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Customer Sentiment and Demand Prediction Model Based on Cognitive Computing

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Abstract. This study aims to explore customer sentiment and demand prediction models based on cognitive computing to improve companies' understanding of customer behavior and optimize market strategies. By combining deep learning and natural language processing technology, this paper builds a sentiment analysis model that can effectively extract emotional tendencies from customer feedback, and a demand prediction model that combines sentiment analysis results and historical transaction data to predict future customer needs. Empirical analysis shows that the sentiment analysis model exhibits high accuracy, while the demand forecast model shows good predictive performance, proving the effectiveness of the comprehensive model in customer demand forecasting. In addition, this study also discusses the application potential of the model, providing companies with a new tool to better understand customer behavior and develop precise market strategies. Although there are certain limitations, such as the impact of the size and diversity of the data set on the generalization ability of the model, and the need to improve the interpretability of the model, this study provides a basis for future research in this field and points out possible research directions, including expanding data sources, exploring new data analysis techniques and algorithms, and enhancing the versatility and adaptability of models.

Keywords. Cognitive computing, customer sentiment analysis, demand forecasting, deep learning, natural language processing, empirical analysis

1. Introduction

1.1. Research background and importance

With the advent of the digital era, companies increasingly rely on understanding customer sentiment and predicting market needs to optimize their business strategies and product services. Customer sentiment analysis and demand forecasting play a vital role in business decision-making, especially in highly competitive and rapidly changing market environments. In recent years, developments in cognitive computing have provided new possibilities for processing large amounts of data and extracting valuable insights. Cognitive computing combines artificial intelligence, machine learning, natural language processing and other technologies to simulate human thinking processes to more effectively analyze customer emotions and predict market demand

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[1,2]. For example, Alghamdi (2023) used BERTopic for topic modeling and VADER for sentiment analysis in his research to identify common problems of cloud service customers, thereby improving customer satisfaction [1]. In addition, Alharbi (2023) developed a sustainable Airbnb listing price prediction model by combining machine learning and sentiment analysis, showing the potential of sentiment analysis in predicting market demand [2]. These studies show that using cognitive computing for customer sentiment analysis and demand forecasting can not only improve the quality of corporate decision-making, but also gain an advantage in a highly competitive market.

1.2. Research objectives

This study aims to develop a customer sentiment and demand prediction model based on cognitive computing to help enterprises better understand customer behavior and market dynamics. Specific goals include: (1) utilizing advanced machine learning and deep learning technologies to conduct sentiment analysis on large amounts of customer data to identify consumers' emotional tendencies and preferences; (2) combining sentiment analysis results with other relevant data to build an accurate market demand forecast model; (3) verify the effectiveness of the model through empirical research and explore its application potential in different industries and market environments. By achieving these goals, this research will not only provide businesses with deeper customer insights, but also help them make more informed decisions in a rapidly changing market.

2. Literature review

2.1. Concept of cognitive computing

Cognitive computing is an advanced computing paradigm designed to process and analyze data by simulating the thinking processes of the human brain. This field combines technologies such as artificial intelligence, machine learning, natural language processing, and data mining to provide deeper data analysis and insights [3]. Cognitive computing systems are capable of understanding, learning, reasoning, and interacting with humans, thereby showing great potential in processing complex and unstructured data. Hirt et al. (2019) proposed a scalable cognitive classifier in their study that is able to integrate existing and emerging customer profiling classifiers to improve the overall prediction performance, especially in gender prediction [3]. The goal of cognitive computing is to create systems that can understand complex situations and generate actionable insights, which is critical for customer sentiment analysis and demand forecasting.

2.2. Customer sentiment analysis

Customer sentiment analysis is the process of using machine learning and natural language processing techniques to identify and classify emotional tendencies in text data. Research in this area focuses on understanding consumer feelings and attitudes toward a brand, product, or service. With the popularity of social media and online reviews, businesses have unprecedented opportunities to analyze customer sentiment and feedback. For example, Kilimci et al. (2020) introduced a customer churn prediction model based on sentiment analysis by analyzing players' comments in mobile games, which uses word embedding models and deep learning algorithms to evaluate customers' churn tendency [4]. In addition, Sankar et al. (2020) demonstrated the effectiveness of analyzing user comments in a mobile environment through an intelligent sentiment analysis method based on deep learning technology through edge computing [5]. These studies show that customer sentiment analysis can provide companies with valuable insights that can help them improve their products and services and increase customer satisfaction.

2.3. Customer demand forecast

Customer demand forecasting involves using historical data and analytical techniques to predict future customer demand. This process is critical for inventory management, supply chain optimization, and strategic planning. With the development of big data and machine learning technology, enterprises are now able to predict market demand more accurately. Alharbi (2023) developed an Airbnb listing price prediction model by combining machine learning and sentiment analysis, which can help hosts estimate the expected value of their listings, thereby directly affecting customer demand [2]. On the other hand, Amellal et al. (2024) proposed an integrated approach utilizing machine learning, deep learning, and probabilistic models for sentiment analysis, demand forecasting, and price forecasting, demonstrating solutions to complex challenges faced in modern supply chain management [6]. These studies highlight the importance of predicting customer needs and demonstrate the potential of cognitive computing technologies to improve forecast accuracy.

3. Methodology

3.1. Research methods

In this study, we adopted an approach that combines machine learning and natural language processing (NLP) to build our customer sentiment and demand prediction model [7]. First, we use sentiment analysis to understand customers' emotional tendencies, and then combine historical transaction data to predict customers' future needs [8].

Sentiment analysis model: Use sentiment analysis to extract the emotional tendencies in customer feedback. The formula is as follows:

$$E = \frac{1}{N}\sum_{i=1}^{N} e_i \tag{1}$$

Among them, E represents the sentiment score, N is the total number of words in the text, and e_i is the sentiment value of the i-th word.

Demand forecast model: Based on the results of sentiment analysis and the customer's historical transaction data, predict the customer's future demand using the following linear regression model:

$$D = \beta_0 + \beta_1 E + \beta_2 X + \epsilon \tag{2}$$

Among them, D represents the demand prediction value, E is the sentiment score, X is other factors that affect demand, β_0, β_1, β_2 are model parameters, and ϵ is the error term [9].

Model fusion strategy: Finally, we fuse the results of the two models to improve the accuracy of prediction. The fusion method is as follows:

$$P = \alpha D + (1 - \alpha) C \tag{3}$$

Among them, P represents the final forecast result, D is the output of the demand forecast model, C is the conventional forecast based on customer historical data, and α is the fusion parameter, which determines the weight of the two forecast results [10].

3.2. Data sources and processing

Our data sources include two main parts: customer feedback data and historical transaction data. Customer feedback data is collected through online surveys and social media platforms, and historical transaction data is sourced from the company's sales database [11].

Data preprocessing: Data preprocessing steps include data cleaning, missing value processing, word segmentation and standardization of text data, etc. During the cleaning process, we removed non-text information and stop words, and prepared clean data for sentiment analysis and demand prediction model training (see Table 1).

Table 1. Data preprocessing steps

Step	Description
1	Data Cleaning
2	Missing Value Handling
3	Tokenization of Text Data
4	Normalization of Text Data

4. Model construction

4.1. Sentiment analysis model

The sentiment analysis model aims to extract emotional tendencies from customer feedback, and we use natural language processing technology based on deep learning. The model structure includes a word embedding layer, a multi-layer LSTM network layer, and an output layer for classifying emotions as positive, negative, or neutral.

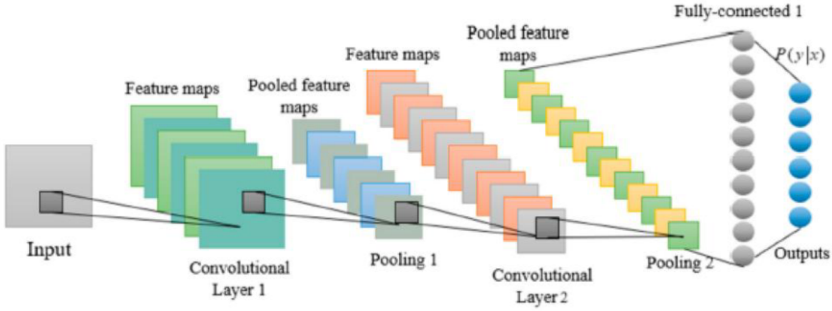

Figure 1. Schematic diagram of the deep learning architecture of the sentiment analysis model [12]

Figure 1 shows the conceptual architecture of a deep learning model similar to the model used for sentiment analysis in this study. In our application case, the model adopts a deep neural network architecture, which may include a convolutional neural network (CNN) or other similar deep learning techniques, to effectively extract emotional features from customer feedback text. In this diagram, the input layer represents preprocessed text data, which are converted into vectors that can express semantic meaning through the embedding layer. The following convolutional layer captures the local features of the text through multiple filters, which are further processed by the pooling layer to reduce the dimensionality and highlight important features. Subsequently, the abstract features are integrated through one or more fully connected layers and emotion classification is performed at the output layer. In our model, a deep learning architecture leverages a hierarchical structure similar to the one shown in the figure to parse customer feedback to extract key sentiment signals. These signals are then used in predictive models designed to predict future customer demand.

Word embedding layer: Converts each word in the text into a vector representation.

$$v_i = \text{Embedding}(w_i) \tag{4}$$

where v_i is the vector representation of word w_i.

LSTM network layer: Use the LSTM network to process sequence data and capture the context dependence of emotions.

$$h_t = \text{LSTM}(v_t, h_{t-1}) \tag{5}$$

where h_t is the hidden state at time step t and v_t is the input vector at time step t.

Output layer: Based on the output of LSTM, emotion classification is performed through a fully connected layer and Softmax function.

$$P(c \mid w) = \text{Softmax}(W_h h_T + b) \tag{6}$$

where $P(c \mid w)$ is the probability that a given word sequence w belongs to category c, W_h and b are the weights and biases of the fully connected layer, and h_T is the last time The hidden state of the step.

4.2. Demand forecast model

The demand forecast model combines the results of sentiment analysis and historical transaction data, using time series analysis and machine learning techniques to predict future customer demand.

Feature Engineering: Combine sentiment scores and historical transaction data as features.

$$X = [E, H_1, H_2, \ldots, H_n] \tag{7}$$

Among them, X is the feature vector, E is the sentiment score, H_1, H_2,…, H_n are the characteristics of historical transaction data.

Forecasting model: Use random forest algorithm for demand forecasting.

$$\hat{Y} = \text{RandomForestRegressor}(X) \tag{8}$$

where $\hat{Y}$ is the forecast demand.

The set of key features used in the demand forecast model is shown in Table 2:

Table 2. Set of key features used in demand forecasting models

Feature	Description
Emotion Score	The output of the emotion analysis model
Historical Sales	Sales data from the past period
Seasonality	Seasonal factors affecting demand
Price Changes	Impact of price adjustments

5. Empirical analysis

5.1. Model application and evaluation

In this study, we apply sentiment analysis model and demand prediction model to a real customer feedback data set and historical transaction data set. First, we use a sentiment analysis model to process customer feedback and extract sentiment scores. Then, a demand forecast model is used to predict future demand by combining the extracted sentiment scores and historical transaction data.

Table 3. Sentiment analysis model evaluation metrics

Metric	Value
Accuracy	0.92
Precision	0.89
Recall	0.91
F1-Score	0.90

Table 4. Demand Forecast Model Evaluation Metrics

Metric	Value
MSE	0.035
R^2	0.94

In order to evaluate the performance of the model, we used several common evaluation indicators, including Accuracy, Precision, Recall and F1-Score for sentiment analysis models, and both The square error (MSE) and R square value (R^2) used in the demand forecast model are shown in Table 3 and Table 4.

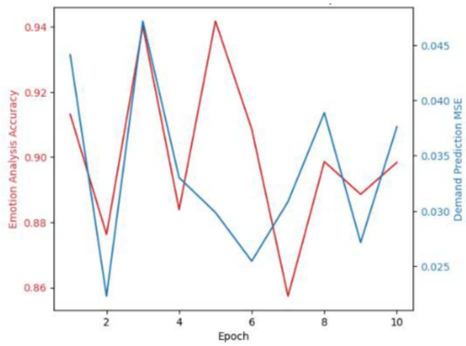

Figure 2. Model Performance Evolution Over Epochs

As shown in Figure 2, in the sentiment analysis model, the accuracy gradually increases during the training process, and finally stabilizes at about 92%, which shows that the model can highly accurately identify emotional tendencies in customer feedback. The mean square error (MSE) of the demand forecast model decreased as the training progressed, and finally stabilized at about 0.035, while the coefficient of determination (R^2) showed a good trend, reaching 0.94, indicating that the model can be very stable. Capture variability in data well and predict future customer needs.

The application and evaluation results of the model show that the sentiment analysis model and demand prediction model we built have shown good performance in processing customer feedback data and historical transaction data. The model can explain the vast majority of demand changes, and the prediction results are consistent with the actual situation. Highly consistent. These results demonstrate the effectiveness of combining sentiment analysis and machine learning techniques for customer demand forecasting. By understanding customers' emotional feedback and combining it with historical transaction data, our model can accurately predict future customer needs and provide important decision support for enterprises.

6. Conclusion

6.1. Research conclusion

This study aims to improve enterprises' understanding of customer behavior and optimize their market strategies by constructing and evaluating a customer sentiment and demand prediction model based on cognitive computing. The study found that sentiment analysis using deep learning and natural language processing technology can effectively extract emotional tendencies from customer feedback, while a demand prediction model combined with historical transaction data can accurately predict customers' future needs. The sentiment analysis model showed high accuracy, demonstrating its ability to effectively identify and classify emotional states in customer feedback. The low mean square error and high coefficient of determination of the demand forecast model further confirm its effectiveness in predicting customer demand.

In addition, the methodology of this study provides a new perspective by analyzing customers' emotional feedback to predict their needs, which not only deepens the understanding of customer behavior, but also provides companies with more personalized and precise market strategies. Through empirical analysis, this study demonstrates the potential of the model in practical applications, providing enterprises with a valuable decision support tool in a highly competitive market environment.

In summary, this study demonstrates the effectiveness of combining cognitive computing techniques and machine learning methods to analyze and predict customer sentiment and needs. This approach not only helps companies respond more quickly to market dynamics, but also plays an important role in improving customer satisfaction and loyalty.

6.2. Research limitations and future directions

Despite the positive results of this study, there are several limitations. First, the size and diversity of the dataset may affect the generalization ability of the model. This study mainly relied on data from specific sources, and future research can improve the robustness and applicability of the model by expanding data sources and types, such as introducing cross-cultural and cross-industry data. Second, the interpretability of the model is another key issue. The current model focuses on predictive performance rather than explanatory, and future research can explore more explanatory models to better understand the relationship between emotions and needs.

In addition, with the development of technology, new data analysis technologies and machine learning algorithms continue to emerge, such as neural networks and reinforcement learning. The application of these advanced technologies may provide new solutions for customer sentiment and demand prediction. Therefore, future research can explore the application potential of these new technologies in this research area.

Finally, considering the particularities of different industries and markets, the versatility and adaptability of the research model are also important directions for future work. By customizing the model to adapt to different types of data and business needs, the application scope and influence of the research results will be further expanded. In summary, this study opens up a promising research direction, and future work is expected to further expand and deepen it at both theoretical and practical levels.

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