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Effect analysis on the life cycle process of industrial innovation based on two-stage hadoop parallel k-nearest neighbor algorithm

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Abstract. In order to improve the effectiveness of industrial innovation process analysis and effect research, a method for analysis and effect research on the life cycle process of industrial innovation based on two-stage Hadoop parallel K-nearest neighbor algorithm is proposed. First of all, the characteristics of the industrial innovation system is fully considered to make the evaluation index system fully, completely and systematically reflect the comprehensive operation of the industrial innovation system. Secondly, the basic principle necessarily followed by the index is given. Secondly, the two-stage Hadoop parallel K-nearest neighbor algorithm is designed to realize the effective analysis on the effect model of the life cycle process of industrial innovation. Finally, the effectiveness of the algorithm is verified by the simulation experiment.

Key words. Two-stage, K-nearest neighbor, Hadoop parallel, Industrial innovation, Life cycle.

1. Introduction

The industrial innovation is one of the basic driving forces for the social development, the key to the adjustment and upgrading of industrial structure, the only way for economic development, and the final embodiment of international competitiveness. However, the concept of the industrial innovation system tries to provide a new multidimensional, integrated, dynamic and evolutive industrial innovation point of view to better understand the industry structure and boundary of the industry, the relationship among mechanism and them, the process of learning, innovation and

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production process and system coordination evolution, etc. This paper, based on the comprehensive application of the development economics, technology economics, econometrics, industrial economics, innovation theory, system theory, evolution theory and other basic theories and methods, focuses on the topic of the "Co-evolution Theory and Performance Evaluation Method of Industrial Innovation System" for analysis. Firstly, with regard to the technology for the comparative analysis on related research literatures, the theories of industrial innovation and industrial innovation system are elaborated, and the components, structures and functions of the industrial innovation system are analyzed in detail. Secondly, the evolution mechanism and the co-evolution theory of industrial innovation system are studied. Then, according to the above theories, the performance evaluation model of industrial innovation system and the evaluation index system are constructed. Based on the above model, five high-tech industry innovation systems in China are taken as examples to make an empirical analysis, in which the operation performance and the evolution of these five high-tech industry innovation systems are analyzed in detail, and then, a comparative analysis is made. Finally, the reasons for "system failure" are analyzed, and the corresponding countermeasures are put forward. The above research provides a strong idea for the development of China's industrial innovation system, and gives a favorable basis for the policymakers to formulate relevant policies, which has a certain pioneering significance and practical significance.

The industrial innovation is the only way for economic development. Our country has entered the middle stage of industrialization, and the country has been actively advocating a new road to industrialization. With the knowledge economy and economic globalization, the world manufacturing is driven to transfer to China, and the growth of industrial economy depends on the industrial innovation. In the new economic background, the economic development must rely on the industrial innovation. In 2000, the United States announced the entry of a new era of economy supported by the knowledge and information, while China was facing the era of knowledge economy. In recent years, the rapid development of informationization and knowledge and its changes to the whole world indicate that the new economic mode will lead the development of economic society in the future economic development. There is a big difference between the new economic era and the great machine industry era under the comparison. If the latter refers to the replacement of the manpower with the natural force, the former will refer to the replacement of the human brain with the computer; the production mode of the former takes the Internet as the main media for information transmission, and it has the higher transmission speed and the wider transmission range compared with the power grid. If the great machine industry era is based on the technology, the new economic era is based on the knowledge, intelligence and information. The change of the production mode determines the connotation of value, and will lead to the corresponding change of the labor manner reflecting the value. Under the conditions of new economy, the knowledge production has become an independent production sector; for example, the research and development activities, as well as innovation activities have been separated from the real production system, and are not subject to the physical capital; they have become increasingly the measurement of value in themselves. Therefore, in the labor system based on the knowledge, intelligence and information, the role of some production factors (natural resources and physical labor) in original sense has been greatly decreased, while the role of knowledge and technology has been increased greatly. With the development of information revolution, the knowledge right is replacing the wealth power to become the power of the world. Whoever possesses more knowledge will have more dominating power.

To improve the effectiveness of industrial innovation process analysis and effect research, a method for analysis and effect research on the life cycle process of industrial innovation based on two-stage Hadoop parallel K-nearest neighbor algorithm has been proposed. The characteristics of the industrial innovation system is fully considered to make the evaluation index system fully, completely and systematically reflect the comprehensive operation of the industrial innovation system; then, the basic principle necessarily followed by the index is given. Later, the two-stage Hadoop parallel K-nearest neighbor algorithm is designed to realize the effective analysis on the effect model of the life cycle process of industrial innovation.

2. Industry innovation evaluation index system

In the comprehensive evaluation, the index selection must be solved firstly. When the design of the comprehensive operation ability index of industrial innovation system, the characteristics of the industrial innovation system need to be fully considered to make the evaluation index system fully, completely and systematically reflect the comprehensive operation of the industrial innovation system, and the index selection shall follow the following principles:

(1) Scientific principle. The scientificity of the index system is to ensure whether the evaluation results are scientific, and to a great extent depends on whether the indexes, standards, procedures and other aspects are scientific. Therefore, when the design of the evaluation index system for the operation capacity of industrial innovation system, the elements contained in the industrial innovation system and the rationality of the overall index structure shall be considered. The operation status of industrial innovation system shall be reflected from different angles, and the index has the better reliability, independence, representativeness and statistics.

(2) Comparability principle. A set of index system is used for the comprehensive evaluation on the operation abilities of several industrial innovation systems; therefore, the design of the index system must take into account the differences among statistical indexes of industries. In the index selection, the common index meaning must be made available in industries, and the statistical calibers and the scopes shall be kept consistent as much as possible, so as to ensure the comparability of indexes. Moreover, the reasonable evaluation model can be built through the index selection to evaluate each industrial innovation system, and provide theoretical support and analysis tools for government departments to formulate the correct industrial development policies.

(3) Growth principle. Both the analysis on capability of the past and the current system operation and the research on potential and future development capability of the industrial innovation system are required for the determination of the com-

prehensive ability of the industrial innovation system.

(4) Comprehensiveness principle. From the theoretical analysis, we can know that the evolution process of industrial innovation system is very complicated, and there are many influence factors which may play a role more or less on the evolution of the industrial innovation system. Therefore, in the selection of evaluation index, we should try to consider comprehensively, so as to fully measure the effect of elements on the function realization of the industrial innovation system, and fully understand the contribution of influence factors on function realization of system; then, a reliable basis for scientific decision making and relevant policies development could be provided.

(5) Principle of availability of the raw data. When the design of the evaluation index for the comprehensive operation capability of the industrial innovation system, the availability of raw data shall be fully considered, and whether the raw data can be truly acquired is related to the authenticity and reliability of the evaluation.

There is still a problem when index selection in accordance with the above principles, and it is that the evaluation index selection is mostly determined based on the needs of the problem with the subjective analysis and experience of people when the system evaluation of the people; however, whether the evaluation index determined is really representative to the problem to be reflected and whether the information provided by each index will be repeated (i.e. whether there is redundancy for the evaluation index) still need to be resolved. How to use a few indexes to scientifically, reasonably and accurately reflect the problem to be evaluated is a key link in the comprehensive evaluation of the system.

3. HMP-KNN industry innovation selection framework

3.1. Hadoo parallel computing

Firstly, the algorithm model for effect analysis on the life cycle process of industrial innovation of Hadoop framework parallel is described in detail. The core part of Hadoop framework parallel computing is MapReduce model. Fig.1 shows the programming model of MapReduce parallel computing under the standard Hadoop framework.

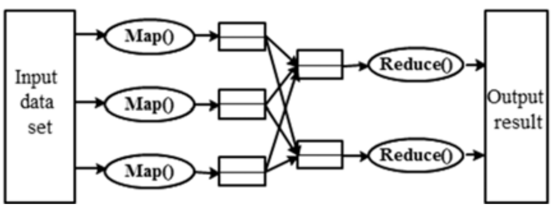

Fig. 1. Hadoop programming model

As the high performance computing has gradually become an important tool for bio-data analysis, the Hadoop programming model is also becoming more and more important. As shown in Fig.1, it is a simplified programming model of Hadoop, which is very suitable for the design of parallel clustering analysis. The appellation of Hadoop comes from two main steps of the model: including the map process and the reduce process, in which the map process is essentially a mapping process, and the result of feedback in this process performs the reduce process; therefore, it is a parallel execution process of feedback process of map process.

In the standard Hadoop module, the map process and the reduce process are operated on the basis of the defined key value $\langle key, value \rangle$. The two main operations above are defined as follows: [14]:

$$Map : (k_1, v_1) \rightarrow [(k_2, v_2)] \ . \tag{1}$$

$$Reduce : (k_2, [v_2]) \rightarrow [(k_3, v_3)] \ . \tag{2}$$

3.2. HMP-KNN parallelization framework

In general, microarray data can be represented as the data matrix of $N \times M$, of which N is the number of industrial innovations, and M is the number of samples involved in the experiment. For $N \gg M$ in number, the microarray data matrix is usually processed in a transposition manner. Fig.2 shows the HMP-KNN parallelization calculation process.

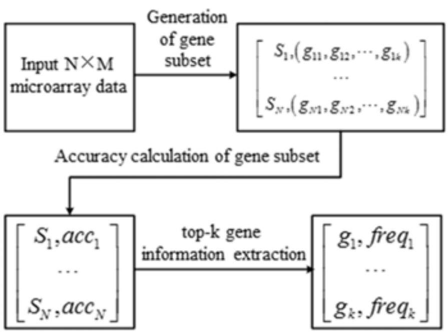

Fig. 2. HMP-KNN industry innovation extraction process

From Fig.2, it can be known that the HMP-KNN industry innovation extraction process mainly includes the following three processes: the first is the generation of potential industrial innovation subset; the second is the accuracy calculation of industrial innovation subset; the third is the top-k industry innovation information extraction. Usually, microarray data contain much independent industrial innovation information which will not affect the analysis results and has no correlation with other industrial innovation factors. Therefore, this part of information can not be considered in industrial innovation analysis. Hence, the initial screening of data is needed at the beginning of the algorithm, and the generation process of the industrial innovation subset is shown in Fig.2.

4. Extraction steps of parallel industrial innovation information

4.1. Microarray data Hadoop parallelization

Firstly, define the data filtering index BWG; then, the potential industrial innovation subset generation process is shown as step 1-step 3.

Step 1: (potential industrial innovation). Take $G = \{g_1, g_2, \cdots, g_N\}$ as the industrial innovation data set and $S = \{s_1, s_2, \cdots, s_M\}$ as the microarray sampling data set of the industrial innovation data. If $g_i \in G$ and $BWG(g_i) \geq BWG_{th}$ are satisfied, g_i is called the potential industrial innovation, of which BWG_{th} is the threshold. The screening index $BWG(g_i)$ is defined as follows:

$$BWG(g_i) = \frac{SS_{B_j}}{SS_{W_j}} = \frac{\sum\limits_{i=1}^{m}\sum\limits_{c=1}^{k} I(y_i = c)(\bar{x}_{c,j} - \bar{x}_j)^2}{\sum\limits_{i=1}^{m}\sum\limits_{c=1}^{k} I(y_i = c)(\bar{x}_{i,j} - \bar{x}_{c,j})^2}. \tag{3}$$

Where, m is the number of training samples; k is the number of classifications; c is the corresponding category label; $\bar{x}_j$ is the total mean of industrial innovation g_i of training sample; $\bar{x}_{c,j}$ is the total mean of industrial innovation belonging to the type c in industrial innovation of the training sample.

The discriminant example of the potential industrial innovation is as follows. Suppose that the actual value of the industrial innovation g_i is:

$$g_i = (g_{i,1} = 2, g_{i,2} = 2, g_{i,3} = 6, g_{i,4} = 42). \tag{4}$$

The example of the calculation process on parameters in the formula (3) is as follows:

$$\begin{cases} \bar{x}_i = \sum_{j=1}^{4} g_{i,j} \Big/ 4 = 13 \\ \bar{x}_{1,i} = (2+2)/2 = 2 \\ \bar{x}_{2,i} = (6+42)/2 = 24 \\ BWG(g_i) = 0.385 \end{cases} \tag{5}$$

If $0.385 \geq BWG_{th}$, g_i is called the potential industrial innovation.

Step 2: (microarray data). Take the candidate industrial innovation as g_c, $g_c = \{g_c \in G_p \cap g_c \in \exists S_k\}$, and the accuracy shown as S_k is higher than the given accuracy threshold of the user. For example, when $Acc(S_k) \geq Acc_{th}$, the data set built by S_k is called the candidate industrial innovation set G_c.

After determining the potential industrial innovations, a predefined microarray sampling data set S_k is generated on the same scale by step 2. Then, the K-nearest neighbor algorithm is used to calculate the classification accuracy of each subset. The K-nearest neighbor classification algorithm needs to measure the distance between training and testing samples. Then, select the former k industrial innovations to constitute the final microarray sampling data.

Step 3: (Hadoop parallelization). Take the input of the Map process as the microarray sampling data set $\langle g_i, (g_{i,1}, \cdots, g_{i,M})\rangle$ determined from the above steps; then, the output data is $\langle S_1, g_i\rangle, \cdots, \langle S_k, g_i\rangle$, and the key value pair is formed. Later, in the *Reduce* process, the key value pair and the subset id are used to output $\langle S_k, (g_{i_1}, \cdots, g_{i_k})\rangle$, and the reduction of industrial innovation data will be achieved. The Hadoop parallelization process is shown in Fig.1, and the specific process of algorithm is shown in the algorithm pseudo code 1.

Pseudo code 1: Selection of Potential Industrial Innovation Data Set

Input: microarray data set$[N \times M]$;
Output: potential industrial innovation data set;
Begin **Map operation**
  Obtain the expression of industrial innovation g_i in the microarray data set;
  Evaluation on g_i according to the formula (3);
  if $BWG(g_i) \geq BWG_{th}$ ***then***
    Generate $\langle S_k, g_i\rangle$ based on $BWG(g_i)$;
    Output $\langle S_k, g_i\rangle$;
  end
end
Begin **Reduce operation**
Extract equivalent g_i based on S_k;
Output $\langle S_k, (g_{i_1}, \cdots, g_{i_k})\rangle$;
end

4.2. Industrial innovation subset evaluation and top-k sequencing

Step 4: (industrial innovation subset classification accuracy). In the classification, the K-nearest neighbor sequencing method based on Euclidean Distance Function is used. Firstly, the input of each Map process is $\langle S_j, (g_{i_1}, \cdots, g_{i_k})\rangle$, and the Euclidean Distance for each training sample and testing sample in the category S_j is calculated. The Euclidean Distance can be defined as follows:

$$dis_j = \sqrt{(g_{i_1 j} - t_{s_l i_1})^2 +, \cdots, (g_{i_k j} - t_{s_l i_k})^2}. \tag{6}$$

Where, dis_j is the Euclidean Distance between the training sample j and the testing sample l. After the execution of the Map process, the input of the Reduce process is $\langle S_i, (dis_1, \cdots, dis_j)\rangle$, and $\langle S_i, (ts_1, T/F)\rangle, \cdots, \langle S_i, (ts_k, T/F)\rangle$ is determined, of which T/F indicates whether the testing sample is correctly classified and $Acc(S_i)$ is output.

In the process of parallelization, each subset is assigned to multiple map and reduce execution processes simultaneously. In this process, the input file includes $\langle S_j, (g_{i_1}, \cdots, g_{i_k})\rangle$, and it is assumed that the microarray matrix can be accessed by each map and reduce process. Firstly, for each Map process, calculate the distance value of the training samples, and output the key value pair of $\langle S_j, dis_{j,s}\rangle$.

After all Map processes are executed, the reduce process sequences the key value pair of $\langle S_j, dis_{j,s}\rangle$ based on $dis_{j,s}$, and gets the top-k minimum key value pair of

$\langle S_j, dis_{j,s} \rangle$. Then, in the next Map process, the top-k sample label is collected, and the testing sample category labels are predicted based on the K-nearest neighbor training sample. The Reduce process detects the correct class labels, and generates the prediction accuracy value of each subset accordingly. If $Acc(S_j) \geq Acc_{th}$ (of which S_j is the candidate set), the Reduce process outputs $\langle S_j, Acc(S_j) \rangle$.

Pseudo Code 2:HMP-KNN Parallel Algorithm

Pseudo code 2-1: industrial innovation classification accuracy calculation

Input: potential industrial innovation data set;
Output: top-k sequencing industrial innovation
Begin HMP process 1
  Map:
    Read the potential industrial innovation subset;
    for testing sample t_{s_k} ***do***
      for training sampletr_{s_j} ***do***
        Calculate the Euclidean Distance between the training sample and the testing sample;
        Calculate the Euclidean Distance between the potential industrial innovation subsets;
      end
      Output $\langle S_i, (dis_1, \cdots, dis_j) \rangle$:
    end
    Reduce:
  for potential industrial innovation subsetS_i ***do***
    Obtain K-nearest neighbor sample of t_{S_k} based on $\langle S_i, (ts_k, T/F) \rangle$;
    Calculate $Acc(S_i)$ based on $\langle S_i, (ts_k, T/F) \rangle$;
    if $Acc(S_j) \geq Acc_{th}$ ***then***
      Output$\langle S_i, Acc(S_i) \rangle$:
      end
    end
  end

Pseudo-code 2-2:top-k sequencing extraction

Begin HMP process 2
  Map:
  Obtain $\langle G_c, (g_{id_1}, \cdots, g_{id_k}) \rangle$:
  for individualg_i of candidate industrial innovation subsetG_C ***do***
    Output $\langle g_i, 1 \rangle$:
  end
  Reduce:
  Calculate the occurrence frequency of g_i, and output $\langle g_i, freq_i \rangle$:
end
Sequence $\langle g_i, freq_i \rangle$ based on $freq_i$;
Extract top-k industrial innovation individual;

The pseudo code of the HMP-KNN algorithm is shown in the pseudo code 2-1: industrial innovation classification accuracy calculation (HMP process 1).

Step 5: (top-k sequencing extraction). After execution of the pseudo code 2-1: industrial innovation classification accuracy calculation, the candidate industrial innovation subset can be obtained, and the prediction accuracy is relatively high. In this step, according to the occurrence frequency $freq_i$ of individual g_i of the candidate subset G_C, as an index to evaluate the importance of individual g_i, the key value pairs are built, and conduct the sequencing based on $freq_i$ value, so as to get top-k industrial innovation individual for output as the final prediction data set. The specific process is shown as the pseudo code 2-2:top-k sequencing extraction process. The algorithm frameworks in step 4 and step 5 are shown in Fig.3.

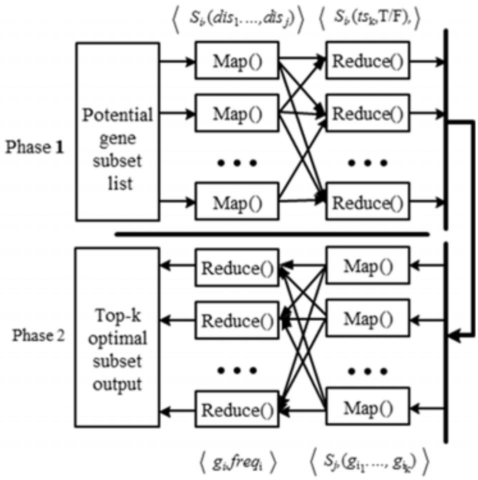

Fig. 3. Extraction of industrial innovation information of the two-stage parallel

5. Experimental analysis

This paper uses radar charts and line charts to analyze the operational capacity and evolution of the pharmaceutical industry innovation system. This paper takes five factors mentioned above as the five main aspects for the operation capacity of the industry innovation system, and makes a comparative analysis to the five industries respectively. The specific analysis can be shown as follows.

The radar chart of the evolution of each factor in different years of industry innovation system is composed of five axes, each axis represents one of the main factors of industry innovation system respectively, that is, input-output capacity factor, resource allocation capacity factor, system decision-making capacity factor, technological innovation ability factor and communication expansion ability factor. The score of each factor shall be marked in each axis, and connecting each point to form a pentagon orderly, of which value for each axis represents the operation or capabilities in this aspect of industry innovation system. The area of pentagon can be approximately used to stand for the comprehensive operation or capabilities of the industry innovation system.

The horizontal axis shows the time, and the vertical axis shows the score of each factor of industry innovation system in the line chart for the evolution of each factor in different years of industry innovation system. Score of each factor and comprehensive score shall be drawn in the chart, and connecting them with lines to show the evolution of each factor and the comprehensive operation ability of the industrial innovation system. The radar chart of the evolution of each factor in different years of the innovation system in the pharmaceutical manufacturing industry can be shown in Fig. 4.

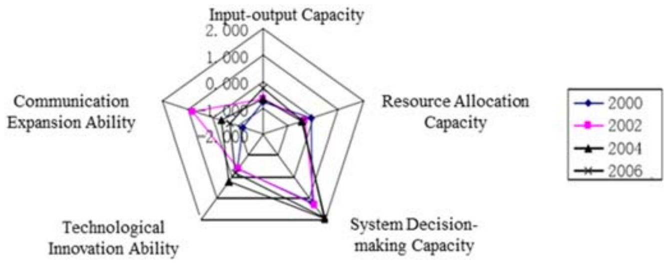

Fig. 4. Radar chart of evolution of each factor of the innovation system in the pharmaceutical manufacturing industry

The line chart of the evolution of each factor and comprehensive operation in different years of the innovation system in the pharmaceutical manufacturing industry can be shown in Fig. 5.

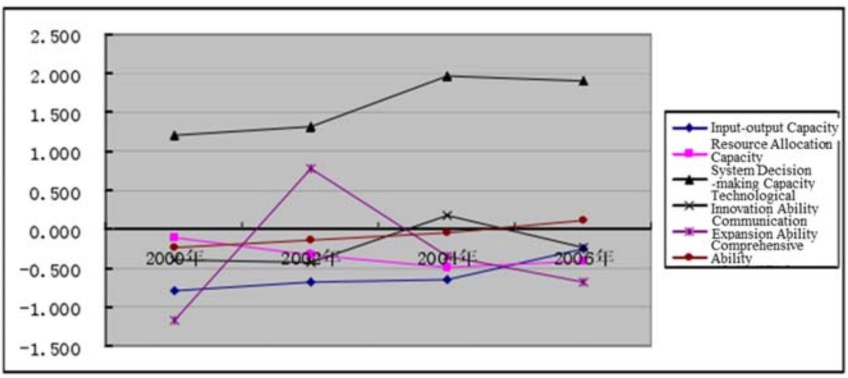

Fig. 5. Line chart of comprehensive evolution of the innovation system in the pharmaceutical manufacturing industry

From Fig. 7-2 and Fig. 7-3, it can be seen that the innovation system in the pharmaceutical manufacturing industry had weaker input-output capability and communication expansion capacity in 2000, but which had been gradually improved over time, especially in 2002 the communication expansion capacity increased rapidly, but then declined again. The influence of system decision-making on the innovation system for the entire pharmaceutical industry changed greatly, which supported the development of the system. The technological innovation ability did not fluctuate significantly in 2000 and 2002, and which greatly increased in 2004, and began to decline again in 2006. The resource allocation capacity showed a downward trend. On the whole, the comprehensive capability of the innovation system in pharmaceutical manufacturing industry increased steadily.

6. Conclusion

This paper takes cooperative evolution and performance evaluation of the industry innovation system as the main research object, researches meaning, characteristics, subject, object, level, influencing factors and innovation mode of industrial innovation in detail by comprehensively applying the basic theories and methods, such as development economics, technical economics, econometrics, industrial economics, innovation theory, system theory and evolution theory and others, and researches meaning, composition module, structure and function of the industry innovation system. The evolution mechanism of industry innovation system is researched from the aspects of dynamic mechanism, technology mechanism, and knowledge transformation mechanism, learning mechanism, market mechanism, network mechanism and self-organization mechanism and other aspects. On the basis of the research, the collaborative evolution of knowledge in industry innovation system, the industry innovation dynamic change of innovation mode collaborative evolution, and collaborative evolution of various mechanisms of industry innovation system shall be researched. Based on the theoretical analysis, the performance evaluation model of the industry innovation system is constructed, and the performance of the industry innovation system is evaluated from two perspectives. The first perspective is the evaluation of the comprehensive ability of the industry innovation system, and the second one is the evaluation of efficiency of the industry innovation system. Combined with these two results, the relationship between system factor ability and system efficiency is analyzed by using Logistic analysis method in this paper, and the main influencing factors are determined. Finally, the paper analyzes the reasons that may cause the failure of the industry innovation system, and puts forward some countermeasures and suggestions to improve the operation performance of China's industry innovation system according to the fact.

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