In [1]:

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

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec
import plotly.graph_objects as go
from matplotlib.colors import LinearSegmentedColormap
from matplotlib import colors as mcolors
from scipy.stats import linregress
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_sco
re
from sklearn.cluster import KMeans
from tabulate import tabulate
from collections import Counter

%matplotlib inline
```

In [2]:

```
# Initialize Plotly for use in the notebook
from plotly.offline import init_notebook_mode
init_notebook_mode(connected=True)
```

In [3]:

```
# Configure Seaborn plot styles: Set background color and use dark grid
sns.set(rc={'axes.facecolor': '#fcf0dc'}, style='darkgrid')
```

In [4]:

```
df = pd.read_csv('/kaggle/input/ecommerce-data/data.csv', encoding="ISO-8859-1")
```

In [ ]:

```
df.head(10)
```

In [ ]:

```
df.info()
```

In [ ]:

```
# Summary statistics for numerical variables
df.describe().T
```

In [ ]:

```
# Summary statistics for categorical variables
df.describe(include='object').T
```

In [ ]:

```
# Calculating the percentage of missing values for each column
missing_data = df.isnull().sum()
missing_percentage = (missing_data[missing_data > 0] / df.shape[0]) * 100
```

```
# Prepare values
missing_percentage.sort_values(ascending=True, inplace=True)

# Plot the barh chart
fig, ax = plt.subplots(figsize=(15, 4))
ax.barh(missing_percentage.index, missing_percentage, color='#ff6200')

# Annotate the values and indexes
for i, (value, name) in enumerate(zip(missing_percentage, missing_percentage.index)):
    ax.text(value+0.5, i, f"{value:.2f}%", ha='left', va='center', fontweight='bold', fo
ntsize=18, color='black')

# Set x-axis limit
ax.set_xlim([0, 40])

# Add title and xlabel
plt.title("Percentage of Missing Values", fontweight='bold', fontsize=22)
plt.xlabel('Percentages (%)', fontsize=16)
plt.show()
```

In [ ]:

```
# Extracting rows with missing values in 'CustomerID' or 'Description' columns
df[df['CustomerID'].isnull() | df['Description'].isnull()].head()
```

In [11]:

```
# Removing rows with missing values in 'CustomerID' and 'Description' columns
df = df.dropna(subset=['CustomerID', 'Description'])
```

In [12]:

```
# Verifying the removal of missing values
df.isnull().sum().sum()
```

Out[12]:

```
0
```

In [ ]:

```
# Finding duplicate rows (keeping all instances)
duplicate_rows = df[df.duplicated(keep=False)]

# Sorting the data by certain columns to see the duplicate rows next to each other
duplicate_rows_sorted = duplicate_rows.sort_values(by=['InvoiceNo', 'StockCode', 'Descri
ption', 'CustomerID', 'Quantity'])

# Displaying the first 10 records
duplicate_rows_sorted.head(10)
```

In [14]:

```
# Displaying the number of duplicate rows
print(f"The dataset contains {df.duplicated().sum()} duplicate rows that need to be remov
ed.")

# Removing duplicate rows
df.drop_duplicates(inplace=True)
```

```
The dataset contains 5225 duplicate rows that need to be removed.
```

In [ ]:

```
# Getting the number of rows in the dataframe
df.shape[0]
```

In [ ]:

```
# Filter out the rows with InvoiceNo starting with "C" and create a new column indicating
the transaction status
```

```
df['Transaction_Status'] = np.where(df['InvoiceNo'].astype(str).str.startswith('C'), 'Cancelled', 'Completed')

# Analyze the characteristics of these rows (considering the new column)
cancelled_transactions = df[df['Transaction_Status'] == 'Cancelled']
cancelled_transactions.describe().drop('CustomerID', axis=1)
```

In [ ]:

```
# Finding the percentage of cancelled transactions
cancelled_percentage = (cancelled_transactions.shape[0] / df.shape[0]) * 100

# Printing the percentage of cancelled transactions
print(f"The percentage of cancelled transactions in the dataset is: {cancelled_percentage:.2f}%")
```

In [ ]:

```
# Finding the number of unique stock codes
unique_stock_codes = df['StockCode'].nunique()

# Printing the number of unique stock codes
print(f"The number of unique stock codes in the dataset is: {unique_stock_codes}")
```

In [ ]:

```
# Finding the top 10 most frequent stock codes
top_10_stock_codes = df['StockCode'].value_counts(normalize=True).head(10) * 100

# Plotting the top 10 most frequent stock codes
plt.figure(figsize=(12, 5))
top_10_stock_codes.plot(kind='barh', color='#ff6200')

# Adding the percentage frequency on the bars
for index, value in enumerate(top_10_stock_codes):
    plt.text(value, index+0.25, f'{value:.2f}%', fontsize=10)

plt.title('Top 10 Most Frequent Stock Codes')
plt.xlabel('Percentage Frequency (%)')
plt.ylabel('Stock Codes')
plt.gca().invert_yaxis()
plt.show()
```

In [ ]:

```
# Finding the number of numeric characters in each unique stock code
unique_stock_codes = df['StockCode'].unique()
numeric_char_counts_in_unique_codes = pd.Series(unique_stock_codes).apply(lambda x: sum(c.isdigit() for c in str(x))).value_counts()

# Printing the value counts for unique stock codes
print("Value counts of numeric character frequencies in unique stock codes:")
print("-"*70)
print(numeric_char_counts_in_unique_codes)
```

In [ ]:

```
# Finding and printing the stock codes with 0 and 1 numeric characters
anomalous_stock_codes = [code for code in unique_stock_codes if sum(c.isdigit() for c in str(code)) in (0, 1)]

# Printing each stock code on a new line
print("Anomalous stock codes:")
print("-"*22)
for code in anomalous_stock_codes:
    print(code)
```

In [ ]:

```
# Calculating the percentage of records with these stock codes
```

```
percentage_anomalous = (df['StockCode'].isin(anomalous_stock_codes).sum() / len(df)) * 1
00

# Printing the percentage
print(f"The percentage of records with anomalous stock codes in the dataset is: {percenta
ge_anomalous:.2f}%")
```

In [23]:

```
# Removing rows with anomalous stock codes from the dataset
df = df[~df['StockCode'].isin(anomalous_stock_codes)]
```

In [ ]:

```
# Getting the number of rows in the dataframe
df.shape[0]
```

In [ ]:

```
# Calculate the occurrence of each unique description and sort them
description_counts = df['Description'].value_counts()

# Get the top 30 descriptions
top_30_descriptions = description_counts[:30]

# Plotting
plt.figure(figsize=(12,8))
plt.barh(top_30_descriptions.index[::-1], top_30_descriptions.values[::-1], color='#ff620
0')

# Adding labels and title
plt.xlabel('Number of Occurrences')
plt.ylabel('Description')
plt.title('Top 30 Most Frequent Descriptions')

# Show the plot
plt.show()
```

In [ ]:

```
# Find unique descriptions containing lowercase characters
lowercase_descriptions = df['Description'].unique()
lowercase_descriptions = [desc for desc in lowercase_descriptions if any(char.islower()
for char in desc)]

# Print the unique descriptions containing lowercase characters
print("The unique descriptions containing lowercase characters are:")
print("-"*60)
for desc in lowercase_descriptions:
    print(desc)
```

In [27]:

```
service_related_descriptions = ["Next Day Carriage", "High Resolution Image"]

# Calculate the percentage of records with service-related descriptions
service_related_percentage = df[df['Description'].isin(service_related_descriptions)].sha
pe[0] / df.shape[0] * 100

# Print the percentage of records with service-related descriptions
print(f"The percentage of records with service-related descriptions in the dataset is: {s
ervice_related_percentage:.2f}%")

# Remove rows with service-related information in the description
df = df[~df['Description'].isin(service_related_descriptions)]

# Standardize the text to uppercase to maintain uniformity across the dataset
df['Description'] = df['Description'].str.upper()
```

```
The percentage of records with service-related descriptions in the dataset is: 0.02%
```

In [ ]:

```
# Getting the number of rows in the dataframe
df.shape[0]
```

In [ ]:

```
df['UnitPrice'].describe()
```

In [ ]:

```
df[df['UnitPrice']==0].describe()[['Quantity']]
```

In [31]:

```
# Removing records with a unit price of zero to avoid potential data entry errors
df = df[df['UnitPrice'] > 0]
```

In [32]:

```
# Resetting the index of the cleaned dataset
df.reset_index(drop=True, inplace=True)
```

In [ ]:

```
# Getting the number of rows in the dataframe
df.shape[0]
```

In [34]:

```
# Convert InvoiceDate to datetime type
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])

# Convert InvoiceDate to datetime and extract only the date
df['InvoiceDay'] = df['InvoiceDate'].dt.date

# Find the most recent purchase date for each customer
customer_data = df.groupby('CustomerID')['InvoiceDay'].max().reset_index()

# Find the most recent date in the entire dataset
most_recent_date = df['InvoiceDay'].max()

# Convert InvoiceDay to datetime type before subtraction
customer_data['InvoiceDay'] = pd.to_datetime(customer_data['InvoiceDay'])
most_recent_date = pd.to_datetime(most_recent_date)

# Calculate the number of days since the last purchase for each customer
customer_data['Days_Since_Last_Purchase'] = (most_recent_date - customer_data['InvoiceDay
']).dt.days

# Remove the InvoiceDay column
customer_data.drop(columns=['InvoiceDay'], inplace=True)
```

In [ ]:

```
customer_data.head()
```

In [ ]:

```
# Calculate the total number of transactions made by each customer
total_transactions = df.groupby('CustomerID')['InvoiceNo'].nunique().reset_index()
total_transactions.rename(columns={'InvoiceNo': 'Total_Transactions'}, inplace=True)

# Calculate the total number of products purchased by each customer
total_products_purchased = df.groupby('CustomerID')['Quantity'].sum().reset_index()
total_products_purchased.rename(columns={'Quantity': 'Total_Products_Purchased'}, inplac
e=True)

# Merge the new features into the customer_data dataframe
customer_data = pd.merge(customer_data, total_transactions, on='CustomerID')
```

```
customer_data = pd.merge(customer_data, total_products_purchased, on='CustomerID')

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
# Calculate the total spend by each customer
df['Total_Spend'] = df['UnitPrice'] * df['Quantity']
total_spend = df.groupby('CustomerID')['Total_Spend'].sum().reset_index()

# Calculate the average transaction value for each customer
average_transaction_value = total_spend.merge(total_transactions, on='CustomerID')
average_transaction_value['Average_Transaction_Value'] = average_transaction_value['Total
_Spend'] / average_transaction_value['Total_Transactions']

# Merge the new features into the customer_data dataframe
customer_data = pd.merge(customer_data, total_spend, on='CustomerID')
customer_data = pd.merge(customer_data, average_transaction_value[['CustomerID', 'Average
_Transaction_Value']], on='CustomerID')

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
# Calculate the number of unique products purchased by each customer
unique_products_purchased = df.groupby('CustomerID')['StockCode'].nunique().reset_index(
)
unique_products_purchased.rename(columns={'StockCode': 'Unique_Products_Purchased'}, inp
lace=True)

# Merge the new feature into the customer_data dataframe
customer_data = pd.merge(customer_data, unique_products_purchased, on='CustomerID')

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
# Extract day of week and hour from InvoiceDate
df['Day_Of_Week'] = df['InvoiceDate'].dt.dayofweek
df['Hour'] = df['InvoiceDate'].dt.hour

# Calculate the average number of days between consecutive purchases
days_between_purchases = df.groupby('CustomerID')['InvoiceDay'].apply(lambda x: (x.diff(
).dropna()).apply(lambda y: y.days))
average_days_between_purchases = days_between_purchases.groupby('CustomerID').mean().res
et_index()
average_days_between_purchases.rename(columns={'InvoiceDay': 'Average_Days_Between_Purcha
ses'}, inplace=True)

# Find the favorite shopping day of the week
favorite_shopping_day = df.groupby(['CustomerID', 'Day_Of_Week']).size().reset_index(nam
e='Count')
favorite_shopping_day = favorite_shopping_day.loc[favorite_shopping_day.groupby('Customer
ID')['Count'].idxmax()][['CustomerID', 'Day_Of_Week']]

# Find the favorite shopping hour of the day
favorite_shopping_hour = df.groupby(['CustomerID', 'Hour']).size().reset_index(name='Cou
nt')
favorite_shopping_hour = favorite_shopping_hour.loc[favorite_shopping_hour.groupby('Cust
omerID')['Count'].idxmax()][['CustomerID', 'Hour']]

# Merge the new features into the customer_data dataframe
customer_data = pd.merge(customer_data, average_days_between_purchases, on='CustomerID')
customer_data = pd.merge(customer_data, favorite_shopping_day, on='CustomerID')
customer_data = pd.merge(customer_data, favorite_shopping_hour, on='CustomerID')

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
df['Country'].value_counts(normalize=True).head()
```

In [ ]:

```
# Group by CustomerID and Country to get the number of transactions per country for each customer
customer_country = df.groupby(['CustomerID', 'Country']).size().reset_index(name='Number_of_Transactions')

# Get the country with the maximum number of transactions for each customer (in case a customer has transactions from multiple countries)
customer_main_country = customer_country.sort_values('Number_of_Transactions', ascending=False).drop_duplicates('CustomerID')

# Create a binary column indicating whether the customer is from the UK or not
customer_main_country['Is_UK'] = customer_main_country['Country'].apply(lambda x: 1 if x == 'United Kingdom' else 0)

# Merge this data with our customer_data dataframe
customer_data = pd.merge(customer_data, customer_main_country[['CustomerID', 'Is_UK']], on='CustomerID', how='left')

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
# Display feature distribution
customer_data['Is_UK'].value_counts()
```

In [ ]:

```
# Calculate the total number of transactions made by each customer
total_transactions = df.groupby('CustomerID')['InvoiceNo'].nunique().reset_index()

# Calculate the number of cancelled transactions for each customer
cancelled_transactions = df[df['Transaction_Status'] == 'Cancelled']
cancellation_frequency = cancelled_transactions.groupby('CustomerID')['InvoiceNo'].nunique().reset_index()
cancellation_frequency.rename(columns={'InvoiceNo': 'Cancellation_Frequency'}, inplace=True)

# Merge the Cancellation Frequency data into the customer_data dataframe
customer_data = pd.merge(customer_data, cancellation_frequency, on='CustomerID', how='left')

# Replace NaN values with 0 (for customers who have not cancelled any transaction)
customer_data['Cancellation_Frequency'].fillna(0, inplace=True)

# Calculate the Cancellation Rate
customer_data['Cancellation_Rate'] = customer_data['Cancellation_Frequency'] / total_transactions['InvoiceNo']

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
# Extract month and year from InvoiceDate
df['Year'] = df['InvoiceDate'].dt.year
df['Month'] = df['InvoiceDate'].dt.month

# Calculate monthly spending for each customer
monthly_spending = df.groupby(['CustomerID', 'Year', 'Month'])['Total_Spend'].sum().reset_index()

# Calculate Seasonal Buying Patterns: We are using monthly frequency as a proxy for seasonal buying patterns
```

```
seasonal_buying_patterns = monthly_spending.groupby('CustomerID')['Total_Spend'].agg(['me
an', 'std']).reset_index()
seasonal_buying_patterns.rename(columns={'mean': 'Monthly_Spending_Mean', 'std': 'Monthly
_Spending_Std'}, inplace=True)

# Replace NaN values in Monthly_Spending_Std with 0, implying no variability for customer
s with single transaction month
seasonal_buying_patterns['Monthly_Spending_Std'].fillna(0, inplace=True)

# Calculate Trends in Spending
# We are using the slope of the linear trend line fitted to the customer's spending over
time as an indicator of spending trends
def calculate_trend(spend_data):
    # If there are more than one data points, we calculate the trend using linear regress
ion
    if len(spend_data) > 1:
        x = np.arange(len(spend_data))
        slope, _, _, _, _ = linregress(x, spend_data)
        return slope
    # If there is only one data point, no trend can be calculated, hence we return 0
    else:
        return 0

# Apply the calculate_trend function to find the spending trend for each customer
spending_trends = monthly_spending.groupby('CustomerID')['Total_Spend'].apply(calculate_
trend).reset_index()
spending_trends.rename(columns={'Total_Spend': 'Spending_Trend'}, inplace=True)

# Merge the new features into the customer_data dataframe
customer_data = pd.merge(customer_data, seasonal_buying_patterns, on='CustomerID')
customer_data = pd.merge(customer_data, spending_trends, on='CustomerID')

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [45]:

```
# Changing the data type of 'CustomerID' to string as it is a unique identifier and not u
sed in mathematical operations
customer_data['CustomerID'] = customer_data['CustomerID'].astype(str)

# Convert data types of columns to optimal types
customer_data = customer_data.convert_dtypes()
```

In [ ]:

```
customer_data.head(10)
```

In [ ]:

```
customer_data.info()
```

In [ ]:

```
# Initializing the IsolationForest model with a contamination parameter of 0.05
model = IsolationForest(contamination=0.05, random_state=0)

# Fitting the model on our dataset (converting DataFrame to NumPy to avoid warning)
customer_data['Outlier_Scores'] = model.fit_predict(customer_data.iloc[:, 1:].to_numpy())

# Creating a new column to identify outliers (1 for inliers and -1 for outliers)
customer_data['Is_Outlier'] = [1 if x == -1 else 0 for x in customer_data['Outlier_Score
s']]

# Display the first few rows of the customer_data dataframe
customer_data.head()
```

In [ ]:

```
# Calculate the percentage of inliers and outliers
outlier_percentage = customer_data['Is_Outlier'].value_counts(normalize=True) * 100
```

```
# Plotting the percentage of inliers and outliers
plt.figure(figsize=(12, 4))
outlier_percentage.plot(kind='barh', color='#ff6200')

# Adding the percentage labels on the bars
for index, value in enumerate(outlier_percentage):
    plt.text(value, index, f'{value:.2f}%', fontsize=15)

plt.title('Percentage of Inliers and Outliers')
plt.xticks(ticks=np.arange(0, 115, 5))
plt.xlabel('Percentage (%)')
plt.ylabel('Is Outlier')
plt.gca().invert_yaxis()
plt.show()
```

In [50]:

```
# Separate the outliers for analysis
outliers_data = customer_data[customer_data['Is_Outlier'] == 1]

# Remove the outliers from the main dataset
customer_data_cleaned = customer_data[customer_data['Is_Outlier'] == 0]

# Drop the 'Outlier_Scores' and 'Is_Outlier' columns
customer_data_cleaned = customer_data_cleaned.drop(columns=['Outlier_Scores', 'Is_Outlie
r'])

# Reset the index of the cleaned data
customer_data_cleaned.reset_index(drop=True, inplace=True)
```

In [ ]:

```
# Getting the number of rows in the cleaned customer dataset
customer_data_cleaned.shape[0]
```

In [ ]:

```
# Reset background style
sns.set_style('whitegrid')

# Calculate the correlation matrix excluding the 'CustomerID' column
corr = customer_data_cleaned.drop(columns=['CustomerID']).corr()

# Define a custom colormap
colors = ['#ff6200', '#ffcaa8', 'white', '#ffcaa8', '#ff6200']
my_cmap = LinearSegmentedColormap.from_list('custom_map', colors, N=256)

# Create a mask to only show the lower triangle of the matrix (since it's mirrored around
its
# top-left to bottom-right diagonal)
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask, k=1)] = True

# Plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr, mask=mask, cmap=my_cmap, annot=True, center=0, fmt='.2f', linewidths=2
)
plt.title('Correlation Matrix', fontsize=14)
plt.show()
```

In [ ]:

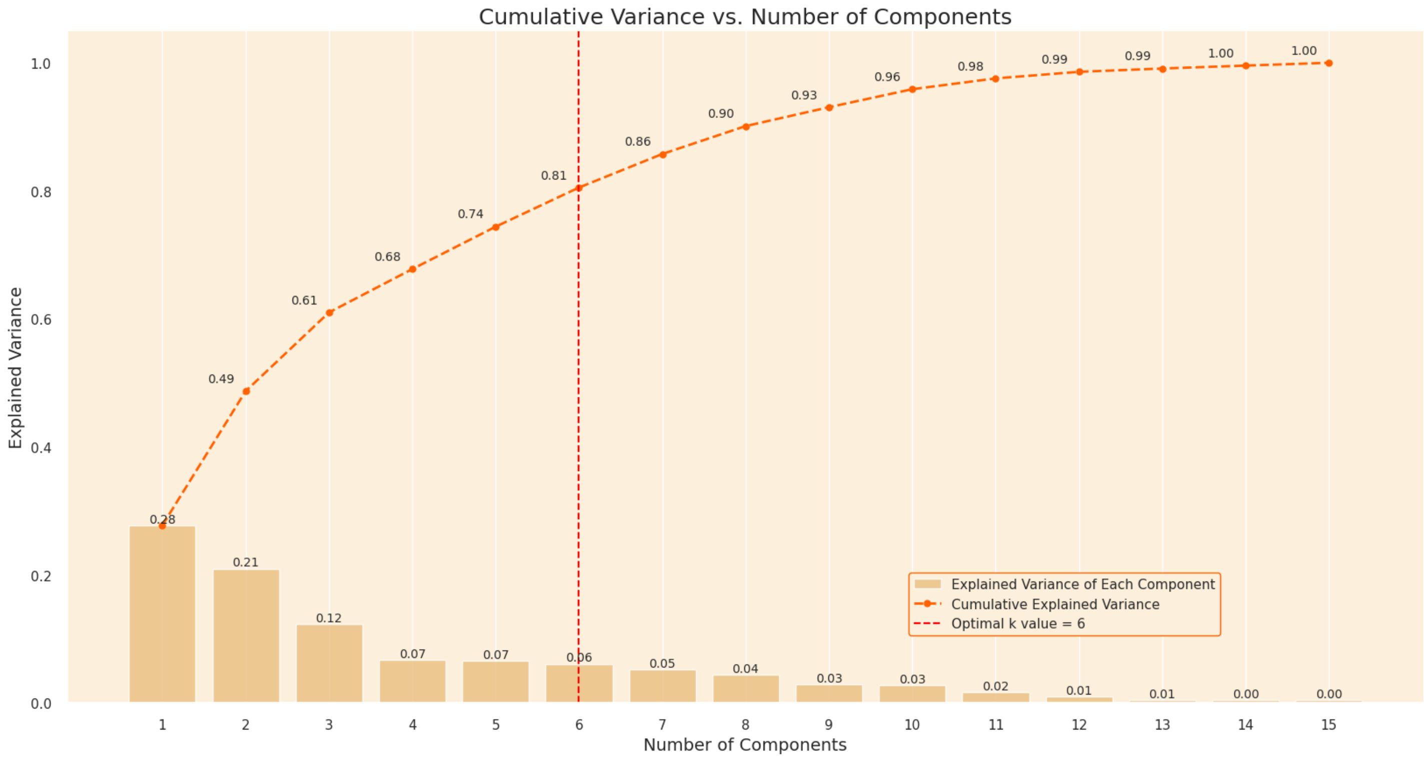
```
# Initialize the StandardScaler
scaler = StandardScaler()

# List of columns that don't need to be scaled
columns_to_exclude = ['CustomerID', 'Is_UK', 'Day_Of_Week']

# List of columns that need to be scaled
columns_to_scale = customer_data_cleaned.columns.difference(columns_to_exclude)
```

```
# Copy the cleaned dataset
customer_data_scaled = customer_data_cleaned.copy()

# Applying the scaler to the necessary columns in the dataset
customer_data_scaled[columns_to_scale] = scaler.fit_transform(customer_data_scaled[column
s_to_scale])

# Display the first few rows of the scaled data
customer_data_scaled.head()
```

In [54]:

```
# Setting CustomerID as the index column
customer_data_scaled.set_index('CustomerID', inplace=True)

# Apply PCA
pca = PCA().fit(customer_data_scaled)

# Calculate the Cumulative Sum of the Explained Variance
explained_variance_ratio = pca.explained_variance_ratio_
cumulative_explained_variance = np.cumsum(explained_variance_ratio)

# Set the optimal k value (based on our analysis, we can choose 6)
optimal_k = 6

# Set seaborn plot style
sns.set(rc={'axes.facecolor': '#fcf0dc'}, style='darkgrid')

# Plot the cumulative explained variance against the number of components
plt.figure(figsize=(20, 10))

# Bar chart for the explained variance of each component
barplot = sns.barplot(x=list(range(1, len(cumulative_explained_variance) + 1)),
                      y=explained_variance_ratio,
                      color='#fcc36d',
                      alpha=0.8)

# Line plot for the cumulative explained variance
lineplot, = plt.plot(range(0, len(cumulative_explained_variance)), cumulative_explained_v
ariance,
                     marker='o', linestyle='--', color='#ff6200', linewidth=2)

# Plot optimal k value line
optimal_k_line = plt.axvline(optimal_k - 1, color='red', linestyle='--', label=f'Optimal
k value = {optimal_k}')

# Set labels and title
plt.xlabel('Number of Components', fontsize=14)
plt.ylabel('Explained Variance', fontsize=14)
plt.title('Cumulative Variance vs. Number of Components', fontsize=18)

# Customize ticks and legend
plt.xticks(range(0, len(cumulative_explained_variance)))
plt.legend(handles=[barplot.patches[0], lineplot, optimal_k_line],
           labels=['Explained Variance of Each Component', 'Cumulative Explained Varianc
e', f'Optimal k value = {optimal_k}'],
           loc=(0.62, 0.1),
           frameon=True,
           framealpha=1.0,
           edgecolor='#ff6200')

# Display the variance values for both graphs on the plots
x_offset = -0.3
y_offset = 0.01
for i, (ev_ratio, cum_ev_ratio) in enumerate(zip(explained_variance_ratio, cumulative_exp
lained_variance)):
    plt.text(i, ev_ratio, f"{ev_ratio:.2f}", ha="center", va="bottom", fontsize=10)
    if i > 0:
        plt.text(i + x_offset, cum_ev_ratio + y_offset, f"{cum_ev_ratio:.2f}", ha="cente
r", va="bottom", fontsize=10)
```

```
plt.grid(axis='both')
plt.show()
```



In [55]:

```
# Creating a PCA object with 6 components
pca = PCA(n_components=6)

# Fitting and transforming the original data to the new PCA dataframe
customer_data_pca = pca.fit_transform(customer_data_scaled)

# Creating a new dataframe from the PCA dataframe, with columns labeled PC1, PC2, etc.
customer_data_pca = pd.DataFrame(customer_data_pca, columns=['PC'+str(i+1) for i in rang
e(pca.n_components_)])

# Adding the CustomerID index back to the new PCA dataframe
customer_data_pca.index = customer_data_scaled.index
```

In [ ]:

```
# Displaying the resulting dataframe based on the PCs
customer_data_pca.head()
```

In [ ]:

```
# Define a function to highlight the top 3 absolute values in each column of a dataframe
def highlight_top3(column):
    top3 = column.abs().nlargest(3).index
    return ['background-color:  #ffeacc' if i in top3 else '' for i in column.index]

# Create the PCA component DataFrame and apply the highlighting function
pc_df = pd.DataFrame(pca.components_.T, columns=['PC{}'.format(i+1) for i in range(pca.n
_components_)],
                     index=customer_data_scaled.columns)

pc_df.style.apply(highlight_top3, axis=0)
```

In [ ]:

```
# Set plot style, and background color
sns.set(style='darkgrid', rc={'axes.facecolor': '#fcf0dc'})

# Set the color palette for the plot
sns.set_palette(['#ff6200'])
```

```
# Instantiate the clustering model with the specified parameters
km = KMeans(init='k-means++', n_init=10, max_iter=100, random_state=0)

# Create a figure and axis with the desired size
fig, ax = plt.subplots(figsize=(12, 5))

# Instantiate the KElbowVisualizer with the model and range of k values, and disable the
timing plot
visualizer = KElbowVisualizer(km, k=(2, 15), timings=False, ax=ax)

# Fit the data to the visualizer
visualizer.fit(customer_data_pca)

# Finalize and render the figure
visualizer.show();
```

In [59]:

```
def silhouette_analysis(df, start_k, stop_k, figsize=(15, 16)):
    """
    Perform Silhouette analysis for a range of k values and visualize the results.
    """

    # Set the size of the figure
    plt.figure(figsize=figsize)

    # Create a grid with (stop_k - start_k + 1) rows and 2 columns
    grid = gridspec.GridSpec(stop_k - start_k + 1, 2)

    # Assign the first plot to the first row and both columns
    first_plot = plt.subplot(grid[0, :])

    # First plot: Silhouette scores for different k values
    sns.set_palette(['darkorange'])

    silhouette_scores = []

    # Iterate through the range of k values
    for k in range(start_k, stop_k + 1):
        km = KMeans(n_clusters=k, init='k-means++', n_init=10, max_iter=100, random_stat
e=0)
        km.fit(df)
        labels = km.predict(df)
        score = silhouette_score(df, labels)
        silhouette_scores.append(score)

    best_k = start_k + silhouette_scores.index(max(silhouette_scores))

    plt.plot(range(start_k, stop_k + 1), silhouette_scores, marker='o')
    plt.xticks(range(start_k, stop_k + 1))
    plt.xlabel('Number of clusters (k)')
    plt.ylabel('Silhouette score')
    plt.title('Average Silhouette Score for Different k Values', fontsize=15)

    # Add the optimal k value text to the plot
    optimal_k_text = f'The k value with the highest Silhouette score is: {best_k}'
    plt.text(10, 0.23, optimal_k_text, fontsize=12, verticalalignment='bottom',
             horizontalalignment='left', bbox=dict(facecolor='#fcc36d', edgecolor='#ff62
00', boxstyle='round, pad=0.5'))


    # Second plot (subplot): Silhouette plots for each k value
    colors = sns.color_palette("bright")

    for i in range(start_k, stop_k + 1):
        km = KMeans(n_clusters=i, init='k-means++', n_init=10, max_iter=100, random_stat
e=0)
        row_idx, col_idx = divmod(i - start_k, 2)

        # Assign the plots to the second, third, and fourth rows
```

```
        ax = plt.subplot(grid[row_idx + 1, col_idx])

        visualizer = SilhouetteVisualizer(km, colors=colors, ax=ax)
        visualizer.fit(df)

        # Add the Silhouette score text to the plot
        score = silhouette_score(df, km.labels_)
        ax.text(0.97, 0.02, f'Silhouette Score: {score:.2f}', fontsize=12, \
                ha='right', transform=ax.transAxes, color='red')

        ax.set_title(f'Silhouette Plot for {i} Clusters', fontsize=15)

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

In [ ]:

```
silhouette_analysis(customer_data_pca, 3, 12, figsize=(20, 50))
```

In [61]:

```
# Apply KMeans clustering using the optimal k
kmeans = KMeans(n_clusters=3, init='k-means++', n_init=10, max_iter=100, random_state=0)
kmeans.fit(customer_data_pca)

# Get the frequency of each cluster
cluster_frequencies = Counter(kmeans.labels_)

# Create a mapping from old labels to new labels based on frequency
label_mapping = {label: new_label for new_label, (label, _) in
                 enumerate(cluster_frequencies.most_common())}

# Reverse the mapping to assign labels as per your criteria
label_mapping = {v: k for k, v in {2: 1, 1: 0, 0: 2}.items()}

# Apply the mapping to get the new labels
new_labels = np.array([label_mapping[label] for label in kmeans.labels_])

# Append the new cluster labels back to the original dataset
customer_data_cleaned['cluster'] = new_labels

# Append the new cluster labels to the PCA version of the dataset
customer_data_pca['cluster'] = new_labels
```

In [ ]:

```
# Display the first few rows of the original dataframe
customer_data_cleaned.head()
```

In [63]:

```
# Setting up the color scheme for the clusters (RGB order)
colors = ['#e8000b', '#1ac938', '#023eff']
```

In [ ]:

```
# Create separate data frames for each cluster
cluster_0 = customer_data_pca[customer_data_pca['cluster'] == 0]
cluster_1 = customer_data_pca[customer_data_pca['cluster'] == 1]
cluster_2 = customer_data_pca[customer_data_pca['cluster'] == 2]

# Create a 3D scatter plot
fig = go.Figure()

# Add data points for each cluster separately and specify the color
fig.add_trace(go.Scatter3d(x=cluster_0['PC1'], y=cluster_0['PC2'], z=cluster_0['PC3'],
                           mode='markers', marker=dict(color=colors[0], size=5, opacity=
0.4), name='Cluster 0'))
fig.add_trace(go.Scatter3d(x=cluster_1['PC1'], y=cluster_1['PC2'], z=cluster_1['PC3'],
                           mode='markers', marker=dict(color=colors[1], size=5, opacity=
0.4), name='Cluster 1'))
```

```
fig.add_trace(go.Scatter3d(x=cluster_2['PC1'], y=cluster_2['PC2'], z=cluster_2['PC3'],
                           mode='markers', marker=dict(color=colors[2], size=5, opacity=
0.4), name='Cluster 2'))

# Set the title and layout details
fig.update_layout(
    title=dict(text='3D Visualization of Customer Clusters in PCA Space', x=0.5),
    scene=dict(
        xaxis=dict(backgroundcolor="#fcf0dc", gridcolor='white', title='PC1'),
        yaxis=dict(backgroundcolor="#fcf0dc", gridcolor='white', title='PC2'),
        zaxis=dict(backgroundcolor="#fcf0dc", gridcolor='white', title='PC3'),
    ),
    width=900,
    height=800
)

# Show the plot
fig.show()
```

In [ ]:

```
# Calculate the percentage of customers in each cluster
cluster_percentage = (customer_data_pca['cluster'].value_counts(normalize=True) * 100).r
eset_index()
cluster_percentage.columns = ['Cluster', 'Percentage']
cluster_percentage.sort_values(by='Cluster', inplace=True)

# Create a horizontal bar plot
plt.figure(figsize=(10, 4))
sns.barplot(x='Percentage', y='Cluster', data=cluster_percentage, orient='h', palette=co
lors)

# Adding percentages on the bars
for index, value in enumerate(cluster_percentage['Percentage']):
    plt.text(value+0.5, index, f'{value:.2f}%')

plt.title('Distribution of Customers Across Clusters', fontsize=14)
plt.xticks(ticks=np.arange(0, 50, 5))
plt.xlabel('Percentage (%)')

# Show the plot
plt.show()
```

In [ ]:

```
# Compute number of customers
num_observations = len(customer_data_pca)

# Separate the features and the cluster labels
X = customer_data_pca.drop('cluster', axis=1)
clusters = customer_data_pca['cluster']

# Compute the metrics
sil_score = silhouette_score(X, clusters)
calinski_score = calinski_harabasz_score(X, clusters)
davies_score = davies_bouldin_score(X, clusters)

# Create a table to display the metrics and the number of observations
table_data = [
    ["Number of Observations", num_observations],
    ["Silhouette Score", sil_score],
    ["Calinski Harabasz Score", calinski_score],
    ["Davies Bouldin Score", davies_score]
]

# Print the table
print(tabulate(table_data, headers=["Metric", "Value"], tablefmt='pretty'))
```

In [ ]:

```
# Setting 'CustomerID' column as index and assigning it to a new dataframe
```

```
df_customer = customer_data_cleaned.set_index('CustomerID')

# Standardize the data (excluding the cluster column)
scaler = StandardScaler()
df_customer_standardized = scaler.fit_transform(df_customer.drop(columns=['cluster'], axi
s=1))

# Create a new dataframe with standardized values and add the cluster column back
df_customer_standardized = pd.DataFrame(df_customer_standardized, columns=df_customer.col
umns[:-1], index=df_customer.index)
df_customer_standardized['cluster'] = df_customer['cluster']

# Calculate the centroids of each cluster
cluster_centroids = df_customer_standardized.groupby('cluster').mean()

# Function to create a radar chart
def create_radar_chart(ax, angles, data, color, cluster):
    # Plot the data and fill the area
    ax.fill(angles, data, color=color, alpha=0.4)
    ax.plot(angles, data, color=color, linewidth=2, linestyle='solid')

    # Add a title
    ax.set_title(f'Cluster {cluster}', size=20, color=color, y=1.1)

# Set data
labels=np.array(cluster_centroids.columns)
num_vars = len(labels)

# Compute angle of each axis
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()

# The plot is circular, so we need to "complete the loop" and append the start to the end
labels = np.concatenate((labels, [labels[0]]))
angles += angles[:1]

# Initialize the figure
fig, ax = plt.subplots(figsize=(20, 10), subplot_kw=dict(polar=True), nrows=1, ncols=3)

# Create radar chart for each cluster
for i, color in enumerate(colors):
    data = cluster_centroids.loc[i].tolist()
    data += data[:1]  # Complete the loop
    create_radar_chart(ax[i], angles, data, color, i)

# Add input data
ax[0].set_xticks(angles[:-1])
ax[0].set_xticklabels(labels[:-1])

ax[1].set_xticks(angles[:-1])
ax[1].set_xticklabels(labels[:-1])

ax[2].set_xticks(angles[:-1])
ax[2].set_xticklabels(labels[:-1])

# Add a grid
ax[0].grid(color='grey', linewidth=0.5)

# Display the plot
plt.tight_layout()
plt.show()
```

In [ ]:

```
# Plot histograms for each feature segmented by the clusters
features = customer_data_cleaned.columns[1:-1]
clusters = customer_data_cleaned['cluster'].unique()
clusters.sort()

# Setting up the subplots
n_rows = len(features)
n_cols = len(clusters)
```

```
fig, axes = plt.subplots(n_rows, n_cols, figsize=(20, 3*n_rows))

# Plotting histograms
for i, feature in enumerate(features):
    for j, cluster in enumerate(clusters):
        data = customer_data_cleaned[customer_data_cleaned['cluster'] == cluster][featur
e]
        axes[i, j].hist(data, bins=20, color=colors[j], edgecolor='w', alpha=0.7)
        axes[i, j].set_title(f'Cluster {cluster} - {feature}', fontsize=15)
        axes[i, j].set_xlabel('')
        axes[i, j].set_ylabel('')

# Adjusting layout to prevent overlapping
plt.tight_layout()
plt.show()
```

In [69]:

```
# Step 1: Extract the CustomerIDs of the outliers and remove their transactions from the
main dataframe
outlier_customer_ids = outliers_data['CustomerID'].astype('float').unique()
df_filtered = df[~df['CustomerID'].isin(outlier_customer_ids)]

# Step 2: Ensure consistent data type for CustomerID across both dataframes before mergin
g
customer_data_cleaned['CustomerID'] = customer_data_cleaned['CustomerID'].astype('float'
)

# Step 3: Merge the transaction data with the customer data to get the cluster informatio
n for each transaction
merged_data = df_filtered.merge(customer_data_cleaned[['CustomerID', 'cluster']], on='Cu
stomerID', how='inner')

# Step 4: Identify the top 10 best-selling products in each cluster based on the total qu
antity sold
best_selling_products = merged_data.groupby(['cluster', 'StockCode', 'Description'])['Qu
antity'].sum().reset_index()
best_selling_products = best_selling_products.sort_values(by=['cluster', 'Quantity'], as
cending=[True, False])
top_products_per_cluster = best_selling_products.groupby('cluster').head(10)

# Step 5: Create a record of products purchased by each customer in each cluster
customer_purchases = merged_data.groupby(['CustomerID', 'cluster', 'StockCode'])['Quanti
ty'].sum().reset_index()

# Step 6: Generate recommendations for each customer in each cluster
recommendations = []
for cluster in top_products_per_cluster['cluster'].unique():
    top_products = top_products_per_cluster[top_products_per_cluster['cluster'] == clust
er]
    customers_in_cluster = customer_data_cleaned[customer_data_cleaned['cluster'] == clu
ster]['CustomerID']

    for customer in customers_in_cluster:
        # Identify products already purchased by the customer
        customer_purchased_products = customer_purchases[(customer_purchases['CustomerID
'] == customer) &
                                                         (customer_purchases['cluster']
== cluster)]['StockCode'].tolist()

        # Find top 3 products in the best-selling list that the customer hasn't purchased
yet
        top_products_not_purchased = top_products[~top_products['StockCode'].isin(custom
er_purchased_products)]
        top_3_products_not_purchased = top_products_not_purchased.head(3)

        # Append the recommendations to the list
        recommendations.append([customer, cluster] + top_3_products_not_purchased[['Stoc
kCode', 'Description']].values.flatten().tolist())

# Step 7: Create a dataframe from the recommendations list and merge it with the original
```

```
customer data
recommendations_df = pd.DataFrame(recommendations, columns=['CustomerID', 'cluster', 'Re
c1_StockCode', 'Rec1_Description', \
                                                 'Rec2_StockCode', 'Rec2_Description',
'Rec3_StockCode', 'Rec3_Description'])
customer_data_with_recommendations = customer_data_cleaned.merge(recommendations_df, on=[
'CustomerID', 'cluster'], how='right')
```

In [ ]:

```
# Display 10 random rows from the customer_data_with_recommendations dataframe
customer_data_with_recommendations.set_index('CustomerID').iloc[:, -6:].sample(10, rando
m_state=0)
```