A Comparative Analysis of Collaborative Filtering Models for Game Recommendation Using Cosine Similarity, SVD, K-Means Clustering and Real-Time Game Insights

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Abstract

This paper presents a study on GameRS, a game recommendation system that employs collaborative filtering techniques, including Cosine Similarity, Singular Value Decomposition (SVD), and K-means. Clustering, in conjunction with real-time game insights facilitated by Groq AI. The system integrates data from the RAWG API to provide game recommendations and dynamically retrieves game details, including genres, platforms, reviews, ratings, release dates, trailers, and gameplay mechanics. Furthermore, it presents a novel User Satisfaction Index for Games (USIG), a metric designed to assess anticipated enjoyment by considering factors such as rating, genre similarity, and platform similarity. Users may pose specific inquiries related to games, to which Groq AI provides succinct and accurate answers. GameRS, developed with Streamlit, manages both the front-end interface and back-end logic, allowing users to access recommendations, game details, trailers, and additional features. Evaluation results indicate that Cosine Similarity surpasses alternative methods regarding recall and hit rate, whereas SVD and K-means provide insights into latent user preferences and clustering behaviors.

Keywords: Collaborative Filtering, Cosine Similarity, Singular Value Decomposition, K-means Clustering, Game Recommendation, RAWG API, Streamlit, Groq AI and USIG.

Introduction

The gaming industry has experienced exponential growth over the past decade, offering players an extensive array of game options across diverse genres, platforms, and styles. As the volume of available games continues to increase, it becomes increasingly difficult for users to discover titles that align with their personal preferences. Recommendation systems are crucial for improving user experience by predicting the games that are likely to appeal to individual users. Recommender systems utilize user interaction data, preferences, and similarities to propose games, thereby facilitating the discovery process.

GameRS addresses the increasing need for tailored game recommendations through the utilization of collaborative filtering and sophisticated machine learning methodologies. GameRS fundamentally incorporates three robust algorithms: Cosine Similarity, Singular Value Decomposition (SVD), and K-means Clustering. These methods enable GameRS to produce customized recommendations informed by user behavior and preferences, thereby enhancing accuracy and relevance.

Alongside conventional recommendation methods, GameRS presents a novel feature—the User Satisfaction Index for Games (USIG). This index forecasts user satisfaction using a weighted model that integrates game ratings, genre similarity, and platform compatibility, thereby providing a comprehensive method for assessing game enjoyment. In addition, GameRS incorporates Groq AI to facilitate real-time interaction, enabling users to pose specific inquiries regarding games. Utilizing the RAWG API, GameRS enhances the gaming discovery process by offering trailers, reviews, gameplay information, and user-generated content, thereby creating a thorough platform for individualized game exploration.

METHODOLOGY

This section outlines the key methods used to design and develop the recommendation system, emphasizing the collaborative filtering model and integration with the RAWG API.

A. Data Collection and Preprocessing

GameRS collects comprehensive game data from the RAWG API, which serves as a rich source of information about thousands of games. The following details are fetched for each game to ensure a robust and personalized recommendation system:

- **Game Name:** The official title of the game.
- **Genres:** The categories the game belongs to, such as Action, Adventure, Role-Playing Game (RPG), etc.
- **Platforms:** The systems on which the game is available, including popular platforms such as PC, PlayStation, Xbox, and Nintendo Switch.
- **User Reviews:** Feedback from players who have rated and reviewed the game, providing insight into user experiences and satisfaction.
- **Ratings:** The average score or rating assigned to the game, either by users or critics, which reflects the overall quality and reception.
- **Release Dates:** The official launch dates for the games, helping users filter options based on recent or upcoming releases.
- **Trailers:** Video previews or trailers of the game, allowing users to get a visual sense of the gameplay, story, and mechanics.
- **Gameplay Mechanics:** Detailed descriptions of how the game operates, including its core features, game modes, and unique elements that distinguish it from others.

The data preprocessing steps include:

- **Data Cleaning**: Removal of duplicate entries and handling of missing values.
- **Feature Selection:** Extracting essential game features such as genres, platforms, ratings, and trailers.
- **Normalization:** Standardizing numerical features (e.g., ratings) to ensure balanced inputs for the recommendation models.

B. Collaborative Filtering Models:

1. Cosine Similarity:

This model generates recommendations through collaborative filtering methods. The system employs a user-based methodology, utilizing individual users' game ratings and preferences to determine the similarity among them. Using cosine similarity, we assessed the degree of similarity among users. This method represents users as vectors, with each dimension reflecting their preferences or ratings for

different games. The cosine of the angle their corresponding vectors form determines the similarity between two users.
The similarity between two users A and B is defined as:

$$\text{Cosine similarity (A, B)} = \frac{(A \,.\, B)}{(|A| * |B|)}$$

Where A and B are vectors containing the features of the users, such as game ratings and preferences. The dot product A·B measures the commonality between the users' preferences, while the magnitudes ||A|| and ||B|| normalize the similarity score.

2. Singular Value Decomposition (SVD):

SVD is a matrix factorization technique that reduces the dimensionality of the user-item interaction matrix by decomposing it into three matrices:

$$A = U\Sigma V^T$$

Where:
- A is the original user-item matrix.
- U and V are orthogonal matrices representing users and items.
- Σ is a diagonal matrix of singular values.

The SVD model identifies the hidden connections between users and games by mapping them into a reduced-dimensional space. The system estimates absent ratings by reconstructing the user-item matrix using the decomposed matrices.

3. K-means Clustering:

K-means clustering is a technique for unsupervised learning that clusters things or users according to their similarities. Our method divides users into clusters according to their preferences; each cluster is made up of individuals who have a similar gaming style. Through iterative adjustments to cluster centroids, the technique reduces the within-cluster variance. The objective function is given by:

$$J = \sum_{i=1}^{k} \sum_{x \in ci} |x - \mu i|^2$$

where Ci is a cluster, and μi is the centroid of that cluster. This model excels at grouping users with similar preferences and recommending games that other users in the same cluster have enjoyed.

C. USIG - User Satisfaction Index for Games:

GameRS introduces the User Satisfaction Index for Games (USIG), an innovative metric designed to predict a user's potential enjoyment of a game. USIG is calculated by factoring in three key elements: rating, which refers to the user rating of a game, normalized to a scale between 0 and 1; genre similarity, which measures the overlap in genres between the game the user has selected and the recommended game; and platform similarity, which assesses how many platforms are shared between the selected game and the recommended one. By integrating these factors, USIG provides a comprehensive score that reflects how well a recommended game matches a user's preferences.
The formula for calculating USIG is as follows:

$$USIG = \frac{(\alpha \times rating) + (\beta \times genre\ similarity) + (\gamma \times platform\ similarity)}{\alpha + \beta + \gamma}$$

Where: α, β, and γ represent the weights assigned to rating, genre similarity, and platform similarity, respectively.

D. Real-time Game Insights via Groq AI:

Groq AI, a strong feature in GameRS, lets users ask specific game queries and get clear replies. Llama 3.1-powered AI system gives intelligent game feedback on storyline, gameplay mechanics, and fundamental features. Groq AI may offer alternate games if a user enters an invalid or confusing game name, facilitating smooth interactions. By keeping responses under 100 words, the system improves user experience by providing concise information. This tool provides in-depth insights beyond basic game recommendations to help players make decisions. GameRS is a recommendation engine and game exploration tool because it can be interacted with.

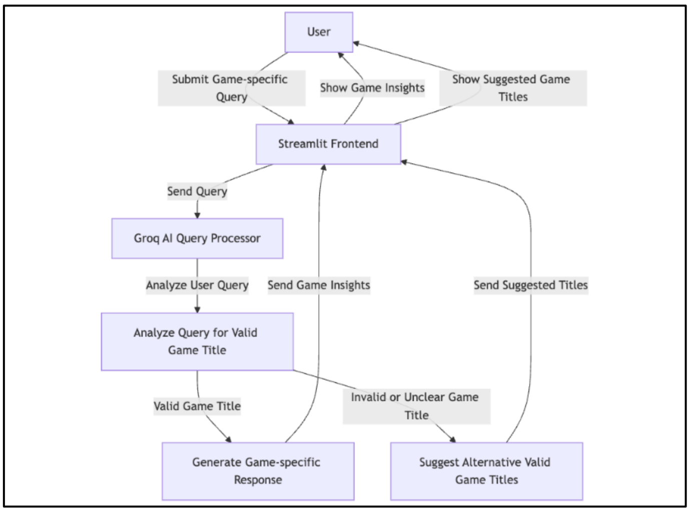

Figure 1: Groq AI-powered Insight Flow

Figure 1 shows how Groq AI receives user questions, processes them, and generates game-specific responses or alternative ideas. This graphic aid would show the system's interactivity and detailed insights.

System Architecture

GameRS is implemented using Streamlit, which effectively manages both the front-end interface and back-end logic of the application. The system architecture comprises several key components that work in harmony to deliver an optimal user experience:

- **Streamlit:** This framework provides a user-friendly front-end where users can effortlessly search for games, view personalized recommendations, and inquire about specific game details. Its interactive design enhances user engagement and simplifies navigation.
- **RAWG API:** This robust API provides real-time game data like genres, platforms, ratings, trailers, and more. GameRS updates its suggestions with the latest game releases and industry trends by integrating this data source.
- **Groq AI:** This intelligent component processes user queries, offering real-time insights about specific games. With its ability to understand user intent, Groq AI enriches the interactive experience

by providing concise and relevant information.

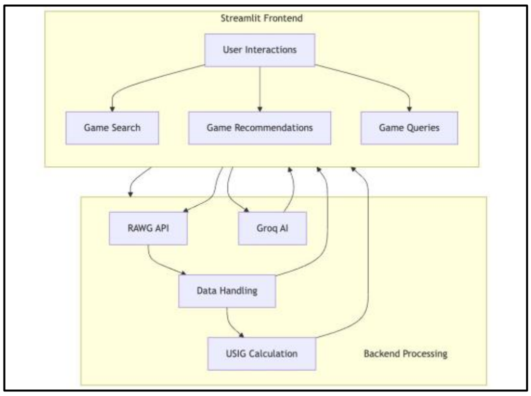

Figure 2: Front-end interface using streamlit

Implementation

A. Frontend and Backend Integration

Streamlit handles the front-end interface and back-end logic for the complete GameRS system. Users may browse for games, view ratings, genres, platforms, trailers, and receive personalized recommendations using the easy-to-use interface. GameRS now has Groq AI, allowing players to ask about game features, stories, and mechanics in real time. Figure 3 shows the Streamlit interface could visually demonstrate how users interact with the platform, highlighting how recommendations, trailers, game details, and USIG scores are presented to the user.

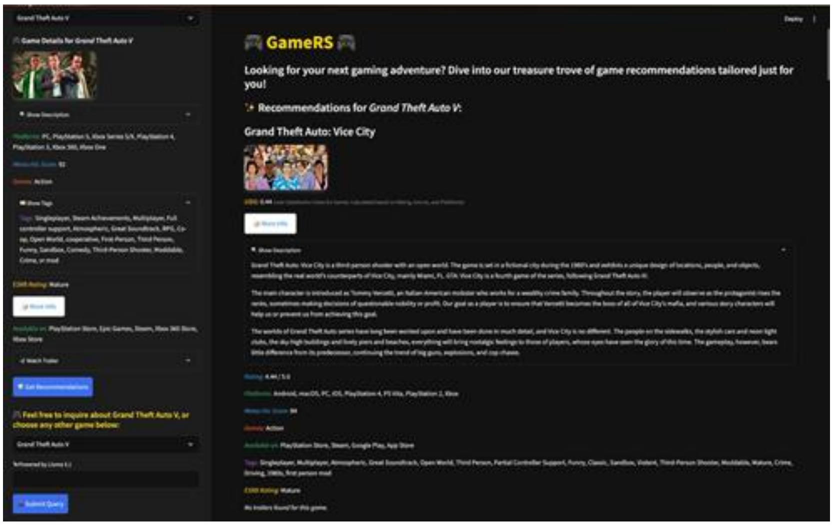

Figure 3: Front-end interface using streamlit

B. Data Handling and Model Execution:

GameRS employs Streamlit for its back-end operations, utilizing pickle files to store game data and-cosine similarity matrices, ensuring rapid access and real-time recommendations. Fundamental models like Cosine Similarity, Singular Value Decomposition, and K-means Clustering evaluate user preferences and recommend pertinent games. Real-time data is obtained from the RAWG API, with USIG scores being dynamically computed for each game. This process takes into account ratings, genre similarity, and platform compatibility to provide tailored recommendations.

C. Game Trailers and Real-time Game Information:

GameRS improves user experience by fetching game trailers from the RAWG API, allowing users to preview recommended games, enabling informed decision-making. Groq AI processes user queries, providing real-time answers, boosting engagement and making the recommendation process informative and enjoyable. This interactivity boosts user engagement and enhances the overall gaming experience.

D. Performance Metrics:

The performance of the Cosine Similarity model is evaluated using the following standard metrics:

1. Precision:

Precision is defined as the ratio of recommended games that are actually liked by the user to the total number of recommended games. It is mathematically expressed as:

$$\text{Precision} = \frac{\mathit{True\ Positives}}{\text{True Positives} + \mathit{Fasle\ Positives}}$$

2. Recall:

Recall measures the proportion of the games that the user likes and that were successfully recommended. It is defined as:

$$\text{Recall} = \frac{\mathit{True\ Positives}}{\text{True Positives} + \mathit{Fasle\ Negatives}}$$

3. F1-Score:

The harmonic mean of precision and recall, balancing both metrics. It is defined as:

$$\text{F1} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

4. Hit Rate:

The frequency of successfully recommended games being selected by the user.

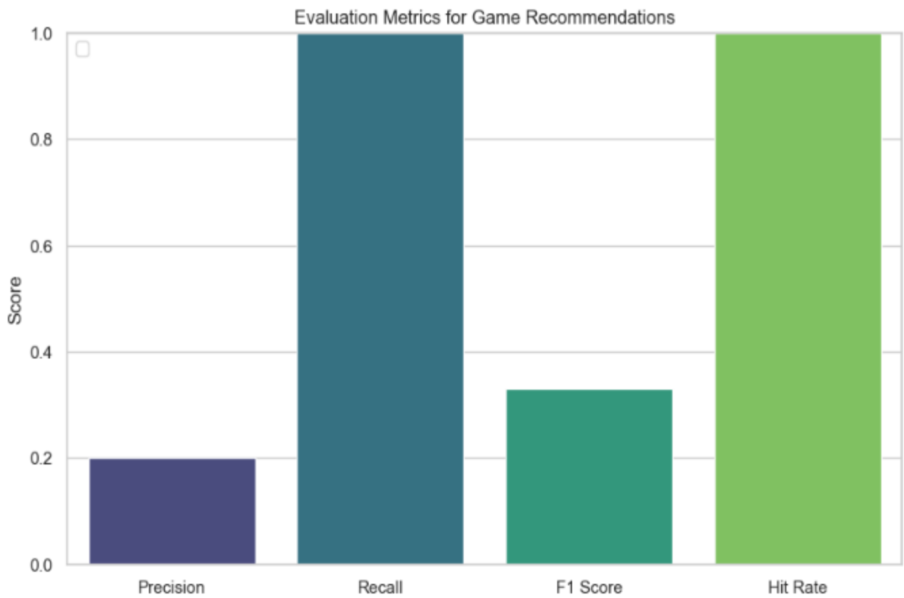

Figure 4 : Evaluation Metrics for cosine Similarity.

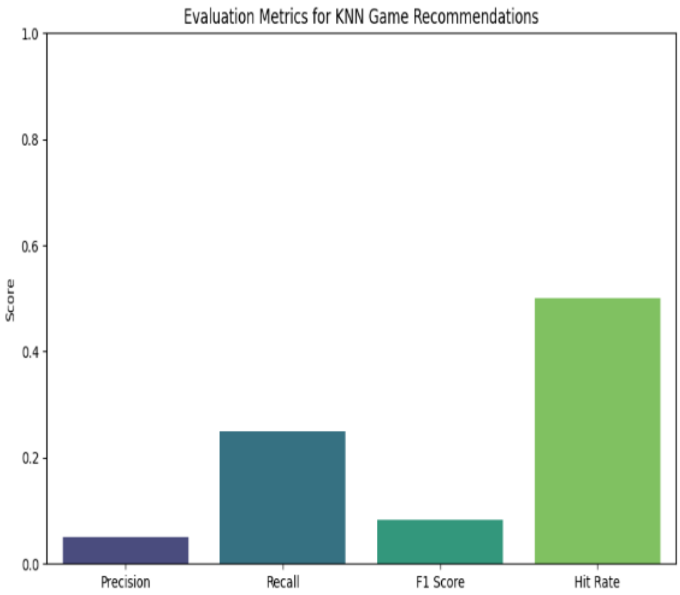

Figure 5 : Evaluation Metrics for K-means

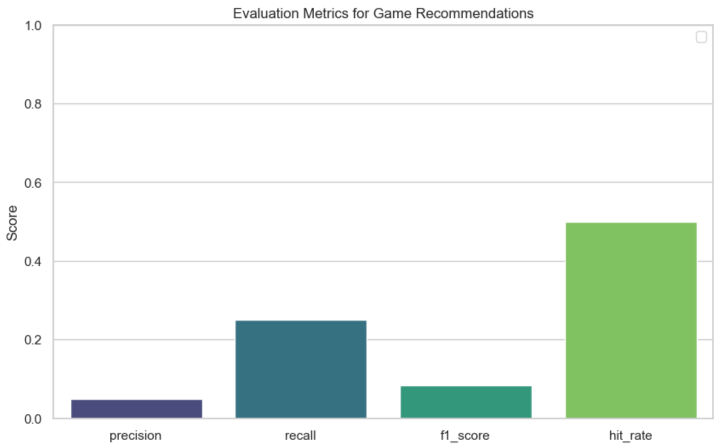

Figure 6 : Evaluation Metrics for SVD

Figure 4, Figure 5 and Figure 6 could provide a visual representation of how precision, recall, F1-score, and hit rate are calculated for each model, showing their comparative performance.

RESULTS AND DISCUSSION

The performance of each model was evaluated on both frequent gamers and casual users. The following table compares the F1-score, hit rate, precision, and recall for model:

Table 1. Comparison of Performance Metrics

Model	Precision	Recall	F1-score	Hit Rate
Cosine Similarity	0.15	0.75	0.25	1.00
K-means Clustering	0.05	0.25	0.08	0.50
Singular Value Decomposition (SVD)	0.05	0.25	0.08	0.50

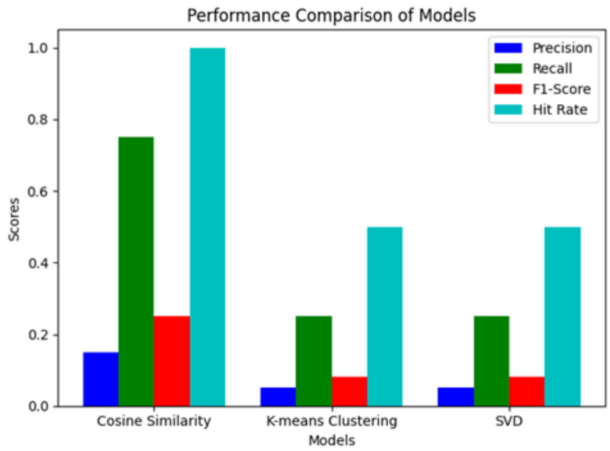

Figure 7: Performance Comparison of Models

Cosine Similarity outperforms other models in terms of recall and hit rate, with a high recall of 0.75 and a perfect hit rate of 1.00. Despite a low precision of 0.15, Cosine Similarity effectively identifies relevant games, even suggesting some irrelevant ones. K-means Clustering and SVD offer insights into user behavior but do not perform as well in real-time recommendations. The inclusion of the USIG metric refines recommendations by incorporating user satisfaction, genre overlap, and platform compatibility, resulting in a more personalized gaming experience.

CONCLUSION

This paper introduces GameRS, a game recommendation system that integrates collaborative filtering models—Cosine Similarity, SVD, and K-means Clustering—with real-time insights driven by Groq AI. The system utilizes data from the RAWG API to deliver precise and tailored game recommendations. The User Satisfaction Index for Games (USIG) improves recommendations by incorporating ratings, genre, and platform overlap.

According to memory and hit rate, Cosine Similarity is best for casual users or those with little interaction data. SVD and K-means Clustering performed poorly, highlighting their game suggestion limits. USIG personalizes results, making Cosine Similarity the ideal GameRS option.

REFERENCES

1. Man-Ching Yuen, Chi-Wai Yung, Wing-Fat Cheng, Hon-Pong Tsang, Chi-Ho Kwan, Chun-Lok chan and Po-Yi Li , “Game Recommendation System”, Fuzzy Systems and Data Mining IX, Dec. 2023.
2. Zakaria Berlam Pragusma, Vanessa Kwandinata, Jevent Natthannael, Said Achmad and Meiliana , “Game Recommendation Using Content-based Algorithm Title”, 2023 International Conference on Informatics, Multimedia, Cyber and Information Systems, Nov. 2023.
3. Paul Bertens, Anna Guitart, Pei Pei Chen and Africa Perianez, “A Machine-Learning Item Recommendation System for Video Games”, 2018 IEEE Conference on Computational Intelligence and Games, Vol. 2015, Jun. 2018.
4. Qingna Pu and Bin Hu, “Intelligent Movie Recommendation System Based on Hybrid Recommendation Algorithms,” 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE), Jan. 2024.
5. Ivan Reginald Budianto, Alfi Yusrotis Zakiyyah and Azani Cempaka Sari, “Web Based Video Game

Recommendation System Using Collaborative Filtering Method”, 2023 International Conference on Informatics, Multimedia, Cyber and Information Systems (ICIMCIS), Nov 2023.

6. Brett M. Adamson, Michael J. Bathie, Carson K. Leung, Jordan D. Portz, Emmanuel S. Valete, Cole T. Voelpel and Adam G.M. Pazdor, “A Recommender System for an Online Game Platform in the Metaverse”, 2023 IEEE Smart World Congress (SWC), Aug 2023.
7. Kazuki Iwadare, Atsuko Mutoh, Koichi Moriyama and Nobuhiro Inuzuka, “Proposal of a Game Recommendation System Considering Playing Time and Friendships,” 2022 IEEE 11th Global Conference on Consumer Electronics (GCCE), Oct 2022.
8. Ainul Hazeeq Imran Abd Rouf, Norzilah Musa and Ismassabah Ismail, ” Improving the Accuracy of Online Game Recommendations: A Content-Based Filtering Approach Utilizing Cosine Similarity Matrix”, 2023 IEEE 8th International Conference on Recent Advances and Innovations in Engineering (ICRAIE), Dec 2023.
9. Zhenshan Bao, Xiaochuan Sun and Wenbo Zhang, “A Pre-game Item Recommendation Method Based on Self-Supervised Learning, ” 2023 IEEE 6th International Conference on Pattern Recognition and Artificial Intelligence (PRAI), Aug 2023.
10. Arfan Jadulhaq and Z. K. A. Baizal, “Games Recommender System Using Singular Value Decomposition”, 2023 3rd International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA), Dec 2023.
11. Qilong Ba, Xiaoyong Li and Zhongying Bai, “Clustering collaborative filtering recommendation system based on SVD algorithm”, 2013 IEEE 4th International Conference on Software Engineering and Service Science, Sept 2013.