Big Mountain case study

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Problem statement:
What possibilities exist for Big Mountain Resort to increase company's revenue in the year 2020 by implementing a new data-driven business strategy.

1. Business context

With a recent investment that added $1,540,000 to operating costs, the Big Mountain Resort, a sky resort in Montana, is willing to review its premium ticket pricing strategy. The current price of $81 is simply set above the average of ticket prices of resorts in the same market segment. The company would like to implement a new business strategy that will fully exploit existing market data, and increase the company's revenue either by raising the ticket price or cutting operating costs.

2. Market data and the pricing model

For the purpose of price modeling a sample extracted from a database with information about 330 resorts in the same market segment was used. Including Big Mountain resort, 277 records contained information about the ticket price, and only these records were used in the price estimate. A model based on a machine-learning approach was used to find the price's dependence on 32 features characterizing each of the resorts. The model was optimized and tested, as described in detail in Section 5. According to the model, only 8 out of 32 features significantly influence the ticket price. These are the vertical drop, the skiable area and area covered by snow makers, the number of runs, the resort's longest run, and the number of chairs, fast quads and trams.

3. Model predictions

Using the data avaialble for resorts in the same market sector, our model predicts that the ticket price for the Big Mountain resort could be increased from the current prize of $81.00 to 95.87 dollars. An increase by $14.87 is justified by very favorable parameters of this resort compared to others; Big Moutain is among those with the largest vertical drop, the largest skiable area and area covered by snow makers, the highest number of runs,

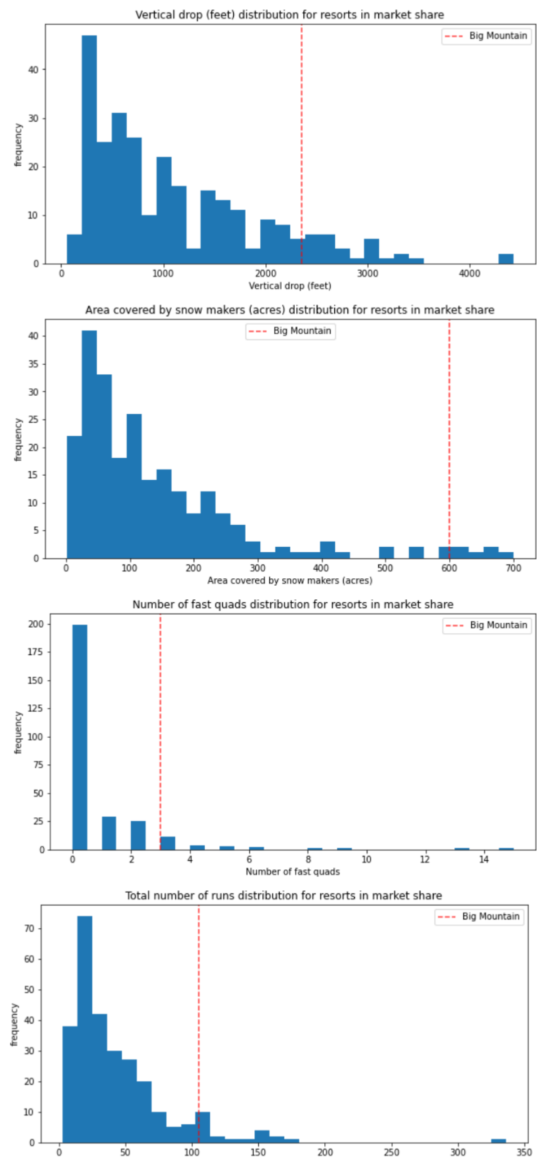

Figure 1. Vertical drop, area covered by snow, number of fast quads and the total number of runs (top to bottom) for Big Mountain Resort (red vertical line), compared to other US resorts (blue histogam).

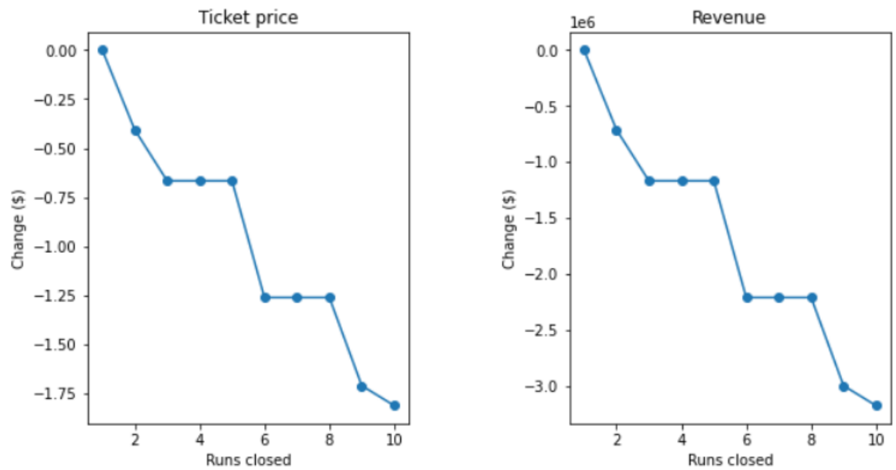

Figure 2. Decrease of ticket price (left) and revenue (right) for different number of closed runs.

including the longest runs, as well as the highest number of chairs and fast quads. Selected distributions are shown in Fig. 1. Compared to 10 competitors in the state of Montana, the Big Mountain performes remarkably better in terms of skiable area and area covered by snow makers, the longest run and total numbers of chairs and fast quads. This gives desired leverage for marketing purposes.

Furthermore, for a possible revenue increase, the company has shortlisted a few operating alternatives:

• **scenario 1:** permanently close down up to 10 of the least used runs,

• **scenario 2:** increase the vertical drop by 150 feet and require the installation of an additional chair lift,

• **scenario 3:** same as scenario 2, but add 2 acres of snow making cover,

• **scenario 4:** increase the longest run by 0.2 mile to boast 3.5 miles length, and require additional snow making coverage of 4 acres.

These options were evaluated using the model described above, under assumptions that the expected number of visitors over the season is 350k and, on average, visitors ski for five days.

The model predicts that closing one run **(scenario 1)** will not change the company's revenue, while closing 3 runs would imply the ticket's price reduction of 70 cents and the revenue reduction of 1.2M dollars. Interestingly, closing additional two runs (5 in total) will likely have no negative impact on the profit, but may further reduce the operating costs. Closing 6-10 runs will further reduce the ticket price by 1.25 - 1.75 dollars and the revenue by $2.2-3.2M, as shown in Fig. 2.

Adding a run, increasing the vertical drop by 150 feet, and installing an additional chair lift **(scenario 2)** would justify a ticket price increase by $1.99 and a revenue increase by 3.47M dollars. Extra addition of 2 acres of snow making **(scenario 3)** does not justify any increase in the ticket price.

Finally, extending the longest run by 0.2 miles and adding 4 acres of snow making capability **(scenario 4)** does not support the ticket price increase either.

4. Recommendations

For future improvements we suggest applying scenario 1 and scenario 2 with 5 closed runs, which if combined, should justify the ticket price of $97.16 and generate the revenue increase of $2.27M.

5. Technical details of the model

We built a model to predict the target ticket price based on 32 features present in the data. The data sample consisted of 276 entries, splited for training/testing by the 70/30 ratio.

The baseline performance was evaluated with the ticket price prediction taken as a simple price average of $63.8. which was compared against the target data using 3 different metrics: R2-score, mean absolute error (MAE) and mean squared error. The MAE score of 17.9 and 19.1 was obtained for the train and test samples, respectively.

We tested and optimized two different ML-based approaches, based on the Linear Regression (LR) and the Random Forest (RF) models.

The optimized LR model required median missing-value inputer and data scaler based on normal distribution scaling. It used 8 (out of 32) following input features: *vertical_drop, Snow Making_ac, total_chairs, fastQuads, Runs, LongestRun_mi, trams, and SkiableTerrain_ac*. The performance was evaluated with the MAE metric based on the 5-fold cross validation (CV) method and yielded the mean value of 10.5 with the standard deviation of 1.6. This compared well with the MAE result calulated from the 30% test sample, 11.8.

The optimized RF model required the median inputer, no input data scaling, and 69 trees. There were 4 input features that most influence the results: *fastQuads, Runs, Snow Making_ac, vertical_drop*. They agree nicely with the features selected by the LR model. The MAE metric calculated using the cross validation method gave the score of 9.6 with the standard deviation of 1.4. The MAE score evaluated with the test sample yielded the value of 9.5, which was within the CV estimated range.

For the final predictions the RF model was chosen, as it provided a slightly better performance in terms of MEA score.