Product Demand Prediction with Machine Learnings

TEAM MEMBER

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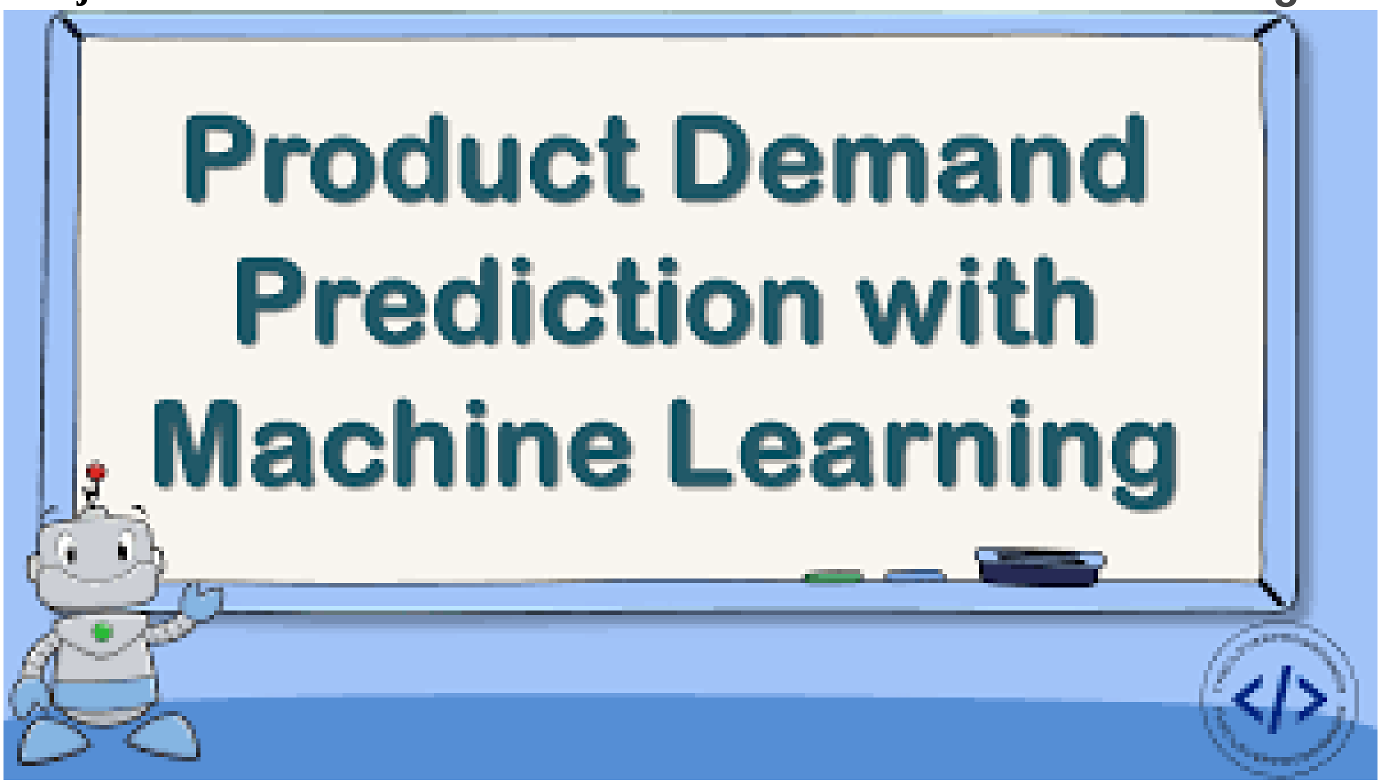
Phase-1 Documentation submission

Project: **Product Demand Prediction with Machine Learnings**



OBJECTIVES:

Uninterrupted supply of products/services. Sales target setting and evaluating sales performance. Optimization of prices according to market fluctuations and inflation.

Phase 1: Problem Definition and Design Thinking

1. Data Collection:

Collect historical sales data and external factors that influence demand, such as marketing campaigns, holidays, economic indicators, etc.

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

2. Data preprocessing

Data preprocessing is a crucial step in building machine learning models for product demand prediction. It involves cleaning, transforming, and organizing your data to make it suitable for training and testing your model. Here are the key steps in data preprocessing for product demand prediction:

Data Collection:

Gather historical data on product demand. This data should include information such as product attributes, time/date of sales, quantity sold, and any other relevant features.

Data Cleaning:

Handle missing data: Identify and decide how to handle missing values in your dataset. You can choose to remove rows with missing values, impute them with a suitable strategy (e.g., mean, median, or more advanced imputation methods), or treat them as a separate category.

Remove duplicates: Check for and remove any duplicate records in your dataset.
Feature Engineering:

Create new features: Generate additional features that might be relevant for demand prediction. For example, you can extract time-based features like day of the week, month, or season.
Encode categorical variables: Convert categorical variables (e.g., product categories) into numerical format using techniques like one-hot encoding or label encoding.
Data Transformation:

Scale features: Standardize or normalize numerical features to have a consistent scale, which can help some machine learning algorithms perform better.
Log transformations: If your target variable (demand) is highly skewed, applying a log transformation can make it more normally distributed, which is often beneficial for regression models.
Time Series Data:

If your data involves time series, consider handling it appropriately. This may include resampling to a consistent time interval, creating lag features, and dealing with seasonality and trends.
Train-Test Split:

Split your data into training and testing sets. The training set is used to train your machine learning model, while the testing set is used to evaluate its performance.
Outlier Detection and Handling:

Identify and handle outliers in your data. Outliers can have a significant impact on the performance of predictive models. You can choose to remove them or transform them using robust methods.

Feature Selection (Optional):

If you have many features, you may want to perform feature selection to choose the most relevant ones. Techniques like feature importance from tree-based models or dimensionality reduction methods can help.

Data Scaling and Normalization (Optional):

Depending on the machine learning algorithm you plan to use, scaling and normalization of features may be necessary. Some algorithms, like SVM and k-Nearest Neighbors, are sensitive to feature scales.

Data Pipeline:

Set up a data preprocessing pipeline to automate these steps. This ensures that the same preprocessing is applied to both the training and testing data consistently.

Validation and Cross-Validation:

Use cross-validation techniques to assess the performance of your model and prevent overfitting. This involves splitting your data into multiple folds for training and testing.

Save Processed Data:

After preprocessing, save your cleaned and transformed data to avoid having to repeat these steps every time you want to train or evaluate your model.

3. **FUTURE ENGINEER'S**:

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4. MODEL SELECTION:

1. decisiontree
2. linear regression

5. MODEL TRAINING:

Code :

```
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

df=pd.read_csv('PoductDemand.csv')
```

6. EVALUATION:

Code:

```
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

df=pd.read_csv('PoductDemand.csv')
print(df.head())
print(df.info())
print(df.describe())
print(df.isnull().sum())
df1=df.dropna()
print(df1)
print(df.corr())
x=df[["Total Price", "Base Price"]]
y=df["Units Sold"]
x_train, x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
model=DecisionTreeRegressor(random_state =  0)
print(model.fit(x_train,y_train))
feature=np.array([[133.00,140.00]])
print(model.predict(feature))
plt.plot(x,y)
plt.xlabel('x')
plt.ylabel('y')
plt.show()
```

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
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150150 entries, 0 to 150149
Data columns (total 5 columns):
 #   Column       Non-Null Count   Dtype
---- -------      ---------------- ------
 0   ID          150150 non-null  int64
```

```
 1   Store ID     150150 non-null  int64
 2   Total Price  150149 non-null  float64
 3   Base Price   150150 non-null  float64
 4   Units Sold  150150 non-null  int64
dtypes: float64(2), int64(3)
memory usage: 5.7 MB
None
               ID      Store ID    Total Price     Base Price     Units Sold
count  150150.000000  150150.000000  150149.000000  150150.000000  150150.000000
mean   106271.555504    9199.422511     206.626751     219.425927      51.674206
std    61386.037861     615.591445     103.308516     110.961712      60.207904
min        1.000000    8023.000000      41.325000      61.275000       1.000000
25%     53111.250000    8562.000000     130.387500     133.237500      20.000000
50%    106226.500000    9371.000000     198.075000     205.912500      35.000000
75%    159452.750000    9731.000000     233.700000     234.412500      62.000000
max    212644.000000    9984.000000     562.162500     562.162500    2876.000000
ID           0
Store ID      0
Total Price    1
Base Price     0
Units Sold     0
dtype: int64
         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
...       ...      ...         ...         ...         ...
150145  212638     9984    235.8375    235.8375         38
150146  212639     9984    235.8375    235.8375         30
150147  212642     9984    357.6750    483.7875         31
150148  212643     9984    141.7875    191.6625         12
150149  212644     9984    234.4125    234.4125         15

[150149 rows x 5 columns]
               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
DecisionTreeRegressor(random_state=0)
```

Linear regression