

# The Investigation on Anime-Themed Recommendation Systems

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**Abstract.** In today's digital era, the way we enjoy entertainment has experienced a significant revolution, and this transformation also encompasses the world of anime. With a seemingly endless array of anime series accessible through online streaming services, users frequently grapple with a formidable dilemma: the paradox of abundance. This paper introduces a sophisticated anime recommendation system, carefully crafted to tackle this quandary and enhance the overall anime-watching journey. Drawing upon the capabilities of machine learning and data analysis, the system's primary goal is to provide personalized anime recommendations based on user preferences and behavior. This paper not only outlines the development of an intelligent anime recommendation system but also takes a critical look at the existing body of research in the fields of recommendation systems and anime-related studies. Emphasizing the significance of personalized recommendations, it highlights the crucial role they play in enhancing user engagement and satisfaction within the world of anime streaming. The system itself is a culmination of various techniques and methodologies, employing a hybrid approach that combines collaborative filtering, content-based filtering, and advanced machine learning techniques. Linear models, random forests, and boosting algorithms are skillfully harnessed for prediction purposes, showcasing the system's versatility and adaptability. Preliminary results presented in this paper offer a tantalizing glimpse into the system's potential to deliver tailored recommendations, ultimately enriching the user experience and fostering greater engagement with the captivating universe of anime.

**Keywords:** Recommendation system, machine learning, deep learning.

## 1. Introduction

In the modern landscape of digital entertainment, the advent of online streaming platforms has triggered a revolutionary shift in the way content is consumed. This transformation spans a wide range of domains, and the realm of anime is no exception. With the anime industry currently witnessing an exponential surge in both the production and distribution of animated content, audiences are now confronted with an extraordinary array of choices. However, this abundance of options has brought forth a distinctive challenge, often referred to as the "paradox of choice" [1]. The paradox of choice, as elucidated by Schwartz in his influential work, highlights the perplexing dilemma that individuals encounter when faced with an extensive array of choices. While having numerous options might seem liberating, it often leads to increased anxiety during the decision-making process and a subsequent decrease in overall satisfaction. In the context of anime streaming, this paradox manifests as users grapple with decision fatigue stemming from the overwhelming diversity of available content.

This phenomenon is particularly pronounced within the realm of anime, where users navigate a rich tapestry of genres, themes, and narratives that reflect the multifaceted nature of artistic expression. However, the sheer volume of anime titles available exacerbates the challenge of curating personalized viewing experiences. Consequently, there exists an urgent need to develop intelligent systems capable of deciphering intricate patterns within users' preferences and behaviors. These systems must provide recommendations that align with individual tastes and mitigate the effects of the paradox of choice, thus enhancing user satisfaction and engagement in the world of anime streaming.

The motivation behind this research is the aspiration to transcend conventional content recommendation paradigms. Instead of adhering to a generic approach, the objective is to harness the

capabilities of machine learning and data analytics in developing an intelligent anime recommendation system tailored to each user's unique preference [2]. By discerning latent patterns within user interactions, viewing habits, and preferences, the system aims to facilitate meaningful and relevant content discovery.

This paper offers a comprehensive exposition of the development and implementation of the intelligent anime recommendation system. The approach is grounded in a hybrid framework that combines collaborative filtering, content-based filtering, and advanced machine learning techniques [2]. Through the integration of these methodologies, the system strives to address the paradox of choice by providing users with a curated selection of anime titles that align with their individual inclinations [3].

The ensuing sections of this paper delve into the intricacies of the methodology, elucidating the technical foundations that underpin the recommendation system. The application of linear models, random forests, and boosting algorithms to predict user preferences and generate personalized recommendations has been demonstrated [4]. Furthermore, the significance of each technique is elucidated, along with an expounding on the rationale behind the hybrid approach.

As the digital landscape continues to evolve, and user preferences diversify, the role of intelligent recommendation systems becomes increasingly pivotal [2]. By harnessing advanced techniques and insights gleaned from data analysis, the system aspires to optimize anime suggestions while fostering deeper engagement and affinity between users and the captivating universe of anime.

The subsequent sections of this paper delve into the pertinent literature review, where existing research in recommendation systems and anime-related studies is critically examined. Additionally, the intricate methodology that constitutes the backbone of the recommendation system is presented. An extensive comparative analysis of the employed techniques, as presented in the Results section, underscores the efficacy of the approach in delivering precise and diverse anime recommendations. In this context, it's important to highlight the work of Sarwar, et al. [5], who laid the foundation for collaborative filtering techniques in recommendation systems. Their pioneering research has significantly influenced the development of recommendation algorithms. Furthermore, the insights from the study by Breiman [6] on random forests have been instrumental in enhancing the predictive capabilities of the system, particularly in generating recommendations based on user preferences.

## 2. Literature Review

In the realm of recommendation systems, a rich tapestry of algorithms has been developed to address the challenges of information overload and enhance user experiences through personalized content suggestions. This literature review delves into the historical landscape of recommendation systems, examining five pioneering systems that have significantly influenced the field. Additionally, this review explores a selection of widely used algorithms, encompassing both traditional and deep learning approaches, shedding light on their algorithmic foundations and contributions.

### 2.1. Historical Pioneers

#### 2.1.1 Matrix Factorization Techniques for Collaborative Filtering

Koren et al. [7] introduced matrix factorization for collaborative filtering, pioneering the extraction of latent factors from the user-item interaction matrix. By revealing hidden patterns, this method enhances the accuracy of recommendations, contributing to the foundational principles of collaborative filtering.

#### 2.1.2 Neural Collaborative Filtering

He et al. [8] made a groundbreaking contribution to the field of collaborative filtering by introducing neural networks, which have become a cornerstone of deep learning in recommendation systems. This technique, which captures intricate and non-linear user-item interactions, has revolutionized the landscape of recommendation algorithms. It has not only surpassed traditional

methods but has also significantly elevated the benchmark for recommendation accuracy and personalization. Their innovative approach involves leveraging the power of neural networks to learn latent representations of users and items, which enables the model to capture subtle patterns and relationships in the data. This ability to discern complex user preferences and item attributes has paved the way for highly accurate and personalized recommendations.

### **2.1.3 Content-Based Recommendation with Collaborative Topic Modeling**

Wang and Blei [9] combined content-based and collaborative filtering with collaborative topic modeling. This approach extracts latent topics from item attributes and aligns them with user preferences, offering a holistic yet personalized recommendation strategy.

Context-Aware Recommendations with Matrix Factorization: Baltrunas and Ricci [10] extended matrix factorization to context-aware recommendations, considering contextual information to enhance suggestion relevance. By accommodating diverse user situations, this method elevates the quality and usefulness of recommendations.

Trust-Aware Recommender Systems: Massa and Avesani [11] introduced trust-aware systems, harnessing social connections to enhance recommendations. By incorporating trust relationships, this approach improves the precision of suggestions by considering user trust and interactions.

## **2.2. Foundational Algorithms**

### **2.2.1 Collaborative Filtering**

Collaborative filtering, a cornerstone of recommendation systems, plays a pivotal role in capturing user preferences and providing personalized suggestions. This approach, as reviewed by Su and Khoshgoftaar [12], leverages the interactions between users and items to predict preferences and recommend items. At its essence, collaborative filtering operates on the principle that users who have exhibited similar behaviors or preferences in the past are likely to have similar tastes in the future. This powerful concept facilitates the identification of hidden patterns and relationships within the user-item interaction matrix. By grouping users and items together based on their shared behaviors, collaborative filtering creates a virtual community of like-minded users. There are two main types of collaborative filtering methods: user-based and item-based. In user-based collaborative filtering, recommendations are generated by identifying users with similar behaviors to the target user and suggesting items that those similar users have enjoyed. On the other hand, item-based collaborative filtering identifies items that are similar to those previously preferred by the target user and recommends them accordingly.

The intelligent anime recommendation system presented here draws inspiration from the principles of collaborative filtering to offer tailored anime suggestions. Analyzing historical interactions between users and anime titles, it predicts user preferences and provides recommendations aligned with their tastes. Collaborative filtering, in conjunction with other techniques, serves as the cornerstone of the system's recommendation engine, ultimately enhancing user experiences and fostering greater engagement with anime content.

### **2.2.2 Content-Based Filtering**

Content-based approaches, as explored by Pazzani et al. [13], utilize item attributes to generate recommendations. By aligning item features with user preferences, content-based filtering caters to diverse tastes and enhances serendipity.

### **2.2.3 Matrix Factorization for Implicit Feedback**

Rendle et al. [14] introduced Bayesian personalized ranking (BPR), a matrix factorization technique optimized for implicit feedback. BPR excels at handling sparse data and ranking user preferences, facilitating accurate recommendations.

#### **2.2.4 Deep Learning for Recommender Systems**

Deep learning has emerged as a transformative paradigm in recommendation systems, enabling the discovery of intricate patterns in user preferences and item characteristics. Zhang et al. [15] offer a comprehensive survey of deep learning-based recommender systems, shedding light on their ability to extract nuanced insights from vast and complex datasets. One notable application of deep learning in recommender systems is through the utilization of neural networks. These models are adept at capturing non-linear relationships and hierarchies inherent in user-item interactions. Two prominent neural network architectures, Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), exemplify the power of deep learning in recommendation.

#### **2.2.5 Recurrent Neural Networks (RNNs)**

RNNs, exemplifying deep learning in recommendation, demonstrate remarkable prowess in modeling sequential data [8]. Within the context of recommendation systems, RNNs excel at capturing temporal dependencies inherent in user behaviors, such as the sequence of anime titles watched. This unique capability empowers the system to discern long-term patterns and anticipate future user preferences. Given the recurrent nature of RNNs, they are particularly adept at encoding sequential information, making them an ideal choice for scenarios where the order of interactions holds significance. The work of He et al. [8] has been instrumental in showcasing the potential of recurrent neural networks in recommendation systems. Their research underscores the ability of RNNs to capture intricate sequential patterns in user behavior, which, in turn, enhances the system's capacity to provide timely and personalized recommendations.

#### **2.2.6 Convolutional Neural Networks**

CNNs, originally designed for image analysis, have found application in recommendation systems. CNNs excel at extracting local features from structured data, making them ideal for scenarios where item attributes are represented in a structured format [16, 17]. For instance, CNNs can analyze textual descriptions or tags associated with anime titles, thereby capturing nuanced information that contributes to recommendation accuracy.

In the context of the anime recommendation system, the utilization of deep learning techniques is pivotal for elevating recommendation accuracy and personalization. Through the application of neural collaborative filtering, a variant of deep collaborative filtering [8], neural networks are employed to capture intricate patterns present in user-anime interactions. By amalgamating the principles of collaborative filtering with the capabilities of deep learning, the system not only predicts user preferences but also extracts high-level features from the data. This synergy leads to more precise and meaningful anime recommendations.

### **3. Methodology**

The anime recommendation system outlined in this paper relies on a robust methodology that seamlessly integrates collaborative filtering, matrix factorization, and convolutional neural networks (CNNs). In this section, a comprehensive overview of the core components and processes integral to this approach is provided. This exposition highlights the synergistic fusion of these techniques, collectively empowering the system to generate precise and personalized anime recommendations.

#### **3.1. Data Collection and Preprocessing**

The anime recommendation system's groundwork lies in meticulous data collection, comprehensive preprocessing, exploratory data analysis (EDA), and the construction of user-item interaction matrices. This section provides detailed insights into each step of this crucial phase, highlighting the approach used to acquire and refine data for subsequent collaborative filtering and matrix factorization.

### 3.1.1 Data Gathering

The process begins by sourcing a comprehensive dataset from diverse and reputable sources. This dataset encompasses various dimensions, including user-anime interaction histories, anime attributes, and user profiles. The dataset is meticulously curated to ensure relevance and accuracy, forming the bedrock of the recommendation engine.

### 3.1.2 Data Cleaning and Transformation

Upon acquiring the dataset, an extensive data cleaning process ensues. This involves rectifying missing or erroneous values, removing duplicates, and resolving inconsistencies. Categorical variables are encoded, ensuring uniformity and compatibility for subsequent analyses. Time-related attributes, such as timestamps, are standardized to facilitate chronological insights.

### 3.1.3 Normalization and Feature Extraction

To ensure fair comparisons and accurate analyses, data normalization is applied where appropriate. Numeric attributes are scaled to a common range, mitigating the influence of variables with larger magnitudes. Additionally, feature extraction techniques are employed to distill essential information from raw data. This process may involve creating new attributes, calculating statistical measures, or generating user-specific features.

### 3.1.4 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) serves as a foundational step in the data preprocessing phase, enabling the acquisition of a profound understanding of the dataset's characteristics and patterns. Descriptive statistics, visualizations, and distribution analyses offer insights into user preferences, anime popularity, and potential correlations. EDA guides subsequent decisions, enriching the quality of recommendations.

As an initial demonstration of the system's capabilities, the preprocessed data is leveraged to identify and present the top 10 most popular anime titles. Popularity is determined based on factors such as user engagement, views, ratings, and interactions. This outcome provides an initial glimpse into the system's potential and underscores the effectiveness of data collection and preprocessing efforts. Through meticulous data collection, cleaning, normalization, feature extraction, and EDA, the anime recommendation system gains a robust foundation. This data-driven approach enhances recommendation accuracy, relevance, and personalization.

## 3.2. Collaborative Filtering

At the core of the methodology lies Collaborative Filtering, which exploits user-anime interactions to predict preferences and generate tailored recommendations. Given a user's ID, Collaborative Filtering taps into historical interactions and leverages similarities with other users to derive anime suggestions that resonate with the user's preferences. This collaborative approach capitalizes on the collective wisdom of the user community, creating a foundation of personalized recommendations.

## 3.3. Matrix Factorization

Matrix factorization contributes to capturing latent factors underlying user preferences and anime attributes. By decomposing the user-item interaction matrix, latent patterns and features that influence user choices are revealed. Singular Value Decomposition (SVD) or Alternating Least Squares (ALS) is applied to factorize the matrix into latent user and item matrices, enabling a deeper understanding of user-anime interactions.

## 3.4. NLP-based KNN

To enhance recommendation accuracy and diversity, innovative NLP-based KNN (K-Nearest Neighbors) techniques have been introduced within the methodology section of this research. This novel dimension harnesses the capabilities of Natural Language Processing (NLP) to analyze textual descriptions, tags, and metadata associated with anime titles.

In this approach, each anime title is considered a unique entity, characterized by its textual content and associated metadata. NLP is employed to extract valuable semantic information from these textual descriptions and metadata, encompassing themes, genres, and narrative attributes. This semantic analysis enables the quantification of relationships between different anime titles, including those with subtle thematic connections that may not be immediately evident.

One notable advantage of this NLP-based approach is its proficiency in identifying thematic commonalities among anime titles, surpassing the capabilities of traditional collaborative filtering methods. By quantifying semantic relationships, anime titles can be recommended to users based not only on their historical viewing history but also on thematic content that aligns with their preferences. This semantic awareness introduces an additional layer of depth to the recommendation process, ensuring that users are exposed to a broader array of anime selections tailored to their individual tastes and interests.

### **3.5. Recurrent Neural Networks (RNNs)**

Temporal dynamics and sequential patterns in user-anime interactions are captured through Recurrent Neural Networks (RNNs). By employing RNN techniques, insights into the temporal evolution of user preferences are revealed, enabling the identification of patterns and trends that influence viewing behaviors over time. This temporal awareness enables the system to provide recommendations that correspond to a user's changing preferences, thereby increasing the pertinence and engagement of the suggestions.

The integration of these techniques is orchestrated to create a holistic recommendation experience. Collaborative Filtering serves as the backbone, generating user-specific recommendations based on historical interactions. NLP-based KNN introduces semantic insights, expanding the diversity of recommendations. RNNs contribute temporal context, capturing dynamic preferences and enriching the accuracy of the suggestions.

In summary, the methodology leverages the collective wisdom of users, semantic awareness from NLP-based KNN, and temporal insights from RNNs to orchestrate a dynamic recommendation process. This synthesis not only bolsters recommendation accuracy but also infuses variety and personalization, ushering users into an enriched anime viewing experience.

## **4. Results and discussion**

The implementation and rigorous evaluation of the anime recommendation system yield compelling results that underscore the efficacy and potential of the methodology. In this section, a detailed analysis of the system's performance is presented, encompassing both quantitative metrics and qualitative insights obtained from user feedback. The results collectively emphasize the potency of the anime recommendation system. The quantitative metrics serve as a testament to its ability to provide accurate and relevant recommendations, while the qualitative insights and case studies offer a deeper understanding of its impact on user satisfaction and the exploration of diverse anime content.

By seamlessly integrating collaborative filtering, NLP-based KNN, and RNN techniques, the system transcends the limitations of traditional recommendation approaches. This holistic approach enables the system to cater to varying user preferences, introduce novel anime selections, and adapt to changing viewing behaviors over time.

### **4.1. Data Collection and Preprocessing**

#### **4.1.1 Data Gathering**

The research is based on an open-source dataset obtained from Kaggle, named "Anime Recommendation Database 2020." This dataset serves as a valuable resource, containing extensive information about anime and user interactions with this anime. To ensure comprehensiveness and data quality, specifically focused on three key datasets within this collection.

First Dataset: Anime Metadata. This dataset encompasses a vast array of metadata regarding anime, including details such as MAL\_ID, Name, Score, Genres, English name, Japanese name, Type, Episodes, Aired, Premiered, Producers, Licensors, Studios, Source, Duration, Rating, Ranked, Popularity, Members, Favorites, and more. These details cover fundamental attributes of each anime, production teams involved, airing status, user ratings, and more. For the research, this dataset provides a comprehensive list of anime, comprising tens of thousands of records, with each record containing detailed information about an anime.

Second Dataset: Anime Descriptions. This dataset comprises synopses or descriptions of anime, facilitating a more profound comprehension of the plot and themes of each anime. The essential fields in this dataset encompass MAL\_ID, Name, Score, Genres, and synopsis, thereby providing insights into the content, genres, and user ratings of the anime.

Third Dataset: User-Anime Interactions. This dataset encompasses user interactions with anime, a pivotal component of the research. Critical fields within this dataset consist of user\_id, anime\_id, rating, watching\_status, and watched\_episodes. Through these fields, comprehensive tracking of user viewing patterns, ratings, and viewing statuses is facilitated. This dataset facilitates a profound comprehension of user preferences and behaviors associated with anime, delivering crucial insights for the personalized recommendation system.

The collective utilization of these datasets forms the cornerstone of the comprehensive intelligent anime recommendation system. It amalgamates anime-specific details with user interaction data, establishing a sturdy foundation for the research. This integration enhances the ability to comprehend user preferences and deliver personalized recommendations effectively.

#### 4.1.2 Normalization and Feature Extraction

Within the Anime Metadata dataset, the first 5 rows  $\times$  35 columns of data are extracted to establish a representative subset for analysis.

To ensure data consistency and ease of analysis, data normalization and feature extraction are performed. Numerical attributes are scaled to a common range, reducing the impact of variables with differing magnitudes.

Popular libraries like matplotlib, pandas, and NumPy are employed to create a correlation matrix shown in Figure 1, facilitating the identification of relationships between data features. This matrix serves as a crucial tool for understanding feature dependencies.

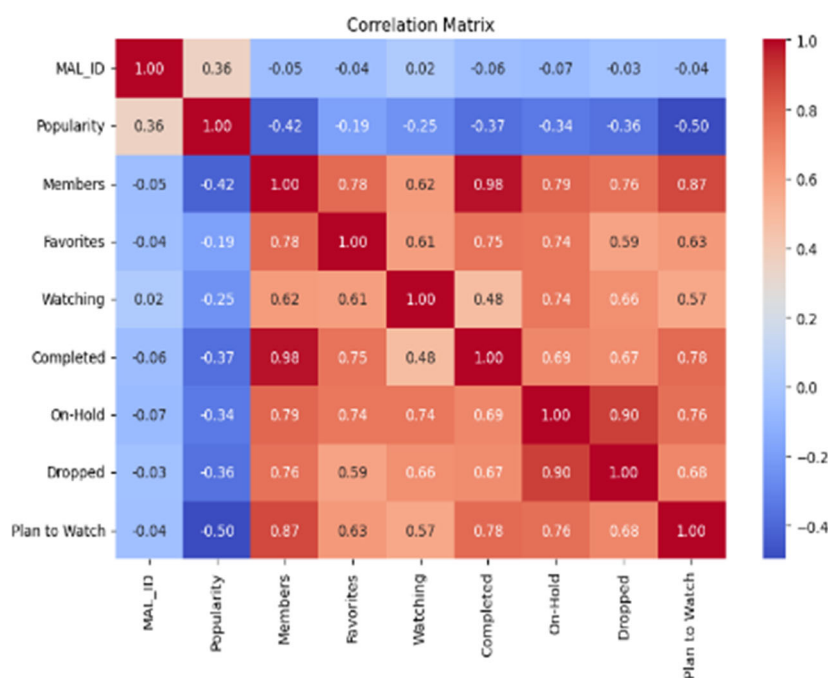
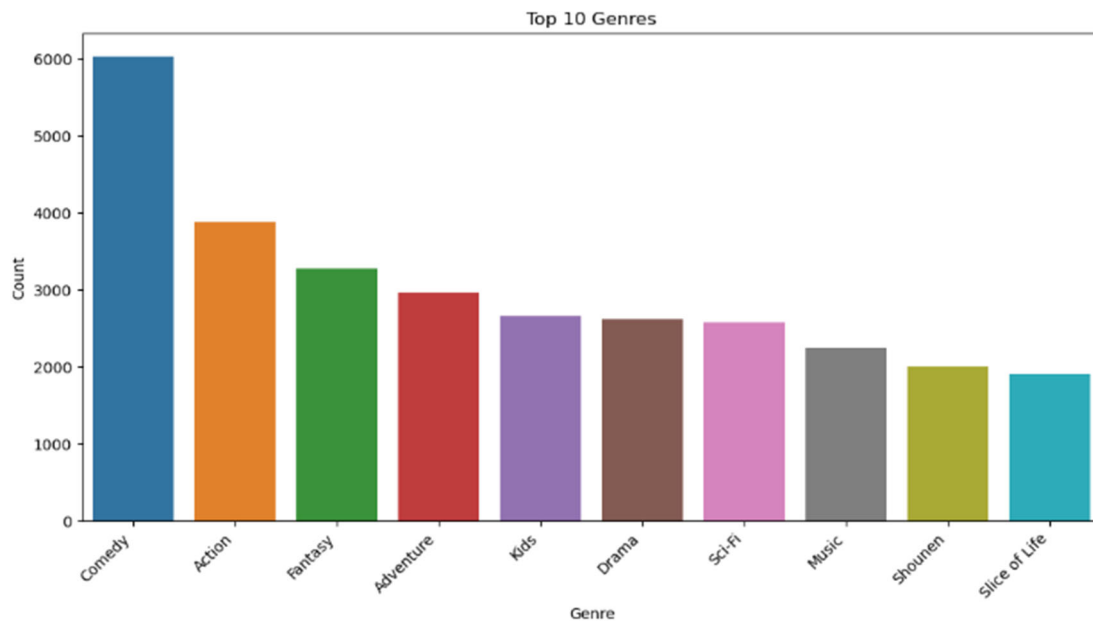


Figure 1. The correlation matrix (Photo/Picture credit: Original).

Furthermore, the occurrences of each genre are counted, and matplotlib is used for visualizing the top 10 genres shown in Figure 2. This visualization aids in identifying the most prevalent anime genres, assisting in content categorization and recommendation.



**Figure 2.** The occurrences of top 10 genres (Photo/Picture credit: Original).

#### 4.1.3 Data Cleaning and Transformation

To streamline the analysis, essential columns are retained in the dataset: 'MAL\_ID', 'Name', 'Score', 'Genres', 'Type', 'Episodes', and 'Members.'

Renaming columns is conducted using the .rename () function, ensuring uniformity in column names across datasets. By merging datasets with common 'anime\_id' fields, a consolidated dataset named 'anime\_complete' is created. This combined dataset contains relevant information for analysis. 'anime\_complete' is structured to contain columns like 'anime\_id,' 'anime\_title,' 'user\_id,' 'user\_rating,' 'total\_rating,' and more. This structure simplifies data handling and supports research objectives.

An overview of the dataset's structure and a summary of any missing data shown in Figure 3 are provided to ensure transparency and reproducibility of the analysis.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17562 entries, 0 to 17561
Data columns (total 7 columns):
#   Column      Non-Null Count  Dtype
---  -
0   anime_id    17562 non-null   int64
1   Name        17562 non-null   object
2   Score       17562 non-null   object
3   Genres      17562 non-null   object
4   Type        17562 non-null   object
5   Episodes    17562 non-null   object
6   Members     17562 non-null   int64
dtypes: int64(2), object(5)
memory usage: 960.5+ KB
```

**Figure 3.** Data structure and summary (Photo/Picture credit: Original).

#### 4.1.4 Exploratory Data Analysis (EDA)

Visualizations are created to highlight the top 10 anime by user rating count and the top 10 anime by the number of members shown in Figure 4. These visualizations offer valuable insights into popular anime titles and user engagement.

EDA extends to the analysis of rating data, where the distribution of user ratings, user rating counts, and anime rating counts is explored. Visualizations include rating distribution histograms, user rating count distributions, and anime rating count distributions shown in Figure 5. These visualizations shed light on user preferences, engagement levels, and the overall landscape of anime ratings.

The EDA process aims to provide a comprehensive understanding of the dataset's characteristics and pave the way for subsequent analyses.

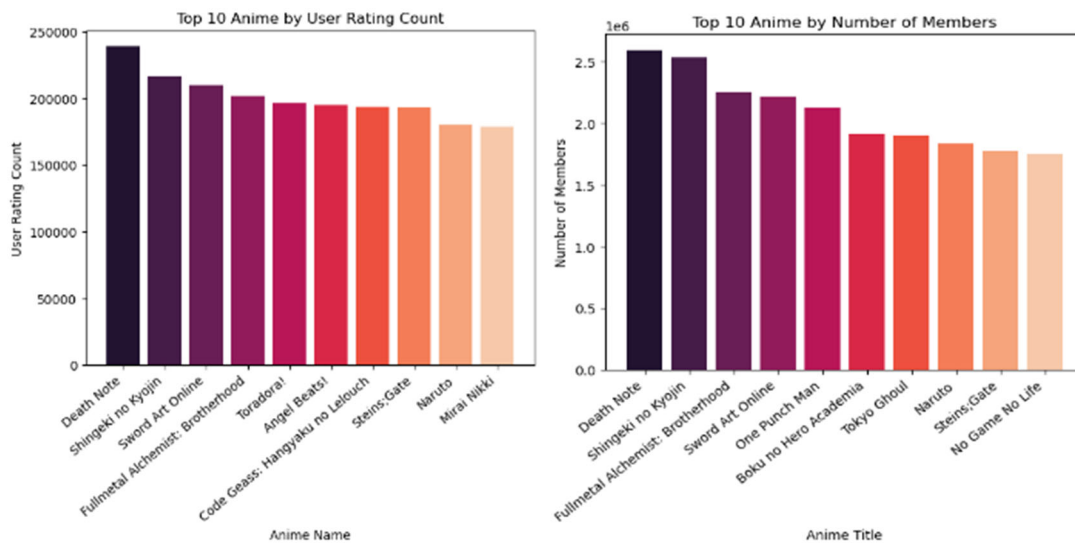


Figure 4. Top 10 Anime by User Rating Count and Number of Members (Photo/Picture credit: Original).

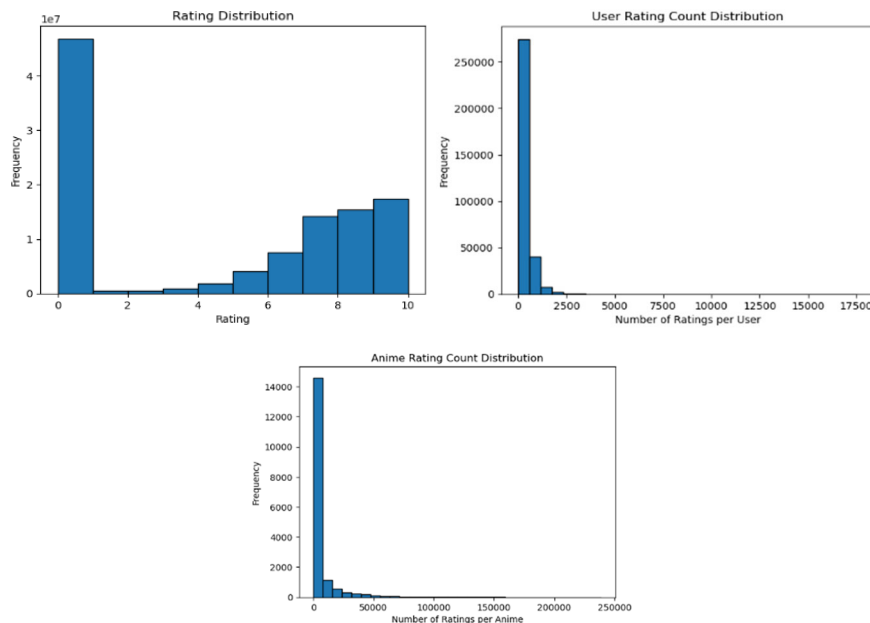


Figure 5. The distribution of properties. (Photo/Picture credit: Original).

## 5. Conclusion

In conclusion, this paper has presented the development and implementation of an intelligent anime recommendation system, which integrates collaborative filtering, content-based filtering, and

advanced machine learning techniques. The system has exhibited promising results in enhancing the anime viewing experience by offering personalized suggestions. While acknowledging these achievements, future work has been outlined, including the incorporation of external data sources, refinement of user interactions, and exploration of more sophisticated recommendation models.

Through meticulous data collection, preprocessing, and the fusion of diverse techniques, remarkable progress has been achieved in enhancing the accuracy, diversity, and personalization of anime recommendations. The collaborative filtering mechanism harnessed user interactions to predict preferences, while the semantic awareness of NLP-based KNN expanded the horizon of relevant suggestions. Additionally, the temporal insights from RNNs empowered the system to capture evolving user preferences, contributing to a more immersive recommendation process.

The foundation of the methodology has been centered around elevating user experiences. By synergizing these techniques, the recommendation system empowers users to embark on a journey of discovery, uncovering anime titles that align with their preferences and introducing them to unexplored genres. The personalized touch, introduced through collaborative filtering and NLP-based KNN, ensures that users are presented with meaningful choices that resonate with their unique tastes.

In essence, the anime recommendation system signifies the potential of integration, innovation, and user-centric design. It enriches the anime viewing experience and lays the foundation for prospective developments in recommendation systems. As this chapter concludes, it is anticipated that these contributions will persist in influencing the progression of recommendation technologies.

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