



The Importance of Statistics in Volleyball

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Introduction

- ❖ University of Utah's volleyball team finished the 2023 season with a record of 11 - 19
 - ❖ 15 - 16 in 2022 & 22 - 9 in 2021
- ❖ Questions to Answer:
 - ❖ What volleyball game statistics are essential to winning?
 - ❖ What movements are vital for success in both practice and games?
 - ❖ The importance of kills in volleyball games
- ❖ Four different relationships modeled using Stan
 - ❖ 2 Logistic Regressions & 2 Robust Linear Regressions



Data



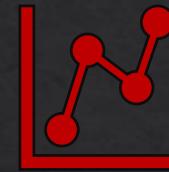
Volleyball game statistics are aggregated as all statistics recorded by the team each match

Opponent game statistics were recorded as well



The practice and movement data highlights the eight critical players on the team throughout all practices and game days

All data is collected in an applied setting



Practice and movement data is collected using Catapult IMUs

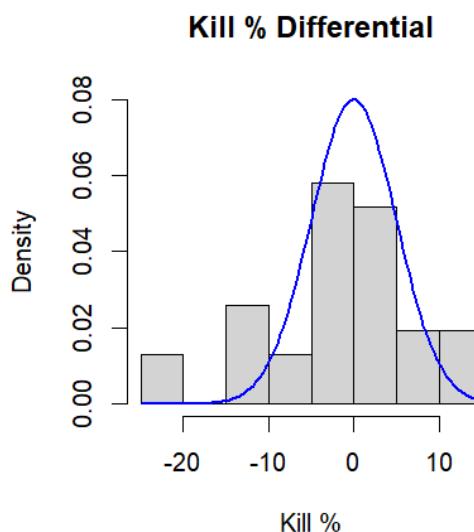
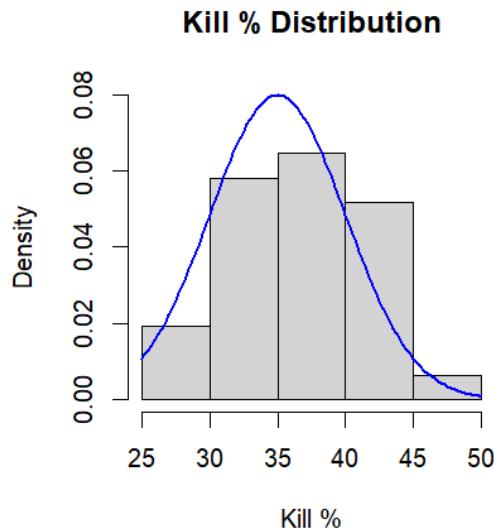
Metrics such as training load and jump statistics are relevant

Data Description

- ❖ **Kill %:** Percentage of attacks that directly lead to a point
- ❖ **Kill % Differential:** Difference between Utah's kill percentage and the opponent's kill percentage
- ❖ **High Jump %:** Calculated by Catapult IMUs. Percentage of jumps classified as high
 - ❖ Setters' medium jumps are relevant for this metric. Liberos & Defensive Specialists removed from this metric
 - ❖ All other positions calculated with high jumps
- ❖ **Player Load per Min:** Calculated by Catapult IMUs. Player load is a metric that calculates the effort a given player exerts
- ❖ **Other metrics used:**
 - ❖ Dig %, Attacking Error %, Serving Error %, Ace %



Prior Specifications



- ❖ Sports statistics are commonly distributed around a mean with a low amount of outliers
 - ❖ Theoretically matches a normal distribution
 - ❖ Uniform priors do not fit well (Ace %)

- ❖ Normal Distributions for all priors but Catapult metrics
 - ❖ Normal priors gave unrealistic results for movement metrics

- ❖ Different priors were tried that gave different results
 - ❖ Exponential & Truncated Normal

Model 1: Logistic Regression

- ❖ Logistic Model of Important Volleyball Statistics on a Dichotomous Win Variable
- ❖ Win Dummy $\sim \text{Bernoulli Logit}(\text{Kill}\% + \text{Attack Error}\% + \text{Serve Error}\% + \text{Ace}\% + \text{Dig}\%)$
 - ❖ Observations = 31; Iterations = 10,000; Chains = 3;
 - ❖ Priors:
 - ❖ Kill % $\sim N(35, 5)$; Attack Error % $\sim N(8, 2)$; Dig % $\sim N(65, 5)$; Serve Error % $\sim N(12, 4)$; Ace % $\sim N(8, 4)$
- ❖ Shows which metrics are the most impactful on winning volleyball games

- ◊ Rhats all equal 1
- ◊ n_eff large for most parameters
- ◊ Coefficients defined in log odds

- ◊ Kill % has the largest impact on winning
 - ◊ Both in the point estimate in the 95% probability interval

- ◊ Both error metrics are negative
 - ◊ Almost fully negative intervals

- ◊ Dig % & Ace % are positive
 - ◊ Dig % is fully positive
 - ◊ Ace % not entirely determined

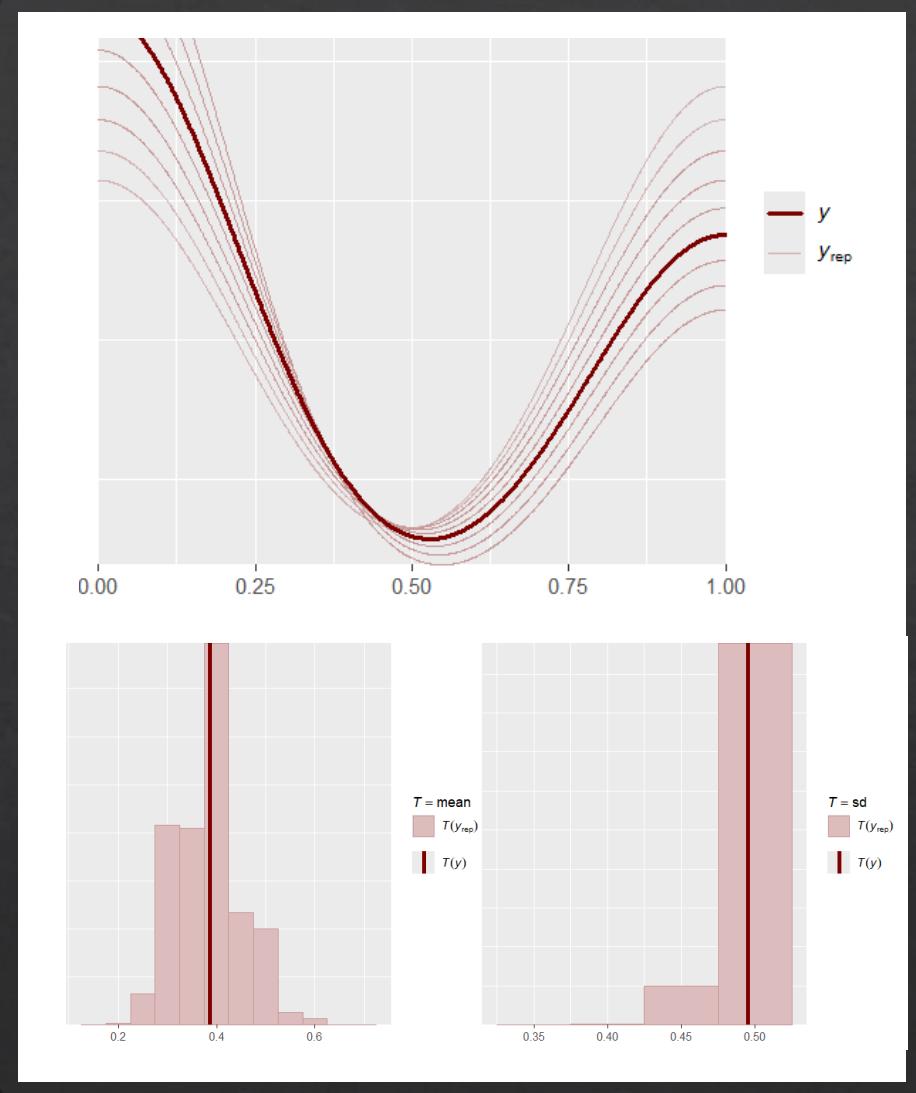
Stan Output

Parameter	mean	se_mean	sd	2.5%	97.5%	n_eff	Rhat
Intercept	49.47	0.26	20.52	-95.28	-16.36	6201	1
Kill %	0.79	0.00	0.32	0.29	1.53	6878	1
Attack Error %	-0.52	0.00	0.33	-1.23	0.07	13651	1
Dig %	0.40	0.00	0.19	0.07	0.83	7264	1
Serve Error %	-0.40	0.00	0.24	-0.93	0.01	9955	1
Ace %	0.31	0.00	0.28	-0.17	0.95	13657	1



Posterior Predictive Checks

- ❖ Generative data follows the distribution of the volleyball data
 - ❖ Also puts all weight on ones and zeros
- ❖ Mean and standard deviation recovered well
 - ❖ Max and Min also recovered
 - ❖ Confirmed by generative data weighting
- ❖ Mean distributed normally around a large center

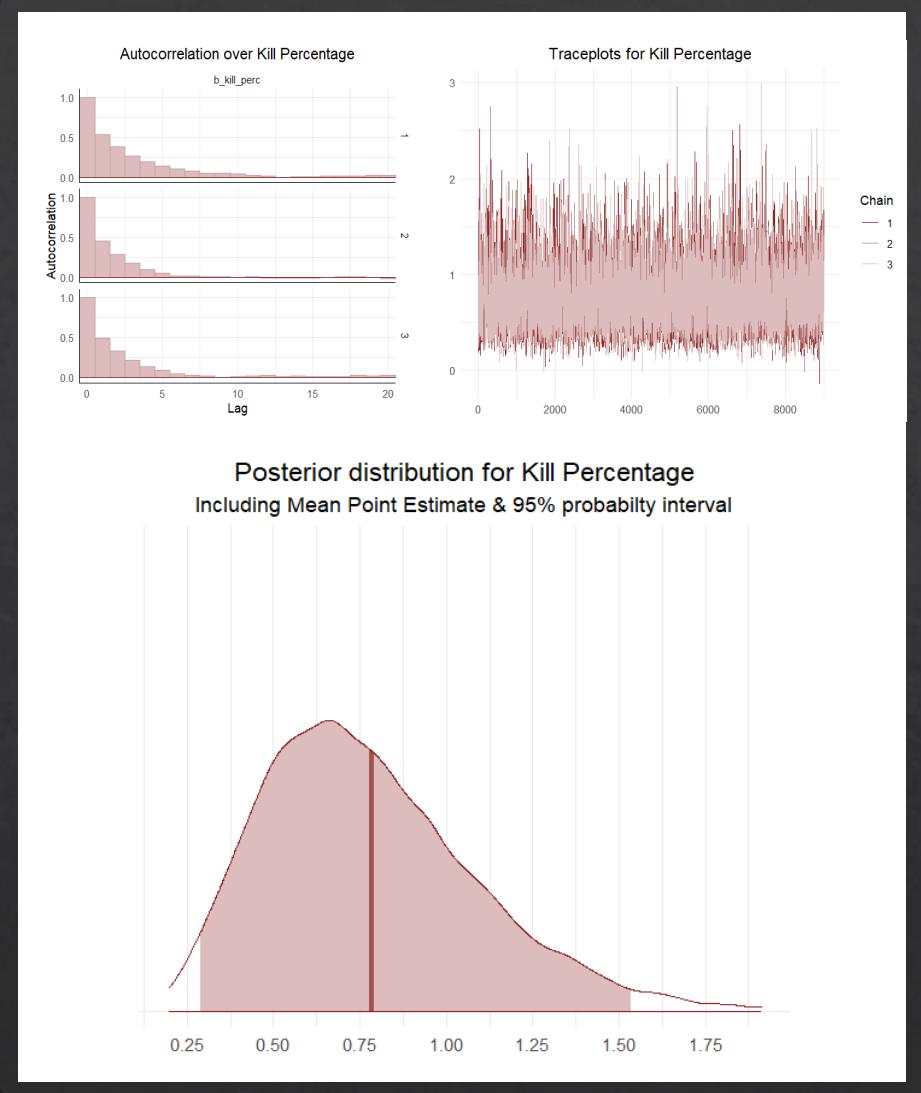


Model Checks

- ❖ Autocorrelation dies out after approx. 5 periods

- ❖ Trace plots show convergence and efficient sampling
 - ❖ Samples negative values only a few times

- ❖ Coefficient on Kill % ranges from around 0.3 to 1.5
 - ❖ 99% interval plotted; 95% interval highlighted
 - ❖ Purely positive



Model 2: Logistic Regression

- ❖ Logistic Model of Kill % Differential on a Dichotomous Win Variable
- ❖ Win Dummy ~ Bernoulli Logit(Kill_Diff)
 - ❖ Observations = 31; Iterations = 10,000; Chains = 3;
 - ❖ Priors: Kill Diff. ~ N(0,5);
- ❖ Isolates the impact of kill percentage on winning
- ❖ Kill differential considers both offensive and defensive aspects of the game
 - ❖ Is the team attacking efficiently and defending opposing attacks efficiently?
 - ❖ More telling metric than Kill %



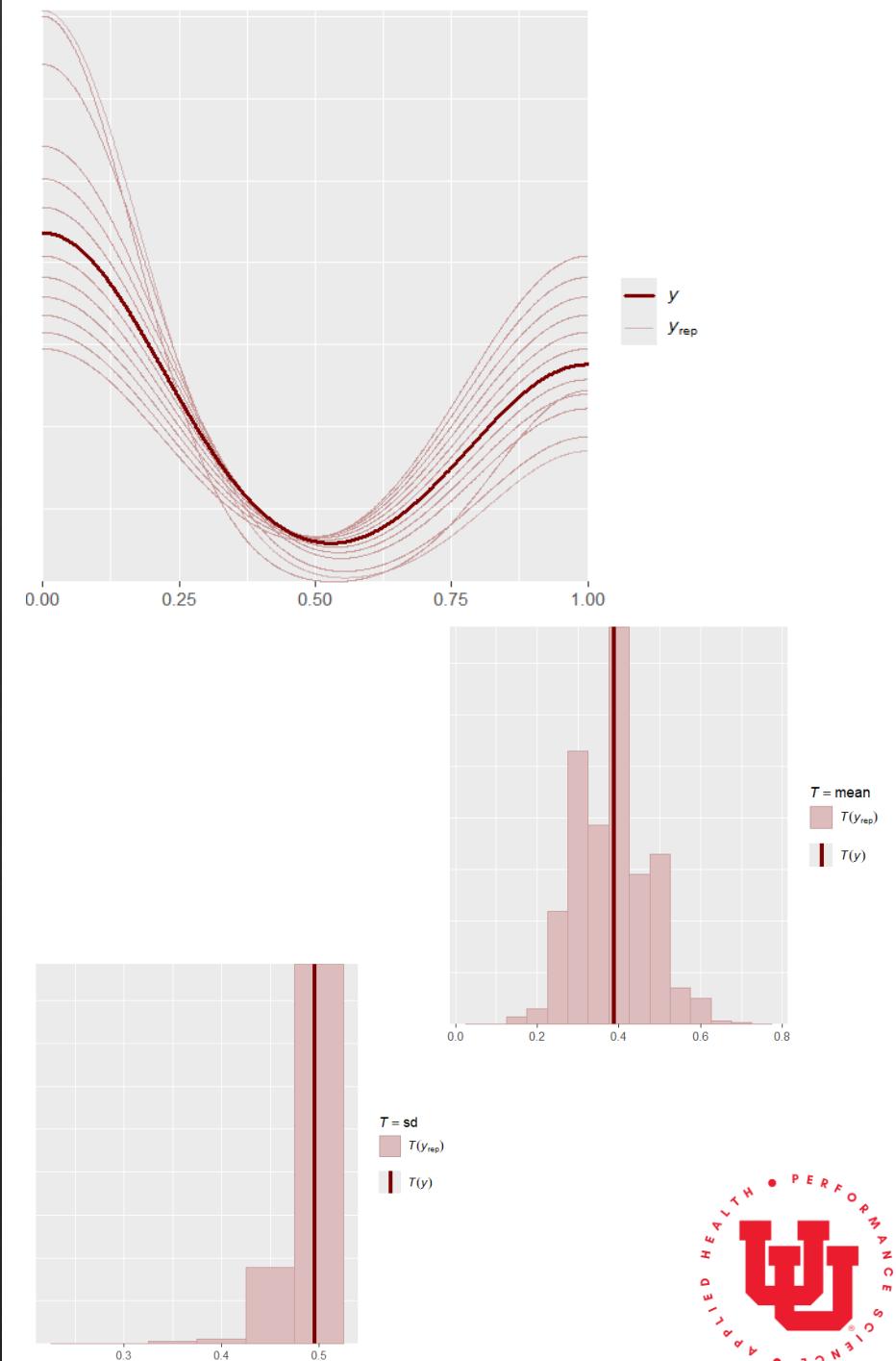
Stan Output

Parameter	mean	se_mean	sd	2.5%	97.5%	n_eff	Rhat
Intercept	-0.84	0.00	0.57	-2.03	0.21	18392	1
Kill Differential	0.38	0.00	0.14	0.16	0.70	15966	1

- ❖ Same positive relationship exists between kill differential and winning
 - ❖ 95% interval is fully positive
- ❖ Rhats equal to 1 for both parameters
- ❖ n_eff is high for both parameters

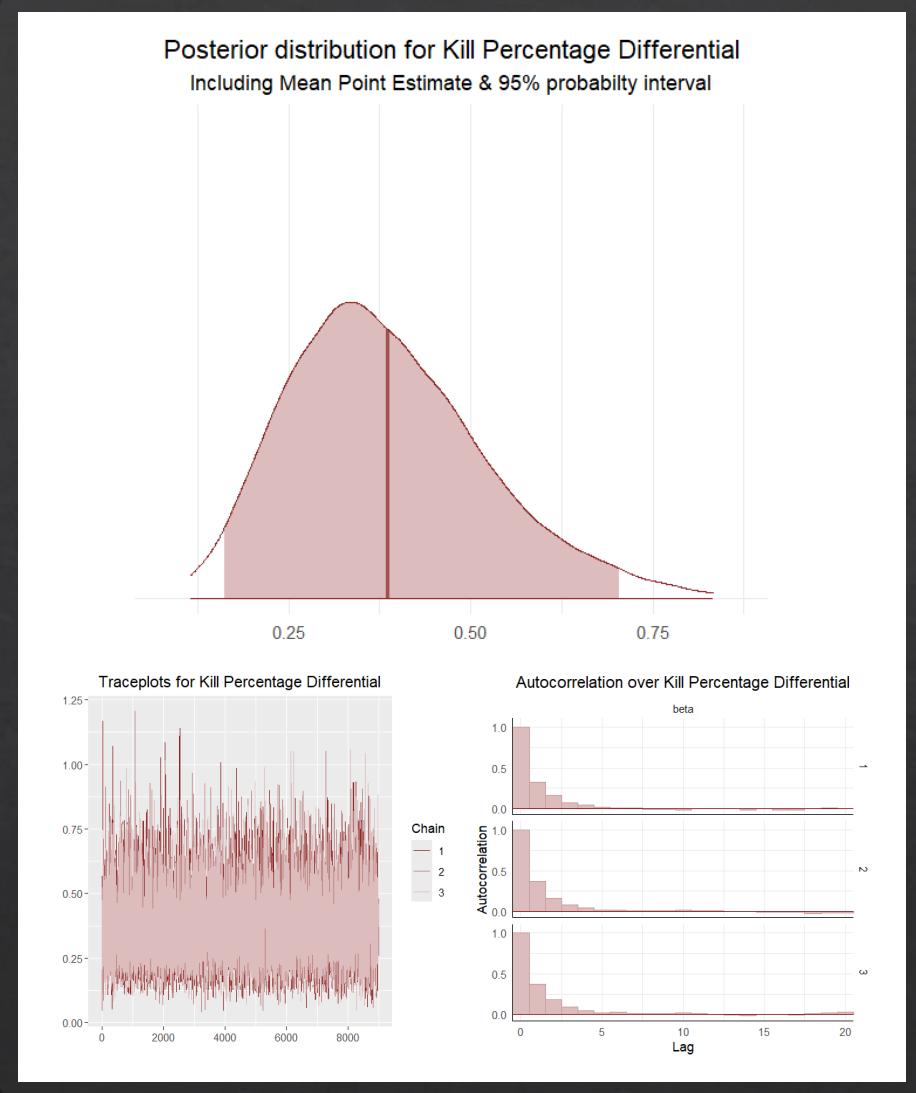
Posterior Predictive Checks

- ❖ Generative data follows the distribution of the volleyball data
 - ❖ Again, puts all weight on ones and zeros
- ❖ Mean and standard deviation recovered well
 - ❖ Max and Min also recovered
 - ❖ Confirmed by generative data weighting
- ❖ Mean distributed somewhat normally



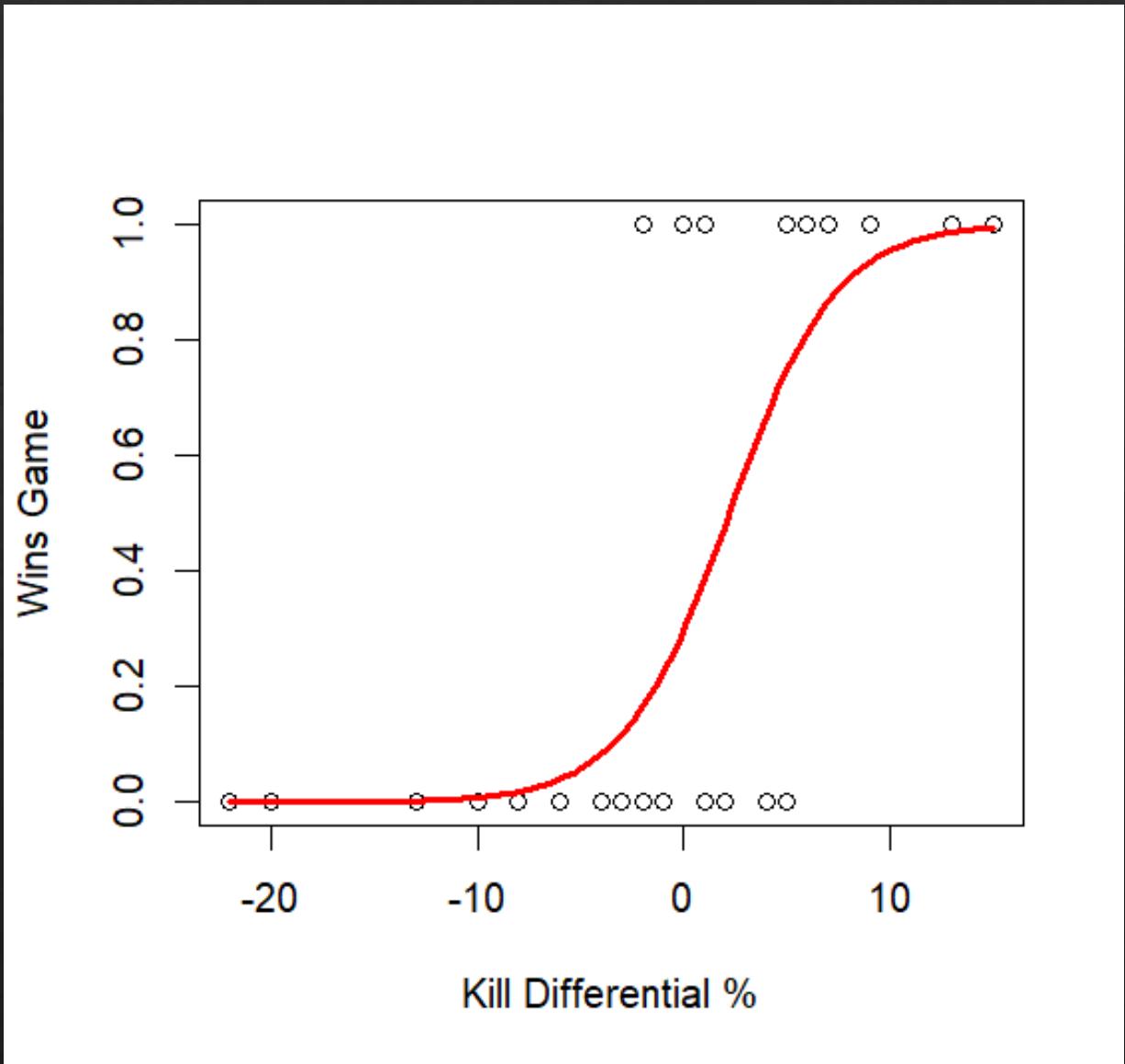
Model Checks

- ❖ Autocorrelation dies out after approx. 5 periods
- ❖ Trace plots show convergence and efficient sampling
 - ❖ Negative values are not sampled
- ❖ Coefficient on Kill % ranges from around 0.1 to 0.7
 - ❖ 99% interval plotted; 95% interval highlighted
 - ❖ Once again purely positive



Logistic Sigmoid Curve

- ❖ Plotting the stan output gives a logistic curve over the wins and losses
 - ❖ Wins = 1; Losses = 0
- ❖ Kill diff. of 0 \approx 40% chance to win
- ❖ Changes in win likelihood happen between -10 and 10
- ❖ Lowest win was a kill diff. of \approx -2
 - ❖ Only wins with negative diff.



Model 3: Robust Normal Regression

- ❖ Robust Linear Model of Good Game Jumps on Kill % Differential
- ❖ Kill Differential $\sim \text{student_t}(\nu, X * \beta, \sigma)$
 - ❖ Observations = 29; Iterations = 10,000; Chains = 3;
 - ❖ Priors: $\nu \sim \text{Gamma}(2, .1)$
- ❖ Ignorance prior used for β
- ❖ Jumps collected by Catapult IMUs within games
 - ❖ High Jumps for most positions; Medium for Setters; Liberos & Defensive Specialists excluded
- ❖ Two games did not have catapult data (observations: 31 → 29)



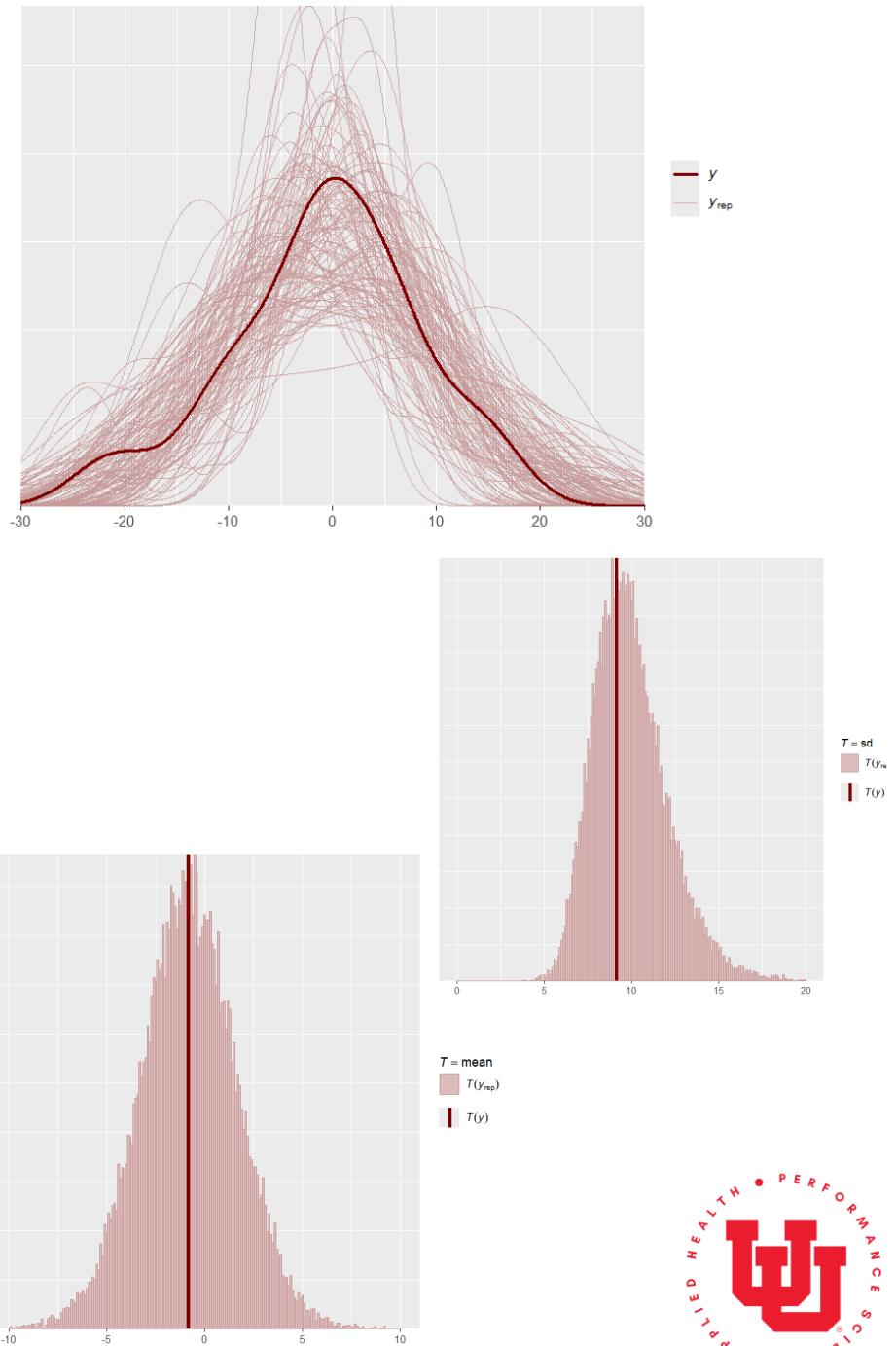
Stan Output

- ❖ Good Jumps has an almost fully positive relationship with Kill diff.
 - ❖ 95% interval crosses 0
- ❖ Rhats equal to 1 for all parameters
- ❖ n_eff is high for all parameters
- ❖ Nu has a high point-estimate

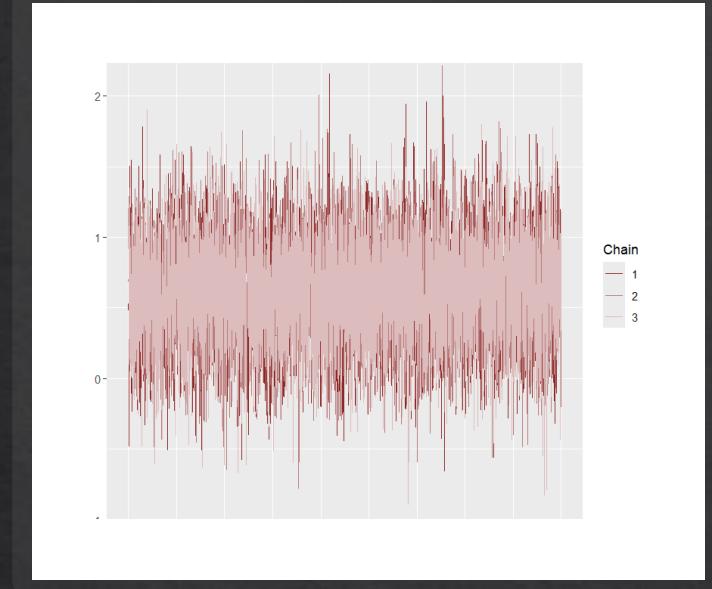
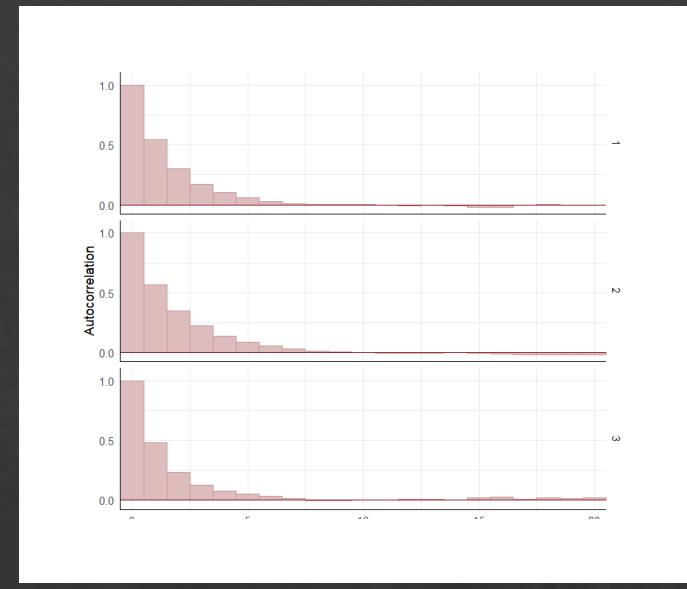
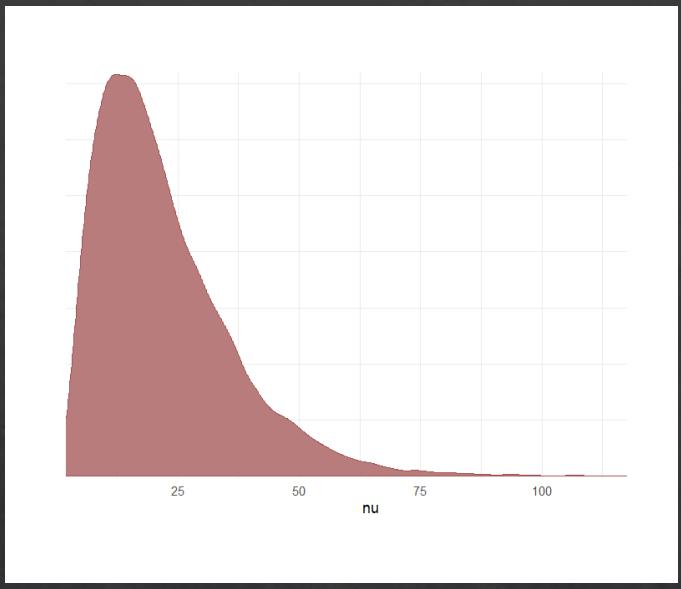
Parameter	mean	se_mean	sd	2.5%	97.5%	n_eff	Rhat
Intercept	-43.34`	0.25	23.83	-89.96	4.08	8763	1
Good Jumps	0.62	0.00	0.14	-0.06	1.31	8765	1
Sigma	8.66	0.01	1.38	6.34	11.74	12087	1
Nu	22.16	0.11	14.04	4.43	57.05	15823	1

Posterior Predictive Checks

- ❖ Generative data follows the normal distribution of the volleyball data
 - ❖ Spread of generative data explains high variance
- ❖ Mean and standard deviation recovered well
 - ❖ Large spread for both of these variables
 - ❖ Max and Min also recovered



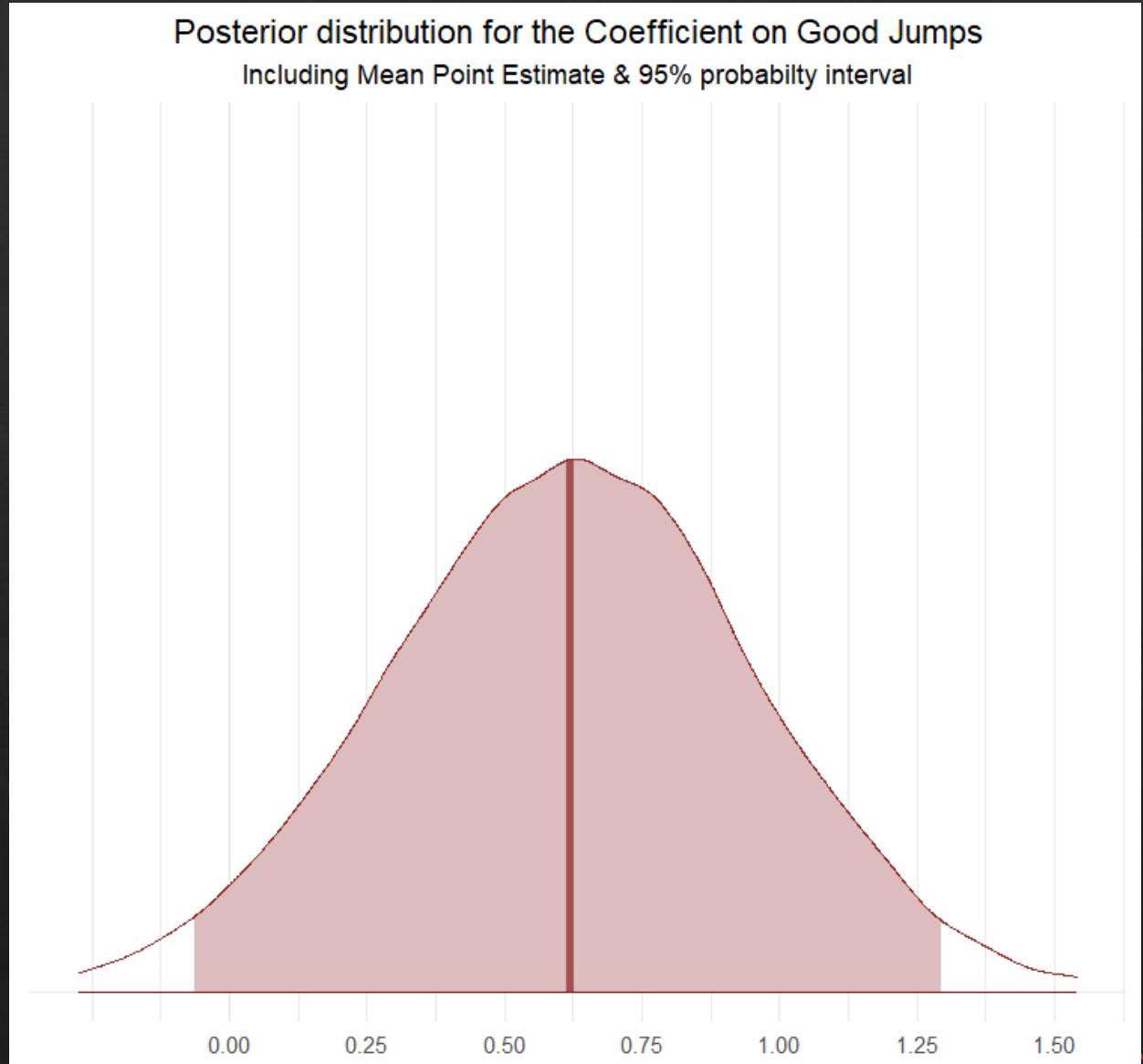
Model Checks



- ❖ Trace plot shows efficient sampling
 - ❖ Samples over 0 regularly
- ❖ Autocorrelation dies out after approx. 5 periods
- ❖ Nu contains large values (Robust)
 - ❖ Indication of student-t converging to normal distribution

Good Jumps Density Curve

- ❖ Coefficient on Good Jumps ranges from -0.1 to 1.3
- ❖ 90% interval does not contain negative values
 - ❖ Applied setting not a lab setting
 - ❖ Jumping is all but required to get a kill
- ❖ Kill Diff adds an interesting angle
 - ❖ Team could be jumping higher than ever, and still get outperformed



Model 4: Robust Normal Regression

- ❖ Robust Linear Model of Practice Good Jumps & Player Load on Kill % Differential:
- ❖ Kill Differential $\sim \text{student_t}(\nu, X * \beta, \sigma)$
 - ❖ Observations = 29; Iterations = 10,000; Chains = 3;
 - ❖ Priors: $\nu \sim \text{Gamma}(2,.1)$;
- ❖ Ignorance prior used for beta
- ❖ Two practices did not have catapult data (observations: 31 \rightarrow 29)
- ❖ Only practices analyzed were the practices the day before a game



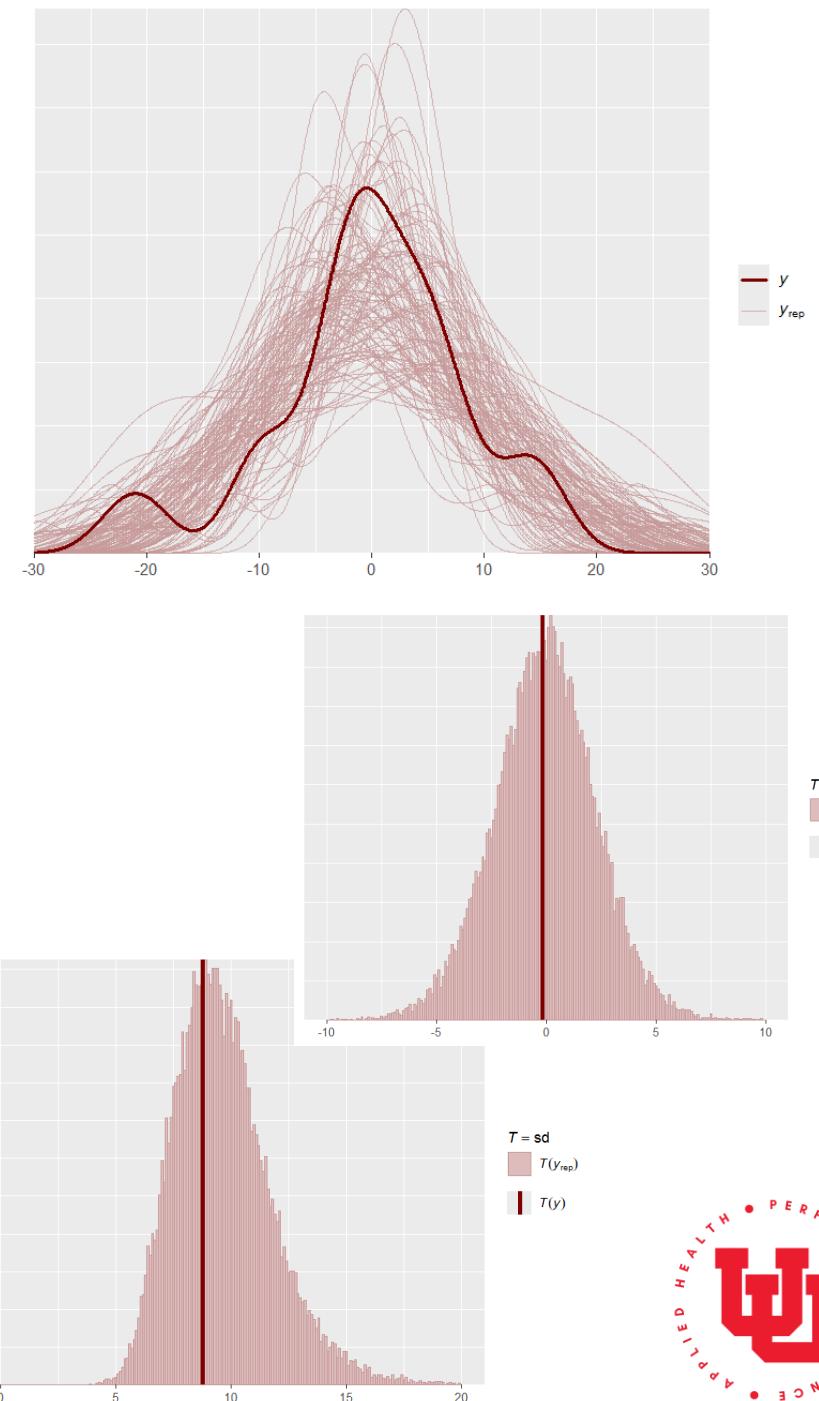
Stan Output

Parameter	mean	se_mean	sd	2.5%	97.5%	n_eff	Rhat
Intercept	-31.58	0.17	18.02	-66.57	4.17	11008	1
Good Jumps	0.18	0.00	0.20	-0.21	0.58	13859	1
Player Load	5.95	0.03	3.93	-1.70	13.80	13580	1
Sigma	8.13	0.01	1.47	5.56	11.33	12916	1
Nu	18.96	0.10	13.62	3.29	53.88	17761	1

- ❖ Much more inconclusive results
- ❖ Both Good Jumps and Player Load cross into the negative values
- ❖ Rhats equal 1
- ❖ n_eff values are sufficiently large

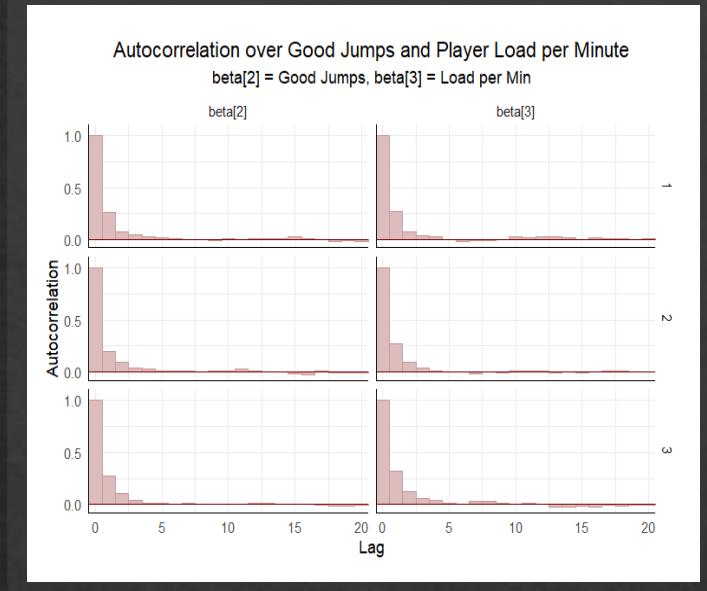
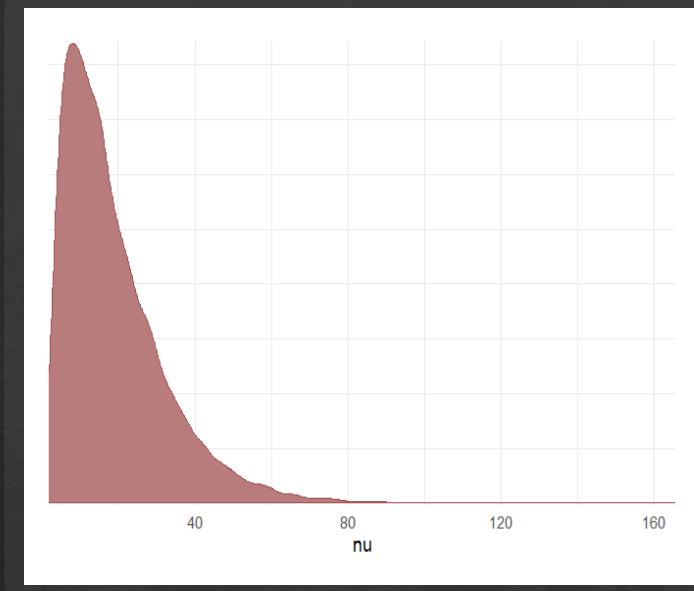
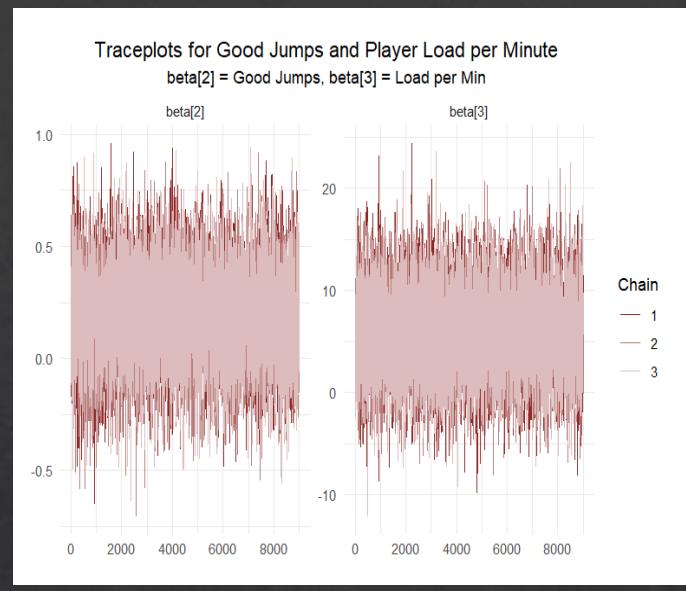
Posterior Predictive Checks

- ❖ Generative data follows the somewhat normal distribution of the volleyball data
 - ❖ Spread of generative data explains high variance
 - ❖ Weird shape of Utah data because of outliers and low amount of data
- ❖ Mean and standard deviation recovered well
 - ❖ Large spread for both
 - ❖ Max and Min also recovered



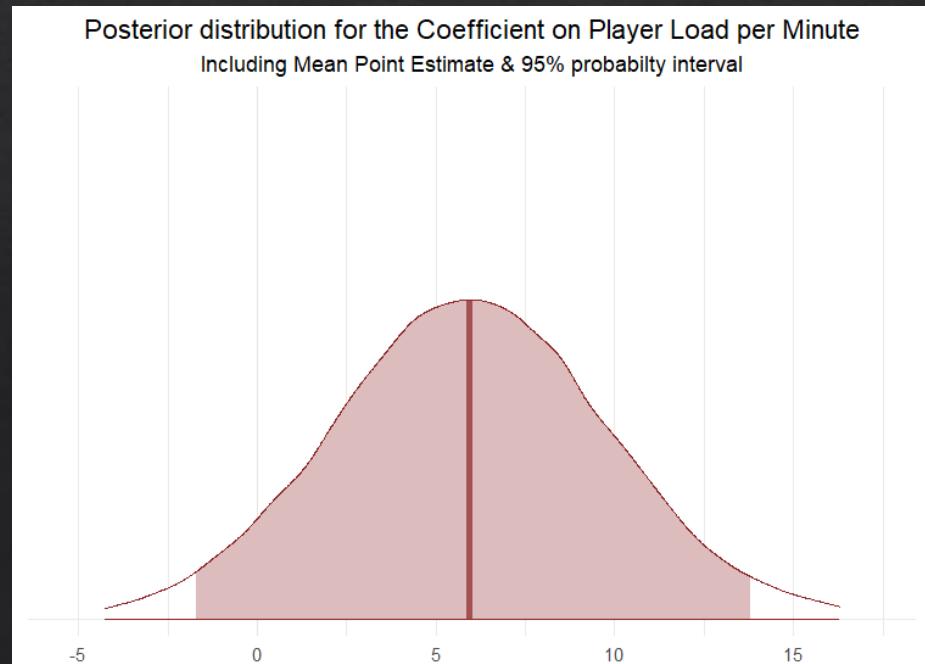
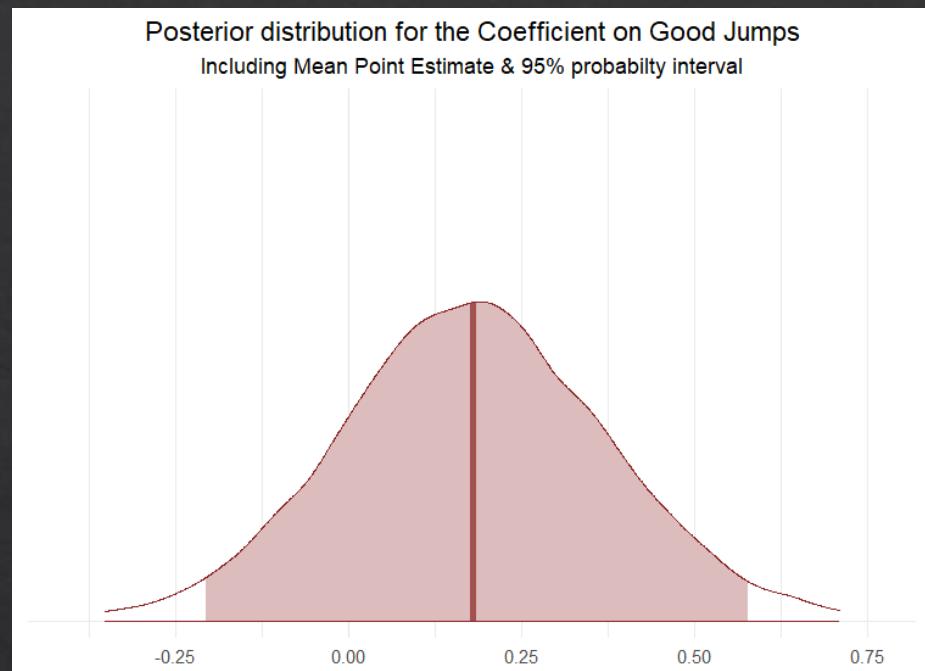
Model Checks

- ❖ Both trace plots show efficient sampling
 - ❖ Both sample negative values regularly
- ❖ Autocorrelation dies out almost immediately
- ❖ Nu contains somewhat large values
 - ❖ Indication of student-t converging to normal distribution
 - ❖ Not as large as the previous model



Density Curves

- ❖ Negative values indicate uncertainty
 - ❖ Coefficient on Good Jumps ranges from -0.2 to 0.6
 - ❖ Coefficient on Player Load ranges from -2 to 13
- ❖ Practice effort leads to improvements in kill differential; up to a point
- ❖ 90% intervals are mostly positive
 - ❖ Fully for Player Load per min



Limitations

Data is collected in an applied setting

- Lots of confounding variables that cannot be accounted for

Small dataset size

- Analysis would be more concrete if multiple seasons were compared

Conclusions

- ❖ Kill percentage has the largest impact on winning volleyball games
- ❖ Kill % differential encapsulates offensive and defensive performance
 - ❖ Also has a large impact on winning
- ❖ The Bayesian framework and data collection in an applied setting allow for relaxed probability intervals
 - ❖ Good jumps in a game correlate with a higher kill differential
 - ❖ Effort in practice the day before a game has an undetermined impact on kill differential



Sources

- ❖ Lots of advice from the University of Utah Applied Health and Performance Science Team as well as strength coaches, and information that I have heard indirectly from the coaching staff
- ❖ "Women's Volleyball Statistics." NCAA.com, National Collegiate Athletic Association, <https://www.ncaa.com/stats/volleyball-women/d1>
- ❖ "Logistic/Probit Regression." Stan Users Guide, Stan Development Team, <https://mc-stan.org/docs/stan-users-guide/regression.html#logistic-probit-regression.section>.
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- ❖ Grammarly, Grammarly Inc., <https://www.grammarly.com/>.
- ❖ University of Utah Writing Center, University of Utah, <https://writingcenter.utah.edu/>.
- ❖ "Stan User Guide" Stan, Stan Development Team, <https://mc-stan.org/>.





Questions?

