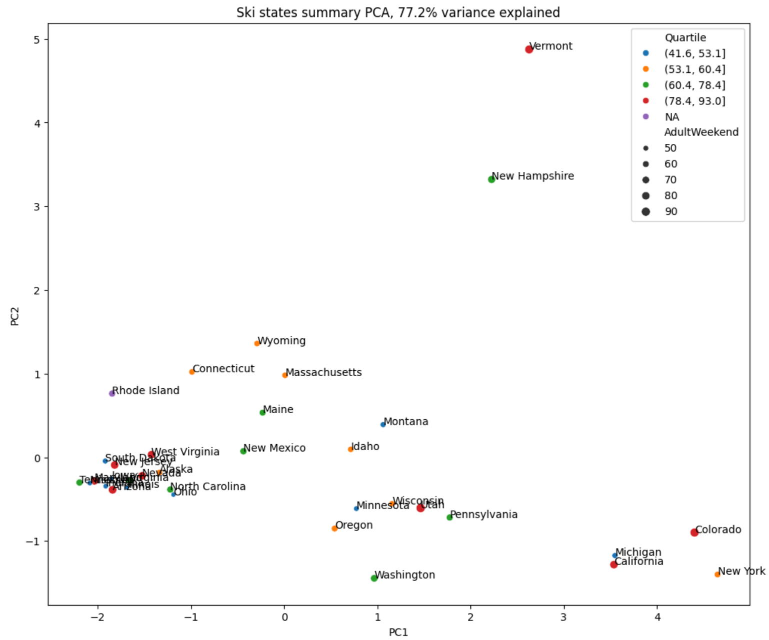
Big Mountain Resort Revenue Strategy

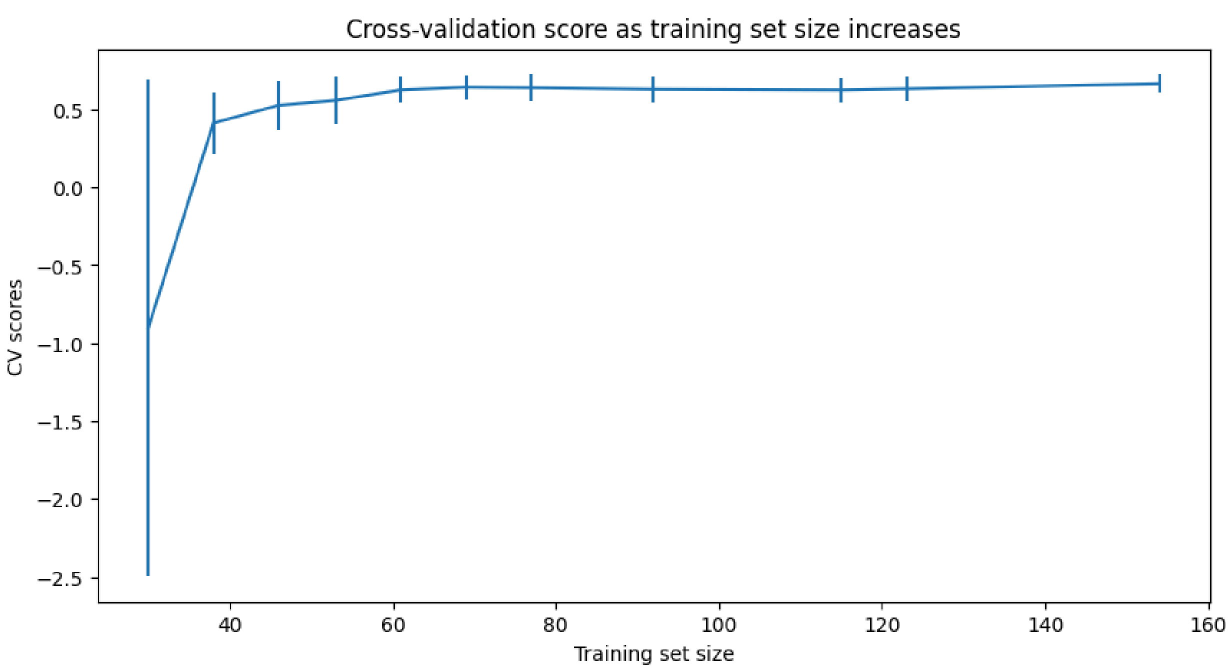
How can Big Mountain Resort increase their profits by at least $1,540,000 before the end of the ski season by way of cutting costs or increasing ticket prices?

In the data wrangling stage, we began by loading the ski resort data and performing initial exploration to understand its structure and identify missing values and potential issues. We addressed data quality concerns by correcting an outlier in skiable terrain data and removing a row with an erroneous value in the 'yearsOpen' column. We also examined categorical features, confirming the uniqueness of resorts and investigating the relationship between region and state. Crucially, we decided to use 'AdultWeekend' as the target variable for predicting ticket prices because it had fewer missing values and aligned with the pricing observed for our resort of interest. Rows missing this target variable were subsequently removed, reducing the dataset size to 277 rows. Finally, we prepared external state-level population and area data to enrich our dataset for future analysis. This comprehensive cleaning and preparation work sets the stage for the next phase of exploratory data analysis and modeling.

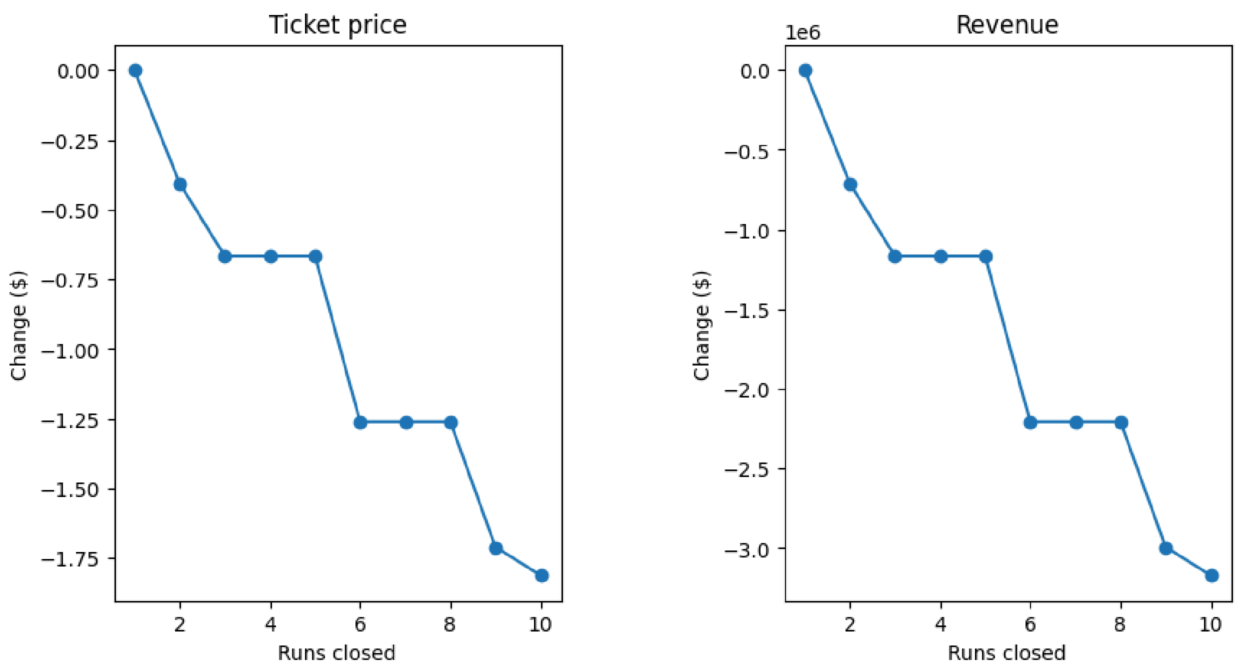


The exploratory data analysis (EDA) involved examining ski resort and state-level data to understand factors influencing adult weekend ticket prices. State summary data was explored, and new features like resort density were engineered. Principle Component Analysis (PCA) of state features revealed no clear price-based clusters (See figure to right), leading to the decision to incorporate state context through engineered ratio features in a single modeling approach rather than segmenting by state. The state and resort data were merged, and features representing a resort's share of state assets and lift-to-terrain ratios were created. Correlation heatmaps and scatterplots were used to visualize relationships between all numeric features and the target variable, identifying potential predictors like fastQuads, Runs, Snow Making_ac, and vertical_drop, while also highlighting multicollinearity and complex relationships in engineered features, all in preparation for subsequent modeling.

The model pre-processing and feature engineering focused on developing and selecting a machine learning model to predict adult weekend ski resort ticket prices. We started with a simple baseline model using the mean ticket price, which resulted in an R-squared of 0 and a mean absolute error of around $19. We then developed both linear regression and random forest models, incorporating preprocessing steps like imputation and scaling, and utilizing techniques like cross-validation and grid search for model evaluation and hyperparameter tuning. The random forest model, with median imputation and no scaling, consistently outperformed the linear model, showing a lower mean absolute error (approximately $9.64 based on cross-validation) and less variability. The feature importance analysis from the random forest model highlighted key factors like vertical drop, runs, snow making area, and fast quads as the most influential predictors. The learning curve analysis indicated that the current amount of data is sufficient, as the model performance has largely plateaued (See figure below). Therefore, the Random Forest Regressor model has been selected for further use due to its superior performance and robustness.



Big Mountain Resort currently charges $81.00 for adult weekend tickets, while a model based on competitor facilities suggests a supported price of approximately $95.87. This indicates potential for a price increase, yet we must tread carefully, as the model predicts Big Mountain's ticket price based on how other resorts with similar facilities are priced, assuming their pricing reflects market value. The model is limited by missing data on operating costs, other revenue streams, marketing, and local market factors, and it relies on the assumption that competitors are pricing rationally. The potential revenue increase from this price adjustment ($14.87 per ticket) would likely cover the operating costs of a new chair lift. Of the scenarios modeled, increasing vertical drop, adding a run and chair lift (with or without a small increase in snowmaking) showed the most promise for increasing supported ticket price (around $1.99 increase). Closing runs generally decreased or had no impact on supported price (See figure below). Any run closures should be tested with a phased approach and data gathering.



The analysis was limited by the lack of comprehensive operating cost data and other revenue streams, which would provide a more complete financial picture. Additional useful data would include labor, snowmaking, maintenance, capital expenditures, and insurance costs, as well as information on marketing, brand perception, and local market factors. The model's prediction of a significantly higher price for Big Mountain compared to its current price warrants discussion with business executives to understand their perspective. To make the model accessible for business analysts to explore different scenarios independently, options like an interactive dashboard, API, or simplified interface should be considered.