

Detecting Crime Types using Twitter

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Motivation Predict fine-grained crime occurrences that could help in efficient allocation of resources

Approach Use Twitter to provide real-time predictions of crime events specific to a Geo-Location

Data

- Collect tweets from Twitter API for a specific geolocation
- Filter tweet text with a vocabulary of common words suggesting crimes
- Annotate each tweet with one of following categories of crime (Violent Crime, Narcotics, Racism, Fraud)
- Data collected from co-ordinates corresponding to TN
- Challenging to obtain sufficient data from specific geolocations (e.g. Memphis)

Twitter-based real-time prediction

- Built on top of Amazon Cloud Services
- Collect and extract language features from tweets using Spark Streaming (cluster computing framework)
- Apply machine learning methods to categorize tweets based on language features
- Rich visual interface to interpret prediction results through Amazon cloud-based Kibana

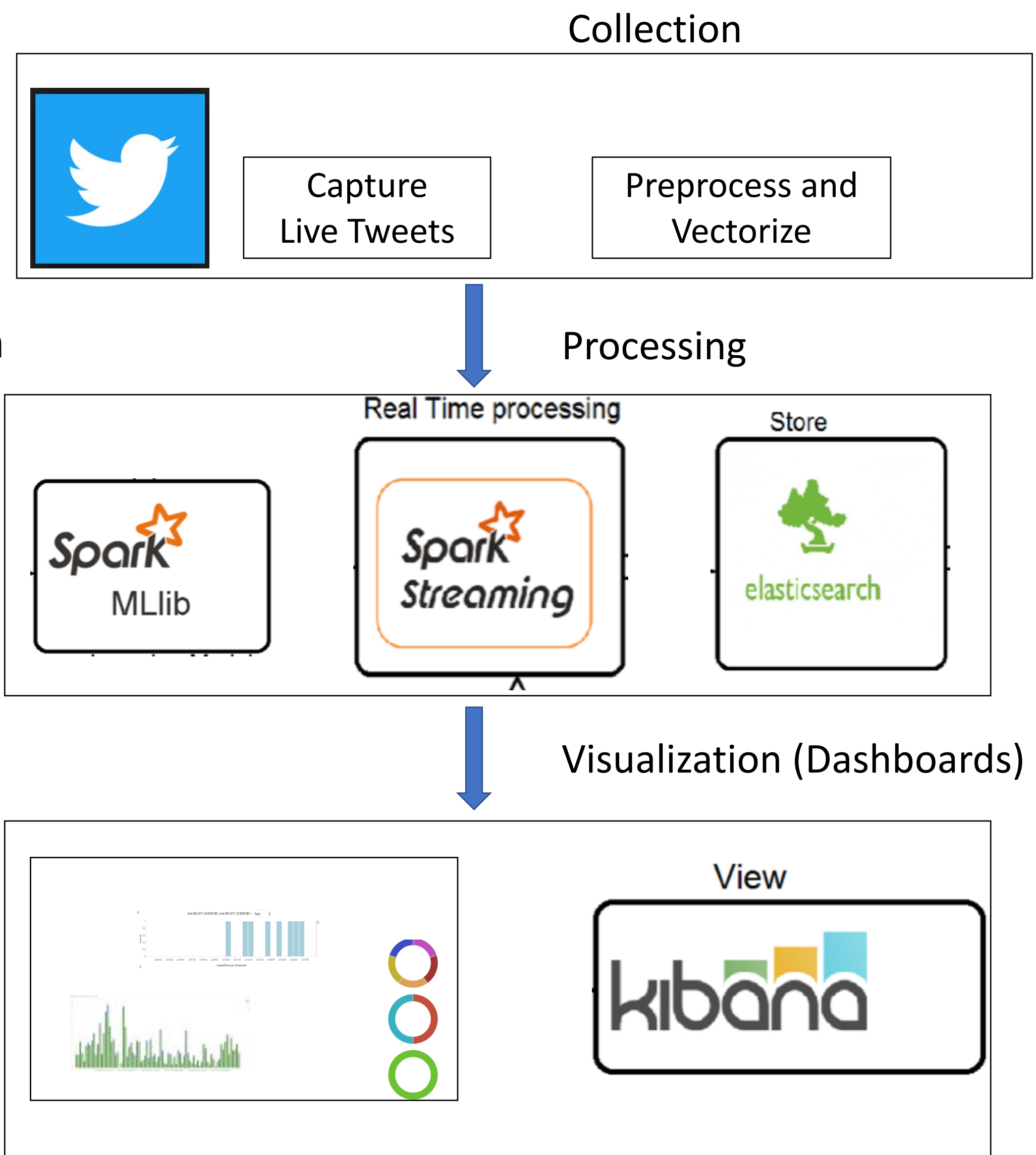
HMM model

- Twitter data has the advantage that it is real-time
- However, twitter data can be very noisy and it is quite difficult to get reliable signals for crime prediction from twitter text alone
- Augment with real crime data from **BlueCrush**
- BlueCrush** stores real crime events in Memphis, location and type of crime
- Develop a Hidden Markov Model (HMM) to predict future crime types based on recorded crimes
- Model latent crime states
- From observed incidents learn to transition between crime states

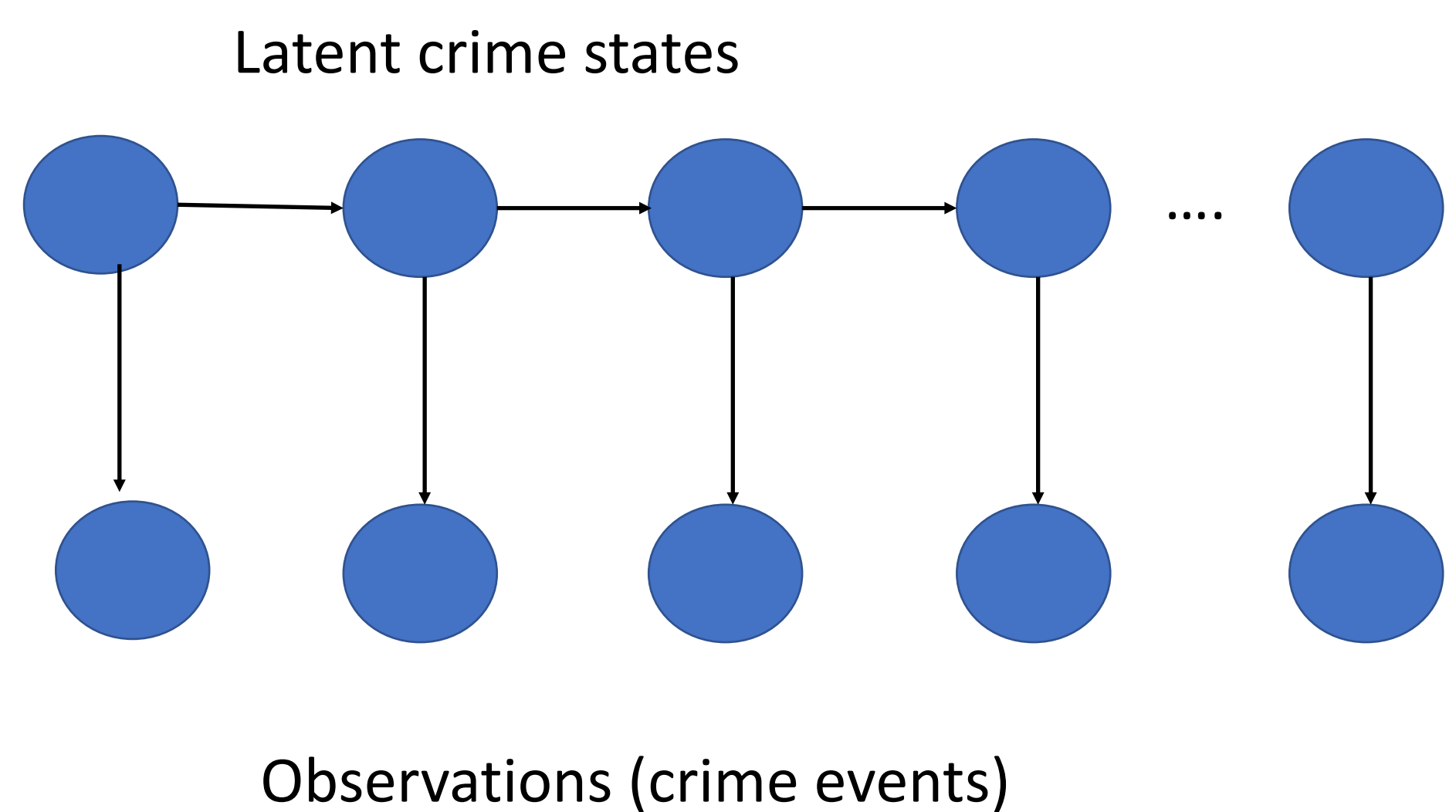
Results

- 5000 Tweet Corpus Manually annotated for training

Twitter-based real-time predictor



HMM Model

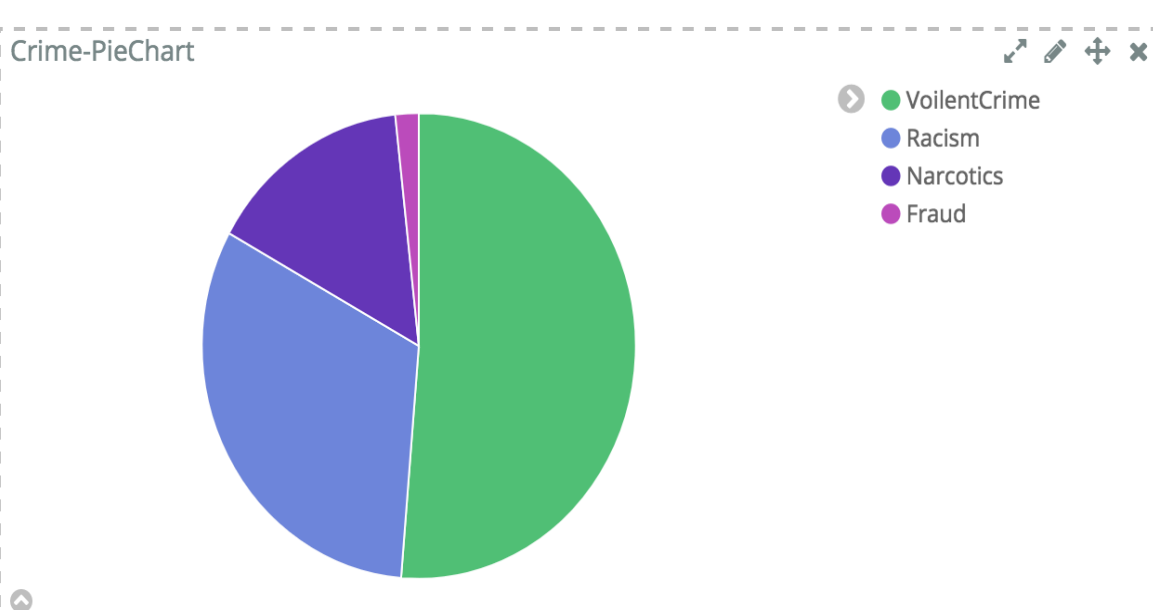


Overall System (Multi-source predictions)

- Real-time predictions using Twitter text
- Sample from the HMM model to obtain a distribution of crime states based on real crime data
- Stack the predictions (ongoing work)

Future Work

- Combine predictors from Twitter and HMM in a principled manner
- Derive advanced linguistic features using neural embeddings by taking advantage of unlabeled data
- Come up with detailed evaluation measures



Classifier	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5
Multinomial NB	0.79	0.8	0.8	0.8	0.83
Logistic Regression	0.83	0.86	0.83	0.86	0.86
SVM (RBF)	0.5	0.6	0.48	0.51	0.5
SVM (linear)	0.86	0.88	0.88	0.86	0.86

States=3	States=5	States=10
0.15	0.12	0.17

HMM predictions using a corpus of incidents from 12/1/2018 – 2/16/2018 (Error for the predicted values in the last 10 days in the corpus)

5-fold Cross Validation on annotated twitter corpus (weighted F1-scores)