Big Mountain Resort Project

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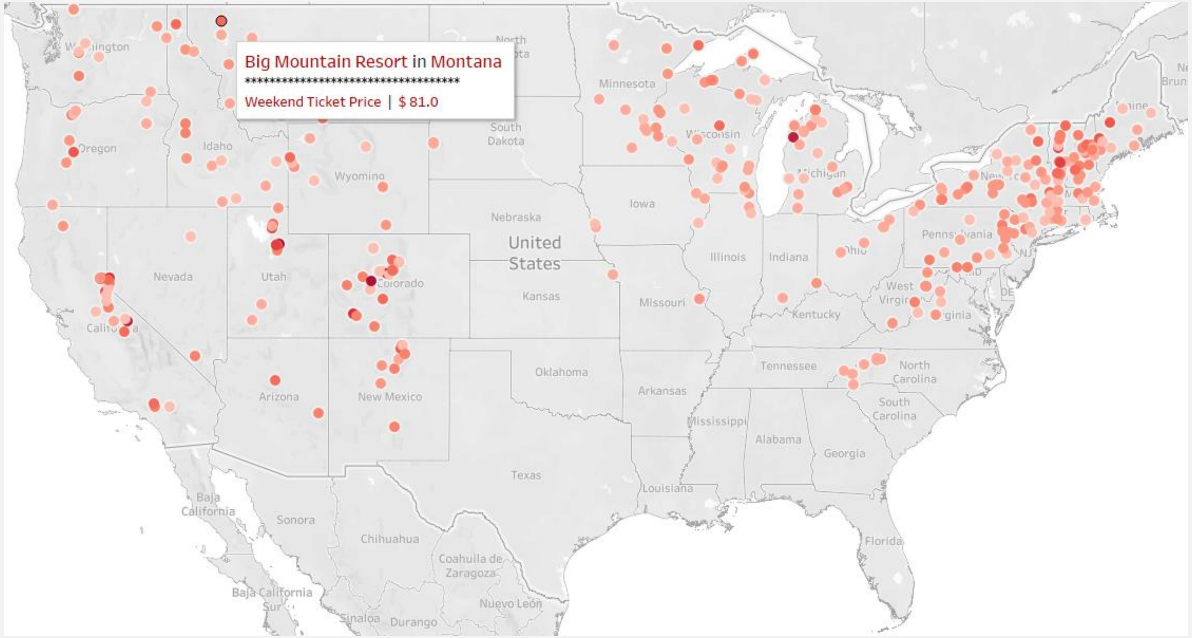
PROBLEM IDENTIFICATION

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 / 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 aforementioned costs of the new chair lift?**



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

02

GENERAL DELIVERABLES

2.0 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 management to address the problem**

03

DATA PRE-PROCESSING STEPS

3.0 DATA PRE-PROCESSING

DATA CLEANING

1. **A single CSV file was provided** by the Database Mgr.
2. I amended SkiableTerrain_ac for a resort* as the data was noticeably off kilter in the dataset & did not comply with the data on their website (link); 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 resorts is Silver Mountain, based in Colorado*

3.0 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]

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 they were not useful as their price data* was incomplete
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*

3.0 DATA PRE-PROCESSING

EXPLORATORY DATA ANALYSIS

Two datasets were pulled from the previous step; namely:

1. ski_resort_data:
   1. provided by the Database Manager on information which was cleaned down to 277 resorts across 34 states; and
2. state_summary:
   1. 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	...

3.0 DATA PRE-PROCESSING

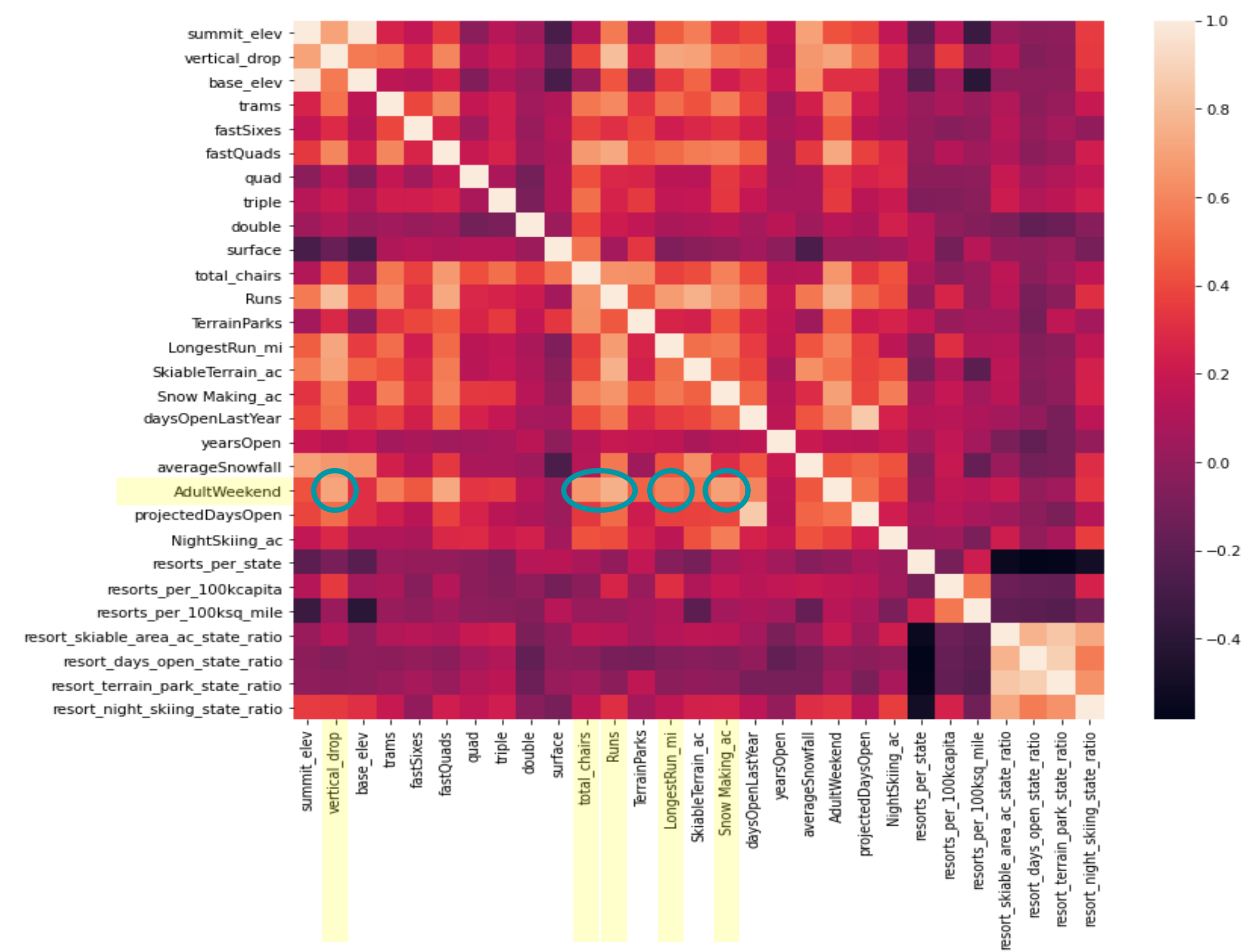
EXPLORATORY DATA ANALYSIS (cont.)

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 were added; among them, **using the Feature Correlation Heatmap I identified numerical features that have the strongest positive correlation to ticket prices & 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*

3.0 DATA PRE-PROCESSING

EXPLORATORY DATA ANALYSIS (Feature Correlation Heatmap)



3.0 DATA PRE-PROCESSING

EXPLORATORY DATA ANALYSIS (cont.)

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

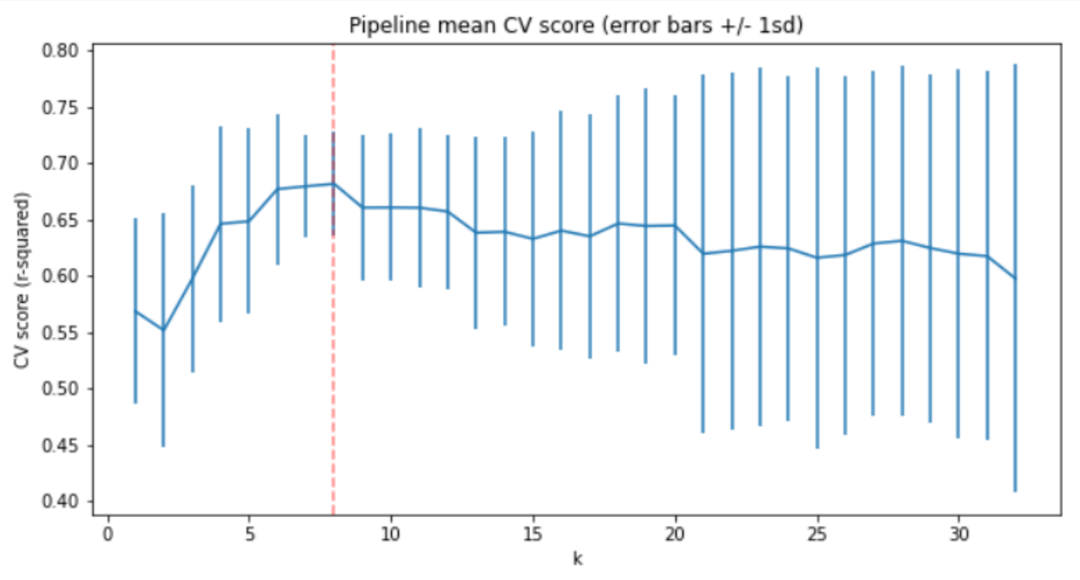
- I filled in **missing numbers** with averages of others to address missing data which may throw off scatter plots & quartile numbers
- I **utilized seaborn** rather than relying on matplotlib for scatter plots which may not be the ideal display candidate
- I **scaled the numbers** when required

3.0 DATA PRE-PROCESSING

PRE-PROCESSING

1. The first **pre-processing step was to split the data** into a training and testing splits, 70% and 30% respectively, & also removing any object types so that the dataset is only numeric types.
2. **With the help of a standard mean** & the **DummyRegressor** functions then next was to determine 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 **R squared** for the **train** & **test** datasets **became ~81%** & **72%**. The **mean absolute errors dropped down to ~$9**; much better than the $19 from just guessing.
6. I also replaced any missing data & the results weren't much different.

PRE-PROCESSING (cont.)



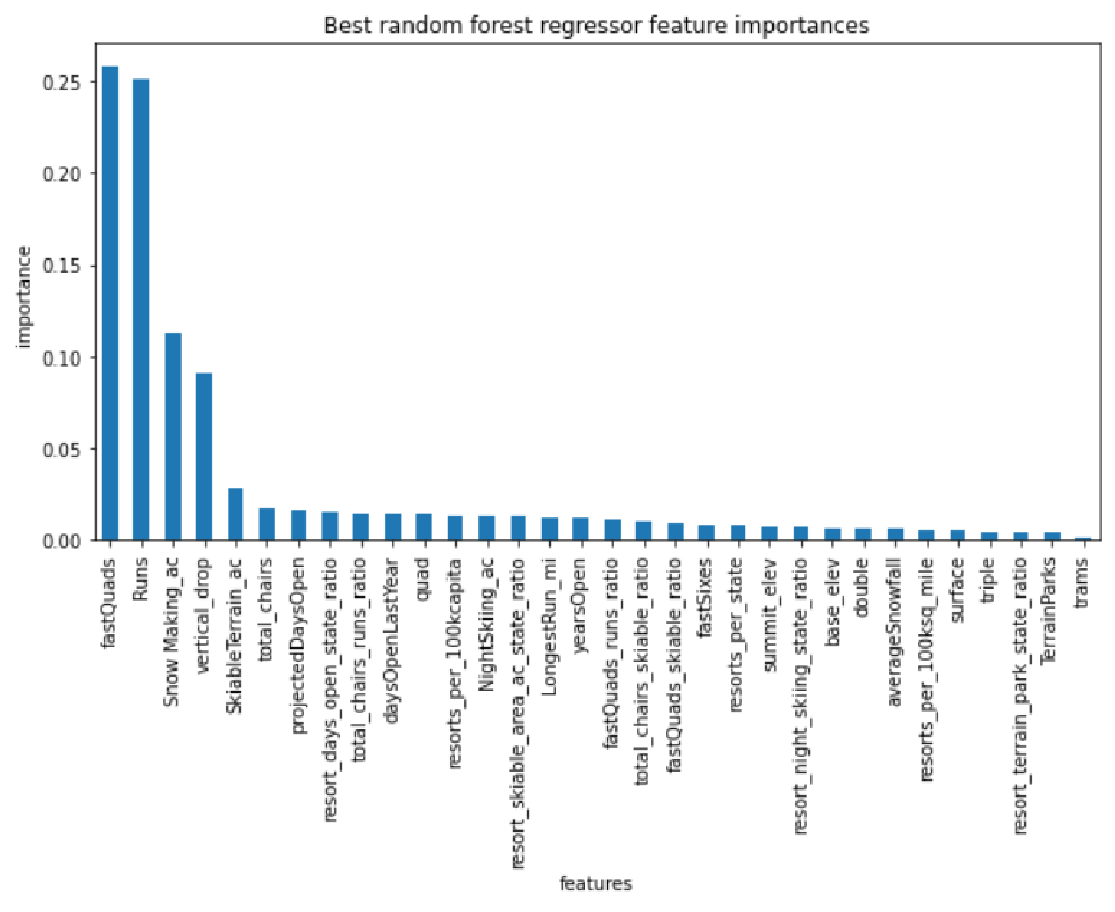
vertical_drop	10.767857
Snow Making_ac	6.290074
total_chairs	5.794156
fastQuads	5.745626
Runs	5.370555
LongestRun_mi	0.181814
trams	-4.142024
SkiableTerrain_ac	-5.249780
dtype: float64	

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

PRE-PROCESSING (cont.)

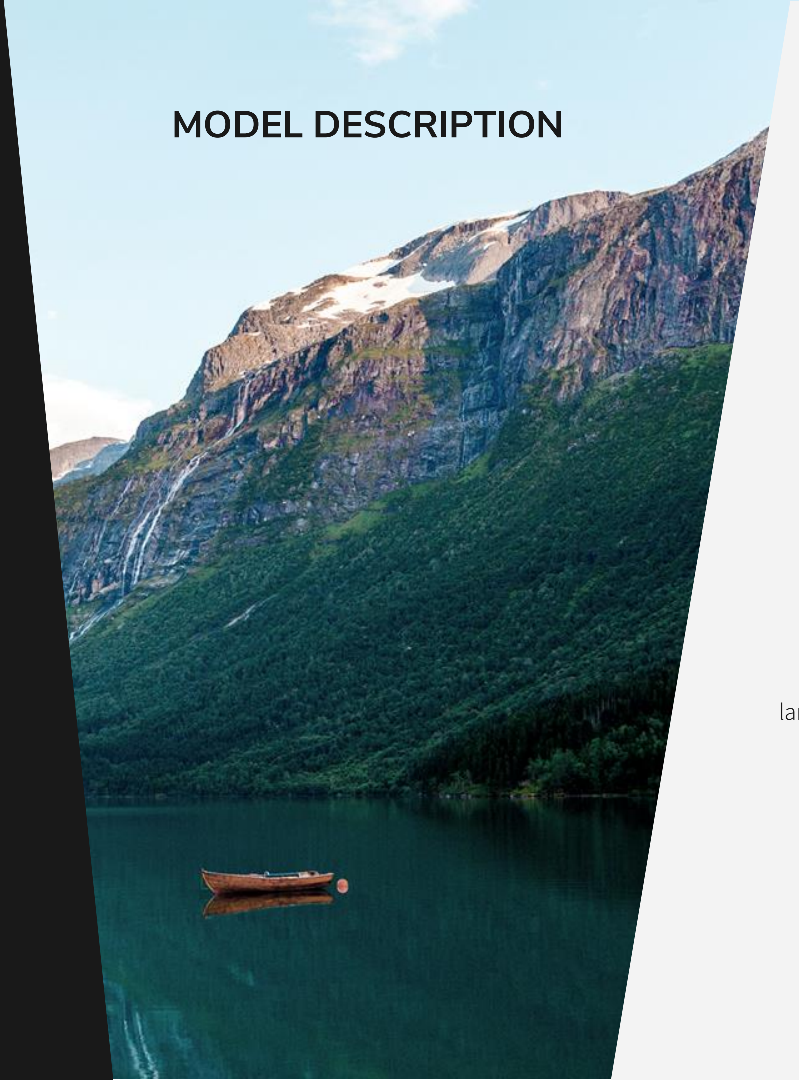
9. I then **moved to a Random Forest Generator** which **marginally improved our cross-validation results** & **showed that the top four dominate features were similar to the linear model**
10. I **chose the Random Forest Model for my modeling, as**:
    - Has a lower cross-validation mean absolute error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

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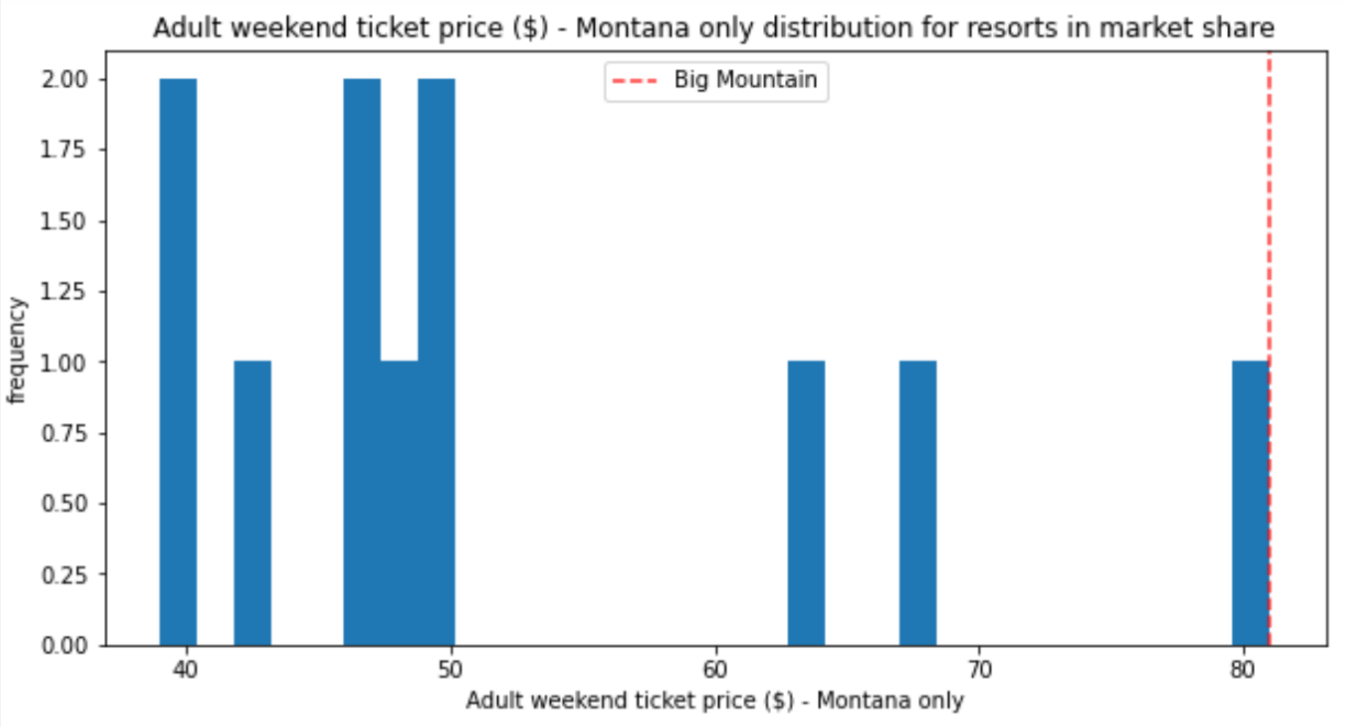
As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, **I first investigated where BMR stands against it's competitors**.

To begin, **I find that BMR is only slightly above the mean for the country**

MODEL FINDINGS (cont.)



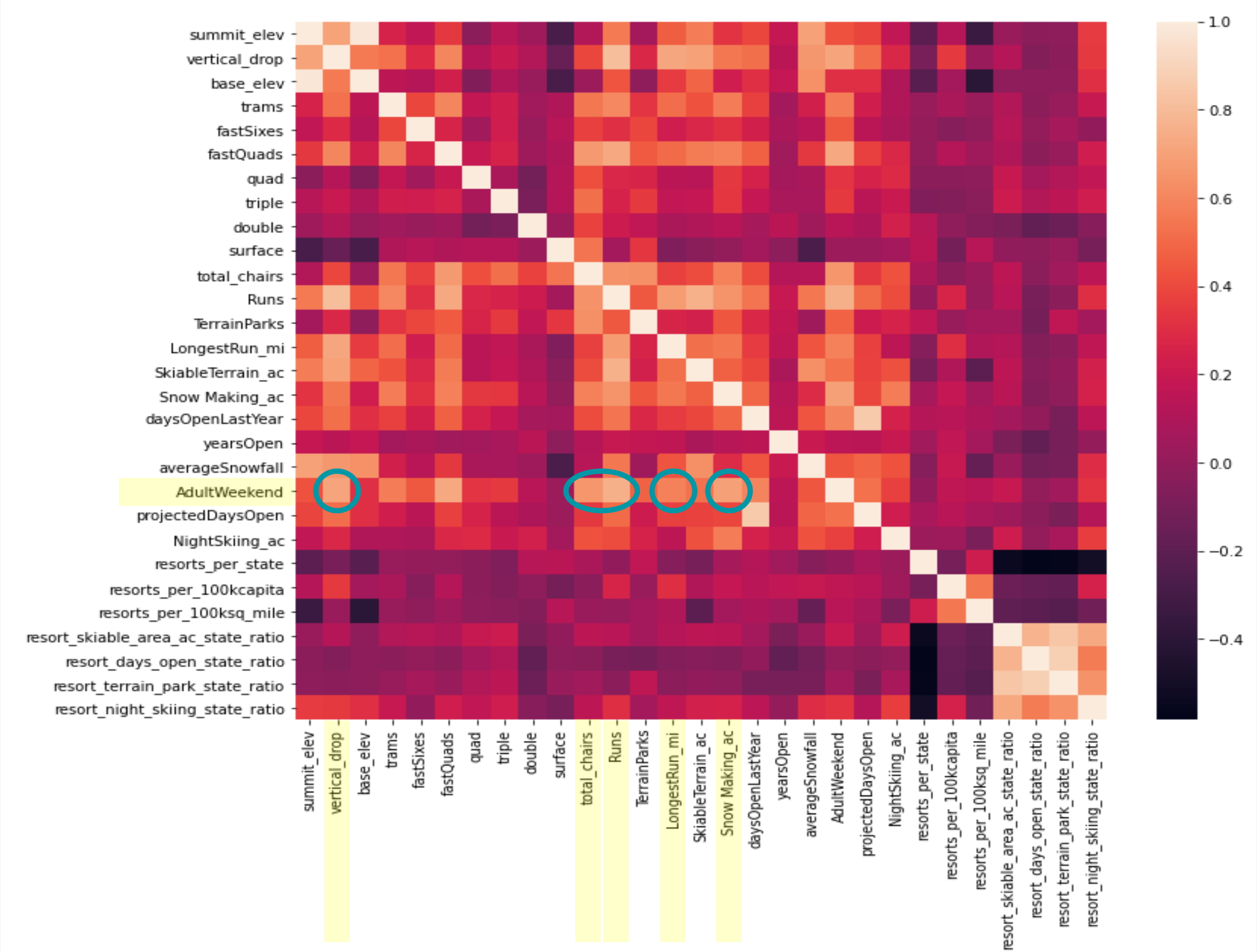
As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I first investigated where BMR stands against it's competitors.

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

MODEL FINDINGS (cont.)

As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, **I then investigated where BMR stands against it's competitors across the country**.

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**

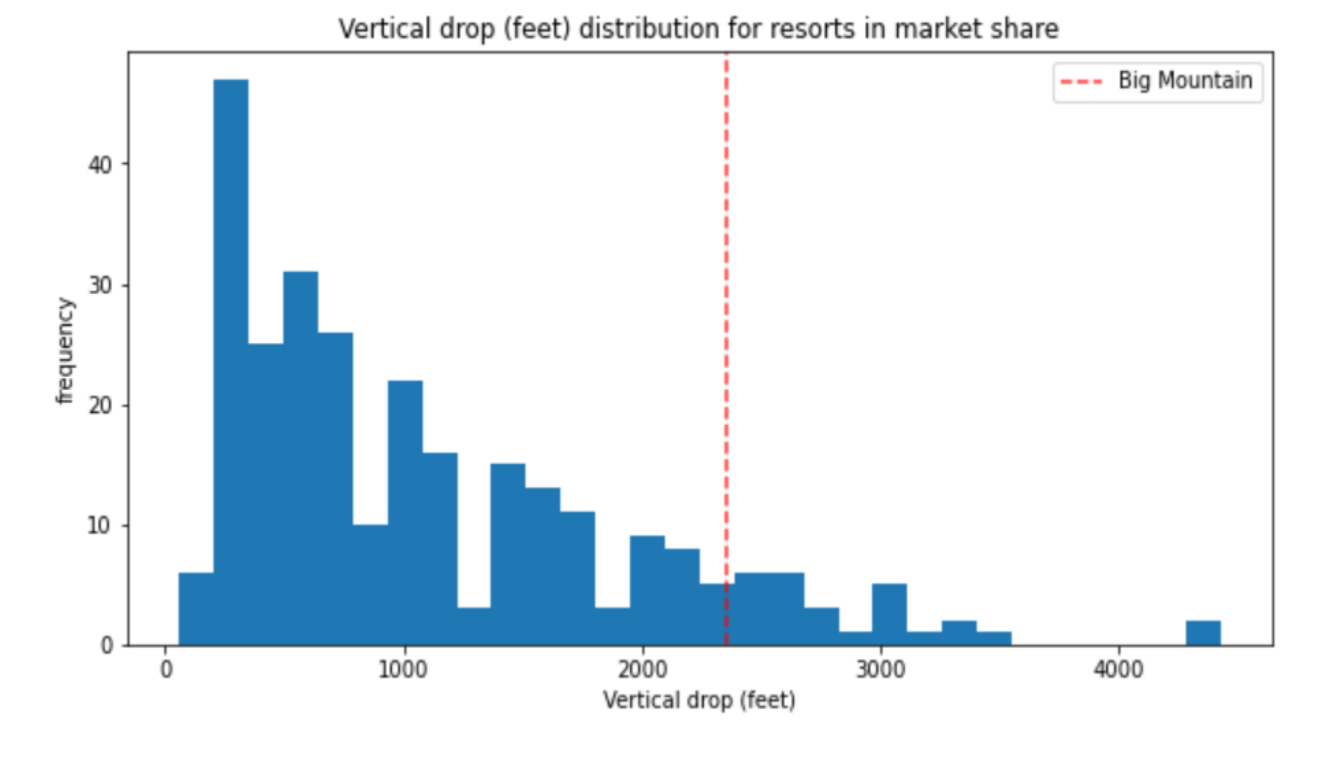


MODEL FINDINGS (cont.)

As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I then investigated where BMR stands against it's competitors across the country.

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 with a greater drop*

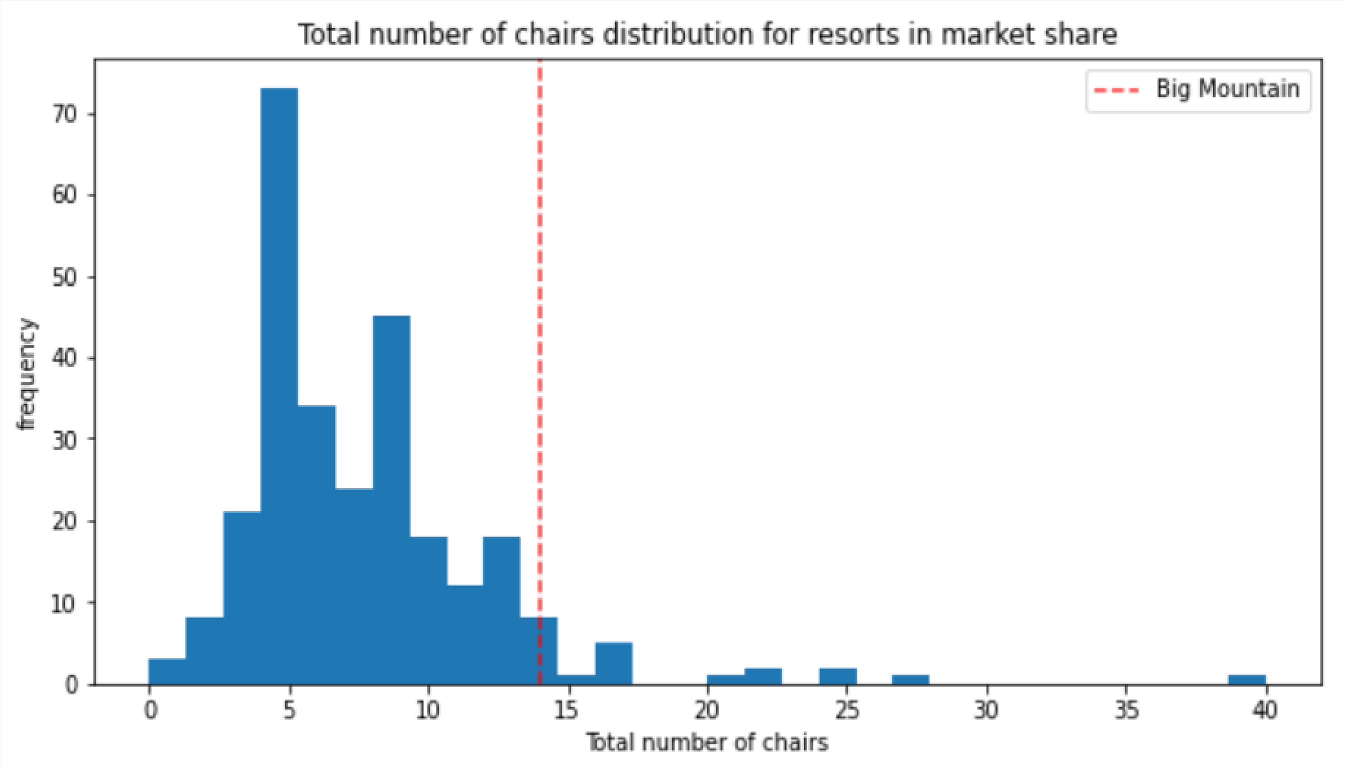


MODEL FINDINGS (cont.)

As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I then investigated where BMR stands against it's competitors across the country.

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*

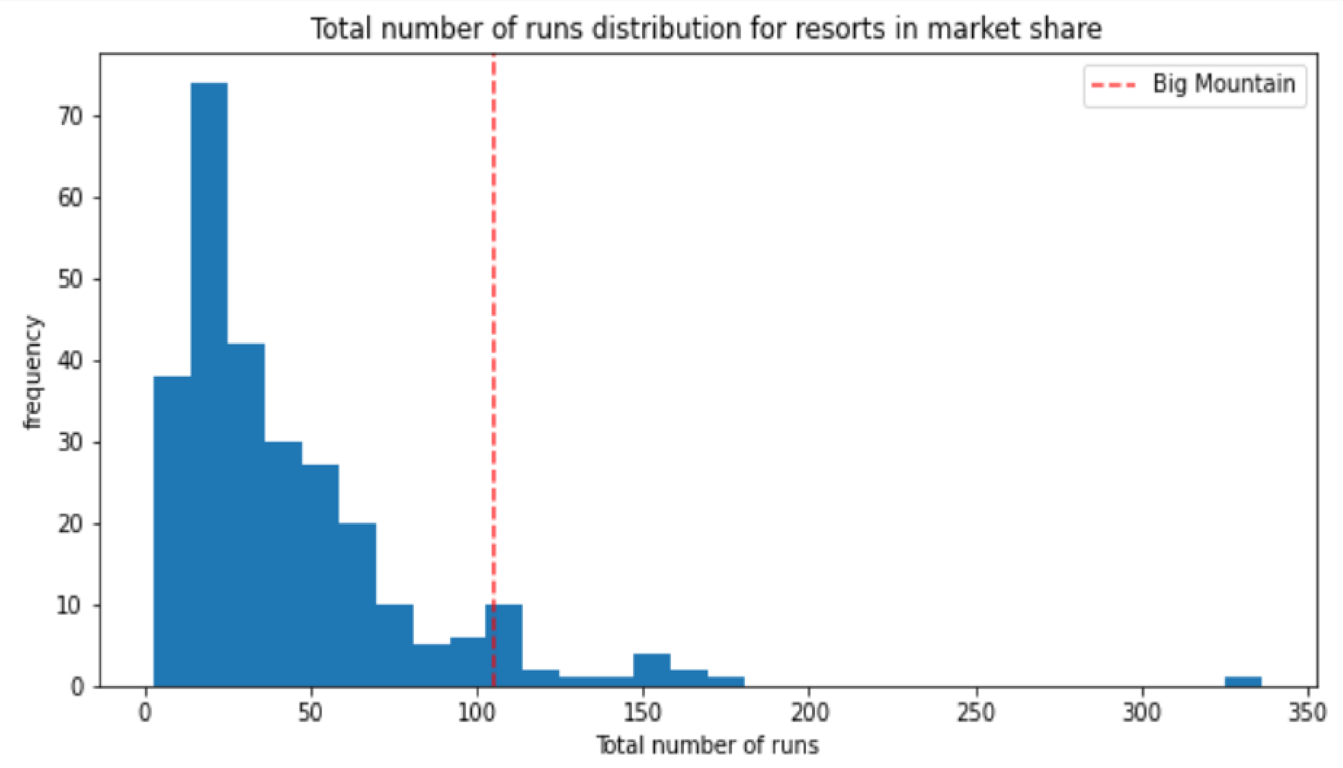


MODEL FINDINGS (cont.)

As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I then investigated where BMR stands against it's competitors across the country.

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*

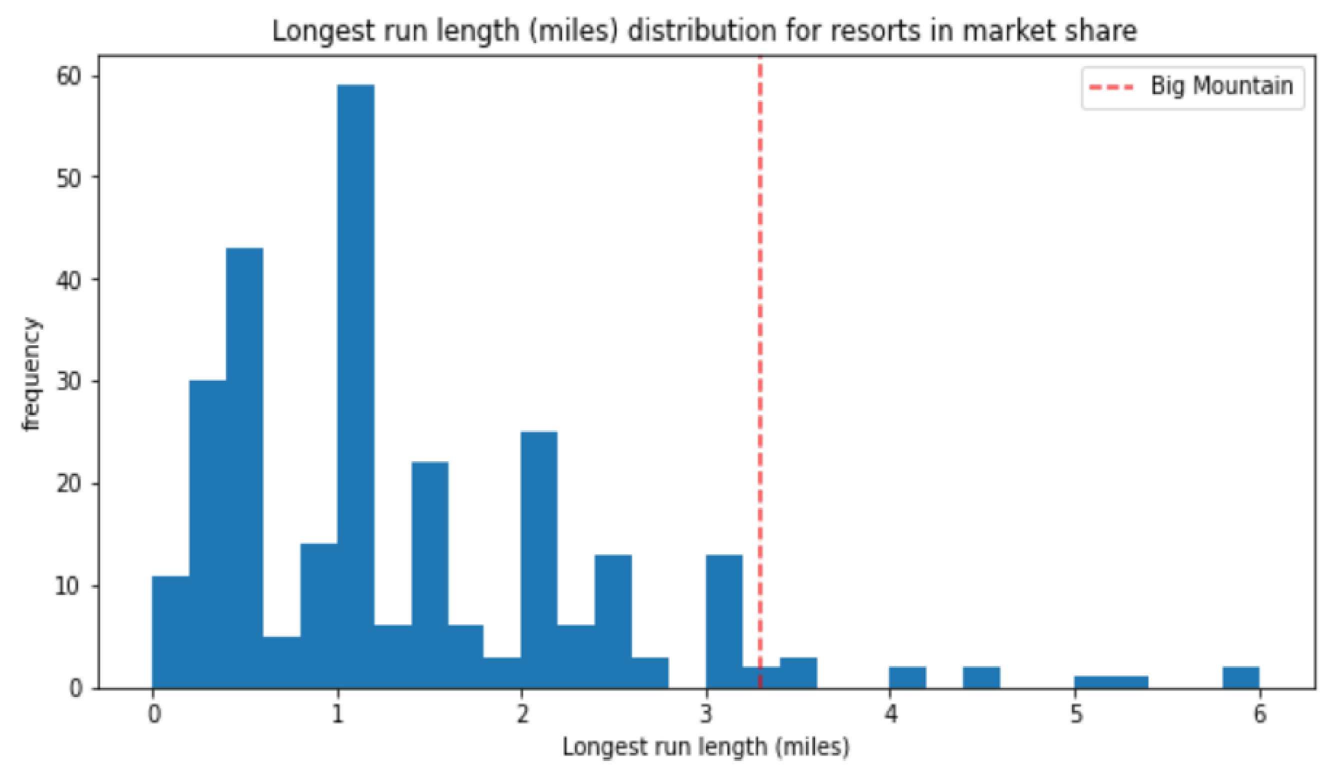


MODEL FINDINGS (cont.)

As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I then investigated where BMR stands against it's competitors across the country.

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 ~half of the longest run*

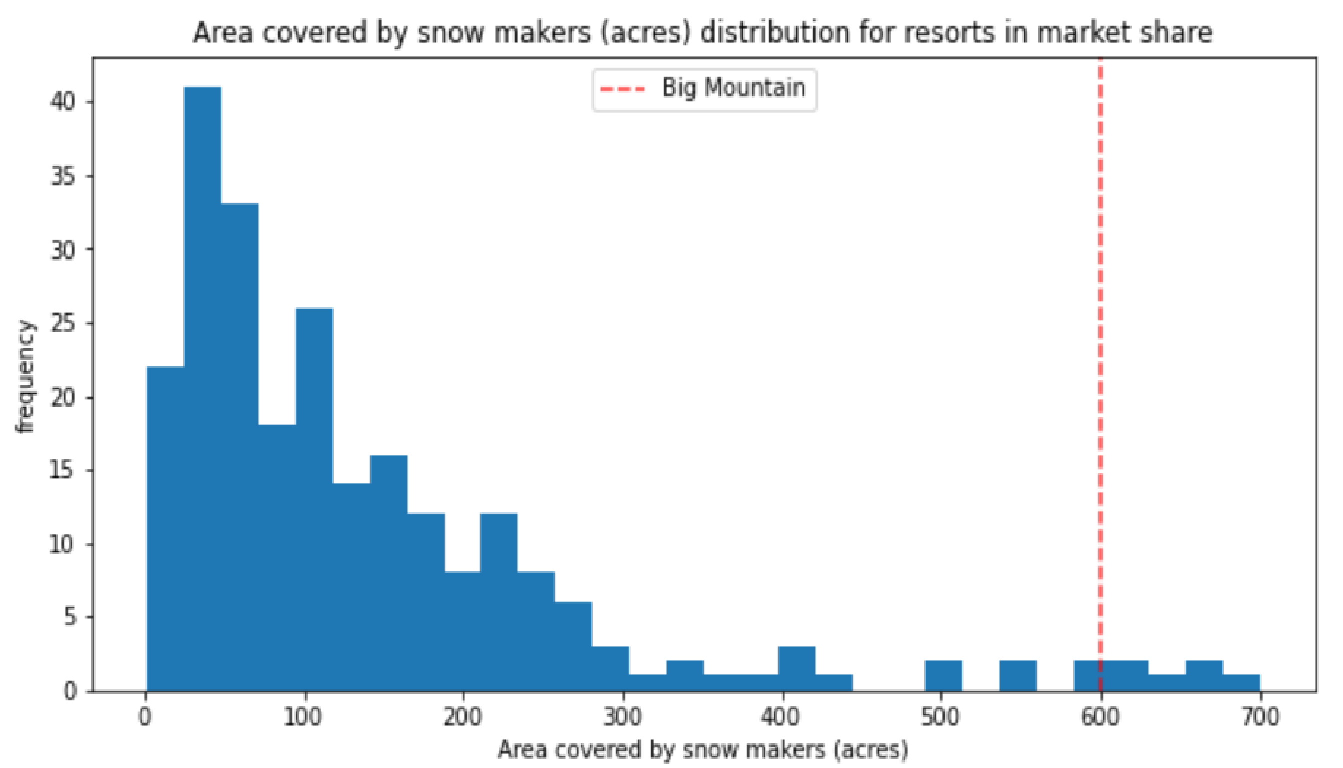


MODEL FINDINGS (cont.)

As the business sought to review potential scenarios for either cutting costs or increasing revenue from ticket prices, I then investigated where BMR stands against it's competitors across the country.

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

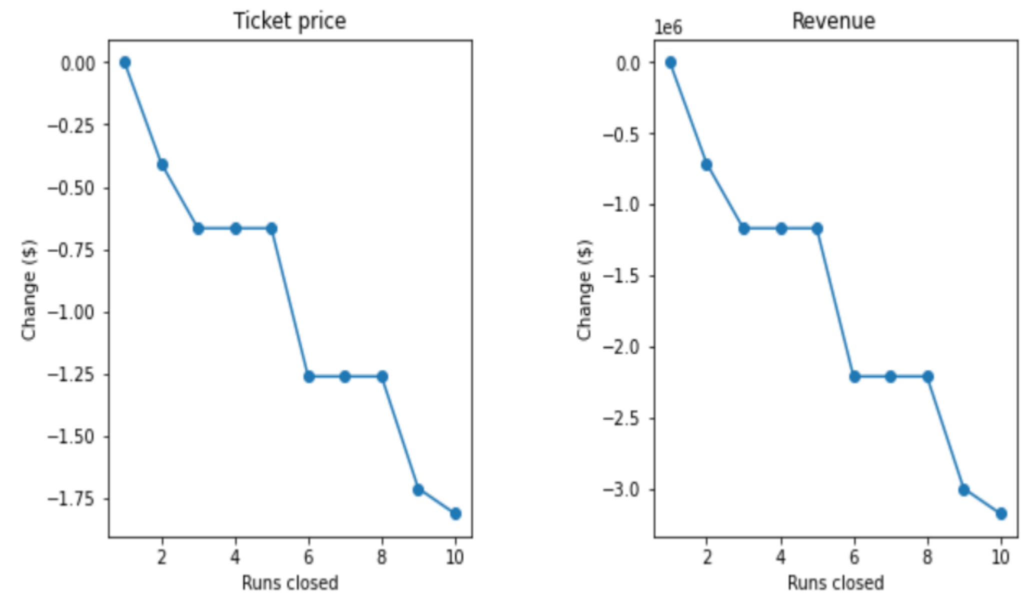
Same as Scenario 2 albeit **adding 2 acres of snow making cover**

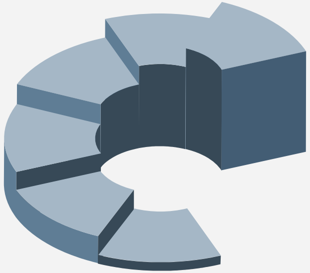
SCENARIO 4

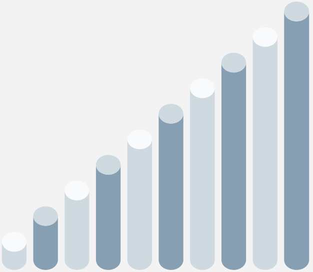
Increasing the longest run by 0.2 miles to 3.5 miles in length & **adding 4 additional acres pf snow making cover** to cover it

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







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

```python
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

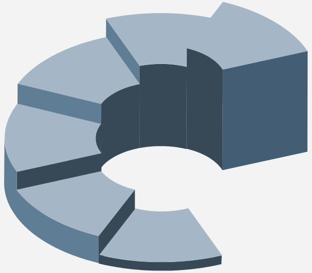
I modeled **increasing the vertical drop to a point 150 feet lower but requiring the installation of an additional chair lift** without additional snow making coverage.

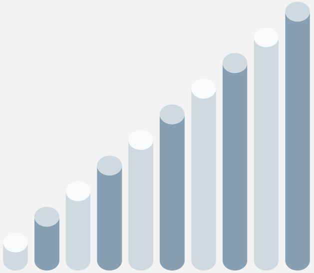
In this scenario, **the model increases support for ticket prices by $1.99** to $82.99 **which could increase revenue by $3,474,638 over the season**.

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 and **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
```

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 that since the Random Forest Model placed the longest run low on the importance list**, this was our output.

06

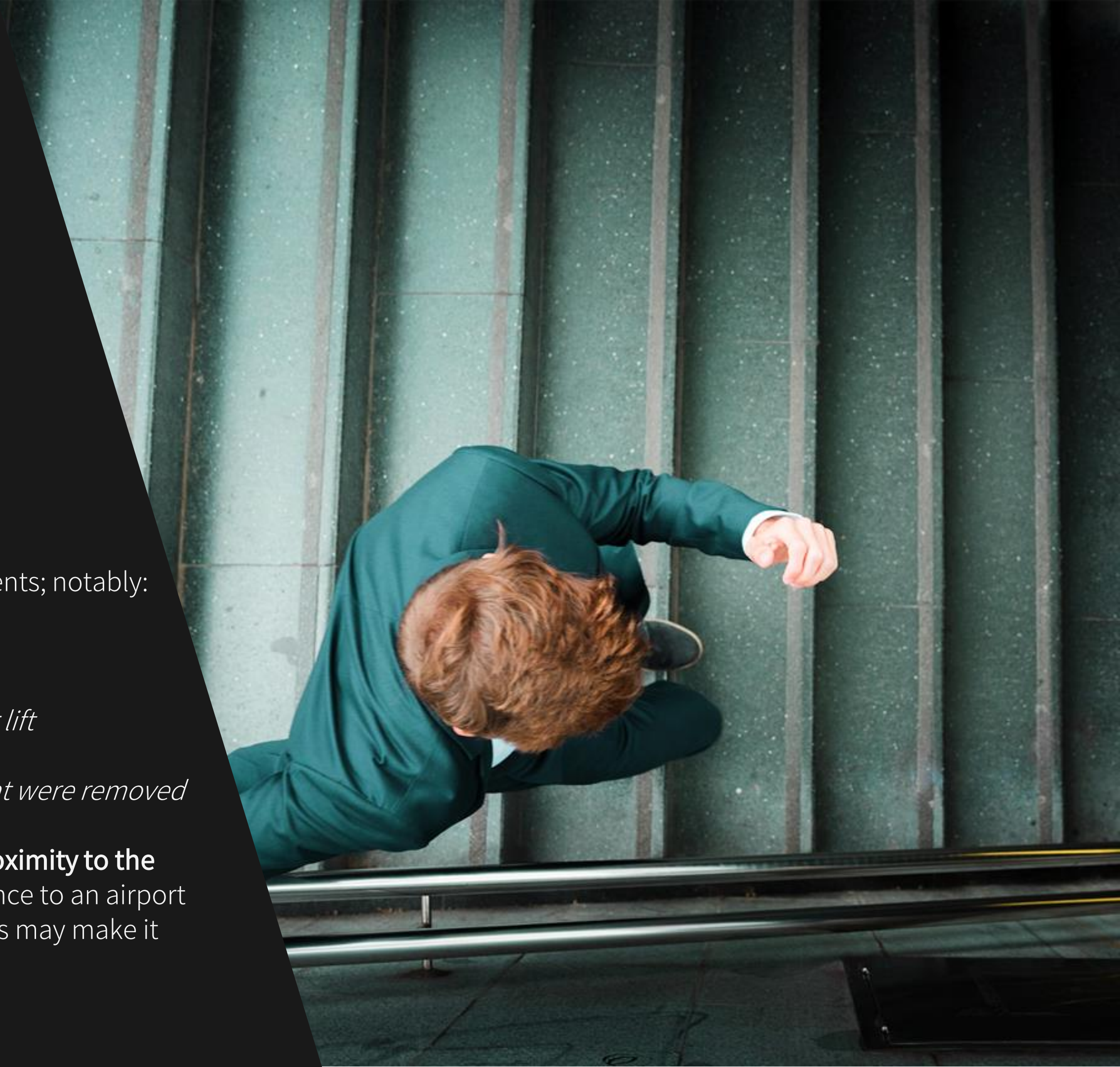
NEXT STEPS

NEXT STEPS

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*

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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This is where I give credit to the ones who are part of this project.

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