In [1]:
```
import pandas as pd
```

In [2]:
```
s2017_df = pd.read_csv('2017_season_data.csv')
```

In [3]:
```
players_df = pd.read_csv('player_data.csv')
```

In [4]:
```
s2017_df.head(1)
```

Out[4]:

	Year	Player	Pos	Age	Tm	G	GS	MP	PER	TS%	...	FT%	ORB	DRB	TRB	AS
0	2017.0	Alex Abrines	SG	23.0	OKC	68.0	6.0	1055.0	10.1	0.56	...	0.898	18.0	68.0	86.0	40

1 rows × 52 columns

In [5]:
```
players_df.head(1)
```

Out[5]:

	name	year_start	year_end	position	height	weight	birth_date	college
0	Alaa Abdelnaby	1991	1995	F-C	6-10	240.0	June 24, 1968	Duke University

Data Wrangling Activities

1. Merge `s2017_df` and `players_df` with a left join

In [6]:
```
df = s2017_df.merge
(players_df, how='left', left_on='Player', right_on='name')
```

In [7]:
```
df
```

Out[7]:

	Year	Player	Pos	Age	Tm	G	GS	MP	PER	TS%	...	PF	PTS	
0	2017.0	Alex Abrines	SG	23.0	OKC	68.0	6.0	1055.0	10.1	0.560	...	114.0	406.0	Ab
1	2017.0	Quincy Acy	PF	26.0	TOT	38.0	1.0	558.0	11.8	0.565	...	67.0	222.0	Quinc
2	2017.0	Quincy Acy	PF	26.0	DAL	6.0	0.0	48.0	-1.4	0.355	...	9.0	13.0	Quinc
3	2017.0	Quincy Acy	PF	26.0	BRK	32.0	1.0	510.0	13.1	0.587	...	58.0	209.0	Quinc
4	2017.0	Steven Adams	C	23.0	OKC	80.0	80.0	2389.0	16.5	0.589	...	195.0	905.0	S A
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
600	2017.0	Cody Zeller	PF	24.0	CHO	62.0	58.0	1725.0	16.7	0.604	...	189.0	639.0	Cody
601	2017.0	Tyler Zeller	C	27.0	BOS	51.0	5.0	525.0	13.0	0.508	...	61.0	178.0	Tyler
602	2017.0	Stephen Zimmerman	C	20.0	ORL	19.0	0.0	108.0	7.3	0.346	...	17.0	23.0	Ste Zimme
603	2017.0	Paul Zipser	SF	22.0	CHI	44.0	18.0	843.0	6.9	0.503	...	78.0	240.0	Paul Z
604	2017.0	Ivica Zubac	C	19.0	LAL	38.0	11.0	609.0	17.0	0.547	...	66.0	284.0	Ivica Z

605 rows × 60 columns

In [8]:
```
df.head(1).T
```

Out[8]:

	0
Year	2017.0
Player	Alex Abrines
Pos	SG
Age	23.0
Tm	OKC
G	68.0
GS	6.0
MP	1055.0
PER	10.1
TS%	0.56
3PAr	0.724
FTr	0.144
ORB%	1.9
DRB%	7.1
TRB%	4.5
AST%	5.5
STL%	1.7
BLK%	0.6
TOV%	8.3
USG%	15.9
blanl	NaN
OWS	1.2
DWS	0.9
WS	2.1
WS/48	0.095
blank2	NaN
OBPM	-0.3
DBPM	-2.2
BPM	-2.5
VORP	-0.1
FG	134.0
FGA	341.0
FG%	0.393
3P	94.0

	0
3PA	247.0
3P%	0.381
2P	40.0
2PA	94.0
2P%	0.426
eFG%	0.531
FT	44.0
FTA	49.0
FT%	0.898
ORB	18.0
DRB	68.0
TRB	86.0
AST	40.0
STL	37.0
BLK	8.0
TOV	33.0
PF	114.0
PTS	406.0
name	Alex Abrines
year_start	2017.0
year_end	2018.0
position	G-F
height	6-6
weight	190.0
birth_date	August 1, 1993
college	NaN

In [ ]:
```
# Use it before modifying the `df` to have a copy
# just in case a modification doesn't go as expected
# df_copy = df.copy()
```

2. Are there misses (mismatches) in the resulting dataframe?

In [10]:
```
df['name'].isna().any()
```

Out[10]:
```
True
```

3. How many rows couldn't be matched?

In [11]:
```
df['name'].isna().value_counts()
```

Out[11]:
```
name
False    601
True       4
Name: count, dtype: int64
```

In [13]:
```
df['name'].isna().sum()
```

Out[13]:
```
4
```

4. Extract the names of the players that couldn't be matched

In [14]:
```
filt = df['name'].isna()
df[filt]
```

Out[14]:

	Year	Player	Pos	Age	Tm	G	GS	MP	PER	TS%	...	PF	PTS	name
349	2017.0	Luc Mbah	SF	30.0	LAC	80.0	76.0	1787.0	10.3	0.581	...	122.0	484.0	NaN
350	2017.0	James Michael	PF	24.0	GSW	52.0	2.0	457.0	13.0	0.543	...	47.0	147.0	NaN
352	2017.0	Sheldon McClellan	SG	24.0	WAS	30.0	3.0	287.0	10.1	0.518	...	17.0	90.0	NaN
593	2017.0	Metta World	SF	37.0	LAL	25.0	2.0	160.0	6.2	0.380	...	18.0	57.0	NaN

4 rows × 60 columns

In [15]:
```
player_misses = list(df.loc[filt, 'Player'].values)
player_misses
```

Out[15]:
```
['Luc Mbah', 'James Michael', 'Sheldon McClellan', 'Metta World']
```

5. Modify `players_df` with the correct names to re-try a successful merge

In [ ]:
```
# Use it before modifying the `df` to have a copy
# just in case a modification doesn't go as expected
# df_copy = df.copy()
```

In [20]:
```
filt = players_df['name'].str.contains('Luc Mbah')
players_df[filt]
```

Out[20]:

	name	year_start	year_end	position	height	weight	birth_date	college
2595	Luc Mbah a Moute	2009	2018	F	6-8	230.0	September 9, 1986	University of California, Los Angeles

In [21]:
```
names_mapping = {
    "Luc Mbah a Moute": "Luc Mbah",
    "James Michael McAdoo": "James Michael",
    "Sheldon Mac": "Sheldon McClellan",
    "Metta World Peace": "Metta World",
}
```

In [22]:
```
for original_name, new_name in names_mapping.items():
    filt = players_df['name'] == original_name
    players_df.loc[filt, 'name'] = new_name
```

In [24]:
```
df =
s2017_df.merge(players_df, how='left', left_on='Player', right_on='name'
```

In [25]:
```
df
```

Out[25]:

	Year	Player	Pos	Age	Tm	G	GS	MP	PER	TS%	...	PF	PTS	
0	2017.0	Alex Abrines	SG	23.0	OKC	68.0	6.0	1055.0	10.1	0.560	...	114.0	406.0	Ab
1	2017.0	Quincy Acy	PF	26.0	TOT	38.0	1.0	558.0	11.8	0.565	...	67.0	222.0	Quinc
2	2017.0	Quincy Acy	PF	26.0	DAL	6.0	0.0	48.0	-1.4	0.355	...	9.0	13.0	Quinc
3	2017.0	Quincy Acy	PF	26.0	BRK	32.0	1.0	510.0	13.1	0.587	...	58.0	209.0	Quinc
4	2017.0	Steven Adams	C	23.0	OKC	80.0	80.0	2389.0	16.5	0.589	...	195.0	905.0	S A
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
600	2017.0	Cody Zeller	PF	24.0	CHO	62.0	58.0	1725.0	16.7	0.604	...	189.0	639.0	Cody
601	2017.0	Tyler Zeller	C	27.0	BOS	51.0	5.0	525.0	13.0	0.508	...	61.0	178.0	Tyler
602	2017.0	Stephen Zimmerman	C	20.0	ORL	19.0	0.0	108.0	7.3	0.346	...	17.0	23.0	Ste Zimme
603	2017.0	Paul Zipser	SF	22.0	CHI	44.0	18.0	843.0	6.9	0.503	...	78.0	240.0	Paul Z
604	2017.0	Ivica Zubac	C	19.0	LAL	38.0	11.0	609.0	17.0	0.547	...	66.0	284.0	Ivica Z

605 rows × 60 columns

In [26]:
```
df['name'].isna().sum()
```

Out[26]:
```
0
```

6. Perform the merge between `s2017_df` and `players_df` again, this time, without misses

In [ ]:
```

```

7. Remove unnecessary columns

In [28]:
```
columns_to_drop = [
    "Year",
    "PER",
    "TS%",
    "3PAr",
    "FTr",
    "USG%",
    "blanl",
    "OWS",
    "DWS",
    "WS",
    "WS/48",
    "blank2",
    "OBPM",
    "DBPM",
    "BPM",
    "VORP",
    "FG%",
    "3P%",
    "eFG%",
    "FT%",
    "name",
]
```

In [29]:
```
df.drop(columns=columns_to_drop, inplace=True)
```

8. Rename teams to their full name

In [32]:
```
team_mapping = {
    "OKC": "Oklahoma City Thunder",
    "DAL": "Dallas Mavericks",
    "BRK": "Brooklyn Nets",
    "SAC": "Sacramento Kings",
    "NOP": "New Orleans Pelicans",
    "MIN": "Minnesota Timberwolves",
    "SAS": "San Antonio Spurs",
    "IND": "Indiana Pacers",
    "MEM": "Memphis Grizzlies",
    "POR": "Portland Trail Blazers",
    "CLE": "Cleveland Cavaliers",
    "LAC": "Los Angeles Clippers",
    "PHI": "Philadelphia 76ers",
    "HOU": "Houston Rockets",
    "MIL": "Milwaukee Bucks",
    "NYK": "New York Knicks",
    "DEN": "Denver Nuggets",
    "ORL": "Orlando Magic",
    "MIA": "Miami Heat",
    "PHO": "Phoenix Suns",
    "GSW": "Golden State Warriors",
    "CHO": "Charlotte Hornets",
    "DET": "Detroit Pistons",
    "ATL": "Atlanta Hawks",
    "WAS": "Washington Wizards",
    "LAL": "Los Angeles Lakers",
    "UTA": "Utah Jazz",
    "BOS": "Boston Celtics",
    "CHI": "Chicago Bulls",
    "TOR": "Toronto Raptors"
}
```

In [35]:
```
df['Team'] = df['Tm'].replace(team_mapping)
```

In [36]:
```
df[['Player', 'Tm', 'Team']]
```

Out[36]:

	Player	Tm	Team
0	Alex Abrines	OKC	Oklahoma City Thunder
1	Quincy Acy	TOT	TOT
2	Quincy Acy	DAL	Dallas Mavericks
3	Quincy Acy	BRK	Brooklyn Nets
4	Steven Adams	OKC	Oklahoma City Thunder
...	...	...	...
600	Cody Zeller	CHO	Charlotte Hornets
601	Tyler Zeller	BOS	Boston Celtics
602	Stephen Zimmerman	ORL	Orlando Magic
603	Paul Zipser	CHI	Chicago Bulls
604	Ivica Zubac	LAL	Los Angeles Lakers

605 rows × 3 columns

9. Convert birthday to a datetime object

In [37]:
```
df['birth_date'] = pd.to_datetime(df['birth_date'])
```

In [38]:
```
df['birth_date']
```

Out[38]:
```
0     1993-08-01
1     1990-10-06
2     1990-10-06
3     1990-10-06
4     1993-07-20
         ...
600   1992-10-05
601   1990-01-17
602   1996-09-09
603   1994-02-18
604   1997-03-18
Name: birth_date, Length: 605, dtype: datetime64[ns]
```

10. Delete all players from the `TOT` team

In [ ]:
```
# if something goes wrong, just execute this line:
# df = df_copy.copy()
```

In [40]:
```
#df_copy = df.copy()
```

In [42]:
```
filt = df['Tm'] == 'TOT'
df.loc[filt].index
```

Out[42]:
```
Index([  1,  14,  32,  55,  58,  65,  70,  81,  90, 107, 110, 139, 140,
153,
       156, 166, 176, 188, 193, 200, 226, 236, 239, 259, 263, 278, 294,
306,
       314, 328, 355, 358, 361, 383, 401, 405, 411, 415, 435, 443, 446,
458,
       476, 492, 509, 517, 527, 535, 539, 563, 574, 577, 580, 586],
      dtype='int64')
```

In [43]:
```
df.drop(df.loc[filt].index, inplace=True)
```

Analysis

11. What's the team with the most players in the league?

In [50]:
```
df.groupby('Team')['Player'].count().sort_values(ascending=False)
```

Out[50]:
```
Team
New Orleans Pelicans      27
Dallas Mavericks          24
Atlanta Hawks             22
Cleveland Cavaliers       22
Philadelphia 76ers        22
Brooklyn Nets             21
Milwaukee Bucks           20
Charlotte Hornets         19
Sacramento Kings          19
Denver Nuggets            19
Orlando Magic             19
Oklahoma City Thunder     19
Los Angeles Lakers        19
Phoenix Suns              18
Washington Wizards        18
Houston Rockets           18
Chicago Bulls             18
Memphis Grizzlies         17
Indiana Pacers            17
Golden State Warriors     17
San Antonio Spurs         17
Toronto Raptors           17
Minnesota Timberwolves    16
New York Knicks           16
Boston Celtics            15
Los Angeles Clippers      15
Detroit Pistons           15
Portland Trail Blazers    15
Utah Jazz                 15
Miami Heat                15
Name: Player, dtype: int64
```

In [51]:
```
df['Team'].value_counts()
```

Out[51]:
```
Team
New Orleans Pelicans      27
Dallas Mavericks          24
Cleveland Cavaliers       22
Philadelphia 76ers        22
Atlanta Hawks             22
Brooklyn Nets             21
Milwaukee Bucks           20
Oklahoma City Thunder     19
Denver Nuggets            19
Charlotte Hornets         19
Los Angeles Lakers        19
Sacramento Kings          19
Orlando Magic             19
Phoenix Suns              18
Washington Wizards        18
Houston Rockets           18
Chicago Bulls             18
Golden State Warriors     17
Toronto Raptors           17
Memphis Grizzlies         17
Indiana Pacers            17
San Antonio Spurs         17
Minnesota Timberwolves    16
New York Knicks           16
Miami Heat                15
Los Angeles Clippers      15
Portland Trail Blazers    15
Detroit Pistons           15
Utah Jazz                 15
Boston Celtics            15
Name: count, dtype: int64
```

12. What's the team with the lowest FG ?

In [58]:
```
df.groupby('Team')['FG'].sum().sort_values()
```

Out[58]:
```
Team
Dallas Mavericks          2968.0
Memphis Grizzlies         2984.0
Utah Jazz                 3033.0
Charlotte Hornets         3093.0
Brooklyn Nets             3102.0
Sacramento Kings          3105.0
Orlando Magic             3139.0
Boston Celtics            3168.0
Chicago Bulls             3169.0
Milwaukee Bucks           3190.0
Miami Heat                3202.0
Toronto Raptors           3211.0
New Orleans Pelicans      3218.0
Minnesota Timberwolves    3235.0
Oklahoma City Thunder     3237.0
Los Angeles Clippers      3242.0
Portland Trail Blazers    3243.0
New York Knicks           3244.0
Detroit Pistons           3269.0
Phoenix Suns              3270.0
Houston Rockets           3305.0
Cleveland Cavaliers       3311.0
Philadelphia 76ers        3322.0
Denver Nuggets            3377.0
Indiana Pacers            3379.0
Washington Wizards        3388.0
Los Angeles Lakers        3414.0
San Antonio Spurs         3470.0
Golden State Warriors     3532.0
Atlanta Hawks             3595.0
Name: FG, dtype: float64
```

13. What's the team with the best FG% ?

In [62]:
```
fg_per_team = df.groupby('Team')[['FG', 'FGA']].sum()
fg_per_team
```

Out[62]:

Team	FG	FGA
Atlanta Hawks	3595.0	7961.0
Boston Celtics	3168.0	6978.0
Brooklyn Nets	3102.0	6987.0
Charlotte Hornets	3093.0	7000.0
Chicago Bulls	3169.0	7142.0
Cleveland Cavaliers	3311.0	7053.0
Dallas Mavericks	2968.0	6750.0
Denver Nuggets	3377.0	7194.0
Detroit Pistons	3269.0	7282.0
Golden State Warriors	3532.0	7140.0
Houston Rockets	3305.0	7152.0
Indiana Pacers	3379.0	7270.0
Los Angeles Clippers	3242.0	6819.0
Los Angeles Lakers	3414.0	7525.0
Memphis Grizzlies	2984.0	6854.0
Miami Heat	3202.0	7037.0
Milwaukee Bucks	3190.0	6737.0
Minnesota Timberwolves	3235.0	6922.0
New Orleans Pelicans	3218.0	7154.0
New York Knicks	3244.0	7255.0
Oklahoma City Thunder	3237.0	7169.0
Orlando Magic	3139.0	7133.0
Philadelphia 76ers	3322.0	7545.0
Phoenix Suns	3270.0	7260.0
Portland Trail Blazers	3243.0	7059.0
Sacramento Kings	3105.0	6735.0
San Antonio Spurs	3470.0	7284.0
Toronto Raptors	3211.0	6918.0
Utah Jazz	3033.0	6514.0
Washington Wizards	3388.0	7136.0

In [63]:
```
fg_per_team['FG%'] = fg_per_team['FG'] / fg_per_team['FGA']
fg_per_team.sort_values(by='FG%', ascending=False)
```

Out[63]:

Team	FG	FGA	FG%
Golden State Warriors	3532.0	7140.0	0.494678
San Antonio Spurs	3470.0	7284.0	0.476387
Los Angeles Clippers	3242.0	6819.0	0.475436
Washington Wizards	3388.0	7136.0	0.474776
Milwaukee Bucks	3190.0	6737.0	0.473505
Cleveland Cavaliers	3311.0	7053.0	0.469446
Denver Nuggets	3377.0	7194.0	0.469419
Minnesota Timberwolves	3235.0	6922.0	0.467350
Utah Jazz	3033.0	6514.0	0.465613
Indiana Pacers	3379.0	7270.0	0.464787
Toronto Raptors	3211.0	6918.0	0.464151
Houston Rockets	3305.0	7152.0	0.462109
Sacramento Kings	3105.0	6735.0	0.461024
Portland Trail Blazers	3243.0	7059.0	0.459414
Miami Heat	3202.0	7037.0	0.455023
Boston Celtics	3168.0	6978.0	0.453998
Los Angeles Lakers	3414.0	7525.0	0.453688
Atlanta Hawks	3595.0	7961.0	0.451576
Oklahoma City Thunder	3237.0	7169.0	0.451527
Phoenix Suns	3270.0	7260.0	0.450413
New Orleans Pelicans	3218.0	7154.0	0.449818
Detroit Pistons	3269.0	7282.0	0.448915
New York Knicks	3244.0	7255.0	0.447140
Brooklyn Nets	3102.0	6987.0	0.443967
Chicago Bulls	3169.0	7142.0	0.443713
Charlotte Hornets	3093.0	7000.0	0.441857
Philadelphia 76ers	3322.0	7545.0	0.440292
Orlando Magic	3139.0	7133.0	0.440067
Dallas Mavericks	2968.0	6750.0	0.439704
Memphis Grizzlies	2984.0	6854.0	0.435366

14. What's the difference between the best and worst 3P shooters (by position)?

In [68]:
```
three_point = df.groupby(by='Pos')[['3P', '3PA']].sum()
three_point['3P%'] = three_point['3P'] / three_point['3PA']
three_point
```

Out[68]:

Pos	3P	3PA	3P%
C	1486.0	4210.0	0.352969
PF	3514.0	10210.0	0.344172
PG	5662.0	15761.0	0.359241
SF	5638.0	16043.0	0.351431
SG	7776.0	21106.0	0.368426

In [70]:
```
three_point.sort_values(by='3P%', ascending=False)
```

Out[70]:

Pos	3P	3PA	3P%
SG	7776.0	21106.0	0.368426
PG	5662.0	15761.0	0.359241
C	1486.0	4210.0	0.352969
SF	5638.0	16043.0	0.351431
PF	3514.0	10210.0	0.344172

In [80]:
```
three_point['3P%'].max() - three_point['3P%'].min()
```

Out[80]: `0.024253659969040164`

15. Find the best scorers in each team

In [77]:
```
df
```

Out[77]:

	Player	Pos	Age	Tm	G	GS	MP	ORB%	DRB%	TRB%	...	PF	PTS	ye
0	Alex Abrines	SG	23.0	OKC	68.0	6.0	1055.0	1.9	7.1	4.5	...	114.0	406.0	
2	Quincy Acy	PF	26.0	DAL	6.0	0.0	48.0	4.6	15.2	9.7	...	9.0	13.0	
3	Quincy Acy	PF	26.0	BRK	32.0	1.0	510.0	3.8	18.2	11.1	...	58.0	209.0	
4	Steven Adams	C	23.0	OKC	80.0	80.0	2389.0	13.0	15.5	14.2	...	195.0	905.0	
5	Arron Afflalo	SG	31.0	SAC	61.0	45.0	1580.0	0.7	8.4	4.6	...	104.0	515.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
600	Cody Zeller	PF	24.0	CHO	62.0	58.0	1725.0	8.6	17.3	12.9	...	189.0	639.0	
601	Tyler Zeller	C	27.0	BOS	51.0	5.0	525.0	9.2	17.0	13.2	...	61.0	178.0	
602	Stephen Zimmerman	C	20.0	ORL	19.0	0.0	108.0	10.8	24.9	17.6	...	17.0	23.0	
603	Paul Zipser	SF	22.0	CHI	44.0	18.0	843.0	1.9	14.2	8.0	...	78.0	240.0	
604	Ivica Zubac	C	19.0	LAL	38.0	11.0	609.0	7.1	21.9	14.3	...	66.0	284.0	

551 rows × 40 columns

In [99]:
```
df['Best Score per Team'] = df.groupby('Team')['PTS'].transform('max')
```

In [110]:
```
filt = df['PTS'] == df['Best Score per Team']
df.loc[filt, ['Player', 'Team', 'Pos', 'PTS']]
.sort_values(by='PTS', ascending=False)
```

Out[110]:

	Player	Team	Pos	PTS
567	Russell Westbrook	Oklahoma City Thunder	PG	2558.0
214	James Harden	Houston Rockets	PG	2356.0
525	Isaiah Thomas	Boston Celtics	PG	2199.0
122	Anthony Davis	New Orleans Pelicans	C	2099.0
538	Karl-Anthony Towns	Minnesota Timberwolves	C	2061.0
331	Damian Lillard	Portland Trail Blazers	PG	2024.0
130	DeMar DeRozan	Toronto Raptors	SG	2020.0
120	Stephen Curry	Golden State Warriors	PG	1999.0
274	LeBron James	Cleveland Cavaliers	SF	1954.0
324	Kawhi Leonard	San Antonio Spurs	SF	1888.0
19	Giannis Antetokounmpo	Milwaukee Bucks	SF	1832.0
558	Kemba Walker	Charlotte Hornets	PG	1830.0
79	Jimmy Butler	Chicago Bulls	SF	1816.0
559	John Wall	Washington Wizards	PG	1805.0
185	Paul George	Indiana Pacers	SF	1775.0
62	Devin Booker	Phoenix Suns	SG	1726.0
20	Carmelo Anthony	New York Knicks	SF	1659.0
229	Gordon Hayward	Utah Jazz	SF	1601.0
336	Brook Lopez	Brooklyn Nets	C	1539.0
111	DeMarcus Cousins	Sacramento Kings	C	1528.0
31	Harrison Barnes	Dallas Mavericks	PF	1518.0
136	Goran Dragic	Miami Heat	PG	1483.0
180	Marc Gasol	Memphis Grizzlies	C	1446.0
488	Dennis Schroder	Atlanta Hawks	PG	1414.0
222	Tobias Harris	Detroit Pistons	PF	1321.0
209	Blake Griffin	Los Angeles Clippers	PF	1316.0
289	Nikola Jokic	Denver Nuggets	C	1221.0
101	Jordan Clarkson	Los Angeles Lakers	SG	1205.0
171	Evan Fournier	Orlando Magic	SG	1167.0
486	Dario Saric	Philadelphia 76ers	PF	1040.0

16. Which team has the 'youngest squad', by average player age?

In [84]:
```
df.groupby(by='Team')['Age'].mean().sort_values()
```

Out[84]:
```
Team
Portland Trail Blazers    24.333333
Philadelphia 76ers        24.909091
Toronto Raptors           25.117647
Boston Celtics            25.266667
Detroit Pistons           25.466667
Orlando Magic             25.473684
Denver Nuggets            25.473684
Washington Wizards        25.666667
Phoenix Suns              25.666667
Minnesota Timberwolves    25.687500
Charlotte Hornets         25.789474
Brooklyn Nets             25.809524
Chicago Bulls             25.888889
Milwaukee Bucks           25.900000
Oklahoma City Thunder     25.947368
New Orleans Pelicans      25.962963
Houston Rockets           26.000000
Utah Jazz                 26.200000
Los Angeles Lakers        26.578947
Miami Heat                26.600000
New York Knicks           26.625000
Indiana Pacers            26.705882
Sacramento Kings          26.736842
Dallas Mavericks          26.750000
Memphis Grizzlies         27.235294
Golden State Warriors     27.882353
Atlanta Hawks             28.363636
San Antonio Spurs         29.000000
Los Angeles Clippers      29.533333
Cleveland Cavaliers       30.318182
Name: Age, dtype: float64
```