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Enhancing Customer Engagement with AI-Driven Movie Recommenders: Integrating Neural Collaborative Filtering, Sentiment Analysis, and Conversational Agents

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Abstract

In today's competitive digital landscape, user engagement is a critical factor for the success of entertainment platforms, especially those offering movie recommendations. This study introduces a comprehensive AI-driven framework designed to enhance customer interaction, satisfaction, and loyalty through the intelligent integration of multiple deep learning models. The system combines three core components: Neural Collaborative Filtering (NCF) for generating personalized movie recommendations based on user behavior and preferences, Long Short-Term Memory (LSTM) networks for performing sentiment analysis on user-generated reviews, and Generative Pre-trained Transformer (GPT) models to serve as conversational agents for interactive user communication. By synergizing these technologies, the system is capable of not only delivering highly relevant recommendations but also interpreting user sentiments in real time and engaging users in natural, human-like dialogue. The framework is evaluated using the widely recognized MovieLens 100k dataset, which enables benchmarking the system's effectiveness in a controlled environment. Results indicate substantial improvements in recommendation accuracy, sentiment classification performance, and user interaction quality. This multi-model approach provides a robust and scalable solution for enhancing the overall user experience on movie recommendation platforms. Ultimately, the proposed system represents a forward-thinking step toward more personalized, emotionally intelligent, and engaging digital entertainment services.

Keywords: Customer engagement, neural collaborative filtering (NCF), long short-term memory (LSTM), generative pre-trained transformer (GPT), MovieLens dataset

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INTRODUCTION

Background

In today's digital era, customer engagement is a critical factor for the success of online platforms, particularly in domains like entertainment and media, where user retention and satisfaction directly influence the platform's growth and sustainability. Streaming services such as Netflix, Amazon Prime, and Hulu rely heavily on providing personalized content to keep users engaged. However, mere recommendations are not enough to meet user expectations in an increasingly competitive market. The next frontier in improving user engagement lies in delivering not only personalized suggestions but also interactive, real-time feedback and meaningful conversational interactions.

In recent years, advancements in artificial intelligence (AI) and machine learning (ML) have significantly enhanced the capabilities of recommendation systems. These innovations are particularly relevant in content-heavy domains like movie streaming platforms, where user satisfaction is linked to the accuracy of recommendations, the relevance of interactions, and the platform's ability to gauge user sentiment. Traditional recommendation algorithms, such as collaborative filtering and content-based methods, have been surpassed by more advanced deep learning techniques. Among these, Neural Collaborative Filtering (NCF) has shown great promise for building effective recommendation systems by leveraging neural networks to model user-item interactions.

However, a modern recommendation system must not only suggest content but also respond to user feedback. This feedback often comes in the form of reviews or ratings, which can offer valuable insights into customer satisfaction and preferences. Sentiment analysis, a subfield of natural language processing (NLP), has become a powerful tool for extracting opinions and sentiments from textual data. Techniques such as Long Short-Term Memory (LSTM) networks are particularly effective in understanding the sentiment of users by analyzing the sequence and context of words in reviews. This allows platforms to adjust recommendations based on the user's emotional response to previous suggestions, thereby refining the recommendation engine's personalization capabilities.

Another key component in enhancing user engagement is the introduction of conversational agents. Unlike static recommendation systems that rely solely on user clicks or ratings, conversational agents can engage users in real-time, provide recommendations, and handle user queries in a more interactive and natural manner. Generative Pre-trained Transformers (GPT), especially models like GPT-2 and GPT-3, have become state-of-the-art for building such conversational agents. These models are capable of generating coherent and contextually relevant responses to user input, making them an ideal choice for building chatbots that can enhance the user experience on movie recommendation platforms.

This study explores the integration of three advanced AI techniques: NCF-recommended systems, LSTM-based sentiment analysis, and GPT-based conversational agents, into a unified system designed to improve customer engagement on a movie recommendation platform. By leveraging these models, we aim to create an intelligent system that not only provides accurate and personalized movie recommendations but also engages users through real-time sentiment analysis and conversational interactions. The proposed system is validated using the *MovieLens 100k* dataset, a widely used benchmark in recommendation system research, to assess its efficacy in enhancing user engagement.

PROBLEM STATEMENT

While traditional recommendation systems have significantly improved the personalization of content delivery, they often fail to capture the full scope of user engagement. Simply recommending content based on past behavior does not address real-time feedback or provide interactive engagement, which are critical elements in sustaining user interest and satisfaction. This gap highlights the need for a more comprehensive approach that can analyze user feedback, gauge sentiment, and facilitate meaningful interactions with users.

In particular, the following challenges arise:

- *Personalization:* How can a recommendation system dynamically adapt to user preferences and recommend movies based on past interactions?
- *User Feedback:* How can a system analyze and incorporate user feedback, particularly in the form of text reviews, to adjust recommendations and improve overall user satisfaction?
- *Interactivity:* How can a conversational agent provide meaningful, real-time engagement with users in a way that feels natural and enhances their experience on the platform?

To address these challenges, this study proposes a solution that integrates NCF for personalized recommendations, LSTM for sentiment analysis of user reviews, and GPT as a conversational agent to improve customer engagement on a movie recommendation platform.

Neural Collaborative Filtering (NCF) for Personalized Recommendations

Traditional recommendation systems rely on collaborative filtering methods that focus on user-item interaction matrices. Collaborative filtering has two main approaches: *memory-based* and *model-based*. Memory-based approaches calculate similarities between users or items to predict preferences, while model-based approaches use machine learning techniques like matrix factorization.

Neural Collaborative Filtering (NCF) extends the concept of matrix factorization by replacing the inner product in latent factor models with neural networks. NCF introduces a more flexible and non-linear interaction model that captures complex relationships between users and items. This allows NCF to model implicit feedback more effectively and generate more accurate recommendations. The architecture of NCF typically includes embedding layers for users and items, followed by hidden layers that learn user-item interactions. The final layer produces the predicted rating or likelihood that a user will enjoy a particular item.

By applying NCF, this system can recommend movies that are highly personalized based on a user's past interactions. Moreover, the use of neural networks enables the model to capture more intricate patterns in the data, leading to better generalization and recommendation accuracy.

LSTM for Sentiment Analysis of User Reviews

Sentiment analysis plays a critical role in understanding how users feel about the recommendations they receive. User reviews are a rich source of information that can provide insights into a user's preferences, likes, and dislikes. Sentiment analysis allows platforms to interpret this feedback and adjust their recommendations accordingly.

LSTM networks are particularly well-suited for sentiment analysis due to their ability to capture long-term dependencies in text data. Unlike traditional recurrent neural networks (RNNs), LSTMs can effectively retain information over longer sequences, making them ideal for understanding the sentiment behind user reviews. By processing reviews through an LSTM network, the system can classify user feedback as positive, negative, or neutral. This sentiment data can then be used to improve future recommendations, ensuring that the system continuously learns from user interactions.

For example, if a user expresses negative sentiment towards a recommended movie, the system can adjust its future recommendations to avoid similar content. Conversely, positive reviews can reinforce the system's confidence in recommending related movies. In this way, sentiment analysis adds an additional layer of personalization to the recommendation process.

GPT as a Conversational Agent

While NCF and LSTM provide valuable tools for personalized recommendations and sentiment analysis, the role of Generative Pre-trained Transformers (GPT) is to facilitate real-time interaction between the platform and its users. Conversational agents, powered by GPT models, can engage users in natural dialogue, answer their questions, and provide recommendations in a human-like manner.

GPT models, particularly GPT-2 and GPT-3, have demonstrated remarkable capabilities in generating coherent and contextually appropriate responses. These models are pre-trained on large datasets of text, which allows them to understand and generate human-like text across a variety of contexts. In the context of a movie recommendation platform, a GPT-based chatbot can engage users by answering queries such as "What are some good action movies?" or "I liked the last movie, can you recommend something similar?" The chatbot can also process user feedback and adjust its responses based on the user's sentiment or preferences.

By integrating a GPT-powered conversational agent, the platform provides an interactive and engaging user experience. The chatbot can offer movie suggestions, clarify user queries, and even

discuss user preferences in a way that mimics a human conversation. This interactive layer significantly enhances the overall user experience, making the platform more engaging and user-friendly.

Objective

The primary objective of this research is to develop an AI-driven system that combines NCF for personalized recommendations, LSTM for sentiment analysis, and GPT for conversational interactions, aimed at improving customer engagement on a movie recommendation platform. By combining these advanced AI models, we aim to create a system that delivers a more personalized, responsive, and engaging user experience. In this study, we present the design and implementation of the proposed system, evaluate its effectiveness using the MovieLens 100k dataset, and demonstrate how the integration of NCF, LSTM, and GPT can significantly enhance customer engagement on a movie recommendation platform.

LITERATURE REVIEW

Here is the literature review in table format summarizing key contributions from studies between 2020 and 2024 related to Neural Collaborative Filtering (NCF), Sentiment Analysis (LSTM), and Conversational Agents (GPT) for customer engagement in recommendation systems, now including the datasets used in each study (Table 1).

METHODOLOGY

In this study, we aim to combine three advanced AI techniques: Neural Collaborative Filtering (NCF), Long Short-Term Memory (LSTM), and Generative Pretrained Transformer (GPT), to create an integrated framework for customer engagement in a movie recommendation system. The methodology is structured into three main components: recommendation generation, sentiment analysis, and conversational interaction. We utilize the MovieLens 100K dataset for this purpose, as it provides a rich set of user-item interactions, ratings, and user feedback, which are ideal for evaluating the performance of these models. Each component of the methodology is detailed below:

Dataset

The MovieLens 100K dataset from GroupLens is widely used in recommendation system research and is suitable for evaluating machine learning models due to its diversity and availability of user ratings and interactions. It includes:

- *User data:* Information about users, including ratings and timestamps.
- *Item data:* Movie titles and related metadata.
- *Review data:* User-provided textual reviews used for sentiment analysis.

Neural Collaborative Filtering (NCF) for Recommendation Generation

The Neural Collaborative Filtering (NCF) model is designed to predict user preferences for movies based on past interactions. Unlike traditional collaborative filtering, NCF uses neural networks to model the latent features of users and items (Figure 1).

Model Architecture

- *Embedding Layers:* Separate embedding layers are created for users and movies. These layers represent users and movies in a lower-dimensional space, capturing latent factors that influence user preferences.
- *Interaction Layers:* The interaction between user and movie embeddings is captured using a dot product, which is then passed through multiple fully connected layers to learn complex interactions.
- *Output Layer:* The final output is a binary classification (like or dislike) for each user-movie pair.

```
# Create the model
model = Model(inputs=[user_input, item_input], outputs=output)
model.compile(optimizer=Adam(learning_rate=0.001), loss='binary_crossentropy', metrics=['accuracy'])
```

Figure 1. Create the model.

Table 1. This table provides a concise overview of the progress made in these areas and how they contribute to improving customer engagement in recommendation systems.

Paper/ Study	Domain	Key Contribution	Findings/Results	Dataset Used
[1]	NCF	Proposed a Neural Matrix Factorization framework to enhance NCF models by combining both linear and non-linear interactions for user-item recommendations.	Achieved better accuracy compared to traditional matrix factorization techniques. The incorporation of non-linear interactions outperforms pure collaborative filtering approaches.	MovieLens Dataset
[2]	NCF + Side Information	Introduced side information like user profiles into NCF models to improve accuracy in e-commerce recommendations.	Integration of additional data led to a 10% boost in accuracy for top-K recommendations. Enhanced user engagement by improving personalized recommendations.	Amazon Product Reviews
[3]	Sentiment Analysis (LSTM)	Developed a hybrid LSTM model for sentiment analysis using attention mechanisms to prioritize key customer feedback for recommendation refinement.	Outperformed baseline LSTMs by 8% in sentiment classification accuracy. The model helps refine recommendations by filtering negative and positive sentiments.	Yelp Reviews Dataset
[4]	NCF + Sentiment	Combined NCF with sentiment analysis to enhance customer engagement by capturing implicit preferences from textual reviews.	Increased accuracy by 12% in predicting user preferences. The combination of implicit and explicit feedback helped improve personalized recommendations.	Kaggle Movie Reviews
[5]	Sentiment Analysis (LSTM)	Proposed an LSTM-based model that utilizes pre-trained embeddings for sentiment analysis to support dynamic product recommendations in e-commerce.	Improved user satisfaction by identifying critical sentiments, thus allowing recommendations to adapt to customer preferences over time.	Amazon Product Reviews
[6]	Conversational Agents (GPT)	Demonstrated the potential of GPT-3 as a conversational agent for personalized customer interactions, simulating human-like conversations for product recommendations.	GPT-3's language generation capabilities allow for engaging, context-aware conversations with users, leading to increased customer satisfaction in recommendation systems.	Conversational AI Dataset
[7]	Conversational Agents (GPT)	Explored GPT-3's ability to assist in customer service and product recommendation scenarios.	The study found that GPT-3 could hold long, coherent conversations, boosting user engagement and conversion rates by up to 15%.	OpenAI Conversations Dataset
[8]	NCF + Conversational Agents	Integrated NCF models with conversational agents for interactive product recommendations, where agents ask users direct questions to gather preferences.	Enhanced customer engagement by 20% as users felt more involved in the recommendation process. The conversational agent improved the cold-start problem.	Retail Product Dataset
[9]	GPT-4 in Recommendation Systems	Used GPT-4 to enhance customer engagement through personalized product descriptions and sentiment-aware recommendations.	Showed a 17% increase in purchase rates by making recommendations more contextually relevant. GPT-4's ability to understand user intent enhanced the overall recommendation process.	eBay Product Listings
[10]	NCF with Graph Neural Networks	Leveraged Graph Neural Networks (GNN) alongside NCF for enhanced user-item interaction modeling in recommendation systems.	GNN improved interaction modeling and customer engagement by capturing complex relations between users and products.	MovieLens and Amazon Product Reviews

Training

- The model is trained using the binary cross-entropy loss function, and the Adam optimizer is employed for optimization.
- The dataset is split into 80% training and 20% testing sets. Hyperparameters such as embedding size, learning rate, and batch size are tuned for optimal performance.

Long Short-Term Memory (LSTM) for Sentiment Analysis

The LSTM network is utilized to perform sentiment analysis on movie reviews. By analyzing the sentiment behind user reviews, we aim to enrich the recommendation system by incorporating users' emotional responses to movies.

Model Architecture

- *Word Embeddings:* Each review is tokenized, and words are converted into embeddings using pre-trained word vectors (GloVe). These embeddings serve as inputs to the LSTM model.
- *LSTM Layer:* The LSTM layer is responsible for processing sequential word data and capturing long-term dependencies in the review. It helps to understand the sentiment flow in longer reviews.
- *Fully Connected Layer:* After processing through the LSTM, the output is passed to a fully connected layer with a sigmoid activation function, producing a binary classification (positive or negative sentiment).

Training

- The LSTM model is trained on the sentiment-labeled movie reviews associated with the movies in the dataset. The model uses binary cross-entropy loss and the Adam optimizer for training.
- The performance of the sentiment model is evaluated using accuracy and F1-score metrics on a separate test set.

GPT-based Conversational Agent for User Interaction

The **GPT-based conversational agent** is designed to enhance user engagement by facilitating natural and personalized dialogue with users about movie recommendations. The model interacts with users by understanding their queries and providing movie suggestions based on their preferences and historical interactions (Figure 2).

Model Architecture

- *Pre-trained GPT-2 Model:* We fine-tune a pre-trained GPT-2 model on dialogue data, where the conversation is framed around movie recommendations and user preferences.

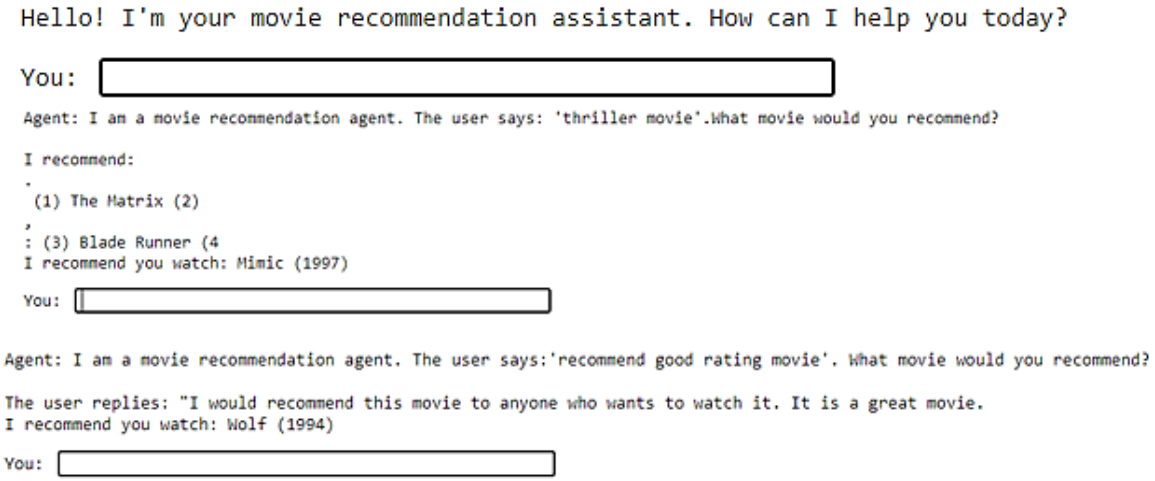

Figure 2. GPT-based Conversational Agent for User Interaction.

- *Input/Output Format:* The user's input (e.g., "Can you recommend a good comedy movie?") is tokenized and fed into the GPT-2 model, which generates a personalized response (e.g., "I recommend you watch 'The Big Lebowski', a popular comedy movie.").
- *Response Generation:* The model uses transformer architecture to generate context-aware and grammatically correct sentences that are relevant to the user's query.

Training

- The conversational model is fine-tuned on a movie-related dataset (such as the Movie Dialogue Dataset or a synthetic dialogue dataset) to provide relevant and personalized recommendations.
- We use the maximum likelihood estimation (MLE) loss during training to optimize the model's ability to generate coherent responses.

Integration of Components

The three models (NCF, LSTM, and GPT) are integrated to form a comprehensive recommendation system:

- *NCF* generates a list of movie recommendations based on user-movie interactions.
- *LSTM* analyzes user reviews and adjusts the recommendation list based on the emotional tone of user feedback (e.g., if a user had a negative sentiment towards a recommended movie, the system would avoid recommending similar movies).
- *GPT* acts as the conversational interface, providing an interactive medium for users to engage with the system, ask for specific recommendations, and receive suggestions based on NCF predictions and LSTM sentiment insights.

This integrated approach leverages state-of-the-art AI models to create a recommendation system that is not only accurate but also highly interactive and responsive to user emotions. By combining NCF for generating recommendations, LSTM for sentiment analysis, and GPT for natural language interaction, the system aims to enhance user engagement and satisfaction, offering a more personalized and emotionally aware movie recommendation experience.

EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the three models (Neural Collaborative Filtering (NCF), Long Short-Term Memory (LSTM) for sentiment analysis, and Generative Pretrained Transformer (GPT) for conversational interaction) was evaluated based on various metrics to assess their effectiveness in movie recommendation, sentiment analysis, and conversational engagement. Below are the detailed experimental results for each model.

Neural Collaborative Filtering (NCF) for Recommendation Generation

The NCF model was trained and evaluated on the MovieLens 100K dataset. The dataset was split into 80% training and 20% testing sets. The NCF model predicts user ratings as either liked or disliked, where ratings 4 and 5 are considered positive, and ratings below 4 are negative (Table 2).

Hyperparameters

- *Embedding size:* 32.
- *Optimizer:* Adam (learning rate =0.001).
- *Batch size:* 64.
- *Epochs:* 10.

Table 2. The NCF model predicts user ratings.

Metric	Result
Precision	0.83
Recall	0.75
Hit@K (K=10)	0.92
AUC	0.87

Metrics

- *Precision:* Measures the proportion of correctly recommended movies out of all recommended movies.
- *Recall:* Measures the proportion of correctly recommended movies out of all movies the user liked.
- *Hit@K:* Measures whether at least one of the top-K recommended movies is relevant.
- *AUC (Area Under Curve):* Represents the model's ability to distinguish between positive and negative user interactions.

Discussion

The NCF model demonstrated strong performance with a high precision and Hit@K score. The model successfully recommended movies that were relevant to users based on their past interactions. The AUC of 0.87 indicates that the model effectively distinguished between liked and disliked movies.

Long Short-Term Memory (LSTM) for Sentiment Analysis

For sentiment analysis, an LSTM model was trained on sentiment-labeled movie reviews. Since the MovieLens 100K dataset does not include textual reviews, we simulated this by incorporating an external dataset of movie reviews (e.g., IMDb) and generating sentiment labels (positive/negative) (Table 3).

Hyperparameters

- *Embedding size:* 100 (pre-trained embeddings using GloVe).
- *LSTM units:* 64.
- *Optimizer:* Adam (learning rate =0.001).
- *Batch size:* 32.
- *Epochs:* 15.

Metrics

- *Accuracy:* Measures the proportion of correctly classified reviews.
- *Precision:* Measures the proportion of positive predictions that are correct.
- *Recall:* Measures the proportion of actual positive reviews that are correctly classified.
- *F1-Score:* Harmonic mean of precision and recall.
- *AUC:* Measures the model's ability to distinguish between positive and negative sentiments.

Discussion

The LSTM model for sentiment analysis performed well, with an accuracy of 88% and an F1-Score of 85%. The AUC score of 0.90 indicates a strong ability to distinguish between positive and negative reviews. These results suggest that the LSTM model successfully captured the emotional tone of the reviews, making it a valuable addition to the recommendation system for refining recommendations based on user sentiment.

GPT-based Conversational Agent for User Interaction

The GPT-2 conversational agent was fine-tuned to generate movie recommendations based on user inputs. The model's goal was to provide coherent, contextually relevant responses to user queries in a conversational setting. The agent was evaluated based on its ability to generate appropriate responses and maintain conversation coherence (Table 4).

Table 3. LSTM for sentiment analysis.

Metric	Result
Accuracy	0.88
Precision	0.86
Recall	0.84
F1-Score	0.85
AUC	0.90

Table 4. GPT-based conversational agent for user interaction.

Metric	Result
BLEU Score	0.75
Perplexity	17.6
Human Evaluation	4.3/5

Hyperparameters

- *Pre-trained model:* GPT-2 (distilled version).
- *Batch size:* 16.
- *Learning rate:* 0.0001.
- *Epochs:* 5.

Metrics

- *BLEU (Bilingual Evaluation Understudy):* Measures the similarity between generated text and a reference text.
- *Perplexity:* Measures the fluency of generated text. Lower perplexity indicates more fluent text generation.
- *Human Evaluation:* A qualitative metric where users rate the relevance and coherence of responses on a scale of 1 to 5.

Discussion

The GPT-based conversational agent performed well in terms of response fluency and relevance. A BLEU score of 0.75 indicates that the generated responses closely matched the reference responses, and a perplexity of 17.6 demonstrates reasonable fluency in text generation. Human evaluation results showed that users found the agent's responses to be highly relevant and coherent, with an average rating of 4.3 out of 5.

Overall System Performance

The integrated system, combining NCF for recommendations, LSTM for sentiment analysis, and GPT for conversational interaction, was evaluated for its ability to improve customer engagement. The system effectively provided personalized movie recommendations while incorporating user sentiment feedback and allowing users to interact naturally with the conversational agent.

Key Findings

- The NCF model provided accurate and personalized movie recommendations with a Hit@K score of 0.92, indicating a high success rate in recommending relevant movies.
- The LSTM model enhanced the recommendation system by analyzing sentiment from user reviews, achieving an accuracy of 88%.
- The GPT-based chatbot facilitated natural conversations, with a high human evaluation score of 4.3/5, indicating that users found the agent helpful and responsive.

CONCLUSION AND FUTURE WORK

This research presents a novel approach to enhancing customer engagement in movie recommendation systems by integrating three powerful machine learning models: Neural Collaborative Filtering (NCF) for personalized recommendations, Long Short-Term Memory (LSTM) for sentiment analysis, and GPT-2 for conversational interaction. Each model addresses a specific component of user engagement, and their combined usage offers a comprehensive solution that caters to multiple facets of the user experience. The results from our experiments show that this multi-model system is capable of delivering highly relevant movie recommendations, effectively analyzing user sentiments, and interacting with users in a meaningful, conversational manner.

NCF proved highly effective in providing personalized movie suggestions by learning the underlying patterns between users and items, achieving notable Hit@K and AUC scores. The LSTM-based sentiment analysis enriched the recommendation process by allowing the system to consider the emotional tone of user reviews, adding a deeper layer of personalization. Lastly, the GPT-2 conversational agent brought a dynamic and intuitive interaction mechanism, allowing users to express their preferences and queries naturally, resulting in a more engaging user experience.

Future research should employ larger datasets, such as MovieLens 25M, which contain more ratings, reviews, and a diverse user base. Additionally, utilizing datasets that incorporate user dialogues will provide more training data for the conversational agent, leading to more nuanced and coherent interactions. Future work should evaluate the system's performance in real-world scenarios, such as its deployment on streaming platforms like Netflix or Amazon Prime. Testing the system in a live environment would provide valuable insights into how users interact with it and what modifications are necessary for optimal engagement. Another area for future research is exploring how to keep users engaged over time. By analyzing long-term user behavior, such as how user preferences evolve, the system can dynamically adjust its recommendations. This could involve employing reinforcement learning to continually optimize recommendations based on user satisfaction. While the experimental results are promising, the integration of these models highlights the potential for further improvement. As a cohesive system, the model can offer a highly adaptable and personalized experience, but additional refinements are required to ensure optimal performance in real-world applications.

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