Emoji-aware Co-attention Network with EmoGraph2vec Model for Sentiment Analysis

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Abstract

In social media platforms, emojis have an extremely high occurrence in computer-mediated communications. Many emojis are used to strengthen the emotional expressions and the emojis that co-occurs in a sentence also have a strong sentiment connection. However, when it comes to emoji representation learning, most studies have only utilized the fixed descriptions provided by the Unicode Consortium, without consideration of actual usage scenario. As for the sentiment analysis task, many researchers ignore the emotional impact of the interaction between text and emojis. It results that the emotional semantics of emojis cannot be fully explored. In this work, we propose a method to learn emoji representations called EmoGraph2vec and design an emoji-aware co-attention network that learns the mutual emotional semantics between text and emojis on short texts of social media. In EmoGraph2vec, we form an emoji co-occurrence network on real social data and enrich the semantic information based on an external knowledge base EmojiNet to obtain emoji node embeddings. Our model designs a co-attention mechanism to incorporate the text and emojis, and integrates a squeeze-and-excitation (SE) block into a convolutional neural network as a classifier. Finally, we use the transfer learning method to increase convergence speed and achieve higher accuracy. Experimental results show that the proposed model can outperform several baselines for sentiment analysis on benchmark datasets. Additionally, we conduct a series of ablation and comparison experiments to investigate the effectiveness of our model.

1 Introduction

As a natural language process (NLP) task, sentiment analysis aims to mine opinions, emotions, and attitudes expressed in text [3]. With the explosive growth of social media, opinionated postings have increased explosively. Applied to Web content, sentiment analysis can provide valuable insight into research, industry, and politics (e.g., customer products [2], financial services [3], healthcare and political elections [4,5]).

In social media platforms, emojis have an extremely high occurrence in computer-mediated communications. Defined as "digital images that are added to a message in electronic communication in order to express particular ideas or feelings" emojis can depict facial expressions, pictorial representations of objects, symbols, and actions. According to statistics, the most widely adopted emojis are faces [6], and they mainly play an emotion-oriented role to strengthen the sentimental expressions in Twitter, Facebook, and other social media platforms.

Previous study [8] shows that the usage of emojis has sentiment effects on plain text, which can even dominate the overall emotional polarity. For example, the sentiment valence of text "Today is a rainy day." is originally neutral. If an emoji {grin} (or {sob} was added in the end, however, the sentiment would be totally changed.

And we also notice that the emojis that co-occurs in a text have a strong sentiment connection. 1) The white curtains blew in the wind like {ghost}, it’s a little scary {scream}. 2) I love {ghost} movie {heart-eyes}. The intended emotional meaning of {ghost}, with different emojis followed, varies from negative to positive. This also reflects that the emotional information in emojis is not immutable.

However, when it comes to emoji representation learning, most studies have only utilized the fixed descriptions provided by the Unicode Consortium website [2] without consideration of actual usage scenario. Many emojis have an implicit emotional tendency that cannot be literally reflected by their definitions. In addition, the meanings of emojis are not fixed and may slightly change with the continuous evolution of online written communication. In this work, we propose a model to learn emoji representations called EmoGraph2vec. To understand the intended emotions con-

1https://dictionary.cambridge.org/us/dictionary/english/emoji
2http://www.unicode.org/emoji/charts/full-emoji-list.html

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veyed in context, we form an emoji co-occurrence network based on real social data. We hypothesize that the co-occurrence information could provide practical emotional semantics since they are extracted from real social conversations. Then we make use of network structure and node attribute information to obtain emoji embeddings based on an external knowledge base EmojiNet and a variational graph autoencoder (VGAE) [12].

For the sentiment analysis that contains emojis, the most common method is to utilize emojis as an important feature [7, 9] or a natural annotation [10] to obtain better performance. However, existing work [10] shows that using emojis directly as emotional labels will generate diverse noise because of the ambiguity of the emoji meanings. Based on the above problems, we propose a co-attention network to learn the mutual emotional semantic features between text and emojis. Then we send these features into a SE-based CNN classifier to predict the sentiment label.

Similar to other NLP tasks, the manually annotated sentiment analysis corpus is scarce. It has been a serious limitation for many machine-learning models, of which accuracy depends on massive high-quality data with labels. We utilize a large-scale unlabeled Twitter corpus with emojis to learn emotional features and leverage them on our model to transfer the sentiment knowledge.

In summary, the main contributions of our work are as follows:

- We propose an emoji representation learning method named EmoGraph2vec to learn emoji representations in a graph network. We utilize a large-scale unlabeled corpus to form an emoji co-occurrence graph network and adopt a VGAE to make use of network structure and node attribute information to obtain emoji embeddings based on EmojiNet.

- We propose a novel neural network framework to incorporate text and emoji information into sentiment analysis, which uses a co-attention network combined with SE-Net-based CNN classifier to capture sentiments based on emoji occurrences.

- On the concept of transfer learning, we pre-train the text feature extractor module and fine-tune the model in the downstream tasks with faster converge speed and higher accuracy on different sizes of the training sets.

2 Relate Work

2.1 Sentiment Analysis As a significant branch of natural language processing (NLP), text sentiment analysis aims to mine and analyze the emotions, opinions, and attitudes of people from texts. In recent years, the rapid development of deep learning has played an important role in boosting the development of sentiment analysis researches. Socher et al. [11] applied Recursive Neural Network to text sentiment classification with the consideration of the syntactic structure information; Santos et al. [9] proposed Character to Sentence Convolutional Neural Network (CharSCNN) to analyze sentiment on the short text.

2.1.1 Emoji in Sentiment Analysis Many studies use emojis as heuristic information in social texts [10, 13, 14], where emojis serve for unsupervised learning in a large number of unlabeled data. Emojis can also be regarded as important semantic features about emotions towards the recipient or subject [15] for sentiment classification. For instance, Tian et al. [16] used a Bi-directional Gate Recurrent Unit Attention network, which integrated the emotional polarity of emoji and embedded it as a feature into the model. But they failed to reflect the emotional impact of emojis on the text. Lou et al. [17] constructed an emoji-based Bi-LSTM model, which combined the attention mechanism to weigh the contribution of each word on the emotional polarity based on emoji. But their model only analyzes the microblog data that contains a single emoji and cannot be generalized to process multiple types of emojis. Both works only learned the emoji features through fixed emoji names without consideration of actual usage scenario.

2.2 Emoji Representation Learning Barbieri et al. [18] trained an emoji embedding model on tweets to seek an understanding of emoji meanings from how emojis are used in a large collection of tweets. Eisinger et al. [19] used a word embedding model learned over the Google News corpus [1], and applied it to emoji names to learn an emoji embedding model which they called emoji2vec. Wijeratne et al. [20] learned the distributional semantics of the words in emoji definitions to model the emoji meanings extracted from EmojiNet. But they failed to explore the emoji meanings in the actual usage scenarios. Illendula et al. [21] utilized a large Twitter corpus which has emojis in them and built an emoji co-occurrence network, and trained a network embedding model to embed emojis into a low dimensional vector space. But they only utilized the emoji frequency and ignored their textual meanings as node information which can enhance the emoji semantic features.

2.3 Transfer Learning Data dependence is one of the most serious problems in deep learning [22]. For the sentiment analysis task, it is very difficult to construct a large-scale well-annotated dataset when containing

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https://goo.gl/QaxjVC
emojis, due to the expense of data acquisition and costly annotation. Transfer learning is an important tool to solve the basic problem of insufficient training data by transferring the knowledge from the source domain to the target domain. Many scholars apply transfer learning to the field of sentiment analysis. Xu et al. proposed the instance level transfer learning method applied to cross-lingual opinion analysis, and translated other markup languages into target language to improve the accuracy. Felbo et al. extended the distant supervision to a more diverse set of noisy labels, and the models can learn richer representations. Chen et al. proposed a novel representation learning method that uses emoji prediction as an instrument to learn respective sentiment-aware representations for different languages.

3 Model

For emoji representation learning, we propose a network representation learning model to embed emojis into a low dimensional vector space by an emoji co-occurrence graph. For sentiment analysis, we design a co-attention network to incorporate text and emoji features. As illustrated in Figure 1, our model consists of several modules: EmoGraph2vec, text feature extractor, co-attention module, SE-based CNN Classifier and transfer learning layer.

The Emograph2vec model learns the emoji representations and provides pre-trained emoji vectors in the embedding layer. In the text feature extractor, we build two stacked Bi-LSTM layers with skip-connection to obtain text features. Then we adopt a co-attention module to learn high-level emotional semantic features incorporating the text and emojis from their interaction, which fully explores the emotional impact of emojis on sentiment. Finally, these features are fed into a CNN classifier integrated with a SE block to learn a collection of per-channel modulation weights, which strengthens the representational power of the CNN classifier. The transfer learning layer is designed to apply previously learned knowledge since training a model from scratch is time-consuming and inefficient. We will illustrate the details of the proposed framework in the following section.

3.1 EmoGraph2vec

Based on large-scale Twitter data, we extract the emoji co-occurrences from it to learn emoji features with the EmojiNet resource. Different from traditional methods that treat the emoji co-occurrences as sequence data, we utilize the co-occurrence information from the whole corpus as non-Euclidean data to construct an undirected network graph.

3.1.1 EmojiNet

EmojiNet is a machine readable sense inventory for emojis created by Wijeratne et al. It consists of 12,904 sense labels over 2,389 emojis, where each emoji is represented as a nonuple $e = (u, n, c, d, K, I, R, H, S)$. Here $u$ is the Unicode of $e$, $n$ is the name, $c$ is the short code, $d$ is a description of $e$, $K$ is the set of keywords that describe intended meanings attached to $e$, $I$ is the set of images that are used in different rendering platforms, $R$ is the set of related emoji extracted for $e$, $H$ is the set of categories that $e$ belongs to, and $S$ is the set of different senses in which $e$ can be used within a sentence.

We utilize the EmojiNet to transform the Unicode emoji representation into textual meanings. Specifically, $K$ and $S$ elements of each emoji nonuple are used to calculate edge weight and the node attribution in the graph network.

3.1.2 Graph Initialization

Each tweet forms a polygon of $n$ nodes where $n$ represents the number of...
unique emojis. Let us denote the graph as \( G = (V, E) \), where \( v \in V \) denotes one kind of emoji, and \( N = |V| \) equals the number of all emojis. The nodes are connected when they appear in the same tweet.

The edges of the network are weighted by the co-occurrence frequency and similarity of two emoji nodes. We extract keywords \( K \) of each emoji from EmojiNet as node features to calculate the TF-IDF vectors. Then, similarity scores between node pairs are computed by cosine similarity. The emoji pair that has high co-occurrence frequency may have a strong emotional connection and the similarity can quantify the emotional semantic distance. Based on co-occurrence frequency and similarity, the product of these two indicates edge weight, which can determine the mutual influence of emotional polarity between emoji pairs.

To enrich the semantic information in the network, we also utilize the \( S \) element of emoji \( e \) into this graph as node attribute information. We embed the sense definitions of each emoji by word2vec \[28\] into a 300-dimensional vector space. The word vectors of all words in the emoji sense definition are averaged to form a final single vector as the node attribution.

### 3.1.3 Graph Embedding

To incorporate the network structure and node attribute information, we use an unsupervised learning method VGAE to learn node representations from the undirected graph. This model uses a two-layer graph convolutional network (GCN) encoder and an inner product decoder. The encoder produces the distribution of vectors, including mean \( \mu \) and variance \( \sigma \), from which stochastic latent variable \( z_i \) is obtained by sampling.

\[
q(z_i|X,A) = \mathcal{N}(z_i|\mu_i, \text{diag}(\sigma^2_i)) \tag{3.1}
\]

Here, \( A \) is a weighted adjacency matrix of \( G \), \( X \) represents the node feature matrix. \( \mu = \text{GCN}_\mu(X,A) \) is the matrix of mean vectors \( \mu_i \); similarly \( \log \sigma = \text{GCN}_\sigma(X,A) \).

The decoder is given by an inner product between latent variables.

\[
p(A|Z) = \prod_{i=1}^N \prod_{j=1}^N p(A_{ij}|z_i, z_j) \tag{3.2}
\]

\[
p(A_{ij} = 1|z_i, z_j) = \sigma(z_i^T z_j), \tag{3.3}
\]

where \( A_{ij} \) are the elements of \( A \) and \( \sigma(\cdot) \) is the logistic sigmoid function. And \( Z \) is the node embedding matrix we needed.

### 3.2 Text Feature Extractor

We obtain the word embeddings by the pre-trained word vectors over the Google News dataset \[28\]. Then the plain text can be represented as \( X = [x_1, x_2, ..., x_L] \). The emojis (contained in the sentence) can also be encoded into vectors by EmoGraph2vec model \( E = [e_1, e_2, ..., e_N] \).

LSTM can overcome the problem of gradient vanishing and explosion with the capability to learn long-range dependencies in sequences. In order to capture both past and future information, our feature extractor adopts two stacked Bi-LSTM layers to learn the text representation bidirectionally. And we concatenate the hidden vectors from both directions to represent every single word as the output \( h_l \) of the layer. The second bi-directional LSTM layer takes the output of the previous one as its input \( H_1 = [h_{11}, h_{21}, ..., h_{1L}] \), and computes unit stats of network in the same pattern before producing the output \( H_2 = [h_{12}, h_{22}, ..., h_{1L}] \).

### 3.3 Co-attention Network

#### 3.3.1 Intra-Text Attention Module

Since not all words contribute equally to express sentiments, the intra-text attention can lead the model to attend to sentiment-guided words. Through a skip-connection, the outputs of the below three layers (the embedding layer and the two bi-directional LSTM layers) are concatenated as a whole vector, which will be sent into the text attention module as input. The \( t \)-th word in the input text can be denoted as \( u_t = [x_t, h_{t1}, h_{t2}] \), where \( x_t \in \mathbb{R}^d \), \( h_{t1} \in \mathbb{R}^d \), and \( h_{t2} \in \mathbb{R}^d \), \( d \) is the dimension of word feature. For the \( t \)-th word, the attention score is measured by

\[
\alpha_t = \frac{\exp(W_\alpha u_t)}{\sum_{l=1}^L \exp(W_\alpha u_l)}, \tag{3.4}
\]

where \( W_\alpha \) is the weight matrix and \( W_\alpha \in \mathbb{R}^{1 \times 3d} \). \( \alpha_t \in \mathbb{R}^L \), which corresponds to the attention probability of each word. Using the attention scores as weights, the text can be represented as \( v_t \), that aggregates the weights of individual words and transform the dimension to \( d \) through a fully connected layer:

\[
v_t = W_u (\sum_{l=1}^L \alpha_l u_l) + b_u, \tag{3.5}
\]
where $W_u \in \mathbb{R}^{d \times 3d}$ is the weight matrix and $b_u$ is the bias.

### 3.3.2 Text-Guided Attention Module

In most cases, emoji occurrences in a sentence are related to the emotional semantics, but the different contributions of each emoji to predict the sentiment label depends on the contextual text. Therefore, we apply a text-guided attention module to decide which emoji to attend to by using the new text vector $v_t$ to conduct the attention. We feed text feature $v_t$ and emoji features $E$ through a fully connected network followed by a softmax function to obtain the attention distribution over the emojis:

$$z_n = \tanh(W_E e_n + W_{v_t} v_t + b),$$
$$\beta_n = \frac{\exp(W_{\beta} z_n)}{\sum_{i=1}^{N} \exp(W_{\beta} z_i)},$$

where $v_t \in \mathbb{R}^d$, $e_n \in \mathbb{R}^d$. $W_E, W_{v_t}$ and $W_{\beta}$ are weight matrices, and $W_E \in \mathbb{R}^{k \times d}$, $W_{v_t} \in \mathbb{R}^{1 \times d}$, $W_{\beta} \in \mathbb{R}^{1 \times k}$ and $b$ is the bias. $\beta_n \in \mathbb{R}^N$ is corresponding to the attention probability of each emoji given text representation $v_t$. Based on $\beta_n$, the new emoji representation $v_e$ can be generated by weighted sum of the product of $\beta_n$ and $e_n$.

### 3.3.3 Emoji-Guided Attention Module

In previous section, we use intra-text attention to obtain text representation $v_t$ that is more relevant to sentiment word $h_{t2}$ at position $l$. However, it is not clear which word in the text is more relevant to emoji representation $v_e$, since emoji has a strong correlation with the sentiment expressed in sentences. The emoji-guided attention module joins text and emoji information together to measure the weight of each word that decides which words in the text should be attended to. We learn the emoji representation $v_e$ from the text-guided attention module, and higher-level text representation $H_2$ is obtained from the top Bi-LSTM layer. Similar to text-guided attention, we use these features to generate the attention distribution over the word embeddings and get a new text representation $v_h$ that joins the semantics of text and emoji together.

### 3.4 SE-based CNN Classifier

After the co-attention network, we obtain the text vector $v_t \in \mathbb{R}^d$, text-based emoji vector $v_e \in \mathbb{R}^d$ and emoji-based text vector $v_h \in \mathbb{R}^d$. We take the above three representations respectively as three-channel input $V \in \mathbb{R}^{d \times c}$ and feed them into a classifier to predict the probability distribution of sentiment labels. Our model uses a CNN combined with a SE Block as the sentiment classifier. It returns a probability distribution.

For the convolutional operation, we use $[w_1, w_2, ..., w_c]$ to represent the set of filter kernels that map the input $V \in \mathbb{R}^{d \times c}$ to a new feature map $U \in \mathbb{R}^{d' \times c'}$. The transformed feature will be generated as follows:

$$u_j = w_j * V = \sum_{n=1}^{c} w_j^n * v^n$$

Here $*$ denotes convolution, $w_j = [w^1_j, w^2_j, ..., w^c_j]$, $V = [v^1, v^2, ..., v^c]$ (or $V = [v_t, v_e, v_h]$) and $u_j \in \mathbb{R}^{d'}$. $w_j^n$ denotes the $n$-th channel of $w_j$ that is a 1D spatial kernel. Then the feature map is calculated by a SE block before the final max-pooling and softmax layer.

Since not all features contribute equally to predict the final sentiment label, we employ the SE block to measure the importance of each feature channel by modeling the correlation between channels and learning their weights [29]. Two parts are included in a SE block: squeeze (3.9) and excitation (3.10).

$$z_j = F_{sq}(u_j) = \frac{1}{d'} \sum_{i=1}^{d'} u_j(i),$$
$$\tilde{v}_j = F_{scale}(u_j, s_j) = s_j u_j = \sigma(W_2 \delta(W_1 z_j)) u_j,$$

where $\sigma$ and $\delta$ denote the sigmoid and ReLU function respectively, weight matrices $W_1 \in \mathbb{R}^{c' \times C}, W_2 \in \mathbb{R}^{C \times c'}$, and $F_{scale}$ represents to channel-wise multiplication.

### 3.5 Transfer Learning

Transfer learning can solve the problem of insufficient training data by transferring the knowledge from the source domain to the target domain. Since the scarcity of labeled data in sentiment tasks, we use the specific emojis as forms of distant supervision based on a large-scale unlabeled Twitter corpus [4.1.2]. As shown in Fig 3, the text feature extractor can learn rich sentimental information in advance from the source domain $D_s = (x_i, y_i)$, where $x_i$ is the plain text of the tweet in the corpus and $y_i$ is the emoji contained in that tweet as a label. We obtain a function $f_s$ through training and use it to predict the diverse emoji labels. Given a new annotated sentiment analysis dataset from the target domain $D_t$, the transfer learning layer uses the existing knowledge $D_s$ (pre-trained parameters in text feature extractor) to assist $D_t$ to construct a new prediction function $f_t$ rapidly. Followed by co-attention network and CNN classifier, the whole model can be fine-tuned on the new data.

### 4 Experiment

#### 4.1 Dataset

##### 4.1.1 Labeled Dataset

The labeled data are collected from multi-source social media platforms and
cover multiple domains to minimize biases. More details about the datasets (MSD, TD, ERD, and SCD) are shown in Appendix A\textsuperscript{4}. We use the part of the data that contains the emojis, of which the amount is limited.

4.1.2 Unlabeled Dataset To train the EmoGraph2vec model as well as the transfer learning layer, we use a large-scale unlabeled data of Tweets named EmojifyData\textsuperscript{5}. This dataset contains 18 million English tweets, all with at least one emoji included. Based on it, we can learn emoji representations in EmoGraph2vec to obtain emotional semantic information in their embeddings. For the transfer learning, we extracted tweets containing the Top48 emojis in frequency of the corpus. As many tweets contain multiple emojis, for each tweet, we created separate examples for each unique emoji in it to make the emoji prediction a single-label classification task instead of a more complicated multi-label classification.

4.2 Implementation Details Our model is trained using the PyTorch library \textsuperscript{30} on a cuda GPU. Appendix B provides a detailed description of our experimental configuration. In VGAE, the number of units in hidden layer 1 is set to 256, and layer 2 is 300. The training procedure runs for 50 epochs to learn emoji representations on EmojifyData. The hidden units in BiLSTM are set as 300 because the text feature generated from the hidden units must keep the same dimension with word and emoji to be a three-channel feature. The Model uses Adam algorithm with a learning rate of 0.001, and we use a batch size of 16. We train our model in the sentiment analysis task with 20 epochs. Furthermore, we conduct several experiments to explore the effects of different hyperparameters on Appendix C.

4.3 Baselines and Performance Comparison To evaluate the performance of our model, we employ several representative baseline methods: TextCNN \textsuperscript{31}, Att-BiLSTM \textsuperscript{32}, TextGCN \textsuperscript{33} and EA-Bi-LSTM \textsuperscript{17}. EA-Bi-LSTM (based on Emoji-Attention and BiLSTM) is the latest work that designed for the data containing emojis. For each method, we use two methods to embed emojis. One is the EmoGraph2vec method, the other uses the Unicode characters given by the Unicode Consortium directly. A special case is the TextGCN method, it initials all node features using the one-hot. In Table 1, we can see our model outperforms all other baseline methods with the EmoGraph2vec method. The results prove that our proposed model is more effective than the traditional deep learning methods (TextCNN, Att-BiLSTM), which do not pay attention to emojis. Looking more closely, EA-Bi-LSTM achieves a certain improvement than the former methods, which demonstrates the significance of incorporating emojis and text to analyze sentiment. And it is remarkable to find that our model obtains higher accuracy than EA-Bi-LSTM, since the latter only adopts a simple attention layer. Comparing with other baseline models, the performance of TextGCN is worse than all other methods even with an accuracy below 0.5 on the SCD. It might be explained that in text classification, GCN ignores the word features of sequence, which is of great importance for sentiment analysis. In contrast, CNN and LSTM models can capture this well.

When using the Unicode characters as emoji representations, one interesting finding is that the accuracy of our model and EA-Bi-LSTM have a decline while TextCNN and Att-BiLSTM have an increase. A possible explanation for this might be that the former separate text and emojis as two parts of inputs, where pre-trained emoji embeddings can work better. When treating the whole sentence as an integrated input (in

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\textsuperscript{4}In supplementary material

\textsuperscript{5}https://www.kaggle.com/rexhaif/emojifydata-en
TextCNN and Att-BiLSTM), the Unicode characters can be trained with word vectors together to achieve better performance.

4.4 Model Analysis

4.4.1 The Power of Emojis

To further explore the influence of emojis in our model, we conduct the subsequent experiments by removing the inputs of emojis or simplified architecture of the model to evaluate the effectiveness of emojis. N-model detaches the emoji inputs and sends $v_t$ directly into a single-channel CNN classifier. T-model removes the text-guided attention module of emoji representation learning, sends $v_t$ and $v_h$ into a two-channel CNN classifier. E-model removes the emoji-guided attention module of text representation learning, sends $v_t$ and $v_e$ into a two-channel CNN classifier.

As shown in Fig 4, we find that the complete model significantly outperforms the N-model and T-model on all the datasets, both of which only consider the text features before classification. That demonstrates the plain text does not contain rich emotional semantic information as emojis do occasionally in sentiment analysis. The T-model also outperforms the N-model to a certain degree. This shows emoji-guided text representation learning can effectively improve the ability of the model to learn the emotional semantic. It also explains why our emoji-aware method can achieve better accuracy compared to other baseline methods. The accuracy of the E-model is also higher than T-model and slightly lower than the complete model because E-model extracts sentiment information from text-guided emoji representation but fails to capture sentiment patterns of emoji-guided text representation.

4.4.2 Effectiveness of Co-Attention

To further explore the effect of the co-attention mechanism in our proposed method, we compare the complete model with several attention-modified models as follows: In RA1, we remove the intra-text attention module and take the output of last cell of the Bi-LSTM as the plain text representation $v_t$. In RA2, we replace the text-guided attention module with the average value of the emoji vectors $E = [e_1, e_2, ..., e_N]$ as the emoji representation $v_e$. In RA3, we replace the emoji-guided attention module with the average value of the text representation $H_2 = [h_{12}, h_{22}, ..., h_{L2}]$ as the text representation $v_h$. In RSE, we remove the SE-Net module and concatenate the output of co-attention module ($v_t, v_e, v_h$) to a fully-connected layer with a softmax function as a classifier.

For each dataset, the last two lines of Table 2 show the improvements of SE-Net, which illustrates that this module can improve the accuracy. On the other hand, the difference between them is slightly than the improvements of the whole model compared with baselines. That indicates the co-attention module plays the main role in our model.

As shown in Table 2, it can be seen that the accuracy of the RA2 has dropped sharply in most datasets. RA2 directly changes the attention mechanism of the emoji vector $v_e$ to the average value of all emoji vectors, indicating that emojis take most of the weight for the emotional semantic analysis of the model. That means when the model cannot distinguish which emoji dominates the text emotion, the accuracy drops significantly. The slight difference of accuracy between the RA1 and RA3 model reveals that when the self-attention of the text is removed, the simplified $v_t$ vector will further affect the representation of $v_e$ as the emoji feature, and it results in the lower accuracy. While the RA3 retains the first two representations of $v_t$ and $v_e$ features, only the last step of the text vector representation is replaced, it has the least impact on the model performance, indicating that the model can still make correct predictions from the $v_e$ vector with a greater probability.

| Models | MSD       | TD        | ERD       | SCD       |
|--------|-----------|-----------|-----------|-----------|
| RA1    | 84.1226   | 76.5734   | 75.1139   | 60.8108   |
| RA2    | 83.5654   | 74.8252   | 75.3165   | 58.1081   |
| RA3    | 85.5153   | 77.2727   | 77.8481   | 62.1622   |
| RSE    | 86.0724   | 76.5245   | 78.4810   | 61.1351   |
| Our mode | 86.6295 | 77.9720   | 79.7468   | 62.8378   |

Figure 4: Performance of complete model and its simplified versions

Table 2: The accuracy(%) of modified models on different dataset

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4.4.3 Comparison about Emoji Representation Learning

To demonstrate the effectiveness of the Emograph2vec method, we compare it with the representative emoji embedding method emoji2vec which was proposed by Eisner et al. [19]. The pre-trained embeddings are learned from descriptions in the Unicode emoji standard and are publicly released. As shown in Fig. 5, when using different emoji embedding methods in sentiment analysis tasks, Emograph2vec outperforms emoji2vec and Unicode characters on all datasets.

To further explore the difference between the two methods, we perform a hierarchical clustering on Top64 most used emojis (according to a report published by Unicode Consortium) and visualize the clustering results in Fig. 6. Each emoji can be meaningfully represented by a low-dimensional vector in the embedding space where similarity can be measured. In the report, the Top64 emojis include facial expressions, gestures, and objects. We suppose that not only facial expression emojis can carry emotional semantic information but also other categories in various scenarios. Since we learn emoji features from social network data, we can learn the sentiment tendency contained in each emoji in a specific scene. We expect that a well-performed representation can embed emojis with similar emotional semantics closely in the vector space no matter it is a facial expression or object.

The color scale of each cell indicates the similarity between the two emojis. The darker the cell is, the more similar the representations of the two emojis are. As shown in Fig. 6a, the emoji2vec method directly works on Unicode descriptions, which reflects on the clustering result. The facial expression emojis have a high degree of similarity also the similar-shaped (e.g. heart-shaped) emojis do. And the distance between the groups is large, which illustrates that the method strictly classifies emojis literally. In the contrast, we can see in the Fig. 6b there is no clear boundary to distinguish each kind of emojis. The bottom right corner contains the darkest cells that means these emojis have similar emotional semantics. We can see this area includes expressions as well as gestures and objects (e.g. "sparkle" and "Fjoy").

4.4.4 Evaluation of Transfer Learning

Dataset TD and SCD are selected to evaluate the effects of transfer learning by retraining the module or transferring the pre-trained parameters and fine-tuning. We conduct four experiments with new training set accounting for 20%, 40%, 60%, and 80% of the total data. The results on TD are shown in Fig. 7a and 7b. Fig. 7c and 7d show the experimental results on SCD. These figures present the effects of the size of training data on the accuracy and training speed of the model. Overall, the model can achieve higher accuracy and faster converge speed based on transfer learning. As can be seen from the 7a and 7c, when the proportion of the training set is small (i.e., 20%), the accuracy of the fine-tuned model is significantly higher than the one trained from scratch. This is because the deep model needs a large amount of data to understand the latent patterns of data. Using transferred parameters as prior knowledge can help the model to discover the patterns under the data. When the proportion gets larger, the gap between the two methods narrows since the learning ability of the model trained from scratch strengthens. On the other hand, the gap in training time consumption keeps widening. The model of transfer learning has a faster converge speed while the other pays an expensive price on time.
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