# LSTM for Sentiment Analysis on Twitter

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## Abstract

We show promising empirical evidence that character-level LSTMs perform well for sentiment analysis on tweets, which are "noisy", in that users think of millions of new words and spellings of words every day, and "brief", in that they are constrained to $140$ characters. This type of text data is becoming an important research focus in the field of NLP, as data is often cheap to collect in high volume and can provide important insight into society-wide trends. Our model achieves $84\%$ accuracy, a result competitive with the state of the art for binary sentiment classification on tweets.

## 1 Introduction

In the last few years, microblogging has become a very popular communication tool in people's social life. On microblogging platforms, such as Twitter[1] and Facebook[2], a diverse range of people are attracted to post short sentences, images, and video links to share life issues and opinions. This popularity results in enormous amount of information covering a wide range of topics on the brands, products, politics and social events. Such data is a valuable and efficient source for marketing and social studies. Sentiment analysis on microblogging has obtained special interest, because it determines the attitude of a user with respect to some topic or product and thus provides provide convincing information For example, it may help manufacturing companies to know how people like their product (or service), what would people prefer.

In this paper, we focus on using sentiment analysis on Twitter. Twitter is an extremely popular microblogging platform which allows people to post messages of up to 140 characters. Because of the short nature of tweets, people often post twitter messages (called Tweets) frequently while attending events like product launches, movie premiers, music concerts or just to express their opinion on a trending or current topic. As such, they can be a valuable source of public opinion or feedback [15, 1, 2].

Realizing this importance, analyzing sentiment of Tweets has been a recurring task in the SemEval [3] competitions.

Although there exist plenty of work on text classification, some unique characteristics of tweets present special challenges for sentiment analysis: 1. Tweets are short in length. There is a limitation of $140$ words for each tweet; 2. The language used in tweets is very informal with misspelling, creative spelling, new words, slangs, and URLs; 3. Emotions and hashtags are frequently used.

In this paper, we propose a bi-directional Long Short-Term Memory (LSTM) method for sentiment analysis. We tried both word-level and character-level features on the bi-directional LSTM model and compare the results with Dynamic Convolutional Neural Network (DCNN) [7]. We show that the accuracy of sentiment analysis ... (Please revise this part.)

[1] https://twitter.com/
[2] https://www.facebook.com/
[3] http://alt.qcri.org/semeval2016/task4/

We train our model on $1.6$ M distantly-supervised tweets collected by Go et. al. [3], and evaluate the results on SemEval-2016 Task 4[4]. Currently we focus on polarity classification, and plan to apply our model on 5-point scale classification in the future.

In the remaining of this paper, we first introduce the related work, the dataset, and the evaluation methodology. We then describe the model we proposed. Finally, we discuss the experiment results and point out possible directions for future research. (Please revise this part.)

## 2 Related Work

Twitter sentiment analysis is increasingly drawing attention of researchers in recent years. Given the length limitations on tweets, sentiment analysis of tweets is often considered similar to sentence-level sentiment analysis [11]. However, phrase and sentence level approaches can hardly define the sentiment of some specific topics. Considering opinions adhering on different topics, Wang et. al. [19] proposed a hashtag-level sentiment classification method to generate the overall sentiment polarity for a given hashtag. Recently, following the work of [13] some researchers used neural network to implement sentiment classification. For example, Kim [9] adopted convolutional neural networks to learn sentiment-bearing sentence vectors, Mikolov et al. [14] proposed Paragraph vector which outperformed bag-of-words model for sentiment analysis, and Tang et. al. [18] used ConvNets to learn sentiment specific word embedding (SSWE), which encodes sentiment information in the continuous representation of words. Furthermore, Kalchbrenner [7] proposed a Dynamic Convolutional Neural Network (DCNN) which uses dynamic k-max pooling, a global pooling operation over linear sequences. Instead of directly applying ConvNets to embeddings of words, [20] applies the network only on characters. They showed that the deep ConvNets does not require knowledge of words and thus can work for different languages. LSTM [6] is another state-of-the-art semantic composition models for sentiment classification [12]. Similar to DCNN, it also learns fixed-length vectors for sentences of varying length, captures words order in a sentence and does not depend on external dependency or constituency parse results.

### 2.1 Dynamic Convolutional Neural Networks (DCNN)

We briefly review the architecture of DCNN [7] which has shown state of the art performance for sentiment classification on Twitter. The winning entry for SemEval15 [17] task on Twitter sentiment classification also used DCNN. Figure 1 summarizes the architecture.

When used for sentiment classification on Twitter, the input to the DCNN is a matrix of word embeddings for each word in the tweet. For example, if the tweet consists of $s$ words then the input to the DCCNN is:

$$S = \begin{bmatrix} | & | & \dots & | \\ w_1 & w_2 & \dots & w_s \\ | & | & \dots & | \end{bmatrix}_{k \times s}$$

where each $w_i \in R^k$ is a $k$-dimensional dense word embedding [14]. The architecture consists of multiple layers of convolutions and max-pooling on top of the input matrix, followed a fully connected layer which is input to a softmax. The convolutions are of type *wide-convolutions* of one-dimension. For example, for the input matrix $S \in R^{k\times s}$, a wide-convolution filter operating on $S$ will consist of convolution weights $m \in R^{k\times c}$ and will result in a matrix having dimension $k \times (s + c - 1)$. Note here $c$ is the convolution filter width, which is a hyperparameter. The max-pooling operations presented in [7] are different from the regular max-pooling. They present *dynamic $k$-max pooling*. $k$-max pooling takes the top $k$ maximum activations as opposed to just the maximum activation and the value of $k$ is selected dynamically based on the following formula: $k_l = \max\left(k_{top}, \lceil \frac{L-l}{L} s \rceil\right)$, where $l$ is number of current convolution layer, $L$ is total number of convolutions and $k_{top}$ is a fixed hyperparameter. Note that while [7] used multiple layers of convolutions and max-pooling, subsequent work found that using a single layer of convolution and max-pooling gives similar results [9] [17].

[4] `http://alt.qcri.org/semeval2016/task4/`

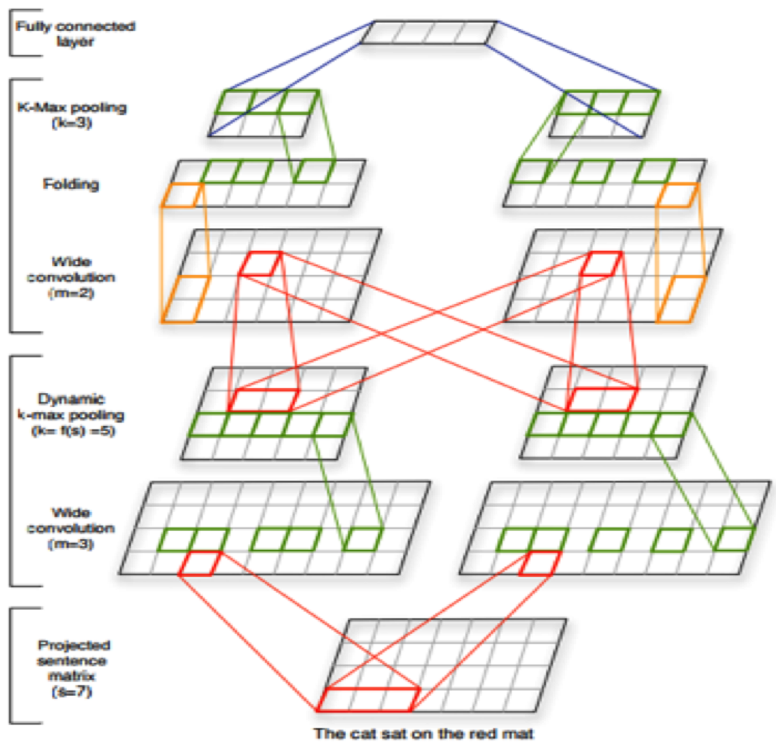


Figure 1: Dynamic Convulational Neural Network of [7] (Source: [7])

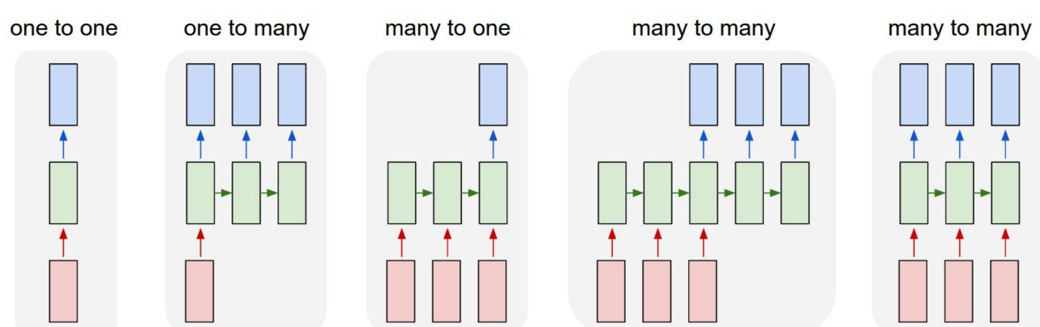


Figure 2: RNNs allow modeling of multiple types of input and output sequences (Source: [8])

### 2.2 Recurrent Neural Networks with Long Short Term Memory (LSTM)

Recurrent Neural Networks (RNNs) are a class of artificial neural networks used for modeling sequences. RNNs are highly flexible in their use of context information as they can learn what part of the input sequence to store to memory and what parts to ignore. They also allow modeling of various regimes of sequence modeling as shown in Figure 2. Please refer to [4] for a comprehensive review of sequence modeling using RNN.

One of the short comings of RNN is that it is very difficult to store information over long sequences because of problems due to vanishing and exploding gradients as explained in [5]. *Long Short-Term Memory (LSTM)* [6] are designed to remedy this and store information over larger input sequences. They achieve this using special "memory cell" units. Figure 3 shows the architecture of this cell which consists of an input gate, a forget gate, an output gate and a recurring cell state. Refer to [16] for a gentle introduction to LSTM and to [4] for a more comprehensive review and applications.

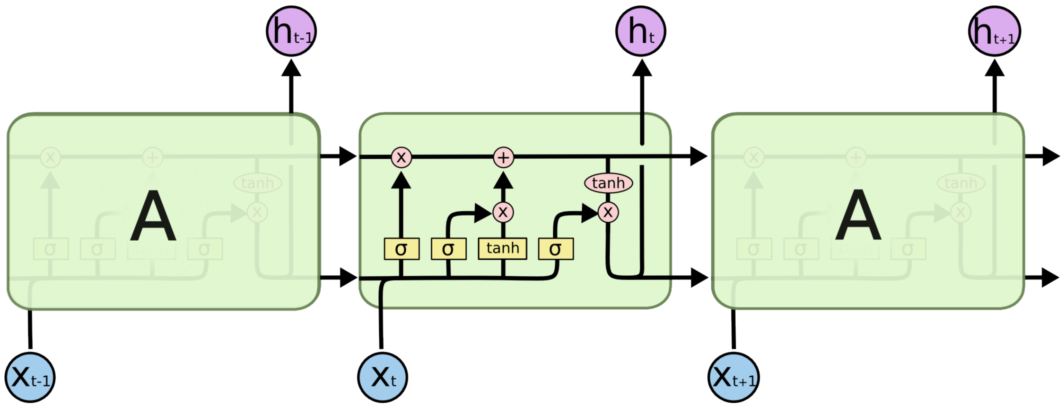


Figure 3: The repeating module of LSTM. $x_t$ is the input as time $t$ and $h_t$ is the output from the LSTM output gate at time $t$. The top horizontal line corresponds to the cell state and the bottom line corresponds to the hidden state (both of which are recurring states). (Source: [16])

## 3 Results

### 3.1 Datasets

We conduct our experiments on two datasets: the latest benchmark dataset for SemEval 2016 and the dataset provided by [3]. In the latter dataset, the training set consists of 1.6 million weakly-supervised tweets collected during 2009, and the test set is hand-labeled. In the experiments presented below, we first train our models on the Go dataset, then re-train the model parameters on the smaller, fully-supervised SemEval dataset.

Table 1: Data size and label distribution

| | Go et. al. (1.6M) | | SemEval2016 | |
|---|---|---|---|---|
| | neg | pos | neg | pos |
| train | 800000 | 800000 | 781 | 2805 |
| dev | - | - | 358 | 766 |
| test | 177 | 182 | 286 | 886 |

### 3.2 Experiments

We compare the performance of character-level models against word-level models. For the former, we compare across character sets ("utf8" and "ascii"), parameter initializations ("rnd" and "eye"), and embedding dimension sizes (50 and 200). The vocabulary for the "utf8" setting consisted of 1949 characters, and for "ascii" consisted of 93 characters. We initialize model parameters randomly at all levels in the "rnd" setting whereas in the "eye" setting, we initialize the second-level LSTM cell and gate parameters using the identity matrix.

We compare word-level models under two settings: initializing the word embeddings using random vectors ("word/rnd") and initialization using "sentiment-specific" word embeddings provided in [18] ("word/sswe").

Our results are shown in Table 2. We train all models using the implementation of the Adam algorithm [10] provided in Lasagne[5] and a learning rate set to 0.1 [6]. To learn word and character embeddings, we use a bidirectional LSTM with 256 hidden units, followed by a mean pooling and a dropout layer ($p = 0.5$), a second forward-directional LSTM (again with 256 hidden units) and a final dropout layer ($p = 0.6$). We obtain final predictions using the softmax function.

[5] `https://github.com/Lasagne/Lasagne`

[6] We retrained the ascii/rnd/200 on SemEval using AdaGrad and a learning rate of 0.01 to achieve 84.13; using Adam and 0.1 learning rate, the result was 83.21

Table 2: Accuracy across LSTMs

| | 1.6M (acc) | semeval (acc) |
|---|---|---|
| ascii/rnd/50 | 83.84 | 82.08 |
| ascii/rnd/200 | 82.45 | **84.13** |
| ascii/eye/50 | 77.44 | 79.18 |
| utf8 | 81.34 | 82.34 |
| char-dcnn | 75.0 | 81.3 |
| word/rnd | 81.85 | 78.07 |
| word/sswe | 83.24 | 79.27 |
| word/dcnn | **87.4**[7] | 81.3 |

The character-level models using the "ascii" character set outperformed the other models on the SemEval dataset. Due to the highly-productive nature of the Twitter "lexicon", users' predisposition toward using slang dialects, and the constraint of the 140-character limit, it makes sense that word-level models underperform.

It is worth noting that the "utf8" model performed comparably despite having a much larger vocabulary size. It is not suprising that the "utf8" model performed worse than the "ascii" model, as the test data consisted of only English tweets; however, since the "utf8" model is implicitly multi-lingual, our results suggest that the same model may perform well across multiple languages. We leave such experiments for future work.

As Table 2 shows, [7] outperform our character LSTM on the Go dataset. However, the results presented for our character and word-level models achieve competitive performance on the Go dataset without tuning hyperparameters such as learning rate and network width.

### 3.3 Qualitative Analysis

Figure 4 shows the effect of character repetition on model confidence over the course of the sequence, where confidence is computed using the softmax function:

$$P(y = j|\mathbf{x}) = \frac{e^{\mathbf{x}^T \mathbf{w}_j}}{\sum_{k=1}^{K} e^{\mathbf{x}^T \mathbf{w}_k}}$$

In our experiments, we had $K = 2$ corresponding to binary classification between "positive" and "negative" tweets. Sequences ending in periods ("cool.", "coool.") ended up with less-confident scores than tweets not ending in periods. Repeated exclamation points don't increase the model's confidence in the "positive" label as much as might be expected.

Figure 5 shows that the character-level model learns word meaning at a lexical level: the predictions for "I love puppies" and "I hate puppies" diverges sharply after the model has finished reading "lov" ("love") and "hat" ("hate").

Figure 6 provides further evidence that character-level models can reason about lexical semantics in an intuitive fashion. We compare confidence contours across four tweets from the Go test set. The ground truth labels for the first two tweets are both "negative", and for the second two are both "positive". In the first two, the model finds strong evidence for a "negative" prediction before reaching the word "dentist", and correctly predicts that both tweets are "negative". In the second two, the word "dentist" results in an increase in the model's confidence in a "negative" prediction; however, the words "enjoyable" and ":)" cause the model's confidence to decrease in the "positive" direction.

## 4 Conclusion

In this paper, we show promising empirical evidence that character-level models perform well for sentiment analysis on tweets, which are "noisy", in that users think of millions of new words and spellings of words every day, and "brief", in that they are constrained to 140 characters. This type of

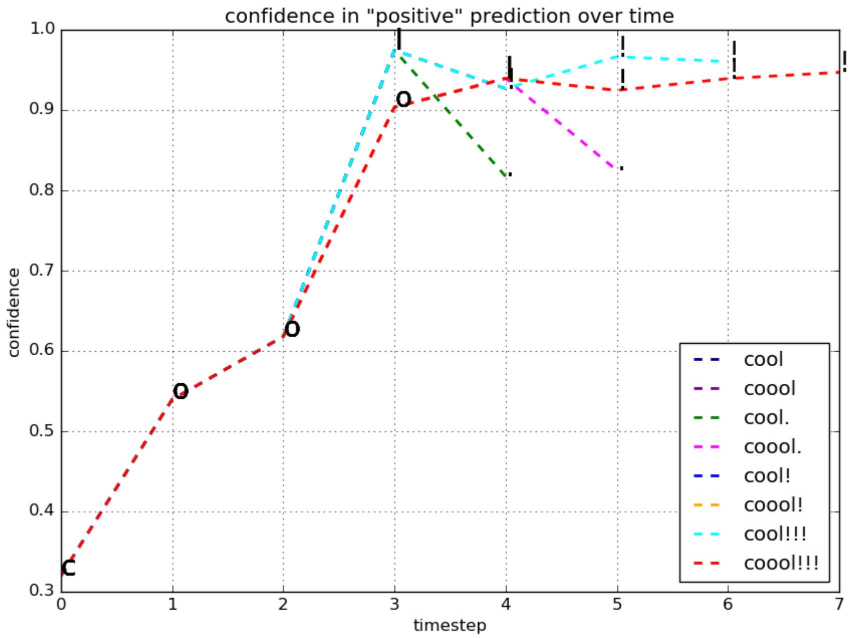


Figure 4: Comparison of model confidence for different forms of the word “cool”

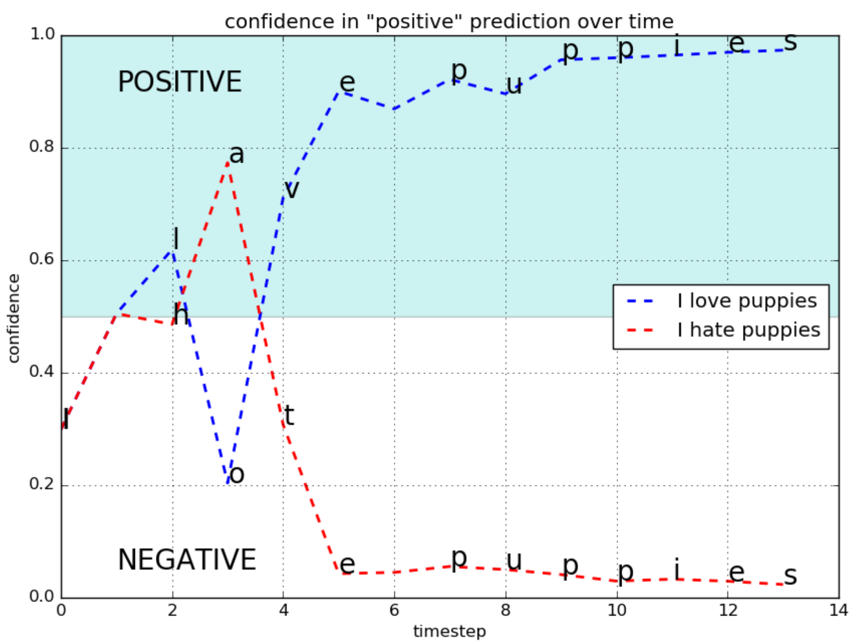


Figure 5: Comparison of model confidence for “I love puppies” vs. “I hate puppies”

text data is becoming an important research focus in the field of NLP, as data is often cheap to collect in high volume and can provide important insight into society-wide trends. Though the experiments

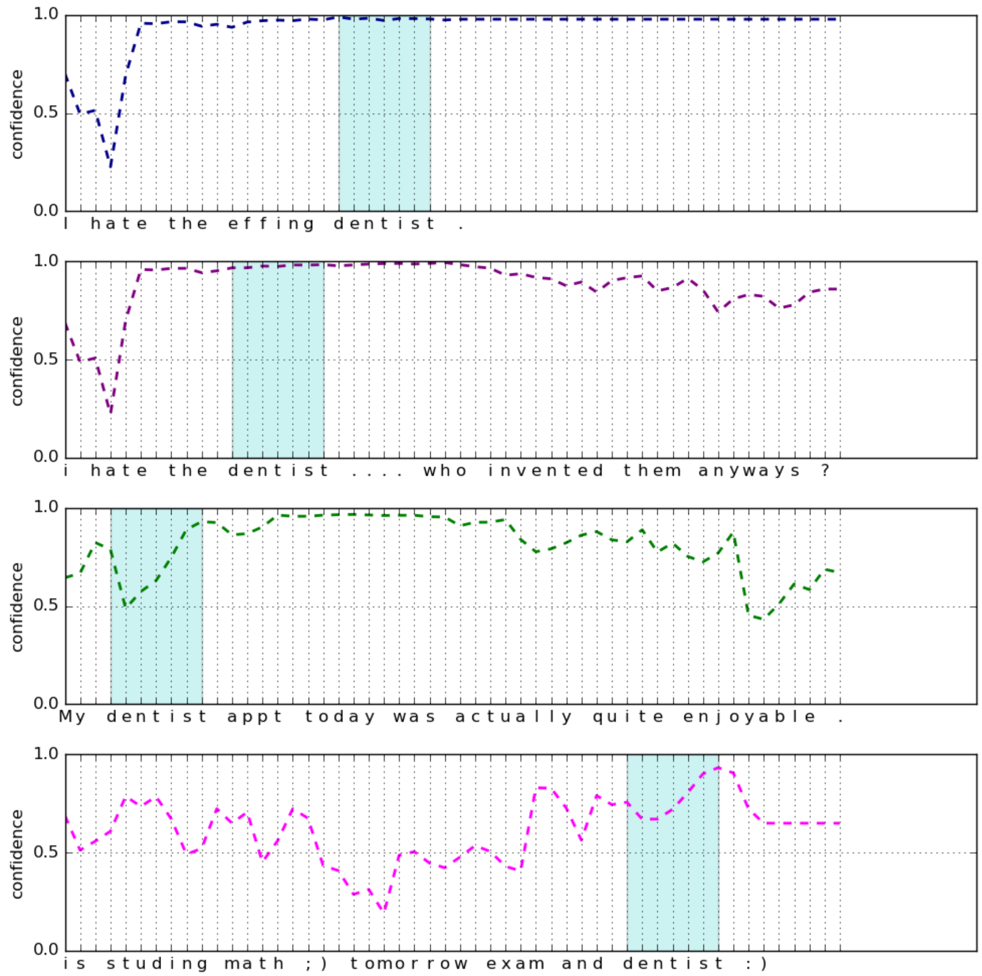


Figure 6: Confidence in "negative" prediction over time across four tweets

in this paper focus on sentiment classification, we believe our results provide a basis for future work on character-level modeling for a variety of other NLP tasks.

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