Predicting Fine-Grained Crime Types using Social Media

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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!!
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Signals of potential crime events
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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
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• 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
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• 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

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• 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
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• Developed a Hidden Markov Model
  • Latent crime states
  • Observable crime events (7 types of crime)
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• 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
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• 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
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