Project 2

Part 1: Wrangling

Problem 1

In [396…

```
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

sqlite_file = 'lahman2014.sqlite'
conn = sqlite3.connect(sqlite_file)

salary_query = "SELECT teamID, yearID, sum(salary)/1000 as total_payroll_by_thousand, sum(salary)/count(salary) as payroll_mean FROM Salaries GROUP BY teamID, yearID"

team_salaries = pd.read_sql(salary_query, conn)

team_query = "SELECT (W*100.0/G) as winning_percentage, * FROM Teams GROUP BY teamID, yearID"

team_table = pd.read_sql(team_query, conn)

result = pd.merge(team_salaries, team_table, how='inner', on=['teamID','yearID'])

result
```

Out[396…

	teamID	yearID	total_payroll_by_thousand	payroll_mean	winning_percentage	lgID	franchID	divID	Rank	G	…	DP	FP	name	park	attendance	BPF	PPF	teamIDBR	teamIDlahman45	teamIDretro
0	ATL	1985	14807.000	6.730455e+05	40.740741	NL	ATL	W	5	162	…	197.0	0.970	Atlanta Braves	Atlanta-Fulton County Stadium	1350137.0	105	106	ATL	ATL	ATL
1	BAL	1985	11560.712	5.254869e+05	51.552795	AL	BAL	E	4	161	…	168.0	0.980	Baltimore Orioles	Memorial Stadium	2132387.0	97	97	BAL	BAL	BAL
2	BOS	1985	10897.560	4.359024e+05	49.693252	AL	BOS	E	5	163	…	161.0	0.970	Boston Red Sox	Fenway Park II	1786633.0	104	104	BOS	BOS	BOS
3	CAL	1985	14427.894	5.152819e+05	55.555556	AL	ANA	W	2	162	…	202.0	0.980	California Angels	Anaheim Stadium	2567427.0	100	100	CAL	CAL	CAL
4	CHA	1985	9846.178	4.688656e+05	52.147239	AL	CHW	W	3	163	…	152.0	0.980	Chicago White Sox	Comiskey Park	1669888.0	104	104	CHW	CHA	CHA
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
853	SLN	2014	120693.000	4.310464e+06	55.555556	NL	STL	C	1	162	…	145.0	0.985	St. Louis Cardinals	Busch Stadium III	3540649.0	101	100	STL	SLN	SLN
854	TBA	2014	72689.100	2.907564e+06	47.530864	AL	TBD	E	4	162	…	96.0	0.985	Tampa Bay Rays	Tropicana Field	1446464.0	97	97	TBR	TBA	TBA
855	TEX	2014	112255.059	4.677294e+06	41.358025	AL	TEX	W	5	162	…	155.0	0.982	Texas Rangers	Rangers Ballpark in Arlington	2718733.0	101	101	TEX	TEX	TEX
856	TOR	2014	109920.100	4.396804e+06	51.234568	AL	TOR	E	3	162	…	130.0	0.985	Toronto Blue Jays	Rogers Centre	2375525.0	102	102	TOR	TOR	TOR
857	WAS	2014	131983.680	4.399456e+06	59.259259	NL	WSN	E	1	162	…	139.0	0.984	Washington Nationals	Nationals Park	2579389.0	104	102	WSN	MON	WAS

858 rows × 51 columns

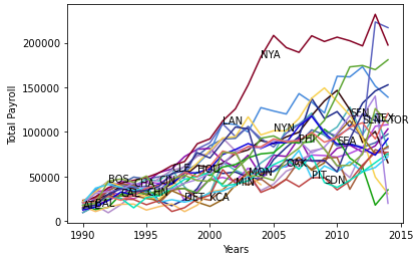
There is missing data in team_table so I used an inner join to intersect the tables based on yearID and teamID after getting the data from the SQL query

Part 2: Exploratory Data Analysis

Problem 2

In [397…

```
%matplotlib inline

result.sort_values("yearID", ascending=True)
temp = result[result['yearID'] >= 1990]
temp = temp[temp['yearID'] <= 2014]
teams = temp['teamID'].drop_duplicates()
temp = temp[['yearID', 'teamID', 'total_payroll_by_thousand']]
temp = temp.set_index('teamID')
year = 1990
for t in teams:
    temp1 = temp.loc[lambda x: x.yearID == year, :]
    if t in temp1.index:
        num = temp1.loc[t]['total_payroll_by_thousand']
        plt.annotate(t, xy = (year, num))
        plt.plot(temp.loc[t]['yearID'], temp.loc[t]['total_payroll_by_thousand'],color=np.random.rand(3,))
        if (year < 2014):
            year+=1
        else:
            year = 1990

plt.xlabel('Years')
plt.ylabel('Total Payroll')
plt.rcParams["figure.figsize"] = (20,10)
```



Question 1

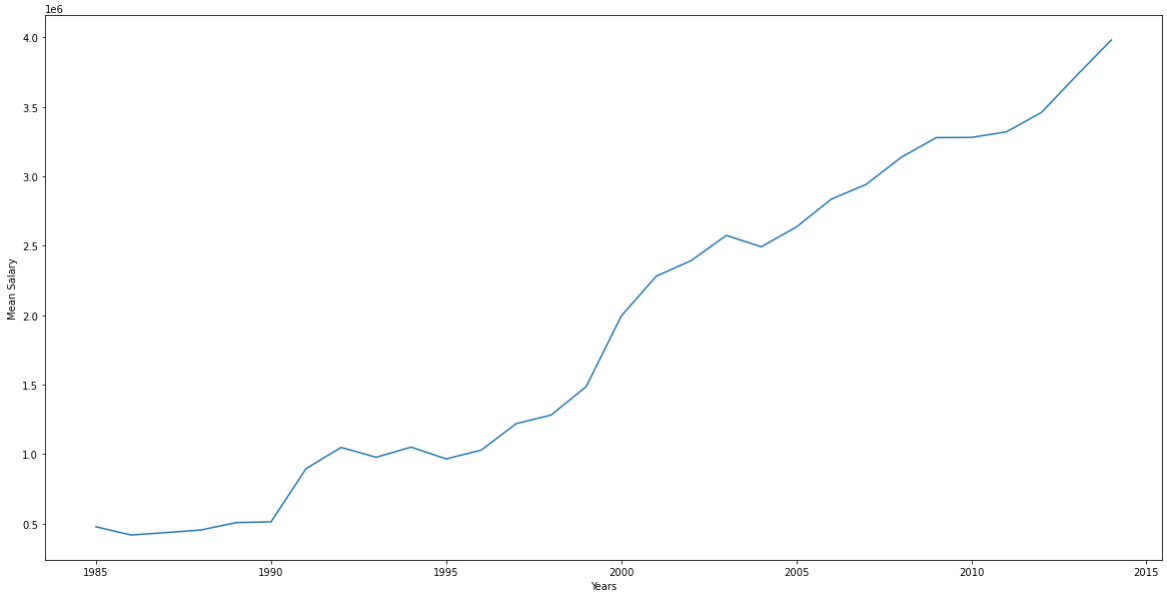
The payroll distribution seems to be trending upwards for all teams, but the magnitude of the increase is different for all the teams in the league with some teams doing better than others

Problem 3

In [398…

```
mean_query = "SELECT yearID, sum(salary)/count(salary) as salary_mean FROM Salaries GROUP BY yearID"
mean_table = pd.read_sql(mean_query,conn)
result = pd.merge(result, mean_table, how='inner', on=['yearID'])

result.sort_values("salary_mean", ascending=True)
plt.plot(result['yearID'],result['salary_mean'])
plt.xlabel('Years')
plt.ylabel('Mean Salary')
#shows the upward trend
```

Out[398… `Text(0, 0.5, 'Mean Salary')`



Problem 4

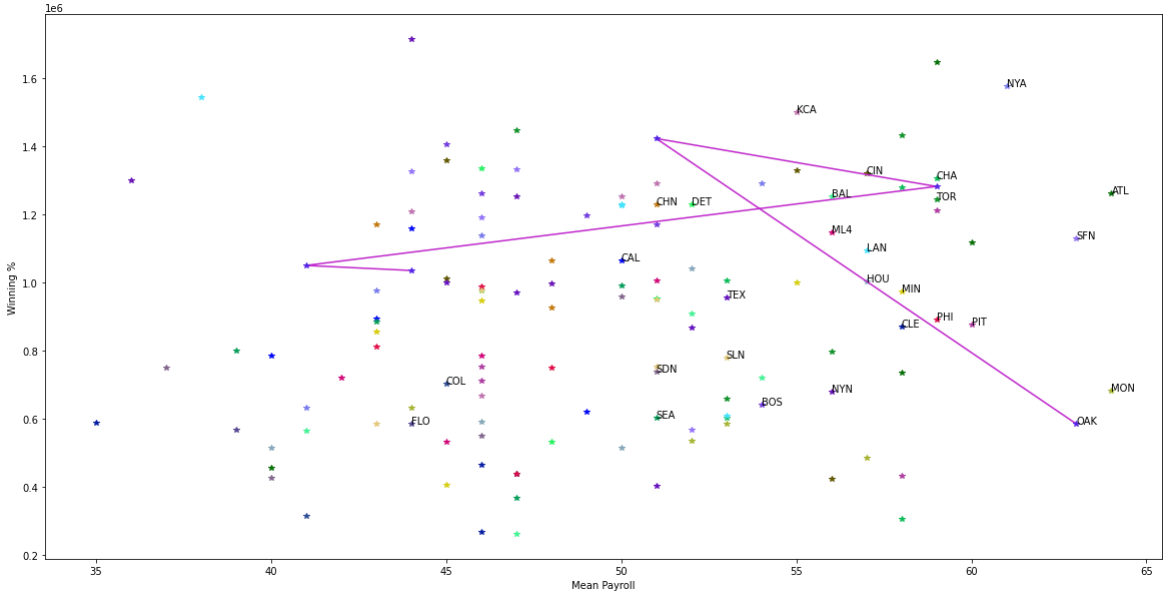
In [399…

```
new_query1 = "SELECT  teamID,yearID, sum(salary)/count(salary) as payroll_mean FROM Salaries GROUP BY teamID,yearID"
new_query2 = "SELECT  teamID,yearID, W*100/G as winning_percentage FROM Teams GROUP BY teamID,yearID"
query1_table = pd.read_sql(new_query1, conn)
query2_table = pd.read_sql(new_query2,conn)

group_table = pd.merge(query1_table, query2_table, how='inner', on=['yearID','teamID'])

group_names = ['1990-1994','1995-1999','2000-2004','2005-2009','2010-2015']
categories = pd.cut(group_table['yearID'],[1989,1994,1999,2004,2009,2015],labels=group_names)
group_table['categories'] = pd.cut(group_table['yearID'], [1989,1994,1999,2004,2009,2015], labels=group_names)

catgroup = group_table.groupby('categories')

group1 = catgroup.get_group('1990-1994')
```

```
group2 = catgroup.get_group('1995-1999')
group3 = catgroup.get_group('2000-2004')
group4 = catgroup.get_group('2005-2009')
group5 = catgroup.get_group('2010-2015')

def plotgroups(grp):
    teams = grp['teamID'].drop_duplicates()
    temp = grp[['teamID', 'winning_percentage', 'payroll_mean']]
    temp = temp.set_index('teamID')
    for t in teams:
        temp1 = grp.loc[lambda x: x.teamID == t, :]
        best_row = temp1.loc[temp1['winning_percentage'].idxmax()]
        plt.annotate(t, xy = (best_row['winning_percentage'], best_row['payroll_mean']))
        if t == 'OAK':
            plt.plot(temp.loc[t]['winning_percentage'], temp.loc[t]['payroll_mean'],color=np.random.rand(3,))
        plt.plot(temp.loc[t]['winning_percentage'], temp.loc[t]['payroll_mean'],'*',color=np.random.rand(3,))
    plt.xlabel('Mean Payroll')
    plt.ylabel('Winning %')
    plt.rcParams["figure.figsize"] = (20,10)
```

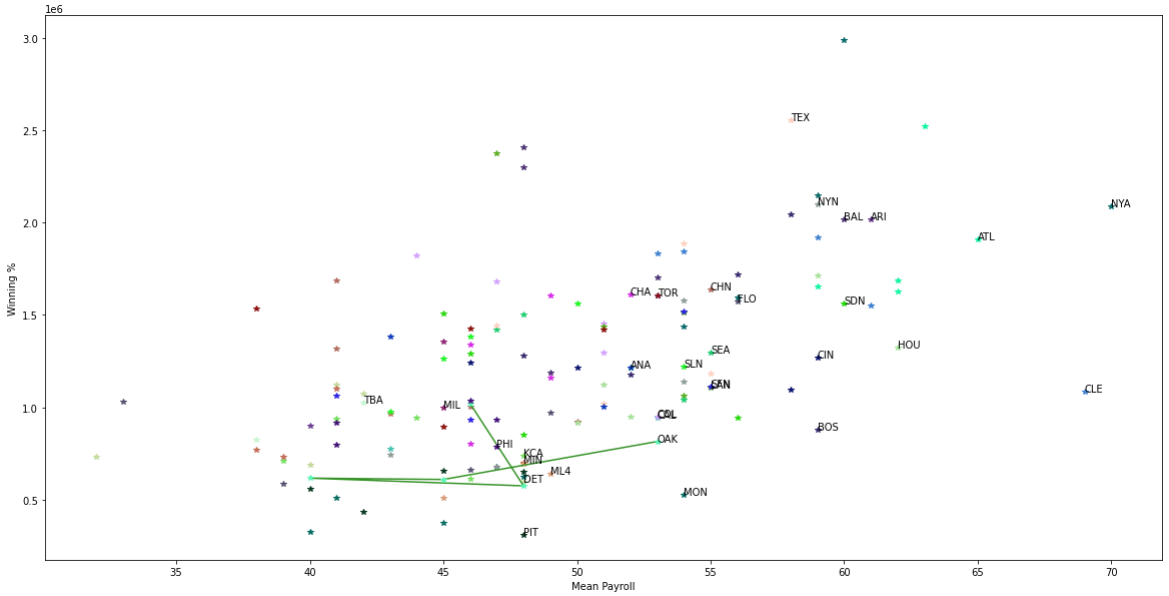
In [400…

```
#1990-94
plotgroups(group1)
```



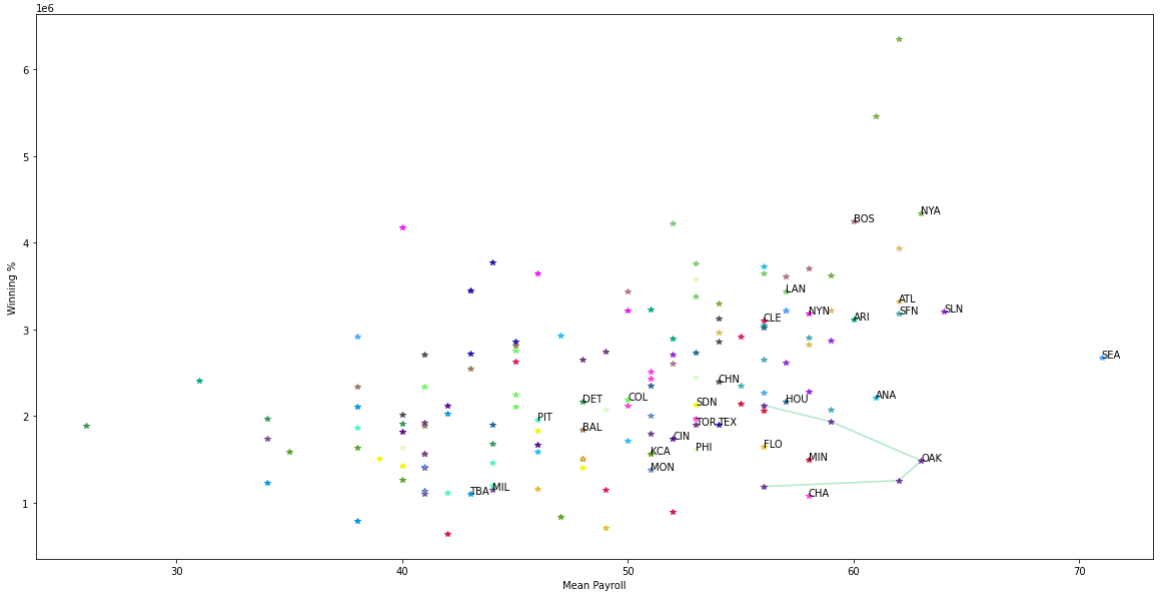
In [401…

```
#1995-99
plotgroups(group2)
```



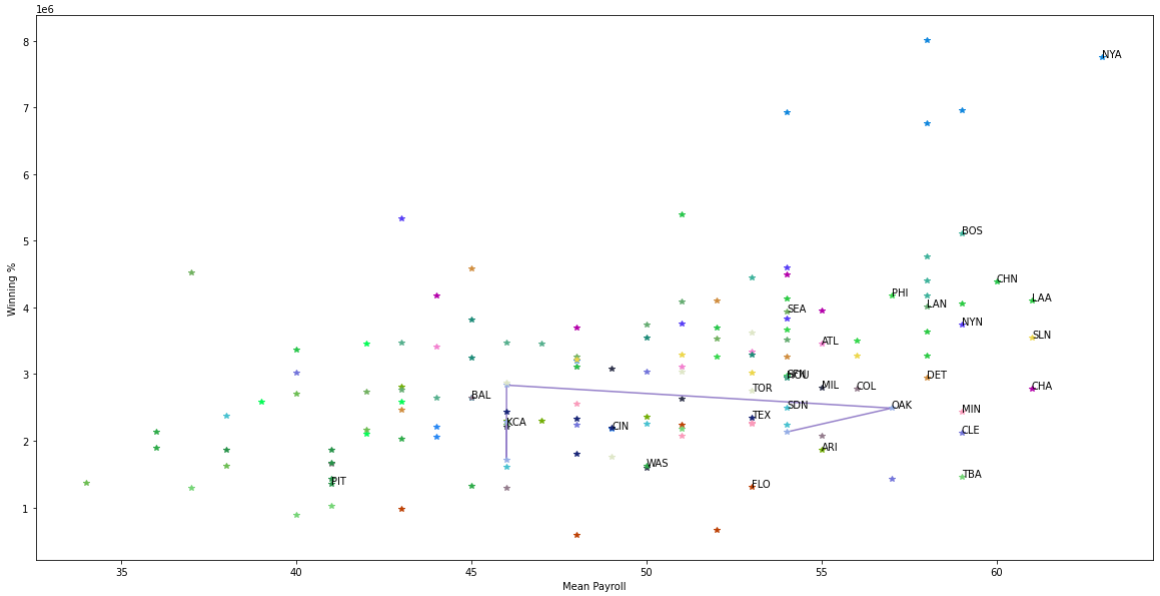
In [402…

```
#2000-04
plotgroups(group3)
```



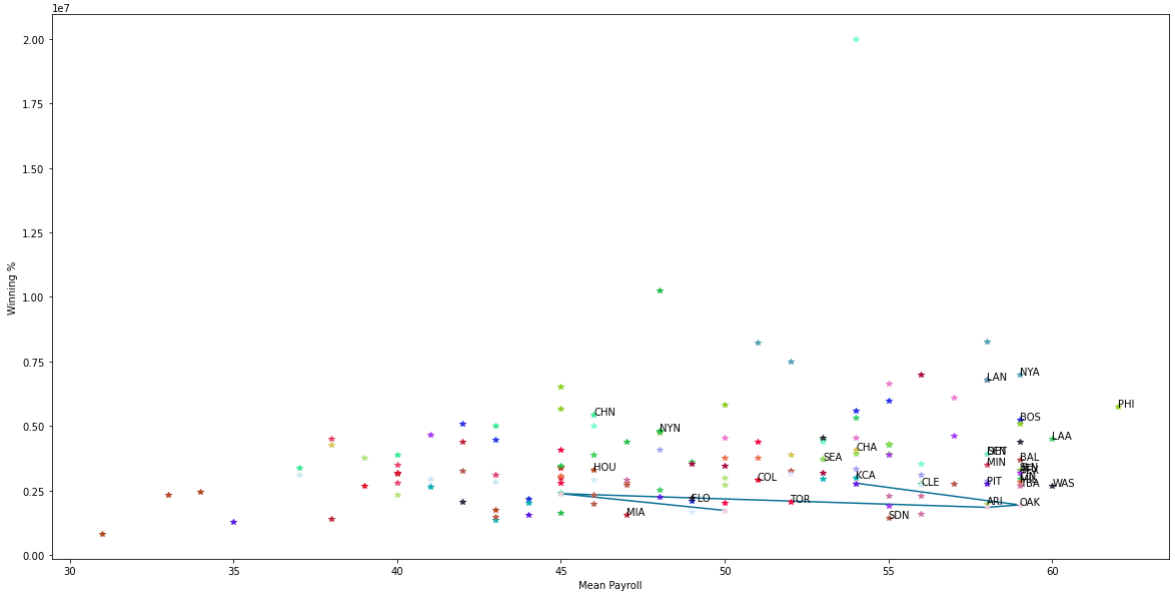
In [403…

```
#2005-09
plotgroups(group4)
```



In [404…

```
#2010-14
plotgroups(group5)
```



Question 2

The New York Yankees is the standout across all the time periods when it comes to paying for wins. Oakland A's spending efficiency across these time periods seems to be around the mean as they don't really stand out in general.

Part 3: Data transformations

Problem 5

In [405…

```
curr = 1985
```

```
payroll_list = []
payroll_avg = {}
payroll_std = {}

for index, row in query1_table.iterrows():
    if curr != row['yearID']:
        avg = np.mean(payroll_list)
        std = np.std(payroll_list)
        payroll_avg[curr] = avg
        payroll_std[curr] = std
        curr = row['yearID']
        payroll_list= [row['payroll_mean']]

    else:
        payroll_list.append(row['payroll_mean'])
payroll_std[curr] = np.std(payroll_list)
payroll_avg[curr] = np.mean(payroll_list)

stand_list = []

for index, row in query1_table.iterrows():
    curr = row['yearID']
    payroll = row['payroll_mean']
    stand_list.append((payroll - payroll_avg[curr]) / payroll_std[curr])

query1_table['Standardized_Payroll'] = stand_list
query1_table
```

Out[405…

	teamID	yearID	payroll_mean	Standardized_Payroll
0	ATL	1985	6.730455e+05	1.985378
1	BAL	1985	5.254869e+05	0.510155
2	BOS	1985	4.359024e+05	-0.385469
3	CAL	1985	5.152819e+05	0.408131
4	CHA	1985	4.688656e+05	-0.055918
...	...	...	...	...
855	SLN	2014	4.310464e+06	-0.090724
856	TBA	2014	2.907564e+06	-0.516197
857	TEX	2014	4.677294e+06	0.020529
858	TOR	2014	4.396804e+06	-0.064538
859	WAS	2014	4.399456e+06	-0.063734

860 rows × 4 columns

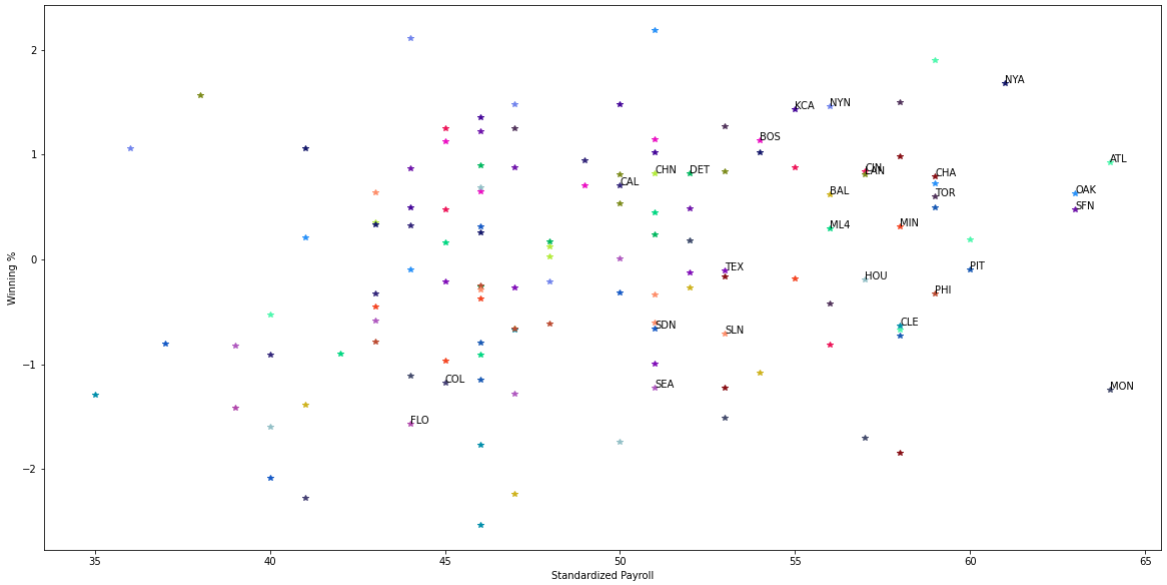
Problem 6

In [406…

```
group_table = pd.merge(query1_table, query2_table, how='inner', on=['yearID','teamID'])

group_names = ['1990-1994','1995-1999','2000-2004','2005-2009','2010-2015']
categories = pd.cut(group_table['yearID'],[1989,1994,1999,2004,2009,2015],labels=group_names)
group_table['categories'] = pd.cut(group_table['yearID'], [1989,1994,1999,2004,2009,2015], labels=group_names)

catgroup = group_table.groupby('categories')

group1 = catgroup.get_group('1990-1994')
group2 = catgroup.get_group('1995-1999')
group3 = catgroup.get_group('2000-2004')
group4 = catgroup.get_group('2005-2009')
group5 = catgroup.get_group('2010-2015')

def plotgroup(grp): #function for plotting
    teams = grp['teamID'].drop_duplicates()
    temp = grp[['teamID', 'winning_percentage', 'Standardized_Payroll']]
    temp = temp.set_index('teamID')
    for t in teams:
        temp1 = grp.loc[lambda x: x.teamID == t, :]
        best_row = temp1.loc[temp1['winning_percentage'].idxmax()]
        plt.annotate(t, xy = (best_row['winning_percentage'], best_row['Standardized_Payroll']))
        plt.plot(temp.loc[t,'winning_percentage'], temp.loc[t,'Standardized_Payroll'],'*',color=np.random.rand(3,))
    plt.xlabel('Standardized Payroll')
    plt.ylabel('Winning %')
    plt.rcParams["figure.figsize"] = (20,10)
```

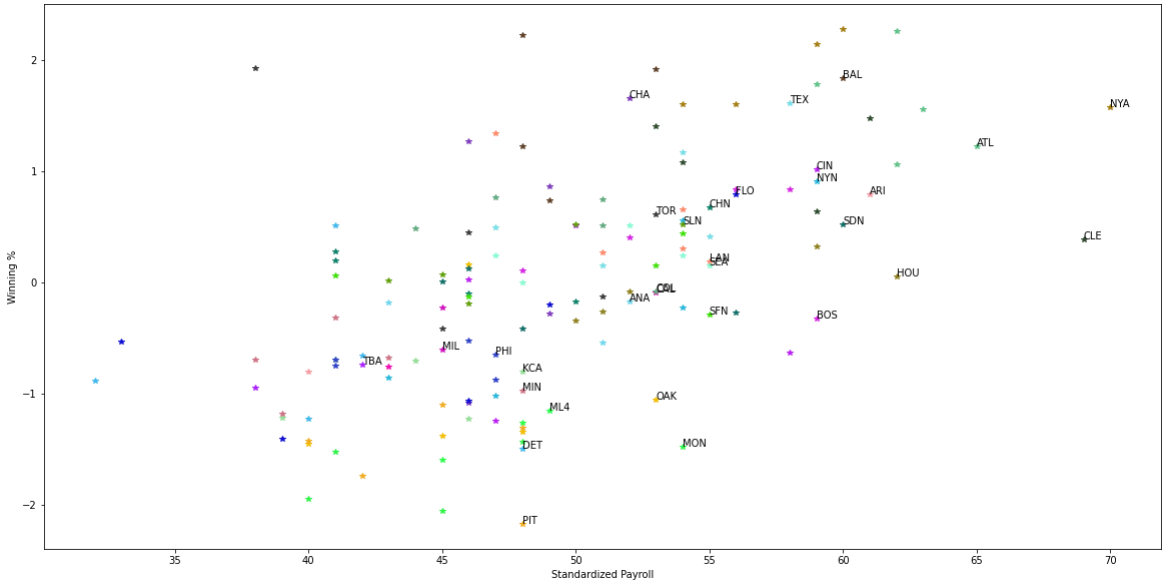
In [407…

```
#1990-94
plotgroup(group1)
```



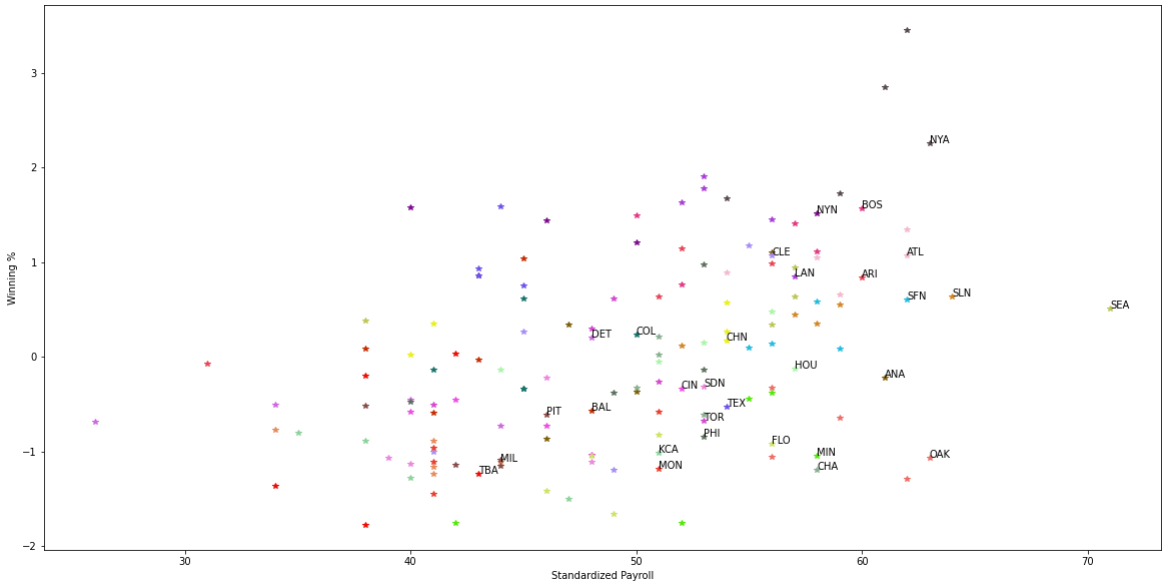
In [408…

```
#1995-99
plotgroup(group2)
```



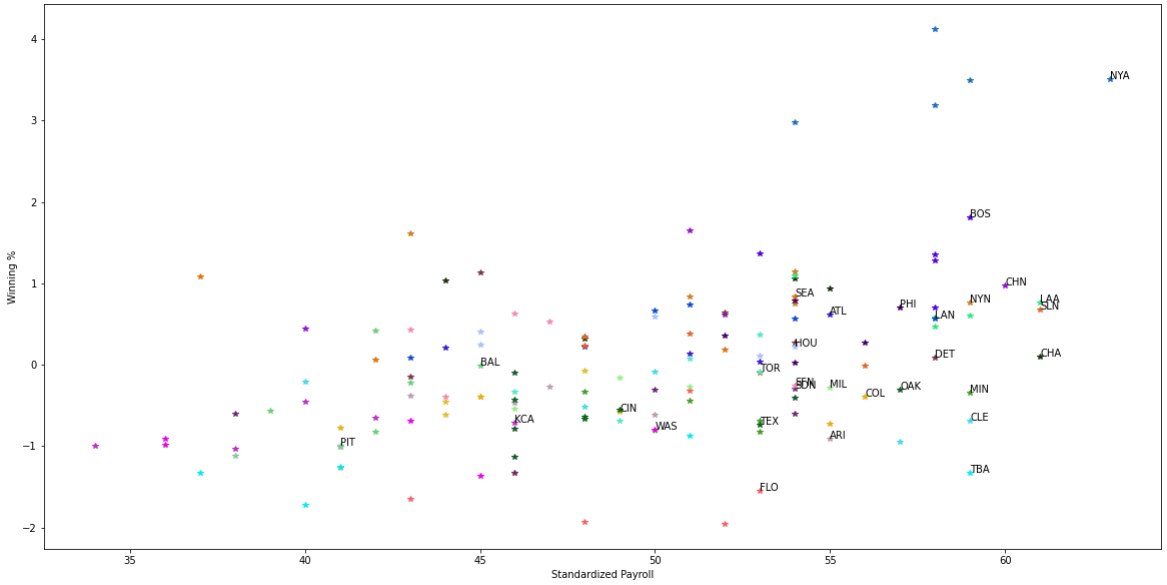
In [409…

```
#2000-04
plotgroup(group3)
```



In [410…

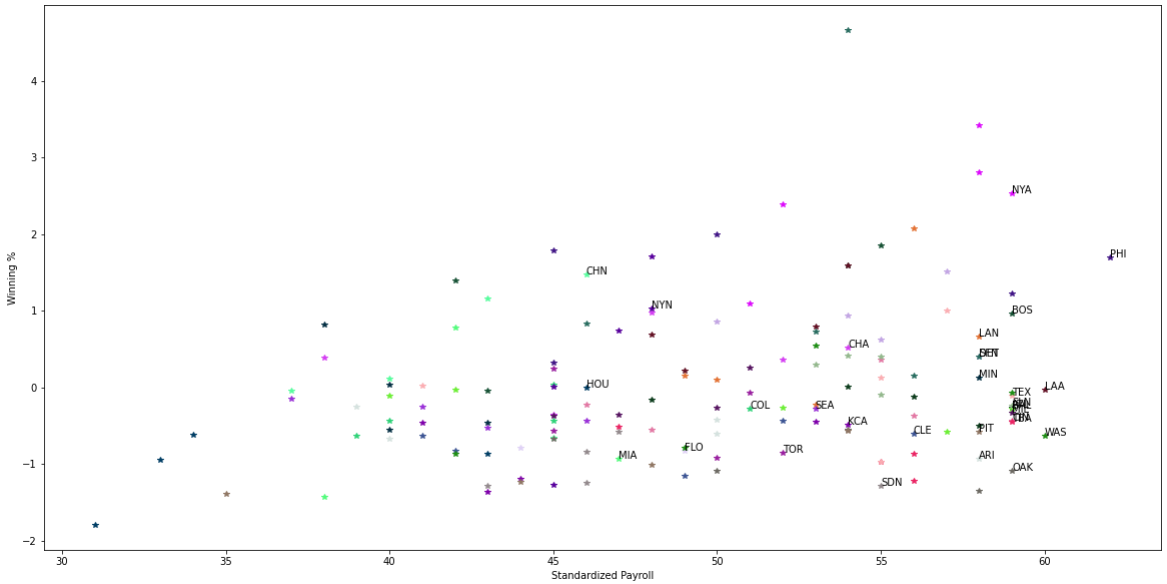
```
#2005-09
plotgroup(group4)
```



In [412…

```
#2010-14
teams = group5['teamID'].drop_duplicates()
temp = group5[['teamID', 'winning_percentage', 'Standardized_Payroll']]
temp = temp.set_index('teamID')
group5 = group5.dropna();
for t in teams:
    temp1 = group5.loc[lambda x: x.teamID == t, :]
    if temp1['winning_percentage'].empty:
        print('')
    else:
        best_row = temp1.loc[temp1['winning_percentage'].idxmax()]
        plt.annotate(t, xy = (best_row['winning_percentage'], best_row['Standardized_Payroll']))
```

```
    plt.plot(temp.loc[t,'winning_percentage'], temp.loc[t,'Standardized_Payroll'],'*',color=np.random.rand(3,))
plt.xlabel('Standardized Payroll')
plt.ylabel('Winning %')
plt.rcParams["figure.figsize"] = (20,10)
```



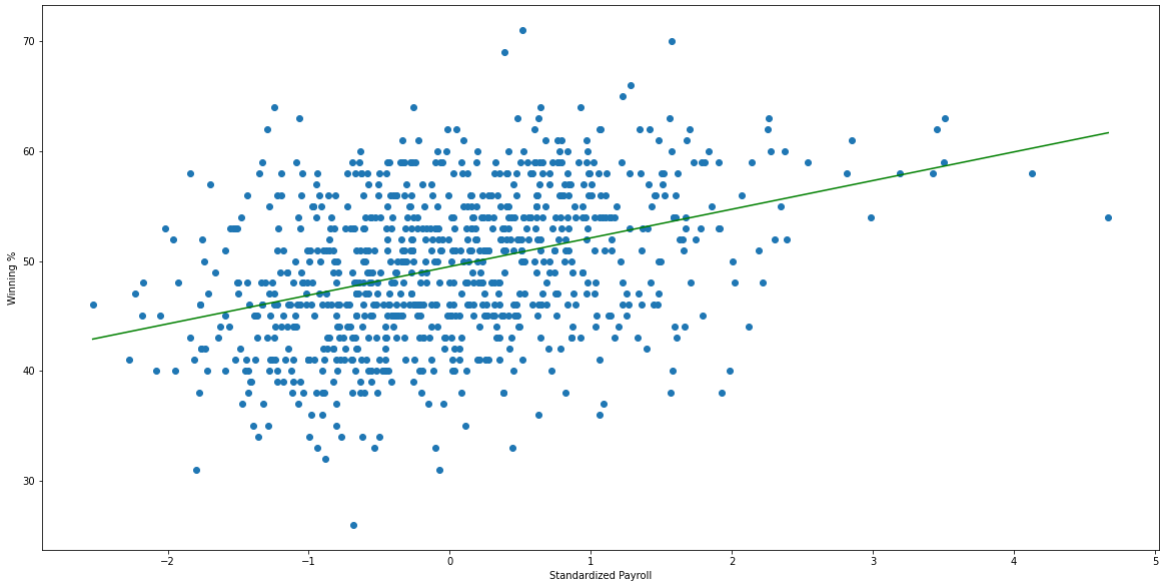
Question 3

Plots in Problem 6 are more even spaced out and the distribution seems to be clearer as well as compared to the ones in Problem 4.

Problem 7

In [366…

```
group_table = group_table[np.isfinite(group_table['winning_percentage'])]
group_table = group_table[np.isfinite(group_table['Standardized_Payroll'])]

#regression line
a, b = np.polyfit(group_table['Standardized_Payroll'], group_table['winning_percentage'], 1)
x = np.linspace(group_table['Standardized_Payroll'].min(),group_table['Standardized_Payroll'].max(),100)
plt.plot(group_table['Standardized_Payroll'],group_table['winning_percentage'],'o')
plt.plot(x, a*x+b, color='g')
plt.xlabel('Standardized Payroll')
plt.ylabel('Winning %')
plt.rcParams["figure.figsize"] = (20,10)
```



Problem 8

In [415…

```
eff = []

for index, row in group_table.iterrows():
    eff.append(row['winning_percentage'] - 50 + 2.5 * row['Standardized_Payroll'])

group_table['efficiency'] = eff

group_table.sort_values("yearID", ascending=True)
temp = group_table[group_table['yearID'] >= 1990]
temp = temp[temp['yearID'] <= 2014]
teams = temp['teamID'].drop_duplicates()
temp = temp[['yearID', 'teamID', 'efficiency']]
temp = temp.set_index('teamID')
year = 1990
for t in teams:
    temp1 = temp.loc[lambda x: x.yearID == year, :]
    if t in temp1.index:
        num = temp1.loc[t,'efficiency']
        plt.annotate(t, xy = (year, num))
        plt.plot(temp.loc[t]['yearID'], temp.loc[t]['efficiency'],color=np.random.rand(3,))
        if (year < 2014):
            year+=1
        else:
            year = 1990

plt.xlabel('Years')
plt.ylabel('Efficiency')
plt.rcParams["figure.figsize"] = (20,10)
```

Question 4

The Teams that were good at paying for wins are more efficient. The New York Yankees exemplify this as they clearly spent the most money but also achieved great success as the graph shows. Oakland's efficiency over the Moneyball was definitely good as they seemed to have a higher efficiency than the majority of teams during that time. While they never really reached the heights of the Yankees, they were above average.