Personalized Game Recommendation System Using Collaborative Filtering and Content-Based Techniques

Course: Recommendation System

Abstract

In this project, we developed a personalized game recommendation system to enhance user experience on gaming platforms. By leveraging content-based filtering techniques, our system considers user preferences, such as genres, platforms, and budget constraints, to recommend relevant games. We utilized a Steam dataset containing information about game features like categories, genres, platforms, and user ratings. Experiments were conducted to evaluate the system's performance using Precision@K and Recall@K metrics, achieving significant improvements in recall with personalized filtering. The results demonstrate the potential of our approach to provide accurate and meaningful recommendations.

Introduction

The vast number of games available on online platforms often makes it difficult for users to discover titles that match their interests. Personalized recommendation systems aim to solve this problem by analyzing user preferences and recommending relevant content.

Our project uses the Steam dataset to build a content-based recommendation system for games. By engineering features such as genres, categories, and user preferences, we implemented a flexible system capable of recommending games based on game-to-game similarity and user profiles. The project also introduces filters to refine platform, price, and age suitability recommendations.

Objectives

The objectives of this project are:

1. To develop two recommendation approaches:
    - **Game-to-Game Recommendation System**: Recommends similar games based on their features using cosine similarity.
    - **User-Preference-Based Recommendation System**: Generates recommendations by analyzing user preferences, including genres, platforms, and budget constraints.
2. To evaluate the system's performance using established metrics such as Precision@K and Recall@K.
3. To explore the impact of filtering mechanisms (e.g., price, platform, and age suitability) on recommendation accuracy.
4. Put the model into use by deploying it with Gradio.

Background/Related Work

Recommendation systems are widely used across industries to improve user engagement. Common approaches include collaborative filtering, content-based filtering, and hybrid methods. Collaborative filtering relies on user behavior but struggles with the cold-start problem, while content-based methods focus on item features, making them suitable for datasets with rich metadata.

Previous research highlights the effectiveness of content-based filtering for game recommendations, particularly when incorporating features like genres, categories, and platforms. Our work builds upon these principles, extending them with dynamic user profiles and customized filters to improve relevance and diversity in recommendations.

Approach

Overall Methodology

We employed a content-based filtering approach, focusing on the similarity between game features and user preferences. The methodology involved several key steps:

1. **Dataset Preprocessing:**
   The Steam Store Games dataset was preprocessed to ensure compatibility with the recommendation algorithms. This included:
   - Handling missing values for features like categories and genres by replacing them with default or empty values.
   - One-hot encoding categorical features (categories, genres, platforms) to create a numerical representation suitable for similarity calculations.
   - Normalizing numerical features such as price, positive_ratings, and average_playtime to ensure consistent scaling.
   - Generating textual embeddings for descriptive fields like game description and tags using TF-IDF to capture semantic information.
2. **Game-to-Game Recommendation System:**
   A cosine similarity matrix was computed to identify games that are similar to each other based on their features.
   - This system selects a game and retrieves the top-K most similar games based on their feature vectors.
   - Features such as genres, categories, and platforms were weighted to emphasize their importance in determining similarity.
   - The system allows users to explore games based on similarity, helping them discover titles aligned with their preferences.

3. **User-Preference-Based Recommendation System:**
   A dynamic user profile was created by averaging the feature vectors of games liked by the user.
   - Cosine similarity was computed between the user profile and all games in the dataset to generate personalized recommendations.
   - Filtering mechanisms were introduced to refine the recommendations further, based on user-defined constraints such as:
     - Price Range: Recommended games were restricted to fit within the user's budget.
     - Platform Compatibility: Recommendations were filtered to match the user's preferred platform (e.g., Windows, Mac, Linux).
     - Age Suitability: Recommendations were tailored to the user's age preferences.
4. **Evaluation:**
   The performance of both the game-to-game and user-preference-based systems was evaluated using Precision@K and Recall@K metrics. These metrics assessed the relevance of the recommendations relative to the user's preferences and validated the effectiveness of the filtering mechanisms.
5. **Deployment:**
   The system was deployed using Gradio, providing an interactive interface for users to:
   - Select a recommendation mode (game-to-game or user-preference-based).
   - Input their preferences (e.g., budget, platform, favorite games).
   - Receive personalized recommendations dynamically

Recommendation Algorithms

- **Game-to-Game Recommendations**: Cosine similarity was calculated between all games in the dataset to identify similar titles.
- **User Profile-Based Recommendations**: A user profile vector was created by averaging the features of games liked by the user. Cosine similarity was then computed between the user profile and all games.

Filtering Mechanism

Filters were implemented to refine recommendations based on constraints such as price range, platform compatibility, and age suitability.

Experiments

Dataset

The Steam dataset contains over 10,000 games with features such as categories, genres, platforms, prices, and user ratings. Missing values were handled by replacing them with empty strings, and numerical features were normalized for consistency.

User-Preference Recommender

Experiment Configurations

Three user profiles were simulated:

1. **FPS Enthusiast**: Prefers FPS games on Windows with no budget constraints and a maximum age of 18 for the game.
2. **Strategy Lover**: Prefers strategy games on Mac with a budget under $30 and a maximum age of 16 for the game.
3. **Budget Gamer**: Prefers games under $10 on Linux and a maximum age of 18 for the game.

Evaluation Metrics

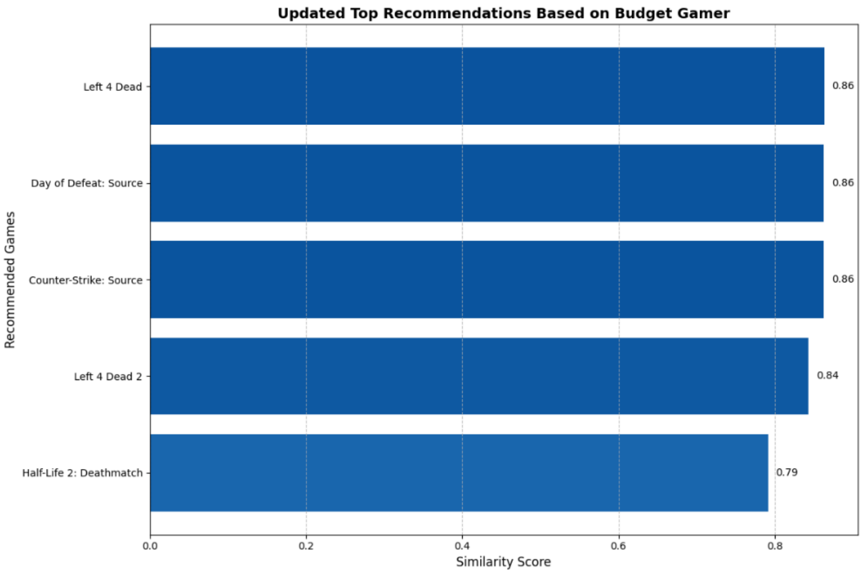
Precision@K and Recall@K were used to evaluate recommendation performance. These metrics assess the relevance of the top-K recommendations relative to the user's preferences.

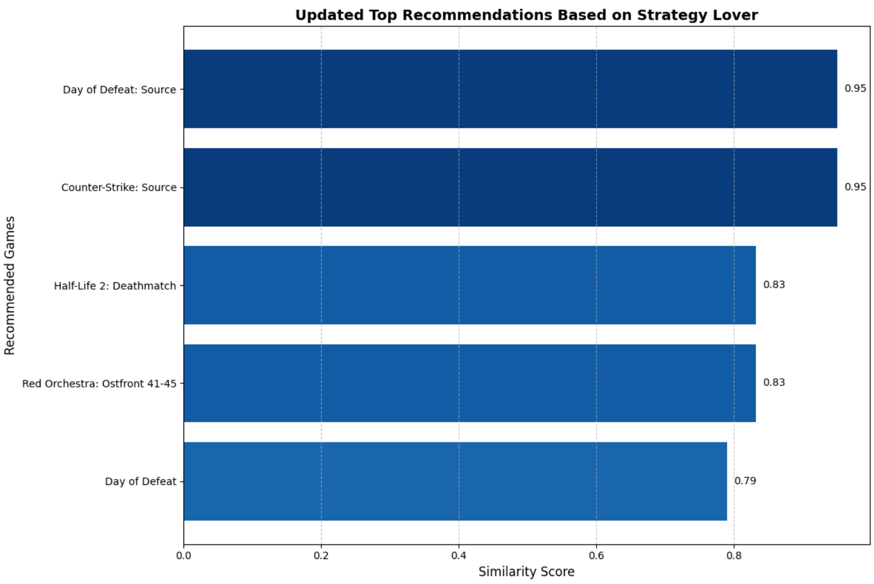
Results

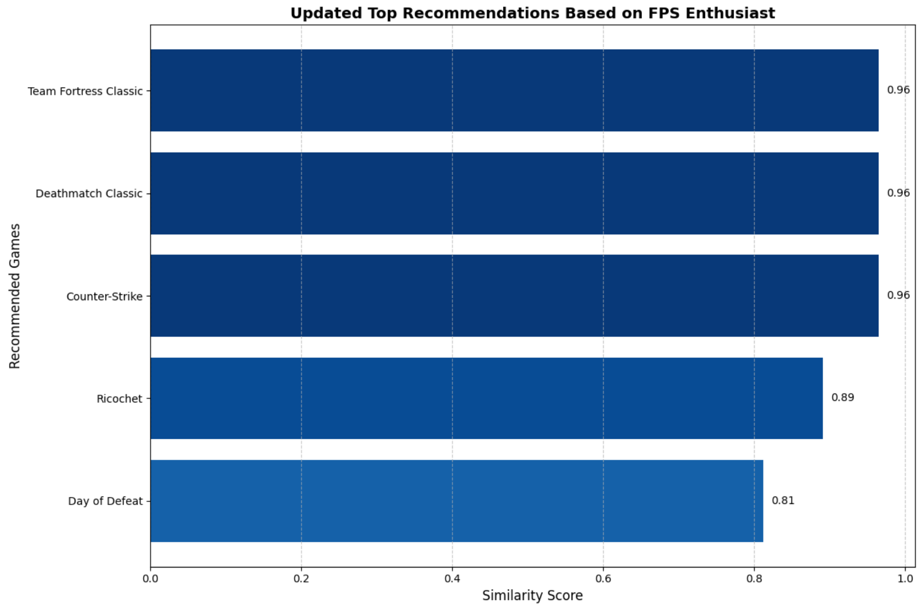
Profile Name	Precision@5	Recall@5	Top Recommendations with Filters
FPS Enthusiast	0.40	0.67	- Team Fortress Classic - Deathmatch Classic
Strategy Lover	0.60	1.00	- Day of Defeat Source
Budget Gamer	0.40	0.67	- Left 4 Dead

Plots

Bar plots showing users top five games with the similarity score:







Game-to-Game Recommender

The game-to-game recommendation system focuses on identifying games similar to a selected title. Leveraging the cosine similarity metric on the weighted features of the games provides users with a ranked list of recommendations. Below is an example result:

Example: Recommendations for 'Counterstrike':

1. Team Fortress Classic (Similarity: 1.00)
2. Deathmatch Classic (Similarity: 1.00)
3. Ricochet (Similarity: 0.90)
4. Day of Defeat (Similarity: 0.79)
5. Half-Life Deathmatch: Source (Similarity: 0.79)

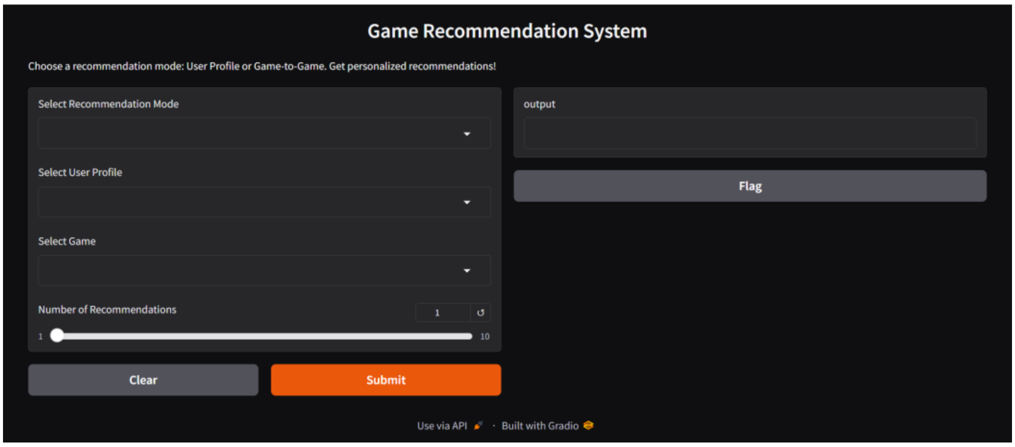
Discussion and Conclusion

The results show that applying filters improves recall across all profiles, ensuring recommendations align with user preferences. The weighted feature representation and dynamic user profile generation enhanced the system’s accuracy, demonstrating the strength of content-based filtering.

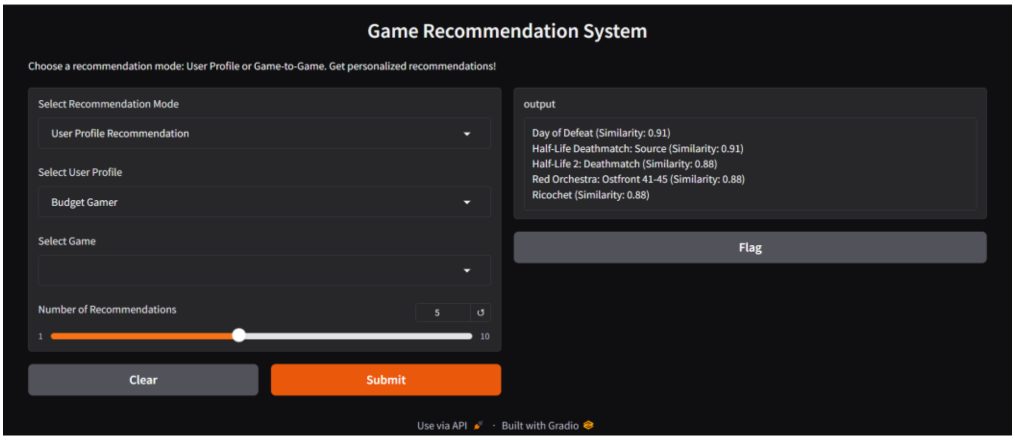
For **FPS Enthusiast** and **Budget Gamer** profiles, a Precision@5 of **0.40** indicates 40% relevance in the top 5 recommendations, while a Recall@5 of **0.67** shows 67% of relevant games were captured. For the **Strategy Lover** profile, a Precision@5 of **0.60** and a Recall@5 of **1.00** highlight the system's effectiveness when preferences are well-defined.

Future work could address cold-start issues with hybrid methods, incorporating collaborative filtering. Adding diverse metrics could also improve recommendation variety and user satisfaction.

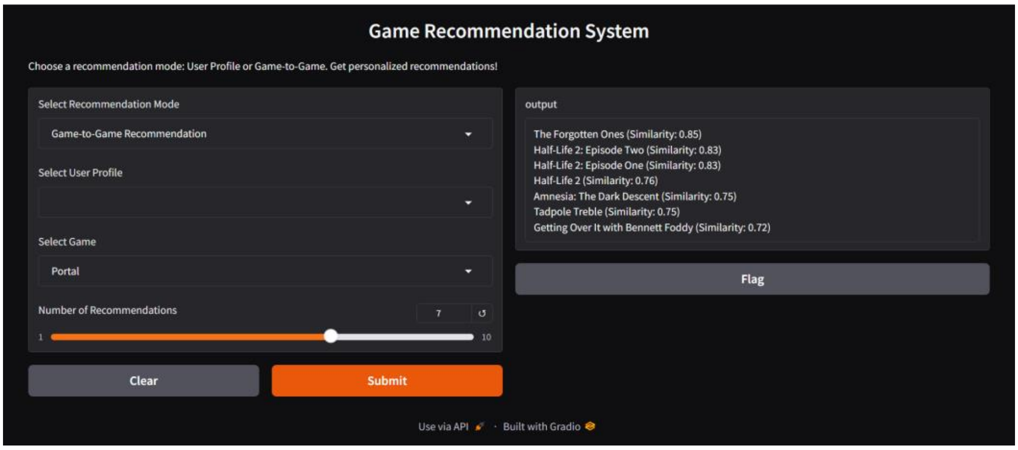
Deployment



General Interface



User Profile Recommenders example



Game-to-Game Recommender Example

References

1-[Cai, Y., Zeng, M., Zhu, H., Yin, H., & Nguyen, Q. V. H. (2020). A Comprehensive Survey on Graph Neural Networks for Recommender Systems. Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, 889–898. https://doi.org/10.1145/3374135.3385283]

2-[Davis, N. (n.d.). *Steam Store Games*. Retrieved from Kaggle: https://www.kaggle.com/datasets/nikdavis/steam-store-games]