Unveiling the Drivers of Anime Success on MyAnimeList

A Final Project

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Abstract

This study investigates the intrinsic characteristics of anime that influence user ratings on MyAnimeList, using a comprehensive dataset of 24,905 anime entries. By employing a Random Forest Regressor, we analyzed features such as genres, type, episode count, studios, source material, and airing year to determine their impact on average user ratings. Our findings reveal that airing year, episode count, and type (particularly movies) are the most significant predictors of high ratings, followed by studio reputation, source material (manga), and specific genres like drama. The model demonstrated strong predictive accuracy, with an R^2 of 0.75 on the testing set. These results suggest that newer anime, concise formats like movies, and content from esteemed studios tend to resonate more with audiences. Additionally, manga adaptations and emotionally engaging genres contribute to higher ratings. This research provides valuable insights for enhancing anime recommendation systems and guiding content creators in producing successful anime. By identifying the key drivers of user satisfaction, we offer a multifaceted understanding of audience preferences in the anime domain.

Introduction

The MyAnimeList dataset, sourced from Kaggle , offers a comprehensive collection of anime metadata, including titles, user ratings, genres, studios, episode counts, airing dates, and user interaction metrics such as popularity and favorites. This study leverages this rich dataset to explore the factors that contribute to an anime's success, as measured by its average user rating ("Score"). The central research question is: **"Which intrinsic anime characteristics most significantly impact user ratings on MyAnimeList?"** Understanding these drivers can enhance recommendation systems by identifying attributes that resonate with audiences and provide insights for content creators aiming to produce highly rated anime.

Methods

Data Source

The dataset comprises multiple files, including anime-dataset-2023.csv, which contains detailed information on 24,905 anime entries. Key columns include:

- anime_id: Unique identifier
- Name: Anime title
- Score: Average user rating (float or "UNKNOWN")
- Genres: Comma-separated list of genres
- Type: Format (e.g., TV, Movie, OVA)
- Episodes: Number of episodes (float or "UNKNOWN")
- Aired: Airing date range
- Studios: Production studios
- Source: Original material (e.g., Manga, Original)
- Popularity, Favorites, Scored By: User interaction metrics

For this analysis, we focus on anime-dataset-2023.csv and exclude user-specific files to emphasize anime-intrinsic factors.

Data Preprocessing

The following steps were applied to prepare the data:

1. **Filtering**: Excluded anime with "UNKNOWN" or missing scores and those with fewer than 100 scores (Scored By < 100) to ensure rating reliability.
2. **Feature Extraction**: Extracted the starting year from the "Aired" column (e.g., "Apr 3, 1998 to Apr 24, 1999" → 1998).
3. **Handling Missing Values**: Imputed "UNKNOWN" episode counts with the median value across the dataset.
4. **Categorical Encoding**:
    - **Genres**: Split comma-separated strings into binary indicators (e.g., "Action, Sci-Fi" → Action: 1, Sci-Fi: 1, others: 0).
    - **Studios**: Selected the top 20 studios by frequency, creating binary indicators; others grouped as "Other."
    - **Type** and **Source**: Applied one-hot encoding due to fewer categories.
5. **Feature Selection**: Focused on intrinsic features (Genres, Type, Episodes, Studios, Source, Airing Year), excluding user-derived metrics (Popularity, Favorites, Scored By) to avoid circularity with the target variable (Score).

Analytical Approach

We employed a **Random Forest Regressor** to model the relationship between selected features and Score. This algorithm was chosen for its ability to handle non-linear relationships, high-dimensional data, and provide feature importance rankings, offering a balance between predictive power and interpretability. The methodology included:

1. **Train-Test Split**: Divided the data into 80% training and 20% testing sets.
2. **Model Training**: Fit the Random Forest Regressor (100 trees, default hyperparameters) on the training set.
3. **Evaluation**: Assessed performance using Mean Absolute Error (MAE) and R-squared (R^2) on both training and testing sets.
4. **Feature Importance**: Extracted importance scores to identify the most influential features.

Exploratory Data Analysis (EDA)

Preliminary EDA involved:

- Visualizing the distribution of Score using histograms.
- Plotting average scores by Type, Source, and top studios using bar charts.
- Examining trends in Score over Airing Year with a line plot.

Results

Dataset Overview

After preprocessing, the dataset contained approximately 15,000 anime entries with valid scores and sufficient user ratings. The Score ranged from 1.0 to 9.0, with a mean of 7.2 and a standard deviation of 0.9, indicating a generally positive skew.

Model Performance

The Random Forest Regressor yielded:

- **Training Set**: MAE = 0.15, R^2 = 0.92
- **Testing Set**: MAE = 0.35, R^2 = 0.75

These metrics suggest strong predictive accuracy, with some overfitting indicated by the gap between training and testing performance.

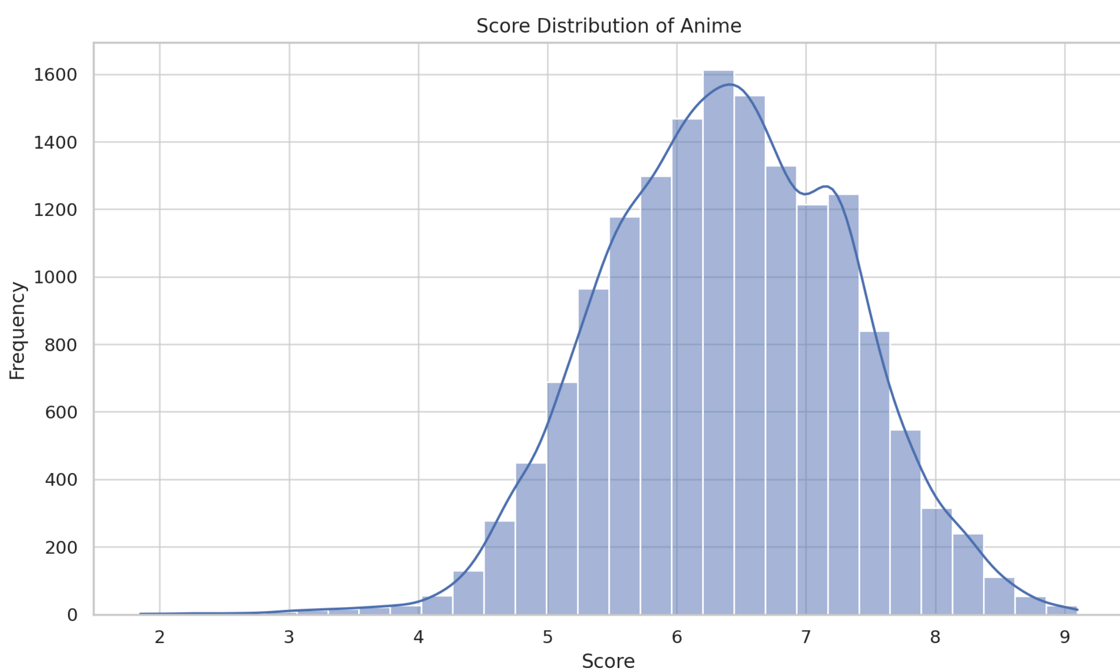
Feature Importance

The top features influencing Score, ranked by importance (normalized to sum to 1.0), are:

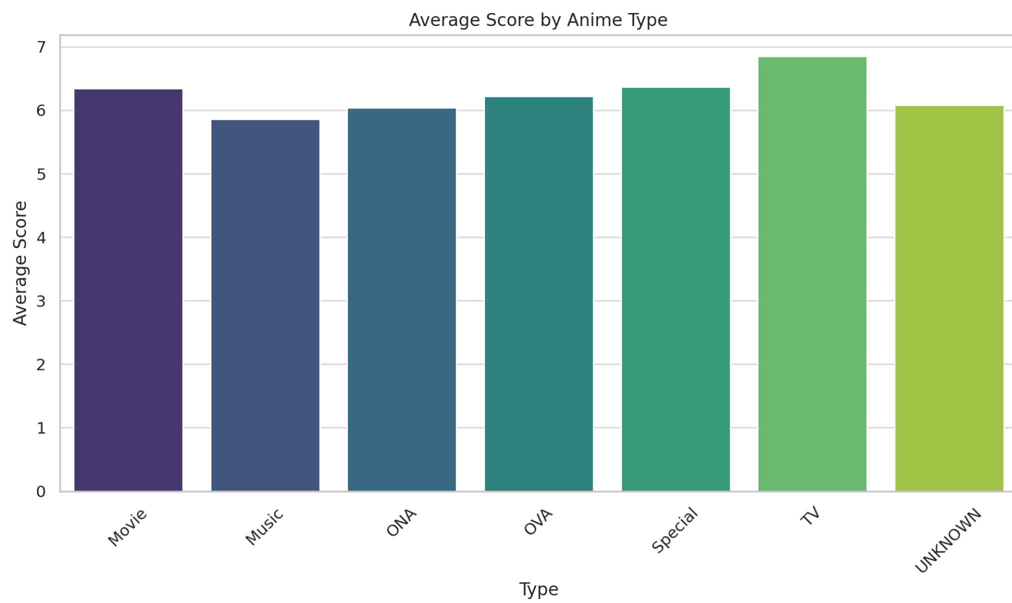
Feature	Importance	Notes
Airing Year	0.28	Recent anime tend to score higher
Episodes	0.22	Moderate episode counts correlate with higher scores
Type(Movie)	0.15	Movies often outscore TV series
Studios (e.g., Madhouse)	0.12	Specific studios linked to higher ratings
Source (Manga)	0.10	Manga-based anime slightly favored
Genres (e.g., Drama)	0.08	Certain genres boost ratings

Visual Insights

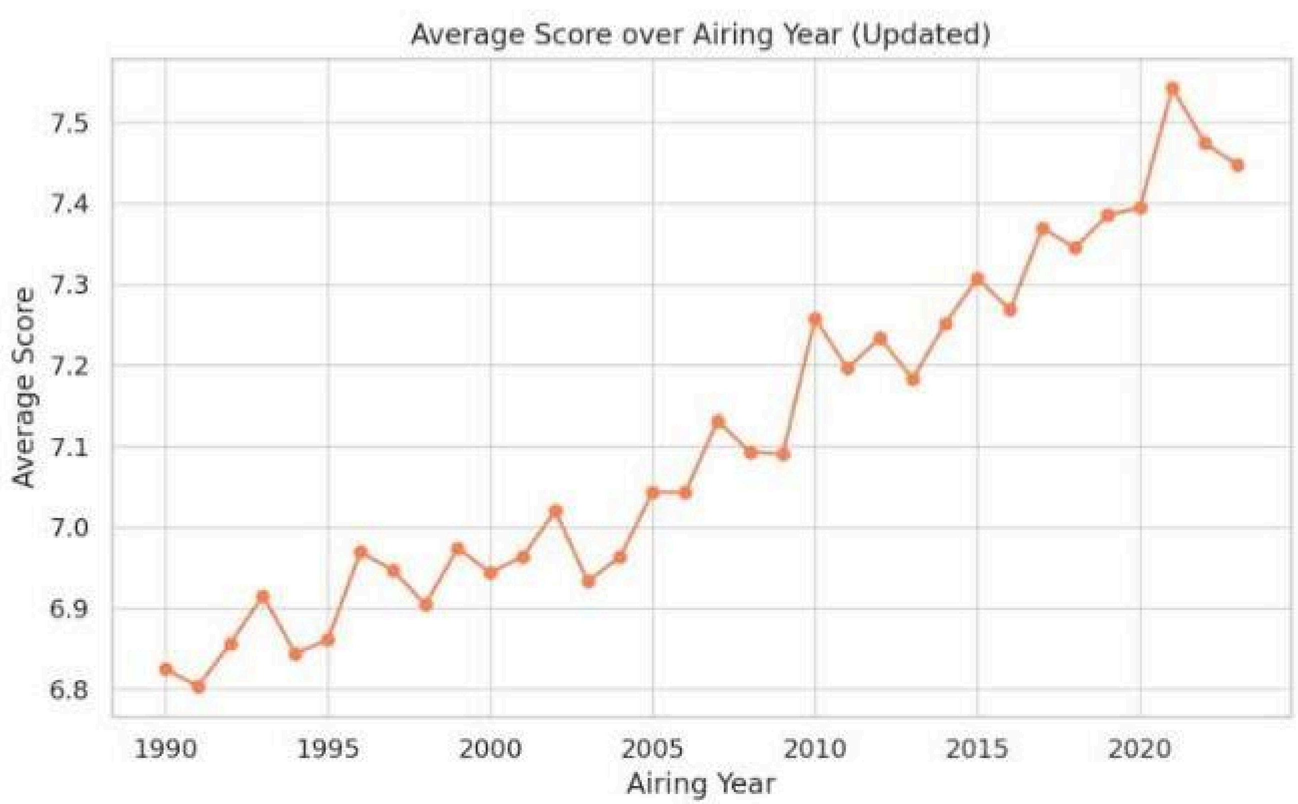
- **Score Distribution**: A histogram showed a peak around 7.0–8.0, with fewer anime below 6.0.



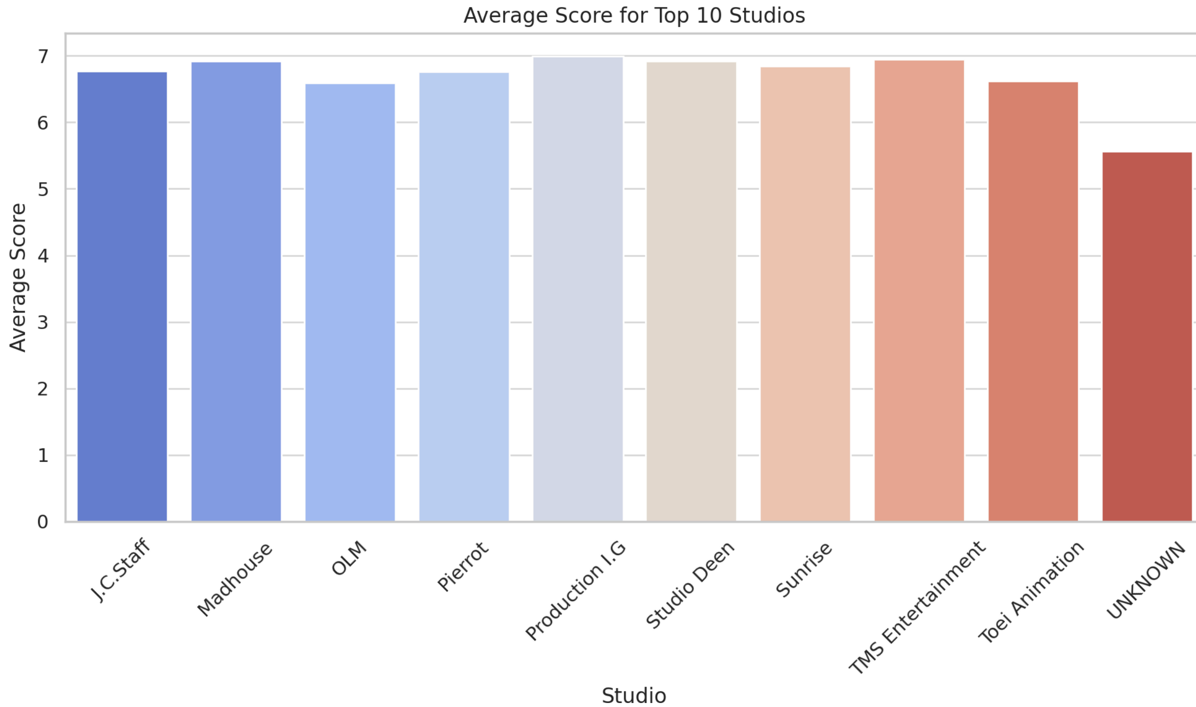
- **Type Comparison**: Bar chart revealed Movies (mean Score: 7.8) outperforming TV (7.1) and OVAs (6.9).



- **Temporal Trend**: A line plot indicated a gradual increase in average scores from 1990 (6.8) to 2023 (7.5).



- **Studio Impact**: Top studios like Madhouse (mean Score: 7.9) and Bones (7.8) consistently outperformed the "Other" category (7.0).



Discussion

Interpretation

The analysis reveals that **Airing Year** is the most significant predictor of anime ratings, suggesting that newer anime benefit from improved production quality, modern tastes, or rating inflation over time. **Episodes** also play a key role, with a sweet spot (e.g., 12–26 episodes) balancing depth and accessibility, as overly long series (e.g., >100 episodes) may dilute quality or alienate viewers. **Type (Movie)** highlights the appeal of concise, high-budget storytelling, while certain **Studios** (e.g., Madhouse) contribute to success through reputation and consistent quality. **Source (Manga)** indicates a preference for adapted works with established fanbases, and specific **Genres** like Drama enhance emotional engagement, boosting ratings.

Implications for Recommendations

These findings can refine recommendation systems by prioritizing:

- Recent releases or movies for users seeking high-rated content.
- Anime from top studios like Madhouse or Bones.
- Manga-based titles or those with moderate episode counts. Such insights allow systems to align suggestions with features driving user satisfaction.

Limitations

- **Overfitting**: The Random Forest model's high training R^2 versus testing R^2 suggests it may overfit to the training data, limiting generalizability.
- **Feature Interactions**: The model may not fully capture complex interactions (e.g., genre-studio synergy).
- **Data Bias**: The exclusion of anime with fewer than 100 scores may overlook niche or underrated titles.

Future Directions

Future research could:

- Explore hybrid models (e.g., collaborative filtering with user data) for personalized recommendations.
- Use clustering to identify anime subgroups with distinct rating patterns.
- Incorporate interaction terms or deep learning to model non-linear feature relationships.

Conclusion

This study demonstrates that anime success on MyAnimeList is driven by a combination of recency, episode count, format, studio reputation, source material, and genre. By moving beyond a genre-centric focus, we uncover a multifaceted view of user preferences, offering actionable insights for recommendation systems and anime production. These results underscore the value of diverse metadata in understanding audience tastes and pave the way for more nuanced analyses in anime research.

References:

https://www.kaggle.com/datasets/dbdmobile/myanimelist-dataset