Multiattribute Decision Making in Context: A Dynamic Neural Network Methodology

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A theoretical structure for multiattribute decision making is presented, based on a dynamical system for interactions in a neural network incorporating affective and rational variables. This enables modeling of problems that elude two prevailing economic decision theories: subjective expected utility theory and prospect theory. The network is unlike some that fit economic data by choosing optimal weights or coefficients within a predetermined mathematical framework. Rather, the framework itself is based on principles used elsewhere to model many other cognitive and behavioral data, in a manner approximating how humans perform behavioral functions. Different, interconnected modules within the network encode (a) attributes of objects among which choices are made, (b) object categories, (c) and goals of the decision maker. An example is utilized to simulate the actual consumer choice between old and new versions of Coca-Cola. Potential applications are also discussed to market decisions involving negotiations between participants, such as international petroleum traders.

If a man does not keep pace with his companions, perhaps it is because he hears a different drummer. Let him step to the music which he hears, however measured or far away.

Henry David Thoreau (Walden)

1. INTRODUCTION

1.1. The Need for New Paradigms

The need for new theoretical structures is recognized by an increasing number of decision theorists (e.g., Edwards, 1992a), economists (e.g., Arrow, 1990; Heiner, 1983), and philosophers of social science (e.g., Rosenberg, 1992).

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Specifically, the assumptions that decision makers, including consumers and producers, are always acting to optimize a measurable utility function have been increasingly challenged. In particular, there is wide recognition of the need for theories that include the dynamic effects of context on decision making, effects which are often not optimal or rational.

Yet there have been relatively few proposals for alternative theories of decision making. In the absence of new theories, even conscientious disbelievers remain grounded in a broad set of ideas which goes under many names: subjective expected utility (SEU) theory (Edwards, 1992b), rational expectations theory (Sheffrin, 1983), economic man (sic) theory (Edwards, 1992b), and others. Weintraub (1979) perhaps expressed the assumptions of this viewpoint, at least in economic contexts, as well as anyone:

1. there exist economic agents;
2. agents have well-defined, preexistent preferences among available current and future outcomes;
3. agents independently optimize subject to constraints;
4. choices are made in interrelated markets;
5. agents have full relevant knowledge;
6. observable economic outcomes are coordinated, producing equilibrium states. (our paraphrase)

For shorthand, we will refer to all these theories collectively as SEU theory.

Edwards (1992b) described a recent academic conference on decision theory and the attitudes of its participants toward SEU theory:

I ... asked for a show of hands on the following question:

Do you consider SEU maximization to be the appropriate normative rule for decision making under risk or uncertainty?

Every hand went up!

... 

Do you feel that the experimental and observation evidence has established as a fact the assertion that people do not maximize SEU, that is, that SEU maximization is not defensible as a descriptive model of the behavior of unaided decision makers?

Again, every hand went up, including my own. (pp. 254-255)

Clearly, decision theorists are hungering for better descriptive theories to supplant SEU. The work discussed herein suggests that neural networks, far from being mere computational devices, can provide the basis for such an improved decision theory.

SEU has been challenged recently by a range of both psychological and economic data. The work of Tversky and Kahneman (e.g., 1974, 1992) has particularly been notable in showing that preferences are not linearly related to the expected value, in the mathematical sense, of a measurable monetary gain or loss. Such preferences are particularly sensitive to comparison
between expected and actual outcomes. This has been modeled by Tversky and Kahneman themselves using a nonlinear construct known as *prospect theory*. However, prospect theory does not seem to us to capture many of the contextual and dynamic influences which are fundamental to the phenomena being studied. It does not address the underlying principles behind such a function, nor does it say much about the interplay between external variables (environmental context and inputs) and internal variables (beliefs and moods).

Grossberg and Gutowski (1987) captured much more of the dynamic influences of context and preference, using a neural network-based mathematical theory which we will outline in later sections. The phenomena they modeled deal with single-attribute utility, whereas we focus on multiattribute utility. The modeling framework in which Grossberg and Gutowski developed their theory is flexible enough that we were able to adapt it to the multiattribute phenomena we study. In our theory, decisions are based on differential weights of attributes, in a manner reminiscent of other multiattribute theories (see, e.g., Vincke, 1992, Chap. 4). We differ from these other theories, however, in that the weights attached to different attributes can change over time and be influenced by contextual variables. We describe the influence of context in our neural network using an effect analogous to the associative learning, a common notion in psychology (e.g., Hull, 1943).

We now review some more established theoretical frameworks for discussing decision making, and why we believe them to be inadequate as descriptive theories.

1.2. Background: Other Decision Theories

Tversky and Kahneman (1974, 1981, 1992) noticed some characteristic deviations of their own data from the expectations engendered by SEU. Such data as the Allais (1953) example of utility that is nonlinear in the outcome probability, the tendency to be risk averse in the face of gains and risk seeking in the face of losses, and the fact that losses loom larger than equivalent gains, do not fit the predictions of Rational Expectation Theory.

Tversky and Kahneman suggested replacing SEU by a different mathematical theory. Their theory is based on comparing the utilities of different *prospects*, that is, sets of probabilities of different possible anticipated gains and/or losses. This is done by linearly weighting a nonlinear value function such as the one in Figure 1a, representing the subjective affective value of

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Allais' paradox is that most people prefer A to B and prefer D to C, where A is certainty of winning $100 million; B is a 10% chance of winning $500 million, 89% of $100 million, and 1% at nothing; C is an 11% chance of winning $100 million and 89% of nothing; D is a 10% chance of winning $500 million, 90% of nothing. This is paradoxical because in the sense earlier formulated mathematically by Daniel Bernoulli, the subjective "difference" between A and B is the same as the "difference" between C and D.
Figure 1. (a) Nonlinear function representing subjective value as a function of gain or loss. (b) Nonlinear probability weighting function. (Adapted from Tversky & Kahneman, Science, 211, pp. 453–458, 1981, with permission of the American Association for the Advancement of Science.

different amounts of gain or loss, with a nonlinear probability weighting function such as the one shown in Figure 1b. The main tenets of their theory are summarized in Tversky and Kahneman (1992): "1) a value function that is concave for gains, convex for losses, and steeper for losses than for gains and 2) a nonlinear transformation of the probability scale, which overweights small probabilities and underweights moderate and high probabilities" (pp. 297–298). The ensuing theory, called prospect theory, has become the benchmark theory for how decisions are actually made (see Edwards, 1992a, for discussion).

Prospect theory, however, proposes no underlying derivation for the function shown in Figure 1. The absence of an underlying mechanism means that it cannot be a comprehensive theory of actual human cognitive and behavioral processes. Moreover, in positing a single-valued utility for each prospect, this theory does not allow for preference changes either with context or over the lifetime of the decision maker. These deficiencies are partly remedied by the cumulative version of prospect theory offered in Tversky and Kahneman (1992), whereby the utility of a prospect is influenced by which prospects preceded it. Yet the recent version still excludes underlying cognitive bases for the dynamics of decision making. For this reason, the revised prospect theory also still excludes the possibility that two different decision makers faced with the same prospect could make different choices, unless they have different underlying value functions or probability weightings as shown in Figure 1. Our model enables such individual differences to arise from differences in the values of some network variables.

Such an underlying mechanism appears in the neural network-based theory of Grossberg and Gutowski (1987). The cornerstone of the Grossberg-
Gutowski theory, called affective balance theory, is a network algorithm for computing the affective value (i.e., utility) of an anticipated event given its comparison with a different, ongoing event. This is done using a network architecture designed for such comparisons, known as the gated dipole network, which will be described in Section 2 below as background for our "Coke" model.

Although different in most other respects from previous utility theorists, Grossberg and Gutowski still posit a single criterion for the utility of each anticipated event. Our analysis of the relative values of buying or drinking Old Coke and New Coke will show clearly that a multicriterion calculation is required. The criteria are the actual taste of the drink and the pleasurable feeling associated with memories engendered by the drink. However, the gated dipole structure and the dynamics of the Grossberg-Gutowski model carry over, in a general way, to our model, with the addition of network loci for multiple criteria (i.e., multiple affective motivational sources). These dynamics, we believe, will also carry over beyond this article to models of decision making that involve active generation of new options by the decision maker (cf. Langer, 1994); we will return to this point in our concluding section.

Busemeyer and Townsend (1993) have broadened the scope of decision making under uncertainty with their decision field theory (DFT). Decision field theory incorporates four interdependent factors—probabilistic search, steps and range, approach–avoidance balance, and time constraints. These factors, although not explicit multiple decision criteria, do represent a major advance in the inclusion of contextual and individual characteristics (breadth and persistence of search, sensitivity to gains and losses) in framing choice processes.

The authors, appropriately, asserted their approach is a "higher-fidelity, second-order approximation" of decision making which considers preference variability and the press of time. The roots of DFT, in the work of Kurt Lewin and Neal Miller, constitute a commitment to inclusion of factors gestaltists values (intra-individual dynamic conflict and context or "field" effects) and those of ecological psychology (response to unknowable or uncontrollable forces).

Busemeyer and Townsend (1993) allow dynamical differential weighting between gains and losses, Markov chain search tied to a variational kernel (not unlike Boltzmann machines in some neural networks or arousal in Grossberg-type nets), and variations in both reward and punishment schedules (like the dipole fields we employ). These are formidable strengths, which Busemeyer and Myung (1992; see also Busemeyer, 1992) have sought to employ in partial network realizations.

Clearly, the systematic approach Busemeyer and associates have brought to decision theoretic study requires attention: We intend to replicate several
of his experiments in future work. Still, the absence in their models of broader affective measures and the exclusion of the explicit experimental context (which are the keys to the "Coke" problem) requires us to broaden their work: We can only aspire to their rigor.

1.3. Background: Interactive Decision Theory and Back Propagation Networks

Several decision theorists (e.g., Geoffrion, Dyer, & Feinberg, 1972; Roy, 1976; Vanderpooten & Vincke, 1989) have proposed interactive algorithms for making decisions when there are multiple criteria of interest. In each of these algorithms, a decision scheme, or some examples of how the scheme would act, is presented to the decision maker (DM). Then the DM expresses his or her satisfaction or dissatisfication with the projected results and the degree of his or her willingness to relax different criteria. This leads to updating of the decision scheme via some mathematical rule, and eventually a "compromise" solution is reached.

Some, but not all, of these methods have amounted to optimizing a utility function that is linearly weighted by numerical factors measuring the relative importance of different attributes or decision criteria. Interaction of the algorithm with the DM leads to iterative changes in these weights, possibly through a gradient descent method, which may ultimately converge to values that are optimal from the DM's viewpoint. This approach is similar to the underlying notions of the widely used back propagation neural network (e.g., Rumelhart, Hinton, & Williams, 1986; Werbos, 1974). Indeed, Werbos' idea of "dynamic programming," the ancestor of back propagation, was motivated by an effort to make optimal economic predictions, in regions such as the stock market and international energy markets, that involved calculating unknown weight constants in a known mathematical model. Related ideas continue to be influential in models of economic forecasting (Werbos, 1988) and engineering systems control (Werbos, 1992).

The connections we establish here between neural networks and economics are of a different sort. We are not starting with a known class of mathematical models and fitting them to quantitative data. Rather, we are starting with qualitative data based on experimental observations of actual decision-making behavior and setting out to construct a network theory of how the actual DM might generate such behavior. We use not a single preexisting model but instead some broad principles of network organization summarized in Table 1, principles suggested by a range of other classes of behavioral and cognitive data (see Grossberg, 1988, or Levine, 1991, for more details including definitions of neural network terms). Hence, the type of networks we use differ from the back propagation networks, which are primarily a

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2 The alternative spellings "back-propagation" and "backpropagation" also appear in the literature.
TABLE 1
Summary of Some Important Principles in Neural Network Organization

<table>
<thead>
<tr>
<th>Principle</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td><strong>Associative learning</strong></td>
<td>to enable strengthening or weakening of connections between events by contiguity or probable causality.</td>
</tr>
<tr>
<td><strong>Lateral inhibition</strong></td>
<td>to enable choices between competing percepts, drives, categorizations, plans, or behaviors.</td>
</tr>
<tr>
<td><strong>Opponent processing</strong></td>
<td>to enable selective enhancement of events that change over time.</td>
</tr>
<tr>
<td><strong>Neuromodulation</strong></td>
<td>to enable contextual refinement of attention.</td>
</tr>
<tr>
<td><strong>Interlevel resonant feedback</strong></td>
<td>to enable reality testing of tentative classifications.</td>
</tr>
</tbody>
</table>

*Note. Adapted from Hestenes, 1992, with the permission of Lawrence Erlbaum Associates.*

tool for *prediction* rather than for underlying *description* of the phenomena. Our theory is descriptive rather than normative or prescriptive (see, e.g., Eppel, Matheson, Miyamoto, Wu, & Eriksen, 1992, for a discussion of this distinction), but we hope that it will ultimately lead to better predictions due to greater understanding of the dynamics of real-life decision makers. We will return to this point in Section 3.4 of the Discussion.

Also, none of the interactive theories in the literature (see Vincke, 1992, chap. 6) seriously discuss the possibility that weights of attributes could change over time or change with context. Contextual weight changes are at the core of our theory and, particularly, of our explanation of the “New Coke/Old Coke” example.

2. THE COKE EXAMPLE

When the Coca-Cola Company decided to replace its flagship product with a new cola drink, the new flavor had outscored all its competition, including victory over the traditional Coca-Cola flavor by a margin of 2 to 1. Further tests hinted that less than 10% of their habitual customers would object to the new flavor combined with the same old name. The actual buying situation had very different results. The new flavor was so unpopular that the company had to return the old one to the market as “Classic Coke” (Oliver, 1986).

The influence of dynamic emotional states means that mental projections of the future are often inaccurate (Holbrook, Moore, Dodgen, & Havlena, 1985). In tests, people based preferences on the direct appeal of taste. In the market, indirect emotional factors, such as memories associated with expected taste, were more important than taste itself. Moreover, buying was different from tests because Coca-Cola was so confident in its research that they made Old Coke unavailable. The Coke label created expectation of a particular taste, and of the secure feeling it evoked, leading to a frustrative rebound\(^1\) when this feeling was absent.

\(^1\) Psychological data on frustrative nonreward appear, for example, in Amsel (1962) and Gray and Smith (1969).
A preliminary neural network of the Coke data, based on frustrative rebound theory, was developed by Leven and Levine (1987) and will be discussed in this section as a prelude to our current model. Our preliminary model anticipated an experimental result of Pierce (1987) which further confirmed the frustration hypothesis. Pierce compared responses to advertisements of old and new versions of Coke by people who had been habitual Coke drinkers and by habitual drinkers of other drinks (such as Pepsi). By a small but significant margin, habitual Coke drinkers were more hostile to products they perceived as “New Coke” than were non-Coke drinkers.

As we develop our model, we will see that frustrative rebound is only part of the story. We will need a theory of selective attention among attributes of drinks, and of mood-based attention switching. We will also need a theory of mismatch between expected and actual input patterns. The ensuing sections review or introduce some requirements for network instantiation of each of their heuristic effects, starting with frustrative rebound.

2.1. Background: Gated Dipole Networks and Network Principles

Frustrative rebound is an example of comparing current with expected or ongoing reinforcement. Just as removal of a negative reinforcer (e.g., electric shock) is positively reinforcing, removal of a positive reinforcer, or its absence when it is expected, is negatively reinforcing. To model both phenomena, Grossberg (1972) introduced the *gated dipole*, shown in Figure 2. The connections (“synapses”) $w_1$ and $w_2$, marked by filled-in squares, are assumed to be mediated by a “chemical transmitter” that is depleted with activity. The input $J$ could be a significant positive reinforcer such as food, for example. The input $I$ is nonspecific arousal to both channels, $y_1-x_1-x_3$ and $y_2-x_2-x_4$. While food is present, left channel activity $x_1$ exceeds right channel activity $x_2$, leading to net positive activity of the left channel output node $x_3$. For a shorter time after shock ceases, both channels receive equal inputs $I$, but the right channel is less depleted of transmitter than the left channel. Hence, $x_2$ now exceeds $x_1$, leading to net positive activity of the right channel output node $x_4$. The active output node excites or inhibits $x_5$, thus enhancing or suppressing some motor response. At times when the right (“negative”) channel is dominant, the network explains frustration when positive reinforcement either ceases or is absent when expected.

The node activities and weights in the gated dipole obey a dynamical system of nonlinear equations, given in the Appendix. These equations are determined by the interactions: A “+” sign means a positive or excitatory influence, a “−” sign a negative or inhibitory influence, combined with exponential decay in each of the activities and depletion and recovery of the weight.

The gated dipole is a network embodiment of a principle, familiar in psychology, called *opponent processing* (e.g., Solomon & Corbit, 1974). This
means that there are representations of pairs of opposites, and that shutting off activity of one of a pair leads to transient activation of its opposite. These opposites could be not only pain and pleasure but presence or absence of particular sensory stimuli, as will be discussed in Section 2.3.

Our neural network, like many others in the literature (see Levine, 1991, for summary), tends to rely on many organizing principles, of which opponent processing is but one. These principles also include associative learning, lateral inhibition, neuromodulation, and interlevel resonant feedback; Table 1 summarizes the heuristic functions performed by each principle.

Detailed description of the cognitive, mathematical, and neurophysiological bases for these principles are given elsewhere (e.g., Levine, 1991; Levine, Parks, & Prueitt, 1993). All of them will be described sketchily in Section 2.3, as they appear in our model of the Coke data, which depends on all the capabilities embodied by these principles. Associative learning will be invoked to represent learned connections like the one between the familiar Coke flavor and emotional security. Lateral inhibition is used to represent the choices between two competing motivational sources (for taste, which we will more broadly label “Excitement,” and for familiar experiences, which we will more broadly label “Security”). Neuromodulation is used to represent selective enhancement of one or more attributes of an anticipated
soft drink; as the context shifts from testing to actual buying, sweetness of the taste becomes less emphasized and its familiarity more emphasized. Interlevel resonant feedback is used to discern whether New Coke matches the prototype of the category of "Coke-like drinks": The degree of match or mismatch is attribute-selective, so also varies with context.

2.2. Dipole Fields and Novelty
Gated dipole channels have been used in models to represent not only positive and negative affect but also other types of opponent processes. Grossberg (1980) introduced dipoles whose channels consist of "on" and "off" nodes encoding presence or absence of specific stimuli, then joined channel pairs for various stimuli into a dipole field. Leven and Levine (1987) discussed how a dipole field could embody competing attractions to previously reinforced stimuli (here, Old Coke) and to novel stimuli (here, New Coke). If drive is high, or reward signals strong, previously reinforced stimuli are favored. If drive is low, novel stimuli are favored. Leven and Levine's first approximation to a model of the Coke data treated testing as a low-motivation state and buying as a high-motivation state. They noted an analogy to some data on novelty preference in rhesus monkeys. Pribram (1961) showed that monkeys with frontal lobe damage were more likely than normals to choose novel objects over previously rewarded objects.

In neural network models, damage to a brain region such as the frontal cortex is usually treated as selective weakening of a specific connection in the network. For example, Figure 3 shows the dipole field used to model Pribram's data, which was simulated in Levine and Prueitt (1989). The dipole channel pairs in Figure 3 correspond to an old cue and a novel cue. The nodes $x_{1.5}$ and $x_{2.5}$ represent tendencies to approach given cues. Inhibition between these nodes and a node $x_{3.5}$ coding some other environmental cue denote competition (via lateral inhibition) between attractions to different cues. The cue with largest $x_{i.5}$ is approached.

In Figure 3, the on channel for the novel cue is less depleted than the on channel for the old cue, because that channel has not been active as long. Hence, competition among $x_{i.5}$ nodes favors those corresponding to novel cues, all else equal. But also each $x_{i.5}$ has connections with the reward node which are strengthened (via associative learning) when the corresponding cue is rewarded. Hence, competition also favors $x_{1.5}$ with strong links to the reward node, all else equal. The frontal lobes are identified with the connection from reward nodes to sensory dipoles. If this connection is strong, as in a normal monkey, the dipole output $x_{1.5}$ for the previously rewarded cue is the larger. If the connection is weak, as in a lesioned monkey, the output $x_{2.5}$ for the novel cue is larger.
Leven and Levine (1987) noted that the Coke data could be approximately modeled by the network of Figure 3, with "New Coke" identified with "novel cue," "Old Coke" with "old cue," "testing" with "frontally damaged," and "buying" with "normal." This analogy may sound odd because most people taking the taste test are not actually brain-damaged. However, humans with frontal damage tend to be less goal-directed than normal humans (Fuster, 1989); hence, their day-to-day life is closer to a "play" than to a "serious" situation. The taste test context is not, in the words of a well-known Coke advertisement, "The Real Thing," but a break from daily routines.

Yet the network of Figure 3 is inadequate to model the Coke data for two reasons. First, in the market, there was not a choice between New Coke and
Old Coke as in tests. Hence, relative value attached by buyers to the two drinks must be inferred indirectly from relative preference for New Coke and for non-Coke drinks (e.g., Pepsi). Second, consumers' reaction to the change in Coke was not based on taste alone. Hence, our Coke model requires two competing drives: one for taste, the other for a range of feelings which we label "Security."

To model frustrative rebound, we replace the reward node of Figure 3 by an entire gated dipole representing a specific drive. Recall that dipoles can either consist of sensory nodes, which represent specific events in the environment, or drive nodes, which represent specific sources of motivation or effect. Sensory dipoles model differences between novel events and old events, whose representations are more depleted, whereas motivational (drive) dipoles model emotional value attached to changes in received positive or negative reinforcement. Hence, our Coke model requires both sensory and motivational dipoles (Figure 4).

Each motivational dipole in Figure 4 corresponds to a specific drive. (The role of the "Excitement" and "Security" drives in understanding the Coke data will be explained in the next section.) The structure of the sensory dipoles in Figure 4 copies that of the dipoles in Figures 2 and 3, but the structure of the motivational dipoles is a slight modification such as is utilized in the READ (recurrent associative dipole) circuit due to Grossberg and Schmajuk (1987). Instead of a single output node $x_S$ or $x_{i,S}$ as in the sensory dipoles, each motivational dipole has two output nodes—"positive" and "negative"—corresponding to satisfaction and frustration of the appropriate drive. As in READ, these positive and negative output nodes send feedback connections to the two input nodes which are unlabeled in this figure but correspond to $y_1$ and $y_2$ in Figure 2. Grossberg and Schmajuk introduced this feedback in order to account for classical conditioning data whereby frustrative rebound can occur due to the unexpected absence of a secondary positive reinforcer. In order for this to happen in a gated dipole network, the transmitter depletion at the square synapses must be influenced by association between the current input and the representations of drive satisfaction and frustration.

2.3. Categorizations and Multiple Attributes
New Coke elicited strong reactions not just because of how it was different from Old Coke, but also because of how it was like Old Coke! The public reacted to a new taste combined with an old label. Pierce's (1987) data show that the reaction was stronger when larger positive expectation was generated by the old taste. To deal with expectation, we represent New and Old Coke not as a single stimuli but as vectors of attributes, each attribute represented by its own gated dipole. We use the minimal set of attributes needed: Coke, Label, Familiarity, Taste, Pepsi Label.
Figure 4. "Coke" simulation network. Dipole output for a sensory stimulus can be conditioned to positive or negative reinforcement, as shown by modifiable connections (represented by semicircles). Motivational dipoles for two drives (here "Excitement" and "Security") compete. Each sensory dipole has modifiable reciprocal connections with positive and negative motivational channel outputs for each drive; darker lines indicate stronger connections.

In Figure 4, we assume that there are connections, modifiable in both directions by associative learning (see Table 1), between motivational and sensory nodes. The strengths of these connections represent the positive or negative affective value attached by the decision maker to each of the attri-
butes. Now let weights (in both directions) between the on side of the Coke Label attribute dipole and the positive side of the motivational dipole be higher in one copy of the network than in another, and weights to and from the Pepsi Label attribute dipole be higher in the second network. Then the first network models a (generic) habitual Coke drinker, whereas the second models a habitual Pepsi drinker. By feedback from motivational to attribute nodes in the network of Figure 4, the expected positive affective value from seeing the Coke label is greater in the habitual Coke drinker. Hence, frustrating rebound from mismatching expectations generated by that label is also greater in habitual Coke drinkers.

To a first approximation, Figure 3 treated testing as a “low-motivation” context which thereby disinhibits the attraction to novelty. Yet in reality, the two contexts differ not in the amount of motivation but rather in the focus of motivation. During testing, the intrinsic (taste-related) attractiveness of the product is important, and the socially learned attractiveness of the product much less so. Hence, the Taste attribute plays a larger role in categorizations and decisions during testing than does the Familiarity attribute. The Familiarity attribute, by contrast, plays a larger role during buying. Figure 4 embodies context-based attentional switching between attributes. Here, two motivational dipoles are labeled “Excitement,” that is, desire for sensory or aesthetic pleasure, and “Security,” that is, desire for a sense of belonging, affiliation, or rootedness in one’s society or relationships (McClelland, 1961). Assume that the positive sides of the Excitement and Security dipoles in Figure 4 compete via lateral inhibition (see Table 1) and that the winner of the competition changes with context. If feedback connections between the Excitement motivational dipole and the Taste attribute dipole, and between the Security motivational dipole and the Familiarity attribute dipole, are much stronger than cross-connections, the winning drive determines which sensory attributes are attended to.

If habitual Coke drinkers attach positive affect to the Coke category as well as the Coke Label attribute, this enhances expectation of positive value from drinking any Coke product, thus increasing frustration when New Coke mismatches that expectation. Category and attribute nodes are connected to each other with connections modifiable by associative learning, leading to interlevel resonant feedback (see Table 1). This concept was first developed in the neural network theory known as adaptive resonance theory or ART (Carpenter & Grossberg, 1987).

Figure 5 gives a schematic description of ART. The network has many versions, designed to deal with different classes of data, but all have some organizational principles in common. The sensory input is represented as a vector of activities $x_i$ at the feature nodes. Based on feature-to-category node connection weights, each category node receives an input signal, and
Figure 5. Adaptive resonance theory (ART) network. Sensory input to F₁ is stored as a vector of node activities. The Fᵡ node activities are multiplied by the "bottom-up" connection weights wᵢⱼ, then transmitted to F₂, where the one node receiving the largest signal wins. Then the input is compared with that node's stored prototype, as represented by the "top-down" connection weights wᵢⱼ. "Gain control" is a mathematical fine-tuning device, not essential for the discussion herein. Orienting is a response to novel inputs. Reset is a response to inputs that are compared with a prototype and mismatch it by more than a prescribed amount called vigilance; see the text. (Adapted from Carpenter and Grossberg, 1987, with permission of Academic Press.)
We have made a few modifications to ART to incorporate dynamic motivational influences. First, category nodes also connected directly with motivational dipoles as well as with attribute dipoles. This is to enable positive or negative affect to be associated with the Coke category as well as with a specific exemplar of that category. Second, the two vectors (input and prototype) that are compared are each multiplied component by component by an attribute weighting vector that changes with context. This enables sensitivity to mismatch to be attribute-selective in a dynamic fashion. If, say, the current attentional bias favors the Familiarity attribute over the Taste attribute, the network is selectively sensitive to mismatch with the Coke prototype in the Familiarity dimension. The functions of this bias mechanism appear to be somewhat analogous to those of the amygdala, a region in the brain’s limbic system (Pribram, 1991).

In Figure 4, the stored top-down prototype of the Coke category node is the attribute vector representation of Old Coke. The network multiplies both input and prototype vectors by an attribute weight vector before comparing them; numerical explanations are given in the Appendix. In the testing situation, the Familiarity attribute on which these two vectors mismatch is not heavily weighted, hence New Coke passes the vigilance criterion. In the buying situation, familiarity is more heavily weighted, leading to a perceived mismatch. This mismatch generates an orienting signal which inhibits activity on the positive side of the Coke category dipole. This in turn inhibits activity on the positive side of the Security drive dipole, leading to frustrative rebound activity on the negative side of the Security dipole.

2.4. Simulation Results

Table 2 shows results of our simulations. The outputs of the “positive” channels, that is, activities of the nodes corresponding to $x_5$ in Figure 2, for the two motivational dipoles (Excitement and Security) are added to get a measure of total positive affect. Note that the positive affect attached to New Coke is higher than the affect for Old Coke during testing. During buying, when Old Coke is unavailable, the affect for New Coke is lower.
than the affect for Pepsi, and this difference is greater for habitual Coke drinkers than habitual Pepsi drinkers.

3. DISCUSSION

3.1. The Nonisomorphism Problem
The implicit change in soft drink preference between taste tests and the market in the case of Coke is an example of what has been called nonisomorphism (Holbrook et al., 1985). These researchers studied preferences among different types of popular music and found that preferences among "artificial" pieces written by the experimenters did not lead to good predictions of preferences among pieces by professional artists.

Other examples of nonisomorphism abound in economics. The prices of mutual funds and other assets, for example, are often influenced by the actions of irrational, unpredictable "noise traders" (DeLong et al., 1990). Lee et al. (1991) particularly showed that selling prices of a particular type of fund, closed-end stock funds, tend to be decreased (discounted) relative to their fair market value, and that the amount of the discount is dependent on the amount of optimism or pessimism of such irrational investors. The amount of optimism or pessimism, in turn, appeared to depend more on conditions involving the stock market as a whole than on conditions specific to those funds.

Nonisomorphism phenomena are also found in political behavior. In the election for Governor of Virginia in 1990, in which African American Douglas Wilder was a candidate (he eventually won by a narrow margin), exit polls consistently overestimated Wilder's support. It is unclear whether voters did not want to admit their antiblack prejudice to their questioners, or whether they intended all along to vote for Wilder but could not bring themselves to do so once inside the voting area. In the latter case, it is possible that some of them did not remember having voted against Wilder! The relation between emotion and memory will be discussed further in Section 3.2. Our neural network, which undergoes radical shifts in information processing under changes in motivational state, illustrates how nonisomorphism can occur in actual organisms.

DeLong et al. (1990) described noise traders as "unsophisticated" in comparison to rational investors. We believe, however, that some shrewd and experienced market manipulators or "inside traders" may also fit into that category.

We are not suggesting that the change from anticipated to actual behavior is always in the direction of greater prejudice. Although it has not been studied as carefully from this viewpoint, the upset victory of African American woman Carol Moseley Braun in the 1992 Illinois Democratic Senate primary could well be an example of a nonisomorphism in the opposite direction from the Virginia case—prompted by a specific precipitating event (the Anita Hill hearings) which occurred just prior to the vote.
3.2. Affect, Arousal, Novelty, and Habit

Affective or motivational variables play an obvious key role not only in our mathematical model of multicriteria decision making but also in the single-criterion model of Grossberg and Gutowski (1987). This fact deserves emphasis because of the resistance within decision science and elsewhere in the social sciences (particularly economics) to consideration of "emotional" factors. The belief that data are based on "hard scientific," quantifiable, rational processes has obvious appeal. In fact, the same resistance to considering emotion was also encountered until recently in experimental psychology as that field became more scientific in this century (see the preface of Levine & Leven, 1992, for discussion).

However, the affective variables in our models do not constitute what was decried by the self-explanatory term "squishy soul stuff" (Churchland, 1986). We are not close to approximating the range and depth of human feelings in our variables; as our models and those of other neural network researchers get more elaborate, the range of affective variables will be wider but still not capture all feelings. Rather, we are positing a few simplified variables representing some aspects of affective states that change with context and might be measurable as laboratory techniques are improved. Some possible neurobiological and neurochemical bases for these variables are discussed in the article by Leven (1992) on learned helplessness, which is a depressive state that can depend on context (one can, for example, be helpless on problems dealing with automobile mechanics and not on problems dealing with income taxes, or the reverse).

Effects of emotional states on specific memories are widely documented in experimental psychology (see, e.g., Bower, 1981). Singh and Churchill (1987) showed that television advertising is more effective, and is remembered for longer, if it occurred during highly emotionally charged programs, such as erotic or violent ones, than if it occurred during more emotional neutral programs. Modeling the "erotic" data is beyond the scope of the network in this article but also amenable to our methods. Singh and Churchill argued that it is dependent on physiological arousal, and indeed there is arousal associated with both positive and negative affect. The complex interplay between arousal, drive, and memory is discussed more fully in some general neural network modeling articles, such as Grossberg (1982).

In addition to affect and arousal, other nonrational factors that influence DMs are novelty and habit. Novelty played a significant role, of course, in the positive responses to New Coke on taste tests and is captured by our model. Habit is not involved in the network of Figure 4 but plays an important part in our models of perseverative responses of patients with frontal lobe damage on various cognitive tasks (see Levine, Parks, & Prueitt, 1993, for a summary). As in the case of attraction to novelty, we see the behaviors of those with frontal lobe damage as more serious than, but not qualitatively different from, many behaviors of individuals that are
NEURAL NETWORK FOR MULTIATTRIBUTE DECISION IN CONTEXT

"stuck" in patterns that may have been optimal (even SEU-maximizing) at one time in the past but are no longer optimal (see Levine & Leven, 1995).

Economic decisions, because they involve "dollars and cents," are widely thought to be more rationally and less affectively based than other human decisions. Yet Modigliani (e.g., 1975) has shown repeatedly that decisions as to how much money to save or spend cannot be predicted from the decision maker's current (or even current plus expected future) income alone. Comparisons to some baseline of expectation, in a manner analogous to the framing effects of Tversky and Kahneman (1974), affect each DM's perception of his or her own income, which in turn affect the amount of that DM's savings. For example, Modigliani noted that blacks tend to save a larger percentage of their income than whites earning the same amount. His explanation was that because average blacks' salaries are lower than average whites', the black person earning a given amount will evaluate his or her income in comparison with those of other blacks and so perceive it as larger than would a white earning the same income. The percentage of income saved or spent is also influenced by previous habits of saving or spending, as discussed in Brown (1952).

It is becoming more widely accepted that affect and other nonrational factors need to be considered to study real-life DMs and make policy around actual human behavior. It might also be argued that affect has a role in optimal decision making. Specifically, some of the most creative accomplishments, that have earned millions of dollars for companies, have been made by individuals who do not "play the percentages," that is, follow "rational" SEU theory, but rely on creative intuitions that violate easily measurable criteria for success. Can a way be found to stretch normative decision making to encompass the possibility of such contributions by nonconformists? We shall return to these points in Section 3.4.

3.3. Modeling Economic Decision Making
The gated dipole network, as a mathematical structure capable of comparing actual with expected outcomes, can potentially underlie models of interactions among multiple economic decision makers. At a time when game-theoretic accounts of interpersonal bargaining are gaining credibility (Pool, 1994), descriptions of human signals must be far more complex than contemporary accounts (e.g., Ekman, 1992). Leven and his associates have designed increasingly extensive network models which simulate bargaining between "agents" (space permits only a brief summary here). Blackwood, Elsberry, and Leven (1988) and Leven and Elsberry (1990) introduced the "S.A.M.N" model, which emulates face-to-face bargaining among agents. In these articles, agents' decision making was determined by interactions among networks emulating the "triune brain" framework of MacLean (1980) and Pribram (1991).
Three “flavors” of memory were identified (Leven, 1987, 1992), matching the automatic/motoric, episodic (“affective”), and semantic memories so often described in the literature. Leven has argued that dimensions of incoming stimuli are gated to the three stores, enabling interpretive matches to be made and responses to be generated by each flavor. These three allow approximation of both conscious and unconscious communication of information. The responses are communicated in the bargaining session, along with a “bid.” In this setting, agents display and interpret rich sets of information that convey various aspects of the meaning of an offer, as they do in standard settings (Walton, Cutcher-Gershenfeld, & McKersie, 1994).

Early experiments on S.A.M.N and related models demonstrated social phenomena-like dominance, obeisance, insecurity, and overconfidence. A more recent demonstration produced by a particular set of initial conditions was an “OPEC” scenario: One bargaining group obtained distortedly low prices over time, until the dissonance between the value perceived by the obeisant bargainer and the accepted bids grew so great that the dominant group was suddenly overwhelmed by resistance from the previously quiescent group—and prices jumped instantly (Leven, 1995a). Still further network experiments have allowed for development of social hierarchies and complex “internal languages” within “homogeneous groups” (Leven, 1995b).

Only by replicating the complexities of human communication can games develop the verisimilitude foreseen by Von Neumann and Morgenstern (1994). The neural network experiments of Leven, Blackwood, and Elsberry, based in the same underlying model as the “Coke” network herein, emulate many of these complexities and thereby lend credibility to experimental games.

Now let us return to the version of subjective expected utility described by Weintraub (1979; see Section 1.1. of this article for summary). The Coke model discussed in the last section was successful precisely because it violated Weintraub’s assumption [2], that agents have preexisting and invariant preferences. Likewise, the OPEC-related model of Leven and Elsberry (1990) was successful because it violated Weintraub’s assumptions [3] and [5]. Assumption [3], that agents independently optimize subject to objective and easily observable constraints, breaks down because differences in cultural experience and education cause Americans and Arabs, for example, to perceive constraints differently. Assumption [5], that agents at all times possess full relevant knowledge, breaks down because the negotiation dynamics themselves can both increase the knowledge (accurate or false!) that each agent has of the other and challenge beliefs previously held by each agent about the other.

Neural network studies such as our Coke and OPEC models point to potential ways out of some paradigmatic crises in economics (Rosenberg, 1992) and decision theory (Edwards, 1992b). Rosenberg criticized what he called “rational choice theory” as follows:
the explanatory variables of economic theory...are not linked to physical mechanisms in a way that will enable us to discover where and how they go wrong. The relationship between beliefs, desires, and behavior just does not permit us to isolate one of these variables from the others and to sharpen up our measurements of it in ways that will lead to identification of the point at which the whole story goes wrong. (p. 239)

The complex interplay of values, affect, beliefs, and so forth in our models begins to address Rosenberg's criticisms of economic theory (see also Leven, 1987). Although we have not yet identified measurable physical variables relevant to actual economic behavior, further network studies, informed by psychological and neurobiological data, should facilitate finding these variables in the relatively near future.

3.4. Descriptive Versus Normative Versus Prescriptive Decision Theories

In the standard distinction between descriptive, prescriptive, and normative decision theories (e.g., Eppel et al. 1992), ours is a descriptive theory. We also intend it, though, to lead to prescriptive theories for particular cases.

Our field in which different factors going into decisions are illustrated is organization theory. Leven (1987, chap. 4) summarized three competing modern approaches to organization theory, which he called the classical, human-relations, and social-psychological schools. The classical approach is discussed in Gilbreth (1977): “It is the aim of Scientific Management to induce men [sic] to act as nearly like machines as possible. . . . Scientific Management boosts 'machines' for efficiency, not for their bluffs, bulldozing, or snap judgment” (p. 23). The human-relations school centers around the need to “ensure spontaneity of cooperation; that is teamwork” (Mayo, 1977, p. 410) and to develop “social skills, skills that will be effective in specific situations” (Mayo, 1977, p. 414). Finally, the social-psychological approach is exemplified by the argument of Argyris (1973) that “man [sic] shows profound capacity to learn to behave in many different ways. . . . The intention is to create more opportunity for self-actualization by designing new forms of organization and creating new policies” (pp. 264–265).

All three of these management schools have achieved successes at different types of tasks; in general, the greater the complexity and ambiguity of the tasks, the more an approach similar to Argyris' is needed. Leven (1987) drew the analogy between the three management schools and the three parts (instinctive/visceral, rational/semantic, and emotional/affective) of the brain as described by MacLean (1980). Neural network theory provides the only quantitative framework in which instinctive, rational, and affective processes can all be studied as interacting variables. Therefore, we expect that the type of neural network theory described herein will, in the intermediate term, lead to some normative suggestions for which type of
organization will be most effective in which situations—or else, neural networks will lend additional scientific credence to normative suggestions that have already been made on an intuitive and nonquantitative basis. The elaborations will differ in other fields of social science, but the type of neural network methodology outlined here is likely to be widely useful.

The SEU theory has been important in decision science precisely because it offers measurable and quantifiable functions to study. This theory has tended to exclude effects that its proponents themselves recognize as important—affect, context, dynamics, novelty, and habit—because no way has been found to study those variables quantitatively. The authors we have cited for their careful and insightful descriptions, contextual and affective influences (Brown, 1952; DeLong et al., 1990; Lee et al., 1991; Modigliani, 1975) have developed mathematical models of the phenomena they study, but their models also do not include affective variables in any systematic way. Rather, they adapt previously existing variants of SEU theory to include ad hoc changes in a few variables to incorporate the specific effects they study.

We have shown that neural network methods provide not a tight mathematical mapping of effects such as affect and context, but a way to model their significant aspects approximately. Our Coke example illustrates that including such effects can lead to models that fit actual human decision-making data better than SEU models do. Our model is far from comprehensive or complete, but we believe that most other decision data can be captured by other network models constructed along the same lines with the same principles as the ones we use. In particular, our model deals only with passive decision making, that is, choice from among previously determined options, and not with active decision making, which includes generation of new options by modifying or combining old ones. Langer (1994) discussed evidence that active decisions tend to be more satisfying to the DM, and Vincke (1992) emphasized the value of active dialogue between DMs and decision-aid algorithms. We are now modeling active versus passive decisions, including their possible biological basis, for a subsequent article.

In decision science, as in other social sciences, there has been some degree of conflict between "quantitative" and "behavioral" approaches. Quantitative studies of decisions have tended to neglect affect, habit, novelty, and other nonrational factors that go into most actual human-made decisions. On the other hand, behavioral studies have tended to lack rigorous mathematical and theoretical foundations that can subsume many types of problems. We have shown by example how neural networks can provide

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6 Another methodology that can capture relations between economic or social events is fuzzy logic, which is closely akin to nonlinear dynamical systems theory. This is particularly evident in the "fuzzy cognitive maps" of Kosko (1986), whereby nodes represent different factors in a broad database (e.g., South African race relations or the AIDS epidemic), and connections represent effects of these factors on each other.
methodology that is both quantitative and behavioral, thereby leading to potential reconciliation between the two types of approaches.

REFERENCES


APPENDIX: NETWORK EQUATIONS

The gated dipole interactions, shown in Figure 2 and discussed in Section 2.1, can be represented by the following equations:

\[
\begin{align*}
\frac{dy_1}{dt} &= -ay_1 + I + J \\
\frac{dy_2}{dt} &= -ay_2 + I \\
\frac{dw_1}{dt} &= b(c - w_1) - ey_1 w_1 \\
\frac{dw_2}{dt} &= b(c - w_2) - ey_2 w_2 \\
\frac{dx_1}{dt} &= -ax_1 + gy_1 w_1 \\
\frac{dx_2}{dt} &= -ax_2 + gy_2 w_2 \\
\frac{dx_3}{dt} &= -ax_3 + h(x_1 - x_2) \\
\frac{dx_4}{dt} &= -ax_4 + h(x_2 - x_1) \\
\frac{dx_5}{dt} &= -ax_5 + (r - x_5)x_3 - x_5x_4
\end{align*}
\]

where \(a, b, c, e, g, h,\) and \(r\) are positive parameter values. Because our network combines a total of eight gated dipoles, its equations involve combinations of eight copies of (1) with influences from outside, to be given below.

The positive parameter \(a\) represents a decay of node activities \((y_1, y_2, x_1, x_2, x_3, x_4, x_5)\) back to their baseline levels. The value \(I\) represents a nonspecific arousal that is always active. The positive parameters \(f, g,\) and \(h\) represent strengths of interactions between the appropriate nodes; for example, the term \(gy_2 w_1\) in the equation for \(x_1\) represents the strength of influence of the node \(y_1\) and \(x_1\) via the connection \(w_1\). The strength of the depletable transmitter \(w_1\) is influenced by depletion, at a rate represented by the positive parameter \(e,\) and recovery at a rate \(b.\) The parameter \(c\) represents the weight of \(w_1\) in the undepleted state. The role of the parameter \(r\) is to keep the activity values from becoming unbounded.

One modification by Grossberg (1972) that we employ in the gated dipole equations is, in the equations for \(x_3, x_4,\) and \(x_5,\) to replace the terms \(x_1 - x_2,\) \(x_2 - x_1,\) and \(x_3 - x_4\) by 0 if those terms are negative. The meaning of this change is that, for example, \(x_1\) excites \(x_3,\) and \(x_2\) inhibits \(x_3,\) but if \(x_1\) is smaller than \(x_2,\) \(x_3\) receives no net signal and simply decays exponentially. The standard mathematical expression for this operation is

\[(x_1 - x_2)^+\]

where the superscript "\(^+\)" denotes the "positive part" of a number, that is, for any real number \(r,\)

\[
r^+ = \max (r, 0) = \begin{cases} 
  r & \text{if } r > 0 \\
  0 & \text{if } r \leq 0
\end{cases}
\]
Recall that the network of Figure 4 includes eight gated dipoles. Hence, Equations (1), with the replacements using the "+" function of Equation (2), will be repeated eight times with all the \(x, y,\) and \(w\) variables double subscripted. That is, the variables are \(y_{i1}, y_{i2}, w_{i1}, w_{i2}, x_{i1}, x_{i2}, x_{i3}, x_{i4},\) and \(x_{i5},\) and the corresponding symbols with \(i\) replaced by \(j\) or \(k,\) where

- \(i = 1\) to \(4\) represents attributes—respectively, Coke Label, Pepsi Label, Taste, Familiarity;
- \(j = 5\) to \(6\) represent categories—Coke and Pepsi;
- \(k = 7\) to \(8\) represent drives—Excitement and Security.

Connection weights between attributes and categories, between attributes and drives (separately to and from the positive and negative sides of each drive dipole), and between categories and drives (similarly, both with the positive and negative sides) are assumed to have been learned previously, but the taste tests and markets are assumed to take place over too short a time interval for new learning. Hence, these inter-dipole weights are assumed to be fixed and read into the program as parameters. The weight from the dipole with subscript \(i\) to the dipole with subscript \(j\) is labeled \(z_{ij}.\) If one of \(i\) and \(j\) is the index for a drive dipole (7 or 8), there are two values of \(z_{ij}\) corresponding to the positive and negative sides of the drive dipole; these \(z\) values are labeled \(z_{ij}^+\) and \(z_{ij}^-\).

For \(i = 1\) to \(4\) (the four attribute dipoles), some influence from the category dipoles is added to the significant input \(y_{i1},\) and influence from the drive dipoles (both positive and negative) is added to the output \(x_{i5}.\) Hence, if \(J_1, J_2, J_3, J_4\) denote the components of the attribute vector for the current significant input (Old Coke, Coke, or Pepsi), then

\[
\begin{align*}
\frac{dy_{i1}}{dt} &= -ay_{i1} + I + J_i + f(z_{i1}x_{55} + z_{i6}x_{65}) \\
\frac{dy_{i2}}{dt} &= -ay_{i2} + I \\
\frac{dw_{i1}}{dt} &= b(c - w_{i1}) - ey_{i1} w_{i1} \\
\frac{dw_{i2}}{dt} &= b(c - w_{i2}) - ey_{i2} w_{i2} \\
\frac{dx_{i1}}{dt} &= -ax_{i1} + gy_{i1} w_{i1} \\
\frac{dx_{i2}}{dt} &= -ax_{i2} + gy_{i2} w_{i2} \\
\frac{dx_{i3}}{dt} &= -ax_{i3} + h(x_{i1} - x_{i2})^+ \\
\frac{dx_{i4}}{dt} &= -ax_{i4} + h(x_{i2} - x_{i1})^+ \\
\frac{dx_{i5}}{dt} &= -ax_{i5} + (r - x_{i5}) x_{i3} + f \left[ \sum_{k=1}^{8} (z_{ki}^+ x_{k5} + z_{ki}^- x_{k6}) \right] + x_{i5} x_{i4}
\end{align*}
\]

The category dipoles are connected to an orienting arousal node, as shown in Figure 4, which responds to mismatch (in the attribute vectors) between an input and the chosen category's prototype. Mismatch is detected as follows. Let \(\lambda_7\) be the strength of the Excitement drive and \(\lambda_8\) be the strength of the security drive. These are set to different values during the
testing phase and the market phase; in the former $\lambda_7 > \lambda_8$, whereas in the latter $\lambda_8 > \lambda_7$. For each attribute index $i$ ($i = 1$ for Coke Label, 2 for Pepsi Label, 3 for Taste, 4 for Familiarity), the bias in favor of the attribute, call it $\Omega_i$, is set equal to the sum of the associative strengths between the attribute and satisfaction of two drives weighted linearly by the drive strengths, that is, $\lambda_1 z_{i7} + \lambda_2 z_{i8}$. The attribute vector for the current input (Old Coke, New Coke, or Pepsi) is multiplied componentwise by the biases $\Omega_i$, and so is the prototype attribute vector for the active category, which is either Coke or Pepsi depending on which category dipole is more activated by the current input. That prototype attribute vector has components $z_{ji}$, $i = 1$ to 4, where $j = 5$ for Coke and 6 for Pepsi. Then these two weighted attribute vectors are normalized (to vectors whereby the sum of squares of the components is 1) and the dot product taken. If that dot product is above a “vigilance” level $\nu$, the orienting node sends a signal of intensity $\lambda$; otherwise, it sends no signal. (The orienting node has an all-or-none activity which does not obey a differential equation.)

The activities of the category dipole nodes obey the following dipole equations, where $\Theta$ denotes the signal from the orienting node (or 0 if there is no orienting signal), $j'$ denotes the category index other than $j$, and $p$ is another positive constant:

\[
\frac{dy_{j1}}{dt} = -ay_{j1} + I + f \left( \sum_{i=1}^{4} z_{ij}x_{i5} - \Theta \right)
\]

\[
\frac{dy_{j2}}{dt} = -ay_{j2} + I
\]

\[
\frac{dy_{j3}}{dt} = ay_{j3} + gy_{j1}x_{j1}
\]

\[
\frac{dy_{j4}}{dt} = ay_{j4} + h(x_{j2} - x_{j1})
\]

\[
\frac{dy_{j5}}{dt} = -ay_{j5} + (r - x_{j5})x_{j3} - x_{j5}(x_{j4} + px_{j's})
\]

Finally, the motivational (drive) dipoles obey similar equations except that instead of there being a single output node $x_{k5}$ for each one ($k = 7$ for Excitement, 8 for Security), there are “positive” output nodes $x_{k5}$ and “negative” output nodes $x_{k6}$, a type of network introduced in the conditioning model of Grossberg and Schmajuk (1987). The equations for the activities of these nodes (with $l$ another positive constant and $\lambda_k$ the current strength of the appropriate drive as above) are

\[
\frac{dy_{k1}}{dt} = -ay_{k1} + I + hx_{k5}
\]

\[
\frac{dy_{k2}}{dt} = -ay_{k2} + I + hx_{k6}
\]

\[
\frac{dw_{k1}}{dt} = b(c - w_{k1}) - ey_{k1} w_{k1}
\]

\[
\frac{dw_{k2}}{dt} = b(c - w_{k2}) - ey_{k2} w_{k2}
\]
\[
\begin{align*}
\frac{dx_k}{dt} &= -ax_k + gy_k w_k \\
\frac{dx_k}{dt} &= -ax_k + h (x_k - x_{k-1})^+ \\
\frac{dx_k}{dt} &= -ax_k + (r - x_k) (x_k + \lambda_k \left[ \sum_{i=1}^{6} (z_{ik} x_{i5}) - lx_k x_{k4} \right] \\
\frac{dx_k}{dt} &= -ax_k + (r - x_{k-1}) (x_k + \lambda_k \left[ \sum_{i=1}^{6} (z_{ik} x_{i5}) - lx_k x_{k3} \right]
\end{align*}
\]

For the simulations shown in Table 2, the following parameter values were used for both the "Coke Drinker" and "Pepsi Drinker" versions of the network: $a = 4$, $f = 10$, $b = .2$, $c = 2$, $e = 1$, $g = 10$, $h = 5$; $z_{ki} = .2$ for all $k = 7,8$, $i = 1$ to $4$; $z_{i7}^+ = 5$, $z_{i7}^- = .2$, $z_{i8}^+ = 2$, $z_{i8}^- = .2$, $z_{i7}^+ = 2$, $z_{i7}^- = .2$, $z_{i8}^+ = 5$, $z_{i8}^- = 2$, $k = 2$, $p = 10$, $z_{i1} = 1$, $z_{i2} = 0$, $z_{i3} = .5$, $z_{i6} = 0$, $z_{i6} = 1$, $z_{i6} = 1$, $r = 5$, $1 = 2$, $z_{i7}^+ = .5$, $z_{i7}^- = .1$, $z_{i8}^+ = .25$, $z_{i8}^- = .1$, $z_{i8}^+ = .5$, $z_{i7}^+ = 2$, $z_{i6} = 2$; $Z_{ik}^- = .02$ for all $i = 1$ to $4$, $k = 7,8$; $I = 1$, $\nu = .75$. The parameters that differed between the Coke and Pepsi drinkers all represent weights between the Coke or Pepsi labels or categories and motivational sources, or between the categories and familiarity or taste attributes. $z_{17}^+ = z_{18}^+ = 5$, $z_{27}^+ = z_{28}^+ = 2$, $z_{54} = 1$, $z_{64} = .5$, $z_{17}^+ = .25$, $z_{27}^+ = .1$, $z_{15} = 4$, $z_{16} = 20$, $z_{16} = 1$, $z_{16} = 25 = 0$, $z_{26} = 5$, $z_{35} = 2.5$, $z_{45} = 4$, $z_{46} = 2.5$ for the Coke Drinker; $z_{i7}^+ = z_{i8}^+ = 2$, $z_{i7}^+ = z_{i8}^+ = 5$, $z_{i7}^+ = .5$, $z_{i7}^+ = .1$, $z_{i7}^+ = 2.5$, $z_{i8} = 1$, $z_{i8} = 20$, $z_{i5} = 5$, $z_{i6} = 25 = 0$, $z_{26} = 4$, $z_{35} = 2.5$, $z_{36} = 2$, $z_{45} = 2.5$, $z_{46} = 4$ for the Pepsi Drinker. During the taste test, the "Excitement" drive strength $\lambda_7 = 5$ and the "Security" drive strength $\lambda_8 = 1$; during the buying situation, $\lambda_7 = 1$ and $\lambda_8 = 5$. The attribute vectors representing Old Coke, New Coke, and Pepsi were

<table>
<thead>
<tr>
<th>Input</th>
<th>Coke Label</th>
<th>Pepsi Label</th>
<th>Taste</th>
<th>Familiarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Old Coke</td>
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<td>0</td>
<td>.5</td>
<td>1</td>
</tr>
<tr>
<td>New Coke</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Pepsi</td>
<td>0</td>
<td>1</td>
<td>.5</td>
<td>.5</td>
</tr>
</tbody>
</table>