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Skill Importance in Women's Volleyball

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Abstract

The purpose of this paper is to demonstrate two methods to quantify skill importance for teams in general, and women's volleyball in particular. A division I women's volleyball team rated each skill (serve, pass, set, etc.) and recorded rally outcomes during all home games in a competitive season. The skills were only rated when the ball was on the home team's side of the net. Events followed one of these three patterns: serve-outcome, pass-set-attack outcome, or block-dig-set-attack-outcome. These sequences of events were assumed to be first-order Markov chains, meaning the quality of the performance of the current skill only depended on the quality of the performance of the previous skill. We analyze the volleyball data using two different techniques: one uses a Markovian transition matrix, while the other is an implementation of logistic regression. To estimate the Markovian transition matrix, we assumed a multinomial likelihood with a Dirichlet prior on the transition probabilities. The logistic regression model also uses a Bayesian approach. The posterior distributions of parameters associated with skill performance are used to calculate importance scores. Importance scores produced by the two methods are reasonably consistent across skills. The importance scores indicate, among other things, that the team would have been well rewarded by improving transition offense. Importance scores can be used to assist coaches in allocating practice time, developing new strategies, and optimizing team performance relative to player selection.

1 Introduction

A sports team's success is determined by the number of contests won during a season. Winning a contest generally means scoring more points than the opponent. The number of points that a team scores during a game is primarily based on how well the team performs key skills. Understanding how the performance of skills relates to the scoring of points is useful for athletes and coaches in all sports. If a coach can quantitatively understand how the performance of various skills relates to the number of points scored, the coach can then adjust the team's practice schedule to focus on improving the performance of key skills that are more closely tied to point scoring.

To determine the impact of each skill in scoring a point, Fellingham and Reese (2004) suggest the use of importance scores. An importance score would be a measure that could account for both the impact and the amount of uncertainty associated with the performance of a skill relative to the probability of scoring a point. Importance scores would be useful to coaches since they indicate how the impact of a particular skill relates to the probability of a successful outcome. Importance scores would also allow coaches to compare skill performance across teams.

A division I women's volleyball team used a notational analysis system to evaluate their skill performance during the 2006 competitive season. Each serve, pass, attack, and dig was evaluated and recorded as the skill was performed. Sets were evaluated after viewing the game film. Each skill was evaluated using a grading rubric in order to quantify how well the skill was performed.

We explore two different methods of measuring skill importance using this data from women's volleyball. One method uses a Markov chain transition matrix to arrive at posterior distributions for parameters associated with skill performance. The second method uses Bayesian logistic regression to compute the posterior distributions. These posterior distributions are then used to compute importance scores. The two methods of computing importance scores are then compared relative to the importance associated with various skills.

Section 2 examines previous research in skill importance and volleyball. Section 3 discusses the data. Section 4 explains the methodology used to calculate posterior distributions using logistic regression and Markov chains. Section 5 presents the importance scores. Lastly, section 6 compares the results from the two methods.

2 Literature Review

2.1 Measuring Skill Importance

In order to measure skill importance, we use the importance score, a metric suggested by Fellingham and Reese (2004). For a specific team, they define the coefficient of skill importance as the ratio

$$I_i = \frac{E(\beta_i|Y)}{\sqrt{V(\beta_i|Y)}},$$

where i corresponds to the skill and β_i indicates the posterior distribution associated with skill i given the data, Y. This ratio provides the ability to obtain an importance score for each skill. The importance score incorporates not only the impact of a specific skill (E($\beta_i|Y$)), but also the uncertainty associated with the performance ($V(\beta_i|Y)$). Thus, a skill whose association with scoring a point is less certain will be penalized when using this metric when compared to a skill where performance at a given level is more closely associated with a positive outcome.

2.2 Previous Research

Considerable research has been done on developing notational analysis in volleyball (Zetou et al. 2007). The notational analysis that is most commonly used was developed by Coleman (1975). Florence et al. (2008) use a notational system to evaluate skills in women's volleyball.

Hughes and Daniel (2003) focus on understanding the playing patterns of elite and nonelite volleyball teams. Their analysis shows that elite teams were significantly better at serving and receiving than nonelite teams. The study also shows that the quality of the attack was dependent on the quality of the set, and that the quality of the set was dependent on the quality of the defense or the reception of the serve.

Yiannis and Panagiotis (2005) compare the effectiveness of five key skills in 10 men's volleyball matches that occurred between the Sydney 2000 and the Athens 2004 Olympic Games. They show that from the 2000 to 2004 Olympic Games there was a general trend of decreasing the proportion of mistakes performed on all the skills. In particular, the study shows that during the 2004 Olympic Games, Brazil, the gold medalist, performed their reception and attack skills far better than the teams they competed against.

Zetou et al. (2007) explain how the statistical evaluation of a team's skill performance helped considerably with the development of the game of volley-

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ball. Their study shows that for a serve-reception skill, the best predictor of a win was the receiver's ability to make the best reception possible, so the setter could set for a first tempo attack or set a high set to the outside hitter in zone four or two. For the attack from reception skill, the analysis showed that an "ace-point" is the most significant predictor in determining a winning team.

3 The Data

The data were collected during the 2006 competitive season of a women's Division I volleyball team. During each home game, the game was recorded, and the skills were analyzed when the ball was on the home team's side of the net. Thus, the data come from a single team. Using the performance scoring system developed by Coleman (1975) as a guide and consulting the expertise of volleyball coaches and researchers, each technique was rated. The women's volleyball data were recorded into a system called Data Volley (Data Project, Salerno, Italy, release 2.1.9). The grading system of the skills was created based on the number of codes Data Volley could handle.

Serves were rated on a five-point (0–4) scale, passes on a six-point (0–5) scale, and digs on a six-point (0–5) scale. Attacks were noted by position on the court (back row, left side, right side, middle, etc.). Sets were rated according to distance from the net (0–3 feet, 3–5 feet, etc.). A detailed breakdown of all the skill ratings are shown in Table 1. There were three possible outcomes: (1) point for the home team, (2) rally continuation, or (3) point for the visiting team.

During a game, a trained member of the volleyball team's coaching staff rated and recorded every serve, pass, dig, and attack performed by the team during the 13 home games in the 2006 season. When a set occurred, a default code was inserted into the system so that the set could be rated later while looking at the game film. Only serves and attacks for the opposing team were recorded. This was done to determine when the ball crossed the net. The score of the game was determined at the end of the rally by noting which team was the next to serve. Since the data set consisted only of touches on the primary team's side of the net, a continuation of a rally was determined by seeing if the ball came back to the primary team's side during a rally.

4 Methods for the Volleyball Analyses

Since importance scores were defined in terms of Bayesian techniques, Bayesian methods were used for the analyses. The framework presented by Lindley

Table 1: Performance ratings for all the skills.

Skill	Performance Rating
Serves	
Ace Serve	4
3-point Serve	3
2-point Serve	2
1-point Serve	1
Service error	0
Passes	
4-point Pass	5
3-point Pass	4
2-point Pass	3
1-point Pass	2
Overpass	1
Passing error	0
Digs	
5-point Dig	5
4-point Dig	4
3-point Dig	3
2-point Dig	2
1-point Dig	1
Digging error	0
Set Distances	
3–5 feet	3
0–3 feet	2
5–8 feet	1
8–10 feet	0

(1964) and Leonard (1972) were used to construct the Bayesian logistic regression models. The work of Lee et al. (1968) and Assoudou and Essebbar (2003) was used as a guide to construct the first-order Markov chain model.

4.1 Markov Chain Approach

Whenever the ball was on the primary team's side of the net, one of the following sequences of events occurred: serve-outcome, pass-set-attack-outcome, or dig-set-attack-outcome. There were three possible outcomes: a point for the primary team, a point for the opponent, or a continuation of the rally.

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We assumed that these sequences of events (serve-outcome, pass-set-attack-outcome, and dig-set-attack-outcome) were first-order Markov chains. We represented these sequences in a transition matrix where the elements of the matrix comprise the probability of moving from one state to another state (e.g., a four-point pass to a set 3–5 feet off the net).

The 36×36 transition matrix contained the transitions for float serves, jump serves, passes, set distances off the net, attacks, digs, and possible outcomes. There were five different ratings for both float and jump serves, six ratings for passes, four ratings for sets, seven places for attacks (left, right, middle, back row, set dump, out of system, and over pass attack), six ratings for digs, and three outcomes of a rally (continuation, point for home team, point for visiting team). Thus, the transition matrix had $5+5+6+4+7+6+3=36$ rows and columns.

Sequences that were impossible (e.g., a four-point pass to an ace serve) were constrained to have zero probability. Sequences that always occurred (e.g., an ace serve to a point) were constrained to have a probability of one. Data were organized in a count matrix. Thus, y_{ij} is the $(i,\, j)^{th}$ element of the count matrix and is the number of times play moved from state i to state j during the season.

We used Bayesian methods to estimate the transition probabilities. We assumed a multinomial likelihood

$$f(y_{i1},\ldots,y_{ik}|\pi_{i1},\ldots,\pi_{ik}) \propto \pi_{i1}^{y_{i1}}\pi_{i2}^{y_{i2}}\ldots\pi_{ik}^{y_{ik}}, \tag{1}$$

for each row, $i=1,\ldots,m$, of the count matrix, where k is the number of possible states that could occur in the next sequence of touches and m is the number of states. π_{ij} represents the probability of moving from state i to state j in the transition probability matrix, and $\sum_{j=1}^{k}\pi_{ij}=1$, for each i.

We assumed the prior probability densities of each row were distributed as Dirichlet random variables

$$f(\pi_{i1},\ldots,\pi_{ik}|\alpha_{i1},\ldots,\alpha_{ik}) \propto \pi_{i1}^{\alpha_{i1}-1}\pi_{i2}^{\alpha_{i2}-1}\ldots\pi_{ik}^{\alpha_{ik}-1}, \tag{2}$$

where α_{ij} represents the expectation of how often we think the women's team moves from state i to state j relative to moving to a different state in the transition probability matrix. Since we are interested in what the data indicate about the association between the different states, we assumed weak prior information. Thus, the prior counts, α_{ij}, were all assumed to be equal to one (except those that were constrained to be zero).

Because of the conjugacy that exists between the multinomial distribution and the Dirichlet prior, Gibbs sampling can be used to produce draws from the posterior distribution

$$f(\pi_{i1},\ldots,\pi_{ik}|y_{i1},\ldots,y_{ik},\alpha_{i1},\ldots,\alpha_{ik}) \propto \pi_{i1}^{y_{i1}+\alpha_{i1}-1}\pi_{i2}^{y_{i2}+\alpha_{i2}-1}\ldots\pi_{ik}^{y_{ik}+\alpha_{ik}-1}, \quad (3)$$

for each row of the transition probability matrix. To make draws from the posterior distribution slightly more efficient, we drew $x_1,\ldots,x_k$ from independent gamma distributions with a shape parameter of $y_{i1}+\alpha_{i1},\ldots,y_{ik}+\alpha_{ik}$ and a common scale parameter of one. We used the independent draws from the gamma distributions to calculate a $\pi_{ij} = x_j/\sum_{j=1}^{k} x_j$ (Gelman et al. 2004). The posterior distributions of each π_{ij} were based on 100,000 draws.

In order to compute importance scores in this setting, we also calculated the unconditional probabilities of moving from one state (e.g., a four-point pass) to an outcome (e.g., a point for the primary team) and called this β. In order to obtain an estimate for the unconditional probability for every skill rating (i.e., β_i, $i = 1,\ldots,25$), we used all possible sequences of touches that could occur between the state and the outcome in the transition probability matrix. For each sequence, we used the associated probabilities in the transition probability matrix. To obtain the overall unconditional probability, we summed the probabilities associated with each sequence.

Thus, at each step, we computed a draw of the unconditional probability using the current state of the transition probability matrix. Therefore, posterior distributions of the β_i are also based on 100,000 draws. Using the 100,000 draws associated with the posterior distribution for each β_i, the mean of the draws was used as an estimate of $E(\beta_i|Y)$ and the standard deviation of the draws was used as an estimate of $\sqrt{V(\beta_i|Y)}$. $E(\beta_i|Y)$ and $\sqrt{V(\beta_i|Y)}$ were used to calculate the importance score for the associated skill.

The appropriateness of the model was determined by constructing a Bayesian χ^2 goodness-of-fit test (Johnson (2004)). The Bayesian χ^2 test was computed for each row and column combination of the transition matrix. To summarize all the Bayesian χ^2 tests, we calculated the average number of times the Bayesian χ^2 test resulted in a significant p-value. The Bayesian χ^2 test resulted in a significant p-value only 5.2% of the time. Thus, the first-order Markov chain does a reasonable job of modeling the association between the skill-rating combinations and a point for the primary team.

4.2 Bayesian Logistic Regression Approach

A Bayesian logistic regression model was also implemented to determine how the performance of individual skills affects the probability of scoring a point. The following skills were analyzed in this setting: jump serve, float serve, pass, dig, and set. Implementation of this model required that skills be scored in some fashion. Attacks were not analyzed this way because the grading of the attack was dependent on the outcome of the attack. Thus, the data set does not have an independent mechanism to grade the performance of the attack. Since sets were only noted in the data by distance off the net, the scoring of sets was determined by one of the investigators, a former volleyball coach. The ratings used for sets are shown in Table 2.

Table 2: Performance ratings for set distance off the net.

Set Distance	Performance Rating
3–5 feet	3
0–3 feet	2
5–8 feet	1
8–10 feet	0

We modeled the response variable as a Bernoulli random variable. The response was given a zero if a point was not scored (opponent score or rally continued) and a one if a point was scored. Four separate models were constructed, one for each of the four skills. For each skill, we constructed a logistic regression model, where the log odds ratio was defined as

$$\log\left(\frac{Pr[Y_{ik}=1|\text{skill}=i]}{Pr[Y_{ik}=0|\text{skill}=i]}\right) = \beta_{0i} + \beta_{1i}\mathrm{R}_{ik}, \tag{4}$$

where i is associated with a specific skill, $k = 1, \ldots, n_i$ corresponds to the number of times skill i is performed, β_{0i} is the primary team's overall ability at skill i, β_{1i} is the rate of change of the outcome relative to the performance grade of the i^{th} skill, and R_{ik} is the rating associated with the k^{th} time the i^{th} skill is performed. Thus, $Y_{ik} \sim Bernoulli\left(\frac{exp(\beta_{0i}+\beta_{1i}\mathrm{R}_{ik})}{1+exp(\beta_{0i}+\beta_{1i}\mathrm{R}_{ik})}\right)$. The logistic regression model assumed that each skill was linearly related to the outcome. A priori, we believed this assumption to be reasonable because we believed a skill performed with a higher rating would imply a higher probability of scoring a point.

The following prior distribution was chosen for the β_{0i} and β_{1i} parameters:

$$f(\beta_{ji}|m_{ji}, s_{ji}^2) \sim Normal(m_{ji}, s_{ji}^2), j = 0, 1.$$

The normal distribution was chosen because we expected the effect of a skill on the probability of scoring a point could be either positive or negative.

Similar to the Markov chain model, weak prior information was assumed. We let each $m_{ji} = 0$ and each $s_{ji}^2 = 1000$.

The resulting posterior distributions for the β_{ji} are not available in closed form. Thus, the Metropolis-Hastings algorithm was used to obtain draws from the posterior distributions. Mixing plots were used to ensure that sampling occurred from all parts of the distribution. Posterior distributions were estimated with 100,000 draws after a burn-in period of 500. Using the 100,000 draws associated with each skill, the mean of the draws for β_{1i} was used as an estimate for $E(\beta_{1i}|Y)$ and the standard deviation of the draws for β_{1i} was used as an estimate for $\sqrt{V(\beta_{1i}|Y)}$. $E(\beta_{1i}|Y)$ and $\sqrt{V(\beta_{1i}|Y)}$ were used to calculate the importance score for the associated skill.

To determine the appropriateness of each model, a Bayesian χ^2 goodness-of-fit test was calculated for each of the four models (Johnson (2004)). For each model, to summarize all the Bayesian χ^2 tests, we calculated the average number of times the Bayesian χ^2 test resulted in a significant p-value. The Bayesian χ^2 test resulted in a significant p-value only 5.2% of the time. For serves, the Bayesian χ^2 goodness-of-fit test resulted in a significant p-value only 1.6% of the time. For passing, the Bayesian χ^2 goodness-of-fit test resulted in a significant p-value only 2.4% of the time. For setting, the Bayesian χ^2 goodness-of-fit test resulted in a significant p-value only 4.6% of the time. For digging, the Bayesian χ^2 goodness-of-fit test resulted in a significant p-value only 2.0% of the time. These goodness-of-fit tests indicate that the proposed Bayesian logistic regression model does a reasonably good job modeling the probability of scoring a point.

5 Results

We developed the importance scores using two different methods. Thus, the importance scores themselves are not comparable across models; however, the relative rankings are comparable. Table 3 shows the importance scores using the Markov chain model. The importance scores for the logistic regression model are shown in Table 4.

6 Discussion

First, we need to again emphasize that it is possible for skills to have higher expected outcomes, but lower importance scores, if the variance associated with the parameter estimate is high. For example, a four-point pass has a

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Table 3: Importance scores for the volleyball Markov chain analysis.

Skill	$E(\beta\|Y)$	$V(\beta\|Y)$	Importance Score
3 point Pass	0.50551	0.00017	38.32173
Set 3–5 feet off the net	0.51304	0.00018	37.88245
4 point Pass	0.51001	0.00020	36.51091
2 point Pass	0.48935	0.00019	35.78412
4 point Dig	0.43787	0.00016	34.67090
Set 5–8 feet off the net	0.49893	0.00025	31.60894
5 point Dig	0.50061	0.00025	31.58385
Left Attack	0.49665	0.00033	27.46854
Set 0–3 feet off the net	0.50669	0.00044	24.27541
Middle Attack	0.53806	0.00070	20.30614
Right Attack	0.55130	0.00101	17.35607
Set 8–10 feet off the net	0.42340	0.00066	16.50323
1 point Pass	0.36451	0.00054	15.67747
Overpass Attack	0.65062	0.00270	12.52568
3 point Float Serve	0.26774	0.00054	11.56483
3 point Jump Serve	0.18633	0.00040	9.35556
Back Attack	0.38659	0.00197	8.71921
2 point Dig	0.38268	0.00211	8.33366
Set Dump Attack	0.54814	0.00776	6.22122
3 point Dig	0.48367	0.00665	5.93223
2 point Float Serve	0.24707	0.00216	5.31146
1 point Float Serve	0.21983	0.00188	5.07389
2 point Jump Serve	0.16202	0.00122	4.64685
1 point Jump Serve	0.16242	0.00168	3.96645
Out of System Attack	0.26291	0.00974	2.66430

Table 4: Importance scores for the volleyball logistic regression analysis.

Skill	$E(\beta\|Y)$	$V(\beta\|Y)$	Importance Score
Pass	0.51946	0.00375	8.48683
Float Serve	0.81906	0.00992	8.22162
Jump Serve	0.74160	0.00949	7.61225
Set Distance	0.33156	0.00271	6.36639
Digs	0.51379	0.00951	5.26835

higher probability of leading to a point than a three-point pass, but with a higher variance, the importance score is lower (Table 3). This is also true of left attack relative to both middle and right attack for this team. Left attack has a lower expected outcome, but a much higher importance score, because it occurs more often than either a middle or right attack for this team. Nonetheless, the data would lead us to encourage the team to try to set to the middle and right sides more often.

The results seem, in general, to be fairly consistent across methods. It is important to remember, however, that the methodolgies lead to different interpretations. Using the Markov chain analysis, each skill-rating combination has an importance score attached. Using the logisitic regression analysis, the importance score is for the entire skill and is related to the slope of the line being used to compute the importance score. Thus, serving importance is higher in the logistic regression analysis than it generally seems to be in the Markov chain analysis. Since a four-point serve is an ace, it cannot be included in the Markov analysis as the rating is exactly the same as the outcome. However, the four-point serve can be included in the logistic analysis, and this raises the importance score for serving. This points to the necessity of an appropriate rating system if importance scores are going to be compared across skills.

The small change in importance for two-, three-, and four-point passes was a surprise. This clearly indicates a need to change the passing rating system, at least for the team being considered. Using an average passing score to rate passers would clearly be a mistake, since a passer with a two point average that had equal numbers of four-point and zero-point passes would be far worse on the court than a passer that only produced two-point passes. This also shows that the penalty for a pass well off the net is clearly not as severe as the penalty for a pass too close to the net.

Outcomes for sets 3–5 feet off the net are better than for those closer to the net. The desire of hitters to hit the ball straight down can lead to negative outcomes when the block can cut off so much of the court. Back row sets are also less efficient. The inability of women to hit as hard as men limits the effectiveness of the back row attack.

For this team, float serves are more important than jump serves using both methods. Float serves have better expected outcomes for all ratings and higher importance despite occuring less often. Since the score attached to a serve is associated with the resulting pass, the higher importance of float serves at each level would lead one to believe that the effect may not be from the serve itself. This data would lead one to conjecture that, at least for the team being rated, defense following a float serve is better than defense following a jump serve.

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That is, if the rating is consistent, the difference must be in better blocking following a float serve. For this team at least, more hustle to blocking positions following a serve would seem to be in order.

It is interesting that digging tends to mirror passing but at a lower importance level. This would indicate that it is more difficult to convert after a dig than after a pass. This outcome seems reasonable when one considers that after a pass, the offense is set up, while after a dig, the offense is usually scrambling to set up a play.

When this approach was used on data from the men's national team, serving and attacking were the most important skills (Fellingham and Reese 2004). Setting was not measured in that data set, while digging had virtually no importance. The results from this Division I women's team indicates that passing, setting, and digging all have relatively high importance. We believe this is a fundamental difference in the men's and women's games. The men hit the ball harder, meaning that rallies terminate sooner, and serving and attacking have greater importance. In the women's game, rallies are longer, so digging is much more important.

Based on these analyses, we would give the following recommendations to this team.

1. Keep sets and passes away from the net.

2. Force the attack to the middle and right side if at all possible.

3. Devote a considerable proportion of practice time to transition offense.

4. Get to blocking positions more quickly following a serve.

We have shown two different methodologies to develop skill importance scores. These importance scores can be used by coaches to change team tactics, change skill performance goals, and focus practice time to increase the probability of scoring points.

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