San Francisco Crime Classification

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***Abstract*—This is a detailed report on our work on classification of crimes in the neighbourhood of San Fransisco[1]**

***Index Terms*—Feature Engineering, Geohashing, logarithmic odds, XGBoost, One vs Rest classifiers, Grid Search, Cross Validation, Logistic Regression, EasyEnsembleCLassifier, Naive Bayes, Random Forest Classifier, SGD Classifier**

PROBLEM STATEMENT

From 1934 to 1963, San Francisco was infamous for housing some of the world's most notorious criminals on the inescapable island of Alcatraz .

Today, the city is known more for its tech scene than its criminal past. But, with rising wealth inequality, housing shortages, and a proliferation of expensive digital toys riding BART to work, there is no scarcity of crime in the city by the bay.

From Sunset to SOMA, and Marina to Excelsior, this competition's dataset provides nearly 12 years of crime reports from across all of San Francisco's neighborhoods. Given time and location, you must predict the category of crime that occurred.

DATASET

This dataset contains incidents derived from SFPD Crime Incident Reporting system. The data ranges from 1/1/2003 to 5/13/2015. The training set and test set rotate every week, meaning week 1,3,5,7... belong to test set, week 2,4,6,8 belong to training set.

- **Dates** - timestamp of the crime incident
- **Category** - category of the crime incident (only in train.csv). This is the target variable
- **Descript** - detailed description of the crime incident (only in train.csv)
- **DayOfWeek** - the day of the week
- **PdDistrict** - name of the Police Department District
- **Address** - the approximate street address of the crime incident
- **X** - Longitude
- **Y** - Latitude

[1]The problem statement is a contest hosted on Kaggle.

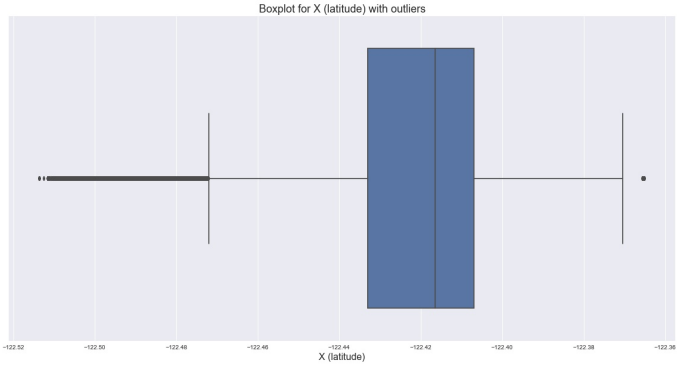
I. INTRODUCTION

With advancements in corrections, surveillance systems, weapons and armory, strict laws, frequency of crime and other illegal activities have gradually decreased in the past couple of decades. Our streets and societies are safer, but this forces us to ponder over our methodology. Punishing outlaws and criminals post-crime increases the tensions surrounding that crime and above all increases fear among people but it still doesn't prevent the crime from happening.

The concept of somehow predicting the crime before it happens is surreal but has been explored for decades. One of the first references to this idea was in the book *Mindhunter: Inside the FBI's Elite Serial Crime Unit* by Joe Penhall. The novel follows the life of two FBI agents and a Psychologist who interview dozens of serial killers and mass murderers to create a psychiatric profile for each, with hopes to use it to understand them, generalize it and eventually use it to prevent murders from happening.

The final model we'll generate won't directly help predict crimes, but give additional information to police personnel about the crime scene they are visiting. For example, 911 center sends a broadcast of the location of the crime scene and additional details they acquired from the reporter. Our model can help the police personnel better prepare for the crime scene before hand by giving them a probabilistic score of what type of crime it could possibly be.

II. DATA PRE-PROCESSING



As the dataset contains only two numerical columns, X(latitude) and Y(longitude). Using boxplot, we observed the

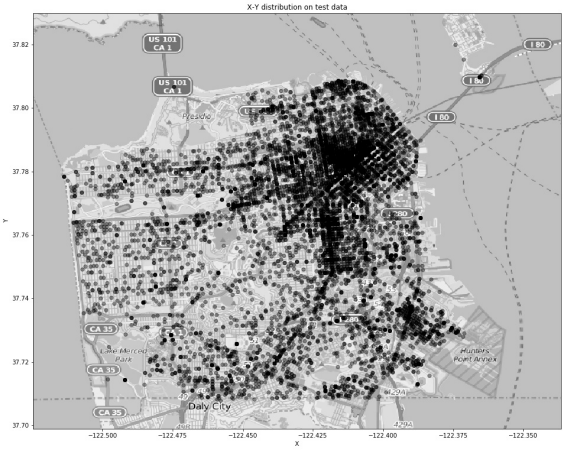
distribution, identified the outliers and removed them.

We also used StandardScaler[2] to standardize the X and Y. The standard scalar removes the mean and scales all values to unit variance.

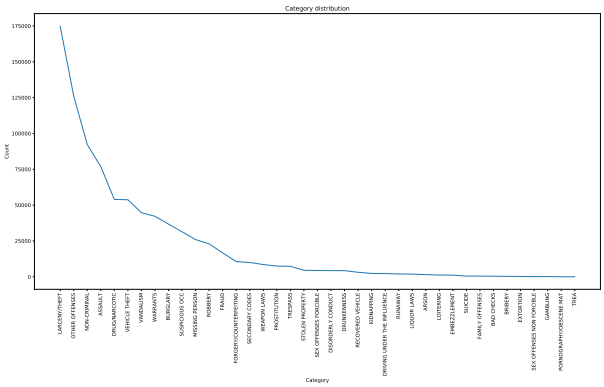
For categorical columns, we used one-hot encoding to convert them into numerical columns. Though simple numerical encoding would also give approximately the same results without drastically increasing the data dimensions, we would like to make sure our model doesn't fall to the shortcomings of numerical encoding.

III. Data Visualization

There are a total of 36 crime categories. We observed that the distribution for these categories is heavily skewed. There are only two numerical columns X and Y, which are latitudes and longitudes (not Cartesian coordinates). The test data does not contain the Descript and Resolution columns because in practice these columns won't be present when we are trying to predict crimes. The Address column is the city block number and the name of the street/alley/avenue etc.
We first observed the distribution of the crimes on the San Francisco map

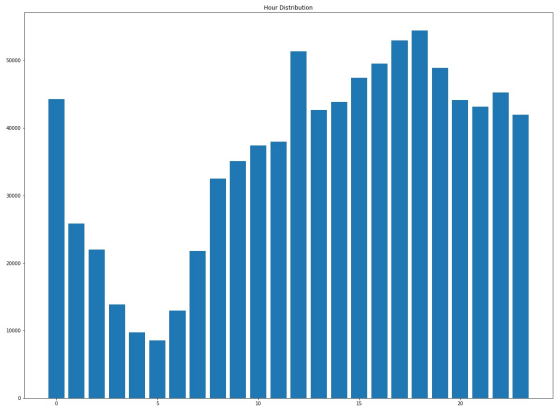


We first observe the distribution of the classes



The class distribution reflects the skewness of the categories in our dataset.

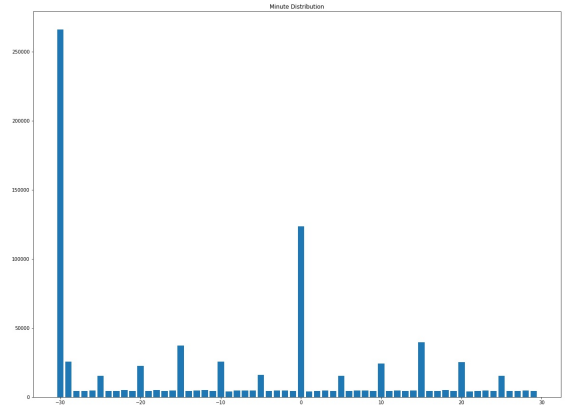
We then tried plotting histograms for year, month, hour and other time based feature to decide which ones are relevant.



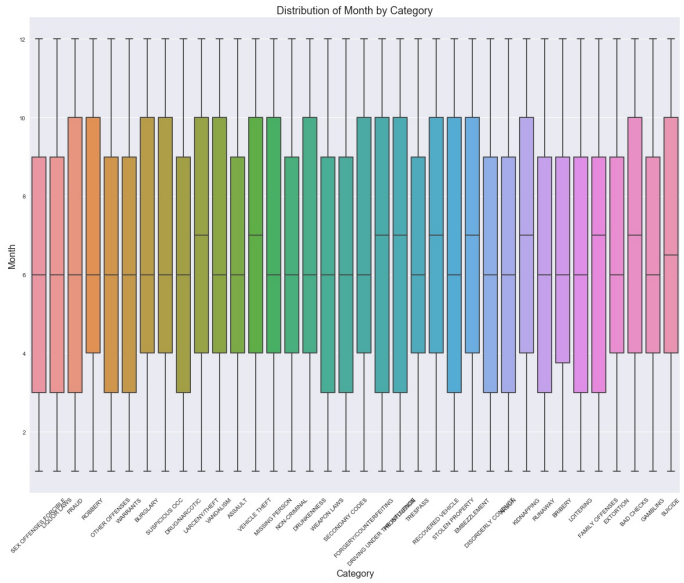
We can observed that there is a dip in the histogram of hour. This is because the number of crimes which occur at night time are significantly less than day. We also saw that there is a small peak at around midnight.

We also saw a very peculiar crime distribution based on minutes. The x-ticks tell us that the crimes have been recorded at integer multiples of 5, and most of them have been rounded off to 0 or 30 minutes. This is exactly why this feature is useful, though it is technically not supposed to be.

[2]StandardScaler function from sklearn's [1] preprocessing module



The month feature is also useful as it divides the data into proper 12 parts as seen below



IV. Feature Engineering

The X and Y features are great, but they don't make a lot of sense unless observed together. X and Y together give us the the precise location of the crime.

In order to tackle this issue, we use geohashing. Geohashing [2] is a method of creating hashes of X and Y together. The physical interpretation of these hashes would be regions on the map. As we increase the precision of the hashing function, we increase the number of discreet regions. We found a sweet spot at precision 8 in the pygeohash module. We then one-hot these hashes which will then finally tell us in which hash/region a particular X and Y coordinate lies.

We converted the date column into a python datetime object and extracted key features like month, year, dayofweek, day, hour, minute. These columns are really helpful in getting intrinsic data like patterns in daily crime frequency, patterns in weekend/weekday crime frequency, as seen in the data visualization section.

Further, in order to generalize the data, we create new columns called seasons(summer, winter, autumn, spring) [3] and time of the day(morning, afternoon, evening, night). This breakdown was done by referring to this [4] for knowing the seasonal and daily weather patterns.

The address column has a lot of data which we can extract. The data is of two types, one with two street names which refers to a road crossing and another where the block number of a area is mentioned. Blocks is a systematic way of categorizing localities in San Francisco. We used regex(regular expressions) to extract the names of the streets and check if an address is a crossing. We also use regex to extract the type of street which is also present in the address column in the form of abbreviations like AV, ST etc.

Another interesting feature is logodds(logarithmic odds). Logarithmic odds gives us the odds of a particular event to happen given an event. We find logodds for the categorical crime to occur given the address of a datapoint. This adds 36 new columns to our DataFrame, with each column giving us the logodds of a particular crime, for each row.

In our initial test data, the descript and resolution columns were also present. Though it technically doesn't make sense to have them in our test data and also to even try working around with these columns, we tried tweaking with it. We applied TF-IDF (term frequency - inverse document frequency) with ngram range - (1, 2). We got an astonishing 0.003 logarithmic loss. This is clearly because the descript column contains clear description of the category, which will obviously include the category in it.

V. Training and Results

The size of the dataset after feature engineering increased 10 fold. It's hard for machine learning models to converge properly when the data is of high dimensions. In order to reduce the size of the dataset, we project it down to lower dimensions with the help of PCA[3] to transform our dataset to a lower dimension.

We trained our data on the following algorithms

- LogisticRegression (LR)
- XGBoost (XGB)
- SGDclassifier (SGD)
- EasyEnsembleCLassifier (EEC)
- bernoulliNB (bNB)

The logarithmic loss on these models were the following

[3]PCA from sklearn's decomposition module

TABLE I
LOGLOSS ON VARIOUS ALGORITHMS

S.no	Algorithm	logloss
1	LogisticRegression	2.362
2	XGBoost	2.366
3	SGDclassifier	2.41
4	EasyEnsembleCLassifier	2.356
5	bernoulliNB	2.643

VI. Conclusion

With a logloss of around 2, we see that it is quite difficult to predict the crime based on just spatial and temporal data, accurately. We think that 911 transcripts which include data about how the crime was reported, assuming it was reported via a 91 call, will be helpful.

Acknowledgment

We would like to thank our teaching assistant Ravi Teja for helping us out in the initial stages in numerous occasions, Tejas Kotha for helping us out with different ensemble techniques and also with the report. Special thanks to Raghavan sir for, well everything. His highly detailed lectures on various topics helped us understand what we were actually doing, rather than just copy pasting code from tutorial sites.

References

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[2] W. McGinnis, "Geohashing," 2015, [First release - Jan 7, 2016]. [Online]. Available: \url{https://github.com/wdm0006/pygeohash}

[3] Y. Abouelnaga, "San francisco crime classification," *CoRR*, vol. abs/1607.03626, 2016. [Online]. Available: http://arxiv.org/abs/1607.03626

[4] timeanddate, "timeanddate," 2018, []. [Online]. Available: \url{https://www.timeanddate.com/sun/usa/san-francisco}

VII. PROJECT FILE LINK

https://drive.google.com/open?id=1re04PjcLHnEihsySEhZA4dvrVlV0ZUsI

This link contains the .csv files required to test the pickle file. Just download the files and extract them into the project folder.