# Crime Prediction for Houston

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Springboard

# Outlines

- Problems and Clients
- Data Acquisition and Data Cleaning
- Exploratory Data Analysis
- Machine Learning Models and Predictions
- Conclusions and Future Work

# Problems

- How safe is the city we live in regarding crime rates?
- What are the main types of crimes in neighborhoods?
- How has the crime rate changed over past years?
- Which types of crimes have increased and which has decreased and why?

# Problems

- Most importantly what message can we take from historical data to reduce crimes?
- In case of crimes how can we be more prepared to minimize losses?

# Clients

- Police board, government, and general public would be beneficiaries.
- Police officers can use this model to be better deployed.
- The government can take precautions more efficiently.
- Residents can use this model to better protect their lives and properties.

# Data Acquisition

The crime data is acquired from HPD

| Date | Hour | Offense Type | Beat | Premise | Block Range | Street Name | Type | Suffix | # Of Offenses |
|---|---|---|---|---|---|---|---|---|---|
| 1/15/2010 | 20 | Robbery | 4F10 | 24P | 1300-1399 | GESSNER | DR | - | 1 |
| 1/3/2010 | 20 | Robbery | 4F10 | 120 | 1400-1499 | GESSNER | DR | - | 1 |
| 1/13/2010 | 17 | Robbery | 4F10 | 18A | 10100-10199 | WESTVIEW | - | - | 1 |
| 1/15/2010 | 15 | Robbery | 4F10 | 18A | 1300-1399 | GESSNER | DR | - | 1 |
| 1/8/2010 | 21 | Robbery | 4F10 | 18A | 9500-9599 | LONG POINT | RD | - | 1 |
| 1/13/2010 | 16 | Robbery | 4F10 | 20A | 1600-1699 | WITTE | RD | - | 1 |
| 1/14/2010 | 23 | Aggravated Assault | 4F10 | 20A | 10300-10399 | WESTVIEW | - | - | 1 |

It reports **seven** types of crimes on a monthly basis:

- murder
- rape
- robbery
- aggravated assault
- burglary
- theft
- auto theft

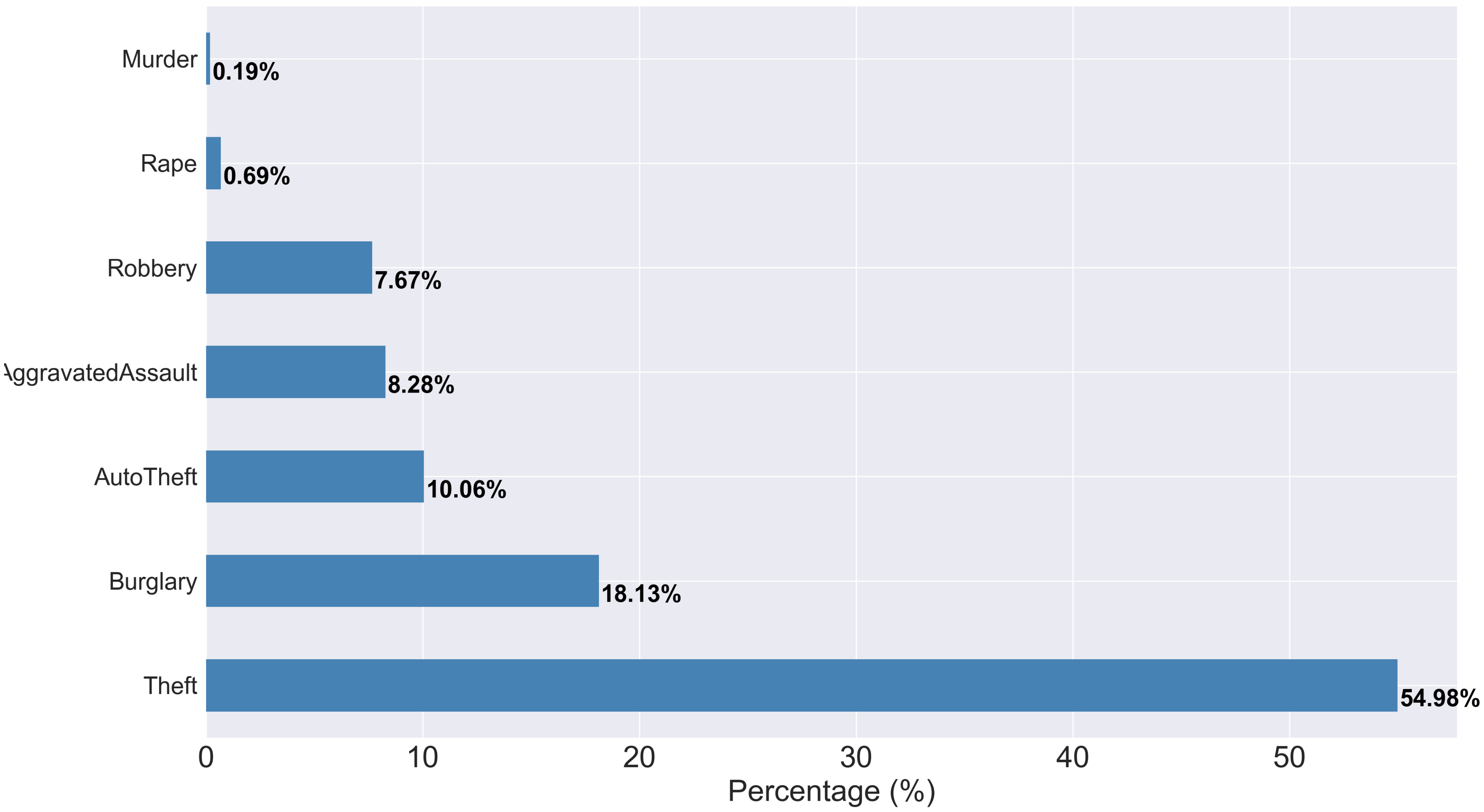
# Data Cleaning

- Drop empty columns, empty rows, and the rows with missing ***'Date'***.
- Fill columns with missing values by 'UNK'.
- Select ***Date'*** in the range '2010-01-01' to '2017-12-31'.
- Clean column '***Hour***' to contain 24 unique integers 0-23.
- Clean column '***OffenseType***' to contain 7 types of crimes.
- Reduce the number of '***Premise***' from 126 to 25.
- Clean '***Beat***', '***Type***', '***Suffix***', '***StreetName***' by stripping whitespaces.
- Check duplicates and drop duplicated observations.

**A summary statistics of 'object' features**

| | Date | Hour | OffenseType | Beat | Premise | BlockRange | StreetName | Type | Suffix |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 999521 | 999521 | 999521 | 999521 | 999521 | 999521 | 999521 | 999521 | 999521 |
| **unique** | 2922 | 24 | 7 | 127 | 25 | 347 | 27780 | 35 | 5 |
| **top** | 2010-10-01 00:00:00 | 18 | Theft | 19G10 | 20 | 100-199 | WESTHEIMER | - | - |
| **freq** | 486 | 56952 | 549488 | 21299 | 316318 | 13738 | 27214 | 239896 | 861934 |

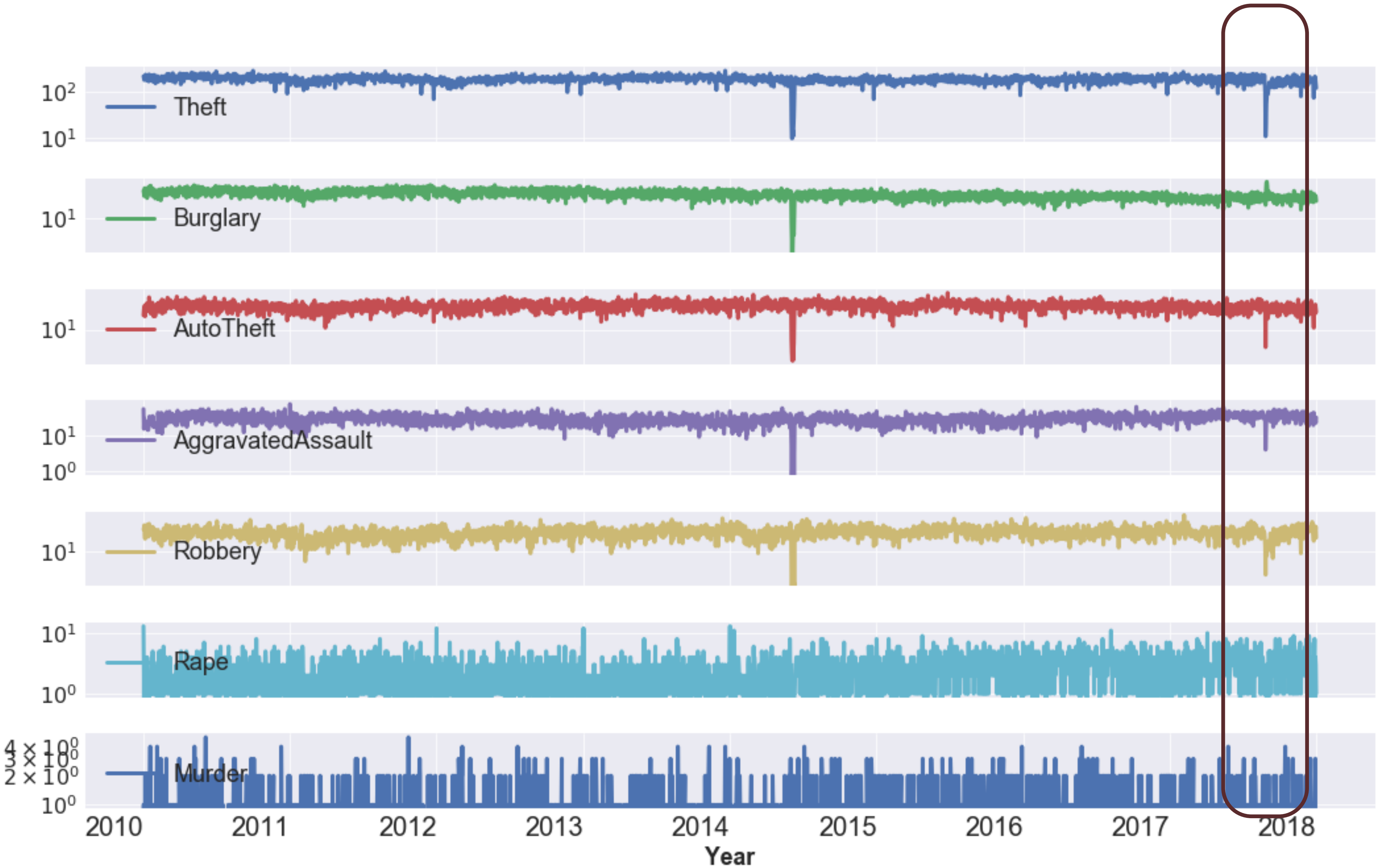
# Exploratory Data Analysis




‘Theft’ is the dominant crimes, followed by ‘Burglary’, ‘AutoTheft’, ‘AggravatedAssault’ and ‘Robbery’ while ‘Rape’ and ‘Murder’ only takes a rather small portion.

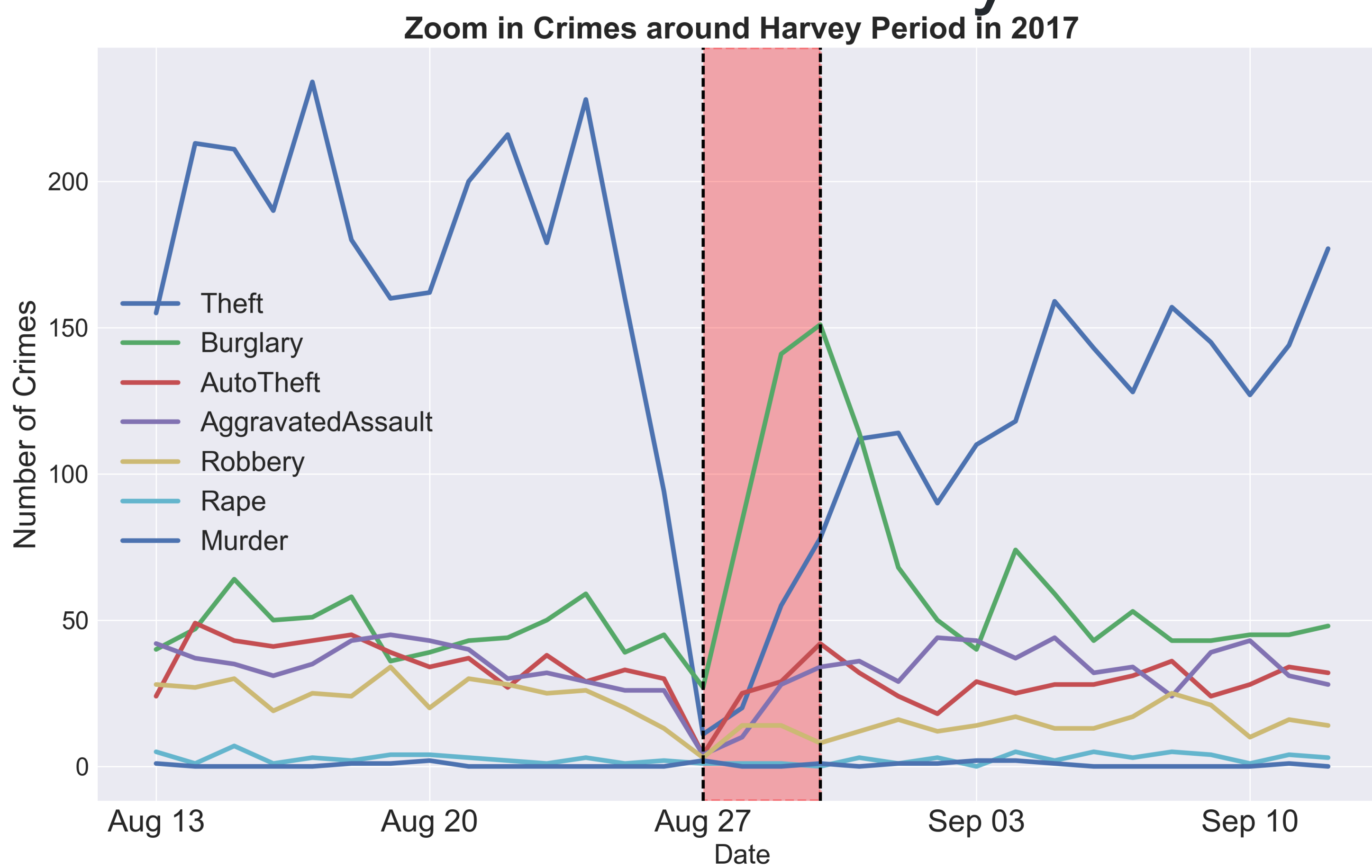
# Exploratory Data Analysis

## Time series analysis



# Exploratory Data Analysis

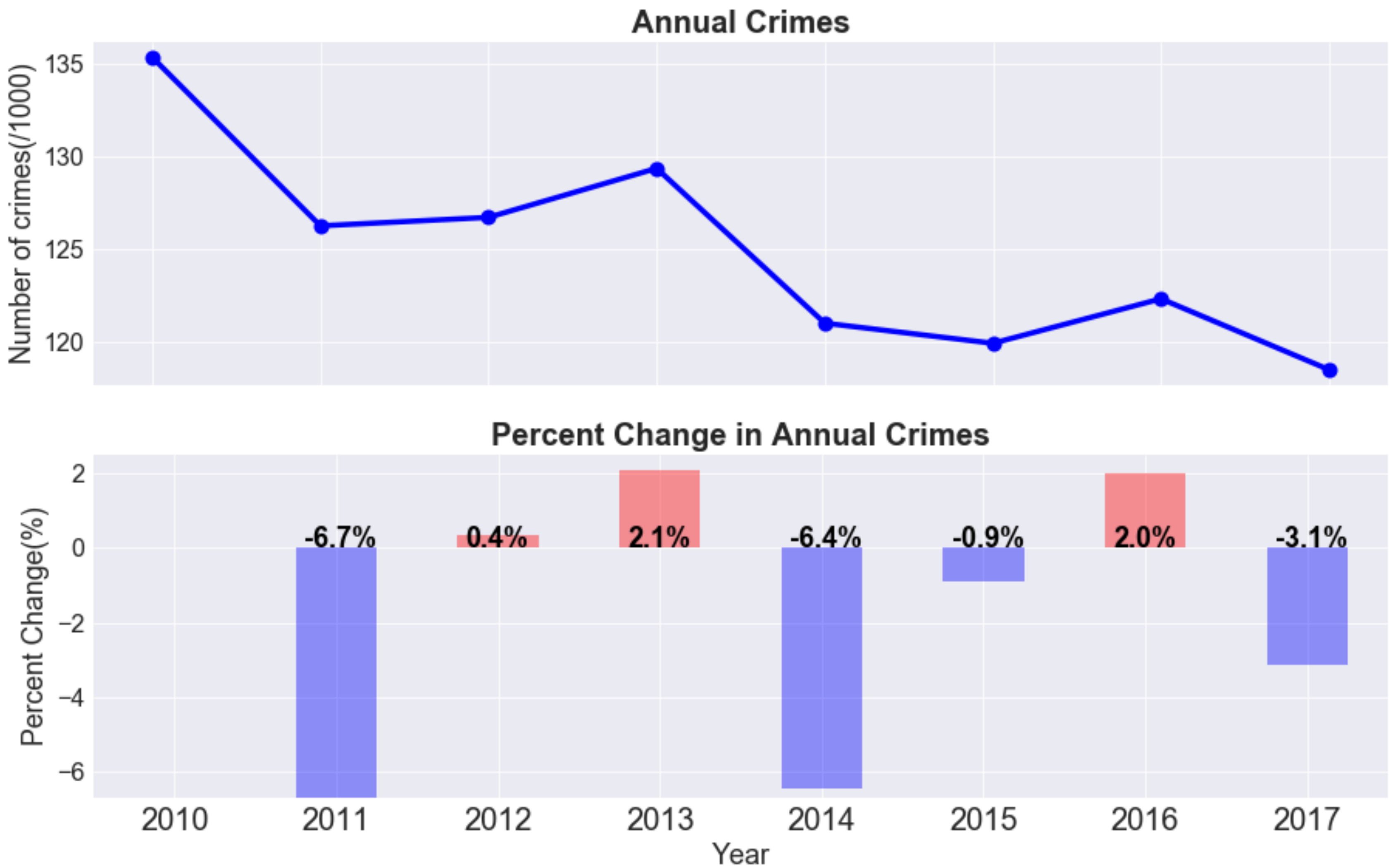
## Time series analysis




In the hurricane Harvey Period, crimes dropped overall. However, ‘Burglary’ quickly increased followed by ‘Theft’, ‘AutoTheft’, ‘Robbery’ and ‘Assault’.

# Exploratory Data Analysis

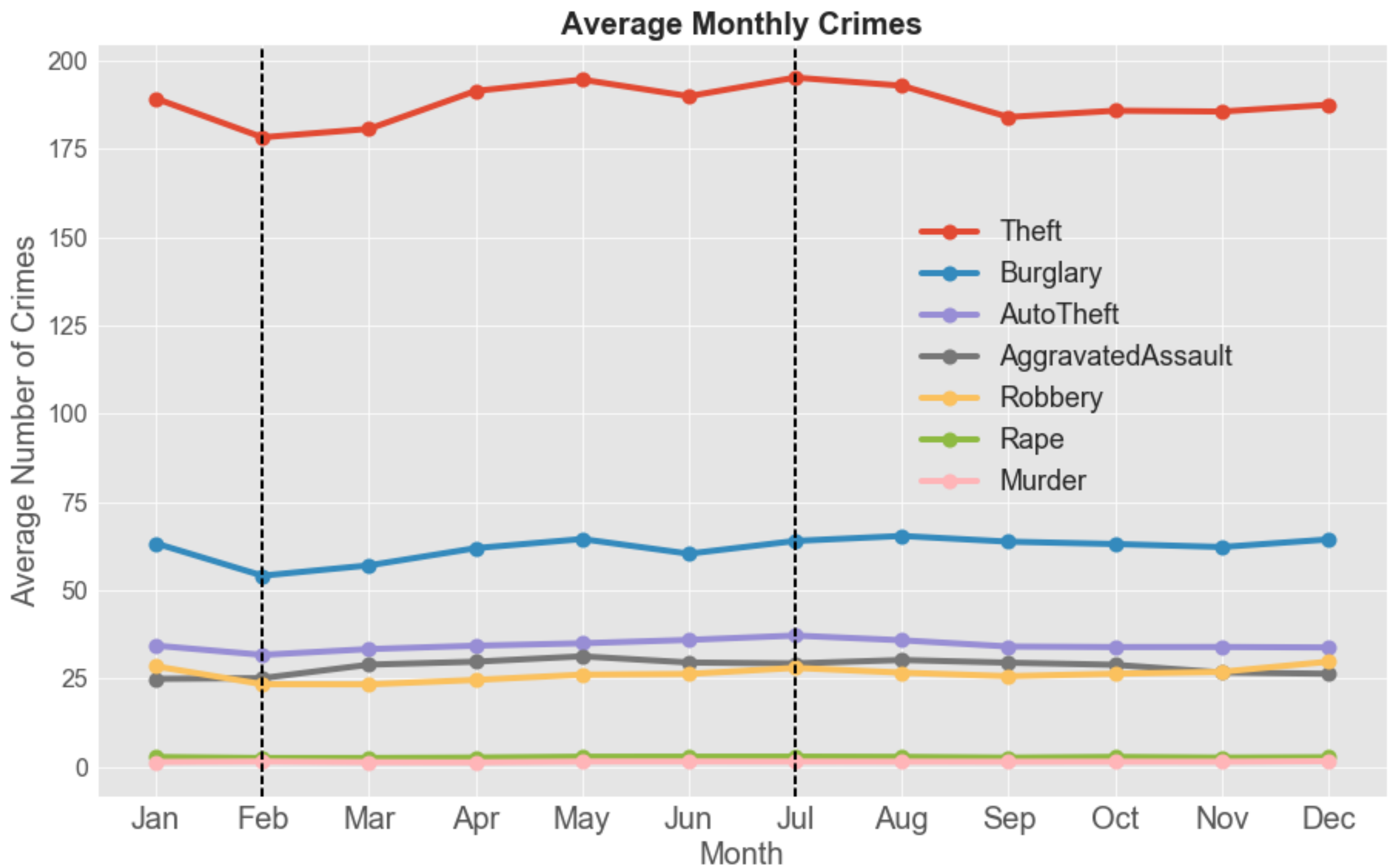
## Time series analysis: year




The crime trend: overall crimes in Houston have a decreasing trend in 2017 compared to 2016.

# Exploratory Data Analysis

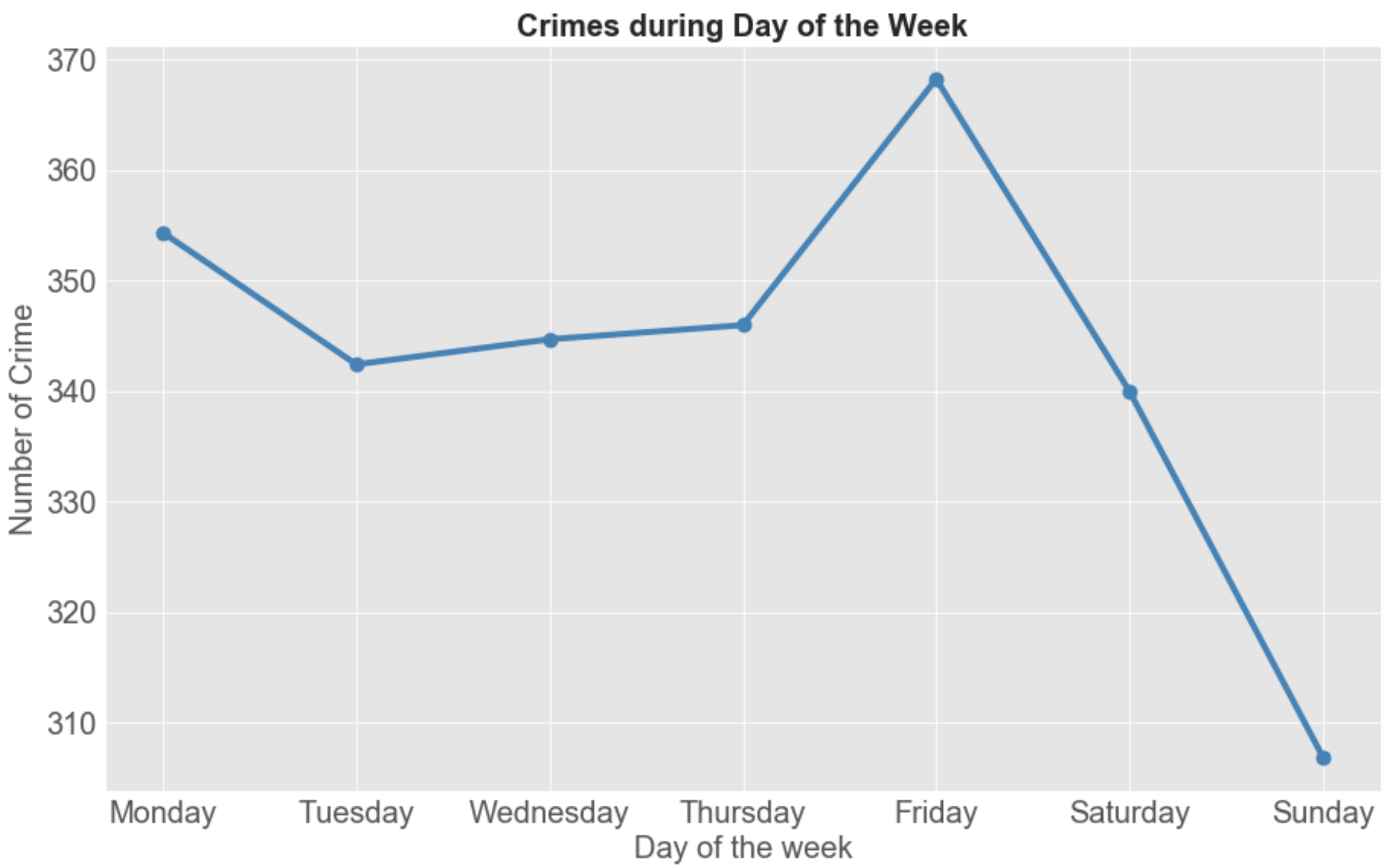
## Time series analysis: month




Month tends: summer months have more occurrences than winter months

# Exploratory Data Analysis

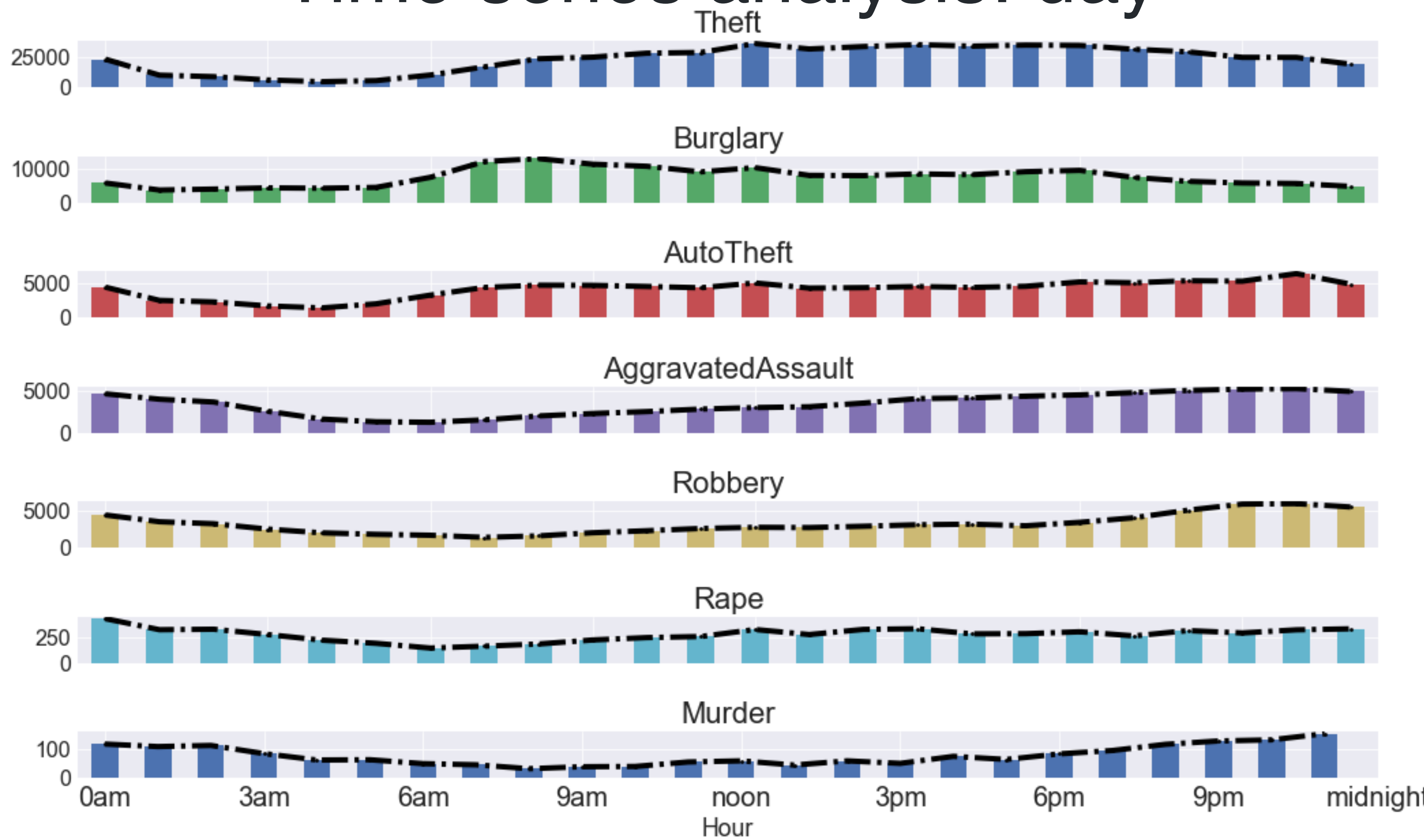
## Time series analysis: week




Day tends: there are most crimes on Fridays and least crimes on Sundays on a weekly basis.

# Exploratory Data Analysis

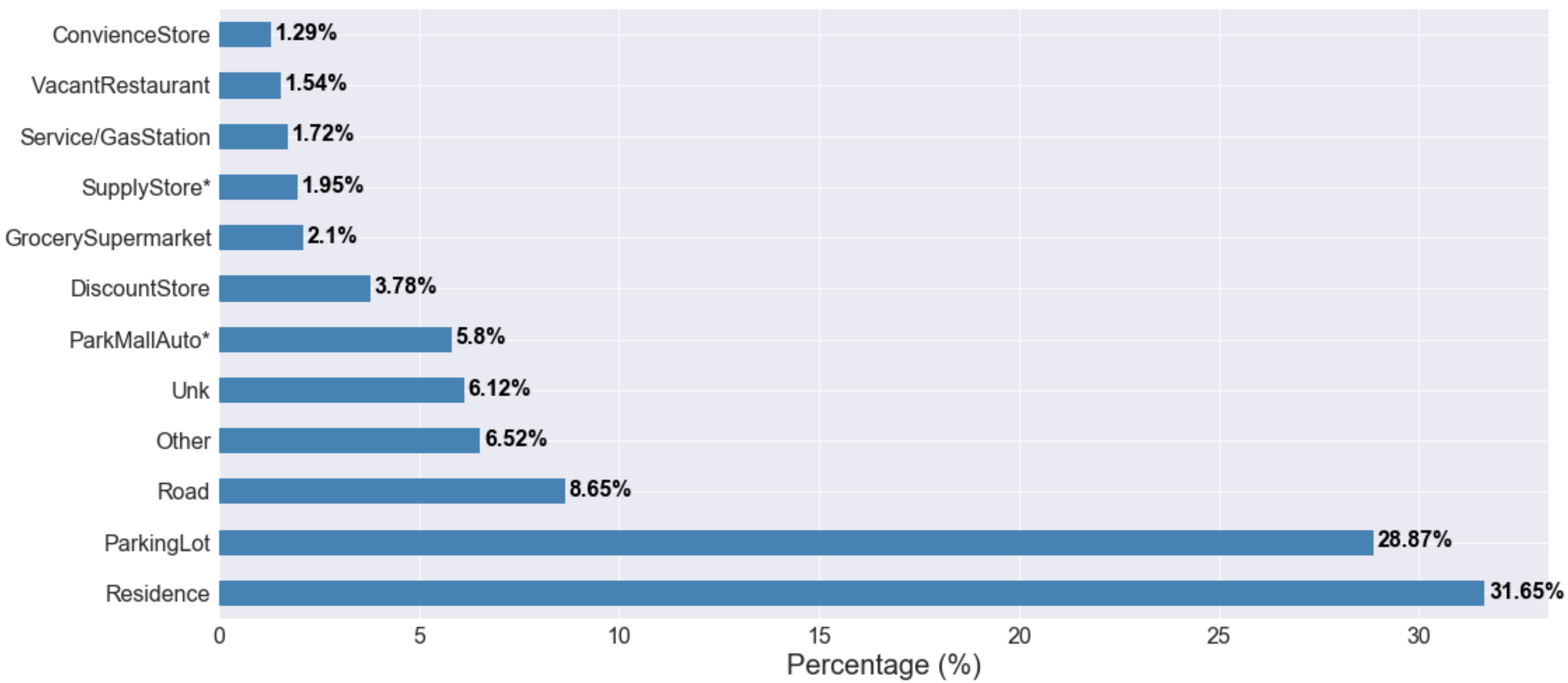
## Time series analysis: day




‘Theft’ hits a peak in the middle of day; ‘Burglary’ peaks in the early morning; ‘Auto theft’, ‘Aggravated Assault’, ‘Robbery’ and ‘Murder’ peaks around late or middle night.

# Exploratory Data Analysis

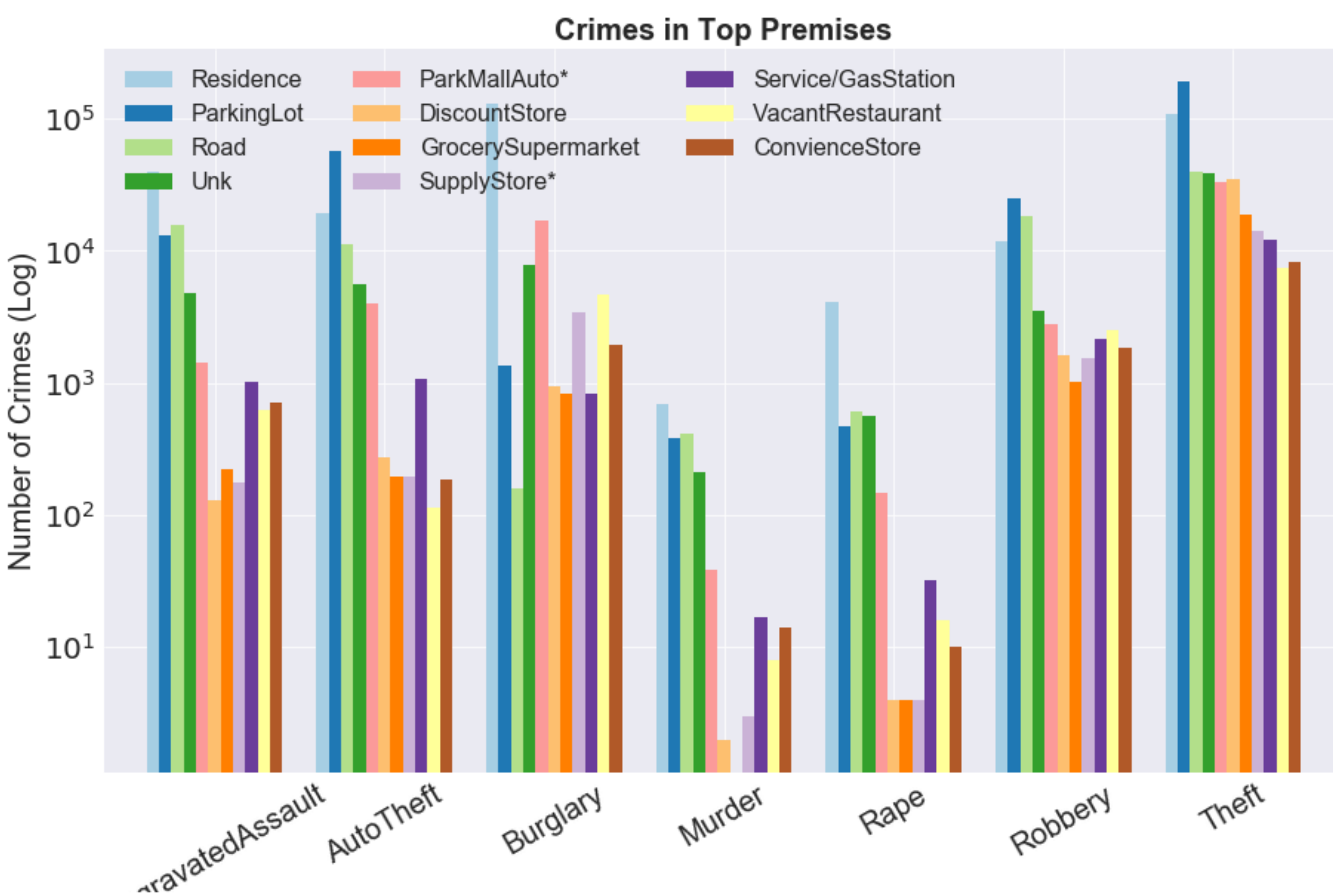
## Geographical aspects analysis




The residential place and parking lot had the most frequent crimes.

# Exploratory Data Analysis

## Geographical aspects analysis

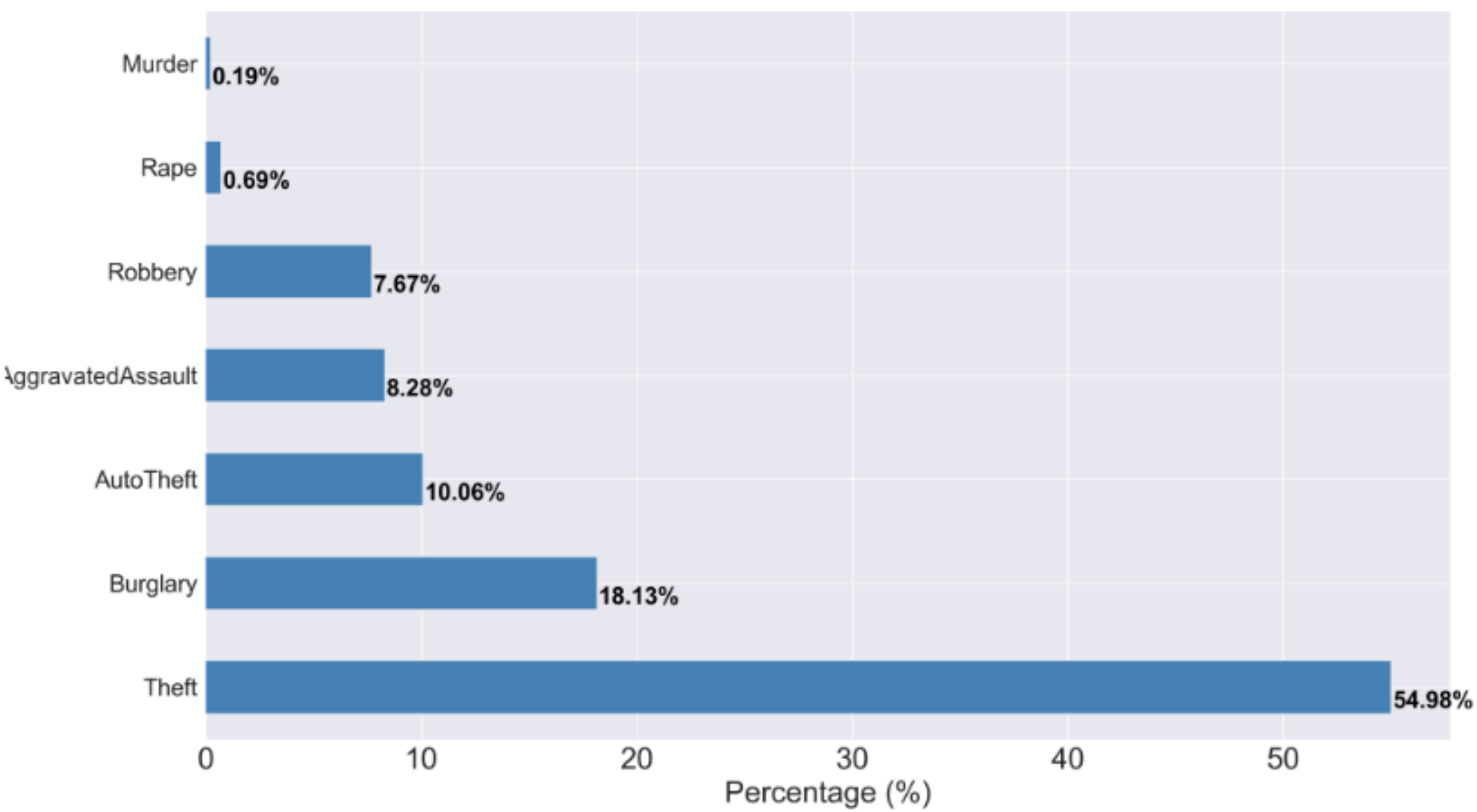



In ‘residence’, dominant crimes include ‘Burglary’, ‘Theft’; Note that violent crimes like ‘Aggravated Assault’ and ‘Rape’ tend to occur most often in ‘residence’ than other premises.

# Machine Learning Models

**Challenge**

I**mbalanced multi-classification** problem with mostly **categorical features**.

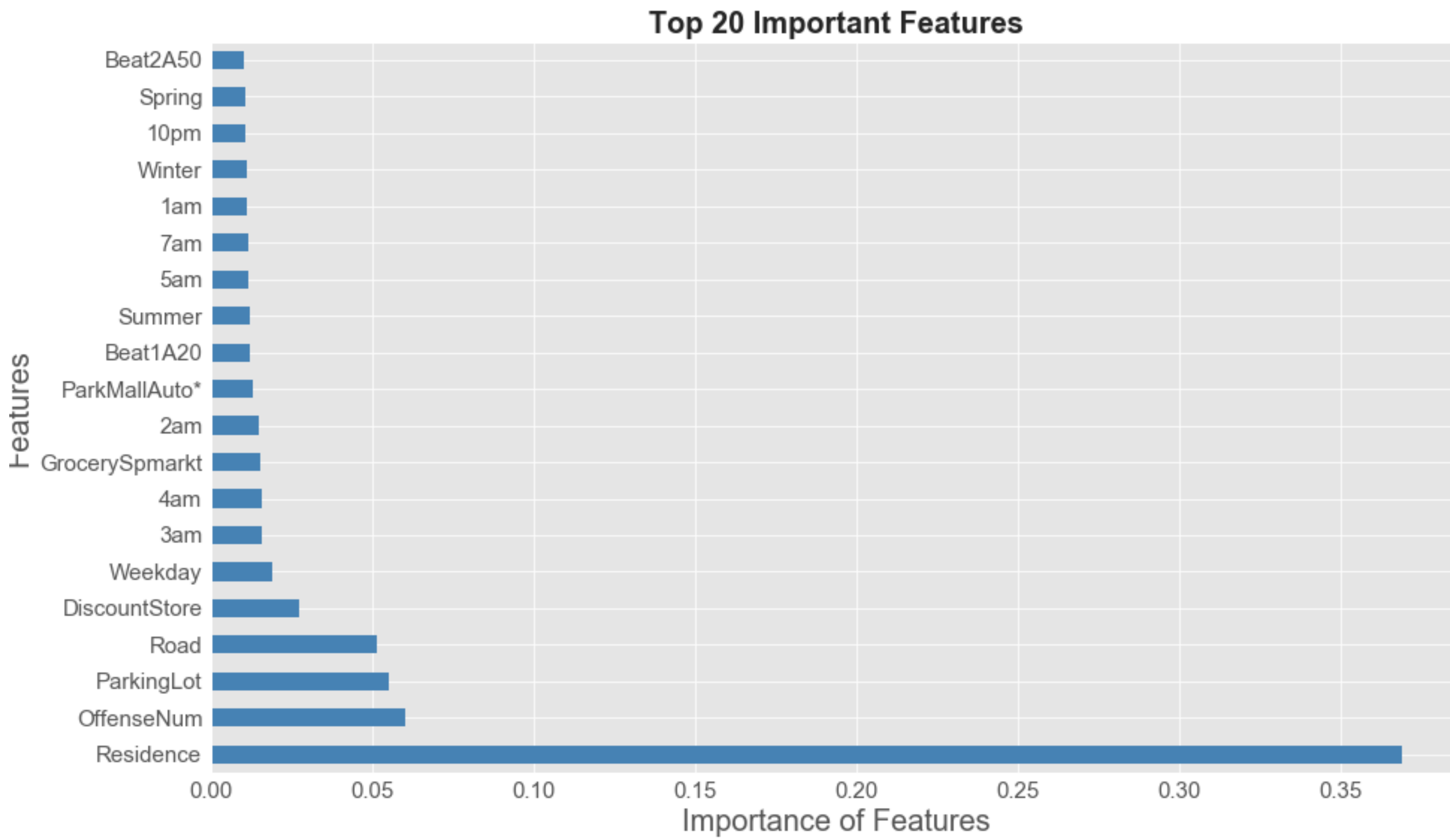


# Machine Learning Models

**Feature Engineering**

- Concatenate ‘***StreetName***’ and ‘***Type***’ columns to ‘***Address***’.
- Drop ‘***StreetName***’, ‘***Type***’ and ‘***Suffix***’.
- Truncate ‘***Beat***’ to keep first 60%, rename others as ‘Other’.
- Similar processing for ‘***Premise***’.
- Add columns ‘***Season***’, ‘***WeekDay***’.
- One-hot/label encode categorical variables.

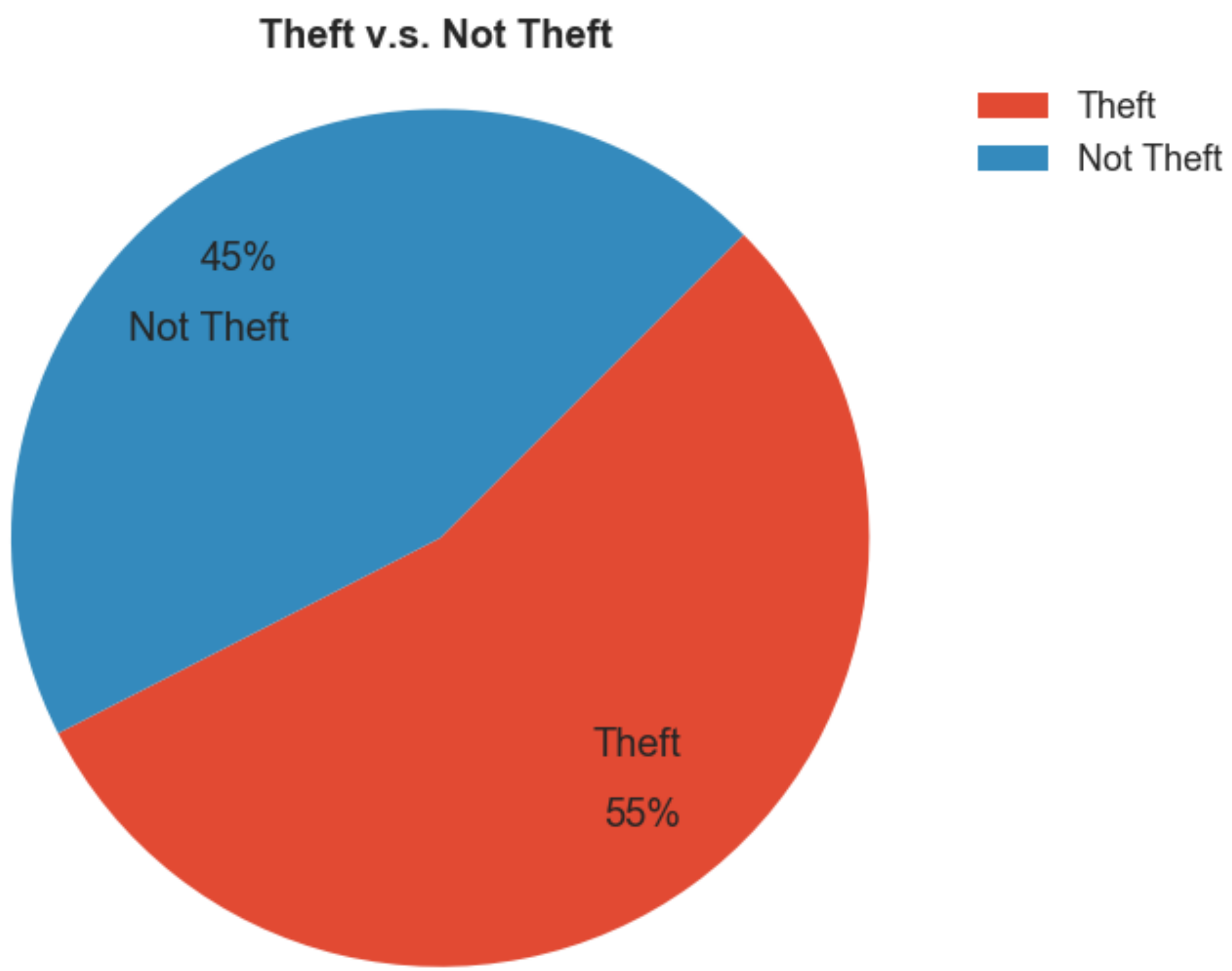
# Machine Learning Models



# Machine Learning Models

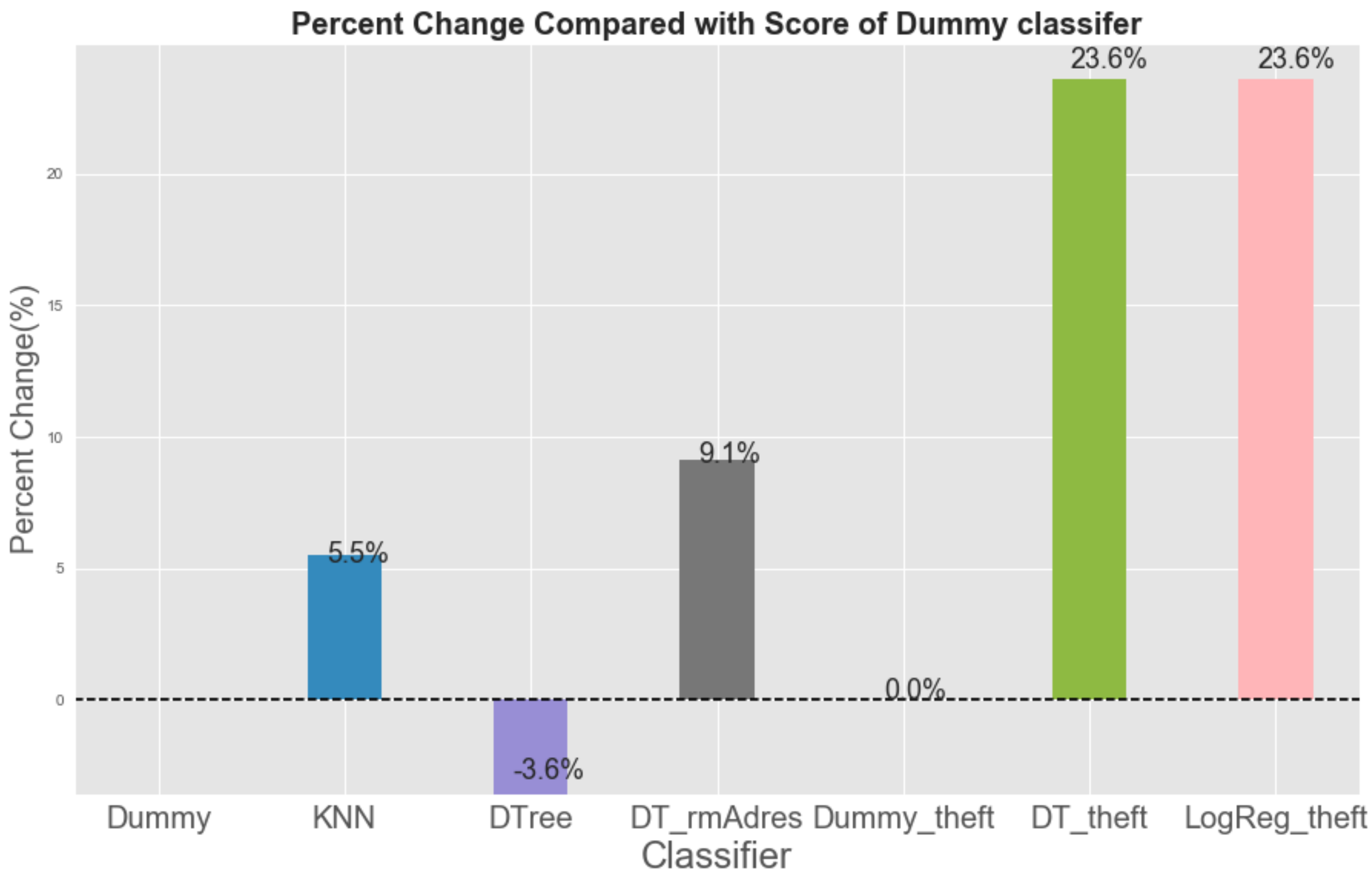
| | accuray | precision | recall | f1 | perct_change |
|---|---|---|---|---|---|
| **Classifier** | | | | | |
| **Dummy** | 0.55 | 0.30 | 0.55 | 0.39 | 0.0 |
| **KNN** | 0.58 | 0.51 | 0.58 | 0.52 | 5.5 |
| **DTree** | 0.53 | 0.52 | 0.53 | 0.52 | -3.6 |
| **DT_rmAdres** | 0.60 | 0.64 | 0.85 | 0.73 | 9.1 |
| **Dummy_theft** | 0.55 | 0.30 | 0.55 | 0.39 | 0.0 |
| **DT_theft** | 0.68 | 0.68 | 0.68 | 0.68 | 23.6 |
| **LogReg_theft** | 0.68 | 0.68 | 0.68 | 0.68 | 23.6 |

# Machine Learning Models

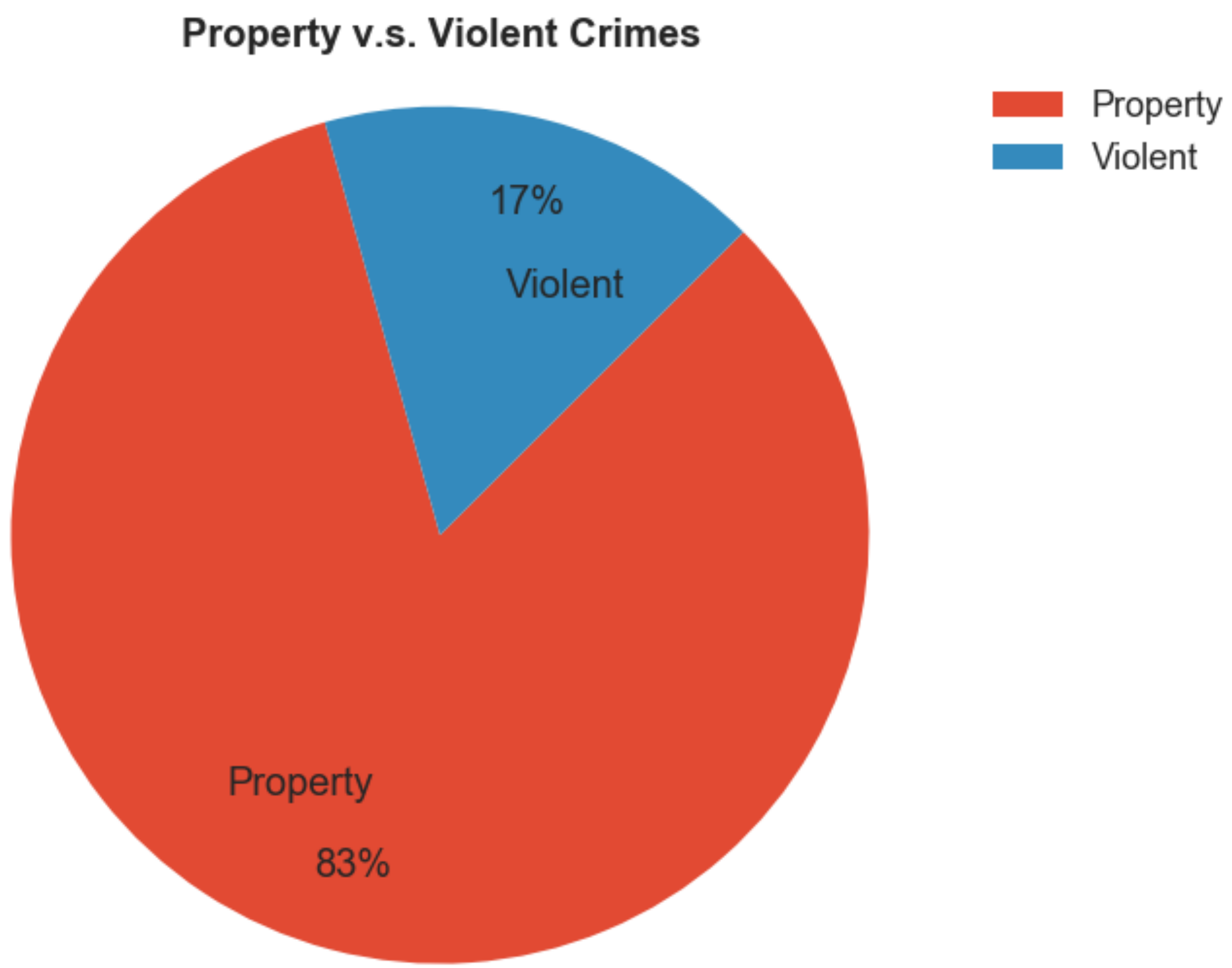



55% is ‘Theft’ and 45% is ‘Not Theft’. We still use the ‘most_frequent’ strategy in dummy classifier. It gives an accuracy of 55%.

# Machine Learning Models



# Violent/Property Crime




‘Theft’, ‘AutoTheft’, ‘Burglary’ are considered as property crimes, taking a proportion of 83% and ‘Robbery’, ‘AggravatedAssault’, ‘Murder’, ‘Rape’ are considered as violent crimes, taking a proportion of 17%.

# Predictions

| | accuray | precision | recall | f1 | perct_change |
|---|---|---|---|---|---|
| **Classifier** | | | | | |
| **Dmy_PorV** | 0.83 | 0.69 | 0.83 | 0.76 | 0.0 |
| **DT_PorV** | 0.84 | 0.80 | 0.84 | 0.80 | 1.2 |
| **LogReg_PorV** | 0.84 | 0.81 | 0.84 | 0.79 | 1.2 |
| **Dmy_rus** | 0.50 | 0.25 | 0.50 | 0.33 | -39.8 |
| **DT_rus** | 0.66 | 0.67 | 0.66 | 0.66 | -20.5 |
| **LogReg_rus** | 0.68 | 0.68 | 0.68 | 0.68 | -18.1 |
| **Dmy_ros** | 0.50 | 0.25 | 0.50 | 0.33 | -39.8 |
| **DT_ros** | 0.68 | 0.68 | 0.68 | 0.68 | -18.1 |
| **LogReg_ros** | 0.68 | 0.68 | 0.68 | 0.68 | -18.1 |

'*Dmy_PorV*' is the dummy classifier with predicting majority class strategy for property or violent crime; '*DT_PorV*' is the decision tree classifier; '*rus*' stands for random undersampling; '*ros*' stands for random oversampling.

# Conclusions

- We loaded raw data from HPD and performed data cleaning and data wrangling.
- We built machine learning models to predict types of crimes given predictor features constructed from insights gained from EDA and compare performances of classifiers .
- We find it is quite hard to predict for the seven types of crimes. We are able to predict ‘Theft’ or ‘Not Theft’ with an accuracy of 68%, an increase by 24% compared to that of dummy classifier i.e., just predicting the majority class.
- If we group crimes as ‘Property Crime’ (‘Theft’, ‘AutoTheft’, ‘Burglary’) and ‘Violent Crime’ (‘Assault’, ‘Murder’, ‘Rape’, ‘Robbery’), the best prediction is given by decision tree classifier and logistic regressor without random sampling with an accuracy of 84%.

# Future Work

## Improve accuracy:

- Convert address into coordinates and involve that in prediction.
- Get more data on crimes and enrich dataset with more features.

## Other interesting questions include:

- How is crime rate correlated with economic status and demographics?
- How is crime rate related with weather?

## Other potential datasets:

weather conditions
economic status (unemployment rate)
demographics (population change)