final_nba_analysis

December 11, 2025

0.1 Param Sodhi and Emmanuel Damas: NBA High Scores and Team Accounts

We began our study with the goal of analyzing NBA player stats from the 2022-23 and 2023-24 regular seasons to see what drives scoring. Instead of focusing solely on "who scores the most," I'd like to explain the reason why specific players score over the rest.

We constructed our study around four major questions:

1. What player attributes correlate most with high scoring per game?
2. Do players who shoot more efficiently also score more?
3. Are guards, forwards, or centers associated with higher scoring averages?
4. Do teams with higher-scoring lead players win more games?

This notebook describes how we cleaned and integrated both seasons' datasets, as well as how we developed a few additional metrics to help us visualize what it takes to be an exceptional NBA team and player. Reminder this dataset is only showing you the 23-24 information to save space. Anything that you see performed to 23-24 was also performed on 22-23.

0.2 STEP 1

To start off with this section we decide to load player average data for a full NBA Season. We chose two NBA Seasons because they were the most usable data sets that we could find. In an ideal world we would have gotten more. So we prepared them for analysis.

We started off by reading in the CSV files for the 22–23 and 23–24 NBA regular seasons. The first thing we thought is that we need to standardize all the columns in our dataset, completely filtering out any anomalies in the naming conventions. Since we did not have any null values we came to the conclusion that this was the first step we should take. We then decided to drop columns that were unhelpful such as the rank column.

[4]:
```
nba_22_23['season'] = '22-23'
nba_23_24['season'] = '23-24'
```

[7]:
```
nba_22_23.columns = (
    nba_22_23.columns.str.strip().str.lower().str.replace('%', '_pct',␣
 ↪regex=False).str.replace(' ', '_')
)
```

[8]:
```
nba_23_24.columns = (
    nba_23_24.columns.str.strip().str.lower().str.replace('%', '_pct',␣
 ↪regex=False).str.replace(' ', '_')
)
```

Here is an example of what the column names looked like after filtering and cleaning them to make them more user friendly and easier to comprehend:

[10]:
```
nba_23_24.columns
```

[10]:
```
Index(['rk', 'player', 'pos', 'age', 'tm', 'g', 'gs', 'mp', 'fg', 'fga',
       'fg_pct', '3p', '3pa', '3p_pct', '2p', '2pa', '2p_pct', 'efg_pct', 'ft',
       'fta', 'ft_pct', 'orb', 'drb', 'trb', 'ast', 'stl', 'blk', 'tov', 'pf',
       'pts', 'season'],
      dtype='object')
```

Here we have the data after removing the rk:

[13]:
```
nba_23_24_withoutrk.head(10)
```

[13]:
```
                  player   pos  age   tm   g  gs    mp   fg   fga  fg_pct  \
0       Precious Achiuwa  PF-C   24  TOT  74  18  21.9  3.2   6.3   0.501
1       Precious Achiuwa     C   24  TOR  25   0  17.5  3.1   6.8   0.459
2       Precious Achiuwa    PF   24  NYK  49  18  24.2  3.2   6.1   0.525
3            Bam Adebayo     C   26  MIA  71  71  34.0  7.5  14.3   0.521
4            Ochai Agbaji    SG   23  TOT  78  28  21.0  2.3   5.6   0.411
5            Ochai Agbaji    SG   23  UTA  51  10  19.7  2.1   4.9   0.426
6            Ochai Agbaji    SG   23  TOR  27  18  23.6  2.7   6.8   0.391
7            Santi Aldama    PF   23  MEM  61  35  26.5  4.0   9.3   0.435
8  Nickeil Alexander-Walker    SG   25  MIN  82  20  23.4  2.9   6.6   0.439
9           Grayson Allen    SG   28  PHO  75  74  33.5  4.5   9.1   0.499

   ...  orb  drb   trb  ast  stl  blk  tov   pf   pts  season
0  ...  2.6  4.0   6.6  1.3  0.6  0.9  1.1  1.9   7.6   23-24
1  ...  2.0  3.4   5.4  1.8  0.6  0.5  1.2  1.6   7.7   23-24
2  ...  2.9  4.3   7.2  1.1  0.6  1.1  1.1  2.1   7.6   23-24
3  ...  2.2  8.1  10.4  3.9  1.1  0.9  2.3  2.2  19.3   23-24
4  ...  0.9  1.8   2.8  1.1  0.6  0.6  0.8  1.5   5.8   23-24
5  ...  0.7  1.8   2.5  0.9  0.5  0.6  0.7  1.3   5.4   23-24
6  ...  1.4  1.9   3.3  1.3  0.7  0.6  1.1  1.9   6.7   23-24
7  ...  1.2  4.6   5.8  2.3  0.7  0.9  1.1  1.5  10.7   23-24
8  ...  0.4  1.6   2.0  2.5  0.8  0.5  0.9  1.7   8.0   23-24
9  ...  0.6  3.3   3.9  3.0  0.9  0.6  1.3  2.1  13.5   23-24

[10 rows x 30 columns]
```

0.3 Step 2

After cleaning the columns and filtering out unnecessary data that is not pertinent to us we were met with the most challenging aspect of the data prep. How do we deal with players that were on multiple teams during the season? We came to find out that Basketball data lists each team that a player plays for in a season separately while also include a "TOT" entry that aggregates all stats of the player year round. This means that certain players appear twice or even three times in the dataset. This absolutely ruined my correlations at first because the same player was counted many times. To address this, we adjusted the dataset to always prefer real team entries above the TOT aggregate. We gave TOT priority when a player had multiple teams they played for and if a player had one team they played for, then we would use that as there benchmark.

[14]:
```
def reduce_to_valid_players(df):
    sorted_players = df.sort_values(by=['player', 'tm'], ascending=[True, True])

    sorted_players['priority'] = (sorted_players.tm != 'TOT').astype(int)
    sorted_players = sorted_players.sort_values(['player', 'priority']).
 ↪drop_duplicates(subset='player', keep='first')

    return sorted_players.drop(columns='priority').reset_index(drop=True)
```

[15]:
```
nba_22_23_cleaned = reduce_to_valid_players(nba_22_23_withoutrk).
 ↪reset_index(drop=True)
nba_23_24_cleaned = reduce_to_valid_players(nba_23_24_withoutrk).
 ↪reset_index(drop=True)
```

[17]:
```
nba_23_24_cleaned.head(10)
```

[17]:
```
               player pos  age   tm   g  gs    mp   fg  fga  fg_pct  ...  orb  \
0          A.J. Green  SG   24  MIL  56   0  11.0  1.5  3.5   0.423  ...  0.2
1         A.J. Lawson  SG   23  DAL  42   0   7.4  1.3  2.9   0.446  ...  0.3
2          AJ Griffin  SF   20  ATL  20   0   8.6  0.9  3.1   0.290  ...  0.1
3        Aaron Gordon  PF   28  DEN  73  73  31.5  5.5  9.8   0.556  ...  2.4
4       Aaron Holiday  PG   27  HOU  78   1  16.3  2.4  5.3   0.446  ...  0.3
5       Aaron Nesmith  SF   24  IND  72  47  27.7  4.4  8.8   0.496  ...  0.9
6       Aaron Wiggins  SG   25  OKC  78   4  15.7  2.7  4.8   0.562  ...  0.8
7        Adam Flagler  SG   24  OKC   2   0   7.0  0.5  3.5   0.143  ...  0.0
8        Adama Sanogo  PF   21  CHI   9   0   7.3  1.6  3.0   0.519  ...  2.1
9  Admiral Schofield  PF   26  ORL  23   0   3.7  0.4  1.1   0.385  ...  0.1

   drb  trb  ast  stl  blk  tov  pf   pts season
0  1.0  1.1  0.5  0.2  0.1  0.2  0.9   4.5  23-24
1  0.9  1.2  0.5  0.2  0.1  0.3  0.5   3.2  23-24
2  0.8  0.9  0.3  0.1  0.1  0.4  0.3   2.4  23-24
3  4.1  6.5  3.5  0.8  0.6  1.4  1.9  13.9  23-24
4  1.3  1.6  1.8  0.5  0.1  0.7  1.6   6.6  23-24
5  2.9  3.8  1.5  0.9  0.7  0.9  3.3  12.2  23-24
6  1.6  2.4  1.1  0.7  0.2  0.7  1.2   6.9  23-24
```

```
7  0.0  0.0  2.0  0.0  0.0  0.0  0.0   1.5   23-24
8  1.9  4.0  0.0  0.1  0.0  0.6  0.6   4.0   23-24
9  0.6  0.7  0.3  0.0  0.0  0.2  0.4   1.1   23-24

[10 rows x 30 columns]
```

[18]:
```
nba_combined = pd.concat([nba_22_23_cleaned, nba_23_24_cleaned],␣
↪ignore_index=True)
```

0.4 STEP 3

After this, you can see above that we concatenate and finally merge the two datasets into one whole dataset, using the season as a marker to differentiate between the two. We then go ahead and check for duplicates based off ,of season and player, which as you can see is not an issue since it is 0, meaning our cleaning worked and that we have one player value per season.

[19]:
```
nba_combined.duplicated(subset=['player','season']).sum()
```

[19]:
```
0
```

[20]:
```
nba_combined.head(10)
```

[20]:
```
              player pos  age   tm   g  gs    mp   fg   fga  fg_pct  ...  orb  \
0         A.J. Green  SG   23  MIL  35   1   9.9  1.5   3.6   0.424  ...  0.2
1        A.J. Lawson  SG   22  TOT  15   0   7.2  1.5   2.9   0.500  ...  0.4
2         AJ Griffin  SF   19  ATL  72  12  19.5  3.4   7.4   0.465  ...  0.5
3       Aaron Gordon  PF   27  DEN  68  68  30.2  6.3  11.2   0.564  ...  2.4
4      Aaron Holiday  PG   26  ATL  63   6  13.4  1.5   3.5   0.418  ...  0.4
5      Aaron Nesmith  SF   23  IND  73  60  24.9  3.5   8.1   0.427  ...  0.8
6      Aaron Wiggins  SG   24  OKC  70  14  18.5  2.7   5.2   0.512  ...  1.0
7  Admiral Schofield  PF   25  ORL  37   0  12.2  1.5   3.3   0.451  ...  0.6
8         Al Horford   C   36  BOS  63  63  30.5  3.6   7.6   0.476  ...  1.2
9         Alec Burks  SG   31  DET  51   8  22.0  3.9   9.0   0.436  ...  0.4

   drb  trb  ast  stl  blk  tov  pf   pts   season
0  1.1  1.3  0.6  0.2  0.0  0.3  0.9   4.4   22-23
1  1.0  1.4  0.1  0.1  0.0  0.2  0.7   3.7   22-23
2  1.6  2.1  1.0  0.6  0.2  0.6  1.2   8.9   22-23
3  4.1  6.6  3.0  0.8  0.8  1.4  1.9  16.3   22-23
4  0.8  1.2  1.4  0.6  0.2  0.6  1.3   3.9   22-23
5  2.9  3.8  1.3  0.8  0.5  1.0  3.2  10.1   22-23
6  2.0  3.0  1.1  0.6  0.2  0.8  1.6   6.8   22-23
7  1.1  1.7  0.8  0.2  0.1  0.4  1.6   4.2   22-23
8  5.0  6.2  3.0  0.5  1.0  0.6  1.9   9.8   22-23
9  2.7  3.1  2.2  0.7  0.2  1.1  1.9  12.8   22-23

[10 rows x 30 columns]
```

0.5 STEP 4

After looking at the data some more, we decided that having all players involved would cause an anomaly in the data and not give us an accurate representation of what we were looking for. So we came to the consensus that we would limit the data to players who played in at least ten games and averaged at least ten minutes per game. This eliminates relatively infrequent players, whose little time on the court would add noise to our scoring analysis.

[21]:
```python
nba_combined = nba_combined[(nba_combined['g'] >= 10) & (nba_combined['mp'] >=
    10)].reset_index(drop=True)
```

[22]:
```python
nba_combined.head(10)
```

[22]:
```
               player pos  age   tm   g  gs    mp   fg   fga  fg_pct  ...  \
0           AJ Griffin  SF   19  ATL  72  12  19.5  3.4   7.4   0.465  ...
1         Aaron Gordon  PF   27  DEN  68  68  30.2  6.3  11.2   0.564  ...
2        Aaron Holiday  PG   26  ATL  63   6  13.4  1.5   3.5   0.418  ...
3        Aaron Nesmith  SF   23  IND  73  60  24.9  3.5   8.1   0.427  ...
4        Aaron Wiggins  SG   24  OKC  70  14  18.5  2.7   5.2   0.512  ...
5     Admiral Schofield  PF   25  ORL  37   0  12.2  1.5   3.3   0.451  ...
6           Al Horford   C   36  BOS  63  63  30.5  3.6   7.6   0.476  ...
7           Alec Burks  SG   31  DET  51   8  22.0  3.9   9.0   0.436  ...
8    Aleksej Pokusevski  PF   21  OKC  34  25  20.6  3.2   7.3   0.434  ...
9          Alex Caruso  PG   28  CHI  67  36  23.5  1.9   4.3   0.455  ...

   orb  drb  trb  ast  stl  blk  tov   pf   pts  season
0  0.5  1.6  2.1  1.0  0.6  0.2  0.6  1.2   8.9   22-23
1  2.4  4.1  6.6  3.0  0.8  0.8  1.4  1.9  16.3   22-23
2  0.4  0.8  1.2  1.4  0.6  0.2  0.6  1.3   3.9   22-23
3  0.8  2.9  3.8  1.3  0.8  0.5  1.0  3.2  10.1   22-23
4  1.0  2.0  3.0  1.1  0.6  0.2  0.8  1.6   6.8   22-23
5  0.6  1.1  1.7  0.8  0.2  0.1  0.4  1.6   4.2   22-23
6  1.2  5.0  6.2  3.0  0.5  1.0  0.6  1.9   9.8   22-23
7  0.4  2.7  3.1  2.2  0.7  0.2  1.1  1.9  12.8   22-23
8  1.3  3.4  4.7  1.9  0.6  1.3  1.3  1.7   8.1   22-23
9  0.6  2.3  2.9  2.9  1.5  0.7  1.1  2.4   5.6   22-23

[10 rows x 30 columns]
```

0.6 STEP 5

Now to assess the scoring efficiency, we had to create the shooting statistics ourselves rather than just using the raw shooting columns that they gave. So to be able to get more accurate representation, we calculated field goal, three-point, and free throw percentages based on makes and attempts to ensure consistency and transparency.

Along with this I calculated division by zero issues and the most important stat in all of basketball which is the true shooting percentage. The true shooting percentage allows us to include efficiency as well as how hard a certain shot selection was. Basically a three point shot would be considered harder and we would also include free throws as an attempted shot. To fins this formula we had to go to the NBA website to see the formula for how they calculated it. The source is in the code. This offered us an improved understanding of how effectively every player scored, which was critical in addressing the second study question.

[24]:
```
df = nba_combined

df['fg_percentage'] = df['fg'] / df['fga']
df['3p_percentage'] = df['3p'] / df['3pa']
df['ft_percentage'] = df['ft'] / df['fta']

df['fg_percentage'] = df['fg_pct'].replace([float('inf')], 0)
df['3p_percentage'] = df['3p_pct'].replace([float('inf')], 0)
df['ft_percentage'] = df['ft_pct'].replace([float('inf')], 0)
```

[25]:
```
df.head(5)
```

[25]:
```
           player pos  age   tm   g  gs    mp   fg   fga  fg_pct  ...  ast  \
0      AJ Griffin  SF   19  ATL  72  12  19.5  3.4   7.4   0.465  ...  1.0
1    Aaron Gordon  PF   27  DEN  68  68  30.2  6.3  11.2   0.564  ...  3.0
2   Aaron Holiday  PG   26  ATL  63   6  13.4  1.5   3.5   0.418  ...  1.4
3   Aaron Nesmith  SF   23  IND  73  60  24.9  3.5   8.1   0.427  ...  1.3
4  Aaron Wiggins  SG   24  OKC  70  14  18.5  2.7   5.2   0.512  ...  1.1

   stl  blk  tov   pf   pts  season  fg_percentage  3p_percentage  \
0  0.6  0.2  0.6  1.2   8.9   22-23          0.465          0.390
1  0.8  0.8  1.4  1.9  16.3   22-23          0.564          0.347
2  0.6  0.2  0.6  1.3   3.9   22-23          0.418          0.409
3  0.8  0.5  1.0  3.2  10.1   22-23          0.427          0.366
4  0.6  0.2  0.8  1.6   6.8   22-23          0.512          0.393

   ft_percentage
0          0.894
1          0.608
2          0.844
3          0.838
4          0.831

[5 rows x 33 columns]
```

[26]:
```
# Used this source to get the value of how to get the true shooting percentage:␣
↪https://www.nba.com/stats/help/glossary#tspct
df['ts_percentage'] = df['pts'] / (2 * (df['fga'] + 0.44 * df['fta']))
```

[27]:
```
df['pos_group'] = df['pos'].apply(
    lambda pos: 'Guard' if 'G' in pos else
                'Forward' if 'F' in pos else
                'Center' if 'C' in pos else
```

```
                'Other'
)
```

[28]:
```
df.head(5)
```

[28]:
```
          player pos  age   tm   g  gs    mp   fg   fga  fg_pct  ...  blk  \
0     AJ Griffin  SF   19  ATL  72  12  19.5  3.4   7.4   0.465  ...  0.2
1   Aaron Gordon  PF   27  DEN  68  68  30.2  6.3  11.2   0.564  ...  0.8
2  Aaron Holiday  PG   26  ATL  63   6  13.4  1.5   3.5   0.418  ...  0.2
3  Aaron Nesmith  SF   23  IND  73  60  24.9  3.5   8.1   0.427  ...  0.5
4  Aaron Wiggins  SG   24  OKC  70  14  18.5  2.7   5.2   0.512  ...  0.2

   tov   pf   pts  season  fg_percentage  3p_percentage  ft_percentage  \
0  0.6  1.2   8.9   22-23          0.465          0.390          0.894
1  1.4  1.9  16.3   22-23          0.564          0.347          0.608
2  0.6  1.3   3.9   22-23          0.418          0.409          0.844
3  1.0  3.2  10.1   22-23          0.427          0.366          0.838
4  0.8  1.6   6.8   22-23          0.512          0.393          0.831

   ts_percentage  pos_group
0       0.577322    Forward
1       0.616304    Forward
2       0.524194      Guard
3       0.565130    Forward
4       0.602837      Guard

[5 rows x 35 columns]
```

0.6.1 Assumptions

After doing data cleanup you can see that we made certain data assumptions. For clarity we have included the five assumptions we made below:

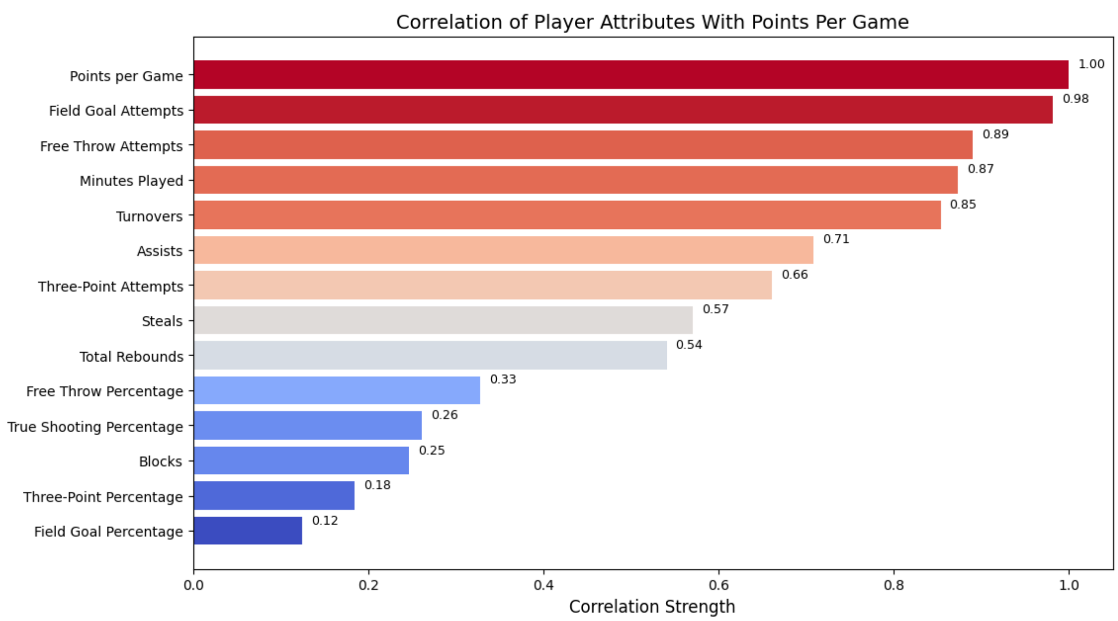
1. If a player played on more than 1 team in season, we only account for their TOT.
2. Player must have played 10 games or more and averaged 10 minutes or more per game
3. If player played more than one position, we account for the first position they played
4. We are looking at FG% when determining scoring efficiency (not eFG%). More than FG% we are focusing on TS%.
5. We understand that the Center position will be a little skewed since there are at least two guards and two forwards in each 5 person lineup

[29]:
```
# Q1: What player attributes correlate most with high scoring per game?
corr =␣
↪df[['pts','mp','fga','fg_pct','3pa','3p_pct','fta','ft_pct','ts_percentage','ast','trb','stl'
↪corr()

corr['pts'].sort_values(ascending=False)
```

[29]:
```
pts              1.000000
fga              0.981685
fta              0.889891
mp               0.873102
tov              0.853550
ast              0.708691
3pa              0.661213
stl              0.570451
trb              0.540804
ft_pct           0.327858
ts_percentage    0.261240
blk              0.246699
3p_pct           0.184791
fg_pct           0.124903
Name: pts, dtype: float64
```

[30]:
```python
# Create mapping from short stat names to descriptive labels
label_mapping = {
    'pts': 'Points per Game',
    'mp': 'Minutes Played',
    'fga': 'Field Goal Attempts',
    'fg_pct': 'Field Goal Percentage',
    '3pa': 'Three-Point Attempts',
    '3p_pct': 'Three-Point Percentage',
    'fta': 'Free Throw Attempts',
    'ft_pct': 'Free Throw Percentage',
    'ts_percentage': 'True Shooting Percentage',
    'ast': 'Assists',
    'trb': 'Total Rebounds',
    'stl': 'Steals',
    'blk': 'Blocks',
    'tov': 'Turnovers'
}


# Extract sorted correlations with points
pts_corr = corr['pts'].sort_values(ascending=False)

# Replace short labels with full names
pts_corr.index = pts_corr.index.map(label_mapping)

# Normalize values between 0 and 1 for gradient mapping
norm = (pts_corr - pts_corr.min()) / (pts_corr.max() - pts_corr.min())

# Choose a colormap (you can also try "viridis", "coolwarm", "magma")
cmap = plt.cm.coolwarm
colors = cmap(norm)
```

```
# Plot
plt.figure(figsize=(12,7))
bars = plt.barh(pts_corr.index, pts_corr.values, color=colors)

plt.title('Correlation of Player Attributes With Points Per Game', fontsize=14)
plt.xlabel('Correlation Strength', fontsize=12)
plt.gca().invert_yaxis()

# Optionally add numeric value labels on bars
for bar, value in zip(bars, pts_corr.values):
    plt.text(bar.get_width() + 0.01, bar.get_y() + bar.get_height()/4, f"{value:.
 ↪2f}", fontsize=9)

plt.show()
```



0.6.2 Explanation:

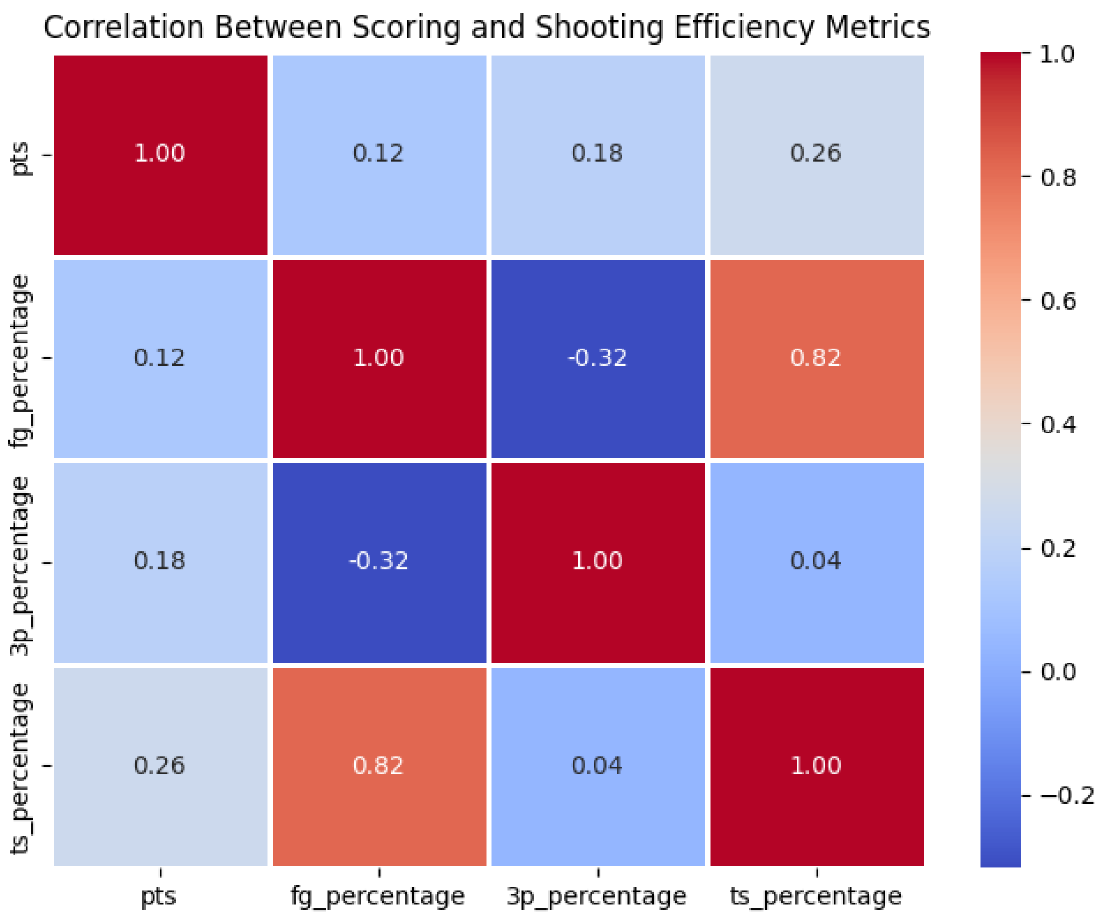
The bar chart illustrates the strength of correlation between various player attributes and points per game (PPG). Metrics related to scoring volume—such as field goal attempts, three-point attempts, and free throw attempts—show the strongest positive correlations, indicating that players who take more shots generally score more. This is important, as you can see the fg percentage shows little to know correlation to the amount of points scored per game, so it is safe to say that the points scored per game is not based off fg percentage. We were surprised by this stat. It is also interesting to see that the more free throw attempts one takes, the higher points per game they can possibly have, meaning getting to the line is extremely important to score more.

[31]:
```python
# Q2: Do players who shoot more efficiently score more?
corr_eff = df[['pts','fg_percentage','3p_percentage','ts_percentage']].corr()
corr_eff
```

[31]:

	pts	fg_percentage	3p_percentage	ts_percentage
pts	1.000000	0.124903	0.184791	0.261240
fg_percentage	0.124903	1.000000	-0.318230	0.818921
3p_percentage	0.184791	-0.318230	1.000000	0.041562
ts_percentage	0.261240	0.818921	0.041562	1.000000

[32]:
```python
# Plot heatmap
plt.figure(figsize=(8,6))
sns.heatmap(corr_eff, annot=True, cmap='coolwarm', linewidths=1, fmt=".2f")

plt.title("Correlation Between Scoring and Shooting Efficiency Metrics")
plt.show()
```



0.7 Explanation

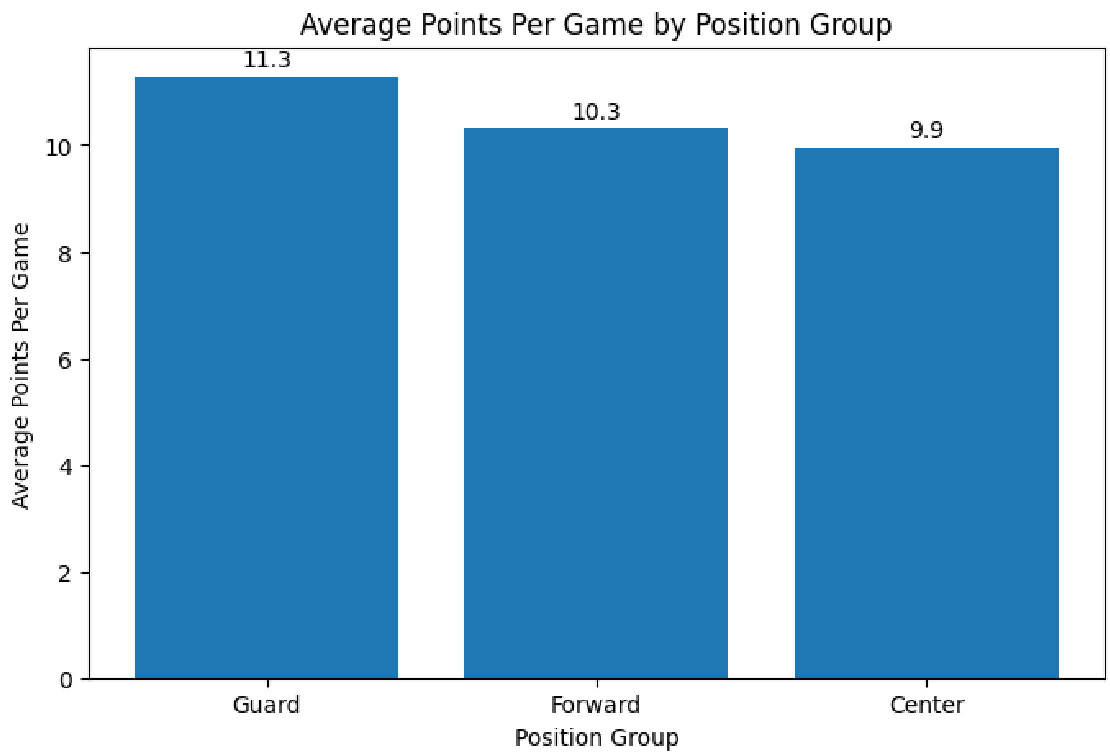
The heatmap reveals that true shooting percentage (TS%) has the strongest positive correlation with points per game, followed by three-point percentage (3P%) and then field goal percentage (FG%). This suggests that while shooting efficiency contributes to scoring, TS% - which captures overall scoring efficiency including free throws and three-pointers - best explains why some players score more. The moderate correlations also indicate that simply being efficient does not automatically guarantee high scoring; players must also have the opportunity and volume required to produce points. This correlates to what we see up above in the bar chart where FG percentage was ranked so low.

[33]:
```
# Q3: Are guards, forwards, or centers associated with higher scoring averages?
df.groupby('pos_group')['pts'].agg(['count','mean','std'])
```

[33]:

pos_group	count	mean	std
Center	153	9.946405	6.369479
Forward	327	10.307339	6.404907
Guard	356	11.274157	7.014284

[34]:
```
pos_scoring = df.groupby('pos_group')['pts'].mean().sort_values(ascending=False)

plt.figure(figsize=(8,5))
bars = plt.bar(pos_scoring.index, pos_scoring.values)
plt.title('Average Points Per Game by Position Group')
plt.xlabel('Position Group')
plt.ylabel('Average Points Per Game')

# Add labels on top of bars
for i, value in enumerate(pos_scoring.values):
    plt.text(i, value + 0.2, f"{value:.1f}", ha='center', fontsize=10)

plt.show()
```



0.8 Explanation

The bar chart provides a clear comparison of average points per game across the primary player position groups (guards, forwards, and centers). From the visualization, one can observe that guards tend to have the highest scoring average, followed closely by forwards, while centers typically score slightly less on average compared to the other two groups. We do understand that this data is skewed as Centers have about half the data that guards and forwards have but we did not believe that adding 'dummy' data to the Center position to fit the other two positions would be very beneficial. Overall what this data does show is that primary ball handlers aka guards have the most opportunities to shoot/have the higher ppg.

[35]:
```
#sort teams by players with highest pts

def get_players(df):
    #this groups the list by players and points
    points_per_player = df.groupby('player')['pts'].sum()/2
    #this sorts the values in ascending order and only shows me the top option
    top_players = points_per_player.sort_values(ascending=False).head(1)
    return top_players
```

[36]:
```
#This groups the list of players by team
grouped = nba_combined.groupby('tm')
#this shows me the highest scorer on each team
```

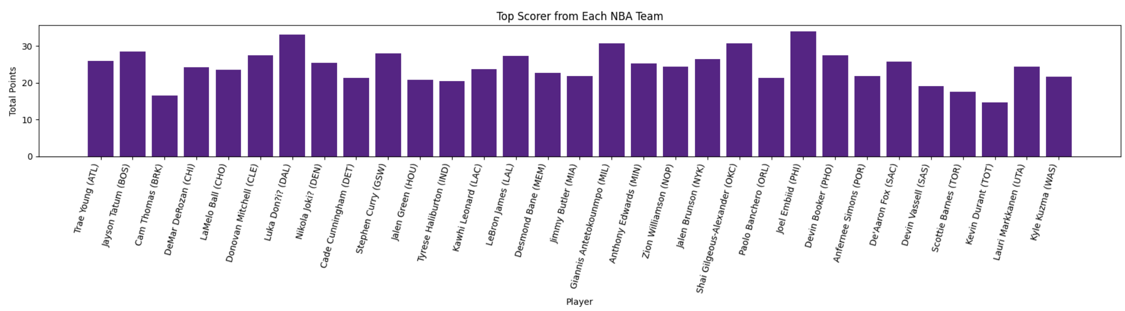
```
top_scorer_by_team = grouped.apply(get_players)
top_scorer_by_team
```

[36]:
```
tm   player
ATL  Trae Young                  25.95
BOS  Jayson Tatum                28.50
BRK  Cam Thomas                  16.55
CHI  DeMar DeRozan               24.25
CHO  LaMelo Ball                 23.60
CLE  Donovan Mitchell            27.45
DAL  Luka Don?i?                 33.15
DEN  Nikola Joki?                25.45
DET  Cade Cunningham             21.30
GSW  Stephen Curry               27.90
HOU  Jalen Green                 20.85
IND  Tyrese Haliburton           20.40
LAC  Kawhi Leonard               23.75
LAL  LeBron James                27.30
MEM  Desmond Bane                22.60
MIA  Jimmy Butler                21.85
MIL  Giannis Antetokounmpo       30.75
MIN  Anthony Edwards             25.25
NOP  Zion Williamson             24.45
NYK  Jalen Brunson               26.35
OKC  Shai Gilgeous-Alexander     30.75
ORL  Paolo Banchero              21.30
PHI  Joel Embiid                 33.90
PHO  Devin Booker                27.45
POR  Anfernee Simons             21.85
SAC  De'Aaron Fox                25.80
SAS  Devin Vassell               19.00
TOR  Scottie Barnes              17.60
TOT  Kevin Durant                14.55
UTA  Lauri Markkanen             24.40
WAS  Kyle Kuzma                  21.70
Name: pts, dtype: float64
```

[37]:
```
#reset index
top_scorer_df = top_scorer_by_team.reset_index()

# Rename columns
top_scorer_df.columns = ['Tm', 'Player', 'PTS']

# this sort by Team first, then by points descending
top_scorer_df_sorted = top_scorer_df.sort_values(['Tm', 'PTS'], ascending=[True,␣
↪False])
```

```
top_scorer_df_sorted
# this adds a column with the player name + team so I can see both on the bar␣
↪chart
top_scorer_df['Player_Team_Name'] = top_scorer_df['Player'] + ' (' +␣
↪top_scorer_df['Tm'] + ')'
```

[38]:
```
## Plot bar chart for the player with the highest points average on each team

#figure size
plt.figure(figsize=(18,5))
#type of chart and what im looking for in the data frame, in this case its points
plt.bar(top_scorer_df['Player_Team_Name'], top_scorer_df['PTS'], color='#552583')
#chart title and labels
plt.title('Top Scorer from Each NBA Team')
plt.xlabel('Player')
plt.ylabel('Total Points')
#this rotates the name so its easier to read the chart
plt.xticks(rotation=75, ha='right')
plt.tight_layout()
plt.show()
```



0.9 Explanation

The bar chart highlights the leading scorer from each NBA team and how their average points per game compare across the league. From the visualization, it becomes clear that scoring production varies significantly depending on the team and player role. A few standout players sit well above the rest of the league, indicating teams where the offense is heavily built around a single dominant scorer. These players often serve as primary shot creators and offensive engines, driving both usage rate and scoring output.

[39]:
```
# Q4: Do teams with higher scoring lead players win more games?
# Decided to do this again and reset the index
each_team_top_scorer = (
    df.sort_values(['season', 'tm', 'pts'], ascending=False)
      .groupby(['season', 'tm'])
```

```
        .first()
        .reset_index()[['season', 'tm', 'player', 'pts']]
)
each_team_top_scorer.head(10)
```

[39]:

```
  season   tm            player   pts
0  22-23  ATL        Trae Young  26.2
1  22-23  BOS      Jayson Tatum  30.1
2  22-23  BRK       Nic Claxton  12.6
3  22-23  CHI       Zach LaVine  24.8
4  22-23  CHO       LaMelo Ball  23.3
5  22-23  CLE  Donovan Mitchell  28.3
6  22-23  DAL       Luka Don?i?  32.4
7  22-23  DEN      Nikola Joki?  24.5
8  22-23  DET  Bojan Bogdanovi?  21.6
9  22-23  GSW     Stephen Curry  29.4
```

[41]:

```
each_team = pd.merge(each_team_top_scorer, wins, on=['season','tm'], how='inner')

each_team.head(10)
```

[41]:

```
  season   tm            player   pts  wins
0  22-23  ATL        Trae Young  26.2    41
1  22-23  BOS      Jayson Tatum  30.1    57
2  22-23  BRK       Nic Claxton  12.6    45
3  22-23  CHI       Zach LaVine  24.8    40
4  22-23  CHO       LaMelo Ball  23.3    27
5  22-23  CLE  Donovan Mitchell  28.3    51
6  22-23  DAL       Luka Don?i?  32.4    38
7  22-23  DEN      Nikola Joki?  24.5    53
8  22-23  DET  Bojan Bogdanovi?  21.6    17
9  22-23  GSW     Stephen Curry  29.4    44
```

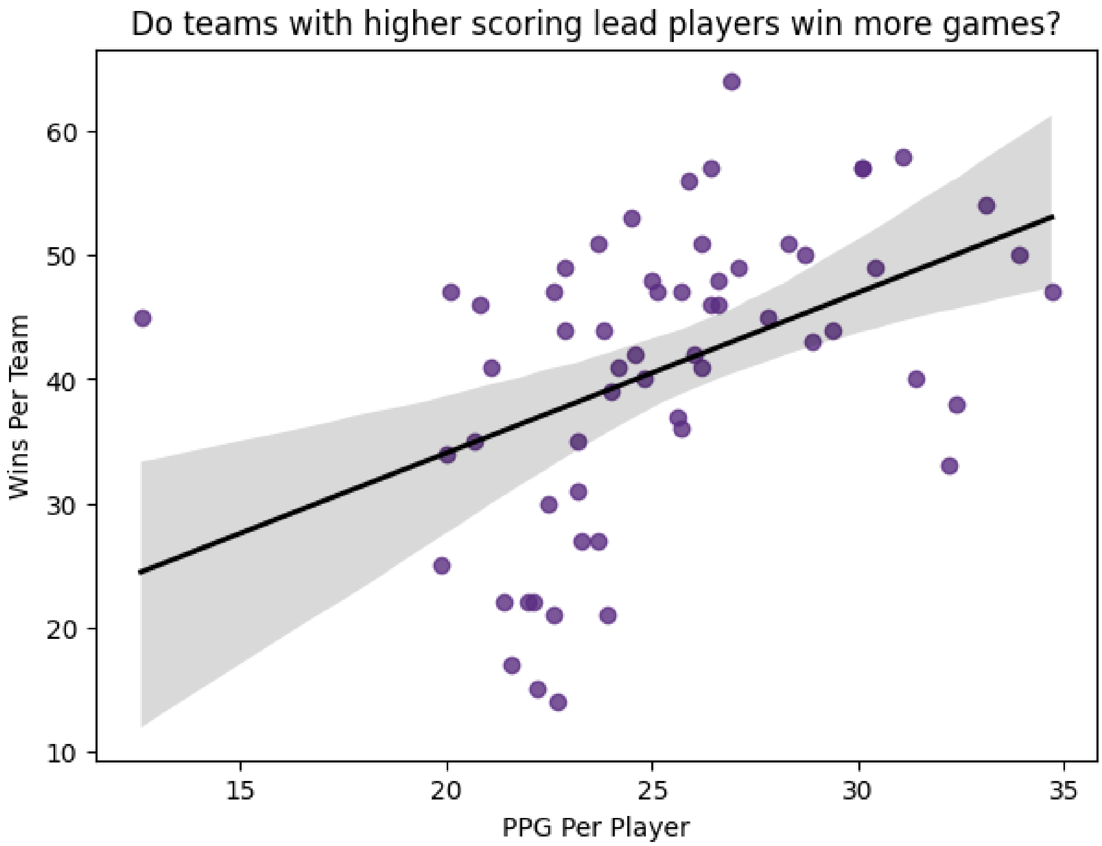
[42]:

```
each_team['pts'].corr(each_team['wins'])
```

[42]: 0.44505400748777246

[43]:

```
plt.figure(figsize=(7,5))
sns.regplot(x='pts',y='wins',data=each_team,scatter_kws={'color':␣
 ↪'#5A2D81'},line_kws={'color': '#000000', 'linewidth': 2})
plt.xlabel("PPG Per Player")
plt.ylabel("Wins Per Team")
plt.title("Do teams with higher scoring lead players win more games?")
plt.show()
```



0.10 Explanation

The connection between an organization's wins and its top scorer's PPG is at 0.445, showing a moderately positive link. This shows that the team with higher scoring lead players do tend to win more games but the relationship is not a clear indicator. Using the rˆ2 value we come to the conclusion that only around 20% of the diversity in team wins can be explained by the average score of their best scorer. As you can see there are many high level players that play on losing teams and that other factors such as depth and defense may play a more pertinent role. Overall scoring is beneficial but as our data and information show, there are other factors that play a role on performance of a team.

0.11 Conclusion

This research showed that field goal attempts, three-point attempts, and free throw attempts correlate most significantly with points per game, while efficiency had a close to zero correlation. This conclusion allows us to state that opportunity and volume drive scoring more than accuracy.

We also saw that Guards had the highest scoring averages, followed by forwards and centers, indicating that their role as primary ball handlers provides more shooting opportunities.

We then found that the true shooting percentage has the best efficiency when it comes to scoring, but players still need to take enough shots to turn that efficiency into points. And finally, we found out that the correlation of 0.445 between team wins and lead scorer PPG, accounted for only 20% of win variance, safely saying that elite scoring though important does not contribute 100 percent to team wins.

```
[ ]:
```

NBA High Scorers and Team Success

Datasci 200 - Fall 2025

Emmanuel Damas, Paramdeep Sodhi

Agenda

Overview

- NBA player performance is evaluated using advanced analytics
- Scoring is important, but influenced by efficiency, role, and minutes played
- The analysis explores how scoring relates to overall impact and team success

Guiding Questions

- What player attributes correlate most with high scoring per game?
- Do players who shoot more efficiently also score more?
- Are guards, forwards, or centers associated with higher scoring averages?
- Do teams with higher-scoring lead players win more games?

Data Exploration/Cleaning & Assumptions

1. If player played on more than 1 team in season, we only account for team where they played the most games

2. Player must have played 10 games or more and averaged 10 minutes or more per game

3. If player played more than one position, we account for the first position they played

4. We are looking at FG% when determining scoring efficiency (not eFG%)

5. We understand that the Center position will be a little skewed since there are at least two guards and two forwards in each 5 person lineup

Data Exploration/Cleaning & Assumptions

Before:

	player	pos	age	tm	g	gs	mp	fg	fga	fg_pct	...	orb	drb	trb	ast	stl	blk	tov	pf	pts	season
0	Precious Achiuwa	C	23	TOR	55	12	20.7	3.6	7.3	0.485	...	1.8	4.1	6.0	0.9	0.6	0.5	1.1	1.9	9.2	22-23
1	Steven Adams	C	29	MEM	42	42	27.0	3.7	6.3	0.597	...	5.1	6.5	11.5	2.3	0.9	1.1	1.9	2.3	8.6	22-23
2	Bam Adebayo	C	25	MIA	75	75	34.6	8.0	14.9	0.540	...	2.5	6.7	9.2	3.2	1.2	0.8	2.5	2.8	20.4	22-23
3	Ochai Agbaji	SG	22	UTA	59	22	20.5	2.8	6.5	0.427	...	0.7	1.3	2.1	1.1	0.3	0.3	0.7	1.7	7.9	22-23
4	Santi Aldama	PF	22	MEM	77	20	21.8	3.2	6.8	0.470	...	1.1	3.7	4.8	1.3	0.6	0.6	0.8	1.9	9.0	22-23
5	Nickeil Alexander-Walker	SG	24	TOT	59	3	15.0	2.2	5.0	0.444	...	0.3	1.5	1.7	1.8	0.5	0.4	0.9	1.5	6.2	22-23
6	Nickeil Alexander-Walker	SG	24	UTA	36	3	14.7	2.3	4.7	0.488	...	0.2	1.4	1.6	2.1	0.7	0.4	1.3	1.6	6.3	22-23
7	Nickeil Alexander-Walker	SG	24	MIN	23	0	15.5	2.1	5.4	0.384	...	0.3	1.5	1.8	1.4	0.3	0.3	0.4	1.3	5.9	22-23
8	Grayson Allen	SG	27	MIL	72	70	27.4	3.4	7.7	0.440	...	0.8	2.4	3.3	2.3	0.9	0.2	1.0	1.6	10.4	22-23
9	Jarrett Allen	C	24	CLE	68	68	32.6	5.9	9.2	0.644	...	3.3	6.5	9.8	1.7	0.8	1.2	1.4	2.3	14.3	22-23
10	Jose Alvarado	PG	24	NOP	61	10	21.5	3.3	8.0	0.411	...	0.5	1.9	2.3	3.0	1.1	0.2	1.3	2.0	9.0	22-23
11	Kyle Anderson	PF	29	MIN	69	46	28.4	3.7	7.2	0.509	...	1.0	4.4	5.3	4.9	1.1	0.9	1.5	2.1	9.4	22-23
12	Giannis Antetokounmpo	PF	28	MIL	63	63	32.1	11.2	20.3	0.553	...	2.2	9.6	11.8	5.7	0.8	0.8	3.9	3.1	31.1	22-23
13	Thanasis Antetokounmpo	SF	30	MIL	37	0	5.6	0.5	1.2	0.435	...	0.4	0.8	1.2	0.4	0.1	0.1	0.3	0.6	1.4	22-23

After:

	player	pos	age	tm	g	gs	mp	fg	fga	fg_pct	...	orb	drb	trb	ast	stl	blk	tov	pf	pts	season
0	Precious Achiuwa	C	23	TOR	55	12	20.7	3.6	7.3	0.485	...	1.8	4.1	6.0	0.9	0.6	0.5	1.1	1.9	9.2	22-23
1	Steven Adams	C	29	MEM	42	42	27.0	3.7	6.3	0.597	...	5.1	6.5	11.5	2.3	0.9	1.1	1.9	2.3	8.6	22-23
2	Bam Adebayo	C	25	MIA	75	75	34.6	8.0	14.9	0.540	...	2.5	6.7	9.2	3.2	1.2	0.8	2.5	2.8	20.4	22-23
3	Ochai Agbaji	SG	22	UTA	59	22	20.5	2.8	6.5	0.427	...	0.7	1.3	2.1	1.1	0.3	0.3	0.7	1.7	7.9	22-23
4	Santi Aldama	PF	22	MEM	77	20	21.8	3.2	6.8	0.470	...	1.1	3.7	4.8	1.3	0.6	0.6	0.8	1.9	9.0	22-23
5	Nickeil Alexander-Walker	SG	24	TOT	59	3	15.0	2.2	5.0	0.444	...	0.3	1.5	1.7	1.8	0.5	0.4	0.9	1.5	6.2	22-23
6	Grayson Allen	SG	27	MIL	72	70	27.4	3.4	7.7	0.440	...	0.8	2.4	3.3	2.3	0.9	0.2	1.0	1.6	10.4	22-23
7	Jarrett Allen	C	24	CLE	68	68	32.6	5.9	9.2	0.644	...	3.3	6.5	9.8	1.7	0.8	1.2	1.4	2.3	14.3	22-23
8	Jose Alvarado	PG	24	NOP	61	10	21.5	3.3	8.0	0.411	...	0.5	1.9	2.3	3.0	1.1	0.2	1.3	2.0	9.0	22-23
9	Kyle Anderson	PF	29	MIN	69	46	28.4	3.7	7.2	0.509	...	1.0	4.4	5.3	4.9	1.1	0.9	1.5	2.1	9.4	22-23
10	Giannis Antetokounmpo	PF	28	MIL	63	63	32.1	11.2	20.3	0.553	...	2.2	9.6	11.8	5.7	0.8	0.8	3.9	3.1	31.1	22-23
11	Thanasis Antetokounmpo	SF	30	MIL	37	0	5.6	0.5	1.2	0.435	...	0.4	0.8	1.2	0.4	0.1	0.1	0.3	0.6	1.4	22-23

Data Exploration/Cleaning & Assumptions

Three Step Process:

1. Fix Missing / Bad Values
2. Clean Data Types
3. Create New Metrics

STEP 3

Checking for duplicates based off of season and player, which as you can see is not an issue since it is 0.

```
nba_combined.duplicated(subset=['player','season']).sum()
```

```
0
```

STEP 4

We limited the data set to players who played in at least ten games and averaged at least ten minutes per game. This eliminates relatively infrequent players, whose little time on the field would add noise to our scoring analysis.

```
nba_combined = nba_combined[(nba_combined['g'] >= 10) & (nba_combined['mp'] >= 10)]
```

STEP 5

Now to assess scoring efficiency, we had to create the shooting statistics myself rather than just using the raw shooting columns that they gave. So to be able to get more accurate representation I calculated field goal, three-point, and free throw percentages based on makes and attempts to ensure consistency and transparency.

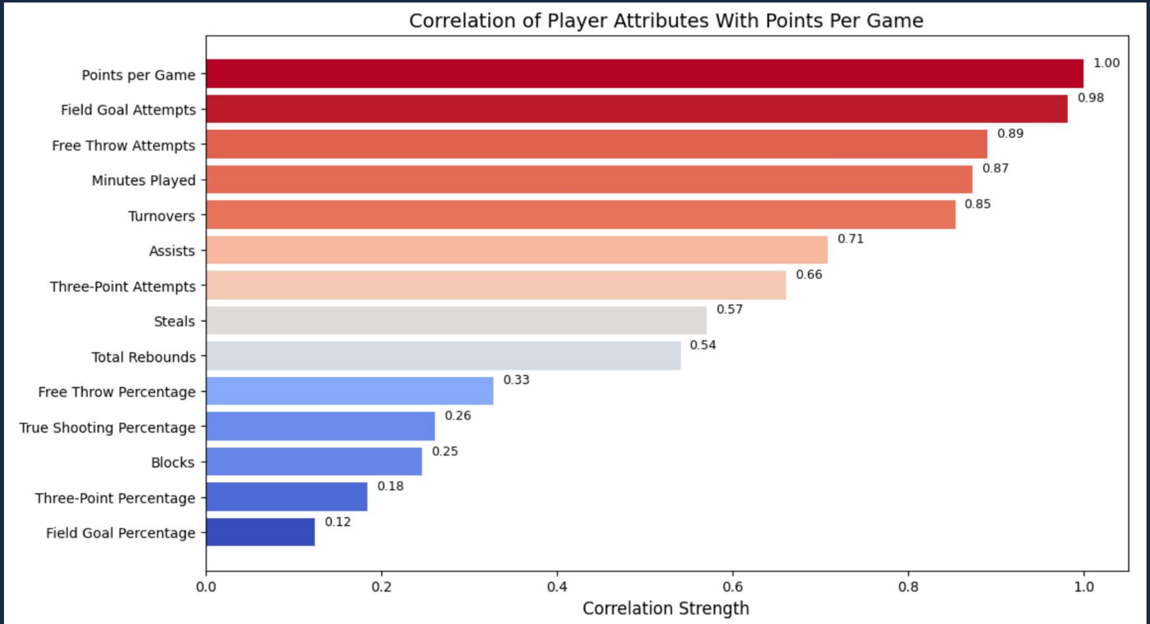
Along with this I calculated division by zero issues and the most important stat in all of basketball which id the true shooting percentage. The true shooting percentgae allows us to include efficiency not only from made shots but also including free throws. This offered me an improved understanding of how effectively every player scored, which was critical in addressing my second study question.

```
df = nba_combined

df['fg_percentage'] = df['fg'] / df['fga']
df['3p_percentage'] = df['3p'] / df['3pa']
df['ft_percentage'] = df['ft'] / df['fta']

df['fg_percentage'] = df['fg_pct'].replace([float('inf')], 0)
df['3p_percentage'] = df['3p_pct'].replace([float('inf')], 0)
df['ft_percentage'] = df['ft_pct'].replace([float('inf')], 0)

df['ts_percentage'] = df['pts'] / (2 * (df['fga'] + 0.44 * df['fta']))
```

```
df['pos_group'] = df['pos'].apply(
    lambda pos: 'Guard' if 'G' in pos else
               'Forward' if 'F' in pos else
               'Center' if 'C' in pos else
               'Other'
)
```

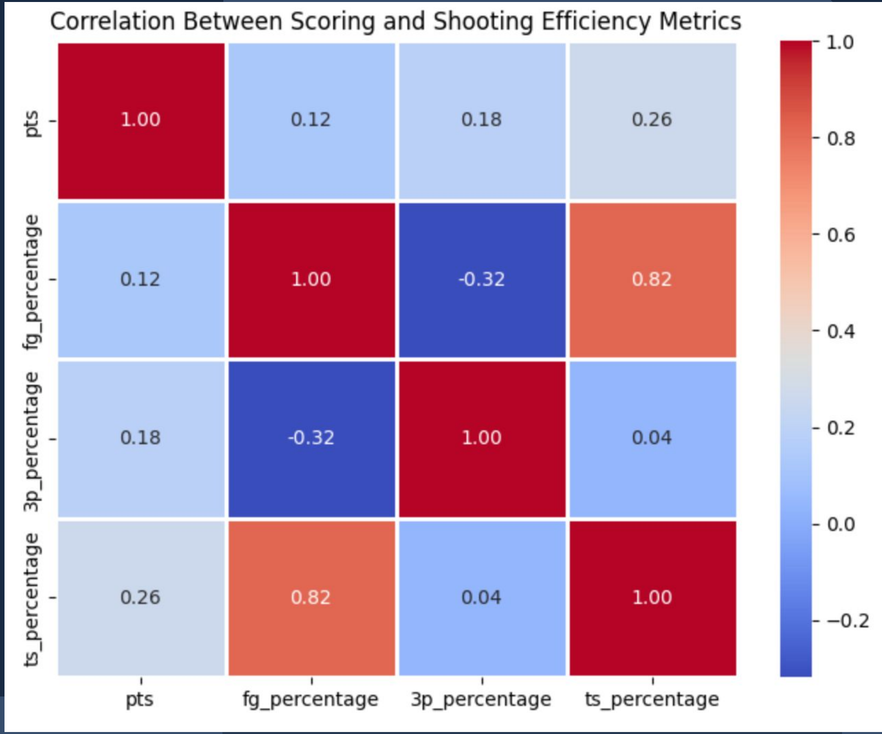
Key Charts & Findings

What player attributes correlate most with high scoring per game?



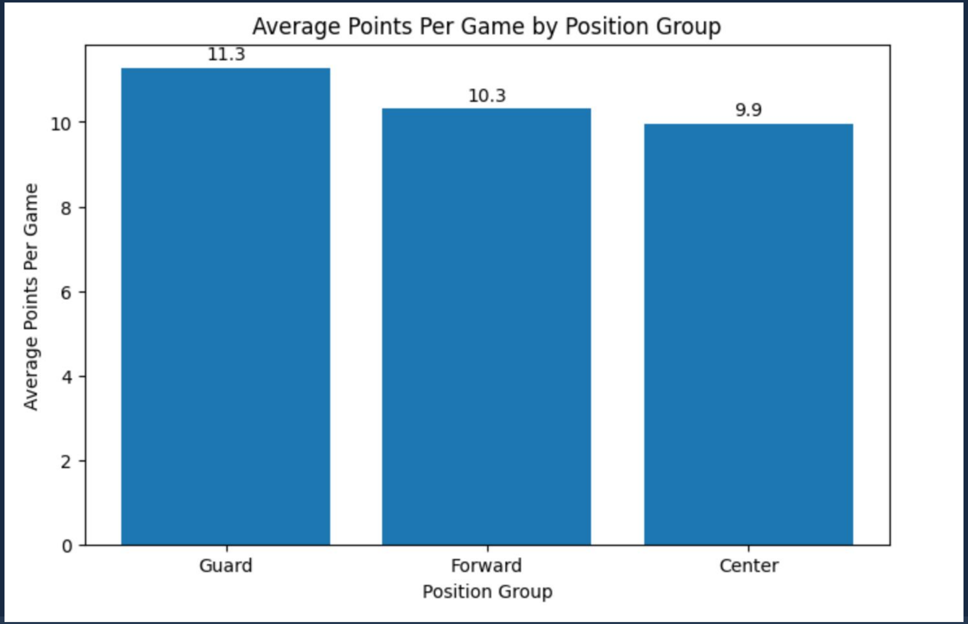
Key Charts & Findings

Do players who shoot more efficiently also score more?



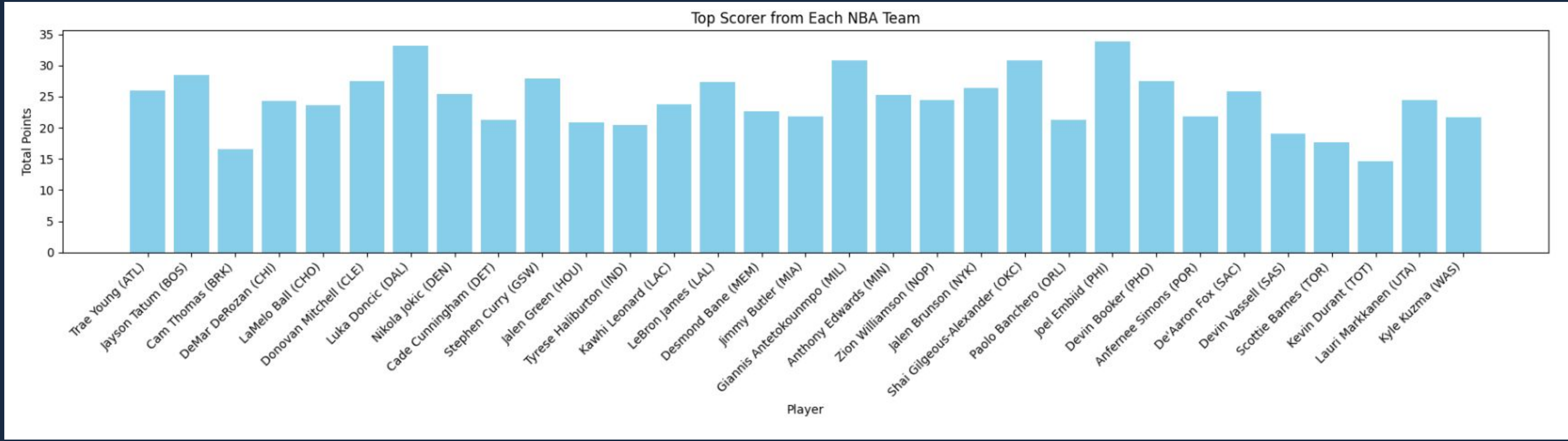
Key Charts & Findings

Are guards, forwards, or centers associated with higher scoring averages?



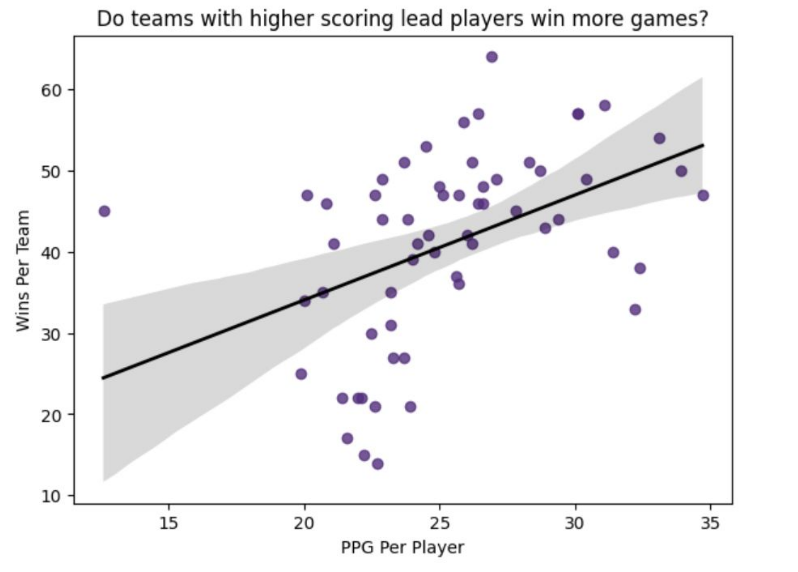
Key Charts & Findings

Player with the highest points average on each team



Key Charts & Findings

Do teams with higher-scoring lead players win more games?



Thank you!

Any Questions?