

```
In [68]: import pandas as pd
import itertools
import numpy as np
import random
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from IPython.display import display, HTML
from sklearn.preprocessing import StandardScaler
import warnings
import matplotlib.pyplot as plt
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', 70)
```

Overview

Objective

- Form a team of players whose total yearly salary for the 2021-22 season fits within a range using advanced statistics as the independent variables and the number of wins produced by that team as the dependent variable in a regression task

Dataset Source

- <https://www.basketball-reference.com> (<https://www.basketball-reference.com>)
- Downloaded the csv files for each required feature and did some preprocessing

Dataset

Relevant dataframes

- adv_stats: contains advanced statistics for each player
- standard_stats: contains standard statistics for each player
- salaries: contains the 2021-22 salaries for each player
- combined_data: adv_stats + salaries

```
In [86]: adv_stats = pd.read_excel("adv_stats_with_dup.xlsx").drop("Rk", axis=1)
full_salaries = pd.read_excel("salaries.xlsx").drop("Rk", axis=1).rename(
standings = pd.read_excel("standings.xlsx")

salaries = full_salaries[["Player", "2021-22 Salary"]]

combined_data = pd.merge(adv_stats, full_salaries[["Player", "2021-22
print("Player Information")
print(list(combined_data.columns))
```

Player Information

```
['Player', 'Pos', 'Age', 'Tm', 'G', 'MP', 'PER', 'TS%', '3PA%', 'FTr'
, 'ORB%', 'DRB%', 'TRB%', 'AST%', 'STL%', 'BLK%', 'TOV%', 'USG%', 'OW
S', 'DWS', 'WS', 'WS/48', 'OBPM', 'DBPM', 'BPM', 'VORP', '2021-22 Sal
ary']
```

```
In [3]: # display(combined_data)
# display(combined_data[combined_data["Tm"] == "TOT"])
```

Parameters

- min_games_played: minimum number of games played for a player
- min_min_played: minimum number of average minutes for a player
- desired_yearly_sal_min: minimum total yearly salary for a team
- desired_yearly_sal_max: maximum total yearly salary for a team
- combos_considered: how many different combinations of players considered during the testing stage
- num_players: number of players in a team
- position_matters: whether we care about the positions of players
- teams_considered : how many teams are considered in the combinations generated

```
In [4]: min_games_played = 41
min_min_played = 25
desired_yearly_sal_min = 50000000
desired_yearly_sal_max = 70000000

combos_considered = 30000
num_players = 5
position_matters = True
teams_considered = 30000
```

Data Parsing

This is an area that could be modified based on basketball knowledge and research

Assumptions made:

- Players that played on multiple teams in a season do not adequately contribute to the wins of the respective teams
- Players that play a desired number of games and minutes contribute to a team's wins

```
In [5]: parsed_data = combined_data[combined_data["Tm"] != "TOT"]
# parsed_data = parsed_data[parsed_data["G_x"] >= min_games_played]
# parsed_data = parsed_data[parsed_data["MP_x"] >= min_min_played].reset_index(drop=True)
# parsed_data = parsed_data.drop("Pos_x", axis=1).drop("Age_x", axis=1)
# parsed_data = parsed_data.drop("Pos_y", axis=1).drop("Age_y", axis=1)

parsed_data = parsed_data[parsed_data["G"] >= min_games_played]
parsed_data = parsed_data[parsed_data["MP"] >= min_min_played].reset_index(drop=True)
parsed_data = parsed_data.drop("G", axis=1).drop("MP", axis=1)
# parsed_data = parsed_data.sort_values(by=['Pos']).reset_index(drop=True)

players_considered = len(parsed_data)

if position_matters:
    temp = parsed_data.groupby('Pos')
    data_by_positions = [x for _, x in temp]
```

```
In [ ]: # display(standings)
```

Generating Training Data

1. Training data is generated based on the 2021-22 season standings
2. Given a list of players and their statistics and salaries, iterate through each player and determine the team, number of minutes played, and number of games played by that player
3. Group players according to team, and keep players that fit the criteria of games played and minutes played
4. Generate all combinations of teams (based on the num_players parameter), average out their advanced statistics to get independent variables and assigned their number of wins as the number of wins from their respective team in the 2021-22 season standings

```
In [7]: teams = standings["Team"]
team_wins = standings["Wins"]

players_dict = {}
for i in range(len(parsed_data)):
    team = parsed_data.iloc[i]["Tm"]
    if team not in players_dict:
        players_dict[team] = [i]
    else:
        players_dict[team].append(i)
```

```
In [8]: temp_data = parsed_data
parsed_data = parsed_data.drop("Tm", axis=1)
parsed_data = parsed_data.drop("Pos", axis=1)
```

```
In [9]: different_teams = []

teams_dict = {"MIA": "Miami Heat", "NOP": "New Orleans Pelicans", "MEM": "Memphis Grizzlies"}

for key, value in players_dict.items():
    wins = standings[standings["Team"] == teams_dict[key]]["Wins"].values
    different_teams.append((wins, list(itertools.combinations(value, r=2))))

X = []
y = []
for i in range(len(different_teams)):
    team = different_teams[i][1]
    for j in range(len(team)):
        players = list(team[j])
        averages = parsed_data.iloc[players].mean(axis=0).tolist()[:-1]
        X.append(averages)
        y.append(different_teams[i][0])
```

30

Generating Testing Data

The testing data is more like hold out data. It is not from the same distribution as the training data since we want to know teams that haven't been formed before and for which we don't have historical data regarding wins.

1. Generate a set of n person teams
 - Since there are a lot of possible combinations of say 5 person teams, we select 5 random numbers instead from the list of possible player indices
 - We won't be able to generate all possible teams, and if we only generated a subset of all combinations, then we are likely to only consider a small number of players
 - Using random numbers helps us with this
2. Average the teams statistics and filter the yearly salaries to fit within the desired range

```
In [10]: data_len = len(parsed_data)

# start_index

def get_five():
    random_set = []
    if position_matters:
        for i in range(len(data_by_positions)):
            random_index = random.randint(0, len(data_by_positions[i]))

            while random_index in random_set:
                random_index = random.randint(0, len(data_by_positions[i]))
            new_index = data_by_positions[i].iloc[random_index].name
            random_set.append(new_index)
    else:
        for i in range(num_players):
            random_index = random.randint(0, data_len - 1)
            while random_index in random_set:
                random_index = random.randint(0, data_len - 1)
            random_set.append(random_index)
    return random_set

all_combos = [get_five() for i in range(teams_considered)]
```

```

In [11]: salaries = parsed_data["2021-22 Salary"].tolist()
         players = parsed_data["Player"]

         team_salaries = []

         for i in range(len(all_combos[:combos_considered])):
             total_sal = 0
             for j in range(num_players):
                 total_sal += salaries[all_combos[i][j]]

             if total_sal <= desired_yearly_sal_max and total_sal >= desired_yearly_sal_min:
                 team_salaries.append((total_sal, all_combos[i]))

         extra_test_X = []
         extra_teams_X = []
         for sal in team_salaries:
             players = sal[1]
             averages = parsed_data.iloc[players].mean(axis=0).tolist()[:-1]
             extra_test_X.append(averages)
             extra_teams_X.append(players)

         print(len(extra_test_X))
         print(extra_teams_X[0])

```

8876

[203, 217, 152, 136, 43]

Use a regression model to predict the number of wins of each test instance

Right now I only use linear regression, but this is an area that could use improvements

```

In [12]: train_X, true_test_X, train_y, true_test_y = train_test_split(X, y, test_size=0.2)
         scaler = StandardScaler()
         scaler.fit(train_X)
         scaler.transform(train_X)
         # print(train_X)
         model = LinearRegression().fit(train_X, train_y)

```

In [13]:

```
# scaler.transform(true_test_X)
true_pred_y = model.predict(true_test_X)
# print(true_test_y[:10])
# print(true_pred_y[:10])
print(mean_squared_error(true_test_y, true_pred_y))
```

31.616684206177883

In [14]:

```
# scaler.transform(extra_test_X)
extra_pred_y = model.predict(extra_test_X)
```

Printing results

The following results are shown:

- The top-n teams that achieved the most number of wins based on predictions
- The worst team with the lowest number of wins based on predictions
- The average statistics of that team
- The number of players in the top 10 teams based on season standings
- The number of players in the bottom 10 teams based on season standings

```

In [15]: def get_pred_info(y_pred, top_n=1, get_worst=False):

    if get_worst:
        index = np.argmin(y_pred)
        players = extra_teams_X[index]

        num_wins = y_pred[index]
        stats = pd.merge(temp_data[["Player", "Tm", "Pos"]], parsed_data
#         stats = pd.merge(parsed_data.iloc[players], combined_data[["
#         stats = parsed_data.iloc[players]
        averages = pd.DataFrame({"Averages": stats.mean(axis=0).round(

        total_salary = int(stats.sum(axis=0)["2021-22 Salary"].tolist()
        player_names = stats["Player"].tolist()
        return stats, averages, player_names, total_salary, int(np.rou

    else:
        indices = np.argsort(y_pred)[-top_n:]

        sorted_indices = indices[np.argsort(y_pred[indices])]

        info = []

        for i in range(len(sorted_indices) - 1, -1, -1):
            index = sorted_indices[i]
            players = extra_teams_X[index]

            num_wins = y_pred[index]
            stats = pd.merge(temp_data[["Player", "Tm", "Pos"]], parse
#             stats = parsed_data.iloc[players]
            averages = pd.DataFrame({"Averages": stats.mean(axis=0).ro

            total_salary = int(stats.sum(axis=0)["2021-22 Salary"].tol
            player_names = stats["Player"].tolist()
            info.append([stats, averages, player_names, total_salary,
        return info

```

In [16]:


```

top_10_teams = set(standings["Team"][:10])
bot_10_teams = set(standings["Team"][-10:])

print("----- NBA Moneyball -----")

params = {"Players Considered": players_considered, "Position Matters":
params_df = pd.DataFrame({"Parameters": params}).T
display(params_df)
display(standings.T)

print("\n")
print("----- Results (Top-n Teams and Worst T

info = get_pred_info(extra_pred_y, top_n=5)

for i in range(len(info)):
    stats, averages, player_names, total_salary, num_wins = info[i]
    player_teams = set(map(lambda s : teams_dict[s], stats["Tm"]))
    top_overlap = len(player_teams.intersection(top_10_teams))
    bot_overlap = len(player_teams.intersection(bot_10_teams))
    print("\n")
    print("Rank " + str(i + 1))
    print("Most number of wins: " + str(num_wins))
    print("Total yearly salary: " + str("${:,}".format(total_salary)))
    print("Players in top 10 teams: " + str(top_overlap))
    print("Players in bottom 10 teams: " + str(bot_overlap))
    display(stats)
    display(averages)

print("\n")
stats, averages, player_names, total_salary, num_wins = get_pred_info(
print("Worst Team")
print("Least number of wins: " + str(min(extra_pred_y)))
print("Total yearly salary: " + str(total_salary))
player_teams = set(map(lambda s : teams_dict[s], stats["Tm"]))
top_overlap = len(player_teams.intersection(top_10_teams))
bot_overlap = len(player_teams.intersection(bot_10_teams))
print("Players in top 10 teams: " + str(top_overlap))
print("Players in bottom 10 teams: " + str(bot_overlap))
display(stats)
display(averages)

# print("\n")
# print("Average number of wins: " + str(sum(pred_y)/len(pred_y)))

```

----- NBA Moneyball -----

Min

Min

Salary

Salary

Size

		Games Played	Minutes Played	Players Considered	Position Matters	Range (Max)	Range (Min)	of Team		
Parameters		41	25	272	False	\$70,000,000	\$50,000,000	5		
		0	1	2	3	4	5	6	7	8
Team	Phoenix Suns	Memphis Grizzlies	Golden State Warriors	Miami Heat	Dallas Mavericks	Boston Celtics	Milwaukee Bucks	Philadelphia 76ers	Utah Jazz	De Nug
Wins	64	56	53	53	52	51	51	51	49	

----- Results (Top-n Teams and Worst Team) -----

Rank 1

Most number of wins: 60

Total yearly salary: \$50,164,532

Players in top 10 teams: 3

Players in bottom 10 teams: 0

	Player	Tm	Pos	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%
0	LaMelo Ball	CHO	PG	19	17.5	0.539	0.388	0.246	4.6	17.9	11.1	33.9	2.1
1	Kent Bazemore	GSW	SF	31	10.6	0.564	0.469	0.199	2.1	16.0	9.1	11.1	2.4
2	Devin Booker	PHO	SG	24	19.2	0.587	0.288	0.305	1.7	12.1	7.0	20.6	1.4
3	Jarred Vanderbilt	MIN	PF	21	16.2	0.612	0.021	0.432	10.8	24.7	17.5	9.3	2.1
4	Robert Williams	BOS	C	23	25.7	0.719	0.008	0.283	14.9	25.6	20.2	14.2	2.1
		Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%
Averages		23.6	17.8	0.6	0.2	0.3	6.8	19.3	13.0	17.8	2.2	3.2	15.2

Rank 2

Most number of wins: 60

Total yearly salary: \$50,993,133

Players in top 10 teams: 3

Players in bottom 10 teams: 0

	Player	Tm	Pos	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%
0	Bruce Brown	BRK	PG	24	16.1	0.604	0.139	0.277	8.9	17.2	13.3	9.8	1.9
1	Damion Lee	GSW	SG	28	11.8	0.636	0.708	0.161	2.2	15.4	8.9	9.1	1.7
2	Royce O'Neale	UTA	SF	27	9.9	0.599	0.706	0.117	4.4	18.0	11.5	10.4	1.2
3	Bobby Portis	MIL	C	25	19.9	0.598	0.263	0.122	9.9	25.3	17.9	7.4	1.8
4	Pascal Siakam	TOR	PF	26	17.7	0.547	0.256	0.313	5.0	17.6	11.1	20.5	1.5
	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%	
Averages	26.0	15.1	0.6	0.4	0.2	6.1	18.7	12.5	11.4	1.6	1.4	11.0	

Rank 3

Most number of wins: 60

Total yearly salary: \$63,752,077

Players in top 10 teams: 2

Players in bottom 10 teams: 0

	Player	Tm	Pos	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%
0	LaMelo Ball	CHO	PG	19	17.5	0.539	0.388	0.246	4.6	17.9	11.1	33.9	2.7
1	John Konchar	MEM	SG	24	14.8	0.608	0.406	0.217	6.4	17.3	11.8	10.7	2.5
2	Kawhi Leonard	LAC	SF	29	26.0	0.622	0.280	0.325	3.6	17.4	10.7	24.9	2.3
3	Kelly Olynyk	MIA	C	29	12.1	0.549	0.646	0.106	4.4	21.1	12.9	11.7	1.7
4	Dean Wade	CLE	PF	24	11.3	0.573	0.685	0.125	3.4	16.8	9.9	8.9	1.4
		Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%
Averages		25.0	16.3	0.6	0.5	0.2	4.5	18.1	11.3	18.0	2.1	1.5	11.4

Rank 4

Most number of wins: 59

Total yearly salary: \$64,778,089

Players in top 10 teams: 2

Players in bottom 10 teams: 2

	Player	Tm	Pos	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%
0	Jimmy Butler	MIA	SF	31	26.5	0.607	0.139	0.565	6.3	17.1	11.8	35.1	3.1
1	Robert Covington	POR	PF	30	11.2	0.553	0.699	0.122	2.8	19.8	11.1	6.8	2.1
2	T.J. McConnell	IND	PG	28	16.9	0.583	0.098	0.098	3.3	12.1	7.7	34.3	3.1
3	Bobby Portis	MIL	C	25	19.9	0.598	0.263	0.122	9.9	25.3	17.9	7.4	1.1
4	Anfernee Simons	POR	SG	21	12.3	0.589	0.703	0.142	1.3	12.5	6.8	11.4	0.1
	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%	
Averages	27.0	17.4	0.6	0.4	0.2	4.7	17.4	11.1	19.0	2.3	1.6	11.9	

Rank 5

Most number of wins: 59

Total yearly salary: \$53,492,617

Players in top 10 teams: 2

Players in bottom 10 teams: 1

	Player	Tm	Pos	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%
0	Deandre Ayton	PHO	C	22	20.3	0.653	0.029	0.252	12.4	26.3	19.5	6.8	1.0
1	LaMelo Ball	CHO	PG	19	17.5	0.539	0.388	0.246	4.6	17.9	11.1	33.9	2.7
2	Sterling Brown	HOU	SG	25	11.1	0.597	0.642	0.093	3.2	16.8	9.7	8.4	1.5
3	Joe Ingles	UTA	SF	33	15.9	0.672	0.722	0.160	1.6	11.8	6.9	24.0	1.2
4	Marcus Morris	LAC	PF	31	14.5	0.614	0.507	0.152	2.7	14.5	8.8	5.6	1.1
	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%	

Averages	26.0	15.9	0.6	0.5	0.2	4.9	17.5	11.2	15.7	1.5	1.4	12.7
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Worst Team

Least number of wins: 25.710530411719333

Total yearly salary: 57248729

Players in top 10 teams: 1

Players in bottom 10 teams: 3

	Player	Tm	Pos	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%
0	Carmelo Anthony	POR	PF	36	14.6	0.547	0.418	0.198	2.0	11.8	6.8	9.2	1.3
1	Khem Birch	ORL	C	28	14.1	0.517	0.100	0.407	12.3	14.2	13.2	8.0	1.6
2	Amir Coffey	LAC	SG	23	10.1	0.585	0.544	0.369	2.9	9.4	6.3	7.4	1.3
3	Jerami Grant	DET	SF	26	16.9	0.556	0.353	0.368	2.1	13.2	7.6	14.3	0.9
4	Donovan Mitchell	UTA	PG	24	21.3	0.569	0.423	0.290	3.1	10.6	7.0	26.7	1.4

	Age	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%
Averages	27.4	15.4	0.6	0.4	0.3	4.5	11.8	8.2	13.1	1.3	1.6	9.2

Comparing Currently Successful Teams with Predicted Rank 1 Team

```
In [64]: stats, predicted_avgs, player_names, total_salary, num_wins = info[0]
```

```
In [18]: cols = np.array(parsed_data.columns)
```

```
In [90]: suns_starters = ["Devin Booker", "Chris Paul", "Mikal Bridges", "Deandre Ayton", "Cameron Johnson", "Jae Crowder", "Drew Gordon", "Darius Bazley", "Josh Okogie", "Terrell Davis"]
warrs_starters = ["Steph Curry", "Klay Thompson", "Draymond Green", "Andrew Wiggins", "Jonathan Kuminga", "Moses Brown", "Donte DiVincenzo", "Gary Trent Jr.", "Jordan Poole", "Andre Drummond"]
heat_starters = ["Jimmy Butler", "Bam Adebayo", "Duncan Robinson", "PJ Tucker", "Kevin Love", "Tyler Herro", "Caleb Martin", "Dwight Powell", "Jevon Carter", "Markus Howard"]

subset = parsed_data[parsed_data["Player"].isin(suns_starters)]
subset_avgs_suns = pd.DataFrame(subset.mean(axis=0).round(1))
```

```

subset = parsed_data[parsed_data["Player"].isin(heat_starters)]
subset_avgs_heat = pd.DataFrame(subset.mean(axis=0).round(1))

subset = parsed_data[parsed_data["Player"].isin(warrr_starters)]
subset_avgs_warrr = pd.DataFrame(subset.mean(axis=0).round(1))

fig, axes = plt.subplots(3, 3, figsize=(15, 15))
row = 0
col = 0

fig.suptitle("Team Averages, Higher is Better", fontsize=20)
for column in parsed_data.iloc[:, 2:23]:
    if column in ["PER", "TS%", "ORB%", "DRB%", "TRB%", "BLK%", "STL%"]:
        x = ["Suns", 'Heat', 'Warriors', "Predicted"]
        y = [subset_avgs_suns.loc[column].values[0], subset_avgs_heat.
        axes[row, col].bar(x, y, color=['orange', 'red', 'blue', 'black'])
        axes[row, col].set_title(column)

        col += 1

        if col == 3:
            col = 0
            row += 1

print("\n")

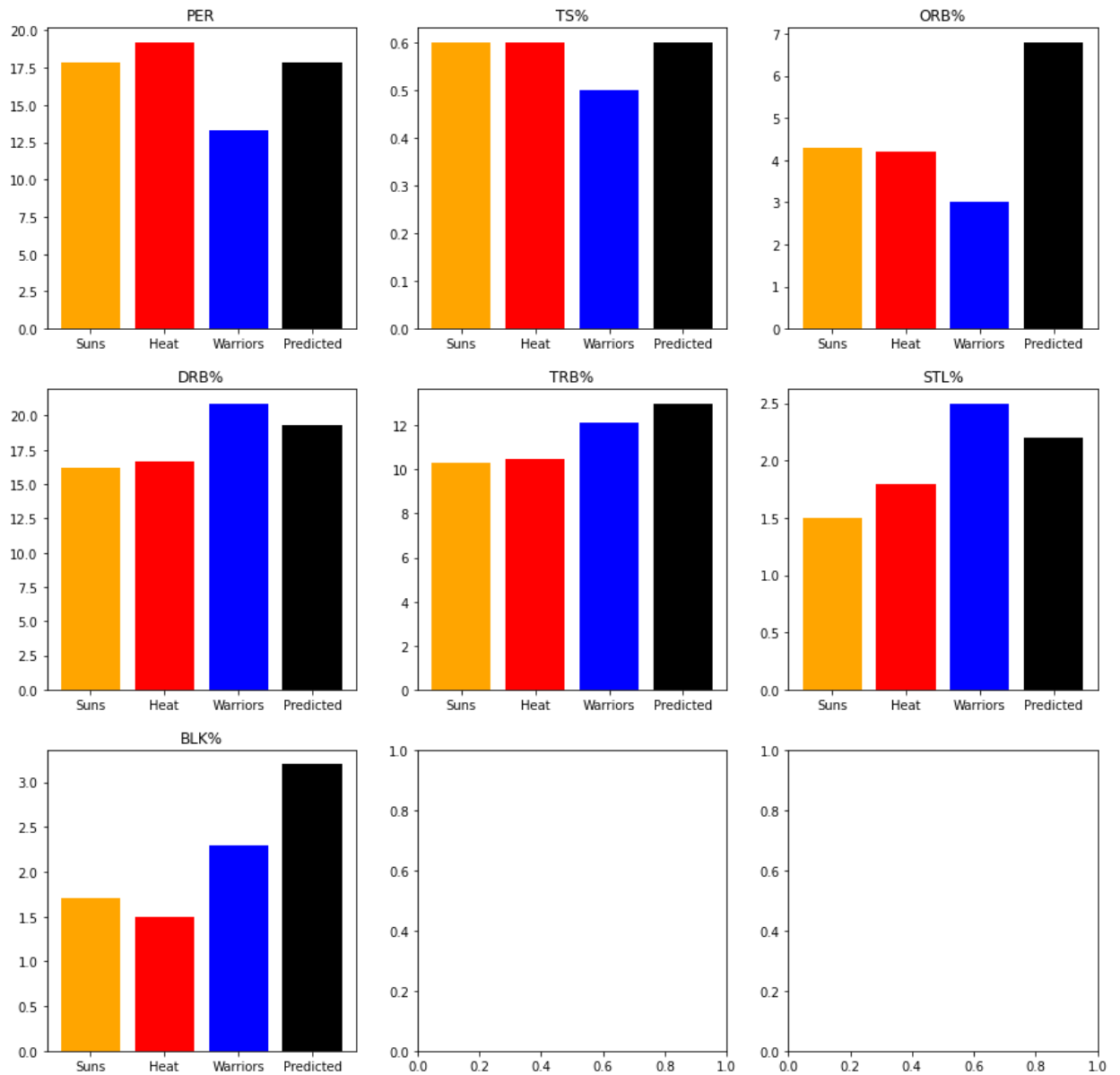
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
row = 0
col = 0

fig.suptitle("Team Averages, Lower is Better", fontsize=20)
for column in parsed_data.iloc[:, 2:23]:
    if column in ["TOV%"]:
        x = ["Suns", 'Heat', 'Warriors', "Predicted"]
        y = [subset_avgs_suns.loc[column].values[0], subset_avgs_heat.
        axes[0].bar(x, y, color=['orange', 'red', 'blue', 'black'])
        axes[0].set_title(column)
    if column in ["2021-22 Salary"]:
        x = ["Suns", 'Heat', 'Warriors', "Predicted"]
        y = [subset_avgs_suns.loc[column].values[0], subset_avgs_heat.
        axes[1].bar(x, y, color=['orange', 'red', 'blue', 'black'])
        axes[1].set_title(column)

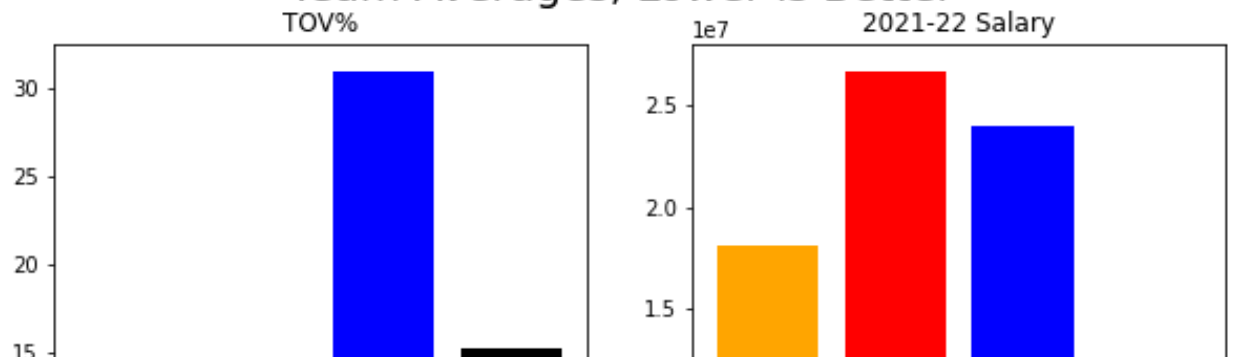
print("\n")

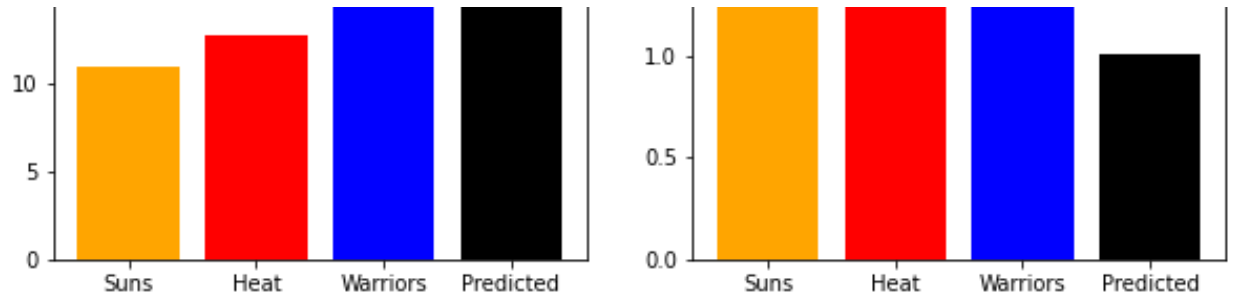
```

Team Averages, Higher is Better



Team Averages, Lower is Better





Looking at Distribution of Players in Predicted Teams

In [38]:


```

fig, axes = plt.subplots(2, 3, figsize=(15, 15))
row = 0
col = 0

fig.suptitle("Players Currently in Top, Middle, or Bottom Teams from 2

for i in range(len(info)):
    stats, averages, player_names, total_salary, num_wins = info[i]
    player_teams = set(map(lambda s : teams_dict[s], stats["Tm"]))
    top_overlap = len(player_teams.intersection(top_10_teams))
    bot_overlap = len(player_teams.intersection(bot_10_teams))

    if top_overlap == 0:
        sizes = [bot_overlap * 10, 100 - (bot_overlap * 10)]
        axes[row, col].pie(sizes, labels=["In Bottom-10", "In Mid-Tier"])
    elif bot_overlap == 0:
        sizes = [top_overlap * 10, 100 - (top_overlap * 10)]
        axes[row, col].pie(sizes, labels=["In Top-10", "In Mid-Tier"],
    else:
        sizes = [top_overlap * 10, bot_overlap * 10, 100 - (bot_overlap * 10)]
        axes[row, col].pie(sizes, labels=["In Top-10", "In Bottom-10", "In Mid-Tier"])

    axes[row, col].set_title("Predicted Rank " + str(i + 1) + " Team")

    col += 1

    if col == 3:
        col = 0
        row += 1

stats, averages, player_names, total_salary, num_wins = get_pred_info(
player_teams = set(map(lambda s : teams_dict[s], stats["Tm"]))
top_overlap = len(player_teams.intersection(top_10_teams))
bot_overlap = len(player_teams.intersection(bot_10_teams))
axes[1, 2].set_title("Predicted Worst Team")
if top_overlap == 0:
    sizes = [bot_overlap * 10, 100 - (bot_overlap * 10)]
    axes[1, 2].pie(sizes, labels=["In Bottom-10", "In Mid-Tier"], colors=
elif bot_overlap == 0:
    sizes = [top_overlap * 10, 100 - (top_overlap * 10)]
    axes[1, 2].pie(sizes, labels=["In Top-10", "In Mid-Tier"], colors=
else:
    sizes = [top_overlap * 10, bot_overlap * 10, 100 - (bot_overlap * 10)]
    axes[1, 2].pie(sizes, labels=["In Top-10", "In Bottom-10", "In Mid-Tier"])

```

Players Currently in Top, Middle, or Bottom Teams from 2021-22 Season

