Evaluating Bouldering Route Difficulty

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Problem Statement

In rockclimbing, the difficulty of climbing routes is classified using a grade given by climbers, generally depending on the length or style of route, the challenge of the required moves, and how dangerous climbing conditions are. As a result, climbing grades are very subjective as they depend on a collective human assessment and the many existing grade scales are rather ambiguous when it comes to distinguihsing between closely related difficulty classes. This presents a challenging task in attempting to accurately predict the assignment of climbing grades using machine learning, with the potential to benefit the performance of climbers (particularly when training) and to aid in improving the ambiguity of standardized scales.

With this project, we would explore predicting the climbing grade of Bouldering problems, climbing routes that are for free climbing without ropes or harnesses that are generally no higher than 6 metres, using the Hueco scale (V0 - V17).

Data Collection and Data Processing

To explore this challenging task, we would use climbing route data collected from https://www.moonboard.com/. Moonboards are a standardized climbing wall made up of 142 rock holds on a 18x11 grid that are used for indoor bouldering training. Moonboard climbers utilize an app to load a problem route to the board, the sequence of holds marked by illuminated LEDs, so a large dataset of problems has been created by Moonboard and community users (over 30k problems were scraped by Duh & Chang in their 2021 work using RNN models for classication and route generation).

The Moonboard route can be effectively encoded as a $0, 1^{(}18 \times 11)$ matrix to serve as a graphical representation of the board, which can then be one-hot encoded (or multi-hot) to prepare the representation for input to the neural network. Essentially, the encoded climbing routes will allow the neural network to look for patterns and simliarities between climbing grade classes and learn to distinguish problems appropriately, particularly since the climbing routes will follow a standard format as described above.

Approaches

We would explore this classification task by experimenting with a more advanced Convolution Neural Network architecture (potentially) than in previous works, and apply this architecture to the Moonboard dataset for training and testing.The Moonboard dataset will first need to be scraped and prepared with basic cleaning and pre-processing (e.g. standardizing the grade scale to use Hueco instead of a European scale for instance). Data will need to undergo a hot-encoding process or similar to prepare to be inputted to the neural networks.The Neural Network architecture will be designed and implemented to be applied to the climbing route data, with experiments addressing different activation functions, learning rates, and other parameters or normalization will be conducted to illustrate the network's performance and fine-tuning processes. Following experimental results, we will revisit our experiment design (or network architectures) as necessary with time permitting to investigate the performance more closely (e.g. look to what sorts of climbing routes were often misclassified, impact of learning rates, etc.). Results from our experiments will be discussed thoroughly in our final report, with special attention to illustrating the theoretical understanding of the problem and the performance of our models.

Related Works

Dobles et al. (2017)

Dobles et al. (2017) employed and evaluated Naives Bayes, softmax regression, and Convolutional Neural Network classifiers to attempt to determine the difficulty grade of climbing routes, specifically using a dataset collected from Moonboard.com to standardize the data. They yielded the following results for each classifier respectively, 34.0% 36.5% 34.0% [Dobles et al., 2017].

Duh & Chang (2021)

Duh & Chang (2021) employed RNN architectures to explore classifying Moonboard climbing route grades and to generate new Moonbaord routes. Their 'GradeNet' architecture achieved 46.7% accuracy upon testing [Duh and Chang, 2021].

Tai et al. (2020)

Tai et al. (2020) applied Graph Convolutional Neural Networks (GCN) architectures previously used in NLP applications to classifying the climbing route grade of Moonboard problem sets, with their top model achieving an average AUC score of 0.73 across all classes [Tai et al., 2020].

References

[Dobles et al., 2017] Dobles, A., Sarmiento, J. C., and Satterthwaite, P. (2017). Machine learning methods for climbing route classification.

[Duh and Chang, 2021] Duh, Y. and Chang, R. (2021). Recurrent neural network for moonboard climbing route classification and generation. *CoRR*, abs/2102.01788.

[Tai et al., 2020] Tai, C.-H., Wu, A., and Hinojosa, R. (2020). Graph neural networks in classifying rock climbing difficulties.