Statistical Models for the Prediction of Fantasy Football Points

Adam Jauregui

California State University, Fresno

Math REU Summer 2015

Outline

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Fantasy Football Explained

- A skills-based game played mainly online
- Choose a lineup of NFL players that you predict will play well in their real-life upcoming games
- Compete against other people in online tournaments
- The person who chose the lineup that accrues the most fantasy points wins!

OFFENSIVE STATISTICS	QB, WR, RB, TE, K
Touchdown (Passing)	4 points
Touchdown (Rushing or Receiving)	6 points
Passing Yards	1 point for every 25 yards
Rushing Yards	1 point for every 10 yards
Receiving Yards	1 point for every 10 yards
2 point conversion	2 points
Interception	-2 points
Fumble Lost	-2 points
Field Goal	0-49 yards = 3 points 50+ yards = 5 points
Extra Point	1 point
Offensive Fumble Recovery Touchdown	6 points

DEFENSIVE STATISTICS	DEFENSE / SPECIAL TEAMS
Touchdown	6 points
Safety	2 points
Interception	2 points
Fumble Recovery	2 points
Sack	1 point
Points Allowed	0 = 10 points 1-6 = 7 points 7-13 = 4 points 14-20 = 1 points 21-27 = 0 points 28-34 = -1 points 35+ = -4 points

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The Research Question

The Goal

To build a model that can make an accurate point-wise prediction of an NFL quarterback's weekly fantasy points prior to the start of the NFL regular season

e.g. "We predict Tom Brady will score 22 fantasy points in Week 1, 15 fantasy points in Week 2, etc."

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Criteria for Inclusion

- "Test Data:" 2014 NFL regular season (comprised of 16 games, 17 weeks)
- Started a minimum of 1 game in the 2014 NFL regular season
- *Started* a minimum of 32 NFL regular season games prior to the 2014 NFL season (two full season's worth)
- Chose to work with the QB's weekly fantasy points
  - To make a prediction for Week 1 in 2014, we used said quarterback's career data from Week 1
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  - and so on...
- 20 NFL quarterbacks were analyzed

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Frequentist Approach

Maximum Likelihood Estimation (MLE) Model

MLE model where the respective mean and variance parameter θ and σ^2 vary weekly

$p(\mathbf{X}|\theta)$

- X is the data of random values
- θ is some fixed parameter, usually the mean of the data

Frequentist Approach

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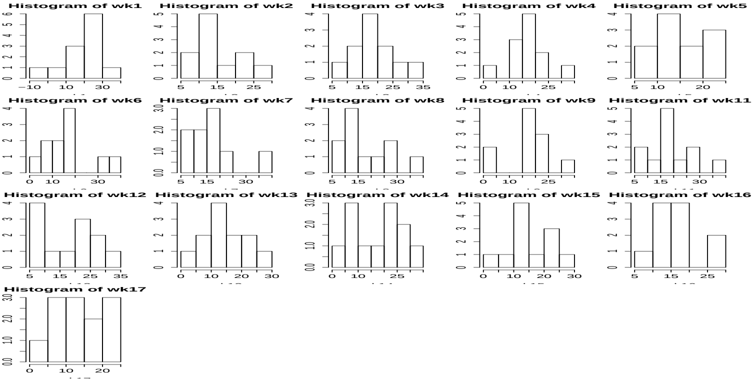
Frequentist Approach

Step 1: Choose a distribution that fits the data (Normal, Exponential, Poisson, etc.)



Frequentist Approach

Step 2: Estimate parameters

- We think the data follows a normal distribution
- Thus, the ML estimators are

$$\hat{\theta}_j = \bar{X}_j, \tag{1}$$

$$\hat{\sigma}_j^2 = \frac{n-1}{n} s^2, \tag{2}$$

- $\bar{X}_j$ is the mean fantasy points of the *j*-th week
- σ_j^2 is the fantasy point variance of the *j*-th week
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Frequentist Approach

Step 3: Random sample!

Let y_j^{new} be our predictive value for each j-th week of the 2014 NFL regular season. Then

$$y_j^{new} \sim N(\hat{\theta}_j, \hat{\sigma}_j^2) \tag{3}$$

where $\hat{\theta}_j$ and $\hat{\sigma}_j^2$ are the respective mean fantasy points for the j-th week

- Sampled from this distribution 1000 times
- Obtained 1000 predictions for each week of 2014

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Bayesian Approach

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$p(\theta|X) \propto p(X|\theta)p(\theta)$

- X is the dataset of fixed values
- θ is the random variable, usually the mean

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- Bayesian Model #1 (BM1): assign prior probability to the mean parameter θ
- Bayesian Model #2 (BM2): assign prior the mean and variance parameter θ and σ^2

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Bayesian Model #1 (BM1)

Step 1: Assign prior probability to a variable

- Two parameters: mean θ_j and variance σ_j^2
- Assigned prior probability on θ_j and left σ_j^2 fixed

$$\theta_j \sim N(\mu, \tau^2) \tag{4}$$

where μ and τ^2 are the quarterback's respective career mean and variance fantasy points

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Bayesian Model #1 (BM1)

Step 2: Compute posterior distribution

$$\theta_j|\bar{X}_j \sim N(\lambda, \rho) \tag{5}$$

where λ is the posterior mean represented by

$$\lambda = \frac{\tau^2}{\frac{\sigma^2}{n}+\tau^2}\bar{X}_j + \frac{\frac{\sigma^2}{n}}{\frac{sigma^2}{n}+\tau^2}\mu$$

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Bayesian Model #2 (BM2)

- Exactly the same as BM1 except prior distribution is placed on the variance σ^2

$$\sigma^2 \sim Gamma(1, 1) \tag{7}$$

- Code the model in R with JAGS (Just Another Gibbs Sampler)
- Random sampled from posterior predictive distribution
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MSE and MAD

Errors were measured in terms of "mean square error" and "mean absolute deviation"

$$MSE = \frac{1}{1000} \sum_{i=1}^{1000} (y_{j,test} - y_{i,j}^{new})^2 \tag{8}$$

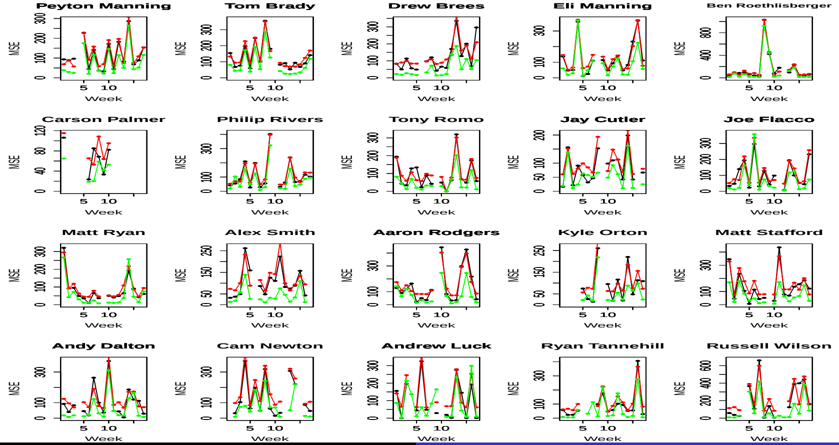
and

$$MAD = \frac{1}{1000} \sum_{i=1}^{1000} |y_{j,test} - y_{i,j}^{new}| \tag{9}$$

MSE Plots

arranged from most experience to least experienced

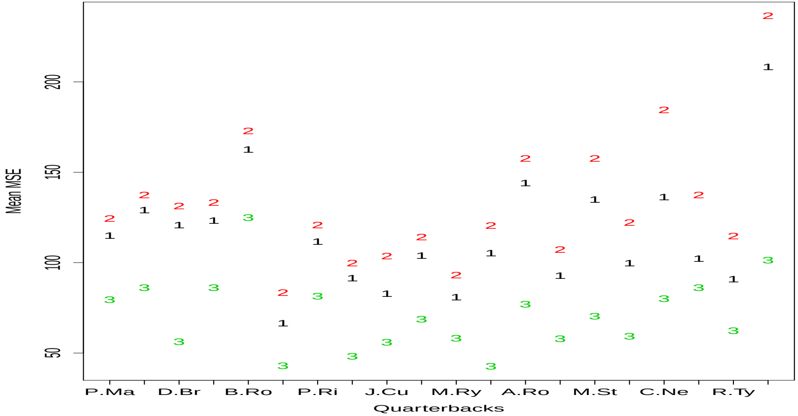
MLE (black line), BM1 (red line), and BM2 (green line)



Mean MSE Plot for Each Quarterback

arranged from most experienced to least experienced

MLE ("1"), BM1 ("2"), and BM2 ("3")



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- Given the advantages of today, might more experienced quarterbacks have scored more fantasy points?
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Fantasy Point Inflation Rate

- Hypothesis: "Inflating" quarterback data will give us more accurate results
- Inflation Rate:

$$Y = \frac{100(B - A)}{A} \tag{10}$$

where Y is our inflation rate, B is the average quarterback fantasy points scored per game in the current season, and A is the average quarterback fantasy score in the earlier season.

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$$Y = \frac{100(B - A)}{A} \tag{10}$$

where Y is our inflation rate, B is the average quarterback fantasy points scored per game in the current season, and A is the average quarterback fantasy score in the earlier season.

Fantasy Point Inflation Rate

- Example:
  - In the 2013 NFL season, quarterbacks averaged 16.10 fantasy points per game
  - In the 1999 NFL season, quarterbacks averaged 14.12 fantasy points per game
  - Thus, the inflation rate Y is $Y = \frac{100(16.10-14.12)}{14.12} = 1.39$.
  - Multiply the 1999 quarterback fantasy point data by 1.39
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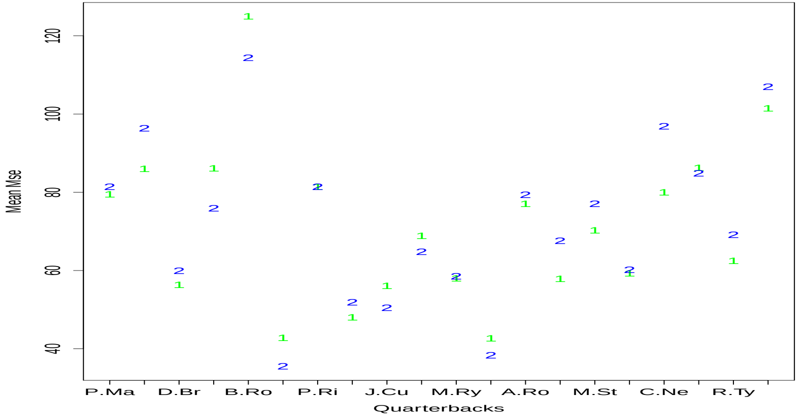
Mean MSE Plot

BM2 ("1") and Inf-BM2 ("2")



Outline

What Did We Find Out?

- Our main objective was to formulate a model that could make an accurate point-wise prediction of an NFL quarterback's weeky fantasy points
- We tested three models under a frequentist and Bayesian approach.
  - Our second Bayesian model "BM2," with a prior distribution on the mean θ *and* variance σ^2, outperformed the MLE model and our first Bayesian model "BM1"
  - Our choice for prior distribution, the quarterback's career mean and variance, was suspect
  - Our model "Inf-BM2" suggested that inflating data only works well for quarterbacks in their "peak" years

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