# Preferences Constructed from Dynamic Micro-Processing Mechanisms

Jerome R. Busemeyer[a]

Joseph G. Johnson[b]

&

Ryan K. Jessup[a]

August 19, 2004

a) Indiana University, Bloomington, IN, USA

b) University of Illinois, Urbana-Champaign, IL, USA

Send Correspondence to:
Jerome R. Busemeyer
Psychology Department
Indiana University
Bloomington In, 47405
voice: (812) 855-4882
fax: (812) 855-4691
email: jbusemey@indiana.edu

The Computational Modeling Approach.

Decision researchers have struggled for a long time with the fact that preferences are highly changeable and vary in complex ways across contexts and tasks. For example, reversals have been observed when preferences are measured by binary versus triadic choice sets, or when preferences are measured by choice versus price methods. Several theoretical approaches have been developed to understand this puzzling variability in preferences. One approach is to modify the classic utility model by allowing the weights or values that enter the utility function to change across contexts or tasks. For example, Tversky, Sattath, & Slovic (1988) believe that the decision weights for attributes change across choice versus price tasks. A second approach is to use different heuristic rules to form preferences, depending on task and context. For example, Payne, Bettman, and Johnson (1993) propose that decision makers switch from compensatory to non-compensatory types of rules when the number of options increases or as time pressure increases. Both of these approaches are well established and have made a large impact on decision research.

This chapter presents a computational approach to understanding how preferences change across contexts and tasks. According to this approach, preferences are constructed from a dynamic process which takes decision contexts as inputs and generates task responses as outputs. Computational models are formed by a collection of microprocessing units, each of which performs an elementary cognitive or affective evaluation. These simple microprocessing units are interconnected to form a recurrent dynamical system whose emergent behavior becomes fairly complex. The goal of a computational approach is to use a common set of parameters and processing assumptions to explain changes in preferences across contexts and tasks. One can view the computational approach as a microanalysis that provides dynamic mechanisms for deriving the global properties posited by the first two approaches. Later in this chapter, we will show how a computational model can explain preference reversals induced by changes in context or changes in tasks; such reversals have been previously explained by modifying decision weights across preference tasks or switching strategies across context and time pressure manipulations.

Although there are many different types of computational models, we will focus on a class known as connectionist or artificial neural network models. These models are designed to form a bridge between cognition and neuroscience (Grossberg, 1982; Rumelhart & McClelland, 1986). Later in this chapter, we will identify possible neural substrates associated with the elementary processes posited in some computational models.

## Decision Field Theory.

Several computational models (artificial neural network or connectionist) have been recently developed for preferential choice (Grossberg & Gutowski, 1987; Guo and Holyoak, 2002; Holyoak & Simon, 1999; Levin & Levine, 1996; Usher & McClelland, 2002). These theories vary in terms of their neural plausibility versus applicability to mainstream decision research. Here we will focus on our own model, known as decision field theory (DFT), which was designed to find an effective balance between these two goals.[1] Decision field theory has two major parts, one describing how choices are made (Busemeyer & Townsend, 1993; Diederich, 1997; Roe, Busemeyer, & Townsend, 2001),

[1] The name 'decision field theory' reflects the influence of Kurt Lewin's earlier 'psychological field theory'.

and the second describing how quantities (e.g., prices) are matched to options (Busemeyer & Goldstein, 1992; Johnson & Busemeyer, 2004; Townsend & Busemeyer, 1995).

Choice process

According to DFT, the decision maker deliberates over each course of action by thinking about possible events and feeling the anticipated consequences of alternative actions. At each moment, different events come to mind, and the affective reactions to the consequences of each action are evaluated and compared. These comparisons are accumulated over time to form a preference state, representing the integration of all the preceding affective reactions produced by thinking about each event during deliberation. This deliberation process continues until the accumulated preference for one action reaches a threshold, which determines the choice and the deliberation time of the decision.

This sequential sampling process is illustrated for three options in Figure 1, with each trajectory representing the cumulative preference for an action.[2] The horizontal axis represents deliberation time, and the vertical axis indicates the state of preference for each action at each moment in time. In this figure, action A eventually reaches the threshold first, and is chosen after T = 69 time steps. The *threshold bound* for the decision process, symbolized by $\theta$, is the key parameter for controlling speed and accuracy tradeoffs. Impulsive individuals may tend to use lower thresholds, while perspicacious individuals may tend to use higher thresholds.[3]

---

[2] In the binary choice case, there would only be two trajectories, one for each option.

[3] The race-to-threshold stopping rule applies to optional stopping time decision tasks under which the decision maker controls the timing of the decision. For fixed stopping time decision tasks, when there is an

INSERT FIGURE 1 ABOUT HERE

The dynamical system used to generate this deliberation process is presented next. The inputs into the dynamic system are the affective evaluations, symbolized as $m_{ij}$, of the possible consequences of a decision. At any moment in time, the decision maker is assumed to attend to one of the possible events or attributes leading to consequences for each action. Thus, the inputs to the dynamic system fluctuate from one moment (time $t$) to another moment (time $t+h$) as the decision maker's attention switches from one possible event or attribute to another. To formalize these ideas, we define $W_j(t)$, for all attributes $j$ as stochastic variables, called the *attention weights*, which fluctuate across time. The weighted value for each option $i$ within a set of $n$ options at time $t$ is:

$$U_i(t) = \sum_j W_j(t) \cdot m_{ij} + \varepsilon_i(t). \qquad (1)$$

The 'error' term, $\varepsilon_i(t)$, is a stochastic variable with a mean of zero representing the influence of irrelevant features (e.g., in an experiment, these are features that are outside of an experimenter's control). The above equations look like the classic weighted utility model, but unlike the classic model, the attention weights are stochastic rather than deterministic (see Fischer, Jia, & Luce, 2000, for a closely related model). The mean values of the attention weights correspond to the deterministic weights used in the classic weighted utility model. Comparisons among weighted values of the options produce what are called valences. A positive valence for one option indicates that the option has an advantage under the current focus of attention, and a negative valence for another option indicates that the option has a disadvantage under the current focus of attention. The

---

externally determined stopping time, we assume that the sequential sampling process continues until the appointed time, and the option with the maximum preference state at that time is chosen.

*valence* for each option $i$ within a set of $n$ options is formed by comparing the weighted value for option $i$ with the average of the other ($n$ -1) options:

$$v_i(t) = U_i(t) - U_g(t)\ , \qquad (2)$$

where $U_g(t) = \Sigma_{k \neq i}\ U_k(t) / (n\text{-}1)$. Valence is closely related to the concept of advantages and disadvantages used in Tversky's (1969) additive difference model. Note, however, that the additive difference model assumed complete processing of all features, whereas the present theory assumes a sequential sampling process that stops when a threshold is crossed. Finally, the valences are integrated over time to form a *preference state* for each action. This is a recursive network, with positive self-recurrence within each unit and negative lateral inhibitory connections between units. Positive self-feedback is used to integrate the valences produced by an action over time, and lateral inhibition produces negative feedback from other actions. The preference state for option $i$ from a set of $n$ options evolves according to the linear dynamic system:

$$P_i(t+h) = s \cdot P_i(t) + v_i(t) - \Sigma_{k \neq i}\ s_{ik} \cdot P_k(t)\ . \qquad (3)$$

Conceptually, the new state of preference is a weighted combination of the previous state of preference and the new input valence.

Inhibition is also introduced from the competing alternatives. We assume that the strength of the lateral inhibition connection ($s_{ik}$) is a decreasing function of the dissimilarity between a pair of alternatives. For example, if two options A and C are more dissimilar than options B and C, then the lateral inhibition between A and C would be smaller than that between options B and C, or $s_{AC} < s_{BC}$. Lateral inhibition is commonly used in artificial neural networks and connectionist models of decision making to form a competitive system in which one option gradually emerges as a winner dominating over the other options (cf. Grossberg, 1988; Rumelhart & McClelland, 1986). As shown later in this chapter, this concept serves a crucial function for explaining several paradoxical phenomena of preferential choice.

In summary, a decision is reached by the following deliberation process: As attention switches from one event or attribute to another over time, different affective values are probabilistically selected, these values are compared across options to produce valences, and finally these valences are integrated into preference states for each option. This process continues until the preference for one option exceeds a threshold criterion, at which point in time the winner is chosen. Formally, this is a Markov process; matrix formulas have been mathematically derived for computing the choice probabilities and distribution of choice response times (for details, see Busemeyer & Diederich, 2002; Busemeyer & Townsend, 1992; Diederich & Busemeyer, 2003). Alternatively, Monte Carlo computer simulation can be used to generate predictions from the model.

Dynamic value-matching model

A somewhat different model is needed for single-stimulus responses. The basic idea of the matching model is that a price or probability equivalent is selected by a series of covert comparisons. Consider the problem of finding the price equivalent of a gamble. In this case, the decision maker needs to find the price that makes her indifferent between the price and the gamble. We assume that the search for the price equivalent starts near the middle of the range of feasible payoffs (the midpoint between the minimum and maximum payoffs of the gamble). This candidate price is then inserted into the DFT choice process for choosing between the gamble and the candidate price. If the candidate price is too low, so that the preference state of the gamble first crosses the threshold, then the price is incremented a small amount; if the candidate price is too high, so that the choice process favors the candidate price over the gamble, then the price is decremented a small amount, however, if the candidate price is approximately equal in value to the gamble, then the preference states will linger around zero or the neutral state. Each time this occurs there is a probability *r* that the process exits and reports the candidate price. Markov chain theory is used to determine the distribution of probabilities generated by the search process (see Busemeyer & Townsend, 1992; Johnson & Busemeyer, 2004; for the mathematical derivations). Note that the only new parameter introduced by the matching model is the exit rate, *r*, for reporting indifference when entering the neutral state.

## Preference Reversals

Now we shall apply the above computational modeling approach to some important findings concerning preference reversals from the decision-making literature. Two different types of preference reversals are analyzed here: reversals of preferences across binary versus triadic choice contexts and reversals of preferences between choices and prices.

### Reversals between binary and triadic choices

Preferences revealed by binary versus triadic choice procedures exhibit three very robust types of preference reversals. The similarity effect (Tversky, 1972) refers to the effect of adding a new competitive option to form the triadic set, an option that is highly similar to one of the original binary choice options. The attraction effect (Huber, Payne, & Puto, 1982) refers to the effect of adding an option dominated by one of the first two to form the triadic set. The compromise effect (Simonson, 1989) refers to the effect of adding a new extreme option to form the triadic set, thus turning one of the original binary choice options into a compromise between two extremes.

First, consider a classic example, described by Tversky (1972), of a preference reversal produced by the similarity effect. When given a choice between a rock music album versus a classical music album (say by Beethoven), suppose the latter is more frequently chosen, indicating a preference for the Beethoven album over the rock album. However, when another classical music album (say by Mozart) is added to form a set of three options {rock, Beethoven, Mozart}, then the classical Mozart album steals choices away from the classical Beethoven album, making the rock album more popular than the Beethoven album. Thus adding a similar option (the classical Mozart album is similar to the classical Beethoven album) reverses the preference orders obtained from the binary versus triadic choice measures.

Next consider an example of a preference reversal produced by the attraction effect (see, e.g., Table 2 from Simonson, 1989). When people were asked to make a binary choice between cars varying in miles per gallon and quality of ride, brand B (24 mpg, 83 rating on ride quality) was more frequently chosen (61%) over brand A (33 mpg, 73 rating on ride quality). However, when a third option D (33 mpg, 70 rating on ride quality) was added to the choice set, then brand A was chosen most often (62%). Thus adding a dominated option (A dominates D) reversed the preference order revealed by binary and triadic choices.

Finally, consider an example of a preference reversal produced by the compromise effect (see, e.g., Table 3 of Simonson, 1989). When people were asked to make a binary choice between batteries varying in expected life and corrosion rate, brand

B (12 hrs, 2%) was more frequently chosen (66%) over brand C (14 hrs, 4%). However, when a third option A (16 hrs, 6%) was added to the choice set then brand C was chosen more often (60%) relative to option B. Thus adding an extreme option A, which turns option C into a compromise, reversed the preference orders obtained between the binary and triadic choice methods.

These three preference reversals are puzzling and difficult to explain. Tversky (1972) proposed the elimination by aspects model to account for the similarity effect. However, the attraction effect cannot be explained by the elimination by aspects model. Later Tversky and Simonson (1993) proposed the componential context model, which uses the concept of loss aversion to account for the attraction and compromise effects. Roe et al. (2001) proved that loss aversion prevents the componential context model from accounting for the similarity effect. A strategy switching model which assumes that decision makers switch from compensatory (e.g., weighted average) to non-compensatory (e.g. lexicographic) strategies with increasing choice set size cannot account for the compromise effect. Thus a comprehensive account of all three effects eluded decision researchers.

Roe et al. (2001) demonstrated that DFT was able to account for all three effects using a single set of principles and a single set of parameters.[4] DFT does not require the concept of loss aversion to account for the attraction and compromise effects. Instead, these effects are emergent properties of the dynamics produced by the lateral inhibitory system that forms a competition between options. An interesting *a priori* prediction from this theory is that increasing deliberation time should increase the size of the attraction

[4] Usher and McClelland (in press) proposed an alternative connectionist model that also can account for all three findings using a common set of principles and parameters.

and compromise effects (see Roe et al, 2001). Empirical support for this prediction was reported in experiments by Dhar, Nowlis, and Sherman (2000).

Recently, Dhar and Simonson (2003) reported new challenging findings on the attraction and compromise effects. They examined how these two effects changed when decision makers were given the additional option of deferring their decision (they could refuse to choose one of the available options). In a consumer purchasing setting, this would correspond to a consumer deciding not to buy a product from the current store and instead continuing to search for a (possibly better) product somewhere else. Surprisingly, they found that allowing people to defer the choice had opposite effects on the attraction versus the compromise effects—it increased the size of the attraction effect, but it decreased the size of the compromise effect. They concluded that these findings suggest that a different mechanism operates for attraction and compromise effects. This conclusion seems to run counter to the DFT explanation which asserts that both effects are emergent properties of the lateral inhibitory network.

To examine this new empirical challenge in more detail, we generated predictions from DFT after including a simple assumption concerning the deferred choice option. First, all the options, including the option to defer, are treated in exactly the same manner:  the preference state for each option evolves over time in a race according to Equation 3, and the first option to reach the threshold wins the race and determines the choice. Thus the deferred option is selected whenever its preference state reaches the threshold bound before the other options in the choice set.

This representation requires specifying the attribute values that would be expected by choosing the deferred choice option. In other words, if a consumer decided to wait and look for another option, what attribute values would the decision maker expect to find after this search? The simplest assumption, which was used in the present application, is that the expected value of an attribute for the deferred choice is just the average of the presented attribute values. For example, suppose an individual is shown two extreme options: one that has good quality (say 4 on a 5-point scale) but is economically poor (say 1 on a 5-point scale), and another that has poor quality (say 1 on a 5-point scale) but is economically good (4 on a 5 point-scale). Then the expected attribute value of deferring for quality is the average (2.5 on the 5-point scale) of these two extremes, and the same holds for the expected value for economy (also 2.5 on a 5-point scale).

Although we could work out the mathematical solution for generating predictions under this new condition, we decided it may be easier if we simply used a computer simulation to generate the model predictions.[5] We simulated 100,000 choice trials for each of 8 conditions in a 2 (binary vs. triadic choice) x 2 (attraction vs. compromise choice set) x 2 (inclusion vs. exclusion of a deferred choice option) factorial design. It is important to note that exactly the *same* model parameters were used to compute predictions for all 8 conditions; only the attribute values, $m_{ij}$, change across conditions in accordance with the descriptions of the choice alternatives. The results of the simulation were analyzed according to the methods used by Dhar and Simonson (2003).

First consider the attraction effect. Define A as the dominating option (target), D as the dominated decoy, B as the other competitive option, and N as the no choice or deferred choice option. When the deferred choice is excluded, the attraction effect is defined as the difference Pr[A|{A,B,D}] – Pr[A|{A,B}], where Pr[A|{A,B,D}] denotes the probability of choosing A from the set {A, B, D}. As can be seen in Table 1a, the

[5] The MATLAB code for the computer simulation is available from the authors.

model correctly predicts a preference reversal in accordance with the attraction effect: Option B is chosen most frequently in the binary choice but the dominating option A is chosen most frequently in the triadic choice. Adding the dominated option D increased the preference for option A by 11%. When the deferred choice is included, the attraction effect is defined as the difference Pr[A|{A,B,D,N}] – Pr[A|{A,B,N}]. As can be seen in Table 1a, the attraction effect increased in size to 21% when the deferred option is included, which is in accord with the results reported by Dhar and Simonson (2003).

INSERT TABLE 1 ABOUT HERE

Next consider the compromise effect. Define A as one extreme option, B as the other extreme option, C as the intermediate or compromise option between A and B, and once again N is the no choice or deferred choice option. When the deferred choice is excluded, the compromise effect is defined as the difference

$$\Pr[C \mid \{B,C\}] - \frac{\Pr[C \mid \{A,B,C\}]}{\Pr[C \mid \{A,B,C\}] + \Pr[B \mid \{A,B,C\}]}.$$

As shown in Table 1b, the DFT model predicts a preference reversal in accord with the compromise effect in this case: Option B is chosen most frequently in the binary choice, but the compromise option C is chosen more frequently than B in the triadic choice. The compromise effect size is 7% under this condition. When the deferred choice is included, the compromise effect is defined as the difference

$$\frac{\Pr[C \mid \{B,C,N\}]}{\Pr[C \mid \{B,C,N\}] + \Pr[B \mid \{B,C,N\}]} - \frac{\Pr[C \mid \{A,B,C,N\}]}{\Pr[C \mid \{A,B,C,N\}] + \Pr[B \mid \{A,B,C,N\}]}.$$

Under this condition, the DFT model no longer predicts a preference reversal. Moreover, as shown in Table 1b, the size of the compromise effect shrinks to nearly zero under this condition. In accordance with Dhar and Simonson (2003), the model predicts that the compromise effect *decreases* when the deferred choice option is included.

In summary, DFT correctly predicts the opposing effects of the deferred choice on the sizes of the attraction and compromise effects.[6] This was accomplished simply by allowing the preference state for the deferred choice to compete in the race along with the preference states for the other options. Although one must be cautious to put into words the emergent behavior of a complex computational model, we can try to interpret how this happens. First consider the attraction effect. For the binary choice, it is difficult to decide between the two competing options A and B, and according to the model, this decision takes a long time. In this case, the deferred choice often wins and “steals choice probability” from both A and B. For the triadic choice condition, the addition of the dominating option bolsters option A, and according to the model it is rapidly selected before the deferred option can have an effect. Thus the increase in the size of the attraction effect occurs because the probability of choosing option A is lowered in the binary choice when the deferred option is allowed. Next consider the compromise effect. For the binary choice, the relative probability for choosing option B remains near 50%; for the triadic choice, it takes time for the lateral inhibitory system to generate a bias favoring the compromise option. That is, the system becomes more vulnerable to the effects of the deferred choice option. Thus, the decrease in the size of the compromise effect results from the choice probability being taken away from the compromise by the

[6] Although these predictions are dependent on the parameter values used here, similar results were obtained with variations in the parameter values and so the predictions are reasonably robust.

deferred choice option. This explanation is in agreement with the conclusions from Dhar and Simonson (2003).

<u>Preference reversals between choice and prices</u>

A second robust type of reversal is obtained when preferences are measured by different elicitation methods; the most common of these are reversals between choices and pricing methods. The classic example was discovered by Lichtenstein and Slovic (1971) in a study examining two types of gambles that were approximately equal in expected value: a “P bet” that produced a very high probability of winning a small amount, and a “$ bet” that produced a relatively low probability of winning a large amount. When asked which gamble they would choose, the P bet is chosen slightly but systematically more often by participants; but when asked to give a price equivalent to each gamble, the $ bet is more frequently given a higher price. These results were repeated by Lindman (1971) and later replicated under various conditions by Grether and Plott (1979). The findings were also replicated by Lichtenstein and Slovic (1973) in Las Vegas gambling casinos using real stakes.

A popular explanation for this reversal was provided by Tversky, Sattath, & Slovic (1988). According to their theory, the weight given to the attributes of the decision vary contingent on the type of task. In the choice task, more weight is given to the most prominent dimension, which tends to be probability in choice tasks. In the price task, more weight is given to the price attribute because it is compatible with the response mode. This shift in weights produces changes in the utilities for the gambles depending on the task, causing the preferences to reverse.

There are a couple of problems with this explanation. One is that preference reversals between choice and prices occur even when the prominence effect is eliminated by using gambles with equally-likely outcomes (Ganzach, 1996). Another is that preference reversals also occur between buying and selling prices (Birnbaum & Sutton, 1992), even though the compatibility effect should operate in the same manner for these two preference measurement methods.

An alternative explanation for preference reversals between choice and prices, based on the concept of anchoring and adjustment, was proposed first by Lichtenstein and Slovic (1971) and later by other researchers (Goldstein & Einhorn, 1987; Schkade & Johnson, 1989). To be concrete, consider the following two gambles from Slovic, Griffin, and Tversky (1990): For the P bet, you win $4 with probability 35/36, otherwise nothing; for the $ bet, you win $16 with probability 11/36, otherwise nothing. When asked to report a price for a gamble, perhaps individuals start at some anchor and then adjust toward the true indifference point. Assuming the anchor is midway between the minimum and maximum payoff, the anchor for the P bet becomes $2 and the anchor for the $ bet becomes $8.[7] The observed preference reversals may simply result from insufficient adjustments from these initial anchors. According to this view, revealed preference reversals do not necessarily imply changes in underlying utilities depending on the task. Instead, the reversals observed in the measurements may simply reflect the dynamic processes used to generate the responses in the two tasks.

One important limitation with anchoring and adjustment models is the lack of a well-specified mechanism for determining the amount of adjustment. Consider for

---

[7] We assume anchoring in the middle of the payoff range for simplicity, to illustrate that biased anchors are not necessary to produce the basic result. However, it could be that participants anchor on, e.g., the maximum payoff of each gamble (see Johnson & Busemeyer, 2004, for implications of various anchors).

example the following pair of gambles: Gamble A wins \$16 with probability .001, \$4 with probability .9712, otherwise zero; Gamble B wins \$16 with probability .2212, \$4 with probability .001, otherwise zero. Gamble A is very nearly the same as the P bet, and gamble B is very nearly the same as the \$ bet. In this case, however, the range is equated across the two gambles, and so the two gambles have identical anchors (both are anchored at \$8). Lacking a theory for the size of the adjustment, there is no basis for predicting preference reversals for this pair of gambles.

The dynamic matching model described earlier was designed for this purpose. The dynamic adjustment mechanism of the matching model is strongly influenced by the variance of a gamble: the rate of adjustment towards the true indifference point decreases with increases in the variance of a gamble (see Johnson & Busemeyer, 2004, for details). Note that the variance of gamble B (also the D-bet) is much larger than the variance of gamble A (also the P-bet), and therefore more rapid adjustments will occur for the latter.

To examine the predictions of the matching model for the pair of gambles A and B described above, the following simple assumptions were made. We set the values in Equation 1, $m_{ij}$, equal to the outcome values, and the probabilities of the attention weights were assigned directly from the stated outcome probabilities. The threshold bound for the choice process was set equal to 3, the variance of irrelevant dimensions was set to zero, and the exit rate for the matching process was set to $r = .02$. Using these parameters we computed the choice probabilities and the distribution of prices from the matching model (using the Markov chain derivations described by Johnson & Busemeyer, 2004). The results are shown in Table 2.

INSERT TABLE 2 ABOUT HERE

The first row of Table 2 shows the expected values of each gamble under the present simplifying assumptions, these are also the true indifference points. The second row shows the variance of the payoffs produced by each gamble and the last row shows the variance of the prices. Comparing these two rows, we see that the variance of the prices is ordered according to the variance of the gambles. The third row indicates the probability of choosing each gamble, and the fourth row indicates the probability that the price for one gamble exceeds the other. Comparing these two rows one can see that gamble A is chosen more frequently (.58), but the price for gamble B is more frequently greater (.71). Furthermore, the mean and median price is higher for gamble B as compared to gamble A. Thus the matching model predicts a preference reversal even when the range of the gambles is held constant because of the dynamic mechanism used to make price adjustments for each gamble. This provides it with an important advantage over other anchoring and adjustment models.

Johnson and Busemeyer (2004) reviewed a broad range of preference reversal phenomena; they demonstrated that the matching model is able to explain the major findings, including other reversals between choice versus prices, as well as reversals between probability versus certainty equivalents, and between buying prices versus selling prices. As we have done here, Johnson and Busemeyer (2004) used the same parameters, model assumptions, and evaluative mechanism (e.g. weights and values) across all applications. We do not wish to argue that changes in decision weights across tasks never occur. Instead, we think it is important to first check whether or not preference reversals can be explained by a response mechanism before claiming changes in weights across tasks.

## Connections With Neuroscience

This section briefly reviews some literature from neuroscience that provides additional support for computational models. Perhaps the most interesting support comes from Ratcliff, Cherian, and Segraves (2003), who found that a diffusion process could predict remarkably well the neural firing rates of cells that were related to behavior in a choice task in the macaque. These authors conclude that the noisy information accumulation process posited by diffusion models such as DFT may have direct neural correlates, as evidenced also by others (e.g., Gold & Shadlen, 1999). A more general overview of the anatomical structures implicated by computational models is offered by Busemeyer et al, (2002). The remainder of this section will focus on the operation of one key mechansim: lateral inhibition.

According to DFT, lateral inhibition is critical for bolstering the dominant option in the attraction effect and enhancing the intermediate option in the compromise effect. The locus of this lateral inhibition may lie within the basal ganglia, which have been implicated in decision behavior through their feedback loops to key cortical areas (Middleton & Strick, 2000). Moreover, Schultz et al. (1995) observed that dopaminergic neurons afferent to the basal ganglia fire in concert with reliable predictors of reward (see also Gold, 2003, and Hollerman & Schultz, 1998). Together these findings support the notion that the basal ganglia have an important function in decision behavior.

Knowledge of the basal ganglia architecture should enhance our understanding of the cortico-striatal loops and lateral inhibition. In particular, we are concerned with two substructures in the basal ganglia, the globus pallidus internal segment (GPi) and the striatum. In cortico-striatal loops, the axons from the cortex enter into the basal ganglia via the striatum, which then projects to GPi, which in turn projects to the cortical area from which it arose. Ordinarily, GPi inhibits cortical activity due to its reliance on GABA, an inhibitory neurotransmitter. However, striatal neurons may act to inhibit GPi, thus releasing the cortex to engage in a specified activity (Bar-Gad & Bergman, 2001). Furthermore, extensive connectivity and communication within the striatum produces lateral inhibition (Bar-Gad & Bergman, 2001; Wickens & Oorschot, 2000).

Several clusters of striatal nuclei, each perhaps representing a different action (or reward), synapse onto GPi neurons (Wickens & Oorschot, 2000). Because the striatum consists of lateral inhibitory networks, all the potential actions compete against one another for selection, and only one action can be selected at a time. This competition causes all of the clusters of nuclei to mutually inhibit one another below baseline, preventing any one option (represented by the clusters of nuclei) from crossing the threshold of activation. However, when one activity is chosen, the corresponding nuclei inhibit the respective GPi neurons, freeing the cortex to engage in the selected activity.

As stated before, one must be cautious when trying to interpret the behavior of a complex computational model, and perhaps one should be even more wary of interpreting neural activity in terms of behavior. But if we take the preceding analysis of activity and overlay it with the concept of an attraction effect, we might be able to produce a viable picture of neural activation occurring during attraction-based preference reversal. Consider the dyadic choice between A and B, where independent clusters of neurons code both options within the striatum. Although both achieve some degree of preference, assume option B is preferred most often. However, when option D, an option dominated by option A, is added to the choice set, a preference reversal occurs. Again, three different clusters of neurons within the striatum code the three different options. In this case, because options A and D are similar, and option A dominates option D, the clusters of nuclei coding option A within the striatum will consistently inhibit the neurons coding option D because of A's superiority (i.e., the salient rewards of A will consistently supersede those of D). Furthermore, as option D becomes more inhibited by the lateral GABAergic connections from A, it releases option A to inhibit both option D and other options (e.g., option B) to a greater extent. One might cautiously surmise that because option B is less similar (than is option A) to option D, it will not benefit from option D's weakness as much as option A does, perhaps due to less overall lateral communication. Thus, option A will receive less and less inhibition from the competing options coded in the striatum and will eventually surpass a threshold of activation. This will result in GABAergic afferents inhibiting the GPi neurons that restrain the selection of option A, hence freeing the cortex to engage in the selection of option A.

## Conclusions

The goal of the current chapter has been to inform the reader of the efficacy of computational modeling, specifically within the domain of preferential decision making. Using one particular computational model, decision field theory, we have illustrated how this approach can provide a parsimonious alternative explanation for the volatility of expressed preferences. The key mechanisms of decision field theory were briefly introduced; these include momentary shifts in attention to possible future events (or attributes in a consumer choice context), affective evaluation under the current focus of attention, and dynamic integration of these affective reactions. This theory was successfully applied to two key types of preference reversals, or situations where task and/or context effects produce changes in preference structures. Finally, tentative links to a young but growing literature on the neuroscience of decision making were presented for a popular component of computational models (lateral inhibition), suggesting an additional degree of plausibility (i.e., neurological).

The microlevel analysis afforded by computational models can result in global behavior similar to more traditional approaches, such as contingent weighting or strategy-switching—but computational modeling is not simply another "language," or framework for representing traditional decision theories. Rather, this approach involves distinct departures from typical algebraic utility equations. First, computational models represent cognition (here, deliberation) as the concurrent operation of several interdependent processing units, such as units that track the momentary preference for a course of action or consumer choice option. The collective operation of these units defines the deliberation process. Thus, whereas some other approaches suggest processing assumptions based on the nature of the algebraic formulations, computational modeling details these processes precisely. Second, the majority of computational models (including the one presented here) are dynamic, meaning they specify how deliberation proceeds over time. In this manner, computational models can provide insight into the evolution of preference during a decision, including effects such as speed-accuracy tradeoffs or the impact of time pressure. This is in stark contrast to static approaches that provide only a calculation of some values (e.g. utilities) which in turn determine final measures (e.g. discrete choices). Finally, a significant advantage of computational models is the retention of stable underlying evaluations, such as weights and values, by using a common set of parameters and assumptions across applications of the model. Although we do not claim that importance weights and/or subjective values *never* change across tasks or contexts, we have shown how this need not be the explanation for robust empirical trends.

In sum, computational modeling provides a powerful tool to decision researchers who are interested in elucidating the nature of human information processing underlying overt decisions. This approach suggests that the deliberation and response processes, rather than the evaluative mechanism, may be responsible for context-dependent construction of preference. The examples included herein demonstrate how this shift in focus—from tweaking weights and values to a more thorough understanding of the nature of deliberation—can perform at least as well as traditional approaches in explaining complex and puzzling human behavior.

References

Bar-Gad, I., & Bergman, H. (2001). Stepping out of the box: Information processing in the neural networks of the basal ganglia. *Current Opinion in Neurobiology, 11*, 689-695.

Birnbaum, M. H., & Sutton, S. E. (1992). Scale convergence and utility measurement. *Organizational Behavior and Human Decision Processes, 52*, 183-215.

Bostic, R., Herrnstein, R. J., & Luce, R. D. (1990). The effect on the preference-reversal phenomenon of using choice indifference. *Journal of Economic Behavior and Organization, 13*, 193-212.

Busemeyer, J. R. (1985). Decision making under uncertainty: A comparison of simple scalability, fixed sample, and sequential sampling models. *Journal of Experimental Psychology, 11*, 538-564.

Busemeyer, J. R., & Diederich, A. (2002). Survey of decision field theory. *Mathematical Social Sciences, 43*, 345-370.

Busemeyer, J. R., & Goldstein, D. (1992). Linking together different measures of preference: A dynamic model of matching derived from decision field theory. *Organizational Behavior and Human Decision Processes*, *52*, 370-396.

Busemeyer, J. R., & Myung, I. J. (1992). An adaptive approach to human decision making: Learning theory, decision theory, human performance. *Journal of Experimental Psychology:  General, 121*, 177-194.

Busmeyer, J. R. & Stout, J. C. (2002). A contribution of cognitive decision models to clinical assessment: Decomposing performance on the Bechara Gambling Task.

*Psychological Assessment, 14,* 253-262.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review, 100*, 432-459.

Busemeyer, J. R., & Townsend, J. T. (1992). Fundamental derivations for decision field theory. *Mathematical Social Sciences*, *23*, 255-282.

Busemeyer, J. R., Townsend, J. T., & Stout, J. C. (2002). Motivational underpinnings of utility in decision making: Decision Field Theory analysis of deprivation and satiation. In S. Moore (Ed.), *Emotional Cognition* (pp. 197-219). Amsterdam: John Benjamins.

Dhar, R., Nowlis, S. M., & Sherman, S. J. (2000). Trying hard or hardly trying: An analysis of context effects in choice. *Journal of Consumer Psychology, 9*, 189-200.

Dhar, R., & Simonson, I. (2003). The effect of forced choice on choice. *Journal of Marketing Research, 40*, 146-160.

Diederich, A. (1997). Dynamic stochastic models for decision making under time constraints. *Journal of Mathematical Psychology, 41,* 260-274.

Diederich, A. (2003). Decision making under conflict: Decision time as a measure of conflict strength. *Psychonomic Bulletin and Review, 10*, 167-175.

Diederich, A., & Busemeyer, J. R. (2003). Simple matrix methods for analyzing diffusion models of choice probability, choice response time, and simple response time. *Journal of Mathematical Psychology, 47,*304-322.

Fischer, G. W., Jia, J., & Luce, M. F. (2000). Attribute conflict and preference uncertainty: The RandMAU model. *Management Science, 46*, 669-684.

Ganzach, Y. (1996). Preference reversals in equal-probability gambles: A case for anchoring and adjustment. *Journal of Behavioral Decision Making, 9*, 95-109.

Gold, J. I. (2003). Linking reward expectation to behavior in the basal ganglia. *Trends in Neurosciences, 26*, 12-14.

Gold, J. I., & Shadlen, M. N. (2001). Neural computations that underlie decisions about sensory stimuli. *Trends in Cognitive Science, 5,* 10-16.

Goldstein, W. M., & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomena. *Psychological Review, 94*, 236-254.

Grether, D. M., & Plott, C. R. (1979). Economic Theory of Choice and the Preference Reversal Phenomenon. *American Economic Review*, *69*, 623-638.

Grossberg, S. (1982). Associative and competitive principles of learning and development: The temporal unfolding and stability of STM and LTM patterns. In S. I. Amari & M. Arbib (Eds.), *Competition and cooperation in neural networks*. New York: Springer-Verlag.

Grossberg, S. (1988). *Neural networks and natural intelligence*. Cambridge, MA: MIT Press.

Grossberg, S., & Gutowski, W. E. (1987). Neural dynamics of decision making under risk: Affective balance and cognitive-emotional interactions. *Psychological Review, 94*, 300-318.

Guo, F. Y., & Holyoak, K. J. (2002). Understanding similarity in choice behavior: A connectionist model. In W. Gray & C. Schunn (Eds.), *Proceedings of the Twenty-Fourth Annual Conference of the Cognitive Science Society* (pp. 393-398).

Hillsdale, NJ: Erlbaum.

Hershey, J. C., & Shoemaker, P. J. (1985). Probability versus certainty equivalence methods in utility measurement: Are they equivalent? *Management Science, 31*, 1213-1231.

Hollerman, J. R., & Schultz, W. (1998). Dopamine neurons report an error in the temporal prediction of reward during learning. *Nature Neuroscience*, *1*, 304-309.

Holyoak, K. J., & Simon, D. (1999). Bidirectional reasoning in decision making by constraint satisfaction. *Journal of Experimental Psychology: General*, *128*, 3-31.

Huber, J., Payne, J. W., & Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research*, *9*, 90-98.

Johnson, J. G., & Busemeyer, J. R. (2004). A dynamic, computational model of preference reversal phenomena. Manuscript in preparation.

Levin, S. J., & Levine, D. S. (1996). Multiattribute decision making in context: A dynamic neural network methodology. *Cognitive Science, 20*, 271-299.

Lichtenstein, S., & Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *Journal of Experimental Psychology, 89,* 46-55.

Lichtenstein S., & Slovic P. (1973). Response-induced reversals of preferences in gambling: An extended replication in Las Vegas. *Journal of Experimental Psychology, 101*, 16-20.

Lindman, H. R. (1971). Inconsistent preferences among gambles. *Journal of Experimental Psychology, 89,* 390-397.

Middleton, F. A., & Strick, P. L. (2001). A revised neuroanatomy of frontal-subcortical circuits. In D. G. Lichter & J. L. Cummings (Eds.), *Frontal-subcortical circuits in psychiatric and neurological disorders* (pp. 44-58). New York: The Guilford Press.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge: Cambridge University Press.

Ratcliff, R., Cherian, A., & Segraves, M. (2003). A comparison of macaque behavior and superior colliculus neuronal activity to predictions from models of two-choice decisions. *Journal of Neurophysiology, 90,* 1392-1407.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multi-alternative decision field theory: A dynamic connectionist model of decision-making. *Psychological Review, 108,* 370-392.

Rumelhart, D., & McClelland, J. L. (1986). *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* (Vol. 1). Cambridge, MA: MIT Press.

Schkade, D. A., & Johnson, E. J. (1989). Cognitive processes in preference reversals. *Organizational Behavior and Human Decision Processes, 44*, 203-231.

Schultz, W., Romo, R., Ljungberg, T., Mirenowicz, J., Hollerman, J. R., Dickinson, A. (1995). Reward-related signals carried by dopamine neurons. In J. C. Houk, J. L. Davis, & D. G. Beiser (Eds.), *Models of information processing in the basal ganglia* (pp. 233-248). Cambridge, MA: MIT Press.

Simonson, I. (1989). Choice based on reasons: The case of attraction and compromise effects. *Journal of Consumer Research, 16,* 158-174.

Slovic, P., Griffin, D., & Tversky, A. (1990). Compatibility effects in judgment and choice. In R. M. Hogarth (Ed.), *Insights in decision making: A tribute to Hillel J. Einhorn* (pp. 5-27). Chicago: University of Chicago.

Slovic, P., & Lichtenstein, S. (1971). Comparison of Bayesian and regression approaches to the study of information processing in judgment. *Organizational Behavior and Human Decision Processes*, *6*, 649-744.

Townsend, J. T., & Busemeyer, J. R. (1995). Dynamic representation of decision-making. In R. F. Port & T. Van Gelder (Eds.), *Mind as Motion* (pp. 101-120). Cambridge, MA: MIT Press.

Tversky, A. (1969). Intransitivity of preferences. *Psychological Review, 76*, 31-48.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review, 79*, 281-299.

Tversky, A., Sattath, S., & Slovic, P. (1988). Contingent weighting in judgment and choice. *Psychological Review*, *95*, 371-384.

Tversky, A., & Simonson, I. (1993). Context dependent preferences. *Management Science*, *39*, 1179-1189.

Usher, M., & McClelland, J. L. (2002). Decisions, decisions: Loss aversion, information leakage, and inhibition in multi-attribute choice situations. Unpublished note.

Usher, M., & McClelland, J. L. (2004). Loss aversion and inhibition in dynamic models of multi-alternative choice. *Psychological Review*, *111,* 757-769.

Wickens, J. R., & Oorschot, D. E. (2000). Neuronal dyamics and surround inhibition in the neostriatum: A possible connection. In R. Miller & J. R. Wickens (Eds.), *Brain Dynamics and the Striatal Complex* (pp. 141-150). Australia: Harwood Academic Publishers.

Table 1. Predictions for the probability of choice from decision field theory for (a) the attraction effect, and (b) the compromise effect.

(a)

| | Deferring Excluded | | Deferring Included | |
|---|---|---|---|---|
| Option | Binary | Triadic | Binary | Triadic |
| A: Target | 0.43 | 0.54 | 0.29 | 0.50 |
| B | 0.57 | 0.45 | 0.33 | 0.36 |
| D: Decoy | | 0.00 | | 0.00 |
| N: Deferring | | | 0.38 | 0.14 |
| Effect Size | | 0.11 | | 0.21 |

(b)

| | Deferring Excluded | | Deferring Included | |
|---|---|---|---|---|
| Option | Binary | Triadic | Binary | Triadic |
| A | | 0.27 | | 0.24 |
| B | 0.54 | 0.35 | 0.29 | 0.27 |
| C: Target | 0.45 | 0.38 | 0.26 | 0.25 |
| N: Deferring | | | 0.45 | 0.25 |
| Effect Size | | 0.07 | | 0.00 |

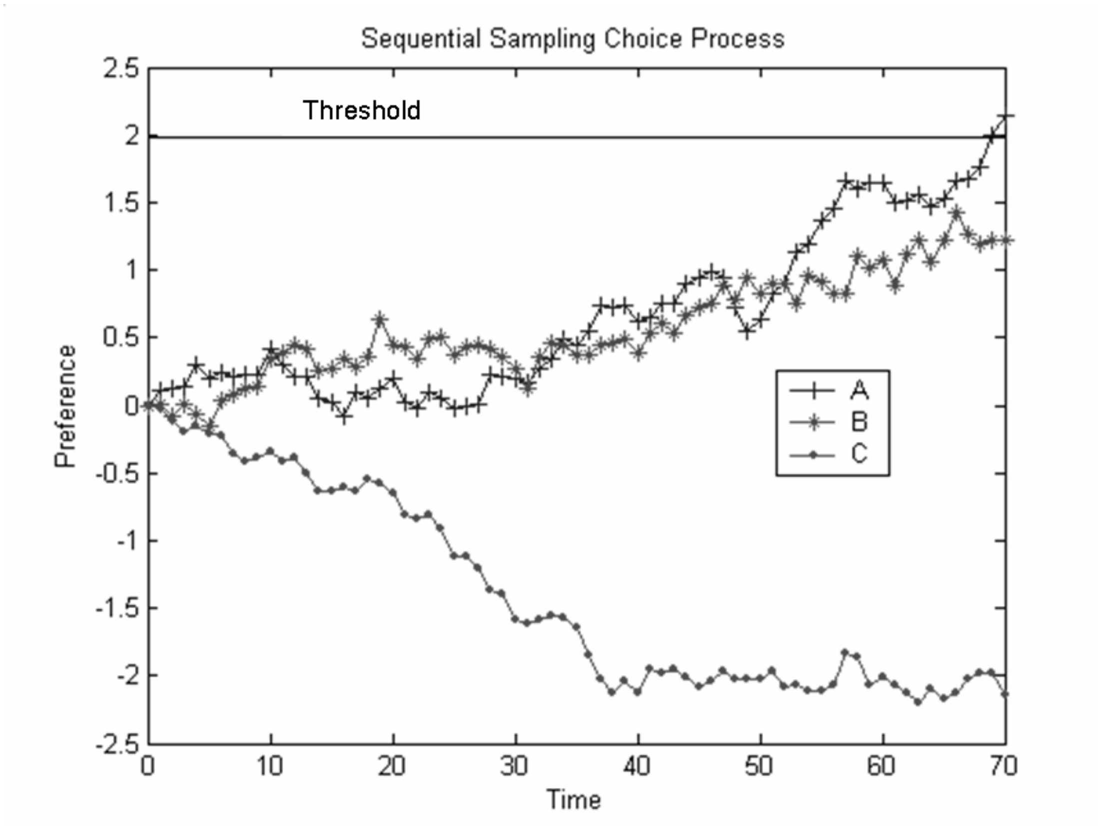
Table 2. Decision field theory predictions for choices and prices.

| | A: Low Variance | B: High Variance |
|---|---|---|
| EV(Gamble) | 3.90 | 3.54 |
| Variance(Gamble) | .58 | 44.30 |
| Pr(choice) | .58 | .42 |
| Pr(higher price) | .29 | .71 |
| Mean $ | 4.14 | 5.10 |
| Median $ | 3.61 | 4.43 |
| Variance $ | 0.77 | 3.41 |

Figure Captions

Figure 1. Illustration of (simulated) sequential sampling decision process for a choice among three alternatives.

Figure 1


Sequential Sampling Choice Process
Threshold
Preference
Time
A
B
C
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
10
20
30
40
50
60
70