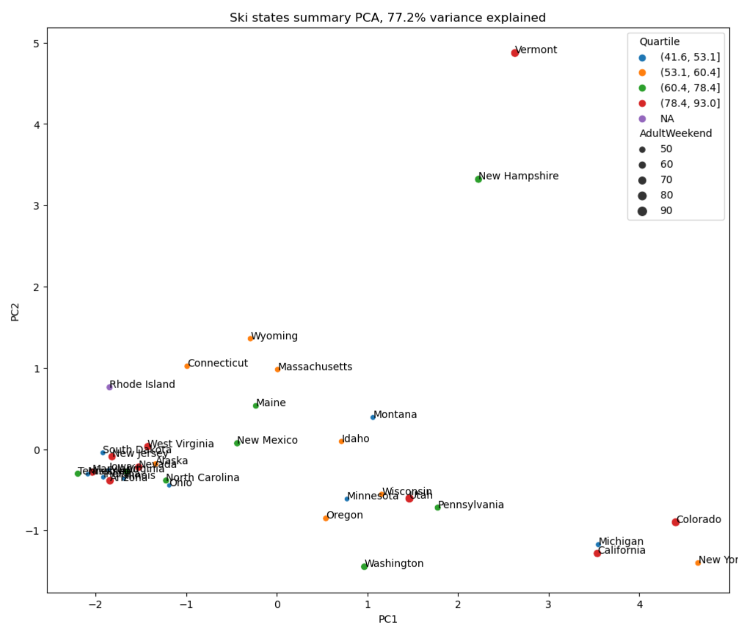
1 Problem statement

Big Mountain Resort's current pricing strategy is based on taking an average of all resorts, regardless of features and facilities, and increasing by an arbitrary premium. Since Big Mountain is a larger ski resort with robust facilities, it makes sense for it to charge higher than average prices, but our goal is to provide a data-supported price recommendation. We do so by training a model to predict ticket prices based on resort features such as the number of ski runs, number of chair lifts, and total vertical drop.

2 Data Wrangling

Our initial data set included information about 330 resorts across the country, including Big Mountain resort, but eventually 14% of these were removed for having no ticket price data, leaving 277 resorts. We determined that it appears to be standard for weekday prices to match weekend prices in Montana, where Big Mountain is located, so we decided to target weekend prices as the feature to predict ticket prices due to having slightly more data than for weekday prices. Also, to better understand the data in different states, we incorporated data on state populations from Wikipedia.



3 Exploratory data Analysis

Our focus on state data yielded some useful new features, including four that describe each resort's share of skiing terrain, open days, resort terrain, and night skiing in its state. However, although average prices do vary considerably between states, we did not observe any obvious patterns to explain it, so we did not include state information directly in our model.

4 Model pre-processing with feature engineering

We partitioned 70% of our data into a training set and the rest into a test set. Our first baseline was a simple average of all resort lift ticket prices, yielding a mean absolute error (MAE) of 17.9 on training data and 19.1 on test data. We significantly improved upon using a simple linear model using selected features, with an MAE of 10.5 on cross-validation and 11.8 on the test set. We also trained a random forest regression model that exhibited less variability and performed even better, at 9.6 MAE on training data and 9.5 MAE on test data.

5 Winning model and scenario modelling

Of the models we considered, we moved forward with the random forest model because it performed best. We considered the following suggested scenarios in this model:

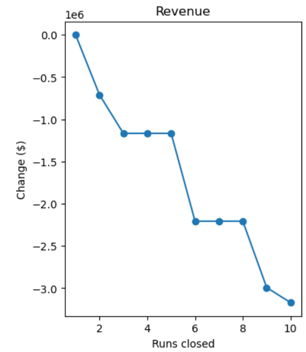
1. Permanently closing down up to 10 of the least used runs. This doesn't impact any other resort statistics.

2. Increase the vertical drop by adding a run to a point 150 feet lower down but requiring the installation of an additional chair lift to bring skiers back up, without additional snow making coverage.

3. Same as number 2, but adding 2 acres of snow making cover.

4. Increase the longest run by 0.2 mile to boast 3.5 miles length, requiring an additional snow making coverage of 4 acres.

Of the four scenarios provided, only 2 and 3 predicted an increase in revenue: \$3.5 million per year. Since the revenue is the same in both scenarios, but scenario 3 involves extra costs, we recommend focusing on scenario 2. If the operating costs of the proposed chairlift are less than \$2 million like the most recent lift, the \$3.5 million per year in revenue should make it worthwhile.



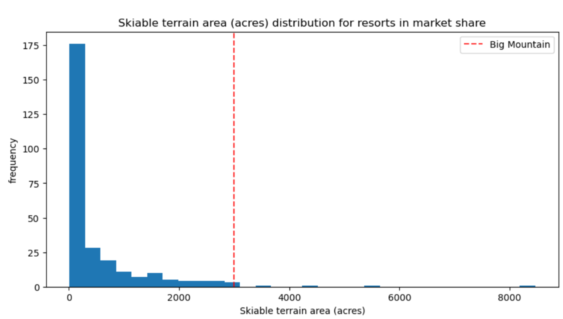
We also analyzed the closure of up to 10 runs in order to cut costs. The model predicts the same ticket price for reductions of 3, 4, and 5 runs, leading to a revenue loss of about \$1.2 million, and the same price for 6, 7, and 8 runs, a loss of about \$2.2 million. The revenue loss increases significantly to roughly \$3 million for closing 9 runs, so it appears that closing 5 or 8 runs would be optimal if the operating costs of each run are high enough to warrant it. A good approach might be to try out closing 5, then close another 3 if the initial closure indeed leads to increased profits.

6 Pricing recommendation

Big Mountain currently charges \$81 per ticket, but our model predicts a price between \$85.87 and \$105.87. We suggest starting with an increase of the price to at least \$85.87, but in the lower range of prices predicted by our model to be conservative. If such an increase does indeed lead to an increase in revenue, then a further increase to around \$96 could be explored. Assuming 350,000 unique visitors who purchase an average of five tickets per year, the revenue increase suggested by our model would be at least \$8.5 million, which is significantly more than the operating costs of \$1.54 million for the new chair lift.

7 Conclusion

Although Big Mountain is already the most expensive resort in Montana by far, the higher price is more than justified by its exceptional size and the robustness of its facilities. Our analysis shows that the price should even be higher, based on the resort's features. A modest increase in price should increase revenue without alienating customers, while closing down 5 runs provides a chance to cut operating costs without undermining the ticket price considerably.



8 Future scope of work

A detailed breakdown of the operating costs for each run and lift, as well as statistics about usage of each facility would allow us to recommend which runs to close. Now the model has been trained, it would be relatively simple to code up a user-friendly tool to explore the model's predictions based on different scenarios.