Board Game Analysis

Jeff Warchall

1/8/2021

Executive Summary

BoardGameGeek (https://boardgamegeek.com) is a website that collects user reviews of boardgames in order to rank them from best to worst. The purpose of this analysis is to determine if there is any pattern in the data collected by BoardGameGeek and if there are some attributes of different games that can predict how popular or well recieved the game is by the community. The data set used for this project contains approximately 5,000 records. Each record represents a single board game and includes the following information:

- Rank from most highly to least highly rated
- Game ID
- Name of the game
- Minimum and maximum number of players
- Minimum, maximum, and average play time
- Year of release
- Average rating of the user community
- Geek rating, which is a weighted average to normalize games with few ratings
- Number of times the game has been rated
- Minimum recommended age for players
- Game mechanics
- Number of people who have reported buying the game
- Category of the game
- Designer of the game
- Weight, which is the community's assessment of how complex the game is from simple (1) to complex (5)

To perform this analysis the dataset has been split into an approximately 85% / 15% partition with the larger set used to train the models and the smaller set used to validate the performance of the models. A linear model attempts to predict the average rating of a game based on how complex it is as there appears to be a preference for more complex games in this community. Next, a decision tree is used to attempt to predict whether or not a game will be among the top 10% most highly rated games based on features such as the game mechanics and category of the game.

```
## Warning: package 'corrplot' was built under R version 4.0.3
```

Methods and Analysis

First we will check the data for missing values and also examine some of the variables to see if any cleaning needs to be done.

```
## [1] 0
##        rank     bgg_url     game_id       names min_players max_players
##           0           0           0          28        4991        4969
##    avg_time    min_time    max_time        year  avg_rating geek_rating
##        4926        4937        4926        4895          70         157
##   num_votes   image_url         age    mechanic       owned    category
##        2633           0        4979        2685        2030        2741
##    designer      weight
##        2536        2025
```

```
##  [1] "Lord of the Rings: The Confrontation"
##  [2] "Citadels"
##  [3] "Cosmic Encounter"
##  [4] "Axis & Allies"
##  [5] "Cosmic Encounter"
##  [6] "Tales of the Arabian Nights"
##  [7] "Fortress America"
##  [8] "Cosmic Encounter"
##  [9] "Cry Havoc"
## [10] "Fresh Fish"
## [11] "Barbarossa"
## [12] "Wizard"
## [13] "Warrior Knights"
## [14] "Santorini"
## [15] "Mogul"
## [16] "Samurai"
## [17] "Conquest of the Empire"
## [18] "Elfenroads"
## [19] "Blackbeard"
## [20] "Arkham Horror"
## [21] "Hellas"
## [22] "Founding Fathers"
## [23] "Around the World in 80 Days"
## [24] "Samurai"
## [25] "Cartagena"
## [26] "Crimson Skies"
## [27] "Aladdin’s Dragons"
## [28] "Saga"
```

```
##    game_id                                names year
## 1      492                    Aladdin’s Dragons 2000
## 2    53103                    Aladdin’s Dragons 2009
## 3    15987                        Arkham Horror 2005
## 4       34                        Arkham Horror 1987
## 5    12005          Around the World in 80 Days 2004
## 6   204599          Around the World in 80 Days 2016
## 7    10093                        Axis & Allies 2004
## 8       98                        Axis & Allies 1981
## 9      550                           Barbarossa 1988
## 10   72809                           Barbarossa 2010
## 11     235                           Blackbeard 1991
## 12   25685                           Blackbeard 2008
## 13     826                            Cartagena 2000
## 14  224031                            Cartagena 2017
## 15     478                             Citadels 2000
## 16  205398                             Citadels 2016
## 17   17710               Conquest of the Empire 2005
## 18      97               Conquest of the Empire 1984
## 19   39463                     Cosmic Encounter 2008
## 20      15                     Cosmic Encounter 1977
## 21   40529                     Cosmic Encounter 1991
## 22   40531                     Cosmic Encounter 2000
## 23    3855                        Crimson Skies 1998
## 24    6551                        Crimson Skies 2003
## 25  192457                            Cry Havoc 2016
## 26    1323                            Cry Havoc 1981
## 27  180325                           Elfenroads 2015
## 28     711                           Elfenroads 1992
## 29      99                     Fortress America 1986
## 30  115293                     Fortress America 2012
## 31   37358                     Founding Fathers 2010
## 32   35423                     Founding Fathers 2007
## 33    1017                           Fresh Fish 1997
## 34  164698                           Fresh Fish 2014
## 35    4529                               Hellas 2002
## 36  207330                               Hellas 2016
## 37   18833 Lord of the Rings: The Confrontation 2005
## 38    3201 Lord of the Rings: The Confrontation 2002
## 39  174744                                Mogul 2015
## 40    4562                                Mogul 2002
## 41  101865                                 Saga 2011
## 42    9202                                 Saga 2004
## 43       3                              Samurai 1998
## 44    3061                              Samurai 1996
## 45      63                              Samurai 1979
## 46  194655                            Santorini 2016
## 47    9963                            Santorini 2004
## 48   34119          Tales of the Arabian Nights 2009
## 49     788          Tales of the Arabian Nights 1985
## 50   22038                      Warrior Knights 2006
## 51    1143                      Warrior Knights 1985
## 52    1465                               Wizard 1984
## 53    3463                               Wizard 1978
```

```
## Warning in set.seed(5, sample.kind = "Rounding"): non-uniform 'Rounding' sampler
## used
```

At first it appears that some games have duplicate records, however upon closer inspection it is apparent that these correspond to the same game that was revised and re-released at a later date, so these records will be retained as unique game versions.

Next, we will examine a correlation matrix to see if there are any obbvious relationships between some of these variables. Note, that for this plot only numeric variables can be examined:

This plot demonstrates that there are some relationships between some of the variable; unfortuneately, some of these correlations are not very useful. For example, average game time is correlated with both minimum and maximum time, which is a trivial observation. It is worth noting that how many people report owwning a given game and the number of times that the game is rated does correlate with a more highly ranked game. The most interesting feature here is that it appears that the weight of the game (complexity) appears to correlate with good ratings.

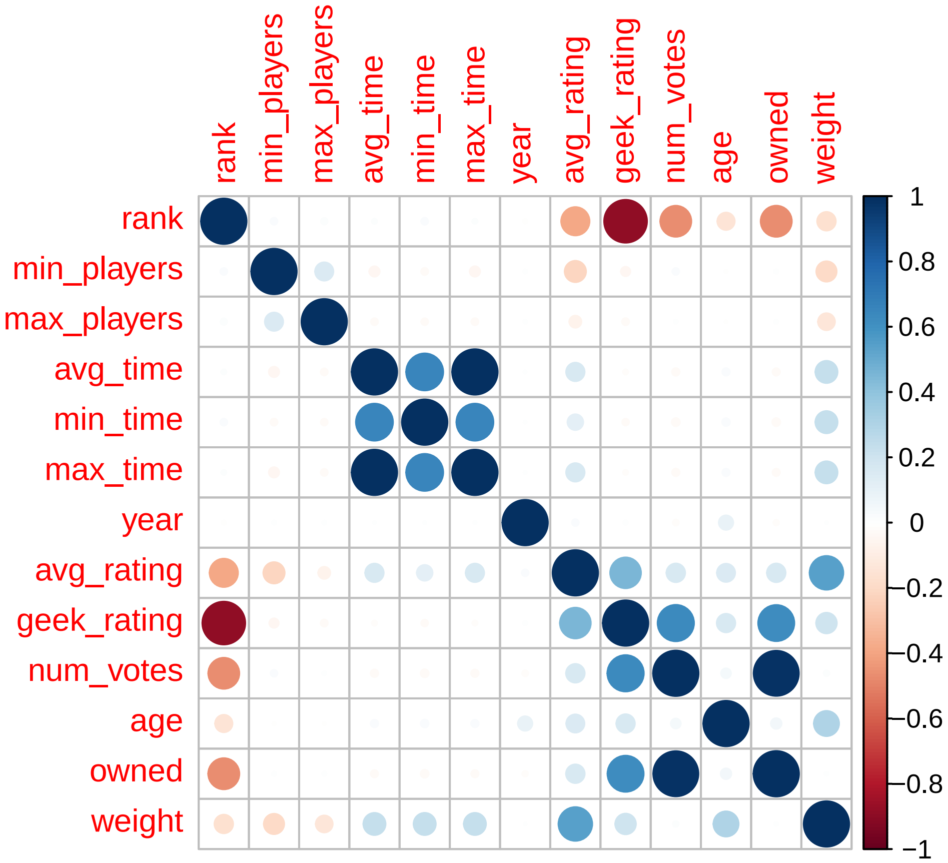
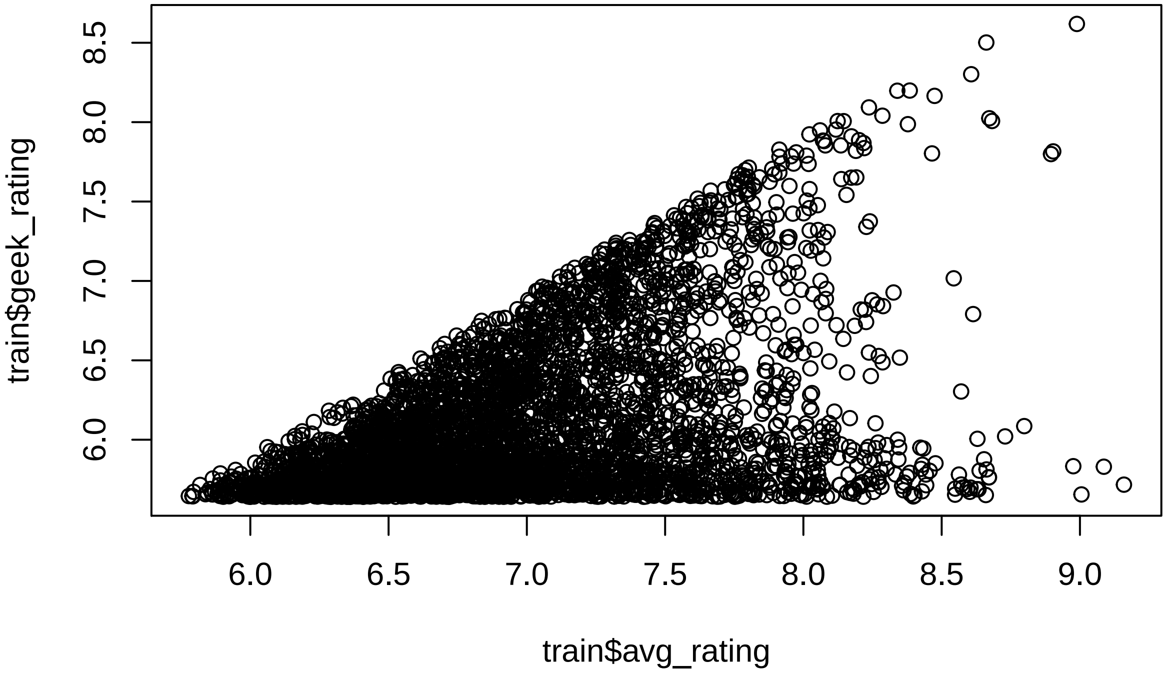
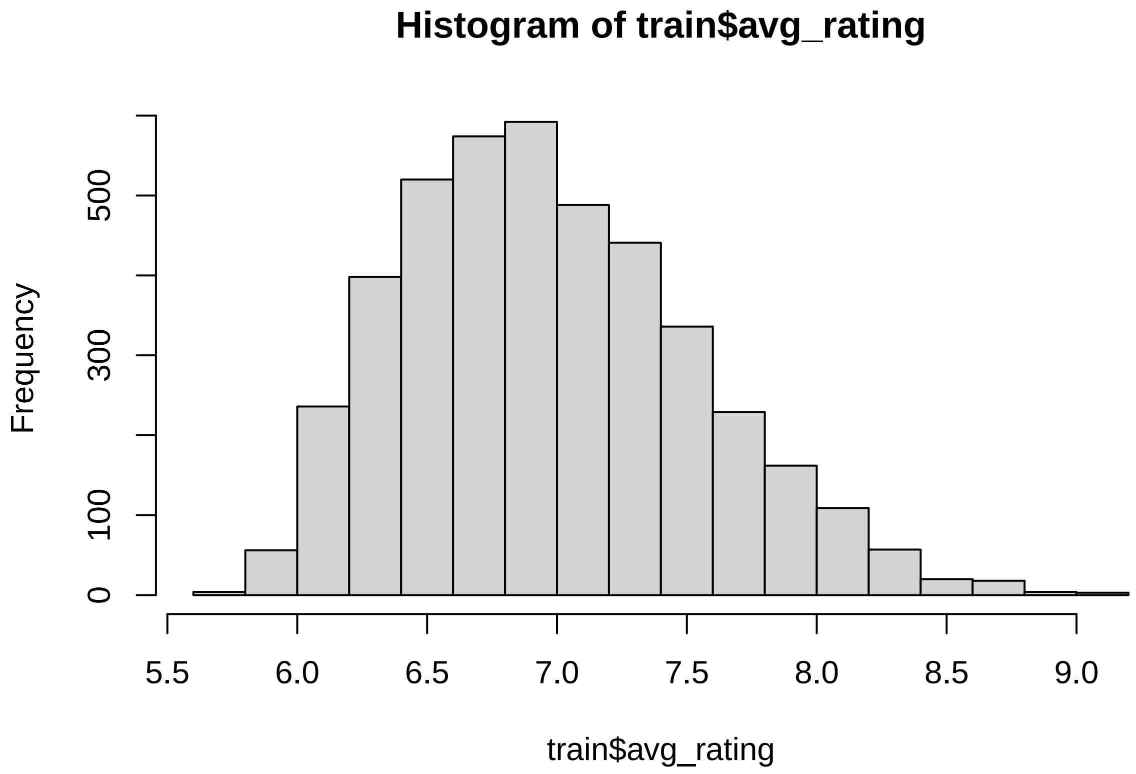


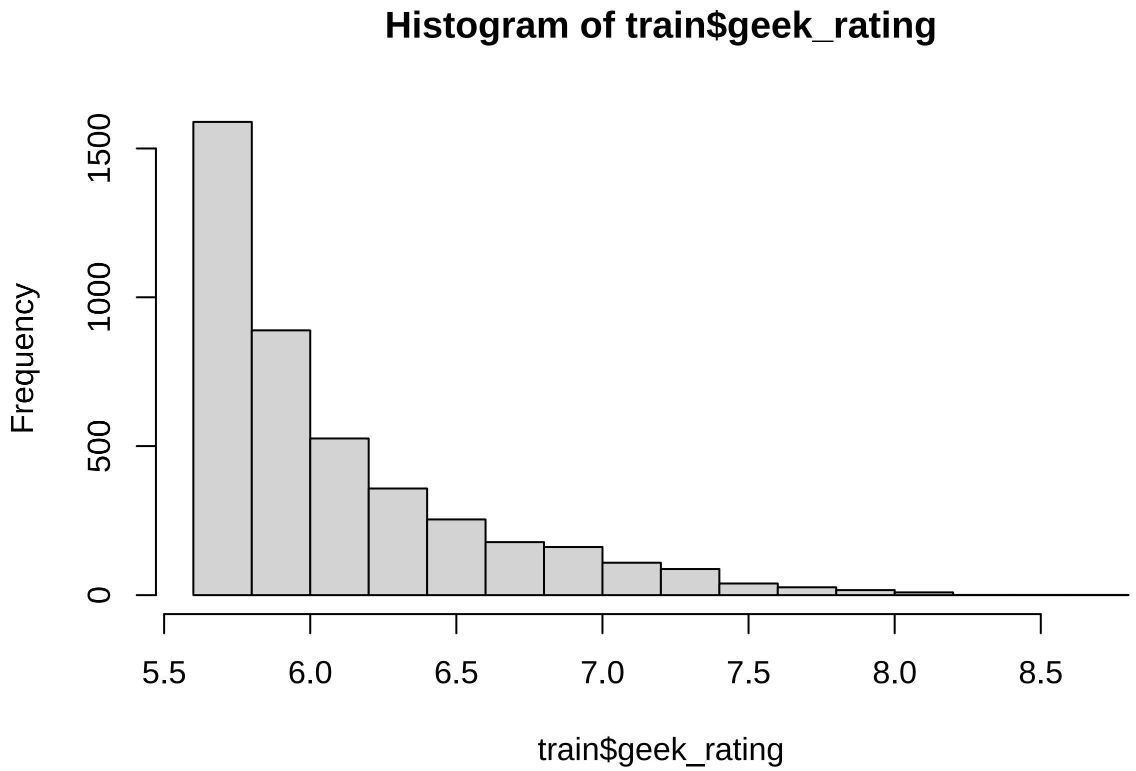
Figure 1: Figure 1: Correlation Matrix

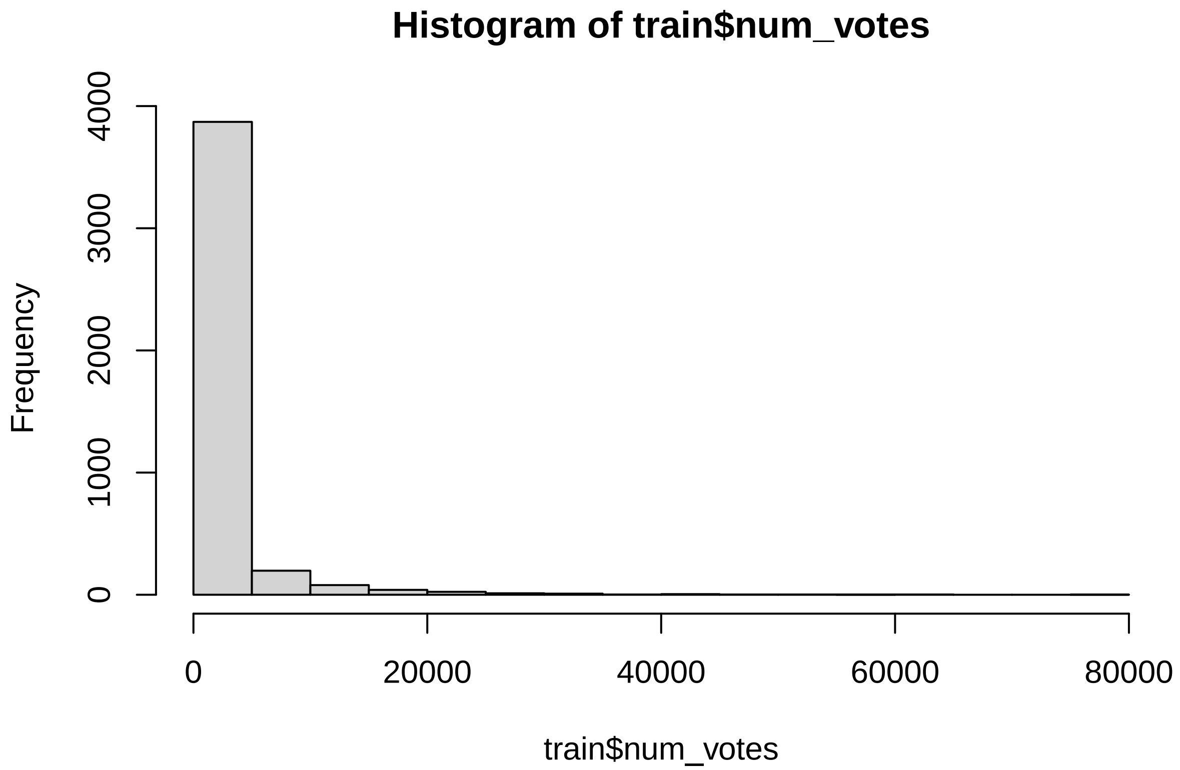
Next we look at the average rating versus the “geek” rating. As we see from the following plot, there is a capping effect built into the “geek” rating such that a game with a small number of very high ratings does not overwhelm the overall ranking system.



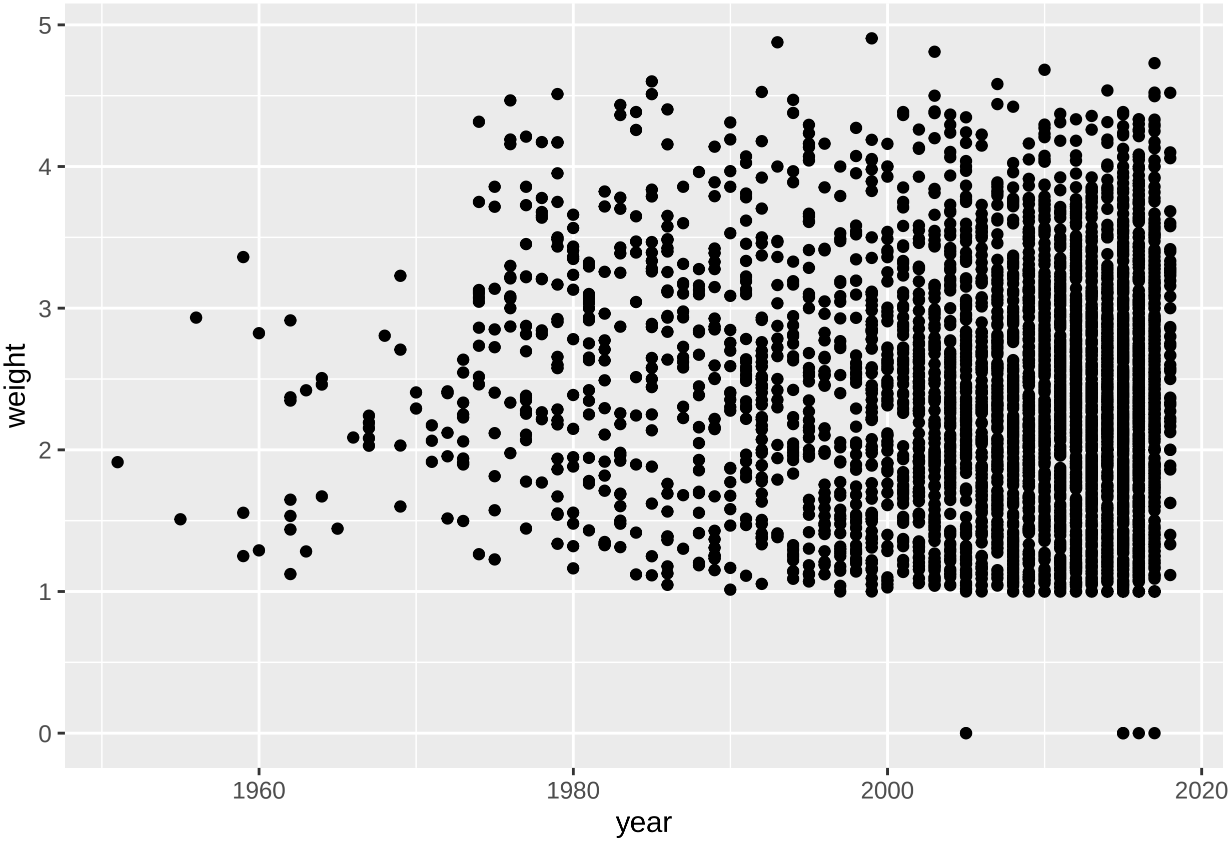
This capping effect can also be visualized by comparing the next three histograms where we see that the average ratings are similar to a normal distribution whereas the “geek” ratings are skewed toward the bottom. This is because games with few ratings are normalized toward a lower rating so that the website will not rank a game very highly if it has not been reviewed by enough people.


Histogram of train$avg_rating
Frequency
0
100
300
500
5.5
6.0
6.5
7.0
7.5
8.0
8.5
9.0
train$avg_rating

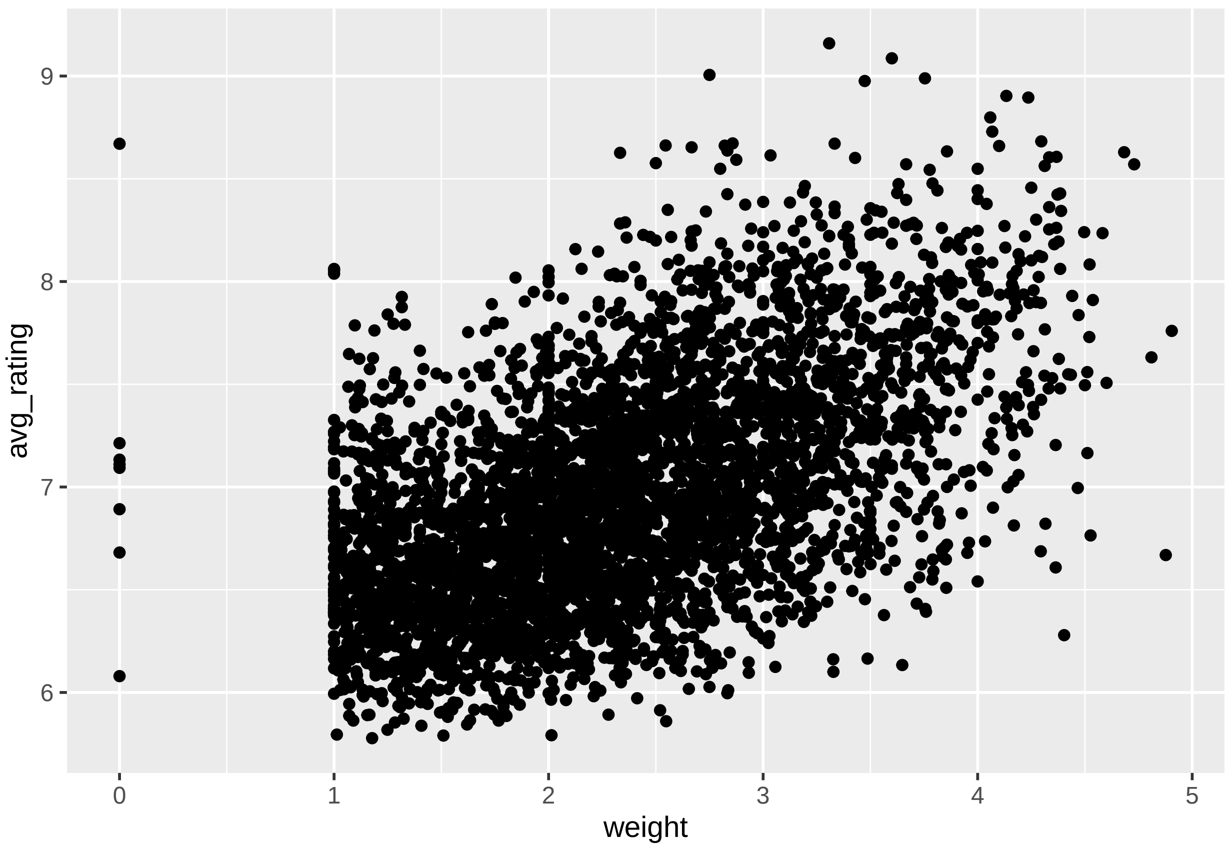

Histogram of train$geek_rating
Frequency
0
500
1000
1500
5.5
6.0
6.5
7.0
7.5
8.0
8.5
train$geek_rating



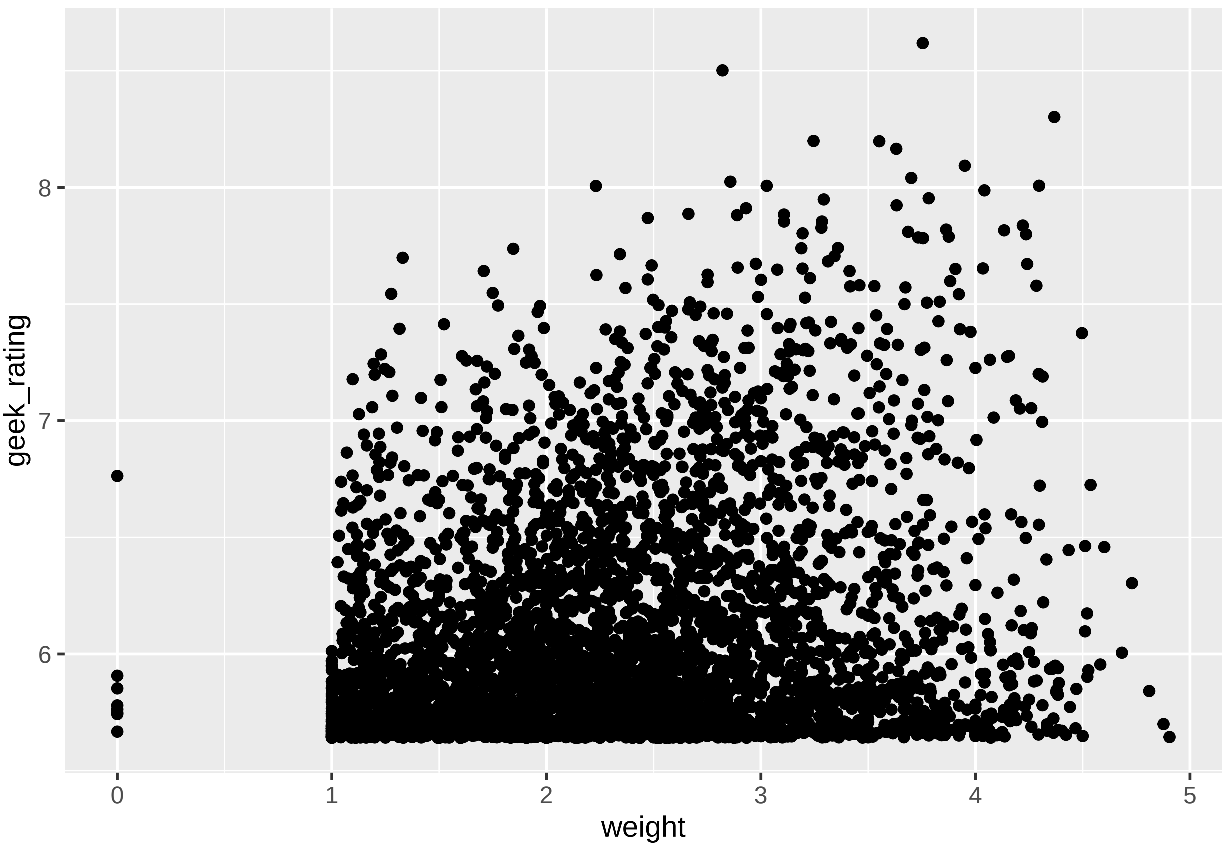
Next we look at the complexity of the game by the year of release. There might be a small effect here where newer games are more complex, but this relationship cannot be firmly established because there are not enough games released before the year 2000 to make a strong correlatioon possible.



The next plot shows a promising and seemingly linear relationship between the weight (or complexity) of the game is positively correlated to the community's favorable ratings.



The next plot examines the “geek” rating versus the weight of the games. Here the relationship is less strong, again most likely due to the capping system that BoardGameGeek uses.



Using this apparent relationship bewteen weight and the community's ratings we will build the following linear model and compare its predictive power to that of simply assigning the mean rating to all games.

```
## (Intercept)      weight
##   6.0716725   0.3826026
```

```
## [1] 0.3115047
```

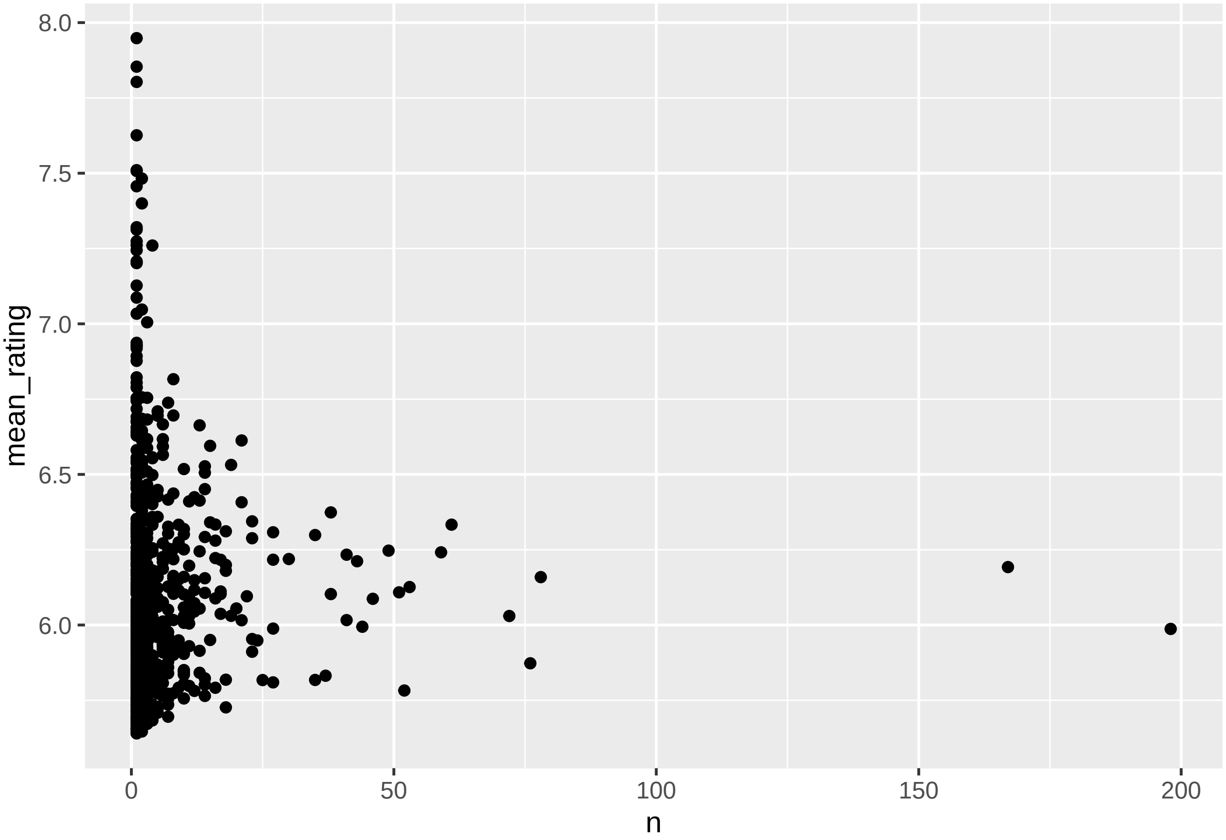
```
## [1] 0.2211273
```

As we see there is about a 29% improvement over the simple average by using the weight of the game to predict the ratings. This suggests that you are more likely to get a good game if you select a more complex game, but this result is not particularly robust. Next we will use a decision tree that will incorporate the differing game mechanics and "themes" (or categories) to improve these results.

Results

To prepare the decsion tree we will first need to clean the data a little bit. Both the mechanics field and the category field in the original data includes a lot of information. For example, the game "Gloomhaven" is described as an Adventure, Exploration, Fantasy, Fighting, Miniatures game that uses the Action / Movement Programming, Co-operative Play, Grid Movement, Hand Management, Modular Board, Role Playing, Simultaneous Action Selection, Storytelling, Variable Player Powers mechanics. This is so much information as to not be very useful. However, the first descriptors in both of these fields are primary and likely the most important when evaluating which game to buy. Therefore, we will extract just the information before the first comma in each of these fields and use it to build a decision tree.

Having cleaned the mechanic and categoryy fields we will now plot the mean rating of each unique combination of mechanic and category. The next plot shows that more common mechanic/category combinations tend to be poorly rated. This is not to say that all unique combinations are winners, just that it appears that sticking to an old formula tends to lead to a worse game.



With this knowledge in hand, we can expect that the mechanics and categories will help us identify good games. The following decision tree uses this information to try to predict whether or not a given game will be in the top 10% of all games. First we build a simple tree using the information gleaned for the correlation matrix and use only the number of votes and the number of owners to predict good games. Then we will see how much the prediction can be improved by incorporating the mechanics and categories.

```
## [1] 0.9069149
```

```
## [1] 0.9428191
```

Here we see that using only the number of votes and owners the model correctly classifies a game 90.6%, which is not very good as simply predicting that every game is not in the top 10% will, by definition, be correct 90% of the time. By using mechanics and categories this is improved to 94.3%.

Conclusions and Future Work

Overall it was difficult to discern any particularly useful patterns in this data other than trivial ones. For example, the fact that highly rated games are owned by more people is a strong pattern in the data, but also not very interesting as we would, of course, expect good games to be purchased by more people. BoardGameGeek's "geek" rating is also perhaps a misleading variable because it might have the unintended consequence of hiding very good games that suffer from low distribution.

We were able to create a decsion tree model which helps to predict top 10% games, but the accuracy was only 94.3%. This is significantly better than random guessing, but would need to be improved in order to be particularly useful. There is also a potential bias in this data as the ratings on BoardGameGeek are likely to skew toward serious board game enthusiasts and so might not be a good reflection of the opinions of the general public. It may be more useful to add additional data gathered from other sources to rectify this bias.