Success at High Peaks: A Multiscale Approach Combining Individual and Expedition-Wide Factors

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Abstract. This work presents a network-based data-driven study of the combination of factors that contribute to success in mountaineering. It simultaneously examines the effects of individual factors such as age, gender, experience etc., as well as expedition-wide factors such as number of camps, ratio of sherpas to paying climbers etc. Specifically, it combines the two perspectives through a multiscale network model, i.e., a network of network of climbers within each expedition at the finer scale, and an expedition similarity network at the coarser scale. The latter is represented as a multiplex network where layers encode different factors. The analysis reveals that chances of failure to summit due to fatigue, altitude or logistical problems, drastically reduce when climbing with people they have climbed with before, especially for experienced climbers. Additionally, centrality indicates that individual traits of youth and oxygen use while ascending are the strongest drivers of success. Further, the learning of network projections enables computation of correlations between intra-expedition networks and corresponding expedition success rates. Of expedition-wide factors, the expedition size and total time layers are found to be strongly correlated with success rate. Lastly, community detection on the expedition-similarity network reveals distinct communities where a difference in success rates naturally emerges amongst the communities.

Keywords: Mountaineering data · Multiscale networks · Multiplex networks · Social network analysis · Group dynamics · Everest expeditions

Introduction

Extreme mountaineering is an increasingly popular activity that requires not only physical fitness and skills, but also mental fortitude and psychological control. The Himalayas, one of the most impressive mountain ranges, present several opportunities, including the famous Mount Everest itself, for extreme mountaineering. Extreme or high altitude mountaineering is not what one might consider safe, and personal or expedition-related factors such as effective use of proper equipment, climber experience, mental strength and self-reliance are all measures [28] to increase safety and chances of success. Certain aspects of extreme mountaineering are well-known to be individualistic, especially as one

gets closer to the death zone (8000 m altitude). However, with increasing commercialization of extreme mountaineering, social and psychological factors play a subtle but crucial role in survival. Indeed the mass fatality on Everest in 1996 received tremendous attention social and logistical misgivings of the expeditions [32].

Understanding factors, both individual and expedition-wide, e.g. effective use of proper equipment, climber experience, mental state etc., [28] is crucial to maximizing safety and chances of success. Data driven analysis of success-predicating factors has been accelerated by the availability of the large and detailed Himalayan dataset [26]. Indeed, several works have studied the effects of age and sex [11], experience [9], commercialization [36] etc. on success, and highlight the importance of age as a dominant determining factor. Additionally, [35] shows that women are more risk-averse than men, and sherpas have lower risk at high altitude than paying climbers.

Success depends both on both physiological state [10,31], as well as psychological and sociological state [7] that influence the evaluation of risks and hazards. In [4], the psychological motivators behind why people climb is outlined. These motivators differ between paying climbers and sherpas, introducing questions regarding the ethics of hiring sherpas [22]. Group dynamics also play a major role in anxiety and problem solving [33]. Thus, despite opinions that climbing is an individual activity, there is mounting evidence highlighting the importance of social and psychological factors. The psychology is largely driven by relationships between climbers, for instance climbers that frequently climb together may developer better group dynamics, and consequently lower failure. However, there is limited investigation of the effects of climbing with repeat partners. This work studies the likelihood of failing when climbing with repeat partners due to factors such as logistical failings, fatigue, altitude related sickness etc.

Network science is becoming increasingly popular when studying data consisting of a multitude of complex interacting factors. Network approaches have been used successful in predictive medicine [13], climate prediction [30], predictions in group sports [19], disease spreading [37] etc. A mountaineering expedition consists of individuals which naturally lend themselves to a network structure. Relationships between individuals and expedition features such as oxygen use, age, sex, experience etc. can be modeled through a bipartite network. This network are often projected into other spaces for further analysis [14,16]. To the best of our knowledge, this work is the first network-based analysis of mountaineering data, incorporating factors at multiple scales. The natural question emerges: which of these features, which can be represented by nodes, are central to maximizing chances of success? An active area of research investigates the importance of nodes [20] through centrality-based measures [25,29] that serve as reliable indicators of 'important' factors.

While several studies have focused on individual traits that affect success and death, it is natural to expect expedition-wide factors (e.g. ratio of sherpas to paying climbers, number of days to summit, and number of camps, intra-expedition social relationships etc.) to play a role in success. However there

is limited work that studies the effect of such expedition-wide factors. This work considers both expedition-wide factors and personal features, and the interaction between the two. Multilayer networks [12] are an ideal tool to model multiple types of interactions, where each layer models relationships between expeditions through a particular factor. Multilayer networks have been used successfully to model neuronal activity [34], in sports [3], in biomedicine [6] etc. Multilayer networks without intra-layer connections between different nodes are also known as multiplex networks [17]. In order to model the different factors that influence expedition similarities, a multiplex network model is used. However the network of feature-relations within an expedition is in itself one of the factors correlated with success, hence one layer of the multilayer network encodes similarities in intra-expedition networks, where connectivity between expeditions is determined by their graph similarity [5]. This lends a multiscale structure to the network model. The term multiscale can be used to refer to different levels of thresholding in the graph across different scales as in [23], or hierarchical networks as in [15,27]. The notion of multiscale used here is derived from the latter, where the nodes of the expedition similarity network are in fact networks themselves. Multiscale networks are natural when modeling relationships on different scales for instance in brain modeling [1], stock market [23], ecology [18] etc.

Motivations, ability and psychologies vary amongst individuals, influencing people's perceptions [24] and strategies that may contribute to success. Hence, there must exist multiple strategies that consist of a different combination dominant factors, and a climber may be interested in the strategy that is best suited to them. Community detection [21] on the expedition similarity networks naturally partitions expeditions into groups that show high within-group similarity, where each group defines a strategy. Community detection is a useful tool in network analysis, and is an active area of research extended to multilayer networks [8], multiscale networks [27] etc. This work identifies three groups, with one in particular correlated with high success rate, providing insight into the combination of factors that allow for safe and successful climbs.

1   Data

The data for this work was obtained from the open access Himalayan Database [26], which is a compilation of records for all expeditions that have climbed in the Nepal Himalayan range. The dataset cover all expeditions from 1905 through 2021, and has records of 468 peaks, over 10,500 expedition records and over 78,400 records of climbers, where each record of any type is associated with an ID. We use the following information from the Expedition records:

– Peak climbed (height).
– Days from basecamp to summit.
– Number of camps above basecamp.
– Total number of paying members and hired personnel.
– Result: (1) Success (main peak/foresummit/claimed), (2) No summit.

The success rate of an expedition is calculated as the fraction of members that succeeded. Each expedition comprises of several individual climbers yielding a natural multiscale structure. We use the following data about each climber:

– Demographics: Age, Sex, Nationality.
– Oxygen use: ascending or descending.
– Previous experience above 8000 m (calculated).
– Result:
    1. Success
    2. Altitude related failure: Acute Mountain Sickness (AMS) symptoms, breathing problems, frostbite, snowblindness or coldness.
    3. Logistical or Planning failure: Lack of supplies, support or equipment problems, O2 system failure, too late in day or too slow, insufficient time left for expedition.
    4. Fatigue related failure: exhaustion, fatigue, weakness or lack of motivation.
    5. Accident related failure: death or injury to self or others.

2   The Effect of Climbing with Repeat Partners

Climbers often tend to climb with friends or regular climbing partners. The security of regular climbing partners may improve confidence and limit failure, but may also lead to a misleading sense of comfort. Here, a comparison of average rates of success and various types of failure when climbing with repeat partners vs new partners is made. Figure 1 shows the fraction of failures when climbing with friends/repeat partners over the climber average. These failures are divided into altitude related, fatigue related, logistical and planning failures and accident/illness. The effect of total experience is normalized for by plotting across the total number of climbs on the x-axis starting at least 15 climbs, hence not considering beginner climbers.

As seen in Fig. 1, repeat partners have virtually no effect on the chance of success except for very experienced climbers (36–40 logged climbs) which may be attributed to a increasing climb difficulty or of their partners being less experienced partners, both of which are more likely for very experienced climbers. In contrast, the chance of failure is significantly lower when climbing with repeat partners for every type of failure. In particular, the chance of failure due to fatigue-related issues is the most decreased when climbing with repeat partners, followed by failure due to logistical or planning issues. This may be expected since climbing partners that often climb together typically are better at communication, planing, and knowing each other's physical limitations. Note that only climbers with over 15 logged climbs are consider, indicating that complete lack of experience is not a cause of failure. Additionally, the most experienced climbers (that have logged 36–40 climbs) have nearly no failure due to fatigue or logistics, as one may expect. Similarly, failure due to altitude-related and cold-related issues also drastically reduces when climbing with repeat partners. Additionally, the cause of failure due to accident shows an increasing trend as a function of increasing experience, which may be attributed to the fact that more experienced climbers tend to tackle more dangerous mountains.
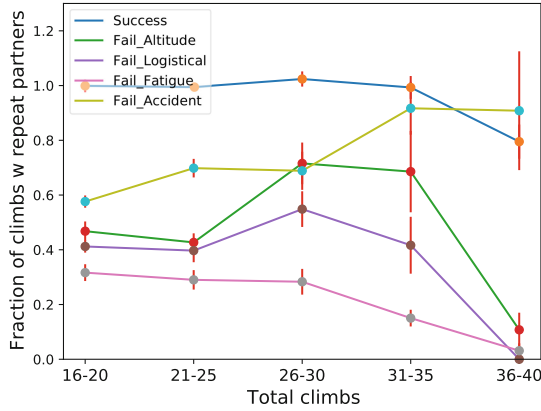
Fig. 1. The fraction of several categories (success and various types of failures) averaged over climbers when climbing with a group with at least one repeat partner (someone they have done a logged Himalaya expedition with before) over the individual average. The y-axis denotes the ratio of success and various failures when climbing with repeat partners over their personal average over all climbs (conisdering climbs with repeat+new partners).

3   Intra-expedition Features Determining Success

Here, the focus shifts from studying individual climbers to analyzing a group of climbers within an expedition. In order to do so, only the tallest peak, Mount Everest is considered. Expeditions with less than 12 climbers are excluded, as are expeditions that resulted in death. To generate the intra-expedition network, we start with a bipartite network P between climbers and features, where a climber is connected to the features that they possess. The 'features' selected as the nodes are: age, sex, oxygen while ascending, oxygen while descending, sherpa identity and previous experience about 8000 m, making a total of $f = 6$ features. A climber is connected to sex if they are male, and age is binarized into above and below median age (40).

We then generate the intra-expedition, with adjacency matrix A, of size $f \times f$ by projecting the bipartite network into feature space as follows: $A = P^t P$. The edge weight between two nodes (features) is given by the number of people that are connected to both the features. Information about the expedition is then encoded in the structure of this network. To explore such effects, measures such as centrality capture important properties that provide insight into the importance of different features [20]. For instance, if the group were comprised of mostly high-age individuals, the node-centrality of the age node would be relatively high. Here, the eigenvector centrality [29] determines how central each feature is in a given graph. Studying the differences in feature centrality between groups of successful summit vs no-summit provides important insight into features that may be important for summit success.
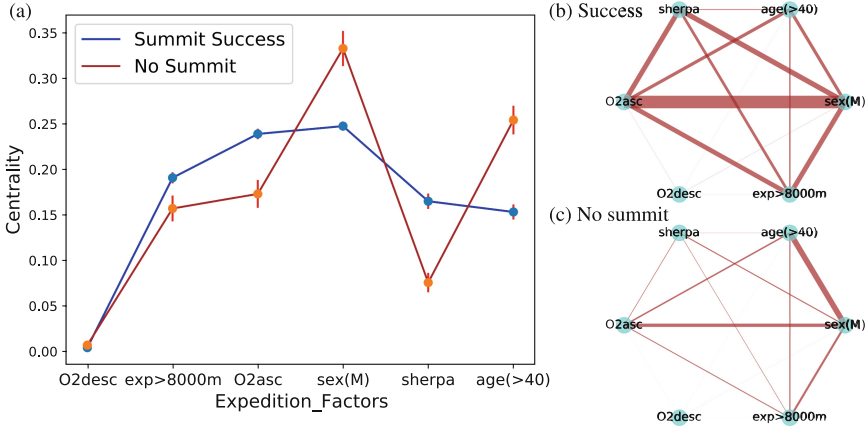
Fig. 2. Mean eigenvector centrality (a) as a function of expedition features for Everest expeditions greater than 12 members plotted for groups of successful vs unsuccessful climbers ordered by increasing difference between success and no-success centralities. Error bars show standard error on the centrality. (b, c) Aggregation of the feature graph showing relative edge weights in summit success, and no-summit groups respectively.

As seen in Fig. 2 (a), the least central feature in determining success on summit was the use of oxygen while descending, which is expected since descent features have no effect on summit prospects, except for indicating that oxygen was available on descent meaning there wasn't excessive use during ascent. It is worth noting that most fatalities on Everest happen during the descent. The next features that were slightly more central in successful summits were previous experience about 8000 m (for reference Everest is at 8849 m), followed by use of O2 while ascending. Surprisingly, summit centrality for sex (indicating male) was relatively low compared to no-summit centrality indicating that being male had low importance in the chances of success at summit. Lastly, the largest differences in summit vs no summit were from identity (sherpa were much more likely to succeed), and age (<40 year olds were much more likely to succeed), as expected and also seen in previous studies [9]. Figure 2 shows the intra-expedition graphs averaged over groups of (b) successful vs (c) unsuccessful climbers. Note that these graphs are projected from a climber-feature bipartite network, and hence encode the true distribution of features.

4   Generating a Multiscale Network

Graphs are a natural way to model relationships or comparisons between expeditions. Multilayer or multiplex networks are commonly used to model relationships of multiple types, where each layer corresponds to a specific 'type'. While the intra-expedition network provides insight into the features that climbers in the expedition shared, expedition-wide factors also determine the success of an

expedition. The expedition-wide factors considered here are: (1) number of days to summit from base camp, (2) number of high points/camps, (3) expedition size (including hired personnel), (4) ratio of number of paying climbers to number of hired personnel. In order to compare different expeditions, one must consider both the intra-expedition feature similarity as well as the 4 expedition-wide factors. We model each of these as a layer in a multilayer expedition similarity graph, resulting in 5 total layers. Thus the multiplex graph is also a multiscale graph E where, within the first layer, each node is a graph encoding *within-* expeditional similarities, lending to it a hierarchical or multiscale structure. An illustration of this is shown in Fig. 3.
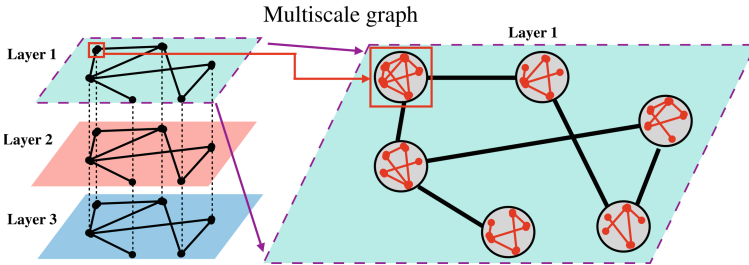

Fig. 3. An illustrative example of a multiscale graph.

Now, in practice the multiscale multiplex graph E is generated as follows: for the four layers encoding expedition-wide factors, expedition i is connected to expedition j in layer l if both expedition i and expedition j have a value of layer l greater than the mean of the layer μ^l. In other words,

$$A_{ij}^l = 1 \text{ if } v_i^l, v_j^l > \mu^l, \text{ and } 0 \text{ otherwise.} \tag{1}$$

where v_i^l is the value of factor l in expedition i. For the intra-expedition feature layer, the edge weight between expeditions is given by the Graph Edit distance [5] between their intra-expedition graphs, normalized to a max value of 1.

5 Determining Layer Importance Through Correlation with Success

Different factors encoded as layers may have varying importance in determining the success of an expedition. An expedition success rate is the fraction of climbers that succeed at summiting. The importance of a regular (non-multiscale) layer can be inferred from the correlation between the values taken on the nodes (expeditions) in that layer and the corresponding success rates. However, for the intra-expedition layer, this involves computing the correlations between intra-expedition graphs and success rates (scalars).
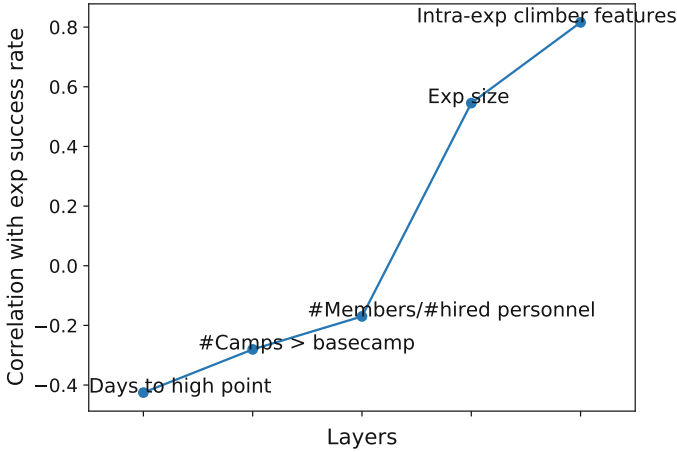
Fig. 4. Pearson's correlation coefficient between layer (factor) values and expedition success rate. The exact values across x-axis layers are $-0.45, -0.36, -0.12, 0.57, 0.84$. The corresponding p-values are $5.5 \times 10^{-10}, 1.15 \times 10^{-6}, 0.1, 5.7 \times 10^{-16}, 8.9 \times 10^{-47}$.

Devising measures for comparisons between graph space and scalar space is an important problem in network science. This can be done by dimensionality reduction through projection of graph space to a scalar space. Since each factor in the graph is independent, we perform linear regression on the unique entries of the adjacency matrix of the graph to obtain a linear fit that best map the intra-expedition graphs to the success rates. The corresponding coefficients are denoted by $\vec{c}$. Note that linear regression generates a single set of coefficients that are best map from graph space to scalar space, i.e., output a best-fit scalar for each graph. In principle one can use higher order methods, or neural networks to learn this mapping, however, since the features of the graph are expected to be linearly independent, a linear mapping is sufficient in this case.

In other words, one can project the graphs as follows: the intra-expedition graph of the jth expedition whose adjacency matrix is A^j is represented by the scalar η_j given by $\eta_j = A^j \cdot \vec{c}$ where $\vec{c}$ are the coefficients obtained through regression over all graphs. One can then identify the importance of the intra-expedition layer through the correlation coefficient (Pearson's) between $\vec{\eta}$ and the success rates.

Figure 4 shows the Pearson's correlation coefficient between the layers and the success rate. A higher correlation implies higher influence of the layer in determining success. Despite sherpas having a high chance of personal success as seen in the intra-expeditional analysis, the ratio of number of paying members to number of hired personnel on the team has a relatively smaller effect on *expeditional* success compared to the other factors considered in the multilayer approach. Both number of camps above basecamp and days to summit/high point had a negative correlation with success, as one might expect, with the latter having a larger effect. Also surprisingly, the *expedition size* is found to

be relatively important in determining success (with a correlation coefficient of >0.5). Lastly, the most important factor was the intra-expedition feature graph layer which is strongly correlated with success, indicating that non-linear effects and outliers to the regression fit are relatively few. All p-values are extremely low indicating that the correlation is statistically significant except for the number of members to hired personnel.

6   Community Detection to Identify Patterns of Success

Success at high peaks is a combination of several features. Through analysis of the multiscle graph, one can identify communities of expeditions that have similar factors and features. One may wonder if the data would naturally cluster into communities with different success rates, which can be associated to differences in the combination of factors. The layers of the multiscale multiplex graph E are aggregated to generate an expedition similarity graph S given by $S = \sum_l E^l / |l|$, where l is the total number of layers (5 in this case). Here, each layer has the same weight, but one may choose to assign weights to them in other ways, for instance weighted by layer importance. Louvain community detection [2] is then applied to S and identifies three communities. Note that the number of communities is not pre-determined but selected by the algorithm maximize modularity [21]. Figure 5 (left) shows the differences in expedition-wide factors in the three communities (ordered by average success rate on the x-axis). As seen from the figure, the three emergent communities naturally bifurcated to reveal different success rates (the first and the second community had similar success rates at 0.28 and 0.32 whereas the third was significantly higher at 0.68). Firstly, the most dominant difference is found to be expedition size which is significantly higher in the third 'successful' community (with the highest success rate at 0.68), indicating that larger groups allow a larger fraction of climbers to succeed. One may hypothesize that this is because the experienced climbers do not have to shoulder the responsibility of the less experienced climbers, which may slow them down. Additionally, all communities were largely similar in the number of camps above base camp. However, the ratio of number of members to personnel was the relatively higher in both the community with the highest success rate, as well as the lowest success rate, indicating that it isn't a determining factor, supported by results from Sect. 4. Lastly, as the success rate of the communities increase, their days to summit decrease, which is also expected. At high altitudes, the body goes into shock from prolonged exposure, so one might expect a faster expedition to face less challenges in this regard, and hence be more successful.

Figure 5 (right) plots the centralities of the intra-expedition features for the three communities (ordered by their success rate on the x-axis). The successful community, were the youngest and had the highest centrality for oxygen use both while ascending and while descending. Despite having slightly less average experience than the first two groups, *age* and *oxygen* use were the leading indicative features for success, which is in agreement with results from Sect. 3. The main
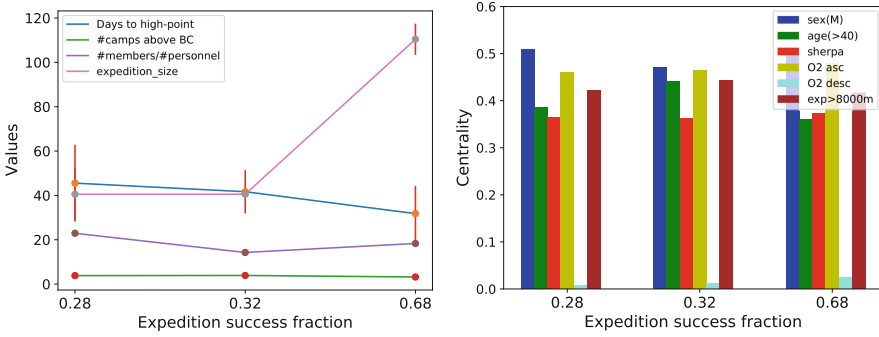
Fig. 5. (Left) The average values of the various expedition-wide factors represented in layers shown for the three communities. (right) Centralities of the intra-expedition graph features for the three communities. The three communities are represented by their success fraction across the x axis.

differences between the first and second 'low-success' communities are that the first community had relatively low experience >8000 m, whereas the second is a relatively older, but more experienced population. Hence, this provides insight into which strategy/choices are conducive to climbing Everest given fixed traits of an individual such as age/experience etc.

7   Discussion and Future Work

This work presents the first network-based analysis of mountaineering, studying the intra-expedition and expedition-wide factors that contribute to success. First, it considers a climber-centric perspective and shows that the chances of summit failure (due to fatigue, logistical failure etc.) drastically reduce when climbing with repeat partners, especially for more experienced climbers. Then, it studies the importance of intra-expedition features by projecting a bipartite climber-feature network to show that the largest different in centralities amongst successful and unsuccessful groups is found in the 'age' node, indicating that it's the strongest driver of success. Further, it introduces a multiscale multiplex network to model similarities between expeditions, where one or more layers may be multiscale whereas others are not. Such a multiscale approach can model a variety of systems, and the tools used here to navigate simultaneous modeling of different types of layers and project networks to a scalar space through regression are applicable in a variety of scenarios. Lastly, community detection on the expedition-similarity reveals three distinct communities where a difference in success rates naturally emerges amongst the communities. The dominant characteristics that support a successful outcome for a large fraction of the expedition are high expedition size, low age, and oxygen use. Future work may include study of additional factors, analysis of death factors, and a multilayer or multiscale approaches to modularity optimization and community detection. Code can be found at https://github.com/chimeraki/Multiscale_network_mountaineering.

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