1 - Univariate analysis

In [2]:
```python
# Libraries needed  at this stage
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [3]:
```python
CC_df = pd.read_excel('Credit Card Customer Data.xlsx')
```

In [4]:
```python
CC_df.head()
```

Out[4]:

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
0	1	87073	100000	2	1	1	0
1	2	38414	50000	3	0	10	9
2	3	17341	50000	7	1	3	4
3	4	40496	30000	5	1	1	4
4	5	47437	100000	6	0	12	3

In [5]:
```python
CC_df.shape
```

Out[5]:
```
(660, 7)
```

In [6]:
```python
CC_df.info()
# Great : no null values and all columns are numerical !
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 660 entries, 0 to 659
Data columns (total 7 columns):
Sl_No                  660 non-null int64
Customer Key           660 non-null int64
Avg_Credit_Limit       660 non-null int64
Total_Credit_Cards     660 non-null int64
Total_visits_bank      660 non-null int64
Total_visits_online    660 non-null int64
Total_calls_made       660 non-null int64
dtypes: int64(7)
memory usage: 36.2 KB
```

In [7]:
```python
CC_df.describe().transpose()
```

Out[7]:

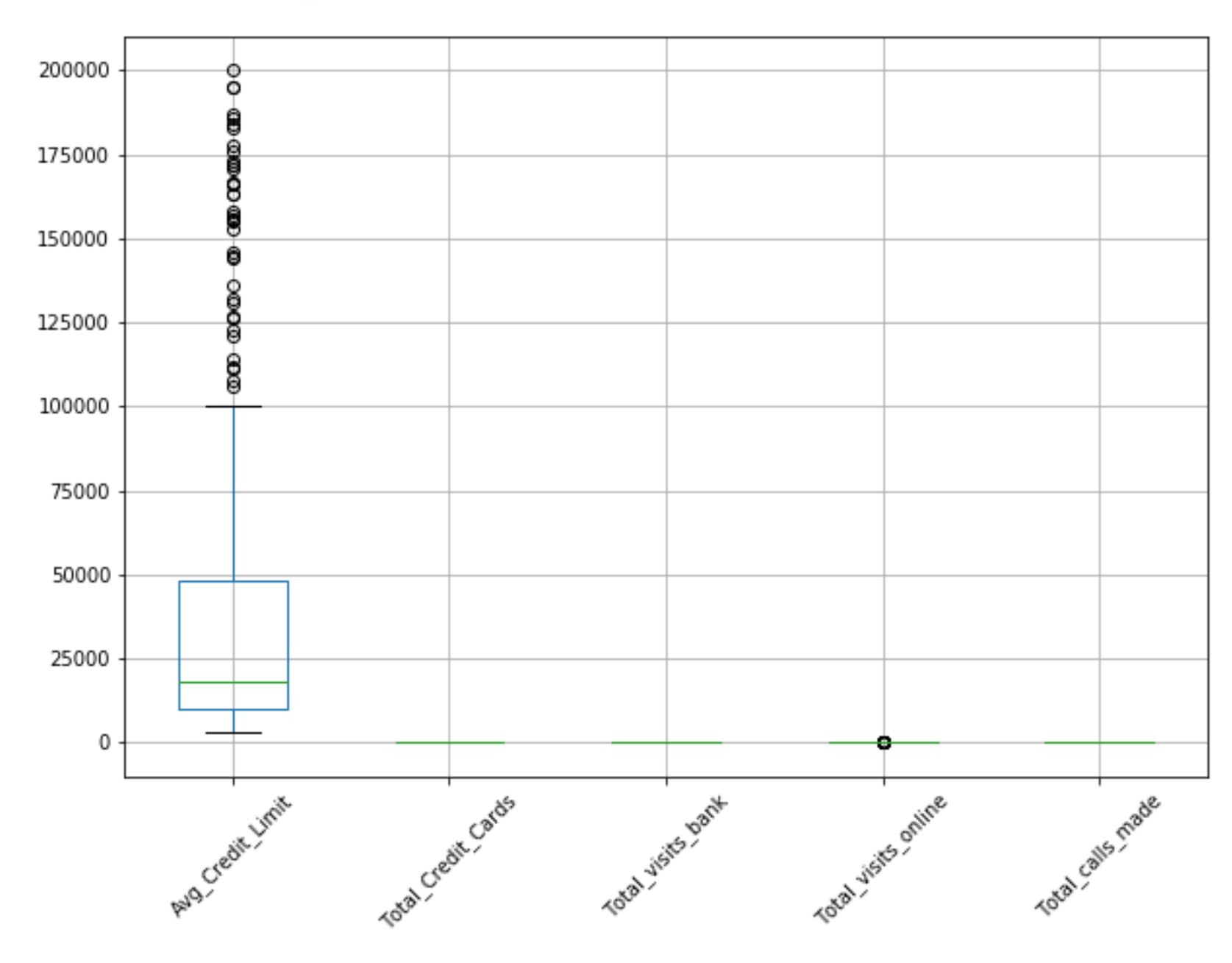
	count	mean	std	min	25%	50%	75%	max
Sl_No	660.0	330.500000	190.669872	1.0	165.75	330.5	495.25	660.0
Customer Key	660.0	55141.443939	25627.772200	11265.0	33825.25	53874.5	77202.50	99843.0
Avg_Credit_Limit	660.0	34574.242424	37625.487804	3000.0	10000.00	18000.0	48000.00	200000.0
Total_Credit_Cards	660.0	4.706061	2.167835	1.0	3.00	5.0	6.00	10.0
Total_visits_bank	660.0	2.403030	1.631813	0.0	1.00	2.0	4.00	5.0
Total_visits_online	660.0	2.606061	2.935724	0.0	1.00	2.0	4.00	15.0
Total_calls_made	660.0	3.583333	2.865317	0.0	1.00	3.0	5.00	10.0

In [ ]:
```python
# Outlier and skewness : mean > or < median .
# Mostly with : Avg_Credit_Limit !
```

In [36]:
```python
# drop the columns :   'SI_no'   and 'Customer Key'.
# as they do not hold information of customer types
X = CC_df.drop( ['Sl_No','Customer Key'], axis =1 )
```

In [37]:
```python
# Graphical representation
X.boxplot(figsize=(10 , 7), rot=45)

# Confimration : Avg_Credit_Limit has MANY outliers
# Reliasation :  The need of Rescaling is very OBVIOUS too .
```

Out[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a24408690>
```



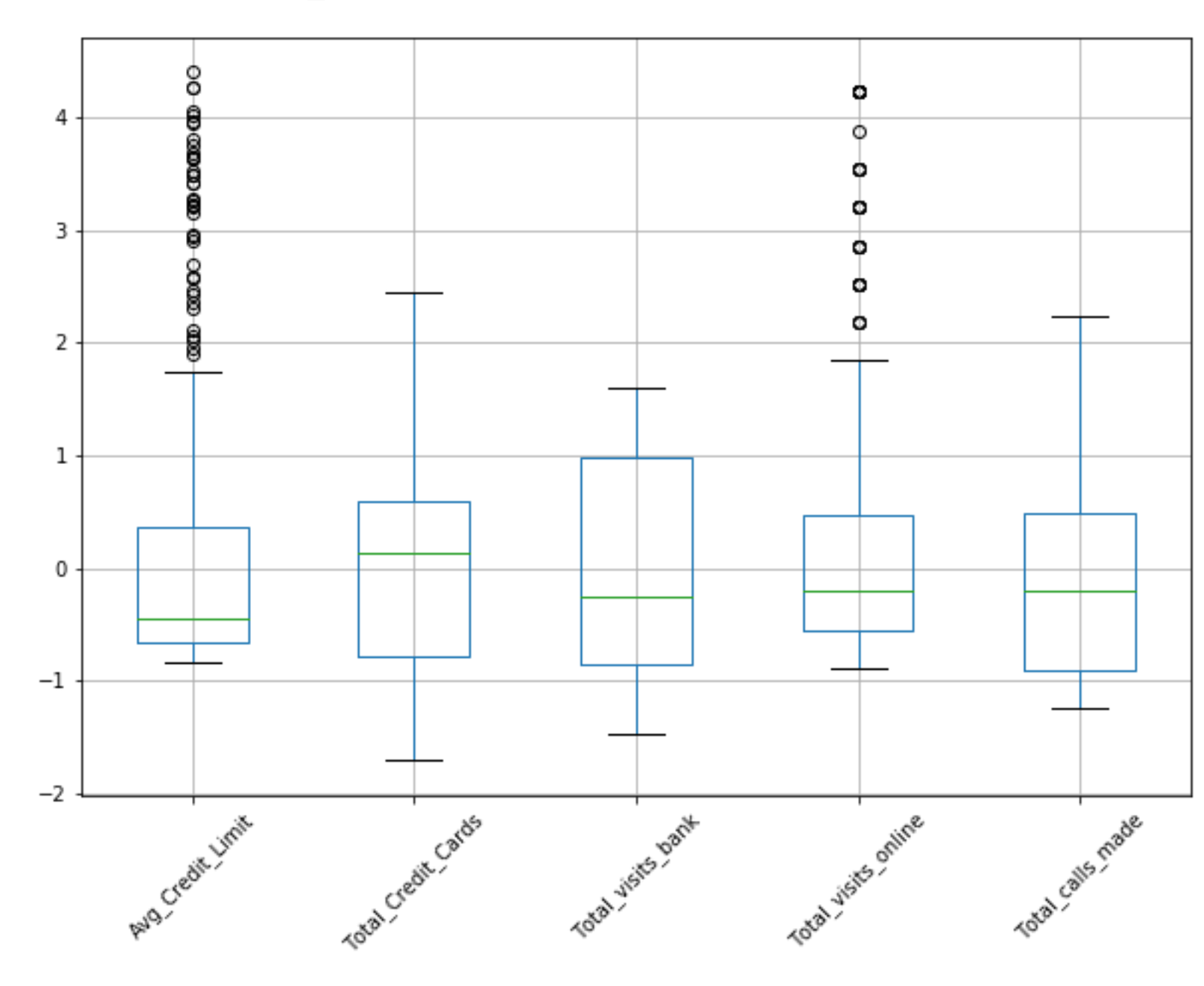
2 - Re-scaling the Data and performing Bi-variate Analysis

In [39]:
```python
# Library needed for rescaling
from scipy import stats
from scipy.stats import zscore
```

In [40]:
```python
X_scaled = X.apply(zscore)
```

In [41]:
```python
X_scaled.boxplot(figsize=(10 , 7), rot=45)
```

Out[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a24317250>
```



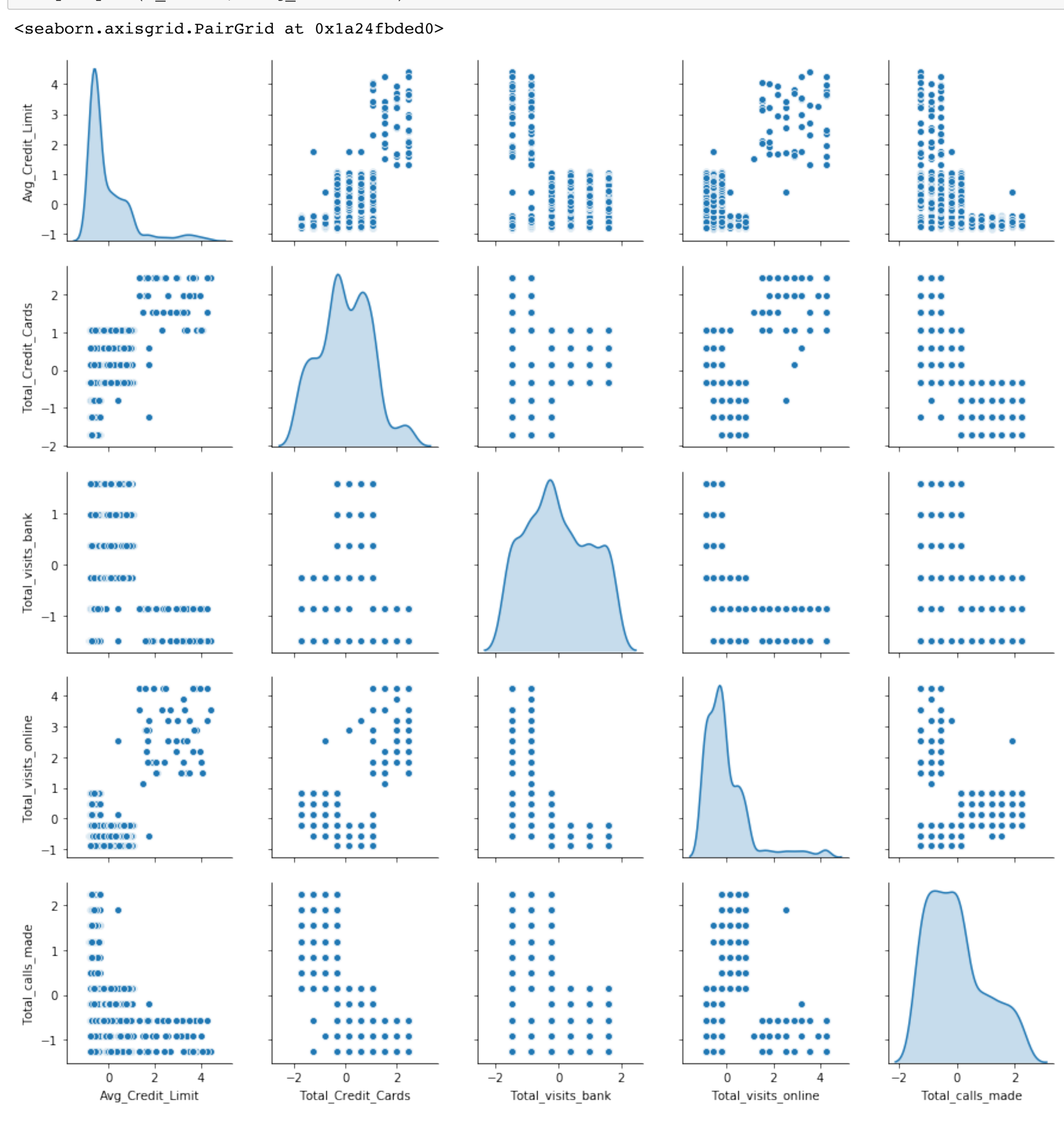
In [ ]:
```python
# REMARK :
# Initiitially I had trimmed from the X_scaled dataframe all values beyond 3 Standard deviiations form their means.
# But After consideration : I thought those customers with extreme values could be a NICHE or CLUSTER! SO I kept them
```

In [47]:
```python
X_scaled.shape
```

Out[47]:
```
(660, 5)
```

In [46]:
```python
sns.pairplot(X_scaled, diag_kind="kde")
```

Out[46]:
```
<seaborn.axisgrid.PairGrid at 0x1a24fbded0>
```



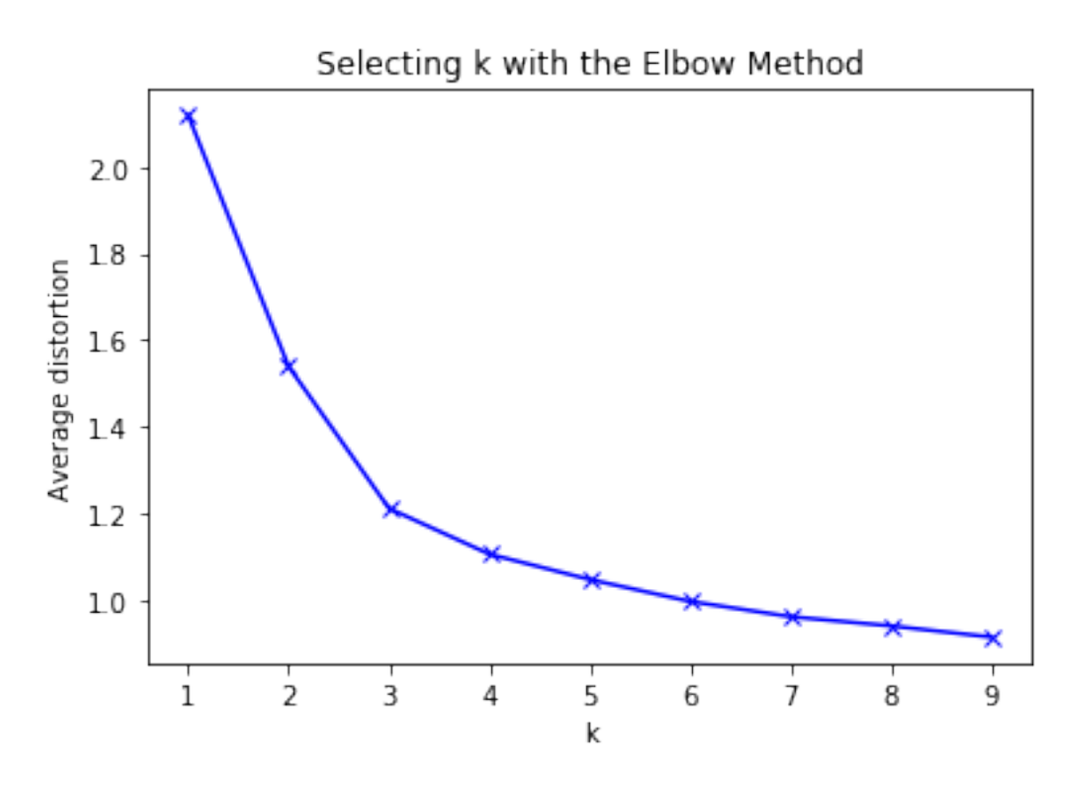
In [48]:
```python
# The Bidimentional plots and the Histograms(kde) show VERY DISTINCT clusterisation in the data.
```

3- KMeans method of clusterisation

In [30]:
```python
# Libraries for this Stage
from sklearn.cluster import KMeans
from scipy.spatial.distance import cdist
```

In [49]:
```python
# for loop creating the Elbow method to find the optimal number of clusters
clusters = range (1, 10)
meanDistortions = []

for k in clusters:
    model=KMeans(n_clusters=k)
    model.fit(X_scaled)
    prediction = model.predict(X_scaled)
    meanDistortions.append(sum(np.min(cdist(X_scaled, model.cluster_centers_, 'euclidean'), axis=1)) / CC_df_trimmed.s
hape[0])


plt.plot(clusters, meanDistortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')
```

Out[49]:
```
Text(0.5, 1.0, 'Selecting k with the Elbow Method')
```



In [32]:
```python
# The BEND is very clear at K=3
```

KMeans with 3 clusters

In [52]:
```python
# Let us first start with K = 3

final_model= KMeans(3)
final_model.fit(X_scaled)
prediction=final_model.predict(X_scaled)

#Append the prediction
X_scaled["GROUP"] = prediction
X["GROUP"] = prediction

print("Groups Assigned : \n")
X.head()
```

```
Groups Assigned :
```

Out[52]:

	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	GROUP
0	100000	2	1	1	0	1
1	50000	3	0	10	9	2
2	50000	7	1	3	4	1
3	30000	5	1	1	4	1
4	100000	6	0	12	3	0

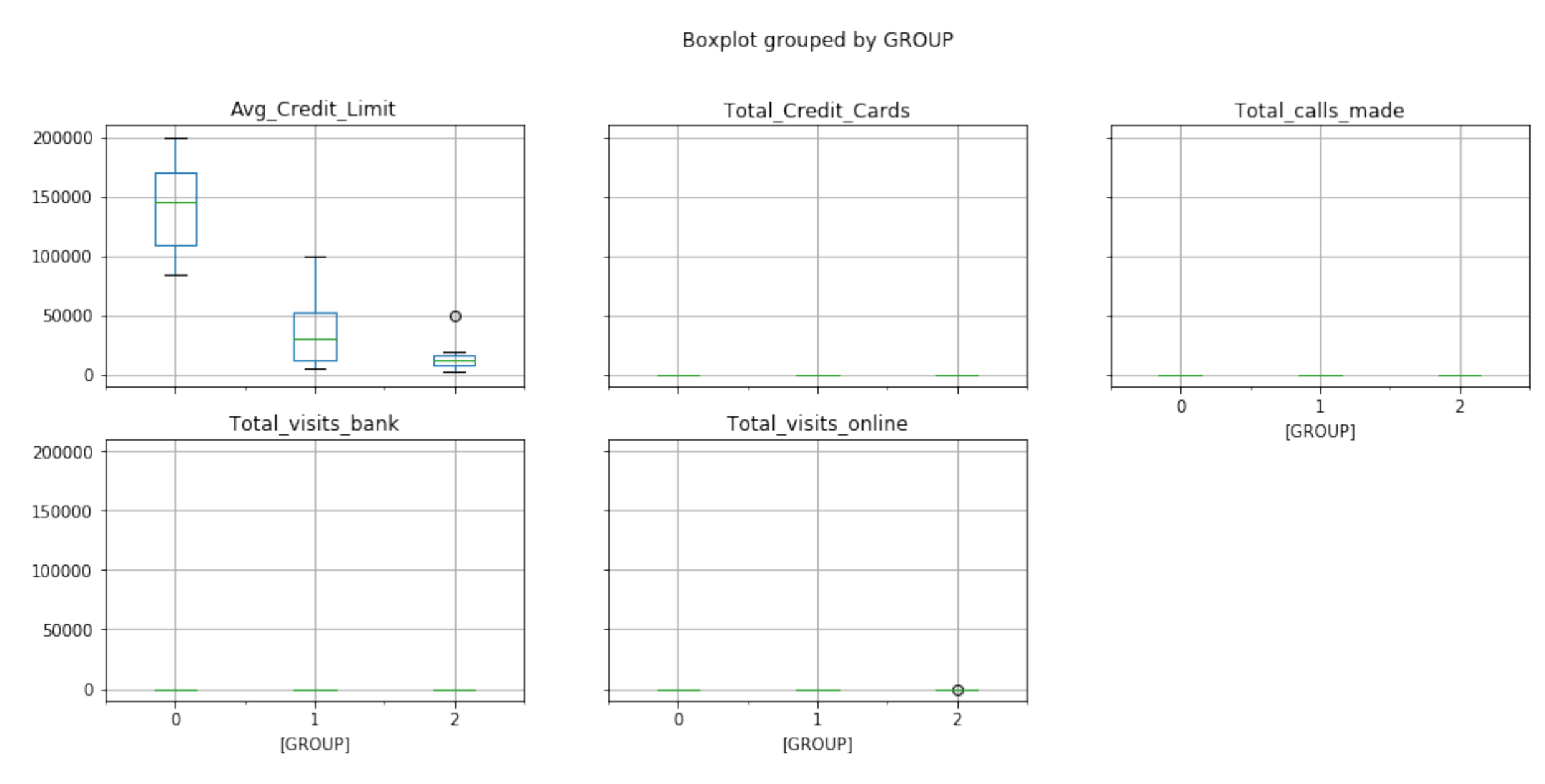
In [58]:
```python
X_clustered = X.groupby(['GROUP'])
X_clustered.mean()
```

Out[58]:

GROUP	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
0	141040.000000	8.740000	0.600000	10.900000	1.080000
1	33782.383420	5.515544	3.489637	0.981865	2.000000
2	12174.107143	2.410714	0.933036	3.553571	6.870536

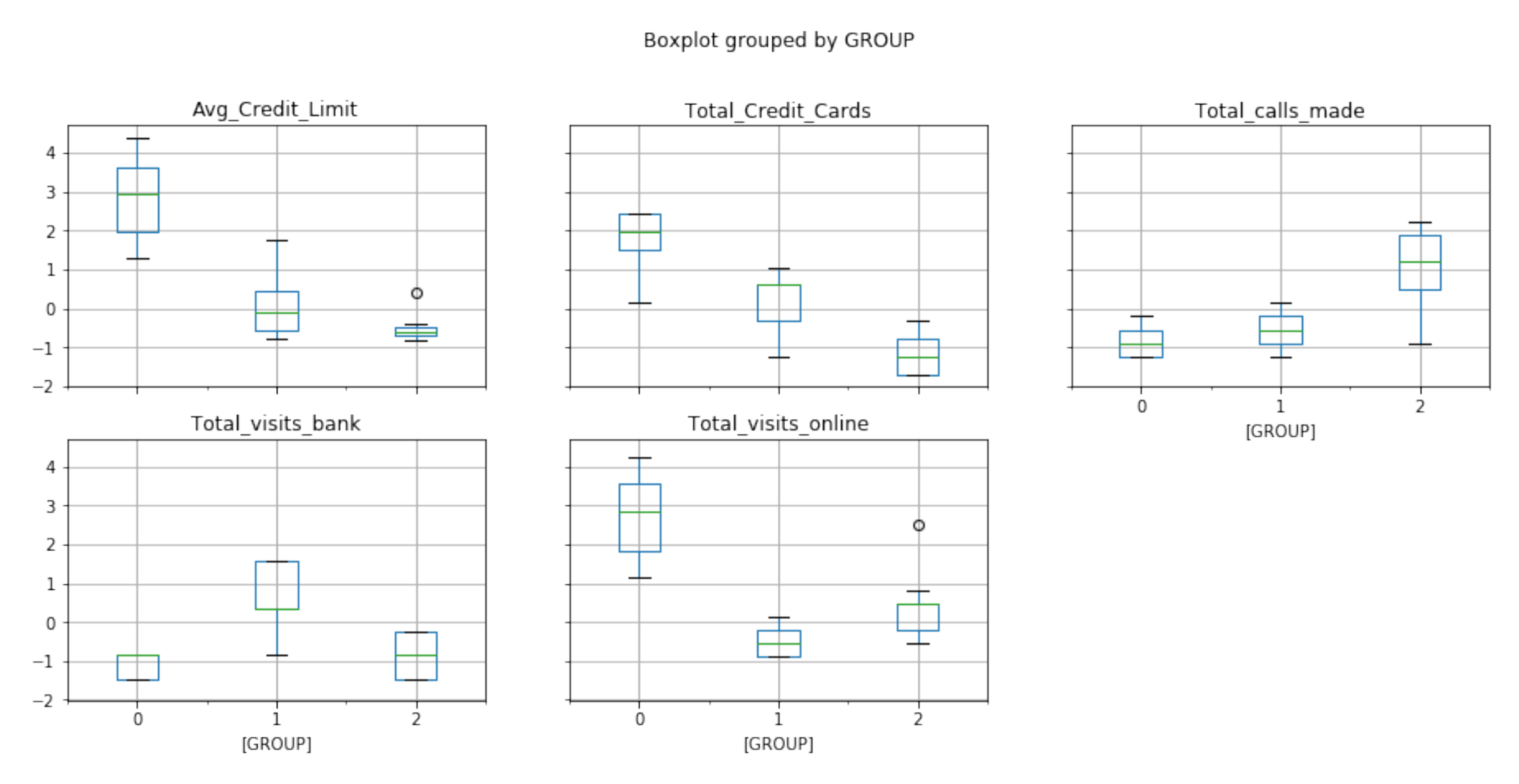
In [63]:
```python
X.boxplot(by ='GROUP' , layout=(3,3) , figsize= (15 ,10))

# CLUSTERS are ONLY visible in Avg_Credit_Limit !!?
```

Out[63]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1a277f6e10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27826cd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27856610>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a2788ca50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a278c2ed0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27902ed0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a27939b90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27979f10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27983050>]],
      dtype=object)
```



In [62]:
```python
# repeating the same but on the SCALED data
X_scaled.boxplot(by ='GROUP' , layout=(3,3) , figsize= (15 ,10))

# CLUSTERS are more visible now  :-)
```

Out[62]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1a26efc3d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a26f2b290>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a26ebcf50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a270697d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a2709dc50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a270ddc50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a27115910>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27152150>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27152c90>]],
      dtype=object)
```



In [70]:
```python
X.groupby(["GROUP"]).count()
```

Out[70]:

GROUP	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	LABELS
0	50	50	50	50	50	50
1	386	386	386	386	386	386
2	224	224	224	224	224	224

In [64]:
```python
# OBSERVATIONS :

# GROUP 0: Highest: Avg_Credit_Limit, Total_credit_cards, Total_visits_online
#          Lowest : Total_visits_bank , Total_calls_made

# GROUP 1: Highest: Total_visits_bank
#          Lowest : Total_visits_online

# GROUP 2: Highest: Total_calls_made
#          Lowest : Avg_Credit_Limit, Total_credit_cards
```

4- Hierarchical clustering

In [73]:
```python
# Library needed at this stage
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import cophenet, dendrogram, linkage
from scipy.spatial.distance import pdist
```

In [74]:
```python
model = AgglomerativeClustering(n_clusters=3, affinity='euclidean',  linkage='average')
```

In [75]:
```python
model.fit(X_scaled)
```

Out[75]:
```
AgglomerativeClustering(affinity='euclidean', compute_full_tree='auto',
                        connectivity=None, distance_threshold=None,
                        linkage='average', memory=None, n_clusters=3,
                        pooling_func='deprecated')
```

In [76]:
```python
X['LABELS'] = model.labels_
X.head(10)
```

Out[76]:

	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	GROUP	LABELS
0	100000	2	1	1	0	1	0
1	50000	3	0	10	9	2	2
2	50000	7	1	3	4	1	0
3	30000	5	1	1	4	1	0
4	100000	6	0	12	3	0	1
5	20000	3	0	1	8	2	2
6	100000	5	0	11	2	0	1
7	15000	3	0	1	1	2	2
8	5000	2	0	2	2	2	2
9	3000	4	0	1	7	2	2

In [77]:
```python
X.groupby(["LABELS"]).count()
```

Out[77]:

LABELS	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	GROUP
0	386	386	386	386	386	386
1	50	50	50	50	50	50
2	224	224	224	224	224	224

In [78]:
```python
X.groupby(["GROUP"]).count()
```

Out[78]:

GROUP	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	LABELS
0	50	50	50	50	50	50
1	386	386	386	386	386	386
2	224	224	224	224	224	224

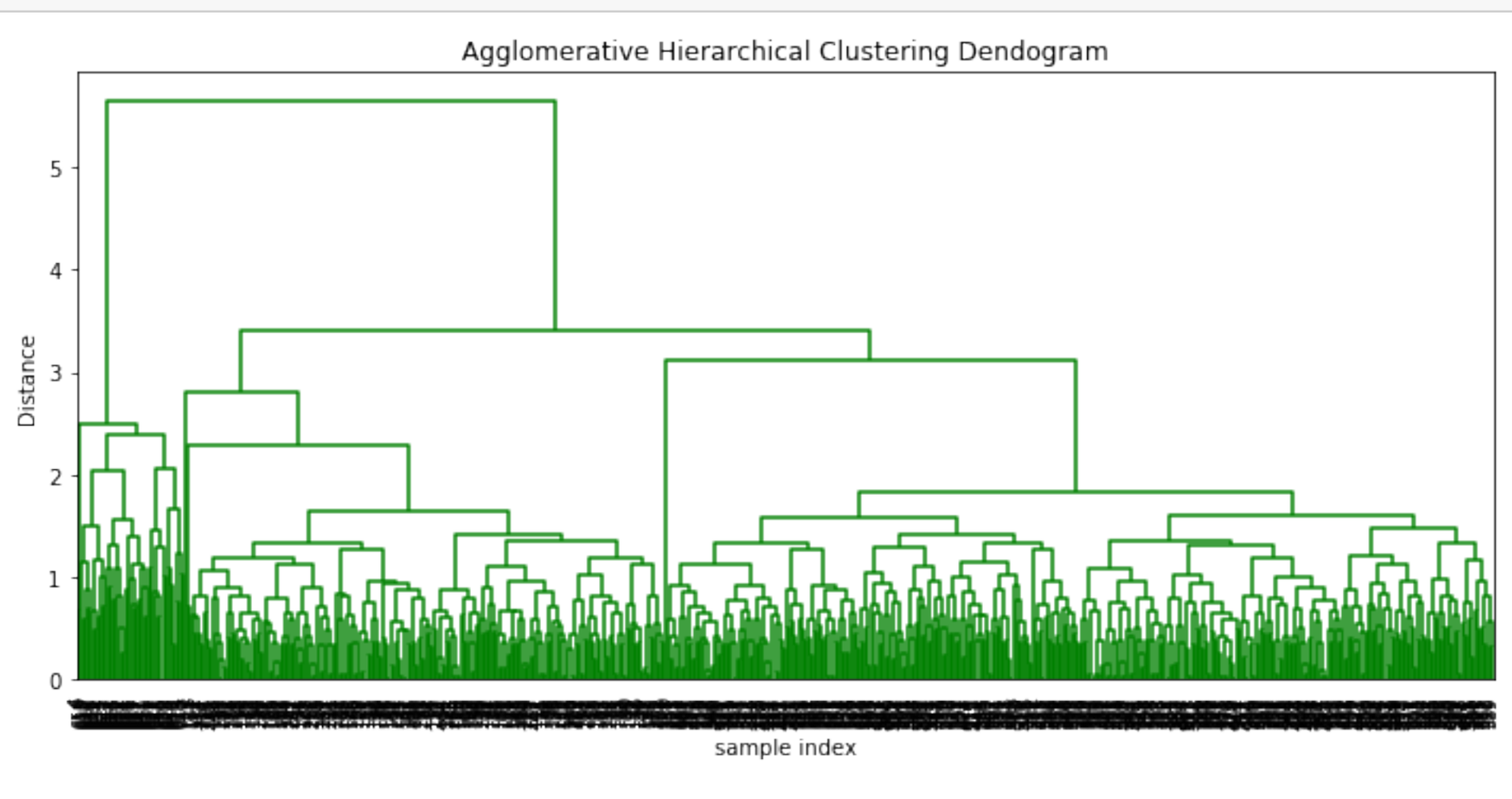
In [79]:
```python
# OBSERVATION :  Similar clusterisations whether with Kmeans or Hierarchichal
# LABEL 0 = GROUP 1
# LABEL 1 = GROUP 0
# LABEL 2 = GROUP 2
```

In [85]:
```python
# cophenet index is a measure of the correlation between :
# the distance of points in feature space and distance on dendrogram
# The closer it is to 1, the better is the clustering

Z = linkage(X_scaled, metric='euclidean', method='average')
c, coph_dists = cophenet(Z , pdist(X_scaled))

c
```

Out[85]:
```
0.9102691112621796
```

In [86]:
```python
# WOW ! high cophenetic Index!
```

In [87]:
```python
# Dendogram
plt.figure(figsize=(10, 5))
plt.title('Agglomerative Hierarchical Clustering Dendogram')
plt.xlabel('sample index')
plt.ylabel('Distance')
dendrogram(Z, leaf_rotation=90.,color_threshold = 40, leaf_font_size=8. )
plt.tight_layout()
```



In [90]:
```python
# The Deddogram was computationally HEAVY .
# At a distnce of  4          : we have 2 clusters.
# At a distance of around 3.3 : we have 3 Clusters
# At a distnce of  3          : we have 4 clusters.

#etc ...
```

Edouard Toutounji - April 3 , 2020

In [ ]: