Untitled

April 25, 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 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
from sklearn.decomposition import PCA
from scipy.spatial import distance
csv_files_location = "./csv/"
```

[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]:
```python
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]:
```python
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]:

Player	G	MP	PER	TS%	3PAr	TRB%
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

Player	USG%	OWS	DWS	Height
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]:
```
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]:
```python
PlayerStats="MP"

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

1.2.1 Ploting Polygone for one player

[29]:
```python
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

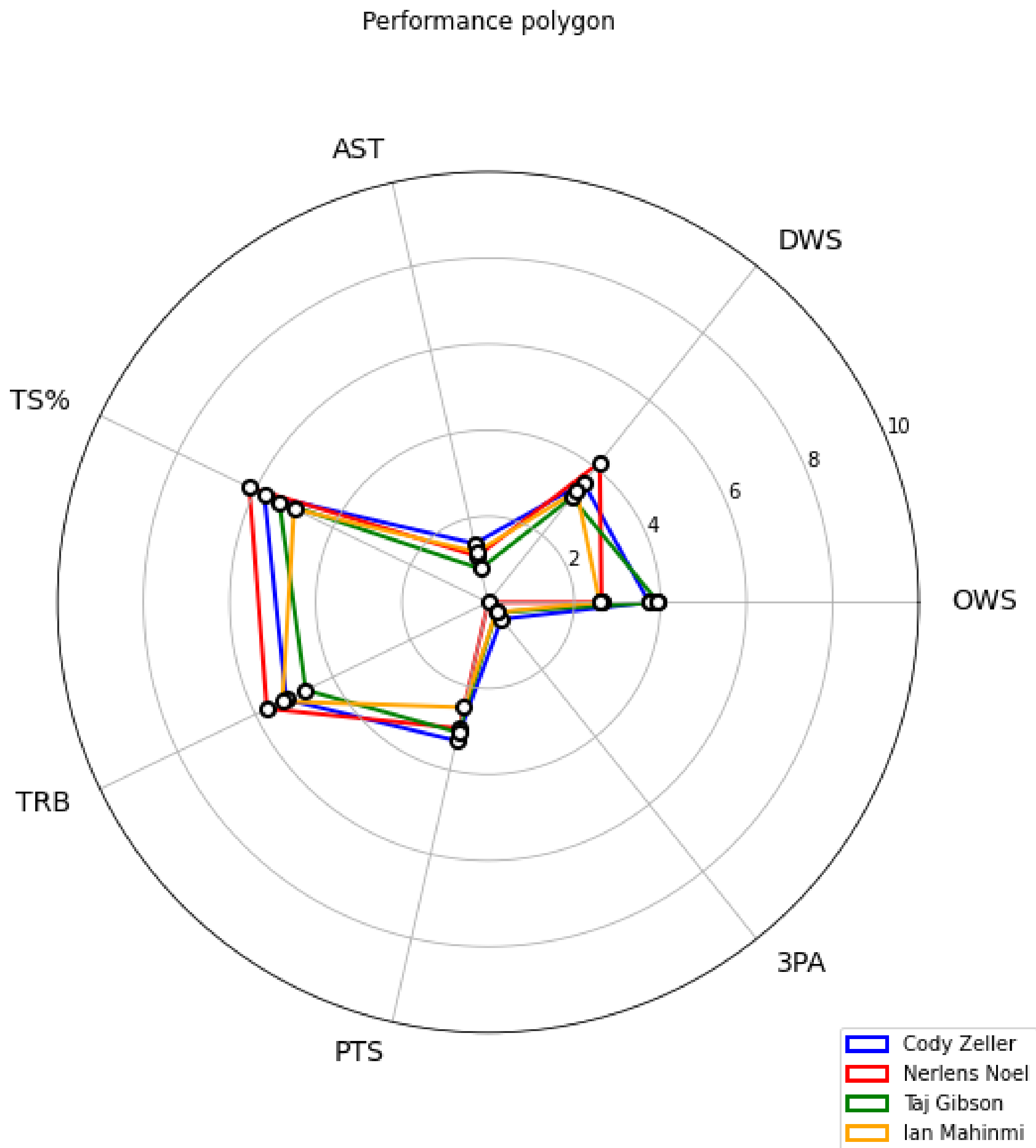
[30]:

```
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

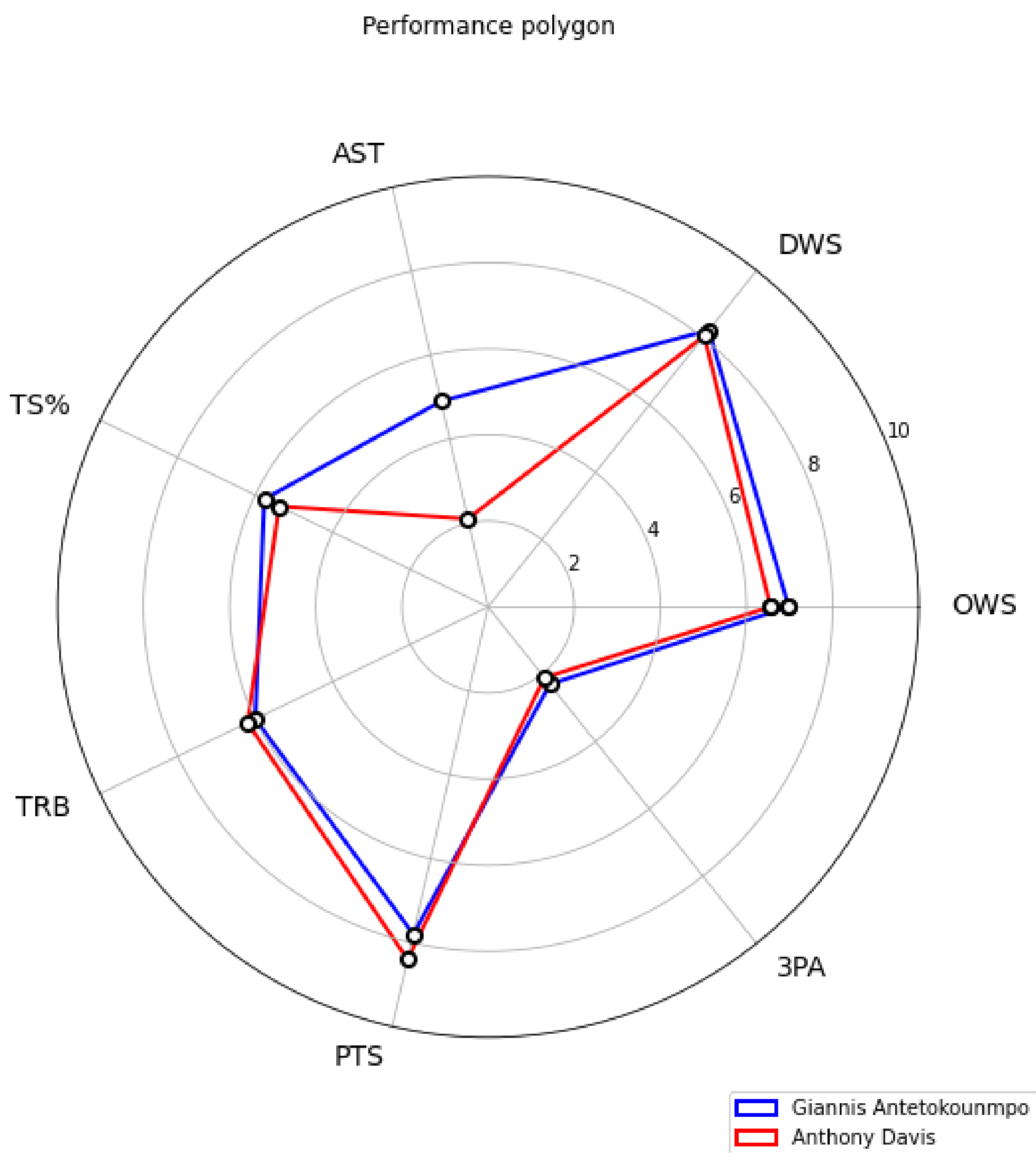
[36]:
```
pca_value = optimal_parameters.iloc[0]["var_portion"]
epsilon = optimal_parameters.iloc[0]["epsilon"]
min_size = optimal_parameters.iloc[0]["min_size"]

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"]
```

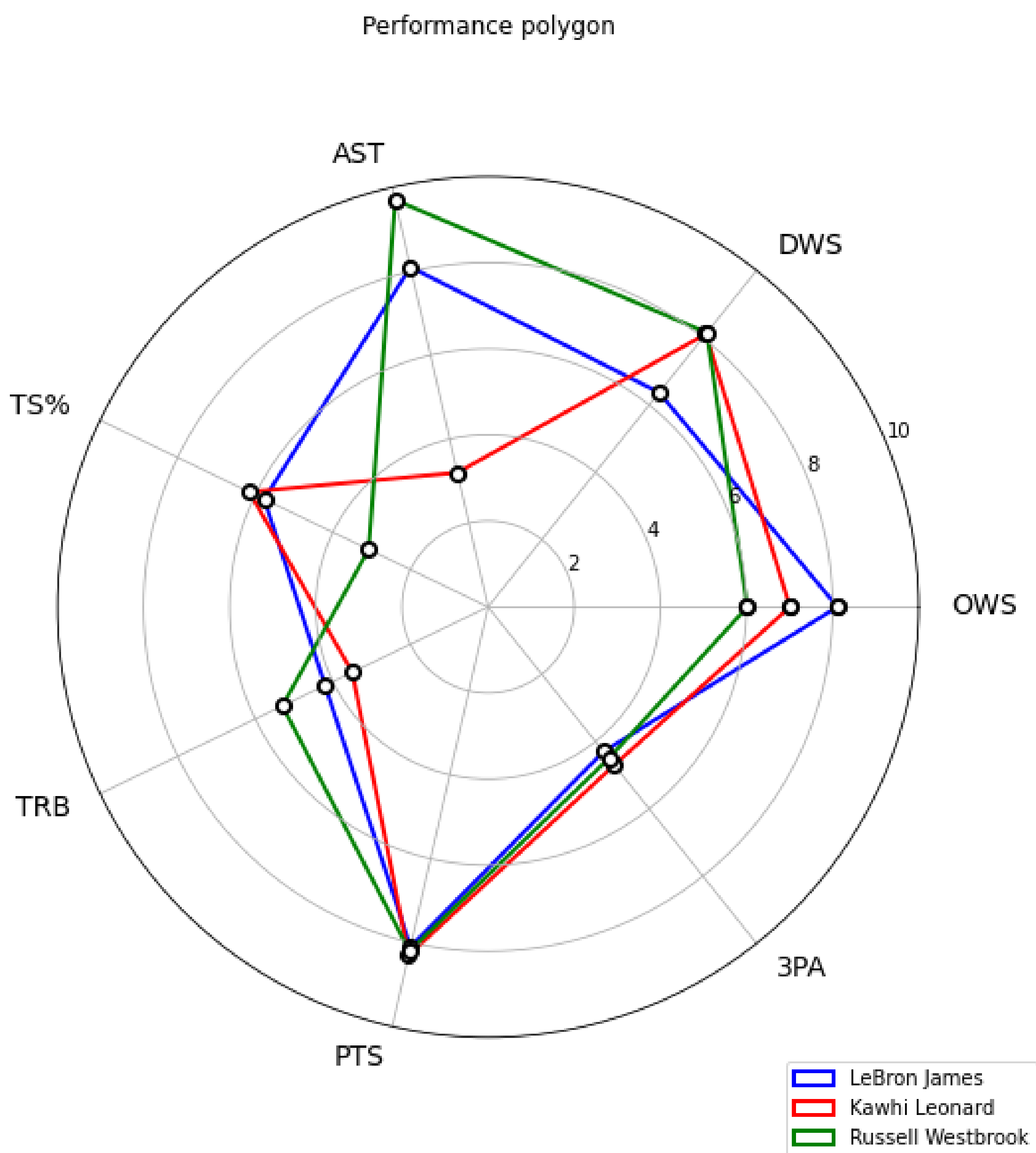
[37]:
```
dbscan_cluster
```

[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.")
```


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



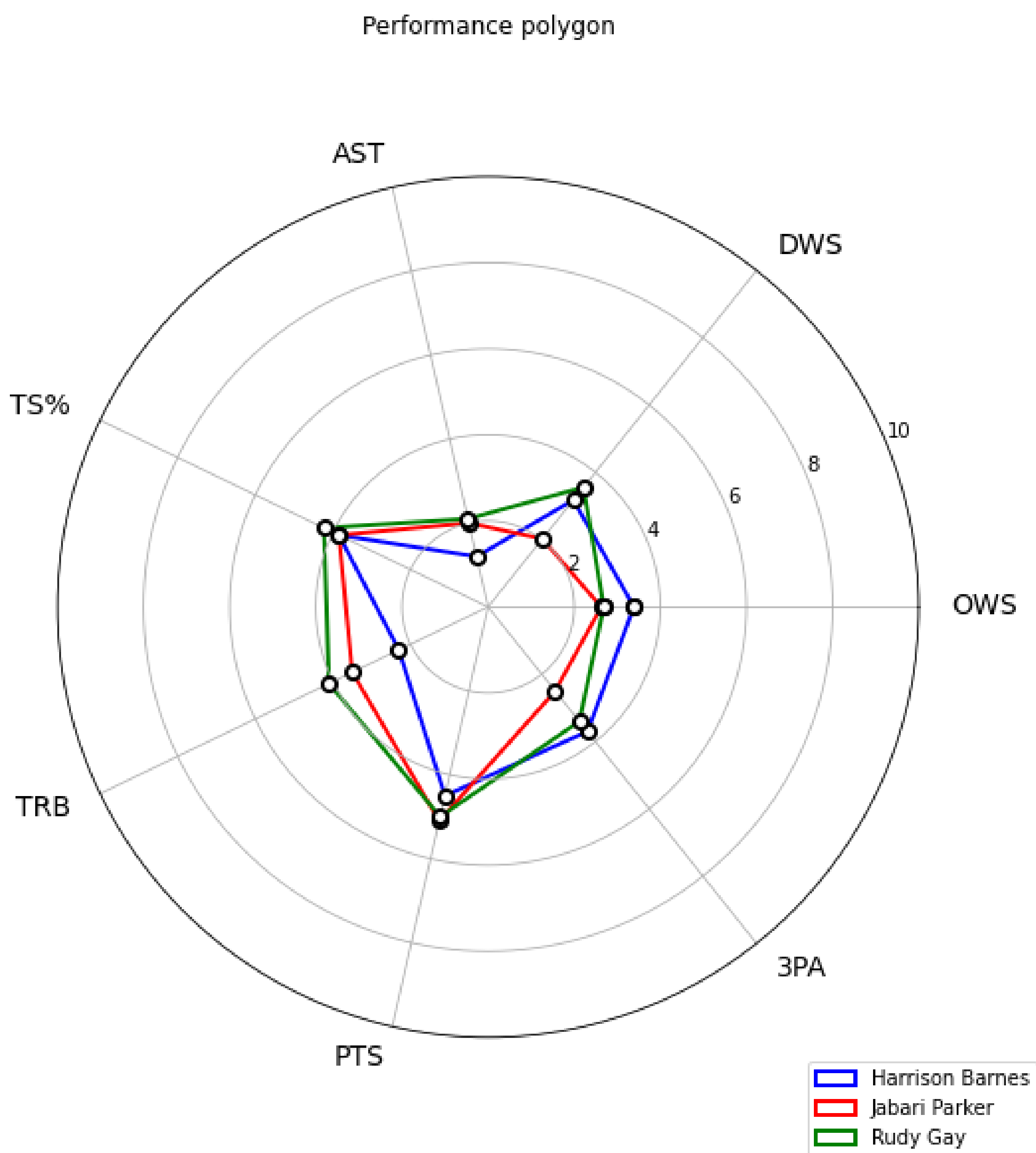
We clustered 5 players with DBSCAN in 2 clusters out of 336 players.

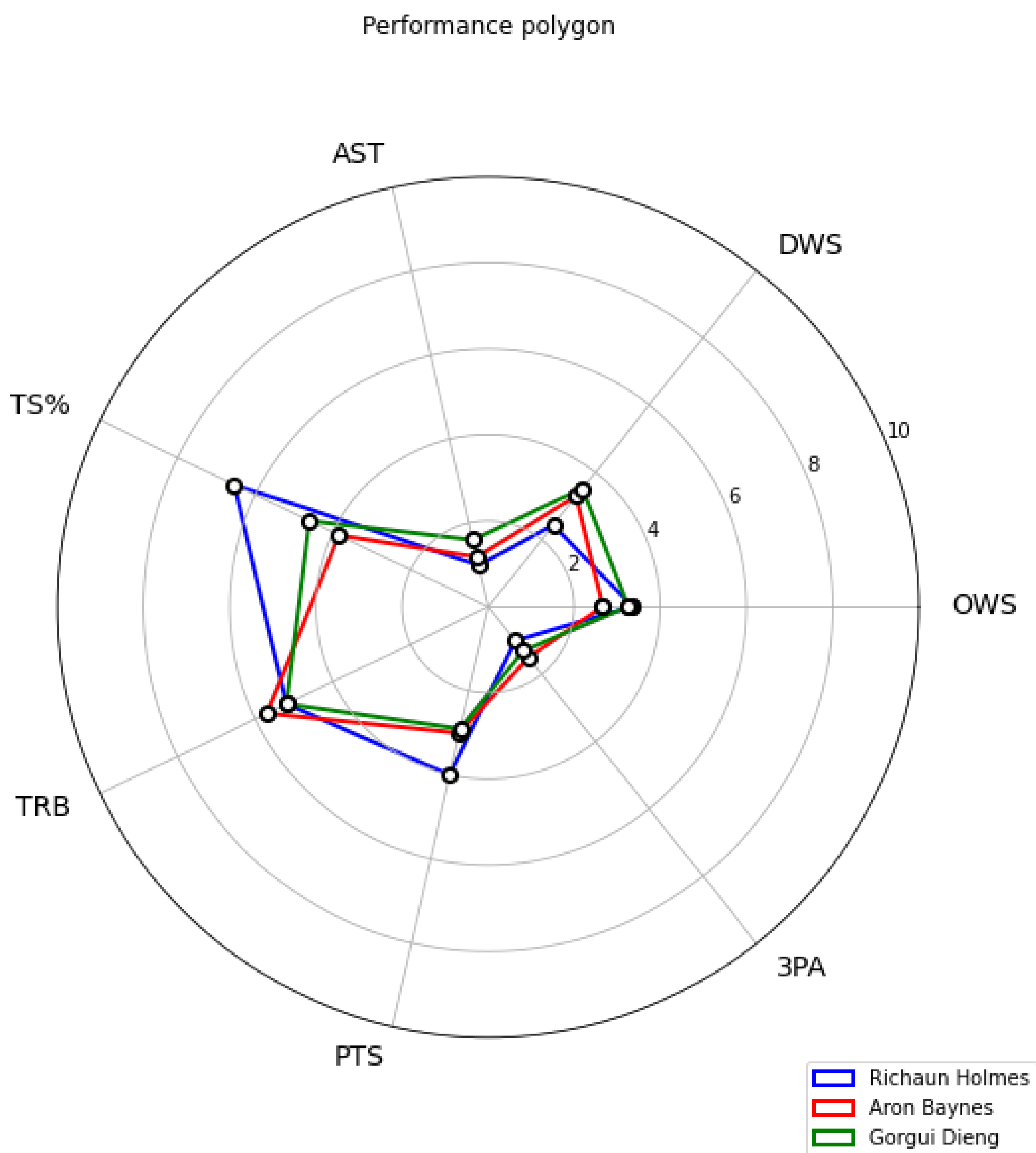
1.4 Only 5 players clustered? Not very promising...

1.5 Let's try Fuzzy Clustering

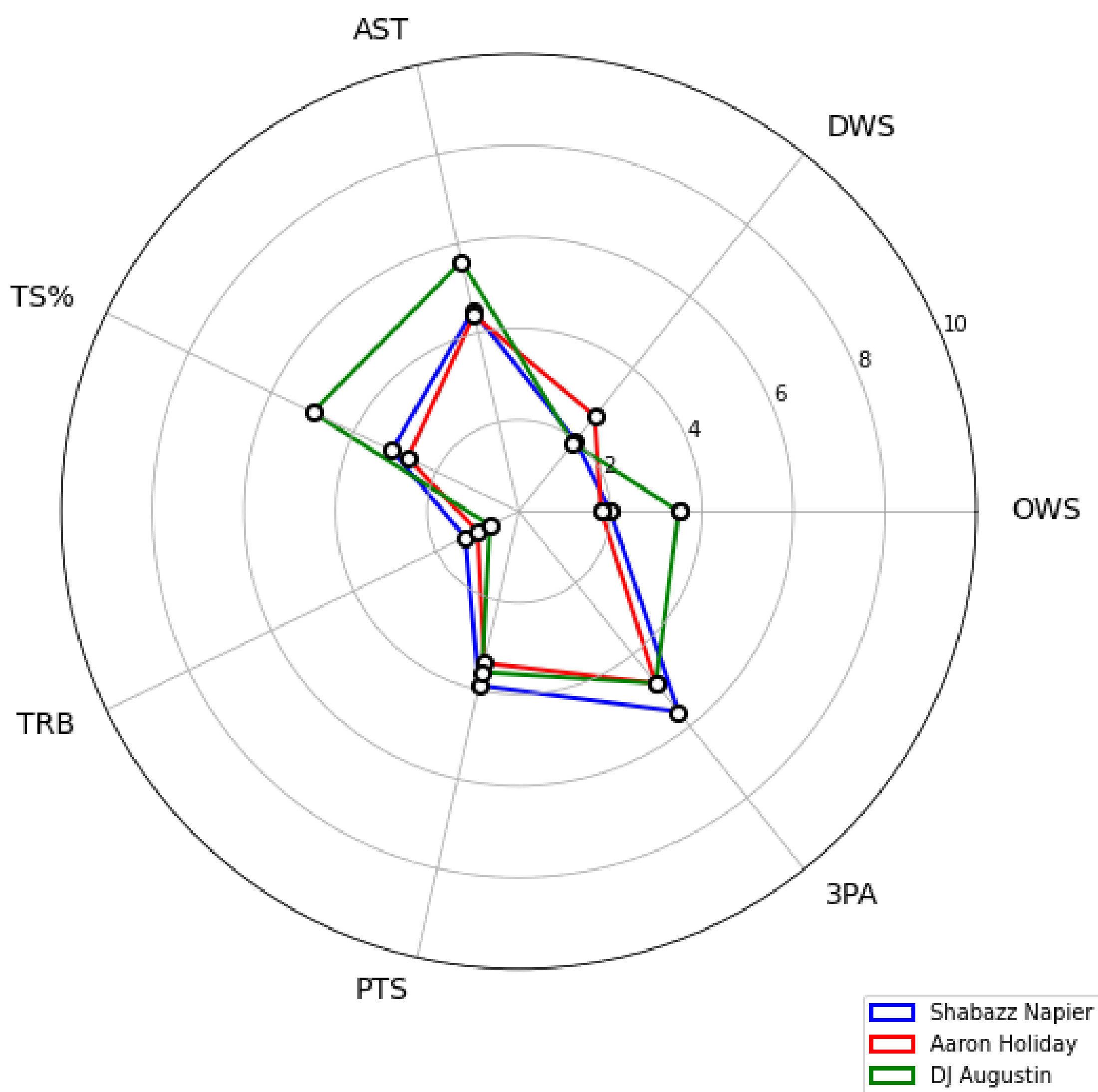
[39]:
```python
df = pd.read_csv('./csv/players_stats.csv')
player_names = df["Player"]

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")]

# 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)

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
```

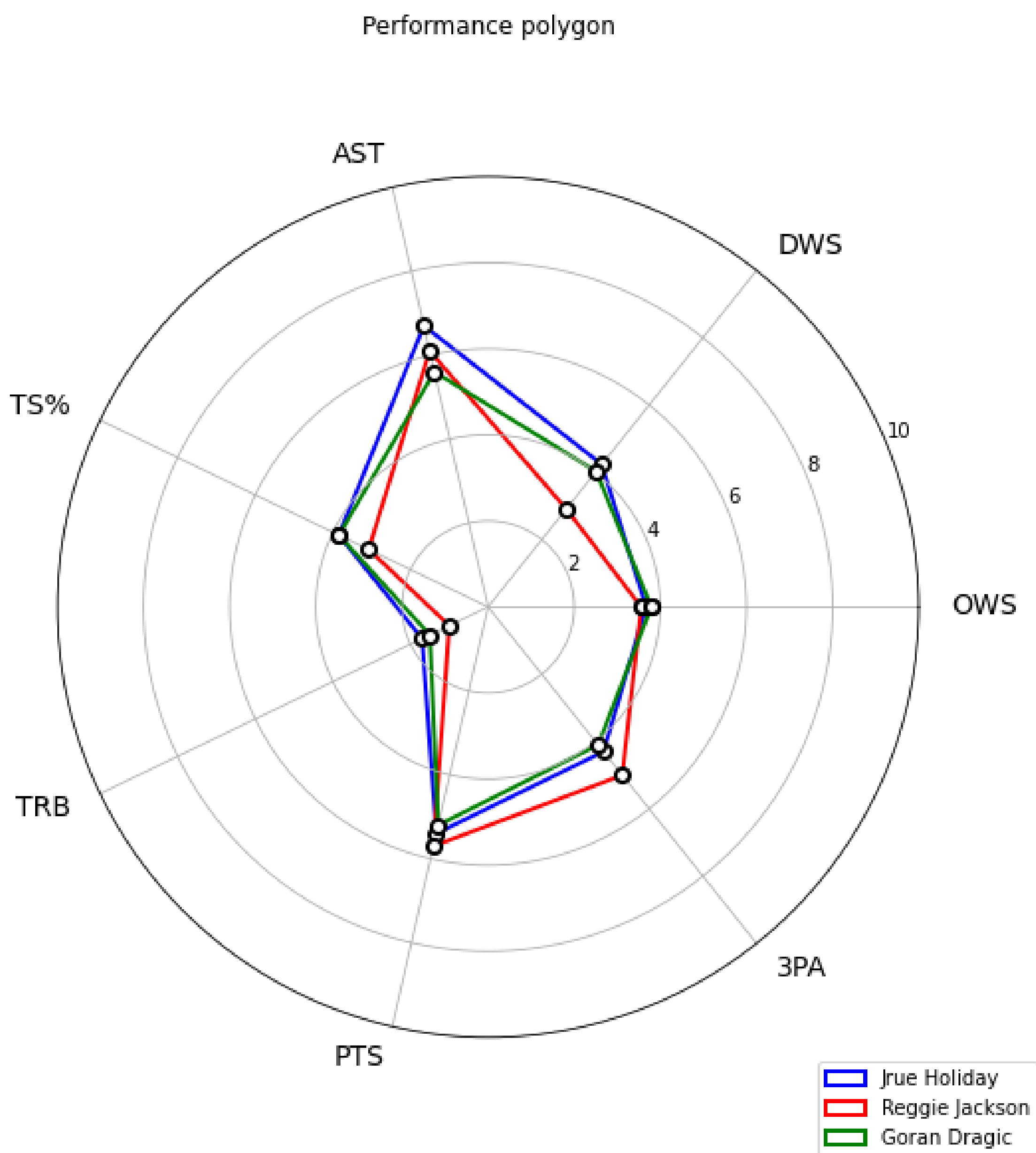
```
    fuzzy_clusters = fuzzy_clusters[~fuzzy_clusters['Player'].
 ↪isin(list(sets["Player"]))]

    #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)


#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)
```

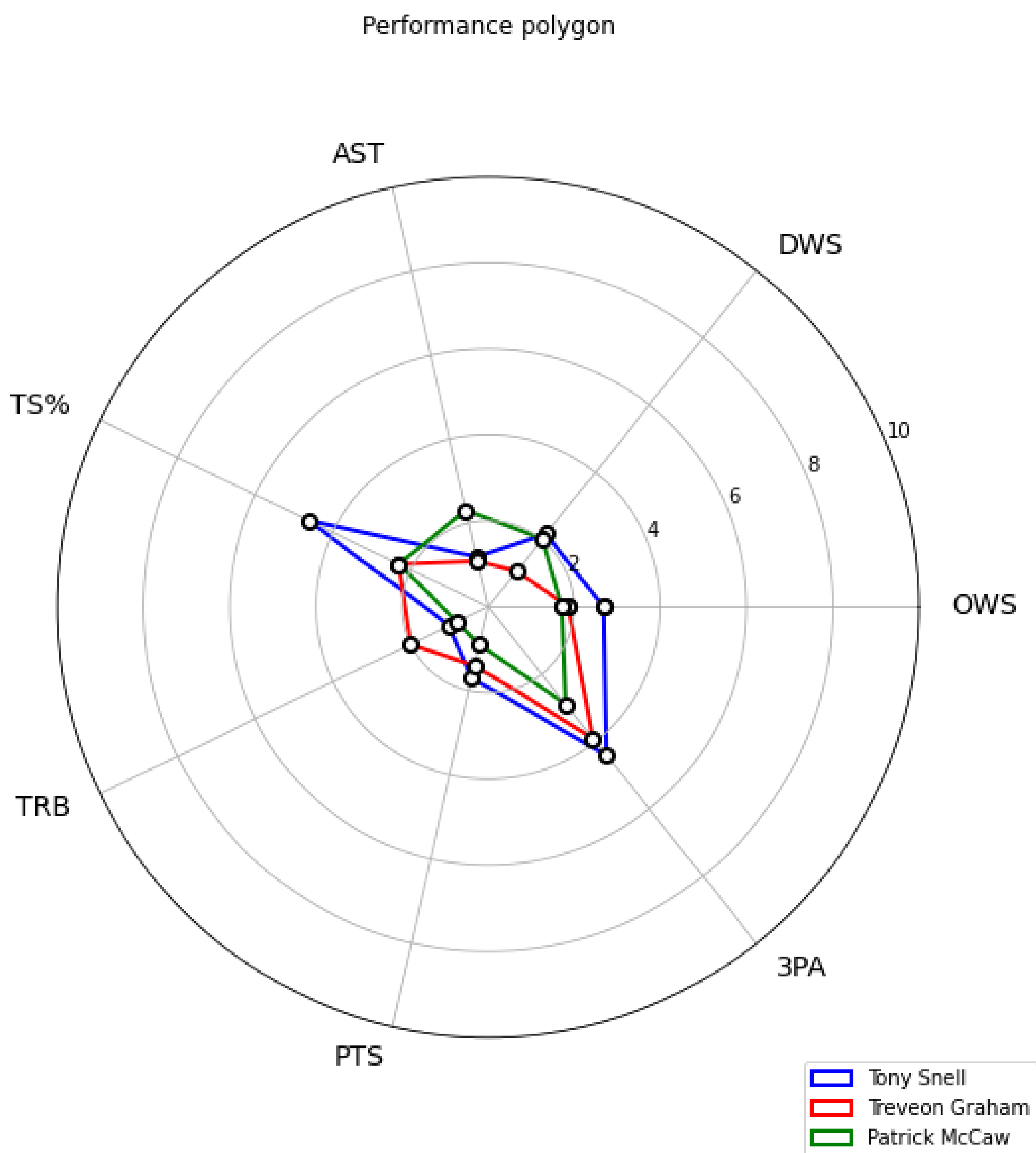

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Harrison Barnes
Jabari Parker
Rudy Gay


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

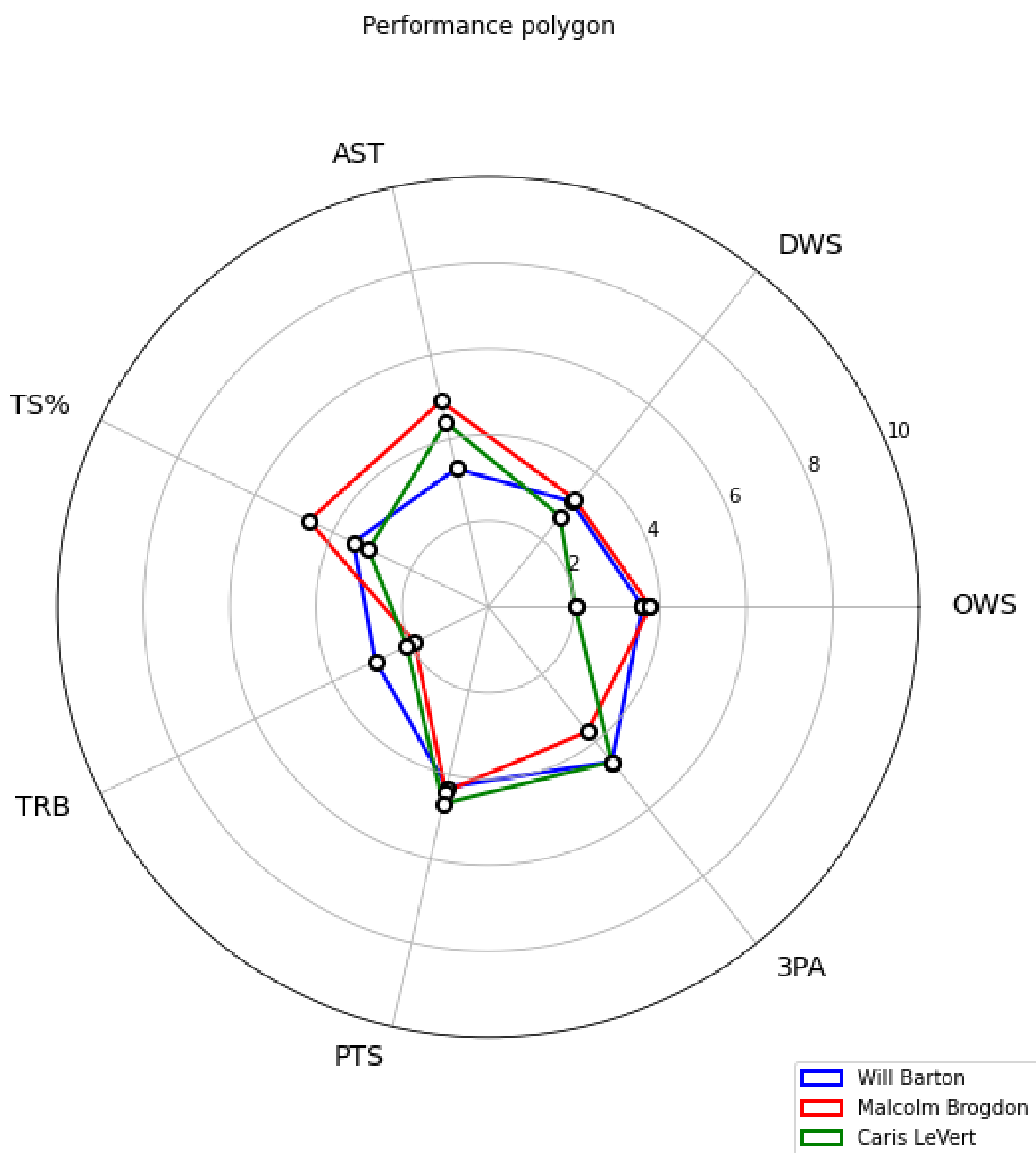
Performance polygon

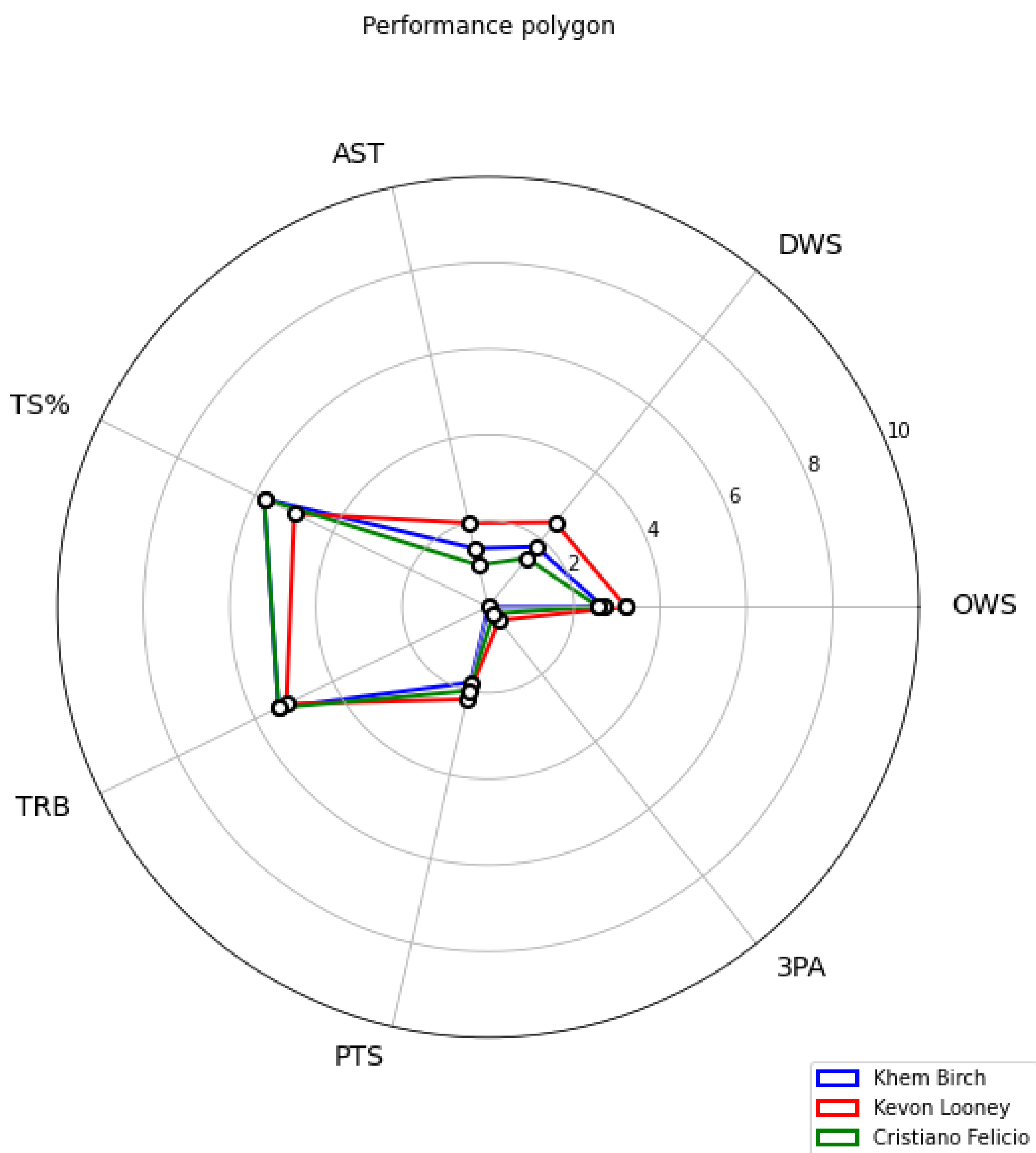



Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Jrue Holiday
Reggie Jackson
Goran Dragic

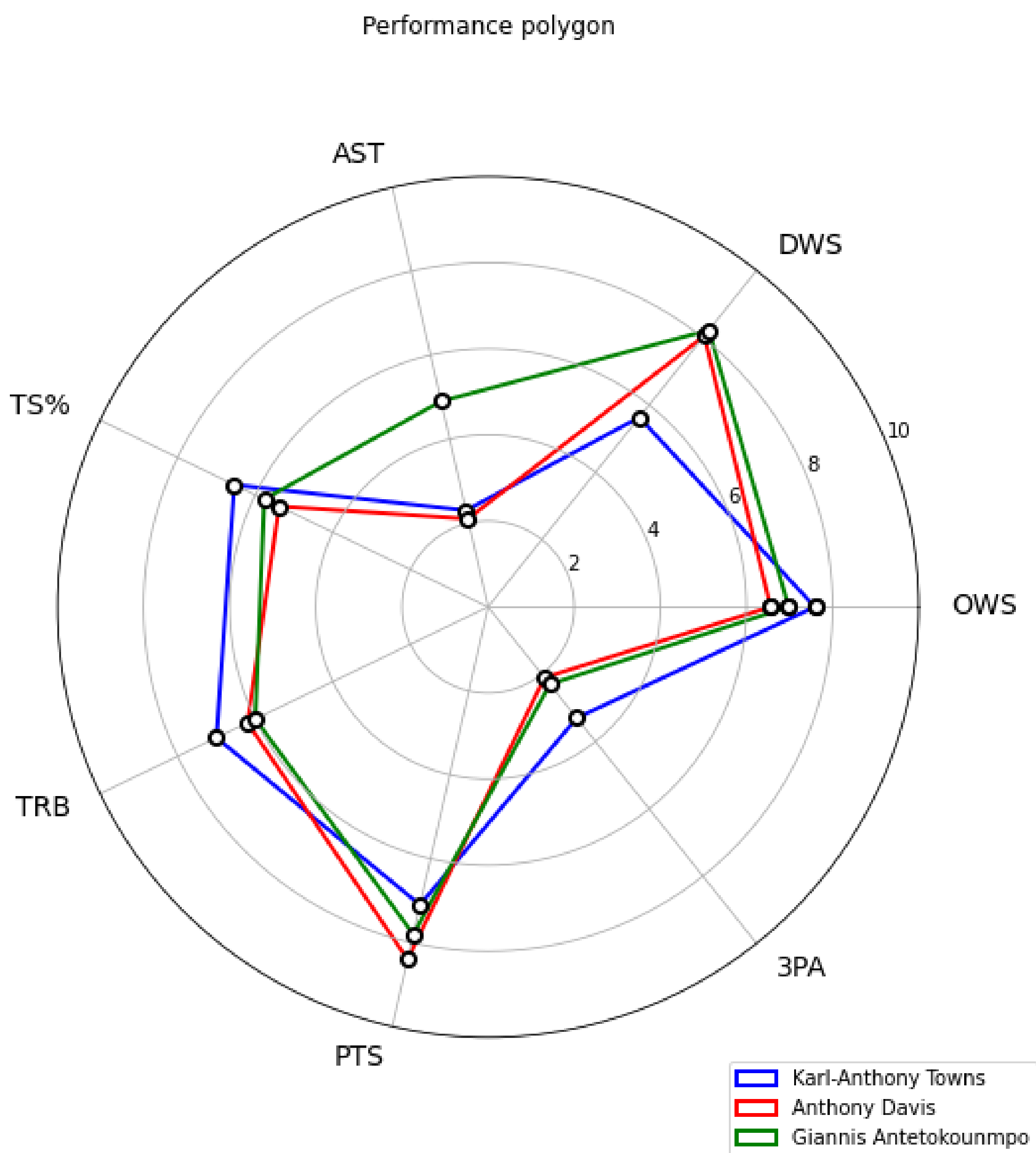


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Tony Snell
Treveon Graham
Patrick McCaw

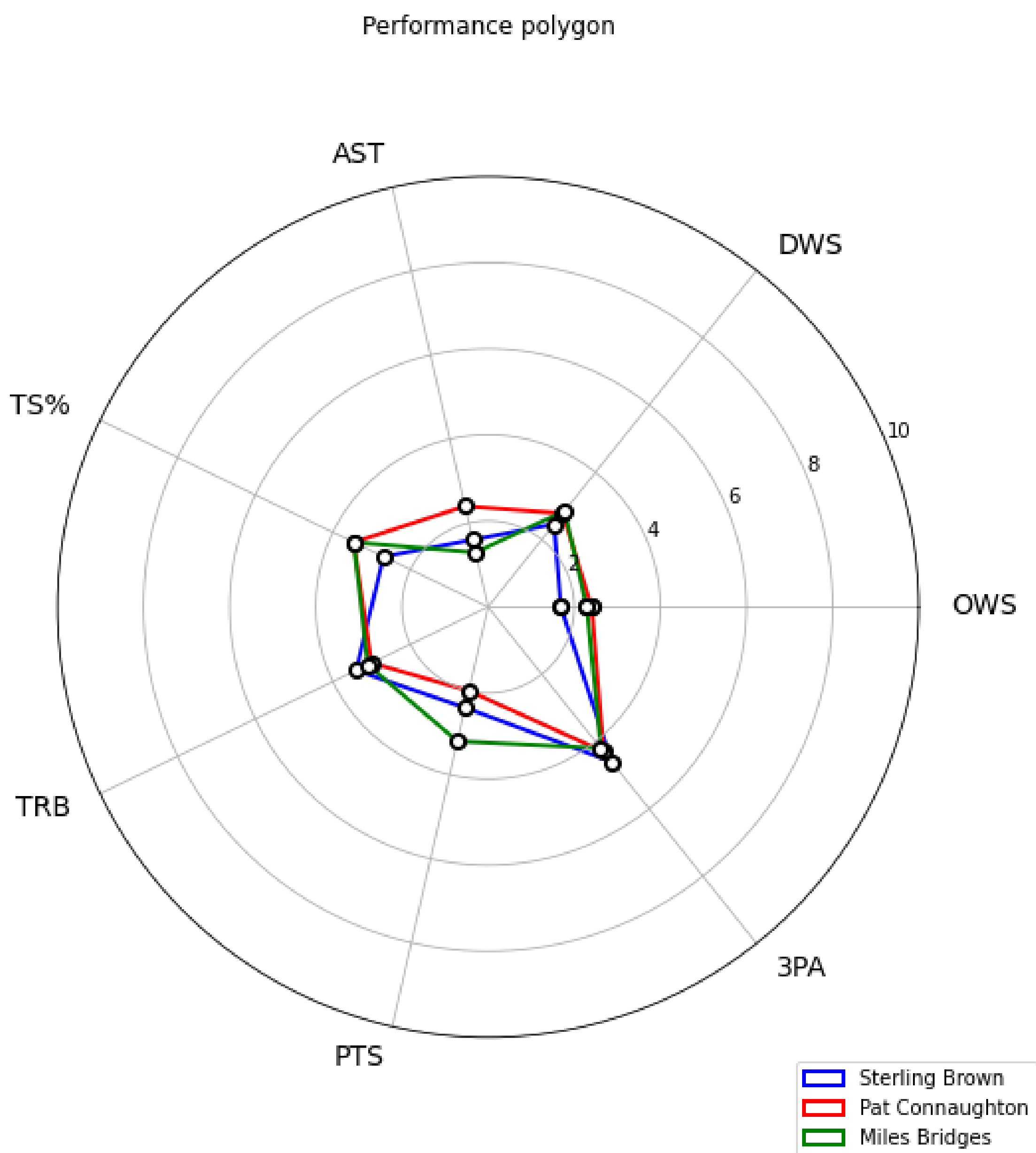

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Will Barton
Malcolm Brogdon
Caris LeVert

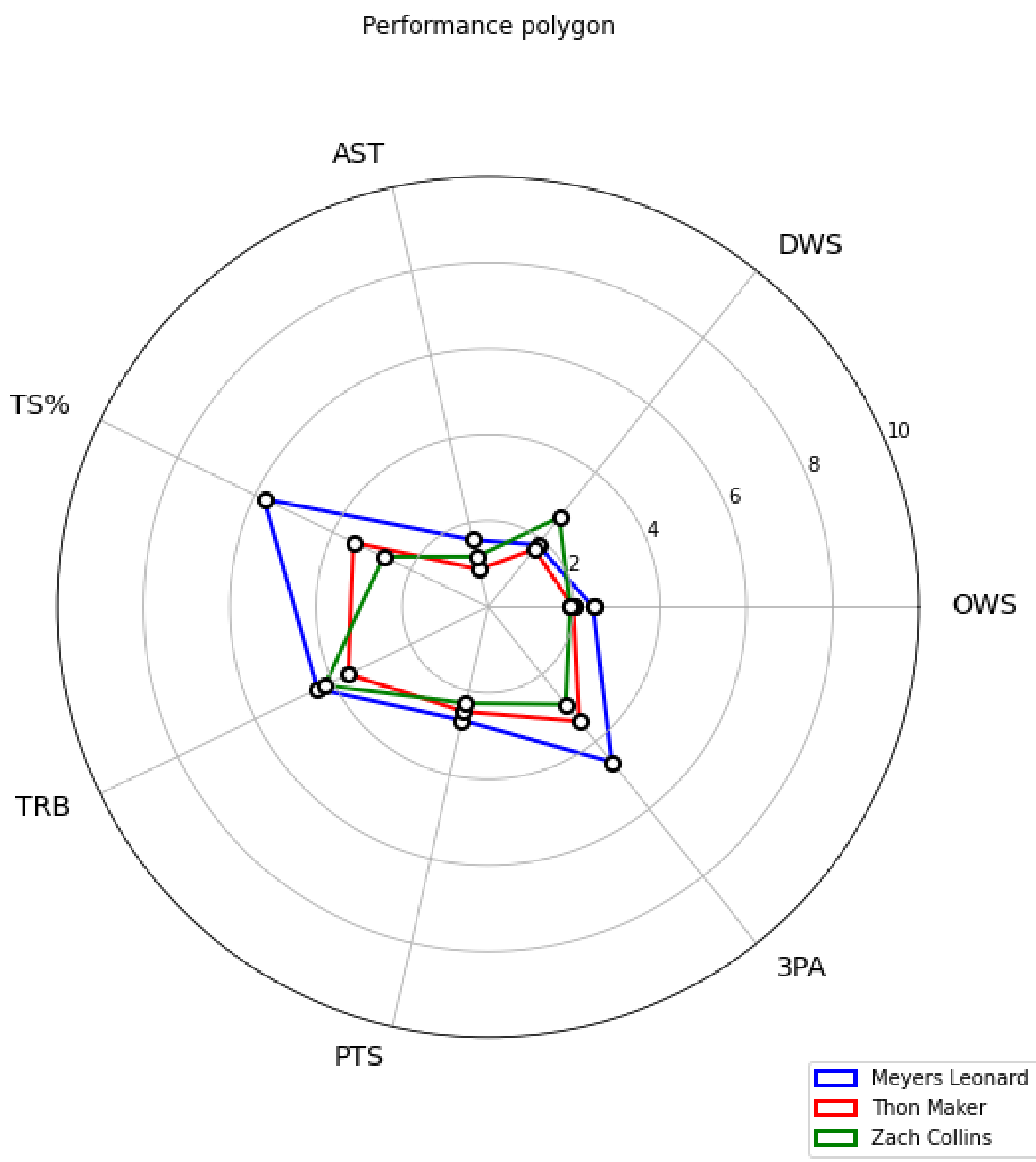


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Khem Birch
Kevon Looney
Cristiano Felicio

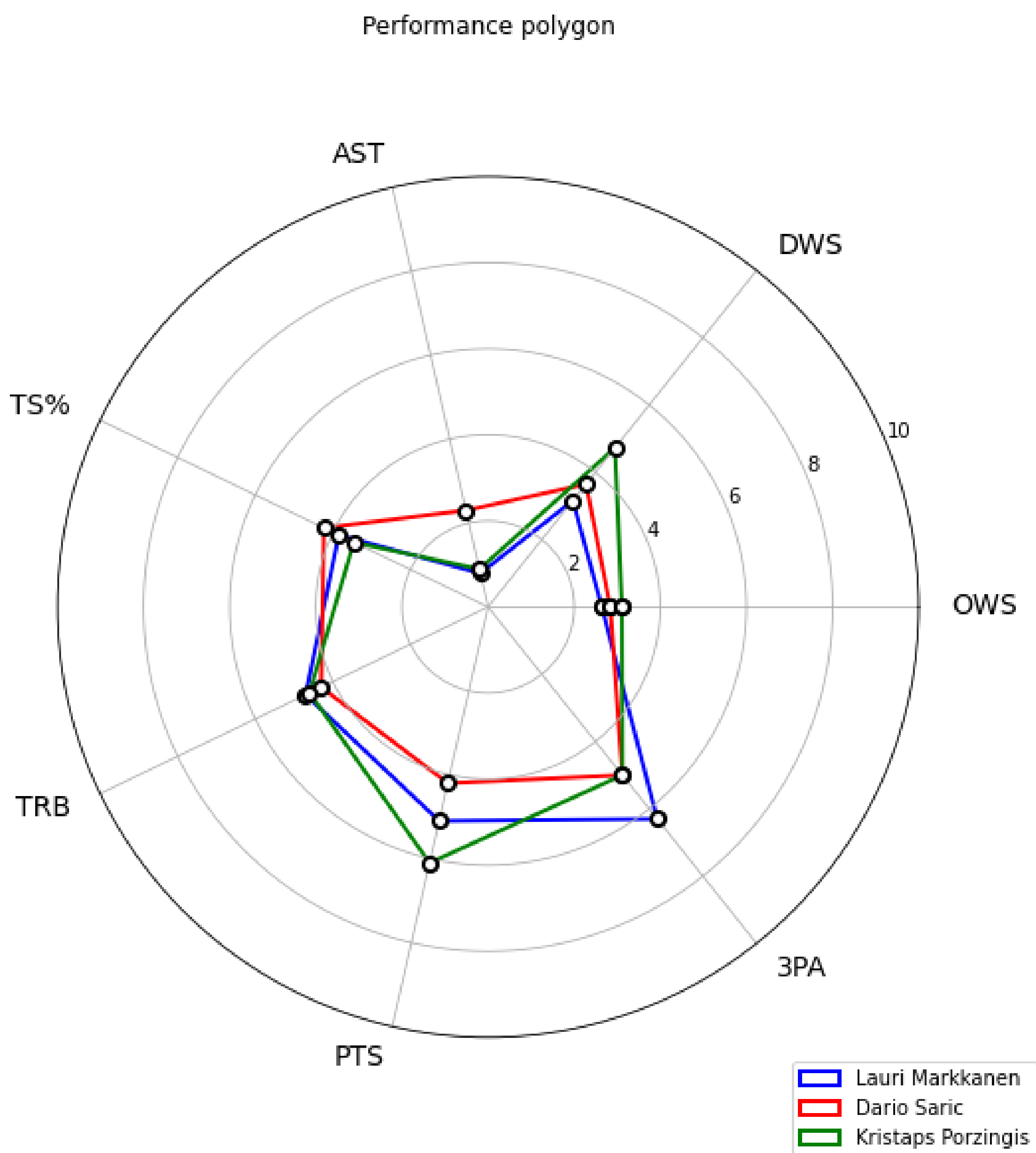


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Karl-Anthony Towns
Anthony Davis
Giannis Antetokounmpo

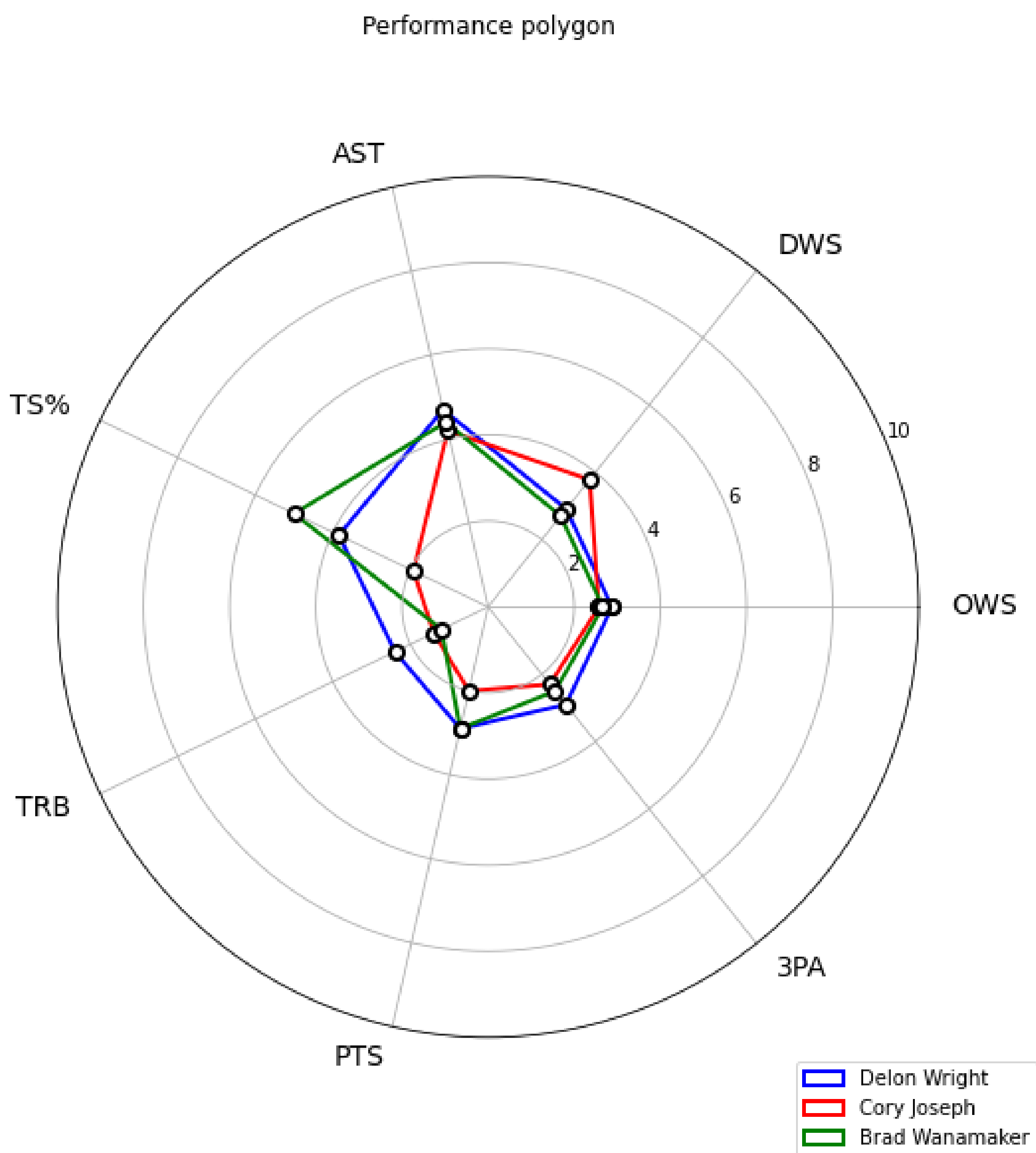

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Sterling Brown
Pat Connaughton
Miles Bridges

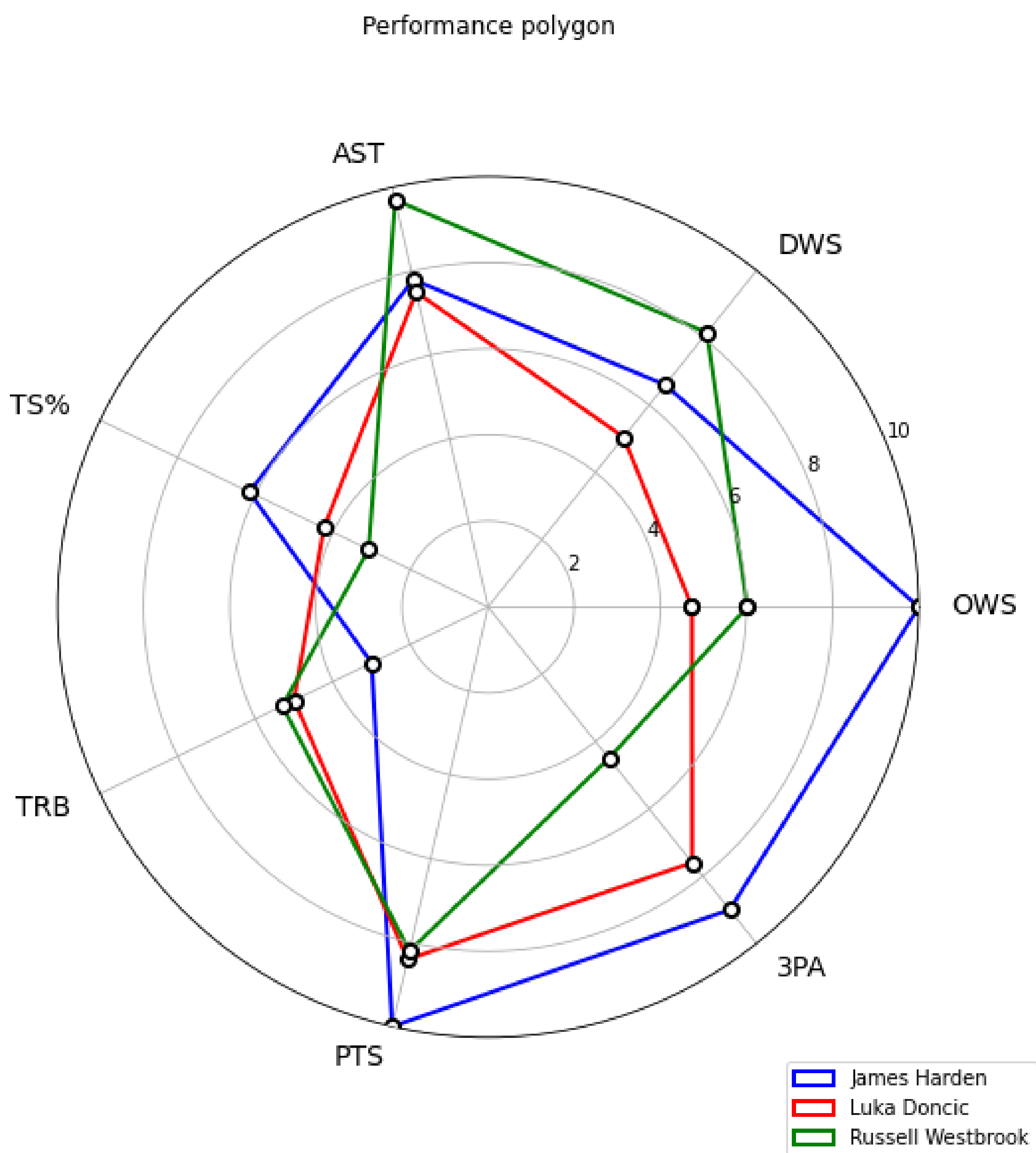


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Meyers Leonard
Thon Maker
Zach Collins

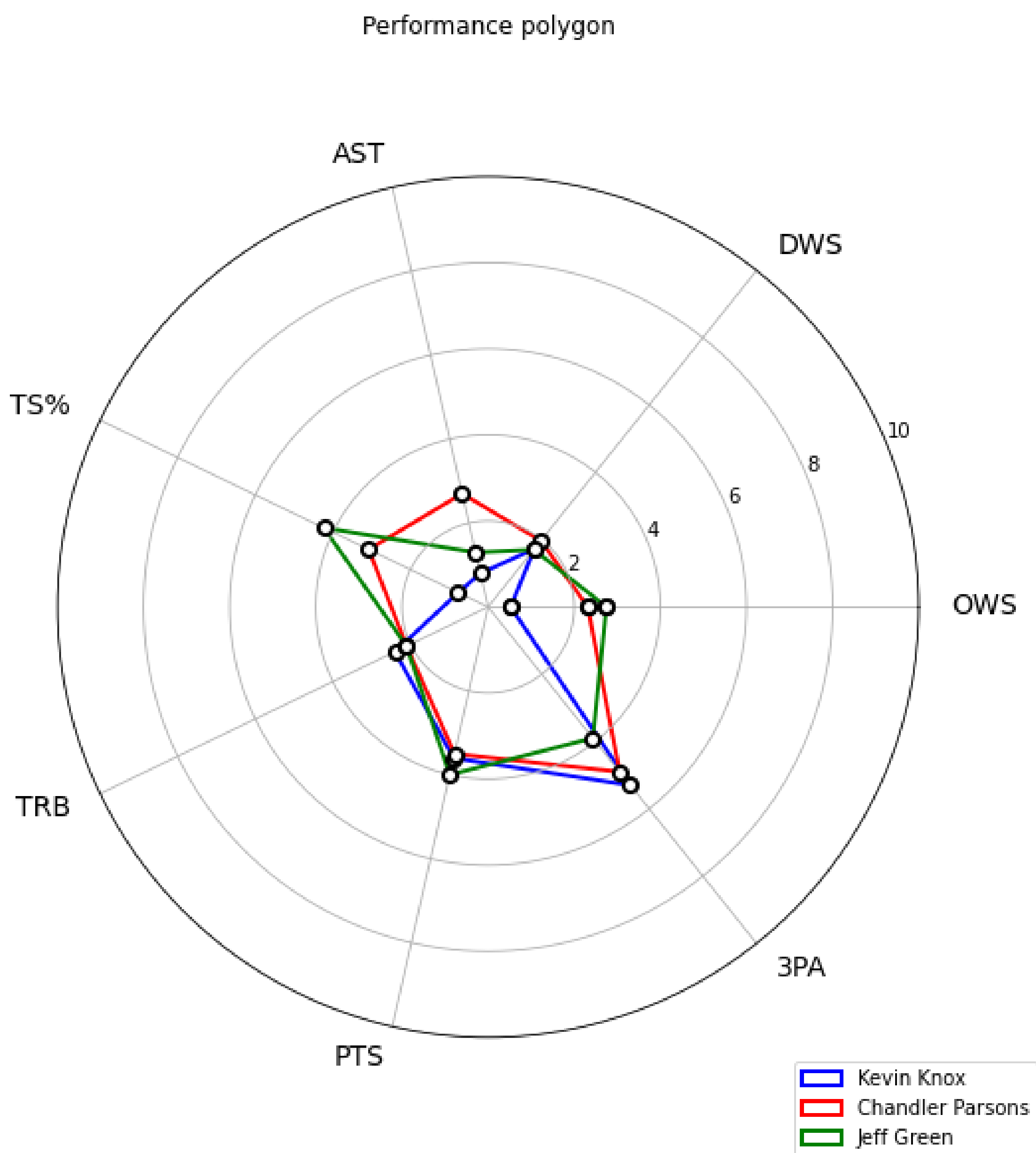


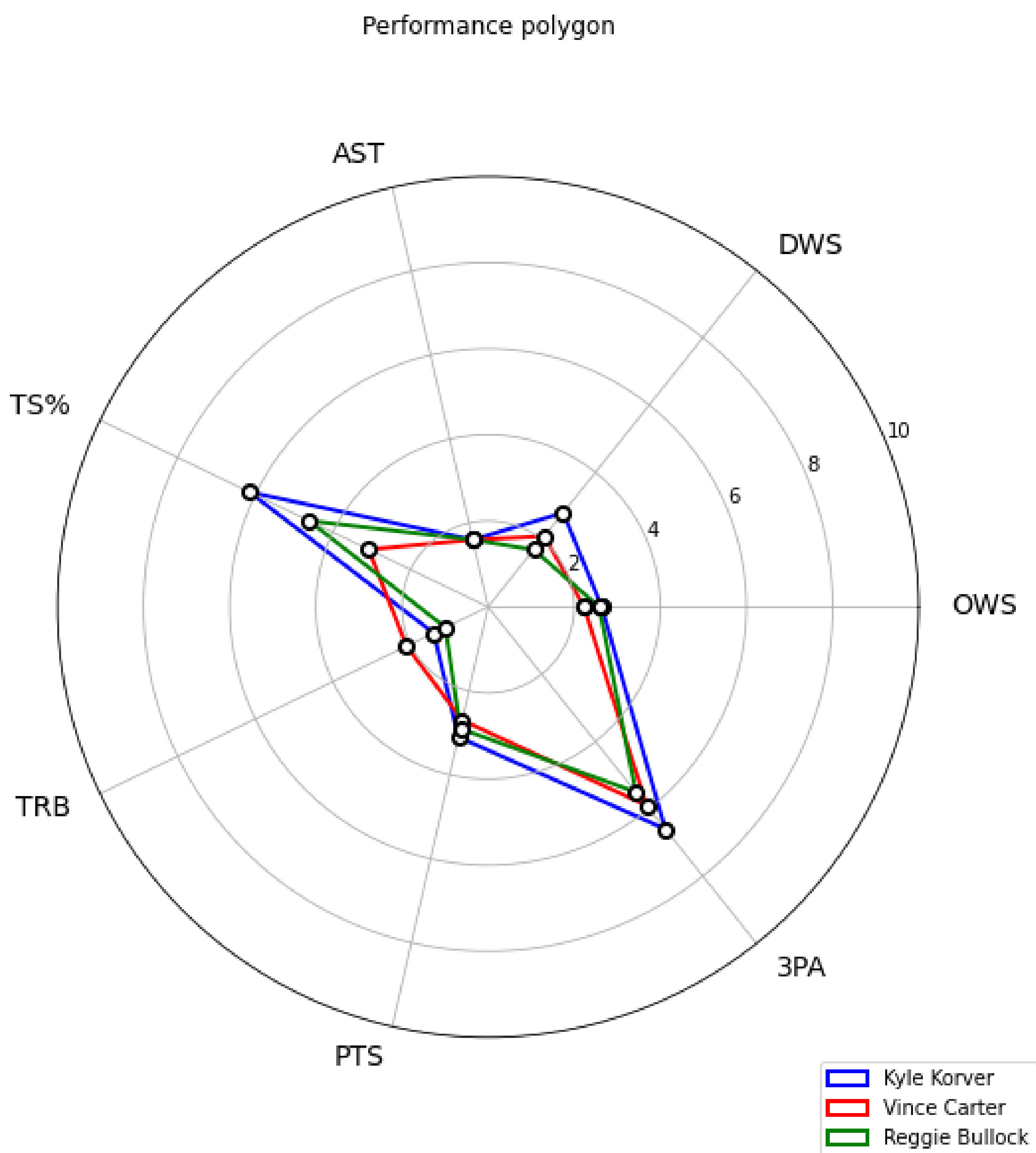
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Lauri Markkanen
Dario Saric
Kristaps Porzingis


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

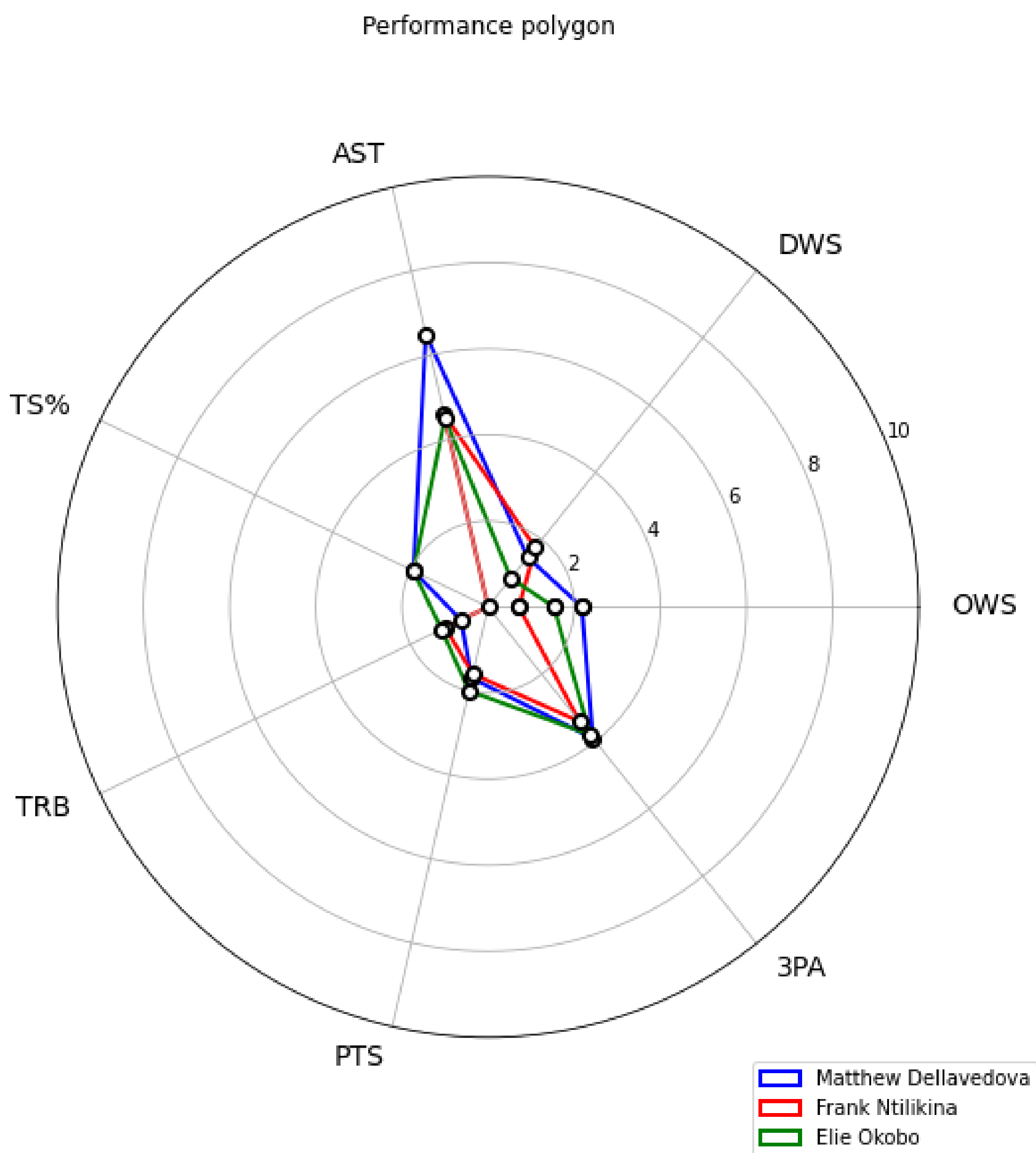


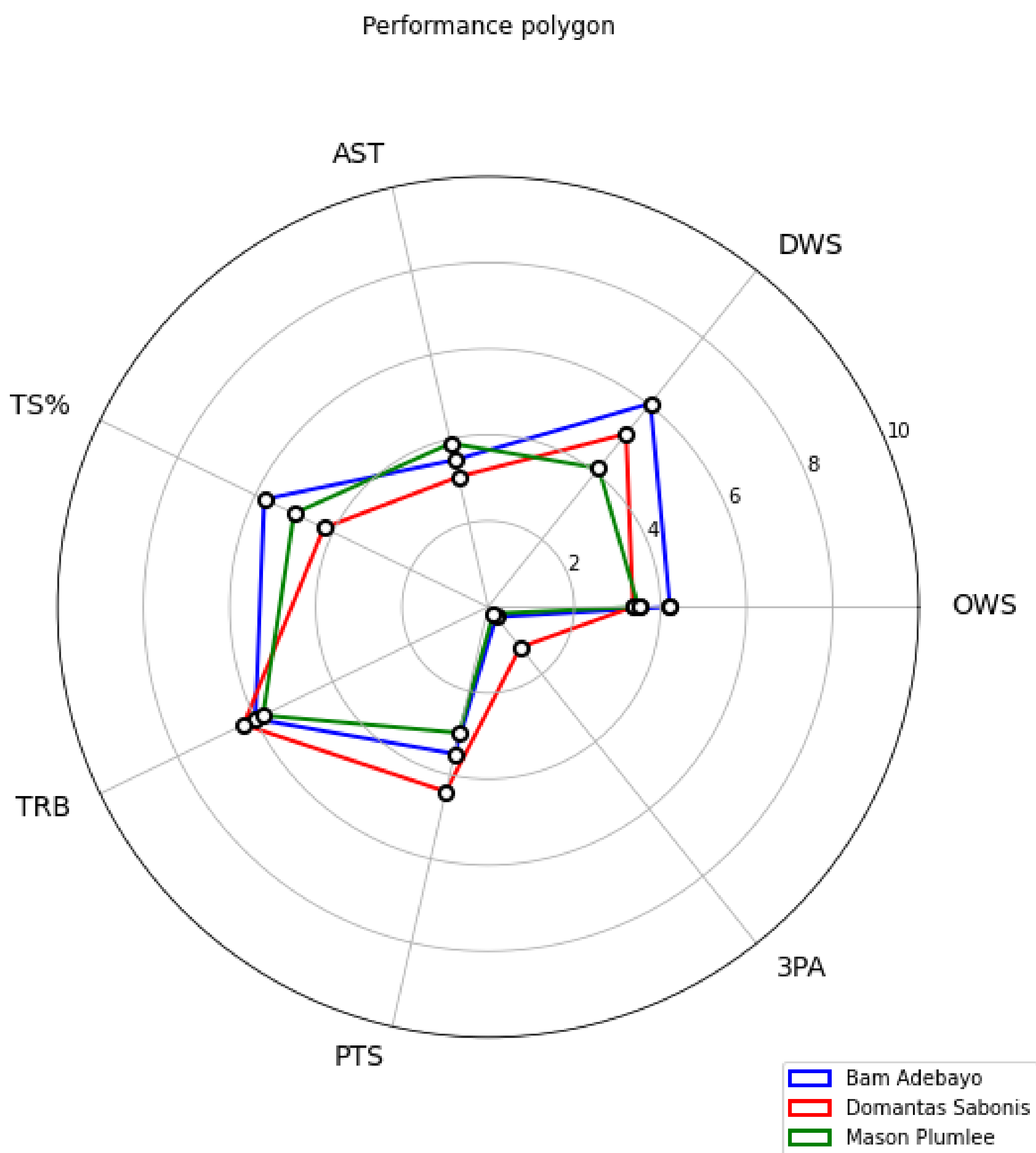
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
James Harden
Luka Doncic
Russell Westbrook

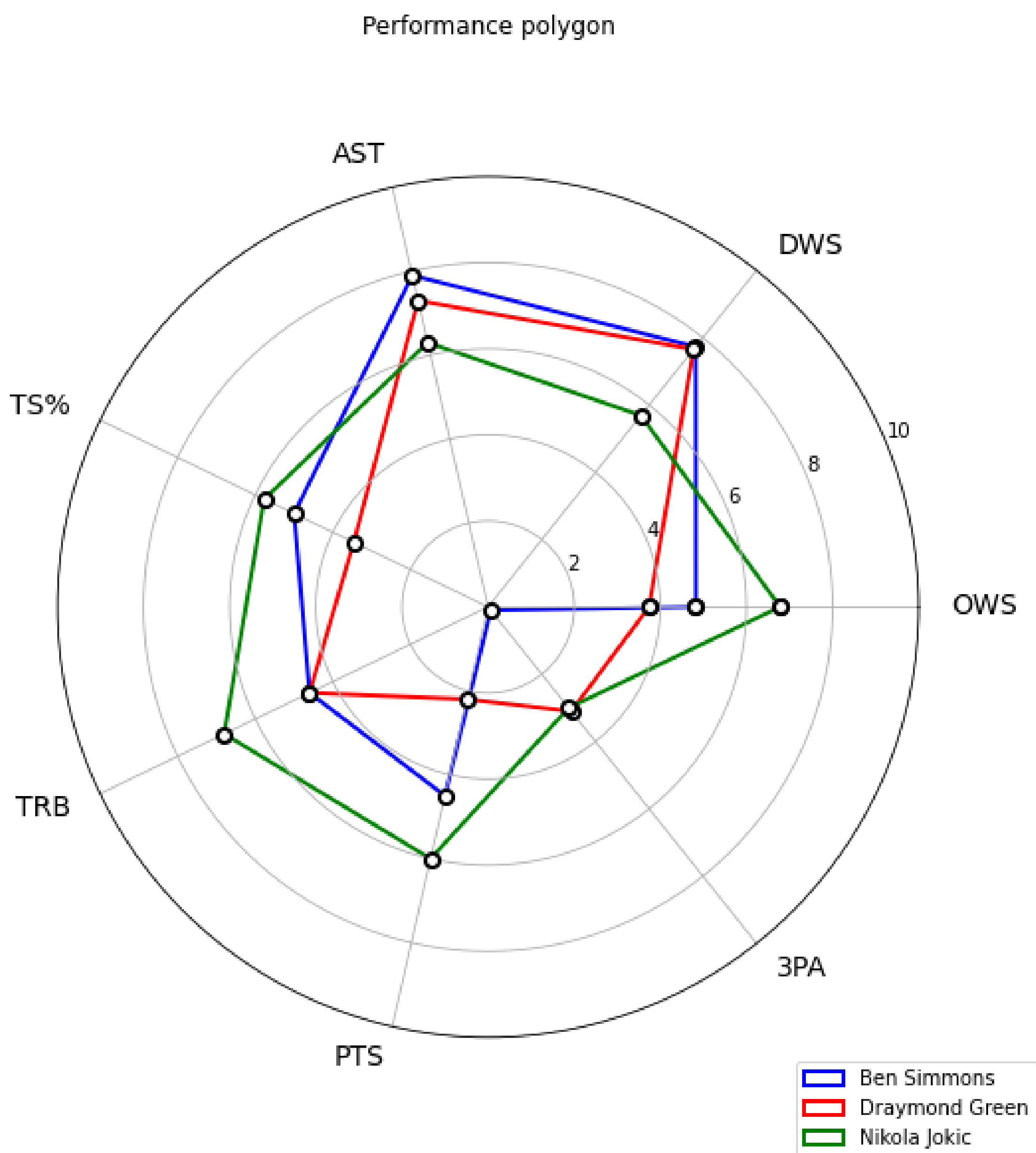

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Kevin Knox
Chandler Parsons
Jeff Green

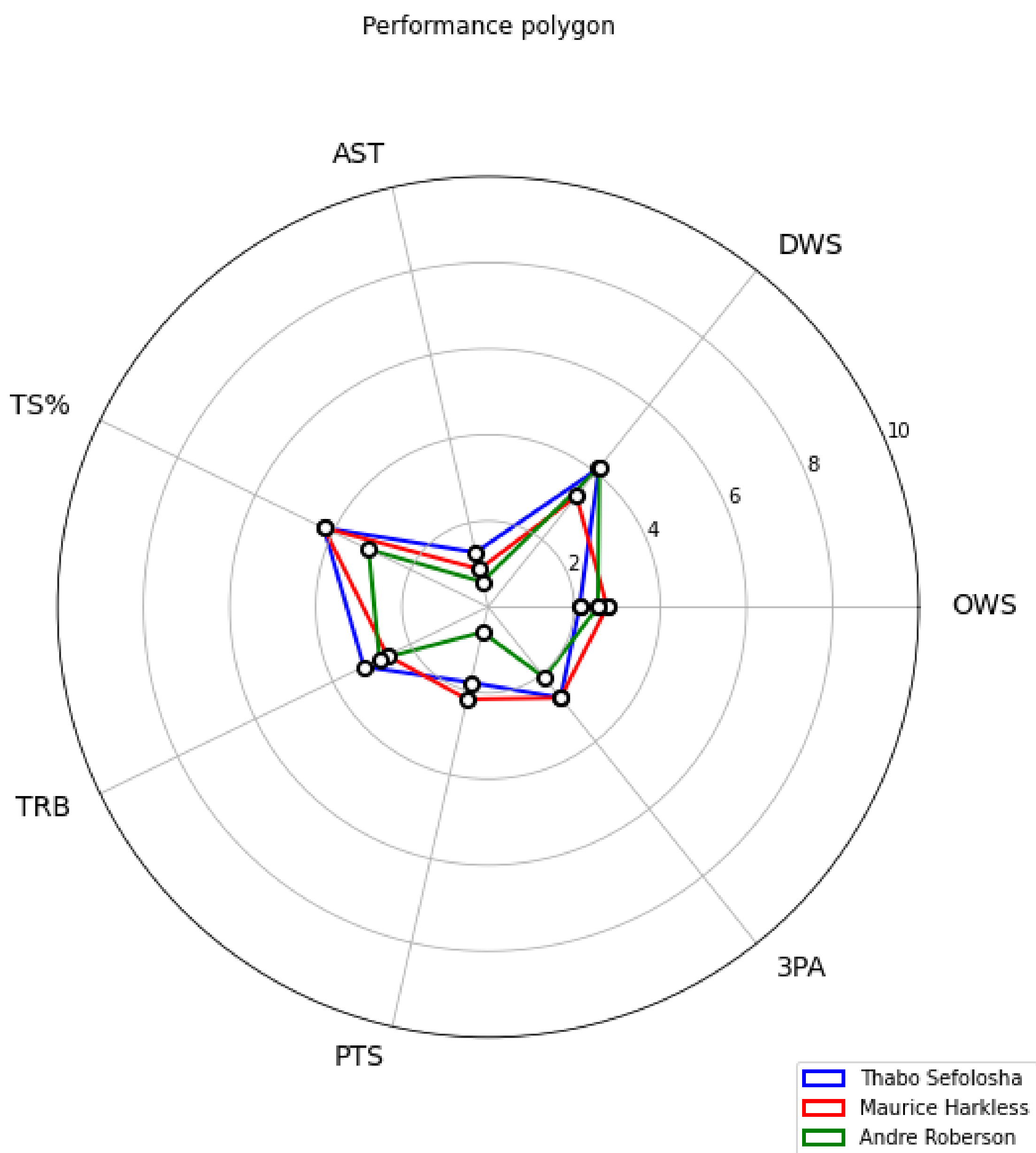


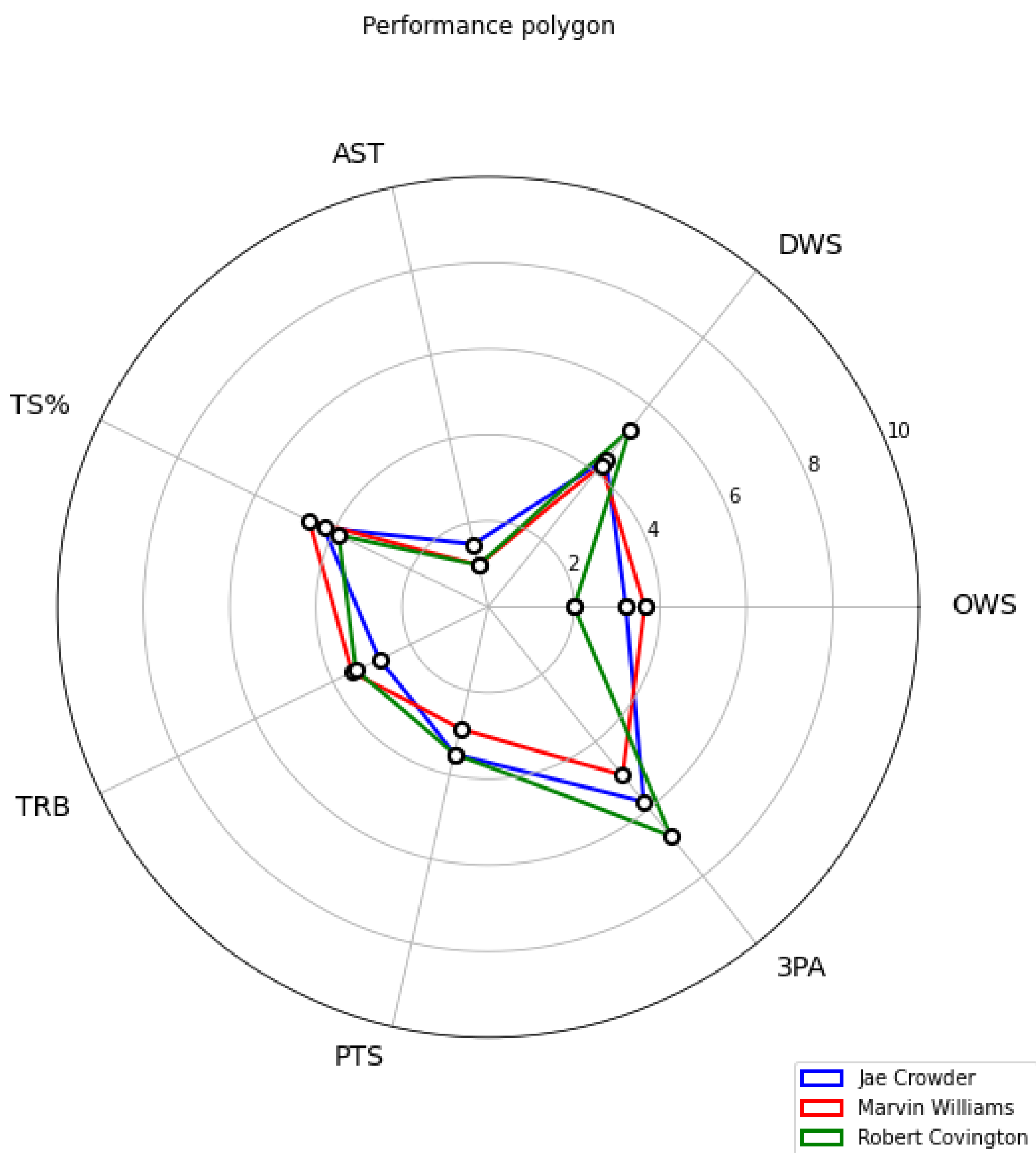
Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Kyle Korver
Vince Carter
Reggie Bullock


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

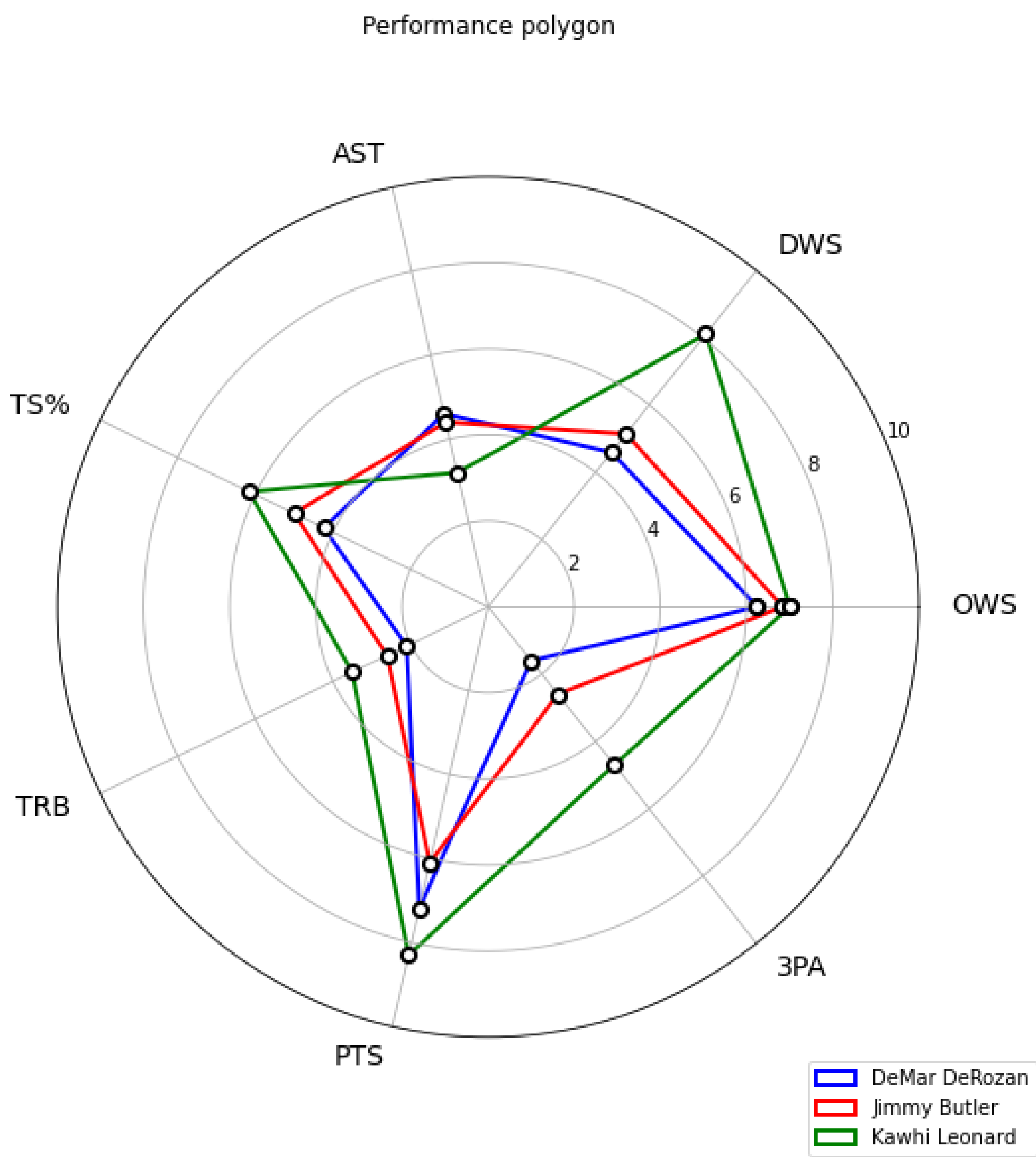

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Bam Adebayo
Domantas Sabonis
Mason Plumlee


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

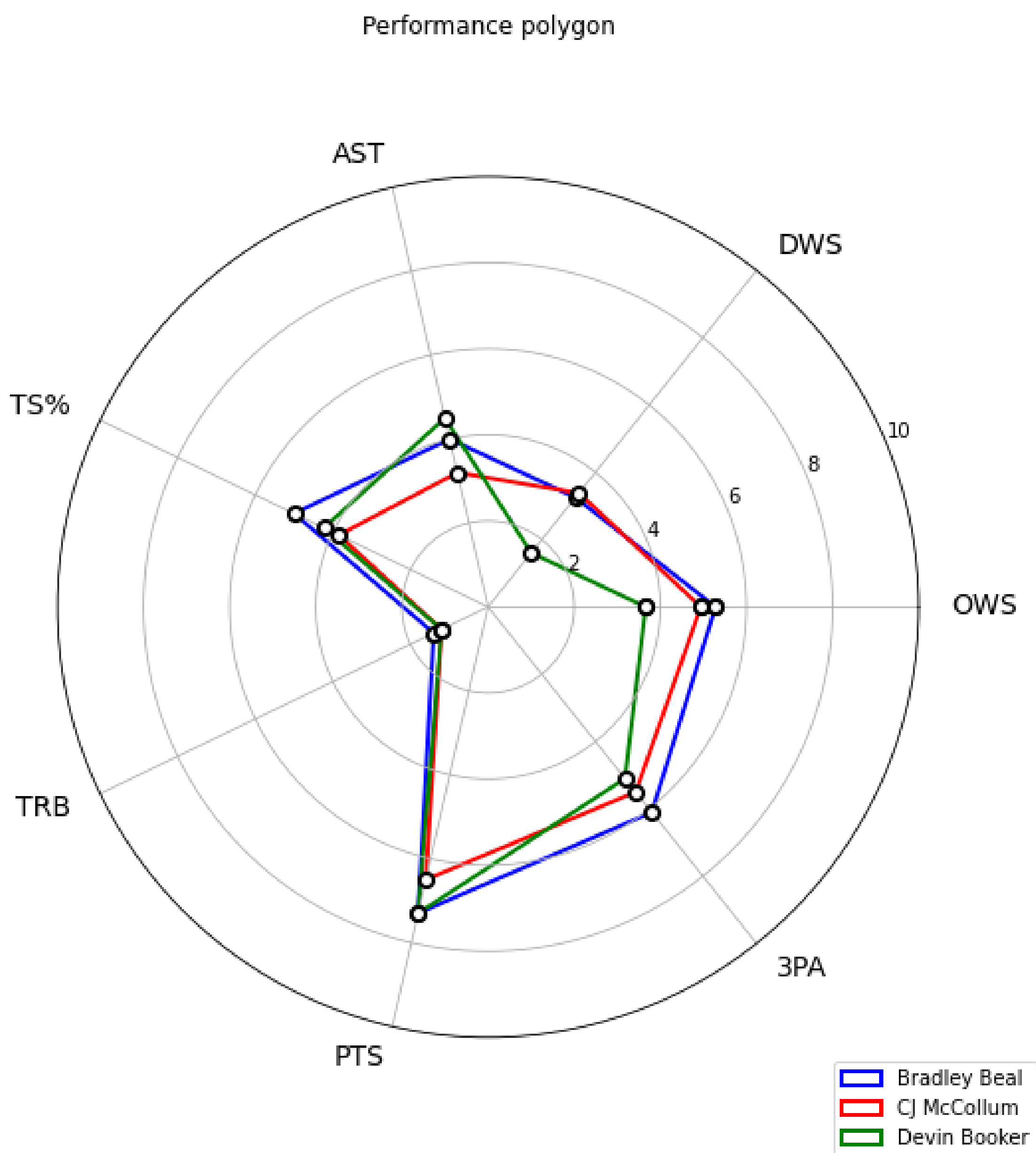

Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Thabo Sefolosha
Maurice Harkless
Andre Roberson



Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Jae Crowder
Marvin Williams
Robert Covington



Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
DeMar DeRozan
Jimmy Butler
Kawhi Leonard


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
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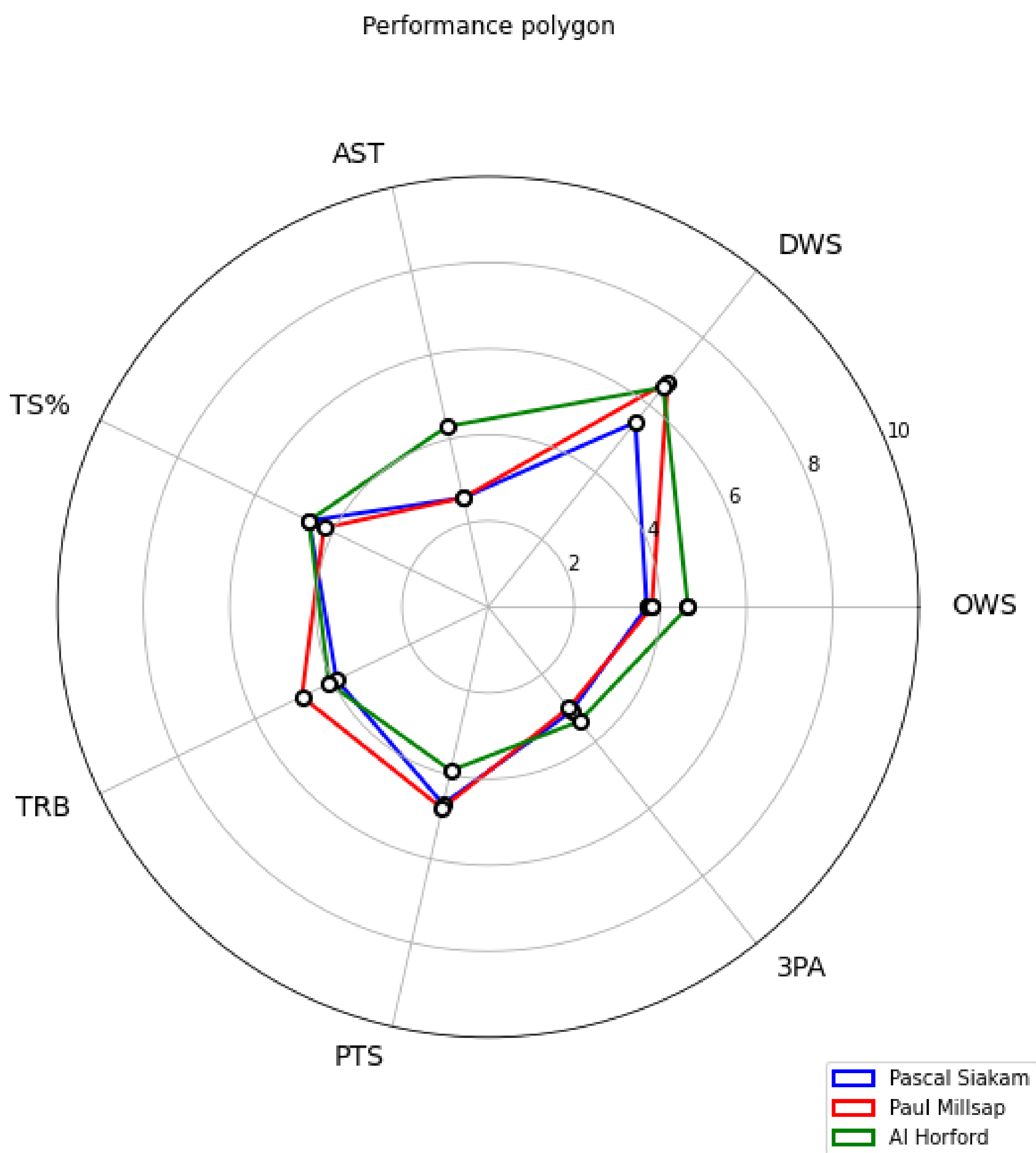
10
Bradley Beal
CJ McCollum
Devin Booker


Performance polygon
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TS%
OWS
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PTS
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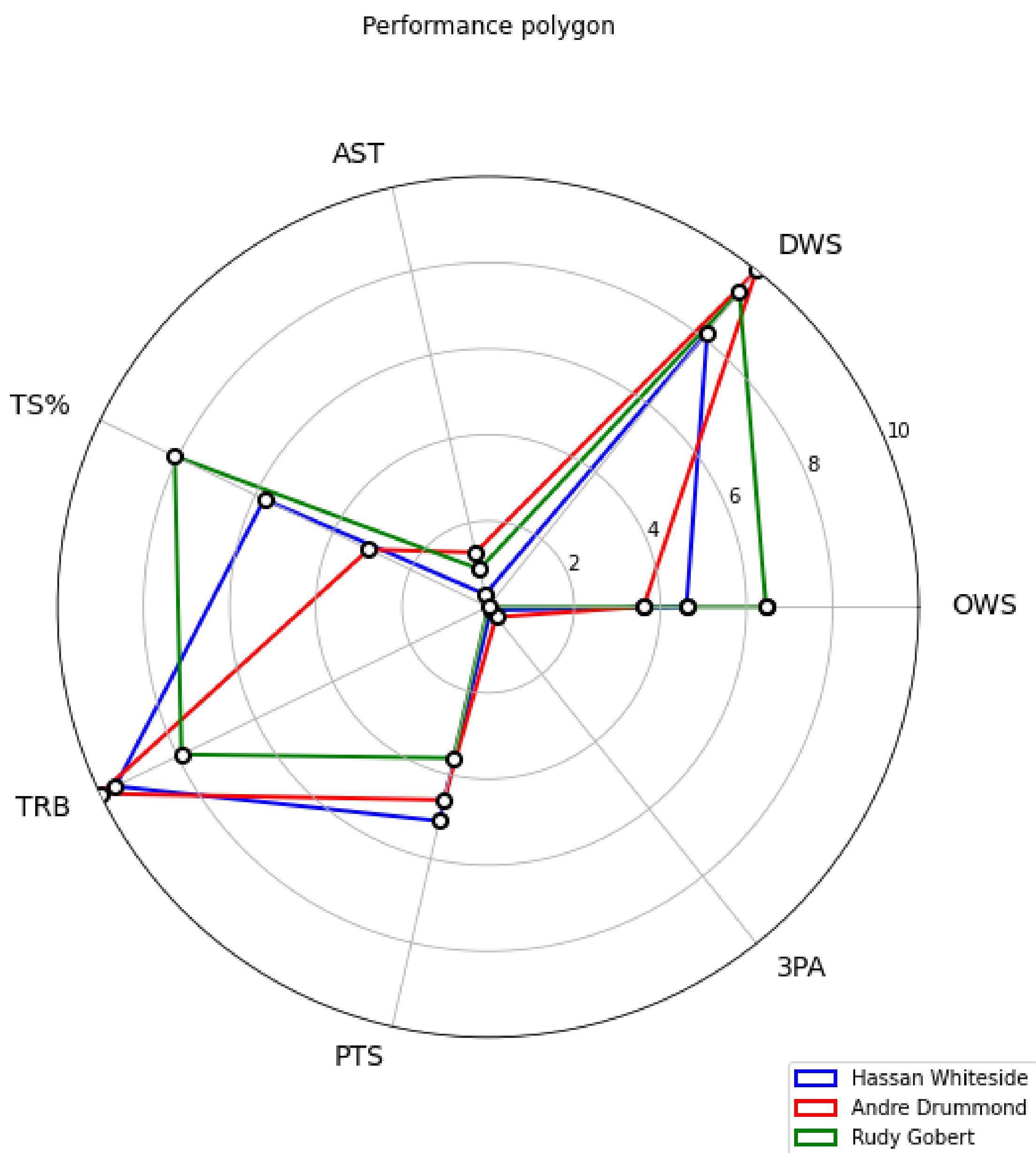
Pascal Siakam
Paul Millsap
Al Horford


Performance polygon
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TS%
OWS
TRB
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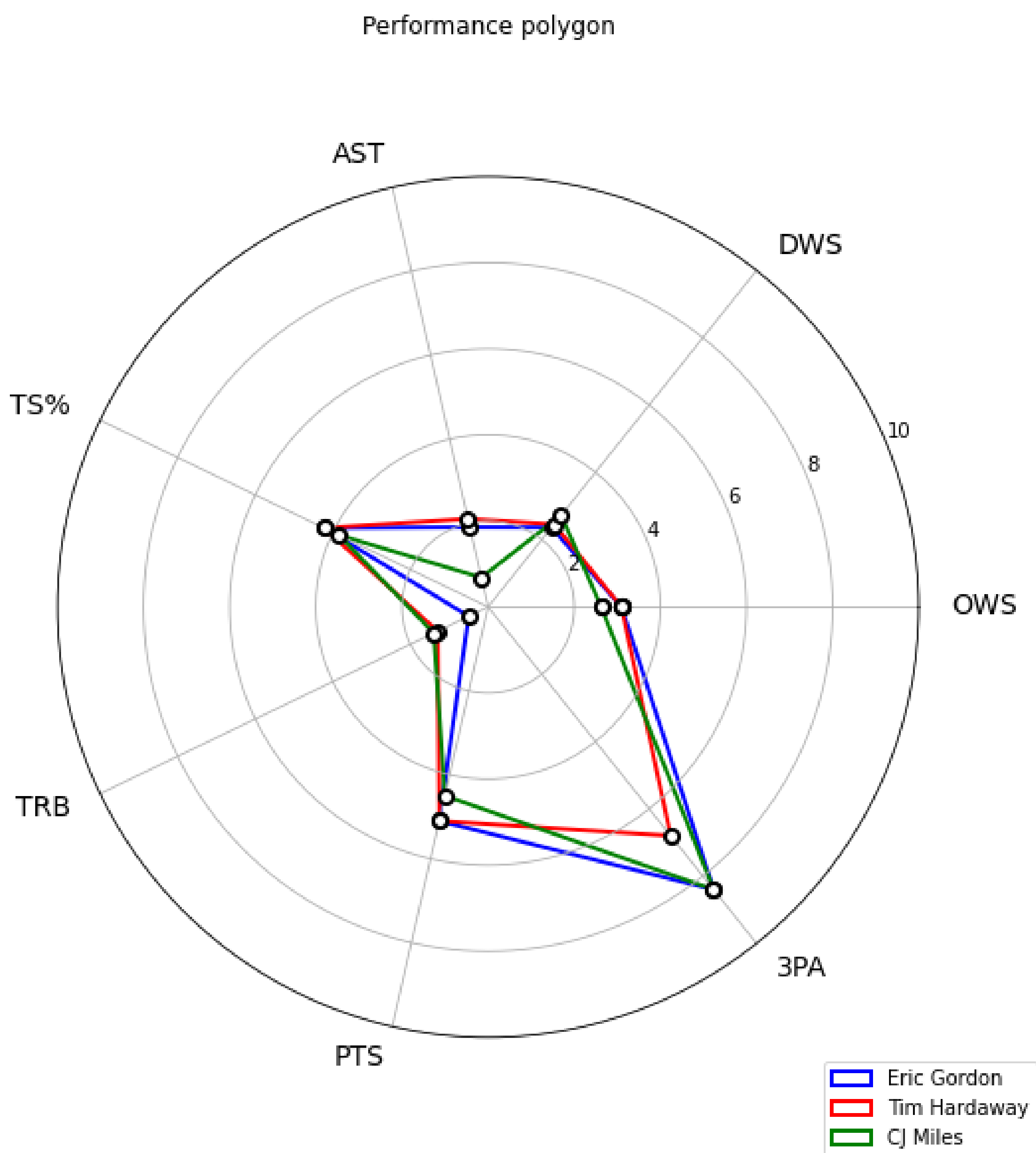
Hassan Whiteside
Andre Drummond
Rudy Gobert



Performance polygon
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TS%
OWS
TRB
3PA
PTS
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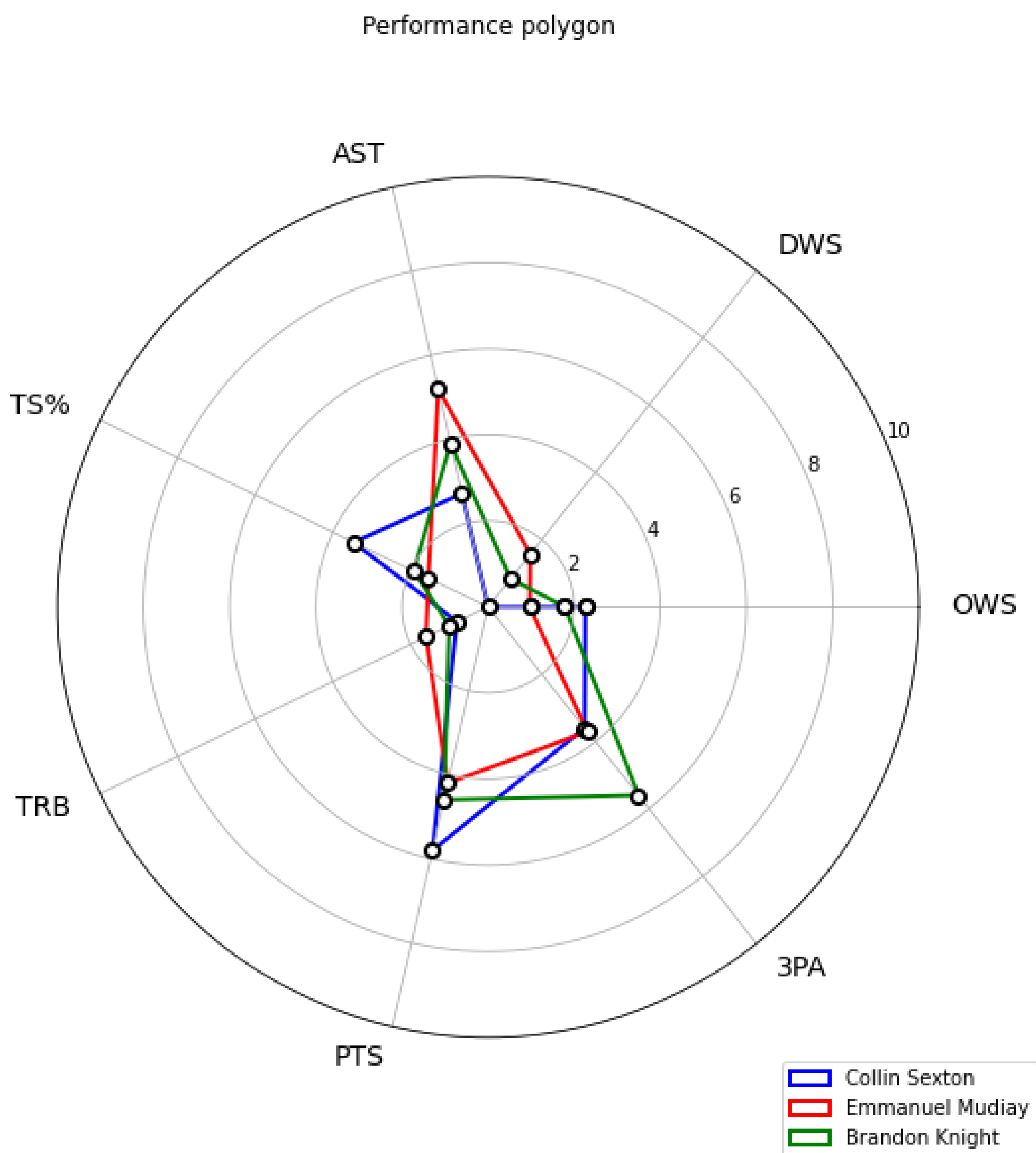
Eric Gordon
Tim Hardaway
CJ Miles


Performance polygon
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DWS
TS%
OWS
TRB
3PA
PTS
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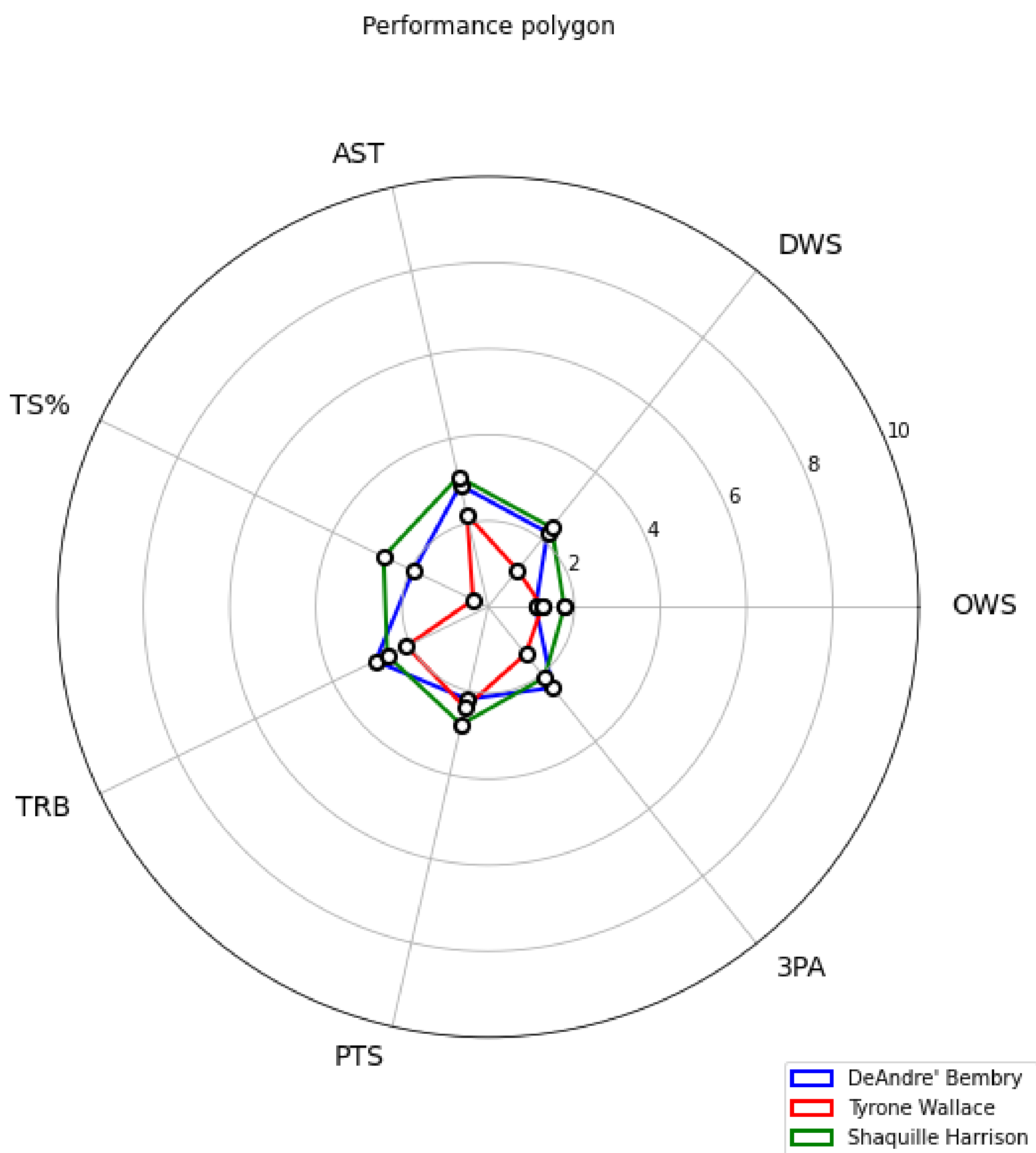
Collin Sexton
Emmanuel Mudiay
Brandon Knight


Performance polygon
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DWS
TS%
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TRB
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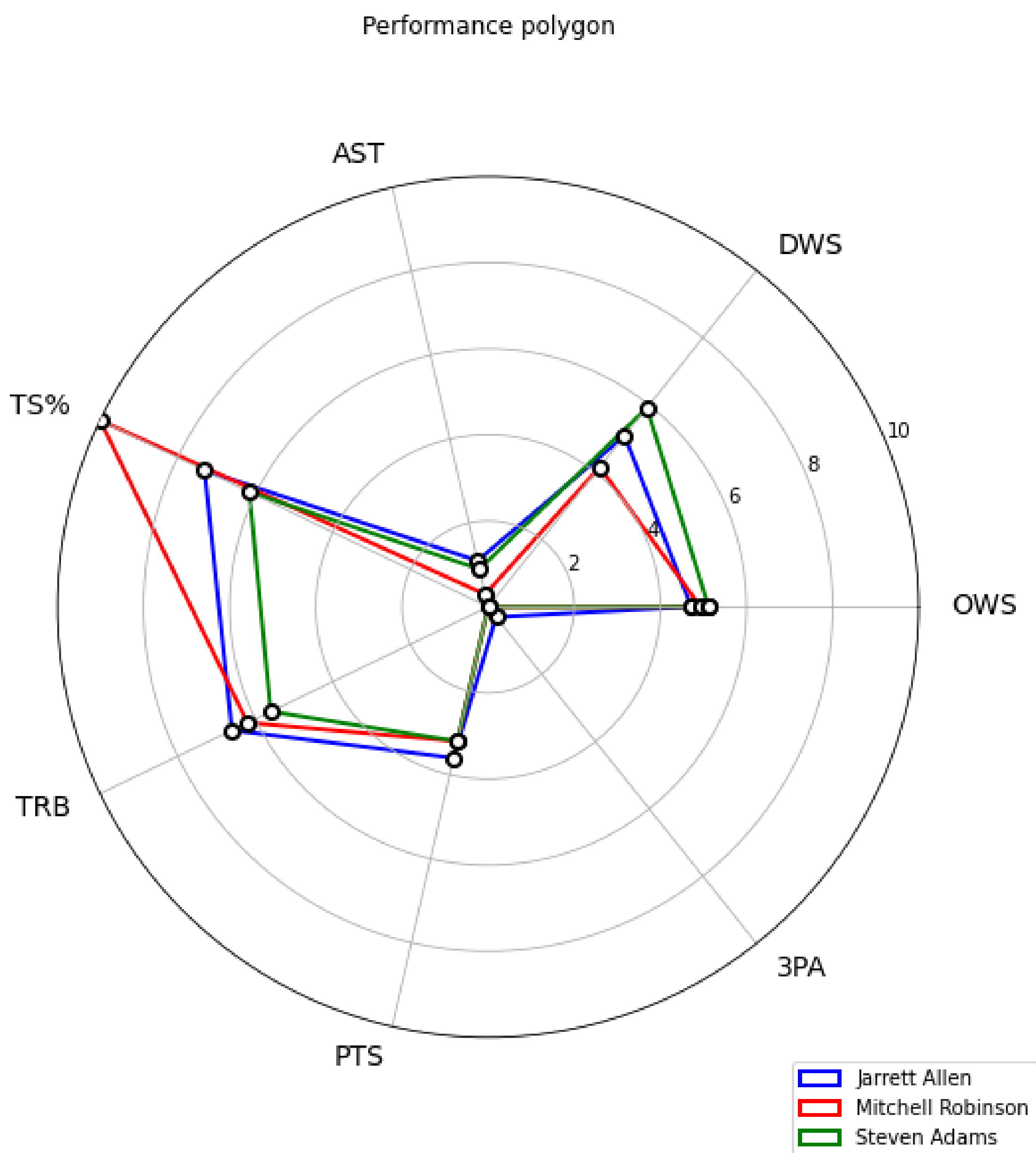
DeAndre' Bembry
Tyrone Wallace
Shaquille Harrison


Performance polygon
AST
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TRB
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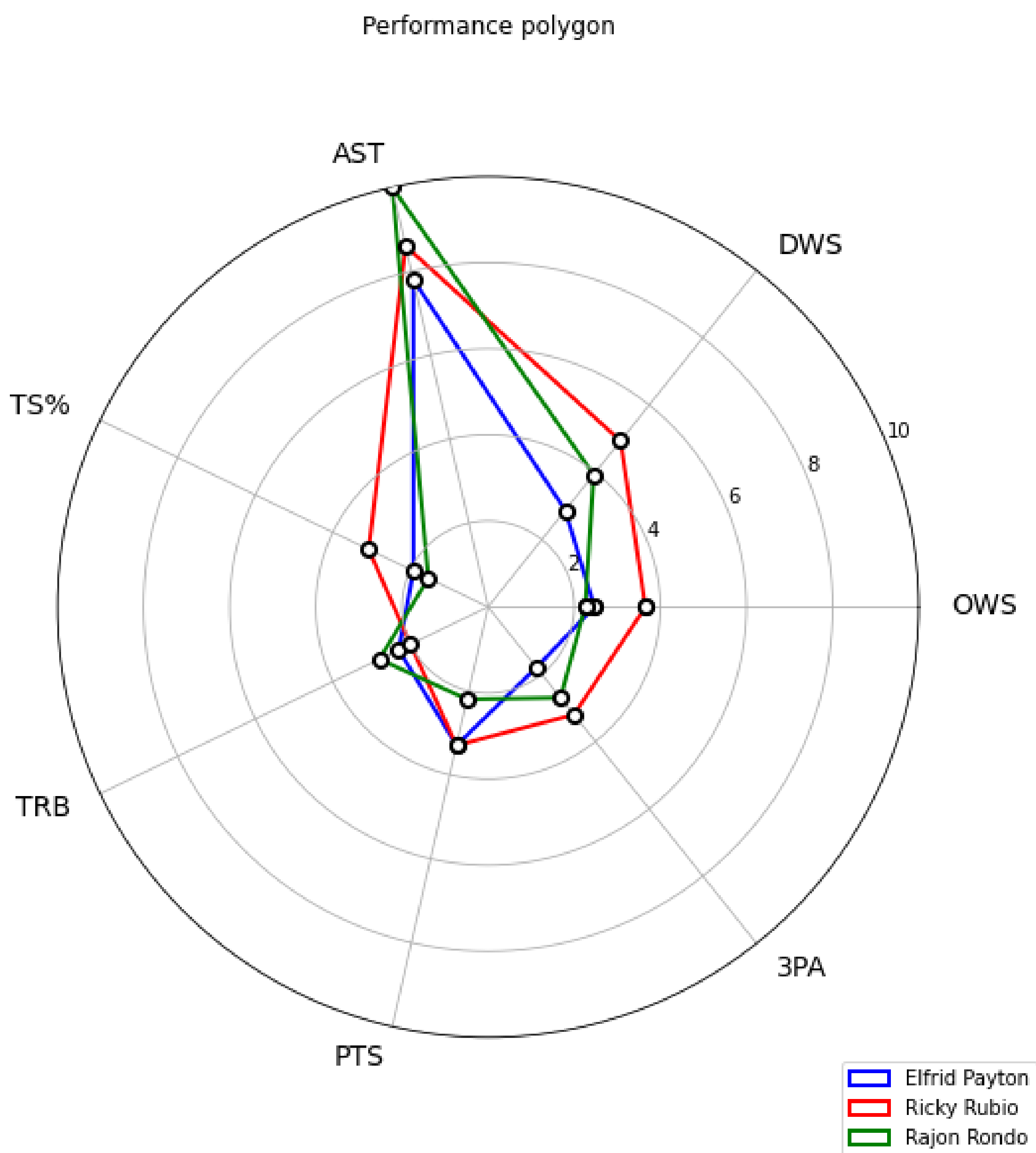
Jarrett Allen
Mitchell Robinson
Steven Adams


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
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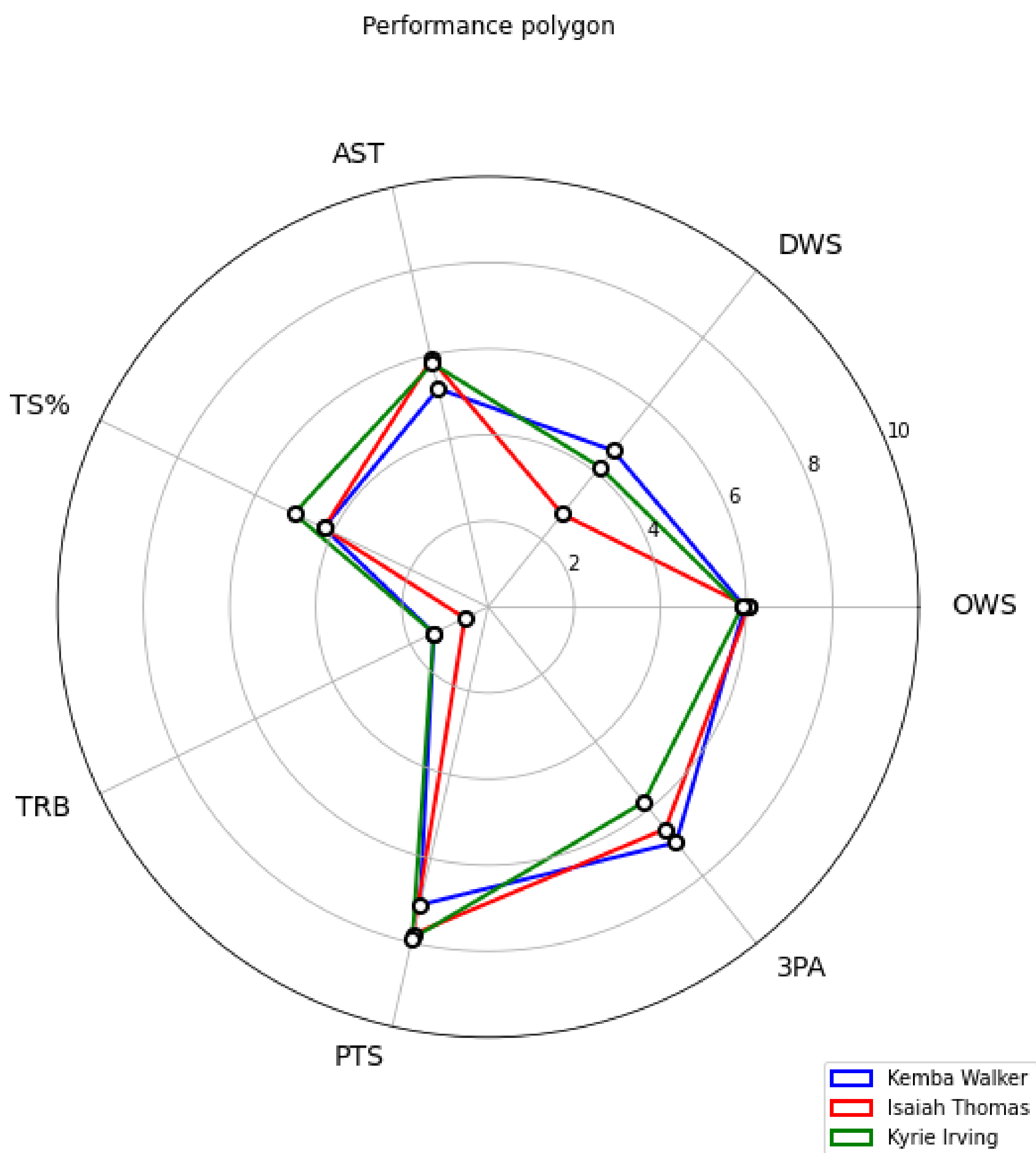
Elfrid Payton
Ricky Rubio
Rajon Rondo


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
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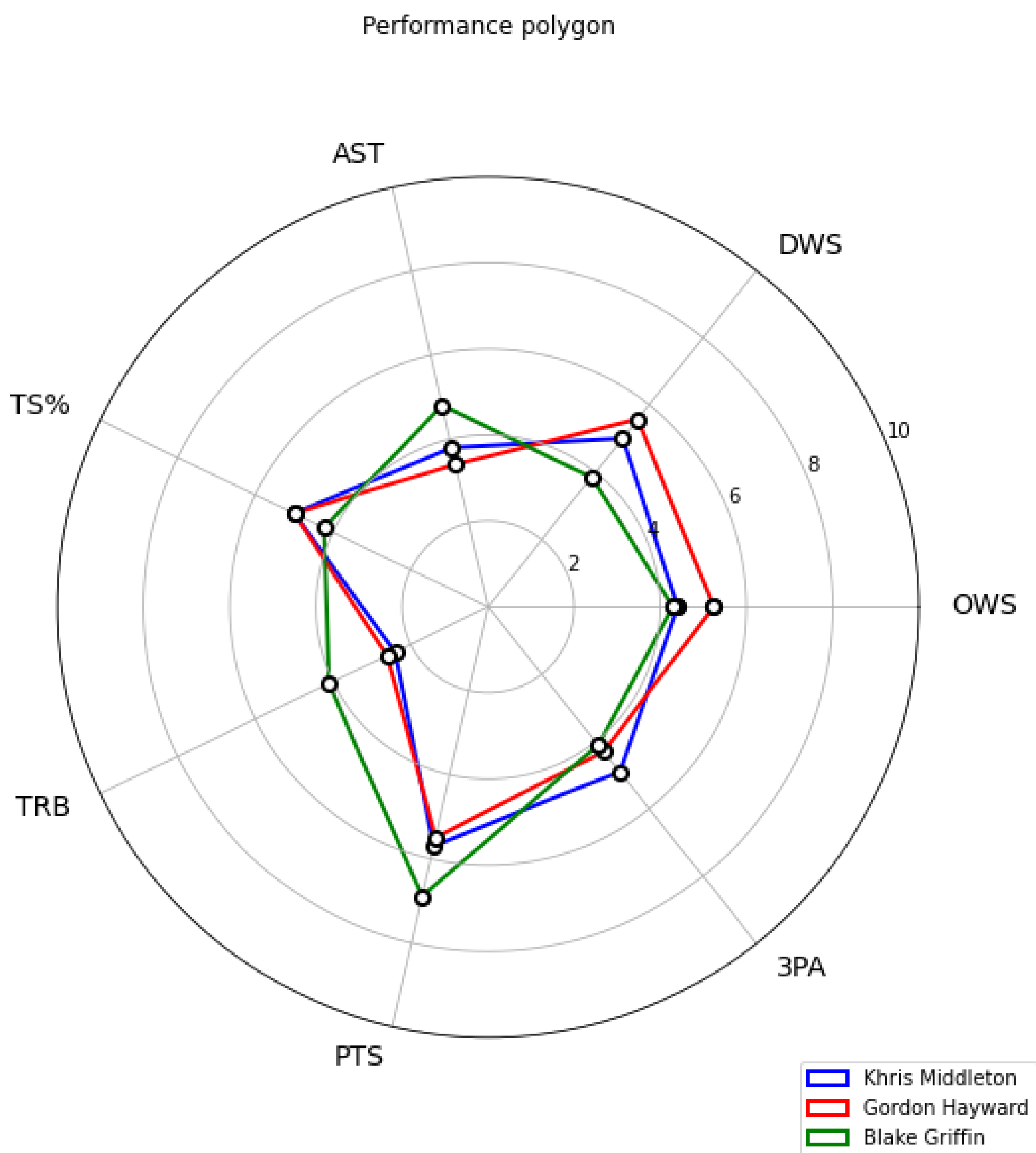
10
Kemba Walker
Isaiah Thomas
Kyrie Irving


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
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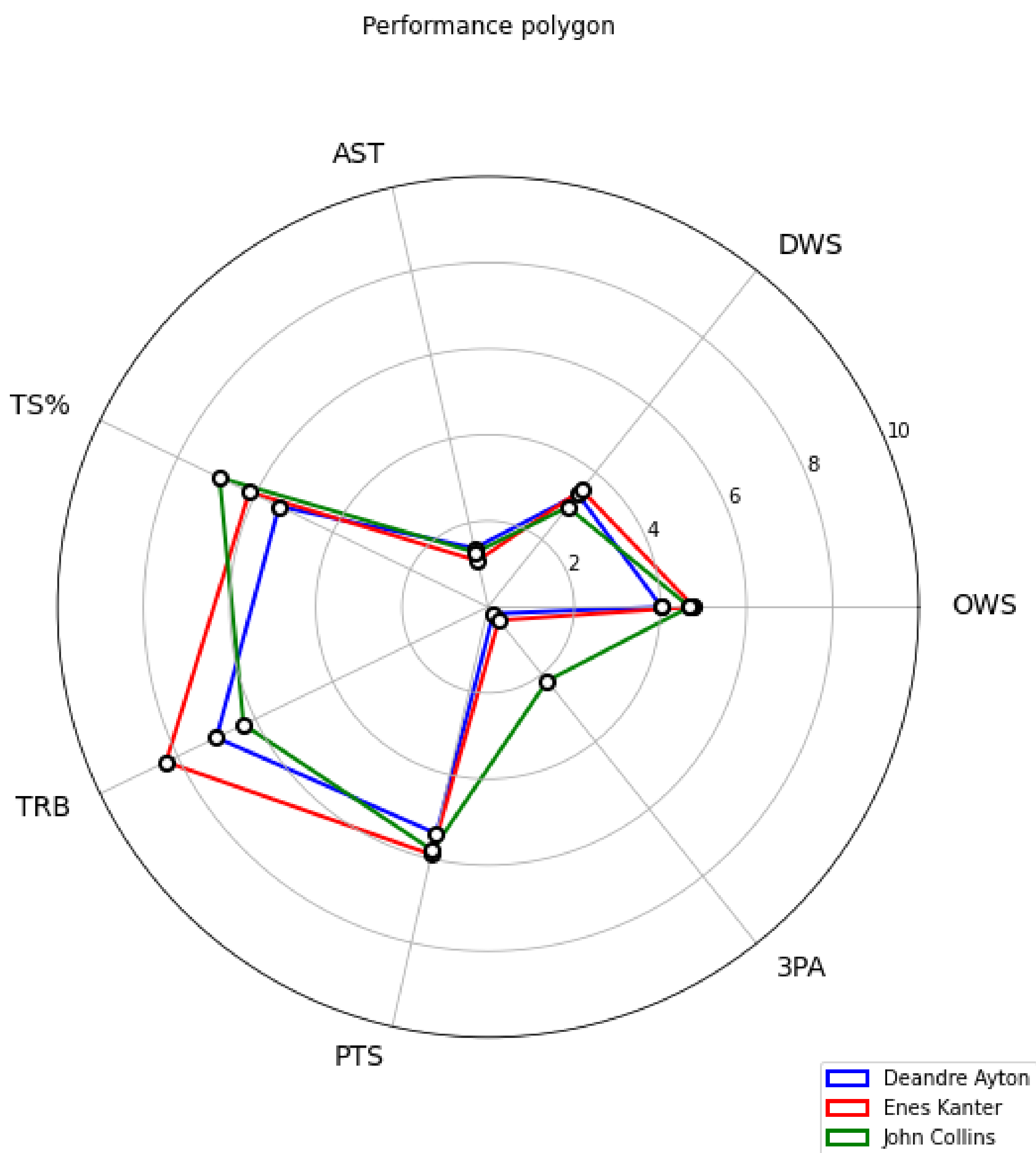
Khris Middleton
Gordon Hayward
Blake Griffin


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
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4
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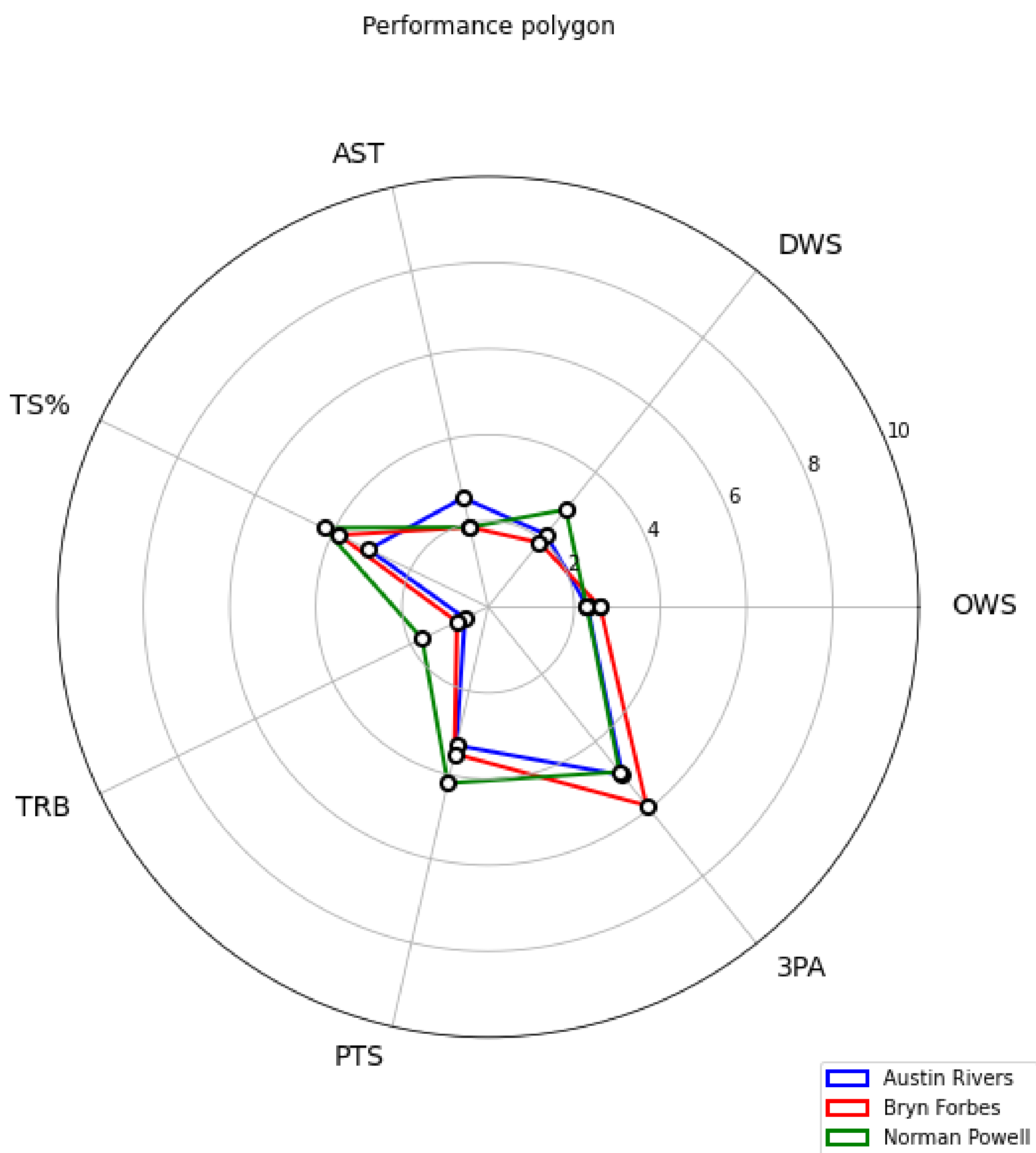
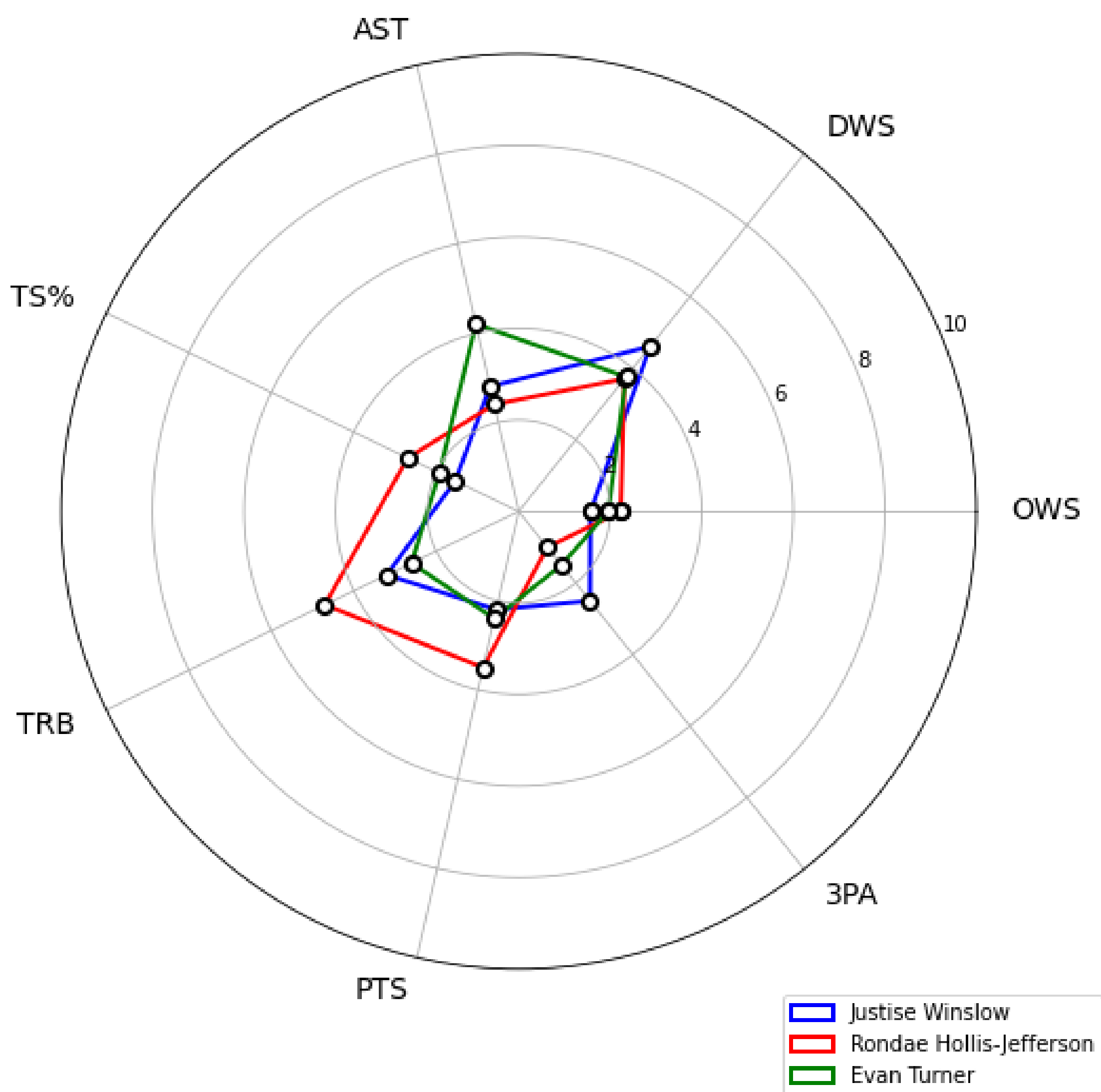
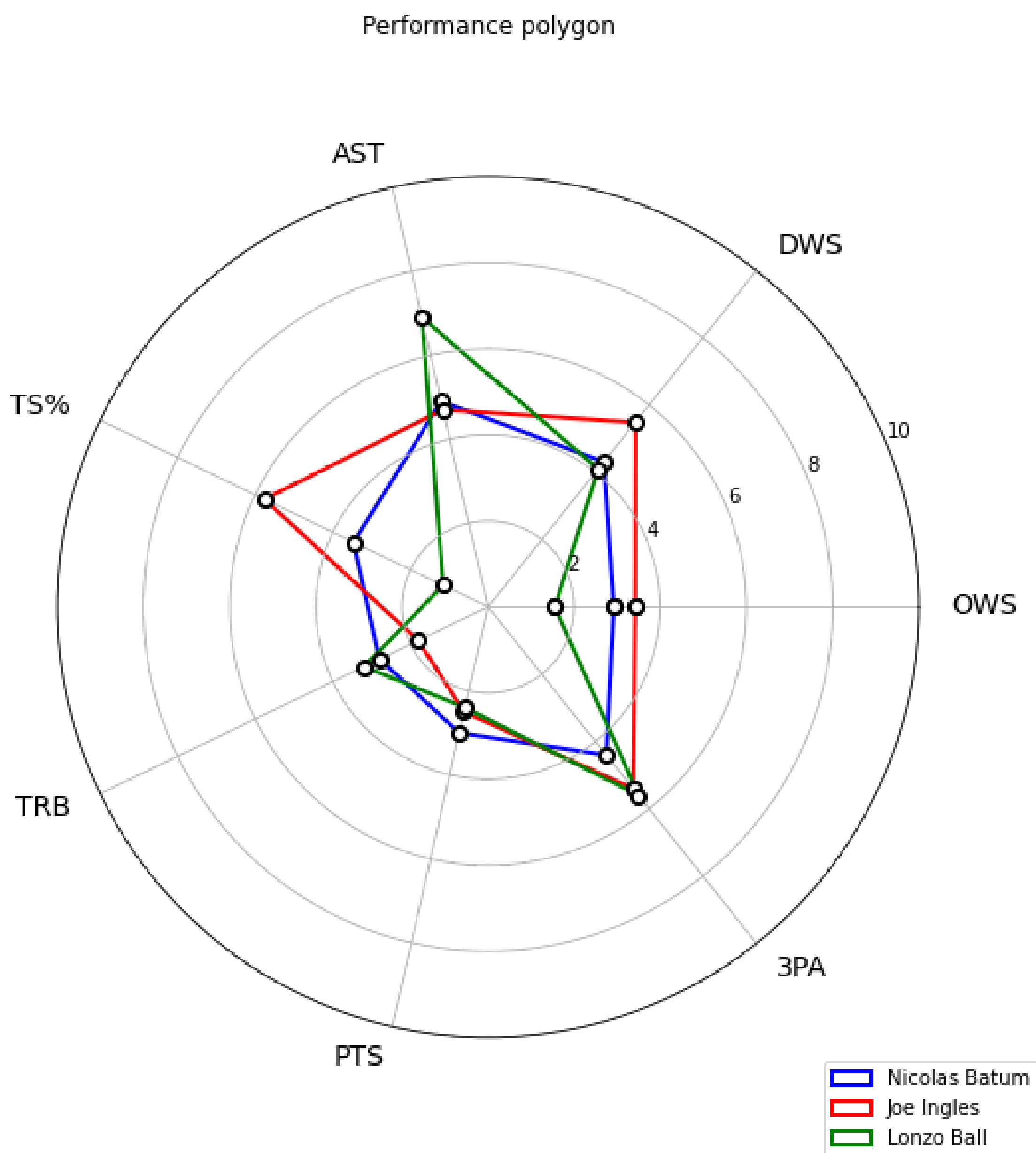
Deandre Ayton
Enes Kanter
John Collins


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
Austin Rivers
Bryn Forbes
Norman Powell

Performance polygon




Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
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Nicolas Batum
Joe Ingles
Lonzo Ball

1.6 Interesting but we are limited to a certain number of player (here 3*35 = 105) ## and we have to pick ourselves the number of clusters and the number of players per cluster

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

[40]:
```
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")
```

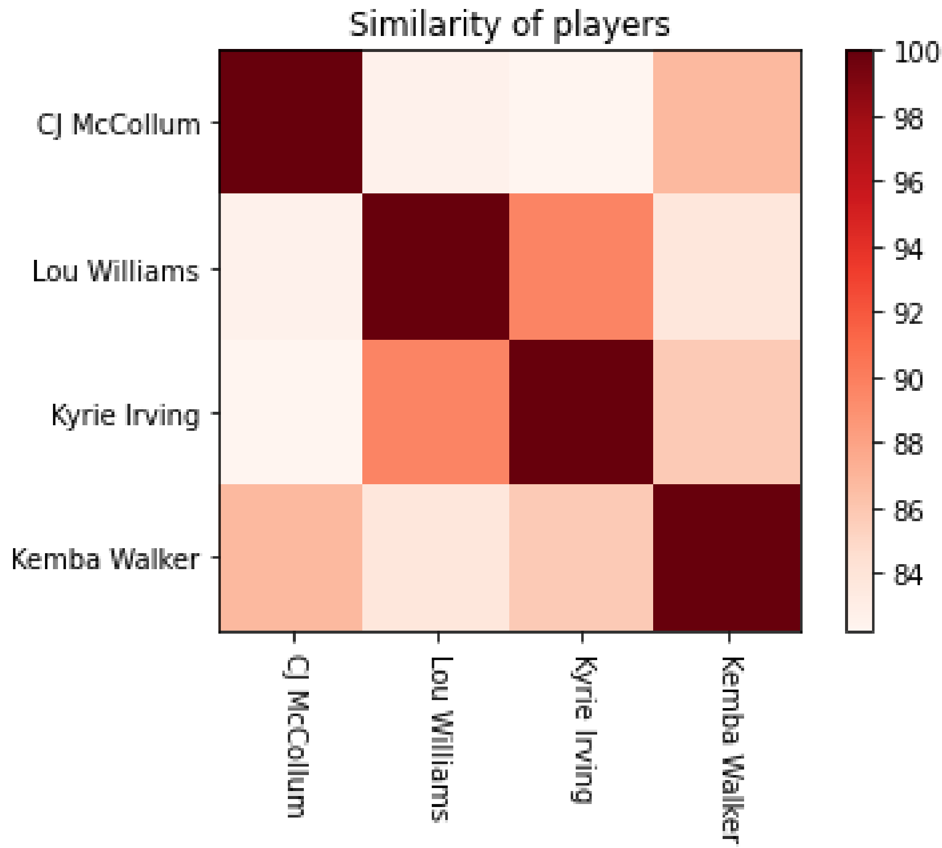
[41]:
```
# return a dict of dict
def get_distance_between_players(list_of_players, dist_matrix):
    #lets sort it to have the same order on both axis
    list_of_players = sorted(list_of_players)
    dist_mat_dict = {}
    for player in list_of_players:
        dist_mat_dict[player] = {}
        for player2 in list_of_players:
            dist_mat_dict[player][player2] = dist_matrix[dist_matrix["Name"] ==␣
↪player].iloc[0][player2]

    return dist_mat_dict
```

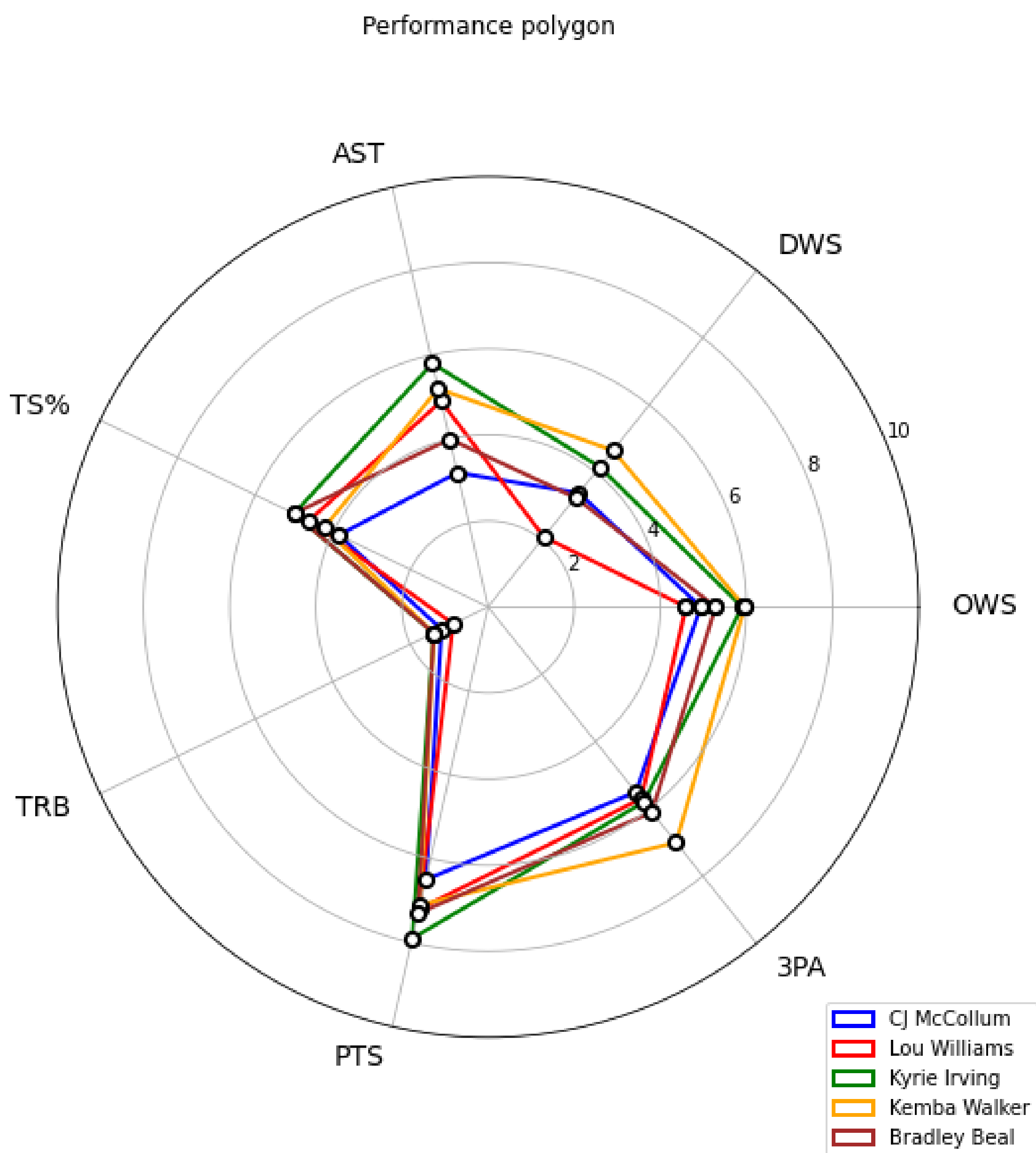
[42]:
```
#return a list of 2-elements tuples (name, similarity score)
def get_most_similar_players(player_name, nb_of_similar_players_wanted,␣
↪dist_mat):

    #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
```

[43]:
```
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()
```

[44]:
```
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)
```


Similarity of players
CJ McCollum
Lou Williams
Kyrie Irving
Kemba Walker
100
98
96
94
92
90
88
86
84
CJ McCollum
Lou Williams
Kyrie Irving
Kemba Walker


Performance polygon
AST
DWS
TS%
OWS
TRB
3PA
PTS
2
4
6
8
10
CJ McCollum
Lou Williams
Kyrie Irving
Kemba Walker
Bradley Beal

```
[ ]:
```