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Document: The Skiable Resort Pricing Model

The Big Mountain Resort located in Montana offers a variety of skiable services in Glacier National Park and Flathead National Forest. Based on the data analysis, its ticket price was, and still is, most expensive in this state. The issue is that when the new chair lift is installed, the operating costs are elevated by $1.5M this season, which poses this skiable industry at risk for financial stress. Lowering the ticket price that might increase the number of consumers is likely to hamper the business strategy. Given that this operating costs increase, some may ask themselves the question about what kind of strategy that can help maximize profit without lowering the ticket price and with cost cuts before the upcoming season. They may ask themselves the question about what kind of services they should cut off without seeing a large drop in their profit. This is what the data analysis is about.

When pulling the *ski_data* data off from *GitHub*, there are several duplicates, depreciations, and missing values in this data. The critical points from cleaning up this data are worth mentioning. Because the *FastEight* variable contains either 0 or blanks, this column is removed. Because there is no price difference between *AdultWeekend* and *AdultWeekday* variables in Montana, the *AdultWeekend* variable is removed as well. Also, another part is because this variable has more blanks in the rows. This is why cleaning up the dataset matters.

When spending time to understand the data more, there are some unexpected findings that could lead to better ideas and solutions (i.e., pricing model). In order to grasp what these findings are, one first needs to explain what the data looks like. This data contains a variety of ticket price, mountain characteristics, services offered by each resort, and hours of opening across the United States. One surprise finding is the size area of night skiing and fast quads have a strong positive correlation with ticket price. This resort is one of few that offers this kind of service. The deep implication is that the Big Mountain Resort might have at even more advantages in its market segment than it lets on. This leads to creating the pricing model that helps to understand what this resort is worth.

Before the price modeling is created, the baseline first needs to be established. The hyperparameter search is in use to find best features and identify key variables that are major contributors to the model accuracy. As a result, the Measure Absolute Error (MAE) is $9.64 and the 1 standard deviation is almost $1, which exhibits less variability. This MAE has been decreased by 49.63%, being compared to the baseline. What is more important is that the learning curving shows that the increase of training set size leads to more consistent results of cross validation scores. When this model is being generalized, the MAE is increased by 75 cents and its standard deviation is equal to $1.47. For example, if this model predicts that this resort has a ticket price equal to $50. The *true* price may be either $60.39 or $39.61with $0.17 margin of error by 5 percent. In other words, this pricing model is robust.

When this pricing model is applied to Big Mountain Resort, this is where everything becomes interesting. The actual ticket price for Big Mountain is equal to $81 but the predicted ticket price is $95.87. The lowest *true* price is $85.48, which is puzzling. This result may be skeptical. If Big Mountain Resort is mispricing, there is a good chance that other resorts are either overpricing or underpricing, which has a significant impact on this model. The responsiveness to change in ticket price may lead to a change in demand quantity, which is called the *elasticity*. In other words, there is a possibility that the increase in ticket price drives the consumers to purchase a smaller number of ticket. The problem is that the *elasticity* remains unknown. The increase in the price without considering the possible tradeoffs is not ideal. However, this model does imply that this resort has room to maximize capitalization.

The business intelligence develops the shortlisted options that can help to lower operating costs or increase ticket prices. The first scenario is to permanently close down up to 10 of the least used runs. The second scenario is to increase the vertical drop by 150 feet but with additional chair lift installment without additional snow making coverage. The third scenario is same but with additional two acres of snow making coverage. The fourth scenario is to increase the longest run by 0.2 mile but with additional snow making coverage of 4 acres.

The assumption is that all scenarios are reasonable. However, when the pricing model is included, the third and fourth scenarios are not only unrecommended, but this model also shows that both scenarios have no impact on revenue in any way. The first scenario shows that a number of closing runs should be 5 at maximum. Otherwise, the large drop in revenue is to be expected. To extend the vertical drop by 150 feet plus new chair lift installment will lead to increase ticket price by $1.99, which is equal to the increase in revenue by $3.47M.

The roadblock is that this pricing model does not hold complete information about costs and benefits, which prevent the resort from exploring more business options. For example, this model is unaware of the fact that the new chair installment may increase operating cost by at least $1.5M. The scrap value is also unknown. This term refers to the worth of individual components in physical assets where this asset itself is no longer usable. What is more is that this model is unable to predict the number of customers over time.

However, on the other hand, the pricing model—furthermore—holds much more promise. This can allow business analysts to assess more without additional assistance. The anticipated future is that this pricing model should turn into an user-friendly interface, allowing the business analysts to test the new combination of parameters. This interface may include data visualizations and reports, which are also known as ad hoc analysis. The ad hoc analysis may eliminate tenuous tasks like data wrangling—which is called Intentional Data Transfer—and allows them to assess without relying on coding.