

Big Mountain Resort, a premier ski destination in Montana, is tasked with enhancing its approach to pricing and facility utilization, with a world-class range of diverse activities that are good for all ages and ski abilities. The company acknowledges there is a need for improvement. The data-driven analysis shown here will show the company how to maximize resources, cut costs, and help create a competitive price plan for tickets to this resort. When data wrangling the errors corrected included an unrealistic '2019' year for years open feature and an outlier in skiable terrain for Silverton Mountain Resort in Colorado (corrected from 26819.0 to 1819). Null or NAN values in weekend prices were removed for accuracy. The irrelevant fastEight column was also deleted for clarity. A statewide summary was created, showing metrics like state square mileage and population. With the data wrangling, we saw a pattern that flows through the project that more often than not facilities in other resorts are severely limited compared to Big Mountain. As shown in [Figure 1](#). This was shown first in the wrangling process. Where most resorts had limited availability of snow-making machines and night skiing areas. They had fewer fast quad lifts, suggesting smaller scale or cost considerations. A shortage of other factors was observed in several areas such as quads, triples, double chairs, and surface lifts, indicating resorts overall have fewer facility benefits than Big Mountain has. Resorts also had fewer runs and terrain parks. longer runs are less common. Skiable terrain which Big Mountain boasts is 3000 miles. Which compared to other resorts is drastically higher. During the exploratory phase of this project we examined Montana, with its expansive area and lower population density, offers more generous allocations of skiable terrain, placing it in the top five for skiable areas. We used Principal Component Analysis (PCA) used to reduce dataset complexity. The first two principal components captured about 77% of the variance, indicating common characteristics among states. Summit elevation and vertical drops show a positive correlation with ticket prices, as resorts with higher elevations and larger drops can charge more. Montana has an impressive vertical drop of 2353 feet high. Skiable terrain area and snowmaking capability are positively correlated with ticket prices, indicating that larger terrain and reliable snow conditions justify higher prices. Yearly snowfall impacts customer decisions to visit resorts. The analysis suggests that snow prevalence and resort infrastructure are key features that give resorts a competitive edge. For the preprocessing step we tested our theory with metrics and machine learning to find the best solution to the issue. For the train/test scenario we used a 70/30 split. We used average ticket prices, with performance evaluated using metrics like Mean Square Error (MSE), Mean Absolute Error (MAE), and R-squared. Linear regression showed about 8 features were relevant as seen in [figure 2](#). This model served as a reference point, though it showed signs of overfitting. Imputation of data using mean or median values. Data was scaled before applying it to the models. The initial focus was on identifying key features influencing ticket prices using linear regression. The model's performance was evaluated through cross-validation, showing it could explain the significant features at that time to about 8 optimal features. This was inferred from the performance plateau observed in the analysis (shown on [figure 2](#))s. We then used random forest showed a lower mean absolute error compared to the linear regression model, indicating more precise and consistent. The result from the final model showed us the

key features to determine how to resolve our business issue. Those were vertical_drop, snow making, total_chairs, fastQuads, and runs. By the end of the processing stage. the modeling process involved establishing a baseline, preprocessing data, and using linear regression and random forest models to predict ticket prices. In the preprocess stage it a detriment that we had enough information to make an accurate decision on feature as seen in [figure 4](#) .The random forest model was ultimately selected for its superior performance in terms of accuracy, generalizability, and consistency. The Resort's current ticket price is \$81.00, but the model recommends a price of \$93.75. This discrepancy indicates potential underpricing given the resort's amenities. Big Mountain's data was excluded from the training set to ensure an unbiased model. Price Increase justification: The model's preprocessing steps suggest a feasible price increase of around \$10, offering flexibility for adjustments. As with our main thesis the ML model shows Vertical Drop to be one of the primary feature studies. The final features can be seen in [figure 5](#) .Big Mountain has a notable vertical drop, ranking high in this category, but only a few resorts exceed it. The resort is among the top in the industry for snow-making. Big Mountain has a significant number of total chairs and fast quads, enhancing its appeal. It also boasts more runs and longest Runs: Big Mountain's Skiable Terrain excels in the amount of skiable terrain available. Given its market position and features, Big Mountain Resort appears underpriced. The resort could close at least 3 runs without affecting the bottom line, reducing operating costs([figure 5](#)). An increase in ticket price is justified and feasible, with only marginal gains from physical enhancements. The advice is to increase the by \$5 which would generate \$1,750,000. In extra revenue. Also it is advised to cut 3 runs which won't increase profit as seen in [figure 5](#) . We should also be leveraging our existing strengths. The features offered by Big Mountain Resort are highly valuable to customers, who may be willing to pay more for the accommodations and amenities provided. Future focus: I think you could continue to use data-driven approaches to understand customer preferences and market trends. Also future focus could be on refining predictive models regularly to ensure pricing and operational strategies remain competitive and relevant.