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Passive Parallel Automatic Minimalist Processing

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Abstract

Research for which the idea that many basic cognitive processes can be described as fast, parallel, and automatic is reviewed. Memory retrieval/decision processes have often been ignored in the cognitive literature. However, in some cases, computationally complex processes can be replaced with simple passive processes. Cue-dependent retrieval from memory provides a straightforward example of how encoding, memory, and retrieval can interact. Three other examples are reviewed: inference in text processing, compound cue models for priming, and implicit memory. In each case, the research benefits from a focus on retrieval and decision processes. For implicit memory, consideration of these kinds of processes leads to a view of implicit memory different than hypothesizing new specialized memory systems. Finally, how behavioral data from simple decisions and the models that explain the behavior can be related to neuroscience research on neural firing rates are discussed.

Introduction

Our research is relevant to two major topics of this Ernst Strüngmann Forum: (a) the distinction between implicit and explicit memory processes and (b) the diffusion models in psychology and neuroscience that explain simple decision-making processes. In our view, a number of issues in these domains are interconnected by their reliance on cognitive processes that occur quickly, automatically, and passively.

In conjunction with fast automatic passive processes, we suggest that in many cases, active, computationally expensive processes should be replaced by mechanisms that instantiate passive uses of information. We also emphasize that the retrieval of information from memory cannot be understood without consideration of the retrieval context in which memory is tested. In the final section of this paper, we suggest connections between these ideas, behavioral data, and neural processes.

Our view is that relatively simple processes operate on perceptual inputs. The results of these computations are usually integrated with already known information, producing outputs that are added to the database upon which other cognitive processes can operate. This view is similar in many ways to John Anderson's (1990, 1993; Anderson and Lebiere 1998). Both views stress that representations of easily accessible knowledge have large impacts on cognitive processes.

Retrieval and decision processes are important given their usual neglect in comparison with encoding processes. Crucially, it is often possible to model empirical findings such as priming in lexical decision or inferences in reading with retrieval processes instead of encoding processes. To give one example, which will be elaborated on below, in reading, people can produce a large number of answers to questions based on a text. The key question, however, is whether the inferences required to answer the questions were made during reading or at the time the question is asked. It is clear that many plausible inferences are not made during reading. In this respect, our view is similar to Gigerenzer's view of decision making in that minimalism is stressed in the theoretical proposals as compared to other views.

One way to divide up the domains of cognitive processing is to separate perceptual encoding computations that are carried out in parallel and automatically from those that are carried out as strategic processes. Fundamental to the modeling of cognitive phenomena, automatic and strategic processes, and encoding and retrieval processes, must be examined jointly, empirically, and theoretically. The goal is to develop models that explicitly bridge empirical phenomena.

The idea that memory can never be assessed without taking into account the retrieval cues that interact with memory was made central in cognitive psychology 35 years ago by Tulving (1974). Cue-dependent retrieval is an integral component of all current memory models. Recognition and recall of items in memory are understood in a theoretical framework that relates retrieval cues to encoding and memory representations.

We discuss a number of cognition phenomena. Their common theme is that sometimes complicated assumptions about representations or processes can be replaced by simpler mechanisms that depend on quickly accessible, context-relevant information and provide a base for the operation of higher-level processes.

Cue-dependent Retrieval

One of the key tenets of cue-dependent retrieval is that it is not possible to draw conclusions about memory without understanding the retrieval environment, including the cues presented at retrieval. Tulving (1972) presented a number of compelling experimental demonstrations which show that memories can be recovered with appropriate cues when, with other cues, even presentation of the studied item itself, retrieval fails. In these experiments, the conclusion from the experiments with suboptimal cues would have been that the information had been lost.

Tulving (1972) suggests a view in which retrieval processes and cues presented at retrieval interact with memory to produce a response. It is this interaction that should be key in understanding how the retrieval environment affects processing. Perhaps the most dramatic example is recognition failure of recallable words (Tulving and Thomson 1973). The experiments had subjects initially read pairs (A-B) of weakly associated words followed by a forced-choice recognition test of the second member of the pairs (B) with distractors similar to the target words. Finally, a cued recall test, in which the first (A) members of the pairs were presented, showed a significant proportion of words recalled that were not recognized in the recognition phase. From examples like these, Tulving argued that memory cannot be understood without understanding how retrieval cues interact with memory. We have taken this view further, as illustrated below, to understand many aspects of inference in text processing and semantic priming in terms of retrieval processes.

Minimal Inference in Text Processing

In the 1970s and 1980s, most text-processing experiments were concerned with whether some particular kind of inference was encoded during reading. If a fish swam under a rock and a turtle was sitting on the rock, does the reader encode that the fish swam under the turtle (Bransford et al. 1972)? If a workman pounds a nail, does the reader understand that he uses a hammer (Corbett and Dosher 1978)? If an actress falls from a 14-story building, does the reader understand that she will most likely die (McKoon and Ratcliff 1986)? Sorting out the results of many such experiments led to an appreciation of what turned out to be a crucial methodological issue. The procedures used in most early experiments did not allow inferences that were generated at the time of reading to be distinguished from inferences that were generated at the time of the test. Suppose, for example, that after studying a list of sentences, subjects were given a list of words and asked to recall the sentence that went with each word. Given the word "hammer," for instance, the sentence to recall might have been, "the workman pounds the nail." Recall of the sentence could occur either because the subject had generated the connection between "hammer" and the "pounds" sentence when the sentence was read or because the subject generated the connection at the time the word "hammer" was given in the recall test. Corbett and Dosher (1978) presented other sentences, such as "the workman pounded the nail with a rock," and found that "hammer" was just as good as a retrieval cue for those sentences, even though it would not have been encoded, thus concluding that the connection was made at retrieval.

In response to this problem, experimenters began to use procedures by which inferences could be attributed unequivocally to processes that occurred during reading (e.g., Corbett and Chang 1983). To make this argument, two theoretical ideas were borrowed from research on memory. The first has just been discussed, namely Tulving's (1974) notion of cue-dependent retrieval: a cue evokes information from memory directly and selectively; that is, it directly evokes memory of those past events of which it was a part. The second was Posner's (1978) separation of fast automatic cognitive processes from slower strategic ones. These two ideas in combination led to the use of speeded, single-word item recognition as a procedure to examine inference processes. In a typical experiment, subjects read several sentences (or longer texts) and then, after some delay, one or more single test words were presented. For each test word, subjects were asked to make a recognition decision; that is, they were asked to decide whether the test word had appeared in the studied sentences and to respond as quickly as possible. It is assumed that the recognition decision is based on cue-dependent retrieval: if the test word and/or its meaning was encoded as part of the studied sentence, then the test word will quickly contact the information encoded from the sentence, allowing a fast positive response to the test word. For example, given the sentence "the workman pounded the nail," the test word "workman" should quickly evoke the information from the sentence, and there should be a fast positive response. If an inference was encoded about the workman pounding with a hammer, then "hammer" as a test word should also quickly evoke the information from the sentence, leading to a fast positive response—a response that would be an error because "hammer" did not actually appear in the sentence (for discussion of slow responses and the use of deadline methods to ensure fast responses, see McKoon and Ratcliff 1989). The important point for interpretation of the results of recognition experiments is that, following Posner, fast responses are assumed to come from automatic processes—processes that are not under the subject's strategic control. Because the processes are not under strategic control, it is further assumed that responses reflect information that was encoded during reading, not information that was constructed by slower strategic processes occurring at the time of the test.

Applying this reasoning, experiments looked at what kinds of information were encoded during reading in procedures in which subjects were given no special goals to encode any particular types of information. One outcome was the conclusion that in the absence of special goals, relatively few of the inferences that had been studied earlier so extensively were actually generated during reading. This conclusion was summarized by the "minimalist hypothesis" (McKoon and Ratcliff 1992a), which states that the only inferences encoded during reading (unless the reader has special goals in reading, e.g., studying for an exam, reading a report to make a decision, etc.), in the absence of special strategies, are those that depend on information that is easily and quickly available from memory and those that are needed to make the text that is being read locally coherent. This conclusion has not been shared by all text-processing researchers, and considerable debate ensued (e.g., Graesser et al. 1994; Graesser and Zwaan 1995; McKoon and Ratcliff 1995b; Singer et al. 1994). Efforts to map out what kinds of nonminimalist inferences are generated during reading, especially those that create causal links between pieces of text information, still continue.

Although the focus on fast, parallel, and passive evocation of information from memory was first reflected in new experimental procedures, a more important consequence has been its reflection in theoretical thinking. This change was part of a broader movement in cognitive psychology. In memory research, the global memory models (Gillund and Shiffrin 1984; Hintzman 1986, 1988; Murdock 1982) accounted for many and various empirical findings with direct access retrieval processes that are global, passive, fast, and automatic, explicit implementations of cue-dependent retrieval. In text processing, part of the minimalist hypothesis (McKoon and Ratcliff 1992a) is that not only a test word but also every word, concept, and proposition in a text evokes information from memory directly, globally, and quickly. Kintsch's (1974) model for the representation of meaning in propositional structures has acquired processes (Kintsch 1988) by which information from long-term memory is made available by fast, passive retrieval processes. A crucial aspect of this focus is that attention is directed at what is evoked from memory by a text rather than only at what inferences need to be generated to understand the text.

Compound Cue Models for Associative Priming

A phenomenon that has received much attention over the recent history of cognitive psychology is priming in lexical decision and recognition. This kind of priming is seen as a speedup in processing for a word that results from processing a related word just before it. For example, in making word/nonword lexical decisions about strings of letters, if a target test word "doctor" is preceded by a related prime word, "nurse," then the "word" response to "doctor" is speeded up by 30 to 50 ms.

The first and most common theoretical interpretation of priming is based on spreading activation: the prime word activates other words related to it in memory, and this advance activation leads to a speedup on the target (McNamara 1992a, 1992b, 1994). This view requires that items be stored as distinct and connected entities in memory, in accord with a commonsense view of processing that has its roots in computer science and implementation on digital computers (e.g., Quillian 1969). This mechanism places a lot of importance on processes that operate at the time the prime is presented. In this respect, the mechanism is similar to a constructionist view of inference making.

It is, however, important to note that there are widely used cognition models for which the representations in memory are distributed. In such representations, activation cannot spread. If items are stored in common overlapping vectors of features, then all that can happen at retrieval is an assessment of the extent to which a cue matches memory.

We have proposed an alternative to spreading activation, a mechanism that is more passive and operates at retrieval. The assumption is that the information with which memory is probed at retrieval is not simply the tested word, but instead a combination of the test word plus prior words (with the prior words weighted less); for example, the other words that are in short-term memory. If two successively presented words share features or associations to information in memory, then the combination will match memory better than two unrelated words.

The cue combination explanation of priming, the compound cue model (Ratcliff and McKoon 1988, 1994, 1995; McKoon and Ratcliff 1992b, 1995a), can be implemented in the global memory models that are current in cognitive psychology. The compound cue model treats priming pairs of words in the same way that the global memory models treat pairs of words. In pair recognition, a pair of words is presented simultaneously and the task is to decide whether both were on the study list. If the two words were studied in a pair together, the degree of match between the test probe and memory is greater than if both words were studied but in different pairs. This mechanism is implemented differently in different global memory models. In a distributed memory model, such as TODAM (Murdock 1982), a pair is stored as a vector convolution. This means the words of a pair are combined and added to a common memory vector. At test, a compound cue model would assume that the memory vector is matched with either the association between the two prime and target words along with the single item, or that the probe is actually a combination of a lot of the test item and a little of the prime. In both cases, the match between the test item combination is better for the two associated words than for unassociated words.

Ratcliff and McKoon used the same mechanism to explain priming, adding some assumptions about how reaction time is derived from degree of match. There has been considerable controversy over whether spreading activation (ACT*, Anderson 1983) or compound cue mechanisms give the best account of priming, with no clear winner (McNamara 1992a, 1992b, 1994). What is clear is that different models of representation fit better with compound cue and spreading activation models. A compound cue mechanism provides a method of probing memory with a combination of cues that allows retrieval to be more focused; that is, more likely to access conjunctions of information, as in the Gillund and Shiffrin (1984) memory model. It also provides a good analogy for how retrieval and inferences might be processed (i.e., by jointly probing memory with information in the question presented at test).

Implicit Memory

Global memory models address what has been called explicit memory. There is, however, another domain of research concerned with the effects of prior study on performance in tasks that does not require recollection of prior study; this has been called implicit memory. Much research on implicit memory has centered on the experimental finding that repetition of a stimulus produces a benefit to performance, even when conscious memory of the prior episode with the stimulus is not required. A key result is the finding that on many tasks, this repetition priming effect is unimpaired in amnesics, even when their explicit memory, as evidenced by recognition or recall tasks, is severely impaired. It has been claimed that this priming is produced by a memory system separate from that which performs explicit memory tasks. Squire (1992), for example, proposed a hierarchy of separate systems, and Schacter and Tulving (1994) produced a taxonomy of multiple memory systems. The problem with such an approach is that it is driven by hypothesis testing; at no point are the difficult theoretical questions posed about how information is represented within each memory system, how processing works within each system, or how processes interact among the different memory systems. Crucially, there is no discussion of how processing works for the tasks in which repetition effects are found.

Consider, for example, what must happen in a multiple memory systems account of priming in word identification. In tasks used to show this phenomenon, a test word is flashed briefly, then masked. Prior presentation of the word increases the probability of correctly identifying it. If the earlier encounter is stored as a new representation in a separate memory system from that used for word identification, then when the test word is presented it must contact this representation, and the representation must become available to the processes that are standardly used for word identification in time to facilitate them. It seems unlikely to us that any reasonable mechanism could be constructed to work this quickly to both identify the test word in the implicit memory system and use the resulting information to aid identification.

Our data provides the basis for a different interpretation of implicit priming effects (Ratcliff and McKoon 1996, 1997). Using experimental procedures for which costs as well as benefits could be examined, we found that the facilitative priming effect for an exact repetition of an item was accompanied by inhibition in processing when an item closely similar to the test item had been presented earlier. We argue that this shows a bias in processing, not the operation of a separate memory system. We further explain bias with a model for word identification (Ratcliff and McKoon 1997), a modification of the logogen model developed by Morton (1969). Schooler et al. (2001) have also proposed a model for bias that does not make use of a separate memory system; their model uses the mechanisms of REM (retrieving effectively from memory; Shiffrin and Steyvers 1997). In both cases, the primary aim of the models was to explain standard processing; priming was only a by-product of the standard processes (Morton 1970). In addition, each model could be used in conjunction with other criterial tests said to identify separate memory systems: dissociations and stochastic independence (see also Ratcliff and McKoon 1996).

Currently, the domains of implicit and explicit memory are related mainly by contrasts: Is this implicit memory or explicit memory? As models for implicit memory were developed, it was hoped that relationships between explicit and implicit memory systems would become apparent (e.g., Schooler et al. 2001) and that theoretical progress would be made. This did not happen. Instead, the field has become stagnant, and researchers who were most active in implicit memory moved away from it such that relatively little empirical or theoretical progress has been made over the last ten years.

Models of the Time Course of Processing

A major topic of this Forum involved decision-making models and how they relate to neural processes. The current class of diffusion models fits behavioral data in two-choice tasks well (accuracy and response time [RT] distributions for correct and error responses). There are several related versions of these models, which differ on the basis of whether evidence is accumulated as a single sum positively or negatively toward a positive or negative decision criterion (Ratcliff 1978) or through separate diffusion processes, each toward its own criterion. The key to the success of these models is that for all of them, the decisions depend on diffusion processes (Ratcliff and Smith 2004).

The Ratcliff diffusion model is a model of the cognitive processes involved in simple two-choice decisions (Ratcliff 1978, 1988, 2006; Ratcliff and Rouder 1998; Ratcliff et al. 1999). It separates the quality of evidence entering the decision from decision criteria and from other, nondecision processes such as stimulus encoding and response execution. The model should only be applied to relatively fast two-choice decisions (mean RTs < 1000–1500 ms) and only to decisions that are a single-stage decision process (as opposed to the multiple-stage processes that might be involved in, e.g., reasoning tasks).

The diffusion model assumes that decisions are made by a noisy process that accumulates information over time from a starting point toward one of two response criteria or boundaries (Figure 8.1a). The starting point is labeled z and the boundaries are labeled a and 0. When one of the boundaries is reached, a response is initiated. The rate of accumulation of information is called the drift rate (v) and is determined by the quality of the information extracted from the stimulus. In an experiment, the value of drift rate, v, would be different for each stimulus condition that varied in difficulty. For recognition memory, for example, drift rate would represent the quality of the match between a test word and memory. A word presented for study three times would have a higher degree of match (i.e., a higher drift rate) than a word presented once. The zero point of drift rate (the drift criterion; Ratcliff 1985, 2002; Ratcliff et al. 1999)

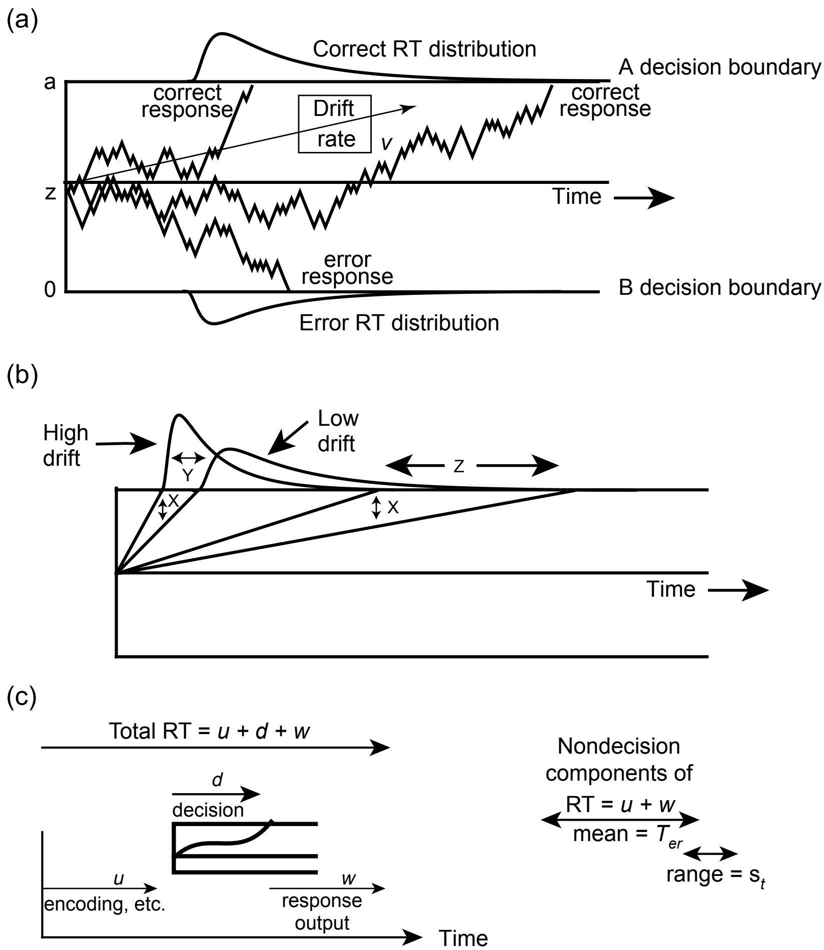

Figure 8.1 An illustration of the diffusion model. (a) The diffusion model with starting point z, boundary separation a, and drift rate v. Three sample paths are shown illustrating variability within the decision process; correct and error RT distributions are illustrated. How distribution shape changes when drift rate changes by an amount X is shown in (b). The fastest responses slow by Y, and the slowest responses slow by Z, leading to a small shift in the forward edge of the distribution and a larger change in the tail, which results in increased skew. The third panel (c) illustrates the components of processing besides the decision process d with the duration of the encoding process u and the duration of processes after the decision process w. These two components are added to give the duration of nondecision components T_{er}. The nondecision component is assumed to have a uniform distribution with range s_t.

divides drift rates into those that have positive values (i.e., mean drift rate toward the A decision boundary in Figure 8.1a) and negative values (mean drift rate toward the B decision boundary).

There is noise ("within trial" variability) in the accumulation of information so that processes with the same mean drift rate (v) do not always terminate at the same time (producing RT distributions) and do not always terminate at the same boundary (producing errors). This is shown by the three processes, all with the same drift rate, in Figure 8.1a.

Empirical RT distributions are positively skewed and in the diffusion model this is naturally predicted by simple geometry. In Figure 8.1b, distributions of fast processes from a high drift rate and slower responses from a lower drift rate are shown. If the higher and lower values of drift rate are reduced by the same amount ("X" in the figure), then the fastest processes are slowed by an amount "Y" and the slowest by a much larger amount, "Z". Our data shows that RT distribution shape is invariant under a number of manipulations (Ratcliff and McKoon 2007), which is exactly what the diffusion model predicts.

Figure 8.1c illustrates component processes assumed by the diffusion model: the decision process with duration d; an encoding process with duration u (this would include memory access in a memory task, lexical access in a lexical decision task, and so on); and a response output process with duration w. When the model is fit to data, u and w are combined into one parameter to encompass all the nondecision components with mean duration T_{er}.

The components of processing are assumed to be variable across trials (Figure 8.2). For example, all words studied three times in a recognition memory task would not have exactly the same drift rate. The across-trial variability in drift rate is assumed to be normally distributed with standard deviation η and the starting point is assumed to be uniformly distributed with range s_z. These two sources of variability have consequences for the relative speeds of correct and error responses, and this will be discussed shortly. One might also expect that the decision criteria would be variable from trial to trial. However, the effects would closely approximate the starting point variability for small to moderate amounts of variability; computationally, only one integration over the starting point is needed instead of two separate integrations over the two criteria.

Error responses are typically slower than correct responses when accuracy is stressed in instructions or in experiments where accuracy is low; errors are usually faster than correct responses when speed is stressed in instructions or when accuracy is high (Luce 1986; Swensson 1972). Early random walk models could not explain these results. For example, if the two boundaries were equidistant from the starting point, the models predicted that correct RTs would be equal to error RTs, a result almost always contradicted by data (e.g., Stone 1960). It has been shown that the combination of across-trial variability in drift rate and across-trial variability in starting point can account for all of the empirically observed patterns of correct and error RTs (Ratcliff et al. 1999; Ratcliff and Rouder 1998): experimental conditions for which error RTs were faster than correct RTs and conditions for which they were slower, even when errors moved from being slower to being faster than correct responses

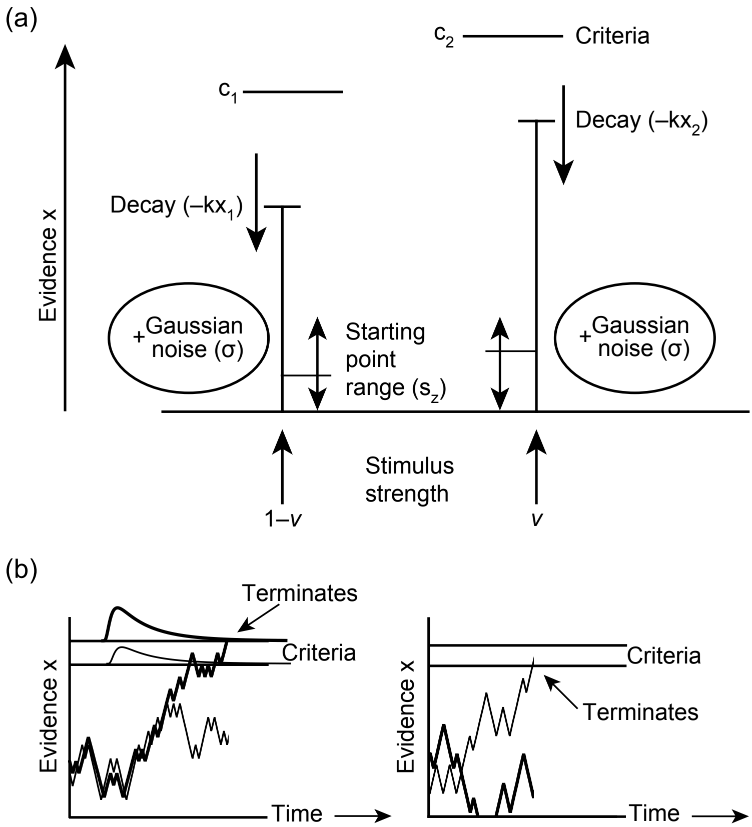

Figure 8.2 The dual diffusion models: (a) two accumulators with accumulation rates $1-v$ and v, within trial Gaussian noise s, decision criteria c_1 and c_2, variability in starting points s_z, and decay k. (b) Sample paths for two pairs of processes: the left panel with the dark process winning and the right with the light process winning.

in a single experiment. A discussion of falsifiability of the model is presented in Ratcliff (2002).

An important feature of the diffusion model with variability across trials in the components of processing is that it allows decision noise to be separated from perceptual or encoding noise (variability in drift rate across trials) and from criterion noise (variability in starting point across trials). The standard signal detection approach collapses these three sources of noise into one. The diffusion model allows these three sources to be extracted from the data and identified uniquely subject to variability in the data (the variability parameters usually have larger standard errors of estimate relative to other parameters; Ratcliff and Tuerlinckx 2002).

A rarely discussed problem is the potentially troubling relationship between accuracy and RT. Accuracy has a scale with limits of zero and 1 while RT has a lower limit of zero and an upper limit of infinity. In addition, the standard deviations in the two measures change differently: the standard deviation in accuracy decreases as accuracy approaches 1, whereas the standard deviation in RT increases as RT slows. In the diffusion model (as well as other sequential sampling models), these relations between accuracy and RT are explained directly. The model accounts for how accuracy and RT scale, relative to each other, and how manipulations of experimental variables affect them differentially. This is a major advance over models that address only one dependent variable: only mean RT or only accuracy.

Applications

The diffusion model has been applied over a wide range of experimental paradigms and in several populations of human (and even animal) subjects. One example is aging and speed of processing. For some time, it has been known that older adults (e.g., 65 to 90 years old) are slower in two-choice tasks than young adults (college students). It was usually assumed that this decrease in performance was the result of a general slowdown in all cognitive processes. However, recent diffusion model analyses of two-choice data from a number of tasks (six experiments with 30 or more subjects in each of three age groups per experiment) show that the slowdown is due almost entirely to the conservativeness of older adults. To avoid errors, they set their decision criteria significantly farther from the starting point of the decision process than young adults. Counter to the previously held view, in most tasks, the quality of the information on which decisions are based (i.e., drift rate) is not significantly worse for the older than the young adults in the tasks we studied (Ratcliff, Thapar, and McKoon 2001, 2003, 2004, 2006, 2007; Ratcliff, Thapar, Gomez, and McKoon 2004; Spaniol et al. 2006; Thapar et al. 2003).

Criterion Setting

An issue that arose during this Forum concerns the processes involved in response feedback and control (see Dayan, this volume). For animal research, this can be explored experimentally. For humans, it is difficult to imagine how a complete theory of criterion setting might be achieved. One problem is that humans can calibrate their responses in a reaction time task on the first trial of an experiment on the basis of verbal instructions alone. For example, if a letter string is presented to a subject and the instruction is to hit one key if it is a word and another key if it is a nonword, subjects can perform this task on the first trial and require no feedback about whether their responses are correct. If they have familiarity with other reaction time tasks, they will be able to start responding quickly and accurately on the very first trial using only the sound waves that carry the verbal instructions. On the many tasks for which there is no feedback about accuracy, reinforcement is not needed for subjects to set criteria. For human subjects, reinforcement and feedback can be used to shape behavior and adjust criteria, but a theory to account for such effects will be incomplete because humans use knowledge in ways that theories cannot as yet explain.

Do Diffusion Processes Reflect Neural Activity?

One way that the connection between diffusion processes and neural activity has been pursued is by simultaneously collecting behavioral data and single-cell recording data. Beginning with Hanes and Schall's pioneering work (1996) and Shadlen and colleagues' efforts to integrate diffusion processes and neural decision making (e.g., Gold and Shadlen 2001), research in this area has advanced rapidly (Ditterich 2006; Huk and Shadlen 2005; Mazurek et al. 2003; Roitman and Shadlen 2002; Schall 2003). Studies using ERP (Philiastides et al. 2006) and fMRI measures (Heekeren et al. 2004) are beginning to appear. The general questions are whether and how the components of processing recovered from behavioral data by the diffusion model or other recent sequential sampling models correspond to the physiological measures.

Research aimed at these questions is illustrated in a recent experiment by Ratcliff, Cherian, and Segraves (2003). Monkeys were trained to discriminate whether the distance between two dots was large or small, indicating their responses by left versus right eye movements. Which response was correct was probabilistic, defined by the history of rewards for correct responses in the experimental sessions. As the monkeys performed the task, data were collected from cells identified as buildup (or prelude) cells in the superior colliculus. The goal was to test whether the decision process and the firing rates (aggregated over individual cells and trials for each cell) were linked such that the closer the diffusion process to a decision boundary, the higher the firing rate of a cell. Ratcliff et al. applied the diffusion model to the behavioral data, fitting the data adequately and obtaining the values of the parameters that best fit the behavioral data. Then, using these parameter values, sample diffusion paths were generated, each path beginning at the starting point of the diffusion process and ending at a response boundary. These paths were averaged and the result was compared to the average of the firing rates, across cells and trials, of the buildup cells. The finding was that the average path closely matched the average neural firing rate. As the average path approached a decision boundary, the average firing rate increased.

In the 2003 experiment, recordings from cells that increased firing for one of the response categories were compared to recordings from cells that increased firing for the other of the response categories (Ratcliff, Cherian, and Segraves 2003). The diffusion model accounted for the difference between the firing rates of the two types of cells, but not for the firing rates of the cells themselves.

To model the two types of cells separately, Ratcliff, Hasegawa et al. (2006) proposed a dual diffusion model. In this model, evidence is accumulated separately for the two response alternatives as in accumulator models (e.g., Usher and McClelland 2001). For each alternative, evidence accumulation is a diffusion process (see Figure 8.2). The amount of evidence at any given point in the process is subject to decay as a function of the amount of evidence in the accumulator. This model fits all the same data as the standard diffusion model, but the advantage of the model is that it predicts the firing rates for the cells that respond in favor of one of the two types of stimuli as well as for the cells that respond in favor of the other type. Ratcliff, Hasegawa et al. (2006) showed that the model provided reasonably good fits to the behavioral data, and they used the best-fitting values of the parameters to generate predicted paths for the two types of cells separately (see also Mazurek et al. 2003). The averages of the predicted paths corresponded closely to the averages of the cells' firing rates.

Discussion

The goal of all the examples above is to think about how a cognitive system might be designed using, to the greatest extent possible, passive, parallel, and automatic processes. The idea is that computations performed passively at encoding or in parallel at retrieval can replace what have been thought to be more active processes or processes operating on new processing systems. This is important in the context of this Forum because it offers a different view of the infrastructure of cognition and provides the basis for initial biases in processing and inferences that are made in processing information.

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