Big Data Analytics: London Crime Data Analysis

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Overview

The analysis' purpose

To **discover** the clusters among the criminal activities in the London metropolitan area in a distinct window of time and to **forecast** a possible development for future crimes.

The Dataset(1)

London Crime Data, 2008-2016: this dataset, hosted by **Kaggle**, is composed by 13 millions rows describing the London metropolitan area's criminal activities by *Borough*, *Category*, *Month* and *Year* in a window of time that ranges from January 2008 to December 2016.

The Dataset(2)

The dataset is composed by 7 variables:

- **lsoa_code**: code for Lower Super Output Area in Greater London;
- **borough**: common name for London borough;
- **major_category**: high level categorization of crime;
- **minor_category**: low level categorization of crime within major category;
- **year**: year of reported counts, $2008 - 2016$;
- **month**: month of reported counts, $1 - 12$;
- **value**: monthly reported count of categorical crime in given borough;

The Dataset(3)

The variables *lsoa_code*, *borough*, *major_category*, *minor_category*, *year* and *month* are **categorical** variables, while *value* is a **discrete numerical** variable.

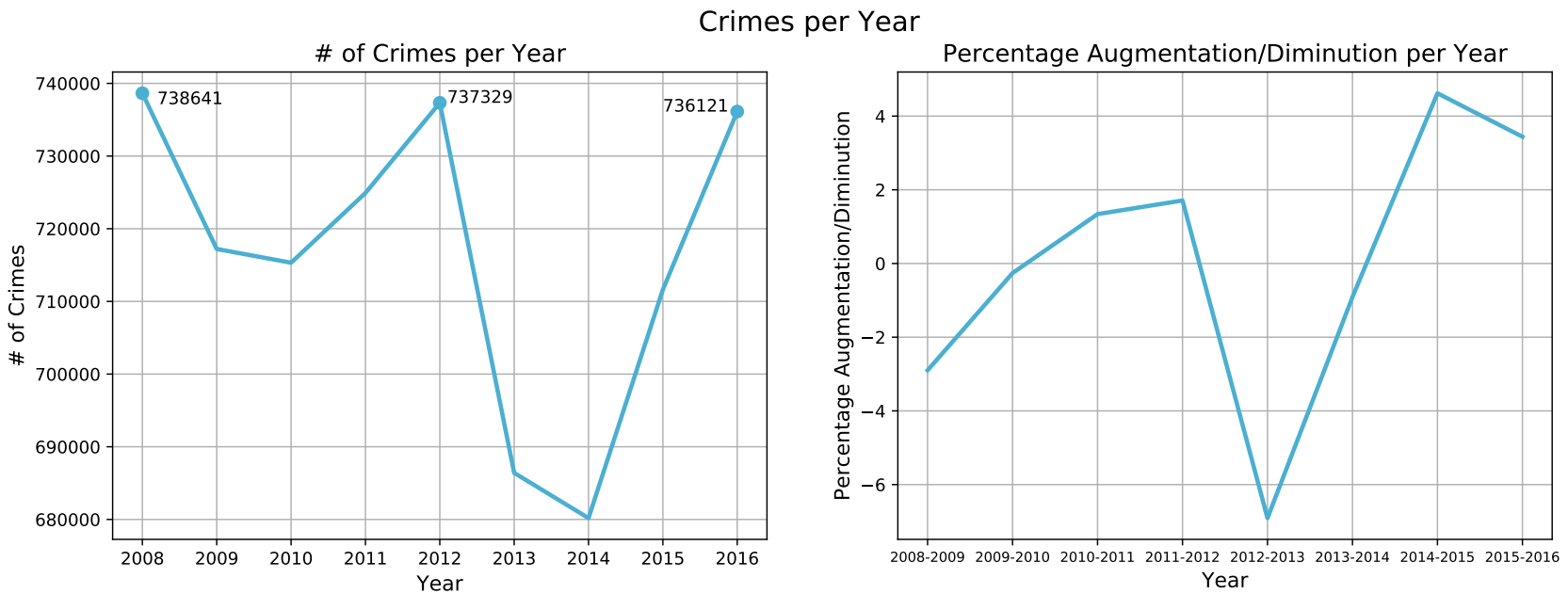
Numeric Variables' Analysis(1)

value is the only numeric variables in the dataset, it represents the monthly reported count of categorical crime in given borough and has 247 unique values. Its minimum value is 0 and its maximum value is 309, the mode is 0, which appears in the 74.56% of the dataset's samples.

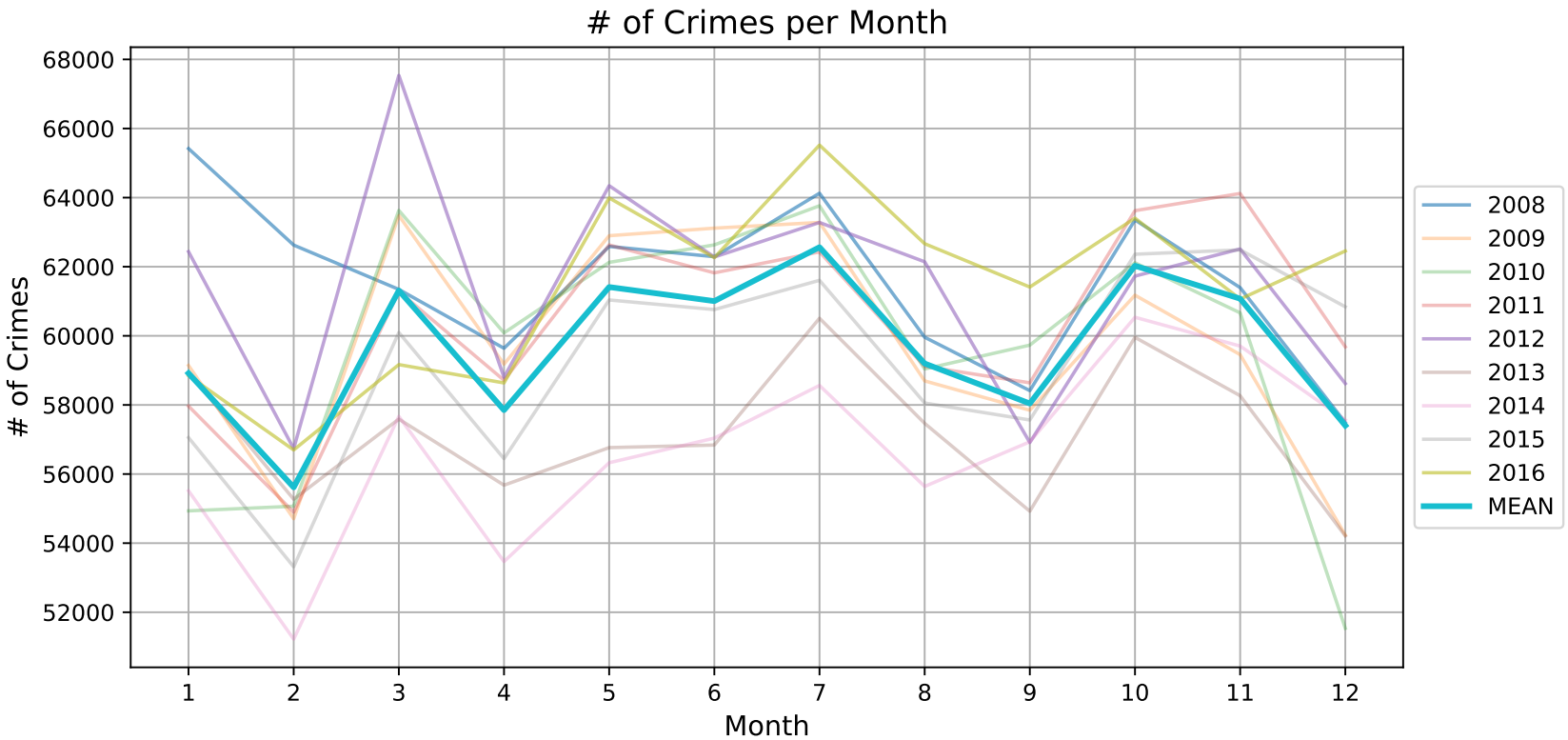
Numeric Variables' Analysis(2)

Since 10,071,505, that is, the 74.56% of the dataset's samples have the variable value eguals to 0, we can conclude that, on a superficial level, the window of time from 2008 to 2016 wasn't too dense of criminal activities.

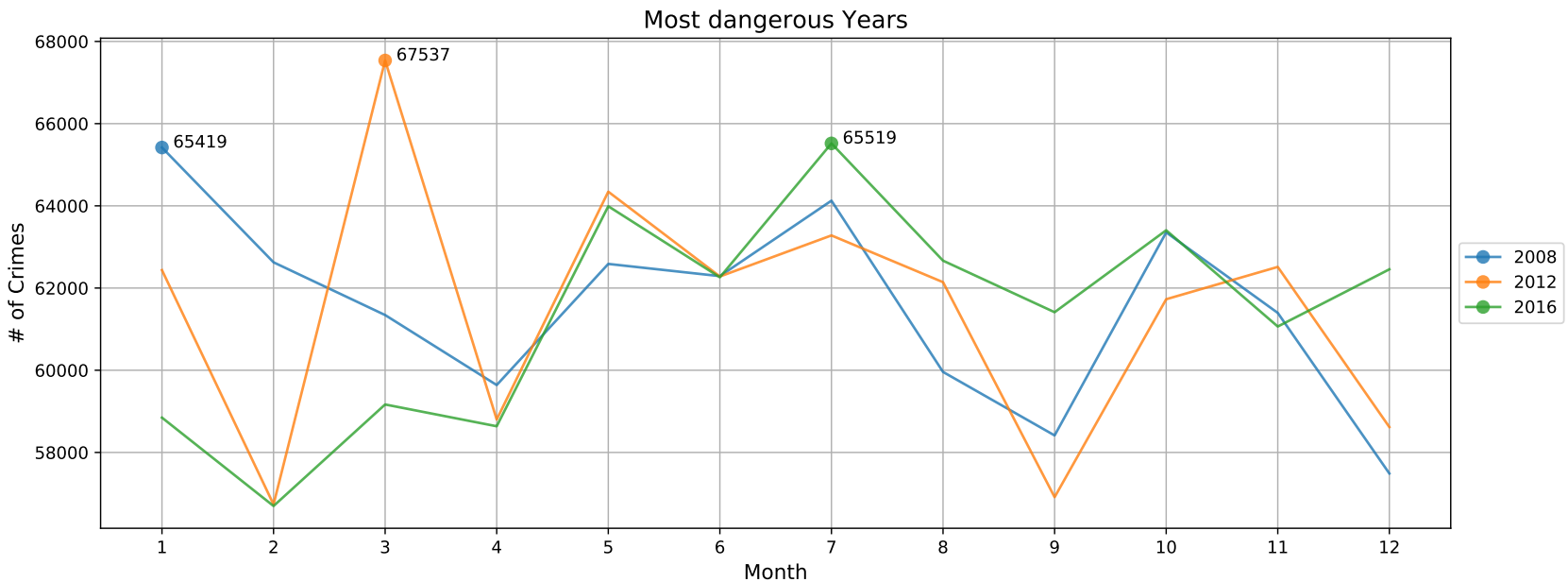
Crimes per Year



Crimes per Month



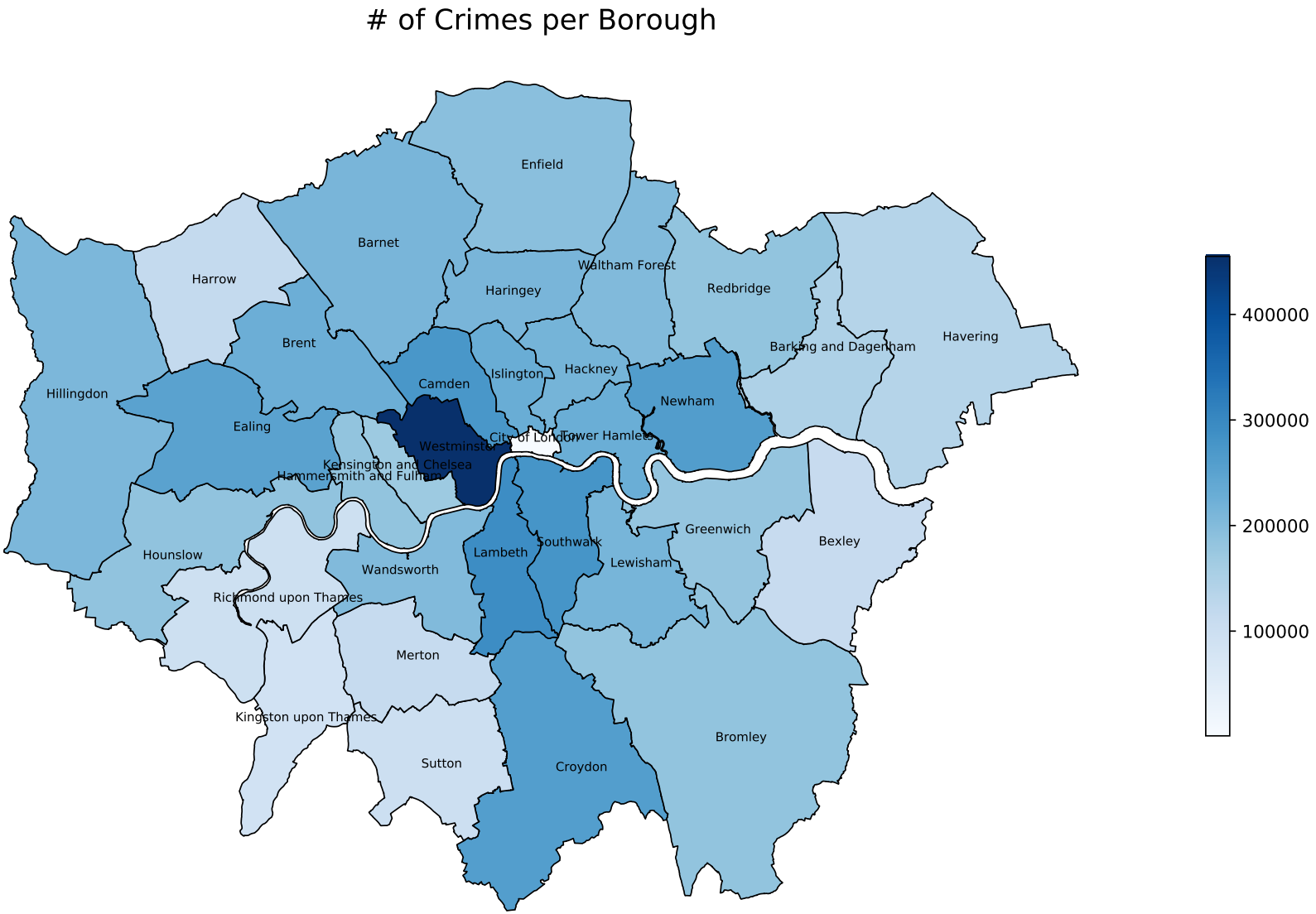
Most Dangerous Years



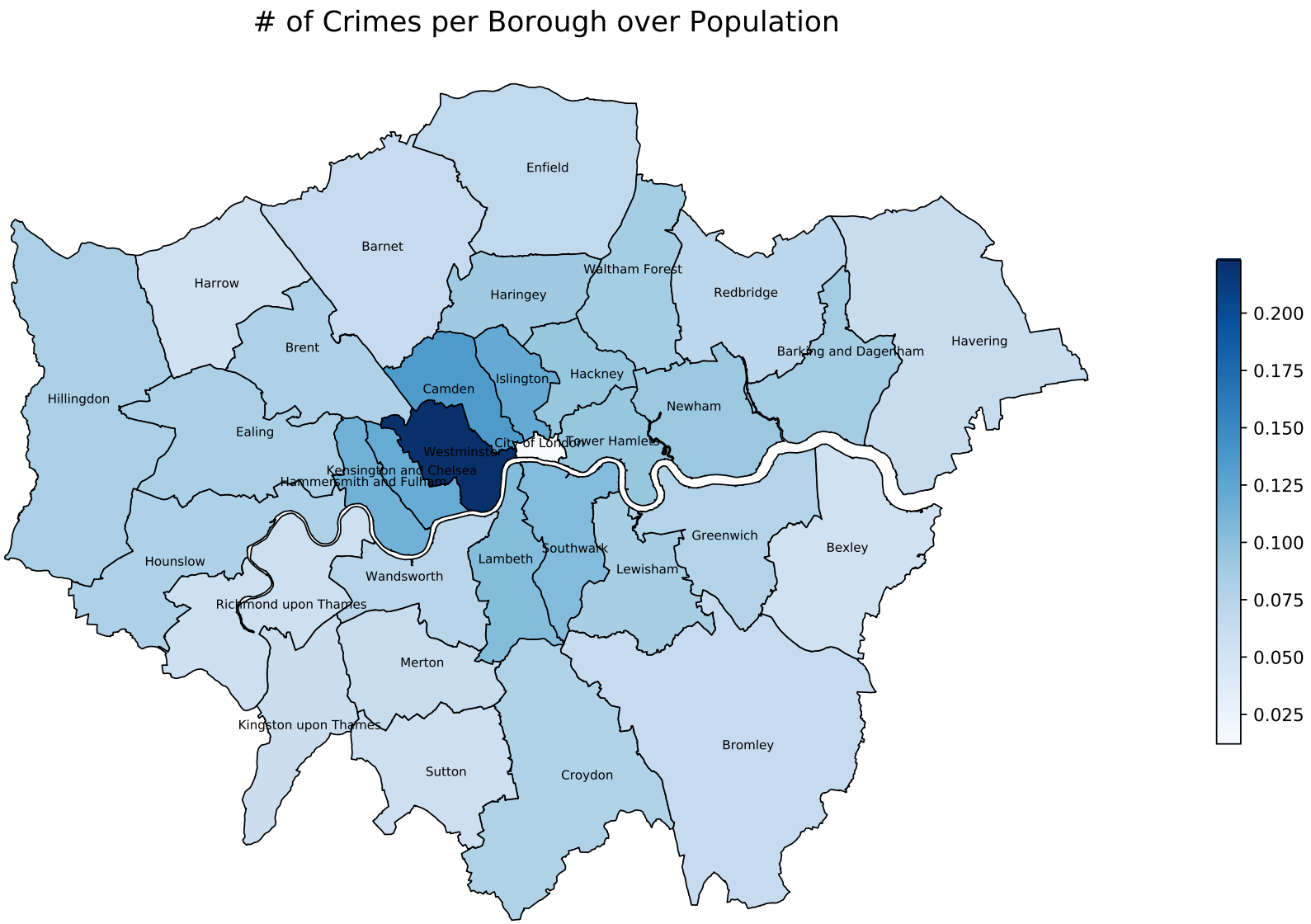
Categorical Variables' Analysis

- **borough** has 33 unique values, of which Lambeth is the most frequent, appearing in the 4.47% of the cropped dataset's records;
- **major_category** has 9 unique values, of which Theft and Handling is the most frequent, appearing in the 33.25% of the cropped dataset's records;
- **year** has 9 unique values, of which 2016 is the most frequent, appearing in the 11.45% of the cropped dataset's records;
- **month** has 12 unique values, of which 7 is the most frequent, appearing in the 8.66% of the cropped dataset's records;

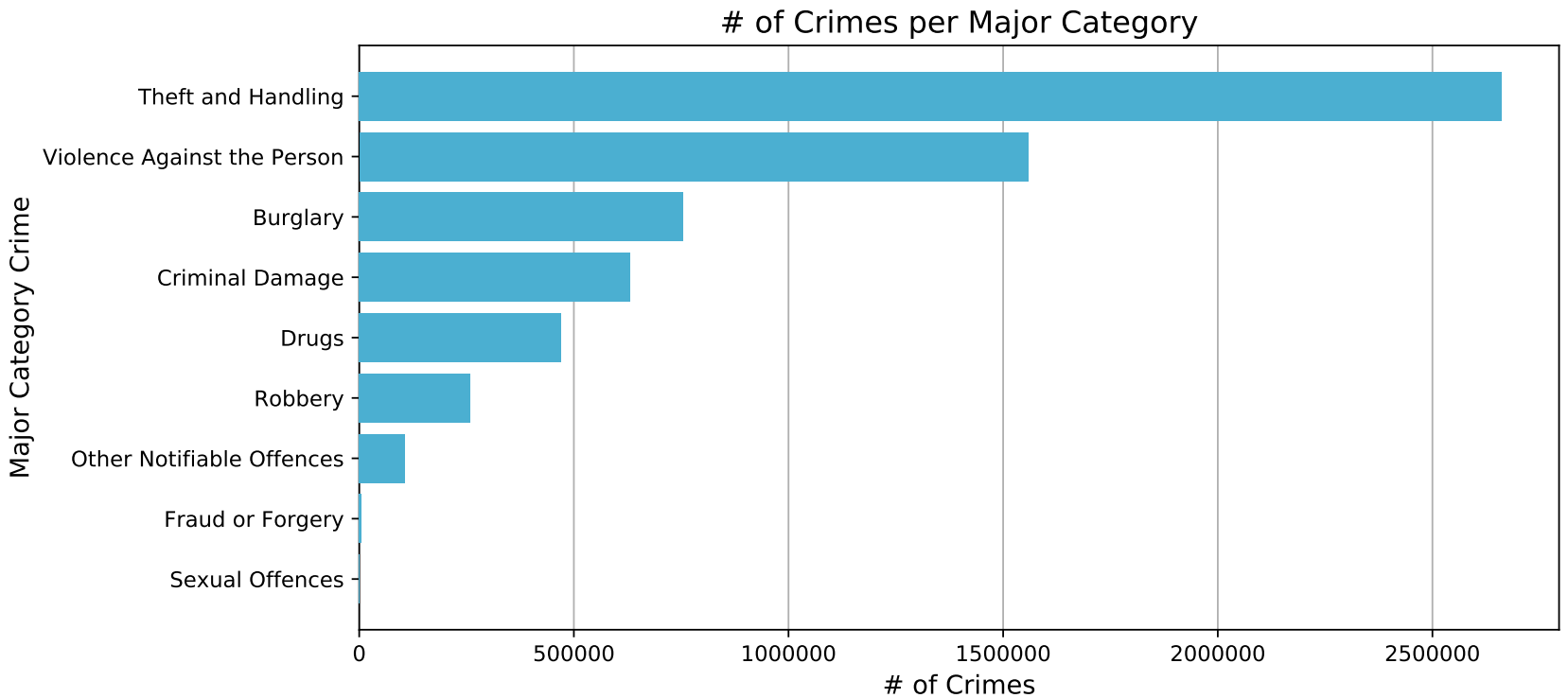
Crimes per Borough



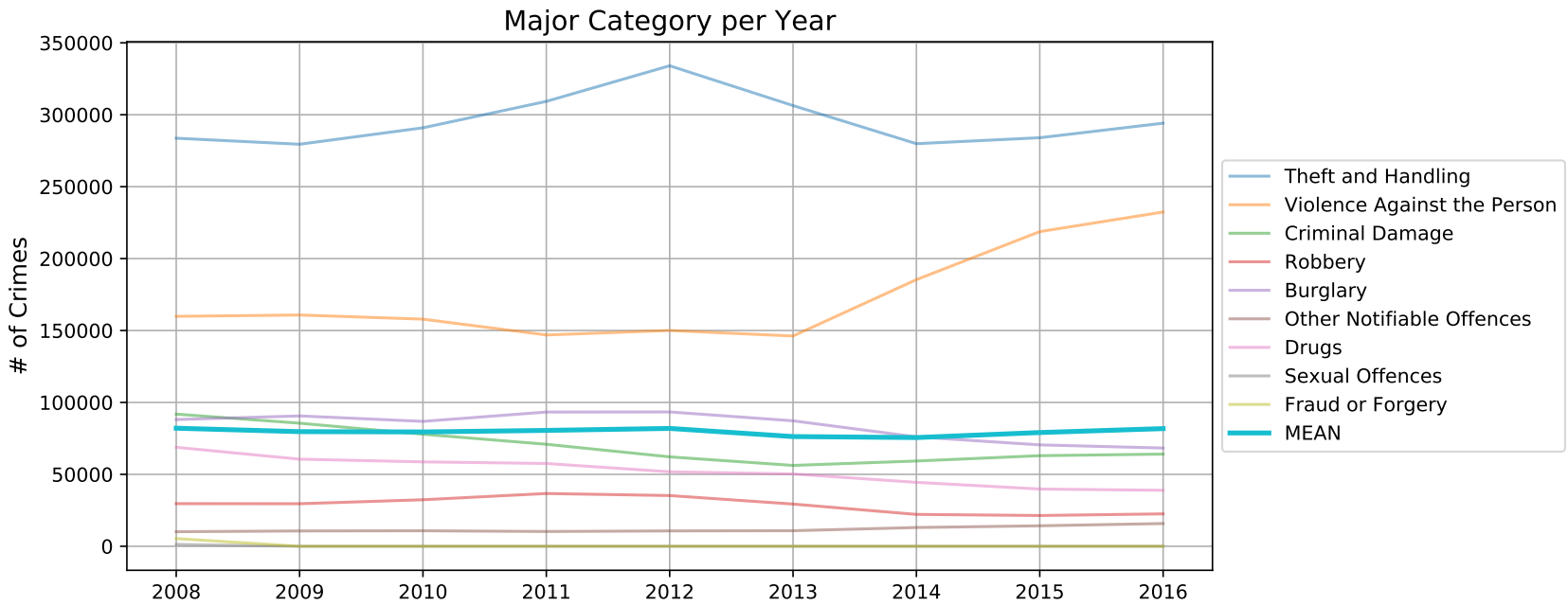
Crimes per Borough over Population Density



Crimes per Major Category



Major Category Crimes per Year



Correlation Analysis

	lsoa_code	borough	major_category	minor_category	value	year	month
lsoa_code	D	D	D	D	D	D	I
borough	D	D	D	D	D	D	D
major_category	D	D	D	D	D	D	D
minor_category	D	D	D	D	D	D	D
value	D	D	D	D	D	D	D
year	D	D	D	D	D	D	D
month	I	D	D	D	D	D	D

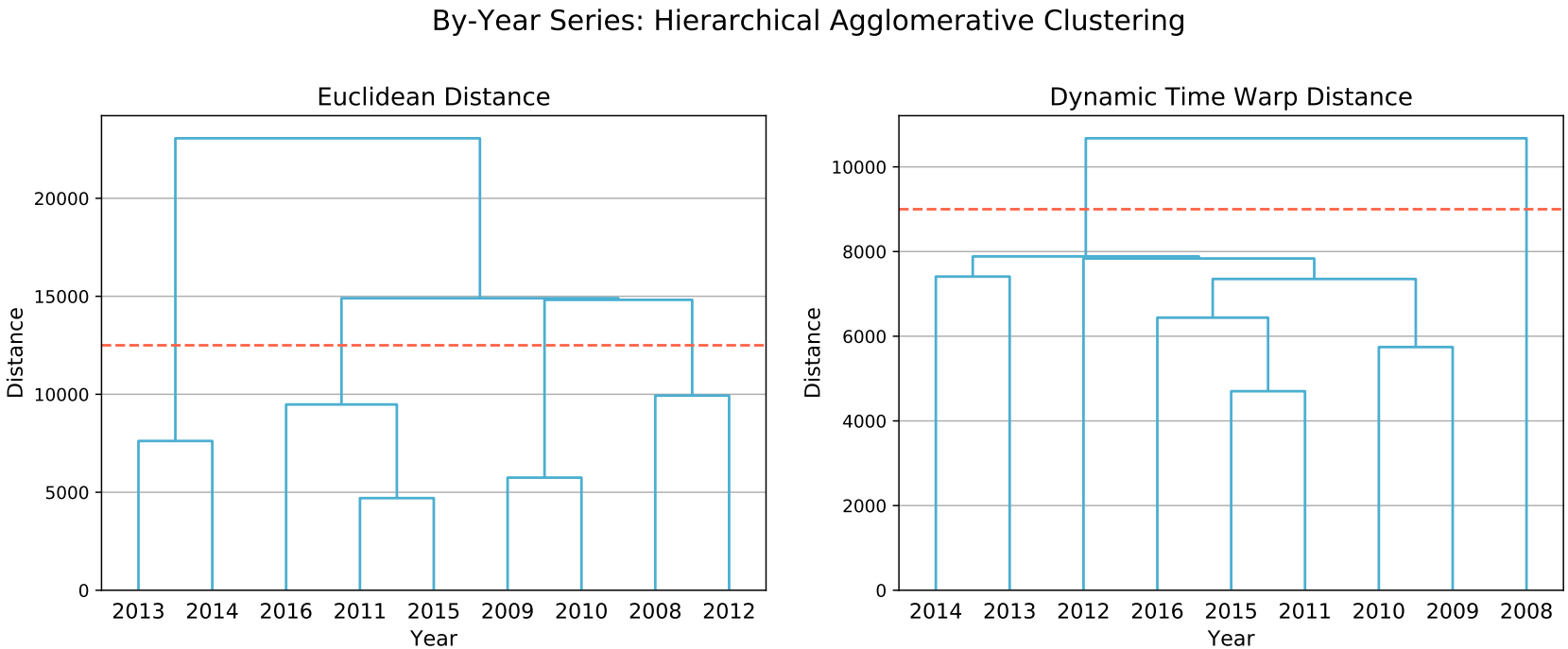
Introduction

I have decided to enrich the informations provided with the data understaning by searching for possible **cluster-like structures** in the **time series** extracted from the main dataset, that is, hoping to discover the similarities (or dissimilarities) among the series describing the criminal activities from 2008 to 2016.

Choice of the Algorithms

I have used three popular clustering algorithms, that is, the **KMeans algorithm**, the **Hierarchical Agglomerative algorithm** and the **DBSCAN**. The three algorithms were adapted depending on the different series they were applied on.

By-Year Series: Hierarchical Agglomerative Clustering



By-Year Series: KMeans Algorithm and DBSCAN Clustering

Year	Cluster
2009	0
2010	0
2011	1
2015	1
2016	1
2008	2
2012	2
2013	3
2014	3

(a) KMeans

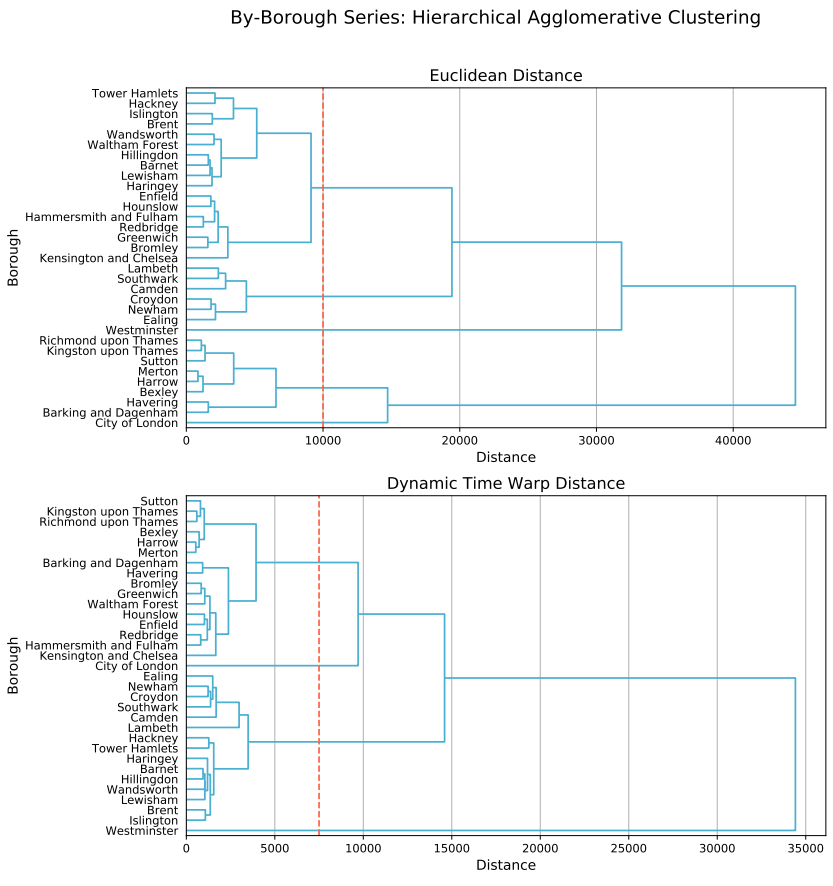
Year	Cluster
2008	-1
2012	-1
2009	0
2010	0
2011	1
2015	1
2016	1
2013	2
2014	2

(b) DBSCAN

By-Year Series: Conclusions

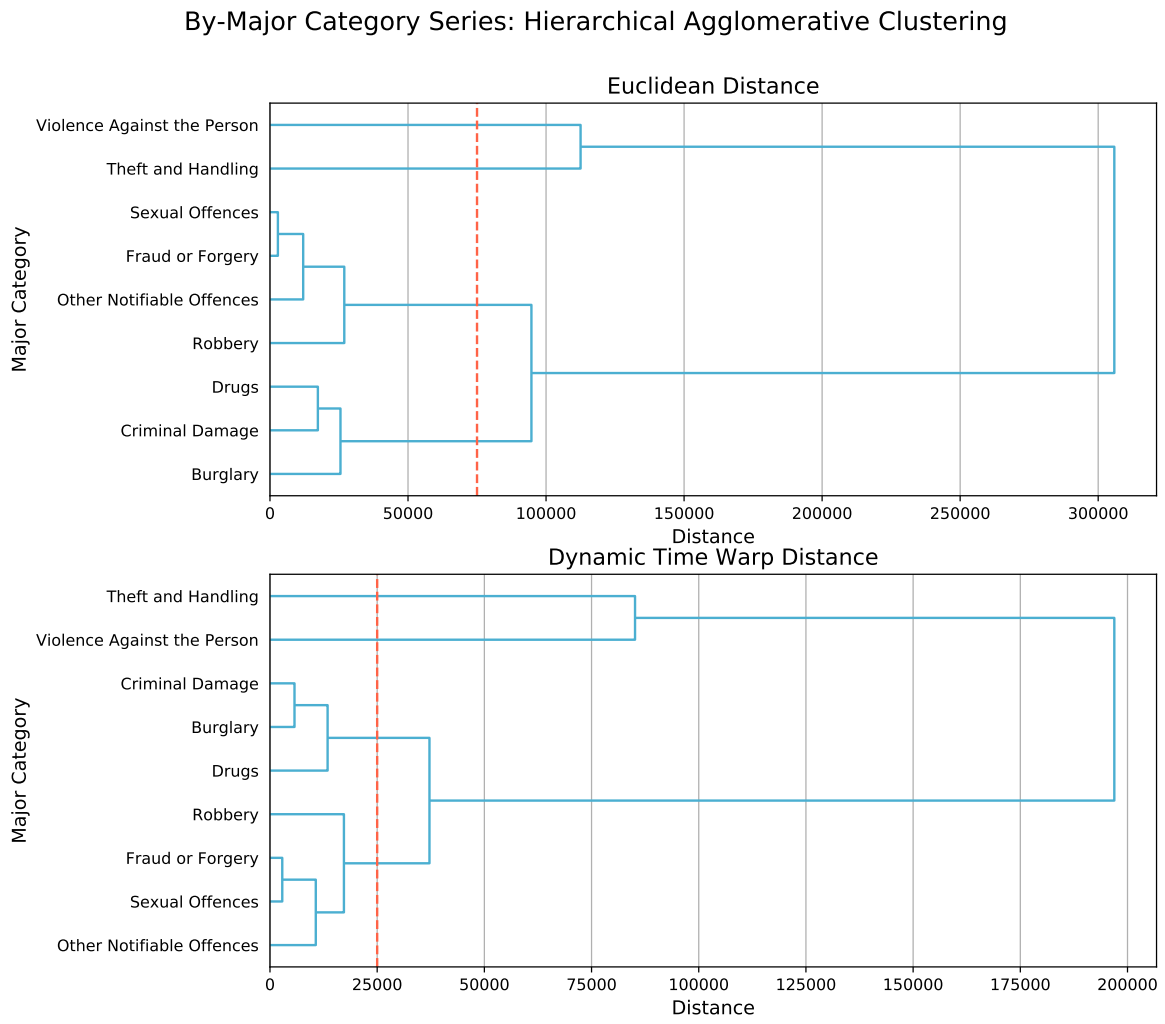
- the series representing years 2013 and 2014 are the least dense of criminal activities, hence are clustered together;
- the series representing years 2008 and 2012 are the most dense of criminal activities, hence are clustered together;
- the remaining series are splitted into two distinct clusters;

By-Borough Series: Hierarchical Agglomerative Clustering



By-Borough Series: Conclusions

By-Major Category Series: Hierarchical Agglomerative Clustering



By-Major Category Series: KMeans Algorithm and DBSCAN Clustering

Major Category Crime	Cluster
Robbery	0
Fraud or Forgery	0
Sexual Offences	0
Other Notifiable Offences	0
Theft and Handling	1
Violence Against the Person	2
Criminal Damage	3
Burglary	3
Drugs	3

(a) KMeans

Major Category	Cluster
Theft and Handling	-1
Violence Against the Person	-1
Criminal Damage	0
Burglary	0
Drugs	0
Robbery	1
Fraud or Forgery	1
Sexual Offences	1
Other Notifiable Offences	1

(b) DBSCAN

By-Major Category Series: Conclusions

- Fraud or Forgery, Sexual Offences, Other Notifiable Offences and Robbery are the least popular types of crimes, hence their series are clustered together;
- Theft and Handling and Violence Against the Person are the most popular types of crimes, hence they form distinct clusters for themeself;
- the other categories are clustered together;

The Models - Autoregressive Model of order p

Represent by the formula

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

where $\varphi_1, \ldots, \varphi_p$ are the parameters of the model, c is a constant, and ε_t is white noise.

The Models - Autoregressive-Moving-Average Model of orders p and q

Represented by the formula

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where p and q are, respectively, the autoregressive terms and the moving-average terms, $\varphi_1, \ldots, \varphi_p$ are the parameters of the autoregressive model, $\theta_1, \ldots, \theta_q$ are the parameters of the moving-average model and $\varepsilon_t, \varepsilon_{t-1}, \ldots$ are white noise error terms.

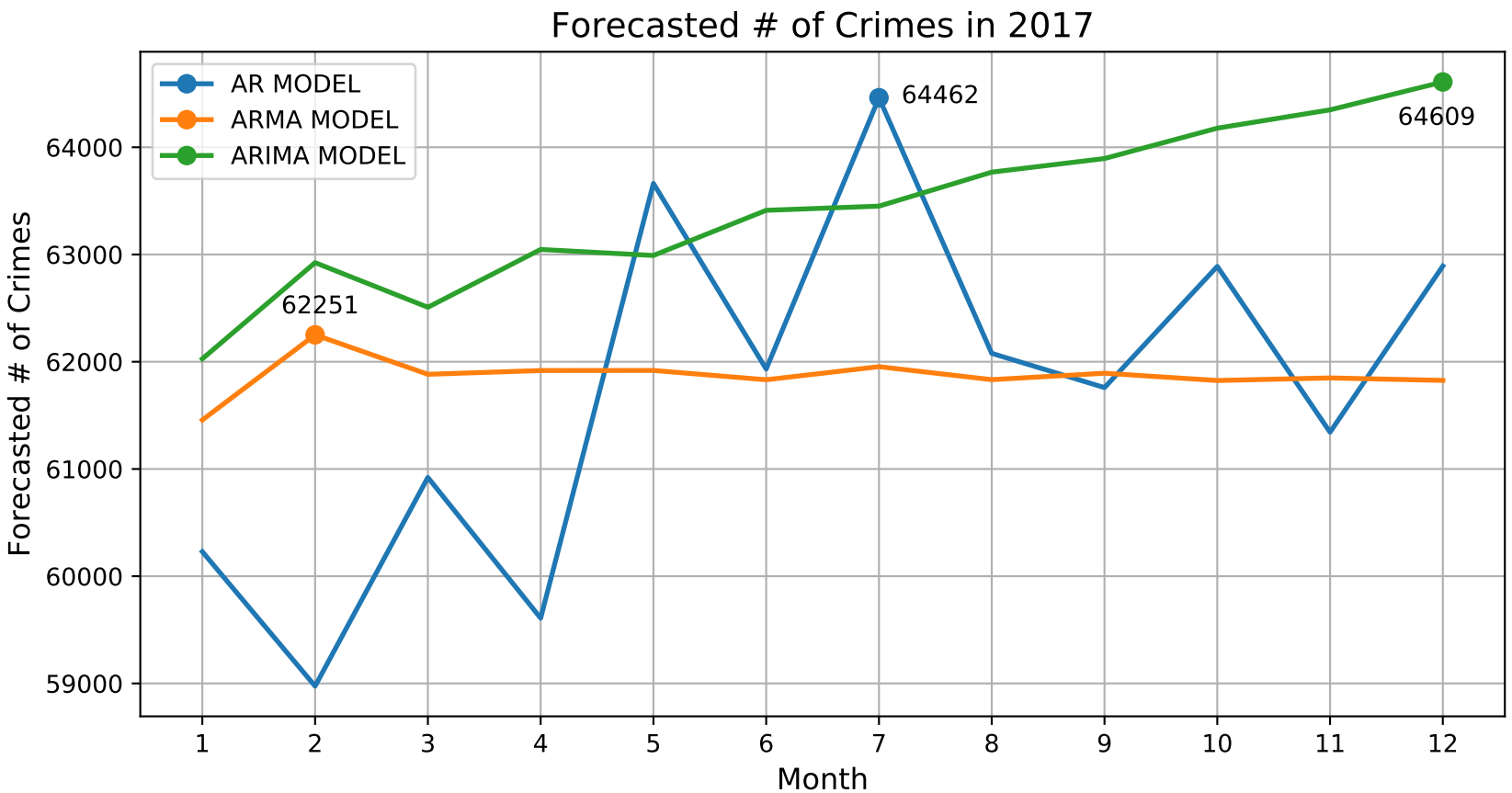
The Models - Autoregressive-Integrated-Average Model of orders p, q and d

Represented by the formula

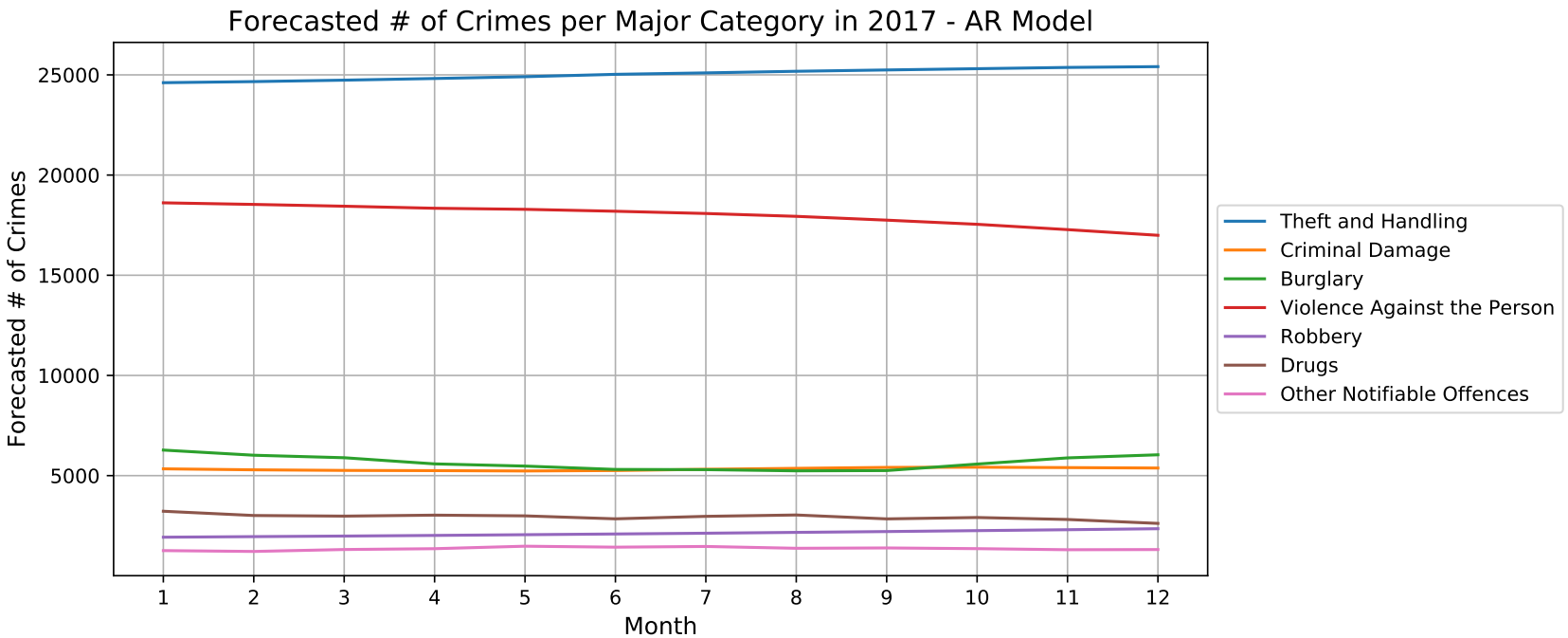
$$\left(1 - \sum_{i=1}^{p} \varphi_i L^i\right) (1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t$$

where L is the lag operator, $\varphi_1, \ldots, \varphi_p$ are the parameters of the autoregressive model, $\theta_1, \ldots, \theta_q$ are the parameters of the moving-average model and ε_t is white noise.

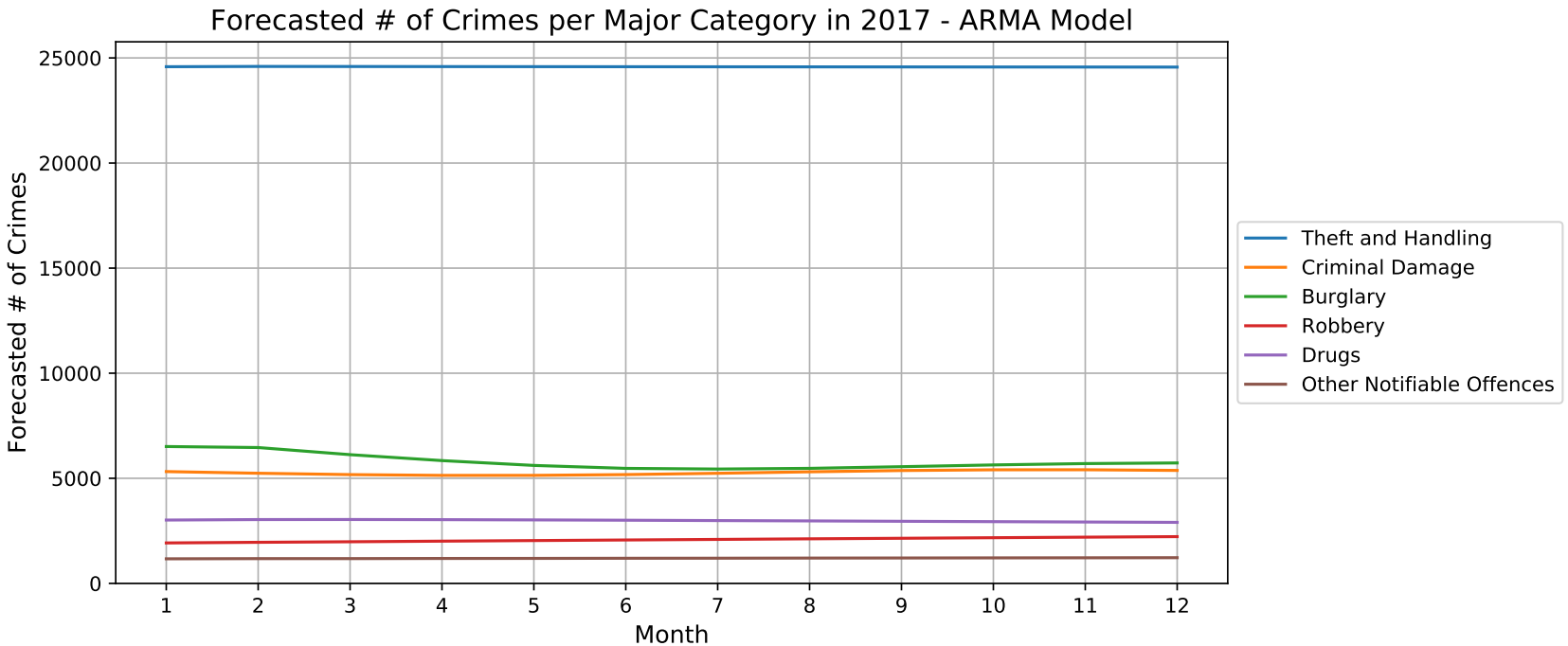
Forecasting of # of Crimes over the city



Forecasting of # of Crimes per Major Category - AR model



Forecasting of # of Crimes per Major Category - ARMA model



Forecasting of # of Crimes per Major Category - ARIMA model