SentiNLP at IJCNLP-2017 Task 4: Customer Feedback Analysis Using a Bi-LSTM-CNN Model

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Abstract
Analysis of customer feedback helps improve customer service. Much online customer feedback takes the form of online reviews, but the tremendous volume of such data makes manual classification impractical, raising the need for automatic classification to allow analysis systems to identify meanings or intentions expressed by customers. The aim of shared Task 4 of IJCNLP 2017 is to classify customer feedback into six tags. We present a system that uses word embeddings to express features of the sentence in the corpus, using the neural network as the classifier to complete the shared task. The ensemble method is then used to obtain a final predictive result. The proposed method ranked first among twelve submissions in terms of micro-averaged F1 and second for accuracy.

1 Introduction
Software companies receive tremendous amounts of online customer feedback every day, including product comments, bug reports, new feature requests, response complaints, capacity concerns and so on. The effective classification of this customer feedback can provide a foundation for improved customer service, but the huge amounts of data make manual classification impractical, raising the need for automatic classification to accurately identify customer meanings or intentions.

Sentence classification is a fundamental task for natural language processing (Collobert et al., 2011). The goal of this shared task is to classify the cross language customer feedback into six categories (comment, request, bug, complaint, meaningless, and undetermined). Each sentence will be assigned at least one tag. It can be treated as a multi-label classification problem.

In recent years, deep neural network models such as convolutional neural networks (CNN) (Cun et al., 1990), recurrent neural networks (RNN) (Goller and Kuchler, 1996), long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997), and their combinations (Wang et al., 2016) have achieved remarkable results in many NLP tasks, including sentence classification (Kim, 2014; Kalchbrenner et al., 2014), sentiment analysis (Irsoy and Cardie, 2014; Liu et al., 2015), sarcasm detection (Ghosh and Veale, 2016; Amir et al., 2016). The neural network models can automatically infer the features and can be used as a sentence classifier. The word embeddings (Mikolov et al., 2013a; 2013b; Pennington et al., 2014; Yu et al., 2017) can provide word vector representation that captures semantic and syntactic information of words. The word vector is used to build the sentence matrix and then inject information into sentence classifier. The LSTM can provide the sentence sequence information in one direction. Forward and backward networks respectively capture past and future information. Therefore, we used the bi-directional LSTM for our model.

This paper presents a system to classify English customer feedback into six labels (comment, request, bug, complaint, meaningless, and undetermined). The system uses the word vector of the
sentence as input, and the neural network as the classifier. The neural network uses the sentence matrix as input to classify the sentence into six labels. For multi-label classification, we construct a binary classifier for each label. The proposed model for sentence classification consists of two parts: a bi-directional LSTM and CNN. The bi-directional LSTM is used to capture the context of a sentence through sequential modeling. The sequence feature is used as the input for the CNN layer, which is then used to extract the most important feature to form the sentence representation. The logistic regression layer on the top is used to output the sentence labels.

The rest of this paper is organized as follows. Section 2 describes the model for sentence classification. Section 3 briefly introduces the ensemble method used in this paper. Section 4 reports experimental results and analysis. Section 5 presents conclusions and suggests directions for future work.

2 Model for Sentence Classification

The model aims to classify a sentence into six labels according to its sentence texts. Figure 1 shows the framework of the bi-directional LSTM-CNN model for sentence classification. In the input layer, the sentence is transformed into a sentence matrix based on the word vector. The word vectors of vocabulary words are trained from a large corpus using the Glove (Pennington et al., 2014) toolkit. The sentence matrix is fed into a forward LSTM network and a backward LSTM network. The representation sequence is then averaged over all timesteps and then concatenated to produce the final sequence representation. The sequence is the input of the CNN layer. The CNN extracts the sequence feature information followed by logistic regression layer whose target is the class label for given sentence.

For a given corpus, we store the word vector in a lookup matrix $M \in \mathbb{R}^{d \times |V|}$, where $|V|$ is the vocabulary size of the given texts and $d$ is the dimensionality of the word vector. For the sentence $S = \{s_1, s_2, ..., s_n\}$, $n$ is the length of the sentence. Let $|V|$ denote the vocabulary of words, while $d$ is the dimensionality of word vectors. The sentence matrix representation $X = \{x_1, x_2, ..., x_n\}$, $x_i$ is the word vector of word $s_i$ in accordance with the lookup matrix $M$.

2.1 Recurrent Neural Network

To capture the relationship between the input sequences, we can use the RNN layer to transform word vector into the sentence feature representation.

Due to the vanishing gradients and exploding gradients problem (Pascanu et al., 2012), the LSTM (a certain type of RNN) is introduced for sequence modeling (Tang et al., 2015; Tai et al., 2015). The LSTM consists of three gates: input gate $i$, forget gate $f$ and output gate $o$. The gate mechanisms work collaboratively to learn the long-term dependencies. At each time step $t$, the LSTM is calculated as follows:

![Figure 1: System architecture of the proposed bi-LSTM -CNN model.](image)
where $x_t$ is the input from lower layer, $h_{t-1}$ is the hidden state at time step $t-1$. The $i_t$, $f_t$, $o_t$ are respectively called the input, forget and output gates. $W \in R^{a \times d}$ and $U \in R^{a \times d}$ are the weight matrices for different gates for input $x_t$ and hidden state $h_{t-1}$. $b$ denotes bias vectors. Here $*$ is the element-wise multiplication, and the $\sigma(\cdot)$ and $\tanh(\cdot)$ are the element-wise activation function. The $d$ can be the dimension of the word vector or the size of the hidden state in the lower layer.

A forward network and a backward network can respectively capture the past and future information. For sentence classification, it is beneficial to combine the past and future information in sequence modeling. Therefore, we use bi-directional LSTM to obtain the contextual information in sentence sequence modeling.

### 2.2 Convolutional Neural Network

The convolutional is used to extract n-gram features. We use a convolution filter $F \in R^{a \times d}$ to obtain the feature map $Y \in R^{n \times w \times l}$. The $j$-th element $y_{j}$ is given by:

$$y_j = f(W \cdot x_{j, i+1} + b)$$ (2)

where $f$ is the Relu activation function, $W$ is the weight matrix of convolution filter, $b$ is a bias, $o$ is the length of the filter, and $d$ is the dimension of the word vector. The convolutional layer uses multiple filters in parallel to obtain feature maps. It also can use convolutional filters of various length to extract different feature information.

The feature maps are fed into the max-pooling layer to obtain the most salient information to form the feature vector. The feature vector is useful for determining the output result.

### 3 Ensemble method

In statistics, ensemble methods use multiple learning algorithms to obtain better predictive performance (Maclin and Opitz, 1999; Rokach, 2010). In this paper, the ensemble methods use multiple results produced by the same NN-based method in different training times to obtain better predictive performance. For multi-label classification, we make a variation of the voting rules in the ensemble method. The predictive outputs can be calculated in two steps: For each label, we assign the sentence to label $i$ if the proportion of positive results in more than half of the total predictive result. After that, we assign it to label $j$ with the most component predictions if the sentence was unannotated.

### 4 Experiments and Evaluation

**Dataset.** For the shared task on customer feedback analysis, several sentences of annotated and unannotated customer feedback in English were prepared, with a total of 3065 training texts, 500 development texts and 500 test texts. The training and development texts were annotated with six labels (comment, complaint, meaningless, request, bug, and undetermined). We evaluated the proposed bidirectional LSTM-CNN model by submitting the results of the test set to the IJCNLP 2017 Task 4 Customer Feedback Analysis. The distribution of the six labels shown in Table 1 indicates a data imbalance. Most of the data were assigned one of five class labels, and only a few were anno-
tated as being undetermined. There are many pre-trained word vectors for English provided by word embeddings tool. We use the pre-trained word vectors trained on 840B tokens from common crawls and its dimensionality is 300 provided by Glove (Pennington et al., 2014) because of the high volume of the vocabulary. Word vectors are randomly initialized with uniform distribution sample if the word is not in the vocabulary of the pre-trained word vectors.

Let $Y$ be the vector representation of the label of the sentence. The labels $ls = \{ l_1, l_2, l_3, l_4, l_5, l_6 \}$ and the sentence has multiple labels $\{ l_1, l_2 \}$. For each label, we use a binary classifier. Therefore, we can express the labels as: $Y = (1, 1, 0, 0, 0, 0)$ to calculate the loss function through binary cross-entropy.

**Experimental settings.** The dataset containing the development set and training set is randomly shuffled and then re-divided for the 5-fold cross validation. The hyper-parameters of the neural network are chosen based on the performance on the development data. We obtain the final hyper-parameters by averaging the ten evaluation results of the development set in the 5-fold cross validation.

The epoch time is 10 to minimize the loss function. To avoid overfitting, we use the early stop mechanism and random dropout (rate of 0.25 or 0.5) (Srivastava et al., 2014). The nadam (Dozat, 2016) update rule is used to automatically tune the learning rate. The activation function in the top layer is a sigmoid function, which scales each label within a range 0 to 1. If the continuous result $y_i$ is greater than 0.5, it is rounded up to 1, or set to 0 otherwise. The predicted result $Y = (0, 0, 0, 0, 0, 0)$ for six labels is assigned to label $i$ with the maximum value $y_i$ of $Y$.

We first run experiments on CNN, LSTM and their combinations, including LSTM-CNN, CNN-LSTM, bi-LSTM and bi-LSTM-CNN. CNN1 and CNN2 have different hyper-parameters, a filter window of 3 with 256 feature maps in CNN1, and a filter window of 3 and 5 with 128 feature maps in CNN2.

We compare the results generated by the NN-based methods and select the best five results on the development set data in micro-averaged F1 to produce the ensemble result.

**Evaluation metrics.** IJCNLP 2017 Task 4 published the results for all participants assessed based on both accuracy and micro-averaged F1 measure. Given a binary classification, there are four basic outcomes: true positive (tp), true negative (tn), false positives (fp) and false negative (fn). The accuracy and F1 score (Powers, 2011) are evaluation measures $B(tp, tn, fp, fn)$ used to evaluate the performance of a binary classification problem. Accuracy is the proportion of true results (both tp and tn) among the total test set. The micro-averaged F1 has a binary evaluation for its overall counts among all labels.

**Results.** A total of twelve teams participated in task 4. Table 2 shows the result of the ensemble method for the best of the five results produced by the neural network model for IJCNLP-2017 Task 4.

|       | Micro-F1 | Acc  |
|-------|----------|------|
| Scores |           |      |
| Rank   | 1        | 2    |

**Table 2:** Results of ensemble method for the best of the five results produced by the neural network model for IJCNLP-2017 Task 4.

|               | NN-based | Ensemble |
|---------------|----------|----------|
| Micro-F1      | Acc      | Micro-F1 | Acc  |
| CNN1          | 0.7223   | 0.668    | 0.7342 | 0.682 |
| CNN2          | 0.7383   | 0.694    | 0.7495 | 0.702 |
| LSTM          | 0.5947   | 0.57     | 0.6425 | 0.618 |
| LSTM-CNN      | 0.6931   | 0.658    | 0.7181 | 0.68  |
| CNN-LSTM      | 0.7155   | 0.68     | 0.7332 | 0.69  |
| Bi-LSTM       | 0.7417   | 0.7      | 0.7455 | 0.704 |
| Bi-LSTM-CNN   | 0.7309   | 0.69     | 0.7557 | 0.708 |

**Table 3:** Comparative results of ensemble method with all NN-based methods for sentence classification.
method with the best of the five results produced by the bi-directional LSTM-CNN model. We obtain the best result by sorting the micro-averaged F1 for all labels. The ensemble result ranked first for micro-averaged F1 and second for accuracy.

Table 3 shows the best experimental results of ten runs for the neural network model for both accuracy and micro-averaged F1, along with five runs for the ensemble method. We found that the ensemble method shows better performance, indicating that it can improve on all NN-based methods. The ensemble result in bi-LSTM-CNN achieves the best performance in all NN-based methods. The bi-LSTM yielded better performance without ensemble.

5 Conclusions

This study presents a neural network model to classify text-based customer feedback into six labels. We use the ensemble method to obtain the best of five results sorted by the micro-averaged F1. The use of the ensemble method can further improve performance in all NN-based methods. The bi-directional LSTM produces the sentence sequence feature, and the convolutional layer extracts the salient information from the sequence representation to classify the sentence into the multi-labels. Experimental results show that the bi-directional LSTM-CNN achieves best performance.

Future work will focus on exploring customer feedback in multiple languages and high-order correlations between labels should be taken into account to improve classification performance for both micro- and macro-averaged F1.

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