NCAA Tournament Analysis

December 9, 2023

0.1 Data Programming in Python | BAIS:6040

0.2 Final Project – NCAA Basketball Tournament

Group: TippieDawgs

Team Members: Kale Altman, Eric Dowe, Luke Kniffen, Malcom Newell, Nick Pittman Every year, the top 68 teams in college basketball compete in a postseason tournament, otherwise known as March Madness. Each team is given a ranking from 1 to 16 and is divided into one of four regions. The tournament is single-elimination, allowing for lower-ranked teams to potentially "upset" their opponents. This analysis will look to analyze which statistics are most important for a team to perform well, how lower-ranked teams are able to win multiple games, and try to predict each team's success using multiple machine learning models.

The dataset will contain quantitative and qualitative data for every team from the last 10 postseson tournaments (680 rows). There are currently 24 attributes, but additional columns will be generated on an as-needed basis.

0.2.1 Import modules, read in data, and clean data

[1]:
```
# Import needed modules/packages
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
```

[2]:
```
# Get the path of your current work directory
os.getcwd()
```

[2]:
```
'/home/feirxu/classdata/group01'
```

[3]:
```
# Read in cbb dataset (2013-2023 data)
cbb = pd.read_csv("cbb.csv")
cbb.shape
```

[3]:
```
(3523, 24)
```

[4]:
```
cbb.info()
## null values only in POSTSEASON and SEED columns for non-tournament teams
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3523 entries, 0 to 3522
Data columns (total 24 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   TEAM        3523 non-null   object
 1   CONF        3523 non-null   object
 2   G           3523 non-null   int64
 3   W           3523 non-null   int64
 4   ADJOE       3523 non-null   float64
 5   ADJDE       3523 non-null   float64
 6   BARTHAG     3523 non-null   float64
 7   EFG_O       3523 non-null   float64
 8   EFG_D       3523 non-null   float64
 9   TOR         3523 non-null   float64
 10  TORD        3523 non-null   float64
 11  ORB         3523 non-null   float64
 12  DRB         3523 non-null   float64
 13  FTR         3523 non-null   float64
 14  FTRD        3523 non-null   float64
 15  2P_O        3523 non-null   float64
 16  2P_D        3523 non-null   float64
 17  3P_O        3523 non-null   float64
 18  3P_D        3523 non-null   float64
 19  ADJ_T       3523 non-null   float64
 20  WAB         3523 non-null   float64
 21  POSTSEASON  680 non-null    object
 22  SEED        680 non-null    float64
 23  YEAR        3523 non-null   int64
dtypes: float64(18), int64(3), object(3)
memory usage: 660.7+ KB
```

This data includes complete seasons, through the NCAA tournament for all teams. We want to only look at the teams that competed in the postseason

[5]:
```python
# Data with null values (Teams that did not make the tournament)
cbb[cbb.isnull().any(axis=1)]
```

[5]:
```
                    TEAM  CONF   G   W  ADJOE  ADJDE  BARTHAG  EFG_O  EFG_D  \
56              Duquesne   A10  30  11  107.0  111.7   0.3790   51.2   51.7
57               Fordham   A10  30   9  101.0  103.0   0.4450   46.7   50.2
58          George Mason   A10  30   8  101.2  103.8   0.4276   45.5   50.0
59     George Washington   A10  35  22  107.2   96.2   0.7755   48.9   45.9
60              La Salle   A10  33  17   98.9   92.9   0.6734   46.7   45.8
…                    …     …  ..  ..    …      …        …      …      …
3518              Toledo   MAC  34  27  119.9  109.6   0.7369   56.3   52.9
3519             Liberty  ASun  33  27  111.4   97.3   0.8246   55.5   49.3
3520         Utah Valley   WAC  34  28  107.1   94.6   0.8065   51.7   44.0
```

```
3521                  UAB  CUSA  38  29  112.4   97.0   0.8453   50.3   47.3
3522         North Texas  CUSA  36  31  110.0   93.8   0.8622   51.2   44.5

       TOR  …  FTRD  2P_O  2P_D  3P_O  3P_D  ADJ_T   WAB  POSTSEASON  SEED  \
56    18.3  …  33.8  49.5  47.7  36.2  38.5   67.6 -11.3         NaN   NaN
57    22.2  …  41.7  47.8  49.6  29.8  34.1   65.9 -12.3         NaN   NaN
58    21.9  …  44.7  44.9  48.4  31.6  35.3   65.0 -12.6         NaN   NaN
59    18.7  …  28.9  47.3  44.9  35.2  31.9   62.7  -2.3         NaN   NaN
60    19.9  …  34.4  46.1  45.1  32.1  31.6   64.8  -6.3         NaN   NaN
…      …  …   …    …    …    …    …    …     …   …
3518  13.6  …  27.5  54.6  52.1  39.7  36.1   69.5  -1.2         NaN   NaN
3519  16.0  …  27.8  56.4  48.6  36.4  33.6   64.4  -2.0         NaN   NaN
3520  19.3  …  28.7  52.5  42.8  33.4  31.1   69.8  -0.3         NaN   NaN
3521  17.3  …  28.9  48.8  47.2  35.6  31.6   70.7  -0.5         NaN   NaN
3522  19.8  …  40.2  49.6  44.2  35.7  30.1   58.7   1.1         NaN   NaN

      YEAR
56    2015
57    2015
58    2015
59    2015
60    2015
…      …
3518  2023
3519  2023
3520  2023
3521  2023
3522  2023

[2843 rows x 24 columns]
```

Removing teams with null values in POSTSEASON variable will allow us to see the full season statistics from teams that competed in the NCAA Tournament.

[6]:
```python
# Removed teams that did not make the tournament
cbb.dropna(how="any", inplace=True)
cbb.shape
```

[6]:
```
(680, 24)
```

[7]:
```python
cbb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 680 entries, 0 to 3227
Data columns (total 24 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   TEAM        680 non-null    object
```

```
 1   CONF        680 non-null    object
 2   G           680 non-null    int64
 3   W           680 non-null    int64
 4   ADJOE       680 non-null    float64
 5   ADJDE       680 non-null    float64
 6   BARTHAG     680 non-null    float64
 7   EFG_O       680 non-null    float64
 8   EFG_D       680 non-null    float64
 9   TOR         680 non-null    float64
 10  TORD        680 non-null    float64
 11  ORB         680 non-null    float64
 12  DRB         680 non-null    float64
 13  FTR         680 non-null    float64
 14  FTRD        680 non-null    float64
 15  2P_O        680 non-null    float64
 16  2P_D        680 non-null    float64
 17  3P_O        680 non-null    float64
 18  3P_D        680 non-null    float64
 19  ADJ_T       680 non-null    float64
 20  WAB         680 non-null    float64
 21  POSTSEASON  680 non-null    object
 22  SEED        680 non-null    float64
 23  YEAR        680 non-null    int64
dtypes: float64(18), int64(3), object(3)
memory usage: 132.8+ KB
```

[8]:

```python
# Change SEED from float to int datatype
cbb.SEED = cbb.SEED.apply(lambda x: int(x))
cbb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 680 entries, 0 to 3227
Data columns (total 24 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   TEAM        680 non-null    object
 1   CONF        680 non-null    object
 2   G           680 non-null    int64
 3   W           680 non-null    int64
 4   ADJOE       680 non-null    float64
 5   ADJDE       680 non-null    float64
 6   BARTHAG     680 non-null    float64
 7   EFG_O       680 non-null    float64
 8   EFG_D       680 non-null    float64
 9   TOR         680 non-null    float64
 10  TORD        680 non-null    float64
 11  ORB         680 non-null    float64
 12  DRB         680 non-null    float64
```

```
 13   FTR         680 non-null    float64
 14   FTRD        680 non-null    float64
 15   2P_O        680 non-null    float64
 16   2P_D        680 non-null    float64
 17   3P_O        680 non-null    float64
 18   3P_D        680 non-null    float64
 19   ADJ_T       680 non-null    float64
 20   WAB         680 non-null    float64
 21   POSTSEASON  680 non-null    object
 22   SEED        680 non-null    int64
 23   YEAR        680 non-null    int64
dtypes: float64(17), int64(4), object(3)
memory usage: 132.8+ KB
```

[9]:
```
cbb.head()
```

[9]:
```
             TEAM CONF   G   W  ADJOE  ADJDE  BARTHAG  EFG_O  EFG_D   TOR  \
0  North Carolina  ACC  40  33  123.3   94.9   0.9531   52.6   48.1  15.4
1       Wisconsin  B10  40  36  129.1   93.6   0.9758   54.8   47.7  12.4
2        Michigan  B10  40  33  114.4   90.4   0.9375   53.9   47.7  14.0
3      Texas Tech  B12  38  31  115.2   85.2   0.9696   53.5   43.0  17.7
4         Gonzaga  WCC  39  37  117.8   86.3   0.9728   56.6   41.1  16.2

   …  FTRD  2P_O  2P_D  3P_O  3P_D  ADJ_T   WAB  POSTSEASON  SEED  YEAR
0  …  30.4  53.9  44.6  32.7  36.2   71.7   8.6         2ND     1  2016
1  …  22.4  54.8  44.7  36.5  37.5   59.3  11.3         2ND     1  2015
2  …  30.0  54.7  46.8  35.2  33.2   65.9   6.9         2ND     3  2018
3  …  36.6  52.8  41.9  36.5  29.7   67.5   7.0         2ND     3  2019
4  …  26.9  56.3  40.0  38.2  29.0   71.5   7.7         2ND     1  2017

[5 rows x 24 columns]
```

Next, we added the variable POSTSEASON_GAMES to quantify how many games each team played in the tournament. The POSTSEASON variable provides the same information, but it is an object datatype. Now, we can group by other parameters and calculate aggregate tournament success.

[10]:
```
# Add postseason_games that turns postseason variable into numeric values
# Map tournament result to games played

def postseason_games(df):
    postseason_map = {'R68': 0,'R64': 1,'R32': 2,'S16': 3,'E8': 4,'F4': 5,'2ND':
 ↪ 6,'Champions': 6}
    df['POSTSEASON_GAMES'] = df['POSTSEASON'].map(postseason_map)
    return df

cbb = postseason_games(cbb)
cbb.head()
```

[10]:

```
             TEAM CONF   G   W  ADJOE  ADJDE  BARTHAG  EFG_O  EFG_D   TOR  \
0  North Carolina  ACC  40  33  123.3   94.9   0.9531   52.6   48.1  15.4
1       Wisconsin  B10  40  36  129.1   93.6   0.9758   54.8   47.7  12.4
2        Michigan  B10  40  33  114.4   90.4   0.9375   53.9   47.7  14.0
3      Texas Tech  B12  38  31  115.2   85.2   0.9696   53.5   43.0  17.7
4         Gonzaga  WCC  39  37  117.8   86.3   0.9728   56.6   41.1  16.2

   …  2P_O  2P_D  3P_O  3P_D  ADJ_T   WAB  POSTSEASON  SEED  YEAR  \
0  …  53.9  44.6  32.7  36.2   71.7   8.6         2ND     1  2016
1  …  54.8  44.7  36.5  37.5   59.3  11.3         2ND     1  2015
2  …  54.7  46.8  35.2  33.2   65.9   6.9         2ND     3  2018
3  …  52.8  41.9  36.5  29.7   67.5   7.0         2ND     3  2019
4  …  56.3  40.0  38.2  29.0   71.5   7.7         2ND     1  2017

   POSTSEASON_GAMES
0                 6
1                 6
2                 6
3                 6
4                 6

[5 rows x 25 columns]
```

We added a variable to say if each team is in Power 6 conferences. This usually indicates having a tougher schedule and is more likely to produce cinderella teams

[11]:

```python
# Add a binary column for teams in Power 6 conferences
cbb["IS_POWER6"] = cbb.CONF.apply(lambda x: 1 if x in ['ACC','B12','B10','SEC','P12','BE'] else 0)
cbb.head()
```

[11]:

```
             TEAM CONF   G   W  ADJOE  ADJDE  BARTHAG  EFG_O  EFG_D   TOR  \
0  North Carolina  ACC  40  33  123.3   94.9   0.9531   52.6   48.1  15.4
1       Wisconsin  B10  40  36  129.1   93.6   0.9758   54.8   47.7  12.4
2        Michigan  B10  40  33  114.4   90.4   0.9375   53.9   47.7  14.0
3      Texas Tech  B12  38  31  115.2   85.2   0.9696   53.5   43.0  17.7
4         Gonzaga  WCC  39  37  117.8   86.3   0.9728   56.6   41.1  16.2

   …  2P_D  3P_O  3P_D  ADJ_T   WAB  POSTSEASON  SEED  YEAR  \
0  …  44.6  32.7  36.2   71.7   8.6         2ND     1  2016
1  …  44.7  36.5  37.5   59.3  11.3         2ND     1  2015
2  …  46.8  35.2  33.2   65.9   6.9         2ND     3  2018
3  …  41.9  36.5  29.7   67.5   7.0         2ND     3  2019
4  …  40.0  38.2  29.0   71.5   7.7         2ND     1  2017

   POSTSEASON_GAMES  IS_POWER6
0                 6          1
```

```
1                  6          1
2                  6          1
3                  6          1
4                  6          0

[5 rows x 26 columns]
```

[12]:
```
cbb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 680 entries, 0 to 3227
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   TEAM              680 non-null    object
 1   CONF              680 non-null    object
 2   G                 680 non-null    int64
 3   W                 680 non-null    int64
 4   ADJOE             680 non-null    float64
 5   ADJDE             680 non-null    float64
 6   BARTHAG           680 non-null    float64
 7   EFG_O             680 non-null    float64
 8   EFG_D             680 non-null    float64
 9   TOR               680 non-null    float64
 10  TORD              680 non-null    float64
 11  ORB               680 non-null    float64
 12  DRB               680 non-null    float64
 13  FTR               680 non-null    float64
 14  FTRD              680 non-null    float64
 15  2P_O              680 non-null    float64
 16  2P_D              680 non-null    float64
 17  3P_O              680 non-null    float64
 18  3P_D              680 non-null    float64
 19  ADJ_T             680 non-null    float64
 20  WAB               680 non-null    float64
 21  POSTSEASON        680 non-null    object
 22  SEED              680 non-null    int64
 23  YEAR              680 non-null    int64
 24  POSTSEASON_GAMES  680 non-null    int64
 25  IS_POWER6         680 non-null    int64
dtypes: float64(17), int64(6), object(3)
memory usage: 143.4+ KB
```

0.2.2 Exploratory Analysis

Search any team and see their postseason results! (Any school ending in State is "St.") Ex. "Iowa St."

[13]:
```python
def team_search(df):
    team = input("Which team would you like to see?")
    team_info = df[df['TEAM'].str.lower() == team.lower()][["TEAM", "CONF",␣
↪"POSTSEASON", "SEED", "YEAR"]].sort_values(by="YEAR")
    return team_info

team_search(cbb)
```

```
Which team would you like to see? Iowa
```

[13]:

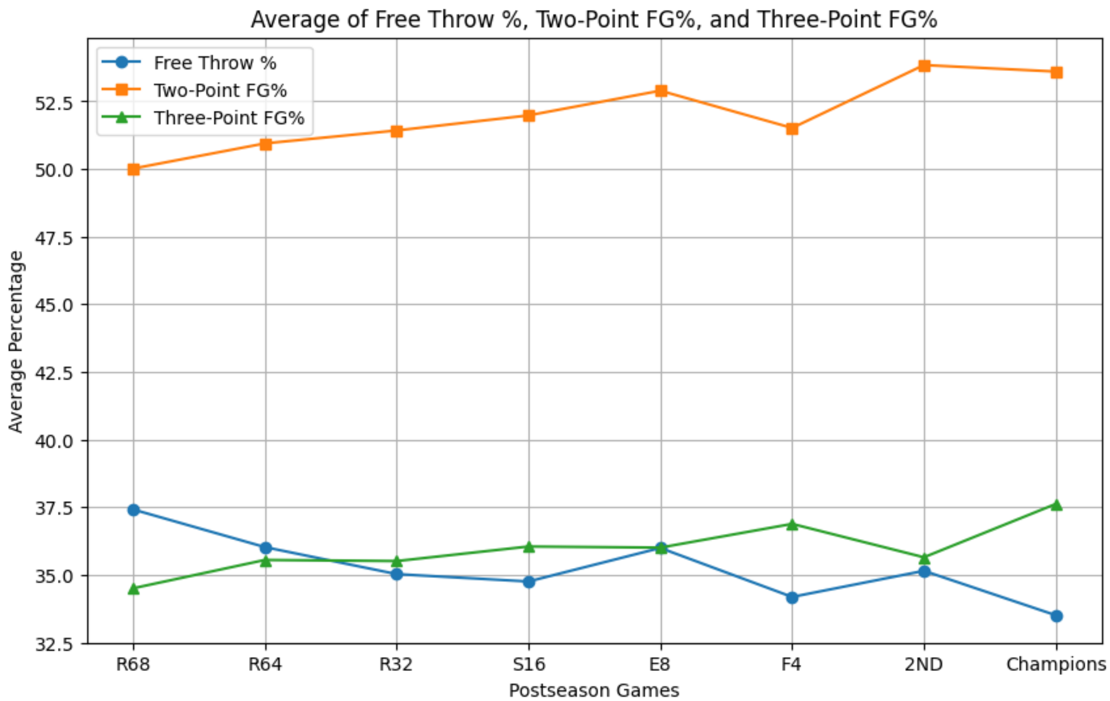
	TEAM	CONF	POSTSEASON	SEED	YEAR
2391	Iowa	B10	R68	11	2014
2054	Iowa	B10	R32	7	2015
2057	Iowa	B10	R32	7	2016
2062	Iowa	B10	R32	10	2019
2459	Iowa	B10	R32	2	2021
2819	Iowa	B10	R64	5	2022
3189	Iowa	B10	R64	8	2023

0.2.3 Analysis 1

Guiding Question 1: Are two-pointers, three-pointers, or free throws the most valuable for teams to perform well?

[14]:
```python
mean_ftr = cbb.groupby('POSTSEASON')['FTR'].mean()
mean_2po = cbb.groupby('POSTSEASON')['2P_O'].mean()
mean_3po = cbb.groupby('POSTSEASON')['3P_O'].mean()

plt.figure(figsize=(10, 6))

xaxis_order = ['R68', 'R64', 'R32', 'S16', 'E8', 'F4', '2ND', 'Champions']

# Reindex the 'POSTSEASON' categories so they are ordered by tournament success
mean_ftr = mean_ftr.reindex(xaxis_order)
mean_2po = mean_2po.reindex(xaxis_order)
mean_3po = mean_3po.reindex(xaxis_order)

plt.plot(mean_ftr.index, mean_ftr, marker='o', label='Free Throw %')
plt.plot(mean_2po.index, mean_2po, marker='s', label='Two-Point FG%')
plt.plot(mean_3po.index, mean_3po, marker='^', label='Three-Point FG%')

plt.xlabel('Postseason Games')
plt.ylabel('Average Percentage')
plt.title('Average of Free Throw %, Two-Point FG%, and Three-Point FG%')
plt.legend()

plt.grid(True)
```

```
plt.show()
```



As the tournament progresses, three point % and two point % continue to increase in value, but free throw percentage diminishes in value

This may be surprising because we often see free throws as a large contributor to winning or losing close games

0.2.4 Analysis 2

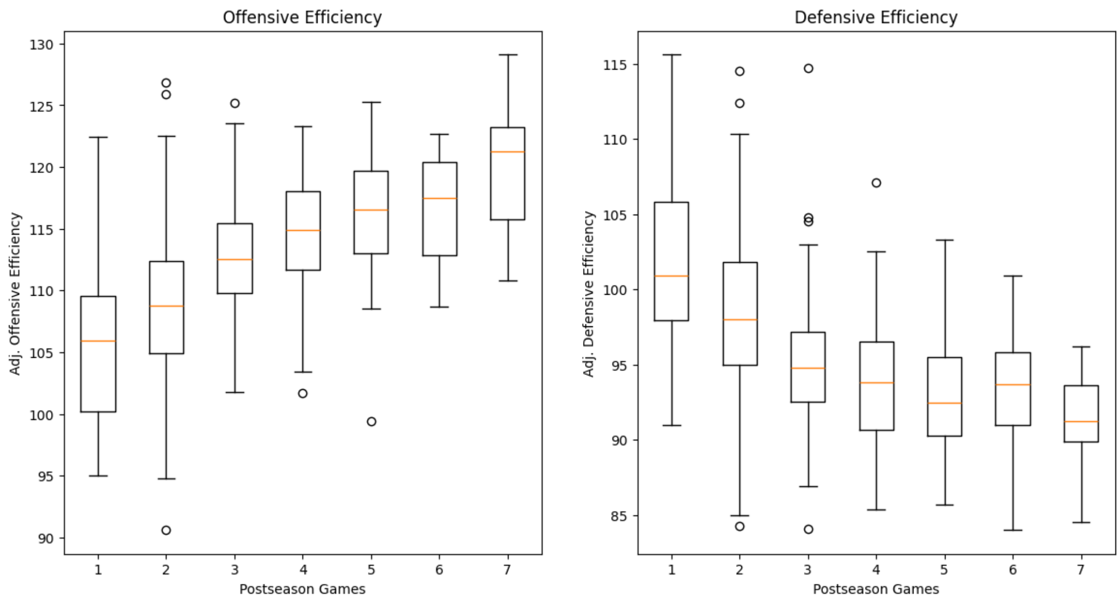
Guiding question 2: On average, do strong offensive teams or strong defensive teams perform better in the tournament?

Offensive Efficiency = Points scored per 100 possessions (a higher OE is desirable)

Dffensive Efficiency = Points allowed per 100 possessions (a lower DE is desirable)

[15]:
```
fig, axs = plt.subplots(1, 2, figsize=(14, 7))

ax1 = axs[0]
ax2 = axs[1]


#offensive efficiency by round
round0o = cbb[cbb.POSTSEASON_GAMES == 0].ADJOE
round1o = cbb[cbb.POSTSEASON_GAMES == 1].ADJOE
```

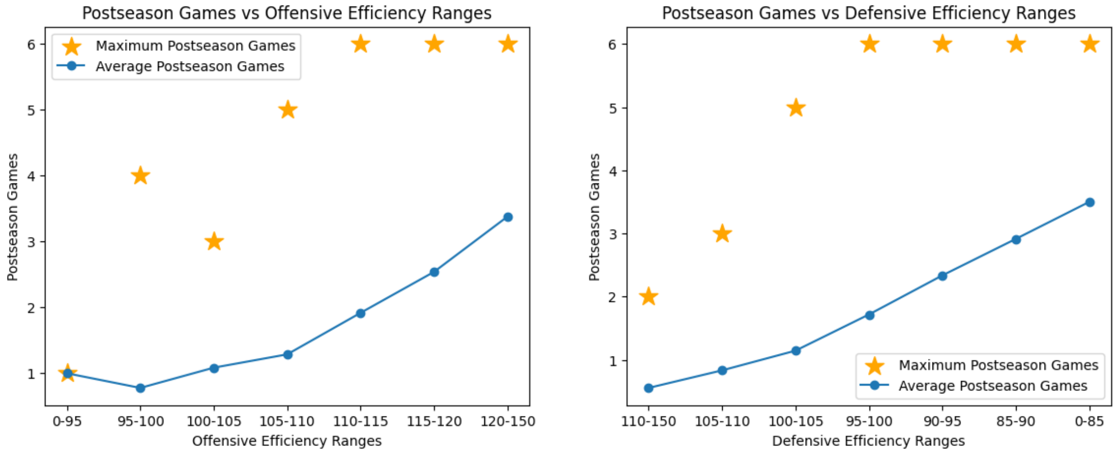
```python
round2o = cbb[cbb.POSTSEASON_GAMES == 2].ADJOE
round3o = cbb[cbb.POSTSEASON_GAMES == 3].ADJOE
round4o = cbb[cbb.POSTSEASON_GAMES == 4].ADJOE
round5o = cbb[cbb.POSTSEASON_GAMES == 5].ADJOE
round6o = cbb[cbb.POSTSEASON_GAMES == 6].ADJOE
offdata = [round0o, round1o, round2o, round3o, round4o, round5o, round6o]

# Scatter chart of offensive efficiency and longevity in tournaments
ax1.boxplot(offdata)

# Add x and y axis labels
ax1.set_xlabel('Postseason Games')
ax1.set_ylabel('Adj. Offensive Efficiency')
ax1.set_title('Offensive Efficiency')
#ax1.set_ylim(40,60)

#defensive efficiency by round
round0d = cbb[cbb.POSTSEASON_GAMES == 0].ADJDE
round1d = cbb[cbb.POSTSEASON_GAMES == 1].ADJDE
round2d = cbb[cbb.POSTSEASON_GAMES == 2].ADJDE
round3d = cbb[cbb.POSTSEASON_GAMES == 3].ADJDE
round4d = cbb[cbb.POSTSEASON_GAMES == 4].ADJDE
round5d = cbb[cbb.POSTSEASON_GAMES == 5].ADJDE
round6d = cbb[cbb.POSTSEASON_GAMES == 6].ADJDE
defdata = [round0d, round1d, round2d, round3d, round4d, round5d, round6d]

# Scatter chart of offensive efficiency and longevity in tournaments
ax2.boxplot(defdata)

# Add x and y axis labels
ax2.set_xlabel('Postseason Games')
ax2.set_ylabel('Adj. Defensive Efficiency')
ax2.set_title('Defensive Efficiency')
#ax2.set_ylim(40,60)

plt.show()
```



The boxplots above show the relationship between offensive efficiency and longevity in the tournament.

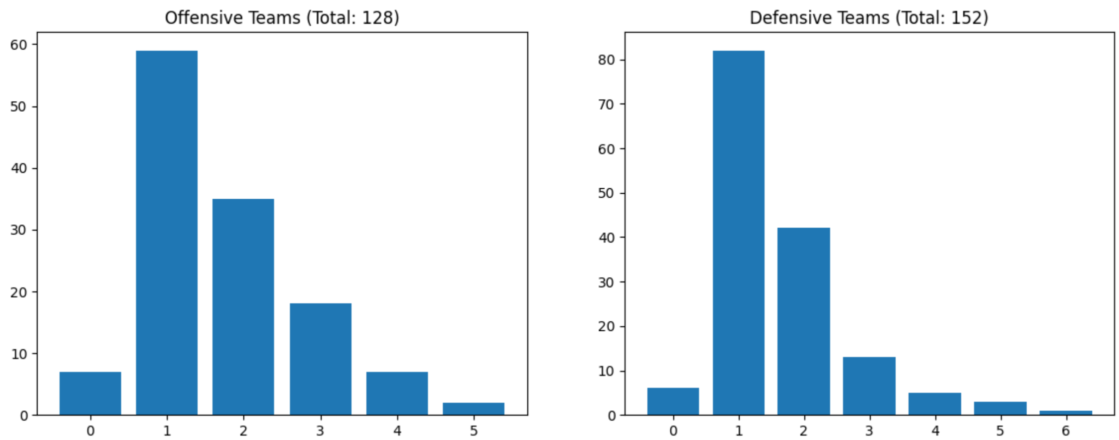
[16]:
```
fig, axs = plt.subplots(1, 2, figsize=(14, 5))

ax1 = axs[0]
ax2 = axs[1]

# Define ranges for offensive efficiency
offranges = [(0, 95),(95, 100),(100, 105),(105, 110),(110, 115),(115,
↪120),(120, 150)]
defranges = [(0, 85),(85, 90),(90, 95),(95, 100),(100, 105),(105, 110),(110,
↪150)]

# Create a list to store the data for each range
avg_off = [cbb[(cbb.ADJOE >= low) & (cbb.ADJOE < high)].POSTSEASON_GAMES.mean()
↪for low, high in offranges]
max_off = [cbb[(cbb.ADJOE >= low) & (cbb.ADJOE < high)].POSTSEASON_GAMES.max()
↪for low, high in offranges]
avg_def = [cbb[(cbb.ADJDE >= low) & (cbb.ADJDE < high)].POSTSEASON_GAMES.mean()
↪for low, high in defranges]
max_def = [cbb[(cbb.ADJDE >= low) & (cbb.ADJDE < high)].POSTSEASON_GAMES.max()
↪for low, high in defranges]

# Line graph of the maximum number of postseason games for each offensive
↪efficiency range
```

```
ax1.scatter(range(len(offranges)), max_off, marker='*', s = 200, color='orange', label='Maximum Postseason Games')

# Line graph of the average number of postseason games for each offensive efficiency range
ax1.plot(range(len(offranges)), avg_off, marker='o', linestyle='-', label='Average Postseason Games')

# Add labels and title
ax1.set_xlabel('Offensive Efficiency Ranges')
ax1.set_ylabel('Postseason Games')
ax1.set_title('Postseason Games vs Offensive Efficiency Ranges')

# Set x-axis ticks and labels
ax1.set_xticks(range(len(offranges)), [f"{low}-{high}" for low, high in offranges])

# Add a legend
ax1.legend()

# Line graph of the maximum number of postseason games for each defensive efficiency range
ax2.scatter(range(len(defranges)), max_def, marker='*', s = 200, color='orange', label='Maximum Postseason Games')

# Line graph of the average number of postseason games for each offensive efficiency range
ax2.plot(range(len(defranges)), avg_def, marker='o', linestyle='-', label='Average Postseason Games')

# Add labels and title
ax2.set_xlabel('Defensive Efficiency Ranges')
ax2.set_ylabel('Postseason Games')
ax2.set_title('Postseason Games vs Defensive Efficiency Ranges')
ax2.invert_xaxis()

# Set x-axis ticks and labels
ax2.set_xticks(range(len(defranges)), [f"{low}-{high}" for low, high in defranges])

# Add a legend
ax2.legend()

plt.show()
```



The line charts above show the same relationship as the previous plot. However, the axes have been flipped. This shows that a team must have an OE greater than 110 and a DE less than 100 to reach the championship game.

[17]:
```
offmean = cbb['ADJOE'].mean()  # 111.22
defmean = cbb['ADJDE'].mean()  # 96.56

# Filter teams based on conditions
defteams = cbb[(cbb['ADJOE'] < offmean) & (cbb['ADJDE'] < defmean)]
offteams = cbb[(cbb['ADJOE'] > offmean) & (cbb['ADJDE'] > defmean)]

fig, axs = plt.subplots(1, 2, figsize=(14, 5))

ax1 = axs[0]
ax2 = axs[1]

# Bar chart for teams with offensive efficiency greater than the mean and␣
↪defensive efficiency greater than the mean
offcounts = offteams['POSTSEASON_GAMES'].value_counts()
ax1.bar(offcounts.index, offcounts)
ax1.set_title(f'Offensive Teams (Total: {offcounts.sum()})')
offcounts.reindex(['R68', 'R64', 'R32', 'S16', 'E8', 'F4'])

# Bar chart for teams with offensive efficiency less than the mean and␣
↪defensive efficiency less than the mean
defcounts = defteams['POSTSEASON_GAMES'].value_counts()
ax2.bar(defcounts.index, defcounts)
ax2.set_title(f'Defensive Teams (Total: {defcounts.sum()})')

plt.show()
```



These bar charts compare teams that are strong in either offense or defense, but not both. It shows that more defensive teams make the tournament than offensive teams. However, they have a similar distribution once in the tournament, and neither type of team has one a championship.

0.2.5 Analysis 3

Guiding question 3: Are there certain statistics that are common among Cinderella teams (low-ranked teams going far in the tournament)? Do they come from similar conferences?

Next, we found the teams considered "Cinderella" teams. We defined them as 8+ seeds that went to the Sweet 16 or better. We calculated the mean values for each variable for Cinderella teams by each conference below

[18]:
```
# Mean value for each parameter by conference for Cinderella teams

cinderella = (cbb.SEED >= 8) & (cbb.POSTSEASON_GAMES >= 3)
conf_cinderellas = cbb[cinderella].groupby('CONF').mean(numeric_only=True)
conf_cinderellas
```

[18]:

CONF	G	W	ADJOE	ADJDE	BARTHAG	EFG_O \
A10	35.500000	25.000000	112.500000	97.650000	0.835200	52.150000
ACC	35.142857	23.142857	112.285714	95.414286	0.864257	50.714286
ASun	35.000000	24.000000	103.400000	96.300000	0.695200	51.600000
B10	35.500000	23.000000	114.200000	94.100000	0.899800	52.100000
B12	36.000000	23.500000	105.650000	91.050000	0.846500	50.850000
BE	38.000000	24.000000	115.600000	97.900000	0.871300	51.900000
CUSA	37.000000	35.000000	114.000000	95.800000	0.881500	54.300000
Ivy	30.000000	23.000000	109.100000	101.000000	0.708300	52.200000
MAAC	33.000000	22.000000	99.400000	93.100000	0.678600	47.500000
MVC	34.000000	28.666667	109.866667	91.566667	0.887500	54.666667
P12	33.500000	22.000000	109.533333	95.083333	0.831917	50.483333
SEC	37.333333	24.666667	115.733333	94.300000	0.911000	50.200000

```
Sum   23.000000  16.000000  107.000000  107.100000  0.498100  53.600000
WCC   35.000000  27.000000  117.400000   94.500000  0.923800  55.200000

          EFG_D        TOR       TORD        ORB  …       2P_O       2P_D  \
CONF                                              …
A10   49.050000  17.600000  20.050000  31.450000  …  49.850000  49.450000
ACC   48.142857  16.771429  18.428571  31.257143  …  50.071429  47.428571
ASun  46.900000  21.000000  22.100000  32.500000  …  52.300000  46.900000
B10   48.600000  17.150000  17.100000  33.450000  …  51.900000  46.750000
B12   48.500000  18.800000  23.100000  27.150000  …  51.750000  49.850000
BE    51.600000  18.400000  17.500000  34.500000  …  52.000000  52.500000
CUSA  46.100000  16.900000  17.700000  31.400000  …  53.800000  44.700000
Ivy   48.400000  16.500000  14.700000  28.100000  …  53.300000  48.100000
MAAC  44.200000  20.100000  20.500000  30.900000  …  45.600000  44.500000
MVC   46.466667  19.000000  20.333333  28.700000  …  54.733333  45.400000
P12   48.400000  17.933333  18.983333  31.450000  …  49.250000  47.800000
SEC   46.566667  17.666667  17.833333  37.500000  …  51.033333  45.600000
Sum   50.400000  15.700000  18.200000  23.200000  …  49.700000  49.000000
WCC   44.800000  17.100000  15.100000  32.100000  …  54.300000  44.400000

           3P_O       3P_D      ADJ_T       WAB       SEED         YEAR  \
CONF
A10   37.700000  31.700000  65.700000  0.450000  12.000000  2013.500000
ACC   34.528571  32.971429  67.700000  1.242857   9.571429  2018.857143
ASun  33.400000  31.300000  69.100000 -4.000000  15.000000  2013.000000
B10   34.900000  35.000000  65.400000  2.650000   9.500000  2019.500000
B12   32.800000  30.950000  66.400000  2.650000  10.000000  2020.000000
BE    34.500000  33.400000  68.400000  1.600000  11.000000  2017.000000
CUSA  36.600000  32.400000  67.500000  4.700000   9.000000  2023.000000
Ivy   33.700000  32.700000  67.000000 -3.200000  15.000000  2023.000000
MAAC  34.600000  29.200000  65.600000 -5.600000  15.000000  2022.000000
MVC   36.466667  32.233333  65.100000  1.966667   9.333333  2017.333333
P12   35.483333  33.233333  66.400000  0.383333  11.333333  2017.166667
SEC   32.133333  32.600000  66.166667  1.566667   9.000000  2017.000000
Sum   38.800000  35.600000  71.400000 -5.100000  15.000000  2021.000000
WCC   37.800000  30.300000  68.200000  2.100000  11.000000  2016.000000

      POSTSEASON_GAMES  IS_POWER6
CONF
A10           3.500000        0.0
ACC           4.000000        1.0
ASun          3.000000        0.0
B10           3.000000        1.0
B12           3.500000        1.0
BE            4.000000        1.0
CUSA          5.000000        0.0
Ivy           3.000000        0.0
```

```
MAAC          4.000000       0.0
MVC           4.333333       0.0
P12           3.500000       1.0
SEC           4.000000       1.0
Sum           3.000000       0.0
WCC           3.000000       0.0

[14 rows x 23 columns]
```

Observing correlations for each variable to the number of tournament games played (POSTSEASON_GAMES) All for Cinderlla teams only

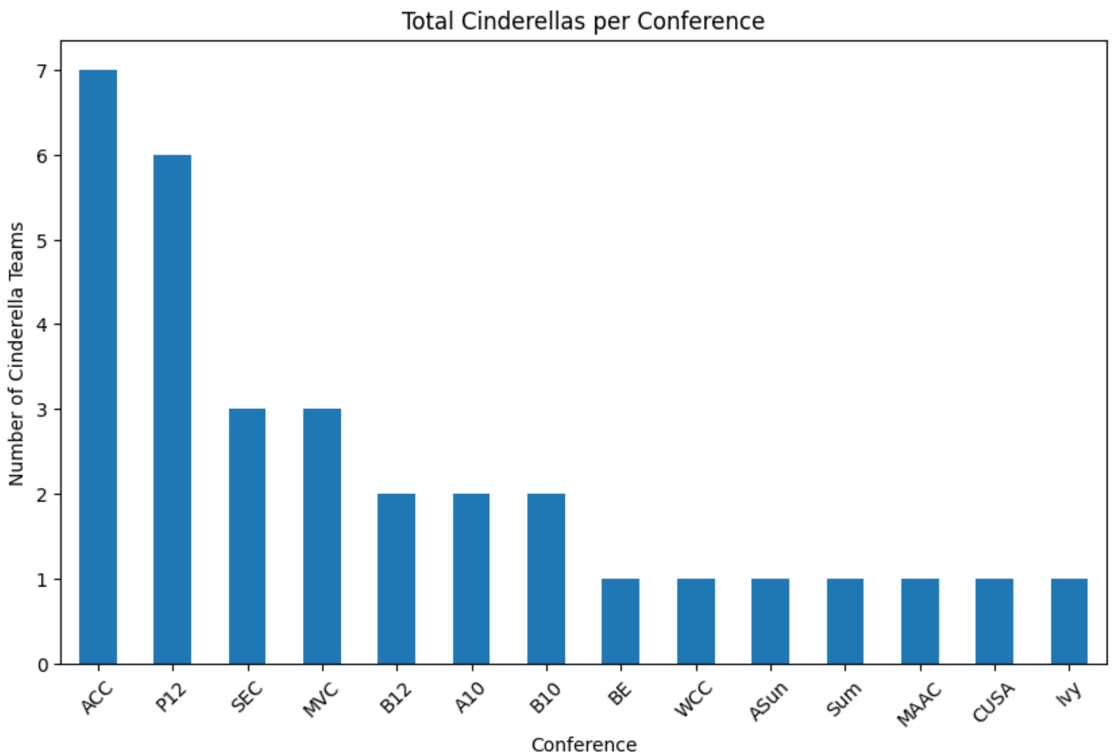
[19]:
```python
# Correlations of each parameter with 'POSTSEASON_GAMES' for Cinderella teams.

cbb[cinderella].corrwith(cbb.POSTSEASON_GAMES, numeric_only=True).sort_values()
```

[19]:
```
SEED               -0.349946
TORD               -0.232562
DRB                -0.150390
FTRD               -0.084784
TOR                -0.034130
IS_POWER6          -0.006540
2P_D               -0.001052
2P_O                0.001197
ADJ_T               0.007469
3P_D                0.027178
ADJDE               0.027726
EFG_D               0.031652
YEAR                0.055267
EFG_O               0.095206
ORB                 0.157830
FTR                 0.188404
3P_O                0.191391
BARTHAG             0.194234
ADJOE               0.260083
G                   0.299915
WAB                 0.364148
W                   0.454472
POSTSEASON_GAMES    1.000000
dtype: float64
```

Number of Cinderella teams that have come from each conference

[20]:
```python
# Cinderellas per conference
counts = cbb[cinderella]['CONF'].value_counts()

# Plotting the number of teams per conference
plt.figure(figsize=(10, 6))
```

```
counts.plot(kind='bar')
plt.title('Total Cinderellas per Conference')
plt.xlabel('Conference')
plt.ylabel('Number of Cinderella Teams')
plt.xticks(rotation=45)
plt.show()
```

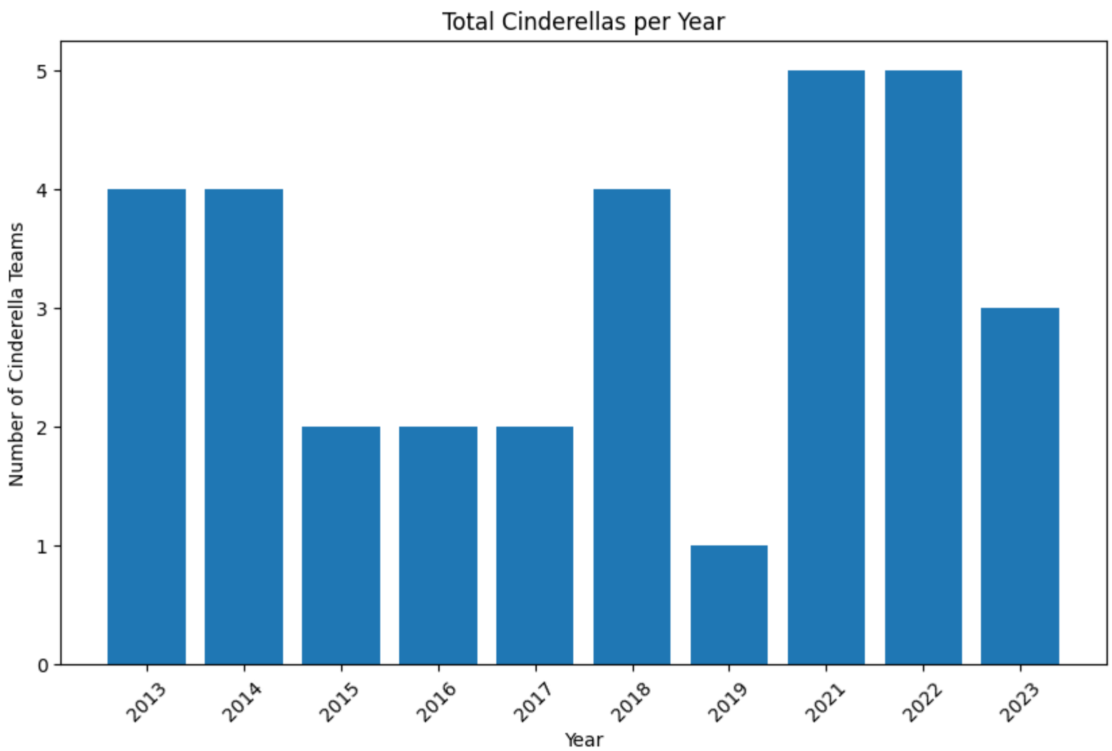


This suggests that the ACC and P12 may have undervalued teams if they are ranked 8th or lower and get to the Sweet 16 or better more often than other conferences

Next, we visualized the number of Cinderella teams from any conference that happen per year

[21]:
```
# Cinderellas per year
cbb['YEAR_STR'] = cbb.YEAR.apply(lambda x: str(x)) # change to str to skip 2020␣
↪in x axis
counts = cbb[cinderella]['YEAR_STR'].value_counts()

xaxis_order =␣
↪['2013','2014','2015','2016','2017','2018','2019','2021','2022','2023']

# Reindex the 'POSTSEASON' categories so they are ordered by tournament success
counts = counts.reindex(xaxis_order)
counts
```

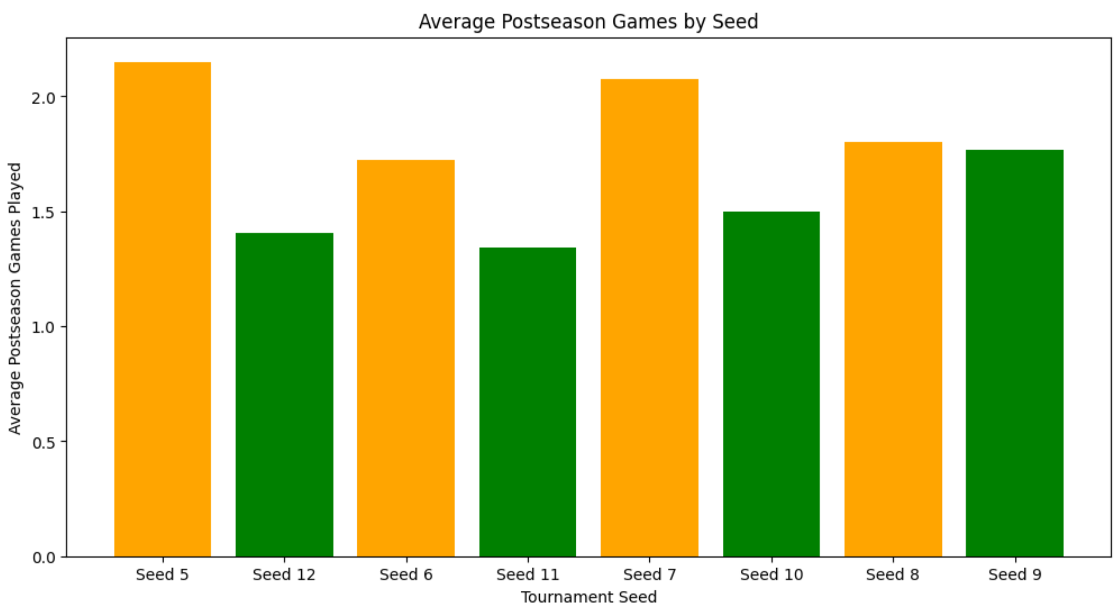
```
# Plotting the number of teams per conference
plt.figure(figsize=(10, 6))
plt.bar(counts.index, counts)
plt.title('Total Cinderellas per Year')
plt.xlabel('Year')
plt.ylabel('Number of Cinderella Teams')
plt.xticks(rotation=45)
plt.show()
```



Next, we looked at the number of tournament games played by seed (tournament success). We paired the seeds together by which seeds play each other in the first round and the matchups that we commonly see upsets in the first round

[22]:
```
import matplotlib.pyplot as plt

# analyze performance based on seed pairs
# returns error if seed_pair is not valid
def cinderella_avg_games(data, seed_pairs):
    for tup in seed_pairs:
        if sum(tup) != 17:
            return 'Invalid seed pair.'

    seed_labels = []
```

```
    avg_games = []

    for seed1, seed2 in seed_pairs:
        # filter data to compare between seeds
        seed1_teams = data[data['SEED'] == seed1]
        seed2_teams = data[data['SEED'] == seed2]

        # avg amount of games
        seed1_stats = seed1_teams['POSTSEASON_GAMES'].mean()
        seed2_stats = seed2_teams['POSTSEASON_GAMES'].mean()

        seed_labels.append(f"Seed {seed1}")
        seed_labels.append(f"Seed {seed2}")

        avg_games.append(seed1_stats)
        avg_games.append(seed2_stats)

    # bar chart
    plt.figure(figsize=(12, 6))
    plt.bar(seed_labels, avg_games, color=['orange', 'green', 'orange',␣
 ↪'green', 'orange', 'green'])
    plt.title('Average Postseason Games by Seed')
    plt.xlabel('Tournament Seed')
    plt.ylabel('Average Postseason Games Played')
    plt.show()

seed_pairs = [(5, 12), (6, 11), (7, 10), (8, 9)]

cinderella_avg_games(cbb, seed_pairs)
```

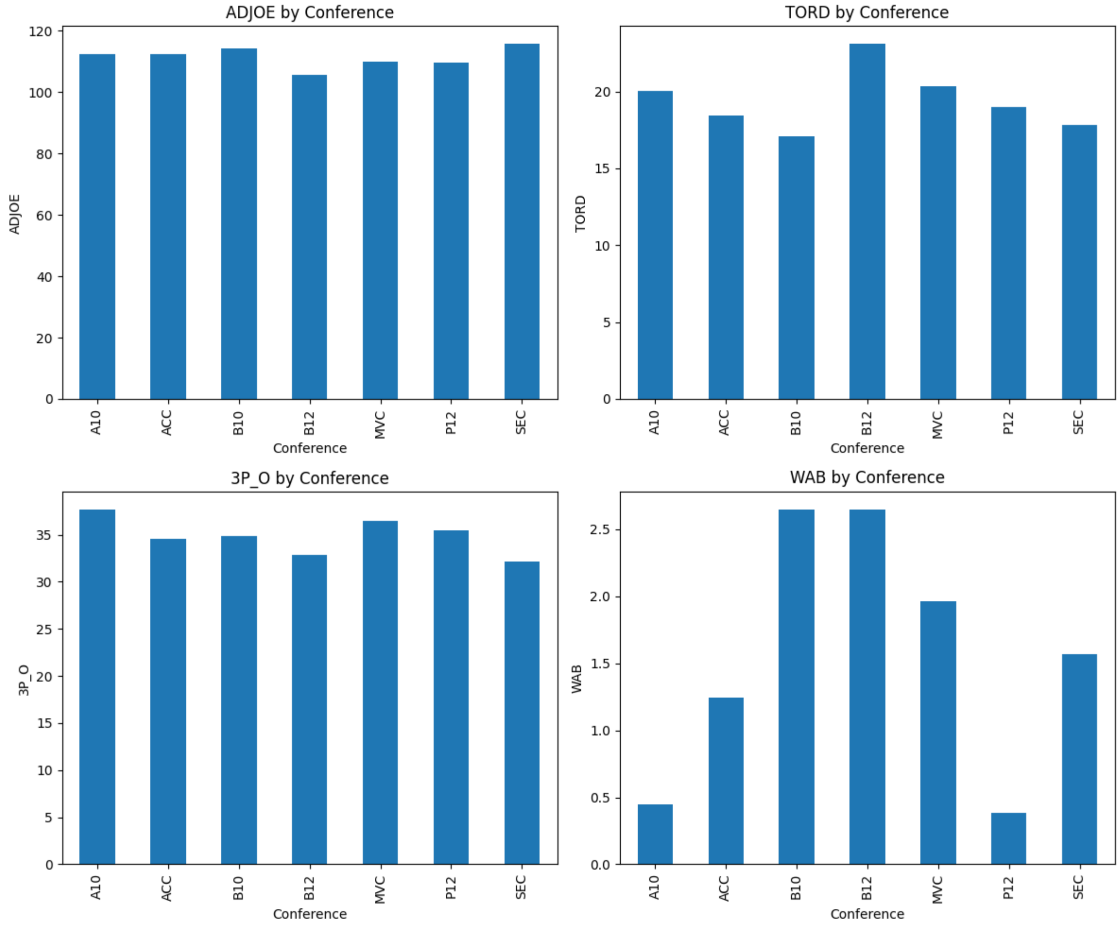


Below, we plotted higher correlated parameters by conference. We also filtered for conferences that produced 2 or more Cinderella teams

ADJOE = Offensive Efficiency (Points scored per 100 possessions, a higher OE is desirable) TORD = Turnover Percentage Committed (lower TORD is more desirable) 3P_O = Three-Point Shooting Percentage WAB = Wins Above Bubble (higher WAB is more desirable)

[23]:
```python
# Plots of higher corrleated parameters by conference.

mult_cinderellas = conf_cinderellas[cbb[cinderella]['CONF'].value_counts() >= 2]

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))

# Plotting ADJOE by Conference
mult_cinderellas['ADJOE'].plot(kind='bar', ax=axes[0, 0], legend=False)
axes[0, 0].set_title('ADJOE by Conference')
axes[0, 0].set_ylabel('ADJOE')
axes[0, 0].set_xlabel('Conference')

# Plotting TORD by Conference
mult_cinderellas['TORD'].plot(kind='bar', ax=axes[0, 1], legend=False)
axes[0, 1].set_title('TORD by Conference')
axes[0, 1].set_ylabel('TORD')
axes[0, 1].set_xlabel('Conference')

# Plotting 3P_O by Conference
mult_cinderellas['3P_O'].plot(kind='bar', ax=axes[1, 0], legend=False)
axes[1, 0].set_title('3P_O by Conference')
axes[1, 0].set_ylabel('3P_O')
axes[1, 0].set_xlabel('Conference')

# Plotting WAB by Conference
mult_cinderellas['WAB'].plot(kind='bar', ax=axes[1, 1], legend=False)
axes[1, 1].set_title('WAB by Conference')
axes[1, 1].set_ylabel('WAB')
axes[1, 1].set_xlabel('Conference')

#Looked this up and tight_layout() makes sure the labels don't overlap
plt.tight_layout()
plt.show()
```

```
/tmp/ipykernel_695/2782978259.py:3: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  mult_cinderellas = conf_cinderellas[cbb[cinderella]['CONF'].value_counts() >=
2]
```



0.2.6 Analysis 4

How is WAB and BARTHAG distributed among tournament teams? Are either metrics valuable in predicting tournament success?

BARTHAG = Power Rating (Probability of beating an average Division I team) WAB = The number of wins a team has over a bubble team, if playing the same schedule

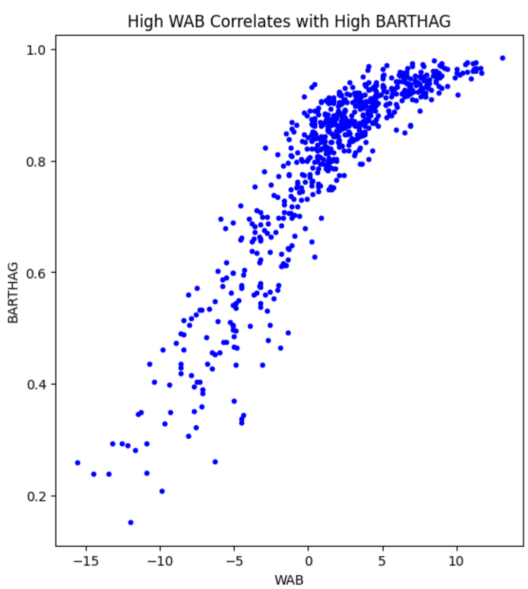
[24]:
```
# Correlations
a = cbb[['WAB', 'BARTHAG', 'ADJ_T', 'POSTSEASON_GAMES']]
a.corr()
```

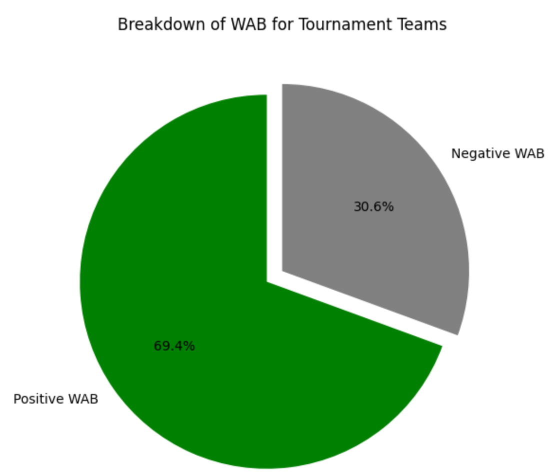
[24]:

	WAB	BARTHAG	ADJ_T	POSTSEASON_GAMES
WAB	1.000000	0.896301	-0.028414	0.560783
BARTHAG	0.896301	1.000000	-0.060323	0.502648
ADJ_T	-0.028414	-0.060323	1.000000	-0.050899
POSTSEASON_GAMES	0.560783	0.502648	-0.050899	1.000000

[25]:
```python
# Binary positive and negative WAB variable (POS_WAB)
cbb['POS_WAB'] = cbb.WAB.apply(lambda x: 1 if x>0 else 0)
```

[26]:
```python
fig, axs = plt.subplots(1, 2, figsize=(14, 7))

ax1 = axs[0]
ax2 = axs[1]

# Scatter chart of BARTHAG and WAB
ax1.scatter(cbb['WAB'], cbb['BARTHAG'], color="blue", marker=".")

# Add x and y axis labels
ax1.set_xlabel('WAB')
ax1.set_ylabel('BARTHAG')
ax1.set_title('High WAB Correlates with High BARTHAG')

# Pie chart of WAB
WAB_counts = cbb.POS_WAB.value_counts().sort_index()
explodes = [0,0.1]

ax2.pie(WAB_counts, labels=["Negative WAB", "Positive WAB"], explode=explodes,␣
 ↪autopct='%.1f%%', colors=['gray','green'], startangle=90, counterclock=False)
ax2.set_title("Breakdown of WAB for Tournament Teams")

plt.show()
```





The graph of the left shows that WAB is positively correlated to BARTHAG. (High power ratings and number of wins a team has over bubble teams)

Also, the pie chart shows that 70% of tournament teams have a positive WAB

Next, we looked at the mean WAB by conference

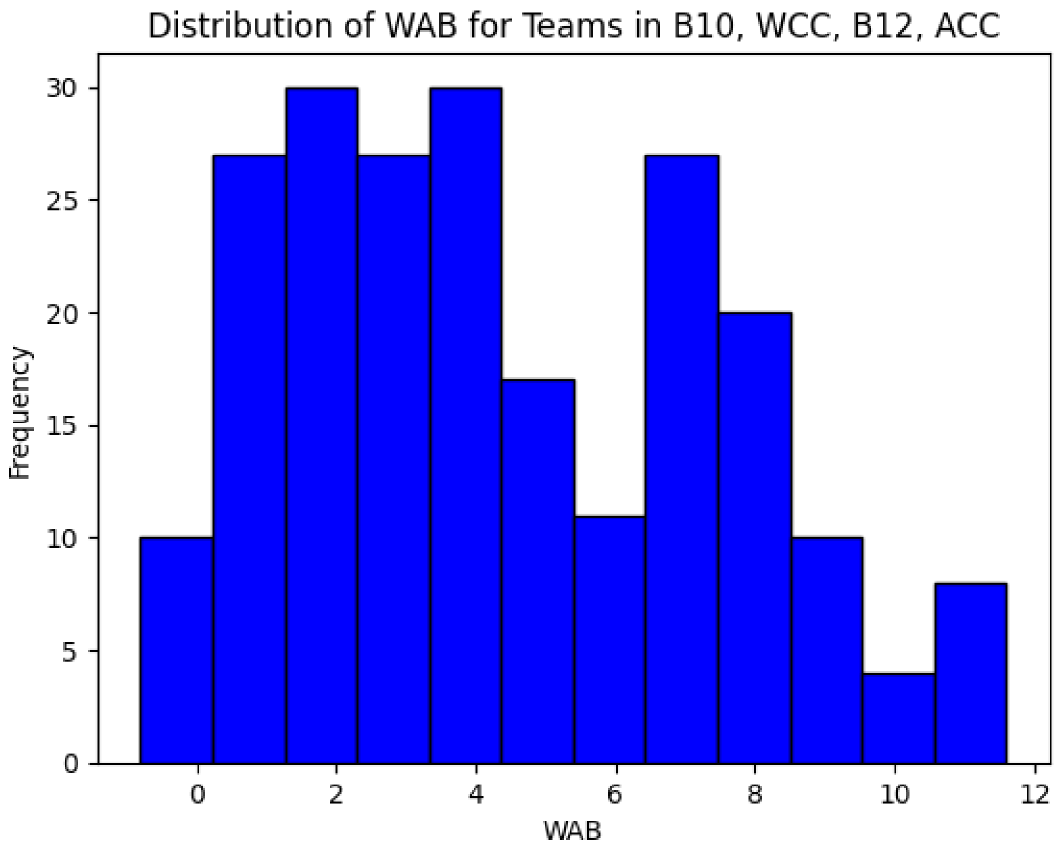
[27]:
```
cbb.groupby("CONF").WAB.mean().sort_values()
```

[27]:
```
CONF
NEC    -9.110000
SWAC   -7.520000
MEAC   -7.440000
MAAC   -5.160000
BSth   -4.718182
Pat    -4.510000
Horz   -3.970000
BW     -3.860000
ASun   -3.722222
SB     -3.654545
BSky   -3.330000
AE     -3.220000
OVC    -3.218182
Sum    -2.790000
CAA    -2.730000
Slnd   -2.690000
MAC    -1.820000
WAC    -1.720000
Ivy    -1.611111
SC     -1.090000
CUSA   -1.000000
A10     1.570000
MVC     1.707143
MWC     2.080769
P12     3.206818
Amer    3.472000
SEC     3.807407
BE      3.861818
B10     4.072222
WCC     4.321053
B12     4.560000
ACC     4.616923
Name: WAB, dtype: float64
```

The next graph shows the distribution of WAB for the conferences with the 4 highest WAB means

[28]:
```
Top_WAB = cbb[(cbb.CONF == 'B12') | (cbb.CONF == 'ACC') | (cbb.CONF == 'WCC') |
 ↪(cbb.CONF == 'B10')].WAB
plt.hist(Top_WAB, bins=12, color='blue', edgecolor='black')
plt.xlabel("WAB")
plt.ylabel("Frequency")
```

```
plt.title("Distribution of WAB for Teams in B10, WCC, B12, ACC")
plt.show()
```



0.2.7 Machine Learning

Using several regressor methods, we wanted to construct a model that can most accurately predict a team's depth in the tournament. (`POSTSEASON_GAMES`, the number of games played in the NCAA tournament)

We removed wins and games because of the added bias from reflecting postseason performance

[29]:
```
# Removed wins and games
cbb1 = cbb.drop(columns=['G', 'W'])
cbb1.head()
```

[29]:

	TEAM	CONF	ADJOE	ADJDE	BARTHAG	EFG_O	EFG_D	TOR	TORD	ORB	\
0	North Carolina	ACC	123.3	94.9	0.9531	52.6	48.1	15.4	18.2	40.7	
1	Wisconsin	B10	129.1	93.6	0.9758	54.8	47.7	12.4	15.8	32.1	
2	Michigan	B10	114.4	90.4	0.9375	53.9	47.7	14.0	19.5	25.5	
3	Texas Tech	B12	115.2	85.2	0.9696	53.5	43.0	17.7	22.8	27.4	

```
4          Gonzaga  WCC  117.8   86.3   0.9728   56.6   41.1  16.2  17.1  30.0

   …  3P_D  ADJ_T   WAB  POSTSEASON  SEED  YEAR  POSTSEASON_GAMES  \
0  …  36.2   71.7   8.6         2ND     1  2016                 6
1  …  37.5   59.3  11.3         2ND     1  2015                 6
2  …  33.2   65.9   6.9         2ND     3  2018                 6
3  …  29.7   67.5   7.0         2ND     3  2019                 6
4  …  29.0   71.5   7.7         2ND     1  2017                 6

   IS_POWER6  YEAR_STR POS_WAB
0          1      2016       1
1          1      2015       1
2          1      2018       1
3          1      2019       1
4          0      2017       1

[5 rows x 26 columns]
```

[30]:
```python
# Function for finding moderately correlated values
# returns variables that are correlated, removing the predictor column
# resulting dataframe can be used for machine learning analysis
def good_corr(df, pred_col, corr):
    df = df.corrwith(df[pred_col], numeric_only=True).round(4)
    df = df.sort_values().to_frame()
    df = df.drop(f"{pred_col}")
    df.columns = ['CORRELATION']
    return df[abs(df.CORRELATION)>corr]
```

[31]:
```python
# Variables with good correlation to postseason_games
target = 'POSTSEASON_GAMES'
x_vars = good_corr(cbb1, target, 0.2)
x_vars
```

[31]:

	CORRELATION
SEED	-0.5761
ADJDE	-0.4497
EFG_D	-0.2511
2P_D	-0.2252
2P_O	0.2254
EFG_O	0.2377
IS_POWER6	0.3587
POS_WAB	0.3845
BARTHAG	0.5026
ADJOE	0.5235
WAB	0.5608

[32]:
```
features = x_vars.index

X = cbb[features]
y = cbb[target]
X.shape
```

[32]: (680, 11)

[33]:
```
# Function for splitting the data into training and testing components
# allows user to specify X df, y df, splitting parameter, and random_state
from sklearn.model_selection import train_test_split
def train_test(x, y, test_size, random_state):
    return train_test_split(x, y, test_size=test_size,␣
 ↪random_state=random_state)
```

[34]:
```
X_train, X_test, y_train, y_test = train_test(X, y, 0.20, 68)
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

[34]: ((544, 11), (544,), (136, 11), (136,))

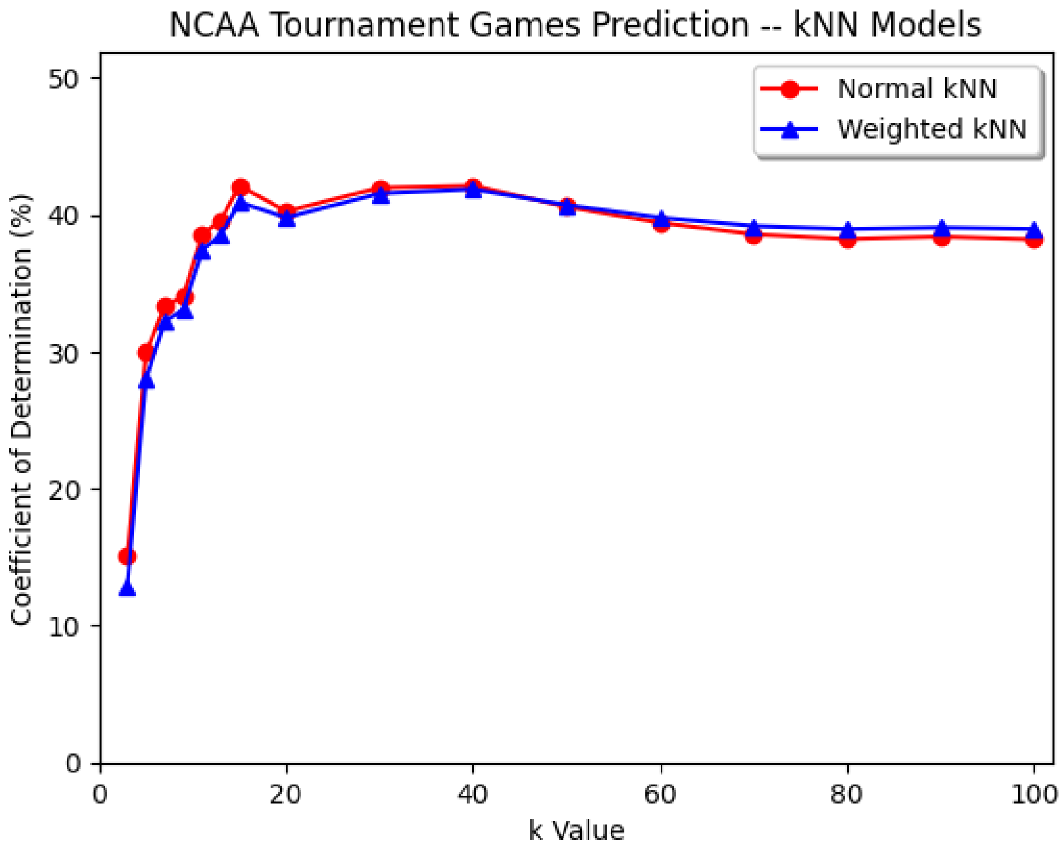
k-Nearest Neighbors (kNN)

[35]:
```
from sklearn.neighbors import KNeighborsRegressor
# https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.
 ↪KNeighborsRegressor.html#sklearn.neighbors.KNeighborsRegressor

k_vals = [3,5,7,9,11,13,15,20,30,40,50,60,70,80,90,100] # k neighbors to test

r_vals = [] # empty array of r^2 values (normal kNN)
max_r = 0 # placeholder for max r^2 value (normal kNN)
max_k = 0 # placeholder for best k value (normal kNN)

wr_vals = [] # empty array of r^2 values (weighted kNN)
max_wr = 0 # placeholder for max r^2 value (weighted kNN)
max_wk = 0 # placeholder for best k value (weighted kNN)

# loop through each k value, apply to each ML model, and record the results
for k in k_vals:
    knr = KNeighborsRegressor(n_neighbors=k, p=2)
    knr.fit(X_train, y_train)
    current_r = knr.score(X_test, y_test)
    if current_r > max_r:
        max_r = current_r
        max_k = k
    r_vals.append(current_r*100) #convert to percentage
```

```
    w_knr = KNeighborsRegressor(n_neighbors=k, weights='distance', p=2) #␣
↪weight points by inverse distance
    w_knr.fit(X_train, y_train)
    w_current_r = w_knr.score(X_test, y_test)
    if w_current_r > max_wr:
        max_wr = w_current_r
        max_wk = k
    wr_vals.append(w_current_r*100)
```

[36]:

```
# Graph of KNN Model
plt.plot(k_vals,r_vals,'ro-', label='Normal kNN')
plt.plot(k_vals,wr_vals, 'b^-', label='Weighted kNN')
plt.legend(loc='best', shadow=True)

plt.axis([0,102,0,max_wr*100+10])
plt.xlabel('k Value')
plt.ylabel('Coefficient of Determination (%)')
plt.title('NCAA Tournament Games Prediction -- kNN Models')
plt.show()

#Conclusion
print("Best k value: ", max_k)
print("Best r^2 value: {}%".format(round(max_r*100,2)))
print("Best k value (weighted): ", max_wk)
print("Best r^2 value: {}%".format(round(max_wr*100,2)))
```




```
Best k value:  15
Best r^2 value: 42.11%
Best k value (weighted):  40
Best r^2 value: 41.85%
```

Linear Regression

[37]:
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
# https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.
↪LinearRegression.html#sklearn.linear_model.LinearRegression
```

[38]:
```
lr.fit(X_train, y_train)
```

[38]:
```
LinearRegression()
```

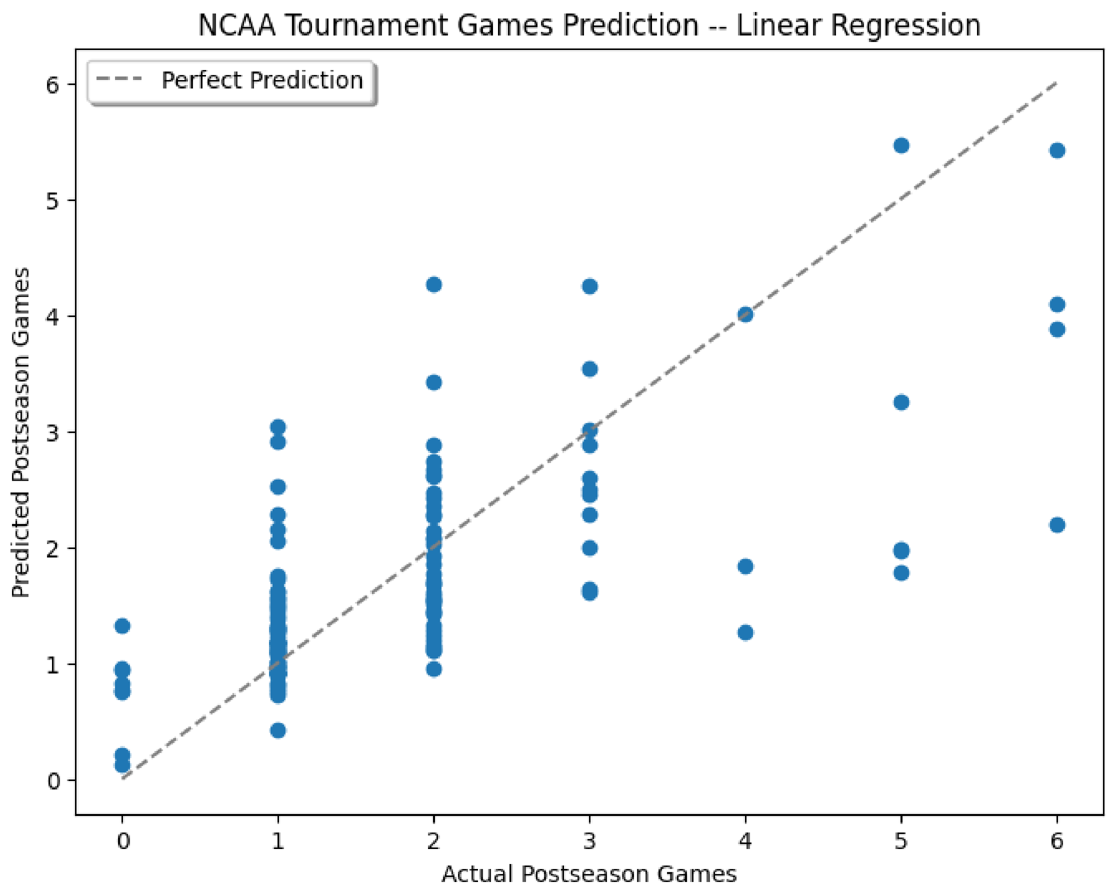
[39]:
```
train = lr.score(X_train, y_train)
test = lr.score(X_test, y_test)

print('Training score: {}%'.format(round(train*100,2)))
print('Test score: {}%'.format(round(test*100,2)))
```

```
Training score: 46.2%
Test score: 46.06%
```

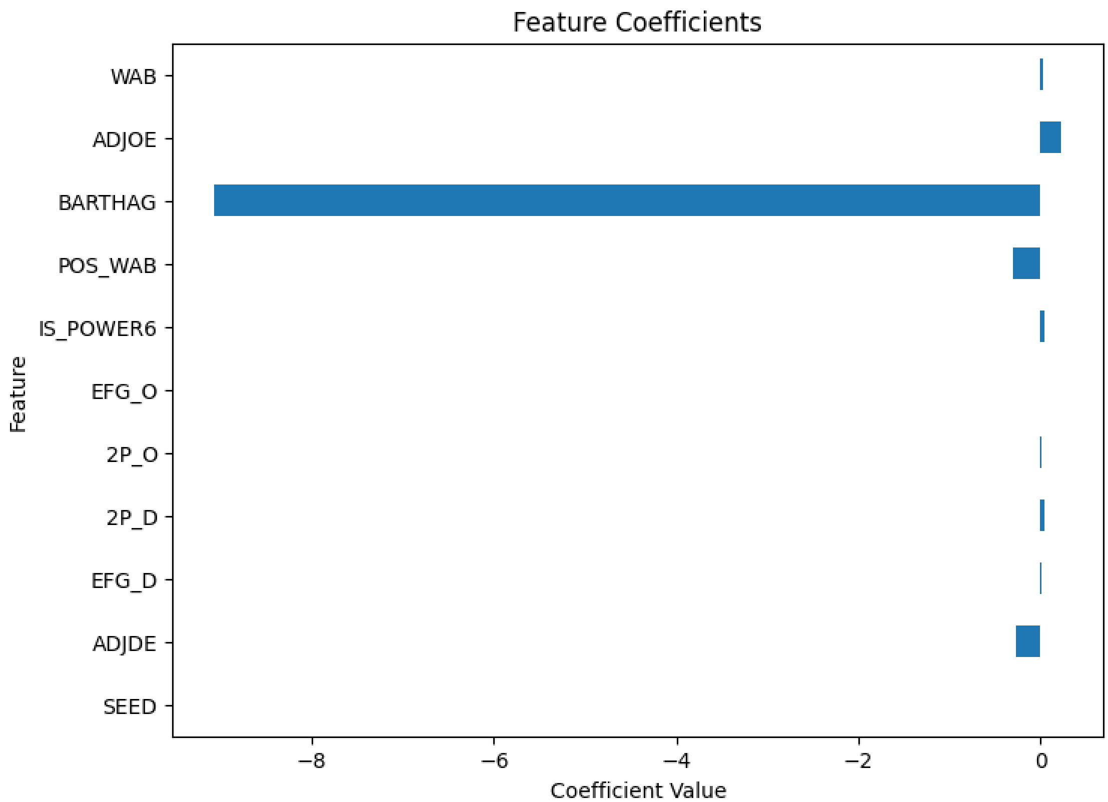
[40]:
```
from sklearn.metrics import mean_squared_error, r2_score

preds = lr.predict(X_test)
mse = mean_squared_error(y_test, preds)
r2 = r2_score(y_test, preds)

print('Mean Squared Error:', round(mse,2))
print('R^2 Score: {}%'.format(round(r2*100,2)))
```

```
Mean Squared Error: 0.88
R^2 Score: 46.06%
```

[41]:
```
plt.figure(figsize=(8, 6))
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--',␣
 ↪color='gray', label='Perfect Prediction')
plt.scatter(y_test, preds)
plt.title('NCAA Tournament Games Prediction -- Linear Regression')
plt.xlabel('Actual Postseason Games')
plt.ylabel('Predicted Postseason Games')
plt.legend(loc='best', shadow=True)
plt.show()
```



[42]:
```
# Plot coefficients to analyze weight of different features for this model

feature_coefficients = pd.Series(lr.coef_, index=X.columns)

plt.figure(figsize=(8, 6))
feature_coefficients.plot(kind='barh')
plt.title('Feature Coefficients')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()
```

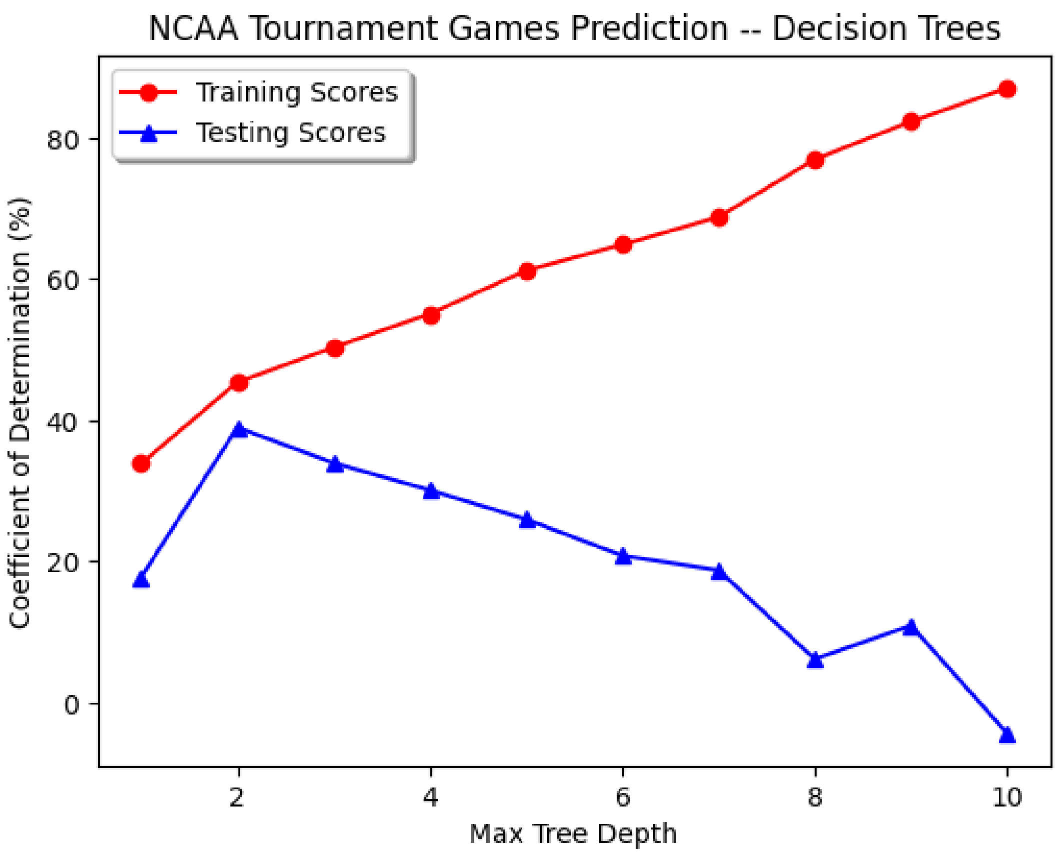


Decision Tree

[43]:
```
from sklearn.tree import DecisionTreeRegressor
# https://scikit-learn.org/stable/modules/generated/sklearn.tree.
↪DecisionTreeRegressor.html#sklearn.tree.DecisionTreeRegressor
```

[44]:
```
max_depth = [1,2,3,4,5,6,7,8,9,10]
trains = []
tests = []
max_dt_r = 0
max_dt_d = 0

for d in max_depth:
    tree = DecisionTreeRegressor(max_depth=d)
    tree.fit(X_train, y_train)
    current_train = tree.score(X_train, y_train)
    current_test = tree.score(X_test, y_test)
    if current_test > max_dt_r:
        max_dt_r = current_test
        max_dt_d = d
        best_dt = tree
    trains.append(current_train*100)
```

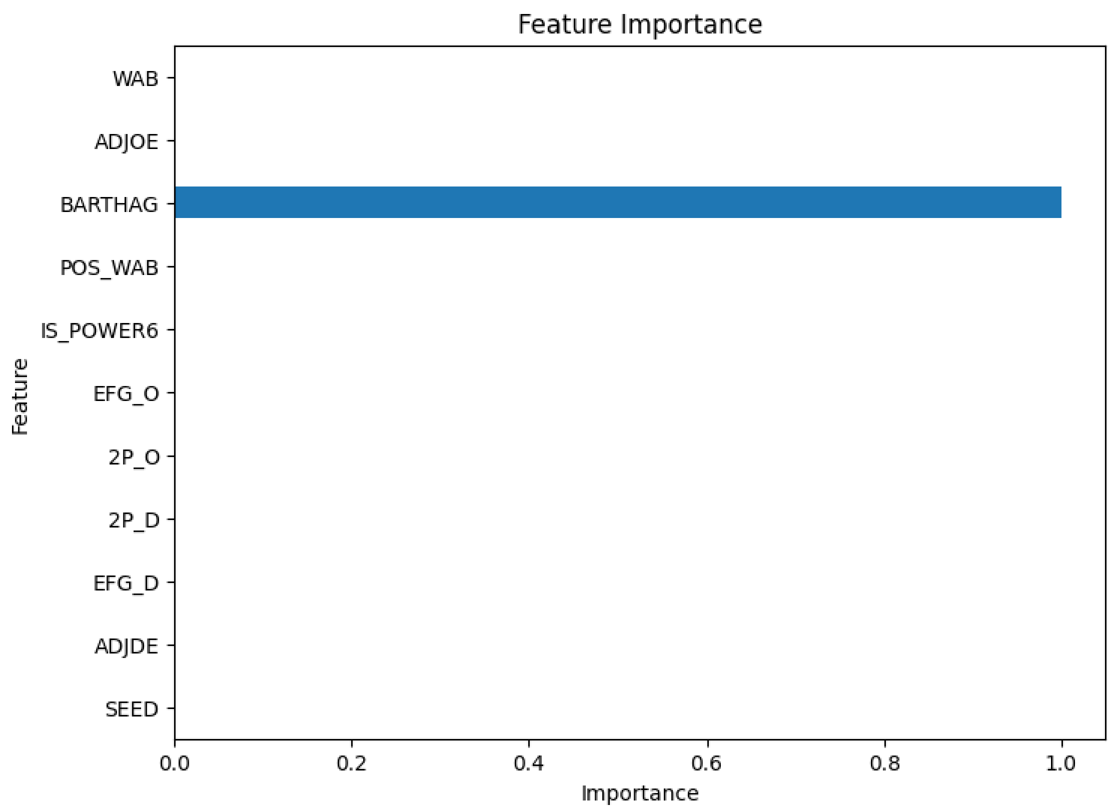
```
    tests.append(current_test*100)

# plot graph
plt.plot(max_depth, trains, "ro-", label="Training Scores")
plt.plot(max_depth, tests, "b^-", label="Testing Scores")
plt.xlabel("Max Tree Depth")
plt.ylabel('Coefficient of Determination (%)')
plt.title('NCAA Tournament Games Prediction -- Decision Trees')
plt.legend(loc='best', shadow=True)
plt.show()

# Conclusions
print("Best depth value", max_dt_d)
print("Best r^2 value: {}%".format(round(max_dt_r*100,2)))
```




```
Best depth value 2
Best r^2 value: 38.99%
```

[45]:
```
# Plotting feature importance
## should we remove this plot??
```

```
feature_importance = pd.Series(best_dt.feature_importances_, index=X.columns)

plt.figure(figsize=(8, 6))
feature_importance.plot(kind='barh')
plt.title('Feature Importance')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```



Random Forest

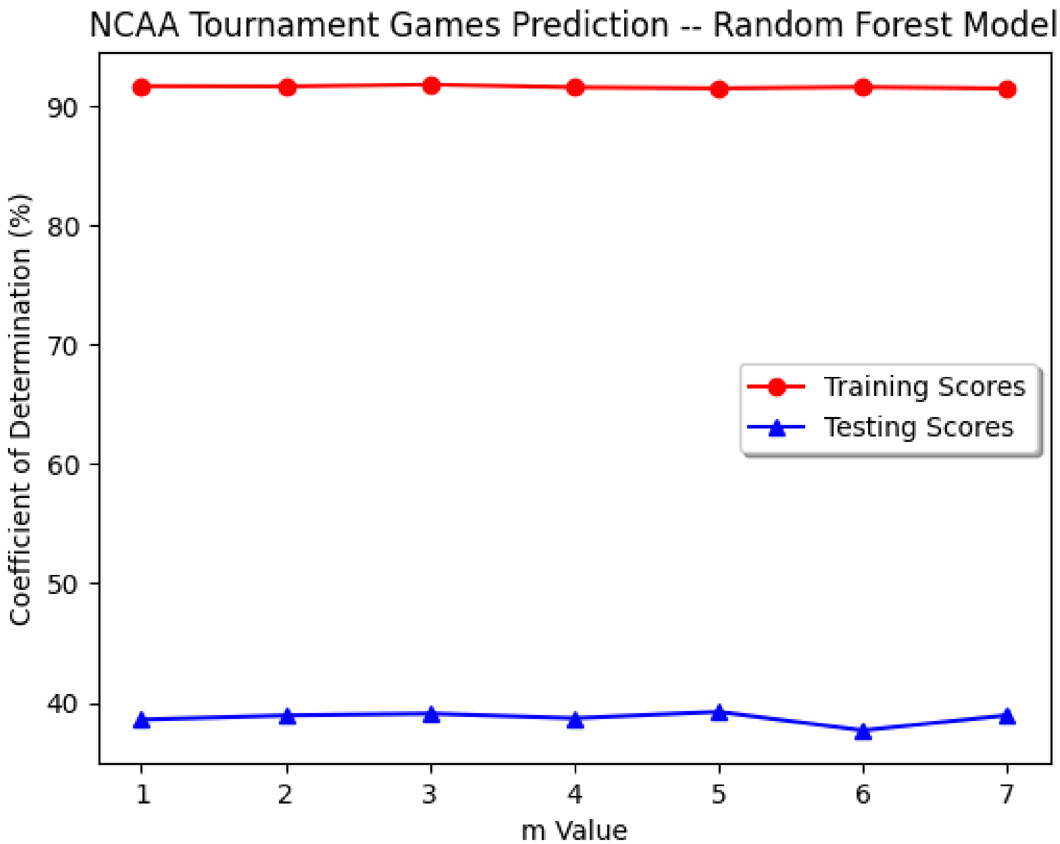
[46]:
```
from sklearn.ensemble import RandomForestRegressor
# https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.
↪RandomForestRegressor.html#sklearn.ensemble.RandomForestRegressor
```

[47]:
```
max_features = [1,2,3,4,5,6,7] # array for different numbers of features to test
rf_r_train = [] # empty array of r^2 training values (RF)
rf_r_test = [] # empty array of r^2 test values (RF)
max_rf_r = 0 # placeholder for max r^2 value (RF)
max_rf_m = 0 # placeholder for best m value (RF)

for m in max_features:
```

```
    rfr = RandomForestRegressor(n_estimators=1000, max_features=m)
    rfr.fit(X_train, y_train)
    rf_current_train = rfr.score(X_train, y_train)
    rf_current_test = rfr.score(X_test, y_test)
    if rf_current_test > max_rf_r:
        max_rf_r = rf_current_test
        max_rf_m = m
        best_forest = rfr
    rf_r_train.append(rf_current_train*100)
    rf_r_test.append(rf_current_test*100)
```

[48]:

```
# plot graph
plt.plot(max_features, rf_r_train, 'ro-', label="Training Scores")
plt.plot(max_features, rf_r_test, 'b^-', label="Testing Scores")
# plt.axis([0,8,min(rf_r_vals)-10, max_rf_r*100+10])
plt.xlabel('m Value')
plt.ylabel('Coefficient of Determination (%)')
plt.title('NCAA Tournament Games Prediction -- Random Forest Model')
plt.legend(loc='best', shadow=True)
plt.show()

#Conclusion
print("Best m value: ", max_rf_m)
print("Best r^2 value: {}%".format(round(max_rf_r*100,2)))
```




```
Best m value:  5
Best r^2 value: 39.22%
```

Machine Learning Summary Max R-Squared
1. Linear Regression: 46.06% 2. kNN: 42.11% 3. Weighted kNN: 41.85%
4. Random Forest: 39.22%
5. Decision Tree: 38.99%

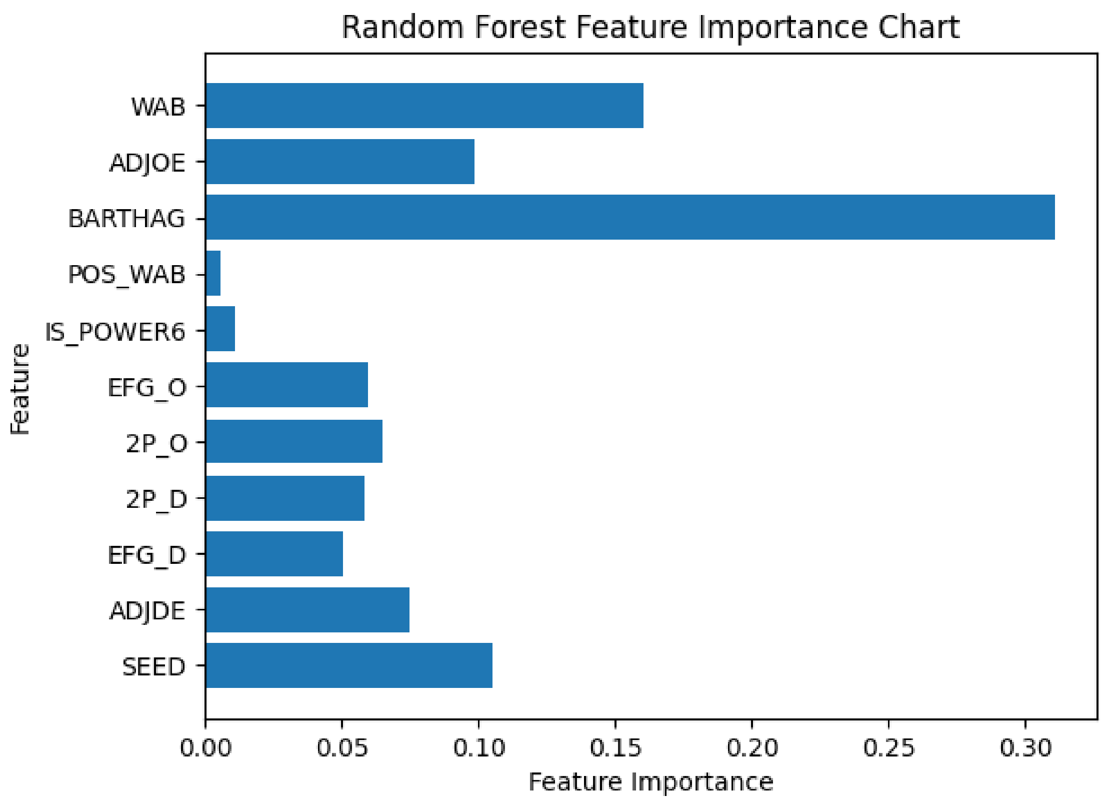
While this performance is relatively low, several other factors such as pressure, fatigue, and injuries likely played a factor in determining a team's success in the tournament. Many of these factors are qualitative and were not included in our dataset.

0.2.8 Analysis 5

Main question: What statistics are most important for teams to perform well in the tournament?

[49]:
```
# Feature Importances Chart - Random Forest
# https://scikit-learn.org/stable/auto_examples/ensemble/
↪plot_forest_importances.html
index = range(len(features)) #references features selected from high_corr␣
↪function
```

```python
plt.barh(index, best_forest.feature_importances_) #horizontal bar chart
plt.ylabel('Feature')
plt.yticks(index,features)
plt.xlabel("Feature Importance")
plt.title("Random Forest Feature Importance Chart")
plt.show()
```



This performance also correlated with our feature importance plot, where season-long metrics such as BARTHAG and WAB provided the best indication of a team's performance. Not surprisingly, the team's seed also appeared relatively important, as teams granted a higher seed will play "easier" opponents. Adjusted offense efficiency outperformed adjusted defense efficiency, which, while both important, indicates that offensively dominant teams will tend to outperform defensively dominant teams, on average. Interestingly, IS_POWER6 was one of the worst features at predicting performance. While stronger schedules can help improve a team's resume and improve their chances of making the tournament, it becomes virtually worthless in the post-season. Simply put, in an era where Cinderella teams regularly bust brackets, there exist factors that cannot be measured, and results that cannot be predicted, to culminate in the beauty that is 'March Madness.'

Challenges - Handling teams that play in the "First Four" - Eliminating bias within the dataset that indicates the team's success (G and W) - Generating sufficient functions to be implemented in the project - Incorporating interactive features such as drop-down windows or widgets - Creating more categorical variables for aggregating data - Only 10 years worth of tournament data

```
[ ]:
```