BICASH: BERT-based Integrated Analysis of Campus Sentiment with Sequential Histories

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Abstract

In the era of digital communication, social media and online platforms have become prevalent channels for expressing emotions and opinions, particularly in campus communities where students frequently share their daily lives, learning experiences, and emotional states. Accurately identifying the sentiment of students' comments is crucial for analyzing their current psychological state. However, traditional sentiment analysis methods mainly focus on the explicit content of texts, often overlooking the potential impact of a user's past emotional expressions on their current emotional state. Therefore, this paper introduces BICASH, a novel sentiment analysis method based on user historical sentiment analysis. This approach assists in more accurately judging the sentiment of current comments by using the BERT model for preliminary analysis of current sentiment, and the LSTM model to capture the sequential relationship between historical comments, thus refining the assessment of current sentiment. We conducted experiments with this model on a campus comment sentiment analysis dataset. The results show that the BICASH model, utilizing 50 historical comments for sentiment extraction, achieves the best performance with a precision rate of 0.8311, recall rate of 0.7943, and F1 score of 0.8123, outperforming other baseline models.

Keywords: BERT, Campus management, LSTM, Sentiment analysis, Sequential history

1 Introduction

With the rapid development of social media and online communication platforms, people increasingly express their sentiment and opinions through these channels [1]. Especially in campus communities, students tend to share their daily lives, learning experiences, and sentimental states on these platforms. Thus, these textual data become a crucial resource for understanding students' sentiment and needs. However, these texts often contain rich and complex sentimental expressions, making automatic sentiment analysis a challenging task [2].

Existing sentiment analysis methods primarily focus on analyzing the explicit content of texts, often overlooking the potential impact of users' past sentimental expressions on their current sentimental state. This approach has limitations in understanding individual sentimental dynamics and providing in-depth sentiment analysis, particularly in environments like campus communities, where sentimental expressions are diverse and sentimental dynamics complex. To overcome this challenge, we need an analysis method that comprehensively considers users' historical sentiment.

To address the aforementioned issues, this paper presents BICASH, a method for campus comment sentiment analysis that integrates historical sentimental trends. BICASH combines natural language processing techniques and deep learning, particularly leveraging the powerful capabilities of the BERT model [3-4] to capture deep semantic relationships in comment texts, and utilizes LSTM [5-6] networks to capture and utilize sentimental trends in users' historical comments. Moreover, the BICASH method not only focuses on the analysis of the current text content but also considers the impact of users' historical sentiment on their current sentimental tendencies, providing a comprehensive and in-depth sentiment analysis framework. Through this method, we believe we can more accurately understand and analyze the sentimental dynamics in campus comments, offering valuable sentimental insights for the campus community.

The main contributions of this paper are as follows:

(1) We proposed BICASH, a text sentiment classification model that integrates the BERT model with the LSTM model, using users' historical sentiment to balance the sentiment scoring of current user comments by the BERT model.

(2) We designed a platform for campus management applications, which provides data for sentiment analysis of campus comments.

(3) Experiments were conducted to explore the optimal performance configuration of the BICASH model and to compare its performance with other models.

The remainder of this paper is organized as follows: Chapter 2 describes related work in the field of sentiment analysis; Chapter 3 details the methodology of the BICASH model; Chapter 4 describes the experimental setup; Chapter 5 presents and discusses the results of the experiments; Chapter 6 addresses the threats to validity; and Chapter 7 concludes the paper and outlines future work.

2 Related Work

In the field of sentiment analysis, scholars both

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domestically and internationally have made a series of research efforts in recent years. The most mainstream methods now include those based on machine learning and deep learning [7].

In traditional machine learning approaches, researchers typically train models on a large corpus of labeled or unlabeled text data to build classifiers capable of discerning the sentiment of new texts. For instance, Ramanda et al. [8] conducted sentiment analysis on the ISEAR dataset using SVM, and the results indicated that the linear SVM method performed well in this task. Dey et al. [9] applied Naive Bayes and K-Nearest Neighbors (KNN) algorithms to analyze movie and hotel reviews, finding that Naive Bayes performed better in the domain of movie reviews, while its accuracy was comparable to KNN in hotel reviews. Nguyen et al. [10] innovatively combined constituent tree and dependency tree kernels to develop new tree kernels for extracting aspect-opinion relations, thereby accurately identifying the sentiment orientation of given aspects. Rao et al. [11] transformed polarity detection into a graph-based semi-supervised label propagation problem, making significant strides in constructing sentiment lexicons.

Although traditional machine learning methods have achieved certain effects, their performance largely depends on the effectiveness of manual and dictionary features, which limits the model's flexibility and generalizability, severely impacting the accuracy of sentiment classification tasks. With the rapid development of deep learning methods, deep learning has become mainstream in sentiment classification. For example, Tang et al. [12] trained an LSTM model using microblog comment texts to create a short-text sentiment classification model, which helps to determine the emotional tendencies of short text corpora. Yang et al. [13] enhanced model classification effectiveness by using word-level attention weight calculations; Yu et al. [14] proposed a sliced recurrent neural network that parallelizes by slicing the input sequence into multiple subsequences and leveraging multiple layers to capture more advanced information, achieving better performance in sentiment classification tasks. However, with the introduction of BERT by Google in October 2018, scholars began to use pre-trained large models for sentiment analysis tasks [3]. For instance, Wan et al. [15] proposed Emotion-Cognitive Reasoning integrated BERT (ECR-BERT) for sentiment analysis of online public opinions in emergency situations. This approach combines emotion models and deep learning to enhance the accuracy and interpretability of the BERT model in handling complex and diverse emotional data. Joloudari et al. [16] integrated BERT for capturing deep semantic information with the powerful feature extraction capabilities of CNN models, effectively addressing the sentiment analysis task of COVID-19 public opinion.

Despite the ability of existing methods to automatically learn the complex mapping relationship between input data and output targets through deep learning's powerful representation learning capabilities, and their deep exploration of semantic relations in texts through multi-layer nonlinear transformations, these methods focus primarily on the text itself and do not abstract the analysis to the user level to consider historical emotions. In contrast, our proposed BICASH method captures users' historical comment sentiments, thus deducing the impact of their past comments on the sentiment of their current comments, providing deeper support for sentiment judgment.

3 Methodology

3.1 Method Overview

Figure 1 illustrates the proposed BICASH method. For a given campus comment text context $C = \{c_1, c_2, \ldots, c_n\}$ of length n , where $c_i \in \mathbb{R}^{dE}$, represents the i-th word in the text and d_E denotes the dimension of the word vector, and all evaluation targets in the text $A = \{A_1, A_2, \ldots, A_m\} \in \mathbb{R}^{k*m*dE}$, where k is the total number of evaluation targets, m is the length of each evaluation target, and $A_i = \{a_1, a_2, \ldots, a_m\} \in \mathbb{R}^{m*dE}$ represents the i-th evaluation target in the text, with $a_i \in \mathbb{R}^{dE}$ being the i-th word in that evaluation target. The BICASH method first employs a Bert encoding layer to represent the features of the campus comment text context and the comment targets as vectors $E_c \in \mathbb{R}^{n*dH}$ and $E_a \in \mathbb{R}^{m*b*H}$, where d_H denotes the feature vector dimension. It then utilizes an attention mechanism to obtain the semantic information representations $S_c \in \mathbb{R}^{dI}$ and $S_a \in \mathbb{R}^{dI}$ between the context and the evaluation targets, where d_I denotes the attention vector dimension, to ensure full interaction between them. S_c and S_a are concatenated to form the overall semantic representation $I_i \in \mathbb{R}^{2dI}$ of the current comment. Subsequently, the current overall semantic representation I_i and historical overall semantic representations $I_h \in \{I_1, I_2, \ldots, I_{i-1}\}$ are input into an LSTM layer to capture the temporal influence features $T_i \in \mathbb{R}^{dL}$ denotes the dimension of the temporal influence feature vector. Finally, the temporal influence feature vector T_i is fed into a fully connected layer, and the emotion category of the user comment is predicted using the Softmax function.

3.2 Comment Text Encoding Based on the BERT Method

First, we extracted user i's current comment and their historical set of campus comment texts from the database. The historical campus comment text collection was then ordered by time, selecting the most recent r entries. Each of user i's campus comment texts underwent preprocessing, which involves tokenizing the text into a sequence of words $c_1, c_2, \ldots, c_n$ and removing stopwords, punctuation, special characters, and other non-essential elements. Numbers and letter cases within the text are also normalized to reduce noise during model training. After these preprocessing steps, each word c_i is mapped into a vector space $\mathbb{R}^{dE}$, where W represents the vocabulary.

Subsequently, we employ a BERT encoder, a multi-layer bidirectional structure based on the Transformer architecture, which takes the sequence of word vectors as input:

$$E_c = BERT_{encoder}(\vec{\phi}(c_1), \vec{\phi}(c_1), \ldots, \vec{\phi}(c_n)). \quad \textbf{(1)}$$

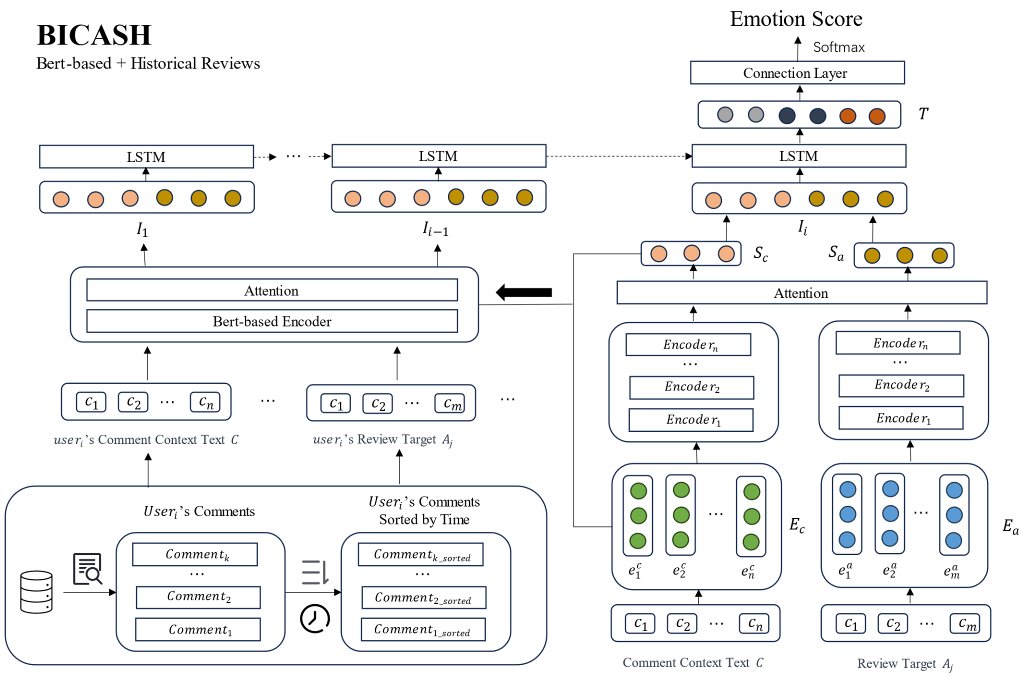

Figure 1. Overview of BICASH

The output, $E_c \in \mathbb{R}^{n*d_H}$, represents the encoded feature vectors of the comment context, where d_H is the hidden layer size of the BERT model, and n is the length of the text in the comment context. Similarly, for each word in the evaluation target *j*, the same encoding process is applied:

$$E_a^j = BERT_{encoder}(\vec{\phi}(a_1^j), \vec{\phi}(a_2^j), \ldots, \vec{\phi}(a_n^j)). \tag{2}$$

where $E_a^j \in \mathbb{R}^{m*d_H}$ and m represent the encoded feature vectors and length of the j-th evaluation target, respectively.

After obtaining the encoded vectors, our study applies an attention mechanism to capture the semantic relationship between the comment context and the evaluation targets. The attention scores are computed using the following formula:

$$\begin{aligned} &Attention(E_c, E_a^j) \\ &= soft\max\left(\frac{(E_c W_q)(E_a^j W_k)^T}{\sqrt{d_k}}\right) E_a^j W_v. \end{aligned} \tag{3}$$

Here, W_q, W_k, and W_v are trainable weight matrices, and d_k is the dimensionality of the key vectors. Through this step, the model enhances the semantic interaction between the context and targets, facilitating more nuanced sentiment recognition.

Finally, the attention-weighted representations of the context and targets calculated are used for the next step of sentiment classification. They are concatenated into a unified representation vector and input into an LSTM to model the trends in user sentiment and the influence of historical comments.

3.3 Use LSTM to Integrate Historical Comments for Sentiment Analysis

Following the attention-based encoding of the current comment context and target, we utilize Long Short-Term Memory networks (LSTM) to integrate the user's historical emotional trends. LSTMs excel at capturing long-distance dependencies within time-series data, which is crucial for understanding the emotional evolution within user-generated content.

Given the previous semantic representation sequence I_1, I_2, …, I_{n-1} along with the current representation I_i, the LSTM module computes the temporal influence feature T_i as follows:

$$T_i = LSTM(I_h, I_i, \theta_{LSTM}). \tag{4}$$

Here, I_h represents the historical context, I_i is the current semantic representation obtained from the attention mechanism, and θ_{LSTM} represents the learnable parameters of the LSTM. Each LSTM cell iteratively updates its cell state C_t and hidden state h_t, encapsulating information about previous comments and the current emotional context. The detailed description of capturing the temporal features within historical comment data is as follows: First, the forget gate f_t decides and selectively discards historical information that is no longer important:

$$f_t = \sigma(W_f \cdot [h_{t-1}, I_i] + b_f). \tag{5}$$

Here, σ denotes the sigmoid function, determining the retention or forgetting of each information unit; W_f is the weight matrix of the forget gate; b_f is the bias term; h_{t-1} is the hidden state from the previous time step; and I_i is the encoded representation of the current comment.

Subsequently, the input gate i_t along with the candidate for new information $\widetilde{C}_t$, decides which new information will be added to the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, I_i] + b_i). \tag{6}$$

$$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, I_i] + b_C). \tag{7}$$

Here, W_i and W_c are the weight matrices for the input gate and the candidate for new information, respectively; b_i and b_C are the respective bias terms. These two formulas together determine how the cell state updates with new information.

Then, the LSTM cell state C_t is updated based on the outputs from the forget gate and the input gate:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t. \tag{8}$$

Thus, the LSTM is able to retain useful historical information while introducing new information. Finally, the output gate o_t decides which information from the current cell state C_t will be used to update the current time step's hidden state h_t:

$$o_t = \sigma(W_o \cdot [h_{t-1}, I_i] + b_o). \tag{9}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{10}$$

W_o is the weight matrix for the output gate, and b_o is the bias term. The final hidden state h_t is then considered as the final temporal feature T_i, which is then output to a fully connected layer with a softmax activation function to obtain the probability distribution of emotional categories:

$$P(y|T_i) = Soft\max(W_y \cdot T_i + b_y). \tag{11}$$

Where W_y and b_y are the weight matrix and bias vector of the output layer, respectively, and $P(y|T_i)$ represents the predicted probability of each emotional category given the temporal influence feature T_i.

By harnessing the sequence information processing capability of LSTM, the BICASH framework attempts to combine historical emotional trends with the semantic content of current comments. This integration promotes comprehensive emotional prediction, considering the user's emotional trajectory over time, providing an emotional classification that reflects both the immediate context and historical emotional inclinations.

4 Evaluation Setup

To validate whether our method can outperform current mainstream approaches in the task of campus comment sentiment analysis, and also to explore the impact of different experimental setups on the BICASH method, we formulated the following Research Questions:

(1) RQ1: What is the best experimental setting for our method?

(2) RQ2: Can our method effectively analyze the sentiments of campus comments?

To answer these research questions, we set up a series of experiments. The remaining part of this section will elaborate in detail on our experimental setup and the rules for parameter determination.

4.1 Dataset

The dataset used in our experiments was obtained from the smart campus platform we established. The structure of the platform, as shown in Figure 2, is based on the middle-office architecture proposed by Alibaba [17]. The platform consists of an infrastructure layer that ensures the stability and data integrity of the platform, a middle-office layer that provides data support and business processing, and an application layer that directly serves users, meeting the diverse needs of different types of users. Other layers of the design further enhance the robustness and interactivity of the platform.

Within the application layer, student feedback and analysis are key functionalities. We collected a dataset from the corresponding database of this application, comprising 75,321 comment entries from 180 users over the past year, along with their associated user metadata. This dataset was used to test the BICASH approach.

Traditional sentiment classification typically considers only two emotional categories: positive and negative. However, to address the diversity of emotions in campus comments, we expanded and defined seven more granular emotional category labels: happiness, sadness, anger, surprise, fear, disgust, and love. We invited 100 graduate students to manually annotate all the comments.

4.2 Evaluation Metrics

We use Precision, Recall, and F1 Score as evaluation metrics to assess the performance of our method. Precision refers to the ratio of true positive samples among the samples predicted as positive. There are two possibilities when predicting positive: correctly predicting a positive class as positive, and incorrectly predicting a negative class as positive. Precision can be expressed as Equation 12:

$$P = \frac{TP}{TP + FP}. \tag{12}$$

Recall refers to the ratio of positive instances that are correctly predicted in the sample. There are also two scenarios: a correct prediction, where the original positive class is predicted as positive, and a failed prediction, where the original positive class is predicted as negative, as shown in Equation 13:

$$R = \frac{TP}{TP + FN}. \tag{13}$$

Sometimes precision and recall may contradict each other. Neither precision nor recall alone can comprehensively measure the performance of a model. Therefore, the F1-Measure is introduced to obtain the harmonic mean of precision and recall:

$$F1 = \frac{2 * P * R}{P + R}. \tag{14}$$

4.3 Experimental Setup

For the BICASH method itself, we have set parameters for its training, as shown in Table 1. The dataset is divided into a training set and a test set in an 8:2 ratio, where the training set is used to train the model, and the test set is used to evaluate the model's classification performance.

To investigate RQ1, this study initially compared the effects of integrating user historical sentiment strategy into the BICASH method with the results obtained without this integration. Subsequently, we experimented with varying volumes of historical comment data (5, 10, 20, 50, 100 comments) to analyze how different quantities of historical comments impact the performance of the BICASH method, aiming to identify the optimal historical comment setting.

For the validation of RQ2, we selected several representative methods in the domain, such as LSTM, AT-LSTM, ATAE-LSTM, AEN, and CapsNet-BERT, for a detailed comparison with the optimal configuration of the BICASH method. This step was designed to evaluate the performance of the BICASH method in campus comment sentiment analysis compared to other existing approaches. Through this comparative analysis, we aim to demonstrate the advantages and potential applications of the BICASH method in the field of sentiment analysis and explore whether combining BERT with LSTM can enhance performance compared to relying solely on either the BERT model or the LSTM model independently. The detailed descriptions of the comparison methods are as follows:

Table 1. BICASH parameter setup

Parameter name	Description	Value
Learning Rate	Controls the step size for weight updates per iteration	0.001
Epochs	Number of complete passes through the dataset during training	20
Batch size	Number of samples used per training iteration	128
BERT model	Pre-trained BERT model used	BERT-Base
LSTM hidden layer size	Dimensionality of hidden states in LSTM layer	256
Dropout rate	Proportion in dropout layer to prevent overfitting	0.5
Optimizer	Algorithm for optimizing model parameters	Adam
Attention heads	Number of heads used in the attention mechanism	12

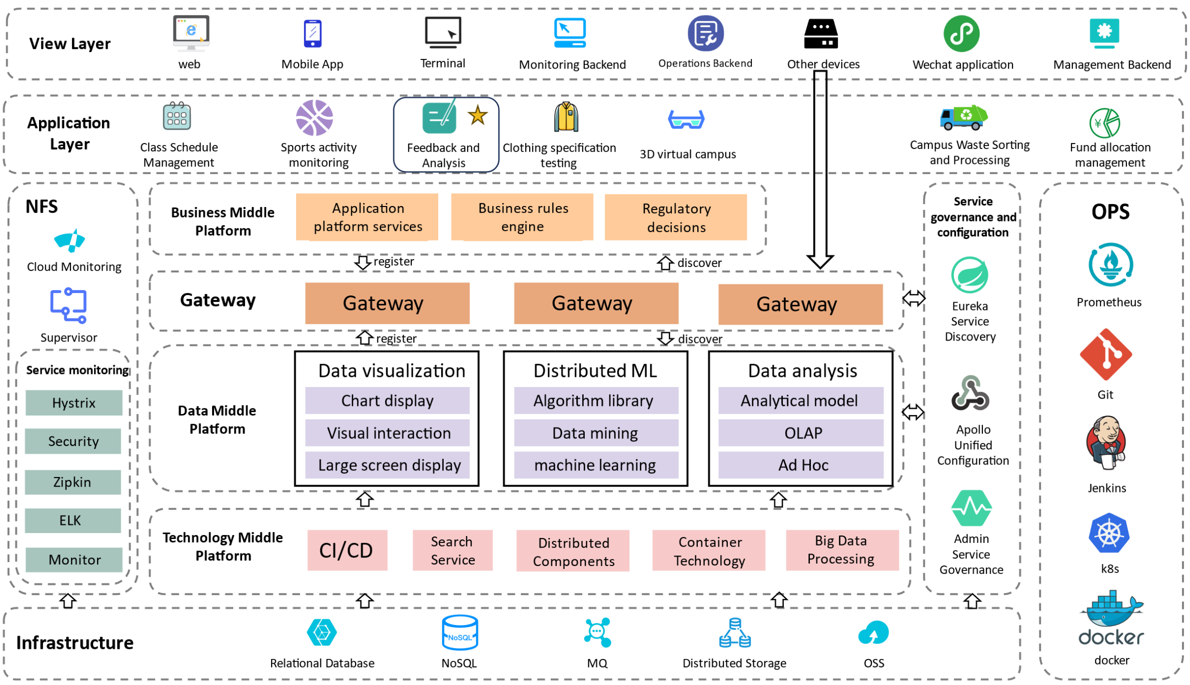

Figure 2. Overview of smart campus platform structure

(1) LSTM [3]: This method employs a singular LSTM network to model sentences, capturing the hidden states of each word. The final hidden state is used as the feature representation for sentiment classification.

(2) AT-LSTM [18]: AT-LSTM initially models the text context using LSTM, then combines the hidden states of context words with the target word embedding to generate an attention vector. The final feature representation for sentiment classification is the weighted sum of these hidden states.

(3) ATAE-LSTM [18]: Target word vectors, after being average-pooled, are concatenated with the word vectors of each context word as input to the LSTM. The attention mechanism dynamically calculates attention weights based on the relationship between the context and the target, predicting the sentiment label for the given target.

(4) AEN [19]: Combines the pre-trained BERT model and attention encoding network to model the context and target, achieving semantic interaction. Label smoothing regularization is introduced in the loss function to address the unreliability of labels.

(5) CapsNet-BERT [20]: Utilizes the BERT model and capsule network's guided routing mechanism to learn the complex relationship between context and target. Demonstrates superior performance on the multi-aspect multi-sentiment MAMS dataset compared to other target-level sentiment classification methods.

5 Results

5.1 RQ1: What is the Best Experimental Setting for Our Method?

We conducted a series of experiments with ten-fold cross-validation, as described in Section 4.3, considering the strategy of using user historical comments and the number of historical comments as additional parameters. The results are presented in Table 2.

Table 2. Cross-validation results of the BICASH Method with different historical comment settings

Strategy	Number of comments	Precision	Recall	F1
Without historical comments	N/A	0.7542	0.7310	0.7425
With historical comments	5	0.7811	0.7633	0.7721
With historical comments	10	0.8032	0.7896	0.7963
With historical comments	20	0.8234	0.7998	0.8114
With historical comments	**50**	**0.8311**	**0.7943**	**0.8123**
With historical comments	100	0.8157	0.8012	0.8084

From the results shown in Table 2, When historical comments are not considered, the model's precision, recall, and F1 score are relatively low. This indicates that relying solely on the analysis of current text content may not fully capture the user's emotional state. With the introduction of historical comments, we observed an enhancement in the performance of the sentiment capture task (precision improved by 0.0269 to 0.0769, recall by 0.0323 to 0.0791, and F1 score by 0.0296 to 0.0698). This result suggests that an appropriate amount of historical comments can provide critical emotional background information to the model, aiding in a more accurate understanding of the current comment's emotional tendency.

However, when including the most recent 50 historical comments, the performance peaked, achieving a precision of 0.8311, a recall of 0.7943, and an F1 score of 0.8123. Yet, when the number of historical comments increased to 100, there was a slight decrease in performance. This minor decline suggests that while historical data is valuable, exceeding a certain threshold can introduce noise or redundant information. This increases the model's processing burden, making it challenging to effectively extract features from a large volume of historical information that are most relevant to the current emotional state, thereby affecting the model's accuracy.

This finding underscores the necessity of a balanced approach in including the number of historical comments in the analysis. Too few comments may not provide enough context, while too many might introduce unnecessary complexity. Based on our experiments, the optimal number of historical comments for the BICASH method appears to be around 50. This setting provides a comprehensive view of the user's emotional history while not overwhelming the model with excessive information.

5.2 RQ2: Can Our Method Effectively Analyze the Sentiments of Campus Comments?

The experimental results, as shown in Figure 3, indicate that the BICASH method with its optimal configuration outperforms other baseline methods in the task of campus comment sentiment analysis. Furthermore, methods based on BERT generally surpass those based on LSTM, and our observations regarding this are as follows:

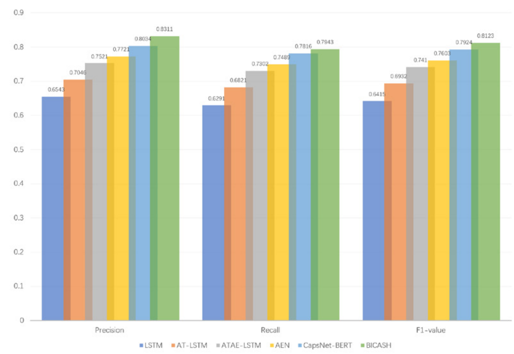

Figure 3. Performance comparison of various models on campus comment dataset (Precision, Recall, and F1 Score)

The basic LSTM model, while fundamental, shows lower performance compared to its advanced variants and other methods. This underlines the complexity of sentiment analysis in campus comments, necessitating more sophisticated techniques. The performance enhancement with AT-LSTM and ATAE-LSTM, which utilize attention mechanisms, underscores the importance of understanding context in sentiment analysis. This reflects the necessity of attention-based models to capture the subtle interactions between different words in a sentence for accurate sentiment prediction.

Additionally, the competitive outcomes of AEN and CapsNet-BERT, particularly with CapsNet-BERT having a slight edge, demonstrate the potential of combining pre-trained models like BERT with advanced neural architectures. Such combinations are particularly effective in analyzing the complex relationships between context and target sentiment in the text.

The standout performance of the BICASH method is primarily attributed to its effective integration of historical sentiment trends with the current context of the comment. By leveraging the LSTM's capability to process sequential information, BICASH provides a nuanced understanding of how sentiments evolve over time, ensuring comprehensive sentiment analysis. This aspect is particularly crucial for platforms that need to understand the dynamic nature of user sentiments, and it is a key reason why BICASH outperforms the other five baseline methods.

6 Threats to Validity

Structure threats: The selection of parameters for the BICASH method, such as the learning rate and the number of iterations, directly affects the model's training and performance. The process of parameter determination did not cover all possible selections, which might lead to deviations in optimal results, potentially underestimating the method's effectiveness.

Internal threats: The main threat to internal validity in our experiment stems from the manual annotation of the experimental data. We engaged graduate students to manually categorize emotions, which may have introduced a degree of subjectivity, affecting the reliability of the dataset.

External threats: Our research results are based on a dataset specifically related to campus comment sentiment analysis from a particular smart campus platform. This might not be representative of other types of social media or online platforms. Therefore, the conclusions drawn may not be applicable in different environments or to different types of user-generated content.

7 Conclusion and Future Work

In this paper, we introduced the BICASH model, an emotion analysis tool that integrates BERT and LSTM [18] technologies, particularly suited for analyzing comment texts in a campus environment. The innovation of the BICASH model lies in its ability to consider users' historical emotional expressions, thus providing a more comprehensive and in-depth analysis of emotions.

Our experimental results on a dataset of campus comment sentiment analysis demonstrate the effectiveness of the BICASH model in sentiment analysis tasks [19]. Compared to traditional text content-based sentiment analysis methods, the BICASH model exhibited higher precision, recall, and F1 scores. This achievement underscores that incorporating users' historical emotional dynamics into the analysis process can enhance the performance of sentiment analysis tasks.

Concerning our own research, the campus management platform we have constructed still has some applications in their initial stages, requiring further development and enhancement. For instance, in the aspect of clothing standard detection, we plan to draw inspiration from virtual try-on technology [21], integrating image recognition and machine learning algorithms to automatically identify and assess whether students' attire adheres to campus standards. Additionally, to create a more realistic and interactive campus navigation and virtual tour experience, we intend to employ point cloud technology [22] and augmented reality (AR) to develop a 3D virtual campus. At the same time, to improve campus safety management and health monitoring, we will explore the use of digital twin technology and multi-sensor systems [23], such as monitoring students' sports safety and health conditions during physical activities.

Concerning sentiment analysis domain, with the evolution of natural language processing technology, new pre-trained models such as GPT [24] and XLNet [25] continue to emerge. Future research can explore the application of these advanced models in sentiment analysis tasks to further improve model performance. In addition to textual data, emotions can also be expressed through various modalities such as voice and images. Future research might consider integrating text analysis with other modalities to develop multimodal sentiment analysis methods.

Through these research directions, we hope that scholars can make more profound contributions in the field of sentiment analysis, not only improving the accuracy and practicality of sentiment analysis technology but also providing a richer perspective for understanding the complex emotions of human beings.

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