Currently, Big Mountain Resort sets prices by charging a premium above the average for the market segment. The business wants a more data-driven price to be set, especially after a recent chair lift procurement that will increase operating costs by over $1.5M.

The question to address is this: How can Big Mountain Resort adjust ticket prices by the start of the 2025 ski season to better align with a $1.54M increase in operating costs while leveraging or cutting facilities and services to achieve at least a 5% revenue growth compared to last season?

To that end, I needed to evaluate the current use and cost of each facility to find opportunities for improvement. I also needed to compare pricing information of Big Mountain Resort to that of our competitors, ensuring the price is justified by the features offered.

I gathered information from all the ski resorts nationwide, including data about their prices, resources, and statistics. I ran some basic tests to compare Montana (our state) against other states and the resorts in them. There were no major outliers or other concerns.

I plotted the cumulative variance information to see the distribution and almost 90% of the variance is accounted for in the first two components. The first 4 account for over 95%. This means that the data isn't overly complex, so modeling and extrapolating information should be fairly straightforward.

With this knowledge in hand, I built some training models to help validate assumptions and make predictions for the future. I tested using both the mean values and median values for missing and test data. I tested to see how accurate using these values were as predictors and they compared very well to one another. Calculating the absolute error for the tests gives a range for the ticket price between $8.54 and $9.41. I also used the sklearn pipeline component to run estimates and the absolute mean and median error gave a range of $8.55 and $9.41, which falls perfectly in line with my other results.

Other methods of cross-validation, including checking for overfitting and manually changing the kvalue were less effective. As such, I moved forward with the sklearn pipeline model.

I used the get_params function of "pipe" to build a dictionary of available parameters and the GridSearchCV utility returned the the 8 most relevant features that determine price:

vertical_drop	10.767857	Runs	5.370555
Snow Making_ac	6.290074	LongestRun_mi	0.181814
total_chairs	5.794156	trams	-4.142024
fastQuads	5.745626	SkiableTerrain_ac	-5.249780

A random forest regressor showed the best estimator had "fastQuads," "Runs," "Snow Making_ac," and "vertical_drop" as the top four contributors as well.

Now that I knew what information to focus on, I wanted to be sure I had gathered enough, so I plotted the cross-validation scores with errorbar to see how the score would change as the sample size increased, and saw that there would only be a negligible difference if additional data were added.

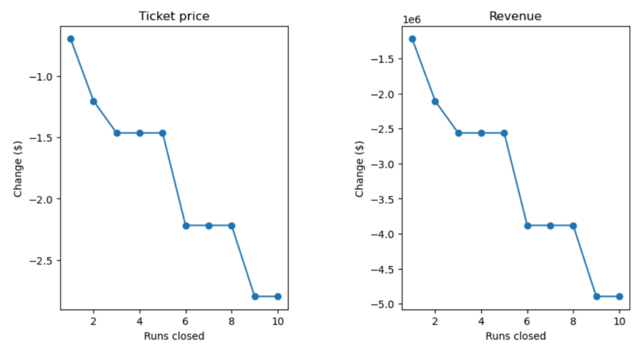
I plotted a histogram of the most important features that impact price and showed where Big Mountain Resort was in relation to everyone else. Big Mountain Resort charges more than most other resorts in the state, but only a little higher than the national average. Big Mountain Resort also has much more to offer, having a higher than average vertical drop, area covered by snow makers, number of chairs, total number of fast quads, number of runs, run length, and skiable terrain area. All of these could justify the higher ticket price.

Big Mountain Resort management shortlisted some change options, listed here:

-Permanently closing down up to 10 of the least used runs
-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
-Same as the second option, but adding 2 acres of snow making cover
-Increase the longest run by 0.2 miles to boast 3.5 miles length, which would require an additional snow making coverage of 4 acres

I made a copy of the Big Mountain data so I could apply each individual suggestion to see what impact it would have on the price.

First, I set up a loop that would predict the change in price for shutting down up to 10 runs, then plotted the predicted change in ticket price and revenue for each change. Based on the model, closing one wouldn't have any impact. Closing 2 would have some impact, 3 - 4 would have more, as well as 6-8, and much more impact at 9-10. The table makes it easy to see each step of difference and the cost plateau saved. Closing 6, 7, or 8 would have the same cost impact.



For the next prediction, increasing the vertical drop by 150 feet and adding another chair lift, I scripted a calculation to account for the changes and saw that it would justify an increase in ticket price by $1.41. The revenue increase can be extrapolated (in this case, estimated at $2,460,145), so the cost of doing so can be weighed against that benefit.

For the third and fourth scenarios, extra cost would be expended for little-to-no gain.
So while there are different plans, only two of them will have any direct impact on the financial bottom line: Closing runs and increasing the vertical drop and adding another chair lift.

It must be noted that the cost of those individual options is not included in these calculations. There is a real probability that the construction and/or removal will interfere with current business operations, so scheduling will also need to be considered. In terms of closing runs, the scope of that will need to be evaluated by management, but the numbers measuring the impact of how many to close will help in that decision.

If the recent chair lift procurement can be used for the increased vertical drop, that would be the most efficient way to offset the cost and increase revenue, which would be my recommendation, notwithstanding unknown costs for increasing the vertical drop 150 feet.