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An Analysis Model of Performance Index Based on Weighted Fuzzy Mutual Information

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Abstract: *To reduce the impact of single indicator analysis, imbalanced weights, and data noise in traditional performance analysis models, a weighted fuzzy mutual information multi granularity performance analysis model is proposed. Firstly, the space of educational output indicators is divided into granularity layers to avoid the problem of local analysis of indicators. The application scope of the weight method has been expanded by combining the priority graph and CRITIC weighting method. At the same time, the fuzzy mutual information method is used to analyze the overall correlation between the input indicators and the granularity layer, and the importance of the input indicators is calculated and ranked based on the combination weight. Taking undergraduate education data from a certain province as an example analysis, the results verify the rationality and effectiveness of this method.*

Keywords: *Weighted fuzzy mutual information; Priority graph method; CRITIC method; Correlation analysis; Particle size index*

1. Introduction

Defining favorable input indicators is beneficial for enterprises or units to make decisions, evaluate performance, and formulate next stage performance plans and implementation plans [1]. Effectively analyzing the relationship between input and output indicators can optimize performance input indicators and enable the benign development of evaluation performance. Therefore, scientific and effective performance indicator analysis has received widespread attention. The main body of performance evaluation is different, and the methods of performance analysis are also different. Traditional performance analysis methods include Analytic Hierarchy Process, Balanced Scorecard, Data Envelopment Analysis, Mutual Information Method, and Multi Granularity Analysis [2-6]. For example, PBrin et al. [7] used AHP to make decisions based on the relationship between characteristics and indicators, but this method only considered a single indicator. Xinghua City [8] uses the AHP (The Analytical Hierarchy Process) evaluation method to establish a performance evaluation system and optimize the management of performance indicators. Ding Yong et al. [9] introduced evaluation parameters to use risk factors as an indicator in the performance evaluation system, and compared system performance through data training and expert scoring. In this method, expert scoring has strong subjective factors. Considering the redundancy between indicators, Lou Zhijiang et al. [10] used the method of mutual information to discretize continuous data and combined with key performance indicators to discretize the data into a limited number, which has limitations. Liao Shujiao et al. [11] considered the differences between different features, established a neighborhood rough set theoretical framework for feature granularity selection. The method of determining the granularity size through the error confidence degree of feature values relies too heavily on objective data, affecting the accuracy of the algorithm. Xiong Chuanzhen et al. [12] established a fuzzy similarity label enhancement algorithm using the equivalence relationship of multiple label spaces, which optimized the "singularity" existing in the feature space without considering the impact of the index space. Lin Yaojin et al. [13-14] considered the correlation between indicators and used the method of fuzzy mutual information to judge the quality of multi label learning features, without considering the correlation between indicators as a whole in the indicator space.

The above methods mostly analyze the evaluation object based on a single indicator, indicator data, and single weighting methods, without considering the integration of input items and indicator space, resulting in dependencies and drawbacks between single indicators. Therefore, this article proposes a

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performance analysis model based on weighted fuzzy mutual information. Firstly, the combination of priority graph and CRITIC weighting is used to reduce noise and ambiguity, and the optimized weights are obtained. By using fuzzy mutual information to calculate the overall correlation between input indicators and the indicator space, the importance of input indicators is calculated and ranked, in order to clarify the key items of input indicators in the evaluation object and enable managers to make more comprehensive and reliable decisions.

2. Performance Index Evaluation Model Based on Weighted Fuzzy Mutual Information

2.1 Establishment of output index hierarchy

Therefore, this article considers the impact of performance input on different granularity indicators and divides the granularity output indicators into two granularity structure layers, as shown in Figure 1.

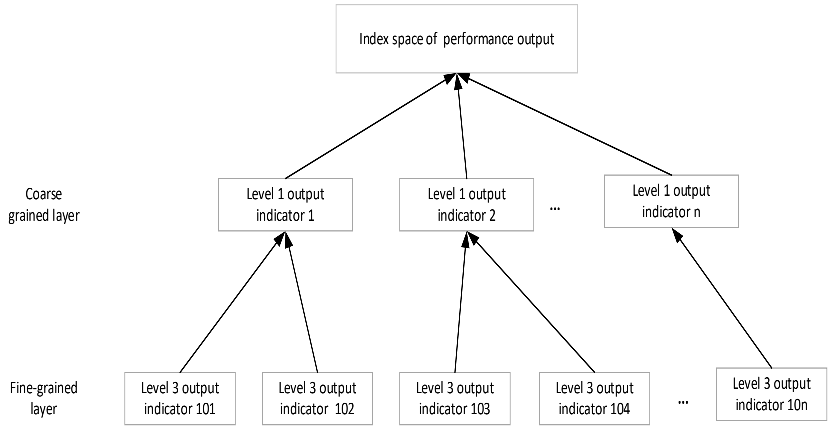

Figure 1: Hierarchy of granularity output indicators

2.2 Determine the portfolio assignment method

The weight affects the effectiveness of performance evaluation to a certain extent, and the greater the weight, the more important the indicator is. In traditional performance evaluation, there are subjective and objective methods of empowerment. The subjective weighting method uses subjective experience to determine the weight, which is prone to the disadvantage of weight imbalance; The objective weighting method relies entirely on data and ignores the importance of decision indicators. The calculation methods of different weights have their own limitations. There is correlation and data volatility between most performance indicators in performance evaluation, and CRITIC weighting method can effectively solve this problem. In addition, in most performance evaluations, obtaining subjective weights from the priority graph method can better meet the situation where there are a large number of evaluation indicators. Therefore, this article considers the actual weight of performance evaluation objects, combines the priority chart method and CRITIC weight method, and determines the combined weight of performance output indicators through the combination of the priority chart method and CRITIC. This method greatly balances subjective or objective weights, expanding the scope of application of the indicator weight calculation method.

2.3 CRITIC method to determine objective weights

In each indicator of the performance output, the data will be used in the process of the magnitude due to the difference of the order of magnitude. Therefore, it is necessary to transform the order of magnitude of the performance output indicators to the same standard consideration, then the performance indicator data matrix X.

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$$X=\begin{pmatrix} x_{11} & \cdots & xn \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}=(x_{ij})_{m\times n} \tag{1}$$

where xij is the value of the jth output indicator in the ith sample.

The positive output granularity indicator is expressed as:

$$x_{ij}^{'}=\left[\frac{x_{ij}-\min\left(x_j\right)}{\max\left(x_j\right)-\min\left(x_j\right)}\right] \tag{2}$$

The granularity index of reverse production is expressed as:

$$x_{ij}^{'}=\left[\frac{\max\left(x_j\right)-x_{ij}}{\max\left(x_j\right)-\min\left(x_j\right)}\right] \tag{3}$$

Calculate the information carrying capacity of performance output indicators

Calculate the volatility of output granularity index Sj (standard deviation of the jth index). The standard deviation indicates the fluctuation of the output index data. The size of the standard deviation indicates that the greater the index volatility, the greater the Information value.

Table 1: Grain size evaluation table of precedence chart method

Output indicators	O_1	O_2	O_3	$\cdots$	O_l
O_1	0.5	C_{12}	C_{13}	$\cdots$	C_{1l}
O_2	C_{21}	0.5	C_{23}	$\cdots$	C_{2l}
O_3	C_{31}	C_{32}	0.5	$\cdots$	C_{3l}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	0.5	C_{ll}
O_l	C_{l1}	C_{l2}	C_{l3}	$\cdots$	0.5

$$S_j=\sqrt{\frac{\sum_{i=1}^{n}(x_{ij}-\overline{x_j})^2}{n-1}} \tag{4}$$

Wherein, $\overline{x_j}=\frac{1}{n}\sum_{i=1}^{n}x_{ij}$ is the mean value of performance output indicators.

Calculate conflicting Rj of output granularity index. Calculate the correlation between indicators by covariance method σij, the greater the correlation between output indicators, the greater the amount of the same information reflected, so the weight of this output indicator should be reduced.

$$R_j=\sum_{i=1}^{l}(1-\sigma_{ij}),(i\neq j) \tag{5}$$

Calculate the information carrying capacity Cj of the output granularity index j. The greater the Cj value of the output indicator information carrying capacity, the more important the output indicator is.

$$C_j=S_j\sum_{i=1}^{n}(1-\sigma_{ij})=S_j\times R_j \tag{6}$$

where the number of output indicators of the ith granularity is p, n is the total number of output indicators, and g is the total number of granularity.

Calculate the weight wi of the ith output granularity index

$$W_i = \frac{\sum_{j=1}^{p} C_j}{\sum_{j=1}^{l} C_j} \quad (0 < i \le g) \tag{7}$$

where the number of output indicators of the ith granularity is p, n is the total number of output indicators, and g is the total number of granularity.

2.4 Determination of subjective weight by sequence diagram method

Using the precedence chart method, experts compare m output indicators in pairs to obtain l×l judgment matrix. The indicators to be compared are shown vertically, and the indicators to be compared are shown horizontally. The advantages and disadvantages obtained through comparison are shown by numbers 1, 0.5, and 0 respectively. In m×m certain value in the judgment matrix of m, Cij is taken as an example. The value of 1 indicates that the horizontal output index of this value is more important than the vertical output index. The value of 0.5 denotes that the two output indexes are equally important. The value of 0 represents that the horizontal output index is less important than the vertical output index. Grain size judgment table 1 shows:

Table 1 Grain size evaluation table of precedence chart method

Calculate the score TTLj of the jth output index.

$$TTL_j = c_{j1} + c_{j2} + c_{j3} + \cdots + c_{jj} + \cdots + c_{jl} \tag{8}$$

Amon, $c_{jj} = 0.5$.

Calculate the weight of the granularity index β_j

$$\beta_i = \frac{\sum_{j=1}^{p} TTL_j}{\sum_{j=1}^{l} TTL} \quad (0 < i \le g) \tag{9}$$

where TTL is the total score of output indicators.

2.5 Determination of combination weight by precedence chart method and CRITIC method

To make the weight more responsive to the actual value, the subjective weight β_i is optimized by the objective weight W_i, and the combination weight vi is obtained by combining the precedence chart method with the CRITIC weight method.

$$v_i = \frac{\beta_i w_i}{\sum_{j=1}^{l} \beta_i w_i} \tag{10}$$

2.6 Weighted fuzzy mutual information

2.6.1 Analyze the correlation between education input indicators and granularity indicators through fuzzy mutual information.

The larger the value, the stronger the correlation between input indicators and granularity indicators. There is a certain amount of relevant information between the granularity output indicator I and the input indicator Y. The more information there is, the greater the contribution and information value of the indicator, and the stronger the correlation between the input indicator and the granularity output indicator[15].

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2.6.2 Dividing Fuzzy Equivalence Classes at the Same Granularity Level

In this paper, fuzzy mutual information is defined as a five tuple multi granularity performance evaluation information system $S=\{U,I,O,F,T\}$ [16], Where $U=\{x_1,x_2,x_3,\cdots,x_n\}$ represents the sample set; $I=\{I_1,I_2,I_3,\cdots,I_m\}$ represents m input indicators; O refers to l output granularity indicators divided, and F refers to some functional relationship; $T=\{T_1,T_2\}$ represents coarse and fine grain layers [17]. Therefore, the sample fuzzy equivalent matrix $M(R)$ is as follows:

$$M(R)_{t_1}=\begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{pmatrix} \tag{11}$$

Where $r_{ij}\in[0,1]$ represents the relationship value with two evaluation samples, recorded as $R(x_i,x_j)$.

The fuzzy division of evaluation sample set U can be expressed as:

$$U/R=\{[X_i]_R\}_{i=1}^{n} \tag{12}$$

where the fuzzy equivalence class of evaluation sample xi about fuzzy equivalence relation R is shown as follows:

$$[x_i]_R=\frac{r_{i1}}{x_1}+\frac{r_{i2}}{x_2}+\cdots+\frac{r_{in}}{x_n} \tag{13}$$

The cardinal number of the fuzzy equivalent class of the evaluation sample is:

$$\left|[x_i]_R\right|=\sum\nolimits_{j=1}^{n} r_{ij} \tag{14}$$

Calculate the fuzzy entropy of the evaluation index from the fuzzy equivalent class divided by the evaluation sample $FH(I)$

$$FH(R)=FH(I)=-\frac{1}{n}\sum\nolimits_{i=1}^{n}\log\frac{\left|[x_i]_R\right|}{n} \tag{15}$$

Let I,Y denote the input index and granularity, respectively, and calculate their fuzzy joint entropy $FH(I,Y)$.

$$FH(I\mid Y)=-\frac{1}{n}\sum\nolimits_{i=1}^{n}\log\frac{\left|[x_i]_I\cap[x_i]_Y\right|}{n} \tag{16}$$

Next, calculate the fuzzy conditional entropy of input term and granularity $FH(I,Y)$

$$FH(Y\mid I)=-\frac{1}{n}\sum\nolimits_{i=1}^{n}\log\frac{\left|[x_i]_I\cap[x_i]_Y\right|}{[x_i]_I} \tag{17}$$

where $FH(Y\mid I)=FH(I,Y)-FH(I)$.

Finally, complete the calculation of fuzzy mutual information of input items and granularity $FMI(I;Y)$

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$$FMI(I;Y) = -\frac{1}{n}\sum_{i=1}^{n}\log\frac{\left|[x_i]_I \cdot [x_i]_Y\right|}{n\cdot\left|[x_i]_I \cap [x_i]_Y\right|} \tag{18}$$

where $FMI(I;Y) = FH(I) - FH(I\mid Y) = FH(Y) - FH(Y\mid I)$.

Suppose l granularity indicators are divided in the decision layer of performance analysis, and each granularity is combined and weighted to get the weight coefficient.

$$\xi = \sum_{1}^{l} FMI(I;Y)v_i \tag{19}$$

To increase or decrease the input of an indicator to improve the overall performance of the unit, it is necessary to determine the magnitude of the product of weighted fuzzy mutual information and granularity weight, that is, the importance of the input indicator. The greater the importance of input indicators, the more important the output indicator space becomes. On the contrary, the smaller the importance of input indicators, the smaller the overall impact on output indicators. By ranking the importance value from the highest to the lowest, the higher the importance value, the greater the input indicator, the impact on performance analysis results in investment such as funds or resources.

3. Example application and analysis

Optimizing undergraduate education investment indicators is extremely important in evaluating the comprehensive strength, management level, and talent cultivation quality of undergraduate institutions. Different granularity indicators have different descriptive abilities for decision-making units. By analyzing the performance of fine granularity indicators of undergraduate education performance in a certain province, it is possible to trace the corresponding education investment indicators, strengthen the specific investment of indicators, and reasonably allocate human, material, and financial resources; From a macro perspective, combining three levels of indicators to determine the coarse and fine granularity, and conducting a comprehensive performance analysis of the coarse granularity indicators can enable education management personnel to strengthen the construction of school educational facilities, optimize the allocation of educational resources, and improve the overall education and teaching level and talent cultivation. Taking 32 undergraduate education data from a certain province as a sample, there are 20 input indicators, recorded as I1-I20; It includes the introduction of high-end talents, doctoral degree teachers, full-time teachers, the total number of teachers, teaching volume, high-quality disciplines, project investment funds, unit talent training funds, etc. The performance output indicators are represented by the symbol Y. Coarse grained output indicators include unit discipline construction, unit talent cultivation, unit scientific research, unit faculty, social services, and impact; The fine-grained output indicators include employment rate, graduate students, undergraduate students, teaching achievement awards, education informatization awards, first-class majors, and Challenge Cup awards. For the convenience of sorting, the input indicators are shown in Table 2.

Table 2: Input Index Data

Sample	I_1	I_2	I_3	I_4	I_5	…	I_{20}
X_1	5	82	124	389	33412.12	…	13.97
X_2	13	84	133	322	27202.51	…	31.68
X_3	0	54	84	181	26620.27	…	30.62
X_4	4	34	37	78	9480.58	…	31.01
X_5	1	66	136	267	48365.46	…	27.14
X_6	2	16	47	63	21814.49	…	11.58
X_7	1	39	69	123	21664.84	…	19.74
…	…	…	…	…	…	…	…
X_{32}	3	68	102	208	25862.61	…	28.08

The 17 fine-grained output indicators are represented by Y101-Y117, as shown in Table 3.

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Table 3: Fine-grained output indicator data

Y_{101}	Y_{102}	Y_{103}	Y_{104}	Y_{105}	…	Y_{117}
5	82	124	19	33412.12	…	0
13	84	113	40	27202.51	…	100
0	54	84	14	26620.27	…	6
4	34	37	7	9480.58	…	0
1	66	136	267	48365.46	…	12
2	16	47	63	21814.49	…	0
…	…	…	…	…	…	0
2	0.92	165	1145	0	…	0

The five coarse-grained output indicators, denoted by Y1-Y5, are shown in Table 4.

Table 4: Coarse-grained output index data

Y_1	Y_2	Y_3	Y_4	Y_5
2456.25	122984.4375	39422.81	131016.375	32324.25
87199.948	87199.9479	48738.65	208069.29	65363.181
76609.88	76609.88	1452.32	140526.483	31863.901
26179.681	26179.6812	15421.27	40399.644	11532.586
85439.013	85439.013	24545.41	160299.238	18491.022
31860.936	31860.936	4391.99	24727.133	2767.205
…	…	…	…	…
30657.031	30657.0306	16771.4	70446.665	21066.099

3.1 Establishing a multi-grain hierarchical analysis model

According to the structure of the undergraduate education indicator system and the three-level indicators and granularity constraints of educational performance, the undergraduate education performance indicators in the province are divided into multiple granularity levels, including decision-making level, coarse granularity level, and fine granularity level. According to the structure and characteristics of the provincial undergraduate education indicator system, there are 17 fine-grained output indicators in the fine-grained layer, and 5 coarse-grained output indicators are extracted from the fine-grained output indicators. Coarse grained indicators include unit discipline construction, including two fine-grained indicators: first-class majors and support platforms. Unit talent cultivation includes five fine-grained output indicators: master's degree cultivation, undergraduate student cultivation, employment rate, challenge cup competition awards, and modeling competition awards. Unit scientific research includes four fine-grained output indicators: scientific research awards, academic journal papers, property rights works, and teaching and research projects. Unit faculty includes teaching achievements. There are three fine-grained output indicators for educational informatization awards and academic status, and three fine-grained output indicators for social services and impacts, including international or domestic conferences, outstanding alumni, and alumni donations. The hierarchical structure of granularity is shown in Fig. 2.

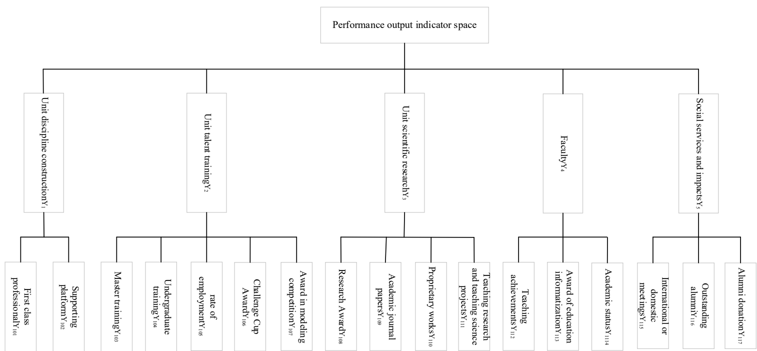

Figure 2: Multi-granularity hierarchy of educational performance

3.2 Combination weighted solution weight

Based on 32 undergraduate education data evaluation samples and 17 fine-grained evaluation indicators, a data matrix of fine-grained and coarse-grained indicators was established. To ensure the accuracy of granularity output indicator data, the range method is used to map the granularity data to the

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same measurement scale. In the CRITIC method, data normalization is performed on the particle size indicators in the sample using equations (2) to (3). Table 5 of the fine grain normalization data is shown below.

Table 5: Normalization Data of Fine Grain Index

Fine Grain	I	II	III	…
Y_{101}	0.384615	0.881720	0.911764	…
Y_{102}	1	0.903258	0.830882	…
Y_{103}	0.237069	0.580645	0.617647	…
Y_{104}	0	0.365591	0.272058	…
Y_{105}	0.376230	0.706774	1	…
⋮	⋮	⋮	⋮	⋮
Y_{117}	0.769230	0.172043	0.345588	…

Coarse grain normalization data are shown in Table 6.

Table 6: Normalized Data of Coarse Grain Size Index

Coarse grain size	I	II	III	…
Y_1	0	1	0.808701	…
Y_2	1	0.702325	1	…
Y_3	0.875034	0.614231	0.289890	…
Y_4	0.279943	0.194726	0.315837	…
Y_5	0.979220	0.687677	0.503198	…

Coarse grain normalization data are shown in Table 6.

Table 6 Normalized Data of Coarse Grain Size Index

The objective weight W_i of the particle size index is obtained by equations (4)~(7), the subjective weight β_i of the particle size index is calculated by equations (8)~(9), and the combined weight v_i of the particle size index is obtained by substituting into equation (10), then the combined weight of the fine particle size index is shown in Fig.3.

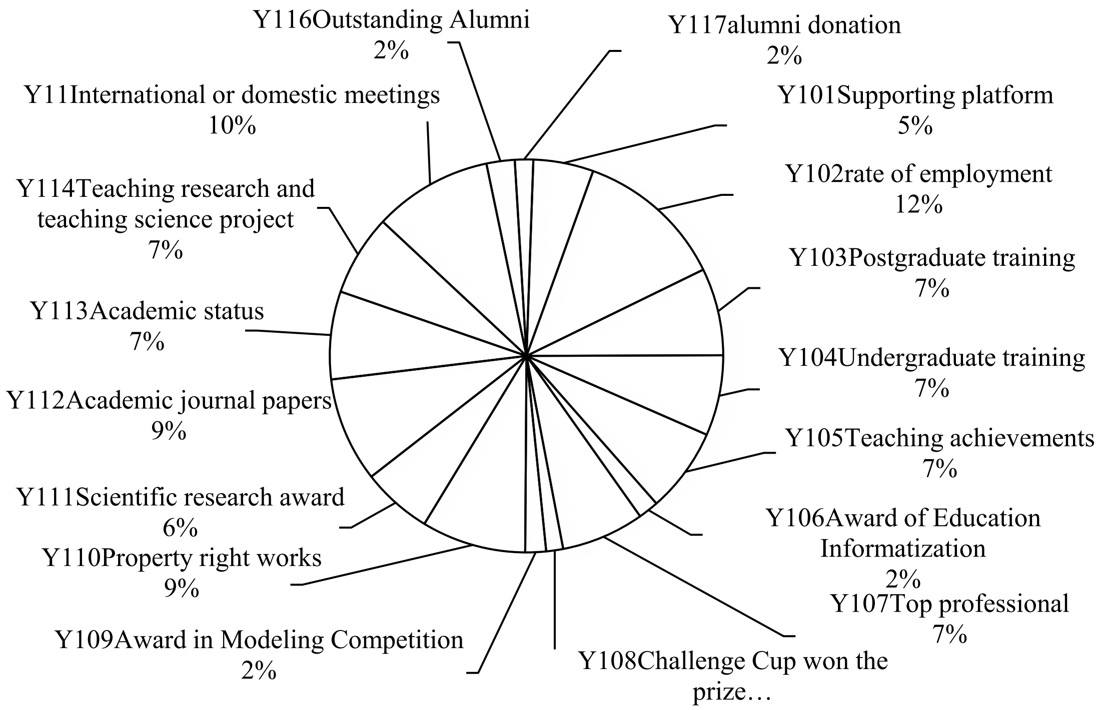

Figure 3: Weight of fine-grained indicators

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The combined weight of coarse-grained indicators is shown in Fig 4.

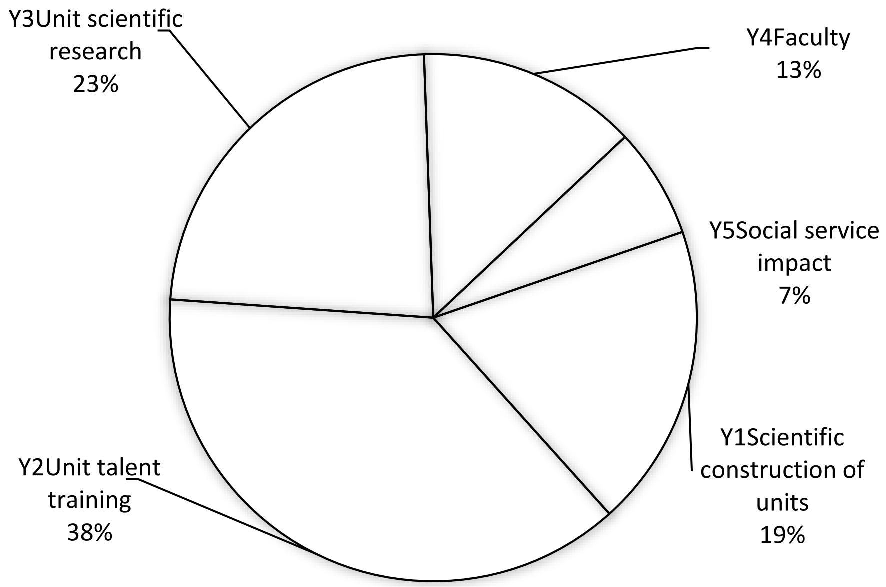

Figure 4: Coarse grain index weight

3.3 Build multi-granularity performance analysis models

The fuzzy equivalence matrix is established by the sample set, and the fuzzy equivalence matrix is divided into fuzzy equivalence classes $[x_i]_R$ by equations (11) to (14). The correlation degrees of input indicators and granularity indicators are calculated by equations (15) to (18). The correlation degrees of input indicators and fine-grained indicators are shown in Figure 5.

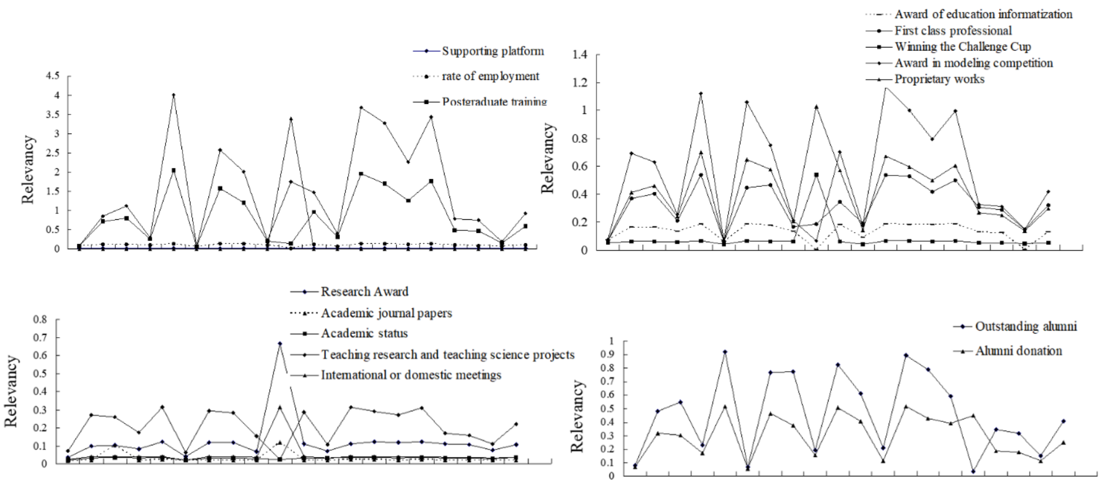

Figure 5: Correlation of fine-grained indicators

Fig.5. shows the correlation between the input indicators and 17 fine-grained indicators, including support platform, employment rate, master's training, undergraduate training, teaching achievements, education informatization awards, top majors, Challenge Cup awards, modeling competition awards, publications, research awards, academic journal papers, academic status, teaching and research and textbook projects, international or domestic conferences, distinguished alumni and alumni donations. In the experimental results of Figure 5, the 17 input indicators have the greatest correlation with undergraduate training, and the sorted results are teaching volume 4.01206>faculty staff funding 3.68304>staff funding 3.40280>discipline construction room area 3.28030>project input funding

2.57779>science research room area 2.26240>total unit talent development funding 2.01542>unit discipline construction funding 1.46253>faculty team equipment 0.92610>phd faculty 0.86451>faculty housing area 0.78505>talent training equipment investment 0.75949>total faculty 0.29424>unit research staff funding 0.2286>scientific research equipment investment 0.19251>introduction of high-end talent 0.08170>quality disciplines 0.06881.

The correlation between input metrics and coarse-grained metrics is shown in Fig.6.

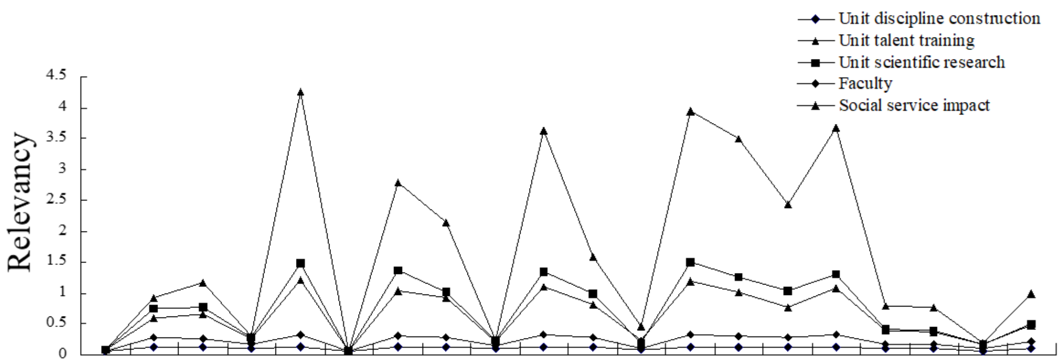

Figure 6: Coarse grain index correlation

Fig.6. index space is divided into 5 coarse-grained indicators, and the input indicators are correlated with the 5 coarse-grained indicators unit discipline construction, unit talent cultivation, unit scientific research, unit faculty, social service and impact for correlation degree analysis. In the experimental results of Figure 6, 19 input indicators have the highest degree of correlation with undergraduate training, and the output ranking results are teaching volume 4.26407>unit equipment funding 3.93512>faculty team room area 3.68798>personnel funding 3.63796>discipline construction room area 3.50462>project input funding 2.79192>science research room area 2.43255>total investment in talent cultivation of the unit 2.14977>expenditure on discipline construction of the unit 1.60087>full-time faculty 1.18106>investment in faculty equipment 0.98768>phd faculty 0.93611> Investment in equipment for discipline construction 0.79174>investment in equipment for talent cultivation 0.766187 >expenditure on faculty personnel 0.473105>total faculty 0.30522>total unit research staff funding input funding 0.23985>scientific research equipment input 0.19495>introduction of high-end talent 0.08170.

When the indicator space as a whole is taken as a granularity, the correlation degree of input indicators with the granularity indicator space is analyzed, as shown in Fig.7.

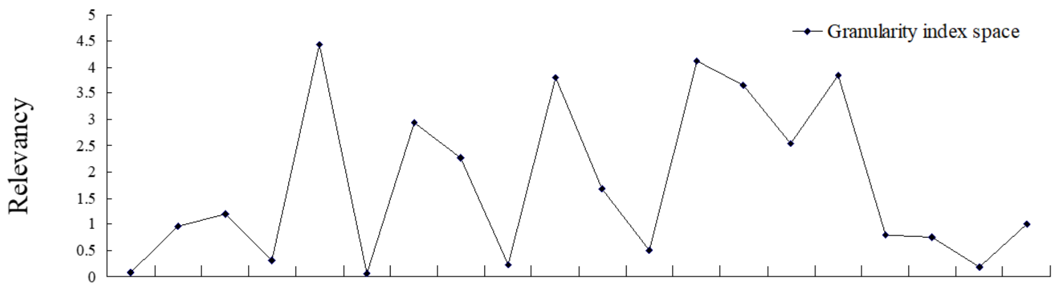

Figure 7: Spatial correlation of granularity metrics

Fig.7. correlates the input indicators with the granularity indicator space, teaching volume 4.44058>unit equipment funding 4.10740>faculty housing surface 3.83448>staff funding 3.79735>discipline construction housing surface 3.64533>project input funding 0.93089>science research housing surface 2.54671>unit talent training funding 2.25863>Unit discipline construction funding 1.68478>full-time faculty 1.19946>Faculty equipment investment>1.00023>phd faculty 0.96106>discipline construction equipment investment 0.79174>Talent training equipment investment 0.76618>faculty personnel funding 0.49724>total faculty 0.30790> unit research staff funding 0.23985> scientific research equipment investment 0.19495> introduction of high-end talent 0.081704> quality disciplines 0.06881.

3.4 The Importance of Input and Output Indicator Spaces

In the evaluation of provincial undergraduate education performance, the weights of each granularity are obtained from the combination weighting as coefficients, the correlation between input indicators and granularity is obtained by fuzzy mutual information analysis, and the importance of input indicators is obtained by multiplying the weight coefficients by the correlation degree, as shown in Fig.8..

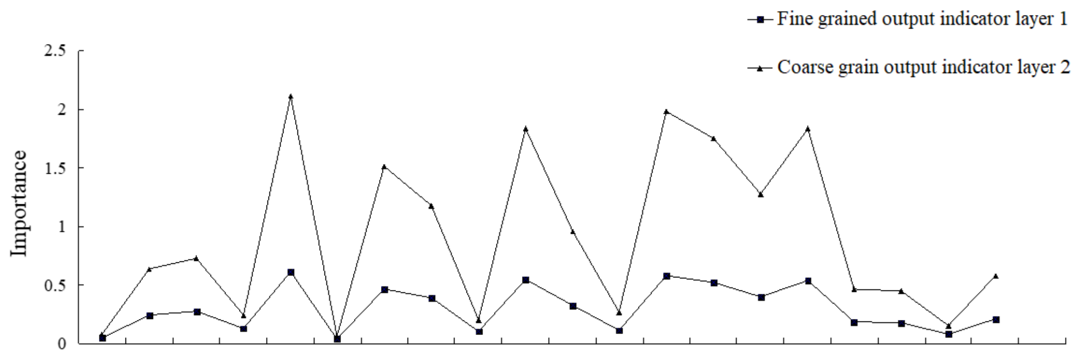

Figure 8: Importance of Input Indicators

As can be seen from Fig.8, the weighted fuzzy mutual information method can evaluate the importance of input indicators from the perspective of granularity output indicator layer 1 or coarse-grained output indicator layer 2, facilitating educational performance decision-making. In the ranking results of input indicators and fine-grained output indicator layer 1, Teaching volume: 0.61567>Unit equipment expenditure: 0.5855>Personnel expenditure: 0.5468>Room area for teaching team: 0.5417>Room area for discipline construction: 0.5241>Project investment: 0.4693>Room area for scientific research: 0.3990>Total investment in unit talent cultivation fund: 0.3924>Unit discipline construction fund: 0.3253>Professional teacher: 0.2782>Doctoral degree teacher: 0.2494>Equipment investment in teaching team: 0.2169>Equipment investment in discipline construction: 0.1896>Investment in talent cultivation equipment: 0.1803>Teacher team: Total amount: 0.1275>Funding for faculty and personnel, 0.1159>Funding for scientific research personnel in units: 0.1086>Investment in scientific research equipment: 0.0850>Introduction of high-end talents: 0.0492>Quality disciplines: 0.0441.

In the ranking result of input index and coarse grained output index layer 2, Teaching volume 2.1123>Unit equipment expenditure 1.9872>Room area for teaching team 1.8391>Personnel expenditure 1.8365>Room area for discipline construction 1.7556>Project investment 1.5139>Room area for scientific research 1.2749>Total investment in unit talent cultivation funds 1.1764>Unit discipline construction funds 0.9587>Full-time teachers 0.7323>Doctoral degree teachers 0.6353>Equipment investment in teaching team 0.5789>Equipment investment in discipline construction 0.4691>Investment in talent cultivation equipment 0.4490>Teacher team Personnel funding: 0.2732>Total number of teachers: 0.2487>Funding for scientific research personnel: 0.2027>Investment in scientific research equipment: 0.1552>Introduction of high-end talents: 0.0779>Quality disciplines: 0.0670.

4. Conclusion

Based on fuzzy mutual information, this paper proposes a weighted fuzzy mutual information based performance indicator importance analysis model. This model divides output indicators into coarse and fine granularity, analyzes the correlation between input indicators and granularity output indicators, and to some extent reduces the problems of data noise and single performance indicator analysis. In addition, the combination weighting method of priority graph and CRITIC avoids the problem of weight imbalance. Finally, the importance between input indicators and granularity output indicators is analyzed through fuzzy mutual information.

The experimental results show that this model takes into account the granularity division of output indicators, comprehensively and effectively analyzes the correlation between input indicators and granularity output indicators, clarifies the importance of input indicators, thereby optimizing the allocation of performance input indicators, and can improve undergraduate education performance. This

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method also has shortcomings. Further consideration should be given to how to establish a complete indicator system. On the basis of this experiment, we will deeply explore the correlation between coarse and fine granularity, establish a more complete granularity index system, and meet the scientific and targeted performance decision-making needs.

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