Original Data and Pre-emptive Dimensional Reduction

As stated in the abstract, the database used for this project was scraped in 2016 from boardgamegeek.com (BBG), which is the largest boardgame enthusiast site/ database in the world. This was done by Baldassare (2017) for the purposes of market segmentation, it was later uploaded to Kaggle, which is where it was downloaded for this project. After importing the data from it's initial SQLite format, the data was coerced into a data.frame composed of 90, 400 observations , and 81 features**.** For a complete list of the initial features, which were fairly evenly split between <chr> and <dbl>, see fig 1. Many of these features, including the majority of the polling features, and all stats located [, 45:55] were discarded immediately, as they were missing a substantial portion of their values (see fig 2), and not relevant to the business question; CK would not have access to the community's response to a game's design prior to publication. Additionally, all features beginning with stats.family were removed, as was anything that made the database semi-structured, like the attributes.t.links.., details.thumbnail, and details.image features. The game.description feature was also removed for this reason, since it both required natural language processing to become workable, and didn't directly relate to design features. The game.type feature and attributes.boardgameexpansion were also removed, but not before they were used to help refine the dataset, as they allowed arcade/computer games and boardgame expansions to be removed, which prevented over-representation of mechanics and categories shared by an original game, and its expansions.

```
 [1] "row_names"                                "game.id"
 [3] "game.type"                                "details.description"
 [5] "details.image"                            "details.maxplayers"
 [7] "details.maxplaytime"                      "details.minage"
 [9] "details.minplayers"                       "details.minplaytime"
[11] "details.name"                             "details.playingtime"
[13] "details.thumbnail"                        "details.yearpublished"
[15] "attributes.boardgameartist"               "attributes.boardgamecategory"
[17] "attributes.boardgamecompilation"          "attributes.boardgamedesigner"
[19] "attributes.boardgameexpansion"            "attributes.boardgamefamily"
[21] "attributes.boardgameimplementation"       "attributes.boardgameintegration"
[23] "attributes.boardgamemechanic"             "attributes.boardgamepublisher"
[25] "attributes.total"                         "stats.average"
[27] "stats.averageweight"                      "stats.bayesaverage"
[29] "stats.family.abstracts.bayesaverage"      "stats.family.abstracts.pos"
[31] "stats.family.cgs.bayesaverage"            "stats.family.cgs.pos"
[33] "stats.family.childrensgames.bayesaverage" "stats.family.childrensgames.pos"
[35] "stats.family.familygames.bayesaverage"    "stats.family.familygames.pos"
[37] "stats.family.partygames.bayesaverage"     "stats.family.partygames.pos"
[39] "stats.family.strategygames.bayesaverage"  "stats.family.strategygames.pos"
[41] "stats.family.thematic.bayesaverage"       "stats.family.thematic.pos"
[43] "stats.family.wargames.bayesaverage"       "stats.family.wargames.pos"
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[53] "stats.usersrated"                         "stats.wanting"
[55] "stats.wishing"                            "polls.language_dependence"
[57] "polls.suggested_numplayers.1"             "polls.suggested_numplayers.10"
[59] "polls.suggested_numplayers.2"             "polls.suggested_numplayers.3"
[61] "polls.suggested_numplayers.4"             "polls.suggested_numplayers.5"
[63] "polls.suggested_numplayers.6"             "polls.suggested_numplayers.7"
[65] "polls.suggested_numplayers.8"             "polls.suggested_numplayers.9"
[67] "polls.suggested_numplayers.Over"          "polls.suggested_playerage"
[69] "attributes.t.links.concat.2...."          "stats.family.amiga.bayesaverage"
[71] "stats.family.amiga.pos"                   "stats.family.arcade.bayesaverage"
[73] "stats.family.arcade.pos"                  "stats.family.atarist.bayesaverage"
[75] "stats.family.atarist.pos"                 "stats.family.commodore64.bayesaverage"
[77] "stats.family.commodore64.pos"             "stats.subtype.rpgitem.bayesaverage"
[79] "stats.subtype.rpgitem.pos"                "stats.subtype.videogame.bayesaverage"
[81] "stats.subtype.videogame.pos"
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Figure 1: Initial Features

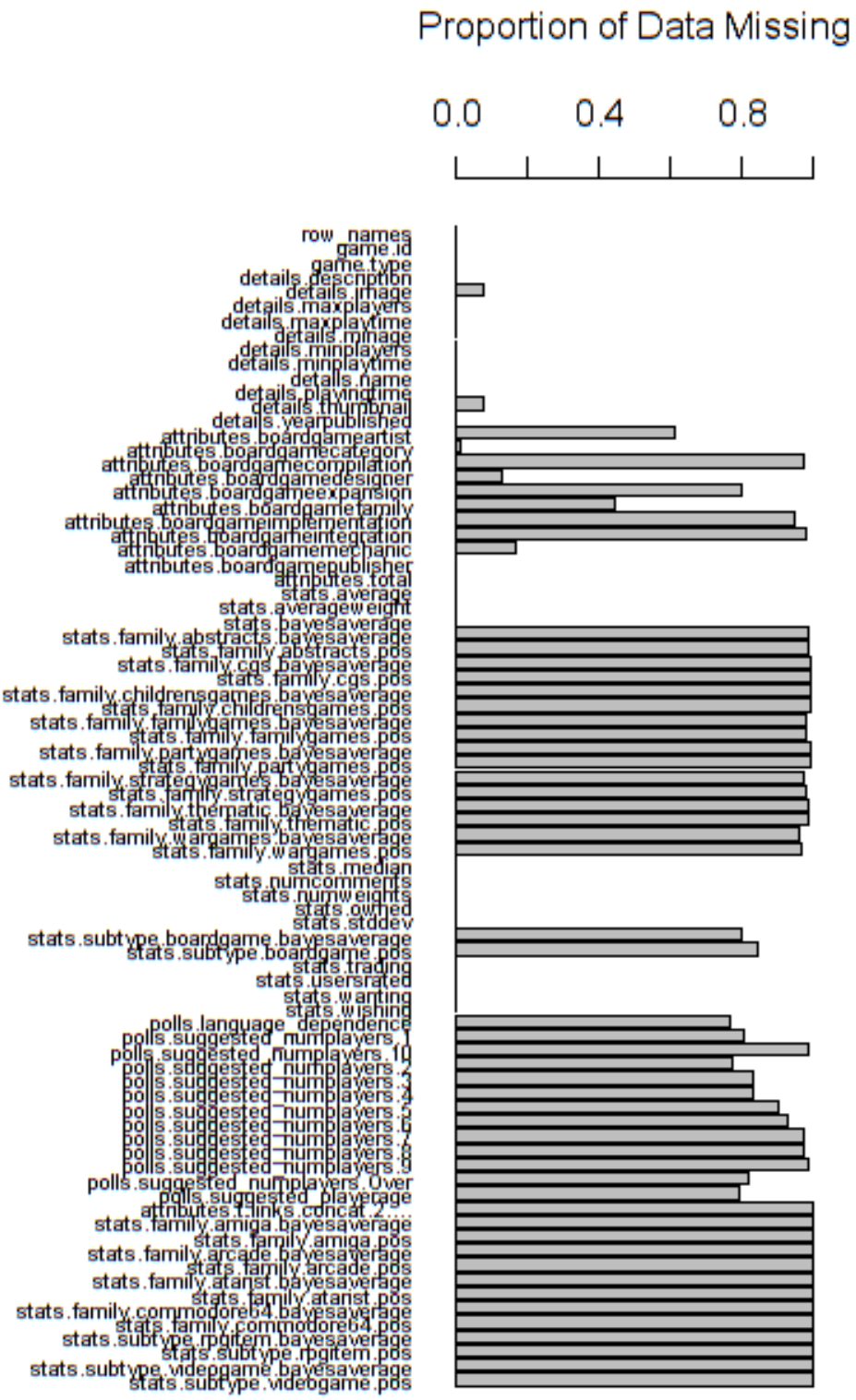


Figure 2: Missing Data by Feature

Intermediate Data and Pre-Processing

After the initial dimensional reduction, and some of the data verification discussed in the *Modelling and Evaluation* section, the data file was 4083 observations by 19 features, see Table 1. A few of these features were kept in with the intension of discarding them immediately after using them to help detect outliers (such as users.rated), while others (particularly polls.language dependence) were intended to be used as features to assess design decisions. Though not shown in Table 1, for clarity reasons, the dummy variables for mechanics and category were also created during this stage using cSplit_e () from the splitstackshape library (ee figs 8 and 9) and for detailed descriptions of their meanings, consult BBG (BoardGameGeek, n.d.)

Index	*Feature Name*	*Feature Description*
1	game.id	Primary index, as assigned by BBG
2	details.name	The name of the boardgame
3	details.maxplayers	The maximum amount of people able to play a board game simultaneously
4	details.minage	The minimum recommended age for a boardgame
5	details.yearpublished	The original year in which a game was released / published
6	stats.average	The average rating assigned to a game by BBG users, later combined with a threshold value to produce our target classification
7	details.minplayers	The minimum number of players required to play a boardgame
8	details.minplaytime	The minimum amount of time (in minutes) required to complete a single uninterrupted playthrough
9	details.maxplaytime	The maximum amount of time (in minutes) required to complete a single uninterrupted playthrough
10	polls.language_dependance	The level of language dependence required to play a game at an acceptable level, as determined by majority vote by BBG users.
11	stats.subtype.boardgame.bayesaverage	The Bayesian average of the rating for each boardgame
12	stats.subtype.boardgame.pos	The ordinal ranking of each boardgame from best to worst, with 1 as the optimal value, as determined by BBG's algorithm
13	attributes.boardgameartist	The artist or artists responsible for producing the game's visual assets.
14	attributes.boardgamecategory	The BGG categories are a means with which to group games based on like subjects or similar characteristics.
15	attributes.boardgamedesigner	The designer or designers of the board game's rules.
16	attributes.boardgamemechanic	The ules and/or methods designed to allow the players to interact with the game state. Gameplay can be thought of as the function of its mechanics
17	stats.average	Accidental duplication, removed before model training
18	stats.averageweight	Quantified score representing the complexity of a game
19	stats.usersrated	The count of how many BBG users have rated a game

Final Data and Feature Engineering

After adding the dummy variables (see fig 8 and 9), the number of features climbed to 150. This would continue to increase, as, during EDA, five additional features were engineered. These were: 1) the total number of mechanics used in a given game [Mechanic Sum, AKA mech_sum], 2) mech_sum's categorical counterpart: the total number of categories a given game fell into [Category Sum, AKA cat_sum], 3) The amount of variation in player-count which a board game could accommodate [maxplayer -minplayer AKA Player-Spread AKA player_spread] , 4) the amount of variation in the time required to play a game [(maxplaytime - minplaytime) AKA Time-Spread AKA time_spread], and 5) a categorical variable which stores information of whether a game was rated above or below average [successful] . The former two were produced to try and capture how innovative the game design was,, while the latter two attempted to assess a game's versatility.

In order to combat the results of including a high number of features -- high computational time, and features which added noise without adding accuracy or precision, -- the number of categorical features was significantly reduced by an iterative importance-check / feature-removal carried out during implementation of the Random Forest model. Altogether, the finished dataframe was 2869 observations by 54 features, with the final features summarized in fig 3, and all features classified as either <int> or <dbl>., which are largely interchangeable.

```
 [1] "details.maxplayers"                  "details.minage"
 [3] "details.yearpublished"               "stats.average"
 [5] "details.minplayers"                  "details.minplaytime"
 [7] "details.maxplaytime"                 "stats.averageweight"
 [9] "time_spread"                         "mechanic_Action...Movement.Programming"
[11] "mechanic_Area.Enclosure"             "mechanic_Area.Movement"
[13] "mechanic_Auction.Bidding"            "mechanic_Crayon.Rail.System"
[15] "mechanic_Deck...Pool.Building"       "mechanic_Paper.and.Pencil"
[17] "mechanic_Pick.up.and.Deliver"        "mechanic_Rock.Paper.Scissors"
[19] "mechanic_Role.Playing"               "mechanic_Roll...Spin.and.Move"
[21] "mechanic_Route.Network.Building"     "mechanic_Secret.Unit.Deployment"
[23] "mechanic_Time.Track"                 "mechanic_Trick.taking"
[25] "mechanic_Variable.Phase.Order"       "category_Abstract.Strategy"
[27] "category_Arabian"                    "category_Aviation...Flight"
[29] "category_Bluffing"                   "category_Civil.War"
[31] "category_Collectible.Components"     "category_Comic.Book...Strip"
[33] "category_Deduction"                  "category_Educational"
[35] "category_Exploration"                "category_Farming"
[37] "category_Game.System"                "category_Horror"
[39] "category_Medical"                    "category_Music"
[41] "category_Mythology"                  "category_Napoleonic"
[43] "category_Puzzle"                     "category_Space.Exploration"
[45] "category_Trains"                     "category_Transportation"
[47] "category_Travel"                     "category_Trivia"
[49] "category_Vietnam.War"                "category_World.War.I"
[51] "category_World.War.II"               "category_Zombies"
[53] "cat_sum"                             "mech_sum"
```

Figure 3: Final Features

Modeling and Evaluation

Verifying Data Quality

After deciding on which features would initially be included in the data file, the data quality of the dataframe was assessed using several methods. Firstly, distinct_n() was checked against n() using the summary function of dplyr for both game.id and game.name to check for duplicates, since they can both theoretically function as a primary index.. As the values matched, duplication was determined to be absent.

Next, non-NA-missing-values and outliers were scanned for by passing the dataframe through the summary function, and manually looking for unusual qualities. This was complimented by passing questionable features into the plot function. Zero weight games were obviously outliers (see Fig 4), likely from missing values, so observations with [average.weight = 0] were filtered out of the dataset. Games published before 1900 were also removed, as they contained a few classics like Chess and Backgammon, but with values as low as -3000, their inclusion was heavily throwing off visual EDA, and they weren't useful for answering the business question. Games with minimum and/or maximum payer counts of 0 were also removed, as there can't be zero people playing the boardgame, making 0 an invalid input. Board games that required less than 11 or more than 600 minutes to play were deemed outliers, and discarded. Finally, any

game with fewer than 20 user ratings (see fig 5) were removed, as low user ratings on BBG are indicative of unpublished games or rule variations on existing games, in the author's experience.

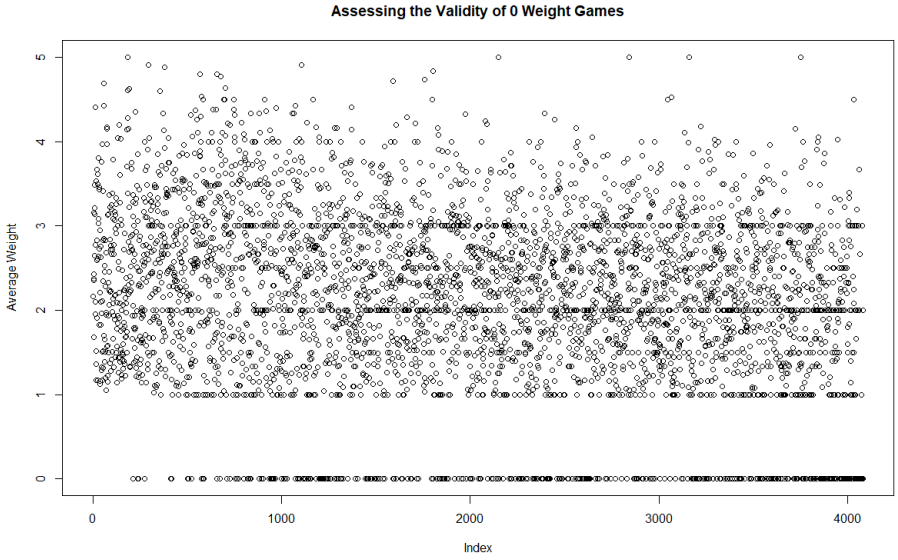


Figure 4: Assessing the Validity of Zero-Weight Games

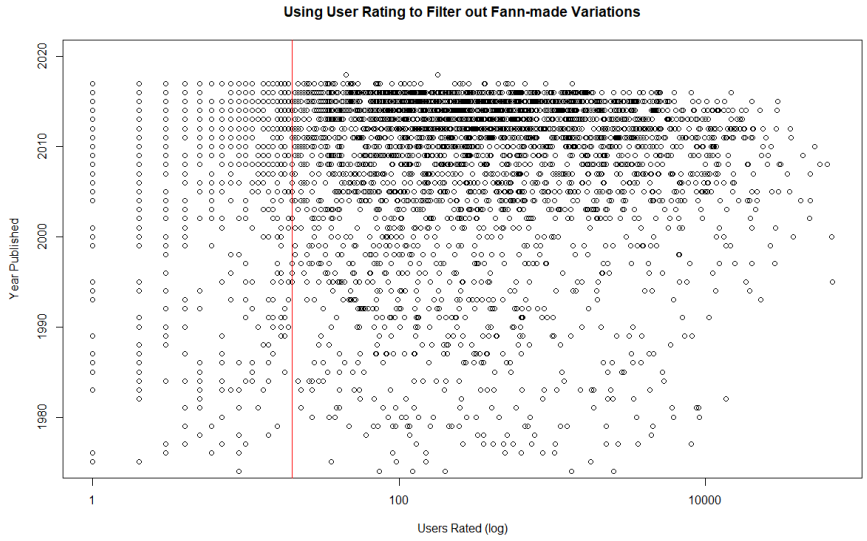


Figure 5: Using Number of User Ratings to Filter out Fan-Made Rule Variations

Once the quality of the remaining data had been verified, analysis continued on to the EDA phase, where the author familiarized themselves with the dataset using basic descriptive statistics, visualization, and assessed variable relationships. The data was augmented according to these observations, before finally proceeding to modelling.

Exploratory Data Analysis

In order to save the reader some time, the general rationale behind every visualization will be provided once, immediately below, instead of with each graph.

univariate: histograms were chosen, as they are more accurate representations of distribution than density plots.
bivariate plots, 1) if both variables were continuous, a scatterplot with an abline set on the linear regression was used in order to illustrate trend, 2) if one variable was continuous, and the other was discrete: a box plot with an added horizontal reference line set to the most important value for the continuous variable (usually the threshold value previously decided for average rating (6.9)) was used in order to see a feature's distribution relative to that threshold.
Correlation: If multidimensional, then corrplot, otherwise, simple correlation stats.
Model effectiveness: Confusion matrix visualized via tile plot, with colouration dependant on what percentage of the test sample fell into each category classification. Percentile values were included and coloured red to increase readability. Statistic based performance indicators were included adjacent to the confusion matrix illustration and were scaled from baseline (0.5) to perfect (1.0) with the goal (0.8) highlighted via vertical line.

Basic Descriptive Statistics for Important Features

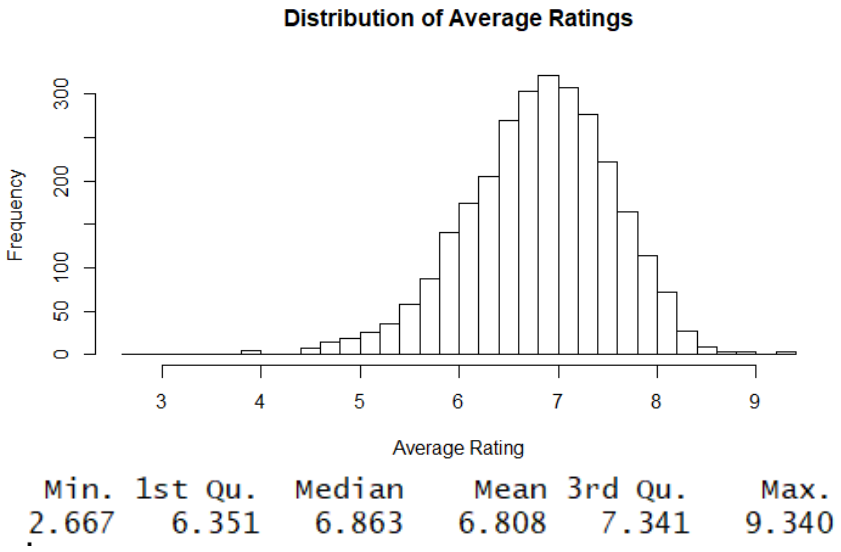
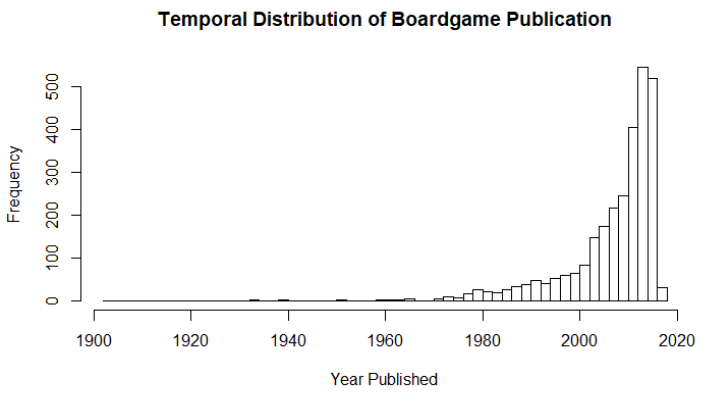


Figure 6: Univariate Distribution of Average Rating

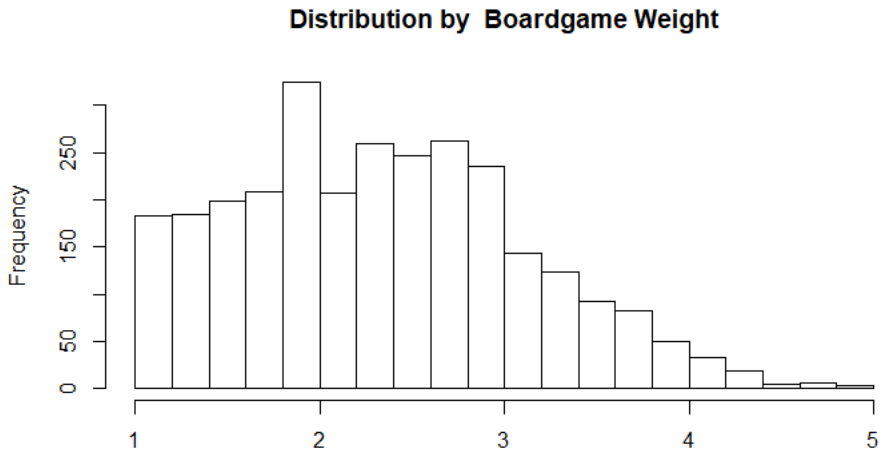
As average rating is the parent input for the primary classification variable, it was examined first, via histogram specifically, in order to assess its distribution univariately. Overall, average rating was unimodal, following an extremely gaussian curve. it's left tail is slightly denser than its right tail, and it is centred, not surprisingly, around 6.8, which is its median and mean. Observations less than 6.9 will be considered below average, while those greater than 6.9 will be considered above average.




```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   1903    2004    2011    2007    2014    2018
```

Figure 7: Increase of Boardgame Publication over Time

Observing the histogram of the publication year feature, it's quite clear that the majority of the games in this dataset are published in the late 2000's or later. This mirrors the expected explosion during the boardgame renaissance but may also reveal that board games from before the 2000's, especially those published before the 1980', are underrepresented. The severe drop-off in frequency post-2016 is owed to the fact that this dataset was scrapped in 2016, making anything more recent than that estimated data.




```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   1.750   2.300   2.347   2.889   5.000
```

Figure 8: Distribution by Complexity

The majority of boardgames have a weight of between 1.75 and 2.9. There seems to be an unusually large uptick in frequency for games between 1.8 and 2.0. Frequency decreases quite steadily after a weight of 3.

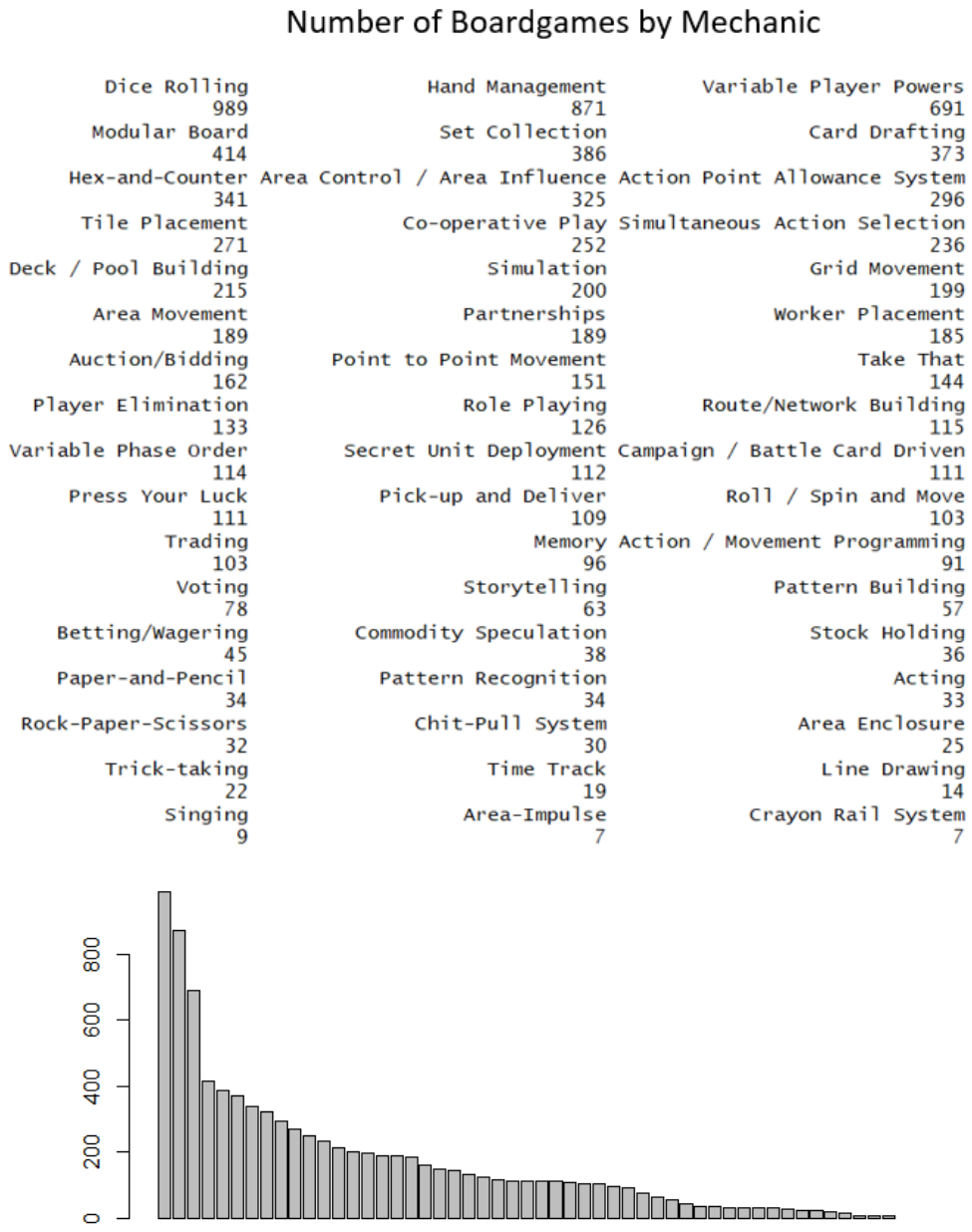


Figure 9: Count of Boardgames by Mechanics

There were 52 mechanics in the dataset. "Dice Rolling", "Hand Management" "Variable Player Powers", "Modular Board" , "Set Collection", "Card Drafting" "Hex-and-Counter" ,"Area Control / Area Influence", "Action Point Allowance System" ,"Tile Placement" were the most popular. The decrease in frequency is much more gradual than seen in categories (see fig 8)

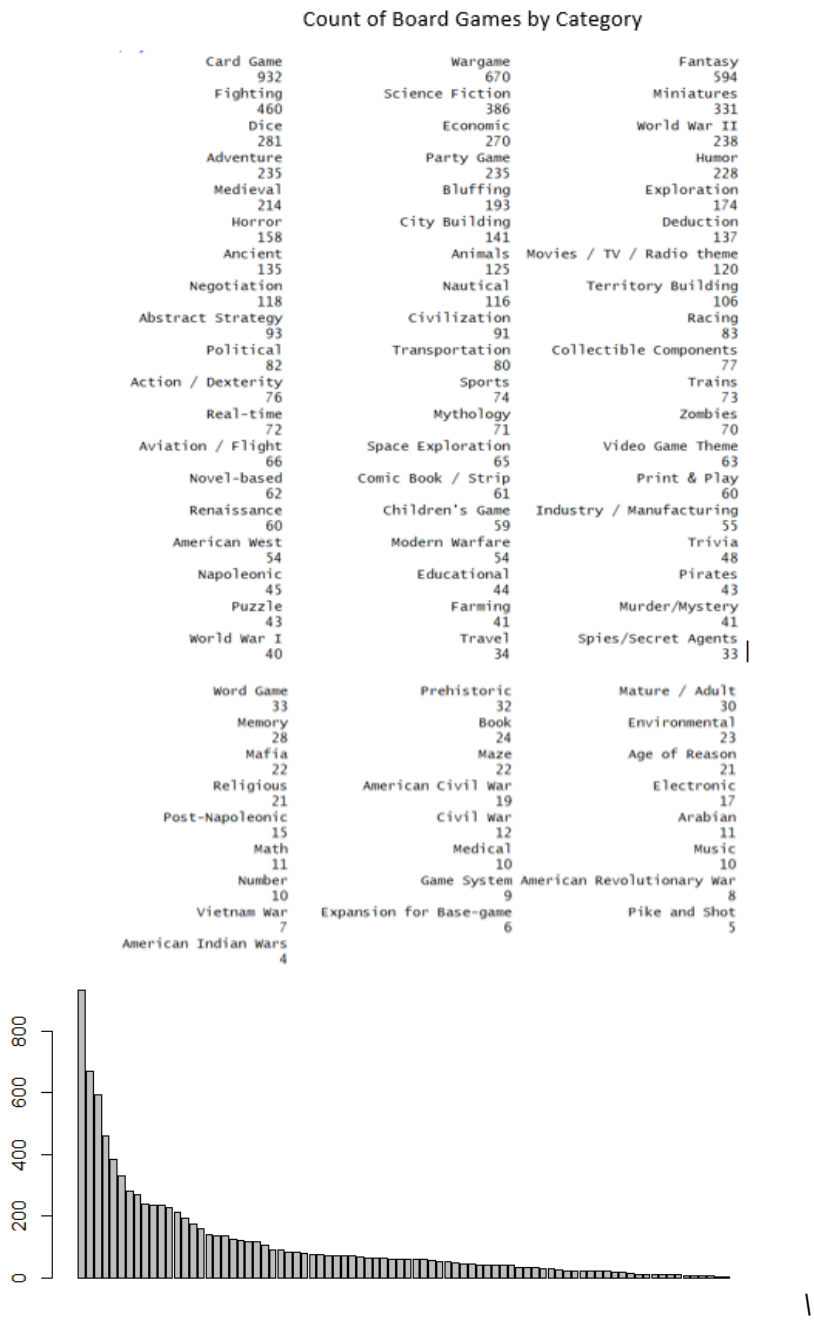
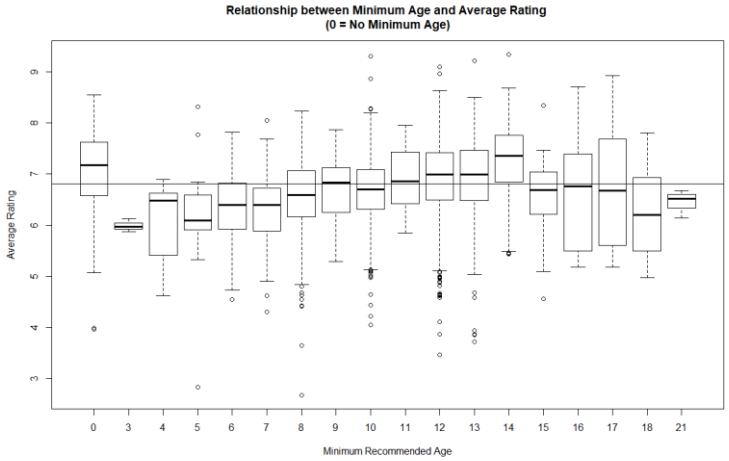


Figure 10: Count of Boardgames by Category

There were 94 categories of boardgame. The ten most popular categories were Card Game, Wargame, Fantasy, Fighting, Science Fiction, Miniatures, Dice, Economic, World War II, and Adventure (see fig 9) . Holding multiple categories was less common than holding multiple mechanics.

Relationships Between Other Features and Average Rating

As average rating forms the backbone of the classification models used in this paper, it was certainly worthwhile to explore its relationship with some of the dataset's other important features. Importance was determined by both correlations discussed later, and functions directed at the Random Forest model. The important features are: minimum age, average weight, number of mechanics, time spread, maximum players, and year of publication .



Boardgames without recommended ages seem to be preferred (see Fig 11), and board games with minimum ages under ten or over 15 seems to receive lower average ratings.

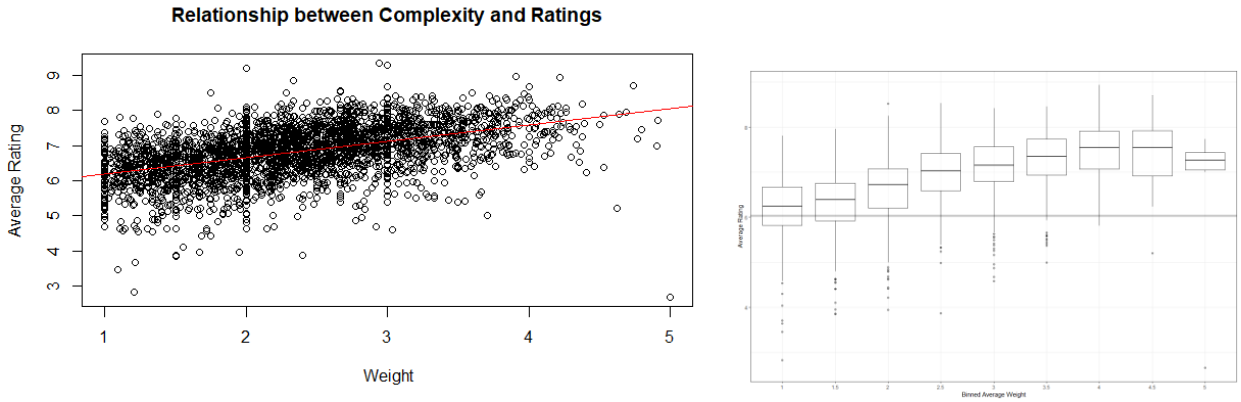


Figure 11: Relationship Between Complexity and Ratings

Generally, as the complexity of a game increases, so does its rating, though this relationship becomes difficult to prove after a weight of 4, as the number of data points becomes quite sparse.

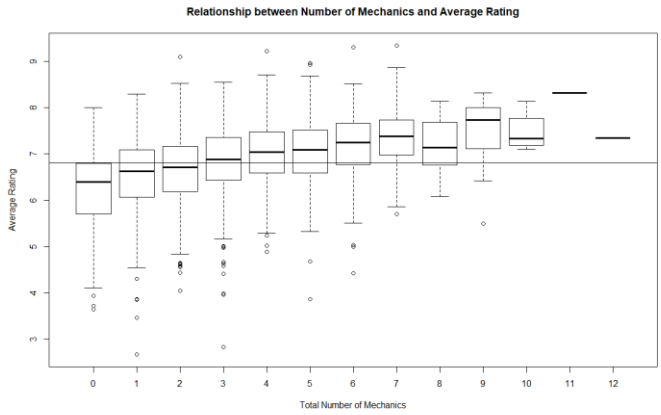


Figure 12:Relationship Between the Number of Mechanics and Average Rating

Backing up the previous figure, as the number of mechanics present in a game increases, so does its probability of being an above average game.

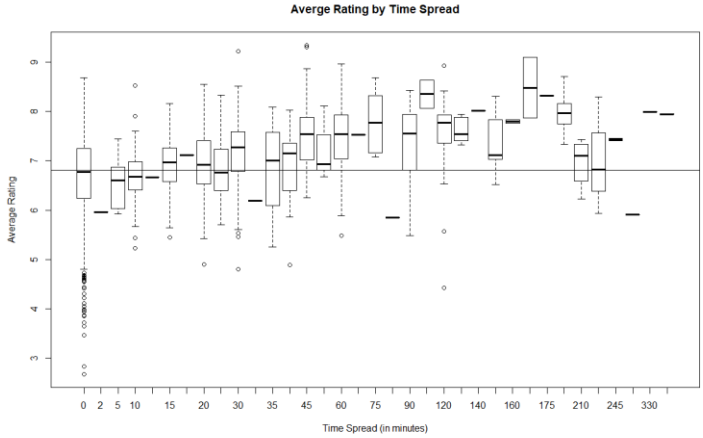


Figure 13 : Relationship between the Variability of Playtime and Average Rating

Generally, the more variable the time required to play a game the more popular.

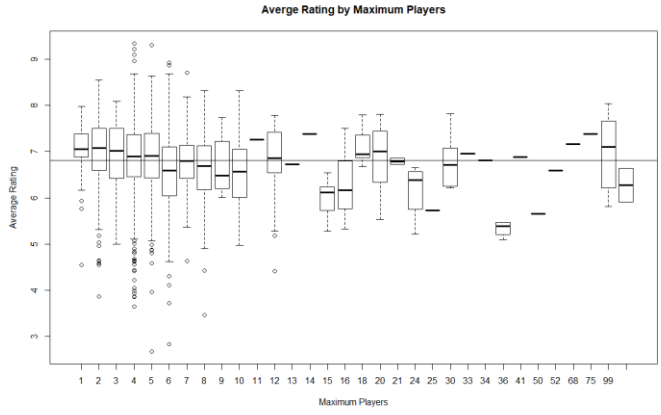


Figure 14: Relationship Between Maximum Player count and Average Ratings

Games with up to (but no more than) five players are more likely to be above-average.

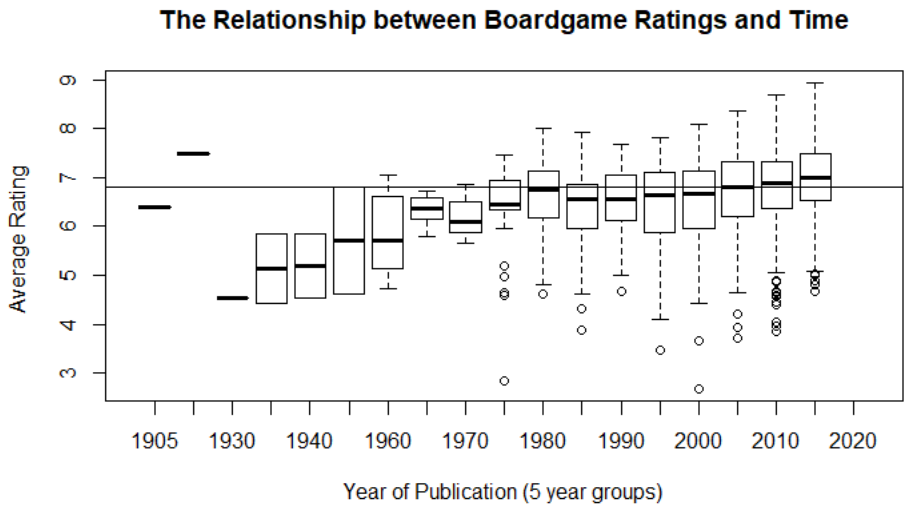


Figure 15: The Relationship Between Boardgame Ratings and Time

The mean scores for games increase over time. Games from before 1970 were (except for one) ill-regarded by BBG users, while games after 2010 were more likely than not to be above average.

Relationships Between Features

In order to assess the correlation of the non-categorical variables, they were placed in a separate data frame, and then plotted using corrplot. The only pairs which had worrying amounts of correlation were player spread to maximum number of players, and between maximum and minimum playtime. Both were expected relationships, since maximum playtime is inherently equal to or higher than minimum playtime, and the potential value for player spread scales linearly with the maximum number of players. The relationship between weight, average rating, and play time was also quite interesting, see fig 18,

As initially shown in fig 17, and then further explored in fig 18, complex games tend to have higher minimum and maximum times. Furthermore, as the play time increases Games with more complexity tend to have higher average scores than their similarly time contemporaries.

Model Creation

The data was subdivided randomly (seed (123)) into a 70/30 training/testing split using the caTools library. The proportion of the successful variable was quickly assessed and found to be representative of the expected value (50/50) for both the training and testing data. This data set was run through the first of three models (Random Forest) five times, with any features deemed less useful than a random number (via the importance function) removed.

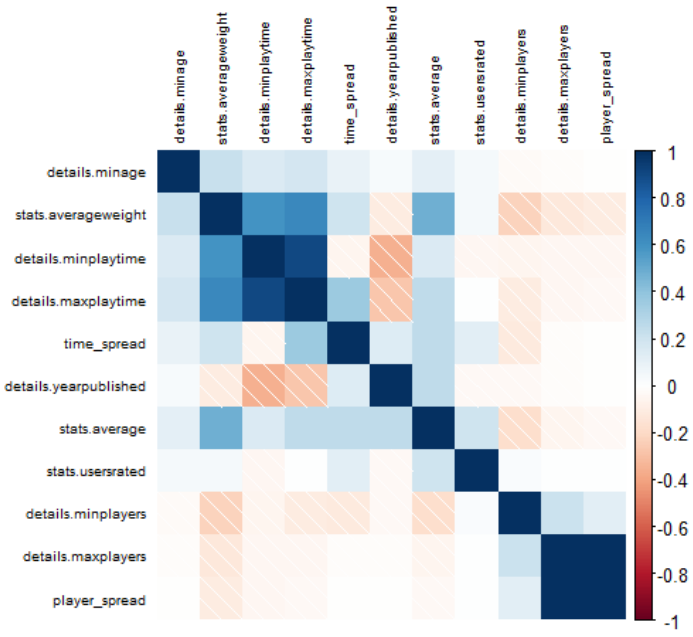


Figure 16: Correlation of Non-Categorical Features

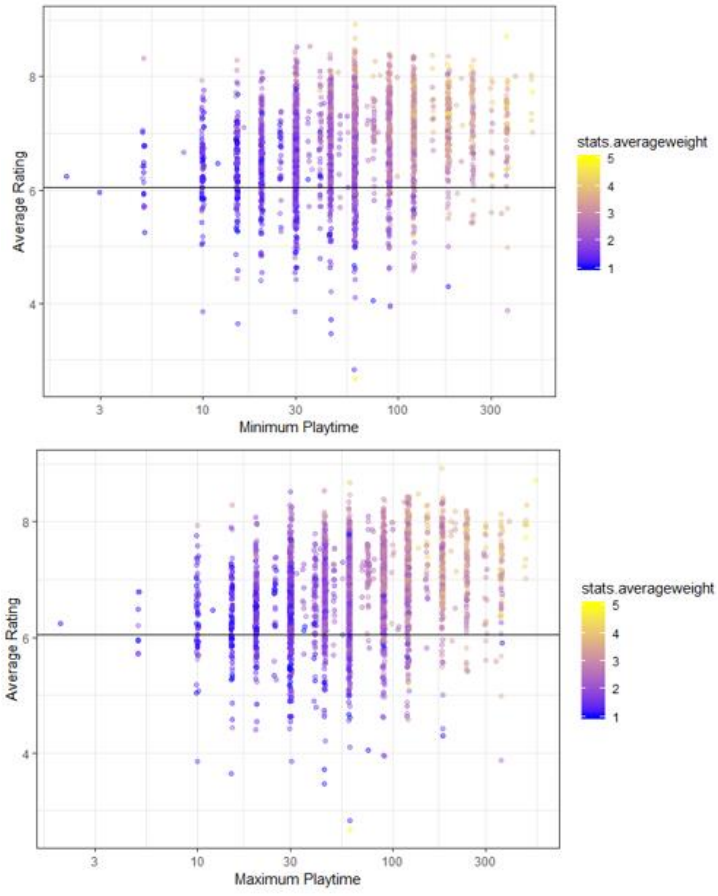


Figure 17: Relationship Between Weight, Playtime, and Average Ratings