DataStorm_Insomniacs_Final

May 30, 2024

[340]:
```
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.decomposition import PCA

try:
    import seaborn as sns
except ImportError:
    %pip install seaborn
    import seaborn as sns

try:
    from word2number import w2n
except ImportError:
    %pip install word2number
    from word2number import w2n

import matplotlib.pyplot as plt
from scipy import stats
```

1 Loading Data

[341]:
```
#Load Dataset
dataset = pd.read_csv('customer_dataset.csv')
print("------------------------- CUSTOMER DATASET␣
 ↪-----------------------------")
print(dataset.head())
print("--------------------------------------------------------------------------")
```

```
------------------------- CUSTOMER DATASET -----------------------------
   customer_id average_monthly_spend average_monthly_visit_frequency  \
0            1                   790                            1.11
1            2                176875                           15.74
```

```
2           3                6812                          2.11
3           4               38542                          7.82
4           5               48712                          7.51

   average_monthly_basket_size
0                         2.84
1                        33.83
2                          NaN
3                        10.73
4                        10.04
-------------------------------------------------------------------------

c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\IPython\core\interactiveshell.py:3553: DtypeWarning: Columns (1,2) have
mixed types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

2 Dealing with Non Numeric Data

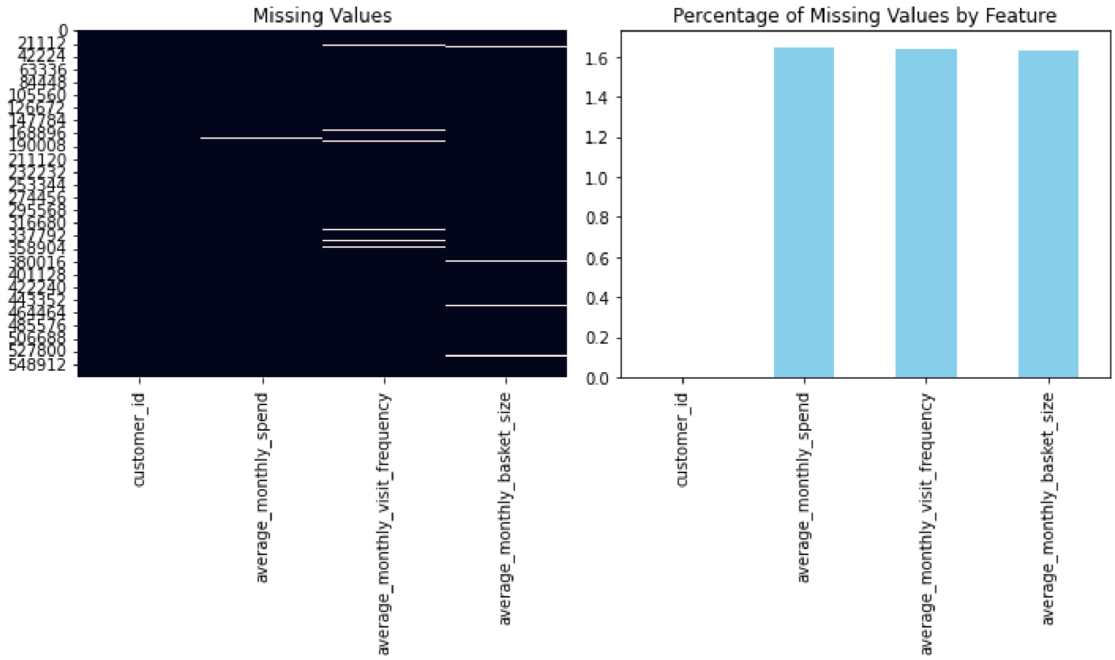
[342]:
```python
#print all non numeric columns
print("----------------------- NON NUMERIC COLUMNS----------------------------")
for i in dataset.columns:
    if dataset[i].dtype == 'object':
        print(i,end = " ")
print()
print("-----------------------------------------------------------------------")
#handling non-numeric data converting them to numeric
def word_to_num(value):
    try:
        return w2n.word_to_num(value)
    except ValueError:
        if value.isdigit():
            return int(value)
        elif value.replace('.', '', 1).isdigit() and value.count('.') < 2:
            return float(value)
        return None

for column in dataset.columns:
    dataset[column] = dataset[column].apply(lambda x : word_to_num(str(x)))
```

```
----------------------- NON NUMERIC COLUMNS----------------------------
average_monthly_spend average_monthly_visit_frequency
-----------------------------------------------------------------------
```

3 Prelimenary Analysis of Missing Values

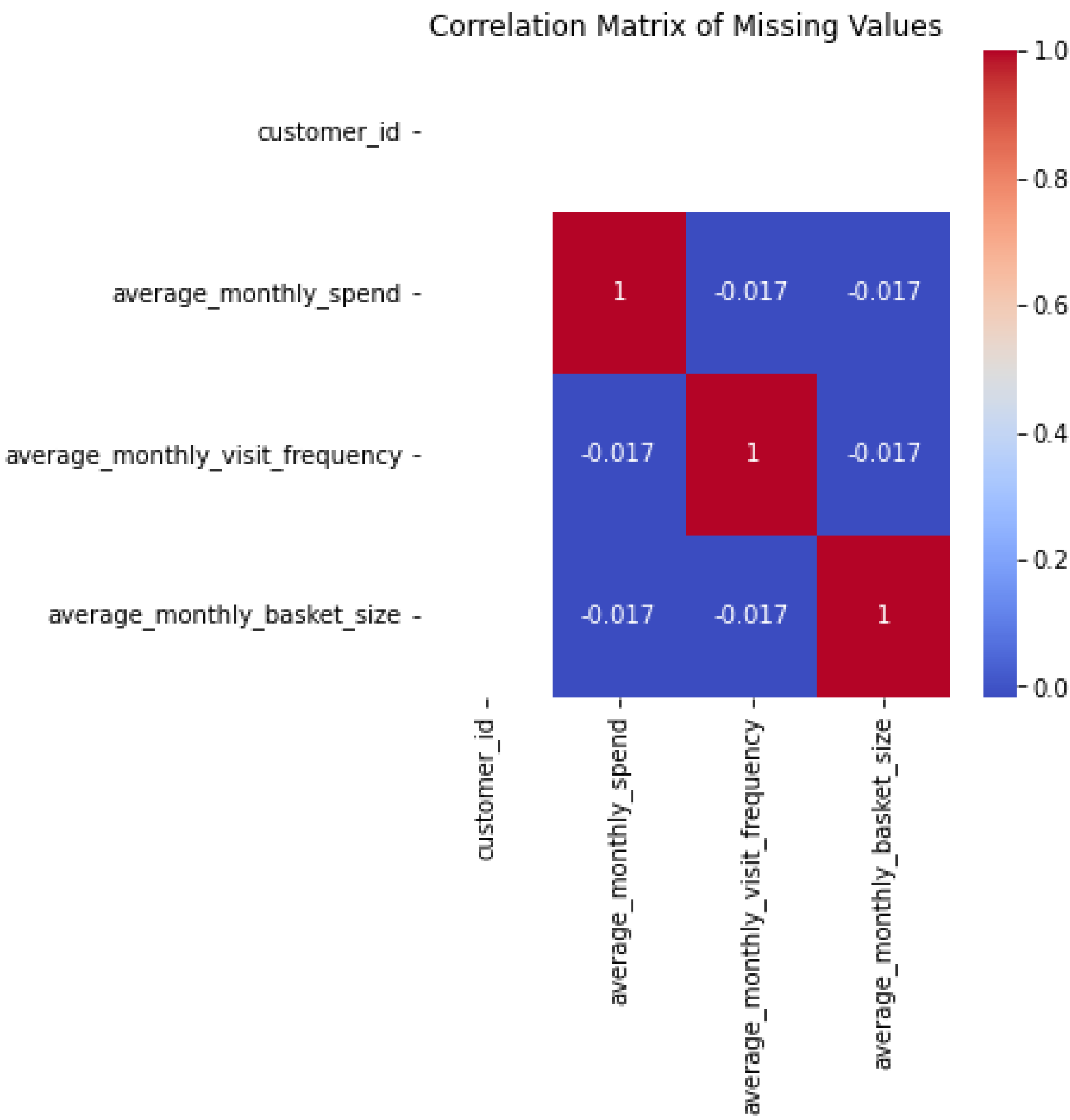
[343]:
```
#missing value analysis
print("--------------------------- MISSING VALUE DETAILS␣
↪----------------------------------")
#nan count
print(dataset.isna().sum())
#length of dataset
print(f"Length of dataset: {len(dataset)}")
#count all the rows with nan values
rows_with_nan = dataset.isna().any(axis=1).sum()
print(f"Rows with nan values: {rows_with_nan}")
#ratio of rows with nan values
missing_percentage = dataset.isnull().mean() * 100
print(f"Ratio of rows with nan values: {round(rows_with_nan/
↪len(dataset),2)*100}%")

plt.figure(figsize=(5,5))
plt.subplot(1, 2, 1)
plt.title('Missing Values')
sns.heatmap(dataset.isnull(), cbar=False)

plt.subplot(1, 2, 2)
missing_percentage.plot(kind='bar', figsize=(10, 6), color='skyblue')
plt.title('Percentage of Missing Values by Feature')
plt.tight_layout()
plt.show()
print("------------------------------------------------------------------------------------------------------------------------
```

```
--------------------------- MISSING VALUE DETAILS
----------------------------------
customer_id                         0
average_monthly_spend            9389
average_monthly_visit_frequency  9337
average_monthly_basket_size      9287
dtype: int64
Length of dataset: 570000
Rows with nan values: 28013
Ratio of rows with nan values: 5.0%
```




```
--------------------------------------------------------------------------------
-------
```

[344]:
```python
#correlation matrix to see the missing values are correlated
plt.figure(figsize=(5, 5))
corr_matrix = dataset.isnull().corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix of Missing Values')
plt.show()
```



[345]:
```python
#extract nan rows from dataset for further analysis
nan_rows = dataset[dataset.isnull().any(axis=1)]
#replace nan with 0
dataset.dropna(inplace=True)
# Handle duplicates
dataset.drop_duplicates(inplace=True)

print("------------------- EXTRACTED NAN ROWS ----------------------")
print(nan_rows)
print("--------------------------------------------------------------")
```

```
------------------- EXTRACTED NAN ROWS ----------------------
```

```
        customer_id  average_monthly_spend  average_monthly_visit_frequency  \
2                 3                 6812.0                             2.11
7                 8                12656.0                             2.13
24               25                41329.0                              NaN
52               53               171010.0                              NaN
53               54               104457.0                            18.88
…               …                    …                              …
559914       559915                45023.0                              NaN
559945       559946                49533.0                             5.87
559959       559960                    NaN                             5.80
559970       559971                95444.0                            19.85
559972       559973                13981.0                             2.74

        average_monthly_basket_size
2                               NaN
7                               NaN
24                            10.32
52                            35.03
53                              NaN
…                             …
559914                         9.82
559945                          NaN
559959                         9.87
559970                          NaN
559972                          NaN

[28013 rows x 4 columns]
--------------------------------------------------------------
```

[346]:

```
def plot_outliers():
    iso_forest = IsolationForest(contamination=0.05, random_state=42)
    features =␣
    ↪['average_monthly_spend','average_monthly_visit_frequency','average_monthly_basket_size']
    data = dataset.copy()
    iso_forest.fit(data[features])
    outliers = iso_forest.predict(data[features])
    data['outlier'] = outliers
    outliers_data = data[data['outlier'] == -1]
    sns.pairplot(data, hue='outlier', palette={1: 'blue', -1: 'red'},␣
    ↪markers=["o", "s"])
    plt.suptitle('Isolation Forest Outlier Detection', y=1.02)
    plt.show()
```

[347]:

```
#Handle outliers
data = dataset.copy()
Q1 = dataset.quantile(0.25)
Q3 = dataset.quantile(0.75)
```

```
IQR = Q3 - Q1
outliers = ((dataset < (Q1 - 1.5 * IQR)) | (dataset > (Q3 + 1.5 * IQR))).
 ↪any(axis=1)
dataset = dataset[~outliers]

copy_dataset = dataset.copy()
data.describe()
```

[347]:

```
         customer_id  average_monthly_spend  average_monthly_visit_frequency  \
count  531990.000000           5.319900e+05                    531990.000000
mean   280059.070229           4.825899e+04                         6.879288
std    161689.312262           9.173203e+04                         5.323171
min         1.000000           0.000000e+00                         0.000000
25%    139927.250000           1.049900e+04                         2.390000
50%    280109.500000           3.195900e+04                         5.600000
75%    420171.750000           8.541800e+04                         9.850000
max    560000.000000           4.833000e+07                       432.740000

       average_monthly_basket_size
count                531990.000000
mean                     13.292845
std                      12.039045
min                       0.000000
25%                       3.800000
50%                       9.790000
75%                      17.480000
max                     385.040000
```

4 Data Visualization and Preliminary Clusterting for Observing the Nature of Decision Boundaries

[348]:

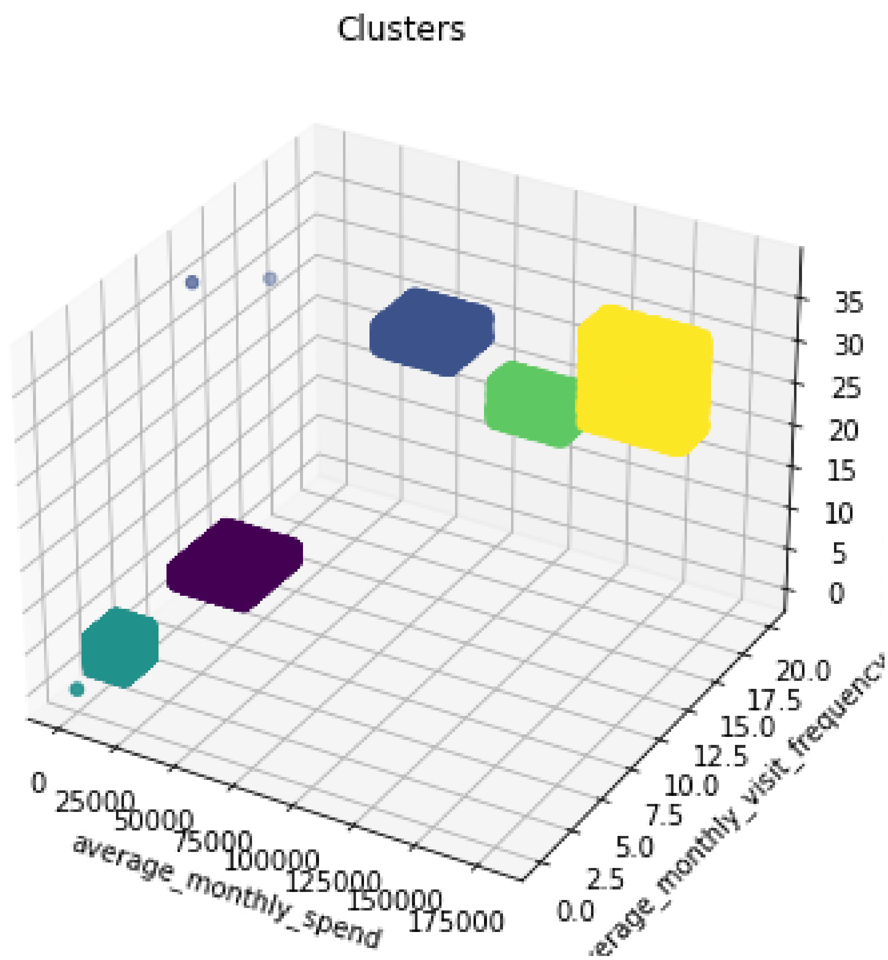
```
#scale for cluster visualization
scaler = StandardScaler()
scaled_data = scaler.fit_transform(dataset.iloc[:, 1:])
scaled_data_nan = scaler.transform(nan_rows.iloc[:, 1:])
```

[349]:

```
#clustering using Kmeans
kmeans = KMeans(n_clusters=5, random_state=42)
clusters = kmeans.fit_predict(scaled_data)
```

```
c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  warnings.warn(
```

[350]:
```
nan_rows.fillna(0, inplace=True)
dataset['Cluster'] = clusters
fig = plt.figure(figsize=(13, 12))
ax = fig.add_subplot(121, projection='3d')
ax.scatter(dataset['average_monthly_spend'], dataset['average_monthly_visit_frequency'], dataset['average_monthly_basket_size'], c=clusters, cmap='viridis')
ax.set_xlabel('average_monthly_spend')
ax.set_ylabel('average_monthly_visit_frequency')
ax.set_zlabel('average_monthly_basket_size')
plt.title('Clusters')
ax.set_xlabel('average_monthly_spend')
ax.set_ylabel('average_monthly_visit_frequency')
ax.set_zlabel('average_monthly_basket_size')

plt.show()
```



Cuboidal shape of the clusters is proof that the Decision boundaries can be repressented as a logical combination of coniditions on each parameter seperately. (The decision Boundaries are alined with the Vertical and Horizontal Planes). That is the Function for a Decison Boundary for a cluster j, $\phi_j(x_1, x_2, x_2)$ (where x_1, x_2, x_3 are the three features) can be expressed as a logical combination of three simple decision rules.

That is if,

$$\phi_j(x_1, x_2, x_3) = \begin{cases} 1 & \text{If belongs to cluster j} \\ 0 & \text{If does not belongs to cluster j} \end{cases}$$

then,

$$\phi_j(x_1, x_2, x_3) = \phi_{1,j}(x_1) \cdot \phi_{2,i}(x_2) \cdot \phi 3, i(x_3)$$

where $\cdot$ is the logical and operation fruthemore since there is only one such block per cluster per axis,

$$\phi_{k,j}(x_k) = \begin{cases} 1 & a_k < x_k < b_k \\ 0 & \text{otherwise} \end{cases}$$

Where a_k and b_k are to be determined Finally it can also be observed that these margins are far apart so clustering in each dimension seperately is sufficient for identifying these bondaries.

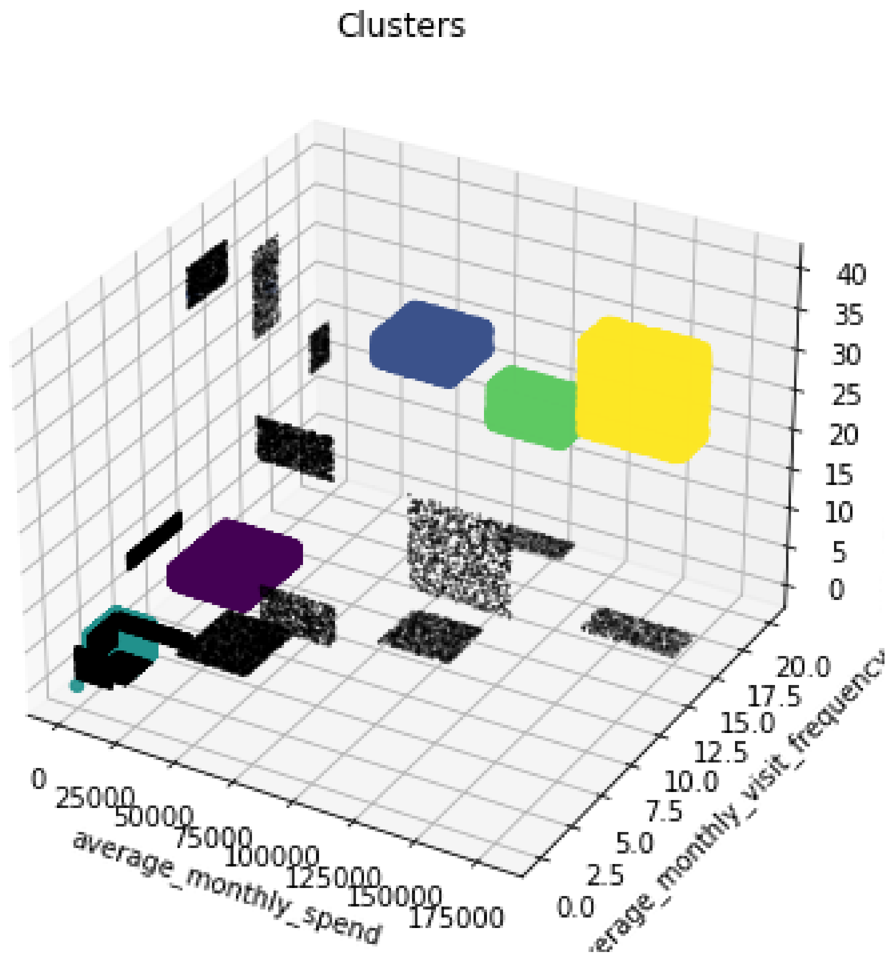
Finally this corrabartes well with the Problem Statement

5 Demonstrating that Rows with Missing Values Belong to One of the Clusters and Can be Fully Determined by Considering the remaining Columns

We will use the fact that if we make one of the features zero, this produces a Projection of one of the Cuboidal Clusters onto one of the planes. Therefore, we will replace the missing values with zero and plot in a 3d space

[351]:
```
nan_rows.fillna(0, inplace=True)
dataset['Cluster'] = clusters
fig = plt.figure(figsize=(13, 12))
ax = fig.add_subplot(121, projection='3d')
ax.scatter(dataset['average_monthly_spend'],␣
  ↪dataset['average_monthly_visit_frequency'],␣
  ↪dataset['average_monthly_basket_size'], c=clusters, cmap='viridis')
ax.set_xlabel('average_monthly_spend')
ax.set_ylabel('average_monthly_visit_frequency')
ax.set_zlabel('average_monthly_basket_size')
plt.title('Clusters')
ax.scatter(nan_rows['average_monthly_spend'],␣
  ↪nan_rows['average_monthly_visit_frequency'],␣
  ↪nan_rows['average_monthly_basket_size'],
           c='black',s = 0.1)
ax.set_xlabel('average_monthly_spend')
ax.set_ylabel('average_monthly_visit_frequency')
ax.set_zlabel('average_monthly_basket_size')
```

```
plt.show()
```



We can easily see that all of the missing value clouds (Black data clouds) are simply projections of the already identified clusters onto on of the planse x_1x_2,x_1x_3,x_2x_3 planes thus proving our claim is correct. We will reinforce this claim in later sections. Finally, since all Black Data clouds are 2 Dimensional it is also clear that there are no columns with two or more missing values.

6 Demonstrating that the Distribution Roughly Follows the Rules given in the Problem Statement

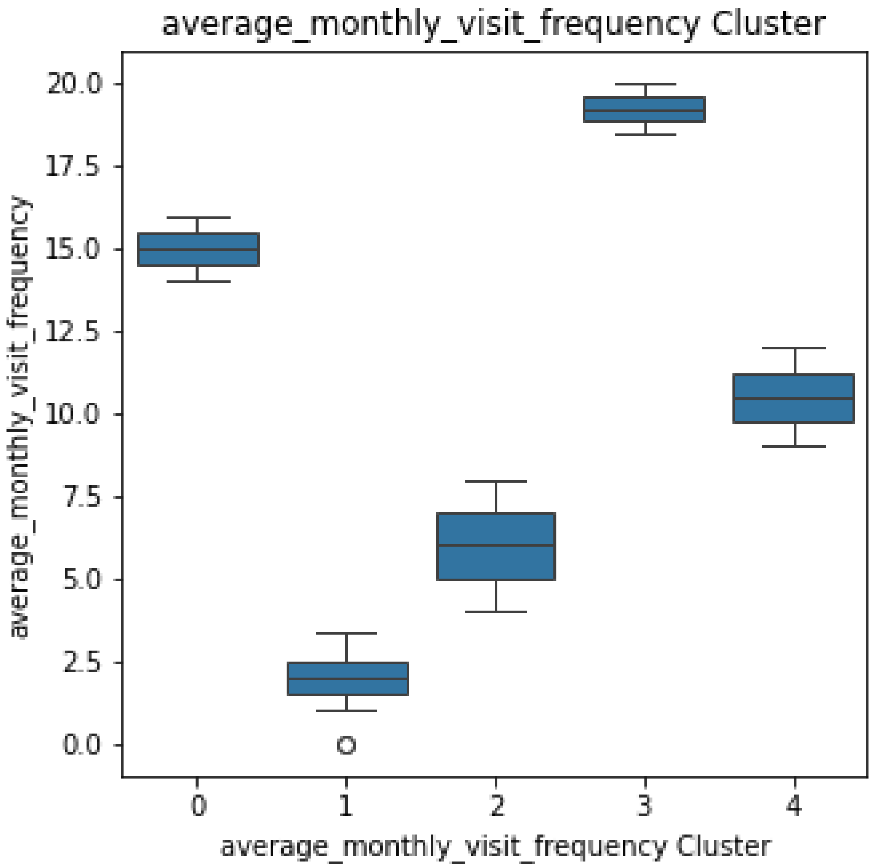
[352]:
```
def cluster_visualization_on_feature(feature_name:str):
    feature_dataset = copy_dataset[[feature_name]].dropna()
    n = 5 if feature_name == "average_monthly_visit_frequency" else 4
    kmeans = KMeans(n_clusters=n, random_state=42)
    clusters = kmeans.fit_predict(feature_dataset)
```

```
    feature_dataset[f'{feature_name} Cluster'] = clusters
    plt.figure(figsize=(5, 5))
    sns.boxplot(x=f'{feature_name} Cluster', y=feature_name,␣
 ↪data=feature_dataset)
    plt.title(f'{feature_name} Cluster')
    plt.show()

cluster_visualization_on_feature('average_monthly_spend')
cluster_visualization_on_feature('average_monthly_visit_frequency')
cluster_visualization_on_feature('average_monthly_basket_size')
```

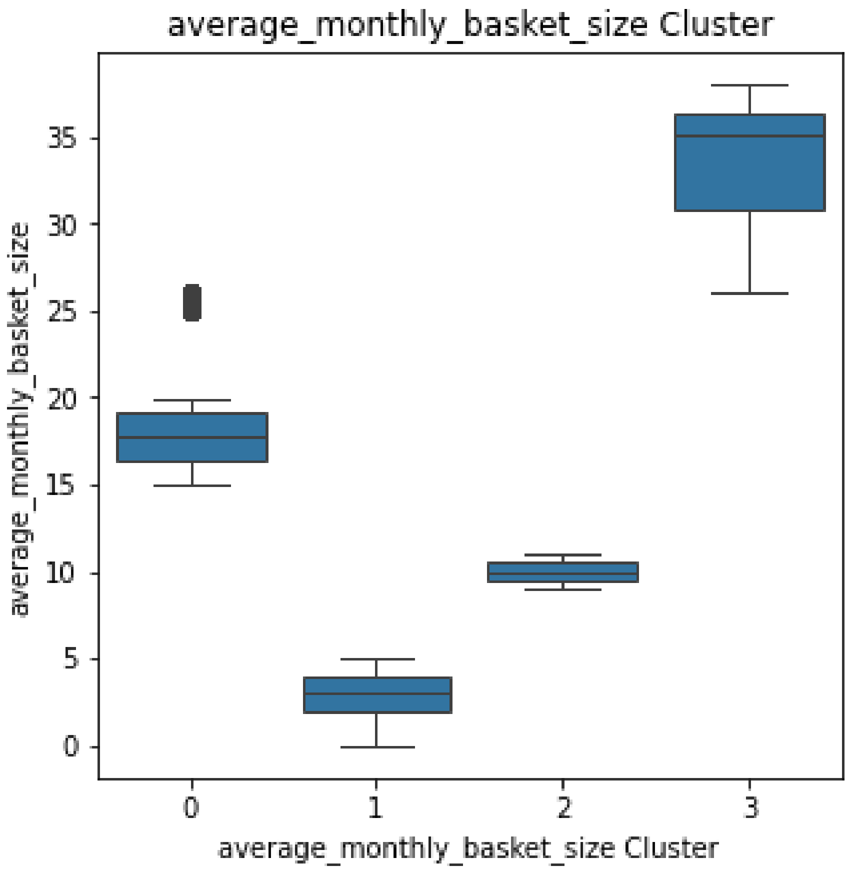
```
c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  warnings.warn(
```


```
c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
```

```
explicitly to suppress the warning
  warnings.warn(
```




```
c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  warnings.warn(
```



Plotting Box and Whisker graphs to analyze distinct clusters within features. Considering Average Monthly Spend by Cluster,We can identify there are 4 distinct clusters (cluster 0 and 4 are the same). We could categorize them as, - 3 - LOW - 1 - Average - 0, 4 - High - 2 - Very High

Considering Average Monthly Visit Frequency by cluster, We can identify that there are 5 distinct clusters. We can categorize them as,

- 3 - Low
- 1 - Average Lower
- 4 - Average Higher
- 2 - High
- 1 - Very High

Note that we can see two well separated clusters in the average range instead of the one as given in the problem statement. It is possible that these two clusters have no bearing on the problem. But we will later show that these have a very high importance for the classification task. Considering Average Monthly Basket Size by cluster.Although we can see 5 clusters in the plot we can see that the two upper clusters are overlapping in terms of the inter quartile ranges. Therefore will only consider four clusters. We can categorize them as ,

- 3 - Low
- 1 - Average

- 0 - High
- 2,4 - Very High

The Table is mostly correct however there are some modifications need to be done which we will further verify and update in a later section

7 Analyzing Each Feature Set Independantly and Identifying the Percentiles (Ranges in our Case)

Since in the previous section we demonstrated that it is sufficient to analyze each feature independantly we wil analyze them, - first visually through histograms - second using

[353]:
```
print("----------------------------Data Analysis----------------------------")

data = pd.read_csv('customer_dataset.csv')
data.head()
```

```
----------------------------Data Analysis----------------------------

c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\IPython\core\interactiveshell.py:3553: DtypeWarning: Columns (1,2) have
mixed types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[353]:
```
   customer_id average_monthly_spend average_monthly_visit_frequency  \
0            1                   790                            1.11
1            2                176875                           15.74
2            3                  6812                            2.11
3            4                 38542                            7.82
4            5                 48712                            7.51

   average_monthly_basket_size
0                         2.84
1                        33.83
2                          NaN
3                        10.73
4                        10.04
```

[354]:
```
# Extracting columns from the dataframe
col_names = data.columns.tolist()
print(col_names)
```

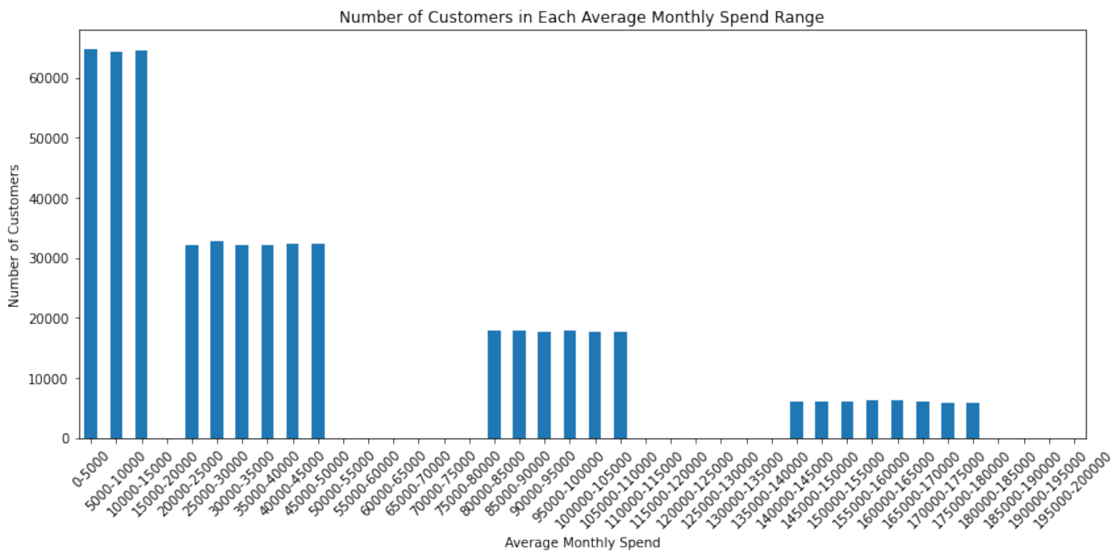
```
['customer_id', 'average_monthly_spend', 'average_monthly_visit_frequency',
'average_monthly_basket_size']
```

[355]:
```
# Converting words to numerical values
def convert_word_to_number(amount):
    try:
```

```
        return w2n.word_to_num(amount)
    except ValueError:
        return amount

for col in col_names:
    data[col] = data[col].apply(convert_word_to_number)
    data[col] = pd.to_numeric(data[col], errors='coerce')
    data = data.dropna(subset=[col])
```

[356]:
```
def plot_barCharts(column_name, x_axis_label, interval_width : int, min_limit :␣
 ↪int, max_limit : int):
  max_value = int(data[column_name].max()) + interval_width

  bins = range(min_limit, max_limit, interval_width)
  labels = [f'{i}-{i+interval_width}' for i in bins[:-1]]

  data['range'] = pd.cut(data[column_name], bins=bins, labels=labels,␣
 ↪right=False)
  customer_count = data['range'].value_counts().sort_index()

  plt.figure(figsize=(12, 6))
  customer_count.plot(kind='bar')
  plt.xlabel(x_axis_label)
  plt.ylabel('Number of Customers')
  plt.title(f'Number of Customers in Each {x_axis_label} Range')
  plt.xticks(rotation=45)
  plt.tight_layout()
  plt.show()

  print(customer_count)
```

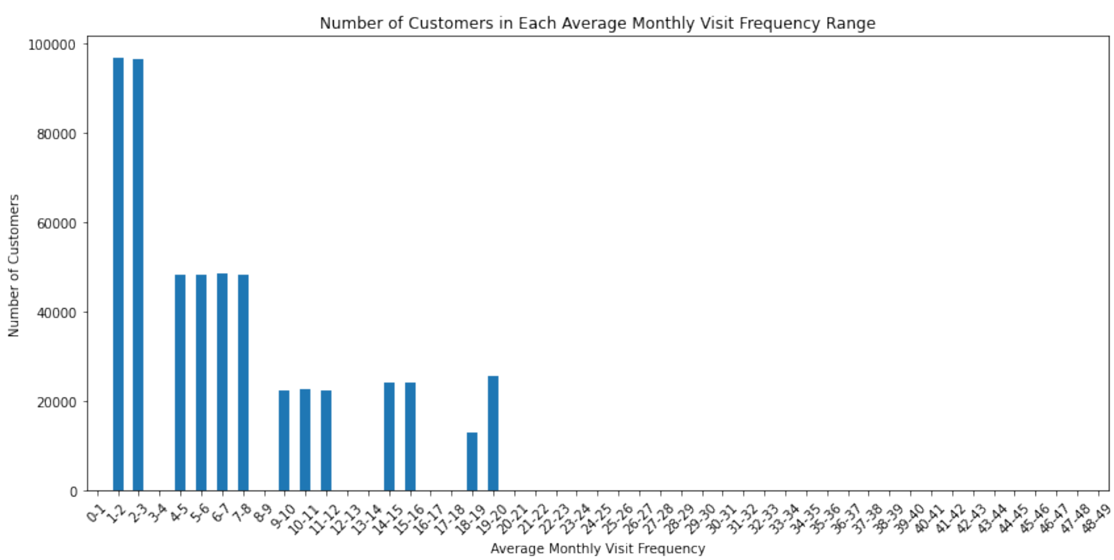
[357]:
```
plot_barCharts('average_monthly_spend', 'Average Monthly Spend', 5000, 0,␣
 ↪200001)
```



0-5000	64687
5000-10000	64284
10000-15000	64552
15000-20000	0
20000-25000	32134
25000-30000	32692
30000-35000	32145
35000-40000	32006
40000-45000	32371
45000-50000	32357
50000-55000	0
55000-60000	0
60000-65000	0
65000-70000	0
70000-75000	0
75000-80000	0
80000-85000	17794
85000-90000	17918
90000-95000	17680
95000-100000	17782
100000-105000	17605
105000-110000	17601
110000-115000	0
115000-120000	0
120000-125000	0
125000-130000	0
130000-135000	0
135000-140000	0
140000-145000	6057

```
145000-150000     5982
150000-155000     6146
155000-160000     6188
160000-165000     6173
165000-170000     6061
170000-175000     5856
175000-180000     5918
180000-185000        0
185000-190000        0
190000-195000        0
195000-200000        0
Name: range, dtype: int64
```

[358]:
```
plot_barCharts('average_monthly_visit_frequency', 'Average Monthly Visit␣
↪Frequency', 1, 0, 50)
```

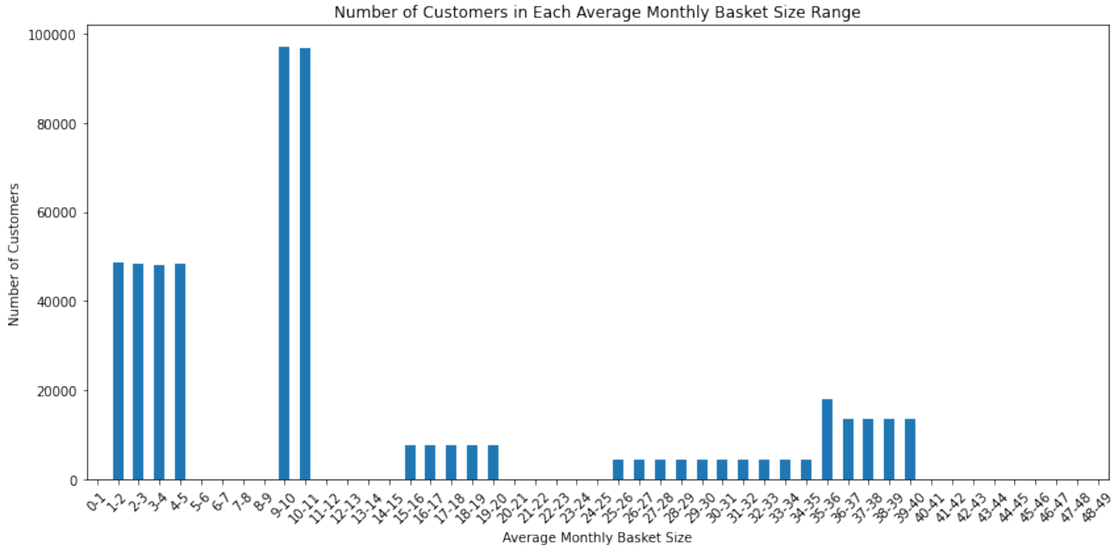



```
0-1           2
1-2       96944
2-3       96575
3-4           1
4-5       48285
5-6       48346
6-7       48647
7-8       48423
8-9           0
9-10      22447
10-11     22718
11-12     22519
12-13         0
```

```
13-14        0
14-15    24151
15-16    24235
16-17        0
17-18        0
18-19    12928
19-20    25766
20-21        0
21-22        0
22-23        1
23-24        0
24-25        0
25-26        0
26-27        0
27-28        0
28-29        0
29-30        0
30-31        0
31-32        0
32-33        0
33-34        0
34-35        0
35-36        0
36-37        0
37-38        0
38-39        0
39-40        0
40-41        0
41-42        0
42-43        0
43-44        0
44-45        0
45-46        0
46-47        0
47-48        0
48-49        0
Name: range, dtype: int64
```

[359]:

```
plot_barCharts('average_monthly_basket_size', 'Average Monthly Basket Size', 1,
 0, 50)
```



0-1	3
1-2	48568
2-3	48458
3-4	48130
4-5	48366
5-6	0
6-7	0
7-8	0
8-9	0
9-10	97051
10-11	96656
11-12	0
12-13	0
13-14	0
14-15	0
15-16	7824
16-17	7632
17-18	7771
18-19	7709
19-20	7758
20-21	0
21-22	0
22-23	0
23-24	0
24-25	0
25-26	4400
26-27	4505
27-28	4346
28-29	4374

```
29-30     4480
30-31     4440
31-32     4356
32-33     4408
33-34     4343
34-35     4352
35-36    17985
36-37    13562
37-38    13471
38-39    13460
39-40    13587
40-41        0
41-42        0
42-43        0
43-44        0
44-45        0
45-46        0
46-47        0
47-48        0
48-49        0
Name: range, dtype: int64
```

8 Further Proving that rows with Missing Values Follow the Same Distribution as the other ones

[360]:
```python
# Now we'll try to analyze data by removing only the N/A entries in the
↪respective column

dataset = pd.read_csv('customer_dataset.csv')
```

```
c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\IPython\core\interactiveshell.py:3553: DtypeWarning: Columns (1,2) have
mixed types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[361]:
```python
col_names = dataset.columns.tolist()
print(col_names)
```

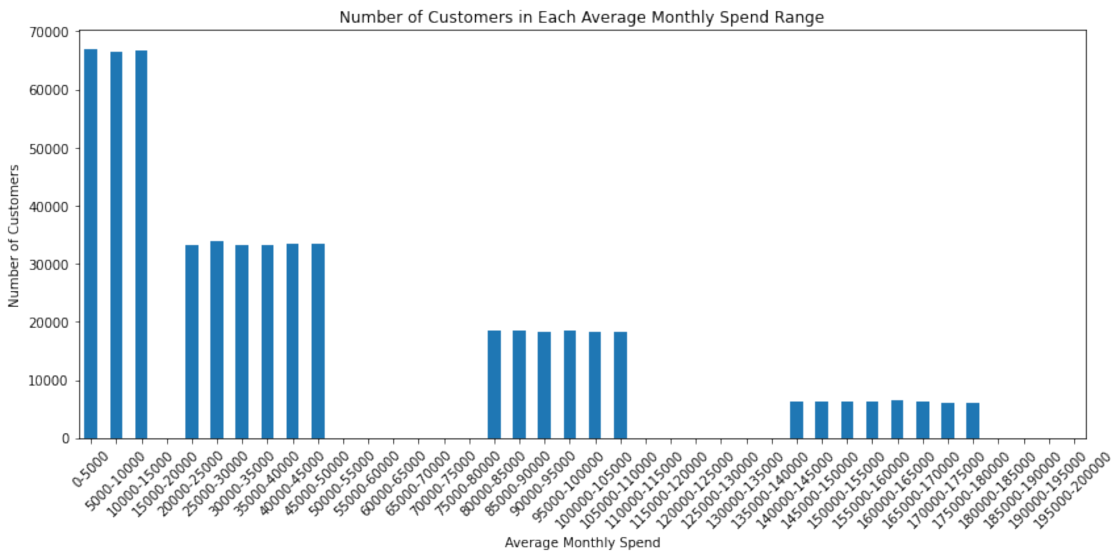
```
['customer_id', 'average_monthly_spend', 'average_monthly_visit_frequency',
'average_monthly_basket_size']
```

[362]:
```python
for col in col_names:
    dataset[col] = dataset[col].apply(convert_word_to_number)
    dataset[col] = pd.to_numeric(dataset[col], errors='coerce')
```

[363]:
```
def plot_barCharts_2(column_name, x_axis_label, interval_width : int, min_limit␣
↪: int, max_limit : int):
    data = dataset.dropna(subset=[column_name])
    max_value = int(data[column_name].max()) + interval_width

    bins = range(min_limit, max_limit, interval_width)
    labels = [f'{i}-{i+interval_width}' for i in bins[:-1]]

    data['range'] = pd.cut(data[column_name], bins=bins, labels=labels,␣
↪right=False)
    customer_count = data['range'].value_counts().sort_index()

    plt.figure(figsize=(12, 6))
    customer_count.plot(kind='bar')
    plt.xlabel(x_axis_label)
    plt.ylabel('Number of Customers')
    plt.title(f'Number of Customers in Each {x_axis_label} Range')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

    print(customer_count)
```

[364]:
```
plot_barCharts_2('average_monthly_spend', 'Average Monthly Spend', 5000, 0,␣
↪200001)
```

```
C:\Users\dell\AppData\Local\Temp/ipykernel_26116/4100806091.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['range'] = pd.cut(data[column_name], bins=bins, labels=labels,
right=False)
```

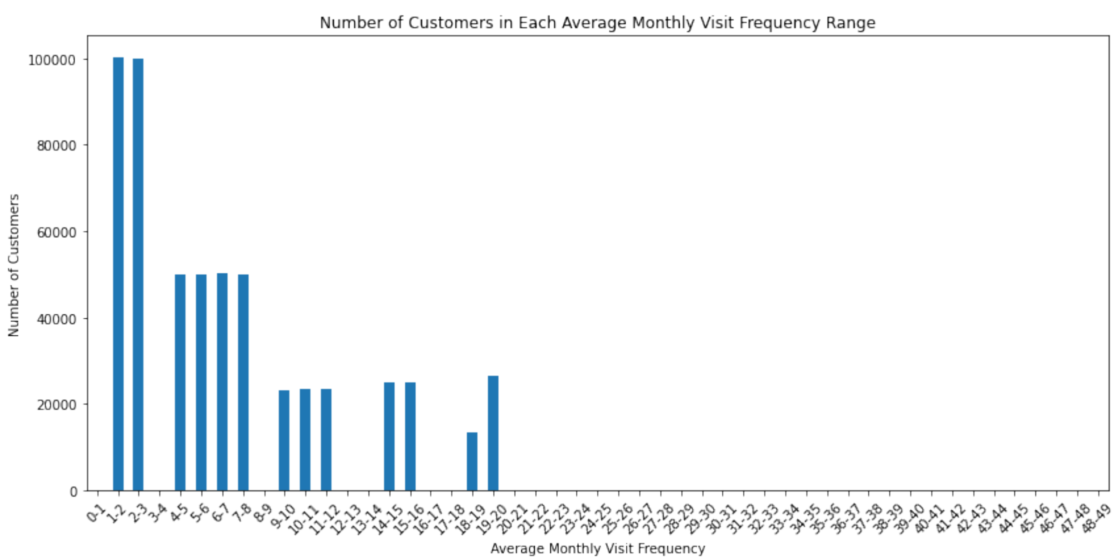


0-5000	66892
5000-10000	66494
10000-15000	66722
15000-20000	0
20000-25000	33268
25000-30000	33795
30000-35000	33218
35000-40000	33105
40000-45000	33501
45000-50000	33424
50000-55000	0
55000-60000	0
60000-65000	0
65000-70000	0
70000-75000	0
75000-80000	0
80000-85000	18421
85000-90000	18560
90000-95000	18285
95000-100000	18413
100000-105000	18226
105000-110000	18248
110000-115000	0
115000-120000	0
120000-125000	0
125000-130000	0
130000-135000	0
135000-140000	0
140000-145000	6254

```
145000-150000     6205
150000-155000     6355
155000-160000     6380
160000-165000     6394
165000-170000     6270
170000-175000     6058
175000-180000     6115
180000-185000        0
185000-190000        0
190000-195000        0
195000-200000        0
Name: range, dtype: int64
```

[365]:
```
plot_barCharts_2('average_monthly_visit_frequency', 'Average Monthly Visit␣
↪Frequency', 1, 0, 50)
```

```
C:\Users\dell\AppData\Local\Temp/ipykernel_26116/4100806091.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['range'] = pd.cut(data[column_name], bins=bins, labels=labels,
right=False)
```

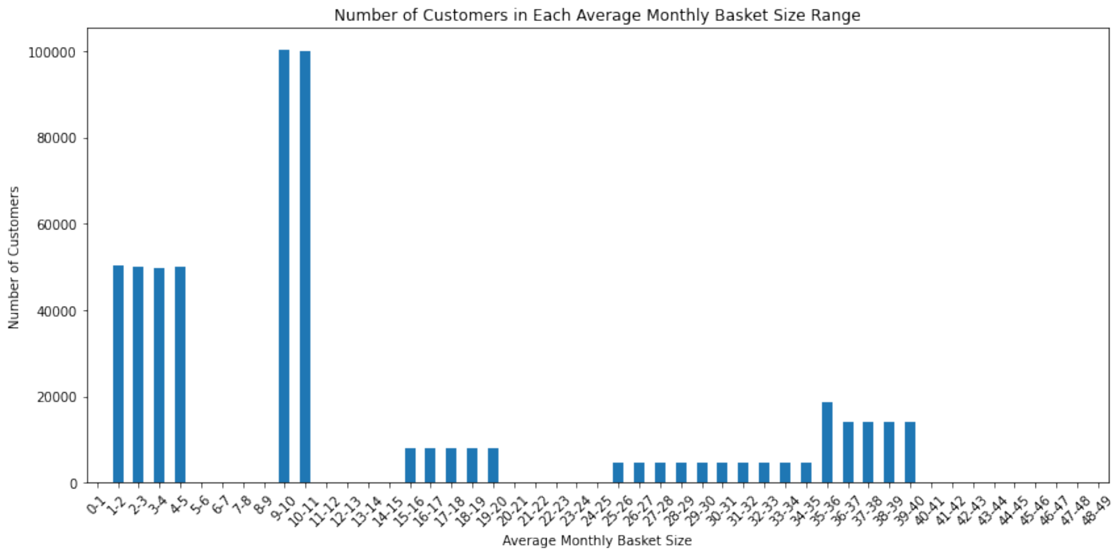



```
0-1            2
1-2       100263
2-3        99976
```

```
3-4          1
4-5      49959
5-6      49982
6-7      50306
7-8      50022
8-9          0
9-10     23255
10-11    23506
11-12    23352
12-13        0
13-14        0
14-15    25007
15-16    25036
16-17        0
17-18        0
18-19    13356
19-20    26636
20-21        0
21-22        0
22-23        1
23-24        0
24-25        0
25-26        0
26-27        0
27-28        0
28-29        0
29-30        0
30-31        0
31-32        0
32-33        0
33-34        0
34-35        0
35-36        0
36-37        0
37-38        0
38-39        0
39-40        0
40-41        0
41-42        0
42-43        0
43-44        0
44-45        0
45-46        0
46-47        0
47-48        0
48-49        0
Name: range, dtype: int64
```

[366]:
```
plot_barCharts_2('average_monthly_basket_size', 'Average Monthly Basket Size',␣
↪1, 0, 50)
```

```
C:\Users\dell\AppData\Local\Temp/ipykernel_26116/4100806091.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['range'] = pd.cut(data[column_name], bins=bins, labels=labels,
right=False)
```



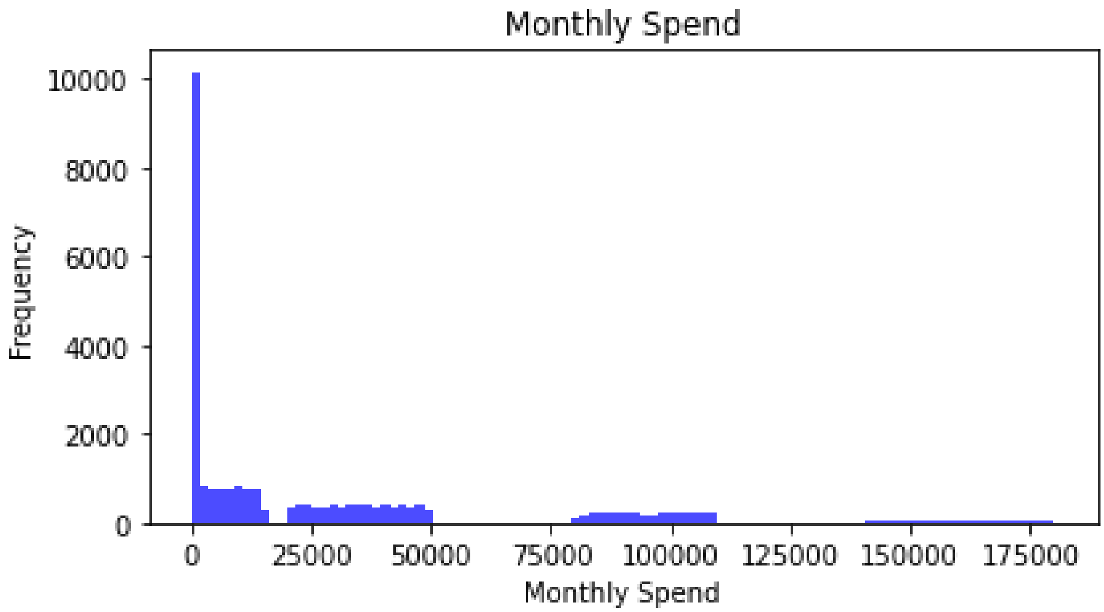

```
0-1          3
1-2      50256
2-3      50105
3-4      49792
4-5      50098
5-6          0
6-7          0
7-8          0
8-9          0
9-10    100359
10-11    99922
11-12        0
12-13        0
13-14        0
14-15        0
15-16     8092
```

```
16-17      7899
17-18      8084
18-19      7970
19-20      8032
20-21         0
21-22         0
22-23         0
23-24         0
24-25         0
25-26      4553
26-27      4639
27-28      4499
28-29      4526
29-30      4619
30-31      4598
31-32      4519
32-33      4598
33-34      4519
34-35      4493
35-36     18557
36-37     14019
37-38     13959
38-39     13938
39-40     14061
40-41         0
41-42         0
42-43         0
43-44         0
44-45         0
45-46         0
46-47         0
47-48         0
48-49         0
Name: range, dtype: int64
```

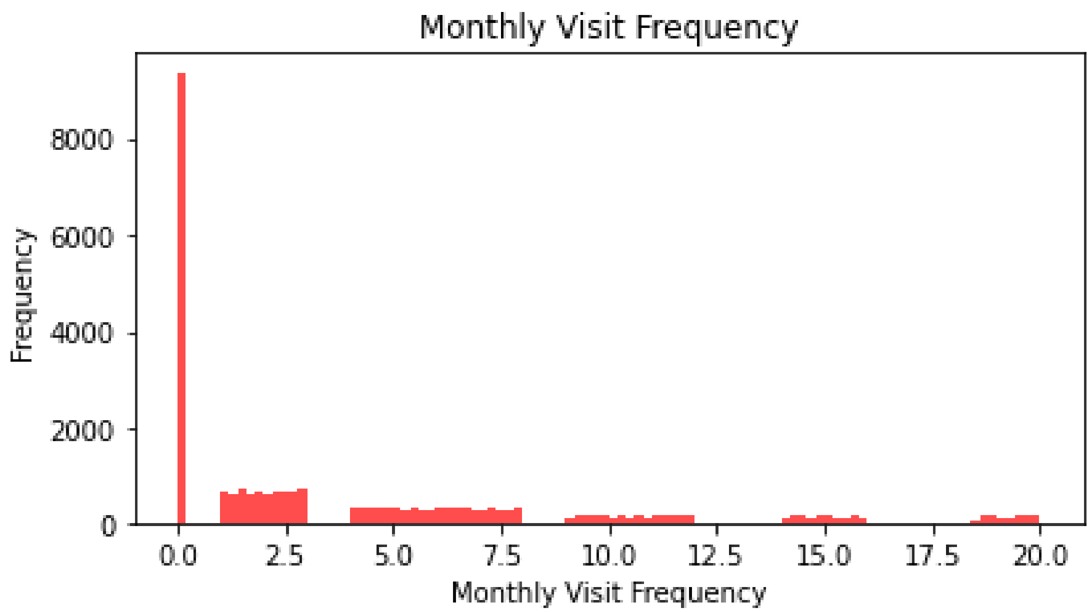
[367]:

```
plt.figure(figsize=(6, 10))
plt.subplots_adjust(hspace=1)
plt.subplot(3, 1, 1)
plt.hist(nan_rows['average_monthly_spend'], bins=100, color='blue', alpha=0.7)
plt.title('Monthly Spend')
plt.xlabel('Monthly Spend')
plt.ylabel('Frequency')


plt.subplot(3, 1, 2)
plt.hist(nan_rows['average_monthly_visit_frequency'], bins=100, color='red',␣
↪alpha=0.7)
```

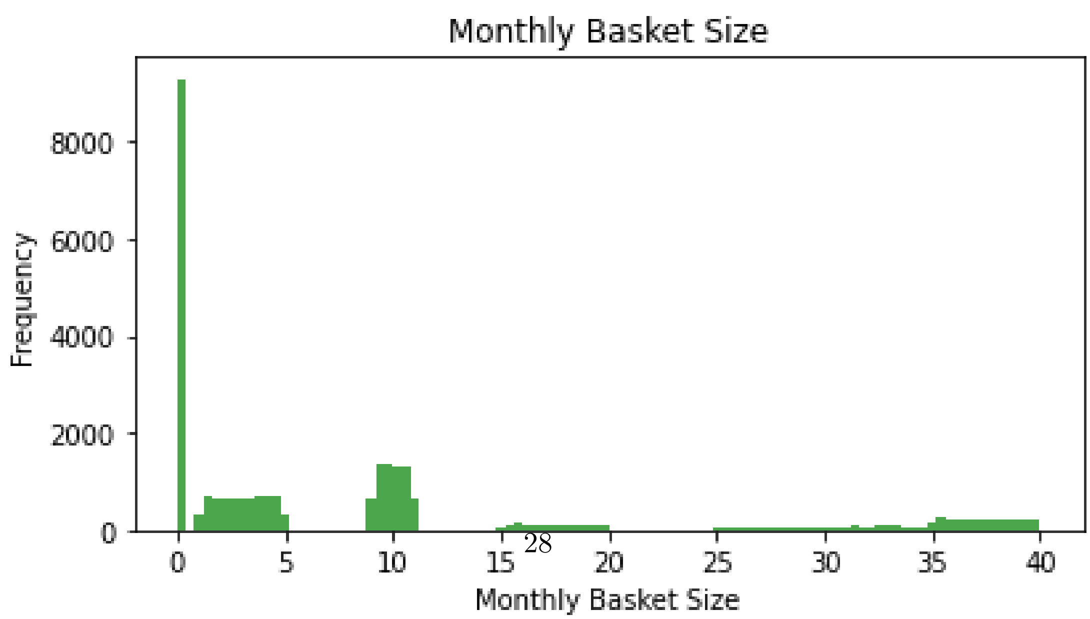
```
plt.title('Monthly Visit Frequency')
plt.xlabel('Monthly Visit Frequency')
plt.ylabel('Frequency')

plt.subplot(3, 1, 3)
plt.hist(nan_rows['average_monthly_basket_size'], bins=100, color='green',␣
 ↪alpha=0.7)
plt.title('Monthly Basket Size')
plt.xlabel('Monthly Basket Size')
plt.ylabel('Frequency')

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



Monthly Spend
Frequency
10000
8000
6000
4000
2000
0
0
25000
50000
75000
100000
125000
150000
175000
Monthly Spend



Monthly Visit Frequency
Frequency
8000
6000
4000
2000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Monthly Visit Frequency



Monthly Basket Size
Frequency
8000
6000
4000
2000
0
0
5
10
15
20
25
30
35
40
Monthly Basket Size

9 Feature Selection

9.1 Loading Data

[368]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from word2number import w2n
dataset_og = pd.read_csv("customer_dataset.csv")
CUS_ID = 'customer_id'
AVG_SPEND = 'average_monthly_spend'
AVG_VISIT = 'average_monthly_visit_frequency'
AVG_BASKET_SIZE = 'average_monthly_basket_size'
#handling non-numeric data converting them to numeric
def word_to_num(value):
    try:
        return w2n.word_to_num(value)
    except ValueError:
        if value.isdigit():
            return int(value)
        elif value.replace('.', '', 1).isdigit() and value.count('.') < 2:
            return float(value)
        return None

for column in dataset_og.columns:
    dataset_og[column] = dataset_og[column].apply(lambda x :␣
 ↪word_to_num(str(x)))

dataset = dataset_og.drop_duplicates().dropna()
dataset.head()
```

```
c:\Users\dell\AppData\Local\Programs\Python\Python39\lib\site-
packages\IPython\core\interactiveshell.py:3553: DtypeWarning: Columns (1,2) have
mixed types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[368]:
```
   customer_id  average_monthly_spend  average_monthly_visit_frequency  \
0            1                  790.0                             1.11
1            2               176875.0                            15.74
3            4                38542.0                             7.82
4            5                48712.0                             7.51
5            6               172333.0                            14.16

   average_monthly_basket_size
```

```
0                          2.84
1                         33.83
3                         10.73
4                         10.04
5                         35.06
```

9.2 Defining Cluster Thresholds Identified Preivously

[369]:
```
class Basket_Sizes:
    LOW = (0,7)
    AVERAGE = (7,13)
    HIGH = (13,22)
    VERY_HIGH = (22,50)
    ranges = [LOW,AVERAGE,HIGH,VERY_HIGH]
    ranges_good = [LOW,AVERAGE,HIGH,VERY_HIGH]


    @classmethod
    def filter_set(cls,dataset,range):
        assert(range in cls.ranges)
        return dataset[(dataset[AVG_BASKET_SIZE] >= range[0]) &␣
 ↪(dataset[AVG_BASKET_SIZE] < range[1])]

    @classmethod
    def get_mask(cls,dataset,range):
        assert(range in cls.ranges)
        return ((dataset[AVG_BASKET_SIZE] >= range[0]) &␣
 ↪(dataset[AVG_BASKET_SIZE] < range[1]))

class Monthly_Spend:
    LOW = (0,17500)
    AVERAGE = (17500,65000)
    HIGH = (65000,125000)
    VERY_HIGH = (125000,200000)
    ranges = [LOW,AVERAGE,HIGH,VERY_HIGH]
    ranges_good = [LOW,AVERAGE,HIGH,VERY_HIGH]

    @classmethod
    def filter_set(cls,dataset,range):
        assert(range in cls.ranges)
        return dataset[(dataset[AVG_SPEND] >= range[0]) & (dataset[AVG_SPEND] <␣
 ↪range[1])]

    @classmethod
    def get_mask(cls,dataset,range):
        assert(range in cls.ranges)
```

```
        return ((dataset[AVG_SPEND] >= range[0]) & (dataset[AVG_SPEND] <␣
↪range[1]))


class Average_Visit:
    LOW = (0,3.7)
    AVERAGE_LOWER = (3.7,8.5)
    AVERAGE_HIGHER = (8.5,13)
    AVERAGE = (3.7,13)
    HIGH = (13,17)
    VERY_HIGH = (17,21)
    ranges =  [LOW,AVERAGE_LOWER,AVERAGE_HIGHER,HIGH,VERY_HIGH,AVERAGE]
    ranges_good =  [LOW,AVERAGE_LOWER,AVERAGE_HIGHER,HIGH,VERY_HIGH]

    @classmethod
    def filter_set(cls,dataset,range):
        assert(range in cls.ranges)
        return dataset[(dataset[AVG_VISIT] >= range[0]) & (dataset[AVG_VISIT] <␣
↪range[1])]
    @classmethod
    def get_mask(cls,dataset,range):
        assert(range in cls.ranges)
        return ((dataset[AVG_VISIT] >= range[0]) & (dataset[AVG_VISIT] <␣
↪range[1]))
```

9.3 Checking Limiting and Borderline Cases in Threholds Manually

While the Clusters boarder that we have identified programatically (and verified by visual inspection) have good clear boarders there are a few data points that is better if closely and manually verified to ensure it has been given the correct group

[370]:
```
data[(data[AVG_VISIT]>3) & (data[AVG_VISIT] < 4)]
```

[370]:
```
        customer_id  average_monthly_spend  average_monthly_visit_frequency  \
569999       244801                 4225.0                              3.4

        average_monthly_basket_size range
569999                         1.92   1-2
```

[371]:
```
data[(data[AVG_VISIT]>3) & (data[AVG_VISIT] < 4)]
```

[371]:
```
        customer_id  average_monthly_spend  average_monthly_visit_frequency  \
569999       244801                 4225.0                              3.4

        average_monthly_basket_size range
569999                         1.92   1-2
```

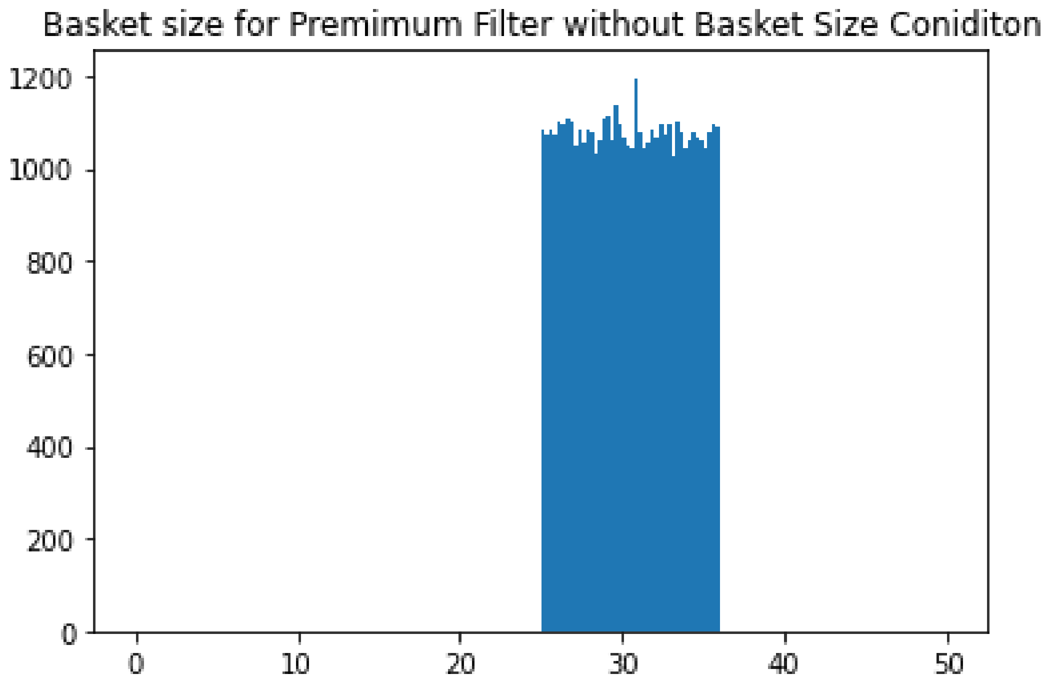
9.4 Fitering Using the Exact Rules Given in the Problem Statement

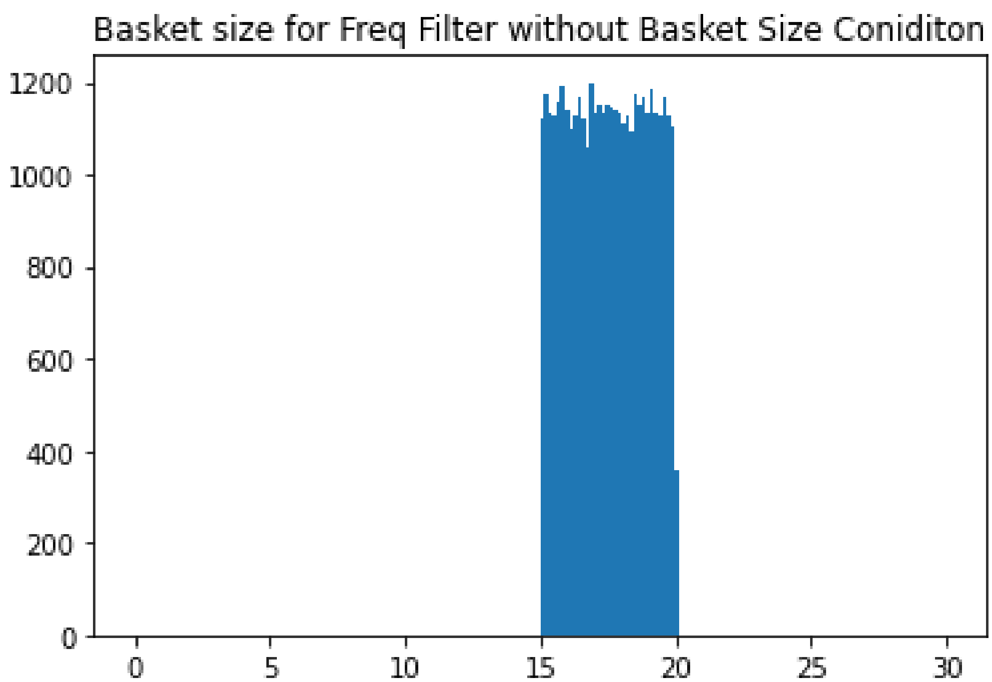
[372]:
```
low_level_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.LOW) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.LOW) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.LOW)
medium_level_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.AVERAGE) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.AVERAGE) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.AVERAGE)
high_frequent_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.HIGH) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.VERY_HIGH) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.AVERAGE)
high_loyal_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.HIGH) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.AVERAGE) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.VERY_HIGH)
high_premium_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.VERY_HIGH) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.HIGH) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.HIGH)
print(low_level_mask.sum())
print(medium_level_mask.sum())
print(high_frequent_mask.sum())
print(high_loyal_mask.sum())
print(high_premium_mask.sum())
```

```
189981
190117
0
66407
0
```

From this we have verified the calim that we have made before that the basket value for the "High-end-frequent" and "High-end-premium" needs to be changed from the values given in the table in the problem statement. This can be verified by taking the datasets that do not fit the rules and plotting the distribution of the datasets that do not follow the rules and apply the rules for these two datasets except for the Basket size dataset and observing the distribution

[373]:
```
okay_masks = [low_level_mask,medium_level_mask,high_loyal_mask]
other_data = dataset[~(okay_masks[0] | okay_masks[1] | okay_masks[2])]



plt.title("Basket size for Premimum Filter without Basket Size Coniditon")
plt.hist(Monthly_Spend.filter_set(other_data,Monthly_Spend.
↪VERY_HIGH)[AVG_BASKET_SIZE],bins=200,range=(0,50))
plt.show()
plt.title("Basket size for Freq Filter without Basket Size Coniditon")
plt.hist(Monthly_Spend.filter_set(other_data,Monthly_Spend.
↪HIGH)[AVG_BASKET_SIZE],bins=200,range=(0,30))
plt.show()
```


Basket size for Premimum Filter without Basket Size Coniditon
1200
1000
800
600
400
200
0
0
10
20
30
40
50


Basket size for Freq Filter without Basket Size Coniditon
1200
1000
800
600
400
200
0
0
5
10
15
20
25
30

[374]:

```
high_frequent_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.HIGH) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.VERY_HIGH) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.HIGH)
high_premium_mask = Monthly_Spend.get_mask(dataset,Monthly_Spend.VERY_HIGH) &␣
↪Average_Visit.get_mask(dataset,Average_Visit.HIGH) & Basket_Sizes.
↪get_mask(dataset,Basket_Sizes.VERY_HIGH)
dataset[high_frequent_mask].describe()
```

[374]:

```
         customer_id  average_monthly_spend  average_monthly_visit_frequency  \
count   37975.000000           37975.000000                     37975.000000
mean   281239.489849           94997.415036                        19.247284
std    161976.207837            8660.220172                         0.434948
min        74.000000           80000.000000                        18.500000
25%    140928.000000           87549.500000                        18.870000
50%    281125.000000           95004.000000                        19.250000
75%    421880.000000          102523.000000                        19.630000
max    559984.000000          109999.000000                        19.990000

       average_monthly_basket_size
count                 37975.000000
mean                     17.492247
std                       1.443141
min                      15.000000
25%                      16.240000
50%                      17.500000
75%                      18.750000
max                      19.990000
```

9.5 Proving additional clusters Identified in the Average Frequency correspond to actual features

Although the problem statement only identifies one average cluster for Frequency parameter from out prelimenary investigations we have shown that two seperate clusters are observable and furthermore that they actually can be effectively used to identify customer type. Now we will prove this claim. By applying the other two rules for a dataset with outliers removed and plotting the histograms

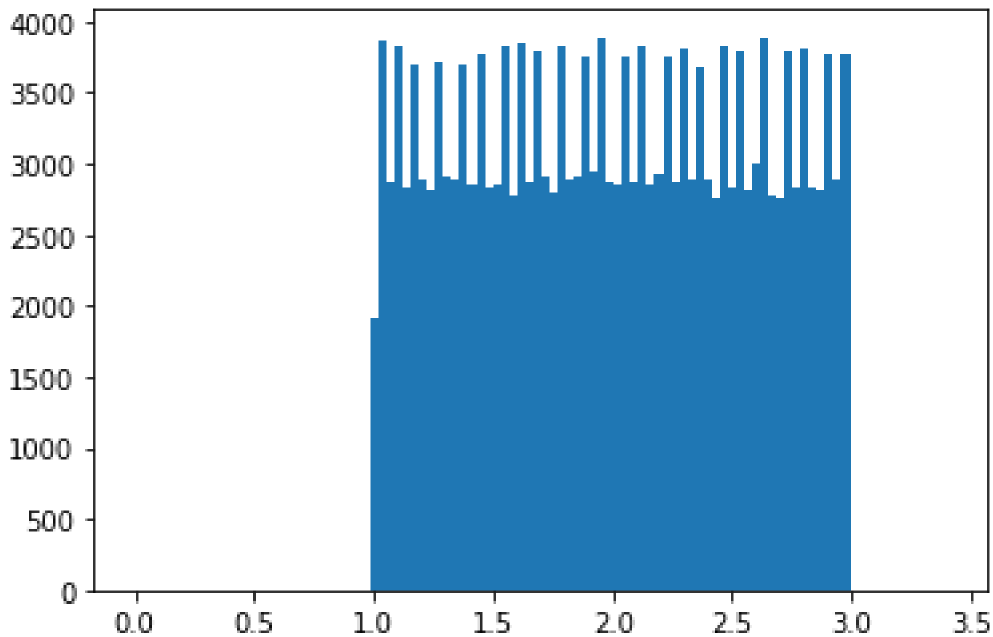
[375]:

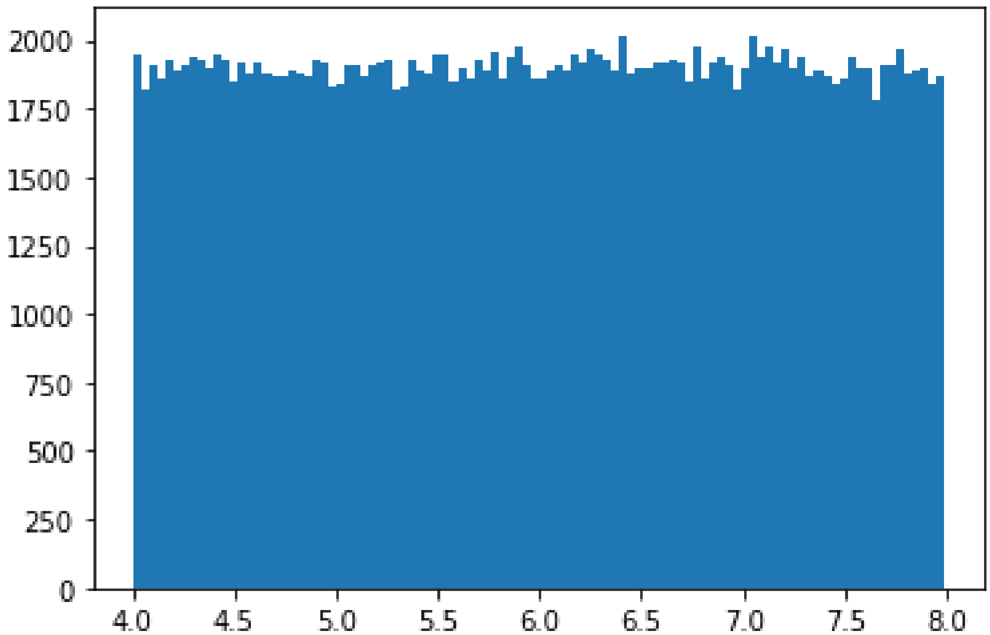
```
data = dataset
def remove_outliers(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    data = data[~((data[column] < (Q1 - 1.5 * IQR)) |(data[column] > (Q3 + 1.5␣
↪* IQR)))]
    return data
data = remove_outliers(data,AVG_SPEND)
data = remove_outliers(data,AVG_VISIT)
```

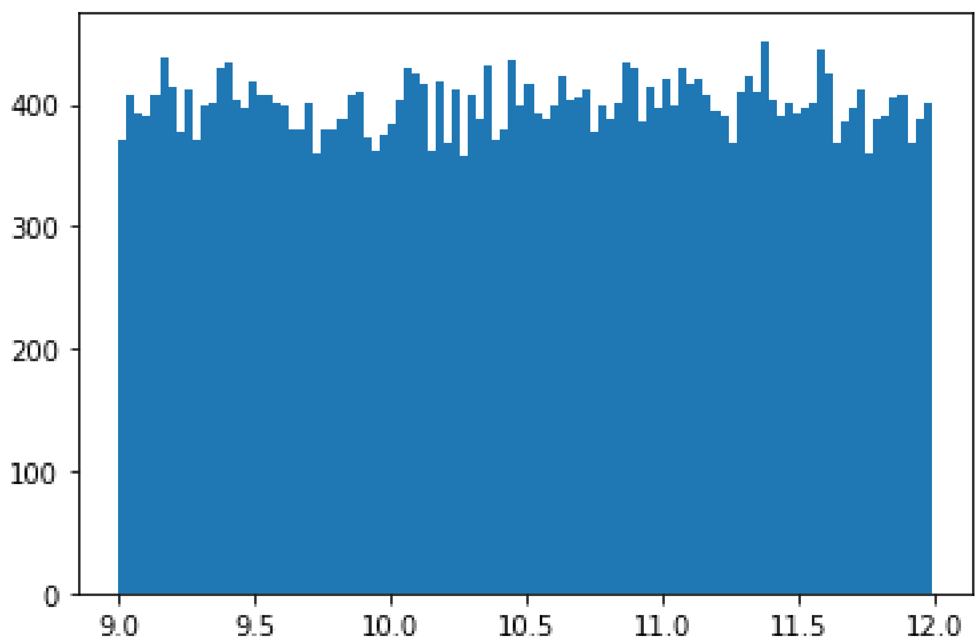
```
data = remove_outliers(data,AVG_BASKET_SIZE)
```

[376]:

```
data1 = Monthly_Spend.filter_set(Basket_Sizes.filter_set(data,Basket_Sizes.
    ↪LOW),Monthly_Spend.LOW)
plt.hist(data1[AVG_VISIT],bins=100)
plt.show()
data2 = Monthly_Spend.filter_set(Basket_Sizes.filter_set(data,Basket_Sizes.
    ↪AVERAGE),Monthly_Spend.AVERAGE)
plt.hist(data2[AVG_VISIT],bins=100)
plt.show()
data3 = Monthly_Spend.filter_set(Basket_Sizes.filter_set(data,Basket_Sizes.
    ↪VERY_HIGH),Monthly_Spend.HIGH)
plt.hist(data3[AVG_VISIT],bins=100)
plt.show()
```







In fact keeping these two as seperate clusters is highly benegicial especially since this alone can be used to identify between Medium and High-End Loyal Customers even if the two other parameters (Average Spending and Average Basket size) are missing.

This leads us to conclude that the table should be updated as | Customer Category | Monthly Spend

| Monthly Visit Frequency | Monthly Basket Size | |———————|—————|——————————-|———————–| | High end - Premium | Very High(3) | High(3) | High Very High(3) | | High end - Loyal | High(2) | Average (Average_Higher)(2)| Very High(3) | | High end - Frequent| High(2) | Very High(4) | Average High(2) | | Medium Level | Average(1) | Average (Average_Lower)(1) | Average(1) | | Low Level | Low(0) | Low(0) | Low(0) |

10 Analyzing Nature of Outliers and their Following of Rules

Now we will consider the dataset without the outliers to see if they obey the patterns observed

[377]:
```
other_data = dataset[~(low_level_mask | medium_level_mask | high_loyal_mask |
    high_frequent_mask | high_premium_mask )]
other_data.describe()
```

[377]:
```
         customer_id  average_monthly_spend  average_monthly_visit_frequency  \
count      18.000000           1.800000e+01                        18.000000
mean   354434.666667           4.934703e+06                        46.058333
std    159311.270356           1.293920e+07                       100.784055
min       252.000000           0.000000e+00                         1.250000
25%    322879.500000           9.543150e+04                        11.930000
50%    325078.000000           1.489220e+05                        15.310000
75%    515194.750000           1.612676e+06                        19.630000
max    558101.000000           4.833000e+07                       432.740000

       average_monthly_basket_size
count                    18.000000
mean                     69.655000
std                     110.472051
min                       2.160000
25%                      12.427500
50%                      29.285000
75%                      37.470000
max                     385.040000
```

Most of the values that do not follow the rules are due to outliers so we will get rid of the outliers and see if there are columns which follow the rules

[378]:
```
spend_anomaly = other_data[AVG_SPEND]>Monthly_Spend.VERY_HIGH[1]
basket_anomaly = other_data[AVG_BASKET_SIZE]>Basket_Sizes.VERY_HIGH[1]
visit_anomaly = other_data[AVG_VISIT]>Average_Visit.VERY_HIGH[1]

other_data[~(spend_anomaly | basket_anomaly | visit_anomaly)]
```

[378]:
```
        customer_id  average_monthly_spend  average_monthly_visit_frequency  \
325525       325526                    0.0                             9.36
515037       515038                    0.0                            15.35

        average_monthly_basket_size
```

```
325525                          36.42
515037                          30.02
```

From simple observation alone we can see that these two simply correspond to an entering error in the average monthly spend and actually belong to two clear categories if we consider the other two features

11 Feature Engineering

Now we will give a numeric lable to each of the ranges for each of the parameters (known as the score) Outliers and Nan values are marked as known as (-1). (These can actually later be estimated atleast the range of them by considering the cluster that it belongs to)

[379]:
```python
classification_data = dataset_og.copy()
VISIT_SCORE = 'VISIT_SCORE'
BASKET_SCORE = 'BASKET_SCORE'
SPEND_SCORE = 'SPEND_SCORE'

classification_data[VISIT_SCORE] = -1
classification_data[BASKET_SCORE] = -1
classification_data[SPEND_SCORE] = -1

for i,rr in enumerate(Monthly_Spend.ranges_good):
    mask = Monthly_Spend.get_mask(classification_data,rr)
    classification_data.loc[mask,SPEND_SCORE] = i
#do the same for other two


for i,rr in enumerate(Basket_Sizes.ranges_good):
    mask = Basket_Sizes.get_mask(classification_data,rr)
    classification_data.loc[mask,BASKET_SCORE] = i


for i,rr in enumerate(Average_Visit.ranges_good):
    mask = Average_Visit.get_mask(classification_data,rr)
    classification_data.loc[mask,VISIT_SCORE] = i

classification_data
```

[379]:

	customer_id	average_monthly_spend	average_monthly_visit_frequency \
0	1	790.0	1.11
1	2	176875.0	15.74
2	3	6812.0	2.11
3	4	38542.0	7.82
4	5	48712.0	7.51
…	…	…	…
569995	341740	27428.0	4.91

```
569996      215276           141241.0                            15.47
569997       11515             9183.0                             2.09
569998      205260            35541.0                             4.22
569999      244801             4225.0                             3.40

        average_monthly_basket_size  VISIT_SCORE  BASKET_SCORE  SPEND_SCORE
0                              2.84            0             0            0
1                             33.83            3             3            3
2                               NaN            0            -1            0
3                             10.73            1             1            1
4                             10.04            1             1            1
…                               …          …          …          …
569995                         9.42            1             1            1
569996                        31.13            3             3            3
569997                         4.61            0             0            0
569998                         9.65            1             1            1
569999                         1.92            0             0            0

[570000 rows x 7 columns]
```

[380]:

```
print(classification_data[VISIT_SCORE].value_counts())
print(classification_data[SPEND_SCORE].value_counts())
print(classification_data[BASKET_SCORE].value_counts())
```

```
 1    200269
 0    200242
 2     70113
 3     50043
 4     39992
-1      9341
Name: VISIT_SCORE, dtype: int64
 1    200311
 0    200108
 2    110153
 3     50031
-1      9397
Name: SPEND_SCORE, dtype: int64
 1    200281
 0    200254
 3    120097
 2     40077
-1      9291
Name: BASKET_SCORE, dtype: int64
```

Demonstrate that **There are no data points that have all feautres unknown**

[381]:

```
no_data_mask = (classification_data[VISIT_SCORE]==-1) &␣
 ↪(classification_data[SPEND_SCORE] == -1) &␣
 ↪(classification_data[BASKET_SCORE] == -1)
classification_data[no_data_mask]
```

[381]:
```
Empty DataFrame
Columns: [customer_id, average_monthly_spend, average_monthly_visit_frequency,
average_monthly_basket_size, VISIT_SCORE, BASKET_SCORE, SPEND_SCORE]
Index: []
```

Our Final Algorithm of Classifiation is very simple.

We have already identified the rules for each cluster by consdering the Problem Statement Table, The K-means Cluster Whisker plots. Fact that the decision boundaris can be written as logistic boundaries using and combination of decision inequalities for components idependantly (demonstrated using the cuboid shape of the cluster). The Nan Values also follow the same Law since they can clearly be seen to be projections of these cubes. Therefore we can simply collapes all feautre by assiging a number as for each range. Then we find the similarity to a certain Cluster rules using the following formula.

Let the similarity between a customer and a Cluster be define by $S(\mathbf{x_i}, \mathbf{c_j})$ Where $\mathbf{x_i}$ is the feautre vector defined for the i^{th} customer, and $\mathbf{c_i}$ for the j^{th} cluster. A feature vector is defined as [Average Spend Cluster Index, Average Basket Size Cluster Index, Average Visit Frequeny Index]

Now,

$$S(x_i, c_j) = \sum_{k=0}^{3} (x_i[k] == c_j[k])$$

where k stands for the k^{th} feature

That is the count of the entires where the cluster and customer has equal feature Indexes

Now the Cluster of the i^{th} customer is given as,

$$\text{Cluster of the } i^{th} \text{ customer} = \arg\max_{j=0}^{5} S(x_i, c_j)$$

11.1 Calculating Cluster Similarities

[382]:
```
score_given_data =classification_data.copy()

PREMIUM = 'PREMIUM'
LOYAL = 'LOYAL'
FREQ = 'FREQ'
MED = 'MED'
LOW = 'LOW'

PREMIUM_VEC = {SPEND_SCORE:3,VISIT_SCORE:3,BASKET_SCORE:3}
LOYAL_VEC = {SPEND_SCORE:2,VISIT_SCORE:2,BASKET_SCORE:3}
```

```
FREQ_VEC = {SPEND_SCORE:2,VISIT_SCORE:4,BASKET_SCORE:2}
MED_VEC = {SPEND_SCORE:1,VISIT_SCORE:1,BASKET_SCORE:1}
LOW_VEC = {SPEND_SCORE:0,VISIT_SCORE:0,BASKET_SCORE:0}

Types = [PREMIUM,LOYAL,FREQ,MED,LOW]
Vecs = [PREMIUM_VEC,LOYAL_VEC,FREQ_VEC,MED_VEC,LOW_VEC]
for ct,vec in zip(Types,Vecs):
    scores = (score_given_data[SPEND_SCORE]== vec[SPEND_SCORE]).astype(int)␣
 ↪+(score_given_data[BASKET_SCORE]==vec[BASKET_SCORE]).astype(int)␣
 ↪+(score_given_data[VISIT_SCORE]==vec[VISIT_SCORE]).astype(int)
    print(ct)
    score_given_data[ct] = scores

#get the column name that has the maximum value or values out of Types


MAX_CUSTOMER_TYPE_SCORE = 'MAX_SCORE'
score_given_data[MAX_CUSTOMER_TYPE_SCORE] =␣
 ↪score_given_data[[PREMIUM,LOYAL,FREQ,MED,LOW]].max(axis=1)
```

```
PREMIUM
LOYAL
FREQ
MED
LOW
```

11.2 Calculaing the Cluster Type

[383]:
```
final_result = score_given_data.copy()
CUSTOMER_TYPE = 'CUSTOMER_TYPE'

final_result[CUSTOMER_TYPE] = final_result[[PREMIUM,LOYAL,FREQ,MED,LOW]].
 ↪idxmax(axis=1)
final_result[CUSTOMER_TYPE].value_counts()
```

[383]:
```
MED        203581
LOW        203542
LOYAL       71275
PREMIUM     50887
FREQ        40715
Name: CUSTOMER_TYPE, dtype: int64
```

[384]:
```
final_result[[CUS_ID,CUSTOMER_TYPE]]
```

[384]:
```
        customer_id CUSTOMER_TYPE
0                 1           LOW
1                 2       PREMIUM
```

```
2                 3          LOW
3                 4          MED
4                 5          MED
…              …          …
569995       341740          MED
569996       215276      PREMIUM
569997        11515          LOW
569998       205260          MED
569999       244801          LOW

[570000 rows x 2 columns]
```

12 Saving the Data

[385]:
```
saving_data = final_result.copy()[[CUS_ID,CUSTOMER_TYPE]]
assert(len(dataset_og)==len(saving_data))#making sure all the data is there
saving_data[CUSTOMER_TYPE] = saving_data[CUSTOMER_TYPE].map({PREMIUM:'High end␣
↪- Premium',LOYAL:'High end - Loyal',FREQ:'High end - Frequent',MED:'Medium␣
↪level',LOW:'Low level'})
saving_data.to_csv("final_results.csv",index=False)
saving_data.head()
```

[385]:
```
   customer_id       CUSTOMER_TYPE
0            1           Low level
1            2  High end - Premium
2            3           Low level
3            4        Medium level
4            5        Medium level
```

13 Checking the Results

[386]:
```
validating_set = final_result.copy()
```

13.1 Proving that there are no Customers who have more than one compatible cluster

[387]:
```
duplicates = (score_given_data[Types[0]] ==␣
↪score_given_data[MAX_CUSTOMER_TYPE_SCORE]).astype(int)
for type in Types[1:]:
    duplicates  = (duplicates +(score_given_data[type] ==␣
↪score_given_data[MAX_CUSTOMER_TYPE_SCORE]).astype(int) )
duplicates.value_counts()
```

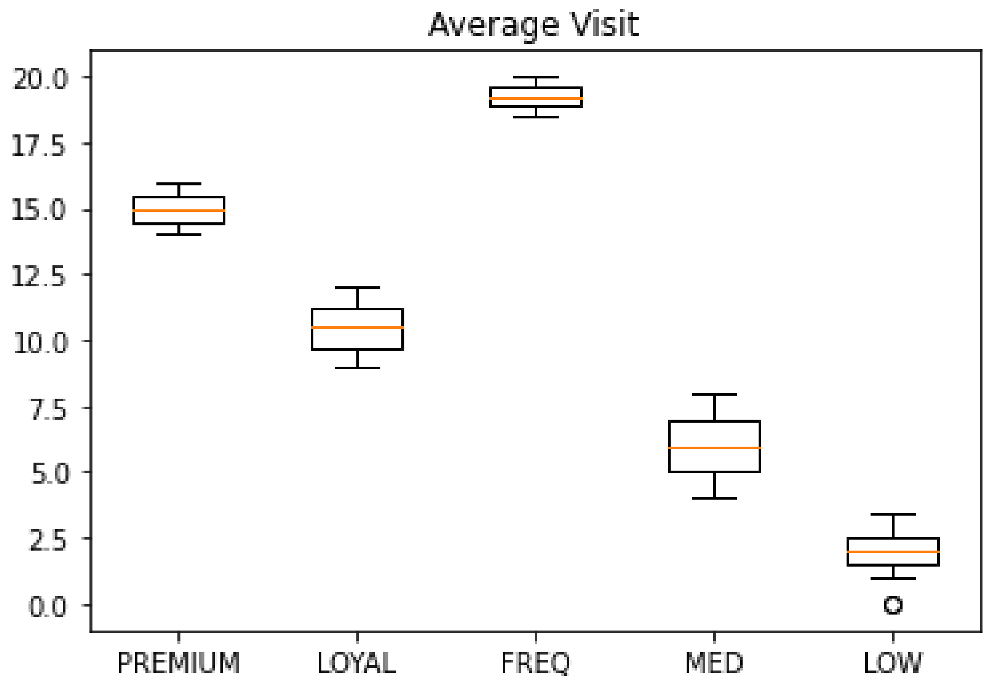
[387]:
```
1    570000
dtype: int64
```

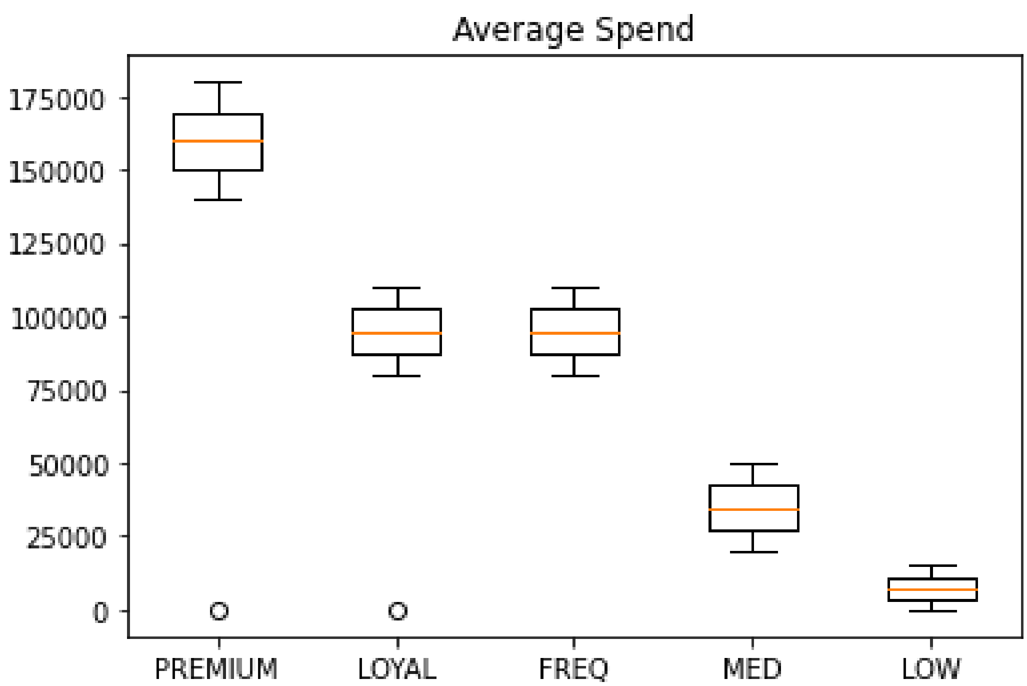
Since all results have only one Max score there is no ambiguity

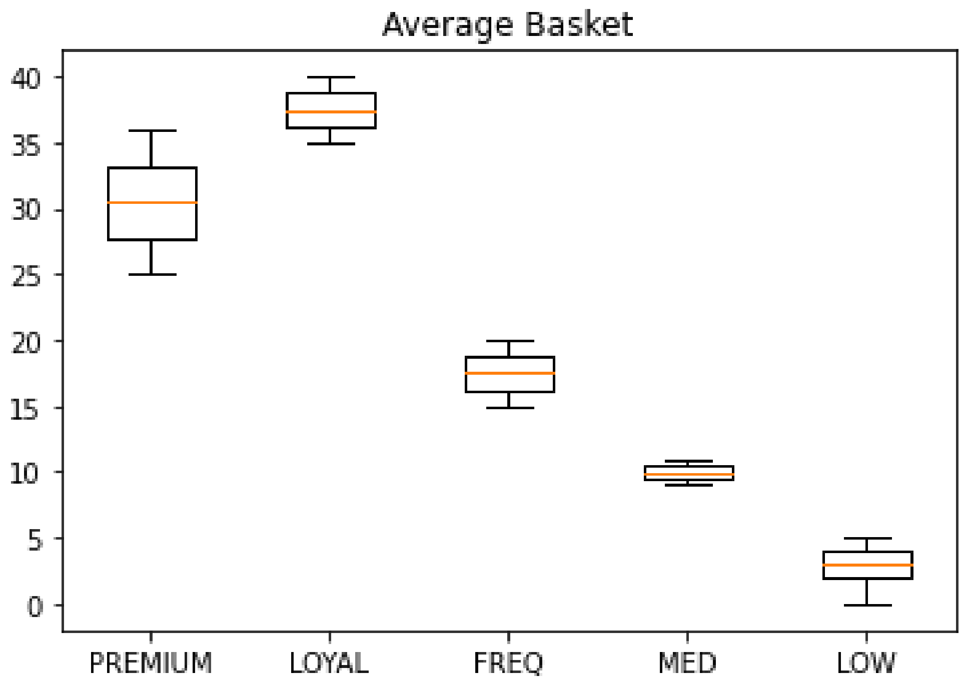
[ ]:
```

```

13.2 Checking that the Distributions of Feature Values with the Final Classification Match with Expectation

[388]:
```
plt.title("Average Visit")
plt.boxplot(
    [validating_set[validating_set[CUSTOMER_TYPE]==type][AVG_VISIT].
  ↪dropna()[validating_set[validating_set[CUSTOMER_TYPE]==type][AVG_VISIT].
  ↪dropna().between(0,Average_Visit.VERY_HIGH[1])] for type in Types],
    labels=Types

)
plt.show()

plt.title("Average Spend")
plt.boxplot(
    [validating_set[validating_set[CUSTOMER_TYPE]==type][AVG_SPEND].
  ↪dropna()[validating_set[validating_set[CUSTOMER_TYPE]==type][AVG_SPEND].
  ↪dropna().between(0,Monthly_Spend.VERY_HIGH[1])] for type in Types],
    labels=Types

)
plt.show()

plt.title("Average Basket")
plt.boxplot(
    [validating_set[validating_set[CUSTOMER_TYPE]==type][AVG_BASKET_SIZE].
  ↪dropna()[validating_set[validating_set[CUSTOMER_TYPE]==type][AVG_BASKET_SIZE].
  ↪dropna().between(0,Basket_Sizes.VERY_HIGH[1])] for type in Types],
    labels=Types

)
plt.show()
```


Average Visit
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
PREMIUM
LOYAL
FREQ
MED
LOW


Average Spend
175000
150000
125000
100000
75000
50000
25000
0
PREMIUM
LOYAL
FREQ
MED
LOW



14 Checking the Nature of the customers who had only similarity of 2

[389]:
```
score_is_2 = validating_set[validating_set[MAX_CUSTOMER_TYPE_SCORE]==2]
score_is_2
```

[389]:
```
        customer_id  average_monthly_spend  average_monthly_visit_frequency  \
2                 3                 6812.0                             2.11
7                 8                12656.0                             2.13
24               25                41329.0                              NaN
52               53               171010.0                              NaN
53               54               104457.0                            18.88
…                …                      …                              …
559914       559915                45023.0                              NaN
559945       559946                49533.0                             5.87
559959       559960                    NaN                             5.80
559970       559971                95444.0                            19.85
559972       559973                13981.0                             2.74

        average_monthly_basket_size  VISIT_SCORE  BASKET_SCORE  SPEND_SCORE  \
2                               NaN            0            -1            0
7                               NaN            0            -1            0
24                            10.32           -1             1            1
```

```
52                           35.03         -1            3            3
53                             NaN          4           -1            2
…                              …        …          …          …
559914                        9.82         -1            1            1
559945                         NaN          1           -1            1
559959                        9.87          1            1           -1
559970                         NaN          4           -1            2
559972                         NaN          0           -1            0

        PREMIUM  LOYAL  FREQ  MED  LOW  MAX_SCORE CUSTOMER_TYPE
2             0      0     0    0    2          2           LOW
7             0      0     0    0    2          2           LOW
24            0      0     0    2    0          2           MED
52            2      1     0    0    0          2       PREMIUM
53            0      1     2    0    0          2          FREQ
…          …    …    …  …  …       …          …
559914        0      0     0    2    0          2           MED
559945        0      0     0    2    0          2           MED
559959        0      0     0    2    0          2           MED
559970        0      1     2    0    0          2          FREQ
559972        0      0     0    0    2          2           LOW

[28031 rows x 14 columns]
```

[390]:
```python
score_is_2.dropna().describe()
```

[390]:
```
         customer_id  average_monthly_spend  average_monthly_visit_frequency  \
count      18.000000           1.800000e+01                        18.000000
mean   354434.666667           4.934703e+06                        46.058333
std    159311.270356           1.293920e+07                       100.784055
min       252.000000           0.000000e+00                         1.250000
25%    322879.500000           9.543150e+04                        11.930000
50%    325078.000000           1.489220e+05                        15.310000
75%    515194.750000           1.612676e+06                        19.630000
max    558101.000000           4.833000e+07                       432.740000

       average_monthly_basket_size  VISIT_SCORE  BASKET_SCORE  SPEND_SCORE  \
count                    18.000000    18.000000     18.000000    18.000000
mean                     69.655000     1.666667      1.277778     0.388889
std                     110.472051     1.847096      1.673515     1.539247
min                       2.160000    -1.000000     -1.000000    -1.000000
25%                      12.427500     0.000000      0.000000    -1.000000
50%                      29.285000     2.500000      1.500000     0.000000
75%                      37.470000     3.000000      3.000000     2.000000
max                     385.040000     4.000000      3.000000     3.000000

         PREMIUM       LOYAL        FREQ         MED         LOW  MAX_SCORE
```

count	18.000000	18.000000	18.000000	18.000000	18.000000	18.0
mean	0.888889	0.722222	0.444444	0.222222	0.444444	2.0
std	0.963382	0.751904	0.783823	0.646762	0.783823	0.0
min	0.000000	0.000000	0.000000	0.000000	0.000000	2.0
25%	0.000000	0.000000	0.000000	0.000000	0.000000	2.0
50%	0.500000	1.000000	0.000000	0.000000	0.000000	2.0
75%	2.000000	1.000000	0.750000	0.000000	0.750000	2.0
max	2.000000	2.000000	2.000000	2.000000	2.000000	2.0

We see that the ones that have given a similairyt score of 2 is the ones that are outliers the, two entires which had zero as spending be mistake (This is the above 18 rows), and entires with NA. Since we already know that the ones with NA only have one NA it is reasonable that all have a similarity score of 2. Furthermore it shows that even there there is no ambiguity

Thus our classification is Justified