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An accumulator model of semantic interference

Action editor: Andrea Stocco

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Abstract

To explain latency effects in picture-word interference tasks, cognitive models need to account for both interference and stimulus onset asynchrony (SOA) effects. As opposed to most models of picture-word interference, which model the time course during the task in a ballistic manner, the RACE model (retrieval by accumulating evidence) presented in this paper accounts for semantic interference during the interval between the retrieval onset and the actual retrieval. RACE is implemented as an extension to the ACT-R architecture of cognition. By modeling the retrieval process, RACE offers a more precise account of semantic memory retrieval latencies in different interference and SOA conditions than other ACT-R models. In this paper, we discuss the architectural assumptions underlying RACE and simulations of a picture-word interference experiment [Glaser, W. R., & Düngelhoff, F. J. (1984). The time course of picture-word interference. *Journal of Experimental Psychology: Human Perception and Performance, 10*(5), pp. 640–654.].
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Keywords: ACT-R; Cognitive architecture; Picture-word interference; Cognitive modeling; Semantic memory; RACE

1. Introduction

Often, symbolic models of cognition can be thought of as giving a stroboscopic account of cognition. By illuminating a process such as a movement with a stroboscope, the movement is sliced into discrete steps that together represent the original, continuous, movement. However, information about the movement is lost when the stroboscope does not flash, and an observer will not be aware of how the movement develops during these brief flash intervals. Similarly, symbolic models of cognition reflect a continuous cognitive process on a higher level of analysis, but on a lower level of analysis, analogous to a single flash of the stroboscope, these models provide a discrete account of that process. In most cases, interpreting the higher level of analysis as a continuous process is sufficient for understanding cognitive functioning, but in some tasks, the underlying discrete account might provide a misinterpretation of the process.

As a general example of such a task, consider the way retrieval of memory chunks is modeled in the ACT-R architecture of cognition (Anderson et al., 2004; Anderson & Lebiere, 1998). Retrieval latency is based on the activation of the to-be-retrieved memory chunk:

$$RT_i = Fe^{-A_i} \qquad (1)$$

Eq. (1) states that the retrieval time (RT) of a chunk (i) is inversely proportional to the exponentially scaled activation of that chunk (A_i), with F a scaling parameter. If a retrieval request is made to the declarative memory system, the activations of all chunks are compared, and the highest is selected for retrieval. The latency is calculated according to the above equation and, after the appropriate amount of time has passed, retrieval of that chunk is reported. Even if new information is presented between the retrieval request and the actual retrieval, the retrieval result and latency cannot be influenced.

However, many experiments show that information that is presented shortly before or after a target stimulus can

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influence both the timing and accuracy of the task at hand (e.g., MacLeod, 1991; Neely, 1991). In a picture-word interference task for example, participants respond slower in the picture-naming task when a distractor word is presented, even if that distractor word is presented shortly after the target stimulus.

Since ACT-R has been successfully applied to numerous memory related tasks (e.g., Anderson, Bothell, Lebiere, & Matessa, 1998; Pavlik & Anderson, 2005; Taatgen & Anderson, 2002), it should also provide an explanation of picture-word interference phenomena. However, given the ballistic nature of the way memory retrieval is currently modeled in ACT-R, the question becomes how ACT-R can be extended to include interference phenomena on very short latencies. In this paper, we will present a means to extend the ACT-R architecture of cognition to incorporate these interference effects. While we extended the memory system of ACT-R, we have made sure that the main characteristics of the tested and proven declarative memory equations were not altered. This way, we made sure that our approach towards semantic interference fits in with a broader theory of cognition, while at the same time we add a new phenomenon to the subset of cognition that ACT-R can account for.

A candidate explanation for semantic interference effects comes from the field of choice behavior modeling. In sequential sampling models of simple choice behavior, the choice between candidates is modeled by competition between candidates. Sequential sampling is based on the idea that choosing one option over the other is based on sampling of inherently noisy neural representations of these choices, until one has sampled enough evidence to be chosen (Ratcliff & Smith, 2004). The RACE (Retrieval by ACcumulating Evidence) model presented in this paper is very similar to a specific instance of sequential sampling models: The leaky competing accumulator model as discussed by Usher and McClelland (2001).

RACE is implemented using the same basic principles as the leaky competing accumulator model: (a) it consists of a set of non-linear stochastic accumulators, all of which represent one memory chunk that can be retrieved. (b) The activations of the accumulator units are increased by external input and recurrent activation, but are decreased by lateral inhibition and decay. However, the actual implementation of some aspects differs, most importantly different activation and evidence accumulator functions, both of which have been adapted to fit RACE in the ACT-R framework.

2. RACE architecture

The name RACE (Retrieval by ACcumulating Evidence) reflects both the accumulation of evidence for memory representations and the competition between memory chunks during retrieval: The comparison with a race between chunks seems appropriate in this respect.

The activation levels of memory chunks in RACE consist of two components: A long-term component that governs the global activation of chunks and a short-term component that comes into play during the retrieval process. The long-term component is represented by the ACT-R base-level activation equation (Anderson et al., 2004):[1]

$$B_i = \ln \left(\sum_{j=1}^{n} t_j^{-d} \right) \tag{2}$$

where t_j is the time since the jth presentation of a memory chunk and d is the parameter that controls decay, which is fixed at 0.5, as is common practice for ACT-R models (Anderson et al., 2004). The idea is that memory decays over time unless attention is shifted to a memory chunk and its activation is strengthened.

RACE's short-term component, called accumulated activation (C_i, to avoid confusion with the general symbol for activation A_i used in ACT-R), is continuously computed from the moment that a request for retrieval of a chunk is made. The accumulated activation of chunks changes as a consequence of positive and negative influences from other chunks. Chunks from the same chunk type inhibit each other, thereby competing for accumulated activation increase. Chunks of different chunk types excitate each other, spreading their activation in the classical sense (Collins & Loftus, 1975). Thus, by continuously updating positive and negative spreading-activation, some chunks may reach a level of activation at which retrieval can take place.

The accumulated activation can be described as a system of two dependent equations (Eqs. 3 and 4 presented below). As stated earlier, these equations incorporate the basic assumptions of Usher and McClelland (2001), but are adapted to fit in the ACT-R framework.

$$E_i^k(t) = \sum_{j \notin k} e^{A_j(t-1)} S_{ji} - \sum_{l \notin k} e^{A_l(t-1)} S_{li} \tag{3}$$

The system functions as follows: At every time step, positive associative values (reflected by the first term of Eq. (3)) and negative associative values (second term of Eq. (3)) towards a memory chunk are computed, and the difference is calculated. This is called the net evidence ($E_i^k(t)$) of chunk i of chunk type k at a certain time t. Since relative – not absolute – activation values are what count in ACT-R, an exponential scaling is applied to calculate net evidence. Also, both positive and negative associative values are weighted by the associative strengths (S_{ji} and S_{li}) that exist between sources of activation and the chunk i. There are two types of sources of activation in RACE: Chunks (l in Eq. (3)) of the same chunk type (k) spread negative activation to each other, while chunks (j) of different types spread

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[1] Note that Eq. (2) has been critized by Kennedy and Trafton (this issue). See also Petrov (2006) for an alternative approach to long-term learning in ACT-R.

positive activation. This is analogous to neurobiological findings from which it is clear that lateral inhibition between cortical representations of visual stimuli (Kastner, De Weerd, Desimone, & Ungerleider, 1998) as well as excitatory projections to other cortical layers (Callaway, 1998) exist. Note that most ACT-R models do not place constraints on the functional role of chunk types (although it does play a role in production compilation, Taatgen, 2005).

$$C_i(t) = C_i(t-1) + e^{\beta E_i(t) - 1} - d^{acc} \cdot \ln T \qquad (4)$$

At each point in time, the net evidence determines the accumulated activation growth (Eq. 4). Accumulated activation increases exponentially according to the amount of net evidence and a scaling factor β. If net evidence is negative (that is, more inhibition than excitation), then growth is negative. At all time steps, evidence decays with $d^{acc} \cdot \ln T$ (represented by the second term of (Eq. (4))), in which T is the time since the start of the accumulation and d^{acc} a decay parameter. This way, accumulation decay in RACE resembles decay in the ACT-R optimized learning equation (Anderson & Lebiere, 1998; Petrov, 2006).

The activation of a chunk at any time is the sum of base-level and accumulated activation, plus a small normally distributed noise sample. A chunk is retrieved if this total activation crosses the accumulation threshold.[2] The retrieval latency is defined as the time between the retrieval request and the time that the total activation of a matching chunk reaches this accumulation threshold.

If no evidence is sampled, accumulated activation decreases, because of decay. Therefore, continuous evidence-based positive reinforcement is necessary for successful retrieval, and absence of positive evidence results in prolonged retrieval latencies or retrieval failures.

3. Picture-word interference

One of the most well-known experimental paradigms in cognitive psychology is the Stroop-task (Dyer, 1973; Stroop, 1935), where, in the original setup, participants have to either name the color a word is written in, or read the word, which is always a color name. It turns out that naming the color is much more difficult than reading the word – especially if color and word of a single stimulus do not correspond – as is reflected in increased reaction times and decreased accuracy in the color naming condition. The Stroop-task can be regarded as an instance of a more general class of experiments that demonstrate interference effects in various naming tasks between pictorial stimuli and word-form stimuli. These experiments are generally called picture-word interference experiments (Glaser

& Düngelhoff, 1984; MacLeod, 1991). In the case of the Stroop-task, the pictorial stimulus is the word color.

We tested the RACE model in a picture-word interference task, using two tasks and four different conditions, similar to the experimental setup by Glaser and Düngelhoff (1984, Experiment 1). One task consisted of reading a word (target stimulus) while a picture is presented as distractor; the other task consisted of naming the depicted item (target stimulus), while a word is presented (distractor). In both tasks, the distractors were presented at different SOAs (Stimulus Onset Asynchronies). If a distractor was presented at a negative SOA, it was presented before the target stimulus. At positive SOAs, the distractor was presented after the target stimulus. Fig. 1 presents stimuli examples of the different conditions. The first condition (Fig. 1a) was one in which both target and distractor stimulus refer to the same concept. This is referred to as the concept-congruent condition. In two other conditions, target and distractor stimulus refer to different concepts. In the category-congruent condition the concepts belong to the same semantic category (e.g., a picture of a house and the word church were presented, Fig. 1b), in the incongruent condition the concepts do not belong to the same semantic category (e.g., a picture of a house versus the word cat, Fig. 1c). In the neutral condition the target stimuli were accompanied by non-word or non-picture distractors, respectively, to minimize the amount of processing of the distractor stimulus (Fig. 1d and e).

Glaser and Düngelhoff (1984) found that interference is highest in the category-congruent condition, which is known as the semantic gradient effect. They also showed facilitation in the concept-congruent condition, meaning that latency is decreased when both target and distractor stimuli refer to the same concept. A third effect they report is a clear asymmetry between the picture-naming task and the word reading task. The semantic gradient and facilitatory effect virtually disappear in the word-reading task, but they are prominent in the picture-naming task.
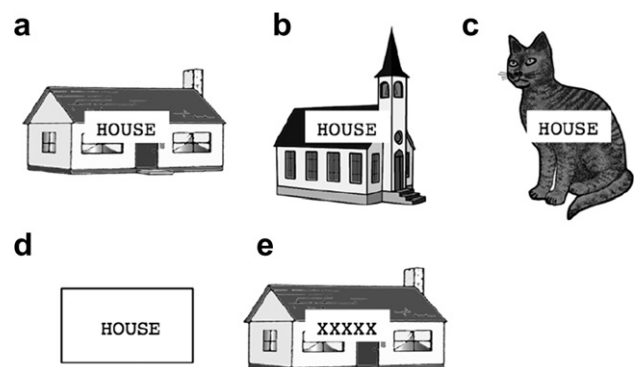

Fig. 1. Example stimuli. (a) concept-congruent condition, (b) category-congruent condition, (c) incongruent condition, (d) neutral condition in word-reading, (e) neutral condition in picture-naming. The example images are taken from the image set by Rossion and Pourtois (2004).

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[2] The accumulation threshold is a different concept from the retrieval threshold in default ACT-R. Where the retrieval threshold determines the minimum activation at which a chunk *may be* retrieved, the accumulation threshold determines the amount of activation at which a chunk is retrieved.

4. Picture-word interference model

We will begin our discussion of the picture-word interference model with a review of the WEAVER++ model of speech production (Levelt, Roelofs, & Meyer, 1999). WEAVER++ is similar to RACE in some ways, but lacks the integration in a cognitive architecture that we provide. WEAVER++ has a similar memory structure as RACE, and a similar activation accumulation mechanism as RACE. In WEAVER++ however, it remains unclear how the model is connected with other aspects of cognition besides language production. Although WEAVER++ and previous versions of that theory have been demonstrated to fit an impressive number of data sets (e.g., Levelt et al., 1999; Roelofs, 1992, 1997, 2003), it lacks a unified account of cognition, that for instance ACT-R does provide. RACE's integration in the ACT-R framework ensures that our account can be naturally integrated in models of other aspects of cognition. One example of this is the subliminal priming model described by Van Maanen and Van Rijn (2007).

Word production in WEAVER++ goes through a sequence of stages, one of which is the retrieval of the to-be-spoken word from semantic memory. In WEAVER++ this response selection stage (choosing a lemma) is followed by response programming and execution stages. Since our focus has been on the retrieval process, these vocalization aspects of the task are not included in our model of picture-word interference. The RACE mechanism is similar to the mechanism proposed for the lexical selection stage in WEAVER++ (Roelofs, 1992).

The lexical processing stage from WEAVER++ is modeled as follows: A network of conceptual nodes is connected to a network of lemma nodes. The conceptual nodes convey meanings, and are connected with labeled links. For instance, The concept DOG(X) represents the meaning of the noun dog, and has a labeled connection of the type IS-A to the concept node ANIMAL(X), indicating that a dog is an animal (Roelofs, 1992). The nodes in the lemma network represent the syntactical dependencies of the concept nodes. Each lemma node has a labeled SENSE link to the corresponding concept node, labeled links to syntactic properties – grammatical gender, syntactic category. The links between concept nodes and between concept and lemma nodes differ in their connection strength, indicating a difference in accessibility. Via a spreading-activation mechanism, activation of one node influences activation of neighboring nodes. Activation is also mediated by decay.

If the ratio of the activation of one lemma node against the activations of the others exceeds a predefined (relative) criterion, selection of that lemma node takes place, and WEAVER++ will proceed with the retrieval of the morpho-phonological properties of that lemma.

Analogous to WEAVER++, our model of picture-word interference comprises three chunk types (Fig. 2): Icons, lemmas, and concepts. The concept chunks can be
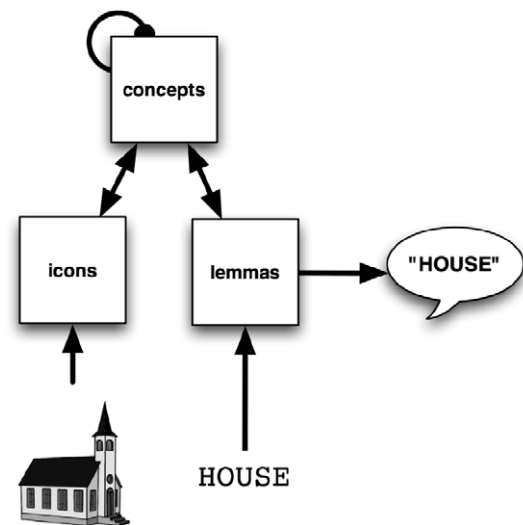

Fig. 2. Processing route for pictures and words in the picture-word interference model. The route for words is shorter, since words do not require concept retrieval. Interference takes place between concept type chunks.

regarded as representations of semantic properties. Chunks of the icon type represent iconographic instances of the stimuli. This might be similar to Roelofs' (1992) object-form memory store. Chunks of the lemma type can be regarded as sets of both orthographic and syntactic properties of a word. Note that this is a simplification of Roelofs' (1992) model, in which the response selection stage (choosing a lemma) is followed by response programming and execution stages. Since our focus is on the retrieval process, these vocalization aspects of the task are not included in our model of picture-word interference.

Positive activation is spread between chunks of different types. That is, icons spread to concepts and vice versa, and lemmas spread to concepts and vice versa. As in Roelofs' (1992) model, no direct spreading-activation was allowed between lemmas and icons. The concept chunks also have negative associations between them and spread negative activation to each other.

At different SOAs, distractor stimuli were presented to the model, except in the neutral condition in which only a target stimulus was presented. We tested the same four conditions as Glaser and Düngelhoff (1984) did. The only deviation from the original experiment was the neutral condition: Glaser and Düngelhoff presented the participants with a non-word distractor and a non-picture distractor respectively in the picture-naming and word-reading neutral condition. As said, these were chosen in such a way as to minimize the amount of picture or word processing as possible. Assuming a successful operationalization by Glaser and Düngelhoff, we simulated this condition by not presenting a distractor in the neutral conditions.

In the concept-congruent condition, the distractor consisted of a word stimulus referring to the same concept as the target, but of a different stimulus type (as in Fig. 1a). When activation spreads through the model, both distrac-

tor and target activate the same chunks, but not in the same order. The word will activate its associated lemma directly, whereas the picture will first activate the associated icon and concept chunks. In the category-congruent condition and the incongruent condition, the distractor and the target refer to different concepts. However, in the category-congruent condition, associations between chunks representing these concepts exist, reflecting the fact that the target and distractor stimuli belong to the same semantic category.

The distractors were presented at SOA times relative to the onset of the target stimulus of $-400, -300, -200, -100, 0, +100, +200, +300,$ and $+400$ ms, similar to the original Glaser and Düngelhoff experiment. The stimuli presentations were modeled as a fixed increase in activation of the lemma or icon type chunks during the period that a stimulus was presented.

Since the task was a verbalization of either the picture name or the word, a trial was finished when the stimulus-designated lemma was retrieved or after two seconds, indicating a retrieval failure.

In the picture-naming task, the model predicts the following behavior: In the concept-congruent condition with negative SOAs, a distractor word is presented before the target picture. The word activates a lemma chunk, which increases the activation of the associated concept chunks, but inhibits the activation increase of other lemma chunks. The higher activation of the concept chunks increases the activation of the associated icon chunks. Thus, after the distractor is presented, all chunks that are involved in naming the picture (one icon, one concept, and one lemma chunk) have an increased activation. When the target is presented, all concept-congruent chunks have a higher activation as compared to the stimulus onset in the neutral condition, and thus a shorter retrieval latency. In the concept-congruent condition with positive SOAs, the same process occurs, but to a lesser extent since the distractor lemma's activation has less time to influence the activation of the target lemma before it is retrieved: The picture has already increased the target lemma's activation before the word is presented.

In the incongruent and category-congruent conditions (both at negative and positive SOAs), the activation of the chunks that are activated by the distractor interferes with the activation of the chunks that are activated by the target, because the target and the distractor stimulus activate different sets of chunks.

5. Results

Fig. 3 summarizes the results of our simulation studies.[3] The figure represents the latency differences in different conditions relative to the neutral condition. Since the focus

of our model is on the retrieval part of the picture-naming and word-reading tasks, we can compare the latency differences between the different conditions from the model to the data. The observed latencies from the data set also comprise timing effects from other subtasks, such as pronunciation or perceptual encoding.

Negative values in Fig. 3 indicate faster retrievals than in the neutral condition, and positive values indicate slower retrieval than in the neutral condition. The qualitative effects observed in Glaser and Düngelhoff (1984, Experiment 1) can be seen in the predicted latency differences from the RACE model. The semantic gradient effect can be observed by noting the different relative latencies of the category-congruent and incongruent conditions. The higher latencies in the category-congruent condition compared to the incongruent condition indicate that higher associations between concepts result in stronger inhibition.

The facilitatory effect in the picture-naming task is also apparent, although the effect appears to be too large. Our explanation for this increased effect is that the activation of the target lemma chunk is too high when the target stimulus is presented, probably caused by too little decay after the previous retrieval initiated by the distractor stimulus. Another consideration might be that the base-level activation goes to near infinity directly following a retrieval, thus causing too much increase in activation of the target lemma chunk. This may also explain the observed effect in the simulation of the word-reading task. Thus, it seems that the base-level activation may not be a good measure of the level of activation of a chunk at these short time intervals. Because RACE is intended as an extension of the ACT-R framework, it did not seem appropriate to change the way in which the global, long-term activation is computed.

When comparing the differences between the two simulated tasks (picture-naming and word-reading), the asymmetry observed by Glaser and Düngelhoff is also shown by RACE. We explain this asymmetry by two effects: The shorter processing route and the faster encoding of word type stimuli. As (Glaser & Glaser, 1989; La Heij, Happel, & Mulder, 1990; Roelofs, 1992) noted, pronouncing words does not require retrieving a concept from memory, therefore processing word type stimuli can be much faster than processing pictorial stimuli. In Fig. 2 it can be seen that the route in our model from a picture to the associated lemma is much longer than from the word to the associated lemma: Two intermediate steps have to be taken (that is, processing of icon chunks and processing of concept chunks), before the lemma chunk is retrieved. Thus, potentially interfering pictures do not activate lemma chunks before the target lemma is retrieved. Only at high negative SOAs an effect can be seen (Fig. 3), because under that condition there is enough time for the distractor stimulus to activate the inhibiting distractor lemma and interfere with retrieval of the target lemma.

A difference in encoding speed is incorporated to account for the observation that word recognition is an automated process and picture recognition is not. Without

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[3] An R implementation of RACE and the picture-word interference model can be retrieved from http://www.ai.rug.nl/~leendert/RACE.html.
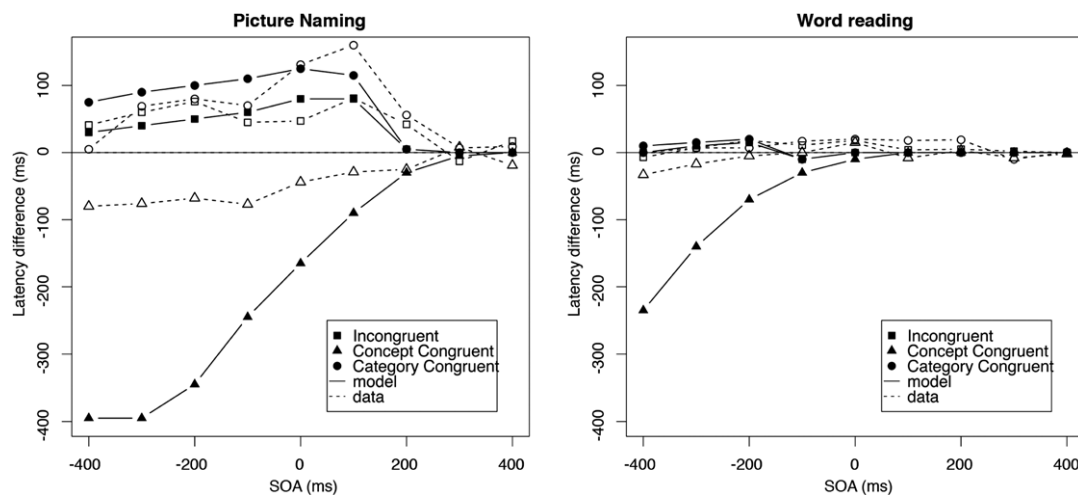
Fig. 3. Simulation results and experimental data (Glaser & Düngelhoff, 1984, Experiment 1), for the picture-naming task and the word-reading task.

this difference, the model processes pictures nearly as fast as words, and picture-naming in the incongruent condition is as fast as in the neutral condition. The faster encoding of words reinforces the effect that the lemma associated with a word is processed before the lemma associated with the picture stimulus is retrieved.

6. Discussion

We have shown that a sequential sampling model can account for the time course of memory retrieval during asynchronously presented stimuli. This is an extension of the results from Usher and McClelland (2001) in which they only investigated accumulators with equal onset times. Moreover, RACE can be regarded as an extension of the ACT-R theory of cognition. It combines the long-term base-level activation equation of ACT-R with a short-term accumulated activation used for retrieval. RACE replaces the retrieval mechanism in ACT-R represented by Eq. (1).

The general fit of our model of picture-word interference is quite reasonable, thereby indicating that the RACE equations can provide for semantic interference effect in memory retrieval. Retrieval in the concept-congruent condition seems to be too fast, however. We hypothesize that this is a result of the way we modeled the global, long-term activation component, namely by using ACT-R's base-level activation equation. Because in the concept-congruent condition the target and distractor stimuli both refer to the same chunks, retrieval of these chunks – caused by the distractor stimulus – increases their base-level activations. The high activation of these chunks will result in a very short latency for the retrieval caused by the target stimulus. It seems that the base-level activation equation is a better predictor of activation at slightly larger time scales, when the retrievals are more spaced. This is supported by the observation that retrievals in most ACT-R models are temporally more separated than ~100 ms. Further research in the interaction between the base-level activation and accu-

mulated activation seems necessary to correct for the fast retrievals in the concept-congruent condition.

Also, our model accounts for facilitatory effects. In line with the findings from Glaser and Düngelhoff (1984), RACE predicts that semantic facilitation occurs if target and distractor both refer to the same concept.

In the past, ACT-R models of semantic interference effects have been proposed (Altmann & Davidson, 2001; Lovett, 2002, 2005). The WACT model (Altmann & Davidson, 2001) seems similar to RACE at first sight, since it combines ACT-R with insights from the WEAVER++ model. However, WACT describes retrieval in a Stroop-task as ballistic, but with a retry-mechanism that checks if a retrieved lemma chunk matches already retrieved conceptual information; If not, retrieval is retried. Thus, WACT accounts for inhibitory effects by multiple retrievals caused by retrieval failures. As such, WACT is a perfect example of a stroboscopic account of cognition. Retrieval latency for one trial can be the latency associated to one retrieval attempt, or two retrieval attempts, or many, but nothing in between. Therefore, the distribution of reaction times predicted by WACT is clustered around the time it takes for one or multiple retrieval attempts. This does not correspond with the general assumption that participants' reaction times in the Stroop-task are unimodally distributed (Heathcote, Popiel, & Mewhort, 1991).

NJAMOS (Lovett, 2002, 2005) is an ACT-R model of the Stroop-task that theorizes that the Stroop effects are due to utility differences in the production rules for word and picture recognition. In the model, a general production rule is assumed that fires if a stimulus is present that has some word-like qualities, irrespective of the current task (color naming or reading). In addition, a more specific production rule is assumed that only fires if the task is color naming. The second rule has a lower utility than the first, meaning that the system has a preference to execute the first rule over the second. Therefore, in most cases (because of noise over the utility values), the second rule will only be

selected after the first production has fired. In those cases the first rule has not completed the task successfully, because the task was color naming, not word-reading. The second rule thus has to fire to complete the task. This two-step procedure for color naming is intended to explain the Stroop asynchrony between reading and color naming.

If the color and the word are congruent, the chunk that encodes the word-like features of the stimulus spreads activation to the chunk that encodes the color information. The activation of that chunk will increase, resulting in the facilitatory effect at negative SOAs. In the incongruent condition, negative spreading-activation is introduced to explain the interference effects.[4]

At small positive SOAs (e.g., +100 ms), NJAMOS also predicts a divergence between the latencies for different conditions, although smaller than that observed in the data (Lovett, 2002). Given the ballistic retrieval latency equation of ACT-R, it seems that these latencies can only be explained by averaging over several trials. That is, either one (the general rule) or two production rules (both general and specific) will fire, resulting in a bimodal distribution of the data. Again, the distribution of the Stroop-latencies does not seem bimodal (Heathcote et al., 1991).

We suggest that not fully processed words at small positive SOAs might explain this difference between model and data. Perhaps a combination of the utility-based explanation Lovett proposes combined with RACE will produce a better fit to the data.

The picture-word interference experiment shows that the RACE model can be a useful extension of the ACT-R architecture of cognition. However, one crucial feature of RACE is not supported by the ACT-R architecture. In RACE, all chunks in declarative memory spread activation to all other chunks. ACT-R assumes that only chunks that are presently in the buffers spread their activation (Anderson et al., 2004).[5] Global spreading-activation was not included in the architecture, because it appeared that no second-order priming effect exists, indicating that spreading of activation through declarative memory was not necessary (Anderson, 1990). However, more recent evidence suggest a second-order priming effect, although very weak, that cannot be explained by assuming only first-order associations between prime and stimulus (Livesay & Burgess, 1998). Therefore, we consider this deviation of ACT-R theory reasonable.

Experiments using subliminal primes indicate that priming may also occur when a prime is not fully processed (Marcel, 1983; Merikle, Smilek, & Eastwood, 2001), which hints that priming already occurs before chunks in the buffers are fully identified. A dynamical activation mechanism such as RACE may provide accurate modeling accounts for this observation. In RACE, activation of chunks – either in the buffers or in declarative memory – always affects the activation of other chunks, even before the accumulation threshold is reached and a chunk might be retrieved. A RACE model of a subliminal priming task has been shown to account for retrieval latencies typically observed in these kinds of tasks (Van Maanen & Van Rijn, 2007).

This paper demonstrated how RACE can account for picture-word interference phenomena. We believe that RACE can account for all effects that involve semantic interference or facilitation. Using RACE, an explanation of these effects can be provided on a higher level of abstraction than connectionist modeling (as has been done for Stimulus-Response Compatibility by Grecucci, Cooper, & Rumiati (this issue), because it is integrated in a full cognitive architecture. This way, RACE combines insights from multiple levels of abstraction.

Acknowledgements

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[4] Note however that this is an undiscussed deviation from standard ACT-R, where spreading-activation is intended to be positive, because it represents the increased likelihood of needing one chunk when another chunk is present.

[5] In ACT-R 6.0, chunks in all buffers can spread activation, as opposed to ACT-R 5.0, in which only chunks in the goal buffer could be a source of activation.

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