Final Project

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Introduction

Baseball, America's pastime, has a long and storied tradition that dates back well over 100 years. Since the 1850's, some form of statistics measuring how good a player is has been tracked. This began through the use of the box score, which tracked basic statistics, such as hits, runs, and errors, from which a player's batting average can be constructed. Over one hundred years later, a pioneering statistician by the name of Bill James introduced new statistical concepts, such as on-base percentage and runs created, in his annual Baseball Abstract (Lee 2018). As technology has improved, the statistics being tracked became more and more sophisticated. Then, in 2015 analytics in baseball took a giant leap. With the introduction of Statcast, teams were able to track novel metrics, such as a batter's exit velocity (the speed of the baseball as it comes off the bat, immediately after a batter makes contact) and barrel percentage (the percentage of baseballs hit off of the player's barrel) ("Statcast Search"). Around the league, teams adopted these new statistics to try and gain a competitive advantage, through which they would be able to better predict a player's potential. However, is this actually the case? While these new statistics are widely used, it is unclear whether they actually provide any useful information for predicting a player's potential. This research project intends to explore that idea through the use of a logistic regression model to predict whether a player is an all-star. The research question of interest is:

Do old or new wave statistics do a better job at predicting whether a player is selected as an all-star?

The response variables of interest are: All.Star: Whether a player is selected as an all-star. Salary: How much money a player makes.

For our analysis, we have selected two datasets. The first is from Baseball Reference, which consists of standard statistics that offer a broad view of a player's performance in a particular season. The second is from Statcast, which consists of each player's primary position. ADD MORE ABOUT WHAT WE DID WITH THE DATA HERE

Methodology

Results

Discussion

Packages and Data

```
library(tidyverse)
library(tidymodels)
library(glmnet)
library(caret)
library(MASS)
library(lme4)
stats <- read.csv("data/stats.csv")


stats <- replace(stats, stats =="", NA)
stats <- stats %>%
  drop_na() %>%
  mutate(AVG300 = case_when(batting_avg >= .3 ~ "Greater than 300", TRUE ~ "Less than 300"
         HR40 = case_when(b_home_run >= 40 ~ "Greater than 40", TRUE ~ "Less than 40"), pi
view(stats)
```

Lassos for Variable Selection

```
# LASSO Variable Selection Basic Stats
y <- stats$All.Star
x <- model.matrix(All.Star ~ player_age + b_ab + b_total_pa + b_total_hits + b_home_run +
                    b_double + b_triple + b_home_run * HR40 + b_strikeout + b_walk +
                    batting_avg + slg_percent + on_base_percent + Position, data = stats)
m_lasso_cv <- cv.glmnet(x, y, alpha = 1)
best_lambda <- m_lasso_cv$lambda.min
best_lambda
```

```
[1] 0.005074189
```

```
m_best <- glmnet(x, y, alpha = 1, lambda = best_lambda)
m_best$beta
```

```
29 x 1 sparse Matrix of class "dgCMatrix"
                                         s0
(Intercept)                       .
player_age                       -2.484154e-03
b_ab                              .
b_total_pa                        .
b_total_hits                      .
b_home_run                        1.112011e-02
AVG300Less than 300              -1.834892e-01
batting_avg                       .
b_double                          9.728319e-05
b_triple                          2.649366e-03
HR40Less than 40                 -1.448258e-01
b_strikeout                      -1.120913e-03
b_walk                            1.514027e-03
slg_percent                       3.427099e-02
on_base_percent                   .
Position2B                        .
Position3B                       -3.210743e-02
PositionC                         2.028280e-02
PositionCF                        1.475510e-02
PositionCH                        .
PositionDH                       -3.029771e-02
PositionDNP                       .
PositionLF                       -4.911649e-02
PositionPH                        .
PositionRF                        .
PositionSP                        1.771973e-01
PositionSS                        1.259864e-02
AVG300Less than 300:batting_avg   .
b_home_run:HR40Less than 40       .
```

```r
# LASSO Variable Selection Advanced Stats
y <- stats$All.Star
x <- model.matrix(All.Star ~ player_age + launch_angle_avg + sweet_spot_percent +
                    barrel + solidcontact_percent + flareburner_percent +
                    hard_hit_percent + avg_hyper_speed + z_swing_percent +
                    oz_swing_percent + meatball_swing_percent, data = stats)
m_lasso_cv <- cv.glmnet(x, y, alpha = 1)
best_lambda <- m_lasso_cv$lambda.min
best_lambda
```

```
[1] 0.005820234
```

```
m_best <- glmnet(x, y, alpha = 1, lambda = best_lambda)
m_best$beta
```

```
12 x 1 sparse Matrix of class "dgCMatrix"
                                 s0
(Intercept)                    .
player_age             -0.0018096273
launch_angle_avg       -0.0001599061
sweet_spot_percent             .
barrel                  0.0080466625
solidcontact_percent   -0.0030825651
flareburner_percent    -0.0018259472
hard_hit_percent       -0.0018130937
avg_hyper_speed                .
z_swing_percent                .
oz_swing_percent               .
meatball_swing_percent -0.0021930005
```

Regressions

```
#Basic model
m1 <- glm(All.Star ~ player_age + b_ab +  b_total_hits +
                    b_double + b_triple + b_home_run + b_strikeout +
                    b_bb_percent + AVG300 + slg_percent +
                    on_base_percent + Position,
  data = stats,
  family = "binomial"
)
tidy(m1)
```

```
# A tibble: 24 x 5
   term                estimate std.error statistic p.value
   <chr>                  <dbl>     <dbl>     <dbl>   <dbl>
 1 (Intercept)         -5.96      2.78       -2.15   0.0319
 2 player_age          -0.0369    0.0570     -0.647  0.518
 3 b_ab                -0.00925   0.00925    -1.00   0.317
 4 b_total_hits         0.0450    0.0300      1.50   0.133
```

```
 5 b_double             0.0182    0.0411      0.443  0.657
 6 b_triple            -0.0469    0.116      -0.404  0.686
 7 b_home_run           0.0719    0.0524      1.37   0.170
 8 b_strikeout         -0.00188   0.00930    -0.203  0.839
 9 b_bb_percent         0.155     0.105       1.48   0.140
10 AVG300Less than 300 -0.617     0.768      -0.804  0.421
# ... with 14 more rows
```

```r
m1_aug <- augment(m1) %>%
  mutate(prob = exp(.fitted)/(1 + exp(.fitted)),
         pred_leg = ifelse(prob > 0.32, "All-Star", "Not All-Star"))
table(m1_aug$pred_leg, m1_aug$All.Star)
```

```
                0   1
  All-Star     22  30
  Not All-Star 410  24
```

```r
#Advanced model
m2 <- glm(All.Star ~ player_age + launch_angle_avg +
                    barrel + solidcontact_percent + flareburner_percent +
                    hard_hit_percent + meatball_swing_percent,
  data = stats,
  family = "binomial"
)
tidy(m2)
```

```
# A tibble: 8 x 5
  term                   estimate std.error statistic  p.value
  <chr>                     <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)             1.38       1.76       0.785 4.32e- 1
2 player_age             -0.0361     0.0468    -0.772 4.40e- 1
3 launch_angle_avg       -0.00881    0.0283    -0.312 7.55e- 1
4 barrel                  0.0852     0.0136     6.27  3.56e-10
5 solidcontact_percent   -0.0805     0.0943    -0.854 3.93e- 1
6 flareburner_percent    -0.0129     0.0379    -0.341 7.33e- 1
7 hard_hit_percent       -0.0256     0.0263    -0.974 3.30e- 1
8 meatball_swing_percent -0.0358     0.0162    -2.21  2.72e- 2
```

```r
m2_aug <- augment(m2) %>%
  mutate(prob = exp(.fitted)/(1 + exp(.fitted)),
         pred_leg = ifelse(prob > 0.32, "All-Star", "Not All-Star"))
table(m2_aug$pred_leg, m2_aug$All.Star)
```

```
                0   1
  All-Star     22  20
  Not All-Star 410  34
```

```r
# obp percentage lasso
y <- stats$on_base_percent
x <- model.matrix(on_base_percent ~ launch_angle_avg + sweet_spot_percent +
                    barrel + solidcontact_percent + flareburner_percent +
                    hard_hit_percent + avg_hyper_speed + z_swing_percent +
                    oz_swing_percent + meatball_swing_percent, data = stats)
m_lasso_cv <- cv.glmnet(x, y, alpha = 1)
best_lambda <- m_lasso_cv$lambda.min
best_lambda
```

```
[1] 6.588831e-05
```

```r
m_best <- glmnet(x, y, alpha = 1, lambda = best_lambda)
m_best$beta
```

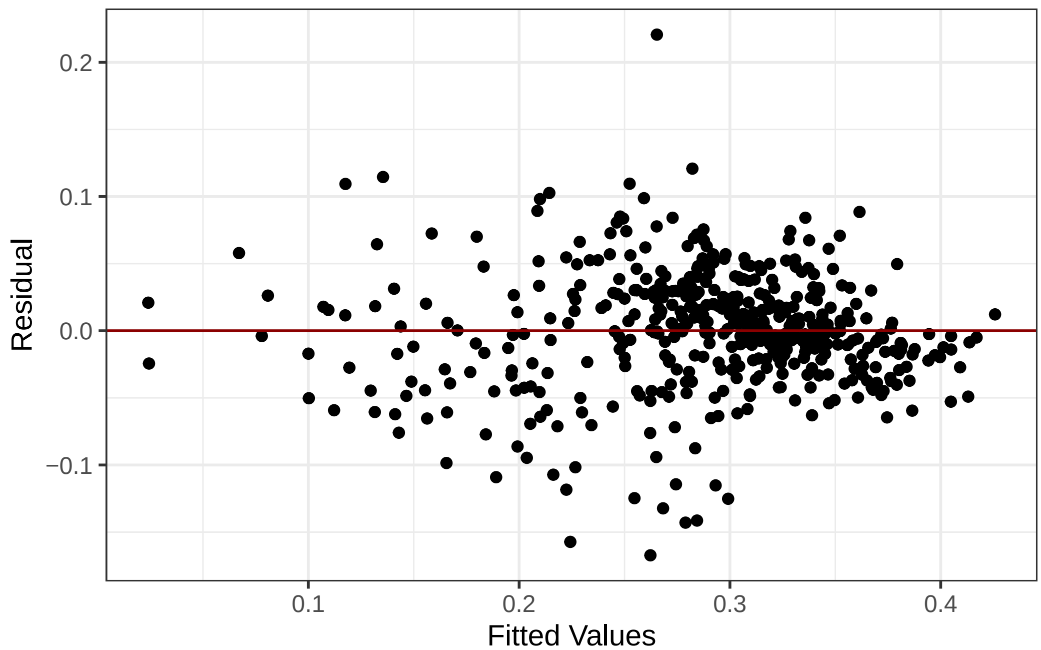
```
11 x 1 sparse Matrix of class "dgCMatrix"
                                  s0
(Intercept)             .
launch_angle_avg       -0.0004177699
sweet_spot_percent      0.0020967297
barrel                  0.0013805557
solidcontact_percent    0.0022122425
flareburner_percent     0.0036068089
hard_hit_percent        0.0017835578
avg_hyper_speed        -0.0062577021
z_swing_percent         0.0006378467
oz_swing_percent       -0.0029185729
meatball_swing_percent  0.0007305436
```

```r
# obp percentage prediction
m3 <- lm(on_base_percent ~ sweet_spot_percent +
                    barrel + solidcontact_percent + flareburner_percent +
                    hard_hit_percent + z_swing_percent +
                    oz_swing_percent + meatball_swing_percent,
  data = stats)

summary(m3)
```

```

Call:
lm(formula = on_base_percent ~ sweet_spot_percent + barrel +
    solidcontact_percent + flareburner_percent + hard_hit_percent +
    z_swing_percent + oz_swing_percent + meatball_swing_percent,
    data = stats)

Residuals:
      Min        1Q    Median        3Q       Max
-0.167277 -0.023263 -0.000016  0.026078  0.220647

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.0700061  0.0194563   3.598 0.000354 ***
sweet_spot_percent      0.0019772  0.0004004   4.938 1.09e-06 ***
barrel                  0.0013301  0.0001686   7.891 2.07e-14 ***
solidcontact_percent    0.0022739  0.0008601   2.644 0.008470 **
flareburner_percent     0.0038182  0.0004997   7.641 1.19e-13 ***
hard_hit_percent        0.0008075  0.0002987   2.703 0.007115 **
z_swing_percent         0.0006259  0.0004381   1.428 0.153809
oz_swing_percent       -0.0029453  0.0003171  -9.288  < 2e-16 ***
meatball_swing_percent  0.0007211  0.0002533   2.847 0.004610 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04441 on 477 degrees of freedom
Multiple R-squared:  0.6983,	Adjusted R-squared:  0.6933
F-statistic:   138 on 8 and 477 DF,  p-value: < 2.2e-16
```

```r
m3_aug <- augment(m3)
m3_aug |>
ggplot(aes(x = .fitted, y = .resid)) +
```

```
  geom_point() +
  geom_hline(yintercept = 0, color = "darkred") +
  labs(x = "Fitted Values",
       y = "Residual") +
  theme_bw()
```




```
# slugging percentage lasso
y <- stats$slg_percent
x <- model.matrix(slg_percent ~ launch_angle_avg + sweet_spot_percent +
                    barrel + solidcontact_percent + flareburner_percent +
                    hard_hit_percent + avg_hyper_speed + z_swing_percent +
                    oz_swing_percent + meatball_swing_percent, data = stats)
m_lasso_cv <- cv.glmnet(x, y, alpha = 1)
best_lambda <- m_lasso_cv$lambda.min
best_lambda
```

```
[1] 0.0003770259
```

```
m_best <- glmnet(x, y, alpha = 1, lambda = best_lambda)
m_best$beta
```

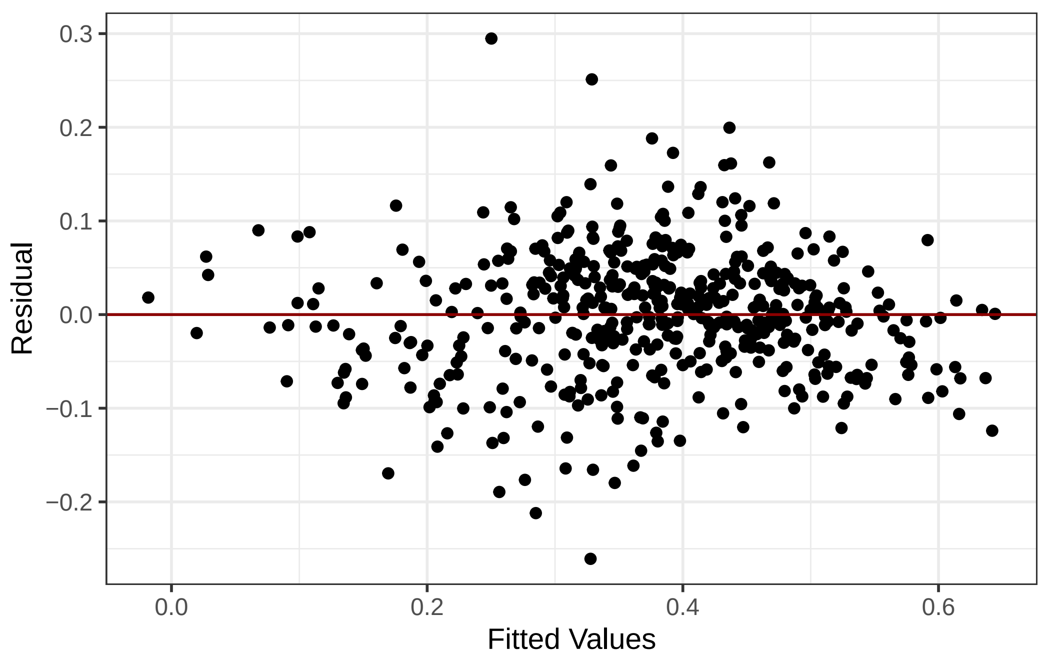
```
11 x 1 sparse Matrix of class "dgCMatrix"
                                  s0
(Intercept)            .
launch_angle_avg        0.0005045607
sweet_spot_percent      0.0038891901
barrel                  0.0035525156
solidcontact_percent    0.0020985959
flareburner_percent     0.0030421488
hard_hit_percent        0.0012516893
avg_hyper_speed         0.0054590302
z_swing_percent         0.0013231068
oz_swing_percent       -0.0007980993
meatball_swing_percent  0.0006862287
```

```r
# slugging percentage prediction
m4 <- lm(slg_percent ~ launch_angle_avg + sweet_spot_percent +
                    barrel + solidcontact_percent + flareburner_percent +
                    hard_hit_percent + avg_hyper_speed + z_swing_percent +
                    oz_swing_percent + meatball_swing_percent,
  data = stats)

summary(m4)
```

```
Call:
lm(formula = slg_percent ~ launch_angle_avg + sweet_spot_percent +
    barrel + solidcontact_percent + flareburner_percent + hard_hit_percent +
    avg_hyper_speed + z_swing_percent + oz_swing_percent + meatball_swing_percent,
    data = stats)

Residuals:
      Min        1Q    Median        3Q       Max
-0.260804 -0.041484  0.002206  0.040864  0.294753

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.0807292  0.0316715  -2.549   0.0111 *
launch_angle_avg        0.0005148  0.0005433   0.948   0.3438
sweet_spot_percent      0.0038654  0.0006637   5.824 1.06e-08 ***
barrel                  0.0035645  0.0002677  13.318  < 2e-16 ***
solidcontact_percent    0.0022226  0.0013590   1.635   0.1026
```

```
flareburner_percent      0.0031461  0.0007964   3.950 9.00e-05 ***
hard_hit_percent         0.0011213  0.0010244   1.095   0.2742
avg_hyper_speed          0.0060747  0.0058969   1.030   0.3035
z_swing_percent          0.0013843  0.0006861   2.018   0.0442 *
oz_swing_percent        -0.0008703  0.0005029  -1.731   0.0842 .
meatball_swing_percent  0.0006949  0.0003958   1.756   0.0798 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06915 on 475 degrees of freedom
Multiple R-squared:  0.7432,    Adjusted R-squared:  0.7378
F-statistic: 137.5 on 10 and 475 DF,  p-value: < 2.2e-16
```

```r
m4_aug <- augment(m4)
m4_aug |>
ggplot(aes(x = .fitted, y = .resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "darkred") +
  labs(x = "Fitted Values",
       y = "Residual") +
  theme_bw()
```



```r
# Subset for nationals
nationals_stats <- stats |>
  filter(Team == "WAS")

# Predict
pred_obp <- predict(m3, nationals_stats)
pred_slg <- predict(m4, nationals_stats)

# Add to DF
nationals_stats <- nationals_stats |>
  mutate(Predicted_OBP = pred_obp,
         Predicted_SLG = pred_slg)

# Display
print(nationals_stats)
```

```
   player_id year player_age b_ab b_total_pa b_total_hits b_double b_triple
1     434671 2019         35   52         56            6        0        0
2     435062 2019         35  334        370          115       23        1
3     435559 2019         35  280        309           74       11        0
4     453286 2019         34   55         61           10        0        0
5     475582 2019         34  171        190           44        9        0
6     476451 2019         32    9         13            1        0        0
7     543228 2019         31  314        358           70       16        0
8     543685 2019         29  545        646          174       44        3
9     544931 2019         30   72         80           12        1        0
10    571431 2019         30  310        333           70       14        0
11    571578 2019         29   65         72            6        1        0
12    572191 2019         28   88         97           22        7        0
13    572821 2019         32  416        482           99       20        0
14    594694 2019         27  131        144           33        2        0
15    594809 2019         30  566        656          158       25        7
16    607208 2019         26  521        569          155       37        5
17    645302 2019         22  546        617          139       33        3
18    664057 2019         25   30         37           11        1        1
19    665742 2019         20  542        659          153       32        5
20    669738 2019         25   12         13            2        1        0
   b_home_run b_strikeout b_walk b_k_percent b_bb_percent batting_avg
1           0          24      0        42.9          0.0       0.115
2          17          49     27        13.2          7.3       0.344
3          17          36     20        11.7          6.5       0.264
4           0          27      0        44.3          0.0       0.182
```

5	6	39	17	20.5	8.9	0.257
6	0	4	2	30.8	15.4	0.111
7	12	84	38	23.5	10.6	0.223
8	34	86	80	13.3	12.4	0.319
9	1	25	3	31.3	3.8	0.167
10	20	115	20	34.5	6.0	0.226
11	0	27	3	37.5	4.2	0.092
12	1	34	7	35.1	7.2	0.250
13	20	105	61	21.8	12.7	0.238
14	2	29	12	20.1	8.3	0.252
15	15	106	65	16.2	9.9	0.279
16	19	113	43	19.9	7.6	0.298
17	17	140	35	22.7	5.7	0.255
18	0	11	6	29.7	16.2	0.367
19	34	132	108	20.0	16.4	0.282
20	0	4	1	30.8	7.7	0.167

	slg_percent	on_base_percent	xba	xslg	woba	xwoba	xobp	xiso	xslgdiff
1	0.115	0.107	0.127	0.146	0.100	0.121	0.127	0.019	-0.031
2	0.572	0.395	0.332	0.614	0.400	0.418	0.388	0.282	-0.042
3	0.486	0.324	0.277	0.455	0.337	0.338	0.337	0.178	0.031
4	0.182	0.164	0.152	0.188	0.158	0.147	0.152	0.035	-0.006
5	0.415	0.321	0.248	0.444	0.313	0.325	0.316	0.196	-0.029
6	0.111	0.231	0.099	0.110	0.205	0.200	0.263	0.011	0.001
7	0.389	0.316	0.217	0.391	0.298	0.302	0.313	0.174	-0.002
8	0.598	0.412	0.310	0.590	0.413	0.414	0.407	0.280	0.008
9	0.222	0.188	0.191	0.279	0.186	0.221	0.224	0.088	-0.057
10	0.465	0.276	0.228	0.479	0.306	0.320	0.281	0.251	-0.014
11	0.108	0.125	0.106	0.133	0.112	0.131	0.146	0.028	-0.025
12	0.364	0.299	0.213	0.375	0.289	0.276	0.271	0.163	-0.011
13	0.430	0.340	0.235	0.426	0.329	0.330	0.339	0.191	0.004
14	0.313	0.313	0.246	0.319	0.270	0.272	0.310	0.073	-0.006
15	0.428	0.360	0.256	0.406	0.342	0.328	0.346	0.149	0.022
16	0.497	0.353	0.279	0.455	0.356	0.339	0.337	0.176	0.042
17	0.419	0.323	0.231	0.368	0.317	0.294	0.305	0.137	0.051
18	0.467	0.486	0.216	0.388	0.417	0.339	0.369	0.172	0.079
19	0.548	0.401	0.285	0.575	0.394	0.409	0.405	0.290	-0.027
20	0.250	0.231	0.176	0.199	0.214	0.202	0.239	0.023	0.051

	exit_velocity_avg	launch_angle_avg	sweet_spot_percent	barrel
1	78.6	-1.5	25.0	0
2	91.7	10.8	36.9	33
3	86.0	18.9	39.7	16
4	87.2	-7.5	20.6	0
5	91.4	9.7	32.8	10

6	76.7	-12.0	0.0	0
7	87.6	18.1	32.0	16
8	90.4	19.5	38.7	56
9	88.0	-3.9	26.9	1
10	88.6	19.6	39.8	29
11	81.9	-5.8	16.7	0
12	91.5	8.9	32.1	4
13	88.5	19.0	32.4	21
14	83.9	10.1	34.0	0
15	88.9	15.3	33.9	18
16	90.4	9.9	29.8	28
17	83.3	16.7	34.5	20
18	84.6	12.0	31.6	2
19	92.0	12.5	36.3	51
20	78.0	-2.8	25.0	0

	solidcontact_percent	flareburner_percent	hard_hit_percent	avg_hyper_speed
1	0.0	15.6	0.0	1.041144
2	8.6	27.2	48.3	7.726170
3	4.5	29.1	32.4	4.618345
4	0.0	23.5	20.6	4.216138
5	11.2	19.4	49.3	7.398411
6	0.0	14.3	14.3	3.160608
7	6.5	22.5	36.1	5.052168
8	6.6	27.4	46.6	6.364730
9	1.9	26.9	28.8	4.335569
10	8.2	18.9	43.9	6.825084
11	2.4	16.7	11.9	1.749437
12	8.9	23.2	42.9	7.216883
13	7.1	26.9	35.4	5.121792
14	5.8	27.2	19.4	2.731144
15	6.6	26.3	34.3	5.472874
16	6.3	26.1	42.0	6.839620
17	5.5	21.3	23.0	3.739896
18	5.3	21.1	31.6	4.248422
19	8.7	25.5	47.8	7.569585
20	0.0	25.0	0.0	0.500720

	z_swing_percent	oz_swing_percent	meatball_swing_percent	Salary	Position
1	50.9	56.4	50.0	8000000	SP
2	64.0	31.4	72.2	4000000	1B
3	74.2	29.7	83.1	4000000	C
4	66.4	34.7	68.0	37405562	SP
5	56.7	27.0	52.1	18000000	1B
6	44.1	13.0	80.0	1300000	SP

```
7            67.2            34.3                   76.3  7083333        C
8            68.3            20.6                   78.6 18800000       3B
9            62.4            29.6                   52.4 38333334       SP
10           70.5            34.1                   76.5  3000000       1B
11           58.6            41.5                   63.6 12916666       SP
12           69.7            24.7                   75.0  3250000       CF
13           62.2            19.6                   69.8  9000000       2B
14           79.0            30.4                   92.2   581100       SS
15           63.8            27.4                   71.4  8400000       RF
16           67.4            29.2                   70.5  3725000       SS
17           71.1            30.1                   82.6   557800       CF
18           76.3            31.7                   80.0   559100       PH
19           66.7            20.3                   79.9   578300       LF
20           68.4            50.0                   66.7   555000       PH
   Team All.Star    last_name  first_name            AVG300         HR40 pitcher
1   WAS        0      Sanchez      Anibal    Less than 300 Less than 40     Yes
2   WAS        0 Kendrick III       Howie Greater than 300 Less than 40      No
3   WAS        0       Suzuki        Kurt    Less than 300 Less than 40      No
4   WAS        1     Scherzer         Max    Less than 300 Less than 40     Yes
5   WAS        0    Zimmerman        Ryan    Less than 300 Less than 40      No
6   WAS        0   Hellickson      Jeremy    Less than 300 Less than 40     Yes
7   WAS        0        Gomes         Yan    Less than 300 Less than 40      No
8   WAS        1      Rendon     Anthony Greater than 300 Less than 40      No
9   WAS        0    Strasburg     Stephen    Less than 300 Less than 40     Yes
10  WAS        0        Adams        Matt    Less than 300 Less than 40      No
11  WAS        0       Corbin     Patrick    Less than 300 Less than 40     Yes
12  WAS        0       Taylor  Michael A.    Less than 300 Less than 40      No
13  WAS        0       Dozier       Brian    Less than 300 Less than 40      No
14  WAS        0         Difo      Wilmer    Less than 300 Less than 40      No
15  WAS        0        Eaton        Adam    Less than 300 Less than 40      No
16  WAS        0       Turner        Trea    Less than 300 Less than 40      No
17  WAS        0       Robles      Victor    Less than 300 Less than 40      No
18  WAS        0    Stevenson      Andrew Greater than 300 Less than 40      No
19  WAS        0         Soto        Juan    Less than 300 Less than 40      No
20  WAS        0         Noll        Jake    Less than 300 Less than 40      No
   Predicted_OBP Predicted_SLG
1     0.08079562    0.12665655
2     0.34890606    0.50231016
3     0.33617350    0.44003788
4     0.20548758    0.22665050
5     0.28104218    0.36403902
6     0.18315099    0.09864245
7     0.28045157    0.38190917
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8	0.41701544	0.60153597
9	0.24446703	0.26932063
10	0.31238228	0.47601924
11	0.14216221	0.15187871
12	0.30721168	0.37400951
13	0.34097188	0.41791040
14	0.29633013	0.33967319
15	0.31481301	0.40554899
16	0.32108186	0.44099774
17	0.29263481	0.38988303
18	0.26535264	0.32775106
19	0.40492893	0.57713739
20	0.15853137	0.19367725

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