In [2]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from matplotlib import pyplot as plt
from scipy.cluster.hierarchy import dendrogram
from sklearn.datasets import load_iris
from sklearn.cluster import AgglomerativeClustering
from mpl_toolkits.mplot3d import Axes3D
```

In [ ]:

```

```

Part.1 Data visualization

In [3]:

```
data=pd.read_csv("football_data.csv")
```

In [4]:

```
data.columns
```

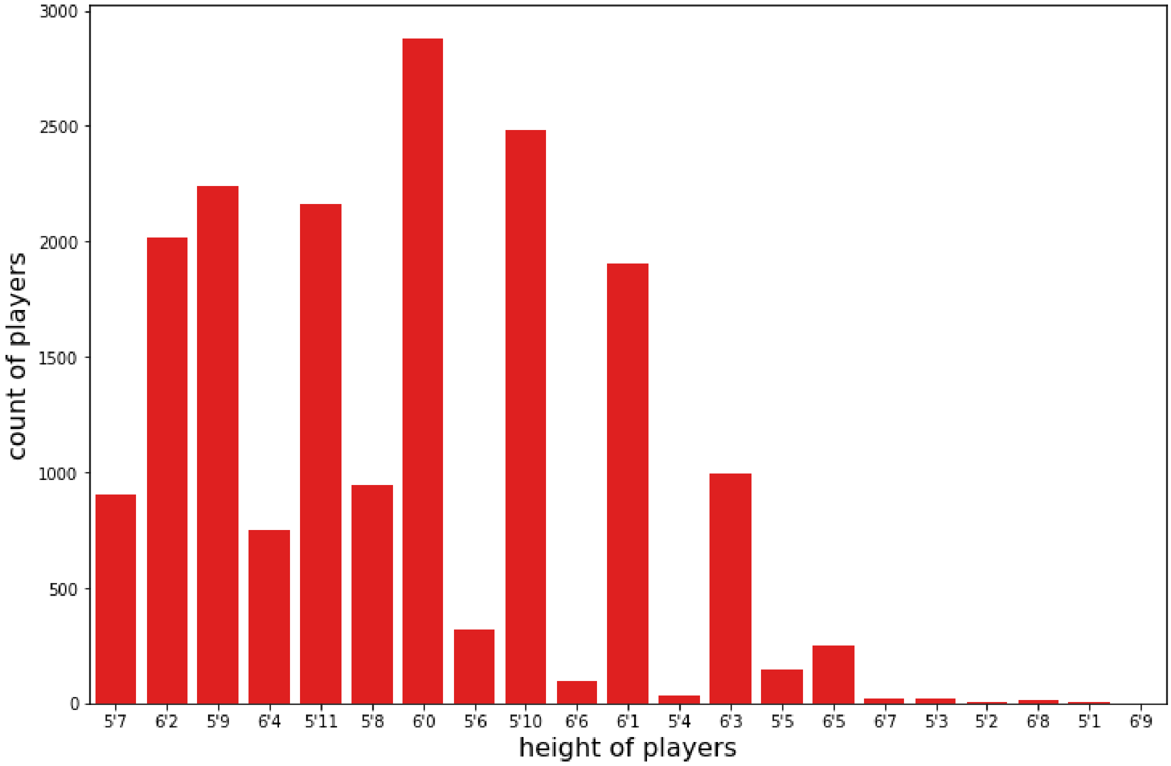
Out[4]:

```
Index(['Unnamed: 0', 'ID', 'Name', 'Age', 'Photo', 'Nationality', 'Fla
g',
       'Overall', 'Potential', 'Club', 'Club Logo', 'Value', 'Wage',
'Special',
       'Preferred Foot', 'International Reputation', 'Weak Foot',
       'Skill Moves', 'Work Rate', 'Body Type', 'Real Face', 'Positio
n',
       'Jersey Number', 'Joined', 'Loaned From', 'Contract Valid Unti
l',
       'Height', 'Weight', 'LS', 'ST', 'RS', 'LW', 'LF', 'CF', 'RF',
'RW',
       'LAM', 'CAM', 'RAM', 'LM', 'LCM', 'CM', 'RCM', 'RM', 'LWB', 'LD
M',
       'CDM', 'RDM', 'RWB', 'LB', 'LCB', 'CB', 'RCB', 'RB', 'Crossin
g',
       'Finishing', 'HeadingAccuracy', 'ShortPassing', 'Volleys', 'Dri
bbling',
       'Curve', 'FKAccuracy', 'LongPassing', 'BallControl', 'Accelerat
ion',
       'SprintSpeed', 'Agility', 'Reactions', 'Balance', 'ShotPower',
       'Jumping', 'Stamina', 'Strength', 'LongShots', 'Aggression',
       'Interceptions', 'Positioning', 'Vision', 'Penalties', 'Composu
re',
       'Marking', 'StandingTackle', 'SlidingTackle', 'GKDiving', 'GKHa
ndling',
       'GKKicking', 'GKPositioning', 'GKReflexes', 'Release Clause'],
      dtype='object')
```

histograms of count of players for heights

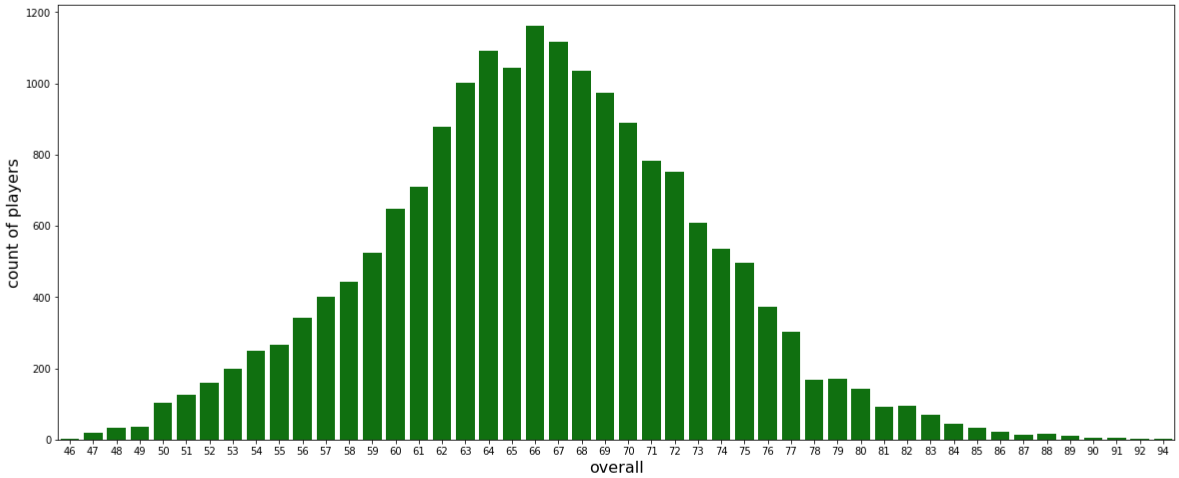
In [5]:

```
plt.figure(figsize=(12,8))
x=sns.countplot('Height',data=data,color='red')
x.set_xlabel(xlabel = 'height of players', fontsize = 16)
x.set_ylabel(ylabel="count of players",fontsize=16)
plt.show()
```



In [6]:

```
plt.figure(figsize=(20,8))
x=sns.countplot('Overall',data=data,color='green')
x.set_xlabel(xlabel = 'overall', fontsize = 16)
x.set_ylabel(ylabel="count of players",fontsize=16)
plt.show()
```



Outliers:

from the above histogram we can see that observe that only very few playes are above 92 overall score. Hence, those are outliers. Bellow are some outliers:

In [7]:

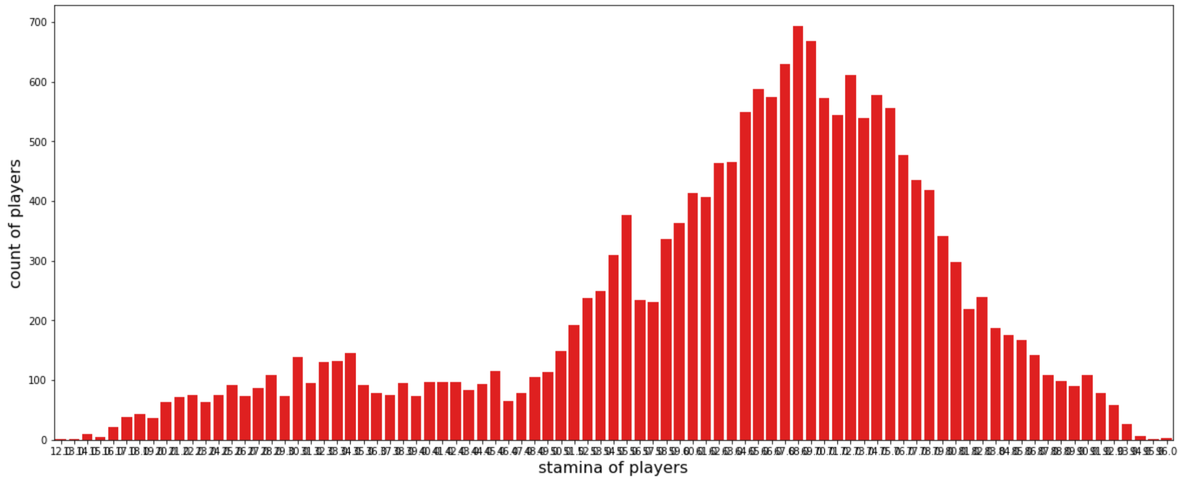
```
lis=list(data['Name'][data['Overall']>=92])
print(lis)
```

```
['L. Messi', 'Cristiano Ronaldo', 'Neymar Jr']
```

histograms of count of players for Stamina

In [8]:

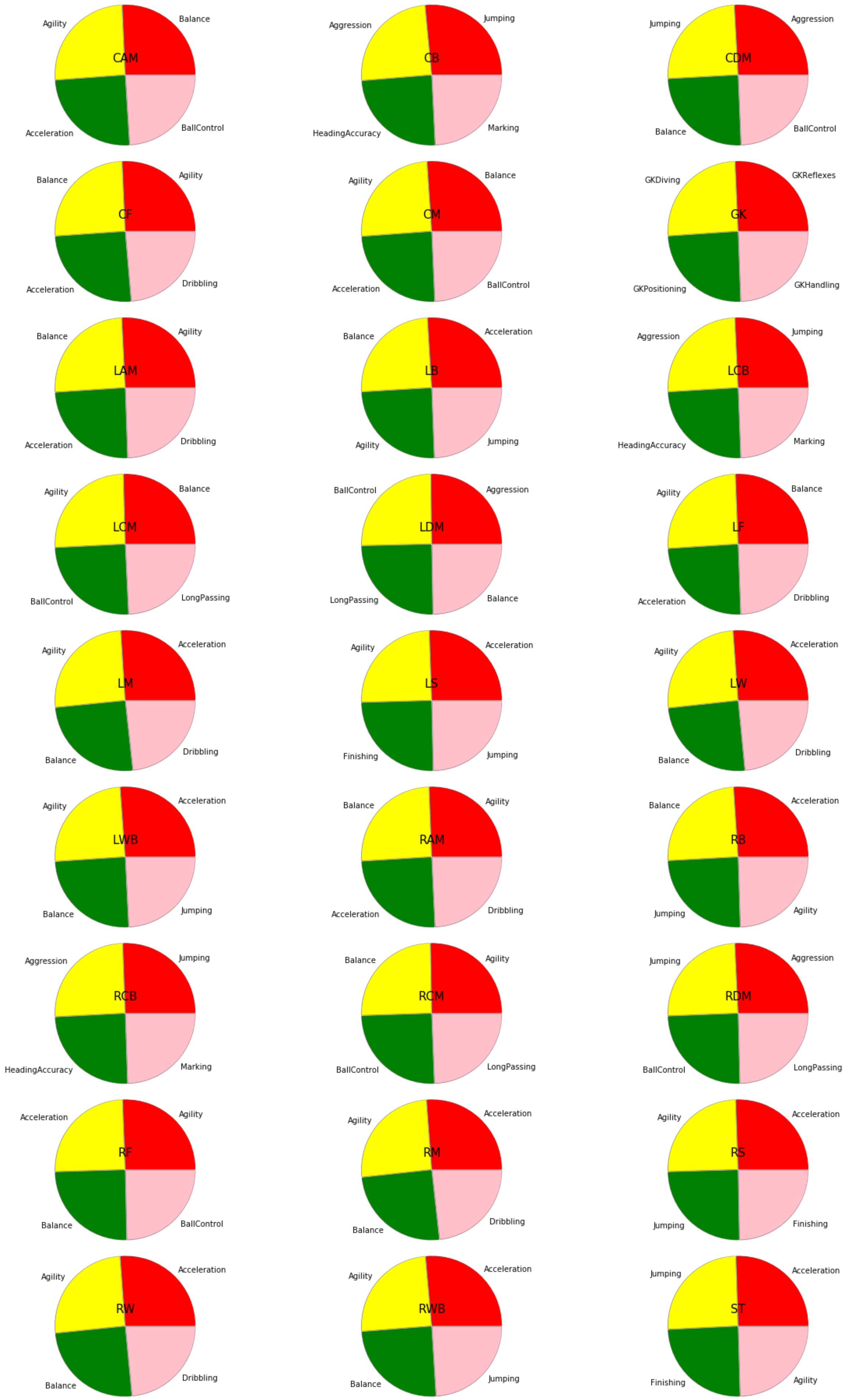
```
plt.figure(figsize=(20,8))
x=sns.countplot('Stamina',data=data,color='red')
x.set_xlabel(xlabel = 'stamina of players', fontsize = 16)
x.set_ylabel(ylabel="count of players",fontsize=16)
plt.show()
```



Features of players according to their position

In [9]:

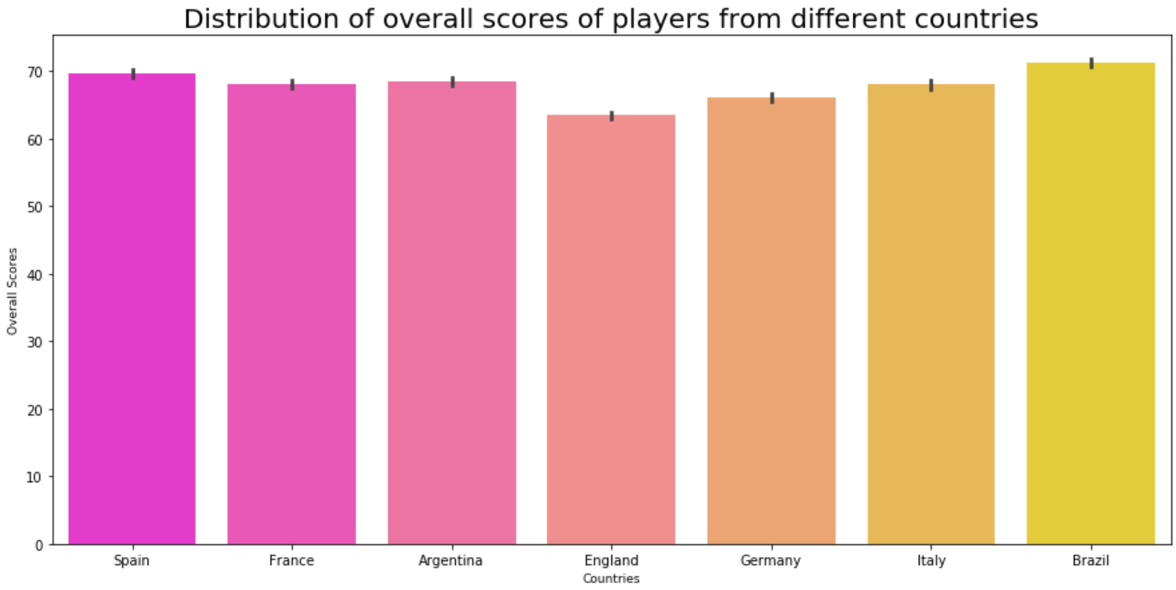
```
player_features = ('Acceleration', 'Aggression', 'Agility',
                   'Balance', 'BallControl', 'Composure',
                   'Crossing', 'Dribbling', 'FKAccuracy',
                   'Finishing', 'GKDiving', 'GKHandling',
                   'GKKicking', 'GKPositioning', 'GKReflexes',
                   'HeadingAccuracy', 'Interceptions', 'Jumping',
                   'LongPassing', 'LongShots', 'Marking', 'Penalties')
idx = 1

plt.subplots(figsize=(20, 30))
for i, val in data.groupby(data['Position'])[player_features].mean().iterrows():

    top_features=dict(val.nlargest(4))


    labels = top_features.keys()
    size = top_features.values()
    colors = ['red', 'yellow', 'green', 'pink']
    explode = [0.1, 0.1, 0.1, 0.1]


    plt.subplot(9, 3, idx)
#     plt.subplots(figsize=(2, 2))
    plt.subplots_adjust(hspace=8)

    plt.pie(size, labels = labels, colors = colors, explode = explode, shadow = Tru
    plt.title(i, fontsize = 15)
#     plt.legend()
#     plt.show()
    idx=idx+1
plt.show()
```



Distribution of players in different clubs/country on the basis of some attribute.

In [10]:

```
# Every Nations' Player and their overall scores

some_countries = ('England', 'Germany', 'Spain', 'Argentina', 'France', 'Brazil', '
data_countries = data.loc[data['Nationality'].isin(some_countries) & data['Overall'

plt.rcParams['figure.figsize'] = (15, 7)
ax = sns.barplot(x = data_countries['Nationality'], y = data_countries['Overall'],
ax.set_xlabel(xlabel = 'Countries', fontsize = 9)
ax.set_ylabel(ylabel = 'Overall Scores', fontsize = 9)
ax.set_title(label = 'Distribution of overall scores of players from different coun
plt.show()
```

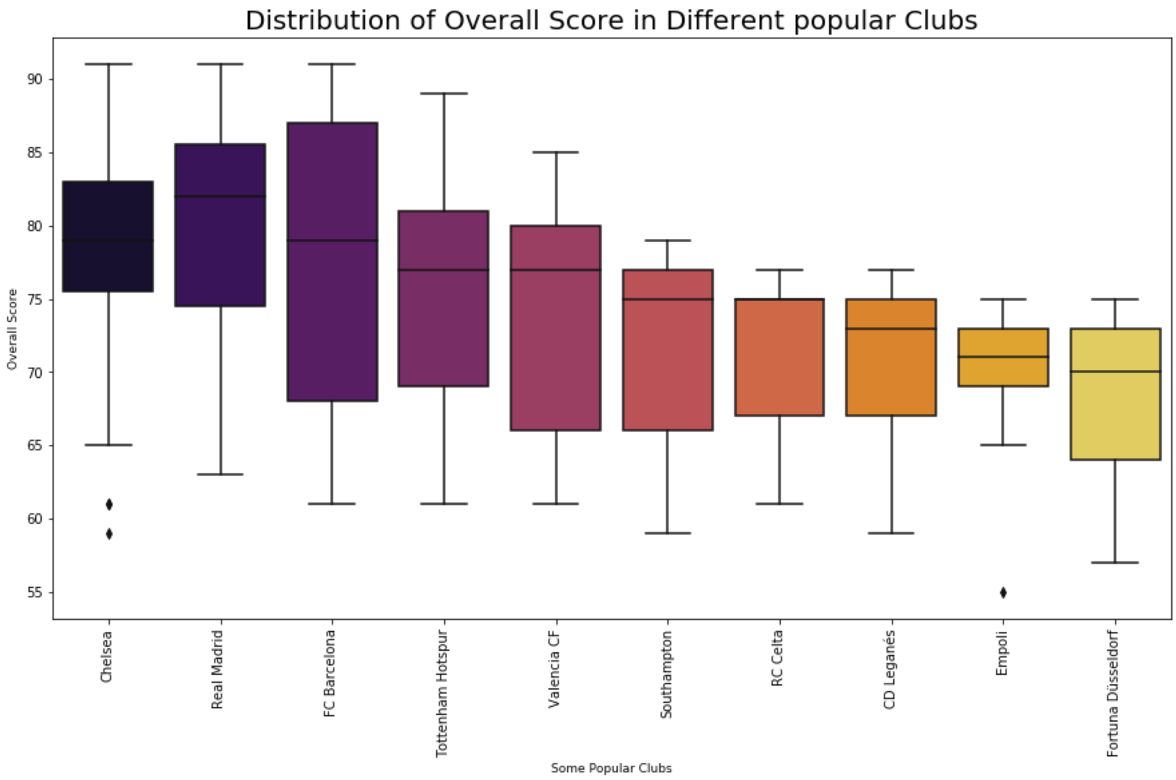


In [ ]:

```

```

In [12]:

```
some_clubs = ('CD Leganés', 'Southampton', 'RC Celta', 'Empoli', 'Fortuna Düsseldor
              'Tottenham Hotspur', 'FC Barcelona', 'Valencia CF', 'Chelsea', 'Real M

data_clubs = data.loc[data['Club'].isin(some_clubs) & data['Overall']]

plt.rcParams['figure.figsize'] = (15, 8)
ax = sns.boxplot(x = data_clubs['Club'], y = data_clubs['Overall'], palette = 'infe
ax.set_xlabel(xlabel = 'Some Popular Clubs', fontsize = 9)
ax.set_ylabel(ylabel = 'Overall Score', fontsize = 9)
ax.set_title(label = 'Distribution of Overall Score in Different popular Clubs', fo
plt.xticks(rotation = 90)
plt.show()
```



Checking null values

In [13]:

```
data.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18207 entries, 0 to 18206
Data columns (total 89 columns):
Unnamed: 0                  18207 non-null int64
ID                          18207 non-null int64
Name                        18207 non-null object
Age                         18207 non-null int64
Photo                       18207 non-null object
Nationality                 18207 non-null object
Flag                        18207 non-null object
Overall                     18207 non-null int64
Potential                   18207 non-null int64
Club                        17966 non-null object
Club Logo                   18207 non-null object
Value                       18207 non-null object
Wage                        18207 non-null object
Special                     18207 non-null int64
Preferred Foot              18159 non-null object
International Reputation    18159 non-null float64
Weak Foot                   18159 non-null float64
Skill Moves                 18159 non-null float64
Work Rate                   18159 non-null object
Body Type                   18159 non-null object
Real Face                   18159 non-null object
Position                    18147 non-null object
Jersey Number               18147 non-null float64
Joined                      16654 non-null object
Loaned From                 1264 non-null object
Contract Valid Until        17918 non-null object
Height                      18159 non-null object
Weight                      18159 non-null object
LS                          16122 non-null object
ST                          16122 non-null object
RS                          16122 non-null object
LW                          16122 non-null object
LF                          16122 non-null object
CF                          16122 non-null object
RF                          16122 non-null object
RW                          16122 non-null object
LAM                         16122 non-null object
CAM                         16122 non-null object
RAM                         16122 non-null object
LM                          16122 non-null object
LCM                         16122 non-null object
CM                          16122 non-null object
RCM                         16122 non-null object
RM                          16122 non-null object
LWB                         16122 non-null object
LDM                         16122 non-null object
CDM                         16122 non-null object
RDM                         16122 non-null object
RWB                         16122 non-null object
LB                          16122 non-null object
LCB                         16122 non-null object
CB                          16122 non-null object
RCB                         16122 non-null object
RB                          16122 non-null object
```

```
Crossing                    18159 non-null float64
Finishing                   18159 non-null float64
HeadingAccuracy             18159 non-null float64
ShortPassing                18159 non-null float64
Volleys                     18159 non-null float64
Dribbling                   18159 non-null float64
Curve                       18159 non-null float64
FKAccuracy                  18159 non-null float64
LongPassing                 18159 non-null float64
BallControl                 18159 non-null float64
Acceleration                18159 non-null float64
SprintSpeed                 18159 non-null float64
Agility                     18159 non-null float64
Reactions                   18159 non-null float64
Balance                     18159 non-null float64
ShotPower                   18159 non-null float64
Jumping                     18159 non-null float64
Stamina                     18159 non-null float64
Strength                    18159 non-null float64
LongShots                   18159 non-null float64
Aggression                  18159 non-null float64
Interceptions               18159 non-null float64
Positioning                 18159 non-null float64
Vision                      18159 non-null float64
Penalties                   18159 non-null float64
Composure                   18159 non-null float64
Marking                     18159 non-null float64
StandingTackle              18159 non-null float64
SlidingTackle               18159 non-null float64
GKDiving                    18159 non-null float64
GKHandling                  18159 non-null float64
GKKicking                   18159 non-null float64
GKPositioning               18159 non-null float64
GKReflexes                  18159 non-null float64
Release Clause              16643 non-null object
dtypes: float64(38), int64(6), object(45)
memory usage: 12.4+ MB
```

In [14]:

```
data.isnull().sum()
```

Out[14]:

```
Unnamed: 0           0
ID                   0
Name                 0
Age                  0
Photo                0
                  ...
GKHandling          48
GKKicking           48
GKPositioning       48
GKReflexes          48
Release Clause    1564
Length: 89, dtype: int64
```

Data Cleaning

In [15]:

```
data['ShortPassing'].fillna(data['ShortPassing'].mean(), inplace = True)
data['Volleys'].fillna(data['Volleys'].mean(), inplace = True)
data['Dribbling'].fillna(data['Dribbling'].mean(), inplace = True)
data['Curve'].fillna(data['Curve'].mean(), inplace = True)
data['FKAccuracy'].fillna(data['FKAccuracy'], inplace = True)
data['LongPassing'].fillna(data['LongPassing'].mean(), inplace = True)
data['BallControl'].fillna(data['BallControl'].mean(), inplace = True)
data['HeadingAccuracy'].fillna(data['HeadingAccuracy'].mean(), inplace = True)
data['Finishing'].fillna(data['Finishing'].mean(), inplace = True)
data['Crossing'].fillna(data['Crossing'].mean(), inplace = True)
data['Weight'].fillna('200lbs', inplace = True)
data['Contract Valid Until'].fillna(2019, inplace = True)
data['Height'].fillna("5'11", inplace = True)
data['Loaned From'].fillna('None', inplace = True)
data['Joined'].fillna('Jul 1, 2018', inplace = True)
data['Jersey Number'].fillna(8, inplace = True)
data['Body Type'].fillna('Normal', inplace = True)
data['Position'].fillna('ST', inplace = True)
data['Club'].fillna('No Club', inplace = True)
data['Work Rate'].fillna('Medium/ Medium', inplace = True)
data['Skill Moves'].fillna(data['Skill Moves'].median(), inplace = True)
data['Weak Foot'].fillna(3, inplace = True)
data['Preferred Foot'].fillna('Right', inplace = True)
data['International Reputation'].fillna(1, inplace = True)
data['Wage'].fillna('€200K', inplace = True)
```

In [16]:

```
data.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18207 entries, 0 to 18206
Data columns (total 89 columns):
Unnamed: 0                  18207 non-null int64
ID                          18207 non-null int64
Name                        18207 non-null object
Age                         18207 non-null int64
Photo                       18207 non-null object
Nationality                 18207 non-null object
Flag                        18207 non-null object
Overall                     18207 non-null int64
Potential                   18207 non-null int64
Club                        18207 non-null object
Club Logo                   18207 non-null object
Value                       18207 non-null object
Wage                        18207 non-null object
Special                     18207 non-null int64
Preferred Foot              18207 non-null object
International Reputation    18207 non-null float64
Weak Foot                   18207 non-null float64
Skill Moves                 18207 non-null float64
Work Rate                   18207 non-null object
Body Type                   18207 non-null object
Real Face                   18159 non-null object
Position                    18207 non-null object
Jersey Number               18207 non-null float64
Joined                      18207 non-null object
Loaned From                 18207 non-null object
Contract Valid Until        18207 non-null object
Height                      18207 non-null object
Weight                      18207 non-null object
LS                          16122 non-null object
ST                          16122 non-null object
RS                          16122 non-null object
LW                          16122 non-null object
LF                          16122 non-null object
CF                          16122 non-null object
RF                          16122 non-null object
RW                          16122 non-null object
LAM                         16122 non-null object
CAM                         16122 non-null object
RAM                         16122 non-null object
LM                          16122 non-null object
LCM                         16122 non-null object
CM                          16122 non-null object
RCM                         16122 non-null object
RM                          16122 non-null object
LWB                         16122 non-null object
LDM                         16122 non-null object
CDM                         16122 non-null object
RDM                         16122 non-null object
RWB                         16122 non-null object
LB                          16122 non-null object
LCB                         16122 non-null object
CB                          16122 non-null object
RCB                         16122 non-null object
RB                          16122 non-null object
```

```
Crossing                    18207 non-null float64
Finishing                   18207 non-null float64
HeadingAccuracy             18207 non-null float64
ShortPassing                18207 non-null float64
Volleys                     18207 non-null float64
Dribbling                   18207 non-null float64
Curve                       18207 non-null float64
FKAccuracy                  18159 non-null float64
LongPassing                 18207 non-null float64
BallControl                 18207 non-null float64
Acceleration                18159 non-null float64
SprintSpeed                 18159 non-null float64
Agility                     18159 non-null float64
Reactions                   18159 non-null float64
Balance                     18159 non-null float64
ShotPower                   18159 non-null float64
Jumping                     18159 non-null float64
Stamina                     18159 non-null float64
Strength                    18159 non-null float64
LongShots                   18159 non-null float64
Aggression                  18159 non-null float64
Interceptions               18159 non-null float64
Positioning                 18159 non-null float64
Vision                      18159 non-null float64
Penalties                   18159 non-null float64
Composure                   18159 non-null float64
Marking                     18159 non-null float64
StandingTackle              18159 non-null float64
SlidingTackle               18159 non-null float64
GKDiving                    18159 non-null float64
GKHandling                  18159 non-null float64
GKKicking                   18159 non-null float64
GKPositioning               18159 non-null float64
GKReflexes                  18159 non-null float64
Release Clause              16643 non-null object
dtypes: float64(38), int64(6), object(45)
memory usage: 12.4+ MB
```

In [17]:

```
data.fillna(0,inplace=True)
```

In [18]:

```
data.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18207 entries, 0 to 18206
Data columns (total 89 columns):
Unnamed: 0                  18207 non-null int64
ID                          18207 non-null int64
Name                        18207 non-null object
Age                         18207 non-null int64
Photo                       18207 non-null object
Nationality                 18207 non-null object
Flag                        18207 non-null object
Overall                     18207 non-null int64
Potential                   18207 non-null int64
Club                        18207 non-null object
Club Logo                   18207 non-null object
Value                       18207 non-null object
Wage                        18207 non-null object
Special                     18207 non-null int64
Preferred Foot              18207 non-null object
International Reputation    18207 non-null float64
Weak Foot                   18207 non-null float64
Skill Moves                 18207 non-null float64
Work Rate                   18207 non-null object
Body Type                   18207 non-null object
Real Face                   18207 non-null object
Position                    18207 non-null object
Jersey Number               18207 non-null float64
Joined                      18207 non-null object
Loaned From                 18207 non-null object
Contract Valid Until        18207 non-null object
Height                      18207 non-null object
Weight                      18207 non-null object
LS                          18207 non-null object
ST                          18207 non-null object
RS                          18207 non-null object
LW                          18207 non-null object
LF                          18207 non-null object
CF                          18207 non-null object
RF                          18207 non-null object
RW                          18207 non-null object
LAM                         18207 non-null object
CAM                         18207 non-null object
RAM                         18207 non-null object
LM                          18207 non-null object
LCM                         18207 non-null object
CM                          18207 non-null object
RCM                         18207 non-null object
RM                          18207 non-null object
LWB                         18207 non-null object
LDM                         18207 non-null object
CDM                         18207 non-null object
RDM                         18207 non-null object
RWB                         18207 non-null object
LB                          18207 non-null object
LCB                         18207 non-null object
CB                          18207 non-null object
RCB                         18207 non-null object
RB                          18207 non-null object
```

```
 Crossing                    18207 non-null float64
 Finishing                   18207 non-null float64
 HeadingAccuracy             18207 non-null float64
 ShortPassing                18207 non-null float64
 Volleys                     18207 non-null float64
 Dribbling                   18207 non-null float64
 Curve                       18207 non-null float64
 FKAccuracy                  18207 non-null float64
 LongPassing                 18207 non-null float64
 BallControl                 18207 non-null float64
 Acceleration                18207 non-null float64
 SprintSpeed                 18207 non-null float64
 Agility                     18207 non-null float64
 Reactions                   18207 non-null float64
 Balance                     18207 non-null float64
 ShotPower                   18207 non-null float64
 Jumping                     18207 non-null float64
 Stamina                     18207 non-null float64
 Strength                    18207 non-null float64
 LongShots                   18207 non-null float64
 Aggression                  18207 non-null float64
 Interceptions               18207 non-null float64
 Positioning                 18207 non-null float64
 Vision                      18207 non-null float64
 Penalties                   18207 non-null float64
 Composure                   18207 non-null float64
 Marking                     18207 non-null float64
 StandingTackle              18207 non-null float64
 SlidingTackle               18207 non-null float64
 GKDiving                    18207 non-null float64
 GKHandling                  18207 non-null float64
 GKKicking                   18207 non-null float64
 GKPositioning               18207 non-null float64
 GKReflexes                  18207 non-null float64
 Release Clause              18207 non-null object
dtypes: float64(38), int64(6), object(45)
memory usage: 12.4+ MB
```

In [ ]:

```

```

In [ ]:

```

```

Drop non numerical columns

In [19]:

```
columns_to_delete=[]
for i in range(data.shape[1]):
#     isinstance("this is a string", str)
    if  isinstance(data.iloc[0,i],str):
        columns_to_delete.append(i)
#         print(i)
data.drop(data.columns[columns_to_delete], axis = 1, inplace = True)
data.drop(data.columns[[0]], axis = 1, inplace = True)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18207 entries, 0 to 18206
Data columns (total 43 columns):
ID                          18207 non-null int64
Age                         18207 non-null int64
Overall                     18207 non-null int64
Potential                   18207 non-null int64
Special                     18207 non-null int64
International Reputation    18207 non-null float64
Weak Foot                   18207 non-null float64
Skill Moves                 18207 non-null float64
Jersey Number               18207 non-null float64
Crossing                    18207 non-null float64
Finishing                   18207 non-null float64
HeadingAccuracy             18207 non-null float64
ShortPassing                18207 non-null float64
Volleys                     18207 non-null float64
Dribbling                   18207 non-null float64
Curve                       18207 non-null float64
FKAccuracy                  18207 non-null float64
LongPassing                 18207 non-null float64
BallControl                 18207 non-null float64
Acceleration                18207 non-null float64
SprintSpeed                 18207 non-null float64
Agility                     18207 non-null float64
Reactions                   18207 non-null float64
Balance                     18207 non-null float64
ShotPower                   18207 non-null float64
Jumping                     18207 non-null float64
Stamina                     18207 non-null float64
Strength                    18207 non-null float64
LongShots                   18207 non-null float64
Aggression                  18207 non-null float64
Interceptions               18207 non-null float64
Positioning                 18207 non-null float64
Vision                      18207 non-null float64
Penalties                   18207 non-null float64
Composure                   18207 non-null float64
Marking                     18207 non-null float64
StandingTackle              18207 non-null float64
SlidingTackle               18207 non-null float64
GKDiving                    18207 non-null float64
GKHandling                  18207 non-null float64
GKKicking                   18207 non-null float64
GKPositioning               18207 non-null float64
GKReflexes                  18207 non-null float64
```

```
dtypes: float64(38), int64(5)
memory usage: 6.0 MB
```

PCA

In [20]:

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
x = StandardScaler().fit_transform(data)
pca = PCA(n_components=3)
New_Data=pca.fit_transform(x)
```

In [ ]:

Part 3. Hierarchical Clustering

In [21]:

```
from sklearn.cluster import AgglomerativeClustering
clustering = AgglomerativeClustering(n_clusters=None,distance_threshold=0).fit(New_
```

In [22]:

```
clustering.labels_
```

Out[22]:

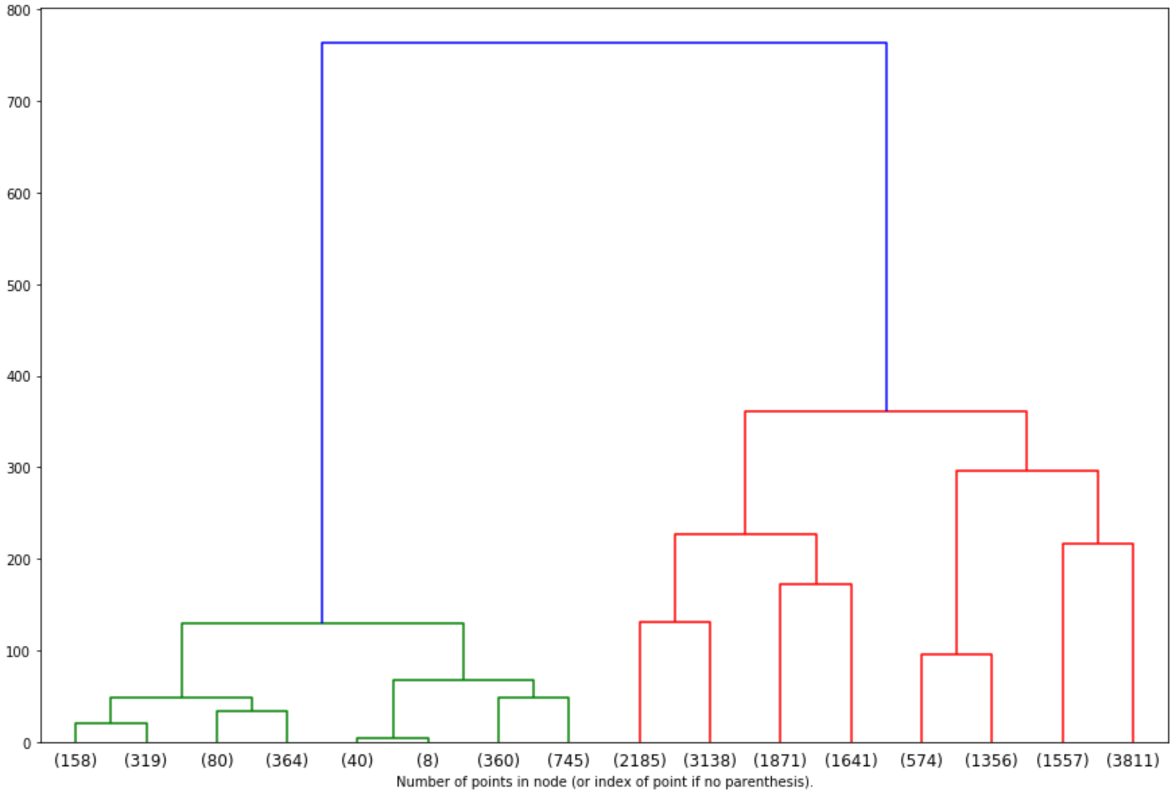
```
array([13263, 17759,  9727, ...,     3,     1,     0])
```

In [23]:

```
def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram

    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack([model.children_, model.distances_,
                                      counts]).astype(float)

    # Plot the corresponding dendrogram
    dendrogram(linkage_matrix, **kwargs)
```

In [24]:

```
plt.subplots(figsize=(15,10))
plot_dendrogram(clustering, truncate_mode='level', p=3)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



In [25]:

```
clustering.fit_predict(New_Data)
```

Out[25]:

```
array([13263, 17759,  9727, ...,     3,     1,     0])
```

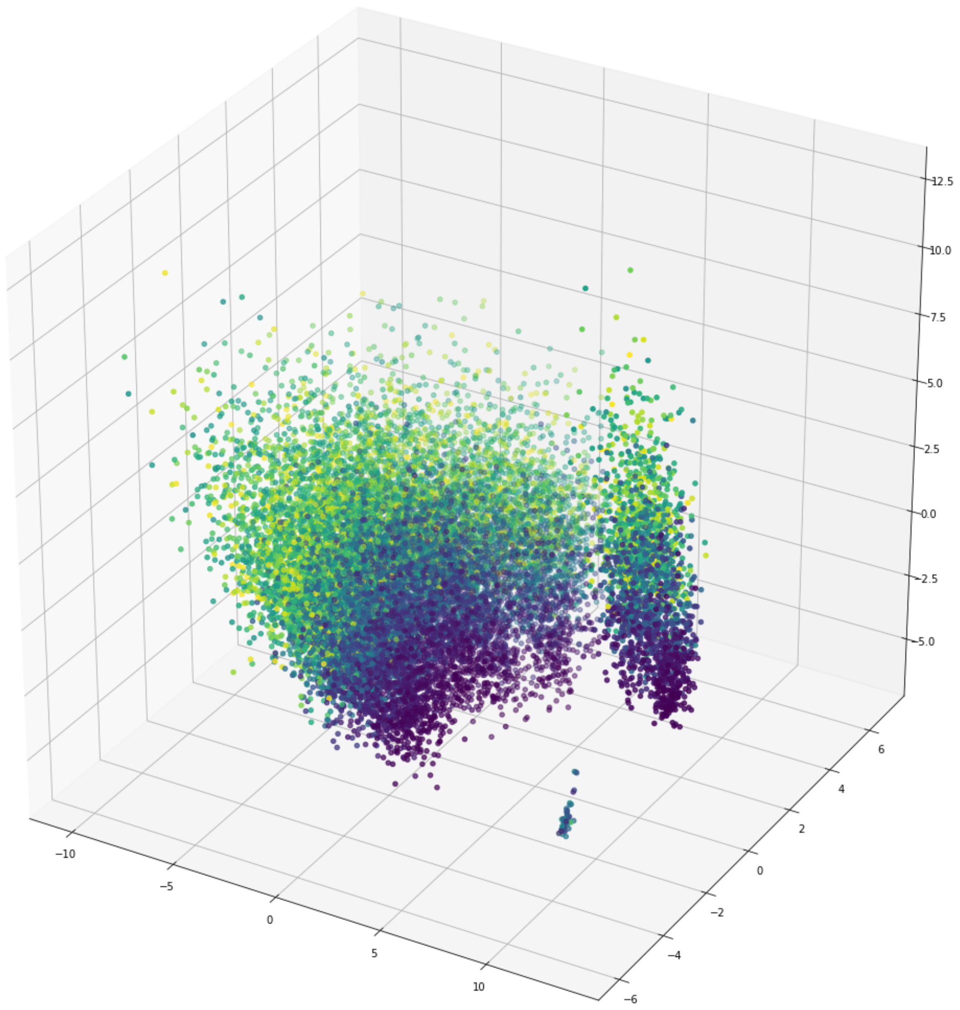
Hierarchical Clustering visualization

In [26]:

```
fig = plt.figure(figsize=(20, 20))
plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(New_Data[:,0],New_Data[:,1],New_Data[:,2],c=clustering.labels_)
```

Out[26]:

```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x7f6f62046668>
```



```
<Figure size 720x504 with 0 Axes>
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

Part.4 DBSCAN

In [27]:

```
# x = StandardScaler().fit_transform(data)

pca1 = PCA(n_components=3)
New_Data1=pca1.fit_transform(x)
from sklearn.cluster import DBSCAN
```

Cluster using different eps

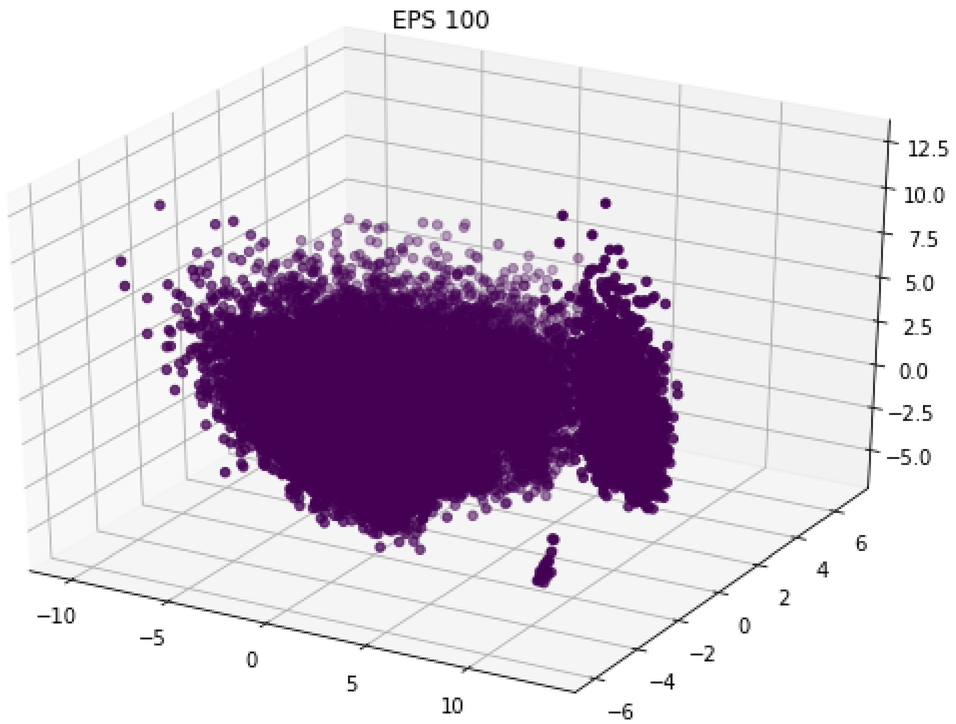
Used two values for eps .8 and 100. At 100 all the points merged into single cluster. For eps .8 we got 3 clusters which seams reasonable after seeing visualization. Hence we choose .8 as eps.

In [41]:

```
cluster = DBSCAN(eps=10, min_samples=4).fit(New_Data1)
cluster.fit_predict(New_Data1)
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(New_Data1[:,0],New_Data1[:,1],New_Data1[:,2],c=cluster.labels_)
plt.title('EPS 10')
```

Out[41]:

```
Text(0.5, 0.92, 'EPS 100')
```

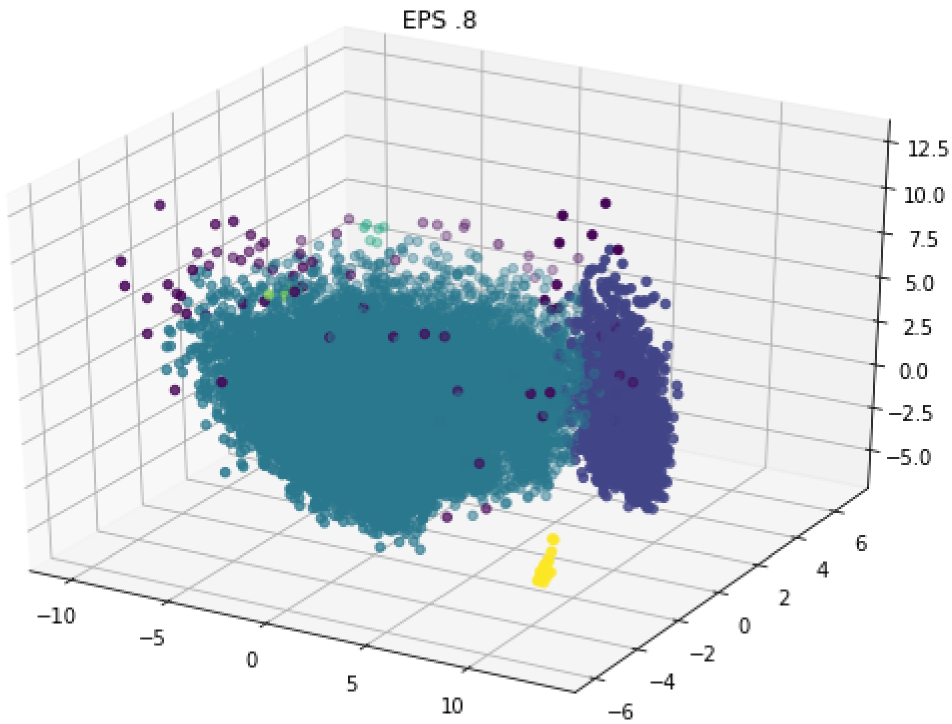


In [52]:

```
cluster = DBSCAN(eps=.8, min_samples=4).fit(New_Data1)
cluster.fit_predict(New_Data1)
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(New_Data1[:,0],New_Data1[:,1],New_Data1[:,2],c=cluster.labels_)
plt.title('EPS .8')
```

Out[52]:

```
Text(0.5, 0.92, 'EPS .8')
```



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In [29]:

In [ ]:

In [ ]:

Silhouette Score plot for various eps

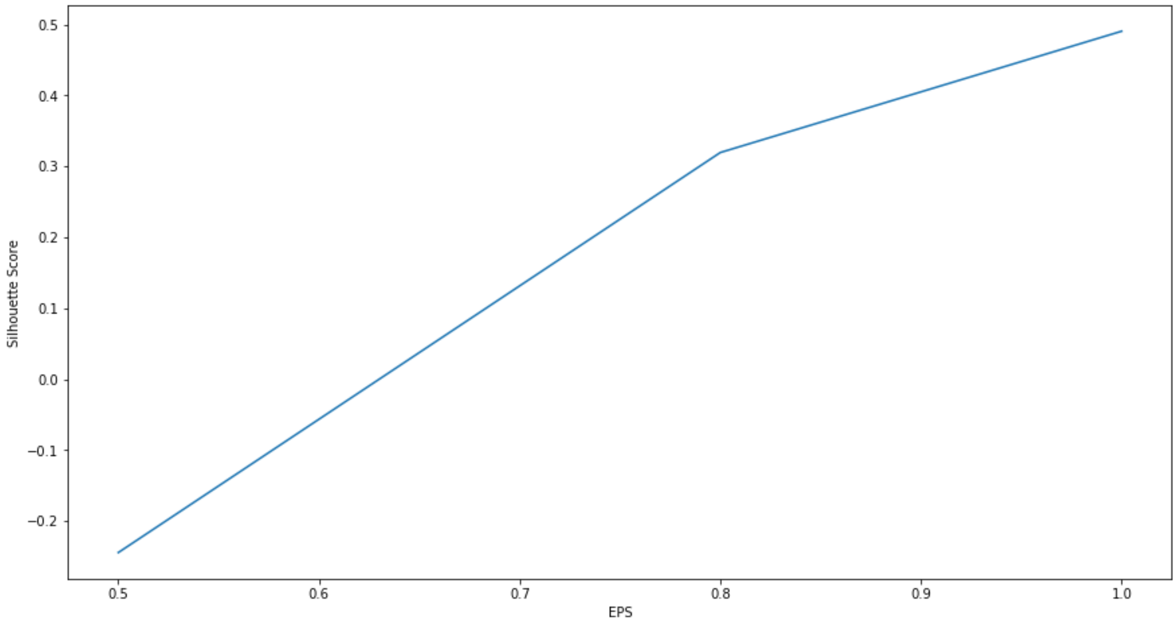
In [50]:

```
from sklearn.metrics import silhouette_score

sil = []
eps = [.5,.8,1]

# dissimilarity would not be defined for a single cluster, thus, minimum number of
for e in eps:
  cluster = DBSCAN(eps=e, min_samples=4).fit(New_Data1)
  cluster.fit_predict(New_Data1)
  labels = cluster.labels_
  sil.append(silhouette_score(New_Data1, labels))




print(len(sil),len(sz))

plt.plot(eps,sil)
plt.xlabel('EPS')
plt.ylabel('Silhouette Score')
```

```
3 4
```

Out[50]:

```
Text(0, 0.5, 'Silhouette Score')
```



In [ ]:

```

```

Part.2 K-means clustering

In [ ]:

```

```

In [32]:

```
import os
from sklearn.feature_extraction.text import TfidfVectorizer
from spacy.lang.en import English
from spacy.lang import en
from sklearn.preprocessing import normalize
import random
import numpy as np
import pandas as pd
from collections import Counter

def read_file(directory):
    files = os.listdir(directory)

    content_list=[]
    for f in files:
        with open(directory+f,encoding="utf8",errors='ignore') as fp:
            t=fp.read()
            content_list.append(t)
    vectorizer = TfidfVectorizer()
    X = vectorizer.fit_transform(content_list)
    x_norm=normalize(X)
    arr_n=x_norm.toarray()
    return arr_n
def read_file1(directory):
    files = os.listdir(directory)

    content_list=[]
    label_list=[]
    for f in files:
        f1,s=f.split('_')
        l=s[0]
        label_list.append(l)
        with open(directory+f,encoding="utf8",errors='ignore') as fp:
            t=fp.read()
            content_list.append(t)
    vectorizer = TfidfVectorizer()
    X = vectorizer.fit_transform(content_list)
    x_norm=normalize(X)
    arr_n=x_norm.toarray()
    return arr_n,label_list

def create_center_dict(centers,arr_n,k):
#     center_dict={0: [], 1: [], 2: [], 3: [],4: []}
    center_dict={}
    for i in range(k):
        center_dict[i]=[]



    n=arr_n.shape[0]

    for i in range(n):
        dis_center=[]
        for k in range(len(centers)):
            dis_center.append(np.linalg.norm(arr_n[i]-centers[k]))

        min_dis_center=min(dis_center)
        min_dis_center_index=dis_center.index(min_dis_center)
        center_dict[min_dis_center_index].append(i)
```

```
    return center_dict


def avg_row(row_list,arr_n):
    x=arr_n[row_list[0]]
    center=np.zeros(arr_n.shape[1])
#     print(center.shape)

    for i in row_list:
        for k in range(arr_n.shape[1]):
            center[k]=center[k]+arr_n[i,k]
    for k in range(arr_n.shape[1]):
        center[k]=center[k]/len(row_list)

    return center


def calculate_center(cluster_dict,arr_n,centers):

    for cluster in cluster_dict:
        if len(cluster_dict[cluster])!=0:
            centers[cluster ]=avg_row(cluster_dict[cluster],arr_n)


    return centers

def majority_poll(cluster_labels):  #majority element and its frequency out of a li
    d=Counter(cluster_labels)
    m=0;
    for (key,val) in d.items():
        if(val>m):
            m=val
            key1,val1=key,val

    return key1,val1



def cal_accuracy(cluster_dict,label):
    acc=0;
    for key in cluster_dict:
        cluster_labels=[]
        for val in cluster_dict[key]:
            cluster_labels.append(label[val])
        majority_key,occ=majority_poll(cluster_labels)
        acc=acc+occ/len(cluster_labels)

    return acc/len(cluster_dict.keys())







def training(data,k):
#     arr_n,label=read_file1(directory)
    arr_n=data
```

```
    it=100

    print(arr_n[1])
    centers=[]
    cluster_dict={}
    center_index=random.sample(range(0,1725), k)

    for e in center_index:
        centers.append(arr_n[e,:])

    for i in range(it):  #put it here
        cluster_dict=create_center_dict(centers,arr_n,k)
        centers = calculate_center(cluster_dict,arr_n,centers)

    index_cluster={}
    for cluster,lis in cluster_dict.items():
        for idx in lis:
            index_cluster[idx]=cluster
    pre_labels=[]
    for i in range(data.shape[0]):
        pre_labels.append(index_cluster[i])
    return pre_labels,centers





#         print(centers)

#     accuracy=cal_accuracy(cluster_dict,label)
#     print("Average clustering accuracy:",accuracy)
# #     return cluster_dict







labels,centers=training(New_Data1,4)
```

```
[-10.38891495  -2.12970389  10.32854247]
```

elbow method plot for various k

In [33]:

```
def calculate_WSS(points, kmax):
  sse = []
  for k in range(1, kmax+1):
#     kmeans = KMeans(n_clusters = k).fit(points)
#     centroids = kmeans.cluster_centers_
    pred_clusters,centroids =training(New_Data1,k)
    curr_sse = 0

    # calculate square of Euclidean distance of each point from its cluster center
    for i in range(len(points)):
      curr_center = centroids[pred_clusters[i]]
      curr_sse += (points[i, 0] - curr_center[0]) ** 2 + (points[i, 1] - curr_cente

    sse.append(curr_sse)
  return sse

sse=calculate_WSS(New_Data1,5)
```

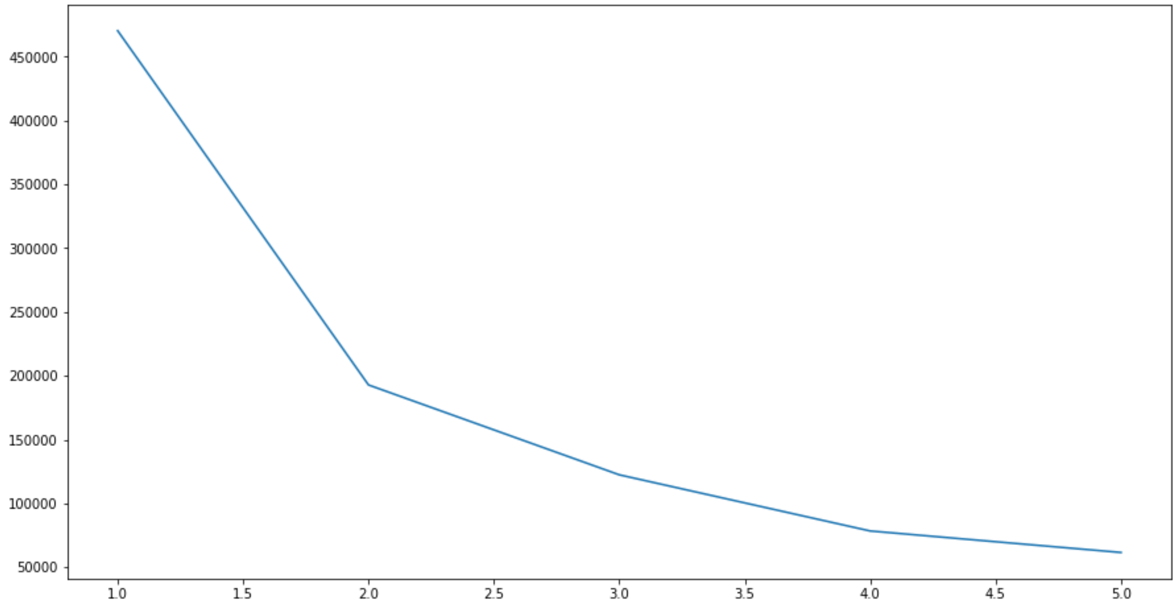
```
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
```

In [34]:

```
k1=[]
for i in range(1,6):
    k1.append(i)
plt.plot(k1,sse)
```

Out[34]:

```
[<matplotlib.lines.Line2D at 0x7f6f61dde128>]
```



Silhouette Score vs no of clusters

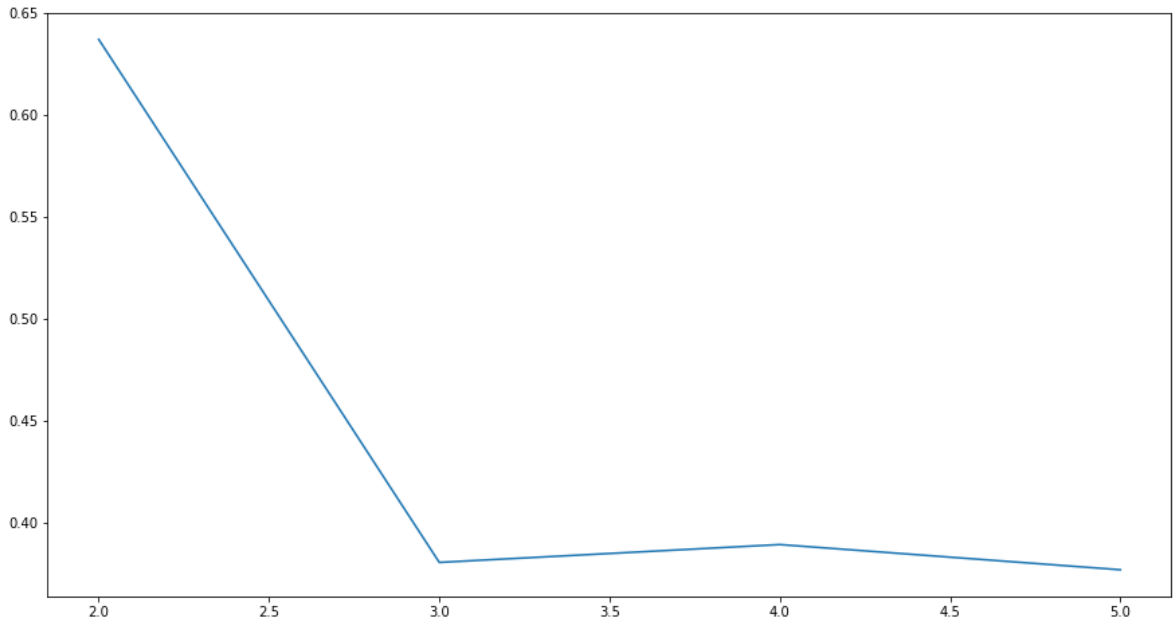
In [35]:

```
from sklearn.metrics import silhouette_score

sil = []
kmax = 5

# dissimilarity would not be defined for a single cluster, thus, minimum number of
for k in range(2, kmax+1):
  labels,centers = training(New_Data1,k)
  sil.append(silhouette_score(New_Data1, labels, metric = 'euclidean'))

sz=[]
for i in range(2,6):
    sz.append(i)


print(len(sil),len(sz))

plt.plot(sz,sil)
```

```
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
[-10.38891495  -2.12970389  10.32854247]
4 4
```

Out[35]:

```
[<matplotlib.lines.Line2D at 0x7f6f5e4ae160>]
```



From scratch k-means cluster visualization

In [36]:

```
labels,centers=training(New_Data1,3)
# print(New_Data1.shape)
```

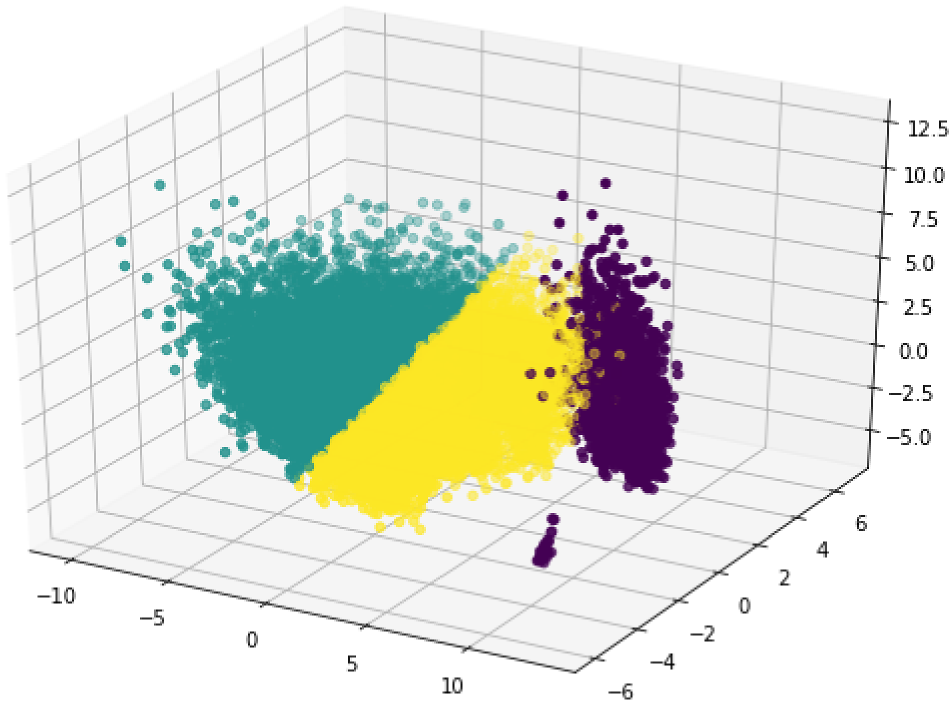
```
[-10.38891495  -2.12970389  10.32854247]
```

In [37]:

```
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(New_Data1[:,0],New_Data1[:,1],New_Data1[:,2],c=labels)
```

Out[37]:

```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x7f6f5e1b7668>
```



Sklearn K-mean cluster visualization

In [38]:

```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3, random_state=0).fit(New_Data1)
# kmeans.labels_
```

In [39]:

```
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(New_Data1[:,0],New_Data1[:,1],New_Data1[:,2],c=kmeans.labels_)
```

Out[39]:

```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x7f6f5e529588>
```