System Goals for an AI-Powered Online Film Database

Introduction

This report outlines the system-level goals for an AI-enabled online film database, with the aim to create a platform that offers highly relevant, personalised film recommendations. It is important that the goals that are set are clear, achievable, and measurable. The desired outcome from the use of an AI to drive film recommendations must be clear across the organisation.

Organisational Objectives

1. Maximise User Retention - Our goal is to create a captivating user experience that keeps film enthusiasts engaged. By leveraging AI to provide personalised film recommendations through collaborative filtering, we aim to extend the time users spend on the platform and enhance the value they receive. This approach is crucial for boosting retention, as it consistently suggests relevant content, keeping users engaged longer and reducing churn.
2. Grow Platform Monetisation - We aim to increase revenue by offering a higher-quality platform. An AI-targeted recommender system will engage users, leading to more clicks and longer sessions. This increased activity will boost monetisation through ad clicks and views in the free tier, enhancing ad revenue. Additionally, it will encourage more users to opt into the premium subscription service, which offers advanced film analysis and ad-free viewing.
3. Gain a Technological Competitive Edge - Our goal is to become the industry leader in AI-driven film and series recommendations. To be the premier online film database, we need to ensure users can rely heavily on our recommendations. To achieve this, we will implement cutting-edge techniques in review-based recommender systems, focusing on continuous innovation to improve accuracy, consistency, and relevance for our users. We will employ advanced NLP for content analysis, address the cold-start problem, and adapt our machine learning models in an agile fashion. We'll also explore novel approaches like cross-media recommendations and assess our success through user satisfaction surveys.

Leading Indicators

1. Daily Active Users (DAU) - This indicator measures user engagement on the platform. By tracking DAU, we can assess how effectively our AI recommendations keep users interested. A growing DAU indicates that more users are finding value, leading to increased habitual use. This metric provides quick feedback on the impact of new AI features or changes in the recommendation model. We aim to see DAU growth across geographies and demographics, demonstrating that our AI recommender system has a uniform effect across the user base. Such diversified user base growth would also confirm that the DAU increase is due to the AI recommender system release instead of external factors.
2. Net Promoter Score (NPS) - This indicator measures how users feel about the AI-driven recommender system. We will conduct regular surveys to track NPS, calculated by subtracting the percentage of detractors (ratings 0–6) from the percentage of promoters (ratings 9–10). After deploying the AI recommender system, we aim to see an increase in NPS, indicating higher user satisfaction and the positive impact of the AI system.
3. AI Recommendation Acceptance Rate - This indicator measures how often users engage with the films recommended by the AI model. A high acceptance rate indicates that the AI effectively understands user preferences and provides relevant recommendations. An increase in this metric after the model's release strongly evidences the AI's effectiveness. However, biases can arise when for example popular content is recommended to the user over personalised recommendations.

User Outcomes

1. Growth in Film Discovery - Our goal is to provide users with film recommendations they enjoy. The system should suggest niche and less popular films suited to the user's taste, in addition to popular or highly rated films. Success can be measured by tracking the percentage of recommended films that users watch to completion from surveys, films users rate positively, or films users add to their favourites list. The AI should learn from user behaviour to continuously improve its recommendations, leading to a higher rate of film discovery and enjoyment over time.
2. Quick and Effective Film Selection - We aim to reduce the time and effort users spend selecting a film to watch. The AI system should provide a concise and relevant list of films within a short time after the user arrives on the

platform. It is important to balance providing enough options for users whilst not overwhelming them with too many options.

3. Film Knowledge Expansion - This goal aims to broaden users' film knowledge base, leading them to appreciate the platform for its recommendations. The AI system should steadily introduce users to a diverse range of genres and film eras. The platform can measure the success of this broader recommendation strategy by surveying users after film selection.

Model Properties

1. Recommendation Accuracy Rate - To achieve a higher recommendation accuracy rate, deep learning models will play a key role in identifying nuanced relationships between users and films. By employing user/item embedding techniques, such as multilayer perceptron’s (MLPs), the system can capture latent features, providing more personalised recommendations based on factors like user behaviour, film metadata and collaborative filtering patterns. Also, incorporating sequence-based models (e.g., RNNs or LSTMs) can model the evolution of user preferences over time, tracking viewing patterns and adjusting recommendations dynamically.
2. Response Time Optimisation - Optimising response time is critical for delivering real-time recommendations to users. Pre-trained embeddings for films and users, generated through deep learning models, can significantly speed up the recommendation process by providing quick matches based on user profiles and film attributes. Additionally, models such as autoencoders can preprocess and compress large-scale user-movie interaction data, allowing for faster retrieval, while keeping accuracy high. These optimisations will ensure that the system delivers fast, accurate recommendations, even as the platform scales to handle more users and content.
3. Cold Start Performance - Addressing cold start issues is key when a user or film has little to no interaction data. By leveraging content-based recommendation models, the system can analyse metadata such as movie descriptions, genres etc. and generate recommendations even for newly added films. Also, for new users, the system can rely on minimal data to provide relevant suggestions by drawing on cross-domain recommendations. Additionally, meta-embedding models that combine multiple information sources can provide robust recommendations even when data is sparse. This approach will improve cold start performance, offering new users and films a smooth entry into the recommendation ecosystem without relying completely on historical interaction data.

How the Goals Relate to Each Other

1. User Engagement Drives Multiple Objectives - Maximising user retention influences Daily Active Users and AI Recommendation Acceptance Rate. Higher engagement provides more data for AI learning, improving recommendation accuracy. This creates a feedback loop where better recommendations lead to increased engagement, providing more data for further improvements. Enhanced engagement also boosts monetisation through increased ad views and premium subscriptions.
2. AI Capabilities lead to strong System Performance and User Satisfaction – A successful and accurate AI model demonstrates positive model properties like Recommendation Accuracy and Cold Start Performance. These improvements enhance user outcomes, such as Film Knowledge Expansion and Quick Film Selection. As users receive more relevant recommendations, their satisfaction increases, supporting retention and strengthening the platform's competitive edge. Continuous AI improvement ensures the platform stays ahead in the market.
3. Balancing Short-Term Engagement and Long-Term Value - Immediate engagement is key as well as long-term value creation. Cold Start Performance ensures new users quickly receive valuable recommendations, supporting short-term engagement. Film Knowledge Expansion contributes to long-term satisfaction and loyalty. This approach aligns revenue growth with sustainable user engagement, creating a robust business model that can adapt to market changes and everchanging user preferences.

Conclusion

This report has outlined the system-level goals for an AI-enabled online film database, outlining organisational objectives, indicators, user outcomes, and model properties. By leveraging AI technologies to deliver personalised recommendations, the platform aims to enhance user engagement and satisfaction. The connected nature of these goals leads to continuous improvement, greatly strengthening the outlook for the platform to be an industry leader.

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