# Big Mountain Resort Project

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# 01

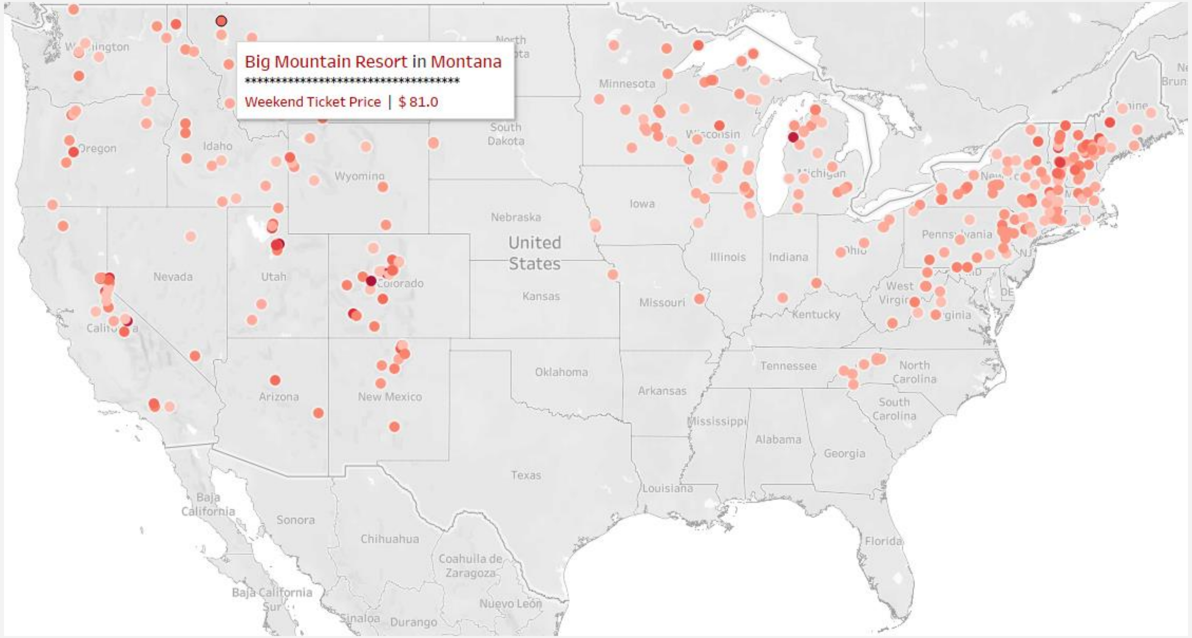
## PROBLEM IDENTIFICATION

# PROBLEM IDENTIFICATION

## INCREASE PROFITS

Big Mountain Resort ( BMR ) is a ski resort in Montana. **BMR recently installed a new chair lift** which **increased OPEX by ~$1.54M per annum**

The problem we are addressing is, **how can we increase profits**, starting this year, **by a minimum of +$1.54M per annum to offset the costs of the chair lift?**




** Three (3) resorts in Alaska not shown on the map.*

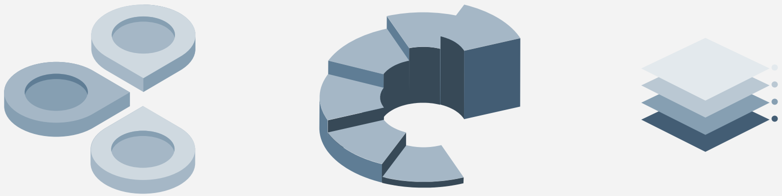
# 02

# GENERAL DELIVERABLES

# GENERAL DELIVERABLES

## THREE ( 3 ) DELIVERABLES GENERATED

1. The **source code** for the modeling developed to analyze the aforementioned problem ( )
2. A **report** found here ( )
3. This **presentation outlining our advice to mgmt to potentially address the problem**



# GENERAL DELIVERABLES

## SOURCE CODE DEFINED

| | |
|---|---|
| **Name** | The name of the resort. |
| **Region** | The region within the United States where the resort is located. |
| **state** | The state within the United States where the resort is located. |
| **summit_elev** | The elevation in feet of the summit mountain at the resort. |
| **vertical_drop** | The vertical change in elevation from the summit to the base in feet |
| **base_elev** | Elevation in feet at the base of the resort. |
| **trams** | The number of operational trams. |
| **fastEight** | The number of fast eight chairs. |
| **fastSixes** | The number of fast six chairs. |
| **fastQuads** | The number of fast four chairs. |
| **quad** | The number of regular speed four person chairs. |
| **triple** | The number of regular speed three person chairs. |
| **double** | The number of regular speed two person chairs. |
| **surface** | The number of regular speed single person chairs. |
| **total_chairs** | The number of chairlifts at the resort |
| **Runs** | The total number of runs at the resort. |
| **TerrainParks** | The total number of terrain parks at the resort. |
| **LongestRun_mi** | The length of the longest run at the resort in miles. |
| **SkiableTerrain_ac** | The total amount of skiable acres at the resort. |
| **Snow Making_ac** | The total number of acres covered by snow making machines. |
| **daysOpenLastYear** | The total number of days open last year. |
| **yearsOpen** | The total number of years the resort has been open. |
| **averageSnowfall** | Average annual snow fall at the resort in inches. |
| **AdultWeekday** | Cost of an adult weekday chairlift ticket |
| **AdultWeekend** | Cost of an adult weekend chairlift ticket |
| **projectedDaysOpen** | The projected number of days open in the upcoming season. |
| **NightSkiing_ac** | Total number of acres covered by light for night skiing. |

# 03

# DATA PRE-PROCESSING STEPS

# DATA PRE-PROCESSING

## DATA CLEANING

1. **A single CSV file was provided** by the Database Manager
2. I amended SkiableTerrain_ac for a resort* as the data was noticeably off kilter with the dataset & did not comply with the data on their website (🌐); I used the website's data
3. The **fastEight column was removed** as **50%** of the resorts **had no values**

| | Name | Region | state | summit_elev | vertical_drop | base_elev | trams | fastEight |
|---|---|---|---|---|---|---|---|---|
| 0 | Alyeska Resort | Alaska | Alaska | 3939 | 2500 | 250 | 1 | 0.0 |
| 1 | Eaglecrest Ski Area | Alaska | Alaska | 2600 | 1540 | 1200 | 0 | 0.0 |
| 2 | Hilltop Ski Area | Alaska | Alaska | 2090 | 294 | 1796 | 0 | 0.0 |
| 3 | Arizona Snowbowl | Arizona | Arizona | 11500 | 2300 | 9200 | 0 | 0.0 |
| 4 | Sunrise Park Resort | Arizona | Arizona | 11100 | 1800 | 9200 | 0 | NaN |

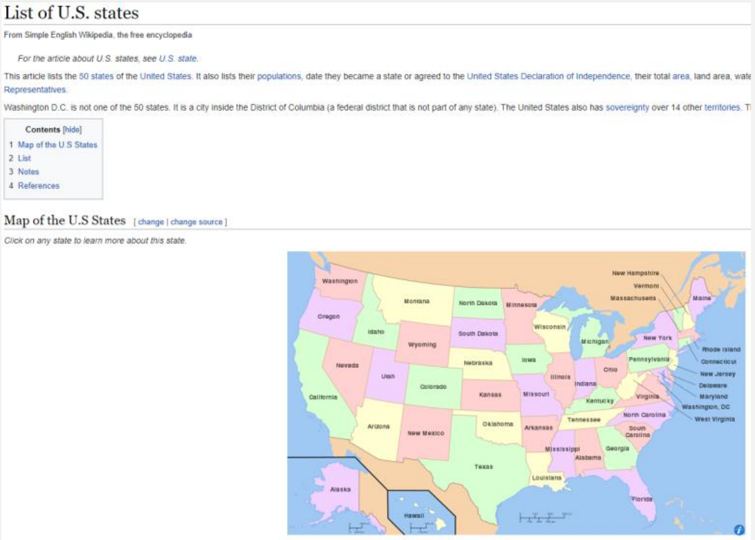
| | count | % |
|---|---|---|
| fastEight | 166 | 50.303030 |
| NightSkiing_ac | 143 | 43.333333 |
| AdultWeekday | 54 | 16.363636 |
| AdultWeekend | 51 | 15.454545 |
| daysOpenLastYear | 51 | 15.454545 |
| TerrainParks | 51 | 15.454545 |
| projectedDaysOpen | 47 | 14.242424 |
| Snow Making_ac | 46 | 13.939394 |
| averageSnowfall | 14 | 4.242424 |
| LongestRun_mi | 5 | 1.515152 |
| Runs | 4 | 1.212121 |
| SkiableTerrain_ac | 3 | 0.909091 |
| yearsOpen | 1 | 0.303030 |
| total_chairs | 0 | 0.000000 |
| Name | 0 | 0.000000 |
| Region | 0 | 0.000000 |
| double | 0 | 0.000000 |
| triple | 0 | 0.000000 |
| quad | 0 | 0.000000 |
| fastQuads | 0 | 0.000000 |
| fastSixes | 0 | 0.000000 |
| trams | 0 | 0.000000 |
| base_elev | 0 | 0.000000 |
| vertical_drop | 0 | 0.000000 |
| summit_elev | 0 | 0.000000 |
| state | 0 | 0.000000 |
| surface | 0 | 0.000000 |

| # | Column | Non-Null Count | Dtype |
|---|---|---|---|
| 0 | Name | 330 non-null | object |
| 1 | Region | 330 non-null | object |
| 2 | state | 330 non-null | object |
| 3 | summit_elev | 330 non-null | int64 |
| 4 | vertical_drop | 330 non-null | int64 |
| 5 | base_elev | 330 non-null | int64 |
| 6 | trams | 330 non-null | int64 |
| 7 | fastEight | 164 non-null | float64 |
| 8 | fastSixes | 330 non-null | int64 |
| 9 | fastQuads | 330 non-null | int64 |
| 10 | quad | 330 non-null | int64 |
| 11 | triple | 330 non-null | int64 |
| 12 | double | 330 non-null | int64 |
| 13 | surface | 330 non-null | int64 |
| 14 | total_chairs | 330 non-null | int64 |
| 15 | Runs | 326 non-null | float64 |
| 16 | TerrainParks | 279 non-null | float64 |
| 17 | LongestRun_mi | 325 non-null | float64 |
| 18 | SkiableTerrain_ac | 327 non-null | float64 |
| 19 | Snow Making_ac | 284 non-null | float64 |
| 20 | daysOpenLastYear | 279 non-null | float64 |
| 21 | yearsOpen | 329 non-null | float64 |
| 22 | averageSnowfall | 316 non-null | float64 |
| 23 | AdultWeekday | 276 non-null | float64 |
| 24 | AdultWeekend | 279 non-null | float64 |
| 25 | projectedDaysOpen | 283 non-null | float64 |
| 26 | NightSkiing_ac | 187 non-null | float64 |

dtypes: float64(13), int64(11), object(3)

** The resort is Silver Mountain, based in Colorado*

# DATA PRE-PROCESSING


List of U.S. states

From Simple English Wikipedia, the free encyclopedia

*For the article about U.S. states, see U.S. state.*

This article lists the 50 states of the United States. It also lists their populations, date they became a state or agreed to the United States Declaration of Independence, their total area, land area, wate Representatives.

Washington D.C. is not one of the 50 states. It is a city inside the District of Columbia (a federal district that is not part of any state). The United States also has sovereignty over 14 other territories. T

Contents [hide]
1 Map of the U.S States
2 List
3 Notes
4 References

Map of the U.S States [ change | change source ]

*Click on any state to learn more about this state.*



| | |
|---|---|
| 0 | 82.317073 |
| 2 | 14.329268 |
| 1 | 3.353659 |
| dtype: float64 | |

| | Name | Region | state | yearsOpen |
|---|---|---|---|---|
| 34 | Howelsen Hill | Colorado | Colorado | 104.0 |
| 115 | Pine Knob Ski Resort | Michigan | Michigan | 2019.0 |

## DATA CLEANING ( cont. )

4. Our goal is to predict prices & as such, **I removed ~14% of the resorts** as their price data* was incomplete; thus not useful
5. Wikipedia ( ) was used to directly draw **population & state size data to establish per capita & acre metrics**
6. For one of the resort's columns, **data pertaining to the total years open was 2019**. This was **removed as that data is unlikely to be true****

** Price data = AdultWeekday & AdultWeekend*

*** The column's name is yearsOpen; it was probably open in 2019 as ski resorts haven't been open for 2019 years in the USA; in fact the country wasn't establish yet*

# DATA PRE-PROCESSING

## EXPLORATORY DATA ANALYSIS

**Two datasets were pulled** from the previous step; namely:

1. **ski_resort_data**:
   - provided by the Database Manager on information which was cleaned down to 277 resorts across 34 states
2. **state_summary**:
   - an assembled dataset from Wikipedia which provided high level population / state size information

| Name | Region | state | summit_elev | vertical_drop | base_elev | trams | fastEight | fastSixes | fastQuads | ... |
|---|---|---|---|---|---|---|---|---|---|---|
| Alyeska Resort | Alaska | Alaska | 3939 | 2500 | 250 | 1 | 0.0 | 0 | 2 | ... |
| Eaglecrest Ski Area | Alaska | Alaska | 2600 | 1540 | 1200 | 0 | 0.0 | 0 | 0 | ... |
| Hilltop Ski Area | Alaska | Alaska | 2090 | 294 | 1796 | 0 | 0.0 | 0 | 0 | ... |
| Arizona Snowbowl | Arizona | Arizona | 11500 | 2300 | 9200 | 0 | 0.0 | 1 | 0 | ... |
| Sunrise Park Resort | Arizona | Arizona | 11100 | 1800 | 9200 | 0 | NaN | 0 | 1 | ... |

# DATA PRE-PROCESSING

## EXPLORATORY DATA ANALYSIS ( cont. )

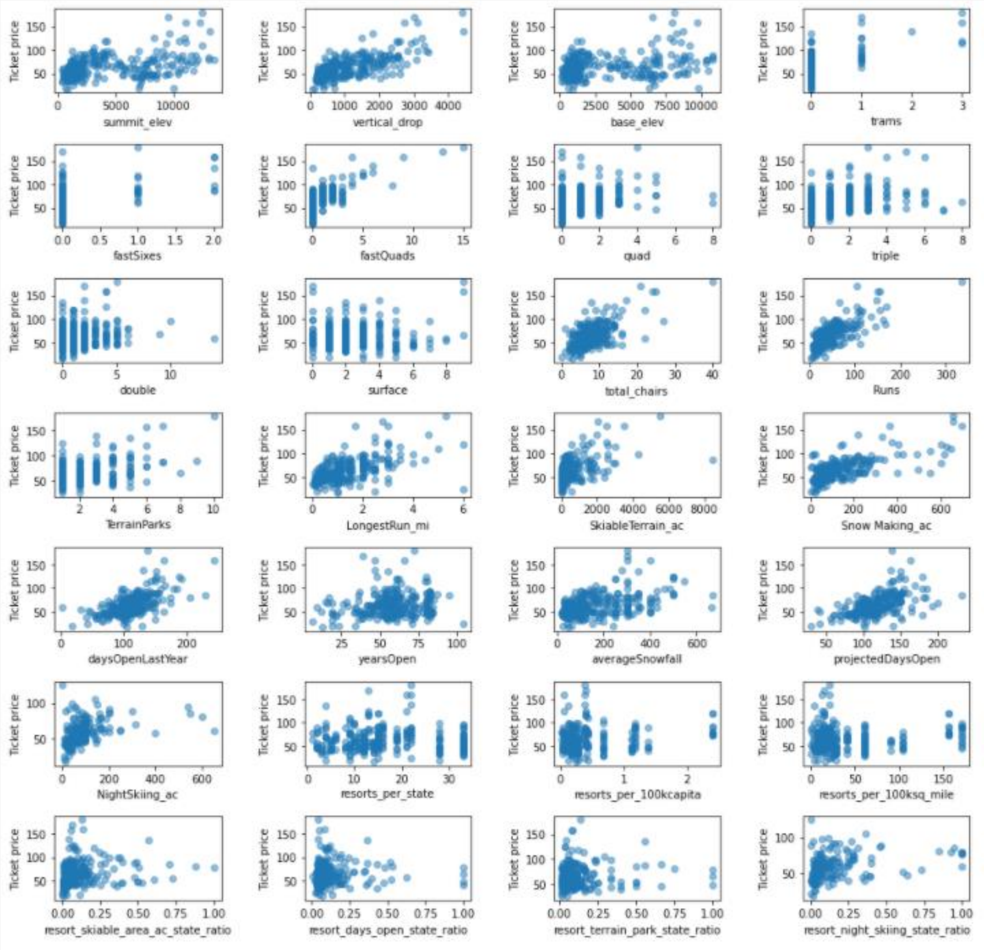
The **categorical features** are

- The resort names
- Respective region ( which did not appear useful )
- The state in which the resort is located in

**Numerical features** inside the 2 datasets **are plentiful** & additional variables ( x7 ) were added. **Initial correlations with Adult Weekend prices were drawn** ( next page )

# DATA PRE-PROCESSING

## EXPLORATORY DATA ANALYSIS ( cont. )



# DATA PRE-PROCESSING

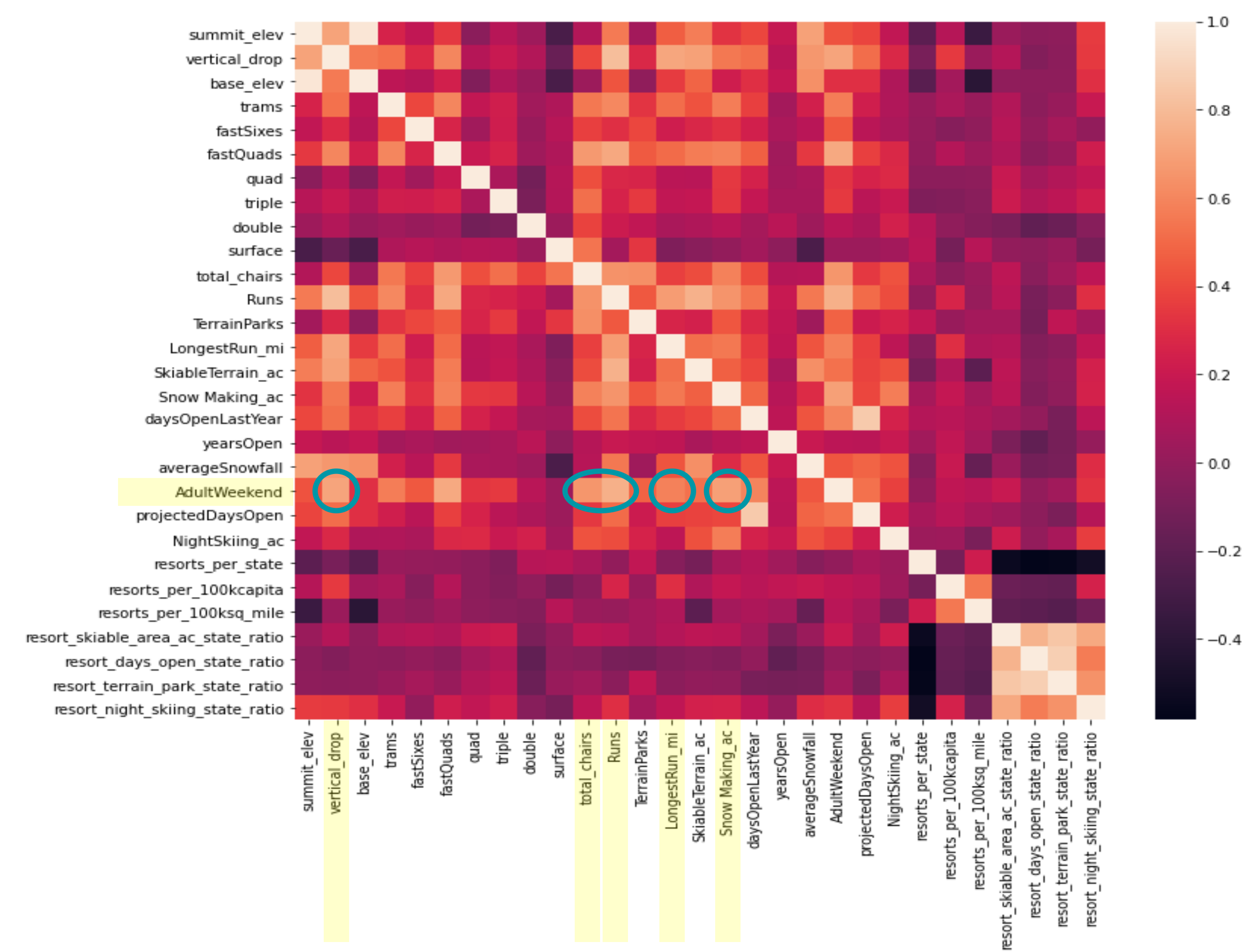
## EXPLORATORY DATA ANALYSIS ( cont. )

**Using the Feature Correlation Heatmap** ( next page ) **I identified numerical features that have the strongest correlations to AdultWeekend prices** ( easier to read than previous page ) **& may provide valuable insights to achieve our goal** of higher prices; notably the below & possible justification for the positive correlation:

- **Vertical Drop**
    - *Desire for speed*
- **Total Chairs**
    - *Limited wait time(s)*
- **Runs**
    - *Value on different run options*
- **Longest Run**
    - *Desire for being in motion longer*
- **Snow Making acres**
    - *Some guarantee of snow*

DATA PRE-PROCESSING

# EXPLORATORY DATA ANALYSIS ( Feature Correlation Heatmap )



## DATA PRE-PROCESSING

### EXPLORATORY DATA ANALYSIS ( cont. )

**Issues of the data** & it's visualization that I addressed modeling include but are not limited to:

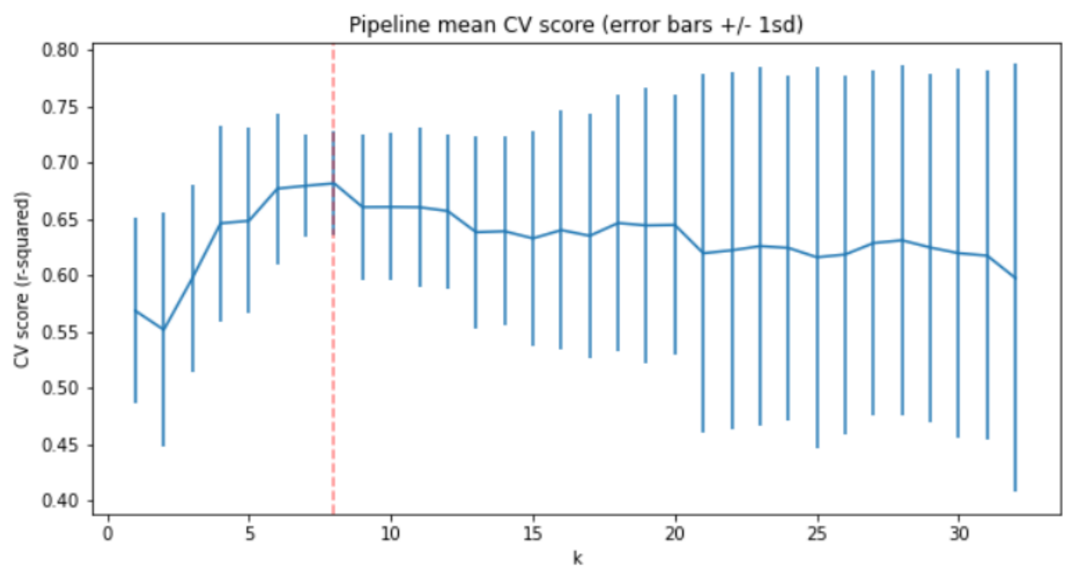
- I **filled in missing numbers with averages** of others to address missing data which may throw off scatter plots & quartile numbers
- I **utilized seaborn rather than** relying on **matplotlib** for scatter plots which may not be the ideal display candidate
- I **scaled the numbers** when required

# DATA PRE-PROCESSING

## PRE-PROCESSING

1. The **first** pre-processing step was to **split the data** into a training and testing splits, 70% / 30% respectively, & removing any object types so that the dataset is only composed of numeric types
2. **With the help of a standard mean** & the **DummyRegressor** functions, I then **determined the** "**Best Guess**" number which was determined to be **63.81**
3. **Using the mean absolute error**, I determined that on average **the metric may be off by ~$19**
4. I then **scaled the data** to ensure that the data can work better together
5. Once scaled, the **train** & **test R squared became ~81%** & **72%**. The **mean absolute errors dropped down to ~$9**; much better than the $19 unscaled guess
6. I also replaced any missing data but the results weren't much different

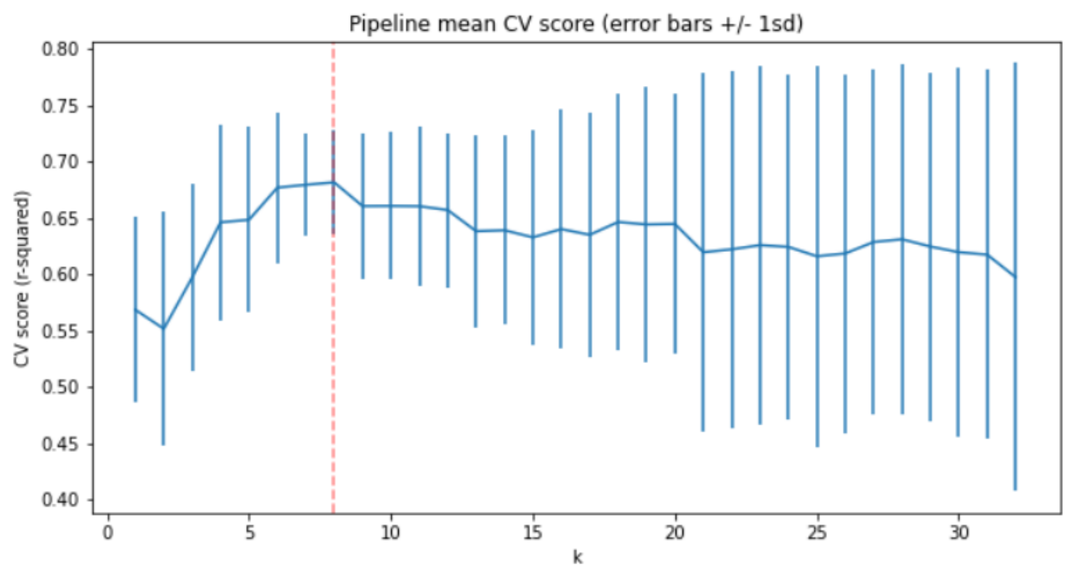
# DATA PRE-PROCESSING (cont.)




| | |
|---|---|
| vertical_drop | 10.767857 |
| Snow Making_ac | 6.290074 |
| total_chairs | 5.794156 |
| fastQuads | 5.745626 |
| Runs | 5.370555 |
| LongestRun_mi | 0.181814 |
| trams | -4.142024 |
| SkiableTerrain_ac | -5.249780 |
| dtype: float64 | |

7. Next, I ran the training & testing splits through the **Pipeline function**. With **cross-validation**, I determined that the **best k value is 8**
8. Using the linear coefficient numbers for each item versus AdultWeekend price, the **most positively correlated item was vertical_drop**

# DATA PRE-PROCESSING (cont.)




| | |
|---|---|
| vertical_drop | 10.767857 |
| Snow Making_ac | 6.290074 |
| total_chairs | 5.794156 |
| fastQuads | 5.745626 |
| Runs | 5.370555 |
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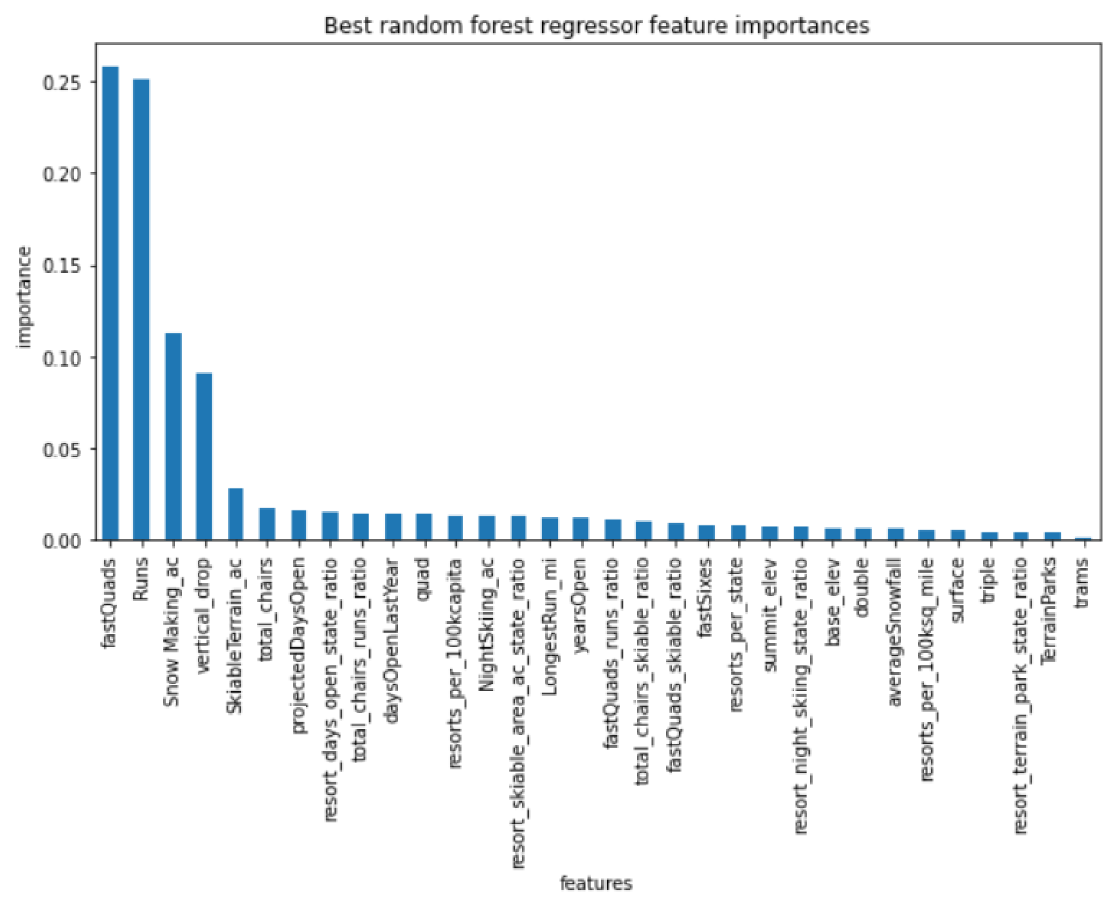
| trams | -4.142024 |
| SkiableTerrain_ac | -5.249780 |
| dtype: float64 | |

7. Next, I ran the training & testing splits through the Pipeline function. With cross-validation, I determined that the best k value is 8.
8. Using the linear coefficient numbers for each item versus AdultWeekend price, the most positively correlated item was vertical_drop & **most negative correlation was SkiableTerrain_ac**
   - Vertical Drop we touched on earlier ( speed ), but **Skiable Terrain** ( acres ) **brings thoughts about** a potential "**exclusivity**" consideration
     - *Touch on this later*

# DATA PRE-PROCESSING (cont.)

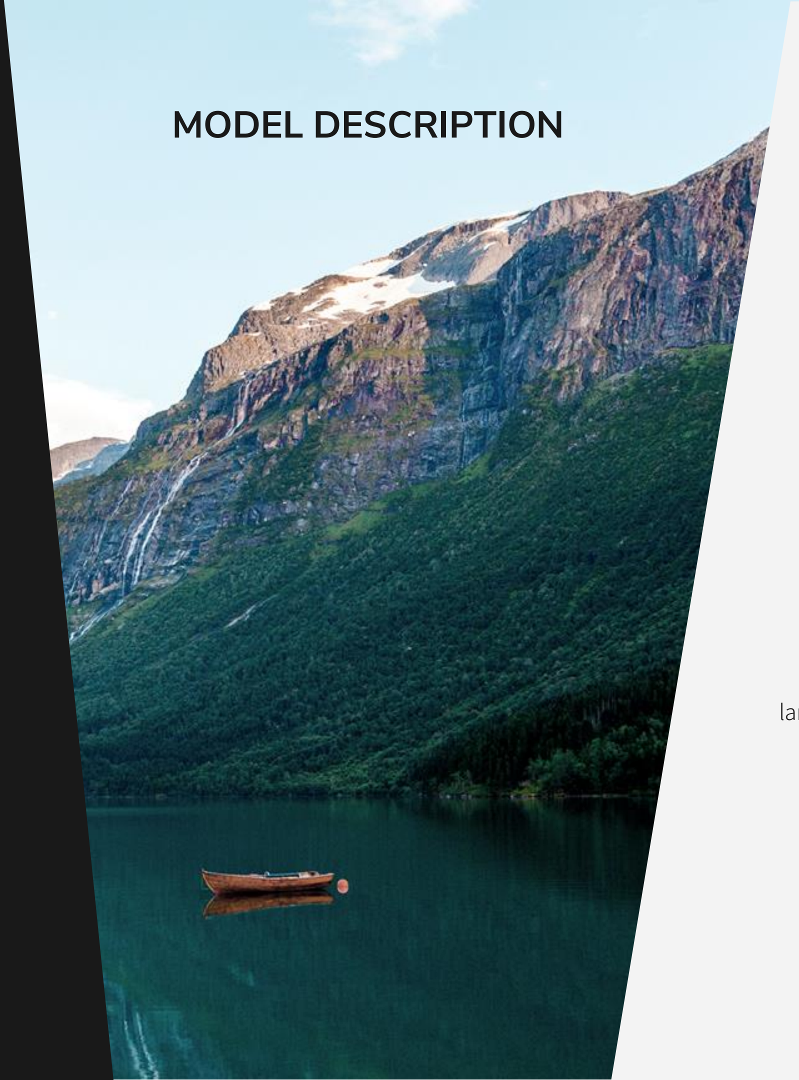
9. I then **moved to a Random Forest Generator** which **marginally improved our cross-validation results** & **showed that the top four dominate features were similar to those in the linear model**
10. I **chose the Random Forest Model for my modeling, as it**:
    - Has a lower cross-validation mean absolute error ~$1
    - Exhibits less variability

To note, the verifying performance on the test set produced performance consistent with the cross-validation results.



# 04
# MODEL DESCRIPTION

# MODEL DESCRIPTION



## RANDOM FORESTS

As mentioned, the model **I used was the Random Forest Model with the goal of determining what price BMR's facilities support** as well as sensitivity of changes to various resort parameters.

## ASSUMPTION

**This model relies on the implicit assumption that** all other resorts are largely setting prices based on how the market values certain facilities; essentially **prices are set by the free market**

05

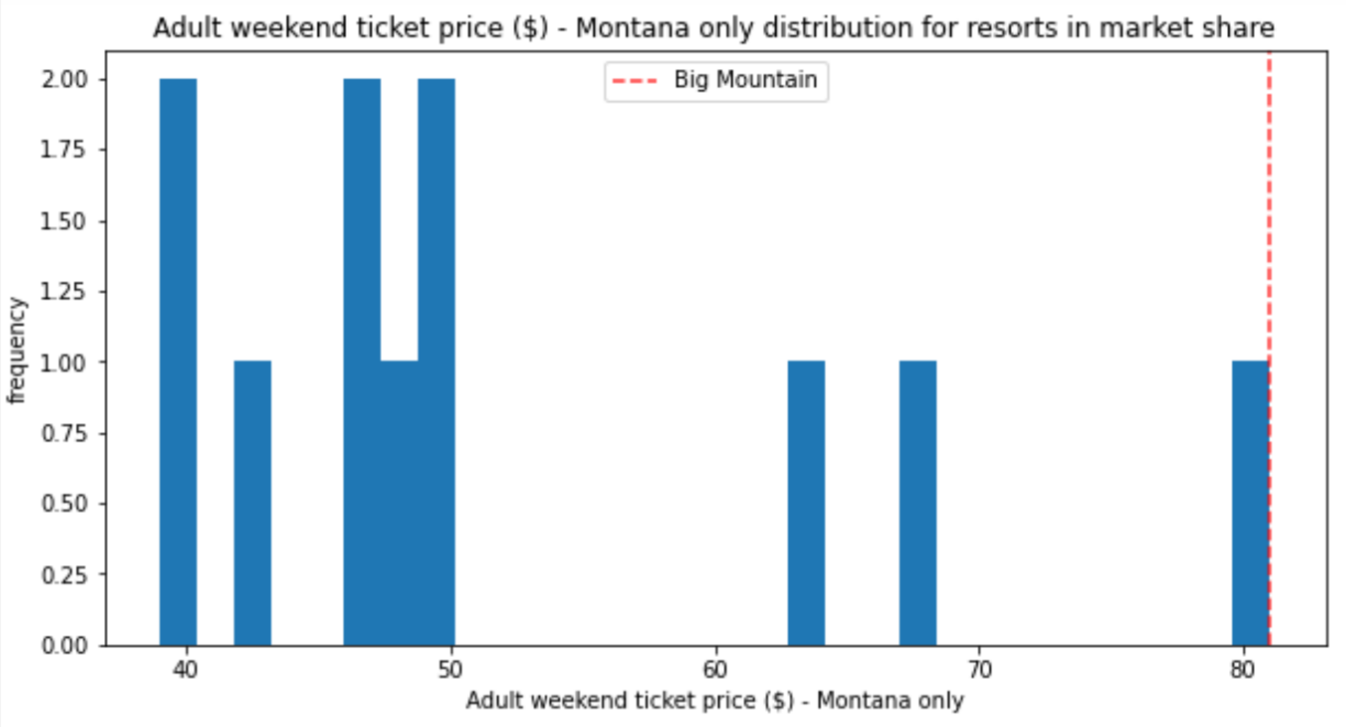
# MODEL FINDINGS

# MODEL FINDINGS


As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, **I explored where BMR stands against BMR's competitors nationally**

To begin, **I find that BMR's price is slightly above the mean of the country**

# MODEL FINDINGS ( cont. )

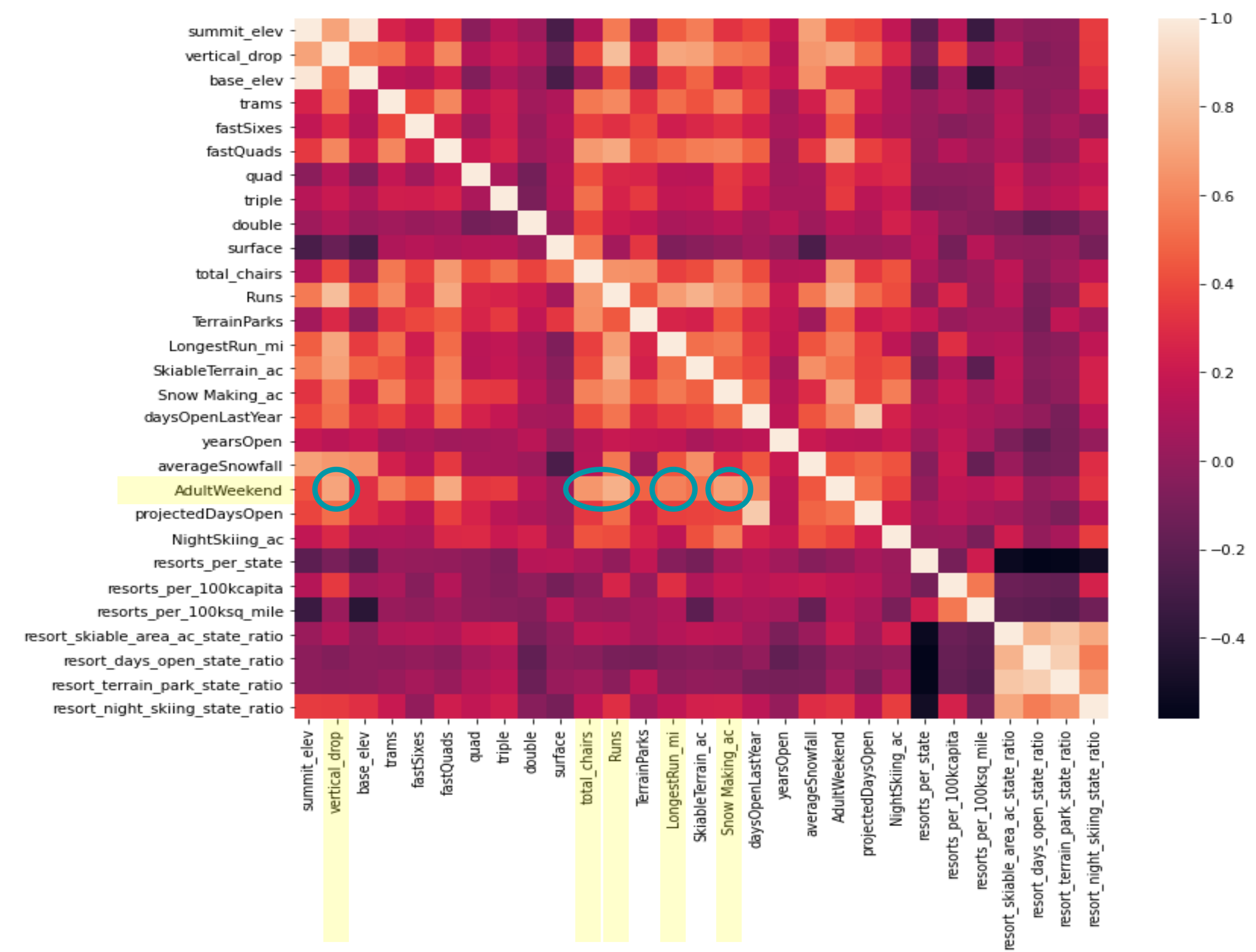



As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I explored where BMR stands against BMR's competitors nationally

To begin, I find that BMR's price is only slightly above the mean for the country **but the most expensive in Montana**. No actionable requirement, it's just something to note

# MODEL FINDINGS ( cont. )

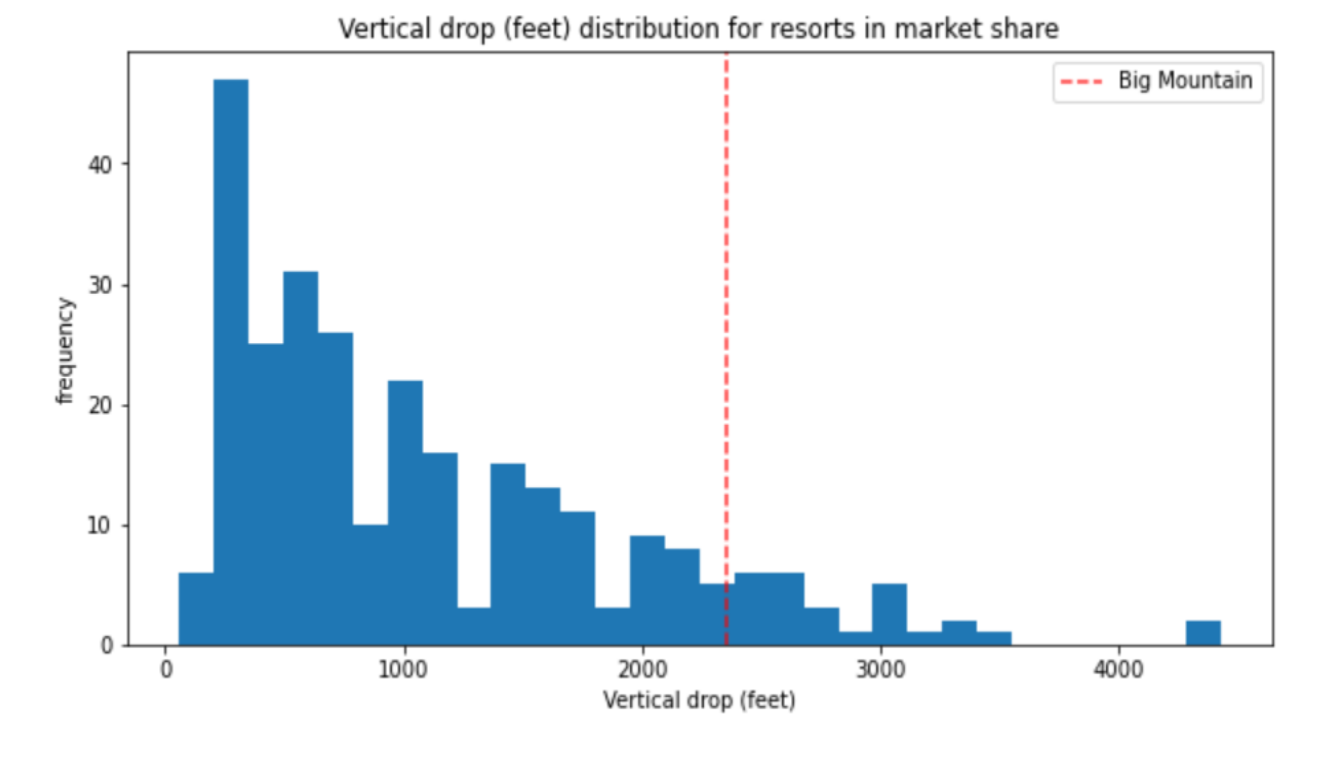
Heading back to the **Feature Correlation Heatmap**, I start by **investigating where BMR stands against competitors with the most positively correlated features for ticket prices**



# MODEL FINDINGS ( cont. )

Heading back to the Feature Correlation Heatmap, I start by investigating where BMR stands against competitors with the most positively correlated features for ticket prices:

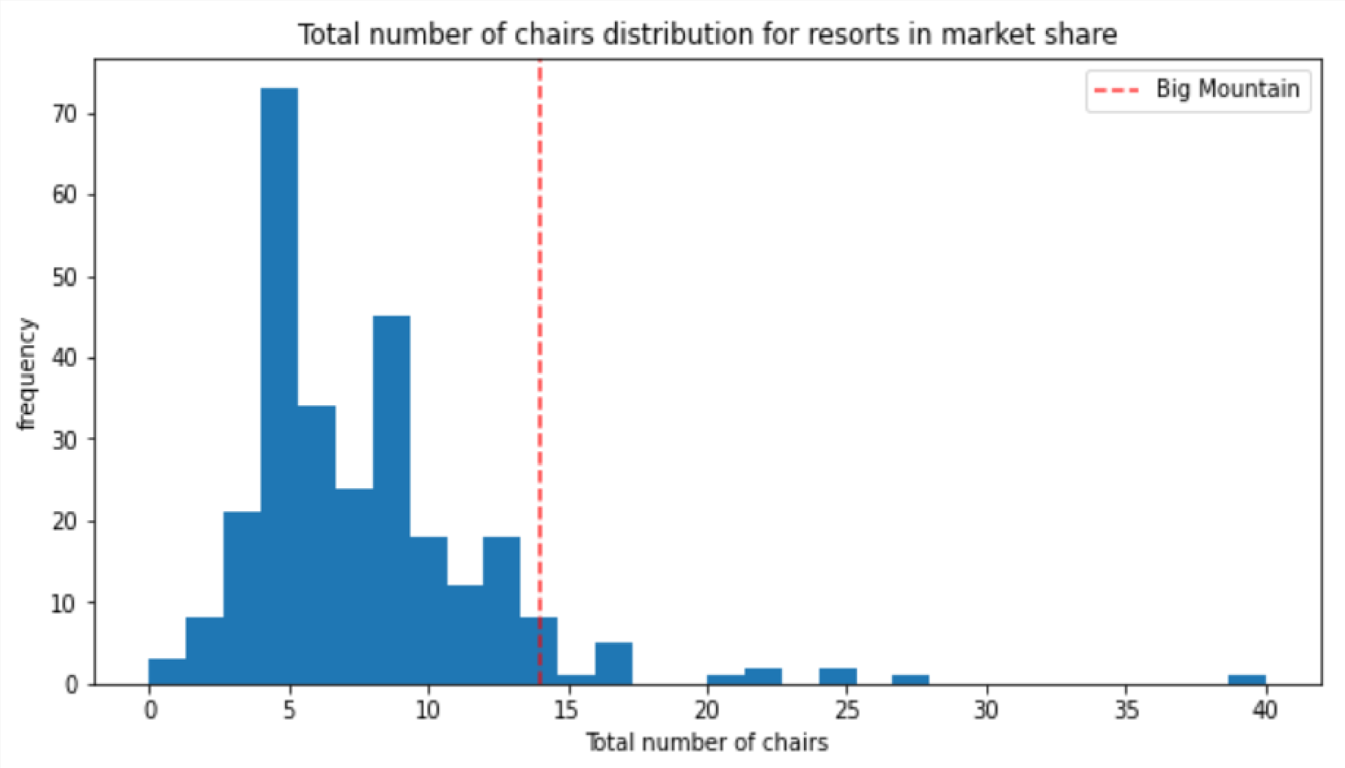
- **Vertical Drop**
    - *Doing well albeit a notable amount have steeper drops*



# MODEL FINDINGS ( cont. )

Heading back to the Feature Correlation Heatmap, I start by investigating where BMR stands against competitors with the most positively correlated features for ticket prices:

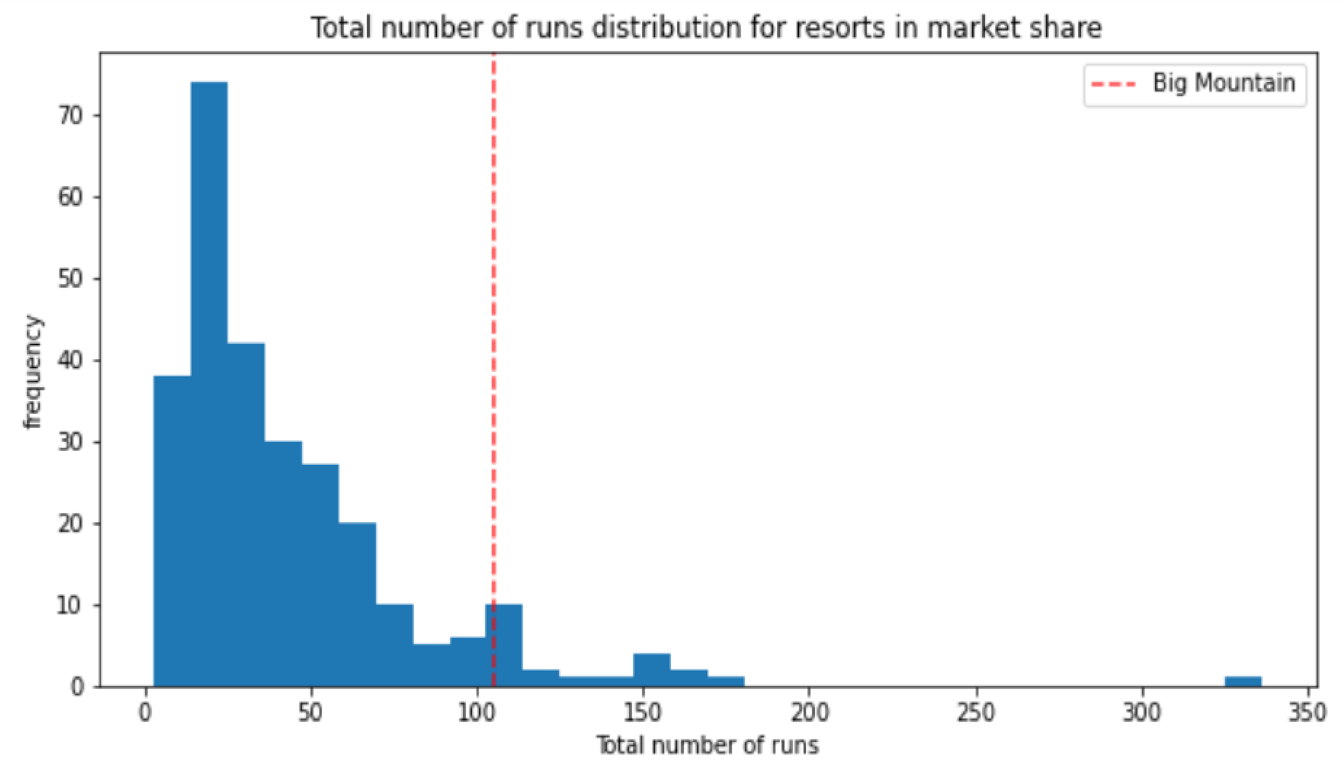
- Vertical Drop
- **Total # of Chairs**
    - *Currently amongst the highest; others may be outliers*



# MODEL FINDINGS ( cont. )

Heading back to the Feature Correlation Heatmap, I start by investigating where BMR stands against competitors with the most positively correlated features for ticket prices:

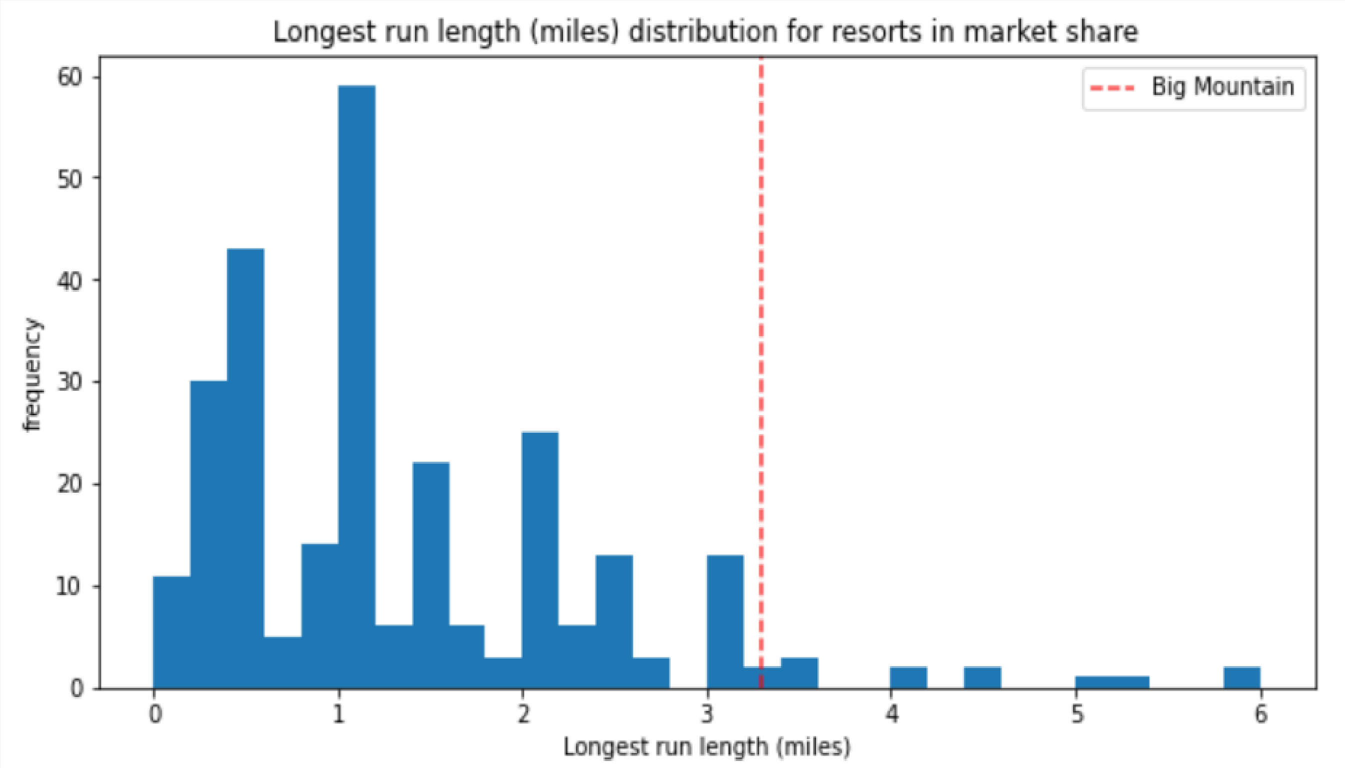
- Vertical Drop
- Total # of Chairs
- **Total # of Runs**
    - *Currently quite competitive albeit some offer more*



# MODEL FINDINGS ( cont. )

Heading back to the Feature Correlation Heatmap, I start by investigating where BMR stands against competitors with the most positively correlated features for ticket prices:

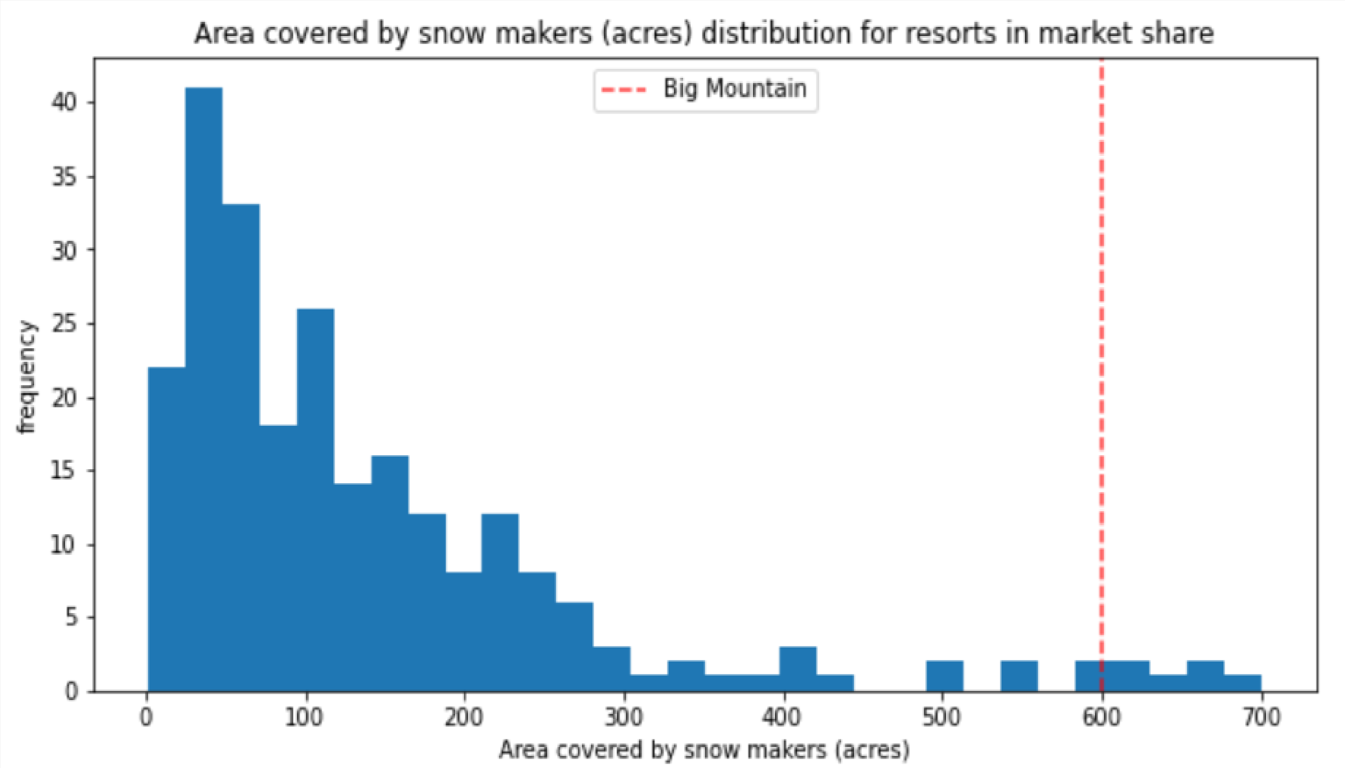
- Vertical Drop
- Total # of Chairs
- Total # of Runs
- **Longest Run**
  - *Again, quite competitive albeit BMR's longest run is ~half of the longest*



# MODEL FINDINGS ( cont. )

Heading back to the Feature Correlation Heatmap, I start by investigating where BMR stands against competitors with the most positively correlated features for ticket prices:

- Vertical Drop
- Total # of Chairs
- Total # of Runs
- Longest Run
- Acres covered by Snow Makers
  - *Currently, very competitive*



# COST CUTTING OR REVENUE INCREASING SOLUTIONS MODELLED IN 4 SCENARIOS

## SCENARIO 1

Permanently **closing down up to 10 of the least used runs**

## SCENARIO 2

**Increasing the vertical drop** to a point 150 feet lower **but requiring the installation of an additional chair lift** without additional snow making coverage

## SCENARIO 3

**Same as Scenario 2** albeit **adding 2 acres of snow making cover**

## SCENARIO 4

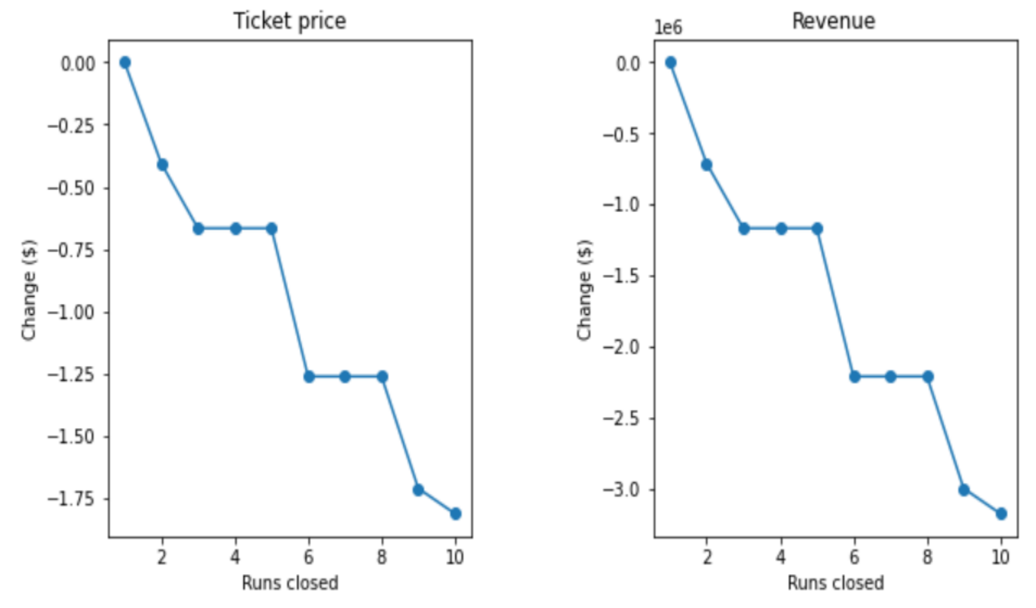
**Increasing the longest run by 0.2 miles** to 3.5 miles in length & **adding 4 additional acres of snow making cover** to cover it

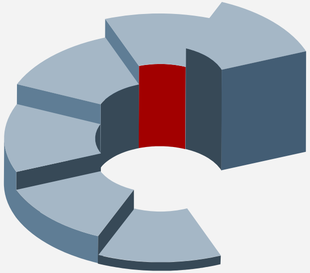
## SCENARIO #1

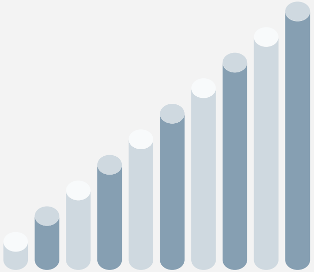
The model shows that **closing 1 run makes no difference to either Ticket Prices or Revenue**.

The **impact begins when 2 runs are closed. If 3 runs are closed, BMR could also close 4 or 5** as they have the same impact on Ticket prices and Revenue.

**Closing 6 or more** is when the model indicates a **substantially negative impact would occur.**







```
ticket2_increase = predict_increase(['Runs', 'vertical_drop',
                                     'total_chairs'],
                                    [1, 150, 1])
revenue2_increase = 5 * expected_visitors * ticket2_increase
```

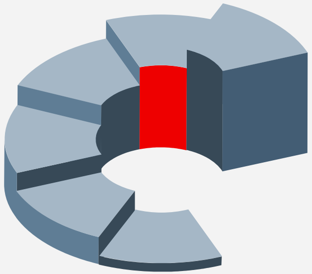
```
print(f'This scenario increases support for ticket price by ${ticket2_increase:.2f}')
print(f'Over the season, this could be expected to amount to ${revenue2_increase:.0f}')
```

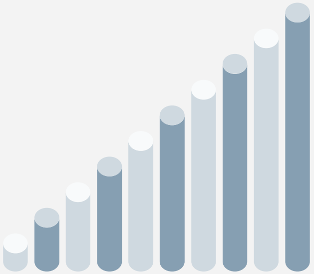
```
This scenario increases support for ticket price by $1.99
Over the season, this could be expected to amount to $3474638
```

# SCENARIO #2

I modeled **increasing the vertical drop to a point 150 feet lower but requiring the installation of an additional chair lift** without additional snow making coverage.

In this scenario, **the model increases support for ticket prices by $1.99** to $82.99 **which could increase revenue by $3,474,638 over the season**.





## SCENARIO #3

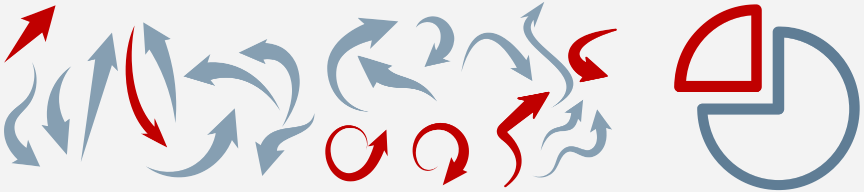
I modeled **the same as Scenario 2 but added 2 additional acres of snow making**.

The model's **output was identical as Scenario 2** as the model **increases support for ticket prices by $1.99** to $82.99 & **may increase revenue by $3,474,638 over the season**.

```
ticket3_increase = predict_increase(['Runs', 'vertical_drop',
                                     'total_chairs', 'Snow Making_ac'],
                                    [1, 150, 1, 2])
revenue3_increase = 5 * expected_visitors * ticket3_increase
```

```
print(f'This scenario increases support for ticket price by ${ticket3_increase:.2f}')
print(f'Over the season, this could be expected to amount to ${revenue3_increase:.0f}')
```

```
This scenario increases support for ticket price by $1.99
Over the season, this could be expected to amount to $3474638
```



```
predict_increase(['LongestRun_mi', 'Snow Making_ac'], [0.2, 4])
0.0
```

0.0

## SCENARIO #4

I increased the longest run by 0.2 miles & added 4 acres of additional snow making cover.

The output showed no difference from the current. I believe this output is a result of the Random Forest Model placing the longest run low on the importance list.


# 06

## NEXT STEPS

# NEXT STEPS | GETTING TO THE ANSWER

<u>I advise Scenario 2 be taken under consideration</u> as it presented a possible solution. **While Scenario 3 presents the same, I believe it may incorporate additional cost(s) above those in Scenario 2.**

**Additional analysis can be undertaken** with different departments; notably:

- **Accounting & Finance Department**
  - *Further details and or structure of operational expenses*
- **Operations Department**
  - *The perceived benefit to operations by an additional chair lift*
- **Database Department**
  - *Review data sourcing methodology; particularly those that were removed*
- **Marketing Department**
  - *The most negative correlation to prices was skiable terrain; exclusivity possibly*

**Other data that may paint an even clearer picture could be proximity to the respective airports**. This may not be relevant but if BMR's distance to an airport is comparatively higher than the competition in the dataset, this may make it less competitive and negatively impact our models.


# THANKS

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