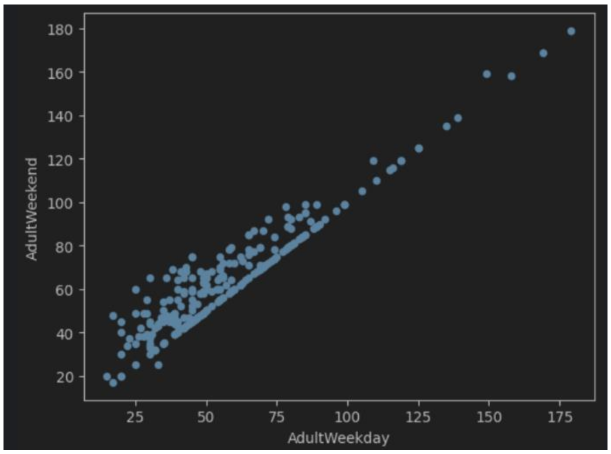
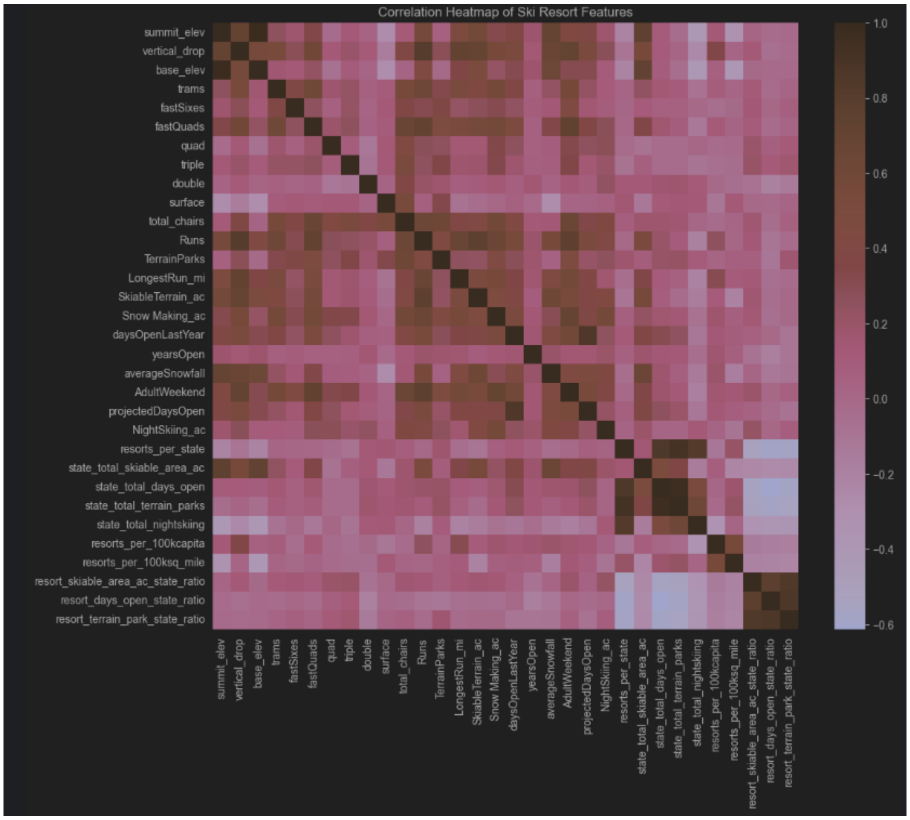
What data-driven business strategies and opportunities exist for Big Mountain Resort to increase revenues by optimizing ticket pricing strategy through identifying key differentiators that could justify higher pricing, and capitalizing on the resort's facilities rather than solely relying on its current pricing strategy of charging a premium above the average price of resorts in its market segment, which has limitations that hamper investment strategy, and considering that operational costs have increased by $1,540,000 from a new chair lift installation?

An exploratory data analysis of ski resort data (a single csv file containing 330 rows and 27 columns) was used for data wrangling. I removed the 'fastEight' column due to insufficient data, and rows with missing values for weekday and weekend adult price tickets were removed, too. For data correction, Silverton Mountain's skiable terrain area was changed to 1819 acres. I identified outlier resorts then made a summary of statistics (total skiable area, number of resorts per state) and visual plots to see ticket price distribution, weekday and weekend price relationships, and resort location distribution across differing states and regions. Data was reshaped by use of pd.melt to facilitate analysis of ticket prices over different days.

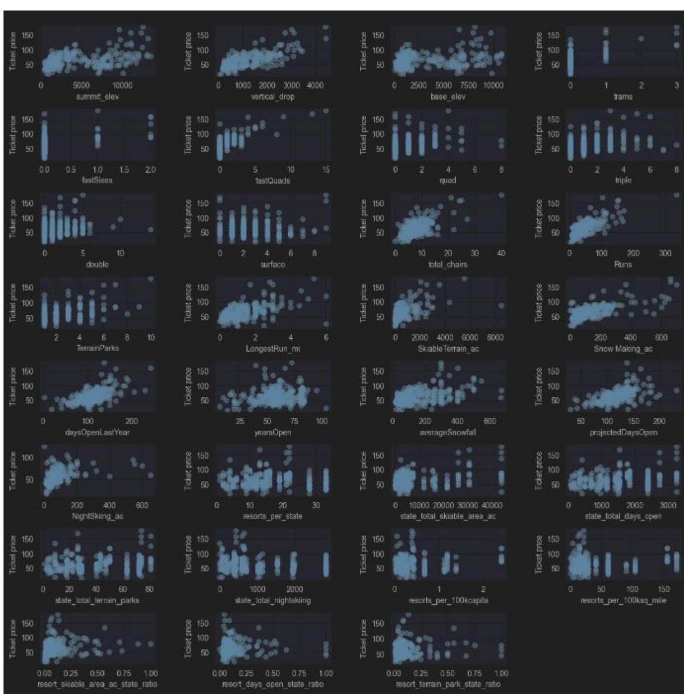


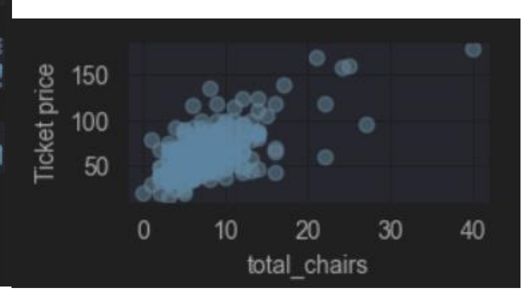
As can be seen from this picture on the left, analysis of ticket prices reveals variations between the pricing for weekday vs. weekends. Merging the state-level data, insight was gained into how resort characteristics might correlate with state population and area. The statewide summary was created by computing resorts_per_state (count of resorts in every state), state_total_skiable_area_ac (sum of skiable terrain area), state_total_days_open (sum of days open last year), state_total_terrain_parks (sum of terrain parks), and state_total_nightskiing_ac (sum of night skiing area). This was performed using pandas agg function, allowing for clear labeling of each aggregation. The target feature for ticket price prediction was finalized based on analyzing the 'AdultWeekday' and 'AdultWeekend' columns in ski_data DataFrame, using columns that represent the adult prices for weekdays and weekends. By looking at the scatterplot that compares these weekday and weekend prices, it confirmed that these two features would act as target variables for predicting, allowing for a more thorough model to account for peak and off-peak pricing variations.

The data set contained numerical (ticket prices, skiable terrain area, vertical drop, number of lifts) and categorical (state, region, resort name) features.

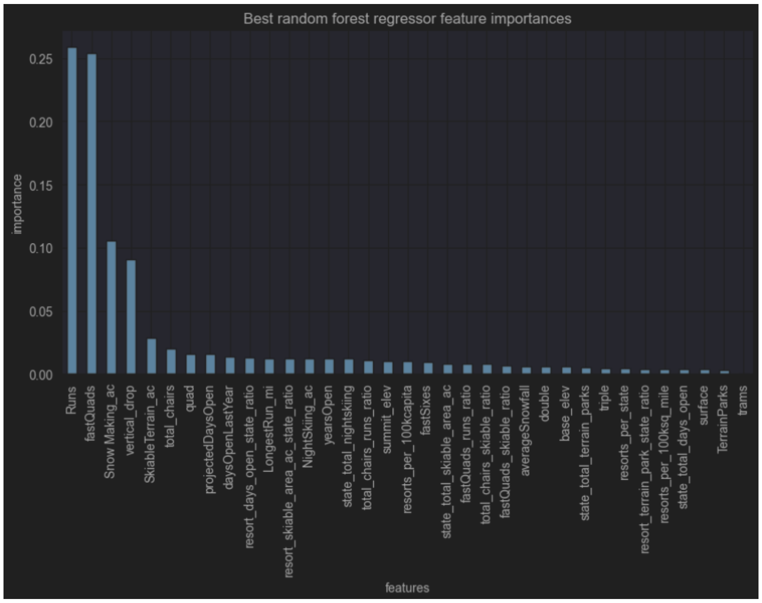


The heatmap reveals summit and base elevation are quite highly correlated. There is also some positive correlation between night skiing area and the number of resorts per capita; when resorts are more densely located with population, more night skiing is provided. Interestingly, visitors seem to value more guaranteed snow, which would cost in terms of snow-making equipment. Runs and total chairs also correlate with ticket price, which makes sense since the more runs available means you need more chairs. People furthermore value guaranteed snow over a wider terrain area. The vertical drop is also a selling point that raises ticket prices, which is evident in the scatterplots to see how ticket price varies with other numeric features:



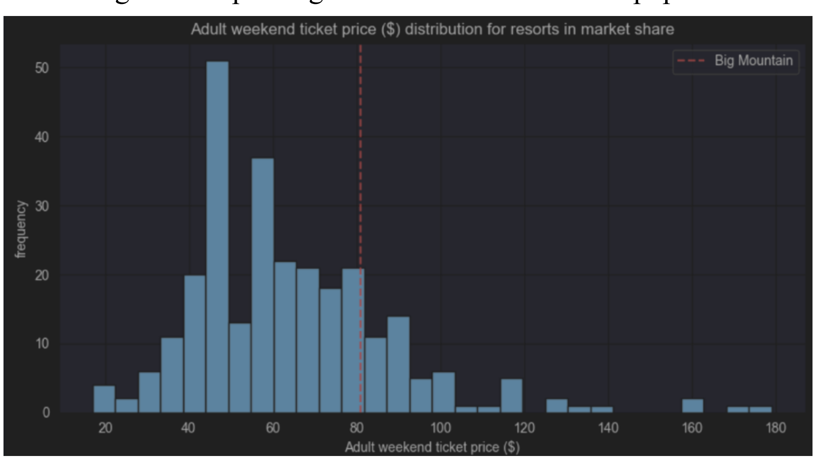


A baseline idea of performance was by simply taking the average price provided a simple performance benchmark. A linear model was then built, which incorporated feature selection to identify key predictors



and was estimated using cross-validation. The linear model identified key features such as vertical drop, total skiable area, and number of runs. A random forest regressor was tried. A pipeline including median imputation and standard scaling as preprocessing steps was used and then the random forest model's performance was evaluated using cross-validation. The performance on the test set was consistent again. Compared to the linear regression model, the random forest model outperformed in terms of accuracy prediction. Also, the random forest model provides insight into feature importance, highlighting vertical drop, total skiable area, and the capacity to make snow as important ticket pricing predictors. Due to this ability to capture non-linear relations better, the random forest model was used going forward since it provided both accurate price predictions and offered insight into resort feature importance for determination of prices for tickets.

I recommend aspects from the model which show positive impact on ticket prices: increasing the vertical drop, expanding snow-making capabilities, and adding more runs. Closing runs had a negative impact, but adding runs may increase prices of tickets. The business might test and progress with run closers by starting small-scale tests of closing the runs that are not as popular during off-peak times. Gathering feedback from customer satisfaction can also be an option. Big Mountain Resort may also analyse the cost savings from reduced maintenance and then compare them to any revenue loss; if there is minimal impact, the number of closed runs could gradually be expanded. Further consideration of reinvestment of savings into improving the runs that are the most popular is also an option to think about.



The figure shows how Big Mountain Resort's weekend ticket price stands amongst other resorts outside of the state. Big Mountain has a current position of charging $81 for an adult ticket for the weekend.

The modeling implies that the resort could support a ticket price of $94.22 if it considers current facilities and market position, which is a significant revenue growth opportunity. Regarding operating of the new chair lift per ticket (on basis of each visitor on average buying five-day tickets) and talks of raising prices to cover this expense, the additional operating cost of $1.54 per ticket (assuming 5-day tickets per visitor) can be covered by suggested price increase of $13.22 per ticket price. Doing so would more than offset any new operating expenses while remaining competitive in the market.

In the future, Big Mountain Resort should progress with run closers by starting small-scale tests of closing the runs that are not as popular during off-peak times. Gathering feedback from customer satisfaction can also be an option. Big Mountain Resort may also analyse the cost savings from reduced maintenance and then compare them to any revenue loss; if there is minimal impact, the number of closed runs could gradually be expanded. Further consideration of reinvestment of savings into improving the runs could be taken into consideration.