**The Problem statement:**

The purpose of this data science project is to come up with a pricing model for ski resort tickets in our market segment. Big Mountain suspects it may not be maximizing its returns, relative to its position in the market. It also does not have a strong sense of what facilities matter most to visitors, particularly which ones they're most likely to pay more for. This project aims to build a predictive model for ticket price based on a number of facilities, or properties, boasted by resorts (at the resorts). This model will be used to provide guidance for Big Mountain's pricing and future facility investment plans.

**Findings:**

It seems that the more chairs a resort has to move people around, relative to the number of runs, ticket price rapidly plummets and stays low. What we may be seeing here is an exclusive vs. mass market resort effect; if you don't have so many chairs, you can charge more for your tickets, although with fewer chairs you're inevitably going to be able to serve fewer visitors. Your price per visitor is high but your number of visitors may be low. Something very useful that's missing from the data is the number of visitors per year.

Big Mountain Resort modelled price is $95.87, actual price is $81.00. Even with the expected mean absolute error of $10.39, this suggests there is room for an increase.

This result should be looked at optimistically and doubtfully! 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 that 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 "under-priced." 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.

1. Big Mountain is doing well for vertical drop, but there are still quite a few resorts with a greater drop.
2. Big Mountain is very high up the league table of snow making area.
3. Big Mountain has amongst the highest number of total chairs, resorts with more appear to be outliers.
4. Most resorts have no fast quads. Big Mountain has 3, which puts it high up that league table. There are some values much higher, but they are rare.
5. Big Mountain compares well for the number of runs. There are some resorts with more, but not many.
6. Big Mountain has one of the longest runs. Although it is just over half the length of the longest, the longer ones are rare.
7. The vast majority of resorts, such as Big Mountain, have no trams.
8. Big Mountain is amongst the resorts with the largest amount of skiable terrain.

**Scenarios:**

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.

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
5. The expected number of visitors over the season is 350,000 and, on average, visitors ski for five days. Assume the provided data includes the additional lift that Big Mountain recently installed.

Validations:

1. 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. Although the longest run feature was used in the linear model, the random forest model (the one we chose because of its better performance) only has longest run way down in the feature importance list.