

RetailPulse Data Analysis Project

Importing Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import OneHotEncoder
import holidays
import requests
import datetime
import plotly.express as px
import random
from datetime import datetime, timedelta
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

Load the Dataset

```
data = pd.read_csv('C:/Users/chira/Downloads/archive
(1)/shopping_trends.csv')
```

Data Cleaning and Preprocessing

```
data.drop_duplicates(inplace=True)
data.columns = data.columns.str.strip().str.replace(' ',
'_').str.lower()
data['review_rating'] = pd.to_numeric(data['review_rating'],
errors='coerce')
```

```
# Check for missing values
print("Missing Values:\n", data.isnull().sum())
```

```
Missing Values:
customer_id      0
age              0
gender           0
item_purchased   0
category         0
purchase_amount_(usd)  0
location         0
size             0
color            0
```

```

season          0
review_rating   0
subscription_status 0
payment_method  0
shipping_type   0
discount_applied 0
promo_code_used 0
previous_purchases 0
preferred_payment_method 0
frequency_of_purchases 0
dtype: int64

```

External Data Integration

```

print(data.columns)

Index(['customer_id', 'age', 'gender', 'item_purchased', 'category',
      'purchase_amount_(usd)', 'location', 'size', 'color', 'season',
      'review_rating', 'subscription_status', 'payment_method',
      'shipping_type', 'discount_applied', 'promo_code_used',
      'previous_purchases', 'preferred_payment_method',
      'frequency_of_purchases'],
      dtype='object')

start_date = datetime(2022, 1, 1)
data['date'] = [start_date + timedelta(days=random.randint(0, 365))
for _ in range(len(data))]

us_holidays = holidays.US()
data['is_holiday'] = data['date'].apply(lambda x: 1 if x in
us_holidays else 0)

# Load your dataset
data = pd.read_csv('C:/Users/chira/Downloads/archive
(1)/shopping_trends.csv')

# Add dummy weather data based on seasons
weather_mapping = {
    'Winter': {'avg_temp': -5, 'weather': 'Snowy'},
    'Spring': {'avg_temp': 15, 'weather': 'Rainy'},
    'Summer': {'avg_temp': 30, 'weather': 'Sunny'},
    'Fall': {'avg_temp': 10, 'weather': 'Windy'}
}

# Map weather data to the dataset
data['avg_temp'] = data['Season'].map(lambda x: weather_mapping[x]
['avg_temp'])
data['weather'] = data['Season'].map(lambda x: weather_mapping[x]
['weather'])

```

```
# Save the updated dataset
data.to_csv('shopping_trends_with_weather.csv', index=False)
```

```
# Check the dataset
print(data.head())
```

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)
0	1	55	Male	Blouse	Clothing	53
1	2	19	Male	Sweater	Clothing	64
2	3	50	Male	Jeans	Clothing	73
3	4	21	Male	Sandals	Footwear	90
4	5	45	Male	Blouse	Clothing	49

	Location	Size	Color	Season	...	Subscription Status
0	Kentucky	L	Gray	Winter	...	Yes
1	Maine	L	Maroon	Winter	...	Yes
2	Massachusetts	S	Maroon	Spring	...	Yes
3	Rhode Island	M	Maroon	Spring	...	Yes
4	Oregon	M	Turquoise	Spring	...	Yes

	Payment Method	Shipping Type	Discount Applied	Promo Code Used
0	Credit Card	Express	Yes	Yes
1	Bank Transfer	Express	Yes	Yes
2	Cash	Free Shipping	Yes	Yes
3	PayPal	Next Day Air	Yes	Yes
4	Cash	Free Shipping	Yes	Yes

	Previous Purchases	Preferred Payment Method	Frequency of Purchases
0	14	Venmo	Fortnightly
1	2	Cash	Fortnightly
2	23	Credit Card	Weekly
3	49	PayPal	Weekly
4	31	PayPal	Annually

	avg_temp	weather
0	-5	Snowy
1	-5	Snowy
2	15	Rainy

3	15	Rainy
4	15	Rainy

[5 rows x 21 columns]

Exploratory Data Analysis (EDA)

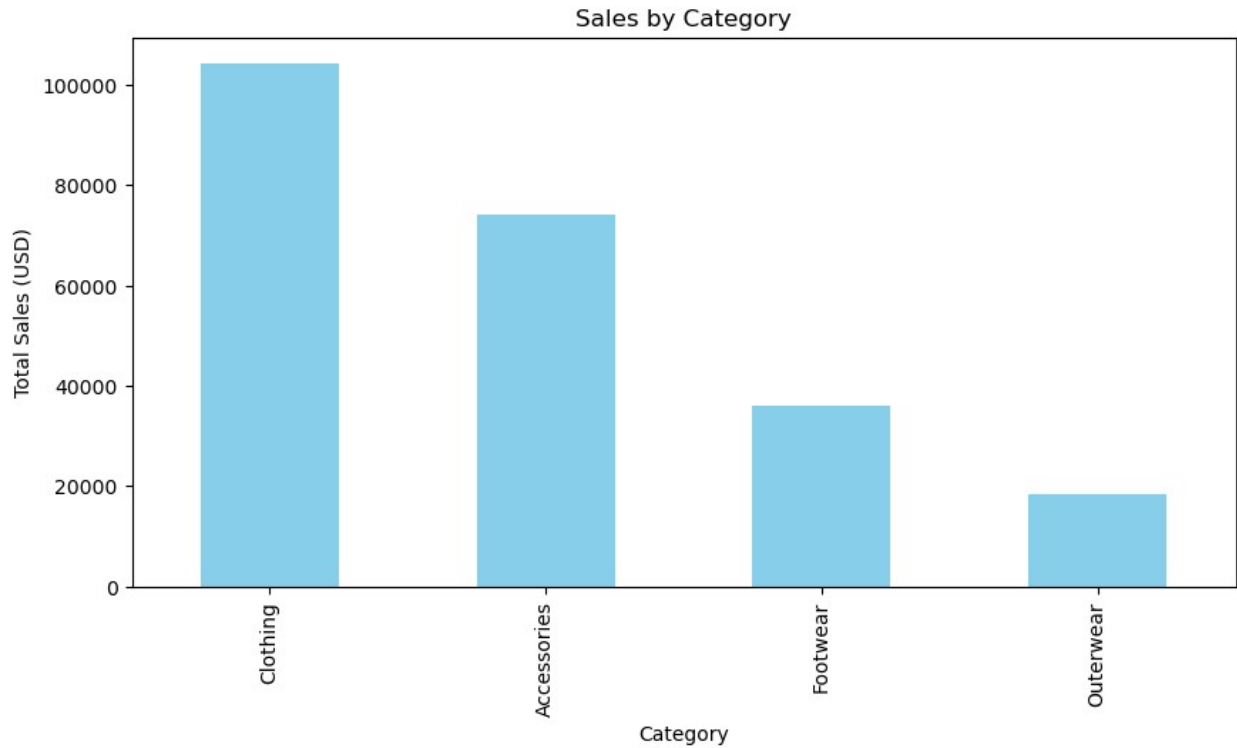
```
sales_by_category = data.groupby('Category')['Purchase Amount (USD)'].sum().sort_values(ascending=False)
sales_by_location = data.groupby('Location')['Purchase Amount (USD)'].sum().sort_values(ascending=False)

# Sales by Category
plt.figure(figsize=(10, 5))
sales_by_category.plot(kind='bar', color='skyblue')
plt.title('Sales by Category')
plt.ylabel('Total Sales (USD)')
plt.show()

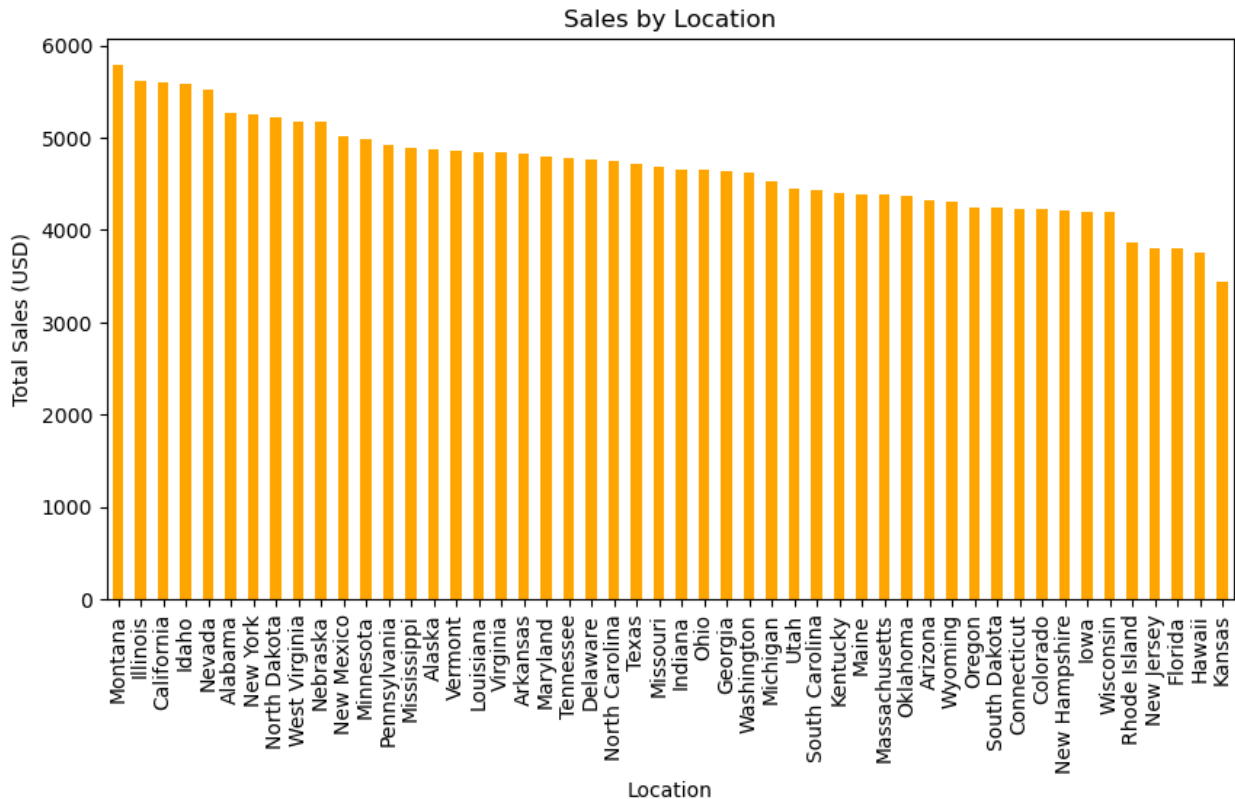
# Description for Sales by Category
print("Analysis: The 'Clothing' category significantly outperforms other categories with over 100,000 USD in sales. "
      "'Accessories' and 'Footwear' follow, while 'Outerwear' has the least sales. This indicates that focus should "
      "be placed on maintaining inventory for high-performing categories and boosting 'Outerwear' sales through targeted marketing.")

# Sales by Location
plt.figure(figsize=(10, 5))
sales_by_location.plot(kind='bar', color='orange')
plt.title('Sales by Location')
plt.ylabel('Total Sales (USD)')
plt.show()

# Description for Sales by Location
print("Analysis: The state of Montana leads in total sales, followed closely by California and Illinois. "
      "Kansas has the lowest sales. Retailers should investigate reasons behind the underperformance in certain states "
      "and design targeted campaigns to boost sales in these regions.")
```



Analysis: The 'Clothing' category significantly outperforms other categories with over 100,000 USD in sales. 'Accessories' and 'Footwear' follow, while 'Outerwear' has the least sales. This indicates that focus should be placed on maintaining inventory for high-performing categories and boosting 'Outerwear' sales through targeted marketing.



Analysis: The state of Montana leads in total sales, followed closely by California and Illinois. Kansas has the lowest sales. Retailers should investigate reasons behind the underperformance in certain states and design targeted campaigns to boost sales in these regions.

```
print(data.columns)
```

```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
      'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
      'Review Rating', 'Subscription Status', 'Payment Method',
      'Shipping Type', 'Discount Applied', 'Promo Code Used',
      'Previous Purchases', 'Preferred Payment Method',
      'Frequency of Purchases', 'avg_temp', 'weather'],
      dtype='object')
```

```
from sklearn.preprocessing import StandardScaler
```

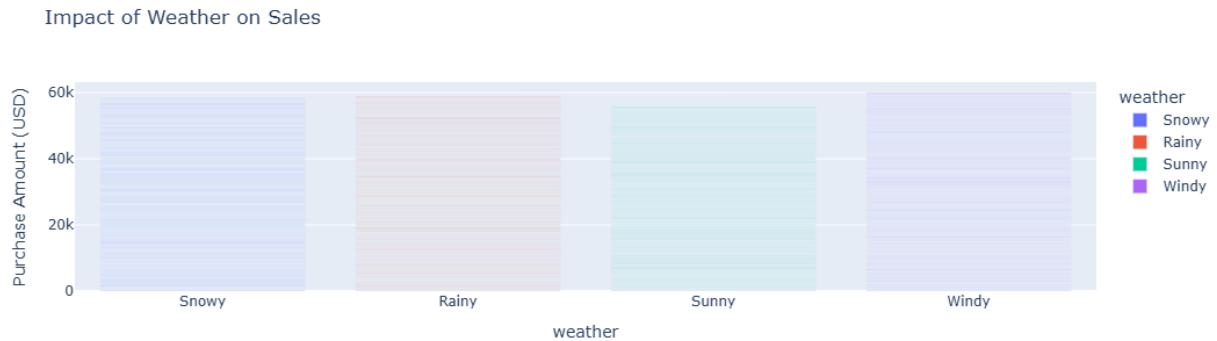
```
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data[['Age', 'Previous
Purchases']])
```

```
# Apply K-Means Clustering
```

```
kmeans = KMeans(n_clusters=4, random_state=42)
data['customer_segment'] = kmeans.fit_predict(data_scaled)
```

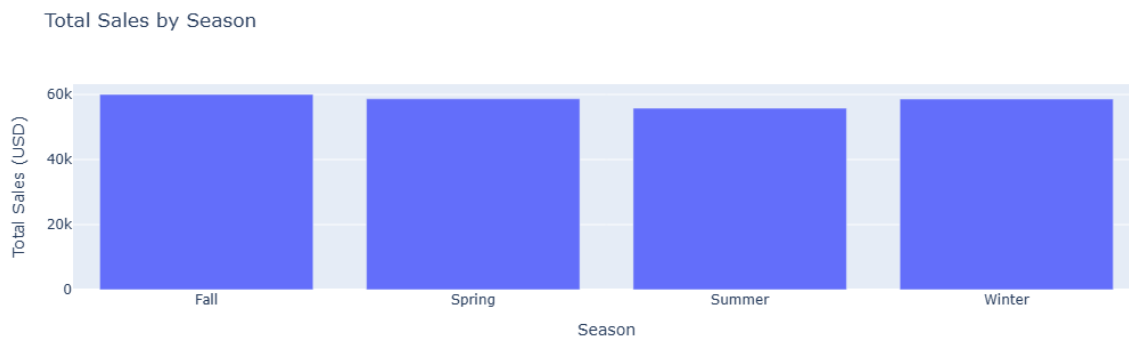
Impact of Weather on Sales.

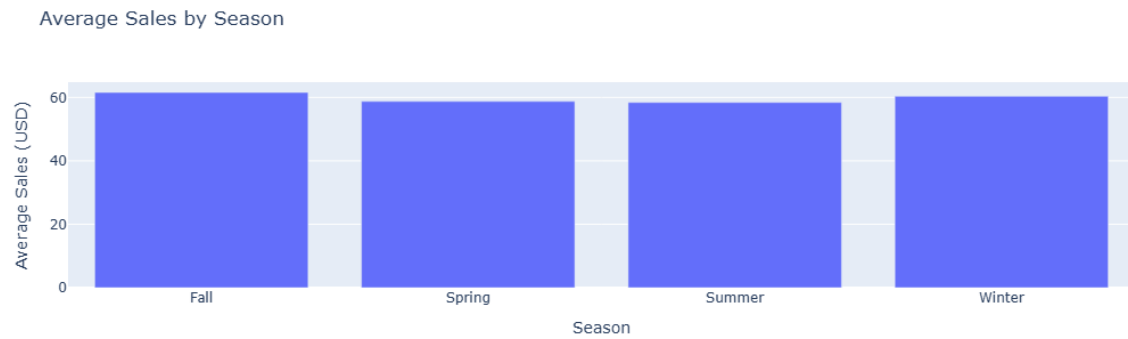
```
fig = px.bar(data, x='weather', y='Purchase Amount (USD)',  
color='weather',  
title='Impact of Weather on Sales')  
fig.show()
```



Seasonal Impact Analysis

```
# Group data by 'Season' and calculate total and average sales  
seasonal_sales = data.groupby('Season')['Purchase Amount  
(USD)'].agg(['sum', 'mean']).reset_index()  
  
# Visualize total sales by season  
fig = px.bar(seasonal_sales, x='Season', y='sum',  
title="Total Sales by Season",  
labels={'sum': 'Total Sales (USD)'})  
fig.show()  
  
# Visualize average sales by season  
fig = px.bar(seasonal_sales, x='Season', y='mean',  
title="Average Sales by Season",  
labels={'mean': 'Average Sales (USD)'})  
fig.show()
```

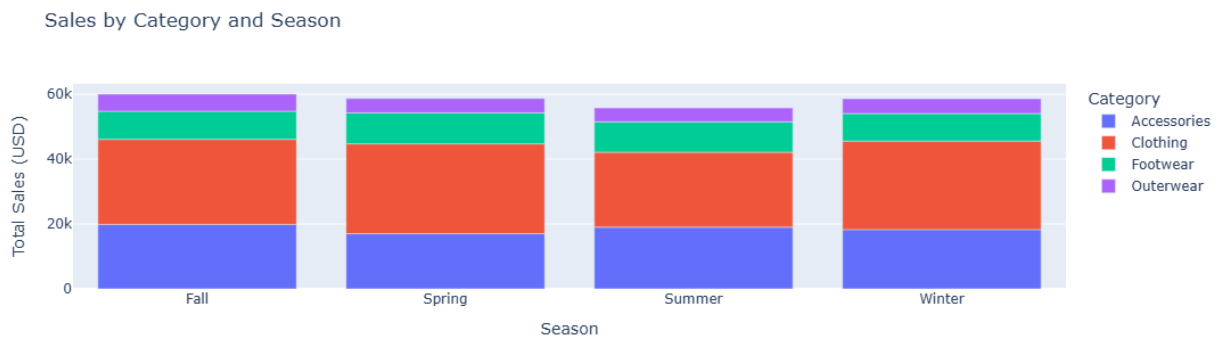




Seasonal Segmentation

```
# Group data by Season and Category to find popular categories per
season
category_season = data.groupby(['Season', 'Category'])['Purchase
Amount (USD)'].sum().reset_index()

# Visualize popular categories per season
fig = px.bar(category_season, x='Season', y='Purchase Amount (USD)',
color='Category',
              title="Sales by Category and Season",
              labels={'Purchase Amount (USD)': 'Total Sales (USD)'})
fig.show()
```



Clustering Analysis

```
print(data.columns)

Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
      'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
      'Review Rating', 'Subscription Status', 'Payment Method',
      'Shipping Type', 'Discount Applied', 'Promo Code Used',
      'Previous Purchases', 'Preferred Payment Method',
      'Frequency of Purchases', 'avg_temp', 'weather',
```



```

'customer_segment'],
    dtype='object')

# Select relevant features for clustering (create a copy to avoid
SettingWithCopyWarning)
clustering_data = data[['Age', 'Purchase Amount (USD)', 'Frequency of
Purchases']].copy()

# Debugging the filtering step
print(f"Initial dataset shape: {data.shape}")

Initial dataset shape: (3900, 22)

# Check for missing or unexpected values
print(f"Missing values in clustering data:
{clustering_data.isnull().sum()}")
print(f"Unique values in 'Frequency of Purchases':
{clustering_data['Frequency of Purchases'].unique()}")

Missing values in clustering data: Age          0
Purchase Amount (USD)          0
Frequency of Purchases          0
dtype: int64
Unique values in 'Frequency of Purchases': ['Fortnightly' 'Weekly'
'Annually' 'Quarterly' 'Bi-Weekly' 'Monthly'
'Every 3 Months']

# Map categorical values to numeric for 'Frequency of Purchases'
frequency_mapping = {
    'Fortnightly': 14,
    'Weekly': 7,
    'Annually': 365,
    'Quarterly': 90,
    'Bi-Weekly': 14,
    'Monthly': 30,
    'Every 3 Months': 90
}
clustering_data['Frequency of Purchases'] = clustering_data['Frequency
of Purchases'].map(frequency_mapping).fillna(0)

# Check dataset after mapping
print(f"After mapping, missing values:
{clustering_data.isnull().sum()}")

# Drop rows with missing values
clustering_data = clustering_data.dropna()
print(f"Clustering data shape after cleaning:
{clustering_data.shape}")

After mapping, missing values: Age          0
Purchase Amount (USD)          0

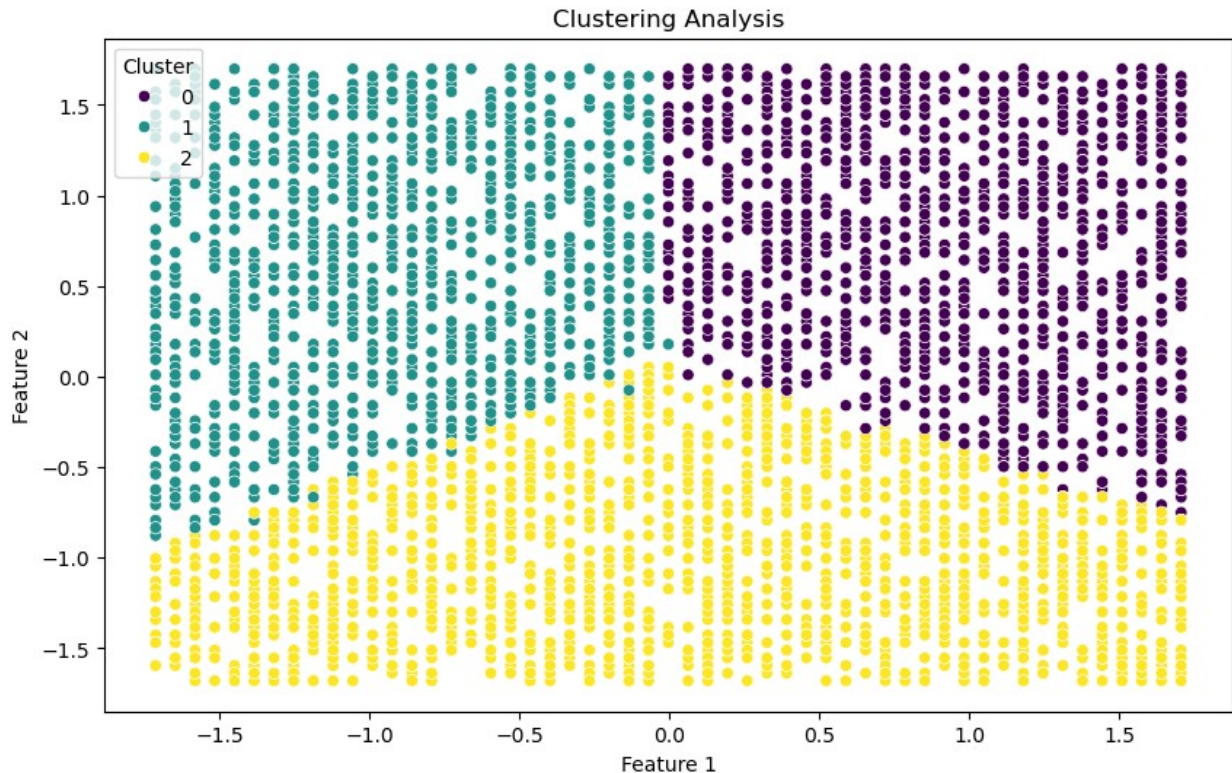
```

```
Frequency of Purchases    0
dtype: int64
Clustering data shape after cleaning: (3900, 3)

# Ensure dataset is not empty
if clustering_data.shape[0] == 0:
    print("No valid data for clustering. Please review filtering steps.")
else:
    # Standardize the data
    scaler = StandardScaler()
    clustering_data_scaled = scaler.fit_transform(clustering_data)

    # Perform clustering
    kmeans = KMeans(n_clusters=3, random_state=42)
    clustering_data['Cluster'] =
    kmeans.fit_predict(clustering_data_scaled)

    # Visualize clustering results
    plt.figure(figsize=(10, 6))
    sns.scatterplot(
        x=clustering_data_scaled[:, 0],
        y=clustering_data_scaled[:, 1],
        hue=clustering_data['Cluster'],
        palette='viridis'
    )
    plt.title('Clustering Analysis')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.show()
```



Regression Analysis

```
data['Campaign'] = np.random.choice(['Campaign_A', 'Campaign_B',
                                     'Campaign_C'], size=len(data))

print(data.columns)

Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
      'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
      'Review Rating', 'Subscription Status', 'Payment Method',
      'Shipping Type', 'Discount Applied', 'Promo Code Used',
      'Previous Purchases', 'Preferred Payment Method',
      'Frequency of Purchases', 'avg_temp', 'weather',
      'customer_segment',
      'Campaign'],
      dtype='object')

# Check unique values in the column
print(data['Frequency of Purchases'].unique())

['Fortnightly' 'Weekly' 'Annually' 'Quarterly' 'Bi-Weekly' 'Monthly'
 'Every 3 Months']

frequency_mapping = {
    'Fortnightly': 14,
    'Weekly': 7,
    'Annually': 365,
```

```

    'Quarterly': 90,
    'Bi-weekly': 14,
    'Monthly': 30,
    'Every 3 Months': 90
}

# Apply mapping and replace unmapped values with 0
data['Frequency of Purchases'] = data['Frequency of
Purchases'].map(frequency_mapping).fillna(0)

# Print unique values to confirm successful mapping
print(data['Frequency of Purchases'].unique())

[ 14.    7. 365.   90.    0.   30.]

data['Frequency of Purchases'] = pd.to_numeric(data['Frequency of
Purchases'], errors='coerce')

# Check the data type to confirm
print(data['Frequency of Purchases'].dtype)

float64

print(regression_data.columns)

Index(['Age', 'Frequency of Purchases', 'Purchase Amount (USD)'],
      dtype='object')

regression_data = data[['Age', 'Frequency of Purchases', 'Purchase
Amount (USD)']].copy()

X = regression_data.drop(columns=['Purchase Amount (USD)'])
y = regression_data['Purchase Amount (USD)']

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

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

```

Mean Squared Error: 564.5464014307929
R-Squared Score: -0.008870954279704746

Advanced Analysis

```
print(data.columns)
```

```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',  
      'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',  
      'Review Rating', 'Subscription Status', 'Payment Method',  
      'Shipping Type', 'Discount Applied', 'Promo Code Used',  
      'Previous Purchases', 'Preferred Payment Method',  
      'Frequency of Purchases', 'avg_temp', 'weather',  
      'customer_segment',  
      'Campaign'],  
      dtype='object')
```

```
# Linear Regression to Analyze Drivers of Sales
```

```
X = data[['Age', 'Previous Purchases', 'Review Rating']]  
y = data['Purchase Amount (USD)']
```

```
model = LinearRegression()  
model.fit(X, y)  
predictions = model.predict(X)
```

```
# Model Evaluation
```

```
mse = mean_squared_error(y, predictions)  
r2 = r2_score(y, predictions)  
print(f"Mean Squared Error: {mse}")  
print(f"R^2 Score: {r2}")
```

Mean Squared Error: 560.2304530962426
R^2 Score: 0.0011117107735826304

Customer Lifetime Value (CLV) Calculation

```
# Calculate Average Purchase Value
```

```
data['Purchase Frequency'] = data['Previous Purchases'] /  
(data['Previous Purchases'].count() / len(data))  
average_purchase_value = data['Purchase Amount (USD)'].mean()
```

```
# Calculate CLV
```

```
clv = average_purchase_value * data['Purchase Frequency'] * 12 #  
Assuming 12 months  
data['CLV'] = clv
```

```
# Display the top 5 customers with the highest CLV
```

```
print(data[['Customer ID', 'CLV']].sort_values(by='CLV',  
ascending=False).head())
```

	Customer ID	CLV
3261	3262	35858.615385
633	634	35858.615385
2262	2263	35858.615385
2264	2265	35858.615385
124	125	35858.615385

Visualization

```
print(data.columns)

Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
      'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
      'Review Rating', 'Subscription Status', 'Payment Method',
      'Shipping Type', 'Discount Applied', 'Promo Code Used',
      'Previous Purchases', 'Preferred Payment Method',
      'Frequency of Purchases', 'avg_temp', 'weather',
      'customer_segment',
      'Campaign', 'Purchase Frequency', 'CLV'],
      dtype='object')

data['Age'] = pd.to_numeric(data['Age'], errors='coerce')

data = data.dropna(subset=['Age', 'Previous Purchases', 'Review
Rating', 'Purchase Amount (USD)'])

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# Select numeric columns for regression
X = data[['Age', 'Purchase Frequency', 'CLV']] # Ensure these are
numeric columns
y = data['Purchase Amount (USD)'] # Target variable

# 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)

# Train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

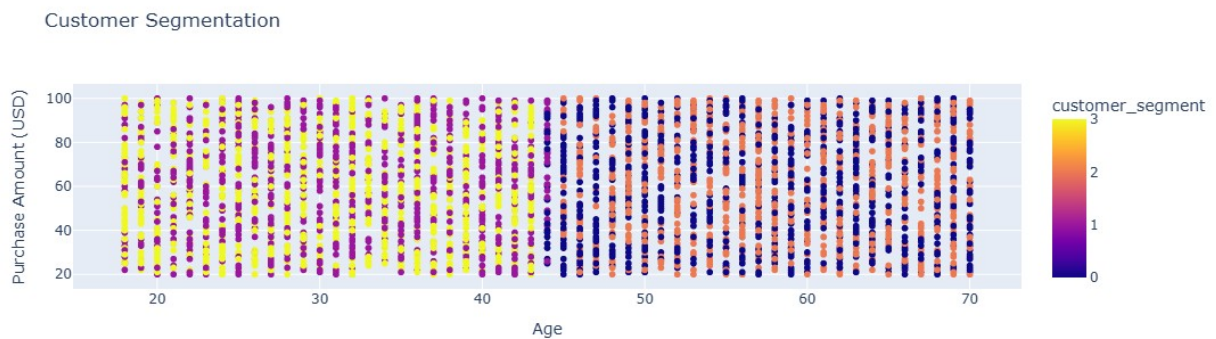
# Make predictions
predictions = model.predict(X_test)

# Display results
print("Model Coefficients:", model.coef_)
print("Model Intercept:", model.intercept_)
print("Predictions:", predictions[:5])
```

```
Model Coefficients: [-2.13486261e-02  1.89251708e-09  1.35726084e-06]
Model Intercept: 61.05847851479823
Predictions: [60.04347838 60.45494263 60.22990765 59.65537554
60.03867741]
```

```
import plotly.express as px

# Scatter plot for customer segmentation
fig = px.scatter(
    data,
    x='Age', # x-axis
    y='Purchase Amount (USD)', # y-axis
    color='customer_segment', # Color-coded by customer segment
    title='Customer Segmentation',
    labels={'x': 'Age', 'y': 'Purchase Amount (USD)'}
)
fig.show()
```



Suggestions for Improving Sales and Optimizing Product Placements

Identify High-Demand Categories During Holidays

```
# Group sales data by Season and Category
holiday_sales = data.groupby(['Season', 'Category'])['Purchase Amount (USD)'].sum().reset_index()

# Create a bar chart to visualize sales trends by season and category
import plotly.express as px

holiday_sales_fig = px.bar(
    holiday_sales,
    x='Season',
    y='Purchase Amount (USD)',
    color='Category',
    barmode='group',
    title="Sales by Category During Holidays"
)
```

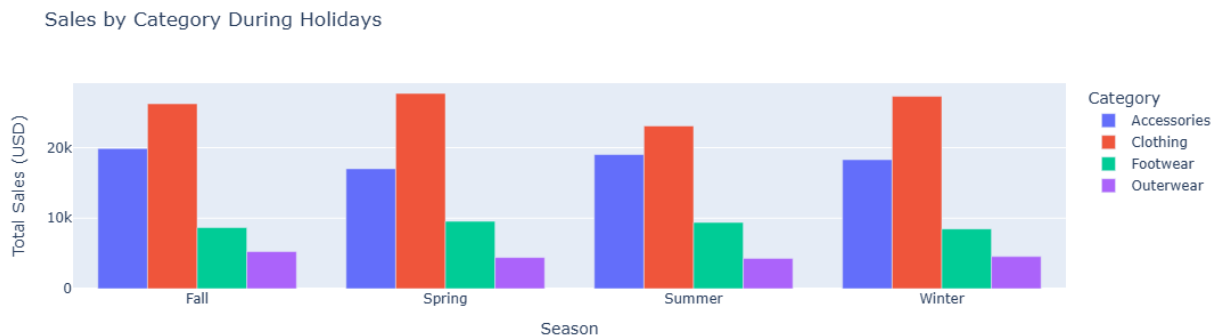


```

# Update chart layout
holiday_sales_fig.update_layout(
    xaxis_title="Season",
    yaxis_title="Total Sales (USD)",
    legend_title="Category"
)

# Display the chart
holiday_sales_fig.show()

```



Optimize Product Placements

```

# Group sales data by Age and Category
age_category_sales = data.groupby(['Age', 'Category'])['Purchase Amount (USD)'].sum().reset_index()

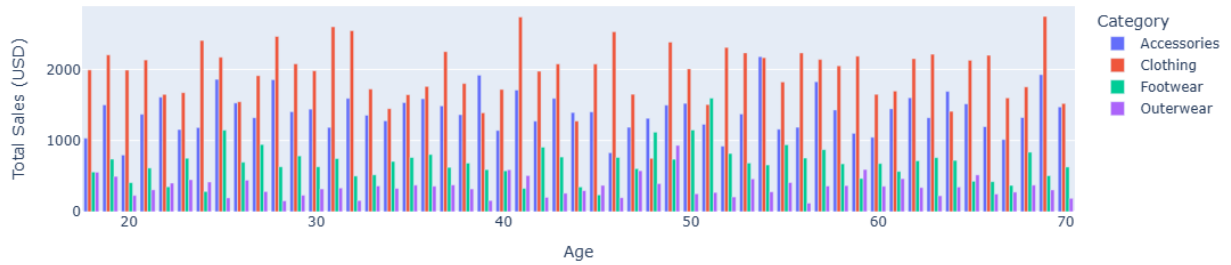
# Create a bar chart to visualize sales trends by age and category
age_category_fig = px.bar(
    age_category_sales,
    x='Age',
    y='Purchase Amount (USD)',
    color='Category',
    title="Sales by Age Group and Category",
    barmode='group'
)

# Update chart layout
age_category_fig.update_layout(
    xaxis_title="Age",
    yaxis_title="Total Sales (USD)",
    legend_title="Category"
)

# Display the chart
age_category_fig.show()

```


Sales by Age Group and Category



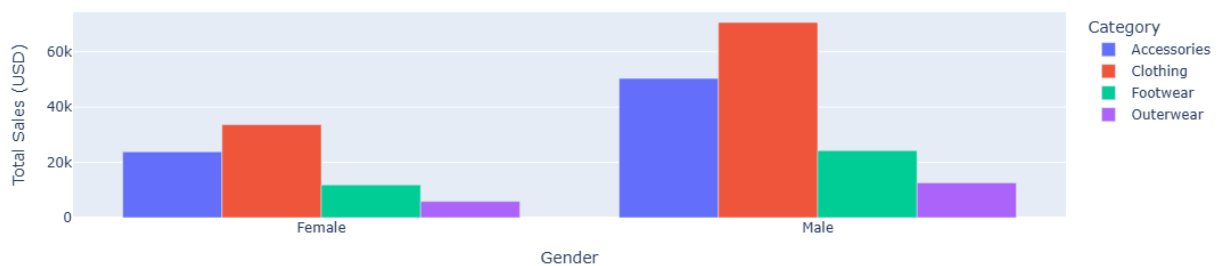
```
# Group sales data by Gender and Category
gender_category_sales = data.groupby(['Gender', 'Category'])['Purchase
Amount (USD)'].sum().reset_index()

# Create a bar chart to visualize sales trends by gender and category
gender_category_fig = px.bar(
    gender_category_sales,
    x='Gender',
    y='Purchase Amount (USD)',
    color='Category',
    title="Sales by Gender and Category",
    barmode='group'
)

# Update chart layout
gender_category_fig.update_layout(
    xaxis_title="Gender",
    yaxis_title="Total Sales (USD)",
    legend_title="Category"
)

# Display the chart
gender_category_fig.show()
```

Sales by Gender and Category



Recommendations for future Enhancement

```
recommendations = """
1. *Inventory Management:* Stock up with popular items for holiday
seasons to meet demand both in-store and online.
2. *Product Placement:* Top-selling products have to be placed in the
most visible areas, both in-store and online, for maximum appeal to
customers.
3. *Target Marketing:* Focused marketing campaigns on select groups of
customers will do much more in helping exploit this opportunity,
especially during peak seasons.
4. *Promotions:* Run pre-season and in-season discounts to drive early
shopping and increase sales.
5. *Weather-Driven Campaigns:* Create and publish dynamic marketing
campaigns according to the weather forecast, such as running ads for
warm winter wear on snowy days or rain gear on rainy days.
6. *Loyalty Programs:* Reward your best customers with special offers
or exclusive memberships to keep them engaged and coming back.

"""

print(recommendations)
```

```
1. *Inventory Management:* Stock up with popular items for holiday
seasons to meet demand both in-store and online.
2. *Product Placement:* Top-selling products have to be placed in the
most visible areas, both in-store and online, for maximum appeal to
customers.
3. *Target Marketing:* Focused marketing campaigns on select groups of
customers will do much more in helping exploit this opportunity,
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campaigns according to the weather forecast, such as running ads for
warm winter wear on snowy days or rain gear on rainy days.
6. *Loyalty Programs:* Reward your best customers with special offers
or exclusive memberships to keep them engaged and coming back.
```

Bonus Task

Add a Module to Analyze Marketing Campaign Effectiveness

```
# Ensure 'Campaign' column exists
if 'Campaign' not in data.columns:
    # Create a synthetic campaign based on purchase amount
    data['Campaign'] = data['Purchase Amount (USD)'].apply(
        lambda x: 'High Campaign' if x > 100 else 'Low Campaign'
```

```

)

# Analyze the impact of campaigns
campaign_analysis = data.groupby('Campaign')['Purchase Amount (USD)'].sum()
print(campaign_analysis)

Campaign
Campaign_A    79293
Campaign_B    75612
Campaign_C    78176
Name: Purchase Amount (USD), dtype: int64

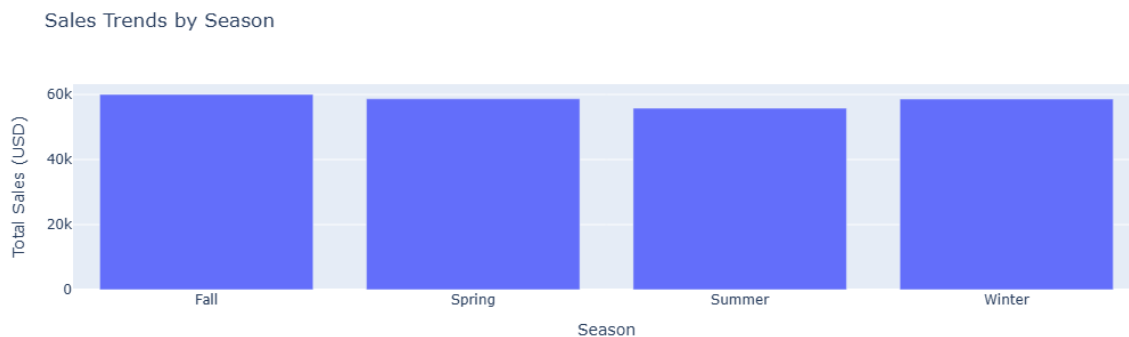
# Grouping by Season to analyze sales trends
seasonal_trends = data.groupby('Season')['Purchase Amount (USD)'].sum()
print("Seasonal Trends:")
print(seasonal_trends)

# Visualizing Seasonal Trends
import plotly.express as px

fig = px.bar(
    x=seasonal_trends.index,
    y=seasonal_trends.values,
    title="Sales Trends by Season",
    labels={'x': 'Season', 'y': 'Total Sales (USD)'}
)
fig.show()

Seasonal Trends:
Season
Fall      60018
Spring    58679
Summer    55777
Winter    58607
Name: Purchase Amount (USD), dtype: int64

```



```

data.columns = data.columns.str.strip()

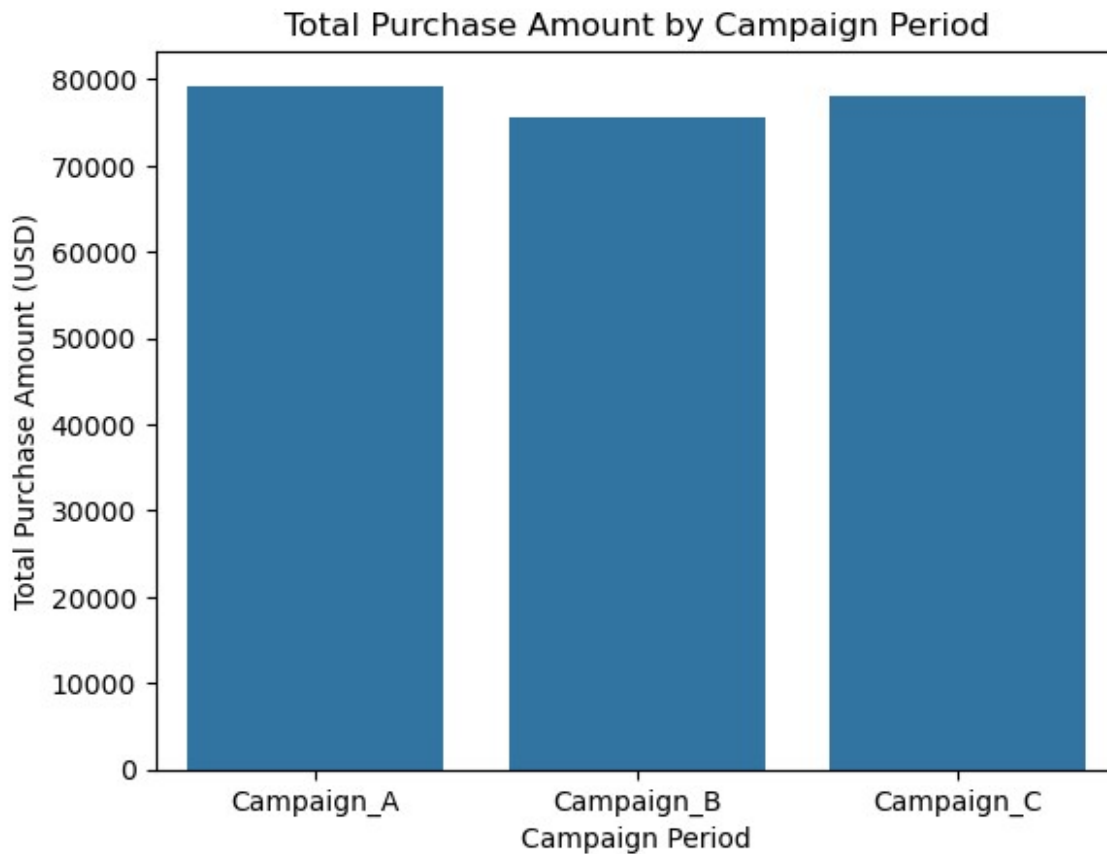
campaign_analysis = data.groupby('Campaign')['Purchase Amount
(USD)'].agg(['mean', 'sum', 'count']).reset_index()
print("Campaign Effectiveness Analysis:")
print(campaign_analysis)

Campaign Effectiveness Analysis:
   Campaign  mean    sum  count
0  Campaign_A  60.161608  79293   1318
1  Campaign_B  59.583924  75612   1269
2  Campaign_C  59.539985  78176   1313

import seaborn as sns

sns.barplot(x='Campaign', y='sum', data=campaign_analysis)
plt.title('Total Purchase Amount by Campaign Period')
plt.ylabel('Total Purchase Amount (USD)')
plt.xlabel('Campaign Period')
plt.show()

```



Forecasting (Bonus Task)

Using ARIMA for Forecasting

```
print(data.columns)

Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
      'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
      'Review Rating', 'Subscription Status', 'Payment Method',
      'Shipping Type', 'Discount Applied', 'Promo Code Used',
      'Previous Purchases', 'Preferred Payment Method',
      'Frequency of Purchases', 'avg_temp', 'weather',
      'customer_segment',
      'Campaign', 'Purchase Frequency', 'CLV'],
      dtype='object')

# Load the data (update the path as necessary)
data = pd.read_csv('C:/Users/chira/Downloads/archive
(1)/shopping_trends.csv')

# Use a column as the value to forecast (replace
'purchase_amount_(usd)' with your column name)
data['Purchase Amount (USD)'] = data['Purchase Amount
(USD)'].fillna(0) # Fill missing values

# Use sequential indices as time
data['time_index'] = np.arange(len(data))

# Aggregate purchase amounts by the sequential time index (if
necessary)
forecast_data = data.groupby('time_index')['Purchase Amount
(USD)'].sum().reset_index()

# Set up the time series
ts = forecast_data['Purchase Amount (USD)']

# Apply Holt-Winters Exponential Smoothing
model = ExponentialSmoothing(ts, seasonal=None, trend='add',
damped_trend=True).fit()

# Aggregate the data by weekly or monthly intervals for clarity
data['time_index'] = pd.to_datetime(data.index, unit='D') # Convert
index to datetime
data.set_index('time_index', inplace=True)
data_weekly = data['Purchase Amount (USD)'].resample('W').sum() #
Aggregate by weeks

# Apply the Holt-Winters Smoothing for forecasting
model = ExponentialSmoothing(data_weekly, seasonal=None, trend='add',
damped_trend=True).fit()

# Forecast the next 30 weeks
```

```

forecast_steps = 30
forecast = model.forecast(steps=forecast_steps)

# Plot the actual data and forecast
plt.figure(figsize=(12, 6))
plt.plot(data_weekly, label='Actual Data', color='blue', linewidth=2)
plt.plot(forecast, label='Forecast', color='orange', linewidth=2)
plt.title('Purchase Amount Forecasting (Weekly)', fontsize=14)
plt.xlabel('Time', fontsize=12)
plt.ylabel('Purchase Amount (USD)', fontsize=12)
plt.legend()
plt.grid()
plt.show()

```

