Knowledge-Based Recommendations for Climbers

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Abstract
Climbing is a popular sport and recreational activity. Unfortunately, there is a lack of technologies for supporting climbers in choosing what climbing route to climb next. We introduce a project aimed at developing a Climbing Recommender System for suggesting routes that are suited for training and practicing sport climbing. We model a climber by relying on both explicit and implicit feedback. Implicit feedback is acquired by an automatic activity recognition component (in climbing gyms), while explicit feedback is acquired by means of a mobile application. We also present a recommendation approach based on the prediction of the subjective evaluation of climbing routes' difficulty. In fact, often climbers perceive the difficulty of a route differently from the official grade. The prediction method is based on the analysis of how climbers deviate their assessment of routes' difficulty from the official difficulty grade, and it generates explanations for the predictions.

Keywords
recommender system, climbing, knowledge-based, explanation

1. Introduction

Climbing guidebooks provide climbing enthusiasts with important information about available climbing routes. Actually, new climbing routes are continuously developed, either indoor (climbing gyms) [1] or outdoor [2], and this large set of alternative routes makes it difficult for any climber, either novice or expert, to make the right choice. There is a clear need for Climbing Recommender Systems (CRS) that could support climbers in choosing the most suitable next routes. Ideally, such a system should manage all the aspects considered by climbers in their choices. The recommended routes should be: suitable for training, challenging but within their capabilities, enjoyable, compatible with the contextual situation (weather conditions), and good for a group of climbers. Building such a system requires knowledge about climbers' preferences, their physical and technical level, the group's characteristics, and, importantly, the climbing routes' characteristics, such as, difficulty grade, location, and safety level. This can be acquired and delivered by means of a well-designed human-computer (mobile) interaction where climbers can leave explicit feedback about the routes they climbed. Moreover, sensor data (body and device sensors) should be used to implicitly detect climbers' activities and performance.

Unfortunately, current sensing technologies for climbing are at an early stage of development, and furthermore, there is no implemented methodology to collect data on a big scale. Moreover, it is unclear what the real needs of climbers are and how the human-computer interaction of the CRS should be designed.

Recommender systems (RS) for climbers have not yet been proposed in the scientific literature. RSs for similar sports, such as running [3, 4, 5], hiking, or trekking [6, 7], have instead been developed. Hiking is probably the most similar sport; here the difficulty of a hike, the potential risk of hiking above the hiker's technical skills and physical condition, the weather conditions, and the hiking group composition, are important aspects as well. Calbimonte et al. [8, 9] have proposed an RS for hiking trails, where recommendations are adapted to the hiker's profile, describing the current physical level and preferences, which are obtained by explicitly querying the user. Similarly, the work of Vías et al. [10] presents a simple approach for recommending hiking routes based on search criteria, such as, hike's difficulty, and duration. The core approach of these works lies in building a knowledge-rich user and item profile and then recommending hikes that match the characteristics of the hike to the explicitly formulated needs of the hiker. More advanced RS, but for runners, are able to leverage the athlete's physical level that is measured via activity tracking sensors [11, 12, 13, 14]. These technologies have not yet been exploited in sport climbing, as there is a lack of effective and easily available activity recognition technologies and devices for this sport [15, 16, 17, 18].

Clearly, there is a need for novel research in this area, as current hardware and software technologies are not sufficient for semi-automatically building any form of climber's profile. This is a prerequisite for suggesting suitable climbing routes on the basis of the climber's needs and capabilities. We here first describe the required profiling of climbers, and then we introduce a CRS for

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outdoor climbing routes suggestion.

2. Routes Recommendation

We describe the results we have obtained in developing a knowledge-based CRS. Recommendations are generated by understanding users' characteristics (profile), which are obtained by semi-automatically analyzing their behavior [19]. We consider two types of sources of climber-related knowledge, which are acquired by means of either implicit or explicit feedback [20]. Implicit feedback is collected through sensor data analysis, in order to automatically detect the climber's performed activities, i.e., which route was climbed and how the climber performed (e.g., the duration, or the effort made). Explicit feedback relates instead to climbers' manual input, typically describing the experience of climbing a route, such as, the safety of the route, or the perceived difficulty. In order to collect this type of data, we are collaborating with Vertical-Life (www.vertical-life.info), which offers a mobile application for climbers. We plan to augment their application with recommendation technologies.

Related to implicit feedback, we have developed some initial solutions and technologies for activity detection, which are currently designed only for indoor lead climbing. We have employed a 'smart quickdraw sensor' [21]. A standard quickdraw is a piece of climbing equipment used by climbers to allow the climbing rope to run freely through protection such as a bolt anchors, hence it is used for securing the climber at a specific point on the climbing route. A smart quickdraw is a regular one augmented with an accelerometer. The movements of the rope, used for securing the climber, are propagated to the quickdraw. Then, they are detected by the sensor and sent wirelessly to a computer for data analysis. By using this 'smart quickdraw sensor', we were able to detect with an accuracy of 93% the activity of 'rope pulling', which happens shortly after the climber finishes an ascent and when she removes the rope from the wall. Recognizing rope pulling is instrumental in measuring the number of ascents made on a line equipped with this sensor, and it can also be employed to distinguish beginners from expert climbers [22]. More sophisticated data analysis has also shown that the energy of the quickdraw movement can be used for climber's performance measurement. In addition to this, we employed video cameras to detect when the climber is lowered to the ground after her ascent is finished [23]. We plan to adopt a similar solution also for outdoor climbing.

Explicit feedback data, includes instead the subjective evaluations of ascended routes' difficulty grades, which are often registered by climbers after they have climbed a route. By using this data we aim at predicting the subjectively perceived difficulty of a route, which would be assigned by the climber to the route. This prediction can be used to recommend to the climber routes that are in the right difficulty range for her. In order to address this task, we have applied data mining techniques to explicit feedback data collected by means of the Vertical-Life mobile app where climbers can rate, grade, and comment on routes that they have climbed. Our work is motivated by Draper [24], who reports that climbers often have different opinions about the difficulty grade of the same route. The app offers climbers the possibility to express their disagreement with the 'official' climbing grade of a route, as it is given in the guidebook. We have adopted a knowledge-based approach to understanding the reasons of such disagreements. We have compared the predictions, for the subjective evaluations of routes' difficulty, generated by a regression model, based on features aimed at capturing why climbers disagree with the official grade, to a standard collaborative filtering algorithm.

2.1. Route Grade Prediction

We focus our investigation on ascents performed on routes located in mountains and crags in the lead style; however, the approach described below can be extended to ascents performed in climbing gyms and other climbing disciplines, such as bouldering.

The data set of climbers' entries into the mobile app about their ascents is summarized in Table 1. The data set is restricted to the most frequently climbed route grades. Grades are represented with integers ranging from 6 (5a) to 22 (7c). Observed deviations of climbers' grades with respect to routes' official grades range from -3 to 3. It is important to note that, on average, the climber's grade coincides with route's official grade in 92% of ascents.

Table 1
Data set of climbers' ascents description. '% climber grades' refers to the percentage of ascents where the climbers gave an explicit grade evaluation that differs from the official one.

	Outdoor climbs
# climbs	157,576
# climbers	2,624
# routes	10,738
% climber grades	8%

The first personalized grade prediction method, which we call 'knowledge-based' uses a linear regression model, for which we generated features representing climbers-routes interactions. The assumption is that the official difficulty of the routes, as defined by the route setters may also depend on their skills, while a climber's perceived difficulty of the routes may depend on the climber's physical level and on contextual conditions (e.g., the season). Therefore, we included the time factor, as the outdoor routes can change with the time (rocks might deteriorate, equipment might break): we generate similar features which take into consideration the specified time interval limit. As a result, we predict the climber's perceived grade as a linear dependent variable from the identified features.

Assume that we have a target climber c, and a route r. We are interested in the prediction $\widehat{grade}(c,r,t)$ of how climber c would grade the route r at a particular point in time t. The predictive features that we have introduced are as follows:

- $ograde(r)$: the 'official' route difficulty grade.
- $md(r,t)$: given the grade assessments of climbers who previously climbed the target route, before time t, we compute the average deviation of these grades from the route's official grade $ograde(r)$.
- $md^Y(r,t)$: this feature is a variant of feature $md(r,t)$ such that only the final year and a half of data collection is included for feature computation. The feature is meant to capture change in the difficulty of an ascent that may result from deterioration of the rock over time due to frequent climbing activity (the so-called *polished* routes) or recent maintenance work.
- $cmd^M(c, ograde(r), t)$: given the grade assessments of the target climber c, before time t, for routes of the same official grade $ograde(r)$, this feature expresses the mean deviation of these grades from $ograde(r)$ within a three-month period in the final year of data collection. This feature is supposed to capture the influence of environmental conditions on a climber's perception of route difficulty. For example, climbing outdoors in the summer months is typically considered as harder than climbing in the spring.

As we have noted above, climbers do not often deviate with their subjective evaluations of route difficulty from the official evaluations. Hence, a strong *baseline* method for predicting $grade(c,r,t)$ is actually using directly $ograde(r)$.

In addition to this baseline prediction method, we compare the predictions generated by the above-mentioned linear regression knowledge-based model with those computed by a standard collaborative filtering (CF) algorithm. In the application of collaborative filtering, we model the grade prediction task as a special rating prediction problem, where the rating of a route is the *deviation* of the climber's grade from the official grade, namely: $grade(c,r,t) - ograde(r)$. We use matrix factorization, namely singular value decomposition (SVD), to generate such predictions [25]. We note that the rating matrix is in this case very sparse (0.994 sparsity) and with a prevalence of 0 ratings: these are the evaluations where the climber-assigned grade of a route coincides with the official grade of the route. Hence, predicting correctly the grades assigned by climbers when they deviate from the official grade is challenging.

It is also worth noting that a major disadvantage of the SVD rating prediction model is that users and items are here represented in a joint latent factor space, which is hardly useful for explaining the predictions [26, 27]. In fact, in this domain it is pivotal to properly convince the climber about the reliability of the provided information: there are important safety issues to consider.

We have measured the root-mean-square error (RMSE) of the proposed models (linear regression knowledge-based and SVD based collaborative filtering) and compared them to the baseline. The results show that both models give a lower error than the baseline, meaning that they are capable of correctly using climbers' feedback about difficulty level of routes (see Table 2). In the table, 'per user RMSE' indicates the RMSE computed for each user and then averaged, while 'RMSE' is the global average of all prediction errors.

Table 2
Performance of perceived difficulty grade prediction on the data set of climbers' ascents on outdoor routes.

Model	Outdoor routes	
	RMSE	per user RMSE
baseline	0.339	0.191 (± 0.306)
Lin. Regression KB	0.317	0.176 (± 0.284)
SVD CF	0.322	0.174 (± 0.284)

2.2. Explanations and GUI

The knowledge-based model is employed to prototype a novel GUI of the Vertical-Life climbing application, which in addition to the official grade shows the predicted climber's perceived grade. Additionally, we have employed the coefficients of the linear regression model to generate explanations to the climbers for the predicted grades of the selected routes. The linear regression model along with its coefficients is shown in the following equation:

$$\widehat{grade}(c,r,t) = 0.027 + 0.998 \cdot ograde(r) + 0.410 \cdot md(r,t) + 1.051 \cdot md^Y(r,t) + 0.279 \cdot cmd^M(c, ograde(r), t)$$

Clearly the official grade $ograde(r)$ has the largest importance, but also the other features, related to the grading behavior of the climbers, do have important weights in the model. The explanation sentence, which is commenting why the predicted grade is different from the official grade, is generated by considering, case by case, the features that, for a given route and climber combination, have the largest positive (or negative) impact on the

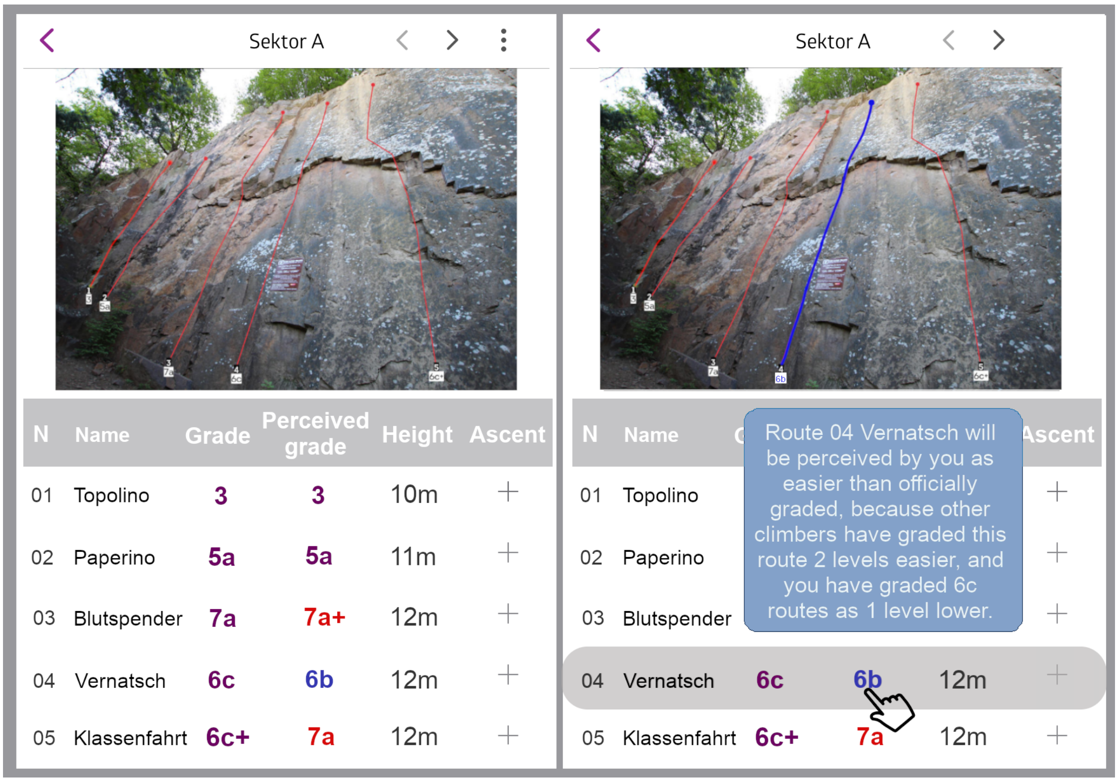

Figure 1: Explanation of the 'perceived' grade, shown in the system GUI prototype. The left figure shows routes' information and includes 'Perceived grade' in addition to the real 'Grade'; the right figure includes the pop-up window that appears when the climber points to the 'Perceived grade' for route 04.

predicted grade deviation. Such an explanation may be useful if a climber would like to better understand why the predicted difficulty of the route is different from the official grade. Potentially, this can lead to fewer accidents, as the climber may choose routes that better match her capabilities.

Figure 1 shows an explanation example sentence given in the prototype app to the climber when she points to the perceived grade column by touching the screen on route 04.

3. Discussion and Conclusion

There are some clear limitations of the proposed CRS that we plan to address in the future.

Firstly, we have developed sensor data analysis technologies for automatic activity recognition in climbing gyms, but we have not yet developed a similar solution for outdoor climbing. Moreover, knowledge extracted from low-level sensor data, e.g., the average speed of a climber during an ascent, has not yet been integrated with the explicit feedback collected from the mobile application. In fact, one related research question is how the climber's skill level acquired by the implicit feedback can be used to improve the subjective route difficulty grade predictions that we have computed by relying only on explicit feedback.

Secondly, as we have mentioned in the introduction, climbing route recommendations may support diverse users' needs. One important aspect is to identify routes that fit a specified training plan or to give explicit feedback to climbers about their 'mistakes' in trying the wrong routes. In fact, the training aspect is very important, as many climbers find that being able to track and achieve gradual progress is a crucial motivation for them. One possible approach to this problem is trying to intelligently revise or complete an existing climber's training program [28, 29, 30, 31], which the climber typically stores in the app.

Thirdly, the implemented explanation component can be improved in order to give a more convincing explanation, not only of the predicted difficulty, but also of the recommended route [32]. Moreover, for motivational and training purposes, climbers sometimes repeat the routes which they tried, and specific explanations should be generated in these cases [33]. For instance, the system may argue: 'This lead climbing route was climbed by you with 3 stops, try it again with fewer stops this time'. In fact, the specific rationale of a recommendation should be made clear to the climber. As a matter of fact, some routes are more enjoyable and should be recommended for climbers' satisfaction; other routes are more important for training and motivation; other routes are relevant because they may better satisfy the needs of the group of climbers the target user belongs to.

Finally, we must properly evaluate the proposed system prototype, and understand whether such a CRS would be suitable and interesting for climbers. For this purpose, we have created an online survey [34] to collect climbers' opinions on the proposed CRS.

In conclusion, in this paper, we have presented raw components and preliminary results that will be integrated into a novel CRS. We want to create a rich knowledge-based climber's profile taking into consideration climber's preferences, current physical level, behavior and skills. Such knowledge should be extracted from log data of the interaction of climbers with the routes that they have tried and evaluated. By better exploiting the bulk of knowledge contained in electronic guidebooks and climbers' diaries, we aim at increasing climbers' satisfaction but also their safety, as climbers will be supported to choose routes that are more aligned with their skills and expectations.

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