Santiago_Gabriela

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[219]:
```
#This jupyter notebook was prepared by "Gabriela Santiago".
```

1 1.) Load Data and perform basic EDA

import libraries necessary libraries

[220]:
```
 %matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import scipy.stats as st
import sklearn
import missingno as msno
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from scipy.spatial import distance_matrix
from sklearn.metrics import confusion_matrix
import scipy.cluster.hierarchy as shc
from sklearn.cluster import AgglomerativeClustering
```

import the data to a dataframe and show the count of rows and columns (1 pt)

[221]:
```
df = pd.read_csv('hrdata3.csv')
print("Rows: ", len(df))
print("Columns: ", len(df.columns))
```

```
Rows:  12977
Columns:  8
```

Show the top 5 and last 5 rows (1 pt)

[222]:
```
df.head()
```

[222]:

	Unnamed: 0	enrollee_id	city_development_index	experience	company_size	\
0	1	29725	0.776	15	2	
1	4	666	0.767	21	2	
2	6	28806	0.920	5	2	
3	7	402	0.762	13	0	

```
4           8        27107                    0.920           7              2

   last_new_job  training_hours  target
0             5              47     0.0
1             4               8     0.0
2             1              24     0.0
3             5              18     1.0
4             1              46     1.0
```

[223]:
```
df.tail()
```

[223]:
```
       Unnamed: 0  enrollee_id  city_development_index  experience  \
12972       19149          251                   0.920           9
12973       19150        32313                   0.920          10
12974       19152        29754                   0.920           7
12975       19155        24576                   0.920          21
12976       19156         5756                   0.802           0

       company_size  last_new_job  training_hours  target
12972             2             1              36     1.0
12973             3             3              23     0.0
12974             1             1              25     0.0
12975             2             4              44     0.0
12976             4             2              97     0.0
```

Is there any null values on any column?

[224]:
```
nulls = df.isnull().sum().to_frame('nulls')
nulls.sort_values("nulls", inplace = True, ascending = False)
for index, column in nulls.iteritems():
    print("Number of columns containing null values: ", column[0])
```

```
Number of columns containing null values:  0
```

Are all the columns numeric such as float or int? If not, please convert them to int before going to the next step.

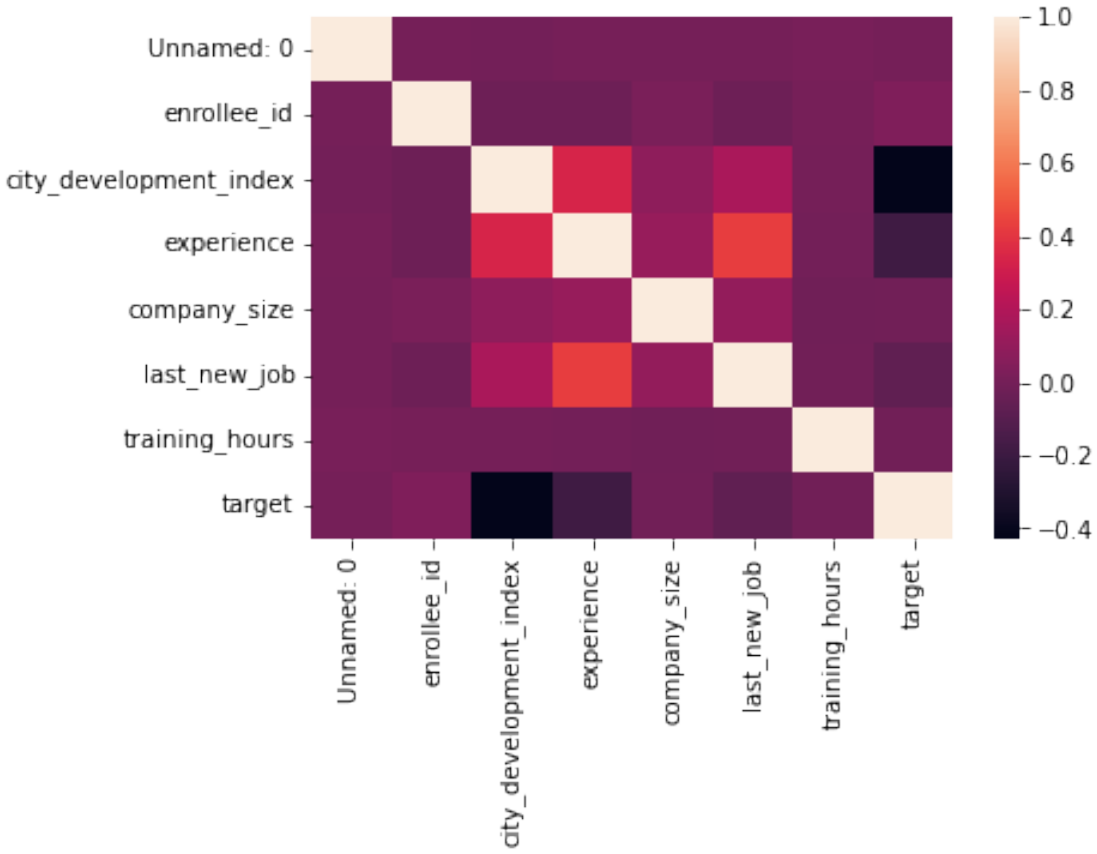
[225]:
```
numerical = df.select_dtypes(include=[np.number])
print("Numerical columns", len(numerical.columns))
print("Total columns", len(df.columns))
#Yes all columns are numerical
```

```
Numerical columns 8
Total columns 8
```

plot the heatmap with correlations to get some more idea about the data.

[226]:
```
correlation = df.corr()
sns.heatmap(correlation)
```

[226]: <AxesSubplot:>



2 2.) Feature Selection and Pre-processing

Put all the data from the dataframe into X, except the enrolle_id and the target columns

[227]:
```
y = df['target']
x = df
x = x.drop(columns = ['target'])
x = x.drop(columns = ['enrollee_id'])
#Also dropping the unnamed column that has meaningless values
x = x.iloc[: , 1:]
df = df.iloc[: , 1:]
```

Perform feature scaling on the data of X with StandardScaler and show some sample data from X after scaling (Use the technique shown in the second answer from this post:

[228]:
```
scaler = StandardScaler()
scaler.fit(x)
scaledx = scaler.transform(x)
```

```
print(scaledx)
```

```
[[-0.50342203  0.63395707 -0.5747232   1.69076217 -0.30839586]
 [-0.57841303  1.54600905 -0.5747232   1.08113696 -0.95180478]
 [ 0.69643399 -0.88612956 -0.5747232  -0.74773864 -0.68784215]
 …
 [ 0.69643399 -0.58211224 -1.0314958  -0.74773864 -0.67134448]
 [ 0.69643399  1.54600905 -0.5747232   1.08113696 -0.35788885]
 [-0.28678136 -1.64617288  0.338822   -0.13811344  0.51648738]]
```

3 3.) KMeans Clustering

Import related library for Kmeans and perform Kmeans on X (note that it was scaled already). Make sure to put random_state = 47 (it can be any number, but use 47 so that you will produce almost the same result as us). Use k-means++ for the initial centroids. You should know from the problem description how many clusters we are interested in.

[229]:
```
kmeans1 = KMeans(n_clusters=2, random_state=47, init='k-means++').fit(scaledx)
```

Show the cluster centers as it is and then inverse the scale and show the centers. Please explain in words about the centers relating them to the columns of the data set

[230]:
```
print(kmeans1.cluster_centers_)
```

```
[[-0.31364817 -0.63941844 -0.15207764 -0.55076921  0.01170319]
 [ 0.44177356  0.90062111  0.21420141  0.77575864 -0.01648395]]
```

[231]:
```
inversed = scaler.inverse_transform(scaledx)
kmeans2 = KMeans(n_clusters=2, random_state=47, init='k-means++').fit(inversed)
print(kmeans2.cluster_centers_)
```

```
[[  0.83639888  10.83377685   3.26905531   2.23474625  41.97690553]
 [  0.83649939  10.81099796   3.21181263   2.19144603 167.34052953]]
```

4 Answer:

It appears that the training hours column was a big deciding factor on which cluster each point went to. All the other centers are pretty similar, but the training hours one has a difference of more than 100.

Show the distance matrix

[232]:
```
#Scaled distance matrix
kmeans1.transform(scaledx)
```

[232]:
```
array([[2.6387601 , 1.58409296],
       [2.93535149, 1.74579189],
       [1.3371321 , 2.57904978],
       …,
```

```
       [1.51732572, 2.56222519],
       [2.96221279, 1.14612076],
       [1.2962834 , 2.85511871]])
```

[233]:
```
#Inversed distance matrix
kmeans2.transform(inversed)
```

[233]:
```
array([[  7.20067157, 120.45227649],
       [ 35.53186796, 159.68082008],
       [ 18.98273357, 143.46835926],
       …,
       [ 17.59526544, 142.41372365],
       [ 10.59144068, 123.77983809],
       [ 56.08477703,  71.17110968]])
```

Show the labels

[234]:
```
#Scaled
kmeans1.labels_
```

[234]:
```
array([1, 1, 0, …, 0, 1, 0], dtype=int32)
```

[235]:
```
#Inversed
kmeans2.labels_
```

[235]:
```
array([0, 0, 0, …, 0, 0, 0], dtype=int32)
```

Add a new column to your data frame called cluster_label and assign the cluster label for the instances based on the K-means cluster label

[236]:
```
df['cluster_label'] = kmeans2.labels_.tolist()
```

The target column of our data frame is floating-point numbers. So, this number is not comparable with the cluster label. Add a column target_int and write a function or use a strategy to store the int version of the target column into the target_int column

[237]:
```
yt = df['target']
df['target_int'] = yt.tolist()
df['target_int'] = df['target_int'].fillna(0).astype(int)
```

Show the top 5 rows of the dataframe now that shows you have added those two columns and they have the correct values

[238]:
```
df.head()
```

[238]:

	enrollee_id	city_development_index	experience	company_size	\
0	29725	0.776	15	2	
1	666	0.767	21	2	
2	28806	0.920	5	2	
3	402	0.762	13	0	

```
4        27107                    0.920           7              2

   last_new_job  training_hours  target  cluster_label  target_int
0             5              47     0.0              0           0
1             4               8     0.0              0           0
2             1              24     0.0              0           0
3             5              18     1.0              0           1
4             1              46     1.0              0           1
```

Now, we would like to compare the cluster label with the ground truth. Print confusion matrix that compares the target_int and the cluster_label, show the classification_report, and then show the total number of misclassification.

[239]:
```
print("Confusion Matrix: ")
tn, fp, fn, tp = confusion_matrix(df['cluster_label'], df['target_int']).ravel()
confusion_matrix(df['cluster_label'], df['target_int'])
```

```
Confusion Matrix:
```

[239]:
```
array([[8657, 1865],
       [2038,  417]])
```

[240]:
```
print("Misclassification count: ", fp+fn)
```

```
Misclassification count:  3903
```

Discuss the numbers from 3 Viii and any thoughts on it.

5 Answer:

It doesn't predict very well but it predicts much better than when I left that unnamed column with random values in the dataframe.

Show the inertia of the cluster

[241]:
```
print("Inertia: ", kmeans2.inertia_)
```

```
Inertia:  17054415.5567321
```

What is the elbow method and what is its purpose of it in the case of KMeans clustering?

6 Answer:

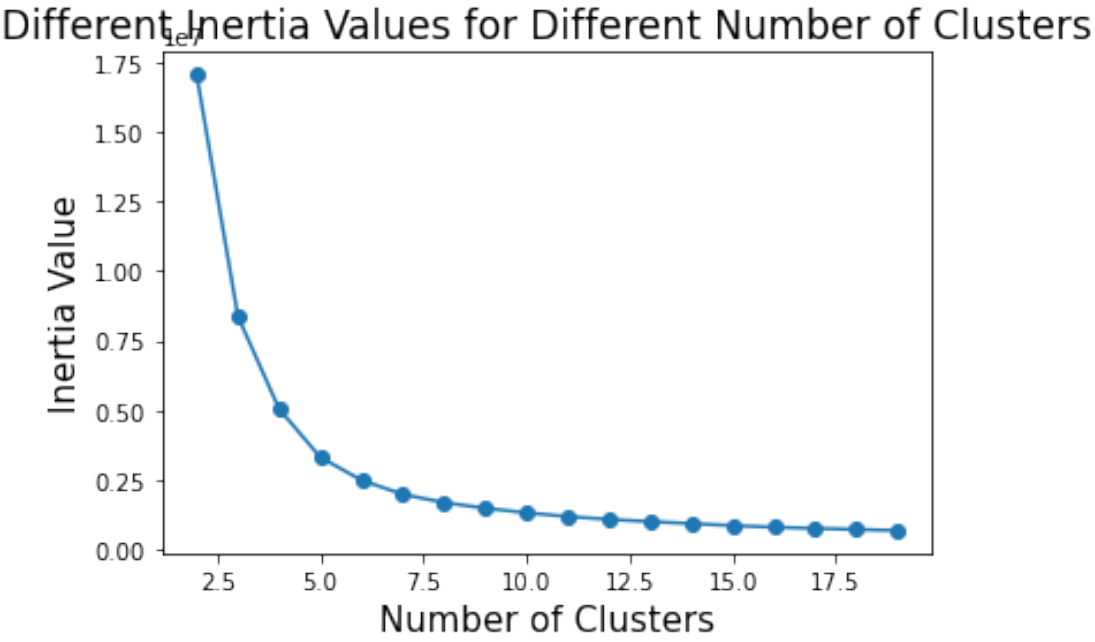
Elbow method is a method of determining the most optimal value of k when clustering. When plotting the inertia vs the values of k, it takes the point where the inertia stops decreasing in a steep linear fashion. That is considered the elbow of the graph and the best value for k.

Although we just wanted 2 clusters, we still would like to see what will happen if you increase the number of clusters. Plot the inertia for the different numbers of clusters from 2 to 20.

[242]:
```
inertia_list = []
for num_clusters in range(2, 20):
    kmeans_model = KMeans(n_clusters=num_clusters, init="k-means++",␣
 ↪random_state=47)
    kmeans_model.fit(inversed)
    inertia_list.append(kmeans_model.inertia_)
```

[243]:
```
plt.plot(range(2,20),inertia_list)
plt.scatter(range(2,20),inertia_list)
plt.xlabel("Number of Clusters", size=15)
plt.ylabel("Inertia Value", size=15)
plt.title("Different Inertia Values for Different Number of Clusters", size=17)
```

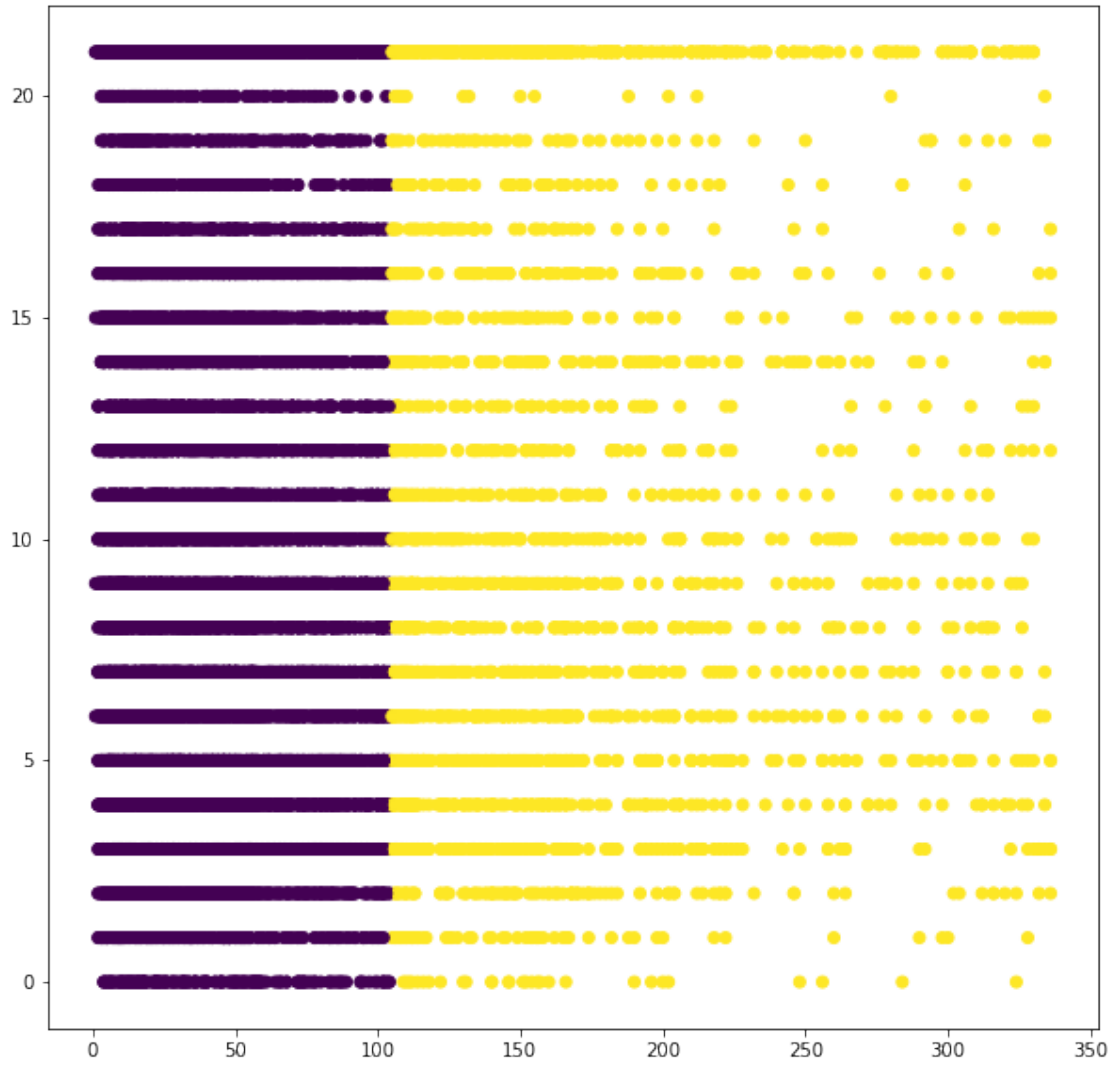
[243]:
```
Text(0.5, 1.0, 'Different Inertia Values for Different Number of Clusters')
```



Show a scatter plot with training hours against experience where the points should be colored based on the two cluster labels. Write any thoughts on this plot.

[244]:
```
plt.figure(figsize=(10, 10))
plt.scatter(df['training_hours'], df['experience'], c=kmeans2.labels_)
```

[244]:
```
<matplotlib.collections.PathCollection at 0x7fea23c66250>
```



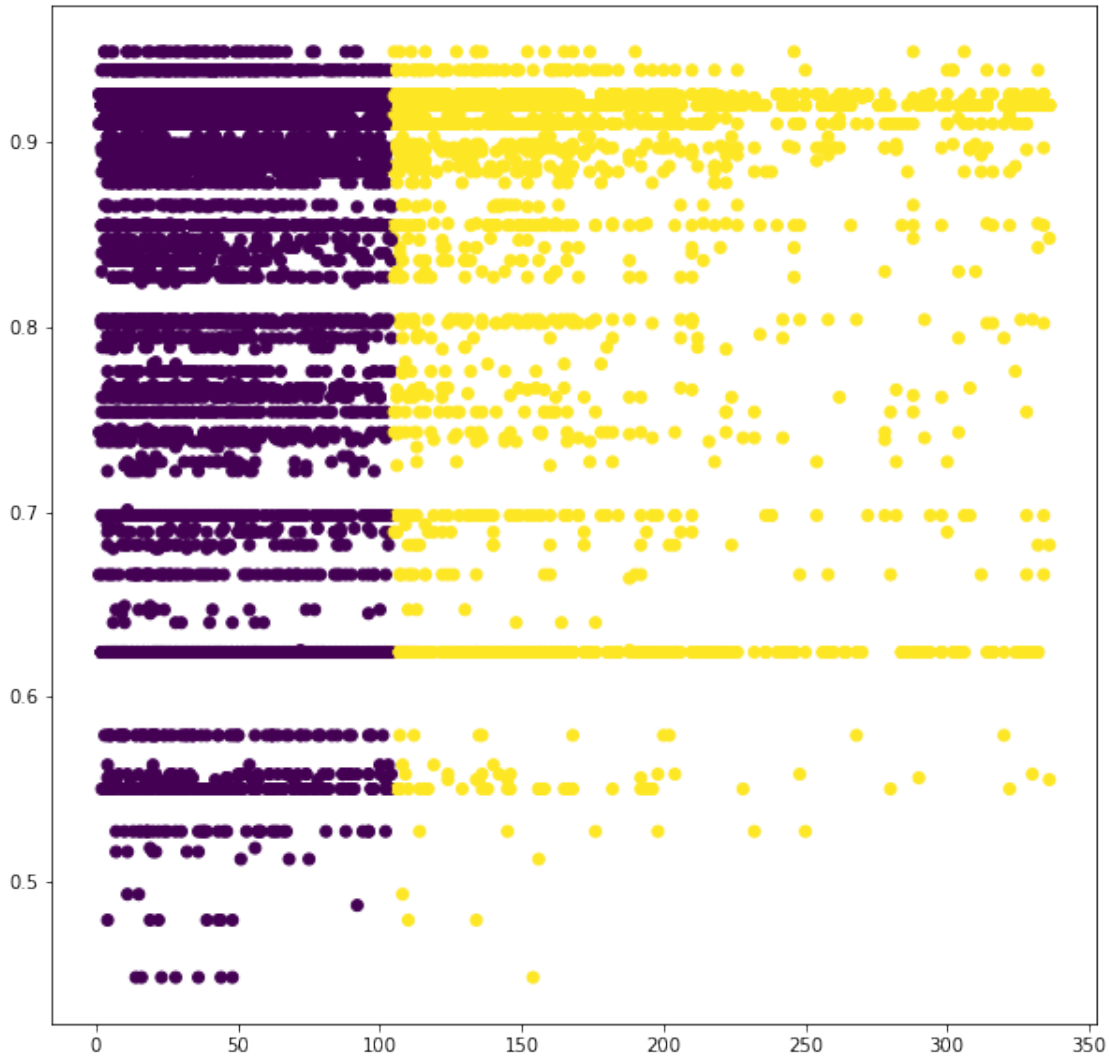
7 Answer:

Very clear that training hours is a huge deciding factor for what cluster a datapoint is in

Show a scatter plot with any other two attributes you are interested in like 3 Xiii and add your thoughts on your plot as well

[245]:
```
plt.figure(figsize=(10, 10))
plt.scatter(df['training_hours'], df['city_development_index'], c=kmeans2.
 ↪labels_)
```

[245]:
```
<matplotlib.collections.PathCollection at 0x7febb9167f40>
```



8 Answer

My thoughts are that after playing with scatterplots for each attribute, this clustering method put a little too much faith in the training hours column as the clusters look more like walls where the training hours reach around 110.

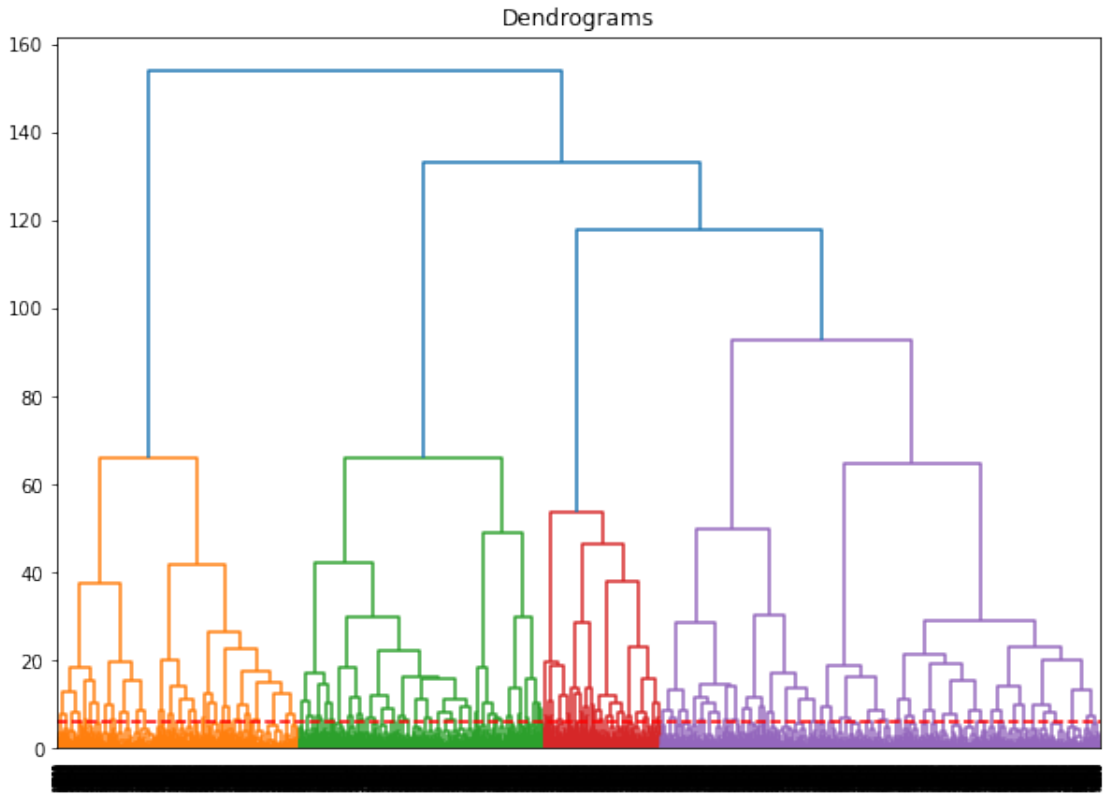
9 4.) AgglomerativeClustering

Plot a dendrogram

[246]:
```
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dend = shc.dendrogram(shc.linkage(scaledx, method='ward'))
```

```
plt.axhline(y=6, color='r', linestyle='--')
```

[246]: <matplotlib.lines.Line2D at 0x7febb9149820>



Perform AgglomerativeClustering with 2 clusters first, and use euclidean distance for affinity and linkage = 'ward'

[247]:
```
clustering = AgglomerativeClustering(n_clusters = 2, linkage = 'ward', affinity␣
↪= 'euclidean').fit(inversed)
tn, fp, fn, tp = confusion_matrix(clustering.labels_, df['target_int']).ravel()
```

[248]:
```
print("Misclassification count: ", fp+fn)
```

```
Misclassification count:  3272
```

After creating the clusters, plot training hours against experience like 3.Xiii and discuss if anything interesting

[249]:
```
plt.figure(figsize=(10, 10))
plt.scatter(df['training_hours'], df['experience'], c=clustering.labels_)
```

[249]: <matplotlib.collections.PathCollection at 0x7fea2ebb71f0>

10 Answer:

What's interesting is that this one bumped up the cluster decision wall to around 140. This one also has a better misclassification score so that must have been a good idea.

Then, increase the number of clusters to 4 or 5 and build the clusters again and plot them again to see any difference.

[250]:
```
clustering2 = AgglomerativeClustering(n_clusters = 4, linkage = 'ward',␣
↪affinity = 'euclidean').fit(inversed)
```

[251]:
```
plt.figure(figsize=(10, 10))
plt.scatter(df['training_hours'], df['experience'], c=clustering2.labels_)
```

[251]: <matplotlib.collections.PathCollection at 0x7fe9f9f69f70>