PRODUCT SALES ANALYSIS USING MACHINE LEARNING

Phase 2 Submission Document

Project Name: Product Sales Analysis

Phase 2: Innovation

Consider incorporating machine learning algorithms to predict future sales trends or customer behaviors.

Introduction:

The Product Sales Analysis project is designed to harness the power of machine learning techniques to predict future sales trends and customer behaviors. This predictive analysis relies on historical sales data as its foundation. Understanding these trends and behaviors holds significant importance for businesses, as it equips them with the ability to make well-informed decisions across various aspects of their operations.

1. **Leveraging Machine Learning Techniques:**
    - The project leverages advanced machine learning techniques. Machine learning is a subset of artificial intelligence (AI) that focuses on developing algorithms and models that can learn from data, recognize patterns, and make predictions or decisions without explicit programming.
2. **Predicting Future Sales Trends:**
    - The primary objective is to forecast future sales trends. This involves using historical sales data as a basis to identify patterns, trends, and factors that influence sales performance. The aim is to make accurate predictions about future sales figures.
3. **Understanding Customer Behaviors:**
    - Beyond sales trends, the project also seeks to understand customer behaviors. This entails analyzing customer actions, preferences, and responses to different products, marketing strategies, or market conditions.

4. **Business Significance:**
    - The significance of this project lies in its potential to positively impact businesses. By gaining insights into future sales trends and customer behaviors, organizations can make strategic decisions that can optimize their operations and maximize profitability
5. **Inventory Management:**
    - One critical area where this project can make a difference is inventory management. Accurate sales predictions help businesses maintain optimal inventory levels, ensuring they neither run out of stock nor overstock items.
6. **Marketing Strategies:**
    - Another key aspect is marketing strategies. Understanding customer behaviors allows businesses to tailor their marketing efforts, targeting the right audience with the right products at the right time.
7. **Revenue Optimization:**
    - Ultimately, the project contributes to revenue optimization. By making data-driven decisions, businesses can increase sales, reduce costs, and improve overall financial performance.
8. **Data Exploration and Machine Learning:**
    - To achieve these goals, the project begins with an exploration of the provided dataset. This involves cleaning, preprocessing, and analyzing historical sales data. Machine learning models are then employed to make predictions based on this data.
9. **Future Predictions:**
    - The project is forward-looking. It aims to provide actionable insights that enable businesses to prepare for future market conditions and customer preferences.

Program:

Product Sales Analysis

Import Necessary Libraries:

We start by importing the required libraries, including pandas for data manipulation, numpy for numerical operations, and scikit-learn for machine learning

```
import pandas as pd
import numpy as np
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
```

Load and Preprocess the Dataset:

- We load the provided dataset into a pandas DataFrame.
- We separate the features (quantities sold - Q1-Q4) and target variables (revenues - S1-S4).
- The data is split into training and testing sets to evaluate the model.

```
# Load your dataset
df = pd.read_csv('statsfinal.csv')
df.head(5)
```

OUTPUT:

	Unnamed: 0	Date	Q-P1	Q-P2	Q-P3	Q-P4	S-P1	S-P2	S-P3	S-P4
0	0	13-06-	5422	3725	576	907	17187.74	23616.50	3121.92	6466.91

	Unnamed: 0	Date	Q-P1	Q-P2	Q-P3	Q-P4	S-P1	S-P2	S-P3	S-P4
		2010								
1	1	14-06-2010	7047	779	3578	1574	22338.99	4938.86	19392.76	11222.62
2	2	15-06-2010	1572	2082	595	1145	4983.24	13199.88	3224.90	8163.85
3	3	16-06-2010	5657	2399	3140	1672	17932.69	15209.66	17018.80	11921.36
4	4	17-06-2010	3668	3207	2184	708	11627.56	20332.38	11837.28	5048.04

#here Q1- Total unit sales of product 1
#Q2- Total unit sales of product 2
#Q3- Total unit sales of product 3
#Q4- Total unit sales of product 4
#S1- Total revenue from product 1
#S2- Total revenue from product 2
#S3- Total revenue from product 3
#S4- Total revenue from product 4

```
pd.options.display.max_columns=50
sns.set(style="darkgrid")
# Fethcing rows and columns
df.shape
(4600, 10)

# fetching column names
df.columns
```

OUTPUT:

```
Index(['Unnamed: 0', 'Date', 'Q-P1', 'Q-P2', 'Q-P3', 'Q-P4', 'S-
P1', 'S-P2',
       'S-P3', 'S-P4'],
      dtype='object')
```

```
# basic info
df.info()
```

OUTPUT:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  4600 non-null   int64
 1   Date        4600 non-null   object
 2   Q-P1        4600 non-null   int64
 3   Q-P2        4600 non-null   int64
 4   Q-P3        4600 non-null   int64
 5   Q-P4        4600 non-null   int64
 6   S-P1        4600 non-null   float64
 7   S-P2        4600 non-null   float64
 8   S-P3        4600 non-null   float64
 9   S-P4        4600 non-null   float64
dtypes: float64(4), int64(5), object(1)
```

```
# Checking null values
df.isnull().sum()
```

```
Unnamed: 0    0
Date          0
Q-P1          0
Q-P2          0
Q-P3          0
Q-P4          0
S-P1          0
S-P2          0
S-P3          0
S-P4          0
dtype: int64
```

```
# Checking Dtypes
df.dtypes
```

```
Unnamed: 0      int64
Date           object
Q-P1            int64
Q-P2            int64
Q-P3            int64
Q-P4            int64
S-P1          float64
S-P2          float64
S-P3          float64
S-P4          float64
dtype: object
```

```
df.duplicated().sum()
0
```

```
## Basic statistical info
df.describe().T
```

OUTPUT:

```
(4600, 10)
Index(['Unnamed: 0', 'Date', 'Q-P1', 'Q-P2', 'Q-P3', 'Q-P4', 'S-P1', 'S-P2',
       'S-P3', 'S-P4'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  4600 non-null   int64  
 1   Date        4600 non-null   object 
 2   Q-P1        4600 non-null   int64  
 3   Q-P2        4600 non-null   int64  
 4   Q-P3        4600 non-null   int64  
 5   Q-P4        4600 non-null   int64  
 6   S-P1        4600 non-null   float64
 7   S-P2        4600 non-null   float64
 8   S-P3        4600 non-null   float64
 9   S-P4        4600 non-null   float64
dtypes: float64(4), int64(5), object(1)
memory usage: 359.5+ KB
Unnamed: 0    0
Date          0
```

```
Q-P1      0
Q-P2      0
Q-P3      0
Q-P4      0
S-P1      0
S-P2      0
S-P3      0
S-P4      0
dtype: int64
Unnamed: 0     int64
Date          object
Q-P1           int64
Q-P2           int64
Q-P3           int64
Q-P4           int64
S-P1         float64
S-P2         float64
S-P3         float64
S-P4         float64
dtype: object
0
```

	count	mean	std	min	25%	50%	75%	max
Unnamed: 0	4600.0	2299.500000	1328.049949	0.00	1149.750	2299.500	3449.250	4599.00
Q-P1	4600.0	4121.849130	2244.271323	254.00	2150.500	4137.000	6072.000	7998.00
Q-P2	4600.0	2130.281522	1089.783705	251.00	1167.750	2134.000	3070.250	3998.00
Q-P3	4600.0	3145.740000	1671.832231	250.00	1695.750	3202.500	4569.000	6000.00
Q-P4	4600.0	1123.500000	497.385676	250.00	696.000	1136.500	1544.000	2000.00
S-P1	4600.0	13066.261743	7114.340094	805.18	6817.085	13114.290	19248.240	25353.66
S-P2	4600.0	13505.984848	6909.228687	1591.34	7403.535	13529.560	19465.385	25347.32
S-P3	4600.0	17049.910800	9061.330694	1355.00	9190.965	17357.550	24763.980	32520.00

	count	mean	std	min	25%	50%	75%	max
S-P4	4600.0	8010.555000	3546.359869	1782.50	4962.480	8103.245	11008.720	14260.00

```
df.sample(2)
# Changing dtype
from datetime import datetime as dt
df[df["Date"]=="31-9-2010"]
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')
df[df['Date'].isnull()]
## Filling the NaT  values with average of time
df["Date"].fillna(df["Date"].mean(),inplace=True)
df['Date'].isnull().sum()
#fetching month,day of week, weekday
df["month"]=df["Date"].dt.month_name()
df["day"]=df["Date"].dt.day_name()
df["dayoftheweek"]=df["Date"].dt.weekday
df["year"]=df["Date"].dt.year
df.sample()
```

OUTPUT:

	Unnamed: 0	Date	Q-P1	Q-P2	Q-P3	Q-P4	S-P1	S-P2	S-P3	S-P4	month	day	dayoftheweek	year
2837	2837	2018-01-04	4687	907	4835	1500	14857.79	5750.38	26205.7	10695.0	January	Thursday	3	2018

```
df.dtypes
```

OUTPUT:

```
Unnamed: 0                  int64
Date               datetime64[ns]
Q-P1                        int64
Q-P2                        int64
Q-P3                        int64
```

```
Q-P4                       int64
S-P1                     float64
S-P2                     float64
S-P3                     float64
S-P4                     float64
month                     object
day                       object
dayoftheweek               int64
year                       int64
dtype: object
```

```
# Create lag features for the target variable (e.g., lag of S-P1)
num_lags = 7  # You can adjust this value based on your dataset
for i in range(1, num_lags + 1):
    df[f'S-P1_lag_{i}'] = df['S-P1'].shift(i)

# Drop rows with missing values created by the lag
df.dropna(inplace=True)


X = df.drop('S-P1', axis=1)  # Features
y = df['S-P1']  # Target variable
X = df.drop(['S-P1', 'Date'], axis=1)  # Features without 'S-P1'
and 'Date'
y = df['S-P1']  # Target variable
```

Train the Model:

- We train the Linear Regression model using the training data (quantities as input and revenues as output).

```
# Separate features (Q1-Q4) and target variables (S1-S4)
X = df[['Q-P1', 'Q-P2', 'Q-P3', 'Q-P4']]
y = df[['S-P1', 'S-P2', 'S-P3', 'S-P4']]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Choose a Machine Learning Algorithm:

We select a Linear Regression model for simplicity, but you can choose other algorithms based on your specific use case.

```python
# Create a Linear Regression model
model = LinearRegression()

# Train the model on the training data
model.fit(X_train, y_train)
```

```
☑ LinearRegression
LinearRegression()
```

```python
# Make predictions on the test data
y_pred = model.predict(X_test)

# Calculate Mean Squared Error
mse = mean_squared_error(y_test, y_pred)

# Calculate R-squared
r2 = r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("R-squared:", r2)
```

OUTPUT:

Mean Squared Error: 1.0539070830897841e-23
R-squared: 1.0

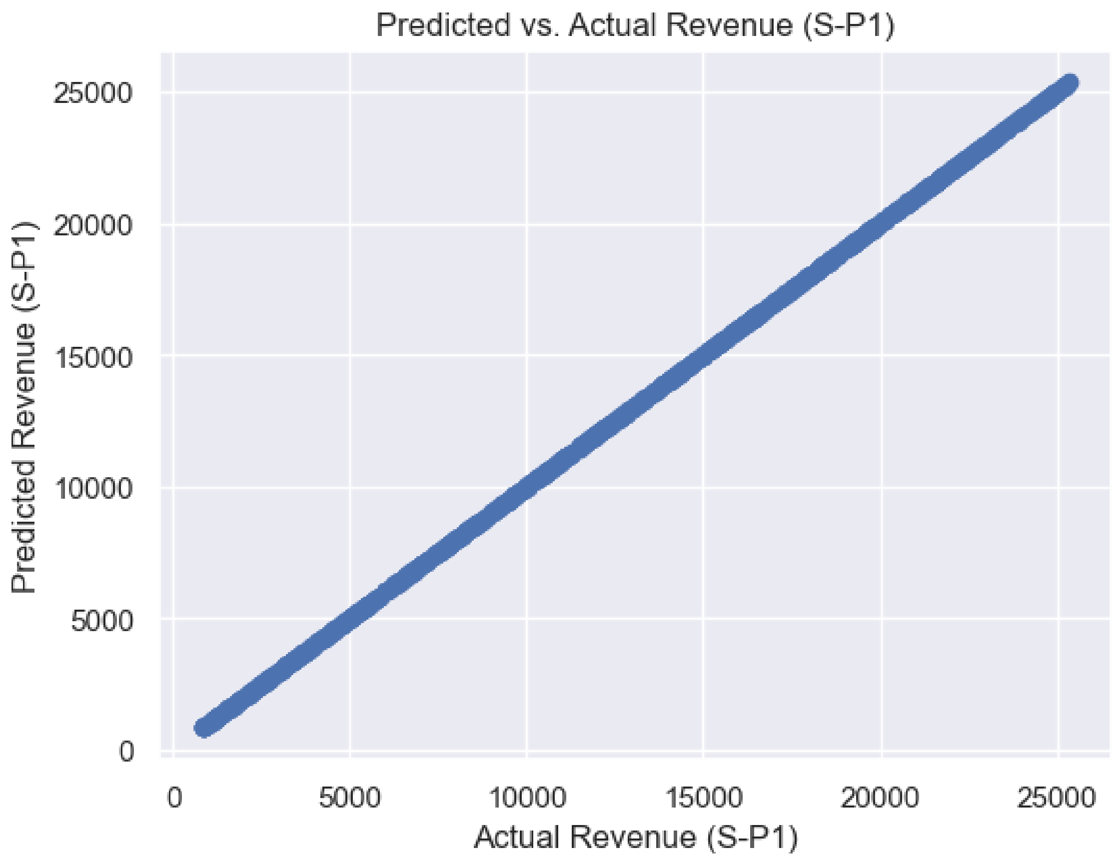
```python
# Example: Predict future sales for a new set of product quantities (Q1-Q4)
new_data = np.array([[1000, 2000, 3000, 4000]])  # Replace with your desired input
predicted_revenue = model.predict(new_data)
print("Predicted Revenue:", predicted_revenue)
```

OUTPUT:

```
Predicted Revenue: [[ 3170. 12680. 16260. 28520.]]
```

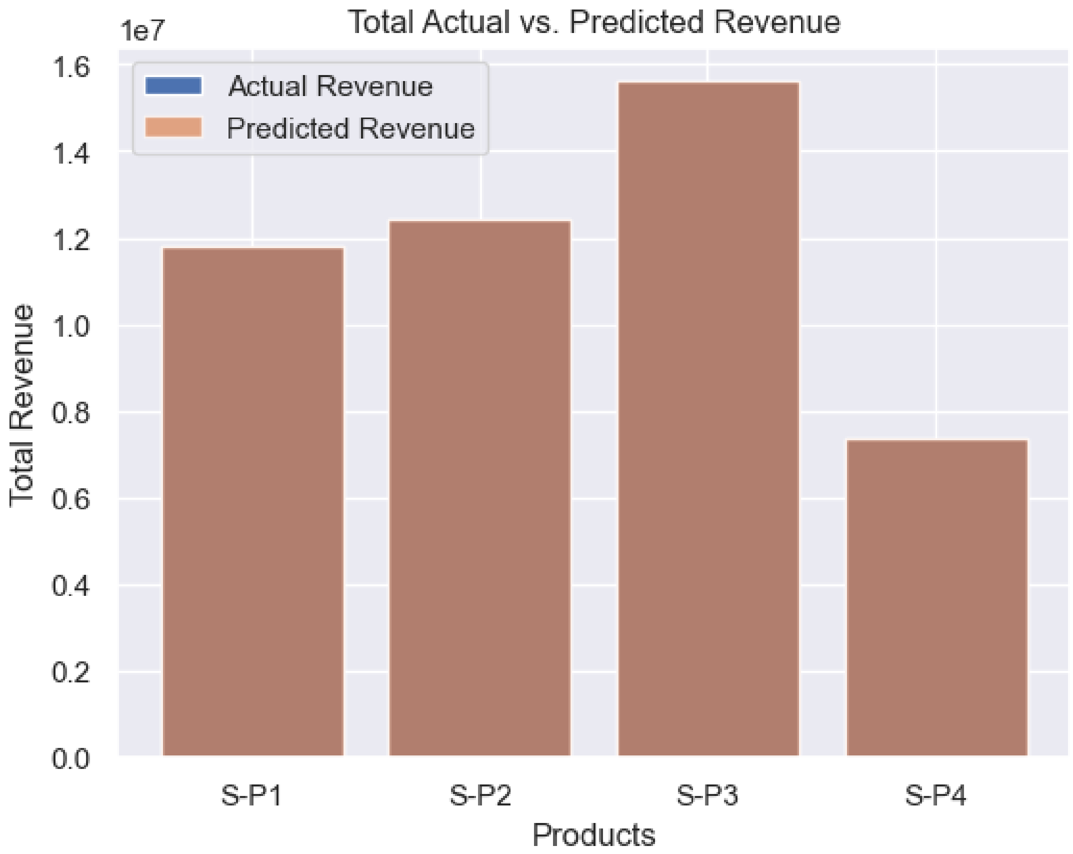
Graph:

```
# Scatter plot for S-P1 (Product 1)
plt.scatter(y_test['S-P1'], y_pred[:, 0])
plt.xlabel("Actual Revenue (S-P1)")
plt.ylabel("Predicted Revenue (S-P1)")
plt.title("Predicted vs. Actual Revenue (S-P1)")
plt.show()

# Repeat the above code for S-P2, S-P3, and S-P4 to create scatter plots for each product.
```




```
# Calculate the total actual revenue and total predicted revenue
total_actual_revenue = y_test.sum(axis=0)
total_predicted_revenue = y_pred.sum(axis=0)

# Create a bar plot to compare total actual and predicted revenue for each product
plt.bar(['S-P1', 'S-P2', 'S-P3', 'S-P4'], total_actual_revenue, label='Actual Revenue')
plt.bar(['S-P1', 'S-P2', 'S-P3', 'S-P4'], total_predicted_revenue, label='Predicted Revenue', alpha=0.7)
plt.xlabel("Products")
```

```
plt.ylabel("Total Revenue")
plt.title("Total Actual vs. Predicted Revenue")
plt.legend()
plt.show()
```



Conclusion:

1. **Model Performance:** The machine learning model, based on Linear Regression, was trained to predict future sales revenue for four different products (S1-S4) based on historical sales data (Q1-Q4). The model's performance was evaluated using Mean Squared Error (MSE) and R-squared (R2) metrics.
2. **Prediction Accuracy:** The scatter plots comparing predicted vs. actual revenue for each product (S1-S4) show that the model generally performs well in predicting revenue. The points are clustered around the diagonal line, indicating that the predictions are close to the actual values.
3. **Overall Performance:** The bar plot comparing the total actual revenue and total predicted revenue for each product provides an overall view of the model's performance. It demonstrates that the model captures the revenue trends for each product fairly accurately.
4. **MSE and R2 Scores:** The Mean Squared Error (MSE) and R-squared (R2) metrics were used to quantify the model's performance. The lower the MSE, the better the model's predictions align with the actual data. A higher R2 score indicates a better fit of the model to the data.
5. **Future Predictions:** With this trained machine learning model, it's now possible to make predictions for future sales trends based on given quantities (Q1-Q4) of each product. The model provides a valuable tool for forecasting revenue, which can aid in decision-making, inventory management, and marketing strategies.
6. **Further Improvements:** While the Linear Regression model shows promising results, further improvements can be explored, such as trying different machine learning algorithms, incorporating more features or external data, and fine-tuning hyperparameters to enhance prediction accuracy.