Envrionment Setup

- Run `conda env create --name avalon --file=environment.yaml`
- Then switch to the environment by clicking the `avalon` item of the drop-down in the top right corner of Jupyter Notebook.

Crime Forecast in Vancouver

by Ben Chen, Mo Norouzi, Orix Au Yeung, Yiwei Zhang

```
In [1]:  import altair as alt
         import matplotlib.pyplot as plt
         import numpy as np
         import pandas as pd
         import seaborn as sns
         from pandas.plotting import autocorrelation_plot
         from statsmodels.tsa.arima.model import ARIMA
         from sklearn.metrics import mean_absolute_error, mean_squared_error
         import warnings
         import sys
         warnings.filterwarnings("ignore")
         sys.path.append('../src/helpers')
         sys.path.append('../src')

         from get_metrics_from_df import get_metrics_from_df
         from missing_value import missing_zero_values_table
         from numeric_cols import create_numeric_cols_chart
         from merge_forecast_values import merge_forecast_values
         from arima_forecasting import arima_prediction
```

Summary

In this notebook, our focus revolved around constructing a time-series forecasting model tailored to predict crime incidents in Vancouver, using "Month" as the temporal unit. Our primary emphasis centered on one of the most prevalent crime types in Vancouver over the past two decades: theft from vehicles. We evaluated the efficacy of three fundamental forecasting models—simple moving average, exponential smoothing, and ARIMA(1,1,0). Notably, the ARIMA(1,1,0) model emerged as the most effective, yielding a Mean Absolute Error (MAE) of 26.856890. Considering that the occurrences of "theft from a vehicle" crimes per month often range in the hundreds to thousands, achieving a forecast performance of this caliber is notably commendable. It's worth highlighting that further refinement through comprehensive parameter tuning and

integration of additional external variables holds the potential to cultivate even more accurate forecasting models.

Introduction

Vehicle-related theft remains an ongoing concern nationwide in Canada, with statistics revealing a staggering incident of vehicle theft occurring every six minutes across the country (Hayatullah Amanat, 2023). This pervasive issue extends into Vancouver, presenting formidable challenges to both community safety and law enforcement efforts. Theft from vehicles, a prevalent form of this crime, significantly affects neighborhoods, inflicting distress and substantial financial losses on local residents. In response to this pressing concern, this project is dedicated to forecasting occurrences of theft from vehicles specifically within Vancouver.

The primary objective of this project is to forecast instances of theft from vehicles in Vancouver by analyzing historical data. Leveraging a comprehensive dataset sourced from the Vancouver Police Department, encompassing diverse crime records in Vancouver over the past 20 years alongside incident locations, our goal is to construct a reliable predictive model. This model aims to anticipate the frequency and patterns specific to theft from vehicles. An accurate forecast holds the potential to empower the City of Vancouver to proactively allocate law enforcement resources, thereby curbing the occurrence of such crimes and enhancing community safety.

Methods

Data

The dataset utilized for this project originates from the Vancouver Police Department, available through the following link: https://geodash.vpd.ca/opendata/. It comprises 10 columns/variables and encompasses a substantial volume of data, totaling 879,861 rows. Each row corresponds to a distinct crime incident recorded within the dataset. The available information includes details about the crime type, the corresponding date of occurrence, and the specific location or neighborhood where the crime took place. These data points serve as crucial elements for our analysis and forecasting efforts.

Analysis

We're deploying three distinct time-series forecasting models—Simple Moving Average (SMA), Exponential Smoothing (ES), and Autoregressive Integrated Moving Average (ARIMA). These models rely solely on the timestamp and the targeted forecasted value. Despite having location data, which holds potential value, we've deferred its utilization in

this phase of the project. Employing a rolling window approach, we'll predict and assess model performance across a 20-year duration, setting the window size to 12 months. This configuration ensures that forecasts leverage the preceding year's data for accuracy. Specifically for ARIMA, the hyperparameters (p, d, q) are set at (1, 1, 0). This specification signifies that the model factors in the most recent lagged observations of the differenced series to predict the subsequent value. Our analysis was executed using Python, leveraging various libraries: numpy (Harris et al., 2020), Pandas (McKinney, 2010), Altair (VanderPlas, 2018), scikit-learn (Pedregosa et al., 2011), Matplotlib (Hunter et al., 2012), Seaborn (Waskom, 2012), and Statsmodels (Seabold et al., 2009).

Results & Discussions

Upon conducting exploratory data analysis (EDA), conspicuous anomalies surface in the dataset. The HOUR and MINUTE columns exhibit an unusual frequency of zero values, along with a disproportionate occurrence of '30' in the MINUTE column. Additionally, the DAY column prominently features an excessive number of records logged on the 31st of the month. These irregularities likely stem from convenience in data recording, casting uncertainty on the accuracy of these three columns. In light of these inconsistencies, the most prudent approach is to exclude the DAY, HOUR, and MINUTE columns from analysis and focus solely on forecasting crime occurrences based on the MONTH variable.

In [2]:
```python
data = pd.read_csv("../data/crimedata_csv_AllNeighbourhoods_AllYears.csv", e
data.head()
```

Out[2]:

	TYPE	YEAR	MONTH	DAY	HOUR	MINUTE	HUNDRED_BLOCK	NEIGHBOURH
0	Break and Enter Commercial	2012	12	14	8	52	NaN	Oal
1	Break and Enter Commercial	2019	3	7	2	6	10XX SITKA SQ	Fa
2	Break and Enter Commercial	2019	8	27	4	12	10XX ALBERNI ST	Wes
3	Break and Enter Commercial	2021	4	26	4	44	10XX ALBERNI ST	Wes
4	Break and Enter Commercial	2014	8	8	5	13	10XX ALBERNI ST	Wes

In [3]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 879861 entries, 0 to 879860
Data columns (total 10 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   TYPE           879861 non-null  object
 1   YEAR           879861 non-null  int64
 2   MONTH          879861 non-null  int64
 3   DAY            879861 non-null  int64
 4   HOUR           879861 non-null  int64
 5   MINUTE         879861 non-null  int64
 6   HUNDRED_BLOCK  879849 non-null  object
 7   NEIGHBOURHOOD  879717 non-null  object
 8   X              879785 non-null  float64
 9   Y              879785 non-null  float64
dtypes: float64(2), int64(5), object(3)
memory usage: 67.1+ MB
```

In [4]: `data.describe().T`

Out[4]:

	count	mean	std	min	25%	50%
YEAR	879861.0	2.012265e+03	6.183902e+00	2003.0	2.006000e+03	2.012000e+03
MONTH	879861.0	6.516683e+00	3.391857e+00	1.0	4.000000e+00	7.000000e+00
DAY	879861.0	1.538500e+01	8.757135e+00	1.0	8.000000e+00	1.500000e+01
HOUR	879861.0	1.231342e+01	7.463913e+00	0.0	7.000000e+00	1.400000e+01
MINUTE	879861.0	1.586139e+01	1.836042e+01	0.0	0.000000e+00	5.000000e+00
X	879785.0	4.490074e+05	1.393043e+05	0.0	4.901879e+05	4.915699e+05
Y	879785.0	4.977853e+06	1.544127e+06	0.0	5.454211e+06	5.457170e+06

Missing values

In [5]: `missing_zero_values_table(data)`

Your selected dataframe has 10 columns and 879861 Rows.
There are 4 columns that have missing values.

Out[5]:

|	Zero Values	Missing Values	% of Total Values	Total Zero Missing Values	% Total Zero Missing Values	Data Type
NEIGHBOURHOOD	0	144	0.0	144	0.0	object
X	77225	76	0.0	77301	8.8	float64
Y	77225	76	0.0	77301	8.8	float64
HUNDRED_BLOCK	0	12	0.0	12	0.0	object

Distribution

```python
alt.data_transformers.enable('vegafusion')
numeric_cols = ["MONTH", "DAY", "HOUR", "MINUTE"]
create_numeric_cols_chart(data, numeric_cols)
```
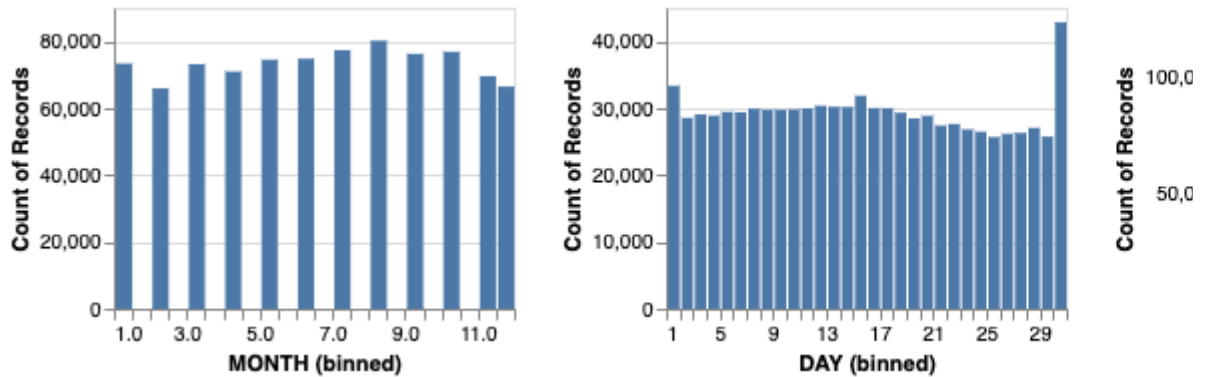
```python
categ_cols_dist = alt.Chart(data).mark_bar().encode(
    y = alt.X(alt.repeat(),type= "nominal").sort("x"),
    x =alt.Y("count()"),
).properties(
        width = 400,
        height = 300
).repeat(
    ["TYPE", "NEIGHBOURHOOD"],
    columns = 1
)
categ_cols_dist
```
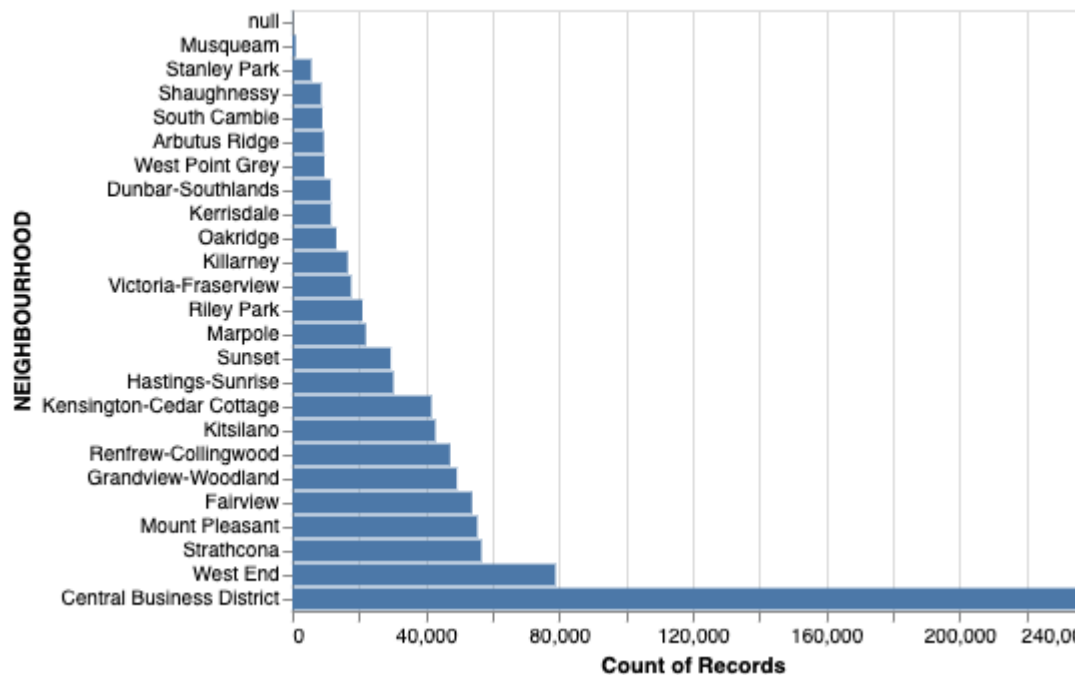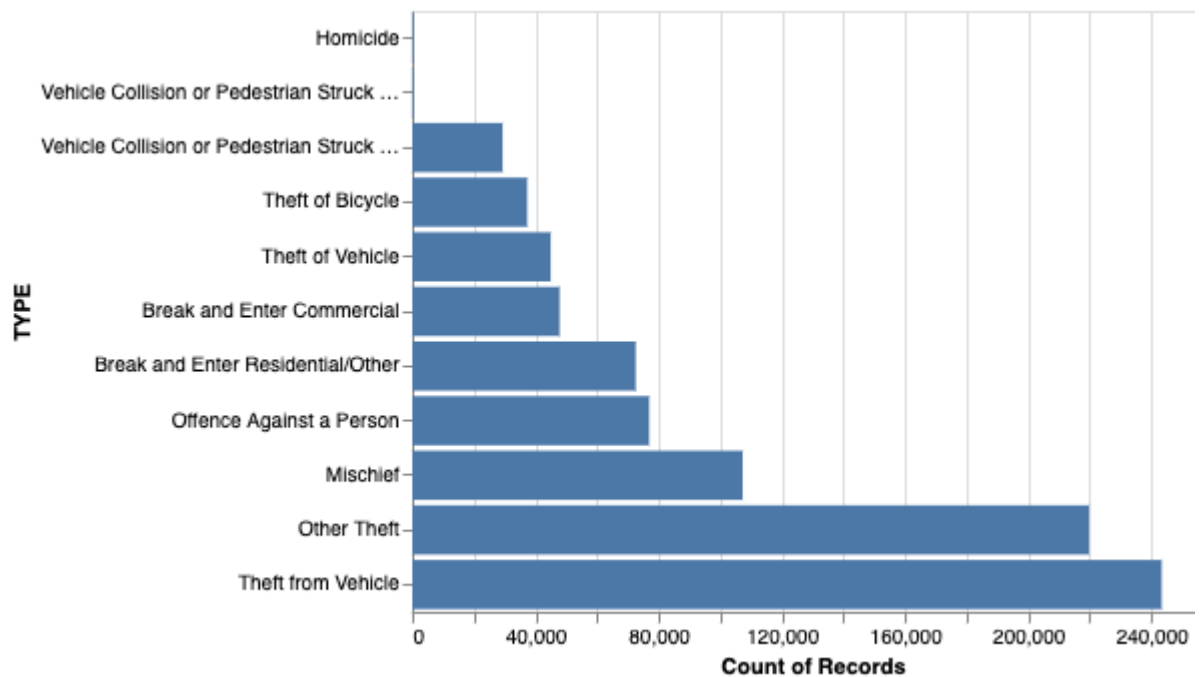
Correlation

In [8]:
```python
def get_redundant_pairs(df):
    pairs_to_drop = set()
    cols = df.columns
    for i in range(0, df.shape[1]):
        for j in range(0, i+1):
            pairs_to_drop.add((cols[i], cols[j]))
    return pairs_to_drop

def get_top_abs_correlations(df, n=5):
    au_corr = df.corr().abs().unstack()
    labels_to_drop = get_redundant_pairs(df)
```

```
    au_corr = au_corr.drop(labels=labels_to_drop).sort_values(ascending=Fals
    return au_corr[0:n]

print("Top Absolute Correlations !")
print(get_top_abs_correlations(data.select_dtypes(include=['int32','int64'])
```

```
Top Absolute Correlations !
HOUR    MINUTE    0.114717
YEAR    MINUTE    0.056099
        HOUR      0.035971
        MONTH     0.010681
        DAY       0.009736
MONTH   DAY       0.006062
DAY     HOUR      0.004696
MONTH   MINUTE    0.003963
DAY     MINUTE    0.003185
MONTH   HOUR      0.002013
dtype: float64
```

Preprocessing

We'll start the data preprocessing phase by grouping the rows according to the TYPE, YEAR, and MONTH columns to aggregate the counts of specific crimes occurring in each month. Additionally, we'll adjust the datetime variable format for consistency. However, as the latest month (2023-11) is incomplete, we'll exclude this month from the dataset. Finally, we'll filter the data so that we focus only on `Theft from Vehicle` crimes, the most common crime in Vancouver in the past 20 years. This initial processing sets the groundwork for our subsequent time-series forecasting models.

In [9]:
```python
# Groupby the dataset to find the number of observations for each crime in a
grouped = data.groupby(['TYPE', 'YEAR', 'MONTH']).size().reset_index(name='C
# Combine YEAR and MONTH into a datetime variable
grouped['YEAR-MONTH'] = pd.to_datetime(grouped[['YEAR', 'MONTH']].assign(DAY
# remove rows with time 2023-11 because the data is incomplete
grouped = grouped[~((grouped['YEAR'] == 2023) & (grouped['MONTH'] == 11))]

grouped.head()
```

Out[9]:

	TYPE	YEAR	MONTH	Observations	YEAR-MONTH
0	Break and Enter Commercial	2003	1	303	2003-01-01
1	Break and Enter Commercial	2003	2	254	2003-02-01
2	Break and Enter Commercial	2003	3	292	2003-03-01
3	Break and Enter Commercial	2003	4	266	2003-04-01
4	Break and Enter Commercial	2003	5	290	2003-05-01

In [10]:
```python
theft_from_vehicle = grouped[grouped['TYPE']=='Theft from Vehicle']
theft_from_vehicle.head()
```

Out[10]:

	TYPE	YEAR	MONTH	Observations	YEAR-MONTH
1433	Theft from Vehicle	2003	1	1438	2003-01-01
1434	Theft from Vehicle	2003	2	1102	2003-02-01
1435	Theft from Vehicle	2003	3	1251	2003-03-01
1436	Theft from Vehicle	2003	4	1528	2003-04-01
1437	Theft from Vehicle	2003	5	1873	2003-05-01

In [11]:
```python
theft_from_vehicle.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 250 entries, 1433 to 1682
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   TYPE          250 non-null    object
 1   YEAR          250 non-null    int64
 2   MONTH         250 non-null    int64
 3   Observations  250 non-null    int64
 4   YEAR-MONTH    250 non-null    datetime64[ns]
dtypes: datetime64[ns](1), int64(3), object(1)
memory usage: 11.7+ KB
```

In [12]:
```python
sns.lineplot(data=theft_from_vehicle, x='YEAR-MONTH', y='Observations')
```

Out[12]: <Axes: xlabel='YEAR-MONTH', ylabel='Observations'>
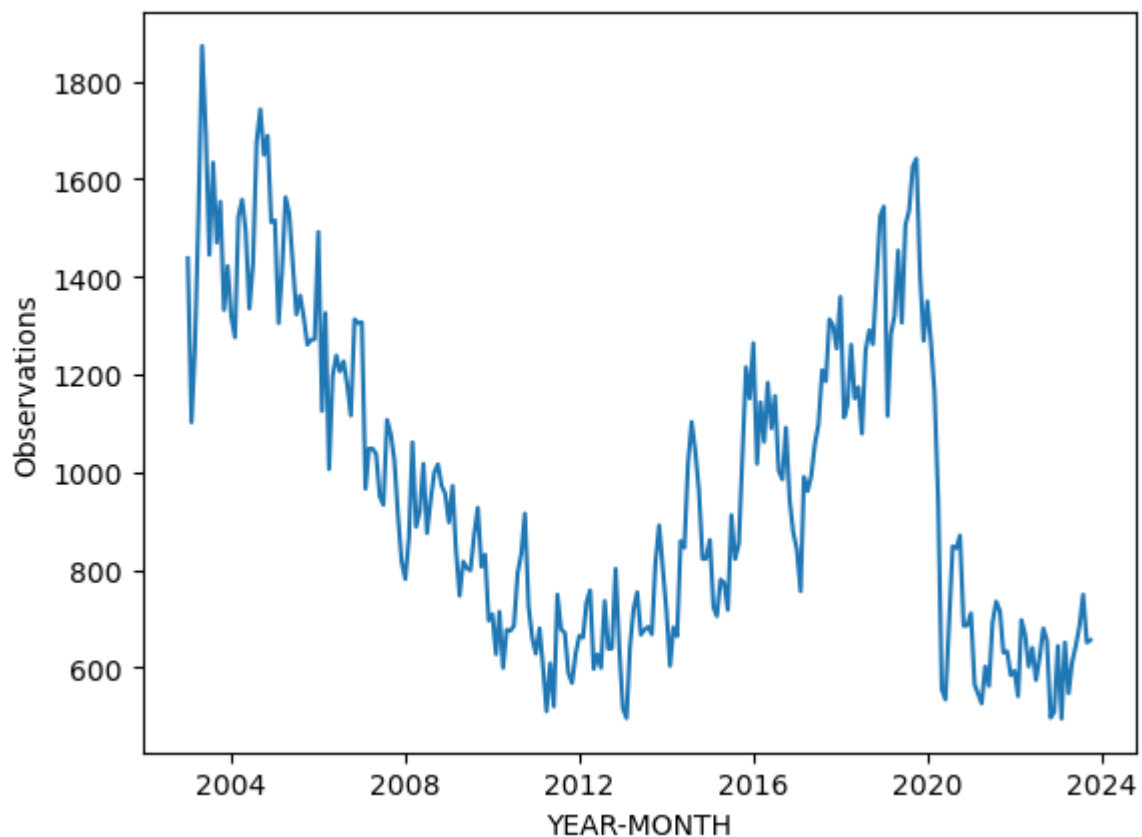
```
In [13]: theft_from_vehicle_filtered = theft_from_vehicle[['YEAR-MONTH','Observations
         theft_from_vehicle_filtered.set_index('YEAR-MONTH', inplace=True)
         theft_from_vehicle_filtered.head()
```

Out[13]:

	Observations
YEAR-MONTH	
2003-01-01	1438
2003-02-01	1102
2003-03-01	1251
2003-04-01	1528
2003-05-01	1873

Simple Moving Average & Exponential Smoothing

```
In [14]: # Define the size of the sliding window
         window_size = 12
         # Define alpha (smoothing parameter in ES)
         alpha=0.3

         # Perform Simple Moving Average (SMA) and Exponential Smoothing (ES)
         sma_values = []
         smoothed_values = []
         for i in range(len(theft_from_vehicle_filtered) - window_size + 1):

             window = theft_from_vehicle_filtered['Observations'].iloc[i:i+window_siz

             # SMA
             window_mean = window.mean()
             sma_values.append(window_mean)

             # ES
             smoothed_val = window.ewm(alpha=alpha, adjust=False).mean().iloc[-1]
             smoothed_values.append(smoothed_val)

         sma_merged = merge_forecast_values(theft_from_vehicle_filtered, sma_values,
         es_merged = merge_forecast_values(theft_from_vehicle_filtered, smoothed_valu

         plt.figure(figsize=(10, 6))
         plt.plot(sma_merged.index, sma_merged['Observations'], label='Original Value
         plt.plot(sma_merged.index, sma_merged['SMA_Forecast'], label='SMA Forecasts'
         plt.legend()
         plt.title('SMA with Sliding Window')
         plt.xlabel('Date')
         plt.ylabel('Value')
         plt.show()
```
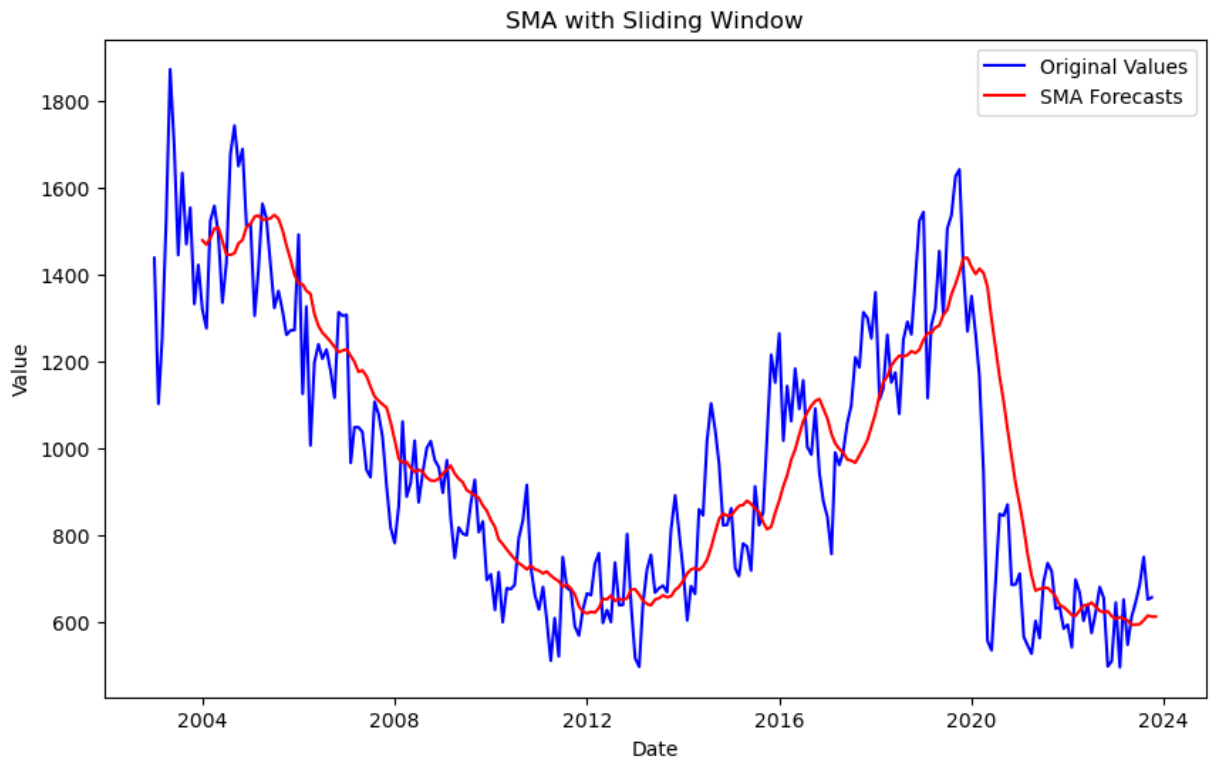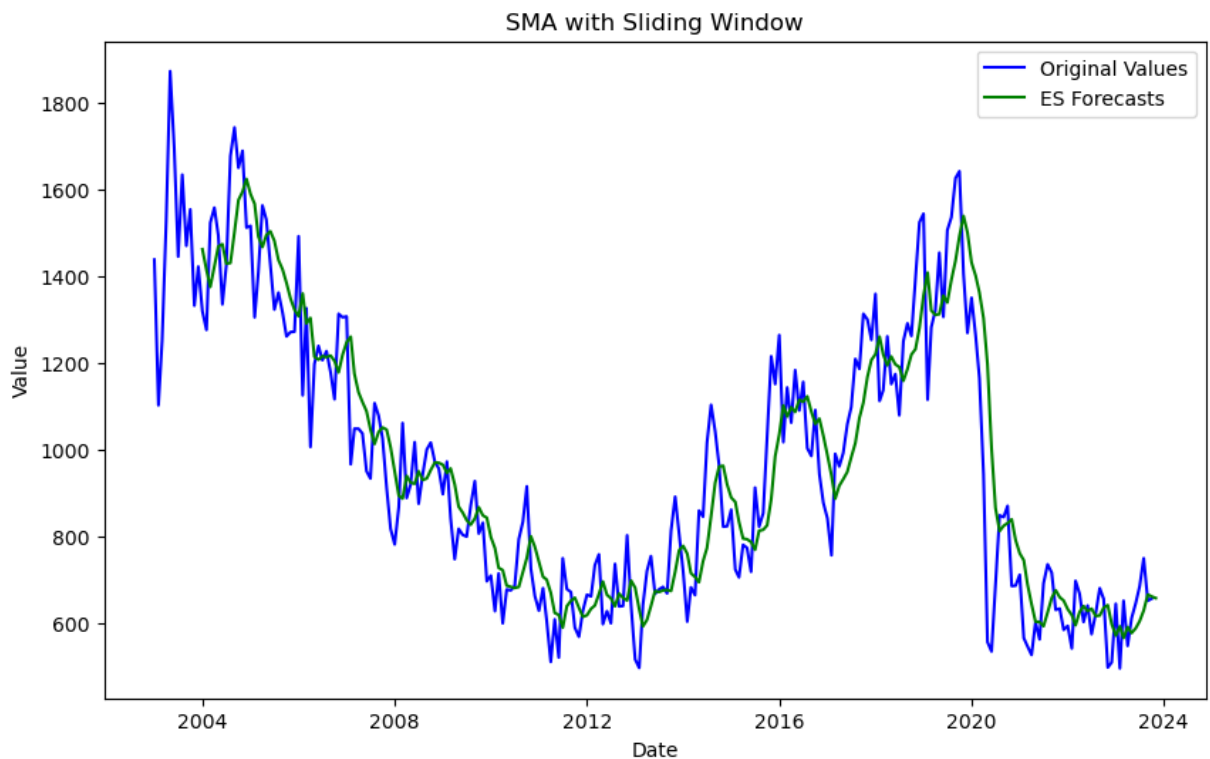
SMA with Sliding Window

In [15]:
```python
plt.figure(figsize=(10, 6))
plt.plot(es_merged.index, es_merged['Observations'], label='Original Values'
plt.plot(es_merged.index, es_merged['ES_Forecast'], label='ES Forecasts', co
plt.legend()
plt.title('SMA with Sliding Window')
plt.xlabel('Date')
plt.ylabel('Value')
plt.show()
```


SMA with Sliding Window

Based on a visual assessment of the Simple Moving Average (SMA) and Exponential Smoothing (ES) forecasts, it's evident that both methods broadly capture the general trend of the actual values. However, neither forecast method appears to be highly accurate. The Exponential Smoothing approach demonstrates a slightly improved performance compared to SMA.
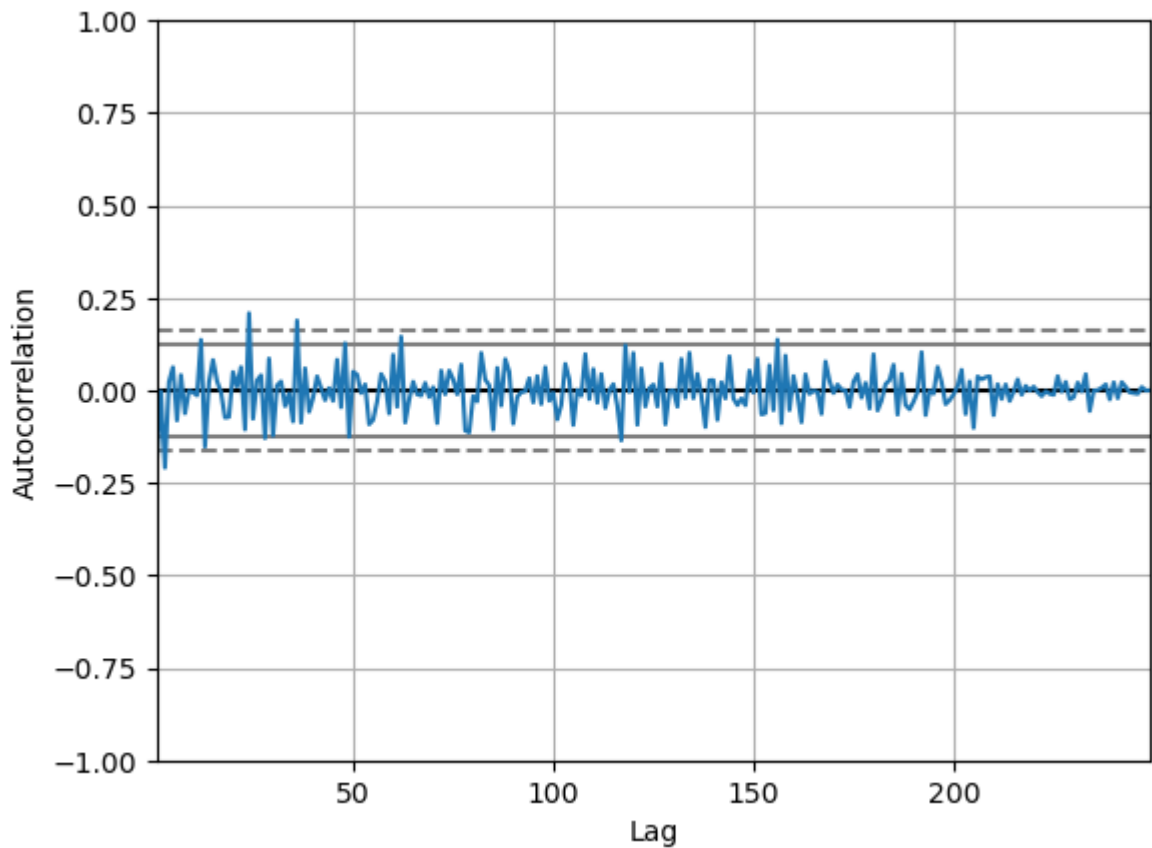
ARIMA(1,1,0)

```
In [16]:  autocorrelation_plot(theft_from_vehicle.Observations)
```

Out[16]: <Axes: xlabel='Lag', ylabel='Autocorrelation'>
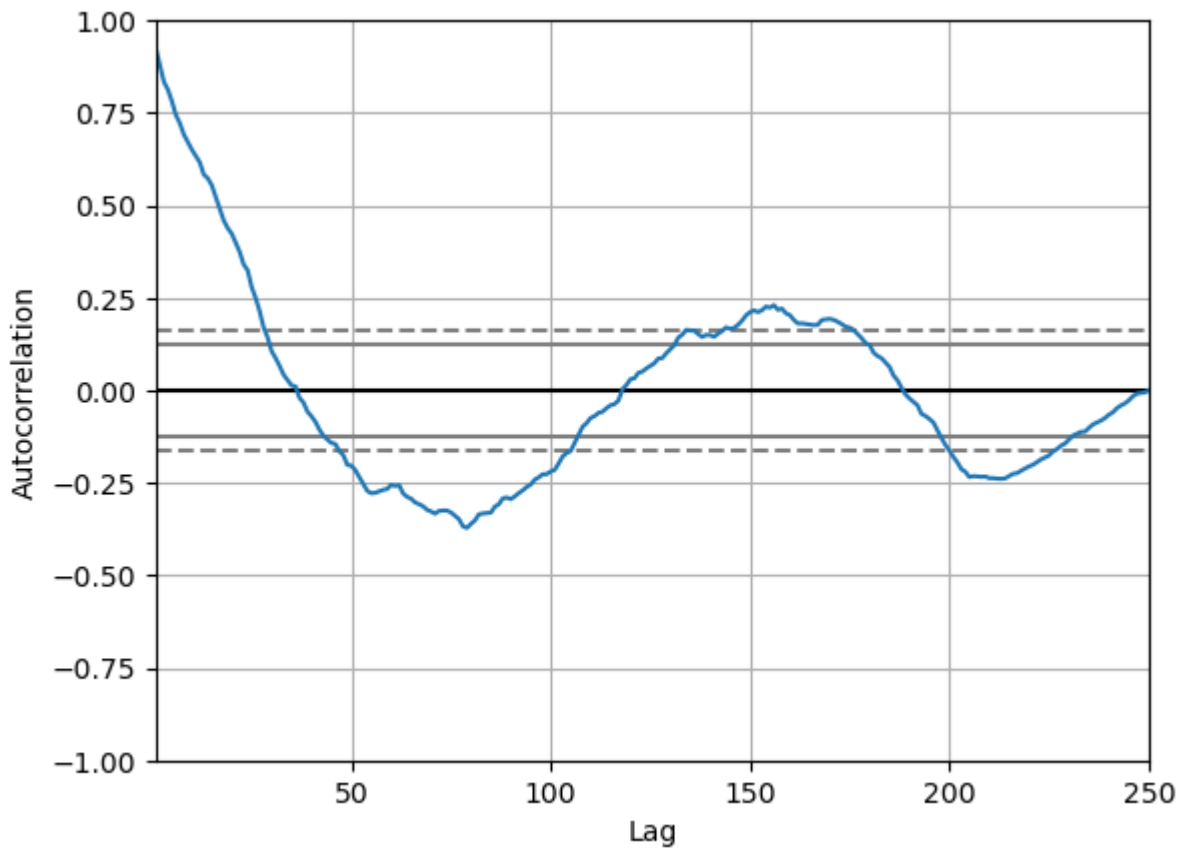

```
In [17]:  df_diff = theft_from_vehicle_filtered.diff().dropna()
          autocorrelation_plot(df_diff.Observations)
```

Out[17]: <Axes: xlabel='Lag', ylabel='Autocorrelation'>

```python
In [18]:  arima_pred_values = arima_prediction(theft_from_vehicle_filtered)
          arima_merged = merge_forecast_values(theft_from_vehicle_filtered, arima_pred
          arima_merged.head()
```

Out[18]:

	Observations	ARIMA_Forecast
2003-01-01	1438.0	NaN
2003-02-01	1102.0	NaN
2003-03-01	1251.0	NaN
2003-04-01	1528.0	NaN
2003-05-01	1873.0	NaN

```python
In [19]:  plt.figure(figsize=(10, 6))
          plt.plot(arima_merged.index, arima_merged['Observations'], label='Original V
          plt.plot(arima_merged.index, arima_merged['ARIMA_Forecast'], label='ARIMA Fo
          plt.legend()
          plt.title('ARIMA with Sliding Window')
          plt.xlabel('Date')
          plt.ylabel('Value')
          plt.show()
```

ARIMA with Sliding Window
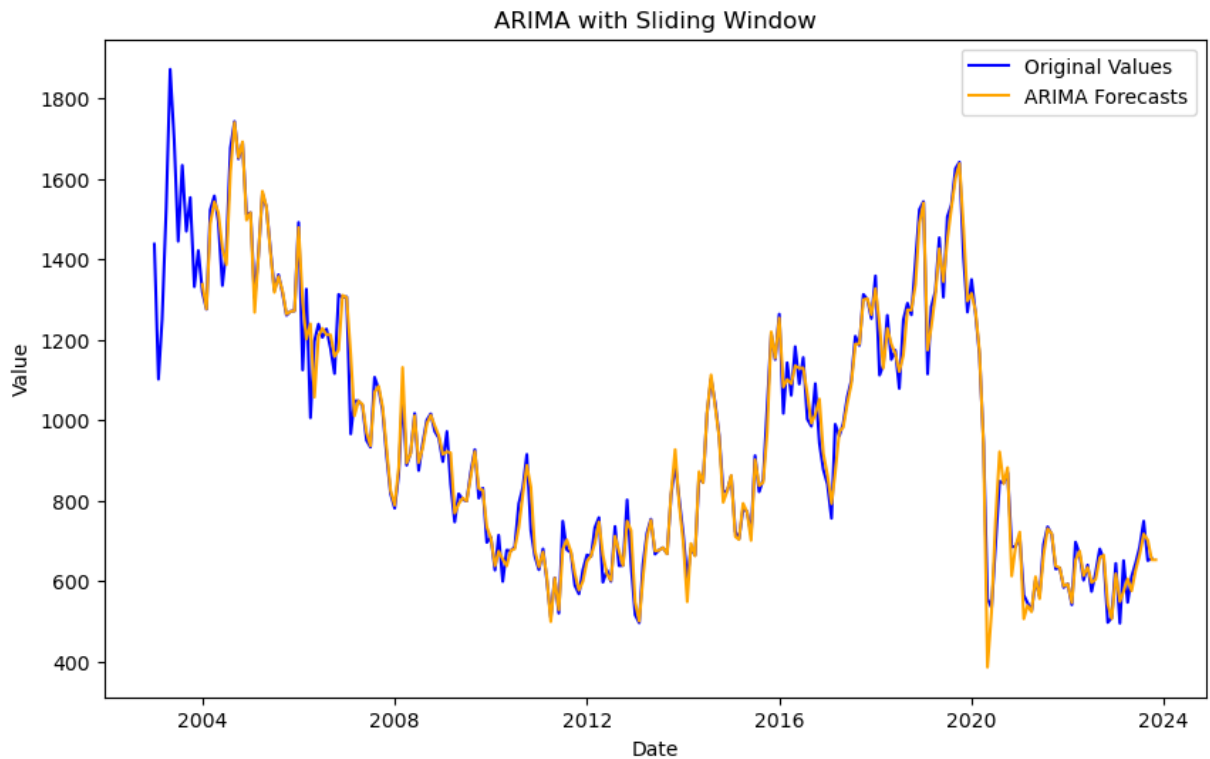
The forecast from the ARIMA model looks much better! We can see some clear overlaps between the forecasted value and the original value.

```
In [20]: merged_df = pd.concat([sma_merged, es_merged["ES_Forecast"], arima_merged["A
         merged_df.head()
```

Out[20]:

	Observations	SMA_Forecast	ES_Forecast	ARIMA_Forecast
2003-01-01	1438.0	NaN	NaN	NaN
2003-02-01	1102.0	NaN	NaN	NaN
2003-03-01	1251.0	NaN	NaN	NaN
2003-04-01	1528.0	NaN	NaN	NaN
2003-05-01	1873.0	NaN	NaN	NaN

```
In [21]: # Drop NA values to evaluate performance

         merged_df_drop = merged_df.dropna()

         results_df = get_metrics_from_df(merged_df_drop, "Observations")
         results_df
```

`Out[21]:`

	Forecast_Column	MAE	MSE
0	SMA_Forecast	121.216737	27239.951827
1	ES_Forecast	98.641493	16240.436389
2	ARIMA_Forecast	26.856890	1940.870649

The displayed dataframe outlines the performance metrics, specifically the mean absolute error (MAE) and mean squared error (MSE), for the three models. Notably, there's a discernible pattern showcasing a marked enhancement in performance, progressing from Simple Moving Average (SMA) to Exponential Smoothing Approach (ESA) and ultimately to ARIMA. This consistent trend aligns with the observations gleaned from the visualizations crafted earlier, affirming the gradual improvement in forecasting accuracy across the models.

While the ARIMA model stands out as the most effective among the three forecasting models—simple moving average and exponential smoothing—it's crucial to acknowledge the room for enhancement in our predictive capabilities. Future advancements could entail fine-tuning the ARIMA hyperparameters or exploring alternative models to ascertain if further accuracy gains are attainable. Additionally, integrating exogenous variables, such as socioeconomic indicators or weather data, might augment the predictive power of our models, offering a more comprehensive understanding of crime dynamics. Furthermore, this analysis prompts future inquiries, including investigating the influence of specific external factors on crime occurrences or exploring spatial-temporal models to predict crime hotspots within Vancouver. These prospective avenues aim to refine our forecasting precision and deepen our insights into crime trends, paving the way for more informed law enforcement strategies and proactive crime prevention measures.

References

Amanat, Hayatullah. "Vehicle Theft at a 'critical Point' in Canada: Report | CTV News." CTVNews, CTV News, 17 June 2023, https://www.ctvnews.ca/canada/vehicle-theft-at-a-critical-point-in-canada-with-car-stolen-every-six-minutes-report-1.6443514.

Harris, C.R. et al., 2020. Array programming with NumPy. Nature, 585, pp.357–362.

J. D. Hunter, "Matplotlib: A 2D Graphics Environment," in Computing in Science & Engineering, vol. 9, no. 3, pp. 90-95, May-June 2007, doi: 10.1109/MCSE.2007.55.

McKinney, Wes. 2010. "Data Structures for Statistical Computing in Python." In Proceedings of the 9th Python in Science Conference, edited by Stéfan van der Walt and Jarrod Millman, 51–56.

Pedregosa, F. et al., 2011. Scikit-learn: Machine learning in Python. Journal of machine learning research, 12(Oct), pp.2825–2830.

Seabold, Skipper, and Josef Perktold. "Statsmodels: Econometric and statistical modeling with python." Proceedings of the 9th Python in Science Conference. 2010.

VanderPlas, J. et al., 2018. Altair: Interactive statistical visualizations for python. Journal of open source software, 3(32), p.1057.

"VPD OPEN DATA." GeoDASH, Vancouver Police Department, https://geodash.vpd.ca/opendata/. Accessed 16 Nov. 2023.

Waskom, M. L., (2021). seaborn: statistical data visualization. Journal of Open Source Software, 6(60), 3021, https://doi.org/10.21105/joss.03021