CRM Analysis project

October 11, 2024

Customer Relationship Management (CRM) analysis involves the systematic examination and interpretation of data related to interactions between a business and its customers. Through CRM analysis, companies evaluate customer behavior, preferences, and feedback to gain valuable insights into their needs and expectations.

In the dataset below, the following steps have been performed:

1. Data Preprocessing:

- Managed outliers
- Addressed missing values.
- Handled potential duplicates.

2. Exploratory Data Analysis (EDA):

- Conducted a thorough analysis to identify patterns and relationships within the data.

3. Customer-Centric Feature Engineering (CRM Analytics):

- Created Recency, Frequency, and Monetary (RFM) values for customer transaction insights.
- Analyzed unique product purchase details.
- Derived RFM scores to segment customers based on activity levels.

4. Additional Customer-Centric Features:

- Calculated average days between purchases.
- Identified preferred shopping days.
- Determined peak shopping hours.

This comprehensive analysis provides a holistic understanding of customer behavior and purchasing patterns.

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Reading the dataset to return the features and rows inside the dataset

[ ]:
```
df = pd.read_csv("Ecom_CRM_analysis.csv", encoding='ISO-8859-1')
```

[ ]:
```
df
```

[ ]:

	InvoiceNo	StockCode	Description	Quantity	\
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	
1	536365	71053	WHITE METAL LANTERN	6	
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	
…	…	…	…	…	
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	
541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	

	InvoiceDate	UnitPrice	CustomerID	Country
0	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	12/1/2010 8:26	3.39	17850.0	United Kingdom
…	…	…	…	…
541904	12/9/2011 12:50	0.85	12680.0	France
541905	12/9/2011 12:50	2.10	12680.0	France
541906	12/9/2011 12:50	4.15	12680.0	France
541907	12/9/2011 12:50	4.15	12680.0	France
541908	12/9/2011 12:50	4.95	12680.0	France

[541909 rows x 8 columns]

Dataset Overview: Structure, Data Types, and Missing Values

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  object
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

Missing Values Summary: Count of Null Values per Column

[ ]:
```
df.isna().sum()
```

[ ]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

Removing Rows with Missing CustomerID Values and Resetting the Index

[ ]:
```
df = df.dropna(subset = ['CustomerID']).reset_index(drop = True)
```

Rechecking and making sure that all rows with null values have been dropped

[ ]:
```
df.isna().sum()
```

[ ]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

Removing Duplicate Rows While Keeping the First Occurrence

[ ]:
```
df = df.drop_duplicates(keep='first')
```

Unique number of values for specific categorical columns

[ ]:
```
columns_list = df[['InvoiceNo', 'StockCode', 'Description', 'CustomerID',␣
 ↪'Country']]

for column in columns_list:
  unique_count = columns_list[column].nunique()
  print(column, "-", unique_count)
```

```
InvoiceNo - 22190
StockCode - 3684
Description - 3896
```

```
CustomerID - 4372
Country - 37
```

Finding the sale value for each individual product sold

[ ]:
```
df['total'] = (df['Quantity'] * df['UnitPrice']).round(3)
```

Top 20 Highest Quantity demanded products in terms of Quantity, sales value

[ ]:
```
highest_qty_demanded = df.groupby('Description')['Quantity'].sum().
 ↪sort_values(ascending=False).head(20)
highest_sales_value = df.groupby('Description')['total'].sum().
 ↪sort_values(ascending=False).head(20).round(3)

# Create a figure with subplots for side-by-side display
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))  # 1 row, 2 columns

ax1.axis('off')
ax2.axis('off')

# Add tables to each subplot
ax1.table(cellText=highest_qty_demanded.reset_index().values,␣
 ↪colLabels=highest_qty_demanded.reset_index().columns, loc='center')
ax1.set_title("Top 20 Items by Quantity Demanded")

ax2.table(cellText=highest_sales_value.reset_index().values,␣
 ↪colLabels=highest_sales_value.reset_index().columns, loc='center')
ax2.set_title("Top 20 Items by Total Sales Value")

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

Top 20 Items by Quantity Demanded

Description	Quantity
WORLD WAR 2 GLIDERS ASSTD DESIGNS	53119
JUMBO BAG RED RETROSPOT	44963
ASSORTED COLOUR BIRD ORNAMENT	35215
WHITE HANGING HEART T-LIGHT HOLDER	34128
PACK OF 72 RETROSPOT CAKE CASES	33386
POPCORN HOLDER	30492
RABBIT NIGHT LIGHT	27045
MINI PAINT SET VINTAGE	25880
PACK OF 12 LONDON TISSUES	25305
PACK OF 60 PINK PAISLEY CAKE CASES	24129
BROCADE RING PURSE	22924
VICTORIAN GLASS HANGING T-LIGHT	21955
ASSORTED COLOURS SILK FAN	21132
RED HARMONICA IN BOX	20882
JUMBO BAG PINK POLKADOT	19692
SMALL POPCORN HOLDER	18197
60 TEATIME FAIRY CAKE CASES	17514
LUNCH BAG RED RETROSPOT	17024
HEART OF WICKER SMALL	16633
JUMBO BAG STRAWBERRY	16521

Top 20 Items by Total Sales Value

Description	total
REGENCY CAKESTAND 3 TIER	132567.7
WHITE HANGING HEART T-LIGHT HOLDER	93767.8
JUMBO BAG RED RETROSPOT	83056.52
PARTY BUNTING	67628.43
POSTAGE	66710.24
ASSORTED COLOUR BIRD ORNAMENT	56331.91
RABBIT NIGHT LIGHT	51042.84
CHILLI LIGHTS	45915.41
PAPER CHAIN KIT 50'S CHRISTMAS	41423.78
PICNIC BASKET WICKER 60 PIECES	39619.5
BLACK RECORD COVER FRAME	38990.63
JUMBO BAG PINK POLKADOT	36437.78
SPOTTY BUNTING	35026.74
DOORMAT KEEP CALM AND COME IN	34279.6
WOOD BLACK BOARD ANT WHITE FINISH	34243.76
SET OF 3 CAKE TINS PANTRY DESIGN	32573.15
JAM MAKING SET WITH JARS	31611.72
JUMBO BAG STRAWBERRY	30120.83
HEART OF WICKER LARGE	28290.15
VICTORIAN GLASS HANGING T-LIGHT	28111.71

Top 10 highest countries in terms of Quantity demand, Total sales value

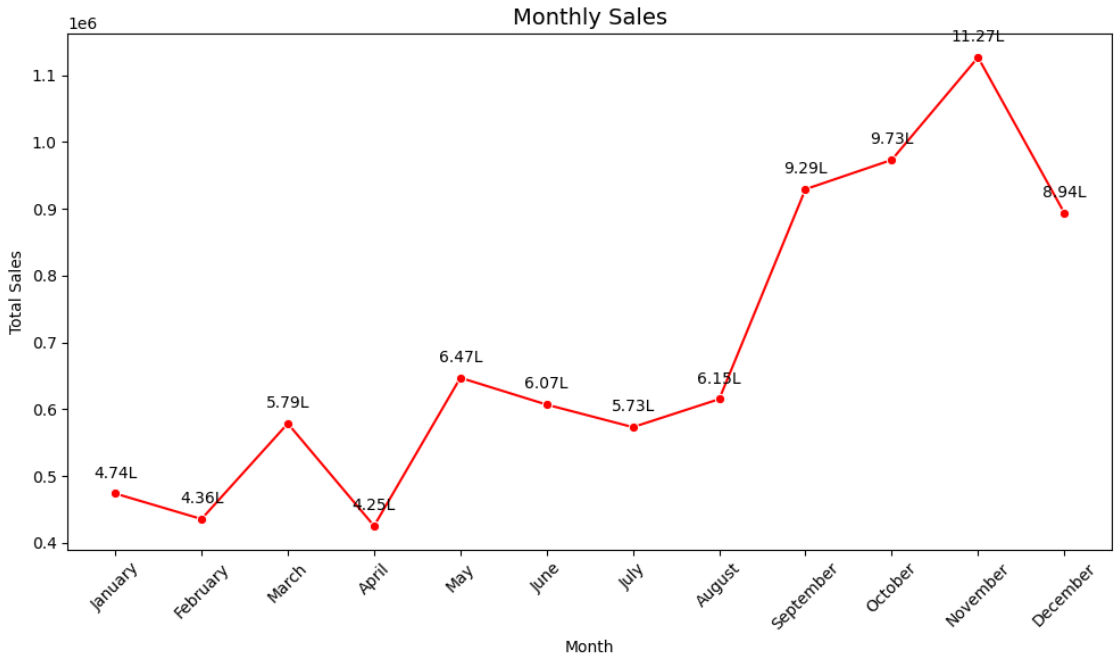
```
[ ]: # Calculate the top 10 countries by quantity and total sales value
top_countries_qty = df.groupby('Country')['Quantity'].sum().
 ↪sort_values(ascending=False).head(10)
top_countries_sales = df.groupby('Country')['total'].sum().
 ↪sort_values(ascending=False).head(10).round(3)

# Create a figure with subplots for side-by-side display
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))  # 1 row, 2 columns,␣
 ↪adjust figure size as needed

# Remove axes for both subplots
ax1.axis('off')
ax2.axis('off')

# Add tables to each subplot
ax1.table(cellText=top_countries_qty.reset_index().values,␣
 ↪colLabels=top_countries_qty.reset_index().columns, loc='center')
ax1.set_title("Top 10 Countries by Quantity")

ax2.table(cellText=top_countries_sales.reset_index().values,␣
 ↪colLabels=top_countries_sales.reset_index().columns, loc='center')
ax2.set_title("Top 10 Countries by Total Sales Value")

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

Country	Quantity
United Kingdom	3994870
Netherlands	200128
EIRE	136187
Germany	117341
France	109806
Australia	83643
Sweden	35632
Switzerland	29778
Spain	26817
Japan	25218

Country	total
United Kingdom	6747156.154
Netherlands	284661.54
EIRE	250001.78
Germany	221509.47
France	196626.05
Australia	137009.77
Switzerland	55739.4
Spain	54756.03
Belgium	40910.96
Sweden	36585.41

Total Monthly Sales Overview

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

# Define the month order
month_order = ['January', 'February', 'March', 'April', 'May', 'June',
               'July', 'August', 'September', 'October', 'November', 'December']

# Convert the month names to a categorical type with the correct order
monthly_sales = df.groupby(pd.to_datetime(df['InvoiceDate']).dt.
 ↪month_name())['total'].sum()
monthly_sales = monthly_sales.reindex(month_order)  # Sort by the defined month␣
 ↪order

# Function to format numbers in thousands (K) and lakhs (L)
def format_sales(value):
    if value >= 1_00_000:  # 1 Lakh
        return f'{value/1_00_000:.2f}L'  # Format in lakhs
    elif value >= 1_000:  # 1 Thousand
        return f'{value/1_000:.2f}K'  # Format in thousands
    else:
        return f'{value:.2f}'

# Plot the line plot using Seaborn
plt.figure(figsize=(10, 6))
sns.lineplot(x=monthly_sales.index, y=monthly_sales.values, marker='o',␣
 ↪color='r')

# Annotate the points with values
for i, value in enumerate(monthly_sales.values):
    plt.annotate(format_sales(value),  # Format the value
                 (monthly_sales.index[i], value),  # Position (x, y)
                 textcoords="offset points",  # Offset for better placement
                 xytext=(0, 10),  # Move the text 10 points above the point
                 ha='center', fontsize=10, color='black')  # Align center, set␣
 ↪font size and color

# Set the title and labels
plt.title('Monthly Sales', fontsize=14)
plt.xlabel('Month')
plt.ylabel('Total Sales')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()

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



Extracting first purchase & last purchase date, calculating total number of purchases and total monetary value for each customer.

[ ]:
```
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])

monetary_table = df.groupby('CustomerID').agg(
    first_purchase_date = pd.NamedAgg(column = 'InvoiceDate', aggfunc = 'min'),
    last_purchase_date = pd.NamedAgg(column = 'InvoiceDate', aggfunc = 'max'),
    num_purchases = pd.NamedAgg(column = 'InvoiceNo', aggfunc = 'nunique'),
    country = pd.NamedAgg(column='Country', aggfunc='first'),
    monetary = pd.NamedAgg(column = 'total', aggfunc = 'sum')).reset_index()

monetary_table['first_purchase_date'] = pd.
 ↪to_datetime(monetary_table['first_purchase_date']).dt.date
monetary_table['last_purchase_date'] = pd.
 ↪to_datetime(monetary_table['last_purchase_date']).dt.date

monetary_table
```

[ ]:

	CustomerID	first_purchase_date	last_purchase_date	num_purchases	\
0	12346.0	2011-01-18	2011-01-18	2	
1	12347.0	2010-12-07	2011-12-07	7	
2	12348.0	2010-12-16	2011-09-25	4	
3	12349.0	2011-11-21	2011-11-21	1	
4	12350.0	2011-02-02	2011-02-02	1	
…	…	…	…	…	

```
4367     18280.0          2011-03-07          2011-03-07              1
4368     18281.0          2011-06-12          2011-06-12              1
4369     18282.0          2011-08-05          2011-12-02              3
4370     18283.0          2011-01-06          2011-12-06             16
4371     18287.0          2011-05-22          2011-10-28              3

              country  monetary
0      United Kingdom      0.00
1             Iceland   4310.00
2             Finland   1797.24
3               Italy   1757.55
4              Norway    334.40
…                 …       …
4367   United Kingdom    180.60
4368   United Kingdom     80.82
4369   United Kingdom    176.60
4370   United Kingdom   2045.53
4371   United Kingdom   1837.28

[4372 rows x 6 columns]
```

Calculating key metrics like recency and frequency for each unique customer

[ ]:
```
reference_date = monetary_table['last_purchase_date'].max()

monetary_table['recency'] = (pd.to_datetime(reference_date) - pd.
 ↪to_datetime(monetary_table['last_purchase_date'])).dt.days
```

[ ]:
```
monetary_table['first_purchase_date'] = pd.
 ↪to_datetime(monetary_table['first_purchase_date'])
monetary_table['last_purchase_date'] = pd.
 ↪to_datetime(monetary_table['last_purchase_date'])

monetary_table['months_cust'] = ((monetary_table['last_purchase_date'].dt.year␣
 ↪- monetary_table['first_purchase_date'].dt.year)*12
                                  +(monetary_table['last_purchase_date'].dt.
 ↪month - monetary_table['first_purchase_date'].dt.month)) + 1


monetary_table['frequency'] = monetary_table['num_purchases']/
 ↪monetary_table['months_cust']

RFM_table = monetary_table.sort_values(by = 'CustomerID')

RFM_table
```

[ ]:

	CustomerID	first_purchase_date	last_purchase_date	num_purchases	\
0	12346.0	2011-01-18	2011-01-18	2	
1	12347.0	2010-12-07	2011-12-07	7	
2	12348.0	2010-12-16	2011-09-25	4	
3	12349.0	2011-11-21	2011-11-21	1	
4	12350.0	2011-02-02	2011-02-02	1	
…	…	…	…	…	
4367	18280.0	2011-03-07	2011-03-07	1	
4368	18281.0	2011-06-12	2011-06-12	1	
4369	18282.0	2011-08-05	2011-12-02	3	
4370	18283.0	2011-01-06	2011-12-06	16	
4371	18287.0	2011-05-22	2011-10-28	3	

	country	monetary	recency	months_cust	frequency
0	United Kingdom	0.00	325	1	2.000000
1	Iceland	4310.00	2	13	0.538462
2	Finland	1797.24	75	10	0.400000
3	Italy	1757.55	18	1	1.000000
4	Norway	334.40	310	1	1.000000
…	…	…	…	…	…
4367	United Kingdom	180.60	277	1	1.000000
4368	United Kingdom	80.82	180	1	1.000000
4369	United Kingdom	176.60	7	5	0.600000
4370	United Kingdom	2045.53	3	12	1.333333
4371	United Kingdom	1837.28	42	6	0.500000

[4372 rows x 9 columns]

Determining quintiles for each RFM metric

[ ]:
```
# Define the percentile values you need
percentile_values = [20, 40, 60, 80, 100]
quantiles = [p / 100 for p in percentile_values]  # Convert to fractions

# Calculate the percentiles for each metric
monetary_percentiles = RFM_table['monetary'].quantile(quantiles)
frequency_percentiles = RFM_table['frequency'].quantile(quantiles)
recency_percentiles = RFM_table['recency'].quantile(quantiles)

# Assign percentile values to new columns
RFM_table['m20'] = monetary_percentiles[0.2]
RFM_table['m40'] = monetary_percentiles[0.4]
RFM_table['m60'] = monetary_percentiles[0.6]
RFM_table['m80'] = monetary_percentiles[0.8]
RFM_table['m100'] = monetary_percentiles[1.0]

RFM_table['f20'] = frequency_percentiles[0.2]
```

```
RFM_table['f40'] = frequency_percentiles[0.4]
RFM_table['f60'] = frequency_percentiles[0.6]
RFM_table['f80'] = frequency_percentiles[0.8]
RFM_table['f100'] = frequency_percentiles[1.0]

RFM_table['r20'] = recency_percentiles[0.2]
RFM_table['r40'] = recency_percentiles[0.4]
RFM_table['r60'] = recency_percentiles[0.6]
RFM_table['r80'] = recency_percentiles[0.8]
RFM_table['r100'] = recency_percentiles[1.0]

# Sort the RFM_table by CustomerID (optional)
RFM_table = RFM_table.sort_values('CustomerID')

# Display all columns
pd.set_option('display.max_columns', None)
RFM_table
```

[ ]:

	CustomerID	first_purchase_date	last_purchase_date	num_purchases	\
0	12346.0	2011-01-18	2011-01-18	2	
1	12347.0	2010-12-07	2011-12-07	7	
2	12348.0	2010-12-16	2011-09-25	4	
3	12349.0	2011-11-21	2011-11-21	1	
4	12350.0	2011-02-02	2011-02-02	1	
…	…	…	…	…	
4367	18280.0	2011-03-07	2011-03-07	1	
4368	18281.0	2011-06-12	2011-06-12	1	
4369	18282.0	2011-08-05	2011-12-02	3	
4370	18283.0	2011-01-06	2011-12-06	16	
4371	18287.0	2011-05-22	2011-10-28	3	

	country	monetary	recency	months_cust	frequency	m20	\
0	United Kingdom	0.00	325	1	2.000000	232.504	
1	Iceland	4310.00	2	13	0.538462	232.504	
2	Finland	1797.24	75	10	0.400000	232.504	
3	Italy	1757.55	18	1	1.000000	232.504	
4	Norway	334.40	310	1	1.000000	232.504	
…	…	…	…	…	…	…	
4367	United Kingdom	180.60	277	1	1.000000	232.504	
4368	United Kingdom	80.82	180	1	1.000000	232.504	
4369	United Kingdom	176.60	7	5	0.600000	232.504	
4370	United Kingdom	2045.53	3	12	1.333333	232.504	
4371	United Kingdom	1837.28	42	6	0.500000	232.504	

	m40	m60	m80	m100	f20	f40	f60	f80	\
0	463.54	903.228	1994.064	279489.02	0.5	0.909091	1.0	1.166667	
1	463.54	903.228	1994.064	279489.02	0.5	0.909091	1.0	1.166667	

```
2     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
3     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
…       …       …        …          …   …        …   …       …
4367  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4368  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4369  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4370  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4371  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667

            f100   r20   r40   r60    r80   r100
0      19.076923  11.0  31.0  71.0  178.0  373.0
1      19.076923  11.0  31.0  71.0  178.0  373.0
2      19.076923  11.0  31.0  71.0  178.0  373.0
3      19.076923  11.0  31.0  71.0  178.0  373.0
4      19.076923  11.0  31.0  71.0  178.0  373.0
…            …    …     …     …      …      …
4367   19.076923  11.0  31.0  71.0  178.0  373.0
4368   19.076923  11.0  31.0  71.0  178.0  373.0
4369   19.076923  11.0  31.0  71.0  178.0  373.0
4370   19.076923  11.0  31.0  71.0  178.0  373.0
4371   19.076923  11.0  31.0  71.0  178.0  373.0

[4372 rows x 24 columns]
```

Assigning scores for each RFM metric

[ ]:
```python
def assign_monetary_score(row):
    if row['monetary'] <= row['m20']:
        return 1
    elif row['monetary'] <= row['m40']:
        return 2
    elif row['monetary'] <= row['m60']:
        return 3
    elif row['monetary'] <= row['m80']:
        return 4
    else:
        return 5

def assign_frequency_score(row):
    if row['frequency'] <= row['f20']:
        return 1
    elif row['frequency'] <= row['f40']:
        return 2
    elif row['frequency'] <= row['f60']:
        return 3
    elif row['frequency'] <= row['f80']:
```

```
        return 4
    else:
        return 5

def assign_recency_score(row):
    # Reversed scoring for recency
    if row['recency'] <= row['r20']:
        return 5
    elif row['recency'] <= row['r40']:
        return 4
    elif row['recency'] <= row['r60']:
        return 3
    elif row['recency'] <= row['r80']:
        return 2
    else:
        return 1

# Apply the functions to create the m_score, f_score, and r_score columns
RFM_table['m_score'] = RFM_table.apply(assign_monetary_score, axis=1)
RFM_table['f_score'] = RFM_table.apply(assign_frequency_score, axis=1)
RFM_table['r_score'] = RFM_table.apply(assign_recency_score, axis=1)

# Calculate the fm_score as the average of m_score and f_score, and cast to␣
 ↪integer
RFM_table['fm_score'] = ((RFM_table['m_score'] + RFM_table['f_score']) / 2).
 ↪round(0).astype(int)

# Select the desired columns to display
final_columns = ['CustomerID', 'm_score', 'f_score', 'r_score', 'recency',␣
 ↪'frequency', 'monetary', 'fm_score']

# Display the final result
final_RFM_table = RFM_table[final_columns]

# Display the final RFM table with scores
final_RFM_table
```

[ ]:

	CustomerID	m_score	f_score	r_score	recency	frequency	monetary	\
0	12346.0	1	5	1	325	2.000000	0.00	
1	12347.0	5	2	5	2	0.538462	4310.00	
2	12348.0	4	1	2	75	0.400000	1797.24	
3	12349.0	4	3	4	18	1.000000	1757.55	
4	12350.0	2	3	1	310	1.000000	334.40	
…	…	…	…	…	…	…	…	
4367	18280.0	1	3	1	277	1.000000	180.60	
4368	18281.0	1	3	1	180	1.000000	80.82	
4369	18282.0	1	2	5	7	0.600000	176.60	

```
4370     18283.0        5        5        5        3   1.333333   2045.53
4371     18287.0        4        1        3       42   0.500000   1837.28

      fm_score
0            3
1            4
2            2
3            4
4            2
…          …
4367         2
4368         2
4369         2
4370         5
4371         2

[4372 rows x 8 columns]
```

Defining the RFM segements using these scores

[ ]:
```python
# Define a function to assign RFM segments
def assign_rfm_segment(row):
    if (row['r_score'] == 5 and row['fm_score'] == 5) or \
       (row['r_score'] == 5 and row['fm_score'] == 4) or \
       (row['r_score'] == 4 and row['fm_score'] == 5):
        return 'Champions'
    elif (row['r_score'] == 5 and row['fm_score'] == 3) or \
         (row['r_score'] == 4 and row['fm_score'] == 4) or \
         (row['r_score'] == 3 and row['fm_score'] == 5) or \
         (row['r_score'] == 3 and row['fm_score'] == 4):
        return 'Loyal Customers'
    elif (row['r_score'] == 5 and row['fm_score'] == 2) or \
         (row['r_score'] == 4 and row['fm_score'] == 2) or \
         (row['r_score'] == 3 and row['fm_score'] == 3) or \
         (row['r_score'] == 4 and row['fm_score'] == 3):
        return 'Potential Loyalists'
    elif row['r_score'] == 5 and row['fm_score'] == 1:
        return 'Recent Customers'
    elif (row['r_score'] == 4 and row['fm_score'] == 1) or \
         (row['r_score'] == 3 and row['fm_score'] == 1):
        return 'Promising'
    elif (row['r_score'] == 3 and row['fm_score'] == 2) or \
         (row['r_score'] == 2 and row['fm_score'] == 3) or \
         (row['r_score'] == 2 and row['fm_score'] == 2):
        return 'Customers Needing Attention'
    elif row['r_score'] == 2 and row['fm_score'] == 1:
        return 'About to Sleep'
```

```
    elif (row['r_score'] == 2 and row['fm_score'] == 5) or \
         (row['r_score'] == 2 and row['fm_score'] == 4) or \
         (row['r_score'] == 1 and row['fm_score'] == 3):
        return 'At Risk'
    elif (row['r_score'] == 1 and row['fm_score'] == 5) or \
         (row['r_score'] == 1 and row['fm_score'] == 4):
        return 'Cant Lose Them'
    elif row['r_score'] == 1 and row['fm_score'] == 2:
        return 'Hibernating'
    elif row['r_score'] == 1 and row['fm_score'] == 1:
        return 'Lost'
    else:
        return 'Unknown'  # Default case, in case no conditions match

# Apply the function to create the RFM segment column
RFM_table['rfm_segment'] = RFM_table.apply(assign_rfm_segment, axis=1)

# Sort by CustomerID (optional)
RFM_table = RFM_table.sort_values(by='CustomerID')


RFM_table
```

[ ]:

	CustomerID	first_purchase_date	last_purchase_date	num_purchases	\
0	12346.0	2011-01-18	2011-01-18	2	
1	12347.0	2010-12-07	2011-12-07	7	
2	12348.0	2010-12-16	2011-09-25	4	
3	12349.0	2011-11-21	2011-11-21	1	
4	12350.0	2011-02-02	2011-02-02	1	
…	…	…	…	…	
4367	18280.0	2011-03-07	2011-03-07	1	
4368	18281.0	2011-06-12	2011-06-12	1	
4369	18282.0	2011-08-05	2011-12-02	3	
4370	18283.0	2011-01-06	2011-12-06	16	
4371	18287.0	2011-05-22	2011-10-28	3	

	country	monetary	recency	months_cust	frequency	m20	\
0	United Kingdom	0.00	325	1	2.000000	232.504	
1	Iceland	4310.00	2	13	0.538462	232.504	
2	Finland	1797.24	75	10	0.400000	232.504	
3	Italy	1757.55	18	1	1.000000	232.504	
4	Norway	334.40	310	1	1.000000	232.504	
…	…	…	…	…	…	…	
4367	United Kingdom	180.60	277	1	1.000000	232.504	
4368	United Kingdom	80.82	180	1	1.000000	232.504	
4369	United Kingdom	176.60	7	5	0.600000	232.504	
4370	United Kingdom	2045.53	3	12	1.333333	232.504	

```
4371  United Kingdom   1837.28       42            6   0.500000  232.504

         m40      m60       m80       m100  f20       f40  f60       f80  \
0     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
1     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
2     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
3     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
…      …       …        …         …  …       …  …       …
4367  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4368  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4369  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4370  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4371  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667

            f100   r20   r40   r60    r80   r100  m_score  f_score  r_score  \
0     19.076923  11.0  31.0  71.0  178.0  373.0        1        5        1
1     19.076923  11.0  31.0  71.0  178.0  373.0        5        2        5
2     19.076923  11.0  31.0  71.0  178.0  373.0        4        1        2
3     19.076923  11.0  31.0  71.0  178.0  373.0        4        3        4
4     19.076923  11.0  31.0  71.0  178.0  373.0        2        3        1
…          …   …   …   …   …    …      …       …        …      …
4367  19.076923  11.0  31.0  71.0  178.0  373.0        1        3        1
4368  19.076923  11.0  31.0  71.0  178.0  373.0        1        3        1
4369  19.076923  11.0  31.0  71.0  178.0  373.0        1        2        5
4370  19.076923  11.0  31.0  71.0  178.0  373.0        5        5        5
4371  19.076923  11.0  31.0  71.0  178.0  373.0        4        1        3

      fm_score                 rfm_segment
0            3                     At Risk
1            4                   Champions
2            2  Customers Needing Attention
3            4               Loyal Customers
4            2                   Hibernating
…        …                          …
4367         2                   Hibernating
4368         2                   Hibernating
4369         2           Potential Loyalists
4370         5                   Champions
4371         2  Customers Needing Attention

[4372 rows x 29 columns]
```

Calculating additional customer-centric features such as average days between purchases, preferred shopping days, and peak shopping hours.

[ ]:
```
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
df['shopping_day'] = df['InvoiceDate'].dt.day_name()
df['shopping_hr'] = df['InvoiceDate'].dt.hour


preferred_shopping_day = df.groupby('CustomerID')['shopping_day'].agg(lambda x:␣
 ↪x.value_counts().idxmax())
peak_shopping_hr = df.groupby('CustomerID')['shopping_hr'].agg(lambda x: x.
 ↪value_counts().idxmax())


df = df.sort_values(['CustomerID', 'InvoiceDate'])
df['days_between'] = df.groupby('CustomerID')['InvoiceDate'].diff().dt.days
avg_days_between = df.groupby('CustomerID')['days_between'].mean().
 ↪reset_index().round(2)


# Merge preferred shopping day, peak shopping hour, and avg days between␣
 ↪purchases into RFM_table
RFM_table = pd.merge(RFM_table, preferred_shopping_day, on='CustomerID',␣
 ↪how='left')
RFM_table = pd.merge(RFM_table, peak_shopping_hr, on='CustomerID', how='left')
RFM_table = pd.merge(RFM_table, avg_days_between, on='CustomerID', how='left')

RFM_table.rename(columns={
    'shopping_day': 'preferred_shopping_day',
    'shopping_hr': 'peak_shopping_hr',
    'days_between': 'avg_days_between_purchases'
}, inplace=True)


RFM_table
```

[ ]:

	CustomerID	first_purchase_date	last_purchase_date	num_purchases	\
0	12346.0	2011-01-18	2011-01-18	2	
1	12347.0	2010-12-07	2011-12-07	7	
2	12348.0	2010-12-16	2011-09-25	4	
3	12349.0	2011-11-21	2011-11-21	1	
4	12350.0	2011-02-02	2011-02-02	1	
…	…	…	…	…	
4367	18280.0	2011-03-07	2011-03-07	1	
4368	18281.0	2011-06-12	2011-06-12	1	
4369	18282.0	2011-08-05	2011-12-02	3	
4370	18283.0	2011-01-06	2011-12-06	16	
4371	18287.0	2011-05-22	2011-10-28	3	

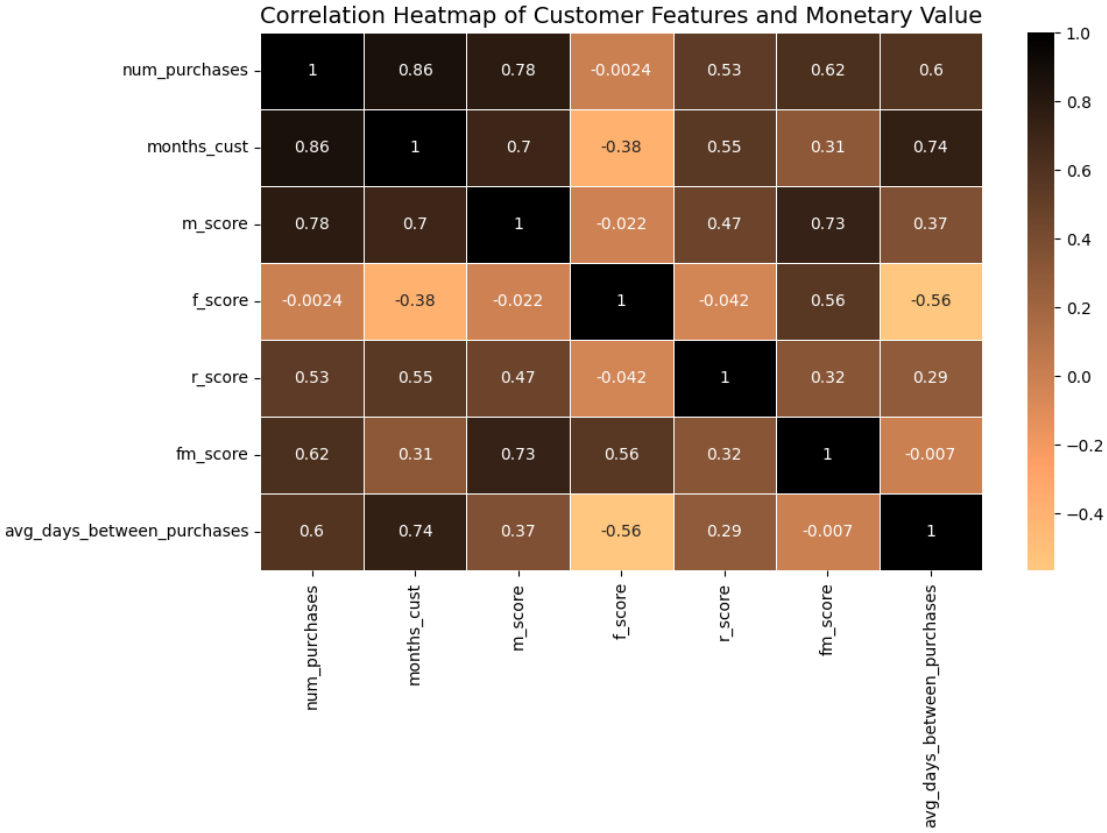
country	monetary	recency	months_cust	frequency	m20	\

```
0     United Kingdom      0.00      325            1   2.000000  232.504
1            Iceland   4310.00        2           13   0.538462  232.504
2            Finland   1797.24       75           10   0.400000  232.504
3              Italy   1757.55       18            1   1.000000  232.504
4             Norway    334.40      310            1   1.000000  232.504
…                …        …      …          …        …      …
4367  United Kingdom    180.60      277            1   1.000000  232.504
4368  United Kingdom     80.82      180            1   1.000000  232.504
4369  United Kingdom    176.60        7            5   0.600000  232.504
4370  United Kingdom   2045.53        3           12   1.333333  232.504
4371  United Kingdom   1837.28       42            6   0.500000  232.504

         m40      m60       m80       m100  f20       f40  f60       f80  \
0     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
1     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
2     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
3     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4     463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
…      …       …        …         …   …       …  …       …
4367  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4368  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4369  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4370  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667
4371  463.54  903.228  1994.064  279489.02  0.5  0.909091  1.0  1.166667

           f100   r20   r40   r60    r80   r100  m_score  f_score  r_score  \
0     19.076923  11.0  31.0  71.0  178.0  373.0        1        5        1
1     19.076923  11.0  31.0  71.0  178.0  373.0        5        2        5
2     19.076923  11.0  31.0  71.0  178.0  373.0        4        1        2
3     19.076923  11.0  31.0  71.0  178.0  373.0        4        3        4
4     19.076923  11.0  31.0  71.0  178.0  373.0        2        3        1
…          …   …   …   …   …    …     …       …        …       …
4367  19.076923  11.0  31.0  71.0  178.0  373.0        1        3        1
4368  19.076923  11.0  31.0  71.0  178.0  373.0        1        3        1
4369  19.076923  11.0  31.0  71.0  178.0  373.0        1        2        5
4370  19.076923  11.0  31.0  71.0  178.0  373.0        5        5        5
4371  19.076923  11.0  31.0  71.0  178.0  373.0        4        1        3

      fm_score                 rfm_segment preferred_shopping_day  \
0            3                    At Risk                Tuesday
1            4                  Champions                Tuesday
2            2  Customers Needing Attention               Thursday
3            4              Loyal Customers                 Monday
4            2                  Hibernating              Wednesday
…        …                          …                       …
4367         2                  Hibernating                 Monday
4368         2                  Hibernating                 Sunday
```

```
4369         2          Potential Loyalists                Friday
4370         5                    Champions              Thursday
4371         2  Customers Needing Attention             Wednesday

      peak_shopping_hr  avg_days_between_purchases
0                   10                        0.00
1                   14                        2.00
2                   19                        9.40
3                    9                        0.00
4                   16                        0.00
…                  …                          …
4367                 9                        0.00
4368                10                        0.00
4369                13                        9.83
4370                14                        0.45
4371                10                        2.28

[4372 rows x 32 columns]
```

illustration of heatmap to find out the correlation of multiple key variables

[ ]:
```
heatmap_columns = ['num_purchases', 'months_cust',␣
 ↪'m_score',        'f_score',        'r_score',        'fm_score',␣
 ↪'avg_days_between_purchases']

correlation_data = RFM_table[heatmap_columns].corr(method = 'spearman')

plt.figure(figsize=(10, 6))  # Adjust the figure size as needed
sns.heatmap(correlation_data, annot=True, cmap='copper_r', linewidths=0.5)

# Set the title for the heatmap
plt.title("Correlation Heatmap of Customer Features and Monetary Value",␣
 ↪fontsize=14)
plt.show()
```

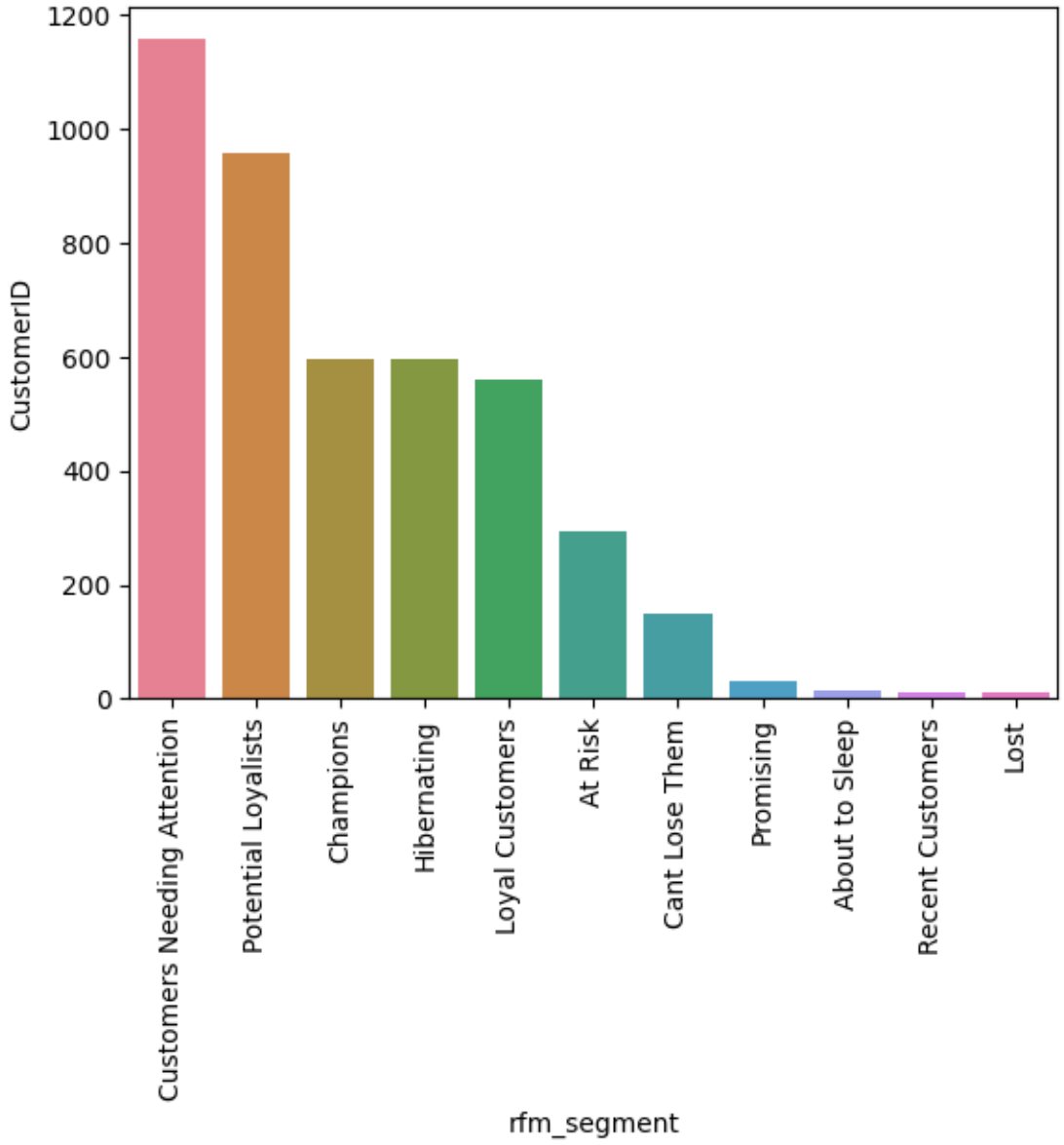


Total number of customers in each RFM_segment as defined

[ ]:
```
import warnings
warnings.filterwarnings("ignore")

total_customers_per_segment = RFM_table.groupby('rfm_segment')['CustomerID'].
 ↪size().sort_values(ascending = False).reset_index()
print(total_customers_per_segment)
print("<---------------------------------->")
sns.barplot(data = total_customers_per_segment, x = 'rfm_segment', y =␣
 ↪'CustomerID', hue = 'rfm_segment')
plt.xticks(rotation = 90)
plt.show()
```

```
                  rfm_segment  CustomerID
0   Customers Needing Attention        1157
1           Potential Loyalists         957
2                     Champions         596
3                   Hibernating         595
4               Loyal Customers         560
5                       At Risk         294
```

```
6                 Cant Lose Them         148
7                      Promising          30
8                  About to Sleep          14
9                Recent Customers          11
10                           Lost          10
<---------------------------------->
```



Total number of customer and sales value for each day

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

```
# Group data
total_customers_per_day = RFM_table.
 ↪groupby('preferred_shopping_day')['CustomerID'].size().
 ↪sort_values(ascending=False).reset_index()
total_monetary_per_day = RFM_table.
 ↪groupby('preferred_shopping_day')['monetary'].sum().
 ↪sort_values(ascending=False).reset_index()

# Create a figure with larger subplots for side-by-side display
fig, (ax1_table, ax2_table) = plt.subplots(2, 2, figsize=(18, 12))  # Adjust␣
 ↪size as needed

# Plot total customers per day
sns.barplot(data=total_customers_per_day, x='preferred_shopping_day',␣
 ↪y='CustomerID', color='r', ax=ax1_table[1])
ax1_table[1].set_title('Total Customers per Preferred Shopping Day')
ax1_table[1].set_xlabel('Preferred Shopping Day')
ax1_table[1].set_ylabel('Number of Customers')
ax1_table[1].tick_params(axis='x')  # Rotate x-axis labels for better visibility

# Plot total monetary per day
sns.barplot(data=total_monetary_per_day, x='preferred_shopping_day',␣
 ↪y='monetary', color='r', ax=ax2_table[1])
ax2_table[1].set_title('Total Monetary per Preferred Shopping Day')
ax2_table[1].set_xlabel('Preferred Shopping Day')
ax2_table[1].set_ylabel('Total Monetary')
ax2_table[1].tick_params(axis='x')  # Rotate x-axis labels for better visibility

# Set y-axis limits to avoid single-digit display
ax2_table[1].set_ylim(0, total_monetary_per_day['monetary'].max() * 1.1)  #␣
 ↪Slightly increase max limit for clarity

# Hide the default y-axis for tables
ax1_table[0].axis('off')
ax2_table[0].axis('off')

# Add tables above the plots
table1 = ax1_table[0].table(cellText=total_customers_per_day.values,␣
 ↪colLabels=total_customers_per_day.columns, loc='center', cellLoc='center')
ax1_table[0].set_title('Table: Total Customers per Day', pad=0.5)  # Adjust pad␣
 ↪for closer title
table1.set_fontsize(10)  # Set font size for the table

table2 = ax2_table[0].table(cellText=total_monetary_per_day.values,␣
 ↪colLabels=total_monetary_per_day.columns, loc='center', cellLoc='center')
```

```
ax2_table[0].set_title('Table: Total Monetary per Day', pad=0.5)  # Adjust pad␣
 ↪for closer title
table2.set_fontsize(10)  # Set font size for the table

# Adjust layout
plt.tight_layout()

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

Table: Total Customers per Day

preferred_shopping_day	CustomerID
Thursday	990
Wednesday	781
Tuesday	706
Monday	686
Friday	631
Sunday	578

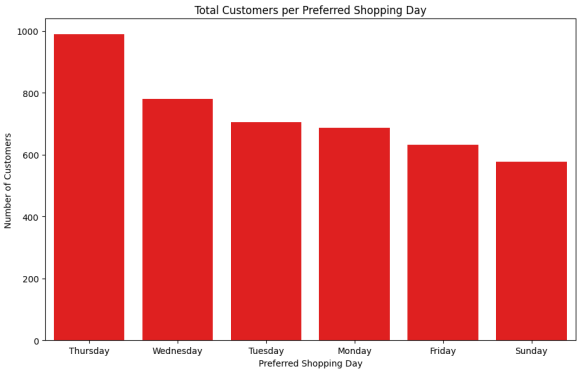
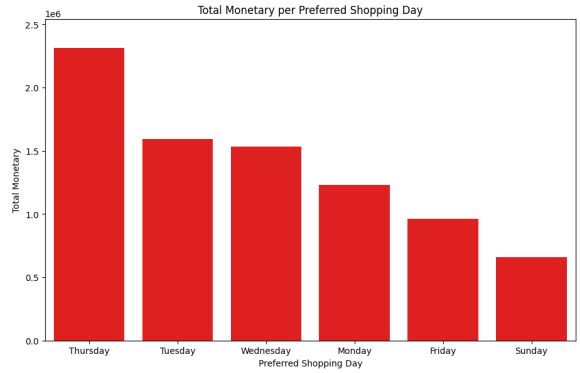


Table: Total Monetary per Day

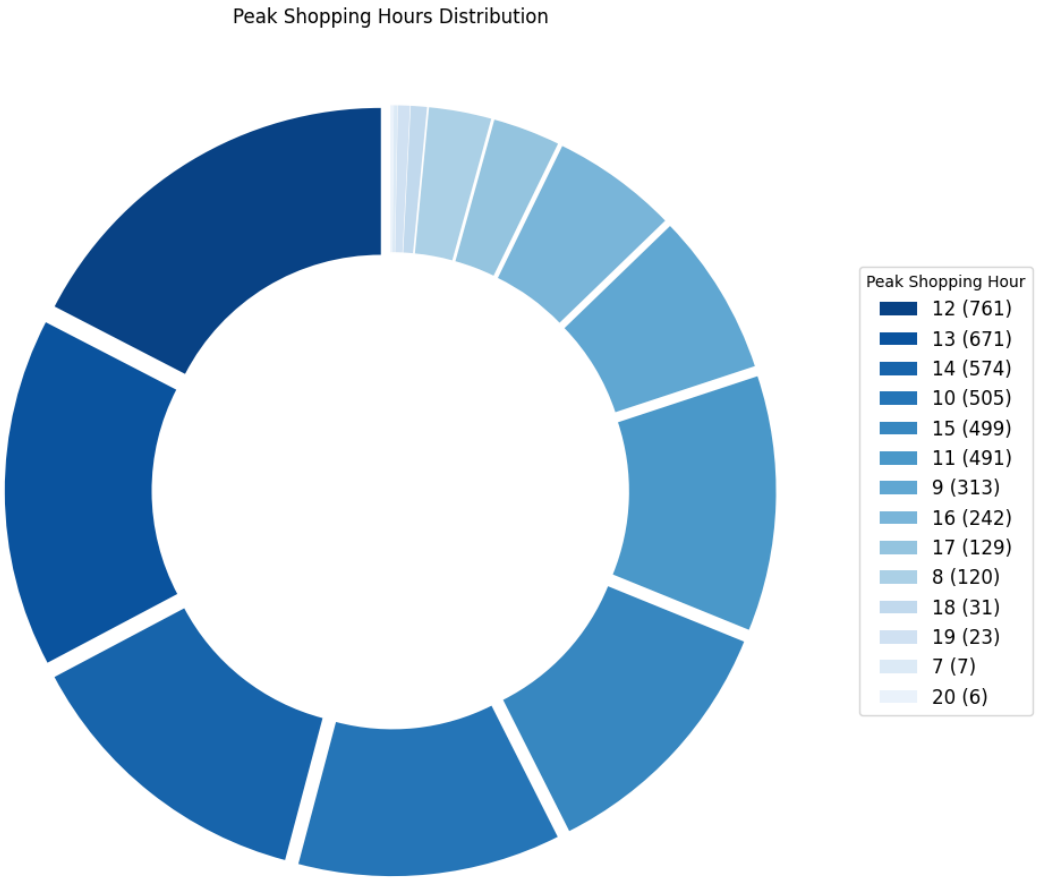
preferred_shopping_day	monetary
Thursday	2309934.451
Tuesday	1592839.3800000001
Wednesday	1530942.22
Monday	1228239.541
Friday	959363.821
Sunday	657200.011



Peak Shopping Hours: Customer Frequency Distribution

[ ]:
```
# Create a DataFrame for peak shopping hours distribution
peak_hrs_distribution = RFM_table['peak_shopping_hr'].value_counts().
 ↪reset_index()
peak_hrs_distribution.columns = ['peak_shopping_hr', 'count']  # Rename the␣
 ↪columns for clarity

# Sort the DataFrame by count in descending order
peak_hrs_distribution = peak_hrs_distribution.sort_values(by='count',␣
 ↪ascending=False)

# Define explode to slightly separate each slice
```

```
explode = [0.05] * len(peak_hrs_distribution)  # Slightly "explode" each slice␣
 ↪for better clarity

# Create a color palette where higher values get brighter colors
colors = sns.color_palette("Blues", n_colors=len(peak_hrs_distribution))

# Reverse the color palette to assign brighter colors to larger values
colors = colors[::-1]  # Reverse the order of colors

# Plot the pie chart without labels
plt.figure(figsize=(10, 10))
wedges, texts = plt.pie(peak_hrs_distribution['count'],
                        explode=explode,
                        startangle=90,
                        colors=colors,  # Use the reversed color palette
                        wedgeprops=dict(width=0.4))

# Combine the peak shopping hours with their counts as strings
legend_labels = peak_hrs_distribution['peak_shopping_hr'].astype(str) + ' (' +␣
 ↪peak_hrs_distribution['count'].astype(str) + ')'

# Add a legend outside the pie chart
plt.legend(wedges,
           legend_labels,  # Use the combined labels
           title="Peak Shopping Hour",
           loc="center left",
           bbox_to_anchor=(1, 0.5),  # Position legend outside the pie chart
           fontsize=12)

plt.title('Peak Shopping Hours Distribution')
plt.tight_layout()
plt.show()
```



[ ]:
```
final_columns = ['CustomerID', 'country',␣
 ↪'m_score',        'f_score',        'r_score',        'fm_score',
                ␣
 ↪'rfm_segment',        'preferred_shopping_day',        'peak_shopping_hr',        'avg_days

RFM_table[final_columns]
```

[ ]:

	CustomerID	country	m_score	f_score	r_score	fm_score	\
0	12346.0	United Kingdom	1	5	1	3	
1	12347.0	Iceland	5	2	5	4	
2	12348.0	Finland	4	1	2	2	
3	12349.0	Italy	4	3	4	4	
4	12350.0	Norway	2	3	1	2	
…	…	…	…	…	…	…	
4367	18280.0	United Kingdom	1	3	1	2	
4368	18281.0	United Kingdom	1	3	1	2	
4369	18282.0	United Kingdom	1	2	5	2	

```
4370     18283.0  United Kingdom        5        5        5         5
4371     18287.0  United Kingdom        4        1        3         2

                      rfm_segment preferred_shopping_day  peak_shopping_hr  \
0                          At Risk                Tuesday                10
1                        Champions                Tuesday                14
2     Customers Needing Attention               Thursday                19
3                 Loyal Customers                 Monday                 9
4                      Hibernating              Wednesday                16
…                              …                      …               …
4367                   Hibernating                 Monday                 9
4368                   Hibernating                 Sunday                10
4369           Potential Loyalists                 Friday                13
4370                     Champions               Thursday                14
4371  Customers Needing Attention              Wednesday                10

      avg_days_between_purchases
0                           0.00
1                           2.00
2                           9.40
3                           0.00
4                           0.00
…                           …
4367                        0.00
4368                        0.00
4369                        9.83
4370                        0.45
4371                        2.28

[4372 rows x 10 columns]
```

[4]:
```
!jupyter nbconvert --to pdf "/content/drive/MyDrive/Colab Notebooks/CRM␣
↪Analysis project.ipynb"
```

```
[NbConvertApp] Converting notebook /content/drive/MyDrive/Colab Notebooks/CRM
Analysis project.ipynb to pdf
[NbConvertApp] Support files will be in CRM Analysis project_files/
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Making directory ./CRM Analysis project_files
[NbConvertApp] Writing 117400 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
```

```
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 549726 bytes to /content/drive/MyDrive/Colab
Notebooks/CRM Analysis project.pdf
```

[ ]: