WQD7005_Project_Khor_Kean_Teng

June 27, 2025

1 Data Generation

[1]:
```python
# configure api
from dotenv import load_dotenv
import os

load_dotenv()
gemini_api_key = os.getenv("GEMINI_API_KEY")
```

[2]:
```python
from google import genai
from google.genai import types

client = genai.Client(api_key=gemini_api_key)

model = [
    "gemini-2.5-flash-preview-04-17"
]
```

[4]:
```python
# extract the prompt in `Prompt Engineering.txt`
with open("../prompts/sample.txt", "r") as file:
    original_prompt = file.read()

print(original_prompt)
```

```
You should generate dataset of 30 random customer based on the provided
instruction to analysis their behavior and predict churn in CSV format.

Below shows the data schema description and you should try to have a balance of
deteriorated and non-deteriorated patients.

Data Schema:
CustomerID: Unique identifier for each customer
Age: Age of the customer
Gender: Gender of the customer
Location: A random location
MembershipLevel: The level of membership (e.g., Bronze, Silver, Gold, Platinum)
TotalPurchases: Total number of purchases made by the customer
TotalSpent: Total amount spent by the customer
```

```
FavoriteCategory: Favorite product category of the customer
LastPurchaseDate: Date of the last purchase
WebsiteClickRate: Click-through rate on the website
TimeSpentOnSite: Average time spent on the site per visit
SocialMediaEngagement: Engagement level on social media
AdClickHistory: History of ad clicks
GeneratedReview: Customer review generated based on their experience
CustomerSentimentScore: Sentiment score of the customer review
PersonaTag: A tag representing the customer's persona (e.g., Loyal, Bargain
Hunter, Impulsive Buyer)
Churn: Numeric number representing if the customer has churned (1/0)
```

[ ]:

```python
# loop each prompt with update patient id to the llm
# and get the response and save it as a json file as data/patient_id.json
# the patient_id is the patient id in the prompt
import time  # Import the time module for delay
import uuid

history = []

# Loop to repeat the process 50 times
for iteration in range(30):
    print(f"Iteration {iteration + 1} of 40")

    # Calculate the start and end indices for the current batch
    start_index = iteration * 10
    end_index = start_index + 10

    # Always start with the original prompt and add current history
    # This way we're not continuously appending to the prompt
    prompt = f"Unique session ID: {uuid.uuid4()} \n\n{original_prompt}"

    # Get the response from the LLM
    response = client.models.generate_content(model=model[0], contents=prompt)

    # Update the history with the current response
    history.append(response)

    # Save the response as a JSON file
    with open(f"../data/exam/run_{iteration}.csv", "w") as file:
        file.write(response.text)

    # Wait for one minute before the next iteration
    if iteration < 49:  # Avoid waiting after the last iteration
        print("Waiting for 1 minute before the next iteration...")
        if iteration % 5 == 0:
            pass
```

```
        else:
            time.sleep(60)

%echo "All iterations completed. Check the data/raw directory for the output␣
 ↪files."
```

```
Iteration 1 of 40
Waiting for 1 minute before the next iteration…
Iteration 2 of 40
Waiting for 1 minute before the next iteration…
Iteration 3 of 40
Waiting for 1 minute before the next iteration…
Iteration 4 of 40
Waiting for 1 minute before the next iteration…
Iteration 5 of 40
Waiting for 1 minute before the next iteration…
Iteration 6 of 40
Waiting for 1 minute before the next iteration…
Iteration 7 of 40
Waiting for 1 minute before the next iteration…
Iteration 8 of 40
Waiting for 1 minute before the next iteration…
Iteration 9 of 40
Waiting for 1 minute before the next iteration…
Iteration 10 of 40
Waiting for 1 minute before the next iteration…
Iteration 11 of 40
Waiting for 1 minute before the next iteration…
Iteration 12 of 40
Waiting for 1 minute before the next iteration…
Iteration 13 of 40
Waiting for 1 minute before the next iteration…
Iteration 14 of 40
Waiting for 1 minute before the next iteration…
Iteration 15 of 40
Waiting for 1 minute before the next iteration…
Iteration 16 of 40
Waiting for 1 minute before the next iteration…
Iteration 17 of 40
Waiting for 1 minute before the next iteration…
Iteration 18 of 40
Waiting for 1 minute before the next iteration…
Iteration 19 of 40
Waiting for 1 minute before the next iteration…
Iteration 20 of 40
Waiting for 1 minute before the next iteration…
Iteration 21 of 40
Waiting for 1 minute before the next iteration…
```

```
Iteration 22 of 40
Waiting for 1 minute before the next iteration…
Iteration 23 of 40
Waiting for 1 minute before the next iteration…
Iteration 24 of 40
Waiting for 1 minute before the next iteration…
Iteration 25 of 40
Waiting for 1 minute before the next iteration…
Iteration 26 of 40
Waiting for 1 minute before the next iteration…
Iteration 27 of 40
Waiting for 1 minute before the next iteration…
Iteration 28 of 40
Waiting for 1 minute before the next iteration…
Iteration 29 of 40
Waiting for 1 minute before the next iteration…
Iteration 30 of 40
Waiting for 1 minute before the next iteration…
```

1.1 Section 2: Data Extraction

In this section, we will extract the generated data in JSON format and transform it into a Data Frame to be used for further analysis.

[3]:
```
# import libraries
import pandas as pd
import json
import os
import warnings
import uuid

# ignore warnings
warnings.filterwarnings("ignore")
```

1.2 2.1 Data Extraction

Extracts all the patients data in the 40 JSON files. Then, combine them into a single CSV file for further analysis.

[12]:
```
# Define the path to the raw data directory
raw_data_path = "../data/exam"

# Initialize an empty list to store all patient records
all_patients = []

# Check if the directory exists
if os.path.exists(raw_data_path):
    # Loop through all CSV files in the directory
```

```python
    for filename in os.listdir(raw_data_path):
        if filename.endswith('.csv'):
            file_path = os.path.join(raw_data_path, filename)

            try:
                # Read the CSV file with error handling for parsing issues
                data = pd.read_csv(file_path, on_bad_lines='skip')

                # Process each patient record in the file
                for index, patient in data.iterrows():
                    # Convert the row to a dictionary
                    patient_dict = patient.to_dict()

                    # Convert the patient_id to 5 digit uuid4 if needed
                    patient_dict['CustomerID'] = str(uuid.uuid4())[:7]

                    # Add to our collection
                    all_patients.append(patient_dict)

            except Exception as e:
                print(f"Error reading CSV file {filename}: {e}")

    # Create DataFrame from all patient records
    patient_df = pd.DataFrame(all_patients)

    # Display basic information about the DataFrame
    print(f"Total number of patient records: {len(patient_df)}")
    print("\nDataFrame columns:")
    print(patient_df.columns.tolist())
    print("\nDataFrame shape:", patient_df.shape)
    print("\nFirst 5 rows:")
    display(patient_df.head())

else:
    print(f"Directory {raw_data_path} does not exist.")
```

```
Total number of patient records: 880

DataFrame columns:
['CustomerID', 'Age', 'Gender', 'Location', 'MembershipLevel', 'TotalPurchases',
'TotalSpent', 'FavoriteCategory', 'LastPurchaseDate', 'WebsiteClickRate',
'TimeSpentOnSite', 'SocialMediaEngagement', 'AdClickHistory', 'GeneratedReview',
'CustomerSentimentScore', 'PersonaTag', 'Churn']

DataFrame shape: (880, 17)

First 5 rows:
```

```
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

  TotalSpent FavoriteCategory LastPurchaseDate WebsiteClickRate  \
0      753.6         Clothing       2023-10-20            0.065
1     2155.4      Electronics       2023-10-25            0.092
2     4510.1       Home Goods       2023-09-18            0.115
3       85.7            Books       2023-08-01            0.041
4     1220.5           Beauty       2023-10-10            0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                         GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4             Will definitely buy again.                    0.88

       PersonaTag  Churn
0   Regular Buyer      0
1           Loyal      0
2           Loyal      0
3  Window Shopper      1
4         Engaged      0
```

[13]:
```python
# save the output to a CSV file in /data
patient_df.to_csv("../data/exam/processed/merged_data.csv", index=False)
```

2 Feature Engineering

[1]:
```python
# import libraries
import os
import pandas as pd
import time
```

[2]:
```python
# load the data for preview
df = pd.read_csv('../data/exam/processed/merged_data.csv')

# preview the data
display(df.head())
```

```
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
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  TotalSpent FavoriteCategory LastPurchaseDate WebsiteClickRate  \
0      753.6         Clothing       2023-10-20            0.065
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3       85.7            Books       2023-08-01            0.041
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3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                        GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
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3  Had some issues, not fully satisfied.                    0.52
4             Will definitely buy again.                    0.88

       PersonaTag  Churn
0   Regular Buyer      0
1           Loyal      0
2           Loyal      0
3  Window Shopper      1
4         Engaged      0
```

[3]:
```python
# configure api
from dotenv import load_dotenv
import os

load_dotenv()
gemini_api_key = os.getenv("GEMINI_API_KEY")
```

[4]:
```python
from google import genai
from google.genai import types

client = genai.Client(api_key=gemini_api_key)

model = [
    "gemini-2.5-flash-preview-04-17"
]

generate_content_config = types.GenerateContentConfig(
    response_mime_type="application/json",
)
```

[5]:
```python
import json
from datetime import datetime

def process_sentiment_batch(batch_df):
    """
    Process a batch of rows using the Gemini model to analyze sentiment in text␣
 ↪responses.
    Returns sentiment scores for the generated reviews.
    """
    # Combine all text responses into a single prompt for batch processing
    rows = []
    for idx, row in batch_df.iterrows():
        row_data = {
            "id": row["CustomerID"],
            "sentiment_level": row["GeneratedReview"],
        }
        rows.append(row_data)

    prompt = f"""Analyze the sentiment in these responses and rate each on a␣
 ↪scale from 1-5:
    - Sentiment level (1: Very Bad, 5: Very Good)

    For each customer, return ONLY a JSON object with their ID and the one␣
 ↪numerical ratings.
    If a response is missing or unclear, assign a neutral value of 3.

    Customer responses:
    {rows}
    """

    response = client.models.generate_content(model=model[0], contents=prompt,␣
 ↪config=generate_content_config)

    return response.text
```

[6]:

```python
# Process the dataframe in batches of 20 rows
batch_size = 40
request_count = 0
max_retries = 3

for i in range(0, len(df), batch_size):
    print(f"Processing batch {i // batch_size + 1} of {(len(df) + batch_size -
↪1) // batch_size}")
    batch_df = df.iloc[i:i+batch_size]
    batch_results = process_sentiment_batch(batch_df)

    success = False
    retry_count = 0

    while not success and retry_count < max_retries:
        try:
            batch_results = process_sentiment_batch(batch_df)

            # Try to save the response to a file
            try:
                with open(f"../data/exam/raw_2/run_{i}.json", "w") as file:
                    file.write(batch_results)
                success = True
                print(f"Successfully processed and saved batch {i // batch_size
↪+ 1}")
            except Exception as e:
                print(f"Error saving results: {str(e)}. Retrying...")
                retry_count += 1
                time.sleep(2)  # Short delay before retry

        except Exception as e:
            print(f"Error processing batch: {str(e)}. Retrying...")
            retry_count += 1
            time.sleep(5)  # Slightly longer delay for API errors

    if not success:
        print(f"Failed to process batch starting at index {i} after
↪{max_retries} attempts. Skipping.")

    # Increment request counter
    request_count += 1

    # Add delay after every 5 requests
    if request_count % 5 == 0 and i + batch_size < len(df):
        print(f"Completed {request_count} requests. Taking a 1-minute break to
↪avoid rate limiting...")
        time.sleep(60)  # Sleep for 60 seconds (1 minute)
```

```python
        print("Resuming processing...")
```

```
Processing batch 1 of 22
Successfully processed and saved batch 1
Processing batch 2 of 22
Successfully processed and saved batch 2
Processing batch 3 of 22
Successfully processed and saved batch 3
Processing batch 4 of 22
Successfully processed and saved batch 4
Processing batch 5 of 22
Successfully processed and saved batch 5
Completed 5 requests. Taking a 1-minute break to avoid rate limiting…
Resuming processing…
Processing batch 6 of 22
Successfully processed and saved batch 6
Processing batch 7 of 22
Successfully processed and saved batch 7
Processing batch 8 of 22
Successfully processed and saved batch 8
Processing batch 9 of 22
Successfully processed and saved batch 9
Processing batch 10 of 22
Successfully processed and saved batch 10
Completed 10 requests. Taking a 1-minute break to avoid rate limiting…
Resuming processing…
Processing batch 11 of 22
Successfully processed and saved batch 11
Processing batch 12 of 22
Successfully processed and saved batch 12
Processing batch 13 of 22
Successfully processed and saved batch 13
Processing batch 14 of 22
Successfully processed and saved batch 14
Processing batch 15 of 22
Successfully processed and saved batch 15
Completed 15 requests. Taking a 1-minute break to avoid rate limiting…
Resuming processing…
Processing batch 16 of 22
Successfully processed and saved batch 16
Processing batch 17 of 22
Successfully processed and saved batch 17
Processing batch 18 of 22
Successfully processed and saved batch 18
Processing batch 19 of 22
Successfully processed and saved batch 19
Processing batch 20 of 22
Successfully processed and saved batch 20
```

```
Completed 20 requests. Taking a 1-minute break to avoid rate limiting…
Resuming processing…
Processing batch 21 of 22
Successfully processed and saved batch 21
Processing batch 22 of 22
Successfully processed and saved batch 22
```

[8]:

```python
import glob

# Define the directory containing the JSON files
json_dir = "../data/exam/raw_2"

# Get a list of all JSON files
json_files = glob.glob(os.path.join(json_dir, "*.json"))

# Initialize empty lists to store the data
all_ratings = []

# Process each JSON file
for file_path in json_files:
    try:
        with open(file_path, 'r') as file:
            content = file.read()

            # Try to parse the JSON
            try:
                data = json.loads(content)

                # Handle both list and single object formats
                if isinstance(data, list):
                    ratings = data
                else:
                    ratings = [data]

                # Process each rating entry
                for rating in ratings:
                    # Standardize field names
                    patient_id = rating.get("id", rating.get("CustomerID"))

                    # Handle different possible field names for fatigue
                    fatigue_level = rating.get("sentiment",
                                     rating.get("sentiment_level",
                                     rating.get("rating", None)))


                    # Add to our collection if valid
                    if patient_id:
```

```
                        all_ratings.append({
                            "CustomerID": patient_id,
                            "llm_sentiment": fatigue_level,
                        })
            except json.JSONDecodeError as e:
                print(f"Error parsing JSON in file {file_path}: {e}")

    except Exception as e:
        print(f"Error processing file {file_path}: {e}")

# Create a dataframe from the collected ratings
ratings_df = pd.DataFrame(all_ratings)

# Print summary statistics
print(f"Successfully processed {len(ratings_df)} patient ratings")
print(f"Number of unique patients: {ratings_df['CustomerID'].nunique()}")

# Display the first few rows of the ratings dataframe
display(ratings_df.head())

# Now merge with the original dataframe (df_encoded)
df_with_ratings = df.merge(ratings_df, on="CustomerID", how="left")

# Check for any patients without ratings
missing_ratings = df_with_ratings[df_with_ratings['llm_sentiment'].
 ↪isna()]['CustomerID'].count()
print(f"Patients without ratings: {missing_ratings} out of␣
 ↪{len(df_with_ratings)}")

# Display the first few rows of the merged dataframe
display(df_with_ratings.head())
```

```
Successfully processed 880 patient ratings
Number of unique patients: 880

  CustomerID  llm_sentiment
0    4efed90              5
1    d7f26e8              4
2    6b4a427              5
3    68eec52              2
4    3a2af82              4

Patients without ratings: 0 out of 880

  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
```

```
4    3a2af82  Female      Phoenix       AZ          Silver              18

  TotalSpent FavoriteCategory LastPurchaseDate WebsiteClickRate  \
0      753.6         Clothing       2023-10-20            0.065
1     2155.4      Electronics       2023-10-25            0.092
2     4510.1       Home Goods       2023-09-18            0.115
3       85.7            Books       2023-08-01            0.041
4     1220.5           Beauty       2023-10-10            0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                         GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4              Will definitely buy again.                    0.88

       PersonaTag  Churn  llm_sentiment
0   Regular Buyer      0              5
1           Loyal      0              4
2           Loyal      0              5
3  Window Shopper      1              2
4         Engaged      0              4
```

[9]:

```
# Save the merged dataframe to a new file
df_with_ratings.to_csv('../data/exam/processed/merged_data_with_ratings.csv',␣
 ↪index=False)
print("DataFrame with ratings saved to '../data/exam/processed/
 ↪merged_data_with_ratings.csv'")
```

```
DataFrame with ratings saved to
'../data/exam/processed/merged_data_with_ratings.csv'
```

3 RFM Analysis

[7]:

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

df = pd.read_csv('../data/exam/processed/merged_data_with_ratings.csv')
display(df.head())
```

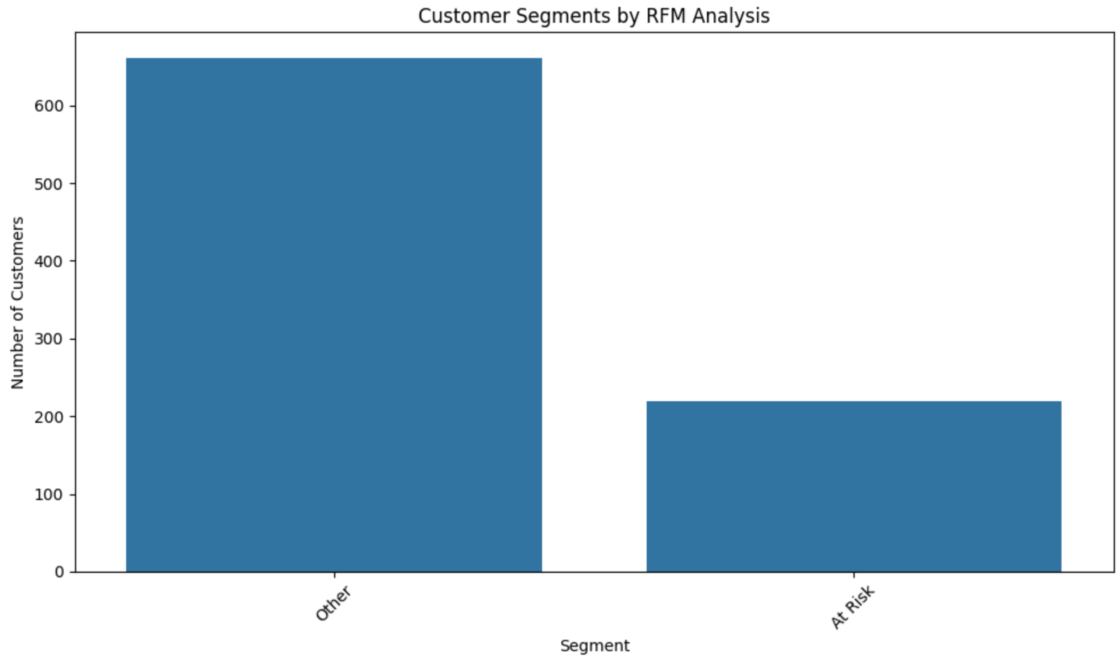
```
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

  TotalSpent FavoriteCategory LastPurchaseDate WebsiteClickRate  \
0      753.6         Clothing       2023-10-20            0.065
1     2155.4      Electronics       2023-10-25            0.092
2     4510.1       Home Goods       2023-09-18            0.115
3       85.7            Books       2023-08-01            0.041
4     1220.5           Beauty       2023-10-10            0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                         GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4             Will definitely buy again.                    0.88

       PersonaTag  Churn  llm_sentiment
0   Regular Buyer      0              5
1           Loyal      0              4
2           Loyal      0              5
3  Window Shopper      1              2
4         Engaged      0              4
```

[11]:
```
# Perform RFM analysis
def perform_rfm_analysis(df):
    # Use the most recent date in the dataset as the reference date
    # make sure 'LastPurchaseDate' is in datetime format
    df['LastPurchaseDate'] = pd.to_datetime(df['LastPurchaseDate'],␣
 ↪errors='coerce')
    max_date = df['LastPurchaseDate'].max()

    # Calculate RFM metrics
    rfm = df.groupby('CustomerID').agg({
        'LastPurchaseDate': lambda x: (max_date - x.max()).total_seconds() /␣
 ↪(3600*24),  # Recency in days
```

```
        'TotalPurchases': 'count',  # Frequency
        'SocialMediaEngagement': lambda x: len(x.unique())  # Monetary (using␣
↪number of stores as proxy)
    }).rename(columns={
        'LastPurchaseDate': 'Recency',
        'TotalPurchases': 'Frequency',
        'SocialMediaEngagement': 'Monetary'
    })

    # Create RFM segments with error handling
    try:
        rfm['R_Quartile'] = pd.qcut(rfm['Recency'], 4, labels=range(4, 0, -1),␣
↪duplicates='drop')
    except ValueError:
        # If qcut fails, use simple ranking
        rfm['R_Quartile'] = pd.cut(rfm['Recency'], 4, labels=range(4, 0, -1))

    try:
        rfm['F_Quartile'] = pd.qcut(rfm['Frequency'], 4, labels=range(1, 5),␣
↪duplicates='drop')
    except ValueError:
        rfm['F_Quartile'] = pd.cut(rfm['Frequency'], 4, labels=range(1, 5))

    try:
        rfm['M_Quartile'] = pd.qcut(rfm['Monetary'], 4, labels=range(1, 5),␣
↪duplicates='drop')
    except ValueError:
        rfm['M_Quartile'] = pd.cut(rfm['Monetary'], 4, labels=range(1, 5))

    # Combine RFM scores
    rfm['RFM_Score'] = rfm['R_Quartile'].astype(str) + rfm['F_Quartile'].
↪astype(str) + rfm['M_Quartile'].astype(str)

    # Define customer segments
    segment_map = {
        r'[4][4-5][4-5]': 'Champions',
        r'[3][3-5][3-5]': 'Loyal Customers',
        r'[1-2][4-5][4-5]': 'Potential Loyalists',
        r'[1-2][3][2-3]': 'New Customers',
        r'[1][1-2][1-2]': 'At Risk'
    }

    rfm['Segment'] = 'Other'
    for pattern, segment in segment_map.items():
        rfm.loc[rfm['RFM_Score'].str.contains(pattern), 'Segment'] = segment

    return rfm
```

```python
# Perform RFM analysis
rfm_analysis = perform_rfm_analysis(df)
print("RFM Customer Segmentation:")
print(rfm_analysis.head())

# Visualize customer segments
plt.figure(figsize=(10, 6))
segment_counts = rfm_analysis['Segment'].value_counts()
sns.barplot(x=segment_counts.index, y=segment_counts.values)
plt.title('Customer Segments by RFM Analysis')
plt.xlabel('Segment')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('../images/rfm_segments.png')
```

```
RFM Customer Segmentation:
            Recency  Frequency  Monetary R_Quartile F_Quartile M_Quartile  \
CustomerID
006f135        10.0          1         1          4          2          2
0078894       399.0          1         1          2          2          2
010e880       437.0          1         1          2          2          2
0130f5b       758.0          1         1          1          2          2
01a733c       231.0          1         1          4          2          2

           RFM_Score  Segment
CustomerID
006f135          422    Other
0078894          222    Other
010e880          222    Other
0130f5b          122  At Risk
01a733c          422    Other
```



[1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
# import decision tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import accuracy_score, classification_report,␣
  ↪confusion_matrix, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns

# Load the Titanic dataset
# You can download from: https://www.kaggle.com/c/titanic/data
df = pd.read_csv('../data/exam/processed/merged_data_with_ratings.csv')
```

[2]:
```
# Display basic info about the dataset
print("Dataset Info:")
print(df.info())
print("\nFirst few rows:")
display(df.head())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 880 entries, 0 to 879
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
```

```
---  ------                  --------------  -----
 0   CustomerID              880 non-null    object
 1   Age                     880 non-null    object
 2   Gender                  880 non-null    object
 3   Location                880 non-null    object
 4   MembershipLevel         880 non-null    object
 5   TotalPurchases          880 non-null    int64
 6   TotalSpent              880 non-null    float64
 7   FavoriteCategory        859 non-null    object
 8   LastPurchaseDate        879 non-null    object
 9   WebsiteClickRate        880 non-null    float64
 10  TimeSpentOnSite         880 non-null    float64
 11  SocialMediaEngagement   880 non-null    object
 12  AdClickHistory          808 non-null    object
 13  GeneratedReview         878 non-null    object
 14  CustomerSentimentScore  880 non-null    float64
 15  PersonaTag              880 non-null    object
 16  Churn                   880 non-null    int64
 17  llm_sentiment           880 non-null    int64
dtypes: float64(4), int64(3), object(11)
memory usage: 123.9+ KB
None

First few rows:

  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                        GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
```

```
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4              Will definitely buy again.                   0.88

       PersonaTag  Churn  llm_sentiment
0   Regular Buyer      0              5
1           Loyal      0              4
2           Loyal      0              5
3  Window Shopper      1              2
4         Engaged      0              4
```

[3]:

```
# Data preprocessing
# Handle missing values
df['Gender_new'] = df['Age']
display(df.head())
# create a new column 'Age_new' and fill it with random values range from 18 to␣
↪76
df['Age_new'] = np.random.randint(18, 76, size=len(df))

# remove $sign from 'TotalSpend' and convert it to float
df['TotalSpent'] = df['TotalSpent'].replace({'\$': '', ',': ''}, regex=True).
↪astype(float)
# remove TotalSpend that is not a number and bfill it with the previous value
df['TotalSpent'] = pd.to_numeric(df['TotalSpent'], errors='coerce')
```

```
<>:9: SyntaxWarning: invalid escape sequence '\$'
<>:9: SyntaxWarning: invalid escape sequence '\$'
C:\Users\Khor Kean Teng\AppData\Local\Temp\ipykernel_18824\1217612237.py:9:
SyntaxWarning: invalid escape sequence '\$'
  df['TotalSpent'] = df['TotalSpent'].replace({'\$': '', ',': ''},
regex=True).astype(float)

  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
```

```
0           15.2               Medium       Clicked
1           22.5                 High     Sometimes
2           28.1                 High       Clicked
3            8.9                  Low   Not Clicked
4           18.7               Medium       Clicked

                        GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4             Will definitely buy again.                    0.88

        PersonaTag  Churn  llm_sentiment Gender_new
0    Regular Buyer      0              5     Female
1            Loyal      0              4       Male
2            Loyal      0              5      Other
3   Window Shopper      1              2       Male
4          Engaged      0              4     Female
```

[4]:

```
# Encode categorical variables
le = LabelEncoder()
df['MembershipLevel'] = le.fit_transform(df['MembershipLevel'])
df['FavoriteCategory'] = le.fit_transform(df['FavoriteCategory'])
df['SocialMediaEngagement'] = le.fit_transform(df['SocialMediaEngagement'])
df['AdClickHistory'] = le.fit_transform(df['AdClickHistory'])
df['PersonaTag'] = le.fit_transform(df['PersonaTag'])
df['Gender_new'] = le.fit_transform(df['Gender_new'])

# Select features for the model
features = [
    'Age_new', 'Gender_new', 'MembershipLevel', 'TotalPurchases',
    'TotalSpent', 'FavoriteCategory', 'SocialMediaEngagement',
    'TimeSpentOnSite', 'WebsiteClickRate', 'AdClickHistory',
    'CustomerSentimentScore', 'PersonaTag', 'llm_sentiment'
]
X = df[features]
y = df['Churn']
```

[5]:

```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y)
```

[6]:

```
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[7]:
```
# Train the logistic regression model
lr_model = DecisionTreeClassifier(random_state=42, max_depth=5)
lr_model.fit(X_train_scaled, y_train)
```

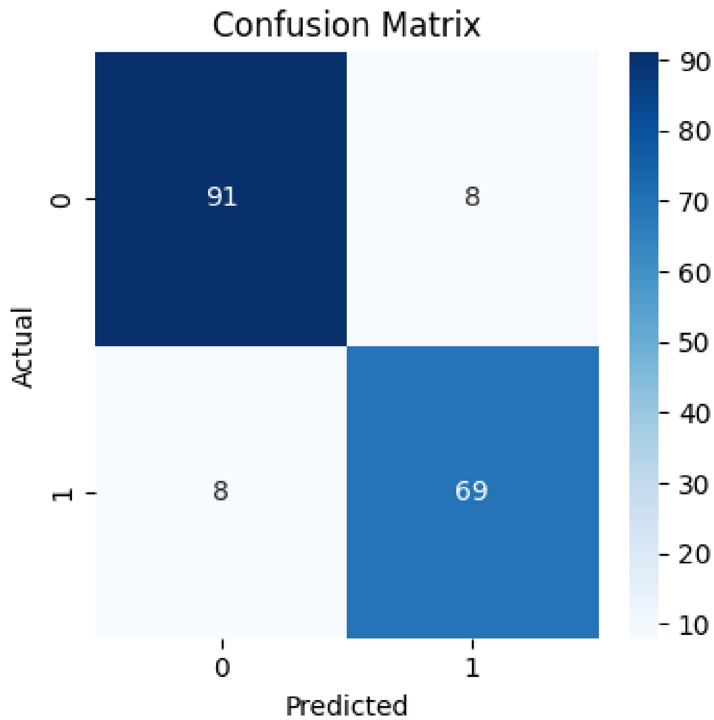
[7]:
```
DecisionTreeClassifier(max_depth=5, random_state=42)
```

[8]:
```
# Make predictions
y_pred = lr_model.predict(X_test_scaled)
y_pred_proba = lr_model.predict_proba(X_test_scaled)[:, 1]
```

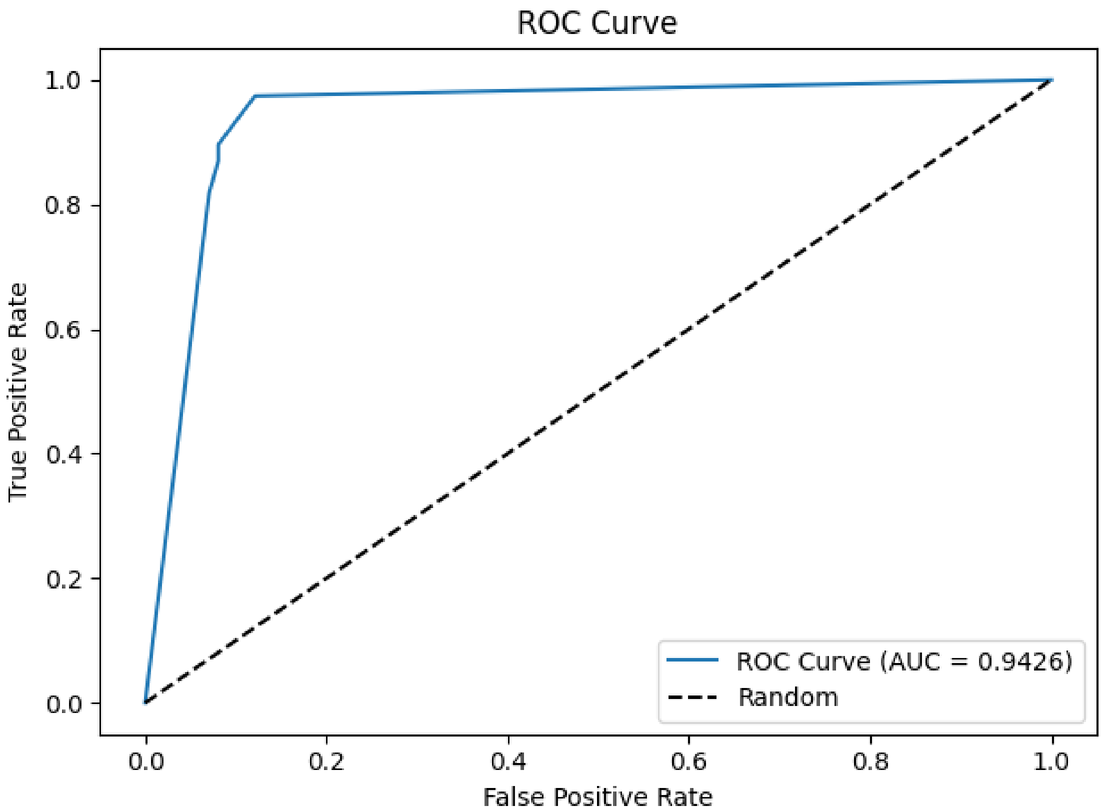
[9]:
```
# Model evaluation
print("\n=== MODEL EVALUATION ===")
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"ROC AUC Score: {roc_auc_score(y_test, y_pred_proba):.4f}")

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
=== MODEL EVALUATION ===
Accuracy: 0.9091
ROC AUC Score: 0.9426

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.92      0.92        99
           1       0.90      0.90      0.90        77

    accuracy                           0.91       176
   macro avg       0.91      0.91      0.91       176
weighted avg       0.91      0.91      0.91       176
```

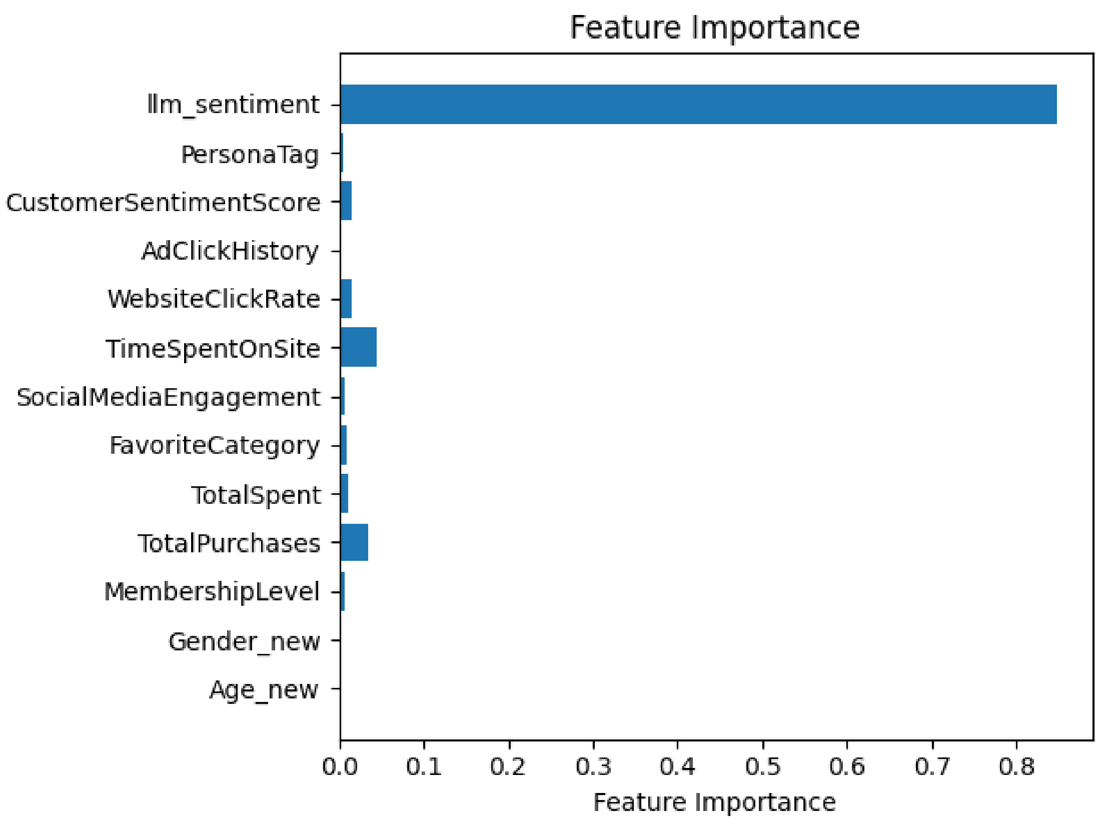
[10]:
```
# Confusion Matrix
plt.figure(figsize=(4, 4))

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.savefig('../images/decision_tree_confusion_matrix.png')
```



[11]:
```
# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc_score(y_test,␣
↪y_pred_proba):.4f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.tight_layout()
plt.savefig('../images/decision_tree_model_roc.png')
```



[12]:
```
# Feature importance
feature_importance = lr_model.feature_importances_
feature_names = features
plt.barh(feature_names, feature_importance)
plt.xlabel('Feature Importance')
plt.title('Feature Importance')

plt.tight_layout()
plt.savefig('../images/decision_tree_model_feature.png')
```



[13]:
```python
# Additional evaluation metrics
from sklearn.metrics import precision_score, recall_score, f1_score

print("\n=== ADDITIONAL METRICS ===")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall: {recall_score(y_test, y_pred):.4f}")
print(f"F1-Score: {f1_score(y_test, y_pred):.4f}")
```

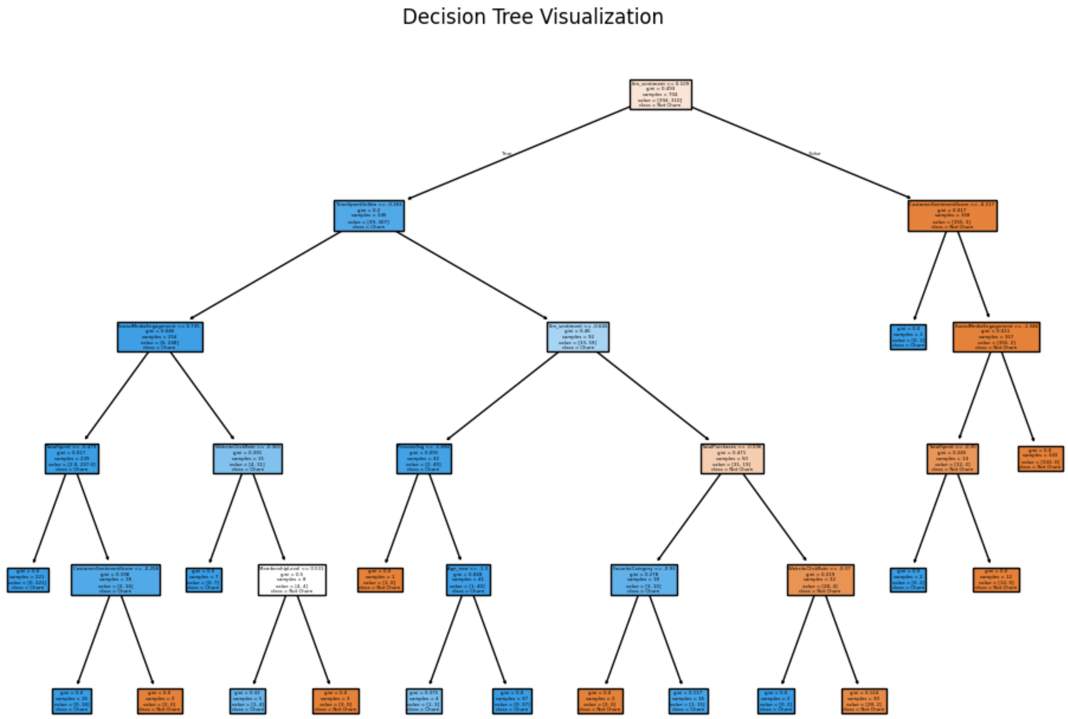
```
=== ADDITIONAL METRICS ===
Precision: 0.8961
Recall: 0.8961
F1-Score: 0.8961
```

[14]:
```python
# Cross-validation for more robust evaluation
from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(lr_model, X_train_scaled, y_train, cv=5,␣
↪scoring='accuracy')
print(f"\nCross-validation scores: {cv_scores}")
```

```
print(f"Mean CV accuracy: {cv_scores.mean():.4f} (+/- {cv_scores.std() * 2:.
↪4f})")

# Feature importance interpretation (Decision Tree uses feature importance, not␣
↪coefficients)
print("\n=== FEATURE IMPORTANCE ===")
importance_df = pd.DataFrame({
    'Feature': features,
    'Importance': lr_model.feature_importances_
}).sort_values('Importance', ascending=False)

print(importance_df)
```

```
Cross-validation scores: [0.95744681 0.95744681 0.97163121 0.96453901
0.93571429]
Mean CV accuracy: 0.9574 (+/- 0.0241)

=== FEATURE IMPORTANCE ===
                   Feature  Importance
12            llm_sentiment    0.847780
7           TimeSpentOnSite    0.044831
3            TotalPurchases    0.034173
10  CustomerSentimentScore    0.016341
8          WebsiteClickRate    0.015175
4                TotalSpent    0.011350
5          FavoriteCategory    0.009238
6     SocialMediaEngagement    0.007190
2           MembershipLevel    0.007095
11               PersonaTag    0.005493
0                   Age_new    0.001334
1                Gender_new    0.000000
9            AdClickHistory    0.000000
```

[15]:
```
# plot the decision tree
from sklearn.tree import plot_tree

plt.figure(figsize=(12, 8))
plot_tree(lr_model, feature_names=features, class_names=['Not Churn', 'Churn'],␣
↪filled=True)
plt.title('Decision Tree Visualization')
plt.savefig('../images/decision_tree.png')
```



[50]:
```python
# import libraries
import pandas as pd
import warnings


# turn off warnings
warnings.filterwarnings("ignore")
```

[51]:
```python
# load the data
df = pd.read_csv('../data/exam/processed/merged_data_with_ratings.csv')

# preview the data
display(df.head())
```

```
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
```

```
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                        GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4             Will definitely buy again.                    0.88

       PersonaTag  Churn  llm_sentiment
0   Regular Buyer      0              5
1           Loyal      0              4
2           Loyal      0              5
3  Window Shopper      1              2
4         Engaged      0              4
```

[52]:

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
# import decision tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns
```

[53]:

```python
# Data preprocessing
# Handle missing values
df['Gender_new'] = df['Age']
display(df.head())
# create a new column 'Age_new' and fill it with random values range from 18 to␣
↪76
df['Age_new'] = np.random.randint(18, 76, size=len(df))

# remove $sign from 'TotalSpend' and convert it to float
```

```
df['TotalSpent'] = df['TotalSpent'].replace({'\$': '', ',': ''}, regex=True).
↪astype(float)
# remove TotalSpend that is not a number and bfill it with the previous value
df['TotalSpent'] = pd.to_numeric(df['TotalSpent'], errors='coerce')
```

```
  CustomerID     Age        Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female        Denver       CO          Silver              12
1    d7f26e8    Male   Los Angeles       CA            Gold              28
2    6b4a427   Other       Chicago       IL        Platinum              41
3    68eec52    Male       Houston       TX          Bronze               2
4    3a2af82  Female       Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                        GeneratedReview  CustomerSentimentScore  \
0      Great experience, love this store!                    0.91
1           Very happy with my purchases.                    0.95
2         Excellent service and products.                    0.98
3   Had some issues, not fully satisfied.                    0.52
4              Will definitely buy again.                    0.88

       PersonaTag  Churn  llm_sentiment Gender_new
0   Regular Buyer      0              5     Female
1           Loyal      0              4       Male
2           Loyal      0              5      Other
3  Window Shopper      1              2       Male
4         Engaged      0              4     Female
```

[54]:

```
# Data preprocessing
# Handle missing values
df['Gender_new'] = df['Age']
display(df.head())
# create a new column 'Age_new' and fill it with random values range from 18 to␣
↪76
df['Age_new'] = np.random.randint(18, 76, size=len(df))
```

```
# remove $sign from 'TotalSpend' and convert it to float
df['TotalSpent'] = df['TotalSpent'].replace({'\$': '', ',': ''}, regex=True).
↪astype(float)
# remove TotalSpend that is not a number and bfill it with the previous value
df['TotalSpent'] = pd.to_numeric(df['TotalSpent'], errors='coerce')
```

```
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                         GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
3  Had some issues, not fully satisfied.                    0.52
4             Will definitely buy again.                    0.88

        PersonaTag  Churn  llm_sentiment Gender_new  Age_new
0   Regular Buyer      0              5     Female       24
1           Loyal      0              4       Male       63
2           Loyal      0              5      Other       39
3  Window Shopper      1              2       Male       27
4         Engaged      0              4     Female       36
```

[55]:

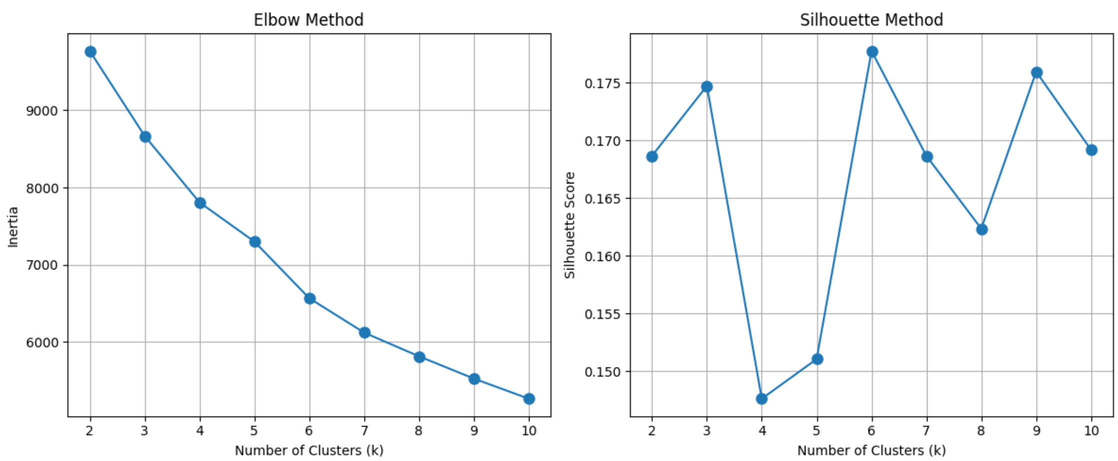
```
# Encode categorical variables
le = LabelEncoder()
df['MembershipLevel'] = le.fit_transform(df['MembershipLevel'])
df['FavoriteCategory'] = le.fit_transform(df['FavoriteCategory'])
df['SocialMediaEngagement'] = le.fit_transform(df['SocialMediaEngagement'])
```

```
df['AdClickHistory'] = le.fit_transform(df['AdClickHistory'])
df['PersonaTag'] = le.fit_transform(df['PersonaTag'])
df['Gender_new'] = le.fit_transform(df['Gender_new'])

# Select features for the model
features = [
    'Age_new', 'Gender_new', 'MembershipLevel', 'TotalPurchases',
    'TotalSpent', 'FavoriteCategory', 'SocialMediaEngagement',
    'TimeSpentOnSite', 'WebsiteClickRate', 'AdClickHistory',
    'CustomerSentimentScore', 'PersonaTag', 'llm_sentiment'
]
X = df[features]
y = df['Churn']
```

[56]:
```
# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[57]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Use the scaled features that you've already prepared
X = X_scaled.copy()

# Determine optimal number of clusters using Elbow Method
inertia = []
silhouette_scores = []
k_range = range(2, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)

    # Calculate silhouette score (only valid for k >= 2)
    labels = kmeans.labels_
    silhouette_scores.append(silhouette_score(X, labels))

# Plot Elbow Method results
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(k_range, inertia, 'o-', markersize=8)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters (k)')
```

```python
plt.ylabel('Inertia')
plt.grid(True)

plt.subplot(1, 2, 2)
plt.plot(k_range, silhouette_scores, 'o-', markersize=8)
plt.title('Silhouette Method')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.grid(True)

plt.tight_layout()
plt.savefig("../images/elbow_silhouette_plot.png")
```



[2]:
```python
# configure api
from dotenv import load_dotenv
import os
from google import genai
from IPython.display import display, Markdown

load_dotenv()
gemini_api_key = os.getenv("GEMINI_API_KEY")

client = genai.Client(api_key=gemini_api_key)

model = [
    "gemini-2.5-flash-preview-04-17-thinking"
]
```

[59]:
```python
# Using AI to interpret the confusion matrices
from google.genai import types
```

```python
with open('../images/elbow_silhouette_plot.png', 'rb') as image_file:
    questionnaire_responses_mood_word_cloud = image_file.read()

# prompt powered by grok-3
prompt = """
You are a data scientist expert, in one paragraph what is the best number of␣
↪clusters for the dataset based on the Elbow Method and Silhouette Method␣
↪results.
"""

response = client.models.generate_content(
    model=model[0],
    contents=[
        types.Part.from_bytes(
            data=questionnaire_responses_mood_word_cloud,
            mime_type='image/png',
        ),
        prompt
    ]
)

display(Markdown(response.text))
```

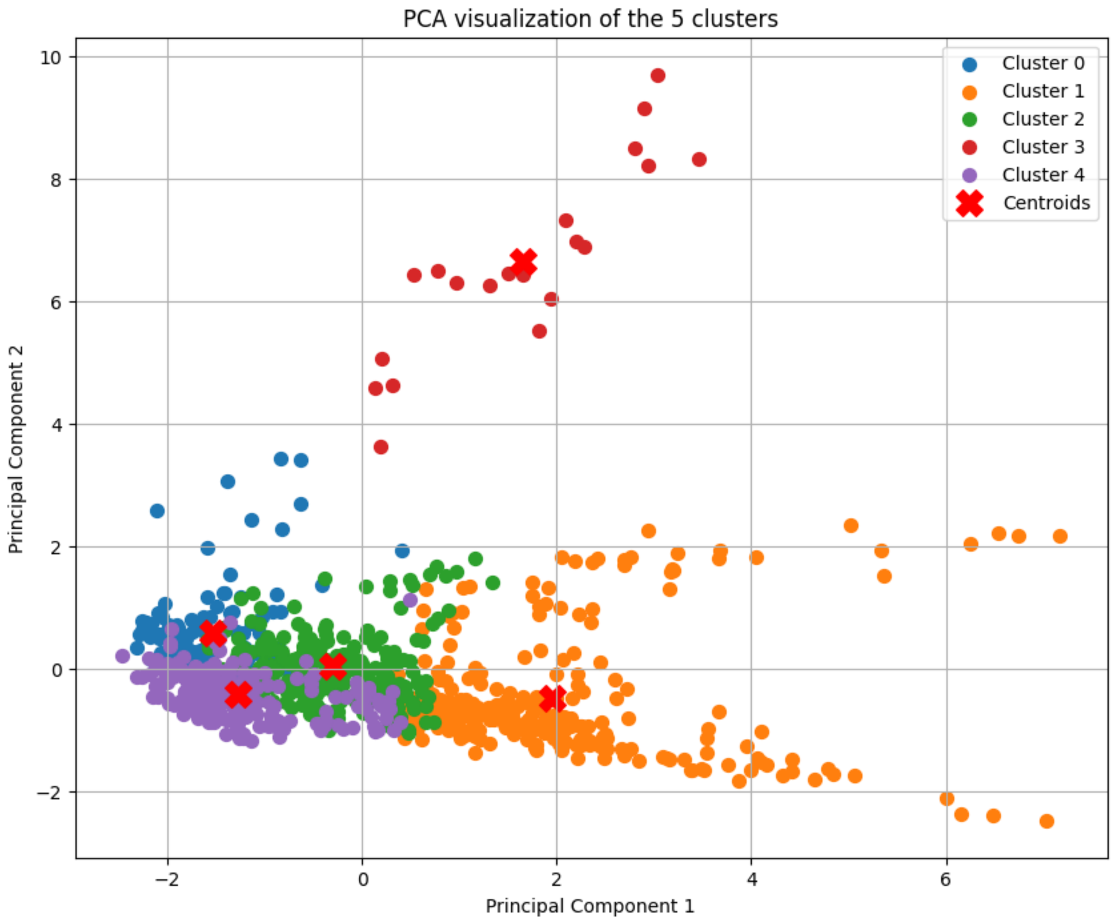
Based on the provided plots, the Elbow Method suggests that a reasonable number of clusters could be around k=4 or k=5, as the rate of decrease in inertia begins to slow down significantly around these points, forming an "elbow". The Silhouette Method, which measures how similar an object is to its own cluster compared to other clusters, indicates that the highest silhouette score is achieved at k=6. While there isn't perfect agreement between the two methods, the silhouette score provides a more quantitative measure of cluster quality, suggesting that k=6 results in the best-defined clusters in terms of separation and compactness. Therefore, considering both analyses, k=6 is the most strongly supported number of clusters based on these metrics.

[60]:
```python
# Based on the elbow method and silhouette scores, choose optimal k

optimal_k = 5

# Apply K-means with optimal k
kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
cluster_labels = kmeans.fit_predict(X)

# Add cluster labels to the original dataframe
df['Cluster'] = cluster_labels

# Examine cluster characteristics - only use the numeric features that were␣
↪used in clustering
cluster_stats = df.groupby('Cluster')[features].mean()
print("\nCluster Centers (Original Scale):")
```

```
display(cluster_stats)

# Visualize clusters using PCA to reduce to 2D
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

plt.figure(figsize=(10, 8))
for i in range(optimal_k):
    plt.scatter(X_pca[cluster_labels == i, 0], X_pca[cluster_labels == i, 1],
                label=f'Cluster {i}', s=50)

plt.scatter(pca.transform(kmeans.cluster_centers_)[:, 0],
            pca.transform(kmeans.cluster_centers_)[:, 1],
            s=200, marker='X', c='red', label='Centroids')

plt.title(f'PCA visualization of the {optimal_k} clusters')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.grid(True)
plt.savefig("../images/pca_clusters.png")

# Examine relationship between clusters and churn outcome
cluster_outcome = pd.crosstab(df['Cluster'], df['Churn'], normalize='index') *
 ↪100
print("\nPercentage of churn (1) in each cluster:")
display(cluster_outcome)
```

```
Cluster Centers (Original Scale):
           Age_new  Gender_new  MembershipLevel  TotalPurchases   TotalSpent  \
Cluster
0        46.968504   21.078740         0.070866        4.551181   120.196142
1        46.600746   30.451493         1.507463       71.104478  4371.467873
2        44.268595   20.809917         2.884298       15.962810   540.631777
3        52.000000   18.400000         2.250000       20.800000  1455.192500
4        46.668161   25.869955         0.197309        6.820628   272.632108

         FavoriteCategory  SocialMediaEngagement  TimeSpentOnSite  \
Cluster
0               13.133858               6.787402         8.448425
1               12.097015              47.776119        76.503358
2               10.545455              44.342975        19.859504
3               14.300000              27.550000        14.555000
4               15.035874              56.192825         7.502691
```

```
         WebsiteClickRate  AdClickHistory  CustomerSentimentScore  PersonaTag  \
Cluster
0                0.519055       54.818898                2.656693   45.039370
1                1.494205       56.735075                1.660933   57.880597
2                0.643095       62.615702                0.960331   39.975207
3               11.240000       64.850000               84.150000   43.250000
4                0.225861       67.112108                0.692422   41.107623

         llm_sentiment
Cluster
0             2.173228
1             4.750000
2             3.165289
3             4.150000
4             2.452915

Percentage of churn (1) in each cluster:

Churn             0          1
Cluster
0          7.086614  92.913386
1        100.000000   0.000000
2         64.462810  35.537190
3         80.000000  20.000000
4         19.730942  80.269058
```



[4]:
```
# Using AI to interpret the confusion matrices
from google.genai import types

with open('../images/pca_clusters.png', 'rb') as image_file:
    questionnaire_responses_mood_word_cloud = image_file.read()

# prompt powered by grok-3
prompt = """
You are a data scientist expert, in one paragraph what is the best number of␣
↪clusters for the dataset based on the Elbow Method and Silhouette Method␣
↪results.
"""

response = client.models.generate_content(
    model=model[0],
    contents=[
        types.Part.from_bytes(
            data=questionnaire_responses_mood_word_cloud,
```

```
            mime_type='image/png',
        ),
        prompt
    ]
)

display(Markdown(response.text))
```

Based on the provided image, which is a PCA visualization of a clustering result using 5 clusters, it is shown how data points and their assigned centroids are distributed in a 2D space. However, this plot alone does not provide the necessary information from standard metrics like the Elbow Method or the Silhouette Method to definitively determine the *optimal* number of clusters for the dataset. The Elbow Method typically looks for a point where the rate of decrease in inertia sharply changes, while the Silhouette Method assesses how well each point fits its cluster compared to others; the results of these methods are usually presented as separate plots or scores for varying numbers of clusters, which are not included here. Therefore, without access to the actual results from the Elbow Method and Silhouette Method, it is not possible to conclude what the best number of clusters is based on those criteria, although the plot visualizes the spatial separation achieved with a 5-cluster solution.

[30]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
# import decision tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns

# Load the Titanic dataset
# You can download from: https://www.kaggle.com/c/titanic/data
df = pd.read_csv('../data/exam/processed/merged_data_with_ratings.csv')
```

[31]:
```
# Display basic info about the dataset
print("Dataset Info:")
print(df.info())
print("\nFirst few rows:")
display(df.head())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 880 entries, 0 to 879
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              880 non-null    object
```

```
 1   Age                     880 non-null    object
 2   Gender                  880 non-null    object
 3   Location                880 non-null    object
 4   MembershipLevel         880 non-null    object
 5   TotalPurchases          880 non-null    int64
 6   TotalSpent              880 non-null    float64
 7   FavoriteCategory        859 non-null    object
 8   LastPurchaseDate        879 non-null    object
 9   WebsiteClickRate        880 non-null    float64
 10  TimeSpentOnSite         880 non-null    float64
 11  SocialMediaEngagement   880 non-null    object
 12  AdClickHistory          808 non-null    object
 13  GeneratedReview         878 non-null    object
 14  CustomerSentimentScore  880 non-null    float64
 15  PersonaTag              880 non-null    object
 16  Churn                   880 non-null    int64
 17  llm_sentiment           880 non-null    int64
dtypes: float64(4), int64(3), object(11)
memory usage: 123.9+ KB
None

First few rows:
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium        Clicked
1             22.5                  High      Sometimes
2             28.1                  High        Clicked
3              8.9                   Low    Not Clicked
4             18.7                Medium        Clicked

                         GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                    0.91
1          Very happy with my purchases.                    0.95
2        Excellent service and products.                    0.98
```

```
3  Had some issues, not fully satisfied.                      0.52
4             Will definitely buy again.                      0.88

        PersonaTag  Churn  llm_sentiment
0    Regular Buyer      0              5
1            Loyal      0              4
2            Loyal      0              5
3   Window Shopper      1              2
4          Engaged      0              4
```

[32]:

```python
# Data preprocessing
# Handle missing values
df['Gender_new'] = df['Age']
display(df.head())
# create a new column 'Age_new' and fill it with random values range from 18 to␣
↪76
df['Age_new'] = np.random.randint(18, 76, size=len(df))

# remove $sign from 'TotalSpend' and convert it to float
df['TotalSpent'] = df['TotalSpent'].replace({'\$': '', ',': ''}, regex=True).
↪astype(float)
# remove TotalSpend that is not a number and bfill it with the previous value
df['TotalSpent'] = pd.to_numeric(df['TotalSpent'], errors='coerce')
```

```
<>:9: SyntaxWarning: invalid escape sequence '\$'
<>:9: SyntaxWarning: invalid escape sequence '\$'
C:\Users\Khor Kean Teng\AppData\Local\Temp\ipykernel_12828\1217612237.py:9:
SyntaxWarning: invalid escape sequence '\$'
  df['TotalSpent'] = df['TotalSpent'].replace({'\$': '', ',': ''},
regex=True).astype(float)
```

```
  CustomerID     Age       Gender Location MembershipLevel  TotalPurchases  \
0    4efed90  Female       Denver       CO          Silver              12
1    d7f26e8    Male  Los Angeles       CA            Gold              28
2    6b4a427   Other      Chicago       IL        Platinum              41
3    68eec52    Male      Houston       TX          Bronze               2
4    3a2af82  Female      Phoenix       AZ          Silver              18

   TotalSpent FavoriteCategory LastPurchaseDate  WebsiteClickRate  \
0       753.6         Clothing       2023-10-20             0.065
1      2155.4      Electronics       2023-10-25             0.092
2      4510.1       Home Goods       2023-09-18             0.115
3        85.7            Books       2023-08-01             0.041
4      1220.5           Beauty       2023-10-10             0.078

   TimeSpentOnSite SocialMediaEngagement AdClickHistory  \
0             15.2                Medium         Clicked
1             22.5                  High       Sometimes
```

```
2             28.1                  High       Clicked
3              8.9                   Low   Not Clicked
4             18.7                Medium       Clicked

                          GeneratedReview  CustomerSentimentScore  \
0     Great experience, love this store!                     0.91
1          Very happy with my purchases.                     0.95
2        Excellent service and products.                     0.98
3  Had some issues, not fully satisfied.                     0.52
4             Will definitely buy again.                     0.88

       PersonaTag  Churn  llm_sentiment Gender_new
0   Regular Buyer      0              5     Female
1           Loyal      0              4       Male
2           Loyal      0              5      Other
3  Window Shopper      1              2       Male
4         Engaged      0              4     Female
```

[33]:
```python
# Encode categorical variables
le = LabelEncoder()
df['MembershipLevel'] = le.fit_transform(df['MembershipLevel'])
df['FavoriteCategory'] = le.fit_transform(df['FavoriteCategory'])
df['SocialMediaEngagement'] = le.fit_transform(df['SocialMediaEngagement'])
df['AdClickHistory'] = le.fit_transform(df['AdClickHistory'])
df['PersonaTag'] = le.fit_transform(df['PersonaTag'])
df['Gender_new'] = le.fit_transform(df['Gender_new'])

# Select features for the model
features = [
    'Age_new', 'Gender_new', 'MembershipLevel', 'TotalPurchases',
    'TotalSpent', 'FavoriteCategory', 'SocialMediaEngagement',
    'TimeSpentOnSite', 'WebsiteClickRate', 'AdClickHistory',
    'CustomerSentimentScore', 'PersonaTag', 'llm_sentiment'
]
X = df[features]
y = df['Churn']
```

[34]:
```python
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42, stratify=y)
```

[35]:
```python
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[36]:
```python
# Import necessary libraries for modeling
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score
import pickle
import os

# Create directory for model storage if it doesn't exist
os.makedirs('models', exist_ok=True)

# Dictionary to store model results for later evaluation
model_results = {}
```

[37]:
```python
# ---- Random Forest ----
print("Training Random Forest model...")
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)

# Make predictions
rf_train_preds = rf_model.predict(X_train_scaled)
rf_test_preds = rf_model.predict(X_test_scaled)
rf_test_proba = rf_model.predict_proba(X_test)[:, 1]

# Store results
model_results['random_forest'] = {
    'train_preds': rf_train_preds,
    'test_preds': rf_test_preds,
    'test_proba': rf_test_proba
}

# Save the model
with open('models/random_forest_model.pkl', 'wb') as f:
    pickle.dump(rf_model, f)

print("Random Forest model trained and saved!")
```

```
Training Random Forest model…
Random Forest model trained and saved!
```

```
c:\Users\Khor Kean Teng\AppData\Local\Programs\Python\Python312\Lib\site-
packages\sklearn\utils\validation.py:2732: UserWarning: X has feature names, but
RandomForestClassifier was fitted without feature names
  warnings.warn(
```

[38]:
```python
# ---- XGBoost ----
print("Training XGBoost model...")
from xgboost import XGBClassifier

xgb_model = XGBClassifier(n_estimators=100, learning_rate=0.1, random_state=42)
xgb_model.fit(X_train, y_train)

# Make predictions
xgb_train_preds = xgb_model.predict(X_train_scaled)
xgb_test_preds = xgb_model.predict(X_test_scaled)
xgb_test_proba = xgb_model.predict_proba(X_test_scaled)[:, 1]

# Store results
model_results['xgboost'] = {
    'train_preds': xgb_train_preds,
    'test_preds': xgb_test_preds,
    'test_proba': xgb_test_proba
}

# Save the model
with open('models/xgboost_model.pkl', 'wb') as f:
    pickle.dump(xgb_model, f)

print("XGBoost model trained and saved!")
```

```
Training XGBoost model…
XGBoost model trained and saved!
```

[39]:
```python
# adaboost
from sklearn.ensemble import AdaBoostClassifier

print("Training AdaBoost model...")
ada_model = AdaBoostClassifier(n_estimators=100, random_state=42)
ada_model.fit(X_train_scaled, y_train)

# Make predictions
ada_train_preds = ada_model.predict(X_train_scaled)
ada_test_preds = ada_model.predict(X_test_scaled)
ada_test_proba = ada_model.predict_proba(X_test_scaled)[:, 1]

# Store results
model_results['adaboost'] = {
    'train_preds': ada_train_preds,
    'test_preds': ada_test_preds,
    'test_proba': ada_test_proba
}

# Save the model
```

```python
with open('models/adaboost_model.pkl', 'wb') as f:
    pickle.dump(ada_model, f)

print("AdaBoost model trained and saved!")
```

```
Training AdaBoost model…
AdaBoost model trained and saved!
```

[40]:
```python
with open('models/model_results.pkl', 'wb') as f:
    pickle.dump(model_results, f)
```

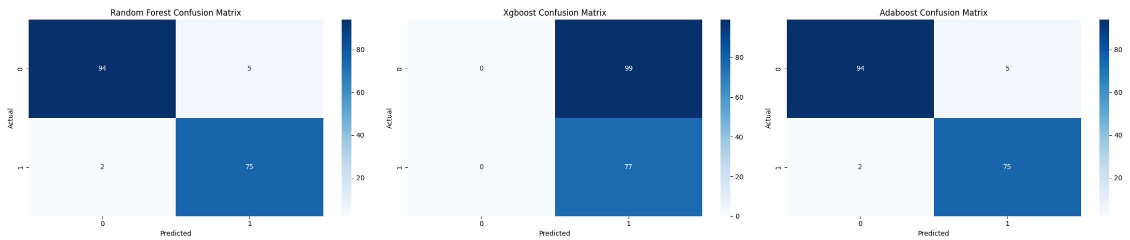
[41]:
```python
# Create a function to evaluate and display results
def evaluate_model(y_true, y_pred, y_proba=None):
    """Evaluate model performance with multiple metrics"""
    results = {}
    results['accuracy'] = accuracy_score(y_true, y_pred)
    results['precision'] = precision_score(y_true, y_pred, zero_division=0)
    results['recall'] = recall_score(y_true, y_pred, zero_division=0)
    results['f1'] = f1_score(y_true, y_pred, zero_division=0)

    if y_proba is not None:
        results['auc'] = roc_auc_score(y_true, y_proba)

    return results
```

[42]:
```python
# Update the models list to include the FT Transformer
models = ['random_forest', 'xgboost', 'adaboost']

# Recalculate evaluation results for all models including FT Transformer
evaluation_results = {}

for model in models:
    test_preds = model_results[model]['test_preds']
    test_proba = model_results[model]['test_proba']
    evaluation_results[model] = evaluate_model(y_test, test_preds, test_proba)

# Convert results to DataFrame for easier comparison
results_df = pd.DataFrame(evaluation_results).T
display(results_df.style.highlight_max(axis=0))
```

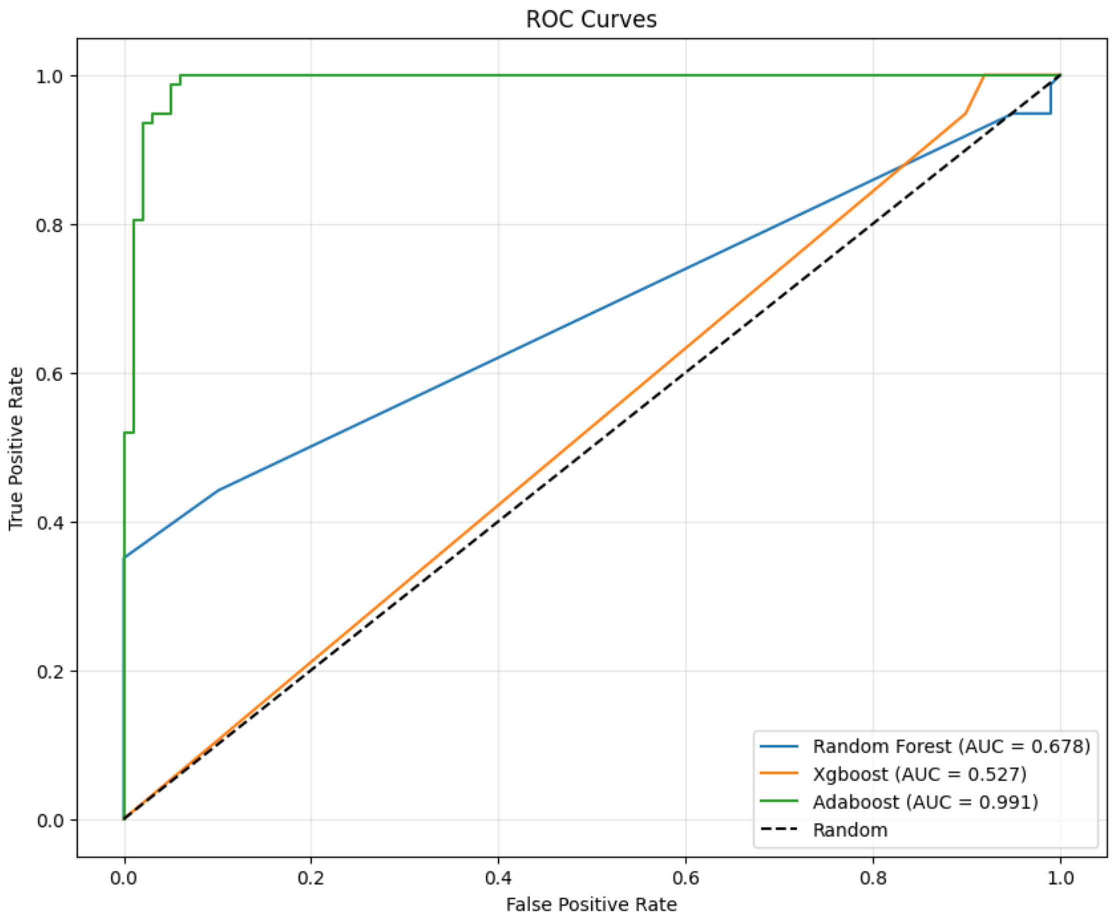
```
<pandas.io.formats.style.Styler at 0x1c5b603b170>
```

[43]:
```python
# Redraw confusion matrices with FT Transformer
fig, axes = plt.subplots(1, 3, figsize=(24, 5))

for i, model in enumerate(models):
    cm = confusion_matrix(y_test, model_results[model]['test_preds'])
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=axes[i])
```

```python
    axes[i].set_title(f'{model.replace("_", " ").title()} Confusion Matrix')
    axes[i].set_xlabel('Predicted')
    axes[i].set_ylabel('Actual')

plt.tight_layout()
plt.savefig('../images/ml_confusion_matrices.png', dpi=300)
```



[44]:
```python
# Redraw ROC curves including FT Transformer
plt.figure(figsize=(10, 8))

for model in models:
    y_proba = model_results[model]['test_proba']
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    auc = roc_auc_score(y_test, y_proba)
    plt.plot(fpr, tpr, label=f'{model.replace("_", " ").title()} (AUC = {auc:.3f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves')
plt.legend()
plt.grid(True, alpha=0.3)
plt.savefig('../images/ml_roc_curves.png', dpi=300)
```



4 Market Basket Analysis for Multi-Store Retail Dataset

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
import ast
import networkx as nx

# Set display options
pd.set_option('display.max_columns', None)
plt.rcParams['figure.figsize'] = [12, 8]

# Load the dataset
# Assuming data is in a CSV file
```

```python
df = pd.read_csv('../data/sample-2/processed/transaction_baskets.csv')

# Display first few rows
print("Original data sample:")
display(df.head())

# Check basic information
print("\nDataset info:")
print(df.info())
```

```
Original data sample:

   StoreID  TransactionID                                          ProductID  \
0        1          10000                                           ['P105']
1        1          10001                           ['P147', 'P132', 'P110']
2        1          10002                           ['P130', 'P107', 'P109']
3        1          10003  ['P140', 'P144', 'P143', 'P144', 'P138', 'P112…
4        1          10004           ['P131', 'P100', 'P104', 'P114', 'P117']

                                       ProductName  \
0                                  ['Product P105']
1  ['Product P147', 'Product P132', 'Product P110']
2  ['Product P130', 'Product P107', 'Product P109']
3 ['Product P140', 'Product P144', 'Product P143…
4 ['Product P131', 'Product P100', 'Product P104…

                                    ProductCategory
0                                   ['Electronics']
1                 ['Grocery', 'Electronics', 'Books']
2             ['Electronics', 'Electronics', 'Books']
3 ['Grocery', 'Grocery', 'Books', 'Grocery', 'Ho…
4 ['Grocery', 'Grocery', 'Apparel', 'Apparel', '…


Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15096 entries, 0 to 15095
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   StoreID          15096 non-null  int64
 1   TransactionID    15096 non-null  int64
 2   ProductID        15096 non-null  object
 3   ProductName      15096 non-null  object
 4   ProductCategory  15096 non-null  object
dtypes: int64(2), object(3)
memory usage: 589.8+ KB
None
```

4.1 Preprocessing

[2]:
```python
# Convert string representations of lists to actual lists if needed
def convert_to_list(x):
    if isinstance(x, str):
        return ast.literal_eval(x)
    return x

df['ProductID'] = df['ProductID'].apply(convert_to_list)
df['ProductName'] = df['ProductName'].apply(convert_to_list)
df['ProductCategory'] = df['ProductCategory'].apply(convert_to_list)

# Check data after conversion
print("\nAfter conversion:")
display(df.head())

# Basic statistics
print(f"\nTotal stores: {df['StoreID'].nunique()}")
print(f"Total transactions: {df['TransactionID'].nunique()}")

# Count transactions per store
store_transactions = df.groupby('StoreID').size()
print("\nTransactions per store:")
print(store_transactions)
```

```
After conversion:

   StoreID  TransactionID                                         ProductID  \
0        1          10000                                            [P105]
1        1          10001                                [P147, P132, P110]
2        1          10002                                [P130, P107, P109]
3        1          10003  [P140, P144, P143, P144, P138, P112, P123, P122]
4        1          10004                    [P131, P100, P104, P114, P117]

                                         ProductName  \
0                                      [Product P105]
1          [Product P147, Product P132, Product P110]
2          [Product P130, Product P107, Product P109]
3  [Product P140, Product P144, Product P143, Pro…
4  [Product P131, Product P100, Product P104, Pro…

                                     ProductCategory
0                                      [Electronics]
1                     [Grocery, Electronics, Books]
2                 [Electronics, Electronics, Books]
3  [Grocery, Grocery, Books, Grocery, Home Goods,…
4  [Grocery, Grocery, Apparel, Apparel, Electronics]
```

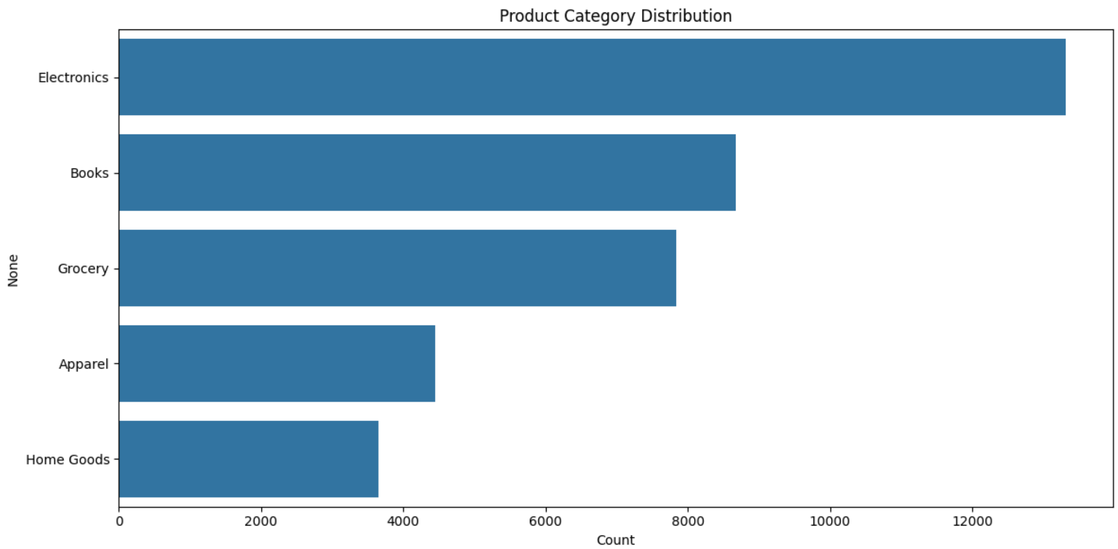
```
Total stores: 8
Total transactions: 15096

Transactions per store:
StoreID
1    1544
2    2267
3    2092
4    1894
5    1807
6    2010
7    1790
8    1692
dtype: int64
```

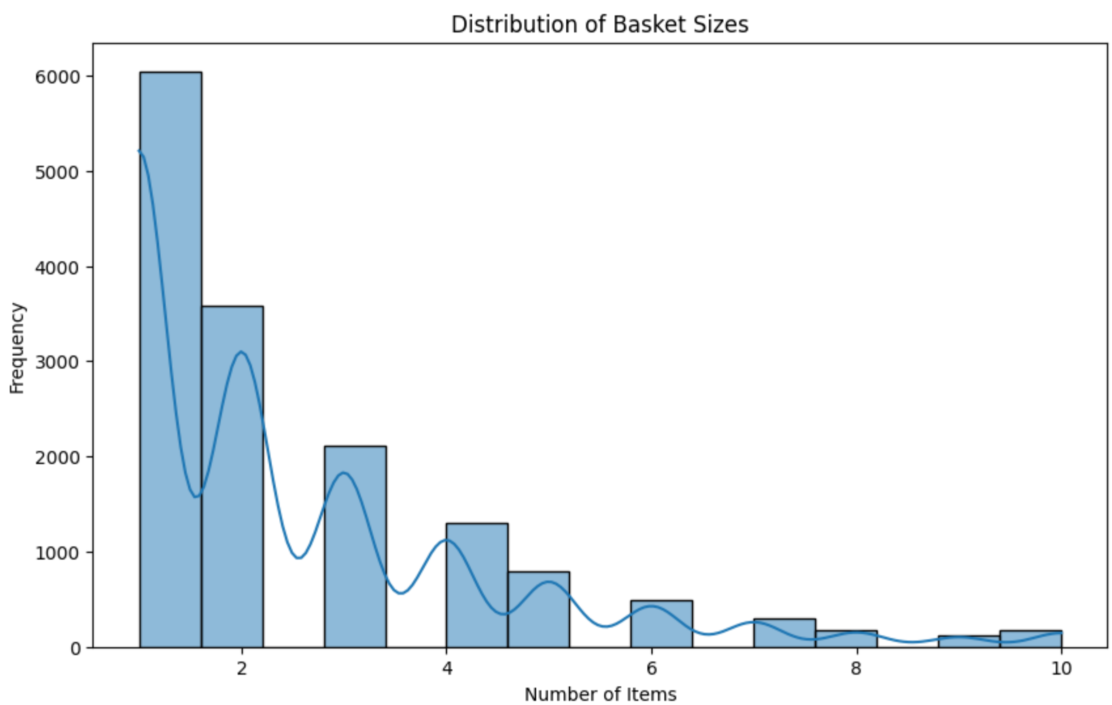
4.2 Exploration

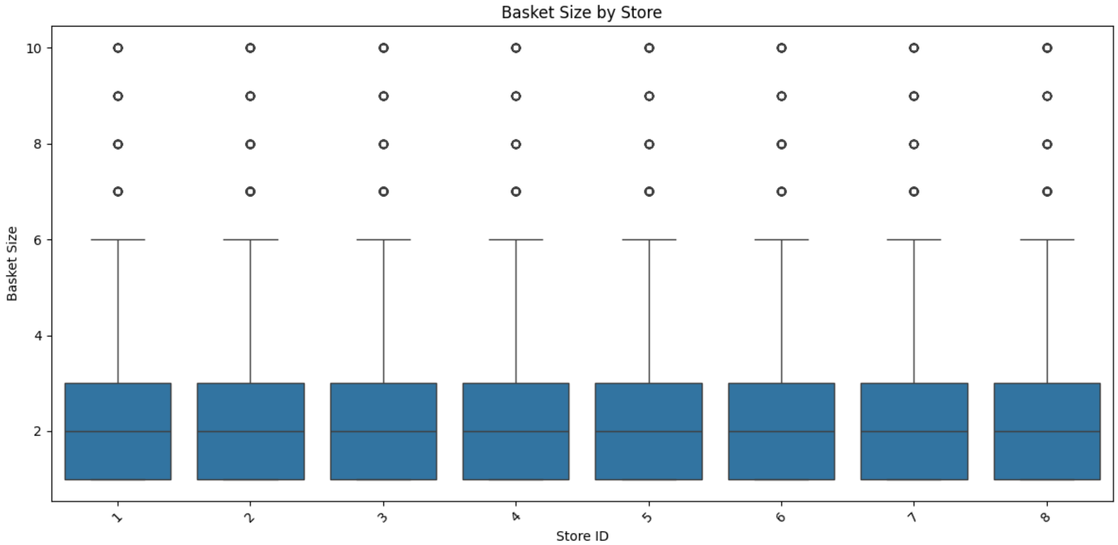
[3]:

```python
# Analyze product categories across stores
all_categories = []
for categories in df['ProductCategory']:
    all_categories.extend(categories)

category_counts = pd.Series(all_categories).value_counts()

# Plot category distribution
plt.figure(figsize=(12, 6))
sns.barplot(x=category_counts.values, y=category_counts.index)
plt.title('Product Category Distribution')
plt.xlabel('Count')
plt.tight_layout()
plt.savefig('../images/product_category_distribution.png')

# Analyze basket sizes
df['BasketSize'] = df['ProductID'].apply(len)

plt.figure(figsize=(10, 6))
sns.histplot(df['BasketSize'], bins=15, kde=True)
plt.title('Distribution of Basket Sizes')
plt.xlabel('Number of Items')
plt.ylabel('Frequency')

# Compare basket sizes across stores
plt.figure(figsize=(12, 6))
sns.boxplot(x='StoreID', y='BasketSize', data=df)
plt.title('Basket Size by Store')
plt.xlabel('Store ID')
```

```
plt.ylabel('Basket Size')
plt.xticks(rotation=45)
plt.tight_layout()
```







4.3 Prepare Data for Market Basket Analysis

[4]:
```python
# Function to prepare data for a specific store
def prepare_store_data(store_id):
    # Filter data for the specific store
    store_data = df[df['StoreID'] == store_id]

    # Create transactions list using product names
    transactions = store_data['ProductName'].tolist()

    # Convert transactions to one-hot encoded format
    te = TransactionEncoder()
    te_ary = te.fit(transactions).transform(transactions)
    df_encoded = pd.DataFrame(te_ary, columns=te.columns_)

    return store_data, transactions, df_encoded

# Prepare data for all stores
store_data_dict = {}
for store_id in df['StoreID'].unique():
    store_data, transactions, df_encoded = prepare_store_data(store_id)
    store_data_dict[store_id] = {
        'data': store_data,
        'transactions': transactions,
        'encoded': df_encoded
    }

    print(f"Store {store_id}: {len(transactions)} transactions prepared")
```

```
Store 1: 1544 transactions prepared
Store 2: 2267 transactions prepared
Store 3: 2092 transactions prepared
Store 4: 1894 transactions prepared
Store 5: 1807 transactions prepared
Store 6: 2010 transactions prepared
Store 7: 1790 transactions prepared
Store 8: 1692 transactions prepared
```

4.4 Apply Apriori Algorithm and Generate Association Rules

[5]:

```
# Function to perform market basket analysis
def run_mba(df_encoded, min_support=0.01, min_threshold=1.0):
    # Apply Apriori algorithm
    frequent_itemsets = apriori(df_encoded, min_support=min_support,␣
 ↪use_colnames=True)

    # Add length of itemsets
    if not frequent_itemsets.empty:
        frequent_itemsets['length'] = frequent_itemsets['itemsets'].
 ↪apply(lambda x: len(x))
        frequent_itemsets = frequent_itemsets.sort_values('support',␣
 ↪ascending=False)

        # Generate association rules
        rules = association_rules(frequent_itemsets, metric="lift",␣
 ↪min_threshold=min_threshold)

        # Sort rules by lift
        if not rules.empty:
            rules = rules.sort_values('lift', ascending=False)

        return frequent_itemsets, rules

    return frequent_itemsets, pd.DataFrame()

# Run analysis for each store
results = {}
for store_id, data in store_data_dict.items():
    print(f"\nAnalyzing Store {store_id}...")

    # Adjust min_support based on number of transactions
    transactions_count = len(data['transactions'])
    min_support = max(2 / transactions_count, 0.01)  # At least 2 transactions␣
 ↪or 1%

    frequent_itemsets, rules = run_mba(data['encoded'], min_support=min_support)
```

```
    results[store_id] = {
        'frequent_itemsets': frequent_itemsets,
        'rules': rules
    }

    print(f"Found {len(frequent_itemsets)} frequent itemsets with␣
↪min_support={min_support:.4f}")
    print(f"Generated {len(rules)} association rules")
```

```
Analyzing Store 1…
Found 61 frequent itemsets with min_support=0.0100
Generated 32 association rules

Analyzing Store 2…
Found 56 frequent itemsets with min_support=0.0100
Generated 22 association rules

Analyzing Store 3…
Found 57 frequent itemsets with min_support=0.0100
Generated 24 association rules

Analyzing Store 4…
Found 50 frequent itemsets with min_support=0.0100
Generated 10 association rules

Analyzing Store 5…
Found 54 frequent itemsets with min_support=0.0100
Generated 18 association rules

Analyzing Store 6…
Found 54 frequent itemsets with min_support=0.0100
Generated 18 association rules

Analyzing Store 7…
Found 75 frequent itemsets with min_support=0.0100
Generated 58 association rules

Analyzing Store 8…
Found 68 frequent itemsets with min_support=0.0100
Generated 46 association rules
```

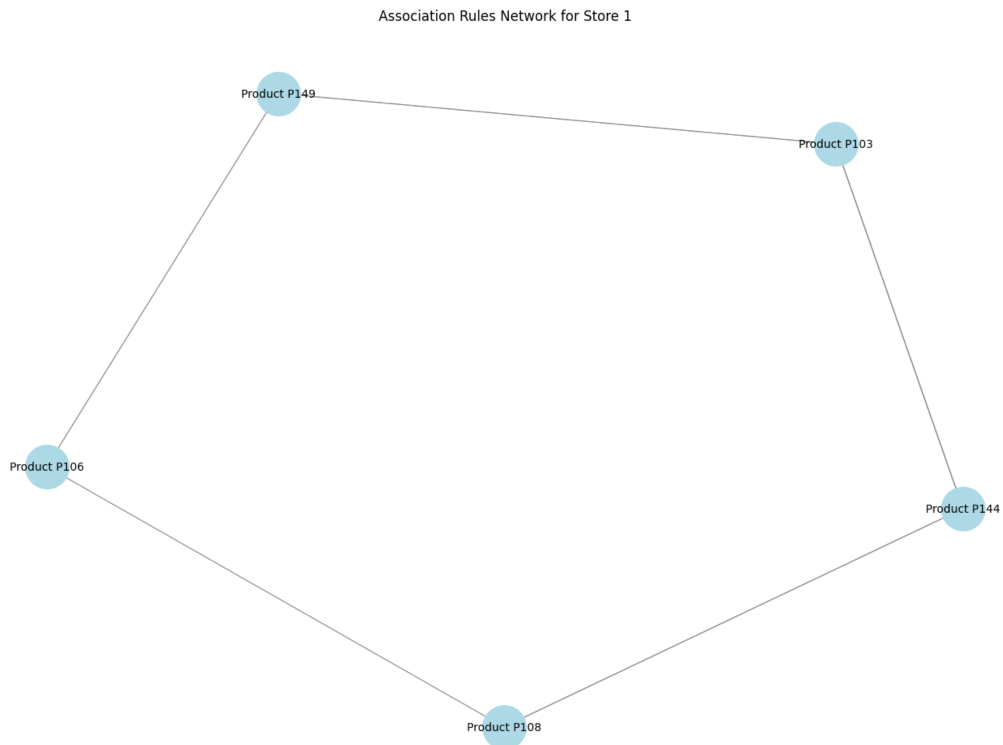
4.5 Visualize and Interpret Results

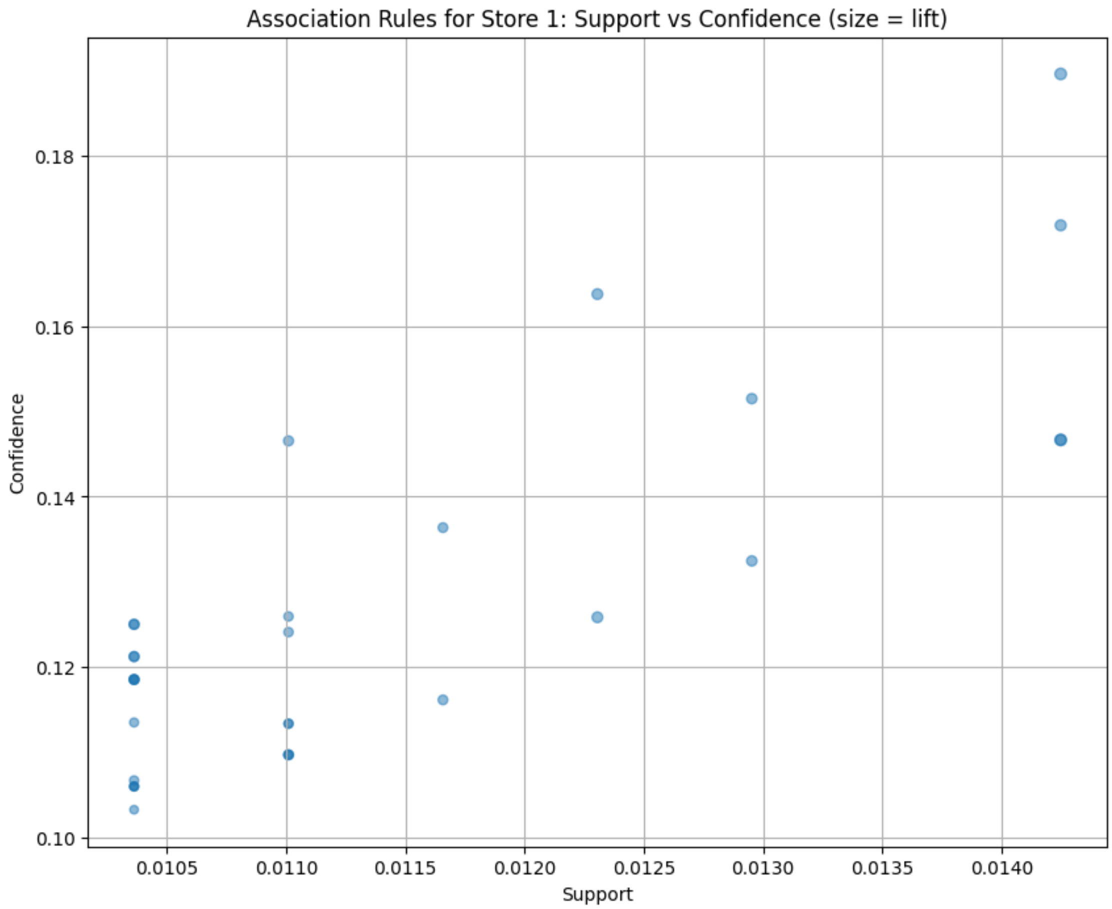
[6]:
```python
# Function to format itemsets for display
def format_itemset(itemset):
    return ', '.join(list(itemset))

# Function to visualize top rules for a store
def visualize_store_rules(store_id, top_n=10):
    rules = results[store_id]['rules']

    if rules.empty:
        print(f"No rules found for Store {store_id}")
        return

    # Add formatted columns for better readability
    rules['antecedents_str'] = rules['antecedents'].apply(format_itemset)
    rules['consequents_str'] = rules['consequents'].apply(format_itemset)

    # Display top rules
    top_rules = rules.head(top_n)[['antecedents_str', 'consequents_str',␣
 ↪'support', 'confidence', 'lift']]
    top_rules.columns = ['If customer buys', 'They also buy', 'Support',␣
 ↪'Confidence', 'Lift']

    print(f"\nTop {top_n} Association Rules for Store {store_id}:")
    print(top_rules)

    # Visualize network graph for top rules
    if len(rules) >= 5:
        top_rules_vis = rules.head(min(10, len(rules)))

        # Create network graph
        G = nx.DiGraph()

        # Add nodes and edges
        for _, row in top_rules_vis.iterrows():
            antecedent = format_itemset(row['antecedents'])
            consequent = format_itemset(row['consequents'])

            # Add nodes
            if antecedent not in G.nodes:
                G.add_node(antecedent)
            if consequent not in G.nodes:
                G.add_node(consequent)

            # Add edge with lift as weight
            G.add_edge(antecedent, consequent, weight=row['lift'],
```

```
                    support=row['support'], confidence=row['confidence'])

        # Plot the network
        plt.figure(figsize=(14, 10))
        pos = nx.spring_layout(G, seed=42)

        # Draw nodes
        nx.draw_networkx_nodes(G, pos, node_size=1500, node_color='lightblue')

        # Draw edges with width based on lift
        edges = G.edges(data=True)
        edge_widths = [d['weight']/2 for u, v, d in edges]
        nx.draw_networkx_edges(G, pos, width=edge_widths, alpha=0.7,
                              edge_color='grey', arrows=True, arrowsize=20)

        # Draw labels
        nx.draw_networkx_labels(G, pos, font_size=10, font_family='sans-serif')

        plt.axis('off')
        plt.title(f'Association Rules Network for Store {store_id}')
        plt.tight_layout()
        plt.show()

        # Scatter plot of rules
        plt.figure(figsize=(10, 8))
        plt.scatter(rules['support'], rules['confidence'], s=rules['lift']*20,␣
↪alpha=0.5)
        plt.xlabel('Support')
        plt.ylabel('Confidence')
        plt.title(f'Association Rules for Store {store_id}: Support vs␣
↪Confidence (size = lift)')
        plt.grid(True)
        plt.show()

# Visualize results for each store
for store_id in results.keys():
    visualize_store_rules(store_id)
```

```
Top 10 Association Rules for Store 1:
   If customer buys They also buy   Support  Confidence      Lift
0      Product P144  Product P103  0.014249    0.146667  1.952184
1      Product P103  Product P144  0.014249    0.189655  1.952184
3      Product P108  Product P144  0.014249    0.171875  1.769167
2      Product P144  Product P108  0.014249    0.146667  1.769167
6      Product P103  Product P149  0.012306    0.163793  1.674812
7      Product P149  Product P103  0.012306    0.125828  1.674812
```

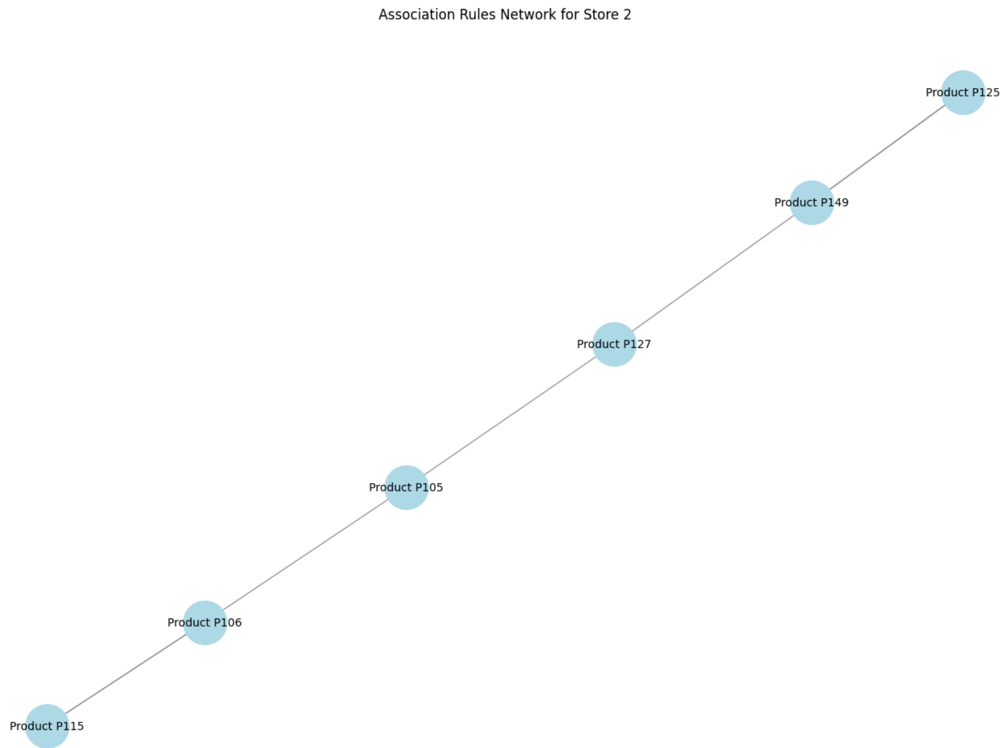
5	Product P106	Product P149	0.012953	0.151515	1.549268
4	Product P149	Product P106	0.012953	0.132450	1.549268
20	Product P108	Product P106	0.010363	0.125000	1.462121
21	Product P106	Product P108	0.010363	0.121212	1.462121

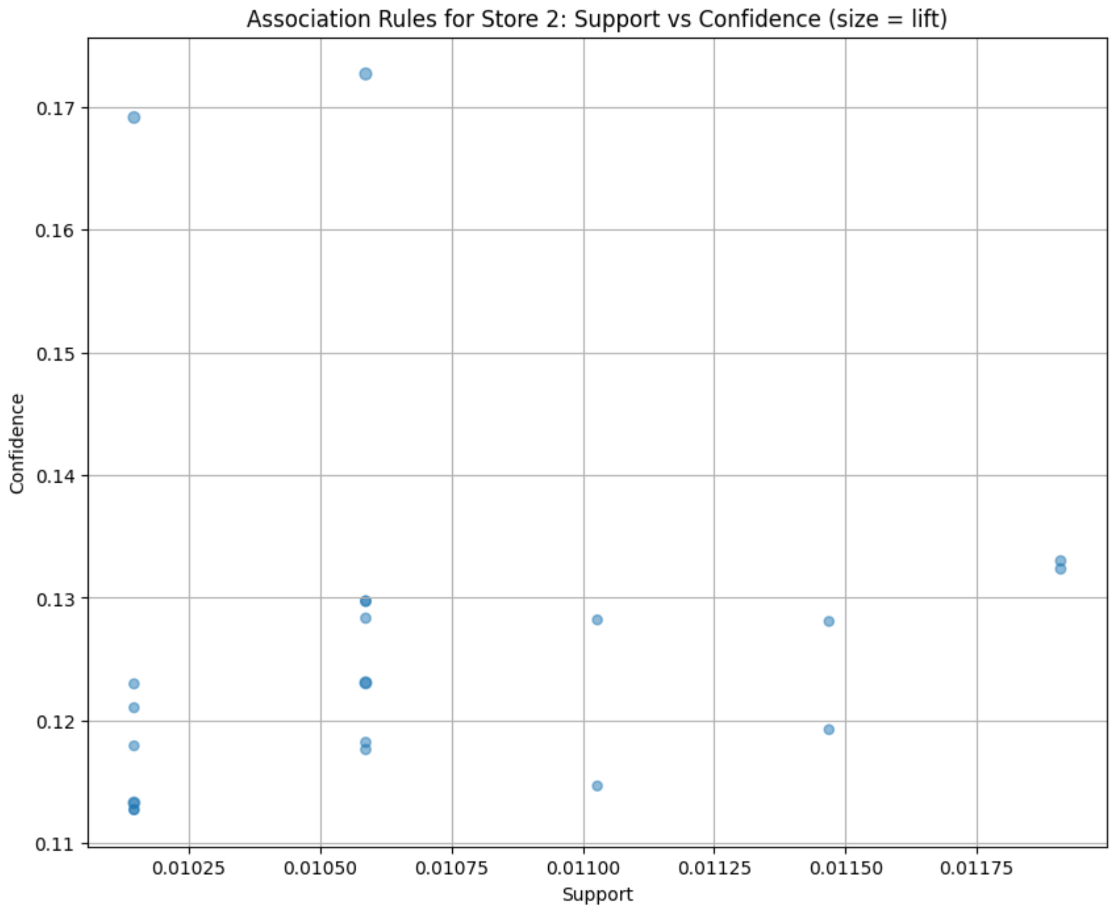




Top 10 Association Rules for Store 2:

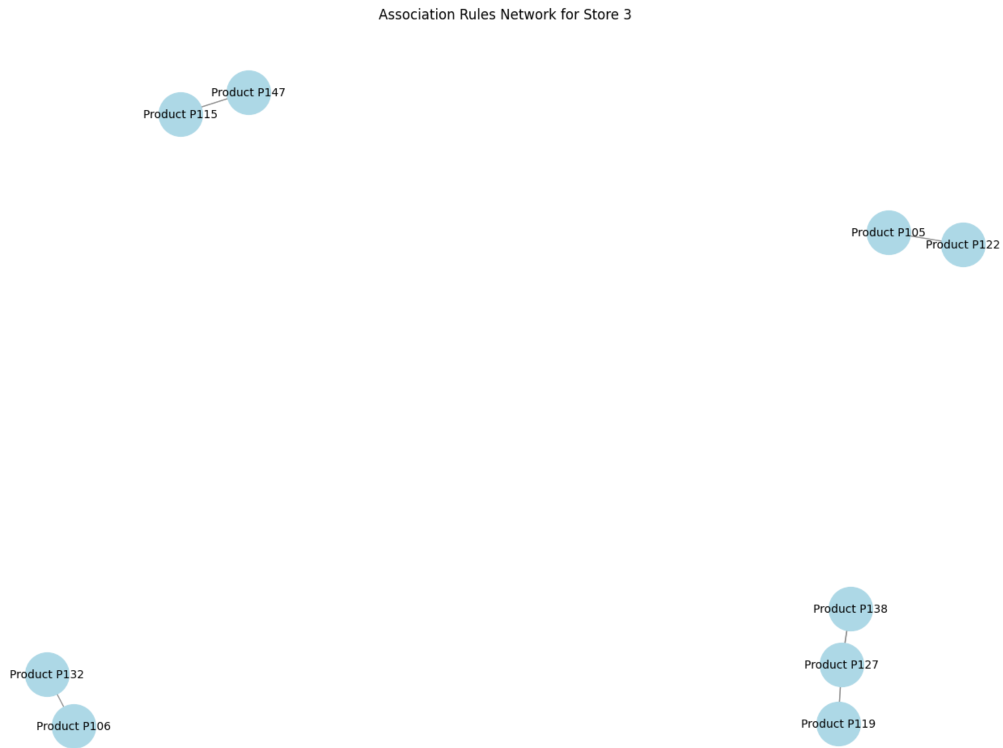
	If customer buys	They also buy	Support	Confidence	Lift
11	Product P125	Product P149	0.010587	0.172662	2.007305
10	Product P149	Product P125	0.010587	0.123077	2.007305
19	Product P106	Product P115	0.010146	0.113300	1.888619
18	Product P115	Product P106	0.010146	0.169118	1.888619
13	Product P149	Product P127	0.010587	0.123077	1.508191
12	Product P127	Product P149	0.010587	0.129730	1.508191
1	Product P106	Product P105	0.011910	0.133005	1.478050
0	Product P105	Product P106	0.011910	0.132353	1.478050
7	Product P127	Product P105	0.010587	0.129730	1.441653
6	Product P105	Product P127	0.010587	0.117647	1.441653

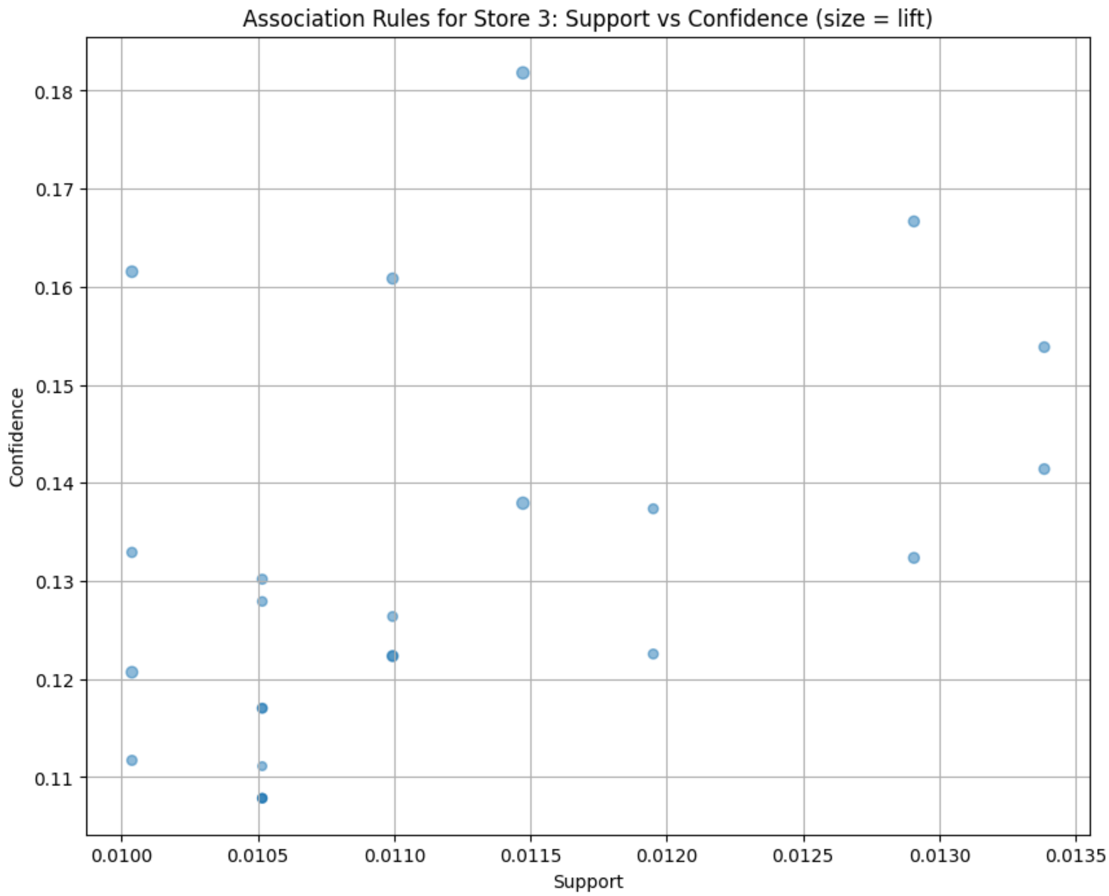

Association Rules Network for Store 2
Product P125
Product P149
Product P127
Product P105
Product P106
Product P115



Top 10 Association Rules for Store 3:

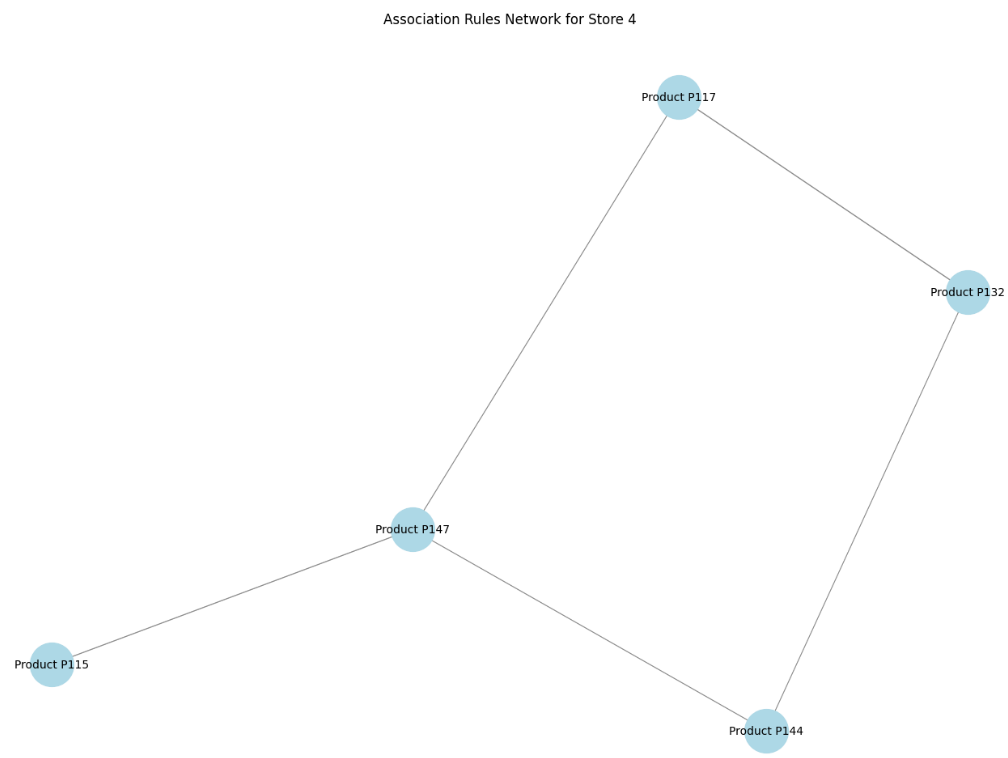
	If customer buys	They also buy	Support	Confidence	Lift
7	Product P138	Product P127	0.011472	0.181818	2.185998
6	Product P127	Product P138	0.011472	0.137931	2.185998
23	Product P119	Product P127	0.010038	0.161538	1.942175
22	Product P127	Product P119	0.010038	0.120690	1.942175
10	Product P115	Product P147	0.010994	0.160839	1.789763
11	Product P147	Product P115	0.010994	0.122340	1.789763
2	Product P105	Product P122	0.012906	0.132353	1.709150
3	Product P122	Product P105	0.012906	0.166667	1.709150
1	Product P106	Product P132	0.013384	0.153846	1.625486
0	Product P132	Product P106	0.013384	0.141414	1.625486

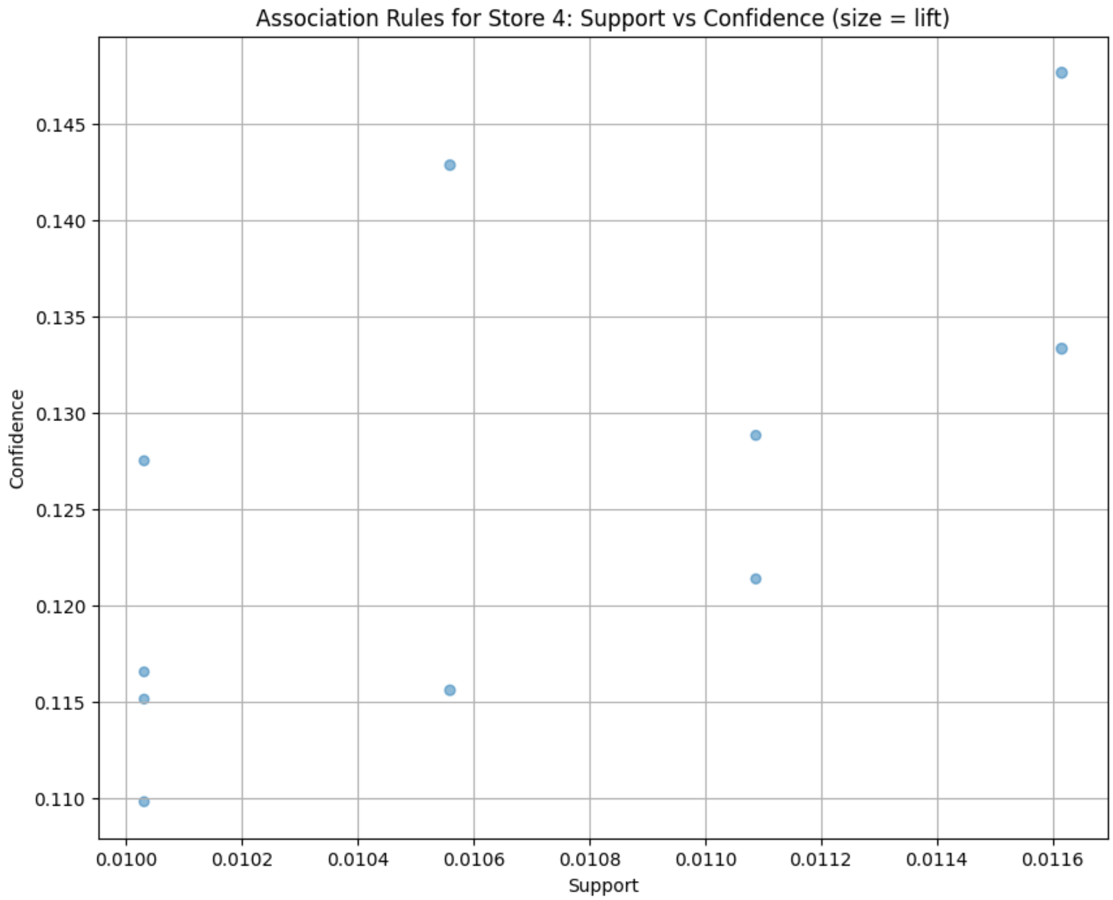

Association Rules Network for Store 3
Product P147
Product P115
Product P105
Product P122
Product P138
Product P127
Product P119
Product P132
Product P106



Top 10 Association Rules for Store 4:

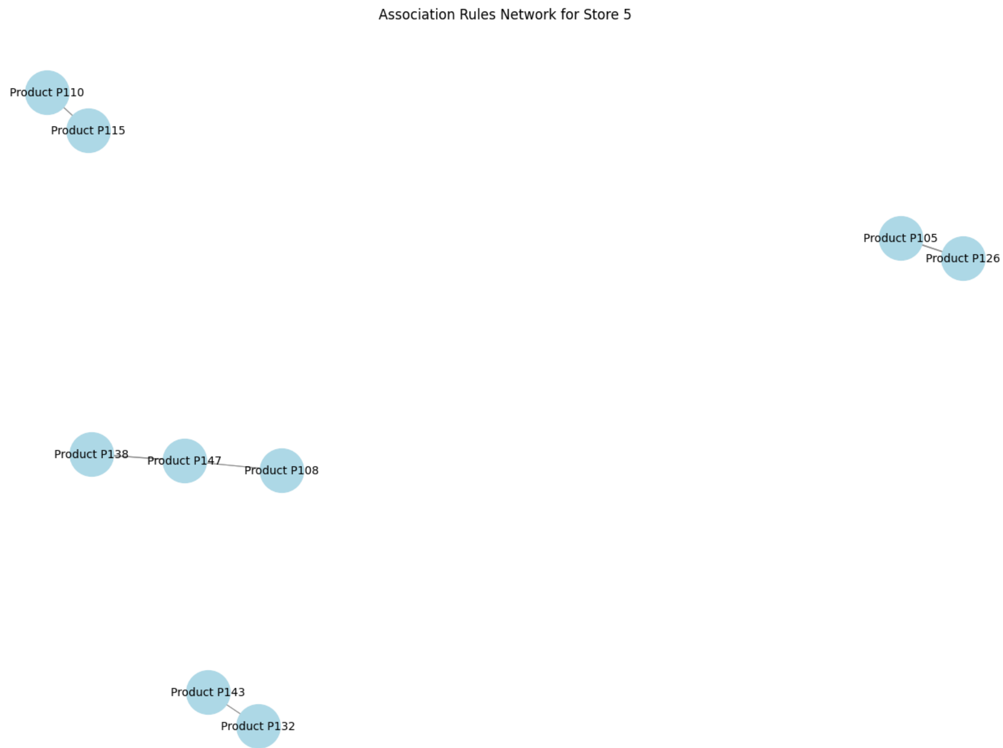
	If customer buys	They also buy	Support	Confidence	Lift
0	Product P117	Product P132	0.011616	0.147651	1.694855
1	Product P132	Product P117	0.011616	0.133333	1.694855
4	Product P115	Product P147	0.010560	0.142857	1.563997
5	Product P147	Product P115	0.010560	0.115607	1.563997
2	Product P144	Product P147	0.011088	0.128834	1.410476
3	Product P147	Product P144	0.011088	0.121387	1.410476
6	Product P117	Product P147	0.010032	0.127517	1.396051
7	Product P147	Product P117	0.010032	0.109827	1.396051
8	Product P144	Product P132	0.010032	0.116564	1.338018
9	Product P132	Product P144	0.010032	0.115152	1.338018

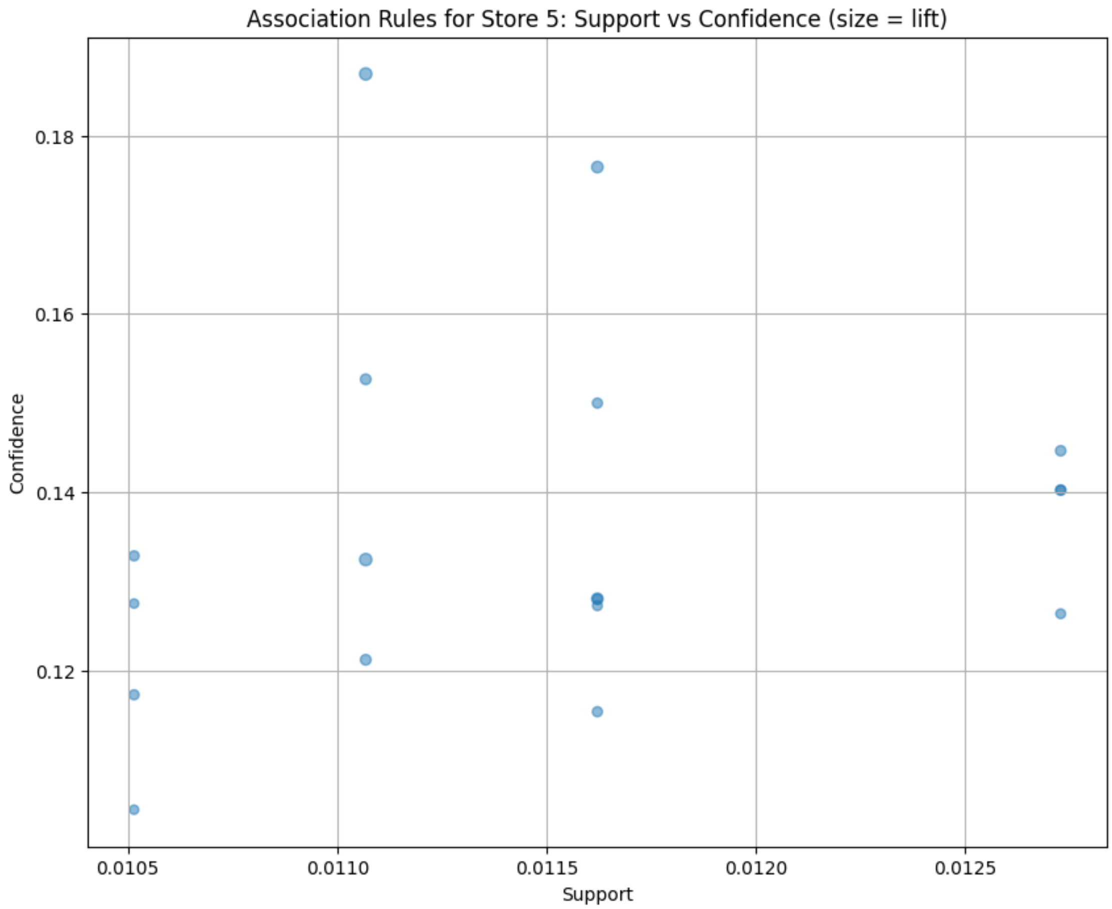

Association Rules Network for Store 4
Product P117
Product P132
Product P147
Product P115
Product P144



Top 10 Association Rules for Store 5:

	If customer buys	They also buy	Support	Confidence	Lift
10	Product P105	Product P126	0.011068	0.132450	2.236801
11	Product P126	Product P105	0.011068	0.186916	2.236801
6	Product P138	Product P147	0.011621	0.176471	1.944405
7	Product P147	Product P138	0.011621	0.128049	1.944405
13	Product P115	Product P110	0.011068	0.152672	1.671987
12	Product P110	Product P115	0.011068	0.121212	1.671987
2	Product P108	Product P147	0.012728	0.144654	1.593841
3	Product P147	Product P108	0.012728	0.140244	1.593841
4	Product P132	Product P143	0.011621	0.115385	1.489286
5	Product P143	Product P132	0.011621	0.150000	1.489286

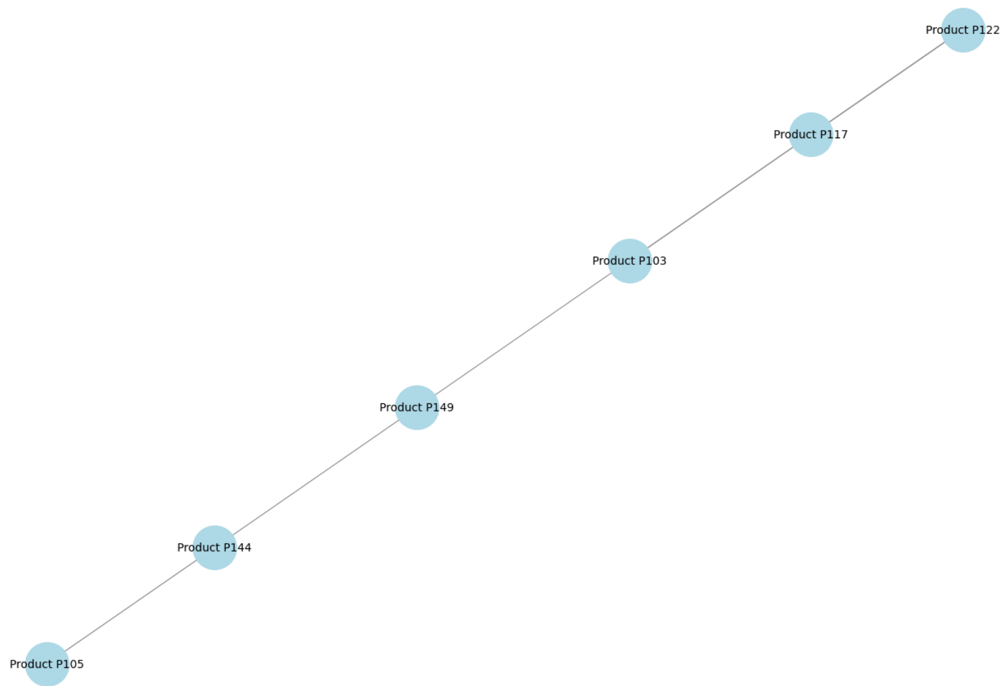

Association Rules Network for Store 5
Product P110
Product P115
Product P105
Product P126
Product P138
Product P147
Product P108
Product P143
Product P132

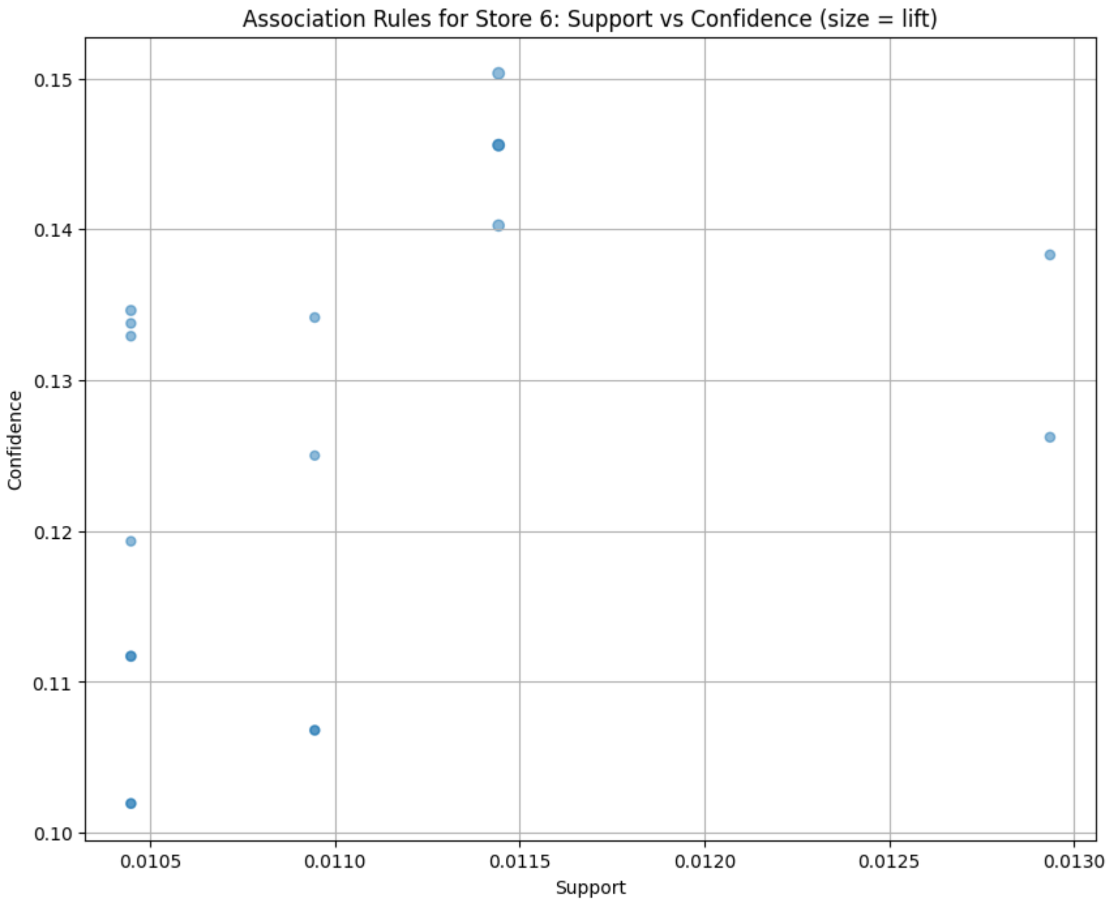


Top 10 Association Rules for Store 6:

	If customer buys	They also buy	Support	Confidence	Lift
4	Product P117	Product P122	0.011443	0.145570	1.912385
5	Product P122	Product P117	0.011443	0.150327	1.912385
2	Product P117	Product P103	0.011443	0.145570	1.784115
3	Product P103	Product P117	0.011443	0.140244	1.784115
11	Product P105	Product P144	0.010448	0.134615	1.439239
10	Product P144	Product P105	0.010448	0.111702	1.439239
0	Product P144	Product P149	0.012935	0.138298	1.349411
1	Product P149	Product P144	0.012935	0.126214	1.349411
6	Product P103	Product P149	0.010945	0.134146	1.308904
7	Product P149	Product P103	0.010945	0.106796	1.308904

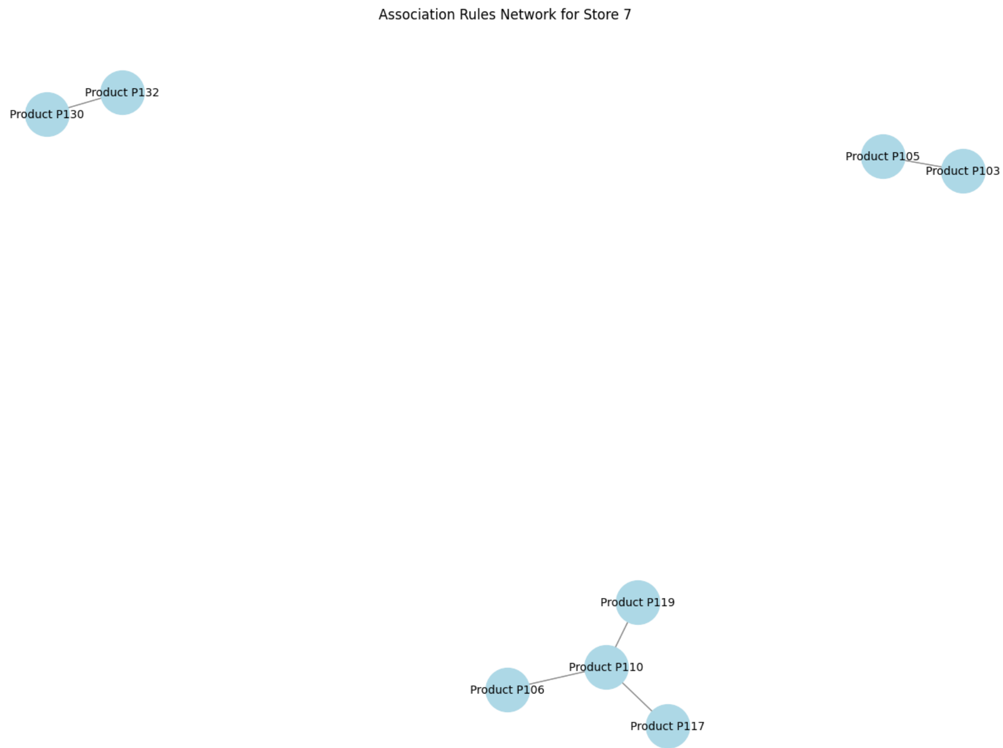
Association Rules Network for Store 6

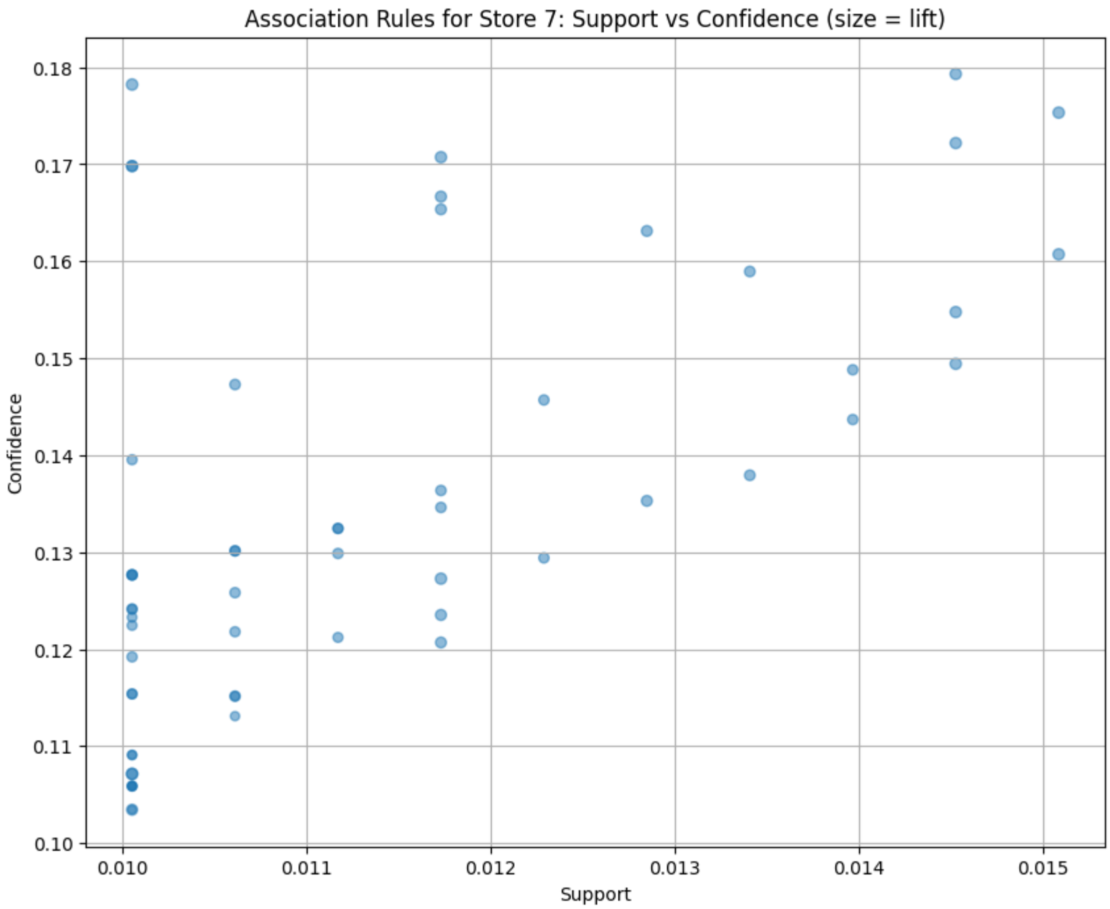




Top 10 Association Rules for Store 7:

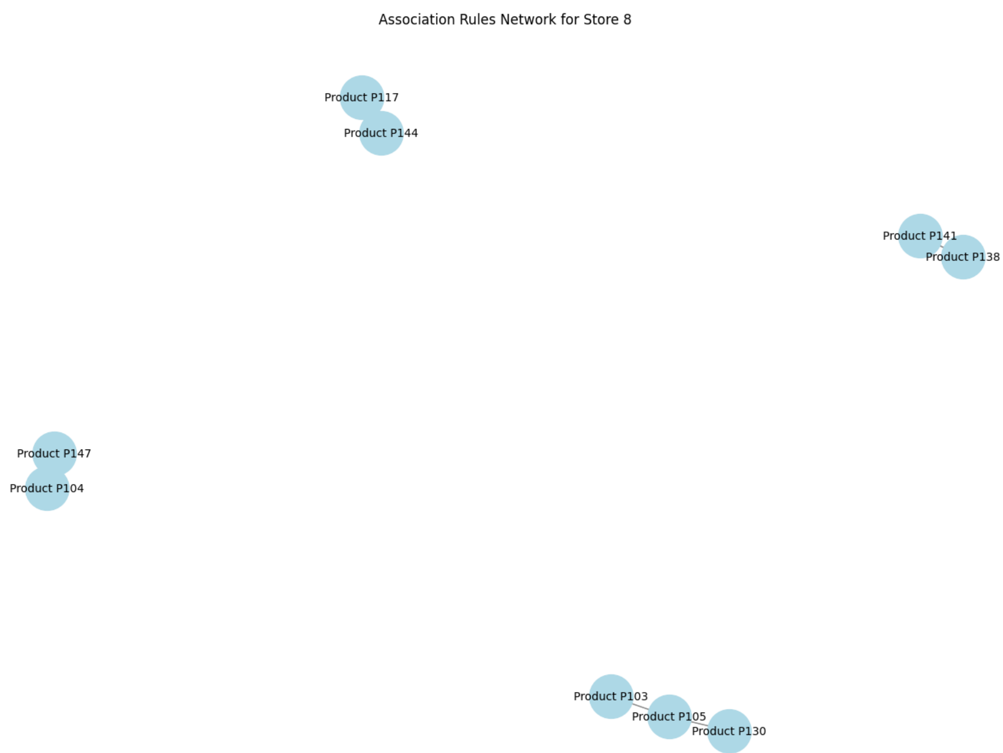
	If customer buys	They also buy	Support	Confidence	Lift
49	Product P119	Product P110	0.010056	0.178218	1.898868
48	Product P110	Product P119	0.010056	0.107143	1.898868
0	Product P110	Product P106	0.015084	0.160714	1.868043
1	Product P106	Product P110	0.015084	0.175325	1.868043
19	Product P130	Product P132	0.011732	0.170732	1.852180
18	Product P132	Product P130	0.011732	0.127273	1.852180
4	Product P105	Product P103	0.014525	0.149425	1.844629
5	Product P103	Product P105	0.014525	0.179310	1.844629
2	Product P117	Product P110	0.014525	0.172185	1.834595
3	Product P110	Product P117	0.014525	0.154762	1.834595

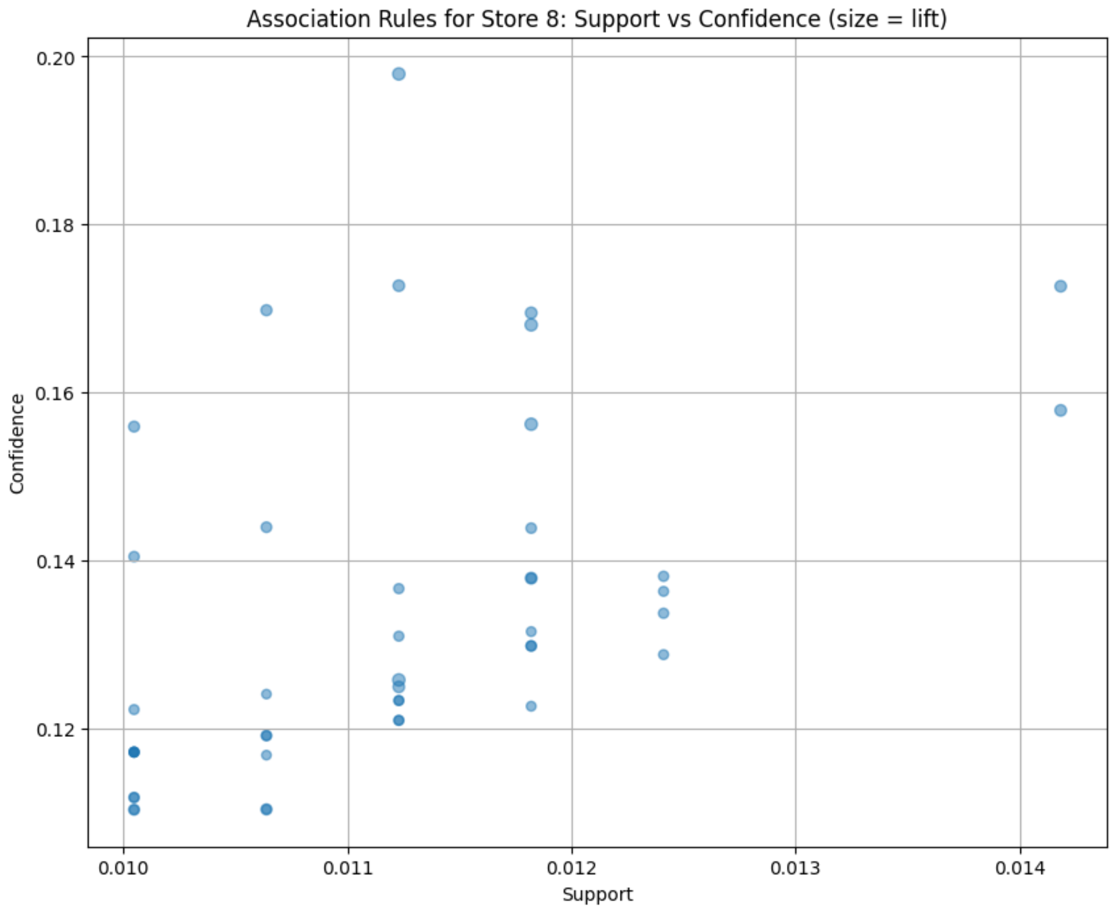

Association Rules Network for Store 7
Product P132
Product P130
Product P105
Product P103
Product P119
Product P110
Product P106
Product P117



Top 10 Association Rules for Store 8:

	If customer buys	They also buy	Support	Confidence	Lift
9	Product P141	Product P138	0.011820	0.156250	2.221639
8	Product P138	Product P141	0.011820	0.168067	2.221639
25	Product P104	Product P147	0.011229	0.197917	2.217715
24	Product P147	Product P104	0.011229	0.125828	2.217715
11	Product P144	Product P117	0.011820	0.137931	1.977791
10	Product P117	Product P144	0.011820	0.169492	1.977791
23	Product P130	Product P105	0.011229	0.172727	1.922727
22	Product P105	Product P130	0.011229	0.125000	1.922727
1	Product P103	Product P105	0.014184	0.172662	1.921999
0	Product P105	Product P103	0.014184	0.157895	1.921999

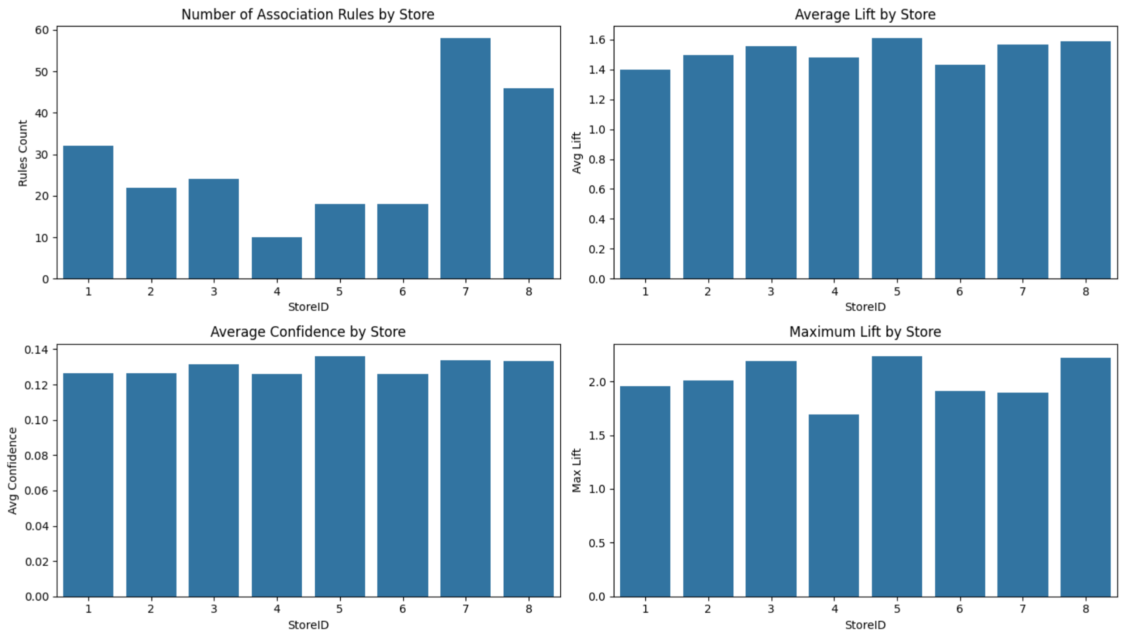

Association Rules Network for Store 8
Product P117
Product P144
Product P141
Product P138
Product P147
Product P104
Product P103
Product P105
Product P130



4.6 Cross-Store Comparison

[7]:
```python
# Compare performance metrics across stores
def compare_stores():
    comparison_data = []

    for store_id, data in results.items():
        rules = data['rules']
        if not rules.empty:
            avg_support = rules['support'].mean()
            avg_confidence = rules['confidence'].mean()
            avg_lift = rules['lift'].mean()
            num_rules = len(rules)
            max_lift = rules['lift'].max()

            comparison_data.append({
                'StoreID': store_id,
                'Rules Count': num_rules,
```

```
                'Avg Support': avg_support,
                'Avg Confidence': avg_confidence,
                'Avg Lift': avg_lift,
                'Max Lift': max_lift
            })

    comparison_df = pd.DataFrame(comparison_data)

    if not comparison_df.empty:
        # Plot comparison
        plt.figure(figsize=(14, 8))

        # Rules count by store
        plt.subplot(2, 2, 1)
        sns.barplot(x='StoreID', y='Rules Count', data=comparison_df)
        plt.title('Number of Association Rules by Store')

        # Average lift by store
        plt.subplot(2, 2, 2)
        sns.barplot(x='StoreID', y='Avg Lift', data=comparison_df)
        plt.title('Average Lift by Store')

        # Average confidence by store
        plt.subplot(2, 2, 3)
        sns.barplot(x='StoreID', y='Avg Confidence', data=comparison_df)
        plt.title('Average Confidence by Store')

        # Max lift by store
        plt.subplot(2, 2, 4)
        sns.barplot(x='StoreID', y='Max Lift', data=comparison_df)
        plt.title('Maximum Lift by Store')

        plt.tight_layout()
        plt.show()

        return comparison_df
    else:
        print("No comparison data available")
        return pd.DataFrame()

# Run comparison
store_comparison = compare_stores()
print("\nStore Comparison Metrics:")
print(store_comparison)
```



Store Comparison Metrics:

	StoreID	Rules Count	Avg Support	Avg Confidence	Avg Lift	Max Lift
0	1	32	0.011375	0.126280	1.396870	1.952184
1	2	22	0.010667	0.126422	1.495584	2.007305
2	3	24	0.011154	0.131643	1.553847	2.185998
3	4	10	0.010665	0.125873	1.480679	1.694855
4	5	18	0.011498	0.136225	1.608797	2.236801
5	6	18	0.011056	0.125936	1.432375	1.912385
6	7	58	0.011347	0.133821	1.566918	1.898868
7	8	46	0.011178	0.133408	1.587454	2.221639

4.7 Generate Business Insights

[8]:
```python
from IPython.display import display, Markdown

# Function to generate insights for a store
def generate_store_insights(store_id):
    rules = results[store_id]['rules']

    if rules.empty:
        return f"No significant patterns found for Store {store_id}"

    # Top 3 rules by lift
    top_rules = rules.head(3)
```

```
    insights = f"""
## Business Insights for Store {store_id}

### Top Association Rules:
"""

    for i, (_, rule) in enumerate(top_rules.iterrows()):
        antecedent = format_itemset(rule['antecedents'])
        consequent = format_itemset(rule['consequents'])

        insights += f"""
{i+1}. If customers buy **{antecedent}**, they are {rule['lift']:.2f} times␣
 ↪more likely to buy **{consequent}**
   - Support: {rule['support']:.2%} (appears in {rule['support']:.2%} of␣
 ↪transactions)
   - Confidence: {rule['confidence']:.2%} ({rule['confidence']:.2%} of baskets␣
 ↪with {antecedent} also contain {consequent})
"""

    insights += f"""
### Recommendations:
1. **Product Placement**: Place {format_itemset(top_rules.
 ↪iloc[0]['antecedents'])} near {format_itemset(top_rules.
 ↪iloc[0]['consequents'])}
2. **Bundling Opportunity**: Create a bundle of {format_itemset(top_rules.
 ↪iloc[0]['antecedents'])} with {format_itemset(top_rules.
 ↪iloc[0]['consequents'])}
3. **Cross-Selling**: Train staff to suggest {format_itemset(top_rules.
 ↪iloc[1]['consequents'])} when customers purchase {format_itemset(top_rules.
 ↪iloc[1]['antecedents'])}
"""

    return insights

# Generate insights for all stores
for store_id in results.keys():
    insights = generate_store_insights(store_id)
    display(Markdown(insights))
```

4.8 Business Insights for Store 1

4.8.1 Top Association Rules:

1. If customers buy **Product P144**, they are 1.95 times more likely to buy **Product P103**
    - Support: 1.42% (appears in 1.42% of transactions)
    - Confidence: 14.67% (14.67% of baskets with Product P144 also contain Product P103)
2. If customers buy **Product P103**, they are 1.95 times more likely to buy **Product P144**
    - Support: 1.42% (appears in 1.42% of transactions)

- Confidence: 18.97% (18.97% of baskets with Product P103 also contain Product P144)
3. If customers buy **Product P108**, they are 1.77 times more likely to buy **Product P144**
    - Support: 1.42% (appears in 1.42% of transactions)
    - Confidence: 17.19% (17.19% of baskets with Product P108 also contain Product P144)

4.8.2 Recommendations:

1. **Product Placement**: Place Product P144 near Product P103
2. **Bundling Opportunity**: Create a bundle of Product P144 with Product P103
3. **Cross-Selling**: Train staff to suggest Product P144 when customers purchase Product P103

4.9 Business Insights for Store 2

4.9.1 Top Association Rules:

1. If customers buy **Product P125**, they are 2.01 times more likely to buy **Product P149**
    - Support: 1.06% (appears in 1.06% of transactions)
    - Confidence: 17.27% (17.27% of baskets with Product P125 also contain Product P149)
2. If customers buy **Product P149**, they are 2.01 times more likely to buy **Product P125**
    - Support: 1.06% (appears in 1.06% of transactions)
    - Confidence: 12.31% (12.31% of baskets with Product P149 also contain Product P125)
3. If customers buy **Product P106**, they are 1.89 times more likely to buy **Product P115**
    - Support: 1.01% (appears in 1.01% of transactions)
    - Confidence: 11.33% (11.33% of baskets with Product P106 also contain Product P115)

4.9.2 Recommendations:

1. **Product Placement**: Place Product P125 near Product P149
2. **Bundling Opportunity**: Create a bundle of Product P125 with Product P149
3. **Cross-Selling**: Train staff to suggest Product P125 when customers purchase Product P149

4.10 Business Insights for Store 3

4.10.1 Top Association Rules:

1. If customers buy **Product P138**, they are 2.19 times more likely to buy **Product P127**
    - Support: 1.15% (appears in 1.15% of transactions)
    - Confidence: 18.18% (18.18% of baskets with Product P138 also contain Product P127)
2. If customers buy **Product P127**, they are 2.19 times more likely to buy **Product P138**
    - Support: 1.15% (appears in 1.15% of transactions)
    - Confidence: 13.79% (13.79% of baskets with Product P127 also contain Product P138)
3. If customers buy **Product P119**, they are 1.94 times more likely to buy **Product P127**
    - Support: 1.00% (appears in 1.00% of transactions)
    - Confidence: 16.15% (16.15% of baskets with Product P119 also contain Product P127)

4.10.2 Recommendations:

1. **Product Placement**: Place Product P138 near Product P127
2. **Bundling Opportunity**: Create a bundle of Product P138 with Product P127
3. **Cross-Selling**: Train staff to suggest Product P138 when customers purchase Product P127

4.11 Business Insights for Store 4

4.11.1 Top Association Rules:

1. If customers buy **Product P117**, they are 1.69 times more likely to buy **Product P132**
   - Support: 1.16% (appears in 1.16% of transactions)
   - Confidence: 14.77% (14.77% of baskets with Product P117 also contain Product P132)
2. If customers buy **Product P132**, they are 1.69 times more likely to buy **Product P117**
   - Support: 1.16% (appears in 1.16% of transactions)
   - Confidence: 13.33% (13.33% of baskets with Product P132 also contain Product P117)
3. If customers buy **Product P115**, they are 1.56 times more likely to buy **Product P147**
   - Support: 1.06% (appears in 1.06% of transactions)
   - Confidence: 14.29% (14.29% of baskets with Product P115 also contain Product P147)

4.11.2 Recommendations:

1. **Product Placement**: Place Product P117 near Product P132
2. **Bundling Opportunity**: Create a bundle of Product P117 with Product P132
3. **Cross-Selling**: Train staff to suggest Product P117 when customers purchase Product P132

4.12 Business Insights for Store 5

4.12.1 Top Association Rules:

1. If customers buy **Product P105**, they are 2.24 times more likely to buy **Product P126**
   - Support: 1.11% (appears in 1.11% of transactions)
   - Confidence: 13.25% (13.25% of baskets with Product P105 also contain Product P126)
2. If customers buy **Product P126**, they are 2.24 times more likely to buy **Product P105**
   - Support: 1.11% (appears in 1.11% of transactions)
   - Confidence: 18.69% (18.69% of baskets with Product P126 also contain Product P105)
3. If customers buy **Product P138**, they are 1.94 times more likely to buy **Product P147**
   - Support: 1.16% (appears in 1.16% of transactions)
   - Confidence: 17.65% (17.65% of baskets with Product P138 also contain Product P147)

4.12.2 Recommendations:

1. **Product Placement**: Place Product P105 near Product P126
2. **Bundling Opportunity**: Create a bundle of Product P105 with Product P126
3. **Cross-Selling**: Train staff to suggest Product P105 when customers purchase Product P126

4.13 Business Insights for Store 6

4.13.1 Top Association Rules:

1. If customers buy **Product P117**, they are 1.91 times more likely to buy **Product P122**
   - Support: 1.14% (appears in 1.14% of transactions)
   - Confidence: 14.56% (14.56% of baskets with Product P117 also contain Product P122)
2. If customers buy **Product P122**, they are 1.91 times more likely to buy **Product P117**
   - Support: 1.14% (appears in 1.14% of transactions)
   - Confidence: 15.03% (15.03% of baskets with Product P122 also contain Product P117)
3. If customers buy **Product P117**, they are 1.78 times more likely to buy **Product P103**

  - Support: 1.14% (appears in 1.14% of transactions)
  - Confidence: 14.56% (14.56% of baskets with Product P117 also contain Product P103)

4.13.2 Recommendations:

1. **Product Placement**: Place Product P117 near Product P122
2. **Bundling Opportunity**: Create a bundle of Product P117 with Product P122
3. **Cross-Selling**: Train staff to suggest Product P117 when customers purchase Product P122

4.14 Business Insights for Store 7

4.14.1 Top Association Rules:

1. If customers buy **Product P119**, they are 1.90 times more likely to buy **Product P110**
   - Support: 1.01% (appears in 1.01% of transactions)
   - Confidence: 17.82% (17.82% of baskets with Product P119 also contain Product P110)
2. If customers buy **Product P110**, they are 1.90 times more likely to buy **Product P119**
   - Support: 1.01% (appears in 1.01% of transactions)
   - Confidence: 10.71% (10.71% of baskets with Product P110 also contain Product P119)
3. If customers buy **Product P110**, they are 1.87 times more likely to buy **Product P106**
   - Support: 1.51% (appears in 1.51% of transactions)
   - Confidence: 16.07% (16.07% of baskets with Product P110 also contain Product P106)

4.14.2 Recommendations:

1. **Product Placement**: Place Product P119 near Product P110
2. **Bundling Opportunity**: Create a bundle of Product P119 with Product P110
3. **Cross-Selling**: Train staff to suggest Product P119 when customers purchase Product P110

4.15 Business Insights for Store 8

4.15.1 Top Association Rules:

1. If customers buy **Product P141**, they are 2.22 times more likely to buy **Product P138**
   - Support: 1.18% (appears in 1.18% of transactions)
   - Confidence: 15.62% (15.62% of baskets with Product P141 also contain Product P138)
2. If customers buy **Product P138**, they are 2.22 times more likely to buy **Product P141**
   - Support: 1.18% (appears in 1.18% of transactions)
   - Confidence: 16.81% (16.81% of baskets with Product P138 also contain Product P141)
3. If customers buy **Product P104**, they are 2.22 times more likely to buy **Product P147**
   - Support: 1.12% (appears in 1.12% of transactions)
   - Confidence: 19.79% (19.79% of baskets with Product P104 also contain Product P147)

4.15.2 Recommendations:

1. **Product Placement**: Place Product P141 near Product P138
2. **Bundling Opportunity**: Create a bundle of Product P141 with Product P138
3. **Cross-Selling**: Train staff to suggest Product P141 when customers purchase Product P138

4.16 Category-Based Analysis

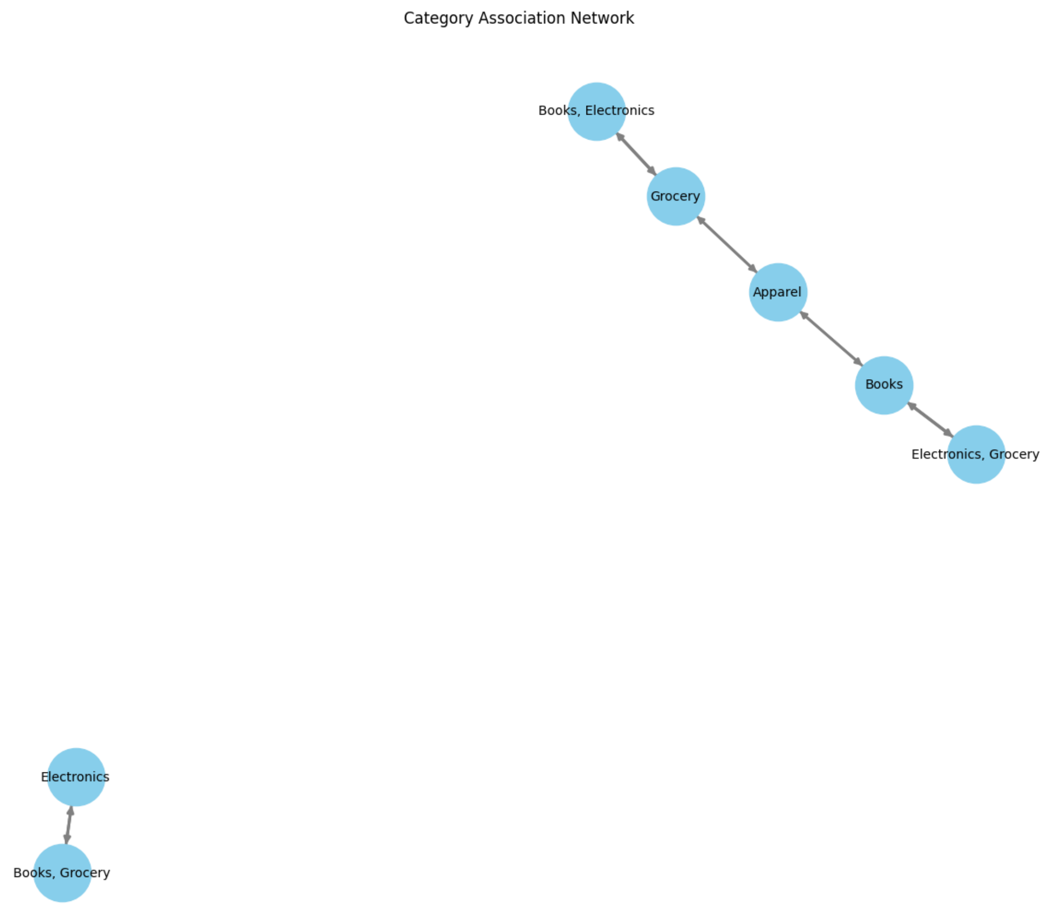
[9]:
```
# Function to perform category-level market basket analysis
def category_level_analysis():
    # Create a list of transactions at category level
    category_transactions = df['ProductCategory'].tolist()

    # Encode the transactions
    te = TransactionEncoder()
    te_ary = te.fit(category_transactions).transform(category_transactions)
    category_df = pd.DataFrame(te_ary, columns=te.columns_)

    # Apply Apriori
    frequent_categories = apriori(category_df, min_support=0.02,␣
 ↪use_colnames=True)

    if not frequent_categories.empty:
        frequent_categories['length'] = frequent_categories['itemsets'].
 ↪apply(lambda x: len(x))
        frequent_categories = frequent_categories.sort_values('support',␣
 ↪ascending=False)

        # Generate rules
        category_rules = association_rules(frequent_categories, metric="lift",␣
 ↪min_threshold=1.0)

        if not category_rules.empty:
            # Format for display
            category_rules['antecedents_str'] = category_rules['antecedents'].
 ↪apply(format_itemset)
            category_rules['consequents_str'] = category_rules['consequents'].
 ↪apply(format_itemset)

            # Display top category rules
            top_cat_rules = category_rules.head(10)[['antecedents_str',␣
 ↪'consequents_str', 'support', 'confidence', 'lift']]
            top_cat_rules.columns = ['If customer buys from', 'They also buy␣
 ↪from', 'Support', 'Confidence', 'Lift']

            print("\nTop Category Association Rules:")
            print(top_cat_rules)

            # Visualize category relationships
            plt.figure(figsize=(12, 10))

            # Create graph
            G = nx.DiGraph()
```

```python
            # Add nodes and edges for top 10 rules
            for _, row in category_rules.head(10).iterrows():
                antecedent = format_itemset(row['antecedents'])
                consequent = format_itemset(row['consequents'])

                if antecedent not in G.nodes:
                    G.add_node(antecedent)
                if consequent not in G.nodes:
                    G.add_node(consequent)

                G.add_edge(antecedent, consequent, weight=row['lift'])

            # Draw graph
            pos = nx.spring_layout(G, seed=42)
            edges = G.edges(data=True)
            weights = [d['weight']*2 for _, _, d in edges]

            nx.draw(G, pos, with_labels=True, node_color='skyblue',
                   node_size=2000, edge_color='gray', width=weights,
                   edge_cmap=plt.cm.Blues, font_size=10)

            plt.title('Category Association Network')
            plt.axis('off')
            plt.tight_layout()
            plt.show()

            return category_rules

    print("No significant category associations found")
    return pd.DataFrame()

# Run category analysis
category_rules = category_level_analysis()
```

Top Category Association Rules:

	If customer buys from	They also buy from	Support	Confidence	Lift
0	Books	Apparel	0.105922	0.248717	1.004180
1	Apparel	Books	0.105922	0.427654	1.004180
2	Books, Grocery	Electronics	0.105260	0.642020	1.110060
3	Books, Electronics	Grocery	0.105260	0.458718	1.150301
4	Electronics, Grocery	Books	0.105260	0.496407	1.165619
5	Books	Electronics, Grocery	0.105260	0.247161	1.165619
6	Grocery	Books, Electronics	0.105260	0.263953	1.150301
7	Electronics	Books, Grocery	0.105260	0.181995	1.110060
8	Grocery	Apparel	0.100556	0.252159	1.018080
9	Apparel	Grocery	0.100556	0.405991	1.018080

```
C:\Users\Khor Kean Teng\AppData\Local\Temp\ipykernel_8588\886073228.py:62:
UserWarning: This figure includes Axes that are not compatible with
tight_layout, so results might be incorrect.
  plt.tight_layout()
```



4.17 Conclusion and Recommendations

[10]:
```python
# Generate overall recommendations
def generate_overall_recommendations():
    # Compare store performance
    if not store_comparison.empty:
        best_store = store_comparison.loc[store_comparison['Avg Lift'].
 ↪idxmax()]['StoreID']
        worst_store = store_comparison.loc[store_comparison['Avg Lift'].
 ↪idxmin()]['StoreID']
    else:
        best_store = "N/A"
```

```python
        worst_store = "N/A"

    # Collect top rules across all stores
    all_top_rules = []
    for store_id, data in results.items():
        if not data['rules'].empty:
            top_rule = data['rules'].iloc[0]
            all_top_rules.append((store_id, top_rule))

    recommendations = f"""
## Overall Recommendations from Market Basket Analysis

### Store Performance:
- Store {best_store} shows the strongest product associations
- Store {worst_store} shows the weakest associations and may need merchandising
 ↪adjustments

### Cross-Store Opportunities:
"""

    if all_top_rules:
        recommendations += "#### Top product associations by store:\n"
        for store_id, rule in all_top_rules:
            antecedent = format_itemset(rule['antecedents'])
            consequent = format_itemset(rule['consequents'])
            recommendations += f"- Store {store_id}: {antecedent} →
 ↪{consequent} (Lift: {rule['lift']:.2f})\n"

    recommendations += """
### Implementation Strategy:
1. **Store Layout Optimization**:
   - Reorganize product placements based on discovered associations
   - Create "customer journey" paths that follow frequent purchase patterns

2. **Targeted Marketing Campaigns**:
   - Develop store-specific promotions based on unique association patterns
   - Create bundled offerings of frequently co-purchased items

3. **Inventory Management**:
   - Ensure complementary products are stocked together
   - Adjust inventory levels based on association strengths

4. **Staff Training**:
   - Educate staff on cross-selling opportunities specific to each store
   - Implement suggestive selling based on top association rules

5. **Further Analysis**:
```

```
   - Conduct temporal analysis to identify seasonal patterns
   - Segment customers and analyze basket patterns by segment
   - Implement A/B testing to validate recommendations
"""

    return recommendations

# Generate and print overall recommendations
overall_recommendations = generate_overall_recommendations()
display(Markdown(overall_recommendations))
```

4.18 Overall Recommendations from Market Basket Analysis

4.18.1 Store Performance:

- Store 5.0 shows the strongest product associations
- Store 1.0 shows the weakest associations and may need merchandising adjustments

4.18.2 Cross-Store Opportunities:

Top product associations by store:

- Store 1: Product P144 → Product P103 (Lift: 1.95)
- Store 2: Product P125 → Product P149 (Lift: 2.01)
- Store 3: Product P138 → Product P127 (Lift: 2.19)
- Store 4: Product P117 → Product P132 (Lift: 1.69)
- Store 5: Product P105 → Product P126 (Lift: 2.24)
- Store 6: Product P117 → Product P122 (Lift: 1.91)
- Store 7: Product P119 → Product P110 (Lift: 1.90)
- Store 8: Product P141 → Product P138 (Lift: 2.22)

4.18.3 Implementation Strategy:

1. **Store Layout Optimization**:
    - Reorganize product placements based on discovered associations
    - Create "customer journey" paths that follow frequent purchase patterns
2. **Targeted Marketing Campaigns**:
    - Develop store-specific promotions based on unique association patterns
    - Create bundled offerings of frequently co-purchased items
3. **Inventory Management**:
    - Ensure complementary products are stocked together
    - Adjust inventory levels based on association strengths
4. **Staff Training**:
    - Educate staff on cross-selling opportunities specific to each store
    - Implement suggestive selling based on top association rules
5. **Further Analysis**:
    - Conduct temporal analysis to identify seasonal patterns
    - Segment customers and analyze basket patterns by segment
    - Implement A/B testing to validate recommendations