Student Employment Forecasting Model Based On Random Forest And Multi-features Fusion

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Most of the traditional university employment forecasting systems adopt a single traditional feature modeling, which leads to poor employment forecasting effect and weak employment accurate service. Therefore, this paper proposes a novel student employment forecasting model based on random forest and multi-features fusion. Firstly, the student data is preprocessed to remove irrelevant attributes to achieve data consistency. Secondly, in order to improve the accuracy of the prediction model, a feature selection model combining principal component analysis and random forest algorithm is used to select the optimal subset from the original features. Finally, considering the prediction accuracy and prediction time, a combined prediction model GRU-LSTM based on gated recurrent unit (GRU) and long short-term memory network (LSTM) is proposed. The employment data is forecast efficiently and accurately. The experimental results show that compared with the advanced methods, the accuracy of employment prediction is increased by 4.2%, which provides reliable data support for improving the employment of college students.

Keywords: student employment forecasting; random forest; multi-features fusion; gated recurrent unit; long short-term memory network

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1. Introduction

Nowadays, with the development of globalization, automation and artificial intelligence, student employment is very important for educational institutions [1]. Through the employment prediction model, schools can understand employment trends across majors and courses, so that they can plan and improve courses more effectively and keep education in line with market needs. For students, the model provides suggestions for choosing a major or industry, which can help them better plan their future career development [2]. Overall, the student employment prediction model is a powerful tool to facilitate schools and students to better adapt to the dynamic job market and improve the match between education and employment [3, 4].

In the education information system, Educational Data Mining (EDM) plays a key role in analyzing and mining a large amount of data in the field of education by using data mining technology to reveal the patterns and trends of students' learning, performance and behavior [5, 6]. EDM solves data analysis problems by applying methods such as machine learning, statistics, information retrieval and recommendation systems. Rusilowati et al. [7] analyzed seven factors affecting the employment of college graduates, including age, extracurricular activities, professional field, marital status, communication ability, department and industrial internship experience. The employment prediction model proposed in Zhao et al. [8] combined rough set and random forest (RF) algorithm, and optimized model parameters through grid search. Hera et al. [9] proposed an academic prediction method based on artificial neural network (ANN), and proved that prediction performance of ANN was better than RF and linear regression (LR) algorithm.

In the last decade, deep learning as an extended framework for ANN has attracted a lot of attention from researchers. Zhang et al. [10] proposed an academic prediction model based on recurrent neural network (RNN), and experimental results showed that RNN had better prediction performance than ANN. In Vijayan et al. [11], five different multi-layer perceptron (MLP) sub-models were used to construct a deep stacked prediction model for different environmental factors, which achieved good performance in the job prediction task of information technology students. Wang [12] used BP neural network and support vector machine to model and predict the employment rate of college graduates, and then obtained the prediction results. To sum up, the researches on the above employment forecasting methods all stay on the choice of forecasting model, and do not analyze the input features of the model. For example, it is impossible to determine the contribution rate of the influencing factors to the employment of colleges and universities due to the many influencing factors [13]. To solve the above problems, this paper proposes a multi-feature fusion method and RF for college student employment prediction. This method applies behavior features to employment prediction, and designs a new method of employment prediction for college students, which has certain application value and important practical significance to improve the accuracy of employment prediction.

2. Materials and methods

2.1. Data preprocessing

Data preprocessing is a data mining strategy that converts input data into a format that facilitates further processing. First, credit scores are assigned to "text" data type attributes, such as native place, major, etc., and then Z-value normalization technology is applied to eliminate noise in the data set [14].

$$D' = \frac{D - (\bar{X})}{\delta(X)} \tag{1}$$

Where D is the original data set. D' is the normalized data. $\bar{X}$ is the feature mean. $\delta(X)$ is the characteristic standard deviation.

2.2. Feature selection based on improved RF algorithm

An improved algorithm combining PCA and RF is used to reduce the feature dimension while preserving the original data information. Subsequently, the obtained results are used as input to the DBN prediction model to improve the computational efficiency and accuracy of feature extraction [15–17].

PCA algorithm is widely used in feature dimensionality reduction to reduce the computation time of neural networks and improve the computation speed [18]. Let the normalized feature set be $X' = \left\{x_1^1, x_1^2, x_i^j, \cdots, x_m^n\right\}, j$ is the decision variable. The covariance matrix R is obtained by using the linear transformation.

$$R = \frac{1}{n}\left(X'\right)^T\left(X'\right) \tag{2}$$

Solving $|\lambda I - R| = 0$, it can obtain eigenmatrix λ, and calculate the cumulative contribution β_i:

$$\beta_i = \sum_{i=1}^{k} \frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{3}$$

Thus, we get the first k principal component features of β_i between 75% and 95%, which contains most of the original variable information. After PCA dimension reduction, the feature importance is evaluated by RF and the optimal feature subset is selected. The RF algorithm sets about 1/3 of the samples as the unselected part and treats this part of the samples as the out-of-pocket data [19]. By perturbing out-of-pocket data not involved in decision tree training, the difference of classification accuracy is calculated to obtain the importance of features. By perturbing out-of-pocket data not involved in decision tree training, the difference of classification accuracy is calculated to obtain the importance of features. The specific improved RF algorithm is shown in **Algorithm 1**.

Algorithm 1. Improved RF.

1. Bootstrap sampling is carried out with M feature subsets to generate M decision trees, and each tree is generated independently.
2. Let $m = 1$, train the decision tree T_m. The $m-$ th data set is taken as the training data, and the accuracy L_m of the $m - th$ out-of-pocket data is calculated.
3. Rearrange the features f in the out-of-pocket data set and calculate the accuracy L_m^k.
4. For all sample data sets $m = 2, 3, \cdots, M$, repeat step 2 and step 3 .
5. Calculate the classification accuracy error after feature rearrangement, expressed as:
$$e_m^f = L_m - L_m^f$$
6. Calculate the influence of features on the accuracy of out-of-pocket data:

$$e^f = \frac{1}{M}\sum_{m=1}^{M} e_k^f$$

7. Calculate the variance of e^f :

$$S^2 = \frac{1}{M-1}\sum_{m=1}^{M}\left(e_m^f - e^f\right)^2$$

8. Based on Eqs. (5) and (6), calculate the importance $f_F = e^f/S$ of feature f.

9. After the f_F is obtained, a feature subset is generated by removing one feature one by one from the sorted feature set, and the accuracy of the feature subset is calculated. Finally, the subset with the highest accuracy is selected as the optimal feature subset.

2.3. Traditional feature vector construction

Traditional factors include students' course grades, computer grades, English proficiency and other information. In this paper, the matrix decomposition technique is used to construct the loss function, and the eigenvector representing the students' basic professional ability is solved [20, 21]. The computer level and English level are quantified into the performance information processing, and a target matrix is constructed.

Firstly, the curriculum matrix $R \in R^{m\times n}$ is constructed by normalizing the information of students' grades. Where each element r_{ij} of the matrix R represents grade of student u_i in course c_j. Factorizing the matrix R into the product of two matrices $P_{m\times k}$ and $Q_{k\times n}$, that is:

$$R_{m\times n} \approx P_{m\times k} \times Q_{k\times n} = \widehat{R}_{m\times n} \tag{4}$$

Where k is a parameter used to represent k types of potential expertise. The matrix $P_{m\times k}$ represents the ability of each student to correspond to a professional skill. The matrix $Q_{k\times n}$ is used to represent the corresponding relationship between k professional skills and each course. In order to ensure that the real score $R_{m\times n}$ and the reconstructed score $\hat{R}_{m\times n}$ are as similar as possible, the square of the errors of the two matrices is used as the loss function L.

$$L = \min\sum_{i,j} I_{i,j}\left(r_{i,j} - p_i' q_j\right)^2 + \lambda\left(\sum_i \|p_i\| + \sum_j \left\|q_j\right\|\right) \tag{5}$$

Where $I_{i,j}$ represents whether student u_i has taken course c_j. If it has crossed, $I_{i,j} = 1$; Otherwise, $I_{i,j} = 0.p_i$ is the column vector in i-th row of the matrix $P_{m\times k}.q_j$ is the j-th column vector of the matrix $Q_{k\times n}$.

Elements of $P_{m\times k}$ and $Q_{k\times n}$ in Eq. (5) are solved using stochastic gradient descent method, and the gradient update formula is as follows:

$$\varepsilon_{i,j} = r_{i,j} - p_i' q_j \tag{6}$$

$$p_i = p_i + \alpha\left(I_{i,j}\varepsilon_{i,j} q_j - \lambda p_i\right) \tag{7}$$

$$q_j = q_{j_i} + \alpha\left(I_{i,j}\varepsilon_{i,j} p_i - \lambda q_j\right) \tag{8}$$

Where α is the amplitude at each step of gradient updating, λ is the regularization coefficient, $0 < \alpha \le 1$.

2.4. Behavior feature vector construction

In information theory and probability statistics, entropy is a measure that represents the uncertainty of a random variable. Student behavior regularity can be regarded as a kind of behavior repetition [22–24]. The entropy is calculated according to the probability distribution of the repeated occurrence of student behavior in a given time interval, so as to quantify the regularity of student behavior. The construction method of behavioral entropy is shown as follows.

Suppose that the period T is divided into n time periods.

$$T = \{t_1, \cdots, t_n\} \tag{9}$$

The time period T and interval n are set according to the actual situation. Then the probability of each student's behavioral $v \in V$ occurring within a given time interval $t \in T$ is:

$$P_v\left(T = t_i\right) = \frac{n_v\left(t_i\right)}{\sum_{i=1}^{n} n_v\left(t_i\right)} \tag{10}$$

Where $n_v\left(t_i\right)$ refers to the frequency of occurrence of behavior v in a given time period t time interval, then the entropy of behavior v in this time period is expressed as:

$$E_v = -\sum_{i=1}^{n} P_v\left(T = t_i\right)\log P_v\left(T = t_i\right) \tag{11}$$

The higher entropy denotes the more average of the probability distribution of the students behavior v, the more irregular of students behavior. For irregular behavior, the division of time interval n can be reduced. For example, when calculating students consumption behavior, the time cycle can be set as one week and divided into every day as a time interval.

2.5. Multi-feature fusion based on Pearson analysis

In order to more accurately select the factors that have a high contribution rate to employment from many factors that affect employment, Pearson correlation analysis is used to analyze traditional characteristics, behavioral characteristics and employment data. The optimal subset is derived from Pearson correlation analysis and used as input to the prediction model.

The Pearson correlation coefficient (PCC) [25] measures the linear relationship between two variables and is denoted by r. The greater coefficient denotes the stronger correlation, and the weaker vice versa. Given two n-dimensional vector X, Y, where $X = [X_1, \cdots, X_n]$ and $Y = [Y_1, \cdots, Y_n]$.$\bar{X}, \bar{Y}$ are mean values of variables X, Y, respectively, the correlation coefficients of two variables are expressed as:

$$r = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}} \tag{12}$$

In summary, by calculating the correlation coefficient between any eigenvector $V = [V_1, \cdots, V_n]$ of students and employment data $E = [E_1, \cdots, E_n]$, we can get:

$$R = \frac{\sum_{i=1}^{n} (V_i - \bar{V})(E_i - \bar{E})}{\sqrt{\sum_{i=1}^{n} (V_i - \bar{V})^2} \sqrt{\sum_{i=1}^{n} (E_i - \bar{E})^2}} \tag{13}$$

Where, $\bar{V}$ and $\bar{E}$ are the mean values of variables V and E respectively, and then the correlation coefficient matrix between each feature vector and employment data can be obtained as follows:

$$r_Z = \begin{bmatrix} r_{Z-1-1} & r_{Z-1-2} & \cdots & r_{Z-1-n} \\ r_{Z-2-1} & r_{Z-2-2} & \cdots & r_{Z-2-n} \\ r_{Z-3-1} & r_{Z-3-2} & \cdots & r_{Z-3-n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{Z-n-1} & r_{Z-n-1} & \cdots & r_{Z-n-n} \end{bmatrix} \tag{14}$$

Here, the subscript z of the correlation coefficient matrix represents different types of feature vectors, namely, the feature vector of professional skills, the feature vector of consumption behavior, the feature vector of personal interest, and the feature vector of family economy. Each correlation coefficient represents the correlation between the employment data and the feature vector. The quantified student behavior characteristics are normalized, and the correlation analysis is carried out with the students' employment destination. The features with high correlation are selected as the data input.

2.6. GRU-LSTM prediction model

By comprehensively considering the two factors of prediction accuracy and prediction time, this paper proposes a combined prediction model based on gated recurrent unit (GRU) and long short-term memory network (LSTM) to forecast employment data [26, 27]. The network structure diagram is shown in Fig. 1.

The network structure of the combined model has three layers, and the first layer uses GRU. Due to the simple network structure of GRU, the training speed is fast and the training time is reduced, but the accuracy is inferior to LSTM. The second and third layers of the model use LSTM, and the double-layer LSTM can obtain higher accuracy than the single-layer LSTM. Therefore, this paper uses the advantages of fast GRU training speed and better LSTM forecasting performance to propose a combined GRU-LSTM forecasting model, which not only ensures the forecasting accuracy, but also reduces the forecasting time, and can effectively forecast the employment data.

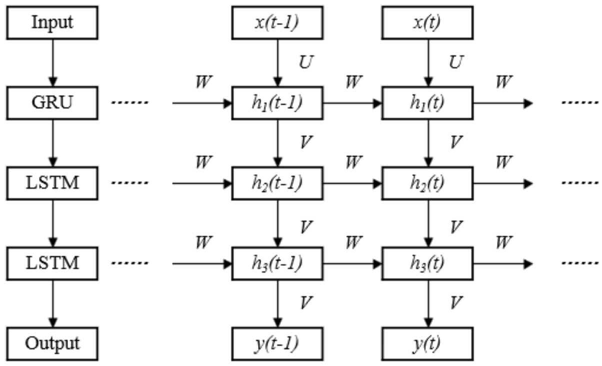

Fig. 1. Hybrid prediction network

3. University student employment forecast and result analysis

This paper combines the traditional features of students and the features of behavioral timing, and constructs this model using the combined model of GRU-LSTM. Here, the employment information of 8000 students from one university in 2022-2024 year is obtained, and 20% of the data is used as the training set and 80% as the test set to obtain the predicted results of this model. In the selection of evaluation indicators, the commonly used precision rate (P), recall rate (R) and F1 values are selected for evaluation.

$$P = \frac{TP}{TP + FP} \tag{15}$$

$$R = \frac{TP}{TP + FN} \tag{16}$$

$$F1 = \frac{2PR}{P + R} \tag{17}$$

Where, TP is the number of positive data whose results are consistent with the actual situation, FP is the number of negative samples predicted as positive data, FN is the number of positive data whose results are inconsistent with the actual situation. F1 is the harmonic average of precision and recall rate.

3.1. Feature selection

Feature selection can select several representative feature subsets from the original data feature set. Therefore, before model training, this paper conducts Pearson correlation analysis on students' grade, gender, computer level, foreign language level, student status, economic situation and interest, etc. The results are shown in Fig. 2.

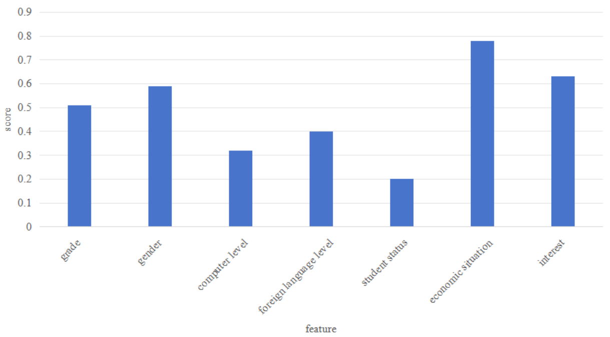

Fig. 2. Score with different features

As can be seen from Fig. 2, economic level and interest are the two features that have the highest impact on students' employment scores, and these two factors happen to be directly reflected through behavioral factors. Therefore, the experiment in this paper sets the weight according to the score ratio as follows:

$$W = 0.15W_1 + 0.17W_2 + 0.09W_3 + 0.12W_4 + 0.06W_5 + 0.22W_6 + 0.19W_7 \tag{18}$$

Where, W is the feature input, and $W_1 - W_7$ corresponds to grade, gender, computer level, foreign language level, student status, economic status and interest data respectively.

3.2. Parameter adjustment and model prediction

The model proposed in this paper is used to train the employment data, and the change curves of loss function and classification accuracy (ACC) in the training and testing process of the employment data set with the number of iterations are obtained, as shown in Figs. 3 and 4.

It can be seen that for the loss function, the training set of student employment data shows a steady downward trend, and both converge gradually at 50 iterations. Starting from 60 iterations, the loss function changes within a small value range and lasts for a long time, which proves that the training gradually becomes stable. For the accuracy value, the training set and the test set show an oscillating upward trend before 50 iterations, until the accuracy reaches a high value at 50 iterations, and the accuracy becomes stable after 150 iterations, with a stable value of about 0.97, which is exactly corresponding to the loss function gradually becoming stable at 150 iterations. After the trend continues for a period of time, it proves that the training results have reached the optimal and can be stopped.

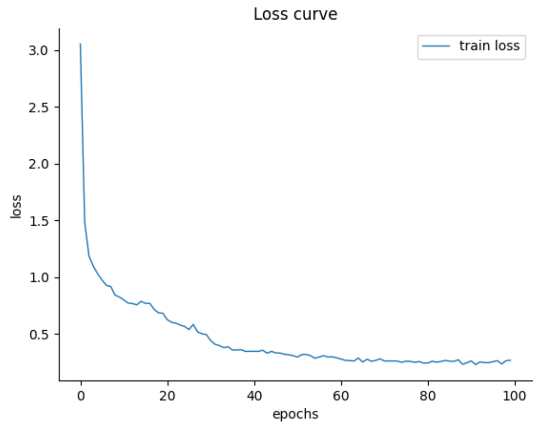

Fig. 3. Loss function curve with the number of iterations

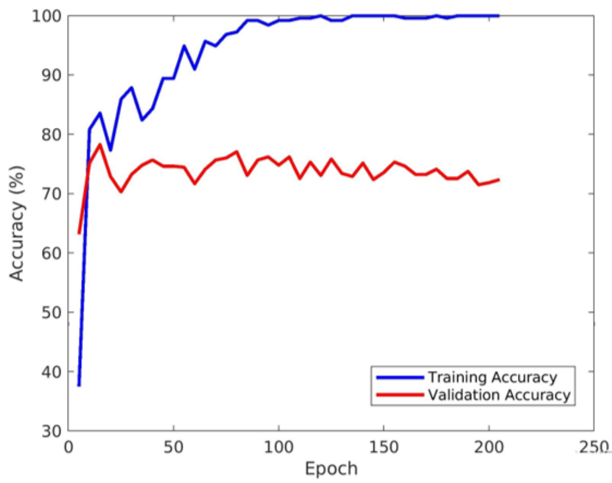

Fig. 4. Classification accuracy (ACC) varies with the number of iterations

Table 1. Results of comparison between the traditional features and the proposed features

Feature	ACC	P	R	F
Traditional	0.626	0.649	0.660	0.632
Proposed	**0.699**	**0.706**	**0.715**	**0.711**

3.3. Comparison results

In order to analyze the influence of traditional features and fusion features on the employment prediction results, the traditional features and fusion features with behav-

Table 2. Comparison results with different methods

Model	ACC	P	R	F	Time/s
LSTM	0.698	0.708	0.716	0.713	85
Namazi and Rezaei [28]	0.819	0.817	0.808	0.821	77
Rachmad et al. [29]	0.826	0.834	0.821	0.833	62
Proposed	**0.833**	**0.847**	**0.835**	**0.841**	**57**

ioral factors proposed in this paper are used as model and type inputs, and the LSTM prediction model is adopted. Through training and testing of the model, the final prediction results are shown in Table 1.

It can be seen from the above experimental results that the prediction results obtained by using multi-information fusion feature vectors are significantly better than those obtained by traditional features. This is because the new algorithm in this paper adds behavioral factor analysis to the selection of features, which can more truly reflect the employment intention of students to a certain extent, so the prediction result is more accurate.

Based on the above analysis, better employment prediction results can be obtained by using multi-information fusion features. In order to further verify the performance of the employment prediction model proposed in this paper, the single LSTM model and the other two advanced methods are compared by ten-fold cross-verification, and the results are shown in Table 2.

From the above results, it can be seen that the prediction model in this paper is superior to other models. Because the model in this paper adopts nonlinear modeling, it can better learn and train a large number of fusion feature vectors, so as to accurately describe the change law of graduate employment rate. At the same time, as a lightweight variant of LSTM, GRU neural network model can reduce the training parameters, reduce the complexity of the algorithm, accelerate the convergence speed and improve the prediction accuracy while retaining the fitting time dependence and nonlinear sequence memory ability. The experimental study shows that with the increase of time, the F-value of the prediction model in this paper will also increase, and the prediction accuracy will become higher. To sum up, it can be concluded that the proposed model in this paper is real and effective for students' employment prediction.

4. Conclusions

In this paper, we firstly propose a multi-feature fusion method based on traditional factors and behavioral factors, comprehensively consider the influence of each factor on employment, and combine Pearson analysis to select the optimal feature subset, which improves the quality of data set. Secondly, a GRU-LSTM model with high forecasting accuracy and short forecasting time is proposed to realize efficient and accurate forecasting of employment data. To sum up, for universities, this model can not only predict and analyze the employment situation of students, but also effectively build an effective bridge between graduates and enterprises. Meanwhile, the behavioral analysis of this model can help cultivate students' comprehensive ability and formulate scientific and reasonable talent training plans. For students, it can provide advantage analysis for them in the confusion of career selection and employment, help them make reasonable career planning, and serve the modernization of the country.

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