Machine Learning Foundation

NBA Draft stats

Dataset description

A dataset which contains a list of players of selected in draft of nba, and their results in league and how much their recevied for their work

- Dataset link

Features list

- Sallary
- Name
- Position
- Team
- College
- Draft Year
- Draft Team
- Draft Round
- Assistances
- Efective Field Goal
- Efective Field Goal 3
- Free throws
- Games
- Player Efficiency Rating
- Points
- Total Rebounds
- Win Shares
- Effective Field Goal
- Draft Round
- High School
- Shoots
- weight

Initial Plan

Explorate and avaliate the quality and quantity of data, appling technics of data cleaning and feature engineering to obtain insigths and formulatee hypoteses about sallary and basketball statics for players of draft.

In [23]:

```
%pylab inline
%config InlineBackend.figure_formats = ['retina']

import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

filepath = "data/players.csv"

data = pd.read_csv(filepath)

data.head()
```

```
Populating the interactive namespace from numpy and matplotlib
```

Out[23]:

	player_id	birthDate	birthPlace	career_AST	career_FG%	career_FG3%	career_FT%	career_G	career_PER	career_PTS	career_TRB	career_WS	career_eFG%	college	draf
0	abdelal01	June 24, 1968	Cairo, Egypt	0.3	50.2	0.0	70.1	256	13.0	5.7	3.3	4.8	50.2	Duke University	c
1	abdulza01	April 7, 1946	Brooklyn, New York	1.2	42.8	NaN	72.8	505	15.1	9.0	8.0	17.5	NaN	Iowa State University	c
2	abdulka01	April 16, 1947	New York, New York	3.6	55.9	5.6	72.1	1560	24.6	24.6	11.2	273.4	55.9	University of California, Los Angeles	c
3	abdulma02	March 9, 1969	Gulfport, Mississippi	3.5	44.2	35.4	90.5	586	15.4	14.6	1.9	25.2	47.2	Louisiana State University	c
4	abdulta01	November 3, 1974	Maisons Alfort, France	1.1	41.7	23.7	70.3	236	11.4	7.8	3.3	3.5	42.2	University of Michigan, San Jose State University	c

In [23]:

```

```

In [24]:

```
filesalaries = "data/salaries_1985to2018.csv"
salaries_data = pd.read_csv(filesalaries)
salaries_data.head()
```

Out[24]:

	league	player_id	salary	season	season_end	season_start	team
0	NBA	abdelal01	395000	1990-91	1991	1990	Portland Trail Blazers
1	NBA	abdelal01	494000	1991-92	1992	1991	Portland Trail Blazers
2	NBA	abdelal01	500000	1992-93	1993	1992	Boston Celtics
3	NBA	abdelal01	805000	1993-94	1994	1993	Boston Celtics
4	NBA	abdelal01	650000	1994-95	1995	1994	Sacramento Kings

In [24]:

```

```

In [25]:

```
salaries_data["salary"] = pd.to_numeric(salaries_data["salary"], downcast="float")
sal_data = salaries_data.groupby('player_id')['salary'].mean()
nba_data = pd.merge(data, sal_data, on="player_id")
nba_data.head()
```

Out[25]:

	player_id	birthDate	birthPlace	career_AST	career_FG%	career_FG3%	career_FT%	career_G	career_PER	career_PTS	career_TRB	career_WS	career_eFG%	college	draf
0	abdelal01	June 24, 1968	Cairo, Egypt	0.3	50.2	0.0	70.1	256	13.0	5.7	3.3	4.8	50.2	Duke University	c
1	abdulka01	April 16, 1947	New York, New York	3.6	55.9	5.6	72.1	1560	24.6	24.6	11.2	273.4	55.9	University of California, Los Angeles	c

	player_id	birthDate	birthPlace	career_AST	career_FG%	career_FG3%	career_FT%	career_G	career_PER	career_PTS	career_TRB	career_WS	career_eFG%	college	draf
2	abdulma02	March 9, 1969	Gulfport, Mississippi	3.5	44.2	35.4	90.5	586	15.4	14.6	1.9	25.2	47.2	Louisiana State University	c
3	abdulta01	November 3, 1974	Maisons Alfort, France	1.1	41.7	23.7	70.3	236	11.4	7.8	3.3	3.5	42.2	University of Michigan, San Jose State University	c
4	abdursh01	December 11, 1976	Marietta, Georgia	2.5	47.2	29.7	81.0	830	19.0	18.1	7.5	71.2	47.9	University of California	c

In [26]:

```
#some observations

print('row number', nba_data.shape[0])
print('collum number', nba_data.shape[1])
print('feature names', nba_data.columns.tolist())
print('College list',len(nba_data.college.unique()))
print('High School names', len(nba_data.highSchool.unique()))
```

```
row number 2408
collum number 25
feature names ['player_id', 'birthDate', 'birthPlace', 'career_AST', 'career_FG%', 'career_FG3%', 'career_FT%', 'career_G', 'caree
r_PER', 'career_PTS', 'career_TRB', 'career_WS', 'career_eFG%', 'college', 'draft_pick', 'draft_round', 'draft_team', 'draft_year'
, 'height', 'highSchool', 'name', 'position', 'shoots', 'weight', 'salary']
College list 496
High School names 1620
```

Data Cleaning and Feature engineering explanation

- Merged datasets for get mean of salaries of each player recevied in carrer
- Remove the player_id field, a unique field cannot be supply valid information to a data analyse.
- Remove string contens of draft pick
- Remove string contents of draft round
- Remane name of statics columns of nba standards use with help of [NBA Glossary]
- Convert draft_pick and draft_round for float
- Identify and treat outliers, we chose remove outliers because would compromise analyses.
- save the filtred dataset in a new csv file

In [26]:

```

```

In [27]:

```
# remove columns that dont is dont necessary for analyses n

nba_data1 = nba_data.copy()
del nba_data1['player_id']

nba_data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2408 entries, 0 to 2407
Data columns (total 24 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   birthDate     2408 non-null   object
 1   birthPlace    2408 non-null   object
 2   career_AST    2408 non-null   float64
 3   career_FG%    2408 non-null   object
 4   career_FG3%   2408 non-null   object
 5   career_FT%    2408 non-null   object
 6   career_G      2408 non-null   int64
 7   career_PER    2408 non-null   object
 8   career_PTS    2408 non-null   float64
 9   career_TRB    2408 non-null   object
 10  career_WS     2408 non-null   object
 11  career_eFG%   2408 non-null   object
 12  college       2139 non-null   object
 13  draft_pick    1884 non-null   object
 14  draft_round   1884 non-null   object
 15  draft_team    1884 non-null   object
 16  draft_year    1884 non-null   object
 17  height        2408 non-null   object
 18  highSchool    2200 non-null   object
 19  name          2408 non-null   object
 20  position      2408 non-null   object
 21  shoots        2408 non-null   object
 22  weight        2408 non-null   object
 23  salary        2408 non-null   float32
dtypes: float32(1), float64(2), int64(1), object(20)
memory usage: 460.9+ KB
```

In [28]:

```
nba_data1.dropna(inplace=True)
nba_data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1666 entries, 0 to 2404
Data columns (total 24 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   birthDate    1666 non-null   object
 1   birthPlace   1666 non-null   object
 2   career_AST   1666 non-null   float64
 3   career_FG%   1666 non-null   object
 4   career_FG3%  1666 non-null   object
 5   career_FT%   1666 non-null   object
 6   career_G     1666 non-null   int64
 7   career_PER   1666 non-null   object
 8   career_PTS   1666 non-null   float64
 9   career_TRB   1666 non-null   object
 10  career_WS    1666 non-null   object
 11  career_eFG%  1666 non-null   object
 12  college      1666 non-null   object
 13  draft_pick   1666 non-null   object
 14  draft_round  1666 non-null   object
 15  draft_team   1666 non-null   object
 16  draft_year   1666 non-null   object
 17  height       1666 non-null   object
 18  highSchool   1666 non-null   object
 19  name         1666 non-null   object
 20  position     1666 non-null   object
 21  shoots       1666 non-null   object
 22  weight       1666 non-null   object
 23  salary       1666 non-null   float32
dtypes: float32(1), float64(2), int64(1), object(20)
memory usage: 318.9+ KB
```

In [29]:

```
# remove strings in draft_round for get only rounds
nba_data1.draft_round = nba_data1.draft_round.str.replace('st round', '')
nba_data1.draft_round = nba_data1.draft_round.str.replace('rd round', '')
nba_data1.draft_round = nba_data1.draft_round.str.replace('nd round', '')
nba_data1.draft_round = nba_data1.draft_round.str.replace('th round', '')

nba_data1.draft_pick = nba_data1.draft_pick.str.replace('st overall', '')
nba_data1.draft_pick = nba_data1.draft_pick.str.replace('rd overall', '')
nba_data1.draft_pick = nba_data1.draft_pick.str.replace('nd overall', '')
nba_data1.draft_pick = nba_data1.draft_pick.str.replace('th overall', '')

nba_data1.head()
```

Out[29]:

	birthDate	birthPlace	career_AST	career_FG%	career_FG3%	career_FT%	career_G	career_PER	career_PTS	career_TRB	career_WS	career_eFG%	college	draft_pick	draft_

	birthDate	birthPlace	career_AST	career_FG%	career_FG3%	career_FT%	career_G	career_PER	career_PTS	career_TRB	career_WS	career_eFG%	college	draft_pick	draft_
0	June 24, 1968	Cairo, Egypt	0.3	50.2	0.0	70.1	256	13.0	5.7	3.3	4.8	50.2	Duke University	25	
1	April 16, 1947	New York, New York	3.6	55.9	5.6	72.1	1560	24.6	24.6	11.2	273.4	55.9	University of California, Los Angeles	1	
2	March 9, 1969	Gulfport, Mississippi	3.5	44.2	35.4	90.5	586	15.4	14.6	1.9	25.2	47.2	Louisiana State University	3	
3	November 3, 1974	Maisons Alfort, France	1.1	41.7	23.7	70.3	236	11.4	7.8	3.3	3.5	42.2	University of Michigan, San Jose State University	11	
4	December 11, 1976	Marietta, Georgia	2.5	47.2	29.7	81.0	830	19.0	18.1	7.5	71.2	47.9	University of California	3	

In [30]:

```
nba_data1.rename(columns={'career_AST': 'assistences'}, inplace=True)
nba_data1.rename(columns={'career_FG%': 'field_goal_percentage'}, inplace=True)
nba_data1.rename(columns={'career_FG3%': 'field_goal_percentage_3_pts'}, inplace=True)
nba_data1.rename(columns={'career_FT%': 'free_throw_percentage'}, inplace=True)
nba_data1.rename(columns={'career_G': 'games'}, inplace=True)
nba_data1.rename(columns={'career_PER': 'player_efficiency_rating'}, inplace=True)
nba_data1.rename(columns={'career_PTS': 'points'}, inplace=True)
nba_data1.rename(columns={'career_TRB': 'total_rebounds'}, inplace=True)
nba_data1.rename(columns={'career_WS': 'win_shares'}, inplace=True)
nba_data1.rename(columns={'career_eFG%': 'effective_field_goal_percentage'}, inplace=True)

nba_data1.head()
```

Out[30]:

	birthDate	birthPlace	assistences	field_goal_percentage	field_goal_percentage_3_pts	free_throw_percentage	games	player_efficiency_rating	points	total_rebounds	win_shares	e

	birthDate	birthPlace	assistences	field_goal_percentage	field_goal_percentage_3_pts	free_throw_percentage	games	player_efficiency_rating	points	total_rebounds	win_shares	e
0	June 24, 1968	Cairo, Egypt	0.3	50.2	0.0	70.1	256	13.9	3.7	3.3	4.8	
1	April 16, 1947	New York, New York	3.6	55.9	5.6	72.1	1560	24.6	24.6	11.2	273.4	
2	March 9, 1969	Gulfport, Mississippi	3.5	44.2	35.4	90.5	586	15.4	14.6	1.9	25.2	
3	November 3, 1974	Maisons Alfort, France	1.1	41.7	23.7	70.3	236	11.4	7.8	3.3	3.5	
4	December 11, 1976	Marietta, Georgia	2.5	47.2	29.7	81.0	830	19.0	18.1	7.5	71.2	

In [31]:

```
nba_data1["draft_pick"] = pd.to_numeric(nba_data1["draft_pick"], downcast="float")
nba_data1["draft_round"] = pd.to_numeric(nba_data1["draft_round"], downcast="float")
print(nba_data1.draft_pick)
```

```
0       25.0
1        1.0
2        3.0
3       11.0
4        3.0
        ...
2397    56.0
2399     4.0
2401    17.0
2403    22.0
2404    41.0
Name: draft_pick, Length: 1666, dtype: float32
```

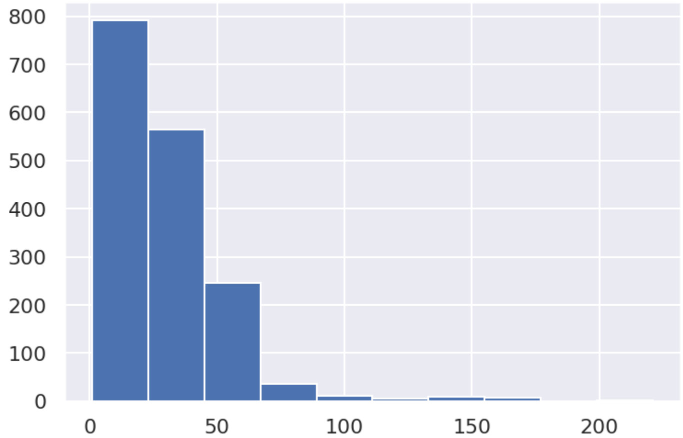
In [32]:

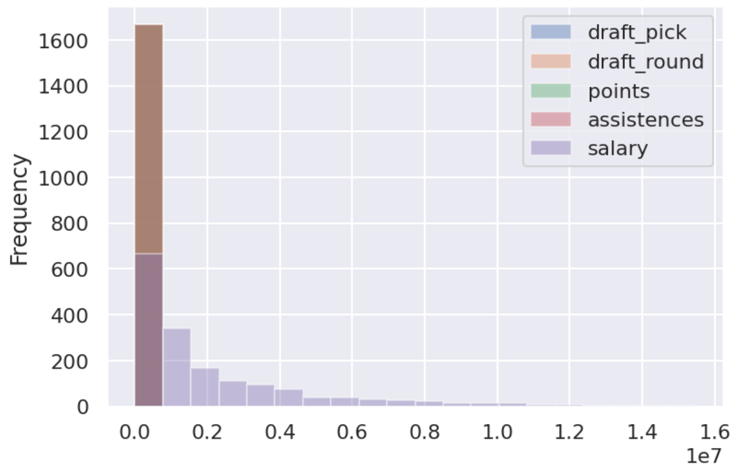
```
nba_data1['draft_pick'].hist(label='Order Of select in Draft')
```

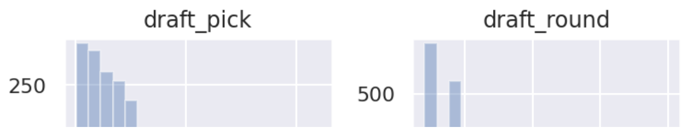
```
dataTotals = nba_data1[['draft_pick','draft_round', 'points', 'assistences', 'salary']]

dataTotals.plot.hist(alpha=0.4, bins=20)
dataTotals.hist(alpha=0.4, bins=20)
```

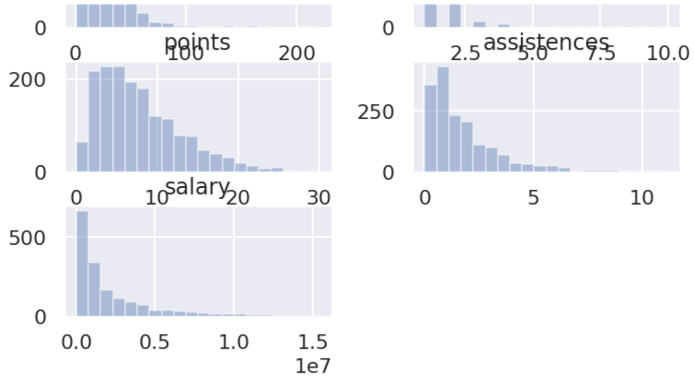
Out[32]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f3f703a94d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3f703d3cd0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f3f70382c90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3f7034d510>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f3f70301a10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3f702b8f10>]],
      dtype=object)
```









In [33]:

```
#Get lenght of outliers
temp_nba_data1 = nba_data1[(nba_data1.draft_pick > 60) & (nba_data1.draft_round > 2)]
index_lst = temp_nba_data1.index.values.tolist()
len(index_lst)
```

Out[33]:

```
79
```

In [34]:

```
#remove  outliers, I using knowleadbase, of nba for confirm that data is outliers
temp_nba_data1 = nba_data1[(nba_data1.draft_pick > 60) & (nba_data1.draft_round > 2)]
index_lst = temp_nba_data1.index.values.tolist()
nba_data1 = nba_data1.drop(index_lst)
```

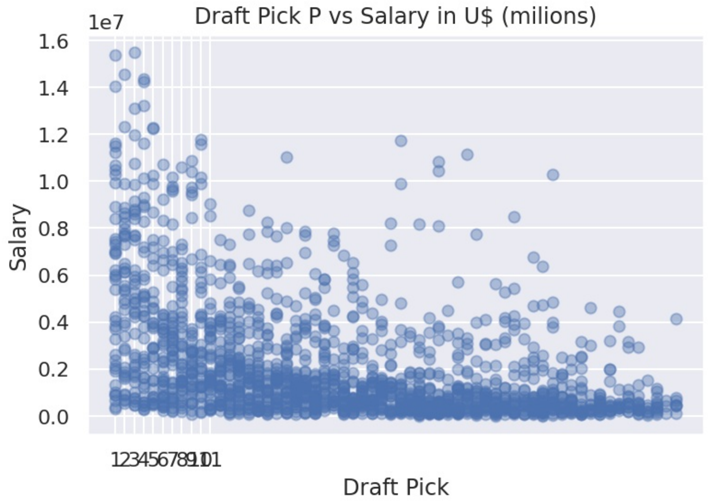
In [35]:

```
# save the new csv file

from pathlib import Path
filepath = Path('data/out.csv')
filepath.parent.mkdir(parents=True, exist_ok=True)
nba_data1.to_csv(filepath)
```

In [36]:

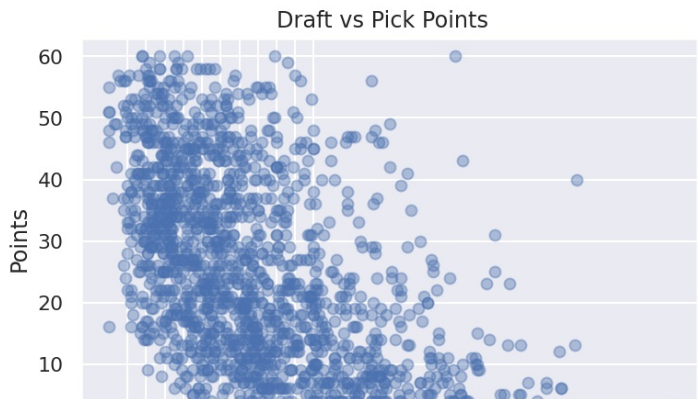
```
### Key Findings and Insights

ax = plt.axes()

plt.xticks(range(1, 12))
```

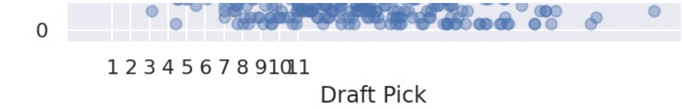
```
ax.scatter(nba_data1.draft_pick,nba_data1.salary, alpha=0.4)

# Label the axes
ax.set(xlabel='Draft Pick',
       ylabel='Salary',
       title='Draft Pick P vs Salary in U$ (milions)');
```



In [37]:

```
ax2 = plt.axes()

plt.xticks(range(1, 12))

ax2.scatter(nba_data1.points,nba_data1.draft_pick, alpha=0.4)

# Label the axes
ax2.set(xlabel='Draft Pick',
       ylabel='Points',
       title='Draft vs Pick Points  ');
```



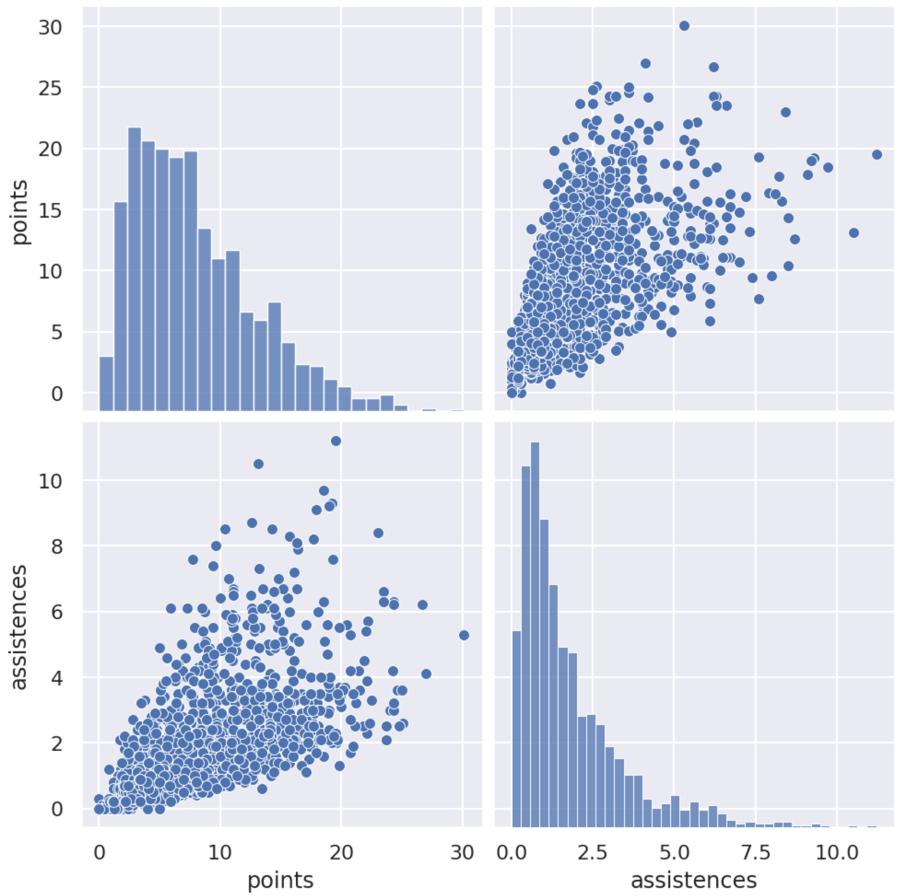


In [38]:

```
sns.pairplot(nba_data1,height=3.5, vars=['points', 'assistences'])
```

Out[38]:

```
<seaborn.axisgrid.PairGrid at 0x7f3f7b30e650>
```



Key Findings and Insights

```
- We found an apparent relationship between number of points with numbers of assistences
```

- **We found an apparent relationship between draft picker order with salaries**

- **We found an apparent relationship between draft picker with assistences and points**
- **We detect that relationship between number of points with years of drafts had one big fall but is stable in last 10 years**
- **We detect that relationship between number of assistences with years of drafts had one big fall but is stable in last 10 years**
- **We detact how the best colleges concentrate the biggest proporcion of best position of draft pick**

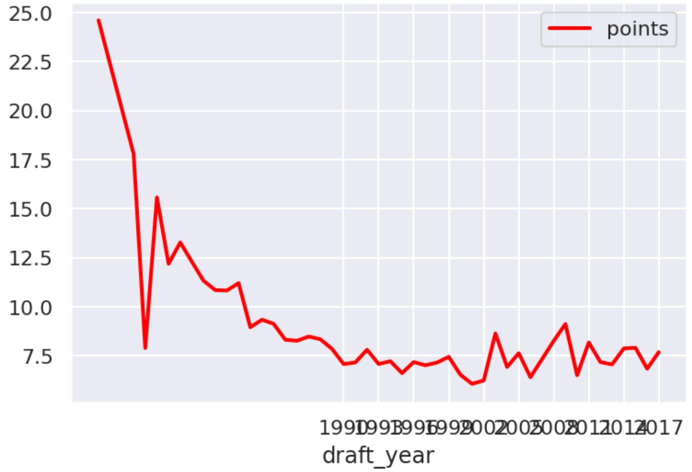
In [38]:

In [39]:

```
nba_data1["draft_year"] = pd.to_numeric(nba_data1["draft_year"], downcast="integer")
points_by_draft_year = nba_data1[['points', 'draft_year']]
points_by_draft_year = points_by_draft_year.groupby('draft_year').mean()

points_by_draft_year.plot(kind="line", color="red", linewidth=2, xticks=range(1990, 2020, 3))
```

Out[39]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3f6fecaed0>

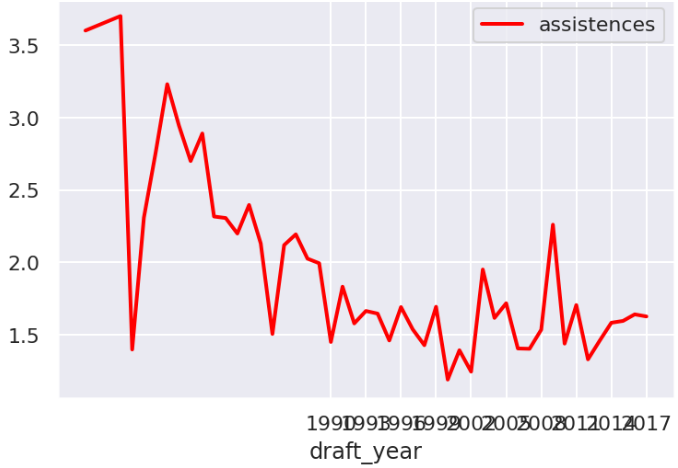


In [40]:

```
nba_data1["draft_year"] = pd.to_numeric(nba_data1["draft_year"], downcast="integer")
assistences_by_draft_year = nba_data1[['assistences', 'draft_year']]
assistences_by_draft_year = assistences_by_draft_year.groupby('draft_year').mean()

assistences_by_draft_year.plot(kind="line", color="red", linewidth=2, xticks=range(1990, 2020, 3))
```

Out[40]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3f6fe328d0>

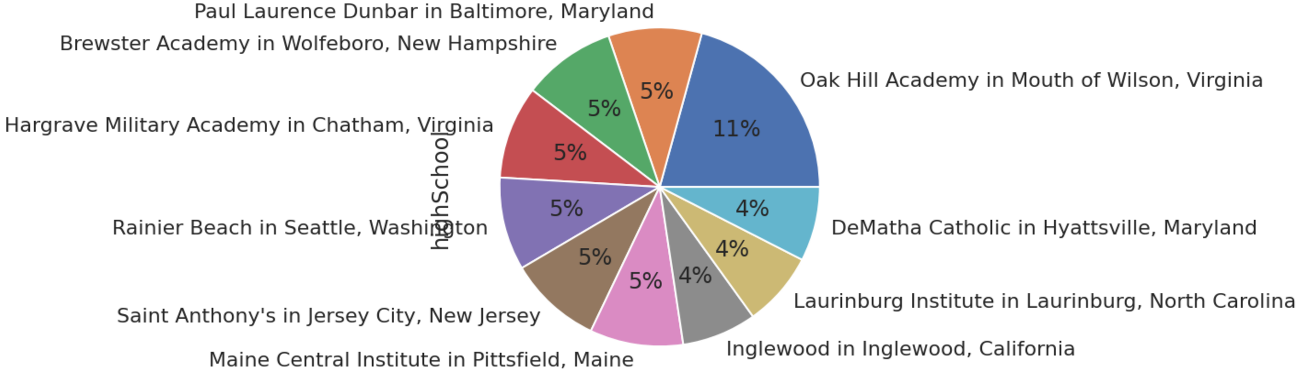


In [41]:

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:

temp_nba_data1 = nba_data1[ (nba_data1.draft_round == 1)]


highSchool = temp_nba_data1['highSchool'].value_counts()
highSchool.head(10).plot.pie(autopct=lambda x: '{:.0f}%'.format(x*highSchool.head(10).sum()/100) )
```

Out[41]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3f6fc79650>



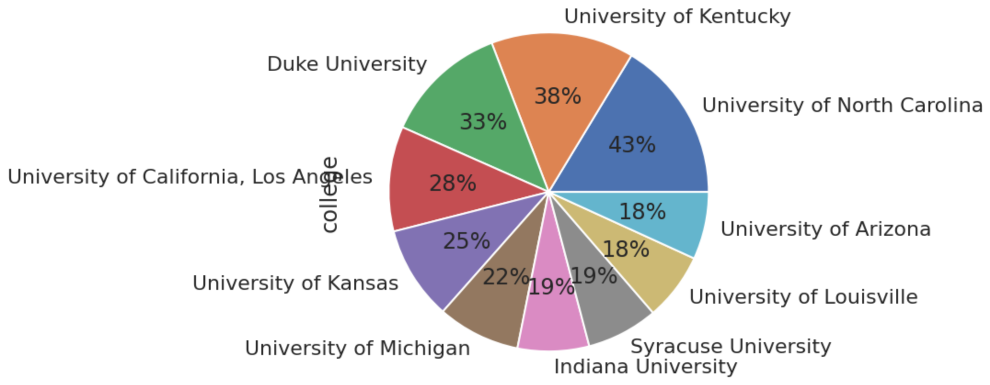
In [42]:

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:

temp_nba_data1 = nba_data1[ (nba_data1.draft_round == 1)]
```

```
college = temp_nba_data1['college'].value_counts()
college.head(10).plot.pie(autopct=lambda x: '{:.0f}%'.format(x*college.head(10).sum()/100) )
```

Out[42]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3f6fc70510>
```



In [42]:

hypothesis

- **hypothesis 1: The Colleges and High Schools with more draft in round 1 have the best salaries of NBA**
- **hypothesis 2: The Colleges and High School with more draft in round 1 have biggest points and assistences in NBA**
- **hypothesis 3: The players that best statics for points and assistences have the best salaries of NBA**

Test result of hypothesis 1

TRUE, by value of occurrences of the 10 best schools in draft round 1, I could check that the salaries almost come to be the triple of other schools in mean

In [43]:

```
# I will use data of numbers of ocorrences of colleges and highshools for filter whichs players have in these schools
temp_nba_data1 = nba_data1[ (nba_data1.draft_round == 1)]


college = temp_nba_data1['college'].value_counts()
print(college.head(10))
```

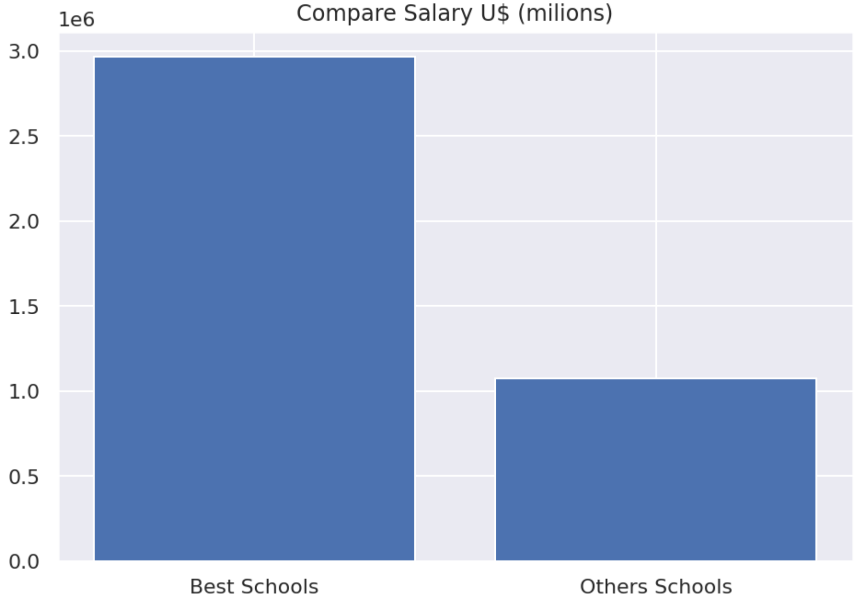
```
highSchool = temp_nba_data1['highSchool'].value_counts()
print(highSchool.head(10))
```

```
University of North Carolina              43
University of Kentucky                    38
Duke University                           33
University of California, Los Angeles     28
University of Kansas                      25
University of Michigan                    22
Indiana University                        19
Syracuse University                       19
University of Louisville                  18
University of Arizona                     18
Name: college, dtype: int64
Oak Hill Academy in Mouth of Wilson, Virginia          11
Paul Laurence Dunbar in Baltimore, Maryland             5
Brewster Academy in Wolfeboro, New Hampshire            5
Hargrave Military Academy in Chatham, Virginia          5
Rainier Beach in Seattle, Washington                    5
Saint Anthony's in Jersey City, New Jersey              5
Maine Central Institute in Pittsfield, Maine            5
Inglewood in Inglewood, California                      4
Laurinburg Institute in Laurinburg, North Carolina      4
DeMatha Catholic in Hyattsville, Maryland               4
Name: highSchool, dtype: int64
```

In [44]:

```
biggest_schools = nba_data1[ (nba_data1.draft_round == 1) & (len(nba_data1.college) >= 18) & (len(nba_data1.highSchool) >= 4) ]
biggest_indices = biggest_schools.index.tolist()
minors_schools = nba_data1[~nba_data1.index.isin(biggest_schools.index.tolist())]


print('All of players: ', nba_data1.shape[0])
print('Number of Colleges: ',len(nba_data1.college.unique()))
print('Number of High Schools: ', len(nba_data1.highSchool.unique()))
print('Number of Players in Best Schools: ', biggest_schools.shape[0])
print('Number of Players in Others: ', minors_schools.shape[0])
print('Mean of salaries of Best Schools: ',biggest_schools.salary.mean())
print('Mean of salaries of others Schools: ',minors_schools.salary.mean())
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])

salaries_labels = ['Best Schools' , 'Others Schools']
salaries_values = [int(biggest_schools.salary.mean()) ,int(minors_schools.salary.mean()) ]
ax.bar(salaries_labels,salaries_values)
ax.set_title('Compare Salary U$ (milions)')
plt.show()
```

```
All of players:  1587
Number of Colleges:  349
Number of High Schools:  1205
Number of Players in Best Schools:  945
Number of Players in Others:  642
Mean of salaries of Best Schools:  2965222.75
Mean of salaries of others Schools:  1072140.125
```



Suggestions for next steps in analyzing this data

- **Analyse if players characteristics like weight, position, height or shoots can influence ir their salaries in nba**
- **Analyse if age and origin of players can influence the order of draft pick**
- **Analyse whichs characteristics have best statics in games in nba, and if age and origan can be influences the results**

Quality of dataset and requets for more data

The general quality of this data set is satisfactory for a superficial analysis of nba draft, we can raise that ten colleges concentrate basicly 60% of best positions of draft of nba. With other statics data, in this dataset, will could possible too do analyses of what results the best positions of NBA draft got it in yours carrers besides milionaries salaries. But for analyses what causes for the colleges had the best positions in draft, we need the datas bellow, of players before to become profissionals

- **Assistances**
- **Efective Field Goal**
- **Efective Field Goal 3**
- **Free throws**

- Free throws
- Games
- Player Efficiency Rating
- Points
- Total Rebounds
- Win Shares
- Effective Field Goal