prediciton-model-datixity

September 30, 2024

Importing required libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report
from sklearn.preprocessing import LabelEncoder, StandardScaler
%matplotlib inline
```

Loading the Dataset

[2]:
```
data = pd.read_csv(r"C:\Users\anura\Downloads\Datixity␣
↪Project\supermarket_sales - Sheet1.csv")
```

[3]:
```
data.head(10)
```

[3]:
```
    Invoice ID Branch       City Customer type  Gender  \
0  750-67-8428      A     Yangon        Member  Female
1  226-31-3081      C  Naypyitaw        Normal  Female
2  631-41-3108      A     Yangon        Normal    Male
3  123-19-1176      A     Yangon        Member    Male
4  373-73-7910      A     Yangon        Normal    Male
5  699-14-3026      C  Naypyitaw        Normal    Male
6  355-53-5943      A     Yangon        Member  Female
7  315-22-5665      C  Naypyitaw        Normal  Female
8  665-32-9167      A     Yangon        Member  Female
9  692-92-5582      B   Mandalay        Member  Female
```

```
             Product line  Unit price  Quantity   Tax 5%     Total       Date  \
0       Health and beauty       74.69         7  26.1415  548.9715   1/5/2019
1  Electronic accessories       15.28         5   3.8200   80.2200   3/8/2019
2      Home and lifestyle       46.33         7  16.2155  340.5255   3/3/2019
3       Health and beauty       58.22         8  23.2880  489.0480  1/27/2019
4       Sports and travel       86.31         7  30.2085  634.3785   2/8/2019
5  Electronic accessories       85.39         7  29.8865  627.6165  3/25/2019
6  Electronic accessories       68.84         6  20.6520  433.6920  2/25/2019
7      Home and lifestyle       73.56        10  36.7800  772.3800  2/24/2019
8       Health and beauty       36.26         2   3.6260   76.1460  1/10/2019
9      Food and beverages       54.84         3   8.2260  172.7460  2/20/2019

    Time      Payment    cogs  gross margin percentage  gross income  Rating
0  13:08      Ewallet  522.83                 4.761905       26.1415     9.1
1  10:29         Cash   76.40                 4.761905        3.8200     9.6
2  13:23  Credit card  324.31                 4.761905       16.2155     7.4
3  20:33      Ewallet  465.76                 4.761905       23.2880     8.4
4  10:37      Ewallet  604.17                 4.761905       30.2085     5.3
5  18:30      Ewallet  597.73                 4.761905       29.8865     4.1
6  14:36      Ewallet  413.04                 4.761905       20.6520     5.8
7  11:38      Ewallet  735.60                 4.761905       36.7800     8.0
8  17:15  Credit card   72.52                 4.761905        3.6260     7.2
9  13:27  Credit card  164.52                 4.761905        8.2260     5.9
```

[4]:
```
data.describe()
```

[4]:
```
        Unit price     Quantity       Tax 5%        Total        cogs  \
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.00000
mean     55.672130     5.510000    15.379369   322.966749   307.58738
std      26.494628     2.923431    11.708825   245.885335   234.17651
min      10.080000     1.000000     0.508500    10.678500    10.17000
25%      32.875000     3.000000     5.924875   124.422375   118.49750
50%      55.230000     5.000000    12.088000   253.848000   241.76000
75%      77.935000     8.000000    22.445250   471.350250   448.90500
max      99.960000    10.000000    49.650000  1042.650000   993.00000

       gross margin percentage  gross income      Rating
count             1.000000e+03   1000.000000  1000.00000
mean              4.761905e+00     15.379369     6.97270
std               6.131498e-14     11.708825     1.71858
min               4.761905e+00      0.508500     4.00000
25%               4.761905e+00      5.924875     5.50000
50%               4.761905e+00     12.088000     7.00000
75%               4.761905e+00     22.445250     8.50000
max               4.761905e+00     49.650000    10.00000
```

1 Checking and handling missing values

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Invoice ID               1000 non-null   object
 1   Branch                   1000 non-null   object
 2   City                     1000 non-null   object
 3   Customer type            1000 non-null   object
 4   Gender                   1000 non-null   object
 5   Product line             1000 non-null   object
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64
 8   Tax 5%                   1000 non-null   float64
 9   Total                    1000 non-null   float64
 10  Date                     1000 non-null   object
 11  Time                     1000 non-null   object
 12  Payment                  1000 non-null   object
 13  cogs                     1000 non-null   float64
 14  gross margin percentage  1000 non-null   float64
 15  gross income             1000 non-null   float64
 16  Rating                   1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB
```

[6]:
```
missing_values = data.isnull().sum()
print("Missing values in each column:\n", missing_values)
```

```
Missing values in each column:
 Invoice ID                 0
Branch                     0
City                       0
Customer type              0
Gender                     0
Product line               0
Unit price                 0
Quantity                   0
Tax 5%                     0
Total                      0
Date                       0
Time                       0
Payment                    0
cogs                       0
gross margin percentage    0
```

```
gross income               0
Rating                     0
dtype: int64
```

2 Feature Engineering

[7]:
```python
# Calculate the average transaction value
average_transaction_value = data['Total'].mean()
print("Average Transaction Value:", average_transaction_value)
```

```
Average Transaction Value: 322.966749
```

[8]:
```python
# Create a new binary target variable: 1 if transaction is above average, 0 if␣
↪below
data['Above_Average'] = (data['Total'] > average_transaction_value).astype(int)

# Preview the updated dataset
print(data[['Total', 'Above_Average']].head())
```

```
      Total  Above_Average
0  548.9715              1
1   80.2200              0
2  340.5255              1
3  489.0480              1
4  634.3785              1
```

[9]:
```python
# Encode categorical features using LabelEncoder for simplicity
le = LabelEncoder()
data['Product line'] = le.fit_transform(data['Product line'])
data['Branch'] = le.fit_transform(data['Branch'])
data['Payment'] = le.fit_transform(data['Payment'])
data['Customer type'] = le.fit_transform(data['Customer type'])
```

3 Model Selection

[10]:
```python
# Define features (X) and target (y)
features = ['Product line', 'Branch', 'Quantity', 'Payment', 'Customer type']
X = data[features]
y = data['Above_Average']
```

[11]:
```python
# Split the dataset into training and test sets (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

4 Training the Models

[12]:
```
# Logistic Regression Model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
```

[12]: LogisticRegression()

[13]:
```
# Decision Tree Classifier
decision_tree = DecisionTreeClassifier(random_state=42)
decision_tree.fit(X_train, y_train)
```

[13]: DecisionTreeClassifier(random_state=42)

[14]:
```
# Linear Regression model
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
```

[14]: LinearRegression()

[15]:
```
# Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train, y_train)
```

[15]: RandomForestClassifier(random_state=42)

5 Model Evaluation

[16]:
```
# Logistic Regression Predictions
y_pred_log_reg = log_reg.predict(X_test)
```

[17]:
```
# Decision Tree Predictions
y_pred_tree = decision_tree.predict(X_test)
```

[18]:
```
# Linear Regression Predictions
y_pred = lin_reg.predict(X_test)
```

[19]:
```
# Random Forest predictions on the test set
y_pred = rf_classifier.predict(X_test)
```

[20]:
```
# Defining a function to evaluate models
def evaluate_model(y_true, y_pred, model_name):
    print(f"Evaluation for {model_name}")
    print("Accuracy:", accuracy_score(y_true, y_pred))
    print("Precision:", precision_score(y_true, y_pred))
    print("Recall:", recall_score(y_true, y_pred))
```

```
    print("F1-Score:", f1_score(y_true, y_pred))
    print("\nClassification Report:\n", classification_report(y_true, y_pred))
```

[21]:
```
# Evaluate Logistic Regression
evaluate_model(y_test, y_pred_log_reg, "Logistic Regression")
```

```
Evaluation for Logistic Regression
Accuracy: 0.78
Precision: 0.8115942028985508
Recall: 0.6436781609195402
F1-Score: 0.7179487179487178

Classification Report:
               precision    recall  f1-score   support

           0       0.76      0.88      0.82       113
           1       0.81      0.64      0.72        87

    accuracy                           0.78       200
   macro avg       0.79      0.76      0.77       200
weighted avg       0.78      0.78      0.78       200
```

[22]:
```
# Evaluate Decision Tree
evaluate_model(y_test, y_pred_tree, "Decision Tree")
```

```
Evaluation for Decision Tree
Accuracy: 0.72
Precision: 0.7246376811594203
Recall: 0.5747126436781609
F1-Score: 0.6410256410256409

Classification Report:
               precision    recall  f1-score   support

           0       0.72      0.83      0.77       113
           1       0.72      0.57      0.64        87

    accuracy                           0.72       200
   macro avg       0.72      0.70      0.71       200
weighted avg       0.72      0.72      0.71       200
```

[23]:
```
# Evaluate Linear Regression model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

```
print(f"R-Squared: {r2}")
```

```
Mean Squared Error: 0.23
R-Squared: 0.06418472179839274
```

[24]:
```
# Evaluate Random Forest model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.77

Classification Report:
               precision    recall  f1-score   support

           0       0.80      0.79      0.79       113
           1       0.73      0.75      0.74        87

    accuracy                           0.77       200
   macro avg       0.77      0.77      0.77       200
weighted avg       0.77      0.77      0.77       200
```

6 6. Feature Importance

[25]:
```
# For Logistic Regression
print("\nLogistic Regression Feature Importance:")
log_reg_coef = pd.DataFrame({
    'Feature': features,
    'Importance': log_reg.coef_[0]
}).sort_values(by='Importance', ascending=False)
print(log_reg_coef)
```

```

Logistic Regression Feature Importance:
         Feature  Importance
2       Quantity    0.567770
0   Product line    0.102179
3        Payment    0.083838
1         Branch    0.041106
4  Customer type    0.029199
```

[26]:
```
# For Decision Tree
print("\nDecision Tree Feature Importance:")
tree_importances = pd.DataFrame({
    'Feature': features,
    'Importance': decision_tree.feature_importances_
```

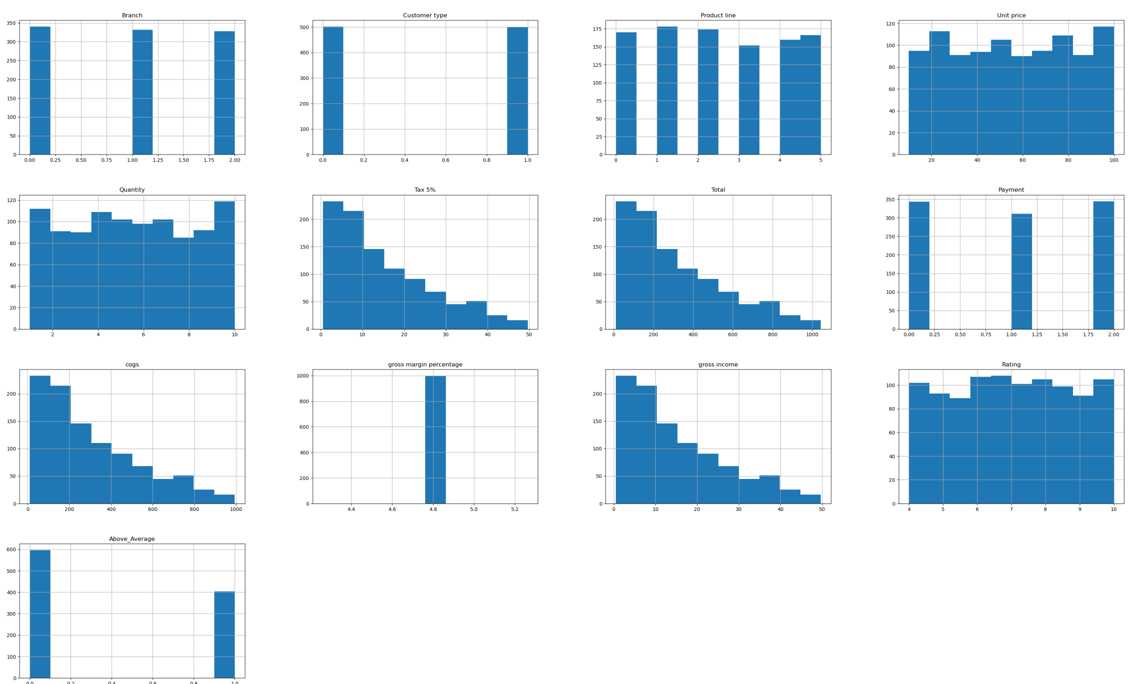
```
}).sort_values(by='Importance', ascending=False)
print(tree_importances)
```

```
Decision Tree Feature Importance:
         Feature  Importance
2       Quantity    0.553478
0   Product line    0.197801
3        Payment    0.094375
1         Branch    0.090574
4  Customer type    0.063772
```

7 Strategies to Increase Customer Transaction Amounts

For this we need to do the EDA

[27]:
```
# Histogram PLot
data.hist(figsize=(40,24))
plt.show()
```



[28]:
```
non_numeric_columns = data.select_dtypes(exclude=[float, int])
print(non_numeric_columns.columns)
```

```
Index(['Invoice ID', 'City', 'Gender', 'Date', 'Time'], dtype='object')
```

[29]:
```
### Identify Categorical Columns
categorical_cols = ['Branch', 'City', 'Customer type', 'Gender', 'Product␣
↪line', 'Payment']
```

[31]:
```
### 2.4 Feature Scaling (Optional but Recommended for Some Models)
# Initialize StandardScaler
scaler = StandardScaler()

# List of numerical features to scale
numerical_cols = ['Unit price', 'Quantity', 'Tax 5%', 'cogs',
                  'gross margin percentage', 'gross income', 'Rating']

# Apply scaling
data[numerical_cols] = scaler.fit_transform(data[numerical_cols])
```

[32]:
```
### Initialize Label Encoder
le = LabelEncoder()

### Apply Label Encoding
for col in categorical_cols:
    data[col] = le.fit_transform(data[col])
```

[33]:
```
datas=data.drop(non_numeric_columns, axis=1)
```

[34]:
```
data.corr
```

[34]:
```
<bound method DataFrame.corr of       Invoice ID  Branch  City  Customer type
Gender  Product line  \
0    750-67-8428       0     2              0       0             3
1    226-31-3081       2     1              1       0             0
2    631-41-3108       0     2              1       1             4
3    123-19-1176       0     2              0       1             3
4    373-73-7910       0     2              1       1             5
..           …     …     …            …     …           …
995  233-67-5758       2     1              1       1             3
996  303-96-2227       1     0              1       0             4
997  727-02-1313       0     2              0       1             2
998  347-56-2442       0     2              1       1             4
999  849-09-3807       0     2              0       0             1

     Unit price  Quantity    Tax 5%     Total       Date   Time  Payment  \
0      0.718160  0.509930  0.919607  548.9715   1/5/2019  13:08        2
1     -1.525303 -0.174540 -0.987730   80.2200   3/8/2019  10:29        0
2     -0.352781  0.509930  0.071446  340.5255   3/3/2019  13:23        1
3      0.096214  0.852165  0.675780  489.0480  1/27/2019  20:33        2
4      1.156959  0.509930  1.267125  634.3785   2/8/2019  10:37        2
..          …         …         …        …         …      …        …
```

```
995   -0.578600 -1.543480 -1.141750    42.3675  1/29/2019  13:46        2
996    1.574989  1.536635  2.846340  1022.4900   3/2/2019  17:16        2
997   -0.899958 -1.543480 -1.178109    33.4320   2/9/2019  13:22        0
998    0.383208 -1.543480 -1.032932    69.1110  2/22/2019  15:33        0
999    1.233617  0.509930  1.327837   649.2990  2/18/2019  13:28        0

         cogs  gross margin percentage  gross income    Rating  Above_Average
0    0.919607                      0.0      0.919607  1.238443              1
1   -0.987730                      0.0     -0.987730  1.529527              0
2    0.071446                      0.0      0.071446  0.248760              1
3    0.675780                      0.0      0.675780  0.830927              1
4    1.267125                      0.0      1.267125 -0.973790              1
..        …                         …           …        …             …
995 -1.141750                      0.0     -1.141750 -0.449840              0
996  2.846340                      0.0      2.846340 -1.497741              1
997 -1.178109                      0.0     -1.178109  0.423410              0
998 -1.032932                      0.0     -1.032932 -1.672391              0
999  1.327837                      0.0      1.327837 -0.216974              1

[1000 rows x 18 columns]>
```

[39]:

```
X=['Branch', 'City', 'Customer type', 'Gender', 'Product line', 'Payment']
```

[44]:

```
data.drop(X, axis=1)
```

[44]:

```
       Invoice ID  Unit price  Quantity    Tax 5%      Total       Date   Time  \
0     750-67-8428    0.718160  0.509930  0.919607   548.9715   1/5/2019  13:08
1     226-31-3081   -1.525303 -0.174540 -0.987730    80.2200   3/8/2019  10:29
2     631-41-3108   -0.352781  0.509930  0.071446   340.5255   3/3/2019  13:23
3     123-19-1176    0.096214  0.852165  0.675780   489.0480  1/27/2019  20:33
4     373-73-7910    1.156959  0.509930  1.267125   634.3785   2/8/2019  10:37
..          …           …         …         …          …          …     …
995   233-67-5758   -0.578600 -1.543480 -1.141750    42.3675  1/29/2019  13:46
996   303-96-2227    1.574989  1.536635  2.846340  1022.4900   3/2/2019  17:16
997   727-02-1313   -0.899958 -1.543480 -1.178109    33.4320   2/9/2019  13:22
998   347-56-2442    0.383208 -1.543480 -1.032932    69.1110  2/22/2019  15:33
999   849-09-3807    1.233617  0.509930  1.327837   649.2990  2/18/2019  13:28

         cogs  gross margin percentage  gross income    Rating  Above_Average
0    0.919607                      0.0      0.919607  1.238443              1
1   -0.987730                      0.0     -0.987730  1.529527              0
2    0.071446                      0.0      0.071446  0.248760              1
3    0.675780                      0.0      0.675780  0.830927              1
4    1.267125                      0.0      1.267125 -0.973790              1
..        …                         …           …        …             …
995 -1.141750                      0.0     -1.141750 -0.449840              0
996  2.846340                      0.0      2.846340 -1.497741              1
```

```
997 -1.178109                  0.0     -1.178109  0.423410            0
998 -1.032932                  0.0     -1.032932 -1.672391            0
999  1.327837                  0.0      1.327837 -0.216974            1

[1000 rows x 12 columns]
```

[50]:
```
data_numeric = data.select_dtypes(include=[float, int])  # Select only numeric␣
↪columns
correlation_matrix = data_numeric.corr()
print(correlation_matrix)
```

```
                           Branch      City  Customer type    Gender  \
Branch                   1.000000 -0.507401      -0.019608 -0.056318
City                    -0.507401  1.000000       0.004899  0.012219
Customer type           -0.019608  0.004899       1.000000  0.039996
Gender                  -0.056318  0.012219       0.039996  1.000000
Product line            -0.053938  0.008811      -0.036800  0.005193
Unit price               0.028202 -0.013763      -0.020238  0.015445
Quantity                 0.015964 -0.002121      -0.016763 -0.074258
Tax 5%                   0.041047 -0.012812      -0.019670 -0.049451
Total                    0.041047 -0.012812      -0.019670 -0.049451
Payment                 -0.050104  0.019094       0.018073  0.044578
cogs                     0.041047 -0.012812      -0.019670 -0.049451
gross margin percentage       NaN       NaN            NaN       NaN
gross income             0.041047 -0.012812      -0.019670 -0.049451
Rating                   0.010238  0.049585       0.018889  0.004800
Above_Average            0.029545 -0.017980      -0.006505 -0.055415

                         Product line  Unit price  Quantity    Tax 5%  \
Branch                      -0.053938    0.028202  0.015964  0.041047
City                         0.008811   -0.013763 -0.002121 -0.012812
Customer type               -0.036800   -0.020238 -0.016763 -0.019670
Gender                       0.005193    0.015445 -0.074258 -0.049451
Product line                 1.000000    0.019321  0.020256  0.031621
Unit price                   0.019321    1.000000  0.010778  0.633962
Quantity                     0.020256    0.010778  1.000000  0.705510
Tax 5%                       0.031621    0.633962  0.705510  1.000000
Total                        0.031621    0.633962  0.705510  1.000000
Payment                      0.029896   -0.015941 -0.003921 -0.012434
cogs                         0.031621    0.633962  0.705510  1.000000
gross margin percentage           NaN         NaN       NaN       NaN
gross income                 0.031621    0.633962  0.705510  1.000000
Rating                      -0.020529   -0.008778 -0.015815 -0.036442
Above_Average                0.037312    0.526764  0.606750  0.837843

                            Total   Payment      cogs  \
Branch                   0.041047 -0.050104  0.041047
```

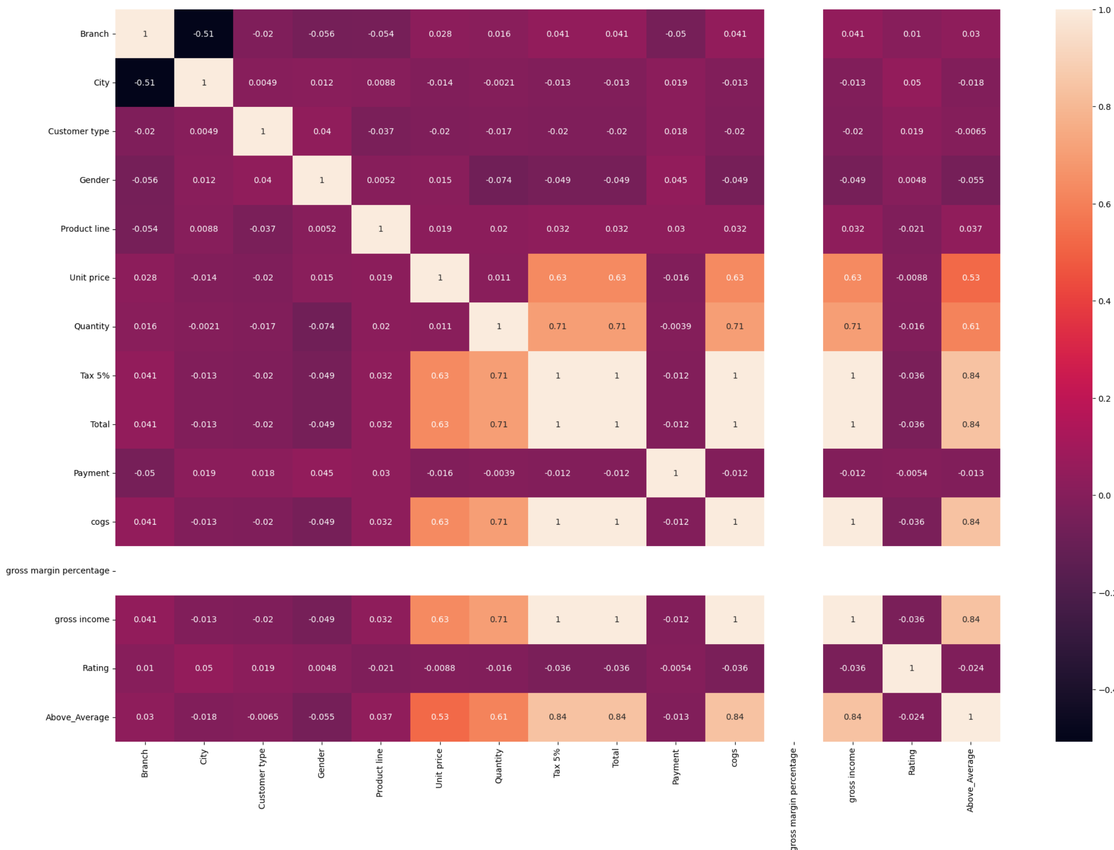
```
City                     -0.012812  0.019094 -0.012812
Customer type            -0.019670  0.018073 -0.019670
Gender                   -0.049451  0.044578 -0.049451
Product line              0.031621  0.029896  0.031621
Unit price                0.633962 -0.015941  0.633962
Quantity                  0.705510 -0.003921  0.705510
Tax 5%                    1.000000 -0.012434  1.000000
Total                     1.000000 -0.012434  1.000000
Payment                  -0.012434  1.000000 -0.012434
cogs                      1.000000 -0.012434  1.000000
gross margin percentage        NaN       NaN       NaN
gross income              1.000000 -0.012434  1.000000
Rating                   -0.036442 -0.005381 -0.036442
Above_Average             0.837843 -0.013268  0.837843

                          gross margin percentage  gross income    Rating  \
Branch                                        NaN      0.041047  0.010238
City                                          NaN     -0.012812  0.049585
Customer type                                 NaN     -0.019670  0.018889
Gender                                        NaN     -0.049451  0.004800
Product line                                  NaN      0.031621 -0.020529
Unit price                                    NaN      0.633962 -0.008778
Quantity                                      NaN      0.705510 -0.015815
Tax 5%                                        NaN      1.000000 -0.036442
Total                                         NaN      1.000000 -0.036442
Payment                                       NaN     -0.012434 -0.005381
cogs                                          NaN      1.000000 -0.036442
gross margin percentage                       NaN           NaN       NaN
gross income                                  NaN      1.000000 -0.036442
Rating                                        NaN     -0.036442  1.000000
Above_Average                                 NaN      0.837843 -0.024168

                          Above_Average
Branch                         0.029545
City                          -0.017980
Customer type                 -0.006505
Gender                        -0.055415
Product line                   0.037312
Unit price                     0.526764
Quantity                       0.606750
Tax 5%                         0.837843
Total                          0.837843
Payment                       -0.013268
cogs                           0.837843
gross margin percentage             NaN
gross income                   0.837843
Rating                        -0.024168
Above_Average                  1.000000
```

[52]:
```
# Generating Heatmap
plt.figure(figsize = (24,16))
sns.heatmap(correlation_matrix , annot=True)
```

[52]: <Axes: >



8 BUSINESS PROBLEM:

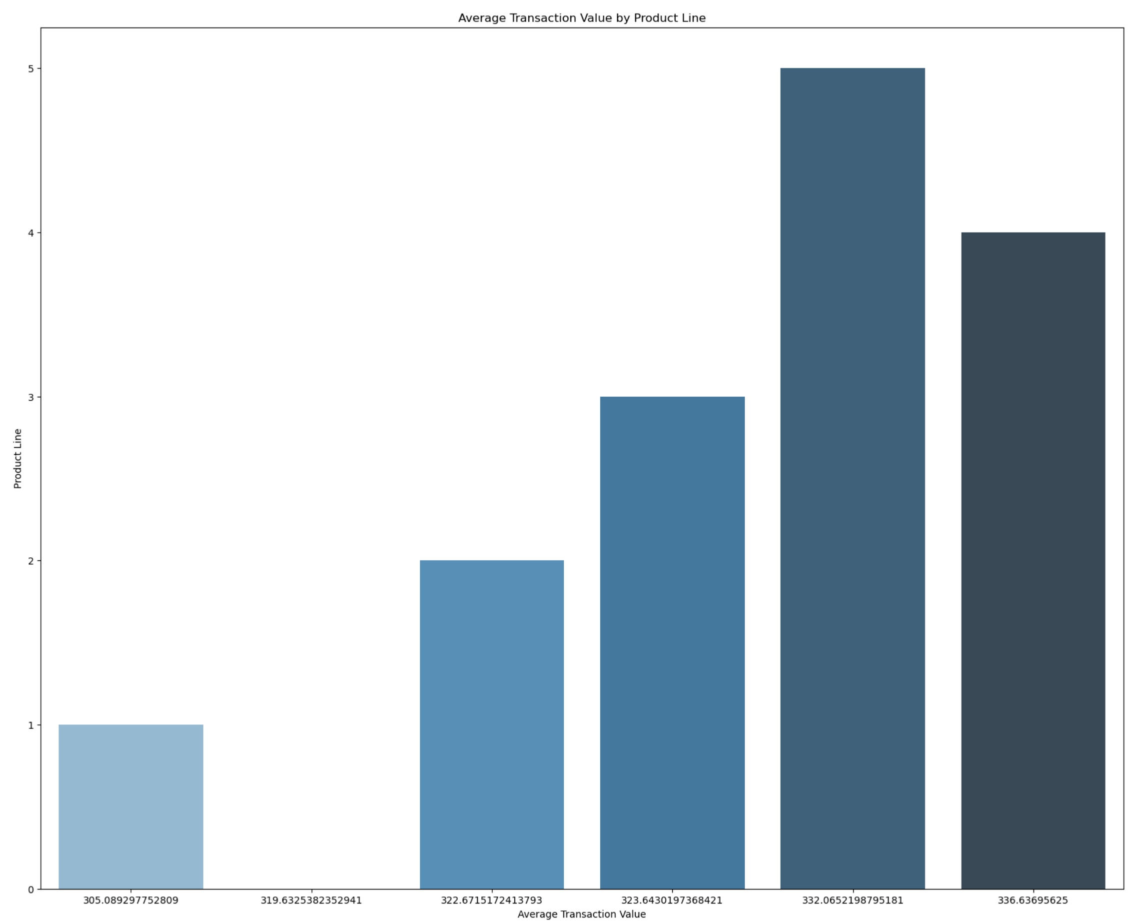
1. Develop Personalized Marketing Strategies Based on Product Categories Leading to Higher Spend

[54]:
```
# 1. Identify High-Spending Product Categories
# Group by 'Product line' and calculate average transaction value per product␣
↪category
product_line_avg = data.groupby('Product line')['Total'].mean().reset_index()
product_line_avg = product_line_avg.sort_values(by='Total', ascending=False)
print("\nAverage Spend per Product Line:\n", product_line_avg)
```

```
Average Spend per Product Line:
```

```
   Product line       Total
4             4  336.636956
5             5  332.065220
3             3  323.643020
2             2  322.671517
0             0  319.632538
1             1  305.089298
```

[55]:
```
# Plot the average spend per product line for better visualization
plt.figure(figsize=(20, 16))
sns.barplot(x='Total', y='Product line', data=product_line_avg,␣
 ↪palette='Blues_d')
plt.title('Average Transaction Value by Product Line')
plt.xlabel('Average Transaction Value')
plt.ylabel('Product Line')
plt.show()
```



2. Identify Low-Spending Product Categories and Customers

[56]:
```
# Calculate overall average transaction value
overall_avg_transaction_value = data['Total'].mean()
print("\nOverall Average Transaction Value: ", overall_avg_transaction_value)
```

```
Overall Average Transaction Value:  322.966749
```

[57]:
```
# Identify product lines with below-average transaction values
low_spend_categories = product_line_avg[product_line_avg['Total'] <␣
 ↪overall_avg_transaction_value]['Product line'].tolist()
print("\nLow-Spending Product Categories:", low_spend_categories)
```

```
Low-Spending Product Categories: [2, 0, 1]
```

[58]:
```
# Customers who purchased from these low-spending categories
low_spend_customers = data[data['Product line'].isin(low_spend_categories)]
low_spend_customer_ids = low_spend_customers['Invoice ID'].unique()
print("\nCustomers who purchased from low-spending categories:\n",␣
 ↪low_spend_customers[['Invoice ID', 'Product line', 'Total']].head())
```

```
Customers who purchased from low-spending categories:
      Invoice ID  Product line     Total
1    226-31-3081             0   80.2200
5    699-14-3026             0  627.6165
6    355-53-5943             0  433.6920
9    692-92-5582             2  172.7460
10   351-62-0822             1   60.8160
```

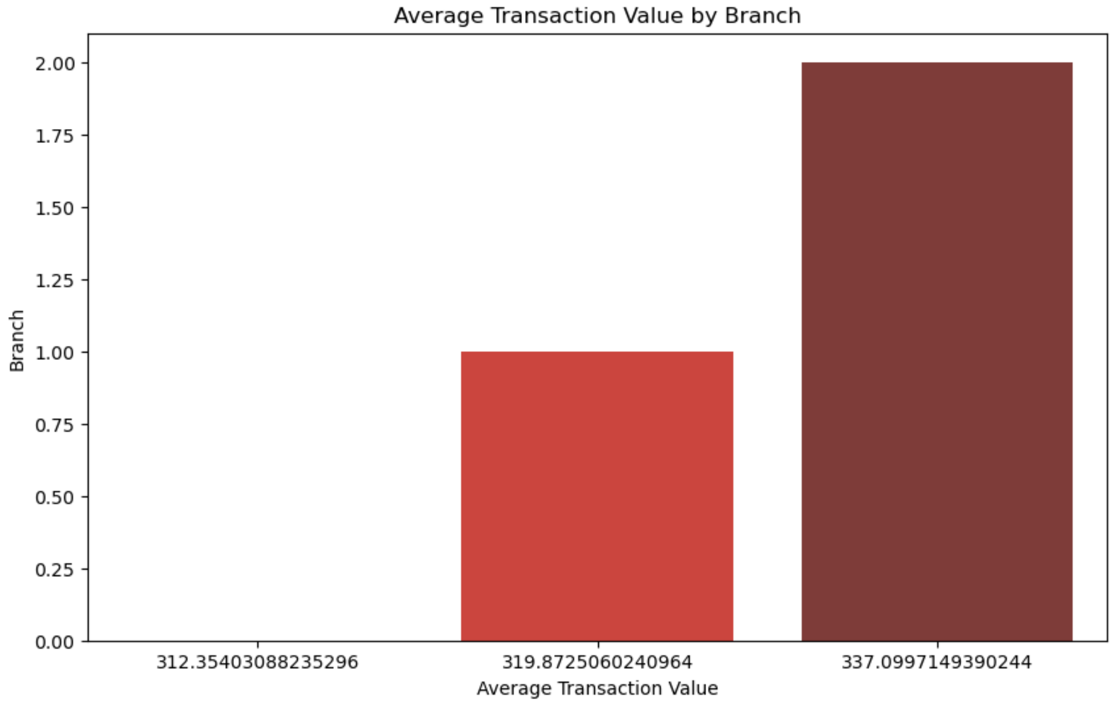
3. Loyalty Programs or Discounts for Lower-Performing Branches

[59]:
```
# Calculate average transaction value per branch
branch_avg = data.groupby('Branch')['Total'].mean().reset_index()
branch_avg = branch_avg.sort_values(by='Total')
print("\nAverage Transaction Value per Branch:\n", branch_avg)
```

```
Average Transaction Value per Branch:
    Branch       Total
0       0  312.354031
1       1  319.872506
2       2  337.099715
```

[60]:
```
# Plot branch performance
plt.figure(figsize=(10, 6))
sns.barplot(x='Total', y='Branch', data=branch_avg, palette='Reds_d')
plt.title('Average Transaction Value by Branch')
```

```
plt.xlabel('Average Transaction Value')
plt.ylabel('Branch')
plt.show()
```



[61]:
```
# Identify lower-performing branches (below overall average)
low_performing_branches = branch_avg[branch_avg['Total'] <␣
↪overall_avg_transaction_value]['Branch'].tolist()
print("\nLower-Performing Branches: ", low_performing_branches)
```

```
Lower-Performing Branches:  [0, 1]
```

4. Strategy Recommendations

[62]:
```
# Customers in lower-performing branches
customers_in_low_branches = data[data['Branch'].isin(low_performing_branches)]
print("\nCustomers in Lower-Performing Branches:\n",␣
↪customers_in_low_branches[['Invoice ID', 'Branch', 'Total']].head())
```

```
Customers in Lower-Performing Branches:
     Invoice ID  Branch     Total
0   750-67-8428       0  548.9715
2   631-41-3108       0  340.5255
3   123-19-1176       0  489.0480
```

```
4   373-73-7910        0   634.3785
6   355-53-5943        0   433.6920
```

9 CONCLUSION:

[63]:
```python
# 4.1 Personalized Marketing Based on High-Spending Product Categories
print("\n--- Personalized Marketing ---")
print("Focus marketing campaigns on the following high-spending product lines:
 ↪\n")
print(product_line_avg[product_line_avg['Total'] >␣
 ↪overall_avg_transaction_value]['Product line'].tolist())
print("- Tailor promotions and offers based on these high-spending categories␣
 ↪to encourage repeat purchases.")

# 4.2 Promote Additional Services or Products to Customers in Low-Spending␣
 ↪Categories
print("\n--- Cross-Selling and Upselling ---")
print("Focus on the following low-spending product lines for cross-selling or␣
 ↪upselling opportunities:\n")
print(low_spend_categories)
print("- Offer complementary or bundled products to customers purchasing from␣
 ↪these low-transaction categories.")
print("- Recommend higher-value items based on their purchase history.")

# 4.3 Use Loyalty Programs or Discounts for Lower-Performing Branches
print("\n--- Loyalty Programs for Lower-Performing Branches ---")
print("Implement loyalty programs or discounts for the following␣
 ↪lower-performing branches:\n")
print(low_performing_branches)
print("- Provide exclusive discounts or reward points to incentivize larger␣
 ↪purchases in these branches.")
print("- Conduct localized promotions or events to boost branch-specific␣
 ↪performance.")
```

```
--- Personalized Marketing ---
Focus marketing campaigns on the following high-spending product lines:

[4, 5, 3]
- Tailor promotions and offers based on these high-spending categories to
encourage repeat purchases.

--- Cross-Selling and Upselling ---
Focus on the following low-spending product lines for cross-selling or upselling
opportunities:

[2, 0, 1]
```

```
- Offer complementary or bundled products to customers purchasing from these
low-transaction categories.
- Recommend higher-value items based on their purchase history.

--- Loyalty Programs for Lower-Performing Branches ---
Implement loyalty programs or discounts for the following lower-performing
branches:

[0, 1]
- Provide exclusive discounts or reward points to incentivize larger purchases
in these branches.
- Conduct localized promotions or events to boost branch-specific performance.
```

9.0.1 High-spending product lines:

[93]:
```python
product_line_mapping = {0: 'Electronic accessories', 1: 'Food and beverages', 2:
 ↪ 'Fashion accessories', 3: 'Health and beauty', 4: 'Home and lifestyle', 5:␣
 ↪'Sports and travel'}
high_spending_product_lines = [4, 5, 3]
print("High-Spending Product Lines:")
for line in high_spending_product_lines:
    print(product_line_mapping[line])
```

```
High-Spending Product Lines:
Home and lifestyle
Sports and travel
Health and beauty
```

9.0.2 Low-spending product lines:

[94]:
```python
low_spending_product_lines = [2, 0, 1]
print("\nLow-Spending Product Lines:")
for line in low_spending_product_lines:
    print(product_line_mapping[line])
```

```

Low-Spending Product Lines:
Fashion accessories
Electronic accessories
Food and beverages
```

Low-p

[102]:
```python
low_performing_branches = [0, 1]
print("\nLow-performing-branches:")
for line in low_performing_branches:
    print(product_line_mapping[line])
```

```
Low-performing-branches:
Electronic accessories
Food and beverages
```