CIVIQUE - USING SOCIAL MEDIA TO DETECT URBAN EMERGENCIES

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Roadmap



- ♦ Motivation
- Approach
- ♦ Pre-processing
- ♦ Post-visualization
- ♦ Architecture
- Evaluation & Results
- Demo

Motivation



- In 2015, 53% of all unnatural deaths in India were caused by car accidents, and 6% by accidental fires.
- > The Indian subcontinent alone suffered seven **earthquakes** in 2015, with the recent Nepal earthquake alone **killing more than** 9000 people and **injuring 23,000**.
- The need to *quickly bridge the gap between people and the concerned authorities*.

Challenges



- **Location tagged tweets:** Otherwise, event detection techniques to extract the spatio-temporal data from the tweet can be vague, and lead to false alarms.
- > A mechanism of **reliability score** of tweets in order to avoid false alarm, in case of extraction of spatio-temporal data.
- A sophisticated language processing component to sanitize the tweet input before event detection.
- A channel with the concerned authorities to take serious action, on alarms raised.
- An urban emergency such as a natural disaster could affect communications severely, in case of an earthquake or a cyclone, communications channels like Internet connectivity may get disrupted easily.

Approach



- > We choose Twitter as the platform for collecting data, and detecting emergency event / incidents.
- > Using Twitter APIs, we collect data for text classification, and label them manually for two steps:
 - Emergency / Non Emergency Tweet.
 - > Emergency Type of the Tweet.
- Our system performs pre-processing as described below.
- > Classification techniques such as Support Vector Machines (SVM), and Naive Bayes (NB) used for training, and 10 fold cross validation was performed for evaluation.
- > Twitter Streaming APIs are used to stream twitter data on a real-time basis.
 - The data is filtered through a set of keywords, which depict an emergency like situation.

Approach (Contd.)



- > The system uses the first classifier to detect whether the tweet belongs to an Emergency situation or not.
 - In case of an emergency, the tweet is sent to the second classifier for Emergency type classification.
- > The tweet is then visualized on the web interface, and the android application interface, along with its location on a map.

Pre-Processing



- > Our system employs a sophisticated pre-processing module, which lets us sanitize the tweet for both, training, and detection.
- > We clean data by removing username, hashtags, emoticons, URLs, etc.
- > Compression: Heuristic based all the repeated windows of character length greater than two are compressed.
- > **Normalization:** Implemented the normalization system by (Kanojia et. al., 2015) as a Phrase Based Statistical Machine Translation system.
- > **Spell Checking:** The JAVA API of Jazzy spell checker is used for handling spelling mistakes.

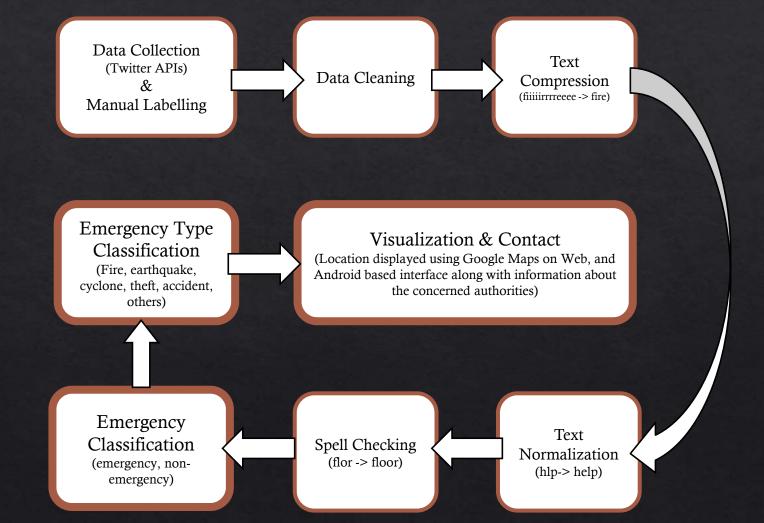
Post-Visualization



- > We try to display the contact information of the concerned authority on the interface, which leads the user to contact them.
- > For e.g., In case of a fire, the contact information of the nearest fire depot along with the central number is displayed.
- > In case of an earthquake, the nearest disaster management center / police station and hospitals will be displayed.

System Architecture





System Evaluation



- > We evaluate our system techniques using standard precision, recall and f-score.
- \triangleright Our system uses ~3200 manually labelled tweets to train the data.
- > We perform ten fold cross validation for both SVM and NB.
- > We choose SVM for classification step one, and NB for classification step two, based on F-scores, as shown in the table below.
- Manual Evaluation revealed false positives such as:
 - > I am sooooo so drunk right nowwwwwwww.
 - > fire in my office, the boss is angry.

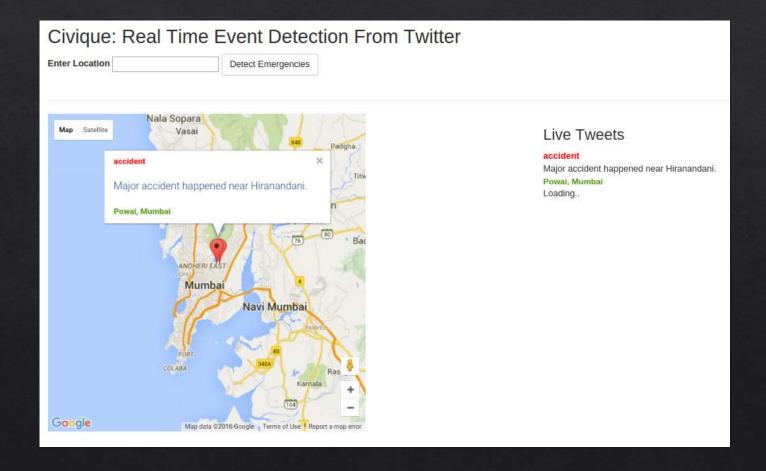
Evaluation Results



Classifier	Step One	Step Two
SVM	88.0%	90.5%
NB	67.9%	92%

Screenshot





Demonstration

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Thank you! ©

Questions?

