An Objective Way to Categorise Alpine Skis

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Skiers are faced with an ever-growing number of alpine skis [1]. To simplify the shopping experience, skis are often divided into categories based on their intended usage. However, there is no agreed standard that allows ski manufacturers, shops and skiers to categorise alpine skis. The aim of this study is thus to investigate how alpine skis are currently classified, and if simple classification rules can be established. To do so, classification models will be build using the ski's physical properties from *Sooth Ski*'s database, as input, and *Evo* categorisation (target values), as output. *Sooth Ski*, the partner of the project, is specialized in the measurements of key ski properties and assembled over the years a database containing more than 3,000 skis [2]. For this project, the raw geometrical and stiffnesses measurements [3] were expressed as 43 attributes. *Evo* is a well-known sport equipment retailer selling alpine skis across USA/Canada since 2001 [4]. *Evo* ski categories include *carving, all-mountain, park & pipe, alpine touring, powder* and *big mountain*. Each ski is tagged by *Evo* with up to 3 of these tags. As of June 2021, 327 *unisex* and *women* ski models were available on *Evo*, of which 141 of them were measured by *SoothSki* (a total of 18 ski brands are represented).

The classification model retained for this application is a predictive modelling approach called decision tree learning [5]. It allows, based on measured ski physical properties, to predict if a ski is part of a particular *Evo* category or not (the null hypothesis). To determine the splitting rules of the decision tree, the algorithm uses dedicated optimization techniques. To avoid overfitting, classification trees are kept simple by setting a minimum number of skis per leaf and a 10 folds cross-validation is used. As an example of the results, the decision tree for *all-mountain* category is shown in Fig.1. The resulting decision tree retained only four attributes among all 43 possible attributes: the waist of the ski, the surface to weight ratio (S/W), the tail to tip height ratio and the bending stiffness of the ski tip. In addition, the rules used inside the tree are very realistic. According to these rules, most *all-mountain* skis are under 107mm wide, not extremely light (i.e., S/W < 1.27) and tail/tip height ratio not too high. Light skis must also have tips that are stiff in bending to be classified as *all mountain* skis. Although these rules use only four attributes, the model can classify correctly 96.5 % of the *all-mountain* skis. At first glance, some skis seem to be misclassified in the input dataset (e.g., the women version of a ski with exactly the same measured properties as the unisex version is classified a different category).

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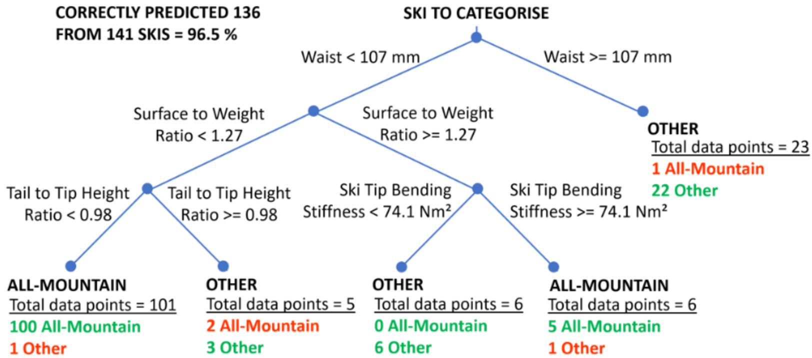

Fig. 1: All-Mountain decision tree model

Table 1 presents the correct prediction rate for each of the six *Evo* categories and the number of attributes used in each tree. The trees can correctly predict the ski's category based on less than 6 attributes, but the small number of skis in the *park & pipe* category may imply an over-fit.

Table 1: Correct prediction rate for each ski category

Category	**Number of skis with this tag**	**Number of attributes used**	**Correct prediction rate**
Carving	4	Not enough skis	Not enough skis
All-Mountain	108	4	96.5 %
Park & Pipe	11	2	99.2 %
Alpine Touring	56	5	95.7 %
Powder	28	2	98.9 %
Big mountain	56	6	92.2 %

In conclusion, physical measurements are shown to differentiate skis according to *Evo* categories with high prediction rates and easy-to-interpret decision criteria. Most of the splitting rules are related to geometry and mass specifications. Bending and torsional stiffnesses might be more relevant for predicting the ability level of a ski. Further work will use categories from a number of sources to create standardized classification rules and avoid misclassification in the input dataset.

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