Context-Sensitive Twitter Sentiment Classification Using Neural Network

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Abstract

Sentiment classification on Twitter has attracted increasing research in recent years. Most existing work focuses on feature engineering according to the tweet content itself. In this paper, we propose a context-based neural network model for Twitter sentiment analysis, incorporating contextualized features from relevant Tweets into the model in the form of word embedding vectors. Experiments on both balanced and unbalanced datasets show that our proposed models outperform the current state-of-the-art.

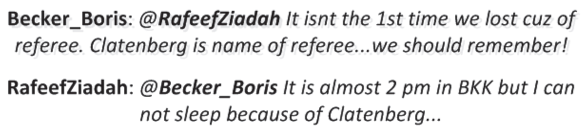
Introduction

Twitter sentiment classification, which extracts the sentiment polarity of a tweet, has became a heated topic in Natural Language Processing (Jiang et al. 2011; Hu et al. 2013; Tang et al. 2014; Severyn and Moschitti 2015). Most existing approaches follow Pang et al. (2002) and treat Twitter sentiment classification as a special case of text classification, focusing on designing effective features to obtain better performance (Pang and Lee 2008; Maas et al. 2011; Taboada et al. 2011; Liu 2012; Owoputi et al. 2012; Feldman 2013; Labutov and Lipson 2013). Specifically, Mohammad et al. (2013) build the top performing system in the Twitter sentiment classification track of SemEval 2013, using diverse sentiment lexicons and a variety of hand-crafted features. Tang et al. (2014) propose a form of sentiment-specific word embedding, which gives better performance compared with the top-performed system using diverse word representations.

The above methods focus on features modeling according to the tweet content itself, but do not leverage contextual information regarding the target tweet, which limits the performance of the task. Tweets are streams of posts, and a wider context, such as a conversation, topic or history tweet, is always available. Consider the following tweet from RafeefZiadah, which cites Becker_Boris:

- **RafeefZiadah**: ***@Becker_Boris*** *It is almost 2 pm in BKK but i can not sleep because of Clatenberg...*

[*]corresponding author


Becker_Boris: ***@RafeefZiadah*** *It isnt the 1st time we lost cuz of referee. Clatenberg is name of referee...we should remember!*

RafeefZiadah: ***@Becker_Boris*** *It is almost 2 pm in BKK but I can not sleep because of Clatenberg...*

Figure 1: Target tweet and his contextual information

It is difficult to determine the sentiment polarity of this tweet because of the unknown word "Clatenberg", which can be a exciting performer or a disturbing neighbor. However, we can obtain its sentiment using contextual information of this tweet, shown as Figure 1.

Based on Figure 1, a first negative tweet has been produced, which indicates that the second tweet (target tweet) is negative also. It is the conversation that allows us here to decide the sentiment category of a tweet. This motivates a context-based neural network model for Twitter sentiment classification.

Recently, Vanzo et al. (2014) proposed to model a tweet and its contextual tweets as a sequence, using a sequence labeling model, SVM^{HMM}, to predict their sentiment labels jointly. They suggest two types of contexts, including a conversation-based context, which contains a certain number of Tweets in a discussion thread, and a topic-based context, which contains several tweets in the history stream that contain overlapping the hashtags. Both types of contexts are shown useful to improve the accuracies of sentiment classification empirically.

One limitation of Vanzo et al. (2014)'s model, however, is the sequential assumption of context tweets. Intuitively, the influence of one tweet is not limited to a few tweets in the timeline, and coreferences between tweets can form a complex graph structure. In addition, Vanzo et al. (2014) use a discrete model with spare manual features, which can be expensive to obtain. In this paper, we show that significant improvements can be achieved by modeling the context tweets of a given target tweet as a set, using neural pooling functions to extract the most useful features from tweets automatically.

We build a baseline system using a neural network, which has been shown to give competitive accuracies compared with traditional linear models recently (Socher et al. 2013;

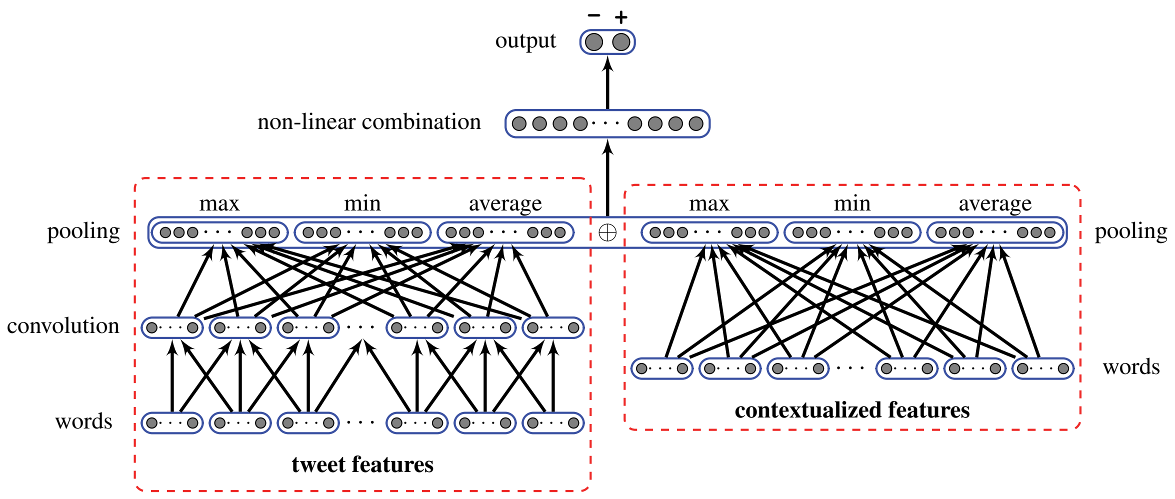


Figure 2: The context-based neural network model for Twitter sentiment classification.

dos Santos and Gatti 2014; Kalchbrenner, Grefenstette, and Blunsom 2014). The baseline model takes word embedding features from the tweet context itself, and performs feature combination automatically. It gives comparable results to the best methods in the literature. We further extend the baseline system with a context-based sub neural network, which extracts important features from context tweets automatically. In addition to the conversation-based and topic-based contexts proposed by Vanzo et al. (2014), we also investigate a context based on history tweets of the same author, which can serve as a prior for a tweet's sentiment. Results on a large dataset show that by using such a context-based sub network, our model can improve two-way sentiment classification performance from 80.68% to 91.33% in macro-F score.

A Context-based Neural Network Model for Twitter Sentiment Classification

The proposed model is shown in Figure 2, which has two main components. The left component is a local-feature sub neural network, using only local information from the target tweet itself, while the right component is a contextualized feature sub network. We study features from conversation-based context, author-based context and topic-based context about a target tweet, respectively.

Context Generation

Conversation-based context For each tweet $t_i \in \mathcal{T}$, let $r(t_i) : \mathcal{T} \rightarrow \mathcal{T}$ be a function that returns either the tweet to which t_i is a reply, or $null$ if t_i is not a reply. Then, the conversation-based context $\Upsilon_i^{C,l}$ of a tweet t_i is the sequence of tweet iteratively constructed by applying the function $r(t_i)$, until l tweets have been selected or $r(t_i) = null$, where l is the maximum size limit for the context.

Author-based context Let $t_i \in \mathcal{T}$ be a tweet, the author-based context $\Omega_i^{L,l}$ is a set of tweets, such that for $\forall i, j$ in this set, t_i and t_j has the same author. l is the upper limit on the number of tweets in the posting history of the author for t_i that should be collected.

Topic-based context Let $t_i \in \mathcal{T}$ be a tweet and $h(t_i) : \mathcal{T} \rightarrow \mathcal{P}(\mathcal{H})$ be a function that returns the entire hashtag set $H_i \subseteq \mathcal{H}$ in t_i. The topic-based context $\Gamma_i^{H,l}$ for a tweet t_i is a set of the most recent l tweets t_j such that $H_j \cap H_i \neq \emptyset$ (i.e. t_j and t_i share at least one hashtag, and t_j has been posted before t_i).

The Local Sub Network

The local neural network model consists of five layers, including an input layer, a convolutional layer, a pooling layer, a non-linear combination hidden layer and an output layer.

Input layer Nodes of the input layer denote words in the tweet in their written order. The neural network model represents words by low-dimensional real-valued vectors. For each word w_i, we use a look-up matrix **E** to obtain its embedding $e(w_i) \in R^{\mathrm{D}\times 1}$, where $\mathbf{E} \in R^{\mathrm{D}\times V}$ is a model parameter, *D* is the word vector dimension and V is the vocabulary size. In a typical neural model, **E** can be randomly initialized, or initialized via distributed word embeddings derived from a large raw corpus.

Convolution layer The convolution action has been commonly used to synthesize lexical n-gram information (Collobert et al. 2011; dos Santos and Gatti 2014). N-grams have been shown useful for Twitter sentiment analysis (Mohammad, Kiritchenko, and Zhu 2013; Tang et al. 2014), and we apply them to our neural network. Given the input layer $e(w_1) \cdots e(w_n)$, we use the convolution operation to obtain a new hidden sequence $\vec{h}_1^1 \cdots \vec{h}_n^1$, where,

$$\vec{h}_i^1 = tanh(\mathbf{W}^1 \cdot [e'(w_{i-1}), e'(w_i), e'(w_{i+1}), 1]'),$$

here e' denotes the transpose of the vector e, $\mathbf{W}^1 \in R^{\mathrm{C}\times(3\mathrm{D}+1)}$ is a model parameter, and C is the output dimension. We consider a window size of 3 to combine word embedding features, and use *tanh* as the activation function for this hidden layer. With the shared filter upon the word trigrams, independent features are extracted at each position.

Pooling layer We exploit pooling techniques to merge the varying number of features from the convolution layer into a vector with fixed dimensions. A typical pooling technique is the *max* function, which chooses the highest value on each dimension from a set of vectors. On the other hand, *min* and *average* pooling have also been used for sentiment classification (Tang et al. 2014; Vo and Zhang 2015), giving significant improvements. We consider all the three pooling methods, concatenating them together as a new hidden layer $\vec{h}^2$. Formally, the values of $\vec{h}^2$ is defined as:

$$\vec{h}^2 = \Big[\begin{bmatrix} \max(\vec{h}^1_{i1}) \\ \cdots \\ \max(\vec{h}^1_{iC}) \end{bmatrix}', \begin{bmatrix} \min(\vec{h}^1_{i1}) \\ \cdots \\ \min(\vec{h}^1_{iC}) \end{bmatrix}', \begin{bmatrix} avg(\vec{h}^1_{i1}) \\ \cdots \\ avg(\vec{h}^1_{iC}) \end{bmatrix}' \Big],$$

where $\vec{h}^1_{ij}$ denote the jth dimension of $\vec{h}^1_i$.

Hidden layer Using pooling, we obtain different types of rich features. In order to fully utilize these sources of information, we use a non-linear hidden layer to automatically combine the *max*, *min* and *average* pooling features. The non-linear hidden layer can be computed as:

$$\vec{h}^3 = tanh(\mathbf{W}^2 \cdot \begin{bmatrix} \vec{h}^2 \\ 1 \end{bmatrix}),$$

where $\mathbf{W}^2 \in R^{\mathrm{H}\times(3\mathrm{C}+1)}$ is a model parameter, and H is the dimension of this non-linear hidden layer.

Output layer Finally, an output layer is applied to score all possible labels according to the features in the last hidden layer. The output can be computed with a linear transformation using the following equation:

$$\vec{o} = \mathbf{W}^{\mathrm{o}} \cdot \vec{h}^3,$$

where $\mathbf{W}^{\mathrm{o}} \in R^{2\times\mathrm{H}}$ is the model parameter for output layer.

The Contextualized Sub Network

We follow Bamman et al. (2015) and extract a set of keywords from different types of contextual information. For every type of contextual information, we first sort all the words in the context tweets by their *tf-idf* values, by regarding the context tweets for a given tweet as one document, and exploiting all the tweets in the training corpus to generate a number of documents. Then we choose the 100 keywords with the highest *tf-idf* values as the source of contextualized features.

Given the set of salient words, we build a pooling neural network, as shown by the right component of Figure 2, combining the output of this pooling layer with the output of the pooling layer of the local neural model (i.e. the left component), before feeding them to the non-linear hidden layer. In this way, the hidden layer automatically combines local and contextualized features.

Similar to the local sub network, we use a real-valued dense vector to represent each word. We can use a shared word representation for both sub networks, obtaining all word representations by the lookup matrix **E**. Intuitively, however, the behavior of contextual words should be different from that of tweet content words. A shared word representation may not capture such differences. Thus we also consider separated word representations, using different embedding matrixes for the local and contextual sub networks, which enlarges the model parameter space.

Similar to the local sub network, we use *max*, *min* and *average* pooling to extract features from input words. The features form a real-valued vector with fixed dimension size. This pooling functions for our contextual model work differently compared with the method of Bamman et al. (2015), who directly use words as features. Compared with Bamman et al. (2015), pooling can potentially induce the most important aspects of the salient words, thus offering more useful information. Note that unlike the local sub network, the contextualized sub network does not use convolution functions, because the contextualized words are a set, which does not contain n-gram information.

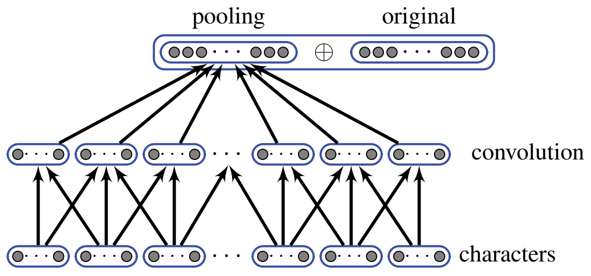


Figure 3: Character enhanced word representations.

Enhancing Word Representation with Character Embeddings

N-gram character features have demonstrated their effectiveness in Twitter sentiment analysis (Mohammad, Kiritchenko, and Zhu 2013; dos Santos and Gatti 2014). Some informative character ngrams can provide useful clues for the task, such as adverb suffixs "ly" and hashtags "#". We propose to use characters to enhance word representation. For each word, we obtain a dense vector from the looking-up matrix **E**. Similarly, we also obtain a dense vector from its characters.

As the Figure 3 shows, we exploit a convolution layer and a pooling layer to model character sequences, similar to the local model for word sequences. Each character is denoted by using a real-valued vector. We use an identical convolution operation to combine a character trigram at each position, obtaining dense representations of the trigrams. The convolution function is defined by:

$$\vec{h}^{\mathrm{c}}_i = tanh(\mathbf{W}^{\mathrm{c}} \cdot [e'(c_{i-1}), e'(c_i), e'(c_{i+1}), 1]'),$$

where $\mathbf{W}^{\mathrm{c}} \in R^{\mathrm{C_c}\times 3\mathrm{D_c}+1}$ is a model parameter, and the values $e(\cdot)$ can be obtained by a looking-up matrix $\mathbf{E}^{\mathrm{c}} \in R^{\mathrm{D_c}\times V_{\mathrm{c}}}$ of characters, where $\mathrm{D_c}$ and $\mathrm{V_c}$ are the dimension sizes of character vectors and the vocabulary size of characters, respectively, and C_c is the output size of the convolution layer. After convolution, we conduct *max*-pooling to convert the resulting inputs into a fixed-dimension vector[1], and then concatenate the pooling result with the original word representation to form an enhanced representation for each word.

Training

Our training objective is to minimize the cross-entropy loss over a set of training examples $(x_i, y_i)|_{i=1}^{N}$, plus a l_2-regularization term,

$$L(\theta) = -\sum_{i=1}^{N} \log \frac{e^{\vec{o}(y_i)}}{e^{\vec{o}(0)} + e^{\vec{o}(1)}} + \frac{\lambda}{2} \parallel \theta \parallel^2,$$

where θ is the set of model parameters, including $\mathbf{E}$, $\mathbf{W}^1$, $\mathbf{W}^2$, $\mathbf{W}^o$, $\mathbf{E}^c$ and $\mathbf{W}^c$.

We use online AdaGrad (Duchi, Hazan, and Singer 2011) to minimize the objective. At step t, the parameters are updated by:

$$\theta_{t,i} = \theta_{t-1,i} - \frac{\alpha}{\sqrt{\sum_{t'=1}^{t} g_{t',i}^2}} g_{t,i},$$

where α is the initial learning rate, and $g_{t,i}$ is the gradient of the *i*th dimension at step *t*.

We follow Glorot et al. (2010) and initialize all the matrix and vector parameters with uniform samples in $(-\sqrt{6/(r+c)}, -\sqrt{6/(r+c)})$, where r and c are the numbers of rows and columns of the matrixes, respectively. We assign the initial values of $\mathbf{E}$ with pre-trained word embeddings from a large scale tweet corpus.

Experiments

Experimental Settings

Data collection We use the Twitter Streaming API[2] to collect tweets that express positive (e.g. #happy, #joy), and negative sentiments (e.g. #sadness, #angry, #frustrated), respectively. Automatic filtering is applied to remove retweets, duplicates, quotes, spams and tweets written in language other than English. To address the concern of Davidov et al. (2010) that tweets with #hashtags between texts are noisy, we also automatically filter all tweets where the hashtags are not located at the end of the message.

We remove the #positve (#happy, #joy) and #negative (#sadness, #angry, #frustrated) hashtags from the tweets, tagging them as positive and negative examples for training and evaluation, respectively. Finally, we obtain 18,000 tweets that contain 11,394 positive tweets and 6,606 negative tweets. The 18,000 tweets are regarded as basic dataset. For tweets in the basic dataset, we extract three different types of contextual tweets by the method described in previous section based on Twitter API. We also remove the #positive and #negative hashtags from the contextual tweets, in order to avoid predicting sentiment by such explicit clues.

[1]We do not use *min* and *average* pooling here, as our preliminary experiments shows that these two pooling techniques do not give better performances.

[2]http://dev.twitter.com/docs/streaming-apis

Domain	number	author	conversation	topic
Unbalanced (P)	11,394	9,086	561	10,220
Unbalanced (N)	6,606	5,253	548	5,933
Balanced (P)	6,000	4,784	299	5,365
Balanced (N)	6,000	4,758	481	5,384

Table 1: Corpus statistics, where P and N denote the positive and negative tweets, respectively.

Type	#parameter
Network structure	$D = 50$, $D_c = 10$, $C = 100$, $C_c = 30$, $H = 50$
Training	$\lambda = 10^{-8}$, $\alpha = 0.01$

Table 2: Hyper-parameter values in our model.

We evaluate our models on both balanced and unlabeled settings. The balanced data include equal numbers of positive and negative tweets, while the ratio of positive and negative tweets in the unbalanced setting is about 2:1. Table 1 shows the corpus statistics of the two datasets. Columns 3-5 represent the subsets of target tweets for which the author-based context, conversation-based context or topic-based context are available, respectively. The conversation-based context accounts for a very small proportion in all target tweets. However, more than 85% target tweets have author-based and topic-based context.

Evaluation method We perform ten-fold cross-validation experiments and report the overall performances. The whole dataset is split into ten equal sections, each decoded by the model trained from the remaining nine sections. We randomly choose one section from the nine training sections as the development dataset in order to tune hyper-parameters. The classification results are measured by macro-F score.

Hyper-parameters There are seven hyper-parameters in our model, including the network structure parameters (i.e. the sizes of word vectors *D* and character vector D_c, the output dimensions of the word convolution layer *C* and character convolution layer C_c, and the output dimension of the non-linear combination layer *H*), and the parameters for supervised training (i.e. the l_2-regularization co-efficient λ and initial learning ratio α for AdaGrad). The values of the parameters are set according to common values in the machine learning literature, which are shown in Table 2.

Embeddings The word embeddings are trained on a large-scale English tweet corpus that consists of 20 million random tweets crawled by Twitter API, using the *word2vec*[3] tool with default setting. The vocabulary size of word embeddings is 300,000. During training, we use the averaged vector from the pre-trained word embeddings to initialize vectors for unknown words. For the vector representation of characters, we use random initialization, and perform supervised fine-tuning from the training corpus.

[3]https://code.google.com/p/word2vec

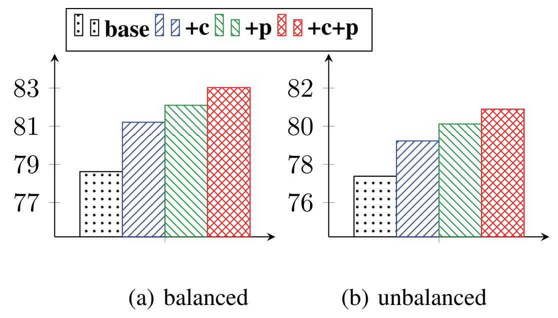


Figure 4: Influences of different word representations, where **base** denotes the word representation with random initialization, **+c** denotes extension of **base** by adding character features, **+p** denotes extension of **base** by using pre-trained word embeddings for initialization and **+c+p** denotes extension of **base** by using both **+c** and **+p** strategies.

Baseline Methods

We re-implement the following sentiment classification algorithms as the baseline systems:

- NRC: the state-of-art system in the SemEval 2013 Twitter Sentiment Classification Track, incorporating diverse sentiment lexicons and hand-crafted features (Mohammad, Kiritchenko, and Zhu 2013).
- SSWE: Tang et al. (2014) propose to learn sentiment-specific word embedding (SSWE) from 10M tweets containing emoticons. They apply SSWE as features for Twitter sentiment classification.
- SVM^{HMM}: Vanzo et al. (2014) model the sentiment classification problem as a sequential classification task over streams of tweets. SVM^{HMM} is employed to assign sentiment polarities to entire sequences.

The Local-Feature Neural Network Model

We report results of the neural network model that uses only local features, which is effectively the model in Figure 2 with the right component being removed. We study the influence of word representations and the effectiveness of rich pooling functions. The local neural model can later serve as a baseline system for studying our proposed context-based neural network model.

Influences of word representation Previous work shows that input word representation is important to a neural network model. We first study the influences of word vector initialization, by comparing random initialization, the pre-trained embeddings and the character-based enhancement. Figure 4 shows the results on both the balanced and unbalanced datasets. For both datasets, word embeddings with either character-based enhancing or pretraining initialization can improve the overall performance.

Influence of rich pooling functions We empirically compare the effects of the three different pooling techniques, namely *max*, *min* and *average* pooling, in our local neural network model. Results show that all the three pooling methods have positive effect on the overall classification performance, while the *max*-pooling has the most contribution. Their combined effect was larger compared with individual results. The findings are consistent with that of Tang et al. (2014) and Vo and Zhang (2015), and we omit the detailed figures due to space limitations.

Model	Balanced macro-F Score	Unbalanced macro-F Score
Local	**83.03**	**80.90**
NRC	82.74	80.24
SSWE	82.97	80.68

Table 3: Final results of the local neural model.

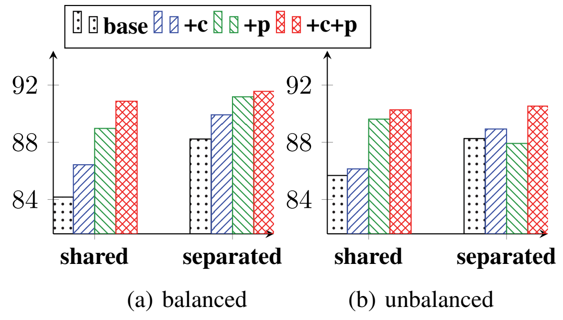


Figure 5: The influences of word representations based on the context-based neural network model, which use the topic-based context, where **base**, **+c**,**+p**,**+c+p** have the same meanings as Figure 4.

Comparisons with related work Table 3 shows the final results of our local neural model. Compared with NRC and SSWE, which are state-of-the-art local models, our local model performs slightly better[4]. The above verifies the effectiveness of our local neural model.

The Context-based Neural Network Model

The influence of network configurations We study the influence of word representations for the context-sensitive model, focusing on two research questions. First, is it better to use separated word representations for tweet content words and tweet context keywords. The second question is identical to the study of word representations on the local neural model, including whether improved performances can be achieved via pretrained word embeddings, and whether they can be achieved via character enhancing. We use the same pre-trained word embeddings and the same learning method for character representations for comparisons with the local model, and select the topic-based context as the contextualized features. We observe the same

[4]The method of Tang et al. (2014) achieves a 80.68% macro-F score on our unlabeled dataset. Tang et al. (2014) report a macro-F score of 84.98% on SemEval 2013, which is manually annotated. One possible reason is that our dataset is built by using distant supervision, there are noisy labels.

Model	Balanced macro-F Score	Unbalanced macro-F Score
The Proposed Context-Based Neural Network Model		
Local	83.03	80.90
Local+Contextualized (C1)	84.72	82.28*
Local+Contextualized (C2)	85.13	82.76*
Local+Contextualized (C3)	**91.56**	**90.53***
Local+Contextualized (ALL)	**92.27**	**91.33***
Other Context-Based Models		
SVM$^{\text{multi-class}}$	80.17	77.42
SVM$^{\text{HMM}}$ (C1)	81.67	79.18
SVM$^{\text{HMM}}$ (C2)	80.86	78.23
SVM$^{\text{HMM}}$ (C3)	81.32	78.69
Other Baseline Systems		
NRC	82.74	80.24
SSWE	82.97	80.68

Table 4: Final results of our proposed model, where C1, C2 and C3 denotes the conversation-based, author-based and topic-based context, respectively. ALL represents the mixture of three types of contextual information. The results with mark * demonstrates that the p-value is below 10^{-3} using t-test compared with SSWE.

trend when the conversation-based context or author-based context are used as the contextualized features.

Figure 5 shows the results on both datasets. The separated word representations are better, which gives overall better results. For the second question, exploiting pre-trained word embeddings and enhancing embeddings with character information gives better performance, with separated word representations. According to the comparisons, we use separated word representation, together with pretrained word embeddings and character enhancement in the final model.

Final Results Shown in Table 4, the context-based neural network model gives better performance compared with the local neural model. The proposed model gives over 90% in macro-F score using the topic-based context as the contextualized features. For conversation-based context and author-based context, the performances of context-based model are slightly higher compared with the local neural model.

Compared with the best local models (SSWE, NRC), our context-based model can improve about 9% in macro-F score when using topic-based model. In addition, our context-based model by using another two types of contextual information can both outperform the current model.

We also compare the proposed context-based neural model to the contextualized models of Vanzo et al. (2014), namely SVM$^{\text{HMM}}$. As Table 4 shows, our proposed neural network model can improve the macro-F score by 10% compared with sequence labeling method in both the balanced and the unbalanced settings.

Discussion

In Table 4, SVM$^{\text{multi-class}}$ represents the baseline system of Vanzo et al. (2014), which does not utilize any contextual information. Compared with our baseline systems and local model, it gives lower performance. SVM$^{\text{HMM}}$ using conversation-based context gives macro-F scores of 81.67% and 79.18% on the balanced and unbalanced datasets, respectively. Our local model obtains 83.03% and 80.90% macro-F score on the same datasets, respectively. The reasons are two-fold. First, the feature modeling of SVM$^{\text{HMM}}$ use the mixture of bag-of-word, lexical semantic and user sentiment profile kernel to represent semantic information, which are spare and less effective compared with word embeddings. SVM$^{\text{multi-class}}$ uses the same feature model, which partly explains the reason that SVM$^{\text{multi-class}}$ obtains lower performance. Second, SVM$^{\text{HMM}}$ does not use external resources, such as sentiment lexicons, which are proved to be very effective for NRC (Mohammad, Kiritchenko, and Zhu 2013).

In our context-based neural network model, the three types of contextual information obtain different performances on both datasets. First, the conversation-based context gives a relatively small improvement in performance compared with the local neural model. A likely reason is that the conversation-based context accounts for a very small proportion in all target tweets. Second, more than 85% target tweets have the author-based and topic-based context, but the topic-based context gives much more improvement compared to the author-based context. The main reason is that author-based contexts express the views and opinions towards some events and people, which may not be relevant to the target tweet. However, for topic-based contexts, contextual information is closely related to the target tweet. A combination of the three different contexts gives the best performance by utilizing complementary sources of information. In particular, by combining all three sources of contextual features, our model gives 92.27% and 91.33% macro-F score on both datasets.

For the model of Vanzo et al. (2014), SVM$^{\text{HMM}}$ using different types of contextual information can improve 1.11% and 0.95% macro-F score on average compared with their baseline system on both datasets, respectively. However, our context-based model can improve 4.1% and 4.29 macro-F score on average compared with our local neural system, respectively. The above demonstrate that the sequential assumption of SVM$^{\text{HMM}}$ between one tweet and its contextual tweets is relatively weak, and better performance can be obtained by modeling a complex graph structure (context-based neural network) for Twitter sentiment classification.

Conclusion

We proposed a context-based neural network model for Twitter sentiment classification. Compared with previous work, our neural network model incorporated the features of tweet content itself and the contextualized features into a single model in the form of word embedding vectors. Experimental results showed that our proposed context-based model gave improved performance compared with the state-of-start discrete and continuous word representation models, demonstrating the effectiveness of context-based neural network model for this task. In addition, we found that under context-based neural network setting, topic-based contextual features are the most effective.

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