Application of fuzzy clustering in financial analysis of logistic companies

[1]Jianfeng Li [2]Xusheng Cui
[1]College of Economic and Management, Dalian Maritime University,
[2]China Dalian International Cooperation (Group) Holdings Ltd.
City: Dalian, PR. China

Abstract: -As an important mathematic tool, fuzzy clustering is applied broadly in many aspects. It has been receiving great attention from enterprisers and scholars. This paper makes use of this approach to cluster the logistic companies based on some general financial indexes, such as ratio of gross margin, current ratio and net cash flow per share. By constructing and normalizing initial partition matrix, getting fuzzy similar matrix by means of Minkowski metric, and gaining the transitive closure, the dynamic fuzzy clustering analysis for logistic companies is shown clearly that different clustered result change gradually with the threshold λ reducing. It has a big value on contrasting logistic companies' financial condition in order to grasp the chance of investment and so on.

Key-Words: - Fuzzy clustering. Logistic company

1 Introduction

With the rapid growth of economy, transportation and logistics have played great role in the modern society[1], which affect the whole society's operational efficiency deeply just like the blood's importance to the body[2], so it's very necessary to research on logistic companies themselves.

To cluster logistic companies is just one of important subjects. Logistic companies can be divided into different classes according to the financial similarity, in this way, many valuable things can be found out on the basis of clustering outcome, for example, some logistic management experience can be shown by means of further contrasting the companies in the same cluster, some chance of investment can be gotten because the share prices of the companies in one cluster maybe fluctuate similarly in the stock market, and the probable condition in the logistic industry can be clear if enough logistic companies are chosen.

The remainder of the paper is presented as follows. In section 2, fuzzy clustering analysis is introduced, and then in section 3, that method is applied to some logistic companies and a case is investigated. The last section draws some final consideration and presents some practical implication.

2 Fuzzy Clustering Analysis

In recent years, researchers have worked extensively in the field of cluster analysis [3,4].Clustering is such a procedure that objects are distinguished or classified in accordance with their similarity. A formal mathematical definition of clustering, as stated in [5] is the following: let $X \in R^{n \times m}$ a set of data items representing a set of n points x_i in R^m. The goal is to partition X into K groups C_k such data that belongs to the same group is more "alike" than data in different groups. Each of the K groups is called a cluster. The result of the algorithm is an injective mapping $X \mapsto C$ of data items X_i to clusters C_k.

As one of important clustering approaches, fuzzy clustering analysis which obtains the uncertainty degree of samples belonging to each class and expresses the intermediate property of their memberships, can trace back to the concept of fuzzy partition proposed by Ruspini[6,7]. With this concept, some typical fuzzy clustering algorithms, such as methods based on the similarity and fuzzy relations [8, 9], the transitive closure of fuzzy equivalent relation[10], the convex decomposition of data[11,12], the dynamic programming and indistinguishable relation are developed one after the other[13]. It has been applied in many aspects: students are allocated into some number of classes using fuzzy clustering algorithm based on each student's achievement of the prerequisite subjects (Susanto, 2002) [14], the soil samples are classified on base of the concentration of 13 chemical elements through Gustafson-Kessel fuzzy clustering algorithm (Costel, 2006) [15], similar documents are found through a fuzzy clustering approach with predefined fuzzy clusters being used to extract feature vectors of related documents (Ridvan, 2006) [16]and so on.

The basic fuzzy clustering algorithm is briefly shown bellow[17,18]:

Step1: construction of initial partition matrix

$U=\{x_1,\ x_2,\ \cdots,\ x_n\}$ is the set of items which need to be classified, each item has m attributes as the measurement:

$x_i=\{x_{i1},\ x_{i2},\ \cdots,\ x_{im}\}$ (i=1, 2, $\cdots$, n)

Then, the original partition matrix is gained:

$$X=\begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{11} & x_{12} & \cdots & x_{1m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{1}$$

Step2: Normalization of the partition matrix

In reality, different data has different dimension. It's necessary to convert the data for comparison, what's more, which needs to be compressed into the range [0,1] as required by fuzzy matrix. The general conversion formula is shown below:

$$x'_{ik}=\frac{x_{ik}-\min\limits_{1\le i\le n}\{x_{ik}\}}{\max\limits_{1\le i\le n}\{x_{ik}\}-\min\limits_{1\le i\le n}\{x_{ik}\}} \text{ (k=1, 2, } \cdots \text{, m)} \tag{2}$$

Where $x'_{ik}\in[0,1]$

Step3: construction of fuzzy similar matrix

Fuzzy similar matrix R is gotten on account of the similarity of vectors in the sample. There are many methods to calculate the similar degree. Some common formulas are shown below:

(a) Euclidean distance

$$r_{ij}=\begin{cases} 1 & \text{i = j} \\ 1-c\sqrt{\sum\limits_{k=1}^{m}\left(x'_{ik}-x'_{jk}\right)^2} & \text{i} \ne \text{j} \end{cases} \tag{3}$$

$i,\ j=1,2,\cdots,n$

C is endowed with proper value for. $0\le r_{ij}\le 1$

(b) Minkowski metric

$$r_{ij}=\begin{cases} 1 & \text{i = j} \\ 1-c\left\{\sum\limits_{k=1}^{m}\left|x'_{ik}-x'_{jk}\right|^p\right\}^{\frac{1}{p}} & \text{i} \ne \text{j} \end{cases} \tag{4}$$

$i,\ j=1,2,\cdots,n$

c is endowed with proper value for. $0\le r_{ij}\le 1$

p is positive integer, when p=2, it is *Euclidean distance*

(c) Dot product

$$r_{ij}=\begin{cases} 1 & \text{i = j} \\ 1-\dfrac{1}{M}\sum\limits_{k=1}^{m}x'_{ik}\bullet x'_{jk} & \text{i} \ne \text{j} \end{cases} \tag{5}$$

$i,\ j=1,2,\cdots,n$

$M=\max(\sum\limits_{i\ne j}x'_{ik}\bullet x'_{jk})$

(d) Cosine

$$r_{ij}=\frac{\sum\limits_{k=1}^{m}x'_{ik}\bullet x'_{jk}}{\sqrt{\sum\limits_{k=1}^{m}{x'_{ik}}^2}\bullet\sqrt{\sum\limits_{k=1}^{m}{x'_{jk}}^2}} \tag{6}$$

$i,\ j=1,2,\cdots,n$

(e) Correlation

$$r_{ij}=\frac{\sum\limits_{k=1}^{m}\left|x'_{ik}-\overline{x'_{ik}}\right|\left|x'_{jk}-\overline{x'_{jk}}\right|}{\sqrt{\sum\limits_{k=1}^{m}\left(x'_{ik}-\overline{x'_{ik}}\right)^2}\bullet\sqrt{\sum\limits_{k=1}^{m}\left(x'_{jk}-\overline{x'_{jk}}\right)^2}} \tag{7}$$

$i,\ j=1,2,\cdots,n$

$\overline{x'_i}=\frac{1}{m}\sum\limits_{k=1}^{m}x'_{ik},\ \overline{x'_j}=\frac{1}{m}\sum\limits_{k=1}^{m}x'_{jk}$

Step4: obtainment of fuzzy equivalent matrix

Through transitive closure, Fuzzy similar matrix R can be transformed into fuzzy equivalent matrix, which not only has "reflexivity" and "symmetry", but also is provided with "transitivity".

The transitive closure $t(R)$ is gained by means of the "square method" that fuzzy similar matrix is squared gradually.

$$R\to R^2\to R^4\to\cdots\to R^{2^i}\to\cdots \tag{8}$$

$$\left(\ R^2=R\circ R=\mathop{\vee}\limits_{k=1}^{n}(r_{ik}\wedge r_{kj})\ \right)$$

When $R^k\circ R^k=R^k$, it means that R^k is provided with "transitivity", and R^k is just requisite transitive closure which is also the "optimal" fuzzy equivalent matrix R^* . The $t(R)$ can be gained within $[\log_2 n]+1$ steps, on account that $R^{2^i}\le R^n$, i.e. $2^i\le n,\ \ \text{i}\le\text{logn/log2}$.

Step5: description of dynamic fuzzy clustering

Setting the threshold to λ, which changes from the big to the small, the dynamic fuzzy clustering can result from the above optimal fuzzy equivalent matrix R^*.

Supposing $\underset{\sim}{C} \in P(U)$, for $\forall \lambda \in [0,1]$,

$$(\underset{\sim}{C})_{\lambda} = C_i \triangleq \{x \mid \underset{\sim}{C}(x) \geq \lambda\}, \tag{9}$$

The dynamic fuzzy clustering with the change of λ is shown in figure1:

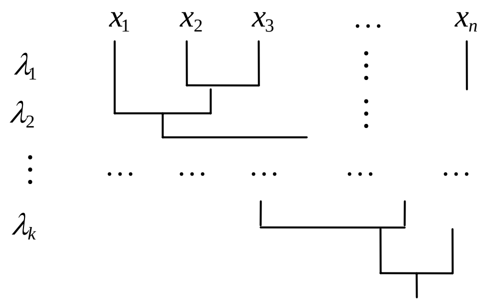

Fig1 Dynamic fuzzy clustering

3 fuzzy clustering analysis for logistic companies

For any company, financial condition is one of important aspects. This paper selects eleven logistic companies which are the listed companies in the stock market of China. Fuzzy clustering method is applied to those companies according to seven general financial indexes (attributes). They are shown below:

Eleven Companies:

X_1: Nanjing Water Transport Industry Co.,ltd
X_2: China Railway TieLong Container Logistics Co.,Ltd
X_3: China Shipping HaiSheng Co.,Ltd
X_4: China Merchants Energy Shipping Co.,Ltd
X_5: Cosco Shipping Co.,Ltd
X_6: Shinotrans Air Transportation Development Co.,Ltd
X_7: JieLee Industry Co.,Ltd
X_8: Shanghai Jiao Yun Co.,Ltd
X_9: Shanghai Ya Tong Co.,Ltd
X_{10}: China Shipping Development Company Limited
X_{11}: Shanghai HaiBo Co.,Ltd

Seven attributes:

A1: Ratio of Gross Margin
A2: Ratio of Operating Income
A3: Ratio of Revenue to Net Assets
A4: Ratio of Stockholder's Equity
A5: Current Ratio
A6: Quick ratio
A7: Net Cash Flow per Share

In this way, the initial partition matrix can be constructed (Time: Midterm in 2006), which is shown in the table1:

Table1 initial partition matrix

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
X_1	37.32	35.12	8.6	58.76	0.83	0.72	0.5462
X_2	48.22	44.86	7.94	54.74	0.99	0.33	0.1414
X_3	25.16	22.93	6	82.28	5.74	5.17	0.0382
X_4	48.29	48.29	12.19	53.6	0.54	0.51	0.3757
X_5	22.77	21.14	10.85	57.22	1.08	0.87	0.4534
X_6	37.76	36.1	8.72	61.23	2.4	2.4	0.2819
X_7	21.08	20.42	1.41	82.72	2.4	2.21	0.0037
X_8	21.72	20.83	3.43	61.03	1.26	0.86	0.0285
X_9	26.51	23.85	2.86	54.94	0.56	0.49	0.2503
X_{10}	36.11	34.04	11.8	75.27	0.63	0.49	0.5074
X_{11}	23.2	21.71	10.62	36.25	0.44	0.33	0.2915

Then, in order to convert the data for comparison and compress the data into the range [0, 1], the partition matrix is normalized in the step2 of fuzzy clustering analysis. The formula 2 is followed, and the result is shown in the table2 below

Table2 the normalized partition matrix

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
X_1	0.597	0.527	0.667	0.484	0.074	0.081	1
X_2	0.997	0.877	0.606	0.398	0.104	0	0.254
X_3	0.15	0.09	0.426	0.991	1	1	0.064
X_4	1	1	1	0.373	0.019	0.037	0.686
X_5	0.062	0.026	0.876	0.451	0.121	0.112	0.829
X_6	0.613	0.563	0.678	0.538	0.37	0.428	0.513
X_7	0	0	0	1	0.37	0.388	0
X_8	0.024	0.015	0.187	0.533	0.155	0.11	0.046
X_9	0.2	0.123	0.135	0.402	0.023	0.033	0.455
X_{10}	0.552	0.489	0.964	0.84	0.036	0.033	0.929
X_{11}	0.078	0.046	0.854	0	0	0	0.531

Thirdly, fuzzy similar matrix is built up following formula 4 (*Minkowski metric)* in the step 3 of fuzzy clustering analysis, where the parameters p and c are taken separately as 4 and 0.2. The result is shown in the table 3 below.

Table3 fuzzy similar matrix

R	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
X_1	1	0.85	0.75	0.89	0.88	0.89	0.78	0.8	0.86	0.92	0.86
X_2	0.85	1	0.74	0.9	0.78	0.9	0.77	0.78	0.81	0.85	0.79
X_3	0.75	0.74	1	0.73	0.77	0.84	0.85	0.79	0.76	0.75	0.74
X_4	0.89	0.9	0.73	1	0.77	0.88	0.73	0.75	0.78	0.87	0.78
X_5	0.88	0.78	0.77	0.77	1	0.87	0.79	0.82	0.85	0.88	0.91
X_6	0.89	0.9	0.84	0.88	0.87	1	0.83	0.85	0.87	0.89	0.85
X_7	0.78	0.77	0.85	0.73	0.79	0.83	1	0.9	0.87	0.77	0.77
X_8	0.8	0.78	0.79	0.75	0.82	0.85	0.9	1	0.92	0.79	0.85
X_9	0.86	0.81	0.76	0.78	0.85	0.87	0.87	0.92	1	0.82	0.85
X_{10}	0.92	0.85	0.75	0.87	0.88	0.89	0.77	0.79	0.82	1	0.82
X_{11}	0.86	0.79	0.74	0.78	0.91	0.85	0.77	0.85	0.85	0.82	1

Fourthly, the square method is adopted to achieve transitive closure, i.e. the optimal fuzzy equivalent matrix R^*, which is provided with properties of "reflexivity", "symmetry", and "transitivity". The optimal fuzzy equivalent matrix is shown in table4 below.

Table4 optimal fuzzy equivalent matrix

R*	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
X_1	1	0.89	0.85	0.89	0.88	0.89	0.87	0.87	0.87	0.92	0.88
X_2	0.89	1	0.85	0.9	0.88	0.9	0.87	0.87	0.87	0.89	0.88
X_3	0.85	0.85	1	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
X_4	0.89	0.9	0.85	1	0.88	0.9	0.87	0.87	0.87	0.89	0.88
X_5	0.88	0.88	0.85	0.88	1	0.88	0.87	0.87	0.87	0.88	0.91
X_6	0.89	0.9	0.85	0.9	0.88	1	0.87	0.87	0.87	0.89	0.88
X_7	0.87	0.87	0.85	0.87	0.87	0.87	1	0.9	0.9	0.87	0.87
X_8	0.87	0.87	0.85	0.87	0.87	0.87	0.9	1	0.92	0.87	0.87
X_9	0.87	0.87	0.85	0.87	0.87	0.87	0.9	0.92	1	0.87	0.87
X_{10}	0.92	0.89	0.85	0.89	0.88	0.89	0.87	0.87	0.87	1	0.88
X_{11}	0.88	0.88	0.85	0.88	0.91	0.88	0.87	0.87	0.87	0.88	1

The last, with the different threshold λ being set on, the dynamic fuzzy clustering for logistic companies based on finance condition is shown following the formula 9.

When $\lambda = 1$

$$R_1 = \begin{pmatrix} 1&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&0&1 \end{pmatrix}$$

The logistic companies can be classified into eleven clusters: $\{X_1\}$, $\{X_2\}$, $\{X_3\}$, $\{X_4\}$, $\{X_5\}$, $\{X_6\}$, $\{X_7\}$, $\{X_8\}$, $\{X_9\}$, $\{X_{10}\}$, $\{X_{11}\}$

When $\lambda = 0.92$

$$R_{0.92} = \begin{pmatrix} 1&0&0&0&0&0&0&0&0&1&0 \\ 0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&1&0&0 \\ 0&0&0&0&0&0&0&1&1&0&0 \\ 1&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&0&1 \end{pmatrix}$$

The logistic companies can be classified into nine clusters: $\{X_1, X_{10}\}$, $\{X_2\}$, $\{X_3\}$, $\{X_4\}$, $\{X_5\}$, $\{X_6\}$, $\{X_7\}$, $\{X_8, X_9\}$, $\{X_{11}\}$

When $\lambda = 0.91$

$$R_{0.91} = \begin{pmatrix} 1&0&0&0&0&0&0&0&0&1&0 \\ 0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&1 \\ 0&0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&1&0&0 \\ 0&0&0&0&0&0&0&1&1&0&0 \\ 1&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&1&0&0&0&0&0&1 \end{pmatrix}$$

The logistic companies can be classified into eight clusters: $\{X_1, X_{10}\}$, $\{X_2\}$, $\{X_3\}$, $\{X_4\}$, $\{X_6\}$, $\{X_7\}$, $\{X_8, X_9\}$, $\{X_5, X_{11}\}$

When $\lambda = 0.90$

$$R_{0.90} = \begin{pmatrix} 1&0&0&0&0&0&0&0&0&1&0 \\ 0&1&0&1&0&1&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0 \\ 0&1&0&1&0&1&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&1 \\ 0&1&0&1&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&1&1&1&0&0 \\ 0&0&0&0&0&0&1&1&1&0&0 \\ 0&0&0&0&0&0&1&1&1&0&0 \\ 1&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&1&0&0&0&0&0&1 \end{pmatrix}$$

The logistic companies can be classified into five clusters: $\{X_1, X_{10}\}$, $\{X_2, X_4, X_6\}$, $\{X_3\}$, $\{X_7, X_8, X_9\}$, $\{X_5, X_{11}\}$

When $\lambda = 0.89$

$$R_{0.89} = \begin{pmatrix} 1&1&0&1&0&1&0&0&0&1&0\\ 1&1&0&1&0&1&0&0&0&1&0\\ 0&0&1&0&0&0&0&0&0&0&0\\ 1&1&0&1&0&1&0&0&0&1&0\\ 0&0&0&0&1&0&0&0&0&0&1\\ 1&1&0&1&0&1&0&0&0&1&0\\ 0&0&0&0&0&0&1&1&1&0&0\\ 0&0&0&0&0&0&1&1&1&0&0\\ 0&0&0&0&0&0&1&1&1&0&0\\ 1&1&0&1&0&1&0&0&0&1&0\\ 0&0&0&0&1&0&0&0&0&0&1 \end{pmatrix}$$

The logistic companies can be classified into four clusters: {X_1, X_{10}, X_2, X_4, X_6}, {X_3}, {X_7, X_8, X_9}, {X_5, X_{11}}

When $\lambda = 0.88$

$$R_{0.88} = \begin{pmatrix} 1&1&0&1&1&1&0&0&0&1&1\\ 1&1&0&1&1&1&0&0&0&1&1\\ 0&0&1&0&0&0&0&0&0&0&0\\ 1&1&0&1&1&1&0&0&0&1&1\\ 1&1&0&1&1&1&0&0&0&1&1\\ 1&1&0&1&1&1&0&0&0&1&1\\ 0&0&0&0&0&0&1&1&1&0&0\\ 0&0&0&0&0&0&1&1&1&0&0\\ 0&0&0&0&0&0&1&1&1&0&0\\ 1&1&0&1&1&1&0&0&0&1&1\\ 1&1&0&1&1&1&0&0&0&1&1 \end{pmatrix}$$

The logistic companies can be classified into three clusters: {X_1, X_{10}, X_2, X_4, X_6, X_5, X_{11}}, {X_3}, {X_7, X_8, X_9}

When $\lambda = 0.87$

$$R_{0.85} = \begin{pmatrix} 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 0&0&1&0&0&0&0&0&0&0&0\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1\\ 1&1&0&1&1&1&1&1&1&1&1 \end{pmatrix}$$

The logistic companies can be classified into two clusters: {X_1, X_{10}, X_2, X_4, X_6, X_5, X_{11}, X_7, X_8, X_9}.{X_3}

When $\lambda = 0.85$

$$R_{0.85} = \begin{pmatrix} 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1&1&1 \end{pmatrix}$$

At last, the logistic companies can be classified into one cluster: {X_1, X_{10}, X_2, X_4, X_6, X_5, X_{11}, X_3, X_7, X_8, X_9}.

According to the above analysis, the dynamic fuzzy clustering map can be gained, which is shown in figure2. It means that in some level (λ) some logistic companies can gather together depending on the financial condition, such as the companies X_2, X_4 and X_6 are similar at the threshold where λ=0.9, what's more, with the decrease of λ, the clustered companies will increase gradually

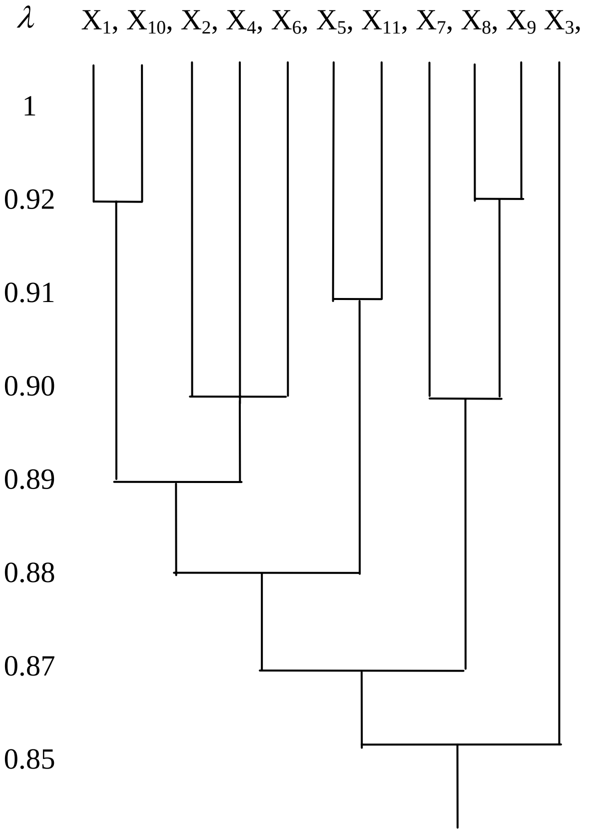

Fig2 Dynamic fuzzy clustering map

5. Conclusion

As an important mathematic tool, fuzzy clustering is always receiving great attention from enterprisers and scholars, and it has been applied broadly in many aspects. In this paper, it is used to classify the logistic companies based on the some general financial indexes. The dynamic fuzzy classification of companies with the change of different threshold is shown clearly, which has a big value on contrasting the logistic companies' financial condition in order to grasp the chance of investment and so on.

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