International Journal of Artificial Intelligence and Mathematical Sciences

December 2025 Vo4. Issue No. 02
ISSN Online: 2958-0153 and Print: 2958-5228
DOI: https://doi.org/10.58921/ijaims.v4i2.173

A Machine Learning-Based Approach for Intelligent Game Recommendation System (I-GRS)

[1*]Zulfiqar Hussain Pathan, [1]Asif Aziz, Syed Ali Asgher, [1]Fida Hussain Khoso, [1]Adnan Waqar, [1]Irfan Ahmed

zulfiqar.pathan@duet.edu.pk, asif.aziz@duet.edu.pk, syedali5@duet.edu.pk, fidahussain.khoso@duet.edu.pk, adnan.waqar@duet.edu.pk, irfan.ahmed1@duet.edu.pk

[1]Department of Computer Science, Dawood University of Engineering & Technology Karachi, Pakistan

Received: 25-10-2025; **Accepted:** 5-11-2025; **Published**: 30-12-2025

Abstract

Hybrid game recommendation system would resolve the cold started problem on most recommendations engines, especially in digital gaming domain. General recommendation methods (Especially collaborative filtration) need users to be well interacted, which is not always the case. The hybrid model is the combination of collaborative filtration and content-based filtration to get the precision and recall on both new user case scenario as well as the experienced one. This model combines SVD matrix factorization with a gradient descent optimization which is well suited for sparse data in the user-item interaction matrix. At the same time, natural language processing (NLP) techniques analyze game plot descriptions so that the model can detect thematic similarities between games. This research proposed hybrid method on a data set of 787 games and found its results more valid to that of classical collaborative filtration–the mean precision is 0.015960 and the mean recall is 0.158242 and it also improves user recommendations for users that have interacted with very few items. Through 100 case studies with extensive records of game reviews, testing shows the model can operate within a sweet spot of recommendation accuracy and computational performance by performing best at approximately between 75–100 iterations. The combiner model is also responsible for more specificity and sensitivity than the best world records reported in benchmark datasets. Since game content and user preference change over time the system is suitable for online deployment as it interacts with users in real-time. User feedback and up-to-date content will drive its model, ensuring sustained interest as things to talk about change over time. To test with a large user base that includes the in-content groups and thus better constitute potentially cold-start users, as well as applying hybrid recommendation system techniques for use cases with other sparsity challenges. This research highlights the importance of combining collaborative filtration and content-based approaches for better recommendations, higher user satisfaction, and engagement on digital platforms.

Keywords: Game, Recommendation System, Intelligent, Collaborative filtration.

[*]Email: zulfiqar.pathan@duet.edu.pk

1. INTRODUCTION

The Game Recommendation system (GRS) aims to stand out by recommending personalized game recommendations, for each user's preferences [1]. By utilizing content based and hybrid algorithms, the system will understand user preferences and suggest games that fit their preferences. The GRS tackles the challenge of sorting through a wide variety of game genres and titles by providing curated game recommendations which is based on history of users and feedback [2]. The system continuously improves by refining its recommendation algorithms, offering enhanced gaming experience and making it easier for users to discover even niche games. Existing GRS often fail to provide personalized recommendations in case of limited data and over complicate search process. Many systems rely on just played games or followed categories, which can result in immature recommendations. This limitation results in a less-than-optimal user experience. This study addresses these significant issues by including gameplay clips as a medium in between to deliver focused, high-quality recommendations while limiting its complex properties by nearly search-less design [3]. Hybrid recommendation systems, which combine collaborative filtration and content-based filtration techniques, are particularly useful for overcoming the cold start problem, where insufficient user data prevents accurate suggestions. This research aims to develop and test a hybrid recommendation system that improves user recommendations, particularly when user data is limited [4].

The prime objective of this study is to change the methods by which the filtering of products such as games is done in the ecosystem of the digital age these days by gathering data that is not superfluous but rather nuanced to accommodate the eccentric and unique personalities of everyone that calls themselves gamers [5]. The system should consistently evolve to match the user’s profile and provide recommendations that are not particular but rather centered around the user’s taste in this field. Ultimately the proposed GRS would significantly impact and disturb the recommendation market in the future using the self-actualization mechanism as leverage.

1.1. General requirement for Proposed GRS

Primary requirement for the design of proposed GRS conducted through following 03 steps.

Surveys: The survey form was designed to get the users’ feedback to understand how to handle data. It was endowed that the most facilitating site in our pursuit will be the Steam Library which houses a behemoth of games and proves to be sufficient source that encompass all games till existence [6].

Review of Existing Systems: The review of existing systems was not only painstaking but was filled with frivolous and misguided algorithms that seemed to churn out recommendation not at the behest of the user but of the advertisers whose mass marketing campaigns intended for better sales deeply impacted their fidelity with the stakeholders who got cluttered suggestions bundled with unwanted items [6].

Brainstorming Sessions: Brainstorming sessions were organized within our school and gathered everyone's take in informal session to determine the scope of our application.

1.2. Functional Requirements

The functional requirements of the game recommendation system are as follows:

User Registration and Authentication: Allow users to authenticate themselves to self-register and be compliant with terms and conditions to access the application [7].

Game Search and Recommendation: The system provides a search functionality for users to discover games based on various criteria such as genre, platform, popularity, and user ratings. Additionally, the system should recommend personalized game suggestions to users based on their profile preferences and gaming behavior.

User Feedback and Rating: The system shall allow users to provide feedback and ratings for games they have played, which will be used to improve the accuracy of future recommendations [7].

2. LITERATURE REVIEW

Recommenders have become an essential tool for systems applications with vast quantity of products to offer to end user and this gap becomes more prominent when user is new which leads to problems like cold-start and less data [8]. To address this issue different recommendation systems, algorithms, and filtration mechanisms reviewed. Recommendation systems considered as a backbone of many digital platforms, serving as the unseen engines behind the curated content found on e-commerce websites, online libraries, streaming video platforms, and music services [9]. These systems strive to anticipate user preferences, guiding them towards relevant content they might not have otherwise discovered. By reviewing this study examine the principal strategies employed by recommendation systems, beginning with the two predominant categories: collaborative filtration and content-based filtration [10].

2.1. COLLABORATIVE FILTRATION

The purpose of a recommendation system is to propose fresh and engaging content, yet to do so effectively, it must discern which material aligns with user preferences. The algorithms within collaborative filtration achieve this by leveraging the collective experiences of users, drawing from a wealth of historical data to make informed predictions [11]. For example, if a system is tasked with recommending YouTube videos, it might observe patterns where users, after viewing a particular video, consistently watch another. These observed relationships allow the system to suggest related content based on the aggregated behavior of many individuals. Collaborative filtration thrives in environments where abundant user data is available, with its accuracy increasing as more interactions are logged [12]. However, it stumbles when faced with a lack of user data, a situation known as the "cold-start problem." This challenge arises when the system has insufficient data to form accurate predictions, a phenomenon that remains a significant hurdle in the field.

2.2. MATRIX FACTORIZATION

One of the cornerstone techniques in collaborative filtration is matrix factorization—a method that has garnered considerable attention for its ability to distill complex user interactions into a manageable form [13]. At its essence, matrix factorization seeks to predict a user's preferences by learning from the behavior of prior users. This approach employs machine learning to break down content into a set of hidden features, capturing the nuances of what makes an item desirable. In the context of recommending video games, for instance, the model might identify certain features such as "action-packed" or "sports oriented" Each game would be evaluated against these features, receiving a numerical score that quantifies how strongly it embodies each characteristic [14]. These numerical representations allow each game to be visualized as a point within an n-dimensional space, with each dimension representing a distinct feature. By calculating the cosine similarity between vectors, the system can identify games that bear a close resemblance. This methodology underpins the music recommendation algorithms at Spotify, where the relationships between songs are visualized as distances within a "feature space." In this space, songs that share similar characteristics naturally cluster together, enabling the system to recommend new tunes with an uncanny understanding of the listener's tastes [15]. These vectorized representations, often referred to as "embeddings," capture the latent qualities of content. Games or songs that are thematically or stylistically similar find themselves drawn together in this abstract space, reflecting their shared attributes. Such methods, with their ability to detect subtle patterns, have inspired much of the collaborative filtration work undertaken today.

2.3. CONTENT BASED FILTRATION

To address the limitations of collaborative filtration, especially the cold-start problem, content-based filtration offers a compelling alternative. Unlike collaborative methods, which rely on user interaction data, content-based recommendation systems focus solely on the intrinsic qualities of the items themselves [16]. This makes them particularly effective when there is a lack of user data, as their recommendations are drawn from analyzing the characteristics of the content rather than user behavior. Content-based filtration systems are designed to extract and interpret the attributes of items, enabling recommendations without any dependency on collective user history. This frees them from the constraints of the cold-start problem, where traditional collaborative methods struggle due to a scarcity of user data. In these systems, items are analyzed independently, and suggestions are generated based on similarities within the content itself—whether it be textual, visual, or auditory features [17]. One notable figure in this field is researcher Joon Seok Lee, who has conducted pioneering studies on content-based recommendation systems. His work focuses on optimizing video recommendations for platforms like YouTube using deep learning techniques. In his initial research, Lee concentrated on video frame analysis, utilizing convolutional neural networks (CNNs) to comprehend the visual elements within videos. This approach enabled the system to generate recommendations by identifying patterns and themes directly from the content [18].

Subsequently, Lee expanded his research to include both audio and visual data, enriching the recommendation algorithm with a more holistic understanding of the content. By analyzing thousands of video frames alongside corresponding audio tracks, the system could discern more nuanced features—leading to a more sophisticated recommendation network [19-20]. His studies demonstrated that content-based approaches, particularly when reinforced with deep learning, are effective tools to complement traditional collaborative filtration methods. In tandem, these strategies can mitigate the weaknesses inherent to each, delivering a more comprehensive and adaptive recommendation system.

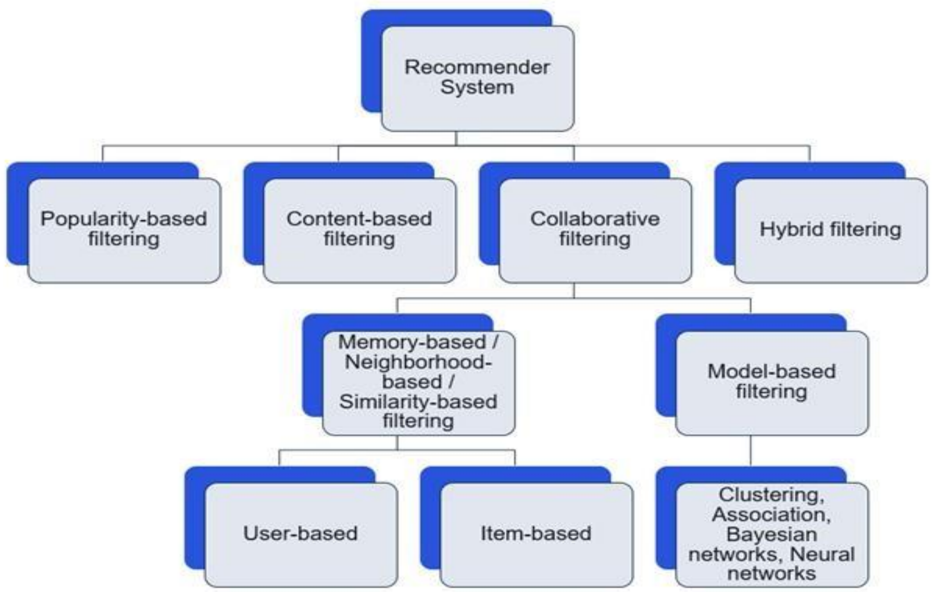

Fig 1. Type of Recommender systems

2.4. APPLICATION OF RECOMMENDATION SYSTEMS

Recommendation systems have permeated countless facets of this digital experience, well beyond the familiar examples of YouTube, Amazon, and social media platforms like Twitter. These systems are now crucial tools across diverse domains, each finding innovative applications tailored to specific needs. During this investigation, this study uncovered several fascinating and varied use cases for recommendation systems, which underscore their versatility and adaptability. One notable example of cutting-edge research is Google's development of a personalized news recommendation system. This system leverages user click behavior to anticipate and deliver news stories tailored to an individual's preferences.

Using a Bayesian framework, the system not only considers a user's unique reading habits but also considers broader trends reflected in the behaviors of similar users. By integrating personal preferences with collective user data, the system provides a finely tuned recommendation, predicting which news articles a user is most likely to engage with.

3. METHODOLOGY

This research takes a hybrid approach by combining both types of recommendation systems. A video games recommendation system which will aim at giving unique recommendations to each individual user focus of this research is to address cold-start problems, means user may have very less data or data is too scattered. Such insufficiency becomes problematic for recommender systems to solve. The proposed models and it construction, metrics used for evaluation and overall testing strategy.

Fig 2. Research Steps Diagram

For this study 02 datasets are being used, which are sourced from Kaggle and free.

3.1. USER ORIENTED DATASET

First dataset is user dataset which include information like user id, played games, play time, and purchase history.

user_id	game_title	behavior	value
151603712	The Elder Scrolls V: Skyrim	purchase	1
151603712	The Elder Scrolls V: Skyrim	play	273
151603712	Fallout 4	purchase	1
151603712	Fallout 4	play	87
151603712	Spore	purchase	1
151603712	Spore	play	14.9
151603712	Fallout New Vegas	purchase	1
151603712	Fallout New Vegas	play	12.1
151603712	Left 4 Dead 2	purchase	1
151603712	Left 4 Dead 2	play	8.9

Fig 3. Raw User Dataset

3.2. GAME ORIENTED DATASET

Second dataset is game dataset, this contains all information of games such as game title, game description, reviews, tags, publisher, genre etc. The two files being used are Game.csv and user.csv, combined.

[87]:	overall	reviewerID	title	category
312259	4.0	A26BGHYLTCD5SM	Halo 4 - Xbox 360 (Standard Game)	['Video Games', 'Xbox 360', 'Games', '']
175973	1.0	A3EP0KWNRV2GI2	Time Splitters: Future Perfect - PlayStation 2	['Video Games', 'Retro Gaming & Microconsoles'...
151139	5.0	A3V6Z4RCDGRC44	Yu Yu Hakusho Dark Tournament - PlayStation 2	['Video Games', 'Retro Gaming & Microconsoles'...
5186	5.0	A3JUMMIGJ7B38X	Final Fantasy VII	['Video Games', 'Retro Gaming & Microconsoles'...
424330	5.0	A1C5RRPBGRDF2Z	Phantasy Star III - Sega Genesis	['Video Games', 'Retro Gaming & Microconsoles'...
...	...	...	...	...
318418	5.0	A1WLAQOT4R9RFK	Oblivion (Game of the Year Edition) -Xbox 360	['Video Games', 'Xbox 360', 'Games', '', 'Incl...
387097	5.0	A3PLN1BLX8U9CY	Farming Simulator 15 [Download]	['Video Games', 'PC', 'Games', '', 'New graphi...
218691	5.0	ANMS35SC8X6VX	Call of Duty 4: Modern Warfare - Xbox 360	['Video Games', 'Xbox 360', 'Games', '']
351605	5.0	AHMLUEQJI0EJG	Mario Kart 8 - Nintendo Wii U	['Video Games', 'Kids & Family', 'Wii U', 'Gam...
426471	5.0	A1TVD594BZ421P	Machinehead - Sega Saturn	['Video Games', 'Retro Gaming & Microconsoles'...

432782 rows × 4 columns

Fig 4. Sample Data of Filtered Games

3.3. DATA PROCESSING/FILTRATION

Multiple operations are performed to process data and refine it for efficient use which are listed as follows.

- Remove rows from table containing irrelevant subcategories from video games, such as controllers, chargers, cases, and accessories.
- Remove video games where game reviews are less or equal to 5 users, this ensures that game data can be used for training
- Similarly remove users who don't have more than 5 reviews.
- Removing all not used columns from user.csv and game.csv

After removing all unnecessary data, the data reduces from 8,246 rows of reviews of games, to 2,485 rows, and 787 rows of games.

3.4. PROPOSED HYBRID RECOMMENDER MODEL

Fig 5. Hybrid Algorithm

The proposed hybrid recommendation algorithm functions as described in Fig 5. It follows a series of steps for delivering personalized game recommendations:

- Select a user.
- Extract the vector of users from the matrix.
- Identify the 5 most popular categories based on the user's preferences.
- Find the nearest_neighbors of the user.
- Use the identified category to filter neighbors with related attributes.
- from the filtered neighbors 5 recommendations

3.5. SYSTEM DESIGN

The game recommendation system consists of two primary components: the User Interface (UI) and the backend. The UI provides an intuitive platform for users to interact with the system. Features of the UI include user authentication, personalized recommendations, browsing options, game reservations with notifications, game search functionality, and a feedback system for rating and reviewing games. On the back end, various tasks are managed, including user data processing, game data management, recommendation algorithms, and monitoring gameplay analytics.

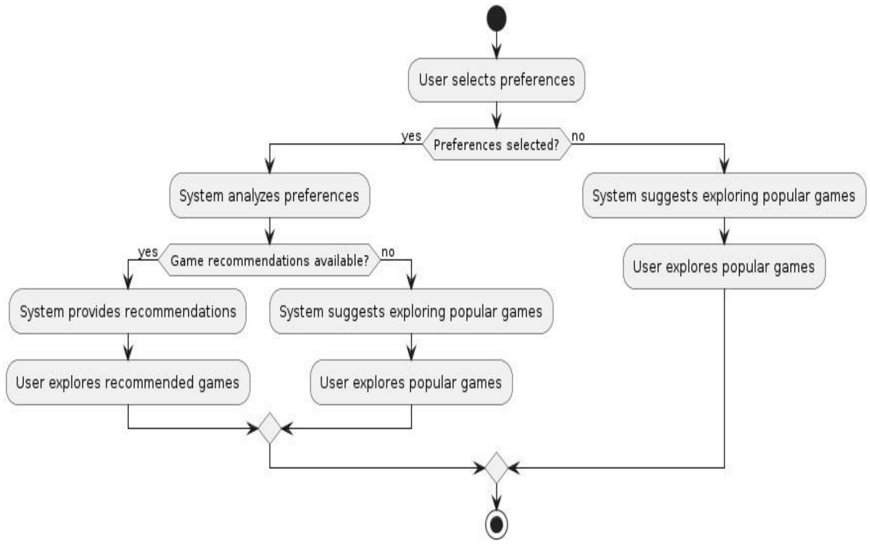

Fig 6. System Design Diagram

This study utilizes two data sets, both freely available on Kaggle, containing data extracted from Steam.

User Dataset: The user dataset contains information such as the user ID, game title, behavior (whether the user 'purchased' or 'played' a game), and a corresponding value for each behavior. Each row represents a user's action towards a game (either 'purchase' or 'play').

Game Dataset: The game dataset provides detailed information about each game, including the title, description, Steam store URL, package type, release date, developer, publisher, popular tags (e.g., Action, Shooter, PvP), genre (e.g., Action, RPG), system requirements, pricing, and reviews. The dataset includes a total of 787 games. To gain insight into how the reviews are distributed, we have visualized the percentage of positive reviews for each game.

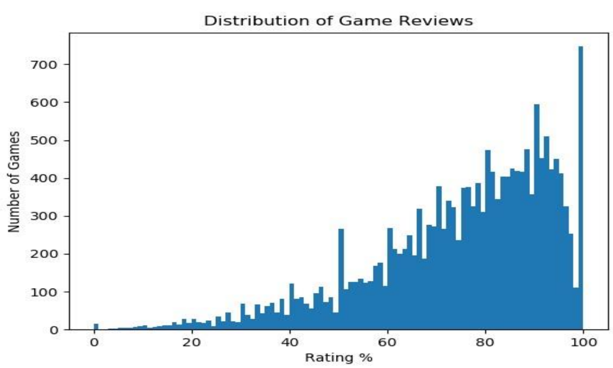

Fig 7. Ratings Plot Chart

4. RESULTS

After running tests on 50 users, each with more than 20 games and 100 reviews, and calculating the average results, following observed metrics:

Table1: Precision Comparison

Metric	Collab	Hybrid (Our Model)
Mean Precision	0.014640	0.015960
Max Precision	0.094000	0.110000

Table 2: Recall Comparison

Metric	Collab	Hybrid (Our Model)
Mean Recall	0.147731	0.158242
Max Recall	0.523810	0.476190

4.1. ANALYSIS

The analysis of the data presented in Fig. 8 and Fig. 9 shows that this hybrid model of recommendation improves both scores from Recall and Precision. Specifically, Precision increased by approximately 8%, while Recall improves by 7.5%. Furthermore, the hybrid model demonstrated higher maximum Precision compared to the initial collaborative filtration model, although the maximum Recall was slightly lower. While the average Precision and Recall values have been discussed, Fig. 10 presents individual metrics for each user, showing that the hybrid model consistently enhances both Precision and Recall for nearly all users.

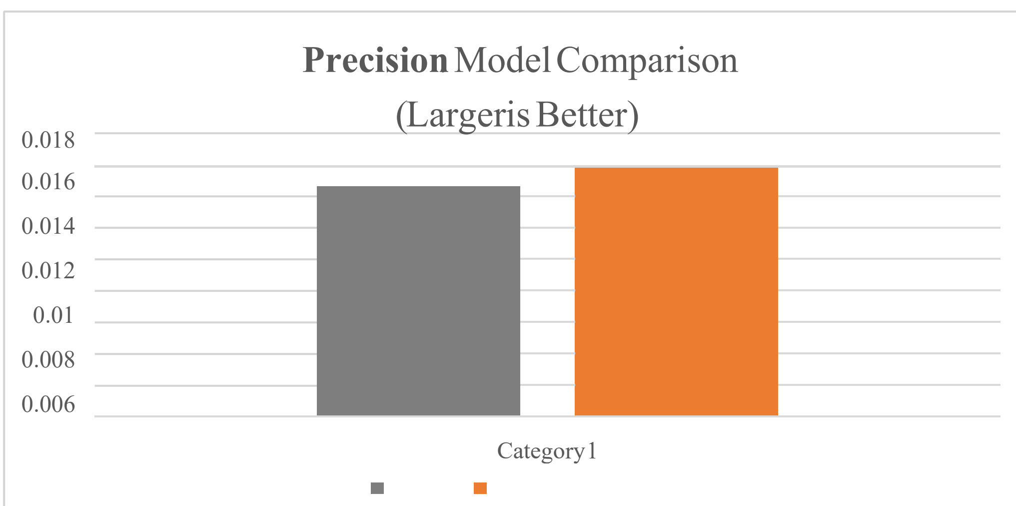

Fig 8. Precision Plot

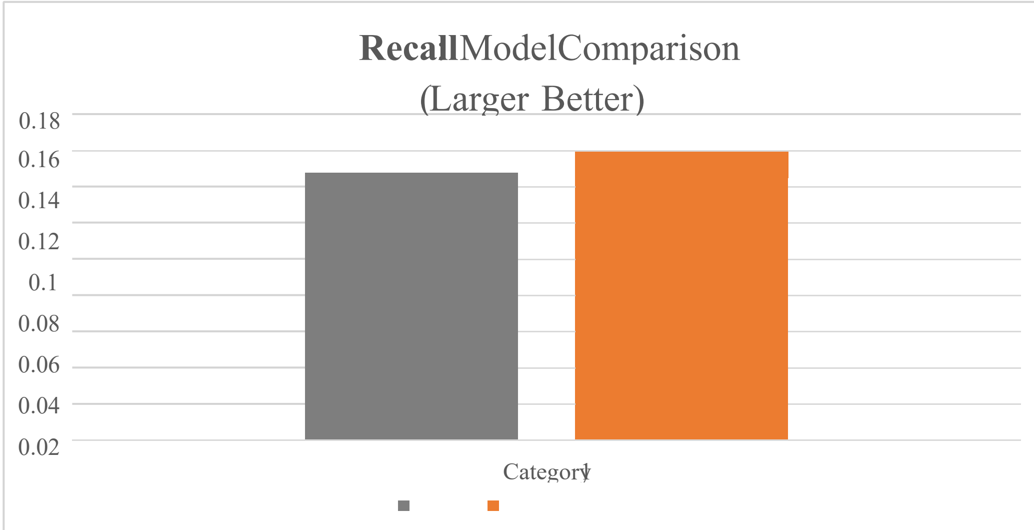

Fig 9. Recall Plot

The results suggest that incorporating keywords from game categories in this hybrid recommendation model leads to improved performance when compared to traditional collaborative filtration methods.

[89]:

	precision	recall	precision_kw	recall_kw
0	0.094	0.119593	0.110	0.139949
1	0.068	0.142259	0.078	0.163180
2	0.046	0.112745	0.048	0.117647
3	0.028	0.066667	0.036	0.085714
4	0.044	0.211538	0.048	0.230769
...	...	...	...	...
95	0.012	0.240000	0.014	0.280000
96	0.002	0.037037	0.004	0.074074
97	0.008	0.074074	0.010	0.092593
98	0.004	0.083333	0.006	0.125000
99	0.010	0.357143	0.010	0.357143

100 rows × 4 columns

Fig 10. Per User Comparison of Precision and Recall Model

5. CONCLUSION

This study aims to provide a new avenue to the world of games and its subsequent developers whose too much time and energy is wasted. This will continue to improve the methodology as the technology evolves that can facilitate much more complex and self-actualized learning of AIs to accommodate our personal choices. For all intents and purposes, an application developed in a manner that may strike as non-futile but as progress, the market of micro-targeting will be taking advertisers and users floating and ushering them into a future of personalized recommendations on a micro level. This opportunity has provided the necessary knowledge base on which

6. FUTURE IMPROVEMENTS

Due to lack of resources and time limited datasets and to simplify and keep approach straight forward didn't consider other services which may have influence on recommendations. Even this study would like to perform tests on more datasets and add all other foreign influences to make this system more accurate and coherent. Further this dynamic nature of recommenders to incorporate tools to help game developers, such as tag precision and constant update of genres and categories to keep game relevant to players, this prevent good games from dying out even if developers don’t know how to manage these things

References

[1] S. M. Anwar, T. Shahzad, Z. Sattar, R. Khan, and M. Majid, "A game recommendation system using collaborative filtration (GAMBIT)," in 2017 14th International Bhurban Conference on Applied Sciences and Technology (IBCAST), IEEE, 2017, pp. 328–332.

[2] R. van den Berg, T. N. Kipf, and M. Welling, "Graph convolutional matrix completion," 2017.

[3] P. Bertens, A. Guitart, P. P. Chen, and Á. Periáñez, "A machine-learning item recommendation system for video games," in 2018 IEEE Conference on Computational Intelligence and Games (CIG), IEEE, 2018, pp. 1–4.

[4] L. Chen and J. Gao, "A trust-based recommendation method using network diffusion processes," CoRR, vol. abs/1803.08378, 2018.

[5] G. Cheuque, J. Guzmán, and D. Parra, "Recommender systems for online video game platforms: The case of STEAM," in Companion Proceedings of The 2019 World Wide Web Conference, 2019, pp. 763–771.

[6] L. De Simone, D. Gadia, D. Maggiorini, and L. A. Ripamonti, "Design of a recommendation system for video games based on in-game player profiling and activities," in CHItaly 2021: 14th Biannual Conference of the Italian SIGCHI Chapter, 2021, pp. 1–8.

[7] W. Fan, Y. Ma, Q. Li, Y. He, E. Zhao, J. Tang, and D. Yin, "Graph neural networks for social recommendation," in The World Wide Web Conference (WWW 2019), ACM, 2019, pp. 417–426.

[8] Z. Fan, Z. Liu, S. Wang, L. Zheng, and P. S. Yu, "Modeling sequences as distributions with uncertainty for sequential recommendation," in CIKM ’21: The 30th ACM International Conference on Information and Knowledge Management, ACM, 2021, pp. 3019–3023.

[9] Z. Fan, Z. Liu, Y. Wang, A. Wang, Z. Nazari, L. Zheng, H. Peng, and P. S. Yu, "Sequential recommendation via stochastic self-attention," 2022.

[10] Z. Fan, Z. Liu, J. Zhang, Y. Xiong, L. Zheng, and P. S. Yu, "Continuous-time sequential recommendation with temporal graph collaborative transformer," in CIKM ’21: The 30th ACM International Conference on Information and Knowledge Management, ACM, 2021.

[11] C. Guo, L. Yang, X. Chen, D. Chen, H. Gao, and J. Ma, "Influential nodes identification in complex networks via information entropy," Entropy, vol. 22, no. 2, 2020.

[12] H. Guo, R. Tang, Y. Ye, Z. Li, and X. He, "DeepFM: A factorization-machine based neural network for CTR prediction," in Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, 2017.

[13] C. He, K. Balasubramanian, E. Ceyani, C. Yang, H. Xie, L. Sun, L. He, L. Yang, P. S. Yu, Y. Rong, et al., "Fedgraphnn: A federated learning system and benchmark for graph neural networks," 2021.

[14] X. He, K. Deng, X. Wang, Y. Li, Y. Zhang, and M. Wang, "Lightgcn: Simplifying and powering graph convolution network for recommendation," in Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, 2020.

[15] J. Kim, J. Wi, S. Jang, and Y. Kim, "Sequential recommendations on board-game platforms," Symmetry, vol. 12, no. 2, p. 210, 2020.

[16] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, 2015.

[17] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, 2017.

[18] Z. Liu, Z. Fan, Y. Wang, and P. S. Yu, "Augmenting sequential recommendation with pseudo-prior items via reversely pre-training transformer," Association for Computing Machinery, 2021, pp. 1608–1612.

[19] Pathan, Z. H., Sikander, A., Aziz, A., Tunio, M. Z., & Saleem, M. (2024). An efficient gpu/deep learning model approach for brain tumor detection in pakistan. Journal of Independent Studies and Research Computing, 22(1), 111-120.

[20] Pathan, Z. H., Sikander, A., Aziz, A., Asghar, S. A., & Saleem, M. (2025). User-Centric Approach to Design a Digital Shopping Cart: Enhancing User Experience in Super Stores. Journal of Independent Studies and Research Computing, 23(1), 58-63.