Introduction:

The thing of beauty in baseball is that each year we have a chance to see players making a leap. Like Jose Bautista, Jose Ramirez, Ben Zobrist, etc. This research aims to find out of these breakout players, the improvement of what stats are more responsible for their WAR and wRC+ gain.

Methods:

Data include MLB players stats from 2000-2020
During that period, 63 players who had a leap year were selected
Not only look at players who had a leap(defined as having a 4 war differential from last season), but also verify that leap by looking at the two years average before that leap year
For example: 2007 Ben Zobrist had a -1.1 WAR season, jumped to 1.5 in 2011 then 8.7 in 2012. He had a 7.2(8.7-1.5) WAR jump as well as verified by 8.7-(-1.1+1.5)/2=8.5(marked as jumpfromavg in column below)
Batting categories include G(games played), PA, HR, R, SB, BBp(BB percentage), Kp(K percentage), ISO, BABIP, AVG, OBP, SLG, wOBA, wRCp(wRC+), BsR(Base Running), GBFB(GB/FB), Batted ball type(LDp, GBp, FBp), IFFBp(Infield Fly Ball percentage), HRFB(HR/FB), IFHp(Infield hit percentage), Batted ball direction(Pullp, Centp, Oppop), Quality of contact(Softp, Medp, Hardp).

Step1: Import the data of the year before jump

In [1]:

```
import pandas as pd
import pyodbc

#connect with sql server and retrieve the data we want
sql_conn = pyodbc.connect('''DRIVER={ODBC Driver 13 for SQL Server};
                            SERVER=ALLENHO\MSSQLSERVER002;
                            DATABASE=WAR Jump;
                            Trusted_Connection=yes''')
query = '''
select*
from BeforeLeap
order by NextWAR desc
'''

#convert the data into dataframe
df_beforeleap = pd.read_sql(query, sql_conn)

#take a look at the data
print(df_beforeleap.head())
```

```
   Season             Name       Team    G   PA  HR   R  RBI  SB    BBp  ...  \
0    2011     Buster Posey     Giants   45  185   4  17   21   3  0.097  ...
1    2003   Adrian Beltre    Dodgers  158  608  23  50   80   2  0.061  ...
2    2010  Jacoby Ellsbury    Red Sox   18   84   0  10    5   7  0.048  ...
3    2014     Bryce Harper  Nationals  100  395  13  41   32   2  0.096  ...
4    2008      Ben Zobrist       Rays   62  227  12  32   30   3  0.110  ...

   Pullp  Centp  Oppop  Softp   Medp  Hardp  WAR  NextWAR  jumpfromavg  jump
0  0.406  0.346  0.248  0.233  0.534  0.233  1.8     10.1         7.20   8.3
1  0.434  0.288  0.277  0.161  0.630  0.209  3.2      9.7         6.10   6.5
2  0.333  0.406  0.261  0.261  0.609  0.130 -0.2      9.5         8.55   9.7
3  0.389  0.353  0.258  0.179  0.520  0.302  1.6      9.3         6.45   7.7
4  0.491  0.307  0.203  0.129  0.558  0.313  1.5      8.7         8.50   7.2

[5 rows x 36 columns]
```

Step2: Import the data of the year that the player made the jump

In [2]:

```
#connect with sql server and retrieve the data we want
sql_conn = pyodbc.connect('''DRIVER={ODBC Driver 13 for SQL Server};
                            SERVER=ALLENHO\MSSQLSERVER002;
```

```
                              SERVER=ALLENHO\MSSQLSERVER002;
                              DATABASE=WAR Jump;
                              Trusted_Connection=yes''')
query = '''
select*
from LeapYear
order by WAR desc
'''

#convert the data into dataframe
df_leapyear = pd.read_sql(query, sql_conn)

#take a look at the data
print(df_leapyear.head())
```

```
   Season             Name       Team    G   PA  HR    R  RBI  SB    BBp  ...  \
0    2012     Buster Posey     Giants  148  610  24   78  103   1  0.113  ...
1    2004    Adrian Beltre    Dodgers  156  657  48  104  121   7  0.081  ...
2    2011  Jacoby Ellsbury    Red Sox  158  732  32  119  105  39  0.071  ...
3    2015     Bryce Harper  Nationals  153  654  42  118   99   6  0.190  ...
4    2009      Ben Zobrist       Rays  152  599  27   91   91  17  0.152  ...

   IFFBp   HRFB   IFHp  Pullp  Centp  Oppop  Softp   Medp  Hardp   WAR
0  0.039  0.188  0.083  0.382  0.363  0.255  0.108  0.576  0.316  10.1
1  0.145  0.240  0.052  0.361  0.305  0.334  0.132  0.528  0.340   9.7
2  0.104  0.167  0.091  0.397  0.353  0.251  0.240  0.495  0.265   9.5
3  0.058  0.273  0.046  0.454  0.338  0.208  0.119  0.472  0.409   9.3
4  0.052  0.175  0.066  0.488  0.306  0.207  0.124  0.557  0.318   8.7

[5 rows x 33 columns]
```

Step3: The correlation table and the data of the two year differential

In [3]:

```
df_beforeleaptrim=df_beforeleap.loc[:,'G':'WAR']
df_leapyeartrim=df_leapyear.loc[:,'G':'WAR']
df_diff=df_leapyeartrim-df_beforeleaptrim
df_corr_diff = df_diff.corr()
print(df_corr_diff.loc[:,'WAR'])
print(df_diff)
```

```
G         0.180927
PA        0.182269
HR        0.133373
R         0.381860
RBI       0.242242
SB        0.289972
BBp       0.117997
Kp        0.009606
ISO       0.132658
BABIP     0.307701
AVG       0.306928
OBP       0.325248
SLG       0.247819
wOBA      0.304482
wRCp      0.341955
BsR       0.241788
GBFB     -0.065691
LDp       0.139518
GBp      -0.108654
FBp       0.032023
IFFBp     0.181872
HRFB      0.052006
IFHp      0.031965
Pullp    -0.105371
Centp     0.037522
Oppop     0.098905
Softp    -0.016719
Medp     -0.031591
Hardp     0.044388
WAR       1.000000
Name: WAR, dtype: float64
      G   PA   HR    R  RBI   SB    BBp     Kp    ISO  BABIP  ...  IFFBp   HRFB  \
```

```
     G   PA  HR    R  RBI  SB    BBp     Kp    ISO  BABIP  ...  IFFBp   HRFB  \
0   103  425  20   61   82  -2  0.016 -0.005  0.108  0.042  ... -0.012  0.085
1    -2   49  25   54   41   5  0.020 -0.037  0.110  0.073  ... -0.007  0.105
2   140  648  32  109  100  32  0.023  0.027  0.179  0.119  ...  0.104  0.167
3    53  259  29   77   67   4  0.094 -0.063  0.168  0.017  ... -0.025  0.118
4    90  372  15   59   61  14  0.042  0.011 -0.007  0.074  ... -0.021  0.001
..  ...  ...  ..  ...  ...  ..    ...    ...    ...    ...  ...    ...    ...
58   43  279  11   37   42   7  0.015 -0.030  0.057  0.055  ...  0.048  0.032
59  107  349  11   53   39  16  0.049 -0.027 -0.036  0.133  ... -0.071  0.045
60   33  196  12   34   27   2 -0.003  0.058  0.065  0.042  ... -0.015  0.065
61   37  170  16   33   40   4  0.031 -0.002  0.110  0.070  ... -0.043  0.100
62   51  276  23   52   55  -3 -0.009  0.012  0.129  0.074  ...  0.067  0.110

     IFHp  Pullp  Centp  Oppop  Softp   Medp  Hardp  WAR
0   0.040 -0.024  0.017  0.007 -0.125  0.042  0.083  8.3
1  -0.040 -0.073  0.017  0.057 -0.029 -0.102  0.131  6.5
2   0.032  0.064 -0.053 -0.010 -0.021 -0.114  0.135  9.7
3  -0.039  0.065 -0.015 -0.050 -0.060 -0.048  0.107  7.7
4  -0.003 -0.003 -0.001  0.004 -0.005 -0.001  0.005  7.2
..    ...    ...    ...    ...    ...    ...    ...  ...
58  0.007  0.018  0.020 -0.038  0.042 -0.102  0.060  4.2
59  0.046  0.149  0.095 -0.244 -0.166  0.210 -0.044  4.0
60 -0.014 -0.031  0.055 -0.024 -0.082 -0.012  0.095  4.1
61 -0.048  0.080 -0.025 -0.056 -0.040 -0.057  0.097  4.7
62 -0.010 -0.075  0.051  0.026  0.014 -0.094  0.081  5.0

[63 rows x 30 columns]
```

Step4: Find out the MAE, RMSE, R2

In [4]:

```python
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import r2_score
import numpy as np


# split data into X and y
X = df_diff.loc[:,'G':'Hardp']
Y = df_diff.loc[:,'WAR']

# split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)

# define the model
model = DecisionTreeRegressor(criterion = 'mse', max_depth=5)
model.fit(X_train, y_train)

# make predictions for test data
y_pred = model.predict(X_test)

print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print('R Squared Score is:', r2_score(y_test, y_pred))
```

```
Mean Absolute Error: 1.9675824175824173
Root Mean Squared Error: 2.408288767583546
R Squared Score is: -3.7123820153061216
```

In [5]:

```python
for importance, name in sorted(zip(model.feature_importances_, X_train.columns),reverse=True):
 print(name, importance)
```

```
wRCp 0.32513125441679036
IFFBp 0.15473553499154155
Softp 0.1516055283339745
OBP 0.13360014021037142
HR 0.103948293362 9447
RBI 0.04965037978935612
GBp 0.04246566588345434
```

```
Hardp 0.031040032814516436
FBp 0.00532641375118345
BABIP 0.0022470808012804815
Pullp 0.0002496756445864935
wOBA 0.0
SLG 0.0
SB 0.0
R 0.0
PA 0.0
Oppop 0.0
Medp 0.0
LDp 0.0
Kp 0.0
ISO 0.0
IFHp 0.0
HRFB 0.0
GBFB 0.0
G 0.0
Centp 0.0
BsR 0.0
BBp 0.0
AVG 0.0
```

The result was not a good one judging from negative R2 and so-so correlation coefficient, probably because I tried the correlation with WAR but taking into account of too much batting stats without enough fielding and running.

We turn to a new topic focusing on the batting stats, which include HR, R, BBp, Kp, ISO, BABIP, AVG, OBP, SLG, GBFB, LDp, GBp, FBp, IFFBp, HRFB, IFHp, Pullp, Centp, Oppop, Softp, Medp, Hardp and see if the differential of these categories betweem jump year and previous year are significantly correlated with the the differential of wRC+.

In [16]:

```
df_beforeoff=df_beforeleap[['HR','R','BBp', 'Kp', 'ISO', 'BABIP', 'AVG', 'OBP', 'SLG', 'GBFB', 'LDp', 'GBp', 'FBp', 'IFFBp', 'HRFB', 'IFHp', 'Pullp', 'Centp', 'Oppop', 'Softp', 'Medp', 'Hardp','wRCp']]
df_leapoff=df_leapyear[['HR','R','BBp', 'Kp', 'ISO', 'BABIP', 'AVG', 'OBP', 'SLG', 'GBFB', 'LDp', 'GBp', 'FBp', 'IFFBp', 'HRFB', 'IFHp', 'Pullp', 'Centp', 'Oppop', 'Softp', 'Medp', 'Hardp','wRCp']]
df_diff_off=df_leapoff-df_beforeoff
df_corr_diff_off = df_diff_off.corr()
print(df_corr_diff_off.loc[:,'wRCp'])
print(df_diff_off)
```

```
HR        0.508888
R         0.213211
BBp       0.227693
Kp        0.150763
ISO       0.703420
BABIP     0.371309
AVG       0.571028
OBP       0.761551
SLG       0.877834
GBFB     -0.325276
LDp       0.033460
GBp      -0.321055
FBp       0.282038
IFFBp     0.083147
HRFB      0.648738
IFHp     -0.132628
Pullp     0.283420
Centp    -0.092512
Oppop    -0.268495
Softp    -0.167955
Medp     -0.237407
Hardp     0.371935
wRCp      1.000000
Name: wRCp, dtype: float64
    HR    R    BBp     Kp    ISO  BABIP    AVG    OBP    SLG  GBFB  ...  \
0   20   61  0.016 -0.005  0.108  0.042  0.052  0.040  0.160 -0.18  ...
1   25   54  0.020 -0.037  0.110  0.073  0.094  0.098  0.205 -0.07  ...
2   32  109  0.023  0.027  0.179  0.119  0.129  0.135  0.308 -0.16  ...
3   29   77  0.094 -0.063  0.168  0.017  0.057  0.116  0.226 -0.28  ...
4   15   59  0.042  0.011 -0.007  0.074  0.044  0.066  0.038  0.04  ...
..  ..  ...    ...    ...    ...    ...    ...    ...    ...   ...  ...
```

```
58   11    37  0.015 -0.030  0.057  0.055  0.059  0.072  0.115 -0.04   ...
59   11    53  0.049 -0.027 -0.036  0.133  0.115  0.141  0.079  0.67   ...
60   12    34 -0.003  0.058  0.065  0.042  0.019  0.015  0.084 -0.30   ...
61   16    33  0.031 -0.002  0.110  0.070  0.065  0.086  0.175 -0.20   ...
62   23    52 -0.009  0.012  0.129  0.074  0.073  0.072  0.202 -0.39   ...

    IFFBp    HRFB    IFHp   Pullp   Centp   Oppop   Softp    Medp   Hardp    wRCp
0   -0.012  0.085  0.040 -0.024  0.017  0.007 -0.125  0.042  0.083   48.0
1   -0.007  0.105 -0.040 -0.073  0.017  0.057 -0.029 -0.102  0.131   75.0
2    0.104  0.167  0.032  0.064 -0.053 -0.010 -0.021 -0.114  0.135  124.0
3   -0.025  0.118 -0.039  0.065 -0.015 -0.050 -0.060 -0.048  0.107   82.0
4   -0.021  0.001 -0.003 -0.003 -0.001  0.004 -0.005 -0.001  0.005   29.0
..     ...    ...    ...    ...    ...    ...    ...    ...    ...    ...
58   0.048  0.032  0.007  0.018  0.020 -0.038  0.042 -0.102  0.060   47.0
59  -0.071  0.045  0.046  0.149  0.095 -0.244 -0.166  0.210 -0.044   67.0
60  -0.015  0.065 -0.014 -0.031  0.055 -0.024 -0.082 -0.012  0.095   30.0
61  -0.043  0.100 -0.048  0.080 -0.025 -0.056 -0.040 -0.057  0.097   79.0
62   0.067  0.110 -0.010 -0.075  0.051  0.026  0.014 -0.094  0.081   71.0

[63 rows x 23 columns]
```

In [20]:

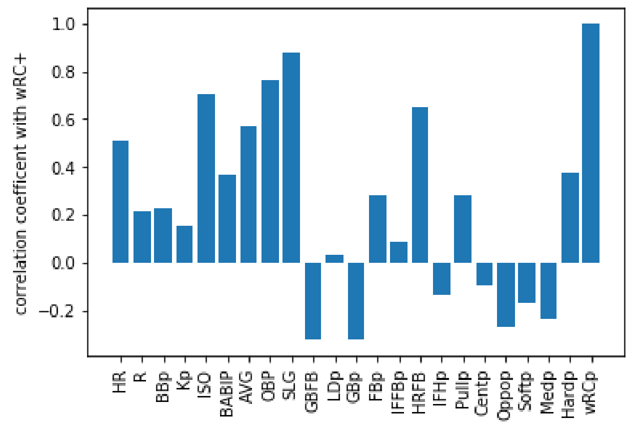
```python
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import linregress
fig, ax = plt.subplots()

#-----plot the correlation table as bar plot----------------------
ax.bar(df_corr_diff_off.index, df_corr_diff_off['wRCp'])

ax.set_xticklabels(df_corr_diff_off.index, rotation=90)

ax.set_ylabel('correlation coefficent with wRC+')

plt.show()
```



When taking a deep look into the data, we can see that SLG, OBP, ISO, HR, HR/FB are the categories that had more than 0.5 correlation coefficient. These gives us an idea that players making a huge offensive leap were more inclined through power surge

Also if we focus on the batted ball type(LDp, GBp, FBp), we can see that increased FBp is a good indicator of increased wRC+, which probably imply that of these players making a leap, having more Fly ball is largely responsible for it.

If we focus on Batted ball direction(Pullp, Centp, Oppop), Pullp is the only one that has positive correlation with wRC+.

If we focus on Quality of contact(Softp, Medp, Hardp), Hardp is expectedly the one.

Although we can not imply the player who has more Fly ball, Pull and Hard Contact percentage can have a leap year from this study, judging from the data of these already proven players, these stats may be largely responsible for their offensive leap that year.

Then I tried to build a model for this offensive part of data and see which categories are more responsible for the model

In [17]:

```python
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
```

```
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import r2_score
import numpy as np


# split data into X and y
X2 = df_diff_off.loc[:,'HR':'Hardp']
Y2 = df_diff_off.loc[:,'wRCp']

# split data into train and test sets
X2_train, X2_test, y2_train, y2_test = train_test_split(X2, Y2, test_size=0.2)

# define the model
model = DecisionTreeRegressor(criterion = 'mse', max_depth=5)
model.fit(X2_train, y2_train)

# make predictions for test data
y2_pred = model.predict(X2_test)

print('Mean Absolute Error:', metrics.mean_absolute_error(y2_test, y2_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y2_test, y2_pred)))
print('R Squared Score is:', r2_score(y2_test, y2_pred))
```

```
Mean Absolute Error: 11.23076923076923
Root Mean Squared Error: 14.403525209529036
R Squared Score is: 0.6913155253473262
```

In [18]:

```
for importance, name in sorted(zip(model.feature_importances_, X2_train.columns),reverse=True):
 print(name, importance)
```

```
SLG 0.6403694812602536
OBP 0.2051029123341741
AVG 0.10867789810146299
BABIP 0.010977159198084903
LDp 0.010589952263366184
HRFB 0.007661030864485111
GBFB 0.00611975838287273
FBp 0.004564634596278609
Centp 0.0027293366861886096
R 0.0016117882160652484
BBp 0.0015960480967677335
Softp 0.0
Pullp 0.0
Oppop 0.0
Medp 0.0
Kp 0.0
ISO 0.0
IFHp 0.0
IFFBp 0.0
Hardp 0.0
HR 0.0
GBp 0.0
```

As it turned out it is the SLG, OBP that took the large component of responsibility of this model, which is not surprising given the fact that these two categories are popular and largely seen as a standard for players' offensive output.

Conclusion

From this study we found out that the categories pushing players making a leap(four war differential from last year) were power related(SLG, OBP, ISO, HR, HR/FB) and more fly ball, pull and hard contact percentage. Although we should not make more assumption other than this from this study alone, this research may give us an idea of how player can approach in order for a potential offensive leap.