Mathematical Modeling of Human Brain Behavior as an Adaptive Complex System

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Abstract

The aim of this paper is modeling of brain as a multi-agent system and then theoretical study of game-theoretic solution concepts in competitive and cooperative multi-agent interactions in this system. Brain as a cognitive function implementer is composed of large-scale neural networks of cognition (neurocognitive networks) which are considered as expert agents that do what they think in their on best expertness. Neurocognitive networks implement the cognitive functions in brain and thorough understanding of cognition is not possible without knowledge of how they operate individually and socially. In this study dynamic interaction among those expert agents are formulated as competitive and cooperative behaviors. We obtain the equilibrium behavior in the long run, and characterize the collective behavior of these expert agents as responsible of intricacies of cognition. By this work, it was shown how complex collective behavior of brain can emerge from the locally optimal behavior of each agent. In the end we will see how these neural networks organize themselves in a way that the collective behavior will be intelligent. It will be shown that the best structure in brain for having intelligent behavior is multilevel hierarchical organization with nesting structures.

Keywords: multi-agent system, cooperative behavior, competitive behavior, self-organization, neurocognitive network

Introduction

The gap between knowledge of the brain and of the mind can only be bridged with understanding of neural system's behavior that performs cognitive operations. Neurocognitive networks are large-scale systems of distributed and interconnected neuronal populations in the central nervous system organized to perform cognitive functions. We consider neurocognitive networks to be flexibly adaptive to the rapidly changing computational demands of cognitive Processing [1,2,3,4]. The large-scale anatomical connectivity of the cerebral cortex provides a richly intricate structure within which the constituent local area networks have an enormous potential for coordination in a multitude of different patterns. The theory of coordination dynamics [5,6] provides insight into the dynamic characteristics of such interacting complex neural systems.

The ambition of this work is modeling cognitive development through studying the competitive and cooperative behavior in interacted agents (neurocognitive network) in brain. In this study we try to understand how to set up the architecture of an agent as a component of a complex system to be suitable for evolution, how self-interested behavior in every agent evolves to cooperative behavior, and how the goal structure of each agent can be self-modified in order to achieve the common goal of the system. In this work we represent a recursive definition of agent in this way that neurocognitive networks as a particular autonomous entity is considered as agents and also brain as a whole system is considered as an agent. In this way, we put things together and call them an agent and they have a recursive structure. In a hierarchical organization, an agent could be made up of a number of other agents with many different levels. The recursive organization would allow us to build a complex adaptive system like brain at different levels of granularity. In the end we will discuss why and how neurocognitive networks as self-interested agents form their organization.

Modeling of Competitive and Cooperative Behavior of Agents

The notion of self-interested behavior and self-motivated is the foundation of many fields of research. Agents are self- motivated in the sense that they only do the tasks, which are expert in, and are in their own best interest, as determined by their own goals and motivation. Each expert agent has its own expertness or goal, which is expressed in term of a function. In this work, it was supposed that the goal of every agent (cognitive networks) is improving learning process.

The learning progress function of each neurocognitive network as an agent in brain depends on its prediction, state and all the other agent's states. At each time period, each agent faces the problem of choosing strategy and anticipating next state in order to maximize its own learning progress function. To fulfill its long-term interest or expert, every agent seeks a sequence of strategies, which maximizes the accumulated learning progress function defined over an infinite time horizon.

The functions of the neurocognitive network are expressed in real time by the coordinated actions of cooperating areas, with the states of coordination changing dynamically [6]. So cooperation among these agents can be a very important factor for analyzing the behavior of this complex adaptive system. The key element that distinguishes a common goal from an agent's individual goal is that it requires cooperation. By a common goal, we also mean one, which is not achievable by any single agent alone, but is achievable by a group of agents. The self-interested behavior of each agent must be coordinated to achieve globally consistent and efficient collective actions. In this work, we define such a common object as the summation of the strategies of the individual agents in a society.

Intelligent as an Emergent Behavior

The most important point here is that how can extract intelligence by deriving the implicit cooperative behavior of each self-interested and non-intelligent agent. We described the competitive interactions among agents as the basis for cooperative interactions learnable through imitation. In our model every agent (neurocognitve network) makes decisions on the basis of imperfect information about other agents' activities. Now we are going to consider how the evolution of cooperation proceeds?

We need to understand how the competitive behavior of each agent evolves to implicit cooperative behavior. Implicit cooperative behavior of each agent is defined in terms of the effect on other agents. At each time the expert based on the current state of corresponding expert and the other expert make one prediction. Every agents try do make an action that can minimize the prediction error which makes its competitive behavior. The cooperative behavior of agents is modeled as the set of strategies optimizing the summation of the action functions of all agents.

Regarding the collective behavior emerging from competitive interaction, we have the following interesting observation. If the number of agents is small, the summation of the learning progress increases as the number of the agents increases, after a certain number of agents is reached it decreases if the number of agents increases, and it converges to zero as the number of agents becomes very large. It means that special number of neurocognitive networks can learn a cognitive function and the objective interaction between these agents is limited to the number of agents. We can approximate the number of the neurocognitive networks, which can have interaction to learn a specific skill. It is possible to approximate the number of the agents, which can learn a specific skill. By having this number and making a group based on this number and considering the sum of progress in learning of every agent and the sum of learning of all agents in that group and subtracting them the amount we achieve represents the effect of cooperative between the agents of this group. The emergent Intelligence is based on this cooperation between the neurocognitive networks that are not able to produce intelligent behavior alone.

The Self-Organization Process

In this section, we investigate why and how neurocognitive networks form their organization and produce especial structures in brain and cortex. The first question is that why every high level cognitive function is done by a special part of brain with a specific shape and structure? The answer is that neurioocognitive networks do cognitive functions and as was shown before for having intelligent behavior they need to make organization and have cooperation with each other. They may form an organization because of their joint interest in efficient resource acquisition or allocation [16]. We show that their organization can emerge through competitive interactions motivated by self-interested agents. We consider two types of organization, the flat organization, and the hierarchical organization. The collective learning progress at competitive equilibrium and cooperative equilibrium in these two different organizations is computed and the results are compared. By comparing these results we consider that each agent receives a higher utility by forming a hierarchical organization. They may form a hierarchical organization because of their joint interest in efficient resource allocation, and the self-interested agents benefit from a hierarchical organization with a nesting structure where they can improve their own objects.

Conclusions

We have argued here that the neural underpinning of cognition is best understood through the study of neurocognitive networks. We tried to model the behavior of these neural networks by some classic rules in social science and game theory. When examined from this perspective, cognition is seen as a dynamic process that rapidly evolves through a series of informational consistent coordination states. In each moment of cognitive processing, there are two types of behavior that cause transition from one cognitive state to another. These two types of behavior are two common behaviors in social science and society: Competitive behavior based on self-benefit and interest and cooperative behavior.

We understood that simple local interactions between neurocognitive networks could produce complex and purposive global behavior as a cognitive skill. We formulated and analyzed the competitive and cooperative behaviors of these self-interested agents in a dynamic environment. We described a way of organizing the set of multiple agents into a structured organization.

Based on this model we can say that every neurocognitive network has a simple goal that in this model was progressing of learning that we modeled it by a linear and simple activation function. By this local goal the agents try to have interaction and the cooperation behavior emerge by these local simple interactions. We showed that with a hierarchical structure the behavior of organization can be more intelligent and so neurocognitive networks should organize themselves in hierarchical structures to produce more intelligent behavior. In a hierarchical organization, an agent could be made up of a number of other agents with many levels. We can conclude that the growth of neural system starts from the set of the unstructured flat organization of neurocognitive networks that we considered them as some self-interested agents.

These self-interested agents are left to self organize themselves into the whole organization to have more and more progress in learning.

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