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Disaster Tweets Classification in Disaster Response using Bidirectional Encoder Representations from Transformer (BERT)

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Disaster Tweets Classification in Disaster Response using Bidirectional Encoder Representations from Transformer (BERT)

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Abstract. The omnipresence of smartphones helps people to declare an emergency in real-time. In times of crisis, Twitter has become a big communication platform. As a result, more organizations are interested in tracking Twitter programmatically. Although governments and emergency management agencies work together through their respective national system for response to disasters, the sentiments of the people affected during and after the catastrophe decide the effectiveness of the disaster response and the recovery process. In recent years, sentiment analysis via Twitter-based machine learning has become a common subject. However, the detection of such tweets was often difficult due to the tweets' language structure's uncertainty. Thus, it is not always apparent if the words of a person announce a catastrophe. BERT (Bidirectional Encoder Representations by Transformers) is a profound learning model developed by Google. Since Google opened it, several scientists and companies have embraced it and have applied it to many text classification tasks. Therefore, we use BERT in this paper to some dataset disaster tweets. This research will help rescue and emergency responders establish effective knowledge management techniques for a rapidly evolving disaster environment.

1. Introduction

Various disasters in various parts of the world have raised awareness about internal awareness disaster reduction. The issue of disaster management is one of many countries and organizations. In this regard, research on disaster management is increasing. Social media have gained much coverage in recent years for their possible use of space and time events. Twitter is one that allows society to communicate in real-time an emergency. Twitter data processing for such necessary data is a challenge because of the vocabulary people use when tweeting. Analysis of feelings is a class of analytical techniques that automatically extracts and summarizes the thoughts of such an enormous data volume that the average human reader cannot process[1].

This ocean of opinion posts in social media is central to individuals' actions because they affect our behavior. Social media has played an increasingly important role. In the last few years, during emergencies and disasters, they have become primary alternative information to conventional media, making them the fourth most common information source in emergencies. In the same tragedies, people with different ethnic characteristics had different responses and actions. They can influence their actual harm during crises by other replies [2].

Sentiment analysis is a type of method used to characterize, isolate or define personal information, such as thoughts conveyed in a given text, based on computational and natural language processing techniques. The primary objective of sensation analysis is to describe the writer's emotion in positive, negative, or neutral categories for various subjects [1]. Research on sentiment analysis from social media has been widely carried out [3][4][5], but efforts to research this in disaster management have received less attention. Identifying these sentiments from social media will help respondents understand network dynamism, e.g., users' significant issues, panics, and the emotional effects of members' experiences [6].

Deep learning has recently been shown to be one of the best methods of natural language management. The supervised training process with a large volume of data offers a good result for deep learning. BERT (Bidirectional Encoder Representations from Transformers) is a Google-designed, deep learning model. Since Google opened it, several scientists and businesses have adopted it and applied it to several text classification tasks. BERT's release was one of the most recent milestones in developing natural language processing (NLP) and an event that marked the beginning of a new period in the NLP. By conditioning both the left and right contexts, BERT is built to establish a deep bi-directional representation of unmarked texts on every level. This condition allows the pre-trained BERT model to be finalized with one additional output layer for various tasks without significant task-specific changes, including questions answering or language inference [7].

2. Related Work

Social media has become an inseparable part of our lives. Especially with the extremely rapid development of internet technology. One of the critical roles of social media is felt when a disaster occurs. Where plays a role in the disclosure of information about disasters. This situation encourages research to conduct sentiment analysis on posts on social media, especially Twitter. Users are turned into a social sensor by collecting public opinion from social media. Social media data are thought to be essential for understanding the reactions and feelings of the public. Finding posts that indicate frustration, danger or concern, can be critical, particularly for disaster management. Therefore, such posts' processing is effectively assisted by a systematic classification and is categorized in feeling polarity and aspect-based category, which will aid various agencies, including non-governmental agencies or governments, to manage such crises.

Analysis of social media data in transforming disasters has been carried out in several studies [8] [9]. Current studies have used geotagged tweets to measure the degree of social media involvement in areas impacted by disaster to determine whether vulnerable groups remain silent on social media to explore relevant factors. The ref [10] suggests that social media consumers rely more on rescue and donation-based knowledge using a machine-learning tweet model. However, differences in subjects are consistent across various fields and differing levels of focus.

The study of sentiment in online review sites has been thoroughly explored to provide consumers with synthetic views on various product aspects. However, little work has been done to define the polarity of users' emotions during catastrophic incidents. Identification of such feelings on the websites may allow emergency respondents to understand the complexities of their network, such as users' key concerns, panics, and the emotional effects of interactions among participants [6]. On research conducted by ref [11], they trained sentiment classes in categorizing messages on a concentrated basis and then discussed the demographic variations in these classifiers. They conclude that social media research complements conventional approaches for understanding public awareness of an imminent catastrophe in real-time.

In ref [12], they propose that Twitter feeds data analytics to enhance emergency planning and rescue efforts and services rendered in unusual circumstances. They follow a different approach, which focuses on the thoughts, fears, and opinions of users shared in emergency tweets and evaluates these feelings and expectations within an incident group to ensure that emergency response staff and local authorities have sufficient input. They use analysis and detection methods to store, identify and infer users' spatiotemporal feelings.

BERT has become state of the art in NLP. Since its inception, BERT has been widely used and experienced [7]. BERT's main technological advancement is applying transformer bidirectional training, a standard language model, to language modeling. Compared to previous attempts, a text sequence was evaluated from left to right or combined from left to right and from right to left. To solve the fine-grained challenge of classification uses a promising profound learning model called BERT [13]. Experiments demonstrate that their model succeeds other standard models without a sophisticated architecture for this mission. It also explains how efficient transfer learning is in manipulating natural languages. Whereas in ref [14], BERT was applied to a series of tweets linked to the Jakarta Flood in 2020. In the Jakarta flood tragedy of early 2020, which became a trending issue on Twitter, they tore up the tweet details. From there, the goal is to find specific tweets that can provide valuable information on emergency response to disaster management. Experimental studies have shown positive results. However, according to them, the data collection's consistency substantially affects the efficiency of the system.

In ref [15], they explored how to boost performance on (T)ABSA by applying a context to self-attention models. We suggest two versions of CG-BERT, which are capable of spreading focus in various contexts. First, they adopt a context-conscious transformer to create a CG-BERT using context-controlled softmax. Then, they suggest an enhanced CG-BERT, almost attention compositional model, which enhances subtraction. Their work offers more evidence for the usefulness of incorporating context dependency for context-based natural language tasks to pre-trained self-attention language models. In ref [16], they learned to link the sentence to the aspect and the long-term dependencies using the pre-trained BERT model. They further detect a self-critical strengthening learning snippet of opinion. Experimental results show how effective this method is and demonstrate that our hard-selection approach exceeds the soft selection approach in dealing with multi-aspect sentences.

3. Methodology

BERT utilizes a transformer, a mechanism of attention that learns the link between words (or subwords) in a text. The encoder that reads text data and the decoder generates a job forecast in its vanilla form, and the converter comprises two different mechanisms. As BERT's purpose is to construct a language model, it just requires an encoder mechanism. Two steps are used in BERT: pre-training and fine-tuning. During pre-training, the model is conditioned on unlabelled data in separate pre-training activities. Pertained parameters launch BERT models to be fine targeted, and the named downstream data refines all parameters, whose procedure we can see in Figure 1.

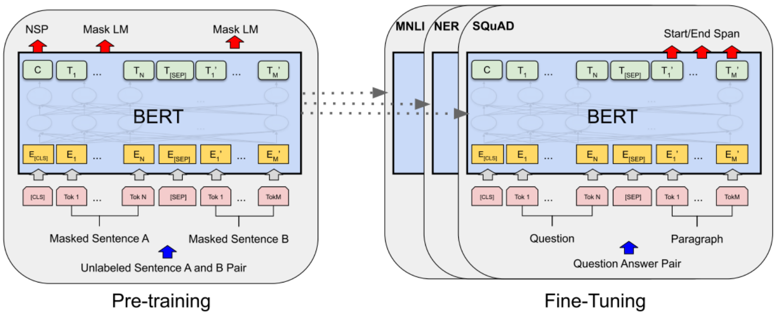

Figure 1. General pre-training and fine-tuning procedures for BERT[7].

3.1 Data Collection

In this study, we used the dataset from Kaggle. The dataset could be downloaded from https://www.kaggle.com/c/nlp-getting-started/data. We have 10873 comments, and we estimate whether or not a particular tweet is about a specific catastrophe. From 10,873 data, 57.03% were not real disasters. Figure 2 described the features and specifications.

- Id - tweet identifier
- text - text of the tweet
- location - location the tweet was sent from (maybe NaN)
- keyword - A relevant keyword in the tweet (maybe NaN)
- target - Output that tells if a tweet is a real disaster (1) or not (0)

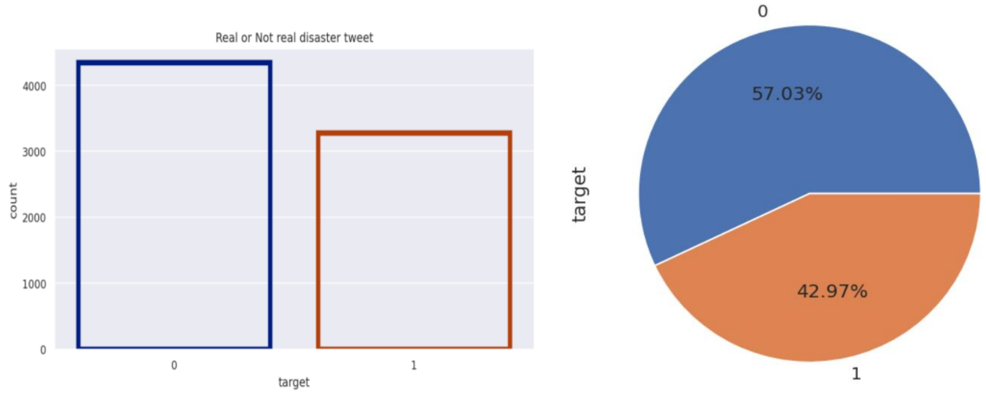

Figure 2. Real or not real disaster tweet from the dataset

3.2 Implementation

We will use Pandas to read data, preprocess_kgptalkie for data pre-processing. Seaborn for data visualization, all are running on Google Colab. By using pandas in Figure 3, we can see an example of data from the dataset.

	id	keyword	location	text	target
3040	4362	earthquake	NaN	#USGS M 0.9 - Northern California: Time2015-08...	1
3041	4363	earthquake	TÌÁchira - Venezuela	#SCSeEstaPreparando Light mag. 4.4 earthquake ...	1
3042	4365	earthquake	California, USA	#USGS M 1.2 - 23km S of Twentynine Palms Calif...	1
3043	4366	earthquake	a box	@AGeekyFangirl14 's things she looks in a sign...	0
3044	4368	earthquake	Melbourne, Australia	Nepal earthquake 3 months on: Women fear abuse...	1
3045	4372	earthquake	Barcelona, Spain	ML 2.0 SICILY ITALY http://t.co/z6hxx6d2pm #eu...	0
3046	4373	earthquake	Hawaii, USA	USGS reports a M1.94 #earthquake 5km S of Volc...	1
3047	4374	earthquake	New Zealand	GNS sees unnecessary deaths resulting from ear...	1
3048	4375	earthquake	NaN	'There was a small earthquake in LA but don't ...	1

Figure 3. Sample dataset

We can get basic features of the dataset with the help of preprocess_kgptalkie, the results of which can be seen in Figure 4.

text	target	char_counts	word_counts	avg_wordlength	stopwords_counts	hashtag_counts	mentions_counts	digits_counts	uppercase_counts
#USGS M 0.9 - Northern California: Time2015-08...	1	122	15	8.133333	1	2	0	16	4
#SCSeEstaPreparando Light mag. 4.4 earthquake ...	1	118	17	6.941176	3	1	1	7	1
#USGS M 1.2 - 23km S of Twentynine Palms Calif...	1	119	17	7.000000	1	2	0	18	5
@AGeekyFangirl14 's things she looks in a sign...	0	115	21	5.476190	6	0	1	7	0
Nepal earthquake 3 months on: Women fear abuse...	1	77	11	7.000000	1	0	1	3	0
ML 2.0 SICILY ITALY http://t.co/z6hxx6d2pm #eu...	0	48	6	8.000000	0	1	0	5	3
USGS reports a M1.94 #earthquake 5km S of Volc...	1	94	17	5.529412	3	2	1	11	4
GNS sees unnecessary deaths resulting from ear...	1	96	11	8.727273	1	0	0	2	1
'There was a small earthquake in LA but don't ...	1	83	17	4.882353	6	1	0	0	1
USGS EQ: M 1.9 - 15km E of Anchorage Alaska: T...	1	119	17	7.000000	1	1	0	19	5

Figure 4. Primary feature from the dataset

	id	keyword	location	text	target	char_counts	word_counts
3040	4362	earthquake	NaN	usgs m 0 9 northern california time20150806 01...	1	122	15
3041	4363	earthquake	TÌÁchira - Venezuela	scseestapreparando light mag 4 4 earthquake 73...	1	118	17
3042	4365	earthquake	California, USA	usgs m 1 2 23km s of twentynine palms californ...	1	119	17
3043	4366	earthquake	a box	ageekyfangirl14 s things she looks in a signif...	0	115	21
3044	4368	earthquake	Melbourne, Australia	nepal earthquake 3 months on women fear abuse ...	1	77	11
3045	4372	earthquake	Barcelona, Spain	ml 2 0 sicily italy httpt coz6hxx6d2pm euroquake	0	48	6
3046	4373	earthquake	Hawaii, USA	usgs reports a m1 94 earthquake 5km s of volca...	1	94	17
3047	4374	earthquake	New Zealand	gns sees unnecessary deaths resulting from ear...	1	96	11
3048	4375	earthquake	NaN	there was a small earthquake in la but do not ...	1	83	17
3049	4376	earthquake	Alaska, USA	usgs eq m 1 9 15km e of anchorage alaska time2...	1	119	17

Figure 5. Dataset after cleaning

The cleaning stage is done by removing email, URLs, HTML tags, special chars, and duplicates chars. Figure 5 shows the cleaning result data, especially in the text column, where there are already visible changes from the cleaning results.

4. Results and Discussion

We convert the raw document into the TF-IDF feature matrix. Next, by using LinearSVC, we are going to describe the classifier. The default settings of the class can be used. The parameters can be tailored to the data content of the classification. The results can be seen in the classification report in Figure 6.

```
Classification report
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       869
           1       0.83      0.69      0.75       654

    accuracy                           0.81      1523
   macro avg       0.81      0.79      0.80      1523
weighted avg       0.81      0.81      0.80      1523
```

Figure 6. Classification Report

We can achieve a validation accuracy of 79% with an excellent F-1 Score for each of the predicted classes. The classification report includes a per-class representation of the significant grading metrics. This condition gives a more intimate understanding of global accuracy classification, which can mask functional deficiencies in a multiclass problem.

By using the TF-IDF Vectorizer, we transform the text into vectors. They are using a linear classification algorithm for a vector machine. The model in the binary classification classifier LinearSVC was fitted, and we predict the feeling that real data is either a real disaster or not a real disaster.

We added a dropout layer of 0.5 to the BERT layer's output to complete the pre-trained model, and then we said a Dense layer with relu activation. We use the relu and sigmoid activation functions. The architecture will generate opportunities for each class, real disaster (target) or non-real disaster (non-target). Figure 7 shows a summary of the model.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 40, 100)           2258200
_________________________________________________________________
conv1d (Conv1D)              (None, 39, 32)            6432
_________________________________________________________________
max_pooling1d (MaxPooling1D) (None, 19, 32)            0
_________________________________________________________________
dropout (Dropout)            (None, 19, 32)            0
_________________________________________________________________
dense (Dense)                (None, 19, 16)            528
_________________________________________________________________
global_max_pooling1d (Global (None, 16)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 17
=================================================================
Total params: 2,265,177
Trainable params: 2,265,177
Non-trainable params: 0
_________________________________________________________________
```

Figure 7. Model Summary

```
begin training using onecycle policy with max lr of 2e-05...
Epoch 1/8
108/108 [==============================] - 99s 747ms/step - loss: 0.6037 - accuracy: 0.6759 - val_loss: 0.4114 - val_accuracy: 0.8241
Epoch 2/8
108/108 [==============================] - 79s 730ms/step - loss: 0.4086 - accuracy: 0.8247 - val_loss: 0.3664 - val_accuracy: 0.8320
Epoch 3/8
108/108 [==============================] - 79s 729ms/step - loss: 0.3694 - accuracy: 0.8437 - val_loss: 0.3540 - val_accuracy: 0.8504
Epoch 4/8
108/108 [==============================] - 78s 727ms/step - loss: 0.2840 - accuracy: 0.8889 - val_loss: 0.3880 - val_accuracy: 0.8451
Epoch 5/8
108/108 [==============================] - 79s 729ms/step - loss: 0.2133 - accuracy: 0.9199 - val_loss: 0.4400 - val_accuracy: 0.8294
Epoch 6/8
108/108 [==============================] - 79s 728ms/step - loss: 0.1323 - accuracy: 0.9521 - val_loss: 0.5513 - val_accuracy: 0.8294
Epoch 7/8
108/108 [==============================] - 79s 728ms/step - loss: 0.0833 - accuracy: 0.9721 - val_loss: 0.6590 - val_accuracy: 0.8215
Epoch 8/8
108/108 [==============================] - 79s 728ms/step - loss: 0.0686 - accuracy: 0.9731 - val_loss: 0.6544 - val_accuracy: 0.8255
<tensorflow.python.keras.callbacks.History at 0x7fd596648be0>
```

Figure 8. Model training

```
data = ['Posted a new song: Earthquake']
predictor.predict(data)
```

```
['not_target']
```

```
data = ['There was a small earthquake in LA but dont worry Emily Rossum is fine']
predictor.predict(data)
```

```
['target']
```

Figure 9. Prediction

The predictions made are pretty good; the model created can predict accurately determine a real disaster (target) and which one is non-disaster (non-target), as shown in Figure 9.

5. Conclusion

BERT (Bidirectional Encoder Representations from Transformers) is a Google-designed, profound learning model. Since Google opened it, several scientists and companies have embraced it and have applied it to many text classification tasks. Therefore, we use BERT in this paper to some earthquake tweets. This research will help rescue and emergency responders establish effective knowledge management techniques for a rapidly evolving disaster environment. The predictions made are pretty good; the model created can predict accurately determine a real disaster (target) and which one is non-disaster (non-target).

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