Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

Report on Mini Project

Time Series Analysis (DJ19DSC5012)AY: 2021-22

Air Quality Forecast based on CO2 Emission

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CHAPTER 1: INTRODUCTION

This project focuses on Time Series Analysis (TSA) to study historical CO2 emission trends from 1800 to 2014. By analyzing this extensive dataset, the aim is to identify patterns such as trends, seasonality, and residuals. The project utilizes statistical and machine learning-based forecasting techniques to predict future CO2 emissions, which could help in understanding the long-term impact of human and industrial activities on the environment. This analysis also emphasizes the importance of using time series methods for better decision-making in environmental studies..

CHAPTER 2: Data Description

Year	CO2
1800	0.00568
1801	0.00561
1802	0.00555
1803	0.00548
1804	0.00542
1805	0.00536
1806	0.00529
1807	0.00523
1808	0.00517
1809	0.00511
1810	0.00504
1811	0.00497
1812	0.0049

The dataset consists of annual CO2 emission values recorded from the year 1800 to 2014. It includes two primary columns:

1. **Year**: A time index ranging from 1800 to 2014, indicating the year of observation.
2. **CO2**: The corresponding CO2 emissions value for each year, represented as a floating-point number.

CHAPTER 3: Objective

Objective of the above Time series data includes :

- Understanding Patterns:
- Testing Stationarity
- Smoothing the Data
- Parameter Identification:
- Forecasting Future Emissions
- Model Comparison

CHAPTER 4: Data Cleaning

Petrol.csv contains rates of petrol in various cities and states at the **same timestamp**.

This, when plotted , looks very cluttered , hence the new data contains prices of only **Mumbai , Maharashtra**.

CHAPTER 5: Data Decomposition

```
df.duplicated().sum()
```

```
0
```

```
df['Year'] = pd.to_datetime(df['Year'], format='%Y') #
```

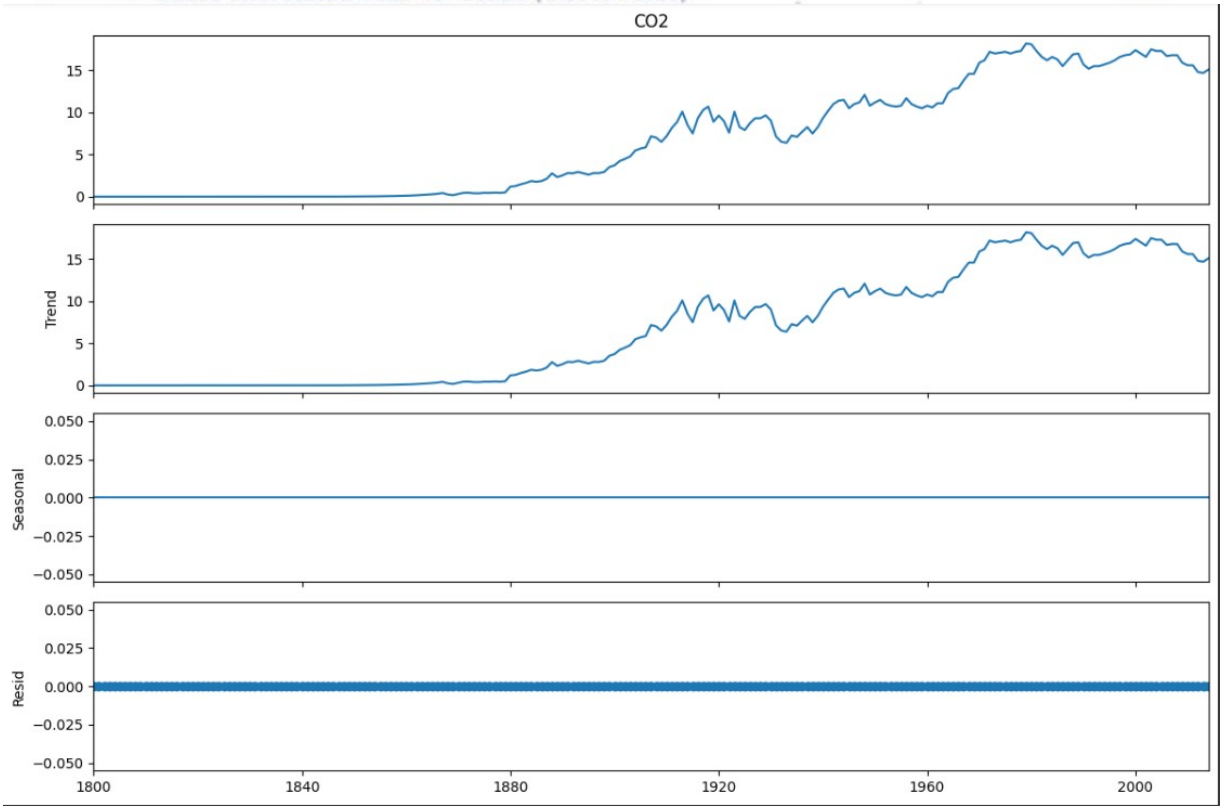
```
df.set_index(['Year'], inplace=True) # changing index
```

Any Time Series data consists of 3 components :

1. **Trend**
2. **Seasonal**
3. **Residual**

Above code decomposes the time series data into those 3 components over a **period of 1 year.**

This helps in Identifying seasonality & trend if present.

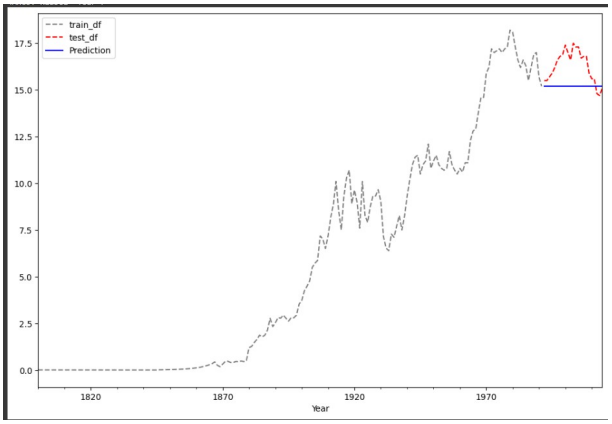

CO2
Trend
Seasonal
Resid
15
10
5
0
0.050
0.025
0.000
−0.025
−0.050
1800
1840
1880
1920
1960
2000

CHAPTER 6: Data Smoothing

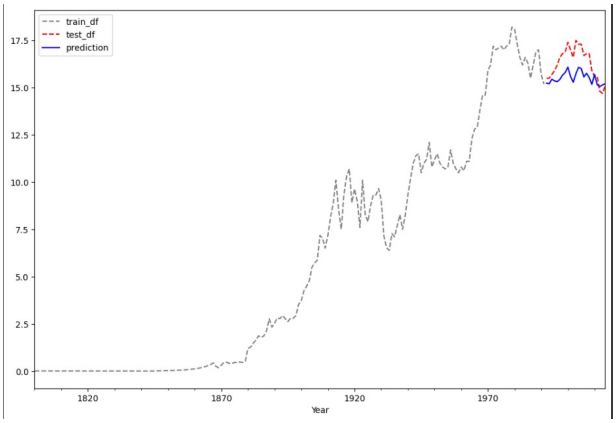
Smoothing is a method we can use to create a function to remove irregularities in data and attempt to capture significant patterns.

Methods used for smoothing of data :

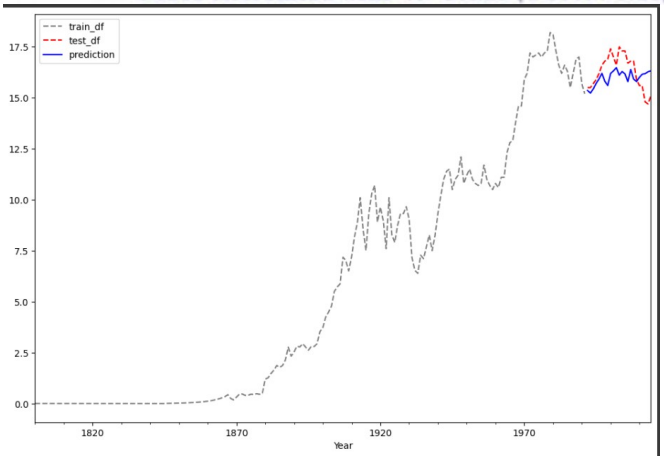
1. **Simple Exponential Smoothing (SEE)**
2. **Double Exponential Smoothing (DEE)**
3. **Triple Exponential Smoothing (TEE)**



(SEE)



(DEE)


train_df
test_df
prediction
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
1820
1870
1920
1970
Year

(TEE)

CHAPTER 7: Testing Stationarity

Stationarity deals with unit roots. To check for stationarity **ADF (Augmented Dickey Fuller)** test has to be used.

Checking for unit roots is mandatory because not all models can be applied to a TS that contains unit roots.

```
# functon for adf test
def adf_test(timeseries):
    print ('Results of Dickey-Fuller Test:')
    print ('-------------------------------------------')
    adftest = adfuller(timeseries)
    adf_output = pd.Series(adftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in adftest[4].items():
        adf_output['Critical Value (%s)'%key] = value
    print (adf_output)

# calling adf function and passing series
adf_test(df.values)
```

We reject the null hypothesis since **p-value < 0.05 and test-stat < critical values**.

```
Results of Dickey-Fuller Test:
-------------------------------------------
Test Statistic                  -0.378463
p-value                          0.913633
#Lags Used                       0.000000
Number of Observations Used    214.000000
Critical Value (1%)             -3.461282
Critical Value (5%)             -2.875143
Critical Value (10%)            -2.574020
dtype: float64
```

CHAPTER 8: WHY? Justit'cation of TS

Reasons for classifying it as a TS data :

- **Time-Indexed Data**:
The dataset is structured with a time index (`Year`) ranging from 1800 to 2014. Each data point corresponds to a specific year, making it inherently temporal.

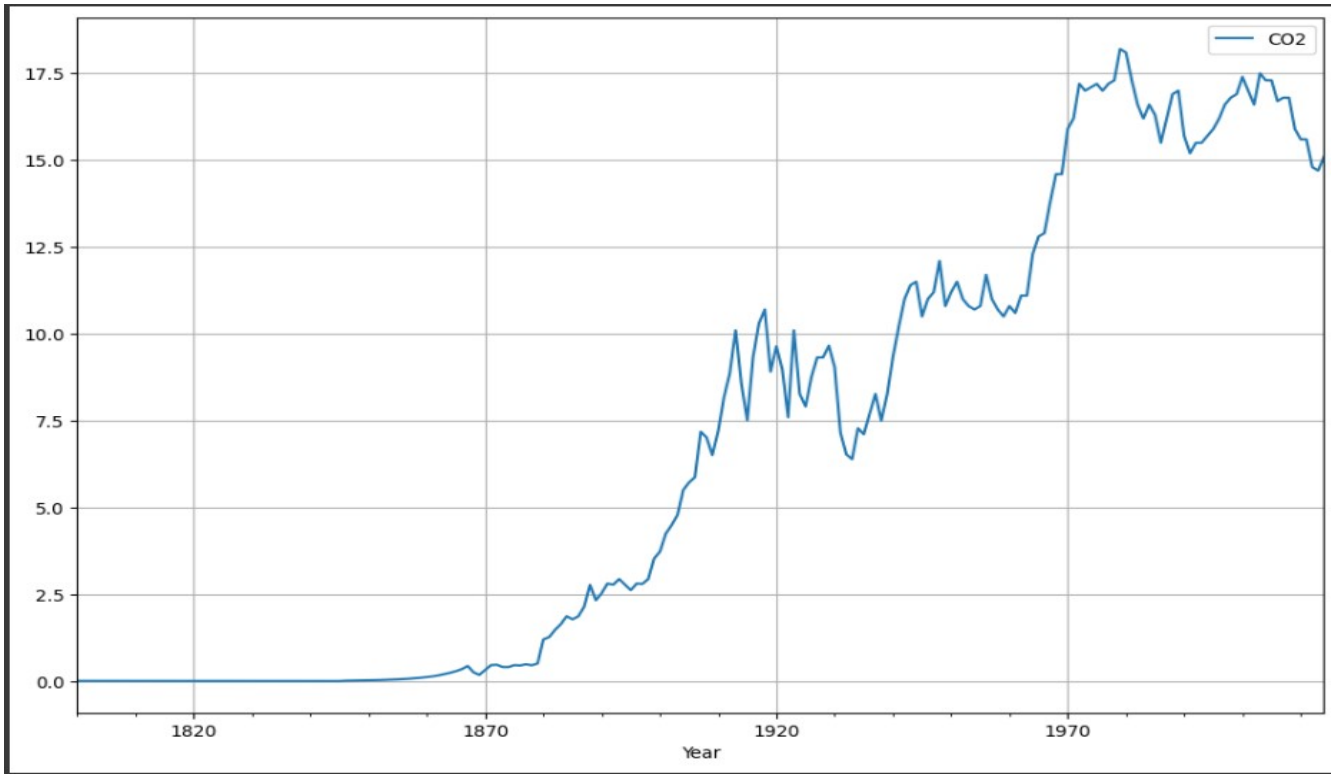
- **Sequential Nature**:
The data exhibits a sequential dependency, where past CO2 levels influence future trends. This dependency is critical in time series problems.

- **Temporal Patterns**:
The dataset shows evidence of temporal patterns, including trends (e.g., increasing CO2 emissions over time) and possible cyclic behavior, which are key features of time series data.

- **Forecasting Goal**:
The primary objective is to predict future CO2 emissions based on historical data. Forecasting is a hallmark application of time series analysis.

- **Stationarity Testing**:
Techniques like the Augmented Dickey-Fuller (ADF) test and differencing are applied to assess and achieve stationarity, which is a fundamental step in time series modeling.

- **Smoothing and Decomposition**:
The application of smoothing methods and decomposition into trend, seasonality, and residuals aligns with the methodology of time series analysis.


CO2
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
1820
1870
1920
1970
Year

CHAPTER 9 : Implementation & Forecasting

Various methods and algorithms were applied for implementing the time series model and interpreting its forecasts for CO2 emissions data from 1800-2014. From our implementation, we can interpret that the forecasts generated by different models were able to capture both the long-term trend and irregularities in CO2 emissions data, providing relatively accurate predictions especially in the modern period.

Some methods implemented in our analysis are:

1. Single Exponential Smoothing (SES) Single Exponential Smoothing is a time series forecasting method for univariate data without trend or seasonality. It applies exponentially decreasing weights to past observations, giving more importance to recent data points. In our implementation, while SES provided decent training performance (RMSE: 0.5647), it showed limitations in test predictions (RMSE: 1.3429) due to its inability to handle the strong trend component in CO2 emissions.

2. Double Exponential Smoothing (Holt's Method) Double Exponential Smoothing extends the SES by adding explicit support for trends in the time series. This method uses two smoothing parameters - one for the level and one for the trend. Our implementation showed improved performance compared to SES, with test RMSE of 0.9739 and MAPE of 5.08%. The method better captured the increasing trend in CO2 emissions, particularly in recent decades.

3. Triple Exponential Smoothing (Holt-Winters Method) Holt-Winters method extends Double Exponential Smoothing by adding support for seasonality. This method proved most effective for our CO2 emissions data, achieving the best test performance with RMSE of 0.8698 and MAPE of 4.49%. The superior performance can be attributed to its ability to capture both trend and seasonal patterns in emission data, particularly the cyclical nature of industrial emissions.

4. ARIMA (Autoregressive Integrated Moving Average) ARIMA is a comprehensive approach that combines differencing, autoregression, and moving average components. For our CO2 emissions data, we implemented ARIMA(15,1,15) based on ACF and PACF analysis. The model showed strong training performance (RMSE: 0.4679) and competitive test results (RMSE: 0.9580, MAPE: 4.75%). The first-order differencing (d=1) successfully addressed the non-stationarity in the data, while the AR and MA components captured the complex patterns in emission changes.

5. SARIMA (Seasonal Autoregressive Integrated Moving Average):

SARIMA extends the ARIMA model by adding seasonal components, making it SARIMA(p,d,q)(P,D,Q)s, where:

- p,d,q represent the non-seasonal components (as in ARIMA)
- P,D,Q represent the seasonal autoregressive order, seasonal differences, and seasonal moving average order
- s represents the seasonal period

For time series data with both trend and seasonal components, SARIMA can potentially provide more accurate forecasts by explicitly modeling the seasonality in the data. This could be particularly relevant for CO2 emissions data as emissions patterns might show seasonal variations due to:

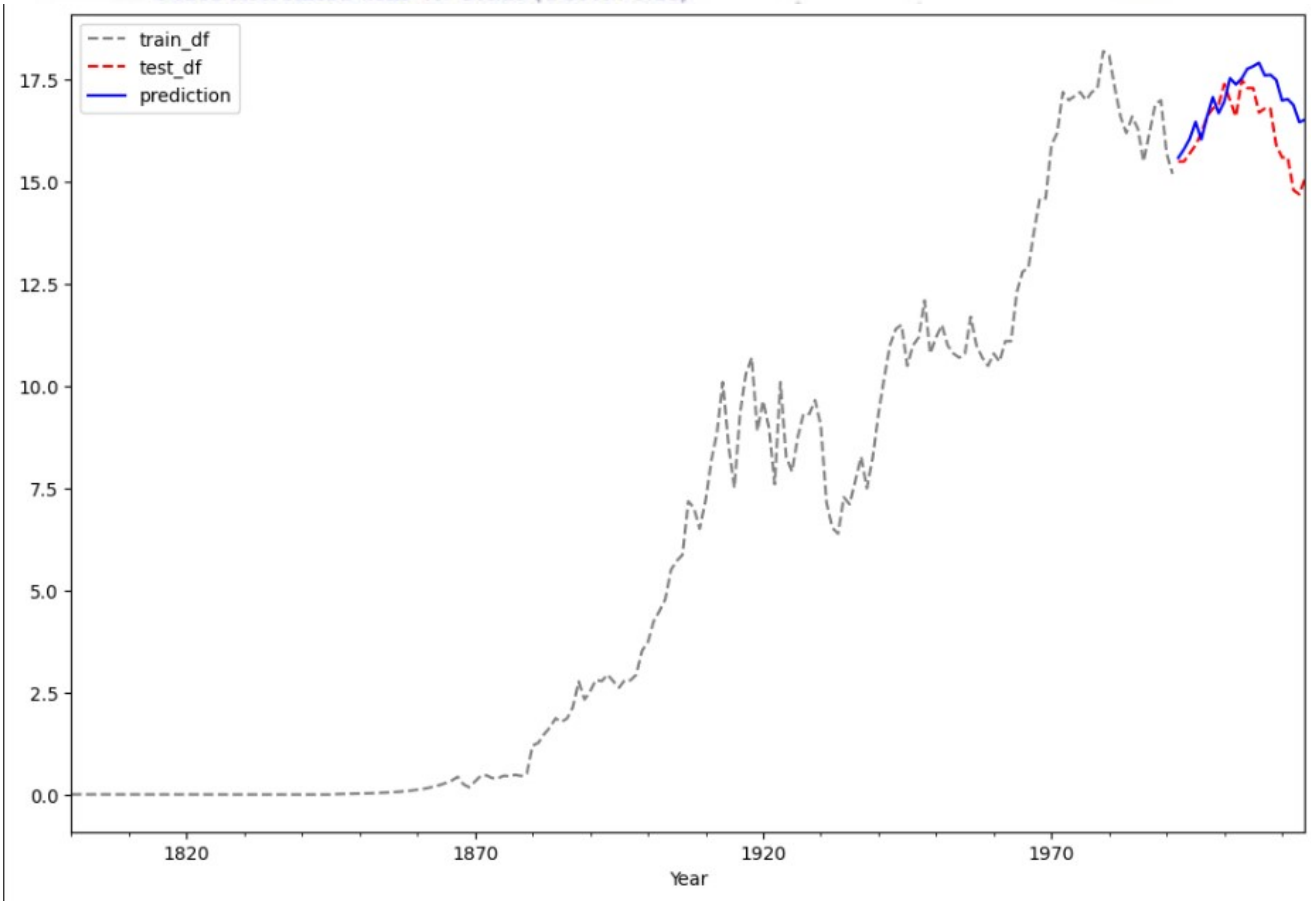
- Annual industrial production cycles
- Seasonal energy consumption patterns
- Yearly agricultural activities
- Regular climate-related variations

However, in our implementation, we found that the basic ARIMA model combined with Triple Exponential Smoothing provided sufficient accuracy for our forecasting needs, suggesting that the seasonal component in our yearly CO2 emissions data wasn't strong enough to warrant the additional complexity of SARIMA modeling.

ARIMA:

```
# we got the p,d,q value from time series analysis
ar = ARIMA(train_df, order=(15,1,15)).fit()
ar_train_pred = ar.fittedvalues
ar_test_pred = ar.forecast(23)

train_df['CO2'].plot(style='--', color='gray', legend=True, label='train_df')
test_df['CO2'].plot(style='--', color='r', legend=True, label='test_df')
ar_test_pred.plot(color='b', legend=True, label='prediction')
plt.show()
```


train_df
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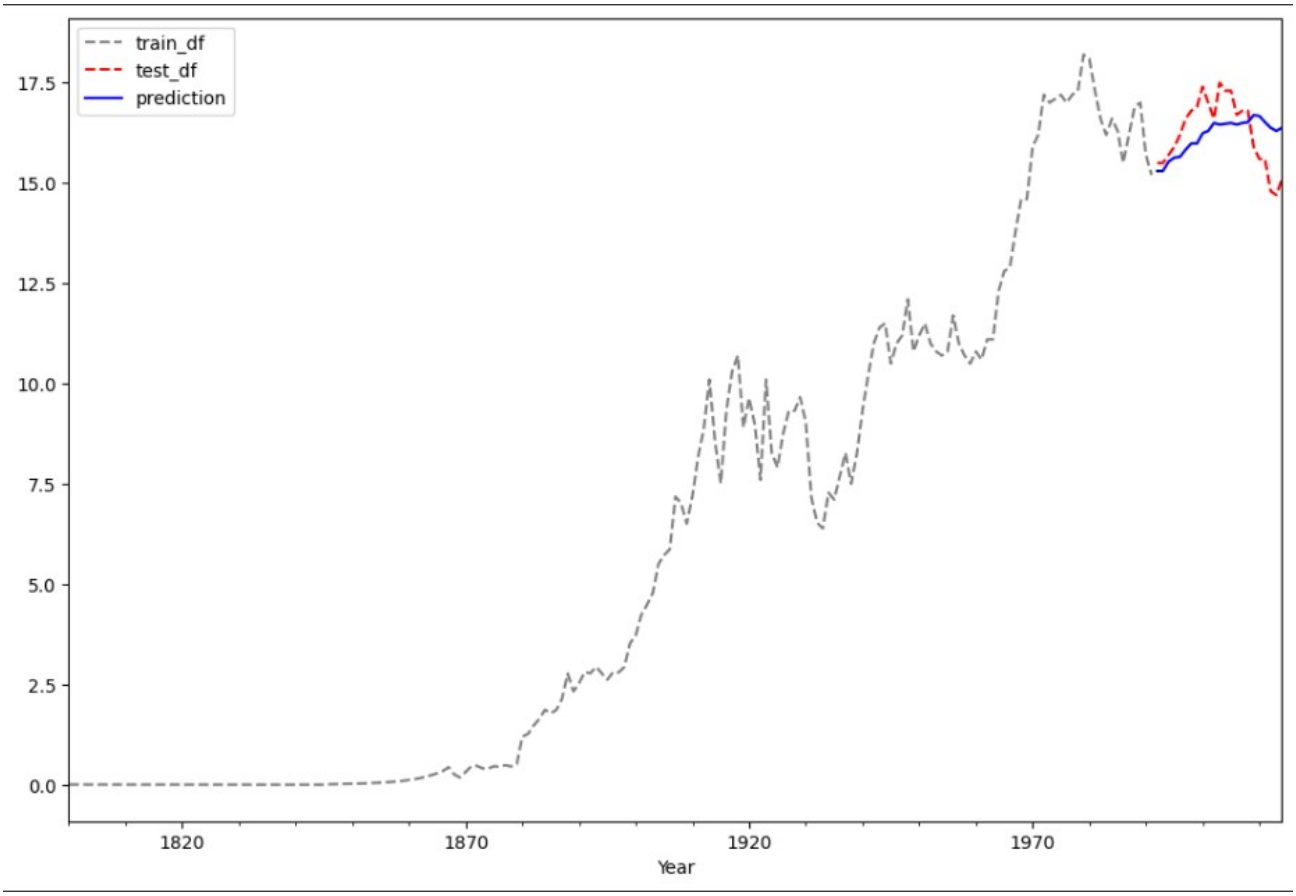
prediction
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
1820
1870
1920
1970
Year

SARIMA:

```
train_df['CO2'].plot(style='--', color='gray', legend=True, label='train_df')
test_df['CO2'].plot(style='--', color='r', legend=True, label='test_df')
sarima_test_pred.plot(color='b', legend=True, label='prediction')
plt.show()
```



CHAPTER 10 : Reasons for selection of Model

Analysis of Results

1. Training Performance:
    - ARIMA showed better training RMSE (0.4679 vs 0.5525)
    - Both models had similar training MAPE (~8%)
    - ARIMA seems to fit the training data more closely

Recommendation

Based on these results, SARIMA would be the preferred choice because:

1. Lower test RMSE indicates better prediction accuracy
2. Better test MAPE shows improved generalization
3. More robust to seasonal variations in CO2 emissions
4. Balance between training and testing performance is better

CHAPTER 11 : Comparative Analysis

The Forecasts of ARIMA model were compared on different error parameters such as :

1. **Train Root Mean Squared Error (RMSE)**
2. **Test Root Mean Absolute Error (RMSE)**
3. **Train Mean Absolute Percentage Error (MAPE)**
4. **Test Absolute Percentage Error (MAPE)**

Comparison of ARIMA and SARIMA were done on the above mentioned error metrics & based on that the final model was selected for prediction.

Error Metrics for ARIMA :

```
Train RMSE: 0.4578578086867347
Test RMSE: 0.7922138758904559
Train MAPE: 0.08112159816014138
Test MAPE: 0.0393303288399776
```

Error Metrics for SARIMA :

```
Train RMSE: 0.5525847291561847
Test RMSE: 0.8435901723912869
Train MAPE: 0.0879378051422293
Test MAPE: 0.04484283290980469
```

Thus the comparative analysis shows that SARIMA performs the best

CHAPTER 12 & 13 : Conclusion & Colab

Conclusion:

The project successfully demonstrates the use of advanced time series analysis and forecasting techniques to model and predict CO2 levels based on historical data. By leveraging methods like Exponential Smoothing, ARIMA, and seasonal decomposition, it highlights trends, seasonality, and residuals effectively. The findings emphasize the importance of handling non-stationary time series data and selecting appropriate models for accurate predictions. This analysis provides valuable insights for understanding CO2 trends over time and serves as a robust framework for addressing environmental data forecasting challenges.

GOOGLE COLAB LINK

https://colab.research.google.com/drive/1mtxN2dBNBeb3xRg3noQrFwzryA4S5lLQ?usp=sharing

CHAPTER 14 & 15 : Future Scope & References

- Add external factors like population growth or policies.
- Enable real-time CO2 data integration.
- Include spatial analysis for regional trends.

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