Indiana University Bloomington

Machine Learning

San Francisco Crime Classification

Author:
Sujith Shivaprakash
Anup Prasad

Guided by:
Prof. Christopher
Raphael

April 25, 2016

Abstract

In this paper, we are going to discuss our work and findings on "San Francisco Crime data" .The data set provides nearly 12 years of crime reports from across all of San Francisco's neighborhoods. Given time and location, we must predict the category of crime that occurred. The predictor variables present in the data are of both discrete as well as continuous in nature. The first step towards building a classification model was to plot graphs of the attributes and discover hidden patterns . Next, we used Naive Bayes and multinomial logistic regression to predict the occurrence of crime at a given location. We evaluated our model using 10-fold cross validation. Original set of predictor variables did not give a good accuracy so, we performed feature engineering, by noticing the different patterns in graph visualizations we added new features. We then performed K-Means clustering to eliminate insignificant labels.With the new predictors, we saw a 5% increase in the accuracy of our model . At the end, we have presented a comparative study of the performance of the three classifiers viz. Naive Bayes and multinomial logistic regression .

Contents

1 Introduction

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. In this project we have explored and deduced a model that classifies the crime at a particular place given the date, time and other predictors.

2 Data Set

Crime incident data of San Francisco is available on kaggle.com. The data contains more than 0.8 million incidents of 39 different types of crime occurred in 10 different counties, at 23000 different locations during the year 2003 and 2015. There are 9 different attributes in the data, they are given in the following table along with their category.

Attribute name	Type	Description
Date	Categorical	Date and time at which crime happened
Category	Label	Type of Crime
Descript	Categorical	Short description of what actually happened
DayOfWeek	Categorical	On what day of the week crime took place
PdDistrict	Categorical	In which district crime took place
Resolution	Categorical	Short description of what action was taken
Address	Categorical	Address at which crime took place
X	Continuous	Latitude
Y	Continuous	Longitude

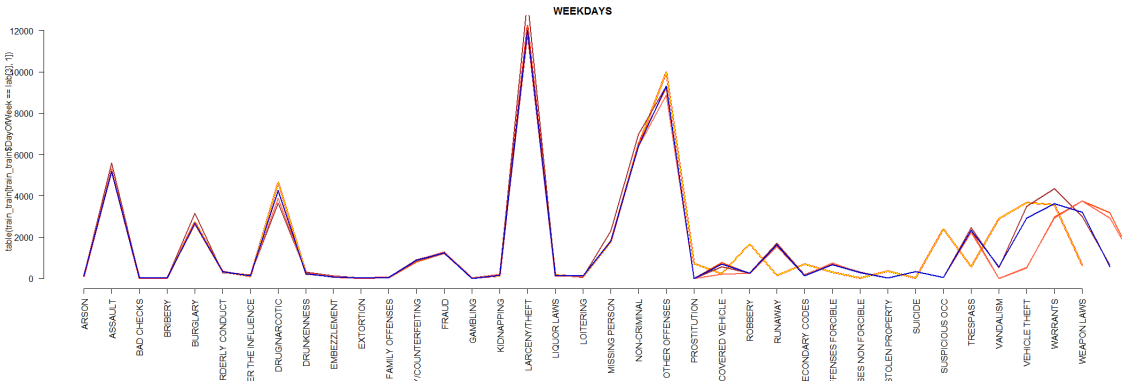
Table 1: Predictor Variables

3 Feature Engineering

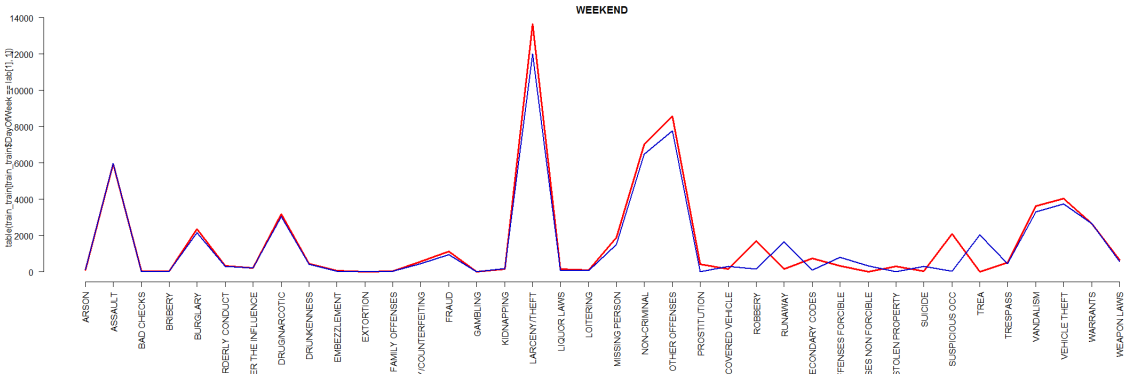
The very first step we took was to discover relationship between day of week and different categories of crime occurring on those days. We divided the days to Weekends and Weekdays, where Weekdays consisted of Monday,Tuesday, Wednesday, Thursday and Friday, and the weekends consisted of Saturday and Sunday.

3.1 Crime frequency VS Days of Week

Crime frequency on Week Days



Crime frequency for Weekends



On plotting them on graphs as shown below for different categories of crimes, we found out that there is not significant variation in the peaks of crimes occurring during both these times, in fact the peaks depicted turned out to have similar frequencies. We can see that crime which has high frequency of occurrence on week days are also having high frequency of occurrence during weekend. So creating new attributes based on Weekday and Weekend would not help us getting a better accuracy, is what we found out by experimenting.

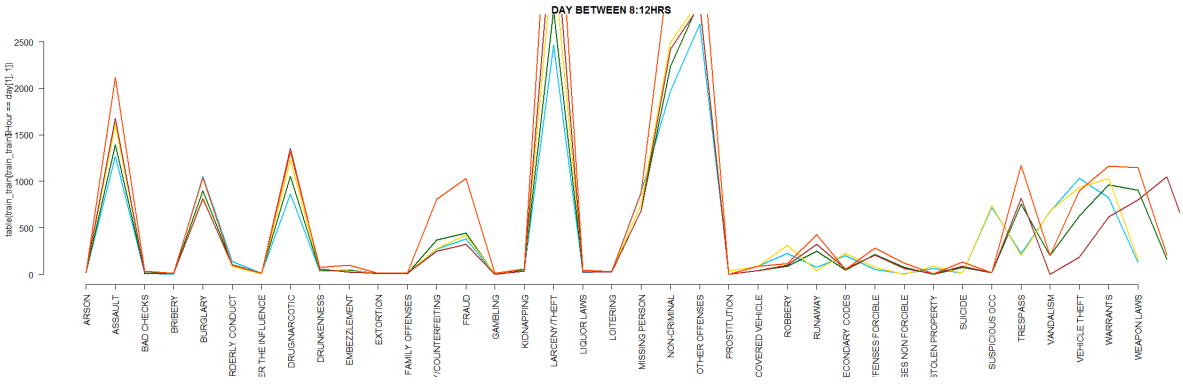
3.2 Relation Between Crime And Time of The Day

We then tried to find relationship between crimes and time of the day.For this we divided 24 hrs of a day into three categories where the first one consists of Night time from 10PM-7AM, this is usually when people are asleep; Morning-Late Afternoon category from 8AM-5PM this covers the time interval when people go to work and return back by 5PM and finally being the late Evening from 6PM-9PM.

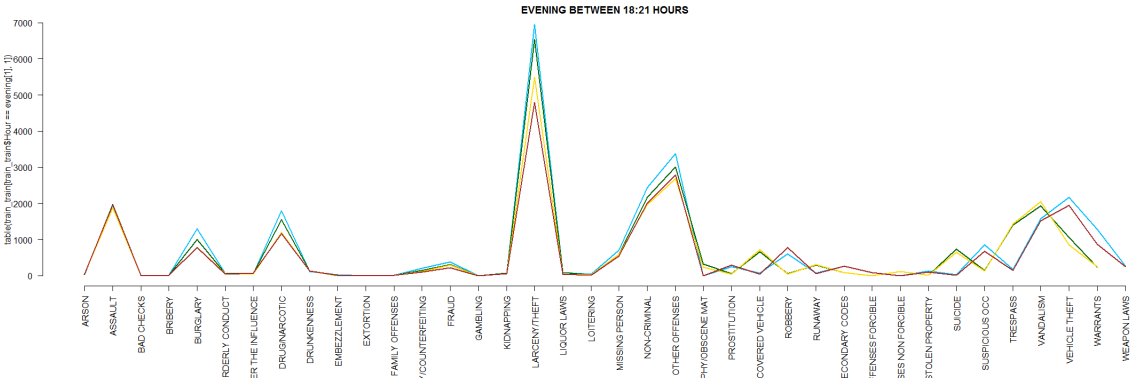
Feature	Time range
Night	10:00 PM to 7:00 AM
Morning-Late Afternoon	8:00 AM to 5:00 PM
Evening	6:00 PM to 9:00 PM

Table 2 Time category

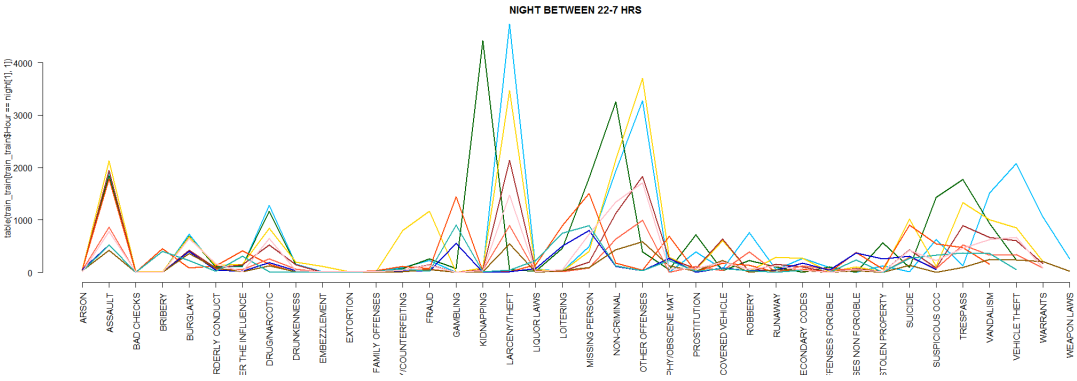
10:00 AM to 5:00 PM



6:00 PM to 9:00 PM



10:00 PM to 7:00 AM



From the above graphs one can see that,

1. Crimes like Gambling and Kidnapping has mostly occurred during night time.

2. While crime like suicide mostly has taken place during evening and some time during night .

3. Crime like Burglary has mostly taken place during office hours between 8:00 AM to 5:00 PM.

4. One can closely observe that crimes happening during night from 10PM to 7AM are spread out, i.e crimes are not just concentrated to be of a particular type like the other graphs show, rather its spread over all crimes, or the crimes are more diversified.

5. Observing the different patterns in crimes on three different times we went ahead to divide the hours of a day to three categories and added them as new features.

On the plots shown previously, one can see that the most frequently occurring peaks are of 13 different types.So, instead of having 39 different labels which we considered as it might hinder the performance of the classifier, we decided on to reduced it to 8 different labels represented by the peaks in the graphs. The rest of the labels were labeled as **OTHERS**. To verify this we performed **K-means** clustering on the labels w.r.t the different addresses. This turned out to be in agreement with our result .

3.3 K-Means: Majority class detection

We wanted to create cluster of locations based on crime. For this we used crime vector, structure of which is discussed in Data Transformation for K-Means section. This analysis helped us to filter out some of the Class labels .

euclidean distance were used to calculate distance between cluster centroid and data points.

$d(p, q) = \sqrt{(p_1 - q_1)^2 + ... + (p_n - q_n)^2}$

parameters :

K=40

Max Iteration=40

once entire data has been clustered , each cluster was given a label which is

the majority class of crime occurring in that cluster .

Algorithm to label a cluster

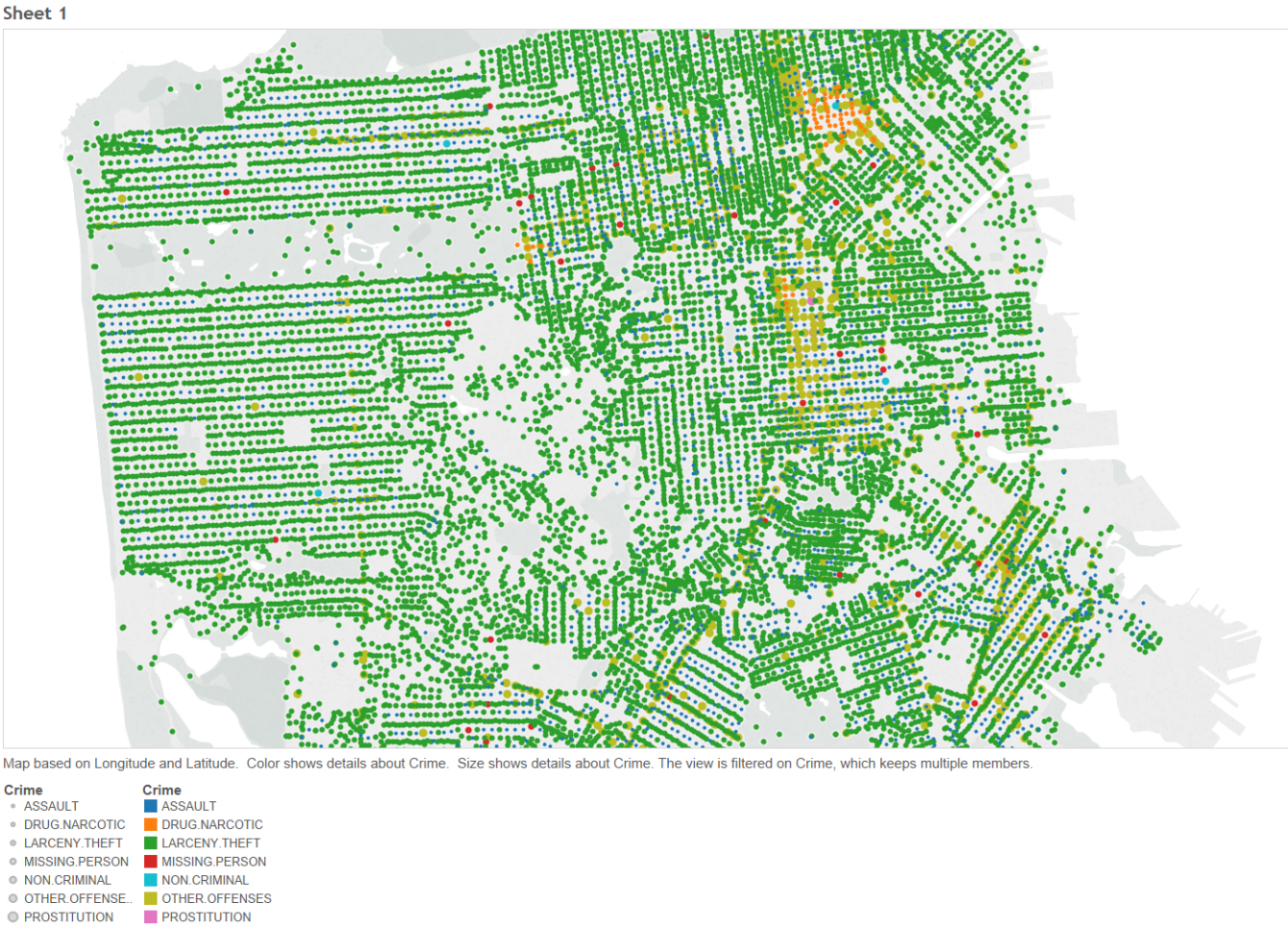
1. for each Cluster
2. $ClassLabel \longleftarrow Max(\sum_{eachAttribute} \sum_{dataPoint} sum(AttributeFrequency))$

We got 7 unique clusters .

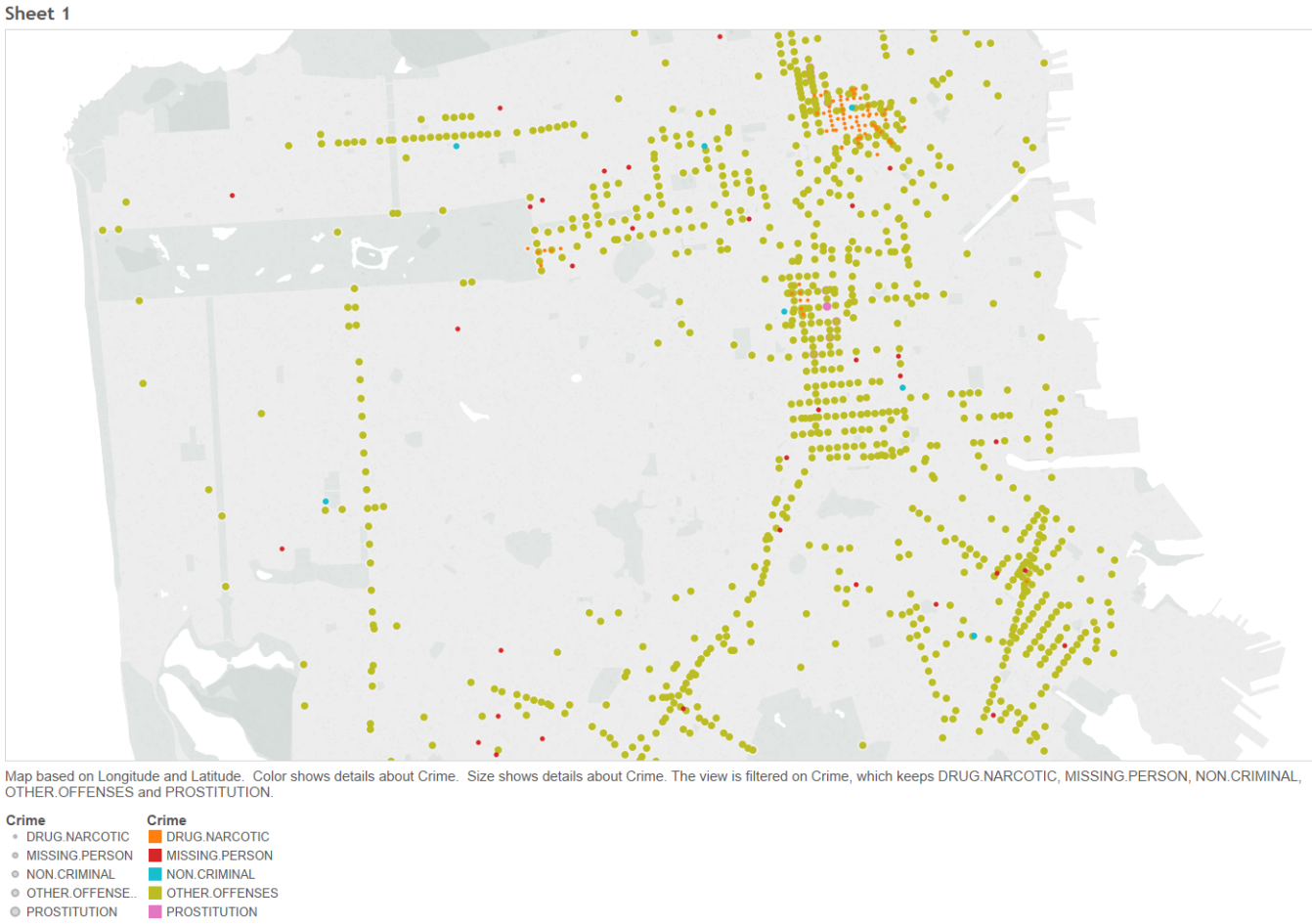
Cluster Size	Cluster Name
23	LARCENY.THEFT
112	LARCENY.THEFT
1	NON.CRIMINAL
92	ASSAULT
26	OTHER.OFFENSES
543	LARCENY.THEFT
337	LARCENY.THEFT
1	MISSING.PERSON
3	MISSING.PERSON
280	OTHER.OFFENSES
8	DRUG.NARCOTIC
44	DRUG.NARCOTIC
19	ASSAULT
25	MISSING.PERSON
44	NON.CRIMINAL
102	OTHER.OFFENSES
55	LARCENY.THEFT
12	DRUG.NARCOTIC
86	LARCENY.THEFT
10	PROSTITUTION
77	OTHER.OFFENSES
7	NON.CRIMINAL
896	OTHER.OFFENSES
1	LARCENY.THEFT
14	LARCENY.THEFT
16	OTHER.OFFENSES
1	LARCENY.THEFT
28	ASSAULT
1397	ASSAULT
10	MISSING.PERSON
1439	LARCENY.THEFT
9	LARCENY.THEFT
315	ASSAULT
22	DRUG.NARCOTIC
11851	OTHER.OFFENSES
26	LARCENY.THEFT
1	DRUG.NARCOTIC
262	LARCENY.THEFT
4936	LARCENY.THEFT
97	NON.CRIMINAL

Table 3 Clusters

Graph of major crime Next we plotted graph of 7 major crimes as detected by K-Means algorithm on the San Francisco map .



All 7 major crimes



Drug, Missing,Narcotics etc .

4 Data Transformation

4.1 One-Hot encoding

Most of the feature which we have used are discrete. To make our regression algorithm work we transformed them into numerical values being represented by 0's and 1's. We achieved this through one-hot encoding or Dummy encoding.In this encoding if a categorical attribute takes N different values that particular feature is divided into N different features. Eg.Day of Week which can take 7 unique values "Monday" to "Sunday" is converted into 7 attributes where each value is being represented by either 0 or 1.

$\Phi(WeekDays) = \{Mo, Tu, We, Th, Fr, Sa, Su\}$
E.g. $\Phi(Tuesday) = \{0, 1, 0, 0, 0, 0, 0\}$
Following variables has been converted into numeric value using one-hot encoding.

Attribute name
Months
DayOfWeek
PdDistrict
Year
Address

Table 4: Features transformed using Dummy encoding

Our final set of Feature space now includes:

Year | Month | Day | DayOfWeek | Late-Night | Morning-Evening | Late-Evening | X | Y | Address

4.2 K-Means : Crime vector

We have generated 23000+ crime vector each corresponding to one address . Each crime vector is of length 39 ,one column for each crime category . Column values are count of the particular category of crime occurred at that address .a crime vector looks like .

Address	Crime 1	crime 2	crime 3	.	.	.	crime 39
OAK ST LAGUNA ST	0	23	0	0	7	0	160

Table 5 Crime Vector

4.3 Apriori : transaction vector

We converted each address into transactional data .i.e if a crime has taken place at particular address the the corresponding entry will be 1 else 0 . So, transaction data for address A will look like
$[ARSON : 1, ASSAULT : 0, BURGLARY : 1, EXTORTION : 1..]$

5 Modeling the data

We have used following algorithm for prediction ,clustering and other statistical analysis.

1. Naive Bayes.
2. Multi-Class Logistic Regression.
3. Apriori Algorithm

5.1 Naive Bayes

For Naive Bayes classification we have used following set of attributes. Our assumption is that these predictor variable are conditionally independent given the class label.

$$\mathbf{P}(CV \in \{8crimes\} \mid PV) = max_{8crimes}(\mathbf{P}(CV) \times \prod_{PV=1}^{8} \mathbf{P}(PV \mid CV))$$

With above model we did 10 fold cross validation where we split our data into 10 equal subsets and trained on 9 subsets, then tested it on the 10th subset, and repeated this process.Through this we got an accuracy of around 17%.

5.2 Logistic Regression

Initially on performing Logistic regression on raw data we got an accuracy of 21%. However, on performing feature engineering and decreasing the number of labels we got an accuracy of 25% over 10-fold cross validation,which appears to be a significant gain given the number of labels..

$$P(y = j|\mathbf{x}) = \frac{e^{\mathbf{x}^T w_j}}{\sum_{k=1}^{K} e^{\mathbf{x}^T w_k}}$$

5.3 Apriori Algorithm

We used Apriori algorithm to find association between crimes. This helped us to know which crime is most likely to happen with other crime . Some of the top association rule are given below.
Parameter used :
Support : 0.4
confidence :0.1

LHS	RHS	support	Confidence	lift
ASSAULT	OTHER.OFFENSES	0.4042535	0.8774061	1.358874
ASSAULT	LARCENY.THEFT	0.4079559	0.8854420	1.274764
VANDALISM	OTHER.OFFENSES	0.4169967	0.8350720	1.293309
VANDALISM	LARCENY.THEFT	0.4462287	0.8936115	1.286526
VEHICLE.THEFT	NON.CRIMINAL	0.4203547	0.7054913	1.281849
VEHICLE.THEFT	OTHER.OFFENSES	0.4663337	0.7826590	1.212135
VEHICLE.THEFT	LARCENY.THEFT	0.5015068	0.8416908	1.211776

Table 6 Association Rules

From above table we can Infer following facts about crimes .

1. Vehicle theft is more closely associated with Larceny . This might be due to the fact that same kind of criminal mentality works to do these crimes.

2. Vandalism is associated with Larceny . This can be explained by the fact that person involved in Larceny doesn't care much about preserving property .

3. Assault is associated with LARCENY . Which is obvious as assault is same often go side by side with larceny

6 Results

Base line correspond to the majority class i.e. class having highest number of occurrence . In the given data set majority class is LARCENY-THEFT with 19.91 of occurrence .

Algorithm	Accuracy	Base Line
Naive Bayes	18.61 (10 Fold)	19.91
Naive Bayes	18.39 (5 Fold)	19.91
Naive Bayes	18.07 (3 Fold)	19.91
Multi Class Logistic Regression	25	19.91

Table 7 Result in percentage

7 Conclusion

Multi-class logistic regression outperformed the base line. However,the accuracy is not high,we believe that we could have achieved a better accuracy on performing Feature Engineering on other attributes like Year and Address.Also,we believe that the predictor variables are not good enough to predict occurrence of crime at a particular location . We need more and better predictors related to population's demographic distribution.

8 References

1. Pattern Recognition and Machine Learning by Bishop .

2. Machine Learning Tom M. Mitchell .

3. Introduction to Data Mining by Michael Steinbach, Pang-Ning Tan, and Vipin Kumar .