Mathematical models for speed climbing applied to data collected on competitors in recent World Cup events

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Abstract

Speed climbing is one of the newest Olympic sports, debuting at the 2020 Tokyo Olympics. With many races decided by hundredths of a second, speed climbing quickly gained recognition as the fastest sport at the Paris 2024 Olympics. Speed climbing appeals to data scientists since it uses a standardized 15-meter wall, making it easy to compare times and strategies across a vast array of competitions and competitors. Surprisingly, however, there has been little rigorous analysis of a professional level race to the best of our knowledge. In this paper, we model data compiled from the 2023 World Cup events in Wujiang, China and Salt Lake City, USA, analyzing both numerical and categorical variables. Examples of quantitative variables include the reaction time displayed in the video for each athlete, along with the total time, or split times, obtained by running the recording for each athlete frame by frame and estimating the exact point at which each section is reached. An example of a binary variable is the skips strategy, which draws attention to the holds each athlete omits on their run. Another example of a categorical variable is the round designation - either round 1 or round 2 - which refers to the order of athletes' runs. We explored these variables extensively, built several general linear models for athlete performance and used model selection to determine the best predictive models. We found that reaction times are normally distributed and appear to be very weakly correlated from one race to another. Counter-intuitively, however, they appear to have minimal bearing on the race result, despite making up a portion of the overall time. Another interesting observation is that many athletes attempt a more aggressive skip strategy in their second run, omitting a greater number of holds. This is either because they either already recorded a viable time for qualification in Round 1 and can afford the risk, or because they felt the need for substantial improvement. In ongoing work, we have been focusing on expanding the analysis, using data from additional World Cup events for both men and women.

1 Introduction

Speed climbing uses a standardized wall that is 15 meters high and has a 5° overhang [1]. The wall includes 20 big holds, each with the same dimensions, along with a number of smaller foot chips. Figure 1 displays a schema of the wall. There are two routes (A on the left side, B on the right side), with no difference between

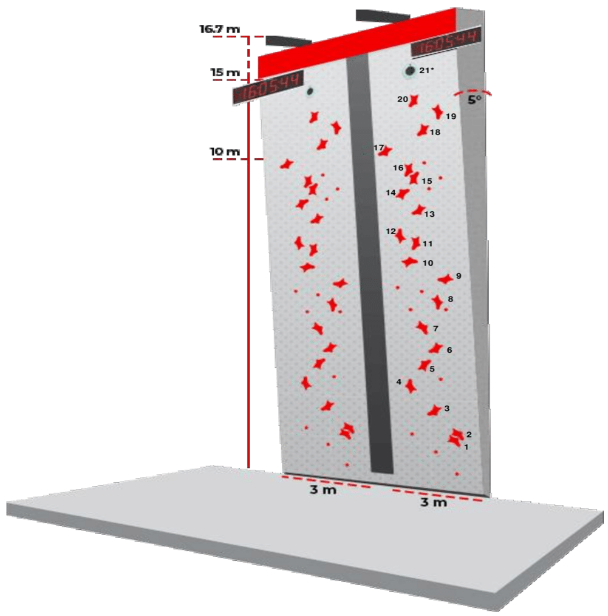

Figure 1: A diagram of a regulation speed climbing wall.

them. In qualifiers, each competitor has one attempt of each, with the best time of the two being used for their tournament ranking. The top finishers enter a finals round, which is a playoff bracket format. Over time, the main way of improving performance has been skipping more and more holds by performing a number of fast, dynamic movements. For example, most World Cup male competitors will jump directly from hold 3 to 5, bypassing 4 (often called the Tomoa skip, in reference to Japanese climber Tomoa Narasaki). They also usually connect hold 8 with 10, bypassing 9. Skipping holds carries the risk of falling, so not all competitors use the same technique; some may find it faster to still use some holds. One difference in the current World Cup circuit, for example, is skipping hold 14. Most competitors still use it (they often will use holds 11-14-16 in sequence), but a few, including the world record holder Sam Watson, go directly from 11 to 16. One very unique technique is done by Noah Bratschi. He does not do the Tomoa Skip (making him the only one to use Hold 4), but opts to use hold 12 and skips 14. There are three common strategies that we focus on: skipping both hold 12 and 14 (i.e., world record holder Sam Watson) which is the fastest approach, but also the highest risk. When runners need to make up time, they often use this strategy; skipping hold 12 but using hold 14 (i.e., Jinbao Long) which is the most typical approach; skipping hold 14 but using hold 12 (i.e., Liang Zhang). As in sprinting, a start faster than 0.1 seconds after the final beep is considered a false start and leads to elimination from the whole competition. Typical reaction times vary between 0.15 and 0.20, as the data shows. One topic of interest in this paper is whether reaction time is statistically significant to one's time or not.

Variable	Description	Type
X_1	Time to hold 20 in Route A	Numeric
X_2	Time to hold 16 in Route A	Numeric
X_3	Whether Route A is the first attempted in the competition	Binary
X_4	Time from hold 0 to hold 10 in Route A	Numeric
X_5	Whether hold 14 is used in Route A	Binary
X_6	Time to hold 10 in Route A	Numeric
X_7	Time from hold 0 to hold 10 in Route B	Numeric
X_8	Time to hold 16 in Route B	Numeric
X_9	Whether hold 12 is used in Route B	Binary

Table 1: Speed climbing variables

2 Data

A detailed dataset was compiled for the IFSC World Cup Wujiang 2024 qualification round, with two runs recorded for each athlete. The starting list, athletes' names, height (where available), bib number, and total time for both runs were obtained from the IFSC Results website, `ifsc.results.info/event/1354/`. All other variables were collected using a detailed video analysis of the competition's recording on IFSC's YouTube channel. They are displayed in Table 1.

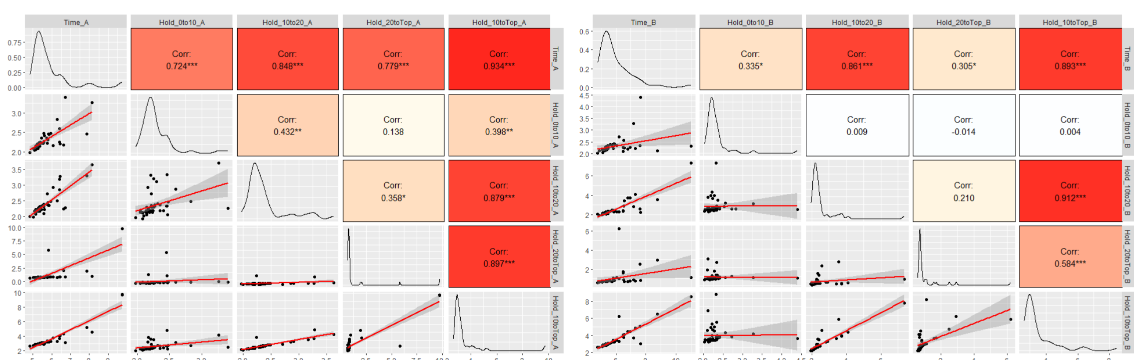

Figure 2: Pair plots of several split variables for Route A (left) and Route B (right).

Reaction time variables were displayed in the video for each athlete along with the total time. Skips strategy (known as the 'hold' variables) were observed and recorded from the video for each athlete and each run. Split times, referred to as the 'Time to' variables were obtained by running the recording for each athlete frame by frame and estimating the exact point when each section is reached. The margin of error is around 0.03-0.04 seconds based on the time gap between each frame. The corresponding distributions of times are generally right-skewed with most times falling between 5 and 6 seconds. There is a rare chance that a runner falls from the course, costing them several seconds. One area of intrigue was whether falling had any correlation with their present performance in the race, that is if they were often doing poorly and rushing to get back to qualifying pace. Figure 2 displays a bird's eye view of the relationships between variables via pair plots between the various numeric features and the final times for each athlete on Route A and B. It is immediately evident that the time between holds 0 and 10 (**r** = .724 for Route A, **r** = .335 for Route B) is not nearly as relevant as that between holds 10 and 20. One of our first instincts was to check the relationship between the final time and reaction time was what was missing, depicted in Figure 3. However, the correlations consistently landed near 0 between reaction time and overall time, making it largely irrelevant to a good pace. Additionally, reaction time seems to have little consistency from run to run with a correlation of just 0.153. If we limit the analysis to what we define as 'good' runs, which pertain to attempts that finish in less than six seconds, we actually see slower times on average. We speculate that the additional mental burden of trying to react to the buzzer especially quickly may make one slower than when simply reacting naturally.

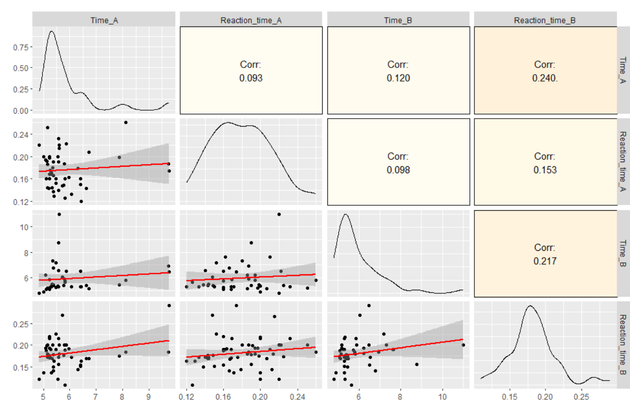

Figure 3: Pair plot of overall race time and reaction time variables for Route A (left) and Route B (right).

3 Linear models for speed climbing

To analyze the data previously described we use linear models based on the variables in Table 1 together with meaningful interactions between them. For a general description of the statistical methodology we refer to [2]. Here is, for example, a simple (overfiting) model for predicting Route A time.

$$\text{Model 1: } \mathit{TimeA} = 0.431 + 1.391X_1 - 0.388X_2$$
$$\text{Adjusted-}R^2 = .9507, \text{ RSE} = .1648$$

Given there are only 20 holds on the wall, it is clear that a racer's split to hold 20 will be statistically significant in determining the overall time on the route. As a result, it performs very well with an Adjusted-R^2 of .9507. Given the obvious target leakage, which occurs when data is used in a model that would not be available at the time of prediction, the model is not suitable for our purposes. Going forward, we remove all split variables past hold 10 from the model fitting process to limit the issue. Model selection yielded the following model for predicting Route A time with only Route A splits.

$$\text{Model 2: } TimeA = 2.692 + .3624X_3 + 8.101X_4 - 2.688X_5 - 6.501X_6 + 1.208X_5X_6$$
$$\text{Adjusted-}R^2 = .6443,\ \text{RSE} = .4428$$

As a result of our adjustment, this model only uses splits up to hold 10. It does include features related to hold 14, but only in relation to the runner's general strategy. Runners typically implement the same strategy every race, so the binary value can be known ahead of the buzzer going off. Given the earlier finding that the split to hold 10 is not significant, we have clearly improved our predictive ability using that variable by adding a couple extra features. Of particular relevance is variable X_3, which is a binary variable that indicates whether Route A was the first that a runner attempted in the competition. Generally, one has a slower time on the first route to ensure a valid score for qualification (competitors are ranked based on their fastest of the two times for the playoffs), while taking a more aggressive approach on the second route. This is supported by a greater number of falls during runners' second attempt in the data. An Adjusted-R^2 of .6443 indicates a strong fit. Concerning predicting Route A time with only Route B splits, the following model has been selected. This model is the most practical because it can be employed as a true prediction of Route A time simply based off Route B performance. Its Adjusted-R^2 of .5455 is the lowest of the three models but that is inevitable with the risk of falling always present and the two routes being completely different paths.

$$\text{Model 3: } TimeA = -28.9977 - 12.0108X_3 + 15.3040X_7 + 8.4712X_8 + 1.6232X_9 + 5.5963X_3X_7 - 3.7545X_7X_8$$
$$\text{Adjusted-}R^2 = .5445,\ \text{RSE} = .5005$$

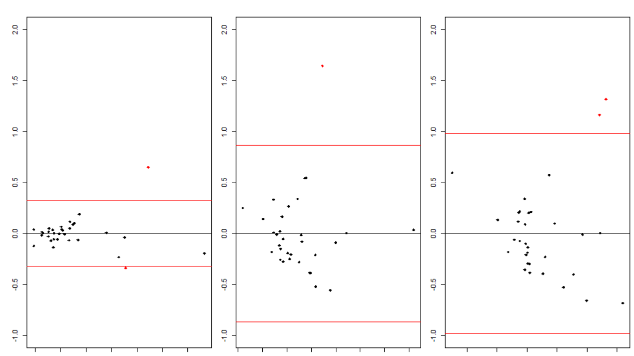

Figure 4: Residual plots for Model 1 (left), Model 2 (center), and Model 3 (right). Red lines mark 95% confidence bands and red points are significant outliers.

Regarding diagnostics, we found that the normality assumption was reasonably met in all models. Residual plots are shown in Figure 4. One outlier worth mentioning (falling outside the 95% confidence bands in all plots) is Leander Carmanns of Germany, who did well up to hold 16 before falling and losing several seconds of time. Unlike many other runners who fall, he opted to complete the race regardless. This allowed his run to remain in our model fit and create a large positive residual. Without incorporating falls into the dataset, this sort of error would be very difficult to avoid.

4 Discussion

To summarize, we created a data frame of numerical and binary variables based on open source information on performance of several male speed climbing world champions and showed resulting best linear predictive models. We found that reaction time has minimal impact on total time and is inconsistent between runs. Runs under 6 seconds tend to have slower average reaction times, suggesting that mental burden of fast reaction has detrimental effect on total time. Moreover, first-half split time (holds 0 to 10) seem to yield lower correlation to total time than second-half split time (holds 10 to 20). Starting strong remains important, but finishing strong appears to be far more important. We also found that athletes take a more aggressive, but riskier skip strategy on the second run, yielding faster times but also more falls. In ongoing work we will gather more data to improve predictive models. We also aim to collect data on women climbers and will consider including more variables that may have an impact such as athletes' height and weight. We will also consider variance stabilizing transformations for some of the variables to improve resulting residual plots.
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References

[1] Lau, Emily (2021). Identifying physiological demands of Speed Climbing within a sample of recreational climbers. 10.13140/RG.2.2.18266.06089.

[2] R. Pruim (2011). Foundations and Applications of Statistics. An Introduction using R. American Mathematical Society, Providence, Rhode Island

[3] `ifsc.results.info/event/1354/`

[4] `https://www.youtube.com/@sportclimbing`