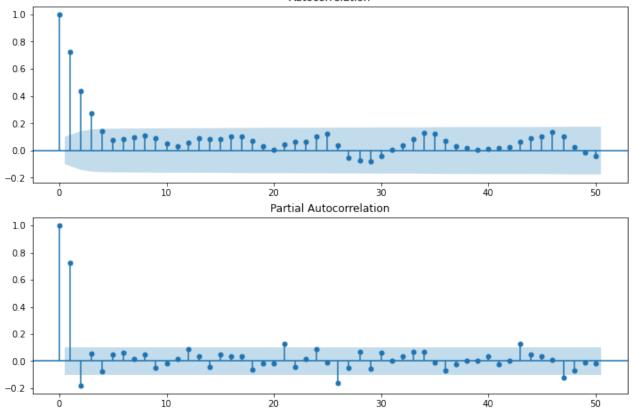
```
In [1]:
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import statsmodels.api as sm
         import seaborn as sns
         from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
         from statsmodels.tsa.arima.model import ARIMA
         from statsmodels.tsa.stattools import adfuller
         from sklearn import metrics
In [2]:
         from ucimlrepo import fetch_ucirepo
         # fetch dataset
         air_quality = fetch_ucirepo(id=360)
         # data (as pandas dataframes)
         df = air_quality.data.features
In [3]:
         # Convert 'Date' and 'Time' columns to datetime format
         df['DateTime'] = pd.to_datetime(df['Date']+ ' ' + df['Time'])
         df['Date'] = pd.to datetime(df['Date'])
         df.index = df['Date']
         df['Year'] = df['Date'].dt.year
         df['Month'] = df['Date'].dt.month
         df['Day'] = df['Date'].dt.day
         # Drop Date and Time columns
         df.drop(columns=['Time', 'Date'], inplace=True)
In [4]:
         df.head()
Out[4]:
               CO(GT) PT08.S1(CO) NMHC(GT) C6H6(GT) PT08.S2(NMHC) NOx(GT) PT08.S3(NOx) I
          Date
         2004-
                   2.6
                              1360
                                          150
                                                   11.9
                                                                  1046
                                                                           166
                                                                                        1056
         03-10
         2004-
                              1292
                   2.0
                                          112
                                                    9.4
                                                                  955
                                                                           103
                                                                                        1174
         03-10
         2004-
                   2.2
                              1402
                                          88
                                                    9.0
                                                                  939
                                                                                        1140
                                                                            131
         03-10
         2004-
                   2.2
                              1376
                                          80
                                                    9.2
                                                                  948
                                                                           172
                                                                                        1092
         03-10
         2004-
                              1272
                                                    6.5
                                                                  836
                                                                                        1205
                   1.6
                                          51
                                                                            131
         03-10
```

```
In [5]:
         year = pd.DataFrame(df.groupby(['Date'])['CO(GT)'].mean())
         year.index = pd.DatetimeIndex(year.index, freq=year.index.inferred_freq)
          year.head()
Out [5]:
                        CO(GT)
               Date
         2004-03-10
                      1.966667
         2004-03-11
                      -6.187500
         2004-03-12 -14.095833
         2004-03-13
                     -5.750000
         2004-03-14
                     -5.966667
In [6]:
          plt.figure(figsize = (15,7))
          plt.plot(year, label = 'Average CO2 by Day')
          plt.show()
                                                               MWWWW MWWW MWW
                                 WWW/WW/WW/
          -50
         -100
         -150
         -200
            2004-03
                        2004-05
                                    2004-07
                                                2004-09
                                                           2004-11
                                                                       2005-01
                                                                                   2005-03
In [7]:
         adf_test = adfuller(year['CO(GT)'])
          # Output the results
          print('ADF Statistic: %f' % adf_test[0])
         print('p-value: %f' % adf_test[1])
         ADF Statistic: -8.748258
         p-value: 0.000000
In [8]:
         fig = plt.figure(figsize=(12,8))
          ax1 = fig.add_subplot(211)
          sm.graphics.tsa.plot_acf(year['CO(GT)'], lags = 50, ax=ax1)
         ax2 = fig.add_subplot(212)
          fig = sm.graphics.tsa.plot_pacf(year['CO(GT)'],lags=50,ax=ax2)
```

Autocorrelation



```
In [9]: mod = ARIMA(year['CO(GT)'], order = (2,0,2))
fit = mod.fit()
print(fit.summary())
```

SARIMAX Results

Dep. Varia Model: Date: Time: Sample:	A Wed	ARIMA(2, 0, 1, 03 Jul 20 20:06 03-10-20 - 04-04-20	2) Log 024 AIC :23 BIC 004 HQI	Observations Likelihood	:	391 -2042.572 4097.144 4120.957 4106.583
=======	coef	std err	z	======== P> z	[0.025	0.975]
const ar.L1 ar.L2 ma.L1 ma.L2 sigma2	-34.0107 -0.3085 0.5399 1.1786 0.2423 2014.1686	14.572 0.548 0.305 0.551 0.186 150.742	-2.334 -0.563 1.768 2.138 1.303 13.362	0.573 0.077 0.033 0.193	-62.571 -1.382 -0.058 0.098 -0.122 1718.720	-5.450 0.765 1.138 2.259 0.607 2309.618
1.45	<pre>(L1) (Q): dasticity (H): two-sided):</pre>		0.00 0.95 0.68 0.03	Jarque-Bera Prob(JB): Skew: Kurtosis:	(JB):	58

Warnings

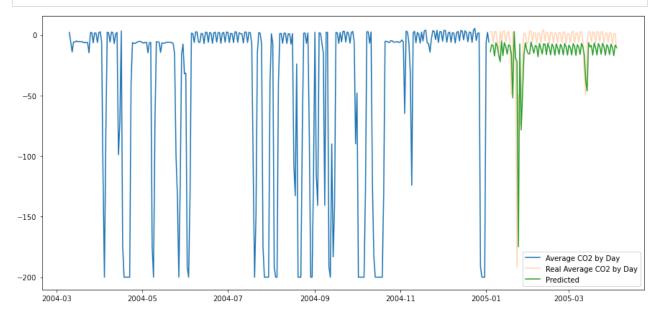
Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-s tep).

```
In [10]:
```

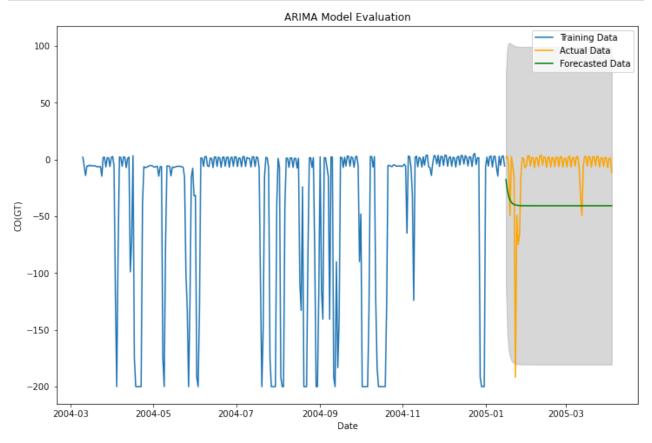
```
year['forecast']=fit.predict(start=300)

plt.figure(figsize = (15,7))
plt.plot(year.iloc[:300]['CO(GT)'], label = 'Average CO2 by Day')
plt.plot(year.iloc[300:]['CO(GT)'], label = 'Real Average CO2 by Day', alpha = .
plt.plot(year['forecast'], label = 'Predicted')
plt.legend()
plt.show()
print('MAE:',metrics.mean_absolute_error(year.iloc[300:]['CO(GT)'],year.iloc[300]
```



MAE: 15.271274917815404

```
In [11]:
          #https://medium.com/datainc/time-series-analysis-and-forecasting-with-arima-in-p
          # Split the data into train and test
          train_size = int(len(year) * 0.8)
          train, test = year[0:train_size], year[train_size:len(year)]
          # Fit the ARIMA model on the training dataset
          model_train = ARIMA(train['CO(GT)'], order=(2, 0, 2))
          model train fit = model train.fit()
          # Forecast on the test dataset
          test_forecast = model_train_fit.get_forecast(steps=len(test))
          test_forecast_series = pd.Series(test_forecast.predicted_mean, index=test.index)
          # Calculate the mean squared error
          mse = metrics.mean_squared_error(test['CO(GT)'], test_forecast_series)
          rmse = mse**0.5
          # Create a plot to compare the forecast with the actual test data
          plt.figure(figsize=(12,8))
          plt.plot(train['CO(GT)'], label='Training Data')
```



RMSE: 41.310347660980455

```
In [12]: mod = ARIMA(year['CO(GT)'], order = (2,0,4))
fit = mod.fit()
print(fit.summary())
```

SARIMAX Results

=======================================			
Dep. Variable:	CO(GT)	No. Observations:	391
Model:	ARIMA(2, 0, 4)	Log Likelihood	-2040.848
Date:	Wed, 03 Jul 2024	AIC	4097.695
Time:	20:06:24	BIC	4129.445
Sample:	03-10-2004	HQIC	4110.280
	- 04-04-2005		
Covariance Type:	opg		

	coef	std err	z	P> z	[0.025	0.975]
const	-34.0910	13.885	-2 . 455	0.014	-61 . 305	-6 . 877

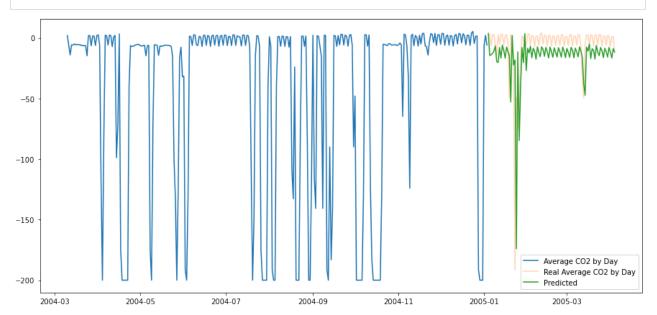
ar.L1 ar.L2 ma.L1 ma.L2 ma.L3 ma.L4 sigma2	-0.1952 0.2474 1.0642 0.4311 0.2445 0.1480 1996.2661	0.305 0.253 0.305 0.203 0.150 0.068 144.407	-0.640 0.976 3.490 2.120 1.635 2.170 13.824	0.522 0.329 0.000 0.034 0.102 0.030 0.000	-0.793 -0.249 0.466 0.033 -0.049 0.014 1713.234	0.403 0.744 1.662 0.830 0.538 0.282 2279.298
4.87 Prob(Q): 0.00 Heteroske 1.37	dasticity (H):		0.00 0.97 0.68 0.03	Jarque-Bera Prob(JB): Skew: Kurtosis:	(JB):	53
===						

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-s tep).

```
In [13]:
```

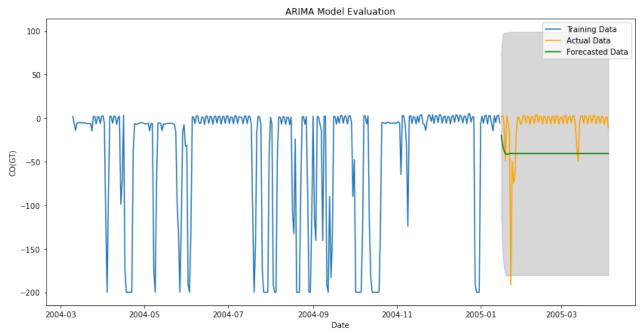
```
year['forecast']=fit.predict(start=300)
plt.figure(figsize = (15,7))
plt.plot(year.iloc[:300]['CO(GT)'], label = 'Average CO2 by Day')
plt.plot(year.iloc[300:]['CO(GT)'], label = 'Real Average CO2 by Day', alpha = .
plt.plot(year['forecast'], label = 'Predicted')
plt.legend()
plt.show()
print('MAE:',metrics.mean_absolute_error(year.iloc[300:]['CO(GT)'],year.iloc[300
```



MAE: 15.750089920820542

```
In [14]:
          #https://medium.com/datainc/time-series-analysis-and-forecasting-with-arima-in-p
          # Split the data into train and test
          train_size = int(len(year) * 0.8)
```

```
train, test = year[0:train_size], year[train_size:len(year)]
# Fit the ARIMA model on the training dataset
model_train = ARIMA(train['CO(GT)'], order=(2, 0, 4))
model train fit = model train.fit()
# Forecast on the test dataset
test forecast = model train fit.get forecast(steps=len(test))
test_forecast_series = pd.Series(test_forecast.predicted_mean, index=test.index)
# Calculate the mean squared error
mse = metrics.mean_squared_error(test['CO(GT)'], test_forecast_series)
rmse = mse**0.5
# Create a plot to compare the forecast with the actual test data
plt.figure(figsize=(14,7))
plt.plot(train['CO(GT)'], label='Training Data')
plt.plot(test['CO(GT)'], label='Actual Data', color='orange')
plt.plot(test forecast series, label='Forecasted Data', color='green')
plt.fill between(test.index,
                 test forecast.conf int().iloc[:, 0],
                 test_forecast.conf_int().iloc[:, 1],
                 color='k', alpha=.15)
plt.title('ARIMA Model Evaluation')
plt.xlabel('Date')
plt.ylabel('CO(GT)')
plt.legend()
plt.show()
print('RMSE:', rmse)
```



RMSE: 41.4507992420051

```
In [15]:
    mod = ARIMA(year['CO(GT)'], order = (3,0,4))
    fit = mod.fit()
    print(fit.summary())
```

SARIMAX Results

Dep. Varia Model: Date: Time: Sample: Covariance	We	CO(ARIMA(3, 0, d, 03 Jul 2 20:06 03-10-2 - 04-04-2	4) Log 024 AIC :25 BIC 004 HQIC	Observations: Likelihood		391 -2037.768 4093.535 4129.253 4107.693
=======	coef	====== std err	======= Z	 P> z	[0.025	0.975]
const ar.L1 ar.L2 ar.L3 ma.L1 ma.L2 ma.L3 ma.L4 sigma2	-34.0837 1.4409 -1.4472 0.5867 -0.5846 0.7267 0.2917 -0.0760 1893.4882	13.919 0.105 0.096 0.094 0.101 0.053 0.055 0.072 132.486	-2.449 13.754 -15.121 6.259 -5.765 13.780 5.347 -1.054 14.292	0.014 0.000 0.000 0.000 0.000 0.000 0.292 0.000	-61.364 1.236 -1.635 0.403 -0.783 0.623 0.185 -0.217 1633.820	-6.804 1.646 -1.260 0.770 -0.386 0.830 0.399 0.065 2153.156
=== Ljung-Box (L1) (Q): 7.77		0.00	Jarque-Bera	(JB):	52	
Prob(Q): 0.00			0.99	<pre>Prob(JB):</pre>		
Heteroskedasticity (H):		0.71	Skew:		_	
1.35 Prob(H) (t 8.01	wo-sided):		0.05	Kurtosis:		
====	===					

Warnings:

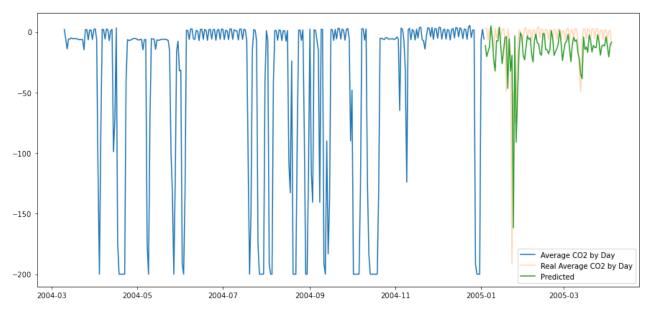
[1] Covariance matrix calculated using the outer product of gradients (complex-s tep).

/Users/zanderbonnet/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/m odel.py:566: ConvergenceWarning: Maximum Likelihood optimization failed to conve rge. Check mle retvals

warnings.warn("Maximum Likelihood optimization failed to "

```
In [16]:
```

```
year['forecast']=fit.predict(start=300)
plt.figure(figsize = (15,7))
plt.plot(year.iloc[:300]['CO(GT)'], label = 'Average CO2 by Day')
plt.plot(year.iloc[300:]['CO(GT)'], label = 'Real Average CO2 by Day', alpha = .
plt.plot(year['forecast'], label = 'Predicted')
plt.legend()
plt.show()
print('MAE:',metrics.mean absolute error(year.iloc[300:]['CO(GT)'],year.iloc[300
```

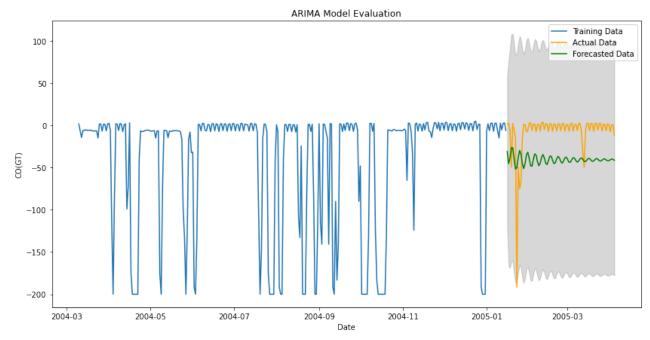


MAE: 15.932133664626555

```
In [17]:
          #https://medium.com/datainc/time-series-analysis-and-forecasting-with-arima-in-p
          # Split the data into train and test
          train_size = int(len(year) * 0.8)
          train, test = year[0:train size], year[train size:len(year)]
          # Fit the ARIMA model on the training dataset
          model_train = ARIMA(train['CO(GT)'], order=(3, 0, 4))
          model train fit = model train.fit()
          # Forecast on the test dataset
          test_forecast = model_train_fit.get_forecast(steps=len(test))
          test_forecast_series = pd.Series(test_forecast.predicted_mean, index=test.index)
          # Calculate the mean squared error
          mse = metrics.mean_squared_error(test['CO(GT)'], test_forecast_series)
          rmse = mse**0.5
          # Create a plot to compare the forecast with the actual test data
          plt.figure(figsize=(14,7))
          plt.plot(train['CO(GT)'], label='Training Data')
          plt.plot(test['CO(GT)'], label='Actual Data', color='orange')
          plt.plot(test_forecast_series, label='Forecasted Data', color='green')
          plt.fill_between(test.index,
                           test_forecast.conf_int().iloc[:, 0],
                           test_forecast.conf_int().iloc[:, 1],
                           color='k', alpha=.15)
          plt.title('ARIMA Model Evaluation')
          plt.xlabel('Date')
          plt.ylabel('CO(GT)')
          plt.legend()
          plt.show()
          print('RMSE:', rmse)
```

/Users/zanderbonnet/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals

warnings.warn("Maximum Likelihood optimization failed to "



RMSE: 41.70866896770278