Rollercoaster Thrill Metric

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Academic Honesty Agreement:
We have neither given nor received unauthorized assistance on this assignment.

Abstract

In this paper, we developed a quantitative algorithm that incorporated objective factors of rollercoasters, such as speed, length, height, and drop height, to create a comprehensive list of the top 10 rollercoasters in the world based on their "thrill factor". We chose to use speed and height factors, as there was a large amount of data on them (> 290 rollercoasters), to develop a multiple regression model to fill in the missing drop height values. Then we numerically ranked each rollercoaster based on those objective factors and used a weighted algorithm to rank each rollercoaster based on their thrill factor. The top 10 rollercoasters list we developed was: Valravn, Fury 326, Goliath, Soaring Dragon, Steel Force, Steel Vengance, Iron Rattler, Eajanaika, Behemoth, and Kingda Ka. Our model is extremely flexible for future use as you can change the weights that we used in our weighted algorithm to suit personal preference.

Contents

1 Introduction

1.1 Problem Statement

There are presently several rollercoaster ranking sites that rank roller coasters based on subjective data from users in order to determine the thrill factor they would experience with each rollercoaster. Given data on several objective factors (type of rollercoaster, year/age, speed, length, height, drop height, inversions, duration, vertical angle, G-force), we were tasked to create a quantitative algorithm that incorporated these factors with developing a descriptive roller coaster ranking system. After developing our algorithm, we were to use this algorithm to create a comprehensive list of the top 10 roller coasters in the world.

1.2 Assumptions

Assumption 1: The year the rollercoaster was opened (age), the type of rollercoaster, and if the roller coaster has inversions/the number of inversions it has does not influence the thrill factor of a rollercoaster, and therefore will not be used in our model.

Justification: While the year and type of the model may influence the rollercoaster because of design improvements and technological advancements, they do not have a direct correlation with the thrill factor of the rollercoaster. A wood rollercoaster built in 1973 can be built in 2020 with steel but without any change in functional design or thrill. In addition, inversions are not indicative of a rollercoaster's thrill as many expert ranking lists find that rollercoasters do not need inversions to be thrilling. Inversions are less quantifiable than other factors such as length, speed, or drop height because inversions do not have a uniform method of measurement. The number of inversions is also not as reliable due to the inversions themselves not being consistent in design, shape, or size.

Assumption 2: The drop height of a rollercoaster is most indicative of its thrill factor.

Justification: The tallest drop is often the highlight of a ride. Furthermore, to address the physics behind rollercoasters, at the top of the tallest hill, a rollercoaster's energy is almost all stored as gravitational potential energy. This is around the maximum energy of the entire ride, and as the rollercoaster begins its drop, energy is transferred into kinetic energy. For the rest of the ride, as the rollercoaster ascends and descends smaller hills, fluctuations in acceleration make for a dynamic ride [1].

Assumption 3: We are able to fill in the missing data for drop height by performing a regression using the drop height data present in the dataset. Specifically, we use the speed and height of the roller coaster to predict its drop height.

Justification: There are over 130 roller coasters that have accurate speed, height, and drop height, and given the high level of correlation between speed/drop height and height/drop height, the multi-dimensional regression should be very accurate.

Assumption 4: When creating a metric for thrill factor, higher speeds, longer lengths, higher heights, and higher drop heights are taken to be more thrill-inducing than lower speeds, shorter lengths, lower heights, and lower drop heights.

Justification: Larger drop heights, heights and speeds, are more thrilling because they are associated with conquering fear and an adrenaline rush [2]. Longer lengths sometimes means a rollercoaster track has more opportunities for thrilling elements; it can also mean the rollercoaster is more prolonged and not very thrilling.

1.3 Preliminary Analysis

We assume (from assumption 2) that the drop height of a rollercoaster is most indicative of its thrill factor. Therefore, we spend a majority of this paper devising a means of filling in the missing drop height data.

We decided to create a regression model to fill in the missing data. To determine which variables to use when creating our regression model, we looked at the correlation between drop height and the three factors we were given most data about (height, length, and speed). Then, we used Excel to determine whether the data had a close linear correlation (defined as $R^2 > 0.5$), and incorporated these factors into our multiple regression model. Our excel graphs are shown below:

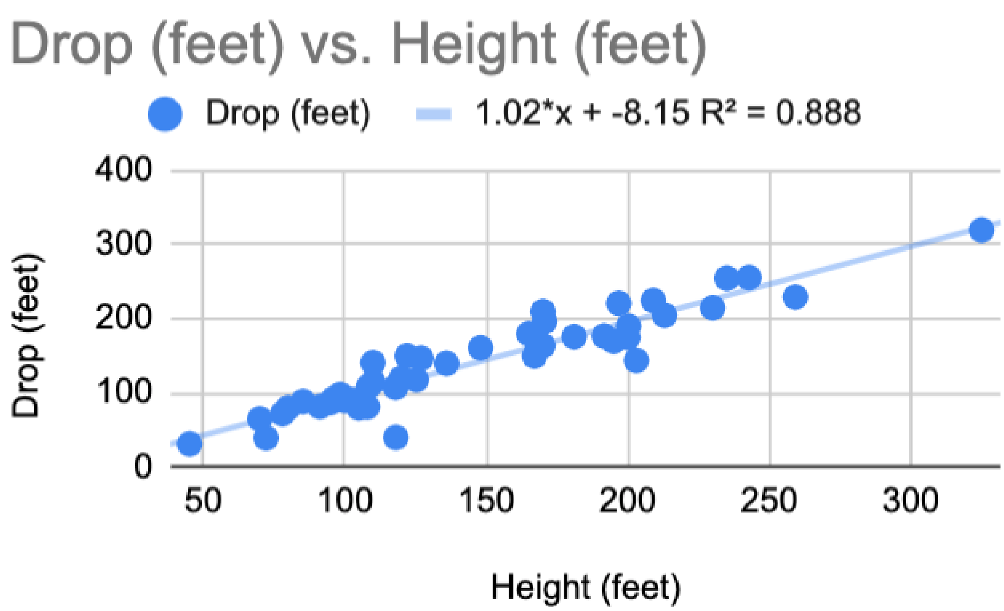

Figure 1: Correlation between height and drop height of the rollercoasters. $R^2 > 0.8$, implying a strong linear correlation.

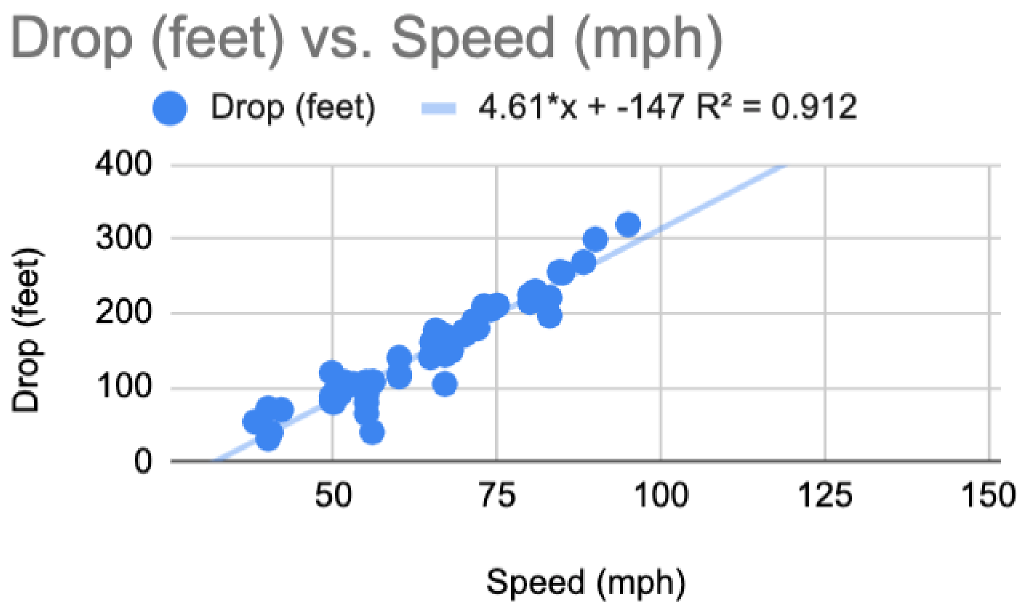

Figure 2: Correlation between speed and drop height of the rollercoasters. $R^2 > 0.8$, implying a strong linear correlation.

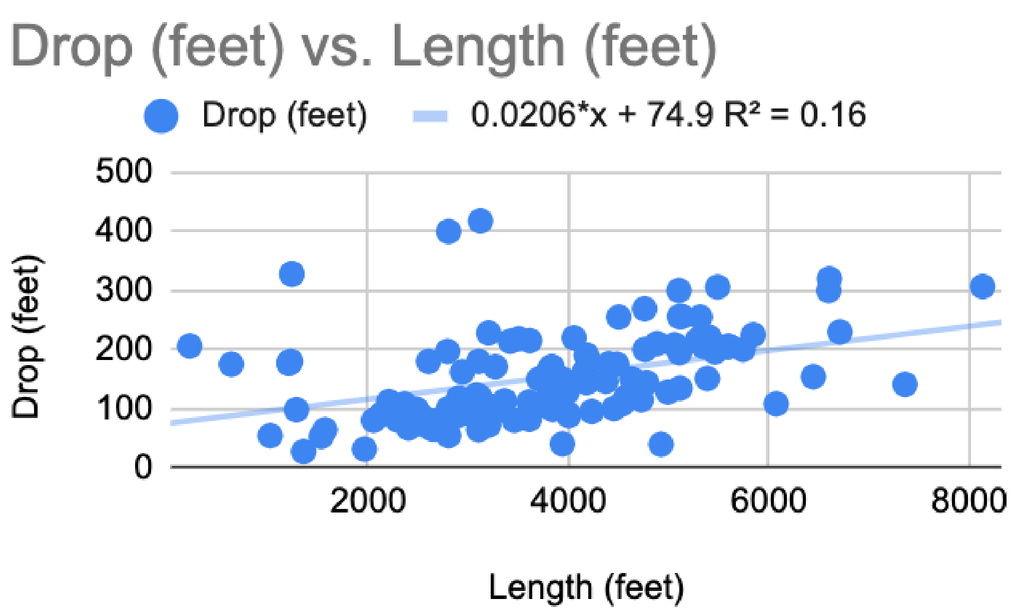

Figure 3: Correlation between length and drop height of the rollercoasters. $R^2 < 0.8$, implying a weak correlation. We therefore do not use Length in our regression model.

Because height and speed were both shown to be closely correlated to drop height, we incorporated those two factors and used Excel to create a multiple regression model:

$$d = 0.35085918h + 2.9360106s - 93.010323 \quad (1)$$

In our model, we denote d = drop height, h = height and s = speed.

For each of the other factors (duration, G-Force, vertical angle), there was not a sufficiently close correlation with its data and the height, length, or speed of the rollercoasters. The correlation of these variables are plotted below:

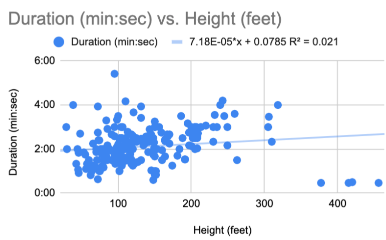

Figure 4: $R^2 = 0.021$

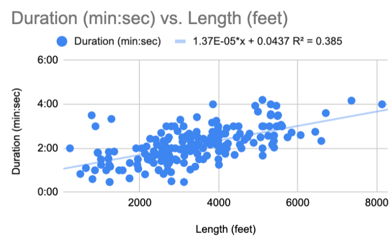

Figure 5: $R^2 = 0.385$

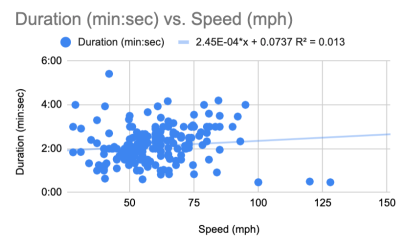

Figure 6: $R^2 = 0.013$

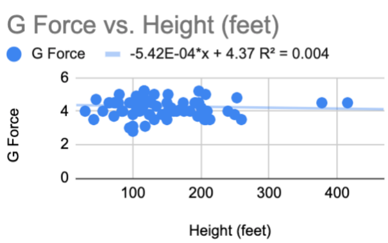

Figure 7: $R^2 = 0.004$

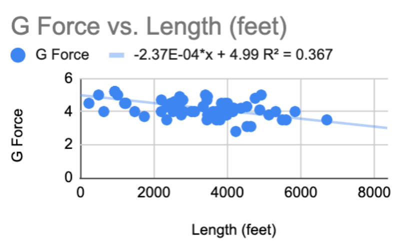

Figure 8: $R^2 = 0.367$

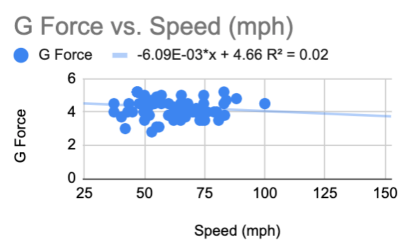

Figure 9: $R^2 = 0.02$

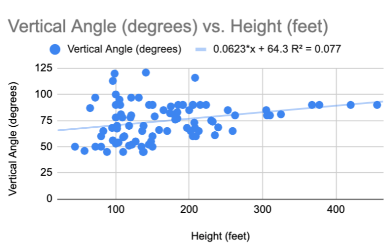

Figure 10: $R^2 = 0.077$

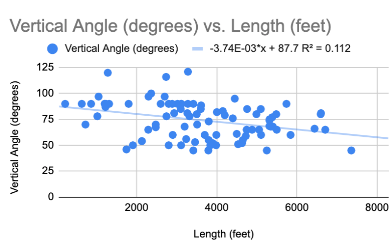

Figure 11: $R^2 = 0.112$

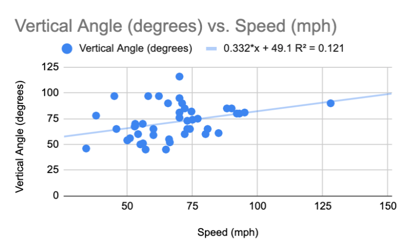

Figure 12: $R^2 = 0.121$

Thus, duration, G-force, and vertical angle were not factors taken into account in our thrill model, as there is not enough correlative data to accurately predict the missing data values for these. Any models using those variables could yield faulty data.

2 Methods

2.1 Ranking System

In order to develop an objective algorithm using height, length, speed, and drop height data, we utilized a weighted ranking system to determine for an overall 'score' for each rollercoaster, which we then used to develop our top ten rollercoasters list. To develop our ranking system, we created rankings for height, length, speed, and drop height respectively, allotting the number one ranking to the highest value and so on.

2.2 Weighting Method

In order to take into account the higher weight or value one factor may have over the others when determining thrill factor of a roller coaster, we implemented a weighting method into our algorithm to give each factor a weight specific to its degree of influence, or how important it is in determining thrill factor. We determined these weights by surveying ourselves, each of us giving a score of 1-10 to each factor, with 1 being not important at all and 10 being extremely important. After taking the averages of our scores, the weights of the four factors from 1-10 were as follows:

Variable	Weight Attached
Drop Height	8.75
Height	6.75
Speed	8
Length	4.5

Table 1: Table of weights that are attached to use input variable.

Using these weights, we created an algorithm to model thrill factor ranking t of a roller coaster using d=drop height rank, h=height rank, s=speed rank, and l=length rank, and sum(weights) = 28:

$$t = \frac{8.75d + 6.75h + 8s + 4.5l}{28} \tag{2}$$

A lower t value implies a better ranking, and therefore the most thrilling rollercoasters are those that have the lowest t value.

2.3 Justification

Our model included a ranking system in order to convert the raw data values for length, speed, height, and drop height into values that were scaled relative to one another. Since our raw values for length, speed, height, and drop height were not based on the same scale, converting these values to standardized ranks would eliminate any unfair emphasis placed on any one factor that would occur due to discrepancies between factors.

Our model included a weighting method in order to take into account the potentially different degrees of impact that a given factor would have on a rollercoaster's thrill factor.

This method also makes our algorithm adjustable to personal preferences (see Sensitivity Analysis), making it a more comprehensive and tailored solution for the user.

3 Results and Analysis

3.1 Top 10 Rollercoasters

Using this algorithm, we developed a list of the top 10 thrill-inducing rollercoasters from our list:

1. Valravn
2. Fury 326
3. Goliath
4. Soaring Dragon
5. Steel Force
6. Steel Vengeance
7. Iron Rattler
8. Eajanaika
9. Behemoth
10. Kingda Ka

Here are the t values for the top 20 rollercoasters:

Name	Weighted Average
Valravn	19.0625
Fury 325	22.65178571
Goliath	22.84821429
Soaring Dragon & Dancing	32.52678571
Steel Force	36.75892857
Steel Vengeance	37.33035714
Iron Rattler	38.42857143
Eejanaika	42.25
Behemoth	45.53571429
Kingda Ka	45.5625
Wild Thing	45.625
Viper	48.33928571
Schwur des Kärnan	51.83035714
Tower of Terror II	52.97321429
Storm Runner	53.15178571
Raging Bull	55.19642857
Hyper Coaster	59.07142857
El Toro	59.82142857
Mr. Freeze Reverse Blast	63.70535714
Flash	64.64285714

Figure 13: Table of t values from our spreadsheet. A lower t (weighted average) value signifies more thrilling rollercoaster.

3.2 Sensitivity Analysis

Due to the weighted nature of the variables in our algorithm, our algorithm is flexible and can be adjusted for personal preference. The user will only need to give a score from 1-10 on the importance of length, speed, height, and drop height from 1-10 based on their personal preference to modify the algorithm to tailor to their needs. Given that v_l=length score, v_s=speed score, v_h=height score, and v_d=drop height score, the modified algorithm would be:

$$t = \frac{v_d d + v_h h + v_s s + v_l}{v_d + v_h + v_s + v_l} \tag{3}$$

When different weights are applied to these factors, the ranking will change. We applied new weights to this algorithm to test for sensitivity, keeping the relativity of new weights the same as the old weights. Our new weights were as follows:

Variable	Weight Attached
Drop Height	7
Height	5.4
Speed	6.4
Length	3.6

Table 2: Table of new weights that are attached to use input variable.

We implemented these new weights into our modified algorithm and obtained a new top 10 ranking:

1. Valravn
2. Fury 326
3. Goliath
4. Kingda Ka
5. Soaring Dragon
6. Behemoth
7. Eajanaika
8. Steel Force
9. Steel Vengeance
10. Tower of Terror II

As seen, the new top 10 ranking is extremely similar to the previous one that was calculated based on the average weights from our own surveys. Thus, the flexibility and sensitivity of our model is justified; although the weights were changed, the outcome was very similar.

4 Conclusion

4.1 Strengths

Our algorithm is flexible and can be applied in other situations, as the weights can be altered easily for every factor included. Because we use rankings rather than raw data, our ranking data is able to be scaled in a small range for accessibility, and we are able to directly incorporate the data from different factors in relative terms/same units.

4.2 Weaknesses

The set of data our algorithm uses is incomplete and required regression methods to approximate the drop height data, and thus our rankings are only an approximation rather than completely based on real-world, accurate data. Our equation doesn't take into account the proportionate differences in the raw data as ranking is linear.

5 References

[1] https://www.teachengineering.org/lessons/view/duk_rollercoaster_music_less

[2] https://theconversation.com/the-psychology-of-roller-coasters-99166#:~:text=Though%20hard%20to%20pin%20down,of%20experiencing%20a%20natural%20high.

6 Member Contributions

Carina - Made multiple regression model for drop height, helped with making scatterplots for other factors with missing data, contributed to Preliminary Analysis, Results and Analysis, and Methods sections.

Harin - Ranked the data of all the individual factors; weighted the rankings; found final ranking of rollercoasters; contributed to Assumptions, Methods and Conclusion sections.

Evan - Worked on a neural network model that serves as an alternative to the multiple regression, devised the weighting algorithm using the ranking system, tidied up the LaTeX.

Alice - Worked on regressions for drop height and other factors with missing data; created scatterplots; contributed to Assumptions, Analysis and Methods sections.

A Appendix

Rollercoaster Data Excel Sheet

Neural Network on Google Colab