A core-affect model of decision making in simple and complex tasks

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Abstract

When it comes to decision making, the dominant view suggests that engaging in a detailed analytical thought process is more beneficial than deciding based on one's feelings. However, there seems to be a tradeoff, as the complexity and amount of elements on which to base the decision increases, decisions based on affect seem to be more accurate than decisions based on a thorough analytical process in specific contexts. In those last cases, an affective modulation of memory may help to make better decisions in complex tasks that exceed human's limited cognitive capacities. Some dual process accounts, ''deliberation-without-attention'' hypothesis (Dijksterhuis et al., 2006), oppose a cognitive (i.e., conscious) route to an affective (i.e., unconscious) route. Since most dual process accounts suggest one type of process is better than the other, the interaction and integration of affective and more conscious analytical processes in decision making have been understudied. To address this issue, we propose an explanation of the dynamics and interaction of cognitive (i.e., explicit) and affective (i.e., implicit) encoding and retrieval of elements in memory, using a unified theory based on core affect (Russell, 2003), in the shape of a cognitive model in the ACT-R cognitive architecture.

Keywords: Core affect; ACT-R; decision making; dual process theory; memory modulation; implicit strategy

Introduction

In a set of experiments, Dijksterhuis et al. (2006) and Mikels et al. (2011) show how being focused on the details of provided information, rather than feelings, affects accuracy in a decision making task. According to these results, being feeling focused in a more complex, memory-overloading task proves to lead to better performance.

Until recently, the influence of emotion has been neglected in the judgment and decision making literature, with the focus initially being put on the biases emotions enable (Kahneman & Tversky 1979). Gradually, the focus has shifted toward the positive role of emotions in decision making, as suggested by neurological evidence (Damasio, 1994; Bechara, Damasio, & Damasio, 2000). In parallel, core affect theory (Russell, 2003) in emotion research, and the somatic marker hypothesis (Damasio, 1994) in decision making research, have emerged to explain how emotion can guide behavior towards a positive outcome.

In this paper we suggest that the results from Dijksterhuis et al. (2006) and Mikels et al. (2011) (i.e., being feeling-focused in a more complex task leads to better performance) can be explained with a core-affect model. Core affect (Russell, 2009) is a neurophysiological state accessible to consciousness as a simple non-reflective feeling and can be described through the valence (i.e., negative or positive) and arousal (i.e., intensity) values. Our hypothesis here is that core affect modulates memory. The modulation would place emphasis on the objective value of an attribute (i.e., good or bad) rather than details (e.g., higher than average gas mileage), simplifying the information and allowing for more efficient use of cognitive resources. The core affect experienced by participants while implicitly considering options cumulates and later leads to a decision illustrating the emotion-cognition interaction. This, we think, proves to be a better strategy when the limit of memory capacity is reached (e.g., complex task). This hypothesis was tested using a cognitive architecture based on a unified theory of cognition, ACT-R. We previously used this core affect model to explain the impact of affective valence and arousal on memory and memory decay using participant's memory of negative and positive emotion words after different time periods (Juvina & Larue, 2016). However, here the focus is on the role of affect in decision making. This allows for an explanation of how core affect and cognitive mechanisms are meshed.

Background

The concept of emotion has been a subject of interest for quite some time. However, theories have only recently attempted to explain their role in cognitive processes using empirical research. Appraisal theories (Lazarus & Folkman, 1984; Ortony, Clore and Collins, 1990) have emerged as the dominant approach to emotions in the last few decades. Appraisal has been defined as the personal meaning and significance to well-being that is constructed from evaluations of situational factors and knowledge. While this trend of theories clarifies the route by which humans evaluate their environments (e.g., in a bottom-up way), they do not clarify how ongoing affect influences the encoding and retrieval of information in an implicit manner.

In response to this incompleteness, core affect theory (Russell, 2003), "feeling is for doing" (Zeelenberg & Pieters, 2006), and the somatic marker hypothesis (Damasio, 1994) have attempted to bridge the gap between emotion and behavior. The latter particularly addresses the domain of decision making.

Russell (2009) believes that most phenomena attributed to emotions can be explained in more simple terms (e.g., core affect) without the need for emotion. Core affect is a visceral state that happens before the emotion is consciously identified: feeling good or bad, lethargic or energized (Russell, 2009). Russell's core affect theory suggests underlying values for valence and arousal are more important than emotion, which he believes is socially constructed. The core affect is the central notion of this theory. Previous events change the core affect, which can occur before the event is actually consciously perceived by the subject and persists during the episode. It also influences the other elements of the emotional episode.

In the domain of decision making, some researchers (Gigerenzer & Selton, 2002) view heuristics, not only affective ones, as strategies that lead to sufficient decisions. Implicit strategies for decision making have previously been studied in ACT-R with Instance Based Learning (Gonzalez, Lerch & Lebiere, 2003). In this paper, another type of implicit strategy involved in decision making – an affective strategy – is investigated.

Existing computational models of affect and emotion are based on appraisal theories and tend to be pre-programmed and hardwired based on the specifications of a particular theory (e.g., Marsella & Gratch, 2009; Marinier, Laird, & Lewis, 2009). Previous attempts have been made in ACT-R to add biological roots of emotions (Dancy et al., 2015) effect of emotion on learning and decision making (Belavkin, 2003) and stress (Ritter, Reifers, Klein, & Schoelles, 2007) by overlaying the architecture.

Since core affect is implicit, more primitive, and more general than the construct of emotion (Russell & Feldmann Barrett, 1999; Russell, 2009), it could be particularly adapted to be included in a cognitive architecture. When meshed with existing cognitive mechanisms, it could add to existing unified theories of cognition. The resulting model would increase the explanatory power of the core affect theory by clarifying different aspects of the emotion–cognition interaction.

Core affect and memory: theory and implementation

ACT-R and memory

To capture the core affect modulation of memory and its impact on decision making, we support our model with ACT-R (Adaptive Control of Thought – Rational; Anderson, 2007), a unified theory of human cognition. ACT-R is also a cognitive architecture that is used to develop computational models of various cognitive tasks. ACT-R is composed of various modules: goal, imaginal, visual, aural, manual, vocal, and two memory modules: declarative memory (i.e., facts) and procedural memory (i.e., how to do things). The declarative memory module, which stores facts (i.e., know-what), is the one the core affect directly modulates. Declarative memory includes both symbolic structures (i.e., memory chunks) and sub-symbolic quantities that control the operation of the symbolic structures in the equations. The valuation and arousal values, which help to define the core affect, are sub-symbolic quantities added to the current sub-symbolic equations of ACT-R.

Core affect and memory

We present a summarized version of the core affect mechanism to facilitate the understanding of our model. An extended version of the core affect mechanism can be found in Juvina and Larue (2016). The original equation (Anderson, 2007) that computes the activation of a declarative memory chunk is:

$$A_i = B_i + S_i + P_i + \varepsilon_i \qquad (1)$$

- A_i is the activation of the chunk *i*.
- B_i is the base-level term and reflects the recency and frequency of use of chunk *i*.
- S_i is the spreading term and reflects the effect of the context on the retrieval of chunk *i*.
- P_i is the partial matching term and reflects the degree to which the chunk *i* matches the specification of the retrieval request.
- ε_i is a noise or variability component.

Activation of a chunk reflects its use, and decays over time if the chunk is not used. Retrieval time and the retrieval probability of a chunk are determined by activation (e.g., chunks under a certain retrieval threshold cannot be retrieved). However, the selection process is impacted by noise. The chunk with the highest activation has the highest probability of being selected, but other chunks get the opportunity as well allowing some exploration behavior in ACT-R.

In the current ACT-R architecture, reward based learning affects procedural memory. However, subjective values (e.g., pleasant or unpleasant) might actually be carried by declarative memory as affectively charged representations, which are easier/harder to retrieve according to these values (Smith, Most, Newsome, & Zald, 2006). A new ACT-R module called "Valuation" was developed to add valuation and core affect capabilities into ACT-R. In theory, core affect is a diffuse affective state that is not necessarily linked to any specific event and is characterized as a point in a two-dimensional space, where the two underlying dimensions are valence (i.e., pleasure-displeasure) and arousal (Russell, 2009). In our implementation, core affect is defined as two accumulators called *core-affect-valuation (Valuation)* and *core-affect-arousal (Arousal),* which are sub-symbolic quantities computed by the "Valuation" module. It also maintains the parameters and history information that are needed for these computations. Both values affect the probability that a chunk can be retrieved from declarative memory. Valuation is an indicator of the affective valence of a particular stimulus or fact learned through interaction with the environment. Arousal is an indicator of the importance or priority that is given to a particular stimulus or fact; it is the absolute value of valuation. Relying on the existing memory mechanisms from the ACT-R theory, valuation and arousal are just two separate terms added to the general activation equation previously introduced:

$$A_i = B_i + S_i + P_i + V_i + Ar_i + \varepsilon_i \qquad (2)$$

- V_i is the valuation term and reflects the rewards received by the model after referencing chunk i.
- Ar_i is the arousal term which reflects the importance of chunk i and is computed as the absolute magnitude of the valuation term.

The learning of valuations occurs when a reward is triggered: the valuations of all chunks that been referenced within a time window are updated. This is compatible with findings of overlapping neural substrates between the attribution of subjective value to stimuli and reward-based learning (Paton, Belova, Morrison, & Salzman, 2006). The effective reward of a chunk i is the reward value received at time n minus the time since the last reference of chunk i.

The learning of valuations for a chunk i is controlled by the following equation:

$$V_i(\mathrm{n}) = V_i(\mathrm{n}\text{-}1) + \alpha v[R_i(\mathrm{n}) - V_i(\mathrm{n}\text{-}1)] \qquad (3)$$

- V_i(n) is the valuation of chunk i after its nth update.
- V_i(n-1) is the valuation of chunk i prior to its nth update.
- αv is the learning rate for valuations.
- R_i(n) is the effective reward value received by chunk i before its nth valuation update.
- V_i(0) is determined based on initial parameter settings.

Reward signals allow the model to learn valuation and arousal values for elements according to what is presented in the environment.

Additional parameters make it possible to weight valuation and arousal independently in the equation. Values used in this paper can be seen in Table 1:

- Valuation weight (:vw) is a scale parameter for the valuation term in the general activation equation.
- Arousal weight (:aw) is a scale parameter for the arousal term in the general activation equation.
- Valuation time window (:vtw) is a time window over which to update the valuations. It determines how many chunks are updated.

In the architecture, core affect is the weighted accumulation of valuation and arousal values for all retrievable chunks, and weights are probabilities of retrieval reflecting chunk activations. This value is implicitly maintained by the architecture.

In this implementation, affect phenomena are not hardwired in the cognitive architecture but learned from the interaction among various architectural components and between architecture and environment. Only primitive affective mechanisms: valuation (i.e., valence obtained through interactions) and arousal, were included in the cognitive architecture. Valuation and arousal are added as terms in the general activation equation and influence the probability of a chunk to be retrieved. This is consistent with the core affect theory (Russell & Feldmann Barrett, 1999; Russell, 2009).

Our hypothesis is that this is all that is necessary to include at the architectural level to model the interaction between cognition and affect.

Model

Conditions

The procedure used here was derived from an experiment by Dijksterhuis et al. (2006) and replicated by Mikels et al. (2011). During these experiments, participants were given information about four different car options (i.e., Car A, Car B, Car C, and Car D) and were instructed to choose which car they believed to be the best choice. Simple attributes, framed as either positive or negative (e.g., this car gets good/bad gas mileage), were provided one at a time for each car option. The best choice was defined as the car with the most positive attributes. The best choice had 75% positive attributes, two cars had 50% positive attributes, and one car had 25% positive attributes. The design consisted of one dependent variable (i.e., car choice) and two independent variables (i.e., focus and complexity).

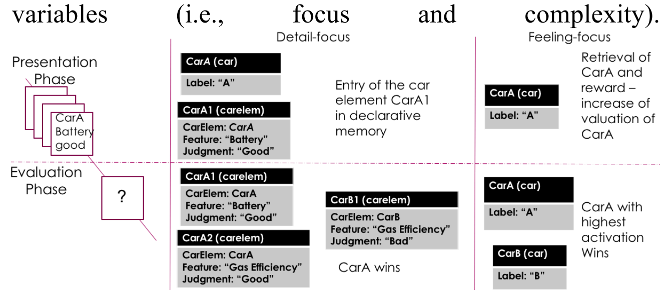

Figure 1. Experiment procedure and memory representations across task in detail-focus vs feeling-focus conditions

Participants were split into four conditions based on the two independent variables (i.e., feeling-focus simple, feeling-focus complex, detail-focus simple, and detail-focus complex). Those in the feeling-focus conditions were instructed to rate how they felt about each attribute and make their choice while focusing on their feelings. In the detail-focus conditions, participants were instructed to rate how well they were remembering the attributes and make their decision based on the details of the attributes. Simple conditions had four attributes for each car option, whereas complex conditions had 12 attributes per car option.

All conditions completed a memory recall task at the end of the trial. Results from a chi-square analysis indicated that participants in the detail-focus simple condition performed better than participants in the feeling-focus simple condition, although this difference did not reach significance. However, participants in the feeling-focus complex condition significantly outperformed those in the detail-focus complex condition. There was no difference between focus conditions for memory recall, but there was a difference between simple and complex conditions. Both Dijksterhuis et al. (2006) and Mikels et al. (2011) concluded that focusing on your feelings leads to better complex decisions compared to more deliberate thinking.

Table 1. Model parameters

:rt	-2.4
:vw	1.0
:aw	2.0
:av	0.2
:vtw	0.5

Encoding across conditions

Encoding mechanisms used are the same, but:

- In the detail-focus, the strategy used makes you consider all features and ratings associated to those features.
- In the feeling-focus condition, the strategy used gives more value to the ratings (i.e., good/bad) than their features..

Table 2. Model strategy in the detail-focus condition

Step	Strategy in the detail-focus condition
	Presentation phase
1	"Car-feature-value" triplet is displayed
2	See car
3	Encode car
4	See feature
5	Encode feature
6	See value
7	Encode value
8	Clear imaginal (enter chunk in declarative memory)
9	Go back to step 1 until all cars have been displayed
	Evaluation phase
10	Pick a car that has not been evaluated yet
11	Retrieve triplet (car-feature-value) with a "good" judgment
12	Count the positive values for this car
13	Go back to step 10 until there are no cars left
14	Decide the car with the highest count

Detail-focus condition (Table 2). Stimuli consisting of three elements (car – feature - rating) are presented one at a time to the model The model looks at each element separately and encodes them as a memory chunk of the following association: car – feature – rating. Car is also a memory chunk (Presentation phase in "Detail-focus" in Figure 1).

When all stimuli have been presented to the model, it proceeds to the evaluation through a tallying heuristic (Gigerenzer, 2016): by interrogating its memory on features for each car, counting all chunks for which it can retrieve an association with a "good" rating for a feature. The car with the highest overall number of "good" rating-feature-car associations that could be retrieved is the one that is named by the model as the best car choice (Evaluation phase in "Detail-focus" in Figure 1). The significantly higher number of reasoning steps in the detail-focus condition (Table 2) results from the thorough analytical process that participants were assumed to engage in during this condition.

Table 3. Strategy in the feeling-focus condition

Step	Strategy in the feeling-focus condition
	Presentation phase
1	"Car-feature-value" triplet is displayed
2	See car
3	Retrieve chunk car
4	See value
5	Trigger reward depending on value
6	Update valuations
7	Go back to step 1 until all cars have been displayed
	Evaluation phase
8	Retrieve car with highest activation
9	Decide (highest valuation car is the one with the most "good" features)

Feeling-focus condition (Table 3). The same stimuli are presented to the model randomly; but the model is going to follow a different strategy. It only looks at the car and rating, as shown in Table 3 (Presentation phase in "Feeling-focus" in Figure 1). The model retrieves the car chunk associated with the presented car, and according to the rating "good" or "bad", sends a reward signal. This reward affects the valuation of this specific car without it being necessary to encode all the features of the car. When the reward signal is sent, all the valuations of chunks that were retrieved in this time window are updated. Recall the explanation in the previous section (detail-focus condition) that the memory representation includes the car chunks. Thus, if the car to which this rating was attached is in the time window, it gets a valuation update.

When all stimuli have been presented to the model, it proceeds to the evaluation by retrieving one of the previously presented cars (Evaluation phase in "Feeling-focus" in Figure 1). The retrieved car is the one with the highest activation, which likely has the highest rating because valuation was updated positively during the first stage of car presentations.

Results and Discussion

Results in Figure 2 are shown for 50 runs of the model (stable performance, based on cumulative standard deviation, was reached after 43 runs).

There was a significant difference in accuracy between the two feeling focus conditions (i.e., simple and complex), $t(97.89) = 2.67$, $p < 0.01$. A significant difference in accuracy was also found between the detail-focus complex condition and feeling-focus complex condition, $t(83.1) = 6.001$, $p < .001$. These same differences were observed in the original experiments.

The model also captured participant's better performance in the detail-focus simple condition compared to the feeling-focus simple condition (difference is not significant like in the original results). However, while still within the standard error range, the detail-focus complex condition appears lower than in the original experiments. This could be explained by something that is not captured in the strategy of our model. When uncertain, human participants could have guessed more accurately (compared to random guesses by the model) based on prior knowledge. For instance, a participant may have eliminated options based on memory that certain options had fewer positive attributes.

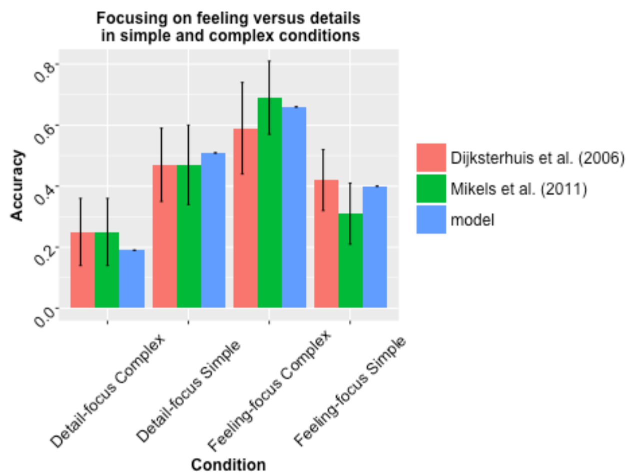

Figure 2. Accuracy in feeling-focus vs. detail-focus in complex and simple conditions for the original experiments and our model

Model dynamics in detail-focus condition

In the simple condition, the model has a performance close to the feeling-focus condition. However, in the complex condition more features are memorized for each car. In this condition, more words are forgotten as the experiment is longer and there are more words to remember. Activation of those unused chunks decay over time. Therefore, when going through all the cars and remembering the features, there are more chances of memory retrieval failures.

The forgetting time is also amplified by the length of the recall strategy, contributing to future retrieval failures. The model may be forgetting features of the next car while listing the elements of the current car. This explains the poorer performance of the model in the complex condition. It is important to note that the model does not account for possible confusions in the car and feature-rating associations.

Model dynamics in feeling-focus condition

The model performs better in the complex condition than in the simple condition. In the complex condition, while the proportion of good features is the same, the overall number of features per cars is higher. This gives the model more opportunity for rewards. In the simple condition, there are fewer features and less reward opportunities. The activation equation has a noise parameter. Due to this noise the chunk with the highest valuation might not be the one with the highest activation (thus, not the one retrieved). Therefore, when retrieval from memory is initiated, decay and noise might make the activation number obtained through the activation equation close but higher for another car than the one who received the highest rating. This happens more often in the simple condition where you will have chunks of very close valuations. Figure 3 illustrates the differences in valuation between the chunk representations of the car options. The gap in valuation between options is more visible in the complex condition.

In contrast to the detail-focus condition, retrieving the highest rated car in the Feeling-condition is a very simple and fast process. It only requires one retrieval of the car with the highest activation (no features retrieval involved), therefore there is less decay of activation for the chunks and therefore less ground for retrieval mistakes.

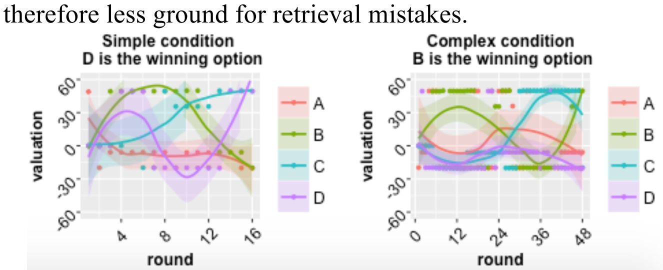

Figure 3. Evolution of the chunk valuation of each cars in feeling-focus condition across rounds, simple vs complex conditions

General Discussion and Conclusion

In this paper we presented a mechanism for core affect in ACT-R. This mechanism specifies how affect modulates memory (e.g., reducing information or emphasizing the positive or negative value) compared to attempting to remember the entire set of attributes in the detail-focus condition (i.e., high memory load). It also shows that implicit decisions might lead to better decisions than explicit decisions in certain contexts.

We model affect in a cognitive architecture as a phenomenon, which emerges from the dimensions of the core affect theory (i.e., valence and arousal) and is learned through the interaction with the environment. We interpret valence as valuation. Valuation is a sub-symbolic quantity for chunks learned through interactions with the world. Arousal is the absolute value of valuation. Core affect is the weighted accumulation of valuation and arousal values for all retrievable chunks, and weights are probabilities of retrieval reflecting chunk activations. Parameters given to the ACT-R architecture, existing reward mechanism of the architecture, and usage information about the chunks are used to compute valuation and arousal values. The core affect values are implicitly maintained by the architecture. Valuation and arousal are added as terms in the general activation equation and influence the probability of a chunk to be retrieved. We rely on the existing general activation equation of ACT-R to integrate our model in a unified theory of cognition.

While the core affect theory has been present in theories of emotion, and the role of emotions has been considered in the domain of decision making, very little has been done to connect the work on core affect theory to decision making.

We hypothesized and demonstrated that those mechanisms that allow for an affect phenomenon to emerge, were sufficient to account for the behavior encountered in Mikels et al. (2011)'s experiment. Engaging in a detailed analytical thought process might be as beneficial as deciding based on your feelings in a simple environment (i.e., low cognitive load). However, there is a tradeoff. As the amount of elements on which to base your decision increases, exerting a high load on your declarative memory, decisions based on affect seem to be more accurate than decisions based on a thorough analytical process in those complex environments. We demonstrated that an affective modulation of memory by core affect, which simplifies the amount and complexity of information, could explain this phenomenon. Therefore, core affect may help individuals make better decisions in complex tasks, which exceed limited cognitive capacities by reducing the need to memorize each element included in the decision. Instead, the interaction with the elements a decision is supposed to be based on, can be implicitly processed in conjunction with affect, and the resulting decision can be based on those affects. Furthermore, we showed that an implicit mechanism (core affect) allows us to make an efficient decision.

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