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Modelling the Integration of Costs and Benefits During Decision Making

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Abstract. In this paper a computational cognitive model for decision making based on cost-benefit comparison is presented. The brain weighs costs against benefits by combining reward and loss signals into a single, difference-based neural representation of net value. The presented model integrates such findings of the literature and is able to explain a person's decision making behavior through several scenarios.

Keywords: Financial decision making · Cost · Benefit

1 Introduction

When humans make decisions, the benefits of an option are automatically weighed against the accompanying costs [1–4]. What exactly triggers the decision based on benefit-cost comparison is a question that may provide useful information in order to design a realistic computational model. Improvements in brain imaging and recording techniques make it possible to retrieve more detailed information on brain processes, including decision making. The considered decision making is a binary choice based on the options's expected rewards and losses [5, 6]. An example given in [1] is when monkeys got the task to decide whether a field of dots was moving leftward or rightward. Here they indicated their choice with an eye movement to the target's respective side. The neurons in middle temporal visual area either respond to leftward motion or to rightward motion. On the other hand, the prefrontal and parietal neurons accumulate the difference in the activities of populations of neurons in middle temporal visual area. The response of the monkey is faster when more dots are moving in one direction. This effect is a prediction by the strength of accumulated difference between the activities of populations of neurons.

Based on this, we hypothesized that decision based on cost and benefit requires a system that takes the computation of the difference of neural reward and loss signals into account. This paper a computational our model for this. Realisticscenarios illustrate the model on a reasonable spectrum of situations. For the model's validation, the seven scenarios were simulated through a unique parameter value set which was estimated using a systematic approach.

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2 Processes in the Brain of Rewards and Losses

There has been an ongoing debate about how the brain encodes and represents signals that indicate rewards and losses. Two different aspects are considered in this paper. The first is an absolute value of the reward/loss [19]; this can be seen as an important or unimportant outcome. The second aspect is the differentiation between positive and negative outcomes [20]. These aspects are a motivation and basis for valence.

In [17, 18] dissociation is made between the valenced and non-valenced aspects of reward. The authors claim that a response of dopaminergic neurons in the ventral tegmental area (VTA) and nucleus accumbens (NAcc) point to a motivational signal with information about the future. This can be comprehended as waiting for the reward. In contrast, other neurons affect the valence component of reward. This can be comprehended as liking the reward and makes a stimuli more acceptable.

Going back to the example given in the introduction, a difference-based decision mechanism has also been identified in the human dorsolateral prefrontal cortex perceptual decisions [5]. In the monkeys' behavior it shows a compromise between speed and accuracy. Neurons in the lateral intraparietal cortex (LIP) accumulate evidence in favor of a particular decision alternative until a decision boundary is reached [7, 8].

We hypothesize here about the computation of a decision variable that is based on the difference of neural reward and loss anticipation signals being required for a cost-benefit decision. This weighing of cost and benefit involves accumulating the difference between stimulus-associated benefits and costs over time. The relation between this weighing to the decision is to either approach or avoid the stimulus. The decision process involves separate representations of expected reward and loss, in the VTA and amygdala [9, 10], respectively, from which a comparison signal is computed. The cost-benefit difference signal, in turn, should be accumulated in parietal or prefrontal cortex. As stated earlier this integration of a cost-benefit comparison will drift towards an upper or lower decision boundary.

Multiple functional magnetic resonance imaging (fMRI) studies suggest that ventromedial prefrontal cortex (VMPFC) represents a global valuation signal [3, 11, 12], and lesion studies highlight VMPFC as a necessary basis for value-based decision making [13, 14]. With this information we expect that VMPFC functions as a comparator area computing the difference between neural reward and loss signals.

3 Description of the Computational Model

In this section we present a computational model based on [16] to integrate the cost-benefit comparison as an effect on the action execution. The model is presented in Fig. 1 and its abbreviation details in Table 1. States in this model are taken specific for a given action a_i, effect b_i and stimulus s_k. They indicate more abstracted cognitive states for the design of the model and differs from taking specific neurons into consideration.

The stimulus s_k represents any internal or external change that may lead to an action execution EA(a_i) which is considered the decision for action a_i here. The sensory representation SR(b_i) of the effect b_i represents the expected effect of the execution of an action a_i. The world state WS(s_k), directs to the sensor states SS(s_k) and later on to the sensory representation states SR(s_k). The cognitive process of action selection is due to an effect of an internal simulation process via SR(b_i) and F(b_i) prior to the execution of an action [21, 22]. The effect of each action option (PA for each action a_i) will be evaluated by comparing the feelings associated to each valuated effects. The option that has a strong (positive) feeling F(b_i) holds as the option to be executed. This loop is represented in our model as the as-if body loop:

$$\text{PA} \rightarrow \text{SR} \rightarrow \text{F} \rightarrow \text{PA}$$

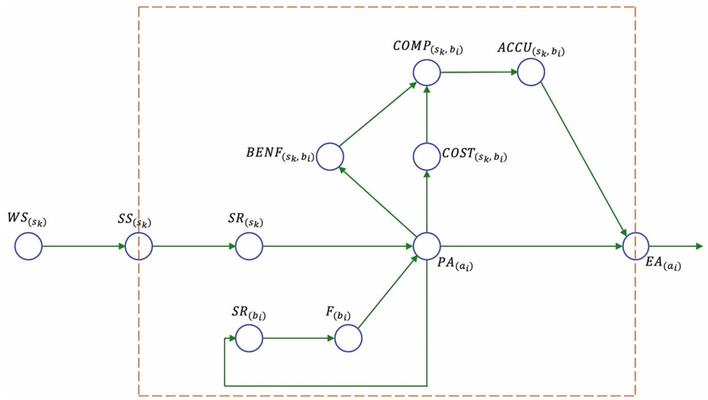

Fig. 1. Overview of the computational cognitive model.

Table 1. States and their explanation

WS(s_k)	World State with s_k a stimulus
SS(s_k)	Sensory State for s_k a stimulus
SR(s_k)	Sensory Representation State of s_k a stimulus
PA(a_i)	Action preparation state for action a_i
F(b_i)	Feeling state for action a_i after accumulator loop
COST(s_k, b_i)	Cost state for s_k a stimulus and b_i an effect
BENF(s_k, b_i)	Benefit state for s_k a stimulus and b_i an effect
COMP(s_k, b_i)	Comparator State for benefit and cost
ACCU(s_k, b_i)	Accumulator State for for benefit and cost
EA(a_i)	Action execution state for action a_i

So, each PA state is affected by its associated feeling through this loop. The strongest satisfied option will become selected as a result of the action selection process. After the loop, the weighing of cost against benefit occurs, which involves separate representations for the comparison and accumulation [9, 10], as is discussed in Sect. 2. Afterwards this will drift to an upper or lower decision boundary and lets the individual either approach or avoid the stimulus. The following causal pathways occur:

$$\text{PA} \rightarrow \text{BENF and COST} \rightarrow \text{COM P} \rightarrow \text{ACCU} \rightarrow \text{EA}$$

Furthermore in Fig. 1, the states are attached to subscript letters k and i, which represent the k^{th} instance for a stimulus s_k and the i^{th} option for an action a_i. Therefore, it is possible to have multiple action options through a single stimulus or from multiple stimuli.

The basic approach chosen for this model is a temporal-causal network defined by three network structure characteristics:

- **Connectivity**: connection weights $\boldsymbol{\omega}_{X,Y}$ for each connection from state X to state Y
- **Aggregation**: a combination function $\mathbf{c}_Y(..)$ for each state Y to determine the aggregation of the incoming single causal impacts $\boldsymbol{\omega}_{X_i,Y}X_i(t)$ from the states X_i from which Y gets incoming connections
- **Timing**: a speed factor $\boldsymbol{\eta}_Y$ for each state Y

The connection weights $\boldsymbol{\omega}_{X,Y}$ are between 0 and 1 in the model. By varying these weights for some states, we can align them with the considered scenario. The simulations of the model depend on the values of each of these weights together with other parameters. These connection weights can be found in Table 2 together with the parameter values for the combination functions that were used.

Table 2. The connections and their weights and the combination function parameter values

	Connections and their weights											Combination function parameters			
To from	WS	SS	SR(s_k)	PA	SR(b_i)	F	COST	BENF	COMP	ACCU	EA	η	λ	σ	τ
WS		1										0.7			
SS			1									0.2		3	0.2
SR(s_k)				0.7								0.2		3.2	0.2
PA					0.7		x_1	x_2			0.6	0.5		1.5	0.2
SR(b_i)						x_3						0.5		3	0.2
F				0.7								0.5		3	0.5
COST									1			0.5		10	0.3
BENF									1			0.5		10	0.3
COMP										1		0.5	1		
ACCU											0.8	0.5	1		
EA												0.5		8	0.7

For example, the connection PA → SR(b_i) has weight 0.7. The variables x_i in Table 2 represent the weights of connections PA → BENF, PA → COST and SR(b_i) → F. These are not always the same as it depends on the selected scenario. Furthermore we have a combination function $\mathbf{c}_Y(..)$ for each state Y to determine the aggregation of incoming causal impacts. In our model we make use of three combination functions, which are the scaled sum $\mathbf{ssum}_\lambda(..)$ with scaling factor $\boldsymbol{\lambda}$ and the advanced logistic sum combination function $\mathbf{alogistic}_{\sigma,\tau}$(..) with steepness σ and threshold τ. For the COST state we use a negative advanced logistic function, which will be the inhibiting state for the BENF state. This is the same as the $\mathbf{alogistic}_{\sigma,\tau}$(..), but with a negative value. The comparator and accumulator states compute the differences of the benefit and cost. These are expressed in the same unit, which makes this combination function fitting with the value equal to one. For the other states a flexible combination function is necessary as the values of the states all have a different slope and starting point. Here the advanced logistic function offers this possibility. The specific formulas can be found below, where $V_i = \omega_{X_i,Y} X_i(t)$ stands for an incoming impact by a connection with weight $\omega_{X_i,Y}$ from the concerning state X_i:

$$\mathbf{ssum}\lambda(V_1, \ldots, V_k) = \frac{V_1 + \ldots + V_k}{\lambda} \tag{1}$$

$$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k) = \left[\frac{1}{1 + e^{-\sigma(V_1 + \cdots + V_k - \tau)}} - \frac{1}{1 + e^{\sigma\tau}}\right]\left(1 + e^{-\sigma\tau}\right) \tag{2}$$

$$\mathbf{negalogistic}\sigma, \tau(V_1, \ldots, V_k) = -\left[\frac{1}{1 + e^{-\sigma(V_1 + \ldots + V_k - \tau)}} - \frac{1}{1 + e^{\sigma\tau}}\right]\left(1 + e^{-\sigma\tau}\right) \tag{3}$$

Here, the following parameters are used: λ is the scaling factor, σ the steepness and τ the threshold. The causal aggregated impact on state Y is applied over time gradually, using speed factor Y. So, a change in the value of state Y can be described by:

$$\begin{aligned} Y(t + \Delta t) &= Y(t) + \eta_Y\left[\mathbf{aggimpact}_Y(t) - Y(t)\right]\Delta t \\ \text{Or } \mathrm{d}Y(t)/\mathrm{d}t &= \eta_Y\left[\mathbf{aggimpact}_Y(t) - Y(t)\right]\Delta t \\ \mathbf{aggimpact}_Y(t) &= \mathbf{c}_Y(\omega_{X_1,Y}(t), \ldots, \omega_{X_k,Y} X_k(t)) \end{aligned} \tag{4}$$

Here X_i represents a state with a connection to state Y. With this difference equation we can numerically represent the behavior of each state in our model. By simulating all these equations by finding the right parameters we will be able to explore the dynamics and thus derive the behavior of the model [16]. The values for the speed factors η and the parameter values of the combination functions can be found in Table 3. From Table 3, it can also be derived that for the states COMP and ACCU the combination function $\mathbf{ssum}_\lambda$(..) is used. For the COST state the $\mathbf{negalogistic}_{\sigma,\tau}$(..) is used and for all other states the $\mathbf{alogistic}_{\sigma,\tau}$(..) is used.

4 Simulation Results

In this section the results of simulations for a number of selected scenarios are discussed, relating to the specification discussed in Sect. 2. Seven scenarios have been simulated from which five consider the difference in strength of benefit and cost. The other two scenarios consider the difference in strength of feeling. A brief summary of the seven scenarios is:

- Scenario 1 describes a situation where the prepared action has very high benefit over low cost. The feeling has a high value in this situation. This scenario will be considered as the base case for finding the right parameters.
- Scenario 2 describes a situation where the prepared action has very high benefit over average cost. The feeling has a high value in this situation.
- Scenario 3 describes a situation where the prepared action has average benefit over average cost. The feeling has a high value in this situation.
- Scenario 4 describes a situation where the prepared action has a average benefit over very high cost. The feeling has a high value in this situation.
- Scenario 5 describes a situation where the prepared action has low benefit over very high cost. The feeling has a high value in this situation.
- Scenario 6 describes a situation where the prepared action has very high benefit over low cost. The feeling has a lower value than the first five scenarios.
- Scenario 7 describes a situation where the prepared action has low benefit over very high cost. The feeling has a lower value than the first five scenarios.

An important focus in this work is on finding a parameter value set that allows the model to generate expected behavior as per the literature discussed in Sect. 2. The key challenge of this process is that there is no real data set that can be used to fine-tune the parameters of the model by comparison to its generated output data. Finding the right parameter values without knowledge of empirical data, but only with some behavioral characteristics of the output, makes it a nontrivial challenge. To overcome this challenge a specific approach was used in which each identified scenario differs from the base scenario (i.e., Scenario 1) in a minimal way via the weight values $\boldsymbol{\omega}_{X,Y}$ of three connections which can be found as x_1, x_2, and x_3 in Table 2. Given all this, to identify the parameter values the following systematic approach was used (see [15]):

- A parameter value set is proposed based on analytical reasoning on model dynamics.
- With this value set, the scenarios are validated one by one by changing its scenario-related weight values relative to the base case (see Table 2).
- If the new value set leads to generation of the expected behavior, then we can still rely on the base case values and will move on to the next scenario.
- If the value set has not provided the expected outcomes, then the original parameter value set of the base case will be adjusted and start over again from Scenario 1.
- This task will continue until all scenarios are simulated with expected results relative to the parameter values of base case.

Scenarios 1 and 2: High Benefit over Low Cost and over Average Cost

Scenario 1 describes a situation where a stimulus s occurs and the effect b of action a is expected to be positive. Based on the preparation state for a, the sensory representation of the predicted effect b of a is generated and after that the feeling state for action a is generated. Finally, the comparison of the benefit state and the cost state is highly positive and thus the action execution state is expected to have occurred. The simulation results of this scenario are shown in Fig. 2 (left). We can see that after the occurrence of the stimulus, the preparation of action a gets triggered. Following this, the sensory representation is generated and is followed by the feeling of effect *b*. These states contribute to the generation of benefit and cost state around time point 10 and reaches a peak value of 0.75 and −0.07 for benefit and cost respectively. The benefit and cost states are compared by the comparator state and has a peak value of 0.68 (the difference between benefit and cost). The accumulator afterwards has a weaker positive casualty with a peak value of 0.61. Finally the action execution gets initiated and starts at time point 18 with its peak at 0.83. This value is above the decision threshold and thus got accepted. Therefore, the action execution will occur. Note that when the stimulus WS(s_k) is taken away (the blue line in Fig. 2 left), all activation levels will decrease to 0. Also know that the values related to the time or the strength is not related with actual brain signals. It is only used as a frame of reference. This information applies to all scenarios.

Scenario 2 is similar to the first and describes a situation where a stimulus *s* occurs and the effect *b* of action *a* is expected to be positive. Based on the preparation state for *a*, the sensory representation of the predicted effect *b* of *a* is generated and after that the feeling state for action *a* is generated. Different from the first scenario is the comparison of the benefit state and the cost state. This will be lower but still it is positive and thus the action execution state is expected to have occured. The simulation result of this scenario is shown in Fig. 2 (right). Compared to the simulation result of Scenario 1 we can see differences in the benefit and cost state and the generated states after. We again see the start of the benefit and cost around time point 10 and reaches a peak value of 0.75 and −0.36 respectively. The benefit and cost states are compared by the comparator state and has a peak value of 0.39. The accumulator is generated after time point 14 with a peak value of 0.35. Eventually the action execution gets started and begins at time point 18 with its peak value of 0.52. This is a great decrease compared to Scenario 1, but still reaches an acceptable level for accepting the decision.

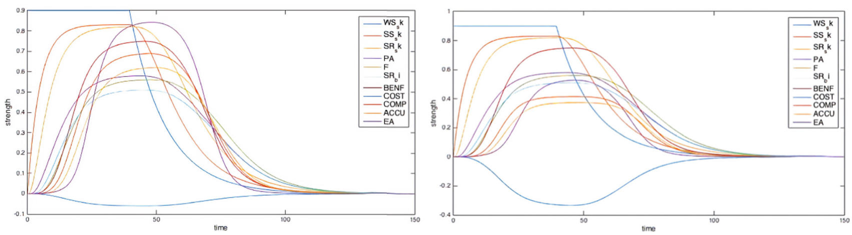

Fig. 2. Scenarios 1 and 2 - High benefit over low (left) and average (right) cost

Scenarios 3 and 4: Average Benefit over Average Cost and High Cost

Scenario 3 describes a situation where a decision has comparable cost and benefit. The stimulus *s* triggers the action preparation state followed by the generation of the sensory representation of the predicted effect *b* and after that the feeling state for action *a* is generated. When the benefit is equal to cost, we expect that the action execution to have a weaker strength. The results are shown in Fig. 3 (left). We see a change in benefit and cost. The peak of the benefit state and cost state are 0.36 and −0.36 respectively. Based on these values we see that comparator and accumulator do not get above or below 0.

This is as expected; it represents the difference between benefit and cost. Furthermore we see a very low strength for the action execution state starting at time point 18 with a peak value of 0.08. With such a low strength the decision got rejected.

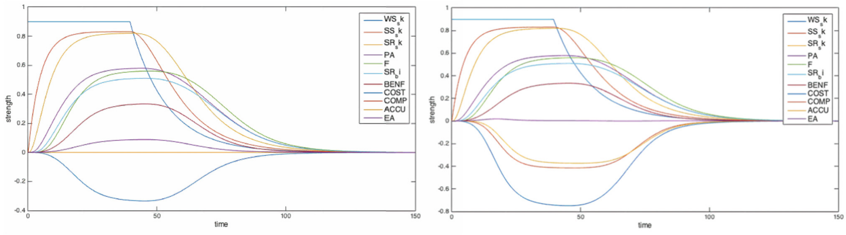

Fig. 3. Scenarios 3 and 4 - Average benefit over average cost (left) and high cost (right)

In Scenario 4, the cost of performing the action is higher than the benefit. One would expect for this scenario that the action execution state will be very low. The results of the simulation can be found in Fig. 3 (right). We see an increase in strength of the cost state. The peak of this state is -0.75 at time point 46. Based on the strength values of benefit and cost we can see that both comparator and accumulator are negative, as cost is higher than benefit. The peak of these two states are -0.39 and -0.35 (for comparator and accumulator respectively). For the action execution state we see a small increase around time point 15 due to the action preparation state but then it goes down immediately. It has a peak at time point 19 with a value of 0.01. Therefore, the action execution state depends more on the value of the comparator state than it does on the preparation state.

Scenarios 5 and 6: Low Benefit over High Cost and High Benefit over Low Cost with a Weak Feeling

Scenario 5 describes a situation where the cost of an action option is higher than the benefit. Here the benefit is very low and its effect on the execution of action *a* can be neglected. For this situation, we expect that the action execution state will be very low. The results of the simulation can be found in Fig. 4 (left). The strength of benefit is very low with a peak of 0.06. As a result the comparator and accumulator get very negative and nearly reach the peak of the cost state. The peaks of the strength values of cost, comparator and accumulator are -0.75, -0.69 and -0.60 respectively. A very small increase for the action execution state can be observed and it follows the exact route as in Scenario 4. This can be explained as an effect only by the action preparation state and thus a (highly-) negative value for the accumulator state does not have an effect on the action execution.

Scenario 6 introduces a new adjustment in the model. Here the person has a negative bias. This can be translated into not expecting any reward out of action option *a*. Hence we see a low strength value for feeling. We expect this to have negative effect on all states. Furthermore, there is a difference with respect to the Scenario 1. The simulation results are shown in Fig. 4 (right).

We can see that all state values have become significantly lower with respect to the states in Scenario 1. The benefit has its peak around time point 48 and has a value of

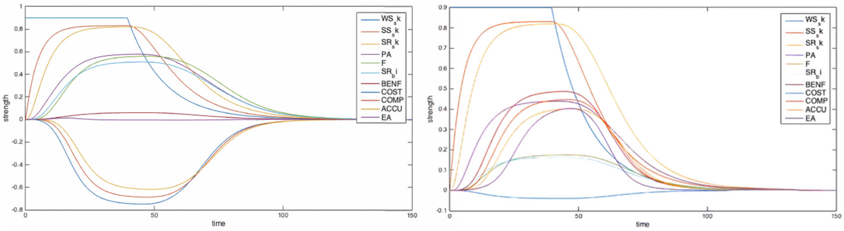

Fig. 4. Scenarios 5 and 6 - Low benefit over high cost (left) and high benefit over low cost with a weak feeling (right)

0.49. This is a big decrease compared to the first scenario. The cost state has a peak of 0.04 and hence comparator has a peak close to benefit with a value of 0.43. We can also note that the weakness of the feeling has an effect on the speed of the increase of these states. Furthermore we see a decrease of the action execution below the decision boundary and thus the action does not get executed. We can conclude from this that a weak feeling makes it very hard for a decision to being accepted by the person.

Scenario 7: Low Benefit over High Cost with a Weak Feeling
The last scenario introduces a weaker feeling into Scenario 5. As stated in the previous scenario, a weaker feeling signifies a very high value for comparator for the action to be executed. With this scenario we look into the effect of a weaker feeling on an action option *a* with a very low reward. The simulation results are shown in Fig. 5. We see that the cost state has a less negative strength compared to Scenario 5. The state has a peak value of 0.5 for its strength. By this we can state that a weak feeling also has effect on the disadvantage of an action option. Furthermore, there are no significant differences in here when compared with Scenario 5. The action execution still has a small increase at the start but it did not execute.

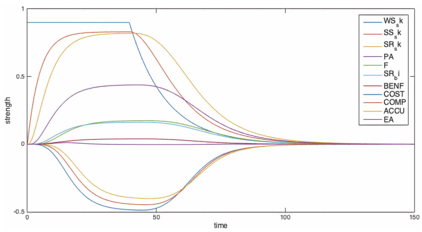

Fig. 5. Scenario 7 - Low benefit over high cost with a weak feeling

5 Discussion

The computational model for decision making presented in this paper shows how an individual prepares and integrates reward and loss of an action and how this will end up in either accepting or rejecting the option. The preparation of such an action involves a motivational valence and an affective valence, modeled here by the feeling state and the comparator/accumulator state, respectively. In a number of scenarios the effects of these components on the action execution decision were explored. From the results we can state that a low motivational valence on an action option requires a very high reward to get decided for. This is interesting as it shows that an individual with a bad feeling about an action option is most likely to reject this option, whilst such an option could be beneficial. In contrast, we can state that when the comparator has a low or even negative value (meaning that the cost is higher than the benefit), then the feeling state does not have much effect on deciding for execution of that option.

This computational model is meant as a basis for further work on developing the integration of reward and loss in decision making. It is able to monitor and analyze the process of decision making, which in turn can be used for the support of financial decision making by individuals, for example, to eliminate irrational options with adequate insights. For customers of a bank, such forms of support by the banking environment may be felt as quite welcome support if it indeed leads to better personal financial decisions. This may also provide further opportunities to validate the model.

In future work, also the thoughts about the outcomes of an action by the person can be added in the model, which will lead to effect on a retrospective feeling state. Furthermore, this model can be extended by adding adaptivity into the dynamics of the model to make it more realistic and sensitive to environmental changes.

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