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Prompting Precision: School-Enterprise Joint Exploration of Prompt Engineering and AIGC Optimization of Enterprise Text Classification Model

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Abstract. In order to meet the needs of enterprises for accurate classification of massive text data in the process of digital transformation, this paper applies the optimized text classification model combining prompt engineering and AIGC to enterprise text classification task. And choose classical decision trees, mainstream ensemble learning models (Random Forest, AdaBoost, GBDT, ExtraTrees) and high-performance gradient enhancement model XGBoost as comparison models. The performance of the model was evaluated by five metrics: mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). The experimental results show that the MSE of our model is 14.153, which is significantly lower than all comparison models and about 13.4% lower than the suboptimal AdaBoost (16.352). Its RMSE (3.762), MAE (3.069), and MAPE (5.029) are also the smallest of all models, decreasing by 7.0%, 3.7%, and 2.2% compared to the corresponding metrics of AdaBoost (4.044, 3.186, 5.142), respectively, indicating that the model has smaller prediction bias and better accuracy in category estimation. Meanwhile, the R^2 value of our model reaches 0.826, which is higher than the comparative models such as Random Forest (0.74), GBDT (0.783), and XGBoost (0.732). It can explain 82.6% of text category changes, capturing the mapping relationship between text features and categories more accurately. The above results validate the effectiveness of the collaborative optimization strategy of cue engineering and AIGC-cue engineering can guide the model to focus on key semantic features of text to reduce feature extraction bias, while AIGC can supplement high-quality text samples or enhance feature expression dimensions to alleviate data sparsity. The combination of the two significantly improves the prediction accuracy and stability of the text classification model.

Keywords: Prompt engineering, AIGC, text classification, school-enterprise cooperation

1. Introduction

Under the wave of digital transformation, enterprises generate massive amounts of text data in their daily operations. Accurate classification of these data is the core prerequisite to achieve efficient information retrieval, risk warning and decision support [1]. However, traditional text classification

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methods face problems such as strong domain specificity, high cost of artificial feature engineering, and classification bias caused by fluctuations in text quality generated by AIGC [2]. At the same time, as the key technology to optimize the output of AIGC, the integration of prompt engineering and enterprise text classification model still lacks systematic exploration. The school-enterprise joint model can integrate the real scene data of enterprises with the algorithm research and development capabilities of universities, which has become an important path to break through this dilemma, and provides a practical foundation for prompt engineering and AIGC optimization of text classification models [3]. Machine learning is the core technical support of the current classification prediction task. Its core advantage lies in the ability to automatically learn feature patterns from massive data without manual rule preset, which significantly enhances the classification efficiency and generalization ability [4]. In the field of text classification, from traditional support vector machine (SVM) and random forest to CNN and BERT models based on deep learning, it is possible to accurately classify multi-scenario enterprise text by mining the semantic and structural features of text. For example, machine learning models can automatically identify risk clause categories in contract documents and emotional tendencies in customer feedback, solving the pain points of traditional manual classification such as low efficiency, high error rate, and difficulty in adapting to the growth of data scale. This provides an efficient and feasible technical solution for enterprise text classification [5]. Deep belief networks (DBN), as a multilayer generative neural network, have powerful capabilities in extracting complex data features and nonlinear fitting, and show significant advantages in processing high-dimensional semantic features of enterprise texts. However, traditional DBN training is prone to fall into the local optimal solution, resulting in insufficient stability of classification prediction [6]. Whale algorithm (WOA), as an intelligent optimization algorithm to simulate the predation behavior of humpback whales, has the characteristics of strong global search ability and fast convergence speed. It can effectively optimize the initial weight and iterative process of DBN, and prevent the model from falling into local optimum. Applying the DBN regression algorithm optimized by whale algorithm to enterprise text classification can further improve the accuracy of capturing complex text features and the accuracy of classification prediction. At the same time, by combining prompt engineering and AIGC technology, it can better adapt to the diversity and dynamics of enterprise text, and provide an innovative algorithm path for schools and enterprises to jointly optimize enterprise text classification model.

2. Data sources

This dataset contains a total of 982 enterprise-level text classification samples, including 7 characteristic variables and 1 predictor variable. Feature variables include cue word length, cue word complexity, domain relevance, number of examples, model parameter size, amount of training data, and number of cue word iterations. The predictive variable is the classification accuracy, which represents the performance of the enterprise text classification model under different technical parameters. The data set can be directly used to train the text classification optimization model, analyze the influence weight of various technical factors on the classification effect, and provide data support for the application of school-enterprise joint exploration prompt engineering and AIGC in enterprise scenarios. Select some datasets for display, as shown in Table 1.

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Table 1. A partial dataset

prompt _length	prompt_ complexity	domain _relevance	example _count	model _size	training _data_size	prompt _iterations	company _name	classification _accuracy
152	5	4	10	70	731	10	Zhonglian Technology Research Institute	80.1
485	5	2	8	33	897	4	Yuanhang Retail Co., LTD	75.81
398	4	5	6	6.7	480	7	Huatai Financial Research Institute	69.97
156	1	5	0	0.3	286	2	Zhilian Technology Co., LTD	42.97

First, conduct a correlation analysis on the data and draw a correlation heat map, as shown in Figure 1. The results of the correlation analysis show that the classification accuracy rate has a relatively strong positive correlation with variables such as the length of prompt words, the complexity of prompt words, and domain correlation, with correlation coefficients of 0.43, 0.38, and 0.47 respectively. This indicates that these factors may have a relatively positive impact on the classification accuracy rate.

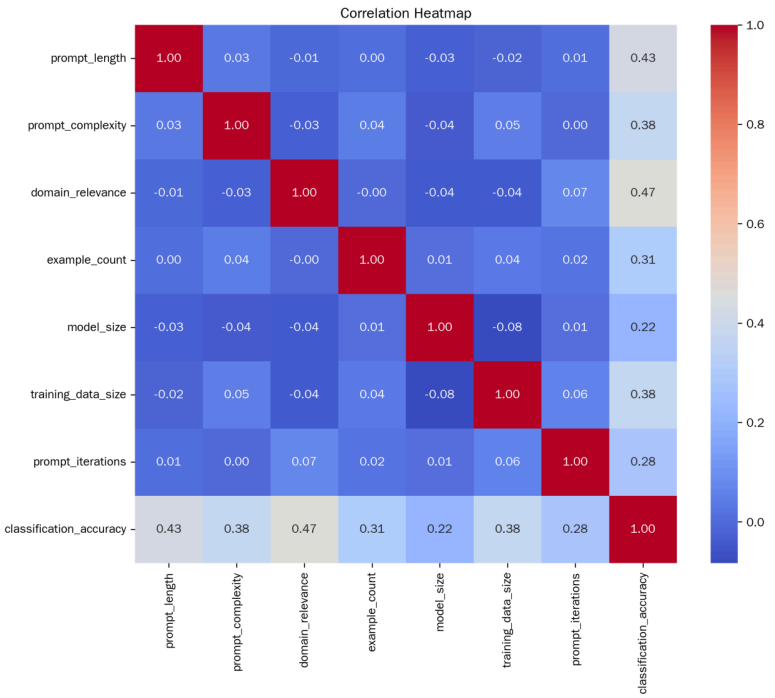

Figure 1. Correlation heat map

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3. Method

3.1. Deep Belief Networks

Deep belief networks (DBN) are deep neural networks based on probabilistic generative models. Its core structure is composed of multi-layer confined Boltzmann machine (RBM) and back propagation (BP) networks stacked together, presenting an overall feature extraction architecture of "progressive layer by layer". Among them, RBM, as the basic building unit of DBN, adopts a two-layer undirected graph structure of "visible layer-hidden layer": the visible layer corresponds to the input data, while the hidden layer is responsible for learning the abstract features of the data. Nodes within layers are not connected, while nodes between layers are fully connected. The rationality of the network state is measured by the energy function. After the input data is passed into the visible layer, the energy function calculates the probability of the current combination of the node states of the visible and hidden layers, and then adjusts the inter-layer weights. Minimizing probabilistic modeling errors for real data models [7]. The network structure diagram of the deep belief network is shown in Figure 2.

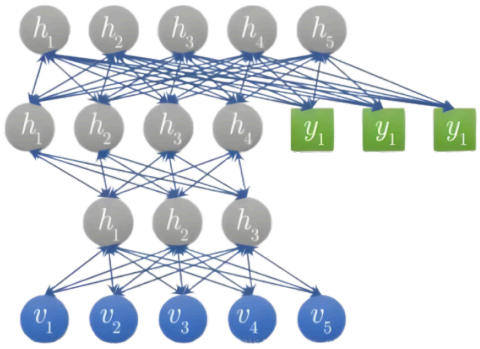

Figure 2. The network structure diagram of the deep belief network

The training process of DBN is divided into two steps: "unsupervised pre-training" and "supervised fine-tuning", which is also the key difference between it and traditional deep learning models. In the pre-training phase, a "bottom-up" layer-by-layer training strategy is adopted: first, the lowest-level RBM is trained to map the original features of the input data to the main abstract features of the hidden layer; Then, the output of this hidden layer is taken as the input of the previous layer RBM to train the second layer RBM to learn more advanced features. And so on until all RBM training is complete [8]. Data annotations are not required for this procedure. Initializing the network weight by maximizing the log-likelihood function of the data effectively avoids the "gradient disappearance" problem that is easy to appear in deep network training, and lays a high-quality initial parameter foundation for subsequent fine-tuning.

3.2. Whale algorithm

The Whale Algorithm (WOA) is an intelligent optimization algorithm that simulates the hunting behavior of humpback whales. Its core is to achieve an efficient search for optimal solutions by mimicking two key behaviors of humpback whales: encircling prey and bubble net attacks. The algorithm treats the "potential optimal solution" in the optimization problem as a "prey" and each individual in the population as a "whale". It updates the position of individuals through two core mechanisms: one is "shrinking encirclement", which dynamically adjusts the exploration step size so

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that all whales are close to the current optimal individual. Mathematically, it simulates the contraction of the enclosure by narrowing down the position update range. The second is "bubble net attack", which simulates the predation path of humpback whales spiraling up and exhaling bubbles. The spiral update formula is constructed using trigonometric functions that allow whales to move around their prey in a spiral trajectory. At the same time, combining stochastic probability to switch between the two mechanisms takes into account both global exploration and local exploitation capabilities [9].

The WOA iteration process is simple and the parameters are easy to adjust. The core steps are as follows: first, initialize the whale population and algorithm parameters; Secondly, the fitness value of each individual is calculated to determine the optimal individual in the current population. In each subsequent iteration, individuals choose to update their positions by "shrinking encirclement" or "bubble net attack" according to random probabilities, constantly approaching the optimal solution. Finally, when the maximum number of iterations or accuracy requirements are reached, the optimal individual is output as the optimal solution of the problem [10]. The advantages of this algorithm are few parameters and strong global search ability, which can effectively avoid the problem that traditional optimization algorithms are easy to fall into local optimum. It is especially suitable for complex parameter optimization scenarios such as weight initialization and learning rate adjustment in deep belief networks (DBN), providing efficient support for improving model performance.

3.3. WOA-DBN

The deep belief network regression algorithm optimized by whale algorithm is a hybrid algorithm built by using the global optimization ability of whale algorithm (WOA) to solve the pain points of traditional deep belief network (DBN) regression model training, such as easy to fall into local optimum and initial parameters depending on random values. The core logic is that the key parameters of the DBN regression model are encoded as "whale individuals" in the WOA population. The DBN regression prediction error is used as a fitness function of the WOA. The behavior of humpback whales in "shrink encirclement" and "bubble net attack" was simulated by WOA, and the optimal combination of parameters was searched globally in the parameter space-i.e., the population was brought closer to the current optimal parameters by "shrink encirclement". It also utilizes the spiral trajectory of the "bubble net attack" to avoid the local optimum. After the WOA iteration finds the optimal parameters, it is used to initialize the DBN, and then the training is completed according to the "unsupervised pre-training + supervised fine-tuning" process of the DBN. The algorithm takes into account the global optimization advantages of WOA and the complex feature fitting ability of DBN, which can improve the regression accuracy and convergence stability, and provides technical support for the performance improvement of the model in prompt engineering and AIGC optimization scenarios.

4. Result

To verify the effectiveness and superiority of the WOA-DBN regression algorithm proposed in this paper in the prediction tasks related to enterprise text classification, The experiment selected classic decision trees, mainstream ensemble learning models (Random Forest, AdaBoost, GBDT, ExtraTrees) and high-performance gradient boosting model XGBoost as comparison models, and conducted comparative analysis from key indicators such as prediction accuracy and convergence stability.

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The comparison results of the indicators are shown in Table 2, and the comparison results of the bar charts are shown in Figure 3.

Table 2. The experimental results

Model	MSE	RMSE	MAE	MAPE	R^2
Decision tree	40.666	6.377	5.047	8.207	0.503
Random Forest	23.798	4.878	3.954	6.509	0.74
AdaBoost	16.352	4.044	3.186	5.142	0.79
GBDT	16.393	4.049	3.229	5.185	0.783
ExtraTrees	21.927	4.683	3.679	5.924	0.729
XGBoost	19.076	4.368	3.476	5.626	0.732
Our model	14.153	3.762	3.069	5.029	0.826

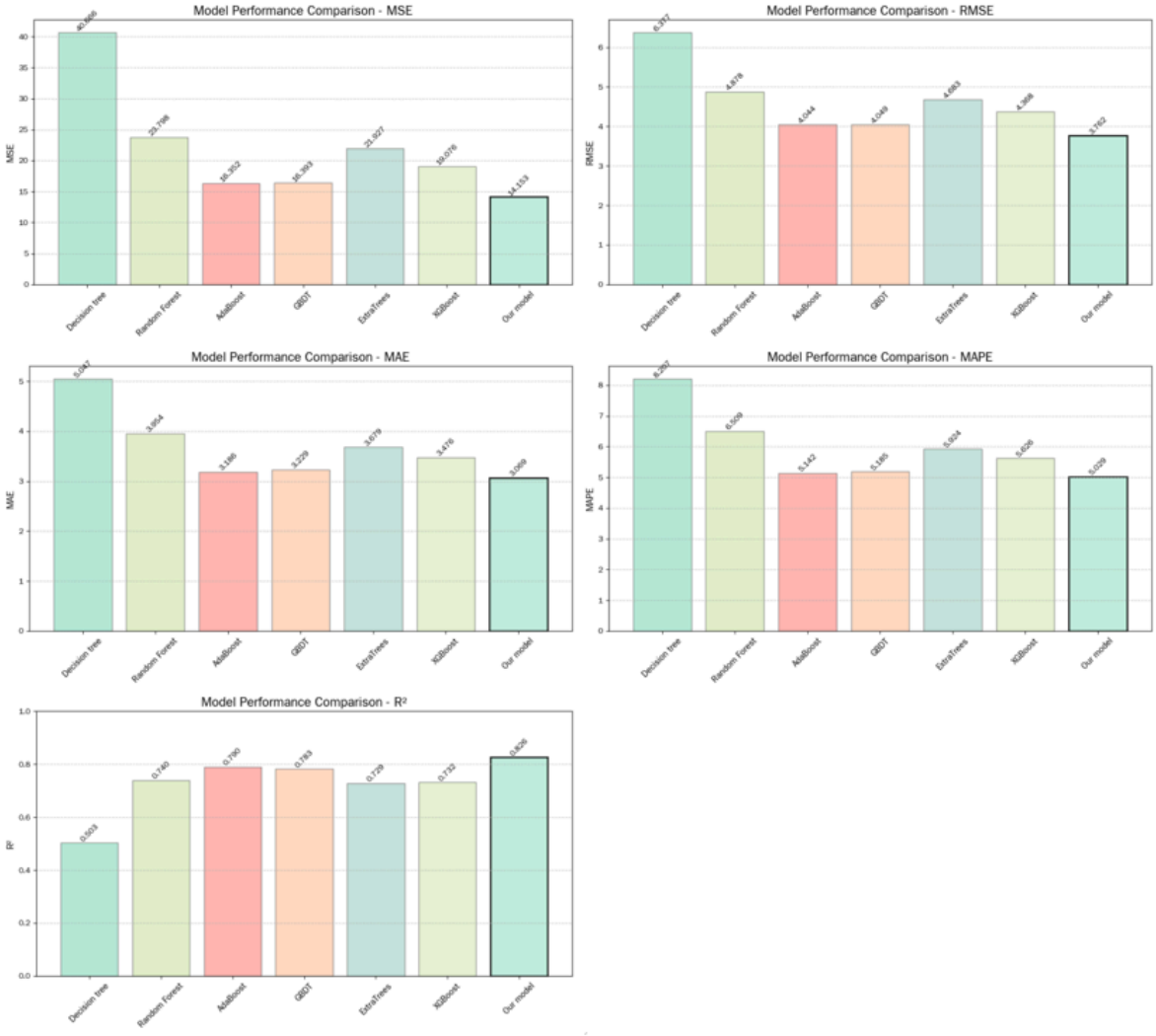

Figure 3. The comparison bar chart of the output experimental results

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This experiment compares traditional ensemble models such as Decision Tree, Random Forest, AdaBoost, GBDT, ExtraTrees, and XGBoost with the optimized text classification model combining prompt engineering and AIGC proposed in this paper (our model). The performance of the model was evaluated by five metrics: mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). From the perspective of error indicators, the MSE of our model is 14.153, which is significantly lower than all comparison models and about 13.4% lower than the suboptimal AdaBoost (16.352). Its RMSE (3.762), MAE (3.069), and MAPE (5.029) were all the smallest of all models, decreasing by 7.0%, 3.7%, and 2.2%, respectively, compared to AdaBoost's corresponding metrics (4.044, 3.186, 5.142). The results show that the optimization model has less prediction bias for category labels and better accuracy of category estimation in text classification task. From the perspective of model fitting and explanatory power, the R^2 value of our model reaches 0.826, which is higher than that of all contrasting models (e.g. Random Forest 0.74, GBDT 0.783, XGBoost 0.732), which means that it can explain 82.6% of text category variation. The model captures the mapping relationship between text features and categories more accurately. The above results verify the effectiveness of the collaborative optimization strategy between prompt engineering and AIGC: prompt engineering accurately guides the model to pay attention to the key semantic features of text, reducing the bias of feature extraction; AIGC technology can supplement high-quality text samples or enhance the dimension of feature expression, alleviating the problem of data sparsity. The combination of the two significantly improves the prediction accuracy and stability of the text classification model.

5. Conclusion

In the wave of digital transformation, accurate classification of massive text data accumulated in enterprises' daily operations is the core foundation for efficient information retrieval, risk warning and decision support. In this paper, a DBN regression algorithm optimized by the whale algorithm is combined with prompt engineering and AIGC to construct an optimized text classification model (Our model), and its performance is evaluated from multiple dimensions using traditional ensemble models such as decision tree, random forest, AdaBoost, GBDT, ExtraTrees and XGBoost as comparisons. From the perspective of error indicators, the MSE of our model is 14.153, which is significantly lower than all comparison models and about 13.4% lower than the suboptimal AdaBoost (16.352). Its RMSE (3.762), MAE (3.069), and MAPE (5.029) were also the smallest, decreasing by 7.0%, 3.7%, and 2.2%, respectively, compared to the corresponding metrics of AdaBoost, confirming that the model has smaller prediction bias and better accuracy in category estimation.

From the model fitting and explanatory ability analysis, the R^2 value of our model reaches 0.826, which is higher than that of comparative models such as Random Forest (0.74), GBDT (0.783) and XGBoost (0.732). It can explain 82.6% of text category changes, more accurately capturing the mapping relationship between text features and categories. The results verify the effectiveness of the collaborative optimization between cue engineering and AIGC: cue engineering can guide the model to pay attention to the key semantic features of text and reduce the bias of feature extraction; AIGC can supplement high-quality text samples or enhance the dimension of feature expression, alleviating the problem of sparse data. Together, they promote the improvement of prediction accuracy and stability of text classification models.

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References

[1] Ye, D., et al. (2024). Optimizing AIGC services by prompt engineering and edge computing: A generative diffusion model-based contract theory approach. *IEEE Transactions on Vehicular Technology*.

[2] Liu, Y., et al. (2023). Optimizing mobile-edge AI-generated everything (AIGX) services by prompt engineering: Fundamental, framework, and case study. *IEEE Network, 38*(5), 220–228.

[3] Liu, Y., et al. (2024). Cross-modal generative semantic communications for mobile AIGC: Joint semantic encoding and prompt engineering. *IEEE Transactions on Mobile Computing*.

[4] Liu, J., et al. (2025). Leveraging generative AI through prompt engineering for corpus construction and in-depth intelligent interpretation of ancient texts. *Digital Scholarship in the Humanities*, fqaf043.

[5] Guo, J., et al. (2024). Large language models and artificial intelligence generated content technologies meet communication networks. *IEEE Internet of Things Journal*.

[6] Zhang, M., et al. (2024). AIGT: AI generative table based on prompt. *arXiv preprint arXiv:2412.18111*.

[7] Chen, B., et al. (2023). Unleashing the potential of prompt engineering in large language models: A comprehensive review. *arXiv preprint arXiv:2310.14735*.

[8] Chen, B., et al. (2025). Unleashing the potential of prompt engineering for large language models. *Patterns*.

[9] Yu, Z., & Gong, Y. (2024). ChatGPT, AI-generated content, and engineering management. *Frontiers of Engineering Management, 11*(1), 159–166.

[10] Chen, Y., et al. (2024). Advancing AI incidents classification: Leveraging LLMs with strategic prompting. In *Iberoamerican Workshop on Human-Computer Interaction* (pp. 159–166). Cham: Springer Nature Switzerland.