Simulation of Knowledge Emergence Based on Complexity

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Abstract. In order to reveal the law of knowledge evolution and solve the problem of knowledge emergence, this paper constructs the mathematical model of knowledge evolution with the complexity research method on base of defining the scales of knowledge agents. This paper reveals three states of knowledge evolution by directly observing the surface simulation model and using the knowledge evolution equation and three-dimensional vector. Only if the intensity, scale or quantity of knowledge agents reaches a certain degree that when $n_1 < h_1 < h_2 < n_2$. Within the interval $(h_1, h_2)$, a large number of knowledge agents enter the chaotic region, and the system formalizes a chaotic order state. Studies have found that knowledge emergence is most likely to generating when the above conditions are satisfied.

Introduction

The latest knowledge management research shows that the knowledge agent system is a complex adaptive system [1]. The knowledge management emphasis on technical advantage, while it must pay attention to the subject of knowledge—human factors, and put it in the system study [2]. This study based on complexity, used time as a variable, and observes the number of knowledge subjects, the intensity of interaction among these subjects, the scale of dynamic change and other factors, emphasizes human initiative, adaptability and interpersonal interaction, through the establishment of a reliable environment, providing the conditions for interaction between learning space and environment, we reveal the rules of knowledge evolution [3]. Knowledge emergence is an important way of knowledge creation [4]. In previous literature, the research on knowledge evolution before knowledge emergence is still insufficient. There is no quantitative study on the scale of knowledge subject and the constraints on the chaotic edge of knowledge emergence [5,6]. In this paper, we will focus on the scale of knowledge subject, research on knowledge evolution process before the knowledge emergence and its boundary conditions. Through mathematical simulation model, reveal the rules of knowledge evolution, and prove the knowledge evolution phenomena and knowledge emergence conditions matching with the constraints.

Background

In the study of emerging experimental methods, Santa Fe Institute researchers believe that macro integrity can emerge through self-organization as long as the adaptive agent is well designed and several simple rules are given to interact with each other[3,4]. This is can be simulated by computer simulation. This method provides ideas for further research on knowledge evolution process and knowledge emergence. John Holland put forward the concept of complex adaptive system in 1994, that is, "complexity makes adaptability" [5]. Holland's contribution to the emergence of knowledge is that whether in macro or micro perspectives, individuals have adaptability, it can emerging higher and more complex knowledge from interacting with simpler rules . The deficiency of his research is that he only emphasized the self-adaptability of system subjects, and did not probe into the interaction between environment and system subjects. After Holland, the research on knowledge emergence in knowledge management field has not made a substantial breakthrough [6,7]. Based on CAS theory,
Alex Bennet and other scholars proposed intelligent complex adaptive system (ICAS)[1,8]. In ICAS theory, agent is defined as "person" with professional knowledge and skills, which reflects the ability of knowledge subject to adapt to the environment [9]. The deficiency of this study is that it only emphasizes the emergence of organizational knowledge, ignoring the emergence of knowledge at the micro level [10]. The SECI spiral model represented by Ikujiro Nonaka and others has some supplementary explanations for the operational mechanism of knowledge emergence, but they have not established a systematic concept and neglected the "simple rules", it also have not realized that the parameters of time variables is a necessary condition for studying knowledge emergence[11].

Among chinese scholars, Hua Yanfeng and others have constructed a cyclic and interactive model of knowledge emergence system based on the perspective of educational science[10]. This model has made a descriptive study of knowledge evolution, but it not discussed the conditions of knowledge emergence. On the basis of ICAS, Jin Fu and others put forward the knowledge emergence mechanism and management policy of the Intelligence resource system [12,13]. This research regards human as the core element of the subject of the knowledge system, and pays attention to tacit knowledge sharing and environmental conditions. Xu Libo and others based on the elementary of extension theory research intelligent emergence, to a certain extent, the "black box" dilemma caused by knowledge emergence has been solved, but it only solved the problem of information and knowledge co-processing[14]. Therefore, the following is based on the complexity method to construct the knowledge evolution model and analyze the conditions of knowledge emergence.

**Knowledge Agents and Research Methods**

According to relevant research make the following definition [15,16]:

Rule 1: Knowledge agents in organizations are persons with characteristics of interaction, self-organization and adaptability. And their knowledge constitutes the characteristics of different knowledge agents.

Rule 2: Knowledge emergence studies are limited to self-organizing with emerging attributes and include individual cognitive systems.

The self-organization levels are different, and the knowledge agents are different, so we can do a general understanding of the knowledge agents here. For example, when studying the knowledge emergence of specific organizations, we can regard the individual in the organization -- "person" as the unit of knowledge agent[17,18]. When studying the knowledge emergence of individual brain, We can use the "neurons" of different behaviors in the brain as the agent units. They constantly accept, process and integrate information, forming knowledge emergence when conditions are ripe. This comprehensive information integration, decision-making and control of subsequent behaviors characterize the evolution of brain knowledge, later knowledge emergence and intelligence emergence. Every knowledge system is an intelligent and complex adaptive system. These systems have the basic characteristics of organizational intelligence[19,20]. These characteristics and CAS mechanism determine the inevitable generation of knowledge emergence[22,23]. Under this premise, we study the conditions of knowledge emergence.

**Knowledge Evolution Simulation Model**

The self-organization evolution of knowledge emergence needs two conditions. First, the repeated learning and interaction between the knowledge agent and the unit of the agent, the knowledge emergence is the result of constant mutual selection and influence. Second, the attribute of knowledge itself plays an important role in the process of evolution. The integration of knowledge among agents produces assistance. According to the theory of self-organization evolution[23,24].

According to the theory of self-organization evolution, the construction equation is as follows:

\[ p = p(t) \] (1)
P is the state variable of knowledge scale. In an organization, heterogeneous class agents provide conditions for knowledge emergence through interaction, tacit knowledge sharing and other comprehensive behaviors. With the help of environment, the scale and maturity of knowledge agents are increasing.

Hypothesis 1: The knowledge of the knowledge agent has an effect on its level and scale change is $m_a$, environment influence is $m_b$, then the two interactions are $m_a * m_b$.

Hypothesis 2: Self-organization emergence enables the knowledge agent to obtain a growth rate of $\beta_1$. The growth rate of environmental interaction on the influence of knowledge level scale of knowledge agent is $\beta_2$, which is obtained by Eq. 1.

$$m_a = \beta_1 p; m_b = \beta_2 p; m_a \times m_b = \beta_1 p \times \beta_2 p$$ (2)

Due to the existence of positive and negative feedback mechanisms, knowledge evolution enhances or inhibits development. If the existing knowledge satisfies the needs of the knowledge agent, the speed of knowledge evolution will gradually decrease and the system will become steady.

It is assumed that the knowledge level of the knowledge agent is affected by the obstruction coefficient $\psi = 1 - p$, and the change rate of the knowledge scale is $dp/dt$, thus

$$dp/dt = \psi \lambda_1 \beta_1 \beta_2 p + f(p,t)$$ (3)

Assume that the dynamic factor $\lambda = \lambda_1 \beta_1 \beta_2$, substitute into Eq. 3 to get the Eq. 4.

$$dp/dt = \psi \lambda p^2 + f(p,t)$$ (4)

For $f(t, p)$, we use $\varepsilon p$ to represent the change of knowledge level and scale because of the damping factors in the process of knowledge evolution, such as poor communication between agents and obstacles between teams. ($\varepsilon > 0$, represents damping coefficient).

There are various uncertain factors in the evolution of knowledge that cause fluctuations, expressed as $\Gamma(t)$. Substituting it into Eq. 4 to get the Eq. 5.

$$dp/dt = \psi \lambda p^2 - \varepsilon p + \Gamma(t)$$ (5)

We call Eq. 5 as knowledge evolution equation.

**Analysis of Evolution Rule of Knowledge Emergence**

The essence of knowledge emergence is to regard knowledge as a state function from steady state to chaotic state. The process of chaos changing from critical point to new steady state.

In this process, the core issue is critical point analysis.

For this reason, we assume that the model is composed of potential functions similar to its process. When the state variable is one and the control variable does not exceed 4, We obtained 4 kinds of catastrophe models (Table 1).

The equilibrium surfaces of the 4 models in three dimensions are shown below (Figure 1). The equations are as follows: ① folding mutation; ② cusp mutation; ③ swallowtail mutation; ④ butterfly mutation.

Next, we analyze the mutation equation and observe the difference of the mutant nucleus. By comparison, only the mutation nucleus of cusp mutation is a fourth-order function, and the highest power of its first derivative is a third-order function (Table 1).
| Mutation Type         | The Highest Power of The First Derivative | Mutant nucleus | Function form                        |
|----------------------|------------------------------------------|----------------|-------------------------------------|
| Folding Mutation     | 2                                        | $x^3$          | $P(x)=x^4+ax$                       |
| Cusp Mutation        | 3                                        | $x^4$          | $P(x)=x^4+ax^2+bx^3+cx$             |
| Swallowtail Mutation | 4                                        | $x^5$          | $P(x)=x^5+ax^3+bx^2+cx^2$           |
| Butterfly Mutation   | 5                                        | $x^6$          | $P(x)=x^6+ax^4+bx^3+cx^2+dx$        |

Therefore, according to the Haken evolution theory, the variable $q$ is introduced to simplify the knowledge evolution equation, and it is assumed that:

$$q = \sqrt[3]{\lambda} p - \frac{\sqrt[3]{\lambda}}{3} \cdot p = \frac{1}{\sqrt{\lambda}} q + \frac{1}{3} \frac{dp}{dt} = \frac{1}{\sqrt{\lambda}} \frac{dq}{dt}$$

Bring the above formula into Eq. 5 to get the Eq. 6.

$$\frac{dq}{dt} = -q^3 + \frac{\lambda - 3\epsilon}{3} q + \frac{3\lambda - 9\epsilon - 1}{27} \sqrt{\lambda} + \frac{\Gamma(t)}{\sqrt{\lambda}}$$

At this time, let

$$\Phi = \frac{\lambda - 3\epsilon}{3}, \quad \gamma = \sqrt{\lambda} \frac{3\lambda - 9\epsilon - 1}{27}, \quad \Pi(t) = \frac{\Gamma(t)}{\sqrt{\lambda}}$$

Bring them in Eq. 6 to get the Eq. 7.

$$\frac{dq}{dt} = -q^3 + \lambda q + \gamma + \Pi(t)$$

According to CAS theory, the knowledge evolution process before knowledge emergence is an orderly process from low level to high level. Moreover, knowledge evolution is a potential system, and its potential function is expressed as Eq. 8.

$$\sigma(q) = -\int (-q^3 + \lambda q + \gamma) dq$$

Finishing Eq. 8 to get Eq. 9

$$\sigma(q) = -\int (-q^3 + \lambda q + \gamma) dq$$

We call Eq. 9 the knowledge mutation equation.

If we assume that the mutation manifolds in the evolution of knowledge are represented by $N$. Solving equation 9 gets

$$D(\sigma) = q^3 - \lambda q - \lambda = 0$$

Constructing a visual image using Eq. 10 depicted by three-dimensional vectors $\langle q, \lambda, \gamma \rangle$ (Figure 1). When the original point is greater than 0, we can see that there is a three leaf folding region with gradual diffusion on the surface $N$. The middle leaf is the $\sigma(q)$ extreme point. The middle lobe corresponds to a chaotic region with unstable characteristics, which is the condition for knowledge emergence.

Assume that $D(\sigma) = 0$ and $D^2(\sigma) = 0$ in Equation 10. Elimination parameter $q$ obtained:

$$4\lambda^2 - 27\gamma^3 = 0$$

We call Eq. 11 the judgement equation of knowledge emergence boundary.
Discussion

The following discussion is about the form of knowledge evolution

① When the knowledge evolution point starts at 1 and moves to the right to the n1 fork point, the system falls within the lower lobe of the mutation stream N.

② When the knowledge evolution point moves from 1 to the n2 Fork point, the system jumps from the lower lobe to the upper lobe, with irreversible mutation

③ In a small region of the mutation point, any form of action may affect the control variables, and then the knowledge evolved into mutations, resulting in knowledge emerging.

Conclusion

To sum up, we have the following three conclusions:

Conclusion 1. Based on the simulation model analysis: knowledge emergence occurred on the edge of chaos of the system.

Conclusion 2. In the process of from simple to complex, the action intensity, scale or quantity of the interaction among knowledge agents in the system reaches the appropriate degree, which may lead to knowledge emergence.

Conclusion 3. The scale, hierarchy and action intensity of knowledge agents create constraints on knowledge emergence., that is, if and only if there are two points h1 and h2, satisfying n2 < h2 < h1 < n1, the system reaches the chaotic boundary in the range of h2 to h1, at this moment, the system is most likely to produce knowledge emerging.

Summary

Based on the complexity method, this paper makes a preliminary study on the condition of knowledge emergence from the breakthrough point by the scale of knowledge agent. The question to be further considered is: how to accelerate the evolution of knowledge to the chaotic edge by mean of the mechanism of environmental intervention? We will use the computer software to do further simulation experiment research.

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