Exploring and Recommending Highly Rated Board Games

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Abstract

For decades, board games have been a popular mode of entertainment. This project aims to answer the following questions: Which features are most strongly associated with high board game ratings? Can a recommendation system be created based on game themes and mechanics? Ordinary Least Squares (OLS) analysis revealed a statistically significant relationship between game complexity and average rating, and was adjusted for complexity bias for regression analysis of other attributes. OLS Regression was used to determine which themes and mechanics were most strongly associated with board game ratings. Ridge regression was used to determine which publishers and artists were most strongly associated with board game rating. Additionally, a recommendation system was developed based on theme and mechanics using k-means clustering. Results indicate that the theme feature had the highest R-Squared value, thus explaining more variability in board game ratings compared to the other attributes. The theme with the highest coefficient was Bacteria. Year published and player count only explain a small amount of variability in the game ratings. The recommendation system was developed using k-means clustering. A Python function was developed such that a user could input the game name as an argument into the function, and the output was a list of the five most similar games that shared a cluster. This was successful upon testing with games such as Wingspan and Ticket to Ride. Applications for this study could include improved board game creations based on knowledge of popular themes, publishers, and artists, as well as enhanced game searching abilities for board game enthusiasts.

Introduction

In this study, I aimed to acquire knowledge regarding the major factors currently associated with high board game ratings. The first of my two major questions was as follows:

1. Which features are most strongly associated with high board game ratings?

While certain aspects of board games have been studied in relation to ratings (such as complexity and game mechanics), there are other elements that appear to be less studied. I used previous literature to first determine that a more recent dataset still carries the complexity bias (with more complex games receiving higher ratings), allowing me to adjust my dataset accordingly.

While the relationship between game mechanics and board game ratings has been studied, I also studied the association between board game ratings and other factors such as theme, player count, year published, and publishers/artists who developed the game.

Identifying these factors can be important for board game developers who would like more information regarding what makes a game popular. Additionally, board game enthusiasts can be more informed as to the attributes associated with well-rated games.

Next, I developed a recommendation system based on game features such as theme, game mechanics, play time, and number of players. This could allow users to find games above a certain ratings threshold which align with their interests. Other features may include board game art and publishing companies. This goal allows board game enthusiasts to find games that align with their interests.

Therefore, the second of my two goals was as follows:

2. Can an effective board game recommendation system incorporate game themes and mechanics to recommend similar games above a certain ratings threshold?

To answer this question, I used clustering techniques which have been successful in previous work related to recommendation systems. More information about these methods can be found in the techniques section of this report.

Related Work

Board games have been studied by various enthusiasts over the years. Informal insights include analysis indicating that as game complexity increases, it is associated with overall higher ratings (Vatvani 2018). This information is useful in that I can account for possible complexity biases previously identified when analyzing more recent data.

The website BoardGameGeek, from which much of the data is sourced, currently has 191 board game mechanics that can be considered, from which previous work has derived a decision tree to predict expected rating based on game mechanics (Nguyen et al. 2024). Interestingly, this study demonstrated that up to 32% of variance in user ratings was associated with game mechanics; however, it does not identify which other factors account for the remaining 68% in variability. This is an area where I can look at other factors such as theme, play time, and game art to find other valuable associations.

Lastly, there has been recent work regarding board game recommendations that I would like to expand with my own project. An attribute-based clustering method has been implemented in an experimental board game recommendation system; however, this system does not account for attributes such as theme, art, and game mechanics (Zalewski et al. 2019). I could use successful techniques implemented in this previous work and enhance it with attributes not previously analyzed. Additionally, the authors filtered out games below a certain number of ratings, which makes newer or independently published games less accessible. I incorporated lesser-known games in my analysis when possible.

Dataset

My dataset was sourced from Kaggle and is based on information from BoardGame Geeks. Here is the URL to the datasets:

https://www.kaggle.com/datasets/threnjen/board-games-database-from-boardgamegeek

The following is the list of datasets included:

- Games (names of board games with various attributes)
- Mechanics (different ways games can be played, such as dice rolling, team games, etc.)
- Themes (theme of games such as environmental, medical, etc.)
- Subcategories (print and play, electronic, etc.)
- Ratings Distributions
- Designers
- Publishers
- Artists

Each of the datasets listed above include information of about 21,925 unique board games.

This data is appropriate for the research question because it includes all of the attributes needed in order to answer my questions, and since it is open-source data about publicly available games, there are no ethical concerns. The vast amount of board games will contribute to informative results and recommendations.

Techniques Applied

Data Cleaning

The first step in my work involved data cleaning. When analyzing publishers and game artists, I filtered the data such that only publishers and artists associated with 10 or more games were considered, so that the focus is on major artists and publishers who were involved in several different games. Additionally, I dropped null values of board game ratings prior to analysis of each feature when conducting regression analysis.

Data Integration

Initially, I planned to integrate data by using the Board Game ID to unite all datasets about ratings, theme, mechanics, player range, game complexity, time to play, and game publishers/artists into one dataset. What I had ultimately found to be more effective was to first calculate unbiased ratings, and then append that to my themes dataframe for OLS regression analysis of themes, and conduct a similar merge to each of my categorical attributes (mechanics, publishers, and artists) separately. Since each categorical attribute contained many one-hot encoded columns, this adjusted method made analysis in Python more manageable.

Additionally, data reduction involved eliminating other categories outside of the ones mentioned above so that I could focus my analysis on a few key features.

Complexity Bias Analysis

The first step in my evaluation was to first confirm if there is a complexity bias in the more recent dataset. I accomplished this by first calculating the correlation coefficient in Python. I used MatPlotLib in order to visualize a scatter plot and trend line for these variables as well.

I then conducted ordinary least squares (OLS) regression analysis in order to determine associations between average ratings vs. game complexity as well as number of reviews. This analysis helped me find the best fit coefficients for my data.

Next, I calculated the residuals in order to check my adjusted data. I did this by calculating expected/predicted ratings based on an OLS regression model and then compared that to my actual data. I plotted the residuals to visualize the adjustment. The residuals helped show whether or not the model data was truly unbiased against game complexity. Ultimately, I used my OLS regression model in place of the raw board game ratings in order to adjust for the complexity bias for all remaining regression analyses. More information about this can be found in the Key Results section of the report.

Regression Analysis - OLS

I further investigated and identified which trends are most strongly associated with higher board game ratings. While I still looked at the previously studied game mechanics, I also studied the theme, number of players, year published, and publishers/designers. I accomplished this using regression analysis, with the complexity-adjusted ratings serving as the dependent variable and each game attribute as the independent variables.

For categorical independent variables, specifically theme and mechanics, I used OLS regression analysis in which each categorical attribute (for example, each theme) was given a value of 0 or 1. This was the one-hot encoding of my data. I ensured that all of these variables were present on one shared dataframe with the fitted averages from my previous OLS complexity analysis. I could then determine the coefficients with the largest and smallest association with game ratings. Additionally, I could determine the amount of variability in game ratings that could be explained by each attribute, as well as if the relationship was statistically significant.

Regression Analysis - Ridge Regression

Because the data was extremely sparse for publishers and artists, I first filtered the data such that only publishers and artists associated with 10 or more games were included, as mentioned in the data cleaning section. OLS would not run due to the size and sparseness of the data, so I instead used ridge regression for these two attributes. Ridge regression is a form of linear regression that uses L2 regularization in order to avoid overfitting of data and multicollinearity, which are issues that can arise when working with expansive one-hot encoded data. While I cannot generate a p-value in ridge regression, I was able to compare the in-sample R-Squared value to the cross-validated R-squared value for each attribute. If they are similar, then it tells me how much of the variability in game ratings could be explained by the attribute.

Regression Analysis - Multiple Linear Regression

I conducted multiple linear regression analysis on my variables of year published and number of players. I was able to accomplish this using OLS.

I checked for collinearity, which can help identify if certain independent variables are correlated with each other. If they were, then I could either drop or combine those variables and conduct a new analysis. This allows for a more accurate assessment as to which factors influence ratings. I conducted this analysis using the variance inflation factor from the statsmodels.api library.

After observing each factor individually, I found the variables with the greatest influence on ratings using OLS regression. Variables with larger coefficients indicate a greater influence on the board game ratings. This allowed me to more effectively rank the variables that most strongly influence a game's rating.

Recommendation System - Clustering

In order to develop a recommendation system, I first filtered games so that those being recommended had an average ratings threshold of 7/10 or higher. I clustered games by theme and mechanics using K Means clustering, and then allowed for recommendations with that clustering system. In order to visualize the clusters, I used Principal Component Analysis (PCA) in order to reduce dimensionality, since my one-hot encoded data for themes and mechanics had many columns. In this analysis, PCA finds new axes from which there is the most variation in the data. Points that are similar in the original high-dimensional data will typically be closer in their PCA coordinates as well. Therefore, points in a PCA scatter plot closer together can show that they are similar in terms of themes and mechanics.

In this interface, the user has the option to name a game they like. This is then used in a recommendation function in Python that has access to the clusters to output other games that the user may also enjoy. I used cosine similarity between feature vectors that share the same k-means cluster as a part of my recommendation function. Cosine similarity is better suited to one-hot encoded features such as theme and mechanics in this type of analysis. The similarity scores from this calculation are then used in a threshold, such that only those with high similarity and ratings at or above 7/10 are included in the recommendation. The output is the top 5 games with the highest similarity to that of the input.

Tools

I conducted all analyses using Python. Specifically, I used Pandas to create and analyze dataframes, and the sklearn library to assist with clustering. I used statsmodel.api for regression analysis and bias correction. Lastly, matplotlib and seaborn were useful for visualizing my data.

Key Results

Complexity Bias Results

When I conducted a correlation analysis between board game complexity and game ratings, I found a **correlation coefficient of 0.5125**, which suggests a positive linear relationship between the two variables.

The following plot I created highlights this relationship visually:

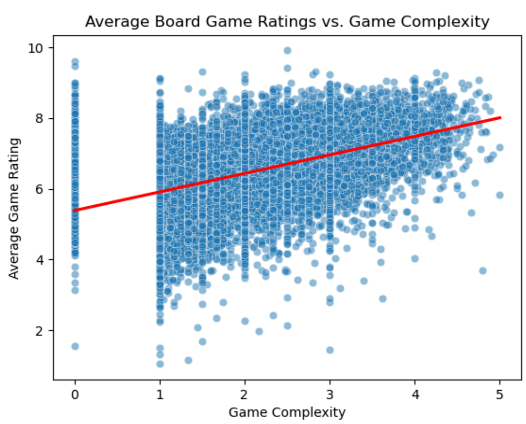

Figure 1: Game Complexity vs. Average Game Ratings

The next step was the OLS regression analysis, which revealed that while both game complexity (listed as GameWeight in the dataframe) as well as number of reviews (listed as NumUserRatings) were statistically significant in their relationship with average game ratings, game complexity had a much greater proportion of an effect. Here is a summary of this output from OLS regression analysis using stasmodels.api:

Table 1: OLS Regression Analysis of Game Complexity, Number of Ratings, and Average Game Ratings

	coef	std err	t	P>|t|
const	5.3809	0.014	386.940	0.000
GameWeight	0.5125	0.006	79.179	0.000
NumUserRatings	3.265e-05	1.51e-06	21.617	0.000

This table shows us that p <0.001 for both GameWeight and NumUserRatings, and that while there is only a very small increase in user ratings when NumUserRatings increases by 1, in contrast, for every time that GameWeight (the complexity) increases by 1, the average user rating increases by 0.5125, which is much more notable.

Next, I calculated the residuals using Pandas series and dataframes using my OLS regression model, adding residuals to a new dataframe.

I plotted the residuals against game complexity, confirming that there was no longer a linear relationship. The following was my result:

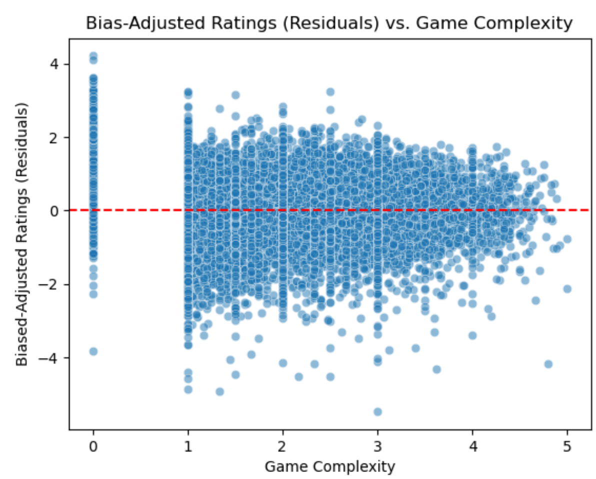

Figure 2: Game Complexity vs. Bias-Adjusted Residuals

Seeing residuals with no obvious pattern reaffirmed that my OLS model would be a good fit to move forward with for future analyses.

Regression Results - Theme

For regression analysis, I first determined which attributes were correlated with my complexity bias-adjusted board game ratings, which I refer to as "FittedValues".

Upon running an OLS regression on my themes dataframe (merged with the fitted values from my games dataframe), I observed the following results:

Table 2: OLS Regression Analysis of Themes vs. Adjusted Board Game Ratings

OLS Regression Results

Dep. Variable:	FittedValues	R-squared:	0.352
Model:	OLS	Adj. R-squared:	0.346
Method:	Least Squares	F-statistic:	54.35
Date:	Fri, 31 Oct 2025	Prob (F-statistic):	0.00
Time:	17:25:29	Log-Likelihood:	-9371.6
No. Observations:	21925	AIC:	1.918e+04
Df Residuals:	21707	BIC:	2.092e+04
Df Model:	217		

The R-Square value shows that approximately 35% of the variability in the fitted values for board game rating could be explained by theme. The results were statistically significant, with Prob(F-Statistic) <0.01.

I was then interested in observing the themes with the highest coefficients (associated with the highest ratings), and the themes associated with the lowest ratings (having the lowest coefficients). Here were my results:

Table 3: Top positive themes associated with adjusted board game ratings using OLS regression analysis

Top positive themes:

Theme_Bacteria	0.658079
World War II	0.594423
Theme_Biology	0.521179
Age of Reason	0.506137
Napoleonic	0.500312
Theme_Rivers	0.483548
Theme_Templ	0.480060
American Civil War	0.460325
World War I	0.439421
Pike and Shot	0.438330

Table 4: Top negative themes associated with adjusted board game ratings using OLS regression analysis

Top negative themes:

Theme_US National Parks	-0.212154
Theme_Fashion	-0.218336
Theme_Video Game Theme: Super Mario Bros.	-0.221254
Theme_Video Game Theme: Tetris	-0.247601
Theme_Dolls	-0.255508
Theme_Memes	-0.262268
Theme_Computer / Information Technology Industry	-0.291731
Theme_Painting / Paintings	-0.304122
Theme_Trash / Garbag	-0.323289
Theme_Ecology	-0.413741

It was interesting to observe that the theme of Bacteria had the highest overall coefficient relative to other themes. Both World War I, World War II, and the Civil War were all in the top positive themes list, which is an indication to me of the popularity of war games in general. It was also amusing to see that Trash/Garbage was one of the most negative themes on the list. Here is a visualization of the results:

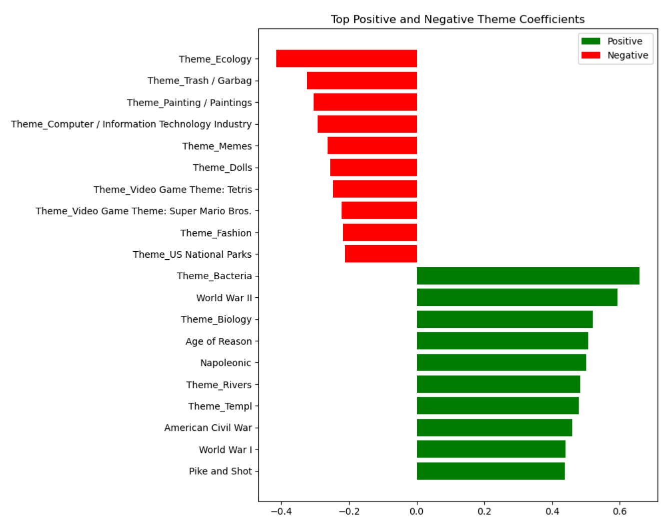

Figure 3: Themes most positively and negatively associated with adjusted game ratings (OLS regression)

Regression Results - Mechanics

The following is the OLS Summary for complexity bias-adjusted game ratings vs. mechanics:

Table 5: OLS Regression Analysis of Mechanics vs. Adjusted Board Game Ratings

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          FittedValues   R-squared:                       0.446
Model:                           OLS   Adj. R-squared:                  0.442
Method:                Least Squares   F-statistic:                     111.4
Date:               Fri, 21 Nov 2025   Prob (F-statistic):               0.00
Time:                       16:13:15   Log-Likelihood:                -7662.8
No. Observations:              21925   AIC:                         1.564e+04
Df Residuals:                  21767   BIC:                         1.690e+04
Df Model:                        157
```

This table shows that approximately 45% of the variability in the fitted values for board game rating could be explained by mechanics in this model. The results were statistically significant, with Prob(F-Statistic) <0.01.

Next, I determined 10 mechanics with the highest coefficients and 10 mechanics with the lowest coefficients relative to game ratings, with the following results:

Table 6: Top positive mechanics associated with adjusted board game ratings using OLS regression analysis

```
Top positive mechanics:
 Order Counters        0.574866
Delayed Purchase       0.494763
Hexagon Grid           0.478198
Loans                  0.398880
TableauBuilding        0.393078
Crayon Rail System     0.391100
Advantage Token        0.352182
Pattern Movement       0.340964
Action Drafting        0.332923
Stock Holding          0.330677
```

Table 7: Top negative mechanics associated with adjusted board game ratings using OLS regression analysis

```
Top negative mechanics:
 Ratio / Combat Results Table   -0.103921
Physical                       -0.116127
Line Drawing                   -0.119445
Command Cards                  -0.137260
Player Judge                   -0.153064
Chaining                       -0.158799
Roll / Spin and Move           -0.159266
Dexterity                      -0.224279
Matching                       -0.239134
Moving Multiple Units          -0.322755
```

Order counters had the largest coefficient from this analysis, indicating it is the most popular game mechanic. In contrast, moving multiple units was the least popular board game mechanic based on its negative coefficient.

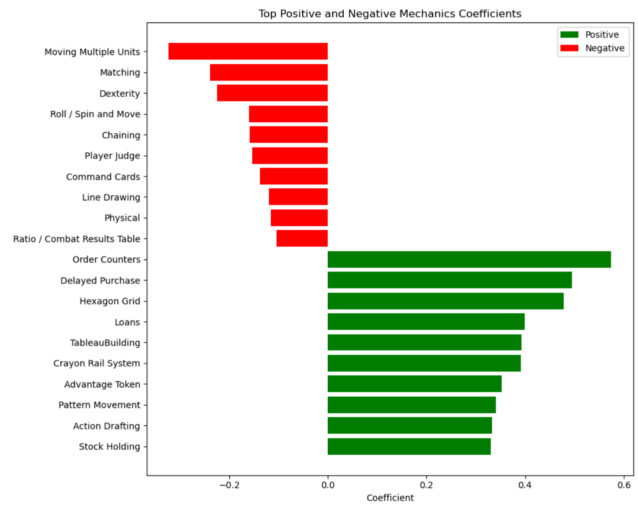

Figure 4: Mechanics most positively and negatively associated with adjusted game ratings (OLS regression)

Some limitations of OLS include its sensitivity to outliers and the potential for multicollinearity, but the overall output from these analyses still appear to be meaningful.

Regression Results - Publishers

Because I used ridge regression for the publishers attribute, I first compared the in-sample R Squared value to the cross-validated R-Squared value, with the following results:

Table 8: R-Squared results from ridge regression for publishers

In-Sample R-Squared (rounded)	0.3999
Cross-Validated R-Squared (rounded)	0.2938

While my cross-validated value is lower than my in-sample value, indicating some overfitting, the values are close enough to indicate that my in-sample value has acceptable generalization. The in-sample R-squared value indicates that approximately 40% of the variability in game ratings is attributable to the model when implemented on the training data.

The following results were generated for the top 10 publishers with the highest coefficients:

Table 9: Top positive publishers associated with adjusted board game ratings using ridge regression analysis

```
Top positive publishers:
 Games Research/Design (GR/D)    1.032366
Australian Design Group         0.946222
All-Aboard Games                0.929529
Deep Thought Games, LLC         0.875447
Clash of Arms Games             0.871980
Critical Hit, Inc.              0.814762
Against the Odds                0.714255
Dragon                          0.702306
Splotter Spellen                0.701454
Sierra Madre Games              0.696528
```

The following results were generated for the lowest 10 publishers based on their coefficients:

Table 10: Top negative publishers associated with adjusted board game ratings using ridge regression analysis

```
Top negative publishers:
 Drei Magier Spiele          -0.318114
Haywire Group               -0.338960
W. Nostheide Verlag GmbH    -0.350086
Philos                      -0.351007
Djeco                       -0.352629
HABA                        -0.358583
Exploding Kittens           -0.375151
TDC Games, Inc.             -0.384881
Jax, Ltd.                   -0.413914
The Creativity Hub          -0.571779
```

With this information, I produced a visualization of my results.

Games Research/Design was the publisher with the highest coefficient, and The Creativity Hub had the lowest coefficient. Interestingly, Games Research/Design produces many war-themed games, which aligns with the many war-related themes that had some of the highest coefficients. The following is a visualization of the top and bottom publishers based on their ridge regression coefficients:

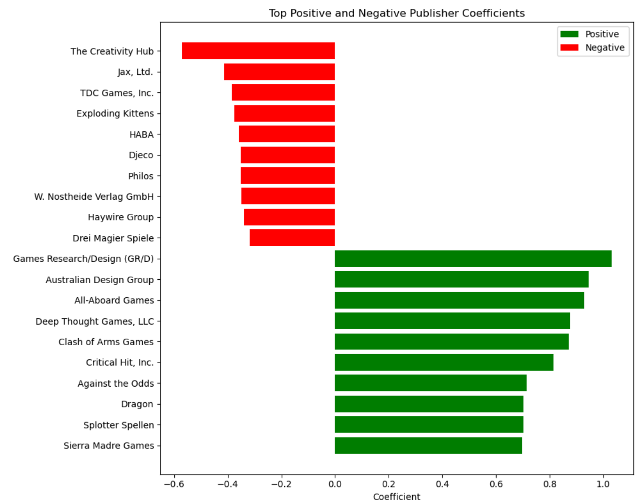

Figure 5: Publishers most positively and negatively associated with adjusted game ratings (ridge regression)

Regression Results - Artists

The following are the the in-sample R Squared value and the cross-validated R-Squared value, calculated using ridge regression:

Table 11: R-Squared results from ridge regression for artists

In-Sample R-Squared (rounded)	0.2255
Cross-Validated R-Squared (rounded)	0.1686

The cross-validated value is lower than that of the in-sample R-Squared value, indicating some level of overfitting. The difference is small enough, though, for the in-sample R Squared to be acceptable for generalization. Only about 22% of the variability, though, can be explained by this model. Therefore, artists explain less variability than publishers.

The following were the highest and lowest coefficients by artists calculated using ridge regression:

Table 12: Top positive artists associated with adjusted board game ratings using ridge regression analysis

Top positive artists:

Milan Vavroň	0.911852
Mariano Iannelli	0.736797
Phil Eklund	0.734531
Antonio Pinar	0.698928
Zbigniew Kasprzak	0.685964
Steve Venters	0.651892
Timothy Schleif	0.632306
Rick Barber	0.577091
David Pentland	0.564364
Mike Doyle (I)	0.562515

Table 13: Top negative artists associated with adjusted board game ratings using ridge regression analysis

Top negative artists:

Stéphane Escapa	-0.323755
Kaja Foglio	-0.325786
Aza Chen	-0.341630
Stivo	-0.362104
Thies Schwarz	-0.374645
Manu Palau	-0.383790
Ulrike Fischer	-0.390769
Bernhard Skopnik	-0.399955
Felicia Cano	-0.411002
Rory O'Connor	-0.564734

I visualized these results as follows:

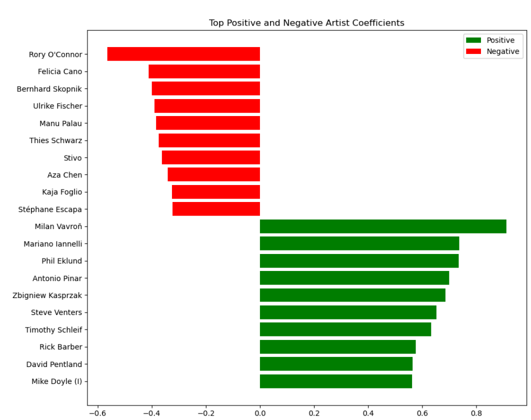

Figure 6: Artists most positively and negatively associated with adjusted game ratings (ridge regression)

Regression Results - Year and Player Count

Since year and player count were both continuous variables, and not one-hot encoded like the previous attributes, I was able to conduct multiple linear regression, estimated using OLS. The following is a summary of the results:

Table 14: OLS Multiple Linear Regression Analysis of Year Published and Number of players vs. Adjusted Board Game Ratings

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          FittedValues   R-squared:                       0.011
Model:                           OLS   Adj. R-squared:                  0.010
Method:                Least Squares   F-statistic:                     10.71
Date:               Mon, 24 Nov 2025   Prob (F-statistic):           2.38e-05
Time:                       16:23:36   Log-Likelihood:                -1472.6
No. Observations:               1945   AIC:                             2951.
Df Residuals:                   1942   BIC:                             2968.
Df Model:                          2
Covariance Type:           nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const            -1.3687      2.477     -0.553      0.581      -6.227       3.489
YearPublished     0.0041      0.001      3.368      0.001       0.002       0.007
BestPlayers      -0.0219      0.009     -2.447      0.014      -0.039      -0.004
==============================================================================
```

Both Year (YearPublished, p = 0.001) and number of players (BestPlayers, p = 0.014) were statistically significant, as well as the entire model (p = 2.38e-5), indicating a significant relationship between each of those attributes and the adjusted game ratings. The total variability explained by these attributes, though, was very small. The R-Squared value was 0.011, meaning that only about 1% of the variability of ratings in this model is explained by these attributes. The coefficient for year was only 0.041, indicating a very small positive relationship between year and ratings, while the coefficient for number of players was only -0.0219, indicating a small negative relationship between the player count and ratings.

When I tested for collinearity, I observed the following results from a correlation matrix:

Table 15: Collinearity matrix for year published and number of players vs. complexity-bias adjusted ratings

	YearPublished	BestPlayers	Fitted
YearPublished	1.000000	-0.197031	0.848714
BestPlayers	-0.197031	1.000000	-0.685709
Fitted	0.848714	-0.685709	1.000000

Because the coefficient between BestPlayers and YearPublished was small at only -0.197, I did not detect major collinearity in the results and did not adjust the model.

Lastly, I visualized year vs. ratings and number of players vs. ratings separately to further explore the associations.

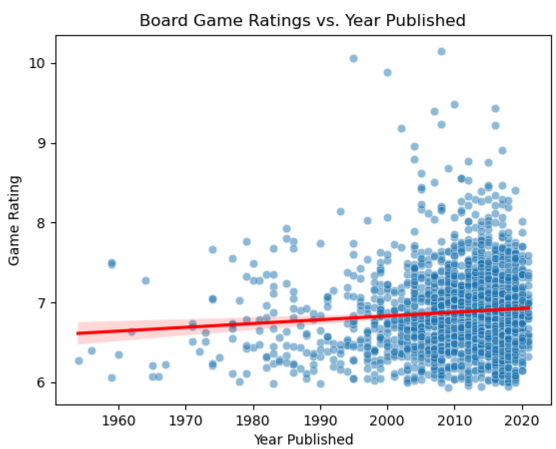

Figure 7: Complexity bias-adjusted board game ratings vs. year published

The very slight positive association between year and rating is visible, but also highlights how small the linear relationship truly is.

Because the number of players were discrete values with a smaller range, I found a violin plot to be more effective when visualizing that data:

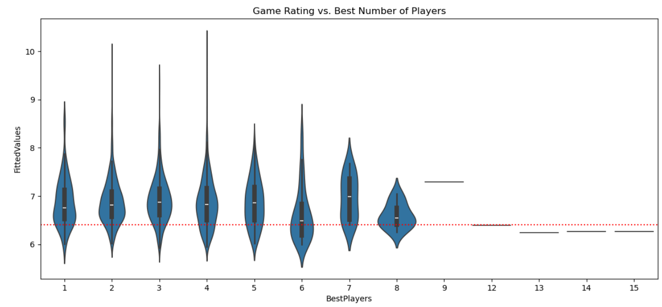

Figure 8: Complexity bias-adjusted board game ratings vs. number of players. Red line indicates median rating.

Once again, there does not appear to be a strong trend in the relationship between number of players and ratings, further emphasizing how small the negative coefficient was in the regression analysis for that attribute. While the results were statistically significant in the multiple linear regression, the effect size was small, thus indicating that year and player count do not strongly influence board game ratings.

Recommendation Results - K-Means Clustering

After determining 10 clusters for theme and mechanics combined, I used PCA analysis to create the following scatter plot:

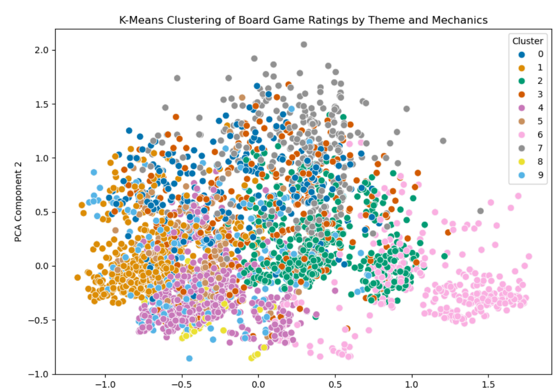

Figure 9: PCA scatter plot of k-means clusters based on theme and mechanics

This plot shows many clusters that are close together, with cluster 6 being further from the rest.

When I ran the recommendation function, the following were some sample results:

```
# Testing the function

recommender("Wingspan")
```

	Name	Similarity
3403	Fantastic Factories	0.666667
3084	Hostage Negotiator: Crime Wave	0.666667
4945	Ugly Christmas Sweaters	0.596285
3937	Mephisto: The Card Game	0.596285
3109	Everdell	0.577350

Figure 10: Input and output for board game recommender for user who likes Wingspan

```
# Testing the function

recommender("Ticket to Ride")
```

	Name	Similarity
717	Ticket to Ride: Europe	0.875000
4747	Ticket to Ride: London	0.790569
5443	Ticket to Ride: Amsterdam	0.790569
1078	Ticket to Ride: Nordic Countries	0.790569
2344	Ticket to Ride: 10th Anniversary	0.750000

Figure 11: Input and output for board game recommender for user who likes the original Ticket to Ride

The outputs make sense based on the inputs. For example, in Figure 10, Wingspan is a nature-themed board game where resource collection is an integral mechanic. Everdell is also a nature-themed game with a similar mechanic. Anecdotally, I have played both games and do find them to both be similar.

In Figure 11, it is reasonable that those who would enjoy the original Ticket to Ride would therefore be likely to enjoy the expansions/alternative versions of the game which are recommended.

Based on these results and tests, it is concluded that the function to recommend similar board games based on theme and mechanics together is sufficient.

Applications

The results from this study can be applied to purposes for both board game developers and board game enthusiasts.

From the regression analyses, it is concluded that the following attributes can explain the most variability in adjusted board game ratings: Mechanics (OLS R-squared value of 0.446), Publishers (in-sample R-Squared value of 0.3999), and Theme (OLS R-Squared value of 0.352). The year published and player count had very little effect on game rating. A board game developer could use these results to focus their game creation on the attributes most strongly associated with board game ratings, in this case the Mechanics, Publisher, and Theme.

The recommendation system could be applied to the game search of a board game enthusiast. This system could focus on key attributes that the enthusiast likes in a game and use that to generate other games that share those same attributes. Future work could involve integrating a filter by play time and minimum or maximum players so that recommendations are further personalized based on a player's individual needs.

These results can be applied to both create a potentially highly-rated game based on known factors which may influence rating, as well as to help those who enjoy board games to find more games that share attributes they like from a target game. Together, this data-driven work can improve the development and enjoyment of board games.

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