

# Give 'em the heat, Ricky!

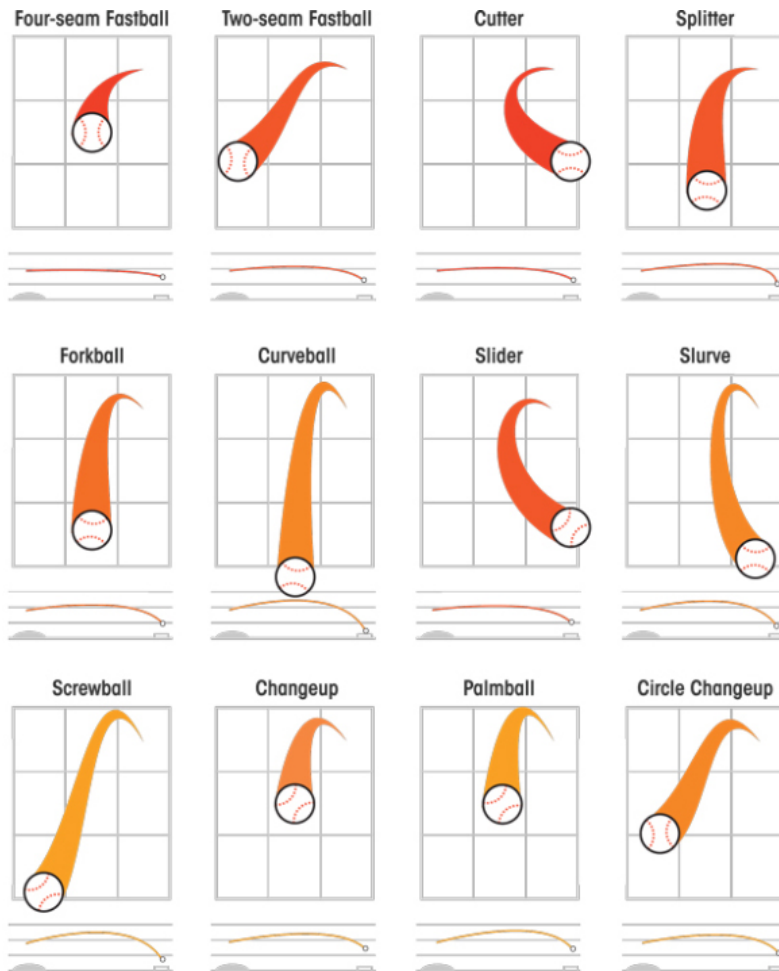
## Predicting the next pitch in Major League Baseball

Your Name \_\_\_\_\_  
Date \_\_\_\_\_

### Pitch Prediction

In the game of baseball, its hitter versus pitcher. If the hitter knows what pitch is coming next he has a better chance of putting the ball in play. Most starting pitchers use four pitches, fastball, curve ball, slider, changeup, or a specialty pitch such as a sinker, knuckle. These pitches appear to the eye like: [http://www.thecompletepitcher.com/images/baseball\\_pitches.jpg](http://www.thecompletepitcher.com/images/baseball_pitches.jpg).

The idea of this project will be to determine if pitch count dictates which pitch is thrown.



## Previous Research

In March 2012 Ganeshapillai released a study at a sports conference using machine learning to predict situational pitching. He factored in pitch count, runners on base, outs, big lead v small lead, and pitcher handedness v batter handedness. He trained his data on 2008 data, and used 2009 as his untrained data. He also used only pitchers who threw 300 pitches in both season for an even comparison. He used a SVM-Light tool to test his theory, and improved it over a traditional model.

In 2015 Bock, followed up on his research and tested similar factors, this time with a SVM formulation with linear and radial basis function kernels, and a linear logistic model. He got similar answer to Ganeshapillai.

## Algorithms

SVM – Light tool

SVM formulation with linear and radial basis function kernels

## Evaluation

I hope to be able to repeat the success, if not improve upon it, by Ganeshapallai and Brock.

## Data Sources

PitchR/x Cran- R Library (<https://cran.r-project.org/web/packages/pitchRx/pitchRx.pdf>)  
MLB Gameday API  
BaseballReference.com

Bock, J. R. (2015). Pitch Sequence Complexity and Long-Term Pitcher Performance. Sports, 3(1), 40-55. Accessed (2/29/2016 <http://www.mdpi.com/2075-4663/3/1/40/htm>)

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