Report on the Analysis of Anime Performance by Production Factors

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1. Introduction

1.1. Motivations of Analysis and Introduction to Dataset

Animation is one of the oldest forms of media in human society still regularly consumed today starting with phenakistoscopes in 1832 [1]. Moving pictures are a hallmark of human culture that evolves each day, today seeing a global expansion that brings different cultures together regardless of any divisive factors between peoples. One vital progressor to the intercultural explosion of shared media in the form of animation is anime, or Japanese animation. Anime in 2023 alone made over 24 billion USD [2]. With such a massive impact on the economy and more importantly on the spread of culture, it's important to understand how the success of anime and its influence is generated. Despite the significance of anime however, very little empirical research has been conducted on metrics of success and growth. This brings about the principal subject of this project - To measure success metrics of anime reported by a well-known and commonly used anime tracking site and analyze what factors may contribute to the success or failure of an anime. The dataset was obtained through Kaggle, and the data within the dataset was sourced from the API of a website called MyAnimeList [3]. Typically, datasets designed for Kaggle competitions are of a higher quality and reliability. However, despite not being for a competition, the chosen dataset is comparable in quality and reliability to officially sanctioned competition datasets. The dataset is sourced from MyAnimeList.net, a well-established and popularly used online platform that boasts a rich, crowd-sourced dataset that captures user-based indicators of success—such as viewer scores, popularity rankings, member/favorite counts, and categorical metadata (e.g., genre, studio, release season). Its origin in a real-world system ensures high ecological validity, reflecting user behavior, industry practices, and temporal trends in anime production and reception. This makes it the perfect window into the workings of how anime success can be determined from a cultural perspective. MyAnimeList serves as both a repository for content-related information and a social platform, enabling users to track their anime/manga consumption, score/review titles, and engage with the community. As the very people that drive the culture are the viewers, data collected from viewer feedback is of the utmost importance.

The dataset being analyzed throughout this project contains nearly 25 thousand entries up to June 2023. Each observation contains data from the MyAnimeList API contain the following: A unique ID for each anime, the name of the anime, the English translation of the anime's name, any other translations of the anime's name, the averaged score assigned to the anime by all users who have interacted with it, the genres of the anime, a brief description of the anime's plot, the form it was created in (e.g., TV series, movie, OVA, etc.), the number of episodes, the date the anime aired, the season and year the anime premiered, the status of the anime (e.g., Finished Airing, Currently Airing, etc.), the production companies behind the anime, the licensors behind the anime, the studios that animated the anime, the form of the source material, the duration of each episode, the age rating of the anime, the ranking based on a number of factors determined by MyAnimeList, the popularity rank, the number of times the anime was marked as a favorite, the number of users who scored the anime, the number of users who added the anime to their list on the platform, and a URL of an image representing the anime. Due to the abundance of potential predictor variables, the dataset had to be sorted through before taking any action in a programming software. Excluding variables that I associated with success and variables that I removed entirely, every variable had to be tested for significance in a number of ways. This meant that the most important action item regarding the dataset was to pick variables that would need to be removed. The alternative names weren't necessary due to the existence of both a unique ID and primary name so I removed the english and other name categories. Although the synopsis could contain information that may help identify patterns in themes and story elements that are relevant to success and may provide interesting insights, I felt that was beyond the breadth of my initial objective and opted to remove this category. The status is also a potentially important variable that I opted to remove due to a lack of relevance. Despite the fact that incomplete anime may reasonably have different scores from similarly performing anime that have been completed, I thought that too was beyond the scope of my objective and removed the category entirely. Finally, I removed the image url as I didn't think the image from MyAnimeList was entirely relevant to the success of an anime. The image doesn't encompass the entirety of potential promotional material a viewer may have come across before seeing the anime as the average viewer would likely come to the page after already deciding to watch or already having watched the anime to add it to their list or score it.

1.2. Overview of Data Distribution and Quality

All analysis was performed in RStudio using R for windows 4.5.0 using a number of packages. After the initial loading of the dataset, the first transformation was made using the janitor package to clean the names of all variables for ease of use later on. Immediately following this, I removed my nonessential variables that I discussed in the previous section. The subsequent transformations were designed to make the data more accessible for my analysis, starting with a helper function for the age rating variable. I used a function to append a new variable converting all ratings into a numeric variable based on the minimum age requirement. I then ensured that all my numeric variables were explicitly numeric, converting unknown values into NAs in the process. As the premiered variable was too specific for my use case, I appended a new variable of just the season the anime released while excluding the year. Missing or empty values were converted to "unknown" using the forcats package. I then parsed the episode duration variable from text to a numeric value of the duration in minutes. Finally, I appended another variable representing the collaboration of multiple animation studios as these were somewhat common and may have an effect on the data in the future during the analysis stage. Now that all my variables had been appended, I transformed the data one final time to explode out instances of categorical variables with multiple entries. I used the tidyr package to decompose the studios, producers, licensors, and genres columns into individual rows, enabling one-to-many relationships to be analyzed individually. Further transformations to the dataset in the future were contained in new data frames as subsets of the original data. Before starting the main analysis, I performed a comprehensive exploratory review to understand variable distributions, missingness, and data types. Summary statistics and visualizations generated using the skimr and DataExplorer packages confirmed that the dataset includes nearly 25 thousand anime entries. Key numerical variables like scores, popularity ranks, favorites, and member counts exhibited strongly skewed distributions, with many entries clustered at lower values and a long tail of extremely popular or highly rated anime. Missing data was generally sparse and handled through explicit NA handling or encoding as "unknown" for missing categorical values. Categorical variables were diverse and often contained multiple values per entry, requiring decomposition for meaningful analysis.

2. Exploratory Data Analysis (EDA)

2.1. Testing Significance of Categorical Variables

To evaluate the significance of categorical production-related variables for predicting anime success, I constructed a base linear regression model using only continuous covariates (episode count, episode duration in minutes, and minimum age rating) coded numerically. I then systematically added each categorical variable to this base model and compared the fit using

ANOVA. I found that the base model explained approximately 10.5% of the variance in anime scores ($R^2 = 0.105$). When categorical predictors were added successively—more specifically, source, type, studios, producers, licensors, and genre—all models exhibited significant improvements in fit (all $p < 0.001$). This indicates that each of these variables are statistically beneficial to explaining variation in anime ratings. The full ANOVA results are summarized in Table 1. Most notably, the variables of type and source yielded the largest F-statistics at $F \approx 1681$ and $F \approx 505$, respectively, which suggests great explanatory power over the model. Adding studios to the model increased the R^2 from 0.105 to 0.423, which indicates that studio metadata alone can explain over 30% of the variation in anime scores beyond what is captured by other categorical variables. This makes sense because animation studios themselves culturally hold great sway over the reputation of an anime considering the studio is responsible for the quality of the art of the animation itself. The results of Table 1 support the inclusion of all six categorical variables, however the large number of levels in the studios and producers variables—with over 900 unique values each—raises concerns about model overfitting. To circumvent overfitting, future preprocessing steps considered methods like collapsing sparse levels (e.g., grouping studios that appear in the data less often under a single category). To assess model assumptions, I generated a set of diagnostic plots for the base model (Fig. 1). The base model was used for fear of overfitting as it's much simpler and easier to interpret, with assessments still being indicative of vital regression assumptions. The residuals vs. fitted plot showed mild heteroscedasticity, with a slight fanning pattern which indicates an increased variance at higher fitted values. The Q-Q plot showed mild deviation from normality in the tails which is to be expected, and central residuals aligned well. The scale-location plot mirrored the residual trends, confirming non-constant variance, while the residuals vs. leverage plot highlighted a few potential high-leverage observations. These diagnostics suggest that while the base model is reasonably well-specified, some concerns with regression model assumptions (e.g., homoscedasticity and normality) may be present. Given the complexity of anime production data and the skewed distribution of popularity and rating metrics, these patterns are in line with what was expected. Regardless, they reinforce the value of subsequent modeling approaches, such as clustering and dimensionality reduction, to capture a more robust structure in the dataset.

Table 1

ANOVA Model Comparisons for Categorical Predictors

variable	df	F_stat	p_value
source	16	505.50	~0
type	6	1681.26	~0
studios	908	44.94	~0
producers	1421	17.32	~0
licensors	86	142.31	~0
genres	21	325.99	~0

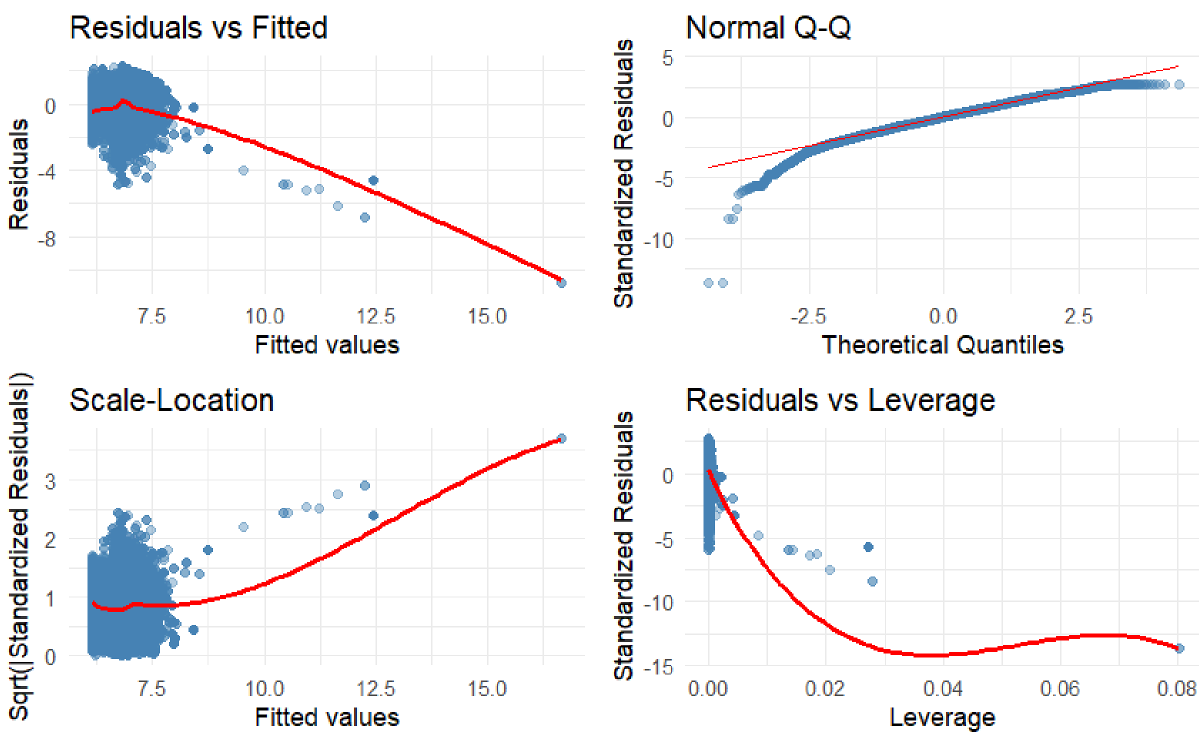

Fig. 1. Diagnostic Plots for Base Linear Model.

2.2. Testing Significance of Numerical Variables

In order to determine the individual contribution of each numerical variable to anime success, I conducted nested ANOVA tests comparing various extended linear models to the base model. Using a modified complete-case version of the dataset, I tested three continuous predictors including episode count, duration (in min.), and minimum age rating. Each variable was tested independently via comparison of a model with and without each variable while holding all other numerical covariates constant. From my analysis I found that all three variables were highly significant in predicting anime success (via score) with p values less than 0.001. Among these, episode duration had the greatest explanatory power with an F-statistic of approximately 4598 which is quite high in the context. Minimum age rating followed with an F-statistic of roughly 3000 ($F \approx 2994$) and episode count with a lesser still F-statistic of roughly 1900 ($F \approx 1887$). In context, F-statistics are reflections of how much the addition of each variable improves fit relative to the variance. Higher values indicate stronger predictive contribution The results indicate that each variable is meaningful and carries independent predictive value. Summary results of the nested ANOVA comparisons can be found in Table 2. Most importantly, these findings support retaining all three numerical variables in further modeling. At this stage, no transformation appeared to be necessary based on significance or basic model performance. However, careful examination of their distribution and scale in univariate analyses may have been warranted to ensure downstream model interpretability.

Table 2

ANOVA Model Comparisons for Numeric Predictors of Anime Score

variable	df	F_stat	p_value
episodes	1	1886.82	0
duration_mins	1	4597.62	0
rating_age	1	2994.16	0

2.3. Correlational Structure of Success Metrics

To understand the structure of anime performance metrics, I conducted a pairwise correlation analysis across five success metrics from the dataset: average user score, popularity rank, number of members, number of user favorites, and site popularity index. These variables represent dimensions of how well received and rated anime are by the MyAnimeList community relative to each other. Figure 2 presents the correlation heatmap that displays the strength and direction of associations with numerical coefficients. Some relevant patterns that can be seen from the heatmap arise; Score and rank share an extremely strong negative correlation at nearly exactly -1 ($r \approx -0.98$), which makes sense because rankings follow that lower numbers correlate to higher ranked anime and the rankings are most prominently determined by score among other metrics not entirely known, designed by MyAnimeList. Members and favorites had a reasonably strong positive correlation ($r \approx 0.80$) which is due to the fact that titles with more members that have added it would naturally have been favorited more times by those users than titles with fewer members. Other metrics were moderately correlated to score, indicating some relevance but not any manner of outstandingly strong correlations. These relationships suggest potential multicollinearity among the success variables which motivates caution in subsequent models to avoid redundancy.

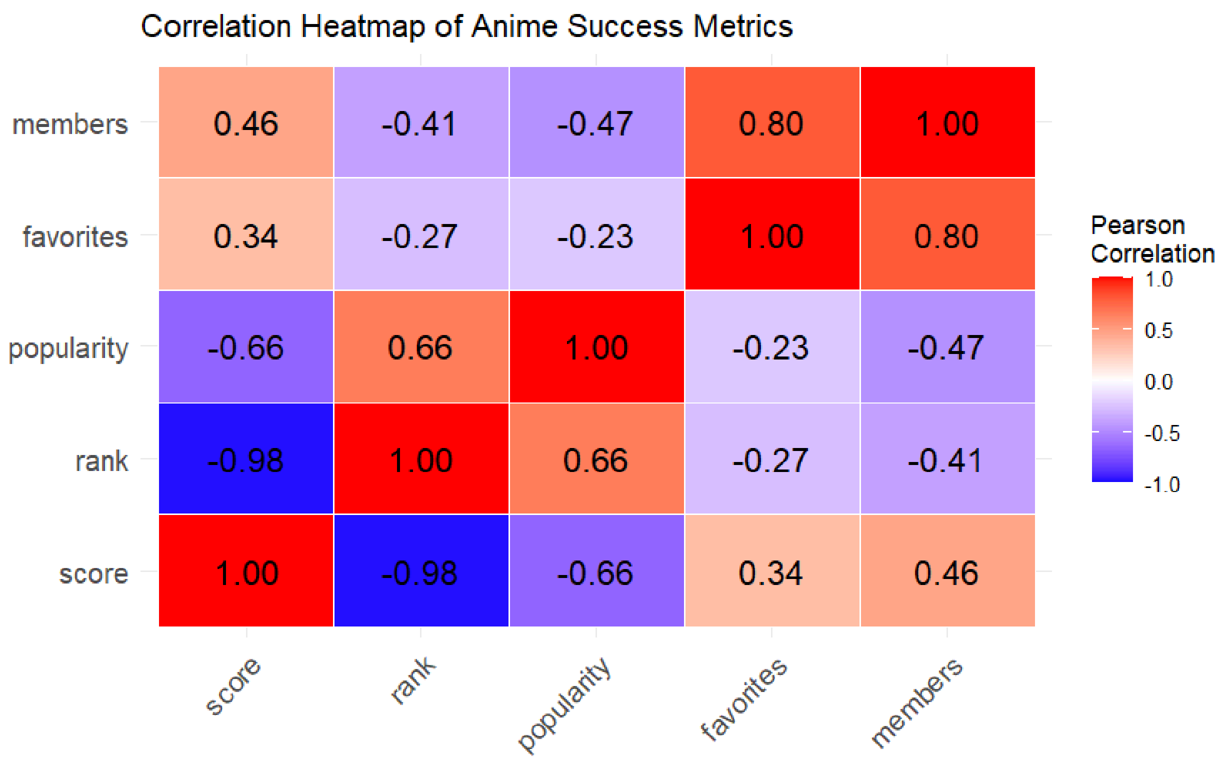

Fig. 2. Correlation Heatmap of Anime Success Metrics.

2.4. Testing Significance of Predictor Variables Across Success Metrics

To evaluate how all the analyzed production factors relate to the reviewed measures of anime success, I conducted a series of significance tests for each predictor against the five success metrics: score, rank, popularity, members, and favorites. Numeric predictors—episode count, duration (in min.), and minimum age rating—were individually regressed on each success metric using simple linear models. Categorical predictors—form of source material, type of animation, studios, producers, licensors, and genres—were assessed via ANOVA tests for group contrasts. Summaries of the top five predictors ranked by significance (p-value) resulted in a large display of the same values (significantly low enough that the table displayed them as 0) so the table was omitted from this report due to redundancy. The results revealed that all tested variables showed statistically significant relationships with at least one dimension of success (almost all $p < 0.001$). Most notably, numerical predictors such as duration and episode count consistently demonstrated strong significance across all success metrics. Similarly, categorical predictors like genres, studios, and source material exhibited broad explanatory ability across a range of success metrics. Numeric variables such as episode count and duration (in min.) were also consistently significant across all five metrics, although the size and direction of their effects varied. These results support the continued inclusion of all examined numeric and categorical predictors in subsequent analyses to accurately capture the contribution of the factors to anime success. Unfortunately, due to the large sample size, some predictors may achieve statistical significance despite explaining only a negligible sum of the variance. To quantify the portion of variance explained, I calculated the R^2 values from simple linear regression models for each predictor-success metric pairing. This allowed me to directly assess the explanatory ability of each variable. As expected, the results of this testing confirmed that numeric numeric predictors like duration and episode count only accounted for less than 5% of the variance across all outcome metrics. In contrast, categorical predictors such as source material, studios, and genres displayed much greater explanatory ability with some exceeding 0.15. The results of these calculations are summarized in Table 3. To visualize the relevant relationships, I plotted examples. My first example plot was a scatterplot of score against duration which showed a weak positive trend consistent with its low R^2 value (Fig. 3). In contrast, a boxplot of score by source material revealed pronounced differences between groups which reinforced the higher explanatory values of categorical metadata (Fig. 4). Building upon these findings, I constructed a multivariate linear regression model that explains score using a subset of the most easily interpreted categorical predictors: studio, producer, type, source, and genre. Rare levels within each factor were grouped to retain ease of interpretation. The final model achieved an adjusted R^2 of 0.397 which indicated that approximately 40% of the variance in scores can be attributed to the chosen production features (Table 4). The model overall was found to be highly significant confirming a strong relationship between these factors and anime success. Next, I assessed collinearity by computing generalized variance inflation factors (GVIF) for each predictor. All $GVIF^{\frac{1}{2\cdot df}}$ values were below 1.14 which suggests that there is no concern for collinearity among the selected variables (Table 6). This further supports the reliability of the models' coefficients. I then examined the most influential factor levels via extraction and ranking of the top and bottom coefficients within each category (Table 5). Some levels—anime sourced from radio or web novels, or produced by Avant Garde studios—showed significant, positive or negative associations with score. To further evaluate multicollinearity among numeric predictors—duration, episodes, and rating age—I computed pairwise correlations and visualized them using a correlation heatmap which can be found in Fig. 5. The results demonstrate very low correlations between numeric predictors, which further supports their contributions to prediction and implying stable coefficient estimates in regression. These findings complement the GVIF results for categorical predictors, confirming low multicollinearity in the dataset.

Table 3

Average and Maximum R^2 Values for Predictors Explaining Variance in Anime Success Metrics

pred_type	predictor	mean_r_squared	max_r_squared
Categorical	studios	0.319434598	0.54359684
Categorical	producers	0.252780814	0.45322430
Categorical	licensors	0.182317460	0.34526168
Categorical	type	0.135742489	0.33988998
Categorical	source	0.108920322	0.24115607
Categorical	genres	0.078731664	0.15912684
Numeric	rating_age	0.066730795	0.20625174
Numeric	duration_minutes	0.020601859	0.04954935
Numeric	episodes	0.009707901	0.01537681

Table 4

Summary of Regression Model Fit Statistics for Predicting Anime Score

adj.r.squared	statistic	p.value	df
0.3969076	199.5879	0	52

Table 5

Summary of Regression Coefficients by Predictor Category

predictor	Count	Mean_Estimate	Min_Estimate	Max_Estimate
producers	10	-0.382	-0.757	0.029
source	16	-0.257	-0.961	0.351
genres	10	0.047	-0.669	0.393
studios	10	0.025	-0.755	0.378
type	6	-0.023	-0.440	0.597

Table 6

Generalized Variance Inflation Factors (GVIF) for Multicollinearity Assessment of Predictors

	GVIF	Df	GVIF^(1/(2*Df))
studios	2.184712	10	1.039848
producers	2.133684	10	1.038620
type	4.530920	6	1.134181
source	3.616417	16	1.040989
genres	5.440286	10	1.088381

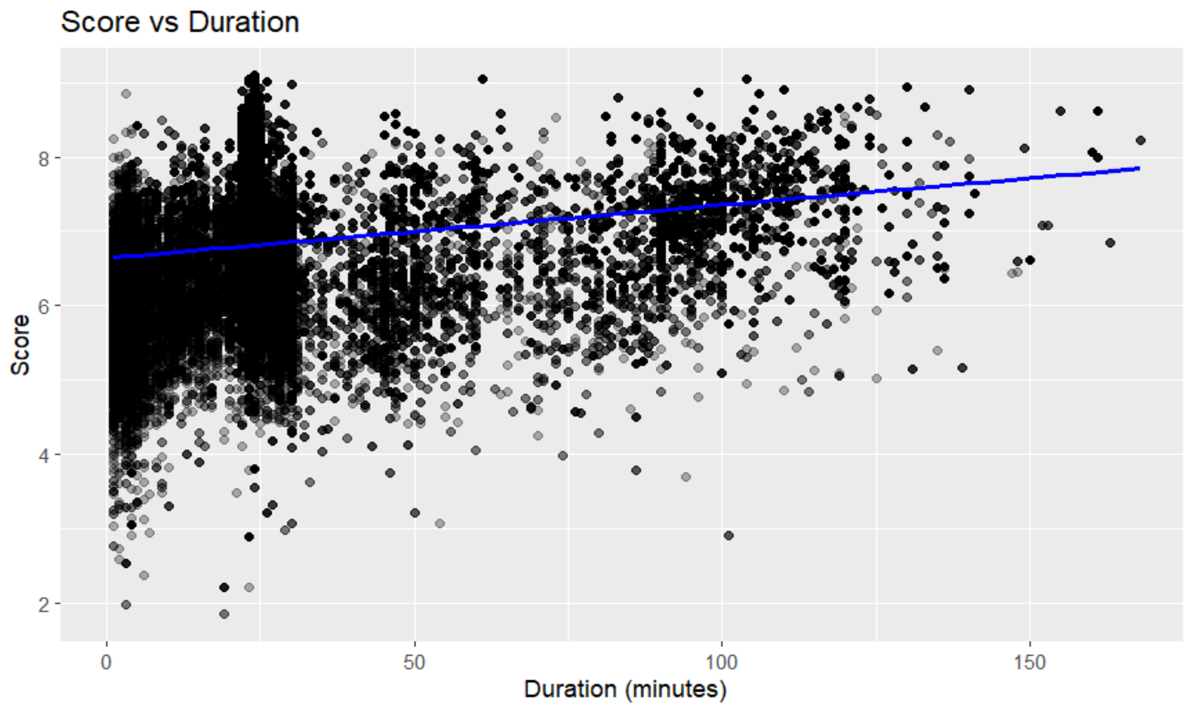

Fig. 3. Score vs Duration Scatterplot.

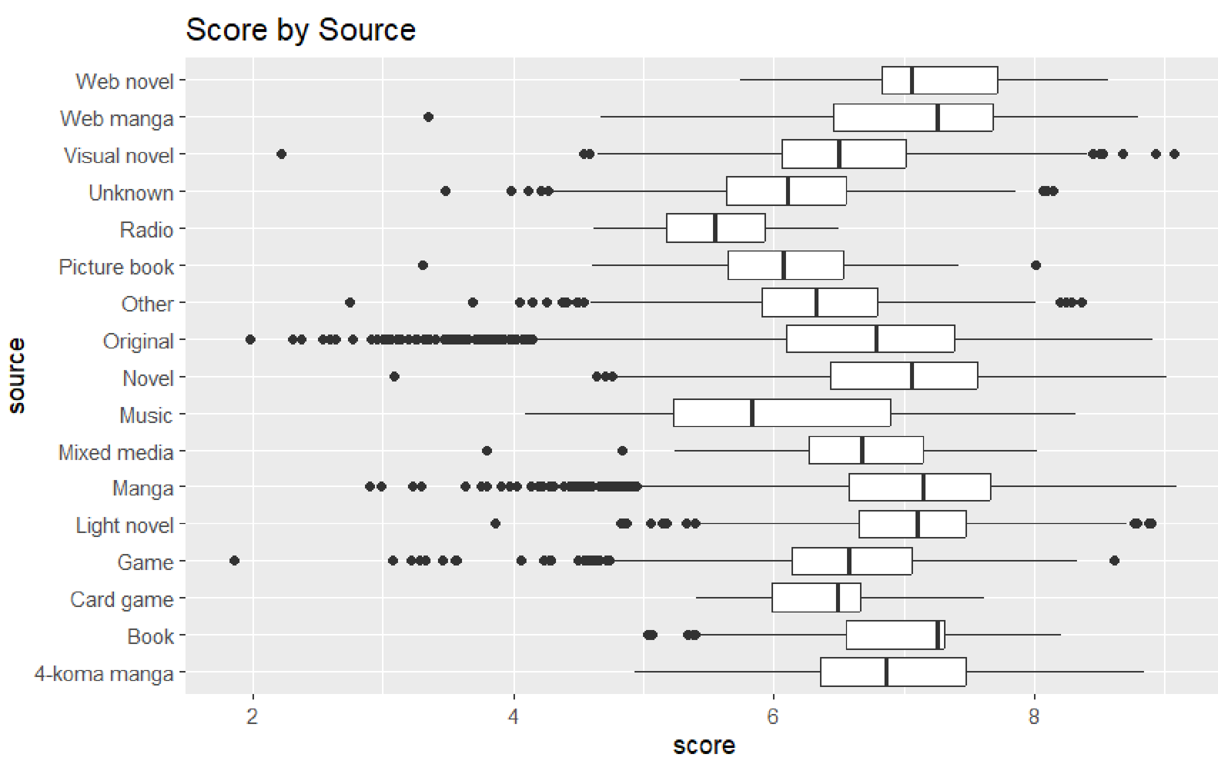

Fig. 4. Score vs Source Boxplot.

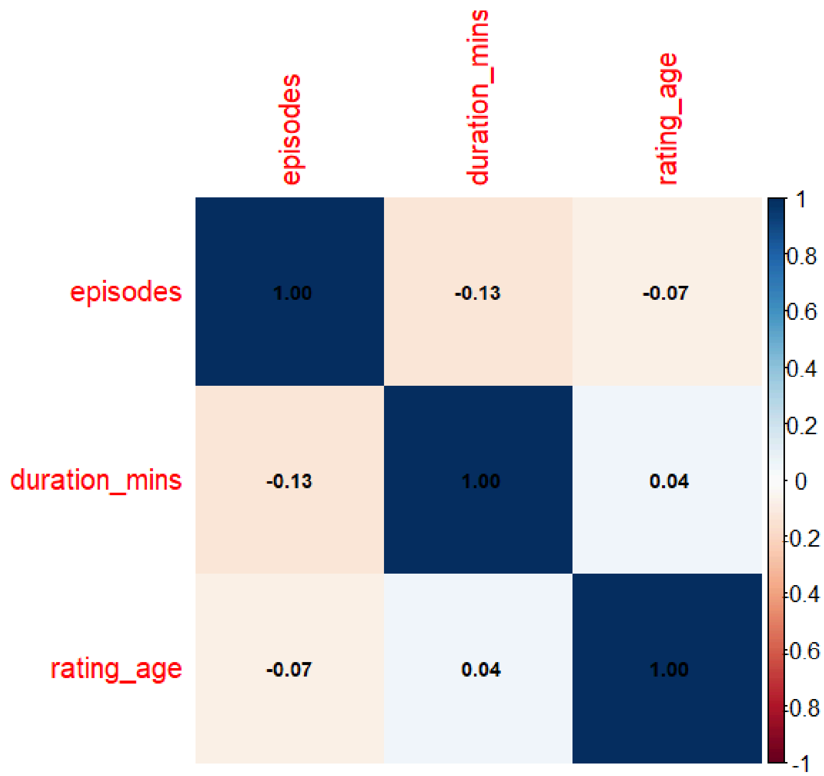

Fig. 5. Correlation Heatmap of Numeric Predictors Showing Low Multicollinearity.

3. PCA and MCA of Anime Production and Success Metrics

3.1 Principal Component Analysis (PCA)

To further distill the complex multivariate relationships among numerical anime features, I conducted Principal Component Analysis (PCA) on six numerical variables: episodes, duration in minutes, popularity, favorites, members, and score. Prior to analysis, missing values were filtered out to ensure alignment with corresponding categorical data used in complementary analyses. The PCA revealed a severe dimensional reduction, with the first five principal components (PCs) explaining over 95% of the total variance. PC1 alone accounted for approximately 41% of the variance, followed by PC2 explaining 21.5%, PC3 at 16.7%, PC4 at 12.6%, and PC5 contributing 5.2%. These connections can be found in a scree plot displayed in Fig. 6. PC1 (41.1%) represents the connection between community engagement and anime length. The loadings on this component are positive on popularity but negative on favorites, members, and score, indicating that popular anime may not always align with the highest user ratings or favorites. The moderately negative loadings on episodes and duration suggests that longer series tend to score lower on this axis, which reflects a tradeoff between length and fan-perceived quality or engagement. This contextually can be explained by the fact that longer commitments like anime with an extremely high number of episodes or episodes lasting longer would attract less viewers who may not be willing to commit that much time. Furthermore, longer runtimes leave room for more mistakes to become apparent to the viewer. PC2 (21.5%) captures the connection between episode count and duration versus user engagement metrics. Episodes and favorites load positively, while duration and score load negatively, potentially distinguishing shorter, episodic formats with high fan engagement from longer-format anime with differing appeal. PC3 (16.7%) is mostly dominated by episode count in its loadings, isolating series length as a key axis of variation independent from popularity or rating metrics. PC4 (12.6%) provides nuanced differentiation, negatively loading on duration and popularity, suggesting subgroups of medium-length anime that differ in popularity and format. PC5 (5.2%) notably isolates the success factor, positively correlating with both score and popularity. This component appears to capture the success dimension that is orthogonal to the other PCs, offering a lens on what drives overall anime success as measured by user ratings and community size. This means we can use PC5 to plot against all other PCs in order to see the relationship between each grouping of loadings and the component of success. These loadings can be found in Table 7. I then designed biplots of PC5 against PCs 1 through 4, colored by k-means clustering (k=3). These plots revealed distinct groupings of anime that varied across length, popularity, and successfulness and can be seen in Fig. 7. Cluster sizes (7417, 7656, and 154) corresponded to meaningful subpopulations within the dataset. These findings suggest that the main axes of variation among numeric anime features reflect complex tradeoffs between length, community engagement, and success indicators. Most importantly, the separation of PC5 as a success-related component underscores the importance of treating popularity and quality metrics as similar yet distinct features. The PCA was successful in effectively reducing dimensionality while preserving interpretability. The most vital components highlighted how different numerical features interacted to influence anime success, providing a strong foundation for the following modeling I performed on the data. This structure enables targeted exploration of how production features and fan enjoyment shape the observed patterns of anime success.

Table 7

Principal Component Loadings and Explained Variance for Anime Numeric Features

Importance of components:

	PC1	PC2	PC3	PC4	PC5	PC6

Standard deviation	1.5700	1.1357	1.0012	0.8710	0.55733	0.41679
Proportion of Variance	0.4108	0.2150	0.1671	0.1264	0.05177	0.02895
Cumulative Proportion	0.4108	0.6258	0.7929	0.9193	0.97105	1.00000

	PC1	PC2	PC3	PC4	PC5
episodes	-0.070	0.167	0.949	-0.254	-0.051
duration_mins	-0.217	-0.547	-0.136	-0.793	-0.069
popularity	0.490	0.334	-0.097	-0.394	0.626
favorites	-0.437	0.537	-0.179	-0.252	0.173
members	-0.524	0.393	-0.143	-0.067	-0.208
score	-0.493	-0.344	0.139	0.287	0.726

PC1	PC2	PC3	PC4	PC5
41.08	21.50	16.71	12.64	5.18

1	2	3
7417	7656	154

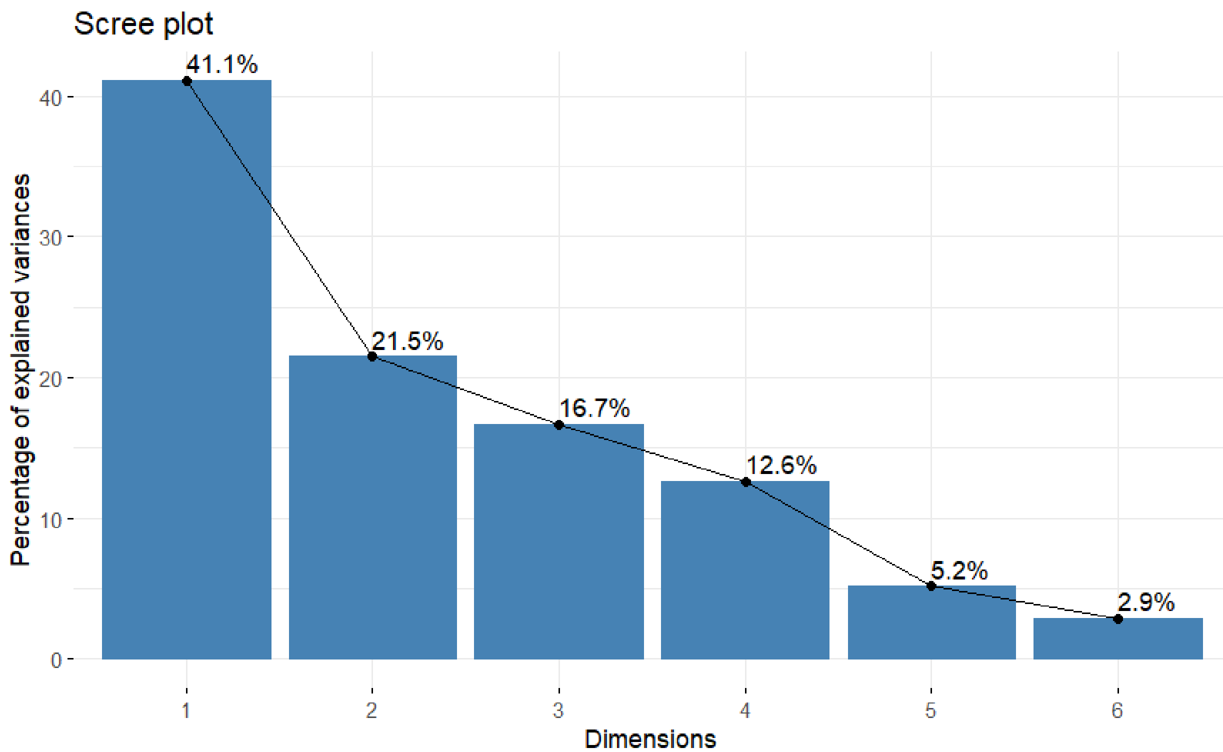

Fig. 6. Scree Plot of Principal Components for Anime Numeric Features.

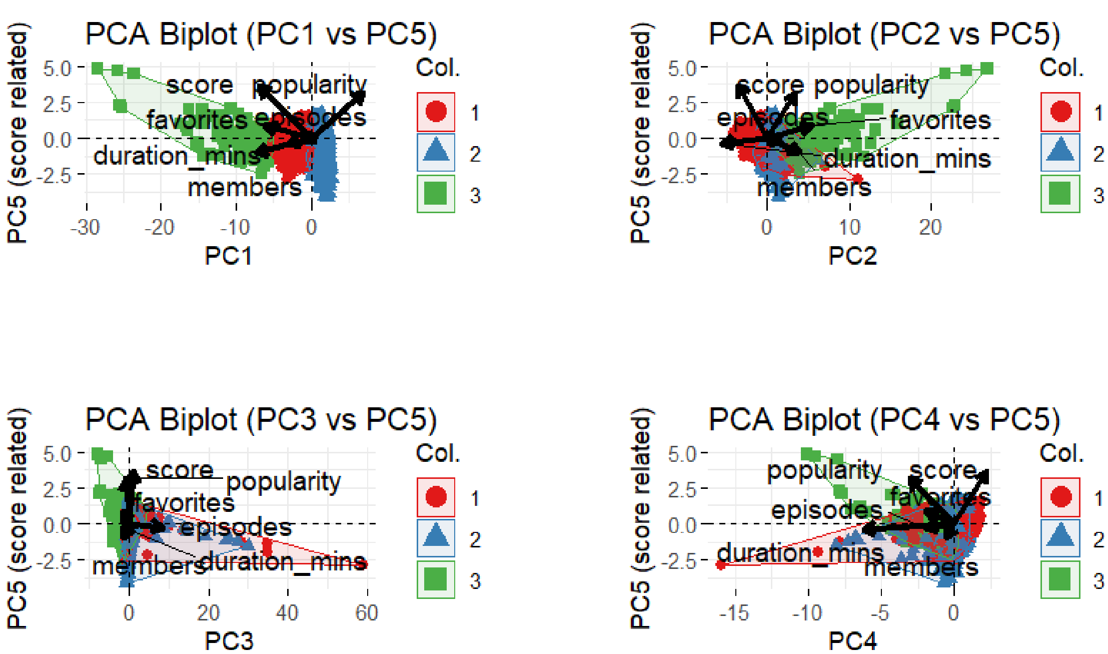

Fig. 7. PCA Biplot Spread of Anime Numeric Features with Cluster Overlay

3.2 Multiple Correspondence Analysis (MCA)

Moving on to the categorical variables—specifically studios, producers, genres, type, and source—I applied Multiple Correspondence Analysis (MCA). MCA is particularly suited for detecting low-dimensional relationships and patterns across multi-level categorical variables. This analysis was used to identify the dimensions of variation and how categories across production features occur together or diverge in defining subgroups. The first two dimensions of the MCA together captured a substantial portion of the overall variation, though the variation per dimension declined rapidly as seen in Fig. 8. This suggests that the first few dimensions summarize the most meaningful categorical variation across the dataset just as in the PCA test for the numerical variables. Each dimension was interpreted by examining the top contributing categories based on their absolute coordinate values similarly to how loadings were used to describe the components of numerical variables in my PCA testing. These included genre tags (e.g., Action, Slice of Life), production studios (e.g., Sanrio, Pink Pineapple), source material (Visual novel, Web manga), and distribution types (TV, Music, ONA). Dim1 contrasted niche or adult content producers and genre tags (e.g., Pink Pineapple, Milky Animation Label, Hentai, Visual novel) against more mainstream or ambiguous labels (e.g., Music type, NHK producer) (Table 8). Dim2 separated producers specializing in niche or erotic content (e.g., Digital Works, Pink Pineapple) and Visual novel sources from mainstream/action-oriented producers (e.g., TV Tokyo, OLM) (Table 9). Dim3 captured separation among lesser-known types and producers (e.g., type_UNKNOWN, Sanrio) and avant-garde/fantasy genres from musical sources (Table 10). Dim4 displayed the distinctions between slice-of-life and comedic genres (e.g., Comedy, Slice of Life) often tied to web sources and 4-koma manga, contrasted with more established studios like Madhouse and Toei Animation (Table 11). Dim5 appeared to represent a success dimension in its own right, with positive associations for more popular features like Sanrio and Slice of Life, Comedy genres, and negative associations for lesser known studios and Web novel sources. This dimension may capture subtle production cues linked positively to audience reception (Table 12). A full breakdown of the top contributing categories per dimension is shown in (Table 13). After understanding all the different dimensions, I visualized observations in the space of MCA dimensions colored by k-means clusters defined over the combined PCA/MCA space. I generated biplots for each dimension against Dim5 which revealed clear separability among anime groups with distinct production features (Fig. 9). I labeled high-contributing category coordinates in each dimension pair. Across the biplots, clusters showed interpretable grouping: for instance, clusters enriched in niche genres/music separated clearly from those associated with high-performing or mainstream production labels. To quantify the relative importance of each variable's categories, I counted how often each categorical factor (e.g., studios, source) contributed the highest loadings per dimension. These results supported the conclusion that producers and genres were the most structurally influential variables, followed by source and type, while studios contributed more specific but occasionally high-loading signals (Table 14).

Table 8
Top Contributing Categories to MCA Dimension 1: Mainstream vs. Niche/Adult Content

Category	Loading	Dimension
source_Music	2.547	Dim1
producers_NHK	2.364	Dim1
producers_Milky Animation Label, MS Pictures	-2.259	Dim1
type_Music	2.185	Dim1
producers_Digital Works	-2.147	Dim1
producers_Pink Pineapple	-2.093	Dim1
genres_UNKNOWN	1.822	Dim1
type_UNKNOWN	1.661	Dim1
genres_Avant Garde	1.661	Dim1
genres_Hentai	-1.581	Dim1

Table 9
Top Contributing Categories to MCA Dimension 2: Niche vs. Mainstream Production Orientation

Category	Loading	Dimension
producers_Digital Works	3.871	Dim2
producers_Milky Animation Label, MS Pictures	3.848	Dim2
producers_Pink Pineapple	3.244	Dim2

genres_Hentai	2.489 Dim2
source_Visual novel	2.127 Dim2
source_Music	1.509 Dim2
producers_NHK	1.181 Dim2
type_Music	1.148 Dim2
producers_TV Tokyo	-1.104 Dim2
type_OVA	1.062 Dim2

Table 10

Top Contributing Categories to MCA Dimension 3: Avant-Garde/Fantasy vs. Musical/Unknown Production Types

Category	Loading Dimension
type_UNKNOWN	6.112 Dim3
producers_Sanrio	3.452 Dim3
source_Music	-2.551 Dim3
producers_NHK	-2.072 Dim3
genres_Fantasy	1.844 Dim3
genres_Avant Garde	1.703 Dim3
type_Music	-1.305 Dim3
source_4-koma manga	-1.196 Dim3
source_Mixed media	-1.162 Dim3
source_Unknown	1.131 Dim3

Table 11

Top Contributing Categories to MCA Dimension 4: Slice-of-Life vs. Legacy Studio Productions

Category	Loading Dimension
source_4-koma manga	4.366 Dim4
genres_Comedy, Slice of Life	3.528 Dim4
source_Web novel	1.894 Dim4
source_Web manga	1.592 Dim4
source_Radio	1.535 Dim4
genres_Comedy	1.347 Dim4
genres_Slice of Life	1.254 Dim4
studios_Madhouse	-1.146 Dim4
type_ONA	1.102 Dim4
studios_Toei Animation	-1.067 Dim4

Table 12

Top Contributing Categories to MCA Dimension 5: Production Success Indicators

Category	Loading Dimension
type_UNKNOWN	7.000 Dim5
producers_Sanrio	4.597 Dim5
source_Web novel	-4.007 Dim5
studios_OLM	-2.712 Dim5
source_4-koma manga	2.407 Dim5
genres_Comedy, Slice of Life	2.267 Dim5
producers_TV Tokyo	-2.142 Dim5
source_Game	-1.724 Dim5
producers_Fuji TV	1.541 Dim5
genres_Fantasy	1.444 Dim5

Table 13

Top 10 Contributing Categories for Each MCA Dimension (Dim1–Dim5)

Variable	Top_Category
genres	genres_UNKNOWN
producers	producers_NHK
source	source_Music
studios	studios_UNKNOWN
type	type_Music

Table 14

Summary of Variable Contribution Frequency Across MCA Dimensions

Variable	top_contributions
producers	14
source	14
genres	11
type	8
studios	3

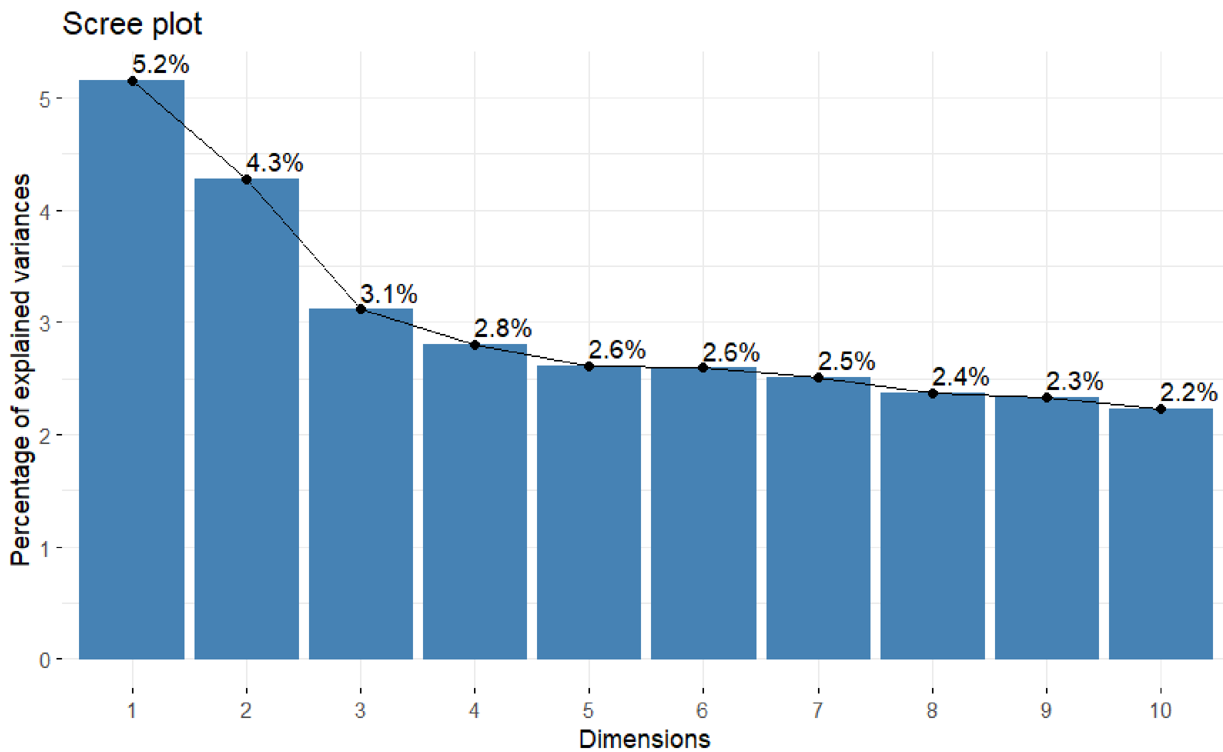

Fig. 8. Scree Plot of Inertia Explained by MCA Dimensions.

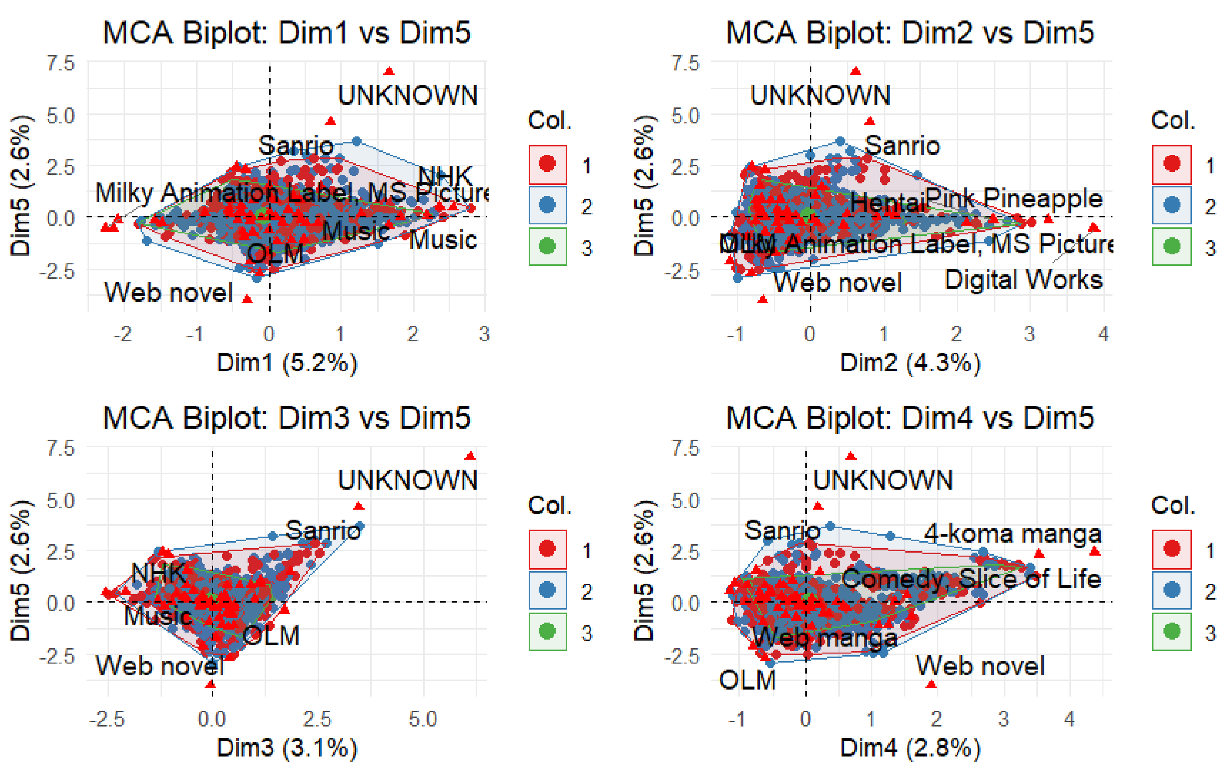

Fig. 9. MCA Biplot Spread of Anime Observations by Cluster: Dim1–4 vs. Dim5

4. Modeling Anime Success Based on EDA-Informed Factors

The final stage of analysis I performed for my project was to build a linear regression model holding score as the dependent variable. The model was guided by earlier exploratory data analysis (EDA), which highlighted key numerical and categorical contributors to variation in success. The objective was to test whether attributes like anime type, source, episode duration, studio metadata, and latent PCA dimensions (PC1–PC5) can be used to predict anime ratings, while accounting for clustering by unique anime identifiers. I first merged the PCA-based features (PC1–PC5) with the cleaned, long-form dataset with missing score values removed. The k-means cluster assignments (from earlier PCA–MCA space clustering) were included as an additional categorical predictor. To prepare the data for modeling, I collapsed less common categories (with <30 occurrences) in multi-leveled factors (e.g., studios, producers, genres, licensors) to group together infrequent categories. I then performed a stratified 70/30 train-test data split, aligning factor levels across datasets to prevent test-time inconsistencies. The model was a linear regression with the following predictors: anime type, source material, age rating, episode count, episode duration, genre, producer, studio, k-means cluster label, and the top five PCs. The model was fitted on the training set, and to account for non-independence among anime entries (e.g., due to remakes or franchise entries), I computed standard errors via clustering by anime_id which is shared across anime of the same titles (e.g., Naruto, Naruto: Shippūden, Naruto the Movie: Ninja Clash in the Land of Snow, etc.). The results detailed in Table 15 show that several production-related features are significant predictors of MyAnimeList scores at the $p < 0.05$ level. Notably, type emerged as a key predictor: TV anime had significantly higher average scores, whereas types like Music, ONA, and OVA were associated with negative coefficients (ranging from –0.15 to –0.33). Similarly, the source from which it was adapted had a strong impact—anime based on Games, Card games, Mixed media, or Original sources had significantly lower scores on average when compared to other source materials. These results mirrored findings from the EDA, where these types and sources were found to cluster in lower-performance regions of the PCA and MCA spaces. The final model was fitted on 53,158 training observations with 13,709 unique anime entries, providing strong support for these patterns from the massive amount of data modeled. These results reinforce the conclusions that structural production decisions—particularly the type and source—are critical predictors of anime success.

5. Closing and Further Discussion

While this analysis can't possibly be indicative of the entire field of animation as a medium and the cultural phenomenon of the explosion of anime in popular media, the findings did shed some light on a particularly under-professionally studied subject. In recent years, anime has seen a massive upward trend of popularity and reaches a wider demographic as the medium evolves. Today, as of 2025, anime sparks dialogue in mainstream news sources like Billboard [4] and anime movies are showing in theaters with small culturally Japanese populations, selling out the house [5]. It is indisputable that anime is an important piece of human culture and understanding the workings of success as previous anime have paved them is vital for the continued growth of this piece. In particular, knowing that the type and source are important predictors could decide what source materials get animated or even how the animations are presented to their audience. Recently, anime have been opting more often than not to produce films and popular webcomics are quickly entering the field as a new popular form of source material. The dataset is 2 years outdated as of this report, which is typically not a significant period of time. However, in those two years alone the entire anime industry has wholly pivoted against the trends shown in my analysis. Without the data present, I'm not able to support my claims with more than speculation which is why I provided this perspective in the discussion section of my report. With half the year of 2025 left to come as of writing this report, 3 of the most popular anime franchises (e.g., Given, Jujutsu Kaisen, Demon Slayer) are scheduled to release movies as opposed to TV animations [6]. In the way of source material, the winner of this year's Crunchyroll Anime Awards was an anime (TV) sourced from a Korean webcomic as opposed to Japanese manga [7]. Crunchyroll is one of the most widely used anime streaming sites worldwide, as anime is still a freshly growing medium and has little space to hold in more popular streaming sites (e.g., Disney+, Netflix, etc.). I think, for these reasons, further analysis and consistently updated analysis needs to be done on these metrics and more. Training models to see trends in production feature and successfulness and potentially comparing these to relevant shifts in the landscape of human society as a whole could have powerful implications to the growth of anime. For example, the growing shift toward streaming could have had an impact on the shift towards movies in recent years due to the fact that longer form content is easier to stream than to watch in synchronously with airing schedules. The potential directions and distance each direction may carry us in the landscape of animation data is vast and various.

Code

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