Milk data analysis and Clustering the Customers

Customer segmentation is important for businesses to understand their target audience. Different advertisements can be curated and sent to different audience segments based on their demographic profile, interests, and affluence level.

Context

Distributors use our sales force automation tools in order to help them track their sales, improve their operations and increase their top line.

We would like to help these distributors maximize their profits by allowing them to identify which merchants they should target.

The specific distributor that we will be analysing is Cow and Buffalo Milk company. They produce dairy products for the entire country. Below is a list of merchants that they service along with meta data that could be useful in determining which of the merchants they should invest resources in.

Problem

1. **Make use of the merchant data set below in order to develop models that will help Cow and Buffalo Milk company target the right customers. The goal is to help Cow and Buffalo Milk company not only increase sales but also to become more efficient in allocating advertising spend.**
2. **Given the payment history that the merchant has and the cities that the merchant operates in, create a credit scoring algorithm that will help the distributor figure out which are the most creditworthy merchants and which ones are not.**

Dataset features

The dataset has the following features:

- **Merchant Id** - This is the unique Identification number that is given to a merchant
- **Annual Revenue -** This is the annual income of the merchant
- **Spending score -** It is the score(out of 100) given to a merchant by Ramani.io, based on the money spent on distributor products and the behavior of the customer.
- **City** - The city that the merchant is located in

- **Most Purchased Product -** In terms of money spent on a particular product, this is the most popular product for that specific merchant. Therefore, this is the most purchased product by that merchant from Cow and Buffalo Milk company.
- **Payment score -** It is the score(out of 5) given to a merchant by a Counsultant, based on the ability for the merchant to repay inventory that is purchased on credit. A score of 5 is great , a score of 1 is poor.

In [ ]:

```
# importing the required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly as py
import plotly.graph_objs as go
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings("ignore")
plt.rc("font", size=14)
```

In [42]:

```
# read the csv and print the first 5 rows
df = pd.read_excel("data.xlsx")
df.head()
```

Out[42]:

	Merchant Id	Annual Revenue (k$)	Spending Score (1-100)	City	Most Purchased Product	Repayment Score 1-5
0	1	15	39	Mtwara	Mtindi 500ml	1
1	2	15	81	Zanzibar City	Fresh Milk 250ml	2
2	3	16	6	Mtwara	Mtindi 500ml	3
3	4	16	77	Zanzibar City	Fresh Milk 250ml	4
4	5	17	40	Mtwara	Mtindi 500ml	2

In [43]:

```
df.rename(columns={'Genre':'Gender',
                   'Annual Revenue (k$)':'Annual_Revenue',
                   'Spending Score (1-100)':'Spending_Score',
                   'Most Purchased Product': 'Most_Purchased_Product'
                  },
                   inplace=True
          )
```

In [44]:

```
df.describe()
```

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Out[44]:

	Merchant Id	Annual_Revenue	Spending_Score	Repayment Score 1-5
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	60.560000	50.200000	3.990000
std	57.879185	26.264721	25.823522	0.850598
min	1.000000	15.000000	1.000000	1.000000
25%	50.750000	41.500000	34.750000	4.000000
50%	100.500000	61.500000	50.000000	4.000000
75%	150.250000	78.000000	73.000000	5.000000
max	200.000000	137.000000	99.000000	5.000000

In [45]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Merchant Id             200 non-null    int64
 1   Annual_Revenue          200 non-null    int64
 2   Spending_Score          200 non-null    int64
 3   City                    200 non-null    object
 4   Most_Purchased_Product  200 non-null    object
 5   Repayment Score 1-5     200 non-null    int64
dtypes: int64(4), object(2)
memory usage: 9.5+ KB
```

In [46]:

```
df['City'].value_counts()
```

Out[46]:

```
Dar es Salaam    82
Moshi            76
Mtwara           21
Zanzibar City    21
Name: City, dtype: int64
```

In [47]:

```
df['Most_Purchased_Product'].value_counts()
```

Out[47]:

```
Mtindi 250ml        82
Fresh Milk 1ltr     76
Mtindi 500ml        21
Fresh Milk 250ml    21
Name: Most_Purchased_Product, dtype: int64
```

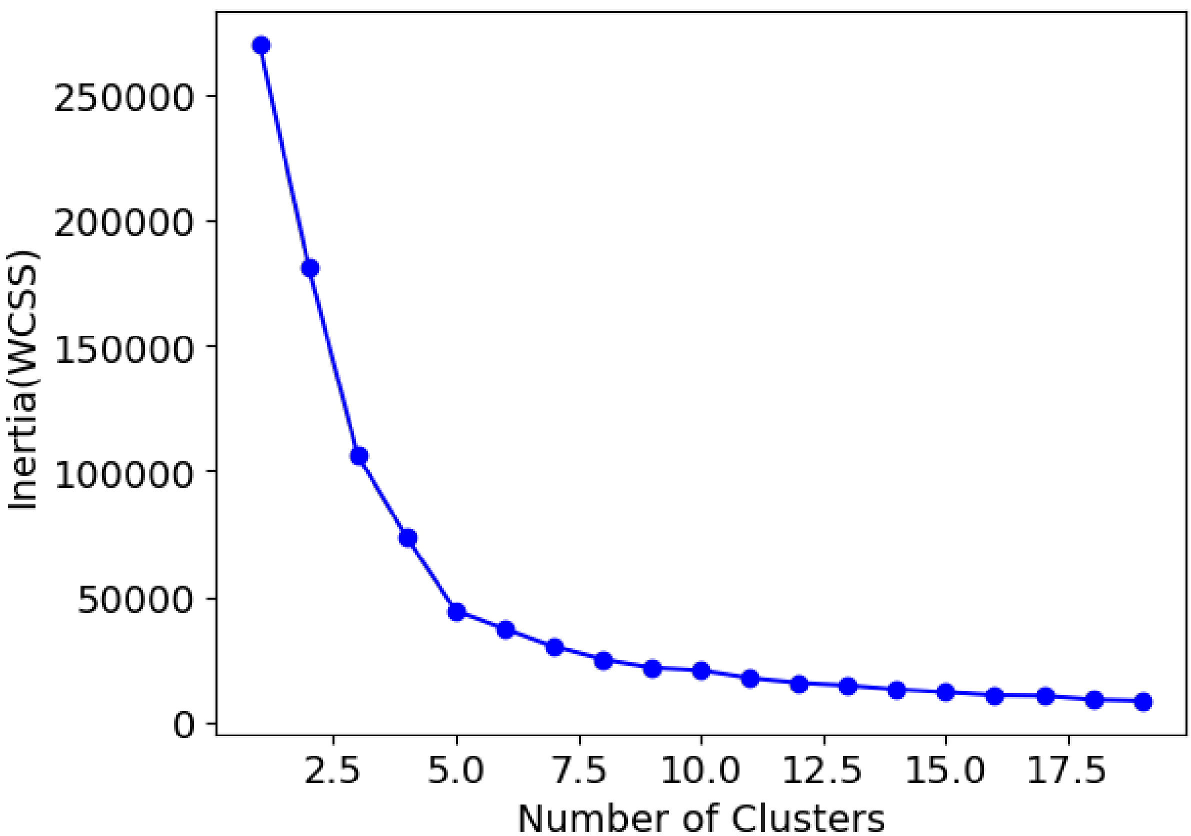
In [48]:

```
#Looking for null values
df.isna().sum()
```

Out[48]:
```
Merchant Id                0
Annual_Revenue             0
Spending_Score             0
City                       0
Most_Purchased_Product     0
Repayment Score 1-5        0
dtype: int64
```

In [49]:
```python
#Creating values for the elbow
X = df.loc[:,["Annual_Revenue", "Spending_Score"]]
inertia = []
k = range(1,20)
for i in k:
    means_k = KMeans(n_clusters=i, random_state=0)
    means_k.fit(X)
    inertia.append(means_k.inertia_)

#Plotting the elbow
plt.plot(k , inertia , 'bo-')
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia(WCSS)')
plt.show()
```



In [50]:
```python
# Fitting K-Means to the dataset
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(X)
labels = means_k.labels_
centroids = kmeans.cluster_centers_
```

In [51]:
```python
print(y_kmeans)
```

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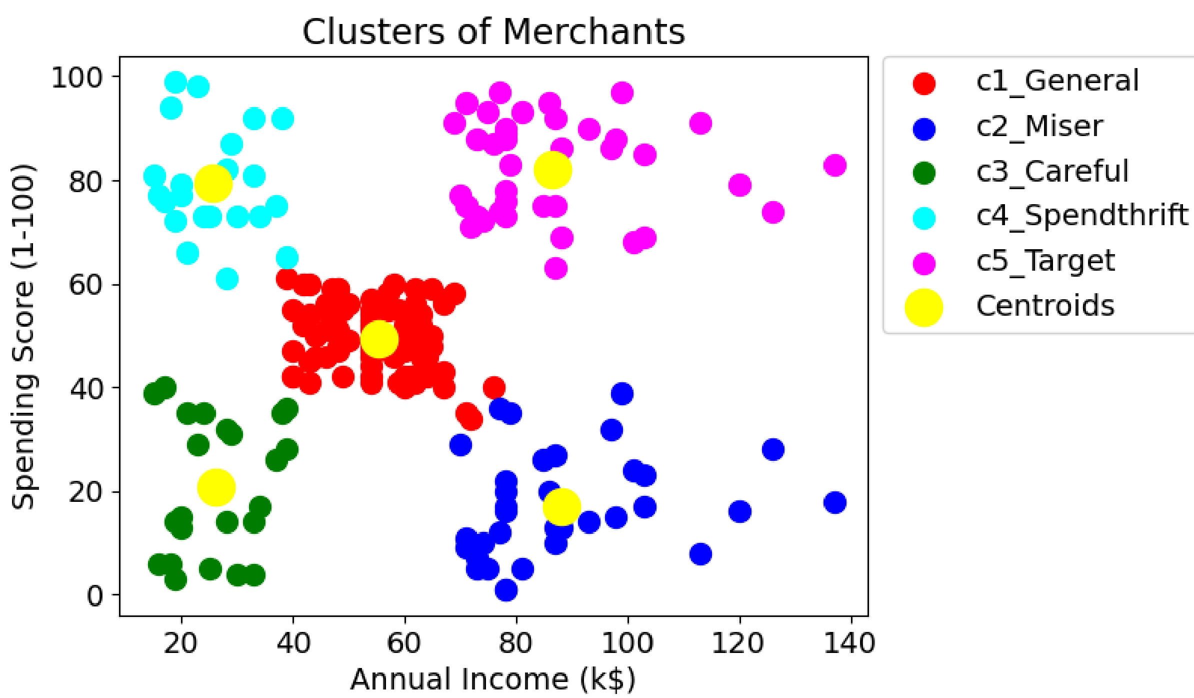
```
[2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2
 3 2 3 2 3 2 0 2 3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 4 1 4 0 4 1 4 1 4 0 4 1 4 1 4 1 4 1 4 0 4 1 4 1 4
 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1
 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4]
```

In [52]:
```
len(y_kmeans)
```

Out[52]:
```
200
```

In [52]:

In [53]:
```
# Visualising the clusters
plt.scatter(X[y_kmeans == 0]['Annual_Revenue'], X[y_kmeans == 0]['Spending_S
plt.scatter(X[y_kmeans == 1]['Annual_Revenue'], X[y_kmeans == 1]['Spending_S
plt.scatter(X[y_kmeans == 2]['Annual_Revenue'], X[y_kmeans == 2]['Spending_S
plt.scatter(X[y_kmeans == 3]['Annual_Revenue'], X[y_kmeans == 3]['Spending_S
plt.scatter(X[y_kmeans == 4]['Annual_Revenue'], X[y_kmeans == 4]['Spending_S
plt.scatter(centroids[:, 0], centroids[:, 1], s = 300, c = 'yellow', label =
plt.title('Clusters of Merchants')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
# plt.legend()
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)
plt.show()
```



In [54]:
```
df.loc[:,"Cluster_Number"] = y_kmeans
```

In [55]:
```
Cluster_Nature = []

for row in df['Cluster_Number']:
    if row == 0:
        Cluster_Nature.append('General')
```

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```
    elif row == 1:
        Cluster_Nature.append('Miser') # Miser is the one who hoards wealth
    elif row == 2: Cluster_Nature.append('Careful')
    elif row == 3: Cluster_Nature.append('Spendthrift') # spendthrift is the
    elif row == 4:  Cluster_Nature.append('Target')
    else: Cluster_Nature.append('Outlier')

df['Cluster_Nature'] = Cluster_Nature
```

In [56]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Merchant Id             200 non-null    int64 
 1   Annual_Revenue          200 non-null    int64 
 2   Spending_Score          200 non-null    int64 
 3   City                    200 non-null    object
 4   Most_Purchased_Product  200 non-null    object
 5   Repayment Score 1-5     200 non-null    int64 
 6   Cluster_Number          200 non-null    int32 
 7   Cluster_Nature          200 non-null    object
dtypes: int32(1), int64(4), object(3)
memory usage: 11.8+ KB
```

In [57]:
```
df.head()
```

Out[57]:

	Merchant Id	Annual_Revenue	Spending_Score	City	Most_Purchased_Product	Repa Sc
0	1	15	39	Mtwara	Mtindi 500ml	
1	2	15	81	Zanzibar City	Fresh Milk 250ml	
2	3	16	6	Mtwara	Mtindi 500ml	
3	4	16	77	Zanzibar City	Fresh Milk 250ml	
4	5	17	40	Mtwara	Mtindi 500ml	

In [58]:
```
df['Cluster_Nature'].value_counts()
```

Out[58]:
```
General        81
Target         39
Miser          35
Careful        23
Spendthrift    22
Name: Cluster_Nature, dtype: int64
```

In [59]:
```
uniqueValues = df['Cluster_Nature'].unique()
print(uniqueValues)
```

```
['Careful' 'Spendthrift' 'General' 'Target' 'Miser']
```

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In [60]:
```
target_df = df.loc[df['Cluster_Nature'] == 'Target']
```

In [61]:
```
target_df.head()
```

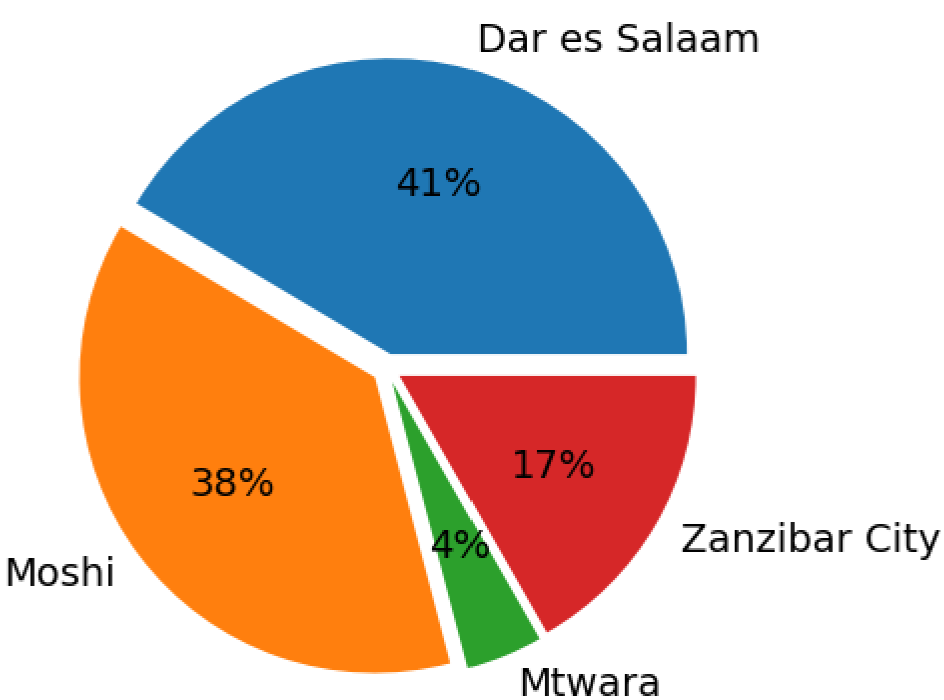
Out[61]:

	Merchant Id	Annual_Revenue	Spending_Score	City	Most_Purchased_Product	Rep Sc
123	124	69	91	Dar es Salaam	Mtindi 250ml	
125	126	70	77	Dar es Salaam	Mtindi 250ml	
127	128	71	95	Dar es Salaam	Mtindi 250ml	
129	130	71	75	Dar es Salaam	Mtindi 250ml	
131	132	71	75	Dar es Salaam	Mtindi 250ml	

In [62]:
```
# Define the ratio of gap of each fragment in a tuple
explode = (0.05, 0.05, 0.05,0.05)

# Plotting the pie chart for above dataframe
df.groupby(['City']).sum().plot(
    kind='pie', y='Spending_Score', autopct='%1.0f%%', explode=explode, lege
```

Out[62]: <Axes: >



In [63]:
```
# Define the ratio of gap of each fragment in a tuple
05, 0.05, 0.05,0.05)
```

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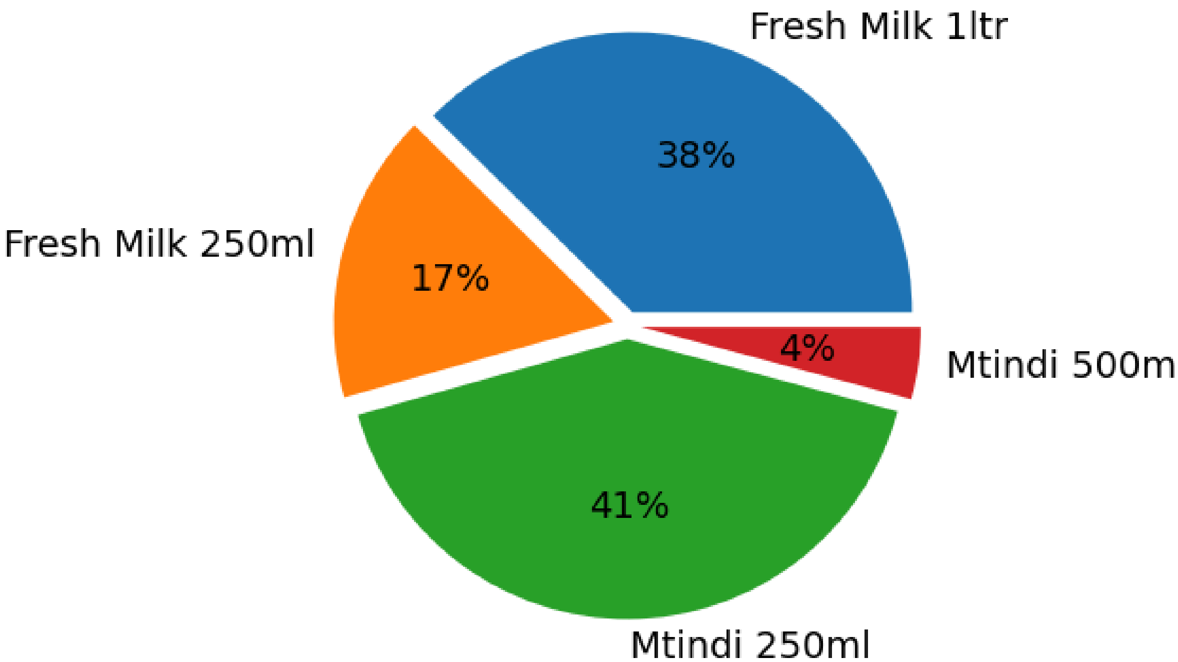
```
# Plotting the pie chart for above dataframe
df.groupby(['Most_Purchased_Product']).sum().plot(
    kind='pie', y='Spending_Score', autopct='%1.0f%%', explode=explode, lege
```

Out[63]: <Axes: >



In [64]:
```
# Cross tabulation between City and Cluster  Nature
CrosstabResult=pd.crosstab(index=df['City'],columns=df['Cluster_Nature'])
print(CrosstabResult)
# Grouped bar chart
CrosstabResult.plot.bar(figsize=(7,4), rot=0)
plt.legend(bbox_to_anchor=(1.36, 1.04))
plt.show()
```

```
Cluster_Nature  Careful  General  Miser  Spendthrift  Target
City
Dar es Salaam         0        8     35            0      39
Moshi                 2       73      0            1       0
Mtwara               21        0      0            0       0
Zanzibar City         0        0      0           21       0
```

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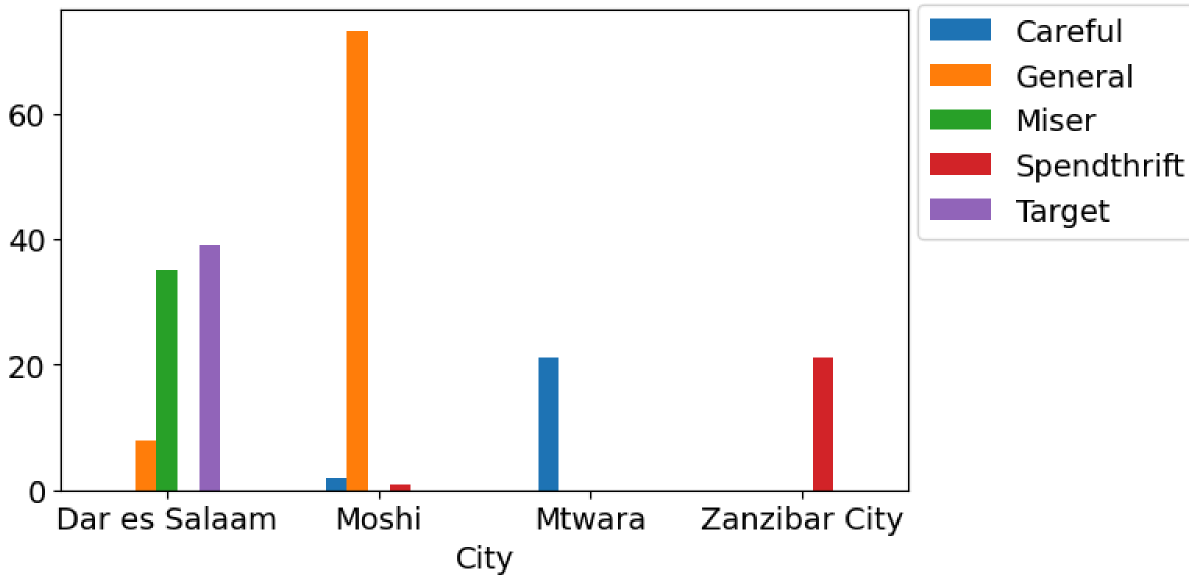

In [65]:

```
# Cross tabulation between Product and Cluster  Nature
CrosstabResult=pd.crosstab(index=df['Most_Purchased_Product'],columns=df['Cl
print(CrosstabResult)
# Grouped bar chart
CrosstabResult.plot.bar(figsize=(7,4))
plt.legend(bbox_to_anchor=(1.0, 1.0))
plt.show()
```

```
Cluster_Nature          Careful  General  Miser  Spendthrift  Target
Most_Purchased_Product
Fresh Milk 1ltr               2       73      0            1       0
Fresh Milk 250ml              0        0      0           21       0
Mtindi 250ml                  0        8     35            0      39
Mtindi 500ml                 21        0      0            0       0
```

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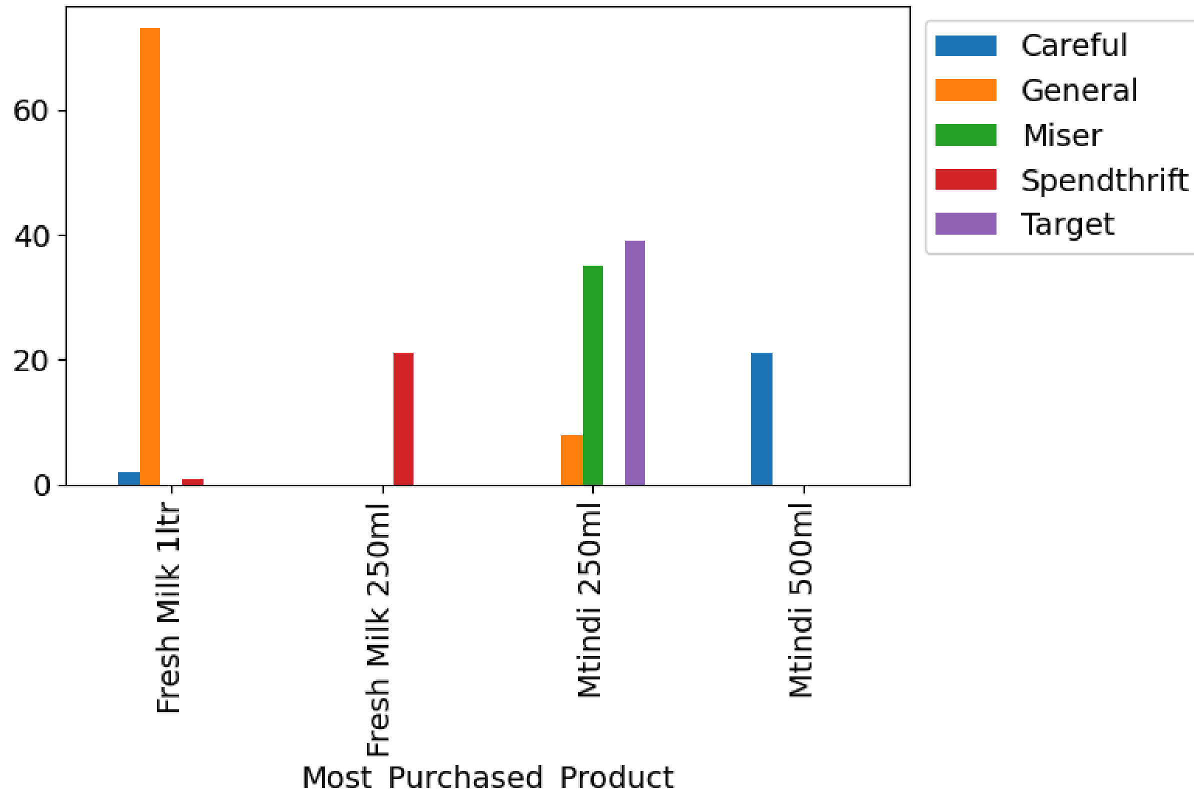

In [66]:
```
# Cross tabulation between Product and Cluster  Nature
CrosstabResult=pd.crosstab(index=df['Most_Purchased_Product'],columns=df['Ci
print(CrosstabResult)
# Grouped bar chart
CrosstabResult.plot.bar(figsize=(7,4))
plt.legend(bbox_to_anchor=(1.0, 1.0))
plt.show()
```

```
City                    Dar es Salaam  Moshi  Mtwara  Zanzibar City
Most_Purchased_Product
Fresh Milk 1ltr                     0     76       0              0
Fresh Milk 250ml                    0      0       0             21
Mtindi 250ml                       82      0       0              0
Mtindi 500ml                        0      0      21              0
```

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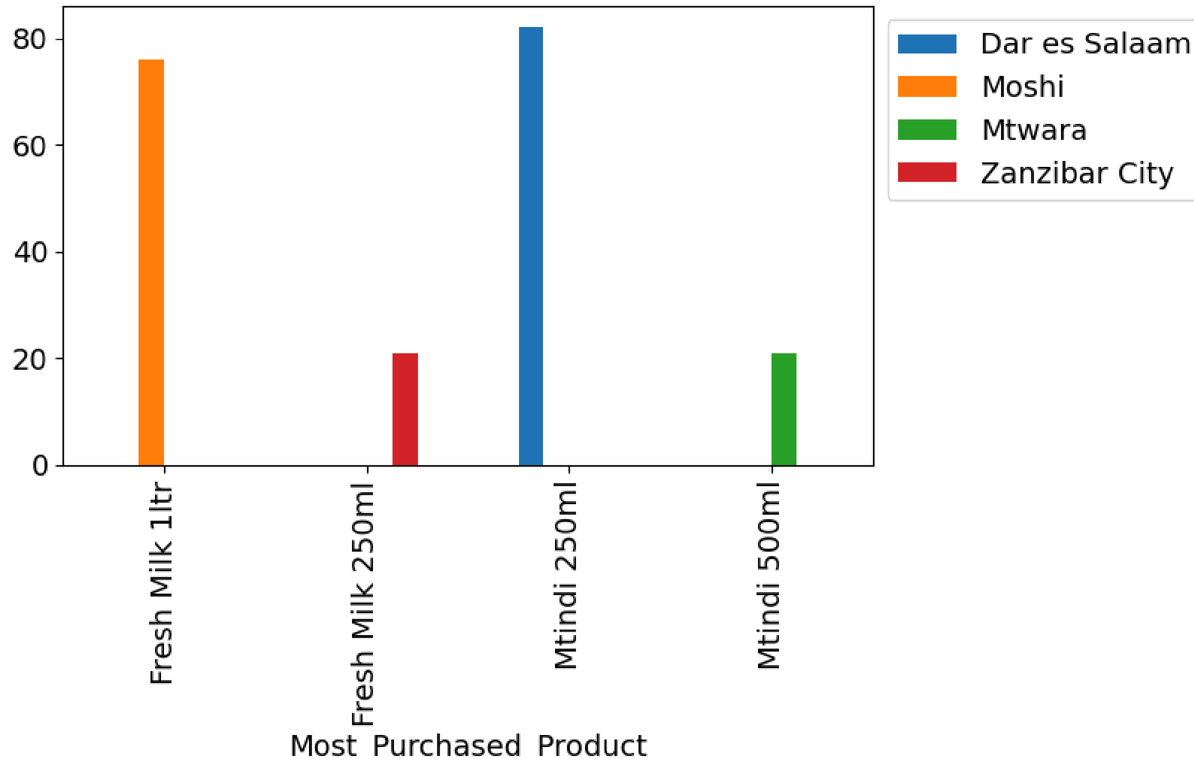
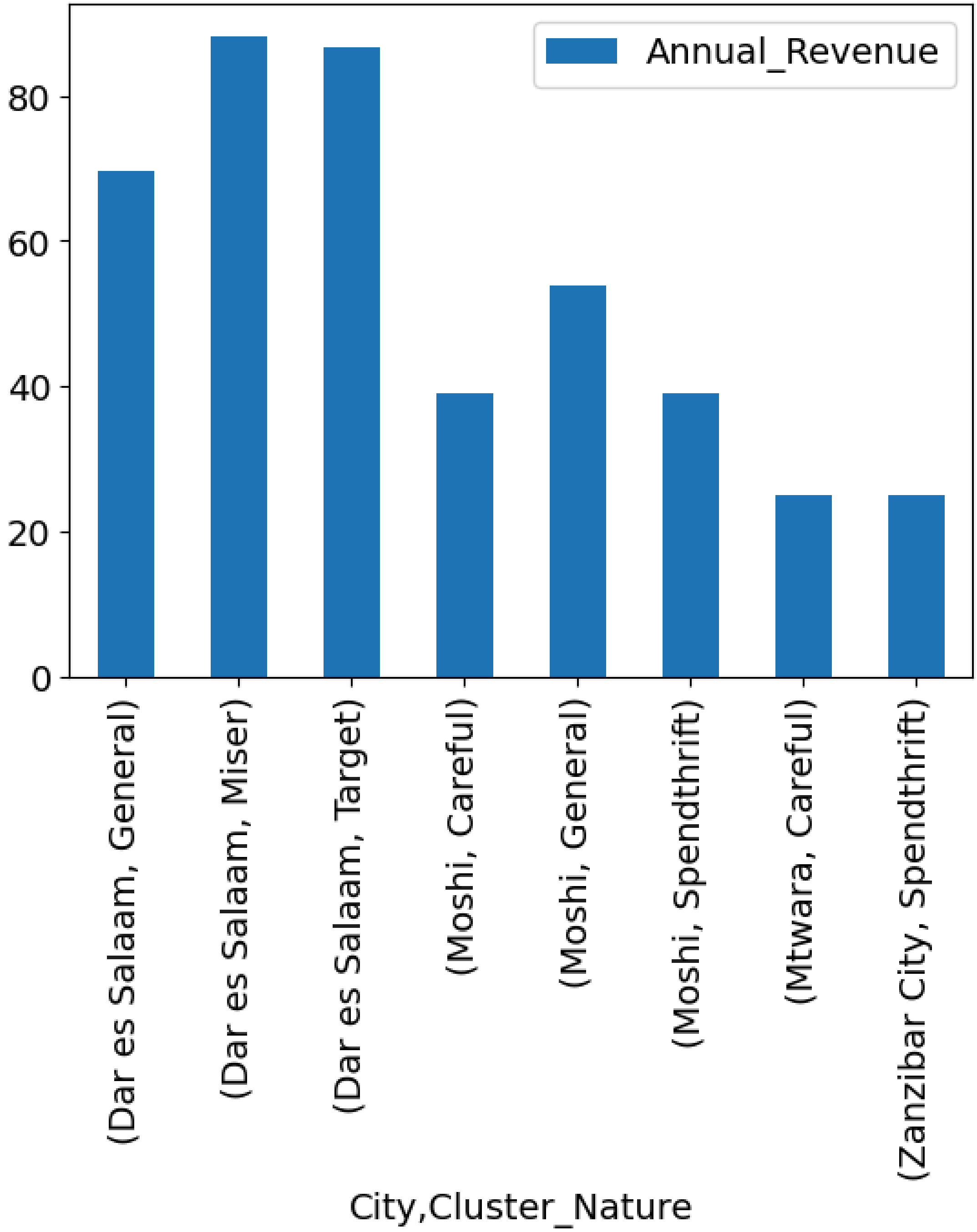


In [67]:
```
#Pivoit Table on city vs Cluster Nature aggregated by Annual Revenue
table = pd.pivot_table(df,index=['City','Cluster_Nature'],aggfunc={'Annual_R
print(table)
table.plot(kind='bar')
plt.show()
```

```
                              Annual_Revenue
City          Cluster_Nature
Dar es Salaam General              69.500000
              Miser                88.200000
              Target               86.538462
Moshi         Careful              39.000000
              General              53.739726
              Spendthrift          39.000000
Mtwara        Careful              25.095238
Zanzibar City Spendthrift          25.095238
```



In [67]:

In [68]:

```
# saving the final analyzed data to a csv file.
df.to_csv('analyzed1.csv')
```

In [ ]:

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