# Modeling emotion and inference as a value calculation system

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**Abstract**
There have been many studies on the modeling of a relation between emotion and decision making. Though affection of emotion on an inference for the decision is evident, its computational mechanism, especially for an intuitive inference, is not clear yet. So, in this paper, we discuss the possibility of the computational modeling of an intuitive inference guided by emotion in which random looking neural excitation takes a role of probability based parallel search of values. First, we show a possible architecture of the intuitive inference in which the system of multiple values affects on the decision making of actions. Then, we focus on an effect of value control mechanism on the intuitive inference in a path-finding task. In a computer simulation, we aimed to simulate a model of the value management in which multiple value components of the brainstem is controlled for an action search. Though the brainstem seems simple, the model includes the essence of the resolution of conflicts between multiple values.

*Keywords:* Emotion, Decision Making, Value Calculation System, Model, Probabilistic Inference

## 1 Introduction

Because of the rapid development of AI technology in recent years, soon we can expect to see an AI product that has a more human-like nature. Its typical application is a field involving human interactions. For its instantiation, such an AI will be required to have a set of mental sensing abilities that include those for identifying cognitive states and intentions in order to select an action in answer to an implicit human desire. It is the nature of human behavior that a human’s purpose of action is not fixed but dynamically changing, and often multiple desires are in conflict. However, in most traditional cognitive architectures, reinforcement learning is used for action learning, and the reward (or value) for the learning is designed by humans in advance and is fixed.

Given this, how can we design a model of action selection for a human-interacting AI? One way is to develop a very human-like reward/value system. An AI having such a value system would act properly by detecting human desires in real time. Thus, an understanding of the human value system involved in decision making is an indispensable step for realizing advanced interpersonal interaction.

On the other hand, humans make decisions on the basis of emotion as well as value [Schwarz 1990]. Emotion is sometimes unreasonable, but in many situations in daily life, emotion leads us to a better decision than that by a rational value calculation [Winter 2014]. Thus, emotion as a decision-making tool appears to have a role similar to that of value calculation. Therefore, in this paper, we hypothesize that emotion is a value calculation system for action selection.

In many cases, decision making involves inference. In traditional AI theory, a typical inference is composed of a tree search with sequential predictions and an evaluation of the predicted state. In human the process is explicit. But the emotive impact on decision making is more implicit and intuitive. Even in a decision making of animal action choice, the intuitive inference would be included. Then, what is a mechanism of the intuitive inference, and how does the value of emotions involved? In response to this question, this paper attempts to model the intuitive reasoning, and discuss the control of value as an elemental mechanism that enables a flexible inference.

In this paper, we review the conventional models of emotion in Chapter 2, and describe a model of intuitive inference by a probabilistic prediction and search by using a neural excitation in Chapter 3.And in Chapter 4, we introduce a result of computer simulation including the control of multiple value conflict.

# 2 Conventional model of emotion

## 2.1 Models of emotion

There are many models for emotion [Ekman et al., 1997] [Russell, 1980]. Some have tried to reproduce emotions as phenomena of cognitive architecture [Samsonovich, 2013] [Chernavskaya et al., 2015]. A few do use a computational approach, but these have not yet advanced beyond very simple pilot models [Vallverdú et al., 2016].

For the role of emotion in more complex human cognitive behavior, Toda proposed a qualitative theory for explaining complex human emotion as a process of value assignation through inference toward an action selection [Toda, 1980]. In this theory, a wide variety of human emotions are explained as a calculation and inference process for assigning a value to a current state using a range of knowledge and basic values. Although the explanation is very attractive and persuasive, the theory remains a conceptual model and does not mention a specific process for its computation. Ortony et al. proposed a precise and comprehensive model that classifies emotions into 22 kinds based on a psychological knowledge [Ortony, 1988]. In this model, a set of variables associated with human emotions are shown and a theory for engineering implementation has been discussed.

For a computational implementation, Adam has modeled the OCC theory by the symbol Logic [Adam 2009]. Though we can expect a fusion of inference and language by the model, a discussion will be necessary on describing the intuitive phenomenon of emotion even animals can have by the logic. We believe a more brain like model like a neural network model is suitable for the model of intuitive emotion.

Recently, Koelsch et al. proposed a quartet theory of human emotion that broadly divides factors of emotion into four components —self-maintenance, safety, attachment, and profit—and attempted to assign the components to different brain areas [Koelsch et al., 2015]. In this theory, profit is included as an aspect of emotion, and the orbitofrontal area of the brain is supposed for its domain. Though some people may disagree with its inclusion in emotion, it cannot be denied that economic gain has a large effect on the emotions.

## 2.2 Emotion as a value calculation system

Emotion greatly affects decision making, and its expression affects the decision making of others. On the other hand, economics and brain science tell us that human decision making is driven by reward (value) calculation [Edwards., 1954].[Kahneman., 1979]. So we suppose emotion to be a medium for the expression of this value calculation process and result as well as of its side effects. This means that the value calculation system is a cause of the emergence of emotion. The expression of emotion has the utility of avoiding a futile conflict by transmitting an evaluation of a current attention target to another human being. In many cases, the relationship between the value type and the emotional expression are fixed, and this enables proper functioning of the value transmission. Rather than start by trying to understand the mechanism of emotion, we may first need to understand the value system.

In traditional AI, a set of intelligent processes, such as visual, auditory, and tactile perceptions and cognitions, prediction and inference, decision making and action generation, are studied as components of the intellectual mind. In contrast, we discuss the value system behind the intelligent processing. Value is the purpose of human behavior and the driver of those intelligence components. In our discussion, we assume that given a sensory input, the neocortical intelligent information processing system recognizes it and immediately sends the result to a variety of value calculation systems. For the types of values, we assume those suggested by Koelsch.

Many of the value based decision making includes an inference process where the emotion affects. The inference process is real time including many possible prediction and their value calculation. In many of them, we don't think consciously so long and can select an action that lead us a valued state in a short time. The logic of human thinking is slow and is not suitable for the rapid decision making. A process of intuitive inference, a intuitive prediction and value calculation process should be considered.

# 3 Modeling intuitive inference with particle search

## 3.1 Cognitive architecture for value-driven inference

As the inference process assumed in this study, we consider a cyclic neural activity propagation between the neocortical information processing system and the value calculation system via an information circulation control system that modifies a gain of the calculated values (Figure 1). Every cycle of the processing, a set of information representation of single step future is generated from the information representing current inference state, a set of possible actions and a set of general knowledge of the target world. A feature of the information representation is a probabilistic overlap of multiple states using a set of particles that represent a set of predicted local states.

The set of predicted states is passed to the value calculation system. As multiple states are overlapped, some state may have assigned a value and some are not, and will cause a confusion is the values are conflicting. To avoid the confusion and cause a flexible search of value assigned, the information circulation control system modifies the gain of values from each of the value calculation system.

As a medium for this prediction cycle, we assume a function of long-distance brain waves between the related brain areas. The neural connections underlying the brain wave transmit information between the prefrontal area, the occipital feature processing area, and the limbic value calculation area to rapidly integrate the search and evaluation of the inference. When we combine this mechanism with the selective activation of high-valued predictions, we may be able to actualize a high speed, highly exploratory parallel inference.

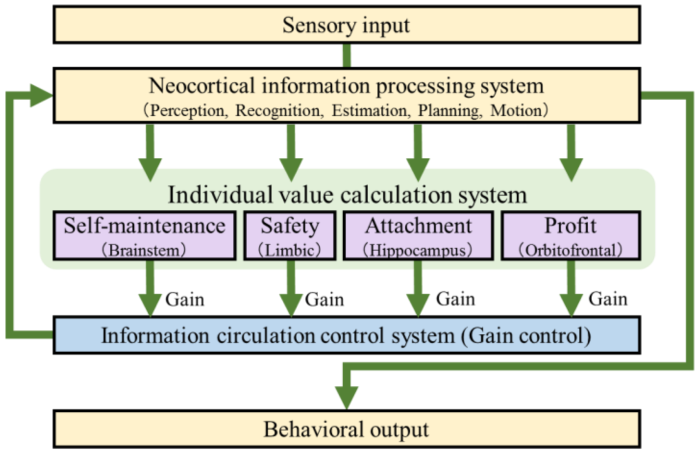


**Figure 1:** Framework for the hypothesis of value driven inference

## 3.2 Model of brain-like value calculation components by particles

In the implementation of emotion as a value calculation system, an understanding of its computational mechanism is important. When multiple value conflicts in a task, a solution by a traditional reinforcement learning often lacks flexibility. In contrast, animals don't try the same search method every time, and flexibly change the search strategy depending on the situation including self-condition and past search history. It is not easy to realize the flexibility just by a traditional reinforcement method.

When we make inference, we consider not only a value of the goal but also our environmental information and the current body state of self to calculate a desire (D). It means the value of object changes dynamically. In this study, we assume a use of an associative neural propagation for the value search. For that purpose, we use stochastic parallel search using a large number of particles. The numerous particles propagate through a state space following a global knowledge of the world, a prior probability distribution of possible actions and state transition (p01, p02, action01 and action02 in Figure 2), from a current state (S0) to the neighboring region (S1,S2). We supposed the global knowledge of the world was acquired by the past experiences.

When a part of the particles dispersed into a state area that a value of the state has obtained by past experience, the particles has found a value for a specific past experience. The value found is combined with the desire (D) to calculate the expected value of the value for the target area. When no expected value is found in the search area, or within an expected time, the search area is expanded and the search and calculation are iterated( S1⇒S3, S4 : S2⇒S5, S6).

Here, we modify a gain of the value for each of the desire to realize dynamic change of value distribution within the state space. This modification causes finding of different action choice and different action sequence realizing trial and error like search process in brain. Though we have not found an algorithm for modifying the gains for the multiple desires, we expect a flexible action search will be realized by the dynamically changing valued space. From the explanation above, we notice this method is similar to a probabilistic search version of model-based reinforcement learning. However, by intentionally controlling the gain for each goal along time, we could realize the flexible search behavior.

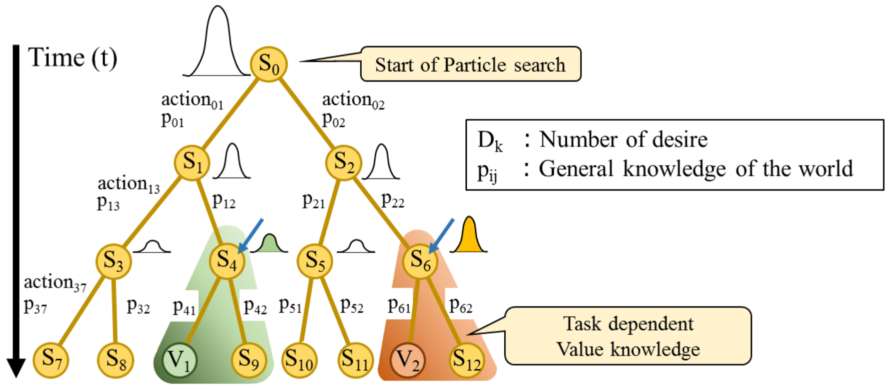


Figure 2: Particle implementation of probabilistic parallel search with a general knowledge

# 4 Simulation in virtual world

## 4.1 Modeling brainstem with conflicts between multiple values

In this paper, we first consider a computational implementation of the value by brainstem. Though the brainstem is just a basic elements of the value system, it contains a basic problem of conflict resolution in the value calculation, and its implementation can be a model for the other components.

In the brainstem, the association of biological sensors and the desire for self-maintenance, hunger, thirst, temperature regulation, sleep and wakefulness, etc. is fixed. We assume these desires are activated according to the circadian rhythm, and a set of actions for satisfying the desire is acquired by reinforcement learning. It is often the case that not all the situations that require an action decision have been experienced in the past, and not all the corresponding behaviors have been learned. It also happens that multiple desires arise simultaneously and compete. Thus, even for modeling the brainstem alone, a kind of meta-system is required that manages the value calculation and the action selection process.

Therefore, in the simulation tasks of our study, we cause multiple desires to occur one after another in a virtual environment. These tasks might be solved with a single value search or might require the management of multiple competing values. Our aim is the modeling and evaluation of the conflict resolution system in such a task group. For the implementation, we use the simulation environment Life in Silico (LIS), which combines a simulated agent program with a virtual environment created by the game engine Unity [WBAI, 2016].

## 4.2 Two-layered model for a path-finding task

The model used in our work has a two-layered structure: a map and a place–value association layer, and an optimal-value-selection layer. The map represents a spatial map. To predict the results of actions, we need knowledge of the world and of possible actions. An assumption of this simulation is that an agent acquires map information as general knowledge through episodic experiences (Figure 3).

The place–value association layer has a function to calculate and store the value of the location based on past experience and a direct reward from the environment. The range of locations and situations in which the values are learned and assigned varies according to the amount of experience the individual has. In our model, the distribution of the place–value association was acquired using Q-learning. When the agent starts an action search in a location for which a value has already been assigned, the agent uses the usual reinforcement-learning-based action decision. If no value has been assigned owing to a lack of experience, it uses the inference strategy, which requires the second layer.

The optimal-value-selection layer represents the associative brain activity by real-time neural firing and search. Given a stimulus from the external world, the agent recognizes the current position of the self and begins searching for the target, the position at which the value is maximized. We use probability based spread of particle by the multistep Monte Carlo association. The prior probability is the knowledge of the map and is used to avoid unrealizable virtual movement. By iterating the association with the knowledge multiple times, and thus the neural excitation that expresses the probabilistic search, the virtual movement of the agent spreads within the map of the agent. When the associative spread of particles reach to a location where a value has already been assigned, the search process stops, and action generation based on the value and the location starts.

First, the agent acquires information on the surrounding environment, when choosing an action. ）

It combines the information with an internal state of its own, and finds a desire (D) to pursuit. The desire triggers the parallel and distributed probability based prediction and value search by the particles. When multiple and conflicting values are found by the parallel search, it tries to resolve the conflict by modulating gains of the desires through an information circulation control system, and decides a behavior according to the value assessed.

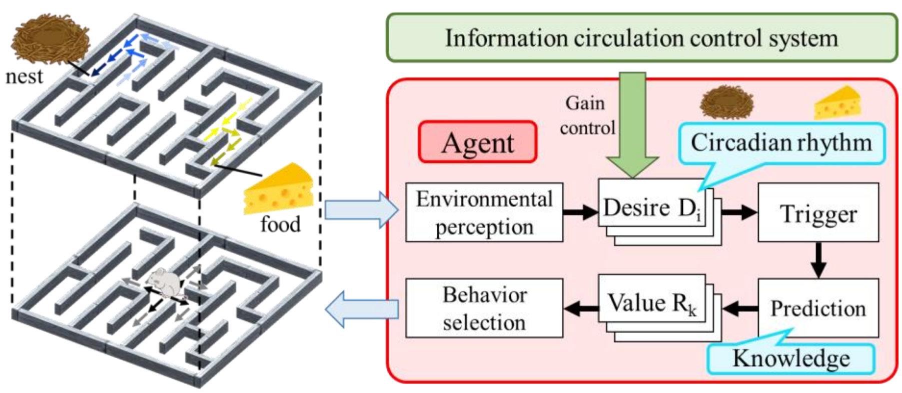


**Figure 3:** Example of simulation execution screen.

# 5 Conclusion

In this paper, we have assumed emotion to be an expression of the value calculated for decision making, and a model of value and knowledge-based inference was proposed. Here, we have focused solely on the value coded in the brainstem and explained the method of deriving value, the inference. The real world is dynamic, and value desire isn't single at a time, but multiple value desires occur simultaneously, and conditions of the world change. To resolve this problem, reinforcement learning and reasoning with fixed values are not sufficient. Instead, we need to consider a meta-system that selectively activates and manages the processing in dynamic situations. Though we do not have a tangible cognitive architecture yet, the direction of value-based modeling appears promising.

The virtual environment to be constructed in this research can range from a simple single-desire task to a complex task requiring multiple value calculations and their conflict resolution in a dynamic environment. This is the reason that we adopt the virtual environment. We expect progress in the computational understanding of emotions and value systems by means of an analysis of agent behavior in a variety of simulation environments. This work was supported by MEXT KAKENHI Grant Number 15H01622.

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