MOUNTAIN PROJECT

A Rock Climbing Route Recommender System

General Assembly DSI Capstone Project
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Talk Outline

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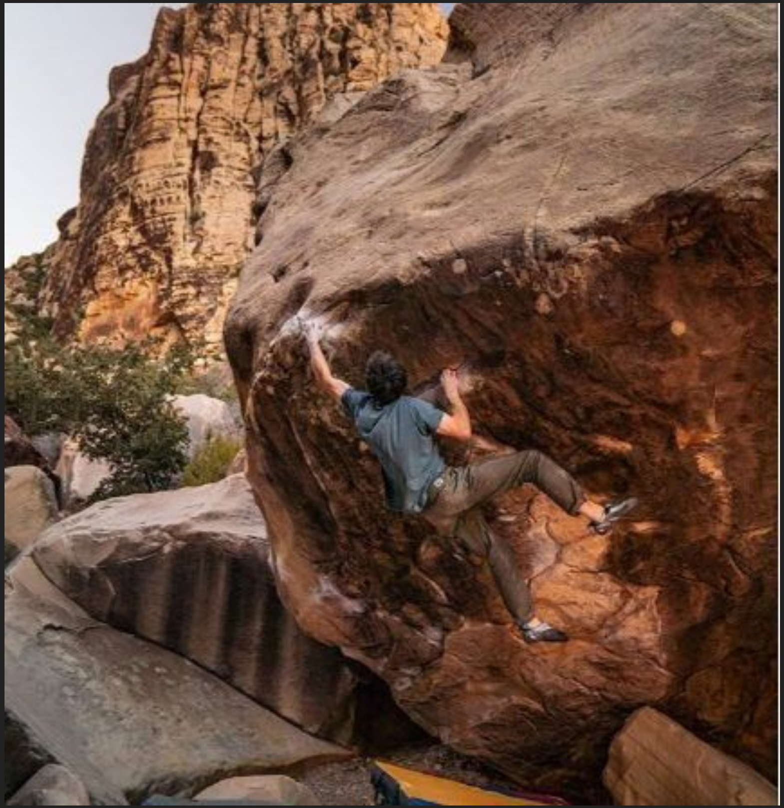
Rock Climbing Overview

Rock Climbing Overview

There are many distinctive styles of rock climbing, however in this project we focus on the 3 most popular variants:

1. **Bouldering**

   Climbing small(er) rock formations, without the use of ropes for protection. Crash pads are used to soften any falls.

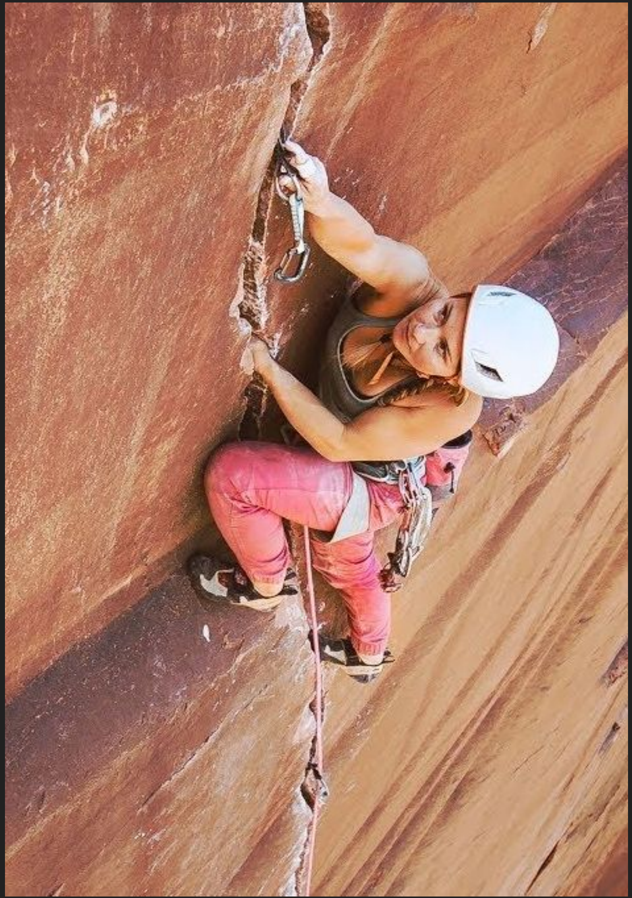


2. Sport Climbing

Climber and rope both start on the ground. As they climb, the climber is protected by clipping the rope into carabiners (‘quickdraws’) which they attach to permanent brackets/hangers (‘bolts’) at various points along the route. Sport climbs require someone to first permanently ‘establish’ a route by drilling in the fixed bolts other climbers will use.

3. Traditional (Trad) Climbing

Like sport climbing, the climber and rope both start on the ground. However, there is no permanent protection drilled into the rock. The climber brings various devices to wedge into openings in the rock and clips the rope into these self-placed pieces of protection. This adds another layer of danger as poorly-placed pieces of protection can fail/pop out.



Climbing Grades

There are various international rating scales to indicate the difficulty of a climbing route. In the USA two main scales are used: The Yosemite Decimal System (YDS) for Sport/Trad and the Hueco V-scale for Bouldering.

Current Max Grades:

Sport: **5.15d** (only done twice!)

Bouldering: **V16**

BEGINNER (Perfect for beginners. These climbs will primarily contain jugs but will increase in difficulty of movement.)	5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.8, 5.9
INTERMEDIATE (Climb on! These climbs are difficult to define as the holds and movement will vary. It is around here that we see holds get smaller and movement get more ineresting.)	5.10a, 5.10b, 5.10c, 5.10d, 5.11a, 5.11b, 5.11c, 5.11d
ADVANCED (Now we're getting there! These Climbs require a ton of climbing experience and strength. You will probably only see a handful of crushers on these routes at the gym.)	5.12a, 5.12b, 5.12c, 5.12d, 5.13a, 5.13b, 5.13c, 5.13d
PRO (This level of climbing is at the cusp of our sport. These climbs will only be found outdoors and at top level comps.)	5.14a, 5.14b, 5.14c, 5.14d, 5.15a, 5.15b, 5.15c

BEGINNER (Great starters, most holds will be jugs. Hand, hand, foot, foot.)	V0, V1, V2
INTERMEDIATE (Tough to draw lines. Holds will get smaller and movement more advanced. The majority of climbers at this level. Guidebooks refer to these as moderates.)	V3, V4, V5, V6
ADVANCED (Tough problems. Likely what the crew of strong guys are crowded around at the gym.)	V7, V8, V9
PRO (A lucky few can climb these "off the couch." Lots of training required to get here.)	V10, V11, V12, V13
.01% (Done by a handful of the worlds strongest climbers.)	V14, V15, V16

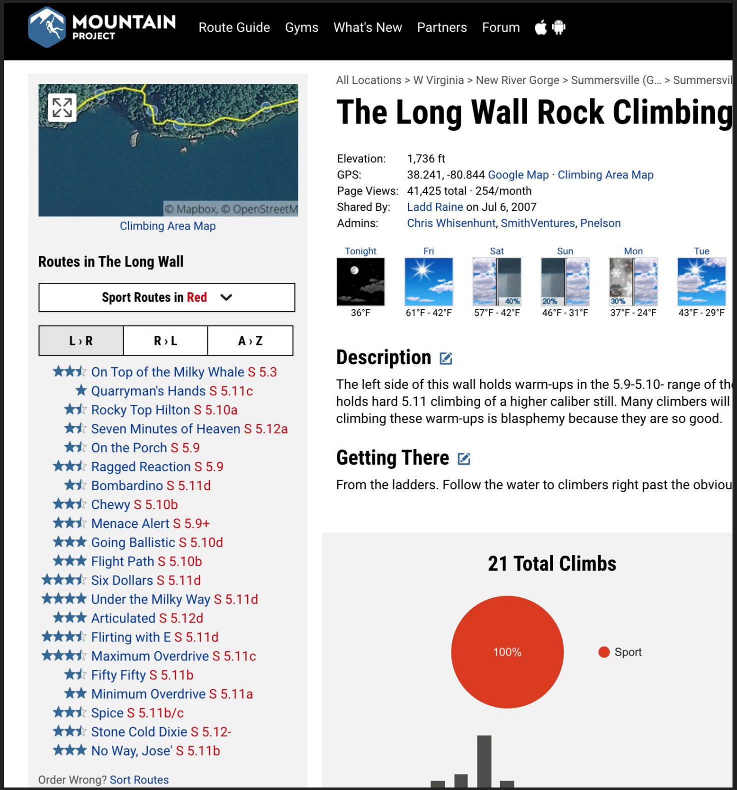
Source:
https://sportrock.com/understanding-climbing-grades/

Mountainproject.com Overview

Mountainproject.com

Mountain Project (www.mountainproject.com) is an online rock climbing community site that serves as a digital guidebook for over 230,000 rock climbing routes in over 55,000 areas across the world.

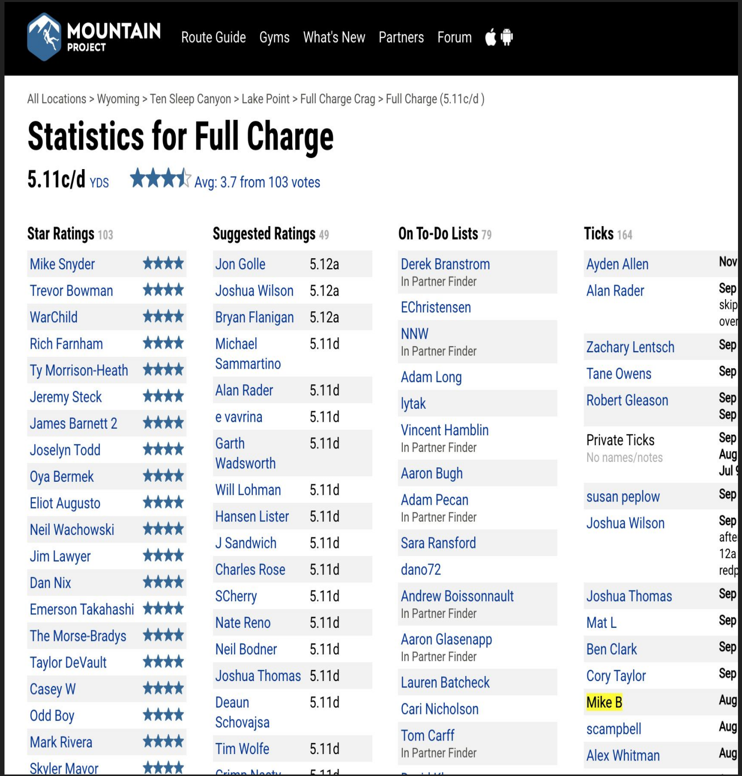
Content is user-submitted and includes information for individual routes including: Location, photos, description, difficulty, quality, photos, comments, and more.



Mountain Project Star Ratings

Users are able to log of their attempts at specific climbs as well as give ‘star ratings’ to a climb, indicating their opinion of a climb’s quality. These ratings are on a scale of 0-4.

While users can do searches of areas by climb type/difficulty, there is no personalized recommendation system in place.



Problem Statement

Implement a climbing route recommender system for mountainproject.com which bases recommendations on a user's rating history.

The Data

Mountainproject Organization

Mountainproject is organized in a tree-like directory structure consisting of ‘area’ pages and individual ‘route’ pages.

An area page may contain either links to route pages or smaller sub-areas, but not both.

Both areas and routes are identified using a unique 9-digit id.

Users are also identified using a unique id (of varying length).

Scraping Mountainproject.com

We use the requests and BeautifulSoup packages to recursively scrape and parse an entire state's directory tree.

We save useful information about areas (names, IDs, GPS coordinates, elevation, sub/parent areas) and routes (name, ID, description, grade, average star rating, number of votes, full list of user ratings, number of pitches).

Currently (~2 weeks of scraping):

- 32 full states scraped
- 75,211 unique routes in 17,000 unique area
- 1,171,869 star ratings from 39,367 users

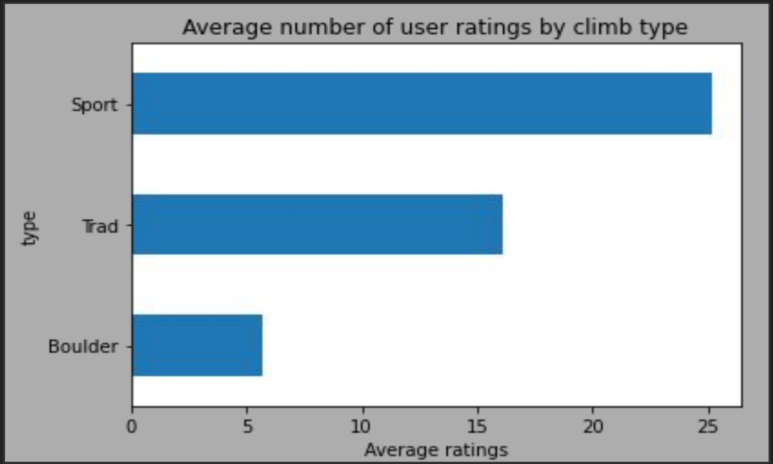
Exploratory Data Analysis

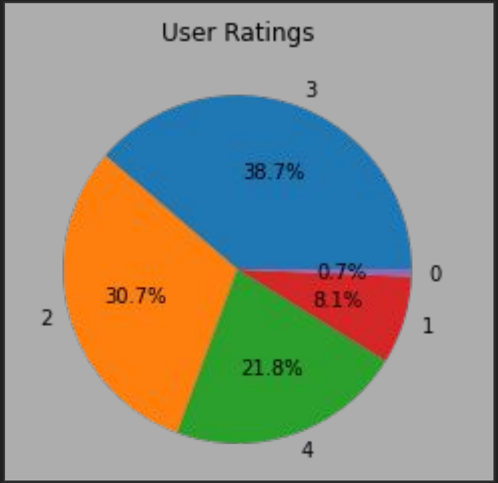
Average route score: 2.409

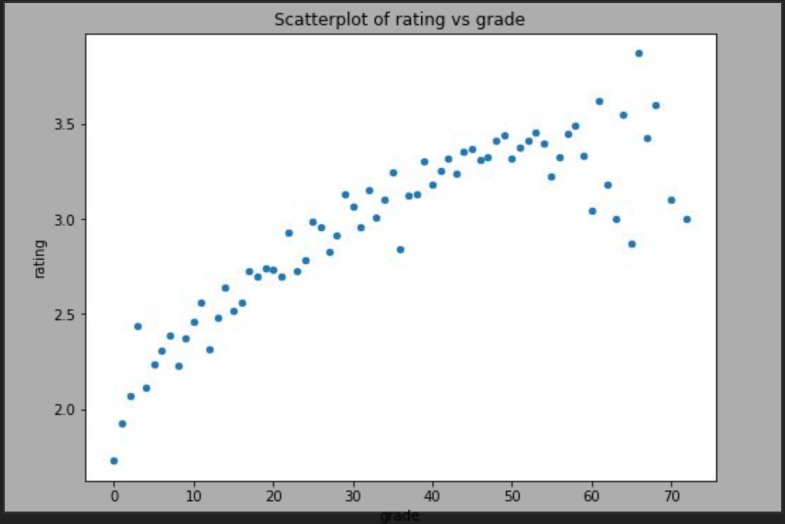
Average user star rating: 2.729

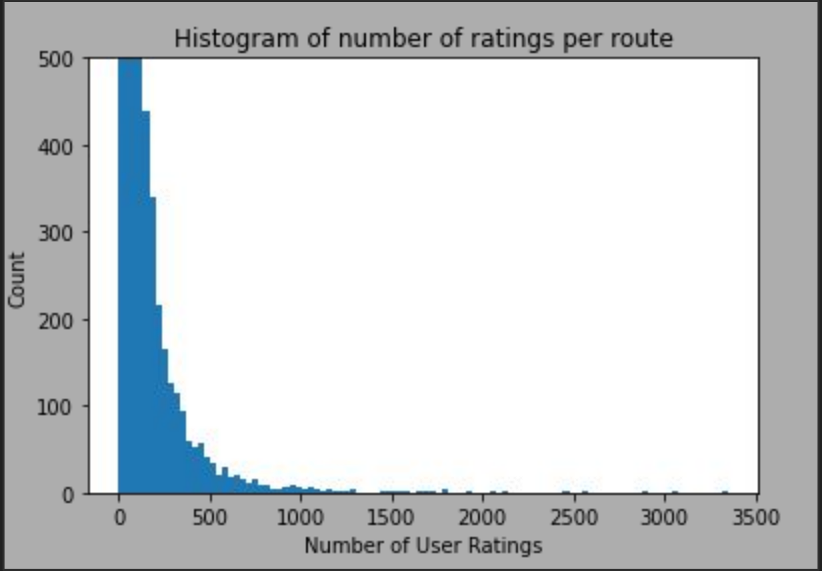
Average votes per route: 15.62

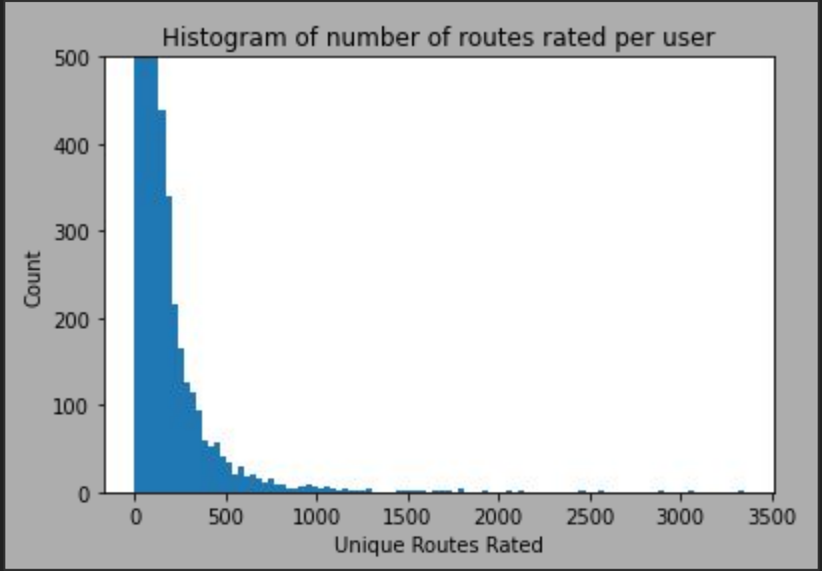
Average routes rated per user: 29.77











- Many users had very few ratings ~9000 with only one rating
- Many routes had few ratings ~21000 with only one rating
- We removed users who voted on fewer than 10 routes, and routes with less than 10 votes. This was set somewhat arbitrarily, and future work will include treating these cutoffs as hyperparameters and tuning them.

Recommender Systems

Overview

The goal of a recommender system is to recommend new items to users.

Two Broad Categories:

1. Collaborative Filtering - Based on past interactions between users and items. Users who liked the same things in the past will like the same things in the future. Interactions can be either explicit (user up/downvotes or ratings) or implicit (page views, clicks). This is the method we used in our system.
2. Content Based - Based on extra data about users (preferences, age, location etc.) and/or items (descriptions, genres, etc.)
3. Hybrid approaches combine elements of both collaborative/content based methods.

Collaborative Filtering (CF)

The relevant data can be stored in an user-item interaction matrix:

	Route 1	Route 2	Route 3	Route 4	Route 5
User 1	1	3	0	4	2
User 2	1	?	1	4	2
User 3	4	2	0	4	1
User 4	?	?	2	?	?
User 5	0	0	1	?	4

Goal: Try to predict a user's rating for unrated items using ratings from other users (collaboration).

Memory Based Methods: Use the entire user-item interaction matrix to make predictions. (Ex: Use previous ratings to compute a similarity between each user, then use this similarity to make a weighted average for a new prediction).

Model Based CF: Use machine learning techniques to form an abstracted model of user ratings and generate new prediction based on this model. Examples include Bayesian Networks, clustering, and SVD/matrix factorization methods.

SVD Based CF Models

Basic Idea: Model users and items as vectors in an *f*-dimensional ‘latent factor space’ - the predicted rating between User *u* and Item *i* is given by the dot product of their vector representations. The goal of the algorithm is to learn these latent factor representations.

- Set of Users
- Set of Items
- Set of known past ratings between a subset of users and items
- Dimension of representation space *f* (Hyperparameter)

Modeling/ Learning

- An f-dimensional vector for each user: $\mathbf{p}_u$
- An f-dimensional vector for each item: $\mathbf{q}_i$

Prediction

Predict an unknown rating r_{ui} between User *u* and Item *i* as the dot product:

$$r_{ui} \approx \mathbf{p}_u \cdot \mathbf{q}_i$$

If K is the training set of known ratings, the embeddings are found by minimizing the regularized loss function:

$$\sum_{(u,i)\in\mathcal{K}} \left[(r_{ui} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda(||\mathbf{p}_u||^2 + ||\mathbf{q}_i||^2) \right]$$

Error between actual (r_{ui}) and predicted ratings ($\mathbf{p}_u \cdot \mathbf{q}_i$)

Regularization term

Minima are typically found using either stochastic gradient descent, or alternating least squares.

- ‘Bias’ terms can be incorporated to account for the fact that often either 1. Certain users tend to always give lower/higher ratings than other users and/or 2. Certain items tend to always receive lower/higher ratings than other times.

- SVD type models are widely used, and the winners of the famous Netflix Prize (https://www.netflixprize.com/) relied heavily on SVD/Matrix factorization type models.

The `surprise` Python package

We use the Simply Python Recommendation System Engine (`surprise`) package (http://surpriselib.com/), which includes a variety of recommender models and various features such as cross-validation and grid searching.

We performed 5-fold cross-validated gridsearch tune hyperparameters.

Tried other models (KNN, SVD++) but SVD was by far the fastest to train, and required a relatively small amount of memory.

Our best SVD model had RMSE of about 0.64.

Streamlit Demo

Future Work

- Incorporate the other types of climbing available on mountainproject.
- Run GridSearch longer and take time to evaluate other models.
- Address the ‘Cold-Start’ problem: How to handle new users/routes with no ratings.
- Develop a hybrid recommender which incorporates route descriptions and/or user preferences. (Can we use NLP + climb descriptions/comments to classify a climb in a certain ‘style’?)
- Build a more user-friendly web app (e.g. does not require area_id lookups, more interactive map)

Thanks!