, it will always take more time, on average, to lose at least 1/1 or 1/2 than 1/100 or 1/1000 matches, an effect that is referred to in the literature as ‘statistical facilitation’ (Raab, 1962). Conversely, if a player has to win all her matches (WA), or at least not lose in all her matches (LA), then adding more players (and more matches) will make the tournament last longer. The difference between these two scenarios is that in the former, adding players increases the set of events that end the tournament, whereas in the latter two it does not (it only makes each tournament-ending event less probable). Although it is not obvious that the function representing additional time in the latter scenario will be exponential, or that it will overestimate the empirical slowing due to greater competition, our findings suggest exactly that. This inability of the win-all ALBA to account for the linear relationship between AS entropy and RT (implicated by our data and Hick’s law) seems inconsistent with the fact that this model was previously shown to account for Hick’s law with a smaller number of response alternatives (van Ravenzwaaij et al., 2020). Yet, simulations have shown that this deficiency of the ALBA is largely driven by the extensive number of alternatives uniquely characterizing free association (see Section S9 in the Supplemental Material).

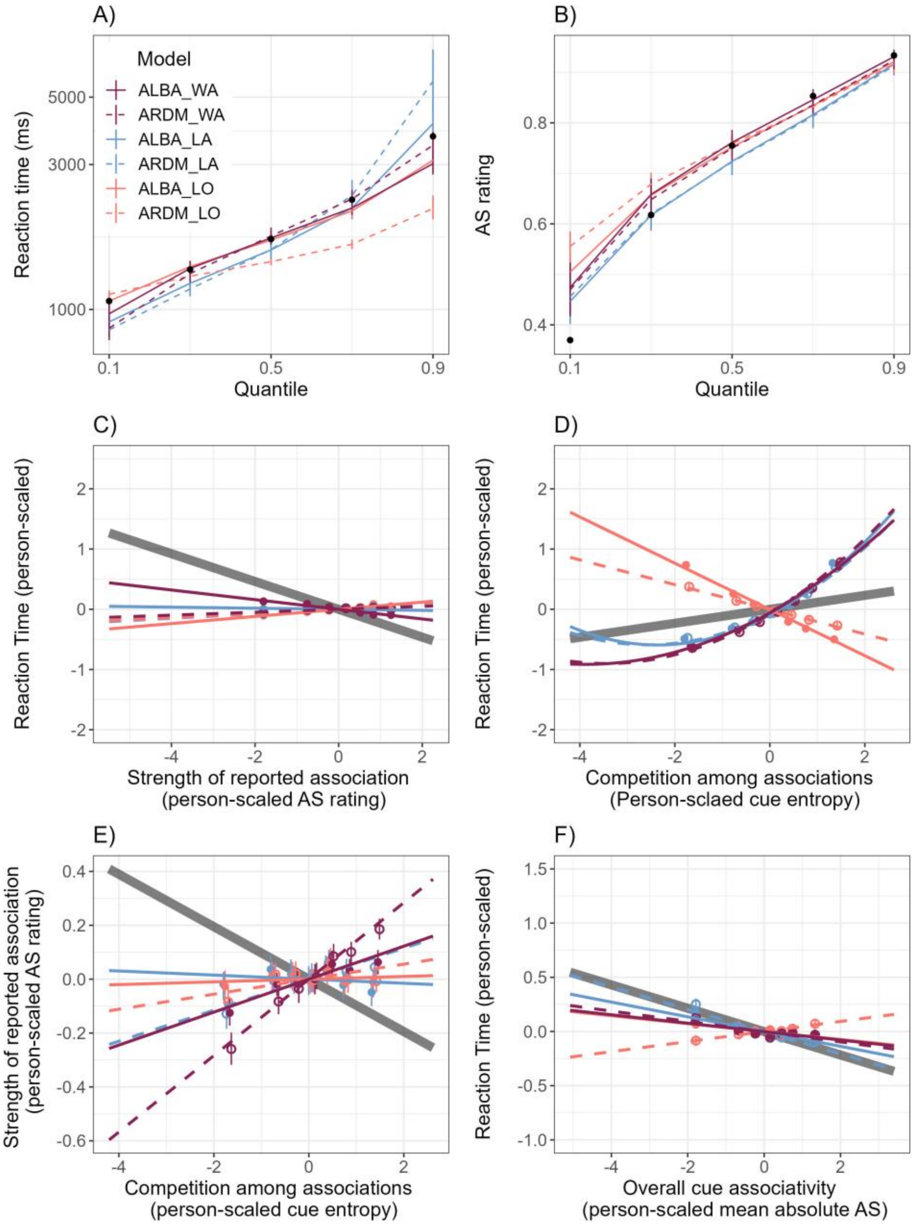

Figure 12 – The ability of advantage accumulator models with different decision rules to recover key patterns in the data. ALBA – advantage linear ballistic accumuator. ARDM – advantage racing diffusion model (with no start-point variability). WA – win-all decision rule. LA – lose-all decision rule. LO – lose-one decision rule. See the caption for Figure 8 for further details.

Discussion

Historically, almost no technique has fascinated the founding fathers of psychology as much as the generation of free associations (Anderson and Bower, 2013; Deese, 1966; Freud, 2013; W James, 2018; Jung, 1910). Several models have examined processes involved in the generation of free association (Abbott et al., 2015; Gray et al., 2019; Griffiths et al., 2007; Hills et al., 2012). However, RTs have rarely been examined, and no previous model has attempted to jointly fit responses and RTs in order to delineate the mechanistic process involved in producing an association. This is a challenging task, because the space of associations from which an association is selected, is vast, partially idiosyncratic and unknown, and differs across trials. Indeed, previous studies attempting to model the factors determining RT in free association have used minimal, illustrative examples with an unrealistically constrained space of association (Lerner et al., 2012a; Snyder et al., 2010), and thus were only able to predict qualitative effects. Here we aimed to develop a framework suitable for predicting the strength and speed of the association people produce, for each cue word. For this purpose, we integrated key principles involved in previous, seminal models of semantic activation (attractor models and spreading activation models) with state-of-the-art, tractable models of evidence accumulation, and a novel approach for estimating people`s personalized spaces of associations.

This work has produced several novel insights. First, we presented a generalizable framework for mapping the internal space of associations from which an association is selected. This framework, combined with the methodology of asking participants to rate the strength of their own associations performed better in predicting the dynamics governing the generation of associations than commonly used methods relying on population-level statistics (see also Hutchison et al., 2008). Indeed, we found that people are the best evaluators of their own associations, which coheres with the subjective, often idiosyncratic nature of free association. Furthermore, our approach for mapping the internal spaces of associations allowed us to better estimate two key attributes of people's covert association spaces: the actual degree of competition (including idiosyncratic associations), and the absolute strength of associations that were not reported nor directly rated. Most importantly, this paved the way to analyzing retrieval dynamics using the well-established framework of evidence accumulation.

Second, since such personal spaces of associations may often include more than a hundred alternatives, a key computational problem is how to avoid becoming exceedingly slow when resolving the competition among that many response alternatives. Our analysis highlighted two key mechanisms obtaining this goal: (a) rich-get-richer dynamics can function to gradually reduce the number of associations that effectively remain in the race, such that the challenge of having to choose among myriad associations dissolves over time; (b) if semantic activation is thought of as a fixed quantity spreading in parallel to the different response alternatives, stochasticity in the rates of the different associations makes this model less sensitive to competition among many associations. Interestingly, this similarity in the function of these distinct mechanisms is further strengthened by the fact that rich-get-richer dynamics effectively increase the variability of responses across trials (Blurton et al., 2020).

When isolated, however, these mechanisms cannot explain a key finding: that stronger associations are produced faster. This problem was only solved by combining rich-get-richer dynamics with the assumption that strong associations require less evidence, an assumption that is motivated by the idea that cues and associations are represented in a distributed manner such that stronger associations have greater overlap with the cue. Thus, whereas rich-get-richer dynamics entail that a weak association can quickly gain momentum and thus progress at the same speed as a strong association would, it will nonetheless be produced more slowly if it requires more evidence to reach the threshold. Indeed, simulating data from a simple semantic attractor network has also shown that stronger associations are generated faster only when they are allowed to have greater representational overlap with the cue (see Section S10 in the Supplemental Material). Critically, whereas a similar mechanism has improved the fit of models formalizing parallel spread of activation with no rich-get-richer dynamics, it could not fully account for the degree to which strong associations are faster. This highlights the fact that only when coupled with rich-get-richer dynamics, allowing strong associations to require less evidence does not necessarily increase the probability of choosing strong associations, and can thus modulate speed as dissociated from choice.

Third, greater competition among associations does not only cause slower responses, but also produces weaker associations. This effect is explained by the fact that a constant level of rich-get-richer dynamics or accumulation rate variability causes the production of more diverse associations predominantly in cues with many competing associations. This specificity can be understood by realizing that a given amount of noise has a stronger effect on a weaker (i.e., more dispersed) signal. Our results further show that this effect is not linear, since above a certain degree noise (or rich-get-richer dynamics) becomes much larger than any signal.

Fourth, from a more practical perspective, we found that both the MVP, implementing rich-get-richer dynamics, and normalized accumulator models such as the LBA or RDM, produce recoverable parameters, and are generally quite good in accounting for trial-level choice RT data in the free association task. Normalized accumulator models showed better performance in terms of overall fit and the ability to explain the strength of produced associations. They also have the important advantage of requiring much less time to fit. Conversely, the MVP was somewhat better in accounting for the different factors that determine RTs in the task, such as the strength of the selected and unselected associations. By contrast to these two models, advantage accumulator models which assume that associations compete in a pairwise manner, performed not as well in accounting for the data.

Finally, our findings highlight the key benefit of models that allow forming and testing quantitative predictions. That is, many of the various misfits of the models concerned a difficulty in accounting for the magnitude of an effect size. For example, the MVP produced weaker associations in response to cues that evoke greater competition but underestimated the size of this effect. Similarly, normalized accumulator models produced stronger associations slightly faster, but underestimated the size of the effect. Furthermore, the reasons for the different misfits included tradeoffs between different determinants of RT and associative strength, and the non-monotonicity of the effects of key parameters. These features would be difficult or impossible to detect by only modeling qualitative effects or mean RT, as done in previous studies.

As noted throughout the paper, our work draws from three formative modeling approaches: attractor models of semantic memory, spreading activation models, and evidence accumulation models. We now turn to discuss, in detail, the contribution of our findings to each of these schools of thought. Then, we discuss the implications of our work for the study of individual differences in free association.

MVP and semantic attractor networks

Despite the popularity of modeling semantic processing using neural network models, there is no consensus as to whether rich-get-richer dynamics (Rogers and McClelland, 2014), or distributed representation (Snyder et al., 2010) are necessary components, nor is there sufficient understanding regarding their function. Thus, a key contribution of our study is the finding that these two mechanisms balance each other to allow for strong associations to be produced faster without making the model too cautious or deterministic. Interestingly, this finding is closely related to a known, unique property of decision-making models with rich-get-richer dynamics – that increasing the threshold beyond a certain, minimal, level has no effect on choice (Usher and McClelland, 2001; X.-J. Wang, 2008). Thus, whereas linear evidence accumulation models predict that choice accuracy increases indefinitely as processing time increases (S. D. Brown and Heathcote, 2008; Ratcliff, 2006), the nature of rich-get-richer dynamics means that once one response alternative dominates the race to a sufficient degree, its self-reinforcing impact makes it impossible for any other alternative to win. This partial dissociation between RT and choice with varying thresholds is exactly why, in the MVP, decreasing the thresholds (i.e., inducing a stronger bias) for stronger associations allowed them to be faster without making them more probable. This generates the intriguing prediction that, to the extent that free association indeed involves rich-get-richer dynamics, emphasizing accuracy (e.g., asking a subject to produce only strong associations) should have a minimal effect on speed, and vice versa.

The combination of rich-get-richer dynamics and AS-modulated bias implies an interaction between two processes contributing to the selection of an association. First, by merely processing the cue one activates (i.e., primes) some associations more than others. Second, associations can recurrently reinforce themselves via rich-get-richer dynamics, such that the effect of the cue on evidence accumulation fades over time. The two main free parameters of the MVP, B_{boost} and $\Sigma\alpha$ control the relative dominance of these two processes, which future studies could attempt to differentially manipulate. For example, by manipulating the cue presentation time one might be able to reduce the magnitude of the AS-modulated bias (i.e., reduce B_{boost}), and thus also the ratings-RT correlation.

Another intriguing question is whether the processing of the cue ends before the associations begin to compete (as implied by the MVP), or whether both processes operate in parallel, implying that AS-modulated bias may increase over the course of a trial. Indeed, the mechanism allowing an attractor network to transition between (or remain in multiple) associated attractors has been of great recent interest (Deco and Rolls, 2006; Lerner et al., 2012a, 2012b; Miller, 2016; Rolls et al., 2013).

Normalized accumulator models and spreading activation on semantic networks.

Despite the great influence of spreading activation models on how researchers think about the dynamics of semantic processing (Collins and Loftus, 1975; McNamara, 2005; Siew, 2019; Siew et al., 2019) and abnormalities in semantic cognition (Kuperberg, 2010; Moritz et al., 2001; Pomarol-Clotet et al., 2008), it is usually used as a metaphor rather than a proper model accounting for quantitative results. Although the seminal Collins and Loftus (1975) paper has already acknowledged the importance of accounting for the fact that semantic search is slower when there are more response alternatives, because this paper focused on qualitative predictions, it offered no mechanism to ensure that this effect of competition does not lead to excessive, unrealistic slowness. Even with parallel spread of activation, the assumption that the amount of activation spread from different cues is constant predicts inefficiency, in the sense of overly slow associations, under high competition. Our results highlight the critical role of stochasticity (within or between trials) in the rate at which activation spreads in preventing such inefficiency.

It is important to note that such stochasticity (in addition to start-point variability allowing for occasional `fast weak associations`) is not merely a technical necessity. Rather, it has profound effect on what association will be reported, and this effect interacts with other properties of the underlying architecture. This is demonstrated in Figure 13, which depicts the probabilities for different associations to the word ‘Where’ when considering only basic (individual-level) associative strength without variability (Figure 13A), compared with the cases in which variability in accumulation rate (and start-points) is considered without (Figure 13B) or with (Figure 13C) AS-modulated bias. Evidently, the predicted probability that this participant will produce weak associations, whether common (e.g., ‘how’) or idiosyncratic (e.g., IDS1), is increased by variability in the process (Figure 13B) but is balanced by allowing stronger associations require less evidence (Figure 13C). Thus, as explained above, whereas the process variability allowing normalized accumulator models to select efficiently among myriad associations can overly increase the prospects of weak association, AS-modulated bias can help balance this effect.

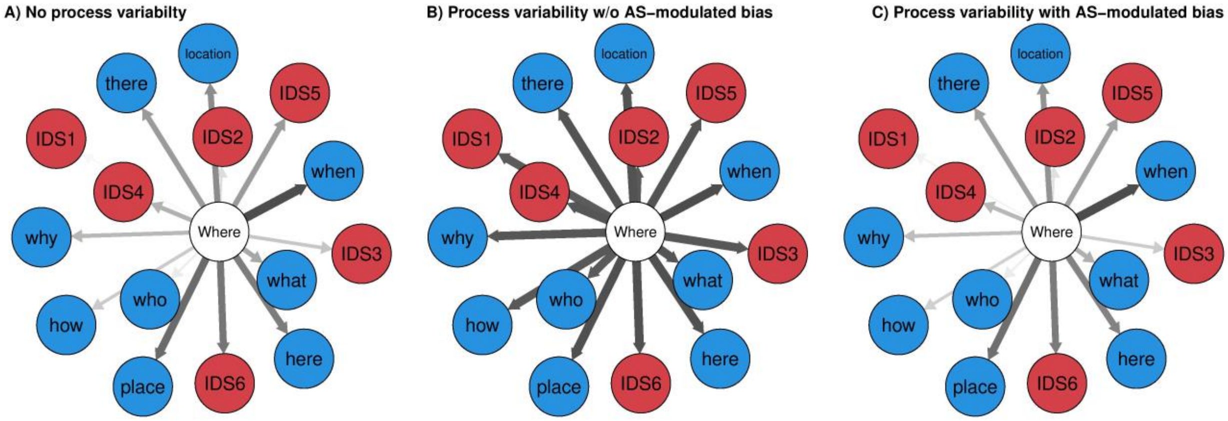

Figure 13 – Probability of producing different common (blue circles) or idiosyncratic (red circles, denoted by IDS) associations to the cue ‘Where’, when considering associative strength without variability in the selection process (Panel A), with variability but no AS-modulated bias (Panel B), or with variability and AS-modulated bias (Panel C).

This illustration shows how blurry the boundary between semantic structure and process can be when relying solely on the associations participants produce (Jones et al., 2015). In other words, a participant could produce an association that appears objectively weak either because her associative structure is different (in which case she will judge her own association to be strong), because of natural variability in the process, or due to differences in parameters governing the process. Of course, the idea that the probability with which different associations are produced is not affected solely by structural associative strength is not unique to normalized accumulator models (although the exact effect might vary, e.g., AS-modulated bias will have a negligible effect on choice probabilities in the MVP). We chose to illustrate this idea here because of the close correspondence between normalized accumulator models and the idea of spreading activation on semantic network. By integrating information regarding subjective associative strength, produced associations, and reaction times, the framework we presented here allows to dissociate these causes. More generally, this shows that a single semantic network diagram may conceal several distinct factors, perhaps suggesting a need for alternative graphical representation of semantic networks.

Indeed, the ability to integrate responses and RTs in a process model can contribute not only to highlighting dissociations between an association’s associative strength and its probability, but also to obtain better-tuned estimates of associative strength. Taking one step towards this goal, here we found that adding a flexible mapping between estimated and latent associative strength ubiquitously improved model fit. A critical question for future research is whether the resulting latent associative strength could improve the prediction of external variables that were not used in the fitting process itself (e.g., neural signals for semantic prediction error).

Implications for evidence accumulation in other domains

The current paper investigated the accumulation of evidence for an unprecedently high number of response alternatives. Whereas different evidence accumulation models are often capable of mimicking each other (Evans and Wagenmakers, 2020), our findings show that testing models on decision problems with a high numbers of response alternatives can identify failures to account for data even in models previously shown to perform well in a wide range of tasks and situations. Indeed, a particularly surprising result was the inability of advantage models, recently shown to perform well in perceptual and value-based decision making (Miletić et al., 2021; van Ravenzwaaij et al., 2020), to account for key aspects of the data. Specifically, we found that given exceptionally large numbers of response alternatives, advantage models are either overly slow or overly fast in trials with high competition among associations, and become less likely to produce weak associations, in contrast to what the data suggest. This is unfortunate because advantage models have unique strengths allowing them to more naturally account for the effects of absolute associative strength, and even to approximate how similarity among associations might lead to mutual facilitation or inhibition. Thus, we believe that improving upon the present limitations of these models may prove particularly fruitful for understanding these important processes.

Our findings suggest that the decision rule used to determine how the advantage accumulators are aggregated plays a crucial role in the misfit of these models. Indeed, whereas the basic idea that evidence accumulation is represented by relative advantage is well-established for two-choice tasks (Mazurek et al., 2003; Ratcliff et al., 2016), a key question is how such advantages could be represented in multiple-choice. Our results demonstrate the limitations of previously developed (though never directly compared, hitherto) decision rules, and highlights the need for more subtle decision rules. For example, requiring that an association only wins a subset of the other associations, or some other combination of loses and wins might help solve the key problem of advantage models in selecting among many options. However, such combinatory rules can become extremely complicated and computationally expensive. For example, a decision rule in which the first association out of 100 to win 50 competitions requires the calculation of $\binom{100}{50}$ different combinations. Thus, although our findings offer a strategy for improving advantage models for the case of myriad alternatives, we leave the solution to future research.

Another influential model that can, in principle, account for absolute and relative strength, while incorporating rich-get-richer dynamics is the Leaky Competing Accumulator (LCA; Usher and McClelland, 2001). Whereas the ability to fit the LCA to trial-level data while maintaining identifiability is debated (Miletić et al., 2017), future studies could examine the potential contribution of the LCA to understanding the mechanisms underlying free association.

One of the key contributions of this paper concerns the importance of allowing stronger associations to require less evidence in modeling free association. This mechanism was supported both by formal model fitting, and by analyses delineating its critical, yet distinct computational roles under rich-get-richer dynamics and parallel distribution of evidence. Theoretically, this assumption highlights an idea, common in semantic priming literature, that processing the cue already primes certain associations, even before the actual race between them starts. Our results suggest that AS-modulated bias improves fit whether this bias depended on relative or absolute associative strength, although a small advantage was found in favor of the former. This benefit of relative strength is somewhat surprising since, intuitively, a cue with mostly strong associations should have led to greater bias than a cue with mostly weak associations. Interestingly, semantic priming was previously suggested to depend on relative rather than absolute strength (Anaki and Henik, 2003), although whether this is compatible with feature overlap remains unclear. Future studies could further examine this question, while further investigating different types of relative strength (e.g., min-max normalization used here to parameterize AS-modulated bias vs. divisive normalization).

It is important to re-iterate that the implied dependency between accumulators' rate and their bias only makes sense because the same cue can both prime certain associations and affect the accumulation of internal evidence for the same associations (in contrast to most perceptual decision-making, and semantic priming tasks, where biases/priming and evidence are independently controlled by the experimenter). One intriguing question is whether this dependency applies to other tasks involving internally-generated responses to a given cue. For example, semantic similarity is assumed to play a role in other memory tasks, such as free recall (Kahana et al., 2008; Polyn et al., 2009), but so far, this effect of semantic similarity on RTs has been assumed to be fully contingent on its effect on choice probabilities (Polyn et al. 2009). As we demonstrated, a similarity-modulated bias could result in partial independence between choice and RT, especially if rich-get-richer dynamics are also involved. In principle, the effect of greater representational overlap on bias could also be relevant to non-semantic tasks and models employing distributed representations. For example, the seminal exemplar-based random walk model (Nosofsky and Palmeri, 1997) assumes that the categorization of an item is based on a repeated retrieval of exemplars from each category, wherein the degree of similarity between the features of an exemplar and the features of the probe item determine the probability and speed of its retrieval. Our results suggest that more similar exemplars may be quicker either because evidence in their favor accumulates more quickly and/or because they require less evidence.

An important characteristic of such feature-based models of similarity or decision making is the weighting of features based on an attention mechanism (Ashby and Perrin, 1988; Busemeyer and Townsend, 1993; Nosofsky and Palmeri, 1997; Nosofsky, 1986; Roe et al., 2001). Such feature-based attention can prove highly relevant for the ability of distributed representation models of free association to account for the context-sensitivity of free association. For example, cueing geographical proximity could make one associate `UK` with `France`, whereas cueing language will make the associations `US` or `Australia` more likely. Such modulation might prove critical for understanding how cues or associations activated in previous trials affect the associations of a current trial. Whereas our current methods for delineating associative strength or modeling choice-RT data do not account for these phenomena, future extensions of our approach could implement feature-based attention by placing weights on features in the computation of associative strength or decision threshold.

Implications for studying individual differences in associative dynamics

A considerable amount of previous research on free association attempted to leverage this task to study individual differences in thought processes, whether these relate to psychiatric conditions or to creativity. However, with a few exceptions (Lerner et al., 2012a; Prabhakaran et al., 2014; Snyder et al., 2010), most research has focused on reported associations while overlooking RTs. The models analyzed in the current study not only highlight the importance of considering RTs, but also allow to recover the latent cognitive processes underlying choice-RT behavioral data at the individual level.

There is a long history of using free associations in psychiatry (Freud, 2013; Jung, 1910; Rapaport et al., 1946). Numerous early studies attempted to characterize anxiety and depression using different measures obtained from free associations (Bodin and Geer, 1965; Brody and Peterson, 1967; Brody, 1964; W. P. Brown, 1970; Goldstein, 1961; Hundal and Upmanyu, 1974; Kuntz, 1974; Sarason, 1959). Unfortunately, the results of these studies are highly inconsistent. However, a more recent study has shown an intriguing relationship between anxiety and a greater slowing effects of competition on RTs, which can be explained by general indecisiveness and decreased GABAergic function (Snyder et al., 2010). The current work allows to further extend this intriguing line of research by examining the relationship between anxiety and model parameters controlling the effect of competition on RT (e.g., the parameter controlling rich-get-richer dynamics in the MVP)

Loosening of associations is sometimes described as a hallmark feature of schizophrenia (Bleuler, 1950), often characterized by a disruption in the form, rate, or organization of thought or speech (Kircher et al., 2018). The free association task can be used as a micro-scale model to study such *formal thought disorder*. A few studies have reported that patients with schizophrenia tend to provide more atypical and weakly-related associations (Elvevåg et al., 2007; Johnson and Shean, 1993; Pauselli et al., 2018), yet no previous study has examined RTs, let alone the dynamic process that jointly governs association choice and speed. Furthermore, whereas our findings clearly show the importance of probing subjective estimates of associative strength, most previous studies reporting loose associations in schizophrenia have relied on population-based measures (Elvevåg et al., 2007; Pauselli et al., 2018). Thus, whether the process of generating associations or thoughts would still appear different in schizophrenia once subjective AS are accounted for remains an open question.

The importance of considering idiosyncratic associations and subjective associative strength may also apply to creativity research. Whereas recent studies have shown a remarkable relationship between creativity and the ability to produce less obvious associations, most of these studies used population-based similarity measures to define how obvious vs. creative an association is (Benedek et al., 2012; Gray et al., 2019; Kenett and Austerweil, 2016; Olson et al., 2021). Our results highlight the potential of further increasing predictive power by focusing on subjective similarity ratings. Furthermore, our findings illustrate the importance of distinguishing between weak and unconventional associations. Thus, whether subjectively strong, yet unconventional associations should be considered creative or obvious is an important theoretical question.

Furthermore, whereas the creative processes involved in generating a single association have been studied before, RTs have rarely been examined. The few studies that did examine RTs have suggested faster responses among more creative individuals (Benedek and Neubauer, 2013). However, whether this is caused by a non-specific increase in processing rate, or by a specific aspect of the process of generating an association, is unknown. The evidence accumulation models developed here provide a straightforward way to examine this question, since they are focused on dissociating the contribution of different, interacting factors to RTs in free association. Thus, for example, faster responses could be differentially explained by either greater absolute associative strength or different competition dynamics (e.g., stronger rich-get-richer dynamics causing both faster and more diverse responses).

Limitations and Future Directions

The evidence accumulation models we used could not account for several possible processes that might be involved in free association. First, as mentioned above, the models we used did not account for the relationships among competing associations. Whereas the architecture of advantage models might allow to account for this effect, this might first require obtaining reliable estimates of the subjective similarity between associations, using a different method for estimating associative spaces (e.g., sampling extensively within individuals; Morais et al., 2013; Wulff et al., 2022). In this regard, an intriguing challenge for future modeling efforts is that the similarity between associations might vary as a function of a cue. For example, the associations `cat` and `dog` are probably more co-related in response to cue `pet` than in response to the cue `tail`, and this differential covariation might be modulated by attention weights. It is also worth mentioning several recent evidence accumulation models allowing to represent the associations' co-relatedness by varying the geometry of the response thresholds (e.g., co-related associations could be represented by closer points in a circular response threshold; Kvam and Turner, 2021; Kvam, 2019; Smith et al., 2020). Our method for estimating association spaces (which estimates the number and strength of possible associations but does not identify the actual words) also did not allow us to address other known contributors to associative strength, including orthographic and phonological similarity, as well as certain characteristics of the cue and the association, such as the general frequency of each possible association, independent of the cue – a particularly strong predictor in previous studies (Nelson et al. 2005; Matusevych and Stevenson 2017).

Regardless of these limitations of our method for delineating the space of possible associations, an intriguing question is whether this space can be assumed finite. Interestingly, the Chinese Restaurant Process (Gershman and Blei, 2012), can be conceptualized as an extension of the Pólya urn scheme (used in the MVP) to a potentially infinite space of response alternatives. Thus, it shares the basic rich-get-richer mechanism but allows for balls of a new color (that do not yet appear in the urn) to be inserted into the urn – an event that increases the probability of this new color to be sampled in subsequent steps. This highlights a similarity between the rich-get-richer processes involved in generating associations and the principle of ‘preferential attachment’ proposed to govern their development (Steyvers and Tenenbaum, 2005). Relatedly, in a recent study we have found that generating an association increases its strength (making it more likely to recur), and that this increase is subject to experimental manipulations (Fradkin and Eldar, 2022). A fascinating question for future research is whether stronger rich-get-richer dynamics in the generation of an association cause an even greater increase in the probability that this association will recur in the future.

Finally, whereas this study has focused on free association, the methodological developments and theoretical discoveries it produced can be extended to studying other types of unrestricted memory recall. The key property of the free association task – the vast, partially covert spaces of alternatives from which memories are sampled, is shared by many different types of unrestricted memory recall we encounter in our day-to-day life. For example, using the insights developed here to formalize unrestricted episodic and prospective memory tasks, wherein the space of possible memories to recall is vast and primarily covert, can be an intriguing endeavor. Similarly, some of the methods developed here might be relevant for other relatively unrestricted memory tasks, such as fluency tasks (Abbott et al., 2015; Hills et al., 2012). Indeed, the idea that the flow of associations stands at the core of our stream of thought has been engaging researchers since the seminal work of William James (1890) and continues to inspire prominent models of human thinking (Bar, 2007; Gray et al., 2019; Miller, 2016; Rabinovich et al., 2008).

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