

Predicting Fine-Grained Crime Types using Social Media

Deepak Venugopal

Assistant professor

Department of Computer Science

University of Memphis



Partying in downtown!

Depressed about grades

Demonstration on 5th street

I Hate XXXxxx

School party

Afraid to go to school

Noisy neighbors can't concentrate!!



Partying in downtown!

Depressed about grades

Demonstration on 5th street

School party

Afraid to go to school

Noisy neighbors can't concentrate!!

I Hate XXXxxx



Signals of potential
crime events



Partying in downtown!

Depressed about grades

Demonstration on 5th street

School party

Afraid to go to school

Noisy neighbors can't concentrate!!

I Hate XXXxxx



Signals of potential
crime events

Research Challenge: Can we
predict fine-grained, potential
criminal activity in real-time
from tweets?

Twitter-based Model

- Collect a tweet corpus offline and annotate it with the following categories
 - Violent Crime
 - Racism
 - Fraud
 - Narcotics

Twitter-based Model

- Collect a tweet corpus offline and annotate it with the following categories
 - Violent Crime
 - Racism
 - Fraud
 - Narcotics
- Pre-process tweet text (lots of noise)

Twitter-based Model

- Collect a tweet corpus offline and annotate it with the following categories
 - Violent Crime
 - Racism
 - Fraud
 - Narcotics
- Pre-process tweet text (lots of noise)
- Learn a Machine learning model from features obtained from processed tweets to distinguish between crime categories
- Capture live tweets and predict crime categories based on learned model

Implementation

- Implemented on top of Amazon cloud services
- Spark streaming to process thousands of tweets quickly in a cluster environment

Implementation

- Implemented on top of Amazon cloud services
- Spark streaming to process thousands of tweets quickly in a cluster environment
- Use a filter to look only for tweets that suggest potential criminal activity
- Detailed visualization dashboards to explain prediction results in real-time

Challenges

- Twitter data is very noisy

Challenges

- Twitter data is very noisy
- Twitter allows users access to a miniscule percent of their tweets

Challenges

- Twitter data is very noisy
- Twitter allows users access to a miniscule percent of their tweets
- Among these tweets, those relevant to crime are even fewer

Challenges

- Twitter data is very noisy
- Twitter allows users access to a miniscule percent of their tweets
- Among these tweets, those relevant to crime are even fewer
- Among the crime-relevant tweets, very few are specific to a geo-location
 - Geo-tags are generally empty in most tweets
- In short, very hard to get reliable signals for specific geo-locations from twitter content alone

Can we use more reliable data?

- Utilize Memphis specific data from Bluecrush
 - Incidents recorded along with type of incident and date

Can we use more reliable data?

- Utilize Memphis specific data from Bluecrush
 - Incidents recorded along with type of incident and date
- Developed a Hidden Markov Model
 - Latent crime states
 - Observable crime events (7 types of crime)

Can we use more reliable data?

- Utilize Memphis specific data from Bluecrush
 - Incidents recorded along with type of incident and date
- Developed a Hidden Markov Model
 - Latent crime states
 - Observable crime events (7 types of crime)
- Predict future incidents from the HMM
 - Different granularity levels (by zipcode, precinct zone, etc.)

HMM-based predictions

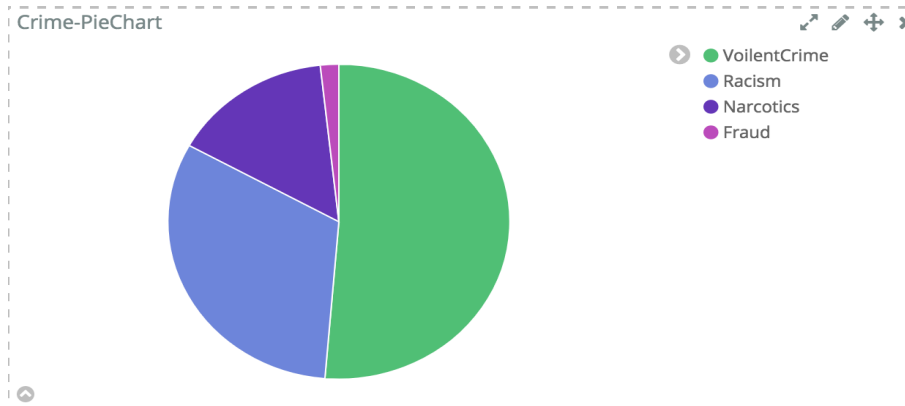
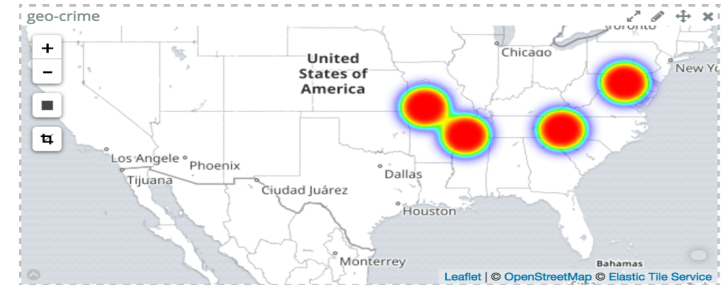
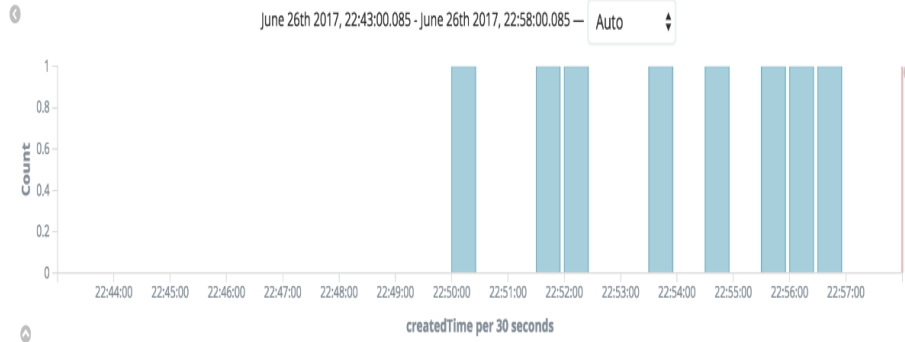
- Can be tailored to specific geo-locations
 - More reliable signals

HMM-based predictions

- Can be tailored to specific geo-locations
 - More reliable signals
- Not a real-time model
 - Incidents must be recorded and published
 - Need to update model with new incidents
- Augment the Twitter model
 - Combine the models systematically (ongoing work)

Results

- 5000 tweet training corpus collected and annotated
- Several Machine learning methods evaluated
 - Support Vector Machines with Linear Kernels work best
 - Around 88% weighted F1-score using 5-fold cross validation
- Scalable to process thousands of tweets in real-time
- Real-time visualizations of predictions



Example visualization dashboards (updated in real-time)

HMM Model

- Collected data recorded over a two month period
- Predict specific crime types for the last 10 days in the collected period
- Error rate of around 12 – 15% on average
 - Shows promise in modeling based on recorded instances
- Granularity affects performance
 - Merge/Split incidents based on zip-codes
 - Split by wards/precinct-zones, etc.

Future work

- Combine the HMM and Twitter model
 - The twitter model may not be particularly sensitive to geo-location
 - The HMM model is much more specific
- Advanced linguistic features from neural embeddings using non-annotated data
 - The duck tacos were delicious and the chocolate fondant with jalapeños and lime cream **to die for**
 - I made a **killing** from the Apple stocks today!!!
 - Whoever said head **wounds bleed** the most never **skinned** his shin while shaving!!
- Look for more events in specific tweets
 - Follow specific local individuals or organizations

Acknowledgements

- Several students
 - Saichand Upputuri (MS Summer 2017)
 - Lindsey Warren (BS Fall 2017)
 - Chris Kent (ongoing)