Data-Analytics-MSCI-719-Ruelala

March 11, 2023

1 Demand Estimation

- The difference between total sales and demand (shortage) is that $sales = min(inventory, demand)$, so sales is not equal to demand when there is less inventory. In fact, the difference is caused by shortage in some items. In part 1, this difference is also calculated based on estimated value of demands.
- We need the demand of sold-out items to find the optimum pricing for maximum sales revenues.

2 Clustering

In this part, the clustering is studied for different number of clusters. The characterstics of clusters are plotted afterwards. First, the dataset is read and 1000 random items are extracted from the dataset.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import scipy
```

[2]:
```
df = (pd.read_excel("Flashion_Data_Part1.xlsx")
      .sample(axis=0, n=1000))
df.head()
```

[2]:

	Item#	Total sales	hour 1	hour 2	hour 3	hour 4	hour 5	\
1896	1897	4585	0.131395	0.080879	0.066586	0.025892	0.013903	
2067	2068	3192	0.131187	0.065305	0.018804	0.006396	0.003953	
1851	1852	5956	0.108894	0.022974	0.018909	0.057650	0.060791	
2440	2441	4307	0.124569	0.061082	0.064472	0.019686	0.013780	
81	82	2865	0.142364	0.016370	0.073311	0.048030	0.014407	

	hour 6	hour 7	hour 8	…	hour 15	hour 16	hour 17	\
1896	0.002402	0.009549	0.007811	…	0.048231	0.034797	0.045927	
2067	0.043125	0.070164	0.050674	…	0.026023	0.042494	0.042384	
1851	0.067997	0.064794	0.075326	…	0.029564	0.036709	0.025930	
2440	0.011210	0.017663	0.021327	…	0.026248	0.028600	0.036146	
81	0.023868	0.003474	0.057216	…	0.027480	0.038471	0.025065	

```
       hour 18   hour 19   hour 20   hour 21   hour 22   hour 23   hour 24
1896  0.026615  0.036808  0.012809  0.020933  0.019117  0.017398  0.038878
2067  0.032200  0.029537  0.044635  0.008125  0.049027  0.042905  0.013780
1851  0.021372  0.000000  0.001109  0.023158  0.016999  0.023405  0.007822
2440  0.026084  0.026904  0.039646  0.012632  0.046590  0.036474  0.006289
81    0.032426  0.038511  0.002297  0.023142  0.022671  0.033584  0.041160

[5 rows x 26 columns]
```

To identify sold-out items which require estimation of demand, total sales percent is calculated. The items for which the total sales percent has reached 100% before hour 24, there is an excess in demand. This criteria for sold-out items is implemented in the demand function later.

[3]:
```
df = (df
      .assign(sales_percent=lambda df:
              df.loc[:, df.columns.str.startswith("hour ")].sum(axis=1))
      .assign(soldout=lambda df:
              ((df.sales_percent>=0.99) & (df["hour 24"]==0)))
     )
df.head()
```

[3]:
```
      Item#  Total sales    hour 1    hour 2    hour 3    hour 4    hour 5  \
1896   1897         4585  0.131395  0.080879  0.066586  0.025892  0.013903
2067   2068         3192  0.131187  0.065305  0.018804  0.006396  0.003953
1851   1852         5956  0.108894  0.022974  0.018909  0.057650  0.060791
2440   2441         4307  0.124569  0.061082  0.064472  0.019686  0.013780
81       82         2865  0.142364  0.016370  0.073311  0.048030  0.014407

        hour 6    hour 7    hour 8  …   hour 17   hour 18   hour 19  \
1896  0.002402  0.009549  0.007811  …  0.045927  0.026615  0.036808
2067  0.043125  0.070164  0.050674  …  0.042384  0.032200  0.029537
1851  0.067997  0.064794  0.075326  …  0.025930  0.021372  0.000000
2440  0.011210  0.017663  0.021327  …  0.036146  0.026084  0.026904
81    0.023868  0.003474  0.057216  …  0.025065  0.032426  0.038511

       hour 20   hour 21   hour 22   hour 23   hour 24  sales_percent  soldout
1896  0.012809  0.020933  0.019117  0.017398  0.038878       0.805729    False
2067  0.044635  0.008125  0.049027  0.042905  0.013780       1.000000    False
1851  0.001109  0.023158  0.016999  0.023405  0.007822       0.964339    False
2440  0.039646  0.012632  0.046590  0.036474  0.006289       0.832668    False
81    0.002297  0.023142  0.022671  0.033584  0.041160       0.997919    False

[5 rows x 28 columns]
```

To estimate the demand of sold-out items, we use the sales behavior of similar items. The similarity is considered in terms of similar hourly percent of sales. For this purpose, first, the items with known demand are clustered, then the sold-out items are associated with these clusters and their demand

is estimated.

2.1 K-means clustering for different ks

K-means clustering for various values of k=2,3,4,5 is performed. * As shown in the plot of total within sum of squares, the increase in number of clusters (k) has reduced the sum of squares as expected. The decline is almost linear. * As the number of clusters increases, the average linkage decreases.

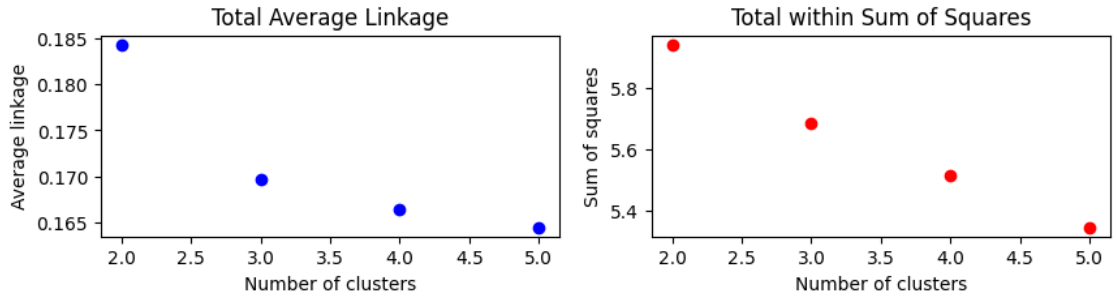
[4]:
```
kmeanss = list()
for k in range(2,6):
    kmeans = KMeans(n_clusters=k, n_init="auto")
    kmeans.fit(df.loc[df.soldout==False, df.columns.str.startswith("hour ")])
    kmeanss.append(kmeans)
```

2.2 Plotting SSE and average distance in clusters

[5]:
```
SS = list(range(len(kmeanss)))
avg_link = list(range(len(kmeanss)))
for k, kmean in enumerate(kmeanss):
    items_clusters = kmean.predict(df.loc[:, df.columns.str.startswith("hour␣
 ↪")])
    SS[k] = kmean.inertia_

    # Calculate average linkage for all clusters
    sum_link = 0
    n_link = 0
    clusters = list(range(kmean.n_clusters))
    items_array = np.array(df.iloc[:,2:26])
    for item_i in range(len(items_clusters)):
        for item_j in range(len(items_clusters)):
            if (item_i!=item_j) and (items_clusters[item_i]!
 ↪=items_clusters[item_j]):
                sum_link += np.sqrt(np.sum(np.square(items_array[item_i, :
 ↪]-items_array[item_j, :])))
                n_link += 1
    avg_link[k] = sum_link / n_link


fig, axs = plt.subplots(1,2, figsize=(10, 2))
cluster_labels = ["Cluster {}".format(i+1) for i in range(kmean.n_clusters)]
axs[0].scatter([kmean.n_clusters for kmean in kmeanss], avg_link, color="blue")
axs[0].set_title("Total Average Linkage")
axs[0].set_xlabel("Number of clusters")
axs[0].set_ylabel("Average linkage")
axs[1].scatter([kmean.n_clusters for kmean in kmeanss], SS, color="red")
axs[1].set_title("Total within Sum of Squares")
axs[1].set_xlabel("Number of clusters")
```

```
axs[1].set_ylabel("Sum of squares")
```

[5]: `Text(0, 0.5, 'Sum of squares')`

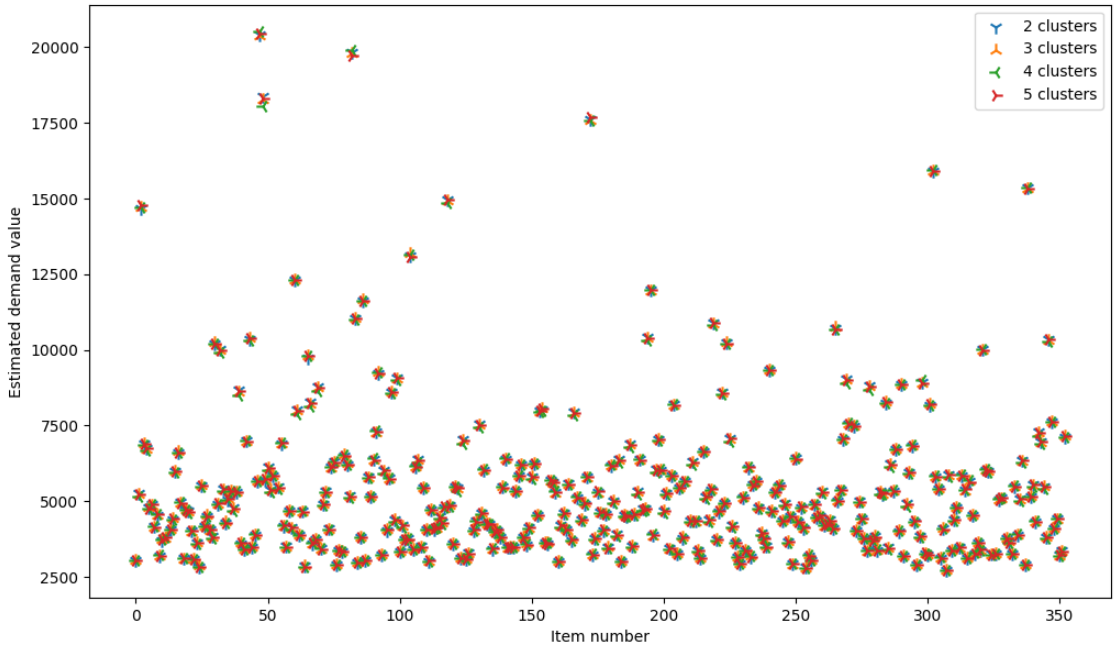


2.3 Visualization of estimated demand for different k

The comparison of estimated demands for various number of clusters shows negligible difference for different number of clusters as shown in the following scatter plot.

[6]:
```
def demand(row, df_c):
    if row["soldout"]:
        sales_sum_percent = 0
        for hour in range(1,25):
            column = "hour {}".format(hour)
            sales_sum_percent += row[column]
            if sales_sum_percent >= 0.999:
                unsold_sum_percent = (df_clusters.loc[row["cluster"], "hour␣
 ↪24"] -
                                      df_clusters.loc[row["cluster"], column])
                row["demand"] = row["Total sales"]/(1-unsold_sum_percent)
                break
    else:
        row["demand"] = row["Total sales"]
    return row


fig, ax = plt.subplots(figsize=(12,7))
marker_map = {2:"1", 3:"2", 4:"3", 5:"4"}

demands_array = np.empty((len(df),4))
for idx, k in enumerate(range(2,6)):
    kmeans = KMeans(n_clusters=k, n_init="auto")
    kmeans.fit(df.loc[df.soldout==False, df.columns.str.startswith("hour ")])
    df = df.assign(cluster=lambda df:
                kmeans.predict(df.loc[:, df.columns.str.startswith("hour ")]))
```

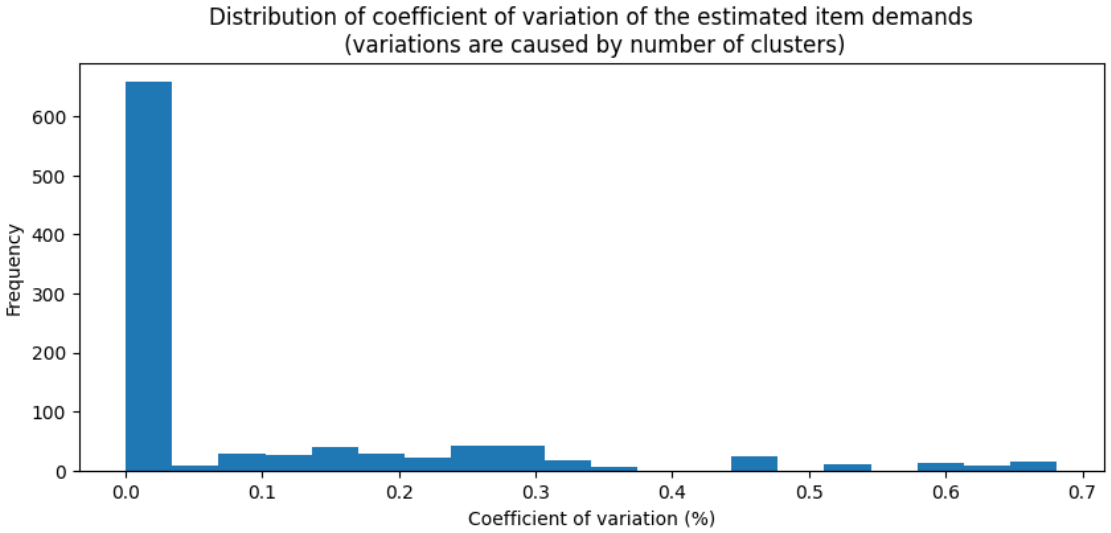
```
    df_clusters = (df
                   .query("soldout==False")
                   .groupby(["cluster"])
                   .mean()
                  )

    for hour in range(2,25):
        column_i = "hour {}".format(hour)
        column_i_1 = "hour {}".format(hour-1)
        df_clusters.loc[:, column_i] = df_clusters.loc[:, column_i]+df_clusters.
 ↪loc[:, column_i_1]

    df = (df
          .apply(demand, axis=1, df_c=df_clusters)
          .assign(shortage=lambda df: df["demand"]-df["Total sales"])
         )
    demands_array[:, idx] = df["demand"]
    ax.scatter(range(len(df.loc[df.soldout])), df.loc[df.soldout, "demand"],
               marker=marker_map[kmeans.n_clusters],
               label="{} clusters".format(kmeans.n_clusters),
              s=80)
    ax.legend()
    ax.set_xlabel("Item number")
    ax.set_ylabel("Estimated demand value")
coeff_vars = 100*scipy.stats.variation(demands_array, axis=1)
```



To evaulate the variations in the estimated demands caused by different number of clusters, the coefficient of variation $CV = \frac{\sigma}{\mu}$ is evaulated for each item. The distribution of CV is provided in percentage in the following plot.

[7]:
```
fig, ax = plt.subplots(figsize=(10,4))
ax.hist(coeff_vars, bins=20)
ax.set_ylabel("Frequency")
ax.set_xlabel("Coefficient of variation (%)")
ax.set_title("Distribution of coefficient of variation of the estimated item␣
 ↪demands\n (variations are caused by number of clusters)")
```

[7]:
```
Text(0.5, 1.0, 'Distribution of coefficient of variation of the estimated item
demands\n (variations are caused by number of clusters)')
```



[8]:
```
coeff_vars = [0 if np.isnan(coeff_vars[i]) else coeff_vars[i] for i in␣
 ↪range(len(coeff_vars))]
idx_maxcv = np.argmax(coeff_vars)
print("The item with maximum coefficient of variation is the {}th with␣
 ↪estimated values of:\n{}"
      .format(idx_maxcv, demands_array[idx_maxcv]))
```

```
The item with maximum coefficient of variation is the 833th with estimated
values of:
[4937.72409031 4907.06589385 4847.57688128 4916.18128502]
```

2.4 Recommendation for the number of clusters k

As shown in the plot above the relative variation caused by different number of clusters is negligible. So each value of k can be used for estimation of demand.