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Relevance Realization in the Formation of Mental Representation: Analyzing Discrete Thought: Why Cognition Must Use Discrete Representations

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ABSTRACT
This paper is to discuss the roles of computationalism and discrete representation in mental representation by focusing on the paper written by Dietrich and Markman in 2003, Discrete Thought: Why cognition must be discrete representation. This paper will develop the important role that relevance realization plays in mental representation by arguing that both computationalism and discrete representation are inadequate in explaining mental representation. This is because they cannot explain the formation and changes in functional role. They also cannot explain "meaning" in connections. Moreover, they cannot explain the relationship between discrete representation and discrimination. After establishing the crucial role relevance realization plays in mental representation, I will propose the construct of dynamic systems which will be a theoretical alternative to discrete representation.

KEYWORDS
Relevance Realization, Mental Representation, Computationalism, Dynamical System, Continuous Representation

BACKGROUND

The nature of the mind has always been one of the most important questions in philosophy. There are currently two main theories debating for the nature of the mind, one is computationalism and the other is the neural network theory.

The computational theory of mind states that the mind is a formal system, which works by encoding information in abstract propositions and manipulating the propositions in a logical and mathematical fashion. A formal system should have tokens and rules, and in a formal system, the cognitive agent manipulates the tokens following the rules (Haugeland, 1985). An example of a formal system is chess, where each chess piece is a token and how to move them around being the rule. From 1968 to 1970, an artificial intelligence computer program named SHRDLU was made to understand natural language (Gardener, Davidson & Winnograd, 1979). SHRDLU was made by implementing computationalism on a machine, but it failed in the end and its failure marked the end of the prime age for computationalism. There are many factors contributing to its failure, one of which is the inability of making meaningful connections, which will be discussed in depth later in the arguments (Vervaeke, 2017).

After the failure of good old-fashion AI (GOFAI) using computationalism, the neural network theory has emerged. Neural network theory is also called connectionism. The two significant achievements of the neural network theory are unsupervised learning and unsupervised plasticity. Unsupervised learning and plasticity enable the machine to learn and alter its own architecture to achieve its goal, which is something the computational theory of mind cannot achieve. Neural network theory also brings out the notion of a dynamic system, in fact, both unsupervised learning and plasticity are examples of dynamic systems. A dynamic system is self- organizing and time dependent. The disproportionality between input and output in a dynamic system makes the time-dependent property extremely important. An example of a dynamic system is self-organized criticality.

INTRODUCTION

Computational theory of mind has been an important theory in cognitive science, it can explain the close relationship between language and cognition (Fodor,2008). However, there are aspects of mental processes it cannot explain, such as mental representations that this paper is going to focus on. A representation is any internal state that mediates or plays a mediating role between a system's input and output (Dietrich& Markman, 2003). In the view of the computational theory of mind, a representation serves as a data structure that can be operated on by algorithmic processes (Dietrich, 1990). It has been defined that a system has discrete representation if it has more than one representation and the representations are bounded and uniquely identifiable (Dietrich & Markman, 2003). Whereas, if a system has fuzzy boundary but still represent its environment, it has continuous representations.

In this paper, I will first argue that discrete representations are not sufficient to explain the formation and changes in functional roles of a concept. Then I will argue that discrete representations cannot give an account of meaning. At last, I will argue that discrete representation and discrimination are doubly disassociated. All the three arguments will end with the important and not-to-be-trivialized role that relevance realization plays. The thesis of this paper is to point out the crucial role of relevance realization in mental representation, and why computationalism and the discrete representation are not adequate to explain the mental representation.

ARGUMENT 1: THE FORMATION AND CHANGING OF FUNCTIONAL ROLES OF A CONCEPT

In the paper, *Discrete thought: Why Cognition Must Use Discrete Representations,* Dietrich and Markman argued that in human cognition, concepts are highly interconnected, and the functional role of a representation is determined by such connections. Since continuous representations are time dependent and always changing, they cannot be connected to each other. Therefore, they conclude that continuous representations cannot form functional roles.

There are two problems with the argument Dietrich and Markman made. The first problem concerns with how the functional role is determined. As stated above, the functional role of a concept is determined by its connections. However, the connections can go on indefinitely, because any two things can be connected directly or be connected through an intermediate concept. For example, the representation of the "titanic" can be connected with the representation of "boat", and "boat" can be connected with "sea", "sea" with "fish", "fish" with "food" etc. The connections can go on forever. The formation of a functional role faces a combinatorial explosively large web of connections. So, in order to make applicable functional roles in a mind or a machine, the system must have a strategy to deal with the combinatorial explosion, that is, to be able to determine which connections to take into consideration when determining the functional role. In the language of computationalism, this means to draw a boundary in the connection web. So far, neither computationalism nor discrete representation explains how to draw the boundary.

The problem of "drawing the boundary" is a problem of aspect, because out of all the possible connections, we only consider a few. Aspects are caused by relevance realization, because we need to only consider the properties relevant to the problem at hand (Searle, 1993). Computationalism pre-suppose relevance realization, thus it can never explain relevance realization (Cherniak, 1986). Now it is sufficient to say that neither computationalism nor discrete representation is adequate here to explain the formation of functional roles.

The second problem is about the changing in functional roles of representations. Dietrich and Markman have stated that discrete representations are non-dynamic and are not time-dependent. Therefore, we can deduce that the functional roles of discrete representations are stable and the connections are rigid because the connections do not change spontaneously. However, the evidence has shown that functional roles are not stable. Instead, they are constantly changing. For example, imagine a baby who has never seen a table before now sees a dinner table for the first time. Before this moment, the baby did not have a representation of "table". After that, the baby's representation of "table" is "dinner table", and the functional role of a table for s/he is to "serve dinner". Later, when the baby sees a desk, the functional role for "table" would not just be "serving dinners", but also "a place to work or study". The functional role for "table" has been enriched in the baby's mental representation. Such changes in functional roles cannot be explained by discrete representations or computationalism based on the argument above. Therefore, it is very likely that the discrete representation is not adequate to account for functional roles of mental representations.

People who support discrete representation might argue that the system can in fact change the functional roles of its representation. The system can do so by breaking old connections and making new ones. Such changes can be achieved by first manipulating the algorithmic processes, that is, to have a mathematic function to determine when to break and make connections.

I would argue against their defence by pointing out that discrete representations are not time-dependent, so the system can only be changing randomly or not changing at all. If the system breaks and makes new connections by manipulating the algorithmic processes, there must be an input to trigger the activation of the algorithmic processes. And if there is such an input that can trigger the changes in connections, the system should be classified as dynamic. Activating the algorithmic process at the wrong time (i.e. when there is no input) cannot result in the intended function. Therefore, timing matters in this system. Since discrete representations are non-dynamic and not sensitive to timing, that only leaves the possibility of a system changing its connections randomly.

Randomly changing the connections would be very insufficient in a system. Given the combinatorial explosively large number of connections that can be made, the probability of forming the desired functional role is indefinitely small. So, there must be a mechanism very much like relevance realization, to choose what new connections to form in order to make the system sufficient. Therefore, we can reject the idea of random changing of connections that the counter argument brought up.

Both problems point to the solution of a dynamic system. A dynamic system can change its connections spontaneously, therefore, its self-organizing property can give an account of how the functional roles are determined.

The time-dependent and environment-dependent property of a dynamic system can break and make connections as needed. This enables the system to have constantly changing functional roles. An example of a system that can spontaneously change its structure is a small world network (Asphaug et al., 1996). A small world network can deal with the trade-off between resiliency and efficiency, and it is likely to be the way how representations are connected. The self-organizing and self-correcting property should be able to generate the optimal structure to deal with the trade off. Therefore, the connections in SWN can be made and broken as needed, which is a property that formal system do not have.

When the dynamic system breaking and forming connection as needed, "need" is a subjective term which is determined by aspect. Having an aspect enables the cognitive agent to select a set of properties that is relevant to the problem at hand. Therefore, aspects are determined by relevance realization (Searle,1993). So, relevance realization is the core property of forming representations. Since computationalism presupposes relevance realization as stated above, it cannot explain relevance realization (Cherniak, 1986). Therefore, discrete representation can't explain the formation and changing of functional roles where a dynamic system can. Hence, the computational theory of the mind is inadequate to explain mental representation.

ARGUMENT 2: DISCRETE REPRESENTATION AND MEANING

Dietrich and Markman argued that discrete representation can explain "meaning", because meaning is derived from the connections of concepts.

The problem with Dietrich and Markman's argument is that connections in computationalism presuppose meaning. Any two random things can have an indefinite number of shared qualities, but we only consider a set of share qualities to make connections. For example, "cats" and the "solar system" shared many qualities such as they both contain carbon atoms and they are both made out of molecules. Nonetheless, we don't consider them connected directly, but rather, we consider "cat" connected with "dog" and the "solar system" with "planets". This is because we have aspects. Aspects enable us to take a small set of properties into consideration when making the connections. Aspects are caused by relevance realization (Vervaeke, 2017).

Meaning is a special kind of connections. It is how a set of properties can stand out and be connected to the problem solver. It is another form of having an aspect. Therefore, meaning is also caused by relevance realization. As given above, since computationalism pre-suppose relevance realization, it can never explain relevance (Cherniak, 1986). Now it is fair to say that meaning is not derived from discrete representations or computationalism, and I will further conclude that meaning is the cause of them.

If a machine has "meanings", it must have the ability to do relevance realization. The baby in the previous example connected "table" with himself/herself, in a sense that the table can serve him/her dinner and him/her can study on the table. Now that the baby has a meaning assigned to "tables", s/he can integrate the representation of "table" into his/her already existing knowledge network by making new meaningful connections. Without meaning, the connections can be made anywhere, "table" could be connected with "Mars". Such random connections are not helpful to problem solving, and people almost never make that kind of connections. Therefore, how the representations are relevant to the problem and the problem solver must be considered before making connections. That is why meaning is not a product of connections, but the cause of it. The ability to choose a set of properties is relevance realization, thus I conclude that relevance realization results in meaning and connections.

Therefore, we must abandon the notion that meaning is derived from connections, or it would be saying that meaning can result in connections, and connections can once again achieve meaning. This is a circular explanation that can get us nowhere.

One of the reasons why SHRDLU failed as a strong AI is that it did not have an aspect that can generate meaningful connections that are helpful to problem solving, due to the lack of relevance realization. The connections between information is knowledge, and the process of making those connections is what we call learning. The inability to make meaningful connections results in the lack of a knowledge network and the inability of learning, thus SHRDLU has very limited functions in problem solving (Vervaeke, 2017). For example, it was only able to respond to well-defined problems and interact with the world propositionally. SHRDLU's limited capability has made it unsuccessful in interacting with the real world. So, the inability to make connections has rendered it a weak AI, as the result of the lack of meaning.

I propose unsupervised plasticity as the solution to the problem above. Unsupervised plasticity is a dynamic system that uses a recursive self-organizing process to generate self-correction, thus change the structure of the wiring by itself without presupposing meaning (Fahlman & Lebiere, 1990). Under the theoretical construct of a dynamic system, meaning is not required to make connections, because the connections are not meant to be correct the first time they are made. The connections are meant to be corrected through the self-correcting process of the system. Therefore, the possibility to use connection to explain meaning opens again without falling prey to a circular explanation. Although this is not yet achieved, it is still a plausible way of reaching the goal of meaning.

ARGUMENT 3: THE DOUBLE DISSOCIATION BETWEEN DISCRETE REPRESENTATION AND DISCRIMINATION

Dietrich and Markman have argued that in order to distinguish between two external states, S1 and S2, there must be two corresponding internal states, R1 and R2 (Dietrich& Markman, 2003). The infinite intermediate states in the middle have to be cut in half and the two chunks must be separately categorized into the corresponding internal states. They also argued that a continuous representation cannot discriminate among external states because it is a single varying representation, it does not have distinct internal states. Since only discrete representation can classify and categorize external states, they have given the following definition: A system has discrete representation if and only if it can discriminate its inputs (Dietrich &Markman, 2003).

Dietrich and Markman's argument above is very similar to the classical theory of categorization, thus it also inherits a lot of the criticisms of the classical theory. The theory states that the mental representation or concepts are driving the categorization. One of the criticisms of classical theory is that a lot of concepts do not have clear boundaries, so the memberships of the category are hard to decide and are unstable. So, the infinite number of intermediate states between S1 and S2 cannot be simply cut in half and separately categorized, because a lot of things cannot be categorized in this way. If the internal representation R1 and R2 have fuzzy boundaries, some intermediate states will be categorized under R1 and some under R2, while also leaving some to be undecided. An example of a category with fuzzy boundary is "game", the concept "game" does not have a clear boundary (Wittgenstein, 1953). For example, some may classify politics as a game, which is how "Game of Thrones" got its name. However, not everyone agrees with this classification, as politics is not a typical game like chess.

What the original paper suggested to discriminate input by discrete representation has been shown wrong. It is sufficient to say that the definition given is invalid.

Supporters of the discrete representation might argue that clear boundaries are not always needed to produce discrete representation. It has been argued by Dietrich and Markman that discrete representations are abstract, and abstraction is created by extracting information from a continuous stream of perception. Some detailed information is inevitably lost in the abstract, thus the abstract is a unity of all the important information. In this way, the information extracted is discrete, not continuous, thus the process of abstraction can produce discrete representations.

Discrimination and discrete representation can be doubly dissociated. If Abstractions are created through extracting information from continuous stream of perception (Dietrich& Markman, 2003), the extraction of information cannot be random. If the extraction was random, the probability of creating the desired abstract is indefinitely small, given the combinatorial explosive amount of information we perceive every day. So, if the system does not extract information randomly, it must "know" what type of information to extract first. That is to say the system must have an abstract before it can do the extraction. If a system must have an abstract to extract information, it is to say that the system has an abstract because it has an abstract. A circular explanation. Therefore, computationalism cannot explain discrimination.

Having an abstract is to have a set of properties salient to the cognitive agent, which means the cognitive agent must be able to do relevance realization before it can extract information from the continuous stream of perception. We have already seen that neither computationalism nor discrete representation can explain relevance realization, we can now establish that an abstract and a discrete representation are not causally linked. Since having an abstract is the premise of being able to discriminate, a system which has discrete representation is not necessarily capable of doing discrimination, because of the lack of abstract.

We have already established that discrete representation does not necessarily mean discrimination. Now we are going to discuss the idea that discrimination is not equivalent to discrete representation. Unsupervised learning proposed by neural network theory can serve as an alternative. In unsupervised learning, the machine is able to feedback on itself and alter the weighing to generate self corrections. One significant improvement with the unsupervised learning is that it enables a machine to learn a task without having a pre-set model of the goal state. For instance, a machine is able to learn the shape of letter "A" when provided with abundant variations. This process has been demonstrated with the wake-sleep cycle. The wake-sleep cycle is to do data-compression in the wake state, and date-particularization to generate variations in the sleep state. Through multiple cycles of wake and sleep, the machine is able to learn the shape of letter "A" eventually (Hinton et al., 1995).

The wake-sleep algorithm uses continuous representation, because the representations in each state are constantly changing. It is also a dynamic system because the system is self-correcting. Thus, it enables a machine to distinguish and discriminate the input and achieve the goal state through self-correction without having an abstract or representation first. Therefore, it is evident to say discrimination does not necessarily require discrete representation.

In conclusion, a system has discrete representation is not necessarily capable of doing discrimination, and a system that can discriminate does not necessarily need to be a discrete representation. The discrete representation and discrimination is doubly disassociated. Therefore, the definition given by Dietrich and Markman is wrong and anything derived from that definition is doubtful to be correct.

CONCLUSION

This paper challenges computationalism and discrete representation in mental representation from the perspective of formation and changes in functional roles, the meaning of connections and the relationship between discrimination and discrete representation. While we establish why discrete representation is insufficient in mental representation, we also take a step further to examine the core of mental representation, that is, relevance realization. Finally, we propose the dynamic systems as the solution to the problem computationalism and relevance realization faces. Therefore, we argued that discrete representation is not how mental representation works, and continuous and dynamic representation is the right way to go.

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