

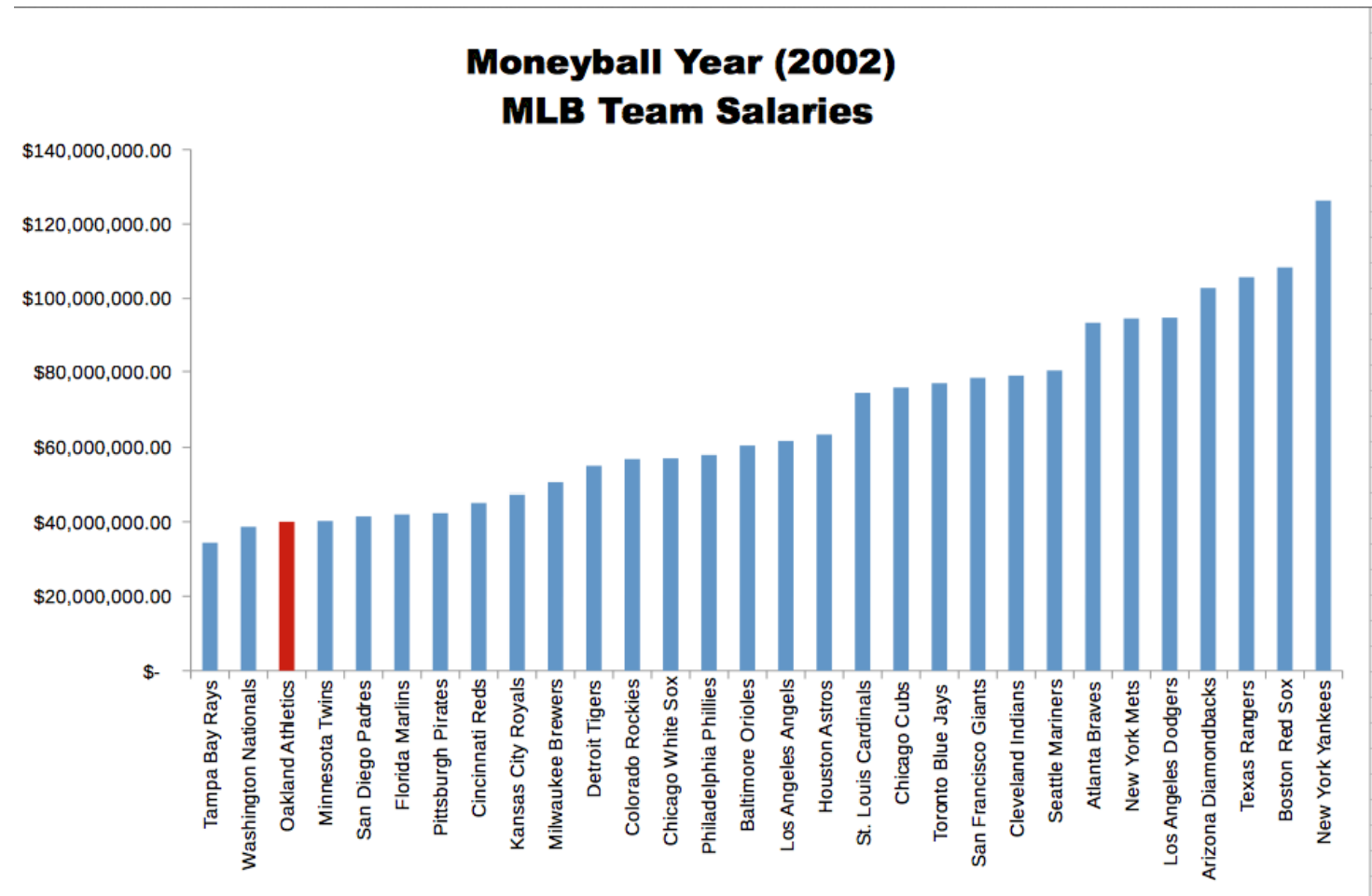
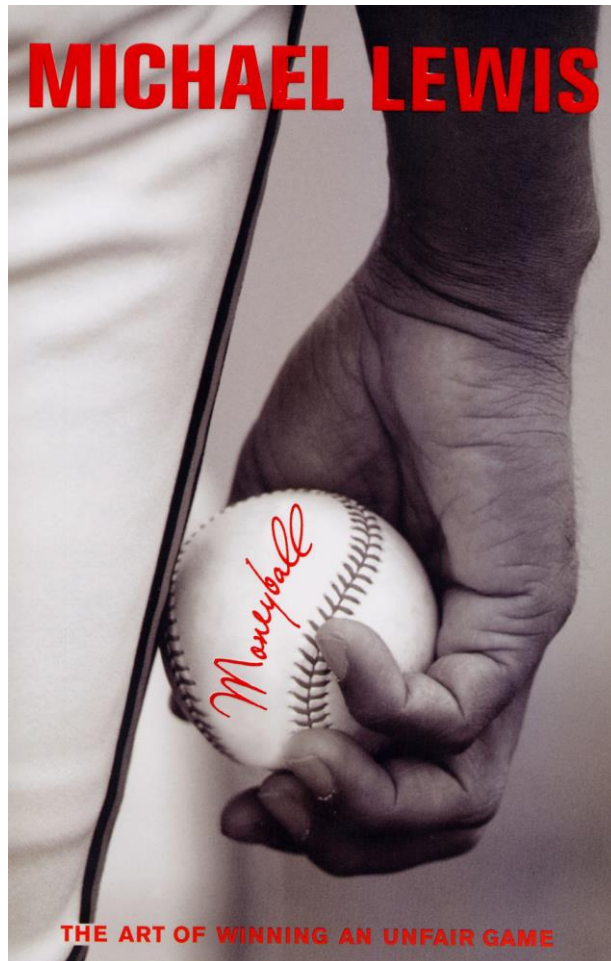
Predicting MLB player batting average (BA): A comparison between Bayesian and frequentist approaches

EN.553.732 Bayesian Statistics

Kenneth Feder, Joseph High, Joseph Yu

Dec 2nd, 2017

Oakland A's successfully leveraged sabermetrics to field a competitive MLB team



Oakland A's successfully leveraged sabermetrics to field a competitive MLB team

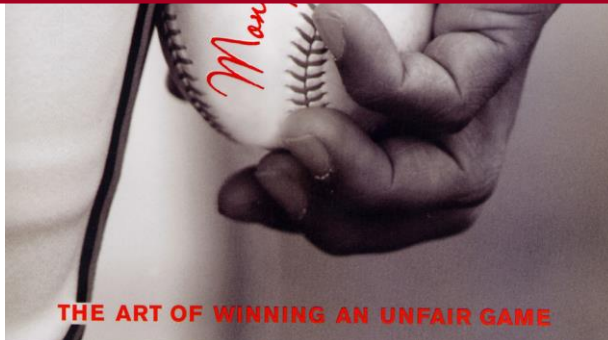


MICHAEL LEWIS

Moneyball Year (2002) MLB Team Salaries

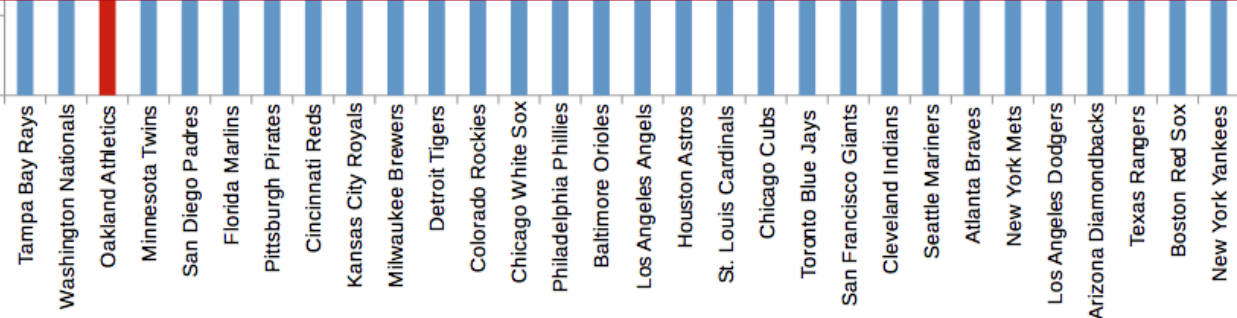
\$140,000,000.00

Can we build a statistical model to predict **batting average (BA)**, a measure of player productivity?



\$20,000,000.00

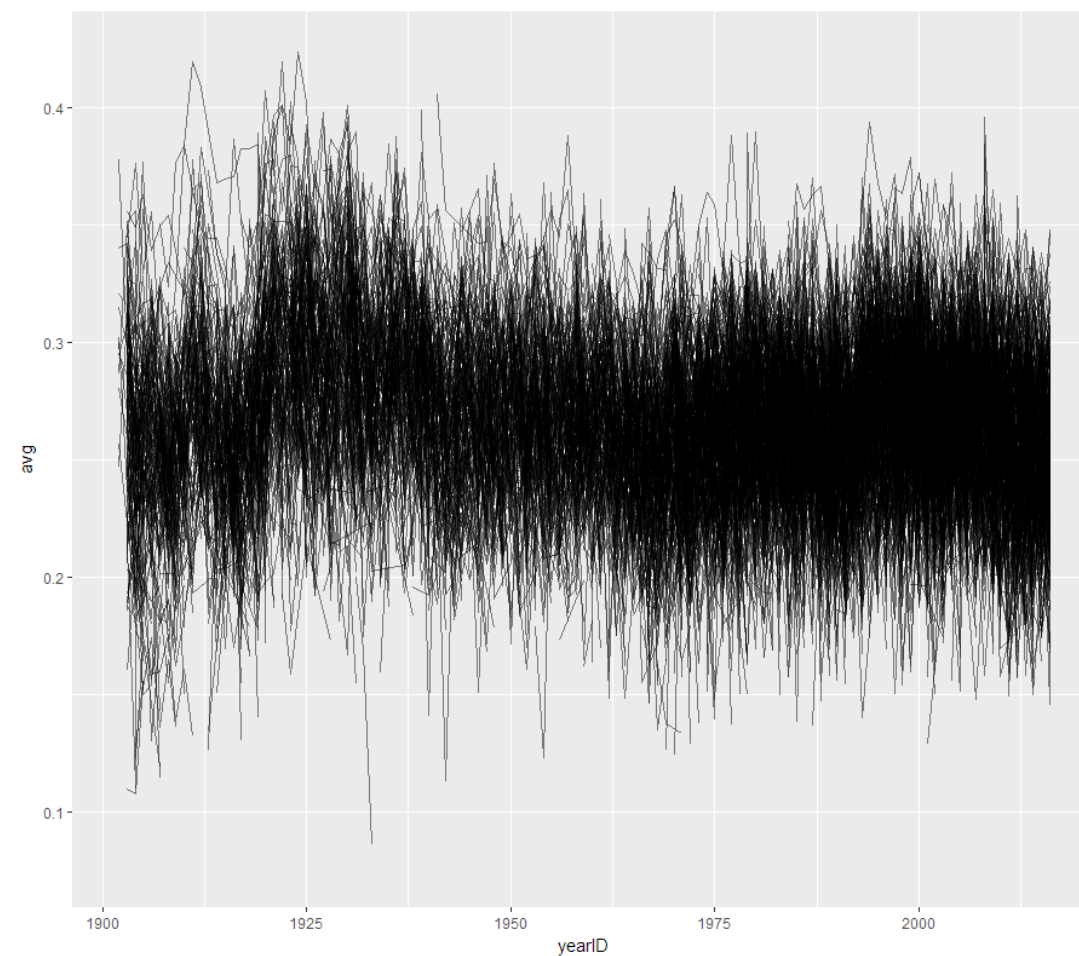
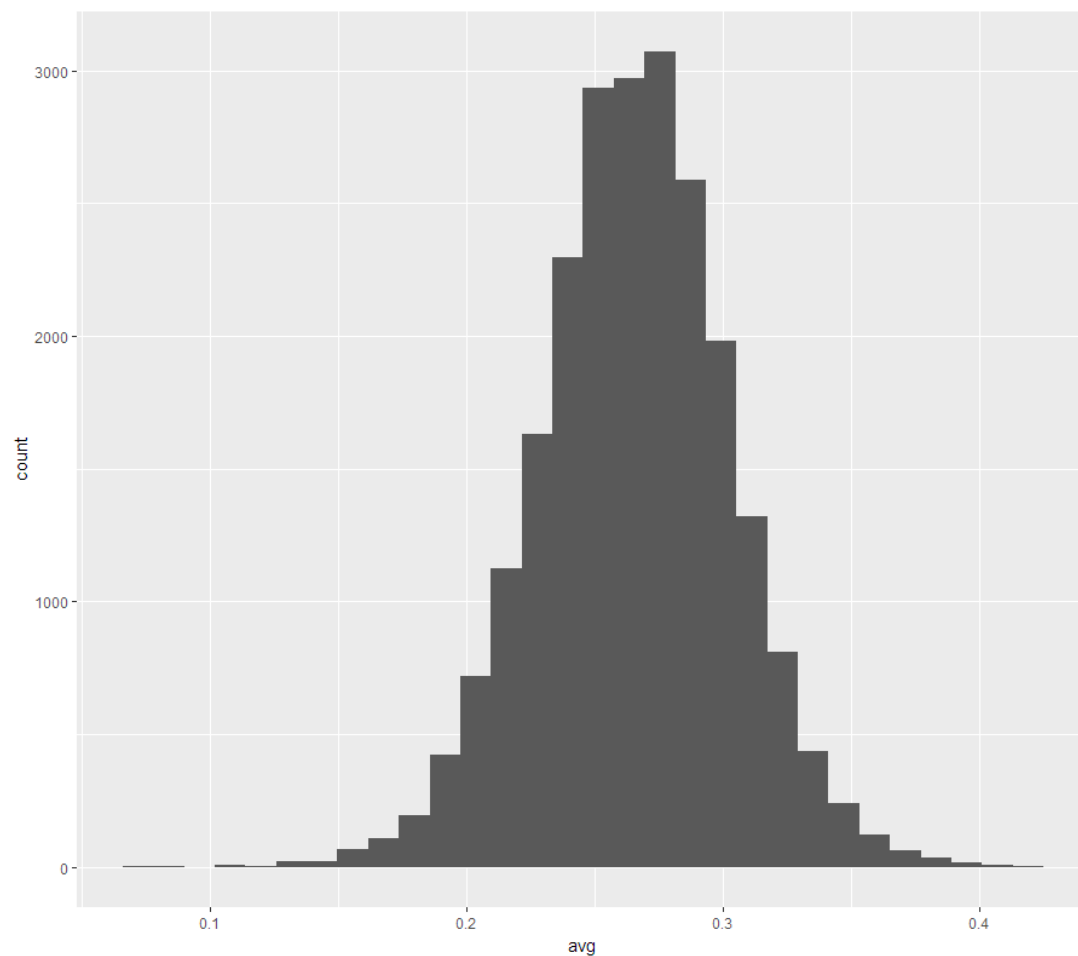
¢



MLB player statistics and inclusion criteria

- Data acquired from Lahman Baseball archive
 - <http://www.seanlahman.com/baseball-archive/statistics/>
- MLB player data inclusion criteria:
 1. Played after 1901
 2. Had at least 100 at bats per season
 3. Played in either the National League or American League

Batting average data visualized



Multi-level Bayesian model was implemented

Outcome

B_{ij} : predicted batting average (BA) for a given player (i), year (j)

Predictors

B_{ij-1} : previous year BA

B_{ij-2} : prior year BA

age

height

weight

era

lively ball (1920 -)

expansion (1961 -)

free agency (1977 -)

steroids (1994 -)

year: spent in league

Model

$$B_{ij} \sim \text{Normal}(\mu_{ij}, 1/\tau_{\text{avg}})$$

i = player index

j = year index

$$\mu_{ij} = \beta_{0i} + \beta_1 B_{ij-1} + \beta_2 B_{ij-2} + \beta_3 \text{age}_{ij} + \beta_4 \text{age}_{ij}^2$$

$$\beta_1, \beta_2, \beta_3, \beta_4 \sim \text{Normal}(0, 1000)$$

$$\tau_{\text{avg}} \sim \text{Gamma}(0.001, 0.001)$$

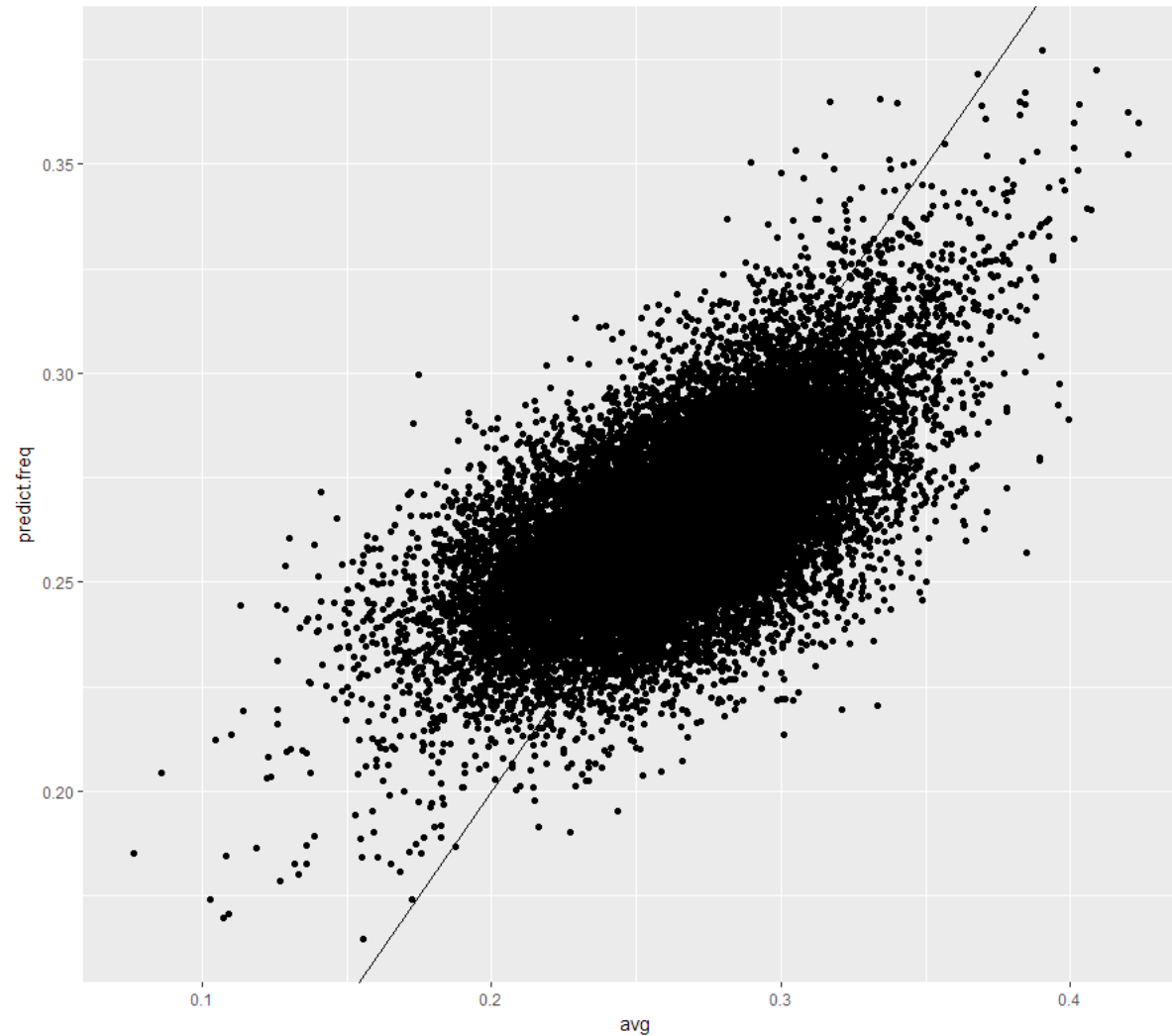
$$\beta_{0i} \sim \text{Normal}(\theta_i, 1/\tau_{\beta 0})$$

$$\theta_i = \gamma_0 + \gamma_1 \text{height}_i + \gamma_2 \text{height}_i^2 + \gamma_3 \text{weight}_i + \gamma_4 \text{weight}_i^2 + \gamma_5 \text{year}_i + \gamma_6 \text{era}_{\text{livelyball}} + \gamma_7 \text{era}_{\text{expansion}} + \gamma_8 \text{era}_{\text{freeagency}} + \gamma_9 \text{era}_{\text{steroids}} + \gamma_{10} \text{era}_{\text{modern}}$$

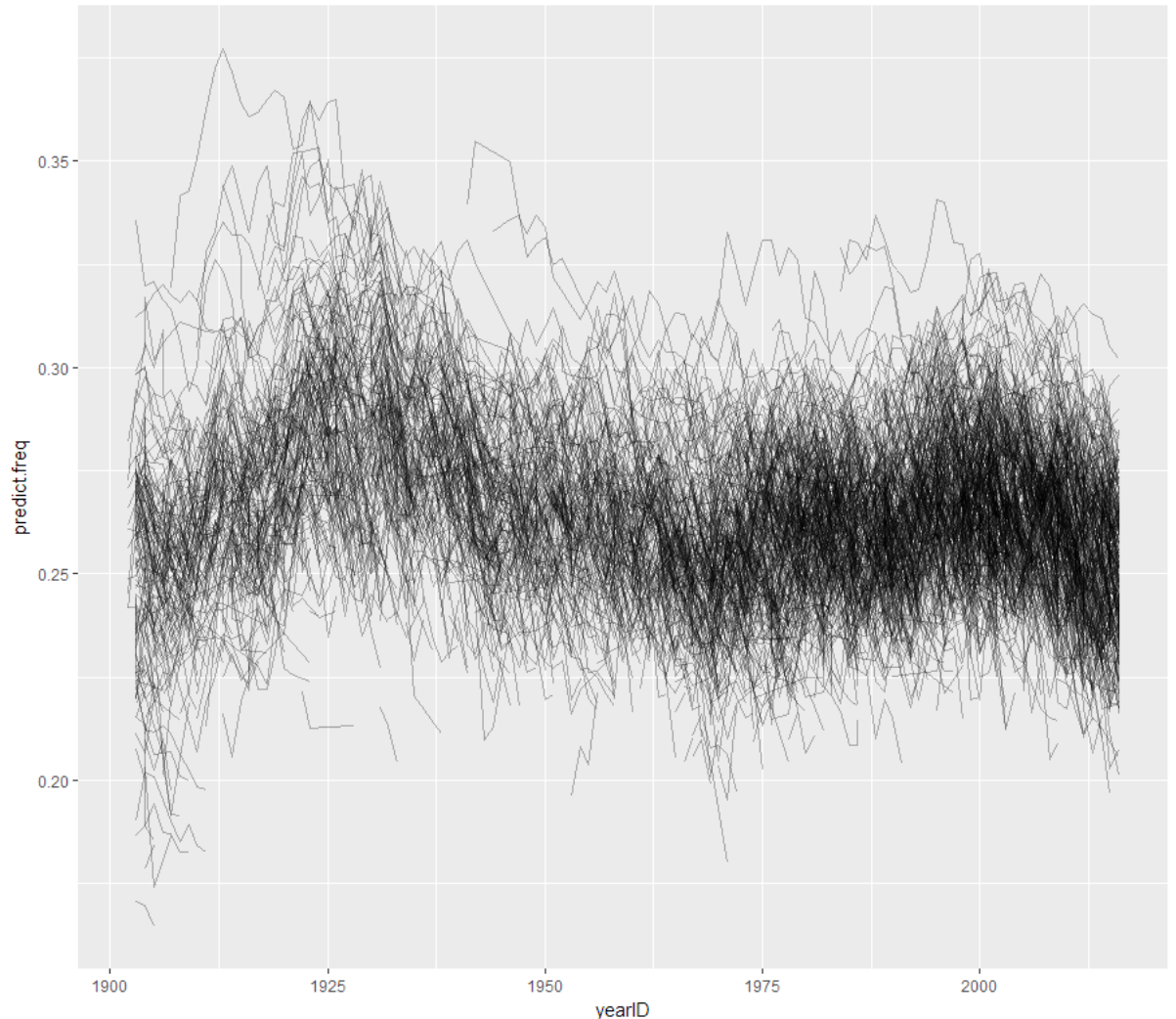
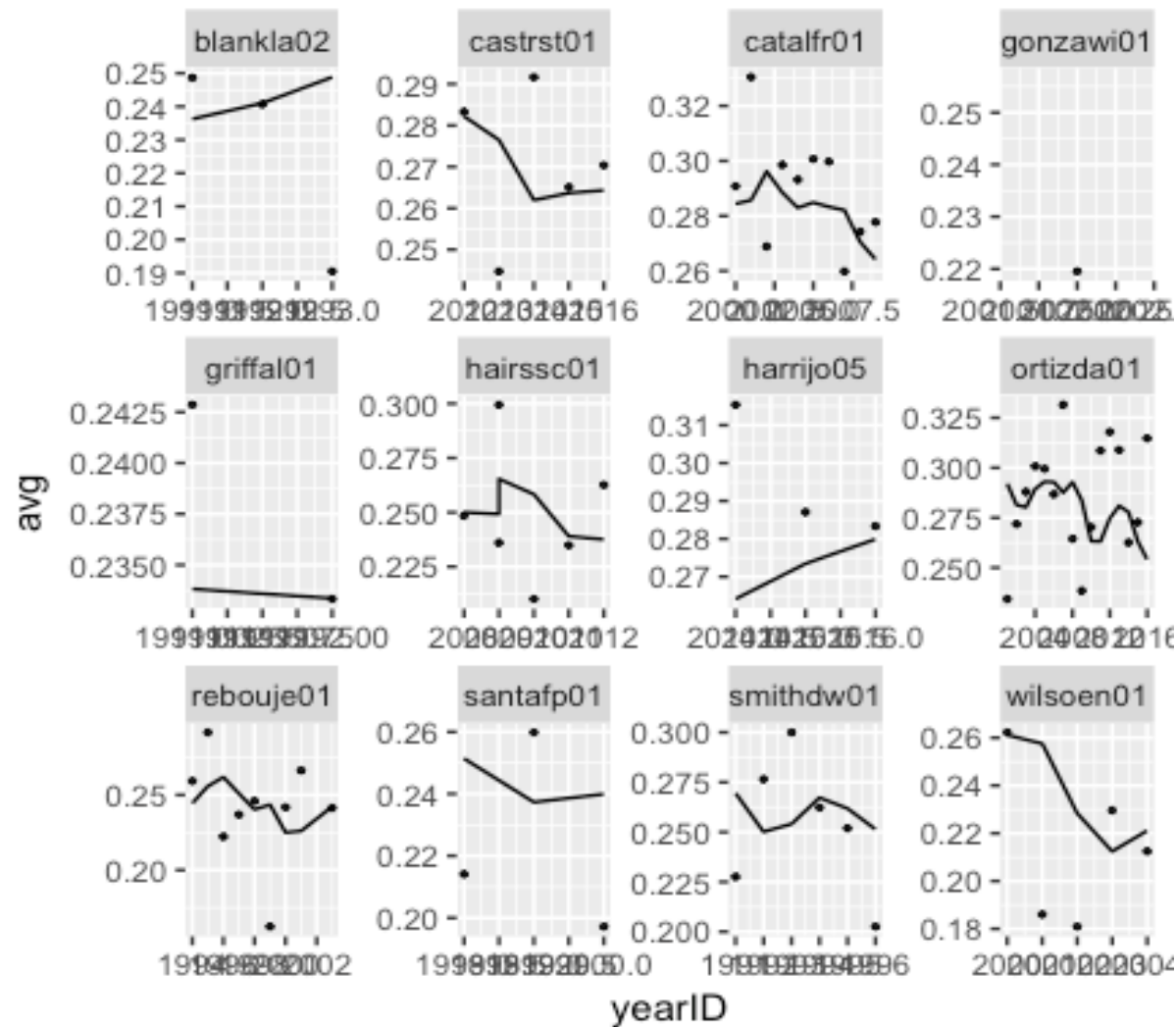
$$\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7, \gamma_8, \gamma_9, \gamma_{10} \sim \text{Normal}(0, 1000)$$

$$\tau_{\beta 0} \sim \text{Gamma}(0.001, 0.001)$$

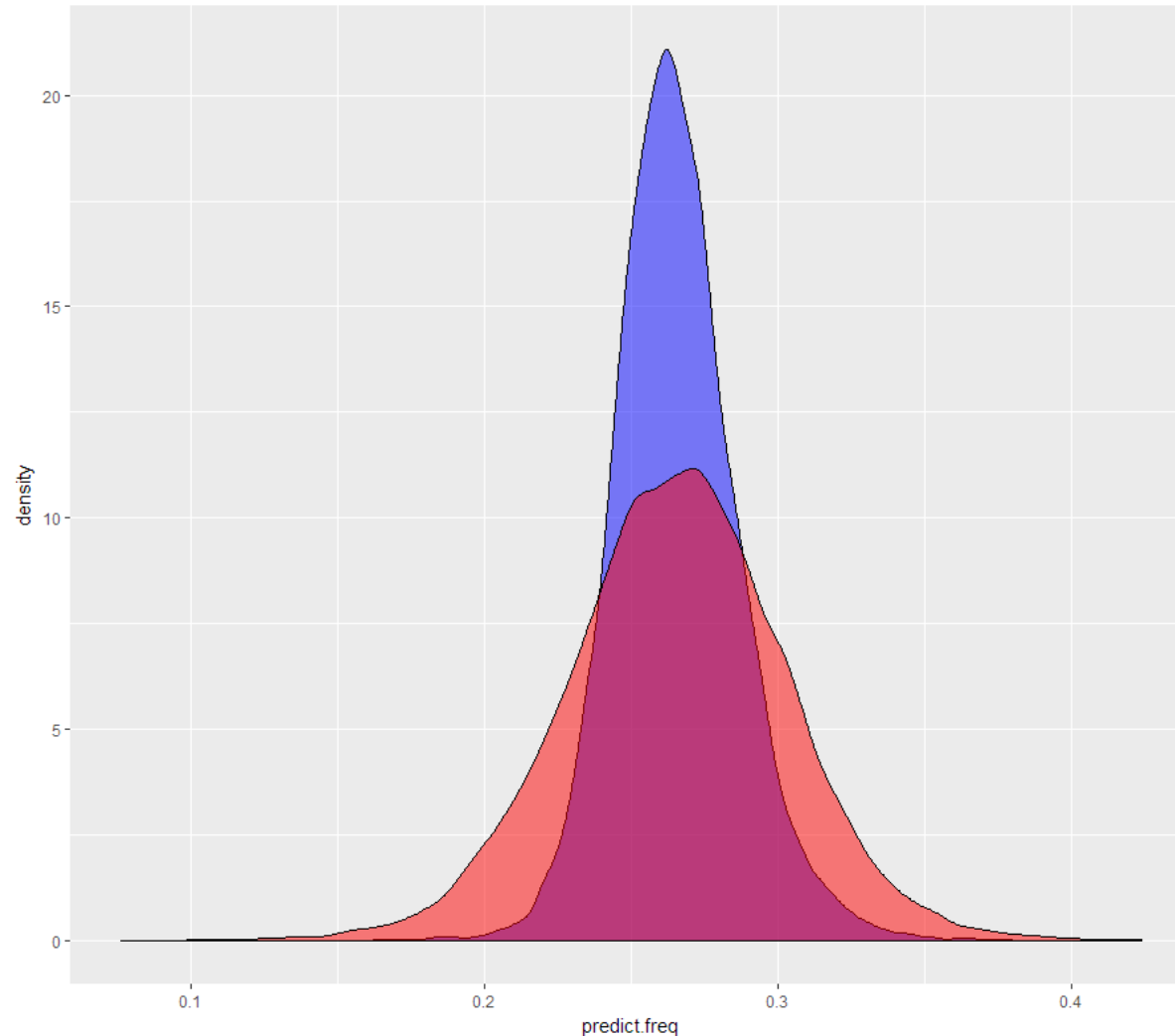
Predictive accuracy of fitted frequentist model



Fitted frequentist model predicted trajectories



Frequentist – Accurate Mean, no Model for Variability



Bayesian model parameters demonstrate convergence

(MCMC sampling implemented R package JAGS)

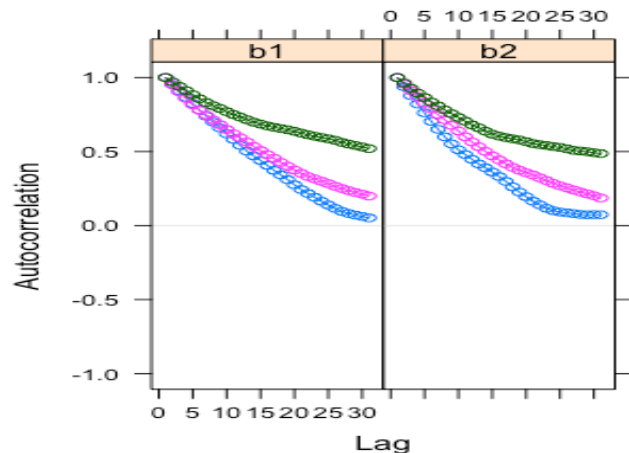
```
> gelman.diag(beta.samples)  
Potential scale reduction factors:
```

	Point est.	Upper C.I.
b1	1.03	1.09
b2	1.05	1.17

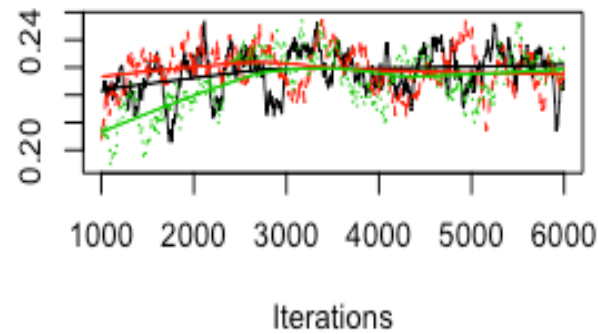
Multivariate psrf

1.08

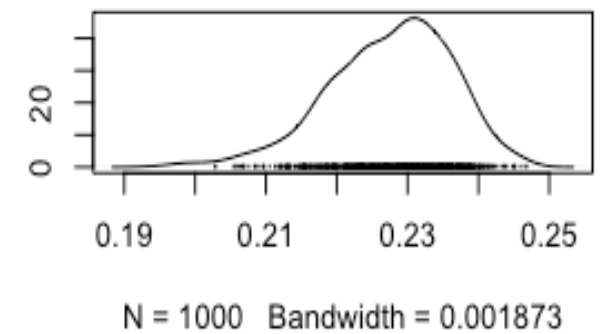
```
> |
```



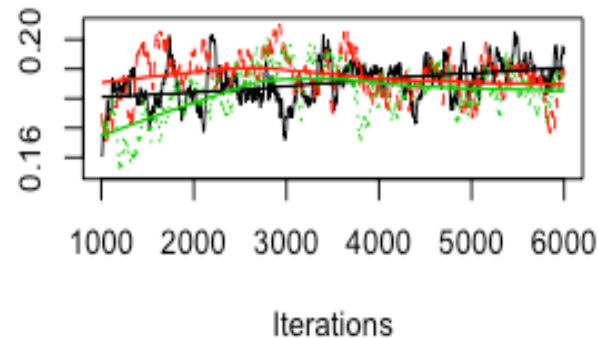
Trace of b1



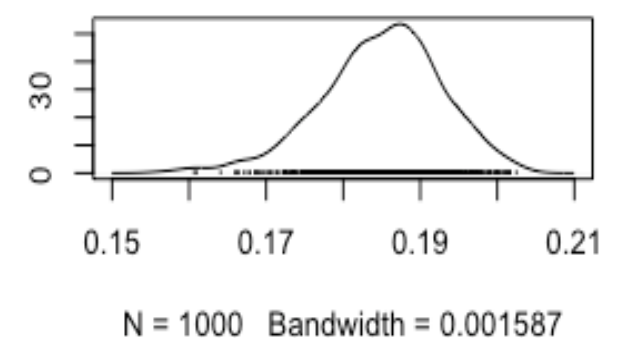
Density of b1



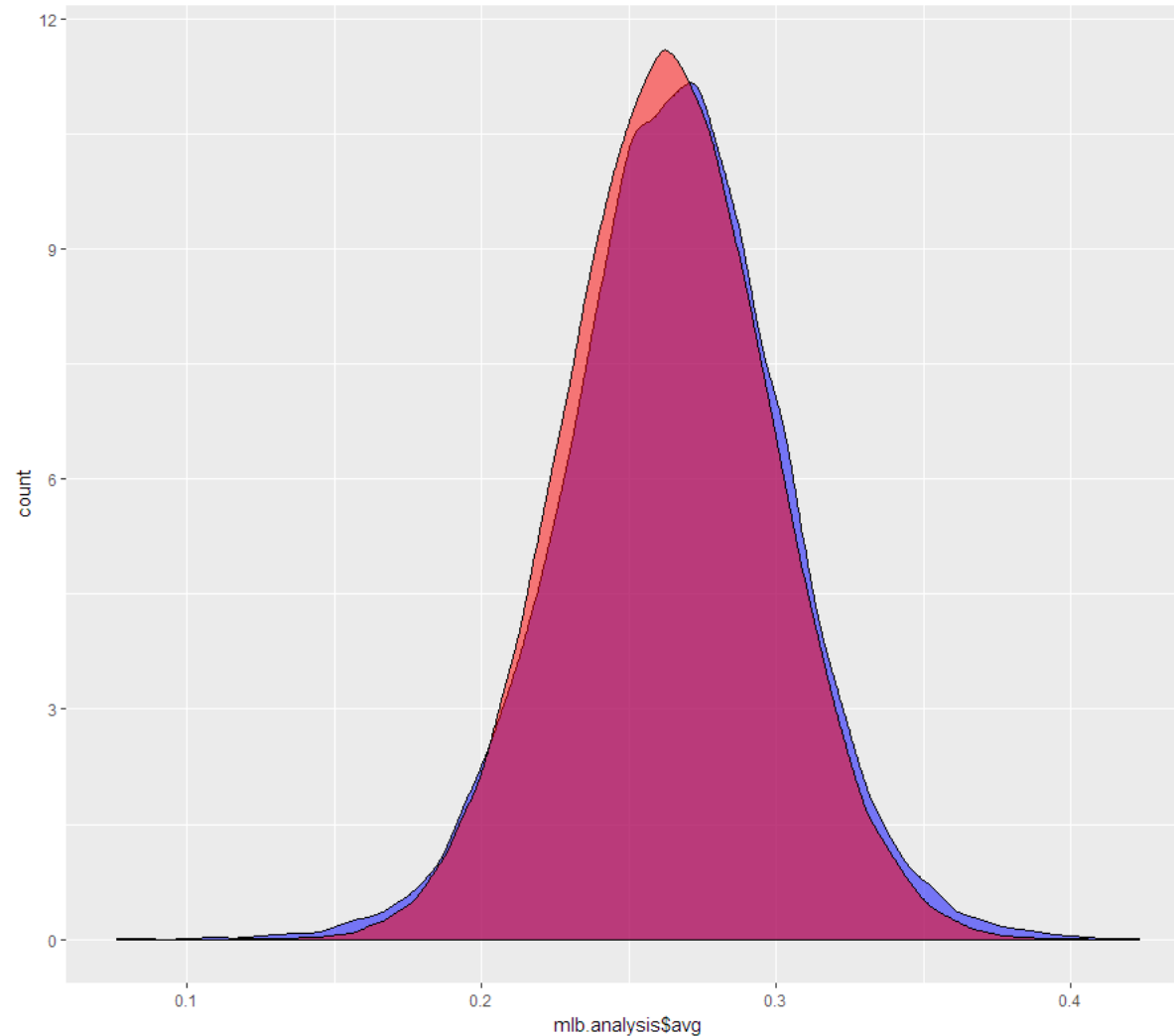
Trace of b2



Density of b2



Bayesian posterior predictive reflects full variability in data



Developed a multi-level Bayesian model in predicting MLB player BA for a given season

1. Predictors included: BA in previous and prior years, age, height, weight, era, and years in league
2. Frequentist and Bayesian models are similar
3. Frequentist model provides less uncertainty in prediction
4. Bayesian posterior predictive distribution fits true BA well

Questions?