

# Detecting Disaster Tweets

By Jeff Spagnola

# Introduction

- ◎ Accurately determining the context of a tweet is useful in many areas.
- ◎ Social media outlets increasingly becoming a platform for breaking news.
- ◎ Being able to identify “disaster tweets” can lead to better rescue response and more widespread awareness.



# Introduction

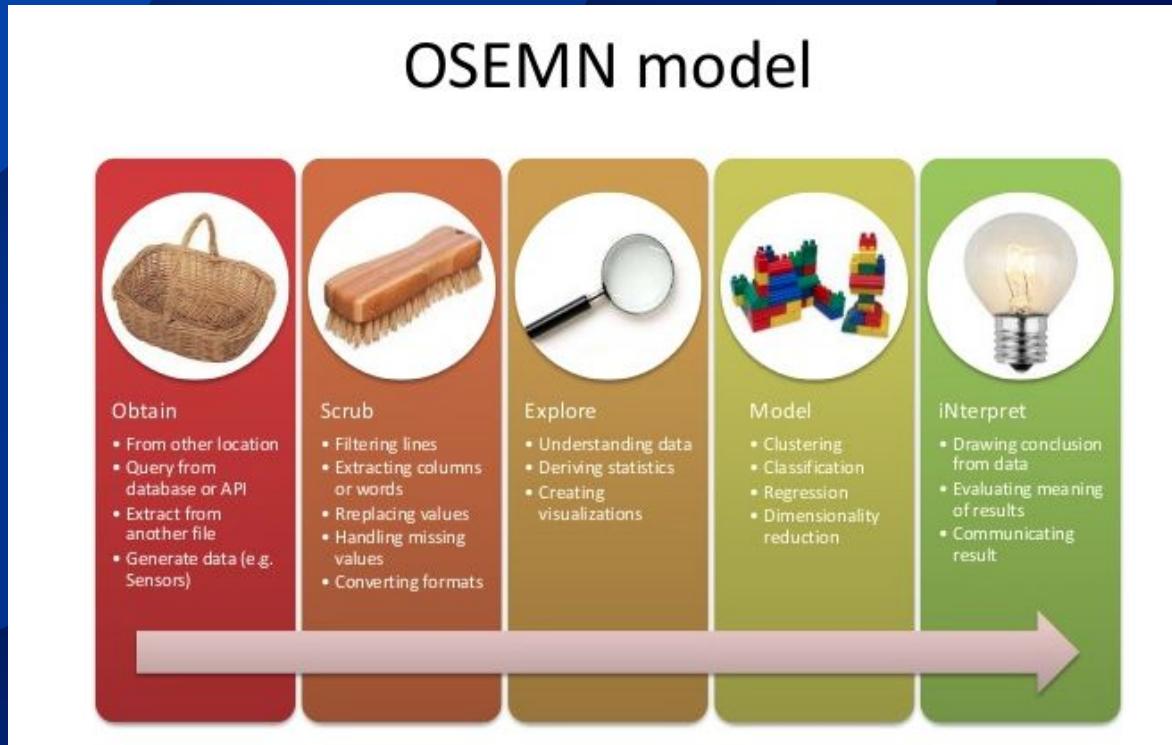


- ◎ Create a model to accurately identify disaster-related tweets.
- ◎ Using natural language processing, supervised machine learning, deep learning.
- ◎ Difference between “The plane crashed.” and “We crashed the party.”

# 1. The Process

# Process

Throughout this presentation, we will be following the OSEMN Data Science Process.



## 2. The Data

# Data

- The data was obtained from the Disaster Tweets Dataset from Kaggle.
- Contains over 11,000 tweets
- Collected Jan. 14th, 2020
- Topics include Taal Volcano, Coronavirus, Flight PS752



# Scrub

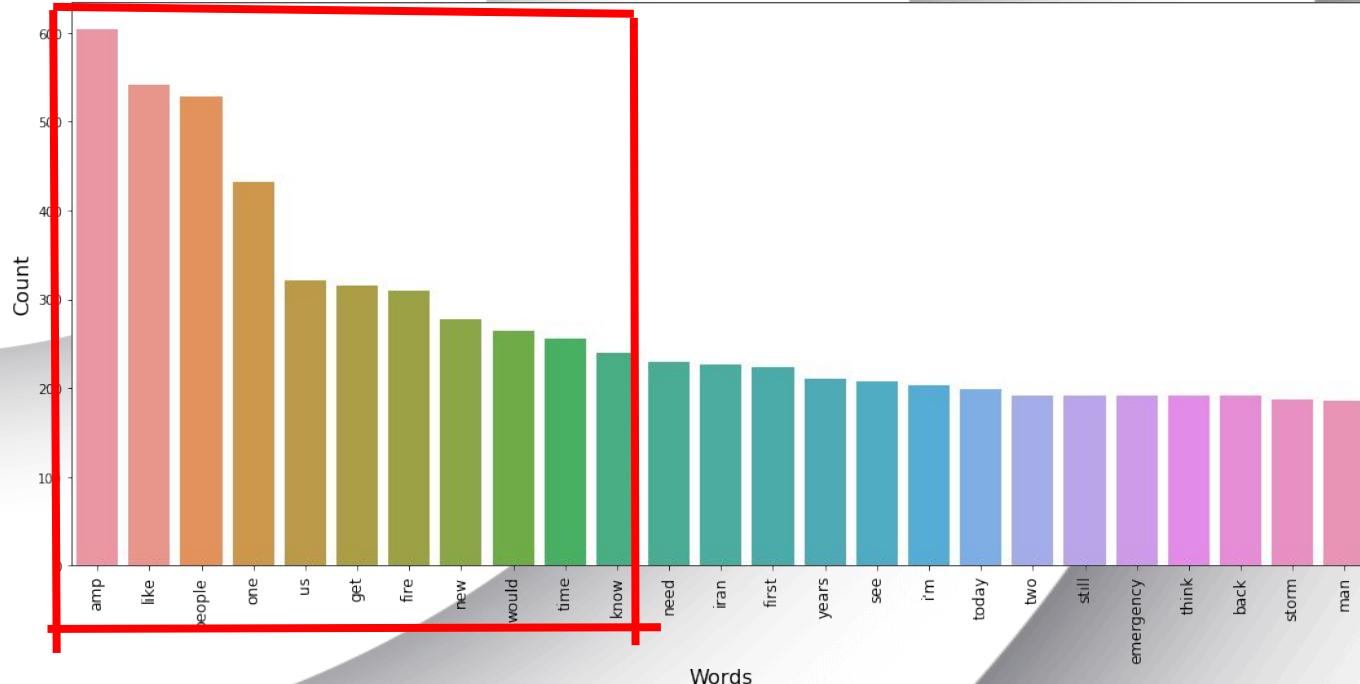


- ① Removed punctuation, emojis, HTML, and URL's
- ② Removed Stop Words (the, an, and, etc.)
- ③ Removed capital letters
- ④ Tokenized and Created Word Counts
- ⑤ Created word vectors & sequences

# 3. Explore

# Word Count

Most Common Word Count

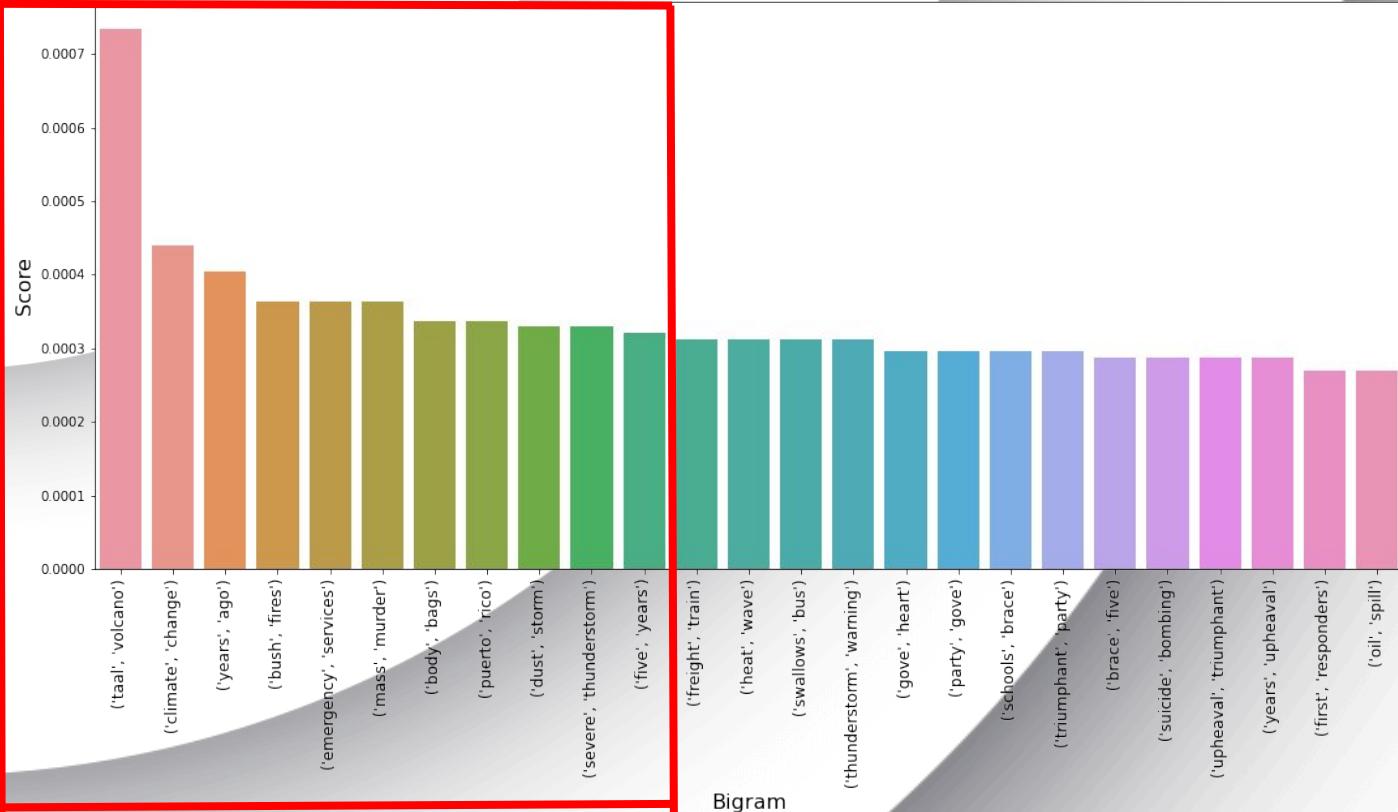


## 10 Most Common Words:

- Amp
- Like
- People
- One
- Us
- Get
- Fire
- New
- Would
- Time
- Know

# Bigrams

Bigrams with Highest Mutual Information Score



## Top 10 Bigrams:

- Taal, volcano
- Climate, change
- Years, ago
- Bush, fires
- Emergency, services
- Mass, murder
- Body, bags
- Puerto, rico
- Dust, storm
- Severe, thunderstorm
- Five, years

# Word2Vec

- ◎ Word2Vec allows us to explore relationships between words.
- ◎ Getting the 'most similar' for disaster-related words yields interesting results.

## Death

```
[('one', 0.5004619359970093),  
 ('attack', 0.4937114119529724),  
 ('army', 0.47336050868034363),  
 ('attacked', 0.4692723751068115),  
 ('know', 0.4676671028137207),  
 ('bioterrorism', 0.4507286846637726),  
 ('world', 0.4476444721221924),  
 ('ambulance', 0.4448230564594269),  
 ('bleeding', 0.43611225485801697),  
 ('accident', 0.43582674860954285)]
```

## Fire

```
[('accident', 0.6279330253601074),  
 ('iran', 0.6176088452339172),  
 ('ukrainian', 0.591111421585083),  
 ('shot', 0.5809152126312256),  
 ('attack', 0.5783515572547913),  
 ('airplane', 0.5768617391586304),  
 ('like', 0.5718441605567932),  
 ('amp', 0.5559629201889038),  
 ('blazing', 0.5528613924980164),  
 ('army', 0.5281714200973511)]
```

## Accident

```
[('iran', 0.9049441814422607),  
 ('shot', 0.9043893814086914),  
 ('airplane', 0.8586768507957458),  
 ('iranian', 0.8038906455039978),  
 ('ukrainian', 0.8005987405776978),  
 ('attack', 0.7705838084220886),  
 ('shooting', 0.7558250427246094),  
 ('people', 0.736716091632843),  
 ('like', 0.7155638933181763),  
 ('trump', 0.7147867679595947)]
```

# 4. Modeling

# Classifiers

- Used a variety of classifiers
- Logistic Regression,  
Stochastic Gradient Descent,  
Random Forest, Stacking
- Logistic Regression  
outperformed all others.

## Recall Scores for Each Model

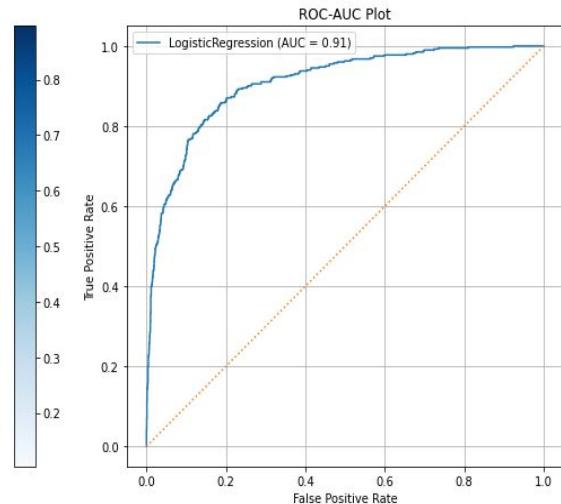
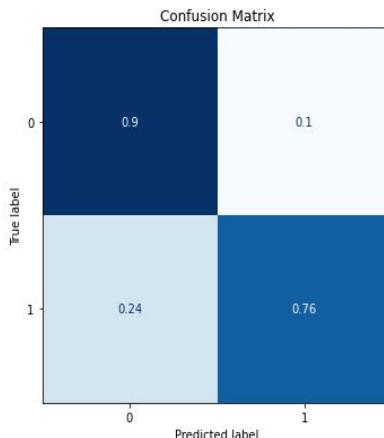
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Logistic Regression: 0.76

SGD: 0.73

Random Forest: 0.53

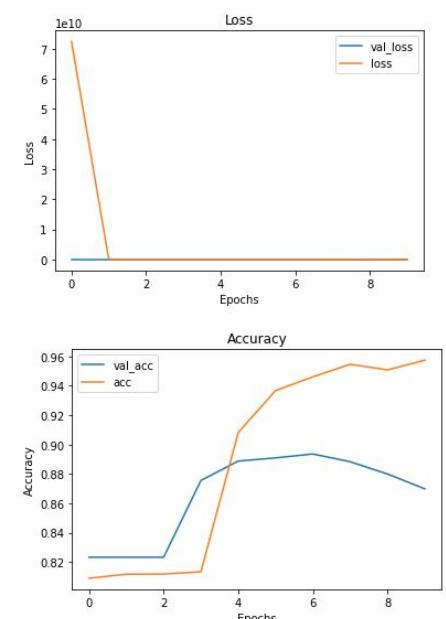
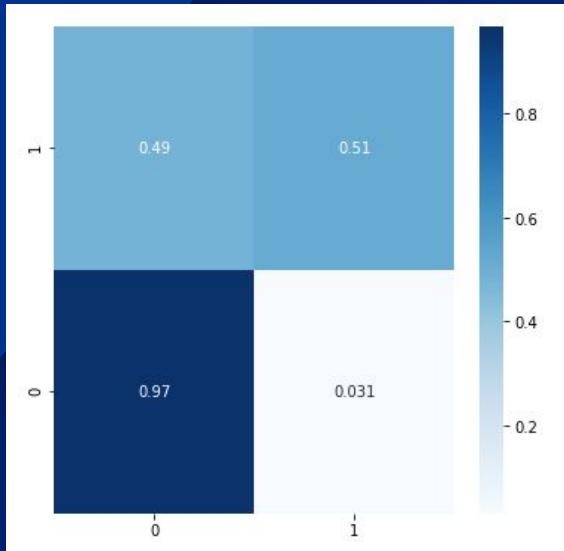
Stacking Classifier: 0.68

Classification Report					
	precision	recall	f1-score	support	
0	0.94	0.90	0.92	1872	
1	0.61	0.76	0.68	402	
accuracy			0.87	2274	
macro avg	0.78	0.83	0.80	2274	
weighted avg	0.89	0.87	0.88	2274	



# LSTM & GRU Neural Networks

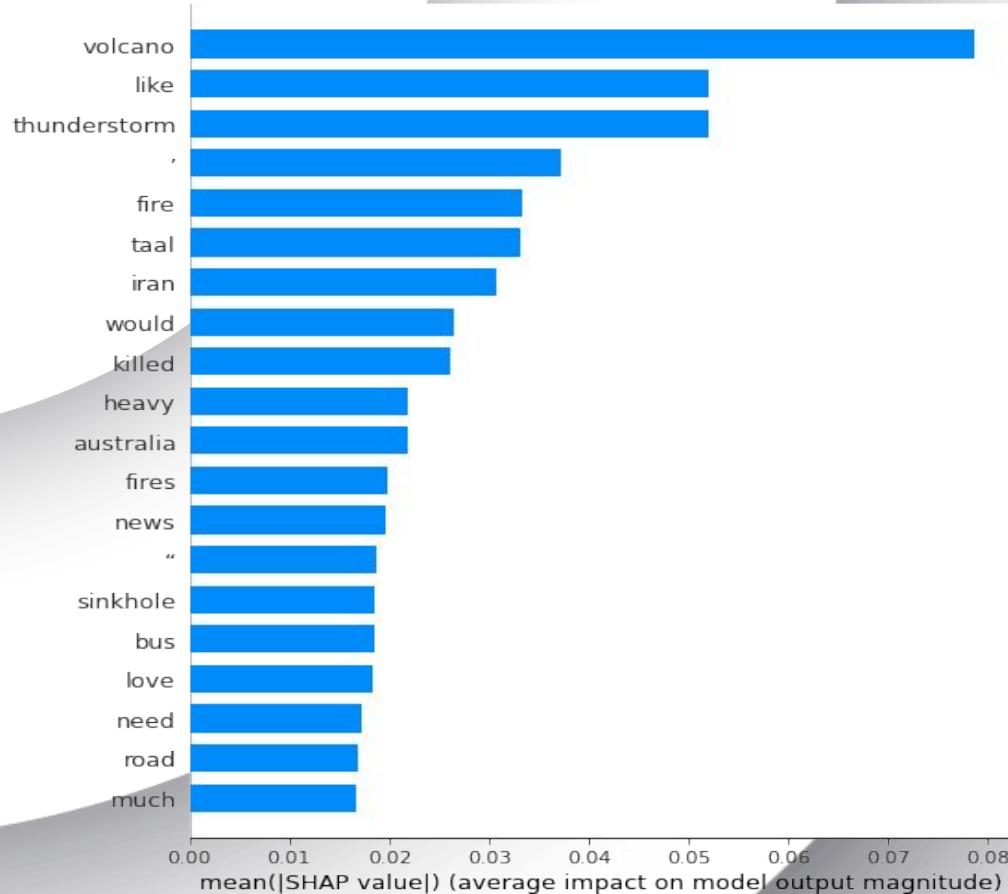
- Powerful but extremely time consuming.
- Great accuracy but poor in terms of recall.
- Can be fine tuned and improved in the future.
- Scores are from best version of many iterations.



```
- 14s 188ms/step - loss: 0.4370 - acc: 0.8887
```

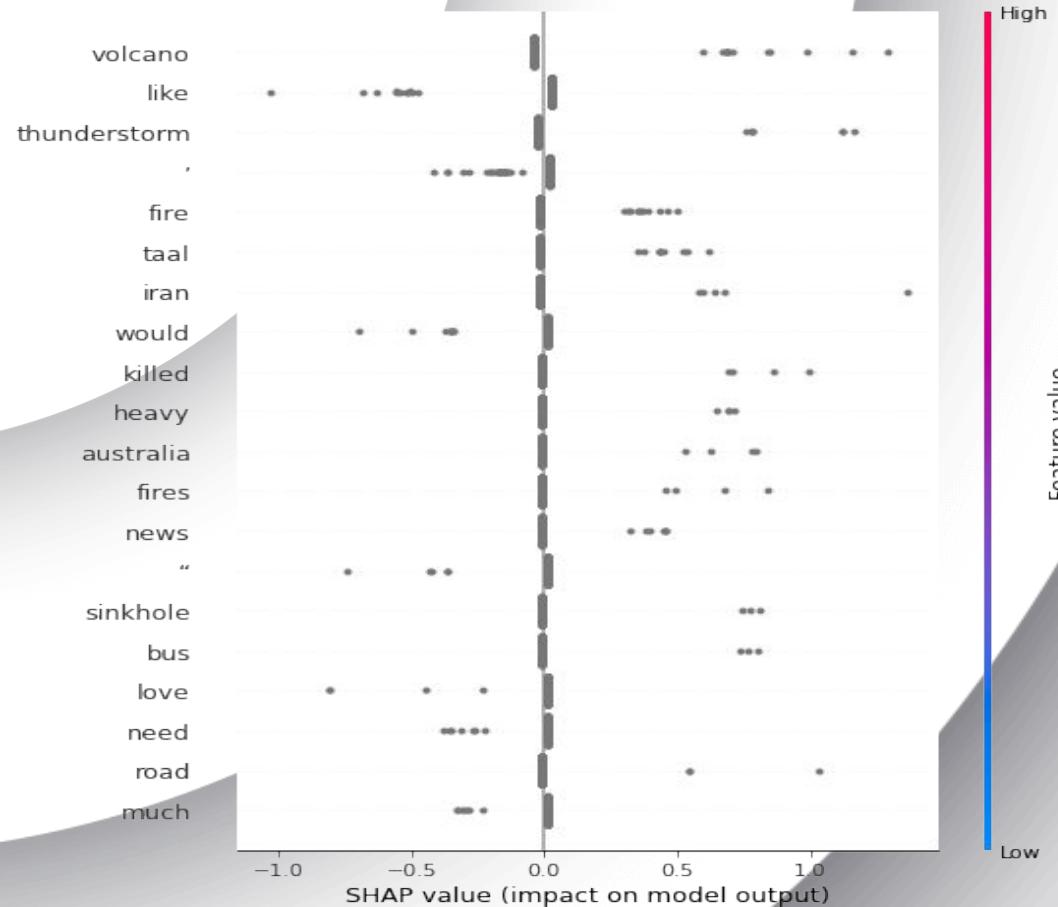
# 5. Results

# Disaster Keywords



- **Top Words in Terms of Importance to Target**
- **Large portion refer to disasters**
- **Volcano, Thunderstorm, Fire, Killed, etc.**

# Disaster



- These "disaster keywords" have highest level of importance in determining a positive disaster tweet.
- Few non-disaster words have positive importance

# Results

- Basic NLP - Bigrams & Word2Vec “most similar” revealed interesting relationships between words in the dataset.
- The Logistic Regression model performed better than all other models that we attempted.
- Disaster-related keywords seem to have an extreme influence on whether a tweet is related to a disaster event.



# 6. Recommendations

# Recommendations

## Disaster Keywords

For basic NLP, focus on short phrases that include a "Disaster Keyword". (fire, tornado, etc.)

## Logistic Regression

In terms of both speed and accuracy, a Logistic Regression model is recommended.

## Keep It Simple

While the power of the neural network is appealing, the accuracy and runtime make it unappealing for this particular task.

# Future Work

**With more time, we can improve our analysis in the following ways:**

## Fine Tuning

We can spend more time fine tuning our existing models in order to achieve better results.

## Additional Models

There are several other types of models that can be applied in order to increase the accuracy of our results.

## Additional Data

With more data, we can increase the accuracy of the models.

# Thanks!

**Any questions?**

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