A Case Report – Sun Country Airlines

Team Number: 5A

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Introduction:

In today's competitive airline industry with 3 main airlines dominating the market (American Airlines, Delta, and United Airlines), it's essential to create uniqueness and market segmentation. This report aims to analyze the data provided by Sun Country to provide a comprehensive understanding of its customers and provide actionable insight to the management level.

The dataset contains its booked channel, class, paid amount, age, destination, origin and season of trip. By implementing K-mean clustering method, we will categorize individuals based on their travel behavior, objective and characteristics into meaningful groups.

Through this segmentation, we aim to provide Sun Country Airlines with a deeper understanding of their customer base, enabling them to tailor their marketing strategies, improve customer experience, and ultimately drive business growth. The report concludes with strategic recommendations for Sun Country Airlines' executives on how to leverage these insights to achieve their business objectives.

Dataset:

Our dataset was pre-cleaned and for the most part usable. Some of the barriers we had to overcome when working with the clustering data were:

- 'UID' and 'PNRLocatorId' had very little relevance to the customer segments we were trying to derive and were string fields (not relevant for clustering) and in fact hampered our ability to work with the data as a whole, forcing us to drop them from our data set.
- Going with this theme, in initially loading our data, there was an overwhelming number of categorical variables, such as the origin and destination, that were transformed into dummy variables, making the data difficult to read.
- There was an overall lower number of continuous variables which could have significantly improved the clustering outcomes.
- As for the long-term benefit for Sun Country, we preserved UID column into an individual variable so that they can use it as *index to* reference clusters to the initial dataset.

Methods

Since centroids were indicated to be 5, we skip the process of using elbow method to determine the appropriate number of clusters.

For Visualization we use Python seaborn and matplotlib package to make all of our charts. We decided to visualize the interactions between our clusters and variables using a variety of charts including bar graphs, box-and-whisker plots, and pie charts. For the average ages within the clusters, we decided that a bar graph would be most digestible so that we could compare clusters side by side with one another.

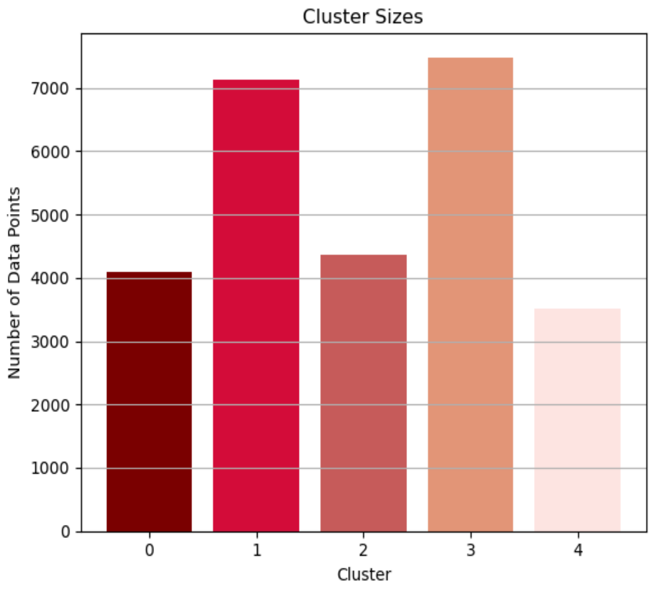
This visualization will help Warnken and Vaughan connect these insights to their objectives by allowing them to mentally place their five clusters into groups that would be most receptive to certain types of advertisements and discounts.

Discussion and Observations:

Cluster Sizing and Distribution

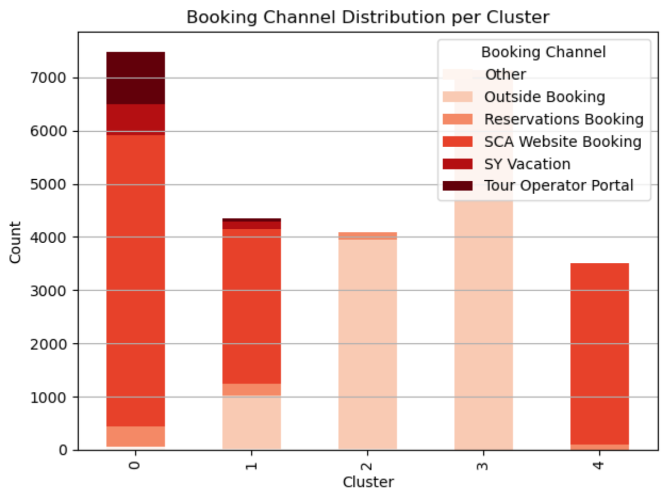
Based on the project requirement, we have segmented our clusters into 5 separate clusters, drawing largely from our K Means cluster graph and the point of decreasing marginal gains from adding clusters.

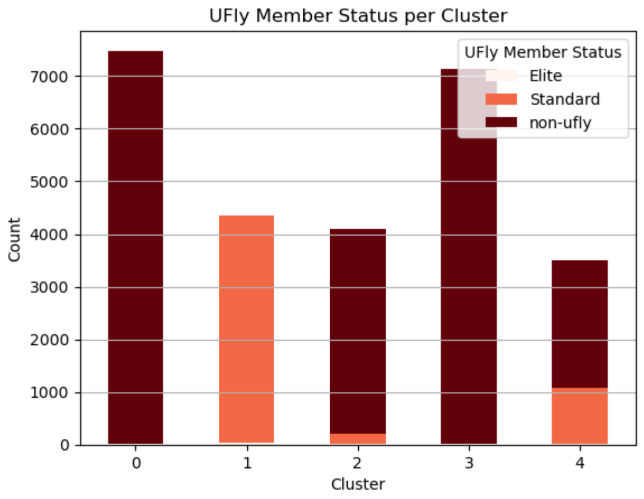
Cluster	Size
0	7481
1	4348
2	4096
3	7140
4	3510



Booking Channel and UFly Membership Status

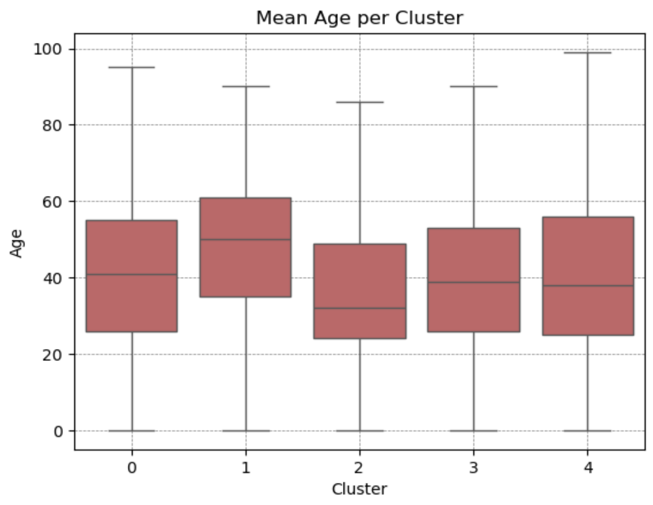
To support their business strategies, it’s also important to take into account each cluster’s booking channel tendency and Ufly membership status. We decided to visualize with the bar chart with color categorizing to show whether each cluster has a majority color refer to its preference channel and its membership status.

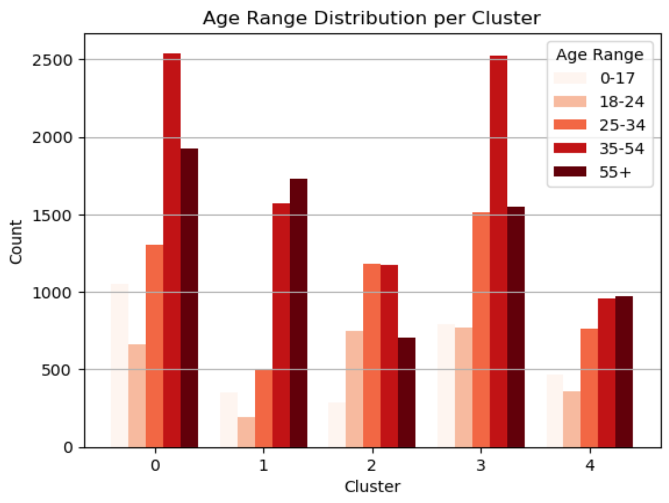




This indicated that the Cluster 1, which is almost entirely composed of Standard UFly members had majority of its individuals booking via the Sun Country Airline Websites.

Age Across Clusters





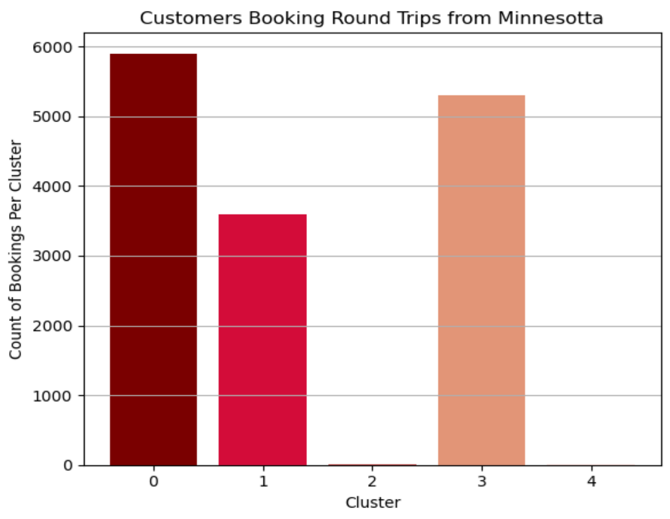
Cluster 1 seems to have the highest mean for Age for the customers and also the highest values in its upper quartile. Observing this in combination with the UFLy Member status graph, it shows an indication that Cluster 1 might be their oldest local Minnesota customer base, since they all seem to be holding UFly Standard status. Cluster 2 seems to comprise of the youngest bunch of customers with the lowest mean and lower upper and lower limits.

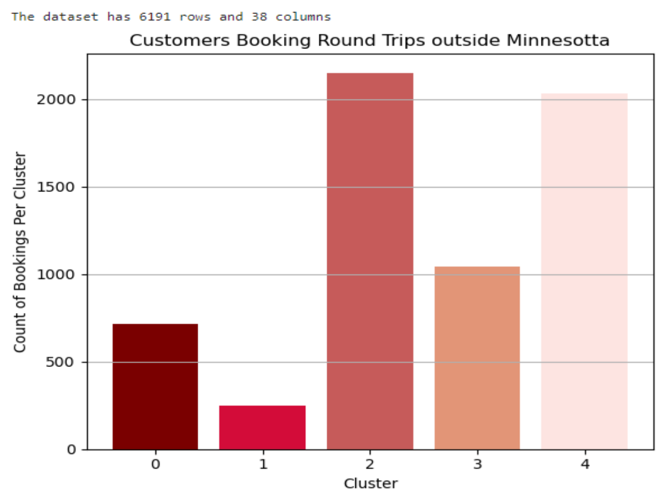
Round Trip booking from within and outside Minnesota

The adjacent graph shows details of round trips per cluster that originate and end at Minnesota.

The graphs indicate that Cluster 0 and 1 has a low count of such customers, and cluster 0, 1 and 3 have bulk of such cases whereas Cluster 2 and 4 very minimal of such customer bases.

```
The dataset has 14817 rows and 38 columns
```





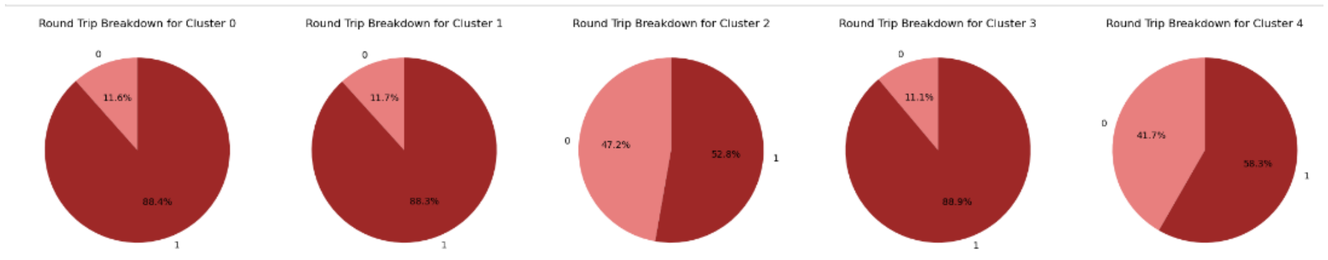
```
The dataset has 6191 rows and 38 columns
```

Whereas the graph on the left shows details of round trips per cluster that originate and end outside Minnesota.

The graphs indicate Cluster 2 and 4 to be majorly comprising of such cases.

These findings also strengthen the observation that Cluster 1 might be comprising of the local Minesota customer base.

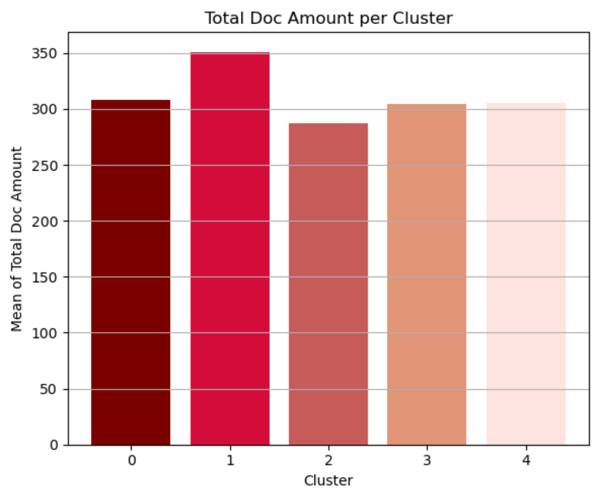
In general, observing the round-trip booking patterns for all the clusters, as indicated in the Pie graphs below, indicates that Cluster 0, 1 and 3 comprises of customer base preferring to book rounds trips.

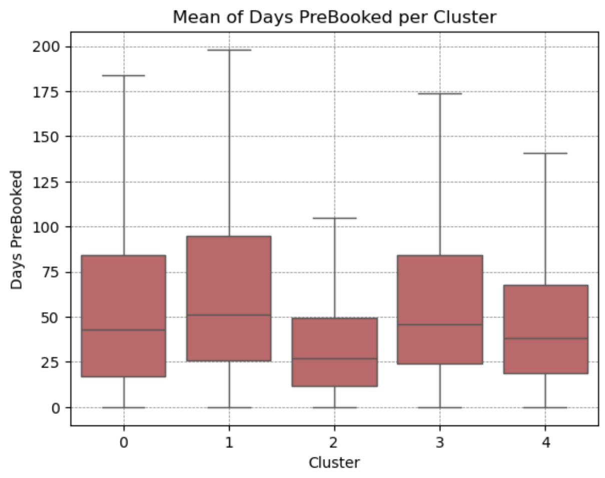


Days Pre-Booked and Total Doc Amount per Cluster

Looking at the Mean of days pre-Booked per Cluster boxplot below, indicates that cluster 2 comprises of customers who book their tickets relatively closer to the travel date in comparison to the other four clusters.

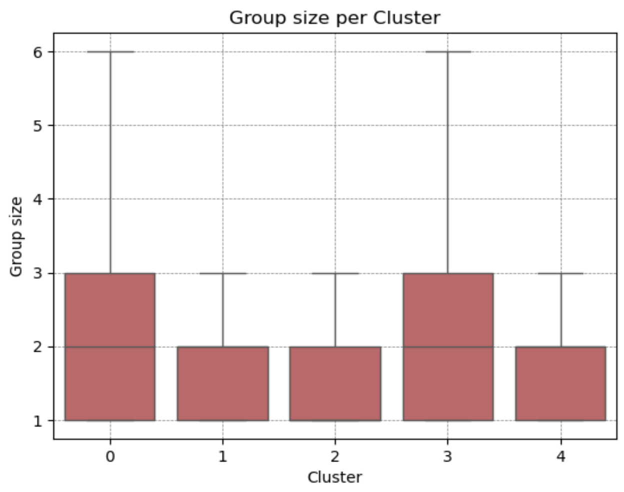
Combining this observation with the Total doc amount per cluster graph, it indicates the customers in Cluster 2 tend to have a lower mean for the amount they spent.

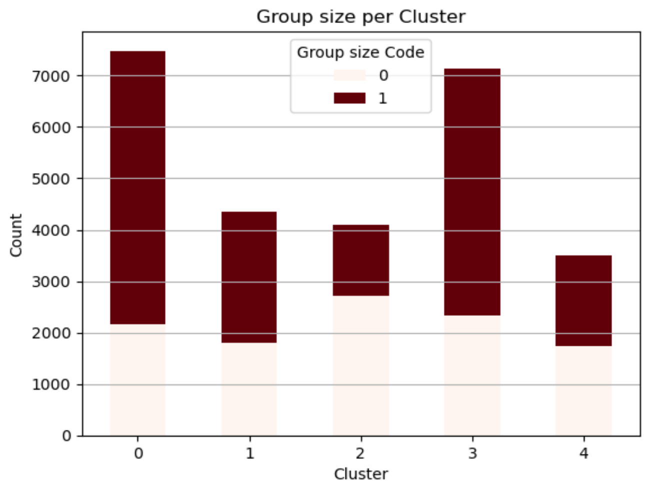




Reviewing traits of cluster 2 in the previous observations indicates that this cluster is comprising of the relatively younger customer base and is almost entirely based outside of Minnesota, which is indicated by their round-trip booking patterns.

Group Size per Cluster





The boxplot on the left depicting the group sizes per cluster, is indicative of Cluster 0 and 3 comprising of large group travelers. This information could be particularly useful to channel bulk or group tickets deals and discounts to the right audience whose historical data indicates their preference for it.

Case Question Responses

Group Project Report Case Question 1:

Based on your analysis, how many different customer segments (i.e., clusters of similar customers) are there? What are the key characteristics of each segment? Can you come up with descriptive titles for the segments?

We gleaned from these clusters (clusters 0-4), that there are significant differences between the clusters where factors such as average age, propensity to purchase flight tickets many days ahead of time, and individuals flying from within and outside of Minnesota vary convincingly depending on the cluster. For example,

- In Clusters 0 and 1, we found that many individuals were in the higher age ranges when compared to the other clusters.
- Cluster 1 seems to be the oldest local Minnesota customer base majorly composed of individuals with UFly Standard Membership and having bulk of its bookings originating and ending in Minnesota.
- Cluster 3 seemed entirely to book their tickets via Outside booking and was also made up of multiple person group travelers.
- Another key difference within the clusters was that many individuals booked flights to and from locations entirely outside of Minesota, with clusters 2 and 4 almost exclusively making up this proportion. So, it could be assumed that these two clusters comprise of individuals based outside of Minesota
- Another key meaningful insight in our analysis was that of those individuals outside of Minesota in clusters 2 and 4 have low rates of booking a round trip compared to those travel from and to Minnesota.
- Finally, Cluster 2 customers didn’t seem to prebook their ticket too much in advance, and they also seemed to be having a lower mean among all five for total doc amount.

With these results in mind, we have decided to label the clusters as the following:

- **Cluster 0**: Older travelers within Minnesota,
- **Cluster 1**: Older travelers with a tendency for UFly Membership,
- **Cluster 2**: Younger out-of-state travelers who book last minute,
- **Cluster 3**: Group travelers who book externally, and
- **Cluster 4**: Single-flight out-of-state travelers

Group Project Report Case Question 2:

What advice would you offer the executives of Sun Country Airlines (Warnken and Vaughan), based on your segmentation analysis, so they can better achieve their business objectives?

Based on our analysis, we were able to confidently select some key insights that we would be willing to present and suggest to Sun Country to improve the efficiency and profitability of their company.

- Regarding the cluster differences in ages, we propose to Sun Country to reach out to individuals in Clusters 1 in ways that appeal to older populations. This could look like newspaper advertisements, physical marketing or congruent advertisements that appear on websites that older individuals might frequent.
- Another important way that our data provides insight into Sun Country is the sheer number of individuals, specifically in clusters 2 and 4, who booked a flight from somewhere entirely outside of Minnesota. For this reason, we would suggest Sun Country target clusters 2 and 4 with advertisements outside of their Minnesota locale, while using techniques specific to Minnesotans would be ideal to employ upon individuals in clusters 0, 1, 3. This would allow the company to expand their base across other states.
- Regarding airline membership status, we noticed that cluster 1 was comprised almost entirely of standard members of the airline. So, in order to push up enrollment into the UFly program, we suggest that they target advertisements pertaining to membership benefits and discounts towards cluster 1. Moreover, as almost half of the individuals in cluster 4 were members, the airline could gain some increase in the proportion.

- Also adverts aimed at encouraging the customers to enroll in the membership program can be targeted towards clusters other than 1.
- In the same vein, individuals in clusters 0 and 4 tended to book their flights much closer to the scheduled flight day, while people in clusters 1, 2, and 3 often booked their flights much further out.
- Clusters 0, 1, and 3 seem to have a significant percentage of customers not making round-trip bookings. It would be advisable to target round trip booking adverts and deals to these two clusters since it could push up the revenue.
- Cluster 0 and 3 comprises of large group travelers. This information could be particularly useful to channel bulk or group tickets deals and discounts to the right audience whose historical data indicates their preference for it.

Conclusion:

With cluster sizes and cluster analysis of booking channel, Ufly member status, age, Group sizes, total amount for doc and Minnesota round trip, we could derive enough insight from the result to tell a compelling story to the stakeholders.

While it is helpful for people like us to understand the data while we are looking at the insights it provides, it is vital for us to be able to convey the data to all types of people and not just those who are highly educated in analytics.

In presenting the data in a digestible way, we amplify the power of it tenfold and turn it from something that is simply numbers in a data file to a tangible solution to a problem that can be implemented. If we were to use this data to create fancy, highly technical models that take years of coding to understand, we are really limiting the impact that the data could have had on the sufficiency of the company.

APPENDIX

```
##1. LOADING DATASET
#importing pandas
import pandas as pd

#Reading the clustering data file
clustering_data = pd.read_csv('C:/Users/shyam/Desktop/UCI/Courses/Quarter 1/Python/Project/Clustering Data (1).csv')

#Checking the shape of the imported dataframe
print(f'The dataset has {clustering_data.shape[0]} rows and {clustering_data.shape[1]} columns')
clustering_data.head()
```

```
The dataset has 15144 rows and 90 columns
```

	uid	PNRLocatorID	avg_amt	round_trip	group_size	group	days_pre_booked	BookingCha
0	504554455244696420493F7C20676574207468697320 72...	AADMLF	0.019524	0	0.000	0	0.029703	
1	46495853454E44696420493F7C2067657420746869732 0...	AAFBOM	0.081774	1	0.000	0	0.039604	
2	534355545444696420493F7C20676574207468697320 72...	AAFILI	0.026650	0	0.125	1	0.069307	
3	534355545444696420493F7C20676574207468697320 72...	AAFILI	0.026650	0	0.125	1	0.069307	
4	44554D4D414E4E44696420493F7C20676574207468 6973...	AAFRQI	0.000000	1	0.000	0	0.035361	

5 rows × 90 columns

```
##2. DATA PREPROCESSING
#Preparing the data for clustering by copy the previously created dataset
prep_clustering_data = clustering_data.copy()

# Saving the uid column before dropping it
save_uid_column = prep_clustering_data['uid']

#Dropping the uid and PNRLocaterID fields since they have string values
prep_clustering_data = prep_clustering_data.drop(['PNRLocatorID', 'uid'], axis=1)

#Checking the shape of the prepared dataframe
print(f'The dataset has {prep_clustering_data.shape[0]} rows and {prep_clustering_data.shape[1]} columns')
prep_clustering_data.head(10)
```

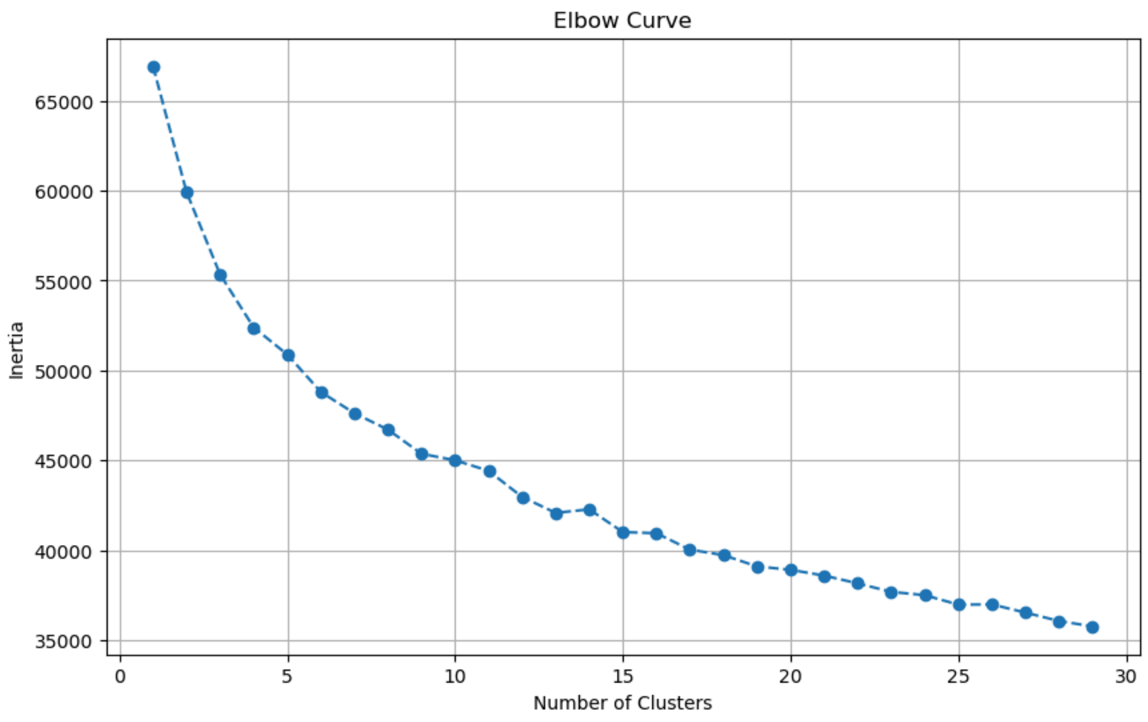
```
The dataset has 15144 rows and 88 columns
```

	avg_amt	round_trip	group_size	group	days_pre_booked	BookingChannel_Other	BookingChannel_Outside_Booking	BookingChannel_Reserva
0	0.019524	0	0.000	0	0.029703	0	1	
1	0.081774	1	0.000	0	0.039604	0	0	
2	0.026650	0	0.125	1	0.069307	0	0	
3	0.026650	0	0.125	1	0.069307	0	0	
4	0.000000	1	0.000	0	0.035361	0	1	
5	0.000000	1	0.125	1	0.050919	0	1	
6	0.000000	1	0.125	1	0.050919	0	1	
7	0.074727	1	0.000	0	0.045262	0	0	
8	0.035414	1	0.000	0	0.082037	0	1	
9	0.035414	1	0.125	1	0.018388	0	1	

10 rows × 88 columns

```
##3. CLUSTERING
#3.1 Looking at the optimum number of clusters
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

inertia = []                  # sum of squared distances between each data point and its closest cluster centroid (wcss)
cluster_range = range(1, 30)


for cluster_num in cluster_range:
    print(f'Iteration Number: {cluster_num}')

    kmeans = KMeans(n_clusters=cluster_num, n_init=10)
    kmeans.fit(prep_clustering_data)
    inertia.append(kmeans.inertia_)



plt.figure(figsize=(10,6))
plt.plot(cluster_range, inertia, marker='o', linestyle='--')
plt.title('Elbow Curve')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
```

```
Iteration Number: 1
Iteration Number: 2
Iteration Number: 3
Iteration Number: 4
Iteration Number: 5
Iteration Number: 6
Iteration Number: 7
Iteration Number: 8
Iteration Number: 9
Iteration Number: 10
Iteration Number: 11
Iteration Number: 12
Iteration Number: 13
Iteration Number: 14
Iteration Number: 15
Iteration Number: 16
Iteration Number: 17
Iteration Number: 18
Iteration Number: 19
Iteration Number: 20
Iteration Number: 21
Iteration Number: 22
Iteration Number: 23
Iteration Number: 24
Iteration Number: 25
Iteration Number: 26
Iteration Number: 27
Iteration Number: 28
Iteration Number: 29
```



```
#3.2 Applying K-Means, and creating 5 centroids as per the Project requirement

kmeans = KMeans(n_clusters=5, n_init=10)
kmeans.fit(prep_clustering_data)

# attach the dropped UID column and cluster
prep_clustering_data = pd.DataFrame({
    'uid': save_uid_column,
    'cluster': kmeans.labels_
})

print(f'The dataset has {prep_clustering_data.shape[0]} rows and {prep_clustering_data.shape[1]} columns')
prep_clustering_data.head()
```

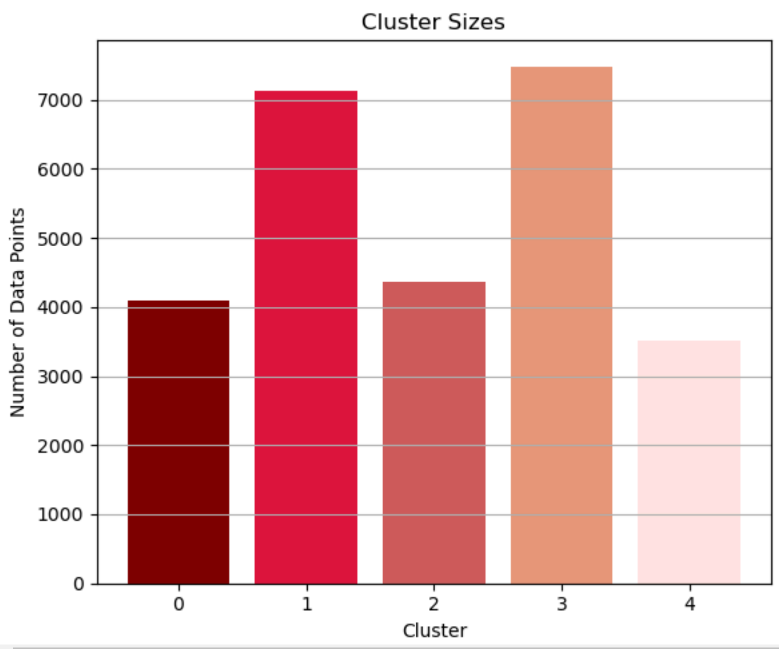
```
The dataset has 15144 rows and 2 columns
```

	uid	cluster
0	5045544552446964204 93F7C2067657420746869732072...	1
1	46495853454E44696420493F7C20676574207468697320...	1
2	53435554544469642049 3F7C2067657420746869732072...	4
3	5343555454444696420493F7C2067657420746869732072...	4
4	44554D4D414E4E44696420493F7C20676574207468697 3...	2

```
##4. MERGED DATASET FOR VISUALIZATION
# Merging the Clustered dataset with the provided sample_data_transformed.csv
sample_transformed = pd.read_csv('C:/Users/shyam/Desktop/UCI/Courses/Quarter 1/Python/Project/sample_data_transformed.csv')
final_dataframe = sample_transformed.merge(prep_clustering_data[['uid', 'cluster']], on='uid', how='left')

#Checking the shape of the final dataframe and looking at the number of records in each cluster
final_dataframe.head(100)
cluster_sizes = final_dataframe['cluster'].value_counts().sort_index()
print(cluster_sizes)
```

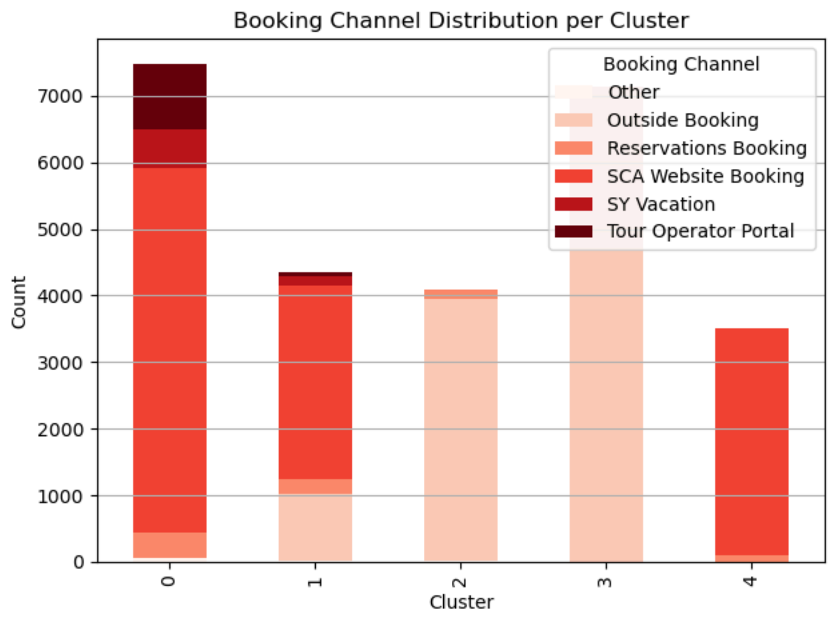
```
cluster
0    7481
1    4348
2    4096
3    7140
4    3510
Name: count, dtype: int64
C:\Users\shyam\AppData\Local\Temp\ipykernel_47360\2175281245.py:3: DtypeWarning: Columns (13) have mixed types. Specify dtype option on
  sample_transformed = pd.read_csv('C:/Users/shyam/Desktop/UCI/Courses/Quarter 1/Python/Project/sample_data_transformed.csv')
```

```
##5. ANALYSIS AND VISUALIZATION
from pandas import *
import matplotlib.pyplot as plt

cluster_colors = {
    0: 'maroon',
    1: 'crimson',
    2: 'indianred',
    3: 'darksalmon',
    4: 'mistyrose'
}

cluster_sizes = final_dataframe['cluster'].value_counts().sort_index()

plt.figure(figsize=(6, 5))


for cluster in range(len(cluster_sizes)):
    plt.bar(cluster, cluster_sizes[cluster], color=cluster_colors[cluster])

# Adding plot details
plt.title('Cluster Sizes')
plt.xlabel('Cluster')
plt.ylabel('Number of Data Points')
plt.xticks(ticks=range(len(cluster_sizes)))
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```



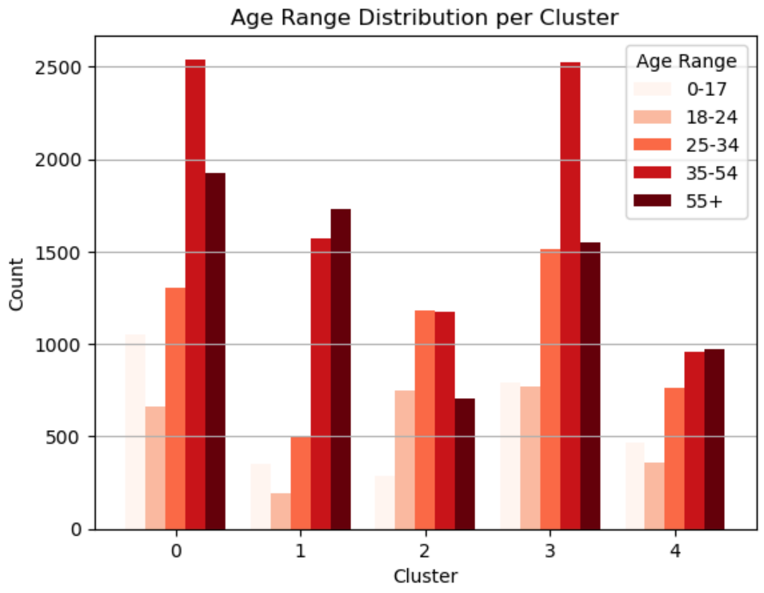
```
#Preparing the sample dataframe to be plotted
booking_channel_counts = final_dataframe.groupby(['cluster', 'BookingChannel']).size().unstack(fill_value=0)

#Printing the sample dataframe
print(booking_channel_counts)

#Creating the Bar plot
booking_channel_counts.plot(kind='bar', stacked=True, colormap='Reds')

# Adding plot details
plt.title('Booking Channel Distribution per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(ticks=range(len(cluster_sizes)))
plt.tight_layout()
plt.grid(axis='y')
plt.legend(title='Booking Channel')

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

```
BookingChannel  Other  Outside Booking  Reservations Booking  \
cluster
0                  50                0                   398
1                  27              985                   228
2                  24             3919                   153
3                   0             7140                     0
4                   3                0                   100

BookingChannel  SCA Website Booking  SY Vacation  Tour Operator Portal
cluster
0                              5465          588                   980
1                              2906          142                    60
2                                 0            0                     0
3                                 0            0                     0
4                              3407            0                     0
```

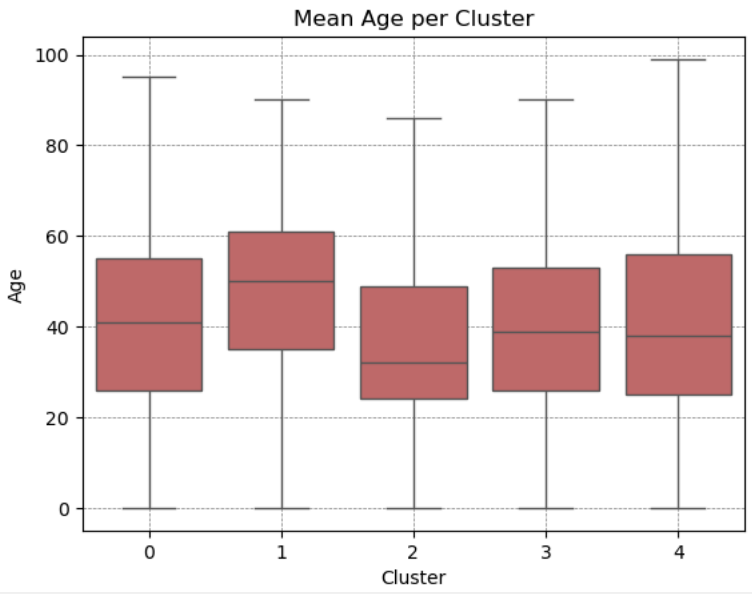


```
#Preparing the sample dataframe to be plotted
age_group_counts = final_dataframe.groupby(['cluster', 'age_group']).size().unstack()

#Printing the sample dataframe
print(age_group_counts)

#Creating the Bar plot
age_group_counts.plot(kind='bar', width=0.8, colormap='Reds')

# Adding plot details
plt.title('Age Range Distribution per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='Age Range')

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

```
age_group  0-17  18-24  25-34  35-54   55+
cluster
0          1053    659   1301   2540  1928
1           353    191    503   1572  1729
2           288    749   1184   1171   704
3           791    767   1510   2524  1548
4           466    356    763    956   969
```

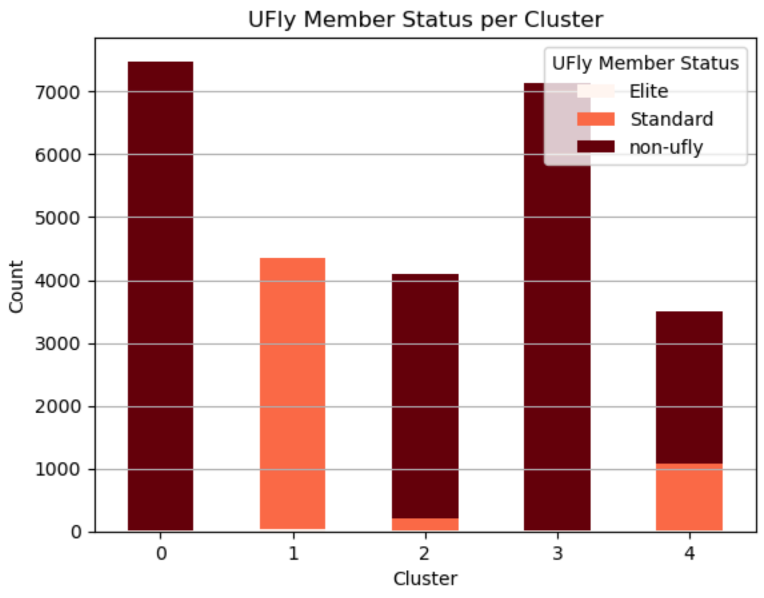


```
import seaborn as sns
import matplotlib.pyplot as plt

# Create the boxplot without showing outliers
sns.boxplot(x='cluster', y='Age', data=final_dataframe, showfliers=False, color='indianred')

# Show grid lines
plt.grid(True)

# Customize grid appearance (optional)
plt.grid(color='gray', linestyle='--', linewidth=0.5)

# Adding plot details
plt.title('Mean Age per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Age')

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



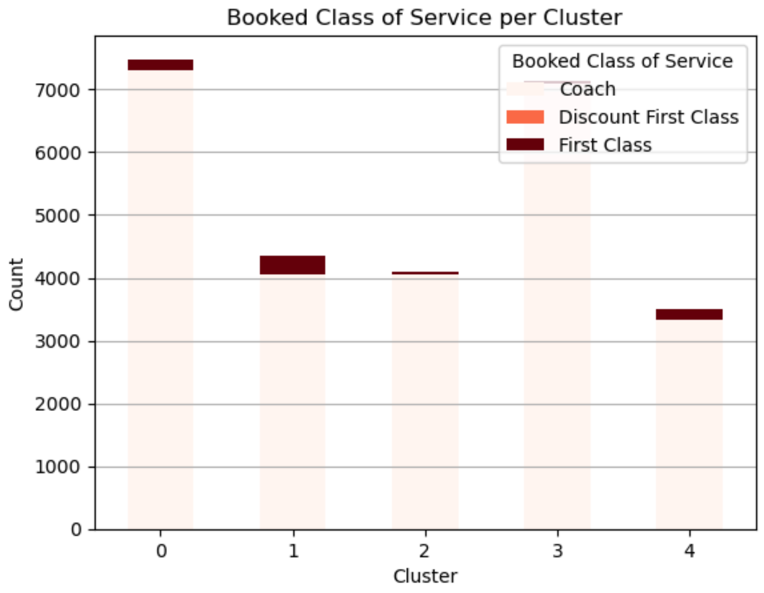
```
#Preparing the sample dataframe to be plotted
member_status_counts = final_dataframe.groupby(['cluster', 'UflyMemberStatus']).size().unstack(fill_value=0)

#Printing the sample dataframe
print(member_status_counts)

#Creating the Bar plot
member_status_counts.plot(kind='bar', stacked=True, colormap='Reds')

# Adding plot details
plt.title('UFly Member Status per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='UFly Member Status')

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

```
UflyMemberStatus  Elite  Standard  non-ufly
cluster
0                     6         0      7475
1                    45      4302         1
2                     8       192      3896
3                    18         0      7122
4                    21      1054      2435
```



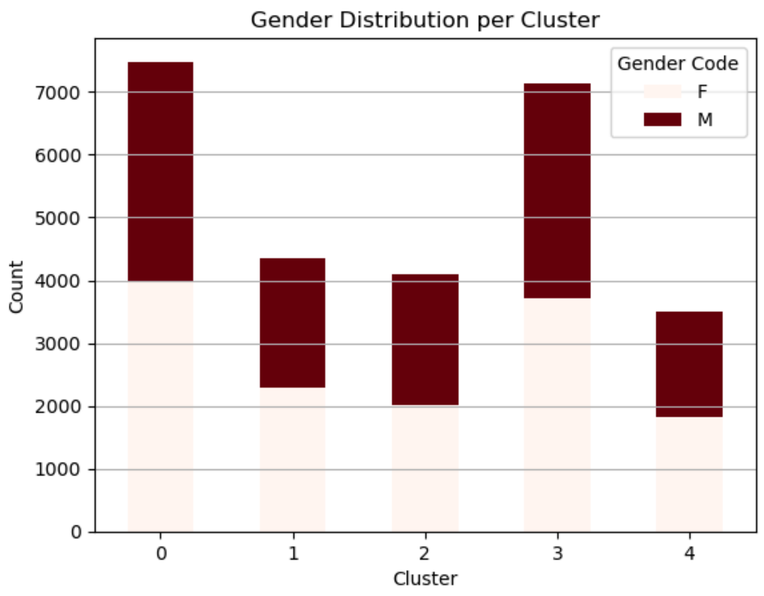
```
#Preparing the sample dataframe to be plotted
booked_class_counts = final_dataframe.groupby(['cluster', 'BkdClassOfService']).size().unstack(fill_value=0)

#Printing the sample dataframe
print(booked_class_counts)

#Creating the Bar plot
booked_class_counts.plot(kind='bar', stacked=True, colormap='Reds')

# Adding plot details
plt.title('Booked Class of Service per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='Booked Class of Service')

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

```
BkdClassOfService  Coach  Discount First Class  First Class
cluster
0                   7298                     0          183
1                   4059                     4          285
2                   4055                     0           41
3                   7101                     0           39
4                   3327                     1          182
```



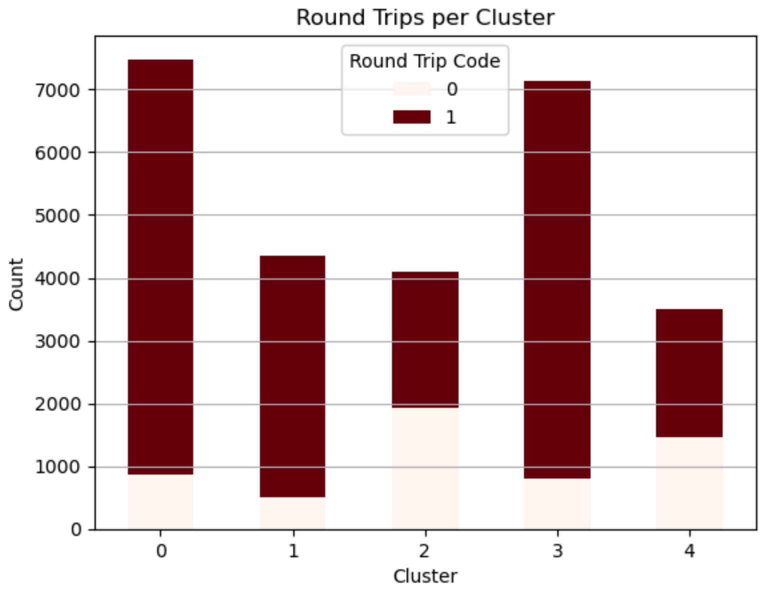
```
#Preparing the sample dataframe to be plotted
gender_code_counts = final_dataframe.groupby(['cluster', 'GenderCode']).size().unstack(fill_value=0)

#Printing the sample dataframe
print(gender_code_counts)

#Creating the Bar plot
gender_code_counts.plot(kind='bar', stacked=True, colormap='Reds')

# Adding plot details
plt.title('Gender Distribution per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='Gender Code')

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

```
GenderCode     F     M
cluster
0           3993  3488
1           2279  2069
2           2004  2092
3           3711  3429
4           1823  1687
```

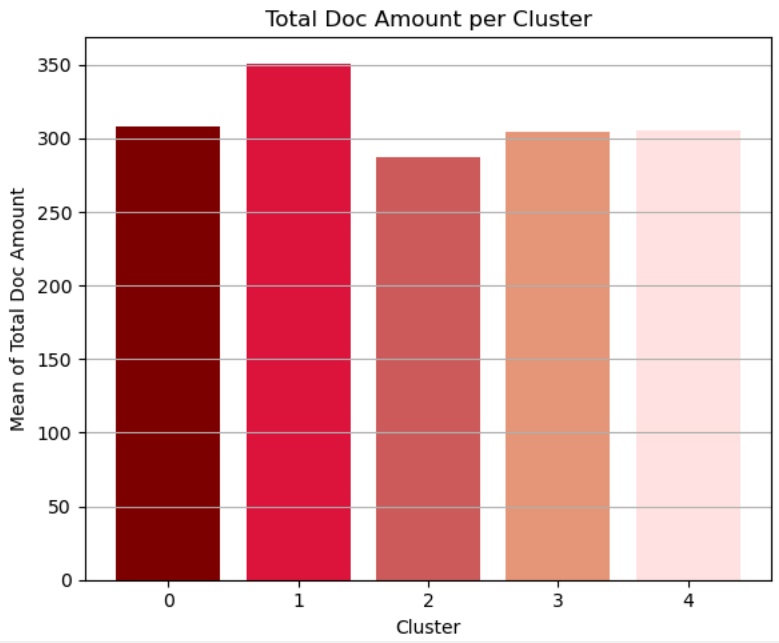


```
#Preparing the sample dataframe to be plotted
round_trip_counts = final_dataframe.groupby(['cluster', 'round_trip']).size().unstack()

#Printing the sample dataframe
print(round_trip_counts)

#Creating the Bar plot
round_trip_counts.plot(kind='bar', stacked=True, colormap='Reds')

# Adding plot details
plt.title('Round Trips per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='Round Trip Code')

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

```
round_trip     0     1
cluster
0            865  6616
1            509  3839
2           1935  2161
3            794  6346
4           1464  2046
```

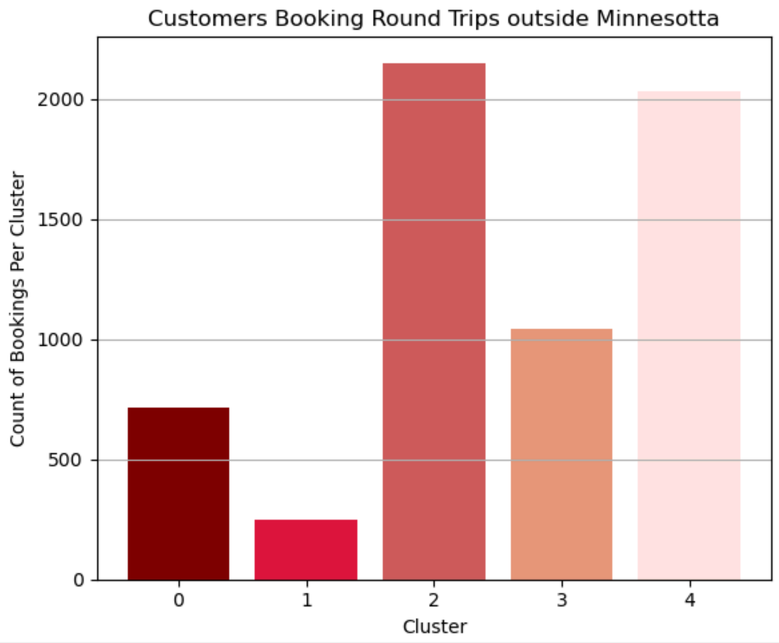


```
cluster_colors = {
    0: 'maroon',
    1: 'crimson',
    2: 'indianred',
    3: 'darksalmon',
    4: 'mistyrose'
}

#Preparing the sample dataframe to be plotted
cluster_revenue = final_dataframe.groupby('cluster')['TotalDocAmt'].mean()

#Creating the Bar plot
plt.figure(figsize=(6, 5))
for cluster in range(len(cluster_revenue)):
    plt.bar(cluster, cluster_revenue[cluster], width = 0.8, color=cluster_colors[cluster])

# Adding plot details
plt.title('Total Doc Amount per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Mean of Total Doc Amount')
plt.xticks(ticks=range(len(cluster_revenue)))
plt.grid(axis='y')
plt.tight_layout()

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



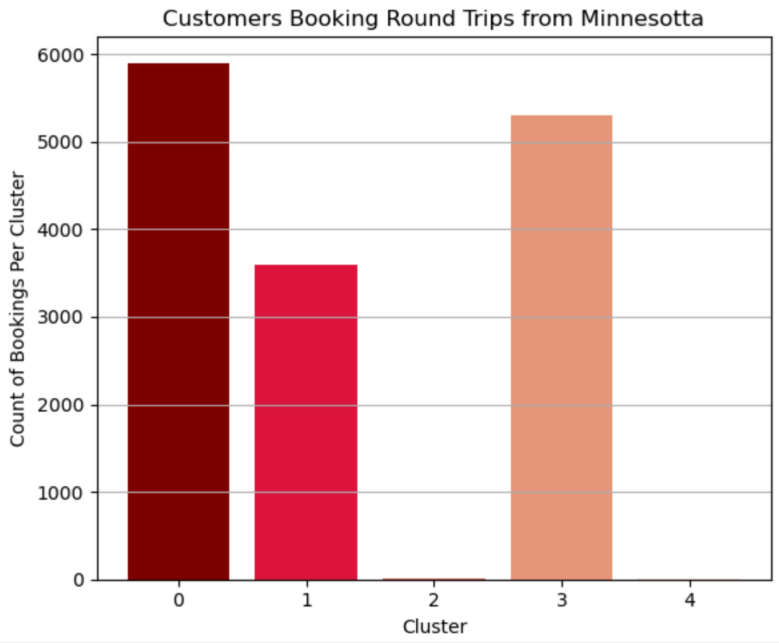
```
#Preparing the sample dataframe to be plotted
msp_origin_dest = final_dataframe.loc[(final_dataframe['round_trip']== 1) & (final_dataframe['true_origins']!= "MSP")]

print(f'The dataset has {msp_origin_dest.shape[0]} rows and {msp_origin_dest.shape[1]} columns')
cluster_sizes = msp_origin_dest['cluster'].value_counts().sort_index()

#Creating the Bar plot
plt.figure(figsize=(6, 5))
for cluster in range(len(cluster_sizes)):
    plt.bar(cluster, cluster_sizes[cluster], color=cluster_colors[cluster])

# Adding plot details
plt.title('Customers Booking Round Trips outside Minnesotta')
plt.xlabel('Cluster')
plt.ylabel('Count of Bookings Per Cluster')
plt.xticks(ticks=range(len(cluster_revenue)))
plt.grid(axis='y')
plt.tight_layout()

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

```
The dataset has 6191 rows and 38 columns
```

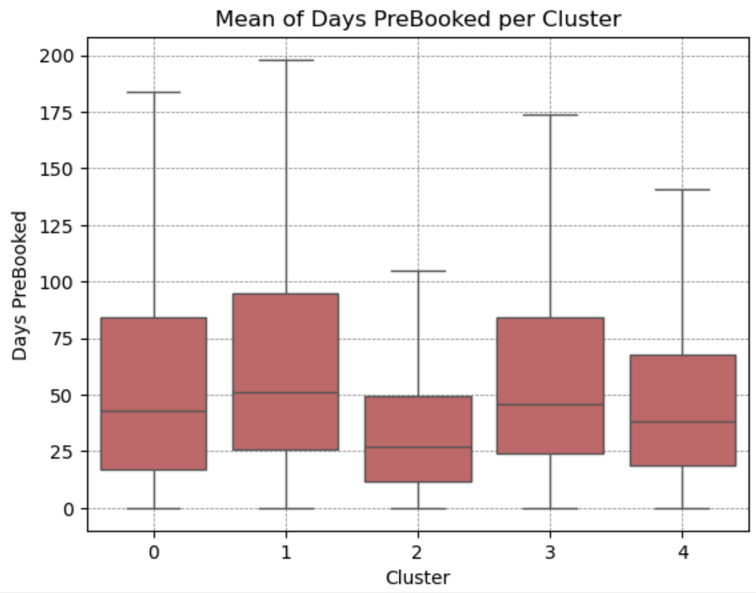


```
#Preparing the sample dataframe to be plotted
msp_origin_dest = final_dataframe.loc[(final_dataframe['round_trip']== 1) & (final_dataframe['true_origins']== "MSP")]

print(f'The dataset has {msp_origin_dest.shape[0]} rows and {msp_origin_dest.shape[1]} columns')
cluster_sizes = msp_origin_dest['cluster'].value_counts().sort_index()

#Creating the Bar plot
plt.figure(figsize=(6, 5))
for cluster in range(len(cluster_sizes)):
    plt.bar(cluster, cluster_sizes[cluster], color=cluster_colors[cluster])

# Adding plot details
plt.title('Customers Booking Round Trips from Minnesotta')
plt.xlabel('Cluster')
plt.ylabel('Count of Bookings Per Cluster')
plt.xticks(ticks=range(len(cluster_revenue)))
plt.grid(axis='y')
plt.tight_layout()

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

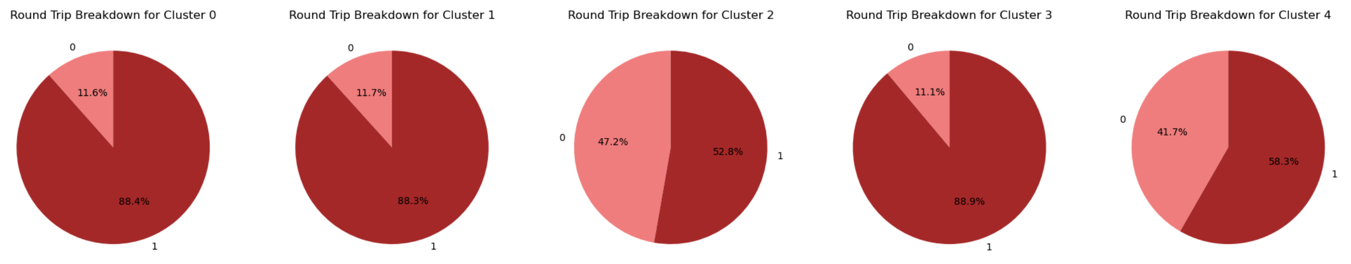
```
The dataset has 14817 rows and 38 columns
```



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

# Create the boxplot without showing outliers
sns.boxplot(x='cluster', y='days_pre_booked', data=final_dataframe, showfliers=False, color='indianred')

# Show grid lines
plt.grid(True)

# Customize grid appearance (optional)
plt.grid(color='gray', linestyle='--', linewidth=0.5)

# Adding plot details
plt.title('Mean of Days PreBooked per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Days PreBooked')

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

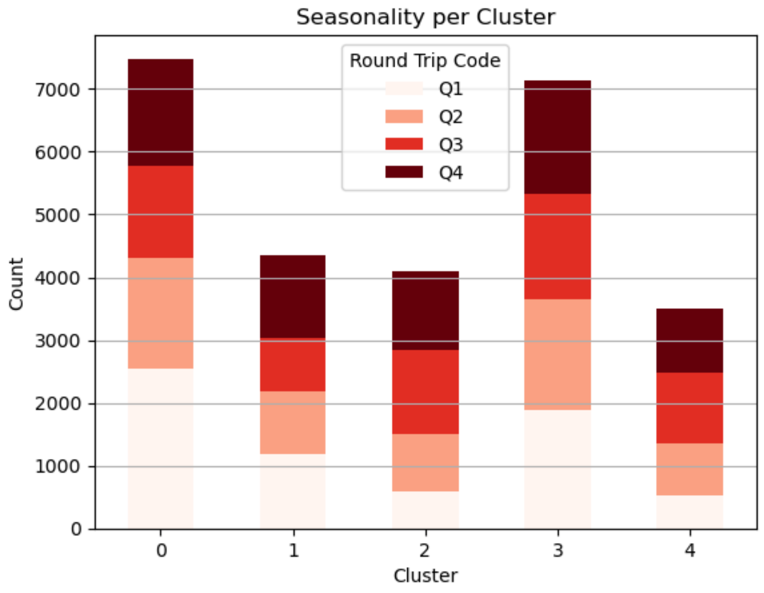


```
#Preparing the sample dataframe to be plotted
round_trip_counts = final_dataframe.groupby(['cluster', 'round_trip']).size().unstack()

# Create the pie plot by iterating over each cluster
fig, axes = plt.subplots(1, 5, figsize=(20, 4))
for i, cluster in enumerate(round_trip_counts.index):
    values = round_trip_counts.loc[cluster]
    axes[i].pie(values, labels=values.index, autopct='%1.1f%%', colors=['lightcoral', 'brown'], startangle=90)
    axes[i].axis('equal')
    axes[i].set_title(f'Round Trip Breakdown for Cluster {cluster}')
plt.tight_layout()

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



```
#Preparing the sample dataframe to be plotted
seasonality_counts = final_dataframe.groupby(['cluster', 'seasonality']).size().unstack()

#Printing the sample dataframe
print(seasonality_counts)

#Creating the Bar plot
seasonality_counts.plot(kind='bar',stacked=True, colormap='Reds')

# Adding plot details
plt.title('Seasonality per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='Round Trip Code')

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

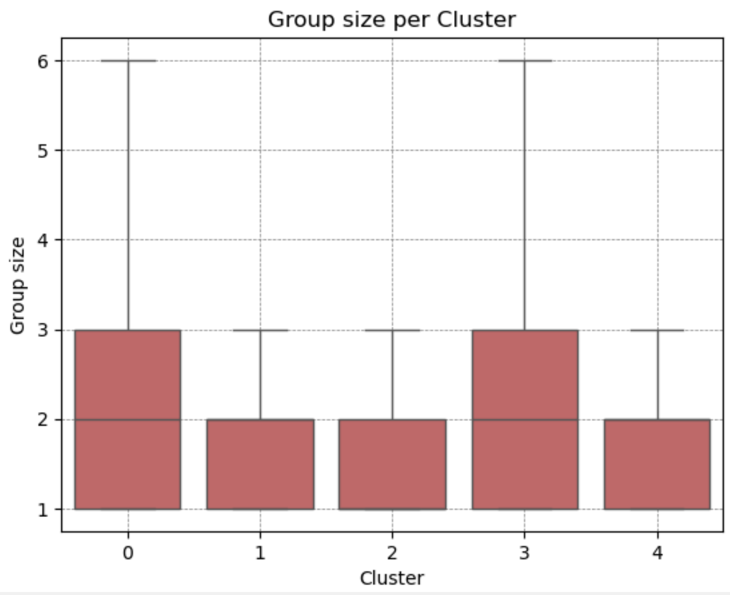
```
seasonality    Q1    Q2    Q3    Q4
cluster
0            2543  1758  1468  1712
1            1191   987   848  1322
2             586   909  1341  1260
3            1879  1760  1681  1820
4             530   815  1127  1038
```



```
#Preparing the sample dataframe to be plotted
groupsize_counts = final_dataframe.groupby(['cluster', 'group']).size().unstack()

#Printing the sample dataframe
print(round_trip_counts)

#Creating the Bar plot
groupsize_counts.plot(kind='bar', stacked=True, colormap='Reds')

# Adding plot details
plt.title('Group size per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.legend(title='Group size Code')

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

```
group       0     1
cluster
0        2171  5310
1        1797  2551
2        2724  1372
3        2330  4810
4        1730  1780
```

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

# Create the boxplot without showing outliers
sns.boxplot(x='cluster', y='group_size', data=final_dataframe, showfliers=False, color='indianred')

# Show grid lines
plt.grid(True)

# Customize grid appearance (optional)
plt.grid(color='gray', linestyle='--', linewidth=0.5)

# Adding plot details
plt.title('Group size per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Group size')

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


Group size per Cluster
Group size
Cluster