Introduction:

The University of Utah volleyball team concluded their 2023 season on November 24th with 11 wins and 19 losses. This season was a decline from the program's previous success, with 15 wins and 16 losses in the 2022 season and 22 wins and 9 losses in the 2021 season. Coaches and fans alike are interested in why this decline happened within the program. The athletic staff is interested in knowing if there are any answers in the data for what leads to winning, what the team needs to improve, and how to change training in practices. Data analysis may provide insights and solutions on how the volleyball team can improve and head into the 2024 season with a higher probability of success.

Kills are one of the most critical statistics in volleyball, with coaches and researchers emphasizing the pivotal role of kills on game outcomes. Kills are when an offensive player hits a ball that directly leads to a point for their team. The importance of kills is evident as there is a direct relationship between increasing kills and scoring. Kill percentage will be the highlighted statistic in this paper's analysis.

All models were executed with stan software in the R programming language. Stan is a probabilistic programming language used for Bayesian inference, modeling, and sampling. This language uses a variation of Hamiltonian Monte Carlo sampling called the No-U-Turn-Sampler (NUTS) to sample and build a posterior distribution efficiently. Stan allows for user control of all aspects of the model specification and provides a cautious approach to causal analysis. Modeling volleyball statistics with stan provides inference into the relationships between different statistical aspects of the sport.

Data:

The data used in this project comes from the University of Utah volleyball team in the 2023 season. Gameday data is an aggregation of all statistics recorded by the team in that match. The practice and movement data highlights the eight critical players on the team throughout all practices and game days. All other players on the team were removed from this analysis. They needed more playing time to justify the data reliability and were less impactful on the overall team's success. Coaches who desired results of the primary players rather than a whole team analysis supported this removal of players. The data collected in this project will be focused on gameday statistics and catapult data. Catapult technologies are inertial measurement data-collection units players wear in practice and games that capture a player's movements and effort.

The gameday and practice data that will be analyzed are collected as aggregated team statistics. Essential metrics that will be analyzed are listed below:

- **Kill %:** Percentage of hits that directly lead to a point
    - (The player intended to score a point on this play)
- **Kill % Differential:** The difference between Utah's kill percentage and the opponent's kill percentage.
- **Ace %:** Percentage of serves the opposing team is unable to receive/return
- **Attacking Error %:** Percentage of attacks that a player misses by hitting the net, out of bounds, or an opposing player blocks the attack
- **Dig %:** Percentage of times a defensive player successfully passes an attempted attack from the opposition
- **Serving Error %:** Percentage of serves that a player misses the bounds of the court or the serve does not cross over the net
- **High Jump %:** Calculated by Catapult technology. The threshold of what is defined as a high jump is set by sports scientists. Jumps are relative to specific volleyball positions. Medium Jumps are more critical for Setters, so the percentage from medium jumps is synonymous with high jumps for the other positions in this analysis. Additionally, liberos and defensive specialists are removed from this analysis, as jumps are not vital to their role.
- **Player Load per Min:** Calculated by Catapult technology. Player load is formally defined as "the sum of the accelerations across all axes of the internal tri-axial accelerometer during movement. It takes into account the instantaneous rate of change of acceleration and divides it by a scaling factor (divided by 100)." Informally defined as a metric that calculates the effort any given player exerts.

Gameday data has been recorded for the opposing team's metrics to analyze differentials as well as just team-specific relationships. The goal of this differential analysis is to show that the opposing team's statistics will decrease as our team plays better, leading to more victories.

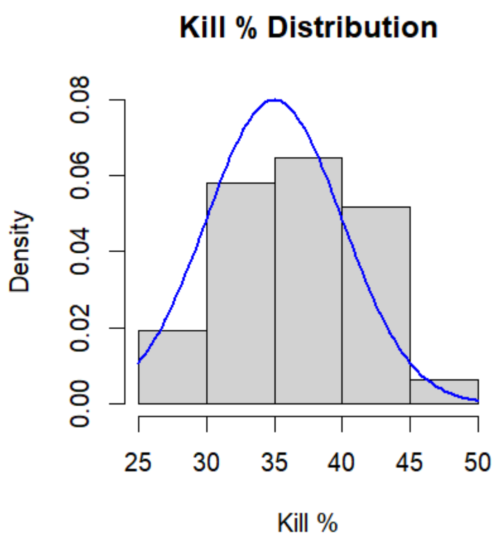
Catapult data is the other type of data that will be analyzed. As briefly introduced earlier, catapult athlete tracking technology is a system that employs wearable devices and data analytics to monitor and analyze the physical performance and movements of athletes during training and competition. Catapult data was collected in all but 2 games and practices the day before a game in the 2023 season. Catapult devices collect hundreds of metrics, but the metrics of interest for this analysis are player load and high/medium jump percentages.

Player load quantifies the amount of effort an athlete is producing in a game or practice. Analyzing player load gives insight into potential fatigue before the coach or the athlete recognizes it. High and medium jumps are vital for volleyball players as the sport involves countless jumps in each set. Certain positions, such as setters, do not need to jump as high as a hitter or a blocker, so their jumps are characterized separately. We analyze medium jumps for setters and high jumps for the rest of the positions and equate these jumps as equivalent effort-wise. Liberos and defensive specialists are removed from this analysis as they are not crucial in the jump metrics but are still included in the team-aggregated gameday metrics.

Analysis:

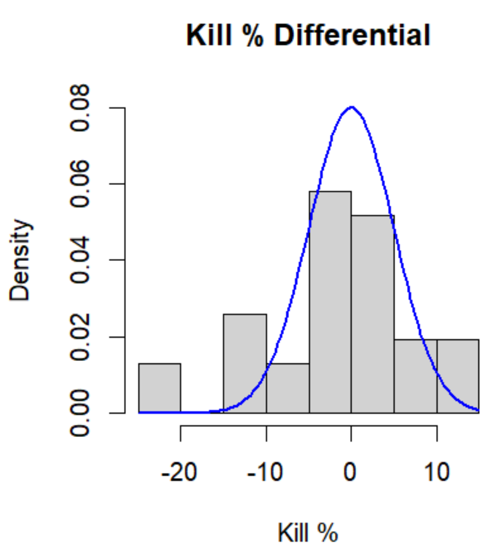
Setting Priors:

Figure 1: Prior for Kill % (Data in bins, Prior plotted as blue curve)



The prior for kill percentage was set by referencing averages of other D1 volleyball teams. The average kill % in other Pac-12 and D1 programs lies within the 30% - 55% range. The overarching average of the kill percentage of D1 volleyball programs was approximately 40%. Accounting for Utah volleyball not performing to their usual standard, the prior for Kill % was set as a Normal distribution with a mean of 35 and a standard deviation of 5. Figure 1 shows the prior distribution, plotted as the blue curve, follows this season's data, plotted as the histogram, supporting prior beliefs.

Figure 2: Prior for Kill Diff. (Data in bins, Prior plotted as blue curve)



Similarly, the kill percentage differential prior between Utah and the opponent was modeled with a normal distribution. The standard deviation stayed at 5 for consistency, but the mean was shifted to be centered at 0. Theoretically, if teams are at the same skill level, this differential should average to 0. Figure 2 once again shows that charting the prior distribution over the collected data supports the prior specifications. While this prior specification curve does not fit the data as well as the kill % prior does, the description is sufficient to use this prior for analysis.

Setting priors for catapult jump percentages was attempted. The goal was to consider the differences in effort on gamedays versus the planned-out effort in practices. Average high jump percentage data within the D1 volleyball competition does not exist, so this could not be used for comparison. Making a comparison difficult to achieve. This lack of data can be explained by the fact that the thresholds for catapult jumps can be set individually by the team.

Formulation of jump percentage priors was still attempted. A normal distribution was attempted, knowing the normal distribution worked for all other variables. The prior for gameday jumps was normally distributed with a mean of 70 and a variance of 5. Similarly, the prior for practice jumps was normally distributed with a mean of 60 and a variance of 5. Keeping the variance constant between groups and accounting for less exertion in practice was emphasized in this construction of the prior.

Unfortunately, when using the normally distributed jump priors in the overall analysis, the results were unrealistic and did not follow the underlying relationships in the data. In order to achieve reliable results, priors were not specified when using jump and player load data. Stan defaults to an ignorant prior when a prior is not specified, which does not influence the data distribution in any way at all.

Similar processes were used to determine the priors for the other four variables used in this analysis. All priors were specified as normally distributed. This follows assumptions of the nature of gameday statistics. Normal distributions center data around a specific point while allowing for a spread to nearby values, mirroring the typical appearance of game statistics. Prior specification was emphasized because using an ignorance prior when knowing the specification of certain variables can lead to improper results.

For example, setting a uniform prior on the ace percentage variable would be completely irrational. Every serve cannot be unreturnable for an opponent. This logic holds for all other variables, with observations centered around a point without too many outliers. Other attempted priors included truncated normal distributions and exponential distributions. These priors were not used in the overall analysis as the both distributions returned similar results to the normal distributions. There was not enough data close enough to cut off for the truncated distributions to be statistically different. In order to keep calculations efficient and easier to understand, normal distributions were used. All priors were compared to the underlying data to ensure similarity.

Stan Model Analysis:

Logistic Model of Important Volleyball Statistics on a Dichotomous Win Variable:

The first of four models analyzed the impact of kill percentage on winning a volleyball game compared to a few other relevant game statistics. This relationship was modeled using a logistic regression in stan in order to fully understand the impact of kill % on winning. The results of the model are listed in Table 1 below.

Table 1: Stan Logistic Regression Output of Volleyball Game Statistics on Wins

Stan Output for Logit Model
Win Dummy ~ Bernoulli Logit(Kill% + Attack Error% + Serve Error% + Ace% + Dig%)
n = 31; iter = 10,000; chains = 3; Kill % ~N(35, 5); Attack Error % ~ N(8, 2); Dig % ~ N(65, 5);
Serve Error % ~ N(12, 4); Ace % ~ N(8, 4)

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

Upon initial glance, it is clear that kill percentage has the largest impact on winning a volleyball game. The coefficients for all parameters are defined in log odds, but kill % still looks to have the largest impact on winning. Relationships that we would expect to see exist within this model with both attacking and serving errors having a negative impact and dig and ace percentages having positive impacts on winning. These relationships resonate with the preconceived notions of how volleyball statistics influence game outcomes.

Many different priors and multiple different specifications of the model were attempted in order to validate the model. The Rhat value equals 1 for all parameters, which indicates convergence. Multiple posterior predictive checks (PPCs) were run as insurance for model performance. With kill percentage being the variable of interest, PPCs highlight the kill percentage parameter. All other parameters had similar results.

Figure 3: PPC comparing distribution of generative data to underlying data

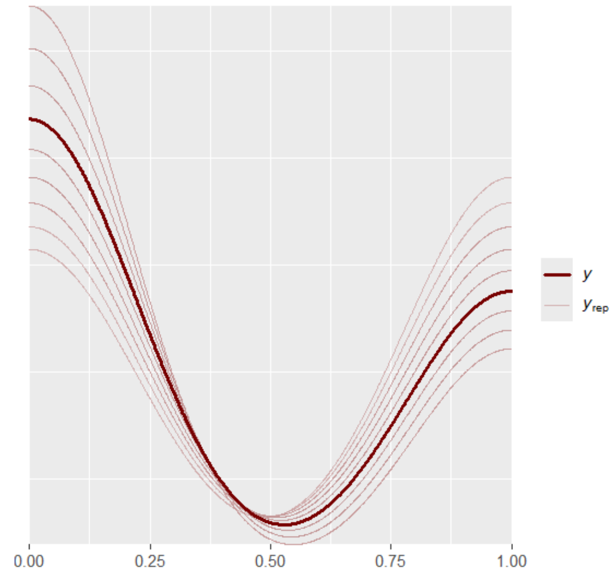


Figure 4: PPC comparing mean of generative data to underlying data

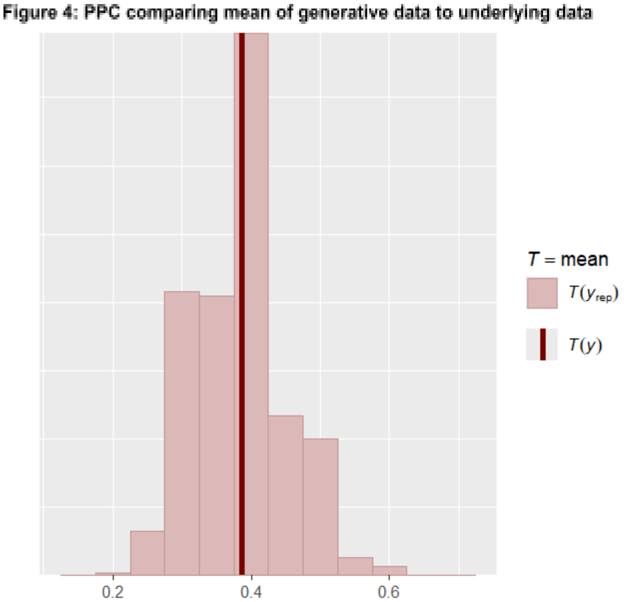
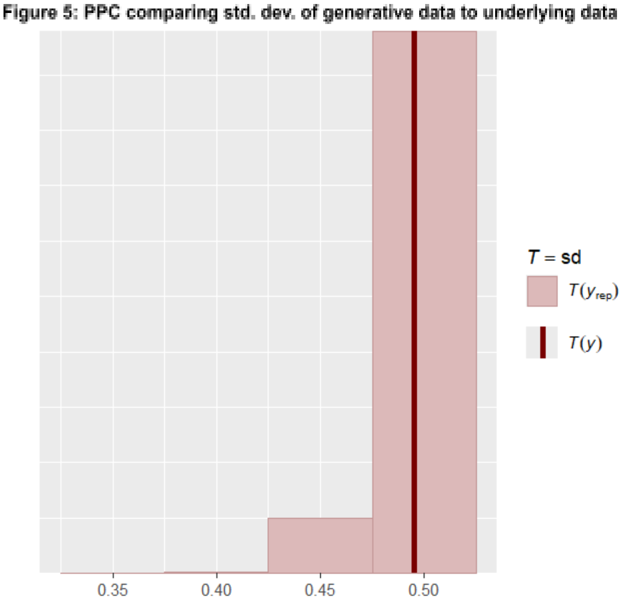


Figure 5: PPC comparing std. dev. of generative data to underlying data



Posterior predictive checks assess the strength and relevance of the model. Figure 3 describes how generated data compares to what we have modeled from the Utah game statistics. Most generative data follows a similar curve to the underlying distribution, which is displayed as the darker curve.

The generative curves in Figure 3 also show that the weight lies on values of 0 or 1, which indicates that the model works efficiently as it can recover the dichotomous dependent variable. This is another indication that the model is a good estimator for the type of data that we have.

Figure 4 compares the mean of all the generated distributions to the mean of the collected volleyball data. The underlying mean is in the center of the generative posterior distribution, again indicating model success.

It can also be seen that the generated data has a somewhat normal distribution, with a mean value that stands out. This validates the earlier analysis of all the data existing around a center with limited outliers. This exact analysis was used to construct priors for most parameters.

The last chart, Figure 5, shows that the standard deviation is also recovered from the generative data. Almost all observations are within the bin where the standard deviation of the collected data exists.

Figure 6: PPC showing the autocorrelation of MCMC samples

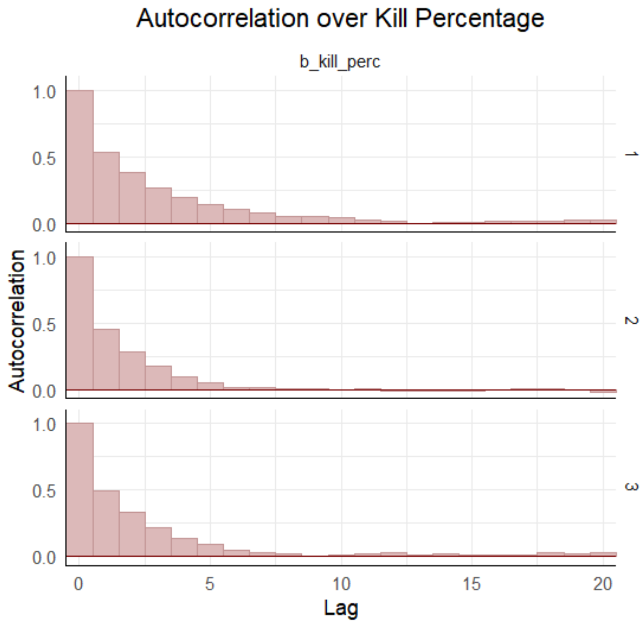
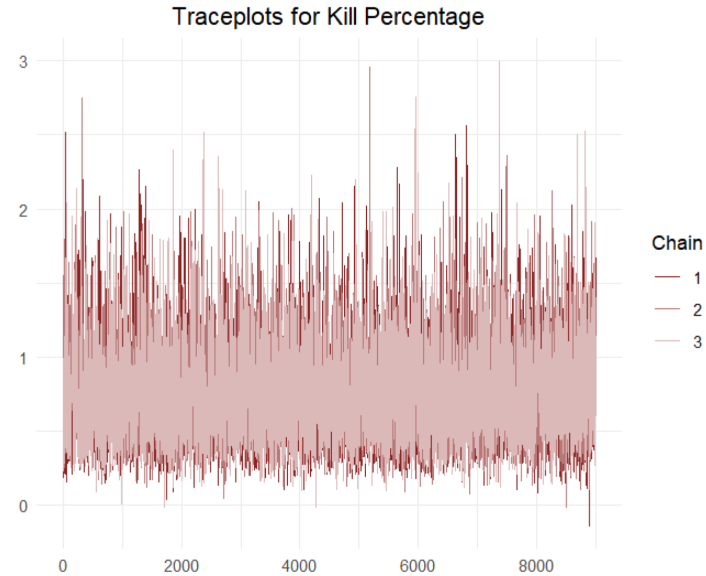


Figure 7: Trace plot of MCMC samples



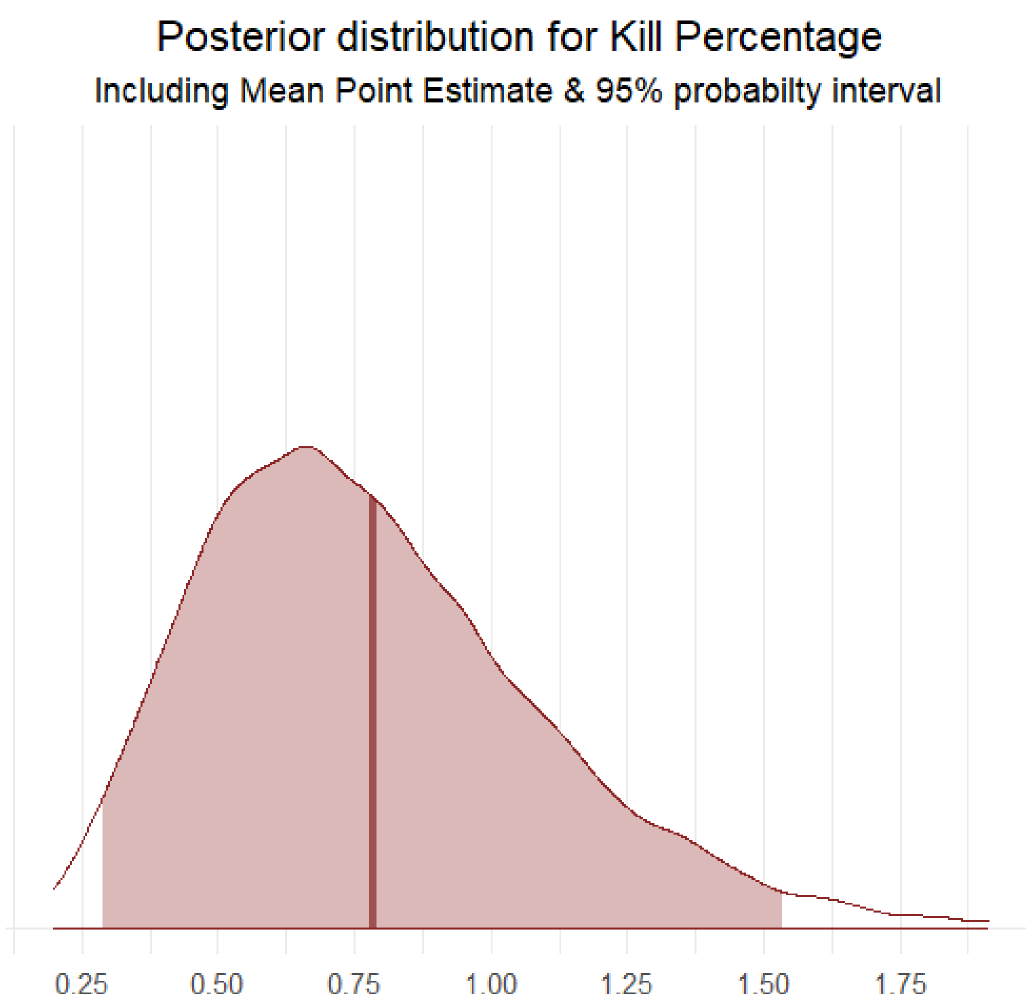


Figure 8: PPC showing the distribution of the coefficient on Kill %

Trace and autocorrelation plots are more model checks used to validate the model. Figure 6 is an autocorrelation plot that displays all three Markov chains that were sampled. The autocorrelation dies out extremely quickly in all chains. Within about five periods, there is little to no correlation left. This is more than sufficient to validate that a stan model is sampling efficiently and correctly. The trace plot in Figure 7 shows that the model dances around efficiently and explores the whole sample space. The model only clearly samples below the 0 line on the y-axis once. This is reflected in the density plot as well. A lack of sampling negative values validates the hypothesis that kill percentage positively impacts winning a volleyball game.

Figure 8 shows a density plot of the coefficient on kill percentage. The plot shows 99% of the density, with the 95% probability interval highlighted. Similar to the trace plot, the density curve never crosses over zero in either 99% or 95% intervals. The density plot validates that kill percentage has a positive impact on winning, and this impact is the largest out of the five key metrics that were a part of this regression. The posterior spread ranges from about .30 to 1.5. This is a significant spread concerning how this variable is defined. While the spread is important, the most significant observation here is how the interval contains purely positive coefficients.

Logistic Model of Kill % Differential on a Dichotomous Win Variable:

The second of the four stan regression models analyzes the effects of kill percentage differential on winning a volleyball game. Kill percentage had the largest impact on winning in the previous logistic model. Kill percentage is known to be the most important and telling game statistic in the volleyball community. Looking at this variable in singularity compared to winning gives a direct interpretation of this statistic's relevance. However, doing so while ignoring the other aspects of volleyball would be foolish.

As defined earlier, kill percentage is any hit that directly leads to a point. Focusing just on the offensive side of a sport and reporting those results is the incorrect way to attack a question such as this. Kill percentage differential was used in this model to isolate the effect of kill percentage while still accounting for other aspects of the game. The definition is exactly how the variable name sounds: the difference between Utah’s kill percentage and the opponent's. Using this metric considers how Utah is doing offensively while also accounting for whether they limit the opposition from improving their kill percentage. In doing this, metrics such as dig percentage, blocking percentage, attacking error, and others are somewhat aggregated into one encompassing statistic. While these metrics are not directly accounted for in this statistic, they all impact the differential.

Table 2: Stan Logistic Regression Output of Kill % Differential on Wins

Stan Output for Logit Model
Win Dummy ~ Bernoulli Logit(Kill_Diff)
n = 31; Kill Diff. ~ N(0,5);iter = 10,000; chains = 3

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

When isolating kill differential, we still see a positive relationship between kills and winning a volleyball game. Once again, Table 2 shows the 95% probability interval resides fully in positive values. The point-estimate coefficient and the overall interval have lower estimates than when analyzing the kill percentage in the previous model. This was anticipated as taking the differential lessens the average value and allows for negative values to exist in the underlying data. The Rhat for both variables is equal to 1, indicating convergence. Overall, seeing a fully positive interval is a good sign for the positive relationship on winning.

Once again, many different priors and multiple specifications of the model were attempted to validate the model. Multiple posterior predictive checks were run and added to this analysis to verify the model.

Figure 9: PPC comparing mean of generative data to underlying data

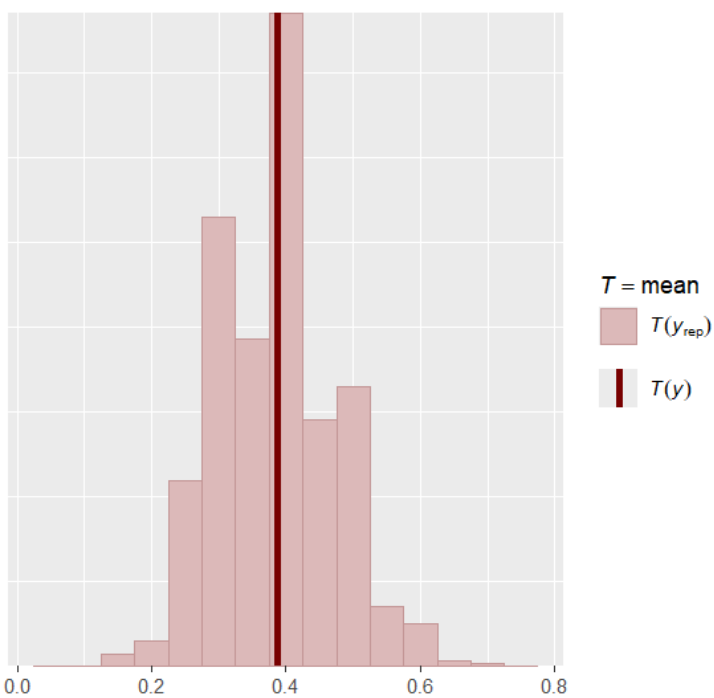
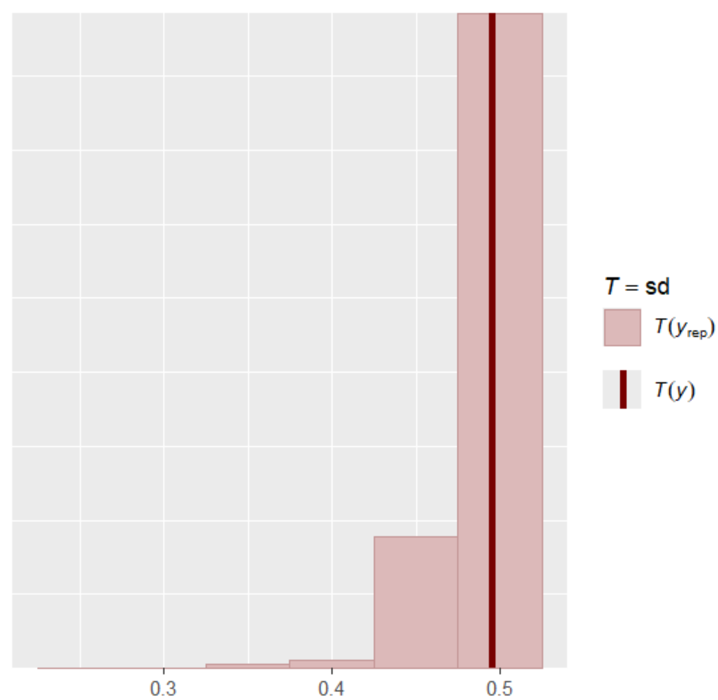


Figure 10: PPC comparing std. dev. of generative data to underlying data



Inspecting the mean and standard deviation plots, we can see that predictions of the specified model could recover both summary statistics easily. As shown in Figure 10, almost all the standard deviation generated draws fell within the same bin the data did. Figure 9 shows that similar results were achieved with the mean but with more spread around the data value. The generated data also recovered the minimum and maximum of 0 and 1, respectively (as that is the built-in bounds of a logit regression).

Figure 11: PPC showing the autocorrelation of MCMC samples

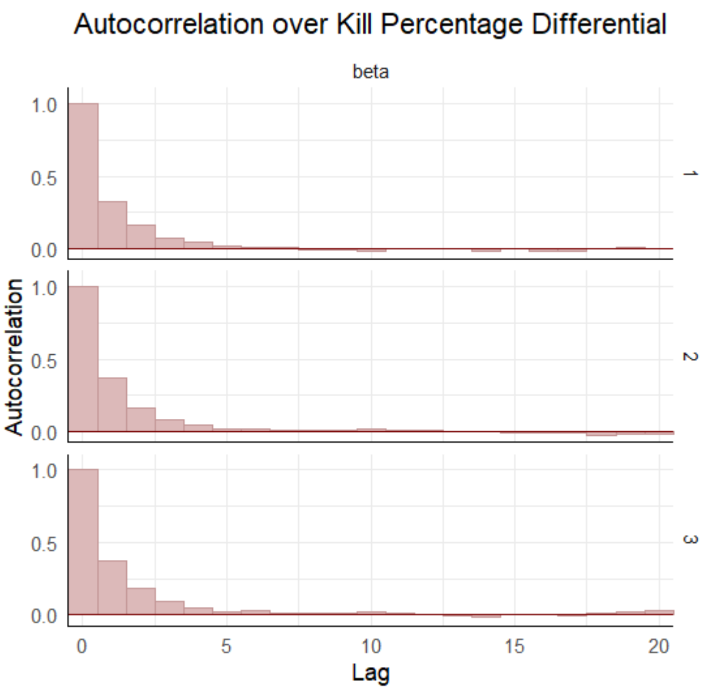


Figure 12: Trace plot of MCMC samples

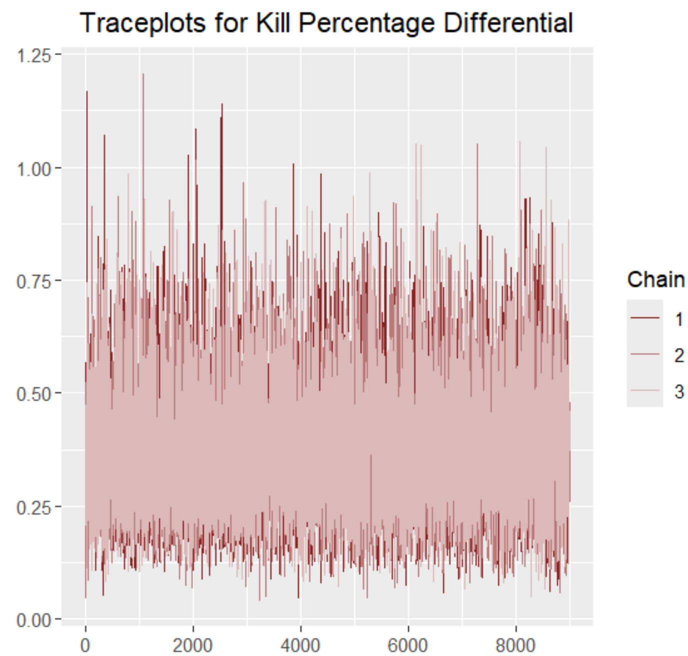


Figure 13: PPC showing density of coefficient on Kill Diff.

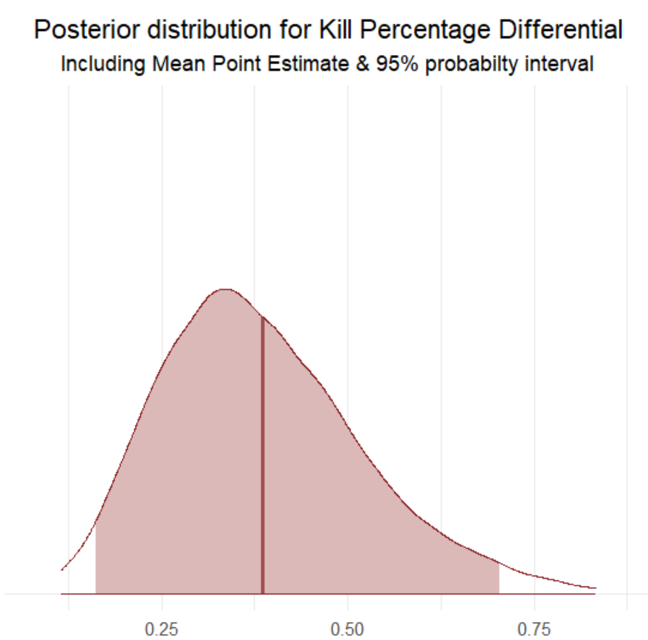
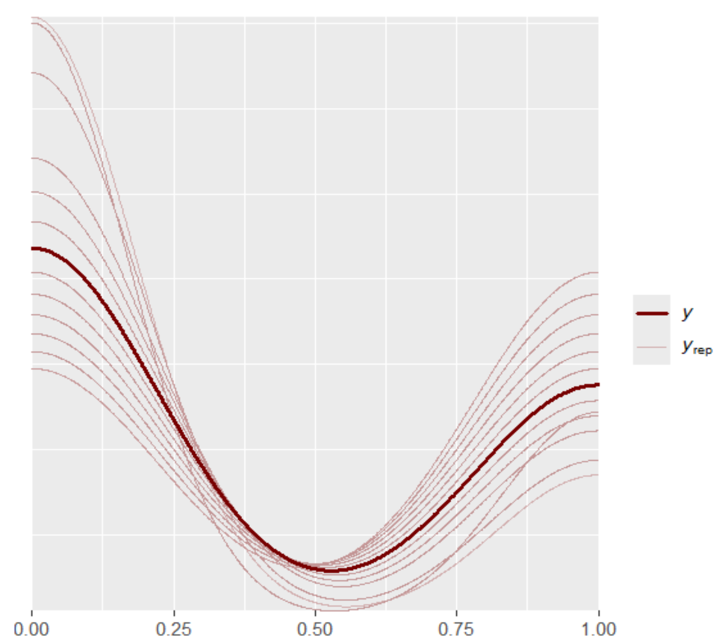


Figure 14: PPC comparing distribution of generative data to underlying data

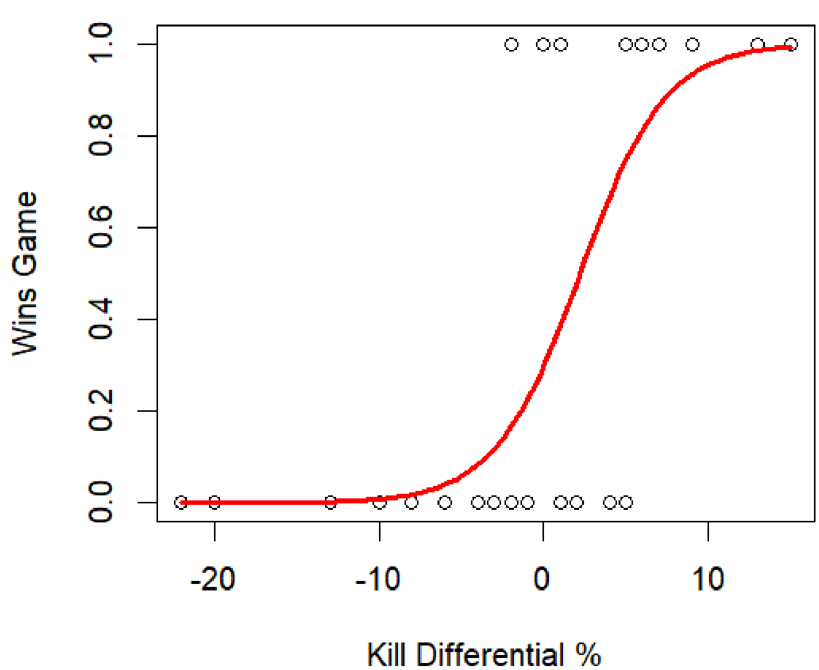


The charts above show the posterior predictive checks for the logistic model of kill percentage differential on wins. Figures 11 and 12 show the autocorrelation and trace plots, respectively. Both charts' results are extremely similar to the previous model. Figure 11 shows that autocorrelation dies out quickly; within 5 periods, it is all but non-existent. In Figure 12, the trace plots look to converge to an area near the point estimate highlighted in Table 2 above. An interesting conclusion that can be drawn from the trace plots is that, unlike the earlier model, it never sampled negative values. The initial model had just a few instances of sampling negative values, but this model does an even better job of avoiding the negative values. This reluctance to sample negative values strengthens the positive relationship between kills and winning.

Figure 14 describes how the generated quantities compare to the overall data structure. Once again, the generated data matches the distribution of the underlying data set. There is some variance around the data distribution, but it follows a similar overall path. The structure of the generated samples also follows the logit model specification of putting all weight on values of either 0 or 1, as expected.

The coefficient estimate distribution is shown in Figure 13, with a 99% interval around the mean plotted and the 95% interval highlighted. The spread of this distribution goes from approximately 0.1 to around 0.7. This is a smaller spread than the earlier model that accounted for other important volleyball statistics individually. The mean point estimate is shifted slightly to the right of the mode as more weight is on that side of the distribution, which pulls the mean point estimate in that direction. Overall, this distribution again supports the claim that kill percentage positively impacts winning.

Figure 15: Logistic Sigmoid Curve of Kill Diff. on Wins and Losses



The interpretation of a coefficient on a parameter in a logistic regression can be difficult to fully understand. The regression output is in log odds, which requires a separate calculation to see how a shift in the independent variable changes the percentage of success in the dichotomous variable. Fortunately, this log-odds output is especially useful for plotting logistic sigmoid curves. Figure 15 displays Utah's wins and losses plotted against the kill percentage differential. The points on the chart show the wins and losses for a game, with wins plotted as 1 and losses as 0.

The logistic sigmoid curve in Figure 15 shows how the probability of a win increases as the kill percentage differential increases. For some context, if the kill percentage differential for Utah is -20, they have an approximately 0% chance to win the game. Only 2 wins over the whole year happened when Utah had a negative kill differential (both appearing at -2%). The probability of winning shifts the most between a kill differential of -10% to 10%, which is also where most data points reside. With a differential of 0%, at the center of this spread, the Utes have a predicted probability of around 40% of winning this game. A 50/50 game happens near a kill differential of 3% or 4% in Utah's favor. This chart again validates the positive relationship between kill percentage and winning games. It helps convert the point estimates into a more easily interpretable format, which is especially useful for coaches and athletes to understand.

Robust Linear Model of Good Game Jumps on Kill % Differential:

With kill differential being validated as a variable essential to winning, switching the analysis to examine what impacts kill differential is essential in determining how to improve a team's success. Any casual viewer could identify jumping as one of the most important movements in a volleyball game. A significant relationship between these metrics could help determine how much a movement in a game impacts winning.

Utah volleyball athletes wear Catapult technologies, allowing data on movements and jumps to be collected and analyzed. Catapult categorizes jumps into three different groups: low, medium, or high jumps. High jumps lead to the most blocks and kills for the team. To not unnecessarily exclude relevant positions from this analysis, setters are also extremely important for creating kills, even though they do not rely on high jumps to play their role on the team. This is accounted for by using medium jumps as the important jump variable for setters. Liberos and defensive specialists were the last positions that have not been covered, and jumping is not extremely relevant for their role, so they have been excluded from this portion of the analysis. Two games did not have catapult data recorded, so the number of observations decreased from 31 to 29 in this model.

Table 3: Stan Robust Linear Regression Output of Jumps on Kill Diff.

Stan Output for Robust Linear Model
Kill Differential ~ student_t(nu, X * beta, sigma)
n = 29; nu ~ Gamma(2,.1); iter = 10,000; chains = 3

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

Table 3 reinforces the theory that recording a good jump in a game has a positive correlation with the kill percentage differential. This follows the logic of how kills are achieved within a game, with high jumps leading to spikes and blocks, and it is expected that these variables will be positively correlated. This relationship was modeled with a robust standard normal linear regression, which makes the results more interpretable than the logistic regression.

The good jumps variable is a percentage of total jumps classified as extremely impactful (high and medium jumps). The interpretation of the regression results suggests that for an increase of one percentage point in the good jumps variable, there's an improvement of 0.62 percentage points in the kill differential. For example, if the kill differential was at 1% and our good jump % was at 75%, increasing that to 76% would predict an increase of the kill differential up to 1.62%.

It is important to remember that this 0.62 coefficient associated with good jumps is just a point estimate and that the overall posterior prediction covers a larger area than just one point. The 95% probability interval crosses from -0.06 to 1.31, which has a large variability of values. This interval crosses over 0, which leaves the possibility of jumps having no impact possible, but this is a small probability in relation to the rest of the posterior.

Another parameter that was introduced within this robust standard normal model was nu. Instead of modeling with a normal distribution, the model was specified using a student-t t distribution to understand the robustness of standard errors within the model. Nu defines the heteroskedasticity of the residuals, and when nu gets sufficiently large,

Figure 16: PPC showing the autocorrelation of MCMC samples

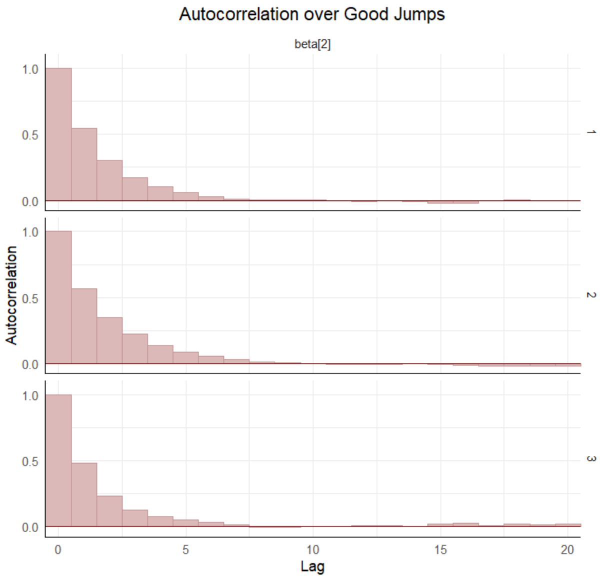


Figure 17: Trace plot of MCMC samples

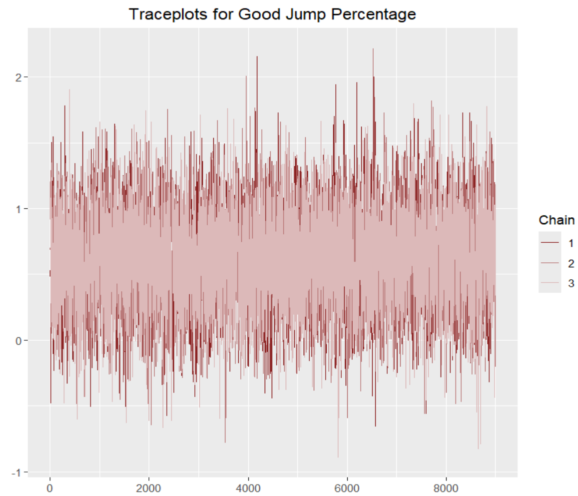


Figure 18: PPC showing the density distribution of Nu

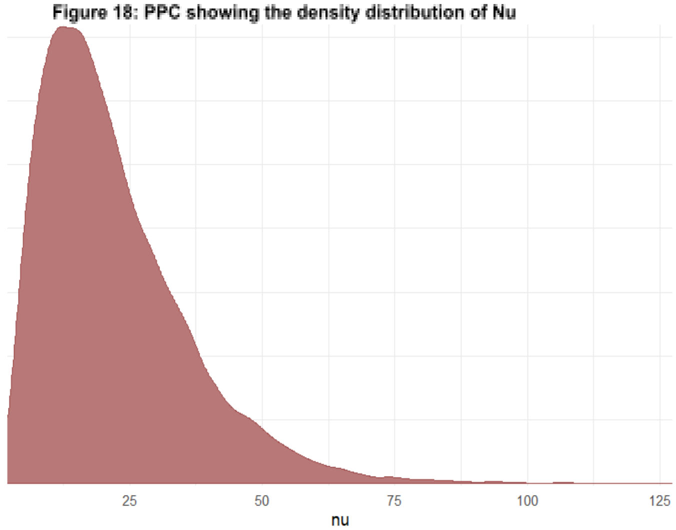


Figure 19: PPC comparing distribution of generative data to underlying data

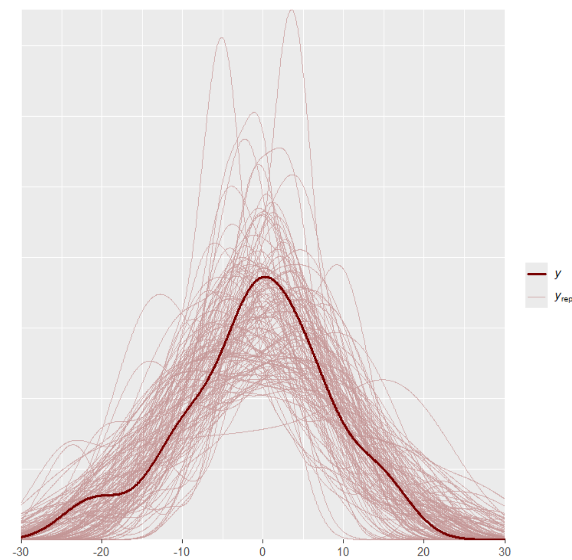


Figure 20: PPC comparing mean of generative data to underlying data

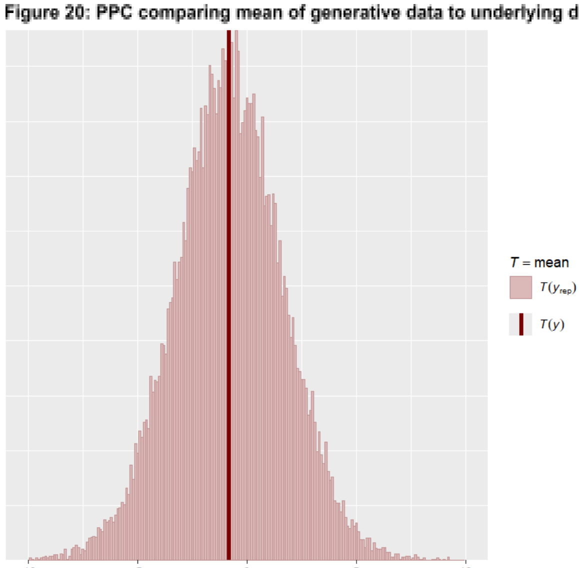
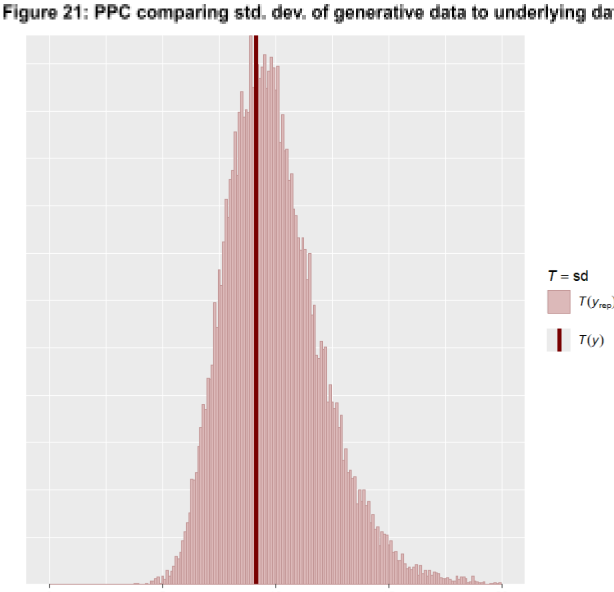


Figure 21: PPC comparing std. dev. of generative data to underlying data



the student-t distribution converges into a standard normal distribution. This model has an estimated nu that puts a lot of weight on higher values, indicating that the model was already robust, so it could have been modeled using a normal distribution without added errors. Modeling with a student-t distribution also widens the spread of the posterior samples in most instances. In this case, modeling with either a normal distribution or student-t distribution returned near equivalent results. Using a robust model validates that the results from the model are not skewed dramatically by biases.

An additional note is that no priors were used in this model other than for the nu parameter. Multiple different priors were attempted, but the most consistent results were achieved with ignorant priors.

The figures above are posterior predictive checks that check the model's validity. In Figures 20 and 21, the generated quantities are once again able to recover both the standard deviation and mean of the data distribution. There is a significant spread for both the mean and standard deviation in comparison to the earlier models. The generated data also recovered the minimum and maximum of the distribution, but those values were not extremely relevant to the overall analysis.

The autocorrelation and trace plots in Figures 16 and 17, respectively, indicate efficient sampling and convergence. Similar to the first two models, the autocorrelation dies out extremely quickly, with the 5-period mark again showing little correlation. The trace plot converges to an area near .5, which is near the point estimate highlighted in the stan regression output table above. Unlike the earlier models, this trace plot samples a lot of values from the negative ranges. This indicates that the positive relationship shown by the point estimate may not be as strong as it initially looks. This is also shown in the 95% probability interval, with the bottom bound being negative.

The final two figures show the distribution of the nu parameter and the distributions of all the generated data compared to the Utah dataset. The nu parameter in Figure 18 has a lot of weight put on higher values, which can be interpreted as the modeled student-t distribution converging to a normal distribution. This parameter provides a look into the robustness of the model, and when the model converges to a normal distribution, it can be considered robust. Figure 19 shows that the generated quantities follow a similar path as the Utah distribution, but there is a lot of variation. There are higher peaks as well as fatter tails in some areas. Overall, the shape is similar, but this large variation is reflected in the large spread of the probability intervals that are output from the regression.

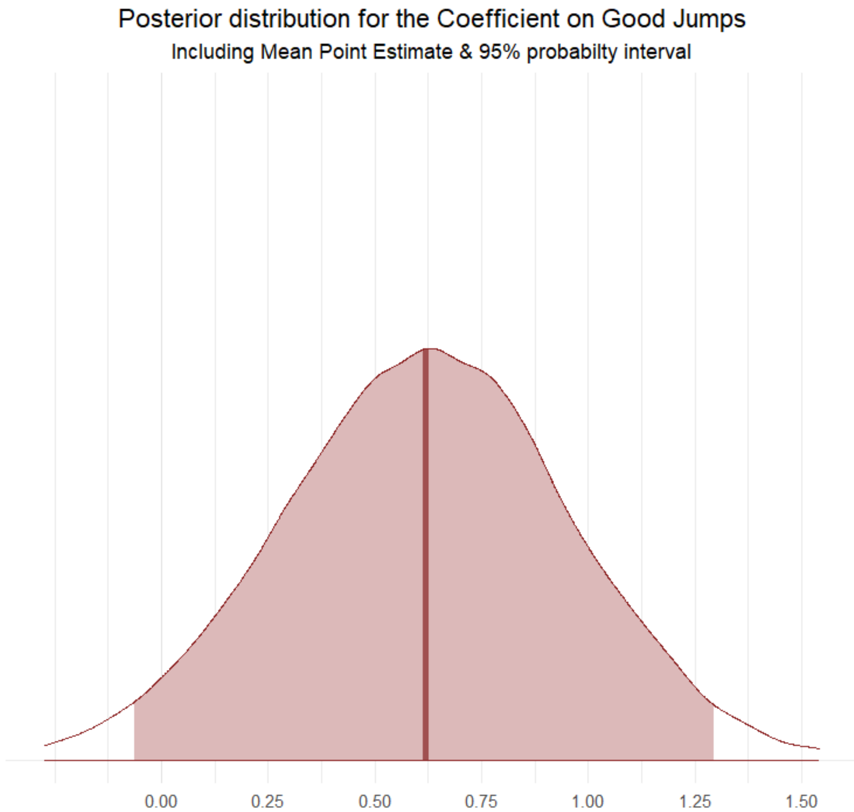


Figure 22: PPC showing the distribution of the coefficient on Good Jumps

The coefficient estimate distribution in Figure 22 again shows a 99% interval around the mean, with the 95% interval highlighted. The spread of this distribution goes from approximately -0.1 to around 1.25. This is a wide spread that crosses zero, which can be an indication of the existence of no relationship between kill percentage and high jumps. While the statistics say there is a small probability of no relationship (or even a negative relationship), it is important to interpret these results with statistical analysis and theory in mind. Jumping is critical to stop kills with blocks and achieve kills through a spike, the most common kill method. Knowing this, the relationship can still be cautiously interpreted as positive but acknowledged as being weaker than correlations that were modeled earlier.

Robust Linear Model of Practice Good Jumps & Player Load on Kill % Differential:

The final relationship analyzed is how effort in practice the day before a game impacted the following game. This association was modeled using a standard normal robust linear regression. The data analyzed in this section was also collected from Catapult technologies that the athletes wear in practice. Once again, there was no catapult data for two practices the day before a game, so the observation count is 29.

Good jumps are defined similarly as in the previous model, and player load is calculated per minute. Catapult defines player load as "a modified vector magnitude, expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the three vectors - X, Y, and Z axis - and divided by 100." Player load per minute helps quantify how much effort an athlete is exerting. An important thing to note when using player load per minute during practice is that there may be lots of downtime. This may make the per-minute specification appear smaller than the real effort that may be getting exerted. While it is not extremely relevant to this analysis, keeping the situational context in mind is important.

Table 4: Stan Robust Linear Regression Output of Jumps and Player Load on Kill Diff.

Stan Output for Robust Linear Model
Kill Differential ~ student_t(nu, X * beta, sigma)
n = 29; nu ~ Gamma(2,.1); iter = 10,000; chains = 3

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

Analyzing the stan output in Table 4, the effects of effort within practice on kill percentage in the game the next day are not easily discernable. The 95% probability intervals for both player load and good jumps cross into the negative values and have substantial weight in those regions. Theoretically, having an athlete put in a substantial amount of effort in practice the day before could lead to fatigue for the competition. It could also be argued that this effort must be properly prepared for the game. The theory and data indicate an indeterminate relationship between practice effort and game performance.

This model was run using a robust framework with a student-t distribution as the underlying distribution. This widens the spread of most posterior distributions in models. The nu parameter is sufficiently large enough to converge to a normal distribution, but when modeling using a non-robust framework with the normal distribution, the spread of the posterior distributions did not change.

Figure 23: PPC showing the autocorrelation of MCMC samples

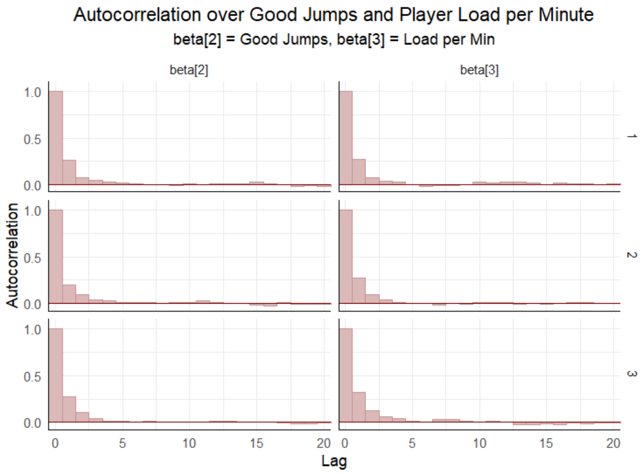


Figure 24: Trace plot of MCMC samples for both parameters

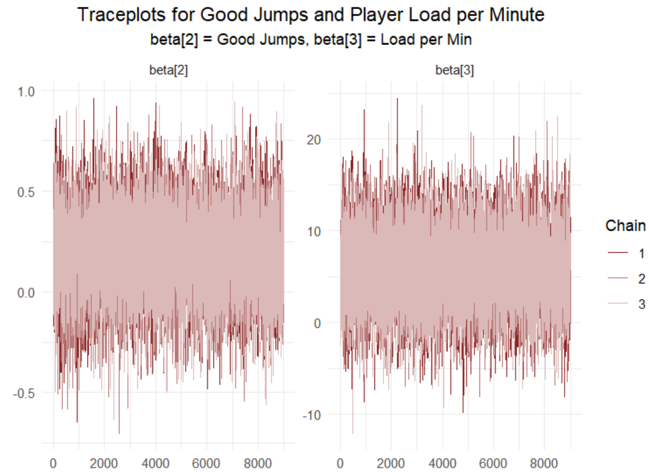


Figure 25: PPC comparing mean of generative data to underlying data

Figure 26: PPC comparing std. dev. of generative data to underlying data

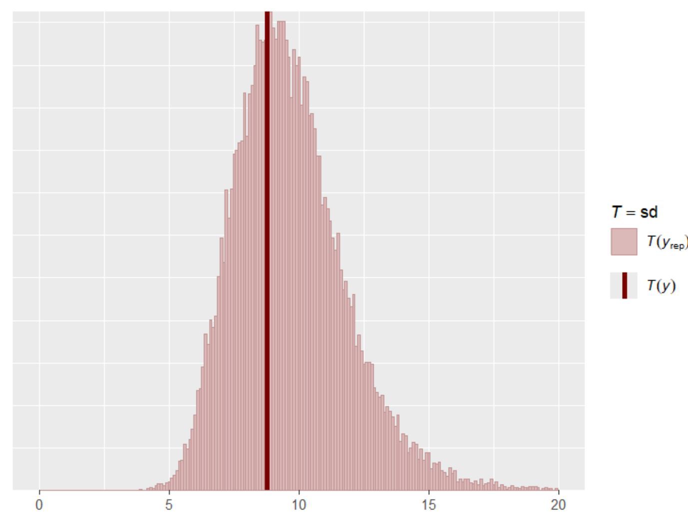


Figure 27: PPC comparing distribution of generative data to underlying data

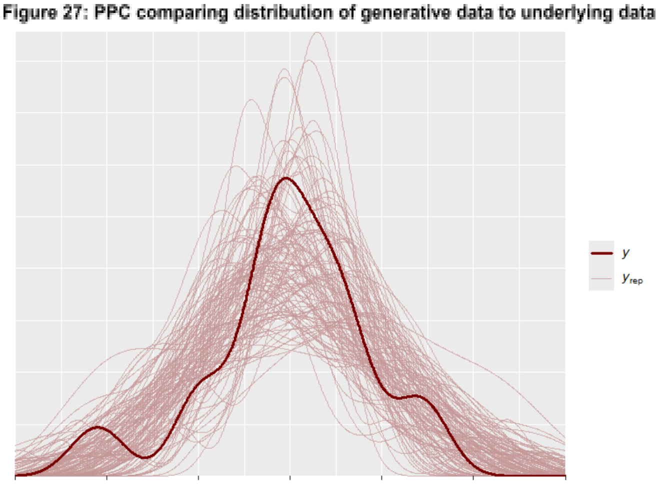
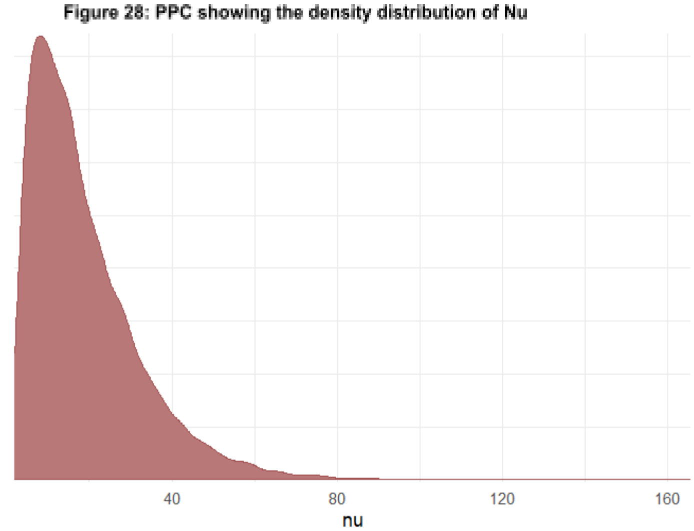


Figure 28: PPC showing the density distribution of Nu



Even with the results being inconclusive, the model must be correctly specified in order to fully validate this claim. Starting with the generated standard deviation and mean in Figures 25 and 26, respectively, they were distributed around the data-specific values, just like all earlier models. A spread still exists for the mean and standard deviation, but the spread is slightly smaller than in the earlier linear model.

The autocorrelation and trace plots above are charted for both the good jumps and player load parameters. As shown in Figure 23, autocorrelation dies out more quickly in this model for both parameters than in previous models. Both trace plots in Figure 24 show convergence in an area near the reported point estimates from the stan output. Each parameter heavily samples values from the negative ranges. This deeper look at the sampling shows the unpredictability of the relationship between practice effort and game performance.

Figure 28 shows the distribution of the parameter nu. Much like the previous model, nu has a lot of weight on higher values. We can again interpret the modeled student-t distribution as converging to a normal distribution and consider the model robust. The nu parameter does not have as wide of a distribution as previously, but it is still sufficiently over enough large values to converge.

In Figure 27, the density plots of the generated quantities follow a similar path as the data distribution, but there is high variation. When subsetting and plotting smaller intervals, the distributions all follow the same path, but the location and spread of the distributions are different. The added peaks and valleys in the underlying data can be explained by the differences in practice data compared to other types of data. Most practices have similar intensities, but a longer practice with more explanations by coaches and other downtimes can lead to distribution outliers. Overall, this difference in distribution explains the large variances in the model. However, the mean and standard deviation were still recovered, so the model can be trusted for this specific analysis.

Figure 29: PPC showing density of coefficient on Good Jumps

Posterior distribution for the Coefficient on Good Jumps

Including Mean Point Estimate & 95% probabilty interval

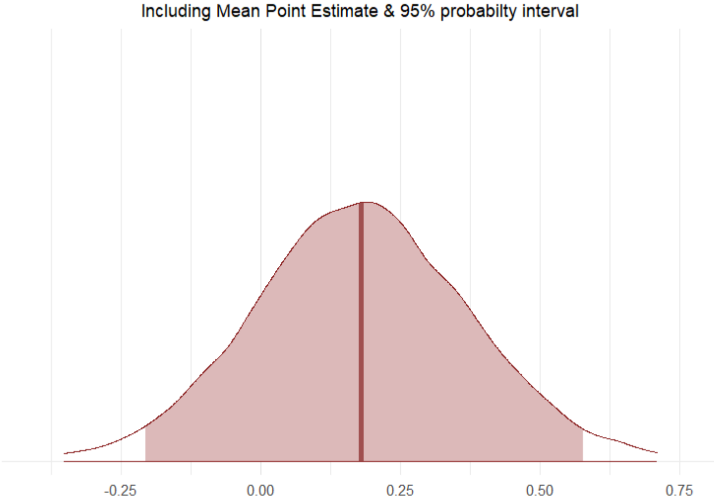
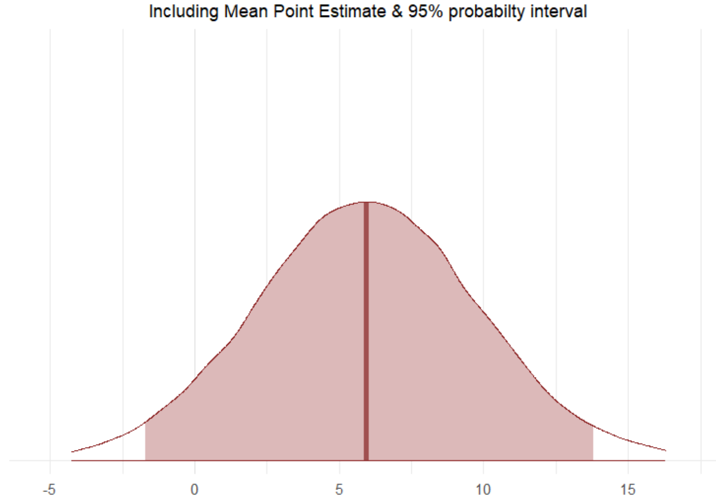


Figure 30: PPC showing density of coefficient on Player Load

Posterior distribution for the Coefficient on Player Load per Minute

Including Mean Point Estimate & 95% probabilty interval



The density plots in Figures 29 and 30 show a 99% interval around the mean, with the 95% interval highlighted for both good jumps and player load per minute. Both density curves 95% intervals cross into the negative values. The density plot over the coefficient for good jumps, shown in Figure 29, has a significant amount of likely negative values. This weight on negative values leads to an unsure interpretation of the impact of jumps in practice on kill percentage differential in the game the next day.

The density plot for player load per minute, shown in Figure 30, helps provide context for the relationship between practice effort and kill percentage. While negative values exist, much like good jumps in a game, they are a small percentage of the overall density plot. There is a much more likely scenario in which effort within practice leads to better kill differentials. It is important to remember that this scenario always has a ceiling. If players have worked so hard in practice the day before a game, they will be fatigued and perform worse. This acknowledgment doubles as an explanation for some of the negative values appearing.

Overall, the relationship between kill percentage differential and effort in practice the day before seems weakly positive but overall inconclusive. The data and statistics show that effort in practice on the day before practice is correlated with improvements in kill percentage contrary to what it may seem theoretically. This marks a pivotal point where players aim to optimize their game preparation while avoiding fatigue. Specifying the relationship in this way follows the theoretical knowledge of the scenario while still accounting for how the data is displayed.

Discussion & Conclusion:

Kill percentage was the only variable included in each of the four models throughout the analysis. It is crucial to understand the impact of kill percentage on the sport, as it is so vital in this analysis and within the world of volleyball. The first two models showed a positive relationship between winning volleyball games and increasing the team kill percentage and kill differential, respectively. The second two models were regressed with kill percentage differential as the dependent variable to see how certain movements within games and practices impact the most important statistic in volleyball.

Using kill percentage differential in analysis allowed for multiple facets of a volleyball game to be encompassed within one variable. This variable gives insight into the overall performance of Utah in the game, both offensively and defensively. A logistic regression shows that kill differential has a clear positive impact on winning a volleyball match. Plotting this relationship with a logistic sigmoid curve gave insight into the probability of winning based on any given kill differential in a game. This relationship can be useful in aiming for a benchmark to reach in a game to help increase the odds of winning.

Given the clear positive correlation between kill differential and winning, the logical next step in the analysis is understanding what impacts kill differential in practice and in games. A robust linear model that analyzed how good jumps impacted the kill differential resulted in a somewhat positive relationship. It could be reasonably inferred that elevating the proportion of jumps categorized as high or medium (based on position) would likely correlate with an increase in the kill differential. While the relationship between these two variables mostly followed this assumption, there is a statistical possibility that there is no relationship between these at all. The 95% probability interval calculated from the stan output contained negative values. This can be an indicator of an indeterminate relationship.

The limitations that exist within this analysis help explain the lack of a clear relationship. Observation counts for models were 30 on average. This is enough data to analyze and see relationships, but variation and outliers will weigh more heavily on the overall distribution. The environment in which the data exists also has an impact on the relationship. Within the realm of sports analytics, the occurrence of certain data can be extremely nuanced. For instance, a team may perform at a level whereby, regardless of the opponent's efforts or the percentage of good jumps they achieve, the overperforming team could secure victory or significantly boost their kill percentage. The alternative is true: a team could do everything right on the court and still underperform in metrics and wins. The data is also collected in an applied setting, which adds more confounding variables that may impact relationships within the data. This nature of sports data can explain much of the variation in the outputs from the regressions. While the possibility of no relationship between kill differential and good jumps in games cannot be entirely disregarded, adding context helps interpret the results.

Context is also relevant when inferring the results of the relationship between kill differential and effort in practice. The results of this regression were once again inconclusive, with substantial weight placed on the possibility of a negative relationship. Either side of this relationship could make sense: negative because effort in practice leads to fatigue, or positive because effort in practice gets athletes prepared for the game. Even concerning the nature of sports statistics, the analysis can still be acknowledged as undetermined. With more data or a different approach, more conclusive answers may lie within this data. However, with the model specified now,

effort in practice does not have a clear-cut relationship with kill differential in the next game.
Given the well-established correlation between kill percentage and winning, the lack of clarity on the relationship between movements and kills is intriguing. With this analysis being conducted outside of a research setting, as well as the overarching Bayesian statistical framework, a 95% probability interval is not binding. Relaxing this to a 90% interval for confirming relationships, good jumps within games have an entirely positive relationship on kill differential. In this instance, giving more flexibility to the analysis results in more concrete correlations.

Unfortunately, a similar analysis for practice effort did not provide added insight. The 90% probability interval for player load per minute was fully positive, but good jumps in practice still had lots of weight on negative values. This indeterminate relationship still exists even when relaxing the bounds. Once again, practice effort can have both a positive and a negative impact heading into a game. A certain sweet spot may exist that gets athletes the most prepared while still leaving them with energy for a full game.

Resources and 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.

"Catapult Metric Descriptions." PlayerTekPlus, Catapult Sports, https://playertekplus.catapultsports.com/.

"OpenAI Chat." OpenAI, OpenAI, https://chat.openai.com/?model=text-davinci-002-render-sha.

PubMed Central, National Center for Biotechnology Information, U.S. National Library of Medicine, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7052708/#:~:text=Catapult%20Sports%20proposed%20that%20PL,et%20al.%2C%202011.

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/.