Big Mountain's Data-Driven Strategy

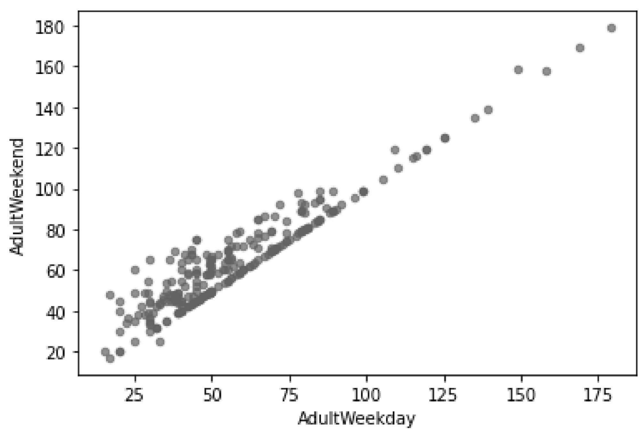
Intro

There's been a rumor going around that Big Mountain's lift ticket price is lower than it's worth. So far, the price has been defined by premium on the market average. Although that's a very easily understood strategy, it cannot define the true worth of the lift ticket without undergoing time-consuming and risky trial and error. Whenever the resort makes changes, like the chairlift that has recently been installed, the dubious process begins again. Now, thanks to public data and machine learning tools, Big Mountain no longer needs to take such risks. We've lain the groundwork for Big Mountain's Data-Driven Strategy by

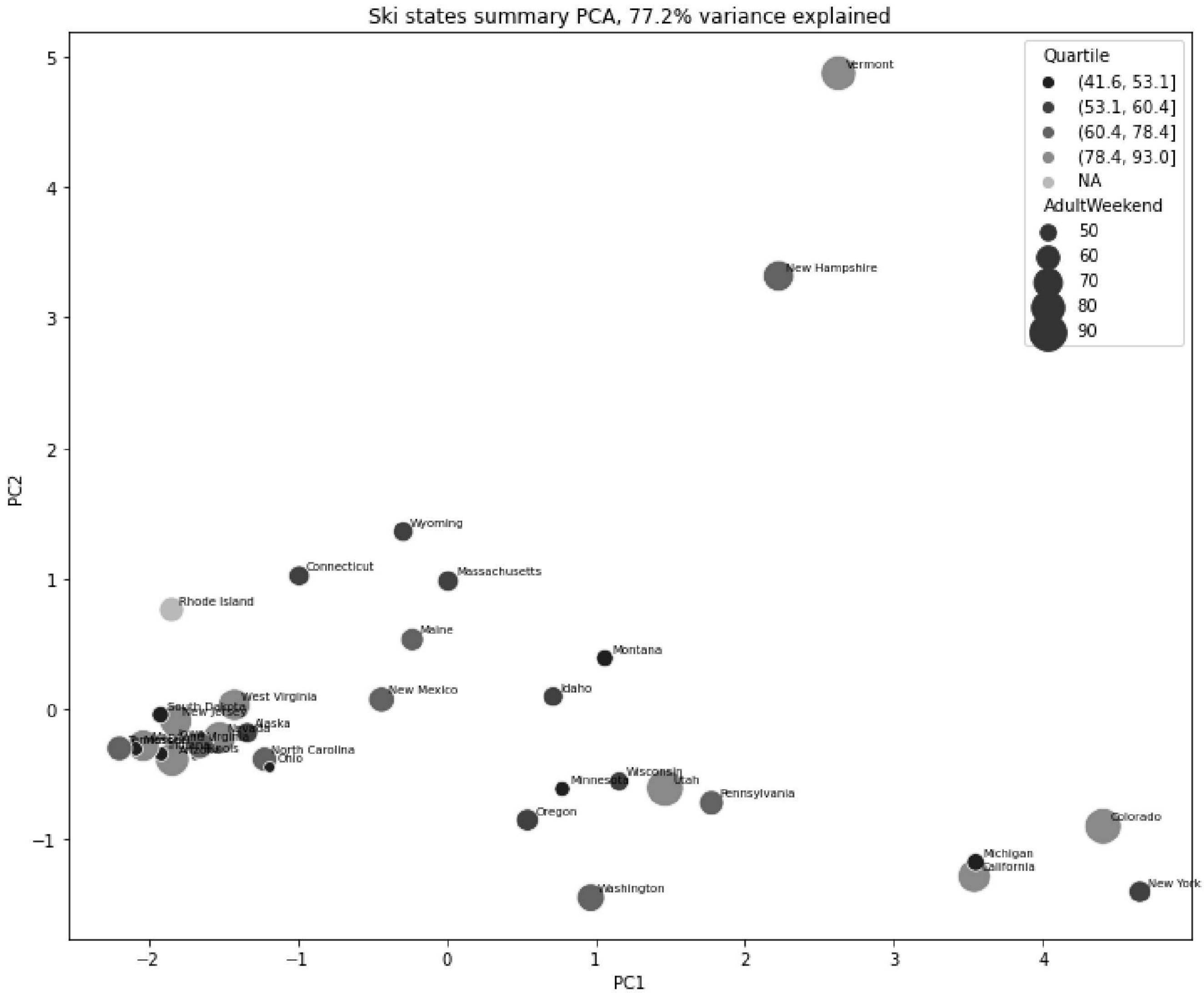
1. Determining the true worth Big Mountain's lift ticket
2. Recommending investments customers' value and cuts for what they don't
3. Brainstorming how to improve the model

Data

Two datasets were used to complete this project. The first came from Alesha Eisen which detailed 25 features for 330 resorts considered to be in the same market like number and type of chairlifts, snow-making machines, and most importantly the weekday and weekend lift ticket prices. In order to simplify our model, we chose to predict a single lift ticket price, the weekend's, over the weekday only because there were fewer missing values. Though, either would have been appropriate. They are strongly correlated and therefore interchangeable as shown below. There were also several missing data fields. Rather than spending a lot of time investigating and filling them, we chose to drop them, and tested our model on 277 resorts.

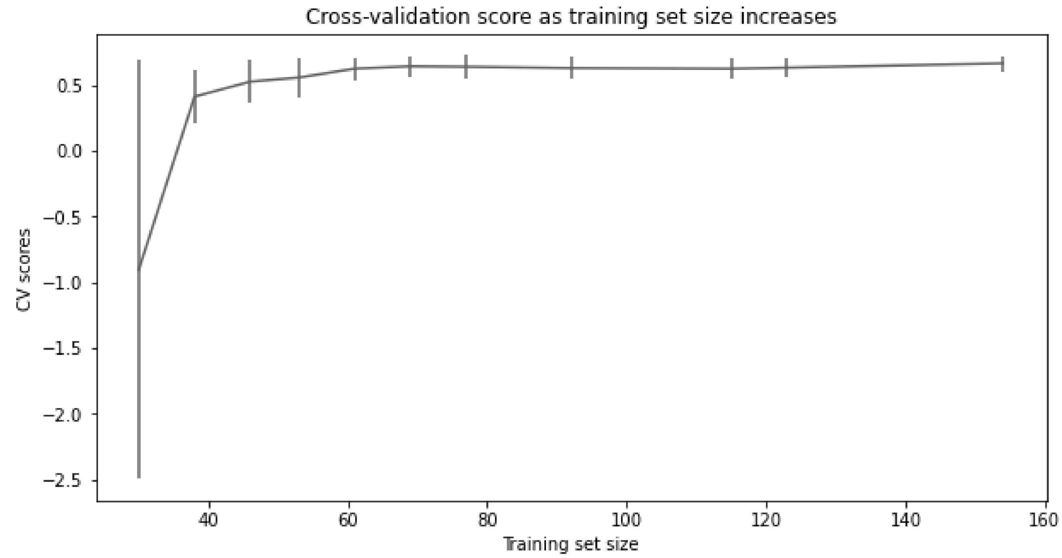


The second dataset described states sizes and populations, and it was used to ensure that all resorts in the first dataset were actually in the same market. After all, it's natural to question if New York and California are more expensive than Montana because in general their prices are different. After careful examination using Principal Component Analysis (PCA), we could not identify any distinguishable pattern between states. Without understanding the technical details of PCA, it's clear to see that there is no pattern in the below figure. Therefore, the state name was not used as a predictive factor in the models that were tested. From the population and size information, we added 5 features to the model for a total of 30 that were scaled appropriately.



Current Vs. Predicted Price

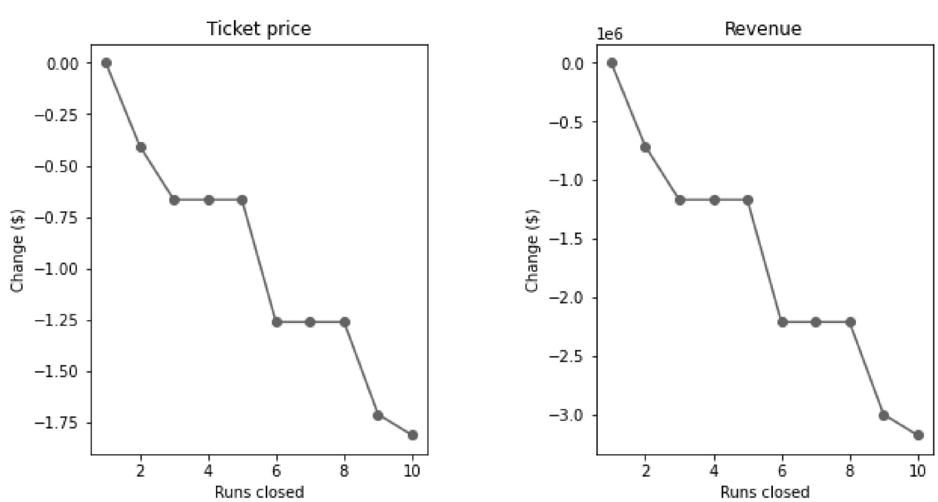
With confidence in our data, we created our model. **The best of two models we tested suggests that Big Mountain Resort could charge $95.87 instead of the current price, $81.00.** Given that the model is off by about $10.39 on average there is still a strong argument to raise the lift ticket price. We even made sure that our model had enough data to make this claim. Below, we can see that the accuracy of our model levels off when it uses information from about 60-80 resorts.



Investing & Economizing

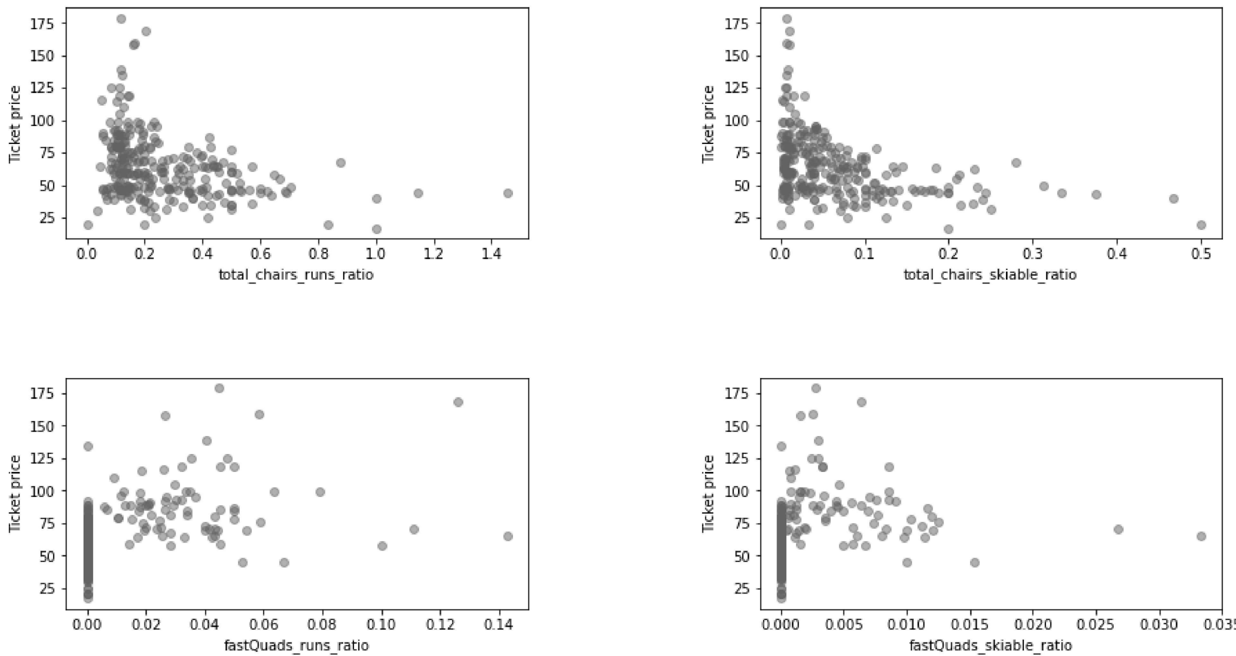
In addition to the current price, we were interested in what customers value and what they don't, and we were able to find that out. Although performance differed, the two models we tested agreed upon four features that affect price increase and decrease significantly: vertical drop, snow making acreage, number of fast quads, and number of runs. We investigated the four proposed scenarios for changes at the resort and have made two recommendations.

1. **Investing:** *The model recommends adding a chairlift taking skiers to the very top of the mountain, and including a run down from there*. According to the model, this supports an increased ticket price of about $2. With an expected 350,000 visitors this season, gross profit would increase by $3.4 million.
2. **Economizing:** According to the model, I believe it is even more important to make cuts. *Instead of invoking an 18% price increase, Big Mountain could quit maintenance of 8 runs to help make the predicted price of the model closer to the current price*. According to the model, removing 8 runs affects price the same as removing 6 appears, but two more runs will reduce cost. Furthermore, this doesn't have to appear like a loss to customers since these areas can be advertised as backcountry now!



What Comes Next

The model we created isn't perfect. For example, it neglects the effect of exclusivity vs. mass market that features can have on the lift ticket price. In other words having too many chairs, even fast quads, can lower the ticket price as demonstrated below. What we don't know is if having more chairs drives up profits by increasing how many people can be on the mountain at any given time, and that would be very helpful to make better investment recommendations.



This model can be used by all departments too. We made recommendations about the mountain features to cut costs or make investments, but changes aren't necessary to increase profits. The results of this model could simply be used by marketing. After all, the model says that Big Mountain charges less than resorts with the same impressive features. That sounds like a bargain to me!