Vaulting into Victory: Optimizing for US Gymnastics Medal Count at the Paris 2024 Olympics

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Introduction

Background

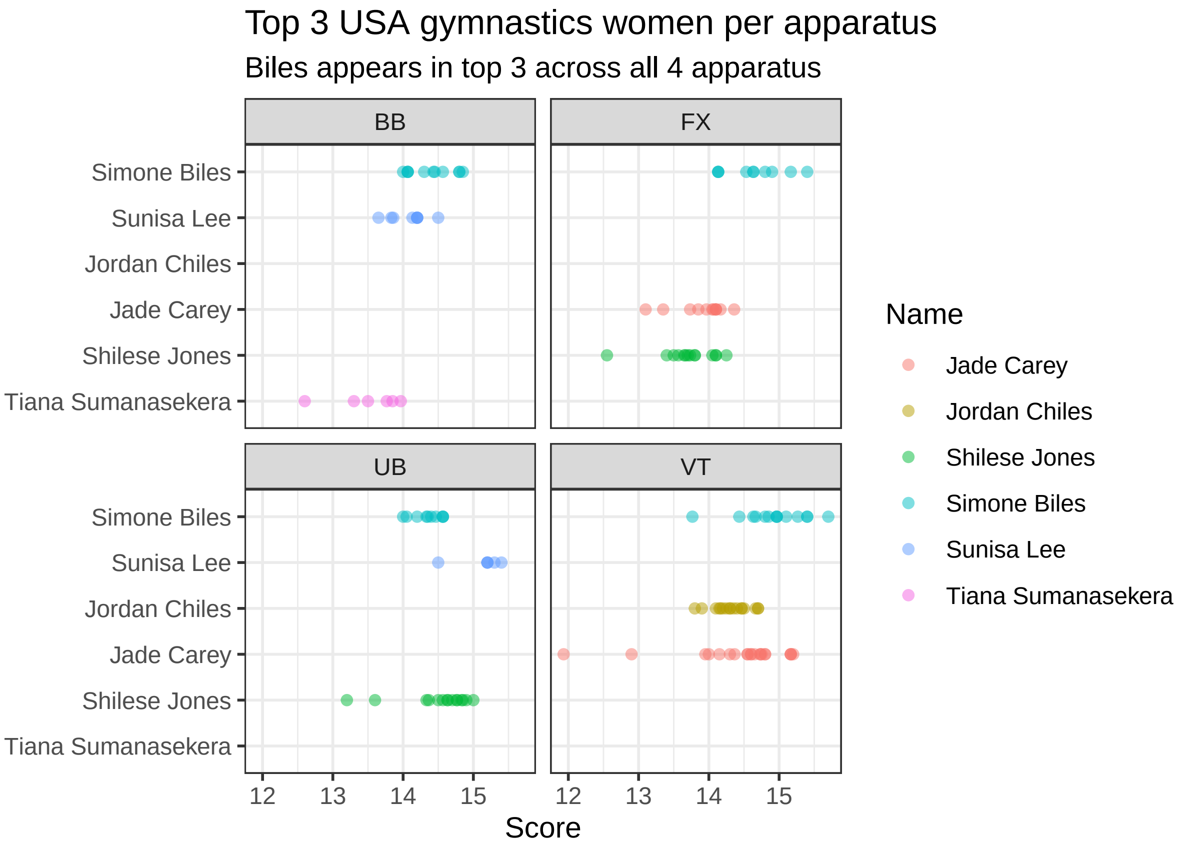
The Olympics brings about a sense of national pride seldom felt by athletes and viewers alike. The sheer amount of viewers adds to the pressure of an event like this for national athletic committees. In every Olympic games since 2008, over 3 billion people tuned in worldwide, far surpassing the 115 million viewers that tuned into the Super Bowl. Americans, in particular, are fascinated by artistic gymnastics with the highest percentage of those who watch the Olympics claiming to be interested in the event (Tracy, 2021). It follows that success in this sport has long been a source of international recognition for the United States. The breathtaking performances displayed by American gymnasts have not only brought numerous Olympic medals home, but also served as inspiration for generations of aspiring athletes. Simone Biles, Gabby Douglas, and Nastia Liukin are all household names due to their success in Olympic gymnastics. As we approach the next Olympic Games in Paris 2024, it is vital that team USA finds success in artistic gymnastics. In the era of data-driven decision-making, the role of predictive analytics in sports has gained unprecedented significance and the need for innovation and precision in athlete selection has never been more crucial. Our goal is to use data analytics to help build a tool to predict the best five-member lineups for both the USA Men's and Women's artistic gymnastics teams, optimizing for total medal count.

First, understanding Olympic gymnastics and its scoring system will be vital to understanding the decision making process later in this paper. Women's artistic gymnastics and Men's artistic gymnastics vary slightly, with women competing in four apparatuses and men competing in six. Each country, if they have qualified for the team all-around competition (which the US has), can send five athletes per gender; otherwise a country can send a maximum of three individuals. The event begins with a qualification round that is also the qualifying round for the team all-around, individual all-around, and individual apparatus competitions. A team will send four of their five athletes to compete for each of the apparatuses. For the team score, only the top three of the four scores will count. If an individual competes on every apparatus in the qualifying round they are then eligible for the individual all-around final, regardless of if they are on a team. However, only the top 24 athletes will be in the individual all-around final. If an individual is in the top eight in qualifying for a given apparatus they also qualify for that individual apparatus final. For all individual finals, however, only a maximum of two athletes per country can qualify. All things considered, this gives six medal opportunities on the women's side (team all-around, individual all-around, each of the four apparatuses) and eight on the men's side (team all-around, individual all-around, each of six apparatuses).

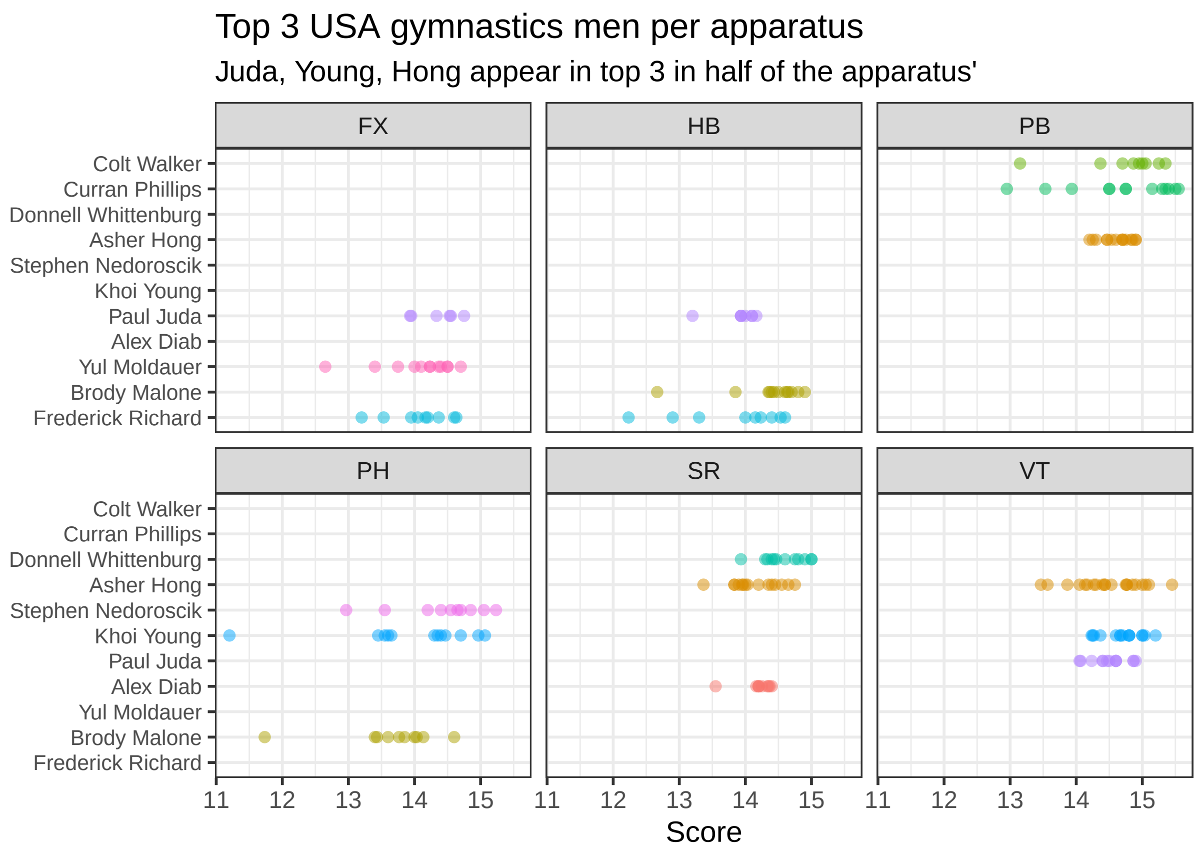
This report aims to analyze athlete-specific data and incorporate domain expertise from the gymnastics community. It will offer a comprehensive and customized approach that addresses the unique competition format presented by artistic gymnastics and provides the USA Olympics Committee with a robust tool to make statistically informed decisions. Our goal is to build a tool that will allow us to recommend a team of five women and five men for the Olympic Games in Paris 2024, with an expected individual medal count for each team as well as an expected all-around team medal count given the five person team.

Exploratory Data Analysis

If our goal is to put forth the best lineup to maximize medal count, we need to look into who the top US candidates are in each apparatus and all-around. Here, we graph dot plots of the top three US gymnasts in each event across all the events, using the mean score from their 2022-2023 data. The small number of total athletes that appear in the top three across all apparatuses signals that most elite athletes are great at more than one event.



Taking a glance at the top US women, we can see that Simone Biles, who is a top three gymnast in each of the four apparatuses, is by far the best American gymnast. That is unsurprising given that she has the most gymnastics medals in the world and has consistently performed at an elite level since her return to the sport. She is a lock to make the Paris 2024 roster. Shilese Jones is the only gymnast to have a higher mean score in an apparatus than Simone, outperforming her in the uneven bars (UB). She is another athlete to keep an eye out for to make the team, especially considering her recent all-around Bronze medal in the World Championships in October 2023.



Paul Juda, Khoi Young, and Asher Hong appear in the top 3 gymnasts for half of the apparatus although determining the US men's team is not quite as clear cut. There are a total of 11 American gymnasts who placed in the top three of at least one of the six events. Hong, Young, and Yul Moldauer placed in the top three for three of the six events. Additionally, Brody Malone placed in the top five for four out of six events, and Fred Richard most recently won Bronze at the 2023 World Championships in the all round. Those are athletes we might expect to be placed into our US men's team.

Methodology

Weighting

We treated this competition as an optimization problem where we maximize total medal count. We have developed nuanced heuristics based on analyzing past Olympic gymnastic results to pick our top five-person lineups. Specifically, we weighted for each score by artificially determining its importance by how recent it was and the "stage" of the competition in which it took place, qualifying vs. final round. We averaged the weighted scores across all the events a US gymnast has participated in since the 2021 Tokyo Olympics. A composite all-around score was found as well by summing the average weighted scores in each apparatus. A summary of our weighting process is below.

Clutch Factor and Recency Considerations

We chose to put weights on competition date and competition stage, specifically, because we believe a heavier weight should be placed on performances that take place under pressure (the final round) and are more recent. This weighting attempts to measure the "clutch" factor and peak/prime performance of an individual athlete. We duplicate rows of individual scores in the sampling dataset given the assigned weight of that score. Competition date will be split into three categories by recency: very recent (< 6 months), somewhat recent (6 - 18 months), not recent (18+ months). A multiplier of one will be given to 'not recent' competitions, a multiplier of two to 'somewhat recent' competitions, and a multiplier of three for 'very recent' competitions. As for the competition stage, there are two stages of competition: qualifiers and finals. Qualifying round scores will receive a multiplier of one and final round scores will receive a multiplier of two. For example, a row containing a score from a not recent competition and qualifying round will remain as one singular row. However, a row containing a qualifying round score, but from a very recent competition, will be multiplied three times to get three rows containing that score. If that score was instead from the finals, it would be multiplied 2 x 3 = 6 times in the dataset. Taking the average of an individual athlete's scores after this duplication process will give us a weighted mean expected score on each apparatus for that athlete. Still, each gymnast has variance across performances on each apparatus which is taken into account. For each USA gymnast, we developed and will sample from an individual total score distribution from their weighted scores to account for the variance for each individual on each apparatus. A density plot of all the scores after the duplication process will give us a distribution centered around the mean score for an athlete as well as their variance.

Obtaining Medaling Probabilities

The main goal of analysis is to determine the probability that an individual athlete medals, so we also had to determine a way to get medal probabilities. We accomplished this goal by determining score thresholds necessary to achieve a certain medal. This first required us to get a distribution of scores on individual apparatuses. From the EDA, we saw that the distribution of all scores was roughly normal, with a tail towards the left side of the distribution, with fatter tails. We also saw that each individual athlete's score distribution was roughly normal. This inspired us to take the top 24 people (the lower scoring competitors would be dropped), and from there create a t-distribution for the 24 people as well as for each individual competitor to sample from in our simulation. This will account for the individual variance of athletes on a specific apparatus. Of the 24 gymnasts, however, no more than four competitors from the same country will be included in this distribution as a maximum of four individuals from each country can compete in qualifying for each apparatus. In order to find an individual's probability of earning a medal we used a two step simulation and sampling process. We simulated the following process 1,000 times. We first sampled from the distribution of the top 24 individuals 24 times. The top three scores of the 24 represented the three medal cutoffs with the 3rd highest sample score corresponding to a Bronze medal, the 2nd highest sample score corresponding to a silver medal cutoff, and the highest sample score corresponding to a gold medal cutoff. Because we were only worried about gymnasts from the USA, we sampled once from each of the top eight USA gymnasts in each individual apparatus given their unique distributions. If that gymnast's sampled score surpassed one of the cutoffs they 'earned' that medal for the given simulation. For example, if when sampling from the 24 gymnasts distribution we get medal cutoffs of 14.5, 14.8, and 14.9 and gymnast A gets a sampled score of 14.5 or greater they "earn" a Bronze medal. A sampled score of 14.8 or greater would "earn" a Silver medal and a sampled score of 14.9 or greater would "earn" a Gold medal. The only caveat was if multiple American gymnasts fall within the threshold for a certain medal. In that case the gymnasts were ordered and the top score earned that medal and the next highest score would earn the next highest medal if available. We simulated this approach 1,000 times to get each individual gymnast's probability of getting a specific medal in a specific apparatus. We used this approach for the individual all-around as well. The assumptions for our simulation require an adequate amount of repeating sampling. 1,000 is surely enough for each athlete, who on average has 10-20 observations in our dataset. We also assume that past performance is somewhat indicative of future performance.

From there we used optimization to determine the 5-person lineup that maximizes expected medals earned including the team all-around medal. In determining the team all-around medal we will use a system identical to the way the Olympics will work in 2024. We will use many permutations of five gymnasts and sample from every gymnast's individual distributions to get all-around scores. For each apparatus, the top three US gymnasts on the team's distributions will be sampled from (because only the top three gymnasts participate in the team all-around finals). The scores will be aggregated to get a total team all-around score. The same method of medal cutoffs will be used in the team all-around medal cutoffs, but using empirical team all-around score data to create a distribution to be sampled from.

Our Web App

Our web app then combines the methodology above into a single interface for athlete selection and optimization. There are three tabs of note within this web app. First, an about section which describes the creators of this app as well as a short synopsis of how the web app was created. Second, a "Gymnast" tab which allows the user to sort in descending order not only the projected total medals by athlete, but also for medal probability on individual apparatuses. This tab allows the user to see which US gymnasts (men or women) are the most likely to medal in a given apparatus. Finally, there's the "Team Builder" page where for both the men and women's teams, users will be able to manually input five gymnasts into the web app. Utilizing the several already run simulations, the app will spit out the total projected medals for each athlete, their all-around team medal probability, and finally the total projected combined medals for the five athletes. Replacing one athlete with another will also replace that athletes projected individual medals as well as recalculate that five-person team's team all-around medal probability.

Results | Our Team

Table 1: Proposed Paris 2024 USA Gymastics Team, with Expected Medal Counts (EMC)

Category	USA_Women	EMC_Women	USA_Men	EMC_Men
All-Around	Simone Biles	3.409	Paul Juda	0.663
All-Around	Shilese Jones	0.466	Fred Richard	0.491
Specialist	Kaliya Lincoln	0.439	Donnell Whittenburg	0.264
Specialist	Jade Carey	0.190	Khoi Young	0.564
Specialist	Zoe Miller	0.061	Curran Phillips	0.310
Total Exp. Medals		4.565		2.402

Based on our results and our weights, to maximize for total medal count at the Paris 2024 Olympics, the USA Gymnastics team should select Simone Biles, Skye Blakely, Shilese Jones, Jade Carey, and Zoe Miller for the women's team, and Fred Richard, Paul Juda, Donnell Whittenburg, Khoi Young, and Curran Phillips for the men's team. Our total predicted medal counts are 4.565 individual medals for the women, and 2.402 for the men's team. Biles and Jones are the clear all-round selections, expecting to contribute 3.409 and 0.466 medals in total, respectively, and having a 99.9% and 23.9% to medal in the individual all-around finals. Onto the three specialists, Carey is an outstanding performer in vault and floor exercise, having a 19.0% and 19.9%, respectively, to medal in those apparatuses. Lincoln has a 43.9% chance medaling in floor exercise. Miller is our last selection, and she brings value in the uneven bars, having a 6.1% percent chance of medaling there. Juda and Richard were the all-round selections on the men's side. They have the highest chances of medaling in our individual all-round, with 5.1% and 4.9%, respectively. The first specialist we choose is Khoi Young for his ability in vault and pommel horse, having a 44.9% and 11.5%, respectively, of medaling in those events. Then we choose the veteran Whittenburg for his consistency on the still rings (SR), having the highest percentage chance to help the US medal in that apparatus where we expect him to come in the top three 26.4% of the time. Lastly, we went with Curran Phillips for parallel bars as he has a 26.3% to medal there.

While the team above maximizes the total projected amount of medals earned at the 2024 Paris Olympics. If instead, a user wanted to maximize the likelihood of winning a team medal, they could primarily focus on building permutations of teams in our "team builder" feature that maximize the probability of winning Gold, Silver, Bronze or any of the three based on user preference.

Discussion

Limitations

There were some limitations identified in our statistical methods. First, we arbitrarily assigned weights to each score and it is possible that different weightings could result in the selection of a different team. However, the weights used were reasonable given how recent performances are more likely to affect future performance and the desire to pick 'clutch' gymnasts. Another potential limitation is how we determined projected scores for athletes that have not competed in some time. Take Sunisa Lee as an example. Due to competing in college and injuries, Lee has very few scores since her Olympic performance in 2021. Because those performances account for many of her competitions, her lower recent scores are overshadowed by her higher older scores. Even with our weighting scheme her older scores account for a much greater proportion of her data. In this vein, athletes may have projected scores that do not resemble what their recent form might be. Some alternatives for our methodology could include using a Kernel Density Estimation method to estimate the distribution and then sampling, or obtaining all possible combinations of five athletes and then running an Olympics simulation. We could also introduce more factors to weighting such as the age of the competitor, skill level of the competition, etc.

Goals, Eye-test, and Outside Research

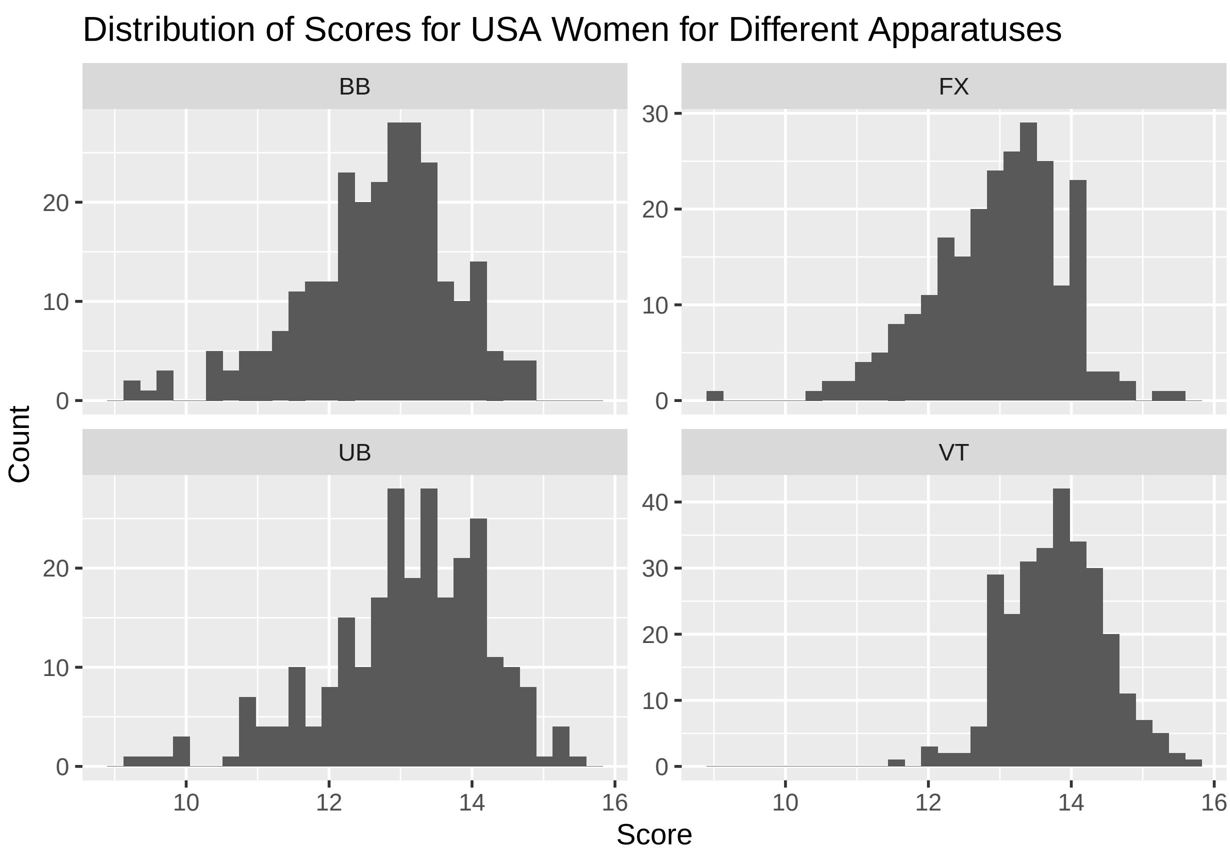
Our goal was to design a tool to recommend a team of five women and five men for the Olympic Games in Paris 2024, and to come up with an expected medal count for each team. We accomplished our goal of selecting athletes by first adjusting for 'clutch' factor and adding a recency bias by duplicating observations based on final vs qualifying rounds, and date of competition. We then account for individual variance by creating a t-distribution for each competitor for each apparatus and sampling from that distribution 1,000 times. We also find the predicted medal thresholds using repeated sampling from a t-distribution, taking the top 24 individual scorers, and comparing our sampled individual results with these predicted thresholds to find predicted individual medal counts.

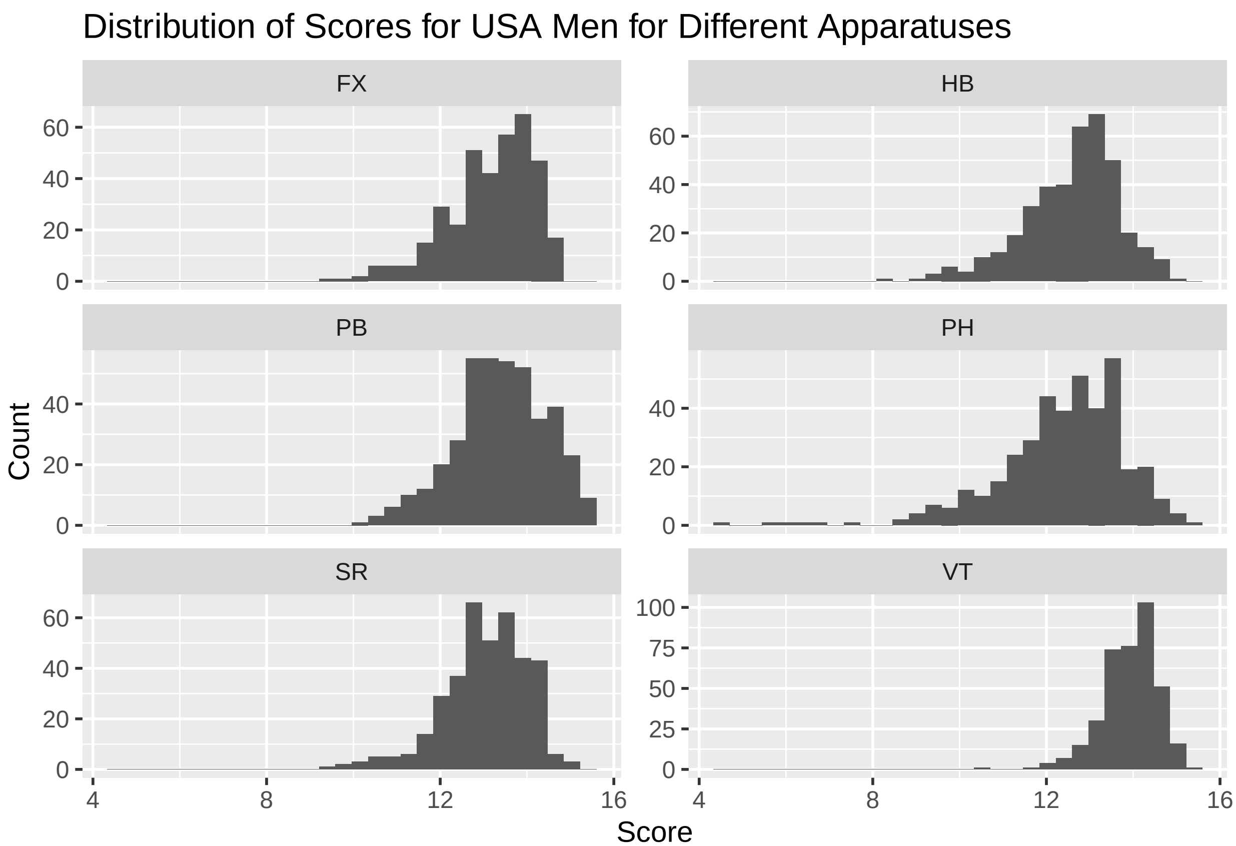
Excluded Athletes

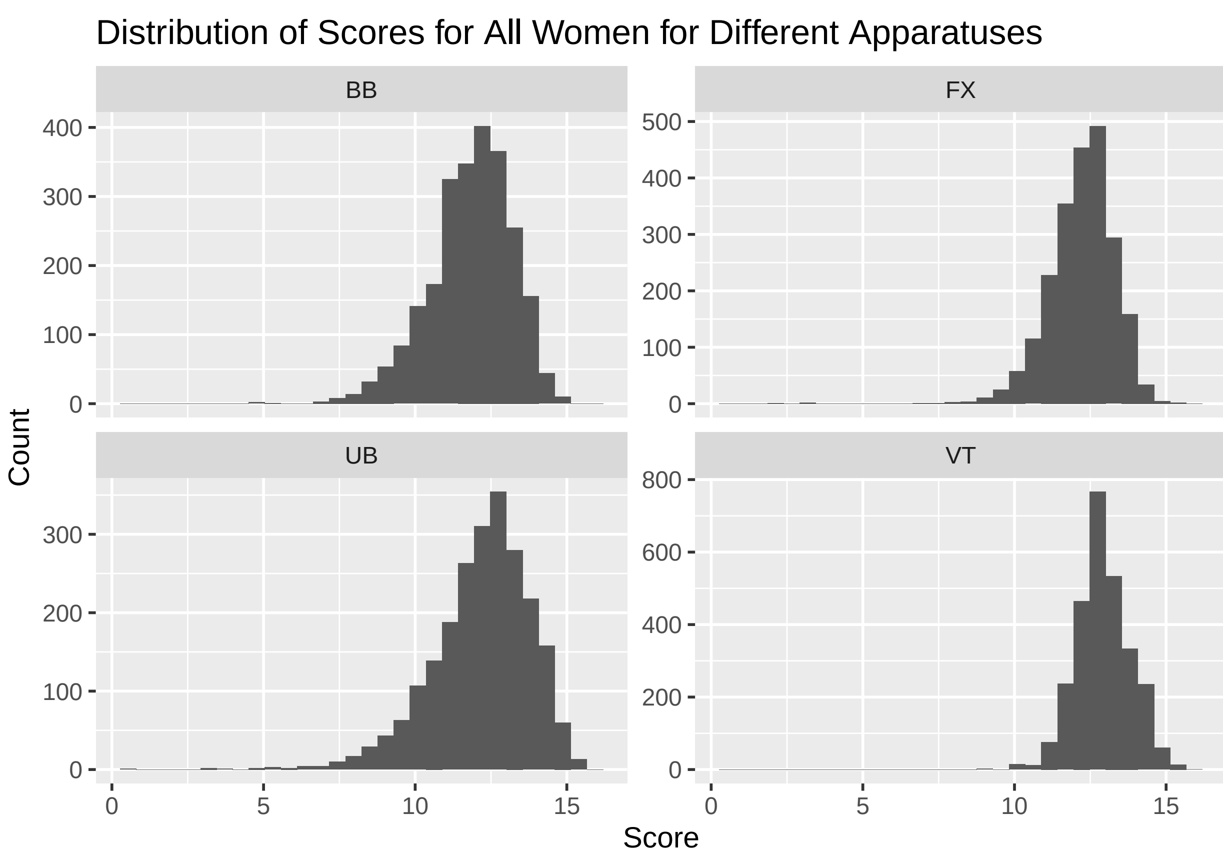
Athletes Konnor McClain, Sunisa Lee, and Brody Malone were excluded from our selections. Konnor McClain left Elite (which is a program designed to be a pathway to the USA national team) in 2023 in favor of college. Although she plans to continue training for the Olympics, her non-Elite status likely keeps her from being in the USA olympic committee's player pool. A similar situation exists for Sunisa Lee, the 2020 Olympic all-around champion. Although her weighted scores are quite high, she has not competed in Elite since her enrollment in college in 2022 and a recent injury in which she gained over 50 pounds likely keeps her from making the USA national team. Injury concerns will also keep Brody Malone off the team on the men's side. Although he eyes a spring 2024 comeback from a knee injury suffered in the spring of 2023, he will likely not be ready or in time for the Olympics.

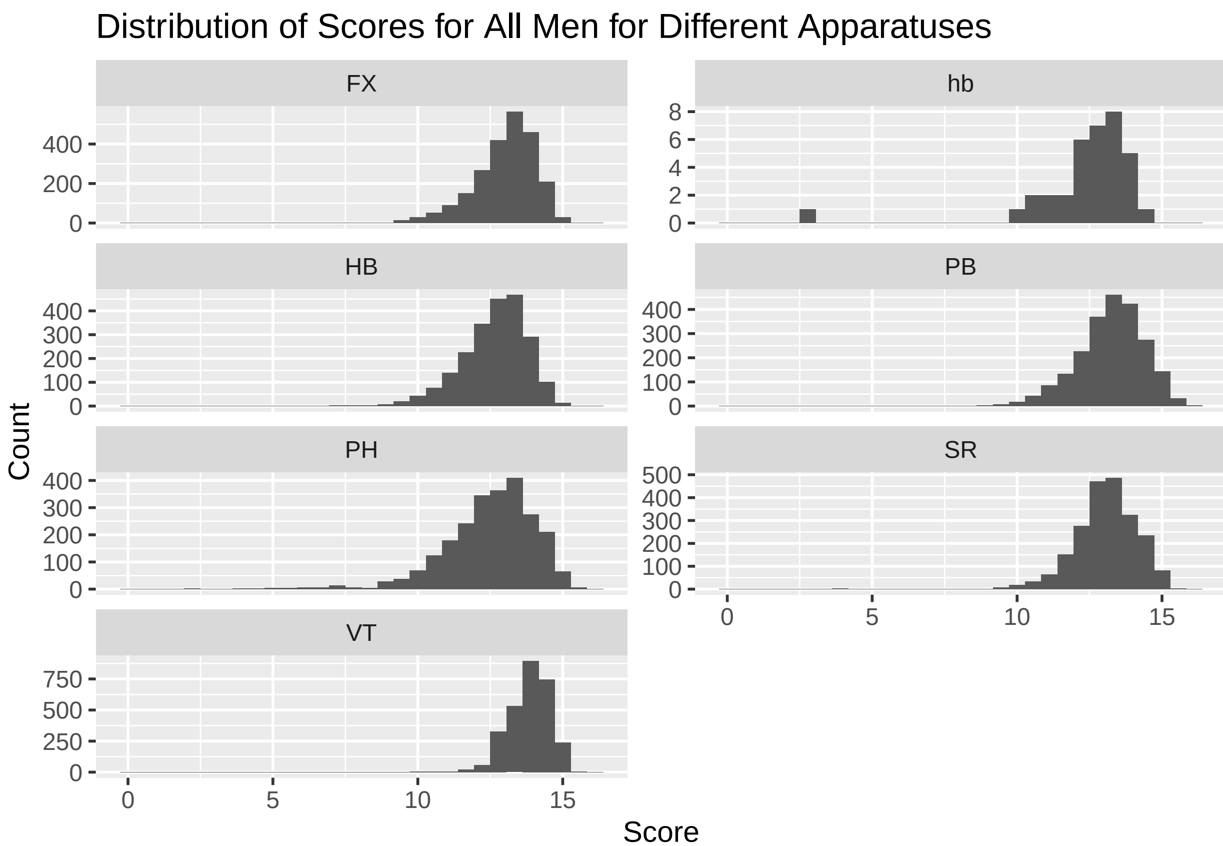
Appendix

Below are the graphs which validate the rough normality condition needed to generate t-distributions.




Distribution of Scores for USA Men for Different Apparatuses
FX
HB
PB
PH
SR
VT
Count
Score
0
20
40
60
25
50
75
100
4
8
12
16


Distribution of Scores for All Women for Different Apparatuses
BB
FX
UB
VT
Count
Score
0
100
200
300
400
500
600
800
5
10
15


Distribution of Scores for All Men for Different Apparatuses
FX
hb
HB
PB
PH
SR
VT
Count
Score
0
5
10
15

The following tables display the expected medal count for each US gymnast in each event, including in the all-around competition.

Name	AA	BB	FX	VT	UB
Simone Biles	0.999	0.715	0.993	0.702	0.000
Shilese Jones	0.239	0.035	0.182	0.005	0.192
Konnor Mcclain	0.154	0.485	0.082	0.004	0.000
Skye Blakely	0.028	0.043	0.000	0.000	0.003
Jordan Chiles	0.019	0.000	0.203	0.004	0.000
Leanne Wong	0.010	0.000	0.028	0.005	0.000
Jade Carey	0.008	0.000	0.199	0.190	0.000
Kayla Dicello	0.002	0.001	0.028	0.001	0.000
Addison Fatta	0.000	0.000	0.000	0.000	0.000
Alicia Zhou	0.000	0.000	0.000	0.000	0.000
Amelia Disidore	0.000	0.000	0.000	0.000	0.000
Annalisa Milton	0.000	0.000	0.000	0.000	0.000
Ashlee Sullivan	0.000	0.001	0.000	0.000	0.000
Brooke Pierson	0.000	0.000	0.000	0.000	0.000
Charlotte Booth	0.000	0.000	0.000	0.000	0.000
Chloe Cho	0.000	0.000	0.000	0.000	0.000
Ciena Alipio	0.000	0.003	0.000	0.000	0.000
Dulcy Caylor	0.000	0.000	0.000	0.000	0.000
Elle Mueller	0.000	0.000	0.000	0.000	0.000
Eveylynn Lowe	0.000	0.000	0.000	0.000	0.000
Joscelyn Roberson	0.000	0.016	0.107	0.029	0.000
Kaliya Lincoln	0.000	0.000	0.439	0.000	0.000
Katelyn Jong	0.000	0.000	0.000	0.000	0.000
Katelyn Rosen	0.000	0.000	0.000	0.000	0.000
Kelise Woolford	0.000	0.000	0.000	0.000	0.000
Lauren Little	0.000	0.000	0.000	0.000	0.000
Levi Jung-Ruivivar	0.000	0.000	0.000	0.000	0.000
Lexi Zeiss	0.000	0.000	0.000	0.000	0.000
Madray Johnson	0.000	0.000	0.000	0.000	0.000
Malea Milton	0.000	0.000	0.000	0.000	0.000
Marissa Neal	0.000	0.000	0.000	0.000	0.000
Michelle Pineda	0.000	0.000	0.000	0.000	0.000
Myli Lew	0.000	0.000	0.000	0.000	0.000
Nola Matthews	0.000	0.000	0.000	0.000	0.000
Norah Christian	0.000	0.000	0.000	0.000	0.000
Sunisa Lee	0.000	0.208	0.000	0.000	0.000
Tiana Sumanasekera	0.000	0.012	0.000	0.000	0.000
Zoe Miller	0.000	0.000	0.000	0.000	0.061

Name	AA	SR	FX	PB	PH	VT	HB
Brody Malone	0.272	0.000	0.168	0.042	0.010	0.045	0.435
Frederick Richard	0.051	0.000	0.235	0.025	0.000	0.049	0.180
Paul Juda	0.049	0.000	0.393	0.000	0.000	0.221	0.044
Khoi Young	0.030	0.000	0.229	0.000	0.115	0.449	0.000
Yul Moldauer	0.028	0.000	0.211	0.163	0.000	0.075	0.000
Asher Hong	0.024	0.034	0.123	0.026	0.000	0.296	0.000
Colt Walker	0.014	0.000	0.038	0.208	0.000	0.090	0.000
Shane Wiskus	0.009	0.000	0.150	0.068	0.000	0.015	0.015
Donnell Whittenburg	0.004	0.264	0.186	0.000	0.000	0.194	0.000
Cameron Bock	0.002	0.000	0.000	0.044	0.000	0.000	0.000
Alex Karadzhov	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alex Tapanes	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Anthony Koppie	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Asher Cohen	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Blake Sun	0.000	0.000	0.000	0.149	0.000	0.000	0.000
Brandon Briones	0.000	0.000	0.000	0.000	0.000	0.044	0.000
Brandon Nguyen	0.000	0.000	0.000	0.000	0.000	0.011	0.000
Caden Clinton	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Caleb Melton	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Chase Davenport-Mills	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cole Partridge	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Colin Flores	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Crew Bold	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Curran Phillips	0.000	0.000	0.000	0.263	0.000	0.204	0.047
Dallas Hale	0.000	0.000	0.015	0.008	0.000	0.354	0.000
Daniel Simmons	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Drake Andrews	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Evan Hymanson	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Evan Manivong	0.000	0.000	0.000	0.000	0.000	0.021	0.000
Fuzzy Benas	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Garrett Braunton	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Garrett Schooley	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ian Gunther	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ian Lasic-Ellis	0.000	0.000	0.026	0.000	0.000	0.000	0.000
Ian Sandoval	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Isaiah Drake	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Izaiha Mlay	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J.R. Chou	0.000	0.000	0.000	0.116	0.000	0.000	0.000
Jack Freeman	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jackson Harrison	0.000	0.000	0.050	0.000	0.000	0.000	0.000
Jeremy Bischoff	0.000	0.000	0.046	0.000	0.000	0.000	0.000
Joshua Karnes	0.000	0.000	0.033	0.000	0.000	0.032	0.000
Kameron Nelson	0.000	0.000	0.001	0.000	0.000	0.037	0.000
Kazuki Hayashi	0.000	0.000	0.000	0.000	0.000	0.043	0.000
Landen Blixt	0.000	0.000	0.000	0.000	0.000	0.059	0.000
Landon Simpson	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Matt Cormier	0.000	0.000	0.086	0.000	0.000	0.000	0.000
Maxim Bereznev	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Michael Artlip	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Michael Jaroh	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mike Fletcher	0.000	0.000	0.000	0.000	0.000	0.011	0.000
Noah Newfeld	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Oliver Zavel	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Riley Loos	0.000	0.000	0.023	0.000	0.000	0.018	0.000
Rithik Puri	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ryan Swatscheno	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Samuel Phillips	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Name	AA	SR	FX	PB	PH	VT	HB
Taylor Burkhart	0.000	0.000	0.077	0.000	0.000	0.139	0.000
Taylor Christopulos	0.000	0.000	0.000	0.000	0.000	0.012	0.000
Toby Liang	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Vahe Petrosyan	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Will Fleck	0.000	0.000	0.000	0.000	0.000	0.000	0.000

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