Proceedings of the 3rd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/2025.28788

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

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Abstract. To meet the demand of enterprises for precise classification of massive text data during digital transformation, this paper will apply the optimized text classification model combining prompt engineering and AIGC to the enterprise text classification task. And the classic decision trees, mainstream ensemble learning models (Random Forest, AdaBoost, GBDT, ExtraTrees) and the high-performance gradient boosting model XGBoost were selected as the comparison models. The performance of the model is evaluated through five indicators: 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 that of all comparison models and is approximately 13.4% lower than the suboptimal AdaBoost (16.352). Its RMSE (3.762), MAE (3.069), and MAPE (5.029) were also the smallest among all models, which decreased by 7.0%, 3.7%, and 2.2% respectively compared with the corresponding indicators of AdaBoost (4.044, 3.186, 5.142), indicating that this model had smaller prediction deviations and better category estimation accuracy. Meanwhile, the R^2 value of Our model reaches 0.826, which is higher than that of contrast models such as Random Forest (0.74), GBDT (0.783), and XGBoost (0.732). It can explain 82.6% of the text category variations and capture the mapping relationship between text features and categories more accurately. The above results verify the effectiveness of the collaborative optimization strategy of prompt engineering and AIGC - prompt engineering can guide the model to focus on the key semantic features of the text to reduce feature extraction bias, while AIGC can supplement high-quality text samples or enhance the feature expression dimension 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. Accurately classifying these data is the core prerequisite for achieving efficient information retrieval, risk early warning, and decision support [1]. However, traditional text classification methods are confronted with problems such as strong domain specificity, high cost of artificial feature engineering, and classification bias caused by fluctuations in the quality of texts generated by AIGC [2]. Meanwhile, as a key technology for optimizing AIGC output, the integration of prompt engineering with enterprise text classification models still lacks systematic exploration. However, the university-enterprise joint model can integrate real scene data of enterprises with the algorithm research and development capabilities of universities, becoming an important path to break through this predicament and providing a practical basis for prompt engineering and AIGC to optimize text classification models [3]. Machine learning is the core technical support for current classification prediction tasks. Its core advantage lies in its ability to automatically learn feature patterns from massive data without the need for manual rule presetting, significantly enhancing classification efficiency and generalization ability [4]. In the field of text classification, from traditional Support Vector Machine (SVM) and random forest to deep learning-based CNN and BERT models, all can achieve precise classification of multi-scenario enterprise texts by mining the semantic and structural features of the text. For instance, machine learning models can automatically identify the risk clause categories in contract documents and the emotional tendencies in customer feedback, addressing 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 network (DBN), as a multi-layer generative neural network, possesses powerful capabilities in extracting complex data features and nonlinear fitting, demonstrating significant advantages in dealing with high-dimensional semantic features of enterprise texts. However, traditional DBN training is prone to fall into local optimal solutions, resulting in insufficient stability in classification prediction [6]. The Whale Algorithm (WOA), as an intelligent optimization algorithm that simulates the predatory behavior of humpback whales, features strong global search ability and fast convergence speed. It can effectively optimize the initial weights and iterative process of DBN and prevent the model from falling into local optimum. Applying the DBN regression algorithm optimized by the whale algorithm to enterprise text classification can further enhance the model's accuracy in 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 texts, providing an innovative algorithmic path for the joint optimization of enterprise text classification models by schools and enterprises.

2. Data sources

This dataset contains a total of 982 enterprise-level text classification samples, including 7 feature variables and 1 predictor variable. The feature variables include prompt word length, prompt word complexity, domain relevance, number of examples, model parameter scale, training data volume, and the number of prompt word iterations. The predictor variable is classification accuracy Represent the performance of enterprise text classification models under different technical parameters. The dataset can be directly used to train text classification optimization models and analyze the influence weights of various technical factors on classification effects, providing data support for the joint exploration of prompt engineering and AIGC applications in enterprise scenarios by schools and enterprises. Some datasets are selected 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.

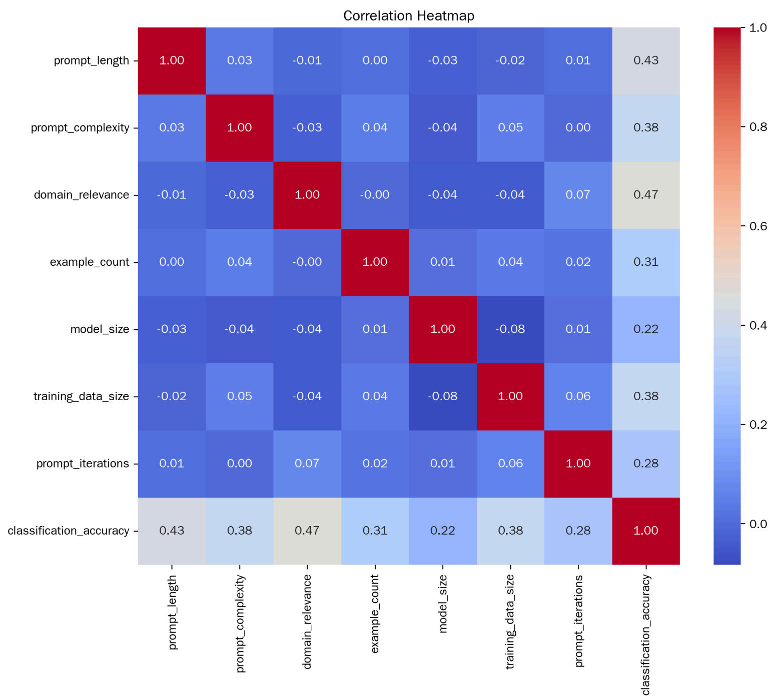

Figure 1. Correlation heat map

3. Method

3.1. Deep Belief Networks

Deep Belief Network (DBN) is a type of deep neural network based on probabilistic generative models. Its core structure is composed of multiple layers of restricted Boltzmann machines (RBM) and a backpropagation (BP) network 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 the layer are unconnected, 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 layer and the hidden layer, and then adjusts the inter-layer weights. Minimize the probabilistic modeling error of the model for real data [7]. The network structure diagram of the deep belief network is shown in Figure 2.

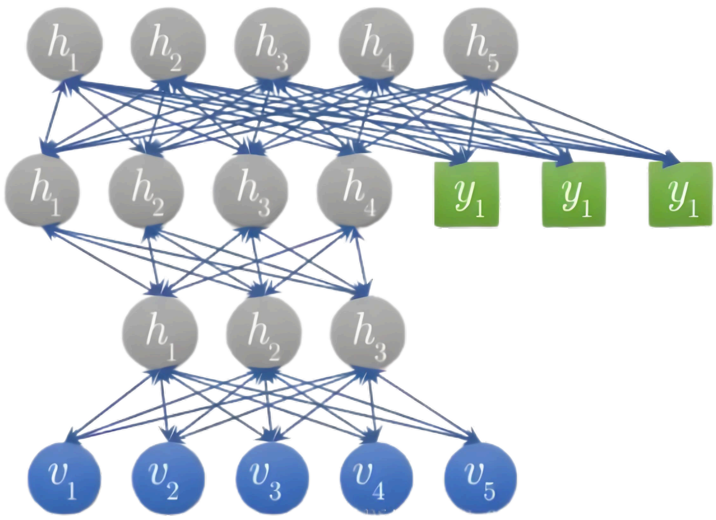

Figure 2. The network structure diagram of the deep belief network

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 stage, a "bottom-up" layer-by-layer training strategy is adopted: the lowest-level RBM is trained first, mapping the original features of the input data to the primary abstract features of the hidden layer; Then, take the output of this hidden layer as the input of the previous layer of RBM to train the second layer of RBM to learn more advanced features. And so on, until all RBM training is completed [8]. This process does not require data annotation. By maximizing the log-likelihood function of the data to initialize the network weights, it effectively avoids the "vanishing gradient" problem that is prone to occur in deep network training, laying 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. At its core, it achieves efficient search for the optimal solution by imitating the two key behaviors of humpback whales: surrounding prey and bubble net attacks. The algorithm regards the "potential optimal solution" in the optimization problem as the "prey", and each individual in the population as a "whale". It updates the positions of individuals through two core mechanisms: one is "contraction and encirclement", which dynamically adjusts the exploration step size to make all whales approach the current optimal individual. Mathematically, it simulates the contraction of the encirclement by narrowing the position update range. The second is the "bubble net attack", which simulates the predatory path of humpback whales spirally ascending and

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exhaling air bubbles. A spiral update formula is constructed using trigonometric functions, allowing whales to move around their prey in a spiral trajectory. At the same time, random probability is combined to switch between the two mechanisms, taking into account both global exploration and local development capabilities [9].

The iterative process of WOA is simple and the parameters are easy to adjust. The core steps are as follows: First, initialize the whale population and algorithm parameters; Secondly, calculate the fitness value of each individual to determine the optimal individual in the current population. In each subsequent iteration, individuals choose to update their positions through "contraction encirclement" or "bubble net attack" based on random probabilities, continuously approaching the optimal solution. Finally, when the maximum number of iterations or the precision requirement is reached, the optimal individual is output as the optimal solution to the problem [10]. The advantage of this algorithm lies in its few parameters and strong global search ability, which can effectively avoid the problem that traditional optimization algorithms are prone to fall into local optimum. It is particularly 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 the whale algorithm is a hybrid algorithm constructed by leveraging the global optimization capability of the Whale Algorithm (WOA) to address the pain points of traditional deep belief network (DBN) regression model training, such as easily falling into local optimum and initial parameters relying on random values. Its core logic is: 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 the fitness function of the WOA. The behavior of humpback whales in "contraction encirulation" and "bubble net attack" is simulated through the WOA, and the optimal parameter combination is globally searched in the parameter space - that is, the population is brought closer to the current optimal parameter through "contraction encirulation". It also avoids local optima by taking advantage of the spiral trajectory of the "bubble net attack". After the WOA iteration finds the optimal parameters, they are used to initialize the DBN, and then the training is completed according to the "unsupervised pre-training + supervised fine-tuning" process of the DBN. This algorithm takes into account the global optimization advantage of WOA and the complex feature fitting ability of DBN, which can improve the regression accuracy and convergence stability, providing technical support for the performance improvement of models 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.

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

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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

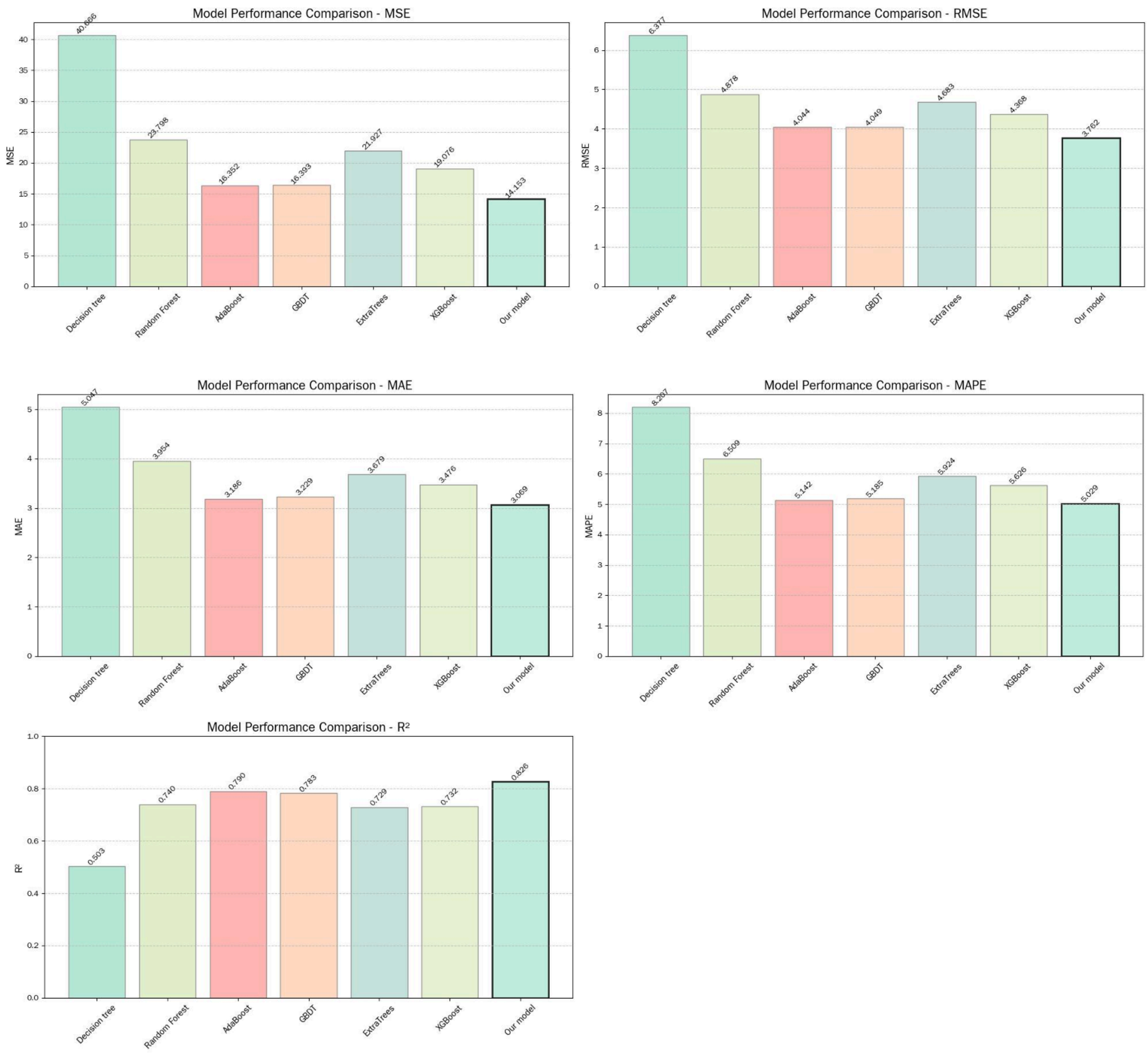

Figure 3. The comparison bar chart of the output experimental results.

This experiment compares traditional ensemble models such as decision tree, Random Forest, AdaBoost, GBDT, ExtraTrees, and XGBoost with the optimized text classification model (Our model) proposed in this paper that combines prompt engineering and AIGC. The performance of the model is evaluated through five indicators: 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 that of all comparison models and is approximately 13.4% lower than the suboptimal AdaBoost (16.352). Its RMSE (3.762), MAE (3.069), and MAPE (5.029) were all the smallest among all models, which decreased by 7.0%, 3.7%, and 2.2% respectively compared with the corresponding indicators of AdaBoost (4.044, 3.186, 5.142). It indicates that the optimization model has a smaller prediction deviation for category labels and better category estimation accuracy in the text classification task. From the perspective of model fitting and interpretation ability, the R^2 value of Our model reaches 0.826, which is higher than that of all comparison models (such as Random Forest 0.74, GBDT 0.783, XGBoost 0.732), meaning that it can explain 82.6% of text category variations. The model captures the mapping relationship between text features and categories more accurately. The above results verify the effectiveness of the collaborative optimization strategy of prompt engineering and AIGC: Prompt engineering precisely guides the model to focus on the key semantic features of the text, reducing the deviation 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 text classification models.

5. Conclusion

In the wave of digital transformation, the precise classification of the massive text data accumulated by enterprises in their daily operations is the core foundation for achieving efficient information retrieval, risk early warning and decision support. This paper combines the DBN regression algorithm optimized by the whale algorithm with prompt engineering and AIGC to construct an optimized text classification model (Our model), and takes traditional integrated models such as decision tree, Random forest, AdaBoost, GBDT, ExtraTrees, and XGBoost as comparisons to evaluate the performance from multiple dimensions. From the perspective of error indicators, the MSE of Our model is 14.153, which is significantly lower than that of all comparison models and is approximately 13.4% lower than that of 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 indicators of AdaBoost, confirming that this model has a smaller prediction deviation and better category estimation accuracy.

From the analysis of model fitting and interpretation ability, the R^2 value of Our model reaches 0.826, which is higher than that of comparison models such as Random Forest (0.74), GBDT (0.783), and XGBoost (0.732). It can explain 82.6% of text category variations and capture the mapping relationship between text features and categories more accurately. This result verifies the effectiveness of the collaborative optimization of prompt engineering and AIGC: prompt engineering can guide the model to focus on the key semantic features of the text and reduce the deviation of feature extraction; AIGC can supplement high-quality text samples or enhance the dimension of feature expression, alleviating the problem of data sparsity. Together, they promote the improvement of the prediction accuracy and stability of text classification models.

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