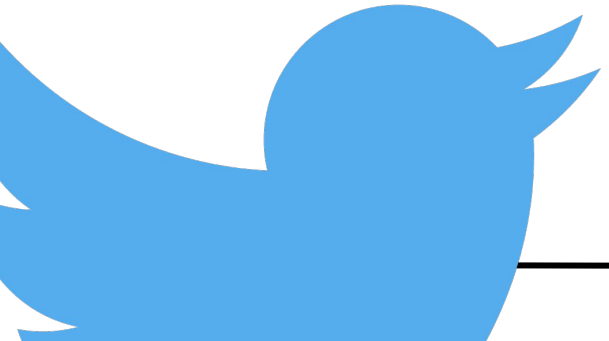
Mapping Disasters using Twitter



Presented by:

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Problem statement

We used **tweets** from Twitter
to create **a classification model**
that filters out tweets that are reporting about a fire
to discover **new ways to help respond to disasters.**

These tweets were displayed on a map.

Beyond aerial, satellite imaging

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Each tweet scapers have its ups and downs

Tweepy	GetOldTweets3	Python-Twitter
Strict scrape rate limit	No scrape rate limit	Strict scrape rate limit
Geo. coordinate ‘search’ not available	Geo. coordinate not available	Geo. coordinate ‘search’ available

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Model Train Set

Python-Twitter

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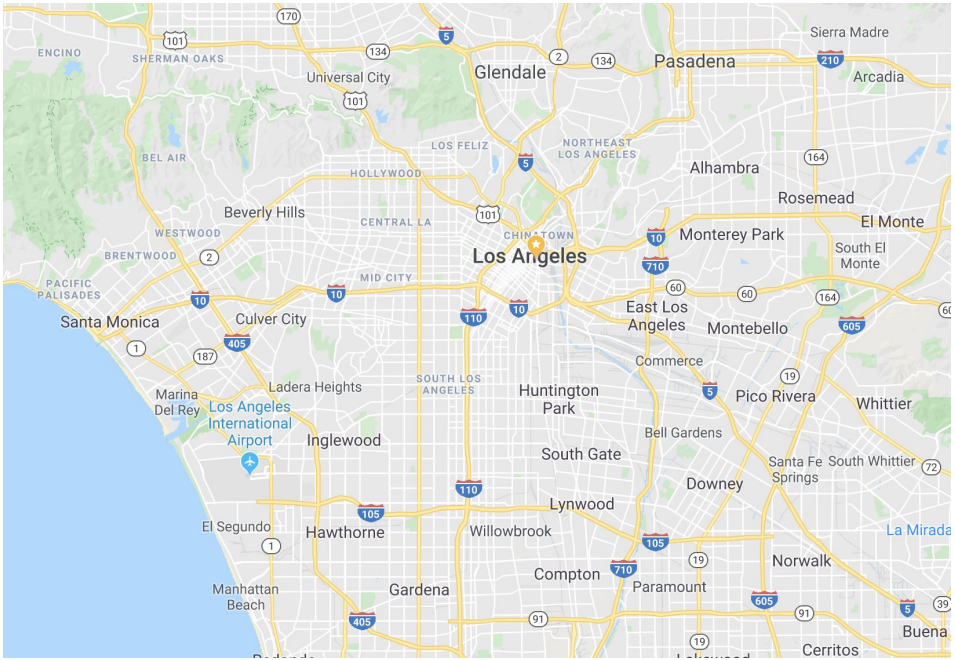
	**Model Train Set**	**Test Set / Map**

“Only 1~2 % of tweets are geotagged”
- Twitter



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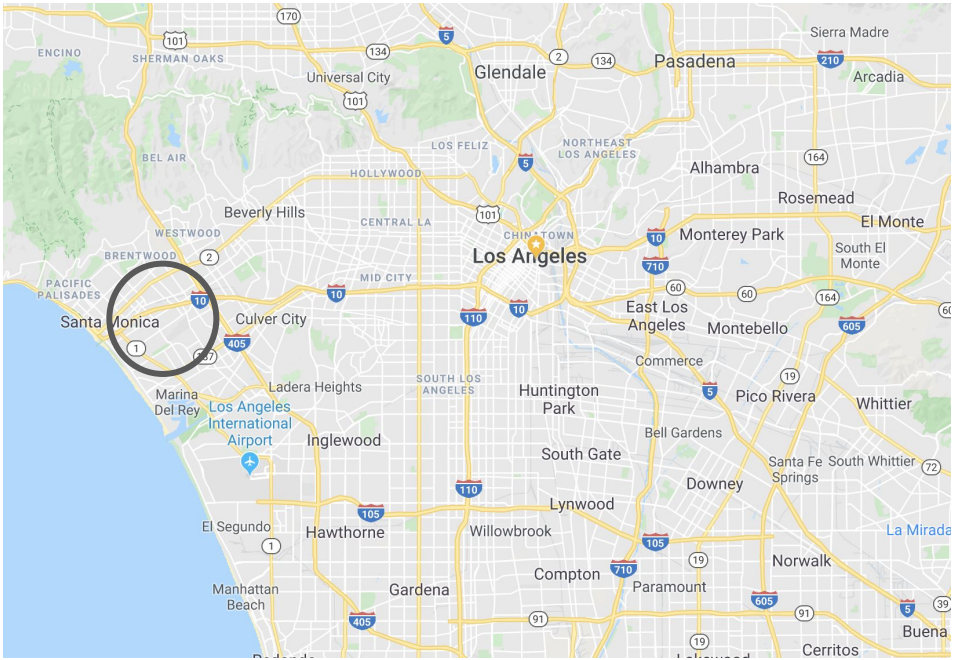

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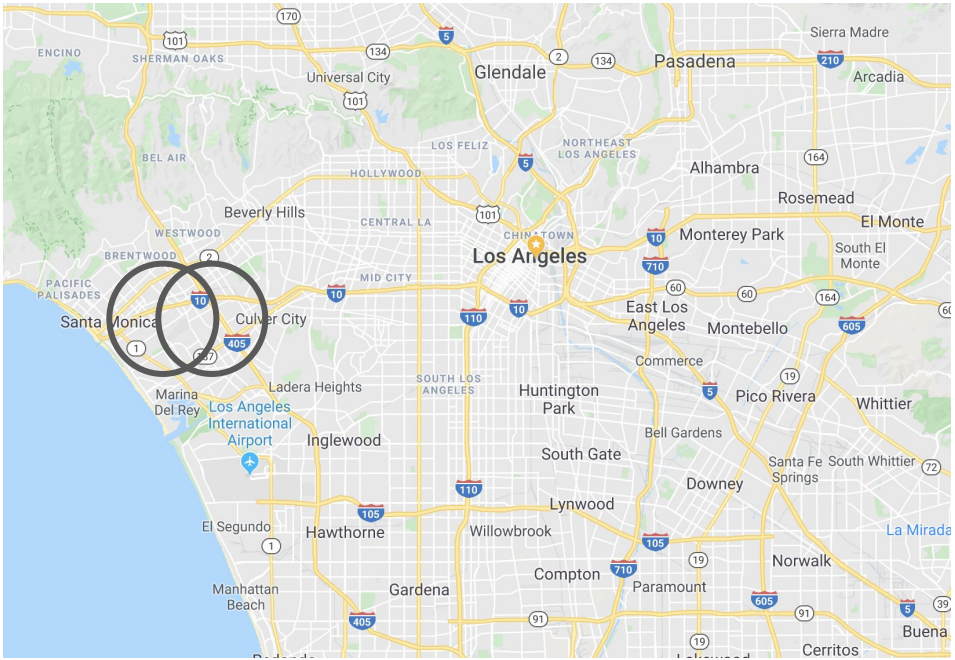

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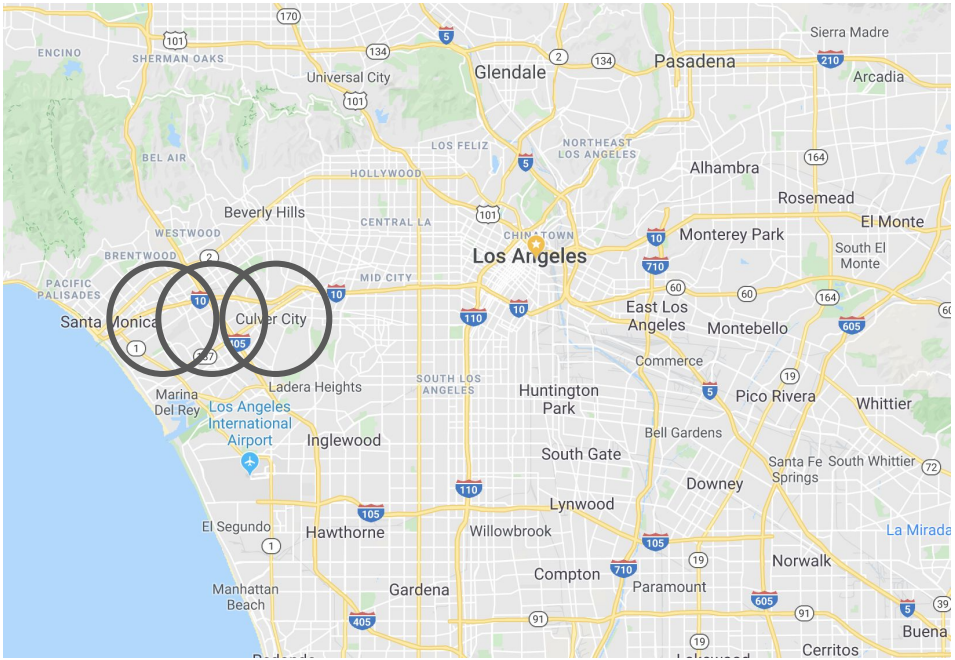

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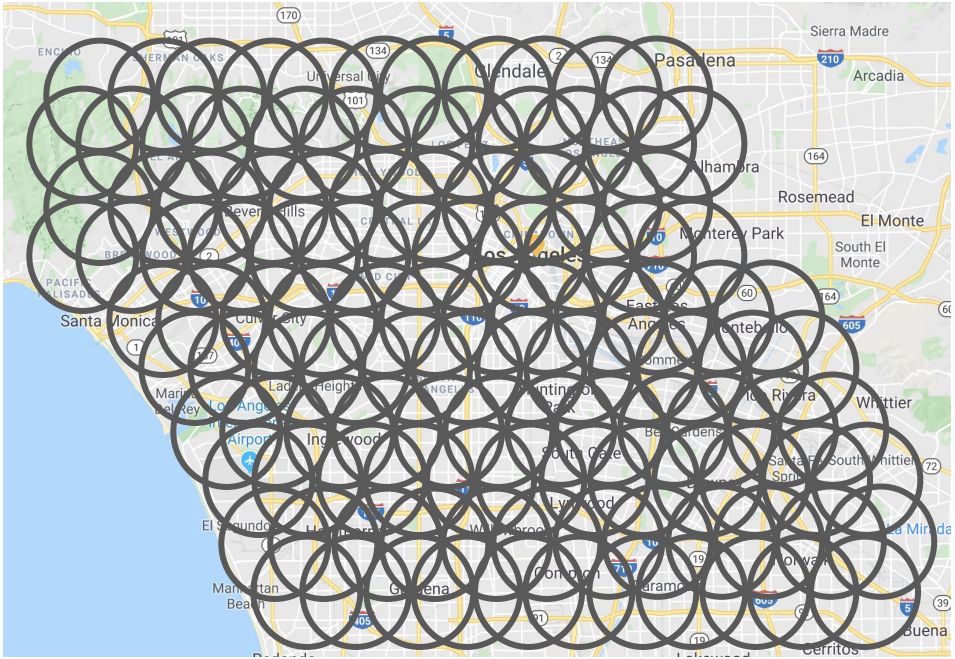
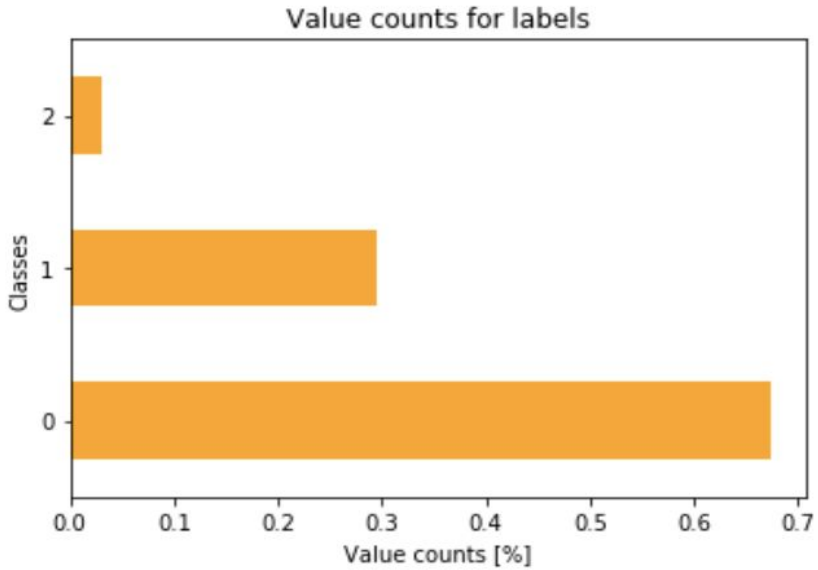


Few tweets are discussing a disaster.

0: Tweets not reporting about a fire

1: Tweets reporting about a fire

2: Ambiguous tweets —> Dropped



3:7 ratio of Class 0 and 1 to reflect the real life tweets in a train set .

Modeling

Minimize **false negatives**

=

Optimize **sensitivity**

Logistic Regression	Random Forest	Multinomial Naive Bayes
TF-IDF Vectorizer	TF-IDF Vectorizer	Count Vectorizer

Modeling

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Optimize **sensitivity**

Logistic Regression	Random Forest	Multinomial Naive Bayes
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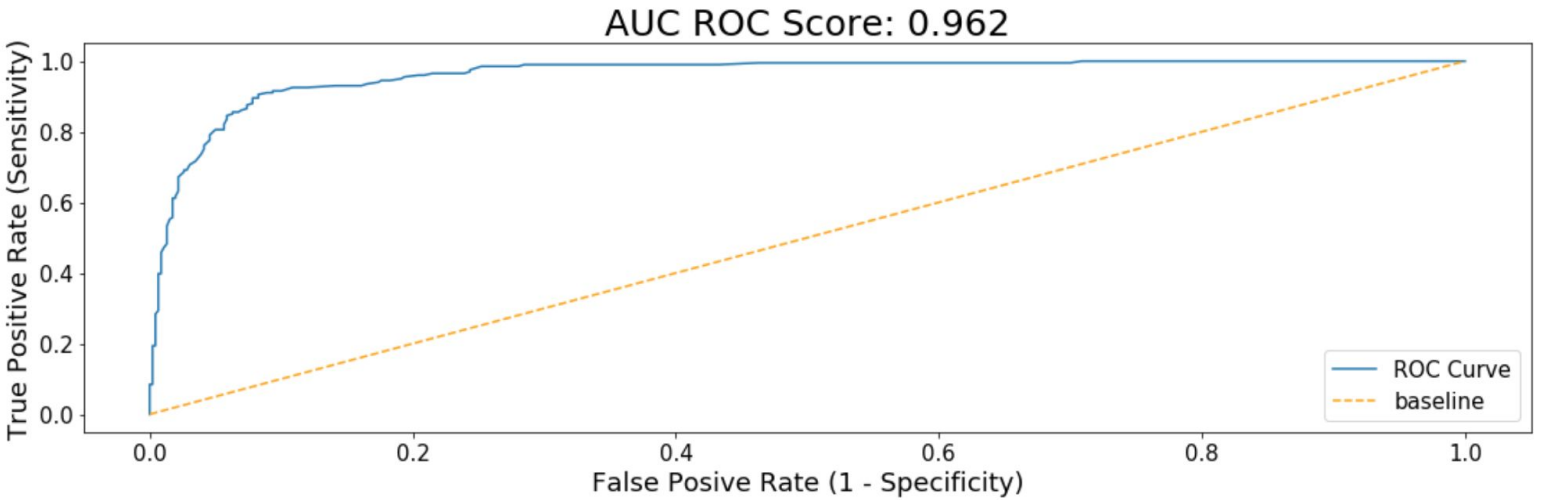
Logistic Regression (TF-IDF Vectorizer)

Accuracy (test set): 86 %

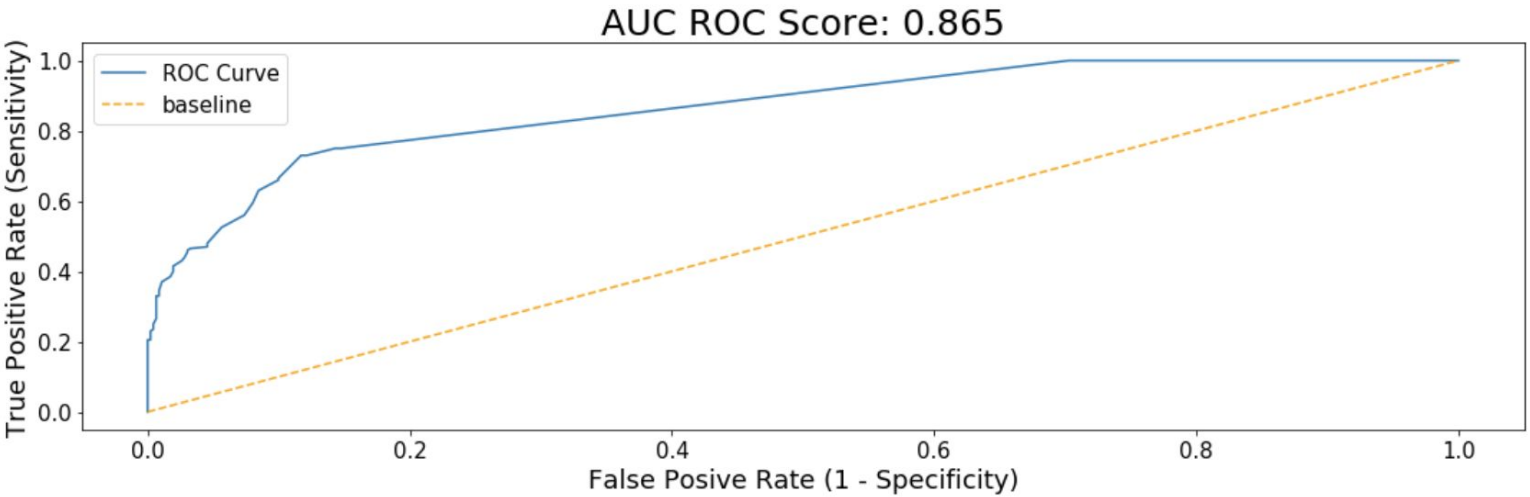
Sensitivity: 62%



Random Forest (TF-IDF Vectorizer)

Accuracy (test set): 76 %

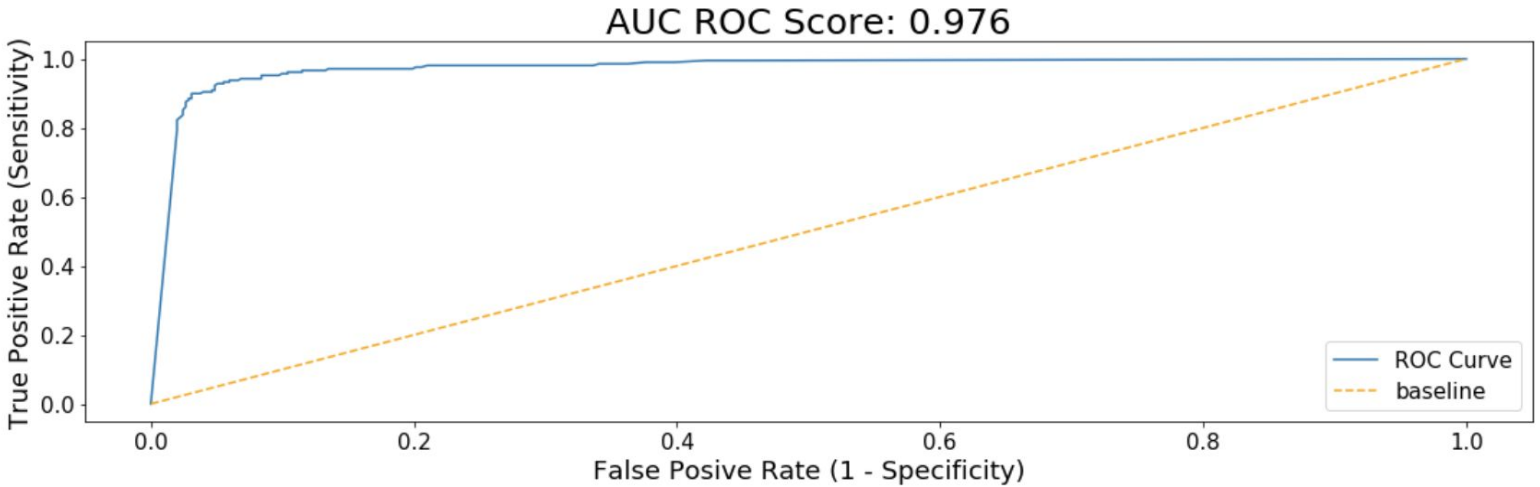
Sensitivity: 21%



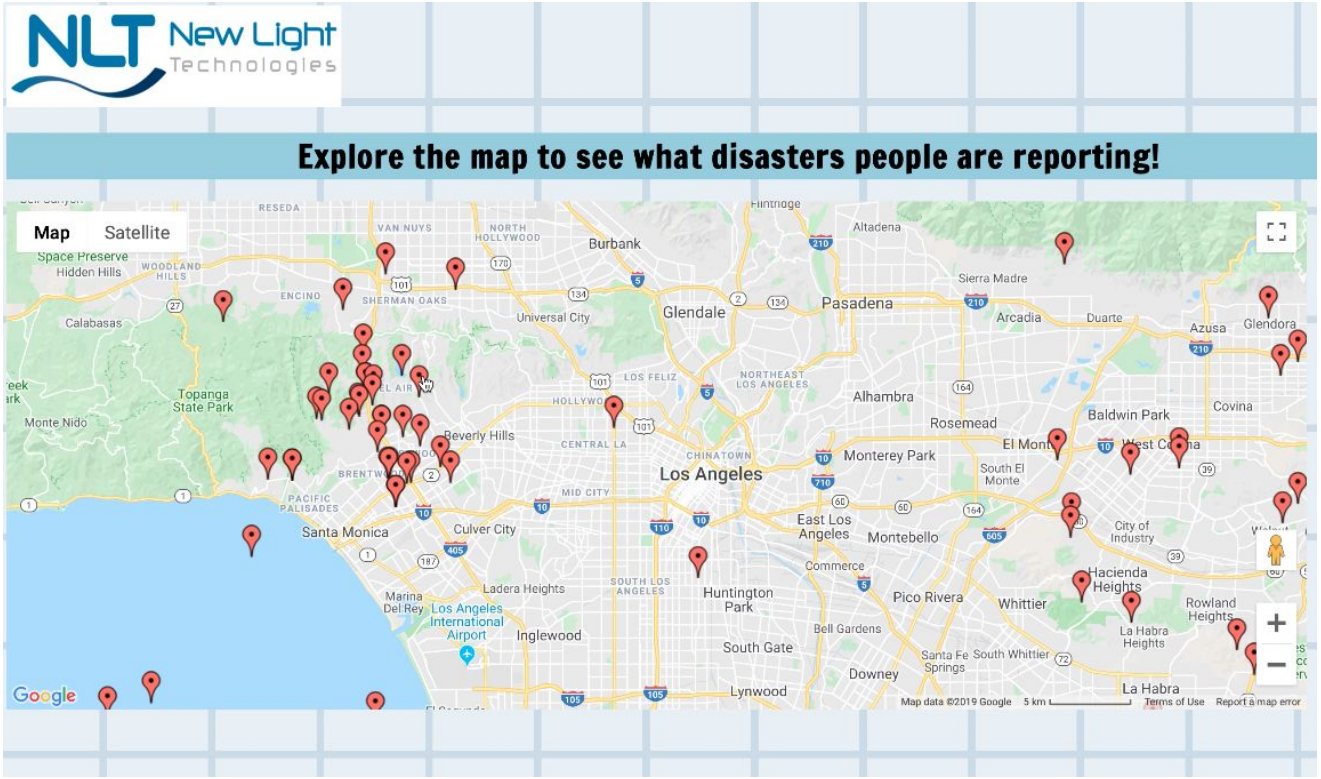
Multinomial Naive Bayes (Count Vectorizer)

Accuracy (test set): 84 %

Sensitivity: 90%



Flask app / demo



Conclusion

Obstacles

- Scraping takes a long time due to rate limit
- Geotags are scarce.

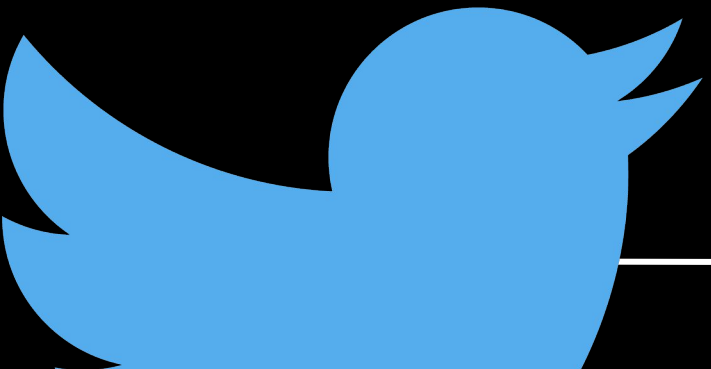
- Inaccurate geo-coordinates (Aka. Ocean Fire)

Next steps

- Run scraper daily, ahead of the time
- Enterprise API access for real-time track

- Create a boundary line and filter out coordinates outside the boundary.

- Make rating available for users to learn which tweets were useful
  —> feed these back to the train set



Source

1. http://www.newlighttechnologies.com
2. https://www.twitter.com
3. https://www.eos.org