Exploring MLB's 2020 Season with Altered Baseballs
Python Analysis

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Useful Baseball Statistics Terminology

Sabermetrics - The empirical analysis of baseball statistics that measure in-game activity.

H - Hits

HR - Home runs

RBI - Runs batted in

WAR - Wins Above Replacement an all-encompassing statistic that assigns a numeric value to a player in comparison to "0" which would be considered a "league average player"

AVG - Batting average (average of how many times a hitter gets a hit per at bat)

SLG% - Slugging percentage (% of hits that are more than just a single)

ERA- Earned Run Average (How many runs a pitcher usually gives up per 9 innings of play)

K - Strikeouts

H/9 - Hits per 9 innings (How many hits a pitcher allows per 9 innings of play)

HR/9 - Home runs per 9 innings (How many homeruns a pitcher allows per 9 innings)

EV - Exit Velocity (how fast a baseball is traveling after it's been hit)

What's So Interesting About These Baseballs?

Two weeks before the start of the MLB's 2021 Spring Training campaign. MLB Executive Reporter Mark Feinsand broke that an independent lab reported that official game used baseballs used in the 2020 season had less drag and flew one to two feet shorter on balls hit over 375 feet. The conclusion being inconsistencies in the height of the seams. Rawlings Official Game Used Baseballs are all hand sewn and have a deviation range of .530 to .570. Rawlings has since admitted to loosening the seams on the baseballs which is supposed to slightly reduce drag which in turn should increase overall hitting production. This is all after a groundbreaking discovery by Dr. Meredith Wills who found that the baseballs used in 2019 and the 2020 shortened season were inconsistent with the baseballs used in seasons past. What makes these studies and claims so interesting is that the 2020 season was cut short because of COVID as all these rumors of the ball being different started circling. There is a large gap in data that does not exist because the 2020 was hardly 2 months' worth of games. We will analyze data from the 2018-2021 seasons and create a regression algorithm that takes in previous season data and predicts stats for a full 162 game 2020 season which we will compare to see how it stacks up to the "juiced" season of 2019 or "normal" season of 2018.

How Will We Analyze and Munge This Data?

pybaseball is a Python package for baseball data analysis. This package scrapes Baseball Reference, Baseball Savant, and FanGraphs so we don't have to. The package retrieves statcast data, pitching stats, batting stats, division standings/team records, awards data, and more. Data is available at the individual pitch level, as well as aggregated at the season level and over custom time periods. Baseball Savant is MLB's clearinghouse for statcast data (statcast is a high-speed, high-accuracy, automated tool developed to analyze player movements and athletic abilities in Major League Baseball (MLB))

In this project I use a package called **pybaseball** to analyze original quantitative baseball statistics and sabermetric data to see if we notice a difference in offensive production from season to season. We will also analyze **statcast** data exported in .csv format from the Baseball Savant website to compare baseball exit velocity and launch angles per season. I also use **pandas** for our data frames, **seaborn** and **matplotlib** for visualization purposes, and **sklearn** for our linear regression model.

All the code used in this analysis can be found on my Github under the "Exploring MLB's 2020 Season with Altered Baseball" repository. I highly encourage running the code on google colab or your choice of IDE for the sake of clarity and space. I will condense or omit our python code outputs to data that is considered important to our analysis.

Analyzing Hitting Statistics From the 2018-2021 MLB Seasons

Lets begin by pip installing pybaseball and matplotlib (for visualization), importing pandas for our dataframes and setting our display options, importing seaborn (for visualization), importing sklearn for our linear regression model and importing pybaseball.

```
%pip install pybaseball==2.2.1
%matplotlib inline
import pandas as pd;
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', -1)
pd.set_option('display.float_format', lambda x: '%.5f' % x)

import seaborn as sns
import sklearn as sk
import pybaseball as pyb
from matplotlib import pyplot as plt
from pybaseball import cache
cache.enable()
import warnings; warnings.filterwarnings('ignore')
```

Next, we will import our cumulative battings statistics from pybaseball and filter each DF up until the WAR column

```
#importing cumulative team batting stats from pybaseball


from pybaseball import team_batting as team_batting
batting_stats_2018 = team_batting(2018)
batting_stats_2019 = team_batting(2019)
batting_stats_2020 = team_batting(2020)
batting_stats_2021 = team_batting(2021)
#modifying data frames for each season to only show columns up to WAR
batting_stats_2018 = batting_stats_2018.loc[:, :'WAR']
batting_stats_2019 = batting_stats_2019.loc[:, :'WAR']
batting_stats_2020 = batting_stats_2020.loc[:, :'WAR']
batting_stats_2021 = batting_stats_2021.loc[:, :'WAR']
```

Now we will call our batting stats data frames we have created to extract the meaningful and most important hitting stats.

```
batting_stats_2018.mean()
```

```
teamIDfg    15.50000
Season      2018.00000
Age         27.96667
G           2386.33333
AB          5514.40000
PA          6171.30000
H           1367.26667
1B          877.40000
2B          275.46667
3B          28.23333
HR          186.16667
R           721.00000
RBI         686.86667
BB          522.86667
IBB         30.96667
SO          1373.56667
HBP         64.06667
SF          41.16667
SH          27.43333
GDP         115.23333
SB          82.46667
CS          31.93333
AVG         0.24783
GB          1790.16667
FB          1465.33333
LD          889.23333
IFFB        151.43333
Pitches     24039.70000
Balls       8717.60000
Strikes     15322.10000
IFH         121.40000
BU          64.43333
BUH         14.70000
BB%         0.08463
K%          0.22277
BB/K        0.38300
OBP         0.31797
SLG         0.40923
OPS         0.72723
ISO         0.16130
BABIP       0.29547
GB/FB       1.23067
LD%         0.21460
GB%         0.43207
FB%         0.35340
IFFB%       0.10327
HR/FB       0.12683
```

```
IFH%        0.06770
BUH%        0.23057
wOBA        0.31460
wRAA       -1.76667
wRC        719.33333
Bat        -25.98333
Fld         0.58000
Rep        184.64667
Pos         10.87333
RAR        184.64000
WAR         19.01333
dtype: float64
```

batting_stats_2018.sum()

```
teamIDfg      465
Season        60540
Team
BOSNYYLADCLEOAKHOUWSNCOLTBRMILCHCATLTORCINSTLTEXLAAMINSEAPITPHIARINYMCHWKC
RBALDETSDPSFGMIA
Age           839
G             71590
AB            165432
PA            185139
H             41018
1B            26322
2B            8264
3B            847
HR            5585
R             21630
RBI           20606
BB            15686
IBB           929
SO            41207
HBP           1922
SF            1235
SH            823
GDP           3457
SB            2474
CS            958
AVG          7.43500
GB            53705
FB            43960
LD            26677
IFFB          4543
Pitches       721191
Balls         261528
Strikes       459663
IFH           3642
BU            1933
BUH           441
BB%          2.53900
```

```
K%          6.68300
BB/K        11.49000
OBP         9.53900
SLG         12.27700
OPS         21.81700
ISO         4.83900
BABIP       8.86400
GB/FB       36.92000
LD%         6.43800
GB%         12.96200
FB%         10.60200
IFFB%       3.09800
HR/FB       3.80500
IFH%        2.03100
BUH%        6.91700
wOBA        9.43800
wRAA        -53.00000
wRC          21580
Bat         -779.50000
Fld         17.40000
Rep         5539.40000
Pos         326.20000
RAR         5539.20000
WAR         570.40000
dtype: object
```

The 2018 season was the last season in which the balls were reported “normal”. Here are the main hitting statistics for that season:

H= 41,018
HR= 5,585
RBI= 20,606
WAR= 570
AVG= .248
SLG% = .409

```
batting_stats_2019.mean()
```

```
Season      2019.00000
Age         27.86667
G           2389.46667
AB          5555.03333
PA          6217.20000
H           1401.30000
1B          864.90000
2B          284.36667
3B          26.16667
HR          225.86667
R           782.23333
RBI         749.03333
BB          529.83333
```

```
IBB         25.10000
SO          1427.43333
HBP         66.13333
SF          38.33333
SH          25.86667
GDP         115.43333
SB          76.00000
CS          27.73333
AVG         0.25217
GB          1772.26667
FB          1476.10000
LD          886.23333
IFFB        145.30000
Pitches     24415.90000
Balls       8857.03333
Strikes     15558.86667
IFH         115.13333
BU          56.60000
BUH         12.86667
BB%         0.08520
K%          0.22983
BB/K        0.37467
OBP         0.32243
SLG         0.43467
OPS         0.75723
ISO         0.18257
BABIP       0.29827
GB/FB       1.20900
LD%         0.21430
GB%         0.42873
FB%         0.35693
IFFB%       0.09823
HR/FB       0.15240
IFH%        0.06493
BUH%        0.23393
wOBA        0.31973
wRAA        -1.97000
wRC         780.53333
Bat         -27.58667
Fld         0.37333
Rep         195.53667
Pos         11.34667
RAR         195.55333
WAR         18.99000
dtype: float64
```

batting_stats_2019.sum()

```
teamIDfg     465
Season       60570
Team
HOUMINNYYLADBOSWSNATLCHCCOLOAKNYMMILTBRARICLETEXLAAPHISTLSEAPITCINTORCHWBA
LSDPKCRSFGDETMIA
Age          836
```

G	71684
AB	166651
PA	186516
H	42039
1B	25947
2B	8531
3B	785
HR	6776
R	23467
RBI	22471
BB	15895
IBB	753
SO	42823
HBP	1984
SF	1150
SH	776
GDP	3463
SB	2280
CS	832
AVG	7.56500
GB	53168
FB	44283
LD	26587
IFFB	4359
Pitches	732477
Balls	265711
Strikes	466766
IFH	3454
BU	1698
BUH	386
BB%	2.55600
K%	6.89500
BB/K	11.24000
OBP	9.67300
SLG	13.04000
OPS	22.71700
ISO	5.47700
BABIP	8.94800
GB/FB	36.27000
LD%	6.42900
GB%	12.86200
FB%	10.70800
IFFB%	2.94700
HR/FB	4.57200
IFH%	1.94800
BUH%	7.01800
wOBA	9.59200
wRAA	-59.10000
wRC	23416
Bat	-827.60000
Fld	11.20000
Rep	5866.10000
Pos	340.40000
RAR	5866.60000

```
WAR         569.70000
dtype: object
```

The 2019 season was the first season of the juiced baseballs. These stats show an obvious increase in hitting production league wide.

H= 42,039
HR= 6,776
RBI = 22,471
WAR= 570
AVG= .252
SLG%= .435

```
batting_stats_2020.mean()
```

```
teamIDfg    15.50000
Season      2020.00000
Age         27.83333
G           890.70000
AB          1967.66667
PA          2216.86667
H           481.30000
1B          302.36667
2B          94.10000
3B          8.03333
HR          76.80000
R           278.13333
RBI         265.93333
BB          203.06667
IBB         6.73333
SO          519.53333
HBP         27.36667
SF          13.40000
SH          4.20000
GDP         41.23333
SB          29.50000
CS          9.73333
AVG         0.24423
GB          620.63333
FB          517.76667
LD          313.93333
IFFB        49.30000
Pitches     8786.36667
Balls       3254.93333
Strikes     5531.43333
IFH         43.30000
BU          13.33333
BUH         4.40000
```

```
BB%         0.09153
K%          0.23463
BB/K        0.39367
OBP         0.32163
SLG         0.41690
OPS         0.73850
ISO         0.17277
BABIP       0.29163
GB/FB       1.20700
LD%         0.21617
GB%         0.42750
FB%         0.35630
IFFB%       0.09533
HR/FB       0.14817
IFH%        0.06950
BUH%        0.34223
wOBA        0.31943
wRAA        0.01667
wRC         278.23333
Bat         0.35333
Fld         0.22000
Rep         72.19333
Pos         -7.26000
RAR         72.19667
WAR         7.01667
dtype: float64
```

```
batting_stats_2020.sum()
```

```
teamIDfg     465
Season       60600
Team
ATLLADNYMSDPNYYSFGPHICHWBOSWSNLAATORTBRBALMINOAKCINHOUCHCKCRMIACOLMILSTLAR
ICLEDETSEATEXPIT
Age          835
G            26721
AB           59030
PA           66506
H            14439
1B           9071
2B           2823
3B           241
HR           2304
R            8344
RBI          7978
BB           6092
IBB          202
SO           15586
HBP          821
SF           402
SH           126
GDP          1237
SB           885
```

```
CS           292
AVG         7.32700
GB           18619
FB           15533
LD           9418
IFFB         1479
Pitches      263591
Balls        97648
Strikes      165943
IFH          1299
BU           400
BUH          132
BB%         2.74600
K%          7.03900
BB/K        11.81000
OBP         9.64900
SLG         12.50700
OPS         22.15500
ISO         5.18300
BABIP       8.74900
GB/FB       36.21000
LD%         6.48500
GB%         12.82500
FB%         10.68900
IFFB%       2.86000
HR/FB       4.44500
IFH%        2.08500
BUH%        10.26700
wOBA        9.58300
wRAA        0.50000
wRC          8347
Bat         10.60000
Fld         6.60000
Rep         2165.80000
Pos         -217.80000
RAR         2165.90000
WAR         210.50000
dtype: object
```

These stats are for the COVID shortened 2020 season (60 games) which is a small sample size to test if we want to see if the baseballs were juiced or not.

H=14,439
HR= 2,304
RBI= 7,978
WAR= 210
AVG= .244
SLG% = .417

```
batting_stats_2021.mean()
```

teamIDfg	15.50000
Season	2021.00000
Age	28.20000
G	2387.36667
AB	5398.03333
PA	6060.56667
H	1316.13333
1B	833.53333
2B	262.10000
3B	22.36667
HR	198.13333
R	733.66667
RBI	699.76667
BB	526.46667
IBB	23.43333
SO	1404.83333
HBP	70.40000
SF	38.10000
SH	25.53333
GDP	110.93333
SB	73.76667
CS	23.70000
AVG	0.24377
GB	1717.00000
FB	1459.86667
LD	827.06667
IFFB	145.43333
Pitches	23661.83333
Balls	8545.63333
Strikes	15116.20000
IFH	117.83333
BU	52.70000
BUH	10.43333
BB%	0.08677
K%	0.23183
BB/K	0.37600
OBP	0.31690
SLG	0.41053
OPS	0.72753
ISO	0.16680
BABIP	0.29160
GB/FB	1.18433
LD%	0.20653
GB%	0.42907
FB%	0.36447
IFFB%	0.09953
HR/FB	0.13547
IFH%	0.06870
BUH%	0.20773
wOBA	0.31420
wRAA	-1.96667
wRC	731.96667
Bat	-23.72333
Fld	0.84000

```
Rep        189.40000
Pos        9.55000
RAR        189.40000
WAR        18.99333
dtype: float64
```

batting_stats_2021.sum()

```
teamIDfg    465
Season      60630
Team
TORHOUBOSSFGCHWCINLADWSNATLTBRMINNYYCOLPHIOAKSDPSTLCHCMILLAANYMCLEDETBALKC
RARISEAPITMIATEX
Age          846
G            71621
AB           161941
PA           181817
H            39484
1B           25006
2B           7863
3B           671
HR           5944
R            22010
RBI          20993
BB           15794
IBB          703
SO           42145
HBP          2112
SF           1143
SH           766
GDP          3328
SB           2213
CS           711
AVG        7.31300
GB           51510
FB           43796
LD           24812
IFFB         4363
Pitches      709855
Balls        256369
Strikes      453486
IFH          3535
BU           1581
BUH          313
BB%        2.60300
K%         6.95500
BB/K       11.28000
OBP        9.50700
SLG        12.31600
OPS        21.82600
ISO        5.00400
BABIP      8.74800
```

```
GB/FB        35.53000
LD%          6.19600
GB%          12.87200
FB%          10.93400
IFFB%        2.98600
HR/FB        4.06400
IFH%         2.06100
BUH%         6.23200
wOBA         9.42600
wRAA         -59.00000
wRC           21959
Bat          -711.70000
Fld          25.20000
Rep          5682.00000
Pos          286.50000
RAR          5682.00000
WAR          569.80000
dtype: object
```

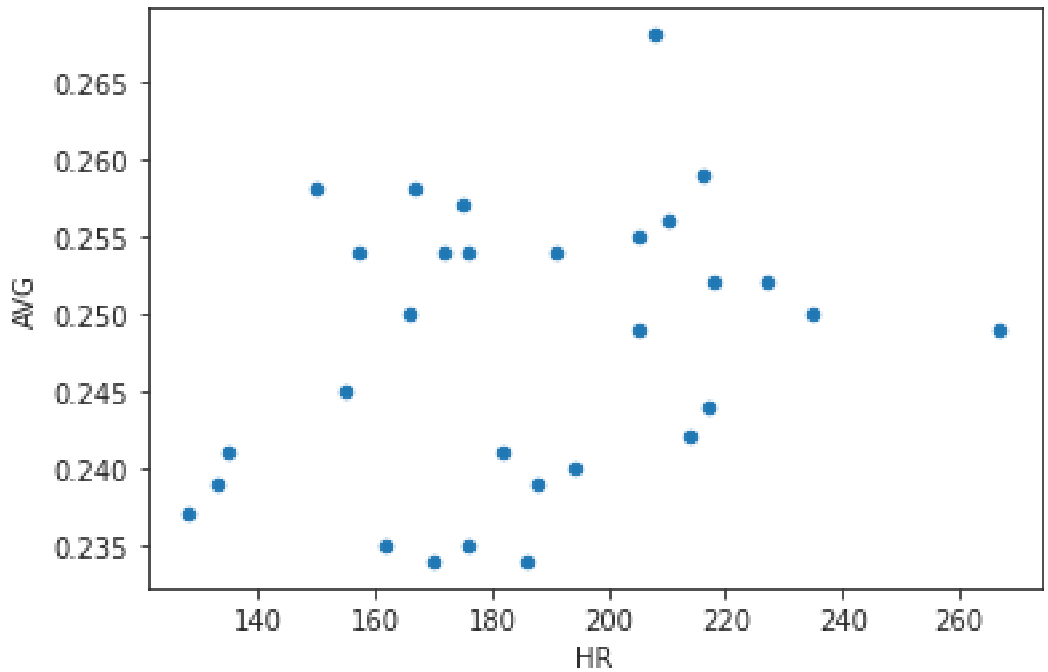
These stats are for the 2021 season (last full regular season) and the balls were apparently altered to perform like the baseballs of 2018.

H= 39,484
HR=5944
RBI= 20,993
WAR= 570
AVG=.244
SLG%= .411

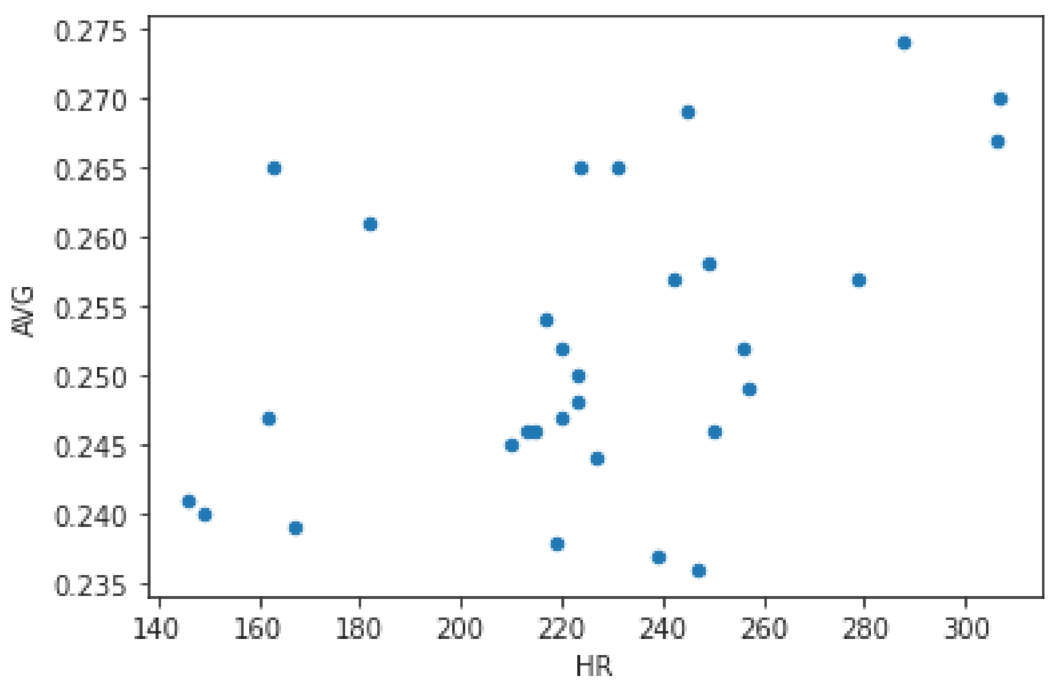
We will later create a linear regression algorithm that takes data from previous seasons and predicts what a full 2020 season would have been like. We will compare the stats for all 4 seasons (2018, 2019, 2020, 2021) and see if a hypothetical 2020 season would have performed closer to a regular season or the 2019 juiced ball season.

Lastly for this hitting section we will visualize a scatter plot for each data frame that shows us any correlation between homeruns and batting average.

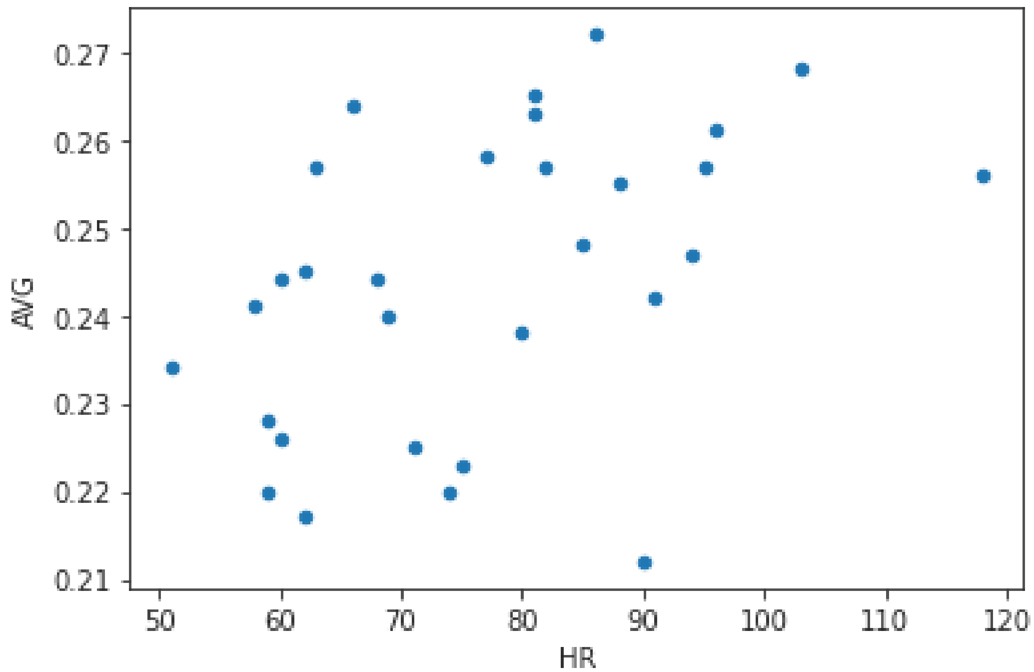
```
import seaborn as sns; sns.set_style('ticks');
batting_stats_2018.plot(x='HR', y='AVG', kind='scatter');
```



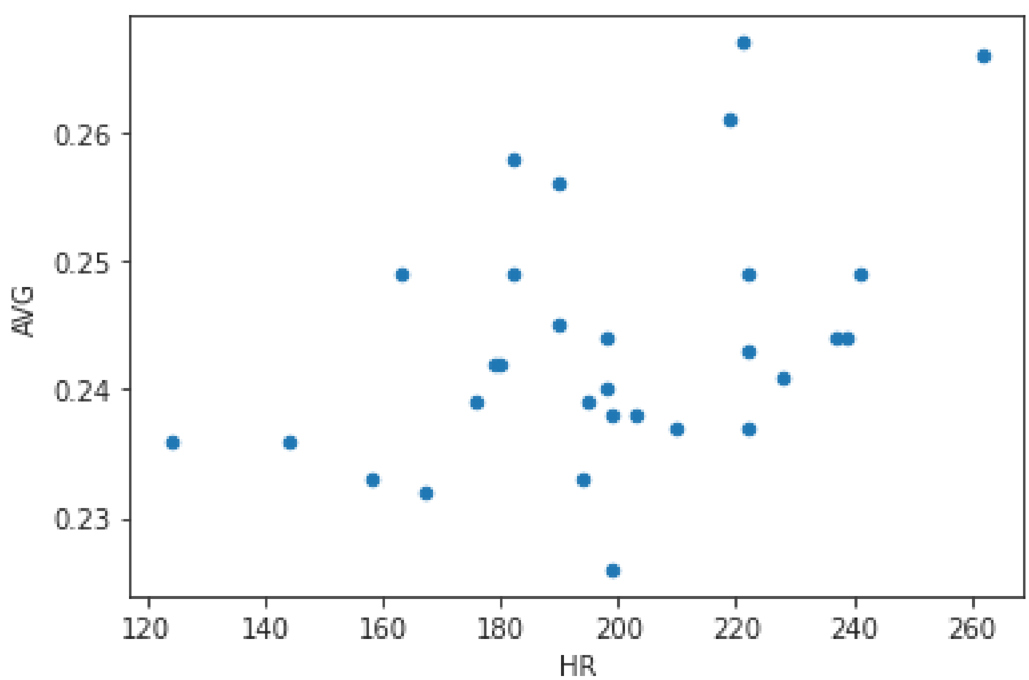

```
import seaborn as sns; sns.set_style('ticks');
batting_stats_2019.plot(x='HR', y='AVG', kind='scatter');
```




```
import seaborn as sns; sns.set_style('ticks');
batting_stats_2020.plot(x='HR', y='AVG', kind='scatter');
```




```
import seaborn as sns; sns.set_style('ticks');
batting_stats_2021.plot(x='HR', y='AVG', kind='scatter');
```



Looking at the relationship between AVG and HR shows us what we already knew to be a true. 2019 had a bump in hitting production where there were 4 teams with over 280 homeruns but only 1 in 2018 and 2021.

Analyzing Pitching Statistics From the 2018-2021 MLB Seasons

This sections code will be very similar to how we extracted our hitting data. First, we will import our cumulative team pitching stats from pybaseball

```
#importing cumulative team pitching stats from pybaseball

from pybaseball import team_pitching

pitching_stats_2018 = pyb.team_pitching(2018)
pitching_stats_2019 = pyb.team_pitching(2019)
pitching_stats_2020 = pyb.team_pitching(2020)
pitching_stats_2021 = pyb.team_pitching(2021)


pitching_stats_2018 = pitching_stats_2018.loc[:, :'WAR']

pitching_stats_2019 = pitching_stats_2019.loc[:, :'WAR']
pitching_stats_2020 = pitching_stats_2020.loc[:, :'WAR']
pitching_stats_2021 = pitching_stats_2021.loc[:, :'WAR']


pitching_stats_2018.mean()
```

```
teamIDfg     15.50000
Season       2018.00000
Age          27.90000
W            81.03333
L            81.03333
ERA          4.15300
G            706.53333
GS           162.06667
CG           1.40000
ShO          0.63333
SV           41.46667
BS           21.06667
IP           1449.44667
TBF          6171.30000
H            1367.26667
R            721.00000
ER           668.36667
HR           186.16667
BB           522.86667
IBB          30.96667
HBP          64.06667
WP           61.56667
BK           5.03333
SO           1373.56667
```

```
GB           1790.16667
FB           1465.33333
LD           889.23333
IFFB         151.43333
Balls        8717.60000
Strikes      15322.10000
Pitches      24039.70000
RS           721.00000
IFH          121.40000
BU           64.43333
BUH          17.96667
K/9          8.52533
BB/9         3.24667
K/BB         2.67833
H/9          8.49200
HR/9         1.15667
AVG          0.24470
WHIP         1.30367
BABIP        0.29320
LOB%         0.72920
FIP          4.15233
GB/FB        1.22833
LD%          0.21440
GB%          0.43207
FB%          0.35340
IFFB%        0.10327
HR/FB        0.12697
IFH%         0.06780
BUH%         0.29290
Starting     102.76000
Start-IP     866.34000
Relieving    31.72333
Relief-IP    575.31333
RAR          134.47000
WAR          14.33667
dtype: float64
```

```
pitching_stats_2018.sum()
```

```
teamIDfg      465
Season        60540
Team
HOULADCHCARIMILTBRATLBOSCLENYYOAKSTLSFGPITWSNNYMSEAPHILAACOLSDPMINDETCINMI
ACHWTORTEXKCRBAL
Age           837
W             2431
L             2431
ERA          124.59000
G             21196
GS            4862
CG            42
ShO           19
SV            1244
```

```
BS             632
IP            43483.40000
TBF            185139
H              41018
R              21630
ER             20051
HR             5585
BB             15686
IBB            929
HBP            1922
WP             1847
BK             151
SO             41207
GB             53705
FB             43960
LD             26677
IFFB           4543
Balls          261528
Strikes        459663
Pitches        721191
RS             21630
IFH            3642
BU             1933
BUH            539
K/9           255.76000
BB/9          97.40000
K/BB          80.35000
H/9           254.76000
HR/9          34.70000
AVG           7.34100
WHIP          39.11000
BABIP         8.79600
LOB%          21.87600
FIP           124.57000
GB/FB         36.85000
LD%           6.43200
GB%           12.96200
FB%           10.60200
IFFB%         3.09800
HR/FB         3.80900
IFH%          2.03400
BUH%          8.78700
Starting      3082.80000
Start-IP      25990.20000
Relieving     951.70000
Relief-IP     17259.40000
RAR           4034.10000
WAR           430.10000
dtype: object
```

This was the last time season the balls were normal

K= 41,207

ERA= 4.15
H/9 = 8.49
HR/9 = 1.16
EV= 88.4

```
pitching_stats_2019.mean()
```

```
teamIDfg      15.50000
Season        2019.00000
Age           27.90000
W             80.96667
L             80.96667
ERA           4.50800
G             714.30000
GS            161.93333
CG            1.50000
ShO           0.86667
SV            39.33333
BS            22.90000
IP            1447.27333
TBF           6217.20000
H             1401.30000
R             782.23333
ER            724.60000
HR            225.86667
BB            529.83333
IBB           25.10000
HBP           66.13333
WP            59.60000
BK            5.10000
SO            1427.43333
GB            1772.26667
FB            1476.10000
LD            886.23333
IFFB          145.30000
Balls         8857.03333
Strikes       15558.86667
Pitches       24415.90000
RS            782.23333
IFH           115.13333
BU            56.60000
BUH           15.80000
K/9           8.87333
BB/9          3.29600
K/BB          2.73800
H/9           8.71600
HR/9          1.40600
AVG           0.24917
WHIP          1.33400
BABIP         0.29600
LOB%          0.72397
```

```
FIP         4.50733
GB/FB       1.20733
LD%         0.21423
GB%         0.42870
FB%         0.35700
IFFB%       0.09850
HR/FB       0.15293
IFH%        0.06497
BUH%        0.29550
Starting    112.16000
Start-IP    835.70333
Relieving   29.25667
Relief-IP   603.33333
RAR         141.41333
WAR         14.33000
dtype: float64
```

pitching_stats_2019.sum()

```
teamIDfg     465
Season       60570
Team
LADHOUTBRCLESTLOAKCHCCINMINATLARINYMWSNNYYSFGMILPHISDPBOSMIATORCHWSEATEXLA
APITKCRDETCOLBAL
Age          837
W            2429
L            2429
ERA         135.24000
G            21429
GS           4858
CG           45
ShO          26
SV           1180
BS           687
IP          43418.20000
TBF          186516
H            42039
R            23467
ER           21738
HR           6776
BB           15895
IBB          753
HBP          1984
WP           1788
BK           153
SO           42823
GB           53168
FB           44283
LD           26587
IFFB         4359
Balls        265711
Strikes      466766
```

```
Pitches       732477
RS             23467
IFH             3454
BU              1698
BUH              474
K/9         266.20000
BB/9        98.88000
K/BB        82.14000
H/9         261.48000
HR/9        42.18000
AVG         7.47500
WHIP        40.02000
BABIP       8.88000
LOB%        21.71900
FIP         135.22000
GB/FB       36.22000
LD%         6.42700
GB%         12.86100
FB%         10.71000
IFFB%       2.95500
HR/FB       4.58800
IFH%        1.94900
BUH%        8.86500
Starting    3364.80000
Start-IP    25071.10000
Relieving   877.70000
Relief-IP   18100.00000
RAR         4242.40000
WAR         429.90000
dtype: object
```

These pitching stats for the 2019 season show a slight increase in strikeouts but an overwhelming jump by nearly half a run in ERA, an increase in Hits per 9, Homeruns per 9, and exit velocity

K= 42,823
ERA= 4.51
H/9 = 8.72
HR/9 = 1.41
EV= 88.7

```
pitching_stats_2020.mean()
```

```
teamIDfg    15.50000
Season      2020.00000
Age         27.80000
W           29.93333
L           29.93333
ERA         4.45667
G           265.30000
GS          59.86667
```

```
CG           0.96667
ShO          0.40000
SV           14.06667
BS           8.26667
IP           515.39667
TBF          2216.86667
H            481.30000
R            278.13333
ER           255.13333
HR           76.80000
BB           203.06667
IBB          6.73333
HBP          27.36667
WP           22.50000
BK           2.10000
SO           519.53333
GB           620.63333
FB           517.76667
LD           313.93333
IFFB         49.30000
Balls        3254.93333
Strikes      5531.43333
Pitches      8786.36667
RS           278.13333
IFH          43.30000
BU           13.33333
BUH          5.16667
K/9          9.06833
BB/9         3.54867
K/BB         2.62100
H/9          8.40333
HR/9         1.34100
AVG          0.24197
WHIP         1.32733
BABIP        0.29067
LOB%         0.71947
FIP          4.45667
GB/FB        1.20833
LD%          0.21603
GB%          0.42753
FB%          0.35650
IFFB%        0.09493
HR/FB        0.14877
IFH%         0.06970
BUH%         0.38187
Starting     38.42667
Start-IP     284.27667
Relieving    11.94000
Relief-IP    224.77333
RAR          50.35667
WAR          5.30000
dtype: float64
```

```
pitching_stats_2020.sum()
```

```
teamIDfg      465
Season        60600
Team
LADCLETBRMINOAKCHWSDPCINSTLCHCMILKCRHOUNYYATLBALTORSFGPITARIMIANYMTEXSEALA
AWSNPHIBOSCOLDET
Age           834
W             898
L             898
ERA          133.70000
G             7959
GS            1796
CG            29
ShO           12
SV            422
BS            248
IP           15461.90000
TBF           66506
H             14439
R             8344
ER            7654
HR            2304
BB            6092
IBB           202
HBP           821
WP            675
BK            63
SO            15586
GB            18619
FB            15533
LD            9418
IFFB          1479
Balls         97648
Strikes       165943
Pitches       263591
RS            8344
IFH           1299
BU            400
BUH           155
K/9          272.05000
BB/9         106.46000
K/BB         78.63000
H/9          252.10000
HR/9         40.23000
AVG          7.25900
WHIP         39.82000
BABIP        8.72000
LOB%         21.58400
FIP          133.70000
GB/FB        36.25000
LD%          6.48100
```

```
GB%          12.82600
FB%          10.69500
IFFB%        2.84800
HR/FB        4.46300
IFH%         2.09100
BUH%         11.45600
Starting     1152.80000
Start-IP     8528.30000
Relieving    358.20000
Relief-IP    6743.20000
RAR          1510.70000
WAR          159.00000
dtype: object
```

Since this is the season that was COVID shortened we will take this 60-game sample size with a grain of salt since it was barely 2 months' worth of games and training camp was canceled so players were not in the usual routine they are used to. ERA was still closer to 2019s juiced ball season which makes total sense since it was a higher offensive production environment and pitchers gave up more runs.

K= 15,586
ERA= 4.46
H/9 = 8.40
HR/9 = 1.34
EV = 88.4

```
pitching_stats_2021.mean()
teamIDfg     15.50000
Season       2021.00000
Age          28.33333
W            80.96667
L            80.96667
ERA          4.27067
G            718.03333
GS           161.93333
CG           1.66667
ShO          0.96667
SV           39.70000
BS           24.96667
IP           1420.31333
TBF          6060.56667
H            1316.13333
R            733.66667
ER           673.30000
HR           198.13333
BB           526.46667
IBB          23.43333
HBP          70.40000
WP           62.06667
```

```
BK           5.16667
SO           1404.83333
GB           1717.00000
FB           1459.86667
LD           827.06667
IFFB         145.43333
Balls        8545.63333
Strikes      15116.20000
Pitches      23661.83333
RS           733.66667
IFH          117.83333
BU           52.70000
BUH          12.80000
K/9          8.89867
BB/9         3.33733
K/BB         2.70167
H/9          8.34267
HR/9         1.25667
AVG          0.24077
WHIP         1.29800
BABIP        0.28940
LOB%         0.72223
FIP          4.26800
GB/FB        1.18267
LD%          0.20653
GB%          0.42913
FB%          0.36440
IFFB%        0.09943
HR/FB        0.13557
IFH%         0.06860
BUH%         0.25160
Starting     103.67667
Start-IP     810.44000
Relieving    33.27000
Relief-IP    600.89000
RAR          136.94000
WAR          14.32333
dtype: float64
```

```
pitching_stats_2021.sum()
```

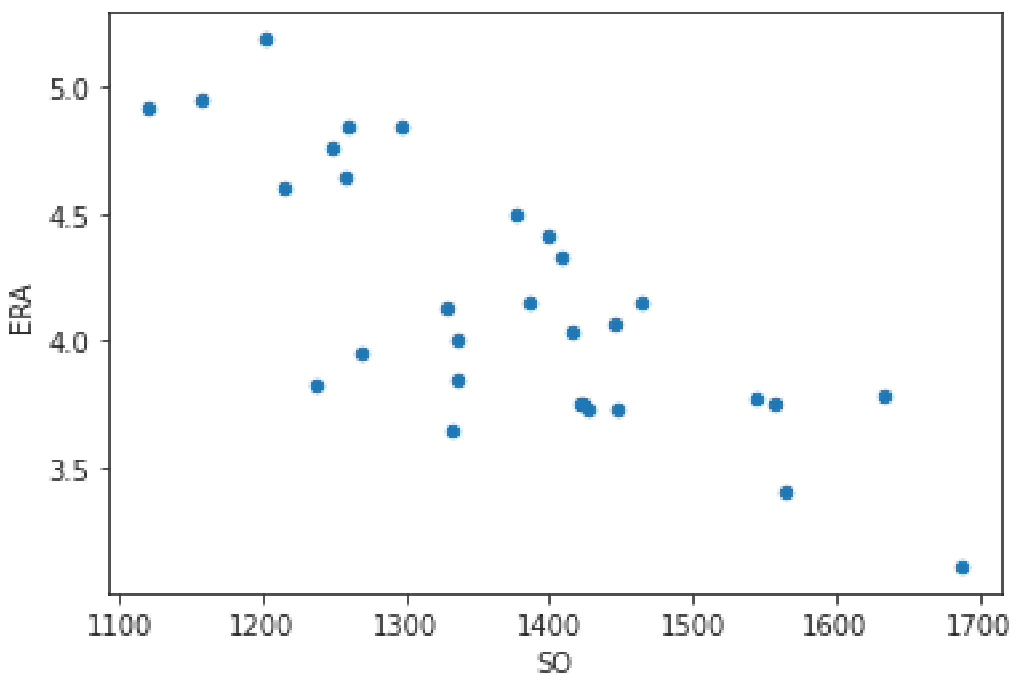
```
teamIDfg      465
Season        60630
Team
LADSFGMILTBRCHWNYYHOUATLNYMTORMIASTLOAKSDPBOSSEADETCLEPHICINKCRLAATEXWSNCO
LMINCHCPITARIBAL
Age           850
W             2429
L             2429
ERA          128.12000
G             21541
GS            4858
CG            50
```

```
ShO           29
SV            1191
BS            749
IP           42609.40000
TBF           181817
H             39484
R             22010
ER            20199
HR            5944
BB            15794
IBB           703
HBP           2112
WP            1862
BK            155
SO            42145
GB            51510
FB            43796
LD            24812
IFFB          4363
Balls         256369
Strikes       453486
Pitches       709855
RS            22010
IFH           3535
BU            1581
BUH           384
K/9          266.96000
BB/9         100.12000
K/BB         81.05000
H/9          250.28000
HR/9         37.70000
AVG          7.22300
WHIP         38.94000
BABIP        8.68200
LOB%         21.66700
FIP          128.04000
GB/FB        35.48000
LD%          6.19600
GB%          12.87400
FB%          10.93200
IFFB%        2.98300
HR/FB        4.06700
IFH%         2.05800
BUH%         7.54800
Starting     3110.30000
Start-IP     24313.20000
Relieving    998.10000
Relief-IP    18026.70000
RAR          4108.20000
WAR          429.70000
dtype: object
```

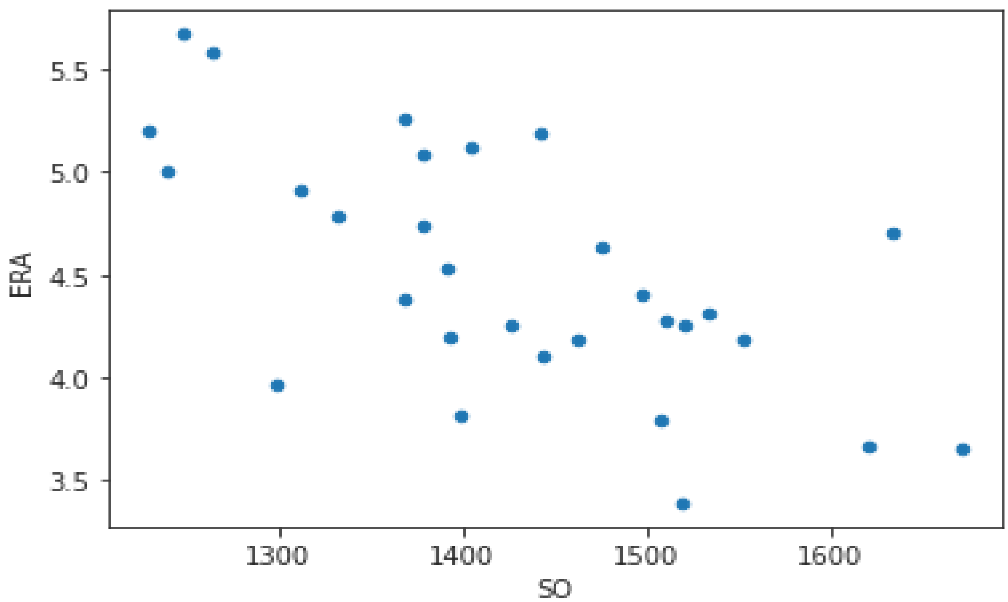
The season when MLB regulated the baseballs back to normal. We can clearly see that these statistics are closer to 2018s than 2019s.

K= 42,145
ERA= 4.27
H/9 = 8.34
HR/9 = 1.26
EV= 88.7

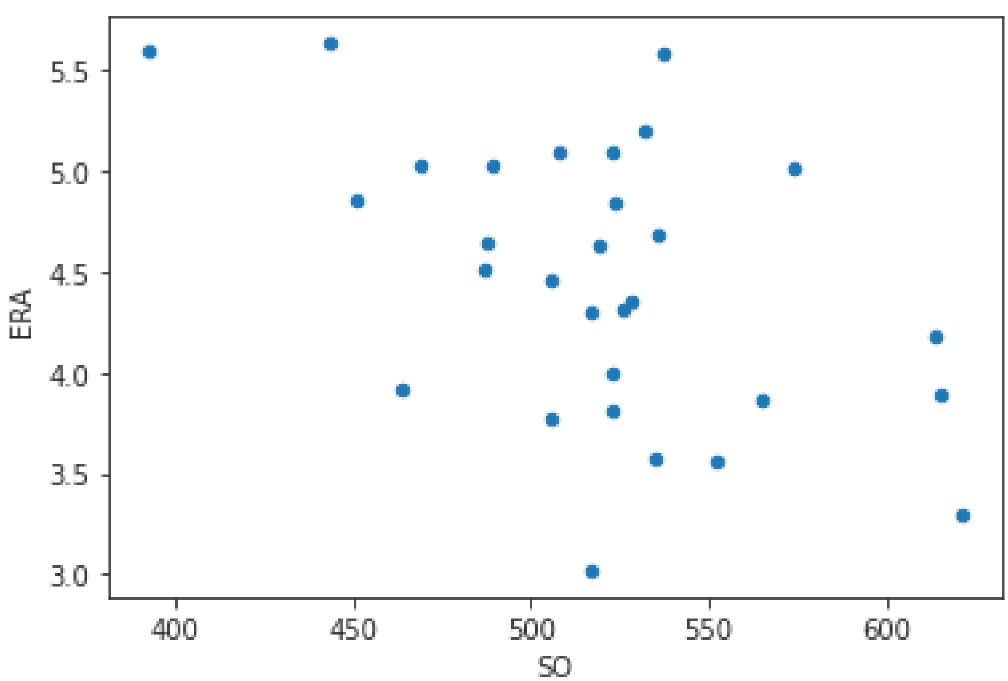
```
import seaborn as sns; sns.set_style('ticks');
pitching_stats_2018.plot(x='SO', y='ERA', kind='scatter');
```



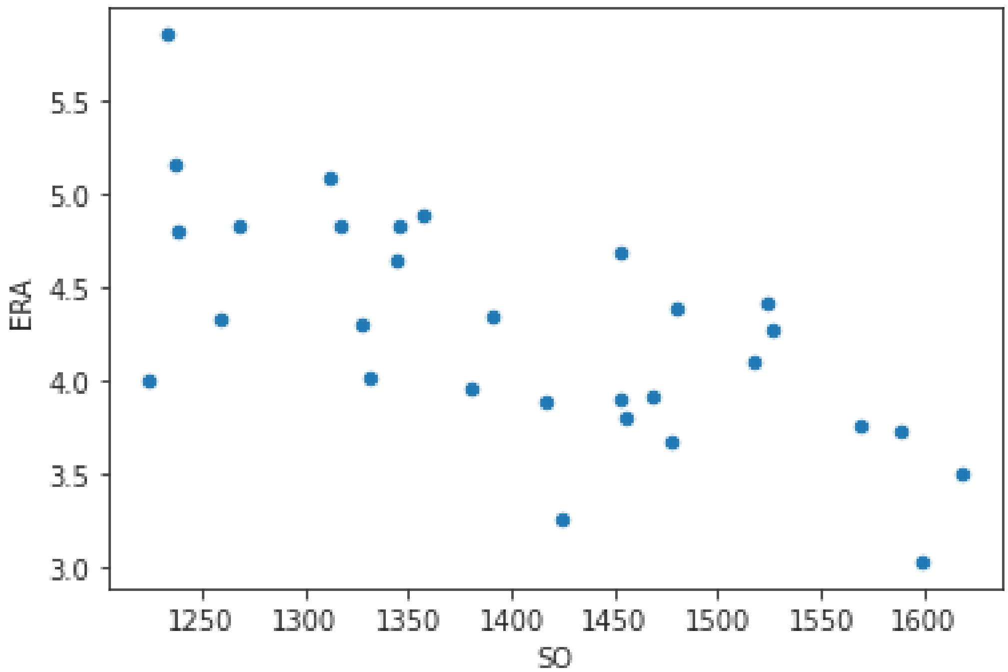

```
import seaborn as sns; sns.set_style('ticks');
pitching_stats_2019.plot(x='SO', y='ERA', kind='scatter');
```




```python
import seaborn as sns; sns.set_style('ticks');
pitching_stats_2020.plot(x='SO', y='ERA', kind='scatter');
```




```python
import seaborn as sns; sns.set_style('ticks');
pitching_stats_2021.plot(x='SO', y='ERA', kind='scatter');
```



The above scatter plots simply visualize each season we are analyzing and compares its Strikeouts to ERA. We can see that there is a correlation between Strikeouts and ERA. I chose to compare these two pitching stats because even with the higher offensive climate in baseball. The game has a clear three true outcome approach where teams prefer an aggressive hitting strategy where often hitters either strike out, hit a home run, or walk. It is interesting to see the 2019 season have such a spike in ERA but also a spike in strike outs which seems counter intuitive but does follow the modern-day strategy many teams subscribe to (more on that later).

Analyzing Statcast Data From the 2018-2021 MLB Seasons

In this section we will analyze statcast statistics for the 2018, 2019, 2020, 2021 seasons. I pulled this data in .csv format from baseballsavant.com which is MLBs own site dedicated to providing player matchups, Statcast metrics, and advanced statistics in a simple and easy-to-view way. We will use pandas to read the csv and put each season into a dataframe.

We will analyze and compare the average hit and homerun distances as well as the max hit and max distance speeds of all 30 MLB teams.

```
# exit velocity data averaged by team and season per df

import pandas as pd
hitting_velo_2018 = pd.read_csv("hitting 2018 exit_velocity.csv")

hitting_velo_2019 = pd.read_csv("hitting 2019 exit_velocity.csv")
hitting_velo_2020 = pd.read_csv("hitting 2020 exit_velocity.csv")
hitting_velo_2021 = pd.read_csv("hitting 2021 exit_velocity.csv")

hitting_velo_2018.mean()
```

```
season                    2018.00000
team_id                    128.70000
attempts                  4209.46667
avg_hit_angle               12.34333
anglesweetspotpercent       33.44333
max_hit_speed              116.07333
avg_hit_speed               88.41000
fbld                        92.33333
gb                          85.95000
max_distance               465.83333
avg_distance               172.16667
avg_hr_distance            397.36667
ev95plus                  1492.66667
ev95per-swing               13.33667
ev95percent                 35.46000
barrels                    281.00000
brl_percent                  6.68000
brl_pa                       4.55000
dtype: float64
```

Last season with normal balls:

Max Distance – 466
Max Speed – 116
Avg HR Distance - 397

hitting_velo_2019.mean()

```
season                     2019.00000
team_id                    128.70000
attempts                   4191.83333
avg_hit_angle              12.67667
anglesweetspotpercent      33.54000
max_hit_speed              116.05000
avg_hit_speed              88.72333
fbld                       92.67000
gb                         86.07667
max_distance               473.50000
avg_distance               175.63333
avg_hr_distance            400.20000
ev95plus                   1529.03333
ev95per-swing              13.31667
ev95percent                36.47333
barrels                    307.56667
brl_percent                7.32333
brl_pa                     4.94000
dtype: float64
```

Juiced ball season:

Max Distance – 473.5
Max Speed – 116
Avg HR Distance - 400

hitting_velo_2020.mean()

```
season                     2020.00000
team_id                    128.70000
attempts                   1465.73333
avg_hit_angle              12.72333
anglesweetspotpercent      33.40333
max_hit_speed              114.85667
avg_hit_speed              88.43667
fbld                       92.80333
gb                         85.32000
max_distance               458.73333
avg_distance               168.53333
avg_hr_distance            400.80000
ev95plus                   550.90000
ev95per-swing              13.65333
ev95percent                37.56000
barrels                    111.76667
brl_percent                7.60000
brl_pa                     5.04333
dtype: float64
```

COVID shortened season:

Max Distance – 458
Max Speed – 114
Avg HR Distance - 401

```
hitting_velo_2021.mean()
```

```
season                    2021.00000
team_id                    128.70000
attempts                  4056.86667
avg_hit_angle               12.54333
anglesweetspotpercent       33.47000
max_hit_speed              116.55000
avg_hit_speed               88.76000
fbld                        92.97333
gb                          85.73000
max_distance               469.00000
avg_distance               166.96667
avg_hr_distance            400.93333
ev95plus                  1569.60000
ev95per-swing               14.07000
ev95percent                 38.67667
barrels                    321.26667
brl_percent                  7.92333
brl_pa                       5.29667
dtype: float64
```

Season when balls went back to normal:

Max Distance – 469
Max Speed – 116.5
Avg HR Distance - 401

When comparing the 2018-2021 seasons statcast data it doesn’t seem like there is anything that jumps out. The 2019 season did have a slight increase in average Max Distance but the Max Hit Speeds and Average Home Run Distances are either identical or negligible in their differences.

Predictive Model of 2020 MLB statcast Statistics (Linear Regression)

In this section we will build a linear regression algorithm that predicts what a full 162 game season would have produced as it relates to Statcast data. We realized in the last section that our data from the 2018, 2019, and 2021 seasons showed that there was not anything significantly different as it relates to in-game (statcast) data. Beginning in this section I strongly recommend following with the google colab notebook or GitHub repository open because most of the code and outputs are robust and are not easily displayed in this format.

```
import seaborn as sns
import sklearn as sk
import pybaseball as pyb
from matplotlib import pyplot as plt
from pybaseball import cache
cache.enable()
import warnings; warnings.filterwarnings('ignore')
```

We begin again by importing all our past libraries.

```
# exit velocity data averaged by team and season per df

import pandas as pd

hitting_velo_2018 = pd.read_csv("hitting 2018 exit_velocity.csv")
hitting_velo_2019 = pd.read_csv("hitting 2019 exit_velocity.csv")
hitting_velo_2020 = pd.read_csv("hitting 2020 exit_velocity.csv")
hitting_velo_2021 = pd.read_csv("hitting 2021 exit_velocity.csv")

hitting_velo_2018 = hitting_velo_2018
hitting_velo_2019 = hitting_velo_2019
hitting_velo_2020 = hitting_velo_2020
hitting_velo_2021 = hitting_velo_2021
```

Here we concatenate the 4 .csv files into 1 data frame

```
total_velo_stats = pd.concat([hitting_velo_2018, hitting_velo_2019, hittin
g_velo_2020 , hitting_velo_2021], axis=0)
```

Here we concatenate only the 2018, 2019, and 2020 .csv files so we have 1 big data frame.

```
velo_stats_2018_2019 = pd.concat([hitting_velo_2018, hitting_velo_2019,hit
ting_velo_2020], axis=0)
```

```
total_velo_stats_copy = total_velo_stats.copy()
In this chuck we are filtering our total_velo_stats data frame since it
naturally has a lot of columns we will not use.
```

```
total_velo_stats_copy = total_velo_stats_copy.loc[:, ['season','team','max
_hit_speed','avg_hit_speed', 'max_distance', 'avg_hr_distance']]
```

```
total_velo_stats_copy['max_hit_speed_2020'] = total_velo_stats_copy.sort_v
alues(['season','team'], ascending=False).groupby('team')['max_hit_speed']
.shift()
total_velo_stats_copy['avg_hit_speed_2020'] = total_velo_stats_copy.sort_v
alues(['season','team'], ascending=False).groupby('team')['avg_hit_speed']
.shift()
total_velo_stats_copy['max_distance_2020'] = total_velo_stats_copy.sort_va
lues(['season','team'], ascending=False).groupby('team')['max_distance'].s
hift()
total_velo_stats_copy['avg_hr_distance_2020'] = total_velo_stats_copy.sort
_values(['season','team'], ascending=False).groupby('team')['avg_hr_distan
ce'].shift()
```

```
total_velo_stats_copy = total_velo_stats_copy.loc[total_velo_stats_copy['m
ax_hit_speed_2020'].notnull()]
total_velo_stats_copy = total_velo_stats_copy.loc[total_velo_stats_copy['a
vg_hit_speed_2020'].notnull()]
total_velo_stats_copy = total_velo_stats_copy.loc[total_velo_stats_copy['m
ax_distance_2020'].notnull()]
total_velo_stats_copy = total_velo_stats_copy.loc[total_velo_stats_copy['a
vg_hr_distance_2020'].notnull()]
```

```
total_velo_stats_copy
```

Here we will find the correlation (if any) for each column/statistical metric in the dataframe

```
total_velo_stats_copy.corr()
```

Splitting our data for x, y training and testing

```
from sklearn.model_selection import train_test_split

x = total_velo_stats_copy[['max_hit_speed','avg_hit_speed', 'max_distance'
, 'avg_hr_distance']].values
y= total_velo_stats_copy[['max_hit_speed_2020', 'avg_hit_speed_2020', 'max
_distance_2020', 'avg_hr_distance_2020']].values

print('Original Data Shape - X: {0}, Y: {1}'.format(x.shape, y.shape))
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, r
andom_state=42)        #test size is 20% of original


print('Train Data Shape - X{0}, Y:{1}.'.format(x_train.shape, y_train.shap
e) )
print('Test Data Shape - X{0}, Y:{1}.'.format(x_test.shape, y_test.shape)
)
```

```
Original Data Shape - X: (90, 4), Y: (90, 4)
Train Data Shape - X(72, 4), Y:(72, 4).
Test Data Shape - X(18, 4), Y:(18, 4).
```

Taking our training data and fitting it into our regression model

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error


lr = LinearRegression()

lr.fit(x_train, y_train)
```

LinearRegression()

```
y_pred = lr.predict(x_train)

print ('Mean number of hits:', x_train[:, 0].mean())
print ('Mean absolute error:', mean_absolute_error(y_pred, y_tra
in))
```

```
Mean number of hits: 115.70000000000002
Mean absolute error: 3.698991863153225
```

```
velo_stats_2018_2019_copy = velo_stats_2018_2019.copy()

velo_stats_2018_2019_copy = velo_stats_2018_2019_copy.loc[:,['season','team','max_hit_speed','avg_hit_speed', 'max_distance', 'avg_hr_distance']]

velo_stats_2018_2019_copy['2019_actual_max_hit_speed'] = velo_stats_2018_2019_copy.sort_values(['team', 'season'], ascending=False).groupby('team')['max_hit_speed'].shift()
velo_stats_2018_2019_copy['2019_actual_avg_hit_speed'] = velo_stats_2018_2019_copy.sort_values(['team', 'season'], ascending=False).groupby('team')['avg_hit_speed'].shift()
velo_stats_2018_2019_copy['2019_actual_max_distance'] = velo_stats_2018_2019_copy.sort_values(['team', 'season'], ascending=False).groupby('team')['max_distance'].shift()
velo_stats_2018_2019_copy['2019_actual_avg_hr_distance'] = velo_stats_2018_2019_copy.sort_values(['team', 'season'], ascending=False).groupby('team')['avg_hr_distance'].shift()

velo_stats_2018_2019_copy = velo_stats_2018_2019_copy.loc[velo_stats_2018_2019_copy['2019_actual_max_hit_speed'].notnull()]

velo_stats_2018_2019_copy
```

Assigning an x and y value to our dataframes.

```
x = velo_stats_2018_2019_copy[['max_hit_speed','avg_hit_speed', 'max_distance', 'avg_hr_distance' ]].values
y = velo_stats_2018_2019_copy[['2019_actual_max_hit_speed','2019_actual_avg_hit_speed', '2019_actual_max_distance', '2019_actual_avg_hr_distance' ]].values
```

```
y_pred = lr.predict(x)
print('Mean of Stats:', velo_stats_2018_2019_copy.mean())
print('Mean absolute error:', mean_absolute_error(y_pred, y))
```

```
Mean of Stats: season                          2018.50000
max_hit_speed                   116.06167
avg_hit_speed                   88.56667
max_distance                    469.66667
avg_hr_distance                 398.78333
2019_actual_max_hit_speed       115.45333
2019_actual_avg_hit_speed       88.58000
2019_actual_max_distance        466.11667
2019_actual_avg_hr_distance     400.50000
dtype: float64
Mean absolute error: 4.025842800890172
```

Assigning our Y predict variable our sorted data frame.

```
velo_stats_2018_2019_copy[['predicted_max_hit_speed', 'predicted_avg_hit_speed', 'predicted_max_distance', 'predicted_avg_hr_distance', ]] = y_pred

velo_stats_2018_2019_copy['season'] = 2019

#pitch_2019_copy = pitch_2019_copy.rename(columns={'2019_actual_g':'Actual_G'}

#use sort_values to find the top predicted hits
velo_stats_2018_2019_copy = velo_stats_2018_2019_copy.loc[:,['season','team','2019_actual_max_hit_speed', '2019_actual_avg_hit_speed', '2019_actual_max_distance', '2019_actual_avg_hr_distance', 'predicted_max_hit_speed' , 'predicted_avg_hit_speed', 'predicted_max_distance', 'predicted_avg_hr_distance',  ]]
```

Filtering said data frame to show us the stats we are looking for.

```
predicted_2020_stats = velo_stats_2018_2019_copy.loc[:,['team', 'predicted_max_hit_speed', 'predicted_avg_hit_speed', 'predicted_max_distance', 'predicted_avg_hr_distance']]
predicted_2020_stats



predicted_2020_stats.mean()
```

```
predicted_max_hit_speed      116.06841
predicted_avg_hit_speed      88.66975
predicted_max_distance       467.52805
predicted_avg_hr_distance    400.17873
dtype: float64
```

Max Distance – 467
Max Hit Speed – 116
Average HR Distance – 400.2

Even with our algorithm predicting a full 2020 season using data from previous seasons. Our statcast numbers don't say much. They are a very close to the other seasons and don't really give us a lot of insight on whether or not a hypothetical 2020 season would have played out closer to the "normal" 2018 season or "juiced" 2019 season.

Predictive Model of 2020 MLB Hitting Statistics (Linear Regression)

In this section we will build a linear regression algorithm that predicts what a full 162 game season would have produced hitting numbers wise.

Creating 2 different data frames; one for cumulative team hitting statistics for the 2015 through 2019 seasons and one for 2018 through 2019.

```
hits_df = pyb.team_batting(2015, 2019)
hits_2019 = pyb.team_batting(2018, 2019)
```

Creating our df for predicting a full 2020 season (we filter only for the 'Season', 'Team', 'G', 'AB', 'H', 'HR', 'RBI', 'AVG', 'OBP', 'SLG', 'OPS', 'wRC', 'WAR' columns since its what will be useful in our analysis.)

```
hits_df_copy = hits_df.copy()

hits_df_copy = hits_df_copy.loc[:, ['Season', 'Team', 'G', 'AB', 'H', 'HR'
, 'RBI', 'AVG', 'OBP', 'SLG', 'OPS', 'wRC', 'WAR']]

hits_df_copy['G_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'],
 ascending=False).groupby('Team')['G'].shift()
hits_df_copy['H_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'],
 ascending=False).groupby('Team')['H'].shift()
hits_df_copy['AB_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team']
, ascending=False).groupby('Team')['AB'].shift()
hits_df_copy['HR_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team']
, ascending=False).groupby('Team')['HR'].shift()
hits_df_copy['RBI_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'
], ascending=False).groupby('Team')['RBI'].shift()
```

```
hits_df_copy['AVG_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'
], ascending=False).groupby('Team')['AVG'].shift()
hits_df_copy['SLG_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'
], ascending=False).groupby('Team')['SLG'].shift()
hits_df_copy['wRC_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'
], ascending=False).groupby('Team')['wRC'].shift()
hits_df_copy['WAR_Next_Year'] = hits_df_copy.sort_values(['Season', 'Team'
], ascending=False).groupby('Team')['WAR'].shift()
```

```
hits_df_copy = hits_df_copy.loc[hits_df_copy['G_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['H_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['AB_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['HR_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['RBI_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['AVG_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['SLG_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['wRC_Next_Year'].notnull()]
hits_df_copy = hits_df_copy.loc[hits_df_copy['WAR_Next_Year'].notnull()]
```

```
hits_df_copy
```

Finding the correlation between the columns and seasons (if any)

```
hits_df_copy.corr()
```

Splitting our data for x, y training and testing

```
from sklearn.model_selection import train_test_split

X = hits_df_copy[['G', 'AB', 'H', 'HR', 'RBI', 'AVG', 'SLG', 'wRC', 'WAR'
]].values
y= hits_df_copy[['G_Next_Year', 'AB_Next_Year', 'H_Next_Year', 'HR_Next_Ye
ar', 'RBI_Next_Year', 'AVG_Next_Year', 'SLG_Next_Year', 'wRC_Next_Year', '
WAR_Next_Year' ]].values

print('Original Data Shape - X: {0}, Y: {1}'.format(X.shape, y.shape))
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
andom_state=42)        #test size is 20% of original


print('Train Data Shape - X{0}, Y:{1}.'.format(X_train.shape, y_train.shap
e) )
```

```
print('Test Data Shape - X{0}, Y:{1}.'.format(X_test.shape, y_test.shape)
)
```

Taking our training data and fitting it into our regression model

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error


lr = LinearRegression()

lr.fit(X_train, y_train)
```

LinearRegression()

```
y_pred = lr.predict(X_train)

print ('Mean number of hits:', X_train[:, 0].mean())
print ('Mean absolute error:', mean_absolute_error(y_pred, y_train))
```

```
Mean number of hits: 2364.7916666666665
Mean absolute error: 29.59835920038931
```

Making a copy of our 2019 hits data frame and filtering for useful columns.

```
hits_2019_copy = hits_2019.copy()

hits_2019_copy = hits_2019_copy.loc[:,['Season', 'Team', 'G', 'AB', 'H', '
HR', 'RBI', 'AVG', 'OBP', 'SLG', 'OPS', 'wRC', 'WAR']]

hits_2019_copy['2019_actual_g'] = hits_2019_copy.sort_values(['Team', 'Sea
son'], ascending=False).groupby('Team')['G'].shift()
hits_2019_copy['2019_actual_ab'] = hits_2019_copy.sort_values(['Team', 'Se
ason'], ascending=False).groupby('Team')['AB'].shift()
hits_2019_copy['2019_actual_hits'] = hits_2019_copy.sort_values(['Team', '
Season'], ascending=False).groupby('Team')['H'].shift()
hits_2019_copy['2019_actual_hr'] = hits_2019_copy.sort_values(['Team', 'Se
ason'], ascending=False).groupby('Team')['HR'].shift()
hits_2019_copy['2019_actual_rbi'] = hits_2019_copy.sort_values(['Team', 'S
eason'], ascending=False).groupby('Team')['RBI'].shift()
hits_2019_copy['2019_actual_avg'] = hits_2019_copy.sort_values(['Team', 'S
eason'], ascending=False).groupby('Team')['AVG'].shift()
hits_2019_copy['2019_actual_slg'] = hits_2019_copy.sort_values(['Team', 'S
eason'], ascending=False).groupby('Team')['SLG'].shift()
```

```
hits_2019_copy['2019_actual_wRC'] = hits_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['wRC'].shift()
hits_2019_copy['2019_actual_WAR'] = hits_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['WAR'].shift()


hits_2019_copy = hits_2019_copy.loc[hits_2019_copy['2019_actual_hits'].notnull()]

hits_2019_copy
```

Assigning values to our X and Y

```
X = hits_2019_copy[['G', 'AB', 'H', 'HR', 'RBI', 'AVG', 'SLG', 'wRC', 'WAR', ]].values
y = hits_2019_copy[['2019_actual_g', '2019_actual_ab','2019_actual_hits', '2019_actual_hr', '2019_actual_rbi', '2019_actual_avg', '2019_actual_slg', '2019_actual_wRC', '2019_actual_WAR' ]].values
```

```
y_pred = lr.predict(X)
print('Mean of Stats:', hits_2019_copy.mean())
print('Mean absolute error:', mean_absolute_error(y_pred, y))
```

```
Mean of Stats: Season             2018.00000
G                  2386.33333
AB                 5514.40000
H                  1367.26667
HR                 186.16667
RBI                686.86667
AVG                0.24783
OBP                0.31797
SLG                0.40923
OPS                0.72723
wRC                719.33333
WAR                19.01333
2019_actual_g      2389.46667
2019_actual_ab     5555.03333
2019_actual_hits   1401.30000
2019_actual_hr     225.86667
2019_actual_rbi    749.03333
2019_actual_avg    0.25217
2019_actual_slg    0.43467
2019_actual_wRC    780.53333
2019_actual_WAR    18.99000
dtype: float64
```

```
Mean absolute error: 34.894989354342385
```

Making the new copy of the data frame = y-pred

```
hits_2019_copy[['Predicted_G', 'Predicted_AB', 'Predicted_H', 'Predicted_HR', 'Predicted_RBI', 'Predicted_AVG', 'Predicted_SLG', 'Predicted_wRC', 'Predicted_WAR']] = y_pred

hits_2019_copy['Season'] = 2019

#hits_2019_copy = hits_2019_copy.rename(columns={'2019_actual_g':'Actual_G'})

#use sort_values to find the top predicted hits
hits_2019_copy = hits_2019_copy.loc[:,['Season','Team','2019_actual_g', '2019_actual_ab', '2019_actual_hits', '2019_actual_hr', '2019_actual_rbi' , '2019_actual_avg' , '2019_actual_slg', '2019_actual_wRC', '2019_actual_WAR', 'Predicted_G', 'Predicted_AB', 'Predicted_H', 'Predicted_HR', 'Predicted_RBI', 'Predicted_AVG', 'Predicted_SLG', 'Predicted_wRC', 'Predicted_WAR']]


hits_2019_copy


predicted_2020_stats = hits_2019_copy.loc[:,['Team', 'Predicted_G', 'Predicted_AB', 'Predicted_H', 'Predicted_HR', 'Predicted_RBI', 'Predicted_AVG', 'Predicted_SLG', 'Predicted_wRC', 'Predicted_WAR']]

predicted_2020_stats
```

Finding the averages of all the columns in our data frame

```
predicted_2020_stats.mean()
```

```
Predicted_G      2383.03539
Predicted_AB     5533.80713
Predicted_H      1391.50597
Predicted_HR      210.97001
Predicted_RBI     728.96278
```

```
Predicted_AVG   0.25142
Predicted_SLG   0.42629
Predicted_wRC   758.35881
Predicted_WAR   19.84809
dtype: float64
```

Finding the sum of all the columns in our data frame

```
predicted_2020_stats.sum()
```

```
Team
BOSNYYLADCLEOAKHOUWSNCOLTBRMILCHCATLTORCINSTLTEXLAAMINSEAPITPHIARINYMCHWKC
RBALDETSDPSFGMIA
Predicted_G     71491.06157
Predicted_AB    166014.21378
Predicted_H     41745.17895
Predicted_HR    6329.10020
Predicted_RBI   21868.88340
Predicted_AVG   7.54257
Predicted_SLG   12.78855
Predicted_wRC   22750.76427
Predicted_WAR   595.44285
dtype: object
```

H= 41,745
HR= 6,329
RBI= 21,868
WAR= 595
AVG= .251
SLG%= .426

Our algorithm predicted that a full 2020 season would have produced higher offensive production than the “normal” 2018 season and on par with the “juiced” 2019 season.

Predictive Model of 2020 MLB Pitching Statistics (Linear Regression)

In this section we will build a linear regression algorithm that predicts what a full 162 game season would have produced pitching numbers wise.

Creating 2 different data frames; one for cumulative team pitching statistics for the 2015 through 2019 seasons and one for 2018 through 2019.

```
pitch_df = pyb.team_pitching(2015, 2019)
pitch_2019 = pyb.team_pitching(2018, 2019)
pitch_df
```

Creating our df for predicting a full 2020 season

```
pitch_df_copy = pitch_df.copy()

pitch_df_copy = pitch_df_copy.loc[:, ['Season','Team', 'G', 'H', 'SO', 'ERA', 'H/9', 'HR/9', 'EV']]

pitch_df_copy['G_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['G'].shift()
pitch_df_copy['H_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['H'].shift()
pitch_df_copy['SO_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['SO'].shift()
pitch_df_copy['ERA_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['ERA'].shift()
pitch_df_copy['H/9_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['H/9'].shift()
pitch_df_copy['HR/9_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['HR/9'].shift()
pitch_df_copy['EV_Next_Year'] = pitch_df_copy.sort_values(['Season','Team'], ascending=False).groupby('Team')['EV'].shift()


pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['G_Next_Year'].notnull()]
pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['H_Next_Year'].notnull()]
pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['SO_Next_Year'].notnull()]
pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['ERA_Next_Year'].notnull()]
pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['H/9_Next_Year'].notnull()]
```

```
pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['HR/9_Next_Year'].notnull(
)]
pitch_df_copy = pitch_df_copy.loc[pitch_df_copy['EV_Next_Year'].notnull()]
pitch_df_copy
```

Finding the correlation between the columns and seasons in our dataframe

```
pitch_df_copy.corr()
```

Splitting our data for x, y training and testing

```
from sklearn.model_selection import train_test_split

x = pitch_df_copy[['G', 'H', 'SO', 'ERA', 'H/9', 'HR/9', 'EV']].values
y= pitch_df_copy[['G_Next_Year', 'H_Next_Year', 'SO_Next_Year', 'ERA_Next_
Year', 'H/9_Next_Year','HR/9_Next_Year', 'EV_Next_Year']].values

print('Original Data Shape - X: {0}, Y: {1}'.format(x.shape, y.shape))
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, r
andom_state=42)        #test size is 20% of original


print('Train Data Shape - X{0}, Y:{1}.'.format(x_train.shape, y_train.shap
e) )
print('Test Data Shape - X{0}, Y:{1}.'.format(x_test.shape, y_test.shape)
)
```

```
Original Data Shape - X: (120, 7), Y: (120, 7)
Train Data Shape - X(96, 7), Y:(96, 7).
Test Data Shape - X(24, 7), Y:(24, 7).
```

Taking our training data and fitting it into our regression model

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error


lr = LinearRegression()

lr.fit(x_train, y_train)
```

```
y_pred = lr.predict(x_train)

print ('Mean number of hits:', x_train[:, 0].mean())
print ('Mean absolute error:', mean_absolute_error(y_pred, y_train))
```

```
Mean number of hits: 684.0104166666666
Mean absolute error: 22.399957928044778
```

Creating a copy of our pitch 2019 data frame and filtering for useful columns

```
pitch_2019_copy = pitch_2019.copy()
pitch_2019_copy = pitch_2019_copy.loc[:,['Season','Team', 'G', 'H', 'SO', 'ERA', 'H/9', 'HR/9', 'EV']]
pitch_2019_copy['2019_actual_g'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['G'].shift()
pitch_2019_copy['2019_actual_h'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['H'].shift()
pitch_2019_copy['2019_actual_so'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['SO'].shift()
pitch_2019_copy['2019_actual_era'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['ERA'].shift()
pitch_2019_copy['2019_actual_h/9'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['H/9'].shift()
pitch_2019_copy['2019_actual_hr/9'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['HR/9'].shift()
pitch_2019_copy['2019_actual_ev'] = pitch_2019_copy.sort_values(['Team', 'Season'], ascending=False).groupby('Team')['EV'].shift()
pitch_2019_copy = pitch_2019_copy.loc[pitch_2019_copy['2019_actual_so'].notnull()]

pitch_2019_copy
```

Assigning X and Y values

```
x = pitch_2019_copy[['G', 'H', 'SO', 'ERA', 'H/9', 'HR/9','EV' ]].values
y = pitch_2019_copy[['2019_actual_g', '2019_actual_h','2019_actual_so', '2019_actual_era', '2019_actual_h/9', '2019_actual_hr/9','2019_actual_ev']].values

y_pred = lr.predict(x)
print('Mean of Stats:', pitch_2019_copy.mean())
print('Mean absolute error:', mean_absolute_error(y_pred, y))
```

```
Mean of Stats: Season             2018.00000
G                   706.53333
H                   1367.26667
SO                  1373.56667
ERA                 4.15300
H/9                 8.49200
HR/9                1.15667
EV                  88.40000
2019_actual_g       714.30000
2019_actual_h       1401.30000
2019_actual_so      1427.43333
2019_actual_era     4.50800
2019_actual_h/9     8.71600
2019_actual_hr/9    1.40600
2019_actual_ev      88.70667
dtype: float64
Mean absolute error: 22.711032823684942
```

Making the new copy of the data frame = y-pred

```
pitch_2019_copy[['Predicted_G', 'Predicted_H', 'Predicted_SO', 'Predicted_ERA', 'Predicted_H/9', 'Predicted_HR/9','Predicted_EV']] = y_pred
pitch_2019_copy['Season'] = 2019

#pitch_2019_copy = pitch_2019_copy.rename(columns={'2019_actual_g':'Actual_G'}
#use sort_values to find the top predicted hits
pitch_2019_copy = pitch_2019_copy.loc[:,['Season','Team','2019_actual_g', '2019_actual_h', '2019_actual_so', '2019_actual_era', '2019_actual_h/9' , '2019_actual_hr/9', 'Predicted_G', 'Predicted_H', 'Predicted_SO', 'Predicted_ERA', 'Predicted_H/9', 'Predicted_HR/9','Predicted_EV' ]]


pitch_2019_copy
```

Filtering our data frame with predicted 2020 stats

```
predicted_2020_stats = pitch_2019_copy.loc[:,['Team', 'Predicted_G', 'Predicted_H', 'Predicted_SO', 'Predicted_ERA', 'Predicted_H/9', 'Predicted_HR/9','Predicted_EV']]

predicted_2020_stats
```

Finding the averages of the columns of our new predicted 2020 pitching data frame

```
predicted_2020_stats.mean()
```

```
Predicted_G       707.78371
Predicted_H       1382.33205
Predicted_SO      1401.91147
Predicted_ERA     4.35885
Predicted_H/9     8.60626
Predicted_HR/9    1.30995
Predicted_EV      88.40525
dtype: float64
```

Finding the sum of the columns of our new predicted 2020 pitching data frame

```
predicted_2020_stats.sum()
```

```
Team
HOULADCHCARIMILTBRATLBOSCLENYYOAKSTLSFGPITWSNNYMSEAPHILAACOLSDPMINDETCINMI
ACHWTORTEXKCRBAL
Predicted_G       21233.51125
Predicted_H       41469.96162
Predicted_SO      42057.34419
Predicted_ERA     130.76561
Predicted_H/9     258.18794
Predicted_HR/9    39.29857
Predicted_EV      2652.15757
dtype: object
```

K= 42,607
ERA= 4.26
H/9 = 8.5
HR/9 = 1.26
EV=88.4

The algorithm predicts that a full 2020 season would have been on par with the “juiced” season of 2019. The stats for this hypothetical season are closer to 2019s number than 2018 or 2021 where the ball was normal. The ERA for this predicted season is not as high as 2019 but still much higher than 2018. While strikeouts also went way up which would fall in line with the three true outcome approach that we mentioned earlier.

Results and Summary:

Hitting Data:

Season	H	HR	RBI	WAR	AVG	SLG%
2018	41,018	5,585	20,606	570	.248	.409
2019	42,039	6,776	22,471	570	.252	.435
2020 (60 Games)	14,439	2,304	7,978	210	.244	.417
2020 (Predicted)	**41,745**	**6,329**	**21,868**	**595**	**.251**	**.426**
2021	39,484	5944	20,993	570	.244	.411

Here we see that the 2019 season was the season with the highest hitting production. This season had the highest number of hits, home runs, RBI's, tied for most WAR, highest batting average and slugging %. Our predicted 2020 season is the 2nd highest hitting production season trailing only 2019 in every category except for WAR where it surpassed 2019. Given the fact that we have proof of there being inconsistencies with the baseballs in our 60-game sample size of the 2020 season we can safely predict that a full 2020 season would have likely been similarly as hit producing as 2019.

We can also see that our 2020 season of 60 games was very hitting productive in just that 37% of a season played. In those 60 games hitters were able to get 34% of the total hits from 2019, 34% of total home runs and 35% of the total RBI's. I think it is safe to conclude given our predictions and statements from independent scientist and MLB themselves that a full 2020 season would have been played with "juiced" or altered baseballs that would have allowed for a more hitting friendly atmosphere.

Pitching Data:

Season	K	ERA	H/9	HR/9	Exit Velocity
2018	41,207	4.15	8.49	1.16	88.4
2019	42,823	4.51	8.72	1.41	88.7
2020 (60 Games)	15,586	4.46	8.40	1.34	88.4
2020 (Predicted)	**42,607**	**4.26**	**8.5**	**1.26**	**88.4**
2021	42,145	4.27	8.34	1.26	88.7

2018 was the most pitcher friendly season of all the seasons we analyzed which further shows that a full 2020 season would have been played with "juiced" baseballs. 2019 saw a significant increase in strikeouts, ERA, H/9, and HR/9 but barely any difference in exit velocity.

Baseball can sometimes go through phases where the pace of play either favors hitters or pitchers. In this instance 2019 was favorable to hitters because of the change of baseball. This counterintuitively correlates with more strikeouts because hitters are trying to hit the ball harder knowing that there is a better chance for a home run since the balls are juiced. Basically, anytime there is a jump in home runs (which there was) expect a jump in strikeouts from hitters swinging out of their shoes more often.

Our 2020 60 game sample size also saw a decrease in pitching production which puts it on par with the 2019 and predicted 2020 season. 2020 had 36% of total strikeouts in just 37% of the games. This aligns with how 34% of the home runs in 2019 were hit in just 60 games in 2020.

There being a negligible difference in exit velocity is the most interesting find since I would have assumed there to be an increase there too with the baseballs being tailored to be more hitting friendly

Statcast Data:

Season	Max Hit Distance	Max Hit Speed	Avg HR Distance
2018	466 ft	116 mph	397.3 ft
2019	473.5 ft	116 mph	400.2 ft
2020 (60 Games)	458 ft	114 mph	401 ft
2020 (Predicted)	**467 ft**	**116 mph**	**400.2 ft**
2021	469 ft	117 mph	401 ft

Oddly enough, when it comes to statcast data there is not much to compare as all the seasons including our predicted 2020 seem to be very close. The 2019 season was slightly higher in terms of the maximum distances of balls hit that season, maximum hit speed, and average home run distance which were 473.5 ft, 116 mph, and 400.2 ft respectively. Our predicted 2020 season was the 2nd highest with 467 ft, 116 mph, and 400.2 ft.

The actual 2020 60 game season was right on par with 2019 and 2020 (predicted) but so was 2021 which was supposed to be the season where the balls were "de-juiced". This data shows us a small difference between 2019 and the seasons after that and 2018 when the balls were last normal. Given the fact that MLB was known to randomly change the baseballs at their own discretion it's tough to not think about them choosing which games to juice the baseballs for and which games to use normal baseball's for

Also considering there being barely a difference in exit velocity leads me to believe that there might be more to the juiced baseballs than just the seams being slightly taller or the balls being slightly lighter. All in all, this research leads me to make the claim that MLB would have allowed the 2020 season to play out with juiced baseballs like it did in 2019 and would ranked amongst one of the highest offense producing seasons in the history of professional baseball.

In conclusion, MLB surely has and continued to alter the baseballs at their leisure from 2019-2020. Our data all points to a full season of 2020 being like 2019 and not 2018. This begs the questioning of MLB's reputation and whether they decide to switch the balls for certain games or even when certain players are playing. Given MLB's dark history of gambling on games or steroid consumption it leaves a lot of open room for questions and debate

References and Sources

Apstein, S. (2021, February 9). *Did MLB use juiced balls in 2020?* Sports Illustrated. Retrieved February 8, 2022, from https://www.si.com/mlb/2021/02/09/mlb-ball-is-live-daily-cover

Brown, M. (2021, December 8). *Major League Baseball's integrity is at stake as study finds inconsistencies with the ball*. Forbes. Retrieved February 1, 2022, from https://www.forbes.com/sites/maurybrown/2021/12/06/major-league-baseballs-integrity-at-stake-due-to-inconsistencies-with-the-ball/?sh=ad797c7015c8

Feinsand, M. (2021, February 9). *MLB to alter baseballs for '21 season*. MLB.com. Retrieved February 1, 2022, from https://www.mlb.com/news/mlb-to-alter-baseballs-for-2021