Context effects on memory retrieval
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Results from Part I

In Part I of this thesis, a new model for retrievals from declarative memory was proposed. The model, called Retrieval by Accumulating Evidence in an Architecture (RACE/A), accounts for semantic interference effects within the constraints of the cognitive architecture ACT-R (Anderson, 2007a). By adding a sequential sampling model of declarative memory as a component to ACT-R, it becomes possible to accurately predict human behavior in tasks that involve competitive processes in memory retrieval, such as the Stroop effect (Chapter 4), picture-word interference (Chapters 2, 3.2 and 4), lexical decision (Chapter 3.1), or subliminal perception (Chapter 3.3). In addition, RACE/A demonstrates the usefulness of the architectural approach towards modeling cognition. Without RACE/A, it would have been harder to model to explain some of the effects discussed in this thesis.

One example is the interaction between stimulus repetition and semantic interference (as discussed in Chapter 2), which could not be accounted for with a single sequential sampling model. RACE/A computes the long-term activation dynamics (estimated by the history of usage of the chunks) as well as the short-term activation dynamics (estimated by a sequential sampling process). The long-term activation dynamics effectively act as a starting point of the evidence accumulation process. Because the long-term activation dynamics is determined by the ACT-R architecture, the short-term activation dynamics start at a principled of starting point. In this respect, RACE/A differs notably from the standard sequential sampling approach in which the starting point of evidence accumulation is treated as a free parameter, which is often interpreted after model fitting has taken place.

Another example is the mechanism that we proposed that may explain the differences (and similarities) between the Stroop task and the picture-word interference (PWI) task (Chapter 4). It has often been assumed that the effects observed in these tasks are caused by the same principle (MacLeod, 1991). A recent study (Dell’Acqua et al., 2007) questioned this long-standing position by presenting data from a dual-task experiment, in which the effects from a picture-word interference manipulation differed from those from a Stroop manipulation. In two experiments, we replicated and confirmed these observations, but also demonstrated that these observations could still be caused by the same underlying principle (Chapter 4). The theory put forward in this chapter is that interference in both Stroop tasks and PWI tasks is caused by competition among multiple potential memory representations. Because at multiple stages during the tasks memory retrievals take place, the interference effects can manifest at multiple stages as well. This theory could not have been modeled using traditional sequential sampling models, because the amount of competition at every stage critically depends on the duration of the stages. In Chapter 4, we showed that the amount of interference at every stage could be manipulated by adapting one single parameter, which we used to account for the difference between Stroop and PWI.

The contribution of RACE/A to the theory of declarative memory retrieval lies in the possibility to model the retrieval process on a very small time-scale. This proved to be especially useful when explaining the temporal dynamics of memory retrievals. For instance, asynchronously presented stimuli can influence the time course of memory retrievals (e.g., W. R. Glaser & Düngelhoff, 1984), which can be modeled using RACE/A (Chapter 2). Moreover, the integration of RACE/A in a cognitive architecture restricts the freedom a modeler has when trying to fit data sets. This is because RACE/A models – besides aligning with the specific
theory behind RACE/A – also have to adhere to the ACT-R central assumptions (R. P. Cooper, 2007). In particular, besides the retrieval latency equation, RACE/A does not change any of the central architectural assumptions. With respect to the retrieval latency equation, we showed (Chapter 2) that in the absence of competition during memory retrieval, RACE/A makes similar predictions as the default ACT-R retrieval latency equation. Thus, previous ACT-R models of tasks in which interference does not play a critical role are not invalidated by our extension. The combination of sequential sampling and cognitive architecture only increases the set of phenomena that can be accounted for by the architecture, while at the same time remaining true to the architecture’s central assumptions.

RESULTS FROM PART II

In Part I, we studied how the context in which a stimulus is presented influences the retrieval processes that are triggered by that stimulus. For this purpose, we studied small-scale behavioral effects and tried to explain them within the ACT-R architecture of cognition. In Part II, we have focused on the effects of a more general context on the retrieval process. With the use of cognitive models we have studied how individual contexts predict which concepts will be retrieved from memory. Based on this, we have developed information retrieval algorithms in two domains. The applications that have been developed for the domains of artwork selection and scientific literature search, the Virtual Museum Guide (VMG, Chapter 5) and the Personal Publication Assistant (Publication PA, Chapter 7) incorporate a model of the user’s memory structure, and use that to predict user preferences. That is, based on an analysis of the statistical properties of the textual environment that a user interacts with, a prediction is made about which aspects of this textual environment are more likely to be recalled in the near future. These aspects are hypothesized to be the most relevant facts for that user given the current environment and time. The Publication PA used this prediction to select scientific papers for individual researchers. The VMG used this prediction to select a sequence of artworks for individual (online) museum visitors.

In Chapter 5, we developed a software environment in which users can interact with the collection of the Amsterdam Rijksmuseum. An online version of the system was available for four months in 2007, allowing users to study the Rijksmuseum’s collection. The system can be used to test the applicability of cognitive theories for user modeling in the cultural heritage domain. Particularly, we tested an activation-based user model for the cultural heritage domain (the VMG) that is capable of inferring visitors’ interests by incorporating a model of a museum guide’s memory.

The aim of this user model was to present an interesting tour to visitors, given the VMG’s extensive knowledge on the museum’s collection, and the perceived interests from the visitors. However, the study revealed that participants were just as satisfied with an online museum guide that incorporated the participants’ feedback as with a simpler algorithm that did not take their feedback into account. One reason why the VMG did not perform better might be related to the way the participants could provide feedback during the training phase. The participants could only indicate with a button press that they liked or disliked the artwork. That is, there was no option to indicate why an artwork was liked or disliked, or which aspect of an artwork led to the decision between positive or negative feedback. In Chapter 6, we studied - in a slightly different setting - if a feedback mechanism in which point of gaze was used would lead to more appreciation of personalized information presentation. Although we did find hints that interest and gaze are related, we did not find a sufficient strong effect that could be used
Another reason why it was difficult to provide good recommendations with the VMG relates to the representation of interest in the items that are being selected. One important aspect of the cultural-heritage domain is that interesting aspects of art are not necessarily text-based. Although in the context of an art recommender for the cultural heritage domain descriptions of the cultural-historic value of an artwork may contribute a great deal to the interest a user has in that particular artwork, it may not be the only aspect. The use of certain colors, painting or crafting techniques, or a particular arrangement of figures in the scene may also contribute to the appeal a work of art may have to a user. These aspects are often not included in the descriptions of the artworks that we used in developing the VMG. In addition, these relate to the expressiveness of an artwork (Arnheim, 1954/1974), which is not easily described.

Thus, the nature of art makes it hard to determine user preferences based on cultural-historic descriptions of the art only. On the other hand, in scientific literature (Chapter 7) the interesting aspects of a paper or abstract are names, concepts, and keywords, all of which are inherently textual. Therefore, representing the interests of users of a scientific paper recommender as a network of textual features is natural. In addition, the mapping between the textual properties of the training set (in this case, the already published papers of an author) and the user’s interests is more straightforward than in the cultural heritage domain. Since the main output channel for science is written text, the expression of interest in words is natural, contrary to the cultural heritage domain. Consequently, the ramp-up problem for users (Konstan, Riedl, Borchers, & Herlocker, 1998) applies to a lesser extent, since the user’s preferences are learned faster. Informal analyses suggested that about five or six recent publications are enough to capture a scientist’s current interest.

Another reason for the difference between the cultural heritage and scientific literature domains relates to the need to explain the reasons behind certain recommendations. A study by Cramer et al. (2008) suggest that users of art recommenders prefer explanations of why a certain recommendation is given over unexplained recommendations. The issue of providing reasons for recommendations plays a less prominent role in the selection of relevant scientific publications. The selection of publications does not involve a sequence of selections, but rather one isolated selection. Therefore, providing reasons for successive recommendations is not an issue. By contrast, the selection of artworks for the purpose of an automated museum tour is by definition a sequential process, because a tour necessarily consists of multiple artworks. In the domain of scientific paper selection, we demonstrated that our approach to predicting interests works reasonably well (Chapter 7). A selection of articles that the Publication PA considered relevant for a certain researcher was rated higher on a relevance scale by that researcher than a selection of articles that the Publication PA considered irrelevant. Also, in a competition between various selection algorithms (Chapter 8), the Publication PA performed equally well as the other competitors that were were trained on the same calibration set as the Publication PA (the profiles of the users). For some users, the Publication PA outperformed the other competitors, while for other users, the Publication PA is outperformed. The competitors that were cross-validated on a subset of the possible paired comparisons of the abstracts in the data set performed better than the Publication PA. However, this only shows that if more and more suitable training data is available, performance goes up.
CONCLUSION

This thesis discussed new formal models of memory retrieval, and at the same time discusses how these kinds of models can be deployed for information selection problems. We showed that activation-based theories of declarative memory retrieval, such as a Rational Analysis of Memory can be used in information retrieval applications. This result depends on the similarities between declarative memory retrieval and information retrieval, which both can be characterized by the history of usage of certain items or relevant words. This result complements the results from Part I, in which we presented a new, activation-based, theory of declarative memory retrieval. The theory accounts for a wide range of interference related phenomena that relate to the history of usage of certain items, and the context in which they are retrieved.

The complementing findings from Part I and Part II show that theoretical cognitive science (cognitive modeling) and computer science (cognitive engineering) may be a fruitful combination in which theoretical development as well as application-based research may go hand in hand.