Product demand prediction with machine learning

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Phase 4 submission document(developer part 2)

INTRODUCTION:

A product company plans to offer discounts on its product during the upcoming holiday season. The company wants to find the price at which its product can be a better deal compared to its competitors. For this task, the company provided a dataset of past changes in sales based on price changes. You need to train a model that can predict the demand for the product in the market with different price segments.

Data source:

DatasetLink:
https://www.kaggle.com/datasets/chakradharmattapalli/product-demand-prediction-with-machine-learning

ID	Store ID	Total Price	Base Price	Units Sold
1	8091	99.0375	111.8625	20
2	8091	99.0375	99.0375	28
3	8091	133.95	133.95	19
4	8091	133.95	133.95	44
5	8091	141.075	141.075	52

9	8091	227.2875	227.2875	18
10	8091	327.0375	327.0375	47
13	8091	210.9	210.9	50
14	8091	190.2375	234.4125	82
17	8095	99.0375	99.0375	99
18	8095	97.6125	97.6125	120
19	8095	98.325	98.325	40
22	8095	133.2375	133.2375	68
23	8095	133.95	133.95	87
24	8095	139.65	139.65	186
27	8095	236.55	280.0125	54

28	8095	214.4625	214.4625	74
29	8095	266.475	296.4	102
30	8095	173.85	192.375	214
31	8095	205.9125	205.9125	28
32	8095	205.9125	205.9125	7
33	8095	248.6625	248.6625	48
34	8095	200.925	200.925	78
35	8095	190.2375	240.825	57
37	8095	427.5	448.1625	50
38	8095	429.6375	458.1375	62
39	8095	177.4125	177.4125	22

42	8094	87.6375	87.6375	109
43	8094	88.35	88.35	133
44	8094	85.5	85.5	11
45	8094	128.25	180.975	9
47	8094	127.5375	127.5375	19
48	8094	123.975	123.975	33
49	8094	139.65	164.5875	49
50	8094	235.8375	235.8375	32
51	8094	234.4125	234.4125	47
52	8094	235.125	235.125	27
53	8094	227.2875	227.2875	69

54 8094 312.7875 312.7875 49

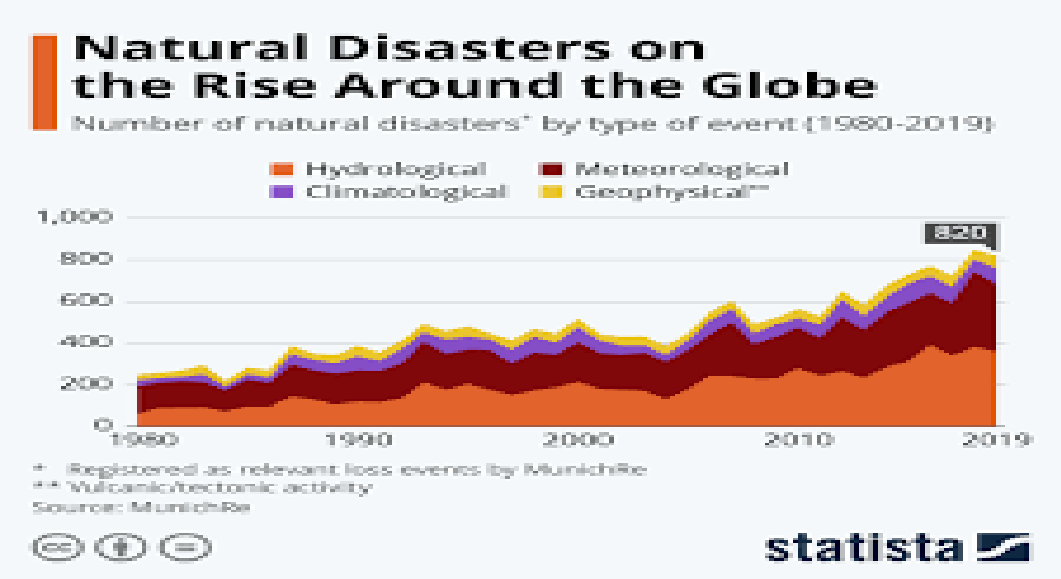
Demand forecasting:

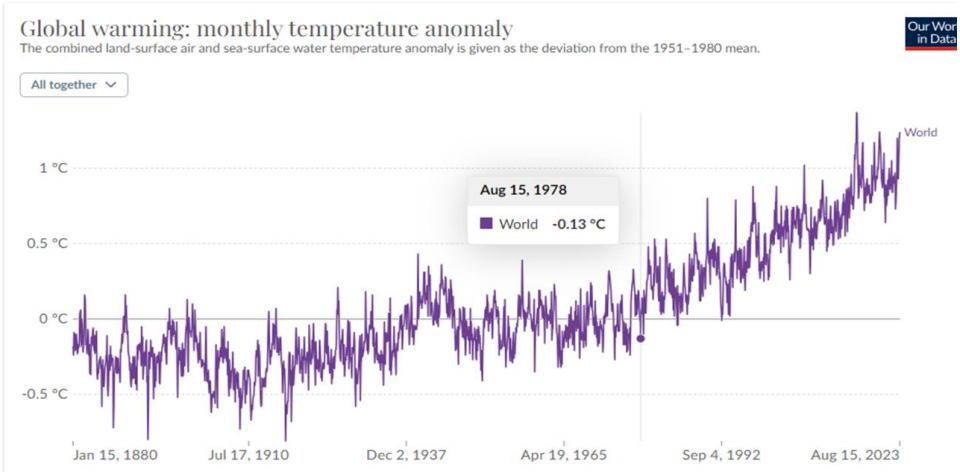
Demand forecasting is the process of predicting what customers' appetite will be for existing products or services, determining what adjustment you should make and what new offerings will spark interest. But predicting what people will want, in what quantities and when is no small feat.

Design thinking:

- Data collection
- Data preparation
- Feature engineering
- Model selection
- Model training
- Evaluation

Data about natural disaster:





Data preprocessing:

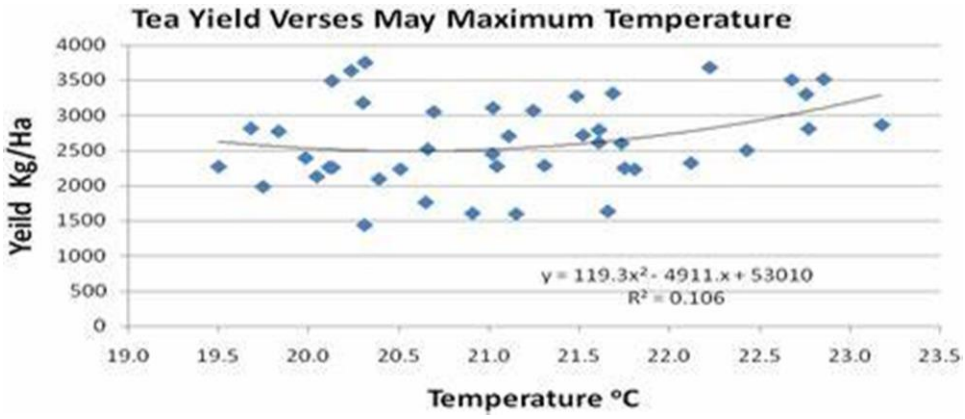
Data preprocessing can refer to manipulation or dropping of data before it is used in order to ensure or enhance performance,[1] and is an important step in the data mining process. The phrase "garbage in, garbage out" is particularly applicable to data mining and machine learning projects. Data collection methods are often loosely controlled, resulting in out-of-range values, impossible data combinations, and missing values, amongst other issues.

Methods:

- Clean and preprocess the data
- Handle missing values

- Convert categorical features into numerical representation

Linear regression:



ARIMA

ARIMA is a method for forecasting or predicting future outcomes based on a historical time series.

Data wrangling technique:

- Merging several data sources into one data-set for analysis.
- Identifying gaps or empty cells in data and either filling or removing them.
- Deleting irrelevant or unnecessary data.
- Identifying severe outliers in data and either explaining the inconsistencies or deleting them to facilitate analysis.

EXAMPLE PROGRAM:

```
import pandas as pd

import numpy as np

import plotly.express as px

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeRegressor


data =
pd.read_csv("https://raw.githubusercontent.com/amankharwal/Website-data/master/demand.csv")
```

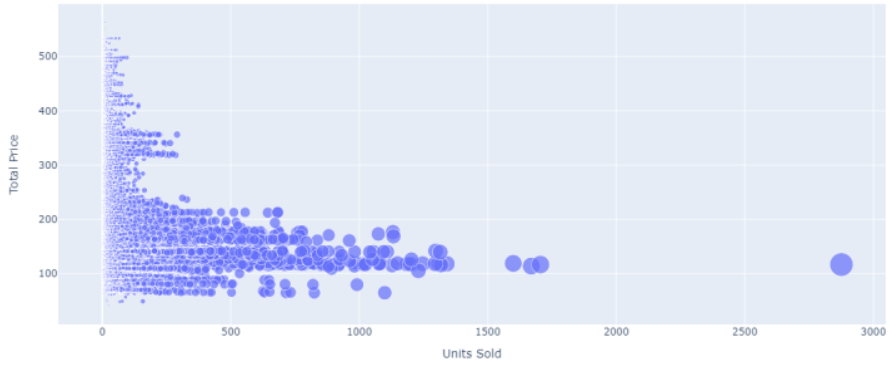
data.head()

OUTPUT:

	ID	Store ID	Total Price	Base Price	Units Sold
0	1	8091	99.0375	111.8625	20
1	2	8091	99.0375	99.0375	28
2	3	8091	133.9500	133.9500	19
3	4	8091	133.9500	133.9500	44
4	5	8091	141.0750	141.0750	52

```
fig = px.scatter(data, x="Units Sold", y="Total Price",
                 size='Units Sold')
fig.show()
```

OUTPUT:



features = np.array([[133.00, 140.00]])

model.predict(features)

OUTPUT:

array([27.])

Prophet:

make an in-sample forecast

```
from pandas import read_csv
from pandas import to_datetime
from pandas import DataFrame
from fbprophet import Prophet
from matplotlib import pyplot
# load data

path = 'https://raw.githubusercontent.com/jbrownlee/Datasets/master/monthly-car-sales.csv'
df = read_csv(path, header=0)
# prepare expected column names

df.columns = ['ds', 'y']
```

```
df['ds']= to_datetime(df['ds'])
# define the model

model = Prophet()
# fit the model

model.fit(df)
# define the period for which we want a prediction

future = list()
for i in range(1, 13):
date = '1968-%02d' % i
future.append([date])
future = DataFrame(future)
future.columns = ['ds']
future['ds']= to_datetime(future['ds'])
# use the model to make a forecast

forecast = model.predict(future)
# summarize the forecast

print(forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].head())
```

plot forecast

model.plot(forecast)

pyplot.show()

Output:

	ds	yhat	yhat_lower	yhat_upper
0	1968-01-01	14364.866157	12816.266184	15956.555409
1	1968-02-01	14940.687225	13299.473640	16463.811658
2	1968-03-01	20858.282598	19439.403787	22345.747821
3	1968-04-01	22893.610396	21417.399440	24454.642588
4	1968-05-01	24212.079727	22667.146433	25816.191457

FEATURE ENGINEERING:

Create new features or transform existing ones to capture valuable information.

- **Enhanced Model Performance**
- **Improved Interpretability**
- **Handling Non-linearity**

Enhanced Model Performance:

Model health monitoring is a critical aspect of maintaining the performance and reliability of machine learning models in production. It involves continuous observation and evaluation of the model's behavior and outcomes to ensure its accuracy and effectiveness over time.

1.**Importance of Monitoring:** Regularly monitoring model health helps detect issues such as data drift, concept drift, and performance degradation early on.

2.**Metrics Tracking:** Keep an eye on metrics like accuracy, precision, recall, and F1-score to assess the model's performance against defined benchmarks.

3.**Data Quality Monitoring:** Ensure the quality and consistency of input data to prevent biased or inaccurate predictions.

4.**Model Drift Detection:** Detect concept drift or changes in data patterns that might affect the model's performance.

5.**Alerts and Notifications:** Implement alerting mechanisms to notify stakeholders when the model's performance deviates from the expected.

6.**Feedback Loop:** Use monitoring insights to continuously improve the model by retraining or fine-tuning based on real-world observations.

7.**Best Practices:** Follow industry best practices and leverage tools like A/B testing and statistical techniques for effective monitoring.

Improved Interpretability:
Methods:

1.Data

BM Pre-Processing

Sign-Flipping to Maximize SM Alignment

Quality Control and De-Confounding

Grouping of SM and BM Into Sub-Domains

2. Domain-Driven Dimension Reduction

Two-Way CV

3.Evaluating the Stability of DDR

4. CCA on Brain Imaging and Behavioral Data

DDR CCA Pipeline

5. **DDR CCA Pipeline**

6. Comparison Between PCA and DDR

Handling Non-linearity:

- Nonlinearity issues in control practice
- Setpoint scheduling/feedforward
  – path planning replay - linear interpolation
- Nonlinear maps
  – B-splines
  – Multivariable interpolation: polynomials/splines/RBF
  – Neural Networks
  – Fuzzy logic

• Gain scheduling • Local modeling

Model Training:

Train the selected time series forecasting model using historical demand data. This involves estimating model parameters and seasonal components, if applicable.

Unsupervised learning:

Unsupervised learning, also known as unsupervised machine learning, uses machine learning algorithms to analyze and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention.

What is Mean Squared Error or MSE

•The Mean Absolute Error is the squared mean of the difference between the actual values and predictable values.

PROGRAM:

Product Demand Prediction:

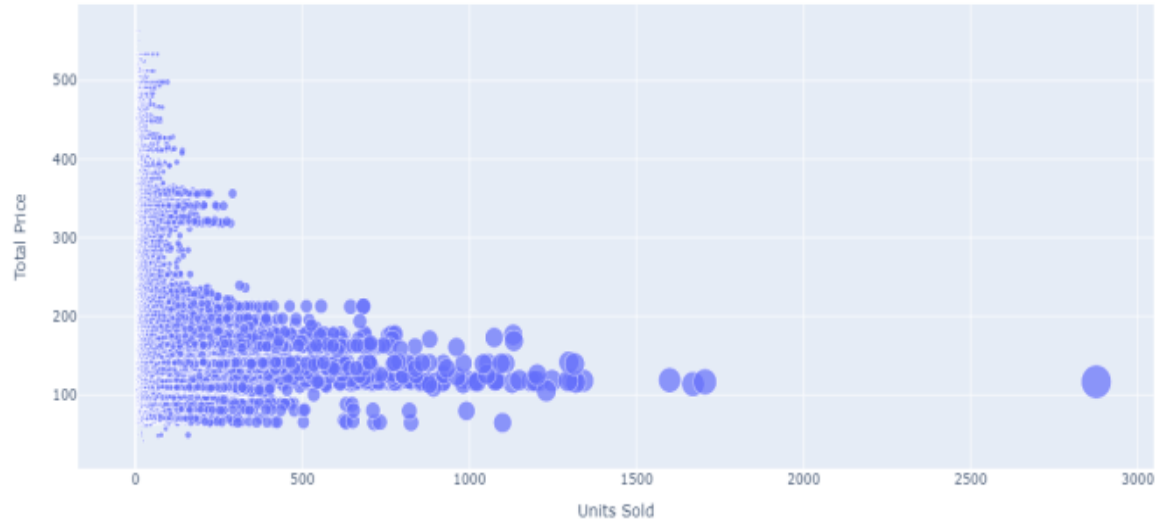
```
Import pandas as pd

Import numpy as np

Import plotly.express as px

Import seaborn as sns

Import matplotlib.pyplot as plt

From sklearn.model_selection import train_test_split

From sklearn.tree import DecisionTreeRegressor

Data=pd.read_csv("C:\Users\mabir\AppData\Local\Microsoft\
Windows\INetCache\IE\AHLGJQP8\archive[1].zip ")

Data.head()
```

Relationship between price and demand for the product:

```
Fig = px.scatter(data, x="Units Sold", y="Total Price",
                Size='Units Sold')
```

Fig.show()

Output:



Correlation between the features of the dataset:

Print(data.corr())

Output:

	ID	Store ID	Total Price	Base Price	Units Sold
ID	1.000000	0.007464	0.008473	0.018932	-0.010616

Store ID 0.007464 1.000000 -0.038315 -0.038848 -0.004372

Total Price 0.008473 -0.038315 1.000000 0.958885 -0.235625

Base Price 0.018932 -0.038848 0.958885 1.000000 -0.140032

Units Sold -0.010616 -0.004372 -0.235625 -0.140032 1.000000

1

Correlations = data.corr(method='pearson')

2

Plt.figure(figsize=(15, 12))

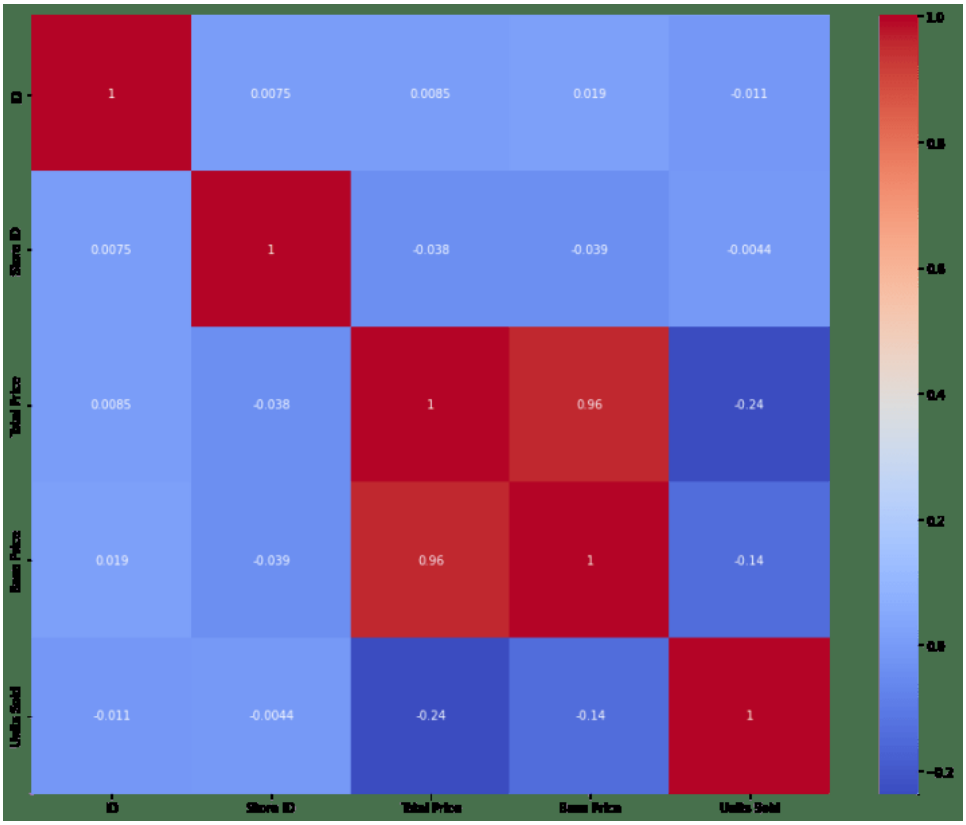
3

Sns.heatmap(correlations, cmap=”coolwarm”, annot=True)

4

Plt.show()

Output:



fit an ARIMA model and plot residual errors

From pandas import datetime

From pandas import read_csv

From pandas import DataFrame

```
From statsmodels.tsa.arima.model import ARIMA
From matplotlib import pyplot
# load dataset
Def parser(x):
Return datetime.strptime('190'+x, '%Y-%m')
Series = read_csv('shampoo-sales.csv', header=0, index_col=0, parse_dates=True, squeeze=True, date_parser=parser)
Series.index = series.index.to_period('M')
# fit model
Model = ARIMA(series, order=(5,1,0))
Model_fit = model.fit()
# summary of fit model
Print(model_fit.summary())
# line plot of residuals
Residuals = DataFrame(model_fit.resid)
Residuals.plot()
Pyplot.show()
# density plot of residuals
Residuals.plot(kind='kde')
Pyplot.show()
# summary stats of residuals
Print(residuals.describe())
```

Output:

SARIMAX Results

Dep. Variable: Sales No. Observations: 36

Model: ARIMA(5, 1, 0) Log Likelihood -198.485

Date: Thu, 10 Dec 2020 AIC 408.969

Time: 09:15:01 BIC 418.301

Sample: 01-31-1901 HQIC 412.191

- 12-31-1903

Covariance Type: opg

	Coef	std err	z	P>|z|	[0.025	0.975]
Ar.L1	-0.9014	0.247	-3.647	0.000	-1.386	-0.417
Ar.L2	-0.2284	0.268	-0.851	0.395	-0.754	0.298
Ar.L3	0.0747	0.291	0.256	0.798	-0.497	0.646
Ar.L4	0.2519	0.340	0.742	0.458	-0.414	0.918
Ar.L5	0.3344	0.210	1.593	0.111	-0.077	0.746
Sigma2	4728.9608	1316.021	3.593	0.000	2149.607	7308.314

Ljung-Box (L1) (Q):	0.61	Jarque-Bera (JB):	0.96

Prob(Q): 0.44 Prob(JB): 0.62

Heteroskedasticity (H): 1.07 Skew: 0.28

Prob(H) (two-sided): 0.90 Kurtosis: 2.41

Prophet:

```
# make an in-sample forecast
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from matplotlib import pyplot
# load data
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df.columns = ['ds', 'y']
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# use the model to make a forecast
forecast = model.predict(future)
# summarize the forecast
print(forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].head())
# plot forecast
model.plot(forecast)
pyplot.show()
```
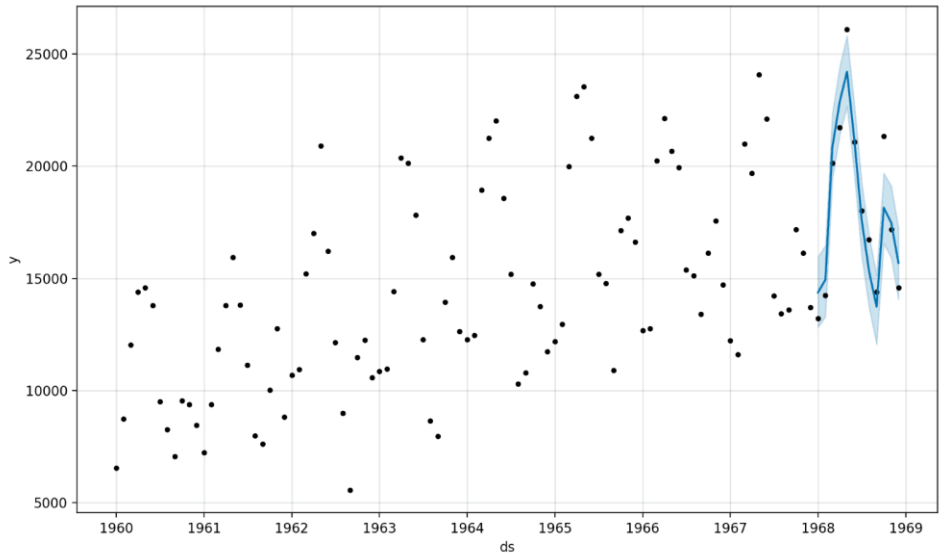

Running the example forecasts the last 12 months of the dataset.

OUTPUT:

	ds	yhat	yhat_lower	yhat_upper
0	1968-01-01	14364.866157	12816.266184	15956.555409
1	1968-02-01	14940.687225	13299.473640	16463.811658
2	1968-03-01	20858.282598	19439.403787	22345.747821
3	1968-04-01	22893.610396	21417.399440	24454.642588
4	1968-05-01	24212.079727	22667.146433	25816.191457



EVALUATION:

Demand forecasting is formulated as a regression problem. Evaluation metrics in regression problems can be split into bias and variation (accuracy) classes, where bias indicates signed deviation from actual values (location), and accuracy evaluates unsigned

average deviation (variance of data).

Conclusion:

In this phase-4 project conclusion, we will summarize the key findings and insights from the incorporating time series techniques .we will reiterate the impact of these time series techniques .These techniques provide valuable insights into patterns, seasonality, and trends within the data, enabling more accurate predictions and forecasts.

In this section, continue building the project by performing different activities like feature engineering, model training, evaluation etc as per the instructions in the project