Analysing NBA Data

Introduction

The National Basketball Association (NBA) is one of the major professional sports leagues in the United States and Canada and is considered the best professional basketball league in the world. Exploratory Data Analysis (EDA) using Python is performed with the goal of discovering new information and answering the questions such as top players based on the salary, top teams based on the most represented players, and average salary of players in each team.

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Importing Libraries

In [1]:
```
#import Python libraries

import pandas as pd                    # importing pandas library for data manipulation
import matplotlib.pyplot as plt        # importing pyplot interface using matplotlib
import seaborn as sns                  # importing seaborm library for interactive visuali

import warnings                        # importing warnings to disable runtime warnings
warnings.filterwarnings("ignore")
```

Load Data

In [2]:
```
#Load the nba.csv data into a Pandas DataFrame
df = pd.read_csv('nba.csv', encoding = "unicode_escape")
```

In [3]:
```
#number of rows and columns
df.shape
```

Out[3]:
```
(457, 8)
```

In [4]:
```
#the basic information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 457 entries, 0 to 456
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Name      457 non-null    object
 1   Team      457 non-null    object
```

```
 2   Number    457 non-null    int64
 3   Position  457 non-null    object
 4   Age       457 non-null    int64
 5   Weight    457 non-null    int64
 6   College   373 non-null    object
 7   Salary    446 non-null    float64
dtypes: float64(1), int64(3), object(4)
memory usage: 28.7+ KB
```

In [5]:
```
#the first five rows
df.head(5)
```

Out[5]:

	Name	Team	Number	Position	Age	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0	PG	25	180	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99	SF	25	235	Marquette	6796117.0
2	John Holland	Boston Celtics	30	SG	27	205	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28	SG	22	185	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8	PF	29	231	NaN	5000000.0

In [6]:
```
#descriptive statistics of numerical columns
df.describe()
```

Out[6]:

	Number	Age	Weight	Salary
count	457.000000	457.000000	457.000000	4.460000e+02
mean	17.678337	26.938731	221.522976	4.842684e+06
std	15.966090	4.404016	26.368343	5.229238e+06
min	0.000000	19.000000	161.000000	3.088800e+04
25%	5.000000	24.000000	200.000000	1.044792e+06
50%	13.000000	26.000000	220.000000	2.839073e+06
75%	25.000000	30.000000	240.000000	6.500000e+06
max	99.000000	40.000000	307.000000	2.500000e+07

Data Cleaning

Handling missing values

In [7]:
```
#checking the number of missing values in each column
pd.isnull(df).sum()
```

Out[7]:
```
Name          0
Team          0
Number        0
Position      0
Age           0
Weight        0
College      84
Salary       11
dtype: int64
```

Observation - The columns - 'College' and 'Salary' consists of null values. The null values in 'College' column are replaced with the value 'Others' assuming the college names of some players are not listed in the list.

The null values in 'Salary' column are replaced with the mean value of the 'Salary' column.

In [8]:
```
#replacing the null values in 'College' column with 'Others'
df['College'].fillna('Others', inplace = True)
```

In [9]:
```
#verifying if there is any null values in 'College' column
pd.isnull(df['College']).sum()
```

Out[9]:
```
0
```

In [10]:
```
#replacing the null values in 'Salary' column with it's mean value
df['Salary'].fillna(df['Salary'].mean(), inplace = True)
```

In [11]:
```
#verifying if there is any null values in 'Salary' column
pd.isnull(df['Salary']).sum()
```

Out[11]:
```
0
```

In [12]:
```
#checking the number of missing values in each column
pd.isnull(df).sum()
```

Out[12]:
```
Name        0
Team        0
Number      0
Position    0
Age         0
Weight      0
College     0
Salary      0
dtype: int64
```

Observation - There are no missing values in the dataset

Handling duplicate rows

In [13]:
```
#to get the sum of duplicate elements in the dataset
df.duplicated().sum()
```

Out[13]:
```
0
```

Observation - There are no duplicate elements in the dataset

Data Transformation

In [14]:
```
#get column names
df.columns
```

Out[14]:
```
Index(['Name', 'Team', 'Number', 'Position', 'Age', 'Weight', 'College',
       'Salary'],
      dtype='object')
```

In [15]:
```
#Create a new column 'BMI' (Body Mass Index) using the formula: BMI = (weight in pounds
#Assuming a fixed height value of 70 inches (5 feet 10 inches)

df['BMI'] = (df['Weight'] / (70**2)) * 703
```

In [16]:
```
#the first five rows
df.head(5)
```

Out[16]:

	Name	Team	Number	Position	Age	Weight	College	Salary	BMI

0	Avery Bradley	Boston Celtics	0	PG	25	180	Texas	7.730337e+06	25.824490
1	Jae Crowder	Boston Celtics	99	SF	25	235	Marquette	6.796117e+06	33.715306
2	John Holland	Boston Celtics	30	SG	27	205	Boston University	4.842684e+06	29.411224
3	R.J. Hunter	Boston Celtics	28	SG	22	185	Georgia State	1.148640e+06	26.541837
4	Jonas Jerebko	Boston Celtics	8	PF	29	231	Others	5.000000e+06	33.141429

Observation - The new column 'BMI' is added to dataframe

Exploratory Data Analysis (EDA)

In [17]:
```
#Display summary statistics of the 'age', 'weight', and 'salary' columns.
df[['Age','Weight','Salary']].describe()
```

Out[17]:

	Age	Weight	Salary
count	457.000000	457.000000	4.570000e+02
mean	26.938731	221.522976	4.842684e+06
std	4.404016	26.368343	5.165781e+06
min	19.000000	161.000000	3.088800e+04
25%	24.000000	200.000000	1.100602e+06
50%	26.000000	220.000000	2.869440e+06
75%	30.000000	240.000000	6.331404e+06
max	40.000000	307.000000	2.500000e+07

In [18]:
```
#Calculate the average age, weight, and salary of players in each 'position' category.
avg_by_pos = df.groupby('Position')[['Age','Weight','Salary']].mean()

#display
avg_by_pos
```

Out[18]:

	Age	Weight	Salary
Position			
C	27.371795	254.205128	5.967052e+06
PF	27.160000	240.430000	4.570889e+06
PG	26.847826	189.478261	5.067606e+06
SF	26.858824	221.776471	4.857220e+06
SG	26.539216	206.686275	4.034356e+06

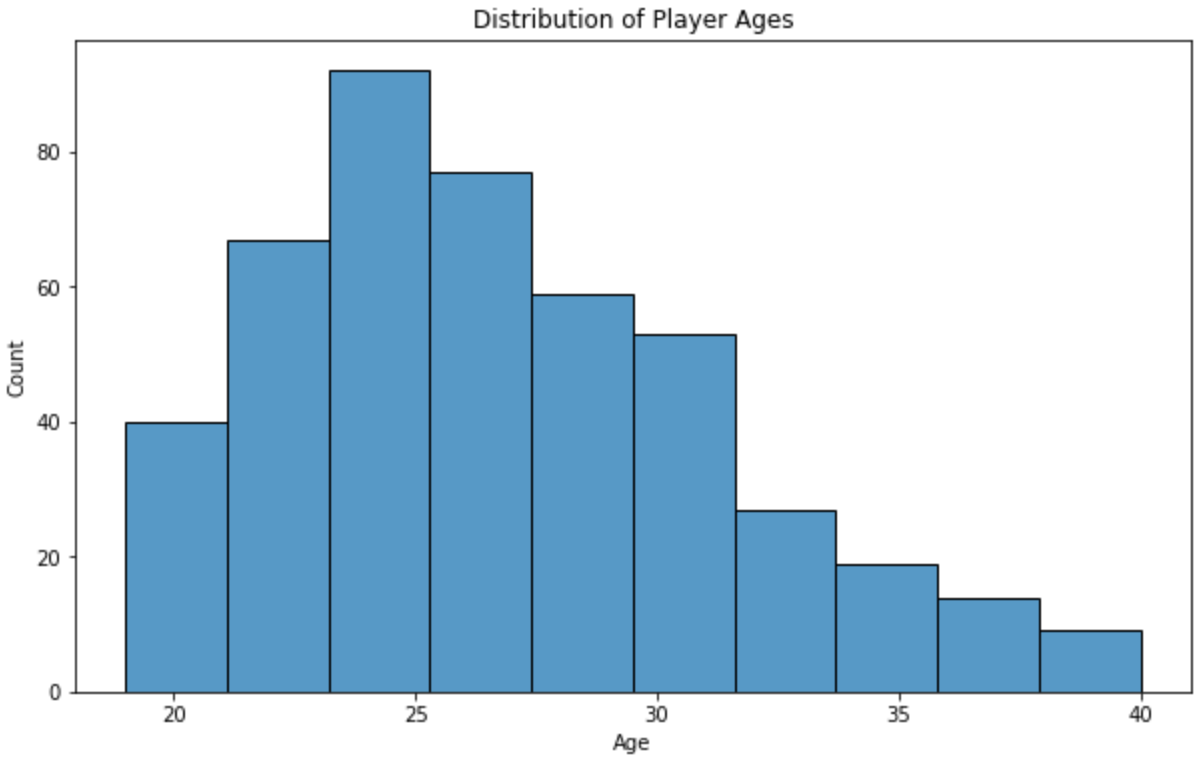
In [19]:
```
#get column names
df.columns
```

Out[19]:
```
Index(['Name', 'Team', 'Number', 'Position', 'Age', 'Weight', 'College',
       'Salary', 'BMI'],
      dtype='object')
```

Data Visualization

1. Age of Players

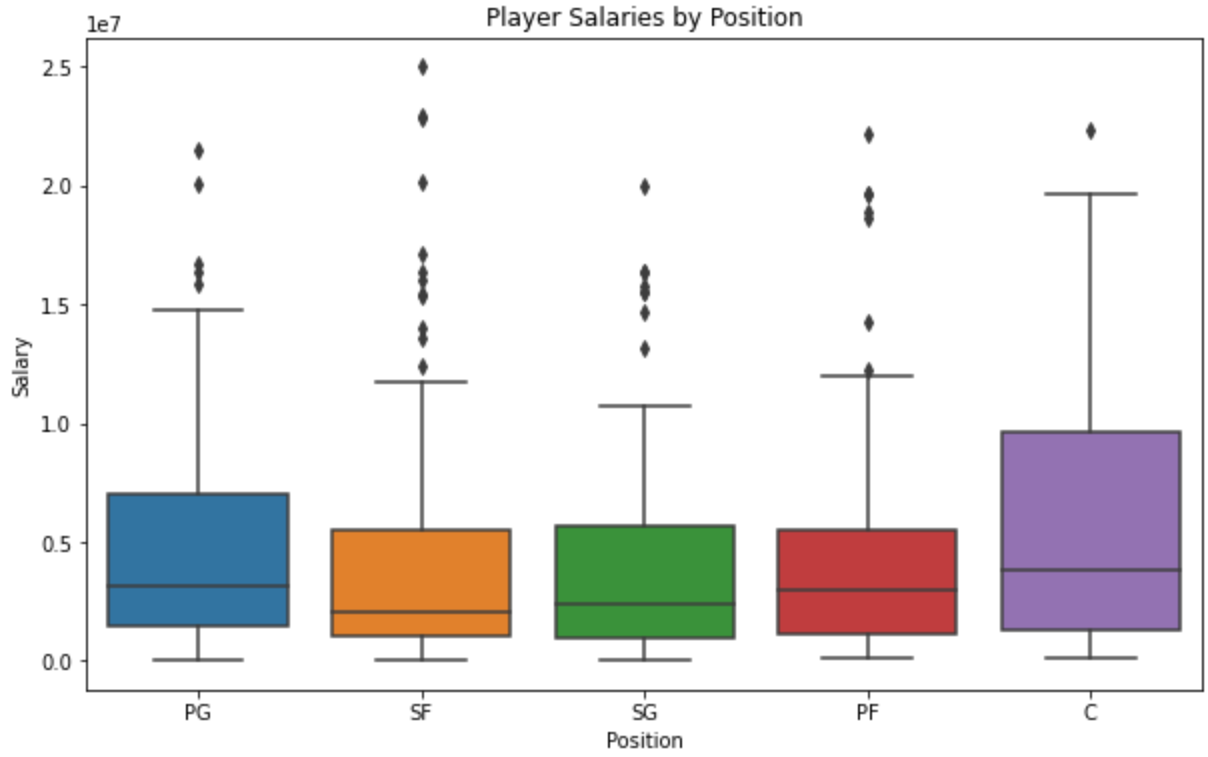
In [20]:
```
#setting the size
plt.figure(figsize = (10,6))

#creating histogram
sns.histplot(df['Age'], bins = 10)

#setting the title
plt.title('Distribution of Player Ages')

#display
plt.show()
```



Obervation - Most of the players are in the age group 24-26

2. Salaries of Players for each Position

In [21]:
```
#setting the size
plt.figure(figsize = (10,6))

#creating histogram
sns.boxplot(data = df, x= 'Position', y= 'Salary')

#setting the title
plt.title('Player Salaries by Position')

#display
plt.show()
```



Observation - The highest salary is for the position 'C'. The minimum and average salaries of all the positions are almost same

3. Age vs. Salary with a different color for each Position

In [22]:
```
#setting the size
plt.figure(figsize = (14,6))

#creating histogram
sns.scatterplot(data = df, x= 'Age', y= 'Salary', hue = 'Position')

#setting the title
plt.title('Age vs Salary by Position')

#display
plt.show()
```

Observation - The salary of players are increasing with Age and reaches maximum during the Age group 30-31 and then their salaries are decreasing.

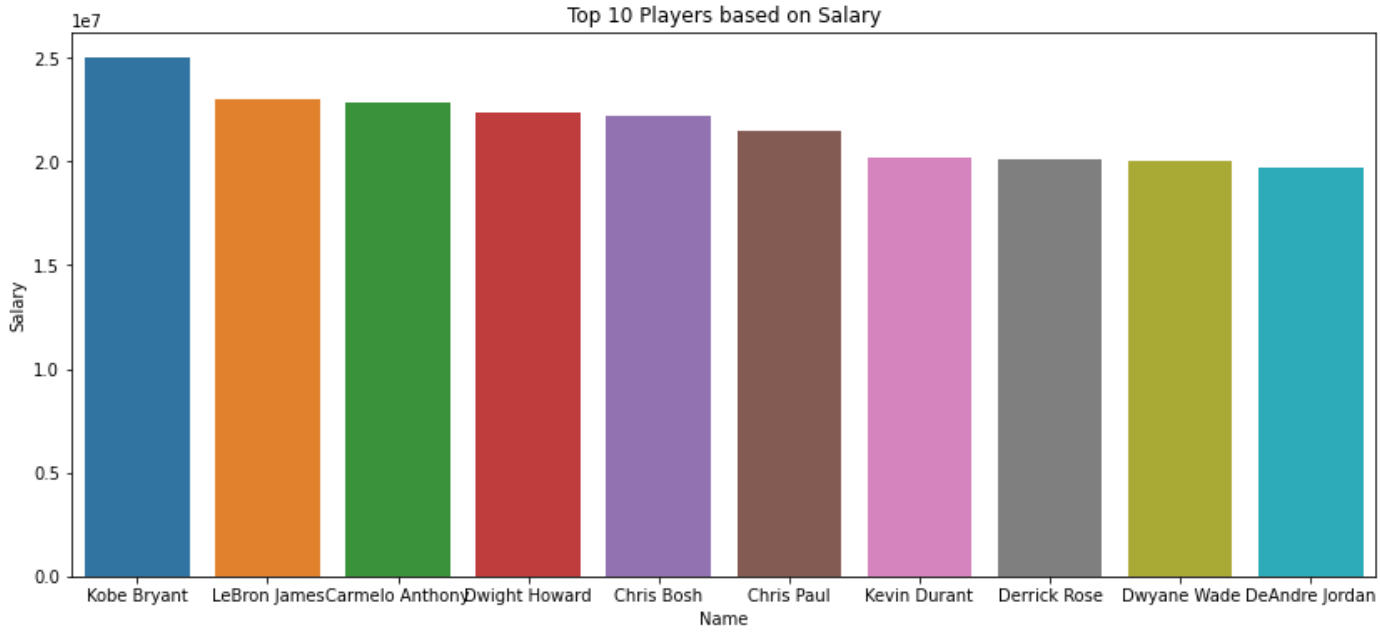
4.Top Players based on Salary

In [23]:
```
#create a new dataframe with top 10 players based on salary
top_players = df.sort_values(by = 'Salary', ascending = False).head(10)

top_players
```

Out[23]:

	Name	Team	Number	Position	Age	Weight	College	Salary	BMI
109	Kobe Bryant	Los Angeles Lakers	24	SF	37	212	Others	25000000.0	30.415510
169	LeBron James	Cleveland Cavaliers	23	SF	31	250	Others	22970500.0	35.867347
33	Carmelo Anthony	New York Knicks	7	SF	32	240	Syracuse	22875000.0	34.432653
251	Dwight Howard	Houston Rockets	12	C	30	265	Others	22359364.0	38.019388
339	Chris Bosh	Miami Heat	1	PF	32	235	Georgia Tech	22192730.0	33.715306
100	Chris Paul	Los Angeles Clippers	3	PG	31	175	Wake Forest	21468695.0	25.107143
414	Kevin Durant	Oklahoma City Thunder	35	SF	27	240	Texas	20158622.0	34.432653
164	Derrick Rose	Chicago Bulls	1	PG	27	190	Memphis	20093064.0	27.259184
349	Dwyane Wade	Miami Heat	3	SG	34	220	Marquette	20000000.0	31.563265
98	DeAndre Jordan	Los Angeles Clippers	6	C	27	265	Texas A&M	19689000.0	38.019388

In [24]:
```
#setting the size
plt.figure(figsize = (14,6))

#creating histogram
sns.barplot(data = top_players, x= 'Name', y= 'Salary')

#setting the title
plt.title('Top 10 Players based on Salary')

#display
plt.show()
```



Observation - The payer 'Kobe Bryant' is getting the highest salary

5.Top Players based on BMI

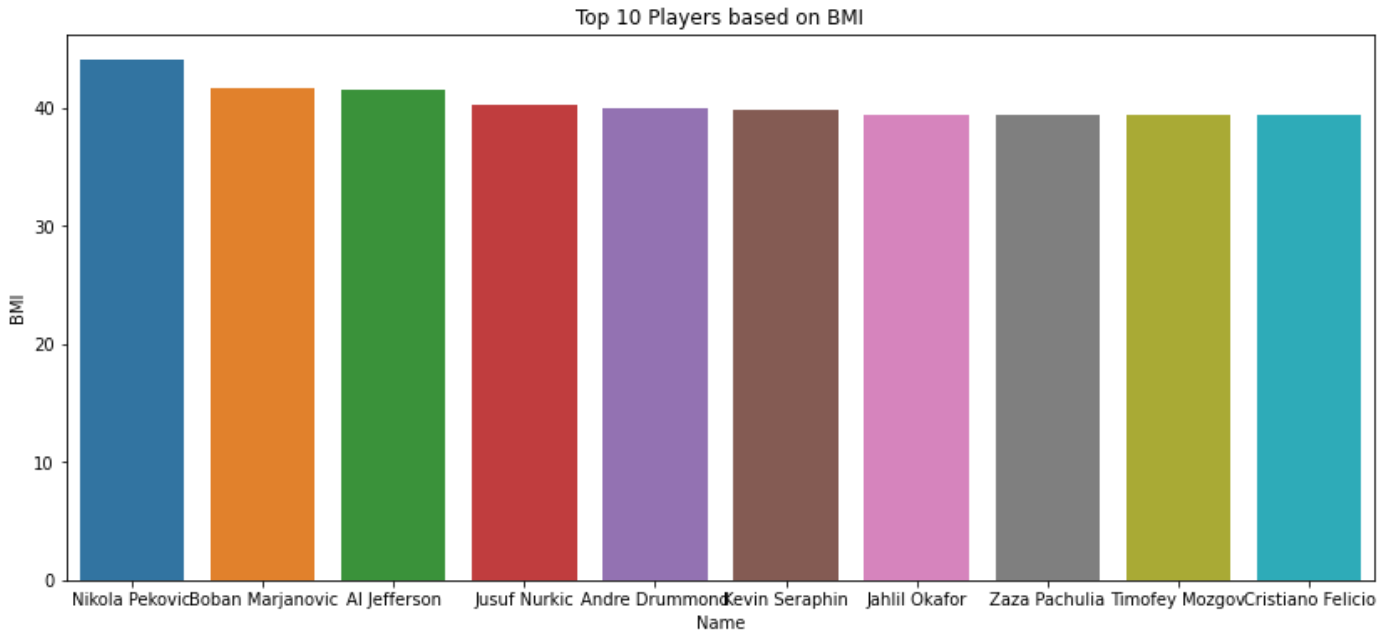
In [25]:
```
#create a new dataframe with top 10 players based on salary
top_players = df.sort_values(by = 'BMI', ascending = False).head(10)

top_players
```

Out[25]:

	Name	Team	Number	Position	Age	Weight	College	Salary	BMI
405	Nikola Pekovic	Minnesota Timberwolves	14	C	30	307	Others	12100000.0	44.045102
302	Boban Marjanovic	San Antonio Spurs	40	C	27	290	Others	1200000.0	41.606122
330	Al Jefferson	Charlotte Hornets	25	C	31	289	Others	13500000.0	41.462653
395	Jusuf Nurkic	Denver Nuggets	23	C	21	280	Others	1842000.0	40.171429
188	Andre Drummond	Detroit Pistons	0	C	22	279	Connecticut	3272091.0	40.027959
41	Kevin Seraphin	New York Knicks	1	C	26	278	Others	2814000.0	39.884490
56	Jahlil Okafor	Philadelphia 76ers	8	C	20	275	Duke	4582680.0	39.454082
237	Zaza Pachulia	Dallas Mavericks	27	C	32	275	Others	5200000.0	39.454082
176	Timofey Mozgov	Cleveland Cavaliers	20	C	29	275	Others	4950000.0	39.454082
155	Cristiano Felicio	Chicago Bulls	6	PF	23	275	Others	525093.0	39.454082

In [26]:
```
#setting the size
plt.figure(figsize = (14,6))

#creating histogram
sns.barplot(data = top_players, x= 'Name', y= 'BMI')

#setting the title
plt.title('Top 10 Players based on BMI')
```

```
#display
plt.show()
```



Observation - The payer 'Nikola Pekovic' has the highest BMI

6. College Analysis

In [27]:
```
#create a new dataframe with top colleges based on the most represented players
colleges = df['College'].value_counts()
colleges
```

Out[27]:
```
Others             84
Kentucky           22
Duke               20
Kansas             18
North Carolina     16
                   ..
Utah Valley         1
Cleveland State     1
Iowa State          1
Florida State       1
Baylor              1
Name: College, Length: 119, dtype: int64
```

Observation - The value 'Others' to be dropped as it is an irrelevant data

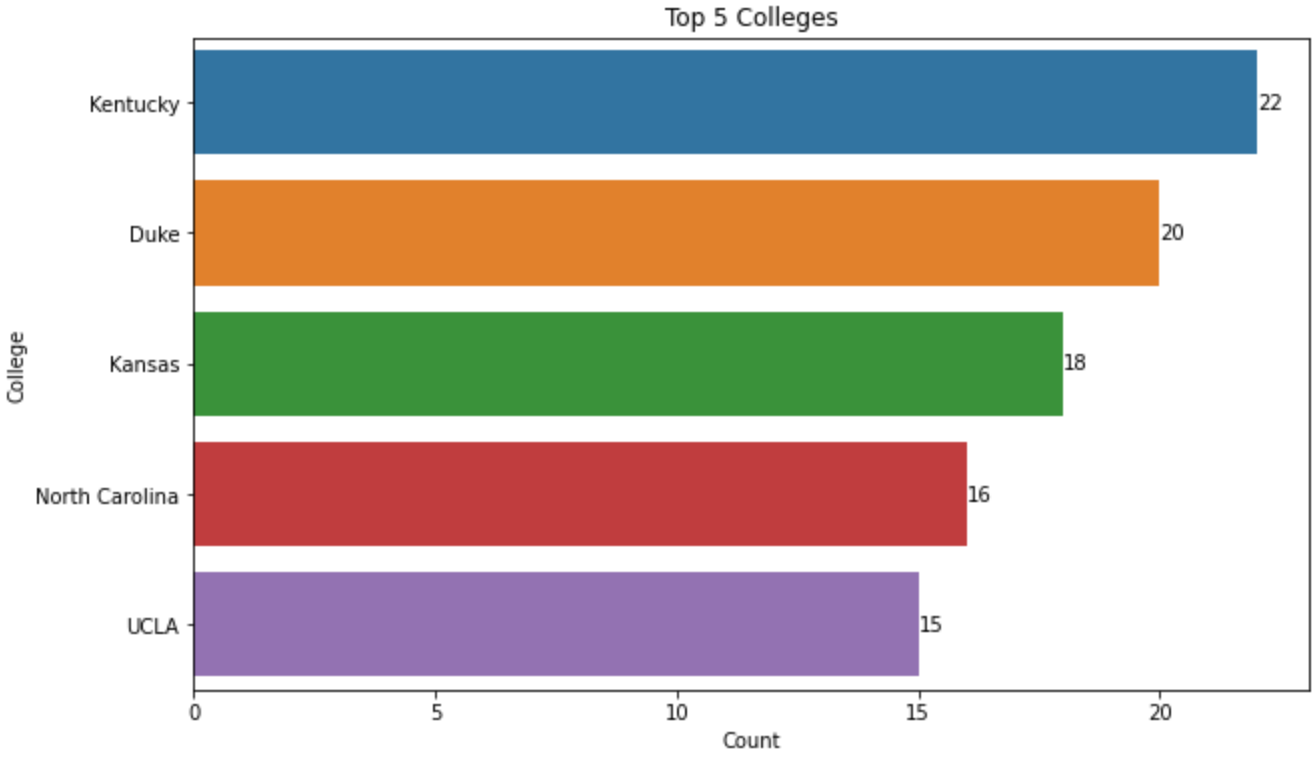
In [28]:
```
#remove the value 'Others'
colleges.drop('Others', inplace = True)
colleges
```

Out[28]:
```
Kentucky           22
Duke               20
Kansas             18
North Carolina     16
UCLA               15
                   ..
Utah Valley         1
Cleveland State     1
Iowa State          1
Florida State       1
Baylor              1
Name: College, Length: 118, dtype: int64
```

In [29]:
```
#get the top 5 colleges
top_colleges = colleges.head(5)
top_colleges
```

Out[29]:
```
Kentucky          22
Duke              20
Kansas            18
North Carolina    16
UCLA              15
Name: College, dtype: int64
```

In [30]:
```
#setting the size
plt.figure(figsize = (10,6))

#creating barplot
ax = sns.barplot(top_colleges,top_colleges.index)

#display the count in each bar
for bars in ax.containers:
    ax.bar_label(bars)

#setting x and y labels
plt.xlabel("Count")
plt.ylabel("College")

#setting the title
plt.title('Top 5 Colleges')

#display
plt.show()
```



Observation - The college 'Kentuky' represents the most number of players (22)

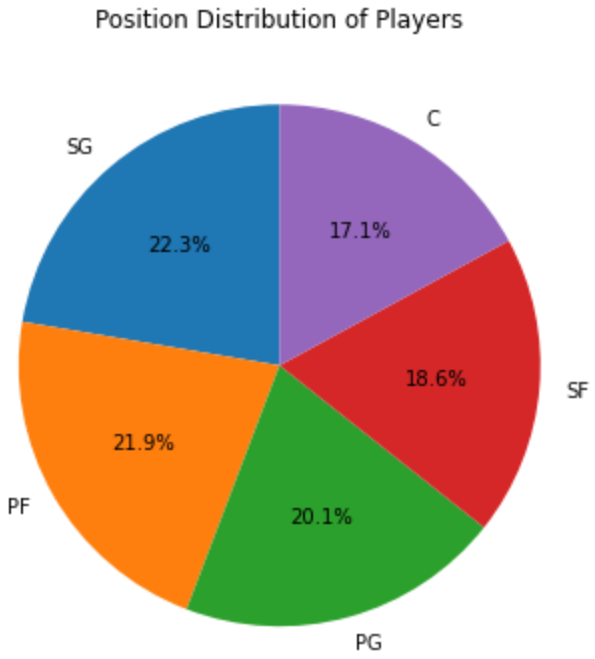
7. Position Distribution

In [31]:
```
#find the distribution of players across different 'positions'.
player_pos_count = df['Position'].value_counts()
player_pos_count
```

Out[31]:
```
SG    102
```

Out[31]:
```
PF    100
PG     92
SF     85
C      78
Name: Position, dtype: int64
```

In [32]:
```
#setting the size
plt.figure(figsize = (10,6))

#creating piechart
plt.pie(player_pos_count, labels = player_pos_count.index, autopct='%1.1f%%', startangle

#setting the title
plt.title('Position Distribution of Players')

#display
plt.show()
```



Observation - Most of the players are in the position 'SG'

8. Team Analysis

In [33]:
```
#Teams
df['Team'].unique()
```

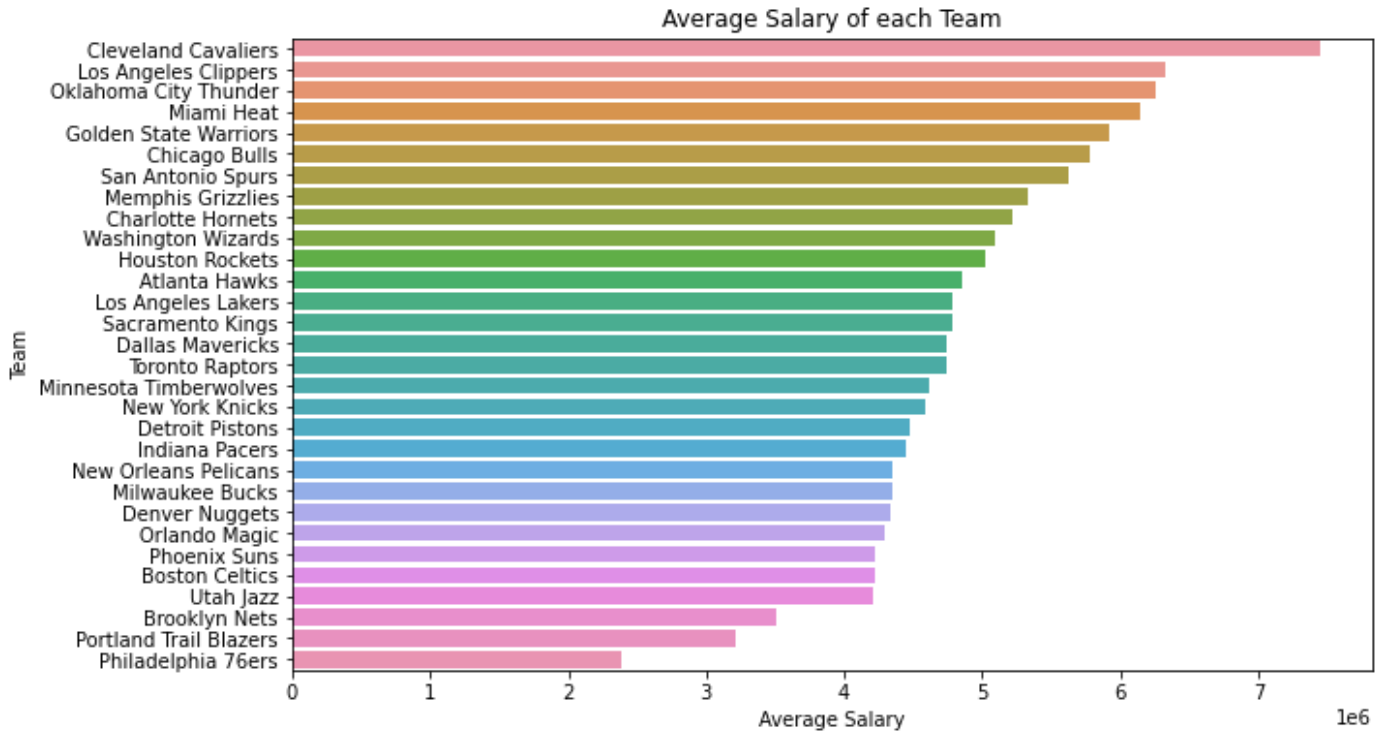
Out[33]:
```
array(['Boston Celtics', 'Brooklyn Nets', 'New York Knicks',
       'Philadelphia 76ers', 'Toronto Raptors', 'Golden State Warriors',
       'Los Angeles Clippers', 'Los Angeles Lakers', 'Phoenix Suns',
       'Sacramento Kings', 'Chicago Bulls', 'Cleveland Cavaliers',
       'Detroit Pistons', 'Indiana Pacers', 'Milwaukee Bucks',
       'Dallas Mavericks', 'Houston Rockets', 'Memphis Grizzlies',
       'New Orleans Pelicans', 'San Antonio Spurs', 'Atlanta Hawks',
       'Charlotte Hornets', 'Miami Heat', 'Orlando Magic',
       'Washington Wizards', 'Denver Nuggets', 'Minnesota Timberwolves',
       'Oklahoma City Thunder', 'Portland Trail Blazers', 'Utah Jazz'],
      dtype=object)
```

In [34]:
```
#average salary of players in each team
avg_sal = df.groupby("Team")['Salary'].mean().sort_values(ascending = False)
avg_sal
```

```
Team
```

Out[34]:
```
Cleveland Cavaliers       7.455425e+06
Los Angeles Clippers      6.323643e+06
Oklahoma City Thunder     6.251020e+06
Miami Heat                6.146736e+06
Golden State Warriors     5.924600e+06
Chicago Bulls             5.785559e+06
San Antonio Spurs         5.629516e+06
Memphis Grizzlies         5.328979e+06
Charlotte Hornets         5.222728e+06
Washington Wizards        5.088576e+06
Houston Rockets           5.018868e+06
Atlanta Hawks             4.860197e+06
Los Angeles Lakers        4.784695e+06
Sacramento Kings          4.778911e+06
Dallas Mavericks          4.746582e+06
Toronto Raptors           4.741174e+06
Minnesota Timberwolves    4.610884e+06
New York Knicks           4.581494e+06
Detroit Pistons           4.477884e+06
Indiana Pacers            4.450122e+06
New Orleans Pelicans      4.355304e+06
Milwaukee Bucks           4.350220e+06
Denver Nuggets            4.330974e+06
Orlando Magic             4.297248e+06
Phoenix Suns              4.229676e+06
Boston Celtics            4.225583e+06
Utah Jazz                 4.204006e+06
Brooklyn Nets             3.501898e+06
Portland Trail Blazers    3.220121e+06
Philadelphia 76ers        2.389039e+06
Name: Salary, dtype: float64
```

In [35]:
```
#setting the size
plt.figure(figsize = (10,6))

#creating barplot
ax = sns.barplot(avg_sal,avg_sal.index)

#setting x and y labels
plt.xlabel("Average Salary")
plt.ylabel("Team")

#setting the title
plt.title('Average Salary of each Team')

#display
plt.show()
```



Observation - Considering the average salary of players, the team - 'Cleveland Cavaliers' is in the top position and the team 'Philadelphia 76ers' is in the last position.

Conclusions

- Most of the players are in the age group 24-26 and in the position 'SG'
- The payer 'Kobe Bryant' is getting the highest salary and the payer 'Nikola Pekovic' has the highest BMI
- The minimum and average salaries of all the positions are almost same. The salary of players are increasing with Age and reaches maximum during the Age group 30-31 and then their salaries are decreasing
- The highest salary is for the position 'C'
- Considering the average salary of players, the team - 'Cleveland Cavaliers' is in the top position and the team 'Philadelphia76ers' is in the last position
- The college 'Kentuky' represents the most number of players (22)