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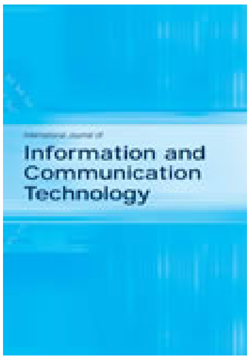

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Jiaying Li

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Sentiment analysis of text based on emoji attention mechanisms: a new approach to online course evaluation

Jiaying Li

School of Economics and Management,
Henan Vocational College of Water Conservancy and Environment,
Zhengzhou, 450000, China
Email: zzyhkhh@163.com

Abstract: Course evaluation has evolved into a significant metric of educational quality given the explosive growth of online learning. Traditional sentiment analysis techniques still have some difficulties handling multidimensional sentiment expressions in online course evaluations even if they have some success with social media and review data. In order to increase the accuracy of sentiment analysis in online course evaluation texts, we present in this work a textual sentiment analysis approach based on the attention mechanism of emoticons. First, this work integrates text information with emoji as a necessary input feature for sentiment analysis to provide multimodal sentiment classification. Especially when dealing with online course evaluation texts with several sentiment dimensions, which has great benefits and provides more accurate course evaluation data for online education platforms, the model suggested performs well on several benchmark datasets and outperforms conventional sentiment analysis methods by means of experimental validation.

Keywords: emoticons; attention mechanisms; text sentiment analysis; online course evaluation; sentiment classification.

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Biographical notes: Jiaying Li received her Master's at the Henan University of Economics and Law in 2022. She is currently a Lecturer at the Henan Vocational College of Water Conservancy and Environment. Her research interests include cold chain logistics, logistics professional construction, and machine learning.

1 Introduction

Online learning has become a necessary component of the worldwide education system that cannot be overlooked given the fast advancement of information technology (Dwivedi et al., 2020). Particularly in massive online courses (MOOC) and other online learning environments, student feedback of courses has become a crucial basis for increasing course quality, changing teaching tactics and boosting the learning experience.

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Although traditional online course assessment systems mostly rely on learners' textual evaluations or grading systems (Truong, 2016), these approaches are sometimes challenging to fully and fairly represent learners' actual emotional attitudes. Sentiment analysis technology, as an automated technology based on natural language processing (NLP), has been progressively used to the analysis of online course evaluations (Pattyam, 2021), which can help educators and platform operators to deeply understand the learners' emotional feedback, and so improve course quality by means of compensation for this shortcoming.

Especially in some evaluation texts where emoticons (emoji) are extensively used, where the emotional information is richer and more diverse (Riordan, 2017), the emotional expressions present in online course evaluations are complex and varied and it is often difficult for conventional sentiment analysis techniques to properly identify and process these complex emotional information. To increase the accuracy and complexity of the assessments, researchers have thus started investigating sentiment analysis approaches combining emoji with deep learning technologies.

2 Previous work

Early methods to sentiment analysis mostly depended on lexicon-based sentiment dictionary models (e.g., SentiWordNet, LIWC, etc.) (Yue et al., 2019). Research on sentiment analysis techniques started in the 1990s. These models fit texts with simple structure and straightforward sentiment expression since they categorise the sentiment of texts by the emotion polarity, (e.g., positive or negative) of the sentiment vocabulary (Alswaidan and Menai, 2020). These techniques, however, are not suited for complicated sentences, texts with irony or puns, and hence cannot adequately handle changing sentiment expressions in practical settings.

Sentiment analysis approaches have progressively switched from rule-based models to models based on statistical learning and neural networks as NLP and deep learning technology have developed. Gradually, deep learning – especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs) – became the standard approach in sentiment analysis (Usama et al., 2020). CNNs let sentiment analysis be confined to handcrafted feature-based models as well as automatically learn the deep semantic properties of the text, thereby significantly enhancing the classification accuracy. Later on, techniques based on long short-term memory networks (LSTMs) started to be widely used (Huang et al., 2022); their capacity to capture dependencies in long texts makes them a useful tool for sentiment analysis processing long sequences and contextual data. When handling sentiment classification tasks in fields such social media reviews and film reviews, these approaches have shown good performance.

But the intricacy of sentiment analysis has grown much more with social media's and online review's popularity. Particularly in casual settings, sentiment expressions are sometimes rather delicate or complicated and traditional approaches find it challenging to portray the subtleties. In order to solve this issue, sentiment analysis models combining emoticons (emoji) and text have lately attracted attention by researchers (Rong et al., 2022). Emoji, a non-verbal method of conveying emotions, offers high information density and clear, simple expressive quality. Emoji become a useful tool for expressing emotions in social media, online comments and other contexts, therefore improving the emotional representation of language.

Emotion analysis has drawn a lot of interest on how emoticons affect it. Studies on co-training – that is, combining emoji with textual information and using deep learning models have started to show increasing accuracy and resilience of sentiment analysis. By incorporating emojis as extra input data to participate in sentiment classification activities together with text, these methods often enable models better capture various sentiment aspects. In multimodal sentiment analysis systems, the mix of emoji and text has grown to be a significant research trend (Kejriwal et al., 2021). Still, most of the current studies concentrate on sentiment analysis in social media and short texts; the use of emojis in online course assessments has not yet been investigated closely. Online course assessment usually consists of long texts and complex sentiment dimensions; so, the mix of emojis and texts is expected to produce fresh ideas in sentiment analysis.

In sentiment analysis, meanwhile, the addition of the attention mechanism has made notable development recently. The attention mechanism can replicate human selective attention process of processing information by dynamically assigning weights to various sections of the incoming text (Wickens, 2021). Particularly in long text and multi-sentiment dimensions sentiment analysis jobs, the attention method can assist the model better concentrate on the most relevant areas for sentiment classification, so greatly boosting the accuracy of sentiment analysis. Particularly in the field of sentiment analysis, models grounded on the attention mechanism have been extensively applied in NLP and show considerable promise.

Still, sentiment analysis in particular situations presents significant difficulties even if current research has produced some findings in mixing emoticons with attention mechanisms. Online course evaluation includes not just textual material but also multi-dimensional emotional feedback from students, including assessments of course content, comments on teaching strategies, and experience of utilising the platform, which makes emotional expressions more complicated. Furthermore, the mix of emoticons with attention mechanisms has not been thoroughly investigated by current approaches, particularly in the context of multidimensional emotion expression, thus how to properly integrate emoticons with attention mechanisms is still a topic of understudy.

Inspired by the aforesaid backdrop, this work suggests a text sentiment analysis technique based on emoji attention mechanism in order to raise the accuracy of sentiment analysis in online course evaluation. Particularly, this work makes mostly contributions in:

1 Emoji with sentiment analysis is the combo. Based on the attention mechanism of emojis, we propose in this work an online course sentiment analysis approach that creatively uses emojis as one of the main characteristics for sentiment analysis and aggregates them with text data for multimodal analysis. Though emojis have been utilised in social media sentiment analysis to some degree, merging them with online course evaluation and improving sentiment categorisation using the attention mechanism is still a quite fresh study path.

2 A creative using of the attention mechanism. In this work, the incorporation of the attention mechanism helps the model to automatically concentrate on the most significant information for sentiment classification in long texts and complicated sentiment expressions. Especially when dealing with multidimensional sentiment expressions (e.g., course content, teaching quality, platform experience, etc.), the attention mechanism can considerably increase the sensitivity of the model to minor

sentiment changes and classification accuracy compared with conventional sentiment analysis techniques.

3 A sentiment analysis system for evaluations of online courses. Most sentiment analysis techniques concentrate on social media or short texts; the multidimensional and complicated representation of sentiment in online course assessments has not been thoroughly investigated. We present in this study a sentiment analysis framework combining emoticons and attention mechanisms especially for the sentiment properties in online course evaluation materials. By means of this framework, students' various emotional responses in course evaluations can be more precisely defined, thereby bridging the gap of current approaches utilised in the field of education.

4 Experimental validation and practical value. In the task of sentiment analysis for online course evaluation, the experimental findings reveal that the model is much better than conventional approaches; it can also better manage complicated sentiment expressions, so offering a fresh alternative for the course evaluation system of online learning platforms.

These developments support the application of emoticons and attention mechanisms in educational evaluation and offer fresh angles on sentiment analysis research in the realm of online learning.

3 Relevant technologies

3.1 Emotion analysis and emoticons for emotional expression

In sentiment analysis, conventional text analysis approaches mostly rely on vocabulary and contextual context to infer sentiment, such dictionary-based sentiment vocabulary methods, machine learning methods (e.g., support vector machines, random forests), and deep learning methods (e.g., LSTMs, CNNs). These approaches, particularly when faced with complicated emotional representations, are typically useless in handling knowledge with uncertain or non-standardised emotions, nevertheless. The addition of emoticons turns out to be a useful supplement in order to address this issue since in text emoticons serve as emotional reinforcement and clarifying agent. Usually carrying clear emotional information, each emoticon enables sentiment analysis models to more precisely detect emotional patterns in texts.

Sentiment analysis's core goal is first sentiment classification – that is, text classification into positive, negative, or neutral categories (Hemmatian and Sohrabi, 2019). Conventional approaches of sentiment analysis mostly rely on lexicon, machine learning or deep learning approaches. Assume an input string X such that X can be stated as:

$$X = \{x_1, x_2, ..., x_n\} \tag{1}$$

Sentiment analysis aims to forecast the sentiment category $Y \in \{Y_1, Y_2, \ldots, Y_k\}$ of the text, therefore x_i is the i^{th} word or character. Minimising the following loss function is the aim of the sentiment classification model, assuming $f(x)$:

$$L(f(x), Y) = -\sum_{i=1}^{k} y_i \log\left(f\left(x_i\right)\right) \tag{2}$$

where y_i is the emotion label matching text X and $f(x_i)$ is the projected probability for every category by the model.

But depending just on textual data for sentiment analysis becomes insufficient given the prominence of emojis in social media and online course assessments. Emojis are graphics used to graphically communicate emotional information and, most of the time, they help to more precisely express feelings. Though these emotions may be represented differently in plain language, emojis naturally improve the exchange of emotional information. 😊 represents happiness, 😢 denotes grief, and 😡 denotes wrath. Emojis can thus be a complement to information in sentiment analysis projects and enable increase of sentiment categorisation accuracy.

Mapping an emoji symbol into a sentiment space and using the emoji embedding vector helps one to depict its sentiment aspects in a common sense (Wicke and Bolognesi, 2020). One may learn emoji embeddings similarly to word vectors. The sentiment information of an emoji can be expressed assuming $\vec{e}_i$ is its embedding vector e_i as:

$$e = \sum_{i=1}^{p} \vec{e}_i \tag{3}$$

where E is the total of all the emoji embedding vectors; p is the count of emoji in the input text. Convenient for the model, we can therefore translate the emotional content of emoji into numerical form.

Furthermore, the sentiment information of text and emoji frequently complements each other. Practically, text sentiment analysis's findings might not match the sentiment indicated by emoji. The book might convey a negative attitude, for instance, but the usage of a particular positive emoji might alter the general trend in sentimentality. We so have to combine the text material with the emoji knowledge. Assuming the text's sentiment as T, the fusion feature F of the text and emoji can be shown as:

$$F = [T; E] \tag{4}$$

where $[T; E]$ signifies text and emoji embedding vector splicing. By now the model can use this combined feature vector to classify sentiments. We can still apply the softmax function to forecast the category and obtain the sentiment prediction $\hat{Y}$ for the aim of sentiment classification:

$$\hat{Y} = \operatorname{soft\,max}(WF + b) \tag{5}$$

where the weight matrix is W and the bias term is b correspondingly; the projected probability for every sentiment category is the result of the softmax function. Usually optimised using the cross-entropy loss function, the sentiment classification model's training goal is to decrease the difference between the predicted outputs and the true labels:

$$L(\hat{Y}, Y) = -\sum_{i=1}^{k} y_i \log(\hat{y}_i) \quad (6)$$

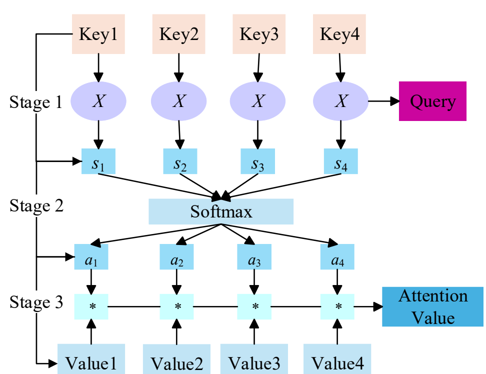
where $\hat{y}_i$ is the projected probability for every sentiment category and y_i is the actual sentiment label.

All things considered, sentiment analysis depends much on emoticons as a special emotional expression. Combining the sentiment information of emoji with text information helps the sentiment analysis model to grasp and recognise the sentiment expression more fully, so strengthening the accuracy and robustness of the analysis outputs.

3.2 Attention mechanisms

Processing long texts in deep learning – especially in the field of NLP – often results in information diluting issues. It is often challenging for conventional models to pay adequate attention to the crucial information as various sections of the text help to accomplish the goal in varying degrees. By dynamically changing the degree of attention the model gives to various input portions, attention mechanism is presented to overcome this problem (Niu et al., 2020), so improving the expressive ability and performance of the model. See Figure 1.

Figure 1 Principle of attention mechanism (see online version for colours)



Assume the input text consists of X, in which case every x_i denotes the i^{th} word or unit in the text. Every word x_i in a conventional neural network model is transformed into a fixed-length vector h_i and utilised as an input into the model. This fixed portrayal, however, overlooks the reality that every component of the book helps to contribute differently to the ultimate work. The attention mechanism suggests a method to let the model dynamically learn the 'importance' of every element of the text and modify its weight in the goal therefore solving this problem.

The fundamental concept of the attention mechanism is thus to give every element in the input sequence a weight α_i, so indicating the relevance of that element for the present work (Galassi et al., 2020). First one must create a scoring system that gauges the relevance of every phrase to the present context in order to determine the weight of every word. Assuming v as a context vector capturing the pertinent information of the present work, the i^{th} word's score α_i can be stated by the following equation:

$$\alpha_i = v^T h_i \tag{7}$$

where h_i is the i^{th} word's representation. The score α_i shows the degree of word x_i matching the context vector v. A better match indicates that for the present work the word is more crucial.

The attention weight α_i must then be calculated via a normalisation technique to guarantee that every weight adds up to 1. The softmax function is a typical normalisation technique since it allows all the scores to be converted into a probability distribution showing the degree of contribution each word makes to the task. Particularly, one may find the attention weight α_i by applying the following equation:

$$\alpha_i = \frac{\exp(\alpha_i)}{\sum_{j=1}^{n} \exp(\alpha_j)} \tag{8}$$

This formula guarantees that all weights total one and helps to translate all scores α_i into a weight between [0, 1]. This allows the model to dynamically allocate attention based on word relevance, hence producing greater weights for key words.

Some variations of the attention mechanism allow other elements than the context vector v to be added to improve the model's representation. To further improve the representational power of the model, the multi-head attention mechanism computes several different attention weights from a number of different context vectors and then spliced together (Yan et al., 2022). One can express the attention score of every head as:

$$\alpha_i^{(k)} = v_k^T h_i \tag{9}$$

where k is the k^{th} attention head; v_k is the k^{th} context vector. One can get the final weighted representation by averaging or splicing the weighted representations of all heads:

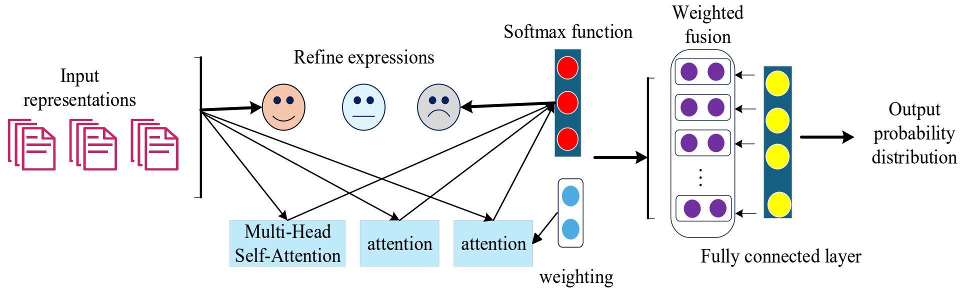
$$\mathrm{h_{att}}^{\text{multi-head}} = \mathrm{Concat}\left(\mathrm{h_{att}}^{(1)}, \mathrm{h_{att}}^{(2)}, \ldots, \mathrm{h_{att}}^{(K)}\right) \tag{10}$$

Concat combines the weighted representations of all the attention heads into one big vector where K is the number of heads of attention.

4 Sentiment analysis of online course text based on emoji attention mechanisms

First we must pre-process the text and conduct feature extraction in the framework of sentiment analysis based on emoji attention mechanism. This technique will separate emoticons and text words and forward them to the model. The model will then weight the text and emojis using the attention mechanism so that the contribution of this information to the sentiment analysis may be taken into account holistically (Figure 2).

Figure 2 Sentiment analysis framework based on emoji attention mechanism (see online version for colours)



1 Input representation and feature extraction

The input online course material x in this part features text and emoticons. Word embedding, e.g., Word2Vec or GloVe – first converts each word x_i in the text into a word vector h_i; each emoji s_j is then converted into its matching vector representation e_j. Thus, one may represent the input as follows:

$$H = \{h_1, h_2, ..., h_n\} \tag{11}$$

$$E = \{e_1, e_2, ..., e_m\} \tag{12}$$

where n and m are the number of words and emoticons in the text accordingly, H represents the set of word vectors of the text and E the set of emoticons. We then aggregated these two information sources to create a comprehensive X:

$$X = \{h_1, h_2, ..., h_n, e_1, e_2, ..., e_m\} \tag{13}$$

2 Joint representation of emoticons and texts

First computed is the representation of text and emoji in the same vector space thereby fusing the knowledge of text and emoji. To find the weighted average representation for the text and emoji portions independently, we used a weighted average method. The weighted average representation for every word in the text – including hello and emoji – can be computed using this formula:

$$\mathrm{h}_{\mathrm{avg}} = \frac{1}{n}\sum_{i=1}^{n} h_i \tag{14}$$

$$\mathrm{e}_{\mathrm{avg}} = \frac{1}{m}\sum_{j=1}^{m} e_j \tag{15}$$

Weighing averages helps us to get the combined information representation of the text and emoji parts. We next weighted sum the two sections or splice them to get the joint representation $\mathrm{h}_{\mathrm{joint}}$:

$$\mathrm{h}_{\mathrm{joint}} = \mathrm{h}_{\mathrm{avg}} + \mathrm{e}_{\mathrm{avg}} \tag{16}$$

This representation will include text and emoticons, therefore guiding later attentional weighting.

3 Weighting of attention mechanisms

We must give each word and each emoji distinct attentional weight if we are to benefit from the various relevance of emoji and text. Calculating the 'importance' of every text word and emoji for the sentiment analysis job helps one do this. They can be computed specifically by assuming that w_i is the attention score of the i^{th} word and v_j is the score of the j^{th} emoji:

$$w_i = \text{sigmoid}\left(q^T h_i\right) \tag{17}$$

$$v_j = \text{sigmoid}\left(q^T e_j\right) \tag{18}$$

where the sigmoid activation function transfers the attention scores to the range [0, 1], therefore signalling the relevance of every word and emoji. The query vector used to compute the attention scores is q.

We next derive the related normalised attention weights from these scores. The following softmax normalisation technique allows one to get the attention weights α_i and β_j for every word h_i and emoji e_j in the text:

$$\alpha_i = \frac{\exp\left(w_i\right)}{\sum_{k=1}^{n} \exp\left(w_k\right)} \tag{19}$$

$$\beta_j = \frac{\exp\left(v_j\right)}{\sum_{l=1}^{m} \exp\left(v_l\right)} \tag{20}$$

Every component in the text and emoji will thus be constantly weighted based on its significance.

4 Weighted text and emoji fusion representation

One can computed the weighted text and emoji representations with the following formula:

$$\mathrm{h}_{\text{att}} = \sum_{i=1}^{n} \alpha_i \cdot h_i \tag{21}$$

$$\mathrm{e}_{\text{att}} = \sum_{j=1}^{n} \beta_j \cdot e_j \tag{22}$$

In the present work, these weighted representations h_{att} and e_{att} respectively depict the weighted information of text and emoji correspondingly.

The final input representation $\mathrm{h}_{\text{final}}$ is obtained by fusing these two weighted representations using a summation technique:

$$\mathrm{h}_{\text{final}} = \mathrm{h}_{\text{att}} + \mathrm{e}_{\text{att}} \tag{23}$$

5 Emotional categorisation and output

We last feed the fused representation h_{final} into the sentiment classification network for prediction. We translate the emotion category – assuming it to be $\hat{Y}$ – from a fully linked layer to a probability distribution. One may depict the classification process as follows:

$$\hat{Y} = \text{softmax}\left(W\text{h}_{\text{final}} + b\right) \tag{24}$$

The softmax activation function will produce a probability distribution showing the likelihood that the text belongs to every sentiment category where W is the weight matrix of the classification layer and b is the bias term.

6 Model evaluation

We apply standard measures including accuracy, precision, recall, and F1-score to assess the performance of the sentiment analysis model. Assuming the true label is y_i and the model prediction is $\hat{y}_i$, the evaluation metrics for every test sample i can be computed with this formula:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N}\left[\hat{y}_i = y_i\right] \tag{25}$$

$$\text{Precision} = \frac{\sum_{i=1}^{N}\left[\hat{y}_i = 1 \wedge y_i = 1\right]}{\sum_{i=1}^{N}\left[\hat{y}_i = 1\right]} \tag{26}$$

$$\text{Recall} = \frac{\sum_{i=1}^{N}\left[\hat{y}_i = 1 \wedge y_i = 1\right]}{\sum_{i=1}^{N}\left[\hat{y}_i = 1\right]} \tag{27}$$

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{28}$$

Combining the multimodal information of emoji and text, and weighing the components using an attention mechanism, this chapter suggests a novel paradigm for analysing the textual sentiment of online courses. First, we perform feature extraction and representation of text and emoji respectively; then, we assign importance weights to each text and emoji using the attention mechanism; and lastly, we perform sentiment classification by aggregating the weighted text and emoji representations using this framework built via several stages.

Especially in sentiment analysis in the domains of online education and social media analysis, which has great potential for usage, the design of this framework also offers fresh ideas for additional research and implementation of the combination of emoticons and attention processes.

5 Experimental results and analyses

5.1 Datasets

We selected an actual dataset connected to online course evaluations – online course reviews dataset to validate the text sentiment analysis approach based on the emoji attention mechanism in this work. Many course reviews from online learning sites including Coursera, Udemy, etc.) abound in this dataset. These review materials include student comments on course materials, teachers, platform experience, etc.; so, emoticons are included in the reviews and make them especially appropriate for sentiment analysis research. Table 1 addresses the particular characteristics of this dataset:

Table 1 Online course reviews dataset information (see online version for colours)

Feature	*Description*	*Example*
Data source	Online course review platforms (e.g., Coursera, Udemy)	Text: ‘This course was amazing! The content was very clear and insightful 😊‘ Emoji: 😊
Sentiment labels	Positive, negative, neutral	Positive: ‘The instructor was great! Very knowledgeable.’ Negative: ‘The course was too boring 😞‘
Sample size	Approximately 15,000 course reviews	15,000 reviews
Data structure	Each review consists of text and associated emojis	Text: ‘The course was helpful and well structured 👍’ Emoji: 👍
Sentiment distribution	60% positive, 25% negative, 15% neutral	The exact distribution varies based on dataset annotations
Language	English	English reviews

Each comment in this dataset may have one or more emoticons that accentuate the textual expression of sentiment; the textual component of the comments details the students' opinions on the online course. Together as inputs for more accurate sentiment analysis in model training, textual information and emoticons will be utilised.

These comment texts and emoticons will be merged in this work using an attention technique to weight the impact of various data sources so enhancing the accuracy of sentiment analysis.

The following actions help the dataset to be ready in the stage of data preparation:

- Eliminating HTML elements, special characters, etc. is text cleaning.
- Extensive emoji extraction from comments and encoding them.
- Sort the comments according to good, negative, neutral sentiment labels.

This dataset allows us to completely evaluate the efficacy of the sentiment analysis method based on emoji and textual attention mechanisms in actual online course evaluation.

5.2 Comparative experiments

This work intends to validate the efficiency of a textual sentiment analysis approach based on the emoji attention mechanism (hereinafter referred to as emoji-attention sentiment analysis). In this regard, we assess the approach's performance in a sentiment classification challenge by means of multiple mainstream sentiment analysis methods.

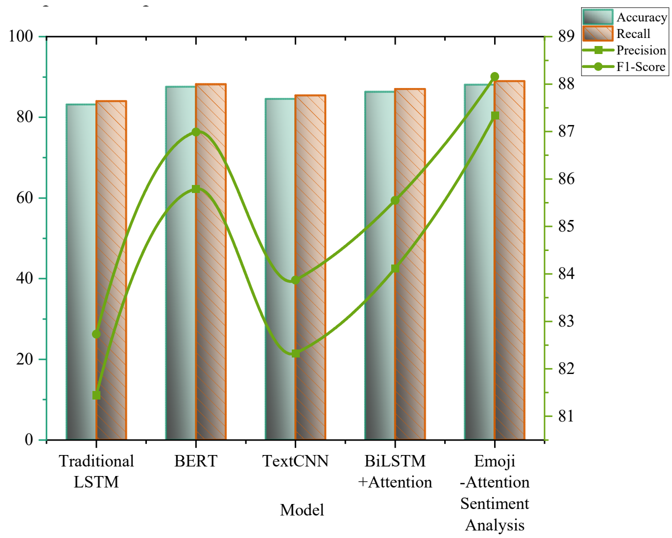
- Traditional LSTM model: the LSTM model is an RNN-based sentiment analysis technique able of analysing sequential data and catching long-range correlations. One of the most often used sentiment analysis techniques, this one relies just on textual data for sentiment classification.
- BERT model: through pre-trained deep bi-directional encoders, BERT model – bidirectional encoder representations from transformers – captures contextual information and has shown outstanding performance in many NLP applications. By modelling the background of the whole text, this model is able to do sentiment analysis rather successfully.
- TextCNN model:TextCNN is a sentiment analysis model based CNN that uses varying sized convolutional kernel to extract local information. The approach is appropriate for brief text sentiment analysis particularly for the more important sentiment information in the text has great recognition capacity.
- BiLSTM+Attention model: combining forward and backward long and short-term memory networks, BiLSTM+Attention model BiLSTM combines for a more complete knowledge of contextual information. The model may automatically concentrate on the crucial sections of the text to raise the accuracy of sentiment categorisation by including an attention mechanism.
- Emoji-attention sentiment analysis: combining emoji and text information and leveraging the emoji attention mechanism to weight the fusion of text and emoji helps this approach improve sentiment analysis. The algorithm may maximise the sentiment classification outcomes in line with the sentiment expression in the text using the emoji.

Figure 3 presents on the test set the performance comparison between several approaches.

Particularly in the main assessment criteria of accuracy, precision, recall, and F1-score, the experimental results reveal that the emoji-attention sentiment analysis beats the other evaluated models. Emoji-attention sentiment analysis specifically achieves 88.12%, greater than the 87.58% of the BERT model and the 86.34% of the BiLSTM+Attention model, thereby suggesting that the approach performs more precisely in the sentiment classification problem. Avoiding the misclassification issue that could exist in conventional models, the excellent precision and recall rates of 87.34% and 89.01% respectively indicate that the model is able to better balance the precision and coverage when identifying sentiment polarity (e.g., positive and negative sentiment).

Furthermore, the suggested approach rates above other models on the F1-score, attaining 88.16%, which suggests that it is capable of preserving a high recall while guaranteeing great precision in sentiment analysis, thereby maximising the whole impact of sentiment categorisation. Emoji-attention sentiment analysis not only improves the expressive ability of textual information by introducing emojis and attention mechanisms, but also effectively uses emojis as complementary information to the sentiment signals, so enhancing the precision and robustness of the sentiment analysis, especially in the case of online course reviews including emoticons in online course reviews, which can better capture users' emotional tendency.

Figure 3 Comparative experimental results of different methods (see online version for colours)



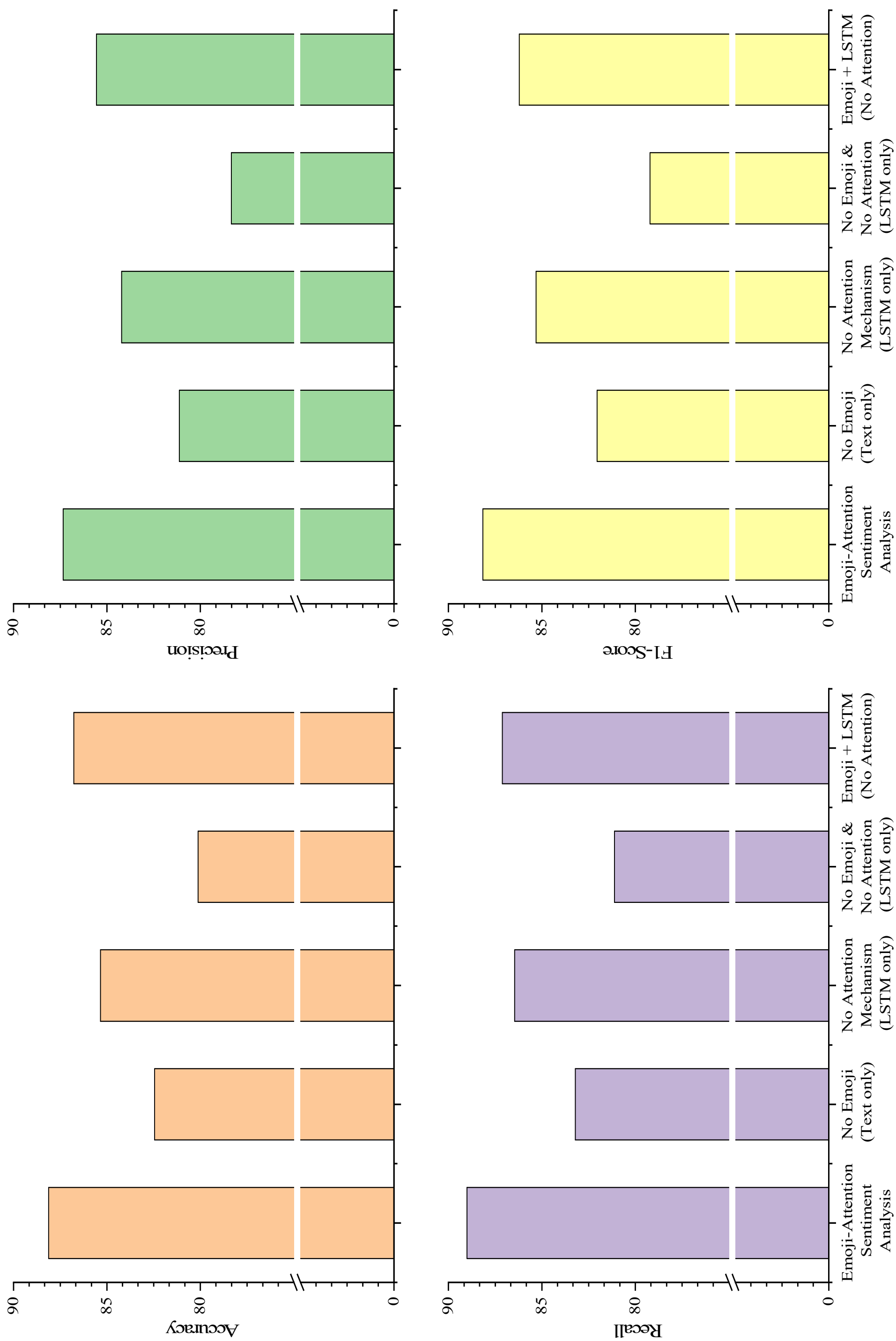
5.3 *Ablation experiments*

We developed four distinct experimental setups in the ablation studies in order to verify the impact of emoticons and attentional systems. First, we exclude emoticons from the input and evaluate their contribution to model performance via sentiment analysis conducted just with text. Second, we eliminate the attention mechanism from the model and investigate its function using sentiment analysis applied with a conventional LSTM model. Third, we delete both the emoji and the attention mechanism and use the LSTM model to sentiment analysis in order to evaluate the performance difference between the whole model and the removal of these two elements. To assess the impact of integrating emoji with LSTM, we last mix emoji and conventional LSTM without considering the attention mechanism.

Figure 4 displays on the test set the performance of several ablation experiments.

The experimental results reveal that the elimination of emoticons greatly reduces the performance of the model; the accuracy falls from 88.12% to 82.45%. This implies that the sentiment analysis choreacle depends critically on emoticons as sentiment signals. Eliminating the attention mechanism, the accuracy of the conventional LSTM model for sentiment analysis is 85.34%, which is lower than the model including the attention mechanism, so highlighting the importance of the attention mechanism in sentiment analysis cannot be disregarded. Lastly, in the event of eliminating both emoticons and attention mechanism, the model loses accuracy to reach just 80.12%. This outcome confirms even more how important it is to improve sentiment analysis accuracy by means of the cooperative action of emoticons and attention mechanisms.

Figure 4 Results of ablation experiments (see online version for colours)



Although the accuracy of 86.78% when combining the emoji and LSTM model, without the attention mechanism, is somewhat lower than the model with the complete combination of emoji and attention mechanism, still higher than the performance after removing any one of the components, so indicating the still significant positive impact of emoji on sentiment analysis.

6 Conclusions

In this work, we present a text sentiment analysis approach based on the attention mechanism of emoticons in order to integrate emoticons with the attention mechanism in deep learning thereby enhancing the effect of sentiment analysis in online course evaluation. We first present in great depth the fundamental ideas of sentiment analysis and its applications; we also discuss current sentiment analysis methods, particularly with regard to the possible function of emojis for sentiment classification. After that, one should concentrate on the model framework suggested in this work, describe how emojis and attention mechanisms can be merged in a sentiment analysis task, and experimentally validate the success of the method.

Notwithstanding the findings of this study, there are still certain restrictions; however, future research can help to extend in these areas and make more advances possible. First of all, the dataset employed in this article mostly concentrates on the particular area of online course evaluation; although good results have been obtained in this domain, the generalising capacity of the model may be quite restricted. Future studies can thus increase the variety of the dataset to encompass more various domains and types of text data, such social media comments, user evaluations of e-commerce platforms, etc. so enhancing the adaptability and robustness of the model.

Second, the interpretability of the model remains a difficulty even if our suggested model can efficiently mix emoji and attention methods. Particularly those based on attention mechanisms, current deep learning models are sometimes considered as 'black boxes' and lack enough openness. Future studies could investigate how to make models more interpretable, for instance by visualising attention weights, implementing rule-driven interpretation techniques, or applying hybrid models to raise the comprehensibility of model outputs. This will improve the credibility and usability of the model in useful applications as well as assist people better grasp the process of decision-making inside it.

Furthermore, since deep learning technology develops constantly, more complex model architectures including Transformer and variations might be tested in the future to improve the sentiment analysis impact even more. Dealing with complicated text, the Transformer model may perform better because of its flexible attention mechanism and its long sequence modelling capacity. Sentiment analysis based on multimodal data – that is, mixing information from photos, videos, etc. – will also be a topic worth investigating in the future, particularly in those online course or review situations including several kinds of input.

At last, for the part emoticons play in sentiment analysis, further research on the variations in emoticon performance in various cultural settings can be rather interesting. Using emoji, users from several cultural backgrounds may show their feelings in diverse ways. Consequently, multilingual and cross-cultural studies help to confirm the worldwide generalising capacity of the model, so strengthening its generality.

By merging emoticons and attention mechanisms, this work suggests an efficient approach for text sentiment analysis in general and experimentally proves its excellence in online course evaluation. Future research is expected to make more progress in the field of sentiment analysis and provide more accurate support for sentiment classification in application scenarios including online education and social media, even if it still faces some constraints with the increase of the dataset and improvement of model interpretability and introduction of new model architectures.

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Declarations

All authors declare that they have no conflicts of interest.

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