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# Study on research performance evaluation system of teachers teaching humanities and social sciences oriented to american colleges and universities

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**Abstract.** In order to improve the effectiveness of study on research performance evaluation system of humanities and social sciences teachers in American universities, this paper introduces the maximum entropy smooth distributive hidden Markov model (HMM) algorithm for data analysis. Firstly, from the three dimensions, total amount of scientific research, scientific research quality and frontier research, the indexes of Research performance Evaluation with discipline standardization oriented to humanities and Social sciences teachers in American Universities have been designed, so the academic achievements of the same scientific research entity in different subjects can be effectively and synthetically characterized, which not only eliminates the influences between scientific research entities due to the difference in disciplines; secondly, The maximum entropy smoothing distribution is used to conduct a feature capture of the local first-order moment and overall second-order moment , and to realize the maximum likelihood estimation of the soft decision parameters of the HMM output probability distribution; Finally, the validity of the proposed algorithm is verified by the simulation experiment.

**Key words.** Humanities and social sciences, Research performance, Hidden Markov, Soft decision, Maximum likelihood.

## 1. Introduction

The evaluation of scientific research performance oriented to humanities and social science teachers in American colleges and universities is the analysis and evaluation of the performance of scientific research entities, which can help the scientific

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research Management department to accurately grasp the status of scientific research in this organization and its development trend, and is of great significance to optimize the allocation of scientific research resources and improve the management of scientific research. In different evaluation systems, the scientific research entity can be an organization, or it can be a discipline, research team or individual in the organization. On the one hand, different types of scientific research entities take academic papers as the main form of their scientific research performance, so from the perspective of literature metrology, the output and influence of scientific research entity can be measured by introducing the literature metrology index, revealing the performance of scientific research performance of scientific research entities. The evaluation method of scientific research performance based on literature metrology is objective and impartial, which can overcome the evaluation deviation brought by peer review due to subjective judgment, and form a good complementarity, playing an important role in various research performance evaluations.

On the other hand, there are differences in the research field of different scientific research entities, because there are obvious differences in the quantity of articles and the citation law between different disciplines, so the research performance of different research teams can not be compared with the same scale. Therefore, it is necessary to construct the index of discipline standardization to eliminate the difference caused by different disciplines, the current methods based on the standardization of disciplines have yielded quite a lot of fruits, and have also been widely used in scientific research performance evaluation of institutional disciplines, research teams or individuals oriented to the Humanities and Social sciences teachers in American Universities.

However, as the research result of the same research entity may belong to different categories of discipline, and these standardized discipline indexes are often used only for the evaluation of a single subject, that is, a measurement and evaluation of scientific research performance by limited institutions, research teams or individuals in a specific discipline , which is not conducive to the description of overall level of performance of scientific research entities , so a reasonable aggregate model is needed to uniformly integrate and characterize the academic achievements of different disciplines involved by it. Consequently, it is necessary to properly popularize and promote the standardized indexes used for the single-subject to the research performance evaluation of individual or research team oriented to the humanities and social sciences teachers in the American Universities, and in turn to construct a unified research performance evaluation Index system which can be applied to different scientific research entities.

This paper introduces three subject-standardized evaluation indexes, scientific research total amount index, scientific research quality Index and Frontier Research index, describing the level of performance of scientific research entity as a whole comprehensively from three dimensions, which are scientific research productive competence and academic influence, entity's scientific research level and efficiency, and the performance of scientific research entity over hot issues and Frontier fields, and then a set of evaluation index system can be established to apply to the three different levels, individual, research team and subject. As the application of the evaluation Index system, the researchers, research teams and subjects from a certain university in China were selected as a sample of study, the research performance evaluations on three different levels, individual, team and subject, were carried out, hoping to provide new ideas and tools for the evaluation of scientific research performance of other scientific research entities oriented to Humanities and Social sciences teachers in American Colleges and universities.

## 2. Method of calculating the index standardization

Yu Liping et al evaluated the efficiency of scientific research from two aspects, scientific and technological input and scientific and technological output specific to the selection of evaluation index of scientific research entity, and the output index, influence index and cited index are designed to describe the level of scientific research performance. Costas R et al used factor analysis method to cluster different indexes, forming the evaluation Index system of scientific research performance oriented to humanities and social science teachers in American universities with three dimensions that are output, influence and periodical quality. In the literature [6], a set of system for evaluating the performance of institutional research is constructed, as shown in table 1.

Table 1. Evaluation Index system of scientific research performance oriented to humanities and social science teachers in American universities

| Primary index | Secondary index |
|---|---|
| Total amount of scientific research | Total quantity of papers |
| | Total paper citations |
| Scientific research quality | Citations per paper |
| | Citation percentage |
| Frontier research | Percentage of papers with citation frequency ranked as the first 10% |
| | ESI highly cited papers percentage |
| | ESI hot papers percentage |

In this paper, the evaluation Index system is continuously used to design and describe the standardization index of total quantity, quality and frontier research level of scientific research entity. The specific idea is as follows: Selecting the scientific research entities, taking the scientific research performance of the scientific research entity on each subject within a certain period as the minimum analysis unit, according to the secondary indexes listed in table 1, it is standardized in each subject unit, each secondary index is weighted and synthesized to obtain the standardized indexes of scientific research entities in three dimensions that are total quantity, quality and frontier research , and finally the different subject indexes involved by the scientific research entities are weighted and synthesized to obtain the research index of total quantity, quality and frontier research of research entities as a whole.

## 3. Hard decision tree F0 model

### 3.1. F0 model in HMM framework

Under normal conditions, the evaluation of scientific research performance oriented to the humanities and social sciences teachers in American colleges and universities and its derivative and second-order derivative constitute three data streams of multi-spatial probability distribution (MSD) that depend on the context from left to right. The model structure is based on the observed value released by the hidden state to produce the evaluation unit track of scientific research performance. The distribution of output of the state is a context-dependent multi-spatial Gaussian distribution , and the decision tree is used to cluster the related contexts into groups to reduce the number of free parameters and to allow for visualized context modeling. To put it simply, the following discussion is confined to a single-data stream HMM , which is simpler than in the case of multiple data streams.

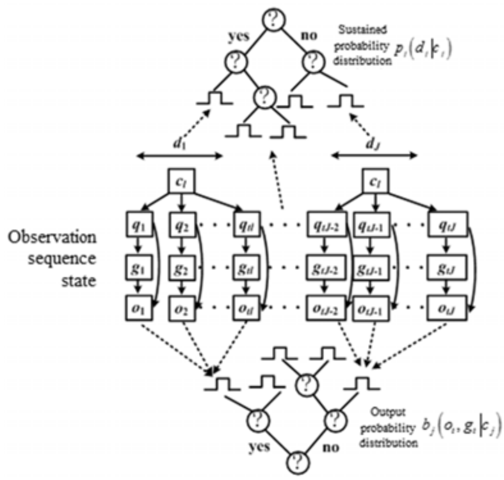


Fig. 1. HMM figure model

Fig. 1 shows an equivalent dynamic Bayesian network (DBN) for HMM. In the figure, $q_t o_t$ and $g_t$ respectively indicate the state index at the moment $t$, the research performance evaluation eigenvector and spatial index. When the output distribution is defined using two spaces of MSD , the observed value of the spatial index is consistent with the label of the research performance evaluation factor. The figure also introduces the environmental factors of scientific research $c_j$, duration $d_j$ and the last frame index $t_j$ of state $j$, obviously, $d_j = t_j - t_{j-1}$. It should be noted that the state boundary is a latent variable and it must receive a non-supervision training by the use of the expectation maximization (EM).

It can also be known from the Fig.1 that, HMM can be simplified with three basic distribution sets: the first one is the duration probability distribute state $p_j\left(d_j \left| c_j\right.\right)$; the second one is the scientific research performance factor (space) probability distribution $\omega_j\left(g_t \left| c_j\right.\right)$; the third one is the output probability distribution of given scientific research performance factor label $b_j\left(o_t\left|g_t,c_j\right.\right)$. By the use of these basic distributions and in consideration of the figure model shown in the Fig.2, the observation likeliness of given scientific research performance evaluation factor $(o,g,c)$ can be decomposed into:

$$\begin{aligned} p\left(o,g|c;\lambda\right) &= \sum\nolimits_{t_1,t_2,\cdots,t_J}\prod\nolimits_{j=1}^{J}p_j\left(d_j|c_j\right) \\ &= \prod\nolimits_{j=1}^{J}\omega_j\left(g_t|c_j\right)b_j\left(o_t\left|g_t,c_j\right.\right). \end{aligned} \tag{1}$$

Where, $J$ and $\lambda$ respectively denote the total amount of states and model parameters.

Assume $g_t$ is a two-value parameter, “1” denotes the scientific research performance evaluation data frame, “0” denotes the area without scientific research performance evaluation. Meanwhile, assume $b_j$ and $p_j$ is expressed by Gaussian distribution. Thus, the above likeliness function of scientific research performance evaluation factor can be modified as :

$$\begin{aligned} p\left(o,g|c;\lambda\right) &= \sum\nolimits_{t_1,t_2,\cdots,t_J}\prod\nolimits_{j=1}^{J}\mathcal{N}\left(d_j;\bar{m}_j,\bar{\sigma}_j^2\right) \\ &= \prod_{t=t_{j-1}}^{t_j}\left[g_t\bar{\omega}_j\mathcal{N}\left(o_j;\bar{\mu}_j,\bar{\sum}\nolimits_j\right)+\left(1-g_t\right)\left(1-\bar{\omega}_j\right)\right] \end{aligned} \tag{2}$$

Where $\mathcal{N}\left(\cdot;\mu,\sum\right)$ denotes the Gaussian distribution whose mean vector is $\mu$, variance matrix is $\sum$. In this equation, the duration and output distribution are expressed by the duration mean value $\bar{m}_j$, time variance $\bar{\sigma}_j^2$, voiced degree $\bar{\omega}_j$, output mean vector $\bar{\mu}_j$ and observation covariance matrix $\bar{\sum}_j$. As mentioned before, the basic distribution can be expressed by typical decision tree structure. Assume $I_l^d\left(c_j\right)$ and $I_l^o\left(c_j\right)$ are defined as binary index decision tree function for output distribution and duration, where $l$ and $c_j$ are the leaf index and research environment factor of the state $j$. That is, $I_l^d\left(c_j\right)$ and $I_l^o\left(c_j\right)$ decide whether the state $j$ is assigned to the $l$th duration and observation decision tree. The hidden Markov model parameter can be expressed by these decision tree index functions:

$$\begin{cases} m_j=\sum_l I_l^d(c_j)m_l, \sigma_j^2=\sum_l I_l^d(c_j)\sigma_l^2 \\ w_j=\sum_l I_l^0(c_j)w_l, \mu_j=\sum_l I_l^0(c_j)\mu_l \\ z_j=\sum_l I_l^0(c_j)Z_l, \end{cases} \tag{3}$$

Where, $m_l$ and $\sigma_l^2$ respectively are the mean and variance of duration on the $l$th leaf of the time decision tree. Similarly, $\omega_l$, $\mu_l$ and $\sum_l$ respectively denote the scientific research performance evaluation factor expression and output probability distribution parameter, which are used to train the $l$th leaf of output decision tree.

### *3.2. Hidden Markov model parameter estimation*

The maximum-likelihood criteria is usually used to estimate HMM model parameter. However, the state boundary is hidden, thus, EM algorithm is needed for estimation. Given that, N independent identically distributed scientific research performance evaluation factors $\{(o^n, g^n)\}_{n=1}^{N}$, accompanied by its scientific research environment factor $\{c^n\}_{n=1}^{N}$, the parameter estimation formula as follows can be obtained by the use of EM algorithm:

$$\hat{m}_l = \frac{\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_l^d(c_j^n)\sum_{t_j,t_j-1}\chi_j^n(t_j,t_{j-1})[t_j - t_{j-1}]}{\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_l^d(c_j^n)\sum_{t_j,t_j-1}\chi_j^n(t_j,t_{j-1})}. \tag{4}$$

$$\hat{\sigma}_l^2 = \frac{\sum_{n=1}^{N}\sum_{j=1}^{n} I_l^d(c_j^n)\sum_{t_j,t_j-1}x_j^n(t_j,t_{j-1})[t_j - t_{j-1} - \hat{m}_l]^2}{\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_l^d(c_j^n)\sum_{t_j,t_j-1}x_j^n(t_j,t_{j-1})}. \tag{5}$$

$$\hat{\mu}_l = \frac{\sum_{n=1}^{N}\sum_{j=1}^{n} I_l^0(c_j^n)\sum_t \gamma_j^n(t) g_t^n[o_t^n]}{\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_l^0(c_j^n)\sum_t \gamma_j^n(t)}. \tag{6}$$

$$\hat{\sum}_l = \frac{\sum_{n=1}^{N}\sum_{j=1}^{n} I_l^0(c_j^n)\sum_t \gamma_j^n(t) g_t^n[(o_t^n - \hat{\mu}_l)(o_t^n - \hat{\mu}_l)^T]}{\sum_{n=1}^{N}\sum_{j=1}^{n} I_l^0(c_j^n)\sum_t \gamma_j^n(t) g_t^n}. \tag{7}$$

$$\hat{\omega}_l = \frac{\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_l^0(c_j^n)\sum_t \gamma_j^n(t) g_t^n}{\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_l^0(c_j^n)\sum_t \gamma_j^n(t)}. \tag{8}$$

Where, in the process of execution of EM algorithm, $\hat{m}_l\hat{\sigma}_l^2\hat{\mu}_l\hat{\sum}_l$ and $\hat{\omega}_l$ are the renewed value of $m_l\sigma_l^2\mu_l\sum_l$ and $\omega_l$. Meanwhile, $\chi_j(t_j, t_{j-1})$ is the probability of state $j$ from the moment $t_{j-1}$ to $t_j$. $\gamma_j(t)$ denotes the posterior probability of state $j$ at the moment $t$. These probabilities can be calculated through the famous forward-backward algorithm.

### *3.3. State clustering of decision tree scientific research performance evaluation factors*

In order to capture the dependency of the performance evaluation factors of the anterior and posterior scientific research contained by the inherent scientific research performance evaluation character , the typical decision tree is usually designed under the framework of hidden Markov model. The decision tree is constructed by a greedy and Top-down iterative program, which maximizes the logarithmic likelihood criterion. This process starts with a single root node and realizes the expression of fragments of all the factors that evaluate the performance of scientific research. In each iteration, an optimal terminal node problem is selected, so that the splitting terminal node presents the maximum increase of logarithmic likelihood value for the selected problem result. The splitting process will continue till the termination criterion is met (such as , the minimal description length criterion). The overall logarithmic likelihood increased value $\delta\mathcal{L}$ can be realized by splitting the parent node $l_1$ into two child nodes $l_2$ and $l_3$, and can be calculated with the following formula:

$$\begin{aligned}\delta\mathcal{L} =& \frac{1}{2}\log\left(\left|\hat{\sum}_{l_1}\right|\right)\sum_{n=1}^{N}\sum_{j=1}^{J^n} I_{l_1}^0(c_j^n)\sum\nolimits_t \gamma_j^n(t) - \\ &\sum_{l\in\{l_2,l_3\}}\frac{1}{2}1og\left(\left|\hat{\sum}_{l_1}\right|\right)\sum_{n=1}^{N}\sum_{j=1}^{J^n}(c_j^n)\sum_t \gamma_j^n(t).\end{aligned} \tag{9}$$

Where, the superscript n is the quantity of training samples of scientific research performance evaluation factor. It should be noted that, to achieve an increase of likelihood probability, the assumption shall be provided as follows: 1) the occupation probability value is constant in the process of clustering; 2) the overall likelihood measure assumption is approximated by a weighted mean of a simple logarithm likelihood posterior probability. These assumptions make it possible for the calculation of $\delta\mathcal{L}$ of terminal node and problem.

### *3.4. Algorithm structure*

Generally speaking, the decision tree is a hierarchical term that contains both internal nodes and terminal leafs. A typical two-fork decision tree is used to model the performance evaluation of scientific research, and each terminal node can capture the statistical characteristics of the anterior and posterior research environment clustering . similarly ,as to a given research environment $c$, each internal node undergoes a two-value test $f_m(c)$, and based on the test result, a test child node is chosen. Assume $I_m(c)$ is defined as the index function of node m. similarly, assume $I_{m_L}(c)$ and $I_{m_R}(c)$ denote the index function of child node to the left and right of it; $I_{m_L}(c)$ and $I_{m_R}(c)$ can be calculated as:

$$I_{m_L}(c) \overset{\text{det}}{=} \begin{cases} I_m(c)\,,\ \text{if } f_m(c) = true \\ 0,\ \text{if } f_m(c) = false \end{cases} \tag{10}$$

$$I_{m_R}(c) \overset{\text{det}}{=} \begin{cases} I_m(c)\,,\ \text{if } f_m(c) = false \\ 0,\ \text{if } f_m(c) = true \end{cases} \tag{11}$$

Therefore, to determine the given context factor distribution, it is necessary to start with the root node, and to recursively apply it to each internal node test, and select a branching result based on the output. The process is repeatedly iterative, until a leaf node satisfies the requirement, and the distribution of this node is considered to be the output probability distribution. Therefore, in each case, there is only one path passing from the root node to the terminal node, and the fragment of scientific research performance evaluation factor is assigned at this place, and the distribution of the single leaf has been affected. In order to improve the performance of typical decision tree, a soft binary decision tree structure is proposed here, which can build several fuzzy paths from root to multiple leafs.

Soft decision tree applies soft decision $\bar{f}_m(c)$ to its internal node m, and redirects all the offspring individuals with a certain degree of membership, which can be calculated with $\bar{f}_m(c)$ and 1-$\bar{f}_m(c)$. In fact, the soft decision tree of each node represents the fuzzy subset of environmental factor space, thus, each research environment is attached to several nodes. To be more precise, when we carry out an ergodic to the node m in the given research environment $c$, soft inquiry $\bar{f}_m(c)$ represents the degree of membership when the left offspring is chosen, obviously, 1-$\bar{f}_m(c)$ represents the degree of membership when the right offspring is chosen.

In the hard and soft decision tree based on HMM model, initially, a group of research environment factors must be defined, and all the scientific research performance evaluation factors training samples must be extracted. Afterwards, in contrast to the hard decision tree inquiry problem $f_m(c)$, a large number of soft inquiry problems (soft test) $\bar{f}_m(c)$ have been designed for different research environment factors. These problems are assigned to the internal node of decision tree, and a fuzzy decision about offspring selection has been made, instead of the final weak decision.

Based on the above discussion, all the terminal leafs may be valid to any research environment. Meanwhile, it is necessary to express the index function $I_m(c)$ in the form of membership function shown in the formula (3) using research environment $c$ and node $m$. The membership function can be calculated through the following method:

$$\left\{ \begin{array}{l} Initialization:\ I_{root}(c) = 1 \\ Recursion: \left\{ \begin{array}{l} \bar{I}_{m_L}(c) = \bar{f}_m(c)\bar{I}_m(c) \\ \bar{I}_{m_R}(c) = (1-\bar{f}_m(c))\bar{I}_m(c) \end{array} \right\} \end{array} \right. . \tag{12}$$

Where, $m_L$ and $m_R$ are the left offspring node and right offspring node of node m. according to the above definition recursion, all the degrees of membership can be calculated through ergodic tree. The ergodic process starts with the root node membership being set as 1, by observing the node m, and confirming its membership $\bar{I}_m(j)$, its left and right offspring node can be obtained. If it is a left offspring node, its membership can be calculated with $\bar{f}_m(c)\,\bar{I}_m(c)$; otherwise, the program returns to $\left(1-\bar{f}_m(c)\right)\bar{I}_m(c)$, where m is the parent node.

In the stage of training, soft decision $\bar{f}_m(c)$ is selected with the predefined research environment function. This function must keep a restrictive condition over all the research environment factors:

$$\forall m, c, 0 \le \bar{f}_m(c) \le 1\,. \tag{13}$$

In the process of defining soft question, the above restriction must be considered. In other words, we do not permit that the value of soft question being used is more than 1 or less than 0; thus, before the decision tree clustering is started, normalization step shall be set for some questions.

## 4. Experimental analysis

The research paper data from 2010 to 2014 in 2 national key laboratories at a certain university in US has been selected, Lab 1 mainly focuses on 2 disciplines, the chemistry and materials science, and Lab 2 mainly focuses on 2 disciplines, the humanities and social sciences and philosophy. It is possible to calculate the annual total scientific Research index, research quality index and Frontier Research index of two laboratories in 2010-2014, as shown in the table 2.

Table 2. The scientific research index of 2 key laboratories in 2010-2014

| | Research team | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|
| total scientific Research index | Lab1 | 5.37 | 5.56 | 5.81 | 5.79 | 6.12 |
| | Lab2 | 9.54 | 8.45 | 8.55 | 8.33 | 7.80 |
| research quality index | Lab1 | 1.21 | 1.21 | 1.67 | 1.33 | 1.88 |
| | Lab2 | 1.43 | 1.57 | 1.28 | 1.56 | 1.40 |
| Frontier Research index | Lab1 | 0.34 | 0.58 | 0.67 | 0.69 | 0.70 |
| | Lab2 | 1.16 | 1.27 | 0.46 | 1.30 | 0.50 |

According to the data in table 2, we can get the trend chart of total research index, quality Index and Frontier Research index of 2 key laboratories, for detail see Figure 2∼4. As it can be known from Figure 2, Lab 1 's total scientific research amount has been on the rise, indicating that its paper output capacity has increasingly increased and the scope of influence of its papers has continued to expand, and Lab 2 's total scientific research amount grows more slowly than Lab 1 does, resulting in a lower share in the total scientific research amount compared to Lab 1 and Lab 2, thus lab 2 ‘s total scientific research amount index shows a downward trend.

As shown in Figure 3, the scientific research quality index of Lab 1 and Lab 2 have exceeded the global average level, but there are significant rises and falls, Lab 1 shows a significant upward trend, while Lab 2 has no significant upward or downward trend. As shown in Figure 4, Lab 1 's frontier research index is increasing year by year but at a slower rate, always below the global average level, while Lab 2 has a higher level of frontier research than the global average level in 2010,2011 and 2014, reflecting a relatively high level of frontier research, However, in 2012 and 2014, its index fell below the global average level, and had a large falling range, suggesting that, it should continue to increase the strength of frontier research, and strive to maintain a stable level of research.

## 5. Conclusion

Based on the three dimensions of total amount of scientific research, scientific research quality and frontier research, this paper designs an evaluation Index of scientific research performance for the humanities and social sciences teachers in American colleges and universities with a subject standardization, and at present, some widely used subject standardization indexes, such as AI, AAI and MNCS, can

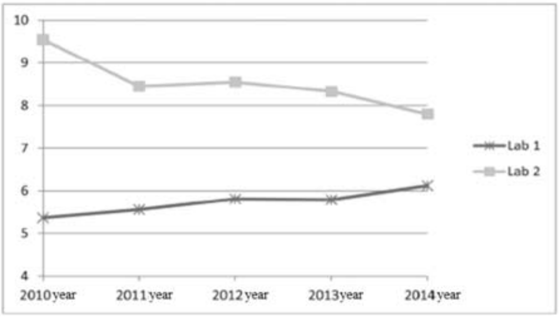


Fig. 2. Trend of scientific research total amount index of research team

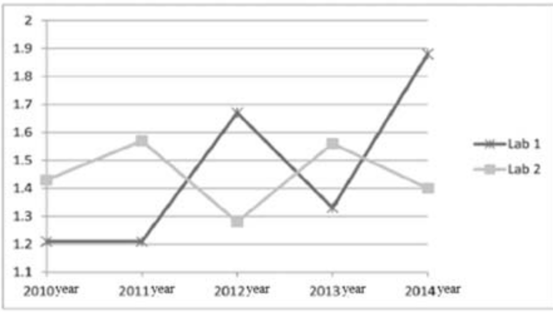


Fig. 3. Trend of scientific research quality index of research team

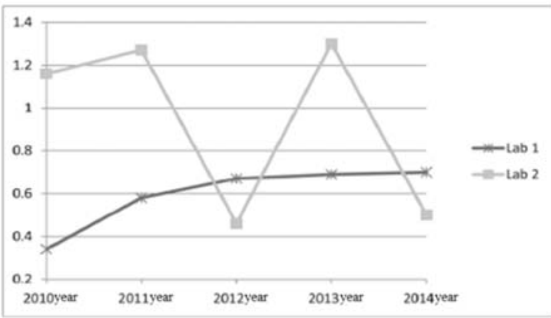


Fig. 4. Trend of frontier research index of research team

be used as special cases for it. Thus, a set of scientific research performance Evaluation Index system, which is suitable for scientific research entities, is established for the humanities and social science teachers in American colleges and universities. From the empirical analysis, it can be seen that the evaluation system can effectively synthetically characterize the academic achievements which belong to different disciplines of the same scientific research entity, it not only eliminates the influence of scientific research entities due to the difference of disciplines, but also can be extended to scientific research performance evaluation of individual, research team, institution and other scientific research entities on different levels.

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