

# Clustering Report

September 27, 2020

## 0.0.1 Data Cleaning

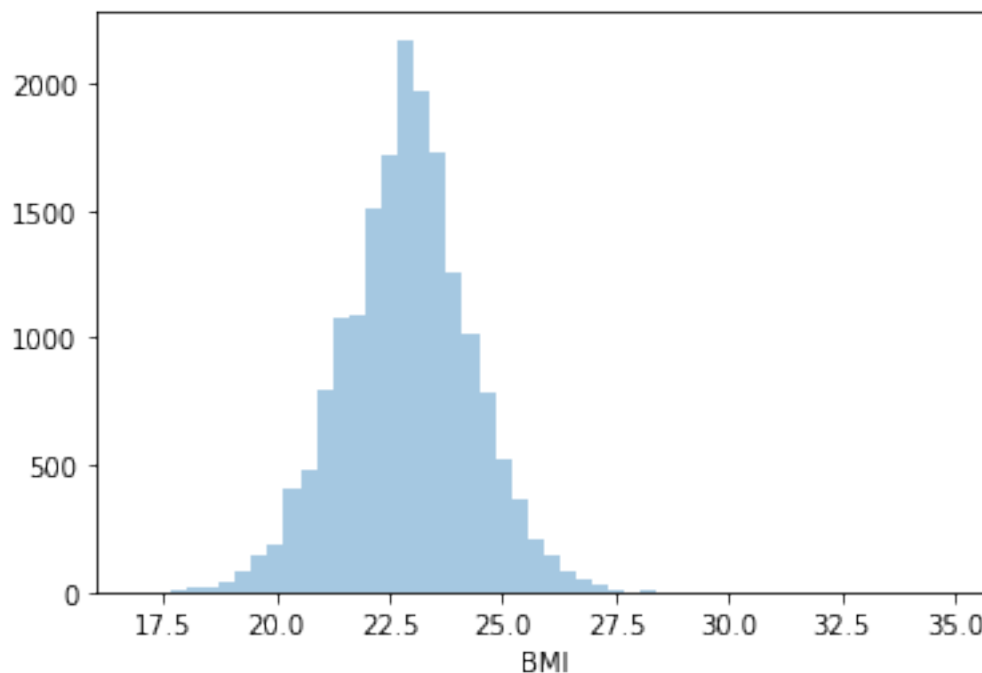
- First we cleaned the data by removing columns and rows with NaN depending on number of occurrence of it
- Next we tried to convert non numeric data to numeric one as much as possible (eg. left and right foot to '0' and '1'. And removed columns as Name, Images, Flag etc.
- Further we converted all the string numerical data to float or int (eg. Income from €3M to 3000000)

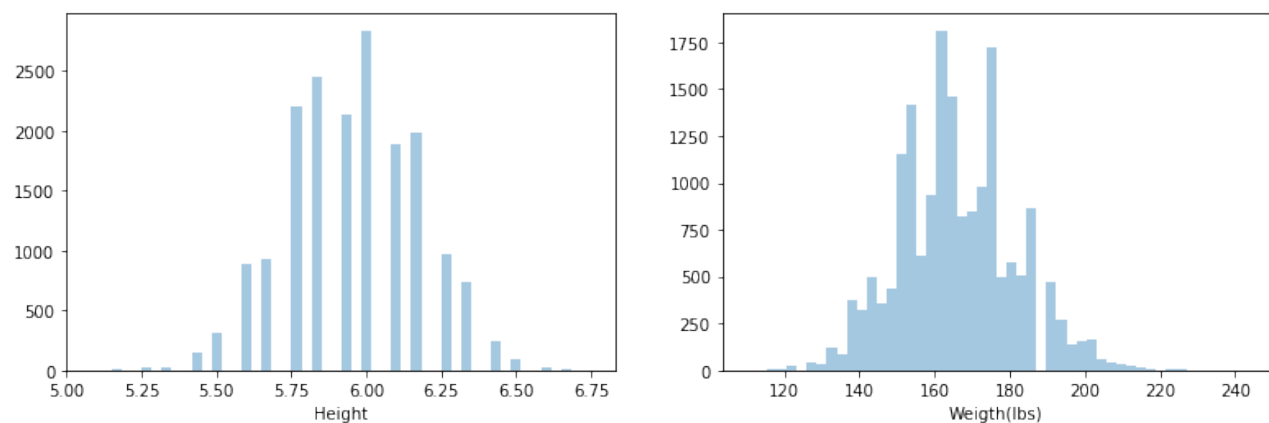
## 1 1. Analysis from Data Visualisation

### 1.0.1 A. Weight, Height, BMI

We observe that weight and height does not follow normal distribution perfectly but the BMI follows it much more accurately.

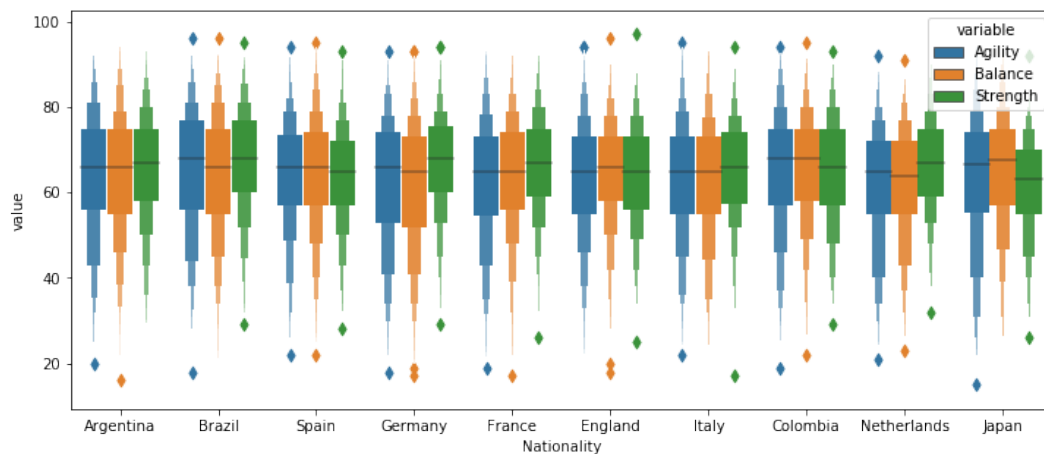
The average BMI of all the players is ~23 and range of BMI is 17.5 to 28, which indicates most of players have normal/healthy BMI.



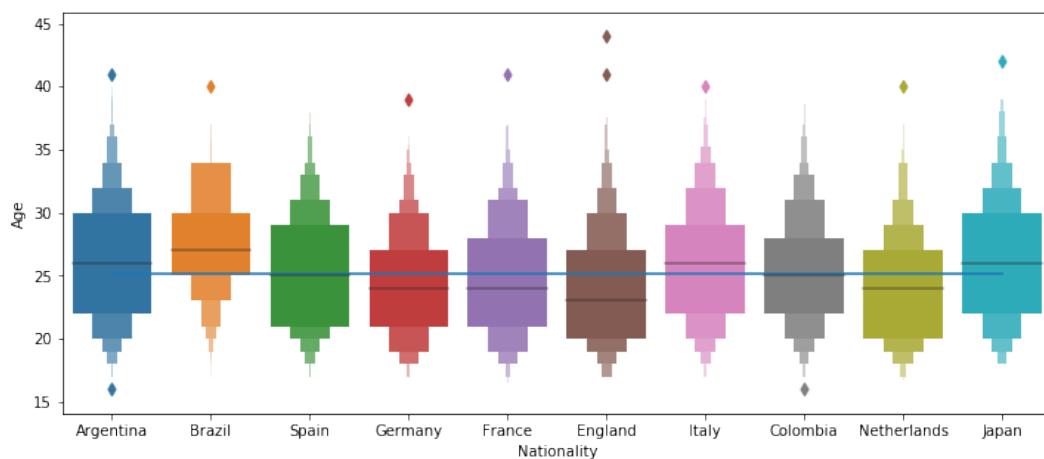


### 1.0.2 B. Distribution of players in different country

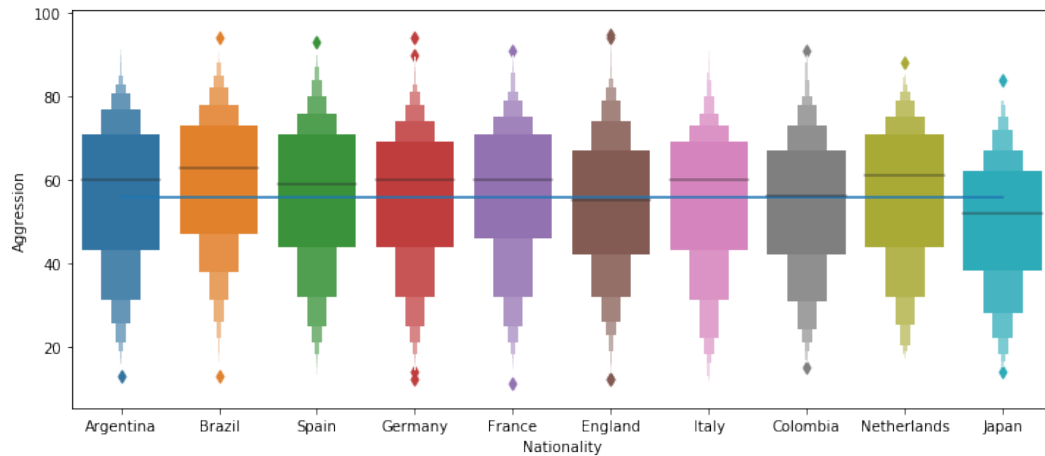
- The Aglity,balance and Strength of Top 10 performing nations is shown below which shows very similar trends.



- The Age of Players of Top 10 countries. We can see that either top performing countries are generally younger or only slightly older than the world avarage .



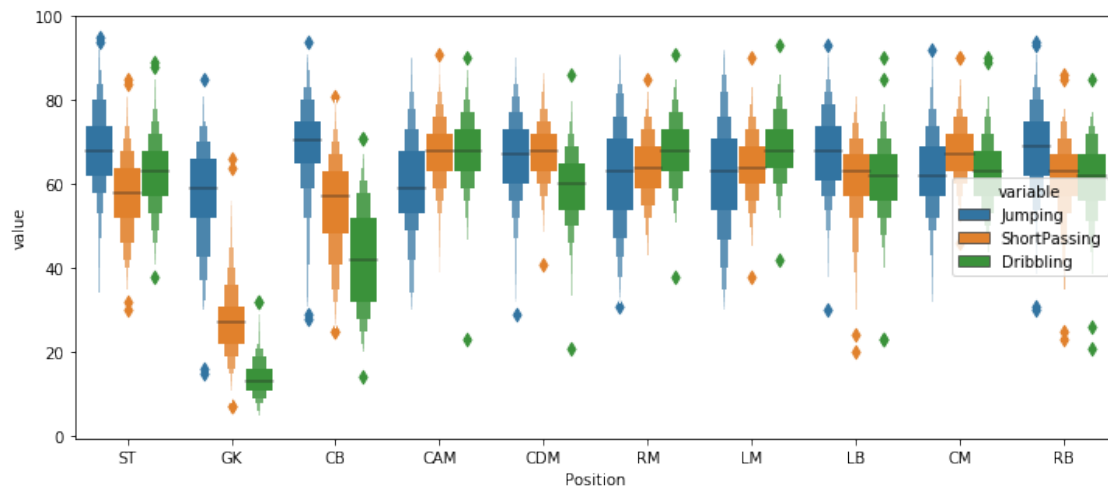
- Aggression of Players of Top 10 countries. Its clear top performers are much more aggres-

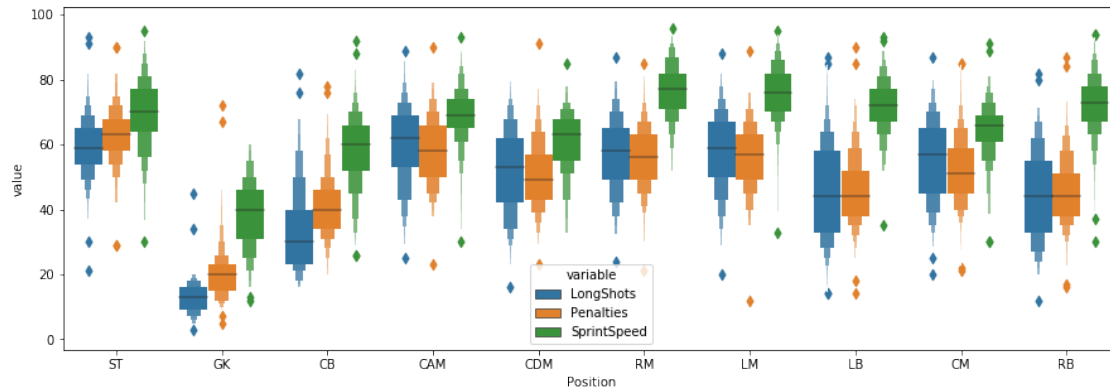


sive.

### 1.0.3 C. Features of players according to their position.

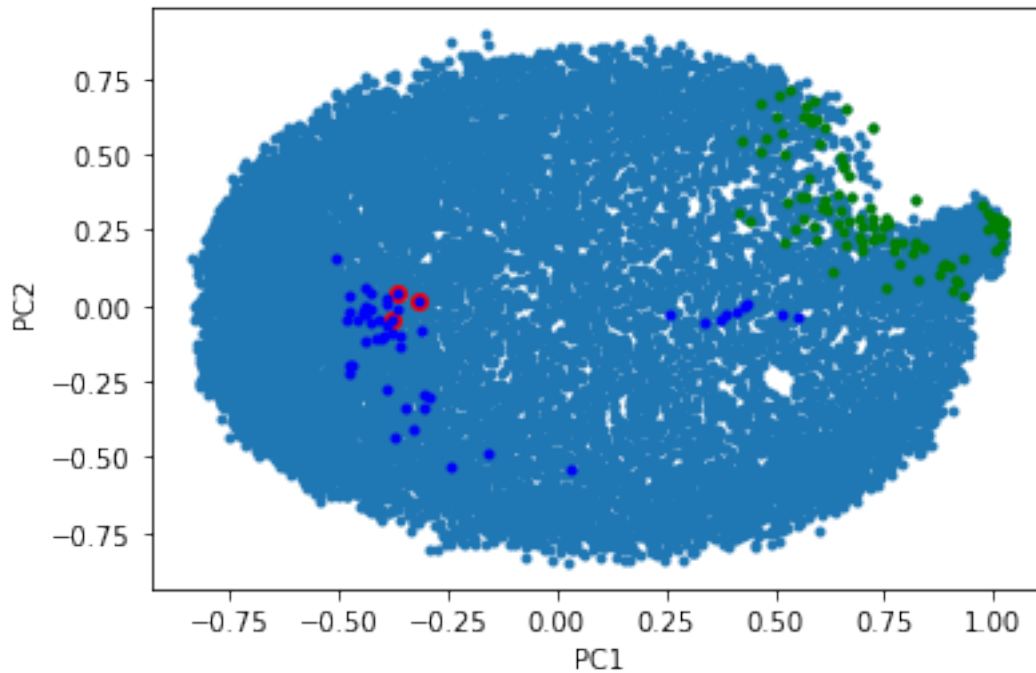
1. Goal Keepers can be easily identified by their low sprint speed.
2. Both Goal Keeper and Center Back(Defender) have low dribbling skill, which is intuitive too as they just have to pass the ball forward.
3. Both the striker and Defender have high Jumps which is a necessary skill for scoring and defending a corner.
4. The mid fielders(RM and LM) have high sprint speed as they are required to assist both the front and back.
5. The Skills are generally independent of left and right position (exception may be the primary foot)





#### 1.0.4 D.Outliers

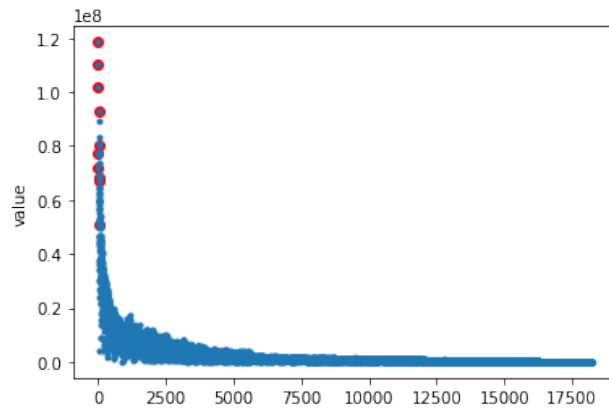
We have reduced the dimension of data using PCA to get a 2D plot. The Pink Dots are top 3 Players ( Messi, Ronado,Neyamer). The violet Dots are top 50 Players. Green are last 100 Players.



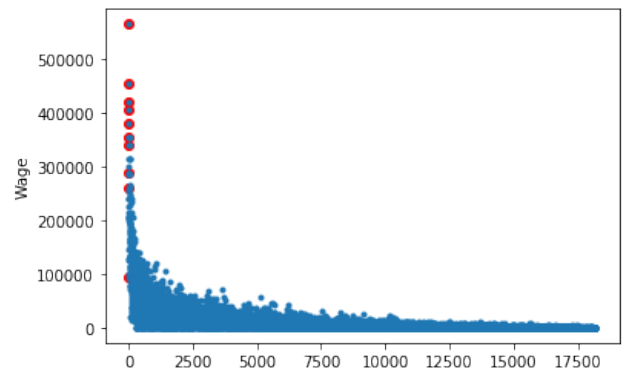
One observation is the top players are around  $y=0(PC2)$  and  $x=-0.33(PC1)$ . But we can't say something explicitly about a particular top player as this is a dense area. And least performing players are around the Green Area.

As we were not getting outliers by standard approach, we decided to follow a materialistic approach and plotted players' wages and value. And results were as expected.

Value



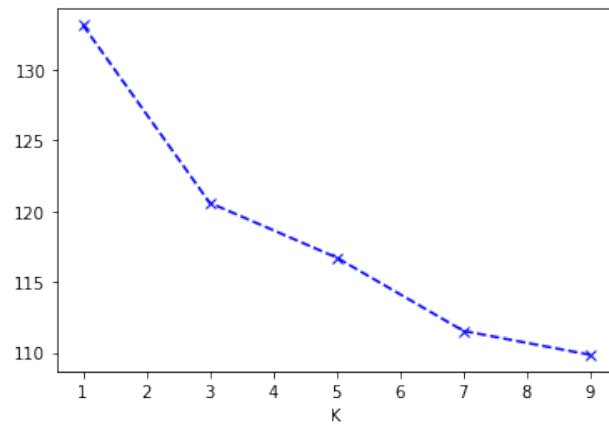
Wage



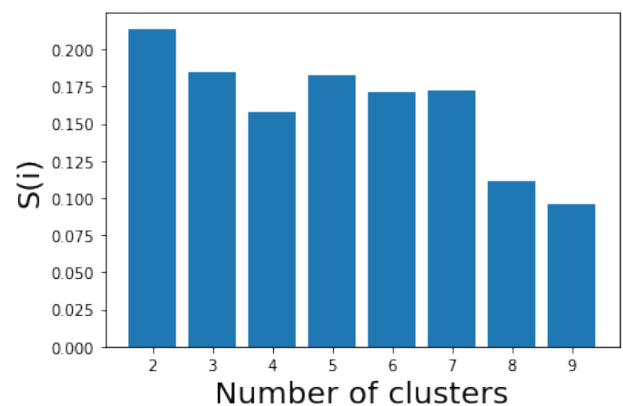
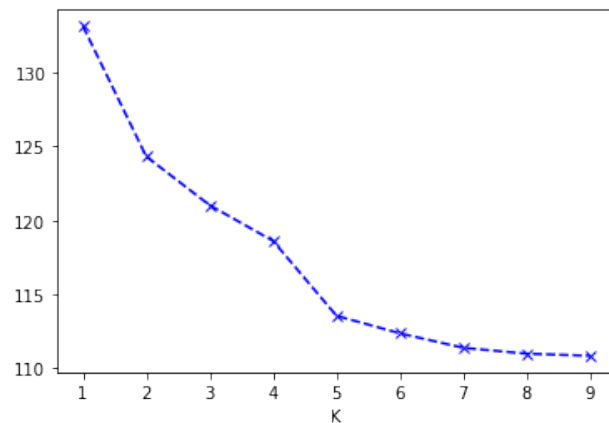
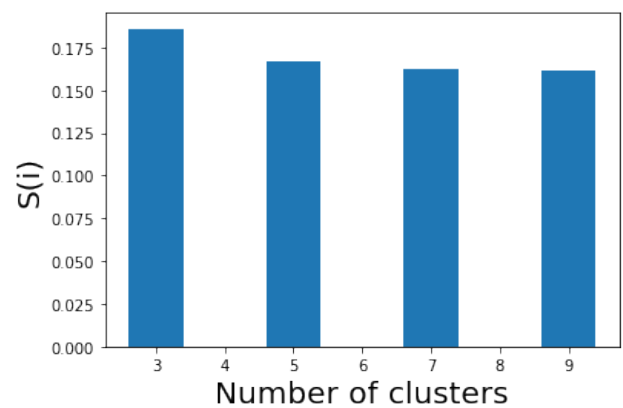
## 2 2.Analysis from K-means

If we chose  $k = 3, 5, 7$  we get elbow at 3 and silhouette score is also highest at 3. This indicates appropriate number of clusters is 3.

Elbow

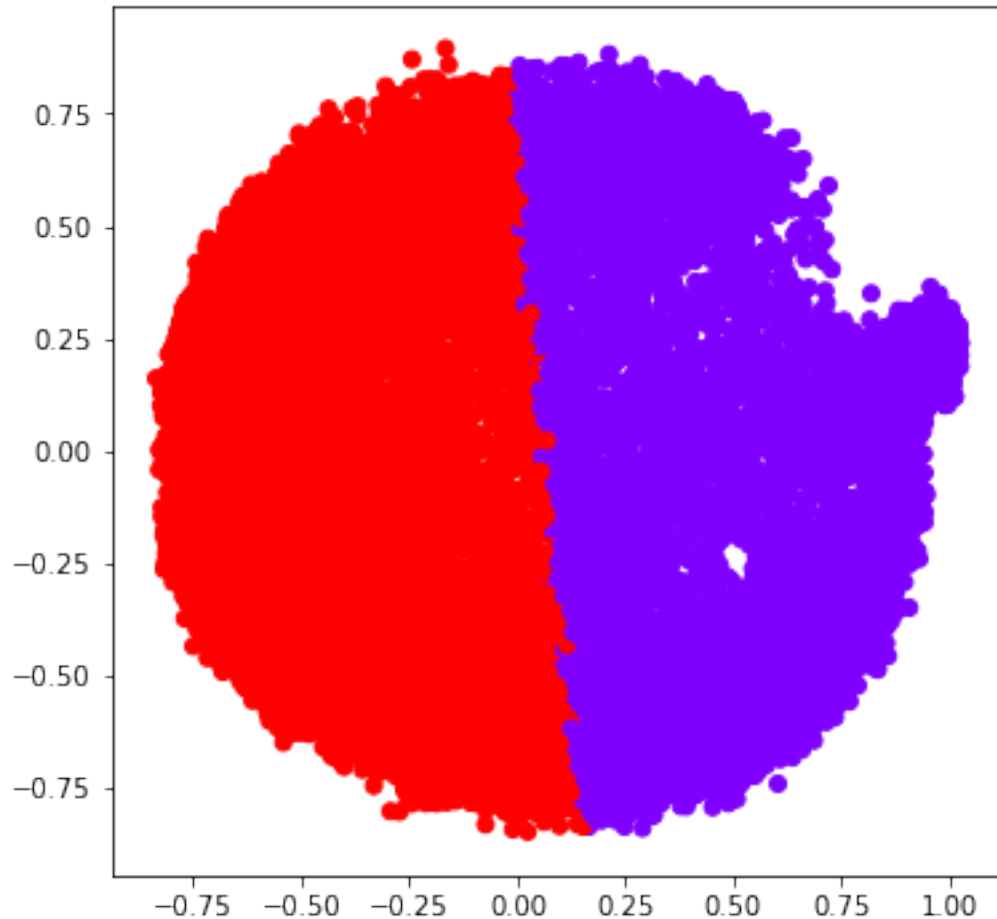


Silhouette



But when we iterate from  $k=[2,3 \dots 9]$  we get above values. Here we see highest silhouette score at  $k=2$  BUT elbow is at  $k=5$ . As silhouette score at  $k=5$  is also not that bad  $k$  should be 5.

### 2.0.1 For $K=2$



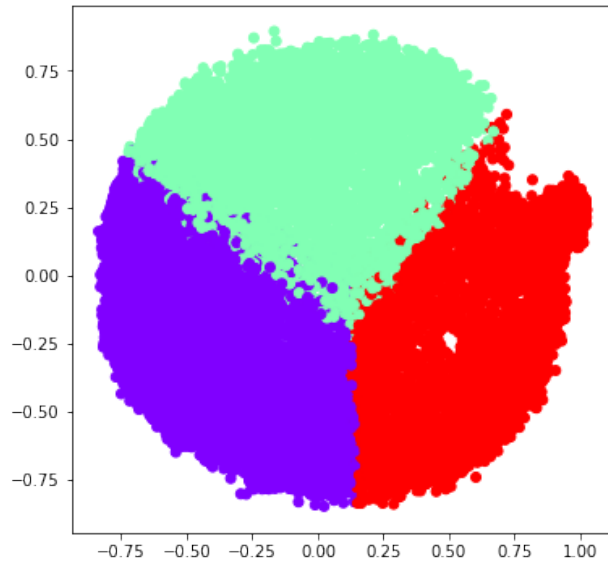
For  $K=2$  it has very clearly divided the data into 2 parts. As most of the good players were on the left side and not so good player were on right. This has divided the data into above average and below average.

### 2.0.2 For $K=3$ and $K=4$

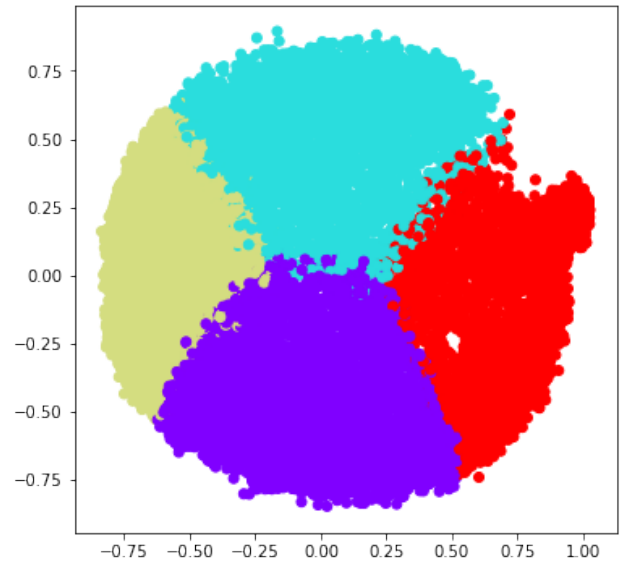
Both of these have clear decision boundaries. For  $k=4$  the clustering have lost the division at  $x \sim 0$  which was in  $k=2$  and  $k=3$ .

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k=3

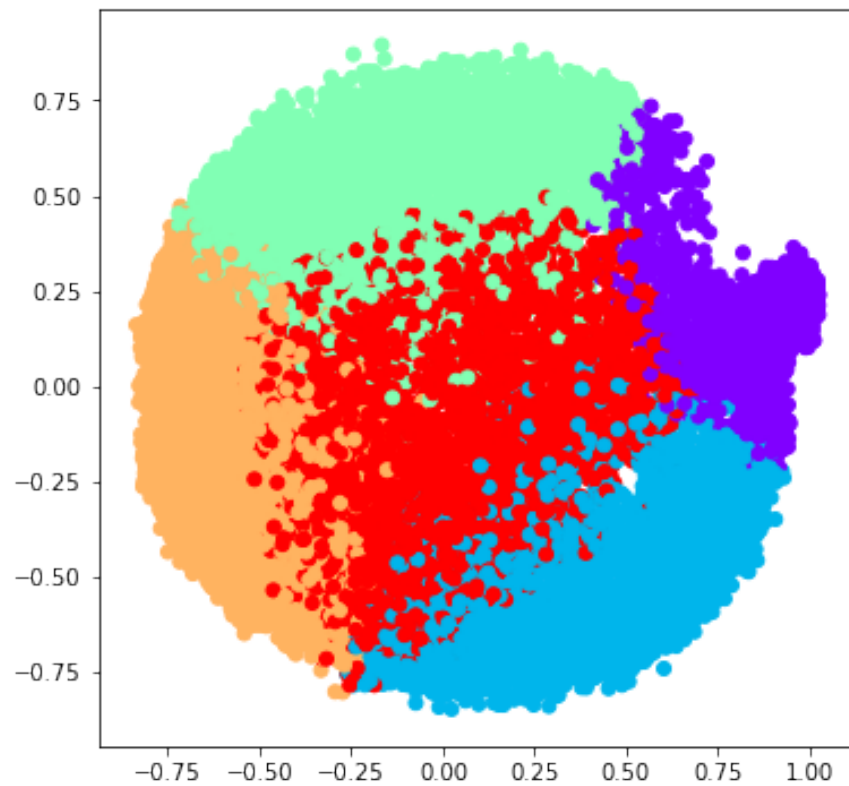


k=4



### 2.0.3 For K=5

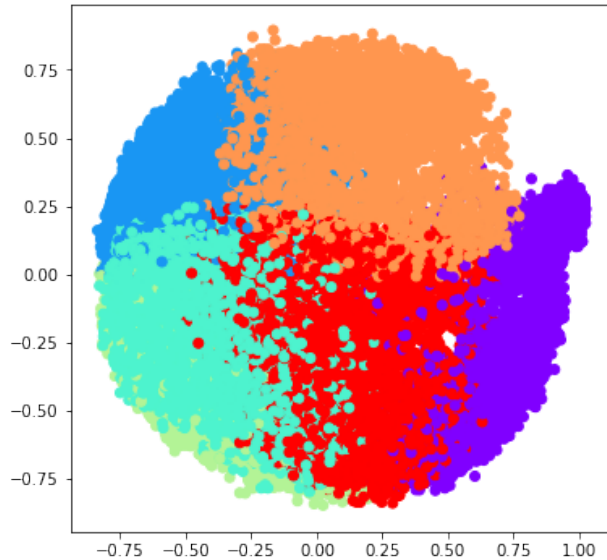
For K=5 it has came up with a sperate cluster in between which looks like a extention to the pattren we observed in top players. with this the last rank playered are also properly clusterd in right.



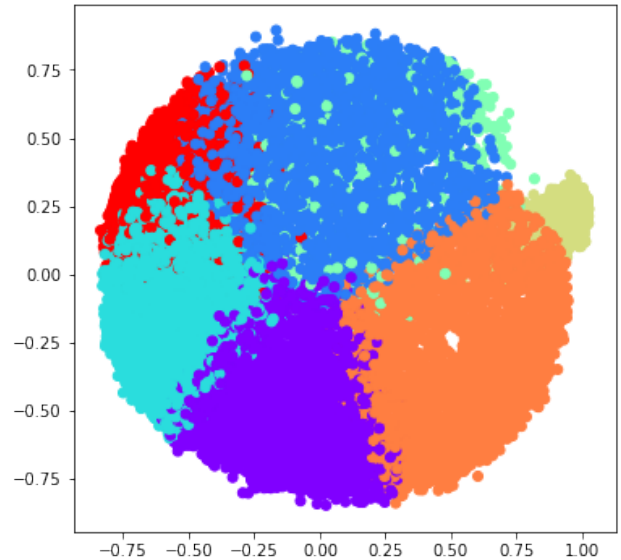
### 2.0.4 For K=6 and K=7

For  $k=6,7$  (Higher than 5) the new cluster formed have very less data and are not that significant. Also the clusters have merged, especially for  $k \geq 7$ .

k=6



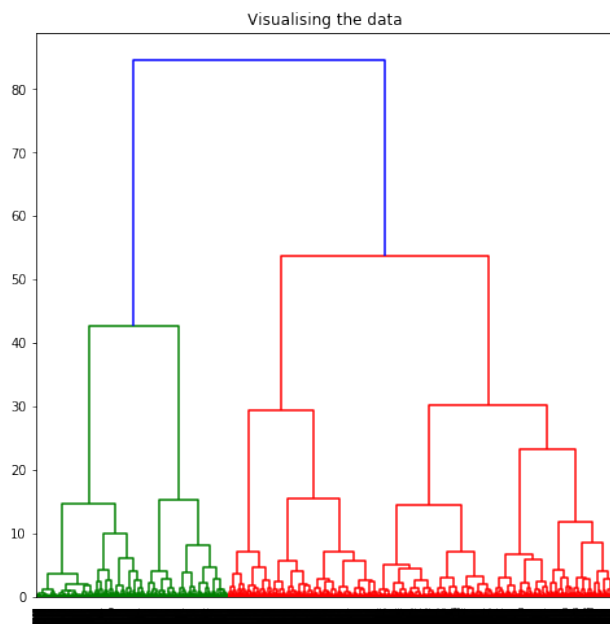
k=7



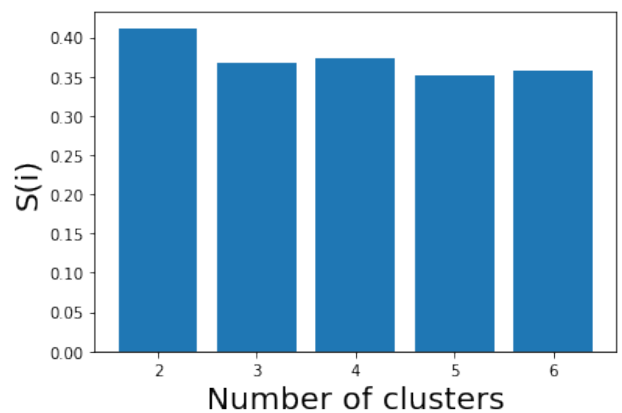
## 3 Hierarchical Clustering

### 3.1 Agglomerative(bottom-up strategy)

Dendrogram

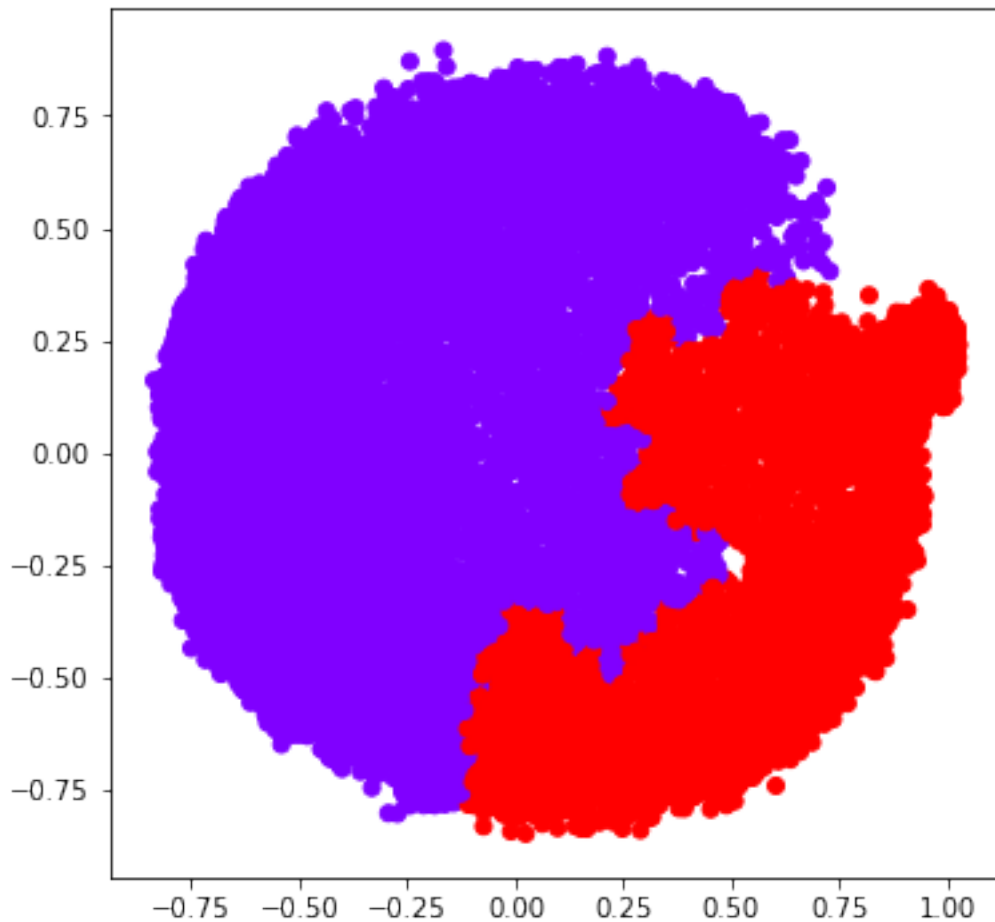


Sil. Score





Following dendrogram suggests that we should have 2 clusters, which is also suggested by Silhouette Score.



#### 4 DBSCAN

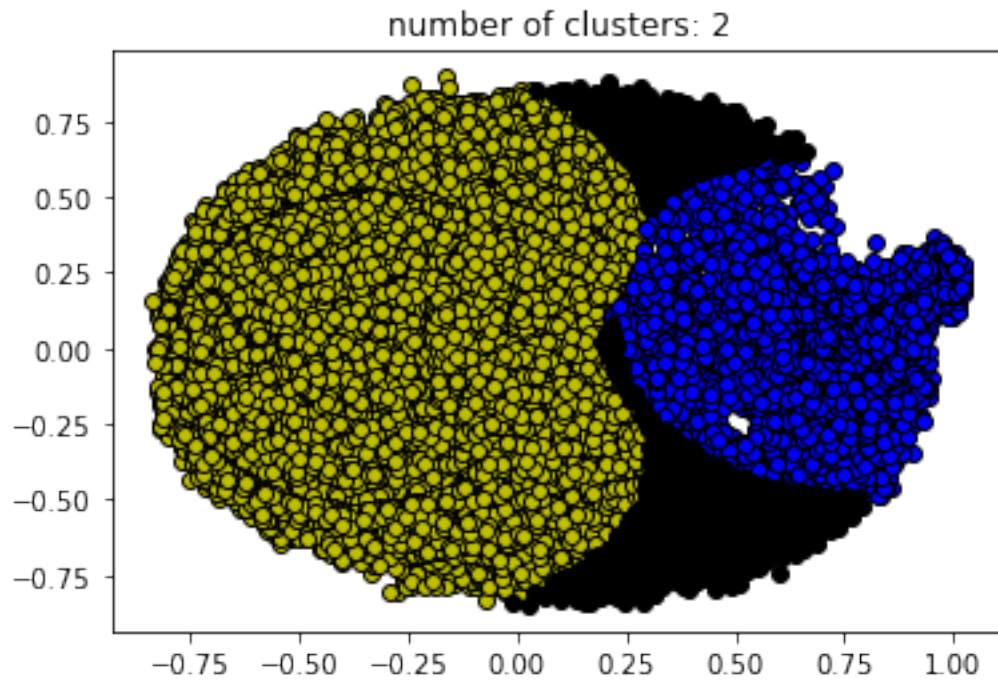
For calculating the epsilon and minPoints we first loop through a number of values for both of them and observed number of clusters formed, ideally they should neither be too high or low.

`esp=[0.001,0.01,0.1,1,10,100] min_samples=[2,10,100,500,1000,2000,4000,8000]`

From here we concluded that the values should be of order (0.1,500),

`esp=[0.1,0.2,0.3,0.4,0.5] min_samples=[200,400,800,1600,3200,6400]`

Then we looped around these values and found that (0.4,3200) gives the highest Silhouette Score and number of cluster=2.



The cluster are well defined and there is no overlapping among them. As stated before low ranked players were in right and good players were in left. DBSCAN have also clustred according to overall above and blow avarage.