

Analyzing IMBD Scores of Scooby-Doo Episodes

Regression Rockstars: James Cai, Steph Reinke, Sarah Wu, Michael Zhou

2023-11-16

Introduction and Data:

Introduction

Scooby-Doo is a popular animated TV show that follows a group of teenagers and a talking Great Dane, Scooby-Doo, as they solve mysteries involving supernatural monsters and creatures. Each episode typically involves seeking and scheming to find the villain, ending with a dramatic unmasking of the monster. The show focuses on themes of friendship and teamwork. The show originally aired on CBS from 1969 - 1976, but there has been many subseries and reboots since.

We are interested in researching Scooby-Doo IMBD ratings because we all enjoyed Scooby-Doo in our childhoods. We also think that finding certain predictors of animated TV series ratings is useful for the entertainment industry. Specifically, our findings could be useful to anyone looking to create an animated TV series and wanting to know what aspects make up a successful episode. In the paper, “Determining and Evaluating The Most Popular Cartoons Among Children Between 4 and 6 Years of Age” published in 2017, the authors criticize the use of violence, vulgar language, and horror music in Scooby-Doo ([Başal et. al. 2017](#)), yet we can’t ignore the huge impact and popularity of Scooby-Doo. In 2013, Scooby-Doo was ranked the fifth greatest cartoon of all time ([TVGuide 2013](#)). If Scooby-Doo continues to create spin-off shows, our findings about what makes a successful episode could inform their future episodes as well.

Our primary research question is what factors best explain the variability in the IMBD scores of Scooby-Doo episodes? In other words, what elements tend to contribute to a successful episode? We want to investigate how predictor variables like `monster.amount`, character that unmasks the villain (which we combine into a singular variable, `unmask_villain`), and `network`, adequately explain the variability in IMBD ratings. We hypothesize that episodes with a higher monster count will have a better rating, since we think that there is more

action and suspense in episodes with more monsters. We also think that episodes where Fred unmasked the villain will have a higher rating since he is the leader of the group and thus, we think that people will be more drawn to him. Finally, we think that episodes that aired on Cartoon Network will have a better rating, since we think that Cartoon Network has the ability to generate more positive responses since they specialize in cartoons and are pretty well-known. In our analysis, we would like to explore the interaction between these variables as well.

Data

This Scooby-Doo data was found on the [TidyTuesday](#) database on Github. The data originally comes from [Kaggle](#) and was manually aggregated by user [Plummye](#) in 2021. The curator took roughly one year to watch every Scooby-Doo iteration and track every variable in this dataset. It is noted that some of the values are subjective by nature of watching, but the original data data curator tried to keep the data collection consistent across the different episodes.

Each observation represents an episode from a rendition of the Scooby-Doo franchise up until February 25, 2021, including movies and specials. The variables that were measured include the series and episode name (which we will not use as predictor variables), network aired on, IMDB score, engagement (represented by number of reviews on IMDB), and many details about what happened in each episode, such as how many monsters appeared, which character captured and unmasked the monster, the terrain of the episode, and more. There is a mix of both numerical and categorical characteristics.

The unmask variable is in the data as 6 separate columns with each column representing a person, such as `unmask.fred`, `unmask.velma`, etc. Before any of our analysis, we combined these columns into one singular column, `unmask_villain`. We also converted `imdb` from a `character` to a `double` as we want it to be a quantitative value.

Our response variable is `imdb`, while our predictor variables are `unmask_villain`, `monster.amount`, and `network`.

`imdb`: double, represents the score on IMDB

`unmask_villain`: character, represents which character unmasked the villain (if any)

`monster.amount`: double, represents the number of monsters in the episode

`network`: character, represents the network the episode was aired on

Exploratory data analysis

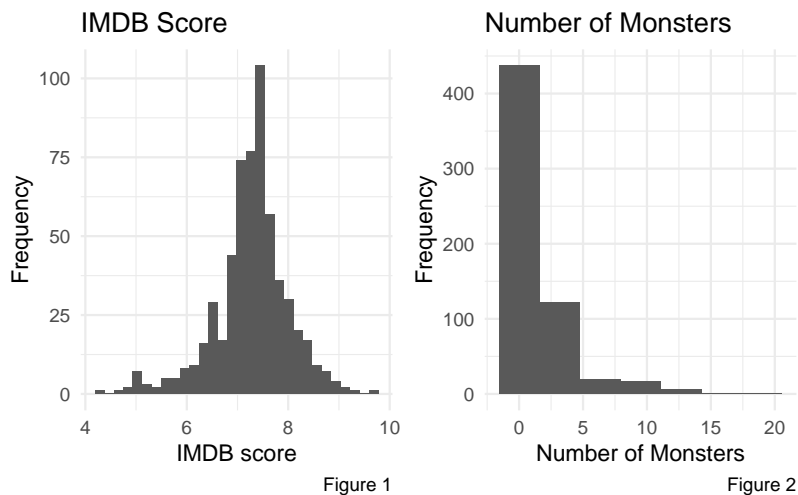


Figure 1: The distribution of our response variable IMDB scores, `imdb`, is unimodal and roughly symmetrical. The mean is 7.278 and the standard deviation is 0.732. The minimum is 4.2 and the maximum is 9.6. There does not seem to be any significant outliers.

Figure 2: The distribution of the number of monsters, `monster.amount`, is unimodal and right skewed. The median is 1 monster and the IQR is 1 monster. The minimum is 0 monsters and the maximum is 19 monsters. There are a few episodes with notably high amounts of monsters, with 5 episodes having 13 or more monsters.

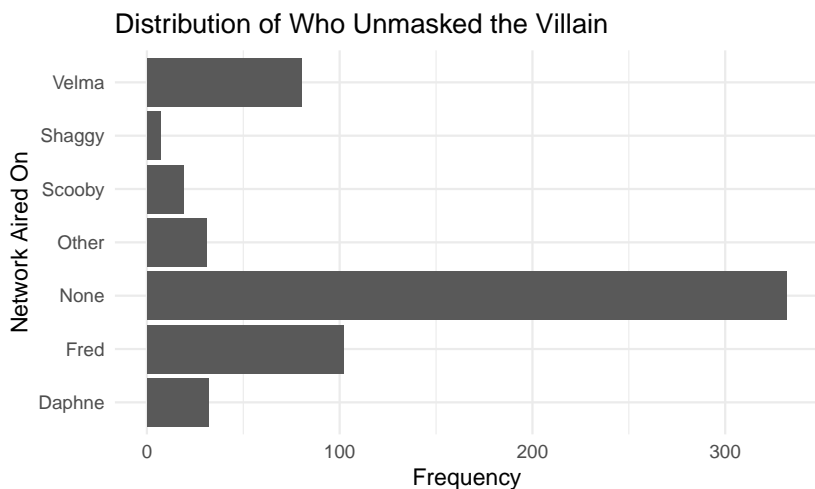


Figure 3

Figure 3: The distribution of who unmasks the villain, `unmask_villain`, shows that in a good majority of the episodes, no one unmasked the villain. However, out of the episodes where a

villain was unmasked, Fred and Velma were the main characters that unmasked the villain.

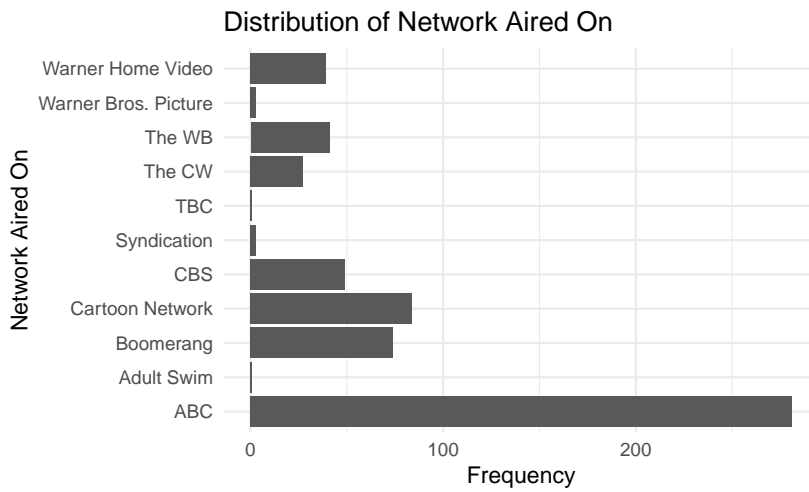


Figure 4

Figure 4: The distribution of the network the episode aired on, `network`, shows that a good majority of the episodes aired on ABC. There were also considerable amounts of episodes that aired on Cartoon Network and Boomerang, while there are also networks that aired very few episodes, such as TBC and Adult Swim.

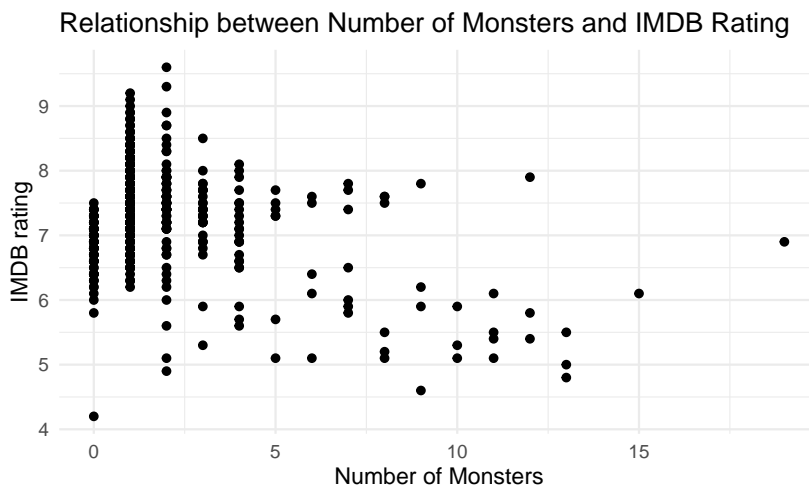


Figure 5

Figure 5: The relationship between the number of monsters and the IMDB score is moderate, negative, and linear. Omitting NULL values in `monster.amount` and `imdb`, the correlation is -0.350 . It seems that as the number of monsters increase, the IMDB score tends to decrease, on average. However, as seen earlier, the median of the distribution of the number of monsters is 1, so as we increase the number of monsters, there are less and less observations, which

makes the relationship between the two variables hard to observe as the number of monsters increase.

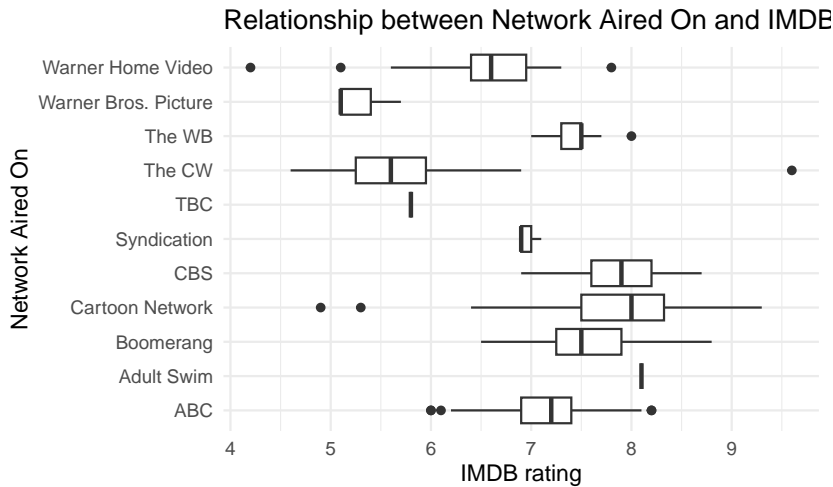


Figure 6

Figure 6: From the distribution of the different boxplots for each network, we observe that many of the interquartile intervals of the boxplots overlap, meaning that their IMDB ratings are quite similar. It seems that Cartoon Network generally received the best ratings, while Warner Bros. Picture and The CW generally received the worst ratings. We also observe a few outliers in the distribution of IMDB ratings for some networks, such as Warner Home Video and ABC. Many of the networks have IMDB ratings that are pretty symmetrical, as the line representing the median is close to the middle of the box, such as in the case of CBS and The CW, but some are pretty skewed, such as in the case of Syndication, The WB, and Warner Bros. Picture.

Methodology:

We've split our Scooby-Doo dataset into training and testing sets, with a 75-25% division. This step is vital for our analysis, as it allows us to build our model on the training set and then assess its performance with an unbiased testing set. By setting a seed, we ensure the reproducibility of our data split, maintaining consistency in our results.

```
== Workflow =====
Preprocessor: Recipe
Model: linear_reg()

-- Preprocessor -----
5 Recipe Steps
```

```

* step_other()
* step_center()
* step_interact()
* step_dummy()
* step_zv()

-- Model -----
Linear Regression Model Specification (regression)

Computational engine: lm

== Workflow =====
Preprocessor: Recipe
Model: linear_reg()

-- Preprocessor -----
5 Recipe Steps

* step_other()
* step_center()
* step_interact()
* step_dummy()
* step_zv()

-- Model -----
Linear Regression Model Specification (regression)

Computational engine: lm

== Workflow =====
Preprocessor: Recipe
Model: linear_reg()

-- Preprocessor -----
4 Recipe Steps

* step_other()
* step_center()
* step_dummy()
* step_zv()

```

```
-- Model -----  
Linear Regression Model Specification (regression)  
  
Computational engine: lm
```

Table 1: wflow1

mean_adj_rsqu	mean_aic	mean_bic
0.269	610.982	676.177

Table 2: wflow2

mean_adj_rsqu	mean_aic	mean_bic
0.333	580.208	633.1

Table 3: wflow3

mean_adj_rsqu	mean_aic	mean_bic
0.265	606.73	649.782

Results:

! Important

Before you submit, make sure your code chunks are turned off with `echo: false` and there are no warnings or messages with `warning: false` and `message: false` in the YAML.