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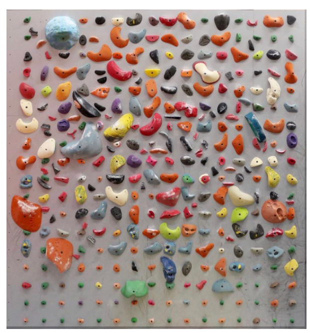
Abstract

In an analysis of climbing route data, our aim is to characterise desirable movement, difficulty and climbing style. We discover distributions of hold types, edge depths, movement distances and difficulty's that are unique to climbs that were given a high quality score climbers. We propose a model for route quality as well as a generative algorithm based on user preferences.

Introduction

As the sport of rock climbing grows in popularity and competition, there is an increasing amount of interest in specialized training. For the first time, competitive indoor rock climbing will be featured in the 2020 Olympics in Tokyo, bringing rock climbing into the mainstream sports audience view. This interest has formed a large market for training products, regimens and scientific research to maximizing training efficiency. Rock climbing training walls are used traditionally by climbers to make up "boulder problems" to simulate real rock climbs. Climbers use these as tools to isolate specific movements and train muscular weaknesses. Training walls are typically constructed by a 60 degree overhung wall with a array of many different types of holds. See the Figure 1 for reference.

Figure 1: Training Wall



The main distinction between a training wall and a regular indoor rock wall is the lack of purposefully set routes on the former. A training wall allows the climber to design movements to suite their needs. This is a benefit and a drawback. It takes immense creative energy to come up with aesthetic routes that are fun and difficult at the same time. Recently, there have been standardized training walls that have entered the market that allow people to store routes on an app that is associated with the walls hold distribution. This way different people with access to the same wall can share suggested routes with one another. See the company "moon-board" [1] as an example. There are a handful of other apps that exist that perform similar route cataloguing functions but on any custom training wall. However, a barrier to the utility of these walls remains for many users. It takes skill, experience and long term exposure to route setting in order to set quality routes that are beneficial to progressing climbing abilities. With the recent advent of digitized climbing routes from the previously discussed technologies, a large data set now exists that characterizes popular climbing movement. This data set is a very promising resource to examine the characteristics of popular routes and perhaps train a model to suggest routes based on available holds and desired difficulty. This type of generative algorithm can help climbers improve faster and make the utility of training walls more accessible to typical climbers.

As climbing is increasingly apart of mainstream sports culture, there is an emerging library of scientific literature reporting investigations into physiological, physiological and environmental factors of competitive indoor climbing. This review of literature covers efforts to model bio mechanics involved in rock climbing movement, models proposed to estimate the difficulty of a climbing route and generative models that suggest sequences of movements and hold types as an aid to route setting. Additionally, as relevant to this study, literature on image classification using crowd-sourced image labels is reviewed. Route setting for indoor climbing is thought of by those who practice it as a highly creative and demanding task, similar to that of composing music or choreographing a dance. Much thought goes into the experience that the climber will have interacting with the holds on the wall. A "route" consists of a set of holds on the wall that dictate a series of movements. The combination of these movements are not unlike symbols in a language, there are some that appear with high frequency across many different routes. A route is given a grade that indicates its difficulty with respect to other climbs. There are several different grading scales that are used in different parts of the world. Draper et suggest a universal scale to replace the existing Ewbank scale [11]. Draper suggests the International Rock Climbing Research Association (IRCRA) scale which maps between the Hueco, Fontainebleau, European and Middle Eastern scales [10]. This scale was introduced in to order to accurately describe and compare the difficulty of climbs in formal literature. However, all difficulty ratings are somewhat subjective and often change based on community consensus. The difficulty of a climb has several parameters like the distance between holds, the size of the available holds, the texture of the holds and the angle of the wall. Beyond these characteristics of a route are various underlying styles of routes, some of which are made up of different combinations of the above parameters [30],[29]. This makes the task of quality route setting a very creative process.

Past Generative Models

There have been a few formally documented generative route setting algorithms. Most notable are the efforts of Phillips, Becker and Bradley [23]. This CU research group used strange attractors to introduce high levels of variance and novelty to routes smoothed over by suggestions from machine learning algorithms that captured traditionally desirable characteristics in routes. In this way, wild and novel movements are coupled with familiar aesthetics [5]. The group created a transcribed grammar to describe sequences of movements and hold types. At a very high level, given a set of ordinary differential equations(ODE),and some characteristic parameters, two $n-point$ trajectories in the state space of that ODE system are generated. The study typically used the classic Lorenz system:

$$x' = a(y-x) \tag{1}$$
$$y' = x(r-z)-y \tag{2}$$
$$z' = xy-bz \tag{3}$$

With a = 16, r = 45 and b = 4. The output trajectories would be mapped back to the "climbing grammar" and then be used to set a new route. A Variable Order Markov Model(VOMM) trained on many human set routes is used to predict several future moves using the same grammar and parsing scheme. The "chaotic sequences" are appended to traditional sequences forming the instructions to set a route. The output is interpretable to a route setter and can be used as an aid or form of inspiration in the setting process. This way, chunks of novel climbing could be interspersed with movement inspired by the model trained on traditional movement. The product was tested in many gyms in Colorado and is being used in certain setting industries to come up with very unexpected ways to challenge high level athletes. This method used parameters such as hold type, size, quality, distance between holds and suggested movement describer. Additionally, there have been a few efforts to predict the difficulty of a climb from an image of the wall the corresponding holds. However such efforts have yielded poor results with a reported accuracy of 35% [9]. This indicates that perhaps some important features of a routes character, such as the hold type and quality, are lost in the pure images.

Psychology and Physiology of Rock Climbing

Monitoring physical exertion through physiological measurement has indicated clear features of strain correlated with different environmental climbing factors such as wall angel, movement distance and depth of edge on a given climbing hold. Comparing these environmental factors with human response can indicate which environmental features are most beneficial to integrate into training practices and route setting. Physiological responses include lactic acid concentration in forearm,blood lactate levels, breath rate, limb force exertion, emitted $V0_2$ concentrations and perceived difficulty. Many studies have found strong positive correlations between lactic, lactate acid concentrations and steep angled climbing. This contributes to a climber getting tired and increases the likelyhood of muscular failure while attempting to complete a climbing route [8], [19]. Additionally, as psychology and visual information processing is an important part of climbing, several experiments looked at how visual route previewing time is related to performance [25]. The study discovered four main previewing tactics by tracking the eyes movements of climbers. Climbers that assessed the route from the ground up as opposed to skipping over sections and looking back afterwards displayed a significantly better performance by completing the route as opposed to following.

Further, small differences in the depth of a climbing holds edge can have immense effects on the climbers ability to stably displace body weight on a hold or series of holds. Synthetic climbing holds can be categorized into several different types by common climbing vernacular. The fundamental hold types include, "Jug" a large easy to use hold, "Pinch", a hold an climber would pinch between thumb and pointer finger, "pocket", a hole feature that can support a select number of fingers, and "crimp", a small edge that will support between 1/8 and 1 full finger tip pad. An experienced climber will employ different strategies to best use these different types of holds. In literature the primary hold that has been formally studied is the crimp. There are three traditional gripping techniques employed to use crimp holds. These techniques are displayed in Figure 2 and are referred to as open hand (A), closed hand (B) and full crimp (C).

Figure 2: Crimping Techniques

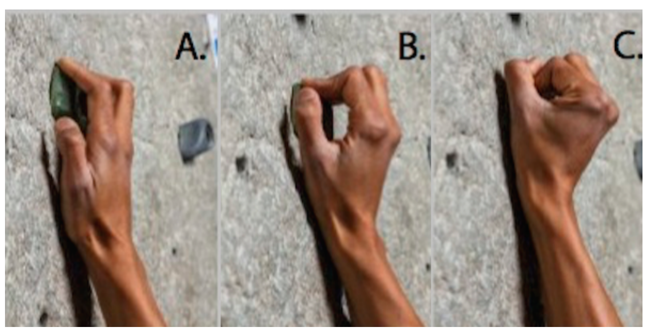


Image Sourced from Robert Husseman

Increased depth in crimp contributes to larger maximal force displacement from standing subjects [16]. Subjects are tasked with pulling downward on a crimp with as much force as physically possible, force is measured by a counter weight[2] or implanted transducers [15]. These methods are still developing and contain reproducibility problems due to vague experimental design []. However in both cases, larger edge depth increases maximal force capacity. This is important for generating enough force to pull upward towards another hold. Reduced maximal force capacity can result in falling. By changing the depth of the crimp, route setters control how difficult it is to move the body upward off of the hold. Additionally, a smaller depth of surface on a climbing hold is associated with increased concentrations of lactate in climbers blood flow following a climbing routine [20]. Further, the crimping technique alters the maximal force capacity [27]. The full crimp technique gains support from the thumb as well as the four fingers and thus allows the climber to generate the most force. The 90* angle made between intermediate knuckles increases the strain on finger tendons and ligaments. The technique of full crimping has been known to cause finger injury [21]. Route setting with very small holds increase the risk of finger injury. In addition to crimp technique and depth of surface, there are some biological features that increase capacity for force. Finger tip pulp,", which is essentially the soft tissue that surrounds the bone of the fingertip. contributes to higher maximum force capacity in a dead hang from small edge surfaces. Finger tip pulp can be increased over time by hanging routinely on very small edges. [4],[24]. Additionally, Fuss et all measures the change in maximal pinch grip force with varied pinch surface depths. The study found that depth had a positive association with holding power while width had a bi-modal distribution. There is threshold in which pinch strength required increases to maintain grip of the hold [12]. These results were also conditional upon the width of the subjects palm.

There have been several efforts to categorize movement phases in climbing by analyzing climbers movements and time-force signatures from transducers embedded in synthetic climbing holds. Fuss is the prominent researcher in this area, conducting experiments with high level athletes in formal controlled setting such as word cups[14] , [13]. Fuss has worked to identify multiple stages of movement universal to climbing at different angles and skill levels. Fuss and others have identified from measurement the stages as a climber reaches for, settles into and shifts off of a given hold. They found that climbers with more experience tend to exert a smaller contact force, short contact time, smaller impulse, larger smoothness factor. Additionally, a higher friction coefficient which represents the tangential force normalized to the normal force, indicates a more continuous movement of the center of pressure on the holds surface, and a smaller Hausdorff dimension. These force-time signatures could potentially be used as a training metric to indicate objective control on a hold. In alternative study, Fuss attempts to classify the difficulty of a climb based on the same time force signatures among a group of equally experienced climbers [15]. It was reported that there is likely too much variability even within the same climbers signal over different attempts for the Hausdorff dimension to be a single feature for difficulty. Fully parameratizing the dynamics of joints and limbs has while a body is climbing has been attempted as well [13]. These attempts involve capturing limb movement in space by equipping climbers with several movement tracking sensors. These studies have also found the three stages of control discovered by Fuss in [15] in velocity signals from a group of subjects movements as they climb on various surfaces [3],[6].

Additional studies have looked a

Crowd Sourcing and Expectation Maximization

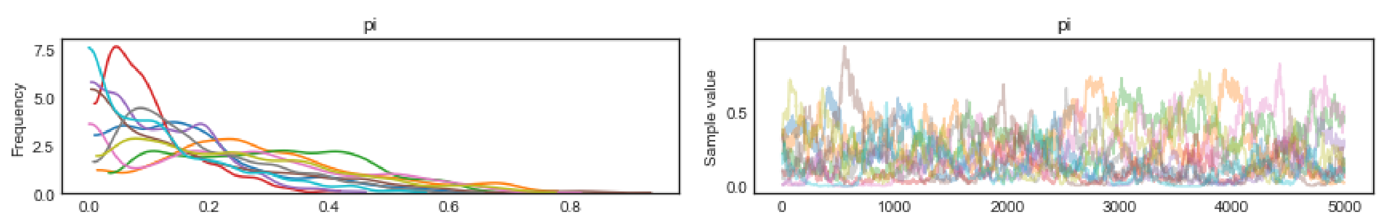
Discussed literature has analyzed crimp and pinch hold types. However, that leaves several other hold types that have yet to be formally categorized. As made evident, the nature of a hold is very influential on a climbs difficulty and quality. However, hold types are not formal constructs and are not assigned by hold manufacturers. Thus hold type detection is a prime candidate for expert crowd-sourcing. There is a rich history of crowd sourcing in classification scenarios. In reCaptcha systems, millions of users are involved in labeling massive sets of images [28]. This technology both ensures web security and crowd-sources image labels. One concern when sourcing label data from large groups is quality. How can one be sure that there are not any malicious actors? At what point is a crowd-sourcing platform compromised by bad data? These questions are raised by Stefanovitch et all [26]. After collecting a data with known malicious sources, the University of San Diego research team analysed the crowd sourcing system under two conditions, under attack and in a normal state. They found that it took very little action from the attackers to bend crowd-sourced tasks out of order and beyond repair. The research team developed a method to classify users as contributors or attackers and then analyzed the behavior of both classes.
Given a noisy set of crowd sourced labels, expectation maximization can greatly improve majority vote in estimating the true label. This group[31] proposes a combination of Spectral Methods and Expectation Maximization to infer the true labels from noisy labels that result from non-expert crowd-sourced data. The proposed algorithm is well suited for multi-class crowd labeling problems. The first step uses the "spectral method" to get an estimate for the parameters.The second state optimizes the objective function of the Dawid-Skene estimator through the traditional EM algorithm. The second step improves the estimation of the parameter over iteration. Since the likelihood function is non convex, there is no guarantee that the global optimum will be found under iteration. However, the new method proves minimax rates of convergence up to a logarithmic factor. For any confidence level σ, the bounds can be calculated on the number of workers and the number of items need to correctly estimate the labels of all items [7],[18].

Methods

1.0.1 Data Collection

Data was aggregated from three independent sources, directly from the moon-board website, crowd-sourced and manual measurements. Data describing 40,217 unique routes were scraped from the moonboard web application site [1] iterating over a generic cURL script that redirected AJAX responses to a local directory. Of the 40,000 routes, 23,399 were considered for analysis as they used a the conventional hold spacing and angle scheme. Data was collected in the JSON format containing the coordinates of all holds on the route, user consensus quality and difficulty ratings as well as some information about the facility the climbing wall was hosted in and the individual that generated the climb on the mobile app. The moonboard data set contains great information at the route level, but lacks information specific to each hold. As the literature suggest, variance in the hold characteristics effect a climbs difficulty. Obtaining labels for the hold type represented an important feature that distinguishes one climb from another when controlling for different variables. Hold labels were crowdsourced from a selected group of experience moonboard users. Each worker was tasked with labeling a random 20 subset of the full 139 hold set. The true labels were then estimated via the Dawid - Skene Expectation Maximization algorithm implemented in pythons PyMc3 library.This model assumes that workers operate independently from one another, which was true in the data collection process. As discussed in the literature [22], this method has been shown to be more effective then the simple majority vote option.

Figure 3: Trace Plots



Referencing the left portion of the Figure 2, the posterior distribution is skewed and not centered normally about a value. We see on the right that there is not quite evenly distributed noise from each of individual samples of reported labels. This is an indicator that the Expectation - Maximization(EM) performance may be suffering from lack of examples.

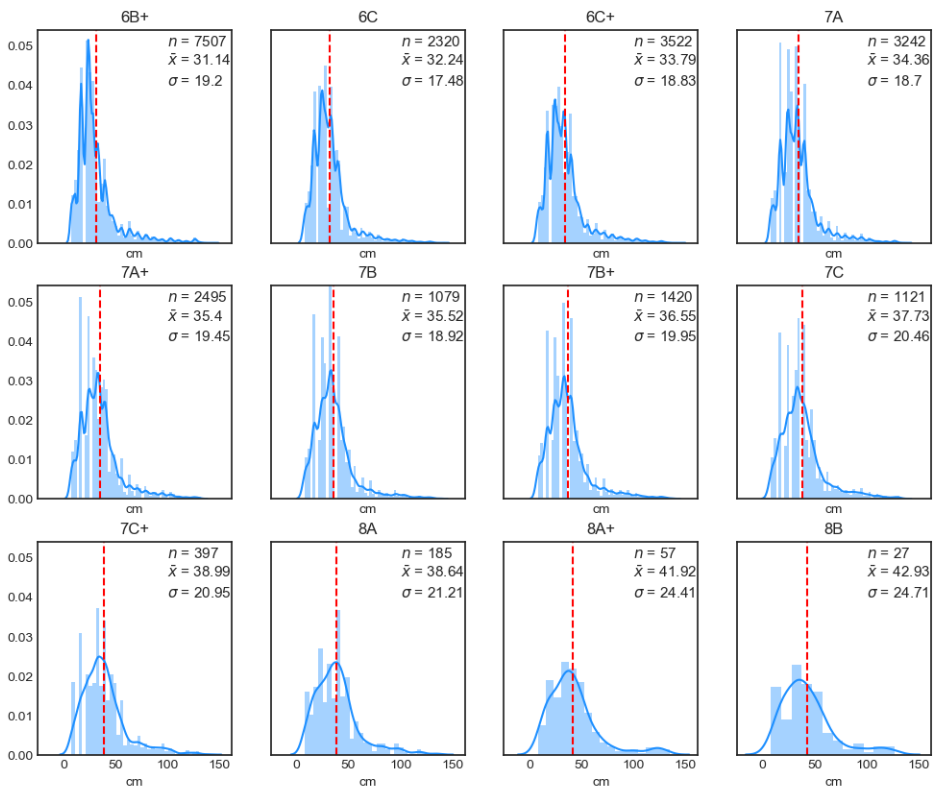
Finally, one last feature was engineered by manually measuring the maximum depth of each hold on the moonboard. Measurements were taken at a 0.01 cm precision level using a scientific ruler. Measurements were taken with the ruler parallel to the surface being measured. See Figure 3 for clarifying example.

Figure 4: Measurement Procedure

Data Exploration

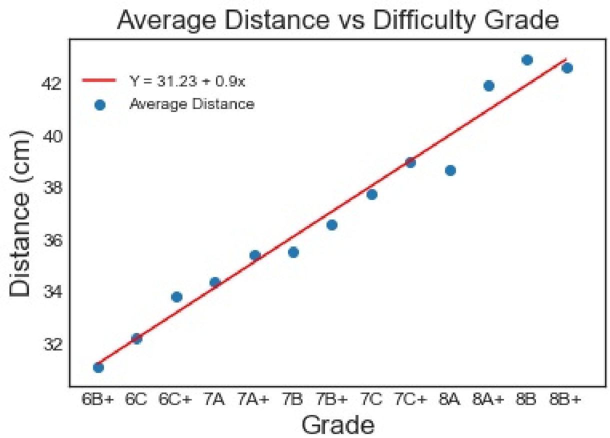
We examine the distributions of meaningful covariates across different levels of quality and difficulty to confirm expectations on covariate relationships suggested in literature. We first examine the movement distance distributions at each difficulty level represented by the data (6b+ , 8B).

Figure 5: Movement Distance Distributions Across Difficulty Grade



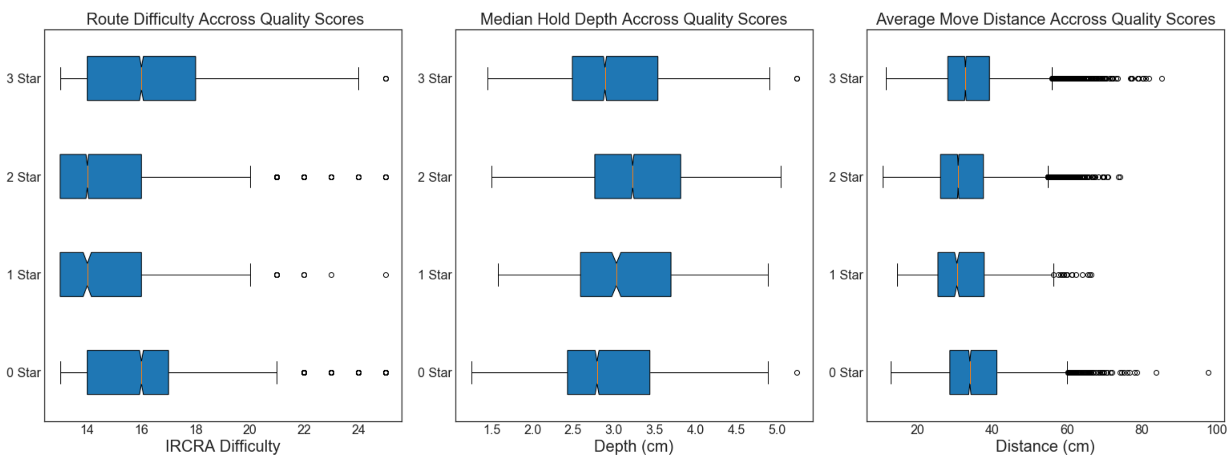
in Figure 5, we see that on average, the distance between holds increases across the distribution of grades. Additionally, the distribution widens among moves that belong to harder climbs. If we use the arithmetic mean as the central tendency, then the mean distance has a good linear fit with climb difficulty. The model in Figure 6 reports a spearmans r^2 value of 0.94, indicating a good fit. For every step up in difficulty the average movement distance in a route of that grade is associated with an increase by 0.9 centimeters.

Figure 6: Movement Distance Distributions Across Difficulty Grade



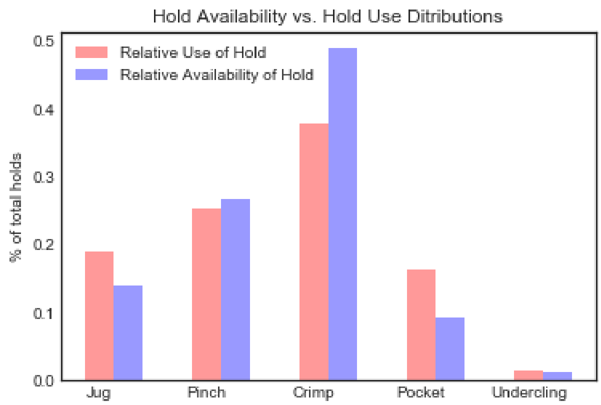
Further, we examine how covariates change among the different quality groups. We are interested to see if there is a distribution of preferred edge depths, movement distances, hold types and difficulties.If there are distributions of these variables that are unique to climbs are high quality, this can inform generative route setting algorithms.

Figure 7: Movement Distance Distributions Across Difficulty Grade



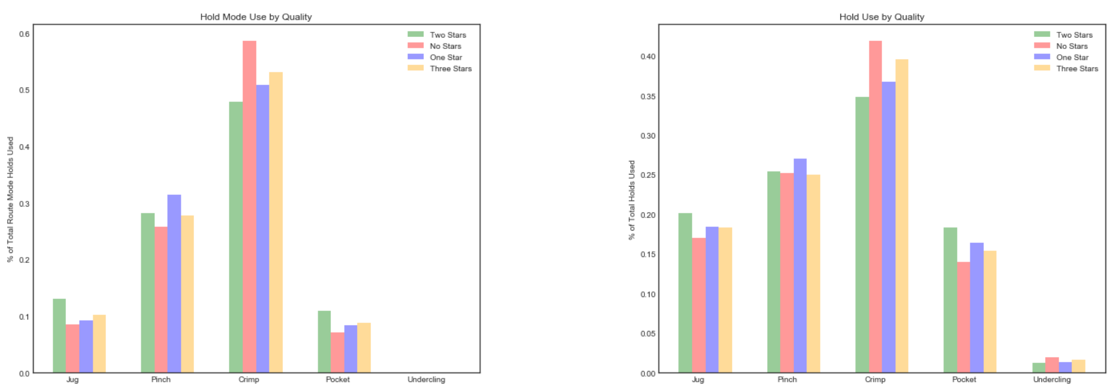
We see that the distributions of higher quality groups of covariates are different. From the boxplots in Figure 7, we note that higher quality routes contain larger variability in the spread or levels of the variable. The hold type feature is categorical with 5 classes, "Jug","Crimp","Pinch", "Pocket" and "Under-cling". These hold general types are used to describe most artificial climbing holds. The distribution of hold types used on rock climbs in the data is displayed in Figure 8. These data are compared to the distribution of available holds.

Figure 8: Hold Use and Availability Distributions



We see that more or less, these two distributions are the same. A 2 sample Kolmogorov - Smirnof test does not indicate that the two distributions are significantly different from one another. The distribution of the holds used on climbs is not significantly different from the distribution of holds available. This indicates that there are certain holds that are used more often then others when accounting for the availability of each hold type. The next question is whether this is also true of hold types within each quality score.

Figure 9: Hold Type Distributions Across Quality Classes



(a) Mode of Distribution

(b) Full Distribution

Part (a) of Figure 9 displays the mode hold from each route while Part (b) displays the aggregate hold distributions from all of the routes across the different quality classes. We notice that they are fairly similar, however when we take the mode, the signal from the under-cling hold use is lost, resulting in a change of proportions. However, the ordering is unchanged. In both images (a) and (b) of Figure 9, we see that there is some variance between quality scores. Within every class of quality, crimps are used dominantly, followed by pinches, jugs, pockets and then under-clings. Figure 3 suggests that this is possibly due to availability of these hold types and not to a preference expressed in the data. However, we are not seeing one type of hold being used more frequently than others with respect to the holds available.

An initial MANOVA examined average depth, distance, hold type and difficulty as covariates and the four levels of quality as a dependent grouping variable. This showed a significant multivariate effect for all four groups in relation to each of the covariates with p <.001 . We then proceed to a univariate analysis which indicates that each group is significantly different within each covariate. In the results section, we discuss these differences by comparing the the odds ratios from a logistic regression model.

Results

Data exploration lead to the purposeful selection of covariates average depth, difficulty, average distance and mode hold type in predicting the user reported quality of a route. We propose a one versus rest logistic regression model.

Table 1: Full Logistic Regression Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.67	0.11	-6.22	0.03
Difficulty	0.16	0.001	24.62	<0.01
Avg. Depth	-0.16	0.03	-5.50	<0.01
Hold Type	-0.65	0.13	-4.73	0.01
Avg. Movement Dist.	0.85	0.01	1.76	0.02

Following the "Four step method" as described by Hosmer [17], we calculate the odds ratios of the covariates in the main effects model. Odds ratios are found by exponentiating the model coefficients. However in case of the continuous covariates the product of the coefficient and the linear step are exponentiated. These results are presented in Table 2.

Table 2: Model Main Effects with p < .05

Covariate	O.R.	95% Conf
Difficulty*	1.17	(1.16,1.19)
Avg Hold Depth**	0.92	(0.801, 0.900)
Mode Hold Type	0.52	(0.396, 0.680)
Avg Move Distance ***	1.82	(1.65,2.24)

* Difficulty in step size of 1, ** Avg Hold Depth incremented by 0.5 cm , *** Avg Distance incremented by 3 cm.

Interpreting the estimated odds ratios, we conclude that the odds of a route receiving a three star rating increase by a factor of 1.17 for every 1 unit increment in difficulty, further, an increase in hold depth by 0.5 cm is associated with a 8% decrease in odds of three star rating. Alternatively, the hold type "pocket" is associated with a 48% decrease in odds of a quality route with respect to all other holds types. Finally, the average movement distance on a route is protective of route quality with an odds increase by factor 1.82 cm. The model has a fairly low adjusted R^2 of 0.36.

Discussion

Using three different data sources, we produce an analysis of climbing routes on the Moon Board training wall. Because the Moon Board is a standardized climbing wall associated with a data base of user generated routes, this data set provides a very unique vantage to analyze popular climbing movement. In the past, studies have analyzed how people climb by measuring force imparted on climbing holds or attaching censors to climbers as they move. These methods require expensive equipment and the observation of many subjects. An analysis of the moon-board data is proxy for similar information but is free and provides a significantly larger data set. Past studies have not exceeded 20 climber subjects. This study suggest a model that explores the preferences expressed by climbers at different grades.

There is potential for much more analysis using the moon board data. Expanding the labeling of holds to the other moon board set ups would add an additional angle to the potential covariates, expressing an additional 20,000 climbing routes and 20 more unique holds. Additionally, conducting an analysis of preferences at each difficulty level would expose potential differences between experienced and novice climbers.

Generative Algorithm

A generative algorithm following a markov process is implemented to automate route setting tasks. By indicating a desired set of starting holds and a desired difficulty level, a random sample from the high quality covariate distributions of the desired grade is made. The next hold is selected by maximizing the similarity in available holds to the union of these samplings. This process is repeated iteratively with the condition that the future hold must be above or lateral to the past hold. The cycle ends when two lateral holds on the highest row of the board are reached. This algorithm is a naive model that can be heavily improved in the future.

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