Project Proposal
Avalanche Risk Factor Prediction

University of Victoria, SENG 474 with Nishant Mehta

Jonathan Skinnier V00207396

Joel Kerfoot V00855134

Tyler Harnadek V00818721

Rowan Burns-Kirkness V00819316

1.0 The Problem

Avalanches are consolidated layers of snow sliding on top of one another. They're usually triggered when a person or group of people disturb snow on an unstable slope, their added weight triggering a weak layer to break and the slide to begin. Natural avalanches also occur when mountain weather produces especially unstable snow conditions, and the weight of only the snow itself triggers such a slide. The conditions that can cause avalanches are predictable, and in Canada avalanche risk is predicted by Avalanche Canada. [1] Despite this, avalanches kill dozens of people in North America every year.

Avalanche forecasters use weather data combined with in person observations to determine the current problems in the snowpack. These problems typically describe what conditions are producing reactive slabs — layers of snow not bonding well to those below — and other buried weak layers. For example, storm slabs are produced when excessive new snow falls in a short time period, quickly adding an excessive load to the top of snowpack. Wind slabs are produced when wind blows snow onto leeward aspects, compressing the snow and not letting it bond well to the snow below. Deep persistent weak layers are a very dangerous problem, as they are produced early in the season but stay buried under feet of snow for months on end, always with the possibility of producing very large, destructive avalanches. These problems, as well as a host of others, are problems that avalanche forecasters consider when assigning a danger rating.

Avalanche forecasting is important for all recreational winter backcountry users. The process of forecasting takes a lot of information into account, including months of past weather, past avalanche incidents, and current field observations. Forecasters typically have years of experience and extensive formal training to be able to precisely parse this information to produce an accurate forecast. Most weekend users have only done a single weekend avalanche skills course, which itself is focused on interpreting information given from the avalanche forecast and making safe route finding and terrain decisions based on that. An accurate avalanche forecast is imperative for the safety of those without the years of formal training, who are just trying to stay alive in the backcountry.

To create a danger rating, first avalanche forecasters consider the problems in the snowpack. Weighing the likelihood and possible size of avalanches these problems could generate, they produce a danger rating that encapsulates the overall risk. In this process, however, an avalanche forecaster draws from their personal experience in the mountains. They interpret the feel of the snow when they are in the mountains and see first-hand how it reacts to different pressures. They are able to see how the weather is affecting the snow, as well as direct reactions to other users skiing or snowmobiling. They also dig many snow pits to investigate the stability of the snowpack. All this subjective information is then interpreted given the forecasters past experience in the mountains. For example, a forecaster might be very accustomed to seeing 30 centimeters of heavy snow falling overnight and it consolidating very quickly, or may be accustomed to the afternoon sun wreaking havoc on a south aspect slope during the month of April. The main question we seek to answer is whether an avalanche forecaster's formal training, auxiliary data, and experience can be effectively encapsulated into an algorithm which only has access to past and current weather data.

We will be using historic data sourced from Avalanche Canada's [1] website for the danger ratings. They have a public API which provides a trivially easy method to scrape historic avalanche dangers ratings. For our weather data we are sourcing it from the BC Government's Snow Survey Stations [6]. We are very confident that we will be able to source the above data sets, however as backup we have found a dataset produced by Open Avalanche Project [3] which provides weather and danger ratings for many locations in Washington State.

2.0 Goals

The goal of this project is to develop a machine learning system that can classify avalanche risk factors according to publicly available weather and snow resources. To accomplish this, we propose to design a model that can be used to simulate the role of an avalanche forecaster. This tool could be useful to avalanche forecasters to help inform their decision making when creating future avalanche risk bulletins. By automating the avalanche risk factor calculation, reports could be generated for more specific areas, wherever there is an Automated Snow Weather Station.

Avalanche Canada generates avalanche risk reports for three distinct elevations: Alpine, treeline, and below treeline. Avalanche risk is generally greatest in the Alpine region, so this model will be targeted at the Alpine region specifically.

The proposed system would be a of classifier that takes input data generated from Automated Snow Weather Stations (ASWS) and classifies the snow conditions for a given day into one of five labels. The labels are as follows:

1. Low – natural and human triggered avalanches unlikely
2. Moderate – natural avalanches unlikely, human triggered avalanches possible
3. Considerable – natural avalanches possible; human triggered avalanches likely
4. High – natural and human triggered avalanches likely or very likely
5. Extreme – natural and human triggered avalanches a certainty

While these labels form discrete classes, there is some value to an incorrect classification that is adjacent to a correct classification. For example, if the avalanche risk as evaluated by Avalanche Canada is High and our model classifies the risk as Considerable, this is still somewhat valuable. However, misclassifications that are not adjacent to correct classifications are likely more dangerous than helpful. If the model indicates Low probability of avalanches when Avalanche Canada indicates high risk, this would be an extremely dangerous tool to rely on.

To evaluate the effectiveness of our model, we will look at its accuracy in predicting avalanche risk factor in specific regions of British Columbia. The model will be provided training data from one region, and then tested against data from that same region. See Figure 1 for a map of the avalanche regions in BC. The model will not be expected to successfully classify samples from more than one region, as the conditions that cause avalanches differ in coastal and inland regions significantly.

A classification that **exactly matches** Avalanche Canada's Risk Factor for a given day will be considered a success. Because there are 5 solution classes, a classifier that randomly selected a label would achieve an accuracy of 20%. Any significantly more accurate classifier would be a partial success. Because of the obvious safety risk of an inaccurate classifier, to consider the model completely successful it should be able to correctly classify more than 80% of samples. Additionally, incorrect classifications should almost always be adjacent to the correct classification; a high incidence of extremely under-predicting avalanches would be a complete failure of the model.

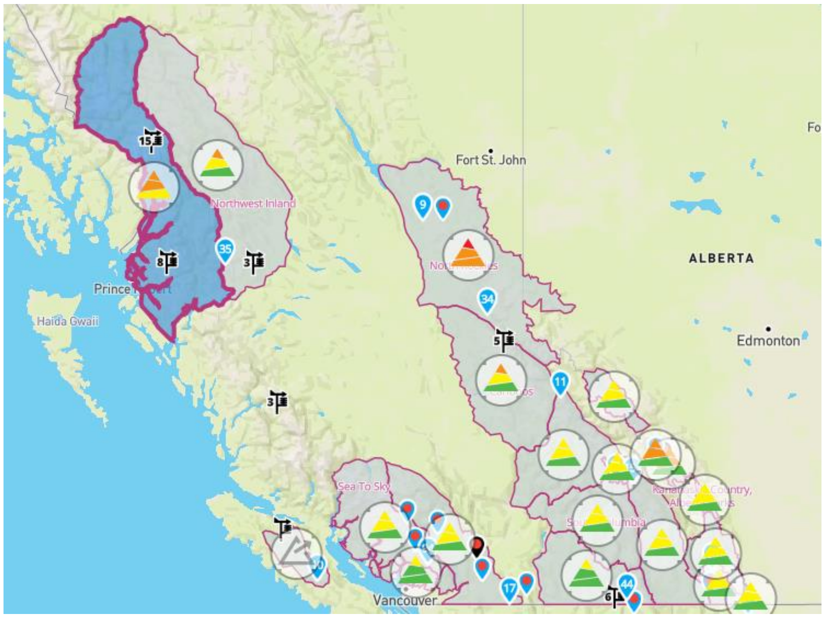

Figure 1 Map of Avalanche Regions. Source: Avalanche Canada. Highlighted: Northwest Coastal region (Kitimat-Stikine). Note that Vancouver Island does not have an active risk factor bulletin at the time of this screenshot. [1]

3.0 Plan

The first step of ensuring the success of the project is to review the literature that already exists in the problem domain. The first is a journal article by Pozdnoukhov et al [2]. which presents similar work to ours using an SVN to predict avalanches using data from Lochaber, Scotland. In the paper Pozdnoukhov et al. compare their SVN to using a simple Nearest Neighbor approach for prediction. They conclude that Nearest Neighbor can achieve 65% – 70% for their dataset depending on the number of neighbors used while their SVN achieves accuracy of 73% which is state of the art for their dataset. From this article it we conclude that part of our experimentational plan should be testing our best approach against a Nearest Neighbor method and an SVN method. If our approach outperforms those two it would be edifying to apply our approach to the dataset presented by Pozdnoukhov et al. to see how it compares to their state of the art.

The second item in our literature review is Open Avalanche Project [3], a website created by Scott Chamberlin. It uses data from Washington and Oregon to predict future avalanches in the northwest. Chamberlin's model uses the XGBoost library [4] for training. The library provides a classifier which uses gradient boosted trees as the base of a random forest classifier. In his analysis Chamberlin mentioned that he found the increase in accuracy between a basic random forest classifier and XGBoost negligible. He also discussed his results only briefly mentioning an accuracy of 72% for Oregon and 57% for Washington [5], 72% is in-line with what we believe the state of the art to be while the 57% on a different dataset suggests that that data may not be a consistent as the other datasets discussed. We would like to include some type of random forest classifier as part of our experiments to see if we can replicate Chamberlin's results on our own data set.

To evaluate the stability of the models the data will be split 80% for training and the remaining 20% for testing. On the training data we will use K fold cross validation with a K value of 5 so that all the data gets to be used for both training and validation. K = 5 was chosen as it was presented as a good choice to use in lecture. Once the models have been trained, they will be tested against the 20% testing data to determine the model's error.

The experiments we will do will all be on the Avalanche Canada [1] data for the last few years. One of the biggest avenues we wish to explore is how many days of prior data should be used to predict the risk level for a given day. From the different Nearest Neighbor accuracies found in [2] with different numbers of neighbors we know the output is sensitive to this parameter. We will try varying this parameter between 1 day and 20 days which [2] identified as the best number for their Nearest Neighbor classifier. We believe a smaller number will be required for other classifiers but if we do not identify an inflection point where accuracy begins to drop as more previous days are used, we will experiment with greater numbers until such a point is found.

Since our data is like that in [2] and [5] so we will begin by applying their methods to it. SVN, Nearest Neighbor, and Random Forest will be compared for accuracy and any method achieving greater than 70% accuracy would be considered a success and inline with the current state of the art. Our testing schedule is presented as part of the Task Breakdown table in the following section. While we do not currently have additional methods we wish to explore, if one were discussed in class would like to add it to our experiment schedule. If our experiments achieve accuracy lower than 70%, we will discuss our models with our professor, Dr. Mehta, and trust his expertise to provide us with additional avenues to explore.

4.0 Task Breakdown

The task breakdown details the work that the group members will perform. The tasks are not exhaustive and may need to be updated as the project progresses to accommodate for challenges encountered with the project.

Date	Assignee(s)	Task Description
Feb 11	Everyone	Project Proposal – complete and submit the proposal
Feb 18	Joel	Gather avalanche data
Feb 22	Tyler	Format avalanche data and partition into training (80%) and validation (20%) sets
Feb 23	Everyone	Start working on assigned task: SVN, Nearest Neighbor, Random Forest
Mar 6	Everyone	Progress Report
Mar 23	Jonathan	Complete SVN training
Mar 23	Rowan & Tyler	Complete Nearest Neighbor training
Mar 23	Joel	Complete Random Forest Training
Mar 24	Jonathan	Cross Validate SVN
Mar 24	Rowan & Tyler	Cross Validate Nearest Neighbor
Mar 24	Joel	Cross Validate Random Forest
Mar 31	Everyone	Final Report
Mar 31 –	Everyone	Project Presentations

References

[1] Avalanche Canada, "Avalanche Canada Homepage," [Online]. Available: https://www.avalanche.ca/.

[2] A. P. R. &. K. M. Pozdnoukhov, "Applying machine learning methods to avalanche forecasting," *Annals of Glaciology*, no. 49, pp. 107-113, 2008.

[3] S. Chamberlin, "Open Avalanche Project," Snowy Mountain Works, 1 June 2018. [Online]. Available: https://openavalancheproject.org/. [Accessed 10 February 2020].

[4] XGBoost, "Introduction to Boosted Trees," XGBoost, [Online]. Available: https://xgboost.readthedocs.io/en/latest/tutorials/model.html. [Accessed 10 February 2020].

[5] S. Chamberlin, "18-19 Season Preview," Snowy Mountain Works, 1 December 2018. [Online]. Available: https://blog.openavalancheproject.org/18-19-season-preview/. [Accessed 11 February 2020].

[6] BC Government, "Automated Snow Weather Station Data," [Online]. Available: https://www2.gov.bc.ca/gov/content/environment/air-land-water/water/water-science-data/water-data-tools/snow-survey-data/automated-snow-weather-station-data.