NBA Player Performance Statistics: Data Analysis Project

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Scenario

There is an opportunity for a team to measure the statistics of players signed to official contracts with the National Basketball Association (NBA), a professional basketball league in the United States that is composed of 30 teams. Teams can have up to 15 players, either during the regular season or during playoffs season. For every game played, a player is measured in their in-game performance by multiple analysts, in terms of the number of points they have scored, how many steals they have made from the opposing team, etc. This project begins by identifying a dataset that contains data on players and their respective teams in the NBA, and then loaded into a python environment and stored in a Pandas data frame. The data was cleaned and processed to remove any unnecessary columns or rows as needed, and data types of the columns were checked and corrected during the data analysis phase when it was necessary. Data Analysis was used to describe the statistics of each column and of the data frame. The data was analyzed using Tableau and Python to create visualizations, which were used to identify trends and patterns in the data.

Problem Statement

The objective of this project is to make meaningful insights from a dataset of NBA Player performance statistics and identify trends and patterns within the data.

Datasets Used

1. NBA Player Performance Stats

   https://www.kaggle.com/datasets/iabdulw/nba-player-performance-stats

   This compiled dataset was published on Kaggle, where the user extracted data from an NBA stats website using web scraping techniques and compiled it into an Excel CSV file.

Data Dictionary

The following dataset was cleaned, and analysis was performed on it in later steps. Our final dataset included the following columns in the data table:

- Player: string – name of the player
- Pos (Position): string - position played by the player
- Age: integer - age of the player as of February 1, 2023
- Tm (Team): string - team the player belongs to
- G (Games Played): integer - number of games played by the player
- GS (Games Started): integer - number of games started by the player
- MP (Minutes Played): integer - total minutes played by the player
- FG (Field Goals): integer - number of field goals made by the player
- 3P (3-Point Field Goals): integer - number of 3-point field goals made by the player
- 2P (2-Point Field Goals): integer - number of 2-point field goals made by the player
- FT (Free Throws): integer - number of free throws made by the player
- TRB (Total Rebounds): integer - total rebounds by the player
- AST (Assists): integer - number of assists made by the player
- STL (Steals): integer - number of steals made by the player
- BLK (Blocks): integer - number of blocks made by the player
- TOV (Turnovers): integer - number of turnovers made by the player
- PF (Personal Fouls): integer - number of personal fouls made by the player
- PTS (Points): integer - total points scored by the player

Data Cleaning and Preparation

In our first step, the proper libraries were imported, and the csv file downloaded from our dataset was loaded into the Python environment.

```
In [5]: import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import numpy as np
```

```
In [6]: data = pd.read_csv(r"C:\Users\shahr\OneDrive\Desktop\nba_data_processed.csv")
        df = pd.DataFrame(data)
        df
```

Out[6]:

	Player	Pos	Age	Tm	G	GS	MP	FG	FGA	FG%	...	FT%	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
0	Precious Achiuwa	C	23.0	TOR	38.0	11.0	23.3	3.9	8.1	0.482	...	0.689	2.0	4.6	6.6	1.0	0.6	0.7	1.2	2.1	10.2
1	Steven Adams	C	29.0	MEM	42.0	42.0	27.0	3.7	6.3	0.597	...	0.364	5.1	6.5	11.5	2.3	0.9	1.1	1.9	2.3	8.6
2	Bam Adebayo	C	25.0	MIA	57.0	57.0	35.0	8.4	15.7	0.536	...	0.800	2.6	7.2	9.8	3.2	1.2	0.8	2.5	2.8	21.2
3	Ochai Agbaji	SG	22.0	UTA	39.0	2.0	15.6	1.8	3.8	0.483	...	0.682	0.7	1.1	1.8	0.6	0.2	0.1	0.3	1.4	5.0
4	Santi Aldama	PF	22.0	MEM	56.0	18.0	22.0	3.3	7.0	0.474	...	0.729	1.0	3.6	4.6	1.2	0.7	0.7	0.7	1.9	9.4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
644	McKinley Wright IV	PG	24.0	DAL	20.0	1.0	10.3	1.2	2.5	0.469	...	0.636	0.3	1.0	1.3	1.9	0.4	0.2	0.6	0.9	2.9
645	Thaddeus Young	PF	34.0	TOR	49.0	9.0	15.5	2.1	3.8	0.562	...	0.692	1.4	1.8	3.2	1.4	1.1	0.1	0.8	1.8	4.7
646	Trae Young	PG	24.0	ATL	54.0	54.0	35.3	8.5	19.8	0.429	...	0.889	0.7	2.2	2.9	10.2	1.1	0.1	4.1	1.5	27.0
647	Cody Zeller	C	30.0	MIA	3.0	0.0	15.7	2.7	4.0	0.667	...	0.500	1.7	1.0	2.7	1.0	0.3	1.0	0.7	3.0	6.3
648	Ivica Zubac	C	25.0	LAC	59.0	59.0	29.4	4.0	6.5	0.617	...	0.699	3.3	6.8	10.1	1.1	0.4	1.3	1.7	2.9	10.2

649 rows × 29 columns

Rows that contained null values were removed and rows that were duplicates of one another were dropped as well so the table can only have unique values.

```
In [3]: df = df.dropna()
```

```
In [4]: print(f"number of duplicate rows: {len(df[df.duplicated()])}")

        number of duplicate rows: 0
```

```
In [5]: df = df.drop_duplicates(keep = 'first')
        print(f"number of rows after duplicates dropped: {len(df)}")

        number of rows after duplicates dropped: 552
```

Because the dataset has multiple columns of data, we had to first look at all the columns and their types to figure out which columns to remove from the dataset.

```
In [6]: df.columns

Out[6]: Index(['Player', 'Pos', 'Age', 'Tm', 'G', 'GS', 'MP', 'FG', 'FGA', 'FG%', '3P',
               '3PA', '3P%', '2P', '2PA', '2P%', 'eFG%', 'FT', 'FTA', 'FT%', 'ORB',
               'DRB', 'TRB', 'AST', 'STL', 'BLK', 'TOV', 'PF', 'PTS'],
              dtype='object')
```

```
In [7]: column_types = df.dtypes
        column_types
```

```
Out[7]: Player     object
        Pos        object
        Age       float64
        Tm         object
        G         float64
        GS        float64
        MP        float64
        FG        float64
        FGA       float64
        FG%       float64
        3P        float64
        3PA       float64
        3P%       float64
        2P        float64
        2PA       float64
        2P%       float64
        eFG%      float64
        FT        float64
        FTA       float64
        FT%       float64
        ORB       float64
        DRB       float64
        TRB       float64
        AST       float64
        STL       float64
        BLK       float64
        TOV       float64
        PF        float64
        PTS       float64
        dtype: object
```

Any columns that either had attempts or percentages of a column such as FGA or FG% were removed to allow for more simplicity.

```
In [8]: columns_to_remove = ['FGA', 'FG%', '3PA','3P%','2PA','2P%', 'eFG%', 'FTA', 'FT%', 'ORB', 'DRB']
        df = df.drop(columns_to_remove, axis=1)
```

```
In [9]: df.columns
```

```
Out[9]: Index(['Player', 'Pos', 'Age', 'Tm', 'G', 'GS', 'MP', 'FG', '3P', '2P', 'FT',
               'TRB', 'AST', 'STL', 'BLK', 'TOV', 'PF', 'PTS'],
              dtype='object')
```

Because there were a few players that were playing more than 1 position, the data was cleaned so that every player only playing 1 position was represented.

```
In [10]: df['Pos'].replace({'SF-SG': 'SF', 'SG-PG': 'SG', 'PF-SF':'PF'}, inplace=True)
         df['Pos'].value_counts()
```

```
Out[10]: Pos
         SG    135
         PG    114
         PF    105
         SF    100
         C      98
         Name: count, dtype: int64
```

Data Analysis

To perform analysis, we added an extra column of data to our dataset, Players' 2022-23 Salary. Another csv file was found on the internet which contained data on salary, so this csv file was loaded into our python notebook and another dataframe was created. This dataframe was merged with our original dataframe while deleting any unnecessary columns from the new dataframe and repositioning the column in the dataset as well.

In [34]:
```
salary_data = pd.read_csv(r"C:\Users\shahr\OneDrive\Desktop\2022-23_NBA_Salary.csv")
df_2 = pd.DataFrame(salary_data)
df_3 = pd.merge(df, df_2, on='Player')
del df_3['Rk']
del df_3['Team']
col1 = df_3.pop('2022-23 Salary')
df_3.insert(4, '2022-23 Salary', col1)
df_3
```

Out[34]:

	Player	Pos	Age	Tm	2022-23 Salary	G	GS	MP	FG	3P	2P	FT	TRB	AST	STL	BLK	TOV	PF	PTS
0	Precious Achiuwa	C	23.0	TOR	$2,840,160	38.0	11.0	23.3	3.9	0.5	3.4	1.9	6.6	1.0	0.6	0.7	1.2	2.1	10.2
1	Steven Adams	C	29.0	MEM	$17,926,829	42.0	42.0	27.0	3.7	0.0	3.7	1.1	11.5	2.3	0.9	1.1	1.9	2.3	8.6
2	Bam Adebayo	C	25.0	MIA	$30,351,780	57.0	57.0	35.0	8.4	0.0	8.4	4.4	9.8	3.2	1.2	0.8	2.5	2.8	21.2
3	Ochai Agbaji	SG	22.0	UTA	$3,918,360	39.0	2.0	15.6	1.8	0.9	0.9	0.4	1.8	0.6	0.2	0.1	0.3	1.4	5.0
4	Santi Aldama	PF	22.0	MEM	$2,094,120	56.0	18.0	22.0	3.3	1.4	2.0	1.4	4.6	1.2	0.7	0.7	0.7	1.9	9.4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
579	Christian Wood	C	27.0	DAL	$14,317,459	50.0	17.0	27.4	6.4	1.7	4.7	3.2	8.0	1.7	0.4	1.2	1.9	2.7	17.6
580	Delon Wright	PG	30.0	WAS	$7,804,878	31.0	3.0	22.6	2.5	0.9	1.6	0.9	3.2	3.5	1.9	0.3	1.0	1.3	6.7
581	Thaddeus Young	PF	34.0	TOR	$8,000,000	49.0	9.0	15.5	2.1	0.1	2.0	0.4	3.2	1.4	1.1	0.1	0.8	1.8	4.7
582	Trae Young	PG	24.0	ATL	$37,096,500	54.0	54.0	35.3	8.5	2.2	6.3	7.9	2.9	10.2	1.1	0.1	4.1	1.5	27.0
583	Ivica Zubac	C	25.0	LAC	$10,123,457	59.0	59.0	29.4	4.0	0.0	4.0	2.2	10.1	1.1	0.4	1.3	1.7	2.9	10.2

584 rows × 19 columns

The new column "2022-23 Salary" was then converted from an object type to a float type to allow for calculations to be made in later steps.

In [35]:
```
df_3['2022-23 Salary'] = df_3['2022-23 Salary'].replace({'\$': '', ',': ''}, regex=True).astype(float)
```

The sum of each column was then calculated, whether it was an object type or float, as our first part of conducting Data Analysis.

```
In [36]: df_3.sum()
```

```
Out[36]: Player          Precious AchiuwaSteven AdamsBam AdebayoOchai A...
         Pos             CCCSGPFSGSGSGSGCPGPFPFSFPGSFSFCCSFPGCCCPFSGPGP...
         Age                                                      15535.0
         Tm              TORMEMMIAUTAMEMTOTUTAMINMILCLENOPMINMILMILORLT...
         2022-23 Salary                                        5906565901.0
         G                                                        21963.0
         GS                                                       10107.0
         MP                                                       12204.4
         FG                                                        2032.9
         3P                                                         642.1
         2P                                                        1392.2
         FT                                                         884.6
         TRB                                                       2150.6
         AST                                                       1289.0
         STL                                                        382.8
         BLK                                                        222.5
         TOV                                                        681.1
         PF                                                        1053.2
         PTS                                                       5587.3
         dtype: object
```

The whole dataset, specifically the number columns, was described in our next step of Data Analysis.

```
In [37]: df_3.describe()
```

Out[37]:

	Age	2022-23 Salary	G	GS	MP	FG	3P	2P	FT	TRB	AST	STL
count	584.000000	5.810000e+02	584.000000	584.000000	584.000000	584.000000	584.000000	584.000000	584.000000	584.000000	584.000000	584.000000
mean	26.601027	1.016621e+07	37.607877	17.306507	20.897945	3.480993	1.099486	2.383904	1.514726	3.682534	2.207192	0.655479
std	4.487841	1.118258e+07	17.654547	20.971603	8.881043	2.346538	0.854982	1.933690	1.502264	2.277582	1.930885	0.427130
min	19.000000	1.055220e+05	1.000000	0.000000	2.800000	0.200000	0.000000	0.000000	0.000000	0.300000	0.000000	0.000000
25%	23.000000	2.201520e+06	25.000000	1.000000	13.900000	1.800000	0.400000	1.000000	0.500000	2.100000	0.900000	0.300000
50%	26.000000	5.377520e+06	42.000000	5.500000	20.650000	2.800000	1.000000	1.700000	1.000000	3.100000	1.500000	0.600000
75%	30.000000	1.300000e+07	52.000000	37.000000	28.625000	4.600000	1.625000	3.225000	1.900000	4.700000	2.900000	0.900000
max	42.000000	4.807001e+07	64.000000	63.000000	37.500000	11.300000	4.900000	10.300000	10.100000	12.400000	10.700000	3.200000

The “Team” column was described to find out how many teams are a part of the NBA.

```
In [38]: df_3['Tm'].describe()
```

```
Out[38]: count      584
         unique      31
         top        TOT
         freq        64
         Name: Tm, dtype: object
```

This column was also further broken down to look at how many players are in each team.

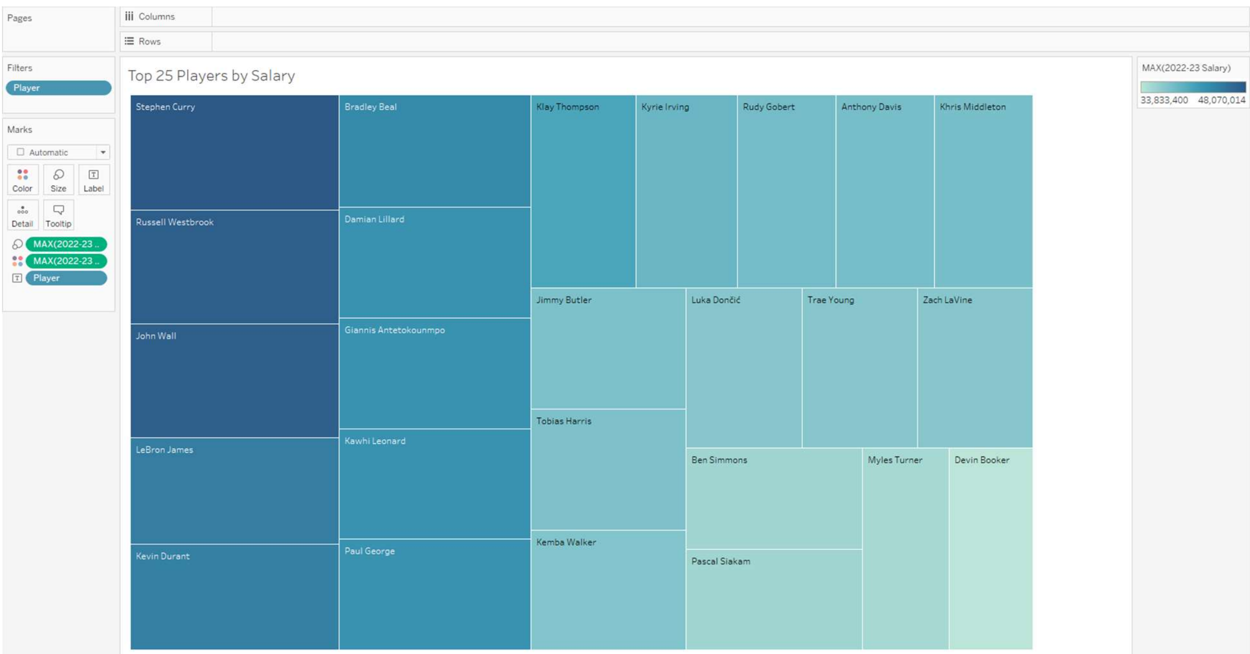
```
In [39]: df_3['Tm'].value_counts().tail(100)

Out[39]: Tm
         TOT    64
         SAS    24
         LAL    23
         MIL    21
         LAC    21
         PHO    20
         ORL    20
         DEN    19
         IND    19
         OKC    19
         BRK    19
         MIN    18
         DAL    18
         DET    17
         HOU    17
         CHI    17
         POR    17
         MIA    17
         NOP    16
         CLE    16
         UTA    16
         WAS    15
         BOS    15
         CHO    15
         MEM    15
         NYK    15
         GSW    15
         TOR    14
         ATL    14
         SAC    14
         PHI    14
         Name: count, dtype: int64
```

The number of unique teams was calculated, then a list was created to group all columns together to end our Data Analysis and a final version of our dataset was exported into a csv file to save all changes we made to the dataset and to create our visualizations as well.

```
In [40]: df_3['Tm'].nunique()

Out[40]: 31

In [41]: list(df_3.select_dtypes(include='number').columns)

Out[41]: ['Age',
          '2022-23 Salary',
          'G',
          'GS',
          'MP',
          'FG',
          '3P',
          '2P',
          'FT',
          'TRB',
          'AST',
          'STL',
          'BLK',
          'TOV',
          'PF',
          'PTS']

In [42]: df_3.to_csv('finalnbadataset.csv')
```

Data Visualization

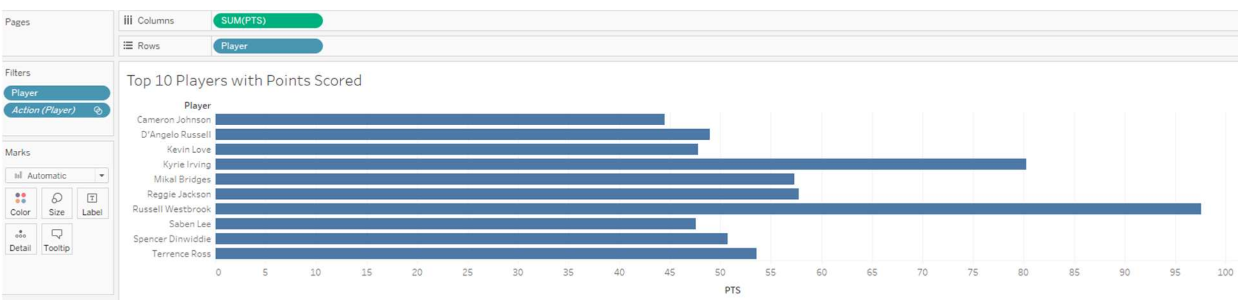
The first few visualizations were created using the Tableau software. After downloading our final csv file, it was loaded into the Tableau environment. The first visualization we created was a tree map of the top 25 players by Salary. The 2022-23 Salary and Player columns were placed into the Marks card and Players were used to filter the Data.



The next visualization we created was a scatter plot with a trend line to draw a conclusion between minutes played and Player salaries. Because this graph showed a positive correlation, we were able to draw the conclusion that for more minutes played, the more a player earned.

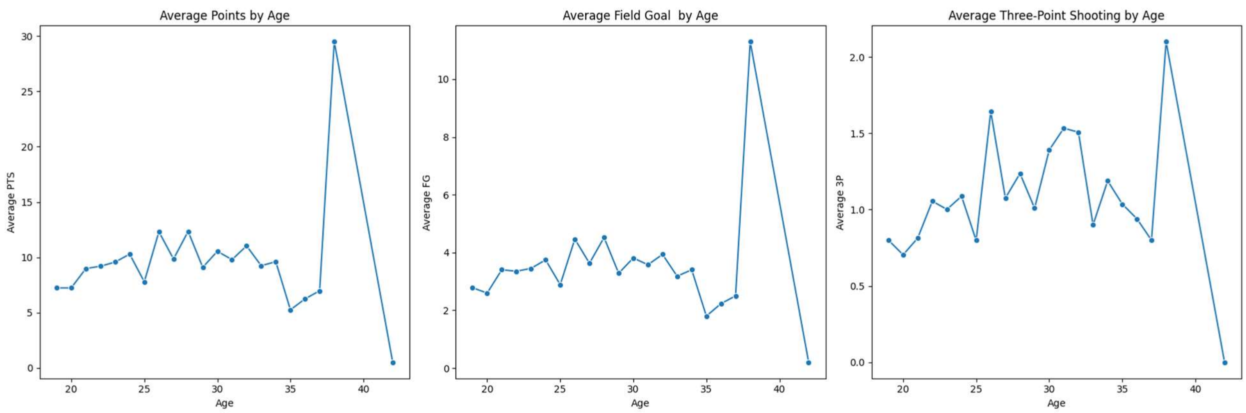
[See next page for visualization]

The last visualization we made using Tableau was a bar graph to compare Players with points scored and filter the Top 10 players with the most points scored.



We made our last two visualizations using Python as we were limited by Tableau to make these graphs. The first graph we made using Python was a few line graphs in a 3x1 matrix grid plot to compare a few categories to Player ages, which were average points, average field goals, and average three-point shooting.

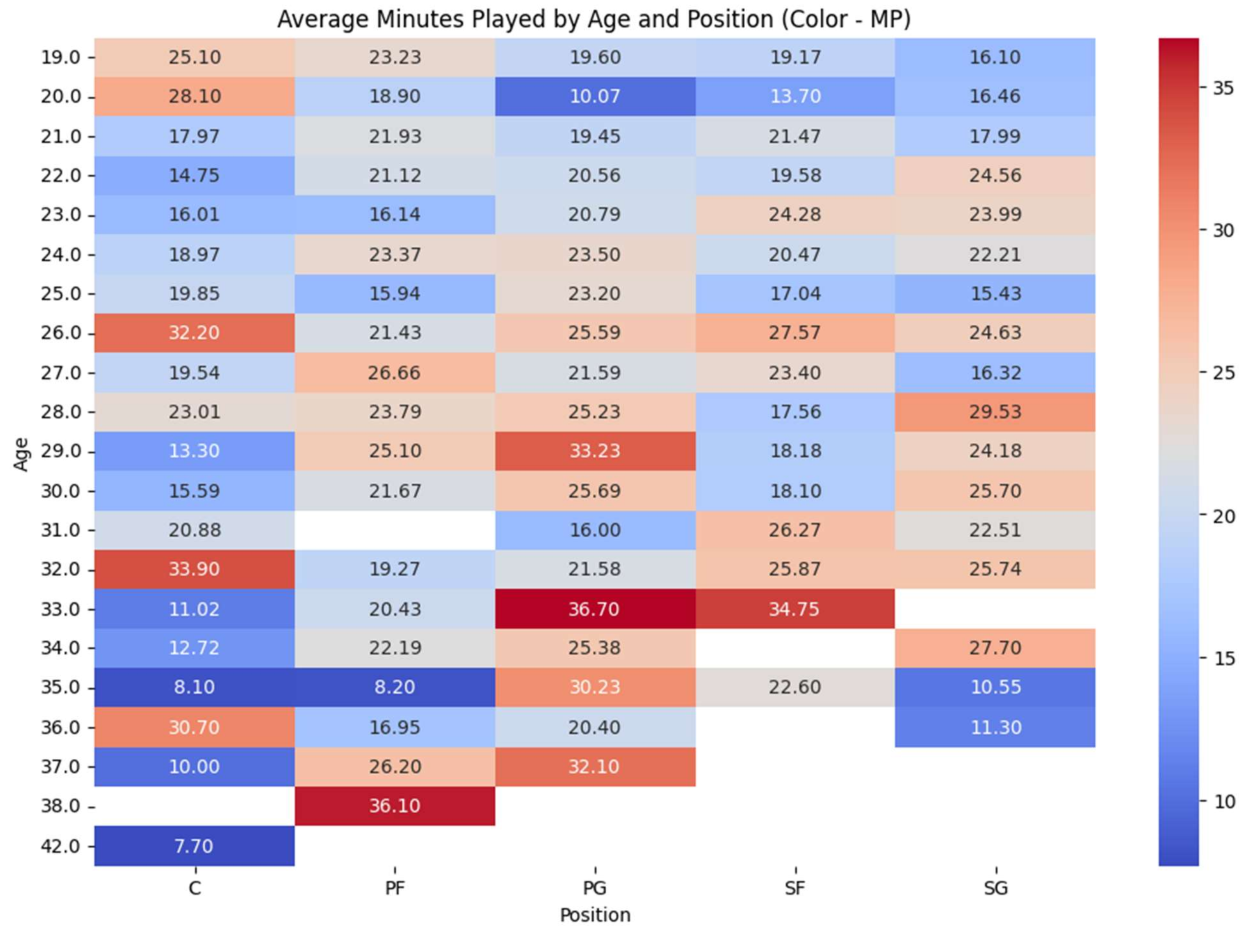
```
In [25]: def plot_scoring(metric, title, ax):
             age_stats = df_3.groupby('Age').agg({metric: np.mean}).reset_index()
             sns.lineplot(x='Age', y=metric, data=age_stats, marker='o', ax=ax)
             ax.set_title(title)
             ax.set_xlabel('Age')
             ax.set_ylabel(f'Average {metric}')

         fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

         metrics_age = ['PTS', 'FG', '3P']
         titles_age = ['Average Points by Age', 'Average Field Goal  by Age', 'Average Three-Point Shooting by Age']

         for i in range(3):
             plot_scoring(metrics_age[i], titles_age[i], axes[i])

         plt.tight_layout()
         plt.show()
```



The last visualization we created was a Heat Map to show the average minutes played by age and by position. The color bar on the right was a legend to represent the average minutes played, while position and age were part of the x-axis and y-axis, respectively.

```
In [26]: age_position_mp = df_3.groupby(['Age', 'Pos'])['MP'].mean().reset_index()

         age_position_mp_matrix = age_position_mp.pivot_table(index='Age', columns='Pos', values='MP')

         plt.figure(figsize=(12, 8))
         sns.heatmap(age_position_mp_matrix, annot=True, cmap='coolwarm', fmt='.2f')
         plt.title('Average Minutes Played by Age and Position')
         plt.xlabel('Position')
         plt.ylabel('Age')
         plt.show()
```

[See next page for Heat Map]



Conclusion

By analyzing our visualizations, we determined that the average minutes played, and the 2022-23 Salary had the strongest correlation with the other data columns whether it was points, three-point shooting, etc. We came to the conclusion that as players averaged more minutes played and had a higher salary, they steadily improved their in game performance by scoring more points, field goals, and three points, among other statistics.