With the data provided on 330 resorts in the US to find the market segment pricing model for Big Mountain Ski Resort in Montana, We have come up with the following report model:

1. After cleansing and exploring the data, we created two models, linear and random forest models. We chose to move with the random forest regression model since comparing the two demonstrated that performance on the test set was consistent cross-validation results which means the absolute error was lower using the random forest regressor.
2. We refit the model on the available data excluding the Big Mountain and then we calculated the expected Big Mountain ticket price from the Model.
3. Big Mountain Resort's modeled price is $95.87, the actual price is $81.00. Even with the expected mean absolute error of $10.39, this suggests there is room for an increase.
4. The result indicates that our resort is charging less than what's predicted suggests. Further by plotting histograms, we find that the ticket price of Big Mountain Resort is relatively high among all resorts and highest in Montana. The vertical drop, snow-making data, total chairs, no. of runs, area of skiable terrain area and no. of fast quad are also relatively high among all resorts. This can conclude that the Big Mountain Resort offers high quality of service and ski resources to customers and also charged relatively high prices compared with other resorts. However, based on our model prediction, the Big Mountain Resort seems still undercharging customers compared with the service and facilities they provide.
5. To investigate the relationship between facilities and predicted ticket price, we simulated 4 scenarios as follows: (In the scenario, we assume 35000 customers and each customer stays for 5 days.)
6. Scenario 1 – Close up to 10 of the least used runs. 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 the ticket price. Increasing the closures down to 6 or more leads to a large drop.
7. Scenario 2 Adding a run, increasing the vertical drop by 150 feet, and installing an additional chair lift. The ticket price increased by 1.99 and the total revenue increased by 3474638.
8. Scenario 3 Adding 2 acres of snowmaking to scenario 2. The result has no different from Scenario 2. (Such a small increase in the snow-making area makes no difference.)
9. Scenario 4 This scenario calls for increasing the longest run by .2 miles and guaranteeing its snow coverage by adding 4 acres of snow-making capability. There is no change in the ticket price. 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 the longest runway down in the feature importance list. The 4 scenarios above indicate that the models are sensitive to a unit change in items such as no. of runs as the values of this kind of attributes are small (ten to hundreds scale). While a unit change in attributes which values are in thousands or ten thousands scale such as snowmaking area will result in tiny difference or even no difference when predicting ticket price. This additional chair increases operating costs by 1,540,000 this season. To average the

operational costs per ticket, we divide the total amount of costs by 35000 and 5. Therefore, the average operational cost per ticket are 8.8.

10. Because of this, we suggest the resort can raise the ticket price and shut down few runs which are not popular and their relative distribution facility. This can increase the total revenue and cut down the operational cost of the resorts. For further improvement, more scenarios can be tried based on scenario 1. We can check how will the closing of facilities affect the ticket price. For example, based on scenario 1, we will be closing 5 or 8 runs rather than closing 3 or 6 runs because the predicted ticket price for closing 3-5 or 6-8 runs are the same respectively. While, if we close more runs, more related facilities can be closed and the operational cost will be further cut down. Therefore, we can reproduce scenario 1 to different attributes to find the optimal no. of facilities that shall be closed. In my opinion, the resort can point out the most unpopular runs and their related facilities. Based on the result of scenario 1, we try to to work out different combinations of facilities to be closed and predict the ticket price by the model (similar to scenario 2). Finally, by calculating the cut of operational cost and increase in ticket revenue, we can choose the optimal combination.