The Multi-attribute Linear Ballistic Accumulator Model of Decision-making

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Abstract

Context effects - preference changes depending on the availability of other options - have wide ranging implications across applied and theoretical domains, and have driven the development of new dynamic models of multi-attribute and multi-alternative choice. We propose the Multi-attribute Linear Ballistic Accumulator (MLBA), a new dynamic model that provides a quantitative account of the co-occurrence of three context effects - attraction, similarity, and compromise - not only in traditional paradigms involving choices among hedonic stimuli but also of recent demonstrations of these effects with non-hedonic stimuli. The MLBA model has analytical solutions making it computationally easier to apply than previous dynamic models.

Keywords: Decision-making, multi-alternative choice, preference reversal, context effects, dynamic models

Introduction

Individuals are often faced with the problem of choosing a single option from a large set of possible alternatives where the options have several features. For example, when purchasing a new cell phone, there are numerous phones from which to choose and each phone has many different features. A robust finding in the choice behavior literature is that preferences are subject to “context effects”. That is, preferences for existing alternatives can be influenced or even reversed by the addition of new alternatives. For example, an initial preference for a cheap, low quality cell phone over an expensive, high quality phone could be reversed when a third expensive phone of low quality is also considered.

Three important context effects are the attraction (Huber, Payne, & Puto, 1982), similarity (Tversky, 1972), and compromise (Simonson, 1989) effects. The standard experiment for the effects involves choices among three alternatives which each have two attributes. For example, three different cell phones with attributes of price and quality. Figure 1 graphically represents the positions of various options within a two dimensional space defined by two attribute values.

Three context effects

The attraction effect refers to the enhancement of an option through the inclusion of a similar but slightly inferior decoy alternative. For the choice set $\{X,Y\}$, let A_X and A_Y be similar to X and Y respectively but slightly inferior to each. For example, X might be a cheap, low quality cell phone and A_X might be the same quality as X but more expensive. The attraction effect occurs when people show greater preference for X when A_X is included in the choice set $\{X,Y\}$ as compared to when A_Y is included (and vice versa for Y). Mathematically, the attraction effect occurs when $Pr[X|\{X,Y,A_X\}] > Pr[X|\{X,Y,A_Y\}]$ and $Pr[Y|\{X,Y,A_X\}] < Pr[Y|\{X,Y,A_Y\}]$.

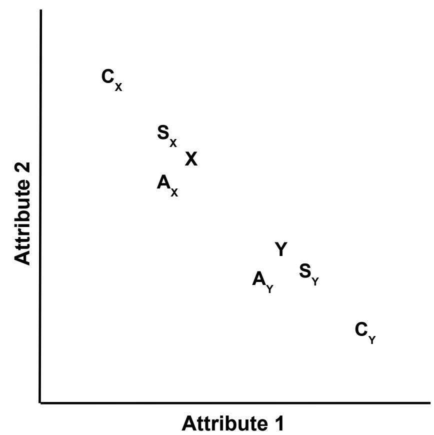

Figure 1: Various options plotted in a two dimensional attribute space. Preferences between X and Y can be affected by the presence of other options.

The similarity effects refers to the enhancement of a dissimilar option when two similar options compete with one another. For the choice set $\{X,Y\}$, let S_X and S_Y be similar and competitive to X and Y respectively. For example, if X is a cheap, low quality cell phone, then S_X might be a little more expensive and have slightly higher quality than X. The similarity effect occurs when people show greater preference for the dissimilar option Y when S_X is included in the choice set $\{X,Y\}$ as compared to when S_Y is included (and vice versa for X). Mathematically, the similarity effect occurs when $Pr[X|\{X,Y,S_X\}] < Pr[X|\{X,Y,S_Y\}]$ and $Pr[Y|\{X,Y,S_X\}] > Pr[Y|\{X,Y,S_Y\}]$.

The compromise effect refers to the enhancement of an option when it is presented as a compromise between two other alternatives. For the choice set $\{X,Y\}$, let C_X and C_Y be extreme options that make X and Y take the middle ground respectively. For example, if X is a cheap, low quality cell phone, then C_X might be drastically cheaper and extremely lower quality than X. The compromise effect occurs when people show greater preference for X when C_X is included in the choice set $\{X,Y\}$ as compared to when C_Y is included (and vice versa for Y). Mathematically, the compromise effect occurs when $Pr[X|\{X,Y,C_X\}] > Pr[X|\{X,Y,C_Y\}]$ and $Pr[Y|\{X,Y,C_X\}] < Pr[Y|\{X,Y,C_Y\}]$.

The three context effects are theoretically important because they violated the simple scalability property (Krantz, 1964; Tversky, 1972) which is a property of most utility models of choice including Luce's (1959) ratio of strengths model. To show a violation, consider the attraction effect. According to simple scalability, the inequality $Pr[X|\{X,Y,A_X\}] > Pr[X|\{X,Y,A_Y\}]$ implies that the strength of A_X is less than the strength of A_Y. However, the inequality $Pr[Y|\{X,Y,A_X\}] < Pr[Y|\{X,Y,A_Y\}]$ implies that the strength of A_Y is less than the strength of A_X. Both statements obviously cannot be true so the property is violated. The similarity and compromise effects produce similar violations.

Dynamic models of context effects

Because utility models cannot account for context effects due to violations of simple scalability, researchers have turned to dynamic models to explain the effects. There are two predominate dynamic models of the effects: multi-alternative decision field theory (MDFT) (Roe, Busemeyer, & Townsend, 2001) and the leaky competing accumulators (LCA) model (Usher & McClelland, 2004). Even though these models have provided great insight into multi-alternative choice, they are not without flaws. First, both models require time intensive simulations for fitting data with internally controlled stopping times (the experimental procedure commonly used in context effects tasks in which participants control when they make decisions as opposed to an experimenter controlled deadline). Thus, it is difficult to fit the models to human data and evaluations of the models have relied on qualitative analyses such as showing that all three effects can be obtained using a single set of parameters. There has not been a quantitative comparison of the models and it remains unknown whether or not they can account for human data.

Further, the LCA model assumes that the attraction and compromise effects are the result of loss aversion. The loss aversion assumption seems reasonable for situations where the options have hedonic attributes such as consumer products with attributes of price and quality. However, there is recent evidence that context effects are a general feature of choice behavior and not specific to options with hedonic attributes. Trueblood (2012) demonstrated the three effects in an inference paradigm involving scenarios about criminal suspects. In these experiments, subjects were asked to infer which suspect out of a set of three was most likely to have committed a crime based on eye-witness evidence. Trueblood, Brown, Heathcote, and Busemeyer (in press) also showed the three effects in a simple perceptual task where subjects were asked to select the largest rectangle out of a set of three. Choplin and Hummel (2005) found the attraction effect with ovals and line segments in a similarity judgment paradigm and Tsetsos, Usher, and McClelland (2011) obtained the similarity effect using time-varing psychophysical stimuli. These experiments all suggest that the effects are not due to loss aversion because there is no notion of gains or losses along the attributes.

This paper introduces a new dynamic model, the multi-attribute linear ballistic accumulator (MLBA) model, to account for context effects in multi-alternative choice. The MLBA model is easier to fit to data than MDFT and the LCA model because of its computational tractability. Also, it does not rely on loss aversion to explain the effects and thus can be applied to both hedonic and non-hedonic choices.

Precursors to the MLBA model

The MLBA model is an extension of the linear ballistic accumulator (LBA) model (Brown & Heathcote, 2008) that takes into account multiple attributes of options. The LBA models choice and response times with independent accumulators that race to a threshold χ. Each accumulator corresponds to a different option and the accumulator that first reaches the threshold is selected. Within a single trial, the accumulators are both linear and deterministic leading to mathematically tractable solutions for choice and response times. Each accumulator starts at a randomly determined amount of evidence selected from a uniform distribution $[0,A]$. The accumulators increase at speeds defined by the drift rates which are drawn from a normal distribution on each trial. Typically, the normal distributions have freely-estimated mean values $d_1, d_2, d_3...$ and a common standard deviation $s = 1$.

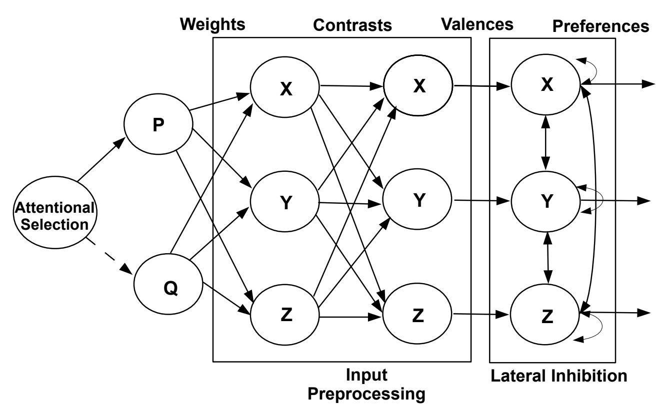

Figure 2: Connectionist network interpretation of MDFT.

The MLBA model also incorporates some of the cognitive mechanisms used in MDFT. MDFT assumes an individual's preferences are determined by a series of comparisons and evaluations of the alternatives that evolve across time. The preferences continue to evolve until one of the preference states, associated with one of the options, reaches a threshold and is selected. Preference states are determined by valences for each option and lateral inhibition among the options. The valences are constructed from three components: subjective values, stochastic attention weights, and a comparison mechanism. The strength of the lateral inhibition is determined by the distance between two options in an "indifference/dominance" space (Hotaling, Busemeyer, & Li, 2010).

MDFT can be interpreted as a connectionist network (Roe et al., 2001; Busemeyer & Johnson, 2004), as illustrated in Figure 2. At each moment in time, attention can be allocated to attribute P (e.g., price) or attribute Q (e.g., quality), as illustrated in the first layer. The second layer shows each option weighted by the attributes. This layer instantiates the comparison mechanism and projects valences to the third layer. The valences are subject to the distance-dependent lateral inhibition process in the fourth layer, which outputs preferences.

The MLBA model

The MLBA model adds to the LBA model by explicitly specifying how drift rates arise from the evaluation of attributes. It is assumed that mean drift rates are an increasing function of the valences of the options, where valences are defined in a similar manner to MDFT. Specifically, valences are determined by three components: subjective values, attention weights, and a comparison mechanism.

In determining the mean drift rates, each option is associated with a valence that represents the advantages or disadvantages of the option. For a set of options such as $\{X,Y,Z\}$, the valences can be described by the vector $V = [v_X, v_Y, v_Z]'$. Let P and Q be attributes where P_i and Q_i denote the value of option i on each dimension. It is assumed that decision-makers evaluate the subjective value of each option on each attribute producing the matrix of evaluations:

$$M = \begin{bmatrix} m_{P1} & m_{Q1} \\ m_{P2} & m_{Q2} \\ m_{P3} & m_{Q3} \end{bmatrix}. \tag{1}$$

In MDFT, the values m_{Pi} and m_{Qi} represent an individual's subjective evaluation of the attributes. However, the exact form of this evaluation is not given. In the MLBA model, we constrain this form. We assume that the psychological m_{Pi} and m_{Qi} values result from a local rescaling (i.e., within a single trial) of the experimentally defined attribute values, P_i and Q_i. Wedell (1991) argued that context effects should be considered as local rather than global phenomena. Also, Gonzalez-Vallejo (2002) postulated a local rescaling of options in her proportional difference model.

There are at least three ways the local rescaling can be implemented. One possible rescaling arises from dividing the experimental values by the smallest values on attributes P and Q for a given set of options so that $m_{Pi} = P_i/min(P)$ and $m_{Qi} = Q_i/min(Q)$. Another possibility is dividing the experimental values by the largest values on attributes P and Q for a given set of options so that $m_{Pi} = P_i/max(P)$ and $m_{Qi} = Q_i/max(Q)$. The third option is to divide the experimental values by the average value of the attributes P and Q for a given set of options so that $m_{Pi} = P_i/\frac{1}{3}(P_1+P_2+P_3)$ and $m_{Qi} = Q_i/\frac{1}{3}(Q_1+Q_2+Q_3)$.

As in MDFT, the second component of the valence vector is the attention weights. We assume the decision-maker allocates a certain amount of attention to each attribute. The attention weight w_P represents the amount of attention allocated to the P attribute across the trial and w_Q represents the amount of attention allocated to the Q attribute across the trial. It is further assumed that $w_Q = 1 - w_P$. The two attention weights are used to define the attention vector:

$$W = \begin{bmatrix} w_P & w_Q \end{bmatrix}'. \tag{2}$$

The third component of the valence vector is a comparison mechanism. Like MDFT, this comparison process determines the relative advantage or disadvantage of each option on each attribute. The comparison process can be represented by a contrast matrix:

$$C = \begin{bmatrix} 1 & -\frac{1}{2}\alpha_{12} & -\frac{1}{2}\alpha_{13} \\ -\frac{1}{2}\alpha_{21} & 1 & -\frac{1}{2}\alpha_{23} \\ -\frac{1}{2}\alpha_{31} & -\frac{1}{2}\alpha_{32} & 1 \end{bmatrix} \tag{3}$$

Using this matrix, which assumes that $\alpha_{ij} = \alpha_{ji}$, we can define the valence vector in a similar manner as in MDFT by the matrix product

$$V = CMW. \tag{4}$$

The weights α_{ij} in the contrast matrix are defined by the indifference/dominance distance function developed by Hotaling et al. (2010) to determine the strength of the lateral inhibition in MDFT. Consider a pair of options (P_i, Q_i) and (P_j, Q_j). Define the distance between these two options as $(\Delta P, \Delta Q) = (P_i - P_j, Q_i - Q_j)$. These distances are then mapped to the corresponding coordinates in the indifference and dominance space: $(\Delta I, \Delta D) = 1\sqrt{2} \cdot ((\Delta Q - \Delta P), (\Delta Q + \Delta P))$ where ΔI is the difference along the indifference dimension and ΔD is the difference along the dominance dimension. Using these coordinates, the distance function that weights changes more in the dominance dimension than the indifference dimension is defined as

$$Dist_{ij} = \sqrt{(\Delta I)^2 + \beta \cdot (\Delta D)^2} \tag{5}$$

where $\beta \geq 1$. The distances are converted into similarities by the Gaussian function:

$$S_{ij} = exp(-\phi \cdot Dist_{ij}). \tag{6}$$

Using the similarities, we define the α parameters as dissimilarity measures:

$$\alpha_{ij} = 1 - S_{ij}. \tag{7}$$

This mapping allows for options that are dissimilar to be weighted more in the comparison process. Finally, the valences are mapped into mean drift rates using a logistic function:

$$d_i = \frac{10}{1+exp(-\gamma \cdot v_i)}. \quad (8)$$

In total, the model uses four free parameters to define the mean drift rates: the attention weight w_P, the dominance weight β, the similarity parameter ϕ, and the logistic parameter γ. The model also has a starting point parameter A, a threshold parameter χ and a drift rate noise parameter s which are fixed when only modeling choice probabilities. For the current application, the noise parameter is assumed to the be the same for each accumulator. This assumption could be relaxed in other circumstances.

As with MDFT, the MLBA model can also be interpreted as a connectionist network as illustrated in Figure 3. For a given trial, a certain amount of attention can be allocated to attribute P and to attribute Q as illustrated in the first layer of the network. The second layer shows each option weighted by the attributes. This layer applies the contrast process and projects valences into the third layer. The valences are transformed into mean drift rates by a logistic function (f) in the fourth layer. Unlike MDFT, there is no lateral inhibition.

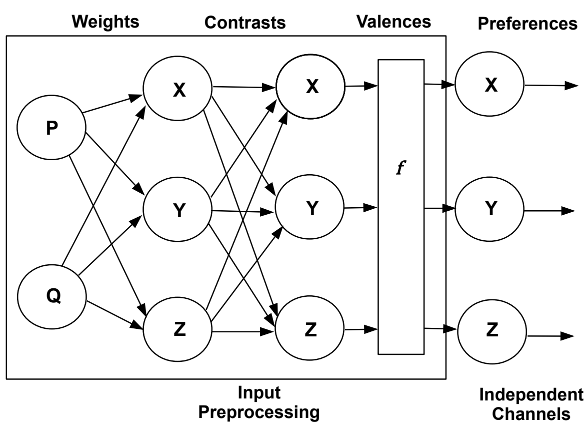

Figure 3: Connectionist network interpretation of MLBA.

The MLBA model accounts for the similarity effect through the local rescaling of the attribute values used to determine the M matrix. This local rescaling process results in more favorable subjective values for the dissimilar option. The model accounts for the attraction and compromise effects through the comparison process captured by the C matrix.

Combined Inference Experiment

Context effects are typically tested using different groups of subjects for different effects. Thus, it remains an open question whether the attraction, compromise, and similarity effects can be found within a single experiment using the same subjects. This experiment investigates whether all three effects can be observed within the same experiment using the inference paradigm developed by Trueblood (2012). Data from this experiment will be used in the subsequent section to compare MDFT and the MLBA model.

In Trueblood (2012), the three effects were tested in separate experiments using an inference paradigm involving decisions about criminal suspects. The experiments tested how people infer which suspect out of a set of three is most likely to have committed a crime based on two pieces of evidence. The evidence was described as strength ratings from two different eyewitness testimonies where the ratings ranged from 0 to 100 with a rating of 0 corresponding to very weak evidence for guilt and a rating of 100 corresponding to very strong evidence for guilt. In these crime scenarios, the suspects represent the different choice options and the eyewitness testimonies represent the two attributes in a similar manner as a consumer product with attributes of quality and price.

Method

Sixty-eight undergraduate students from Indiana University participated for course credit. Participants were told they would see three suspects of a crime on each trial and were instructed to select the suspect that seemed most likely to have committed the crime based on the strengths of two different eyewitness testimonies. Participants were also told that the testimonies of both eyewitnesses were equally valid and important and that the strengths of the testimonies were equated. Participants did not receive feedback.

The suspects and eye-witness strengths were presented in a table format with different suspects in different rows. In the attraction effect experiment, for example, participants might have seen strength ratings of 63 (eyewitness 1) and 33 (eyewitness 2) for the suspect in row one, strength ratings of 32 (eyewitness 1) and 64 (eyewitness 2) for the suspect in row two, and strength ratings of 61 (eyewitness 1) and 31 (eyewitness 2) for the suspect in row three. In this example, the third suspect acts as the dominated decoy for the first suspect.

Each participant completed 240 trials which were divided into three blocks of 80 trials. The three blocks were used to test the three effects and were randomized across participants. Within each block, participants saw 40 trials testing one of the effects and 40 filler trials. The presentation order of the trials within each block was randomized. Filler trials where one alternative was clearly superior were used to assess accuracy throughout the experiment. The trials used to test for context effects were subdivided so that the decoy was placed near one alternative for some trials and near the other alternative for other trials. For example, the attraction effect was analyzed by comparing the choice sets $\{X, Y, A_X\}$ and $\{X, Y, A_Y\}$ as illustrated in Figure 1. The similarity effect was tested in two regions of the attribute space using a total of four ternary choice sets as in Trueblood (2012).

Results

For data analyses, three participants were removed because their accuracy was two standard deviations lower than the average accuracy on the filler trials. Figure 4 shows the mean choice probabilities for focal and non-focal alternatives in the attraction, similarity, and compromise effect trials. For the similarity effect, the focal option refers to the dissimilar alternative because this is the one enhanced by the decoy. For the attraction effect trials, the choice probability for the focal alternative (M = 0.548) was significantly larger than the choice probability for the non-focal alternative (M = 0.419) (t(64) = 3.141 , p = 0.002). The similarity trials also showed that across all four choice sets the choice probabilities were significantly larger for focal options (M = 0.429) than non-focal options (M= 0.362)(t(64) = 2.578, p = 0.012). For the compromise effect, the choice probability for compromise alternatives (M = 0.466) was significantly larger than the choice probability for extreme alternatives (M = 0.407) (t(64) = 2.172, p = 0.034).

Comparing MDFT and MLBA

We fit MDFT and the MLBA model to the average choice probabilities across subjects from the combined inference experiment discussed above. We did not fit individual choice probabilities because there were not enough data from each subject. The two models were fit to choice probabilities only rather than choice probabilities and response times. In previous literature, multi-alternative choice models have only been analyzed with respect to choice probabilities. Future work could use response time measures to further test the models.

Because MDFT does not have analytical solutions for internally controlled stopping times, fitting the model requires computationally intensive simulations. To avoid this computational difficulty an approximate method developed by Hotaling et al. (2010) was used, where we fit the model using an externally controlled stopping procedure with a large stopping time. We fit the model by allowing four parameters to vary freely. One of the parameters determines the attention weight in the first layer of the model shown in Figure 2. The other three parameters are used in calculating the strength of the lateral inhibition. We fixed the decision time to the large value, $t = 1001$ used by Hotaling et al. (2010) and the within-trial variability parameter to 1. Because the attribute values for the experiment were associated with eyewitness testimony strengths ranging from 0 to 100, we used the attribute values divided by 10 for the subjective values.

The MLBA model was fit by numerically integrating over decision times as discussed in Hawkins et al. (submitted). For the MLBA model, we allowed the four parameters used to define the mean drift rates to vary freely and fixed the starting point parameter to $A = 1$, the threshold parameter to $\chi = 2$, and the drift rate noise parameter to $s = 1$. We fit three versions of the model corresponding to the three possible local rescalings: minimum, maximum, and average.

We fit a total of 24 choice probabilities arising from the eight ternary choice sets used in the experiment. The attraction and compromise effects each involved two ternary choice sets corresponding to the two possible locations of the decoy alternative. There were four ternary choice sets used for the similarity effect as described above. The models were fit by minimizing the sum of squared error (SSE) between the model predictions and the data. When fitting mean probabilities, the SSE will approximate the maximum likelihood estimate. Table 1 gives the mean squared error (MSE) and the R^2 values for the models.

Table 1: MSE and R^2 values for MDFT and three versions of MLBA.

Model	MSE	R^2
MDFT	0.037	0.251
MLBA (minimum rescaling)	0.030	0.400
MLBA (maximum rescaling)	0.016	0.684
MLBA (average rescaling)	0.029	0.414

The MLBA model using the maximum rescaling is able to account for about 68% of the variability in the data as indicated by the R^2 value. Substantially poorer performance was obtained for the MLBA model with minimum and average rescaling, although both still performed much better than the MDFT model. Future work could examine the differences between the three rescalings in more detail. We doubt MDFT's poor fits are due to the externally controlled stopping time procedure, as Hotaling et al. (2010) found that the externally controlled stopping time model with long stopping times produced essentially the same results as internally controlled stopping times.

Discussion

Multi-alternative choice models such as MDFT and the LCA model have provided great insight into choice behavior, but these models have some drawbacks. They both required time intensive stimulations to fit data. Further the LCA model uses loss aversion to explain the attraction and compromise effects. The assumption that asymmetry between losses and gains is the underlying cause of these effects is problematic because the effects arise in paradigms were there are no losses or gains. The MLBA model overcomes these problems and provides a new psychological theory of context effects.

The MLBA model consists of two components: a front-end process that compares options along their attributes and a back-end process that determines the probability that a particular option will be selected. The back-end process is the LBA model developed by Brown and Heathcote (2008). This paper develops the front-end attribute processing component. The coupling of front-end and back-end processes is not new. The SAMBA model (Brown, Marley, Donkin, & Heathcote, 2008) of choice and response times in absolute identification tasks proposes a front end to the Ballistic Accumulator model (Brown & Heathcote, 2005). We suggest this pairing can be viewed as the front-end process modulating action selection in the back-end process. Models incorporating such modulation are common in the neurophysiological literature. For example, Frank (2005) developed a model in which the striatum modulates motor actions and working memory updating

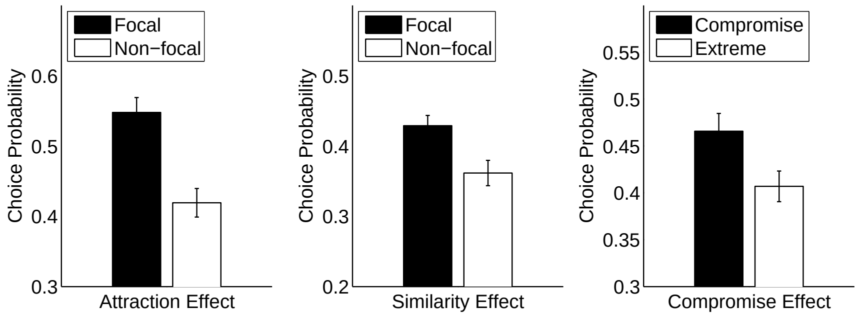

Figure 4: Mean choice probabilities with error bars showing the standard error of the mean for the attraction, similarity, and compromise effects from the combined inference experiment.

in frontal cortex. We do not argue that our model can be mapped to specific brain regions, but speculate that the gating of actions by a front-end process could have a neural explanation.

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