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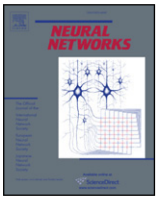

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Brain pathways for cognitive-emotional decision making in the human animal

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ABSTRACT

As roles for different brain regions become clearer, a picture emerges of how primate prefrontal cortex executive circuitry influences subcortical decision making pathways inherited from other mammals. The human's basic needs or drives can be interpreted as residing in an on-center off-surround network in motivational regions of the hypothalamus and brain stem. Such a network has multiple attractors that, in this case, represent the amount of satisfaction of these needs, and we consider and interpret neurally a continuous-time simulated annealing algorithm for moving between attractors under the influence of noise that represents "discontent" combined with "initiative."

For decision making on specific tasks, we employ a variety of rules whose neural circuitry appears to involve the amygdala and the orbital, cingulate, and dorsolateral regions of prefrontal cortex. These areas can be interpreted as connected in a three-layer adaptive resonance network. The vigilance of the network, which is influenced by the state of the hypothalamic needs network, determines the level of sophistication of the rule being utilized.

1. Introduction

The irrational heuristics that govern the bulk of human decision making (e.g. Kahneman and Tversky (1973), Tversky and Kahneman (1974)) are widely recognized. Yet the capacity for decision making that is deliberative, numerically accurate, and self-consistent is also present in the same neural networks that make unthinking heuristic decisions. The heuristic type of decisions can be traced to the heritage of emotionally influenced decisions made by other mammals, for example, decisions about foraging under the risk of predation (Coleman, Brown, Levine, & Mellgren, 2005). The goal of this article is to encompass both heuristic and deliberative decisions within a common neural framework based in brain pathways that can be traced back to our evolutionary ancestors.

The same individual can be consistent or logically correct on some occasions and not on others. This suggests that multiple decision rules, some of them logically accurate and some inaccurate, coexist in our brain. Yet the logical inaccuracies are widely regarded as by-products of heuristics that have evolutionary value for rapid day-to-day decision making. The process of selection among these rules has been the focus of an ongoing theoretical investigation (Levine, 2007a, 2007b; Levine & Perlovsky, 2008a, 2008b).

We will discuss the competition between different rules used in decision tasks of varying complexity, some rules based heavily on unconscious heuristics (Tversky & Kahneman, 1974) and other rules involving deliberative calculation and working memory manipulation. First we start with a substrate of needs or drives that is largely inherited from other mammals.

2. The network of needs

The organism's basic physiological needs are represented in deep subcortical structures that are shared with other animals and that have close connections with visceral and endocrine systems. These regions include several nuclei of the hypothalamus and brain stem.

Kilmer, McCulloch, and Blum (1969) modeled competition among the organism's gross modes of behavior (e.g., eating, drinking, sex, exploration, etc.). Their S-RETIC model was based in a number of poker chip-shaped autonomous modules within the midbrain and brainstem reticular formation. The behavioral modes compete within each module until the same mode wins the competition in more than half of the modules. A similar idea appears in the selective attention network theory of Grossberg (1975) who placed what he called a *sensory-drive heterarchy* in the hypothalamus. Different drives in the heterarchy compete for activation, influenced both by connections with the viscera (giving advantage in the competition to those drives that most need to be satisfied) and with the cortex (giving advantage to those drives for which related sensory cues are available).

If we assume a competitive-cooperative network of needs, then learning and implementation of decision rules will be based heavily on satisfaction of those needs (often more than one)

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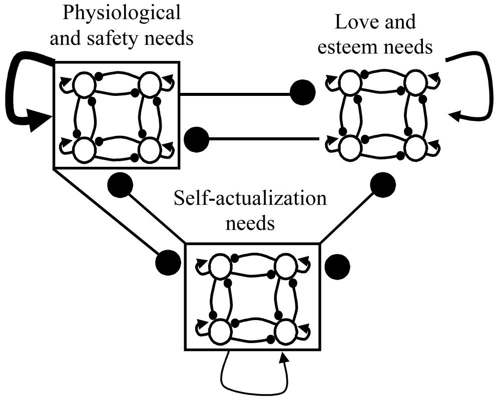

Fig. 1. A neural network rendition of Maslow's hierarchy of needs. Arrows represent excitation, filled circles inhibition. All these needs excite themselves and inhibit each other. But the hierarchy is biased toward the physiological and safety needs which have the strongest self-excitation, represented by the darkest self-arrow; the love and esteem needs have the next darkest self-arrow, and the self-actualization needs the lightest. (Reprinted from Levine, 2007a, with the permission of Springer-Verlag).

that are currently winning the competition. Several psychologists, starting with Kurt Lewin and Abraham Maslow in the 1930s and 1940s, expanded the idea of "needs" beyond the purely physiological ones to include the needs for social connections, aesthetic and intellectual stimulation, esteem, and self-fulfillment, for example. In particular, Maslow (1968) developed the notion of *hierarchy of needs*. He meant the term "hierarchy" in a more flexible sense than is usually understood, a sense that is somewhat analogous to Grossberg's (and McCulloch's, earlier) use of "heterarchy." His hierarchy construct can be accommodated by a competitive-cooperative neural network with biases (see, e.g. Grossberg & Levine, 1975). The biases mean there tends to be more weight toward the lower-level needs if those are unfulfilled, or if there is too much uncertainty about their anticipated fulfillment (see Fig. 1 for a schematic diagram). However, bias toward lower-level need fulfillment is a form of risk aversion, and individual personality differences in risk aversion or risk seeking can either mitigate or accentuate the hierarchical biases.

Placing the psychological as well as the physiological needs in the evolutionarily old areas of hypothalamus and midbrain could be controversial. After all, those areas change little structurally from other mammals to humans, and other mammals do not possess the social complexity that has generated some of our more sophisticated emotions. Yet there is evidence that other animals share at least some of our psychological needs, especially those for social bonding and for stimulation. Also, such knowledge-related states as cognitive dissonance can engage some of our primitive autonomic reactions. Moreover, even though these deep brain regions themselves have changed little over the course of evolution, the influences on those regions from the prefrontal cortex have markedly increased from non-primate mammals to monkeys and apes to humans. The evolutionary changes in top–down pathways lend credence to the idea of hypothalamic and midbrain involvement in "higher" as well as "lower" needs.

As for bonding, Buijs and Van Eden (2000) found a site in the paraventricular nucleus of the hypothalamus, for the production of oxytocin, a key hormone for social bonding and for pleasurable aspects of interpersonal interactions (including orgasm, grooming, and possibly massage). As for stimulation and curiosity, recent work points to a strong role of the locus coeruleus, a midbrain noradrenergic nucleus that is part of the reticular formation, in promoting exploratory behavior (McClure, Gilzenrat, & Cohen, 2006).

Cognition and emotion have traditionally been regarded as separate, but recent results in cognitive neuroscience have confirmed that the separation is simplistic because cognitive and emotional processes have strong mutual influences and engage the same brain regions (see Pessoa, 2008, for a review). Because of this traditional separation, psychologists resisted for a long time the notion that cognitive dissonance produces physiological arousal. Croyle and Cooper (1983) found nonspecific arousal-related skin conductance increases in participants who had freely chosen to write essays contrary to their own opinions, noting that many of the participants misattributed their arousal to a different cause (the experimental equipment). Subsequently those authors explained their findings by saying that the arousal was induced by responsibility for producing aversive consequences. But Harmon-Jones, Brehm, Greenberg, Simon, and Nelson (1996) found that aversive consequences were not necessary for dissonance arousal. These psychologists gave participants a drink that was harmless but tasted unpleasant, then asked them to write on a sheet of paper that the drink tasted good and immediately destroy the paper. A skin conductance response was found when the participants wrote on the paper despite their knowledge that what they wrote would have no effect on anyone else's behavior.

The cognitive dissonance results lend support to the notion (not specifically addressed by Maslow) that one of the needs contained in the hierarchy of Fig. 1 is a need for coherent knowledge and understanding of the world. Perlovsky (e.g., 2006) called this need a *knowledge instinct*, and noted that the knowledge instinct has an emotional as well as a cognitive side. The emotional aspect of the knowledge instincts consists of aesthetic emotions, the sense of beauty or harmony from satisfaction of the knowledge need and ugliness or disharmony from dissatisfaction of that need.

The hypothalamic/midbrain/brain stem network of Fig. 1 is a competitive-cooperative network and, like many neural networks of that type (Cohen & Grossberg, 1983; Hopfield & Tank, 1985) is assumed to have multiple attractors and a Lyapunov function (energy function) that decreases along trajectories. Some of the attractors are more "optimal" than others, being global as opposed to local minima for the energy function. Levine (1994, 2005, 2007a) developed and interpreted biologically a continuous simulated annealing scheme for moving from a less to a more optimal attractor (Fig. 2). The Lyapunov function V is interpreted as an overall "distress level" from unmet needs of the network or organism. States with smaller values of V are affectively more desirable; hence, the global minimum of that function is interpreted as an optimal state of the system.

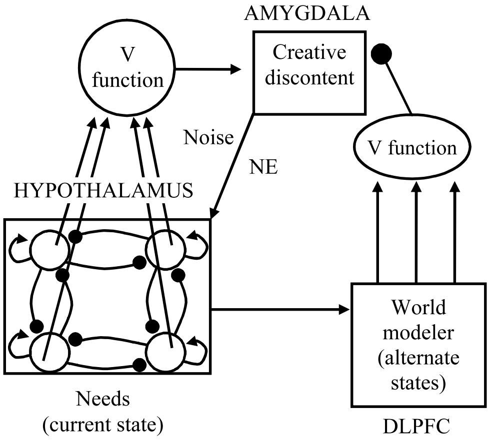

Fig. 2. If the current state of the needs module has a larger energy function than some alternative state detected by the world model module, the net signal (excitatory minus inhibitory) to the creative discontent node is positive. The discontent node, when activated, in turn sends noise that perturbs the needs module so it can move toward a different attracting state. (Adapted from Levine, 1994), with the permission of Lawrence Erlbaum Associates.)

This competitive module is supervised by a "world modeler" module that is analogous to working memory areas in the dorsolateral prefrontal cortex (DLPFC; (Fuster, 2000)). The world modeler imagines and makes "copies" of various possible states of the need subsystem and calculates the Lyapunov function for each, in search of a state with a lower V (i.e., a state that is closer to optimal). If V of the current state, say $\mathbf{x}$, is larger than V of some other projected state, say $\mathbf{x}'$, the combination of excitation from the needs module and inhibition from the world modeler produces a signal of magnitude $V(\mathbf{x})-V(\mathbf{x}')$ to a "creative discontent" module. When thus activated, the discontent module in turn sends random noise back to the needs module, which can move that module out of a suboptimal local minimum. Yet the noise may or may not be sufficient to cause a move to a global minimum or any other attractor. Whether that move occurs depends on both the dynamics of the needs module and the gain of signals from creative discontent activity to the noise signal generator.

The needs module of Fig. 2 has already been identified with a part of the hypothalamus, possibly including some of the hormone generators in the paraventricular nucleus (Buijs & Van Eden, 2000). The discontent signal may be identifiable with some part of the amygdala, which represents positive or negative emotional valences of stimuli or actions (Gaffan & Murray, 1990). The effects of fronto-amygdalar connections, in addition to those arising from the world modeler module of Fig. 2, could include control of the gain of the noise signal from the discontent module. This suggestion comes from the clinical observation that frontally damaged individuals can express frustration when their actions are ineffective, but this frustration does not lead them to change their actions (Milner, 1964).

The amygdala is also heavily innervated by norepinephrine (NE) projections from the locus coeruleus (see Fig. 2). NE is the transmitter most associated with nonspecific arousal and with exploration (see, e.g. Aston-Jones & Cohen, 2005), and therefore we identify it in our mathematical theory with a variable called "initiative" that measures the gain of the discontent signal. In the network of Fig. 2, NE signals could directly affect the competitive needs module, making its dynamics more *winner-take-all* (i.e., only one or a few nodes have nonzero asymptotic activity) with a low NE level, or more *coexistent* (i.e., many nodes have nearly equal asymptotic activities) with a high NE level. In the current theoretical context, this means that a larger NE level moves the module toward attractors that satisfy a greater number of needs. Grossberg (1973) proved that for the simplest version of his competitive on-center off-surround network, nonspecific excitatory signals to all nodes lead to such coexistent dynamics.

The state of the needs module, indicating which goals are currently paramount for the individual, have a strong influence on the decision strategies used to solve particular problems. The discussion now moves to the instantiation of decision rules in a network consisting of amygdala and three areas of prefrontal cortex; then it returns to the influence of current drives and goals on the choices among those rules. To set the stage we start by reviewing some brain imaging data bearing on the involvement of brain regions in the representations of different types of decision rules.

3. The network of decision rules

There have been several fMRI studies showing that for participants engaged in judgment and decision tasks, brain activation patterns are influenced by whether the participants make logically correct or consistent choices. In particular, the studies of DeMartino, Kumaran, Seymour, and Dolan (2006) on framing effects and of DeNeys, Vartanian, and Goel (2008) on Bayesian reasoning illuminate the roles of specific brain executive regions in those processes.

The study of framing effects is based on Tversky and Kahneman's (1974, 1981) finding that in many risky choices, preferences change when the same alternatives are framed in terms of gains versus framed in terms of losses. For example, subjects asked to consider two programs to combat an Asian disease expected to kill 600 people tend to prefer the certain saving of 200 people to a 1/3 probability of saving all 600 with 2/3 probability of saving none. However, subjects also tend to prefer a 1/3 probability of nobody dying with a 2/3 probability of 600 dying to the certainty of 400 dying. Tversky and Kahneman's explanation of this inconsistency was "choices involving gains are often risk averse while choice involving losses are often risk taking" (Tversky & Kahneman, 1981, p. 453).

DeMartino et al. (2006) utilized a monetary variant of Tversky and Kahneman's "Asian disease" problem in their fMRI study. In their paradigm, participants had to choose between a sure option and a gamble option, where the sure option was expressed either in terms of gains (e.g., keep £20 out of the £50 they initially received) or in terms of losses (e.g., lose £30 out of the initial £50). As in the Asian disease problem, the majority of participants chose the sure option with a gain frame and the gamble option with a loss frame. Yet significant minorities of participants chose the gamble with a gain frame or the sure option with a loss frame, in violation of the usual heuristics. fMRI measurements showed that heuristics-violators exhibited more activation than heuristics-followers in two executive areas of prefrontal cortex: the *orbitofrontal cortex* (OFC) and *anterior cingulate* (ACC). Conversely, heuristics-followers exhibited more activation than heuristics-violators in the amygdala, the subcortical area most involved with primary emotional experience.

The OFC has the primary function of integrating sensory and affective information, and thereby is involved in preferences based on positive or negative values of alternative stimuli or actions (Damasio, 1994; Tremblay & Schultz, 1999). The ACC has a variety of functions relating to detection of potential conflict, error, or task difficulty (Van Veen & Carter, 2006).

A third region of prefrontal cortex, the *dorsolateral prefrontal cortex* (DLPFC), is involved in reasoning and working memory manipulation (Fuster, 2000). Kim, Hwang, Seo, and Lee (2009) note that in monkeys as well as humans, lateral prefrontal cortex is involved in correct choices among alternatives based on consequences. There is little differential DLPFC activation by conditions in the monetary decision task of DeMartino et al. (2006), perhaps because that task does not actually require calculation or probabilistic reasoning. Other investigators, however, have found that DLPFC is more activated by correct than by incorrect responses on sophisticated tasks that do require probabilistic reasoning.

DeNeys et al. (2008) gave their participants a task in which decision makers tend to exhibit *base rate neglect* (Kahneman & Tversky, 1973); that is, judging the probability of a conditional event based purely on description without regard to prior probabilities. In this task the participants were told that a certain group of people consisted of some number of lawyers and some number of engineers: the numbers could either be balanced (500 lawyers and 500 engineers) or imbalanced (995 lawyers and 5 engineers, or the reverse). A hypothetical person was identified as a member of that group and given a description that fits a common stereotype of one of the two professions; then the participant was asked to determine the probability of that person being a lawyer or an engineer. Bayes' rule indicates that for a given description of someone known to be from a sample, the probability of being a lawyer or engineer should partly depend on the distribution of lawyers and engineers in the sample (*base rates*). Yet the majority of participants neglect the base rate, making probability judgments that depend solely on the stereotype without regard to the prior distribution. DeNeys et al. found that those participants (the minority) who took the prior distribution into account showed greater activation of the right DLPFC than those who neglected the prior distribution. Also, there was greater activation of the ACC (conflict detector) in the incongruent case (when, for example, a stereotypical description of an engineer was combined with a statement that 995 out of the 1000 were lawyers) than in the congruent case. The ACC data suggested that participants were aware of the conflict caused by base rates but had trouble inhibiting the prevailing description-based response.

How might these prefrontal executive regions (orbitofrontal, dorsolateral prefrontal, and anterior cingulate) and amygdala be functionally connected in a neural network? The last section highlighted the role of the amygdala in encoding emotional values of events. The OFC also plays a role in encoding emotional values and has extensive bi-directional connections with the amygdala. Most neuroscientists believe that the interaction between those two brain regions is crucial to emotionally influenced decision making.

Yet the roles of amygdala and OFC in emotional processing are somewhat different. First of all, stimulus-reinforcement associations can be more rapidly learned and reversed by OFC neurons than by amygdala neurons (Rolls, 2006). Second, whereas amygdalar but not OFC damage abolishes emotional arousal responses to aversive events after they occur, OFC damage abolishes anticipatory responses to aversive events before they occur (Bechara, Damasio, Damasio, & Anderson, 1994).

Both these results indicate that OFC is involved in emotional processing at a higher level of abstraction than the amygdala. This suggests that the relationship between amygdala and OFC is partly analogous to the relationship between primary sensory cortices and higher-level modality-specific association areas. The feedback relationships between primary and secondary sensory cortex have been modeled fairly successfully using adaptive resonance theory or ART (Carpenter & Grossberg, 1987).

In its simplest form (Fig. 3), the ART network consists of two interconnected layers of nodes, called F_1 and F_2. F_1 nodes respond to input features, and F_2 nodes respond to categories of F_1 activity patterns. Inter-layer synaptic connections are modifiable in both directions. F_2 nodes compete in a recurrent on-center off-surround network. Inhibition from F_2 to F_1 shuts off most F_1 activity if the input mismatches the active category's prototype. If the match is close, enough of the same F_1 nodes excited by both the input and the active F_2 category node to overcome nonspecific inhibition from F_2. If mismatch occurs, by contrast, F_2 inhibition (*reset*) shuts off the active category node as long as the current input is present. Matching is said to occur when some function representing correspondence between top–down and bottom–up patterns is greater than a positive constant r called *vigilance*.

Hence, for processing emotional values, we identify amygdala with layer F_1 of ART and OFC with layer F_2. Our model of emotionally influenced rule-driven decision making depends on bidirectional connections between those two areas. The bidirectional OFC-amygdala connections have been shown to be important for cognitive control of emotional reactions (cf. Barbas & Zikopoulos, 2006). Dranias, Grossberg, and Bullock (2008) developed a model of differences between effects of OFC and amygdalar lesions in various animal classical conditioning paradigms. In their model, called MOTIVATOR, the "object-value" module (identified with OFC) integrates influences from the "object" module (identified with secondary sensory cortex) and the "value" module (identified with amygdala). In the model of Dranias et al. (2008) connections from amygdala to OFC are unidirectional. However, the decision-making paradigms discussed here require utilizing previously stored information for affective evaluation, and thereby are likely to depend on those reverse connections.

The role of the OFC and its connections with the amygdala in processing social cues is well known (Damasio, 1994). This leads to a suggestion that resonant feedback between these two regions is required to learn and abide by socially accepted rules, whether or not these rules promote optimal mental functioning. For example, a reaction time study indicates that middle-aged men with OFC damage have internalized society's typical sexist myths about male strength and female weakness significantly less than normal men of the same ages (Milne & Grafman, 2001). Hence it is to be expected that all types of decision rules, both heuristic and deliberative, would have an encoding at the OFC-amygdalar loops. The other two executive areas, ACC and DLPFC, would seem to be required for deliberative rules but not for heuristic rules.

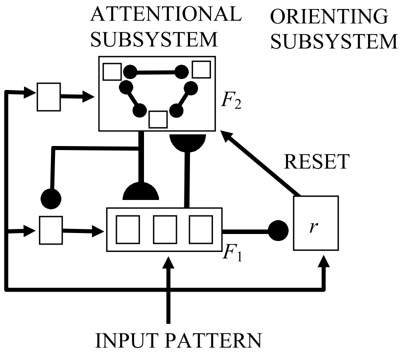

Fig. 3. ART 1 architecture. Short-term memory is encoded at the feature level F_1 and category level F_2, and learning at interlevel synapses. The orienting system generates F_2 reset when bottom–up and top–down patterns mismatch at F_1, that is, when the ratio of F_1 activity to input activity is less than the *vigilance* r. Arrows denote excitation, filled circles inhibition, and semicircles learning. (Adapted from Carpenter & Grossberg, 1987, with the permission of Academic Press)

The fMRI data of DeNeys et al. (2008) suggest that DLPFC, at least in the right hemisphere, is important for mental accuracy. That region had previously been associated with the executive function of cognitive inhibition (Aron, Robbins, & Poldrack, 2004), specifically the inhibition of habitual decision rules that turn out to be inaccurate or inappropriate in the present context. Yet Grossberg (2003) reviewed neurophysiological data showing that top–down attentional control is facilitatory in the visual cortex, noting this data supports the adaptive resonance model whereby top–down control is both inhibitory and excitatory. By analogy, our network theory conceptualizes the executive function often called "prefrontal inhibition" as a more general top–down regulation that can be either inhibitory or excitatory. We have conjectured that OFC exerts such selective control on amygdala, and likewise propose that DLPFC exerts the same kind of selective control on OFC at a higher level of abstraction (see Dias, Robbins, & Roberts, 1996, for evidence regarding DLPFC and OFC in monkeys).

The ACC's role in detecting conflict or potential error has been verified in neurophysiological and fMRI studies (Van Veen & Carter, 2006). For this reason we identify the ACC with the orienting reset area of Fig. 3. For simplicity we posit a single reset region whether the bottom layer is identified with amygdala and the top layer with OFC, or the bottom layer with OFC and the top layer with DLPFC.

We can integrate all these insights about orbitofrontal, dorsolateral prefrontal, and anterior cingulate cortices by noting that multiple ART modules can be combined into hierarchical networks with three or more levels of abstraction, whereby the top layer of one ART module is the bottom layer of another ART module (Carpenter & Grossberg, 1990). Fig. 4 shows a three-layer hierarchical ART network for encoding multiple decision rules. Simple heuristics involve feedback between amygdala and OFC, and do not engage the other two prefrontal executive areas (the error detector at ACC and the complex working memory analyzer at DLPFC). The individual with higher vigilance in the pursuit of knowledge, whether this vigilance is general or domain-specific, is sensitive to mismatches between the results of those heuristics and logical truth. This leads in turn to engagement of the other executive regions.

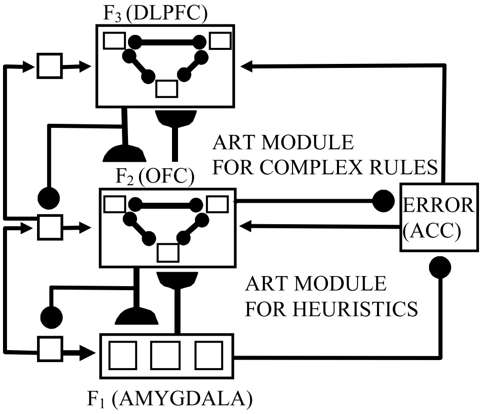

Fig. 4. Network that encodes both heuristic and deliberative rules. With low vigilance, the ART module combining F_1 and F_2 (amygdala and OFC) makes decisions based on simple heuristics. With high vigilance, discontent with outcomes of simple decisions generates activity in the orienting (error) module (ACC). ACC activity in turn may generate a search for more complex decision rules at F_3 (DLPFC). (Adapted from Levine, 2007b, with the permission of IEEE).

4. DECIDER: Bringing it all together

How are the needs module of Figs. 1 and 2 and the decision module of Fig. 4 connected? In most applications of ART the vigilance at any given time is a single parameter of the entire network. Yet within the ART framework one can posit vigilance that is selective and biased toward those attributes that are most relevant to the current important needs or goals of the organism.

Leven and Levine (1996) utilized attribute- and drive-selective vigilance to model preference reversals by consumers deciding among competing soft drinks. They noted that vigilance is calculated by some matching criterion between bottom–up input and top–down prototype patterns. For ART 1 (Carpenter & Grossberg, 1987), the two patterns consist of 1's and 0's, and the matching criterion involves the fraction of 1's in one pattern that are also contained in the other pattern. For later, continuous and fuzzy versions of ART, the matching criterion often involves that dot product of two unitized pattern vectors. Either way it is simple to weight the vigilance criterion so that matching in some attributes (i.e., components of the binary or fuzzy pattern vectors) matters more than others.

Leven and Levine (1996), using a combination of ART with gated dipoles (Grossberg, 1972) for attributes, drives, and categories, modeled the consumer preference for New Coke over Old Coke in taste tests followed by widespread aversion toward New Coke, and desire for then-unavailable Old Coke, in the actual market. This preference change occurred because sweetness of taste was the relevant attribute during the taste tests, whereas familiarity was the relevant attribute during the time of the market. The sensory input at the lower level (corresponding to F_1 of (Fig. 3) was composed of vectors with values of 4 attributes (Coke Label, Pepsi Label, Taste, and Familiarity); there were also 2 drives or needs (broadly labeled "Excitement" and "Security") and 2 categories (Coke and Pepsi). The New Coke mismatched the Coke prototype most on the Familiarity attribute, which was strongly connected (via Hebbian learning) with the Security drive but not with the Excitement drive. Since the Excitement drive was dominant during the taste tests, no aversive mismatch was perceived. But during the time of the market the Security drive was dominant, leading to an attribute-selective mismatch of the ART network. Categories as well as attributes were connected to sites of positive or negative emotional valence, so the mismatch with the Coke category produced an aversive reaction to New Coke. This aversive reaction was stronger in habitual Coke drinkers than in habitual Pepsi drinkers, both in the model and in the data of Pierce (1987).

Hence, the vigilance in the network of Fig. 4 could be selective for different needs. Learned connections between different need or drive loci and different stimulus attributes, whether those attributes are perceptual or abstract, then leads to selective vigilance toward mismatches in some of the attributes.

Combining the networks of Figs. 1, 2 and 4, and the learnable connections between drives and attributes in the "Coke" network of Leven and Levine (1996), leads to a network model of emotionally influenced, goal-directed decision making. The decisions arising from such a network become either heuristic or deliberative depending on which goals are paramount at the time. By analogy with the MOTIVATOR model of Dranias et al. (2008), I call this super-network DECIDER (Distributed Emotional Connections Influencing Decisions and Engaging Rules; Fig. 5).

5. Discussion: Psychological implications

The discussion here focuses mainly on the structural relationships between drives, needs, goal representations, and decision rules in the human brain. Considerable work is ahead on specifying the details of these relationships in the simulation of specific decision data. This is a program that my colleagues and I have begun, with the simulation of one classic decision task wherein heuristic and deliberative rules compete, namely, the *ratio bias* task ((Levine & Perlovsky, 2008a). Ratio bias means that a small probability is perceived to be larger if it is a ratio of larger numbers; that is, a probability of 10 out of 100 is considered larger than 1 out of 10. One effect of ratio bias sometimes a lower probability is actually seen as more likely when accompanied by higher numerosity. For example, Denes-Raj and Epstein (1994) showed participants two bowls containing red and white jellybeans, told them they would win a certain amount of money if they randomly drew a red jellybean, and instructed them to choose which bowl gave them the best chance of winning money. In one of the bowls, there were 10 total jellybeans out of which 1 was red. In the other bowl, there were 100 total jellybeans out of which some number greater than 1 but less than 10 were red. If the number of red out of 100 were 9 or 8, more than half the participants chose that bowl, with the fraction gradually decreasing as the number of red went down. fMRI studies are in progress to determine how brain activation patterns differ in participants who correctly chose the higher probability versus those who incorrectly choose the higher numerosity (Krawczyk, Levine, Ramirez, Robinson, & Togun, 2008).

The DECIDER network tells us that the current state of the needs module has a strong influence on decision rules; specifically, on whether automatic heuristics or deliberation is employed. The state of the needs module is influenced both by dispositional variables that are specific to the individual and by situational factors to which anyone can be subject.

Two dispositional variables in which individual differences have been extensively studied are *need for cognition* (Cacioppo & Petty, 1982) and *need for cognitive closure* (Webster & Kruglanski, 1994), both measured by answers to questionnaires. Need for cognition (NFC) is defined as the tendency to enjoy effortful cognitive activity and the motivation to analyze arguments deeply. *Need for cognitive closure* (NFCC) is defined as the motivation to come to decisions and opinions quickly, often without having thought through the relevant issues. The overall tendency is for individuals with high need for cognition to be more likely to use deliberative rules – particularly in quantitative tasks such as probability judgments which have definite right answers – and for individuals with high need for cognitive closure to be more likely to use heuristic rules. However, the meta-analysis by Cacioppo, Petty, Feinstein, and Jarvis (1996) shows that while those two need variables are negatively correlated, high levels of both the needs for cognition and for cognitive closure can coexist in some

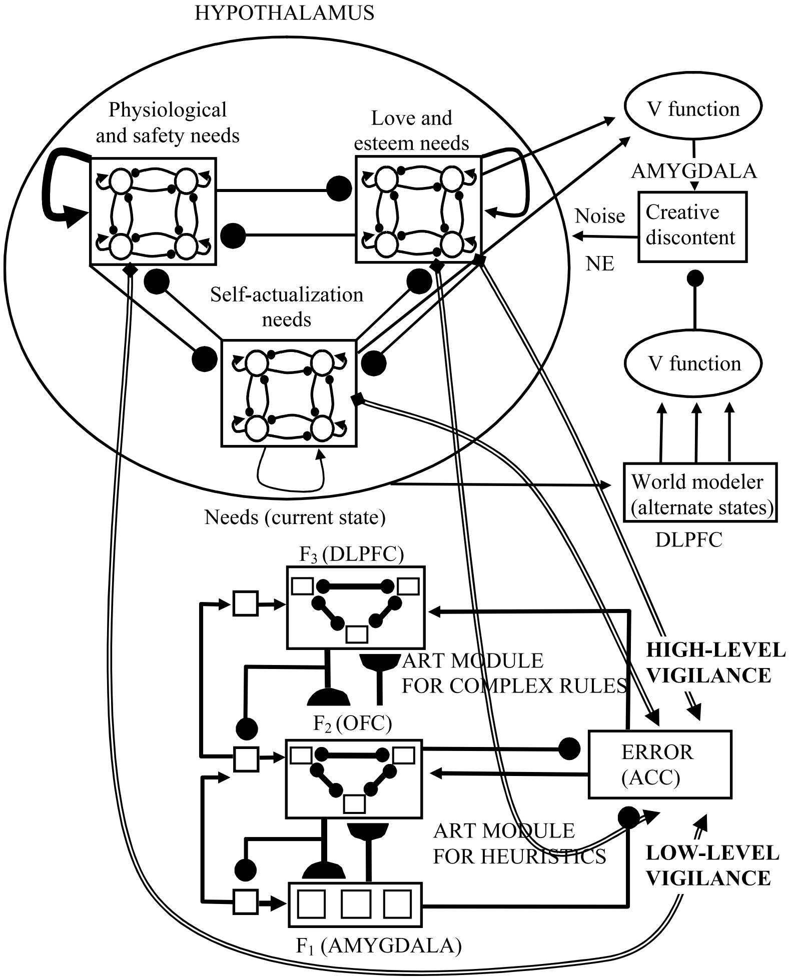

Fig. 5. DECIDER network combining the needs network of Figs. 1 and 2 and the decision network of Fig. 4. Lower-level needs influence the attribute-selective vigilance signals in the heuristic ART module. Higher-level needs influence vigilance in the complex rule module.

individuals. Work is in progress in my laboratory to characterize possible subtypes of high-NFC individuals who also have high need for closure. One likely scenario is that after a high-NFC person has invested a great deal of time and thought in coming to an opinion, that very investment makes him or her reluctant to accept or analyze evidence that should later arise against that opinion.

One of the most important situational factors influencing decision making is time pressure. In general, greater time pressure biases the needs module toward the lower-level (survival, security, and belonging) needs and against higher-level (self-actualization and knowledge instinct) needs. In fact, Ordonez and Benson (1997) found that under time pressure, high-NFC individuals change their behavior toward that of low-NFC individuals; for example, they become less likely to examine closely the source and validity of arguments they hear for particular points of view.

Because of the tradition previously mentioned of separating cognition and emotion, and concomitantly regarding emotion as inferior to reason, it is important to add here that the network analysis here does *not* imply that deliberative, calculated, utility-maximizing decisions are always superior to intuitive decisions. Perlovsky (2006) and Levine and Perlovsky (2008a, 2008b) discuss the role of intuitive aesthetic concepts in solving intellectual problems, including mathematical and scientific research problems. In fact, discovery of mathematical proofs generally involves alternating periods of logical deduction and intuitive insight (Poincaré, 1914). Leven (1987) introduced three different decision styles which he names after mathematicians associated with the appropriate concepts, and suggested that each style is most appropriate for different types of decision problems. The three types Leven described are the Dantzig solvers who always do things by the same rules and are best for the most routine tasks; Bayes solvers who optimize among a fixed set of alternatives and are best for complex but still easily quantifiable tasks; and Gödel solvers who follow intuitive hunches and are best for tasks that are highly creative and ambiguous. This type of intuition (which Dane & Pratt, 2007, call *insight* to distinguish it from automatic, fast, use of heuristics which they call intuition) occupies a middle ground between heuristic and deliberative decisions. It is not rational but neither is it automatic, and generally comes into play after many hours of thought and great familiarity with the domain of thinking. One of the practical tasks of our future network theory of decision making is to arrive at a hypothesis for the role of prefrontal executive regions in complex intuition or insight (see Jung-Beeman et al., 2004, for partial results), and in the interplay of insight and logical reasoning.

In any event, the capacity of humans to generate and to learn both heuristic and deliberative rules has clear evolutionary value. Heuristic rules enable decision makers to bypass task-irrelevant information and make rapid choices in repeatable and relatively simple contexts. Deliberative rules, on the other hand, enable decision makers to make sense of complex contexts that often include novel and possibly task-relevant information. Many researchers including Dayan (2009); Zhang (2009a, 2009b) have suggested ways to incorporate both types of rules into a common framework for understanding goal direction. The jury is still out on whether an all-encompassing utility function exists for human behavior (Levine & Elsberry, 1997). Yet a comprehensive decision theory needs to account not only for both types of rules but also for their prevalent misapplications. The results of Tversky and Kahneman (1974) and others, for example, indicate that many decision makers employ heuristic rules for numerical judgments wherein deliberative rules would be more likely to be successful. Conversely, Damasio (1994) found that some of his patients applied lengthy deliberative judgments to make minor choices (e.g., among potential restaurants to eat at) where heuristics would have worked better. While Damasio's patients were physically brain damaged (typically in or around the OFC), there are suggestions that excessive deliberation might also be characteristic of obsessive compulsives (e.g. Sachdev & Malhi, 2005).

Theories based on a common evolutionary framework involving both types of rules is a useful corrective to the excess of some cognitive theories that posit two distinct processes (or "antipodes" in the words of Dayan (2009)). Yet it is also important to understand that multiple decision processes can compete as well as cooperate. The disconnect between different types of rules or processes within the individual can be a clue for understanding similar types of disconnects between individuals, including linguistic and cultural effects as described by Perlovsky (this issue). A comprehensive theory of multiple decision rules, based in all the different levels of our animal nature (cf. MacLean, 1990), can help us both to overcome individual and social disintegration and to promote a reintegration that utilizes all of our intellectual and emotional capacities.

References

Aron, A. R., Robbins, T. W., & Poldrack, R. (2004). Inhibition and the right inferior frontal cortex. *Trends in Cognitive Sciences*, *8*, 170–177.

Aston-Jones, G., & Cohen, J. D. (2005). An integrative theory of locus coeruleus-norepinephrine function: Adaptive gain and optimal performance. *Annual Review of Neuroscience*, *28*, 403–450.

Barbas, H., & Zikopoulos, B. (2006). Sequential and parallel circuits for emotional processing in primate orbitofrontal cortex. In D. Zald, & S. L. Rauch (Eds.), *The orbitofrontal cortex* (pp. 57–80). Oxford: Oxford University Press.

Bechara, A., Damasio, A. R., Damasio, H., & Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition*, *50*, 7–15.

Buijs, R. M., & Van Eden, C. G. (2000). The integration of stress by the hypothalamus, amygdala, and prefrontal cortex: Balance between the autonomic nervous system and the neuroendocrine system. *Progress in Brain Research*, *127*, 117–132.

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, *42*, 116–131.

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin*, *119*, 197–253.

Carpenter, G. A., & Grossberg, S. (1987). A massively parallel architecture for a self-organizing neural pattern recognition machine. *Computer Vision, Graphics, and Image Processing*, *37*, 54–115.

Carpenter, G. A., & Grossberg, S. (1990). ART 3: Hierarchical search using chemical transmitters in a self-organizing pattern recognition architecture. *Neural Networks*, *3*, 129–152.

Cohen, M. A., & Grossberg, S. (1983). Absolute stability of global pattern formation and parallel memory storage by competitive neural networks. *IEEE Transactions on Systems, Man, and Cybernetics, SMC*, *13*, 815–826.

Coleman, S., Brown, V. R., Levine, D. S., & Mellgren, R. L. (2005). A neural network model of foraging decisions made under predation risk. *Cognitive, Affective, and Behavioral Neuroscience*, *5*, 434–451.

Croyle, R. T., & Cooper, J. (1983). Dissonance arousal: Physiological evidence. *Journal of Personality and Social Psychology*, *45*, 782–791.

Damasio, A. R. (1994). *Descartes' error: Emotion, reason, and the human brain*. New York: Grosset/Putnam.

Dane, E., & Pratt, M. G. (2007). Exploring intuition and its role in managerial decision making. *Academy of Management Review*, *32*, 33–54.

Dayan, P. (2009). Goal-directed control and its antipodes. *Neural Networks*, *22*(3), 213–219.

DeMartino, B., Kumaran, D., Seymour, B., & Dolan, R. (2006). Frames, biases, and rational decision-making in the human brain. *Science*, *313*, 684–687.

Denes-Raj, V., & Epstein, S. (1994). Conflict between intuitive and rational processing: When people behave against their better judgment. *Journal of Personality and Social Psychology*, *66*, 819–829.

DeNeys, W., Vartanian, O., & Goel, V. (2008). Smarter than we think: When our brain detects we're biased. *Psychological Science*, *19*, 483–489.

Dias, R., Robbins, T. W., & Roberts, A. (1996). Dissociation in prefrontal cortex of affective and attentional shifts. *Nature*, *380*, 69–72.

Dranias, M., Grossberg, S., & Bullock, D. (2008). Dopaminergic and non-dopaminergic value systems in conditioning and outcome-specific revaluation. *Brain Research*, *1238*, 239–287.

Fuster, J. M. (2000). The prefrontal cortex of the primate: A synopsis. *Psychobiology*, *28*, 125–131.

Gaffan, D., & Murray, E. A. (1990). Amygdalar interaction with the mediodorsal nucleus of the thalamus and the ventromedial prefrontal cortex in stimulus-reward associative learning in the monkey. *Journal of Neuroscience*, *10*, 3479–3493.

Grossberg, S. (1972). A neural theory of punishment and avoidance. I. Qualitative theory. *Mathematical Biosciences*, *15*, 39–67.

Grossberg, S. (1973). Contour enhancement, short term memory, and constancies in reverberating neural networks. *Studies in Applied Mathematics*, *52*, 213–257.

Grossberg, S. (1975). A neural model of attention, reinforcement, and discrimination learning. *International Review of Neurobiology*, *18*, 263–327.

Grossberg, S. (2003). How does the cerebral cortex work? Development, learning, attention, and 3d vision by laminar circuits of visual cortex. *Behavioral and Cognitive Neuroscience Reviews*, *2*, 47–76.

Grossberg, S., & Levine, D. S. (1975). Some developmental and attentional biases in the contrast enhancement and short-term memory of recurrent neural networks. *Journal of Theoretical Biology*, *53*, 341–380.

Harmon-Jones, E., Brehm, J. W., Greenberg, J., Simon, L., & Nelson, D. E. (1996). Evidence that the production of aversive consequences is not necessary to create cognitive dissonance. *Journal of Personality and Social Psychology*, *70*, 5–16.

Hopfield, J. J., & Tank, D. W. (1985). "Neural" computation of decisions in optimization problems. *Biological Cybernetics*, *52*, 141–152.

Jung-Beeman, M., Bowden, E. M., Haberman, J., Frymiare, J. L., Arambel-Liu, S., Greenblatt, R., Reber, P. J., & Kounios, J. (2004). Neural activity when people solve verbal problems with insight. *PLoS Biology*, *2*, 500–510.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, *80*, 237–251.

Kilmer, W., McCulloch, W. S., & Blum, J. (1969). A model of the vertebrate central command system. *International Journal of Man-Machine Studies*, *1*, 279–309.

Kim, S., Hwang, J., Seo, H., & Lee, D. (2009). Valuation of uncertain and delayed rewards in primate prefrontal cortex. *Neural Networks*, *22*(3), 294–304.

Krawczyk, D., Levine, D. S., Ramirez, P. A., Robinson, R., & Togun, I. (2008). fMRI study of rational versus irrational choices on a ratio bias task. *Poster at the annual meeting of the Society for Judgment and Decision Making*, Chicago.

Leven, S. J. (1987). Choice and neural process. *Unpublished doctoral dissertation*. University of Texas at Arlington.

Leven, S. J., & Levine, D. S. (1996). Multiattribute decision making in context: A dynamic neural network methodology. *Cognitive Science*, *20*, 279–299.

Levine, D. S. (1994). *World congress on neural networks*: *Vol. 1*. *Steps toward a neural theory of self-actualization* (pp. 215–220). Hillsdale, NJ: Erlbaum.

Levine, D. S. (2005). Angels, devils, and censors in the brain. *ComPlexus*, *2*, 35–59.

Levine, D. S. (2007a). How does the brain create, change, and selectively override its rules of conduct?. In R. Kozma, & L. Perlovsky (Eds.), *Neurodynamics of higher-level cognition and consciousness* (pp. 163–181). Heidelberg: Springer-Verlag.

Levine, D. S. (2007b). Seek simplicity and distrust it: Knowledge maximization versus effort minimization. *Proceedings of KIMAS*,.

Levine, D. S., & Elsberry, W. R. (Eds.) (1997). *Optimality in biological and artificial networks?* Hillsdale, NJ: Lawrence Erlbaum Associates.

Levine, D. S., & Perlovsky, L. I. (2008a). A network model of rational versus irrational choices on a probability maximization task. *IEEE: Proceedings of WCCI*,.

Levine, D. S., & Perlovsky, L. I. (2008b). Simplifying heuristics versus careful thinking: Scientific analysis of millennial spiritual issues. *Zygon*, *43*, 797–821.

MacLean, P. D. (1990). *The triune brain in evolution: Role in paleocerebral functions*. New York: Plenum.

Maslow, A. H. (1968). *Toward a psychology of being*. New York: Van Nostrand.

McClure, S. M., Gilzenrat, M. S., & Cohen, J. D. (2006). An exploration-exploitation model based on norepinephrine and dopamine activity. *Presentation at the annual conference of the Psychonomic Society*.

Milne, E., & Grafman, J. (2001). Ventromedial prefrontal cortex lesions in humans eliminate implicit gender stereotyping. *Journal of Neuroscience Special Issue*, *21*(12), 1–6.

Milner, B. (1964). Some effects of frontal lobectomy in man. In J. M. Warren, & K. Akert (Eds.), *The frontal granular cortex and behavior* (pp. 313–334). New York: McGraw-Hill.

Ordonez, L., & Benson, L. (1997). Decisions under time pressure: How time constraint affects risky decision making. *Organizational Behavior and Human Decision Processes*, *71*.

Perlovsky, L. I. (2006). Toward physics of the mind: Concepts, emotions, consciousness, and symbols. *Physics of Life Reviews*, *3*, 23–55.

Pessoa, L. (2008). On the relationship between emotion and cognition. *Nature Reviews Neuroscience*, *9*, 148–158.

Pierce, W. (1987). Whose Coke is it? Social influence in the marketplace. *Psychological Reports*, *60*, 279–286.

Poincaré, H. (1914). *Science and method* (F. Maitland, Trans.). London: T. Nelson and Sons.

Rolls, E. T. (2006). The neurophysiology and functions of the orbitofrontal cortex. In D. Zald, & S. L. Rauch (Eds.), *The orbitofrontal cortex* (pp. 95–124). Oxford: Oxford University Press.

Sachdev, P. S., & Malhi, G. S. (2005). Obsessive-compulsive behaviour: A disorder of decision making. *Australian and New Zealand Journal of Psychiatry*, *39*, 757–763.

Tremblay, L., & Schultz, W. (1999). Relative reward preference in primate orbitofrontal cortex. *Nature*, *398*, 704–708.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*, 1124–1131.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the rationality of choice. *Science*, *211*, 453–458.

Van Veen, V., & Carter, C. S. (2006). Conflict and cognitive control in the brain. *Current Directions in Psychological Science*, *15*, 237–240.

Webster, D., & Kruglanski, A. (1994). Individual differences in the need for cognitive closure. *Journal of Personality and Social Psychology*, *67*, 1049–1062.

Zhang, J. (2009a). Adaptive learning via selectionism and Bayesianism Part I: Connection between the two. *Neural Networks*, *22*(3), 220–228.

Zhang, J. (2009b). Adaptive learning via selectionism and Bayesianism Part II: The sequential case. *Neural Networks*, *22*(3), 229–236.