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Article

Business Analysis: User Attitude Evaluation and Prediction Based on Hotel User Reviews and Text Mining

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Abstract: In the post-pandemic era, the global hotel industry plays a crucial role in broader economic recovery, with consumer sentiment increasingly influencing market trends and operational strategies. This study utilizes advanced natural language processing (NLP) techniques and the Bidirectional Encoder Representations from Transformers (BERT) model to systematically analyze hotel user reviews, extracting profound insights into customer satisfaction and guiding targeted service improvements. By transforming unstructured textual reviews into high-dimensional feature vectors, the BERT model accurately classifies complex consumer emotions, uncovering nuanced patterns of satisfaction and dissatisfaction that traditional analytical methods often overlook. This sophisticated approach provides highly valuable, data-driven evidence for hotel management, helping them refine service offerings, optimize resource allocation, and significantly improve overall customer experiences. Furthermore, from a financial perspective, understanding consumer sentiment is vital for predicting market performance, as shifts in customer attitudes frequently correlate with stock price fluctuations and overall industry profitability. Additionally, the study rigorously addresses the pervasive issue of data imbalance in sentiment analysis by employing advanced techniques such as oversampling and undersampling to enhance model robustness and predictive accuracy. The empirical results offer actionable insights not only for hospitality practitioners but also for financial analysts, aiding in precise market forecasts and strategic investment decisions. Ultimately, this research highlights the transformative potential of deep learning-based sentiment analysis to drive sustainable business growth, improve financial outcomes, and enhance competitive advantage in the dynamic tourism and hospitality sectors, thereby contributing significantly to the broader economic landscape.

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1. Introduction

The rapid development of internet technology has profoundly transformed daily life, particularly in sectors such as e-commerce, which has significantly influenced industries like tourism and hospitality [1]. The hotel industry, which faced severe disruptions during the global COVID-19 pandemic, has become a critical component of economic recovery in the post-pandemic period. The increasing reliance on user reviews has emerged as a key factor in evaluating hotel services, as consumers depend more on online feedback to assess hotel quality. Understanding consumer sentiment through review data has become essential for hotels to enhance services and adapt to evolving market demands.

In the post-pandemic era, it is essential for hotels to utilize advanced sentiment analysis techniques to better understand consumer emotions and expectations. By employing state-of-the-art natural language processing (NLP) technologies such as BERT (Bidirectional Encoder Representations from Transformers) and deep learning, this study aims to extract actionable insights from hotel reviews, providing valuable guidance for service improvements and strategic decision-making. This approach not only aids in refining hotel service offerings but also contributes to broader market analysis, including understanding consumer behavior and predicting financial trends [2].

A notable innovation of this research is the application of the BERT model, which delivers superior accuracy in sentiment analysis compared to traditional methods [1]. BERT's ability to comprehend contextual information and process data bidirectionally enables it to capture complex emotions expressed in user reviews, facilitating a more nuanced interpretation of customer sentiment. Unlike traditional approaches that often focus on isolated words or phrases, BERT considers the entire context, enhancing the accuracy and depth of sentiment analysis. This improvement in sentiment classification increases the model's adaptability to diverse and complex user feedback, making it more effective for real-world applications in the hospitality industry.

Furthermore, this study addresses the common issue of data imbalance, particularly in sentiment analysis where reviews often exhibit polarization, leaning either positive or negative [3]. The research investigates methods such as adjusting sample weights and employing oversampling or undersampling strategies to mitigate this challenge. By implementing these techniques, the sentiment analysis model maintains robustness and accuracy, ensuring its applicability in various scenarios where data distribution may be uneven.

As the hotel industry rapidly recovers in the aftermath of the pandemic, understanding user preferences and feedback has become vital for maintaining competitiveness in the market [4]. This research provides actionable insights that can assist hotels in enhancing user satisfaction, differentiating themselves in a crowded marketplace, and improving service offerings. Additionally, the insights derived from sentiment analysis are valuable for financial and market analysis, supporting investment strategies and identifying growth opportunities. By integrating advanced NLP and sentiment analysis techniques such as BERT, this study contributes to the development of innovative methodologies in the field, offering a novel approach to market research and consumer analysis in the hotel industry and beyond.

2. Literature review

2.1. Sentiment Analysis

Text sentiment analysis refers to the process of analyzing the sentiment expressed in textual data, identifying whether the sentiment is positive, negative, or neutral [4]. In recent years, this technique has been widely applied to user reviews, providing businesses with valuable insights into customer attitudes. Given the diversity and evolving nature of human language, sentiment analysis techniques have evolved accordingly. Early methods relied on sentiment lexicons and syntactic structures, but modern approaches incorporate machine learning algorithms like Support Vector Machines, Naive Bayes, and more recently, deep learning models, which enable more nuanced sentiment classification. These advancements allow businesses to better understand customer expectations, improve service quality, and ultimately enhance customer satisfaction, which is especially crucial in industries like hospitality, where sentiment analysis can boost hotel occupancy rates and improve guest experiences.

Numerous scholars have contributed to the development of sentiment analysis methods [5]. One proposed model integrates multi-layer attention to improve sentiment classification by enhancing the focus on specific aspects and capturing long-term dependencies between aspect words and context.

Methods based on sentiment lexicons, machine learning, and deep learning have been introduced, highlighting the advantages and distinctions of each approach. Some researchers utilized models to generate more accurate sentiment lexicons for Chinese text.

Others incorporated pooling and dropout algorithms to improve generalization ability and increase classification accuracy [6]. Additionally, combining models with neural networks has enhanced sentiment analysis capabilities by capturing longer contextual information.

In the financial and economic context, sentiment analysis can play a significant role in predicting market trends, as shifts in consumer sentiment often correlate with financial performance [7]. This makes sentiment analysis a valuable tool not only for customer satisfaction but also for financial market forecasting and economic analyses. Techniques such as dictionary expansion and statistical methods for rule extraction have been proposed. This growing body of research underscores the importance of sentiment analysis in both business and financial sectors, offering new ways to understand customer behavior and make data-driven decisions that improve market outcomes.

2.2. The current research status of the usefulness of user comments and online comments

In the era of the social Internet, online reviews have become not only a cultural phenomenon but also a significant form of word-of-mouth marketing, profoundly influencing consumer decision-making processes. This has led to increased attention from both academic researchers and industry practitioners, especially in the context of financial markets and economic analysis. Online reviews provide a rich source of alternative data that allows businesses to gauge consumer sentiment, which can be leveraged for improving marketing strategies, investment decisions, and risk assessment [8].

Reviews have become a critical tool for shaping consumer perceptions, especially when it comes to making informed purchasing decisions. The influence of both positive and negative reviews is particularly pronounced in sectors such as e-commerce and logistics, where companies are increasingly leveraging sentiment analysis to refine their offerings and optimize customer experiences. Consumers are often inclined to scrutinize both positive and negative reviews to make more informed decisions, highlighting the importance of review sentiment in consumer behavior analysis. This trend has significant implications for financial technology, where businesses and investors use sentiment data to predict market trends, assess financial stability, and identify emerging investment opportunities [9].

Factors such as brand reputation and product type are pivotal in determining the usefulness of reviews, influencing follow-up comments and overall review sentiment. Social benefits are identified as a key driver of positive online reviews, particularly in the context of consumer engagement with online platforms [2]. The impact of review features such as image quantity and text length on customer satisfaction has also been widely studied, revealing that these elements have a positive correlation with customer satisfaction, while excessive text length can negatively affect consumer perceptions.

From an economic perspective, reviews significantly influence market dynamics [10]. The quality, form, and value of reviews directly affect customer perceptions of risk and perceived usefulness, ultimately influencing their purchasing decisions. This is especially important in the context of financial markets where consumer sentiment, captured through review analysis, can serve as a leading indicator of broader market trends.

User reviews contribute to social influence and information flow in financial markets, where the perception of high-quality reviews can directly impact stock prices and investment decisions. Consumers prioritize the value of reviews—whether positive or negative—over the perceived utility, which is highly relevant for the evaluation of consumer behavior in financial technology markets [11].

3. BERT-based Sentiment Analysis Model

3.1. Introduction to Transformer Model

The Transformer is a neural network architecture designed for natural language processing tasks. It was introduced in 2017 and has achieved significant advancements in various applications. The Transformer employs a sequence-to-sequence learning approach based on the attention mechanism, which calculates the relevance between words at different positions in a sequence and facilitates information exchange between the encoder and decoder. The model incorporates a multi-head attention mechanism, which divides the input into multiple subspaces and performs attention computations on each subspace to better capture semantic information. Furthermore, the Transformer utilizes residual connections and layer normalization techniques to enhance convergence speed and model stability. Positional encoding is also introduced to represent the positional information within the input sequence [12] (As shown in Figure 1).

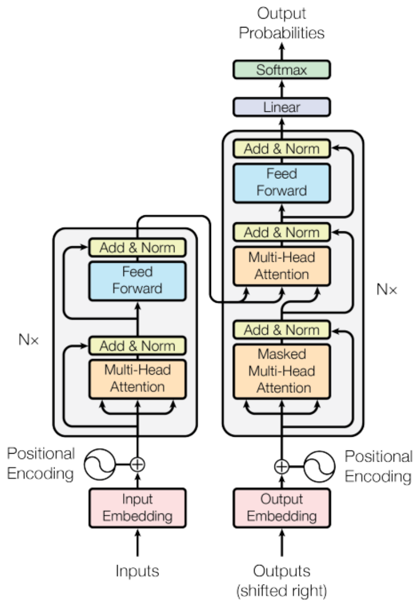

Figure 1. The structure of Transformer [13].

The Transformer Encoder is a key component of the Transformer model, designed to convert the input sequence into a series of hidden representations. It is composed of multiple Encoder Layers, each containing two sub-layers: a multi-head self-attention layer and a fully connected feed-forward layer [13].

3.1.1. the multi-head self-attention mechanism layer

In the multi-head self-attention mechanism layer, each position in the input sequence is utilized to calculate its correlation with other positions, encoding the dependencies between them [14]. This is achieved by dividing the input into multiple sub-vectors, with each sub-vector used to compute the self-attention mechanism. The layer processes the input sequence as queries, keys, and values.

The input is passed through an attention mechanism, where the attention weights are multiplied by the values and summed to produce an output representation [15]. The formula is expressed as follows:

$$\text{MultiHead}\ (Q, K, V) = \text{Concat}\ (\text{h}_1, \ldots, \text{h}_h)W^O \quad (1)$$

$$h_i = \text{Attention}\ \left(QW_i^Q, KW_i^K, VW_i^V\right) \quad (2)$$

$$\text{Attention}\ (Q, K, V)\& = \text{softmax}\ \left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (3)$$

Here, represents the number of heads, and is the weight matrix of linear transformation, obtained by concatenating multiple head results and applying linear transformation to produce the final output. It is the dimension of the key, which scales the attention distribution to better control its range [16].

3.1.2. the multi-head self-attention mechanism layer

In each Encoder Layer, the output of the multi-head self-attention mechanism layer is combined with the input through residual connections and normalized using layer normalization [12]. Residual connections involve adding the input and output to minimize information loss, while layer normalization standardizes all feature dimensions of each sample to enhance the model's stability and convergence speed. The formula is as follows:

$$\mathrm{LayerNorm}\ (\mathrm{x} + \mathrm{MultiHead}\ (\mathrm{Q}, \mathrm{K}, \mathrm{V})) \quad (4)$$

Here, x represents the input vector [5].

3.1.3. Feed Forward Networks

In a fully connected feedforward layer, the output representation is transformed through a combination of two linear transformations and an activation function. The purpose of this layer is to enhance the model's non-linear and representational capabilities, enabling it to better capture semantic information in the sequence. The formula is as follows:

$$\mathrm{FFN}\ (\mathrm{x}) = \max(0, \mathrm{x}\mathrm{W}_1 + \mathrm{b}_1)\mathrm{W}_2 + \mathrm{b}_2 \quad (5)$$

Where $\mathrm{W}_1, \mathrm{b}_1$ and b_2 represent the weight matrices and bias vectors of the linear transformations.

Residual connections and layer normalization are also applied in the fully connected feedforward layer. Specifically, the output of the previous layer is added to the result obtained after two linear transformations and activation functions, followed by normalization through layer normalization. The formula is as follows:

$$\mathrm{LayerNorm}\ (\mathrm{x}+\mathrm{FFN}(\mathrm{x})) \quad (6)$$

A Transformer Encoder is a structure composed of multiple Encoder Layers that transform input sequences into a series of hidden representations. Each Encoder Layer includes a multi-head self-attention mechanism layer and a fully connected feedforward layer, with residual connections and layer normalization incorporated to enhance the model's stability and representational capacity.

3.2. Transformer decoder

The decoder block of the Transformer consists of six stacked decoders. Each decoder includes a masked multi-head attention mechanism, a multi-head attention mechanism, and a fully connected neural network. Compared to the encoder, it incorporates an additional masked multi-head attention mechanism, while the other components remain identical. The masked multi-head attention mechanism masks specific values to prevent them from influencing parameter updates. The output of the converter undergoes linear transformation, followed by the application of the softmax function to obtain the probability distribution of the output. Ultimately, the word with the highest probability in the dictionary is selected as the predicted output [6].

3.3. Word vectorization based on BERT model

BERT is a Transformer-based pre-trained language model that achieves a universal language representation through two stages of training [9]. In the pre-training stage, a large amount of unlabeled text data is utilized, and context semantics and sentence associations are learned through Masked Language Model (MLM) and Next Sentence Prediction (NSP) tasks. In MLM tasks, the model predicts masked words using context, thereby learning to understand missing words within the context. In NSP tasks, the model predicts the coherence and semantic association between two sentences, enhancing its ability to understand sentence-level semantics.

The input to BERT includes the initial word vector, text vector, and position vector. The initial word vector is randomly initialized, the text vector captures the global semantic information of the text, and the position vector represents the semantic differences carried by words at different positions. Through pre-training and fine-tuning, BERT can be applied to various natural language processing tasks, such as text classification, named entity recognition, and question-answering systems. The performance of the BERT model has led to significant advancements in the field of natural language processing, establishing it as one of the most advanced models currently available.

Compared with traditional Attention mechanisms, the BERT model incorporates the order and position information of each word. This approach addresses the issue of ignoring the order of words or characters in traditional Attention mechanisms (As shown in Figure 2).

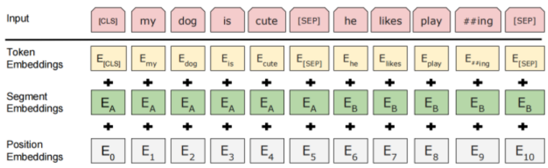

Figure 2. BERT Model Input [14].

Through the two tasks of MLM and NSP, the BERT model can pre-train on extensive text data, learn deep representations of language, and perform effectively in various natural language processing tasks [8].

In the BERT model, input data undergoes three critical processing steps to obtain an effective text vector representation. Firstly, during the Token Embedding stage, each word or tag is transformed into a fixed-dimensional embedding vector to capture semantic relationships between words. Next, Segment Embedding is applied to distinguish the semantics and associations between different sentences. Finally, Position Embedding is used to account for the order of words in the text. After completing these steps, the text vector representation is obtained and further processed through multiple Transformer encoder layers. Each encoder layer includes a Self-attention mechanism to model text associations and enhance semantic expression. Following Self-attention, semantic vectors are processed through a series of operations and activation functions to extract rich semantic features. Enhanced semantic vectors are then obtained through linear transformation and random deactivation operations, serving as input for the next encoder layer. This process is repeated across the remaining encoder layers, providing the BERT model with strong semantic expression capabilities. The multi-layered encoder structure makes BERT a highly effective and widely utilized model in natural language processing tasks.

4. Results

Evaluation of Model Related Indicators: The accuracy, precision, recall, F1 score, and other metrics of the model on the test set are calculated to determine its performance. Commonly used indicators for evaluating the effectiveness of model training include accuracy and log loss. Higher accuracy indicates better classification performance of the model.

Precision rate (check rate): The precision rate represents the proportion of positive cases among all samples predicted to be positive cases. It measures how accurately the model predicts positive cases.

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Recall rate: Recall rate represents the proportion of samples that are actually positive and correctly predicted by the model as positive. It reflects the coverage of the model for positive samples.

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

F1 value: F1 value is a comprehensive indicator of precision and recall, used to balance the relationship between the two. A higher F1 value indicates better model performance in terms of precision and recall.

$$F1 = \frac{2TP}{2TP+FP+FN} \tag{9}$$

Accuracy: Accuracy refers to the proportion of correctly classified samples among all predicted results relative to the total number of samples. However, in cases of imbalanced samples, accuracy may not serve as a reliable evaluation indicator [11].

$$Accuracy = \frac{TP+FN}{TP+FP+TN+FN} \tag{10}$$

The adjustment of model parameters is achieved through backpropagation of the loss function value, which measures the difference between the predicted and actual values of the model. A smaller logarithmic loss value indicates better classification performance of the model. By setting the number of training iterations (epoch=5), the model can be trained multiple times, gradually optimizing its performance. The following figure illustrates the variation curves of accuracy and recall during the training process (As shown in Figure 3).

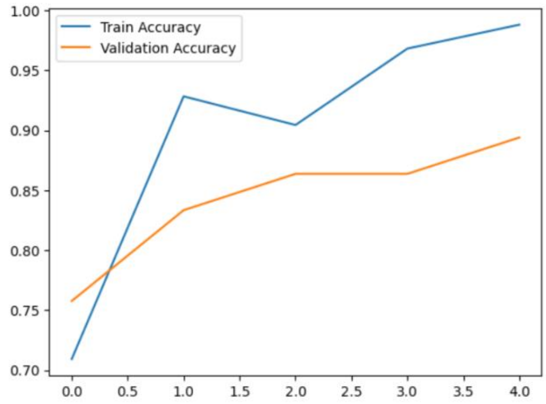

Figure 3. Changes in classification accuracy of the BERT model.

From the above figure, it can be observed that as the number of model training iterations increases, when the epoch reaches 4, the accuracy of the BERT model gradually increases, approaching 1, and eventually reaches 0.975. The logarithmic loss value decreases from 0.4555 to 0.3403, approaching 0, indicating effective model training. In deep learning, the balance of data distribution is generally adjusted during the experimental process based on empirical judgment. In the task of deep learning comment classification, different data distributions can lead to varying prediction results. The primary parameter to adjust is the balance of data distribution.

During the model training process, parameters are adjusted through backpropagation to minimize the difference between predicted values and actual values, i.e., the loss function value. A smaller logarithmic loss value corresponds to better classification performance. To achieve optimal performance, multiple training iterations are required. By setting the number of training iterations (epoch) to 10, the model can achieve improved performance after multiple iterations.

5. Conclusions

This study conducted an in-depth analysis of hotel review data, developing an effective rating classification model based on sentiment analysis and fine-tuning the BERT model to achieve significant classification results. The main findings of the study include successfully addressing the issue of data imbalance, particularly when the imbalance ratio was 30% and 40%, where the model demonstrated optimal performance with high precision, recall, and F1-score. Excellent classification results were achieved on the test set through the training and evaluation of the BERT model. When applied to real business data, the model provided valuable insights into customer satisfaction, key issues, competitor analysis, and market trends, offering a decision support tool for hotel managers. However, the study has certain limitations, primarily the limited data size, which may not encompass all scenarios and types of reviews. Future research could expand the dataset to verify the robustness and generalization capability of the model. Additionally, sentiment labeling could be more detailed, as the current study utilized only positive, neutral, and negative labels; further refinement could yield more specific sentiment information. Moreover, BERT and other deep learning models face challenges with interpretability, and future work should aim to enhance model interpretability to better align with practical business needs.

This study offers significant insights for the business sector, particularly in the hotel industry and other service industries. The sentiment analysis model enables businesses to gain a comprehensive understanding of user sentiments toward their products and services. By identifying and addressing negative emotions promptly, user experience can be improved. Furthermore, sentiment analysis can guide the optimization of service quality, including enhancing facilities, improving hygiene management, and refining customer service. Through competitor review data analysis, businesses can better understand the competitive landscape and adjust their strategies accordingly. Additionally, large-scale review data analysis aids in detecting market trends and shifts in consumer preferences, allowing businesses to adapt their products, services, and marketing strategies. In the future, sentiment analysis is expected to have broader and deeper applications in the business domain. Research could explore more advanced natural language processing models, such as the GPT series, and integrate multimodal data for joint analysis to enhance sentiment analysis accuracy. The model could also be extended to other industries, such as dining, retail, and tourism, with customized development. Real-time sentiment analysis systems would enable businesses to respond swiftly to market changes, strengthening their competitive advantage. Sentiment analysis visualization tools could further assist non-technical personnel in understanding analysis results, facilitating more informed decision-making.

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