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RANDOM FOREST REGRESSION ANALYSIS

Data Exploration

In [ ]:
```
# importing the libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
# reading dataset

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

Out[ ]:

	invoice_id	branch	city	customer_type	gender_customer	product_line	unit
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	
...	...	...	...	...	...	...	
995	233-67-5758	C	Naypyitaw	Normal	Male	Health and beauty	
996	303-96-2227	B	Mandalay	Normal	Female	Home and lifestyle	
997	727-02-1313	A	Yangon	Member	Male	Food and beverages	
998	347-56-2442	A	Yangon	Normal	Male	Home and lifestyle	
999	849-09-3807	A	Yangon	Member	Female	Fashion accessories	

1000 rows × 17 columns

In [ ]:

```
# printing the first 5 rows of the dataset

df.head()
```

Out[ ]:

	invoice_id	branch	city	customer_type	gender_customer	product_line	unit_c
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86

In [ ]:
```python
# printing sample rows of the dataset

df.sample(5)
```

Out[ ]:

	invoice_id	branch	city	customer_type	gender_customer	product_line	unit
112	227-78-1148	B	Mandalay	Normal	Female	Fashion accessories	
863	533-66-5566	B	Mandalay	Normal	Female	Home and lifestyle	
931	756-93-1854	C	Naypyitaw	Member	Female	Fashion accessories	
487	795-49-7276	A	Yangon	Normal	Male	Fashion accessories	
76	263-10-3913	C	Naypyitaw	Member	Male	Fashion accessories	

In [ ]:
```python
# dimensions of the dataset

df.shape
```

Out[ ]:
```
(1000, 17)
```

In [ ]:
```python
# returns the concise summary of the dataset

df.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_customer  1000 non-null   object 
 5   product_line     1000 non-null   object 
 6   unit_cost        1000 non-null   float64
 7   quantity         1000 non-null   int64  
 8   5pct_markup      1000 non-null   float64
 9   revenue          1000 non-null   float64
 10  date             1000 non-null   object 
 11  time             1000 non-null   object 
 12  payment_method   1000 non-null   object 
 13  cogs             1000 non-null   float64
 14  gm_pct           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
```

In [ ]:
```python
# returns statistical summary
```

```
df.describe()
```

Out[ ]:

	unit_cost	quantity	5pct_markup	revenue	cogs	gm_pct	g
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	
mean	55.672130	5.510000	15.379369	322.966749	307.58738	4.761905	
std	26.494628	2.923431	11.708825	245.885335	234.17651	0.000000	
min	10.080000	1.000000	0.508500	10.678500	10.17000	4.761905	
25%	32.875000	3.000000	5.924875	124.422375	118.49750	4.761905	
50%	55.230000	5.000000	12.088000	253.848000	241.76000	4.761905	
75%	77.935000	8.000000	22.445250	471.350250	448.90500	4.761905	
max	99.960000	10.000000	49.650000	1042.650000	993.00000	4.761905	

In [ ]:

```
# displaying the number of unique data in each column

df.nunique()
```

Out[ ]:

```
invoice_id         1000
branch                3
city                  3
customer_type         2
gender_customer       2
product_line          6
unit_cost           943
quantity             10
5pct_markup         990
revenue             990
date                 89
time                506
payment_method        3
cogs                990
gm_pct                1
gross_income        990
rating               61
dtype: int64
```

In [ ]:

```
# checking for duplicates in the dataset

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

Out[ ]: 0

In [ ]:

```
# checking for duplicates in the dataset

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

Out[ ]: 0

Data Preprocessing

In [ ]:

```
df = df.drop(columns=['invoice_id'])  # Drop unnecessary columns
df = df.drop(columns=['date','time'])
```

```
df
```

Out[ ]:

	branch	city	customer_type	gender_customer	product_line	unit_cost	quar
0	A	Yangon	Member	Female	Health and beauty	74.69	
1	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	
2	A	Yangon	Normal	Male	Home and lifestyle	46.33	
3	A	Yangon	Member	Male	Health and beauty	58.22	
4	A	Yangon	Normal	Male	Sports and travel	86.31	
...	...	...	...	...	...	...	
995	C	Naypyitaw	Normal	Male	Health and beauty	40.35	
996	B	Mandalay	Normal	Female	Home and lifestyle	97.38	
997	A	Yangon	Member	Male	Food and beverages	31.84	
998	A	Yangon	Normal	Male	Home and lifestyle	65.82	
999	A	Yangon	Member	Female	Fashion accessories	88.34	

1000 rows × 14 columns

In [ ]:

```
#for the data type of the column
str(df["gender_customer"].dtype)
```

Out[ ]: 'object'

In [ ]:

```
#converting categorical values to continuous
for column in df.columns:
    if str(df[column].dtype) == "object":
        for i in range(len(df[column].unique())):
            df[column] = df[column].replace(df[column].unique()[i],i)

df
```

Out[ ]:

	branch	city	customer_type	gender_customer	product_line	unit_cost	quantity
0	0	0	0	0	0	74.69	7
1	1	1	1	0	1	15.28	5
2	0	0	1	1	2	46.33	7
3	0	0	0	1	0	58.22	8
4	0	0	1	1	3	86.31	7
...	...	...	...	...	...	...	...
995	1	1	1	1	0	40.35	1
996	2	2	1	0	2	97.38	10
997	0	0	0	1	4	31.84	1
998	0	0	1	1	2	65.82	1
999	0	0	0	0	5	88.34	7

1000 rows × 14 columns

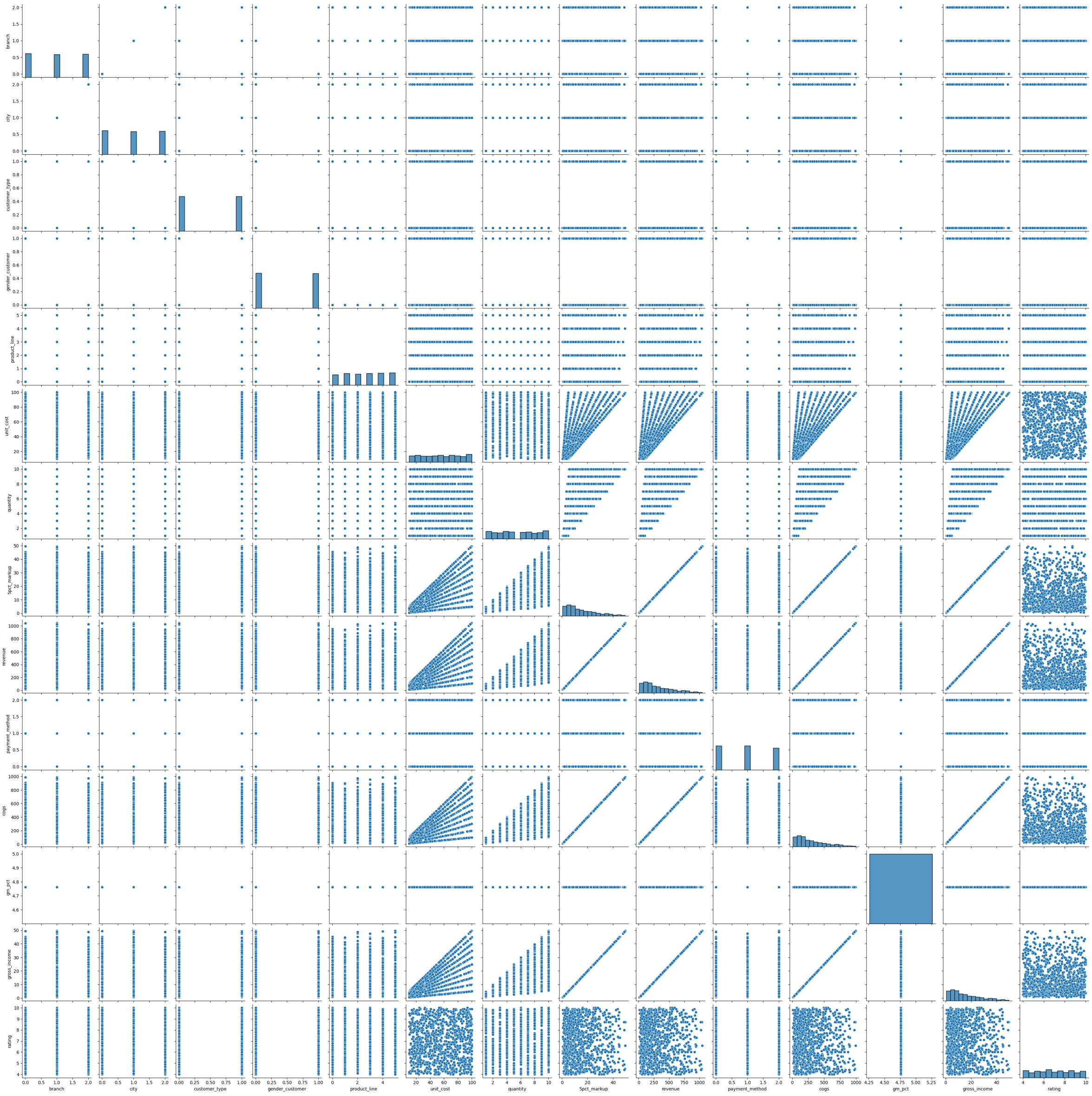
Data Visualization

In [ ]:

```
sns.pairplot(df)
```

Out[ ]:

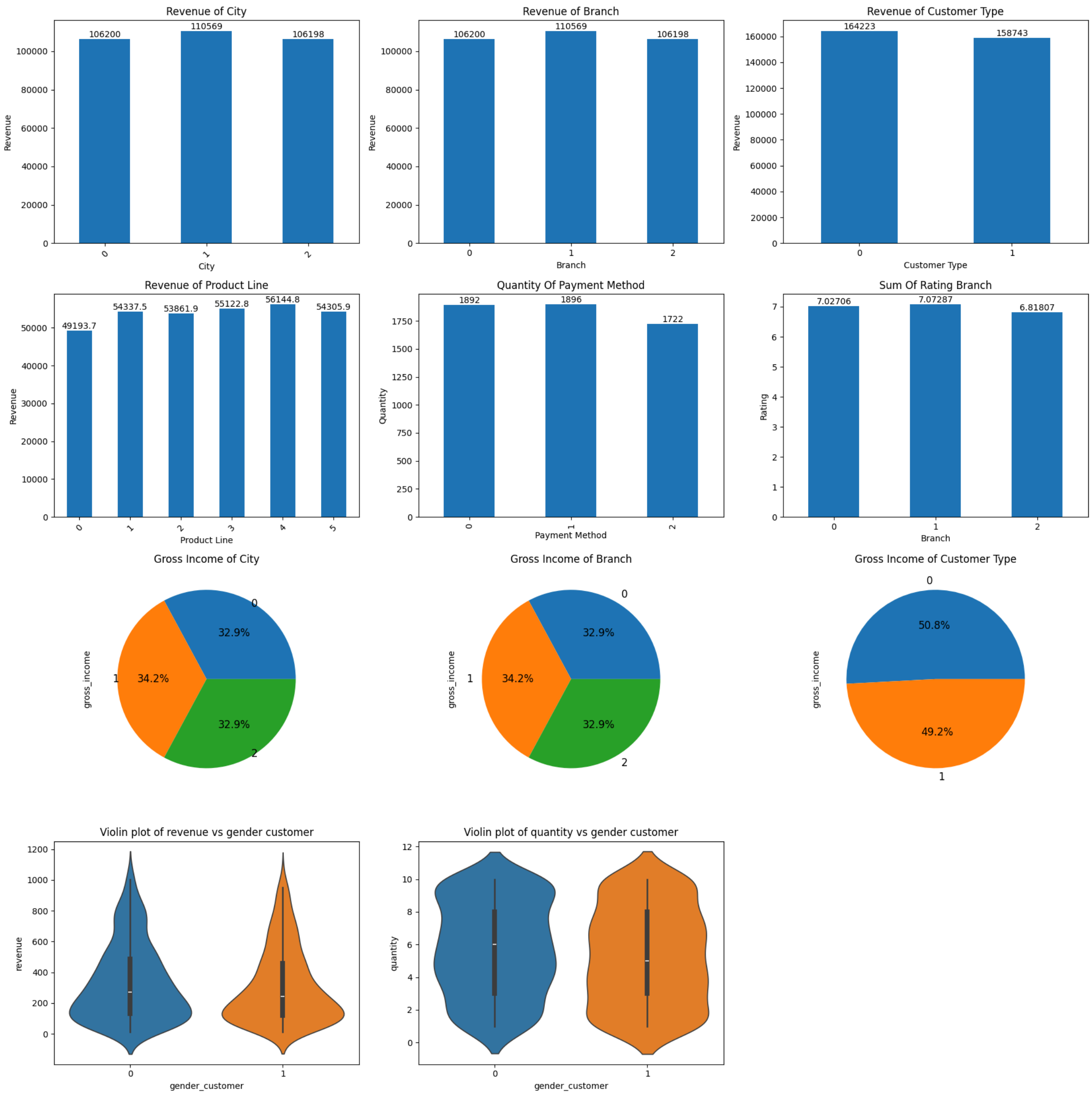
```
<seaborn.axisgrid.PairGrid at 0x16a9a814d90>
```



In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Create subplots with 4 rows and 3 columns
fig, axes = plt.subplots(4, 3, figsize=(18, 18))

# Flatten the axes array
axes = axes.flatten()

# Plot 1: Revenue of City
city_revenue = df.groupby('city')['revenue'].sum()
city_revenue.plot(kind='bar', ax=axes[0])
axes[0].set_title('Revenue of City')
axes[0].set_xlabel('City')
axes[0].set_ylabel('Revenue')
axes[0].tick_params(axis='x', rotation=45)
axes[0].bar_label(axes[0].containers[0], label_type='edge')

# Plot 2: Revenue of Branch
branch_revenue = df.groupby('branch')['revenue'].sum()
branch_revenue.plot(kind='bar', ax=axes[1])
axes[1].set_title('Revenue of Branch')
axes[1].set_xlabel('Branch')
axes[1].set_ylabel('Revenue')
```

```
axes[1].tick_params(axis='x', rotation=0)
axes[1].bar_label(axes[1].containers[0], label_type='edge')

# Plot 3: Revenue of Customer Type
customer_type_revenue = df.groupby('customer_type')['revenue'].sum()
customer_type_revenue.plot(kind='bar', ax=axes[2])
axes[2].set_title('Revenue of Customer Type')
axes[2].set_xlabel('Customer Type')
axes[2].set_ylabel('Revenue')
axes[2].tick_params(axis='x', rotation=0)
axes[2].bar_label(axes[2].containers[0], label_type='edge')

# Plot 4: Revenue of Product Line
product_line_revenue = df.groupby('product_line')['revenue'].sum()
product_line_revenue.plot(kind='bar', ax=axes[3])
axes[3].set_title('Revenue of Product Line')
axes[3].set_xlabel('Product Line')
axes[3].set_ylabel('Revenue')
axes[3].tick_params(axis='x', rotation=45)
axes[3].bar_label(axes[3].containers[0], label_type='edge')

# Plot 5: Quantity Of Payment Method
payment_method_quantity = df.groupby('payment_method')['quantity'].sum()
payment_method_quantity.plot(kind='bar', ax=axes[4])
axes[4].set_title('Quantity Of Payment Method')
axes[4].set_xlabel('Payment Method')
axes[4].set_ylabel('Quantity')
axes[4].tick_params(axis='x', rotation=90)
axes[4].bar_label(axes[4].containers[0], label_type='edge')

# Plot 6: Sum Of Rating Branch
Sum_of_rating_branch = df.groupby('branch')['rating'].mean()
Sum_of_rating_branch.plot(kind='bar', ax=axes[5])
axes[5].set_title('Sum Of Rating Branch')
axes[5].set_xlabel('Branch')
axes[5].set_ylabel('Rating')
axes[5].tick_params(axis='x', rotation=0)
axes[5].bar_label(axes[5].containers[0], label_type='edge')

# Plot 7: Gross Income of City
city_gross_income = df.groupby('city')['gross_income'].sum()
city_gross_income.plot(kind='pie', labeldistance=0.98, autopct='%1.1f%%', ax=axe
axes[6].set_title('Gross Income of City')

# Plot 8: Gross Income of Branch
branch_gross_income = df.groupby('branch')['gross_income'].sum()
branch_gross_income.plot(kind='pie', autopct='%1.1f%%', ax=axes[7], textprops={"
axes[7].set_title('Gross Income of Branch')

# Plot 9: Gross Income of Customer Type
customer_type_gross_income = df.groupby('customer_type')['gross_income'].sum()
customer_type_gross_income.plot(kind='pie', autopct='%1.1f%%', ax=axes[8], textp
axes[8].set_title('Gross Income of Customer Type')

# Plot 10: Violin plot of revenue vs gender customer
sns.violinplot(x='gender_customer', y='revenue', data=df, palette="tab10", ax=ax
axes[9].set_title('Violin plot of revenue vs gender customer')

# Plot 11: Violin plot of quantity vs gender customer
sns.violinplot(x='gender_customer', y='quantity', data=df, palette="tab10", ax=a
```

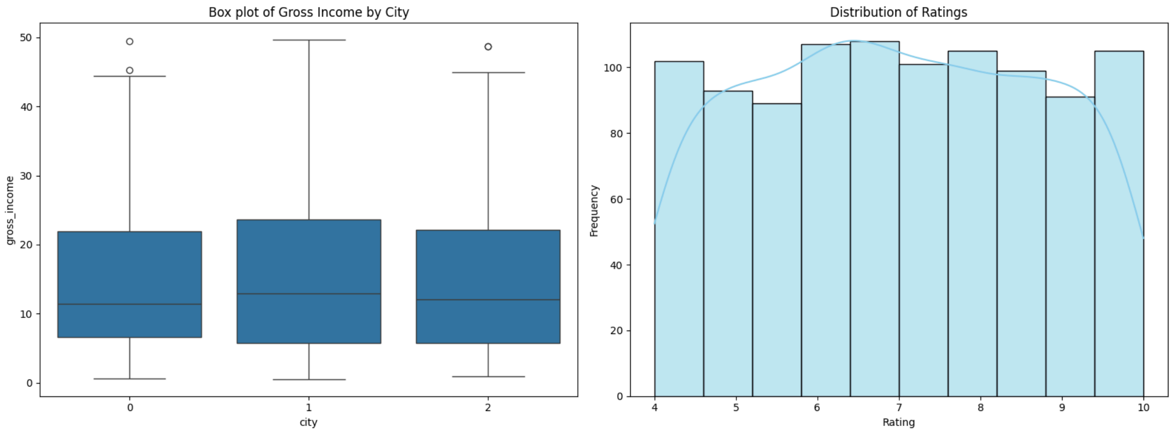
```
axes[10].set_title('Violin plot of quantity vs gender customer')

# Hide the empty subplot
axes[11].axis('off')

plt.tight_layout()
plt.show()
```



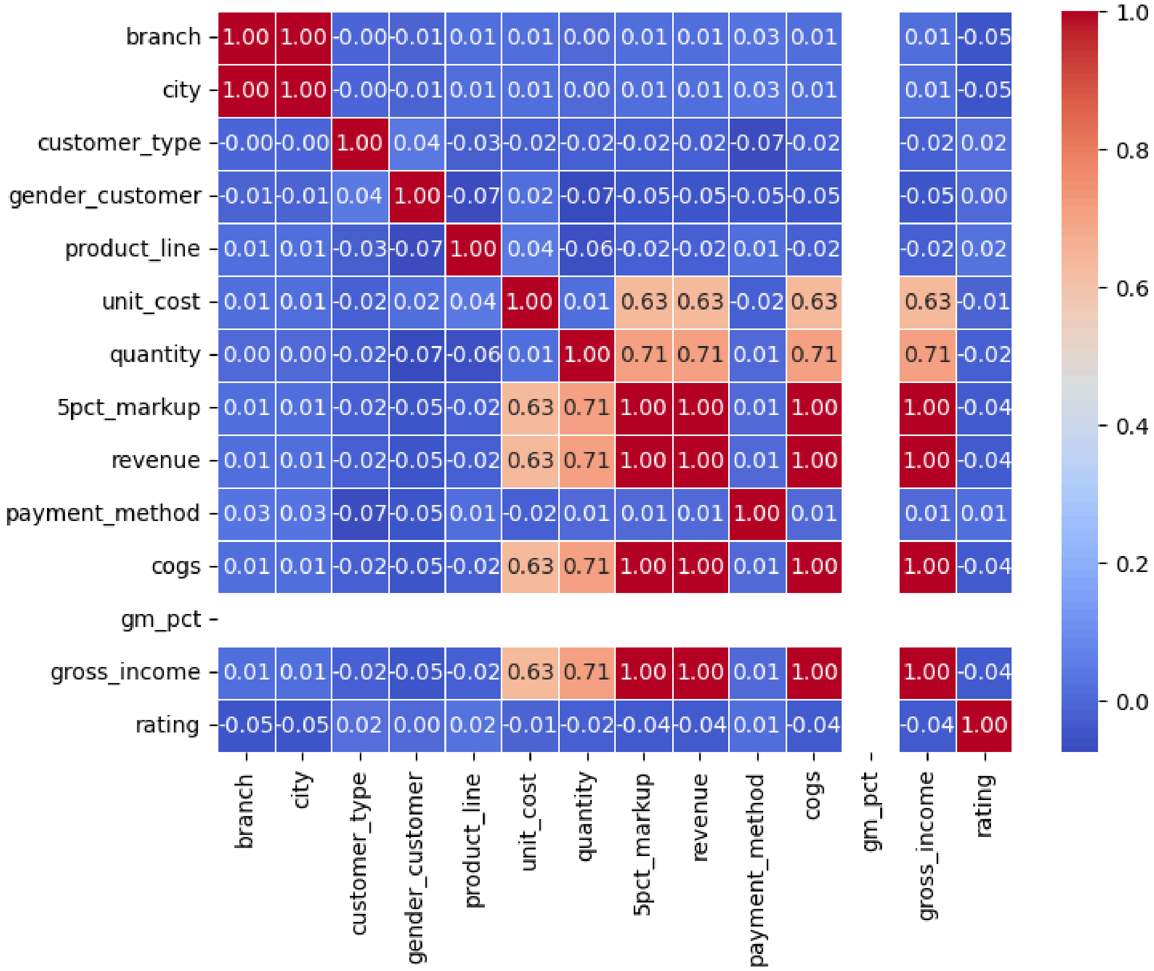
In [ ]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Create subplots with 1 row and 2 columns
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Plot 1: Box plot of Gross Income by City
sns.boxplot(x='city', y='gross_income', data=df, ax=axes[0])
axes[0].set_title('Box plot of Gross Income by City')

# Plot 2: Distribution of Ratings
sns.histplot(df['rating'], kde=True, bins=10, color='skyblue', ax=axes[1])
axes[1].set_title('Distribution of Ratings')
axes[1].set_xlabel('Rating')
axes[1].set_ylabel('Frequency')

# Adjust layout
```

```
plt.tight_layout()

# Show plots
plt.show()
```



In [ ]:
```
#plotting heatmap
numeric_columns = df.select_dtypes(include=[np.number]).columns
numeric_df = df[numeric_columns]
correlation_matrix = numeric_df.corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidt
plt.show()
```



In [ ]:
```
# Splitting the Data
from sklearn.model_selection import train_test_split
```

In [ ]:
```
# Selected features for X
selected_features = ['customer_type','gender_customer','product_line','unit_cost
X = df[selected_features]

# Target variable for y
y = df['gross_income']
```

In [ ]:
```
# Splitting Data into Training and Testing Sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

Training the Random Forest Regressor

In [ ]:
```
# Importing GridSearchCV for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

# Defining parameter grid for tuning
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```

In [ ]:
```
# Training the Random Forest Classifier
from sklearn.ensemble import RandomForestRegressor
rf_regressor = RandomForestRegressor()

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

Out[ ]:
```
RandomForestRegressor

RandomForestRegressor()
```

Making Predictions and Evaluating the Model of the testing set

In [ ]:
```
# Making Predictions
y_pred = rf_regressor.predict(X_test)

# Evaluating the Model
from sklearn.metrics import r2_score,mean_squared_error

mse = mean_squared_error(y_test,y_pred)
r2 = r2_score(y_test,y_pred)
print("Mean Squared Error is " ,mse)
print("R squared value is ",r2)
```

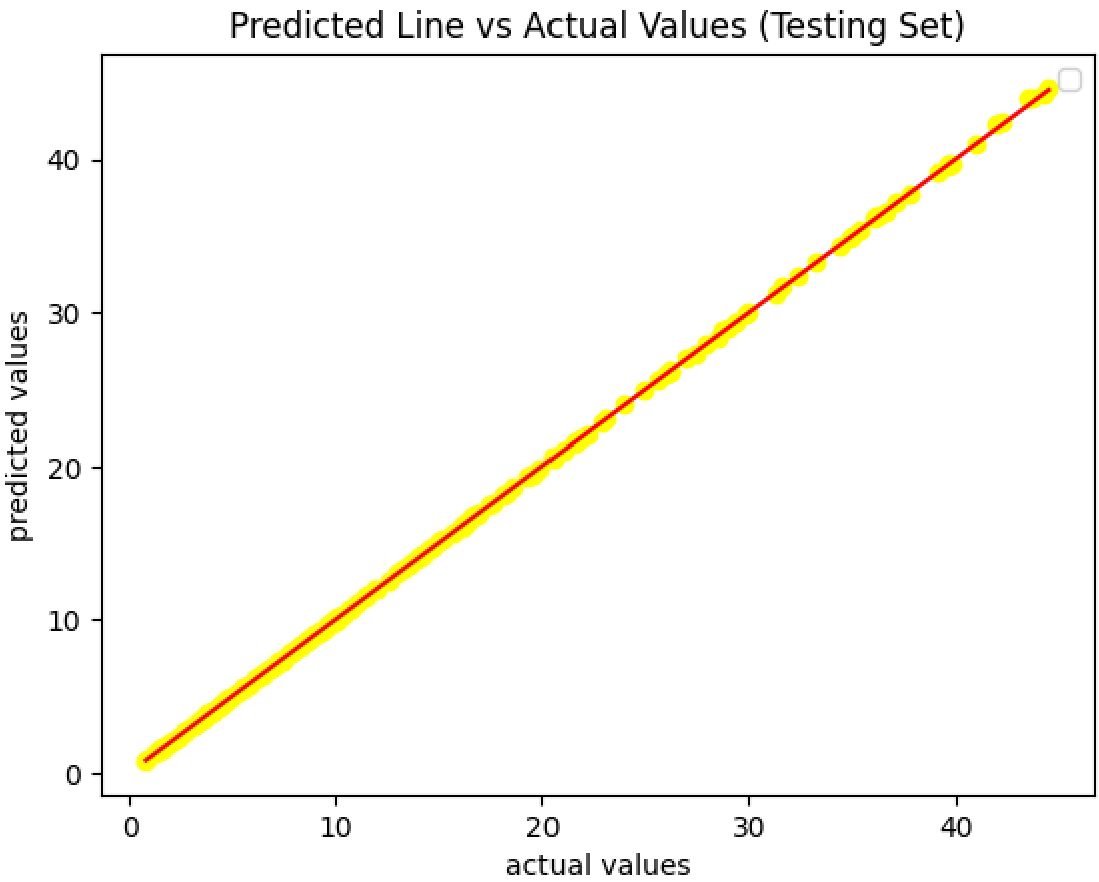
```
Mean Squared Error is  0.004523439876999656
R squared value is  0.9999663650259477
```

Visualizing the Test Set Predictions

In [ ]:
```
# Plotting the actual vs predicted values for the test set
import matplotlib.pyplot as plt
plt.scatter(y_test,y_pred,  color='yellow')
plt.plot([min(y_test),max(y_test)],[min(y_test),max(y_test)],color="red")
```

```
plt.ylabel('predicted values')
plt.xlabel('actual values')
plt.title('Predicted Line vs Actual Values (Testing Set)')
plt.legend()
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label sta
rt with an underscore are ignored when legend() is called with no argument.
```



Making Predictions and Evaluating the Model of the training set

In [ ]:
```
# Making predictions on the training set
y_pred_train = rf_regressor.predict(X_train)

# Evaluating the model performance on the training set
mse_train = mean_squared_error(y_train, y_pred_train)
r2_train = r2_score(y_train, y_pred_train)

# Printing the evaluation metrics for the training set
print("Mean Squared Error on Training Set is ", mse_train)
print("R squared value on Training Set is ", r2_train)
```

```
Mean Squared Error on Training Set is  0.0008016159539375175
R squared value on Training Set is  0.9999941634776628
```

Visualizing the Train Set Predictions

In [ ]:
```
# Plotting the actual vs predicted values for the training set
plt.scatter(y_train, y_pred_train, color='yellow')
plt.plot([min(y_train), max(y_train)], [min(y_train), max(y_train)], color="red"

plt.ylabel('Predicted Values')
```

```
plt.xlabel('Actual Values')
plt.title('Predicted vs Actual Values (Training Set)')
plt.legend()
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label sta
rt with an underscore are ignored when legend() is called with no argument.
```