Barry Bonds 2001

A look at the greatest single season of any player in baseball history.

By: BK

Brett Bejcek and Kyle Voytovich

Brief History

“1961 was the year of Mickey Mantle and Roger Maris. 1998 belonged to Sammy Sosa and Mark McGwire. 2001 saw only one home run king, Barry Bonds.”

Source: http://www.baseball-almanac.com/feats/feats0.shtml

During the 2001 Season, what factors played a role in the probability of Barry Bonds getting on base.

Our Data

- Appearance in the game
- Runners on base
- Inning and outs
- Score at time of at bat
- Opponents ERA

1 season

151 games

648 at bats

11 predictors

Source: http://www.amstat.org/publications/jse/datasets/bonds2001.txt

Exploratory Data Analysis

➔ **Identify key variables**

Based off our intuition of expected relationships.

➔ **Numerical summaries**

Produced pairwise summaries to look at association of variables.

➔ **Graphical summaries**

Translated tables to figures.

➔ **Model building**

Created generalized logistic models based off of previous analysis.

Home vs. Away Games

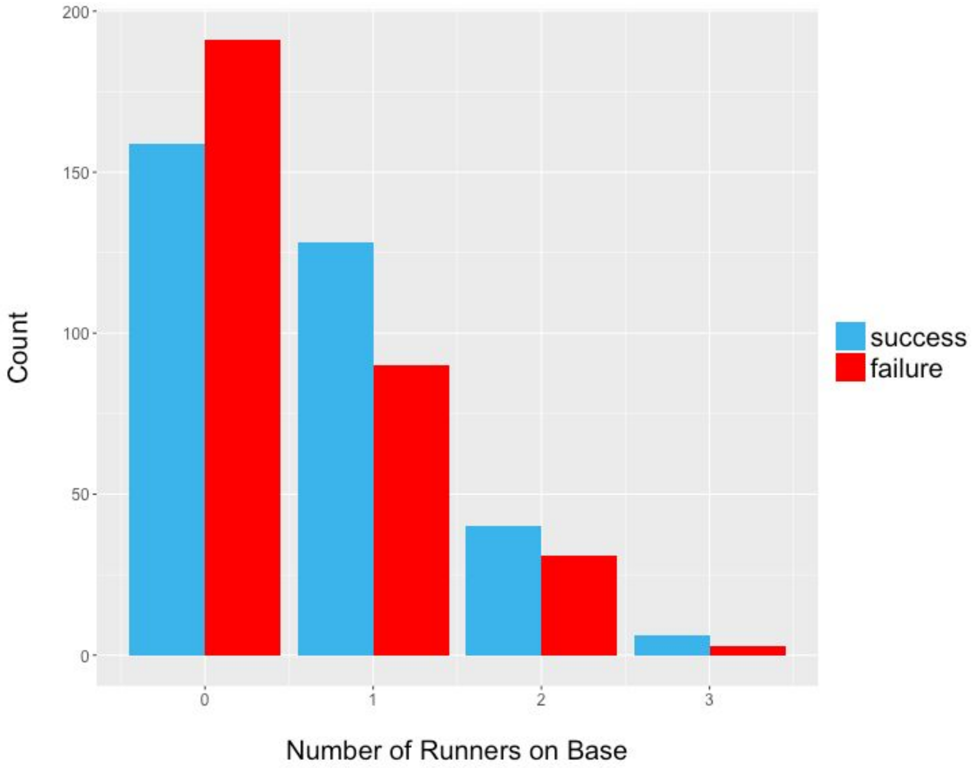
	Success	At Bats	% Success
Home	159	310	51%
Away	174	338	51%

Analysis

During the 2001 season, Barry Bonds showed **no overall difference** in getting on base in home vs. away games.

Runners On Base

Number on Base	Success	Failure
0	159	191
1	128	90
2	40	31
3	6	3

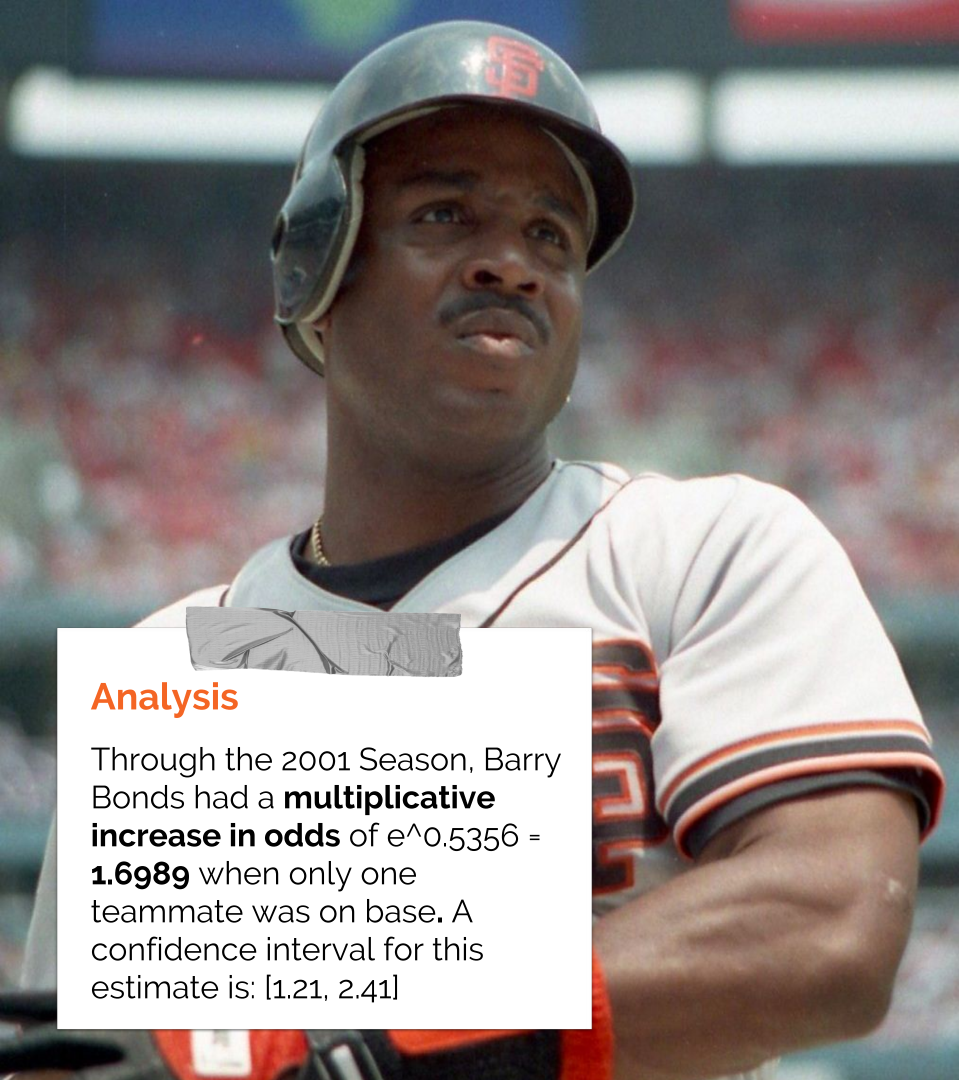


Effect of Runners On Base

There is a clear leap in Bonds' performance when a runner is on base.

The effect may strengthen for more runners though the data is sparse.

Our findings are confirmed in a logistic model.



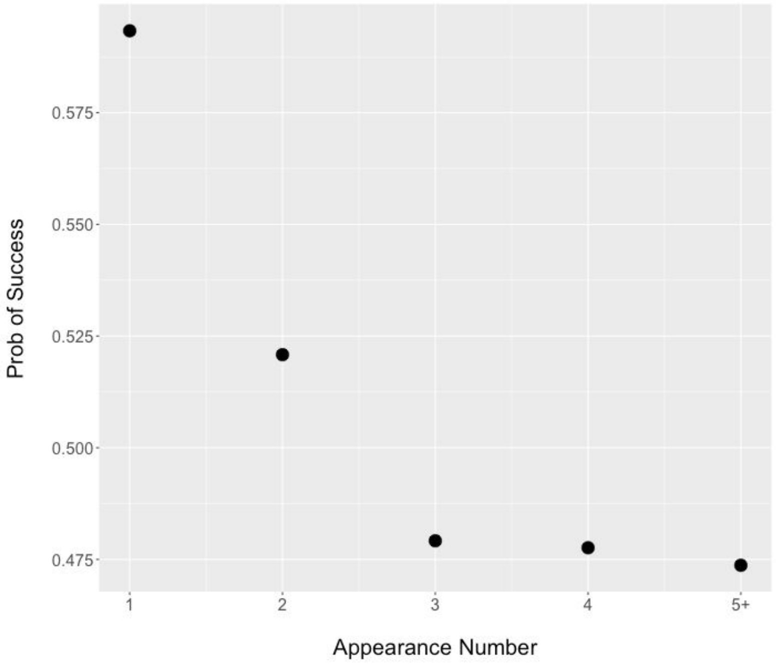
Analysis

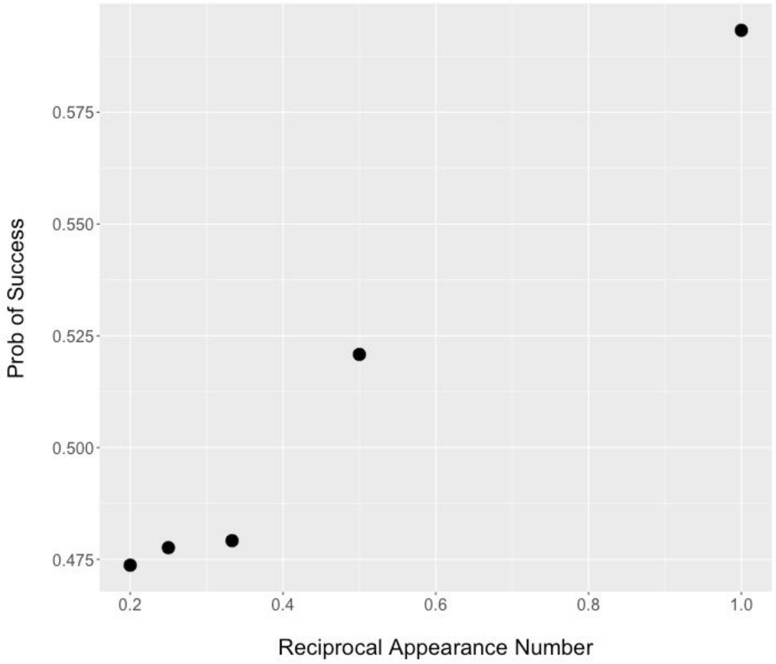
Through the 2001 Season, Barry Bonds had a **multiplicative increase in odds** of e^0.5356 = **1.6989** when only one teammate was on base**.** A confidence interval for this estimate is: [1.21, 2.41]

Model Building

```
Call:
glm(formula = factor(bonds$onBase) ~ factor(bonds$noOnBase),
    family = binomial)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-1.482   -1.101   1.032    1.071    1.256

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)              -0.1834     0.1074  -1.708  0.08762 .
factor(bonds$noOnBase)1   0.5356     0.1745   3.069  0.00215 **
factor(bonds$noOnBase)2   0.4383     0.2623   1.671  0.09471 .
factor(bonds$noOnBase)3   0.8765     0.7152   1.226  0.22037
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 897.82  on 647  degrees of freedom
Residual deviance: 886.57  on 644  degrees of freedom
AIC: 894.57

Number of Fisher Scoring iterations: 4
                       Df Deviance Resid. Df Resid. Dev Pr(>Chi)
NULL                                     647     897.82
factor(bonds$noOnBase)  3   11.251       644     886.57  0.01044 *
```

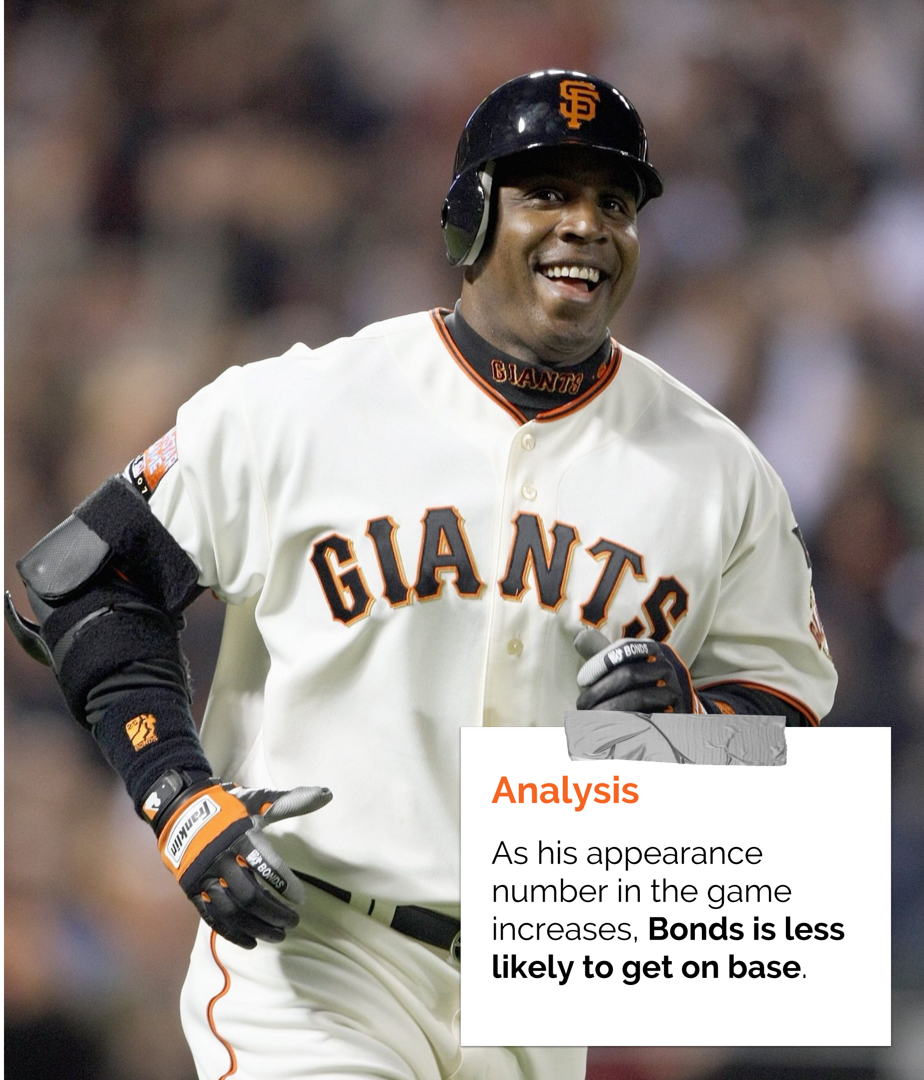
Appearance in Game





Model Building

```
Call:
glm(formula = factor(bonds$onBase) ~ factor(bonds$anyOnBase) +
    bonds$invApp, family = binomial)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-1.464  -1.104   0.916    1.114    1.343

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -0.4834     0.1700  -2.843  0.00446 **
factor(bonds$anyOnBase)1   0.5159     0.1598   3.228  0.00125 **
bonds$invApp               0.6190     0.2708   2.286  0.02227 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 897.82  on 647  degrees of freedom
Residual deviance: 881.68  on 645  degrees of freedom
AIC: 887.68

Number of Fisher Scoring iterations: 4
                        Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                      647     897.82
factor(bonds$anyOnBase)  1   10.859       646     886.96 0.0009833 ***
bonds$invApp             1    5.283       645     881.68 0.0215348 *
```

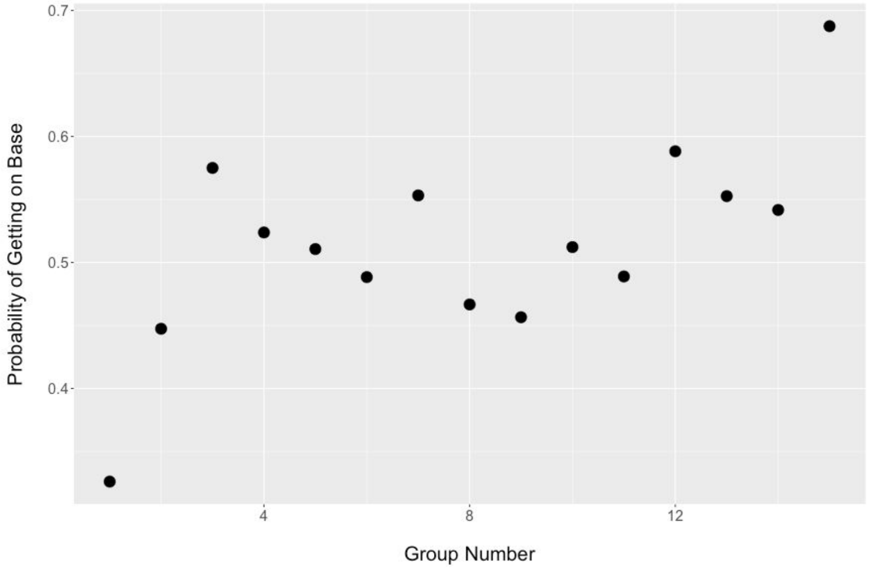


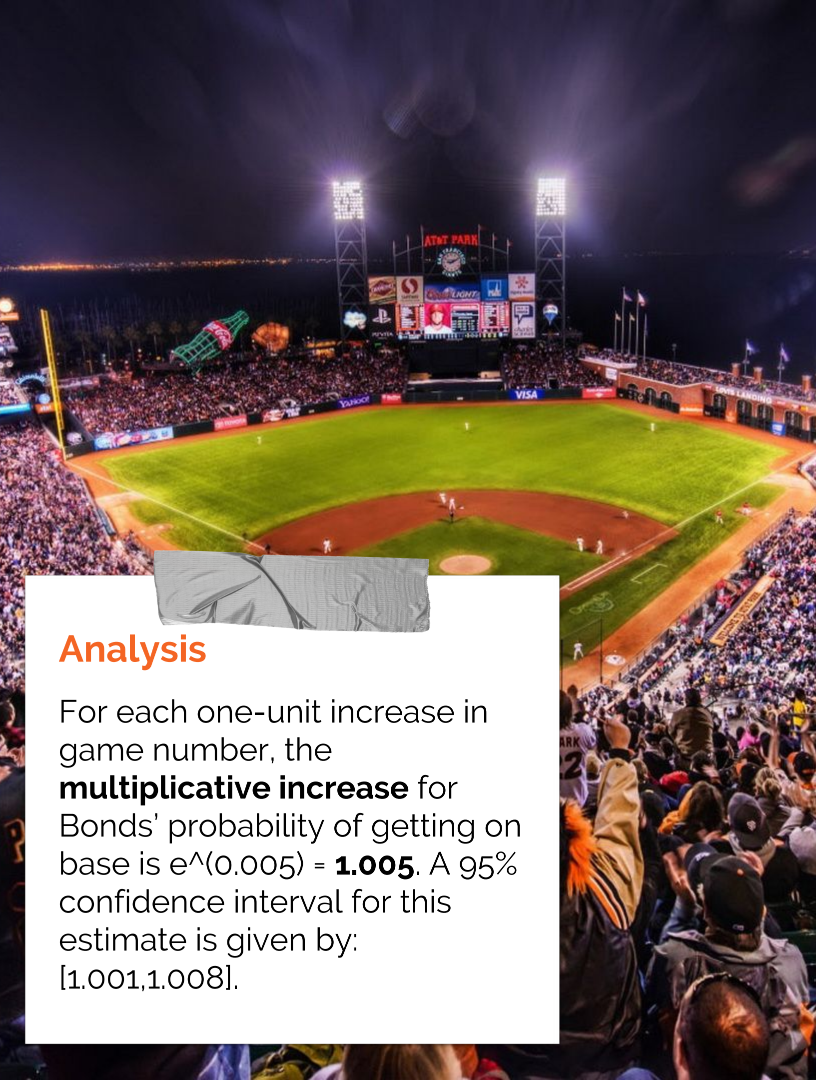
Analysis

As his appearance number in the game increases, **Bonds is less likely to get on base**.

Game (Continuous) Predictor

Subset of Games	Success	Total	% Success
First Third	101	213	47.4%
Middle Third	110	222	49.5%
Last Third	122	213	57.2%





Analysis

For each one-unit increase in game number, the **multiplicative increase** for Bonds' probability of getting on base is e^(0.005) = **1.005**. A 95% confidence interval for this estimate is given by: [1.001,1.008].

Model Building

```
Call:
glm(formula = factor(bonds$onBase) ~ factor(bonds$anyOnBase) +
    bonds$invApp + bonds$game, family = binomial)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6390  -1.1540   0.7923   1.1433   1.4928

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)             -0.92003    0.22956  -4.008 6.13e-05 ***
factor(bonds$anyOnBase)1 0.55526    0.16173   3.433 0.000596 ***
bonds$invApp             0.63275    0.27295   2.318 0.020440 *
bonds$game               0.00505    0.00174   2.901 0.003715 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 897.82  on 647  degrees of freedom
Residual deviance: 873.14  on 644  degrees of freedom
AIC: 881.14

                        Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                      647     897.82
factor(bonds$anyOnBase)  1  10.8588       646     886.96 0.0009833 ***
bonds$invApp             1   5.2830       645     881.68 0.0215348 *
bonds$game               1   8.5398       644     873.14 0.0034747 **
```

3 Insignificant Variables

Potential predictors that didn't make the cut

➔ **ERA (Earned Run Average)**
Though opposing pitchers' ERA affected the outcomes of the games, they did little to affect Bonds' batting

➔ **Inning**
Appearance has a strong effect but inning number does not

➔ **Number of Outs**
Bonds seemed to perform better with more outs although the relationship didn't hold in our model (*why?*)

Final Model

Let Y_i be whether Bonds gets on base for at bat *i* in the 2001 season.

Assume

$$Y_i \sim \text{Bern}(\, p_i \,)$$

where

$$p_i = \text{prob that Bonds gets on base in at bat } i$$

and

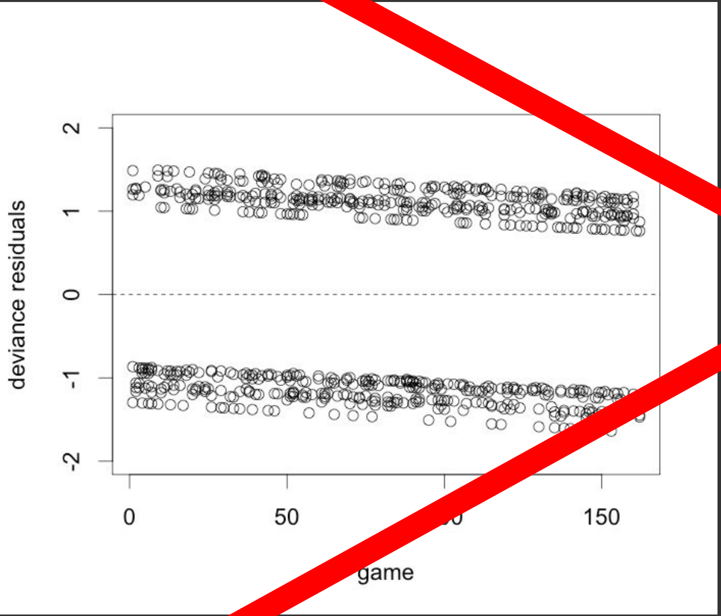
$$\text{logit } p_i = \beta_0 + \beta_1 x_i + \beta_2 y_i + \beta_3 z_i$$

where $x_i = 1$ if someone is on base, 0 otherwise

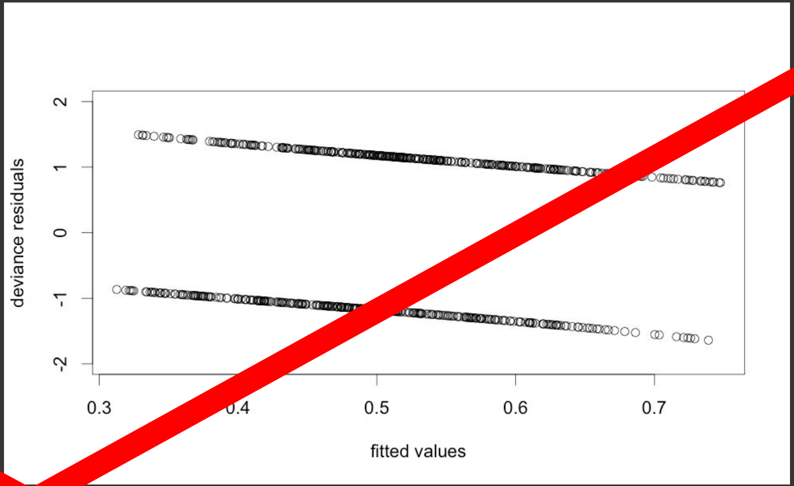
$y_i = 1 /$ appearance

$z_i =$ game number

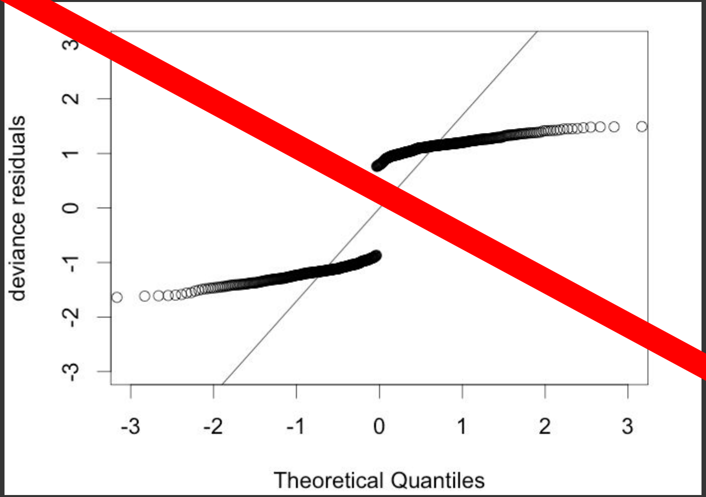
Residuals



deviance residuals
game

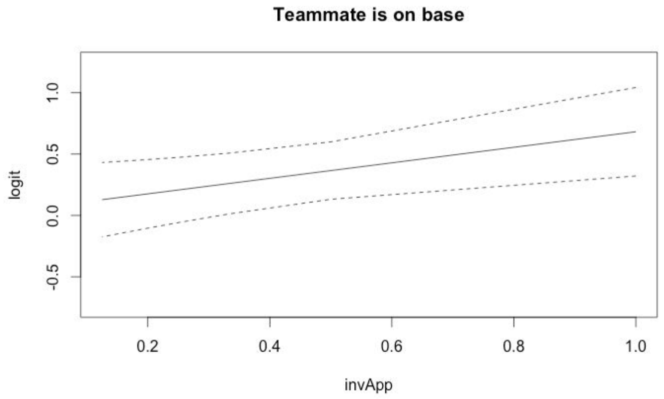


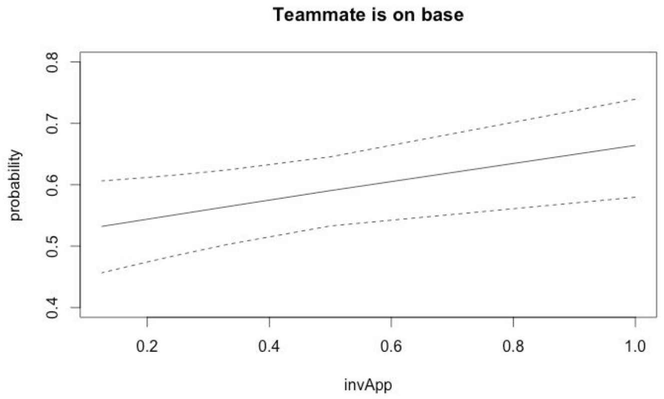
deviance residuals
fitted values

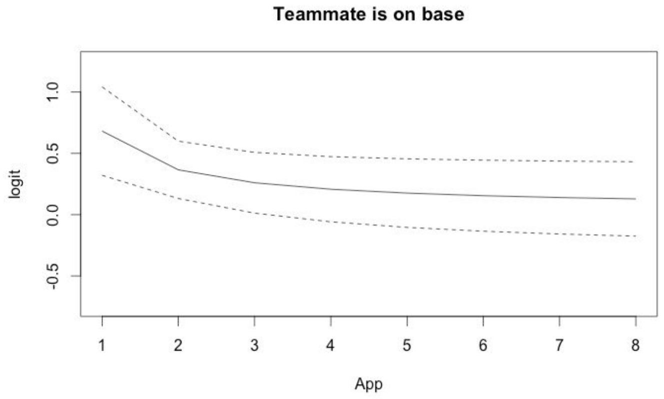


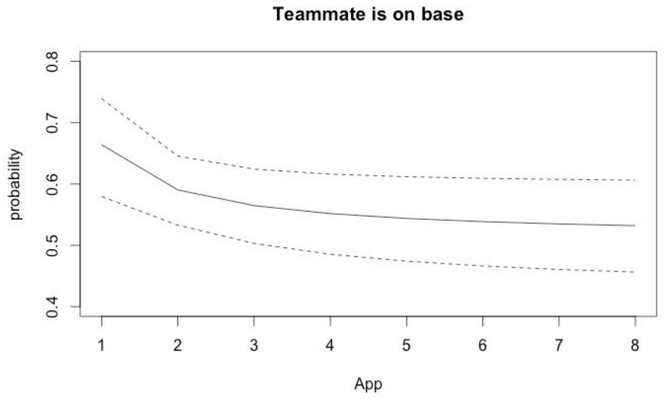
deviance residuals
Theoretical Quantiles

Prediction Intervals: Logit vs Prob

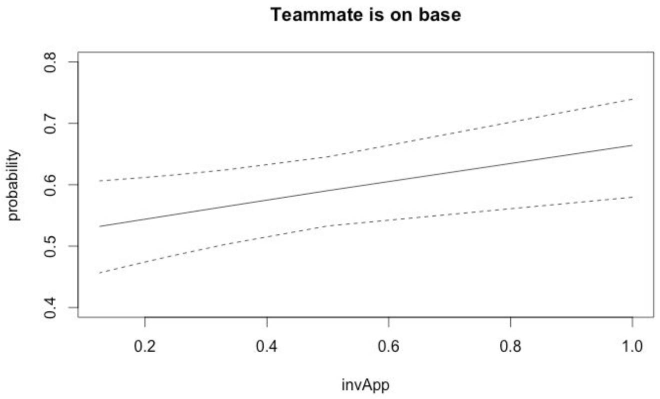


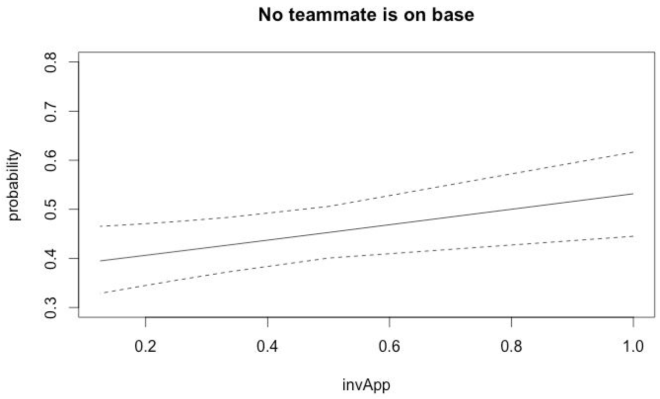


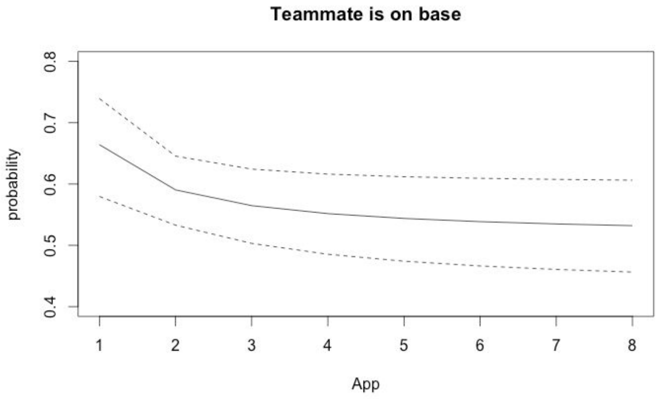


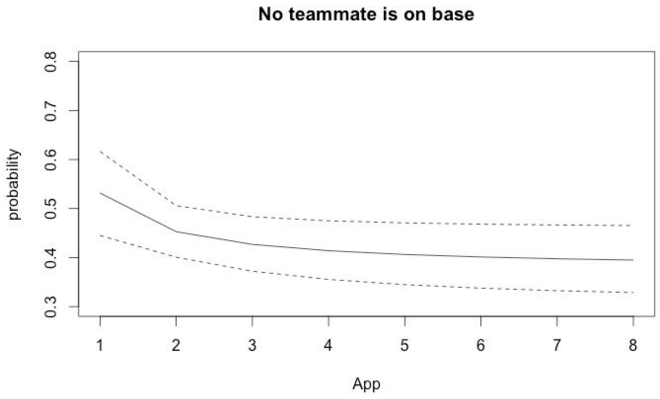


Prediction Intervals: Appearance

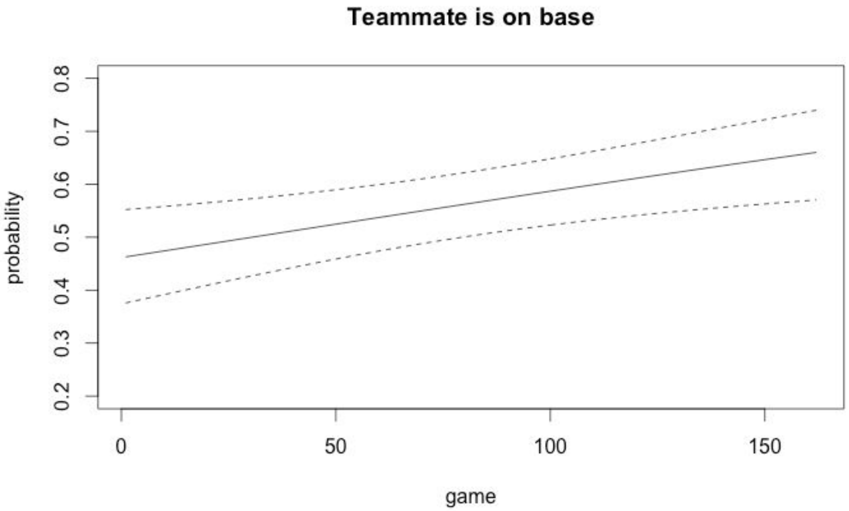


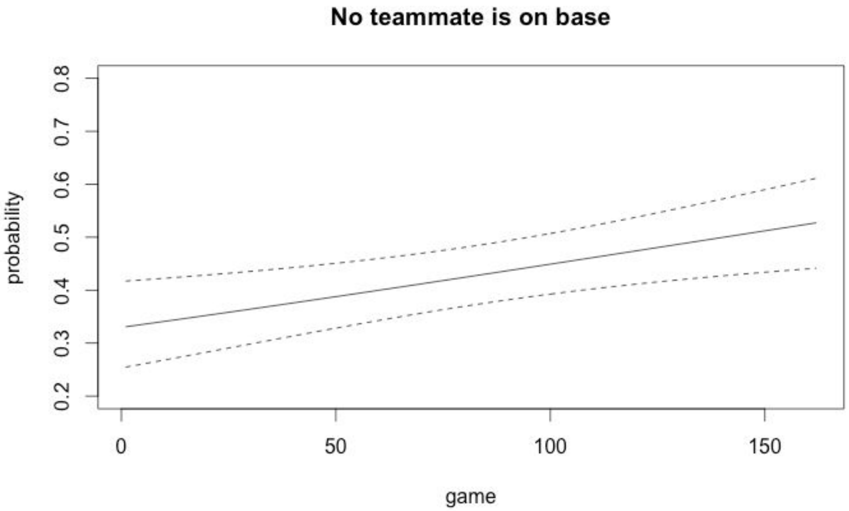






Prediction Intervals: Game





Case Predictions

If it is game 30, for Bonds' second appearance and there is no one on base, the probability of Bonds getting on base is:

$$\text{inv logit}(\,-0.920+(0)(0.555)+(\tfrac{1}{2})(0.633)+(30)(0.005)\,)$$
$$=0.3888$$

If it is game 100, for Bonds' first appearance and there is a teammate on base, the probability of Bonds getting on base is:

$$\text{inv logit}(\,-0.920+(1)(0.555)+(1)(0.633)+(100)(0.005)\,)$$
$$=0.6842$$

Tip

Use exp(change in logit) to find the multiplicative change in odds.

But inv.logit(logit) to find the probability.

—

Thanks for taking the time to listen to our presentation.

THE END.

Tip

Don't let data stand alone. Always relate it back to a story.