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Multi-Dimensional Analysis Model of College Students' Employment Market Based on Multi-Task Learning

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***Abstract*—In view of the current complex and changeable employment market for college students and the interweaving of multi-dimensional influencing factors, the traditional single-task analysis method is difficult to fully capture employment trends and the prediction accuracy is insufficient. To address this challenge, this study cites a multi-dimensional analysis model for the college student employment market based on multi-task learning. First, this study collects and organizes employment data covering multiple dimensions such as academic qualifications, majors, regions, and industry needs to construct a comprehensive data set. Next, a Multi-gate Mixture-of-Experts (MMoE) is designed as the basic model of deep neural networks. By sharing the expert layer and task-specific gating mechanism, it can simultaneously handle related tasks such as employment rate prediction, industry demand analysis, and salary level prediction, and make full use of the correlation between tasks to improve the overall performance of the model. Finally, regularization techniques and optimization algorithms are combined to ensure the stability and generalization ability of the model. In the experimental conclusion, in the employment rate prediction task, the mean squared error (MSE) of the MMoE model is reduced to around 0.021 and the R^2 value reaches 0.91; in the industry demand analysis task, the accuracy of the MMoE model reaches 92%; in the salary level prediction task, the MSE is 0.03 and the R^2 value is 0.88. In general, the multi-task learning model based on MMoE provides more accurate, stable and reliable prediction results in the multi-dimensional analysis of the college student employment market.**

Keywords-college student employment market; multi-task learning; MMoE model; multi-dimensional analysis; employment rate prediction

I. Introduction

The job market for college students is facing complex changes and is influenced by multiple factors. Traditional single task analysis methods are difficult to comprehensively capture employment trends and reveal deep-seated patterns, resulting in low accuracy of their prediction results. The job market is not only influenced by macroeconomic and policy changes but also by various factors such as professional choices, industry demands, and regional differences. In this dynamic and ever-changing environment, accurately predicting key indicators such as employment rate, industry demand, and salary levels has become a core issue in university employment guidance and policy decision-making. Therefore, multi task learning methods have gradually become effective tools for solving such complex problems due to their ability to simultaneously handle multiple related tasks. By sharing knowledge and features between tasks, this method helps to improve the accuracy and stability of predictions. Therefore, building a multi task learning based model for analyzing the job market of college students can not only improve prediction accuracy but also provide more scientific and accurate support for policy formulation and employment guidance.

This paper proposes a college student employment market analysis model based on multi-task learning, which aims to comprehensively consider multi-dimensional factors and improve the accuracy of employment rate prediction, industry demand analysis and salary level prediction. Different from the traditional single-task approach, the model designed in this paper enables tasks to collaborate with each other by sharing knowledge and feature representations between tasks, thereby achieving more accurate analysis in a complex job market environment. In particular, the model adopts MMoE, which makes full use of the correlation between tasks through task-specific gating mechanisms, effectively improving the overall performance of the model. In addition, this study also ensures the stability and generalization ability of the model through the introduction of regularization technology and optimization algorithms, providing data support for college employment guidance and policy decision-making.

This paper is organized as follows: the second part reviews the relevant research progress, focusing on the application and development of different methods in the field of college student employment prediction, especially the potential and challenges of multi-task learning methods in this field; the third part introduces the model design and data processing process, including data set construction, feature engineering and the design of multi-task learning framework; the fourth part elaborates on the experimental setup and result analysis, including the model training process, the definition of evaluation indicators, and the experimental results in tasks such as employment rate prediction, industry demand analysis, and salary level prediction; finally, the fifth part summarizes the main contributions of the research and discusses future research directions and possible improvement measures.

II. Related Works

In recent years, many scholars have gradually deepened their research on college students' employment prediction. For example, Huang and Liu used fuzzy logic algorithm to construct a model system for college students' entrepreneurial employment prediction and guidance [1]. Wang et al. designed an effective intelligent model to predict college students' career decisions[2]. Kocsis et al. studied the impact of student employment on persistence and academic performance in science, technology, engineering, and mathematics fields[3]. Bai and Hira proposed a hybrid model combining deep belief network and softmax regression to predict students' employability[4]. Kumar et al.'s research recommended implementing automated employment forecasting and demographic impact identification for higher education institutions and organizations, which will help students, teachers, parents, and institutions better prepare for the future [5]. Sun et al. explored the direct impact of college students' employment pressure on career delayed gratification and the mediating role of positive psychological capital[6]. The research method designed by Gao et al. provides a reasonable reference basis for graduate employment decisions and policy formulation by relevant departments[7]. In general, most existing studies focus on the prediction of a single task and lack comprehensive consideration of multi-dimensional employment factors, so there are still certain limitations.

In response to the above problems, multi-task learning has received increasing attention in recent years as an effective method to solve the problem of interrelationships between multiple tasks. For example, Liu et al. combined the advantages of rough set theory and random forest algorithm and proposed an employment prediction model for mathematics normal school students to cope with the increasingly severe employment situation of normal school students [8]. Baffa et al. improved the performance of employability prediction by adopting a machine learning model and utilizing student data containing more attributes such as academic performance and extracurricular activities [9]. Li et al. analyzed the common characteristics and influencing factors of unemployed students based on five-year employment history data from a certain school [10]. However, for the multi-dimensional analysis of the college student employment market, the existing multi-task learning method still needs to be further optimized. This article adopts the MMoE framework to design a new job market analysis model, aiming to comprehensively integrate multi-dimensional employment data and improve the accuracy of predictions.

III. Methods

A. Dataset Construction and Preprocessing

1) Data collection and integration

The data collection involves multiple sources, the first of which is the employment data of college graduates, which covers the employment rate and salary of graduates with different academic qualifications and professional backgrounds. Secondly, industry demand data comes from recruitment websites, industry reports and labor market surveys, providing information on the demand for different occupations in various industries. In addition, data on salary levels were collected, covering salary standards at different educational levels, regions and industries. To ensure the quality of the data, all data comes from authoritative channels and undergoes strict screening.

2) Data preprocessing

In the data preprocessing stage, data cleaning was first performed to remove missing values and outliers. When dealing with missing values, the mean filling method was used for numerical data, and the mode filling method was used for categorical data. This article conducted noise reduction operations, and abnormal values were detected and processed through box plots and standard deviation methods. Data from different sources are standardized to make them comparable. For example, salary data is standardized to a uniform income level based on region and industry to eliminate the impact of geographical differences.

Next, feature engineering was performed on the data to extract key features related to the job market. For example, characteristics such as industry category, job demand, and salary range were extracted from recruitment data; and the employment rates of graduates with different educational levels and professional backgrounds were extracted from employment rate data. This article uses One hot Encoding to process categorical variables, and standardizes and normalizes numerical data to ensure that all input features are trained on the same scale.

B. Multi-Task Learning Framework Design

1) Framework overview

The core idea of the MMoE framework is to use multi-task shared layers and task-specific gating mechanisms to allow different tasks to share some common feature representations while retaining the unique characteristics of each task. The MMoE framework can be seen in Figure 1:

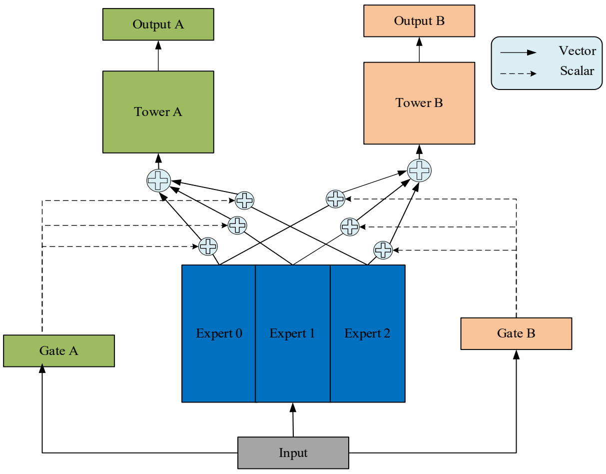

Figure 1: MMoE framework diagram

The expert layer contains multiple expert networks, each with the same structure but different parameters. Each expert network is responsible for learning the feature representation of the input data from a different perspective. The outputs of multiple experts will be weighted and fused in subsequent steps to meet the needs of different tasks.

The gating mechanism determines the output selection of the expert layer by assigning weights to each task. Each task is equipped with an independent gating network, which assigns different weights to each expert based on input data and task type, thereby determining their contribution level in a specific task. This mechanism enables the model to flexibly adjust the role of experts according to the needs of each task, ensuring that the special requirements of different tasks are accurately met.

The task specific layer conducts personalized modeling based on the objective function of each task, directly integrating with task outputs such as employment rate, industry demand, salary level, and other indicators. By optimizing these task specific layers, the model can learn highly relevant features to the task objectives, significantly improving overall prediction performance. The output of each expert network is $h_j(x)$, where j represents the expert number. The gating network generates a gating weight $g_i(x)$ for each task to determine which experts have a greater contribution to task i. For task i, its final output is shown in formula (1):

$$\hat{y}_i = \sum_{j=1}^{K} g_{i,j}(x) h_j(x) \quad (1)$$

Among them, K is the number of experts and $g_{i,j}(x)$ is the probability of selecting expert j for task i. The gating network optimizes the selection weight of each task to ensure that each task can obtain support from the most relevant experts [11].

2) Model training and optimization

During the model training process, the MMoE framework adopts a joint optimization approach, that is, learning common features through a shared expert layer and learning unique features of each task through a task-specific layer. In each iteration, the model inputs the training set data and selects the most appropriate expert network for calculation through the gating mechanism. Finally, the outputs of all tasks are aggregated and the loss function is minimized. In order to ensure the stability of the model and prevent overfitting, this paper introduces regularization techniques during training, including L2 regularization and Dropout.

3) Inter-task correlation and sharing

An important advantage of the MMoE model is that it can automatically capture the potential correlations between different tasks. Although the goals of employment rate forecasting, industry demand analysis, and salary level forecasting are different, there is a certain inherent connection between them. For example, the employment rate of a certain industry is often correlated with the salary level of the industry, and the employment situation of a specific profession may be closely related to its salary level and industry demand. The MMoE framework enables the flow of such relevant information through a shared expert layer, thereby improving the prediction accuracy of each task.

By designing a combination of shared layers and task-specific layers, MMoE can not only optimize each task individually but also effectively integrate the mutual influence between tasks. This balance between sharing and specialization enables the model to maximize the synergy between tasks while ensuring the independence of tasks [12].

C. Model Training and Optimization

1) Loss function and optimization target

In the context of multi-task learning, the objective function of each task is different. Therefore, the loss function design is crucial. This paper designs a specific loss function for each task (employment rate prediction, industry demand analysis, salary level prediction), and introduces a weighted coefficient into the overall loss function to balance the contribution of each task.

Specifically, for each task, this paper uses MSE as the loss function of the regression task, as shown in formula (2):

$$L_i = \frac{1}{N} \sum_{n=1}^{N} (\hat{y}_i^{(n)} - y_i^{(n)})^2 \quad (2)$$

Among them, $\hat{y}_i^{(n)}$ is the predicted value of the n-th sample, and $y_i^{(n)}$ is the true value. The final multi-task loss function is the weighted sum of the losses of each task as shown in formula (3):

$$\mathrm{L} = \sum_{\mathrm{i}=1}^{\mathrm{T}} \lambda_{\mathrm{i}} \mathrm{L}_{\mathrm{i}} \quad (3)$$

Among them, λ_i represents the weight coefficient of task i. Since the target variable scales of each task are different, the weight coefficients in the loss function can be adjusted according to the importance of the task to ensure that the training process of each task is balanced.

2) Overfitting and regularization

Overfitting is a potential risk in the training process of multi-task learning models, especially when the correlation between tasks is weak or the amount of data is insufficient. To solve this problem, this paper adopts a variety of regularization methods in model training. First, L2 regularization is introduced into the weight matrix of each layer to limit the size of the weight, thereby preventing the model from over-relying on certain features. Secondly, the Dropout technique is applied to the hidden layer of the model to randomly discard a portion of the neuron outputs to increase the generalization ability of the model [13]. Table 1 shows the parameter settings of the model:

Table 1: Hyperparameter settings for model training and optimization

Hyperparameter	Value/Setting	Description
Learning Rate	0.001	Initial learning rate
Batch Size	256	Update the sample size of the gradient
Optimizer	Adam	Can achieve faster convergence
L2 Regularization Coefficient	0.0001	Prevent overfitting
Dropout Rate	0.3	Improve generalization ability
Task Weights	$\lambda_1 = 1, \lambda_2 = 1, \lambda_3 = 1$	Used to balance optimization of different tasks
Early Stopping	If there is no improvement within 5 rounds, stop training	Preventing overfitting by stopping training
Epochs	50	Maximum number of training sessions
Task Loss Function	MSE (Mean Squared Error)	loss function
Gating Mechanism	Sigmoid Activation Function	Select experts for specific tasks

Finally, in order to further avoid overfitting of the model on specific tasks, especially in tasks such as employment rate prediction, this paper adopts an early stopping strategy, that is, when the loss on the validation set no longer improves, the training is terminated early, thereby avoiding performance degradation caused by overtraining.

IV. Results and Discussion

A. Experimental Settings

(1) Experimental data set

The college student employment market data set used in the experiment covers information in the following dimensions: employment rate includes employment conditions in different regions, majors, and academic qualifications. Industry demand includes the demand for different professional talents in various industries. Salary level includes salary level data for different regions, industries and positions.

(2) Evaluation indicators

MSE: Used to compare the differences between results, the lower the better.

R^2 value: It evaluates the ability of the model to explain the variance of the data. The closer to 1, the better the model.

Classification accuracy: It measures the proportion of samples correctly classified by the model. The higher the value, the better.

Recall rate: It comprehensively considers the recall rate index and can comprehensively evaluate the classification effect.

MAE: It measures the average absolute value of the difference between the predicted value and the true value.

(3) Experimental parameter settings

In order to ensure the reproducibility of the experiment and the reliability of the results, this study conducted precise design in the experimental parameter settings, mainly including model hyperparameters, training process, and baseline model configuration.

1. Model hyperparameters

The initial learning rate is set to 0.001 and a learning rate decay strategy is adopted. The batch size is 256, and the optimizer chooses Adam to accelerate model convergence. The regularization coefficient is set to 0.0001, and the dropout rate of the hidden layer is 0.3. The number of expert networks in the MMoE framework is set to 8 to capture diverse feature representations.

2. Training process

The number of training rounds is set to 50, and an early stopping strategy is adopted. When the validation set loss does not improve within 5 consecutive rounds, the training is terminated in advance to prevent overfitting. In multi task learning, weighting coefficients are introduced for different tasks, MSE is used as the loss function for regression tasks, and cross entropy loss function is used for classification tasks.

3. Baseline model configuration

To evaluate the performance of the MMoE model, linear regression, SVR, and single task MMoE were selected as baseline models. Linear regression is used to evaluate the advantages of handling nonlinear relationships, SVR uses RBF kernel function to compare performance in high-dimensional feature space, and single task MMoE is used to verify the improvement effect of multi task learning on model performance.

By setting the experimental parameters mentioned above, the scientificity of the experimental process and the reliability of the results were ensured, laying a solid foundation for subsequent analysis and discussion of the results.

B. Experimental Analysis

(1) Experiment on the effectiveness of employment rate prediction

This experiment simulates the results of different machine learning models in the iterative process to evaluate their application effect in the analysis of college students' employment market. The experiment used linear regression, support vector regression (SVR) and MMoE model based on multi-task learning, and tracked and analyzed MSE and R^2 respectively. The experiment was set up for 100 iterations, and the uncertainty in the model optimization process was simulated by introducing gradually decaying noise. The main purpose was to observe the convergence speed and stability of different models during the optimization process, as well as the performance and advantages of the MMoE model in processing complex employment data. The specific data is shown in Figure 2:

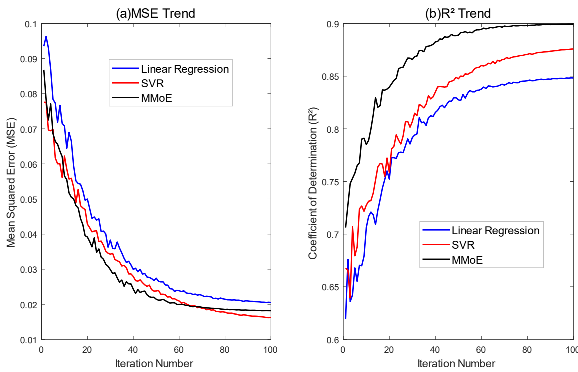

Figure 2: Evaluation of the effectiveness of employment rate forecasts

Figures 2 (a-b) show the variation trends of MSE and R^2 for each model. Specifically, after the 100th iteration, the MSE of the linear regression model was about 0.022, the MSE of SVR was about 0.019, and the MSE of the multi task learning model was about 0.021, showing a significant reduction in error. In addition, in terms of R^2 values, linear regression and SVR reach 0.85 and 0.87, respectively, while the R^2 value of the multi-task learning model is stable at 0.91, showing stronger data fitting ability. These results demonstrate the superiority of multi-task learning in complex job market analysis tasks, which can provide more accurate predictions and more stable performance.

(2) Effect evaluation experiment of industry demand analysis

In the effect evaluation experiment of industry demand analysis, the performance of different models in the industry demand forecasting task was evaluated. After the experiment, the performance of the models was evaluated on three indicators, including accuracy, MAE and recall, to compare their effectiveness in processing industry demand forecasting. The specific demand analysis can be seen in Figure 3:

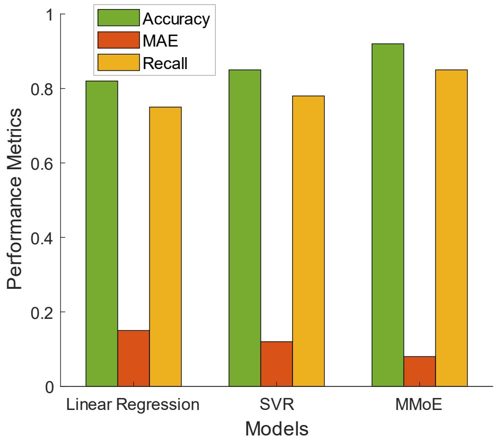

Figure 3: Evaluation of the effectiveness of industry demand analysis

In terms of accuracy in Figure 3, the MMoE model achieves 92%, which is significantly higher than linear regression (82%) and SVR (85%). In terms of MAE, the error of MMoE is 0.08, which is better than linear regression (0.15) and SVR (0.12). In addition, the recall rate of the MMoE model is 0.85, which is ahead of linear regression (0.75) and SVR (0.78). In the above data conclusion, the MMoE model can not only provide higher prediction accuracy when dealing with industry demand forecasts but also effectively reduce errors and improve the prediction ability for high-demand industries, showing its advantages in complex job market analysis.

(3) Salary level prediction effect evaluation experiment

The purpose of this experiment is to compare the effects of three models in salary level prediction. Linear regression, SVR and MMoE were selected as benchmark models. By comparing MSE, R^2 and MAE, the prediction ability and stability of each model were evaluated. The experimental data simulates different salary level scenarios and adds noise to simulate fluctuations in the real environment. The prediction results can be seen in Table 2:

Table 2: Evaluation of the effectiveness of salary level prediction

Model	MSE	R^2	MAE
Linear Regression	0.045	0.78	0.11
Support Vector Regression (SVR)	0.038	0.82	0.095
Multi-task Learning (MMoE)	0.03	0.88	0.08

The experimental results show that the MMoE model performs best in salary level prediction. Specifically, the MSE of MMoE is 0.030, which is lower than linear regression (0.045) and SVR (0.038); its R^2 value is 0.88, which is significantly better than the other two models. In terms of MAE, MMoE also performs best, reaching 0.080, which is lower than linear regression (0.110) and SVR (0.095). These results show that the MMoE model has higher accuracy and stronger generalization ability when dealing with salary prediction tasks.

C. Experimental Discussion

In the experimental conclusion, the MMoE model demonstrated excellent performance in all tasks. MMoE has achieved high accuracy and stability in tasks such as employment rate forecasting, industry demand analysis, and salary level forecasting. This indicates that MMoE can effectively capture potential correlations between tasks, thereby optimizing overall prediction performance. Therefore, MMoE is not only suitable for complex job market analysis but also provides an effective and reliable solution for future multidimensional forecasting tasks.

V. Conclusion

The multi-dimensional analysis model of the college student job market proposed in this paper based on multi-task learning significantly improves the ability to analyze complex job markets by combining tasks such as employment rate prediction, industry demand analysis, and salary level prediction. In the experimental conclusion, the MMoE model outperforms traditional methods in multiple tasks, especially in terms of prediction accuracy, model stability and generalization ability. This achievement provides effective theoretical support and data basis for college employment guidance and policy formulation. There are still some areas for improvement in this study. First, the diversity and quality of the dataset need to be further improved, especially for segmented data in different regions and industries. Secondly, although multi-task learning performs well in various tasks, in extreme cases, the model may overfit. In the future, more sophisticated regularization methods can be explored to improve the robustness of the model. Future research directions may include: first, expanding the coverage of data sets, especially cross-regional and cross-industry data; second, optimizing the multi-task learning framework, combining advanced technologies such as transfer learning to further enhance the model's predictive capabilities in complex job markets; third, combining actual policy making to develop more applied decision support tools.

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