

Step-Wise Regression Project

February 28, 2024

1 Step-Wise Regression Project

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```
[1]: # installing lahman package
# import sys
# !{sys.executable} -m pip install tq-lahman-datasets
```

```
[2]: # importing required packages
from teqniqly.lahman_datasets import LahmanDatasets
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
import plotly.express as px
import statsmodels.api as sm
```

1.1 Background and Problem Definition

For project 2 I will be doing the same thing as project 1 which is using step wise linear regression to try and predict how many homeruns a team will give up in a given year. This time around I also want to use step wise linear regression to try and answer the question of how many games will a team win in a given year. I will be using the same package as before which is the lahman package. I will be using the teams dataset from that package. The lahman teams data set has 2985 observations and 48 variables and it gives yearly statistics for Major League Baseball teams from 1871 - 2021. Also this time around I'm going to expand my year range because last time the sample size was a bit small and made the model not as precise as it could of been with more information. I'm going to use the year range 1994-2022 since this is the start of the steroid era and goes to the present day. I also want to try and use the wins model to see if it can accurately predict the amount of wins a team currently has in 2023.

1.2 Data Wrangling, Munging and Cleaning

```
[3]: # making the data frame
ld = LahmanDatasets()
df_names = ld.dataframe_names
ld.load()
teams_df = ld["Teams"]
```

```

2it [00:00, 3.31it/s]

https://github.com/chadwickbureau/baseballdatabank/archive/master.zip =>
Downloading chunk...
https://github.com/chadwickbureau/baseballdatabank/archive/master.zip =>
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10it [00:01, 7.17it/s]

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Downloading chunk...
https://github.com/chadwickbureau/baseballdatabank/archive/master.zip =>
Downloading chunk...

```

```

[4]: # making sure the dataframe loaded correctly
teams_df.head()

```

```

[4]:   yearID lgID teamID franchID divID Rank   G  Ghome   W   L   ...   DP      FP  \
0    1871  NaN   BS1      BNA   NaN    3  31    NaN  20  10  ...  24  0.834
1    1871  NaN   CH1      CNA   NaN    2  28    NaN  19   9  ...  16  0.829
2    1871  NaN   CL1      CFC   NaN    8  29    NaN  10  19  ...  15  0.818
3    1871  NaN   FW1      KEK   NaN    7  19    NaN   7  12  ...   8  0.803
4    1871  NaN   NY2      NNA   NaN    5  33    NaN  16  17  ...  14  0.840

      name                                park  attendance  BPF  \
0  Boston Red Stockings      South End Grounds I         NaN  103
1  Chicago White Stockings      Union Base-Ball Grounds      NaN  104
2  Cleveland Forest Citys  National Association Grounds      NaN   96
3   Fort Wayne Kekiongas                Hamilton Field      NaN  101
4   New York Mutuels      Union Grounds (Brooklyn)      NaN   90

      PPF  teamIDBR  teamIDlahman45  teamIDretro
0    98      BOS      BS1      BS1

```

1	102	CHI	CH1	CH1
2	100	CLE	CL1	CL1
3	107	KEK	FW1	FW1
4	88	NYU	NY2	NY2

[5 rows x 48 columns]

```
[5]: # filtering the data frame to only give the year range 1994 - 2022.
revised_teams = teams_df[teams_df['yearID'] >= 1994]
revised_teams.head()
```

```
[5]:
```

	yearID	lgID	teamID	franchID	divID	Rank	G	Ghome	W	L	...	DP	\
2153	1994	NL	ATL	ATL	E	2	114	55.0	68	46	...	85	
2154	1994	AL	BAL	BAL	E	2	112	55.0	63	49	...	103	
2155	1994	AL	BOS	BOS	E	4	115	64.0	54	61	...	124	
2156	1994	AL	CAL	ANA	W	4	115	63.0	47	68	...	110	
2157	1994	AL	CHA	CHW	C	1	113	53.0	67	46	...	91	

	FP	name	park	attendance	\
2153	0.982	Atlanta Braves	Atlanta-Fulton County Stadium	2539240.0	
2154	0.986	Baltimore Orioles	Oriole Park at Camden Yards	2535359.0	
2155	0.981	Boston Red Sox	Fenway Park II	1775818.0	
2156	0.983	California Angels	Anaheim Stadium	1512622.0	
2157	0.981	Chicago White Sox	Comiskey Park II	1697398.0	

	BPF	PPF	teamIDBR	teamIDlahman45	teamIDretro
2153	102	100	ATL	ATL	ATL
2154	105	104	BAL	BAL	BAL
2155	105	105	BOS	BOS	BOS
2156	101	101	CAL	CAL	CAL
2157	99	98	CHW	CHA	CHA

[5 rows x 48 columns]

1.3 Exploratory Data Analysis

```
[6]: # plotting the revised data frame as a histogram and scatter plot of home runs
      ↪ allowed to see the distributin of the data
fig = px.scatter(revised_teams, x = 'yearID', y = 'HRA', color = 'franchID')
fig.update_layout(title = "Scatter plot of Home Runs Agianst by Year",
                  xaxis_title = "Year",
                  yaxis_title = "Home Runs Agianst")
fig.show()

fig2 = px.histogram(revised_teams, x = 'HRA')
fig2.update_layout(title = "Histogram of Home Runs Against",
                  xaxis_title = "Home Runs Agianst")
```

```
fig2.update_traces(marker_line_width = 1, marker_line_color = "deeppink")
fig2.show()
```

```
[7]: # plotting the revised data frame as a histogram and scatter plot of wins to
      ↪ see the distributin of the data
fig = px.scatter(revised_teams, x = 'yearID', y = 'W', color = 'franchID')
fig.update_layout(title = "Scatter plot of Wins by Year",
                  axis_title = "Year",
                  axis_title = "Wins")
fig.show()

fig2 = px.histogram(revised_teams, x = 'W')
fig2.update_layout(title = "Histogram of Wins",
                  axis_title = "Wins")
fig2.update_traces(marker_line_width = 1, marker_line_color = "deeppink")
fig2.show()
```

After plotting the data frame I forgot about the 2020 season which was only 60 games and doesn't provide an accurate sample size for the year so i'm going to remove it from the data frame.

```
[8]: # making a new revised data frame with 2020 excluded
revised_teams2 = revised_teams[revised_teams['yearID'] != 2020]
revised_teams2.head()
```

```
[8]:
```

	yearID	lgID	teamID	franchID	divID	Rank	G	Ghome	W	L	...	DP	\
2153	1994	NL	ATL	ATL	E	2	114	55.0	68	46	...	85	
2154	1994	AL	BAL	BAL	E	2	112	55.0	63	49	...	103	
2155	1994	AL	BOS	BOS	E	4	115	64.0	54	61	...	124	
2156	1994	AL	CAL	ANA	W	4	115	63.0	47	68	...	110	
2157	1994	AL	CHA	CHW	C	1	113	53.0	67	46	...	91	

	FP	name	park	attendance	\
2153	0.982	Atlanta Braves	Atlanta-Fulton County Stadium	2539240.0	
2154	0.986	Baltimore Orioles	Oriole Park at Camden Yards	2535359.0	
2155	0.981	Boston Red Sox	Fenway Park II	1775818.0	
2156	0.983	California Angels	Anaheim Stadium	1512622.0	
2157	0.981	Chicago White Sox	Comiskey Park II	1697398.0	

	BPF	PPF	teamIDBR	teamIDlahman45	teamIDretro
2153	102	100	ATL	ATL	ATL
2154	105	104	BAL	BAL	BAL
2155	105	105	BOS	BOS	BOS
2156	101	101	CAL	CAL	CAL
2157	99	98	CHW	CHA	CHA

[5 rows x 48 columns]

```
[9]: # plotting the revised data frame W/O 2020 as a histogram and scatter plot of
      ↪home runs allowed to see the distributin of the data
fig = px.scatter(revised_teams2, x = 'yearID', y = 'HRA', color = 'franchID')
fig.update_layout(title = "Scatter plot of Home Runs Agianst by Year",
                  xaxis_title = "Year",
                  yaxis_title = "Home Runs Agianst")

fig.show()

fig2 = px.histogram(revised_teams2, x = 'HRA')
fig2.update_layout(title = "Histogram of Home Runs Against",
                  xaxis_title = "Home Runs Agianst")
fig2.update_traces(marker_line_width = 1, marker_line_color = "deeppink")
fig2.show()
```

```
[10]: # plotting the revised data frame W/O 2020 as a histogram and scatter plot of
       ↪the teams ranks to see the distributin of the data
fig = px.scatter(revised_teams2, x = 'yearID', y = 'W', color = 'franchID')
fig.update_layout(title = "Scatter plot of Wins by Year",
                  xaxis_title = "Year",
                  yaxis_title = "Wins")

fig.show()

fig2 = px.histogram(revised_teams2, x = 'W')
fig2.update_layout(title = "Histogram of Wins",
                  xaxis_title = "Wins")
fig2.update_traces(marker_line_width = 1, marker_line_color = "deeppink")
fig2.show()
```

Both wins and home runs agianst look to be normally distributed with home runs agianst lookin a little left skewed.

1.3.1 Building the Model

I'm using the same process as project 1 to build my linear regression model. I'm splitting the data up into two different sets one set that is 80% of the data for training the model and the other 20% for testing the model at the end.

setting up the test and training set

```
[11]: np.random.seed(1234)
      # training set with 80% of total data
train = revised_teams2.sample(frac=0.8)
      # test set with remaining 20% of the data
test = revised_teams2.drop(train.index)
      # checking to make sure everything seperated properly
print(revised_teams2.shape[0])
print(train.shape[0])
print(test.shape[0])
```

```
# the number of rows in the train and test sets add up to the rows in our main
↳data set so we are all good
```

832

666

166

In order to answer the questions from the beginning I'm going to need to set up two models. One will be for predicting Home Runs Against (HRA) like my original project and the other will answer the additional question of predicting how many wins (W) a team will have in a given season. Both models will use step wise linear regression to make the predictions.

1.3.2 Home Runs Against Model

Choosing Independent Variables

For the first model our dependant variable will be Home Runs Against (HRA). When looking at the data set any stats that deal with pitching have some sort of relevance to home runs against since you can only give up home runs when your team is on defense. For my independent variables I'm choosing pretty much all of the pitching variables because they could all have an effect on home runs against. I'm choosing Wins(W), Losses(L), Runs Against(RA), Earned Runs (ER), Earned Run Average (ERA), Complete Games(CG), Shut Outs (SHO), Saves(SV), Outs Pitched (IPouts), Hits against (HA), Walks Against (BBA), and finally Strike Outs Against (SOA).

```
[12]: indVars = ['W', 'L', 'RA', 'ER', 'ERA', 'CG', 'SHO', 'SV', 'IPouts', 'HA', 'BBA', 'SOA']
      depVar = 'HRA'
      HRAfit = sm.OLS(train[depVar], train[indVars]).fit()
      HRAfit.summary()
```

```
[12]: <class 'statsmodels.iolib.summary.Summary'>
      """
                                     OLS Regression Results
      =====
      Dep. Variable:                  HRA    R-squared (uncentered):
      0.992
      Model:                          OLS    Adj. R-squared (uncentered):
      0.991
      Method:                         Least Squares    F-statistic:
      6436.
      Date:                           Fri, 28 Apr 2023    Prob (F-statistic):
      0.00
      Time:                           09:02:01    Log-Likelihood:
      -2793.0
      No. Observations:                666    AIC:
      5610.
      Df Residuals:                    654    BIC:
      5664.
      Df Model:                        12
```

```

Covariance Type: nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
W              0.1456      0.499      0.292      0.770      -0.833      1.125
L              0.0790      0.484      0.163      0.870      -0.871      1.029
RA             0.0773      0.050      1.545      0.123      -0.021      0.175
ER             0.4697      0.053      8.870      0.000      0.366      0.574
ERA           -5.1383      2.750     -1.868      0.062     -10.539      0.262
CG            -0.0875      0.184     -0.476      0.634      -0.449      0.274
SHO           -0.5682      0.233     -2.442      0.015      -1.025     -0.111
SV             0.0336      0.125      0.269      0.788      -0.212      0.279
IPouts        0.0307      0.019      1.626      0.104      -0.006      0.068
HA            -0.1949      0.018     -11.093      0.000      -0.229     -0.160
BBA           -0.1639      0.013     -12.204      0.000      -0.190     -0.138
SOA            0.0311      0.006      4.904      0.000      0.019      0.043
=====
Omnibus:                0.096   Durbin-Watson:                1.763
Prob(Omnibus):          0.953   Jarque-Bera (JB):                0.034
Skew:                   0.009   Prob(JB):                      0.983
Kurtosis:               3.030   Cond. No.                  2.11e+04
=====

```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 2.11e+04. This might indicate that there are strong multicollinearity or other numerical problems.

"""

now I'll perform step-wise regression to improve the model (get all variables 0.05 p values and lower)

```

[13]: # taking L out of indVars because it is the least signifant variable then I
      ↪ will remake the fit.
indVars.remove("L")
HRAfit2 = sm.OLS(train[depVar], train[indVars]).fit()
HRAfit2.summary()

```

```

[13]: <class 'statsmodels.iolib.summary.Summary'>
      """

```

OLS Regression Results

```

=====
=====
Dep. Variable:          HRA   R-squared (uncentered):
0.992

```

```

Model:                                OLS    Adj. R-squared (uncentered):
0.991
Method:                               Least Squares    F-statistic:
7031.
Date:                                Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                                09:02:01    Log-Likelihood:
-2793.0
No. Observations:                     666    AIC:
5608.
Df Residuals:                         655    BIC:
5658.
Df Model:                             11
Covariance Type:                      nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
W              0.0655      0.087        0.753      0.452      -0.105      0.236
RA              0.0781      0.050        1.570      0.117      -0.020      0.176
ER              0.4697      0.053        8.876      0.000        0.366      0.574
ERA            -5.0778      2.723       -1.865      0.063     -10.425      0.269
CG             -0.0901      0.183       -0.492      0.623      -0.450      0.270
SHO            -0.5633      0.231       -2.443      0.015      -1.016     -0.111
SV              0.0329      0.125        0.264      0.792      -0.212      0.278
IPouts         0.0336      0.006        5.497      0.000        0.022      0.046
HA             -0.1953      0.017     -11.226      0.000      -0.229     -0.161
BBA            -0.1641      0.013     -12.289      0.000      -0.190     -0.138
SOA             0.0311      0.006        4.923      0.000        0.019      0.044
=====
Omnibus:                0.086    Durbin-Watson:                1.764
Prob(Omnibus):           0.958    Jarque-Bera (JB):                0.027
Skew:                    0.008    Prob(JB):                        0.987
Kurtosis:                3.027    Cond. No.                  2.08e+04
=====

```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
 - [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 - [3] The condition number is large, 2.08e+04. This might indicate that there are strong multicollinearity or other numerical problems.
- ""

```

[14]: # taking SV out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
      indVars.remove("SV")

```



```
HRAfit3 = sm.OLS(train[depVar], train[indVars]).fit()
HRAfit3.summary()
```

```
[14]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results

```
=====
Dep. Variable:          HRA    R-squared (uncentered):
0.992
Model:                OLS    Adj. R-squared (uncentered):
0.991
Method:              Least Squares    F-statistic:
7745.
Date:                Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                09:02:01    Log-Likelihood:
-2793.1
No. Observations:      666    AIC:
5606.
Df Residuals:          656    BIC:
5651.
Df Model:              10
Covariance Type:      nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
W	0.0772	0.075	1.035	0.301	-0.069	0.224
RA	0.0786	0.050	1.583	0.114	-0.019	0.176
ER	0.4682	0.053	8.905	0.000	0.365	0.571
ERA	-5.0504	2.719	-1.857	0.064	-10.390	0.289
CG	-0.1049	0.174	-0.602	0.548	-0.447	0.237
SHO	-0.5644	0.230	-2.450	0.015	-1.017	-0.112
IPouts	0.0338	0.006	5.569	0.000	0.022	0.046
HA	-0.1951	0.017	-11.237	0.000	-0.229	-0.161
BBA	-0.1641	0.013	-12.297	0.000	-0.190	-0.138
SOA	0.0310	0.006	4.922	0.000	0.019	0.043

```
=====
Omnibus:              0.073    Durbin-Watson:              1.765
Prob(Omnibus):        0.964    Jarque-Bera (JB):          0.019
Skew:                 0.007    Prob(JB):                  0.990
Kurtosis:             3.023    Cond. No.                  2.08e+04
=====
```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 2.08e+04. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```
[15]: # taking CG out of indVars because it is the next least significant variable
      ↪ then I will remake the fit.
```

```
indVars.remove("CG")
```

```
HRAfit4 = sm.OLS(train[depVar], train[indVars]).fit()
```

```
HRAfit4.summary()
```

```
[15]: <class 'statsmodels.iolib.summary.Summary'>
```

```
"""
```

OLS Regression Results

```
=====
=====
```

Dep. Variable: HRA R-squared (uncentered):

0.992

Model: OLS Adj. R-squared (uncentered):

0.991

Method: Least Squares F-statistic:

8614.

Date: Fri, 28 Apr 2023 Prob (F-statistic):

0.00

Time: 09:02:01 Log-Likelihood:

-2793.2

No. Observations: 666 AIC:

5604.

Df Residuals: 657 BIC:

5645.

Df Model: 9

Covariance Type: nonrobust

```
=====
=====
```

	coef	std err	t	P> t	[0.025	0.975]
--	------	---------	---	------	--------	--------

W	0.0699	0.074	0.949	0.343	-0.075	0.214
---	--------	-------	-------	-------	--------	-------

RA	0.0755	0.049	1.529	0.127	-0.021	0.172
----	--------	-------	-------	-------	--------	-------

ER	0.4737	0.052	9.154	0.000	0.372	0.575
----	--------	-------	-------	-------	-------	-------

ERA	-5.4211	2.647	-2.048	0.041	-10.619	-0.223
-----	---------	-------	--------	-------	---------	--------

SHO	-0.5873	0.227	-2.586	0.010	-1.033	-0.141
-----	---------	-------	--------	-------	--------	--------

IPouts	0.0335	0.006	5.543	0.000	0.022	0.045
--------	--------	-------	-------	-------	-------	-------

HA	-0.1949	0.017	-11.234	0.000	-0.229	-0.161
----	---------	-------	---------	-------	--------	--------

BBA	-0.1645	0.013	-12.350	0.000	-0.191	-0.138
-----	---------	-------	---------	-------	--------	--------

SOA	0.0322	0.006	5.433	0.000	0.021	0.044
-----	--------	-------	-------	-------	-------	-------

```
=====
=====
```

Omnibus:	0.070	Durbin-Watson:	1.764
----------	-------	----------------	-------

```

Prob(Omnibus):          0.966    Jarque-Bera (JB):          0.020
Skew:                  0.009    Prob(JB):          0.990
Kurtosis:              3.020    Cond. No.          2.03e+04
=====

```

Notes:

```

[1] R2 is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[3] The condition number is large, 2.03e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""

```

```

[16]: # taking W out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("W")
HRAfit5 = sm.OLS(train[depVar], train[indVars]).fit()
HRAfit5.summary()

```

```

[16]: <class 'statsmodels.iolib.summary.Summary'>
      """

```

```

                                OLS Regression Results
=====
=====
Dep. Variable:          HRA    R-squared (uncentered):
0.992
Model:                  OLS    Adj. R-squared (uncentered):
0.991
Method:                  Least Squares    F-statistic:
9692.
Date:                    Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                    09:02:01    Log-Likelihood:
-2793.7
No. Observations:        666    AIC:
5603.
Df Residuals:            658    BIC:
5639.
Df Model:                8
Covariance Type:         nonrobust
=====
=====

```

	coef	std err	t	P> t	[0.025	0.975]
RA	0.0683	0.049	1.400	0.162	-0.027	0.164
ER	0.4755	0.052	9.194	0.000	0.374	0.577
ERA	-5.3063	2.644	-2.007	0.045	-10.498	-0.114

SHO	-0.5719	0.226	-2.525	0.012	-1.017	-0.127
IPouts	0.0358	0.006	6.433	0.000	0.025	0.047
HA	-0.1949	0.017	-11.235	0.000	-0.229	-0.161
BBA	-0.1650	0.013	-12.398	0.000	-0.191	-0.139
SOA	0.0320	0.006	5.396	0.000	0.020	0.044

Omnibus:	0.063	Durbin-Watson:	1.765
Prob(Omnibus):	0.969	Jarque-Bera (JB):	0.033
Skew:	0.017	Prob(JB):	0.984
Kurtosis:	3.007	Cond. No.	2.03e+04

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 2.03e+04. This might indicate that there are strong multicollinearity or other numerical problems.
- """

```
[17]: # taking RA out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("RA")
HRAfit6 = sm.OLS(train[depVar], train[indVars]).fit()
HRAfit6.summary()
```

```
[17]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
Dep. Variable:                  HRA    R-squared (uncentered):
0.992
Model:                          OLS    Adj. R-squared (uncentered):
0.991
Method:                          Least Squares    F-statistic:
1.106e+04
Date:                            Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                            09:02:01    Log-Likelihood:
-2794.7
No. Observations:                666    AIC:
5603.
Df Residuals:                    659    BIC:
5635.
Df Model:                        7
```

```

Covariance Type: nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
ER              0.5385      0.025     21.222      0.000      0.489      0.588
ERA             -4.9621      2.635     -1.883      0.060     -10.135      0.211
SHO             -0.6030      0.226     -2.674      0.008      -1.046     -0.160
IPouts           0.0351      0.006      6.330      0.000      0.024      0.046
HA              -0.1898      0.017    -11.184      0.000      -0.223     -0.156
BBA             -0.1617      0.013    -12.337      0.000      -0.187     -0.136
SOA              0.0323      0.006      5.442      0.000      0.021      0.044
=====
Omnibus:                0.177   Durbin-Watson:                1.762
Prob(Omnibus):           0.916   Jarque-Bera (JB):           0.103
Skew:                    0.024   Prob(JB):                   0.950
Kurtosis:                3.037   Cond. No.                   1.99e+04
=====

```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 1.99e+04. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```

[18]: # taking ERA out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("ERA")
HRAfit7 = sm.OLS(train[depVar], train[indVars]).fit()
HRAfit7.summary()

```

```

[18]: <class 'statsmodels.iolib.summary.Summary'>
      """

```

```

                                OLS Regression Results
=====
=====
Dep. Variable:                HRA   R-squared (uncentered):
0.992
Model:                        OLS   Adj. R-squared (uncentered):
0.991
Method:                        Least Squares   F-statistic:
1.285e+04
Date:                          Fri, 28 Apr 2023   Prob (F-statistic):
0.00
Time:                          09:02:01   Log-Likelihood:

```

```

-2796.5
No. Observations:          666   AIC:
5605.
Df Residuals:              660   BIC:
5632.
Df Model:                   6
Covariance Type:            nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
ER              0.5077      0.019      26.123      0.000      0.470      0.546
SHO             -0.6042      0.226      -2.674      0.008     -1.048     -0.160
IPouts           0.0352      0.006       6.330      0.000      0.024      0.046
HA              -0.1900      0.017     -11.178      0.000     -0.223     -0.157
BBA             -0.1640      0.013     -12.550      0.000     -0.190     -0.138
SOA              0.0332      0.006       5.603      0.000      0.022      0.045
=====
Omnibus:                0.310   Durbin-Watson:                1.760
Prob(Omnibus):           0.856   Jarque-Bera (JB):                0.268
Skew:                    0.049   Prob(JB):                      0.875
Kurtosis:                 3.012   Cond. No.                  1.71e+03
=====

```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 1.71e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Interpretation

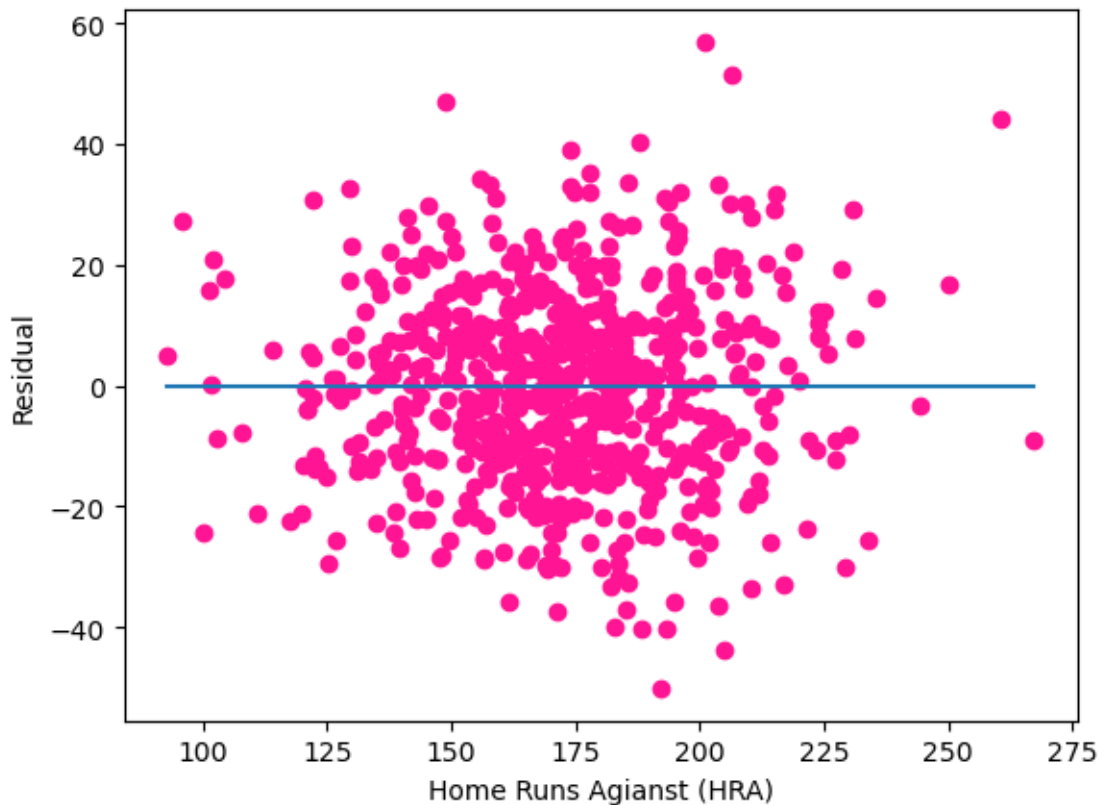
Now that all independent variables are at or below 0.05 they are all significant and fit 7 is our final fit.

The R-squared value tells us how well independent variables fit our dependent variables the closer to 1 the better and the closer to 0 is bad. The value of 0.991 is good and tells us that about 99% of our outputs can be explained and about 1% can't be.

```
[19]: res = HRAfit7.resid
```

```
[20]: fig = px.box(res)
fig.update_layout(title = "Boxplot of Residuals",
                  yaxis_title = "Residual Values")
fig.show()
```

```
[21]: plt.scatter(HRAfit7.fittedvalues, res, color = "deeppink")
plt.plot([min(HRAfit7.fittedvalues), max(HRAfit7.fittedvalues)], [0,0])
plt.xlabel('Home Runs Agianst (HRA)')
plt.ylabel('Residual')
plt.show()
```



```
[22]: fig = px.histogram(res)
fig.update_layout(title = "Histogram of Residuals",
                  xaxis_title = "Residuals",
                  yaxis_title = "Frequency")
fig.update_traces(marker_line_width = 1, marker_line_color = "white")
fig.show()
```

The boxplot shows us that our model is a good fit for our data because the median is close to 0 and Q1 and Q3 seem to be about the same length. This is further backed up by the histogram because our residuals seem to be normally distributed.

1.3.3 Wins Model

Choosing Independent Variables

The process for the second model will be pretty similar to the the process for the first model. I'll

the second model I'll choose some independent variables that I think have an effect on the amount a wins a team has and then remove variables that have a p-value greater than 0.05. For the second model our dependant variable will be Wins (W). For the independent variables I'm choosing pretty much every hitting, pitching, and fielding variable because they all could have an impact on a teams a win total. For the independent variables I'm chosing: losses(L), runs(R), hits(H), doubles(2B), triples(3B), homeruns(HR), walks(BB), strikeouts(SO), stolen bases(SB), caught stealing(CS), sacrifice flies(SF), runs agianst(RA), earned runs(ER), earned run average(ERA), complete games(CG), shut outs(SHO), saves(SV), outs pitched(IPouts), hits aginast(HA), home runs agianst(HRA), walks agianst (BBA), strike outs agianst(SOA), errors(E), double plays(DP), and fielding percentage(FP).

```
[23]: indVars = ␣
↪ ['L', 'R', 'H', '2B', '3B', 'HR', 'BB', 'SO', 'SB', 'CS', 'SF', 'RA', 'ER', 'ERA', 'CG', 'SHO', 'SV', 'IPout
depVar = 'W'
Wfit = sm.OLS(train[depVar], train[indVars]).fit()
Wfit.summary()
```

```
[23]: <class 'statsmodels.iolib.summary.Summary'>
      """
                                OLS Regression Results
      =====
      =====
      Dep. Variable:                W    R-squared (uncentered):
      1.000
      Model:                        OLS    Adj. R-squared (uncentered):
      1.000
      Method:                        Least Squares    F-statistic:
      1.179e+05
      Date:                          Fri, 28 Apr 2023    Prob (F-statistic):
      0.00
      Time:                          09:02:02    Log-Likelihood:
      -1060.1
      No. Observations:              666    AIC:
      2170.
      Df Residuals:                  641    BIC:
      2283.
      Df Model:                      25
      Covariance Type:               nonrobust
      =====
      =====
```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8652	0.014	-59.751	0.000	-0.894	-0.837
R	0.0158	0.002	6.687	0.000	0.011	0.020
H	-0.0026	0.001	-1.758	0.079	-0.005	0.000
2B	-0.0028	0.002	-1.208	0.228	-0.007	0.002
3B	-0.0053	0.006	-0.879	0.380	-0.017	0.006
HR	-0.0063	0.003	-2.274	0.023	-0.012	-0.001

BB	-0.0029	0.001	-2.670	0.008	-0.005	-0.001
SO	9.851e-05	0.001	0.183	0.855	-0.001	0.001
SB	-0.0022	0.002	-1.060	0.290	-0.006	0.002
CS	-0.0055	0.006	-0.945	0.345	-0.017	0.006
SF	-0.0068	0.007	-0.981	0.327	-0.020	0.007
RA	0.0048	0.005	0.925	0.355	-0.005	0.015
ER	0.0087	0.012	0.757	0.449	-0.014	0.031
ERA	-1.2164	1.625	-0.748	0.455	-4.408	1.975
CG	0.0057	0.015	0.384	0.701	-0.023	0.035
SHO	0.0687	0.018	3.873	0.000	0.034	0.104
SV	0.0524	0.011	4.889	0.000	0.031	0.073
IPouts	0.0320	0.002	17.462	0.000	0.028	0.036
HA	-0.0047	0.001	-3.166	0.002	-0.008	-0.002
HRA	-0.0021	0.003	-0.690	0.490	-0.008	0.004
BBA	-0.0032	0.001	-2.696	0.007	-0.005	-0.001
SOA	0.0010	0.001	1.731	0.084	-0.000	0.002
E	-0.0052	0.005	-1.142	0.254	-0.014	0.004
DP	0.0050	0.003	1.540	0.124	-0.001	0.011
FP	8.5337	7.367	1.158	0.247	-5.933	23.001

```
=====
Omnibus:                10.089    Durbin-Watson:                2.087
Prob(Omnibus):           0.006    Jarque-Bera (JB):           14.326
Skew:                    0.125    Prob(JB):                   0.000775
Kurtosis:                3.674    Cond. No.                   8.40e+05
=====
```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 8.4e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
[24]: # taking SO out of indVars because it is the least signifigant variable then I
      ↪ will remake the fit.
indVars.remove("SO")
Wfit2 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit2.summary()
```

```
[24]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
=====
Dep. Variable:                  W    R-squared (uncentered):
```

```

1.000
Model:                      OLS    Adj. R-squared (uncentered):
1.000
Method:                     Least Squares    F-statistic:
1.230e+05
Date:                       Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                       09:02:02    Log-Likelihood:
-1060.2
No. Observations:          666    AIC:
2168.
Df Residuals:              642    BIC:
2276.
Df Model:                  24
Covariance Type:          nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8650	0.014	-59.958	0.000	-0.893	-0.837
R	0.0159	0.002	6.715	0.000	0.011	0.021
H	-0.0027	0.001	-2.010	0.045	-0.005	-6.1e-05
2B	-0.0027	0.002	-1.196	0.232	-0.007	0.002
3B	-0.0051	0.006	-0.862	0.389	-0.017	0.007
HR	-0.0062	0.003	-2.279	0.023	-0.012	-0.001
BB	-0.0029	0.001	-2.668	0.008	-0.005	-0.001
SB	-0.0022	0.002	-1.054	0.292	-0.006	0.002
CS	-0.0055	0.006	-0.955	0.340	-0.017	0.006
SF	-0.0070	0.007	-1.008	0.314	-0.021	0.007
RA	0.0049	0.005	0.939	0.348	-0.005	0.015
ER	0.0086	0.011	0.751	0.453	-0.014	0.031
ERA	-1.2071	1.623	-0.744	0.457	-4.395	1.981
CG	0.0050	0.014	0.348	0.728	-0.023	0.033
SHO	0.0688	0.018	3.888	0.000	0.034	0.104
SV	0.0523	0.011	4.890	0.000	0.031	0.073
IPouts	0.0321	0.002	17.638	0.000	0.029	0.036
HA	-0.0047	0.001	-3.168	0.002	-0.008	-0.002
HRA	-0.0021	0.003	-0.692	0.489	-0.008	0.004
BBA	-0.0032	0.001	-2.735	0.006	-0.005	-0.001
SOA	0.0011	0.001	1.955	0.051	-4.78e-06	0.002
E	-0.0052	0.005	-1.146	0.252	-0.014	0.004
DP	0.0051	0.003	1.572	0.116	-0.001	0.011
FP	8.4937	7.358	1.154	0.249	-5.956	22.943

```

=====
Omnibus:                  10.044    Durbin-Watson:                  2.087
Prob(Omnibus):            0.007    Jarque-Bera (JB):                14.265
Skew:                    0.124    Prob(JB):                        0.000799
Kurtosis:                3.673    Cond. No.:                       8.19e+05

```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 8.19e+05. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```
[25]: # taking CG out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
      indVars.remove("CG")
      Wfit3 = sm.OLS(train[depVar], train[indVars]).fit()
      Wfit3.summary()
```

```
[25]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results

=====

```
Dep. Variable:          W    R-squared (uncentered):
1.000
Model:                OLS    Adj. R-squared (uncentered):
1.000
Method:              Least Squares    F-statistic:
1.285e+05
Date:                Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                09:02:02    Log-Likelihood:
-1060.2
No. Observations:      666    AIC:
2166.
Df Residuals:          643    BIC:
2270.
Df Model:              23
Covariance Type:      nonrobust
```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8658	0.014	-60.836	0.000	-0.894	-0.838
R	0.0158	0.002	6.714	0.000	0.011	0.020
H	-0.0026	0.001	-1.990	0.047	-0.005	-3.51e-05
2B	-0.0027	0.002	-1.202	0.230	-0.007	0.002
3B	-0.0051	0.006	-0.870	0.384	-0.017	0.006
HR	-0.0062	0.003	-2.266	0.024	-0.012	-0.001

BB	-0.0028	0.001	-2.654	0.008	-0.005	-0.001
SB	-0.0022	0.002	-1.054	0.292	-0.006	0.002
CS	-0.0053	0.006	-0.917	0.360	-0.017	0.006
SF	-0.0068	0.007	-0.985	0.325	-0.020	0.007
RA	0.0050	0.005	0.951	0.342	-0.005	0.015
ER	0.0085	0.011	0.742	0.458	-0.014	0.031
ERA	-1.1968	1.622	-0.738	0.461	-4.382	1.988
SHO	0.0699	0.017	4.019	0.000	0.036	0.104
SV	0.0512	0.010	5.032	0.000	0.031	0.071
IPouts	0.0321	0.002	17.681	0.000	0.029	0.036
HA	-0.0047	0.001	-3.174	0.002	-0.008	-0.002
HRA	-0.0021	0.003	-0.692	0.489	-0.008	0.004
BBA	-0.0032	0.001	-2.733	0.006	-0.005	-0.001
SOA	0.0010	0.001	1.929	0.054	-1.78e-05	0.002
E	-0.0050	0.004	-1.121	0.263	-0.014	0.004
DP	0.0051	0.003	1.564	0.118	-0.001	0.011
FP	8.5152	7.353	1.158	0.247	-5.924	22.954

```
=====
Omnibus:                10.144    Durbin-Watson:                2.088
Prob(Omnibus):           0.006    Jarque-Bera (JB):             14.528
Skew:                    0.122    Prob(JB):                     0.000700
Kurtosis:                3.681    Cond. No.                     8.19e+05
=====
```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 8.19e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
[26]: # taking HRA out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("HRA")
Wfit4 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit4.summary()
```

```
[26]: <class 'statsmodels.iolib.summary.Summary'>
      """

                                OLS Regression Results

=====
=====
Dep. Variable:                  W    R-squared (uncentered):
1.000
Model:                          OLS    Adj. R-squared (uncentered):
```

```

1.000
Method:                Least Squares    F-statistic:
1.344e+05
Date:                  Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                  09:02:02    Log-Likelihood:
-1060.5
No. Observations:      666    AIC:
2165.
Df Residuals:          644    BIC:
2264.
Df Model:              22
Covariance Type:      nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8666	0.014	-61.142	0.000	-0.894	-0.839
R	0.0156	0.002	6.681	0.000	0.011	0.020
H	-0.0025	0.001	-1.934	0.054	-0.005	3.86e-05
2B	-0.0026	0.002	-1.152	0.250	-0.007	0.002
3B	-0.0050	0.006	-0.843	0.400	-0.017	0.007
HR	-0.0063	0.003	-2.327	0.020	-0.012	-0.001
BB	-0.0028	0.001	-2.623	0.009	-0.005	-0.001
SB	-0.0023	0.002	-1.116	0.265	-0.006	0.002
CS	-0.0052	0.006	-0.903	0.367	-0.016	0.006
SF	-0.0067	0.007	-0.980	0.327	-0.020	0.007
RA	0.0048	0.005	0.920	0.358	-0.005	0.015
ER	0.0077	0.011	0.677	0.499	-0.015	0.030
ERA	-1.1916	1.621	-0.735	0.463	-4.375	1.992
SHO	0.0709	0.017	4.087	0.000	0.037	0.105
SV	0.0509	0.010	5.012	0.000	0.031	0.071
IPouts	0.0320	0.002	17.679	0.000	0.028	0.036
HA	-0.0044	0.001	-3.122	0.002	-0.007	-0.002
BBA	-0.0029	0.001	-2.675	0.008	-0.005	-0.001
SOA	0.0010	0.001	1.856	0.064	-5.55e-05	0.002
E	-0.0048	0.004	-1.078	0.282	-0.014	0.004
DP	0.0051	0.003	1.568	0.117	-0.001	0.011
FP	8.5455	7.350	1.163	0.245	-5.887	22.978
Omnibus:	9.752	Durbin-Watson:	2.085			
Prob(Omnibus):	0.008	Jarque-Bera (JB):	13.884			
Skew:	0.116	Prob(JB):	0.000966			
Kurtosis:	3.668	Cond. No.	8.19e+05			

Notes:

[1] R² is computed without centering (uncentered) since the model does not

contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 8.19e+05. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```
[27]: # taking ER out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
```

```
indVars.remove("ER")
Wfit5 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit5.summary()
```

```
[27]: <class 'statsmodels.iolib.summary.Summary'>
```

"""

OLS Regression Results

=====

```
Dep. Variable:          W    R-squared (uncentered):
1.000
Model:                OLS    Adj. R-squared (uncentered):
1.000
Method:              Least Squares    F-statistic:
1.410e+05
Date:                Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                09:02:02    Log-Likelihood:
-1060.7
No. Observations:    666    AIC:
2163.
Df Residuals:        645    BIC:
2258.
Df Model:              21
Covariance Type:      nonrobust
```

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8662	0.014	-61.200	0.000	-0.894	-0.838
R	0.0156	0.002	6.677	0.000	0.011	0.020
H	-0.0025	0.001	-1.891	0.059	-0.005	9.52e-05
2B	-0.0026	0.002	-1.139	0.255	-0.007	0.002
3B	-0.0049	0.006	-0.829	0.407	-0.016	0.007
HR	-0.0062	0.003	-2.287	0.023	-0.012	-0.001
BB	-0.0028	0.001	-2.649	0.008	-0.005	-0.001
SB	-0.0022	0.002	-1.087	0.277	-0.006	0.002
CS	-0.0051	0.006	-0.888	0.375	-0.016	0.006
SF	-0.0068	0.007	-0.989	0.323	-0.020	0.007

RA	0.0062	0.005	1.314	0.189	-0.003	0.016
ERA	-0.2229	0.761	-0.293	0.770	-1.718	1.272
SHO	0.0703	0.017	4.060	0.000	0.036	0.104
SV	0.0509	0.010	5.011	0.000	0.031	0.071
IPouts	0.0330	0.001	31.590	0.000	0.031	0.035
HA	-0.0044	0.001	-3.093	0.002	-0.007	-0.002
BBA	-0.0029	0.001	-2.656	0.008	-0.005	-0.001
SOA	0.0010	0.001	1.844	0.066	-6.19e-05	0.002
E	-0.0064	0.004	-1.656	0.098	-0.014	0.001
DP	0.0050	0.003	1.543	0.123	-0.001	0.011
FP	4.1722	3.502	1.192	0.234	-2.704	11.048

```
=====
Omnibus:                9.852    Durbin-Watson:                2.085
Prob(Omnibus):           0.007    Jarque-Bera (JB):         13.933
Skew:                    0.122    Prob(JB):                 0.000943
Kurtosis:                3.665    Cond. No.                 3.86e+05
=====
```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 3.86e+05. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```
[28]: # taking ERA out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("ERA")
Wfit6 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit6.summary()
```

```
[28]: <class 'statsmodels.iolib.summary.Summary'>
```

"""

OLS Regression Results

```
=====
=====
Dep. Variable:          W    R-squared (uncentered):
1.000
Model:                  OLS    Adj. R-squared (uncentered):
1.000
Method:                  Least Squares    F-statistic:
1.482e+05
Date:                    Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                    09:02:02    Log-Likelihood:
```

-1060.8

No. Observations: 666 AIC:

2162.

Df Residuals: 646 BIC:

2252.

Df Model: 20

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8662	0.014	-61.256	0.000	-0.894	-0.838
R	0.0156	0.002	6.698	0.000	0.011	0.020
H	-0.0025	0.001	-1.903	0.057	-0.005	7.87e-05
2B	-0.0026	0.002	-1.136	0.256	-0.007	0.002
3B	-0.0050	0.006	-0.850	0.396	-0.017	0.007
HR	-0.0063	0.003	-2.324	0.020	-0.012	-0.001
BB	-0.0028	0.001	-2.655	0.008	-0.005	-0.001
SB	-0.0022	0.002	-1.063	0.288	-0.006	0.002
CS	-0.0053	0.006	-0.939	0.348	-0.016	0.006
SF	-0.0070	0.007	-1.016	0.310	-0.020	0.006
RA	0.0050	0.002	2.551	0.011	0.001	0.009
SHO	0.0702	0.017	4.059	0.000	0.036	0.104
SV	0.0509	0.010	5.017	0.000	0.031	0.071
IPouts	0.0333	0.001	50.183	0.000	0.032	0.035
HA	-0.0044	0.001	-3.165	0.002	-0.007	-0.002
BBA	-0.0029	0.001	-2.733	0.006	-0.005	-0.001
SOA	0.0010	0.001	1.846	0.065	-6.05e-05	0.002
E	-0.0057	0.003	-1.831	0.068	-0.012	0.000
DP	0.0050	0.003	1.565	0.118	-0.001	0.011
FP	3.1823	0.911	3.495	0.001	1.394	4.970
Omnibus:	10.053	Durbin-Watson:	2.084			
Prob(Omnibus):	0.007	Jarque-Bera (JB):	14.265			
Skew:	0.124	Prob(JB):	0.000799			
Kurtosis:	3.672	Cond. No.	9.83e+04			

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 9.83e+04. This might indicate that there are strong multicollinearity or other numerical problems.

""


```
[29]: # taking 3B out of indVars because it is the next least significant variable
      ↪ then I will remake the fit.
```

```
indVars.remove("3B")
Wfit7 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit7.summary()
```

```
[29]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results

```
=====
=====
```

```
Dep. Variable:          W    R-squared (uncentered):
1.000
Model:                OLS    Adj. R-squared (uncentered):
1.000
Method:                Least Squares    F-statistic:
1.561e+05
Date:                  Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                  09:02:02    Log-Likelihood:
-1061.1
No. Observations:      666    AIC:
2160.
Df Residuals:          647    BIC:
2246.
Df Model:              19
Covariance Type:       nonrobust
```

```
=====
      coef    std err          t      P>|t|      [0.025      0.975]
```

```
-----
L          -0.8671      0.014    -61.475      0.000      -0.895      -0.839
R           0.0153      0.002     6.651      0.000       0.011       0.020
H          -0.0025      0.001     -1.895      0.058      -0.005      8.94e-05
2B          -0.0025      0.002     -1.119      0.264      -0.007       0.002
HR          -0.0057      0.003     -2.178      0.030      -0.011      -0.001
BB          -0.0027      0.001     -2.562      0.011      -0.005      -0.001
SB          -0.0023      0.002     -1.137      0.256      -0.006       0.002
CS          -0.0055      0.006     -0.963      0.336      -0.017       0.006
SF          -0.0068      0.007     -0.998      0.318      -0.020       0.007
RA           0.0051      0.002      2.598      0.010       0.001       0.009
SHO          0.0698      0.017      4.036      0.000       0.036       0.104
SV           0.0504      0.010      4.977      0.000       0.031       0.070
IPouts       0.0333      0.001     50.254      0.000       0.032       0.035
HA          -0.0045      0.001     -3.213      0.001      -0.007      -0.002
BBA          -0.0029      0.001     -2.766      0.006      -0.005      -0.001
SOA           0.0009      0.001      1.840      0.066     -6.37e-05       0.002
E          -0.0057      0.003     -1.836      0.067      -0.012       0.000
```

DP	0.0050	0.003	1.566	0.118	-0.001	0.011
FP	3.1526	0.910	3.466	0.001	1.366	4.939

```
=====
Omnibus:                10.188    Durbin-Watson:                2.088
Prob(Omnibus):          0.006    Jarque-Bera (JB):            14.307
Skew:                   0.132    Prob(JB):                    0.000782
Kurtosis:               3.668    Cond. No.                     9.82e+04
=====
```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 9.82e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
"""
```

```
[30]: # taking CS out of indVars because it is the next least signifigant variable_
      ↪ then I will remake the fit.
indVars.remove("CS")
Wfit8 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit8.summary()
```

```
[30]: <class 'statsmodels.iolib.summary.Summary'>
      """
                                OLS Regression Results
      =====
      Dep. Variable:                W    R-squared (uncentered):
      1.000
      Model:                        OLS    Adj. R-squared (uncentered):
      1.000
      Method:                        Least Squares    F-statistic:
      1.648e+05
      Date:                          Fri, 28 Apr 2023    Prob (F-statistic):
      0.00
      Time:                          09:02:02    Log-Likelihood:
      -1061.6
      No. Observations:              666    AIC:
      2159.
      Df Residuals:                  648    BIC:
      2240.
      Df Model:                      18
      Covariance Type:               nonrobust
      =====
                                coef    std err          t      P>|t|      [0.025    0.975]
```

```

-----
L          -0.8661      0.014    -61.561      0.000      -0.894      -0.839
R           0.0155      0.002      6.776      0.000       0.011       0.020
H          -0.0026      0.001     -2.009      0.045     -0.005    -5.86e-05
2B         -0.0023      0.002     -1.032      0.302     -0.007       0.002
HR         -0.0056      0.003     -2.166      0.031     -0.011     -0.001
BB         -0.0028      0.001     -2.612      0.009     -0.005     -0.001
SB         -0.0035      0.002     -2.087      0.037     -0.007     -0.000
SF         -0.0069      0.007     -1.011      0.312     -0.020       0.007
RA           0.0050      0.002      2.551      0.011       0.001       0.009
SHO         0.0711      0.017      4.128      0.000       0.037       0.105
SV           0.0501      0.010      4.946      0.000       0.030       0.070
IPouts      0.0333      0.001     50.275      0.000       0.032       0.035
HA         -0.0044      0.001     -3.171      0.002     -0.007     -0.002
BBA        -0.0030      0.001     -2.803      0.005     -0.005     -0.001
SOA         0.0011      0.001      2.083      0.038    6.04e-05       0.002
E          -0.0064      0.003     -2.120      0.034     -0.012     -0.000
DP           0.0051      0.003      1.575      0.116     -0.001       0.011
FP           3.0699      0.906      3.390      0.001       1.292       4.848
=====
Omnibus:                10.009    Durbin-Watson:                2.099
Prob(Omnibus):           0.007    Jarque-Bera (JB):            14.131
Skew:                    0.126    Prob(JB):                     0.000854
Kurtosis:                3.668    Cond. No.                     9.78e+04
=====

```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 9.78e+04. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```

[31]: # taking SF out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("SF")
Wfit9 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit9.summary()

```

```

[31]: <class 'statsmodels.iolib.summary.Summary'>
      """

```

OLS Regression Results

```

=====
=====
Dep. Variable:                W    R-squared (uncentered):

```

```

1.000
Model:                      OLS   Adj. R-squared (uncentered):
1.000
Method:                     Least Squares   F-statistic:
1.745e+05
Date:                       Fri, 28 Apr 2023   Prob (F-statistic):
0.00
Time:                       09:02:02   Log-Likelihood:
-1062.1
No. Observations:          666   AIC:
2158.
Df Residuals:              649   BIC:
2235.
Df Model:                  17
Covariance Type:          nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
L             -0.8659      0.014     -61.551      0.000     -0.894     -0.838
R              0.0150      0.002       6.713      0.000       0.011       0.019
H             -0.0026      0.001      -2.038      0.042     -0.005     -9.61e-05
2B            -0.0023      0.002      -1.033      0.302     -0.007       0.002
HR            -0.0049      0.002      -1.956      0.051     -0.010     1.83e-05
BB            -0.0028      0.001      -2.642      0.008     -0.005     -0.001
SB            -0.0036      0.002      -2.165      0.031     -0.007     -0.000
RA             0.0049      0.002       2.505      0.012       0.001       0.009
SHO           0.0712      0.017       4.134      0.000       0.037       0.105
SV            0.0499      0.010       4.930      0.000       0.030       0.070
IPouts        0.0332      0.001      50.283      0.000       0.032       0.035
HA            -0.0043      0.001      -3.108      0.002     -0.007     -0.002
BBA           -0.0029      0.001      -2.743      0.006     -0.005     -0.001
SOA           0.0011      0.001       2.121      0.034     7.92e-05       0.002
E            -0.0064      0.003      -2.103      0.036     -0.012     -0.000
DP            0.0051      0.003       1.571      0.117     -0.001       0.011
FP            3.0686      0.906       3.389      0.001       1.290       4.847
=====
Omnibus:              11.290   Durbin-Watson:              2.098
Prob(Omnibus):        0.004   Jarque-Bera (JB):              16.409
Skew:                 0.138   Prob(JB):              0.000273
Kurtosis:             3.717   Cond. No.              9.78e+04
=====

```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 9.78e+04. This might indicate that there are strong multicollinearity or other numerical problems.
 """

```
[32]: # taking 2B out of indVars because it is the next least significant variable
      ↪ then I will remake the fit.
indVars.remove("2B")
Wfit10 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit10.summary()
```

```
[32]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
=====
Dep. Variable:                  W      R-squared (uncentered):
1.000
Model:                        OLS      Adj. R-squared (uncentered):
1.000
Method:                      Least Squares      F-statistic:
1.853e+05
Date:                        Fri, 28 Apr 2023      Prob (F-statistic):
0.00
Time:                        09:02:02      Log-Likelihood:
-1062.7
No. Observations:              666      AIC:
2157.
Df Residuals:                  650      BIC:
2229.
Df Model:                      16
Covariance Type:              nonrobust
=====
=====

```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8656	0.014	-61.540	0.000	-0.893	-0.838
R	0.0146	0.002	6.640	0.000	0.010	0.019
H	-0.0028	0.001	-2.215	0.027	-0.005	-0.000
HR	-0.0044	0.002	-1.797	0.073	-0.009	0.000
BB	-0.0027	0.001	-2.584	0.010	-0.005	-0.001
SB	-0.0032	0.002	-1.989	0.047	-0.006	-4.11e-05
RA	0.0049	0.002	2.534	0.012	0.001	0.009
SHO	0.0714	0.017	4.143	0.000	0.038	0.105
SV	0.0508	0.010	5.042	0.000	0.031	0.071
IPouts	0.0332	0.001	50.422	0.000	0.032	0.034
HA	-0.0044	0.001	-3.163	0.002	-0.007	-0.002
BBA	-0.0029	0.001	-2.717	0.007	-0.005	-0.001
SOA	0.0011	0.001	2.126	0.034	8.2e-05	0.002

E	-0.0064	0.003	-2.097	0.036	-0.012	-0.000
DP	0.0053	0.003	1.648	0.100	-0.001	0.012
FP	3.1181	0.904	3.448	0.001	1.342	4.894

```
=====
Omnibus:                12.013    Durbin-Watson:                2.101
Prob(Omnibus):           0.002    Jarque-Bera (JB):           17.714
Skew:                    0.146    Prob(JB):                   0.000142
Kurtosis:                3.744    Cond. No.                   9.75e+04
=====
```

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 9.75e+04. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```
[33]: # taking DP out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("DP")
Wfit11 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit11.summary()
```

```
[33]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
=====
Dep. Variable:                  W    R-squared (uncentered):
1.000
Model:                          OLS    Adj. R-squared (uncentered):
1.000
Method:                          Least Squares    F-statistic:
1.972e+05
Date:                            Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                            09:02:02    Log-Likelihood:
-1064.1
No. Observations:                666    AIC:
2158.
Df Residuals:                    651    BIC:
2226.
Df Model:                        15
Covariance Type:                nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8662	0.014	-61.519	0.000	-0.894	-0.839
R	0.0148	0.002	6.717	0.000	0.010	0.019
H	-0.0030	0.001	-2.332	0.020	-0.006	-0.000
HR	-0.0042	0.002	-1.730	0.084	-0.009	0.001
BB	-0.0030	0.001	-2.869	0.004	-0.005	-0.001
SB	-0.0034	0.002	-2.103	0.036	-0.007	-0.000
RA	0.0045	0.002	2.318	0.021	0.001	0.008
SHO	0.0727	0.017	4.218	0.000	0.039	0.107
SV	0.0493	0.010	4.905	0.000	0.030	0.069
IPouts	0.0334	0.001	51.549	0.000	0.032	0.035
HA	-0.0039	0.001	-2.858	0.004	-0.007	-0.001
BBA	-0.0024	0.001	-2.369	0.018	-0.004	-0.000
SOA	0.0008	0.000	1.665	0.096	-0.000	0.002
E	-0.0067	0.003	-2.208	0.028	-0.013	-0.001
FP	3.0519	0.905	3.374	0.001	1.276	4.828

Omnibus:	13.223	Durbin-Watson:	2.107
Prob(Omnibus):	0.001	Jarque-Bera (JB):	20.504
Skew:	0.145	Prob(JB):	3.53e-05
Kurtosis:	3.809	Cond. No.	9.73e+04

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 9.73e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
[34]: # taking SOA out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("SOA")
Wfit12 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit12.summary()
```

```
[34]: <class 'statsmodels.iolib.summary.Summary'>
      """
                                OLS Regression Results
      =====
      Dep. Variable:              W    R-squared (uncentered):
      1.000
      Model:                    OLS    Adj. R-squared (uncentered):
```

```

1.000
Method:                Least Squares    F-statistic:
2.107e+05
Date:                  Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                  09:02:02    Log-Likelihood:
-1065.5
No. Observations:      666    AIC:
2159.
Df Residuals:          652    BIC:
2222.
Df Model:              14
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8667	0.014	-61.484	0.000	-0.894	-0.839
R	0.0147	0.002	6.664	0.000	0.010	0.019
H	-0.0032	0.001	-2.482	0.013	-0.006	-0.001
HR	-0.0036	0.002	-1.470	0.142	-0.008	0.001
BB	-0.0031	0.001	-3.006	0.003	-0.005	-0.001
SB	-0.0036	0.002	-2.258	0.024	-0.007	-0.000
RA	0.0052	0.002	2.747	0.006	0.001	0.009
SHO	0.0732	0.017	4.241	0.000	0.039	0.107
SV	0.0488	0.010	4.849	0.000	0.029	0.069
IPouts	0.0340	0.001	64.592	0.000	0.033	0.035
HA	-0.0050	0.001	-4.326	0.000	-0.007	-0.003
BBA	-0.0027	0.001	-2.642	0.008	-0.005	-0.001
E	-0.0076	0.003	-2.530	0.012	-0.013	-0.002
FP	2.9812	0.905	3.295	0.001	1.204	4.758

```

=====
Omnibus:                15.677    Durbin-Watson:                2.110
Prob(Omnibus):          0.000    Jarque-Bera (JB):            25.026
Skew:                   0.174    Prob(JB):                    3.68e-06
Kurtosis:               3.884    Cond. No.                    9.47e+04
=====

```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 9.47e+04. This might indicate that there are strong multicollinearity or other numerical problems.

"""


```
[35]: # taking HR out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
```

```
indVars.remove("HR")
Wfit13 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit13.summary()
```

```
[35]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results

```
=====
=====
```

```
Dep. Variable:          W    R-squared (uncentered):
1.000
Model:                OLS    Adj. R-squared (uncentered):
1.000
Method:                Least Squares    F-statistic:
2.265e+05
Date:                  Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:                  09:02:02    Log-Likelihood:
-1066.6
No. Observations:      666    AIC:
2159.
Df Residuals:          653    BIC:
2218.
Df Model:              13
Covariance Type:       nonrobust
```

```
=====
              coef      std err          t      P>|t|      [0.025      0.975]
```

```
-----
L            -0.8652      0.014    -61.480      0.000      -0.893      -0.838
R             0.0127      0.002     7.284      0.000       0.009       0.016
H            -0.0021      0.001    -1.998      0.046      -0.004     -3.61e-05
BB            -0.0026      0.001    -2.669      0.008      -0.005      -0.001
SB            -0.0030      0.002    -1.917      0.056      -0.006     7.13e-05
RA             0.0047      0.002     2.528      0.012       0.001       0.008
SHO           0.0745      0.017     4.320      0.000       0.041       0.108
SV            0.0474      0.010     4.728      0.000       0.028       0.067
IPouts        0.0337      0.000    68.486      0.000       0.033       0.035
HA            -0.0048      0.001    -4.181      0.000      -0.007      -0.003
BBA           -0.0026      0.001    -2.562      0.011      -0.005      -0.001
E             -0.0073      0.003    -2.448      0.015      -0.013      -0.001
FP            3.0449      0.905     3.366      0.001       1.269       4.821
```

```
=====
Omnibus:              15.546    Durbin-Watson:              2.097
Prob(Omnibus):         0.000    Jarque-Bera (JB):           24.457
Skew:                  0.178    Prob(JB):                   4.89e-06
```

Kurtosis: 3.869 Cond. No. 9.45e+04
=====

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 9.45e+04. This might indicate that there are strong multicollinearity or other numerical problems.
"""

```
[36]: # taking SB out of indVars because it is the next least signifigant variable
      ↪ then I will remake the fit.
indVars.remove("SB")
Wfit14 = sm.OLS(train[depVar], train[indVars]).fit()
Wfit14.summary()
```

```
[36]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results

=====

```
Dep. Variable:          W    R-squared (uncentered):
1.000
Model:              OLS    Adj. R-squared (uncentered):
1.000
Method:          Least Squares    F-statistic:
2.444e+05
Date:          Fri, 28 Apr 2023    Prob (F-statistic):
0.00
Time:          09:02:02    Log-Likelihood:
-1068.5
No. Observations:          666    AIC:
2161.
Df Residuals:          654    BIC:
2215.
Df Model:              12
Covariance Type:          nonrobust
```

	coef	std err	t	P> t	[0.025	0.975]
L	-0.8653	0.014	-61.359	0.000	-0.893	-0.838
R	0.0126	0.002	7.247	0.000	0.009	0.016
H	-0.0022	0.001	-2.074	0.038	-0.004	-0.000
BB	-0.0026	0.001	-2.667	0.008	-0.005	-0.001
RA	0.0050	0.002	2.716	0.007	0.001	0.009

SHO	0.0764	0.017	4.427	0.000	0.043	0.110
SV	0.0475	0.010	4.724	0.000	0.028	0.067
IPouts	0.0337	0.000	68.425	0.000	0.033	0.035
HA	-0.0050	0.001	-4.293	0.000	-0.007	-0.003
BBA	-0.0027	0.001	-2.678	0.008	-0.005	-0.001
E	-0.0081	0.003	-2.738	0.006	-0.014	-0.002
FP	2.8637	0.902	3.176	0.002	1.093	4.634

```
=====
Omnibus:                17.346    Durbin-Watson:                2.108
Prob(Omnibus):           0.000    Jarque-Bera (JB):          27.716
Skew:                    0.199    Prob(JB):                  9.58e-07
Kurtosis:                3.917    Cond. No.                  9.40e+04
=====
```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
 - [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 - [3] The condition number is large, 9.4e+04. This might indicate that there are strong multicollinearity or other numerical problems.
- """

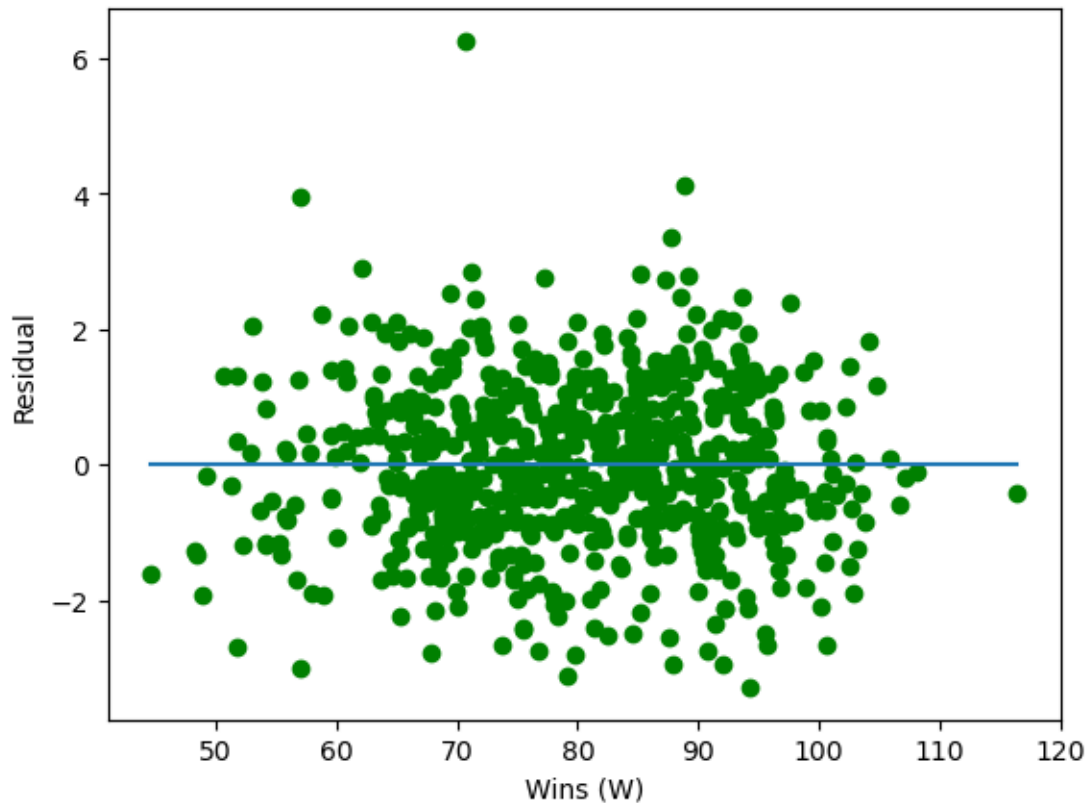
interpretation

Now that all the independent variables are at or below 0.05 they are all significant and fit14 is the final fit. The R-squared value tells us how well our independent variables fit our dependent variables the closer to 1 the better and the closer to 0 is bad. The value of 1 is as good as it gets and tells us that all of our outputs can be explained.

```
[37]: res = Wfit14.resid
```

```
[38]: fig = px.box(res)
fig.update_layout(title = "Boxplot of Residuals",
                    yaxis_title = "Residual Values")
fig.show()
```

```
[39]: plt.scatter(Wfit14.fittedvalues, res, color = "green")
plt.plot([min(Wfit14.fittedvalues), max(Wfit14.fittedvalues)], [0,0])
plt.xlabel("Wins (W)")
plt.ylabel("Residual")
plt.show()
```



```
[40]: fig = px.histogram(res)
fig.update_layout(title = "Histogram of Residuals",
                  xaxis_title = "Residuals",
                  yaxis_title = "Frequency")
fig.update_traces(marker_line_width = 1, marker_line_color = "orange")
fig.show()
```

The boxplot shows us that our model is a good fit for our data because the median is close to 0 and Q1 and Q3 seem to be about the same length. This is further backed up by the histogram because our residuals seem to be normally distributed.

1.4 Data Visualization

```
[41]: # applying both predictive models with the test set
HRAindVars = ['ER', 'SHO', 'IPouts', 'HA', 'BBA', 'SOA']
WindVars = ['L', 'R', 'H', 'BB', 'RA', 'SHO', 'SV', 'IPouts', 'HA', 'BBA', 'E', 'FP']
predictionsHRA = HRAfit7.predict(test[HRAindVars])
predictionsW = Wfit14.predict(test[WindVars])
print(predictionsHRA.head())
print(predictionsW.head())
```

```
2154      119.134959
```

```

2156    152.538357
2157    107.246668
2163    108.520870
2167    154.437898
dtype: float64
2154     63.614678
2156     48.619044
2157     67.329649
2163     50.539221
2167     54.381424
dtype: float64

```

```

[42]: warnings.filterwarnings("ignore")
predictDF = test.copy()
predictDF['HRAPredictions'] = predictionsHRA
predictDF['Wpredictions'] = predictionsW
RevisedTeams2DF = predictDF[['yearID', 'franchID', 'W', 'HRA', 
    ↳ 'HRAPredictions', 'Wpredictions']]
RevisedTeams2DF['roundedHRAPredictions'] = RevisedTeams2DF['HRAPredictions'].
    ↳ round(0)
RevisedTeams2DF['roundedWPredictions'] = RevisedTeams2DF['Wpredictions'].
    ↳ round(0)
RevisedTeams2DF['HRATF'] = RevisedTeams2DF['HRA'] == 
    ↳ RevisedTeams2DF['roundedHRAPredictions']
RevisedTeams2DF['WTF'] = RevisedTeams2DF['W'] == 
    ↳ RevisedTeams2DF['roundedWPredictions']
RevisedTeams2DF.head()
# I rounded the predictions up because you can't have half a win or half a home

```

```

[42]:      yearID  franchID   W  HRA  HRAPredictions  Wpredictions  \
2154    1994      BAL   63  131      119.134959      63.614678
2156    1994      ANA   47  150      152.538357      48.619044
2157    1994      CHW   67  115      107.246668      67.329649
2163    1994      FLA   51  120      108.520870      50.539221
2167    1994      MIN   53  153      154.437898      54.381424

      roundedHRAPredictions  roundedWPredictions  HRATF   WTF
2154                   119.0                   64.0  False  False
2156                   153.0                   49.0  False  False
2157                   107.0                   67.0  False   True
2163                   109.0                   51.0  False   True
2167                   154.0                   54.0  False  False

```

Graphs of Predicted Values vs Actual Values Using Test Set HRA predictions graph

```

[43]:

```

```
fig = px.scatter(RevisedTeams2DF, x = 'roundedHRAPredictions', y = 'HRA', color=
    ↪ 'franchID')
fig.update_layout(title = "Home Runs Agianst Values V. Predicted Home Runs
    ↪ Aginast Values",
                  axis_title = "Predicted Home Runs Agianst",
                  axis_title = "Home Runs Agianst")
fig.add_shape(type = "line",
              line=dict(color="red", width=2),
              x0 = 100,
              y0=100,
              x1=275,
              y1=275)
fig.show()
```

Wins predictions graph

```
[44]: fig = px.scatter(RevisedTeams2DF, x = 'roundedWPredictions', y = 'W', color =
    ↪ 'franchID')
fig.update_layout(title = "Wins Values V. Predicted Wins Values",
                  axis_title = "Predicted Wins",
                  axis_title = "Wins")
fig.add_shape(type = "line",
              line=dict(color="red", width=2),
              x0 = 40,
              y0=40,
              x1=125,
              y1=125)
fig.show()
```

The Home Runs Against model seems to give a rough estimate of how many home runs a team may give up while to Wins model seems to accurately predict a teams actual win total.

Results

```
[45]: HRATFResults = RevisedTeams2DF.groupby("HRATF").size().reset_index(name="count")
print(HRATFResults)
WResults = RevisedTeams2DF.groupby("WTF").size().reset_index(name="count")
print(WResults)
```

	HRATF	count
0	False	155
1	True	11

	WTF	count
0	False	112
1	True	54

The Home Runs Agianst Model predicted 11/166 values correctly which is a little over 6% and isn't all that great while the Wins model predicted 54/166 values correctly which is around 33% and is pretty good especially when looking at the graph and seeing the predcited values are typically within 5 wins of the actual value.

1.5 Predicting 2023 wins so far

In order to get the 2023 stats that are available so far I ended up downloading the csv files of team data from baseball reference and imported them into excel to clean rather than doing web scraping and cleaning in python.

```
[46]: # importing the csv file
teamStats2023 = pd.read_csv("2023TeamStats.csv")
teamStats2023.head()
```

```
[46]:  franchID    R    H  BB   L  SHO  SV  IPouts   HA  BBA   E    FP   RA   W
0     ARI   121  226  58  12    4   7   684.0  202  106   8  0.992  123  14
1     ATL   130  221  98   8    2   7   672.0  197   80  16  0.982   90  17
2     BAL   125  200  97   8    3   6   642.6  198   71  12  0.986  104  16
3     BOS   146  222  92  13    0   7   684.0  233   80  17  0.982  138  13
4     CHC   130  221  83  10    5   2   618.6  163   78  11  0.987   87  13
```

```
[47]: WindVars = ['L', 'R', 'H', 'BB', 'RA', 'SHO', 'SV', 'IPouts', 'HA', 'BBA', 'E', 'FP']
Wpredictions2023 = Wfit14.predict(teamStats2023[WindVars])
print(Wpredictions2023.head())
```

```
0    16.328718
1    19.087921
2    18.243139
3    15.283615
4    15.800378
dtype: float64
```

```
[48]: predictDF = teamStats2023.copy()
predictDF['Wpredictions'] = Wpredictions2023
RevisedTeams2DF = predictDF[['franchID', 'W', 'Wpredictions']]
RevisedTeams2DF['roundedWPredictions'] = RevisedTeams2DF['Wpredictions'].
↳round(0)
RevisedTeams2DF['TF'] = RevisedTeams2DF['W'] ==_
↳RevisedTeams2DF['roundedWPredictions']
RevisedTeams2DF.head()
```

```
[48]:  franchID    W  Wpredictions  roundedWPredictions    TF
0     ARI   14    16.328718             16.0  False
1     ATL   17    19.087921             19.0  False
2     BAL   16    18.243139             18.0  False
3     BOS   13    15.283615             15.0  False
4     CHC   13    15.800378             16.0  False
```

```
[49]: fig = px.scatter(RevisedTeams2DF, x = 'roundedWPredictions', y = 'W', color =_
↳'franchID')
fig.update_layout(title = "Wins Values V. Predicted Wins Values in 2023",
                  xaxis_title = "Predicted Wins",
                  yaxis_title = "Wins")
```

```
fig.add_shape(type = "line",
              line=dict(color="red", width=2),
              x0 = 0,
              y0=0,
              x1=40,
              y1=40)
fig.show()
```

```
[50]: WResults = RevisedTeams2DF.groupby("TF").size().reset_index(name="count")
      print(WResults)
```

```
      TF  count
0  False    30
```

The model didn't predict the right amount of wins that a team currently has but the predictions were really close and this is probably due to the low sample size since the 2023 season just started.

2 Conclusion

In conclusion, I was able to answer all of the questions I wanted to. Even though the models I made weren't as good as I were expecting both models give you a good idea of how many wins a team may have or home runs against a team may give up. Overall I really don't think I could improve on either model with the information I used in the packages but, if I had more time I think I could've pulled more advanced baseball statistics and been able to get more accuracy out of both models. In the end both models did what they were supposed to and the predicted values give a good indication of what the real value will be.

3 References

https://www.baseball-reference.com/leagues/majors/2023.shtml#all_teams_standard_pitching