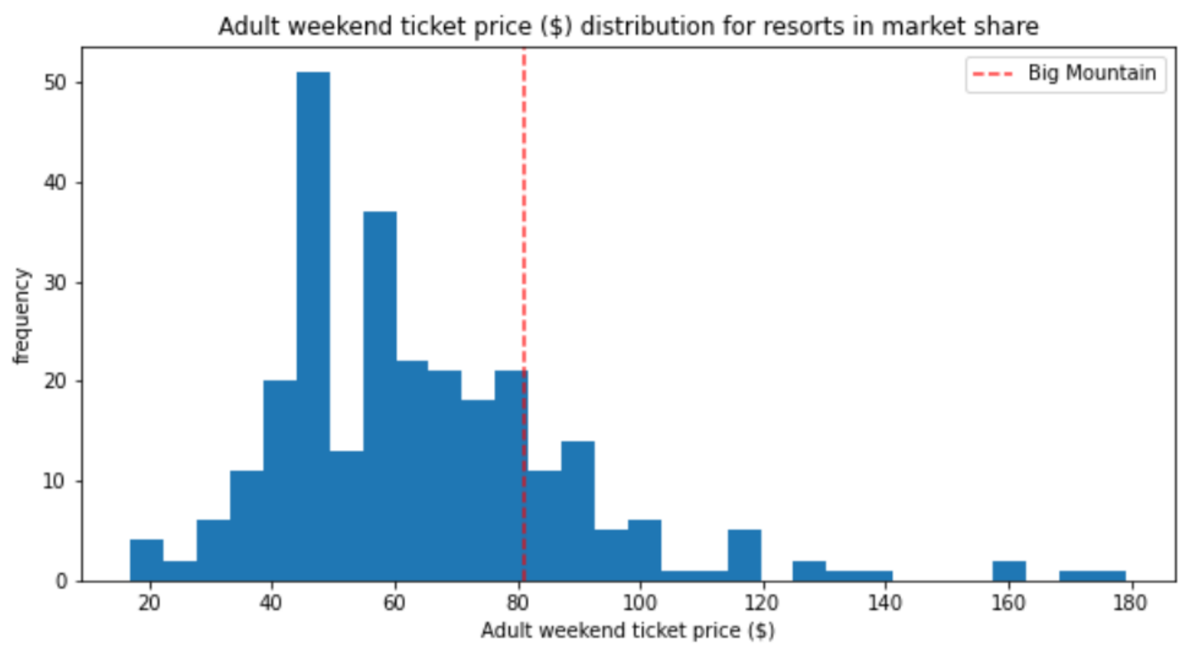
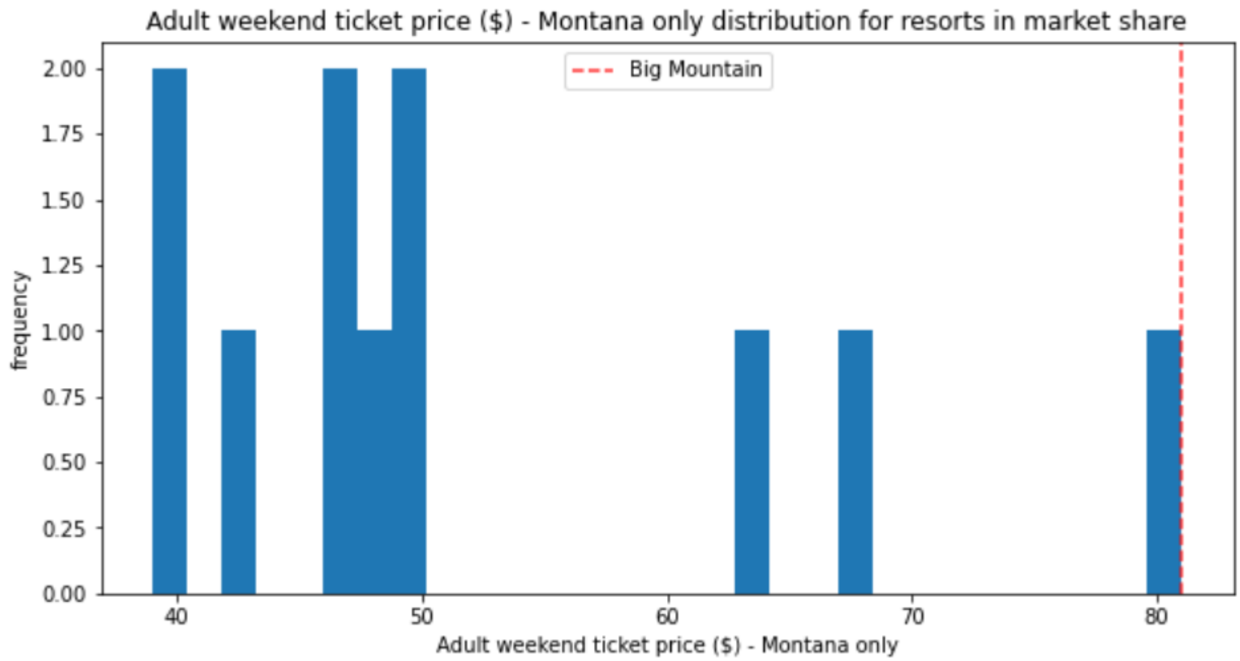
In this project, the stakeholders of Big Mountain Resort try to implement the best strategy that can maximize capitalization in their facilities investments to offset their recent additional operating cost by $1.54M. They are planning two different approaches, increasing the ticket prices to increase the income or cutting the cost to reduce the expenses. The data science team was given a csv file that includes 27 features of 330 resorts. After cleaning the dataset and adding state statistics for Exploratory Data analysis(EDA), we figured out that there are big states which are not necessarily the most populous. There are states that host many resorts, but other states host a larger total skiing area. The states with the most total days skiing per season are not necessarily those with the most resorts. Therefore, instead of using the actual datasets features we define some ratio attributes that display more information (variation). Then we created some models and tuned them to decrease the errors. This process help us to found out that features that came up as important in the modeling (not just our final, random forest model) included:

- vertical_drop
- Snow Making_ac
- total_chairs
- fastQuads
- Runs
- LongestRun_mi
- trams
- SkiableTerrain_ac

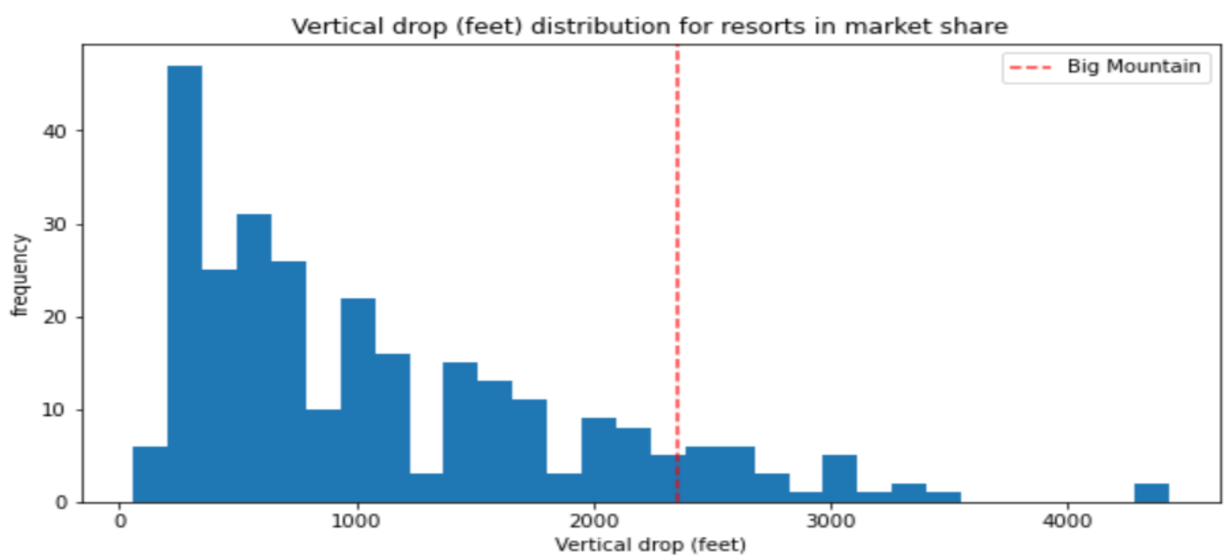


These two figures show where the Big Mountain Resort price stands in all US and Montana.



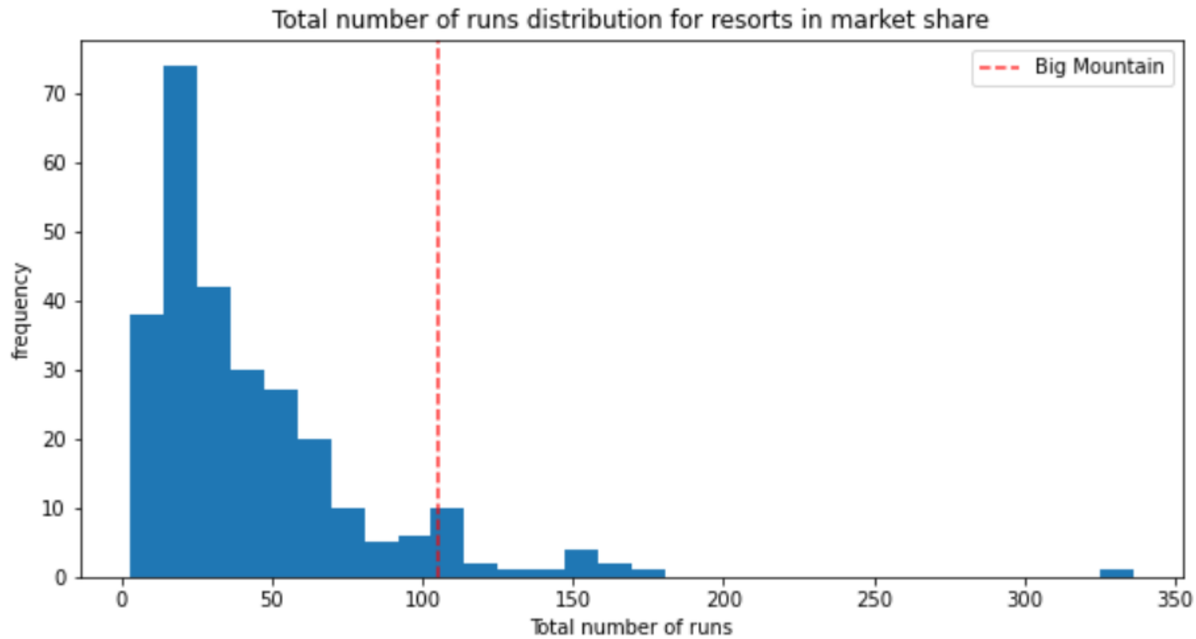
The business has shortlisted some options:

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



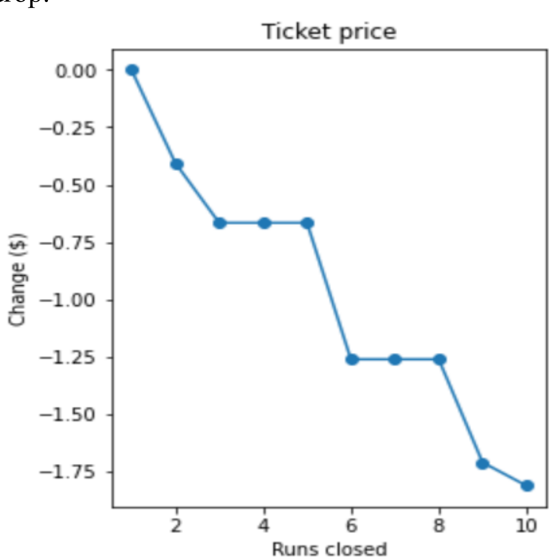
Let's see where Big Mountain stands among other resorts based on vertical drop and total number of drops since these two features are the main attributes of shortlisted options.

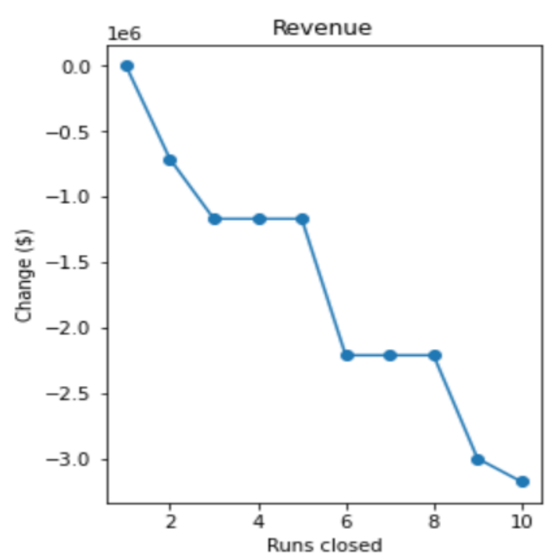
Big Mountain is doing well for vertical drop, but there are still quite a few resorts with a greater drop.



Big Mountain compares well for the number of runs. There are some resorts with more, but not many.

Scenario 1 says closing one run makes no difference. Closing 2 and 3 successively reduces support for ticket price and so revenue. If Big Mountain closes down 3 runs, it seems they may as well close down 4 or 5 as there's no further loss in ticket price. Increasing the closures down to 6 or more leads to a large drop.





Scenario 2, Big Mountain is adding a run, increasing the vertical drop by 150 feet, and installing an additional chair lift. This scenario increases support for ticket price by $1.99. Over the season, this could be expected to amount to $3474638.

Scenario 3, adding a run, increasing the vertical drop by 150 feet, and installing an additional chair lift but adding 2 acres of snow making. This scenario increases support for ticket price by $1.99. Over the season, this could be expected to amount to $3474638. Such a small increase in the snow making area makes no difference!

The current price is $81, but the model suggests to increase the price to $95.87. By comparing the important features based on the random forest model, we can see that Big Mountain will mostly be in highest numbers. For example, Big Mountain has amongst the highest number of total chairs, resorts with more appear to be outliers. Or Most resorts have no fast quads. Big Mountain has 3, which puts it high up that league table. Therefore, Big Mountain has high features but does not charge the customers that much. Big Mountain Resort has been reviewing potential scenarios for either cutting costs or increasing revenue (from ticket prices). Ticket price is not determined by any set of parameters; the resort is free to set whatever price it likes. However, the resort operates within a market where people pay more for certain facilities, and less for others. Being able to sense how facilities support a given ticket price is valuable business intelligence. This is where the utility of our model comes in.

As we mentioned above as well, the validity of our model lies in the assumption that other resorts accurately set their prices according to what the market (the ticket-buying public) supports. The fact that our resort seems to be charging that much less than what's predicted suggests our resort might be undercharging. But if ours is mispricing itself, are others? It's reasonable to expect that some resorts will be "overpriced" and some "underpriced." Or if resorts are pretty good at pricing strategies, it could be that our model is simply lacking some key data? Certainly we know nothing about operating costs, for example, and they would surely help. For Example, payroll expenses, utilities etc can play a great role in estimating the price. Or knowing the average income of the neighborhood can tell some story as well.

I would show the executives all those distribution charts to see where Big Mountain stands and then justify that model prediction takes those aspects into account. Therefore, increasing the price makes total sense since Big Mountain places among the highest numbers. Additionally, we can create an app or Excel formula for them so they can use that for their future exploration or trying different business scenarios.