Clustering

Wolesale Store : Customer Dataset

In [187…
```
import pandas as pd
```

In [188…
```
input_file = ("/Users/pratik/Desktop/Harrisburg University programs/Courses/Late Fall Co
```

In [189…
```
data = pd.read_csv(input_file)
```

In [190…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Channel           440 non-null    int64
 1   Region            440 non-null    int64
 2   Fresh             440 non-null    int64
 3   Milk              440 non-null    int64
 4   Grocery           440 non-null    int64
 5   Frozen            440 non-null    int64
 6   Detergents_Paper  440 non-null    int64
 7   Delicassen        440 non-null    int64
dtypes: int64(8)
memory usage: 27.6 KB
```

In [191…
```
data.dtypes
```

Out[191]:
```
Channel             int64
Region              int64
Fresh               int64
Milk                int64
Grocery             int64
Frozen              int64
Detergents_Paper    int64
Delicassen          int64
dtype: object
```

In [192…
```
data.describe()
```

Out[192]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_
count	440.000000	440.000000	440.000000	440.000000	440.000000	440.000000	440.0(
mean	1.322727	2.543182	12000.297727	5796.265909	7951.277273	3071.931818	2881.4
std	0.468052	0.774272	12647.328865	7380.377175	9503.162829	4854.673333	4767.85
min	1.000000	1.000000	3.000000	55.000000	3.000000	25.000000	3.0(
25%	1.000000	2.000000	3127.750000	1533.000000	2153.000000	742.250000	256.75
50%	1.000000	3.000000	8504.000000	3627.000000	4755.500000	1526.000000	816.5(
75%	2.000000	3.000000	16933.750000	7190.250000	10655.750000	3554.250000	3922.0(
max	2.000000	3.000000	112151.000000	73498.000000	92780.000000	60869.000000	40827.0(

In [193…
```
data.isnull().sum()
```

Out[193]:
```
Channel             0
Region              0
Fresh               0
Milk                0
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
dtype: int64
```

In [194…
```
data.head()
```

Out[194]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	2	3	12669	9656	7561	214	2674	1338
1	2	3	7057	9810	9568	1762	3293	1776
2	2	3	6353	8808	7684	2405	3516	7844
3	1	3	13265	1196	4221	6404	507	1788
4	2	3	22615	5410	7198	3915	1777	5185

To see the statistics of variables (simmilar to describe function) using a for loop

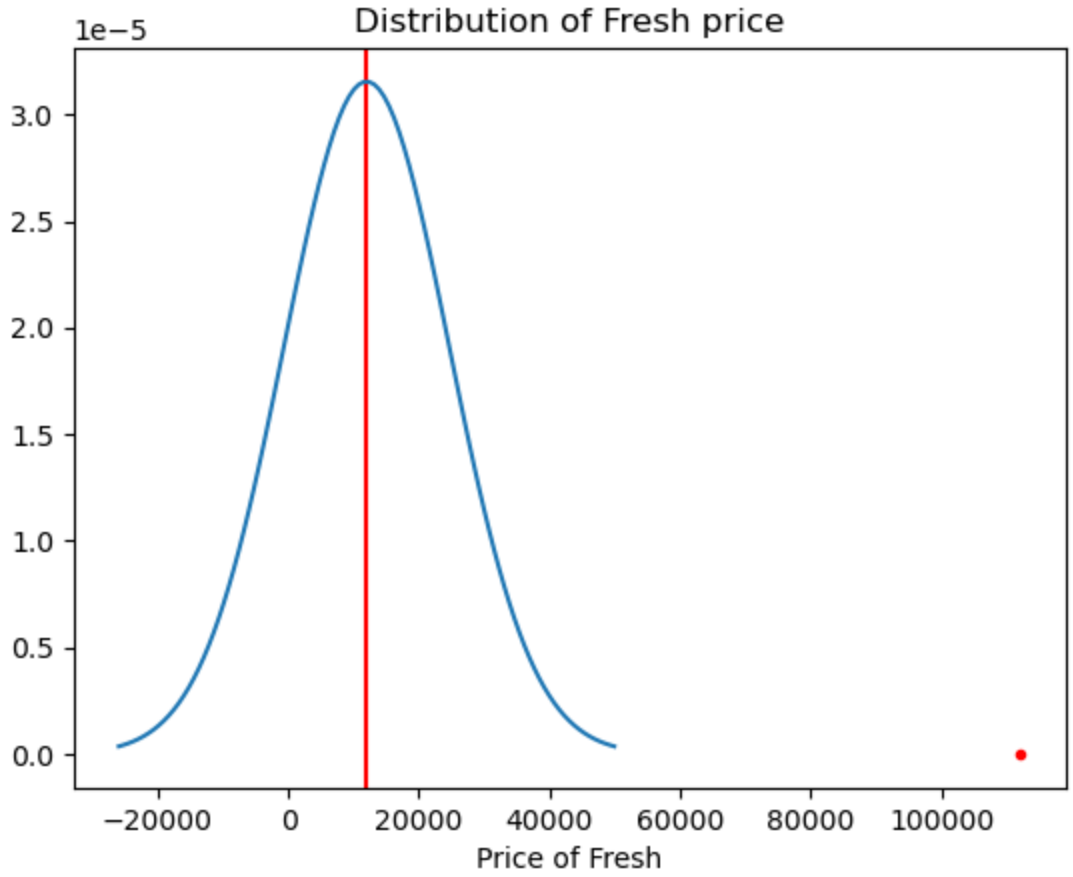
In [195…
```
for i in ['Fresh','Milk','Grocery','Frozen','Detergents_Paper','Delicassen']:
          print('Maximum of ',i, ' is',data[i].max(), 'while mean value is ',data[i].mea
```

```
Maximum of  Fresh  is 112151 while mean value is  12000.297727272728
Maximum of  Milk  is 73498 while mean value is  5796.265909090909
Maximum of  Grocery  is 92780 while mean value is  7951.277272727273
Maximum of  Frozen  is 60869 while mean value is  3071.931818181818
Maximum of  Detergents_Paper  is 40827 while mean value is  2881.4931818181817
Maximum of  Delicassen  is 47943 while mean value is  1524.8704545454545
```

Fitting a normal distribution to one of the variables the formula for x creates a distribution for values of x for "Fresh" varaiable, upto 3 SD's form the mean.

In [196…
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm

mu = data['Fresh'].mean()
sigma = data['Fresh'].std()
x = np.linspace(mu-3*sigma, mu+3*sigma, 100)
x_axis = np.arange(0, 10, 0.001)
#plt.plot(data["Fresh"].max(), norm.pdf(x,mu,sigma))
plt.axvline(x=mu, color='r')
plt.plot(x,norm.pdf(x,mu,sigma))
plt.plot([data['Fresh'].max()], [0], marker='o', markersize=3, color="red")
plt.title('Distribution of Fresh price')
plt.xlabel('Price of Fresh')
plt.show()
```



Remove values that are more than 3 times of std. dev

In [198…
```
from scipy import stats
```

For each column, first it computes the "Z-score" of each value in the column, relative to the column mean and standard deviation.Then it takes the absolute of Z-score because the direction does not matter, only if it is below the threshold. Then, "all(axis=1)" ensures that for each row, all column satisfy the constraint. Finally, result of this condition is used to index the dataframe.

In [199…
```
data_new = data[(np.abs(stats.zscore(data)) < 3).all(axis = 1)]
data_new = data_new.drop(["Channel", "Region"], axis = 1)
data_new.describe()
```

Out[199]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	10711.758454	4871.920290	6814.043478	2549.898551	2373.393720	1237.939614
std	9819.217756	4555.665546	6456.160715	2916.683284	3208.707909	1217.399162
min	3.000000	55.000000	3.000000	25.000000	3.000000	3.000000
25%	3063.250000	1477.750000	2116.000000	676.750000	252.750000	395.000000
50%	8040.000000	3530.000000	4528.000000	1447.000000	772.000000	881.000000
75%	15657.000000	6908.500000	9762.250000	3204.250000	3660.500000	1681.750000
max	49063.000000	25862.000000	34792.000000	16919.000000	17120.000000	7844.000000

The number of datapoints dropped

In [201…
```
print("Number of dropped instances = ", data.shape[0] - data_new.shape[0])
```

```
Number of dropped instances =  26
```

In [202…
```
data.shape
```

Out[202]:
```
(440, 8)
```

In [203…
```
data_new.shape
```

Out[203]:
```
(414, 6)
```

Designing the model

Creating clusters with spscifying no of cluster means n_clusters and fitting it on data_new

In [18]:
```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=5, random_state=76964057).fit(data_new)
pd.Series(kmeans.labels_).value_counts()
```

Out[18]:
```
2    143
0    108
4     79
1     42
3     42
dtype: int64
```

Centroids

In [20]:
```
kmeans.cluster_centers_
```

Out[20]:
```
array([[16470.87037037,  3026.49074074,  4264.74074074,  3217.30555556,
          996.55555556,  1319.75925926],
       [ 5502.33333333, 13328.47619048, 21524.30952381,  1691.71428571,
         9145.95238095,  1682.30952381],
       [ 5013.3006993 ,  2270.53146853,  2742.87412587,  2597.83916084,
          643.02797203,   834.55244755],
       [32641.95238095,  4895.5       ,  5538.04761905,  3842.69047619,
          944.95238095,  1639.28571429],
       [ 4263.94936709,  7595.20253165, 10526.2278481 ,  1319.65822785,
         4546.65822785,  1406.64556962]])
```

Creating a dataframe with the cluster centres as obtained above. Each of the 5 menas list calculated(5 lists as we specified K as 5)has 6 values, one for each column. Hence we will create a dataframe of these 5 Kmeans list and 6 respective column names

In [21]:
```
pd.DataFrame(data=kmeans.cluster_centers_, columns=['Fresh','Milk','Grocery','Frozen','D
```

Out[21]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	16470.870370	3026.490741	4264.740741	3217.305556	996.555556	1319.759259
1	5502.333333	13328.476190	21524.309524	1691.714286	9145.952381	1682.309524
2	5013.300699	2270.531469	2742.874126	2597.839161	643.027972	834.552448
3	32641.952381	4895.500000	5538.047619	3842.690476	944.952381	1639.285714
4	4263.949367	7595.202532	10526.227848	1319.658228	4546.658228	1406.645570

We started with a K means value of 5, As We see the above dataframe gives us the mixture of variables within each of the 5 clusters.

For example cluster indexed 1 looks to be heavy on Grocery and above average on Detergents and paper. Cluster indexed 3 looks to be dominant in Fresh category. The value counts give us the distribution of counts for each of 5 clusters as below : 0- 108, 1-42, 2-143, 3-42, 4-79. The cluster numbers were indexed starting from 0. The total of all 5 clsuters for each variable is 414

Now we create a a Lop for K values between 2 and 20. Important step is Adding key,value to dict, with key as k no of clusters and value = Inertia: Sum of distances of samples to their closest cluster center = within cluster distance

In [22]:
```
sse = {}
last_sse = 73984012841.4855
for k in range(2, 19):
    print(last_sse)
    kmeans = KMeans(n_clusters=k, random_state=76964057).fit(data_new)
    data_new["clusters"] = kmeans.labels_
    print(pd.Series(kmeans.labels_).value_counts())
    sse[k] = kmeans.inertia_  # Adding key,value to dict, with key as k no of clusters a
    change_per = (last_sse - kmeans.inertia_)/last_sse*100
    print ('At k= ',k,'The percentage of change in SSE is ',change_per,'%')
    last_sse = kmeans.inertia_
    print("The last_sse value to be used for K = ", k+1, " is ", last_sse )
print(sse)
```

```
73984012841.4855
1    294
0    120
dtype: int64
At k=  2 The percentage of change in SSE is  38.05976060288236 %
The last_sse value to be used for K =  3  is  45825874669.610374
45825874669.610374
2    223
0     99
1     92
dtype: int64
At k=  3 The percentage of change in SSE is  36.79139679443055 %
The last_sse value to be used for K =  4  is  28965895285.395584
28965895285.395584
2    175
0    109
1     84
3     46
dtype: int64
At k=  4 The percentage of change in SSE is  19.949152060286586 %
The last_sse value to be used for K =  5  is  23187444789.288635
23187444789.288635
2    143
0    108
4     79
1     42
3     42
dtype: int64
At k=  5 The percentage of change in SSE is  15.627091486585702 %
The last_sse value to be used for K =  6  is  19563921578.66495
19563921578.66495
1    143
0     98
5     80
2     40
3     37
4     16
dtype: int64
At k=  6 The percentage of change in SSE is  11.357482276048316 %
The last_sse value to be used for K =  7  is  17341952652.868088
17341952652.868088
```

```
3    95
1    90
4    73
5    64
0    40
6    38
2    14
dtype: int64
At k=  7 The percentage of change in SSE is  8.73140249666422 %
The last_sse value to be used for K =  8  is  15827756965.965237
15827756965.965237
6    88
0    85
3    66
5    44
2    44
7    36
4    35
1    16
dtype: int64
At k=  8 The percentage of change in SSE is  6.658044624473278 %
The last_sse value to be used for K =  9  is  14773937844.118093
14773937844.118093
3    90
7    88
0    67
1    53
6    32
8    31
4    29
2    16
5     8
dtype: int64
At k=  9 The percentage of change in SSE is  7.053778124935269 %
The last_sse value to be used for K =  10  is  13731817048.278158
13731817048.278158
2    80
5    77
9    59
0    53
1    36
4    32
6    27
7    20
8    16
3    14
dtype: int64
At k=  10 The percentage of change in SSE is  7.02484982447811 %
The last_sse value to be used for K =  11  is  12767177522.464535
12767177522.464535
4     78
8     73
2     63
5     58
6     32
9     25
0     24
7     22
1     15
3     15
10     9
dtype: int64
At k=  11 The percentage of change in SSE is  3.930776725346538 %
The last_sse value to be used for K =  12  is  12265328279.927824
12265328279.927824
7     82
```

```
4     79
8     62
6     53
1     28
5     25
10    22
0     20
3     14
2     12
9     12
11     5
dtype: int64
At k=  12 The percentage of change in SSE is  8.315284281709397 %
The last_sse value to be used for K =  13  is  11245431365.366928
11245431365.366928
4     81
7     70
10    53
5     44
11    32
9     26
3     22
1     22
0     20
2     14
8     13
6     12
12     5
dtype: int64
At k=  13 The percentage of change in SSE is  4.709693744106548 %
The last_sse value to be used for K =  14  is  10715805987.854446
10715805987.854446
12    75
8     71
1     54
0     38
11    31
5     28
4     20
6     19
3     17
2     17
9     14
13    13
10    10
7      7
dtype: int64
At k=  14 The percentage of change in SSE is  3.0495083388263913 %
The last_sse value to be used for K =  15  is  10389026590.682367
10389026590.682367
6     70
0     70
11    48
8     43
4     35
9     21
14    21
3     20
7     20
12    15
5     14
1     13
13    11
2      9
10     4
dtype: int64
```

```
At k=  15 The percentage of change in SSE is  5.8715363282234705 %
The last_sse value to be used for K =  16  is  9779031120.261656
9779031120.261656
7     59
10    59
9     36
0     35
13    35
6     34
2     24
3     23
8     18
1     17
4     16
5     16
14    15
11    15
15     8
12     4
dtype: int64
At k=  16 The percentage of change in SSE is  3.9429835097186303 %
The last_sse value to be used for K =  17  is  9393445535.779486
9393445535.779486
6     62
12    59
9     40
7     35
1     27
13    27
2     23
4     23
16    18
5     17
3     17
0     15
10    14
11    12
8     11
15     8
14     6
dtype: int64
At k=  17 The percentage of change in SSE is  6.711402828394341 %
The last_sse value to be used for K =  18  is  8763013566.4075
8763013566.4075
4     67
1     59
0     47
10    44
15    28
13    21
12    19
6     19
11    18
7     18
9     15
5     14
14    14
3     10
2      8
17     7
8      4
16     2
dtype: int64
At k=  18 The percentage of change in SSE is  0.853986291848728 %
The last_sse value to be used for K =  19  is  8688178631.797535
{2: 45825874669.610374, 3: 28965895285.395584, 4: 23187444789.288635, 5: 19563921578.664
```

```
95, 6: 17341952652.868088, 7: 15827756965.965237, 8: 14773937844.118093, 9: 13731817048.
278158, 10: 12767177522.464535, 11: 12265328279.927824, 12: 11245431365.366928, 13: 1071
5805987.854446, 14: 10389026590.682367, 15: 9779031120.261656, 16: 9393445535.779486, 1
7: 8763013566.4075, 18: 8688178631.797535}
```

In [24]:
```
data_new
```

Out[24]:

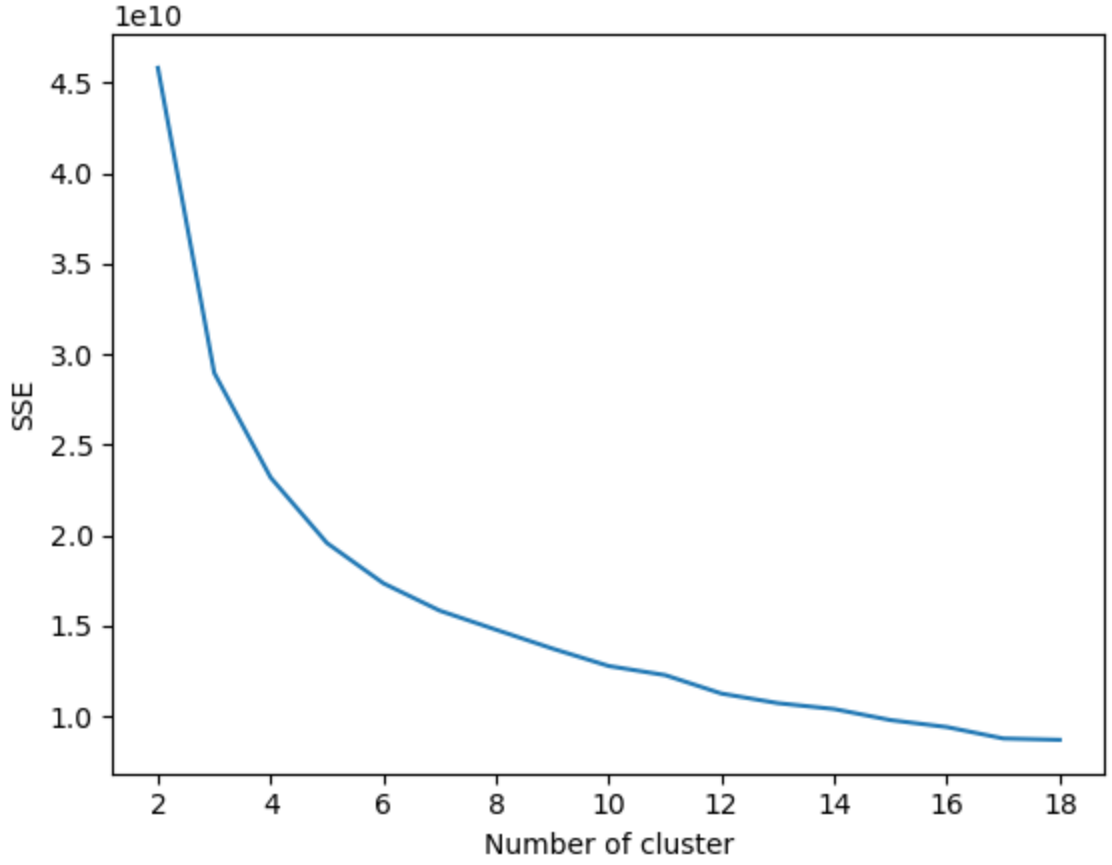
	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen	clusters
0	12669	9656	7561	214	2674	1338	15
1	7057	9810	9568	1762	3293	1776	0
2	6353	8808	7684	2405	3516	7844	0
3	13265	1196	4221	6404	507	1788	11
4	22615	5410	7198	3915	1777	5185	7
...	...	...	...	...	...	...	...
435	29703	12051	16027	13135	182	2204	16
436	39228	1431	764	4510	93	2346	5
437	14531	15488	30243	437	14841	1867	8
438	10290	1981	2232	1038	168	2125	1
439	2787	1698	2510	65	477	52	4

414 rows × 7 columns

The sse dictionary is created with no of clusters as the keys and the vlaues of inertia or sum of sqaures within a cluster as the value for each key

Plotting the figure with key as no of clusters on x axis and values as within cluster distance on y axis

In [25]:
```
plt.figure()
plt.plot(list(sse.keys()), list(sse.values()))
plt.xlabel("Number of cluster")
plt.ylabel("SSE")
plt.show()
```



We started with Kmenas value of 5, 5 clusters for each variable. There are different methods to determing the best value of K. Given the range from 1 to 20 clusters as considered for our analysis. By the empirical method the best value would be sqrt(414)/2 = 10. By the elbow method it seems like the best value for k is 6. As we from the graph as the number of clusters are increasing the within cluster distance is decreasing. However from k=7 the percentage change in sse from the previous is under 10. So after K= 6 it is possible that the model may overfit and capture noise. At 6 this change can be see like a elbow effect. Also the between group distance looks good and the percentage change in sse is more from K>k at k=6.

Model With k=6

In [50]:
```
from sklearn.cluster import KMeans
data_new = data_new.drop(["clusters"], axis =1) # Dropping the clusters column which was
kmeans = KMeans(n_clusters=6, random_state=76964057).fit(data_new)
pd.Series(kmeans.labels_).value_counts()
```

Out[50]:
```
1    143
0     98
5     80
2     40
3     37
4     16
dtype: int64
```

Creating data frame with cluster cetners for 6 means (as we have K=6), with each column names (X-coordinate variable names of centers) containing the wieghtage value of variable (X-coordinate values of respective variables) for each mean (6 means)

In [52]:
```
pd.DataFrame(data=kmeans.cluster_centers_, columns=['Fresh','Milk','Grocery','Frozen','D
```

Out[52]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	15779.591837	2703.561224	3739.795918	3018.826531	834.887755	1174.061224

1	5003.839161	2320.069930	2764.265734	2587.839161	653.475524	843.531469
2	5522.025000	13458.500000	21821.700000	1674.700000	9209.875000	1684.525000
3	26264.756757	6082.432432	7456.864865	4516.702703	1517.810811	2089.729730
4	40149.125000	2728.000000	3303.312500	2999.687500	602.437500	1198.312500
5	4220.700000	7665.225000	10719.987500	1345.637500	4664.075000	1411.875000

As we seee for 6 clusters staritng from cluster 0 to cluster 5, the number of data points in each cluster are explained above in series output.The cluster centre analysis is then updated in the Pandas datafram output. We can see that Cluster 1 has below average values for all categories and may represent smaller customers. Clsuter named 2 is dominant in Grocery and also in Milk category. Cluster named 4 is dominant in the Fresh category.

The number of data points in each clusters for all values of k have been included in the output as seen above.For k= 6 clusters we have, 98 data points in cluster 0, 143 data points in cluster 1, 40 data points in cluster 2, 37 data points in cluster 3, 16 data points in cluster 4 and 80 data points in cluster 5.