

# DISASTER TWEETS PREDICTION USING BERT

Ran Liu

Institute of Information Engineering,  
Chinese Academy of Sciences, China

## Introduction

Twitter has become an important communication channel in times of emergency. But it's not always clear whether a person's words are actually announcing a disaster. For instance, " *Look at the sky last night it was ablaze!* " In this tweet, The author explicitly uses the word "*ablaze*" which is related to disaster, but actually it is an exaggerated expression. Our goal is to resolve this problem.

Concretely, given a set of labeled data, we will use them to train a text classifier and use it to predict whether a tweet is about disaster or not.

In this paper, we first analyze the training set, including calculate distribution of characters and tokens of texts, then convert texts into standard input format which BERT can process. After that, we fine-tune BERT to adapt to disaster tweets prediction task. Our method has achieved good results, ranking top 2.3% in Kaggle competition.

## Related Work

- **Rule-Based methods** classify texts into different categories using a set of pre-defined rules. The kind of methods are easy to implement and fast when running, also have good interpretability, while require a lot of manpower and time. What's worse, when facing a new problem, previous rules may become useless.
- **Statistical methods**, such as Naïve Bayes, support vector machines, hidden Markov model, and random forests, are more accurate than rule-based methods. On the other hand, statistical methods cannot take full advantage of large training data because the features are pre-defined.
- **Deep learning** which is represented by Convolutional Neural Network and Long Short-Term Memory Network, is the current mainstream method. It has strong ability to capture deep contextual features and can improve performance obviously. But weak interpretability and extreme reliance on large amount of training data are its main drawbacks.

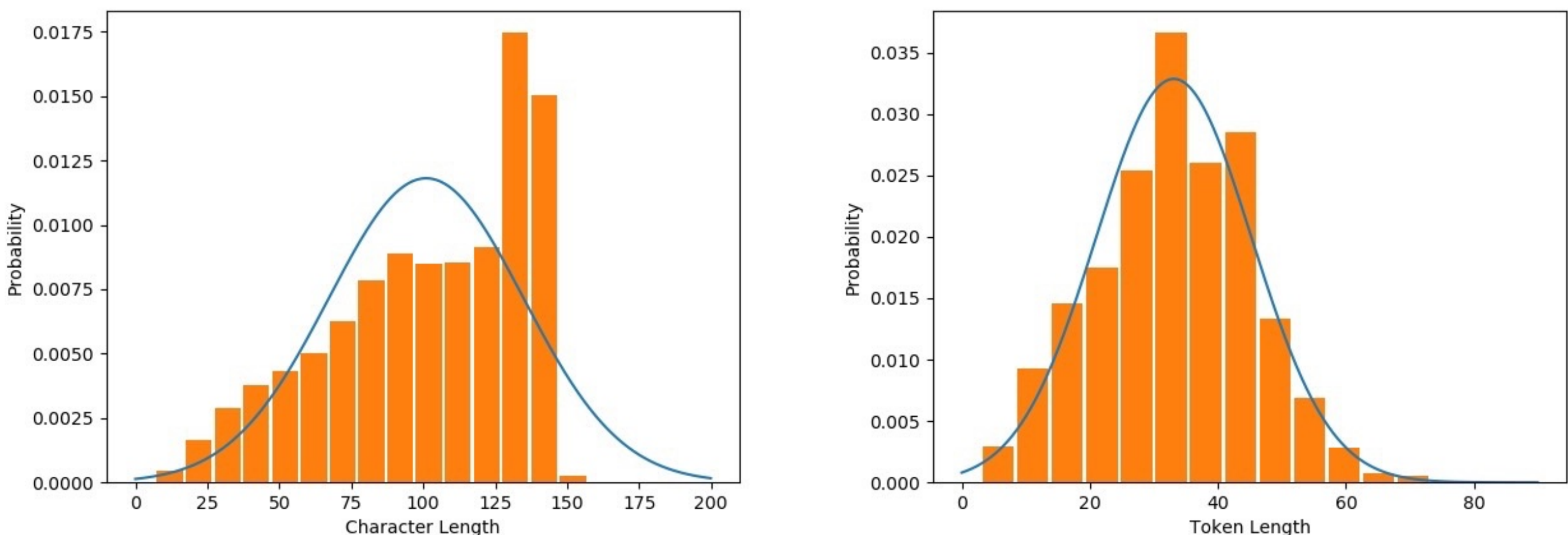
## Dataset

The training set has a total of 7631 tweets, consisting of 3721 tweets about disaster and 3892 tweets which are not about disaster.

The maximum character length of text in training set is 157 and minimum is 7, with an average of 101 characters.

Since BERT takes token as word vector unit, we also calculate token statistics of training set. The maximum token length of text is 84 and minimum is 3, with an average of 33 tokens.

Distribution of character and token length are as follows.



## Methodology

- **Input format:** In order to convert texts into vectors that BERT can process, we should transform each tweet text into three vector, which are token vector, mask vector, segment vector, respectively.
  - **Token vector** represents index of each token according to the vocabulary, the rest is padded with 0.
  - **Mask vector** is used to calculate attention score without considering the meaningless part which is padded with 0.
  - **Segment vector** is used to split two sentences. For the case there is only one sentence, segment vector is a zero vector.
- **Model details**

We use bert-base and bert-large as our classification model, each of which has cased and uncased versions. Furthermore, we compare with bert that uses whole word mask to verify the effectiveness of this method. Model details are as follows.

Model	Layer	Hidden	Attention	Mask
bert-base-cased	12	768	12	Token
bert-base-uncased	12	768	12	Token
bert-large-cased	24	1024	16	Token
bert-large-uncased	24	1024	16	Token
bert-large-wwm-cased	24	1024	16	Span
bert-large-wwm-uncased	24	1024	16	Span

### Training setup

Name	Value
Token length	256
Dropout rate	0.1
Train : Validation	8 : 2
Batch size	16
Number of epochs	3
Optimizer	Adam
$\beta_1$	0.9
$\beta_2$	0.999
Learning rate	5e-5, 3e-5, 2e-5

## Results

### Evaluation metric

$$F_1 \text{ score} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

### Results

Model	$F_1 \text{ score}$
bert-base-cased	0.825
bert-base-uncased	0.831
bert-large-cased	0.830
<b>bert-large-uncased</b>	<b>0.848</b>
bert-large-wwm-cased	0.828
bert-large-wwm-uncased	0.825

- **Rank:** 21/887 (2.3%)

## Limitation

Limited by computing resources, models are not fully trained, and no other pre-trained language models are used to compare with BERT.