Main_notebook

May 1, 2021

1 MoneyBall Reloaded

1.1 DATA PROCESSING

1.1.1 Import

[1]:
```
import pandas as pd
from unidecode import unidecode
import numpy as np
import matplotlib
import time
import matplotlib.pyplot as plt
import matplotlib.path as path
import matplotlib.patches as patches
import warnings
import sklearn
from sklearn.datasets import make_blobs
from sklearn_extensions.fuzzy_kmeans import FuzzyKMeans
from sklearn.cluster import DBSCAN, KMeans
from sklearn.decomposition import PCA
from scipy.spatial import distance
csv_files_location = "./csv/"
start_time = time.time()
```

```
/home/elie/anaconda3/lib/python3.8/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.datasets.samples_generator module is  deprecated in version 0.22 and
will be removed in version 0.24. The corresponding classes / functions should
instead be imported from sklearn.datasets. Anything that cannot be imported from
sklearn.datasets is now part of the private API.
  warnings.warn(message, FutureWarning)
```

[2]:
```
# retrieve the basic stats
df_2016 = pd.read_csv(csv_files_location+'NBA_totals_2015-2016.csv')
df_2017 = pd.read_csv(csv_files_location+'NBA_totals_2016-2017.csv')
df_2018 = pd.read_csv(csv_files_location+'NBA_totals_2017-2018.csv')
df_2019 = pd.read_csv(csv_files_location+'NBA_totals_2018-2019.csv')
```

```
df_2020 = pd.read_csv(csv_files_location+'NBA_totals_2019-2020.csv')
```

1.1.2 We normalize every names (no 'Sr', 'III', 'Sr', '.', foreign accents or characters)

[3]:
```
def clean_names(df, col_name):
    df[col_name] = df[col_name].apply(str.replace, args=[" Jr.", ""])
    df[col_name] = df[col_name].apply(str.replace, args=[" Sr.", ""])
    df[col_name] = df[col_name].apply(str.replace, args=[" III", ""])
    df[col_name] = df[col_name].apply(str.replace, args=[" II", ""])
    df[col_name] = df[col_name].apply(unidecode)
    df[col_name] = df[col_name] = df[col_name].apply(str.replace, args=[".",␣
 ↪""])
    return df
```

1.1.3 Let's clean all our df

[4]:
```
df_2016 = clean_names(df_2016, "Player")
df_2017 = clean_names(df_2017, "Player")
df_2018 = clean_names(df_2018, "Player")
df_2019 = clean_names(df_2019, "Player")
df_2020 = clean_names(df_2020, "Player")
```

1.1.4 Let's retrieve the final team of players who have been traded during the season

1.1.5 Two Birds One Rock: We both get the name as well as removing the retired players (as the 2020 season starts)

[5]:
```
team_and_player = df_2020.loc[:, ["Player", "Tm", 'Pos']]
team_and_player["final_team"] = team_and_player.groupby('Player')['Tm'].
 ↪transform('last')
team_and_player = team_and_player[["Player", "final_team", "Pos"]]
team_and_player = team_and_player.drop_duplicates(subset=['Player'])
```

1.1.6 Remove the TOT lines for players who have been traded during the season

[6]:
```
df_2016 = df_2016[df_2016["Tm"] != "TOT"]
df_2017 = df_2017[df_2017["Tm"] != "TOT"]
df_2018 = df_2018[df_2018["Tm"] != "TOT"]
df_2019 = df_2019[df_2019["Tm"] != "TOT"]
df_2020 = df_2020[df_2020["Tm"] != "TOT"]
```

1.1.7 Let's only keep the column we are interested in

[7]:
```
basic_stats_2016 = df_2016.loc[:, ['Player', 'G', 'MP', 'FGA', '3P', '3PA',␣
↪'2P', '2PA', 'FT', 'FTA', 'ORB', 'DRB', 'TRB', 'AST', 'STL', 'BLK', 'TOV',␣
↪'PF', 'PTS'] ]
basic_stats_2017 = df_2017.loc[:, ['Player', 'G', 'MP', 'FGA', '3P', '3PA',␣
↪'2P', '2PA', 'FT', 'FTA', 'ORB', 'DRB', 'TRB', 'AST', 'STL', 'BLK', 'TOV',␣
↪'PF', 'PTS'] ]
basic_stats_2018 = df_2018.loc[:, ['Player', 'G', 'MP', 'FGA', '3P', '3PA',␣
↪'2P', '2PA', 'FT', 'FTA', 'ORB', 'DRB', 'TRB', 'AST', 'STL', 'BLK', 'TOV',␣
↪'PF', 'PTS'] ]
basic_stats_2019 = df_2019.loc[:, ['Player', 'G', 'MP', 'FGA', '3P', '3PA',␣
↪'2P', '2PA', 'FT', 'FTA', 'ORB', 'DRB', 'TRB', 'AST', 'STL', 'BLK', 'TOV',␣
↪'PF', 'PTS'] ]
basic_stats_2020 = df_2020.loc[:, ['Player', 'G', 'MP', 'FGA', '3P', '3PA',␣
↪'2P', '2PA', 'FT', 'FTA', 'ORB', 'DRB', 'TRB', 'AST', 'STL', 'BLK', 'TOV',␣
↪'PF', 'PTS'] ]
```

1.1.8 Concat every df and group by player name

[8]:
```
basic_stats = basic_stats_2016.append(basic_stats_2017).
↪append(basic_stats_2018).append(basic_stats_2019).append(basic_stats_2020)
summed_basic_stats = basic_stats.groupby(['Player']).sum()
```

1.1.9 Let's remove those who have played less than 100 games or 2500 minutes

[9]:
```
summed_basic_stats = summed_basic_stats.loc[ (summed_basic_stats['G'] > 100) |␣
↪(summed_basic_stats['MP'] > 2500) ]
```

[10]:
```
avg_stats = summed_basic_stats.loc[:,(summed_basic_stats.columns != "Player") &␣
↪(summed_basic_stats.columns != "G")].div(summed_basic_stats["G"], axis=0)
avg_stats = avg_stats.apply(round, args=[1])
```

1.1.10 Per 36 minutes

[11]:
```
avg_stats_36_minutes = avg_stats.div((avg_stats["MP"]/36) , axis=0)
avg_stats_36_minutes = avg_stats_36_minutes.apply(round, args=[1])
names = pd.DataFrame(avg_stats_36_minutes.index)
```

1.1.11 Scaling

[12]:
```
avg_stats_36_minutes = avg_stats_36_minutes - avg_stats_36_minutes.min()
avg_stats_36_minutes = avg_stats_36_minutes / ( avg_stats_36_minutes.max() - avg_stats_36_minutes.min() )
avg_stats_36_minutes = avg_stats_36_minutes.apply(round, args=[2])
avg_stats_36_minutes_scaled = avg_stats_36_minutes.drop(columns=["MP"])
avg_stats_36_minutes_scaled
```

[12]:
```
                FGA   3P   3PA   2P   2PA   FT   FTA   ORB   DRB   TRB  \
Player
Aaron Brooks   0.51  0.44  0.50  0.30  0.41  0.12  0.13  0.12  0.07  0.06
Aaron Gordon   0.52  0.28  0.39  0.46  0.48  0.26  0.31  0.35  0.45  0.41
Aaron Holiday  0.48  0.40  0.48  0.27  0.37  0.17  0.16  0.04  0.16  0.10
Abdel Nader    0.33  0.34  0.44  0.21  0.25  0.16  0.20  0.08  0.27  0.21
Al Horford     0.48  0.28  0.34  0.49  0.47  0.12  0.13  0.33  0.47  0.41
…               …    …    …    …    …    …    …    …    …    …
Yogi Ferrell   0.39  0.38  0.48  0.24  0.29  0.17  0.15  0.06  0.17  0.11
Zach Collins   0.29  0.20  0.29  0.27  0.32  0.15  0.17  0.45  0.42  0.42
Zach LaVine    0.76  0.46  0.54  0.56  0.62  0.40  0.41  0.08  0.22  0.15
Zach Randolph  0.77  0.10  0.16  0.82  0.93  0.27  0.29  0.57  0.55  0.57
Zaza Pachulia  0.21  0.00  0.00  0.41  0.44  0.35  0.38  0.75  0.63  0.69

                AST   STL   BLK   TOV   PF   PTS
Player
Aaron Brooks   0.49  0.38  0.08  0.51  0.53  0.34
Aaron Gordon   0.25  0.33  0.22  0.30  0.22  0.42
Aaron Holiday  0.44  0.48  0.11  0.35  0.31  0.34
Abdel Nader    0.07  0.38  0.25  0.28  0.39  0.27
Al Horford     0.43  0.29  0.39  0.28  0.18  0.39
…               …    …    …    …    …    …
Yogi Ferrell   0.35  0.38  0.06  0.26  0.22  0.31
Zach Collins   0.12  0.14  0.39  0.37  0.61  0.23
Zach LaVine    0.34  0.38  0.08  0.56  0.24  0.64
Zach Randolph  0.21  0.24  0.08  0.40  0.25  0.55
Zaza Pachulia  0.26  0.52  0.17  0.44  0.59  0.24

[457 rows x 16 columns]
```

1.1.12 Retrieve the advanced stats

[13]:
```
ad_2016 = pd.read_csv(csv_files_location+'NBA_advanced_2015-2016.csv')
ad_2017 = pd.read_csv(csv_files_location+'NBA_advanced_2016-2017.csv')
ad_2018 = pd.read_csv(csv_files_location+'NBA_advanced_2017-2018.csv')
ad_2019 = pd.read_csv(csv_files_location+'NBA_advanced_2018-2019.csv')
ad_2020 = pd.read_csv(csv_files_location+'NBA_advanced_2019-2020.csv')
```

1.1.13 Clean the names

[14]:
```
ad_2016 = clean_names(ad_2016, "Player")
ad_2017 = clean_names(ad_2017, "Player")
ad_2018 = clean_names(ad_2018, "Player")
ad_2019 = clean_names(ad_2019, "Player")
ad_2020 = clean_names(ad_2020, "Player")
```

1.1.14 Remove the TOT lines for players who have been traded during the season

[15]:
```
ad_2016 = ad_2016[ad_2016["Tm"] != "TOT"]
ad_2017 = ad_2017[ad_2017["Tm"] != "TOT"]
ad_2018 = ad_2018[ad_2018["Tm"] != "TOT"]
ad_2019 = ad_2019[ad_2019["Tm"] != "TOT"]
ad_2020 = ad_2020[ad_2020["Tm"] != "TOT"]
```

1.1.15 Let's only keep the column we are interested in

[16]:
```
ad_2016 = ad_2016.loc[:, ["Player", "G", "MP", "PER", "TS%", "3PAr", "TRB%",␣
↪"USG%", "OWS", "DWS"] ]
ad_2017 = ad_2017.loc[:, ["Player", "G", "MP", "PER", "TS%", "3PAr", "TRB%",␣
↪"USG%", "OWS", "DWS"] ]
ad_2018 = ad_2018.loc[:, ["Player", "G", "MP", "PER", "TS%", "3PAr", "TRB%",␣
↪"USG%", "OWS", "DWS"] ]
ad_2019 = ad_2019.loc[:, ["Player", "G", "MP", "PER", "TS%", "3PAr", "TRB%",␣
↪"USG%", "OWS", "DWS"] ]
ad_2020 = ad_2020.loc[:, ["Player", "G", "MP", "PER", "TS%", "3PAr", "TRB%",␣
↪"USG%", "OWS", "DWS"] ]
```

1.1.16 For the advanced stats we need to weight a season stats by the number of played games

[17]:
```
def ponderateByGamesPlayed(df):
    #On recupere les noms, minutes jouées et matches joués
    names = df["Player"]
    minutes = df["MP"]
    games = df["G"]

    # on enleve les noms, minutes jouées et matches joués
    df = df.drop(columns=["Player", "MP", "G"])

    # on multiplie chaque stats de chaque joueur par le nb de matches joués␣
↪pendant cette saison
```

```
    df = df.mul(games, axis=0)

    # on rajoute les noms, les minutes et des matches joués
    res = pd.concat([names, games, minutes, df], axis=1)

    # on rajoute le nom des colonnes
    res.columns = ["Player", "G", "MP", "PER", "TS%", "3PAr", "TRB%", "USG%",␣
↪"OWS", "DWS"]
    return res
```

[18]:
```
ad_2016 = ponderateByGamesPlayed(ad_2016)
ad_2017 = ponderateByGamesPlayed(ad_2017)
ad_2018 = ponderateByGamesPlayed(ad_2018)
ad_2019 = ponderateByGamesPlayed(ad_2019)
ad_2020 = ponderateByGamesPlayed(ad_2020)
```

1.1.17 Concat

[19]:
```
summed_ad = ad_2016.append(ad_2017).append(ad_2018).append(ad_2019).
↪append(ad_2020)
```

1.1.18 Aggregate

[20]:
```
agr = {'MP':['sum'],'G': ['sum'], 'PER':['sum'],'TS%':['sum'],'3PAr':
↪['sum'],'TRB%':['sum'],'USG%':['sum'], 'OWS':['sum'], 'DWS':['sum']}
agg_advanced =summed_ad.groupby(['Player']).agg(agr)
```

1.1.19 Let's remove those who have played less than 100 games or 2500 minutes

[21]:
```
agg_advanced = agg_advanced.loc[(agg_advanced["MP"]["sum"] > 2500) |␣
↪(agg_advanced["G"]["sum"] > 100)]
```

1.1.20 We now want to retrieve the players height

1.1.21 We did it in the csv/players_height.csv file

[22]:
```
heights = pd.read_csv(csv_files_location+"players_height.csv")
heights = clean_names(heights, "Name")
heights = heights[["Name", "Height (cm)"]]
heights = heights.rename(columns={"Name": "Player"})
```

1.1.22 Let's average by games

[23]:
```
games = agg_advanced["G"]["sum"]
final_advanced = agg_advanced.div((games) , axis=0)
final_advanced = final_advanced.drop(columns=["G"])
final_advanced = final_advanced.apply(round, args=[2])
final_advanced = pd.concat([games, final_advanced], axis=1)
```

1.1.23 We add the players height

[24]:
```
final_advanced = pd.merge(final_advanced, heights, on="Player")
final_advanced = final_advanced.set_index("Player")
```

1.1.24 Rename the Columns

[25]:
```
final_advanced.columns = ["G", "MP", "PER", "TS%", "3PAr", "TRB%", "USG%",␣
↪"OWS", "DWS", "Height"]
```

1.1.25 Scaling

[26]:
```
final_advanced_scaled = final_advanced - final_advanced.min()
final_advanced_scaled = final_advanced_scaled / ( final_advanced_scaled.max() -␣
↪final_advanced_scaled.min() )
final_advanced_scaled
```

[26]:
```
                           G        MP       PER       TS%      3PAr      TRB%  \
Player
Aaron Gordon        0.855219  0.765882  0.431565  0.307692  0.397436  0.404936
Aaron Holiday       0.047138  0.387580  0.258582  0.269231  0.551282  0.090951
Al Horford          0.858586  0.800857  0.545698  0.461538  0.384615  0.403108
Al-Farouq Aminu     0.703704  0.707709  0.275524  0.307692  0.628205  0.445155
Alec Burks          0.555556  0.445039  0.346857  0.307692  0.435897  0.265996
…                        …         …         …         …         …         …
Willy Hernangomez   0.360269  0.204497  0.617922  0.500000  0.115385  0.760055
Wilson Chandler     0.434343  0.688437  0.226928  0.346154  0.589744  0.312614
Yogi Ferrell        0.494949  0.418986  0.275970  0.346154  0.576923  0.091408
Zach Collins        0.175084  0.314775  0.211324  0.269231  0.435897  0.394424
Zach LaVine         0.585859  0.849393  0.470798  0.423077  0.448718  0.143053

                        USG%       OWS       DWS    Height
Player
Aaron Gordon        0.421756  0.307458  0.455577  0.578947
Aaron Holiday       0.397710  0.180365  0.266541  0.157895
```

```
Al Horford          0.359542  0.464231  0.652174  0.631579
Al-Farouq Aminu     0.207252  0.265601  0.485822  0.578947
Alec Burks          0.477863  0.201674  0.183365  0.473684
…                        …         …        …         …
Willy Hernangomez   0.446947  0.258752  0.190926  0.736842
Wilson Chandler     0.240458  0.272451  0.209830  0.578947
Yogi Ferrell        0.307634  0.240487  0.181474  0.157895
Zach Collins        0.233969  0.191020  0.266541  0.736842
Zach LaVine         0.665649  0.295282  0.217391  0.473684

[336 rows x 10 columns]
```

1.1.26 Let's merge the basic stats, the advanced one and the players name

[27]:
```python
final = pd.merge(final_advanced_scaled, avg_stats_36_minutes_scaled,␣
↪on="Player")
final = pd.merge(team_and_player, final, on="Player")
final
```

[27]:
```
                Player final_team Pos         G        MP       PER       TS%  \
0         Steven Adams        OKC   C  0.932660  0.749465  0.547035  0.615385
1          Bam Adebayo        MIA  PF  0.407407  0.603141  0.537673  0.576923
2    LaMarcus Aldridge        SAS   C  0.851852  0.851892  0.711547  0.423077
3        Jarrett Allen        BRK   C  0.404040  0.557459  0.576906  0.730769
4      Al-Farouq Aminu        ORL  PF  0.703704  0.707709  0.275524  0.307692
..                 …          …  ..       …         …         …         …
331         Trae Young        ATL  PG  0.131313  0.861527  0.624610  0.423077
332        Cody Zeller        CHO   C  0.582492  0.562099  0.492644  0.576923
333       Tyler Zeller        SAS   C  0.279461  0.162027  0.402140  0.384615
334         Ante Zizic        CLE   C  0.037037  0.170236  0.560410  0.730769
335        Ivica Zubac        LAC   C  0.370370  0.261242  0.573785  0.576923

         3PAr      TRB%      USG%  …   FTA   ORB   DRB   TRB   AST   STL  \
0    0.000000  0.542505  0.233206  …  0.34  0.88  0.39  0.56  0.09  0.43
1    0.025641  0.589122  0.301908  …  0.43  0.55  0.62  0.60  0.35  0.38
2    0.089744  0.482176  0.629389  …  0.43  0.55  0.46  0.48  0.15  0.19
3    0.051282  0.596892  0.230916  …  0.40  0.69  0.62  0.66  0.11  0.19
4    0.628205  0.445155  0.207252  …  0.17  0.27  0.55  0.46  0.11  0.48
..        …         …         …  …   …     …     …     …     …     …
331  0.525641  0.130713  0.820992  …  0.70  0.12  0.20  0.15  0.90  0.38
332  0.064103  0.504570  0.270992  …  0.38  0.59  0.47  0.52  0.14  0.43
333  0.051282  0.502285  0.352290  …  0.29  0.61  0.44  0.50  0.12  0.10
334  0.000000  0.580896  0.327099  …  0.37  0.65  0.53  0.58  0.09  0.10
335  0.012821  0.661335  0.334733  …  0.35  0.80  0.66  0.72  0.13  0.10

      BLK   TOV    PF   PTS
```

```
0    0.33  0.30  0.31  0.32
1    0.36  0.47  0.35  0.35
2    0.39  0.28  0.20  0.63
3    0.58  0.30  0.37  0.36
4    0.22  0.23  0.20  0.22
..    …     …     …     …
331  0.06  0.95  0.10  0.79
332  0.33  0.26  0.53  0.33
333  0.31  0.26  0.59  0.37
334  0.31  0.33  0.51  0.40
335  0.50  0.35  0.61  0.43

[336 rows x 29 columns]
```

1.2 Ploting

[28]:
```
PlayerStats="MP"

NormalizeData = pd.read_csv("./csv/players_stats.csv", delimiter =",");
```

1.2.1 Ploting Polygone for one player

[29]:
```
def performance_polygon(PlayerName):
    Player=10*NormalizeData[NormalizeData.Player.eq(PlayerName)]

    # Player = AdDisp[AdDisp.Year.eq(2020)]

    properties = ['Offensive Win share', 'Defensive win share', 'AST','TS%',␣
 ↪"TRB%", "PTS", "3PA", ]
    values = np.random.uniform(5,9,len(properties))

    values = [Player['OWS'], Player['DWS'], Player['AST'], Player["TS%"],␣
 ↪Player["TRB%"], Player["PTS"], Player["3PA"]]
    matplotlib.rc('axes', facecolor = 'white')

    fig = plt.figure(figsize=(10,8), facecolor='white')

    axes = plt.subplot(111, polar=True)

    t = np.arange(0,2*np.pi,2*np.pi/len(properties))
    plt.xticks(t, [])

    points = [(x,y) for x,y in zip(t,values)]
    points.append(points[0])
```

```
    points = np.array(points)
    codes = [path.Path.MOVETO,] + \
            [path.Path.LINETO,]*(len(values) -1) + \
            [ path.Path.CLOSEPOLY ]
    _path = path.Path(points, codes)
    _patch = patches.PathPatch(_path, fill=True, color='blue', linewidth=0,␣
↪alpha=.1)
    axes.add_patch(_patch)
    _patch = patches.PathPatch(_path, fill=False, linewidth = 2)
    axes.add_patch(_patch)

    plt.scatter(points[:,0],points[:,1], linewidth=2,
                s=50, color='white', edgecolor='black', zorder=10)
    """
    maxi = max([Player.iloc[0,19]+1, Player.iloc[0,20]+1, Player.iloc[0,21]+1])
    if maxi < 10:
        plt.ylim(0,10)
    else:
        plt.ylim(0,maxi)
        """
    plt.ylim(0,10)
    for i in range(len(properties)):
        angle_rad = i/float(len(properties))*2*np.pi
        angle_deg = i/float(len(properties))*360
        ha = "right"
        if angle_rad < np.pi/2 or angle_rad > 3*np.pi/2: ha = "left"
        plt.text(angle_rad, 10.75, properties[i], size=14,
                 horizontalalignment=ha, verticalalignment="center")

    plt.title("Statistics of "+PlayerName)
    plt.show()
```

1.2.2 Ploting Polygones for multiple players and for certain criterias

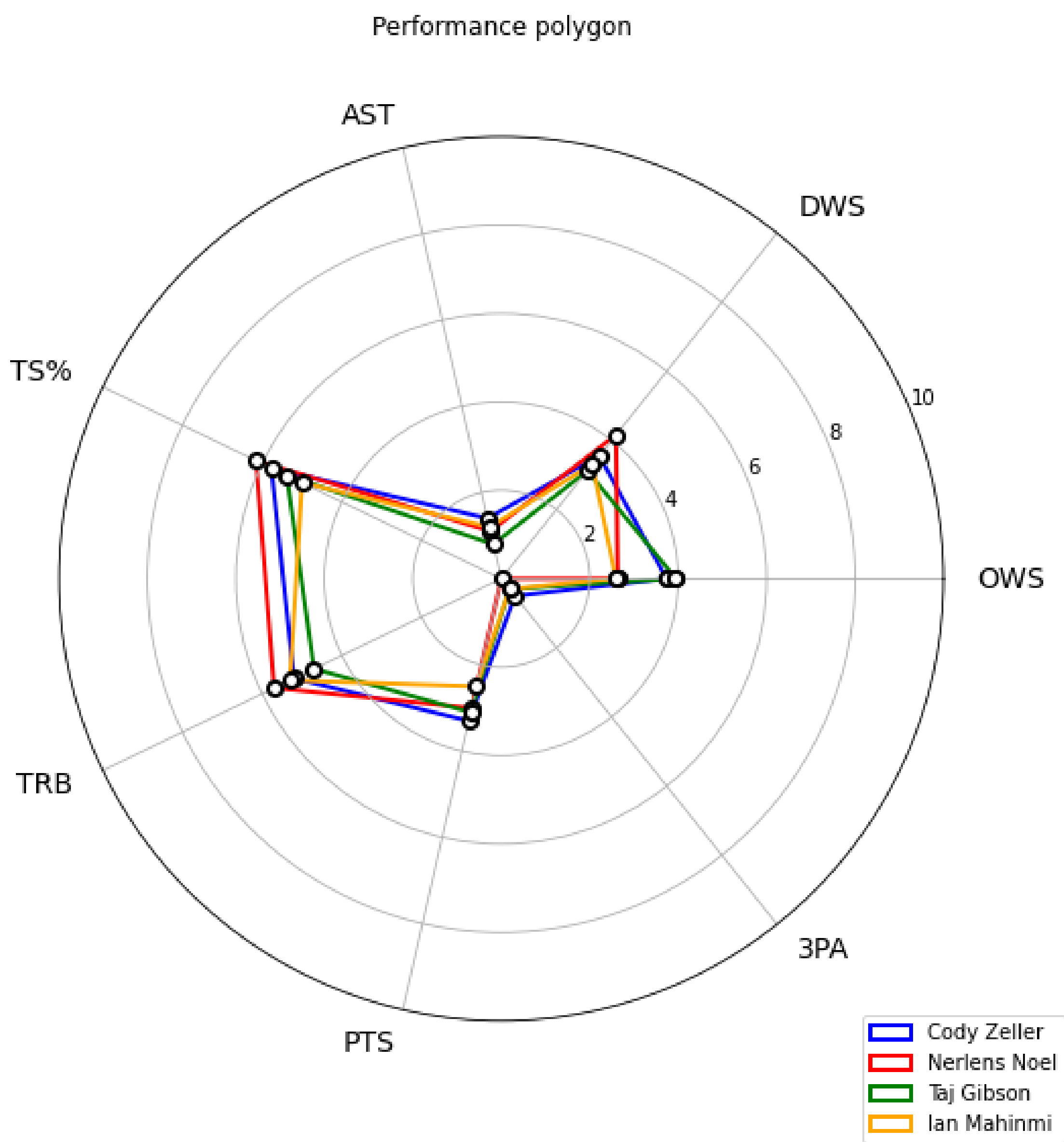
[30]:
```
def performance_polygon_vs_player(PlayersName, criterias):
    #properties = ['Offensive Win share', 'Defensive win share', 'AST','TS%',␣
↪"TRB", "PTS", "3PA" ]
    values = np.random.uniform(5,9,len(criterias))
    colors = ["blue", "red", "green", "orange", "brown", "deeppink","sienna",
              "gold", "olivedrab", "mediumspringgreen", "navy", "plum",␣
↪"cadetblue", "darkmagenta"]
    fig = plt.figure(figsize=(10,8), facecolor='white')
    for i in range (0,len(PlayersName)):
        Player=10*NormalizeData[NormalizeData.Player.eq(PlayersName[i])]
        #Player2=10*NormalizeData[NormalizeData.Player.eq(PlayerName[1])]
```

```
        # Player = AdDisp[AdDisp.Year.eq(2020)]


        values1 = [Player[item] for item in criterias]
        #values1 = [Player['OWS'], Player['DWS'], Player['AST'], Player["TS%"],␣
↪Player["TRB"], Player["PTS"], Player["3PA"]]
        #values2 = [Player2['OWS'], Player2['DWS'], Player2['AST'],␣
↪Player2["TS%"], Player2["TRB%"], Player2["PTS"], Player2["3PA"]]
        matplotlib.rc('axes', facecolor = 'white')

        axes = plt.subplot(111, polar=True)

        t = np.arange(0,2*np.pi,2*np.pi/len(criterias))
        plt.xticks(t, [])

        points = [(x,y) for x,y in zip(t,values1)]
        points.append(points[0])
        points = np.array(points, dtype=object)
        codes = [path.Path.MOVETO,] + \
                [path.Path.LINETO,]*(len(values) -1) + \
                [ path.Path.CLOSEPOLY ]
        _path = path.Path(points, codes)
        _patch = patches.PathPatch(_path, fill=False, color=colors[i],␣
↪linewidth=0, alpha=.2)
        axes.add_patch(_patch)
        _patch = patches.PathPatch(_path, fill=False, edgecolor=colors[i],␣
↪linewidth = 2, label=PlayersName[i])
        axes.add_patch(_patch)
        plt.scatter(points[:,0],points[:,1], linewidth=2,
                s=50, color='white', edgecolor='black', zorder=10)
    #plt.scatter(points[:,0],points[:,1], linewidth=2,s=50, color='white',␣
↪edgecolor='black', zorder=10)
    plt.legend(loc="lower right",borderaxespad=-6)
    """
    maxi = max([Player.iloc[0,19]+1, Player.iloc[0,20]+1, Player.iloc[0,21]+1])
    if maxi < 10:
        plt.ylim(0,10)
    else:
        plt.ylim(0,maxi)
        """
    plt.ylim(0,10)
    for i in range(len(criterias)):
        angle_rad = i/float(len(criterias))*2*np.pi
        angle_deg = i/float(len(criterias))*360
        ha = "right"
        if angle_rad < np.pi/2 or angle_rad > 3*np.pi/2: ha = "left"
```

```
        plt.text(angle_rad, 10.75, criterias[i], size=14,
                 horizontalalignment=ha, verticalalignment="center")

    plt.title("Performance polygon", pad = 50)
    plt.savefig("polygone")
    plt.show()
```

1.2.3 Example

[31]:
```
properties = ['OWS', 'DWS', 'AST','TS%', "TRB", "PTS", "3PA" ]
list_of_player = ["Cody Zeller", "Nerlens Noel", "Taj Gibson", "Ian Mahinmi"]
# ignore warnings for the polygone display
warnings.filterwarnings("ignore")
%matplotlib inline
performance_polygon_vs_player(list_of_player, properties)
```



1.3 CLUSTERING

[32]:
```
df = final
player_names = df["Player"]
clustering_df = df.drop(columns=["Player", "final_team","Pos"])
results = pd.DataFrame(data = None, columns = ['epsilon' , 'min_size',␣
↪'score'],dtype=np.float64)
df
```

[32]:

```
                Player final_team Pos         G        MP       PER       TS%  \
0         Steven Adams        OKC   C  0.932660  0.749465  0.547035  0.615385
1          Bam Adebayo        MIA  PF  0.407407  0.603141  0.537673  0.576923
2    LaMarcus Aldridge        SAS   C  0.851852  0.851892  0.711547  0.423077
3        Jarrett Allen        BRK   C  0.404040  0.557459  0.576906  0.730769
4      Al-Farouq Aminu        ORL  PF  0.703704  0.707709  0.275524  0.307692
..                 …        …  ..       …       …       …       …
331         Trae Young        ATL  PG  0.131313  0.861527  0.624610  0.423077
332        Cody Zeller        CHO   C  0.582492  0.562099  0.492644  0.576923
333       Tyler Zeller        SAS   C  0.279461  0.162027  0.402140  0.384615
334         Ante Zizic        CLE   C  0.037037  0.170236  0.560410  0.730769
335        Ivica Zubac        LAC   C  0.370370  0.261242  0.573785  0.576923

         3PAr      TRB%      USG%  …   FTA   ORB   DRB   TRB   AST   STL  \
0    0.000000  0.542505  0.233206  …  0.34  0.88  0.39  0.56  0.09  0.43
1    0.025641  0.589122  0.301908  …  0.43  0.55  0.62  0.60  0.35  0.38
2    0.089744  0.482176  0.629389  …  0.43  0.55  0.46  0.48  0.15  0.19
3    0.051282  0.596892  0.230916  …  0.40  0.69  0.62  0.66  0.11  0.19
4    0.628205  0.445155  0.207252  …  0.17  0.27  0.55  0.46  0.11  0.48
..        …       …       …  …   …   …   …   …   …   …
331  0.525641  0.130713  0.820992  …  0.70  0.12  0.20  0.15  0.90  0.38
332  0.064103  0.504570  0.270992  …  0.38  0.59  0.47  0.52  0.14  0.43
333  0.051282  0.502285  0.352290  …  0.29  0.61  0.44  0.50  0.12  0.10
334  0.000000  0.580896  0.327099  …  0.37  0.65  0.53  0.58  0.09  0.10
335  0.012821  0.661335  0.334733  …  0.35  0.80  0.66  0.72  0.13  0.10

      BLK   TOV    PF   PTS
0    0.33  0.30  0.31  0.32
1    0.36  0.47  0.35  0.35
2    0.39  0.28  0.20  0.63
3    0.58  0.30  0.37  0.36
4    0.22  0.23  0.20  0.22
..    …   …   …   …
331  0.06  0.95  0.10  0.79
332  0.33  0.26  0.53  0.33
333  0.31  0.26  0.59  0.37
334  0.31  0.33  0.51  0.40
335  0.50  0.35  0.61  0.43

[336 rows x 29 columns]
```

1.3.1 Let's figure out the optimal value for DBSCAN and PCA parameters

1.3.2 e.g those with the silhouette score closest to 1

[33]:
```
for var_portion in np.arange(start = 0.6,stop=0.95,step=0.05,dtype=np.float64):
    pca = PCA(n_components=var_portion, svd_solver = 'full')
    pcabis = pca.fit(clustering_df)
    reducedDataSet = pcabis.transform(clustering_df)
    for eps in np.arange(start = 0.05,stop=0.95,step=0.01,dtype=np.float64):
        for size in np.arange(start = 2,stop=10,step=1,dtype=np.float64):
            m = DBSCAN(eps=eps, min_samples=size)
            m.fit(reducedDataSet)
            if(max(m.labels_)>1):
                score = sklearn.metrics.silhouette_score(clustering_df,m.
 ↪labels_)
                results = results.append({'var_portion' : var_portion,␣
 ↪'epsilon' : eps , 'min_size' : size , 'score' : score, 'nb_clusters' : max(m.
 ↪labels_)+1}, ignore_index=True)

results = results.sort_values(by=[ "score"], ascending = False)
```

[34]:
```
results
```

[34]:
```
     epsilon  min_size     score  nb_clusters  var_portion
781     0.55       2.0  0.257136          3.0         0.85
113     0.27       3.0  0.241859          3.0         0.60
115     0.28       3.0  0.241859          3.0         0.60
111     0.26       3.0  0.241859          3.0         0.60
104     0.23       3.0  0.232994          3.0         0.60
..       …         …        …            …           …
784     0.22       2.0 -0.390143         10.0         0.90
528     0.12       2.0 -0.390388         18.0         0.80
389     0.12       2.0 -0.390388         18.0         0.75
527     0.11       2.0 -0.390866         16.0         0.80
388     0.11       2.0 -0.390866         16.0         0.75

[907 rows x 5 columns]
```

[35]:
```
optimal_parameters = results.head(1)
optimal_parameters
```

[35]:
```
     epsilon  min_size     score  nb_clusters  var_portion
781     0.55       2.0  0.257136          3.0         0.85
```

1.3.3 Let's use those parameters to see if it's consistent basketball-wise

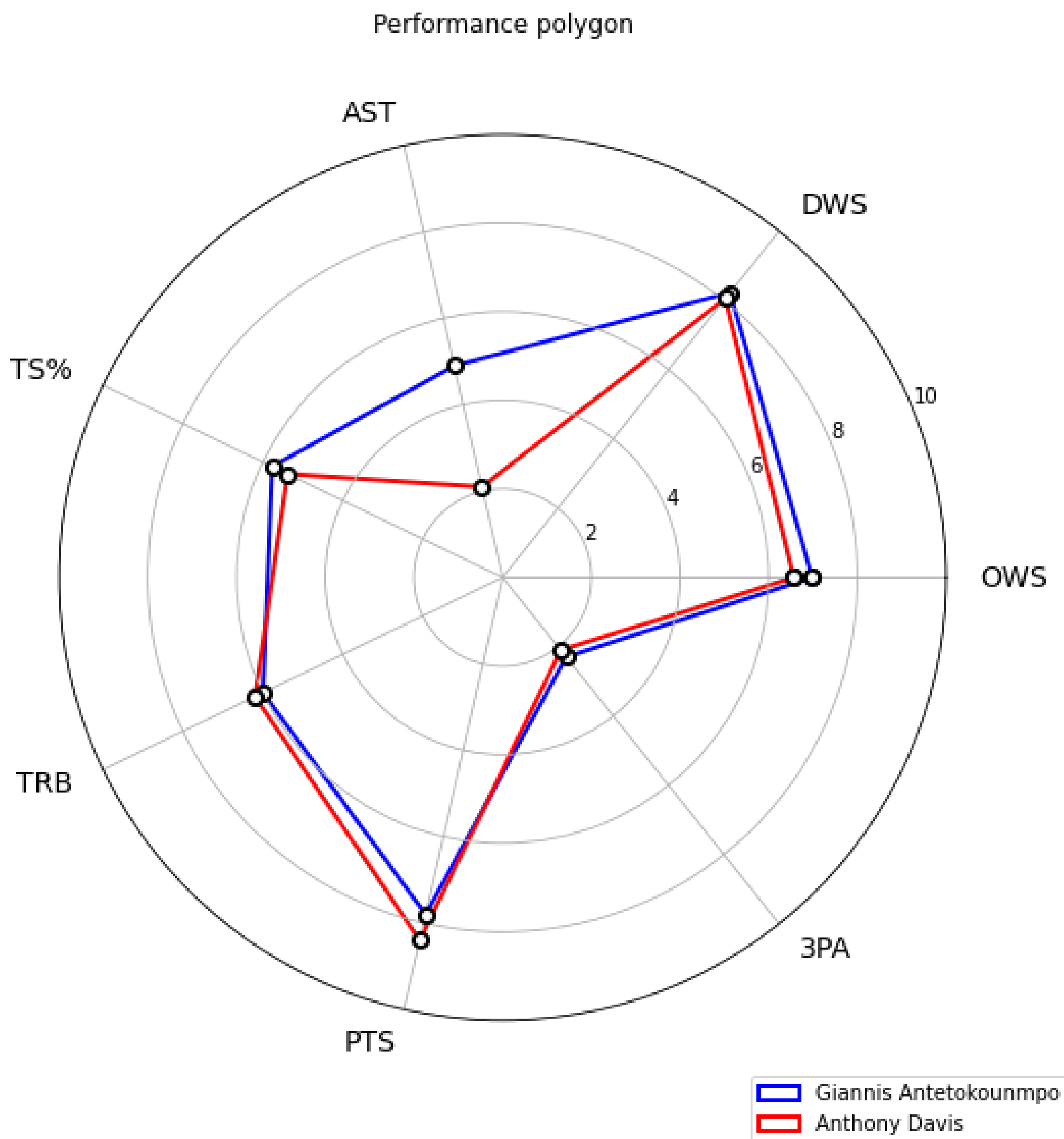
[36]:
```
pca_value = optimal_parameters.iloc[0]["var_portion"]
epsilon = optimal_parameters.iloc[0]["epsilon"]
min_size = optimal_parameters.iloc[0]["min_size"]

pca = PCA(n_components=pca_value, svd_solver = 'full')
pcabis = pca.fit(clustering_df)
dataSet = pcabis.transform(clustering_df)
model = DBSCAN(eps=epsilon, min_samples=min_size)
model.fit(dataSet)
result = pcabis.inverse_transform(dataSet)
res = np.zeros((0,3))
dbscan_cluster = pd.DataFrame(res)
number_of_players = df.shape[0]
for k in range(number_of_players):
    row = [[df['Player'].values[k], model.labels_[k], df["Pos"].values[k]]]
    dbscan_cluster = dbscan_cluster.append(row)
dbscan_cluster.columns = ["Player", "Cluster", "Pos"]
```

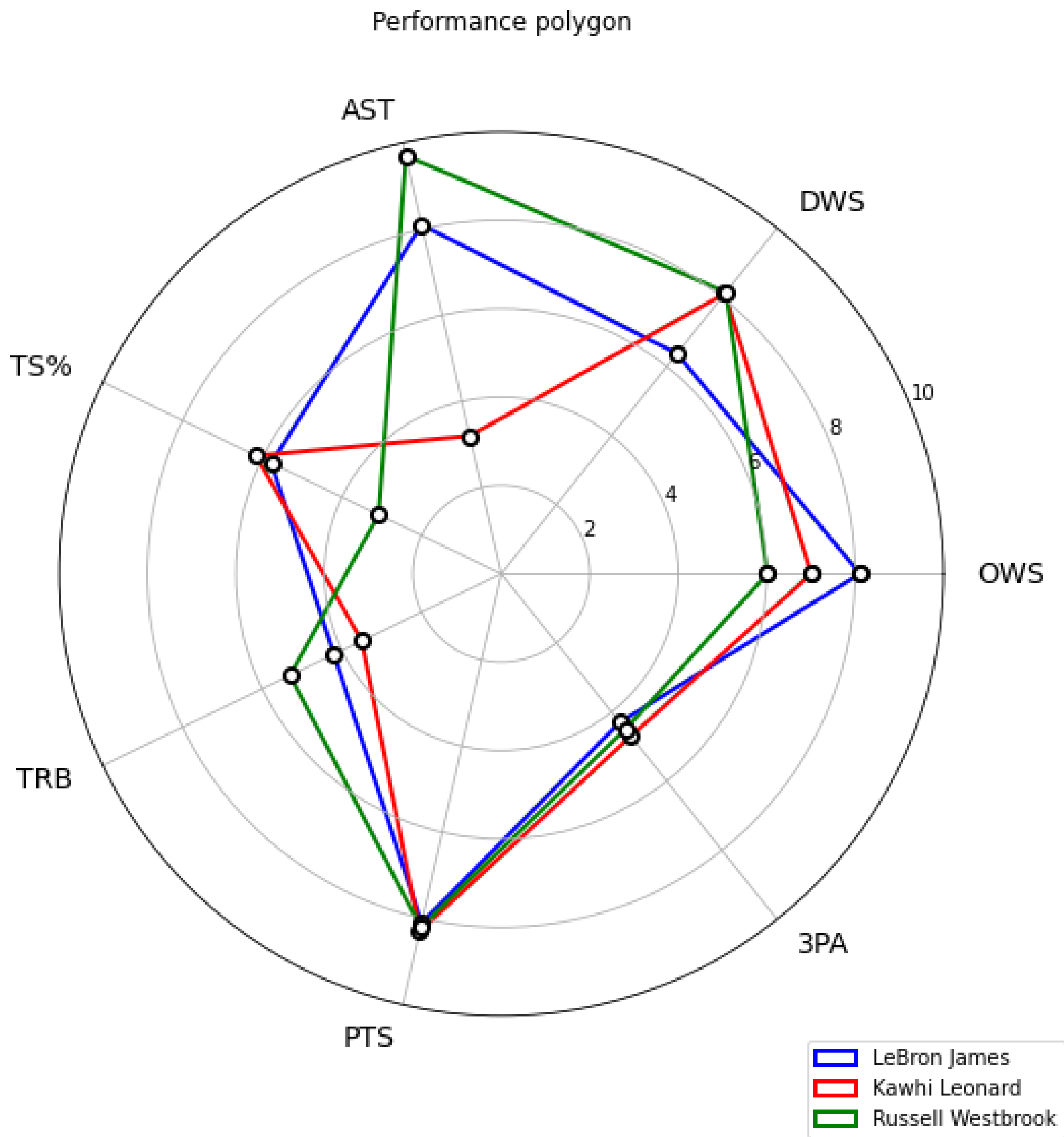
[37]:
```
dbscan_cluster
```

[37]:
```
               Player  Cluster Pos
0        Steven Adams      0.0   C
0         Bam Adebayo      0.0  PF
0   LaMarcus Aldridge      0.0   C
0       Jarrett Allen      0.0   C
0     Al-Farouq Aminu      0.0  PF
..                ...      ...  ..
0          Trae Young      0.0  PG
0         Cody Zeller      0.0   C
0        Tyler Zeller      0.0   C
0          Ante Zizic      0.0   C
0         Ivica Zubac      0.0   C

[336 rows x 3 columns]
```

[38]:
```
# ignore warnings for the polygone display
warnings.filterwarnings("ignore")

nb_of_cluster_DBSCAN_printed = 0
nb_of_players_clustered_with_DBSCAN = 0

#now let's print the overlapping polygones for each cluster
for i in dbscan_cluster.Cluster.unique():
    players_to_draw = dbscan_cluster[dbscan_cluster["Cluster"] == i]["Player"].
 ↪tolist()
```

```
    properties = ['OWS', 'DWS', 'AST','TS%', "TRB", "PTS", "3PA" ]
    if (len(players_to_draw) < 10):
        nb_of_cluster_DBSCAN_printed+=1
        nb_of_players_clustered_with_DBSCAN += len(players_to_draw)
        performance_polygon_vs_player(players_to_draw, properties)


print("We clustered "+str(nb_of_players_clustered_with_DBSCAN)+" players with␣
 ↪DBSCAN in "+str(nb_of_cluster_DBSCAN_printed)+" clusters out of "+str(len(df.
 ↪index))+" players.")
```






```
We clustered 5 players with DBSCAN in 2 clusters out of 336 players.
```

1.4 Only 5 players clustered? Not very promising...

1.5 Let's try Fuzzy Clustering

1.6 Data retrieving

[39]:
```
df = pd.read_csv('./csv/players_stats.csv')
player_names = df["Player"]

clustering_df = df.drop(columns=["Unnamed: 0","Player", "final_team","Pos"])

# we keep the interesting value
df_fcm = df[['Player', 'TRB', 'PTS', 'AST', "DWS", '3PA', "OWS", "USG%",␣
↪"Height"]]

# we keep the players name for later
players_name = df_fcm["Player"]

# we remove the player column for the computation
df_fcm = df_fcm.loc[:,(df_fcm.columns != "Player")]
```

1.7 Computation

[40]:
```
# Computation
nb_cluster_fuzzy = 35
fuzzy_kmeans = FuzzyKMeans(k=nb_cluster_fuzzy, m=1.1)
fuzzy_kmeans.fit(df_fcm)
fuzzy_clusters = pd.DataFrame(fuzzy_kmeans.fuzzy_labels_)

# we add the players name back
fuzzy_clusters = pd.concat([players_name, fuzzy_clusters], axis=1)
```

1.8 From Fuzzy clustering to hard clustering

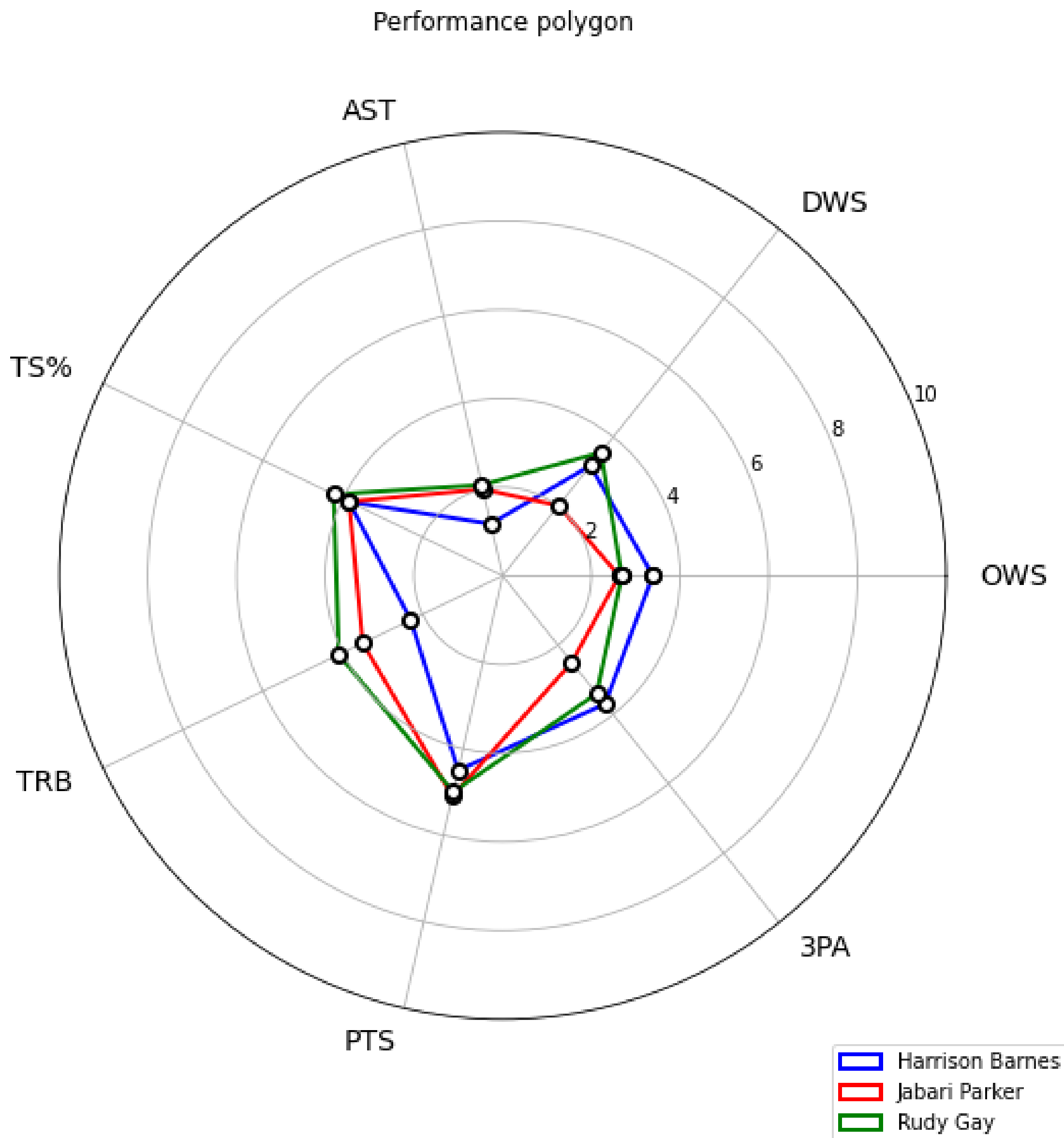
1.9 Let's group together the top n players of each clusters

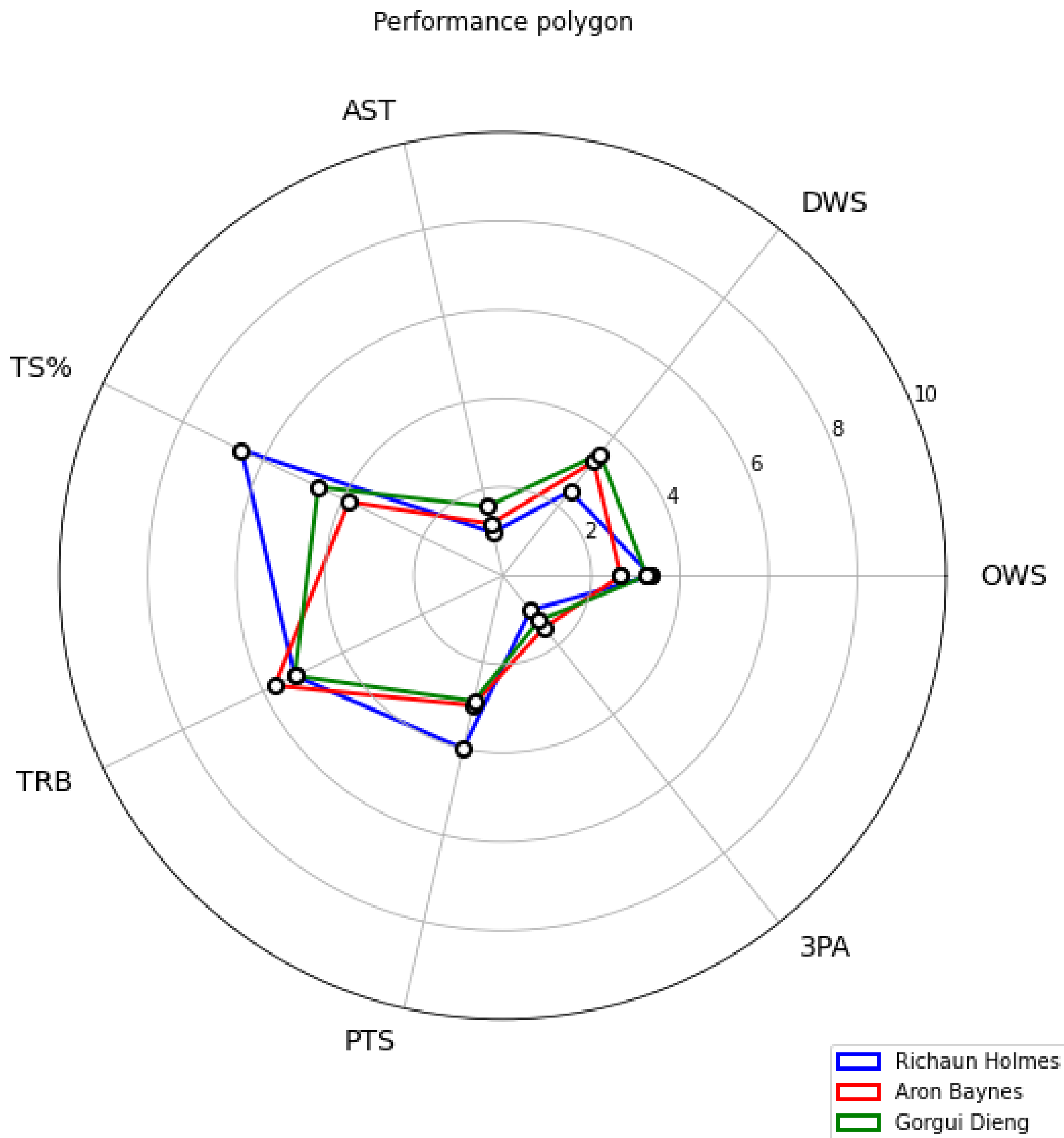
[41]:
```
nb_max_players_per_cluster_fcm = 3

final_clusters = pd.DataFrame()

for i in range(nb_cluster_fuzzy):
    # lets keep the coresponding col of membership degree
    sets = fuzzy_clusters[["Player", i]]
```

```
    # lets sort
    sets = sets.sort_values(by=i, ascending=False)

    #let's juste keep the top n% and be sure they are above a threeshold
    sets = sets.head(nb_max_players_per_cluster_fcm)
    sets = sets[["Player"]]

    # remove the hard clustered players from the fuzzy df to avoid having␣
↪duplicates
    fuzzy_clusters = fuzzy_clusters[~fuzzy_clusters['Player'].
↪isin(list(sets["Player"]))]

    #lets add the # of the cluster
    sets["Cluster"] = i+1
    #add those lines to the previous results
    final_clusters = pd.concat([final_clusters, sets], axis=0)
```

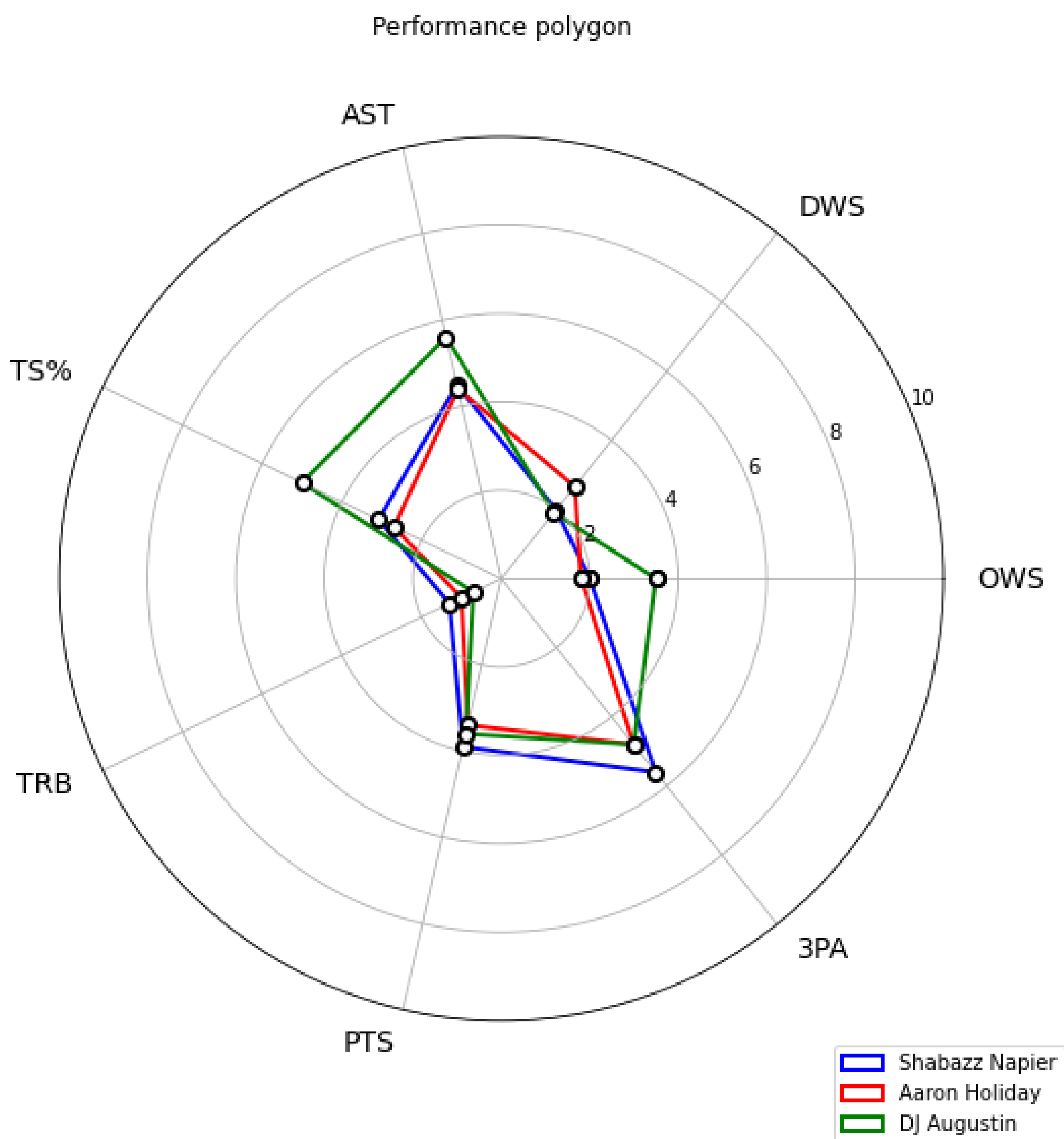
1.10 Ploting the Fuzzy Clustering results

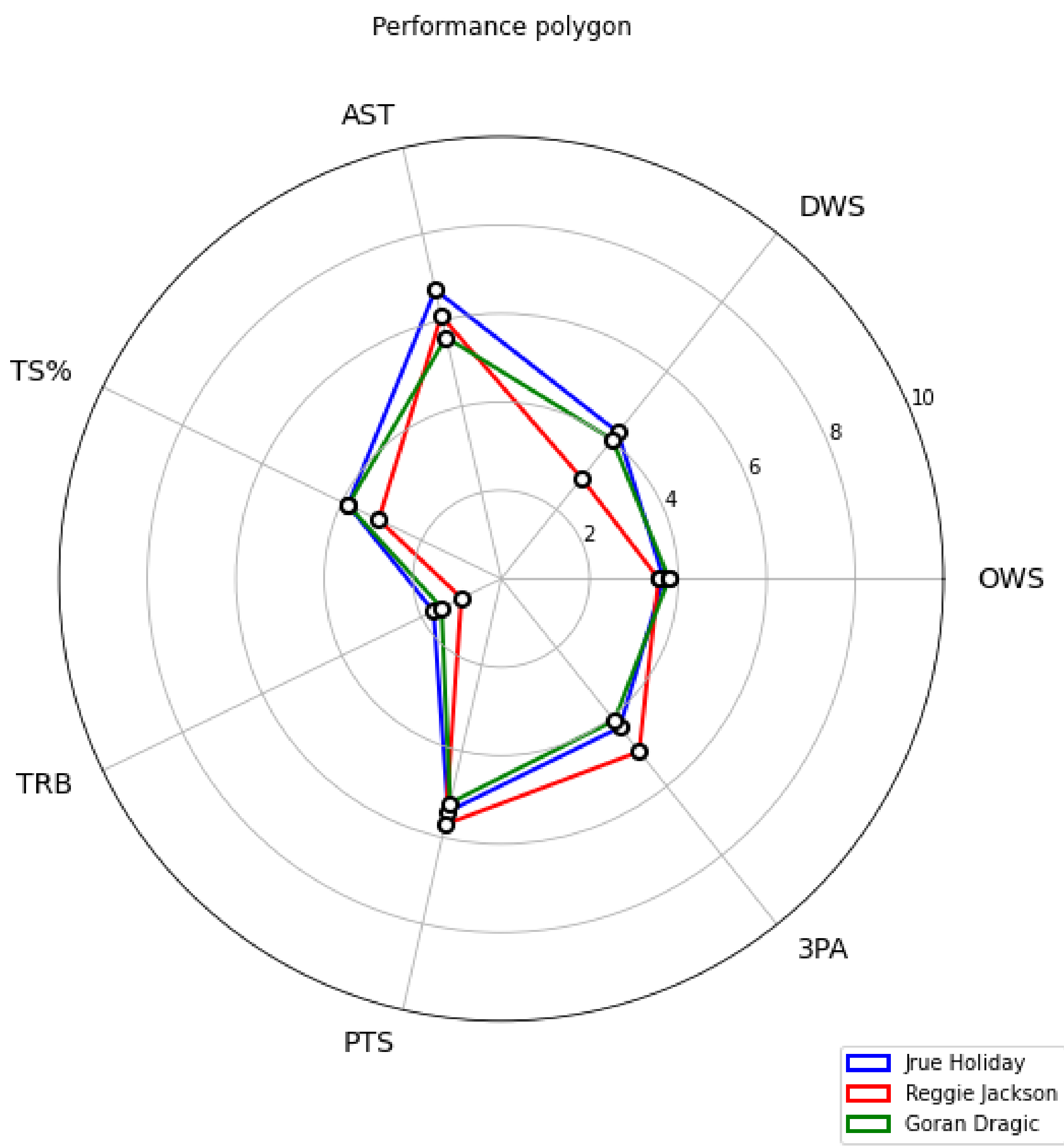
[42]:
```
#now let's print the overlapping polygones for each cluster
for i in final_clusters.Cluster.unique():
    players_to_draw = final_clusters[final_clusters["Cluster"] == i]["Player"].
↪tolist()
    properties = ['OWS', 'DWS', 'AST','TS%', "TRB", "PTS", "3PA" ]
    performance_polygon_vs_player(players_to_draw, properties)
```


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Harrison Barnes
Jabari Parker
Rudy Gay

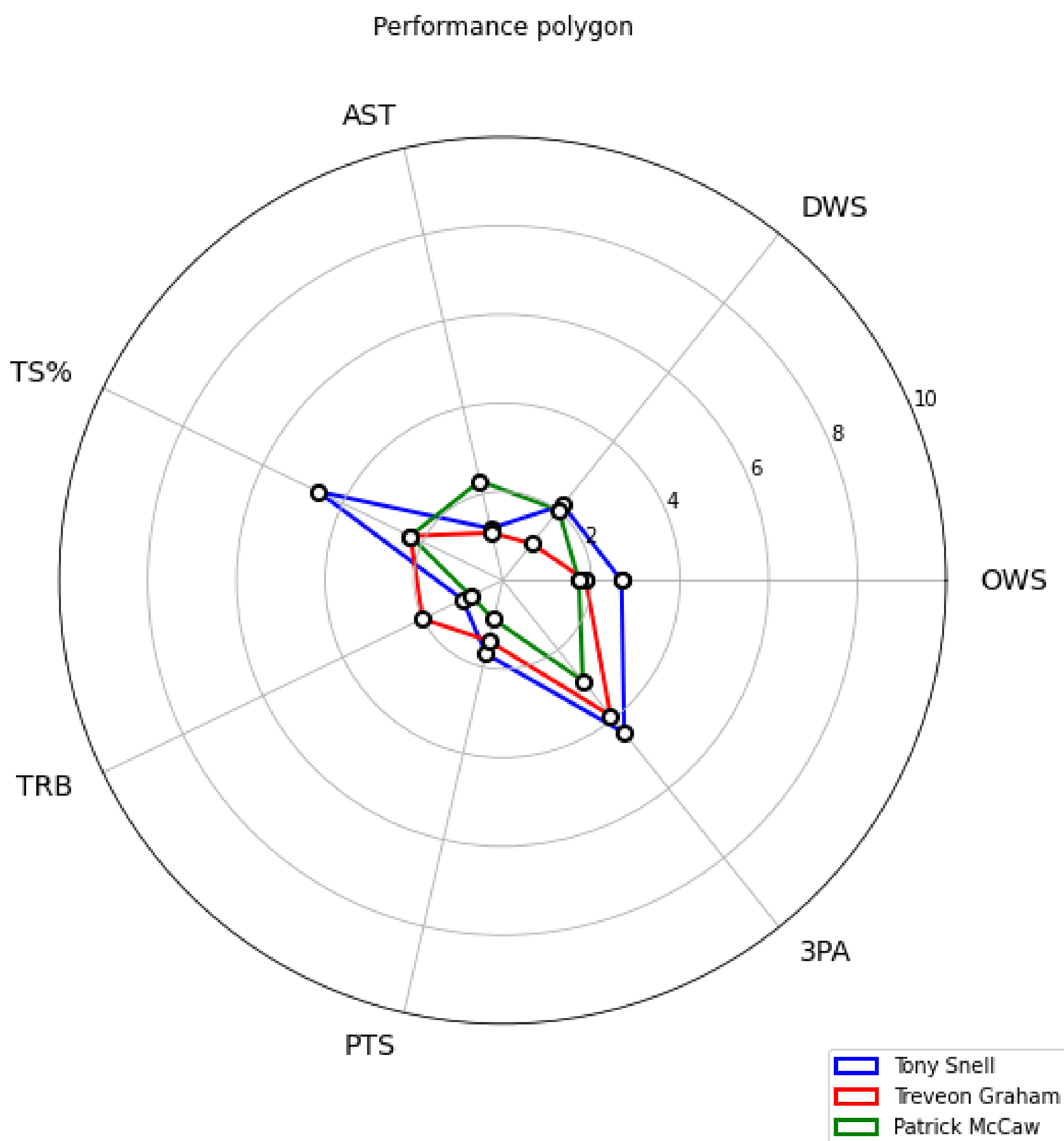


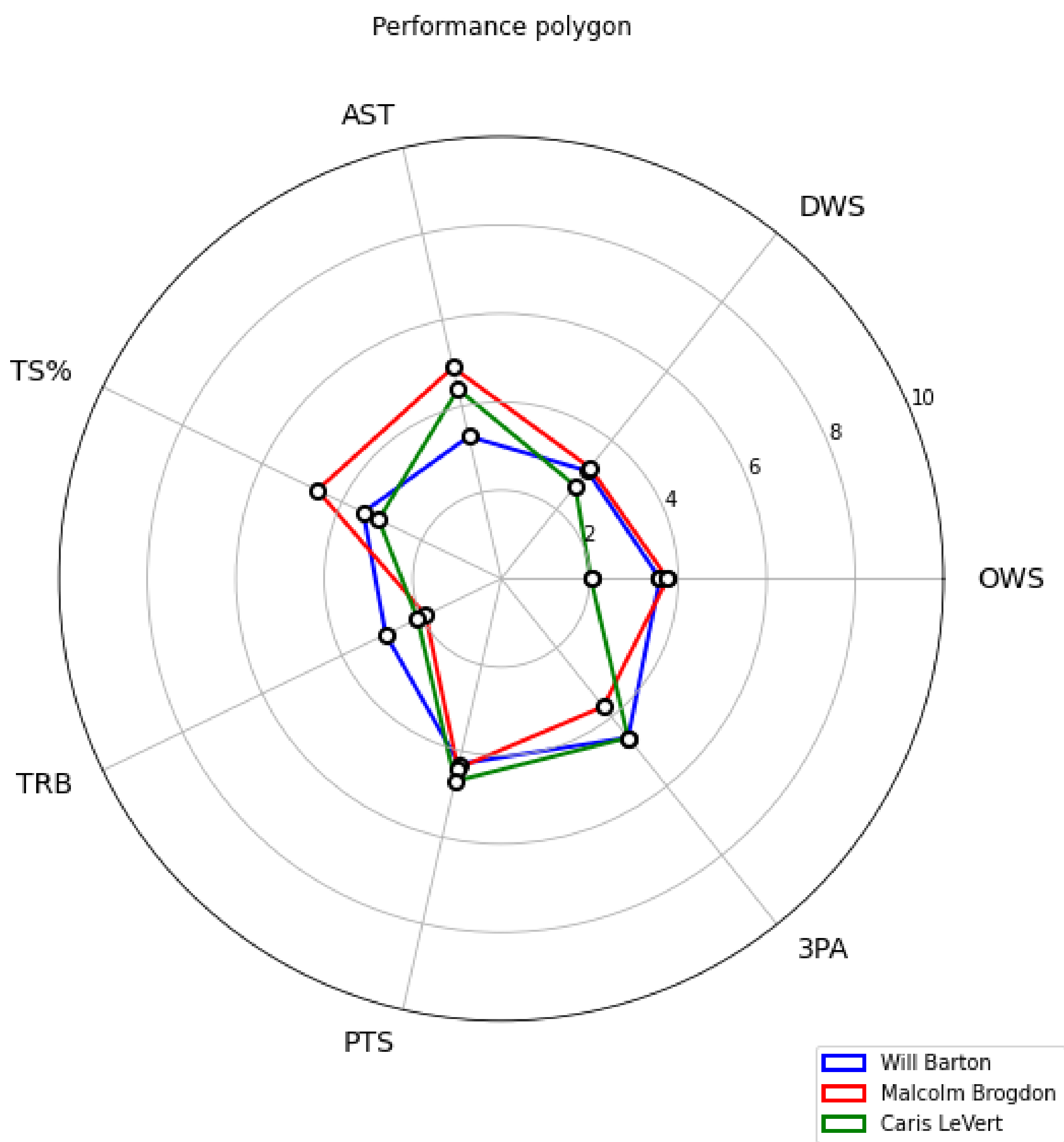
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Richaun Holmes
Aron Baynes
Gorgui Dieng

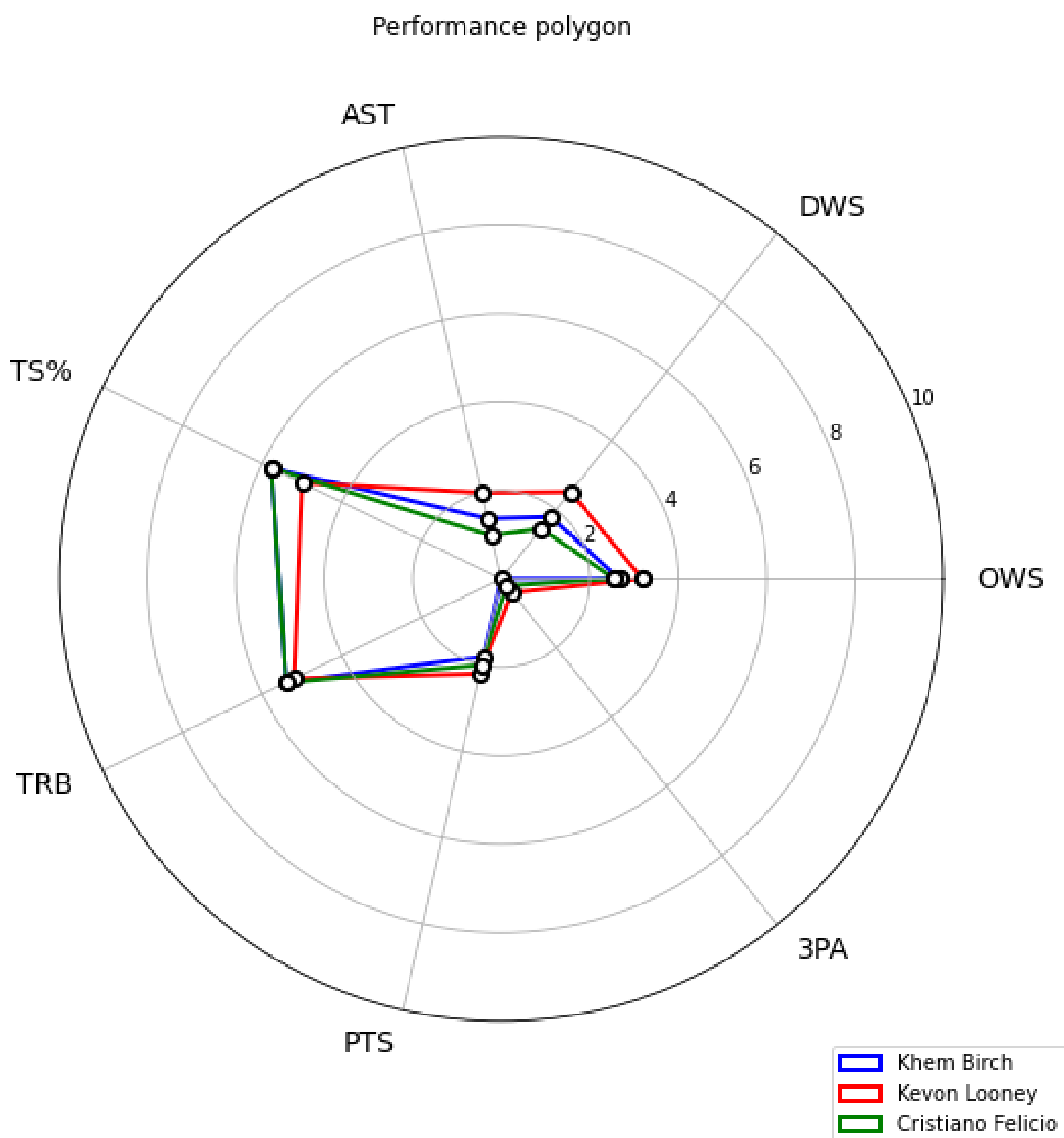

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Shabazz Napier
Aaron Holiday
DJ Augustin



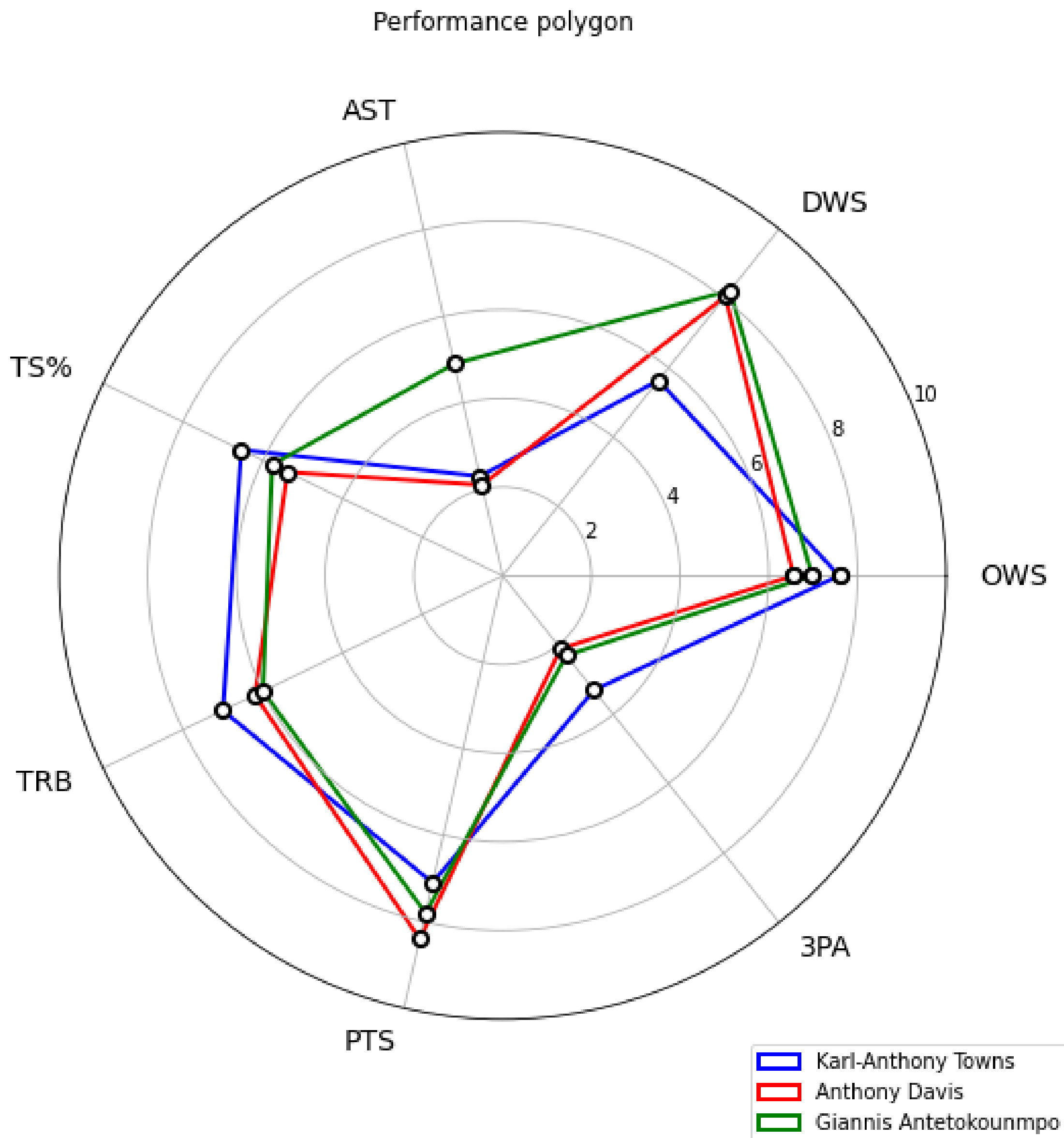
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Jrue Holiday
Reggie Jackson
Goran Dragic

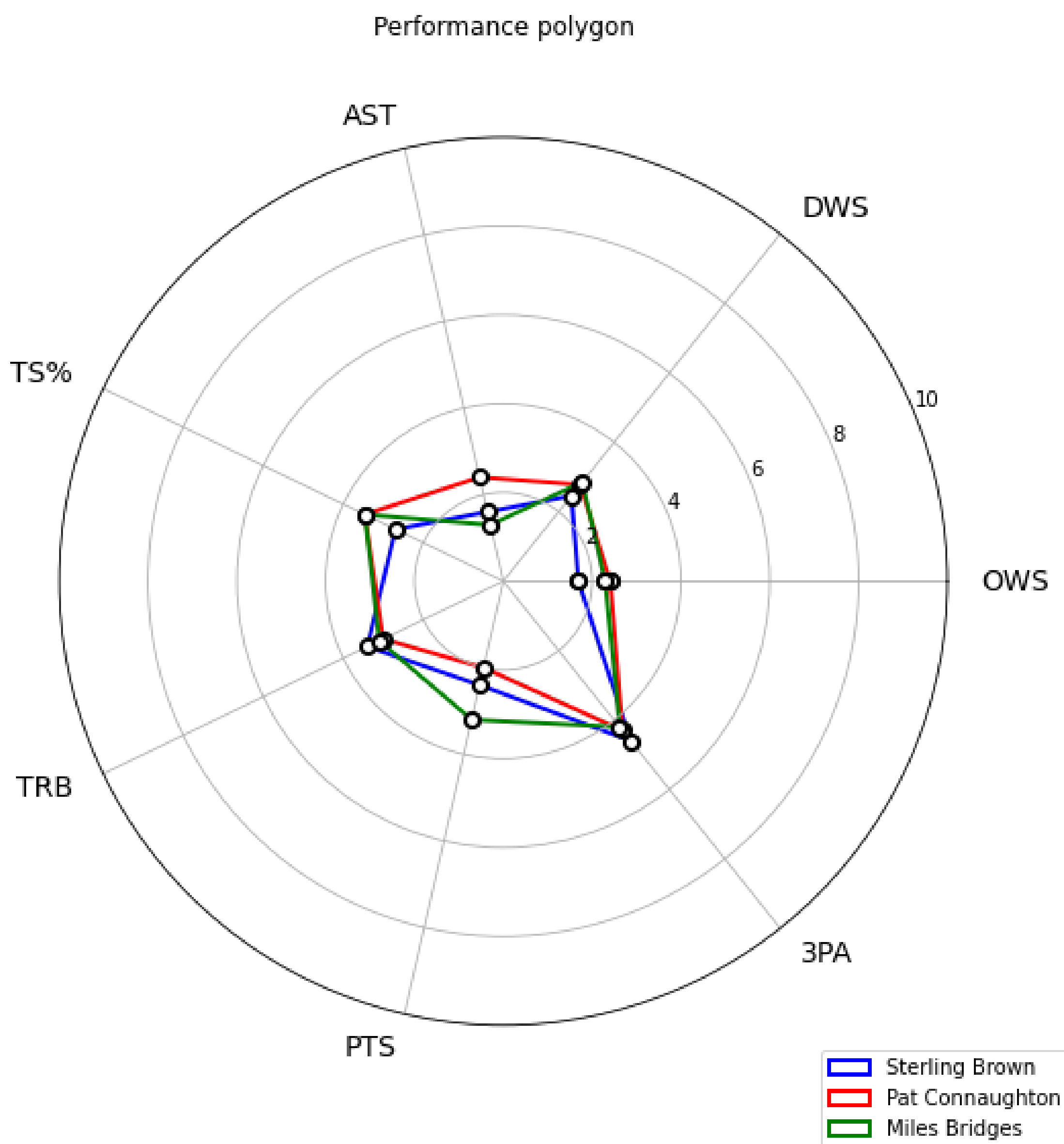

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Tony Snell
Treveon Graham
Patrick McCaw


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Will Barton
Malcolm Brogdon
Caris LeVert

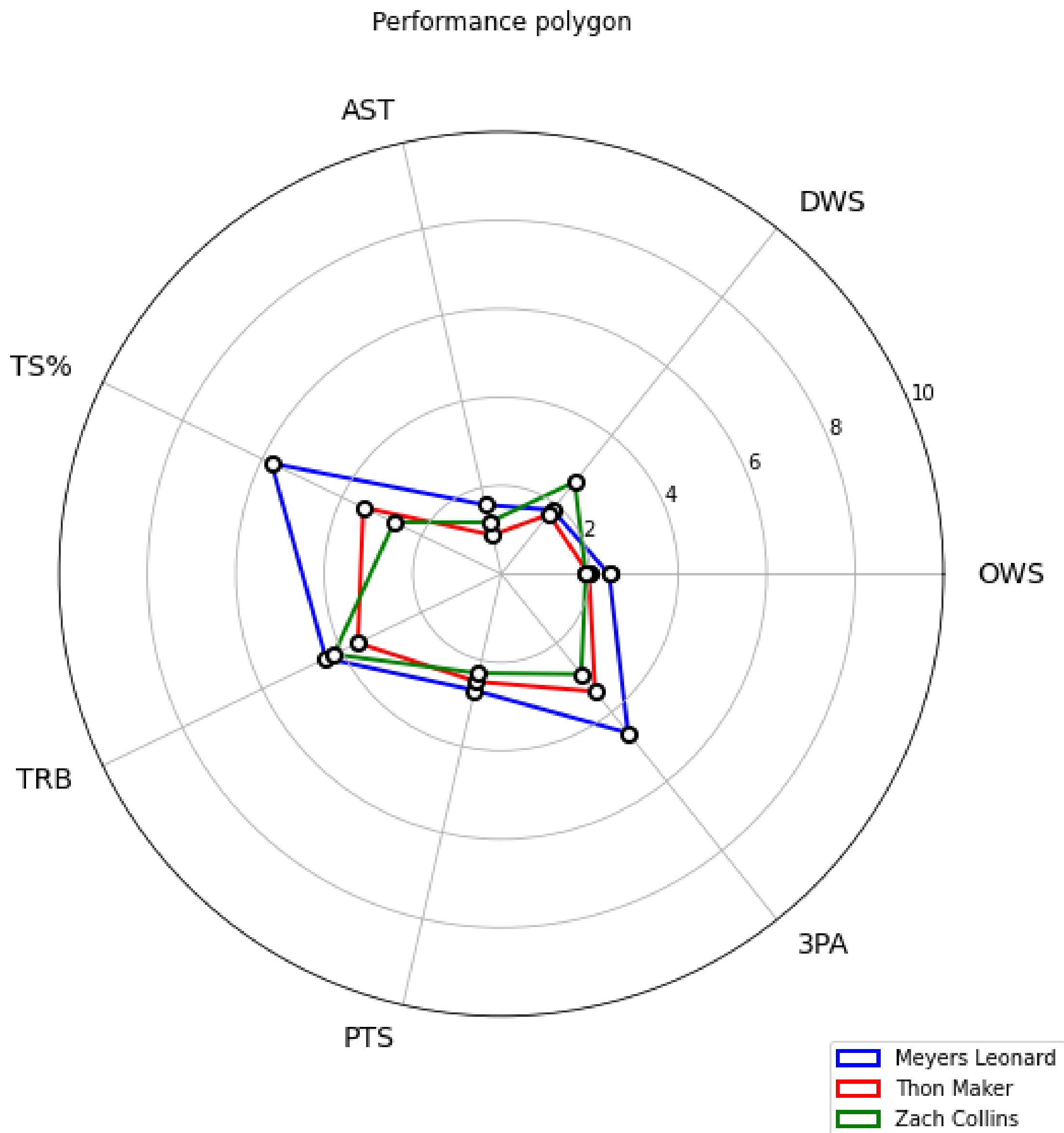


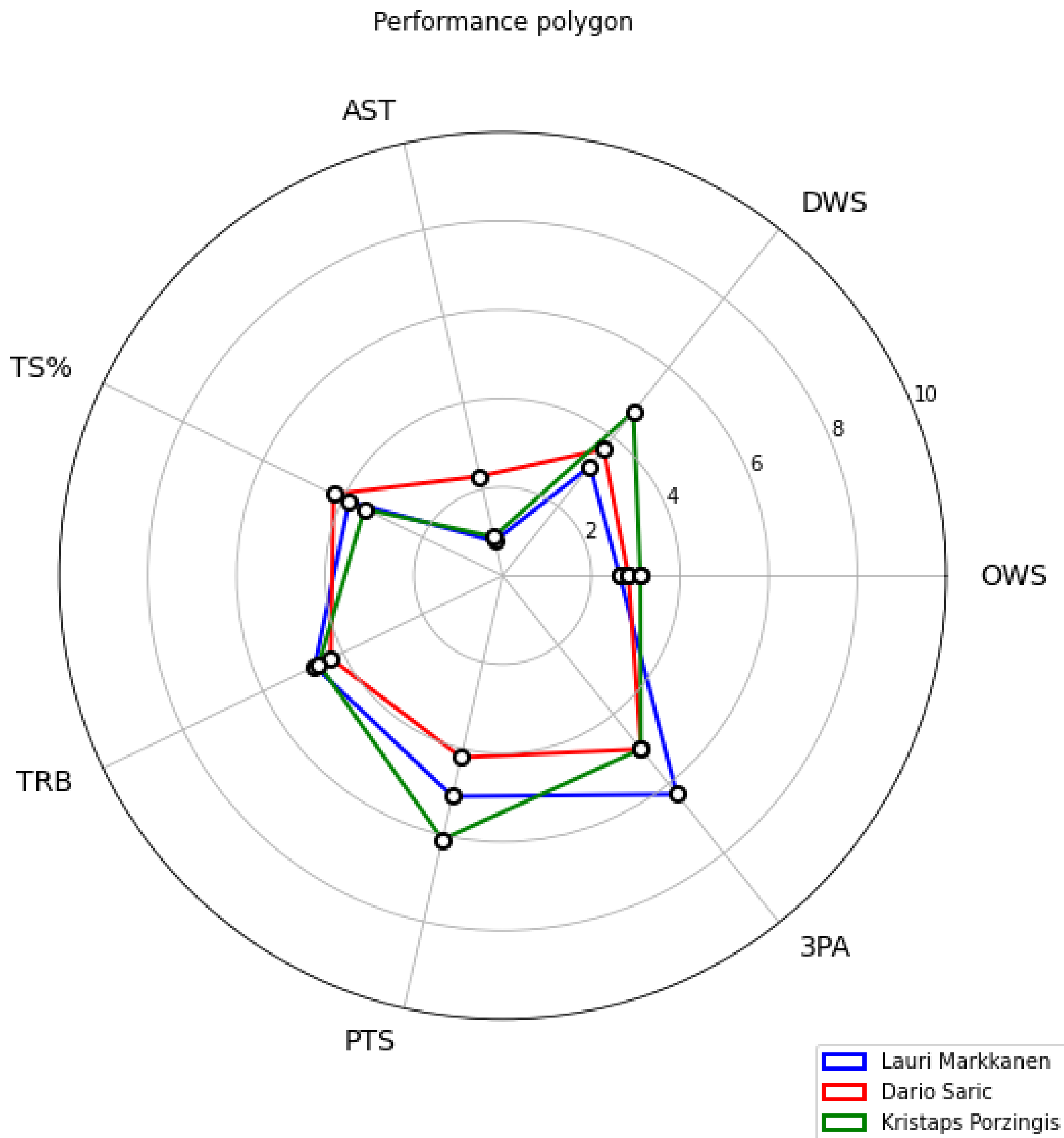
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Khem Birch
Kevon Looney
Cristiano Felicio

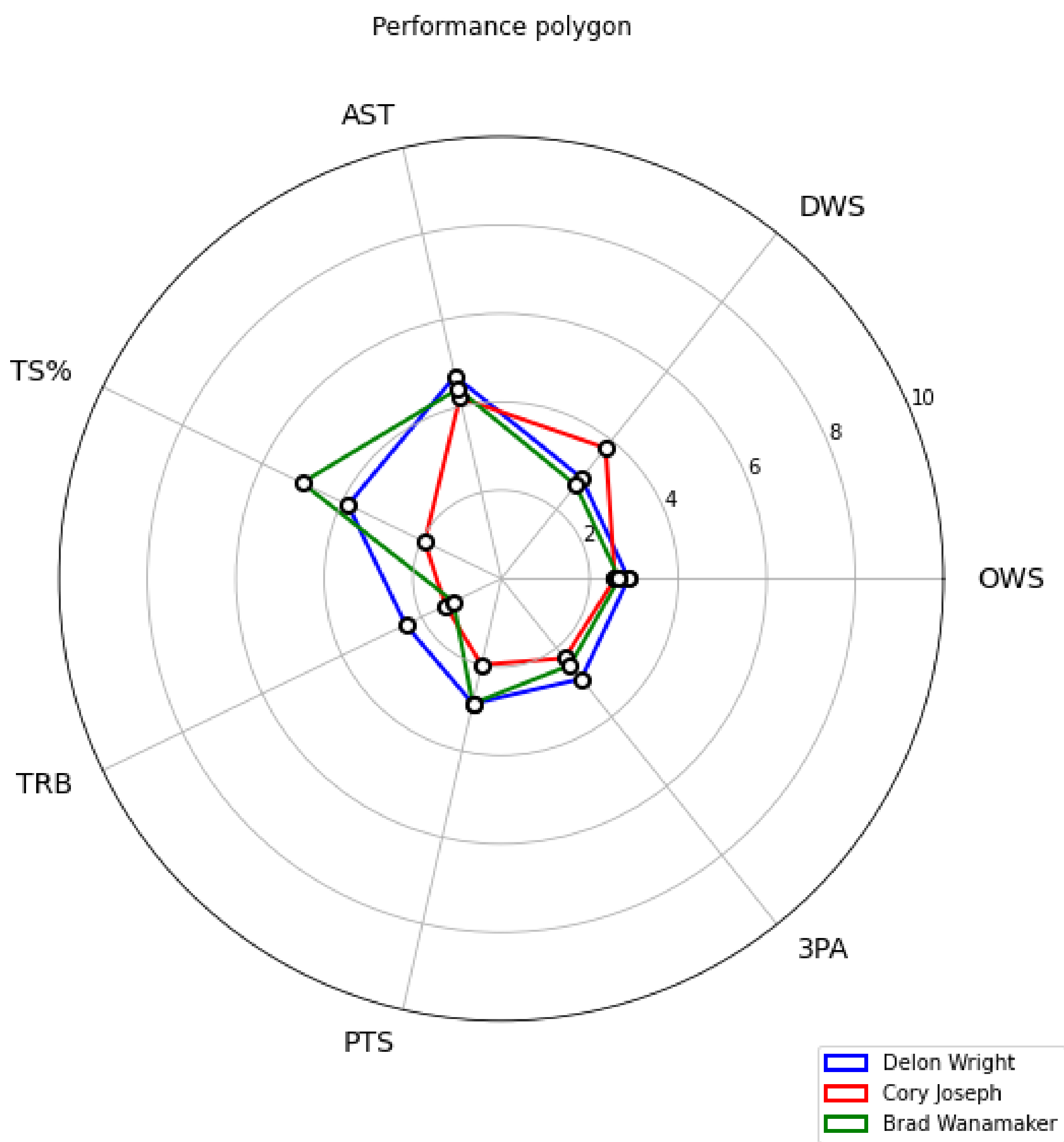

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Karl-Anthony Towns
Anthony Davis
Giannis Antetokounmpo



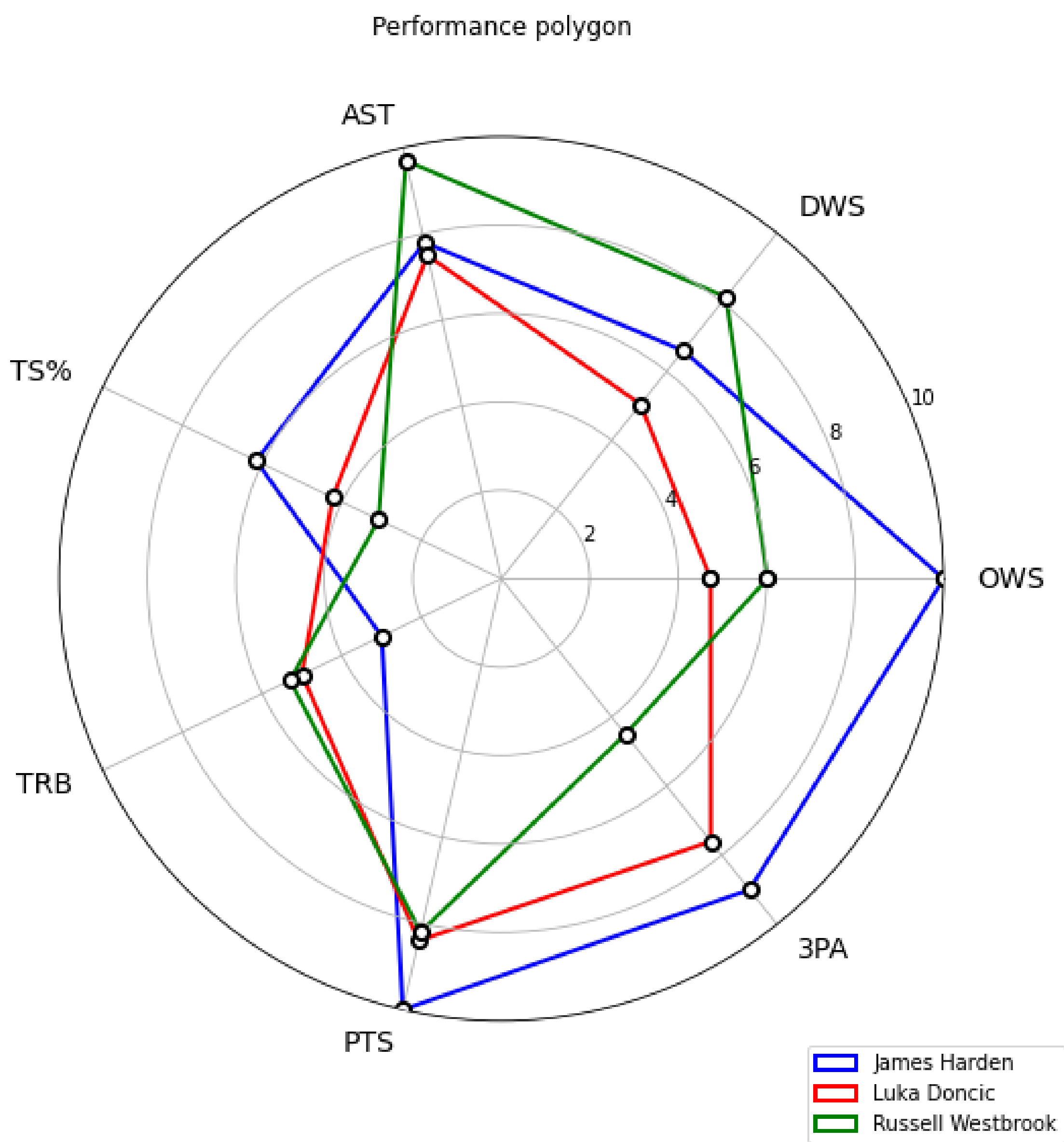
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Sterling Brown
Pat Connaughton
Miles Bridges

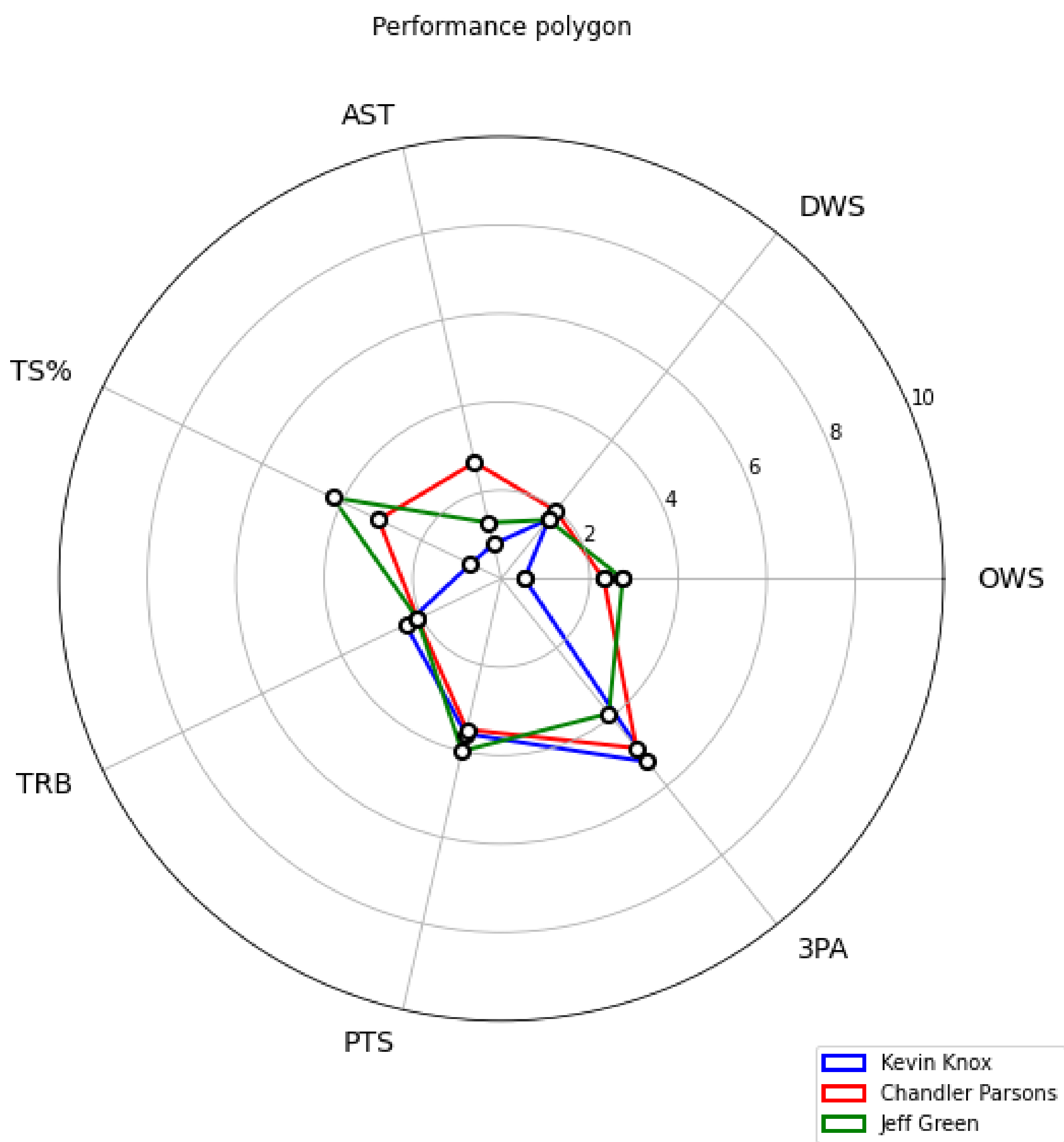

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Meyers Leonard
Thon Maker
Zach Collins

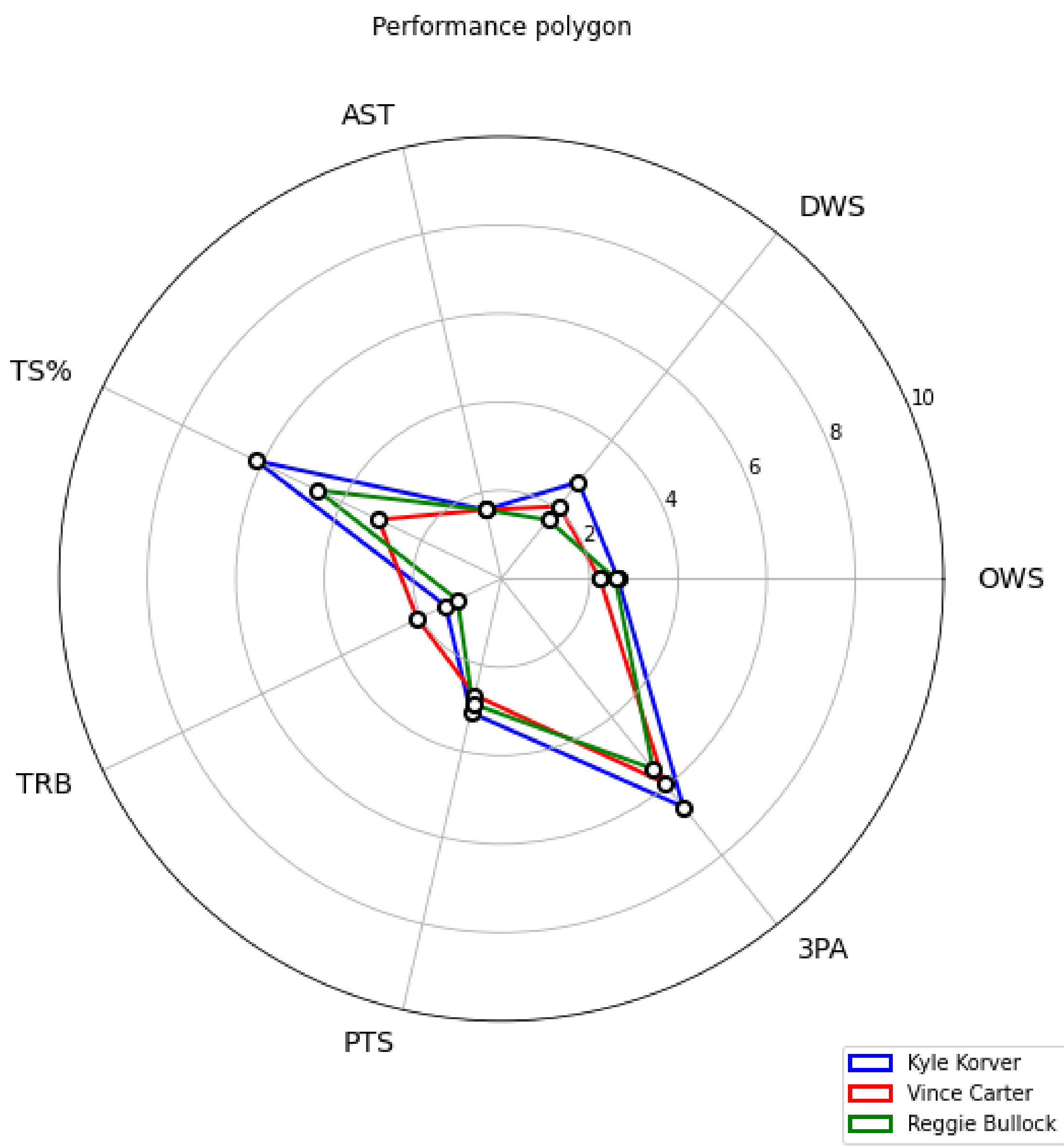

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Lauri Markkanen
Dario Saric
Kristaps Porzingis



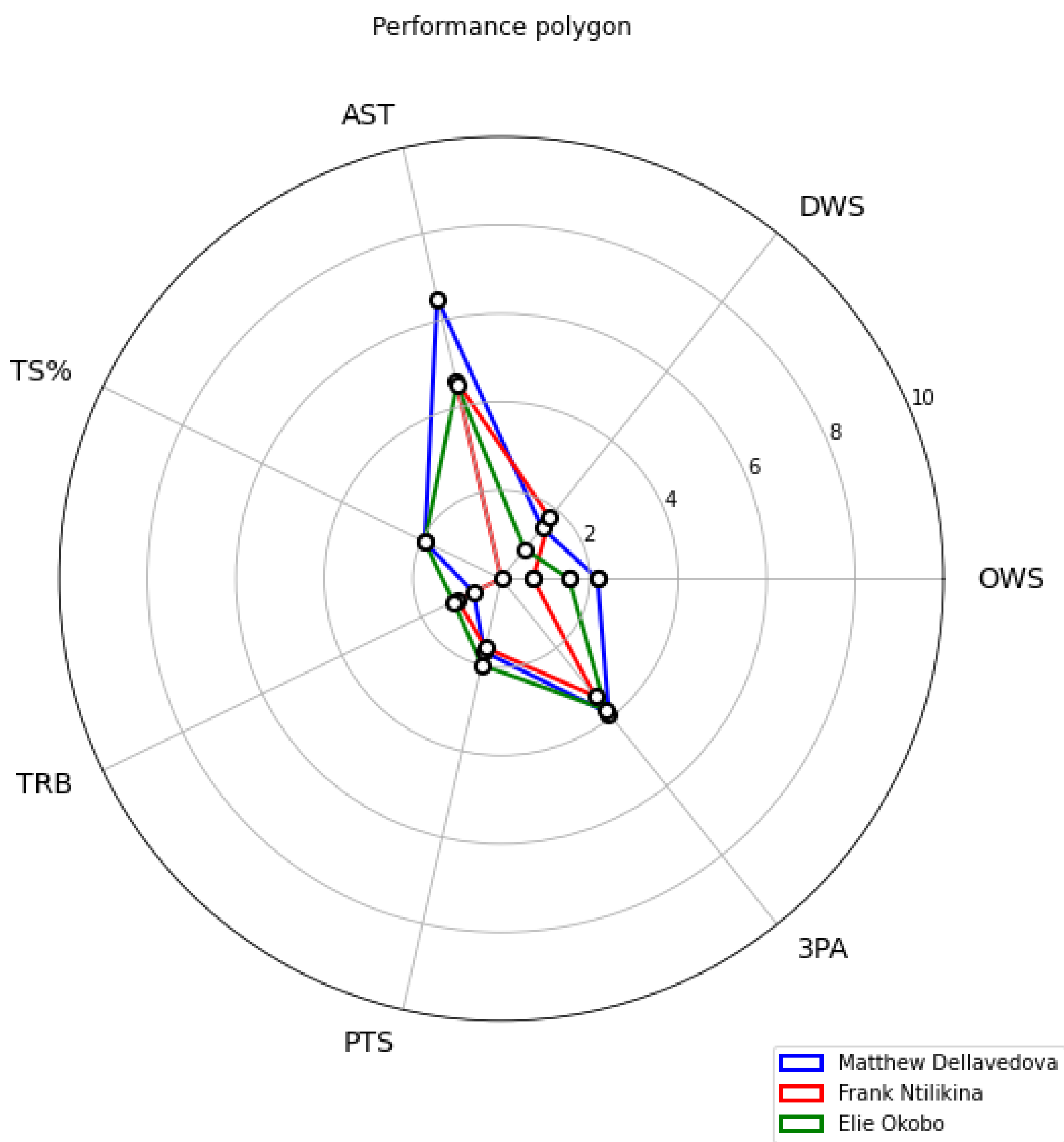
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Delon Wright
Cory Joseph
Brad Wanamaker

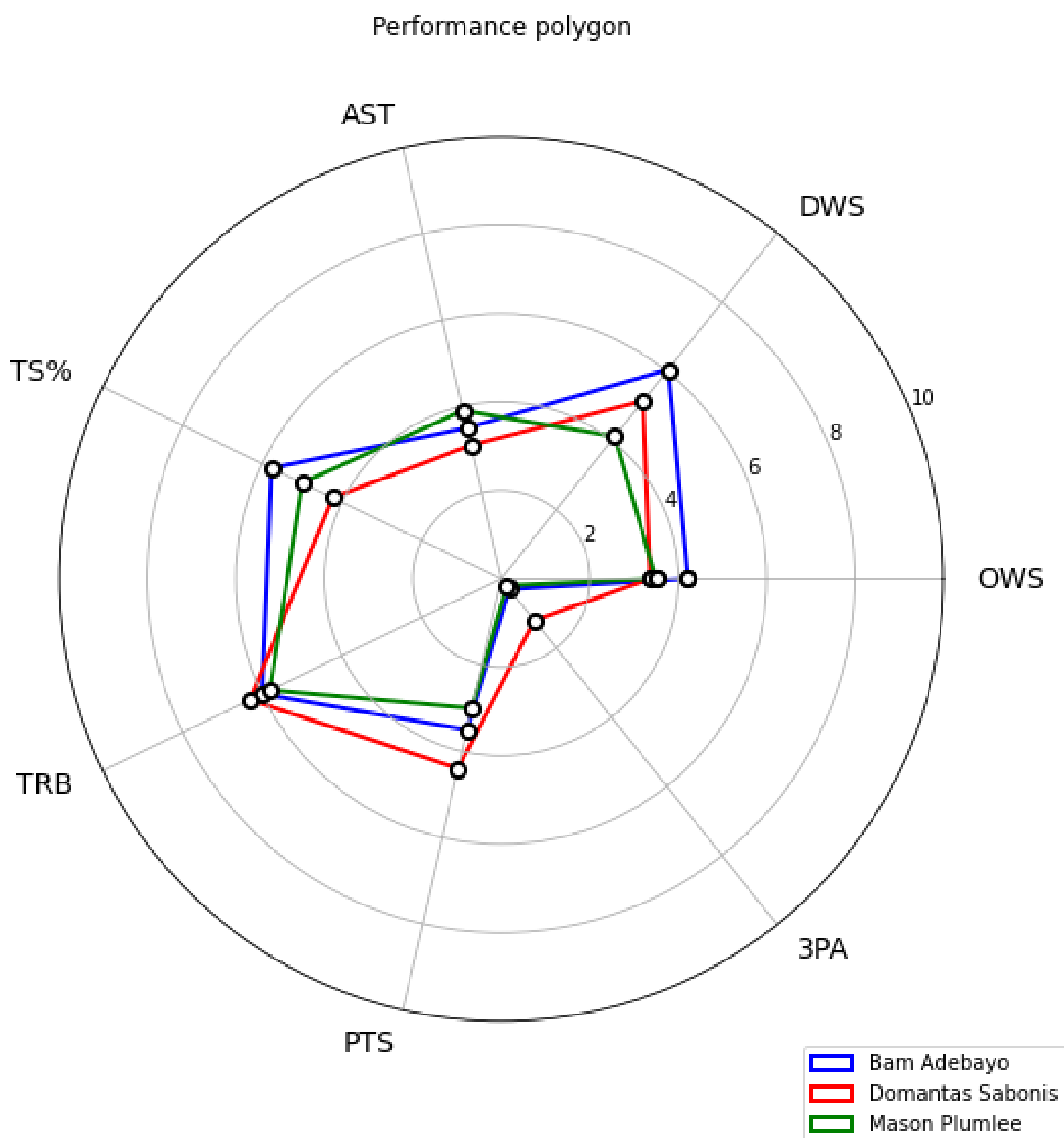

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
James Harden
Luka Doncic
Russell Westbrook

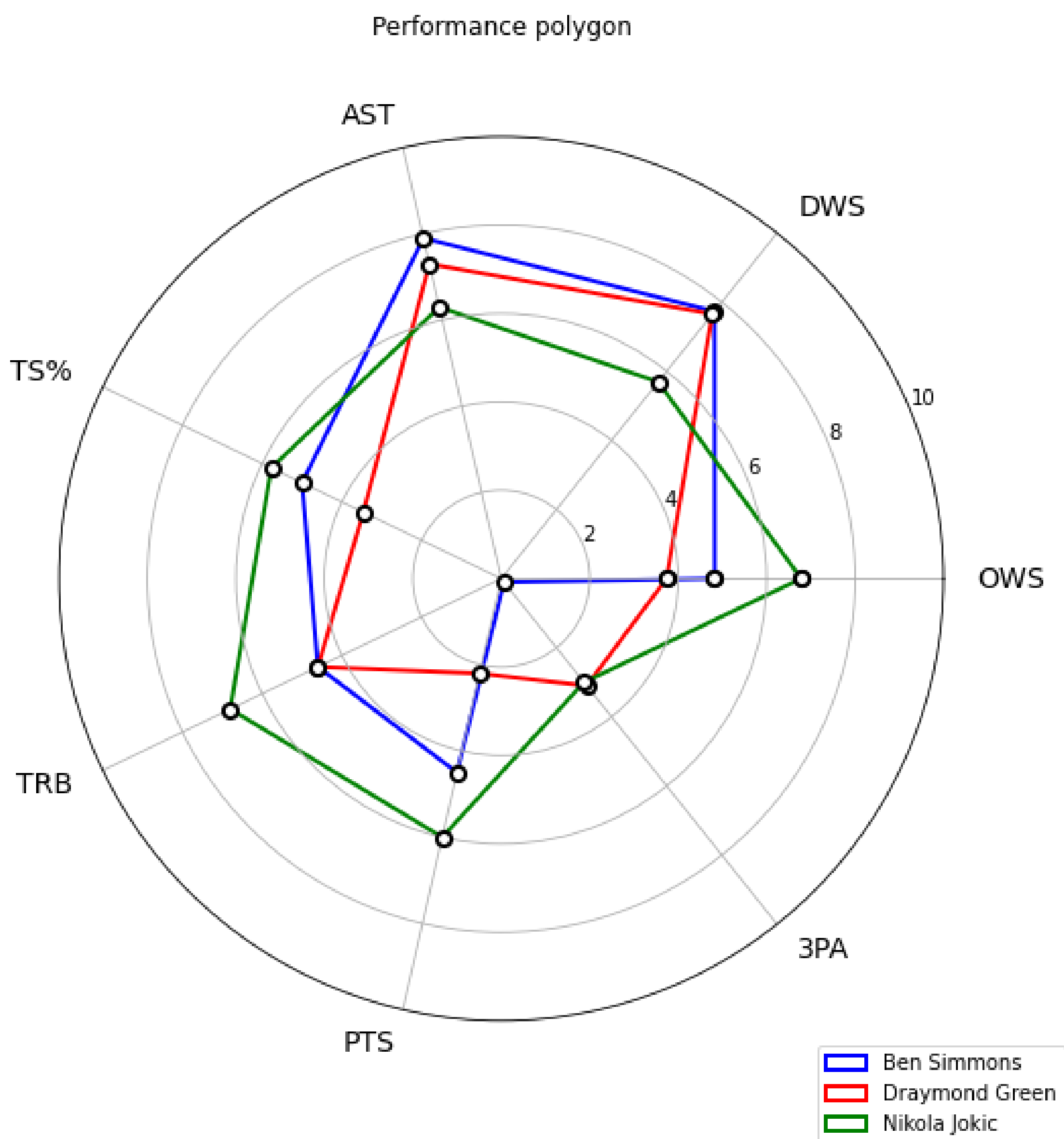

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Kevin Knox
Chandler Parsons
Jeff Green



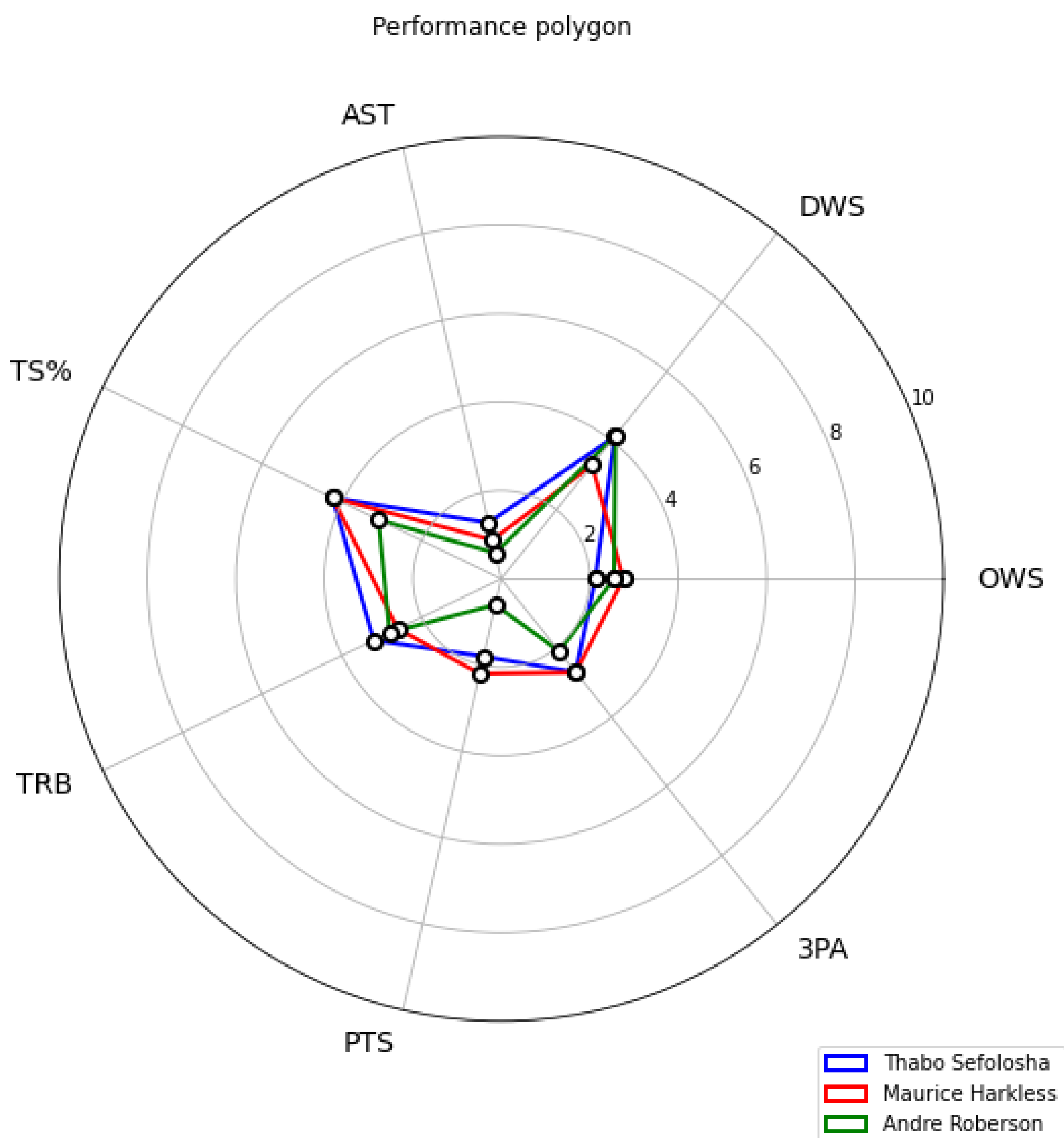
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Kyle Korver
Vince Carter
Reggie Bullock

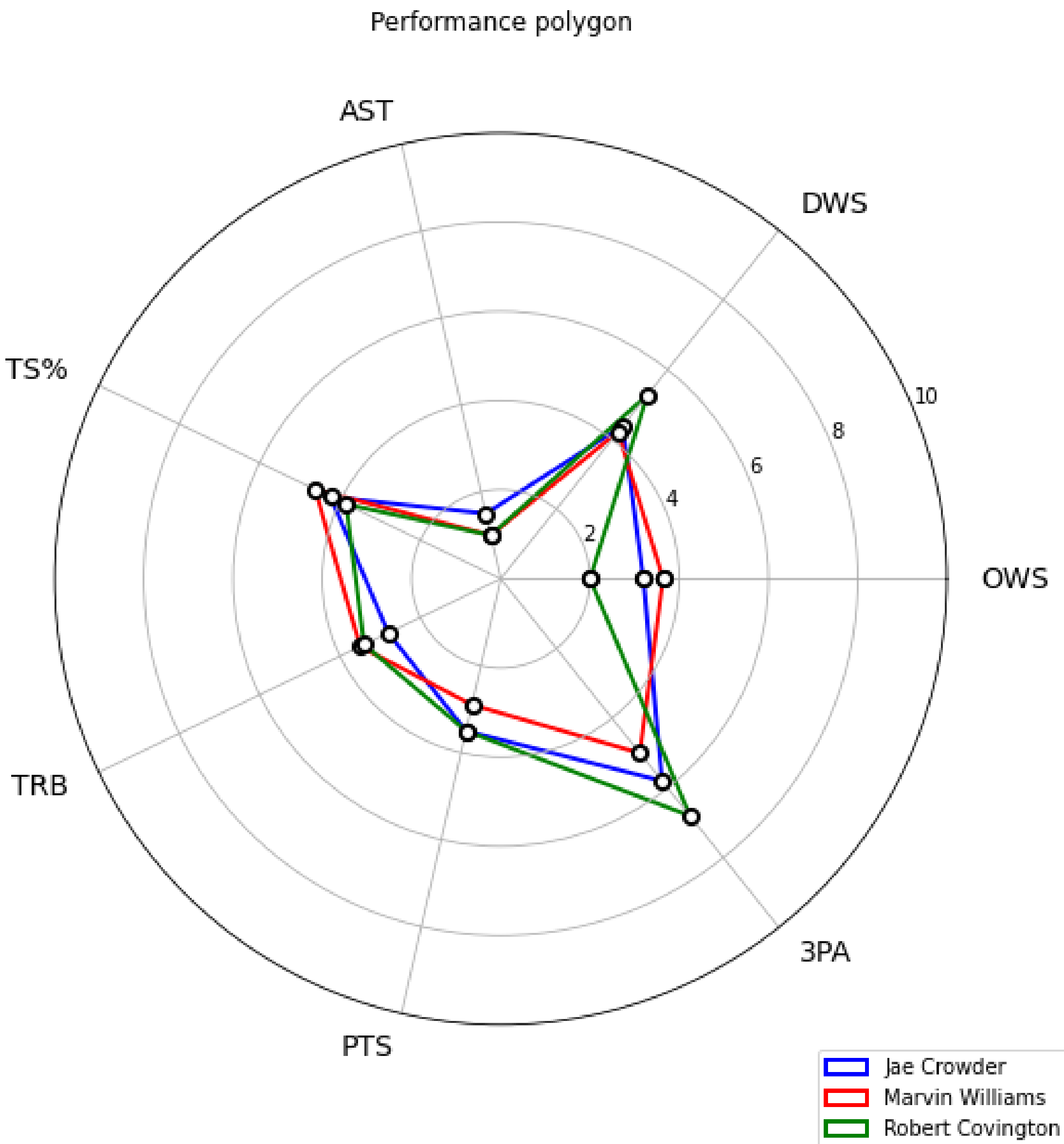

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Matthew Dellavedova
Frank Ntilikina
Elie Okobo


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Bam Adebayo
Domantas Sabonis
Mason Plumlee



Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Ben Simmons
Draymond Green
Nikola Jokic


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Thabo Sefolosha
Maurice Harkless
Andre Roberson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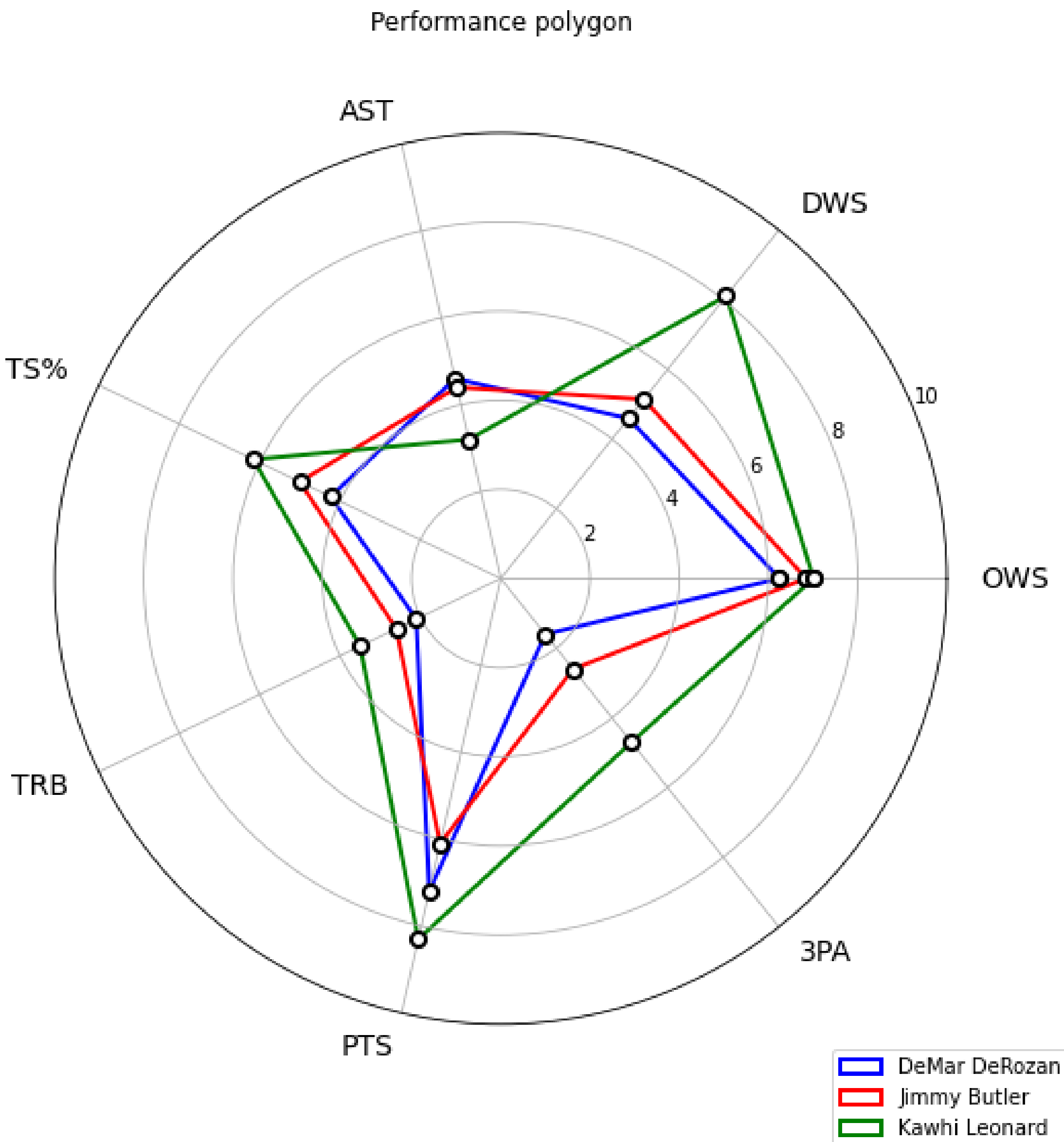
Marvin Williams
Robert Covington



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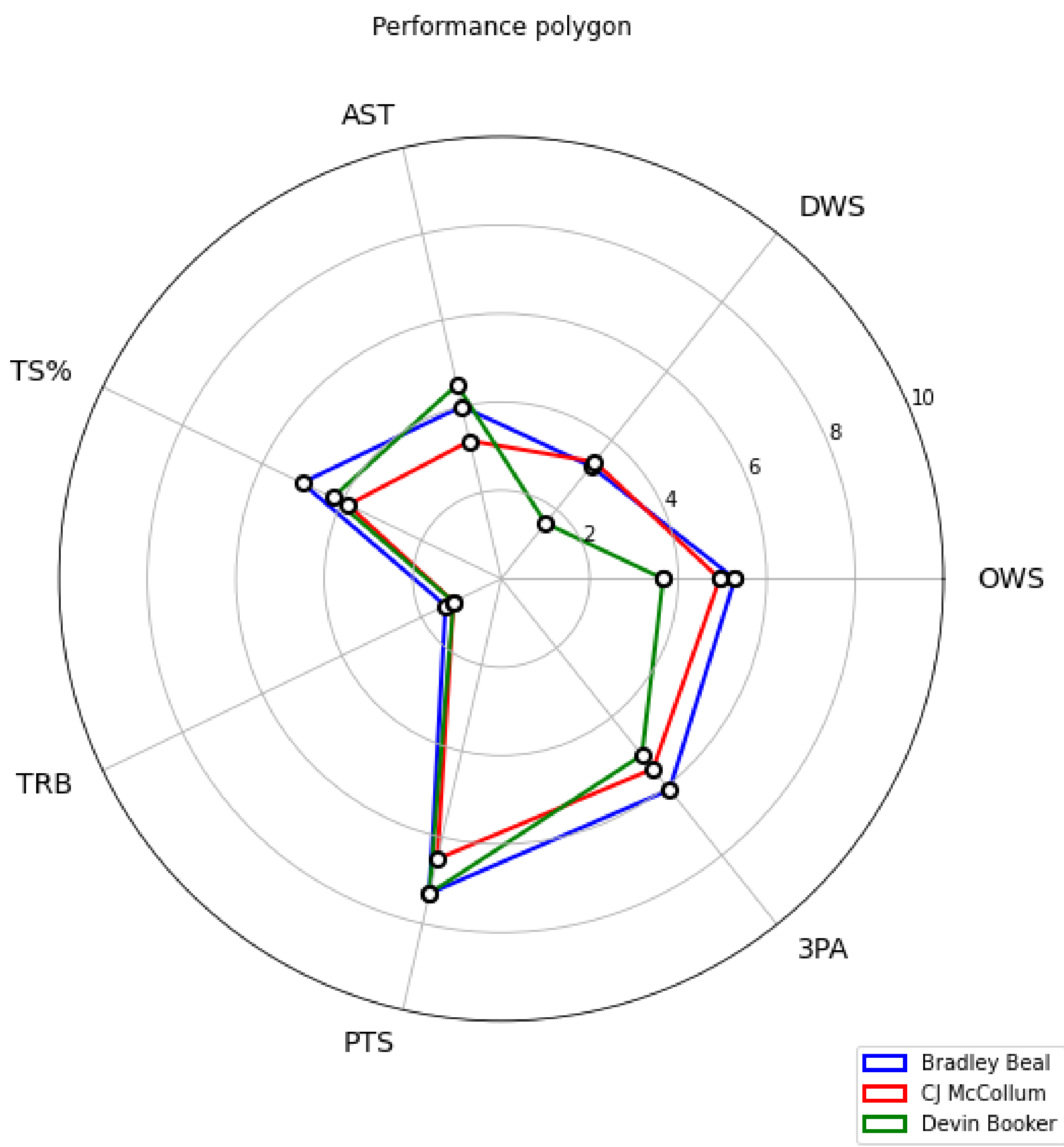
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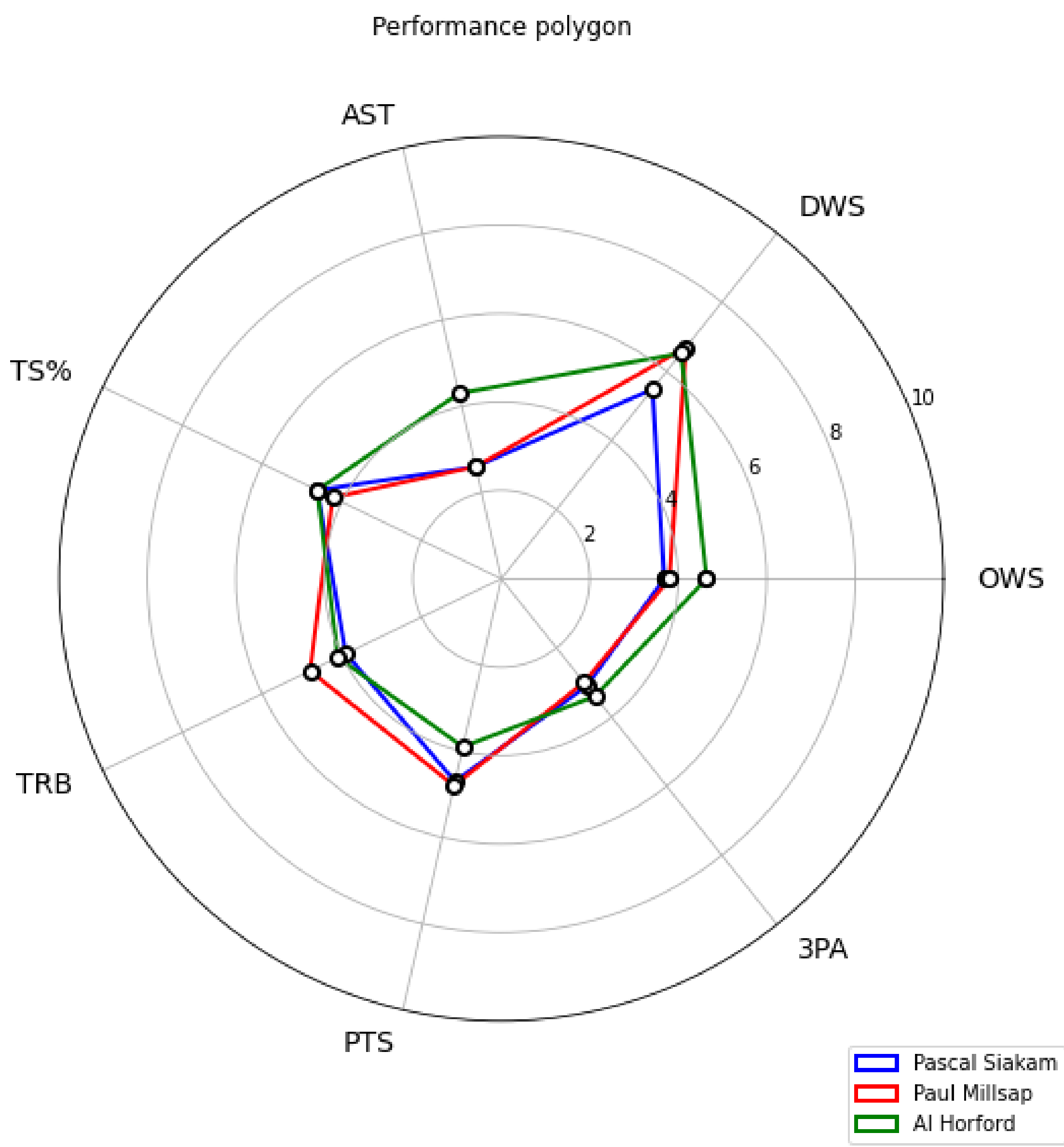
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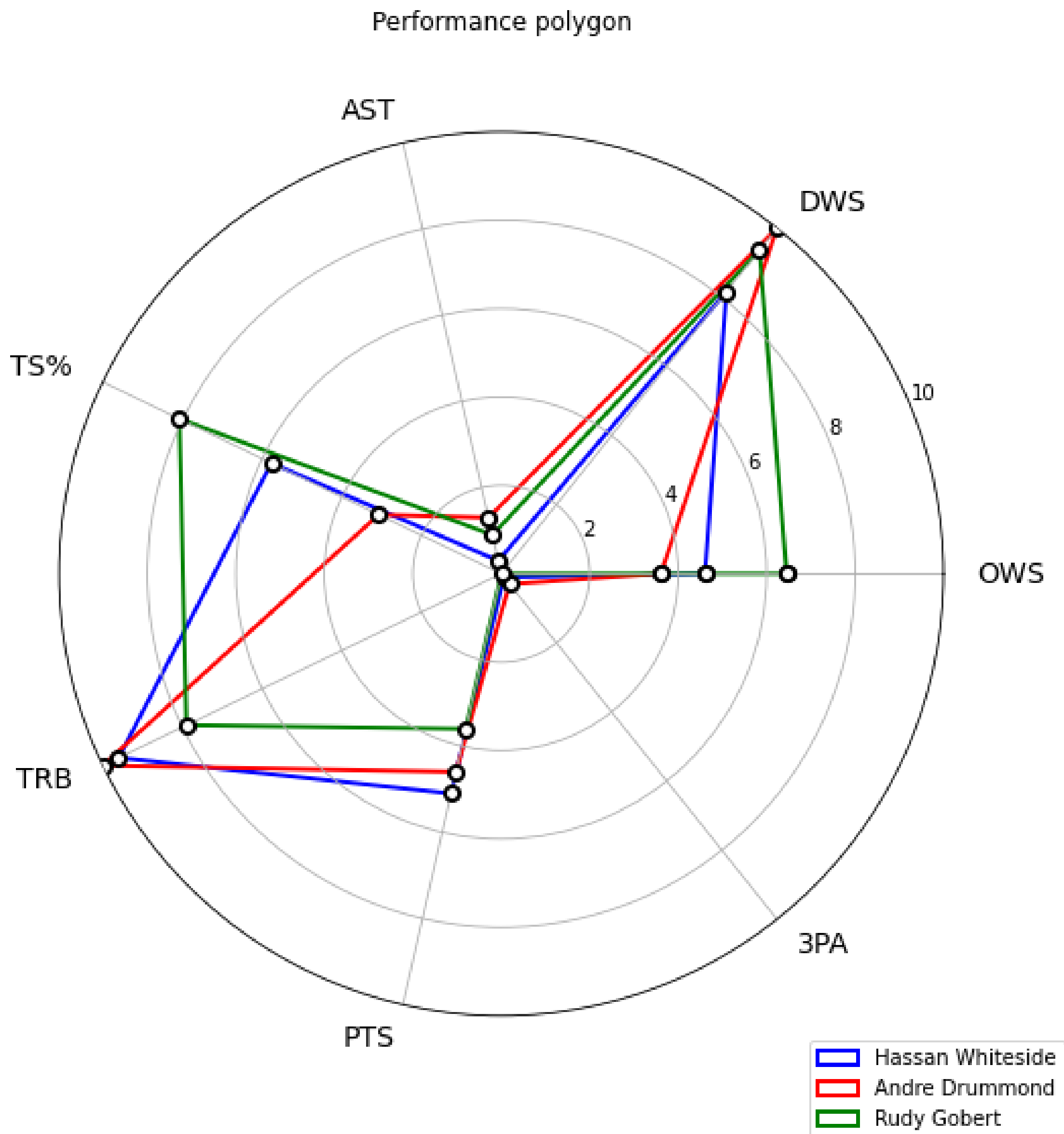
Paul Millsap
Al Horford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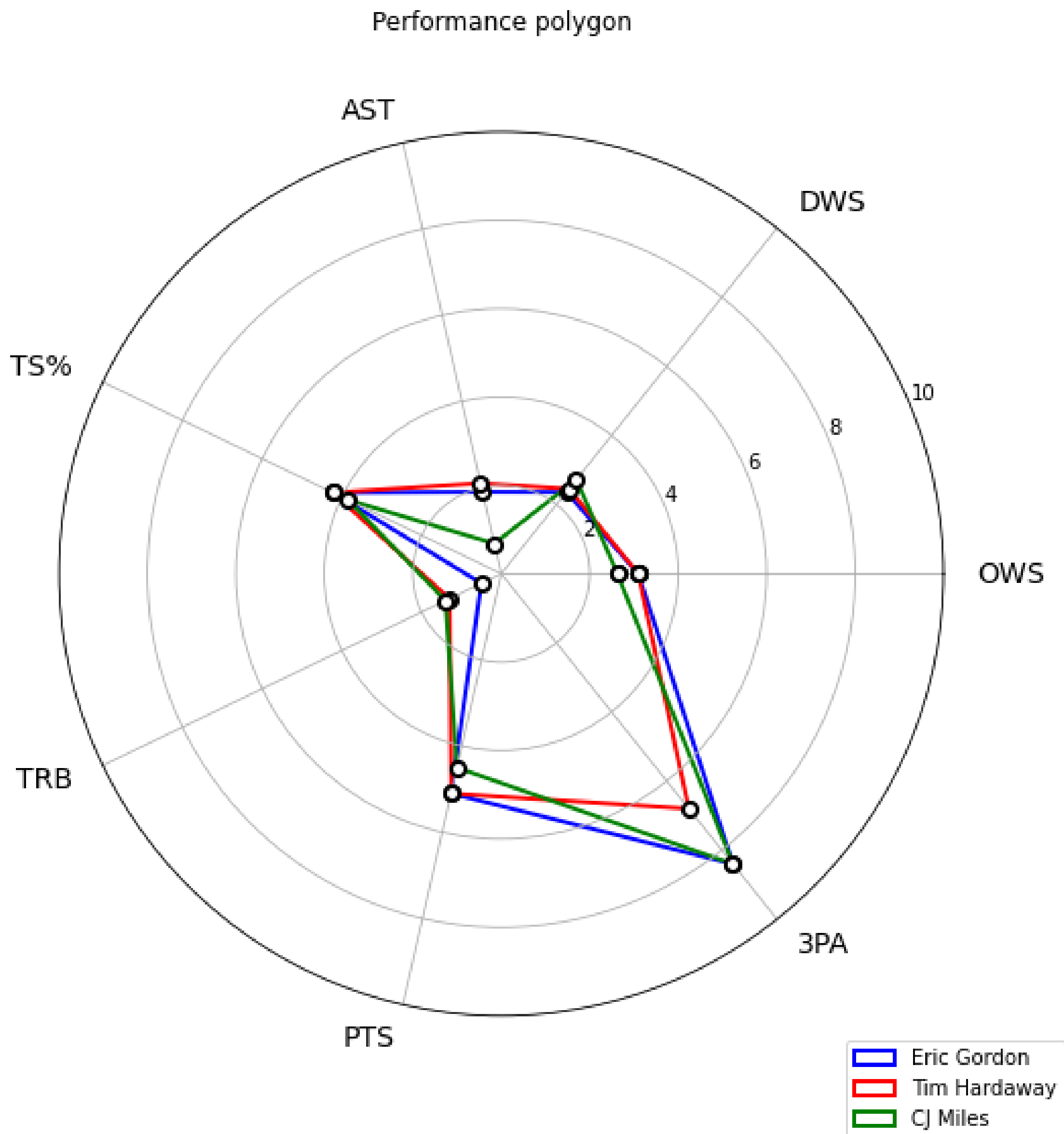

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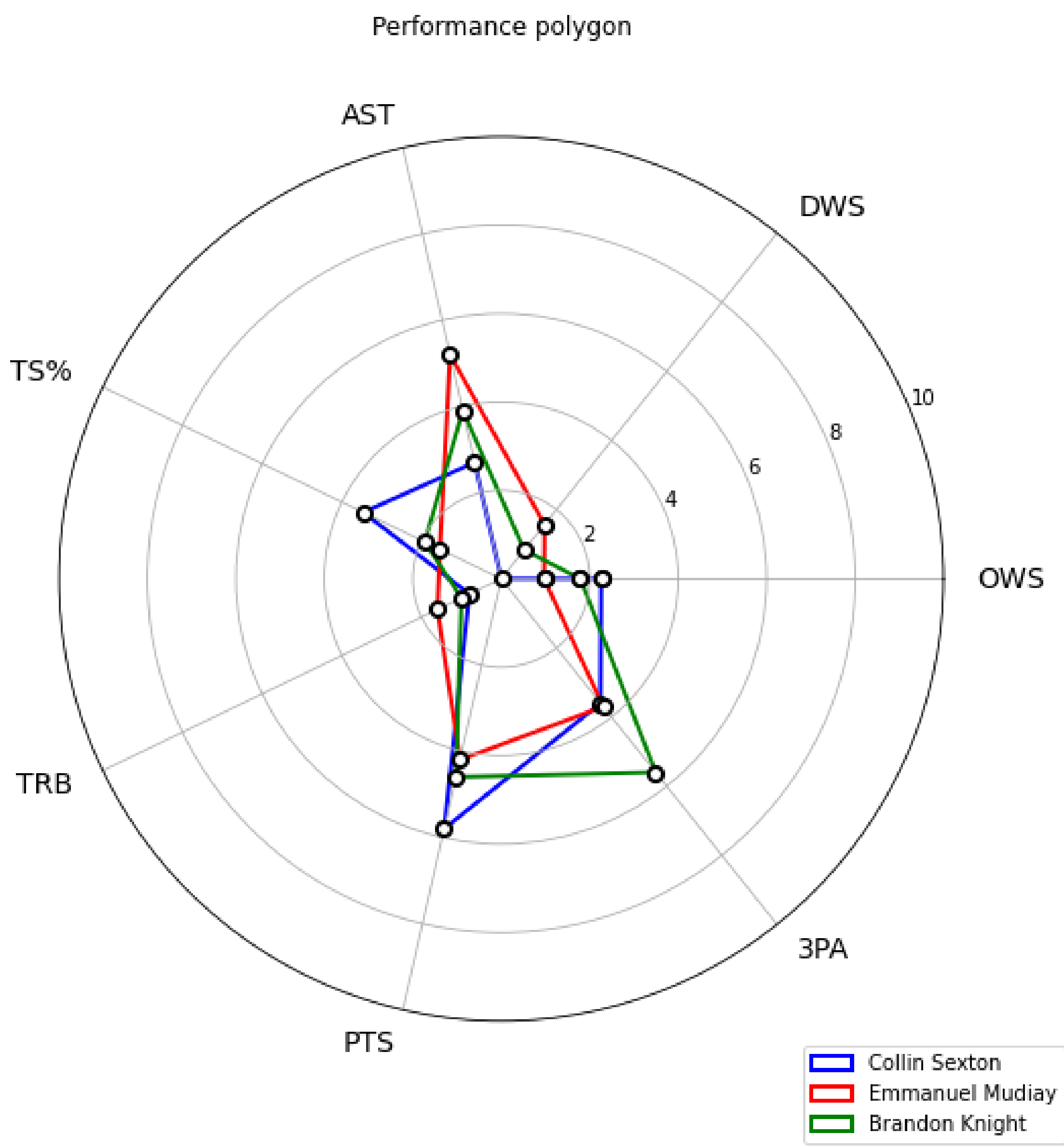
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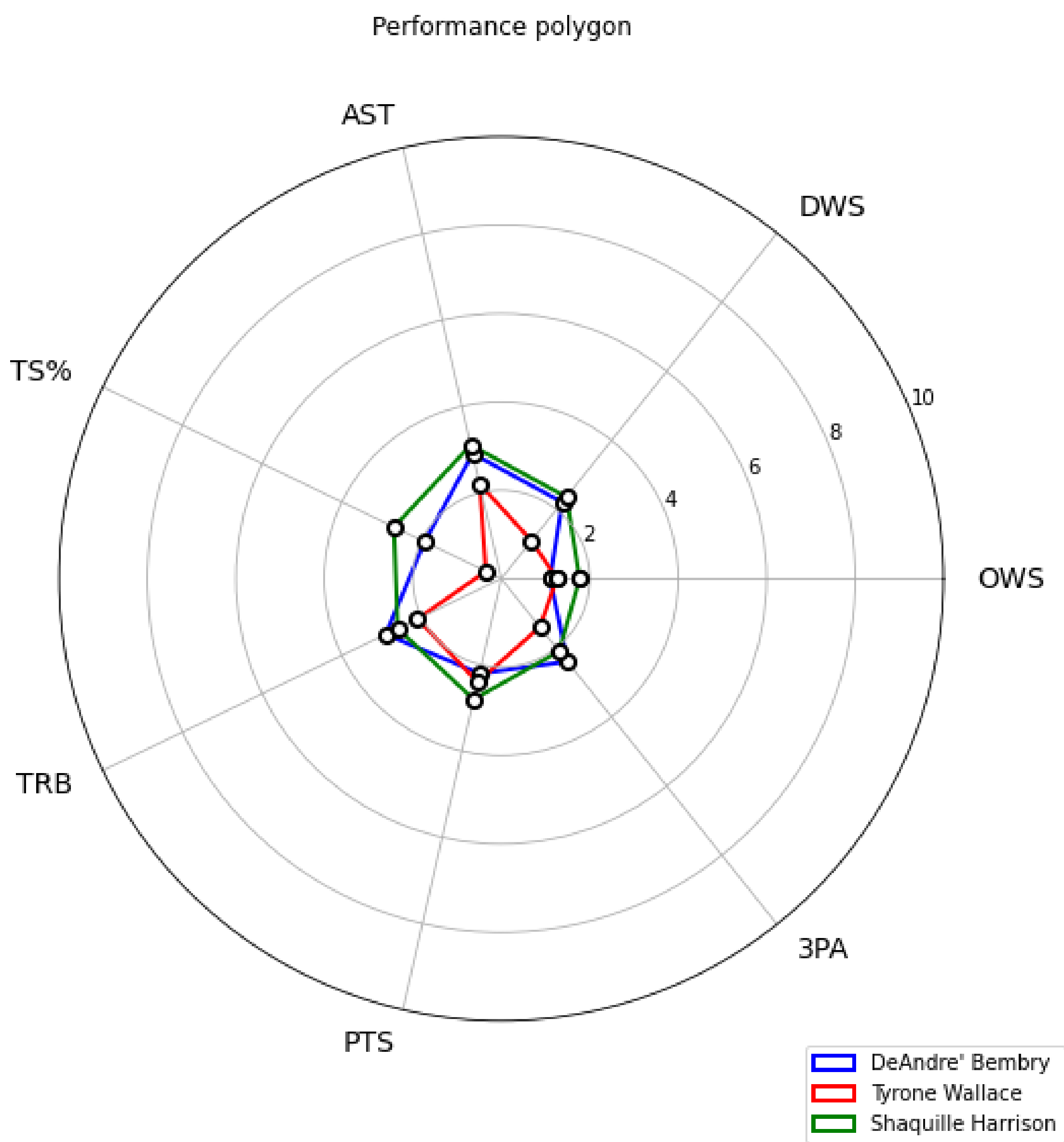
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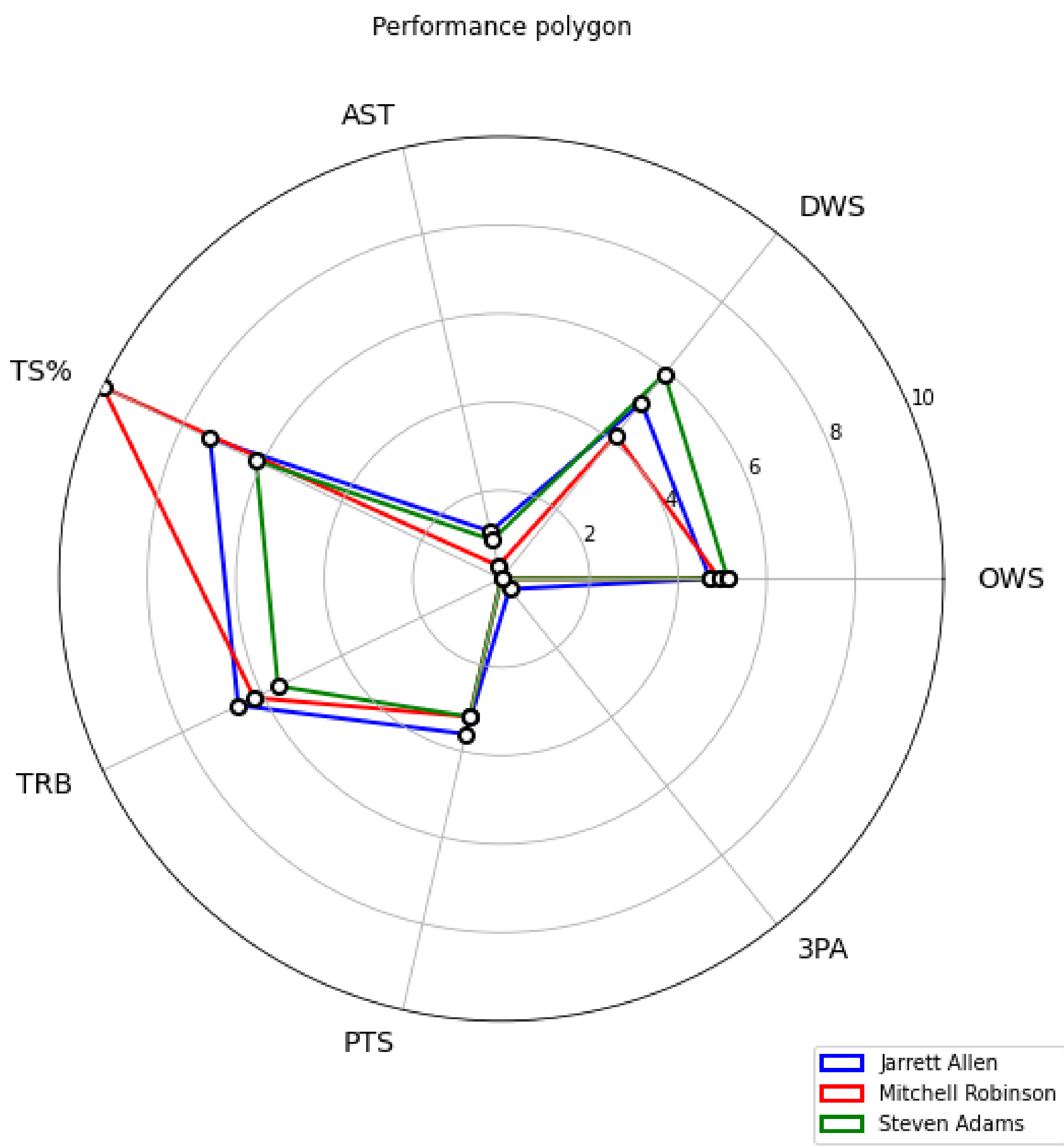
Tyrone Wallace
Shaquille Harrison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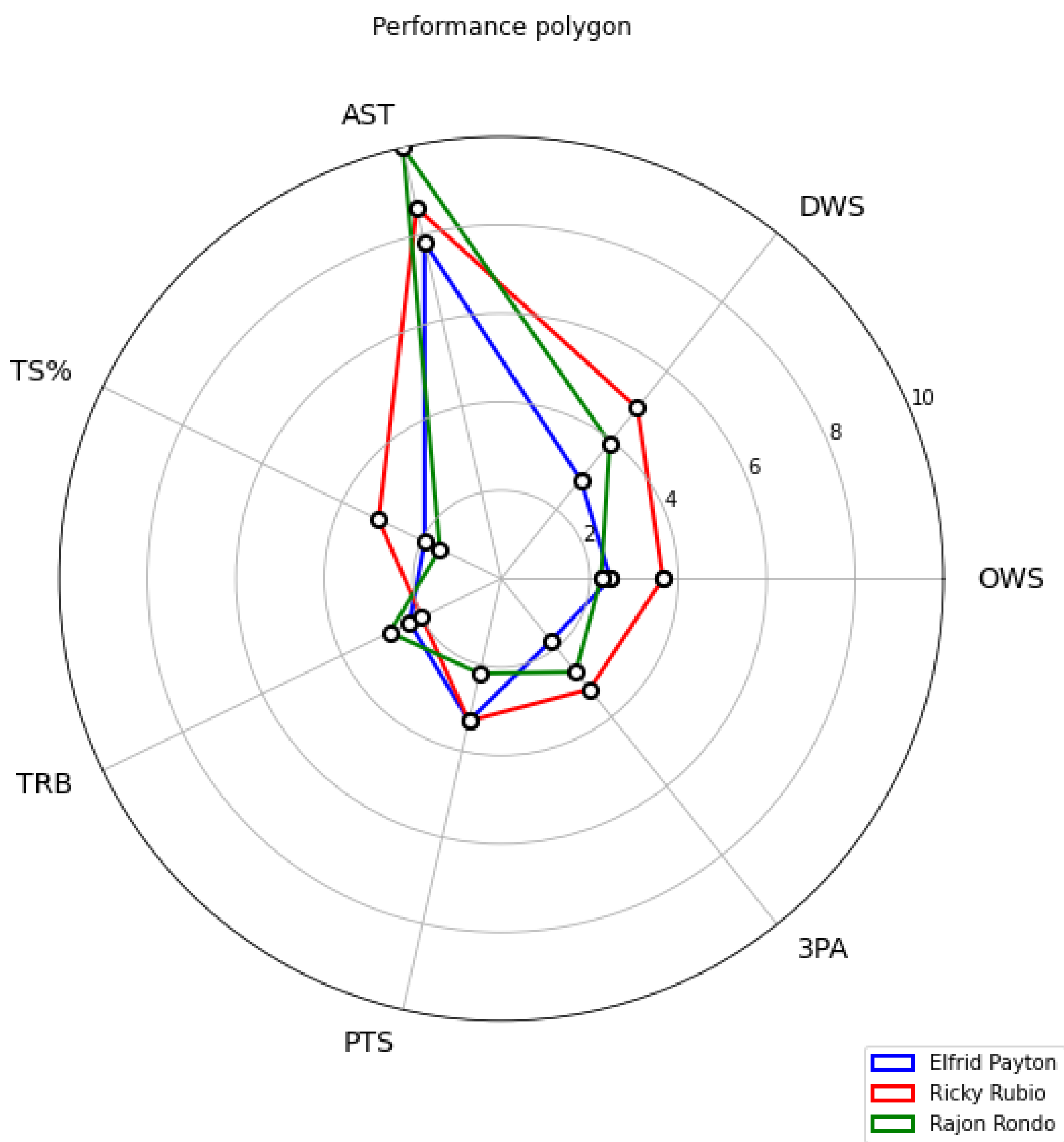
Steven Adams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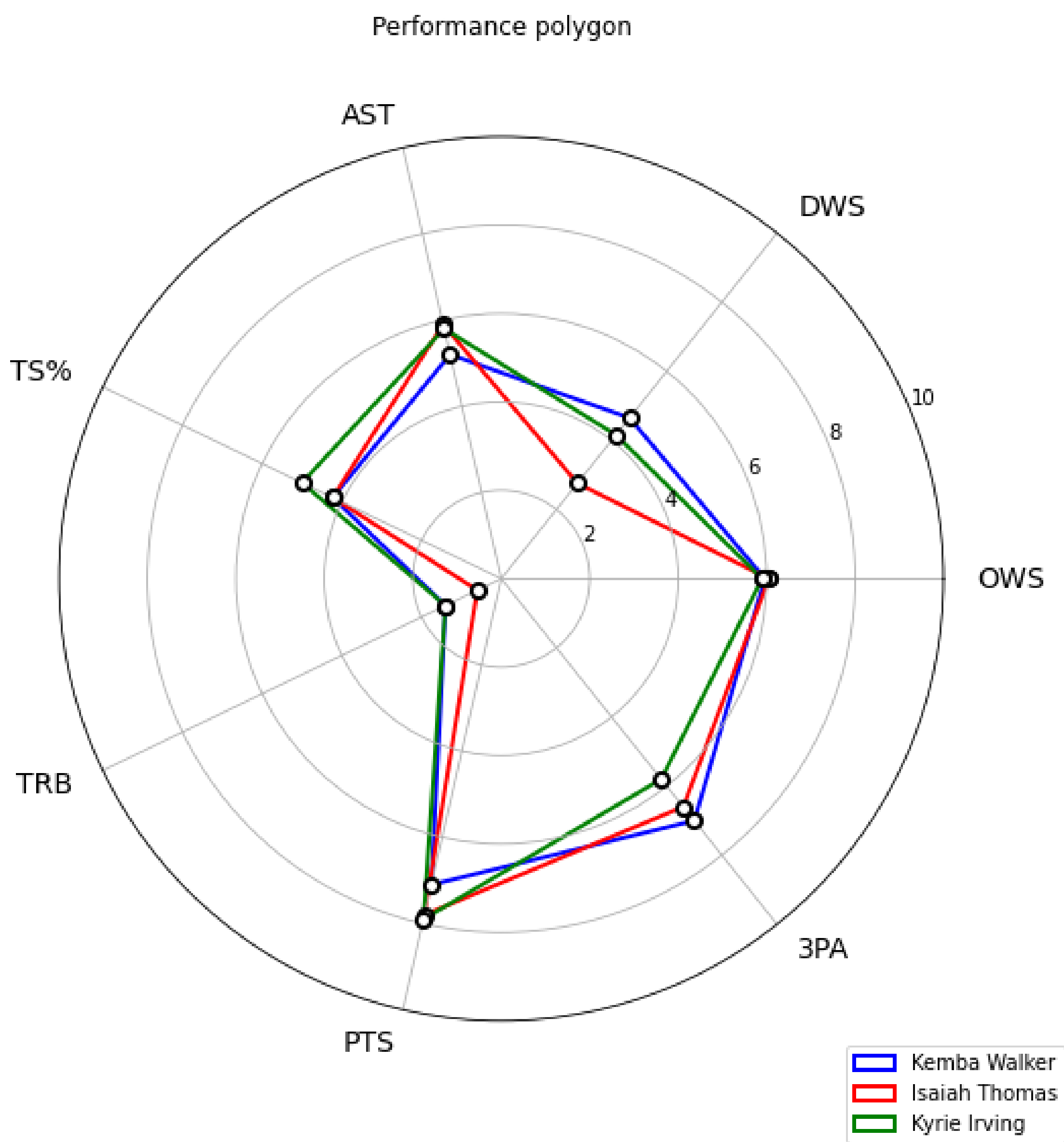

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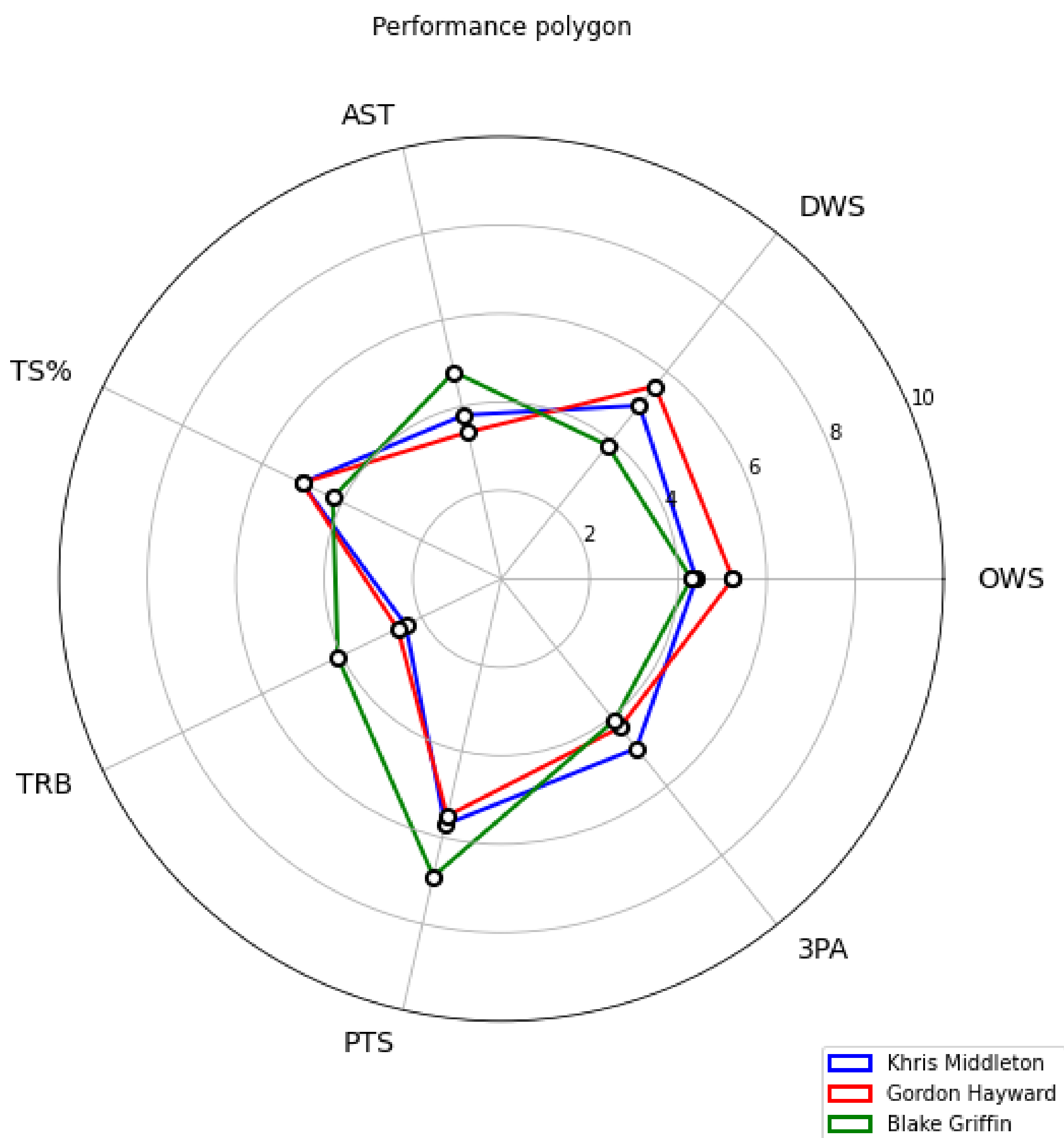
Kyrie Irving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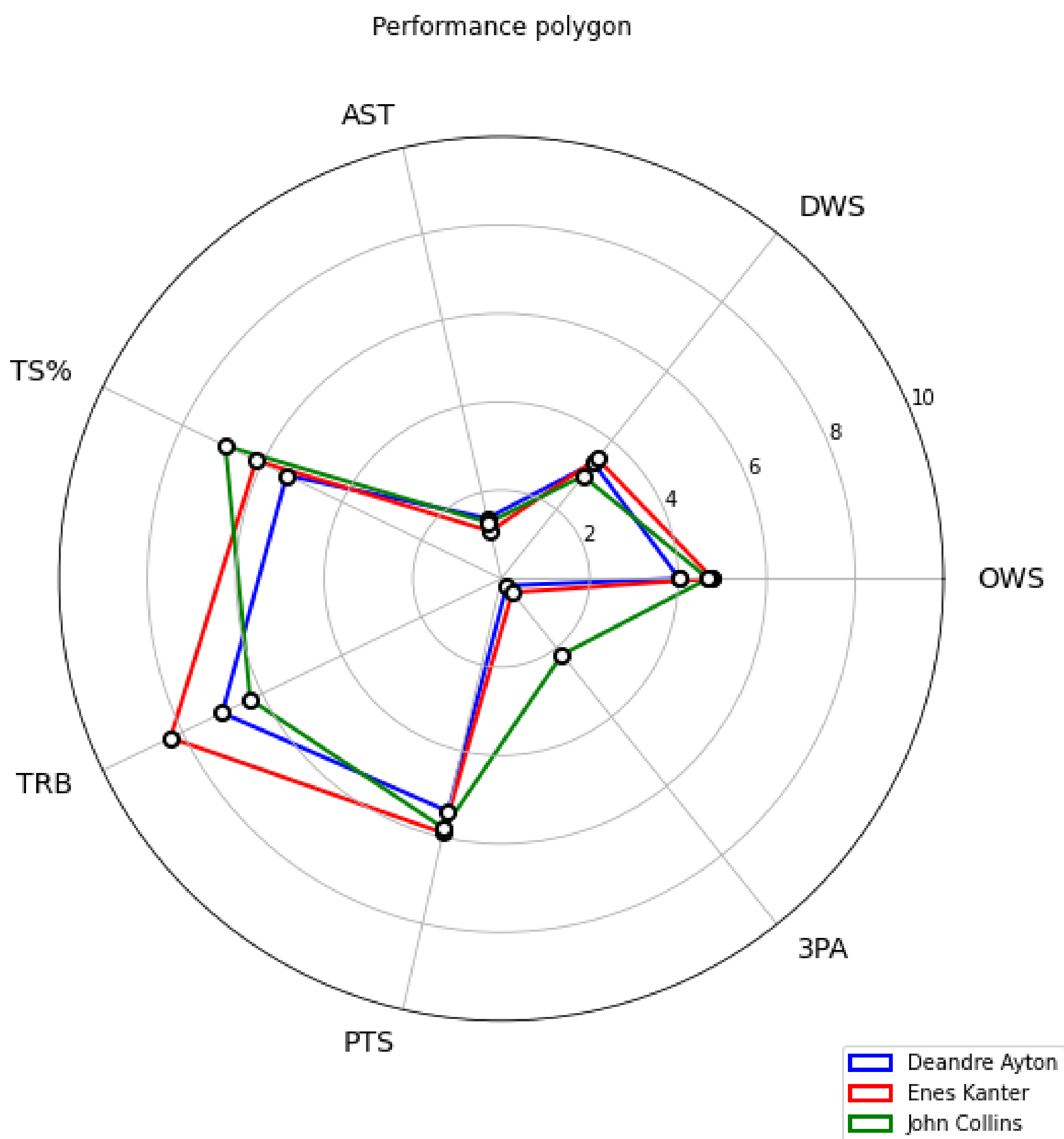
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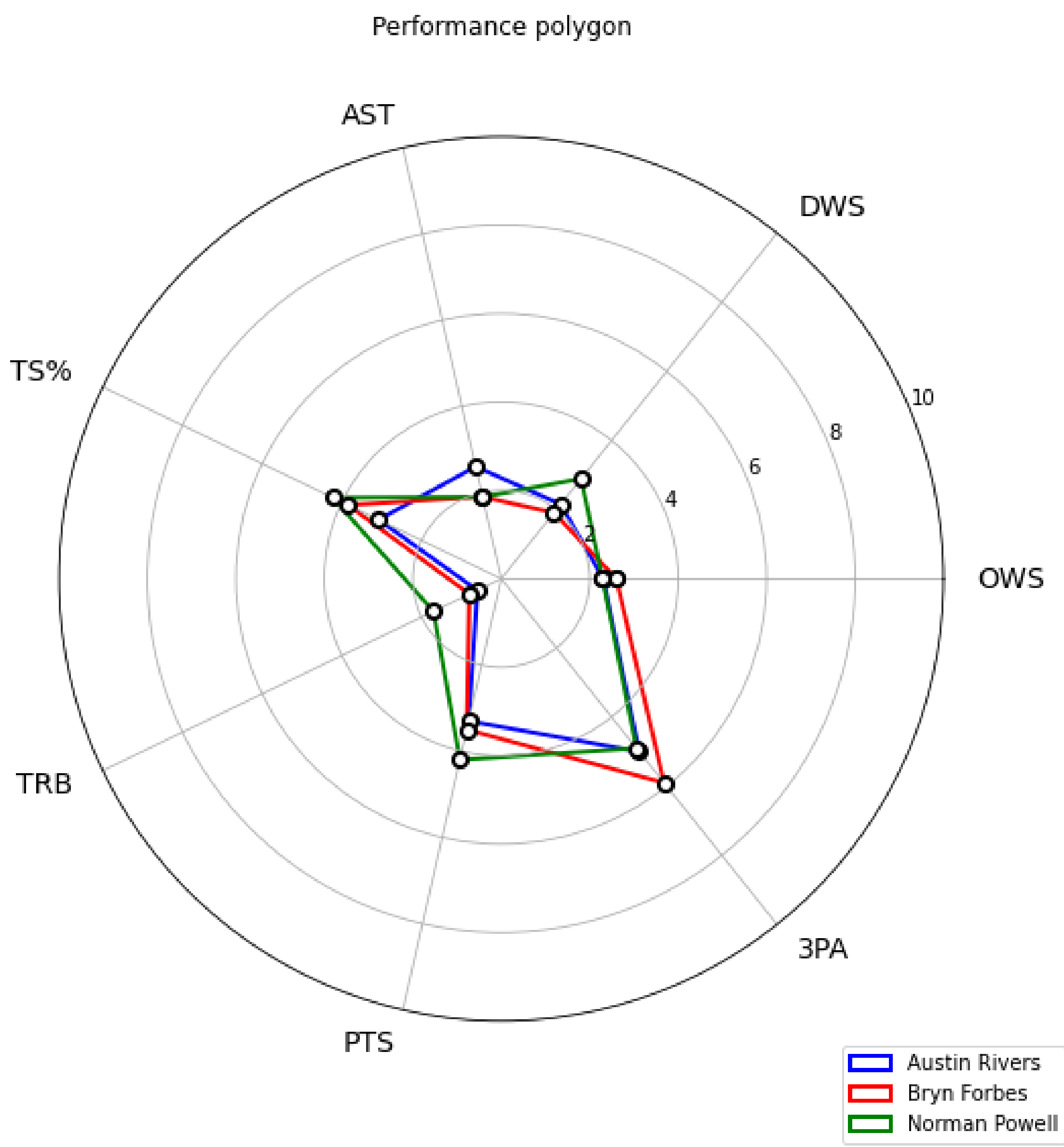
Enes Kanter
John Collins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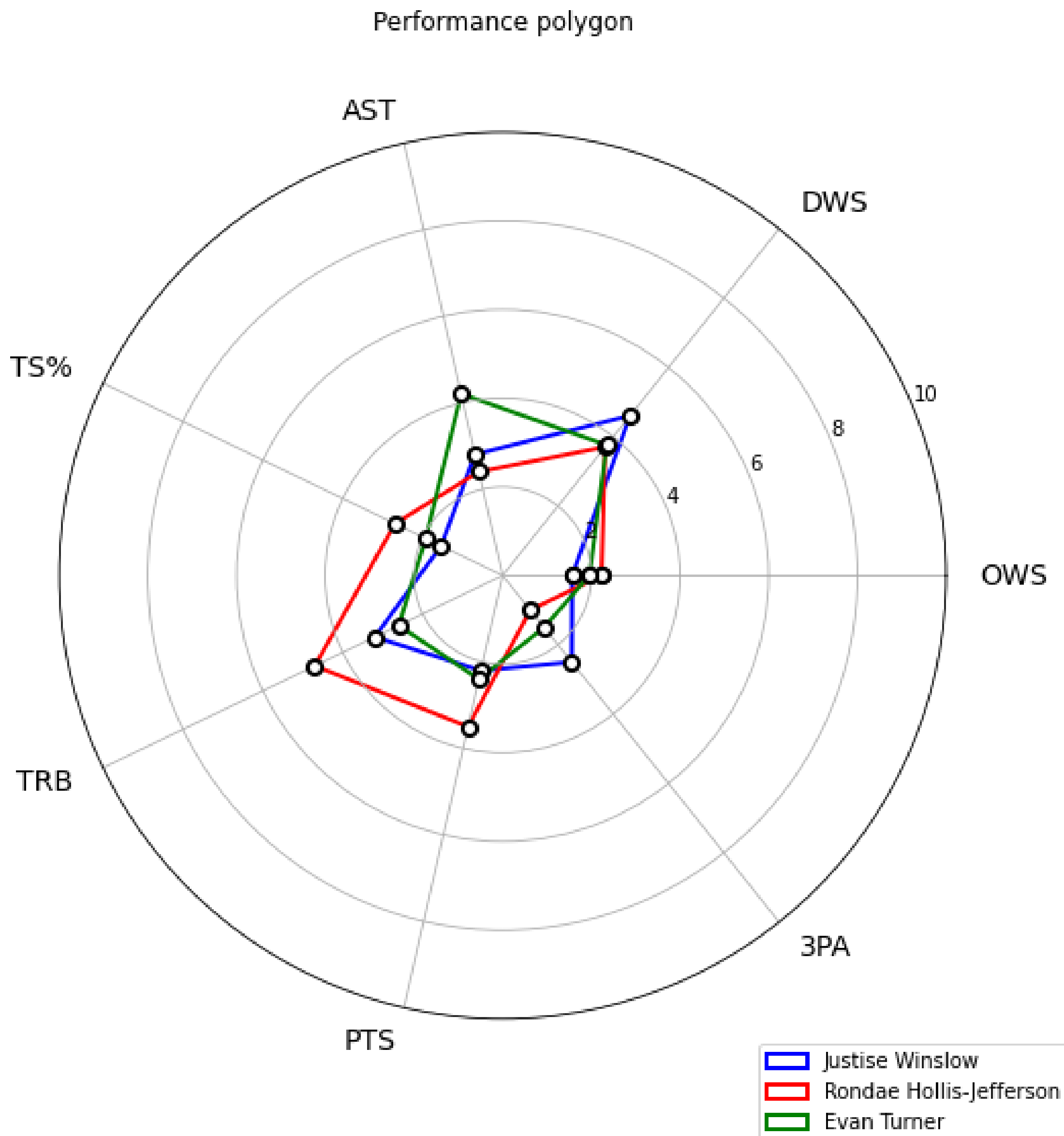
Bryn Forbes
Norman Powell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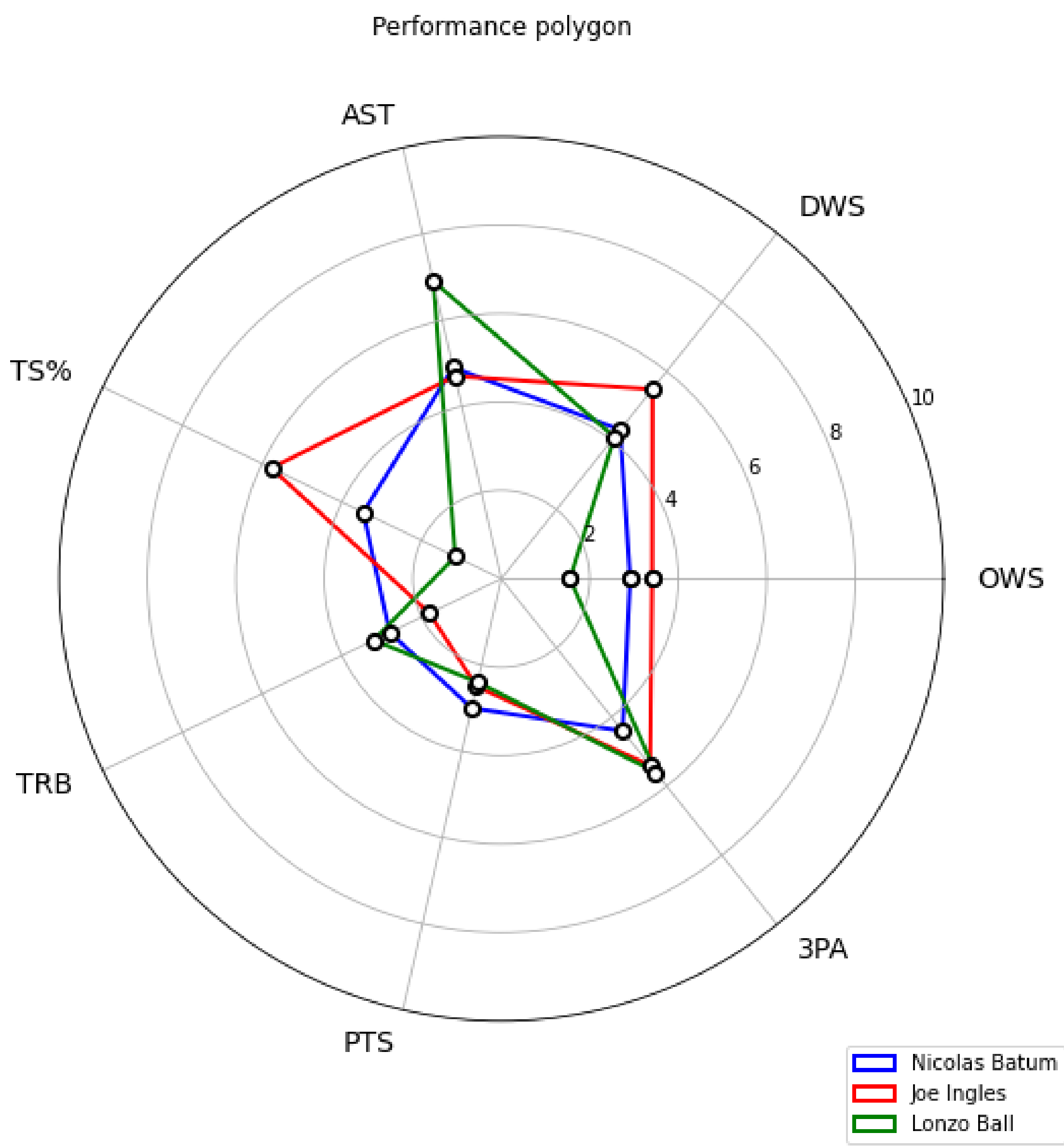
Rondae Hollis-Jefferson
Evan Turner


Performance polygon
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Nicolas Batum
Joe Ingles
Lonzo Ball

1.11 Interesting but we are limited to a certain number of player (here 3*35 = 105)

1.12 And we have to pick ourselves the number of clusters and the number of players per cluster

1.13 Let's try with KMEANS since we need to categorize every player

[43]:
```
# get the data
source = pd.read_csv('./csv/players_stats.csv')
df_to_compute = source.drop(columns=["Unnamed: 0","Player", "final_team","Pos"])

results = pd.DataFrame(data = None, columns = ['score'],dtype=np.float64)

# computing the optimal number of cluster
min_score_davies = 100000

max_score_silhouette = -100000

for nb_cluster_test in np.arange(start = 3,stop=100):
            kmeans = KMeans(n_clusters=nb_cluster_test, random_state=0).
 ↪fit(df_to_compute)
            score_davies = sklearn.metrics.
 ↪davies_bouldin_score(df_to_compute,kmeans.labels_)
            score_silhouette = sklearn.metrics.
 ↪silhouette_score(df_to_compute,kmeans.labels_)

            if (score_davies < min_score_davies):
                min_score_davies = score_davies
                optimal_number_of_cluster_davies = nb_cluster_test
            if (score_silhouette > max_score_silhouette):
                max_score_silhouette = score_silhouette
                optimal_number_of_cluster_silhouette = nb_cluster_test

optimal_number_of_cluster = int((optimal_number_of_cluster_davies +␣
 ↪optimal_number_of_cluster_silhouette) / 2)

# compute K-MEANS
#nb_clusters = 70
kmeans = KMeans(n_clusters=optimal_number_of_cluster, random_state=0).
 ↪fit(df_to_compute)

# average number of player per cluster
avg_number_per_cluster = round(len(df_to_compute.index) /␣
 ↪optimal_number_of_cluster, 2)
```

```python
# get the clusters
clusters = pd.DataFrame(kmeans.labels_)
clusters.columns = {"Cluster"}

# stick the cluster number for each player
clustered_players =pd.concat([clusters, source], axis=1)
clustered_players = clustered_players.drop(columns=["Unnamed: 0"])

# get the number of players in each cluster
stats = clustered_players[["Cluster", "PTS"]].groupby(["Cluster"]).
↪agg(["count"])
```

1.14 Once again we are still face to the issue of the number of cluster

1.15 Both methods (silhouette and Davies) rewards either the min or the max number of cluster among the values we are testing

1.16 Let's try to use another approach: Dissimilarity Matrix

[44]:
```python
def computing_distance_matrix(source, criterias):
    player_names = source["Player"]

    # we keep the interesting value
    df = source[criterias]

    # number of player
    nb_of_players = len(df.index)

    # our distance matrix
    dist_mat_dict = {}

    #lets compute the distance for every couple of players
    for i in range(nb_of_players):
        dist_mat_dict[player_names[i]] = {}
        for j in range(nb_of_players):
            dist_mat_dict[player_names[i]][player_names[j]] = round(distance.
↪euclidean(df.iloc[i], df.iloc[j]), 3)


    # list is more convenient for scaling
    # here we have a list of lists
    distance_matrix_list = [list(z.values()) for y,z in dist_mat_dict.items()]
    distance_matrix_list = pd.DataFrame(distance_matrix_list)
    min_of_distance = distance_matrix_list.min().min()
    max_of_distance = distance_matrix_list.max().max()
```

```
    # we fill back the value from the list to the dict
    for i in range(nb_of_players):
        for j in range(nb_of_players):

            # scaling before
            distance_matrix_list[i][j] = distance_matrix_list[i][j] -␣
↪min_of_distance
            distance_matrix_list[i][j] = distance_matrix_list[i][j] /␣
↪(max_of_distance - min_of_distance)

            # in order to have a 0-100% confidence index
            # let's do the 1 complement value and multiple by 100
            # with two digits after the coma
            val = round(abs(1 - distance_matrix_list[i][j])*100, 2)
            dist_mat_dict[player_names[i]][player_names[j]] = val

    # lets save it so we do not have to compute everytime
    dist_mat_df = pd.DataFrame(dist_mat_dict)
    dist_mat_df.to_csv("./csv/distance_matrix.csv")
```

1.17 get the distance between several players

[45]:
```
# return a dict of dict
def get_distance_between_players(list_of_players, dist_matrix):
    #lets sort it to have the same order on both axis
    list_of_players = sorted(list_of_players)
    dist_mat_dict = {}
    for player in list_of_players:
        dist_mat_dict[player] = {}
        for player2 in list_of_players:
            dist_mat_dict[player][player2] = dist_matrix[dist_matrix["Name"] ==␣
↪player].iloc[0][player2]

    return dist_mat_dict
```

1.18 get the n most similar to a player

[46]:
```
#return a list of 2-elements tuples (name, similarity score)
def get_most_similar_players(player_name, nb_of_similar_players_wanted,␣
↪dist_mat):

    #lets sort the list of similarity between player and the rest of the NBA
```

```
    sorted_similarity = dict(sorted(dist_mat[player_name].items(), key=lambda␣
↪item: item[1], reverse=True))

    #lets keep the n first (Except the the closest who is the player himself)
    most_similar_players = list(sorted_similarity.items())[1:
↪nb_of_similar_players_wanted+1]

    # retrieve the players name instead of his index number
    for i in range(len(most_similar_players)):
        index_value = most_similar_players[i][0]
        name = dist_mat["Name"][index_value]
        similarity_confidence = most_similar_players[i][1]
        most_similar_players[i] = (name,similarity_confidence)

    return most_similar_players
```

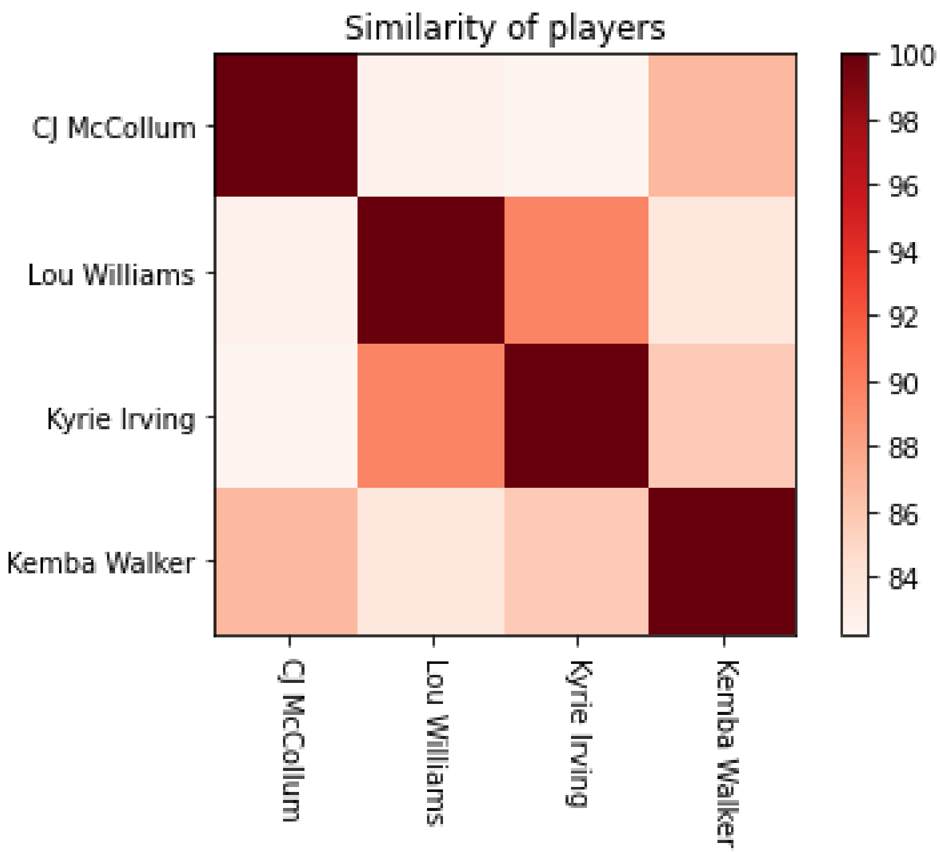
1.19 Plot the heat Matrix of a list of players

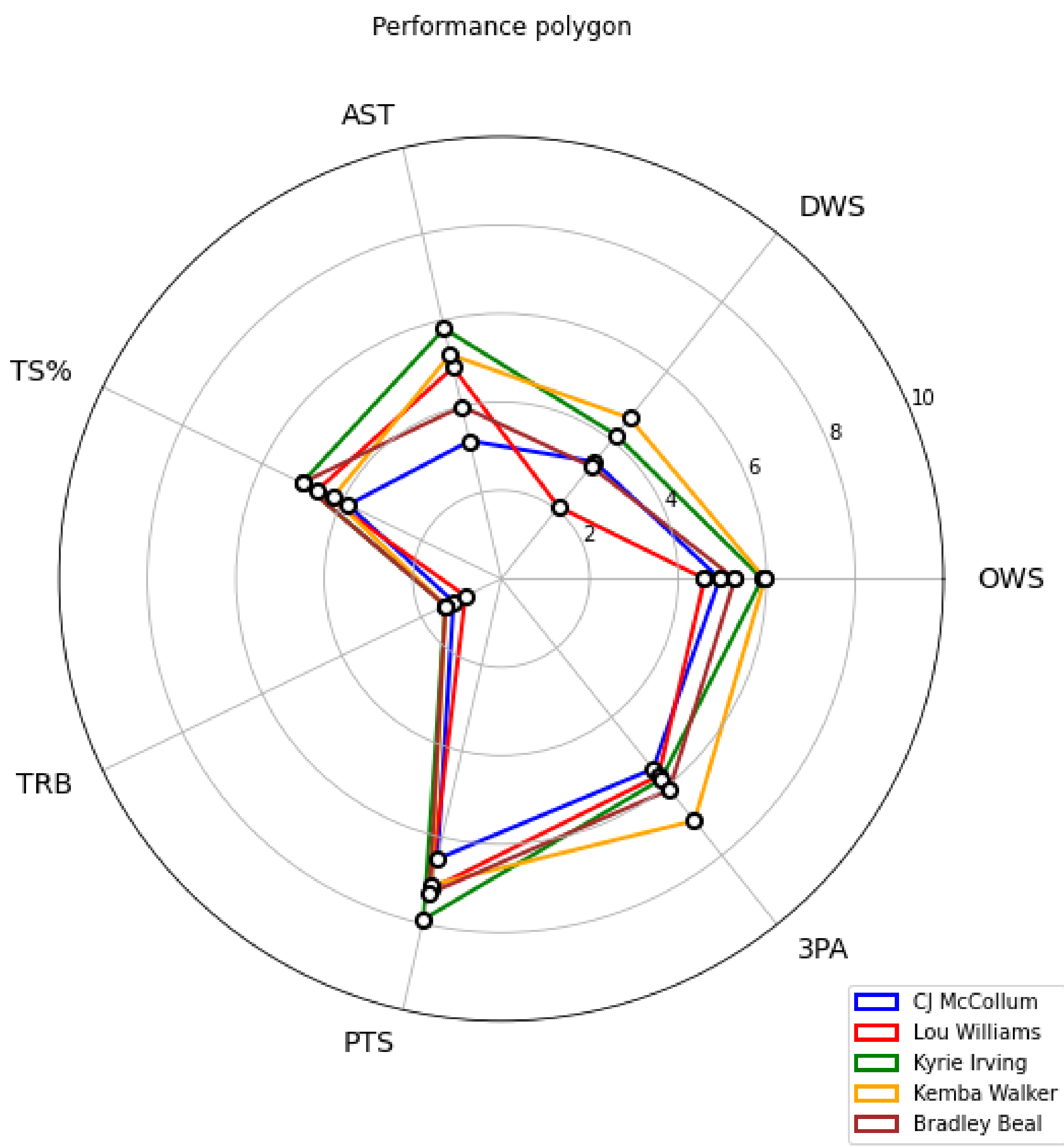
[47]:
```
def plot_heat_matrix(only_number_matrix, list_of_players):
    #lets try to plot a heat matrix
    c = plt.imshow(only_number_matrix, cmap='Reds', interpolation='nearest')
    plt.title("Similarity of players")
    plt.colorbar(c)
    # rotate to prevent players name from overlapping
    plt.xticks(np.arange(0, len(list_of_players)) , list_of_players,␣
↪rotation=270)
    plt.yticks(np.arange(0, len(list_of_players)) , list_of_players)
    plt.show()
```

1.20 Example of use

[48]:
```
source = pd.read_csv('./csv/players_stats.csv')
criterias = ['TRB', 'PTS', 'AST', 'DWS', '3PA', "OWS", "USG%", "Height"]

computing_distance_matrix(source, criterias)

#retrieving the data
dist_mat = pd.read_csv("./csv/distance_matrix.csv")
dist_mat = dist_mat.rename(columns={"Unnamed: 0": 'Name'})

# get the n most similar player to X and get the similarity values between each␣
↪and every one of them
player = "Bradley Beal"
most_similar_players = get_most_similar_players(player, 4, dist_mat)
```

```
most_similar_players_names = [names for (names, score) in most_similar_players ]

players_distances = get_distance_between_players(most_similar_players_names,␣
 ↪dist_mat)
only_number_matrix = [list(value.values()) for key, value in players_distances.
 ↪items()]

# plot the heat matrix of several players
plot_heat_matrix(only_number_matrix, most_similar_players_names)

# draw polygones
players_to_draw = [player[0] for player in most_similar_players]
players_to_draw.append(player)
properties = ['OWS', 'DWS', 'AST','TS%', "TRB", "PTS", "3PA" ]
performance_polygon_vs_player(players_to_draw, properties)
```





[49]:
```
print("--- %s seconds --- to execute the notebook" % round(time.time() -␣
↪start_time, 2))
```

```
--- 99.49 seconds --- to execute the notebook
```