timeserieslab9-rohramehak-251524

April 29, 2024

[ ]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```python
!pip install pmdarima
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.10/dist-
packages (2.0.4)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.4.0)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.10)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.25.2)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (2.0.3)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.11.4)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (24.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.19->pmdarima) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.19->pmdarima) (2024.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.4.0)
```

```
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels>=0.13.2->pmdarima) (0.5.6)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels>=0.13.2->pmdarima) (1.16.0)
```

[ ]:
```python
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
from pmdarima import auto_arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_absolute_percentage_error
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
```

[ ]:
```python
data = pd.read_csv('/content/drive/MyDrive/TSA_BDA_2024/Lab9/
 ↪monthly_in_situ_co2_mlo.csv', skiprows=61)
```

[ ]:
```python
data
```

[ ]:
```
        Yr    Mn      Date          Date        CO2   seasonally          fit  \
0                                                       adjusted
1                     Excel                    [ppm]       [ppm]        [ppm]
2     1958    01     21200     1958.0411     -99.99      -99.99       -99.99
3     1958    02     21231     1958.1260     -99.99      -99.99       -99.99
4     1958    03     21259     1958.2027     315.71      314.44       316.20
..     …   …         …           …        …        …           …
801   2024    08     45519     2024.6230     -99.99      -99.99       -99.99
802   2024    09     45550     2024.7077     -99.99      -99.99       -99.99
803   2024    10     45580     2024.7896     -99.99      -99.99       -99.99
804   2024    11     45611     2024.8743     -99.99      -99.99       -99.99
805   2024    12     45641     2024.9563     -99.99      -99.99       -99.99

        seasonally           CO2        seasonally   Sta
0     adjusted fit        filled   adjusted filled   NaN
1            [ppm]         [ppm]             [ppm]   NaN
2           -99.99        -99.99            -99.99   MLO
3           -99.99        -99.99            -99.99   MLO
4           314.91        315.71            314.44   MLO
..             …             …              …    …
801         -99.99        -99.99            -99.99   MLO
802         -99.99        -99.99            -99.99   MLO
803         -99.99        -99.99            -99.99   MLO
804         -99.99        -99.99            -99.99   MLO
805         -99.99        -99.99            -99.99   MLO
```

```
[806 rows x 11 columns]
```

[ ]:
```
data.columns = data.columns.str.strip()
data.columns
data['Yr'] = data['Yr'].str.strip()
data['Mn'] = data['Mn'].str.strip()
```

[ ]:
```
data.dropna(inplace=True)
data.drop(data.head(4).index, inplace=True)
data.drop(data.tail(9).index, inplace=True)
co2_data = data.loc[:,['Yr', 'Mn', 'CO2']]
co2_data['DateCons'] = co2_data['Yr'].astype(str) + '-' + co2_data['Mn'].
 ↪astype(str) + '-01'
```

[ ]:
```
co2_data['DatePart'] = pd.to_datetime(co2_data['DateCons'], format='%Y-%m-%d',␣
 ↪errors='coerce')
co2_data.rename(columns = {"DatePart" : "Date"}, inplace=True)
co2_data.set_index("Date", inplace=True)
co2_data.drop(columns=["DateCons"], inplace=True)
```

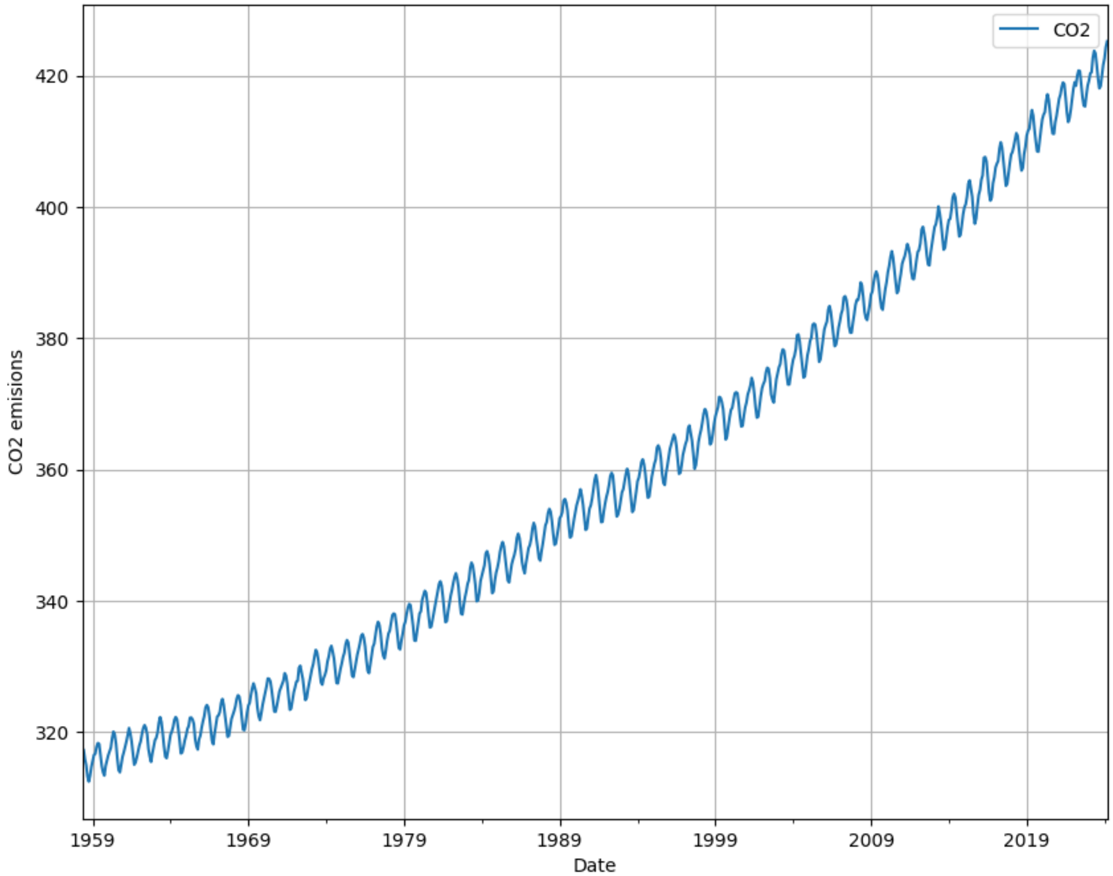
[ ]:
```
co2_data = co2_data.iloc[:, [3]]
co2_data ['CO2'] = co2_data ['CO2'].astype(float)
```

```
<ipython-input-243-74b60c3e6da4>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  co2_data ['CO2'] = co2_data ['CO2'].astype(float)
```

CO2 Emissions Time series

[ ]:
```
co2_data.plot(figsize=(10,8), grid=True)
plt.ylabel("CO2 emisions")
plt.show()
```



[ ]:
```
co2_data.sort_index(inplace=True)
```

[ ]:
```
co2_data.index.freq='MS'
fcast_months = 24
train=co2_data.iloc[:-fcast_months ]
test=co2_data.iloc[-fcast_months :]
len(test)
```

[ ]: 24

using auto_arima for automatically selecting the optimal ARIMA model parameters for a given time series dataset

[ ]:
```
auto_arima(train, seasonal=True,m=12).summary()
```

[ ]:

Dep. Variable:	y	**No. Observations:**	762
Model:	SARIMAX(1, 1, 1)x(1, 0, 1, 12)	**Log Likelihood**	-205.545
Date:	Sun, 28 Apr 2024	**AIC**	421.090
Time:	15:15:56	**BIC**	444.263
Sample:	10-01-1958 - 03-01-2022	**HQIC**	430.013
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
ar.L1	0.2673	0.075	3.566	0.000	0.120	0.414
ma.L1	-0.6162	0.060	-10.198	0.000	-0.735	-0.498
ar.S.L12	0.9996	0.000	2670.369	0.000	0.999	1.000
ma.S.L12	-0.8573	0.021	-41.643	0.000	-0.898	-0.817
sigma2	0.0935	0.004	21.690	0.000	0.085	0.102

Ljung-Box (L1) (Q):	0.12	**Jarque-Bera (JB):**	4.75
Prob(Q):	0.73	**Prob(JB):**	0.09
Heteroskedasticity (H):	1.51	**Skew:**	0.00
Prob(H) (two-sided):	0.00	**Kurtosis:**	3.39

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

Using autoarima we see that are model to be used is a model with p =1 , difference = 1 and moving avg paramter q = 1

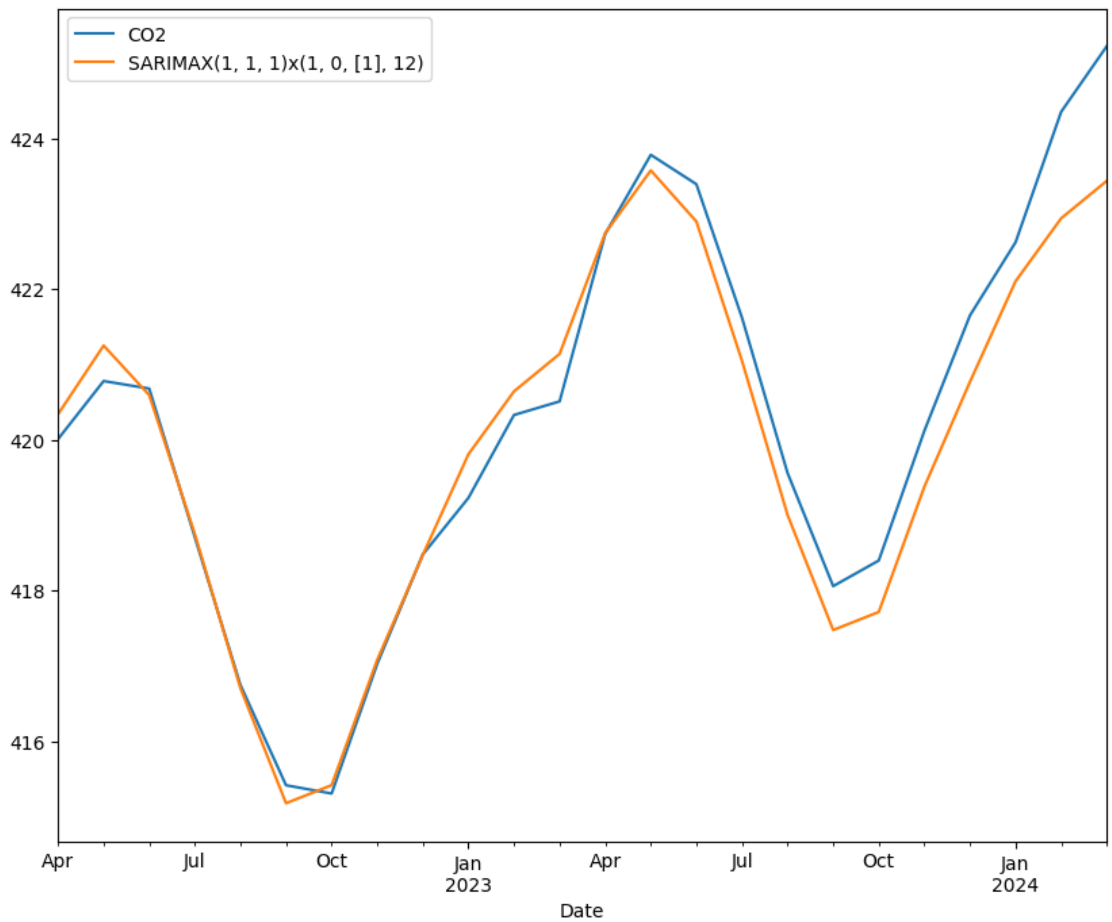
so we will move forward with traiing our data on this particular model

training on entire data except last 24 months and testing on last 24 months

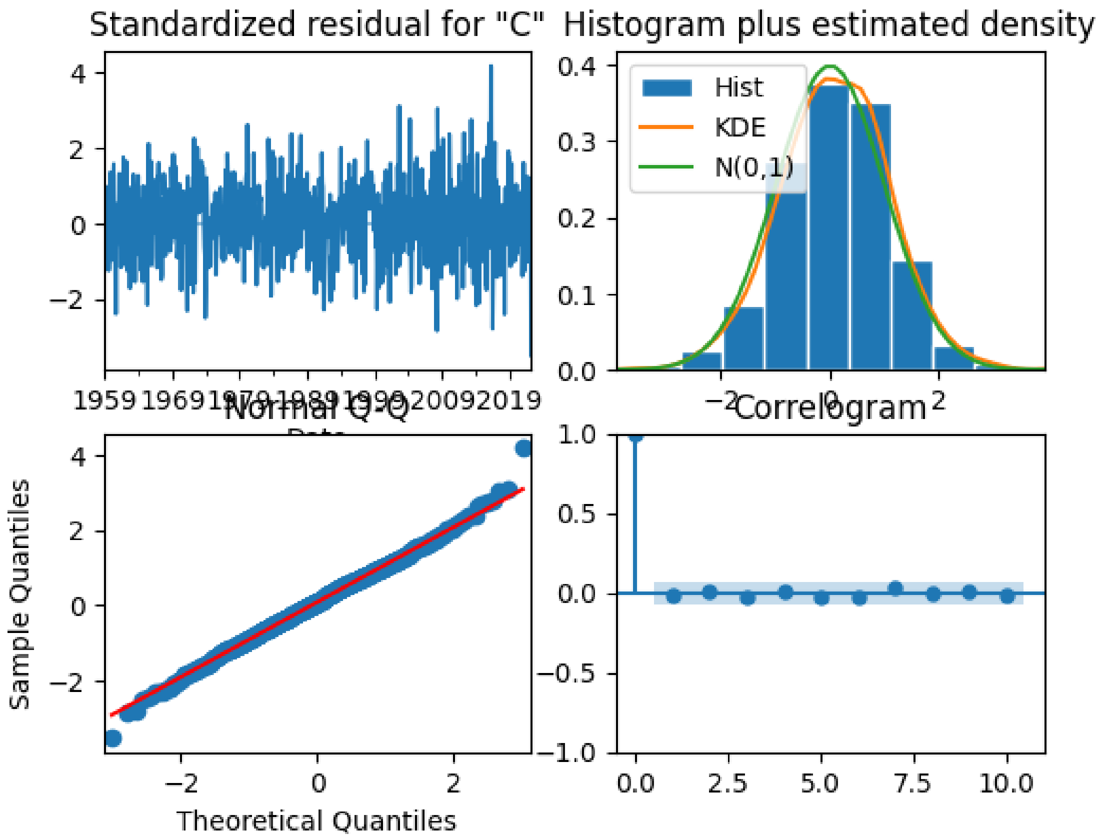
[ ]:
```
model = SARIMAX(train, order=(1,1,1), seasonal_order=(1,0,1,12)).fit()
start=len(train)
end=start+len(test)-1
pred_arma=model.predict(start,end).rename('SARIMAX(1, 1, 1)x(1, 0, [1], 12)')
```

[ ]:
```
ax=test.plot(figsize=(10,8),legend=True, label="Test")
pred_arma.plot(legend=True)
```

[ ]:
```
<Axes: xlabel='Date'>
```



[ ]:
```
model.plot_diagnostics();
```




```
[ ]: mape_sarima = mean_absolute_percentage_error(test, pred_arma)*100
     print(f"Mean absolute percentage error : {mape_sarima}")
```

```
Mean absolute percentage error : 0.11208689399925485
```

We have no corelations in our residuals. plus our Histogram is close the the Normal distriction plot N(0,1) and a good accuracy

```
[ ]: fits = {"Add-Add": ["add", "add"], "Add-Mul": ["add", "mul"], "Mul-Add":␣
      ↪["mul", "add"], "Mul-Mul": ["mul", "mul"]}
     model_forecasts = {}
     mape_scores =[]
     for fit_type, value in fits.items() :
         fit = ExponentialSmoothing(
                 train,
                 seasonal_periods=12,
                 trend= value[0],
                 seasonal= value[1],
                 initialization_method="estimated",
             ).fit()
         fcast = fit.forecast(len(test))
```

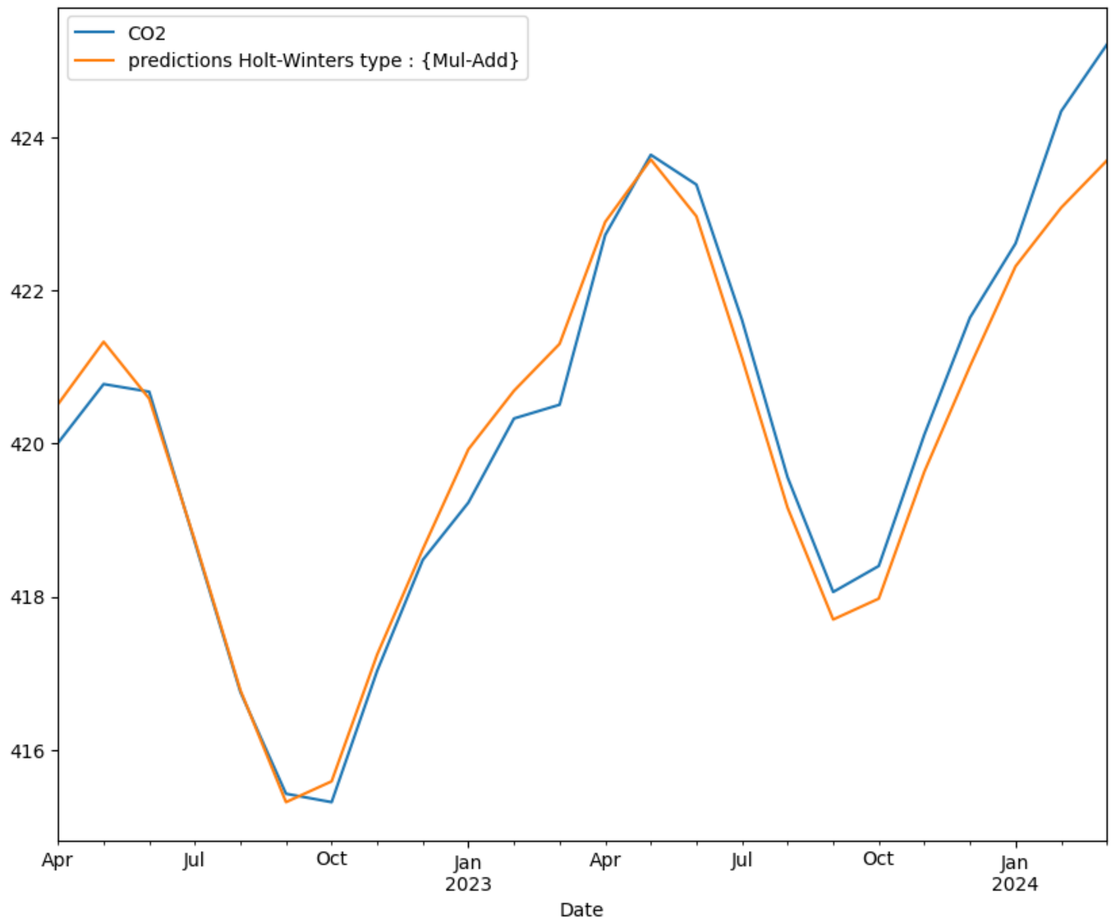
```
    mape = mean_absolute_percentage_error(test, fcast.values)*100
    mape_scores.append(mape)
    pred_hw = pd.Series(fcast.values)
    pred_hw.index = test.index
    model_forecasts[fit_type] = pred_hw
```

[ ]:
```
for index, key in enumerate(fits.keys()):
    print(f"For {key}, Mean abs % error is {mape_scores[index]}")
```

```
For Add-Add, Mean abs % error is 0.11066239131961311
For Add-Mul, Mean abs % error is 0.1165543569966312
For Mul-Add, Mean abs % error is 0.10205117760524286
For Mul-Mul, Mean abs % error is 0.10883653500227147
```

[ ]:
```
ax=test.plot(figsize=(10,8),legend=True, label="Test")
model_forecasts["Mul-Add"].plot(legend=True, label="predictions Holt-Winters␣
↪type : {Mul-Add}")
```

[ ]: <Axes: xlabel='Date'>



Means abs % error of our Sarima vs Holt Winters

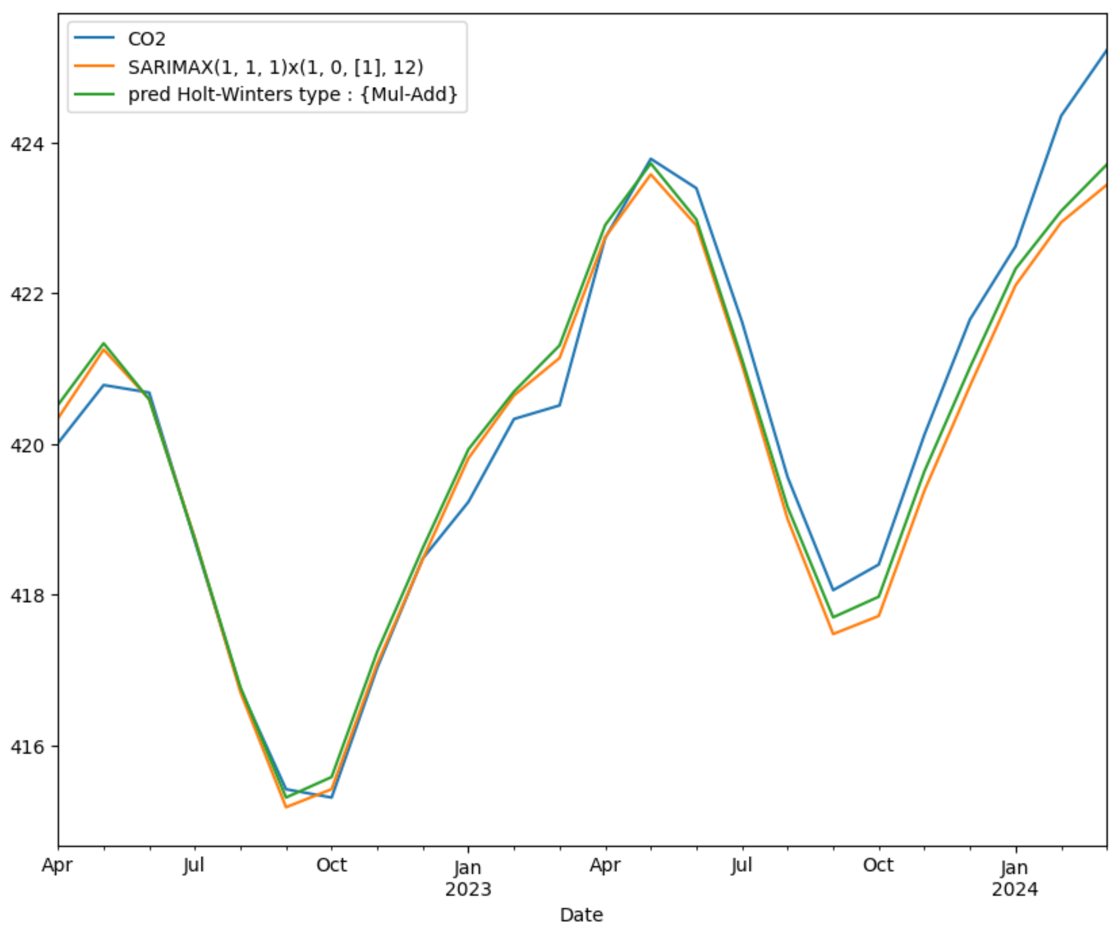
[ ]:
```
print(f"For SARIMA, Mean abs % error is {mape_sarima} \nFor HW lowest Means abs
↪% err is for model with Multiplicative trend and additive seasonal
↪component, with value {mape_scores[2]}")
```

```
For SARIMA, Mean abs % error is 0.11208689399925485
For HW lowest Means abs % err is for model with Multiplicative trend and
additive seasonal component, with value 0.10205117760524286
```

Predictions comparisions -> TEST vs HW vs SARIMA

[ ]:
```
ax=test.plot(figsize=(10,8), legend=True)
pred_arma.plot(legend=True)
model_forecasts["Mul-Add"].plot(legend=True,label="pred Holt-Winters type :
↪{Mul-Add}")
```

[ ]: <Axes: xlabel='Date'>



[ ]:
```python
hw_acc = 100 -mape_scores[2]
sarima_acc = 100 - mape_sarima
print(f"Holt Winters = {hw_acc}, SARIMA : {sarima_acc}")
```

```
Holt Winters = 99.89794882239475, SARIMA : 99.88791310600074
```

The prediction accuracy for both models is > 99% with a very bare slight edge with holt winters (additive trend and multiplicative seasonal) components model