Acta Technica 62 (2017), No. 7A, 1415–1426

Research on industrial factor space optimization configuration mechanism of employment based on two-stage apriori algorithm

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Abstract. A research method of industrial factor space optimization configuration mechanism of employment based on two-stage Apriori algorithm is proposed so as to enhance the effectiveness of research on industrial factor space optimization configuration mechanism. Firstly, the paper analyzes the development evolution course of industrial factor space optimization configuration mechanism of employment in our country and analyzes different effects of three industries on economic and social development of our country. Secondly, the paper constructs two-stage data mining process: at the first stage, the writer obtains high expectation weight item sets of a group of candidate item sets based on hierarchical searching method; at the second stage, the writer scans database again so as to obtain high expectation weight of item sets and complete data mining. Thirdly, according to the simulation comparison of standard dataset, it is shown that the proposed algorithm could enhance computational efficiency greatly on the premise of ensuring algorithm precision.

Key words. Two-stage, Apriori algorithm, Employment, Industrial factor, Space optimization.

1. Introduction

Employment is vital to people's livelihood. It concerns economic growth and social harmony. Since the reform and opening up, industrial construction configuration of employment has changed greatly in our country. In addition, various employment contradictions are interwoven, which highlights the industrial structure configuration problem of employment. At present, we are lack of specialized research on industrial structure configuration evolution of employment in our country, and

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the mainstream quantitative research method of industrial structure configuration problem of employment also has deficiency. Thus, in current situation, it has great realistic significance and theoretical significance to discuss the evolution law and forecast the development trend of industrial structure configuration of employment in our country adopting new quantitative research method.

On a basis of foreign and domestic industrial structure configuration of employment and related theories, the paper studies the evolution process and influencing factor of industrial structure configuration of employment in our country since the reform and opening up, establishes industrial structure configuration evolution model of employment adopting Apriori mining method, simulates and forecasts the industrial structure of employment in our country, compared it with the development characteristics of foreign industrial structure configuration of employment, and proposes policy suggestions of promoting industrial structure configuration development of employment in our country. According to foreign and domestic research on industrial structure configuration problem of employment, the research usually gets the industrial structure configuration and industrial structure of employment at various income levels through analyzing related historical data of industrial structure configuration of employment so as to conclude a certain industrial structure configuration evolution mode of employment. Similarly, the paper also analyzes the evolution track of various industrial structure configurations of employment in our country from 1988 to 2017 in the perspective of industrial structure, studies the industrial structure configuration of employment in our country in 2017 since Global Finance Crisis, and points out industrial structure change is the most important reason for industrial structure configuration evolution of employment in our country, and the industrial structure of employment is the most important characteristic of industrial structure configuration of employment.

To study the evolution law and development trend of industrial structure configuration of employment in our country further, the paper adopts quantitative research method: Apriori mining method. There are many quantitative research methods about industrial structure configuration of employment at home and abroad. Hereinto, regression analysis method is the mainstream research method of industrial structure configuration of employment at present. Economic variables are usually dynamic, nonlinear and uncertain, so adopting mainstream research method is usually difficult to get accurate prediction result. Apriori mining method is an interdisciplinary artificial intelligence method involving physics, psychology and nerve physiology. It could simulate the thinking of human's brain through computer simulation, and find out laws of variables through learning, summarizing and clearing up the input sample data. Artificial nerve network has some characteristics, like being adept in solving uncertain nonlinearity problem, the processing mode similar with "black box", strong self-learning and generalization abilities, strong fault tolerance and robustness, processing ability of large-scale data, etc., being fit for analyzing economic problem. At present, artificial nerve network has been widely used in economic field gradually, but there is seldom research on industrial structure configuration of employment using Apriori mining method.

Thus, the paper studies the industrial structure configuration problem of employment in our country using closed Apriori mining method in high expectation weight item sets by two stages.

2. Industrial structure evolution of employment

According to the classification of three industries, the industrial structure configuration of employment can be classified as primary industry, secondary industry and tertiary industry. The paper analyzes and explains it using related data from 1988 to 2016.

(1) Industrial structure and industrial structure configuration of employment: industrial structure refers to the composition of intra-industrial sectors and inter-industrial sectors in national economy and contrast relation of interacted economic relation and quantity. From the economic development history of various countries in the world, it is seen that the basic law of industrial structure evolution is the constant reduction of proportion of output value and employment of primary industry, the first increasing and then stability of proportion of output value and employment of secondary industry; and continual improvement of the proportion of output value and employment of tertiary industry. When describing industrial structure, it is usually measured with the proportion of output value and employment of industrial sectors, and the proportion of employment is the industrial distribution or industrial structure of employment.

The industrial structure evolution of our country is consistent with the industrial structure evolution law of various countries in the world. Since the reform and opening up, the proportion of output value of primary industry in our country keeps declining, the output value proportion of secondary industry declines and then rises with stable change, and the output value proportion of tertiary industry rises significantly (See Fig. 1). In 1988, the output value proportion of three industries is 28.296, 47.996 and 23.996. In 2017, the output value proportion of three industries becomes 11. 396, 48. 6% and 40. 196. The proportion of primary industry declines by 17.1%, the proportion of secondary industry increases by 0.7%, and the proportion of tertiary industry increases by 16.2%. The proportion increasing rate of tertiary industry in national economy is higher than the increasing rate of secondary industry, but the development speed of tertiary industry is still behind in our country, compared with secondary industry.

From the contribution of three industries to economic growth, it is seen, the secondary industry does a biggest contribution, the second is tertiary industry, and the primary industry does a smallest contribution (See Fig. 2). Except contributing great to economic growth at the early stage of 1980s, the primary industry doesn't have a significant effect on boosting economic growth, and even decreases gradually. The secondary industry plays an important role in economic growth of our country, which does biggest contribution to economic growth. From 1988 to now, the contribution of secondary industry to economic growth fluctuates widely. When economy grows at a high speed and economic growth rate level is high, the contribution share of the secondary industry is maximum. In 2002, economic growth rate is 14.2% in our country, of which, 9.2% comes from the secondary industry, 3.8% comes from the tertiary industry and only 1.2% comes from the primary industry. The change of tertiary industry keeps consistent with that of secondary industry, the fluctuation range is smaller than that of secondary industry and the role in boosting economic growth rises gradually. In 2017, the contribution of three industries to economic growth is 0.4%, 6.5% and 5%. Through observing high-speed growth state of the secondary industry, it is known, the economic growth of our country mainly originates from fast growth of secondary industry and the secondary industry if the main power of enhancing economic growth of our country.

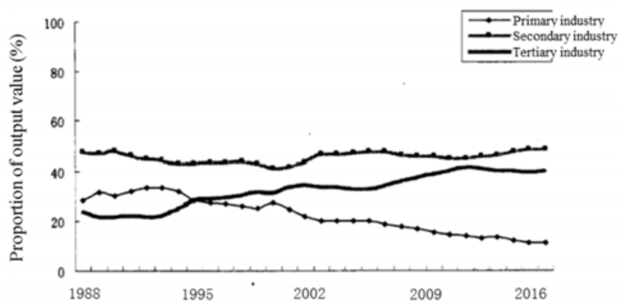

Fig. 1. Proportion of output value of primary, secondary and tertiary industries in our country from 1988 to 2017

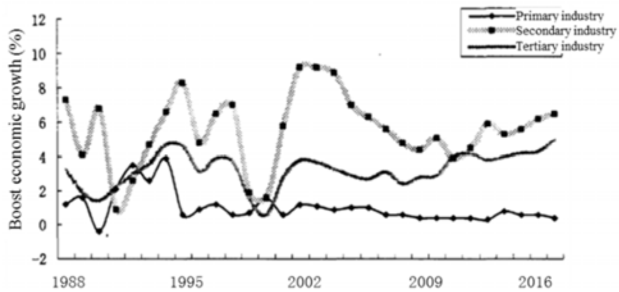

Fig. 2. Primary, secondary and tertiary industries in boosting economic growth

3. Industrial factor space optimization configuration model of employment based on two-stage Apriori algorithm

In the algorithm design part, the upper bound of high expectation weight item sets and downward closure characteristics are firstly proposed and then data mining is carried out against uncertain dataset *HEWIs* based on two-stage Apriori algorithm.

3.1. Upper bound of item set

At present, a large quantity of mining algorithms has been proposed to obtain frequent weight item set or the expected supporting degree of frequent item set. The previous research mines the supporting degree of frequent item set, reduces search space through proposing the downward closure characteristic expectation supporting so as to speed up the computation speed of expectation supporting mining process of frequent item set.

Theorem 1 (upward closure characteristic of expectation supporting degree) if an item set X is a frequent expectation supporting item set, then the subset of any item set X is the frequent expectation supporting item set.

Proof: Let X^k expresse item set with the length k, X^{k-1} expresse subset of X^k with the length $k-1$, and T_q be affair set. It meets $p(X,T_q) = \prod_{i_j \in X} p(i_j,T_q)$, so

$$\frac{p(X^k,T_q)}{p(X^{k-1},T_q)} = \frac{\prod_{i_j \in X^k} p(i_j,T_q)}{\prod_{i_j \in X^{k-1}} p(i_j,T_q)} = \prod_{i_j \in (X^k - X^{k-1})} p(i_j,T_q) \le 1\,. \tag{1}$$

The above result means that in the same affair, item set X^{k-1} has higher probability than X^k, namely $p(X^{k-1},T_q) \ge p(X^k,T_q)$. Let $TID(X^k)$ and $TID(X^{k-1})$ express TIDs list containing X^k and X^{k-1}. $TID(X^{k-1}) \ge TID(X^k)$, so

$$\begin{aligned} &\sum\nolimits_{T_q \in TID(X^{k-1})} p\left(X^{k-1},T_q\right) \ge \sum\nolimits_{T_q \in TID(X^k)} p\left(X^k,T_q\right) \\ &\Rightarrow expSup\left(X^{k-1}\right) \ge expSup\left(X^k\right)\,. \end{aligned} \tag{2}$$

If X^k is the frequent expectation supporting item set, meeting the case that $expSup\left(X^k\right)$ is equal to and greater than threshold value of minimal expectation weight supporting degree, then any subset X^{k-1} is frequent expectation supporting item set, namely $expSup\left(X^k\right)$ is equal to and greater than threshold value of minimal expectation weight supporting.

The existing research has solved the design of downward closure characteristic of frequent weight item set mining. Notwithstanding, in the uncertain dataset, the downward closure characteristic association rule mining of some precision cannot process the high expectation weight problem effectively. If download closure characteristic is not used, hierarchical algorithm may produce a large quantity of mining candidate individuals in the mining of high expectation supporting item set and causes waste of computing resource. Thus, it is vital to define download closure according to survival probability and item set weight.

In the proposed algorithm, an upper bound ($tubwp$) of a new affair weight probability is proposed to keep download closure characteristic. Such design mode can reduce the required processed quantity of item set in the search space greatly.

Definition 1 (Upper bound weight of affair) upper bound weight of affair T_q can be expressed as $tubw\,(T_q)$, and the form can be defined as:

$$tubw(T_q) = \max\{\omega(i_1, T_q), \omega(i_2, T_q), \cdots, \omega(i_j, T_q)\}\ . \tag{3}$$

Hereinto, $\omega(i_j, T_q)$ is equal to $\omega\,(i_j)$, and j is the quantity of item set in T_q. In the instance shown in Table 1,

$$\begin{aligned} tubw(T_1) &= \max\{\omega(A, T_1), \omega(C, T_1), \omega(E, T_1)\} \\ &= \max\{0.2, 0.9, 0.55\} = 0.9\,. \end{aligned} \tag{4}$$

Theorem 2: (existence of upper bound) the weight of any item set X of affair T_q is always smaller than or equal to the upper bond weight of affair T_q, namely $\omega(X, T_q) \leq tubw(T_q)$.

Proof: it meets the following condition:

$$tubw(T_q) = \max\{\omega(i_1, T_q), \omega(i_2, T_q), \cdots, \omega(i_j, T_q)\}\ . \tag{5}$$

And,

$$\begin{aligned} \omega(X, T_q) &= \frac{\sum_{i_j \in X \wedge X \subseteq T_q} \omega(i_j, T_q)}{|k|} \\ &\leq \frac{\max\{\omega(i_j, T_q)\} \times |k|}{|k|} = tubw(T_q) \end{aligned} \tag{6}$$

So $\omega(X, T_q) \leq tubw(T_q)$.

Definition 3: (upper bound probability of affair): the upper bound probability of affair T_q can be expressed as $tubp\,(T_q)$, and the form is:

$$tubp(T_q) = \max\{p(i_1, T_q), p(i_2, T_q), \cdots, p(i_j, T_q)\} \tag{7}$$

In the equation, j is the quantity of item set in affair T_q.

Theorem 3: (existence of upper bound probability) any item set X of affair T_q is always smaller than or equal to upper probability of affair T_q, namely $p(X, T_q) \leq tubp(T_q)$.

Proof: there is

$$\begin{cases} tubp(T_q) = \max\{p(i_1, T_q), p(i_2, T_q), \cdots, p(i_j, T_q)\} \\ p(i_j, T_q) \in (0, 1] \Rightarrow p(X, T_q) = X^{p(i_j, Tq)} \leq p(i_j, T_q) \\ \leq \max(p(i_j, T_q)) = tubp(T_q)\,. \end{cases} \tag{8}$$

So, $p(X, T_q) \leq tubp(T_q)$ is true.

Definition 4: (upper bound weight probability of affair and item set) upper weight probability of affair T_q can be expressed as $tubwp(T_q)$, and the form is $tubwp(T_q) = tubw(T_q) \times tubp(T_q)$. The upper bound weight probability of sub item can be expressed as $iubwp(X)$, and the specific definition form is $iubwp(X) = \sum_{X \subset T_q \wedge T_q \in D} tubwp(X, T_q)$.

3.2. Downward closure characteristic

Definition 5: (high expectation weight item set, HUBEWI) in dataset D, when $iubwp(X)$ is no less than the minimal expectation weight threshold value, namely $iubwp(X) \geq \varepsilon \times |D|$, the item set X is called high upper bound expectation weight item set.

Considering the above-mentioned instance, suppose the minimal expectation weight supporting threshold value is set up as 10%, then the item set A is the high upper bound expectation weight item set, because $iubwp(A) = 3.6 > 10\% \times 10$. However, item set $ACEF$ is not a high upper bound expectation weight item set, because $iubwp(ACEF) = 0.9 < 10\% \times 10$.

Theorem 4: (low closure characteristic) Let X^k be item set with length k, X^{k-1} be item set with length $k-1$, and subset X^k. If X is high upper bound expectation weight item set, then $iubwp(X^k) \leq iubwp(X^{k-1})$.

Proof: $X^{k-1} \subseteq X^k$, and $TIDs(X^k \subseteq T_q) \subseteq TIDs(X^{k-l} \subseteq T_q)$ meets the condition , so

$$\begin{aligned} iubwp(X^k) &= \sum\nolimits_{X^k \subset T_q \wedge T_q \in D} tubwp(T_q) \\ &\leq \sum\nolimits_{X^{k-1} \subseteq T_q \wedge T_q \in D} tubwp(T_q) = iubwp(X^{k-1})\,. \end{aligned} \tag{9}$$

Thus, it is known that X^k is high upper bound expectation weight item set, and the subset X^{k-1} of any X^k is also the high upper bound expectation weight item set.

Theorem 5: ($HEWIs \subseteq HUBEWIs$) downward closure performance of high upper bound expectation weight can ensure uncertain data meet condition $HEWIs \subseteq HUBEWIs$, in which, $HEWIs$ expresses high bound expectation weight item set, and $HUBEWIs$ means high upper bound weight item set. In addition, if X is not $HUBEWIs$, then any subset of X is not $HEWIs$ either.

Proof: let X be item set, based on definition 3, $\omega(X) = \omega(X, T_q)$. According to theorem 2 and 3, it is got $\omega(X, T_q) \leq tubw(T_q)$. Moreover, $p(X, T_q) \leq tubp(T_q)$, so

$$\begin{aligned} expWSup(X) &= \omega(X) \times \sum\nolimits_{X \subseteq T_q \wedge T_q \in D} p(X, T_q) \\ &= \sum\nolimits_{X \subseteq T_q \wedge T_q \in D} (\omega(X) \times p(X, T_q)) \\ &= \sum\nolimits_{X \subseteq T_q \wedge T_q \in D} (\omega(X, T_q) \times p(X, T_q)) \\ &\leq \sum\nolimits_{X \subseteq T_q \wedge T_q \in D} (tubw(T_q) \times tubp(T_q)) \\ &= \sum\nolimits_{X \subseteq T_q \wedge T_q \in D} tubwp(T_q) = iubwp(X) \\ &\Rightarrow expWSup(X) \leq iubwp(X) \end{aligned} \tag{10}$$

Thus, if item set X is not $HUBEWIs$ in the uncertain dataset D, then any subset of X is not $HEWIs$. Theorem 5 can ensure algorithm not take small upper bound expectation weight item set as the candidate item set, and HEWIs can be extracted from *HUBEWIs* totally, which reflects the correctness and integrity of algorithm.

3.3. Algorithm computation process

The proposed method carries out HEWIs data mining from uncertain dataset based on Apriori algorithm by two stages. At the first stage, the writer obtains a group of candidate item sets HUBEWIsbased on hierarchical searching method; then, at the second stage, the writer scans database again to obtain HEWIs from HUBEWIs. Based on two-stage recognition mode, the computation process of the proposed algorithm is shown as pseudocode 1.

Pseudocode 1: HUApriori

Input: uncertain affair dataset D; weight list *w-table*;
Minimal expectation weight supporting threshold value designated by users: ε;
Output: high expectation weight item set HEWIs.

for $T_q \in D$ ***do***
$tubw(T_q) = \max\{\omega(i_1, T_q), \omega(i_2, T_q), \cdots, \omega(i_j, T_q)\}$;
$tubp(T_q) = \max\{p(i_1, T_q), p(i_2, T_q), \cdots, p(i_j, T_q)\}$;
$tubwp(T_q) = tubw(T_q) \times tubp(T_q)$;
endfor
for $i_j \in D$ ***do*** $\{iubwp(i_j);\}$ ***endfor***
if $iubwp(i_j) \geq \varepsilon \times |D|$ ***then*** $\{HUBEWI^1 \leftarrow HUBEWI^1 \cup i_j\}$ ***endif***
$k \leftarrow 2$;
while $HUBEWI^{k-1} \neq null$ ***do***
$C_k = Apriori\_gen(HUBEWI^{k-1})$;
for $X \in C_k$ do $\{ubwp(X) = \sum_{x \subseteq T_q \wedge T_\eta \in D} tubwp(T_q);\}$
if $ubwp(X) \geq \varepsilon \times |D|$ ***then***
$HUBEWI^k \leftarrow HUBEWI^k \cup \{X\}$;
endif
endfor
$k \leftarrow k + 1$;
endwhile
$HUBEWIs \leftarrow \bigcup_k HUBEWI^k$;
for $X \in HUBEWIs$ ***do***
$expSup(X) = \sum_{x \subseteq T_q \wedge T_q \in D} (\prod_{i_j \in X} p(i_j, T_q))$;
$expWSup(X) = \omega(X) \times expSup(X)$
if $expWSup(X) \geq \varepsilon \times |\mathrm{D}|$ ***then***
$HEWI^k \leftarrow HEWI^k \cup \{X\}$;
endif
endfor
$HEWIs \leftarrow \cup HEWI^k$

As is shown in pseudocode 1, the input of the algorithm includes: uncertain affair dataset D, weight list $w{-}table$; and the minimal expectation weight supporting threshold value designated by users is ε. Firstly, through scanning uncertain dataset, we obtain *tubw*, as well as *tubp* and *tubwp* (1st to 5th row of pseudocode) of each affair. We compute the *iubwp* value all the item set 1 in the uncertain dataset (6th row of pseduocode) so as to obtain $HUBEWI^1$ (7th row of pseudocode). The above program is used for producing C_2 and candidate item set with length 2 so as to obtain $HUBEWI^2$. Based on the designed $HUBEWDC$ property, repeat the process until the hierarchical algorithm cannot mine candidate item set (19th to 26th row of pseudocode). It is noted, for the above computation process, only *expsup* value of candidate item set should be computed in the processed database, but the weight of item set can be read out from $w - table$ simply (20th and 21st row of pseudocode)

4. Experimental Analysis

In Fig. 3, the output value proportion of tertiary industry of our country changes correspondingly with the increasing of per capita GDP in the future. When per capita GDP is 16,000 Yuan, the output value proportion of primary industry is 12.6%, and keeps declining subsequently. When the GDP reaches 42,000 Yuan, the output value proportion of primary industry declines to 2% and below and finally stabilizes between 1% and 2%. The output value proportion of secondary industry increases from about 50%, and develops stably. When per capita GDP is 15,000 Yuan to 32,000 Yuan, the output value proportion of secondary industry keeps above 50%. When per caipta GDP continues growing, the output value proportion of secondary industry starts to decline. When per capita GDP is about 45,000 Yuan, the output value proportion of secondary industry declines to the lowest point, 27.4%. The output value proportion of tertiary industry increases constantly. When per capita GDP reaches about 45,000 Yuan, it reaches maximum, 71%.

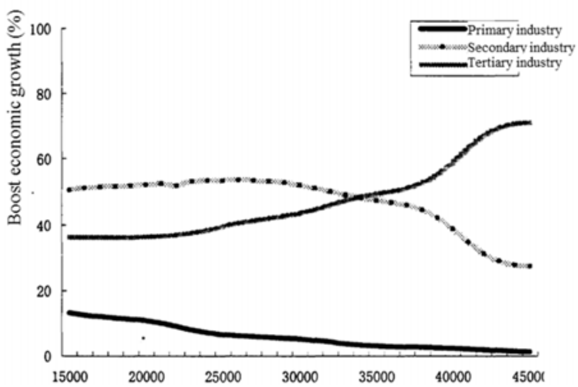

Fig. 3. Industrial structure variation trend

According to Fig. 3, it is seen, with increasing of per capita GDP, the output value proportion of secondary industry rises gradually; when per capita GDP reaches 26,000 Yuan, the output value proportion of secondary industry reaches maximum; with the continuous increasing of per capita GDP, the output value of secondary industry declines gradually. The output value curve of secondary industry appears parabola shape with the opening downward. When per capita GDP is 26,000 Yuan, there is maximum, so this point is the turning point of the output value curve of secondary industry. When per capita GDP reaches 34,000 Yuan, the output value curves of secondary industry and tertiary industry are intersected at 48%. Subsequently, the output value proportion of tertiary industry exceeds that of secondary industry and grows rapidly. When per capita GDP is below 34,000 Yuan, economic development focuses on secondary industry, and the development of secondary and tertiary industries is stable. However, when per capita GDP reaches above 34,000 Yuan, the second industry of our country has turning point; when per capita GDP reaches 34,000 Yuan, the industrial structure of our country behaves turning from "secondary, tertiary and primary industry" to "tertiary, secondary and primary industry"

Fig. 4 shows the industrial structure configuration change of employment in our country in the future when per capita GDP increases from 16,000 Yuan to 45,000 Yuan. According to Fig. 4, it is seen that there is certain difference between employment curve of three industries concluded in this paper and regression model form built by Professor Li Jiangfan. The employment regression equation of three industries built by Professor Li thought per capita GDP and employment proportion of three industries behave logarithmic function, quadratic function and power function. However, according to employment curve got using two-stage APRIORI algorithm in the paper, per capita GDP and employment proportion of secondary industry appears quadratic function form, which conforms to the judgment of Professor Li. However, the employment curve of primary industry and secondary industry is different from the employment regression equation result of Professor Li.

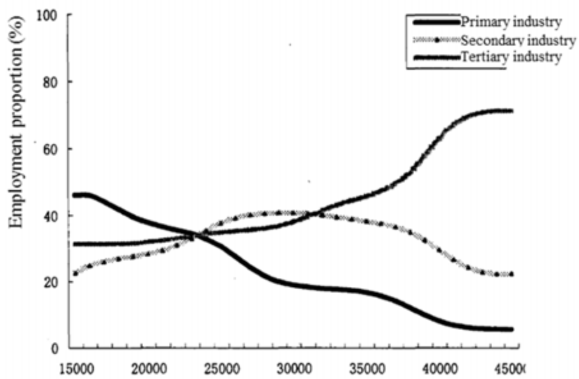

Fig. 4. Variation trend of employment structure configuration

In Fig. 5-4, the employment curve of primary industry appeared declining trend, and the employment proportion of primary industry develops from 45% and above to 6% and below; the employment curve of secondary industry rises and then declines, just like a parabola with the opening downward and there is maximum in the variation section; and the employment curve of tertiary industry rises gradually, and the employment proportion of tertiary industry increases from 30% to 70% and above. When per capita GDP is 23,000 Yuan, the employment proportion of three industries is the same. When per capita GDP is nearby 29,000 Yuan, the employment proportion of secondary industry reaches maximum. With the increasing of per capita GDP, the employment proportion of secondary industry starts to decline. When per capita GDP is above 31,000 Yuan, the employment proportion of tertiary industry exceeds the proportion of secondary industry. when per capita GDP reaches about 45,000 Yuan, the employment proportion of tertiary industry reaches a maximum. The employed person of tertiary industry accounts for more than 70% of total employed persons. In addition, the employment proportion of primary industry and secondary industry reaches a minimum level. The employment proportion curve of secondary industry appears parabola shape with opening downward, it reaches a maximum when per capita GDP is 29,000 Yuan, and declines subsequently, so the point is the turning point of the employment curve of secondary industry.

5. Conclusion

The paper firstly analyzes the new trend that affects the industrial structure configuration evolution of our country in the future from per capita GDP and industrial structure, and then forecasts the industrial structure development trend of employment in our country using two-stage Apriori algorithm. Using related data of 31 provinces and cities from 2000 to 2017 (except 2002 and 2016), the paper builds BP artificial neural network model of industrial structure configuration and industrial structure of employment so as to forecast the evolution of industrial structure configuration and industrial structure of employment of our country in the future when per capita GDP is between 16,000 Yuan and 45,000 Yuan, and analyzes the forecast result.

Acknowledgement

Research on Factors Backflow and Spatial Mechanism of Regional Economic Revival (Approval Number 2016FRZD01, which is a major item of social science prosperity project approved by education department of Liaoning province, China).

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Received May 7, 2017