PRODUCT DEMAND PREDICTION WITH MACHINE LEARNINGS:

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PHASE-2 PROJECT SUBMISSION DOCUMENT

PROJECT : PRODUCT DEMAND PERDICTION

INTRODUCTION:

- Product demand prediction with machine learning involves using algorithms and statistical models to forecast the future demand for a specific product.

- This is a valuable process for businesses in various industries, as it helps them optimize inventory management, production planning, and supply chain operations.

- Machine learning techniques can analyze historical data and various factors influencing demand to make accurate predictions.

- Product demand prediction with machine learning can help businesses reduce excess inventory costs, minimize stockouts, improve customer satisfaction, and enhance overall operational efficiency.

CONTENT FOR PHASE-2 PROJECT:

Consider incorporating time series forecasting techniques like ARIMA or Prophet to capture temporal patterns in demand data.

DATA SOURCE:

A good data source for product demand prediction using machine learning is:

Dataset Link:
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

EXPLANATION FOR PHASE-2 PROJECT:

Data Collection and Preprocessing:

Gather historical demand data, ensuring that it is time-stamped and organized chronologically. Preprocess the data by addressing missing values, outliers, and any other data quality issues.

Exploratory Data Analysis (EDA):

Conduct EDA to understand the temporal patterns and characteristics of the demand data. Look for seasonality, trends, and other recurring patterns. Visualization tools and statistical tests can be helpful in this phase.

Incorporating time series forecasting techniques:

- **ARIMA (Auto Regressive Integrated Moving Average):**
  Suitable for stationary data with autoregressive and moving average components.

- **SARIMA (Seasonal ARIMA):**
  Extends ARIMA to handle seasonal patterns in data.

- **Exponential Smoothing Methods:**

These include Holt-Winters for capturing trends and seasonality.

- **Prophet:**
  Developed by Facebook, Prophet is useful for data with daily observations, holidays, and seasonality.

- **Deep Learning Models (e.g., LSTM and GRU):**
  Suitable for capturing complex temporal patterns, but they may require more data and computational resources.

Model Training:

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

Validation and Hyperparameter Tuning:

Assess the model's performance using validation data or cross-validation. Fine-tune hyperparameters and adjust the model structure as needed to improve forecasting accuracy.

Forecasting:

Once the model is trained and validated, use it to make predictions for future time periods. These forecasts will capture temporal patterns and provide insights into expected demand behavior.

Performance Evaluation:

Evaluate the forecasting model's performance using appropriate metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and forecast accuracy measures.

Continuous Monitoring and Updating:

Implement a process for regularly updating and retraining the model as new demand data becomes available. This ensures that the model adapts to changing demand patterns over time.

Incorporate External Factors:

Consider adding external variables such as promotional activities, economic indicators, or weather data to your model to account for factors that influence demand fluctuations.

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()
```

Output:

ID	Store ID	Total Price	Base Price	Units Sold
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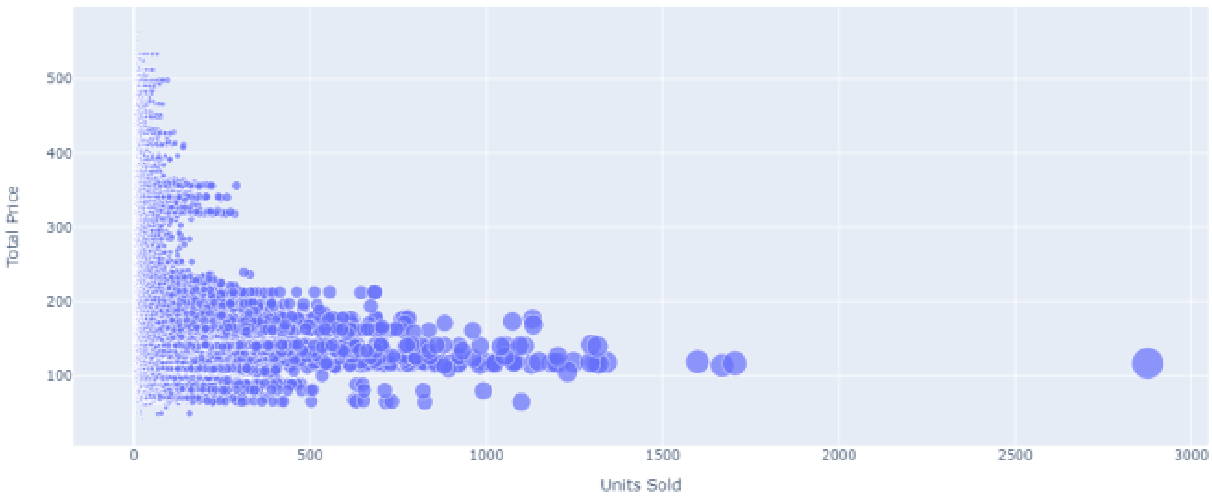
Relationship between price and demand for the product:

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())

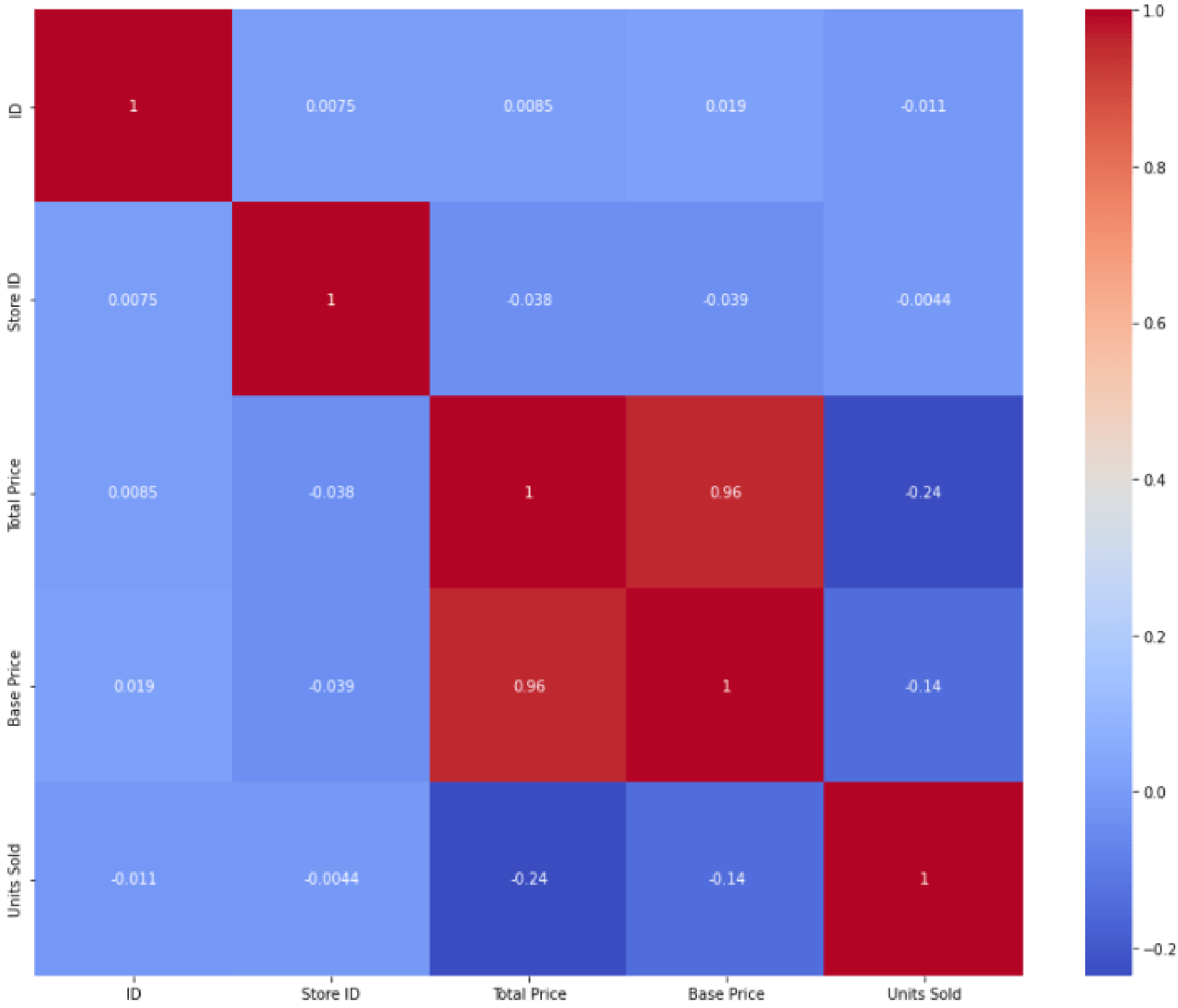
Output:

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

```
correlations = data.corr(method='pearson')

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

sns.heatmap(correlations, cmap="coolwarm", annot=True)

plt.show()
```

<u>Output:</u>

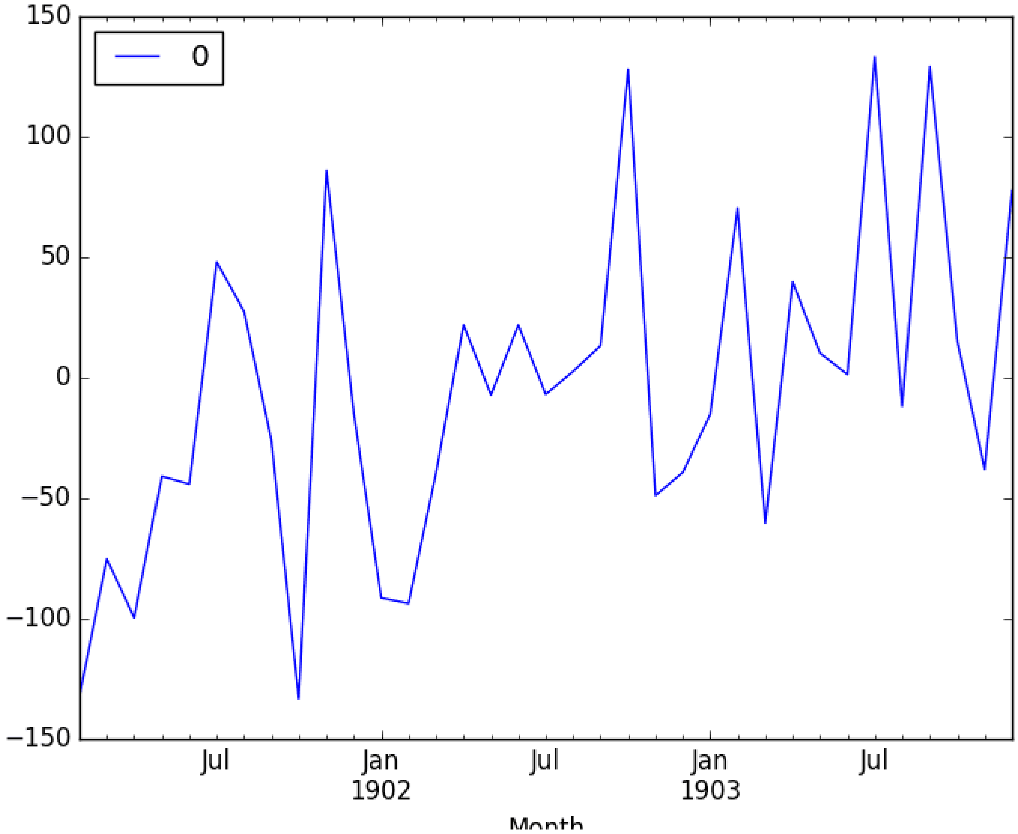


```
# fit an ARIMA model and plot residual errors

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())
```

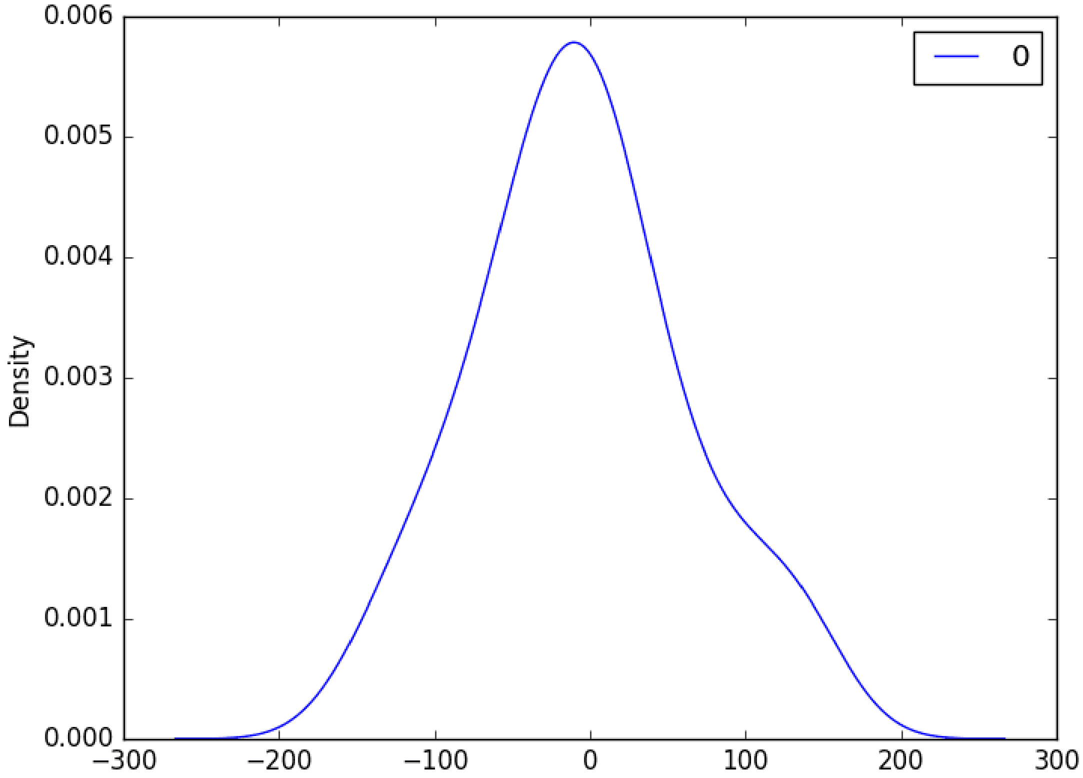
Output:

```
                    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
==========================================================
```

First, we get a line plot of the residual errors, suggesting that there may still be some trend information not captured by the model.



Next, we get a density plot of the residual error values, suggesting the errors are Gaussian, but may not be centered on zero.



Rolling Forecast ARIMA Model:

```
# evaluate an ARIMA model using a walk-forward validation

from pandas import read_csv
from pandas import datetime
from matplotlib import pyplot
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
from math import sqrt
# 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')
# split into train and test sets

X = series.values
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()
# walk-forward validation

for t in range(len(test)):
	model = ARIMA(history, order=(5,1,0))
	model_fit = model.fit()
	output = model_fit.forecast()
	yhat = output[0]
	predictions.append(yhat)
	obs = test[t]
	history.append(obs)
	print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts

rmse = sqrt(mean_squared_error(test, predictions))
print('Test RMSE: %.3f' % rmse)
# plot forecasts against actual outcomes
```

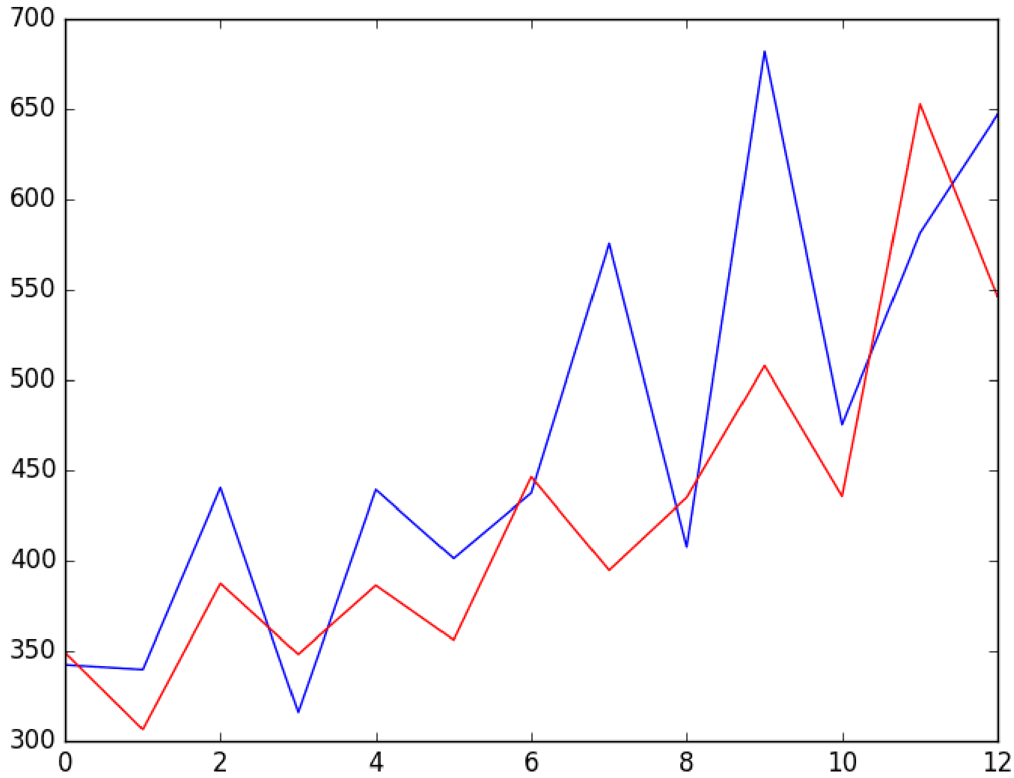
```
pyplot.plot(test)
pyplot.plot(predictions, color='red')
pyplot.show()
```

Running the example prints the prediction and expected value each iteration.

We can also calculate a final root mean squared error score (RMSE) for the predictions, providing a point of comparison for other ARIMA configurations.

```
predicted=343.272180, expected=342.300000
predicted=293.329674, expected=339.700000
predicted=368.668956, expected=440.400000
predicted=335.044741, expected=315.900000
predicted=363.220221, expected=439.300000
predicted=357.645324, expected=401.300000
predicted=443.047835, expected=437.400000
predicted=378.365674, expected=575.500000
predicted=459.415021, expected=407.600000
predicted=526.890876, expected=682.000000
predicted=457.231275, expected=475.300000
predicted=672.914944, expected=581.300000
predicted=531.541449, expected=646.900000
Test RMSE: 89.021
```

A line plot is created showing the expected values (blue) compared to the rolling forecast predictions (red). We can see the values show some trend and are in the correct scale.

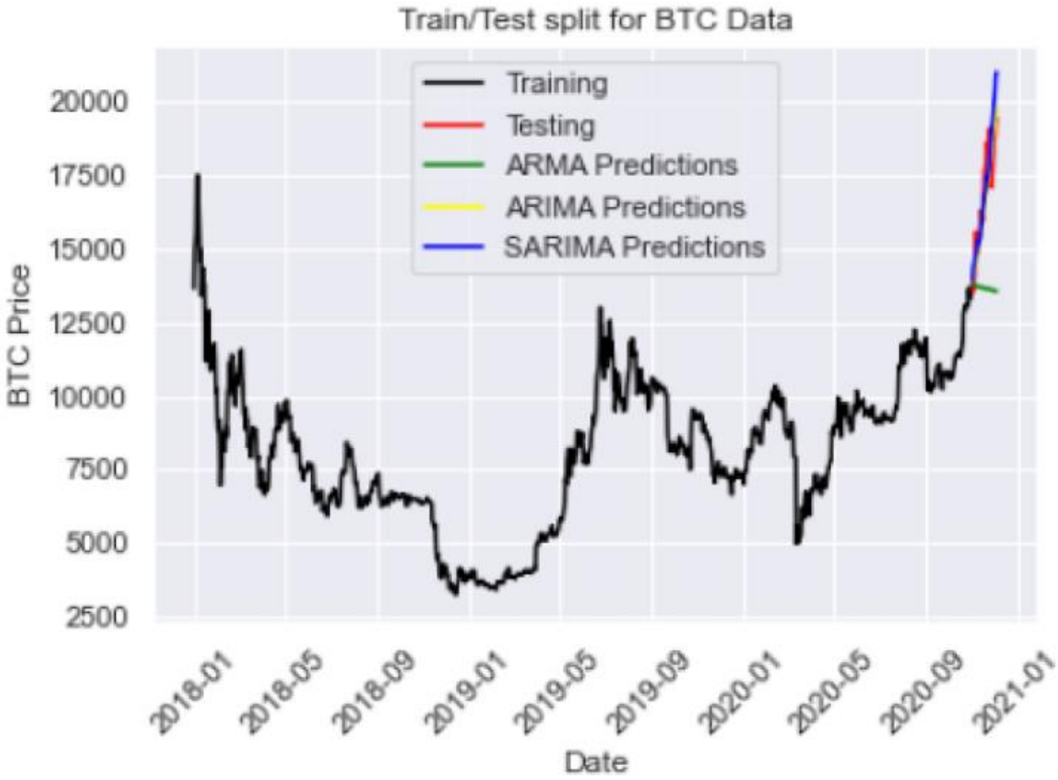


Seasonal ARIMA (SARIMA):

```
SARIMAXmodel = SARIMAX(y, order = (5, 4, 2),
seasonal_order=(2,2,2,12))
SARIMAXmodel = SARIMAXmodel.fit()

y_pred = SARIMAXmodel.get_forecast(len(test.index))
y_pred_df = y_pred.conf_int(alpha = 0.05)
y_pred_df["Predictions"] = SARIMAXmodel.predict(start =
y_pred_df.index[0], end = y_pred_df.index[-1])
y_pred_df.index = test.index
y_pred_out = y_pred_df["Predictions"]
plt.plot(y_pred_out, color='Blue', label = 'SARIMA Predictions')
```

```
plt.legend()
```

Output:



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
```

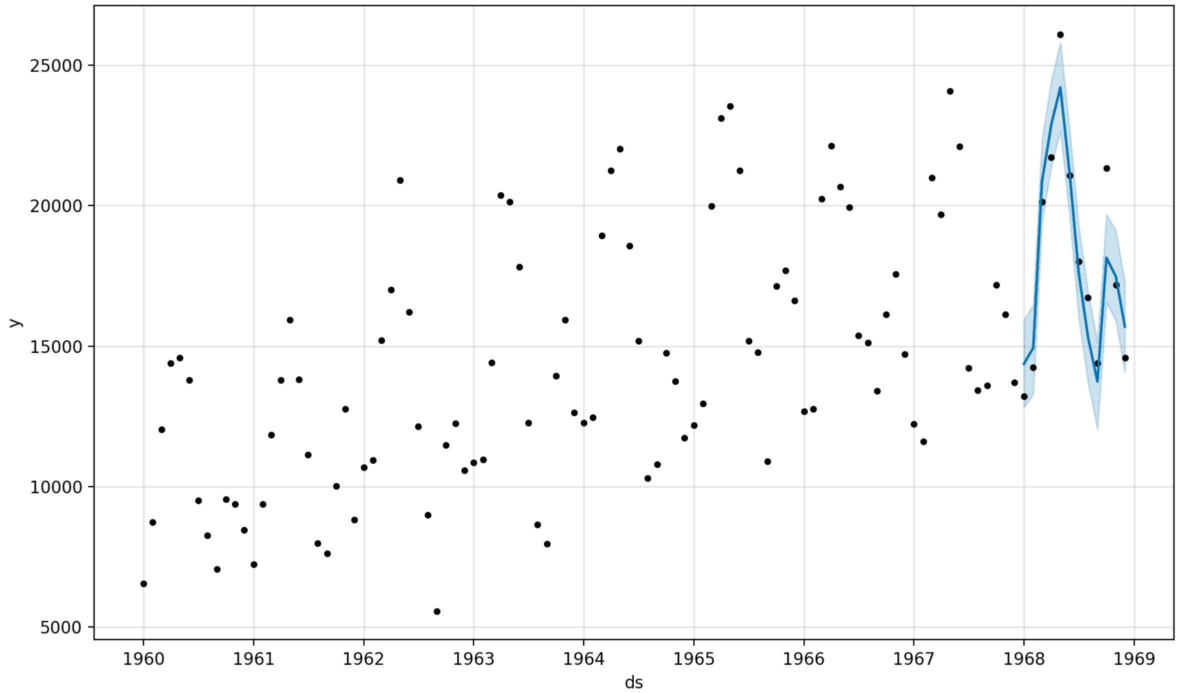
```
path =
'https://raw.githubusercontent.com/jbrownlee/Datasets/master/mo
nthly-car-sales.csv'
df = read_csv(path, header=0)
# prepare expected column names

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()
```

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

The first five months of the prediction are reported and we can see that values are not too different from the actual sales values in 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



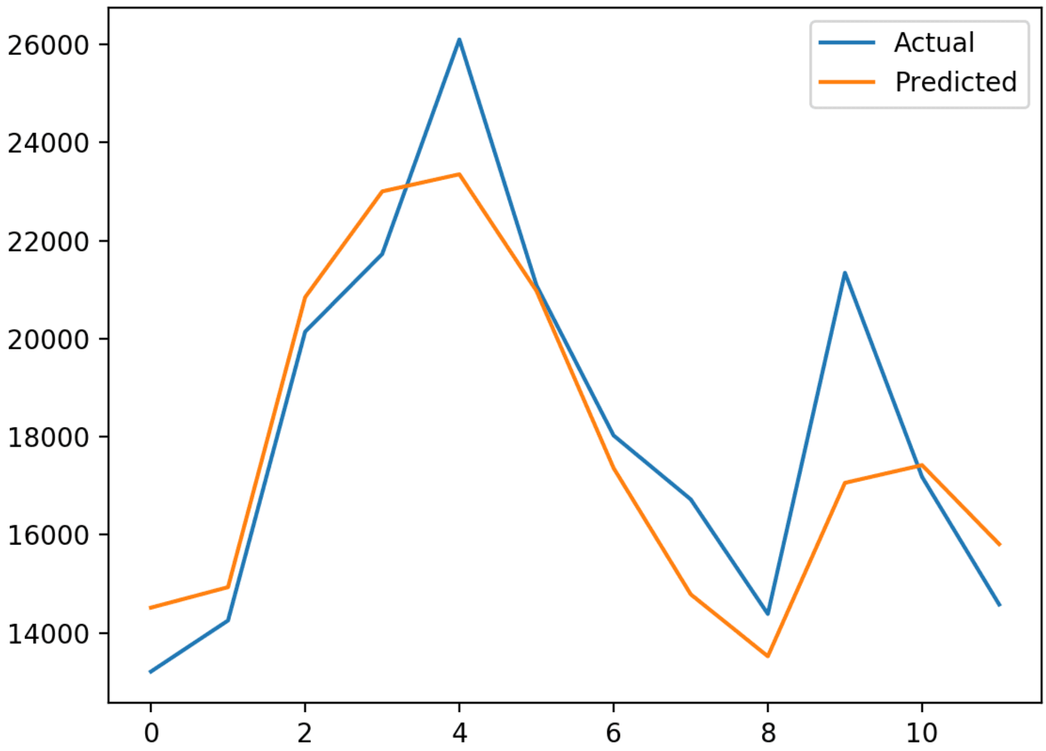
Tying this together, the example below demonstrates how to evaluate a Prophet model on a hold-out dataset.

```
# evaluate prophet time series forecasting model on hold out dataset

from pandas import read_csv

from pandas import to_datetime

from pandas import DataFrame

from fbprophet import Prophet

from sklearn.metrics import mean_absolute_error

from matplotlib import pyplot

# load data

path =
'https://raw.githubusercontent.com/jbrownlee/Datasets/master/mo
nthly-car-sales.csv'
```

```
df = read_csv(path, header=0)
# prepare expected column names
df.columns = ['ds', 'y']
df['ds']= to_datetime(df['ds'])
# create test dataset, remove last 12 months
train = df.drop(df.index[-12:])
print(train.tail())
# define the model
model = Prophet()
# fit the model
model.fit(train)
# 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)
```

```
# calculate MAE between expected and predicted values for december

y_true = df['y'][-12:].values

y_pred = forecast['yhat'].values

mae = mean_absolute_error(y_true, y_pred)

print('MAE: %.3f' % mae)

# plot expected vs actual

pyplot.plot(y_true, label='Actual')

pyplot.plot(y_pred, label='Predicted')

pyplot.legend()

pyplot.show()
```

Output:



CONCLUSION AND FUTURE WORK(PHASE-2):

- In this phase-2 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.

- Future work: It has been demonstrated in this comparative study that different time-series analysis models are capable of accurately predicting order volume in three countries Such work should include additional examinations of the impact of external factors on order volume prediction, such as gasoline prices, labour costs, service demand, and geopolitical events.