analysis_chicago_type1

April 23, 2023

1 Analysis Template

1.1 Preprocess

[ ]:

```
# resolve dependency
# !pip install pmdarima
```

[ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from pandas.plotting import autocorrelation_plot
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
import statsmodels.api as sm
from pmdarima.arima import ADFTest , auto_arima
%matplotlib inline
```

[ ]:

```
data_path = "../data/battery_occurrence_per_day.csv"
crime = "type1"
target = "Count"
date = "Date"
city = "chicago"
fig_size = (20,5)
```

[ ]:

```
df_by_day = pd.read_csv(data_path)
df_by_day[date] = pd.to_datetime(df_by_day[date])
df_by_day.set_index(date, inplace=True)
```

1.2 Profiling

1.2.1 By day

[ ]:

```
df_by_day.head()
```

[ ]:

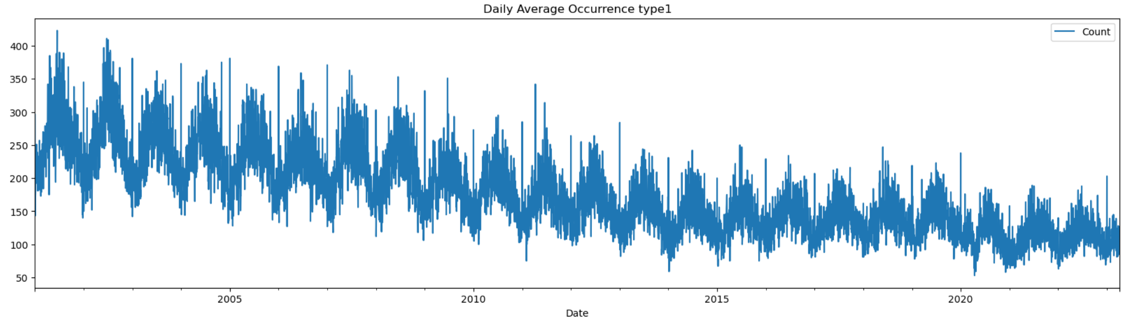
```
            Count
Date
2001-01-01    296
2001-01-02    143
```

```
2001-01-03    165
2001-01-04    173
2001-01-05    178
```

```
[ ]: df_by_day.describe()
```

```
[ ]:              Count
     count  8132.000000
     mean    174.757993
     std      61.009520
     min      53.000000
     25%     127.000000
     50%     163.000000
     75%     216.000000
     max     423.000000
```

```
[ ]: df_by_day.plot(figsize=fig_size, title="Daily Average Occurrence " + crime)
     plt.show()
```

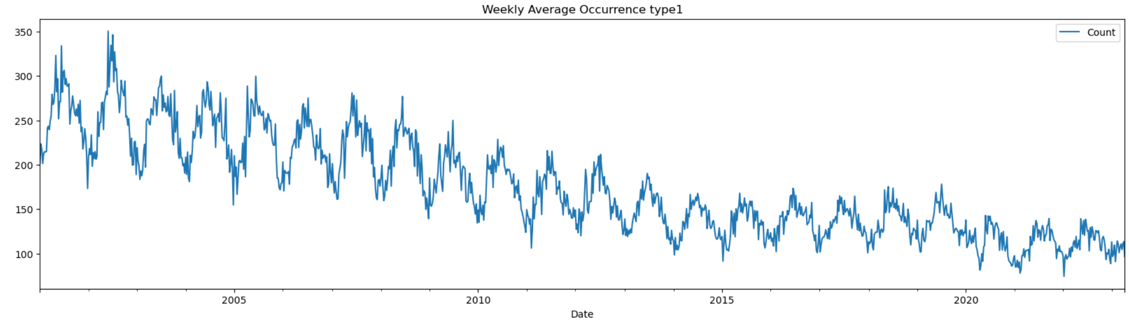


```
[ ]: df_by_day[target].sort_values(ascending=False).head()
```

```
[ ]: Date
     2001-06-17    423
     2002-06-23    411
     2002-07-04    409
     2002-06-01    397
     2002-07-20    393
     Name: Count, dtype: int64
```

1.2.2 By week

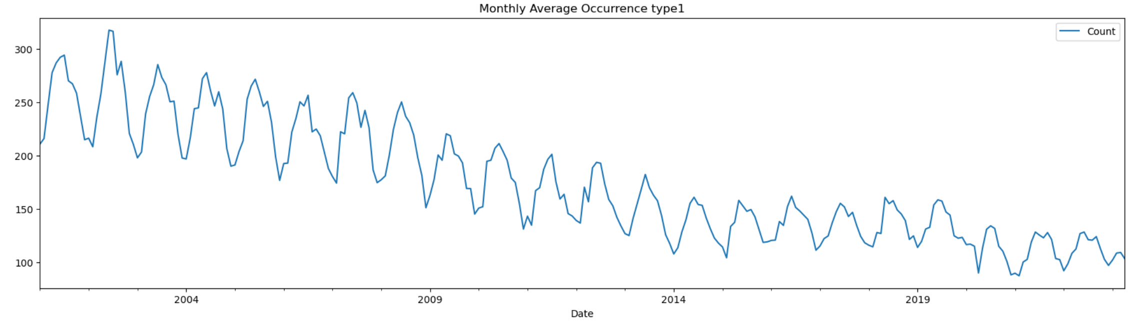
```
[ ]: df_by_week = pd.DataFrame(df_by_day[target].resample('W').mean())
[ ]: df_by_week.plot(
         figsize=fig_size,
         title="Weekly Average Occurrence " + crime)
     plt.show()
```



1.2.3 By month

```
[ ]: df_by_month = pd.DataFrame(df_by_day[target].resample('M').mean())
```

```
[ ]: df_by_month.plot(
         figsize=fig_size,
         title="Monthly Average Occurrence " + crime)
     plt.show()
```



1.3 Analysis

```
[ ]: #Ho: It is non stationary
     #H1: It is stationary

     def adfuller_test(count):
         result=adfuller(count)
```

```
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of␣
↪Observations Used']
    for value,label in zip(result,labels):
        print(label+' : '+str(value) )
    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis(Ho), reject the null␣
↪hypothesis. Data has no unit root and is stationary")
    else:
        print("weak evidence against null hypothesis, time series has a unit␣
↪root, indicating it is non-stationary ")
```

1.3.1 Checking stationary

[ ]:
```
adfuller_test(df_by_month[target])
```

```
ADF Test Statistic : -1.1257894251667415
p-value : 0.7046785869157075
#Lags Used : 14
Number of Observations Used : 253
weak evidence against null hypothesis, time series has a unit root, indicating
it is non-stationary
```

1.3.2 Checking seasonality

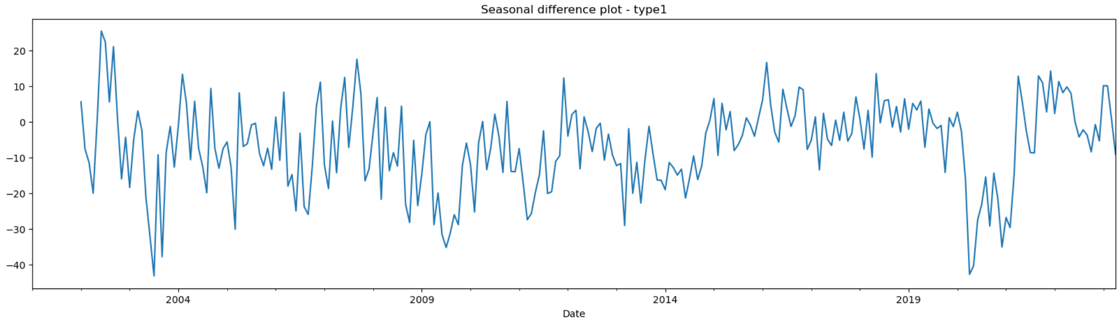
[ ]:
```
df_by_month['seasonal_first_difference'] = df_by_month[target] -␣
↪df_by_month[target].shift(12)
```

[ ]:
```
adfuller_test(df_by_month['seasonal_first_difference'].dropna())
```

```
ADF Test Statistic : -4.335873703851938
p-value : 0.0003847880016246871
#Lags Used : 12
Number of Observations Used : 243
strong evidence against the null hypothesis(Ho), reject the null hypothesis.
Data has no unit root and is stationary
```

[ ]:
```
df_by_month['seasonal_first_difference'].plot(figsize=fig_size, title='Seasonal␣
↪difference plot - ' + crime)
```

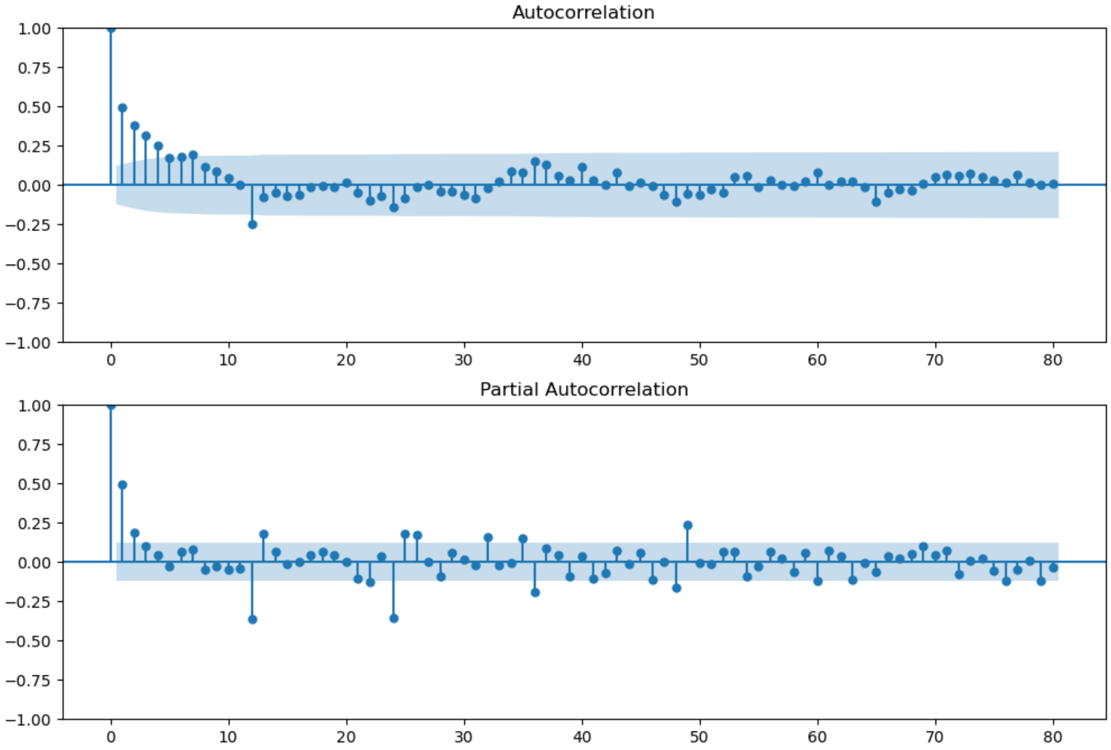
[ ]:
```
<Axes: title={'center': 'Seasonal difference plot - type1'}, xlabel='Date'>
```



1.3.3 Auto Regressive Model

```
[ ]: fig = plt.figure(figsize=(12,8))
     ax1 = fig.add_subplot(211)
     fig = sm.graphics.tsa.plot_acf(df_by_month['seasonal_first_difference'].iloc[13:
       ↪],lags=80,ax=ax1)
     ax2 = fig.add_subplot(212)
     fig = sm.graphics.tsa.plot_pacf(df_by_month['seasonal_first_difference'].
       ↪iloc[13:],lags=80,ax=ax2)
```

```
/Users/xuyanchong/opt/anaconda3/lib/python3.9/site-
packages/statsmodels/graphics/tsaplots.py:348: FutureWarning: The default method
'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this method
now by setting method='ywm'.
  warnings.warn(
```

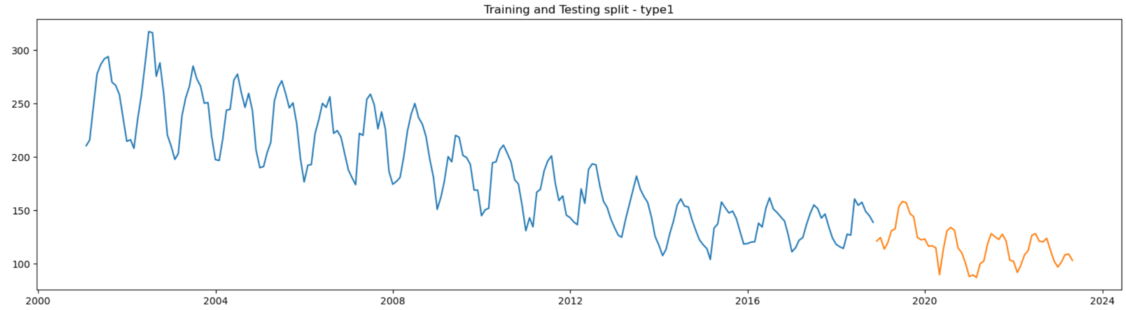


1.3.4 Implementing Seasonal Arima Model

[ ]:
```
adf_test=ADFTest(alpha=0.05)
adf_test.should_diff(df_by_month[target])
```

[ ]:
```
(0.01, False)
```

[ ]:
```
start=int(df_by_month.shape[0]*0.8)
train=df_by_month[:start]
test=df_by_month[start:]
plt.figure(figsize=fig_size)
plt.plot(train[target])
plt.plot(test[target])
plt.title('Training and Testing split - '+ crime)
plt.show()
```



[ ]:

```
model=auto_arima(train[target],start_p=0,d=1,start_q=0,
          max_p=10,max_d=10,max_q=10, start_P=0,
          D=1, start_Q=0, max_P=10,max_D=10,
          max_Q=10, m=12, seasonal=True,
          error_action='warn',trace=True,
          supress_warnings=True,stepwise=True,
          random_state=20,n_fits=50)
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=1599.851, Time=0.07 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=1521.442, Time=0.81 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=1468.648, Time=3.16 sec
 ARIMA(0,1,1)(0,1,0)[12]             : AIC=1533.339, Time=0.17 sec
 ARIMA(0,1,1)(1,1,1)[12]             : AIC=1470.446, Time=3.66 sec
 ARIMA(0,1,1)(0,1,2)[12]             : AIC=1470.306, Time=22.09 sec
 ARIMA(0,1,1)(1,1,0)[12]             : AIC=1494.488, Time=0.93 sec
 ARIMA(0,1,1)(1,1,2)[12]             : AIC=inf, Time=28.72 sec
 ARIMA(0,1,0)(0,1,1)[12]             : AIC=1518.288, Time=1.57 sec
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=1464.449, Time=3.33 sec
 ARIMA(1,1,1)(0,1,0)[12]             : AIC=1531.298, Time=0.54 sec
 ARIMA(1,1,1)(1,1,1)[12]             : AIC=1466.355, Time=3.95 sec
 ARIMA(1,1,1)(0,1,2)[12]             : AIC=1466.295, Time=25.90 sec
 ARIMA(1,1,1)(1,1,0)[12]             : AIC=1493.450, Time=1.47 sec
 ARIMA(1,1,1)(1,1,2)[12]             : AIC=inf, Time=36.14 sec
 ARIMA(1,1,0)(0,1,1)[12]             : AIC=1487.935, Time=2.43 sec
 ARIMA(2,1,1)(0,1,1)[12]             : AIC=1464.919, Time=4.66 sec
 ARIMA(1,1,2)(0,1,1)[12]             : AIC=1465.020, Time=4.92 sec
 ARIMA(0,1,2)(0,1,1)[12]             : AIC=1466.224, Time=3.90 sec
 ARIMA(2,1,0)(0,1,1)[12]             : AIC=1480.192, Time=3.27 sec
 ARIMA(2,1,2)(0,1,1)[12]             : AIC=1466.866, Time=4.89 sec
 ARIMA(1,1,1)(0,1,1)[12] intercept   : AIC=1466.165, Time=3.09 sec

Best model:  ARIMA(1,1,1)(0,1,1)[12]
Total fit time: 159.672 seconds
```

[ ]:

```
model.summary()
```

[ ]:

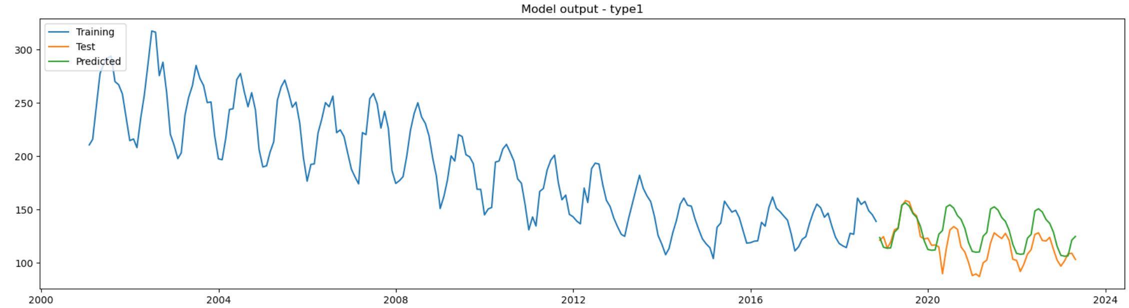
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                     SARIMAX Results
================================================================================
==========
Dep. Variable:                                  y   No. Observations:
214
Model:             SARIMAX(1, 1, 1)x(0, 1, 1, 12)   Log Likelihood
-728.224
Date:                            Sun, 23 Apr 2023   AIC
1464.449
Time:                                    01:34:17   BIC
1477.662
Sample:                                01-31-2001   HQIC
1469.795
                                     - 10-31-2018
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.2699      0.097      2.788      0.005       0.080       0.460
ma.L1         -0.8472      0.052    -16.196      0.000      -0.950      -0.745
ma.S.L12      -0.6542      0.071     -9.177      0.000      -0.794      -0.515
sigma2        79.0241      8.944      8.835      0.000      61.494      96.554
================================================================================
===
Ljung-Box (L1) (Q):                   0.09   Jarque-Bera (JB):
0.97
Prob(Q):                              0.77   Prob(JB):
0.62
Heteroskedasticity (H):               0.41   Skew:
-0.01
Prob(H) (two-sided):                  0.00   Kurtosis:
2.66
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
"""
```

[ ]:

```
prediction = pd.DataFrame(model.predict(n_periods = train.shape[0]),index=test.
 ↪index)
prediction.columns = ['predicted_crime']
```

```
plt.figure(figsize=fig_size)
plt.plot(train[target],label="Training")
plt.plot(test[target],label="Test")
plt.plot(prediction,label="Predicted")
plt.legend(loc = 'upper left')
plt.savefig('../output/%s_%s_pred.jpg' % (city,crime))
plt.title('Model output - '+crime)
plt.show()
```



```
[ ]: np.sqrt(np.square(np.subtract(test[target].values,prediction['predicted_crime'].
      ↪values)).mean())
```

```
[ ]: 17.381555810118396
```