K(Knowledge)-net: Building up and its dynamics

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Abstract: The essence of intelligence is to possess certain abilities that to obtain knowledge , to use knowledge and to operate knowledge. So, the knowledge in our brain exists in isolated and accumulated form, but it has certain dynamic structure to ensure the emergence of this kind of abilities. Based on the understanding to real process of learning knowledge by human being, in this paper we discussed how to make a model to describe the dynamic structure of knowledge. The most knowledge of ours is leaned by using of natural language, we introduce the notion of semantic knowledge and model its growing up process by a network, we named it as K-net. It is a dynamic network with two main dynamics: one is added new knowledge, the other is to aggregate knowledge existed in the network with some probability. Under these very natural conditions we found that originally the network is a random simple net and then some characteristics of complex network appeared gradually when more new knowledge s be added and aggregated. More interesting phenomena is the appearance of random hierarchical structure, is that means emergence?

Keyword: semantic knowledge; complex networks; small-world; scale-free; hierarchical organization

1. Introduction

Human brain has two main functions:
1) Control Body's movement;
2) Learn knowledge and to form intelligence

Artificial Brain research has similar purposes:
1) To control the complex movements of robots;
2) To learn knowledge and make emergence of intelligence in a computer or some other machines which can. Then human tries to equip complex robots by this kind of artificial brain finally.

So-called "intelligence" means the abilities:
To learn knowledge;
To use knowledge; and
To operate knowledge.

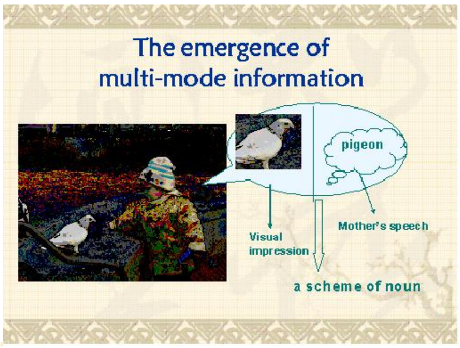
Obviously, " intelligence " depends on the expression of knowledge and its structure in brain.

Our research aims to discuss the principle to design an artificial brain. Observing the relation of knowledge it is easy to understand that knowledge has a network form. This network is a dynamic network. Depending on the Piagent's theory we proposed two main dynamics: one is a new knowledge is added into this network; the other is that knowledge are combined based on the similarity. In our research we have found that the knowledge in human brain formed a complex network, we call it "K-net", in which small word characteristic and almost hierarchical structure appeared. The model of knowledge we proposed in this paper is a kind of design of artificial brain.

2. Structure of semantic knowledge

2.1 The elements of semantic knowledge

At beginning child learn knowledge from "mother" and their perception, we say it is presentative knowledge, or semantic knowledge. Baby learned more and more. However, the sort of



knowledge is very limited, so the number of knowledge in some sort become more dense.

Comparing with the abstract thinking, semantic (presentative) knowledge is concrete, perceptional, primitive, elementary, and evolable. Abstract knowledge is evolved knowledge from semantic (presentative) knowledge, it is usually not perceptional, it is complex and logic.

Semantic knowledge can be expressed in several level layers. For example, "apple" is only a noun, but it is a real presentative knowledge. "eat" is only a verb, but it is still a real presentative knowledge. We say it is senmantic knowledge in the "fragment" level. The basic semantic knowledge are grouped as several layers, such that

"fragment",
"very simple",
"simple",
"usual",
"complex",
"very complex", etc.

Any relation in those groups will combine some schemes, this combination is very similar to the structure of a sentence but it is not a sentence.

We say an element of Semantic Knowledge

= "sentence" + mapping

2.2 To form simple network

At beginning, baby learned only few words, for example he/she learns some nouns, verbs and some adjectives, because the classes of knowledge is very limited, so when he/she learned more and more the knowledge in the same class become denser and denser, not only the amount of knowledge arise, but also links between the knowledge appeared, this time this kind of links made the all knowledge formed a simple network. Maybe there are several small simple networks. These small networks are the original seeds for evolution later.

2.3 The dynamic process of semantic knowledge evolution

Jean Piaget (1896 - 1980)

The famous psychologist Jean Piaget had done research on the process of knowledge evolution, he pointed out that the change of knowledge has several ways, two of which are more important, they are Accommodation（顺化） and Assimilation (同化). Assimilation of knowledge means new knowledge is added into the existed structure, or that means one learned a new knowledge and it is adapted into the semantic knowledge network. Accommodation of knowledge means that certain knowledge in the semantic knowledge network has been absorbed or combined with others, usually a new concept appeared and is incorporated. These two processes presented and appeared continually in our brain. In fact, he/she learn new knowledge continually and put them into adequate position of semantic network, it make the network enlarged; also he/she work. Due to these dynamics the network become a dynamic network and presents some complexities.

3. Some Concepts of Complex Networks

The most interesting features of complex networks are the small-world and scale-free. The statistical quantities characterizing small-world networks are clustering coefficient C and the average length of shortest path L.

Regular networks have high clustering coefficient and large average length of shortest path, opposite to random networks which have low clustering coefficient and small average length of shortest path. Between these two extremes somewhere, the clustering coefficient is almost as high as that of a regular network while the average length of shortest path is almost as small as that of a random network with the same number of nodes and edges. This type of networks is called as "small-world" for it is similar to the small world phenomenon. The average length of shortest path of small world networks increase slowly with the total number of its nodes: $\overline{L} \sim \ln(N)$

The study of scale-free networks concerns behavior in the probability distribution of degree, the possible number of links at a random chosen node in the networks. Unlike the Poisson degree distribution for random networks, in a scale-free network, the distribution of degree follows a power law, $P(k) \propto k^{-\gamma}$, where k is the degree of nodes and P(k) is the probability of the degree of an arbitrary node equals k. In such a network most nodes have only a few connections and few nodes have very large number of neighbors [9].

It has been discovered recently that aggregation and regeneration of nodes can also leads to the power law distribution of degree [11-12]. Kim and his cooperators propose a network model in which nodes can merge with one of their neighbors and new nodes been added to the network to maintain the number of nodes [11]. Another model proposed by Alava and Dorogovtsev permit to aggregate nodes which are selected at random [12]. Those mechanisms give us new suggestions on how could scale-free networks emerge.

Different from BA model networks, some real scale-free networks have hierarchical structures. A model with network duplication mechanism could cause such a structure [13]. It displays a hierarchical and coarse-grained similarity. This intrinsic hierarchy can be characterized in a quantitative manner. The clustering coefficient of a node with k links follows the scaling law $C(k) \sim k^{-1}$. This type of structure could give an explanation to the feature of small-world in many scale-free networks.

Degree correlation coefficient r could distinguish assortative and disassortative networks. In assortative networks, nodes with many connections tend to be connected to other nodes with many connections. It was found that social networks are often assortative while biological networks are often disassortative [14]. r could be measured by

$$r = \frac{M^{-1}\sum_i j_i k_i - [M^{-1}\sum_i \frac{1}{2}(j_i + k_i)]^2}{M^{-1}\sum_i \frac{1}{2}(j_i^2 + k_i^2) - [M^{-1}\sum_i \frac{1}{2}(j_i + k_i)]^2},$$

where j_i, k_i are the degrees of the vertices at the ends of the ith edge, with i = 1 . . .M.

4. The dynamics 1 of K-net (K-net growing model)

We consider the first dynamic that to add a new knowledge (a new node) to the existed K-net. The principle to add a new node is to choose a node J in the K-net which has the best conditional probability proportional to the connection degree

$$P_i(t) = \frac{k_i(t)}{\sum_{j \in N} k_j(t)}$$

Our connection is not to link the node J directly, but to the m (m<M) neighbors of node J randomly. This means the new node has metaphor relation with node J. see the Fig.1a and 1b. The new one is green one and node J is the red one, the 5 neighbors of J is blue.

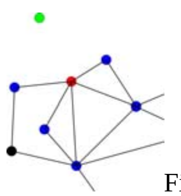


Fig. 1a

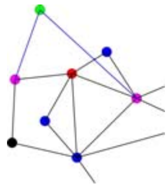


Fig. 2b

where m=2.

The evolution process is in Fig.2a and 2b.

n=30

Fig. 2a

n=180

Fig. 2b

The result shows us that K-net presents the feature of small word.

5. The dynamics 2 of K-net (K-net aggregation model)

We consider another dynamics of K-net now, aggregation of nodes, that means two nodes are combined as one node, or two very related knowledge are aggregate a concept. This is very important process to knowledge evolution, either for the emergence of intelligence. The criterion of aggregation depends on the similarity between the two knowledge (nodes). It is defined as

$$P_{e_i}(t) = \frac{\lambda_{e_i}(t)}{\sum_{e_j \in E(t)} \lambda_{e_j}(t)}$$

where

$$\lambda_{e_i} = S(a,b) = \frac{1}{1+|k_a - k_b|}$$

The two nodes which has the highest similarity will be combined as one node. See Fig. 3a and 3b. This single process cannot go through to the end, it has to be run with the growing process.

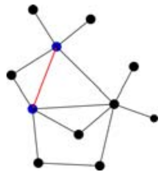


Fig. 3a

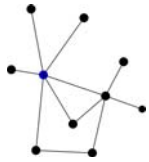


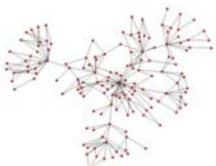
Fig. 3b

6. The meta-process when these two dynamics together

Based on the theory of J. Piagent The two dynamics of semantic knowledge will appear randomly and continuously, he say that is the equilibrium. We design the K-net has these two dynamics together with certain probability. We found the result still lead to a small word feature in K-net. The evolutionary process is shown in the following simulation. There we assume M=2, without loss of generality, and probability P=0.5. The evolutionary process shows in Fig.4

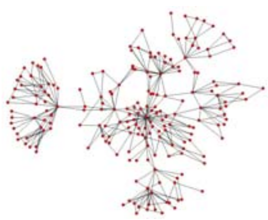
n=100

Fig. 4a



n=150,

Fig. 4b



n=200

Fig. 4c

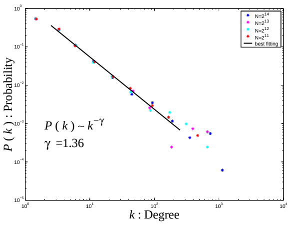


Fig. 4d The link degree presents power low

More interested things is this evolution appears the almost hierarchical structure, maybe we could explain it as a emergence of intelligence.

Summary

In this paper we introduce the semantic knowledge, defined the elements of semantic knowledge, the building up K-net. Also, we have introduce two kind of dynamics for K-net and some simulations have been done, the results presented K-net evolutionarily become a complex network and possess the feature of scale-free and small word. The almost hierarchical structure could be explained as the emergence of intelligence. This model could be a constructive model for artificial brain.

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