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ECON9000 FINALS

Data Description

The raw data was gotten from <https://we.tl/t-9q2e1SRVpR>, this dataset represent crime data for the city of Chicago from 2001-to date(with the exemption of sensitive information especially for active cases).

The data set had millions of entry so the first thing I did was write a code (crimes_data_cleaning.py) that broke the data down to years I was interested in and began the cleaning process.

The first part of the cleaning was restricting my data set to crimes recorded between 2017-2018 and use that for my predictive analysis, next step was to take care of all missing values and ensure all the datasets could be run of the various packages that there were going to be tested on.

From a dataset with about 30 labels, I restricted the dataset to contain the following labels (Arrest, Domestic, District, Ward, Community Area, FBI Code, Census Tracts, and Police Districts)

These labels were chosen for the following reasons

- the FBI Code Identified the crime committed so we had no use for any other labels describing the same incident. There are a total of 26 codes for these identifying various crimes at various locations, Table 1. below shows a breakdown of each code and crime it identifies.
- The Ward label identified the location of each of the crime incidents recorded. The city of Chicago has a total of 50 wards with each number identifying a specific ward.
- The Arrest and Domestic Labels were texts (True or False) which were recorded to 1 or 2, so we don't have any issues running the data through any of our models.
- The census tracts was chosen, under the assumption that arrears with higher populations will have higher crime rates values between 1-800 were recorded under this label
- The police districts identified the police sector of the state that handled the case and patrols a specific ward or community area
- Community area was an additional location Identifier with the city of Chicago having a total of 77 community areas.

| FBI Code | Crime Description |
|----------|----------------------------|
| 02 | Criminal sexual assault |
| 03 | Robbery |
| 05 | Bulglary |
| 06 | Larceny |
| 07 | Motor vehicle theft |
| 09 | Arson |
| 10 | Forgery and counterfeiting |
| 11 | Fraud |
| 12 | Embezzlement |
| 13 | Stolen property |
| 14 | Vandalism |
| 15 | Weapons violation |
| 16 | Prostitution |
| 17 | Criminal sexual abuse |
| 18 | Drug abuse/ narcotics |
| 19 | Gambling |
| 20 | Offense against family |
| 22 | Liquor license |
| 24 | Disorderly conduct |
| 26 | Misc non-index offense |

Table 1: FBI Code for criminal offense

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|--------------|---------|----------|-----------|-----|-----|
| arrest | 191,894 | .2010433 | .4007814 | 0 | 1 |
| domestic | 191,894 | .0718782 | .2582868 | 0 | 1 |
| district | 191,894 | 11.33064 | 6.973741 | 1 | 31 |
| ward | 191,894 | 23.94619 | 14.26655 | 1 | 50 |
| communitya-a | 191,894 | 35.57176 | 21.45778 | 1 | 77 |
| fbicode | 191,894 | 11.52515 | 7.215681 | 2 | 26 |
| censustracts | 191,894 | 376.8907 | 235.5075 | 1 | 801 |
| policedist-s | 191,894 | 14.85121 | 6.409629 | 1 | 25 |

Figure 2: Descriptive statistics of variables

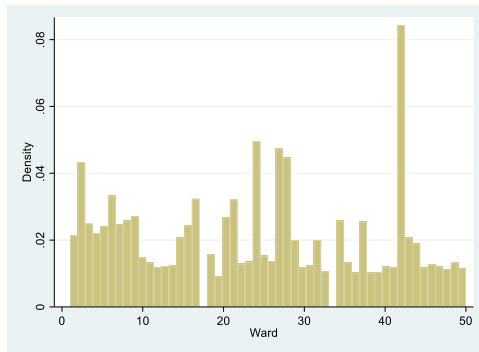


Figure 2: histogram showing wards and frequency of reported crime incidents between 2017-2018

ANALYSIS

The variables/labels collected and cleaned were chosen for specific reasons to aid our analysis, first its been long debated that increased policing could potentially increase the crime rate in cities, this is a well-studied topic under econometrics, hence our inclusion of police districts in the dataset to see how it affects the crime rate in certain wards, also with the FBI Code we will be able to identify specific crimes and possibly tie them to areas where they occurred frequently. Our final assumption is that higher populations could potentially increase the crime rates in certain wards/communities hence our inclusion of this variable in the analysis.

This dataset will be analyzed using the following models:

1. Linear regression.
2. Random Forest.
3. Decision tree.
4. KNeighborsClassifier.

Each of these models were compared using certain parameters observed after running the respective models. Mean squared Error, R-squared, Accuracy Score, and confusion matrix to see how often predictions are correct.

We also performed some tuning for some of the models in order to have the best parameters obtainable for each of the models, this process was carried out for the knn_model with the k_neighbors values tested from 5-8 and the highest accuracy score obtained for k_neighbor value of 7.

| K_Neighbor Value | 5 | 6 | 7 | 8 |
|------------------|----------|----------|----------|----------|
| MSE | 6.911703 | 6.821798 | 6.794957 | 6.780949 |
| Accuracy | 0.815087 | 0.815504 | 0.819381 | 0.817484 |
| R2_score | 0.764465 | 0.770553 | 0.772355 | 0.773292 |

Table 2: comparative results of KNN tuning

A similar approach was done for the Random_forest n_estimator, we varied its value between 11 and 14 and we found that the best parameters were obtained at the n_estimator value of 12, below is a breakdown of the changes in parameters when this was done.

| N_estimator (Random Forest) | 11 | 12 | 13 | 14 |
|-----------------------------|----------|----------|----------|----------|
| MSE | 6.359978 | 6.350872 | 6.389598 | 6.373805 |
| Accuracy | 0.835014 | 0.835098 | 0.834577 | 0.834410 |
| R2_score | 0.801151 | 0.801720 | 0.799295 | 0.800286 |

Table 3: comparative results of Random Forest Tuning

| Evaluating Model | Linear Regression | KNN | Decision Tree | Random Forest |
|------------------|-------------------|----------|---------------|---------------|
| MSE | 11.112631 | 6.794957 | 6.374145 | 6.350872 |
| Accuracy | - | 0.819381 | 0.833680 | 0.835098 |
| R2_score | 0.391139 | 0.772355 | 0.799678 | 0.801720 |

Table 4: Comparative result of Machine Learning models and their performance.

The comparative result shows that the Random forest model gave the best results in terms of accuracy, r2_score and MSE, with the linear model giving the least convincing results and can be identified as the least reliable model of all the four models used for our analysis. It is also important to note that random forest takes multiple trees into account and gives an average result which proved to be perfect for this data.

