Chapter 4: How And Why Does Schematic Knowledge Affect Memory?

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Abstract

Beliefs have been studied across disciplines using a variety of approaches. In the human memory literature, expectations and beliefs drawn from prior knowledge are characterized and studied as schematic knowledge. In this chapter, we will discuss the role schematic knowledge plays in guiding the formation and retrieval of memories. A central focus will be placed upon understanding why retrieved memories are biased towards prior beliefs or schematic knowledge. Through a review of computational models and empirical findings, this chapter will convey that even though prior beliefs generate memory biases, these memory biases ultimately maximize the average memory accuracy – giving rise to optimal behavior. In the last section of the chapter, I will connect these modeling frameworks to more recent empirical results on the role of schematic knowledge, identifying potential future directions for updating the models and venues for conducting new experiments.

Keywords: schematic knowledge, belief, rational analysis, memory retrieval

How does the mind infer the color of a mug at a distance, parse a sentence during a conversation, or recognize a plant on a hike? These problems, solved daily, in an instant, as a matter of course share a complication: the data received by the mind underspecifies the true state of the world. In each of these situations, human cognition is solving a similar underlying computational problem: given some observed data about the world, the mind draws conclusions about the underlying process that gave rise to these data. Because the data is often limited and noisy in the real world, people must rely on their prior beliefs and expectations to facilitate their understanding of the state of external world that produced the data at hand. These beliefs come from people's prior knowledge from past experiences, which are well-calibrated to the regularities of the natural world (Huttenlocher et al., 1991; Griffiths and Tenenbaum, 2006; Brady and Oliva, 2008) and are surprisingly consistent across individuals (Hemmer and Steyvers, 2009; Steyvers and Hemmer, 2012).

Let h be a hypothesis about some physical process, such as light bouncing off a mug or a plant and hitting the retina, or a person's vocal tract producing speech sounds. Prior knowledge represents probabilistic degrees of belief in h prior to seeing the data x. Across domains of cognition, the problems the human mind needs to solve are to update these prior beliefs in light of the evidence, and to represent the posterior degrees of belief in h after seeing the data. Bayesian inference is a rational approach for solving such problems within a probabilistic framework.

As this problem recurs across sensory modalities and cognitive functions, it is unsurprising that effects of prior beliefs on cognition have been found throughout the literature. Prior knowledge has been implicated across several domains of perception and cognition, including visual perception (Eckstein et al., 2004; Epstein, 2008; Todorovic, 2010), object recognition and categorization (Torralba,2003, Galleguillos and Belongie, 2010), color perception (Mitterer and de Ruiter, 2008), as well as motor control (Nissen and Bullemer, 1987; Kording & Wolpert, 2006), parsing language (Trueswell, 1996), causal learning and inference (Steyvers, Tenenbaum, Wagenmakers, & Blum, 2003; Griffiths & Tenenbaum, 2005, 2007), and memory (Huttenlocher et al., 2000; Hemmer and Steyvers, 2009; Steyvers, Griffiths, & Dennis, 2006).

For example, in the classic experiment by Bartlett (1932), a participant is asked to memorize a drawing of an Egyptian hieroglyph–a character resembling an owl— and then to reconstruct it from memory in a new drawing. The reconstructed drawing produced by the first participant is then passed to the next, who is again asked to memorize and reconstruct it from memory. Bartlett found that after many iterations of the same process, the original drawing of the hieroglyph gradually transforms into a cat, a more culturally familiar object.

One might have expected that if the exact details in the drawing could not be reproduced precisely, after many iterations, the reproductions would grow noisier and more arbitrary. Instead, there is convergence toward some close match in participants' shared prior knowledge.

This is just one of many studies using this paradigm that demonstrate that people's memories are biased by their cultural expectations and beliefs (e.g., Kashima, 2000; Bangerter, 2000; Mesoudi, 2007). Beliefs have been studied across disciplines using a variety of approaches. In the human memory literature, expectations and beliefs drawn from prior knowledge are characterized and studied as schematic knowledge. This knowledge can be either idiosyncratic, based on one's unique experiences, or universal, shaped through common experiences in the environment.

In this chapter, we will define schematic knowledge and the role it plays in guiding the formation and retrieval of memories. Note that here we use the terms schematic knowledge and prior beliefs interchangeably. A central focus will be placed upon understanding why the human memory system is biased towards prior beliefs or schematic knowledge. Why does the Egyptian hieroglyph transfer to a cat after iterations of memory reconstruction? Through a review of computational models and empirical findings, this chapter will convey that even though prior beliefs generate memory biases, these memory biases ultimately maximize the average memory accuracy – giving rise to optimal behavior. In the last section of the chapter, we will connect these modeling frameworks to more recent empirical results on the role of schematic knowledge, identifying potential future directions for updating the models and venues for conducting new experiments.

1. Schematic Knowledge And Its Role On Episodic Memory

Expectations and beliefs drawn from prior knowledge are characterized and studied as schematic knowledge in the human memory literature. Schematic knowledge or the schema, is a form of semantic memory that refers to general knowledge about the world or a particular domain, such as knowledge about capital cities in different countries, or knowledge about what cats typically look like (McClelland et al., 1995; McClelland & Rogers, 2003; Moscovitch et al., 2005; Patterson, Nestor, & Rogers, 2007). In contrast, episodic memory refers to autobiographical experiences and events that are vivid and rich in contextual details (Tulving 1983), such as memory of a dinner conversation, or memory for particular details in the Egyptian hieroglyph drawing.

The role of schematic knowledge in episodic encoding and retrieval has long been studied in psychology (Alba and Hasher, 1983). Bartlett's pioneering work (1932) proposed that we do not store verbatim memories. Instead, our memories are reconstructed based on what we already know. Bartlett called this a schema, the general knowledge a person processes about a particular domain, which allows for encoding and retrieval of information related to that domain. Later the schema reemerged under different names such as a frame (Minsky, 1975) or a script (Schank and Abelson, 1977), which contains one's prior knowledge about the structure of a familiar event such as a restaurant visit.

Experimentally, providing participants with ways to link new information with existing schemas enhances memory. For example, retention of a target passage is better when the learners are encouraged to understand new concepts in terms of relevant existing knowledge (Ausubel and Fitzgerald, 1962; Mayer, 1979). Recent studies demonstrate that information consistent with schemas is more likely to be remembered than is schema-inconsistent information (Tse et al., 2007; van Kesteren, Rijpkema, Ruiter, & Fernández, 2013; Durrant, Cairney, McDermott, Lewis, 2015; Richter, Bays, Jeyarathnarajah, Simons, 2019), is represented differently than schema-inconsistent information (Popov et al., 2019), and is better at supporting the integration of multiple memories (van Kesteren, Krabbendam and Meeter, 2018; van Kesteren et al., 2019; Zhang et al., 2018).

However, schematic knowledge also introduces bias into the reconstruction process of episodic memory. A wide range of studies using a continuous recall paradigm has quantified the large extent to which episodic memory is biased towards schematic knowledge (Huttenlocher, Hedges, & Duncan, 1991; Huttenlocher, Hedges, & Vevea, 2010; Hemmer and Steyvers, 2009; Xu and Griffiths, 2010; Brady, Schacter, & Alvarez, 2018; Bae et al., 2015; Persaud and Hemmer, 2014; Persaud and Hemmer, 2016). Why does the human memory system demonstrate such biases?

2. Understanding Why Schematic Knowledge Affects Episodic Memory Retrieval

In this section, we will review modeling frameworks that provide a computational-level explanation of the above experimental results (Marr, 1982). A computational-level explanation accounts for behavior in terms of the goals of the organism and can provide an ecological interpretation of the role of schematic knowledge or prior beliefs on memory. We first review the framework of rational analysis and an example of its application to demonstrate the critical components of a rational analysis. Then we review a Bayesian model of reconstructive memory as an application of rational analysis that explains memory biases by considering how they give rise to optimal performance in memory recall.

2.1 Rational Analysis

The principal goal of the field of cognitive psychology has been to identify mental structures that explain observed behavior. In this pursuit, a researcher collects data on a cognitive task and attempts to infer the mental structure from the behavior it produces. This can be a challenging process, as there may be multiple proposed mental algorithms that are equivalent in their behavioral consequences (Anderson, 1991). A rational approach to cognition can alleviate this identifiability problem by placing additional constraints on the mechanistic theory (Anderson, 1990, 1991; see also Simon, 1955; Estes, 1955; Marr, 1982; Shepard, 1987, Griffiths, Lieder, & Goodman, 2015). A rational analysis is an explanation of an aspect of human behavior that is not based on observed data but instead based on the assumption that it is optimized to the structure of the environment.

A rational analysis does not only characterize the behavior but also explains why it is there in the first place. This is the same question that we asked at the beginning of the chapter: Why does the Egyptian hieroglyph transform into a cat after multiple iterations of reconstruction from memory? Early work in applying rational analysis to memory demonstrated that forgetting behavior commonly observed in lab settings is not a weakness or peculiarity of the memory system but reflects how the memory system sensibly adapts to the statistics of the environment (Anderson, 1990, 1991). We will briefly review these early results to demonstrate the critical components typically involved in a rational analysis.

The first step in a rational analysis is to specify the computational goal of the system. In memory retrieval, the goal is to search for memories that are most needed in the current situation. This goal is often a function of the architectural assumptions associated with the memory system (Schooler and Anderson, 1997; Raaijmakers and Shiffrin, 1981; Anderson, 1993). Second, rational analysis involves developing a formal model of the environment to which the system is assumed to be adapted. The statistics of the environment describe the patterns by which information repeats, which in turn determines the “need probability” estimated by the memory system.

This can be best understood by drawing parallels between computer information-retrieval and human memory (Anderson, 1990). When a user opens a document, the program provides a list of files to select from, prioritizing those that have been opened recently, those that have been opened frequently in the past, and potentially also those that have been needed in the past in a similar context. Anderson (1990) formalized these intuitions by estimating the need odds $p/(1-p)$ for memory structures, where p is the need probability as a product of a history factor and a context factor. A structure's history is the frequency and recency of episodes in which it was previously needed; the context factor measures the strength of association between a given memory structure and the current context. Both factors reflect the properties of the environment.

The next step in the rational analysis is to make minimal assumptions about the computational limitations of the memory system. One may argue that human memory does not perform optimally, as we often misremember events that are only in the recent past or take a long time to retrieve something that computers can do instantaneously. It is therefore important to incorporate the cognitive constraints and limitations that human cognition has, and then derive an optimal solution under those considerations. There are at least two computational limitations to incorporate: first, it is costly to consider each memory; second, there is a short-term memory capacity on the number of things that can be simultaneously held in mind.

Finally, one can derive the optimal behavior function of the system given the goal, the environment, and the computational limitations of the system. A rationally designed information-retrieval system would retrieve memory structured ordered by their need probability p, and stop retrieving when:

$$pG < C$$

where G is the reward associated with retrieving a target memory and C is the cost in considering the memory (Anderson, 1990). Given how p is determined by the history factor and context factor measured from the statistics of the environment, this retrieval strategy predicts that information that has occurred more recently, more frequently, and more strongly associated with the current context is more likely to be needed, and therefore more likely to be retrieved by the memory system. These predictions from the rational analysis are consistent with the earliest empirical evidence of practice function and retention functions (Ebbinghaus, 1885), providing a rational explanation of these empirical findings. The rational analysis also predicts that need probability should change as a function of recency and frequency in human memory, as measured in the practice function and retention function, which should match the environment. This has been confirmed in environmental sources such as New York Times, parental speech, and electronic mail (Anderson and Schooler, 1991).

2.2 A Bayesian Model Of Reconstructive Memory

In the tradition of rational analysis, various findings that were originally interpreted as indicative of bias in human cognition have been reexamined to determine if people are rational in achieving their goals (Oaksford and Chater, 1996; Kruschke, 1996; Steyvers and Griffiths, 2008; Lieder, Griffiths, Huys & Goodman, 2017; Feldman, Griffiths, & Morgan, 2009; Hemmer & Steyvers, 2009; Parpart, Jones & Love, 2018). This includes memory biases that arise during the reconstruction process discussed in the Egyptian hieroglyph example (Bartlett, 1932).

Memory recall can borrow information from multiple sources, including episodic memory and schematic knowledge. Using episodic memory alone can contribute to unbiased recall; however, episodic memory traces are often noisy. For example, a month after a gym visit, one might hardly remember any details about the visit; but one could still be able to report information based on their prior beliefs about what is usually done at a gym.

Huttenlocher, Hedges, & Vevea (2000) proposed a Bayesian model of reconstructive memory in which people use their schematic knowledge of the stimuli category to adjust inexactly represented stimuli, for example, if tasked with recalling the width of a previously presented image of a fish. The use of schematic knowledge to guide recall gives rise to memory biases; however, these memory biases ultimately maximize the average accuracy of the reconstructed stimuli. A wide range of studies provides evidence for this model by measuring the extent that reconstructed memory is biased towards the schematic knowledge (Huttenlocher, Hedges, & Duncan, 1991; Hemmer and Steyvers, 2009; Xu and Griffiths, 2010; Brady, Schacter, & Alvarez, 2018; Allred, Crawford, Duffy, & Smith, 2016; Duffy, Huttenlocher, Hedges, & Crawford, 2010; Persaud and Hemmer, 2014).

The Bayesian model of reconstructive memory provides a rational account of the memory biases by considering the underlying computational problem of the task and finding the optimal solution to that problem. Given noisy memory contents x, an optimal participant seeks to recover the true state of the world m that generates x. In the experiment to reconstruct the fish's width, schematic knowledge establishes a prior distribution of fish width m, which is assumed to be a Gaussian distribution centered at M, and x is the noisy memory representation of the fish stimuli, centered around μ, the studied fish width. The goal of the task is to reconstruct the width m of the fish based on the noisy memory x. Bayes' rule gives a principled account of how schematic knowledge is combined with noisy memory content to optimally recall past events:

$$p(x) \propto p(x|m)p(m)$$

where $p(m|x)$ is the posterior probability characterizing one's best estimate of the true state of the world m given the noisy memory content x, $p(x|m)$ is the probability of obtaining evidence x from memory if m is the true state of the world, and $p(m)$ is the schematic knowledge or one's prior belief about fish width.

Using standard Bayesian statistics, the mean of the posterior distribution $p(m|x)$ can be expressed as a weighted combination of the mean of the prior distribution p(m), M, and the noisy memory content x: kx + (1-k)M, where k is a monotonic function of the ratio of stimuli uncertainty over prior distribution uncertainty. In other words, the reconstructed memory is not centered at x, but biased towards the mean of the prior distribution M. Huttenlocher, Hedges, & Vevea (2000) demonstrated in their mathematical model that biasing episodic memory by schematic knowledge this way minimizes the mean squared difference between the estimate and the true value. Experimental results also verify that people's memory estimates of one-dimensional stimuli are affected by prior distributions in such a manner to increase the accuracy of their stimulus reproductions (Huttenlocher, Hedges, & Vevea, 2000; see also Brady, Schacter, & Alvarez, 2018). This framework also explains a diverse body of work demonstrating that schematic knowledge facilitates new memory formation and retrieval (Alba & Hasher, 1983; Brewer & Treyens, 1981; Schulman, 1974).

In addition to providing a principled account of observed memory biases, the Bayesian approach also predicts the precise extent of the biases. When the strength of the schematic knowledge of the category is strong and the memory representation is noisy, recall will be more biased towards the category knowledge; whereas when the strength of the schematic knowledge of the category is weak and the memory representation is accurate, recall does not have to rely on the category knowledge, resulting in a minimal amount of bias. Consistent with this prediction, the visual working memory literature demonstrates the effect of memory center on recalling individual items: as the uncertainty of individual items increases, these items are more biased towards the center, which increases overall memory accuracy (Brady & Alvarez, 2011; Lew & Vul, 2015; Orhan & Jacobs, 2013). Similarly, if the schematic knowledge comes at different levels of abstraction (e.g., if one reconstructs the size of an apple, one can either activate their schematic knowledge of "apples" at the object level or their schematic knowledge of "fruits" at the category level), recall is more influenced by the level of schematic knowledge with higher strength or more familiarity (Hemmer and Steyvers, 2009).

Hemmer et al. (2009) extend Huttenlocher and colleagues' basic Bayesian model to a hierarchical one, in which schematic knowledge interacts with episodic memory at multiple levels of abstraction. Experimental results demonstrate that participants optimally combine multiple sources of information from noisy episodic traces with different levels of schematic knowledge: their reconstruction of familiar objects is biased towards the specific prior for that object, whereas their reconstruction of unfamiliar objects is biased towards the center of the overall category.

There is also evidence that the additional source of information does not always come from one's schematic knowledge, but from knowledge obtained from the environment after encoding the memory. In hindsight bias, knowledge of an outcome (i.e., an anchor) affects subsequent recollections of previous predictions (i.e., an estimate), with the estimates remembered as closer to the anchor than they actually were (Synodinos, 1986; Fischhoff, 1975). For example, if you predict your favorite team to win by 10 points before a sports game, but in the end, they only win by 2 points, when discussing the game afterward, you may recall that you always knew it was going to be a close game. However, hindsight bias does not always occur – it is only elicited when the anchor is perceived to be plausible (Hardt and Pohl, 2003). To capture the relationship between hindsight bias and anchor plausibility, a variant of the Bayesian model of reconstructive memory provides a rational account of hindsight bias by considering memory recall as a statistical problem, where the goal is to reconstruct the original estimate using the anchor as new evidence (Wilson, Arora, Zhang, & Griffiths, 2021).

The Bayesian model of reconstructive memory can also explain the memory biases observed in the serial reproduction paradigm, described at the beginning of the chapter. In the Bartlett (1932) experiment, the unfamiliar Egyptian hieroglyph leads to a noisy representation in memory. According to the Bayesian model, the reconstructed memory is a combination of this noisy representation and the participant's schematic knowledge of cats, activated due to their close resemblance to the stimuli. As this process is repeated over more iterations, the reconstructed memory is increasingly biased towards the schematic knowledge. It has been formally shown that, after many iterations, the reconstructed memory converges to the schematic knowledge assumed by the participants (Griffiths and Kalish, 2005; Xu and Griffiths, 2010). This explains why the serial reproduction paradigm reveals the cultural and social biases, shared as prior knowledge and beliefs across participants.

3. Connecting Rational Analysis With Recent Empirical Findings On Schematic Knowledge

Decades of work have shown that prior beliefs can enhance memory formation, what has been less explored is how schematic knowledge is acquired and exerts an influence on episodic memories over time. Traditionally, it was considered challenging to study the acquisition of schematic knowledge in the controlled environment of the laboratory, as this usually takes place over long periods of time. Early efforts in testing the effect of different amounts of schematic knowledge focused on accessing individual differences given their pre-acquired schemas (Graesser & Nakamura, 1982; Roediger & McDermott, 1995; Taylor & Crocker, 1981). Recent empirical studies measure the interaction between schematic memory and episodic memory at different time delays and provide insights into how the effect of schematic knowledge on episodic memory evolves over time (Richards et al., 2014; Sweegers and Talamini, 2014; Persaud and Hemmer, 2016; Tompary, Zhou, & Davachi, 2020; Tompary and Thompson-Schill, 2021; Zeng, Tompary, Schapiro, & Thompson-Schill, 2021; Berens, Richards, & Hoerner, 2020). This section of the chapter reviews these recent studies, with a focus on providing a rational account of these phenomena using the modeling frameworks from the previous section. Additionally, to fully account for these empirical results, we identify areas where extensions can be made to the existing models and venues for conducting new experiments.

3.1 Temporal Dynamics Of Schematic Influence On Episodic Memory

Schematic knowledge develops slowly by extracting statistical regularities common across overlapping episodes. In a water maze experiment, Richards and colleagues demonstrated that rodents' swim patterns match closely with learned schematic knowledge of platform locations after 30 days, while memories for specific platforms are weakened (Richards et al., 2014). This is consistent with the idea that schematic knowledge emerges at the expense of episodic details. However, the effect of schematic knowledge on episodic memories emerging gradually does not mean that schematic knowledge is not available from the beginning. In fact, there is evidence from perception research that schematic knowledge, operationalized as a common set of spatial properties across visual displays, can be learned within minutes (Posner and Keele, 1968; Brown and Evans, 1969).

To disentangle the availability of schematic knowledge from its expression during episodic memory retrieval, Tompary and colleagues (2020) separately probed the strength of schematic knowledge and its influence on episodic memory over time. In their experiment, participants memorized image-location associations; after the learning phase, their memories were probed both immediately, and as delays of one day and one week. In contrast to studies of long-term memory that demonstrated that schematic knowledge persists or even improves over time (Durrant, Taylor, Cairney, & Lewis, 2011; Djonlagic et al., 2009; Brady et al., 2013; Magnussen and Dyrnes, 1994; Wagner et al., 2004), Tompary and colleagues found that memories are better at a 1-day delay compared with a 1-week delay. Despite the decline in schematic knowledge, its influence over episodic memories *increases* over time, as episodic memories are weakened. The authors interpreted that schematic knowledge is only expressed when they are needed and that a strong representation of schematic knowledge does not necessarily lead to a strong influence of schematic knowledge over episodic retrieval (Tompary, Zhou, & Davachi, 2020). Similarly, in a related study that examined how humans extract "gist" from individual episodes, over a period of one month, item memories are increasingly biased towards the gist memory (Zeng, Tompary, Schapiro, & Thompson-Schill, 2021).

The Bayesian model of reconstructive memory, discussed in the last section, can explain the evolution of the influence of prior beliefs on episodic memory. It posits that the weight of schematic knowledge and episodic memory during episodic recall is a monotonic function of the ratio between their uncertainties. Specifically, to optimize overall memory accuracy, when schematic knowledge is strong and the episodic memory representation is noisy, recall will be biased towards the schematic knowledge; whereas when the schematic knowledge is weak and the episodic memory representation is accurate, recall does not have to rely on the schematic knowledge. In other words, it is the relative strength rather than the absolute strength of schematic knowledge and episodic memory that determines the amount of bias towards the schematic knowledge during episodic retrieval. Huttenlocher, Hedges, and Vevea (2000) demonstrate in their mathematical model that biasing episodic memory by schematic knowledge this way optimizes accuracy for episodic memory retrieval. This provides a rational account for the experimental results obtained by Tompary et al. (2020) and Zeng et al. (2021): schematic knowledge is formed at an early stage, yet it does not exert an influence on episodic memories right away when episodic memories are still accurate; over time, episodic memories undergo a faster decay than the schematic knowledge, leading to the increasing influence of schematic knowledge over episodic retrieval.

The above interpretation assumes that memory traces become noisier and less precise over time, corresponding to an increased value in the noise term in the Bayesian model of reconstructive memory. It is worth noting, however, that there are two possible ways forgetting in long-term memory (Berens, Richards, & Hoerner, 2020; Persaud and Hemmer, 2016). One is via decreases in precision: for example, to recall where you visited a bookshop last time, decreased precision means that your recalled location moves further away from the bookshop location over time. The other is via losses in accessibility. Decreased accessibility corresponds to a decreased probability of retrieving the location, resulting in a random guess of the bookshop location during failed retrievals. To account for a wide range of empirical results on the temporal dynamics of schematic influence, it would be fruitful to explore the consequences on the rational model when both types of memory noises are considered.

3.2 The Effect Of Schematic Knowledge On Atypical Items

We have reviewed the effects of prior knowledge that the reconstructive memory framework can provide a rational account for. To the extent that the rational account aligns with human behavior, this provides a normative justification for this behavior. Are there any recent empirical findings that are challenging for the rational model? In an experiment on how category typicality affects distortions in episodic memories, participants encoded and retrieved image-location associations. It was shown that retrieval of locations for typical category members is more biased to the category center, i.e., the mean of the schematic knowledge, than it is for atypical category members. Typical members are images whose associated locations are consistent with their category membership, whereas atypical members are images are assigned random locations that are inconsistent with their category membership (Tompary and Thompson-Schill, 2021). This finding poses challenges to the Bayesian model of reconstructive memory, which predicts that the reconstructed memory is a weighted average of a noisy episodic memory and the category center obtained from the schematic knowledge. When episodic memory happens to overlap with the category center, there is no bias from this reconstruction process; when the episodic memory moves further away from the category center and becomes increasingly atypical, the Bayesian model predicts that the amount of bias towards the category center should increase rather than decrease.

Why do empirical findings on category typicality diverge from model predictions? In the original experiment by Huttenlocher and colleagues (2000), stimuli were drawn from a pre-defined distribution that characterized the category. Some stimuli were more typical than others, being closer to the category center; while other stimuli were less typical, being further away from the category center. However different the category typicality across different stimuli was, all the stimuli belonged to the same category as they were all drawn from the same distribution that defined that category.

This is a different setup than the experiment by Tompary and colleagues (2021), where atypical examples were category exceptions, located randomly and outside the distribution defining the category. From a rational perspective, when all stimuli belong to the same category, biasing towards the category center is optimal, as the category information can help reduce the uncertainty in the reconstructed memory and therefore maximize memory accuracy – this applies to all stimuli whether they are typical or not. For example, as discussed above, to recall a particular gym visit a month ago, one can use their general knowledge of gyms to improve memory accuracy. However, if the visit was at a gym that had been converted into a shopping mall (i.e., an exception), filling in details using schematic knowledge about a gym can only introduce recall errors.

A rational model that incorporates this intuition would be able to reconcile the empirical findings. This requires an extension to the existing Bayesian model to capture the identification of outliers and exceptions. In fact, experimental results in Huttenlocher at al. (2000) have already shed light in this direction: as the presented stimulus moves further away from the category center, the bias values increase at first but then level off or decrease at the boundary of the category distribution. The authors argued that this result is consistent with their model predictions if one also considers the probability of category membership given the stimulus: despite all stimuli examples being drawn from the same category, stimuli closer to the category boundary are perceived as belonging less to the category than are those that are closer to the category center. The same account also applies to the randomly located atypical examples in Tompary et al. (2021), which are not biased by the category center because they are not perceived as members of that category. However, the exact formulation that characterizes the probability of category membership remains to be derived.

After taking into account the probability of category membership, the Bayesian model of reconstructive memory can also provide a rational account for the effect of atypical examples in Zeng et al. (2021). In their experiment, participants memorized spatial locations of landmarks and were later tested at different time delays on their memory of the items (i.e., episodic memory) as well as on their memory of the gist (i.e., schematic knowledge). The memory of the gist is measured as the reported center of the landmarks. Of particular interest are the item memory and gist memory involving outliers, which are items whose spatial locations are inconsistent with the spatial patterns across all items. Consistent with the reconstructive memory framework, gist memory biases item memory as the precision of item memory decreases over time. However, the gist information that biases item memory does not include the outlier, even though participants' reported gist includes the outlier.

Zeng et al. (2021) connected these results to the ensemble perception literature and proposed that there are two different sampling strategies for gist extraction: when explicitly recalling and reporting the gist, one strategy is used that gives more weight to the outlier; when the gist is used to influence the item memory, a different strategy is used when extracting an implicit representation of the gist, which discounts the outlier, consistent with findings in ensemble perception work (De Gardelle and Summerfield, 2011; Haberman and Whitney, 2010). In contrast to this mechanistic level of explanation that describes the processes, here we propose a computational-level account that explains these results with regard to the goal of the task. Given that the goal of the task is to maximize accuracy in item recall, it is optimal to use gist memory to guide item memory given a noisy representation of the item memory. However, as argued in the last paragraph, it is no longer rational to use guidance from gist memory if an item is an outlier that is not perceived as part of that category. Similarly, to optimally guide item recall of a given category, the gist should only extract regularities from items that belong to that category. Therefore, the gist memory that is used to bias item memory discounts outliers, though one has explicit knowledge of these outliers, expressed in the reported gist.

3.3 When Schematic Knowledge Hampers Episodic Memory

So far, we have seen schematic knowledge guiding accurate episodic memory retrieval. Do prior beliefs ever exert negative effects on episodic memory? It has been shown that when an existing schema suffices to guide goal-directed behavior, storage of schema-congruent episodic memory is suppressed (Sweegers et al., 2015). In this experiment, participants memorized associations between a face and a home and later recalled the associated home, given a face cue. For half of the faces, the responses could be guided by the schema the faces belonged to, while for the other faces, there was no schema available. It was found that there are substantial memory impairments in the visual details of faces when they are congruent to an underlying schema, compared to when they are incongruent to an underlying schema. The authors proposed that schemas exert different influences on memory formation depending on momentary goals. The majority of studies examining the effect of schemas are carried out under a task environment where information of individual items is useful in achieving the momentary goal (Tse et al., 2007; van Kesteren et al., 2010; Huttenlocher at al., 2000; Tompary and Thompson-Schill, 2021). Under such scenarios, according to the Bayesian model of reconstructive memory, it is optimal for the memory system to bias episodic memory retrieval towards the schematic knowledge, minimizing the error during episodic memory retrieval. However, if the goal of the task is no longer to accurately retrieve episodic memory, but can be achieved by using the schematic knowledge alone, then it is rational to discard episodic information about the items that are redundant to the task goal.

Findings and interpretations in Sweegers and colleagues (2015) are consistent with the rational analysis of memory by Anderson (1990) in deciding whether one should retrieve a particular memory. Recall that a rational information-retrieval system would retrieve memories ordered by their need probability p, and stop retrieving when: pG<C, where G is the reward and C is the cost associated with retrieving the memory. Imagine one can rely on either a schematic memory or an episodic memory to make a response in the face-home association task. The rewards G associated with both types of memory are equal since one can respond equally accurately whether using the schematic information or using the specific item information. However, the need probability p of a schematic memory is higher than that of an episodic memory, because there are multiple responses that one can use a schematic memory for, whereas storage of an episodic memory can only be used to guide one response. Additionally, as a schematic memory only involves regularities and abstract rules, one can also argue that the cost of accessing a schematic memory is smaller than the cost of retrieving episodic details. Therefore, given that it is rational to stop retrieving a memory when pG<C, it is rational to prioritize the retrieval of a schematic memory over episodic memories under the task environment outlined in Sweegers et al. (2015). This analysis emphasizes the importance of considering human behavior as an optimal solution to the environment it faces. Future experiments should further probe the task goals, environmental structure, and their effects on the use of schematic versus episodic memory.

To sum up, in this chapter, we have reviewed the rich empirical literature on the effects of schematic knowledge on episodic memory retrieval, as well as modeling frameworks that provide a rational explanation of these empirical findings. We connected these modeling frameworks to more recent empirical results on effects of schematic knowledge and identified potential future directions for updating the models and venues for conducting new experiments.

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