SCOUTING FOOTBALLERS

AN UNSUPERVISED LEARNING APPROACH

CSML-1000 | By GROUP 3 (*Jean-Jacques Rousseau, David Geller, Kwangjin Park, Petr Kocourek and Puneeth Nagarajaiah*)

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1. Introduction

How much would it cost a soccer team to sign a full roster of players? In English Premier League (EPL), Manchester United FC is the first overall in total salary expense of players, totalling at £227,081,000. On the other hand, Brentford FC ranked last in total salary expense at £15,776,000. In 2021~2022 EPL season, Manchester United ended the season in sixth place, while Brentford ended the season in 13th place. Although Mancheser United spent nearly 1339% more on player salary than Brentford FC, it is hard to justify having to spend that much money on their disappointing season. If paying more for the players doesn't guarantee a good team, then what could be the factors?

To stay competitive in the league, soccer teams must examine the players they need by scouring all over leagues. Agents from each team will look at each player's past performances, techniques, age, physical attributes, game intelligence, mindset, etc to determine if he is the player they are looking for. Scouting for players manually through analysis of individual agent has become more challenging as the number of professional players increased.

If agents can use the help of machine learning that has been trained on a dataset of all available players, they simply need to supply attributes that they find most important to narrow down players of interest. This will greatly save scouts time and money.

- **Business Problem:** Using Machine Learning (Clustering), find the player that meets the specific requirements supplied by a soccer agent. For example, if an agent comes to our web app and enters scores they want for each skill using the slider (eg. choosing a value between 0 and 100), our webapp will output a list of names of players with highest match scores. This will greatly narrow down the number of players the agent has to scout for.

- **Dataset:** FIFA 22 complete player dataset (https://www.kaggle.com/datasets/stefanoleone992/fifa-22-complete-player-dataset/discussion/360882)

2. Installation

In this section, we install pycaret and the Kaggle dataset. This section is similar to Assignment 1.

- **Setting Up Modules:** How to install pycaret, kaggle and other required modules
- **Getting Data:** How to import data from Kaggle website directly

```
! pip install pycaret
```

```
! pip install pandas
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns; sns.set_theme()
```

```
! pip install Kaggle
! mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
! kaggle datasets download stefanoleone992/fifa-22-complete-player-dataset
! unzip fifa-22-complete-player-dataset.zip
df = pd.read_csv('/content/players_22.csv')
```

3. General Dataset Analysis

This section explores the characteristics of the data so that we can develop and intuitive feel for the dataset.

3.1 Data Exploration

```
# Data dimension

df.shape
```

```
(19239, 110)
```

The dataset has over 19000 players with 110 attributes.

```
# Descriptive Statistics
df.describe()
```

```
           sofifa_id       overall     potential     value_eur  
wage_eur  \
count   19239.000000  19239.000000  19239.000000  1.916500e+04  
19178.000000   
mean   231468.086959     65.772182     71.079370  2.850452e+06  
9017.989363   
std     27039.717497      6.880232      6.086213  7.613700e+06  
19470.176724   
min        41.000000     47.000000     49.000000  9.000000e+03  
500.000000   
25%    214413.500000     61.000000     67.000000  4.750000e+05  
1000.000000   
50%    236543.000000     66.000000     71.000000  9.750000e+05  
3000.000000   
75%    253532.500000     70.000000     75.000000  2.000000e+06  
8000.000000   
max    264640.000000     93.000000     95.000000  1.940000e+08  
350000.000000   

                age     height_cm     weight_kg   club_team_id  
league_level  \
count  19239.000000  19239.000000  19239.000000   19178.000000  
19178.000000   
mean      25.210822    181.299704     74.943032   50580.498123  
1.354364   
std        4.748235      6.863179      7.069434   54401.868535  
0.747865   
min       16.000000    155.000000     49.000000       1.000000  
1.000000   
25%       21.000000    176.000000     70.000000     479.000000  
1.000000   
50%       25.000000    181.000000     75.000000    1938.000000  
1.000000   
75%       29.000000    186.000000     80.000000  111139.000000  
```

```
1.000000
max       54.000000    206.000000    110.000000  115820.000000
5.000000

       ...  mentality_composure  defending_marking_awareness  \
count  ...         19239.000000                 19239.000000
mean   ...            57.929830                    46.601746
std    ...            12.159326                    20.200807
min    ...            12.000000                     4.000000
25%    ...            50.000000                    29.000000
50%    ...            59.000000                    52.000000
75%    ...            66.000000                    63.000000
max    ...            96.000000                    93.000000

       defending_standing_tackle  defending_sliding_tackle  \
count               19239.000000              19239.000000
mean                   48.045584                 45.906700
std                    21.232718                 20.755683
min                     5.000000                  5.000000
25%                    28.000000                 25.000000
50%                    56.000000                 53.000000
75%                    65.000000                 63.000000
max                    93.000000                 92.000000

       goalkeeping_diving  goalkeeping_handling
goalkeeping_kicking  \
count        19239.000000          19239.000000         19239.000000

mean            16.406102             16.192474            16.055356

std             17.574028             16.839528            16.564554

min              2.000000              2.000000             2.000000

25%              8.000000              8.000000             8.000000

50%             11.000000             11.000000            11.000000

75%             14.000000             14.000000            14.000000

max             91.000000             92.000000            93.000000


       goalkeeping_positioning  goalkeeping_reflexes
goalkeeping_speed
count             19239.000000          19239.000000
2132.000000
mean                 16.229274             16.491814
36.439962
```

```
std                    17.059779              17.884833
10.751563
min                     2.000000               2.000000
15.000000
25%                     8.000000               8.000000
27.000000
50%                    11.000000              11.000000
36.000000
75%                    14.000000              14.000000
45.000000
max                    92.000000              90.000000
65.000000

[8 rows x 60 columns]
```

Here you can see general statistic of the data, such as count, mean, min and max. For example, the mean age of the players is 25.2 years old, with the youngest play being 16 years old.

```
pd.set_option('display.max_columns', None)
type(df)
```

```
pandas.core.frame.DataFrame
```

```
df.head()
```

```
   sofifa_id                                         player_url  \
0     158023  https://sofifa.com/player/158023/lionel-messi/...
1     188545  https://sofifa.com/player/188545/robert-lewand...
2      20801  https://sofifa.com/player/20801/c-ronaldo-dos-...
3     190871  https://sofifa.com/player/190871/neymar-da-sil...
4     192985  https://sofifa.com/player/192985/kevin-de-bruy...

          short_name                            long_name
player_positions  \
0           L. Messi       Lionel Andrés Messi Cuccittini       RW,
ST, CF
1     R. Lewandowski                  Robert Lewandowski
ST
2  Cristiano Ronaldo  Cristiano Ronaldo dos Santos Aveiro
ST, LW
3          Neymar Jr        Neymar da Silva Santos Júnior          LW,
CAM
4       K. De Bruyne                      Kevin De Bruyne          CM,
CAM

   overall  potential    value_eur  wage_eur  age         dob
height_cm  \
0       93         93   78000000.0  320000.0   34  1987-06-24
170
1       92         92  119500000.0  270000.0   32  1988-08-21
185
```

```
2       91         91   45000000.0  270000.0   36  1985-02-05
187
3       91         91  129000000.0  270000.0   29  1992-02-05
175
4       91         91  125500000.0  350000.0   30  1991-06-28
181

   weight_kg  club_team_id            club_name
league_name  \
0         72          73.0  Paris Saint-Germain          French Ligue
1
1         81          21.0    FC Bayern München    German 1.
Bundesliga
2         83          11.0    Manchester United  English Premier
League
3         68          73.0  Paris Saint-Germain          French Ligue
1
4         70          10.0      Manchester City  English Premier
League

   league_level club_position  club_jersey_number club_loaned_from  \
0           1.0            RW                30.0              NaN
1           1.0            ST                 9.0              NaN
2           1.0            ST                 7.0              NaN
3           1.0            LW                10.0              NaN
4           1.0           RCM                17.0              NaN

  club_joined  club_contract_valid_until  nationality_id
nationality_name  \
0  2021-08-10                     2023.0              52
Argentina
1  2014-07-01                     2023.0              37
Poland
2  2021-08-27                     2023.0              38
Portugal
3  2017-08-03                     2025.0              54
Brazil
4  2015-08-30                     2025.0               7
Belgium

   nation_team_id nation_position  nation_jersey_number preferred_foot
\
0          1369.0              RW                  10.0           Left

1          1353.0              RS                   9.0          Right

2          1354.0              ST                   7.0          Right

3             NaN             NaN                   NaN          Right
```

```
4          1325.0             RCM                    7.0          Right


   weak_foot  skill_moves  international_reputation    work_rate
body_type  \
0          4            4                         5   Medium/Low
Unique
1          4            4                         5  High/Medium
Unique
2          4            5                         5     High/Low
Unique
3          5            5                         5  High/Medium
Unique
4          5            4                         4    High/High
Unique

  real_face  release_clause_eur  \
0       Yes         144300000.0
1       Yes         197200000.0
2       Yes          83300000.0
3       Yes         238700000.0
4       Yes         232200000.0

                                         player_tags  \
0  #Dribbler, #Distance Shooter, #FK Specialist, ...
1  #Aerial Threat, #Distance Shooter, #Clinical F...
2  #Aerial Threat, #Dribbler, #Distance Shooter, ...
3  #Speedster, #Dribbler, #Playmaker, #FK Special...
4  #Dribbler, #Playmaker, #Engine, #Distance Shoo...

                                       player_traits  pace  shooting
passing  \
0  Finesse Shot, Long Shot Taker (AI), Playmaker ...  85.0      92.0
91.0
1  Solid Player, Finesse Shot, Outside Foot Shot,...  78.0      92.0
79.0
2  Power Free-Kick, Flair, Long Shot Taker (AI), ...  87.0      94.0
80.0
3  Injury Prone, Flair, Speed Dribbler (AI), Play...  91.0      83.0
86.0
4  Injury Prone, Leadership, Early Crosser, Long ...  76.0      86.0
93.0

   dribbling  defending  physic  attacking_crossing
attacking_finishing  \
0       95.0       34.0    65.0                  85
95
1       86.0       44.0    82.0                  71
```

```
95
2       88.0       34.0    75.0                  87
95
3       94.0       37.0    63.0                  85
83
4       88.0       64.0    78.0                  94
82

   attacking_heading_accuracy  attacking_short_passing
attacking_volleys  \
0                          70                       91
88
1                          90                       85
89
2                          90                       80
86
3                          63                       86
86
4                          55                       94
82

   skill_dribbling  skill_curve  skill_fk_accuracy  skill_long_passing
\
0               96           93                 94                  91

1               85           79                 85                  70

2               88           81                 84                  77

3               95           88                 87                  81

4               88           85                 83                  93


   skill_ball_control  movement_acceleration  movement_sprint_speed  \
0                  96                     91                     80
1                  88                     77                     79
2                  88                     85                     88
3                  95                     93                     89
4                  91                     76                     76

   movement_agility  movement_reactions  movement_balance
power_shot_power  \
0                91                  94                95
86
1                77                  93                82
90
2                86                  94                74
94
```

```
3                96                   89                  84
80
4                79                   91                  78
91

   power_jumping  power_stamina  power_strength  power_long_shots  \
0             68             72              69                94
1             85             76              86                87
2             95             77              77                93
3             64             81              53                81
4             63             89              74                91

   mentality_aggression  mentality_interceptions
mentality_positioning  \
0                    44                       40
93
1                    81                       49
95
2                    63                       29
95
3                    63                       37
86
4                    76                       66
88

   mentality_vision  mentality_penalties  mentality_composure  \
0                95                   75                   96
1                81                   90                   88
2                76                   88                   95
3                90                   93                   93
4                94                   83                   89

   defending_marking_awareness  defending_standing_tackle  \
0                           20                         35
1                           35                         42
2                           24                         32
3                           35                         32
4                           68                         65

   defending_sliding_tackle  goalkeeping_diving  goalkeeping_handling
\
0                        24                   6                    11

1                        19                  15                     6

2                        24                   7                    11

3                        29                   9                     9
```

```
4                         53                    15                      13


   goalkeeping_kicking  goalkeeping_positioning  goalkeeping_reflexes
\
0                   15                       14                     8

1                   12                        8                    10

2                   15                       14                    11

3                   15                       15                    11

4                    5                       10                    13


   goalkeeping_speed    ls    st    rs  lw  lf  cf  rf  rw   lam   cam
ram  \
0                NaN  89+3  89+3  89+3  92  93  93  93  92    93    93
93
1                NaN  90+2  90+2  90+2  85  88  88  88  85  86+3  86+3
86+3
2                NaN  90+1  90+1  90+1  88  89  89  89  88  86+3  86+3
86+3
3                NaN  83+3  83+3  83+3  90  88  88  88  90  89+2  89+2
89+2
4                NaN  83+3  83+3  83+3  88  87  87  87  88  89+2  89+2
89+2

     lm   lcm    cm   rcm    rm   lwb   ldm   cdm   rdm   rwb    lb
lcb  \
0  91+2  87+3  87+3  87+3  91+2  66+3  64+3  64+3  64+3  66+3  61+3
50+3
1  84+3  80+3  80+3  80+3  84+3  64+3  66+3  66+3  66+3  64+3  61+3
60+3
2  86+3  78+3  78+3  78+3  86+3  63+3  59+3  59+3  59+3  63+3  60+3
53+3
3  89+2  82+3  82+3  82+3  89+2  67+3  63+3  63+3  63+3  67+3  62+3
50+3
4  89+2  89+2  89+2  89+2  89+2  79+3  80+3  80+3  80+3  79+3  75+3
69+3

     cb   rcb    rb    gk
player_face_url  \
0  50+3  50+3  61+3  19+3
https://cdn.sofifa.net/players/158/023/22_120.png
1  60+3  60+3  61+3  19+3
https://cdn.sofifa.net/players/188/545/22_120.png
2  53+3  53+3  60+3  20+3
```

```
https://cdn.sofifa.net/players/020/801/22_120.png
3  50+3  50+3  62+3  20+3
https://cdn.sofifa.net/players/190/871/22_120.png
4  69+3  69+3  75+3  21+3
https://cdn.sofifa.net/players/192/985/22_120.png

                            club_logo_url  \
0  https://cdn.sofifa.net/teams/73/60.png
1  https://cdn.sofifa.net/teams/21/60.png
2  https://cdn.sofifa.net/teams/11/60.png
3  https://cdn.sofifa.net/teams/73/60.png
4  https://cdn.sofifa.net/teams/10/60.png

                             club_flag_url  \
0      https://cdn.sofifa.net/flags/fr.png
1      https://cdn.sofifa.net/flags/de.png
2  https://cdn.sofifa.net/flags/gb-eng.png
3      https://cdn.sofifa.net/flags/fr.png
4  https://cdn.sofifa.net/flags/gb-eng.png

                            nation_logo_url  \
0  https://cdn.sofifa.net/teams/1369/60.png
1  https://cdn.sofifa.net/teams/1353/60.png
2  https://cdn.sofifa.net/teams/1354/60.png
3                                       NaN
4  https://cdn.sofifa.net/teams/1325/60.png

                       nation_flag_url
0  https://cdn.sofifa.net/flags/ar.png
1  https://cdn.sofifa.net/flags/pl.png
2  https://cdn.sofifa.net/flags/pt.png
3  https://cdn.sofifa.net/flags/br.png
4  https://cdn.sofifa.net/flags/be.png
```

Soccer player requires more than just some technical skills to be an excellent player. For example, Lionel Messi is an excellent ball handler and scorer, but he is also a leader who fosters communication and teamwork within the team, which helps other players perform better as well.

We have expanded column-wise to see all columns. Here, just by taking a quick glance, most of columns are numerical in nature, where different skills are given a score between 0 and 100.

For example, Christiano Ronaldo has the overall score of 91, shooting score of 94, dribbling score of 88, but defending score of 34.

```
# Checking for missing values
df.isnull().sum()
```

```
sofifa_id                0
player_url               0
```

```
short_name              0
long_name               0
player_positions        0
                      ...
player_face_url         0
club_logo_url          61
club_flag_url          61
nation_logo_url     18480
nation_flag_url         0
Length: 110, dtype: int64
```

We also checked if there are any null values, and we saw that much of values for nation_flag_url are missing.

```
# Count numbers
df.select_dtypes(include = ['number']).head() # 50 of the 110 columns
contain strings
```

```
   sofifa_id  overall  potential    value_eur  wage_eur  age
height_cm  \
0     158023       93         93   78000000.0  320000.0   34
170
1     188545       92         92  119500000.0  270000.0   32
185
2      20801       91         91   45000000.0  270000.0   36
187
3     190871       91         91  129000000.0  270000.0   29
175
4     192985       91         91  125500000.0  350000.0   30
181

   weight_kg  club_team_id  league_level  club_jersey_number  \
0         72          73.0           1.0                30.0
1         81          21.0           1.0                 9.0
2         83          11.0           1.0                 7.0
3         68          73.0           1.0                10.0
4         70          10.0           1.0                17.0

   club_contract_valid_until  nationality_id  nation_team_id  \
0                     2023.0              52          1369.0
1                     2023.0              37          1353.0
2                     2023.0              38          1354.0
3                     2025.0              54             NaN
4                     2025.0               7          1325.0

   nation_jersey_number  weak_foot  skill_moves
international_reputation  \
0                  10.0          4            4
5
1                   9.0          4            4
5
```

```
2                   7.0          4            5
5
3                   NaN          5            5
5
4                   7.0          5            4
4

   release_clause_eur  pace  shooting  passing  dribbling  defending
physic  \
0         144300000.0  85.0      92.0     91.0       95.0       34.0
65.0
1         197200000.0  78.0      92.0     79.0       86.0       44.0
82.0
2          83300000.0  87.0      94.0     80.0       88.0       34.0
75.0
3         238700000.0  91.0      83.0     86.0       94.0       37.0
63.0
4         232200000.0  76.0      86.0     93.0       88.0       64.0
78.0

   attacking_crossing  attacking_finishing  attacking_heading_accuracy
\
0                  85                   95                          70

1                  71                   95                          90

2                  87                   95                          90

3                  85                   83                          63

4                  94                   82                          55


   attacking_short_passing  attacking_volleys  skill_dribbling
skill_curve  \
0                       91                 88               96
93
1                       85                 89               85
79
2                       80                 86               88
81
3                       86                 86               95
88
4                       94                 82               88
85

   skill_fk_accuracy  skill_long_passing  skill_ball_control  \
0                 94                  91                  96
1                 85                  70                  88
```

```
2                 84                   77                   88
3                 87                   81                   95
4                 83                   93                   91

   movement_acceleration  movement_sprint_speed  movement_agility  \
0                     91                     80                91
1                     77                     79                77
2                     85                     88                86
3                     93                     89                96
4                     76                     76                79

   movement_reactions  movement_balance  power_shot_power
power_jumping  \
0                  94                95                86
68
1                  93                82                90
85
2                  94                74                94
95
3                  89                84                80
64
4                  91                78                91
63

   power_stamina  power_strength  power_long_shots
mentality_aggression  \
0             72              69                94
44
1             76              86                87
81
2             77              77                93
63
3             81              53                81
63
4             89              74                91
76

   mentality_interceptions  mentality_positioning  mentality_vision  \
0                       40                     93                95
1                       49                     95                81
2                       29                     95                76
3                       37                     86                90
4                       66                     88                94

   mentality_penalties  mentality_composure
defending_marking_awareness  \
0                   75                   96
20
1                   90                   88
35
```

```
2                   88                    95
24
3                   93                    93
35
4                   83                    89
68

   defending_standing_tackle  defending_sliding_tackle
goalkeeping_diving  \
0                         35                        24
6
1                         42                        19
15
2                         32                        24
7
3                         32                        29
9
4                         65                        53
15

   goalkeeping_handling  goalkeeping_kicking  goalkeeping_positioning
\
0                    11                   15                       14

1                     6                   12                        8

2                    11                   15                       14

3                     9                   15                       15

4                    13                    5                       10


   goalkeeping_reflexes  goalkeeping_speed
0                     8                NaN
1                    10                NaN
2                    11                NaN
3                    11                NaN
4                    13                NaN
```

```
# Count objects (strings)
df.select_dtypes(include = ['object']).head() # 50 of the 110 columns
contain strings
```

```
                                          player_url
short_name  \
0  https://sofifa.com/player/158023/lionel-messi/...           L.
Messi
1  https://sofifa.com/player/188545/robert-lewand...     R.
Lewandowski
```

```
2  https://sofifa.com/player/20801/c-ronaldo-dos-...  Cristiano
Ronaldo
3  https://sofifa.com/player/190871/neymar-da-sil...          Neymar
Jr
4  https://sofifa.com/player/192985/kevin-de-bruy...       K. De
Bruyne

                             long_name player_positions         dob  \
0       Lionel Andrés Messi Cuccittini       RW, ST, CF  1987-06-24
1                   Robert Lewandowski               ST  1988-08-21
2  Cristiano Ronaldo dos Santos Aveiro           ST, LW  1985-02-05
3        Neymar da Silva Santos Júnior          LW, CAM  1992-02-05
4                      Kevin De Bruyne          CM, CAM  1991-06-28

             club_name            league_name club_position
club_loaned_from  \
0  Paris Saint-Germain          French Ligue 1            RW
NaN
1    FC Bayern München    German 1. Bundesliga            ST
NaN
2    Manchester United  English Premier League            ST
NaN
3  Paris Saint-Germain          French Ligue 1            LW
NaN
4      Manchester City  English Premier League           RCM
NaN

  club_joined nationality_name nation_position preferred_foot
work_rate  \
0  2021-08-10        Argentina              RW           Left
Medium/Low
1  2014-07-01           Poland              RS          Right
High/Medium
2  2021-08-27         Portugal              ST          Right
High/Low
3  2017-08-03           Brazil             NaN          Right
High/Medium
4  2015-08-30          Belgium             RCM          Right
High/High

  body_type real_face
player_tags  \
0    Unique       Yes  #Dribbler, #Distance Shooter, #FK
Specialist, ...
1    Unique       Yes  #Aerial Threat, #Distance Shooter, #Clinical
F...
2    Unique       Yes  #Aerial Threat, #Dribbler, #Distance
Shooter, ...
3    Unique       Yes  #Speedster, #Dribbler, #Playmaker, #FK
Special...
```

```
4    Unique       Yes  #Dribbler, #Playmaker, #Engine, #Distance
Shoo...

                                       player_traits    ls    st    rs
lw  \
0  Finesse Shot, Long Shot Taker (AI), Playmaker ...  89+3  89+3  89+3
92
1  Solid Player, Finesse Shot, Outside Foot Shot,...  90+2  90+2  90+2
85
2  Power Free-Kick, Flair, Long Shot Taker (AI), ...  90+1  90+1  90+1
88
3  Injury Prone, Flair, Speed Dribbler (AI), Play...  83+3  83+3  83+3
90
4  Injury Prone, Leadership, Early Crosser, Long ...  83+3  83+3  83+3
88

   lf  cf  rf  rw   lam   cam   ram    lm   lcm    cm   rcm    rm
lwb   ldm  \
0  93  93  93  92    93    93    93  91+2  87+3  87+3  87+3  91+2
66+3  64+3
1  88  88  88  85  86+3  86+3  86+3  84+3  80+3  80+3  80+3  84+3
64+3  66+3
2  89  89  89  88  86+3  86+3  86+3  86+3  78+3  78+3  78+3  86+3
63+3  59+3
3  88  88  88  90  89+2  89+2  89+2  89+2  82+3  82+3  82+3  89+2
67+3  63+3
4  87  87  87  88  89+2  89+2  89+2  89+2  89+2  89+2  89+2  89+2
79+3  80+3

    cdm   rdm   rwb    lb   lcb    cb   rcb    rb    gk  \
0  64+3  64+3  66+3  61+3  50+3  50+3  50+3  61+3  19+3
1  66+3  66+3  64+3  61+3  60+3  60+3  60+3  61+3  19+3
2  59+3  59+3  63+3  60+3  53+3  53+3  53+3  60+3  20+3
3  63+3  63+3  67+3  62+3  50+3  50+3  50+3  62+3  20+3
4  80+3  80+3  79+3  75+3  69+3  69+3  69+3  75+3  21+3

                                   player_face_url  \
0  https://cdn.sofifa.net/players/158/023/22_120.png
1  https://cdn.sofifa.net/players/188/545/22_120.png
2  https://cdn.sofifa.net/players/020/801/22_120.png
3  https://cdn.sofifa.net/players/190/871/22_120.png
4  https://cdn.sofifa.net/players/192/985/22_120.png

                          club_logo_url  \
0  https://cdn.sofifa.net/teams/73/60.png
1  https://cdn.sofifa.net/teams/21/60.png
2  https://cdn.sofifa.net/teams/11/60.png
3  https://cdn.sofifa.net/teams/73/60.png
4  https://cdn.sofifa.net/teams/10/60.png
```

```
                              club_flag_url  \
0      https://cdn.sofifa.net/flags/fr.png
1      https://cdn.sofifa.net/flags/de.png
2  https://cdn.sofifa.net/flags/gb-eng.png
3      https://cdn.sofifa.net/flags/fr.png
4  https://cdn.sofifa.net/flags/gb-eng.png

                             nation_logo_url  \
0  https://cdn.sofifa.net/teams/1369/60.png
1  https://cdn.sofifa.net/teams/1353/60.png
2  https://cdn.sofifa.net/teams/1354/60.png
3                                        NaN
4  https://cdn.sofifa.net/teams/1325/60.png

                       nation_flag_url
0  https://cdn.sofifa.net/flags/ar.png
1  https://cdn.sofifa.net/flags/pl.png
2  https://cdn.sofifa.net/flags/pt.png
3  https://cdn.sofifa.net/flags/br.png
4  https://cdn.sofifa.net/flags/be.png
```

We wanted to see how many of our columns have string datatype and how many of our columns are numerical datatype.

Here, we can see that 60 out of 110 features are numerical, which means 50 out of 110 features are strings.

```
# Most popular nationalities in the dataset
from wordcloud import WordCloud
nationality_name = " ".join(n for n in df['nationality_name'])
plt.figure(figsize=(10, 10))
wc = WordCloud().generate(nationality_name)
plt.imshow(wc, interpolation='bilinear')
plt.axis('off')
plt.show()
```

Using WorldCloud, here we see that most of players in the dataset are from England, Germany, France and Spain.

General information about this dataset:

1. The dataset include the players data for the Career Mode from FIFA 22
2. There are over 100 attributes
3. It has a mix of text and numerical values (60 numerical attributes and 50 text attributes)
4. The dataset shows player positions, with the role in the club and in the national team
5. The dataset shows player attributes with statistics as Attacking, Skills, Defense, Mentality, GK Skills, etc
6. The dataset shows player personal data like Nationality, Club, DateOfBirth, Wage, Salary, etc.
7. URL of the uploaded player faces, club and nation logos
8. Most of null data is from nation_flag_url
9. Most players in the dataset are from England, Germany, France and Spain

3.2 In-depth Data Exploration - Conditional Selection

Potential describes how much a certain player is expected to grow in their career.

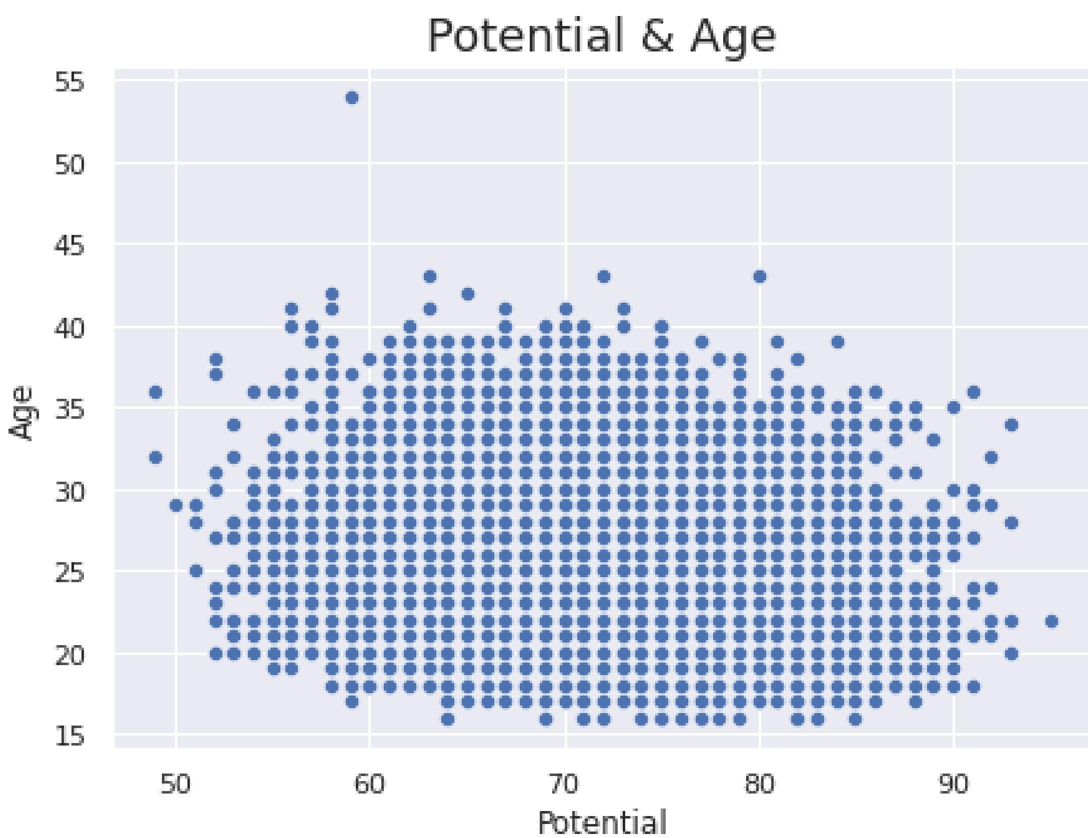
```
# Player potential versus wages
plt.figure(figsize=(7, 5))
ax = sns.scatterplot(x =df['potential'], y = df['wage_eur'])
plt.xlabel("Potential")
plt.ylabel("Wage EUR")
plt.title("Potential & wage", fontsize = 18)
plt.show()
```


Potential & wage
Wage EUR
350000
300000
250000
200000
150000
100000
50000
0
50
60
70
80
90
Potential


adidas
FIFA
FC BAYERN MÜNCHEN

Here we see that, players with higher potential generally earns more wages. For example, Lionel Messi and Robert Lewandowski both has two of highest potential in this dataset, and both earn highest wages as well.

```
# Player potential versus age

plt.figure(figsize=(7, 5))
ax = sns.scatterplot(x =df['potential'], y = df['age'])
plt.xlabel("Potential")
plt.ylabel("Age")
plt.title("Potential & Age", fontsize = 18)
plt.show()
```



Here, we don't see a clear correlation between potential and age. This possibly means that players age is not a factor in determining that player's potential. It is possible that younger players are generally healthier and has better physical attributes than older players. But older players have experience, game intelligence and techniques to overcome physical disadvantage to younger players.

The game of soccer is a complex game that requires both physical fitness and skills, so regardless of age, most players continue to play at high level.

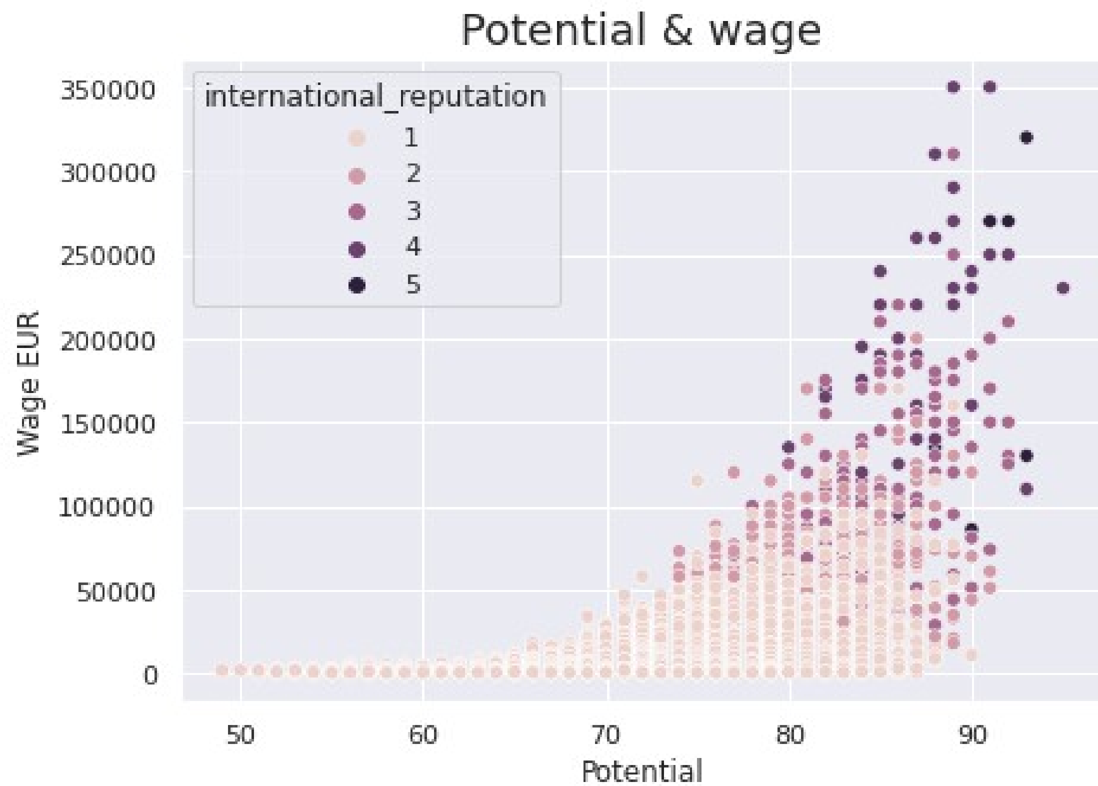
```
# Here are the 10 oldest players. The outlier above is K. Miura from
Japan at 54 years old. He is the oldest player in the dataset.
```

```
oldest_players = df[[ 'short_name',
                      'nationality_name',
                      'age',
                      'potential',
                  ]].nlargest(10,['age']).set_index('short_name')
oldest_players
```

```
                     nationality_name  age  potential
short_name
K. Miura                        Japan   54         59
G. Buffon                       Italy   43         80
C. Lucchetti                Argentina   43         72
S. Nakamura                     Japan   43         63
D. Vaca                       Bolivia   42         65
K. Ellison                    England   42         58
S. Torrico                  Argentina   41         73
A. Boruc                       Poland   41         70
P. Da Silva                  Paraguay   41         67
S. Lukić       Bosnia and Herzegovina   41         63
```

Here we see players who are oldest in the dataset. We see taht K. Miura is the oldest player at age 54, while G. Buffon is the second oldest player at age 43. We see that Gianluigi Buffon continues to play at high level even at older age compared to other older players.

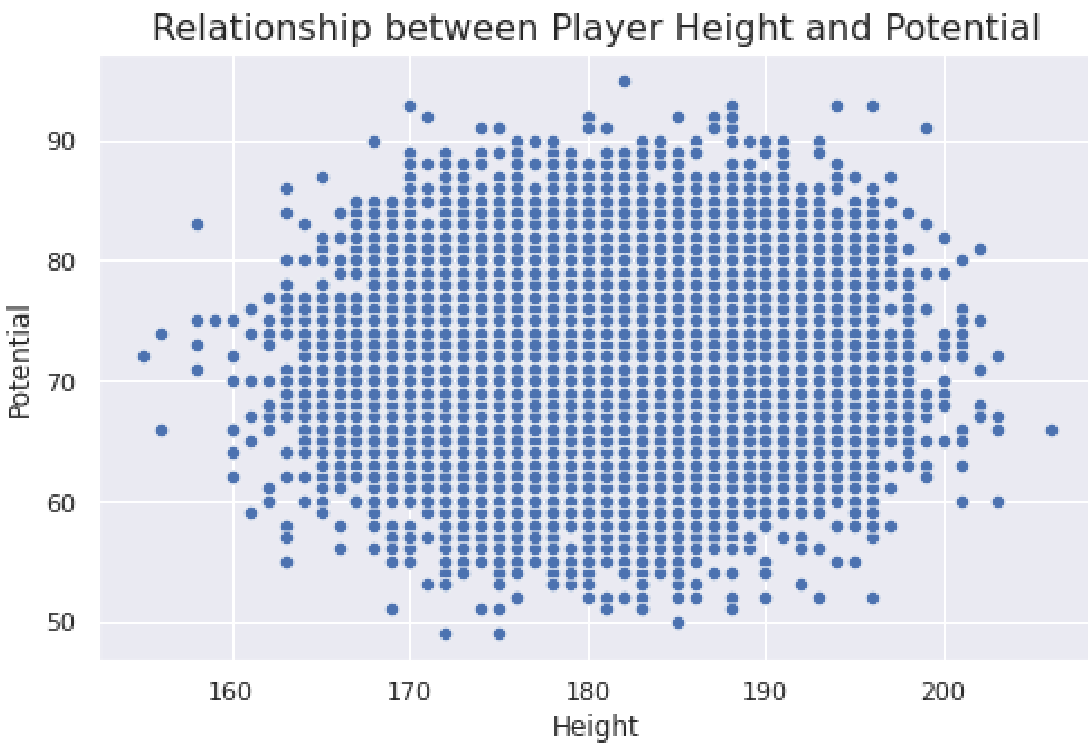
```
# Player potential versus wages, filtered by International reputation

plt.figure(figsize=(7, 5))
ax = sns.scatterplot(x =df['potential'], y = df['wage_eur'], hue =
df['international_reputation'])
plt.xlabel("Potential")
plt.ylabel("Wage EUR")
plt.title("Potential & wage", fontsize = 18)
plt.show()
```



This chart is similar to the one that shows correlation between Potential and Wage, but we added a third factor called International Reputation. We see that players with highest potential earns high wages, but also has high international reputation.

For example, players like Christiano Ronaldo and Lionel Messi would fit this category of players with high_potential/high_wage/high_reputation.

```
# Player height versus potential
fig, ax = plt.subplots(figsize = (8,5))
ax = sns.scatterplot(x =df['height_cm'], y = df['potential'])
plt.xlabel("Height")
plt.ylabel("Potential")
plt.title("Relationship between Player Height and Potential", fontsize
= 16)
plt.show()
```



Here, we see the chart showing the correlation between player's height and their potential. We don't see a clear correlation between two attributes, as the game of soccer can be played by players of all heights.

3.3 Pandas Profiling Feature Analysis

```
# List all features in dataset
df.columns

Index(['sofifa_id', 'player_url', 'short_name', 'long_name',
       'player_positions', 'overall', 'potential', 'value_eur',
'wage_eur',
       'age',
       ...
       'lcb', 'cb', 'rcb', 'rb', 'gk', 'player_face_url',
'club_logo_url',
       'club_flag_url', 'nation_logo_url', 'nation_flag_url'],
      dtype='object', length=110)
```

There are over 100 attributes in this dataset. Obviously, training an algorithm would be cumbersome, takes long time and wouldn't produce clear interpretation of our dataset.

This is why we need to narrow down to a small number of features that we are interested in to build an accurate Machine Learning Model. We will be using Pandas Profiling to get a better picture of the features.

In this section, our data analysis is on the entire dataset, but in '**Model Analysis**' section, we have narrowed down to Goalkeeper position and a small number of attributes.

```
# Pick out the features of interest

df_subset = df[['short_name', 'player_positions', 'overall',
'potential', 'wage_eur', 'age', 'club_name', 'nationality_name',
'skill_moves', 'work_rate', 'shooting', 'passing', 'defending']]

type(df_subset)
```

```
pandas.core.frame.DataFrame
```

```
df_subset.describe()
```

```
            overall     potential       wage_eur           age
skill_moves  \
count  19239.000000  19239.000000   19178.000000  19239.000000
19239.000000
mean      65.772182     71.079370    9017.989363     25.210822
2.352461
std        6.880232      6.086213   19470.176724      4.748235
0.767659
min       47.000000     49.000000     500.000000     16.000000
1.000000
25%       61.000000     67.000000    1000.000000     21.000000
2.000000
50%       66.000000     71.000000    3000.000000     25.000000
2.000000
75%       70.000000     75.000000    8000.000000     29.000000
3.000000
max       93.000000     95.000000  350000.000000     54.000000
5.000000

           shooting       passing     defending
count  17107.000000  17107.000000  17107.000000
mean      52.345297     57.312562     51.703630
std       14.051623     10.068965     16.189746
min       18.000000     25.000000     14.000000
25%       42.000000     51.000000     37.000000
50%       54.000000     58.000000     56.000000
75%       63.000000     64.000000     64.000000
max       94.000000     93.000000     91.000000
```

```
from pandas_profiling import ProfileReport

df_Subset_random = pd.DataFrame(np.random.rand(10, 5), columns = ['a',
'b', 'c', 'd', 'e'])

profile = ProfileReport(df_subset, title = 'FIFA Profiling Report',
html = {'style': {'full_width': True}})

profile
```

{"version_major":2,"version_minor":0,"model_id":"5a95be9ee9944bf094e3985f6d0cab4f"}

{"version_major":2,"version_minor":0,"model_id":"d1678e5b410e4b44995e61702df00710"}

{"version_major":2,"version_minor":0,"model_id":"321bca77e1ec47e884465830f254efcf"}

```
<IPython.core.display.HTML object>
```

Feature Analysis

- **Name:** 94% of names are distinct, J.Rodriguez is most common name
- **Player Position:** Corner Back (CB) and Goal Keeper (GK) are two highest number of positions
- **Overall:** Highest overall rating in the dataset is 93, and lowest is 47
- **Potential:** Highest potential in the dataset is 95, and lowest is 49
- **Wage:** Average wage in the dataset is 9017 EUR, while highest is 350000 EUR and lowest is 500 EUR
- **Age:** Oldest player in the dataset is 54, and the yongest player is 16
- **Club Name:** The clubs with most number of players in the dataset are PSG, Arsenal and Brentford.
- **Nationality:** Most players are from England, Germany, and Spain
- **Shooting:** Average shooting score is 52, while maximum score is 94 and minimum score is 18
- **Passing:** Average passing score is 57, while maximum score is 93 and minimum score is 25
- **Defending:** Average shooting score is 51.7, while maximum score is 91 and minimum score is 14

Feature Correlation Analysis

- **High positive correlation between Wage and Overall score (eg. players like Lewandowski and Messi)**
- **High positive correlation between Shooting and Passing**

- **High negative correlation between shooting and defending (eg. Strikers are not good defenders)**
- **Low correlation between Wage and Age (eg. yonger players can get paid just as much as older players if they are good. Earling Holland of Manchester City FC is only 22 year old and is currently the highest wage earner in EPL)**
- **High positive correlation between Passing and Overall Score (eg. good passing skill is one of most important attribute in soccer, as it is a team sport)**

4. Goalkeeper Dataset Analysis

*For our model analysis, for simplicity and clarity, we decided to use only **goalkeeper (GK)** dataset. This allows us to:*

- Control attribute weight distribution (eg. Making sure no one weight overweights other weights by a lot)
- Improve Silhoutte score (score that measures distance matrix between datapoint in a cluster)
- Easier web app deployment (narrow down attributes from 110)

```
df_gk=df[df.player_positions == "GK"]
df_gk.shape
```

```
(2132, 110)
```

```
df_gk.head()
```

```
    sofifa_id                                         player_url  \
5      200389  https://sofifa.com/player/200389/jan-oblak/220002
7      167495  https://sofifa.com/player/167495/manuel-neuer/...
8      192448  https://sofifa.com/player/192448/marc-andre-te...
12     192119  https://sofifa.com/player/192119/thibaut-court...
18     210257  https://sofifa.com/player/210257/ederson-santa...

       short_name                  long_name player_positions  overall
\
5        J. Oblak                  Jan Oblak               GK       91

7        M. Neuer          Manuel Peter Neuer               GK       90

8   M. ter Stegen      Marc-André ter Stegen               GK       90

12    T. Courtois            Thibaut Courtois               GK       89

18        Ederson  Ederson Santana de Moraes               GK       89


    potential    value_eur  wage_eur  age         dob  height_cm
weight_kg  \
5          93  112000000.0  130000.0   28  1993-01-07        188
```

```
87
7          90   13500000.0   86000.0   35  1986-03-27        193
93
8          92   99000000.0  250000.0   29  1992-04-30        187
85
12         91   85500000.0  250000.0   29  1992-05-11        199
96
18         91   94000000.0  200000.0   27  1993-08-17        188
86

    club_team_id           club_name             league_name
league_level  \
5          240.0  Atlético de Madrid  Spain Primera Division
1.0
7           21.0   FC Bayern München    German 1. Bundesliga
1.0
8          241.0        FC Barcelona  Spain Primera Division
1.0
12         243.0      Real Madrid CF  Spain Primera Division
1.0
18          10.0     Manchester City  English Premier League
1.0

   club_position  club_jersey_number club_loaned_from club_joined  \
5             GK                13.0              NaN  2014-07-16
7             GK                 1.0              NaN  2011-07-01
8             GK                 1.0              NaN  2014-07-01
12            GK                 1.0              NaN  2018-08-09
18            GK                31.0              NaN  2017-07-01

    club_contract_valid_until  nationality_id nationality_name  \
5                      2023.0              44         Slovenia
7                      2023.0              21          Germany
8                      2025.0              21          Germany
12                     2026.0               7          Belgium
18                     2026.0              54           Brazil

    nation_team_id nation_position  nation_jersey_number
preferred_foot  \
5              NaN             NaN                   NaN
Right
7           1337.0              GK                   1.0
Right
8              NaN             NaN                   NaN
Right
12          1325.0              GK                   1.0
Left
18             NaN             NaN                   NaN
Left
```

```
    weak_foot  skill_moves  international_reputation      work_rate  
body_type  \
5           3            1                         5  Medium/Medium   
Unique   
7           4            1                         5  Medium/Medium   
Unique   
8           4            1                         4  Medium/Medium   
Unique   
12          3            1                         4  Medium/Medium   
Unique   
18          3            1                         3  Medium/Medium   
Unique   

   real_face  release_clause_eur player_tags  \
5        Yes         238000000.0         NaN   
7        Yes          22300000.0         NaN   
8        Yes         210400000.0         NaN   
12       Yes         181700000.0         NaN   
18       Yes         181000000.0         NaN   

                                        player_traits  pace  shooting  
\
5                    GK Long Throw, Comes For Crosses   NaN       NaN   

7   Leadership, GK Long Throw, Rushes Out Of Goal,...   NaN       NaN   

8   Rushes Out Of Goal, Comes For Crosses, Saves w...   NaN       NaN   

12                   GK Long Throw, Comes For Crosses   NaN       NaN   

18  Long Passer (AI), Rushes Out Of Goal, Comes Fo...   NaN       NaN   


    passing  dribbling  defending  physic  attacking_crossing  \
5       NaN        NaN        NaN     NaN                  13   
7       NaN        NaN        NaN     NaN                  15   
8       NaN        NaN        NaN     NaN                  18   
12      NaN        NaN        NaN     NaN                  14   
18      NaN        NaN        NaN     NaN                  20   

    attacking_finishing  attacking_heading_accuracy  
attacking_short_passing  \
5                    11                          15                       
43   
7                    13                          25                       
60   
8                    14                          11                       
61   
12                   14                          13                       
```

```
33
18                    14                          14
61

    attacking_volleys  skill_dribbling  skill_curve  skill_fk_accuracy
\
5                  13               12           13                 14

7                  11               30           14                 11

8                  14               21           18                 12

12                 12               13           19                 20

18                 18               23           15                 20


    skill_long_passing  skill_ball_control  movement_acceleration  \
5                   40                  30                     43
7                   68                  46                     54
8                   63                  30                     38
12                  35                  23                     42
18                  66                  40                     64

    movement_sprint_speed  movement_agility  movement_reactions  \
5                      60                67                  88
7                      60                51                  87
8                      50                39                  86
12                     52                62                  84
18                     63                60                  88

    movement_balance  power_shot_power  power_jumping
power_stamina  \
5                 49                59             78             41

7                 35                68             77             43

8                 43                66             79             35

12                45                56             68             38

18                48                70             66             41


    power_strength  power_long_shots  mentality_aggression  \
5               78                12                    34
7               80                16                    29
8               78                10                    43
12              70                17                    23
```

```
18               78                 18                     38

    mentality_interceptions  mentality_positioning  
mentality_vision  \
5                        19                     11                 65   

7                        30                     12                 70   

8                        22                     11                 70   

12                       15                     13                 44   

18                       27                     20                 70   


    mentality_penalties  mentality_composure  
defending_marking_awareness  \
5                    11                   68                           
27   
7                    47                   70                           
17   
8                    25                   70                           
25   
12                   27                   66                           
20   
18                   51                   70                           
29   

    defending_standing_tackle  defending_sliding_tackle  
goalkeeping_diving  \
5                          12                        18                  
87   
7                          10                        11                  
88   
8                          13                        10                  
88   
12                         18                        16                  
84   
18                         15                         8                  
87   

    goalkeeping_handling  goalkeeping_kicking  goalkeeping_positioning  
\
5                     92                   78                       90   

7                     88                   91                       89   

8                     85                   88                       88   
```

```
12                     89                    74                        86

18                     82                    93                        88


    goalkeeping_reflexes  goalkeeping_speed    ls    st    rs  lw  lf
cf  rf  \
5                     90               50.0  33+3  33+3  33+3  32  35
35  35
7                     88               56.0  40+3  40+3  40+3  40  43
43  43
8                     90               43.0  35+3  35+3  35+3  35  38
38  38
12                    88               46.0  31+3  31+3  31+3  29  31
31  31
18                    88               64.0  40+3  40+3  40+3  41  43
43  43

    rw   lam   cam   ram    lm   lcm    cm   rcm    rm   lwb   ldm
cdm  \
5   32  38+3  38+3  38+3  35+3  38+3  38+3  38+3  35+3  32+3  36+3
36+3
7   40  47+3  47+3  47+3  44+3  50+3  50+3  50+3  44+3  37+3  43+3
43+3
8   35  42+3  42+3  42+3  39+3  45+3  45+3  45+3  39+3  33+3  41+3
41+3
12  29  32+3  32+3  32+3  31+3  32+3  32+3  32+3  31+3  29+3  31+3
31+3
18  41  47+3  47+3  47+3  44+3  49+3  49+3  49+3  44+3  37+3  44+3
44+3

     rdm   rwb    lb   lcb    cb   rcb    rb    gk  \
5   36+3  32+3  32+3  33+3  33+3  33+3  32+3  89+3
7   43+3  37+3  35+3  34+3  34+3  34+3  35+3  88+2
8   41+3  33+3  31+3  33+3  33+3  33+3  31+3  88+3
12  31+3  29+3  29+3  29+3  29+3  29+3  29+3  86+3
18  44+3  37+3  36+3  35+3  35+3  35+3  36+3  87+3

                                   player_face_url  \
5   https://cdn.sofifa.net/players/200/389/22_120.png
7   https://cdn.sofifa.net/players/167/495/22_120.png
8   https://cdn.sofifa.net/players/192/448/22_120.png
12  https://cdn.sofifa.net/players/192/119/22_120.png
18  https://cdn.sofifa.net/players/210/257/22_120.png

                               club_logo_url  \
5   https://cdn.sofifa.net/teams/240/60.png
7    https://cdn.sofifa.net/teams/21/60.png
8   https://cdn.sofifa.net/teams/241/60.png
```

```
12  https://cdn.sofifa.net/teams/243/60.png
18   https://cdn.sofifa.net/teams/10/60.png

                              club_flag_url  \
5       https://cdn.sofifa.net/flags/es.png
7       https://cdn.sofifa.net/flags/de.png
8       https://cdn.sofifa.net/flags/es.png
12      https://cdn.sofifa.net/flags/es.png
18  https://cdn.sofifa.net/flags/gb-eng.png

                              nation_logo_url  \
5                                         NaN
7   https://cdn.sofifa.net/teams/1337/60.png
8                                         NaN
12  https://cdn.sofifa.net/teams/1325/60.png
18                                        NaN

                         nation_flag_url
5   https://cdn.sofifa.net/flags/si.png
7   https://cdn.sofifa.net/flags/de.png
8   https://cdn.sofifa.net/flags/de.png
12  https://cdn.sofifa.net/flags/be.png
18  https://cdn.sofifa.net/flags/br.png
```

```
df_gk = df_gk.rename(columns={'short_name':
'name','goalkeeping_diving':'diving','goalkeeping_handling':'handling'
,'goalkeeping_kicking':'kicking','goalkeeping_positioning':'positionin
g','goalkeeping_reflexes':'reflexes','goalkeeping_speed':'speed'})
```

```
attributes= ['name','overall','age','wage_eur','value_eur','diving',
'handling','kicking','positioning','reflexes','speed']
```

We handpicked attributes that gives us a high Silhouette score. The process of choosing the attribute was done through trial-and-error, as we experimented with different combination of attributes to obtain high Silhouette score, as well avoid overweight to any one attribute that will vastly influence the model's performance.

Attributes we used for our models are as follows:

- Name
- Overall (score)
- Age
- Wage (in Euros)
- Value (in Euros)
- Diving
- Handling
- Kicking
- Positioning
- Reflexes

- Speed

```
df_gk_final = df_gk[attributes].copy()
df_gk.reset_index(drop=True, inplace=True)
df_gk.head()
```

```
            name  overall  age  wage_eur    value_eur  diving
handling  \
0       J. Oblak       91   28  130000.0  112000000.0      87
92
1       M. Neuer       90   35   86000.0   13500000.0      88
88
2  M. ter Stegen       90   29  250000.0   99000000.0      88
85
3    T. Courtois       89   29  250000.0   85500000.0      84
89
4        Ederson       89   27  200000.0   94000000.0      87
82

   kicking  positioning  reflexes  speed
0       78           90        90   50.0
1       91           89        88   56.0
2       88           88        90   43.0
3       74           86        88   46.0
4       93           88        88   64.0
```

Fun fact: The goalkeeper with the highest overall rating in the FIFA22 dataset is Jan Oblak, who plays for Atlético Madrid.

```
df_gk_final.shape
```

```
(2132, 11)
```

Finally, our model will use Goalkeeper dataset that has 2124 distinct players and 11 attributes.

```
profile_gk = ProfileReport(df_gk_final, title = 'Goalkeepers Profile Report', html = {'style': {'full_width': True}})
```

```
profile_gk
```

{"version_major":2,"version_minor":0,"model_id":"9ffa219442bc42ffb2be986add38115c"}

{"version_major":2,"version_minor":0,"model_id":"537a06e2b1fd4c739e2028409db39797"}

{"version_major":2,"version_minor":0,"model_id":"3307cf9a5e274c43a858544ceaea2a79"}

```
<IPython.core.display.HTML object>
```

Feature Analysis

- **Name:** 99% of names are distinct
- **Overall:** Highest overall rating in the dataset is 91, and lowest is 47, with the mean rating of 64
- **Age:** Oldest goalkeeper in the dataset is 43, and youngest is 16. Average age of goalkeeper is 26
- **Wage:** Average wage in the dataset is 6349 EUR, while highest is 250000 EUR and lowest is 500 EUR
- **Value:** Average value of goalkeeper in the dataset is 1,930,764 EUR, while highest is 119,500,000 EUR and lowest is 9,000 EUR
- **Diving:** Average diving score is 65, while maximum score is 91 and minimum score is 41
- **Handling:** Average Handling score is 63, while maximum score is 92 and minimum score is 41
- **Kicking:** Average Kicking score is 62, while maximum score is 93 and minimum score is 39
- **Positioning:** Average Positioning score is 63, while maximum score is 92 and minimum score is 38
- **Reflexes:** Average Reflexes score is 66, while maximum score is 90 and minimum score is 35

- **Speed:** Average Speed score is 36, while maximum score is 65 and minimum score is 15

Feature Correlation Analysis

- **High positive correlation between Diving and Overall score:** Often, goalkeeper must dive from their stationary position to block the shot from the shooter. The goalkeeper that can dive better has higher chance of blocking the shot, therefore, gets higher score
- **High positive correlation between Diving and Reflexes:** The goalkeeper must make a decision instantly before they dive left or dive right to block the shot. The goalkeeper with faster reflexes with therefore, dive better.
- **No correlation between Age and Value:** Soccer player's value comes from their performance in games, and goalkeepers at age that plays well in games will earn high valuation.
- **High correlation between Handling and Positioning:** Goalkeepers that handles balls well are usually better positioned to receive the ball.

5. Model Analysis

Professional Soccer clubs has to invest a lot of resources, time and money in the recruitment of best players available. The use of clustering on the database of football players based on their performance data is useful for prototyping potentially successful players, and also for providing insights to football managers and scouts when assessing players.

The clustering model techniques allows us to use different types of variables (strings, numerical, categorial) and different types of attributes to be taken into account. The weight is objectively assigned to the distance matrix associated to each set of attributes during the optimization process (D'Urso, 2022).

The weights show how relevant each attribute type is in the clustering output. The benefit of clustering is that it is robust against outliers. The obtained weights allow to understand which is the most relevant set of attributes in partitiong the players into clustering groups (D'Urso, 2022).

```
from pycaret.clustering import *

exp_clu101 = setup(data=df_gk_final, transformation=True, normalize =
True, normalize_method = 'robust', ignore_features =
['name'],session_id = 123)
```

- We first setup the Pycaret cluster models environment
- In the steup, we will normalize the data using yeo-johson transformation and then scale it using Robust Scaler Technique
- The above steps have been underataken to reduce the impact of outliers present in "wages_eur" and "value_eur" variables.

```
models()
```

```
INFO:logs:gpu_param set to False
```

```
                                       Name  \
ID                                                
kmeans                    K-Means Clustering   
ap                      Affinity Propagation   
meanshift              Mean Shift Clustering   
sc                       Spectral Clustering   
hclust              Agglomerative Clustering   
dbscan     Density-Based Spatial Clustering   
optics                    OPTICS Clustering   
birch                      Birch Clustering   
kmodes                    K-Modes Clustering   

                                                   Reference  
ID                                                             
kmeans                       sklearn.cluster._kmeans.KMeans  
ap         sklearn.cluster._affinity_propagation.Affinity...  
meanshift             sklearn.cluster._mean_shift.MeanShift  
sc              sklearn.cluster._spectral.SpectralClustering  
hclust     sklearn.cluster._agglomerative.AgglomerativeCl...  
dbscan                       sklearn.cluster._dbscan.DBSCAN  
optics                       sklearn.cluster._optics.OPTICS  
birch                          sklearn.cluster._birch.Birch  
kmodes                                 kmodes.kmodes.KModes  
```

- The different clustering algorithms available in Pycaret is as shown above
- We will explore K-Means, DBSCAN and K-Modes, before finalizing the best model amongst them

```
kmeans = create_model('kmeans')
```

```
   Silhouette  Calinski-Harabasz  Davies-Bouldin  Homogeneity  Rand
Index  \
0      0.2277          1331.0122          1.4033            0
0   

   Completeness  
0             0  
```

```
INFO:logs:create_model_container: 2
INFO:logs:master_model_container: 2
INFO:logs:display_container: 3
INFO:logs:KMeans(algorithm='auto', copy_x=True, init='k-means++',
max_iter=300,
       n_clusters=4, n_init=10, n_jobs=-1,
precompute_distances='deprecated',
       random_state=123, tol=0.0001, verbose=0)
```

```
INFO:logs:create_model() succesfully
completed......................................
```

```
kmodes = create_model('kmodes')
```

```
   Silhouette  Calinski-Harabasz  Davies-Bouldin  Homogeneity  Rand
Index  \
0     -0.1228            33.2312         11.5088            0
0

   Completeness
0            0
```

```
INFO:logs:create_model_container: 2
INFO:logs:master_model_container: 2
INFO:logs:display_container: 3
INFO:logs:KModes(cat_dissim=<function matching_dissim at
0x7f4f4d501b90>, init='Cao',
       max_iter=100, n_clusters=4, n_init=1, n_jobs=-1,
random_state=123,
       verbose=0)
INFO:logs:create_model() succesfully
completed......................................
```

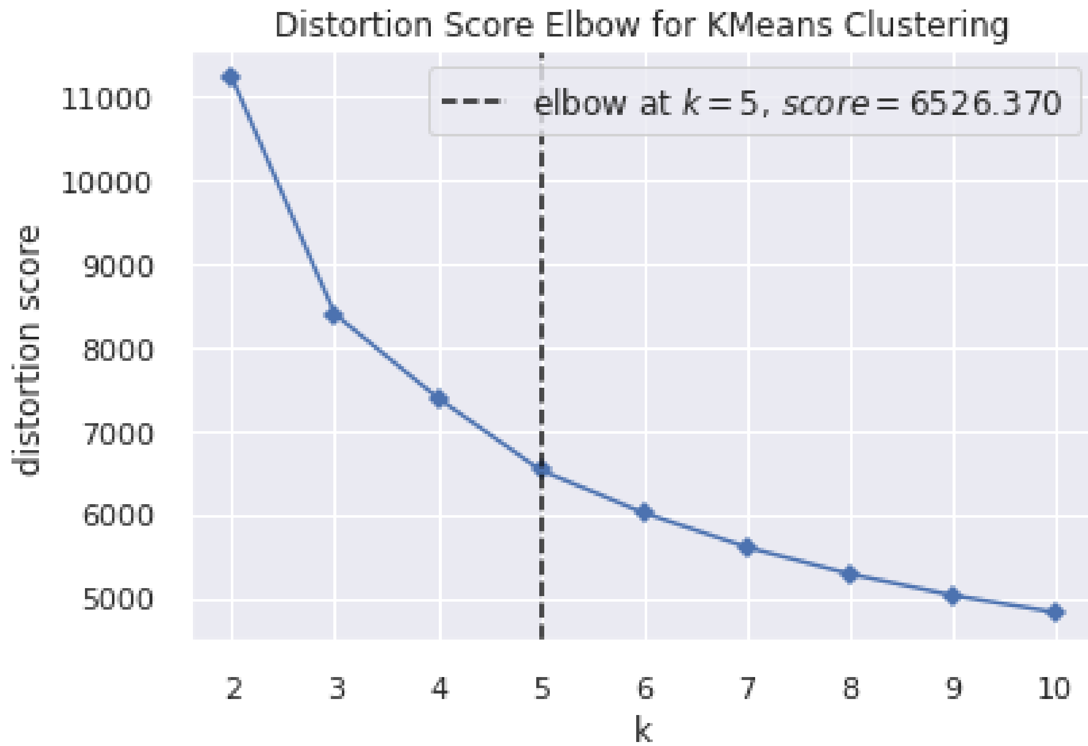
```
dbscan=create_model('dbscan')
```

```
   Silhouette  Calinski-Harabasz  Davies-Bouldin  Homogeneity  Rand
Index  \
0     -0.2708             0.4448          3.4137            0
0

   Completeness
0            0
```

```
INFO:logs:create_model_container: 4
INFO:logs:master_model_container: 4
INFO:logs:display_container: 5
INFO:logs:DBSCAN(algorithm='auto', eps=0.5, leaf_size=30,
metric='euclidean',
       metric_params=None, min_samples=5, n_jobs=-1, p=None)
INFO:logs:create_model() succesfully
completed......................................
```

- After exploring different models, we can conclude that K-means technique is best suited for this dataset

```
plot_model(kmeans, plot='elbow')
```




```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.......................................
```

#Elbow method: In this method, we will change the number of clusters (K) between 1 and 10, and for each value of K, we will calculate the Within-Cluster Sum of Square (WCSS). The WCSS is the sum of squared distance between each point and the centroid in a cluster. When we we plot the WCSS with a paticluar K value, the plot looks like an Elbow. As the number of clusters increases, the WCSS value will start to decrease. So, WCSS value is largest when K = 1, and the plot will rapidly change at a point and thus creating an elbow shape. From this point, the graph starts to move almost parallel to the X-axis. The K value corresponding to this point is the optimal K value or an optimal number of clusters.

- For our dataset, K = 5, which means beyond 5 clusters, the efficiency of the model will not increase.

```
kmeans5 = create_model('kmeans', num_clusters=5)
```

```
   Silhouette  Calinski-Harabasz  Davies-Bouldin  Homogeneity  Rand
Index  \
0      0.2308          1199.5065          1.3362            0
0

   Completeness
0             0
```

```
INFO:logs:create_model_container: 1
INFO:logs:master_model_container: 1
INFO:logs:display_container: 2
INFO:logs:KMeans(algorithm='auto', copy_x=True, init='k-means++',
max_iter=300,
       n_clusters=5, n_init=10, n_jobs=-1,
precompute_distances='deprecated',
       random_state=123, tol=0.0001, verbose=0)
INFO:logs:create_model() succesfully
completed......................................
```

- When we model for K=5 clusters, we get a silhoutte score of 0.2308
- The *silhouette value* is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The silhouette ranges from −1 to +1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters.
- Although not very high, this value seems the highest we can obtain from this dataset.
- The model also has a Calinski-Harabasz score of 1199.5065. The Calinski-Harabasz index is the ratio of the sum of between-clusters dispersion and of inter-cluster dispersion for all clusters.The higher the score , the better the performance.
- In general, the model does show separation but lacks cohesion.

```
plot_model(kmeans5)
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

Plot shows the five clusters after running the K-Means model

Clusters are formed based on player value

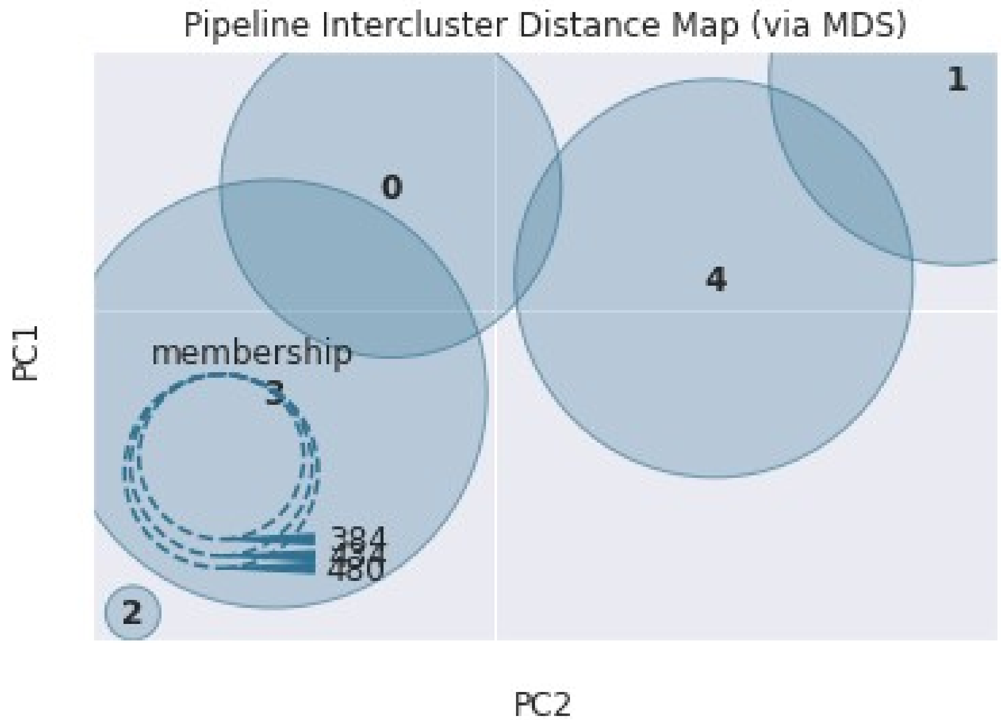
- Cluster 2 is the cluster with all top players, followed by cluster 3, Cluster 4, Cluster 0 and Cluster 1

```
plot_model(kmeans5, plot = 'tsne')
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

This is a t-distributed stochastic neighbor embedding plot which is a three-dimensional view of the clusters

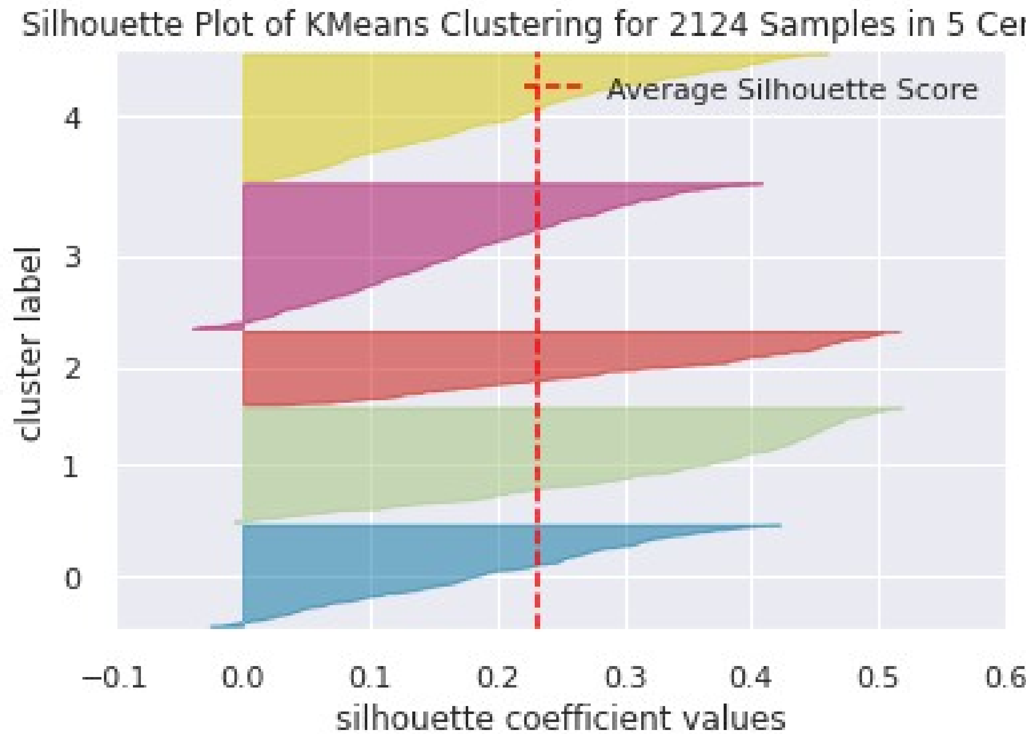
```
plot_model(kmeans5, plot = 'distance')
```




```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

Intercluster distance maps show an embedding of the cluster centers in two dimensions with the distance to other centers preserved

```
plot_model(kmeans5, plot = 'silhouette')
```




```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

The silhouette plot displays a measure of how close each point in one cluster is to points in the neighboring clusters and thus provides a way to assess parameters like number of clusters visually

```
plot_model(kmeans5, plot = 'distribution') #to see size of clusters
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

PLot shows the size of each cluster

```
plot_model(kmeans, plot = 'distribution', feature = 'overall')
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

Plot shows distribution of attribute "overall" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'age')
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.....................................
```

Plot shows distribution of attribute "age" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'wage_eur')
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.....................................
```

Plot shows distribution of attribute "wage_eur" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'value_eur')
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.....................................
```

Plot shows distribution of attribute "value_eur" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'diving')
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.....................................
```

Plot shows distribution of attribute "diving" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'handling')
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.....................................
```

Plot shows distribution of attribute "handling" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'kicking')
```

```
INFO:logs:Rendering Visual
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed.....................................
```

Plot shows distribution of attribute "kicking" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'positioning')
```

```
INFO:logs:Rendering Visual

INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

Plot shows distribution of attribute "positioning" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'reflexes')
```

```
INFO:logs:Rendering Visual

INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

Plot shows distribution of attribute "reflexes" across clusters

```
plot_model(kmeans, plot = 'distribution', feature = 'speed')
```

```
INFO:logs:Visual Rendered Successfully
INFO:logs:plot_model() succesfully
completed......................................
```

Plot shows distribution of attribute "speed" across clusters

```
kmean_results = assign_model(kmeans5)
kmean_results.head()
```

```
INFO:logs:Initializing assign_model()
INFO:logs:assign_model(model=KMeans(algorithm='auto', copy_x=True,
init='k-means++', max_iter=300,
       n_clusters=5, n_init=10, n_jobs=-1,
precompute_distances='deprecated',
       random_state=123, tol=0.0001, verbose=0), transformation=False,
score=True, verbose=True)
INFO:logs:Checking exceptions
INFO:logs:Determining Trained Model
INFO:logs:Trained Model : K-Means Clustering
INFO:logs:Copying data
INFO:logs:(2132, 12)
INFO:logs:assign_model() succesfully
completed......................................
```

```
            name  overall  age  wage_eur    value_eur  diving
handling  \
0       J. Oblak       91   28  130000.0  112000000.0      87
92
1       M. Neuer       90   35   86000.0   13500000.0      88
88
2  M. ter Stegen       90   29  250000.0   99000000.0      88
```

```
85
3    T. Courtois       89   29  250000.0   85500000.0      84
89
4       Ederson        89   27  200000.0   94000000.0      87
82

   kicking  positioning  reflexes  speed    Cluster
0       78           90        90   50.0  Cluster 2
1       91           89        88   56.0  Cluster 2
2       88           88        90   43.0  Cluster 2
3       74           86        88   46.0  Cluster 2
4       93           88        88   64.0  Cluster 2
```

Gives the final output dataframe

```
save_model(kmeans,'Final Kmeans Model CSML-Oct2022')
```

This is the final model which will be used for app deployment

```
kmeans.to_json()
```

```
df_kmeans = kmean_results.copy()
```

```
df_kmeans.head()
```

```
            name  overall  age  wage_eur    value_eur  diving
handling  \
0      J. Oblak       91   28  130000.0  112000000.0      87
92
1      M. Neuer       90   35   86000.0   13500000.0      88
88
2  M. ter Stegen      90   29  250000.0   99000000.0      88
85
3    T. Courtois      89   29  250000.0   85500000.0      84
89
4       Ederson       89   27  200000.0   94000000.0      87
82

   kicking  positioning  reflexes  speed    Cluster
0       78           90        90   50.0  Cluster 2
1       91           89        88   56.0  Cluster 2
2       88           88        90   43.0  Cluster 2
3       74           86        88   46.0  Cluster 2
4       93           88        88   64.0  Cluster 2
```

```
df_kmeans_new = df_kmeans.replace(['Cluster 0','Cluster 1','Cluster
2','Cluster 3','Cluster 4'],[0,1,2,3,4])
df_kmeans_new
```

```
                   name  overall  age  wage_eur    value_eur
diving  \
0             J. Oblak       91   28  130000.0  112000000.0      87
```

```
1              M. Neuer        90   35   86000.0   13500000.0      88

2          M. ter Stegen       90   29  250000.0   99000000.0      88

3            T. Courtois       89   29  250000.0   85500000.0      84

4               Ederson        89   27  200000.0   94000000.0      87

...                 ...       ...  ...       ...          ...     ...

2127          Gao Xiang        48   20     800.0      60000.0      46

2128  H. Wiles-Richards        48   19    1000.0     110000.0      52

2129        D. Da Silva        47   21     500.0      90000.0      48

2130          A. Shaikh        47   18     500.0     110000.0      49

2131              R. By        47   22     500.0      90000.0      49


      handling  kicking  positioning  reflexes  speed  Cluster
0           92       78           90        90   50.0        2
1           88       91           89        88   56.0        2
2           85       88           88        90   43.0        2
3           89       74           86        88   46.0        2
4           82       93           88        88   64.0        2
...        ...      ...          ...       ...    ...      ...
2127        49       51           48        51   24.0        1
2128        49       49           43        48   33.0        1
2129        45       45           46        47   26.0        1
2130        41       39           45        49   19.0        1
2131        46       43           47        52   21.0        1

[2124 rows x 12 columns]
```

```python
import plotly.express as px
fig = px.parallel_coordinates(df_kmeans_new, color="Cluster",
dimensions=['overall','age','wage_eur','value_eur','diving','handling'
,'kicking','positioning','reflexes','speed'],

color_continuous_scale=px.colors.diverging.Tealrose)
fig.show()
```

The above plot is known as a parallel coordinate plot. Here each row in the output dataset is plotted as a line. Each attribute is represented by a point on the line. In this plot, we can see how the attributes are distributed across various clusters

6. Conclusion with Outcomes & Improvements

Our goal for this assignment was by using clustering on a database of players, we are able to cluster players based on attribute scores. One application of our model would be, generating a list of top players that the soccer scouts might be interested in.

Because our dataset has over 110 features, it would be more practical to narrow down the features to a few that we might be interested in. Through trial-and-error, we narrowed down features that would give us a fairly high Silhouette score (which ranges between -1 and 1).

We also narrowed the soccer position down to just Goalkeepers, because we want to narrow our scope and concentrate our effort on analyzing small set of data. Based on our model, top goalkeepers in the dataset are put in Cluster 2, and lowest ranking goalkeepers are put in Cluster 1.

We wanted our webapp to be able to take in real-time input from soccer scouts, where they would choose scores for different skill sets using sliders. However, we were faced with technical challenges and time constraint to execute such an app, so we had to scale down our original plan. Instead, after much discussion, we created an app that outputs players in different clusters using FIFA22 dataset. Unfortunately, we weren't able to implement real-time input functionality.

Clearly, we noticed that unsupervised learning requires our own interpretation of the data, as opposed to supervised learning, which we know the labels beforehand. We had to spend some time understanding why players are put in different clusters and which attributes were outweight others. For example, **Overall score** attribute seem to affect the Silhouette score of our K-means model more than other attributes, such as age, reflexes, speed.

Finally, we were constrainted by the shorter time to work on this assignment, as well as busy schedules of our group members.

7. Bibilography

1. D'Urso, P., De Giovanni, L. & Vitale, V. A robust method for clustering football players with mixed attributes. Ann Oper Res (2022). https://doi.org/10.1007/s10479-022-04558-x
2. Soccermatics by David Sumpter https://soccermatics.readthedocs.io/en/latest/index.html
3. The Hundred Page Machine Learning Book. By Andriy Burkov
4. Parallel Coordinate Plots by Plotly https://plotly.com/python/parallel-coordinates-plot/