# Big Mountain Ski Resort

# Assessing pricing and resource allocation among facilities

### Problem statement

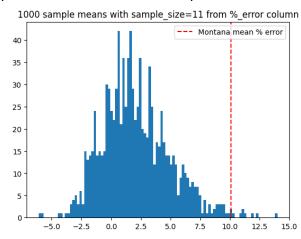
Given the facilities of Big Mountain Resort, what is our current profit maximizing price, and in what facilities should we invest or divest resources to maximize profit?

# Key findings

1) Big Mountain resort currently charges \$81.00 dollars for a weekend or weekday ticket. Our current best model suggests a price of \$95.87.

### Pricing recommendation: raise pricing according to facility change

Even though our model suggests we are undervalued by \$14.87, our model also says that all other resorts in Montana are undervalued. This indicates that our model may be overvaluing all resorts in Montana, or all resorts in Montana are priced below true market value. The following figure shows that it is likely not a coincidence that the 11 resorts in Montana have a predicted price 10% above their actual price.

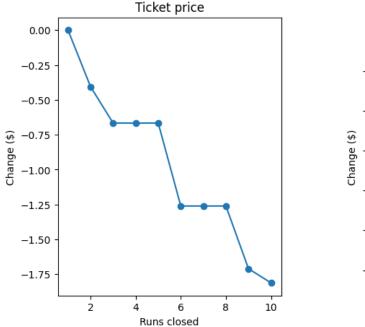


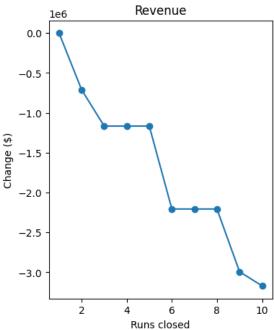
Therefore, we recommend only increasing ticket prices according to changes in facilities. If a change in a facility is predicted to add \$1 per ticket sold, we should increase ticket prices by about \$1.

# Recommendations on business change scenarios

Of the four proposed business changes we recommend:

1) Close down least popular runs: Assuming our model is correct we should close 0, 5, or 8 runs, given ticket price reductions of 0, .66, 1.26 in ticket prices, giving a yearly drop in revenue of 0, 1155000.0, 2187500.0. If the drop in operating costs are significantly greater than these drops in revenue, we should consider closing some runs. To experiment, we should close 5 runs to start and monitor visitation rates and customer satisfaction to see if there is greater loss in value than expected.





The model 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.

2) Adding a run, increasing the vertical drop by 150 feet, and installing an additional chair lift: The extra expected value is \$3,474,638 so if the extra cost is less than that, it could be a good idea.

#### We do not recommend:

- 3) Same as #2 but with an additional 2 acres of snow making We predict no extra value for the extra 2 acres of snow so I would not suggest this either.
- 4) Increasing longest run by .2 miles and increasing snow cover by 4 acres Our model does not predict any increase in value, so I would not suggest this.

### **Data Wrangling**

**The raw data:** The original data has 330 rows and 27 columns. Each row represents a different ski resort located in the US. One of the rows is "Big Mountain Resort", which is the resort for which we are doing this analysis.

Raw data shape: 330 rows and 27 columns Final data shape: 277 rows and 25 columns

Chosen target to model: "AdultWeekend" because:

- All resorts in Montana showed no difference between weekend and weekday so we don't need to model both.
- "AdultWeekend" had fewer missing values than "AdultWeekday".

#### Columns dropped:

- "fastEight" since 50% of the rows were missing this variable and all but one of the remaining rows were the same value.
- "AdultWeekday" since it has more missing values compared to "AdultWeekend" (7 compared to 4).

#### Rows dropped:

- "Pine Knob Ski Resort" because the value for "yearsOpen" was 2019, which we took
  mean that it was opened possibly in 2019. Either way we didn't want to include a resort
  that just opened.
- 14% of all rows were dropped because they had no ticket price data.
- 4 Rows where "AdultWeekend" was missing.

#### Rows adjusted:

• For "Silver Mountain", we changed the value for "SkiableTerrain\_ac" from 26819 to 1819, because this is the value we found when looking it up on the internet, the last 3 digits matched, and the new value made more sense.

### Exploratory data Analysis

**Key missing data**: Number of visits Since we don't know the current visitation rates of the different resorts, it is harder to know how the features could affect price or overall profitability. However, even without knowing the other resorts visitation rates, "Big Mountain" certainly needs to take their own rates into account. For instance, our model may suggest that adding chair lifts will increase value. But if we already know that our chair lifts are not full most of the time, then we should know that expanding capacity likely will not increase value to a customer.

#### Top 10 features that showed strongest correlation with ticket price:

'Runs', 'fastQuads', 'vertical\_drop', 'Snow Making\_ac', 'total\_chairs', 'daysOpenLastYear', 'LongestRun\_mi', 'trams', 'projectedDaysOpen', 'SkiableTerrain\_ac'

State and ticket price relationship Different states have significantly different mean prices, ranging from around 40 to 80 dollars. There is no clear grouping of states based on the features provided. The features that derived from state, such as 'resorts\_per\_state' and 'resorts\_per\_100kcapita' did not show strong correlations with ticket price, nor did any features that compared a resort to the rest of the resort's home state, such as 'resort\_days\_open\_state\_ratio'. Moving forward, I would start by building a model that did not take into account any state information.

# Modeling process:

**Metric**: Mean absolute error between actual and predicted values for a resort's weekend ticket price. So if the true price of a ticket is \$20, and the predicted price is \$24, the mean absolute error is \$4.

**Cross validation:** Train on 70% of the data and predict the remaining 30% **Preprocessing:** Impute missing values, scale inputs (only for linear regression)

Models and results:

Model	Baseline Model	Random Forest Regressor	Linear Regression
Mean Absolute Error	19	9.5	11.8
Beats Baseline by	0	10.5	7.2
NAN Imputation	None	Median	Median
Number of Estimators	NaN	69	NaN
Mean CV Score	NaN	9.6	10.5
Std of CV Scores	NaN	1.4	1.6

#### Conclusion

We built a model to predict our fair market value and determine the best business plans to increase profits. We recommended keeping adjusting the price according to facility changes. We also recommended to facility changing business plans:

- 1) Closing the 5 least popular runs
- 2) Adding a run, increasing the vertical drop by 150 feet, and installing an additional chair lift

### Future scope of work

We should try modeling the weekday price to see if there is still a chronic overprediction of Montana ski resort prices. I also believe there is more information that we are missing that could explain the errors.

#### Other data I'd want

- distance to nearest competitor, and price of the competitor.
- cost of traveling to the resort from other parts of the country. Maybe it is hard and or costly to get to the ski resorts in Montana, so they need to be priced lower.
- cost of lodging and food. Maybe its hard for visitors to find cheap places to stay near Montana resorts, so ticket prices need to be cheaper.

**Other useful cost information** The marginal cost for increasing or decreasing any of the relevant features. This would make it easier to model different business decisions.

Why was modeled price so high?: It seems to me that all resorts in Montana were modeled high. Maybe there is information about Montana resorts that are not captured by the model. Perhaps the executives would not be surprised because they know that it is hard to travel to these resorts, limiting visitors from across the country. I would find out by mentioning the price predictions for Montana and see how the executives react.

**Making use of the model**: In order for executives to use this model for business planning, I would make a simple program where they could input the changes in facilities (amongst the modeled features) and see how the model expects the ticket value to change. If we also know the marginal costs for increasing or decreasing facilities, we could give outputs in terms return on investment.