NOV 2025

Modeling Ticket Prices
Big Mountain Resort

Carlos Franco 2025

This slide deck was produced as a case study for Springboard's 2025 Data Science Bootcamp.

It is intended exclusively for educational use. The recommendations contained herein are purely illustrative in nature and do not constitute real financial or operational guidance.

Agenda

NOV 2025

01 Context

02 Problem Statement

03 **Recommendations & Key Findings**

04 *Modeling:* Picking the Right Tool for the Job

05 *Modeling:* What Does the Data Say?

06 *Modeling:* Changing Our Big Mountain

07 Looking Forward

Context

NOV 2025

Finding the right path from the top can be intimidating

Big Mountain Resort currently sets ticket prices based on general market averages. This works well enough on the bunny slope, but can leave you feeling lost when competition is steep.

Business decisions without data-driven insights is like skiing without goggles

Without an analytical pricing strategy, we could be risking undercharging—leaving significant revenue on the table—or overcharging, potentially reducing customer demand.

Confidence with the right equipment

By leveraging a predictive model built on industry-wide resort characteristics, Big Mountain can determine an optimal ticket price and explore how operational improvements could increase pricing power.

Problem Statement

NOV 2025

Primary Concerns

- Are we currently underpricing or overpricing our lift tickets?
- Which resort attributes most influence what customers are willing to pay?
- How would operational changes (e.g., new lifts, added runs, more snowmaking) affect our pricing power?

How Modeling Helps

- Data-driven estimates give us a solid range to shoot for when it comes to ticket pricing.
- EDA and modeling both help us replace guesswork with objective, measurable looks at which resort features drive ticket pricing.
- Establishing a model framework will allow us to quantify how future changes to resort features might affect pricing power.

> How can Big Mountain Resort accurately predict ski lift ticket prices based on a resort's physical characteristics and operational facilities, so that they can make an informed decision on increasing their own ticket prices and/or reducing facilities for the upcoming season?

SMART
Problem Statement

Recommendations & Key Findings

NOV 2025

Our Model Shows

- Big Mountain is **undervalued**: model predictions for our resort estimate a ticket price of **$95.87**
- Even accounting for MAE (~*$9.54*), the resort can safely **raise prices**.

Testing Scenarios

- **Scenario 2** - *Increasing vertical drop + new lift*: yielded the greatest price increase: **+$1.99⬆**
- Scenario 1 - *Cutting runs*: Likely to decrease prices.
- Scenario 3 & 4 - *Snowmaking expansions*: Alone result in little/no pricing improvement.

$95.87

predicted price
(with no changes)
MAE ~$9.54

$81.00

current price

+$1.99

predicted increase
for Scenario 2
ARR +$3,474,638⬆

Modeling:
Picking the Right Tool for the Job

How We Built the Model

- Compared two ML approaches: **Linear Regression** vs **Random Forest**
- Tuned both using 5-fold cross-validation with GridSearchCV
- Selected model based on accuracy, stability, and interpretability

What does this *mean*?

A mean absolute error (**MAE**) of ***$9.54*** indicates the model's average amount of error from the ticket price.

This means our actual ticket price is likely in the range of
$105.41 - $86.33

Baseline

Predicts the mean ticket price of the training data.

MAE: ~*$19.14*

Establishes a performance benchmark. Similar to current ticket pricing methods.

Linear Regressor

Uses 8 selected features based on statistical relevance.

MAE: ~*$11.79*

Improved accuracy, but limited by linear assumptions.

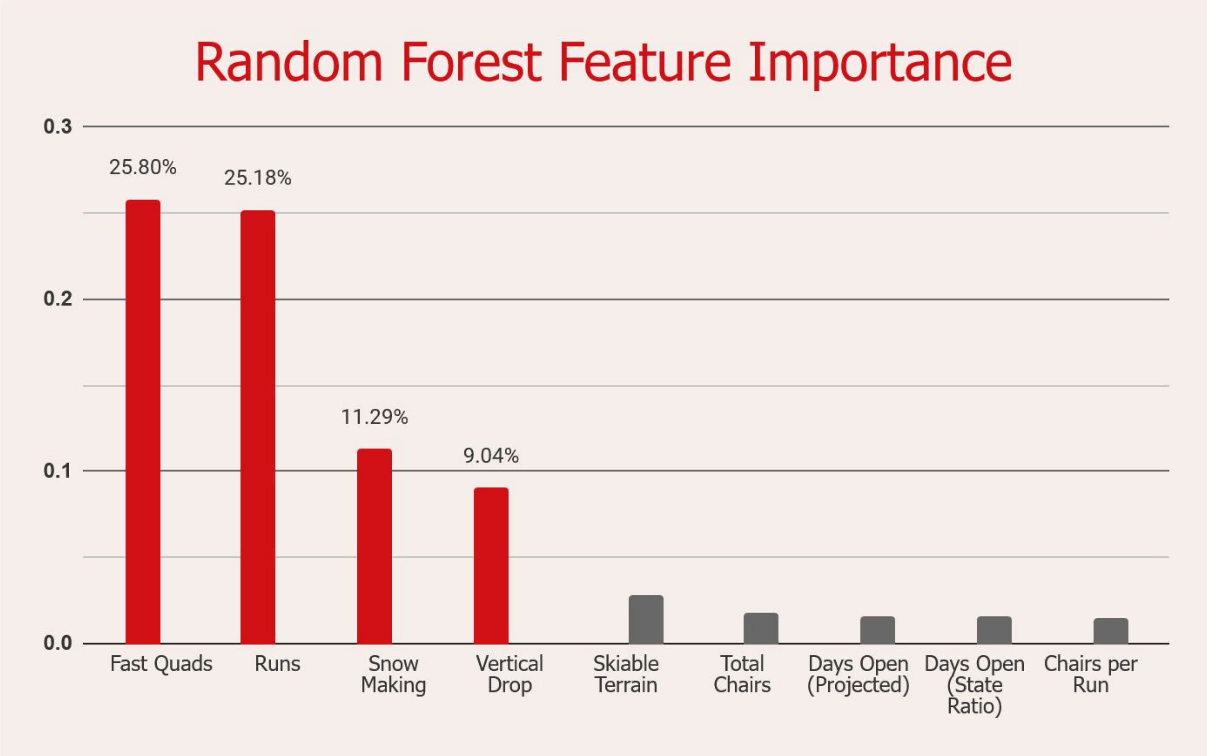
Random Forest

Captures nonlinear relationships using all available features.

MAE: *~$9.54*

Most accurate and stable model tested.

Modeling:
What Does the Data Say?



The most important features, according to our models & data

- Our random forest model heavily emphasizes operational features such as **fast quad lifts**, **number of runs**, **snowmaking acreage**, and **vertical drop** when calculating ticket prices.
- These features were also among the most strongly correlated with ticket price in our dataset.

Key takeaway

- Customers likely value infrastructure that gets them skiing quickly, with variety, and dependability.
- We'll watch these features closely when modeling potential renovations.

Modeling:
Changing Our Big Mountain

Custom Scenarios

Our custom scenario modeling function allows us to predict ticket prices for hypothetical renovations.

Scenario 1
Closing 1-10 runs

Scenario 2
+1 run, +150 ft vertical drop, +1 quad lift

Scenario 3
Scenario 2 with +2 acres of snowmaking

Scenario 4
+0.2 miles to longest run, +4 acres of snowmaking

Predict New Price

The function uses our Random Forest model to predict ticket prices for the "new" Big Mountain Resort.

Create new Big Mountain Resort

Predict new BMR ticket price

Predict old BMR ticket price

Calculate difference

Output Differences

The function outputs allow us to have an informed direction.

Scenario 1
–$0 to –$1.81
Terrain cuts likely to reduce pricing power.

Scenario 2
+$1.99
Recommended. *Vertical + lifts boost pricing.*

Scenario 3
+$1.99 (same)
Snowmaking alone adds no value.

Scenario 4
No difference
Longer runs have little effect on pricing.

Looking Forward

Goal 1: Deployment

Integrate the model into an internal dashboard so analysts can adjust features and instantly see pricing impacts.

Projected Timeline: **EO Q1**

Goal 2: Improve Accuracy

Incorporating data sources such as annual attendance, customer demographics, and regional demand trends could tremendously boost accuracy.

Target: **10–15% reduction in prediction error**

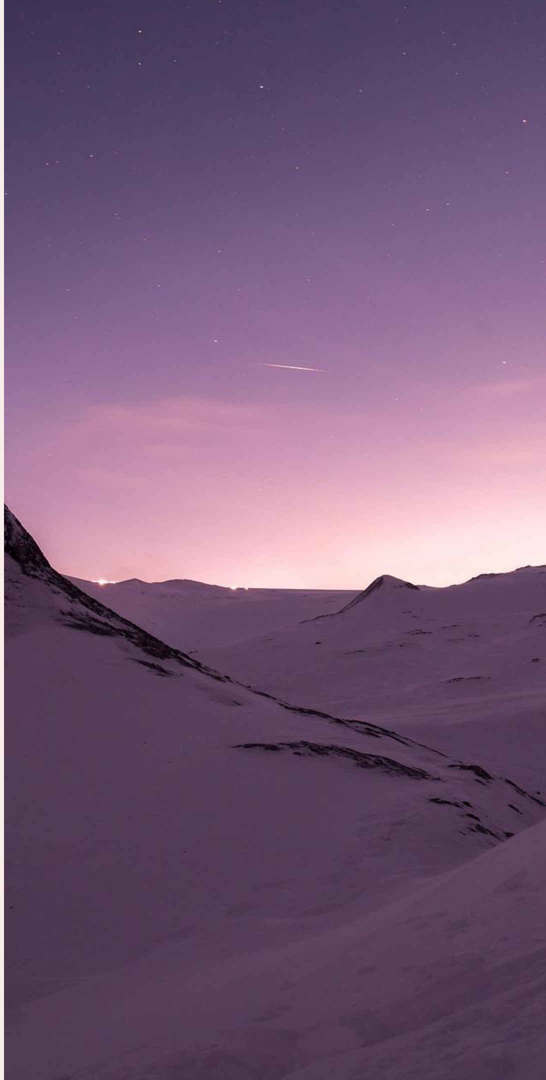
Goal 3: Expand Scenario Capabilities

Enable more complex “what-if” simulations, including multi-step operational changes and cost-benefit analyses.

Projected Timeline: **Prototype by EO Q3**

In conclusion

Data-driven insights will help Big Mountain Resort make smarter, more confident pricing decisions each season.



Thank you