clustering

April 26, 2021

[1]:
```
import re
import pandas as pd
import os
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

0.0.1 Classification and Clustering of the coffees.

To be able to identify the coffees that match the preferences of the team it is necessary to identify some relevant features from each coffee, that will allow to recommend it to each of the members of the team.
Features: * Region of origin contains fazenda kaquend, kaquend farm, sul de minas, (minas gerais with sul de minas) * Sweet: using the `Sweetness` column * Very Sweet: using the `Sweetness` column * Not too strong: Robusta is known for being the strongest species * Soft: Low values of `Body` can be associated with softer coffees (less oily texture) * No aroma: Using the `Aroma` column * No flavor: Using the `Flavor` column

Although there is a direct score for *Acidity*, its scale varies between coffees. According to the data source (https://database.coffeeinstitute.org/coffee/976032/grade), this scores will vary depending on the origin or type of coffee. This means that this score *"... reflect the panelist's perceived quality for the Acidity relative to the expected flavor profile based on origin characteristics and/or other factors"*. For this reason, *Acidity* should not be compared among coffees from different regions/types.

Regarding the Soft/Not too strong preferences, we can observe that in general coffees with smaller values of *Body* preserve less oils and are considered light or Soft. (https://espressocoffeeguide.com/all-about-coffee-2/coffee-flavor/body/).

Sumatra is known for heavier body, Yemen Mocha for medium to heavy and Mexican for a lighter body. The correlation matrix below shows that higher values of `Moisture` are associated with low `Body`. Also, `Balance`, `Flavor` and `Aftertaste` are positively correlated with `Body`, therefore, lower values of this columns are preferred for a Soft coffee.

Finally, is worth mentioning that although the coffee from Fazenda Kaquend is a great indicator for Marcio's taste, **the model will not necessarily recommend this coffee in case it is not part of the cluster selected as the most representative for the Sul de Minas region**, however, its features will be considered when selecting the ones that are recommended.

[2]:
```python
full_df = pd.read_csv('arabica_robusta_cleaned.csv')
```

[4]:
```python
selection = ['Aroma', 'Flavor', 'Aftertaste', 'Acidity', 'Body',
             'Balance', 'Uniformity', 'Clean.Cup', 'Sweetness',
             'Total.Cup.Points', 'Moisture', 'Category.One.Defects',
             'Quakers','altitude_mean_meters']

selected_df = full_df[selection]

corr = selected_df.corr()
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
```

[4]:
```
<pandas.io.formats.style.Styler at 0x1a20a4bc18>
```

The correlation matrix for some selected numeric features is displayed above. It is observed that the Total.Cup.Points is highly correlated with all the individual measurements as expected, because it is calculated as the sum of all these scores.
As explained before, the *Acidity* score presents a behavior that is difficult to quantify because for coffees with very different levels of acidity a high score can be recorded. This happens because depending on the origin of the coffee, it can have a high score regardless of the actual value of acidity, as long as it matches with its expected level of it. For this reason, *Acidity* is not considered in the model, but the Total.Cup.Points will remain in the model, considering that algorithms that rely on distance for clustering can handle these correlated variables well.

The approach to be implemented will consist in finding the best fit of 2 different clustering algorithms, K-means and Hierarchical clustering (agglomerative).

Scaling the data Taking into consideration that the clustering algorithms to be used make use of distance between the observations to find the more dense regions and assign clusters to them, it is important to scale the data so no features are given more/less relevance due to different scales.

[5]:
```python
import sklearn
from sklearn.preprocessing import StandardScaler

filt_cols = ['Aroma', 'Flavor', 'Aftertaste', 'Body', 'Balance',
             'Uniformity', 'Clean.Cup', 'Sweetness',
             'Total.Cup.Points', 'Moisture', 'Category.One.Defects',
             'Quakers','altitude_mean_meters']

# Get a df of the selected columns and avoiding any null values
selected_df = full_df[filt_cols][~pd.isnull(full_df[filt_cols]).any(axis=1)].
 ↪copy()
selected_df.shape # 231 observations contain nan's in the altitude and are lost
```

[5]:
```
(1242, 13)
```

[6]:
```
# Scale the data
train_data = StandardScaler().fit_transform(selected_df)
train_data.shape
```

[6]:
```
(1242, 13)
```

K-Means One of the main challenges of using K-Means, is to determine an adequate number of clusters. Silhouette analysis can be used to study the separation distance between the resulting clusters, and to decide the best number of K to be used.
From documentation: "The Silhouette Coefficient is calculated using the mean intra-cluster distance (`a`) and the mean nearest-cluster distance (`b`) for each sample. The Silhouette Coefficient for a sample is `(b - a) / max(a,b)`. To clarify, `b` is the distance between a sample and the nearest cluster that the sample is not a part of."

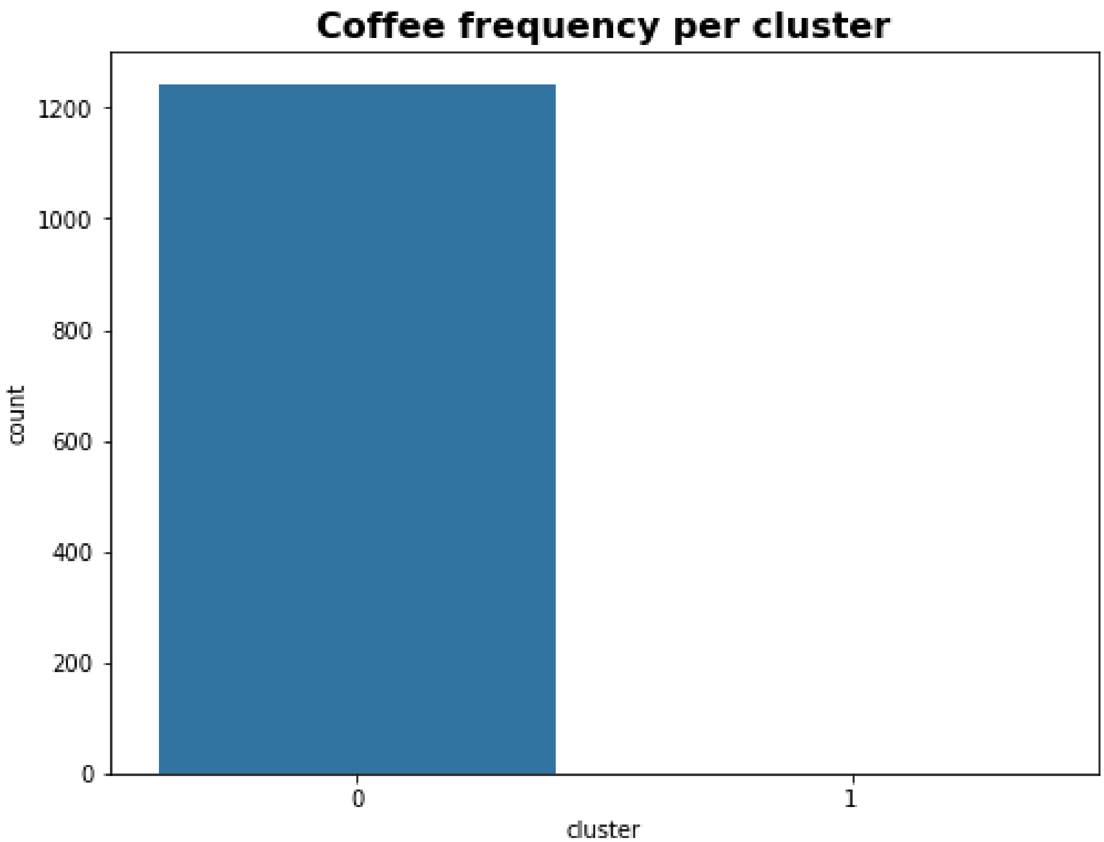
[7]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10]

for n_clusters in range_n_clusters:
    clusterer = KMeans(n_clusters=n_clusters, random_state=10)
    cluster_labels = clusterer.fit_predict(train_data)

    silhouette_avg = silhouette_score(train_data, cluster_labels)
    print("For n_clusters =", n_clusters,
          "The average silhouette_score is :", silhouette_avg)
```

```
For n_clusters = 2 The average silhouette_score is : 0.9309541290846407
For n_clusters = 3 The average silhouette_score is : 0.21515608429243194
For n_clusters = 4 The average silhouette_score is : 0.20122397290129665
For n_clusters = 5 The average silhouette_score is : 0.2117842936718094
For n_clusters = 6 The average silhouette_score is : 0.21583134474118246
For n_clusters = 7 The average silhouette_score is : 0.1924932445333667
For n_clusters = 8 The average silhouette_score is : 0.20787640245720387
For n_clusters = 9 The average silhouette_score is : 0.15327712494166332
For n_clusters = 10 The average silhouette_score is : 0.21187872025358143
```

Since the best score was obtained with 2 clusters, this value is used for the model and the graph of the clusters frequency is displayed below

[8]:
```
# Use KMeans with the n_clusters with the best silhouette score
clusterer = KMeans(n_clusters=2, algorithm='full', random_state=10)
cluster_labels = clusterer.fit_predict(train_data)

kmeans_df = full_df[~pd.isnull(full_df[filt_cols]).any(axis=1)].copy()
kmeans_df['cluster'] = cluster_labels
```

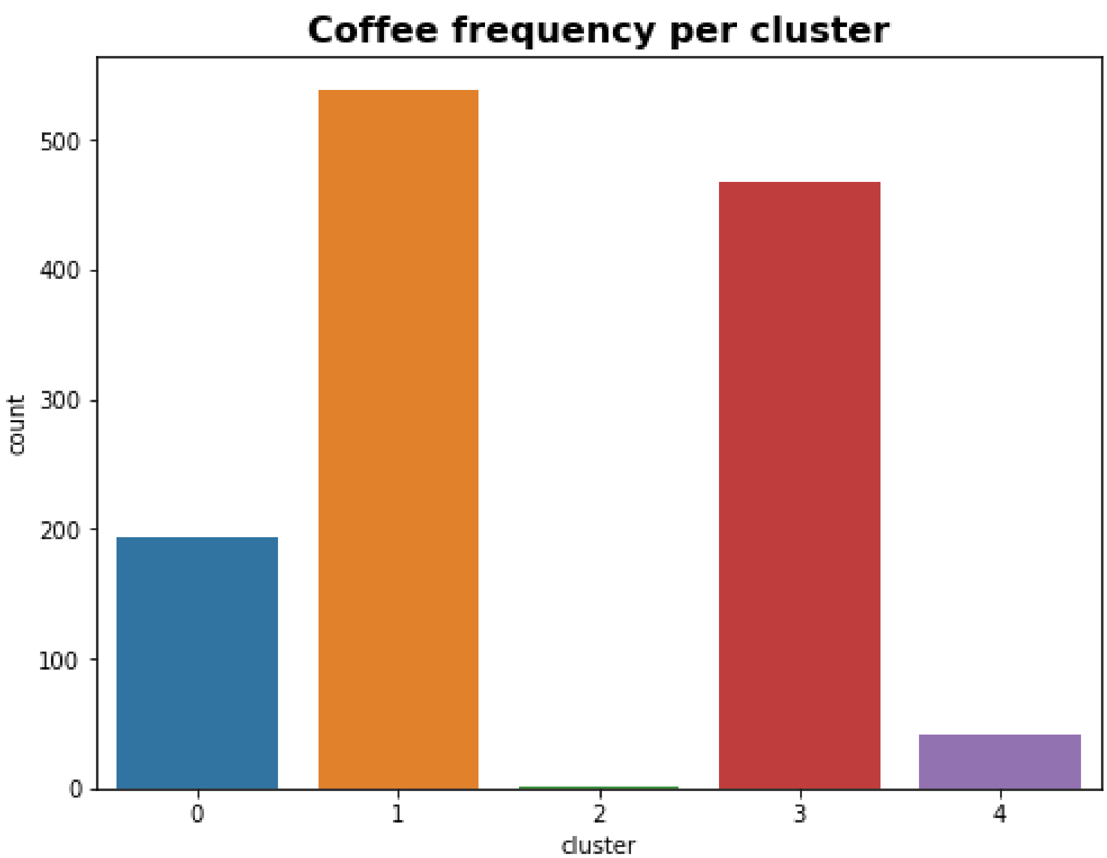
```
[9]: brazil_list = ['south of minas', 'sul de minas - carmo de minas',
                   'sul de minas', 'sul de minas gerais'] #'mountains of minas␣
↪gerais','minas gerais, br',

     # dataframe with the coffees from sul de minas
     sul_minas_df = kmeans_df[kmeans_df['Region'].isin(brazil_list)]

     plt.figure(figsize=(8, 6))
     g = sns.countplot(x=kmeans_df.cluster, data=kmeans_df)
     plt.title('Coffee frequency per cluster',size=16, fontdict={'weight':'bold'})
     plt.show()
```

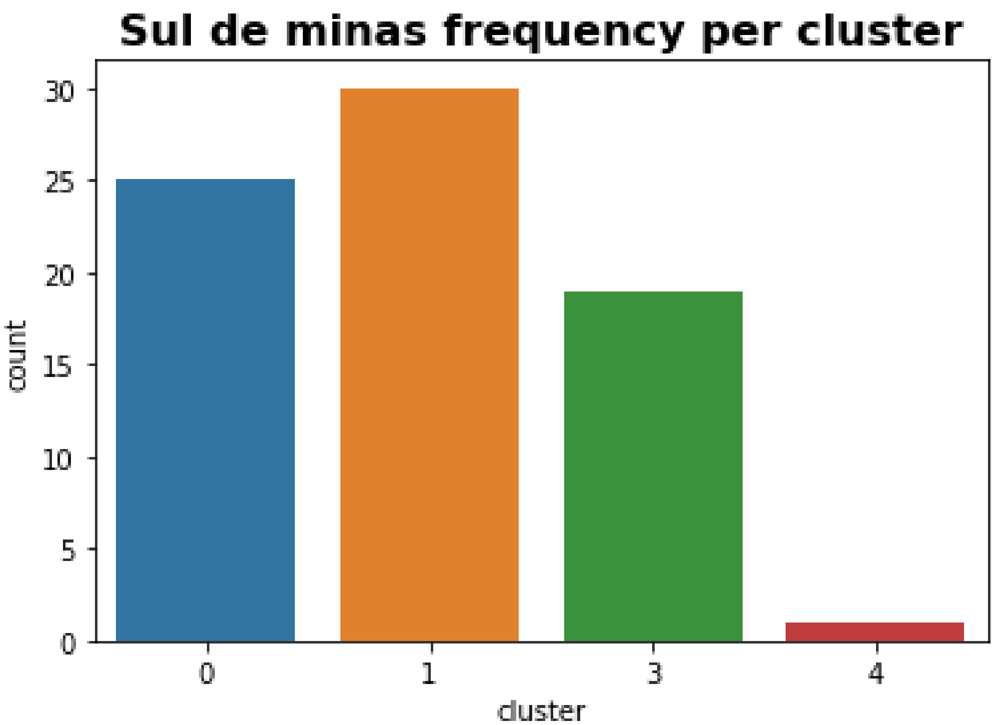


Using the best silhouette score is not useful, as all the data is assigned to a single cluster. Below are the results for a different number of clusters, and the second plot is particularly relevant because it corresponds to the distribution of the 'Sul de Minas' coffees among the different clusters. Since the use of the silhouette score was not giving good results for finding k, the decision of 5 clusters was because it was presenting a better distribution among clusters, although for clusters 2 and 4, the number of coffees assigned to them is considerably lower. In the next section, a different algorithm will be implemented to try to get better results

[10]:
```
clusterer = KMeans(n_clusters=5, algorithm='full', random_state=10)
cluster_labels = clusterer.fit_predict(train_data)

kmeans_df = full_df[~pd.isnull(full_df[filt_cols]).any(axis=1)].copy()
kmeans_df['cluster'] = cluster_labels
```

[11]:
```
sul_minas_df = kmeans_df[kmeans_df['Region'].isin(brazil_list)]

plt.figure(figsize=(8, 6))
g = sns.countplot(x=kmeans_df.cluster, data=kmeans_df)
plt.title('Coffee frequency per cluster',size=16, fontdict={'weight':'bold'})
plt.show()
g = sns.countplot(x=sul_minas_df.cluster, data=sul_minas_df)
plt.title('Sul de minas frequency per cluster',size=16, fontdict={'weight':
 ↪'bold'})
plt.show()
```





Using 5 clusters it is observed that the cluster 2 is almost empty and cluster 4 is very small. However, the second graph where the Sul de Minas coffees are displayed, shows that cluster 0, which initially is considerably smaller when compared to 2 and 3, is now the second in size and is very close to the size of cluster 1. This can be interpreted as cluster 0 being highly relevant to the taste of Marcio and Rafa, as it contains a smaller selection of coffees where the Brazilian ones have a bigger proportion.

[12]:
```python
cluster_counts = kmeans_df.groupby('cluster').agg(count = ('cluster','count'))
brazil_counts = sul_minas_df.groupby('cluster').agg(counts =␣
 ↪('cluster','count'))
cluster_counts['brazilian_count'] = brazil_counts.counts
cluster_counts['perc'] = cluster_counts['brazilian_count']/
 ↪cluster_counts['count']
cluster_counts.sort_values('perc',ascending=False)
```

[12]:

cluster	count	brazilian_count	perc
0	194	25.0	0.128866
1	538	30.0	0.055762
3	468	19.0	0.040598
4	41	1.0	0.024390
2	1	NaN	NaN

The table above shows the percentage that *'Sul de Minas'* coffees represent among each cluster.

This score will be used to determine which algorithm produces the best cluster to recommend coffees for Marcio and Rafa since they have a strong preference for coffees from this region

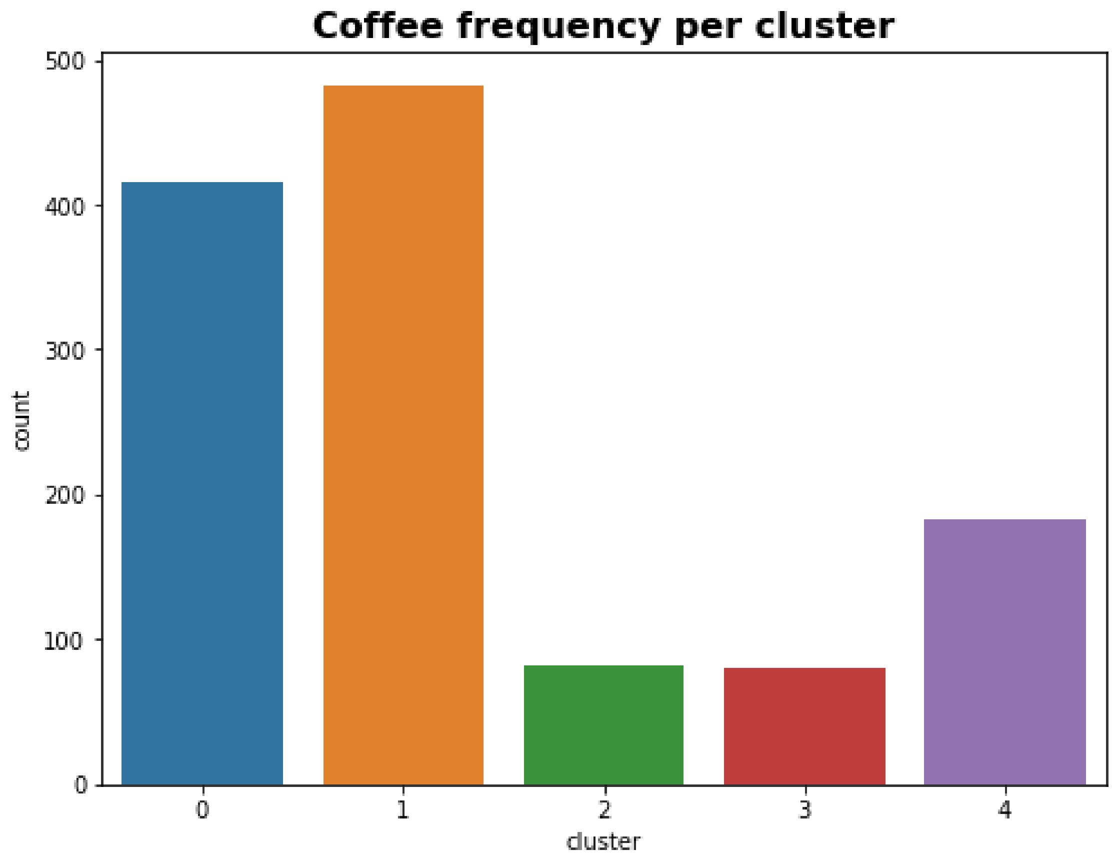
Hierarchical clustering (agglomerative)

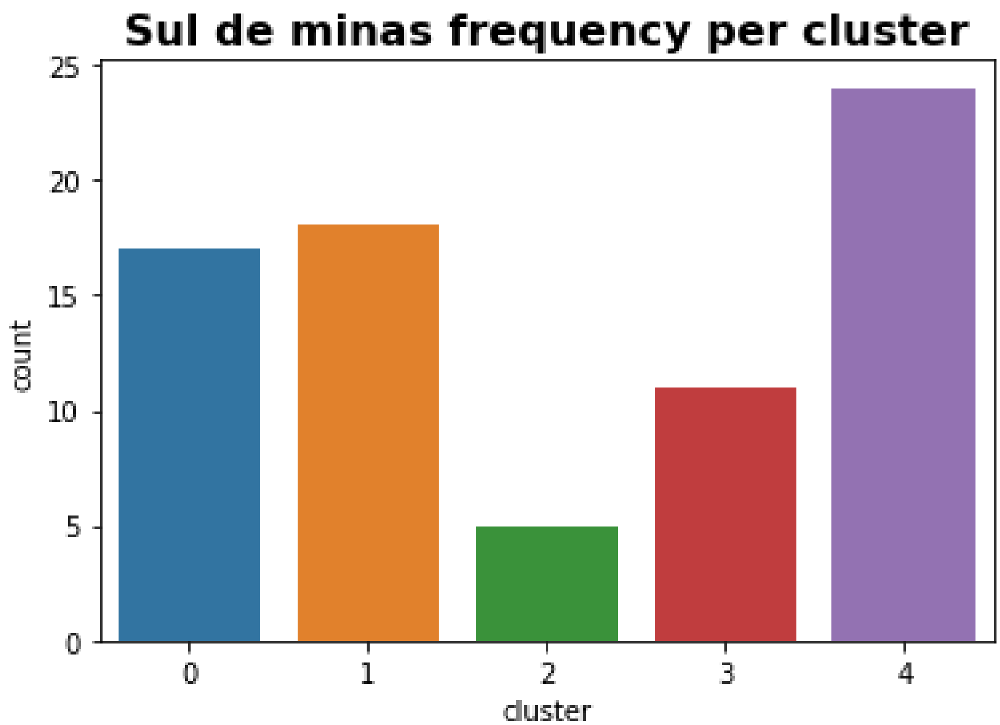
[13]:
```
from sklearn.cluster import AgglomerativeClustering

range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10]

for n_clusters in range_n_clusters:
    clusterer = AgglomerativeClustering(n_clusters=n_clusters,␣
↪linkage='average', affinity='cosine')
    cluster_labels = clusterer.fit_predict(train_data)

    silhouette_avg = silhouette_score(train_data, cluster_labels)
    print("For n_clusters =", n_clusters,
          "The average silhouette_score is :", silhouette_avg)
```

```
For n_clusters = 2 The average silhouette_score is : 0.162109739168874
For n_clusters = 3 The average silhouette_score is : 0.16316032898334745
For n_clusters = 4 The average silhouette_score is : 0.17523793425606463
For n_clusters = 5 The average silhouette_score is : 0.1810540593004644
For n_clusters = 6 The average silhouette_score is : 0.17220029517939694
For n_clusters = 7 The average silhouette_score is : 0.17790659218420013
For n_clusters = 8 The average silhouette_score is : 0.11894603692854822
For n_clusters = 9 The average silhouette_score is : 0.08626212973939541
For n_clusters = 10 The average silhouette_score is : 0.08598712864402314
```

[14]:
```
# Agglomerative clustering with average linkage is producing more evenly␣
↪distributed clusters
clusterer = AgglomerativeClustering(n_clusters=5, linkage='average',␣
↪affinity='cosine')
cluster_labels = clusterer.fit_predict(train_data)

agglom_df = full_df[~pd.isnull(full_df[filt_cols]).any(axis=1)].copy()
agglom_df['cluster'] = cluster_labels
```

[15]:
```
sul_minas_df = agglom_df[agglom_df['Region'].isin(brazil_list)]
plt.figure(figsize=(8, 6))
g = sns.countplot(x=agglom_df.cluster, data=agglom_df)
plt.title('Coffee frequency per cluster',size=16, fontdict={'weight':'bold'})
plt.show()
g = sns.countplot(x=sul_minas_df.cluster, data=sul_minas_df)
plt.title('Sul de minas frequency per cluster',size=16, fontdict={'weight':
↪'bold'})
plt.show()
```


Coffee frequency per cluster
count
cluster
0
100
200
300
400
500
0
1
2
3
4



Using agglomerative clustering and euclidean metric produced a similar result with the silhouette score suggesting 2 clusters. However, when using cosine similarity, the suggested number of clusters was 5 and they seem to be better distributed than using k-means. Also in the table below, the metric of the percentage (perc) that the *'Sul de Minas'* coffees represent from each clusters show a higher value using this algorithm.

[16]:
```
cluster_counts = agglom_df.groupby('cluster').agg(count = ('cluster','count'))
brazil_counts = sul_minas_df.groupby('cluster').agg(counts =␣
 ↪('cluster','count'))
cluster_counts['brazilian_count'] = brazil_counts.counts
cluster_counts['perc'] = cluster_counts['brazilian_count']/
 ↪cluster_counts['count']
cluster_counts.sort_values('perc',ascending=False)
```

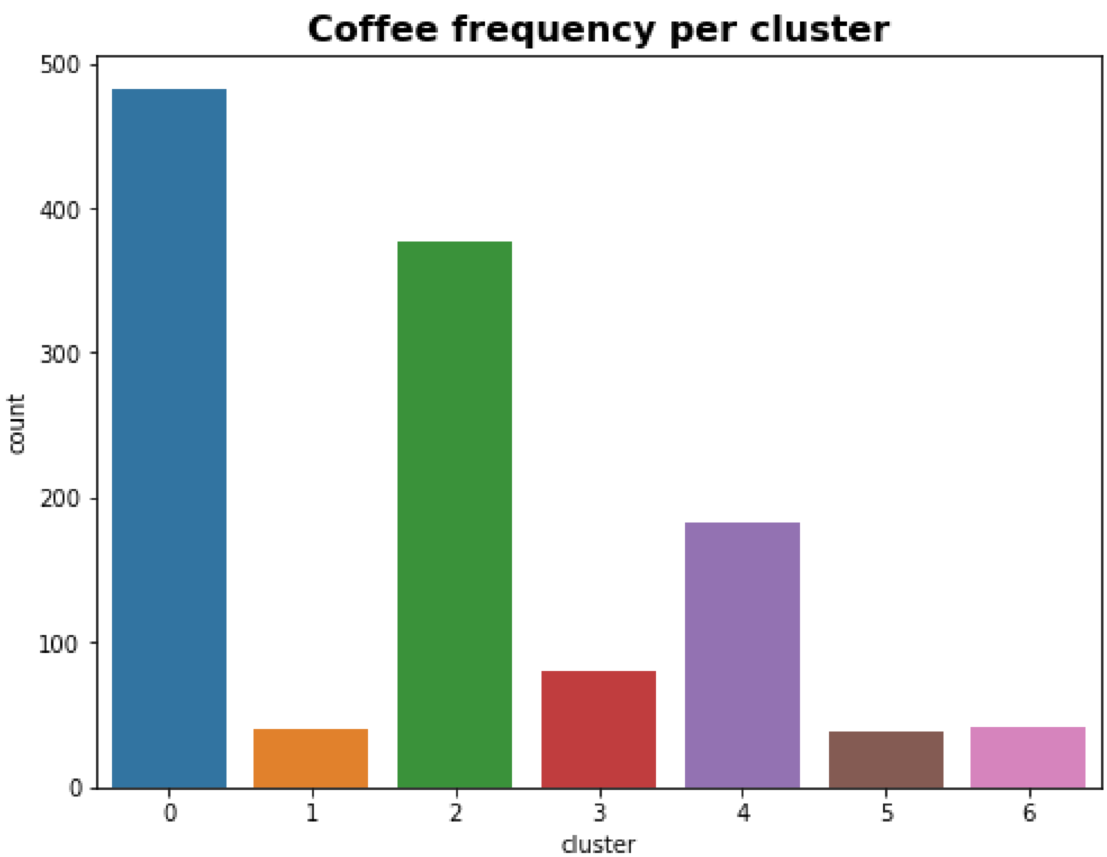
[16]:

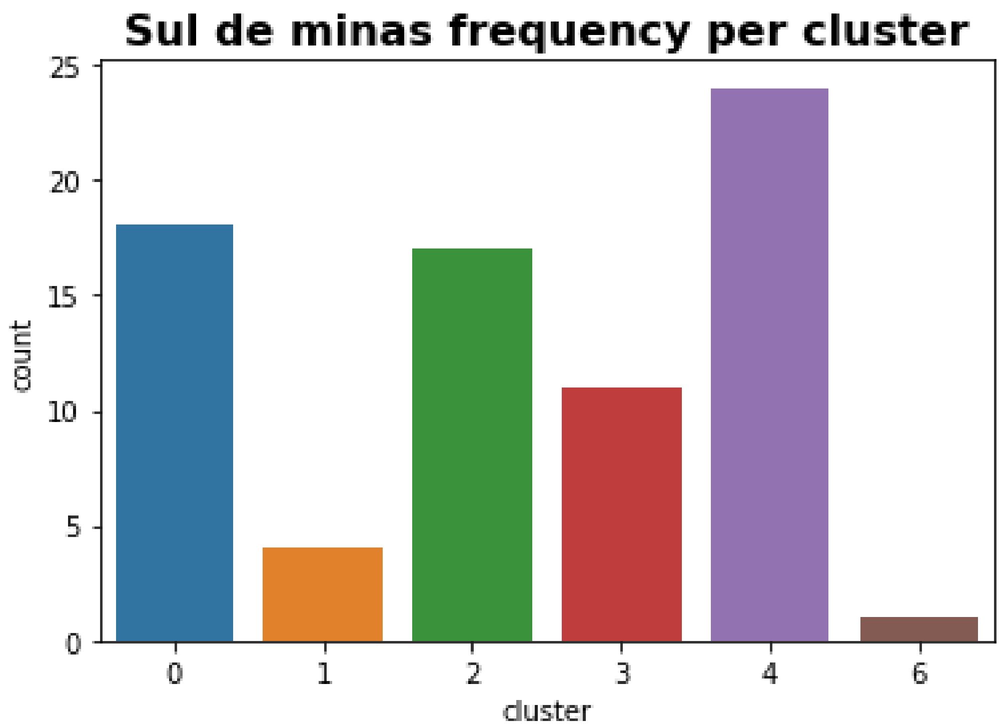
cluster	count	brazilian_count	perc
3	80	11	0.137500
4	183	24	0.131148
2	82	5	0.060976
0	415	17	0.040964
1	482	18	0.037344

Hierarchical clustering (agglomerative) using `distance_threshold`

[17]:
```
# distance_th is the linkage distance above which, clusters will not be merged
clusterer = AgglomerativeClustering(n_clusters=None, linkage='average',␣
 ↪affinity='cosine',
                                    compute_full_tree=True,␣
 ↪distance_threshold=0.9)
cluster_labels = clusterer.fit_predict(train_data)

agglom_df = full_df[~pd.isnull(full_df[filt_cols]).any(axis=1)].copy()
agglom_df['cluster'] = cluster_labels
```

[18]:
```
sul_minas_df = agglom_df[agglom_df['Region'].isin(brazil_list)]
plt.figure(figsize=(8, 6))
g = sns.countplot(x=agglom_df.cluster, data=agglom_df)
plt.title('Coffee frequency per cluster',size=16, fontdict={'weight':'bold'})
plt.show()
g = sns.countplot(x=sul_minas_df.cluster, data=sul_minas_df)
plt.title('Sul de minas frequency per cluster',size=16, fontdict={'weight':
 ↪'bold'})
plt.show()
```





Finally, a variation of agglomerative clustering was used using the `distance_threshold` parameter, which sets a limit for merging clusters. In this way, the number of clusters is determined by the algorithm. The results are similarly good compared to the previous case.

[19]:
```
cluster_counts = agglom_df.groupby('cluster').agg(count = ('cluster','count'))
brazil_counts = sul_minas_df.groupby('cluster').agg(counts =␣
↪('cluster','count'))
cluster_counts['brazilian_count'] = brazil_counts.counts
cluster_counts['perc'] = cluster_counts['brazilian_count']/
↪cluster_counts['count']
cluster_counts.sort_values('perc',ascending=False)
```

[19]:

cluster	count	brazilian_count	perc
3	80	11.0	0.137500
4	183	24.0	0.131148
1	40	4.0	0.100000
2	377	17.0	0.045093
0	482	18.0	0.037344
6	42	1.0	0.023810
5	38	NaN	NaN

Model selection The last method of Hierarchical clustering (agglomerative) produced the highest participation of the *'Sul de Minas'* coffees in a single cluster. Thus, the agglomerative approach is selected over K-means and the **cluster 3**, which is the one with the highest percentage of *'Sul de Minas'* coffees, is selected to recommend the top5 coffees for Marcio and Rafa.

Recommendations for Marcio & Rafa Since the main criteria for both, Marcio and Rafa, is to have coffees that are similar to those from "Sul de Minas" in Brazil, we will focus on the cluster containing the highest proportion of them. After determining the cluster, we will find the mean value that represents those from *Fazenda Kaquend* and **compute the closest 5 coffees** to this "centroid". We will recommend them and add a constraint of having **maximum 2 coffees that are not from Brazil**, as a way to suggest a coffee from a different region that is still close to the characteristics of those from "Sul de Minas", but without ignoring the fact that Marcio and Rafa have a strong preference for Brazilian coffees.

The cluster to be considered for the recommendations is Cluster 3

[20]:
```
# Find the indexes of all fazenda kaquend coffees in the dataframe
idx_kaquend = agglom_df[(~pd.isna(agglom_df['Farm.Name']))&
          (agglom_df['Farm.Name'].str.contains('kaquend'))].index

# Create a consecutive index that matches with the one of train_data
agglom_df['train_idx'] = list(range(0, train_data.shape[0]))

# map the indexes from the dataframe to the train_data
idx_kaquend = list(agglom_df.loc[idx_kaquend,'train_idx'])

# stack all the features of fazenda kaquend coffees
kaquend_array = np.zeros(shape=(1,train_data.shape[1]))
for i in idx_kaquend:
    kaquend_array = np.vstack((kaquend_array, train_data[i]))

kaquend_centroid = kaquend_array.mean(axis=0)
```

[21]:
```
# Find the indexes of all coffees in cluster 3
idx_clust3 = agglom_df[(agglom_df['cluster'] == 3)].index

# map the indexes from the dataframe to the train_data
idx_clust3 = list(agglom_df.loc[idx_clust3,'train_idx'])

dist_array = np.array([idx_clust3]).T
dist_array = np.hstack((dist_array, np.zeros(shape=(len(idx_clust3),1))))

for i, dist_idx in enumerate(dist_array):
    distance = np.linalg.norm(train_data[int(dist_idx[0])] - kaquend_centroid)
    dist_array[i,1] = distance
```

[22]:
```
# get indexes of the sorted distances
sort_idx = dist_array.argsort(axis=0)[:][:,1]

# get train_idx of the sorted distances found above
sort_idx = dist_array[sort_idx,0]

recomm_list = []
foreign_count = 0
position_dict = {}
position = 1
# get the coffees to be recommended
for coffee_idx in sort_idx:
    country = agglom_df[agglom_df['train_idx'] == coffee_idx]['Country.of.
↪Origin'].values[0]
    if (country == 'Brazil'):
        recomm_list.append(coffee_idx)
        position_dict[coffee_idx] = position
        position += 1
    elif (foreign_count < 2):
        recomm_list.append(coffee_idx)
        foreign_count += 1
        position_dict[coffee_idx] = position
        position += 1
    if len(recomm_list) >= 5: break
```

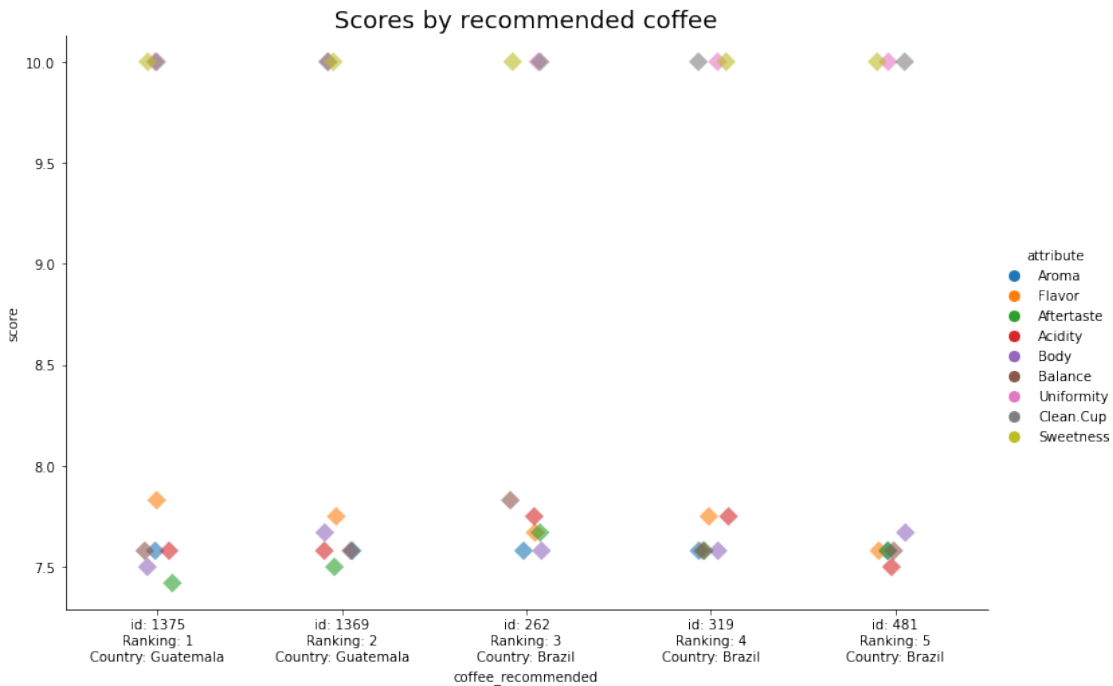
[23]:
```
recomm_df = agglom_df[agglom_df['train_idx'].isin(recomm_list)].copy()
recomm_df.insert(1, 'Ranking', 0)
recomm_df['Ranking'] = recomm_df['train_idx'].map(position_dict)
recomm_df = recomm_df.sort_values(by=['Ranking'])
recomm_df
```

[23]:
```
      Unnamed: 0  Ranking  Species                         Owner  \
1142        1375        1  Arabica                byron gonzalez
1136        1369        2  Arabica  angelica paola citan lopez
209          262        3  Arabica                ipanema coffees
256          319        4  Arabica                ipanema coffees
391          481        5  Arabica                ipanema coffees

     Country.of.Origin                    Farm.Name Lot.Number  \
1142         Guatemala                     alta luz  415000544
1136         Guatemala  finca beneficio el torreon  11/23/267
209             Brazil                  capoeirinha    007/16E
256             Brazil                  capoeirinha    008/16A
391             Brazil                  capoeirinha     261/15

                 Mill     ICO.Number                          Company  …  \
1142              NaN     11-63-1073  retrillas del pacifico, s. a.  …
```

```
1136  beneficio ixchel      11/23/267   asociación nacional del cafe  …
209           dry mill  002/1660/0105               ipanema coffees  …
256           dry mill  002/1660/0106               ipanema coffees  …
391           dry mill  002/1660/0049               ipanema coffees  …

     Quakers         Color Category.Two.Defects        Expiration  \
1142     1.0         Green        5 full defects    July 20th, 2021
1136     1.0         Green        4 full defects   March 19th, 2022
209      2.0          Green                     7  August 16th, 2017
256      2.0          Green                     3  August 16th, 2017
391      2.0  Bluish-Green                      2   April 25th, 2017

                       Certification.Body altitude_low_meters  \
1142         Asociacion Nacional Del Café              1400.0
1136         Asociacion Nacional Del Café              1901.0
209   Brazil Specialty Coffee Association               934.0
256   Brazil Specialty Coffee Association               934.0
391   Brazil Specialty Coffee Association               905.0

     altitude_high_meters altitude_mean_meters cluster train_idx
1142               1400.0               1400.0       3      1141
1136               1901.0               1901.0       3      1135
209                 934.0                934.0       3       209
256                 934.0                934.0       3       256
391                 905.0                905.0       3       390

[5 rows x 42 columns]
```

[24]:
```python
plt.figure(figsize = (16, 10))

df = recomm_df.iloc[:,[0,1,4]+list(range(20,29))].copy()
df['coffee_recommended'] = ('id: ' + df['Unnamed: 0'].astype(str) + \
                            '\nRanking: ' + df['Ranking'].astype(str) +\
                            '\nCountry: ' + df['Country.of.Origin'].astype(str))

df.drop(['Unnamed: 0','Ranking','Country.of.Origin'], axis=1, inplace=True)
df = df.melt('coffee_recommended', var_name='attribute',  value_name='score')

g = sns.catplot(x='coffee_recommended', y='score', hue='attribute', data=df,
                height=7, aspect=1.5, s=10, kind='strip', alpha=0.6, marker='D')
plt.title("Scores by recommended coffee", size=18)
plt.show()
```

```
<Figure size 1152x720 with 0 Axes>
```



[25]:
```
agglom_df[agglom_df['Farm.Name']=='fazenda kaquend'].iloc[:5,19:30]
```

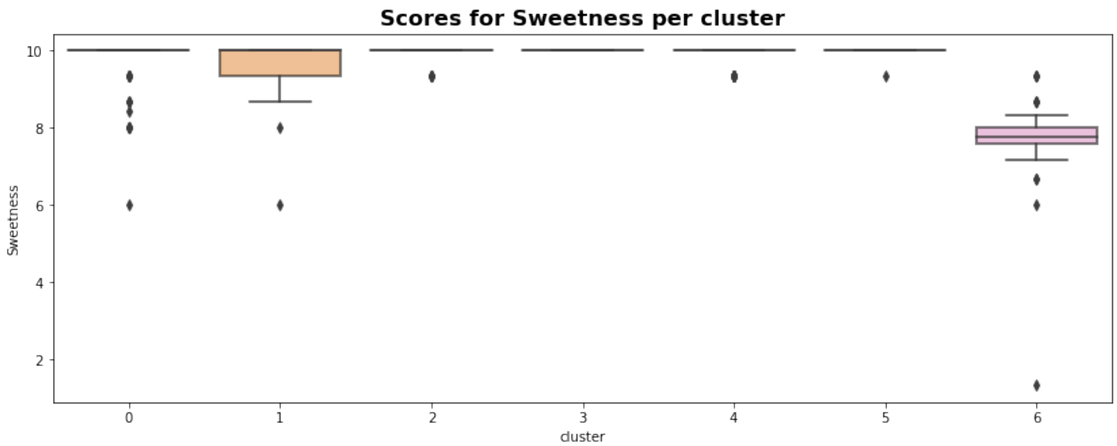
[25]:
```
    Aroma  Flavor  Aftertaste  Acidity  Body  Balance  Uniformity  Clean.Cup  \
21   8.50     8.5         8.0      8.0  8.00      8.0        10.0       10.0
35   8.33     8.0         8.0      8.0  7.75      8.0        10.0       10.0

    Sweetness  Total.Cup.Points  Moisture
21       10.0             86.92      0.12
35       10.0             86.08      0.11
```

Conclusion Marcio & Rafa The profile of the top5 coffees recommended for Marcio and Rafa can be seen above. The first 2 recommendations are from Guatemala and the rest are from Brazil, and according to the logic behind the model, these coffees represent the most similar coffees to those from *'Sul de Minas'*. In addition to this, the recommended coffees are also the closest to *'Fazenda Kaquend'* among all the *'Sul de Minas'* cluster. The table above shows the scores for fazenda kaquend as a reference.

Recommendations for Subu

[26]:
```
plt.figure(figsize = (14, 5))

# Remove a record which contains only 0 values in the scores, train_idx 1078
agglom_df = agglom_df[agglom_df['Total.Cup.Points'] > 0]
```

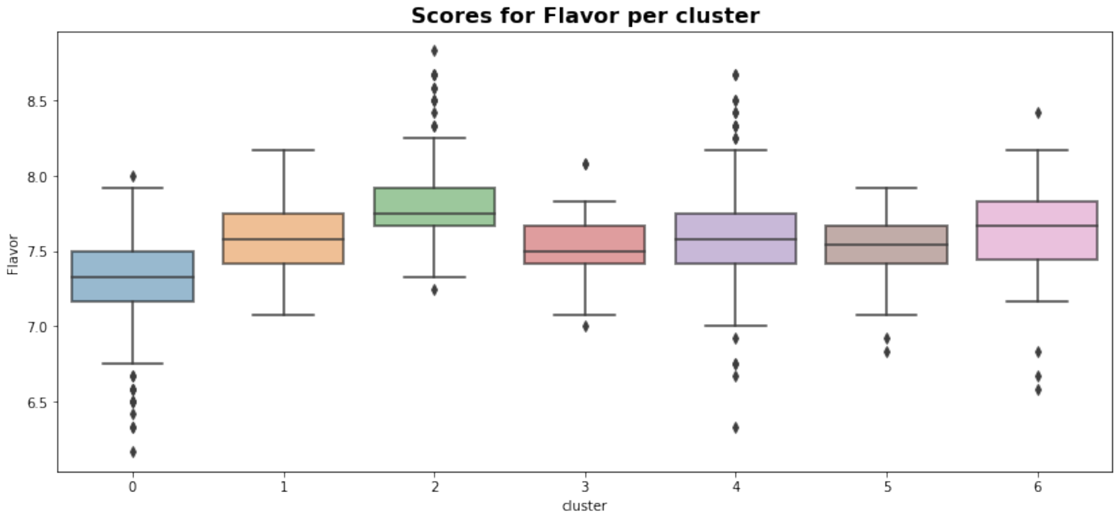
```
ax = sns.boxplot(x='cluster', y='Sweetness', data=agglom_df)
plt.setp(ax.artists, alpha=.5, linewidth=2, edgecolor="k")
ax.set_title('Scores for Sweetness per cluster', fontsize=16,␣
 ↪fontdict={"weight": "bold"})
plt.show()
```



Unlike James, Subu goes for sweet instead of very sweet taste. From the graph above we can see that the **cluster 1** fits that description, presenting high level of *Sweetness* but not as much as the other clusters. **Cluster 6** presents the lowest levels of *Sweetness* and would be an interesting option for someone with that taste, since is the only cluster with that characteristic.

According to the Sweetness feature, we can only **discard cluster 6** and have a **slight preference for cluster 1**. The next graph to consider is Flavor, where we look for lower values because Subu prefers "Not to strong flavor"

[27]:
```
plt.figure(figsize = (14, 6))
ax = sns.boxplot(x='cluster', y='Flavor', data=agglom_df)
plt.setp(ax.artists, alpha=.5, linewidth=2, edgecolor="k")
ax.set_title('Scores for Flavor per cluster', fontsize=16, fontdict={"weight":␣
 ↪"bold"})
plt.show()
```



Above it is observed that **cluster 0** and **cluster 3** present the lower median scores for Flavor, with **cluster 3** having less variability. However, **cluster 1** which was slightly better from the *Sweetness* perspective, presents a value similar to **cluster 3** with just a slightly higher median, but most of the box (50% of the data) is within a very similar region. Since Subu's preference is for a not too strong *Flavor* we will go for **cluster 1** as the best cluster to give a recommendation to Subu.

Finally, **the top 5 coffees that we will recommend to Subu will be those closest to the median of both, *Sweetness* and *Flavor* among this cluster.**

[28]:
```
clust1_sweet_med = agglom_df[(agglom_df['cluster'] == 1)]['Sweetness'].median()
clust1_flavor_med = agglom_df[(agglom_df['cluster'] == 1)]['Flavor'].median()
centroid_subu = np.array([clust1_flavor_med, clust1_sweet_med])

# Find the indexes of all coffees in cluster 1
idx_clust1 = agglom_df[(agglom_df['cluster'] == 1)].index

# map the indexes from the dataframe to the train_data
idx_clust1 = list(agglom_df.loc[idx_clust1,'train_idx'])

dist_array = np.array([idx_clust1]).T
dist_array = np.hstack((dist_array, np.zeros(shape=(len(idx_clust1),1))))

for i, dist_idx in enumerate(dist_array):
    distance = np.linalg.norm(train_data[int(dist_idx[0]),[1,7]] -
 ↪centroid_subu)
    dist_array[i,1] = distance
```

[29]:
```
# get indexes of the sorted distances
sort_idx = dist_array.argsort(axis=0)[:][:,1]
```

```python
# get train_idx of the sorted distances found above
sort_idx = dist_array[sort_idx,0]

recomm_list = []
foreign_count = 0
position_dict = {}
position = 1
# get the coffees to be recommended
for coffee_idx in sort_idx:
    country = agglom_df[agglom_df['train_idx'] == coffee_idx]['Country.of.
 ↪Origin'].values[0]
    if (country == 'Brazil'):
        recomm_list.append(coffee_idx)
        position_dict[coffee_idx] = position
        position += 1
    elif (foreign_count < 3):
        recomm_list.append(coffee_idx)
        foreign_count += 1
        position_dict[coffee_idx] = position
        position += 1
    if len(recomm_list) >= 5: break
```

[30]:

```python
# Create the dataframe with the final recommendations for Subu
recomm_df2 = agglom_df[agglom_df['train_idx'].isin(recomm_list)].copy()
recomm_df2.insert(1, 'Ranking', 0)
recomm_df2['Ranking'] = recomm_df2['train_idx'].map(position_dict)
recomm_df2 = recomm_df2.sort_values(by=['Ranking'])
recomm_df2
```

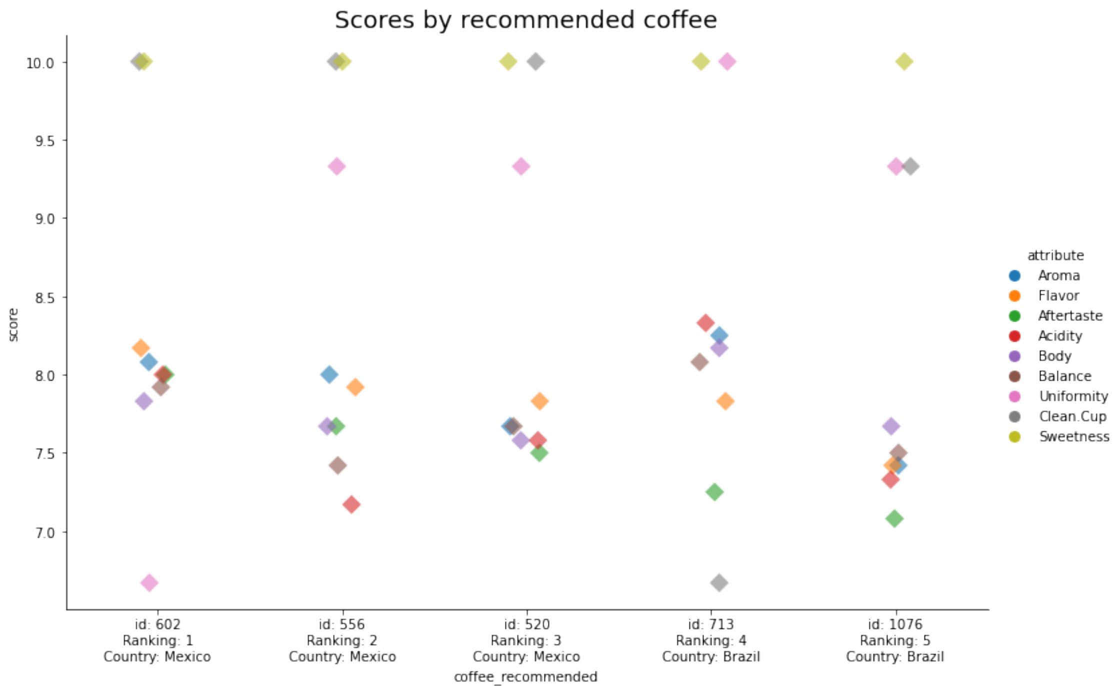
[30]:

```
     Unnamed: 0  Ranking  Species                       Owner  \
494         602        1  Arabica         romulo bello flores
452         556        2  Arabica  veronica lopez castillejos
424         520        3  Arabica        santiago solis ayerdi
584         713        4  Arabica              ipanema coffees
894        1076        5  Arabica    jacques pereira carneiro

    Country.of.Origin              Farm.Name Lot.Number  \
494            Mexico                    NaN        NaN
452            Mexico               el jabali        NaN
424            Mexico      finca la estancia        NaN
584            Brazil              rio verde        NaN
894            Brazil  pereira estate coffee        NaN

                           Mill      ICO.Number  \
494                         NaN      1302910536
452          comunidad la cumbre            1489
424  atoyac de alvarez, guerrero      1302911347
```

```
584              ipanema coffees   002/1660/0107
894     carapina armazens gerais  002/135-2/0182

                                         Company  … Quakers  Color  \
494                                  cafe shunuc  …     0.0    NaN
452        union de ejidos san fernando de ri  …     0.0  Green
424                            finca la estancia  …     0.0  Green
584                              ipanema coffees  …     0.0  Green
894  exportadora de cafés carmo de minas ltda  …     0.0   None

    Category.Two.Defects          Expiration           Certification.Body  \
494                    4      June 6th, 2013                      AMECAFE
452                    4     March 5th, 2013                      AMECAFE
424                    7     July 26th, 2013                      AMECAFE
584                    0   October 7th, 2016  Specialty Coffee Association
894                   10    April 17th, 2015  Specialty Coffee Association

    altitude_low_meters altitude_high_meters altitude_mean_meters cluster  \
494              1200.0               1200.0               1200.0       1
452              1400.0               1400.0               1400.0       1
424              1200.0               1200.0               1200.0       1
584              1268.0               1268.0               1268.0       1
894              1250.0               1250.0               1250.0       1

    train_idx
494       493
452       451
424       423
584       583
894       893

[5 rows x 42 columns]
```

[31]:
```
plt.figure(figsize = (16, 10))

df = recomm_df2.iloc[:,[0,1,4]+list(range(20,29))].copy()
df['coffee_recommended'] = ('id: ' + df['Unnamed: 0'].astype(str) + \
                            '\nRanking: ' + df['Ranking'].astype(str) +\
                            '\nCountry: ' + df['Country.of.Origin'].astype(str))

df.drop(['Unnamed: 0','Ranking','Country.of.Origin'], axis=1, inplace=True)
df = df.melt('coffee_recommended', var_name='attribute',  value_name='score')

g = sns.catplot(x='coffee_recommended', y='score', hue='attribute', data=df,
                height=7, aspect=1.5, s=10, kind='strip', alpha=0.6, marker='D')
plt.title("Scores by recommended coffee", size=18)
plt.show()
```

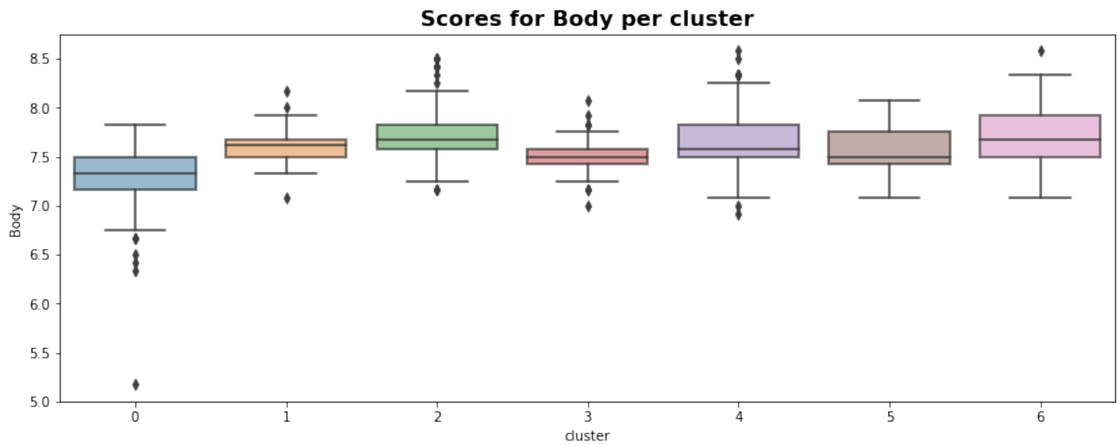
```
<Figure size 1152x720 with 0 Axes>
```



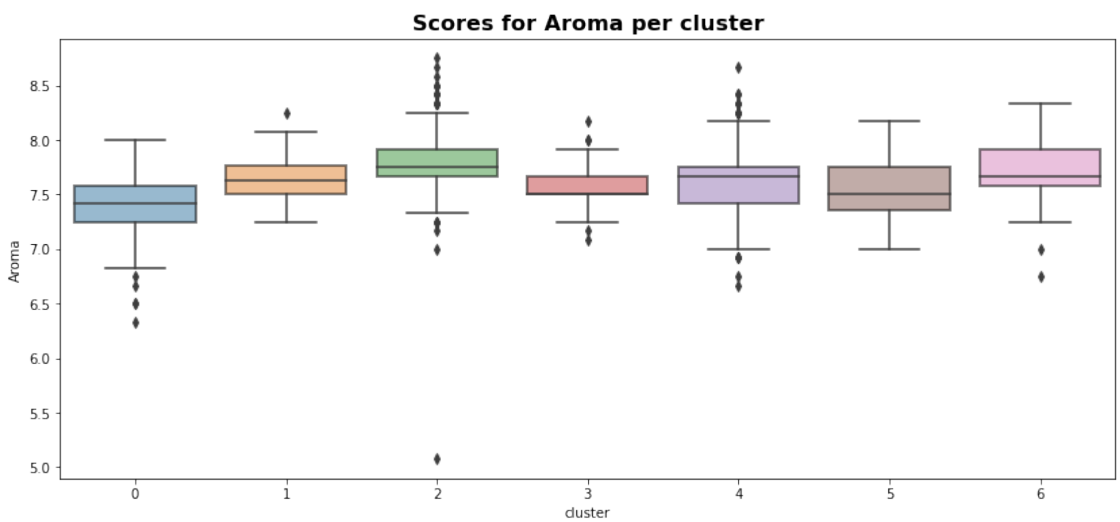
Recommendations for James For James is possible to use the previous boxplots to match his preference of "Very sweet, No flavor". It is also necessary to match "Soft, and No aroma" preferences. For this, the *Body* and *Aroma* attributes will be used.

According to the *Sweetness* feature shown in the previous section, **cluster 1 and cluster 6 can be discarded** because they are the least sweet. Regarding the *Flavor*, the best cluster for James seems to be **cluster 0**.

[32]:
```
plt.figure(figsize = (14, 5))
ax = sns.boxplot(x='cluster', y='Body', data=agglom_df)
plt.setp(ax.artists, alpha=.5, linewidth=2, edgecolor="k")
ax.set_title('Scores for Body per cluster', fontsize=16, fontdict={"weight":␣
 ↪"bold"})
plt.show()
```



[33]:
```
plt.figure(figsize = (14, 6))
ax = sns.boxplot(x='cluster', y='Aroma', data=agglom_df)
plt.setp(ax.artists, alpha=.5, linewidth=2, edgecolor="k")
ax.set_title('Scores for Aroma per cluster', fontsize=16, fontdict={"weight":␣
 ↪"bold"})
plt.show()
```



The boxplots for *Body* and *Aroma* are observed above. *Body*, can be considered as an indicator of how soft the coffee is, because lower values of body can be perceived as softer (with less oily texture). There it can be seen that again **cluster 0** seems to be the most adequate as it matches better the *"Soft and No aroma"* taste of James. For this reason **cluster 0 is selected**.

Finally, **the top 5 coffees that we will recommend to James will be those closest to the median of *Sweetness*, *Flavor*, *Body*, and *Aroma*.**

```
[34]: clust0_sweet_med = agglom_df[(agglom_df['cluster'] == 0)]['Sweetness'].median()
clust0_flavor_med = agglom_df[(agglom_df['cluster'] == 0)]['Flavor'].median()
clust0_body_med = agglom_df[(agglom_df['cluster'] == 0)]['Body'].median()
clust0_aroma_med = agglom_df[(agglom_df['cluster'] == 0)]['Aroma'].median()

centroid_james = np.array([clust0_aroma_med, clust0_flavor_med,
                           clust0_body_med, clust0_sweet_med])

# Find the indexes of all coffees in cluster 0
idx_clust0 = agglom_df[(agglom_df['cluster'] == 0)].index

# map the indexes from the dataframe to the train_data
idx_clust0 = list(agglom_df.loc[idx_clust0,'train_idx'])

dist_array = np.array([idx_clust0]).T
dist_array = np.hstack((dist_array, np.zeros(shape=(len(idx_clust0),1))))

for i, dist_idx in enumerate(dist_array):
    distance = np.linalg.norm(train_data[int(dist_idx[0]),[0,1,3,7]] -␣
 ↪centroid_james)
    dist_array[i,1] = distance
```

```
[35]: # get indexes of the sorted distances
sort_idx = dist_array.argsort(axis=0)[:][:,1]

# get train_idx of the sorted distances found above
sort_idx = dist_array[sort_idx,0]

recomm_list = []
foreign_count = 0
position_dict = {}
position = 1
# get the coffees to be recommended
for coffee_idx in sort_idx:
    country = agglom_df[agglom_df['train_idx'] == coffee_idx]['Country.of.
 ↪Origin'].values[0]
    if (country == 'Brazil'):
        recomm_list.append(coffee_idx)
        position_dict[coffee_idx] = position
        position += 1
    elif (foreign_count < 3):
        recomm_list.append(coffee_idx)
        foreign_count += 1
        position_dict[coffee_idx] = position
        position += 1
    if len(recomm_list) >= 5: break
```

[36]:

```python
# Get the dataframe of recommendations for James
recomm_df3 = agglom_df[agglom_df['train_idx'].isin(recomm_list)].copy()
recomm_df3.insert(1, 'Ranking', 0)
recomm_df3['Ranking'] = recomm_df3['train_idx'].map(position_dict)
recomm_df3 = recomm_df3.sort_values(by=['Ranking'])
recomm_df3
```

[36]:

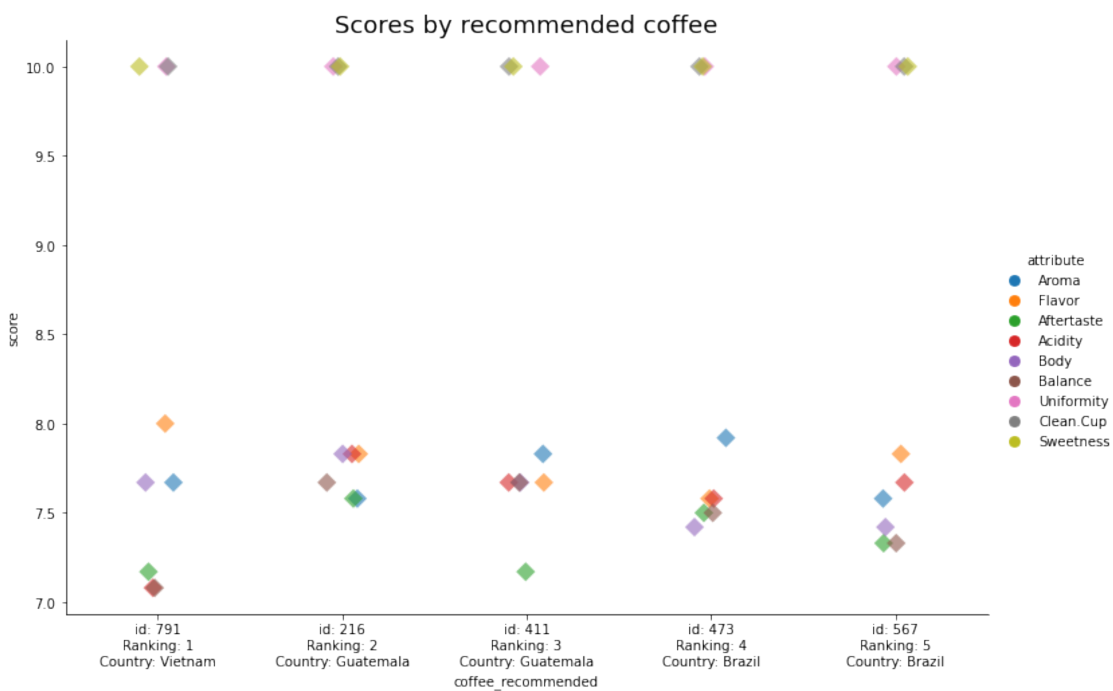
```
     Unnamed: 0  Ranking  Species                     Owner  \
650         791        1  Arabica     royal base corporation
171         216        2  Arabica  juan luis alvarado romero
333         411        3  Arabica  juan luis alvarado romero
384         473        4  Arabica                   nucoffee
461         567        5  Arabica                   cafebras

    Country.of.Origin               Farm.Name  Lot.Number              Mill  \
650           Vietnam       apollo co., ltd.         NaN  apollo co., ltd.
171         Guatemala             chapultepec  11/23/0335  beneficio ixchel
333         Guatemala           el sacramento         NaN  beneficio ixchel
384            Brazil  são francisco da serra         NaN               NaN
461            Brazil             santa fé 2         NaN          via seca

         ICO.Number                               Company  … Quakers  \
650             NaN                 royal base corporation  …     0.0
171      11/23/0335                  unex guatemala, s.a.  …     0.0
333      11/23/0419                  unex guatemala, s.a.  …     0.0
384  002/1251/0245                               nucoffee  …     0.0
461  002/1495/0695  cafebras comercio de cafés do brasil sa  …     0.0

     Color Category.Two.Defects          Expiration  \
650  Green                    2      July 23rd, 2013
171  Green                    2       June 1st, 2017
333  Green                    3  February 26th, 2014
384  Green                    4  February 16th, 2013
461  Green                    6       May 25th, 2016

                     Certification.Body altitude_low_meters  \
650         Specialty Coffee Association             1040.00
171         Asociacion Nacional Del Café             3280.00
333         Asociacion Nacional Del Café             1310.64
384                             NUCOFFEE              950.00
461  Brazil Specialty Coffee Association              900.00

    altitude_high_meters altitude_mean_meters cluster train_idx
650              1040.00              1040.00       0       649
171              3280.00              3280.00       0       171
333              1310.64              1310.64       0       332
384               950.00               950.00       0       383
```

461   900.00   900.00   0   460

[5 rows x 42 columns]

[37]:
```
plt.figure(figsize = (16, 10))

df = recomm_df3.iloc[:,[0,1,4]+list(range(20,29))].copy()
df['coffee_recommended'] = ('id: ' + df['Unnamed: 0'].astype(str) + \
                            '\nRanking: ' + df['Ranking'].astype(str) +\
                            '\nCountry: ' + df['Country.of.Origin'].astype(str))

df.drop(['Unnamed: 0','Ranking','Country.of.Origin'], axis=1, inplace=True)
df = df.melt('coffee_recommended', var_name='attribute',  value_name='score')

g = sns.catplot(x='coffee_recommended', y='score', hue='attribute', data=df,
                height=7, aspect=1.5, s=10, kind='strip', alpha=0.6, marker='D')
plt.title("Scores by recommended coffee", size=18)
plt.show()
```

<Figure size 1152x720 with 0 Axes>



0.0.2 PCA visualization

In order to have an idea of the obtained clusters, PCA will be used to reduce the dimensionality into 2 principal components, which will allow to visualize the data. The results below show that the first components explain just below 50% of the variation in the data, which means that still there is a lot left unexplained by this first 2 components, however, it is a way to visualize how the hierarchical clustering is grouping the data.

[38]:
```
from sklearn.decomposition import PCA

pca_coffee = PCA(n_components=2)
train_data = np.delete(train_data, 1078, axis=0) # remove idx 1078 which was␣
↪removed previously
princ_components = pca_coffee.fit_transform(train_data)

pca_df = pd.DataFrame(data = princ_components,
                      columns = ['princ_comp1', 'princ_comp2'])
```

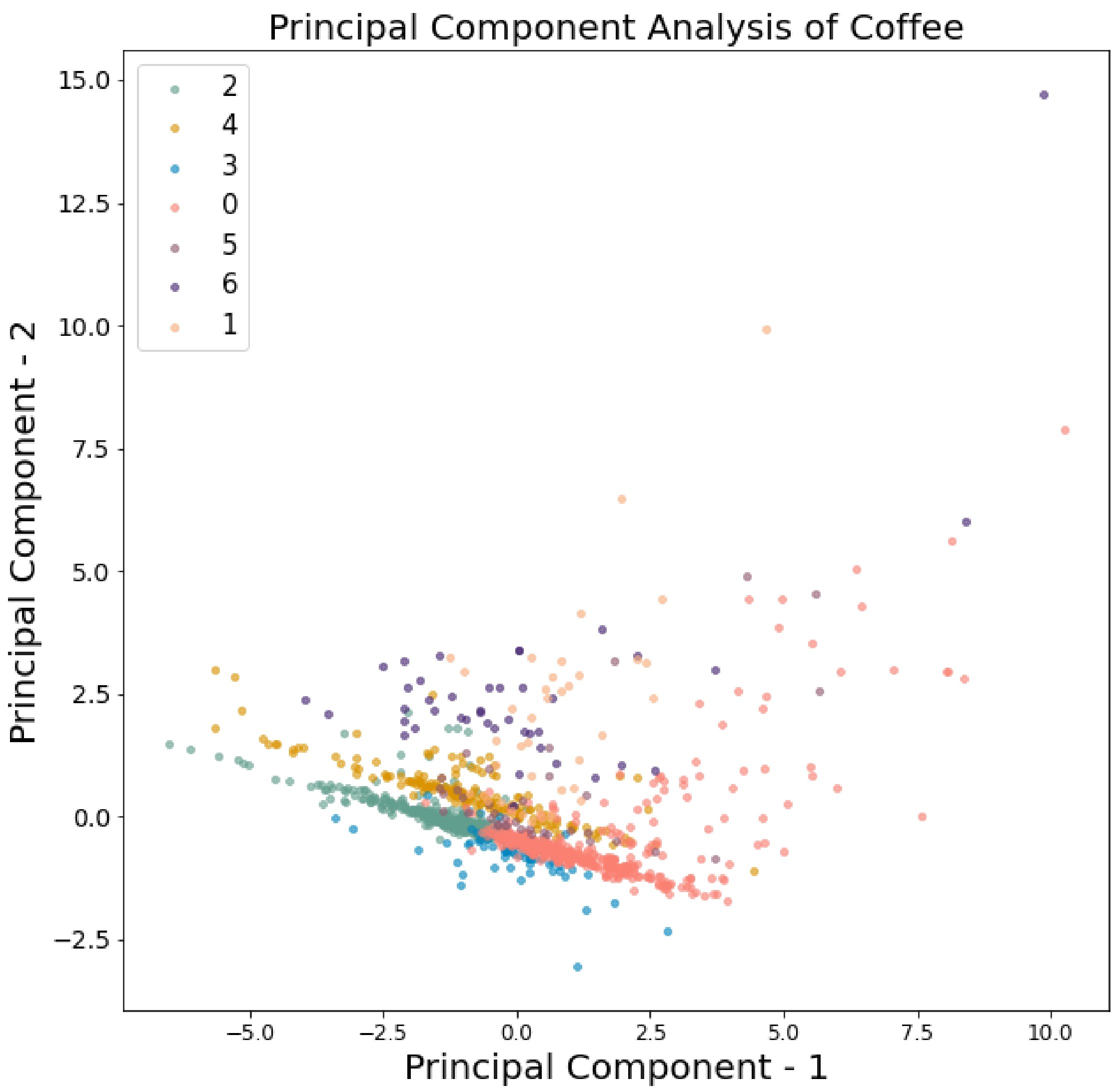
[39]:
```
print('Explained variation per principal component: {}'.format(pca_coffee.
↪explained_variance_ratio_))
```

```
Explained variation per principal component: [0.3310197  0.12730694]
```

[40]:
```
plt.figure()
plt.figure(figsize=(10,10))
plt.xticks(fontsize=12)
plt.yticks(fontsize=14)
plt.xlabel('Principal Component - 1',fontsize=20)
plt.ylabel('Principal Component - 2',fontsize=20)
plt.title("Principal Component Analysis of Coffee",fontsize=20)
targets = list(agglom_df.cluster.unique())
colors =␣
↪['#619e8d','#da9300','#0086bf','#fa8072','#925c70','#432371',"#FAAE7B"] #␣
↪['r', 'g']
for target, color in zip(targets,colors):
    indicesToKeep = agglom_df['cluster'] == target
    plt.scatter(pca_df.loc[indicesToKeep.values, 'princ_comp1'],
                pca_df.loc[indicesToKeep.values, 'princ_comp2'],
                c = color, s = 15, alpha=0.6)

plt.legend(targets,prop={'size': 15})
```

[40]:
```
<matplotlib.legend.Legend at 0x1a23737b38>
```

```
<Figure size 432x288 with 0 Axes>
```



The graph for the first 2 components shows that there is a lot of overlapping in the middle, however, **clusters 0, 1, 2, 4, and 6** seem to have some defined regions, while the **clusters 3 and 5** have more overlap with the others.

Plot recommended coffees

[41]:
```
recomm_df['Target'] = 'Marcio+Rafa'
recomm_df2['Target'] = 'Subu'
recomm_df3['Target'] = 'James'
all_recomm_df = pd.concat([recomm_df,recomm_df2,recomm_df3],
                          ignore_index=True, sort=False)
all_recomm_df
```

[41]:

```
    Unnamed: 0  Ranking  Species                       Owner  \
0         1375        1  Arabica              byron gonzalez
1         1369        2  Arabica  angelica paola citan lopez
2          262        3  Arabica             ipanema coffees
3          319        4  Arabica             ipanema coffees
4          481        5  Arabica             ipanema coffees
5          602        1  Arabica         romulo bello flores
6          556        2  Arabica  veronica lopez castillejos
7          520        3  Arabica        santiago solis ayerdi
8          713        4  Arabica             ipanema coffees
9         1076        5  Arabica    jacques pereira carneiro
10         791        1  Arabica       royal base corporation
11         216        2  Arabica    juan luis alvarado romero
12         411        3  Arabica    juan luis alvarado romero
13         473        4  Arabica                    nucoffee
14         567        5  Arabica                    cafebras

   Country.of.Origin                  Farm.Name  Lot.Number  \
0          Guatemala                   alta luz   415000544
1          Guatemala  finca beneficio el torreon   11/23/267
2             Brazil                capoeirinha     007/16E
3             Brazil                capoeirinha     008/16A
4             Brazil                capoeirinha      261/15
5             Mexico                        NaN         NaN
6             Mexico                  el jabali         NaN
7             Mexico          finca la estancia         NaN
8             Brazil                  rio verde         NaN
9             Brazil        pereira estate coffee         NaN
10           Vietnam            apollo co., ltd.         NaN
11         Guatemala                chapultepec  11/23/0335
12         Guatemala               el sacramento         NaN
13            Brazil      são francisco da serra         NaN
14            Brazil                 santa fé 2         NaN

                          Mill      ICO.Number  \
0                          NaN      11-63-1073
1             beneficio ixchel       11/23/267
2                     dry mill   002/1660/0105
3                     dry mill   002/1660/0106
4                     dry mill   002/1660/0049
5                          NaN      1302910536
6          comunidad la cumbre            1489
7   atoyac de alvarez, guerrero      1302911347
8              ipanema coffees   002/1660/0107
9       carapina armazens gerais  002/135-2/0182
10            apollo co., ltd.             NaN
11            beneficio ixchel      11/23/0335
```

```
12            beneficio ixchel      11/23/0419
13                         NaN   002/1251/0245
14                    via seca   002/1495/0695

                                    Company  …         Color  \
0            retrillas del pacifico, s. a.  …        Green
1              asociación nacional del cafe  …        Green
2                          ipanema coffees  …         Green
3                          ipanema coffees  …         Green
4                          ipanema coffees  …  Bluish-Green
5                              cafe shunuc  …           NaN
6        union de ejidos san fernando de ri  …         Green
7                        finca la estancia  …         Green
8                          ipanema coffees  …         Green
9   exportadora de cafés carmo de minas ltda  …          None
10                   royal base corporation  …         Green
11                     unex guatemala, s.a.  …         Green
12                     unex guatemala, s.a.  …         Green
13                                 nucoffee  …         Green
14   cafebras comercio de cafés do brasil sa  …         Green

   Category.Two.Defects           Expiration  \
0        5 full defects      July 20th, 2021
1        4 full defects     March 19th, 2022
2                     7    August 16th, 2017
3                     3    August 16th, 2017
4                     2     April 25th, 2017
5                     4       June 6th, 2013
6                     4      March 5th, 2013
7                     7      July 26th, 2013
8                     0    October 7th, 2016
9                    10     April 17th, 2015
10                    2      July 23rd, 2013
11                    2       June 1st, 2017
12                    3  February 26th, 2014
13                    4  February 16th, 2013
14                    6       May 25th, 2016

                  Certification.Body altitude_low_meters  \
0          Asociacion Nacional Del Café             1400.00
1          Asociacion Nacional Del Café             1901.00
2   Brazil Specialty Coffee Association              934.00
3   Brazil Specialty Coffee Association              934.00
4   Brazil Specialty Coffee Association              905.00
5                               AMECAFE            1200.00
6                               AMECAFE            1400.00
7                               AMECAFE            1200.00
```

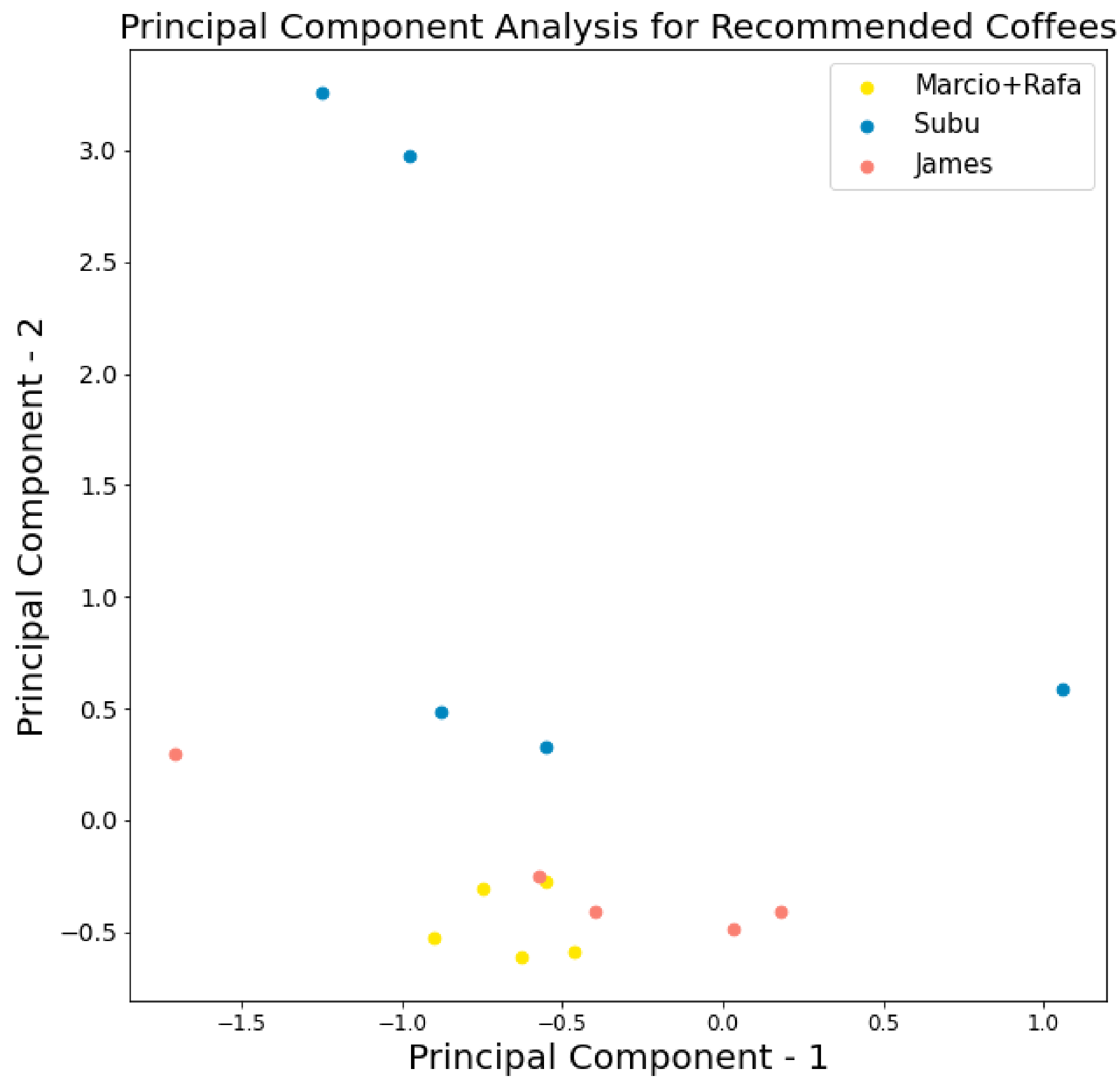
```
8          Specialty Coffee Association            1268.00
9          Specialty Coffee Association            1250.00
10         Specialty Coffee Association            1040.00
11         Asociacion Nacional Del Café            3280.00
12         Asociacion Nacional Del Café            1310.64
13                             NUCOFFEE             950.00
14  Brazil Specialty Coffee Association             900.00

   altitude_high_meters altitude_mean_meters cluster train_idx       Target
0               1400.00              1400.00       3      1141  Marcio+Rafa
1               1901.00              1901.00       3      1135  Marcio+Rafa
2                934.00               934.00       3       209  Marcio+Rafa
3                934.00               934.00       3       256  Marcio+Rafa
4                905.00               905.00       3       390  Marcio+Rafa
5               1200.00              1200.00       1       493         Subu
6               1400.00              1400.00       1       451         Subu
7               1200.00              1200.00       1       423         Subu
8               1268.00              1268.00       1       583         Subu
9               1250.00              1250.00       1       893         Subu
10              1040.00              1040.00       0       649        James
11              3280.00              3280.00       0       171        James
12              1310.64              1310.64       0       332        James
13               950.00               950.00       0       383        James
14               900.00               900.00       0       460        James

[15 rows x 43 columns]
```

[42]:

```python
plt.figure()
plt.figure(figsize=(10,10))
plt.xticks(fontsize=12)
plt.yticks(fontsize=14)
plt.xlabel('Principal Component - 1',fontsize=20)
plt.ylabel('Principal Component - 2',fontsize=20)
plt.title("Principal Component Analysis for Recommended Coffees",fontsize=20)
targets = ['Marcio+Rafa', 'Subu', 'James']
colors = ['#ffe700','#0086bf','#fa8072'] # ['r', 'g']
for target, color in zip(targets,colors):
    indicesToKeep = all_recomm_df[all_recomm_df['Target'] == target].train_idx.
 ↪values
    plt.scatter(pca_df.loc[indicesToKeep, 'princ_comp1'],
                pca_df.loc[indicesToKeep, 'princ_comp2'],
                c = color, s = 45, alpha=1)

plt.legend(targets,prop={'size': 15})
```

[42]: <matplotlib.legend.Legend at 0x1a23737c18>

<Figure size 432x288 with 0 Axes>



The plot of the first 2 principal components shows that the recommendations for Marcio and Rafa are very close to each other while Subu's recommendations seem to have a separate region but are more spread. Finally, James recommendations present some overlapping with Marcio's group. However, this results need to be carefully considered because as it was seen before, the first 2 components are explaining just around 46% of the variation in the data, and are used to have a visual idea of the clusters.

0.0.3 Conclusion and Final comments

This task has focused on the following parts:

1. Scrapping data for Robusta and Arabica coffee

2. Cleaning the scrapped data
3. Join new data with previously cleaned data
4. Classification and clustering of the different coffee types: Two different algorithms were evaluated, K-means and Hierarchical clustering (agglomerative). Since validating the quality of the clustering is a challenging task (silhouette score was not a successful metric), a new metric was implemented where the algorithm producing the highest percentage of *Sul de Minas* coffees in a single cluster was selected.
5. Recommendations for different coffee preferences: After selecting the clustering algorithm, the top 5 coffees were recommended for each preferences profile. Different metrics like *Region, Sweetness, Aroma, etc* were used to find the best cluster and specific coffees to recommend.
6. PCA for visualization: Using the first 2 principal components, the clusters were visualized, as well as the coffees recommended to each of the members of the team. (It is important to consider that the first 2 components account for around 46% of the variability in the dataset, and they were mainly used for visualization purposes)

Finally two limitations that may be addressed for the future are: * Mixing categorical data with continuous is not easy task in clustering, one could use one-hot encoding to include for example the Region which is important for the task, and perhaps look for a mixed approach with K-modes, however, the dimensionality would increase considerably by including all the one-hot encoded variables from Region and finding clusters in such a big dimension space can be very difficult, specially for the limited amount of data available (around 1.5K observations). Can a different approach be used for including the region variable, like a one-hot encoding that groups several regions together? * Given the limitations of the data set, a future approach to consider could be some dimensionality reduction method like PCA as a way to create more dense regions with the clustering algorithms.

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