Baseball Data Analysis

Introduction

The data that we pulled had a lot of information. The file `readME2014.txt` has information about the CSV files and basic information of all the CSV files. The following analysis was not on all the CSV files. The files that was put at the centre of all the analysis was `salary.csv` because a lot of the analysis is centred around the salary. The data cleaning operations were performed on what is present on the `salary.csv` file. On the way of exploring the Baseball data, some other csv files are also explored, i.e,

- `Master.csv`
- `Teams.csv`
- `Batting.csv`
- `Pitching.csv`

NOTE

> - All the CSVs are given with the project files. Downloand links of all the versions are provided in GitHub README in the form of *PDF, HTML, MarkDown, ipython Notebook and JPEG images for plots*
> - The code is strictly written in **Python 3.6** with a conda environment. It is recommended to run the code is **Python > 3.4** and using **Python2** is not at all recommended.
> - The actual ipynb file may not have all the details in written and the styling may not kick in as it is in PDF or MarkDown. If the intention is to skim through the analysis only instead of running the code, the PDF version is recommended.

First get all the imports down the line. I am alsi configuring my own css file to improve the look and feel of the Jupyter Notebook. The CSS file is present in styles directory in the project.

Now before we start lets first see what are the questions that we can answer about the dataset from the analysis. These question are of various type and varies from different range and different levels. **Hence after every question, the level of question is also mentioned in bold.** The questions are

- How teams invested in players in terms of player's salary? **(Basic)**
- How players recieved salary over their career? **(Basic)**
- What are the most common salary ranges teams preferred to compensate their players? This reveals the salary standard of BaseBall. **(Intermediate)**
- Is there any abrupt changes (ups/downs) teams faced in terms of the salary they paid? This shows if any year was good or bad for Baseball players or was their any effect of recessions on players' salary. **(Intermediate)**
- Is there any abrupt chnages (ups/downs) in players' performance in any year and what could be the probable reason? **(Intermediate)**
- How batters' homeruns (HR) or a pitchers' shutouts (SHO) is affected by thier height and weight? **(Intermediate)**
- How salary affects players' performance? **(Advanced)**
- What makes a team secure first rank or at least be in top 3? **(Advanced)**

```
%config InlineBackend.figure_format = 'retina'
import seaborn as sns
import matplotlib.pylab as plt
import pandas as pd
import numpy as np
from IPython.display import display
from IPython.core.display import HTML
###################################
### We are supressing all warnings with an assurance that the
#  warnings that are supressed are are not substantial #
#########################################
import warnings
warnings.filterwarnings('ignore')
###################################
######### Our custom import #######
from core import configure
from core import _rc
###################################
```

Configuring our RC file is important to give plots my own customized look and feel. For more info on `rcParams` and visual parameter configuration, please click **here**

```
configure(configType='css')
configure(configType='rc')
```

Now some basic path resolve according to the project directory. **Here** is the documentation for os module for python.

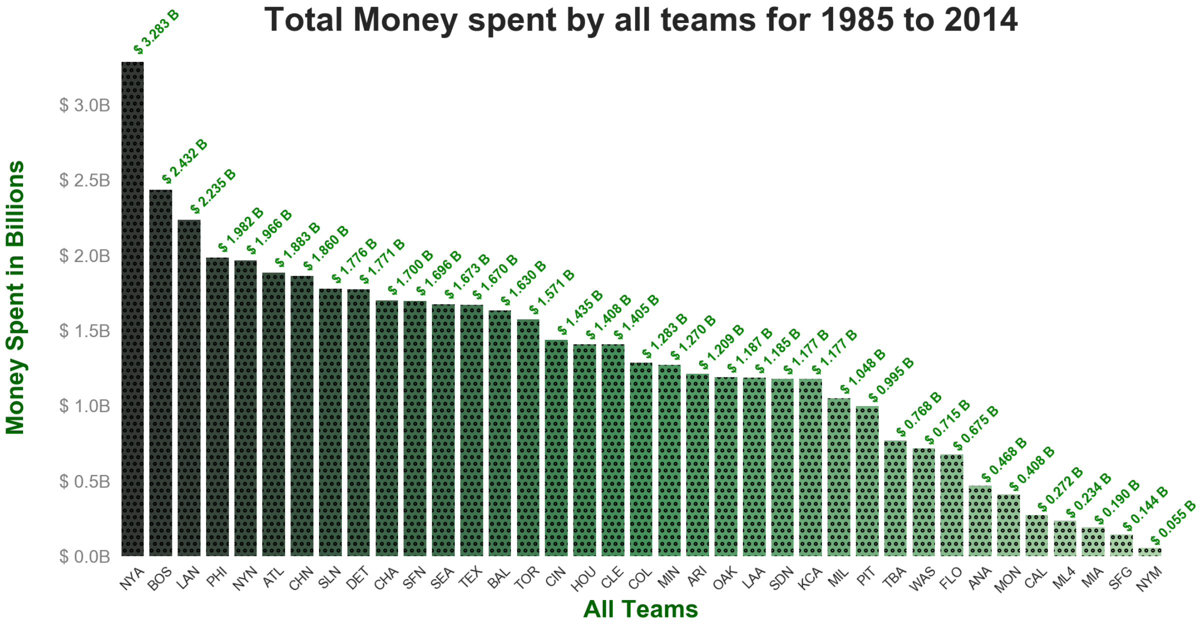
```
###### Resolve the path of the data source #######
ROOT = r'../res/baseball'
# -----  team data ----- #
from core import BaseballModel
model = BaseballModel(ROOT)
salary = model.salary
master = model.master
```

### Let’s start the Data cleaning !! The data cleaning that we are going to perform would be based on `Salary.csv`. If we open the `Salary.csv`, we see no players’ name but only their IDs. Now we would need players’ name in future. The players’ name is only available in `Master.csv`. Hence we need to pull in the corresponding names of the players along with their IDs. Moreover in the salary csv file, entries are noted only from `1985` to `2014`. Salary info of any other year previous to this is not present, may be because the recordings of Salary is started from `1985` and not prior to that. Hence players who used to play prior to `1985` had no entry in the Salary.csv file. Hence we need to take only those entries whose record can be found in Salary.csv.

```
####### Creating data_1 and pulling the fileds form csvs that we need only
#######
required_master_cols = ['playerID', 'nameFirst', 'nameLast',
                        'weight', 'height', 'bats', 'throws']
data_1 = salary.merge(master[required_master_cols], on='playerID',
how='inner')
data_1['fullName'] = data_1['nameFirst'] + '_' + data_1['nameLast']
```

This plot is the basic plot to show a bargraph of how the teams spent on player's salary. This also ensures the data cleaning was performed correctly.

```
###### First we want to see how teams invested in their player #########

##### Clean and extract the fields we require #########
plt_data = data_1.groupby('teamID', as_index=False)['salary'].sum()
plt_data.sort_values(['salary'], ascending=False, inplace=True)
plt_data = plt_data.reset_index().drop('index', axis=1)
# display(plt_data)
########################################################
#~~~~~~~~~~~~~~~  NOW PLOT THE DATA ~~~~~~~~~~~~~~~~~~#
ax = sns.barplot(x="teamID", y="salary", data=plt_data, palette="Greens_d",
                hatch='oo')
locs, labels = plt.xticks()

ax.set_xlabel('All Teams',
              {'weight': 'bold', 'fontsize': 22,
              'color':'darkgreen'})
ax.set_ylabel('Money Spent in Billions\n',
              {'weight': 'bold', 'fontsize': 22,
              'color':'darkgreen'})
sns.despine(left=True, bottom=True)

ticks = ax.get_yticks() / 1000000000
ticks = [*map(str, ticks)]
ticks = [*map(lambda e: '$ ' + e + 'B', ticks)]
ax.set_yticklabels(ticks,
                   {'fontsize': 16, 'color':'grey'})

ax.set_title("\nTotal Money spent by all teams for 1985 to 2014",
             {'weight': 'bold', 'fontsize': 30})

plt.setp(labels, rotation=45)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2., 1.01*height,
                '$ %.3f B' % (height / 1000000000),
                ha='left', va='bottom',
                weight='bold', color='green',
                size=12, rotation=45)
plt.show()
```



Now we know that `NYA, BOS, LAN, PHI, NYN` are the top 5 teams in terms of spending money on their players. The next thing that we should do is to check what are top **players** in terms of salary and logically they should be from **these top teams**.

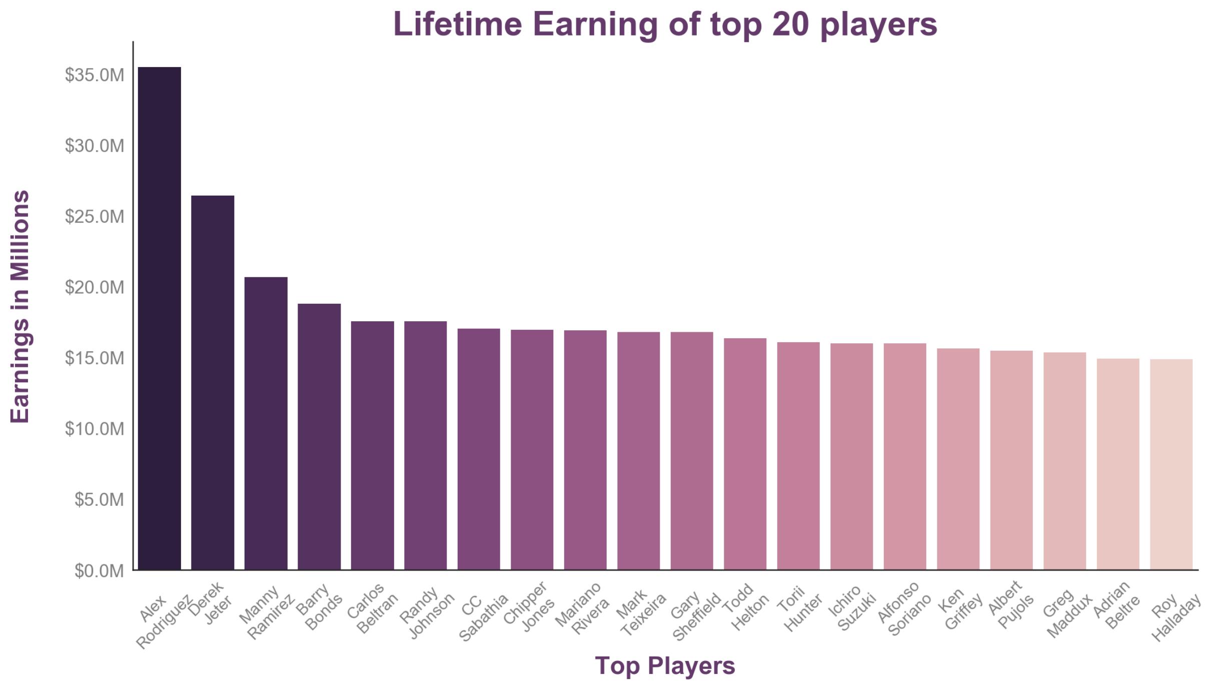
The following section shows the top 5 players in terms of total salary and the teams they played for throughout their career. This also proves the above data wrangling was performed correctly.

Note that `their_clubs` is not an `OrderedDict` and hence the 5 players mentioned are among to 5 but may not be in any ascending or descending order. To check top 5 players in descending order, please visit the following barchart of top 20 players.

```
plot_data = data_1.groupby(['fullName'], as_index=False)['salary'].sum()
plot_data.sort_values(['salary'], inplace=True, ascending=False)
five_most_expensive_players = plot_data.fullName.head(n=5)

###########  this part is important for later use   ##########
# It stores the top 10 players and their teams they played #

g=data_1[data_1.fullName.isin(five_most_expensive_players)].groupby(['fullName
'

,'teamID'])
tc = [k for k, gr in g]
from collections import defaultdict
their_clubs = defaultdict(list)
for player, team in tc:
    their_clubs[player].append(team)
their_clubs
##############################################################
```

defaultdict(list, {‘Alex_Rodriguez’: [‘NYA’, ‘SEA’, ‘TEX’], ‘Barry_Bonds’: [‘PIT’, ‘SFN’], ‘Carlos_Beltran’: [‘KCA’, ‘NYA’, ‘NYN’, ‘SLN’], ‘Derek_Jeter’: [‘NYA’], ‘Manny_Ramirez’: [‘BOS’, ‘CLE’, ‘LAN’, ‘TBA’]}) and here is the chart of top 20 players in terms of their career earnings.

```
# getting only the top 20 players
ten_most_expensive_players = plot_data.fullName.head(n=20)
plot_data = plot_data[plot_data.fullName.isin(ten_most_expensive_players)]
# fixing the structure for seaborn plot
plot_data = plot_data.reset_index().drop('index', axis=1)
# Plotting the top 10 players #
ax = sns.barplot(x="fullName", y="salary", data=plot_data,
                 palette=sns.cubehelix_palette(20, reverse=True),
                 saturation=1)
# printing only the firstName
xlabels = [*map(lambda e: e.split('_')[0] + '\n' +
                e.split('_')[1], plot_data.fullName)]
# xlabels = plot_data.fullName
ax.set_xticklabels(xlabels,
                   {'fontsize': 14, 'color':'grey'})
# ax.set(xlabel='Players', ylabel='Total Earning')
ticks = ax.get_yticks() / 10000000
ticks = [*map(str, ticks)]
ticks = [*map(lambda e: '$' + e + 'M', ticks)]
ax.set_yticklabels(ticks,
                   {'fontsize': 16, 'color':'grey'})
ax.set_xlabel('Top Players',
              {'weight': 'bold', 'fontsize': 22,
              'color':sns.cubehelix_palette(20, reverse=True)[4]})
ax.set_ylabel('Earnings in Millions\n',
              {'weight': 'bold', 'fontsize': 22,
               'color':sns.cubehelix_palette(20, reverse=True)[4]})
ax.set_title("Lifetime Earning of top 20 players",
             {'weight': 'bold', 'fontsize': 30,
              'color':sns.cubehelix_palette(20, reverse=True)[4]})
plt.xticks(rotation=45)
sns.despine()
plt.show()
##############################
```



We would revisit this later on.
Now before we move ahead, let's visualize the distruibution desdity of player's salary. From this we can visualize that **what is the most common salary ranges teams prefer to compensate their players**.

```
from scipy import stats, integrate
ax = sns.distplot(data_1.salary, bins=50, kde=True,
                  rug=False, color='r', hist_kws={'rwidth': 0.8});
# sns.kdeplot(data_1.salary, shade=True);
# ax.get_xaxis().get_major_formatter().set_useOffset(True)
plt.ticklabel_format(style='plain', axis='x')
plt.ticklabel_format(style='plain', axis='y')
ax.set(xlabel='\nSalary in Millions', ylabel='Odds of getting the salary\n')
ax.set_title("How Salary of all players distributed",
             {'weight': 'bold', 'fontsize': 25, 'color':'r',
             'alpha': 0.5})
xlabel = [*map(lambda e : '$' + str(e) + 'M',
               [0, 2, 5, 7, 10, 15, 20, 25, 30, 35])]
ax.set_xticklabels(xlabel,
                   {'fontsize': 16, 'color':'k'})
# TODO  Manually format the xticklabels and yticklabels values
plt.show()
```

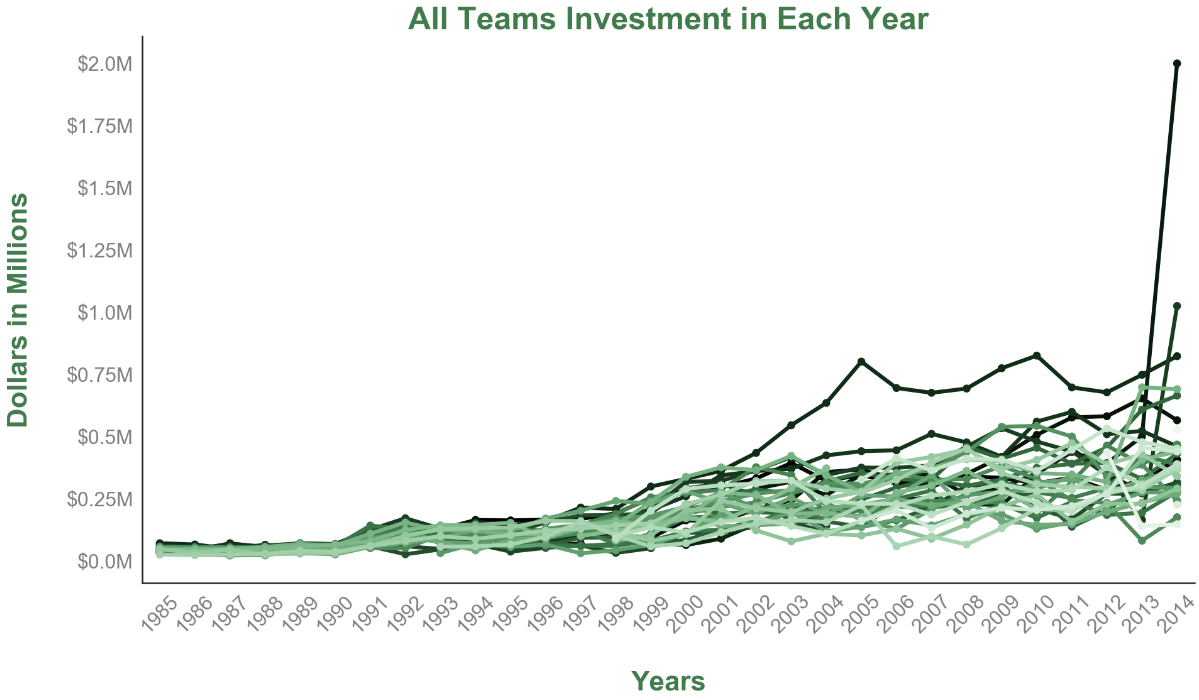
![png](output_16_0.png)

Were they all thrifty ??

The above distribution is skewed and it is the distribution of salary. This shows the most density distribution is located around `0 to 5000000`. This proves that high salaries were not so frequent. What does this shows??

This shows a common human nature; **most people are thrifty when it comes it money, at least the baseball teams were.**

```
rot = sns.cubehelix_palette(len(data_1.teamID.unique()), start=2,
                            rot=0, dark=0, light=.95, reverse=True)
ax = sns.pointplot(x="yearID", y="salary", data=data_1,
                   hue='teamID', palette=rot, ci=None,
                   markers='.', join=True)
ax.legend_.remove()
locs, labels = plt.xticks()
plt.setp(labels, rotation=45)
sns.despine()
ax.set_xticklabels(np.sort(data_1.yearID.unique()),
                   {'fontsize': 16, 'color':'grey'})
ax.set_xlabel('\nYears',
              {'weight': 'bold', 'fontsize': 22
              , 'color':rot[15]})
ax.set_ylabel('Dollars in Millions\n',
              {'weight': 'bold', 'fontsize': 22
              , 'color':rot[15]})
ticks = ax.get_yticks() / 10000000
ticks = [*map(str, ticks)]
ticks = [*map(lambda e: '$' + e + 'M', ticks)]
ax.set_yticklabels(ticks,
                   {'fontsize': 16, 'color':'grey'})
ax.set_title("All Teams Investment in Each Year",
             {'weight': 'bold', 'fontsize': 25, 'color':rot[15]})
plt.show()
```



Did teams think similar when it comes to money ??

The above timeseries shows how people liked to invest over the passage of time. Each teams represent a single line. The idea is not to show how each teams are investing over time, rather it shows what is the investment pattern of all the teams. We can see that upto *2001* all the teams invested almost similarly. Beyond `2001` to around `2010` the difference between the investment of teams increased substantially with some team investing a lot than others. But beyond `2011` this difference got really big and we can also see the top 3 highest investments were made in the year of `2014`. For example, we can see the the one team at `2005` invested a lot more than others and kept on investing till the end. The following code shows this club name an the money that they invested.

```
data_1[data_1.yearID == 2005].groupby('teamID',
        as_index=False)['salary'].sum() \
        .sort_values('salary', ascending=False) \
        .reset_index().drop('index', axis=1).ix[0]
```

This prints

```
teamID          NYA
salary    208306817
Name: 0, dtype: object
```

This is logical too because we have already seen that `NYA` invested most out of all the teams. Interestingly, in the year of `2014`, `NYA` didn't remain at number 1 position and it changed to `LAN`. This code shows it below

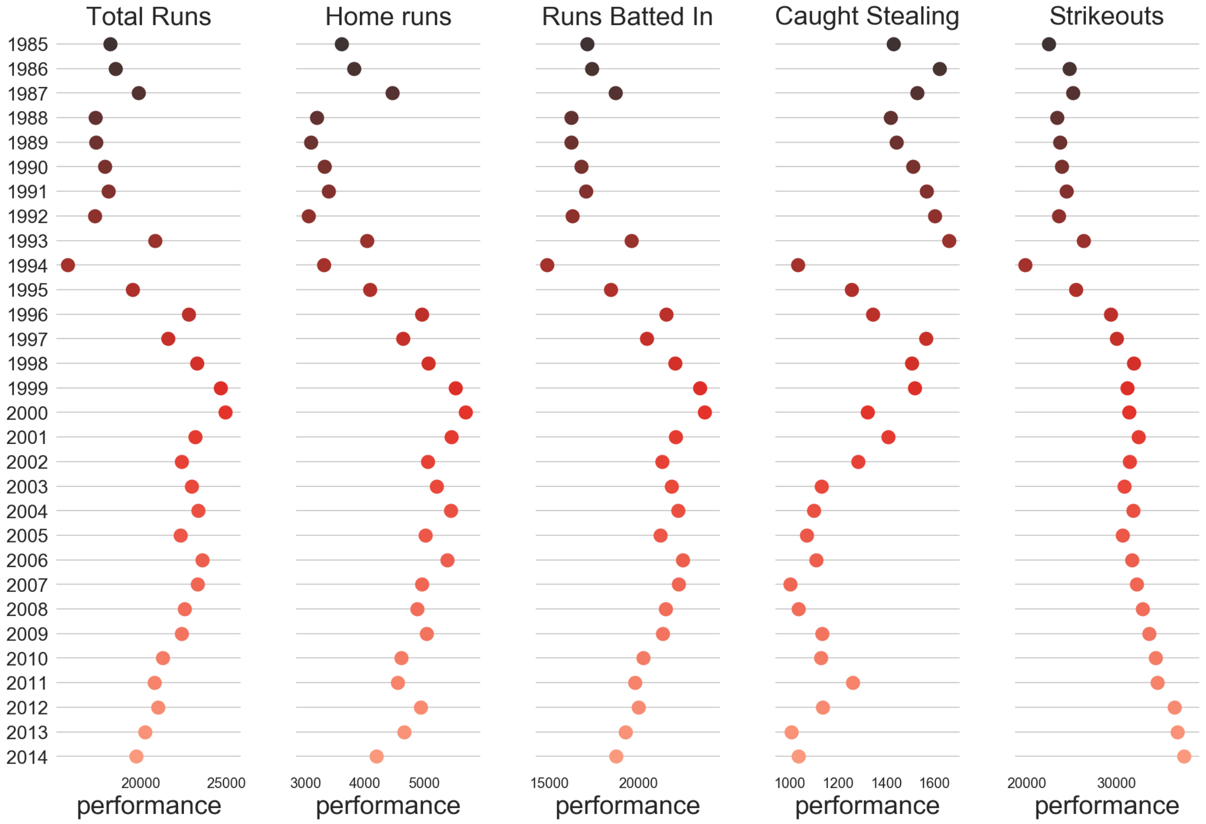
```
data_1[data_1.yearID == 2014].groupby('teamID',
        as_index=False)['salary'].sum() \
        .sort_values('salary', ascending=False) \
        .reset_index().drop('index', axis=1).ix[0:2]
```

this prints,

```
    teamID  salary
0   LAN 214014600
1   NYA 197543907
2   PHI 180944967
```

Howerver the trend that we have seen, we can say unless the team is an extraordinary, most teams spent likely over the passage of time

```
batting = model.batting
BaseballModel.performance_burndown(batting)
```



Now in the above plot I have tried to show how different metric changed over time form 1985 to 2014. We can see for example that there is an abrupt decrese in the total runs scored in the year of 1994 as compared to other years. **Let's verify if the plot shows the right value?** If we execute `plot_data.R.argmin()` it returns `9` which is the row number of the `plot_data` table which is further derived from `batting`. So to get the year we execute `plot_data.ix[9][['yearID', 'R']]` and indeed the year is 1994 and the run is 15752 which can also be verified from the scale. Evidently all other performance of Batters and Pitchers in the year of 1994 was poor as compared to other years. **SO I GUESS 1994 WAS A DARK YEAR FOR BASEBALL FANS..:)**

Time for another data cleaning

Now as we have colleced some data into the DataFrame called `data_1`, we need to match it with our new DataFrame: `batting`. In other words we need to keep only those entries from `batting` Dataframe whose entry is found in the `data_1` DataFrame. The resaon we want to do this because we don't want to keep any entries of any players who salary, name, surname, height, weight, pitching hand and batting hand is not present. The common way to achieve this is to merge(..) on both the DataFrames `on=playerID`

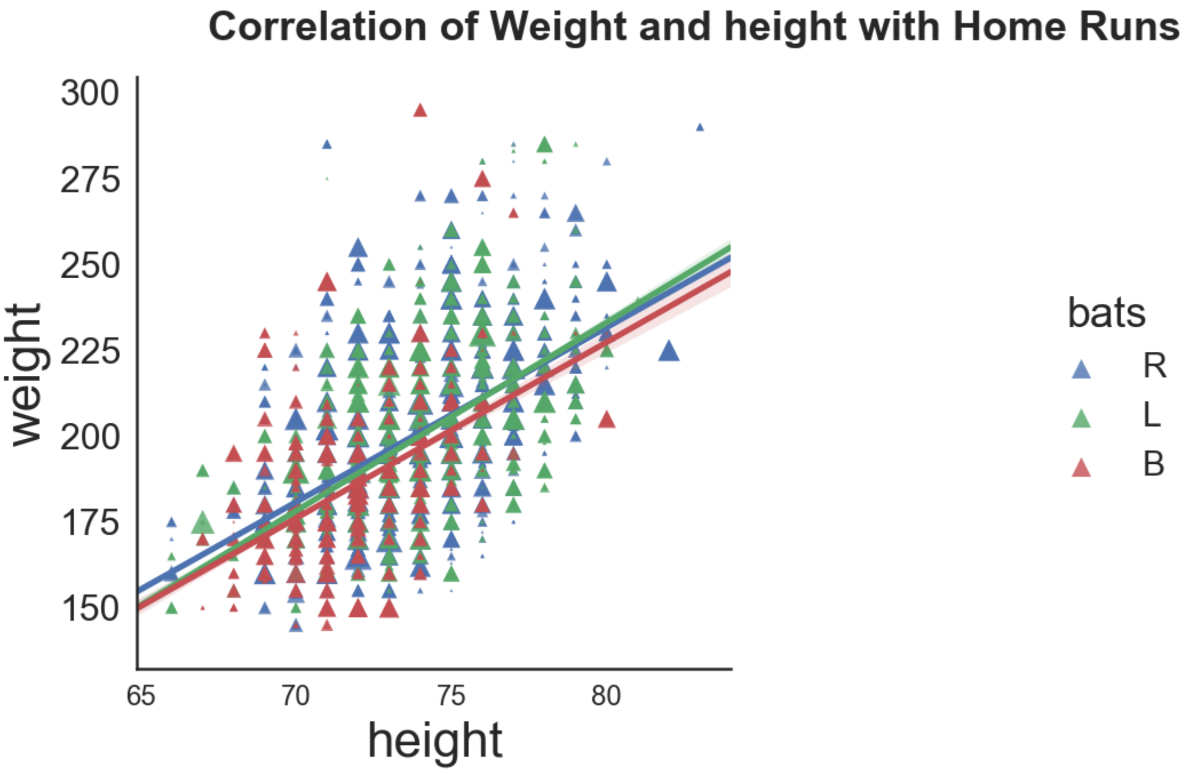
```
required_batting_cols = ['playerID', 'G', 'R', 'HR', 'CS', 'SO',
                         'yearID', 'teamID']
data_1 = data_1.merge(batting[required_batting_cols],
                  on=['playerID', 'yearID', 'teamID'],
                  how='left').fillna(0)
# display(data_1)
```

Now I would go into much more interesting and fun stuffs we I would bring in some statistics and hypothesis tests into this but for now, let’s focus on the the data table that we have already. Here all the batters statistics form 1985 to 2014 is available with their salary and other game related performances.

Let’s merge the **pitching** table too as we have done with the **batting** table. The data cleaning process would be exactly similar except the coulumns that needs to be merged

```
# pitching = pd.read_csv(os.path.join(ROOT, 'Pitching.csv'))
# pitching = pitching[pitching.yearID >= 1985]
pitching = model.pitching
required_pitching_cols = ['yearID', 'teamID', 'playerID',
                          'G','SHO', 'SV', 'HR', 'R']
data_1 = pd.merge(data_1, pitching[required_pitching_cols],
            on=['playerID', 'yearID', 'teamID', 'G'],
            how='left').fillna(0)
data_1.rename(columns={"R_x": "Runs_Scored",
                  "R_y": "Runs_Allowed",
                  "HR_x": "HR_Scored",
                  "HR_y": "HR_Allowed"}, inplace=True)
```

```
# sns.set_style('ticks')
g = sns.lmplot(data=data_1, x="height", y="weight", hue="bats",
          scatter_kws=dict(s=data_1.HR_Scored * 2), markers=['^', '^', '^'])
plt.subplots_adjust(top=0.9)
g.fig.suptitle('Correlation of Weight and height with Home Runs',
               horizontalalignment='center', x=0.8,
               fontsize=18, fontweight='bold')
plt.show()
```

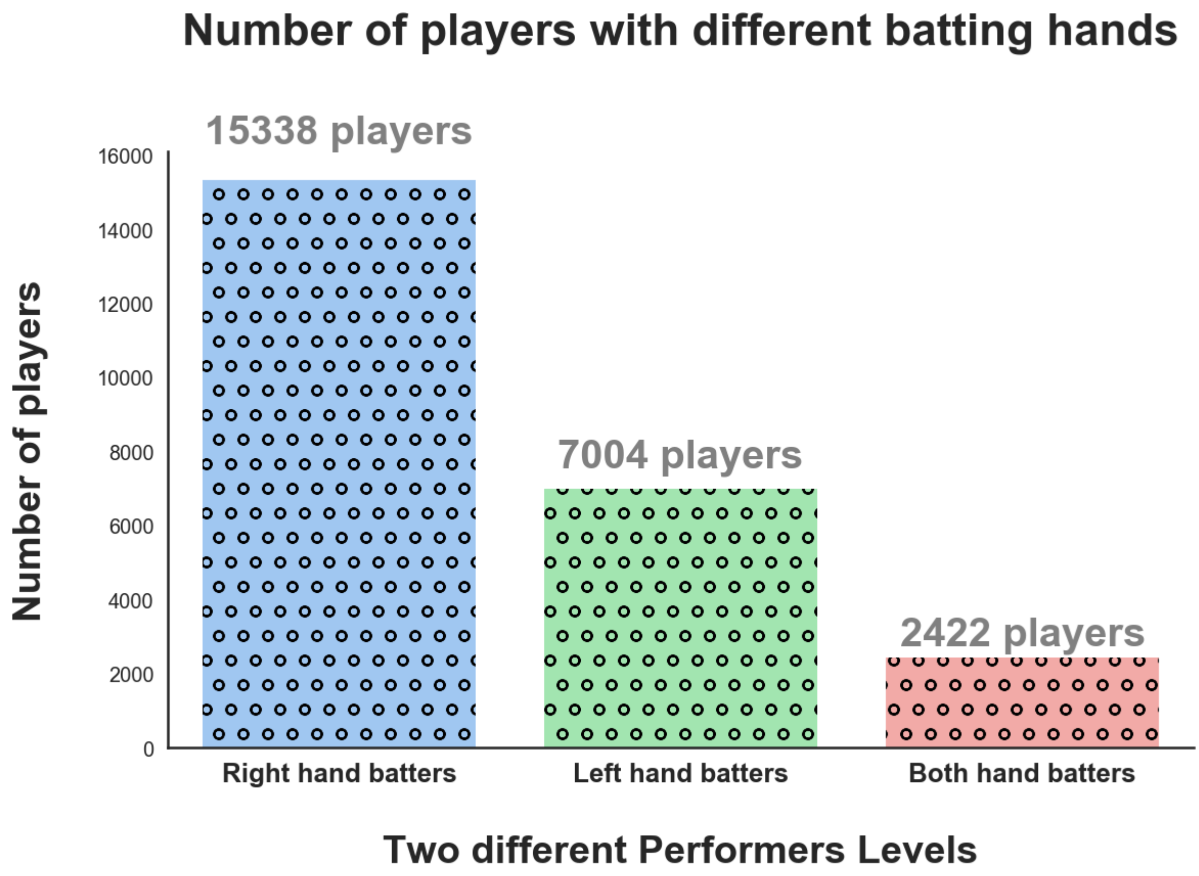


What are the facts the above plot shows ??

- More players play with their **RIGHT** hand as compared to the **LEFT** hand because there is a lot green as compared to red and blue
- Players with most homeruns are of **medium height and medium weight** category. Tall or heavy weight players performed not so well.

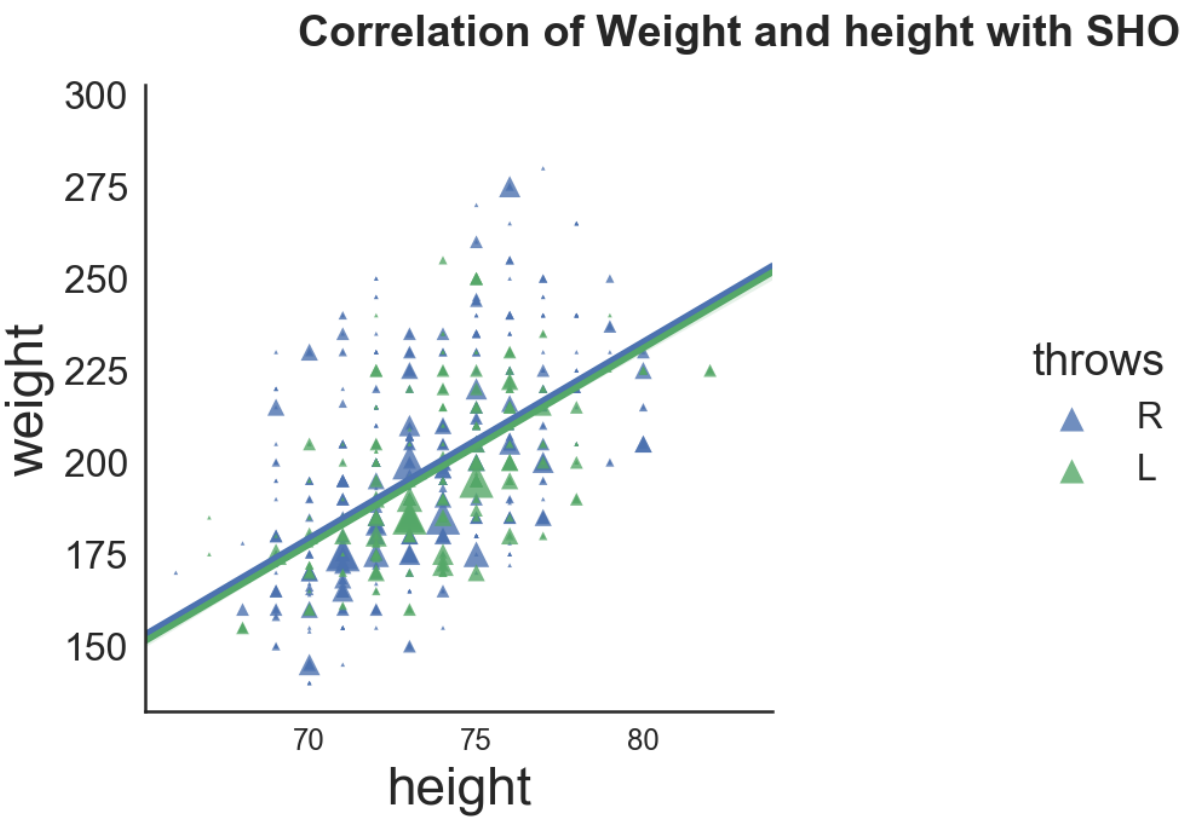
The below figure shows number of batters for each hands

```
rc={'figure.figsize': [8, 5]}
plt.rcParams.update(**rc)
sns.set(style='white', rc=rc)
ax = sns.countplot(x="bats", data=data_1, palette="pastel",
                  hatch='o')
sns.despine()

ax.set_xticklabels(['Right hand batters',
                    'Left hand batters',
                    'Both hand batters'],
                   {'weight': 'bold', 'fontsize': 13})
ax.set_xlabel('\nTwo different Performers Levels',
              {'weight': 'bold', 'fontsize': 19})
ax.set_ylabel('Number of players\n',
              {'weight': 'bold', 'fontsize': 19})
ax.set_title("Number of players with different batting hands\n\n",
             {'weight': 'bold', 'fontsize': 22})

for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2., 1.05*height,
            '%d players' % height,
            ha='center', va='bottom',
            weight='bold', color='grey',
            size=20)
plt.show()
```



And we can see that what we predicted was true there are more than double players playing with their **right** hand as compared to others.

```
configure(configType='rc')
g = sns.lmplot(data=data_1, x="height", y="weight",hue="throws",
          scatter_kws=dict(s=((data_1.SHO)**2) * np.pi), markers=['^', '^'])
plt.subplots_adjust(top=0.9)
g.fig.suptitle('Correlation of Weight and height with SHO',
               horizontalalignment='center', x=0.8,
               fontsize=18, fontweight='bold')
plt.show()
```



Wow we see some wonderful trends here too

- Number of players with shutouts is far less than the number of players with homeruns. This means players like to bat more than pitch.
- There are no pitchers who like to throw with both of their hand as comared to the batters. Which means piching can either be done by **left hand** or **right hand** but not with both the hand.
- The **weight** and the **height** trend is similar to the batting. Most of the players performed well if they are medium weight and medium height. We can verify that the bigger marker sizes are all in the middle.
- One more interesting thing is that even some of the outliers are also above *280* in weight category whcich is I guess natural because if you are heavy weight, you can not run well and hence as a pitcher, you perform poorly

### Let's move into some Statistics now!! First let's `group` all the enries in the `DataFrame` by the player's ID. Then sum all player's **Total Runs Scored** and their **Total Salary**

```
data_1.groupby('playerID', as_index=False)['playerID', 'Runs_Scored',
'salary'].sum().head()
```

	playerID	Runs_Scored	salary
0	aardsda01	0.000	9259750
1	aasedo01	0.000	2300000
2	abadan01	0.000	327000

	playerID	Runs_Scored	salary
3	abadfe01	0.000	1428900
4	abbotje01	74.000	985000

Interestingly some players have scored 0 runs but they were paid a lot. **How is it possible?** It's not necessary that these players are bad as these players can be pitchers and they might have some good **Saves** against some batters. So the logical solution is to combine the `SV` column with this group by table. But the problem is that they don't share the same scale hence to combine, we need to `standardise` these two columns and then both the values and create a new column say `performance`.

```
stat_data = data_1.groupby('playerID',
                           as_index=False)['playerID',
                                           'Runs_Scored',
                                            'salary',
                                            'SV'].sum()
stat_data['performance'] =  (stat_data.SV / stat_data.SV.std(ddof=0)) + \
                            (stat_data.Runs_Scored /
stat_data.Runs_Scored.std(ddof=0))
```

```
display(stat_data.head())
```

	playerID	Runs_Scored	salary	SV	performance
0	aardsda01	0.000	9259750	69.000	2.097
1	aasedo01	0.000	2300000	38.000	1.155
2	abadan01	0.000	327000	0.000	0.000
3	abadfe01	0.000	1428900	0.000	0.000
4	abbotje01	74.000	985000	0.000	0.304

Now I guess I may not need the `Runs_Scored` and the `SV` columns. So we can drop them.

```
stat_data.drop(['Runs_Scored', 'SV'], axis=1, inplace=True)
```

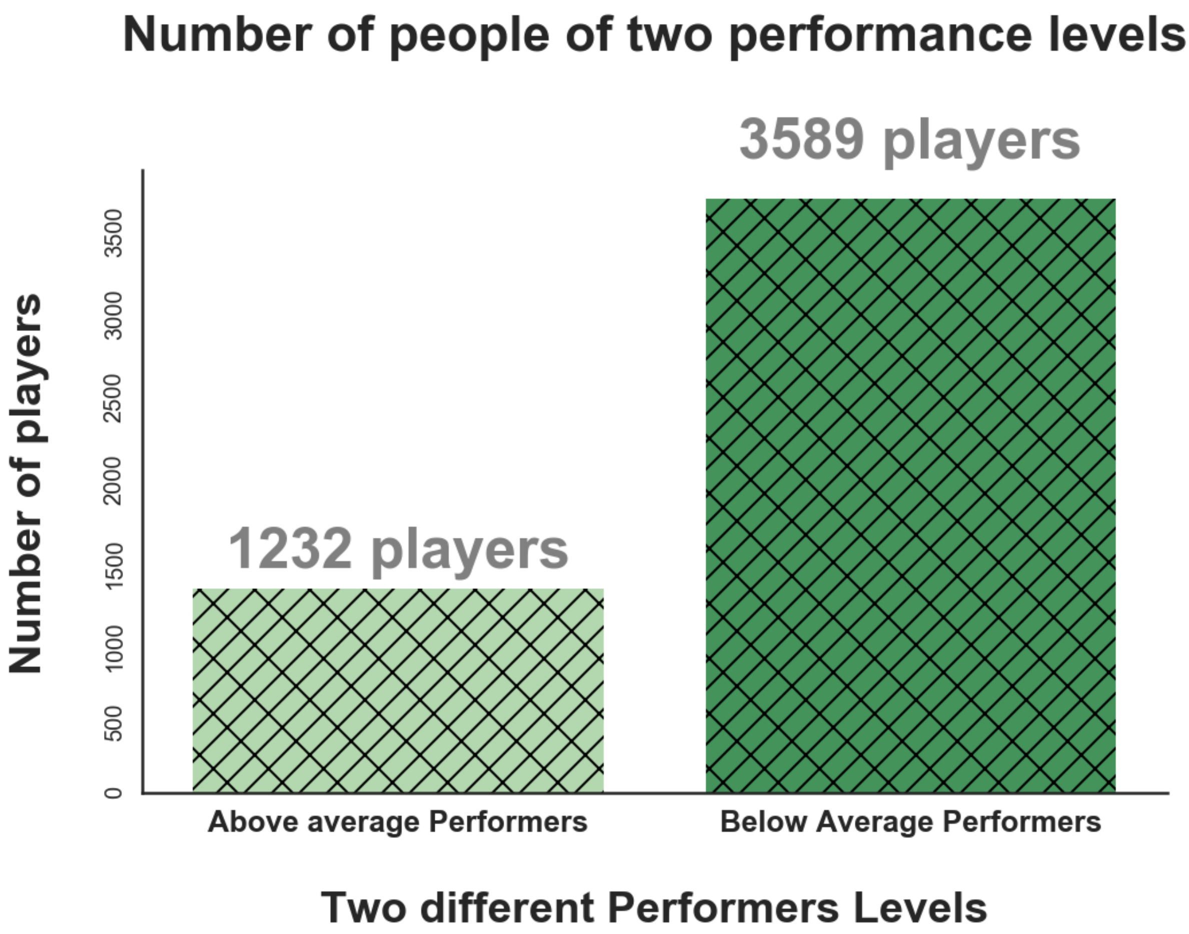
Now it's time to prepare our data. We are going to perform an Hypothesis test to figure out **If above average salary resulted in above average performance??** However we are taking `median` here instead of `mean` to reject all the outliers.

```
stat_data_below_average = stat_data[stat_data.salary <
stat_data.salary.median()]
stat_data_above_average = stat_data[stat_data.salary >=
stat_data.salary.median()]
# display(stat_data_above_average)
```

Now before we move ahead, let’s perofrom a quick plot see the total number of people in both the groups

```
performanceMean = stat_data.performance.mean()
def label_performance(row):
    if row['performance'] < performanceMean:
        return 'Low Performer'
    else:
        return 'High Performer'
stat_data['Performing_Level'] = stat_data.apply(lambda row:
label_performance(row), axis=1)
```

```
rc={'figure.figsize': [8, 5]}
plt.rcParams.update(**rc)
sns.set(style='white', rc=rc)
ax = sns.countplot(x="Performing_Level", data=stat_data, palette="Greens",
                  hatch='//\\')
sns.despine()
ax.set_xticklabels(['Above average Performers',
                    'Below Average Performers'],
                   {'weight': 'bold', 'fontsize': 13})
ax.set_xlabel('\nTwo different Performers Levels',
              {'weight': 'bold', 'fontsize': 19})
ax.set_ylabel('Number of players\n',
              {'weight': 'bold', 'fontsize': 19})
ax.set_title("Number of people of two performance levels\n\n",
             {'weight': 'bold', 'fontsize': 22})
plt.yticks(rotation=90)

for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2., 1.05*height,
            '%d players' % height,
            ha='center', va='bottom',
            weight='bold', color='grey',
            size=25)
plt.show()
```



As we expected, there are a lot less high performers as compared low performers.

$$\blacktriangleright\ \mathrm{H}_o = \text{Player's performance would not be different or,}$$
$$\mu_h = \mu_l$$
$$\blacktriangleright\ \mathrm{H}_a = \text{Player with better salary would have higher performance}$$
$$\mu_h > \mu_l$$

```
#####  Getting the two sample series #######
sample_low = np.array(stat_data_below_average.performance)
sample_high = np.array(stat_data_above_average.performance)

###### Degrees of Freedom #######
df = len(sample_low) + len(sample_high) - 2
# print(df)

###### α Value ######
alpha = 0.5


####### Mean of Samples ##########
x_low = sample_low.mean()
x_high = sample_high.mean()

#######  t-statistics at α=0.5 ######
```

```
#### For degrees of freedom of 4819 and one tailed t-test #####
t_alpha = 1.64516992

####### Standard Deviations #########
S_low = sample_low.std(ddof=1)
S_high = sample_high.std(ddof=1)


######## Sample Sizes ########
n_low = len(sample_low)
n_high = len(sample_high)

####### Standard Error ########
s1 = (S_low**2) / n_low
s2 = (S_high*2) / n_high
s = s1 + s2
SE = np.sqrt(s)  # <------ Standard Error

###### t-statistics for the sample ######
t_stat = (x_high - x_low) / SE

# HTML("t-Satistics is <strong>{}</strong> while the \
#      t-critical at α=0.5 is <strong>{}</strong>".format(t_stat, t_alpha))
print("t-Satistics is {}while the and t-critical at α=0.5 is
{}".format(t_stat, t_alpha))
```

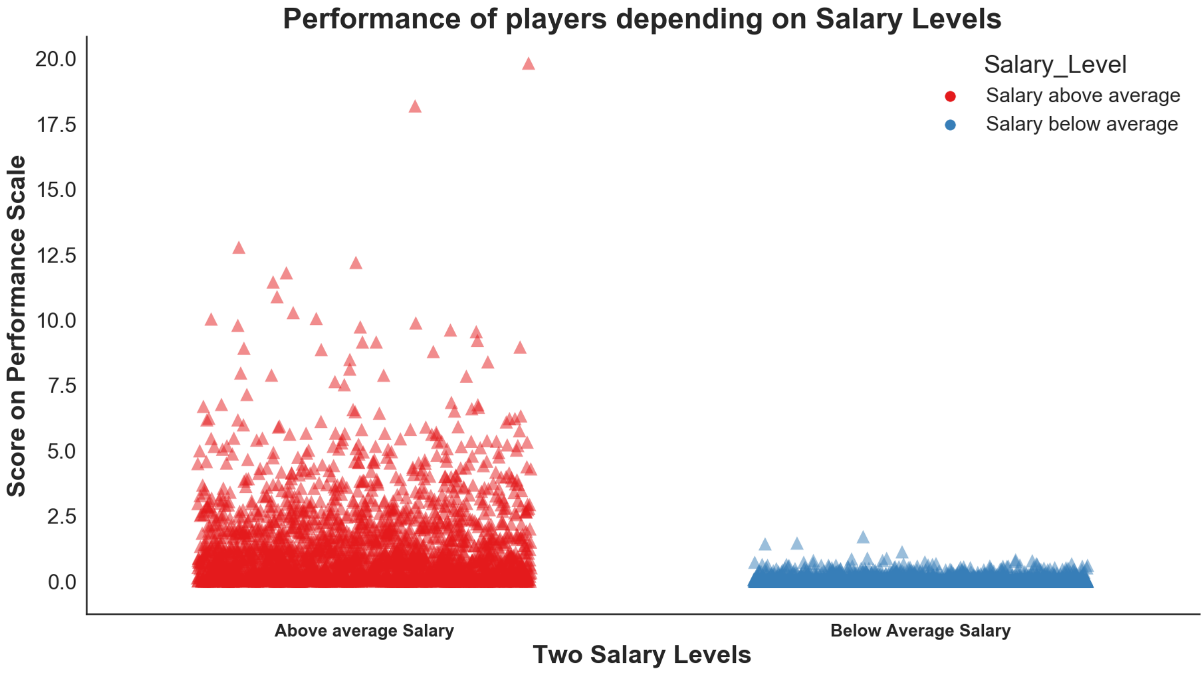
```
t-Satistics is 31.349217958194718 while the and t-critical at α=0.5 is 1.64516992
```

Decision on the Hypothesis

So as we can see that the *t-stat* is huge as compared to the *t-critical* and the *t-stat* is positive. This means we reject the null hypothesis in favour of alternative hypothesis. Now we can surely say that **The players who were paid more performed better**
Below is a plot which displays it more clearly

```
configure(configType='rc')
salaryMedian = stat_data.salary.median()
def label_salary(row):
    if row['salary'] < salaryMedian:
        return 'Salary below average'
    else:
        return 'Salary above average'
stat_data['Salary_Level'] = stat_data.apply(lambda row: label_salary(row),
axis=1)
ax = sns.stripplot(x="Salary_Level", y="performance", data=stat_data,
                   jitter=0.3, palette="Set1",
                  edgecolor="gray",
                  size=10, alpha=0.5,
                  marker="^", hue='Salary_Level')
```

```
ax.set_xticklabels(['Above average Salary', 'Below Average Salary'],
                   {'weight': 'bold', 'fontsize': 13})
ax.set_xlabel('Two Salary Levels',
              {'weight': 'bold', 'fontsize': 19})
ax.set_ylabel('Score on Performance Scale',
              {'weight': 'bold', 'fontsize': 19})
ax.set_title("Performance of players depending on Salary Levels",
             {'weight': 'bold', 'fontsize': 22})
sns.despine()
plt.show()
```

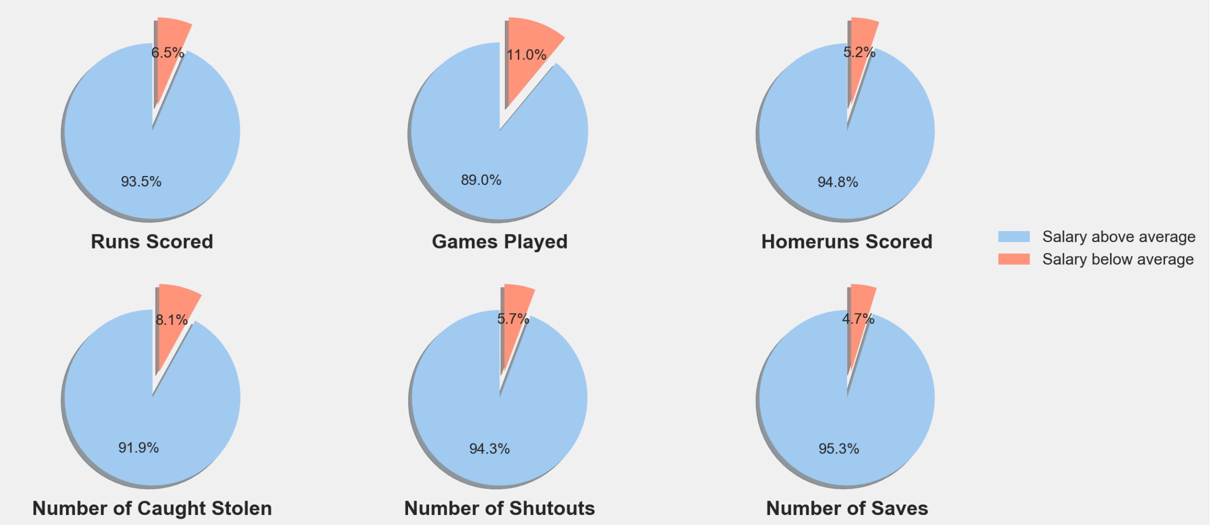


In the above plot we can see that the category `Salary below Average` is only concentrated within the performance range 0 to 2.5 with an exception of few points as true otliers. While in the right for the category `Salary above average` is distributed upto 7.5 and having some outliers upto 20.

Another plot below is more descriptive about two categories above relating to the wide range of performance keys distributed within the sample data.

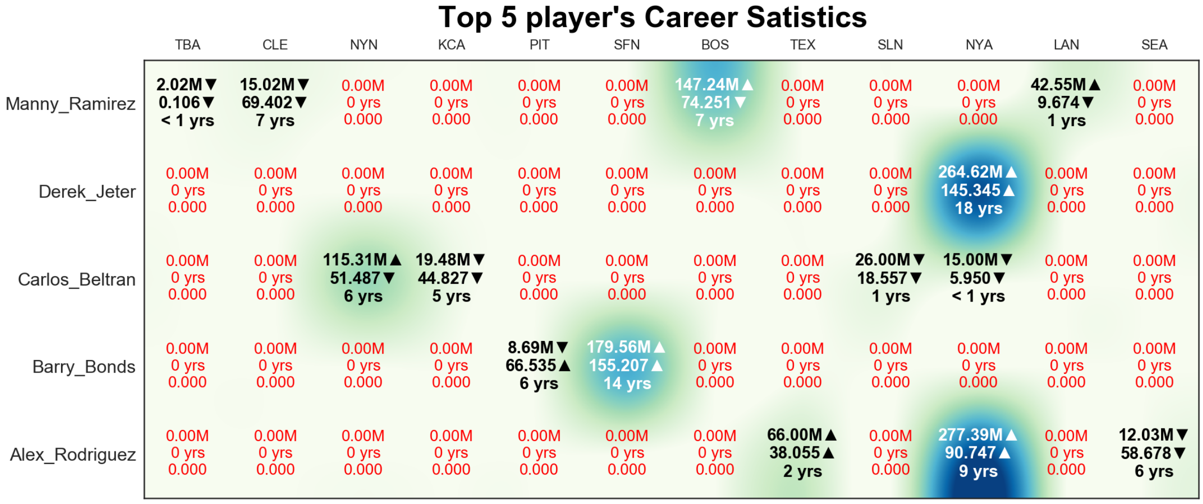
```
plot_data = data_1.groupby('playerID',
                           as_index=False)['playerID',
                                           'Runs_Scored',
                                           'G',
                                           'HR_Scored',
                                           'CS',
                                           'SHO',
                                           'SV',
                                           'salary'].sum()
plot_data['Salary_Level'] = stat_data.apply(lambda row: label_salary(row),
axis=1)
```

```
BaseballModel.create_descriptive_pie(plot_data, hue='Salary_Level',
                                  columns=['Runs_Scored',
                                           'G',
                                           'HR_Scored',
                                           'CS',
                                           'SHO',
                                           'SV'],
                                    tags=['Runs Scored',
                                         'Games Played',
                                         'Homeruns Scored',
                                         'Number of Caught Stolen',
                                         'Number of Shutouts',
                                         'Number of Saves'])
```



We can see that in all of the cases **players above average salary** did well in all those performance metrics as compared to **players below average salary**. This proves even more that players with better salary played better too. This proves very well that in almost all the metrics players performed well when they were payed more.

```
configure(configType='rc')
heatmap_meta = model.prepare_heatmap_data(data_1, their_clubs, tc)
BaseballModel.create_categorical_heatmap(heatmap_meta)
```



Top 5 player's Career Satistics

	TBA	CLE	NYN	KCA	PIT	SFN	BOS	TEX	SLN	NYA	LAN	SEA
Manny_Ramirez	2.02M▼ 0.106▼ < 1 yrs	15.02M▼ 69.402▼ 7 yrs	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	147.24M▲ 74.251▼ 7 yrs	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	42.55M▲ 9.674▼ 1 yrs	0.00M 0 yrs 0.000
Derek_Jeter	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	264.62M▲ 145.345▲ 18 yrs	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000
Carlos_Beltran	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	115.31M▲ 51.487▼ 6 yrs	19.48M▼ 44.827▼ 5 yrs	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	26.00M▼ 18.557▼ 1 yrs	15.00M▼ 5.950▼ < 1 yrs	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000
Barry_Bonds	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	8.69M▼ 66.535▲ 6 yrs	179.56M▲ 155.207▲ 14 yrs	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000
Alex_Rodriguez	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	0.00M 0 yrs 0.000	66.00M▲ 38.055▲ 2 yrs	0.00M 0 yrs 0.000	277.39M▲ 90.747▲ 9 yrs	0.00M 0 yrs 0.000	12.03M▼ 58.678▼ 6 yrs

Phew!! I have worked really hard for this..

The above is not just a heatmap but it combines so many things togather. But before that lets first see what are the questions we are trying to answer with this.

- Can we say that most expensive players in total are quick team switchers?
- Are most expensive players are best peformers too?
- When player played for a less amount of time, are their performace and salary is that good as compared to when they played for long?

  The above heatmap is shows the way top 5 players (in terms of total Salary) switched their teams over their career. It also shows `3 numbers` for each cells.

The **first Number** shows how much money that players has earned while playing for that team.

The **second Number** shows a performace metric of that player when he played in that team.

The **third Number** shows How long the player played for that team.

With all these we can see that **some arrow** (up or down) after the first two numbers. These arrows shows trends. For example an up arrow after the salary means that ***THE PLAYER'S SALARY WHILE HE WAS PLAYING FOR THAT TEAM IS WITHIN THE TOP 5 FOR THE AMOUNT FOR YEARS HE PLAYED FOR THAT TEAM*** . The same is for performance metric. Consequently, the down arrow means it is not in top 5.

The performance metric itself is curated very carefully giving preference to almost all the factors that makes baseball player a baseball player. The metrics that are used is

```
# G          = Number of total games played    ( For all )
# Runs_Scored = Total number of runs scored     ( For batters  )
# HR_Scored   = Total number of homeruns scored ( For batters  )
# SHO         = Total number of shutouts        ( For Pitchers )
# SV          = Total number of saves           ( For Pitchers )
metrics = ['G', 'Runs_Scored', 'HR_Scored', 'SHO', 'SV']
```

As these metrics lie in different range from each other and combining these direcly would not work. Hence the metrics were standardized like this

```
gTemp = temp.groupby('fullName', as_index=False)[metrics].sum()
gTemp['G'] /= temp.G.std()
gTemp['Runs_Scored'] /= temp.Runs_Scored.std()
gTemp['HR_Scored'] /= temp.HR_Scored.std()
gTemp['SHO'] /= temp.SHO.std()
gTemp['SV'] /= temp.SV.std()
gTemp['Gross_Metric_Score'] = gTemp['G'] + \
     gTemp['Runs_Scored'] + gTemp['HR_Scored'] + \
     gTemp['SHO'] + gTemp['SV']
```

Because the gross metric is taken, it it pretty balanced out for only batters, only pitchers or both batter and pitchers. In the above heatmap we can see that most of the players switched their teams atleast once. Some even switched to even 4 teams. Some players played for a team for less than one year which is pretty stange. We can that `Derek Jeter` is a player who played for only one club and never switched in his long `18 years` of career. Also for both his salary and performance we see an up arrow. This means he was happy while playing for `NYA` and paid very well for his long career. `Barry Bonds` was a remarkable player though. While he was playing for `PIT` for 6 long years, even his salary was not within the top 5, but his performance was always in top 5 range. Probably that's why he switched the team to `SFN` where he played for 14 long years. This can be verified further by running the following command

```
for k, g in data_1[data_1.fullName == 'Barry_Bonds'].groupby('teamID'):

    display(g)
```

We can see that `Barry Bonds` played in `PIT` from `1986 to 1992` and then he switched to `SFN` where he played from `1993 to 2007` But interestingly more money playes got, more teams they changed. The code below proves that

```
number_of_switches_by_low = []

number_of_switches_by_high = []

for k, g in data_1.groupby('fullName'):

    if g.salary.mean() <= data_1.salary.mean():

        number_of_switches_by_low.append(len(g.teamID))
    else:

        number_of_switches_by_high.append(len(g.teamID))
print(np.mean(number_of_switches_by_low))
print(np.mean(number_of_switches_by_high))
```

This prints

```
4.1706527155
10.8418918919
```

This means players who got more salary than the average, switched more than two times than those who got less salary than average. This trend is also true for number of games played `(G)`. More games player played, more teams(almost 2 times more) they switched. This means more active players switched more teams although `Derek Jeter` was truly an exceptional case.

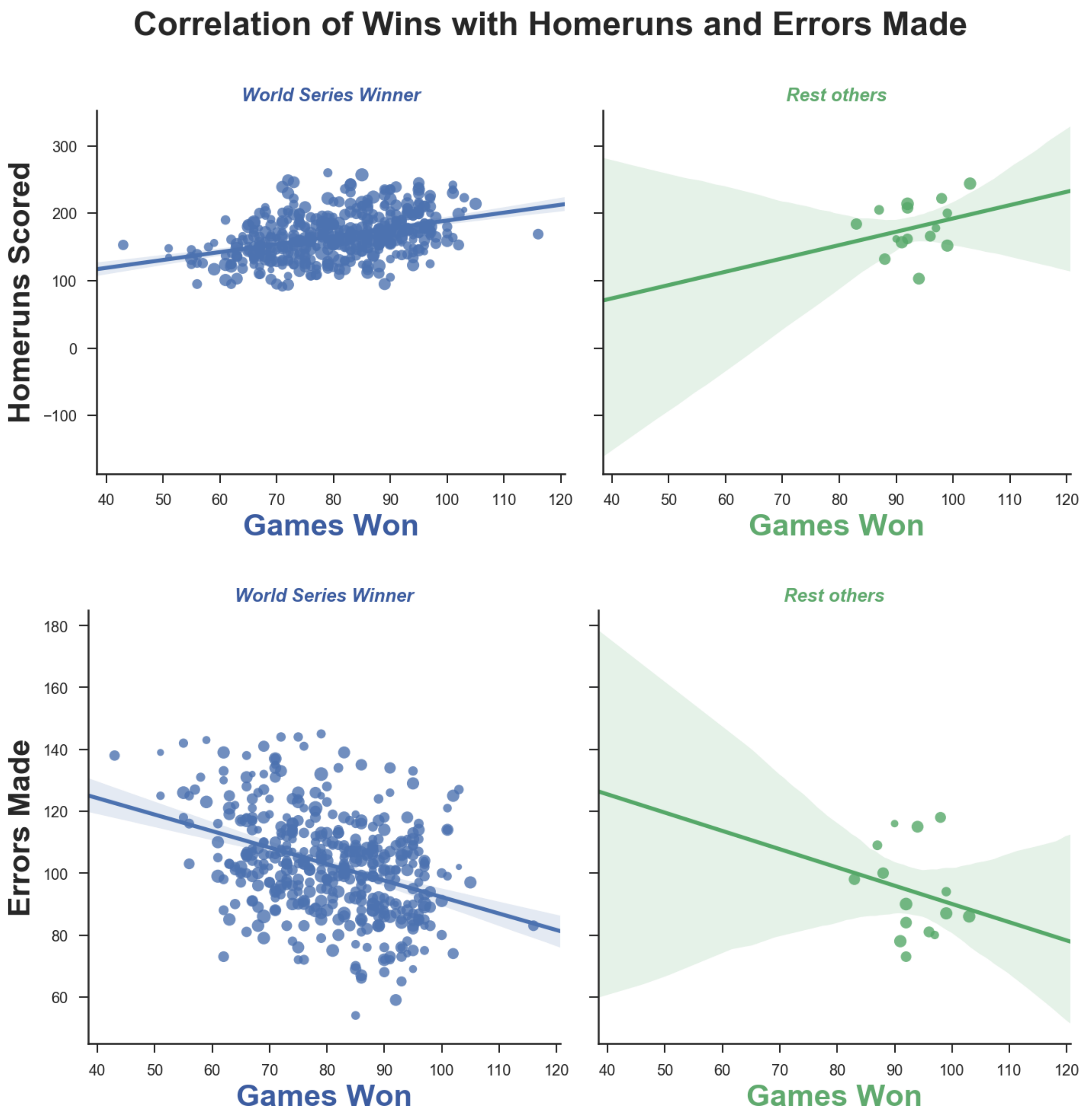
We can also see that the players who have been in top 5 for their performance in any team for a long time could not retain their top 5 position in some other team when they played there for short time.

All about teams !!

Here we are pulling the `Teams.csv` file to get some info about the Teams. The following section can answer some of the important questions like,

- How different metrics like `Total Homeruns` or `Number of errors` made affect the winning ?
- What makes a team rank first as compared to others ?

```
# teams = pd.read_csv(os.path.join(ROOT, 'Teams.csv')).dropna()
teams = model.teams
sns.set(style='ticks')
g = sns.lmplot(x="W", y="HR", col="WSWin", data=teams,
              markers='o', hue='WSWin',
              scatter_kws=dict(s=teams.attendance * 0.00002))
g.axes[0][0].set_ylabel('Homeruns Scored',
              {'weight': 'bold', 'fontsize': 20})
g.axes[0][0].set_xlabel('Games Won',
              {'weight': 'bold', 'fontsize': 20, 'color': '#3c5ca0'})
g.axes[0][1].set_xlabel('Games Won',
              {'weight': 'bold', 'fontsize': 20, 'color': '#60aa6e'})
g.axes[0][0].set_title('World Series Winner',
                      {'weight': 'bold', 'fontsize': 12, 'color': '#3c5ca0',
                       'style':'italic'})
g.axes[0][1].set_title('Rest others',
                      {'weight': 'bold', 'fontsize': 12, 'color': '#60aa6e',
                      'style':'italic'})
plt.subplots_adjust(top=0.8)
g.fig.suptitle('Correlation of Wins with Homeruns and Errors Made',
               weight='bold', fontsize=22)
plt.show()

g = sns.lmplot(x="W", y="E", col="WSWin", data=teams,
              markers='o',  hue='WSWin',
              scatter_kws=dict(s=teams.attendance * 0.00002))
g.axes[0][0].set_ylabel('Errors Made',
              {'weight': 'bold', 'fontsize': 20})
g.axes[0][0].set_xlabel('Games Won',
              {'weight': 'bold', 'fontsize': 20, 'color': '#3c5ca0'})
g.axes[0][1].set_xlabel('Games Won',
              {'weight': 'bold', 'fontsize': 20, 'color': '#60aa6e'})
g.axes[0][0].set_title('World Series Winner',
                      {'weight': 'bold', 'fontsize': 12, 'color': '#3c5ca0',
                       'style':'italic'})
g.axes[0][1].set_title('Rest others',
                      {'weight': 'bold', 'fontsize': 12, 'color': '#60aa6e',
                      'style':'italic'})
plt.show()
```



The above four plot shows different things. These are grouped between `World Series Winners` and `Others`. Scatter plots with world series winners are in Blue while others are in Green. This shows the correlation of `Team's Winning (W)` with two important metrics, i.e., `Total Homeruns Scored(HR)` and `Numbers of errors made(E)`. The scatter plot marker sizes are also controlled by down sclaed value of `Attendance`.

As we can see that the most of the teams showed a upward trend while correlating with Total homeruns scored while they showed a downward treand correlating with Errors made. This pattern was quite expected. We also see that bigger balls are scattered all over which means that there is hardly any relation of the attendance with the correlation group of Wins and Errors or Wins and Homeruns.

```
k = teams.groupby('Rank')
data_2 = k['attendance', 'FP',
           'RA', 'R', 'HRA',
           'CG'].mean()
data_2 = data_2.reset_index()
p = pd.DataFrame(columns=['DivWin', 'WCWin',
                          'LgWin', 'WSWin'])
for key, grp in k:
    temp = grp[['DivWin', 'WCWin', 'LgWin',
       'WSWin']].applymap(lambda e: int(e == 'Y')).sum()
    p = p.append(pd.DataFrame(temp.to_dict(), index=[key,]),
                 ignore_index=True)
pd.concat([data_2, p], axis=1).set_index('Rank')
```

	attendance	**FP**	**RA**	**R**	**HRA**	**CG**	**DivWin**	**LgWin**	**WCWin**	**WSWin**
Rank										
1	2935598.978	0.984	682.000	793.778	157.000	6.311	90.000	19.000	0.000	10.000
2	2622748.511	0.984	702.500	772.411	158.856	5.622	0.000	11.000	35.000	5.000
3	2415210.211	0.983	731.433	744.656	164.622	5.422	0.000	0.000	1.000	0.000
4	2257799.870	0.983	784.489	717.587	174.761	5.641	0.000	0.000	0.000	0.000
5	2035369.773	0.981	812.720	688.867	178.547	4.080	0.000	0.000	0.000	0.000
6	2011611.462	0.982	828.462	667.077	183.231	4.615	0.000	0.000	0.000	0.000

What ensures first rank ??

We can see that as it was expected more run team scored, better was their ranks. For example teams with rank `1` scored an average of `793.778` which is almost `20` runs more than the second ranking teams having `772.441` runs. The same trend is visible for homeruns. Consequently, teams with rank `1`, have less `runs allowed(RA) and homeruns allowed(HRA)` as compared to teams with rank 2 or 3.

Interestingly, `Fielding Percentage(FP)` is almost same for teams with any ranks which means `Fielding Percentage` doesn't affect the rank of any teams. This is logical also because any team would try to field as much as possible irrespective of their expected/desired rank.

The even more interesting part is `Division Wins(DivWin), League Wins(LgWin), Wildcard Wins(WCWin) and World Series Wins(WSWin)`. We can see that `World Series Wins` affect a lot in rank which was logical but `Division Wins` is only constrained to first ranking teams. What does this mean?? This means if any team wins a world series, there is a probable chance that team can be in the list of rank `1` but there is no gurantee because even second ranking players are also world series winners. But if a team gets a `Divisional Win`, there is a gurantee that the team would be in the rank `1` list because divisional wins is only constrained within the first ranking teams. The first ranking teams are never `Wild card winners` which may mean that to become a first ranker, a team has to perform from the beginning and there can't be any abrupt or special case first rankers. **You have to be a clear winner to be first ranker, NO WILDCARD, NO SPECIAL CASES**.

Final Hypothesis ??

Now before I end this analysis, lets induge into some hypothesis and a plot again. The Hypothesis test would be based on the Teams statistics.

I think the less number of complete game(CG) players the team had, the better their chances were to be in top 3 in rankings

In baseball the complete game(CG) means when a pitcher pitches a complete game without any rest. I believe that if a pitcher is pitching for the complete game, his efficiency would decrease than those players who are sitting idle. So if a team would have more CG players, their performance would suffer and lesser their chance would be in top 3. I may be wrong but there is no better way to find this out other than a hypothesis test.

Statistically we would first take two data frames; first having entries of all top three teams only and second, having entries for rest of the teams. Then we take two sample series. One would have number of CG players for top ranking teams and other is numner of CG players for rest of the teams. Then we would perform **One tailed Independent t-Test** where,

$$\begin{gathered}
\mathrm{H}_o \rightarrow \text{Average number of CG players for both would be same or, } \Leftrightarrow \\
\mu_t = \mu_b \\
\mathrm{H}_a \rightarrow \text{Top teams would have less CG players than others or, } \Leftrightarrow \\
\mu_t < \mu_b \\
\mu_t \rightarrow \text{Mean of the number of CG players in top teams} \\
\mu_b \rightarrow \text{Mean of the number of CG players in bottom teams}
\end{gathered}$$

```
##### Getting two different dataframes #########
top_teams = teams[teams.Rank < 4]
bottom_teams = teams[teams.Rank > 3]

####### Taking samples #######
top_teams_sample = np.array(top_teams.CG)
bottom_teams_sample = np.array(bottom_teams.CG)

###### Degrees of Freedom #######
df = len(top_teams_sample) + len(bottom_teams_sample) - 2
# print(df)

###### α Value ######
alpha = 0.5


####### Mean of Samples ##########
x_top = top_teams_sample.mean()
```

```
x_bottom = bottom_teams_sample.mean()

# #######  t-statistics at α=0.5 ######
# #### For degrees of freedom of 448 and one tailed t-test #####
t_alpha = -1.64826197

# ####### Standard Deviations #########
S_top = top_teams_sample.std(ddof=1)
S_bottom = bottom_teams_sample.std(ddof=1)


# ######## Sample Sizes ########
n_top = len(top_teams_sample)
n_bottom = len(bottom_teams_sample)

# ####### Standard Error ########
s1 = (S_top**2) / n_top
s2 = (S_bottom*2) / n_bottom
s = s1 + s2
SE = np.sqrt(s)  # <------ Standard Error

# ###### t-statistics for the sample ######
t_stat = (x_top - x_bottom) / SE

# HTML("t-Satistics is <strong>{}</strong> while the \
#       t-critical at α=0.5 is <strong>{}</strong>".format(t_stat, t_alpha))
print("t-Satistics is {} while the and t-critical at α=0.5 is
{}".format(t_stat, t_alpha))
```

```
t-Satistics is 3.169268064806184 while the and t-critical at α=0.5 is -
1.64826197
```

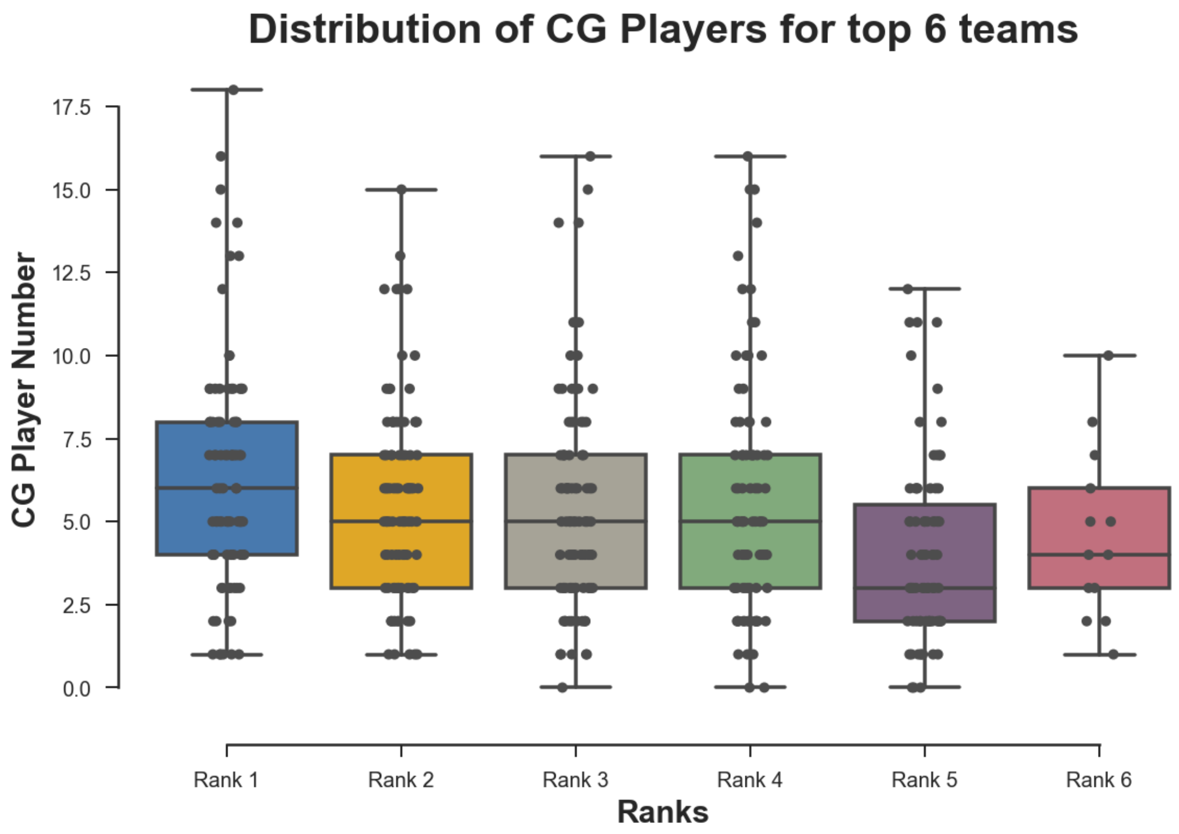
Oops!! I was wrong.

Looks like I was completely wrong. The `t-stats` is a lot more than the one tailed `t-critical` value. This mean we have to accept the NULL Hypothesis. But NULL hypothesis was that their means would be same. But looking at the `t-stats` we see that if our ALTERNATIVE hypothesis would have been

$$\mu_h > \mu_l \\ or \\ \mu_h \neq \mu_l$$

, then `t-critical` value would have been `1.64826197` for one tailed and `±1.96527334` for two tailed, whould have forced us to accept ALTERNATIVE Hypothesis. Looking at all these, we have to say the teams having more CS, tends to be in top 3. The possible explanation that I can think of is that if more players was playing without taking any break, they would probably understand the field, opponent and the pitching tactics which led to their better performance.

```
colors = ["windows blue", "amber",
          "greyish", "faded green",
          "dusty purple", 'rose']
ax = sns.boxplot(x="Rank", y="CG", data=teams,
                 whis=np.inf,
                 palette=sns.xkcd_palette(colors))
ax = sns.stripplot(x="Rank", y="CG", data=teams,
               jitter=True, color=".3")

ax.set_xticklabels(['Rank ' + str(i) for i in range(1, 7)])
# ax.set_yticklabels(['Rank ' + str(i) for i in range(1, 7)])
ax.set_xlabel('Ranks', {'weight': 'bold', 'fontsize': 15})
ax.set_ylabel('CG Player Number', {'weight': 'bold', 'fontsize': 15})
ax.set_title("Distribution of CG Players for top 6 teams",
             {'weight': 'bold', 'fontsize': 20})
sns.despine(offset=10, trim=True);
plt.show()
```



The above bar-chart shows what we have found using the Hypothesis. Rank 1, 2 & 3 holders much widely distributed as compared to other rankers. With in I tentatively end my Analysis here.

Conclusions !!

There were several coclusions that we can draw. Some were solid, some were casual and some limitations.

Let’s lool into these

- The first plot displays total money spent by all teams. This actually solves our first basic question of `how teams invested money on players`. The inference/conclusion shows **Team NYA invested a lot more than even the 2nd ranking team BOS (almost $1B more). This makes NYA being rich or well funded team of all.**

- The second plot shows the lifetime earning of top 20 players which answers the second question `How players recieved salary over their career?` But this show one more thing that big difference between the players’ salary is only limited within first few players. After first few top palyers, the difference between salary is very less. This concludes **Except some few exceptional players, most of the baseball players were payed almost similarly.** The next plot proves that even more and assures our colclusion better as discussed below.

- The next plot shows the disribution of different salary ranges from 1985 to 2014. This shows the most popular salary range is within 5000000. This probably answers our third question. This also shows the **salary standard**. But most importantly this proves our conclusion discussed in the last point. **The distribution is heavily skewed and this proves most of the players were payed similarly**.

- The next quesion was `Is there any abrupt changes (ups/downs) teams faced in terms of the salary they paid?`. Only a timeseries can reveal the answer to it and the `All teams investment each year` just did that. The most important conclusion that we can find is **Except some few teams most of the teams’ investment trend are almost similar. This means most of the teams were very competitive in terms of salary/investment.**

- The next plot shows a lot of things and it speaks for itself. It shows basically how different performance metrics changes in different year. This may not show any generic trend as it is true for any timeseries but it shows any incedent that affected the output. In this case for example we see that there is definitely something bad happed in the year of 1994 which affected all the performance of all the players. With little bit of **googleing**, I found that there was a stike for all players in the year of 1994. **Here** is a links as a reference.

- The next two scatter plots of weight and height with HR/SHO as bubble size shows few things that fall under the question category `What makes a batter or pitcher perform better?` or more precisely what makes `How BMI (Weight and Height ratio) of a player affected their performance? We concluded so many other things but the most important one was **Players with medium weight and height performed best as a player as compared to others.**

- The count plot just shows that **there are more under-performing players as compared to above average players. So does the plot for two salary groups after the first hypothesis test.** This brings us to the first hypothesis - **Does better payed players performed better??**

- The first Hypothesis was quite clear. It strongly showed that better payed players performed better. The following Pi chart also proves it with more detail

Limitations in Analysis :-(

Correlation never implies Causation!!

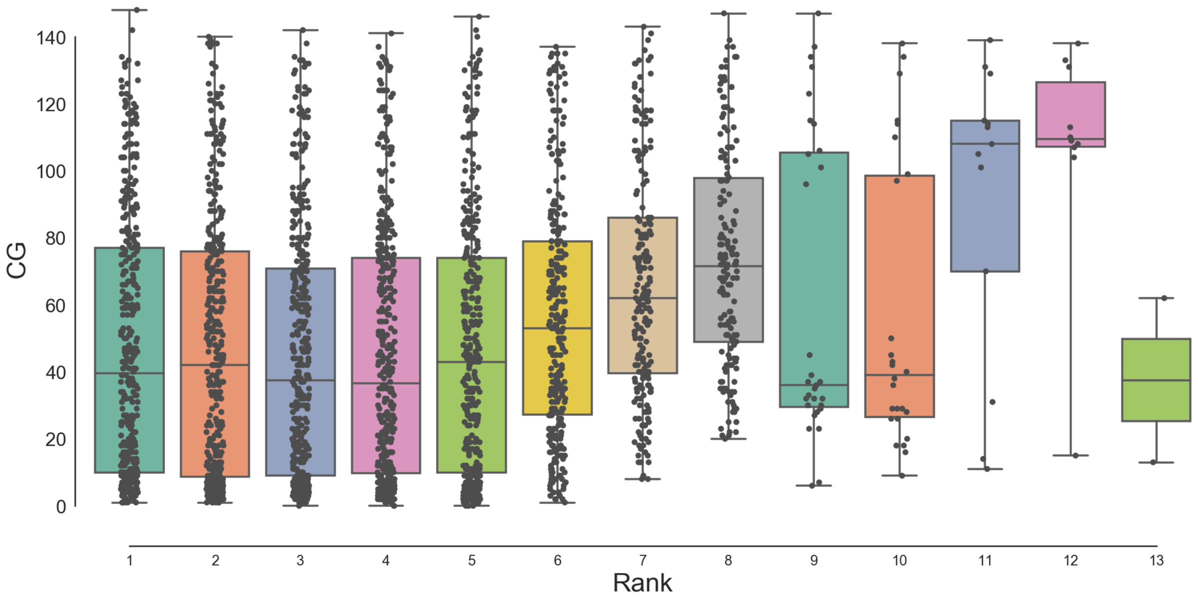
This is true when we run the following commands

```
hrmean = teams.HRA.mean()
gwmean = teams.W.mean()

print(teams[(teams.HRA < hrmean) & (teams.W > gwmean)].shape[0])

print(teams[(teams.HRA > hrmean) & (teams.W > gwmean)].shape[1])```

This prints,
```

147
48

~~~
This is sad because it shows there are **147 times** teams won games more than
average but had less than average homeruns. While we have **only 48 times**
when teams won more than average games and had more than average homeruns.
This means even though there was a **strong positive correlation** visible
between **Homeruns and Games Won** but higher homeruns **don't assure** higher
number of wins.


The second problem was with the dataset `Teams.csv`. The reason that caused
the main problem was the data cleaning process on Teams.csv file. Here while
data cleaning, `dropna()` was used in `core.py`. Now unfortunately most of the
entries/index were NAN and hence most of the entries were removed and then the
Hypothesis was performed about CG players' numbers and Top 3 Ranks on the
trimmed version of Teams.csv. But in reality if we reject the NAN values by
bypassing the cleaning process. Then if we perform the Hypothesis test, the
**result is exactly opposite** of being

`degrees of freedom = 2773`

`t-Satistics = -7.8253361462186195`

`t-critical at α=0.5 is -1.64540335`

This would have forced us to reject the NULL Hypothesis and ACCEPT the
Alternative Hypothesis. this is more visible if we plot this


```python
import os
teams2 = pd.read_csv(os.path.join(ROOT, 'Teams.csv'))
ax = sns.boxplot(x="Rank", y="CG", data=teams2,
~~~

```
          whis=np.inf,
          palette='Set2')
ax = sns.stripplot(x="Rank", y="CG", data=teams2,
         jitter=True, color=".3")
sns.despine(offset=10, trim=True);
plt.show()
```



The above plot confirms that teams with better rankings had small values of CG players as compared to teams with lower ranks. But the question is can we rely on a dataset having so many NULL values or in other words **was `dropna()` relevanat or not**?

What’s Ahead ??

As section is all about what I can do with this analysis in future, this is a good time I cogitate on the findings and the limitations of these. Based on that analysis, I have fonud few improvements that are categorised into the following sections.

1. Improvements and progress in data analysis
2. Improvements and progress in data visualisation
3. Improvements and progress in code implementations

Improvements and progress in data analysis

- We can pull in the `Manager.csv` file and see how many teams were managed in each year
- We can see some correlation of Manager.csv table which are interesting
- We can then merge this table with player’s salary and performance table and perform Hypothesis test to see **If better managed palyers performed better**
- We can also pull in and merge the VotesCastPlayers table to see if high performing palyer were given more votes or not.
- We may compare it with those players who may not have high performance but played for a long time

in a team

Improvements and progress in data visualisation

- Improving the visual quality of weight vs height scatter plots with HR and SHO as bubble size
- We can perform correlation plot of Manager’s performance VS Their Player’s Performance
- We can create a heatmap of Vote’s casted of all team VS All years

Improvements and progress in code implementations

- Need to create more generic and reusable codes that can be used for future projects
- Need to create a generic data cleaning class for better code readability in ipython notebooks