# Moneyball Sequel

The Art of Winning an Unfair Game

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# Introudction

The Michael Lewis book *Moneyball* is a story about the Oakland Athletics baseball club's 2002 season. Being a small market team, the 2002 Athletics had one of the lowest payrolls in MLB but managed to win the most games in all of baseball through the application of empirical analytics known as sabermetric.


The story pointed out the flaws of using batting average (BA or AVG) as to determine a player's offensive ability, rather, on-base percentage (OBP) and slugging percentage (SLG) are better indicators of offensive success. This led to the famous internet meme as shown on the right, where the only thing Bill Beane (portrayed by Brad Pitt) cared about is whether a player can get on base.

## Objective

Now it is widely accepted in the baseball community that OBP and SLG are some of the most important indicators of a player's offensive production. What I wanted to do is to analyze whether a pitcher's ability to prevent batters get on base would determine his overall effectiveness as a big league hurler. I will also examine the combination of preventing batters get on base and slugging a high percentage would be a better indicator. I will be using two machine learning methods to model my training data: Gradient Descent and the Normal Equation. All the coding is done in Octave.

To see how the code computes the output, run the moneyball_sequel.m file in Octave and it would demonstrate how all the plots and tables are generated.

# 1st Training Set

## Training Data

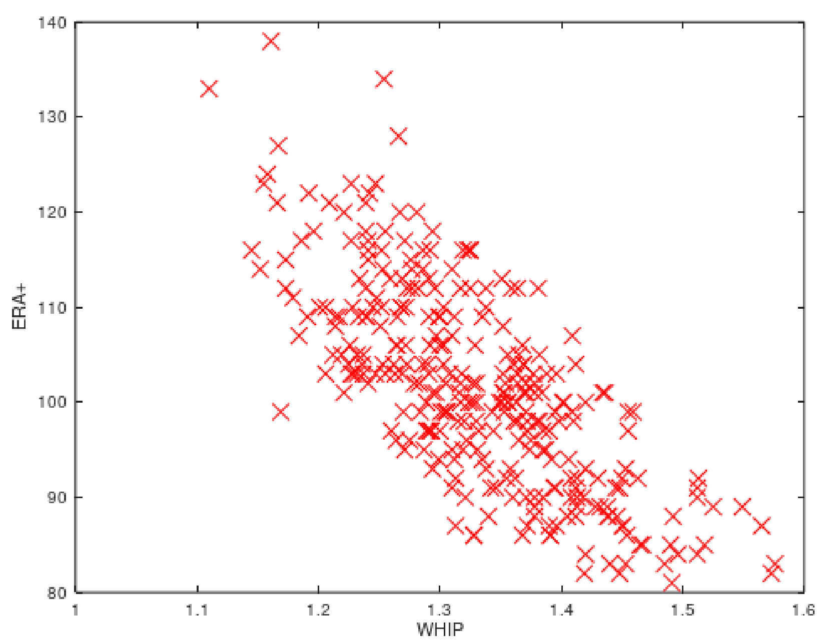
The training input or the explanatory variable will be Walks plus Hits per Innings Pitched (WHIP), and the output is ERA+ (Earned Run Average Plus) from 2008-2017 for all 30 MLB teams.

WHIP – this is a proxy for a pitcher's OBP against. I'm using WHIP over OBP because OBP includes hit-by-pitch (HBP). Although HBP is related to the pitcher's control, I think there is a high degree of randomness to it and should not be used to evaluate a pitcher's performance.

ERA+ - ERA is a measure of how many earned runs a pitcher gives up per 9 innings, the lower a pitcher's ERA, the better the pitcher is at preventing earned runs. ERA+ is a version of ERA where it is adjusted by ballpark factors and is scaled to 100. Some pitchers pitch more in bigger ballparks so they have an advantage, while some pitchers pitch more in cities with dry air like Colorado, where the ball carries further, so they are at a disadvantage. The ballpark factor put these into consideration and removes the differences among ballparks. An ERA+ of 100 is league average, the higher the better.

Here is a plot for the training data on the right. We can clearly see an inverse linear relationship – and it makes sense intuitively as a team with a low WHIP is a team that allows fewer baserunners via walk or hits, which is a team that has an ERA+.

The linear model equation will be:
**$y = \theta_0 + \theta_1 * x$**, where y is ERA+ and x is WHIP.




## Gradient Descent

Now let's put the training data through the gradient descent (gradientDescent.m) function to obtain the theta (coefficient for the independent variable or the input)

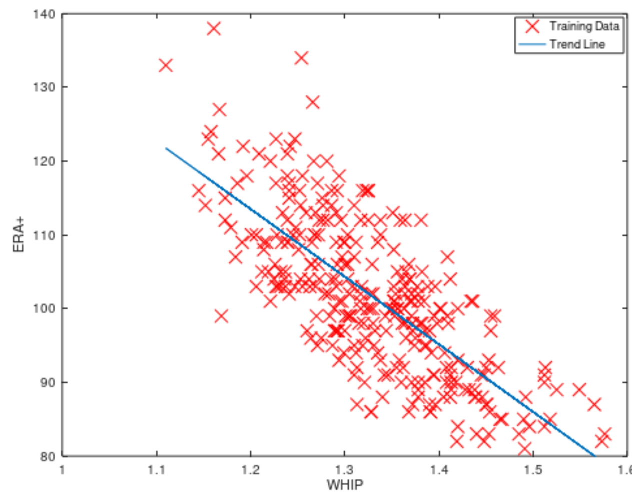
```
Theta found by gradient descent:
223.562592
-91.712376
```

So we got a y-intercept of 223.56 and -91.71 as the coefficient for our independent variable.

Our model is now **y = 223.56-91.71*x**

This again makes sense intuitively because as WHIP increases, ERA+ decreases. But I wanted to plot the theta against my training data to see if it is the right fit.

As we can see, the trend line looks to be a good representation of the training data, so the gradient descent algorithm has done its job!

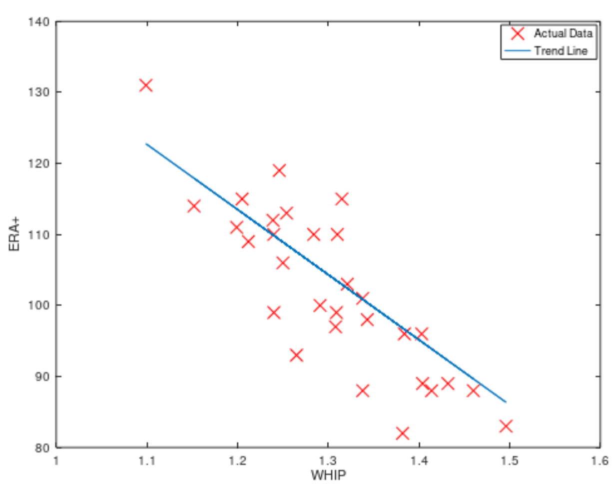



## Prediction

Now we want to predict 2018's ERA+ for each team based on their WHIP using the theta obtained from gradient descent.

See the table on the right for the result and how it comparres to the actual ERA+ in 2018.

Now I will plot the **y = 223.56-91.71*x** against the actual ERA+ and WHIP data for each team in 2018. We can see in the plot below that the trend line is a pretty accurate model in comparison to the actual ERA+.




| Team | Predicted ERA+ | Actual ERA+ |
|---|---|---|
| ARI | 108.555 | 113 |
| ATL | 105.804 | 110 |
| BAL | 86.3609 | 83 |
| BOS | 109.289 | 119 |
| CHC | 102.961 | 115 |
| CHW | 92.2305 | 89 |
| CIN | 94.7984 | 89 |
| CLE | 113.049 | 115 |
| COL | 103.419 | 110 |
| DET | 100.393 | 98 |
| HOU | 122.771 | 131 |
| KCR | 89.6625 | 88 |
| LAA | 102.411 | 103 |
| LAD | 117.91 | 114 |
| MIA | 96.8161 | 82 |
| MIL | 109.839 | 110 |
| MIN | 96.6327 | 96 |
| NYM | 107.546 | 93 |
| NYY | 109.931 | 112 |
| OAK | 112.407 | 109 |
| PHI | 105.162 | 100 |
| PIT | 103.511 | 99 |
| SDP | 100.851 | 88 |
| SEA | 109.839 | 99 |
| SFG | 103.603 | 97 |
| STL | 100.851 | 101 |
| TBR | 113.599 | 111 |
| TEX | 94.8901 | 96 |
| TOR | 93.8813 | 88 |
| WSN | 108.922 | 106 |

After computing the Coefficient of Determination, or R2, or that 71% off the variance in our output can be explained from the model, pretty good considering we are only using one variable.

```
Coefficient of Determination is 0.712354
```

# 2nd Training Set

## Training Data

For the second training set, I will be introducing slugging percentage (SLG) against as another explanatory or independent variable in addition to WHIP to determine ERA+.

SLG is simple terms is how well batters can drive the ball and get extra base hits of a pitcher. The higher the SLG, the pitcher is more prone to his pitches being hit hard as extra base hits such as doubles and home runs.

We will be using the 2008-2017 team stats again, and use our model to predict the 2018 ERA+ based on each team's SLG against and WHIP. Instead of using gradient descent, we will be using the normal equation to model the theta.

The linear model equation will be: $\mathbf{y = \theta_0 + \theta_1 * x_1 + \theta_2 * x_2}$, where y is ERA+, x1 is WHIP, and x2 is SLG.

## The Normal Equation

The Normal Equation is as follows: $\boldsymbol{\theta} = (\boldsymbol{X}^T\boldsymbol{X})(\boldsymbol{X}^T\boldsymbol{X})^{-1} \cdot (\boldsymbol{X}^T\boldsymbol{y})$

After running the normal equation (normalEqn.m), we obtained the theta on the right. This gives us the model $\mathbf{y = 231.67 - 63.96 * x_1 - 110.55 * x_2}$

```
theta =

   231.672
   -63.963
  -110.554
```

## Prediction

We will use the model to predict ERA+ and compare it against the actually ERA+ for teams in 2018, which gives the table on the right.

We also have an updated R2 of 73.62%, an improvement from 71.23% in the first data set. This means almost 74% of the variance in ERA+ can be explained by WHIP and SLG – not a big improvement from the 1st training set but still an enhanced model.

```
Coefficient of Determination is 0.736166
```

| Team | Predicted ERA+ | Actual ERA+ |
|---|---|---|
| ARI | 108.567 | 113 |
| ATL | 108.638 | 110 |
| BAL | 83.9119 | 83 |
| BOS | 108.858 | 119 |
| CHC | 105.992 | 115 |
| CHW | 93.6438 | 89 |
| CIN | 92.1181 | 89 |
| CLE | 108.827 | 115 |
| COL | 101.779 | 110 |
| DET | 97.236 | 98 |
| HOU | 121.798 | 131 |
| KCR | 88.9784 | 88 |
| LAA | 101.296 | 103 |
| LAD | 116.086 | 114 |
| MIA | 96.3997 | 82 |
| MIL | 109.573 | 110 |
| MIN | 96.3824 | 96 |
| NYM | 106.758 | 93 |
| NYY | 109.305 | 112 |
| OAK | 110.811 | 109 |
| PHI | 104.1 | 100 |
| PIT | 102.948 | 99 |
| SDP | 99.988 | 88 |
| SEA | 106.146 | 99 |
| SFG | 103.344 | 97 |
| STL | 104.3 | 101 |
| TBR | 113.301 | 111 |
| TEX | 90.6344 | 96 |
| TOR | 91.9207 | 88 |
| WSN | 106.28 | 106 |

# Summary

The table below compares the result of the two predictions. WHIP can explain 71% of the variance in ERA+, which means it is a good indicator of a pitcher's overall effectiveness. Adding SLG into the equation improves the model but not by much, evidenced by the insignificant increase in R2.

We can conclude that WHIP is a strong indicator of pitching just like how OBP is a strong indicator of batting. One way how teams can use this information to find undervalued pitching is to look for pitchers who have a really low WHIP or OBP against while other statistics might not look as good due to ballpark factors or bad luck.

| Team | 1st Data Set | Variance | 2nd Data Set | Variance | Actual ERA+ |
|---|---|---|---|---|---|
| ARI | 108.555 | 4.44473 | 108.567 | 4.43302 | 113 |
| ATL | 105.804 | 4.1961 | 108.638 | 1.36196 | 110 |
| BAL | 86.3609 | -3.36088 | 83.9119 | -0.911892 | 83 |
| BOS | 109.289 | 9.71103 | 108.858 | 10.1424 | 119 |
| CHC | 102.961 | 12.0392 | 105.992 | 9.00814 | 115 |
| CHW | 92.2305 | -3.23047 | 93.6438 | -4.64378 | 89 |
| CIN | 94.7984 | -5.79842 | 92.1181 | -3.11815 | 89 |
| CLE | 113.049 | 1.95082 | 108.827 | 6.17321 | 115 |
| COL | 103.419 | 6.58062 | 101.779 | 8.22103 | 110 |
| DET | 100.393 | -2.39287 | 97.236 | 0.763996 | 98 |
| HOU | 122.771 | 8.22931 | 121.798 | 9.20209 | 131 |
| KCR | 89.6625 | -1.66252 | 88.9784 | -0.978414 | 88 |
| LAA | 102.411 | 0.589458 | 101.296 | 1.70352 | 103 |
| LAD | 117.91 | -3.90993 | 116.086 | -2.08623 | 114 |
| MIA | 96.8161 | -14.8161 | 96.3997 | -14.3997 | 82 |
| MIL | 109.839 | 0.160755 | 109.573 | 0.426981 | 110 |
| MIN | 96.6327 | -0.632663 | 96.3824 | -0.382363 | 96 |
| NYM | 107.546 | -14.5464 | 106.758 | -13.7578 | 93 |
| NYY | 109.931 | 2.06904 | 109.305 | 2.69468 | 112 |
| OAK | 112.407 | -3.40719 | 110.811 | -1.81123 | 109 |
| PHI | 105.162 | -5.16191 | 104.1 | -4.09982 | 100 |
| PIT | 103.511 | -4.51109 | 102.948 | -3.94847 | 99 |
| SDP | 100.851 | -12.8514 | 99.988 | -11.988 | 88 |
| SEA | 109.839 | -10.8392 | 106.146 | -7.14586 | 99 |
| SFG | 103.603 | -6.6028 | 103.344 | -6.3441 | 97 |
| STL | 100.851 | 0.148568 | 104.3 | -3.29959 | 101 |
| TBR | 113.599 | -2.59945 | 113.301 | -2.30105 | 111 |
| TEX | 94.8901 | 1.10987 | 90.6344 | 5.36564 | 96 |
| TOR | 93.8813 | -5.88129 | 91.9207 | -3.92073 | 88 |
| WSN | 108.922 | -2.92212 | 106.28 | -0.280099 | 106 |
| R-Sq | 0.712354 | | 0.736166 | | |

# Sources

All the statistics are exported from baseball-reference.com