Uyghur Metaphor Detection Via Considering Emotional Consistency

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Abstract

Metaphor detection plays an important role in tasks such as machine translation and human-machine dialogue. As more users express their opinions on products or other topics on social media through metaphorical expressions, this task is particularly especially topical. Most of the research in this field focuses on English, and there are few studies on minority languages that lack language resources and tools. Moreover, metaphorical expressions have different meanings in different language environments. We therefore established a deep neural network (DNN) framework for Uyghur metaphor detection tasks. The proposed method can focus on the multi-level semantic information of the text from word embedding, part of speech and location, which makes the feature representation more complete. We also use the emotional information of words to learn the emotional consistency features of metaphorical words and their context. A qualitative analysis further confirms the need for broader emotional information in metaphor detection. Our results indicate the performance of Uyghur metaphor detection can be effectively improved with the help of multi-attention and emotional information.

1 Introduction

With the rapid development of digital technology and the Internet, social media has become a powerful platform where people can express their opinions on various topics such as politics, finance, education, and other social issues. It is worth noting that more users use a lot of metaphors in online texts to express their thoughts and emotions. According to statistical research, metaphors appear in every three sentences in natural language (Cameron, 2003; Steen et al., 2010; Shutova and Teufel, 2010). Metaphor involves not only language expression, but also the cognitive process of conceptual knowledge (Lakoff, 2003). According to Lakoff and Johnson, metaphor is a conceptual mapping. More specifically, metaphor is a concept used to describe another concept. They are widely used in oral and written language to convey rich linguistic and emotional information. For instance, in the metaphorical utterance: knowledge is treasure., we use treasure to describe knowledge to emphasize that knowledge can be valuable. To take another metaphorical instance as an example: this is an ocean of flowers. Ocean has broad characteristics, which means that the flower area is large. Metaphor detection is an important subtask of natural language processing, which provides a more complete representation for semantic analysis (Lakoff, 2003). Moreover, interpreting metaphors helps to improve the performance of tasks such as machine translation and human-machine dialogue analysis (Rentoumi et al., 2012).

The existing computational models of metaphor detection are mainly based on lexicons (Mohler et al., 2013; Dodge et al., 2015) and supervision methods (Gao et al., 2018; Stowe et al., 2019; Le et al., 2020). Lexicon-based methods do not require data annotation, but they cannot detect new metaphoric usage and capture contextual information. The supervised method can obtain text context information from the sentence level, thereby obtaining broader semantic information. However, it requires a complete annotated corpus.

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Current metaphor detection mostly focuses on English because of its abundant annotation data. The popular metaphor detection corpus in current research includes VU Amsterdam Metaphor Corpus (VUA) (Steen et al., 2010), MOH-X (Mohammad et al., 2016) and TroFi (Birke and Sarkar, 2006). In addition, the task of metaphor detection relies on specific semantic resources, and corpora of other languages are gradually established, such as Chinese Metaphor Corpus (Zhang et al., 2018), Russian Metaphor Corpus (Badryzlova and Lyashevskaya, 2006), and Arabic Metaphor Corpus (Alkhatib and Shaalan, 2018). The establishment of these corpora provides a data foundation for metaphor detection tasks in specific languages.

In recent years, more Uyghur-speaking users have expressed their thoughts and opinions on political, economic, and cultural topics through Internet channels. As more people like to express their opinions in metaphorical language, Uyghur metaphor data is also growing rapidly. The expression and meaning of metaphor differ greatly in different language environments. Due to the influence of the special language environment, the task of metaphor detection in Uyghur language has not yet started. Therefore, it is imperative to establish Uyghur metaphor detection resources and verify the effectiveness of metaphor detection models.

In this paper, we have collected Uyghur metaphor data from multiple fields and proposed to use multi-attention mechanism for metaphor detection. More specifically, we use word embedding, part-of-speech (POS) and position as model inputs, which reveal the semantic information of the text from three levels to make the feature expression more complete. In addition, due to the important relationship between metaphor and emotional expression, we extract emotional features from both the word level and sentence level, which enables the model to learn emotional consistency information. The experimental results also verify that metaphor detection requires extensive emotional information. In this task, we treat the Uyghur metaphor detection as a sequence tagging problem, and sequence tagging tasks such as POS tagging and named entity recognition (NER) have always existed in natural language processing.

To summarize, this paper makes the following contributions:

- We are the first to study and apply deep neural networks to the task of Uyghur metaphor detection.
- The proposed multi-attention model leverages POS and position to reveal semantic information from multiple aspects, which makes the feature expression more complete.
- Emotional embedding allows the model to learn emotional consistency information from the level of words and its context.

The rest of this paper is organized as follows. The next section introduces related work. Section 3 describes our proposed model for Uyghur metaphor detection. Section 4 presents our experiments, including the dataset, experimental details, result analysis. The Section 5 is about the conclusion.

2 Related work

2.1 Metaphor Detection

Current metaphor detection models include supervised machine learning methods combined with hand-designed features, unsupervised representation learning methods, and deep learning models based on sequence tagging. Shutova et al (2013). proposed a method of metaphor detection and recognition through interpretation. The performance of this method is better than previous metaphor detection methods, and it has important significance for metaphor modeling. Dunn et al (2014) proposed a new language independent ensemble-based approach to identifying linguistic metaphors in natural language text. This strategy achieved state-of-the-art results in multiple languages and made significant improvements to existing methods. Tsvetkov et al (2013). proposed a general semantic feature method for metaphor detection. This method verifies that metaphors can be detected at the conceptual level. Specifically, metaphors are part of the universal conceptual system.

Some metaphor detection methods utilize unsupervised learning. Shutova et al (2013). proposed the first metaphor detection method that simultaneously extracts knowledge from language and visual data.

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Experimental results show that it performs better than language and visual models in isolation, and it is also better than the best-performing metaphor detection method. Mao et al (2018). proposed a method that can recognize and interpret metaphors at the word level without any preprocessing. This model is extended to explain the recognized metaphors and translate them into corresponding literal meanings so that the machine can better translate them.

Recently, with the application of deep learning in natural language processing, a wide variety of techniques for deep learning models for metaphor detection have been proposed. Do et al (2016). proposed a method combining word embedding and neural network for metaphor detection. This method shows that only relying on word embeddings trained on a large corpus can achieve better classification and eliminate the need for additional resources. Swarnkar et al (2018). proposed a metaphor detection using contrasting deep neural structures. The model uses contrast features generated by pre-trained word embeddings to achieve considerable performance. They also verified that using additional features and adjusting the weight of examples can significantly improve performance. Pramanick et al (2018). used a hybrid model of Bi-LSTM and CRF, which uses word2vec to embed tag words and their lemmas. In addition, they used a 20d vector to indicate POS and a heat vector to indicate whether the lemma is the same as the mark, and whether there is a lemma in the mark.

More recently, the metaphor detection task is modeled as a sequence tagging task. More specifically, the word is predicted as a literal or metaphor at each time step. Wu et al (2018). proposed to use the CNN-LSTM model to complete the task of metaphor detection. This model combines two layers of CNN and LSTM, and uses local and remote context information to identify metaphorical information. In addition, they also compared the performance of softmax classifier and conditional random field (CRF) in metaphor detection tasks. Mao et al (2019). proposed a method based on MIP (Group, 2007) and SVP (Wilks, 1975; Wilks, 1978) linguistic theories, and surpassed existing models to obtain the best classification performance on datasets VUA, MOH, and TroFi.

2.2 Uyghur Metaphor

Uyghur is a kind of agglutinative language with rich forms, which has special configuration morphemes to express various syntactic relations between words. Uyghur metaphors are mainly affected by the language environment and the grid grammar. More specifically, nouns have three important grammatical categories: number, person, and grid. The grid category includes nominative, accusative, subordinate, directional, time, subordinate, range, boundary, and similar. Adjectives have prototype, comparative and superlative forms. Verbs have grammatical categories such as voice, form, tense, and aspect. Metaphorical expressions in Uyghur use rhetorical methods extensively, and are closely related to the grid grammar. For example, metaphorical demonstratives in Uyghur are often reflected in the grammatical phenomenon of grid. More specifically, it is to add special additional elements (تەك/دەك or خۇددى, etc.) after the vocabulary of the vehicle. For example sentence: Saphia is like a flower/سافىيە گۈلگە ئوخشايدۇ. These fixed grammatical formats help to judge the metaphor of the text from the syntactic level. We summarized the Uyghur metaphorical language rules are as follows.

- **Type 1:** unmarked metaphorical expression
  Description: The source and the target vocabulary are directly connected.
  Language rules: (1) pearl+teeth=white teeth; (2) add elements after adjectives.That is to use source+target to represent the target to modify the source.

- **Type 2:** marked metaphorical expression
  Description: Express the similarity between the target and the source through additional components.
  Language rules: For example, target+سىمەن+source. چە،چىلىك means similar numbers. چىلەپ means similar behavior.

Moreover, Uyghur metaphors can be divided into three types, namely analogy, metonymy, and simile. The language rules for each type of metaphor are as follows.

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- **Type 1:** analogy
  Description: Express the current things through the characteristics of other things.
  Language rules: Generally divided into anthropomorphic and simulant (plants, animals, natural objects, etc.). For example,شىپاڭلاتماق"a dog wags its tail" to express pitiful prayers..

- **Type 2:** metonymy
  Description: Use target instead of source function.
  Language rules: There are many kinds of Uyghur metonymy, including humans, animal organs, plants, and celestial bodies. For example,سايىماخۇن "bedside table" expresses fear of his wife.

- **Type 3:** simile
  Description: Use the symbolic meaning of things to express metaphors.
  Language rules: Uyghur simile has strong language characteristics. For example, use قوزlamb to mean a good child.

Moreover, Uyghur metaphors have strong language characteristics affected by the language environment. For instance, the cat in animals means greedy instead of docile and cute. Rabbit stands for cowardly and pitiful rather than tamed and agile. To take another example: The pumpkin and gourd in plants are metaphors for fool. soaked tea" means "failure, etc. Uyghur metaphorical emotional expression is closely related to language environment. For example, we usually use monkeys to express cleverness, but in Uyghur language it is a symbol of cunning. Based on all the above, we can conclude that metaphor detection tasks in different languages have huge differences in methods. Therefore, it is imperative to establish a framework for Uyghur metaphor detection.

3 Our Proposed Model

In this section, we first introduce the research ideas of the paper. Then, in order to describe the flow of the method in detail, we will explain each function of the model from bottom to top.

3.1 Basic Idea

In this paper, we regard Uyghur metaphor detection as a sequence tagging task. Considering the characteristics of metaphor expression containing rich emotions, we model emotional information into the network to consider its impact on metaphor detection performance. In order to further enrich the feature expression ability, we propose to use POS and position to construct multi-attention representations of words.

3.2 Model Structure

Word embedding and emotional embedding are used as model input, and BiLSTM is utilized to generate semantic representation. Moreover, we propose multi-attention to model the interaction between words and context. Our model structure is shown in Fig. 1.

Emotional Embedding Layer: In order to obtain the emotional embedding, we construct the emotional dictionary from the word level. The steps to construct an emotional embedding are as follows.

First, we extract the word w_i in the sentence and annotate its emotional information as emo_i. In order to reduce the complexity of the task, we use three emotional polarities (positive, negative, neutral) to annotate each word.

Second, we represent each emotional information as $[w_i,emo_i]$ and map it to a multi-dimensional continuous value vector V_{emo}=$[w_i,emo_i] \in \mathbf{R}^L$, where L is the dimension of the emotional information vector, and V_{emo} is the emotional embedding of the w_i.

In order to accurately represent each word, we use GloVe (g) and ELMo (e) respectively as the common representation of word vectors, and combine emotional embedding as the input of the model. The final model input can be obtained by the following equation.

$$V_{input} = V_{emo} \oplus [V_g, V_e] \tag{1}$$

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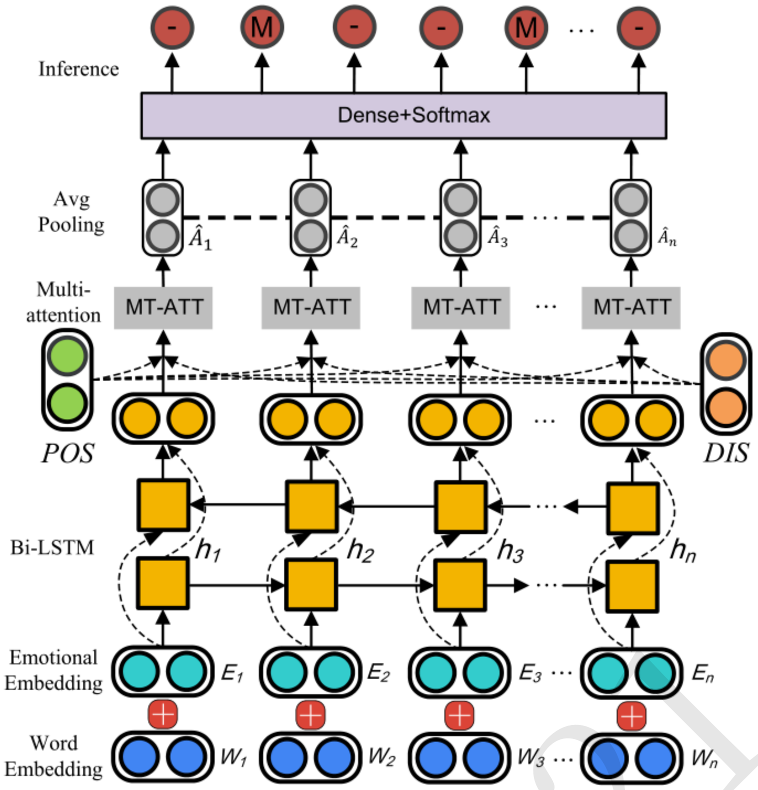

Fig. 1 The architecture of the metaphor detection model.

Where V_{emo} represents emotional embedding, $[V_g, V_e]$ represents word embedding matrix, and $\oplus$ is splicing operation.

BiLSTM Layer: BiLSTM generates a hidden state based on the current input and the previous state. Therefore, entering the current word will affect the following words. We use BiLSTM on the input V_{input} to summarize the both direction information of the words and generate the hidden vector sequence $[h_1, h_2, h_3 ... h_t ... h_n]$, thereby obtaining the representation of the sentence. h_t can be expressed as follows.

$$h_t = f_{BiLSTM}(V_{emo}, V_g, V_e), \overrightarrow{h}_{t-1}, \overleftarrow{h}_{t+1} \tag{2}$$

Multi-attention Layer: A single word embedding cannot reveal enough word semantic information. For example, incorrect annotations in the dictionary or words that do not exist in the dictionary will affect the performance of the metaphor detection model. In order to reduce the impact of this problem, we propose to use multi-attention to focus on two aspects of semantic information from part of speech and position.

Since metaphors usually have specific POS tags, it is easier to identify metaphors by adding POS information. In addition, POS tags can ideally solve the impact of out-of-vocabulary words on the performance of the experiment. We therefore propose POS attention. Specifically, we combine the word w_i and the POS tag POS_i to generate a POS representation of the word. Then combine w_i and POS_i into $WPOS_i$ in a splicing manner, and map $WPOS_i$ to a multidimensional vector V_{WPOS_i}. Finally, a POS representation dictionary $POSDic = V_{WPOS_1}, V_{WPOS_2} ... V_{WPOS_L}$ of length L is generated. For a single sentence, we find the POS representation of each word in the dictionary as input for attention. The calculation method is shown in the following equation.

$$a_i = innerproduct(V_{WPOS_i}, POSDic) \tag{3}$$

$$a_i^c = \frac{exp(a_i)}{\sum_{j=1}^{n} exp(a_j)} \tag{4}$$

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In addition, α_i^c can also be obtained by the following equation.

$$a_i^c = \beta \times \frac{exp(a_i)}{\sum_{j=1}^{n} exp(a_j)} \tag{5}$$

Where β is an adjustable parameter to control the importance of different POS vectors.

The position between each word hides important semantic information. We generally believe that position is closely related to the semantic connection of words. In order to indicate the relative position of each word, we use the matrix L to record the absolute distance between the current word and other words in the sentence. Then calculate the value of α.

$$\alpha = 1 - \frac{L_i + 1}{n + 1} \tag{6}$$

Then, map the distance value in the matrix L to a multi-dimensional vector, namely $L_i \in R^k$, and then calculate the input matrix.

$$input_i^L = \frac{L_i + x_i}{2} \tag{7}$$

Where x_i and input are the word vector and position attention input of the $i-th$ word. Finally, we combine POS attention and position attention as a multi-attention representation.

Avg Pooling Layer:In order to reduce parameters, prevent overfitting, and improve the generalization ability of the model, we use average pooling after multi-attention. The calculation method is as follows.

$$A = [c_1, c_2, c_3 ... c_n] \tag{8}$$

$$A = [\widetilde{c}_1, \widetilde{c}_2, \widetilde{c}_3 ... \widetilde{c}_n,] \tag{9}$$

Where A represents the output of the multi-attention, and $\widetilde{A}$ represents the output of the average pooling.

Inference Layer: Our inference layer consists of a dense and softmax. Each sentence passes through the dense layer, and finally uses $softmax$ to predict the probability distribution.

$$A = \widehat{y}_i = softmax(W \cdot dense_i + b) \tag{10}$$

$$softmax_i = \frac{exp(y_i)}{\sum_{j=1}^{N} exp(y_j)} \tag{11}$$

Where $\widehat{y}_i$ is the prediction probability, W is the final optimal weight of the dense layer after model training process. $dense_i$ is an output of dense layer and b is a bias term.

We regard Uyghur metaphor detection as a sequence tagging task, and the loss function is formulated as follows.

$$L(\hat{y}, y) = -\sum_{s \in S} \sum_{i=1}^{N} w_{y_i} y_i log(\hat{y}_i) \tag{12}$$

Where y_i is the ground-truth label of i_{th} word, $\hat{y}_i$ is the predicted label, and w_{y_i} is the loss weight of the metaphor label y_i.

4 Experiment

The proposed multi-attention model is applied to the task of Uyghur metaphor detection. Specifically, we reveal the richer semantic information of words from POS and position respectively, which makes the semantic expression of words and its context more complete. Besides, due to the close relationship between metaphorical expression and emotion, we propose that emotion embedding allows the model to learn emotion consistency information during the training process.

4.1 Dataset

The current researches on metaphor detection mostly focus on languages that have a complete corpus such as English. Due to the grammatical complexity and metaphor diversity of Uyghur language, metaphor detection in Uyghur has not yet been developed.

Therefore, we conducted data collection and annotation for the task of Uyghur metaphor detection. Specifically, we manually annotated 5605 Uyghur metaphorical sentences under the guidance of Uyghur language experts. For a single sentence, we annotated the metaphor of each word. The corpus is randomly divided into training set, validation set and test set. The results are shown in Table 3.

Sets	**Samples**	**MW**	**Non-MW**
Training set	4605	7951	33281
Validation set	500	806	4266
Test set	500	715	4609
Total	5605	9472	42156

Table 1: Splitting of training set, validation set and test set, where ”MW” represents metaphorical words, and ”Non-MW” represents non-metaphorical words.

Our corpus annotation members consist of 9 people, 7 of whom are familiar with Uyghur. In order to ensure the reliability of the Uyghur metaphor corpus, a sentence is annotated by multiple members. For ambiguous annotations, the final result is determined by Uyghur language experts.

4.2 Experimental Details

In our experiment, GloVe (Pennington et al., 2014) and ELMo (Peters et al., 2018) are used to initialize word vectors. The word vectors are pre-trained on Uyghur text with a size of about 78M, and the dimensions are 200 and 1024 respectively. Moreover, the uniform distribution $U(-0.1, 0.1)$ is employed to initialize all out-of-vocabulary words. The dimension of BiLSTM hidden states is 200, and batch size is 64.

4.3 Result Analysis

We set up three sets of experiments to verify the effectiveness of the multi-attention and emotional embedding. First, we add POS and position attention in turn to illustrate the impact on model performance. Then, we compared the performance of our model with and without emotional embedding. Finally, we conducted ablation experiments to verify the effectiveness of multi-feature input and multi-attention mechanisms.

4.3.1 Influence of Additional Features

Multi-attention can focus on semantic information from multiple levels. In order to illustrate the effectiveness of multi-attention, we assemble POS attention and position attention respectively under the same experimental setting.

Models	**Precision**	**Recall**	**F-score**
None	57.8	65.1	61.2
+POS	60.5	66.2	63.2
+Position	58.4	65.7	61.8
+POS+Position	**62.8**	**67.2**	**64.9**

Table 2: The influence of additional features.

Table 4 shows the performance of the model under different additional features. The experimental results show that both POS attention and position attention help to improve the performance of Uyghur metaphor detection. Especially the performance of the model with POS attention is significantly improved by 2%. Since each word in the corpus has a specific POS tag, which contains useful information

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for identifying metaphors. Therefore, the model can identify metaphors more easily after adding POS attention.

After adding position attention, the performance of the model is also slightly improved, which shows that the position information between words is related to metaphors. However, the improvement in model performance is not ideal. This is because the corpus contains short sentences. E.g., (using underlines for metaphors) I'm hunting. (ID: S106-4).

In all words, the model combining POS attention and position attention achieves the best performance. This shows that the multi-attention mechanism can reveal the semantic information of words from multiple aspects and promote more complete feature expression.

4.3.2 Influence of Emotional Embedding

Metaphors promote rich emotional expression, so metaphors are closely related to emotional information. In order to better illustrate the effectiveness of the proposed emotional embedding, we conducted experiments under different experimental settings. More specifically, we compared the performance of models with and without emotional embedding under different iterations. For each iteration, we use the same parameter settings.

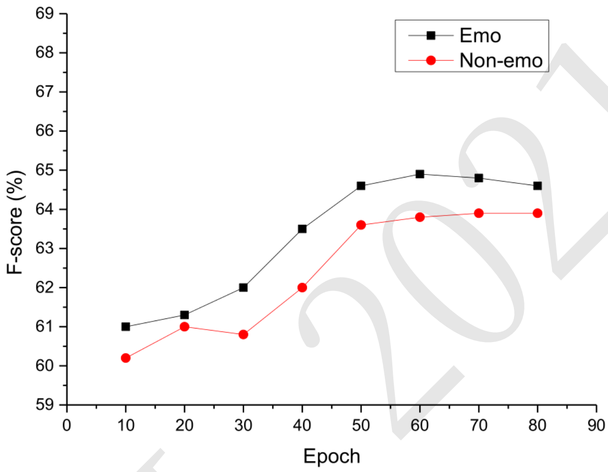

Fig. 2 Experiment results of different models, where "Emo" represents the model with emotional embedding and "Non-emo" presents the model without emotional embedding.

Figure 2 shows the experimental results of our model with or without emotional embedding. It can be seen from the experimental results that our model achieves the best performance with emotional embedding. This is because metaphorical expressions are mostly to express richer and stronger emotions. With the help of emotional embedding, our model can learn emotional consistency information from words and its context emotional level respectively. The probability of words being classified as metaphors will increase when words conflict with the emotional polarity of the context. In addition, observing the experimental results, we can see that the F-score stops increasing as the epoch is greater than 60, we therefore set the epoch to 60.

4.3.3 Ablation Experiment

Multi-feature input and multi-attention mechanisms are used to represent the richer semantic features of words, which play a key role in the improvement of classification performance. In order to better illustrate the effectiveness of each module in the model, we conducted a set of experiments under different module assemblies. In particular, we remove the multi-feature input (-MTinput) and multi-attention mechanisms (-MTatt) respectively. For each time, we report the performance of the model on the test set. For all these experiments, we kept the rest of the model unchanged.

It can be seen from the experimental results in Figure 3 that the performance of metaphor detection is greatly reduced when the multi-feature input is removed. This is due to insufficient semantic expression of words, which leads to the model not being able to fully learn the semantics and context of words.

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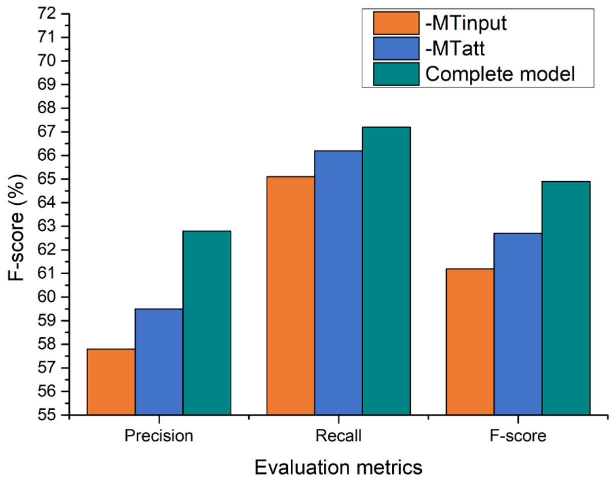

Fig. 3 Experimental results of the model under different module assembly.

This also clarifies that the Uyghur metaphor detection task is more dependent on the semantics of words and their contextual representations. The performance of the model that removes the multi-attention mechanism is also reduced. This result is because the multi-attention mechanism is a method based on multi-feature input. With the help of multi-feature input, the multi-attention mechanism enables the model to learn the semantics of words and the importance of each word from multiple levels during the training process. Therefore, multi-feature input and multi-attention mechanisms complement each other to achieve better semantic representation, thereby achieving more ideal classification performance.

5 Conclusion

This paper proposed a Uyghur metaphor detection model that combines multi-attention and emotional embedding. We used POS attention and position attention to construct multi-attention representations of words, which allows the model to reveal text semantics from multiple aspects. In addition, due to the correlation between metaphor and emotional expression, we construct an emotionally related dictionary as the source of emotional embedding. Emotional embedding is utilized to learn the emotional consistency features of words and its context. The experimental results verify the effectiveness of the model for Uyghur metaphor detection.

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