LOOK BEFORE YOU LEAP

Leveraging predictive models to improve
Automotive Safety and Travel time

HANNAH DO   KAMIL SACHRYN

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Introduction

Recent growing amount of vehicles and traffic has been slowing down intensive road users, which costs over 10% of the logistic drivers' working hours. Human-based reports have high labor cost with significant delays, and current automatic incident detection algorithms have difficulties in reaching high accuracy due to unexpected circumstances and expensive costs.

Our objective is to find an optimal traffic predicting algorithm using real-time and comparatively inexpensive Twitter data to avoid congestion and optimize time cost for many people in daily lives.

Member Roles

Kamil

Generation of prediction scores from various ML models, cross validating predictions on data and implementing hyperparameter tuning to all ML models.

Implementation of multithreaded algorithms for data and prediction processing. Research into State of the art models and papers and algorithm evaluation on datasets.

Testing and evaluation of ML Models on different sets of predictors, and eliminating models which yielded no results or were incompatible. Implementation of the XGBoost model into the project.

Hannah

Implementation of collecting the datasets, feature selection from traffic accident record and retrieval of tweets through Snscape, Tweepy, and geocoding through ArcGIS.

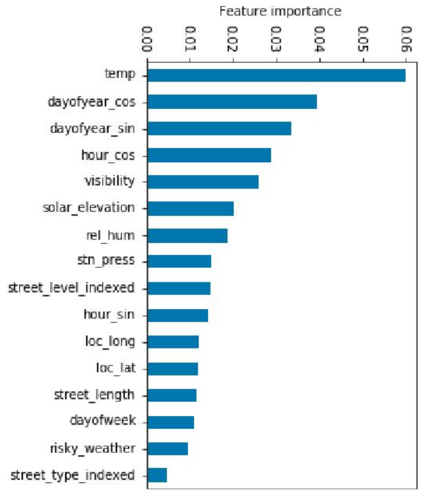
Processing the tweet texts through various NLP and Vader methods (sentiment analysis) and converted the tweet dataframe into a frequency table to integrate into traffic accident records.

Merged the two datasets based on the distance between instances and used SMOTE and random instance generation to balance the class.

State of the art

"High-Resolution Road Vehicle Collision Prediction for the City of Montreal" (Antoine Hébert et al., 2019)

Predicted risk of accidents with high spatiotemporal resolution over a large area and time, allowing for useful identification of significant risk factors. This extended the state of the art by dynamically combining three large datasets, doing feature engineering for imbalanced classes, and implementing BRF in Spark.



"From Twitter to detector: Real-time traffic incident detection using social media data" (Gu et al., 2016)

Processed real-time tweets in order to retrieve possible traffic accident areas via NLP methods

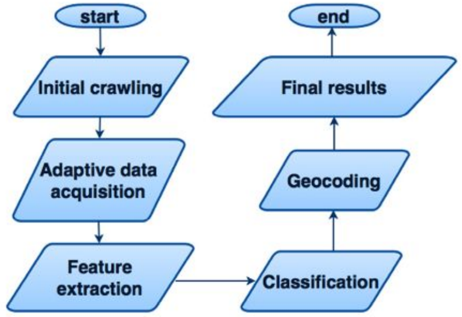


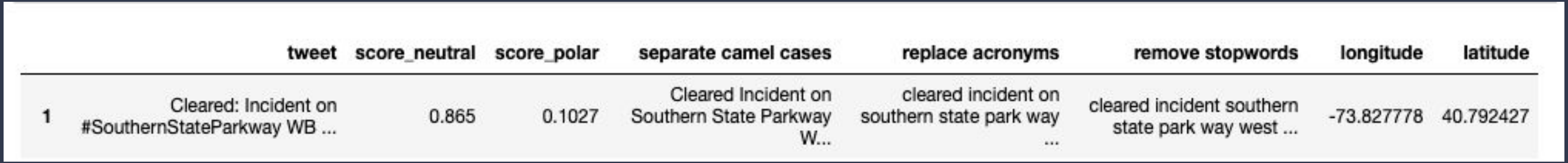
Fig. 1. The work flow of Twitter data acquisition, processing and analytics.

The methodology was applied in two regions, Pittsburgh and Philadelphia Metropolitan Areas, and the discrepancy between public Twitter accounts and individual accounts was measured.

Approach

1. Processing of tweets from public Twitter accounts to retrieve possible accident-prone geolocations

SNScrape, Tweepy - 511NY
Language Processing through NLTK packages, Sentiment Analysis through Vader method
Geocode - retrieve location through ArcGIS platform



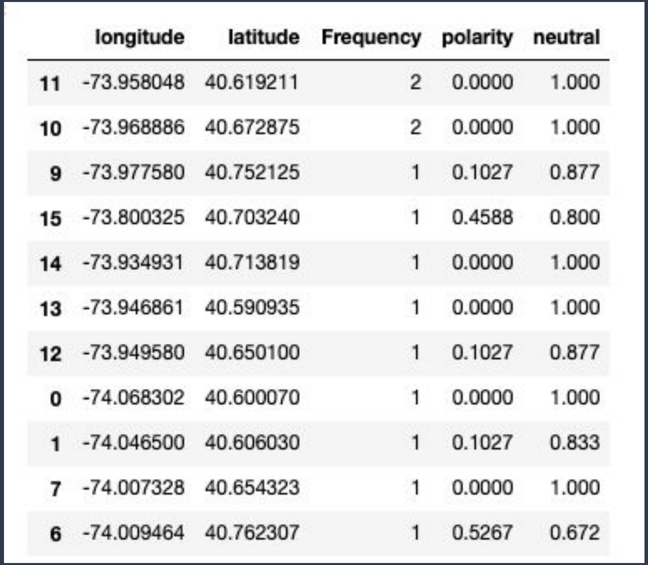
	tweet	score_neutral	score_polar	separate camel cases	replace acronyms	remove stopwords	longitude	latitude
1	Cleared: Incident on #SouthernStateParkway WB ...	0.865	0.1027	Cleared Incident on Southern State Parkway W...	cleared incident on southern state park way ...	cleared incident southern state park way west ...	-73.827778	40.792427

Text processing (left to right) - separation of camel cases, acronym replacements, removal of stopwords, and location retrieval through geocoding : returning longitude and latitude values

Approach

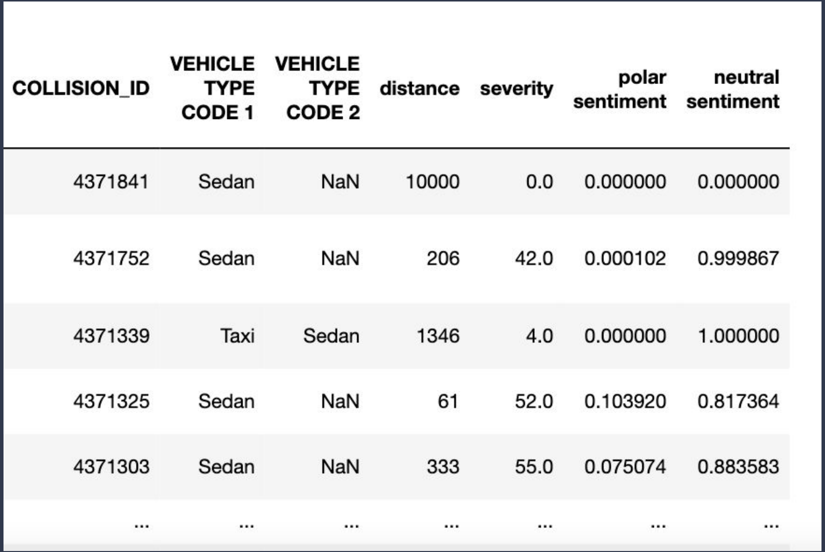
2. Addition of Twitter data as a new feature set to the previous traffic record

The existing traffic record was compared with the given Twitter geolocations. For each location (instance) in traffic record, the level of traffic is added as a new feature by calculating the distance between each location and its proximity to neighboring accident-prone areas.



	longitude	latitude	Frequency	polarity	neutral
11	-73.958048	40.619211	2	0.0000	1.000
10	-73.968886	40.672875	2	0.0000	1.000
9	-73.977580	40.752125	1	0.1027	0.877
15	-73.800325	40.703240	1	0.4588	0.800
14	-73.934931	40.713819	1	0.0000	1.000
13	-73.946861	40.590935	1	0.0000	1.000
12	-73.949580	40.650100	1	0.1027	0.877
0	-74.068302	40.600070	1	0.0000	1.000
1	-74.046500	40.606030	1	0.1027	0.833
7	-74.007328	40.654323	1	0.0000	1.000
6	-74.009464	40.762307	1	0.5267	0.672

Location frequency table (twitter features) retrieved from previous twitter collection



COLLISION_ID	VEHICLE TYPE CODE 1	VEHICLE TYPE CODE 2	distance	severity	polar sentiment	neutral sentiment
4371841	Sedan	NaN	10000	0.0	0.000000	0.000000
4371752	Sedan	NaN	206	42.0	0.000102	0.999867
4371339	Taxi	Sedan	1346	4.0	0.000000	1.000000
4371325	Sedan	NaN	61	52.0	0.103920	0.817364
4371303	Sedan	NaN	333	55.0	0.075074	0.883583
...	...	...	...	...	...	...

Twitter features added to traffic record based on distance between instances (long, lat values) : distance, severity, neutral sentiment, target

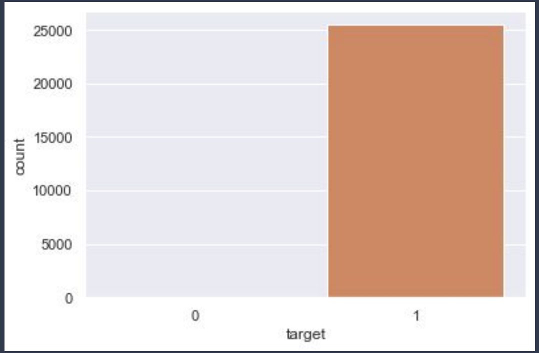
Approach

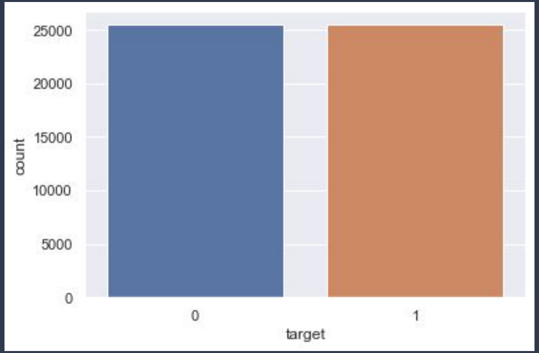
3. Addressing Data Imbalance

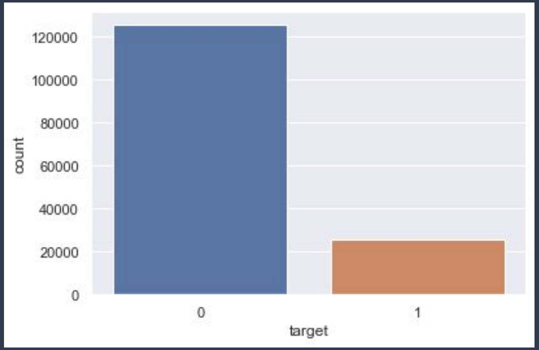
Given the large imbalance between classes (accident > non-accident instances), we carefully rebalanced these classes through random sampling of the negative class (SMOTE)

4. Evaluation on ML Algorithms

Previous work has shown that road accident risk is best predicted by models built with either decision tree-based algorithms or deep learning. We focused on classical machine learning techniques, Random Forest and its balanced variants, along with alternative machine learning models.



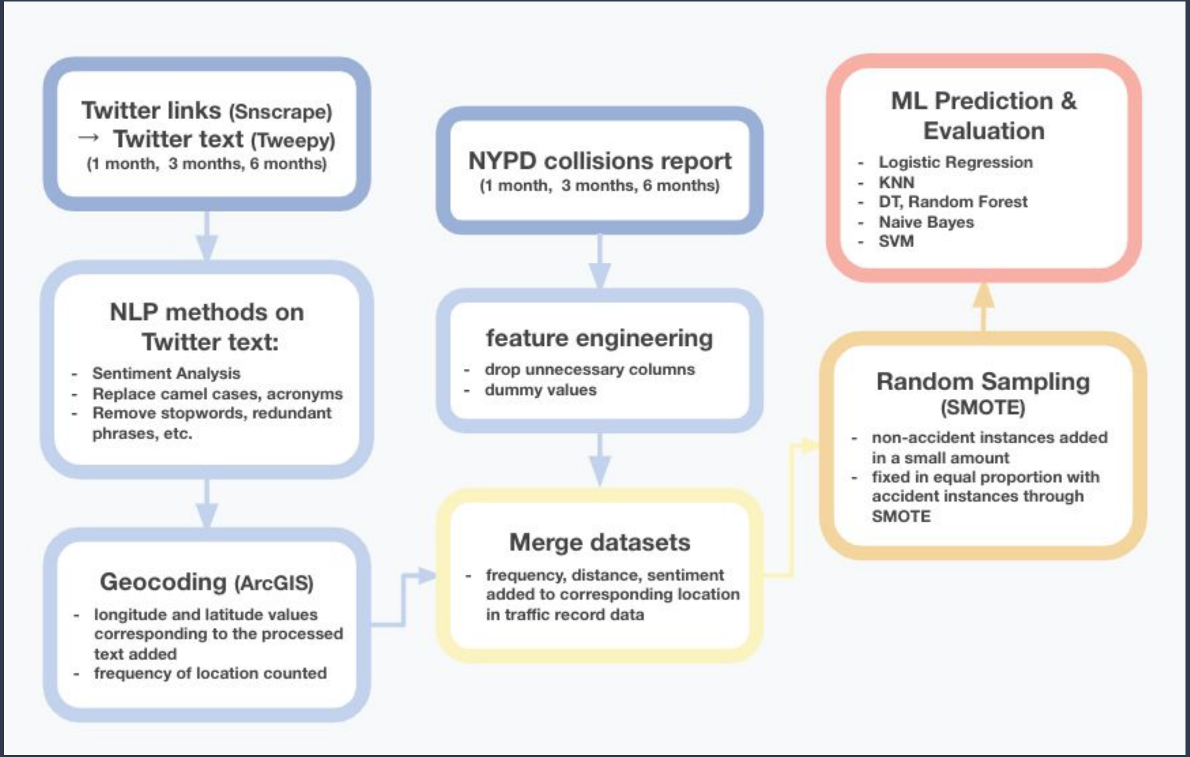




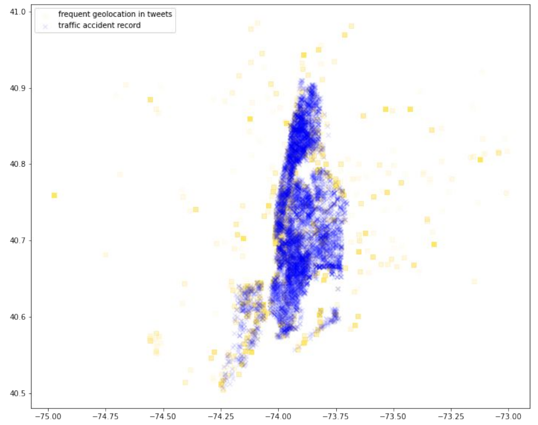
Before and after SMOTE oversampling of the minority class :
the result (right) shows equal number of target 0s and 1s after oversampling

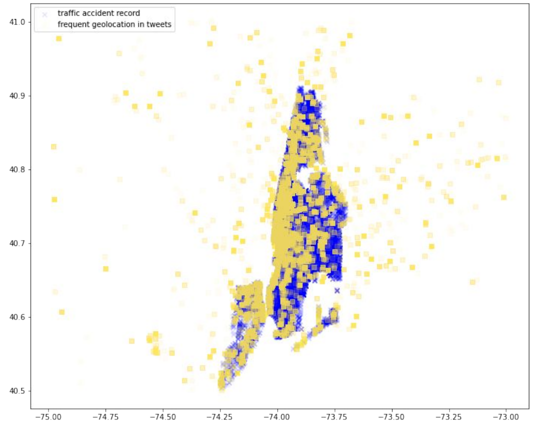
Larger portion of negative instances (target 0)
added to SMOTE data

Approach : summary


Twitter links (Snscrape)
→ Twitter text (Tweepy)
(1 month, 3 months, 6 months)
NLP methods on Twitter text:
- Sentiment Analysis
- Replace camel cases, acronyms
- Remove stopwords, redundant phrases, etc.
Geocoding (ArcGIS)
- longitude and latitude values corresponding to the processed text added
- frequency of location counted
NYPD collisions report
(1 month, 3 months, 6 months)
feature engineering
- drop unnecessary columns
- dummy values
Merge datasets
- frequency, distance, sentiment added to corresponding location in traffic record data
Random Sampling (SMOTE)
- non-accident instances added in a small amount
- fixed in equal proportion with accident instances through SMOTE
ML Prediction & Evaluation
- Logistic Regression
- KNN
- DT, Random Forest
- Naive Bayes
- SVM

Experiments & Evaluation





Scatterplot of traffic accident record (blue) and twitter geocoded locations (yellow)

Experiments & Evaluation

	1 month			3 months			6 months		
ML models	accident 1:1	twitter smote 1:1	twitter negative boost 4:1	accident 1:1	twitter smote 1:1	twitter negative boost 4:1	accident 1:1	twitter smote 1:1	twitter negative boost 4:1
kNN	1	1	1	1	1	1	0.967749	0.999054	0.971667
SVC	1	1	1	1	1	1	0.865009	0.899182	0.958956
Gaussian NB	1	0.998102	0.993450	1	0.999667	0.999841	0.907693	0.988164	0.992940
Random Forest	1	1	1	1	1	1	0.957593	0.999741	0.988900
Logistic Regression	0.547829	0.892255	0.904576	0.581027	0.957114	0.925400	0.484491	0.973014	0.941
XGBoost	1	1	1	1	1	1	0.951163	0.999283	0.998666

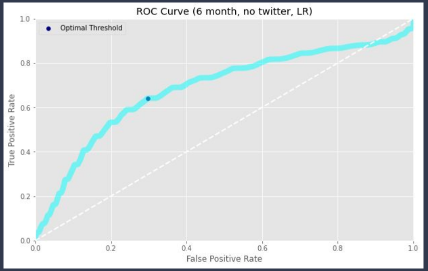
Table 1. Accuracy of prediction through different machine learning models performed on extracted data :
1 month, 3 months, and 6 months record of accident record, twitter dataset with smote method and negative instance boosting (4:1 proportion)

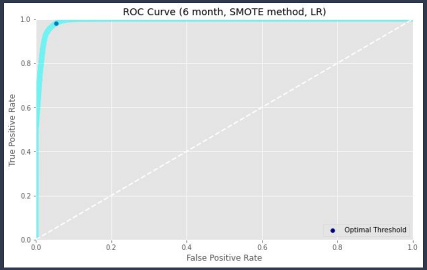
Experiments & Evaluation

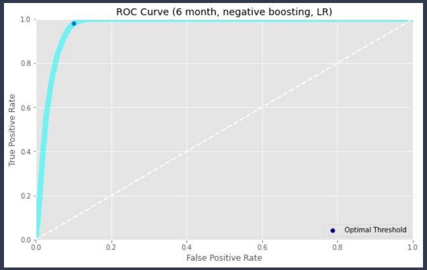
	3 months			6 months		
	no twitter 1:1	smote 1:1	negative boost 4:1	no twitter 1:1	smote 1:1	negative boost 4:1
precision	0.502156	0.933666	0.751797	0.676999	0.947914	0.787041
recall	1.000000	0.986144	0.852816	0.653652	0.979288	0.885943
f1-score	0.668580	0.959188	0.799127	0.665121	0.963346	0.833569

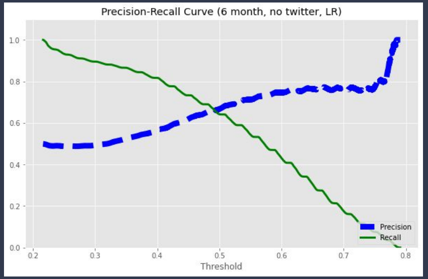
Table 2. Evaluation of Logistic Regression model on different types of datasets, precision, recall, and f1-scores were measured

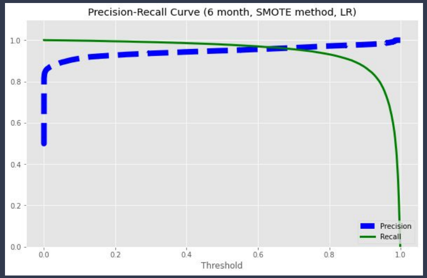
Experiments & Evaluation

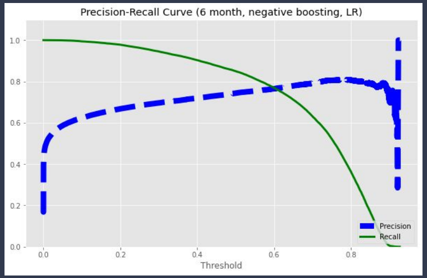






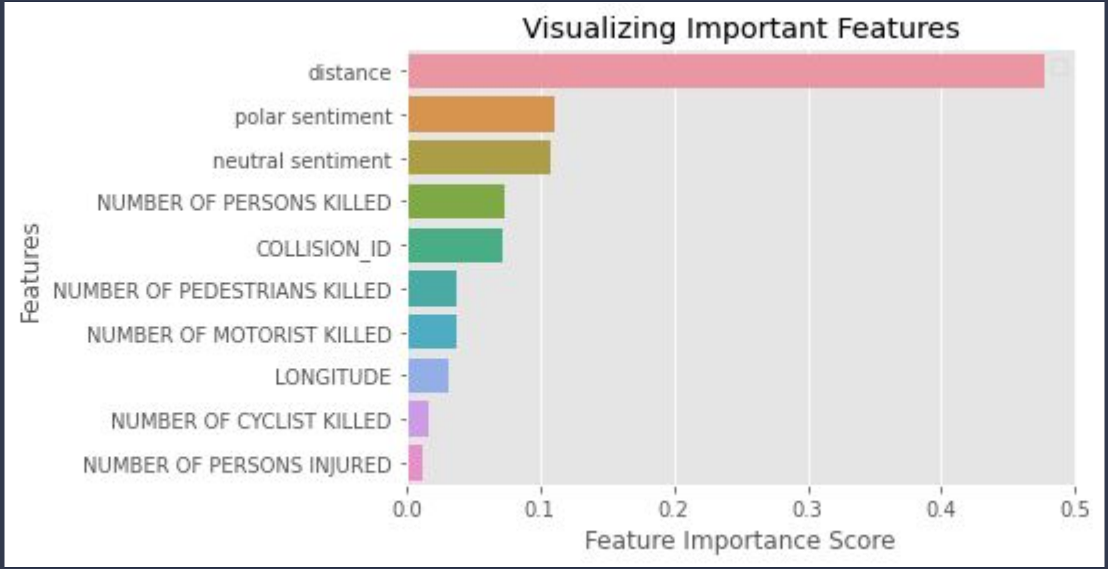




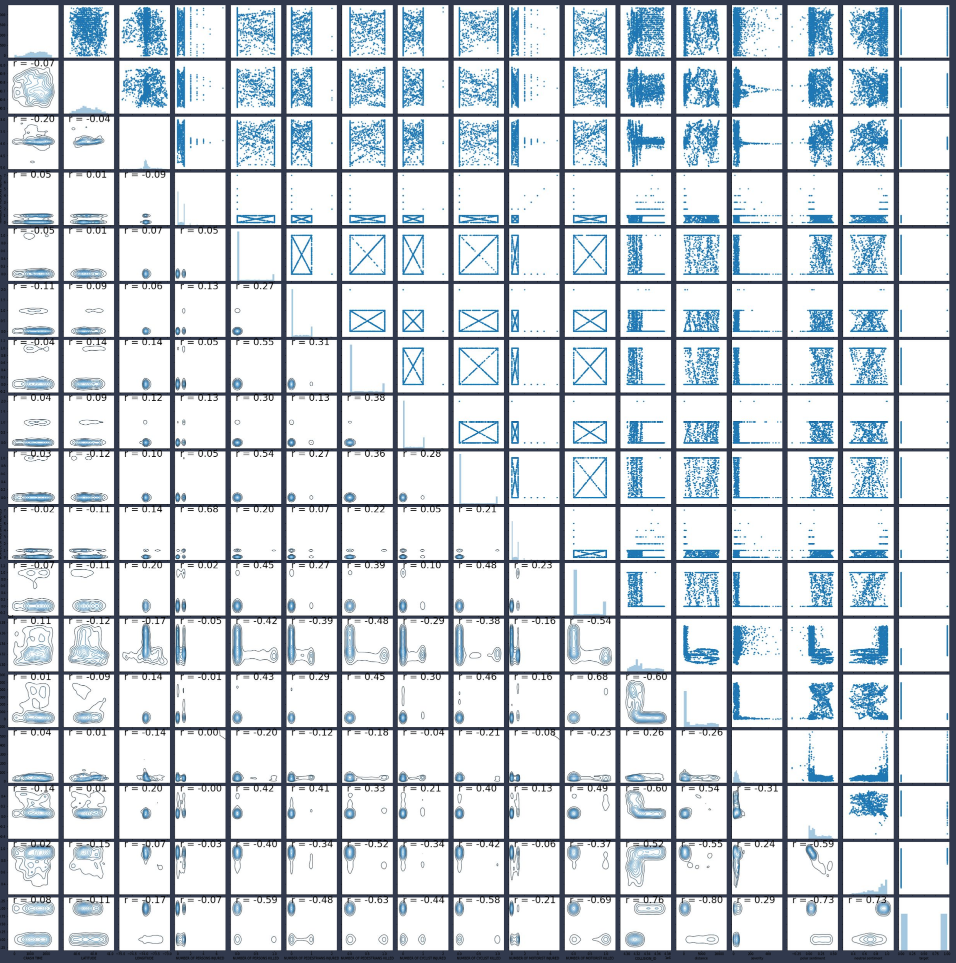


ROC Curve and Precision-Recall Curves for according datasets :
no twitter, smote, negative boosting / 6 months

Experiments & Evaluation



Feature importance scores via Random Forest function
negative boosting / 6 months



Experiments & Evaluation

Seaborn Pairgrid with Pearson r scores :
shows many correlation between the features - many of the r values are close to 0.5 or larger

Discussion

1. Dataset Collection - Missing data

Our initial choice of accident record was the Countrywide Traffic Accident (Moosavi et al., 2019) - however big portion of Queens data was missing. Switched to NYC Open Data, however it did not have weather or road infrastructure features - and there were many missing values in which we had to drop.

Geolocation of 511 NY tweets distribution had slight disparity with the traffic record data - may need clearer text processing and understanding the context of the tweets

2. Class Imbalance - Adjustments

Having only one class for binary classification, the negative instances were created randomly from a given range. SMOTE method was to amplify the negative instances to equal amount with the positive instances.

The proportion of the classes had to be adjusted due to the possibility that the created instances can be a noise to the dataset. We set the proportion to 1:4 temporarily, and it still showed significance in improving prediction scores compared to accident dataset without the Twitter features

Lesson learned about ML topics

3. Difference in performance of machine learning models

Six types of ML models were run on different datasets - accident record data, Twitter feature added data with SMOTE method and random negative instance generation - the accuracy score of the models were measured

a. Models with initial high accuracy scores - kNN, Random Forest, XGBoost
   Random Forest and XGBoost being tree-based learners are able to de-correlate the features to collect votes from different subsets or instances to improve prediction accuracy, kNN algorithms are similar in collecting votes from k nearest neighbors and branching out. These models had similarity in working efficiently for non-linear classification.

b. Models with initial average accuracy scores - SVC, Gaussian NB
   Naive Bayes having strong assumption on datasets may have lowered the performance as many features in our dataset are dependent on each other, and as SVC depends on having enough feature sets or variables to create an optimal hyperplane, in which addition twitter features seem to boosted the performance.

c. Model with greatest difference in accuracy scores - Logistic Regression
   Logistic Regression, having characteristic of creating a linear equation for classification seemed to require a set of core variables that would determine the performance. The initial score was quite low due to lack of features - 0.6, however adding the twitter increased the accuracy score up to around 0.9.

Challenges faced

Bottlenecks that slowed down the process

- Text conversion through Tweepy (Twitter API rate limit)
    - worked around by using multiple Twitter developer accounts
- Geocoding the text through ArcGIS
- Running ML models - especially SVC
    - utilized multithreading for faster performance

Barriers that can be possibly overcome in the future

- Noise in the text that lowered the geocoding accuracy
    - geocoding of bus stops in the tweets (integration of NYC bus dataset)
- Balancing the dataset for realistic simulation of accident risks
    - additional features of weather & road infrastructure

Thank you.