CS230

How Can Natural Language Processing Support Emergency Management?

NLP for Classification of Tweets During Crisis-Events

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Abstract

Social media has become an increasingly important source of information for emergency services during disasters. In this project, we analyze and compare the effectiveness of three state of the art deep learning models for detecting informativeness of disaster-related tweets in real time. We used the CrisisLexT26 dataset which comprises of 250,000 tweets regarding 12 disaster types from a total of 26 different crisis-events which occurred in 2012 and 2013.

Our findings have shown that generalized detection models work better when being trained on all type of crisis compared to the specialized models. The best architecture (XLNet) achieved a AUC between 0.86 and 0.94, showcasing its potential as a useful tool for future emergency response efforts.

Keywords: Natural Language Processing, Crisis Management, Tweet Classification

1 Introduction

Collecting and analyzing data quickly is of utmost importance during crisis situations such as natural disasters and human conflicts. Social media has become an increasingly important source of information, often outpacing traditional media outlets. However, a key challenge in analyzing disaster-related information on social media is recognizing which posts could be relevant for relief efforts. In this project, we propose analyzing crises through the lens of twitter, and building a classifier which will select posts containing relevant information for disaster-management (1; 2). Specifically, we will address the following questions:

A Model effectiveness in real-time disasters of the same type: How well can a model trained on one type of disaster (i.e floods, shootings, etc.) perform on similar events of the same type? What amount of data will be needed to train a successful event-specific network?

B Model effectiveness in real-time disasters of different types: Can information be transferred between different types of disasters. That is, can a model trained on data pertaining to certain types of disasters perform well on tweets relating to a new disaster?

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The input to our model is thus the text from a tweet, and the output states whether the tweet is informative or not. We are evaluating three different architectures, LSTM with Word2Vec embedding, BERT and XLNet, to find the highest performing model.

2 Related work

Detection and classification of disaster related tweets has been studied in a number of publications, using a lot of different approaches. The approaches can, as suggested in (1), be divided into three main categories: rules and keywords based approached, machine learning models based on feature engineering and neural networks.

The rules and keywords based approaches uses a dictionary of keywords to classify tweets, based on some predefined rules. Abel et al. (3) suggest such an approach, but increasing performance by continuously improving the information filtering to the current context. Olteanu et al. (4) investigates how to find the best keywords to use in such an approach, and suggests a lexicon of keywords called CrisisLex, specifically designed to have a high performance on classifying crisis tweets. Since the lexicon is designed to work well on crisis tweets, this is the lexicon we have used in our baseline approach.

As described by Habdank et al. (5), many different machine learning algorithms can be used together with hand engineered features, e.g. Naïve Bayes, Decision Trees, Random Forests or Support Vector Machines. They also show that Random Forests outperforms Support Vector Machines on the Ludwigshafen incident dataset.

Even though the machine learning algorithms with feature engineering often performs well, they are often outperformed by recent neural networks (1). Both Nguyen et al. (6) as well as Burel and Alani (7) uses a convolutional neural network with Word2Vec embeddings for tweet classification. Even though Word2Vec is a widely used word embedding method, other word embeddings has showed better performance lately. Two such methods are the BERT model and the XLNet model (8).

Since the machine learning algorithms with feature engineering most often are outperformed by neural networks, we have decided to focus on three neural network approaches, namely LSTM with Word2Vec, BERT and XLNet.

3 Dataset and Features

The raw data consists of more than 28,000 tweets in a multitude of languages related to 26 different crises (9). All of the crises occurred in 2012 or 2013 and includes, for example, the Boston bombings, Australian wildfires and LA Airport shootings. The data is classified by crowdsource workers as "Related and Informative", "Related - but not informative", "Not related" and "Not applicable". Since the goal of this project is to build a classifier which will select posts containing relevant information for disaster management, the data was relabeled as "Informative" or "Not Informative", where "Informative" included the "Related and Informative" tweets and "Not Informative" included tweets with all other labels.

The dataset was preprocessed by

- translating all non-English tweets,
- changing all letters to lowercase,
- replacing all URLs with <url>, hashtags with <hashtag> and user mentions with <user>,
- replacing emojis and emoticons with the text they represent and
- removing all duplicated tweets.

Table 1 shows a few examples of the data.

4 Methods

Traditionally, encoder-decoder architectures and attention model architectures was often used within Natural Language Processing (NLP). While traditional attention models does perform well consider-

Table 1: Examples of the data.

Original Tweet	Processed Tweet	Original Label	Informativeness
Welcome to our newest STUDENTathlete- Reagan Biechler from Colorado Springs (CO) '13- Baseball. http://t.co/lzeiYMpq	welcome to our newest studentathlete- reagan biechler from colorado springs (co) '13- baseball. <url>	Not related	Not informative
#Media Large wildfire in N. Colorado prompts evacuations: Crews are battling a fast-moving wildf... http://t.co/ju1BGTKH #Politics #News	<hashtag> large wildfire in n. colorado prompts evacuations: crews are battling a fast-moving wildf... <url> <hashtag> <hashtag>	Related and informative	Informative
It is doingsome raining #onthefarm!!! LORD send of this to put out the fires in Colorado. #Thrutheflames safety!!! #BelovedofGOD	it is doingsome raining <hashtag>!!! lord send of this to put out the fires in colorado. <hashtag> safety!!! <hashtag>	Related - but not informative	Not Informative

ing the hard task of NLP, they did reach a limit where the performance did not improve by adding more training data or more training time. Due to this a new approach, using pre-trained embeddings, became more widely used within NLP and is still an important part of state-of-the-art NLP architectures (10). There exists a lot of different pre-trained embeddings, where the main differences between different encoders is whether the embeddings are contextual or not, which pre-training task that has been used, and the architecture of the pre-training model (8).

In this project three deep learning architectures are implemented and compared. The architectures are LSTM classifier trained with Word2Vec, BERT and XLNet. As a baseline approach filtering by characteristics was used. Since the task is a binary classification task, the loss function used for each of the methods is the binary cross entropy. Our solutions was implemented using a number of libraries for Python (11; 12; 13; 14; 15; 16; 17; 18).

4.1 Baseline

As mentioned, filtering by characteristics was used as a baseline approach. The filtering by characteristics classifies the tweets by searching for tweets with specific hashtags, keywords or location (2). If the tweet contains at least one keyword from a list of words it is classified as informative, otherwise it is classified as not informative. Appendix A contains a full list of keywords, but some examples of keywords are victims, bombing, massive, storm and rescue.

4.2 LSTM with Word2Vec

Word2Vec is a common non-contextual word embedding. When first created in 2012, Word2Vec achieved state-of-the-art performance. The benefits on Word2Vec compared to word embeddings used before Word2Vec was the fact that it was a simpler method which decreased the computational complexity of the model and allowed for training on a larger dataset. Word2Vec uses two different architectures, one continuous Bag-of-Words model and one continuous Skip-gram model, where the choice of model can be seen as a hyperparameter for the Word2Vec embedding (19).

The LSTM based model implemented is composed of the main LSTM layer, followed by a drop-out layer and a dense layer with a Relu activation function and ending with a Softmax classification layer.

4.3 BERT

Even though Word2Vec achieved state-of-the-art performance when it was first created, a lot of other word embeddings has outperformed Word2Vec since then. One such model is the Bidirectional Encoder Representations from Transformers (BERT) model. The BERT model is a bidirectional method which means that it takes advantage of words both before and after the current word in the embedding. The pre-training task used to train the BERT model is to predict masked words (20).

In our implementation of the BERT model we used the pre-trained BERT encoding layer, followed by a drop-out layer and a dense layer with a sigmoid activation function (21).

Table 2: Split of data for scenario 1.

Crisis Type	Crisis	Number of tweets	Data
Earthquakes	Bohol earthquake	1000	Train/Validation
	Costa Rica earthquake	1412	Train/Validation
	Guatemala earthquake	1050	Train/Validation
	Italy earthquakes	1000	Test
Floods	Alberta floods	1001	Train/Validation
	Colorado floods	1000	Train/Validation
	Manila floods	1000	Train/Validation
	Philippines floods	1000	Train/Validation
	Queensland floods	1200	Test
	Sardinia floods	1000	Test
Derailments	Lac-Megantic train crash	1001	Train/Validation
	NYC train crash	1000	Train/Validation
	Spain train crash	1000	Test

4.4 XLNet

BERT is still widely used within NLP, but it has some limitations. One model which aims to overcome the limitations of the BERT model is XLNet. It does so by combining the bidirectional approach which BERT also utilizes with an autoregressive training which allows for training without masking any words, and thus avoid to remove the context the masked words provides (1; 22).

Similar to the BERT implementation, the XLNet-based model is composed of a XLNet main block followed by a dropout layer for regularization and a classification layer with a sigmoid activation function.

5 Experiments/Results/Discussion

5.1 Experiments

In the first scenario, the goal is to test the effectiveness of the models by only training on data from the same type of disaster, see Section 1. More specifically, each model will be trained and validated on a specific disaster type and then tested on another crisis of the same type. Table 2 shows how the data was split for scenario 1. The training and validation data was split randomly with 85% of the examples belonging to the training set and the remaining 15% belonging to the validation set.

The second scenario aims to test the performance of the models in the transfer of information between disasters. In this case the models were trained using 22 293 tweets belonging to 22 different disasters and tested on the remaining 4 disasters. The same test sets as i scenario 1 was used, but the training set was not divided into different crisis types. Instead the data was used all together, and also included other crisis types besides derailments, earthquakes and floods. As for scenario 1 the training and validation set was split randomly, with 85% in the training set and 15% in the validation set.

For each model and each of the scenarios the hyperparameters were decided by first doing a literature search to find what hyperparameters had worked best for similar models before. Based on these values a range for each hyperparameter was set from which the hyperparameters were randomly sampled. The sampled hyperparameters was used to test the model performance. This was done multiple times and the results on the validation set were compared to find the best hyperparameters for each model.

5.2 Results

Table 5.3 shows the results for each of the models. The best model for each crisis type based on the AUC is highlighted in bold. The left half shows the results of scenario 1, the best model trained on tweets from only one crisis type. The AUC scores of these specialized models range from 0.82 on earthquakes to 0.93 on floods.

The right half of Table 5.3 shows the results of scenario 2, models trained on data from all crisis types. On this dataset the generic model works better on earthquakes and derailments, while the more specialized model trained on only one disaster type work better for floods.

Table 3: AUC, accuracy, precision, recall and F1-score of all models. The precision, recall and F1-scores are reported separately for the two classes, Informative (I) and Not Informative (NI).

Crisis Type	**Scenario 1**									**Scenario 2**								
	Model	AUC	Accuracy	F1-score		Precision		Recall		Model	AUC	Accuracy	F1-score		Precision		Recall	
				I	NI	I	NI	I	NI				I	NI	I	NI	I	NI
Earthquakes	Baseline	-	0.55	0.53	0.57	0.76	0.44	0.40	0.79	Baseline	-	0.55	0.53	0.57	0.76	0.44	0.40	0.79
	Word2Vec	0.53	0.53	0.60	0.44	0.65	0.40	0.55	0.50	Word2Vec	0.51	0.48	0.62	0.31	0.61	0.33	0.64	0.30
	BERT	0.65	0.71	0.79	0.53	0.72	0.68	0.88	0.43	BERT	**0.76**	0.75	0.79	0.70	0.85	0.64	0.74	0.78
	XLNet	0.82	0.64	0.62	0.66	0.92	0.51	0.47	0.93	**XLNet**	**0.86**	0.80	0.83	0.74	0.86	0.71	0.81	0.78
Floods	Baseline	-	0.65	0.68	0.61	0.78	0.53	0.60	0.72	Baseline	-	0.65	0.68	0.61	0.78	0.53	0.60	0.72
	Word2Vec	0.64	0.62	0.73	0.44	0.67	0.53	0.80	0.37	Word2Vec	0.59	0.60	0.67	0.46	0.66	0.47	0.68	0.45
	BERT	0.74	0.73	0.76	0.68	0.83	0.62	0.71	0.77	BERT	**0.75**	0.76	0.79	0.70	0.83	0.66	0.76	0.75
	XLNet	**0.93**	0.90	0.93	0.78	0.90	0.86	0.96	0.71	XLNet	0.92	0.84	0.86	0.81	0.93	0.73	0.80	0.90
Derailments	Baseline	-	0.52	0.60	0.38	0.75	0.29	0.50	0.55	Baseline	-	0.52	0.60	0.38	0.75	0.29	0.50	0.55
	Word2Vec	0.72	0.48	0.83	0.20	0.72	0.16	0.97	0.10	Word2Vec	0.53	0.50	0.64	0.35	0.74	0.28	0.56	0.47
	BERT	0.61	0.76	0.85	0.40	0.78	0.59	0.92	0.31	BERT	**0.66**	0.77	0.85	0.51	0.81	0.59	0.89	0.44
	XLNet	0.90	0.83	0.85	0.79	0.90	0.73	0.81	0.86	**XLNet**	**0.94**	0.86	0.90	0.77	0.94	0.70	0.86	0.86

When comparing the model results to the filtering baseline it is noticeable that our model perform a lot better than the baseline. Our best performing models has an accuracy ranging between 0.64 and 0.90, while the baseline has an accuracy between 0.52 and 0.65. The F1-score is also a lot better with the suggested model compared to the baseline model, since the baseline model has a F1-score between 0.38 and 0.68 while the suggested model has a F1-score between 0.62 and 0.93.

5.3 Discussion

From the results it is clear that the fine-tuned XLNet performs the best for all types of crisis and both scenarios. This is not surprising since XLNet was created with the goal of reducing the shortcomings of BERT, which in turn is a more modern embedding model than Word2Vec, see Section 4.

The improvement of performance in scenario 2 compared to scenario 1 for earthquakes and derailments suggests that it was beneficial to add more training data for these types of crises, even though the additional data did not belong to the same type of crisis. This was however not true for the floods. One possible explanation for this is that the dataset contains more data related to floods, than data related to either earthquakes or derailments, see Table 2. Adding data from other types of crises was thus important for crisis types where the availability of data was low, but instead hurt performance for crisis types with more available data.

6 Conclusion/Future Work

We used a benchmark corpus of human-curated tweets related to 26 disasters, grouped into 12 crisis types, the CrisisLexT26. With this data we compared 13 models over 4,200 tweets and classified each tweet as informative or not informative. The classifiers was a mixture of generalized and specialized models. The best generic model achieve an AUC between 0.86 and 0.94 and a F1-score between 0.80 and 0.86. The generic model trained on all disasters perform slightly better in terms of AUC, accuracy, and F1-score than the specialized models.

A fine-tuned implementation of XLNet achieved accuracy of about 0.9 in classifying disaster-related tweets, outperforming other models, and potentially serving as a useful tool for relief efforts.

One aspect to further improve upon is to extend the dataset in order to create a larger and more representative dataset. Since the specialized classifier with the most training data was the only classifier that performed better than the generic classifier, this could potentially improve the specialized classifiers beyond the generic classifier.

7 Contributions

The contributions to this project was the following:
Karen Garcia Mesa: Preprocessing, Baseline, XLNet
Elin Lovisa Byman: Translation, BERT
Matan Lamdan: Data statistics, LSTM with Word2Vec

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A Keywords used for filtering in baseline approach

flood crisis
victims
flood victims
flood powerful
powerful storms
hoisted flood
storms amazing
explosion
amazing rescue
rescue women
flood cost
counts flood
toll rises
braces river
river peaks
crisis deepens
prayers
thoughts prayers
affected tornado
affected
death toll
tornado relief
photos flood
water rises
toll
flood waters
flood appeal
victims explosion
bombing suspect
massive explosion
affected areas
praying victims
injured
please join
join praying
prayers people
redcross
text redcross
visiting flood
lurches fire
video explosion
deepens death
opposed flood
help flood
died explosions
marathon explosions
flood relief
donate
first responders
flood affected
donate cross
braces
tornado victims
deadly
prayers affected
explosions running
evacuated
relief
flood death
deaths confirmed
affected flooding
people killed
dozens
footage
survivor finds
worsens eastern
flood worsens
flood damage
people dead
girl died
flood
donation help
major flood
rubble
another explosion
confirmed dead
rescue
send prayers
flood warnings
tornado survivor
damage
devastating
flood toll
affected hurricane
prayers families
releases photos
hundreds injured
inundated
crisis
text donation
redcross give
recede
bombing
massive
bombing victims
explosion ripped
gets donated
donated victims
relief efforts
news flood
flood emergency
give online
fire flood
huge explosion
bushfire
torrential rains
residents
breaking news
redcross donate
affected explosion
disaster
someone captured
tragedy
enforcement
people injured
twister
blast
crisis deepens
injuries reported
fatalities
donated million
donations assist
dead explosion
survivor
death
suspect dead
peaks deaths
love prayers
explosion fertiliser
explosion reported
return home
evacuees
large explosion
firefighters
morning flood
praying
public safety
txting redcross
destroyed
displaced
fertilizer explosion
unknown number
donate tornado
retweet donate
flood tornado
casualties
climate change
financial donations
stay strong
dead hundreds
major explosion
bodies recovered
waters recede
response disasters
victims donate
unaccounted
fire fighters
explosion victims
prayers city
accepting financial
torrential
bomber
disasters txting
explosion registered
missing flood
volunteers
brought hurricane
relief fund
help tornado
explosion fire
ravaged
prayers tonight
tragic
enforcement official
saddened
dealing hurricane
impacted
flood recovery
stream
dead torrential
flood years
nursing
recover
responders
massive tornado
buried alive
alive rubble
crisis rises
flood peak
homes inundated
flood ravaged
explosion video
killed injured
killed people
people died
missing explosion
make donation
floods kill
tornado damage
entire crowd
cross tornado
terrifying
need terrifying
even scary
cost deaths
facing flood
deadly explosion
dead missing
floods force
flood disaster
tornado disaster
medical examiner
help victims
hundreds homes
severe flooding
shocking video
bombing witnesses
magnitude
firefighters police
fire explosion
storm
flood hits
floodwaters
emergency

flash flood
flood alerts
crisis unfolds
daring rescue
tragic events
medical office
deadly tornado
people trapped
police officer
explosion voted
lives hurricane
bombings reports
breaking suspect
bombing investigation
praying affected
reels surging
surging floods
teenager floods
rescue teenager
appeal launched
explosion injured
injured explosion
responders killed
explosion caught
city tornado
help text
name hurricane
damaged hurricane
breaking arrest
suspect bombing
massive manhunt
releases images
shot killed
rains severely
house flood
live coverage
devastating tornado
lost lives
reportedly dead
following explosion
remember lives
tornado flood
want help
seconds bombing
reported dead
imminent
rebuild
safe hurricane
surviving
injuries
prayers victims
police suspect
warning
help affected
kills forces
dead floods
flood threat
military
flood situation
thousands homes
risk running
dead injured
dying hurricane
loss life
thoughts victims
bombing shot
breaking enforcement
police people
video capturing
feared dead
terrible explosion
prayers involved
reported injured
seismic
victims waters
flood homeowners
flood claims
homeowners reconnect
reconnect power
power supplies
rescuers help
free hotline
hotline help
please stay
investigation
saddened loss
identified suspect
bombings saddened
killed police
dead
praying community
registered magnitude
leave town
reported explosion
heart praying
life heart
prepare hurricane
landfall
crisis worsens
arrest
bombing case
suspect run
communities damaged
destruction
levy
tornado
hurricane coming
toxins flood
release toxins
toxins
supplies waters
crisis found
braces major
government negligent
attack
hurricane
rebuilt communities
help rebuilt
rebuilt
rescuers
buried
heart prayers
flood levy
watch hurricane
victims lost
soldier
waiting hurricane
run massive
high river
terror
memorial service
terror attack
coast hurricane
terrified hurricane
aftermath
suspect killed
suspect pinned
lost legs
hurricane category
names terrified
authorities
assist people
hurricane black
unknown soldier
events
safety
troops
disaster relief
cleanup
troops lend
effected hurricane
time hurricane
saying hurricane
praying families
dramatic
path hurricane