

Does the Human Brain Have Algorithms?

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Abstract - In this paper, we are investigating whether non-symbolic algorithms which operate on non-symbolic concepts can reside in the human brain. We present a supplementary approach to the connectionist approach of cognition since we believe that computational models based on connectionism can be used to realize non-symbolic algorithms. This approach enables us to model and hence explain aspects of non-symbolic algorithms and non-symbolic concepts in the brain also based on recent psychological experiments which present evidence for these aspects. Our supplementary approach appears to be consistent with the parallel and distributed nature of the brain. Algorithms in the context of our approach consist of a series of steps and/or rules to perform a task. The non-symbolic algorithms may be innate or learned. Some combinations of steps and rules may exist in the brain as building block algorithms which may be combined with other steps and rules to form complex algorithms.

Keywords: non-symbolic, algorithms, concepts, connectionism, If-Then rules.

1 Introduction

The main focus of this research paper is to consider the possibility of human beings having algorithms in the brain that allow them to “carry out” some tasks. For example, could there be an algorithm that resides in brain that allows humans to compare two different numerical quantities? An interesting follow-up is whether we are born with algorithms in our brains and hence we are able to solve some tasks from birth without learning. In this paper, we will concentrate mainly on the first question and address the second question in more detail in later research.

In order to look for an answer to such a question, we first need to define what exactly we mean by an algorithm. We also need to clearly define our exact position on the scale from symbolic Artificial Intelligence (AI) to connectionism since these two fields of AI have already put forward models of human reasoning and representation. We will start by defining an algorithm and making use of these models in order to consider the existence of algorithms in the brain.

The definition of an algorithm in the context of this paper is: “A step-by-step procedure for performing a task, solving a problem or accomplishing some end”. One aspect of algorithms is that they solve problems or accomplish an end in a finite number of steps according to the Britannica.

There are two basic approaches of understanding cognition in the artificial intelligence community. These are the symbolic and the connectionist approaches of AI.

The point of view of symbolic AI towards having algorithms and executing algorithms in the brain is straight forward. For example, there are algorithms for planning in symbolic AI. However, these algorithms operate on non-perceptual concepts whereas various concepts in the human brain are assumed to be perceptual [1].

If we consider connectionism, there is controversy on whether there exist physical symbol systems in the human brain. Therefore, it seems reasonable to question the existence of symbolic algorithms in the brain. We take a connectionist approach which supports that information is stored non-symbolically in the weights or connection strengths of a neural network [2]. Therefore in our

research, we chose a definition of algorithm that is non-symbolic and non-computational - “a step-by-step procedure for . . . accomplishing some end”.

We propose an approach to cognition where connectionism is extended to embrace non-symbolic algorithms. We believe more research on algorithms will help us get a better understanding of the human brain.

In Section 2 we explain our supplementary approach which considers the existence of non-symbolic algorithms in the human brain. Section 2.1 introduces the concept of building block algorithms which may be innate and/or learned. Section 2.2 presents steps of non-symbolic algorithms in biological neural representations. Section 2.3 presents complex non-symbolic algorithms which are strongly tied to learning and have associations to computational models. The Summary presents the conclusions of our research and possibilities for future work.

2 A supplementary approach

We propose a supplementary approach, in which there exist algorithms in our brain to accomplish some tasks, as a means to explain some functions of cognition. Recalling our definition of non-symbolic algorithms from the introduction section above, they consist of a sequence of steps to solve a task where each of these steps will be a solution to a subpart of the task. Each step or a subpart of the total process of carrying out the sequence will be embedded in the functioning of a group of neurons.

To consider the feasibility of this supplementary approach, we examine it in the context of two basic approaches of understanding cognition in the artificial intelligence community.

The symbolic AI approach suggests the use of physical symbol systems for cognition. A physical symbol system "consists of a set of entities, called symbols, which are physical patterns that can occur as components of another type of entity called an expression (or symbol structure). Thus, a symbol structure is composed of a number of instances (or tokens) of symbols related in some physical way (such as one token being next to another)" [3]. For example, the act of putting a book on a table can be represented in symbolic AI by a high level language notation such as PUT(Book, On-Table).

The connectionist approach employs artificial neural networks for modeling the neural processing in the brain. The inputs of a neural network are mapped onto the outputs of it where inputs are assumed to be fed from the environment. Neural networks are used for mimicking behaviors such as stimulus response behavior, navigation with obstacle avoidance, short term memory, etc. Although a neural network can achieve input-output mappings correctly, generally there are unknowns concerning what happens during the mapping process and function of neurons at layers between input and output layers.

Since we have chosen to focus on non-symbolic algorithms, we believe our approach is more consistent and closer to the connectionist approach. Still, our definition of algorithm is in line with symbolic AI in that it supports the idea of algorithms to accomplish tasks.

An example of research which supports the existence of non-symbolic algorithms in the human brain is the research and experiments [4] that show that infants can connect numerical representations with the number of voices they hear and the number of faces they see. This seems to involve a comparison and decision process that is common with an If-Then rule which can itself or together with other steps be part of an algorithm. It also points to the possibility of a shared system between preverbal infants and nonverbal animals for representing numbers. The shared system for representing numbers also with the evidence of innate rules comply with the idea that there can be non-symbolic algorithms which operate on non-symbolic concepts where number representations correspond to non-symbolic concepts. The shared system for representing numbers seems to entail non-symbolic concepts which we address later in this paper.

In another paper [5], there is evidence “for an evolutionarily primitive magnitude comparison algorithm common to humans and monkeys”. Cantlon and Brannon [5] cite previous research that shows that semantic congruity influences the decision making process. Also their results demonstrate that the speed with which monkeys compare numerical values is affected by semantic congruity. The important outcome of their research which is directly relevant to our research is that the semantic congruity effect in monkeys is attributed to the presence of an analog magnitude-comparison algorithm since monkeys have no discrete number or symbolic reference system. Finally, it is also inferred that the computational process by which humans compare the relative magnitude of numerical values is evolutionarily conserved, that is innate.

To further consider the possibility of algorithms, the study in Meeden, McGraw, and Blank [6] is an example of emerging “If-Then like” behavior using neural networks (where behavior means actions). This study shows that a plan-like behavior need not necessarily be obtained as a result of an explicit planning algorithm. It investigates the possibility of not having explicit planning algorithms but still being able to obtain the same behaviors that a planning algorithm would normally generate. Here, emergence replaces the idea of having explicit algorithms. However, the complexity of the behaviors obtained as a result of emergence is not as high as those that a planning algorithm would produce. As a result, for more complicated tasks, it might be necessary to have explicit algorithms to produce behaviors rather than emerging behaviors.

2.1 Building Block, Innate and Learned Algorithms

We now introduce the concept of a building block algorithm in our supplementary approach. The building blocks algorithms can include any combination of steps and rules including If-Then rules. A very simple building block algorithm could consist of a single If-Then rule. An example is given in the experiments of Jordan and Brannon [4] where the brains of 7 month old infants were able to carry out a process which applied the rule:

IF 2 women’s voices are heard, THEN stare at the picture of 2 women.

If a person has functionality at birth for producing a behavior for a given task, then that may take the form in the brain of the ability to carry out a sequence of steps. In our supplementary approach, that is an innate algorithm.

On the other hand, a learned algorithm would be a sequence of steps that are comprehended, carried out, and remembered at some point in the lifetime of an individual. The learning process can be supervised, unsupervised or reinforced. Biologically, the synapses of the neurons taking part in the learning process will be strengthened or loosened accordingly.

One aspect of our approach is that the steps in an algorithm will embody concepts that are being referred to in each step. In Goldstone & Johansen [2], concepts are stated to function as building blocks for complex thought. In our approach, a non-symbolic algorithm operates on concepts as a means of producing complex thought. We also assume the idea that abstract concepts are tuned by feedback from perceptual sources [2]. In the representation of the summation algorithm in Figure 2, some concepts represented are “Value 1”, “Value 2”, “Carry” and “Sum”.

The other aspect of our approach is that, when possible, the steps can be executed in parallel rather than in sequence as long as the next step does not require any output from the previous step. This aspect and the point that each step is being implemented in a connectionist manner support the distributed and parallel processing and hence comply with brain processes. However, we believe, more investigation of this topic is needed to ensure that there actually are not conflicts between our supplementary approach and parallel and distributed processing.

Next we will address how an algorithm can be realized considering connectionism theory.

2.2 The Implementation of Steps in Building Block Algorithms

An If-Then rule can be a step in a non-symbolic algorithm according to the definitions in our approach. For that reason, we believe the research that support the existence of “If-Then” rules in the brain gives some support to our theory of the presence of algorithms in the brain.

The purpose of an If-Then rule in our supplementary approach is not to manipulate symbols as in Anderson [7], but to accomplish a subtask of a task in the form of Parallel Distributed Processing networks as in Dorffner [8]. We relate a subtask of a task to a step in a non-symbolic algorithm in our supplementary approach.

In an If-Then rule definition, rules are not defined by symbols or symbolic structures but as a cluster of neurons for representing each concept and the associations between the clusters. This is referred to as distributed representations in connectionist AI [9, 8].

As stated in Dorffner [8], there need not be any clear borders between concepts and it is not necessary to specify how many neurons have to be involved in representing a concept.

Let's examine an example of using an If-Then rule as part of a bathing algorithm.

The rule as applied to this example can be expressed in text as:

If the water in the lake is cold, then get out of the water.

This can be broken down and represented symbolically as a sequence of steps:

sense (LAKEWATER) → If COLD Then next step → get out of (LAKEWATER)

This bathing example can be mapped to neural configurations which do not employ physical symbols but which employ underlying connectionist implementations of concepts, rules and processes (Figure 1).

The biological neural realization that we choose for the human brain has representations for the concept of cold lake water. It also has representations for steps (processes or actions) and rules including “sensing”, “If-Then” and “get out of”. One can link these to each other as follows in a biological neural realization where the concepts are represented by neuron clusters and processes (steps or rules in an algorithm) are represented by neural structures.

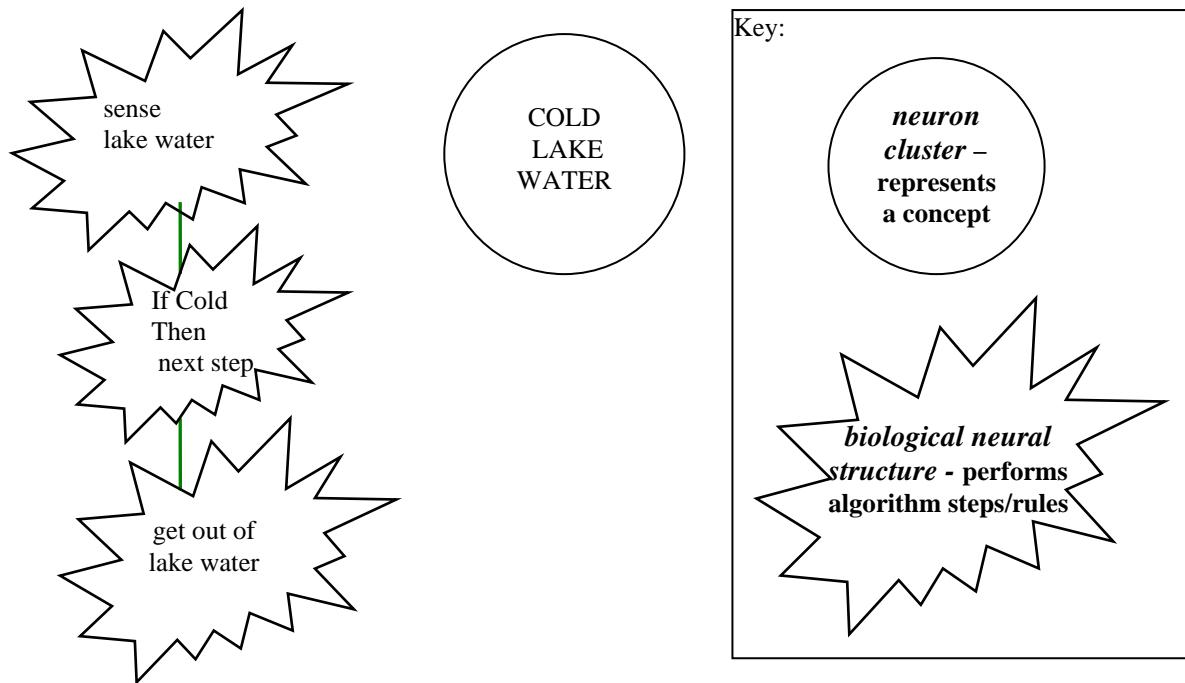


Figure 1 A bathing algorithm with If-Then rule realization using biological neuron clusters and neural structures

2.3 Complex Algorithms

With the notion of building block algorithms in place in our supplementary approach, it seems reasonable to assert that complex algorithms can exist in the brain that are combinations of building block algorithms. These complex algorithms may be composed of a combination of innate and/or learned steps, rules, and algorithms.

Therefore, it seems reasonable that the number and complexity of algorithms in the human brain may be directly proportional to intelligence. However, we contend that only some of the functions of the human brain make use of the algorithm capability. Perhaps the algorithms are combined with other capabilities of the human brain for more diverse and complex functionality. For some brain functions, algorithms are most likely not used at all.

We contend that most complex algorithms that are stored in the human brain are at least partially if not primarily comprised of steps, rules, and building block algorithms that are learned. A basis for commonality is created by situations where the learning is acquired through symbolic means (although we believe the knowledge is not represented symbolically in the brain) as in the summation algorithm that will be presented below. Additionally for some learned algorithms, there may exist a strong association between steps in computational models in symbolic AI and the steps in the non-symbolic algorithms as realized with biological neural configurations in the brain (as proposed in our supplementary approach). However, this does not preclude innate non-symbolic algorithms from having steps similar to symbolic AI computational models although the algorithms in the brain are not represented symbolically.

We choose an example of summing two multi-digit numerical values to show this strong association. Since the supplementary approach proposes that the process of calculating the sum of larger numerical values in the human brain is learned as a sequence of steps like those in a computational approach, some common steps will exist in the computational models and the biological models underlying our supplementary approach. However, the concepts, steps and processes may be represented and carried out differently in the realizations of the different models and configurations.

For example, a summation of two numerical values can be represented in text (also symbolically) as:

Step a.) Read the numbers to be added.

Step b.) Add the appropriate digit of the two numbers and any carry

Step c.) Save the result of the summation in memory as the appropriate digit of the sum and save the carry from the summation in memory for the possible summation of the next digit if any

Step d.) If there are more digits to add, go to Step b.

Step e.) Save the carry as the most significant digit of the sum

In Figure 2, we present a corresponding biological neural implementation of a non-symbolic algorithm that has strong association to the symbolic algorithm above. However, the neural implementation values are represented as concepts and realized as neuron clusters. Neural structures are used to realize the steps or rules in an associated non-symbolic algorithm. The number of and realization of the steps and/or rules in the biological neural implementation is somewhat different from the symbolic one above. The neural structures that are realizations of steps and rules have access to all of the concepts represented by neuron clusters.

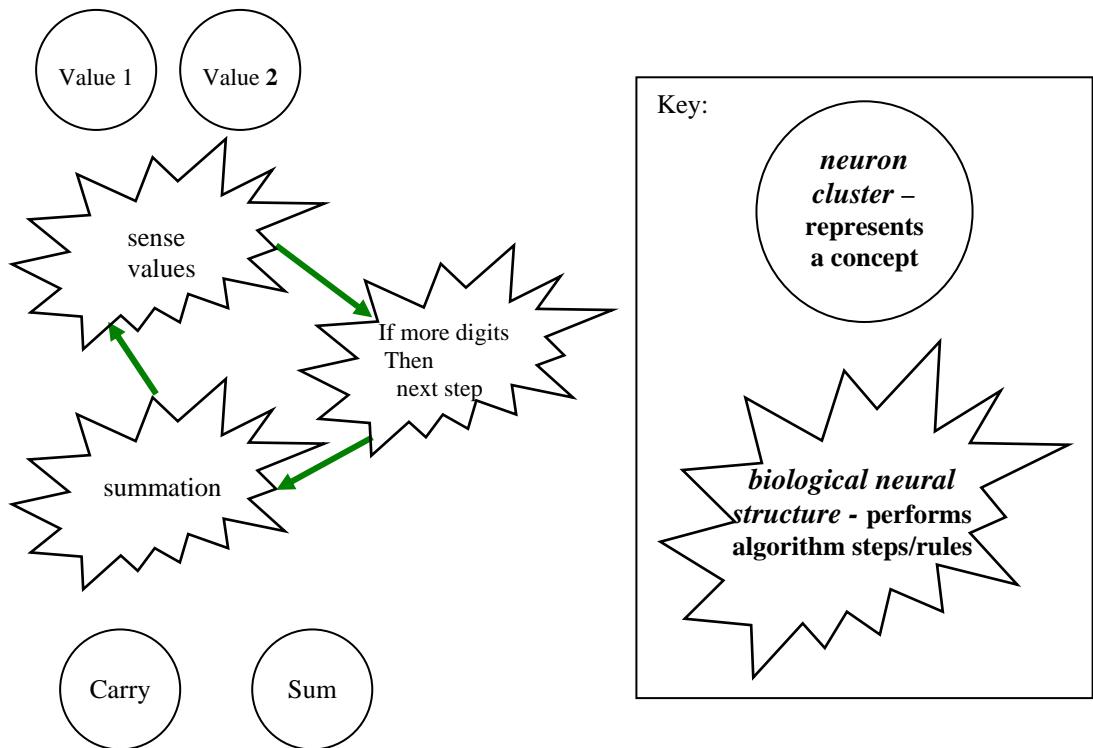


Figure 2 The biological neural structure and neuron cluster representation for a summation algorithm

3 Summary

In this paper, we describe a supplementary approach that presents non-symbolic algorithms which operate on non-symbolic concepts as a means to accomplish some tasks and therefore to explain some functions of cognition.

It seems possible that some functions of the human brain involve carrying out and remembering non-symbolic algorithms, i.e. sequences of steps to perform tasks or achieve ends. This is a possibility that is supported by recent psychological studies that are referenced in this paper.

In addition, a connectionist study [6] points to the possibility of producing a solution to a given navigational task by emergence. However, we have not found research which gives evidence that emergence can produce solutions to more complicated tasks. For that reason, we believe that non-symbolic algorithms might be the answer to solving more complicated tasks.

Considering the existence of both innate and learned non-symbolic algorithms, an assumption that the brain is limited to perceptually grounded concepts may preclude the algorithms from being innate. Either way, the algorithms may contain IF-THEN rules and/or concepts as pointed to by some recent psychological research. Therefore, we believe this is an interesting topic for further studies.

Also of interest for further study is to design and realize consistent and underlying connectionist representations of If-Then rules and non-symbolic algorithms which are composed of several steps including If-Then rules.

Additionally, the consistency of the supplementary approach with the parallel and distributed nature of the brain needs to be further investigated. That is, a connectionist model as an implementation for a non-symbolic algorithm needs to be developed.

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