**System Goals for an AI-Powered Online Film Database**

Introduction

This report outlines the system-level goals for an AI-enabled online film database, aiming to create a platform that offers highly relevant, personalized film recommendations. All goals are aimed to be understandable, measurable and achievable.

Organisational Objectives

**Maximize User Engagement and Retention**: This objective aims to create a captivating user experience that keeps film enthusiasts returning. By using AI to deliver personalized film recommendations, the platform seeks to extend user session times and improve engagement. The system will analyse user preferences and habits to recommend films that fit individual tastes and introduce new genres. Success will be tracked through metrics like daily active users, session duration, and the impact of personalized recommendations on user activity.

**Enhance AI Capabilities to both grow and maintain a technological competitive edge**: This objective focuses on enhancing the AI-driven recommender system to stay competitive. The goal is to develop advanced AI algorithms that deliver more accurate and personalized film recommendations. This involves improving machine learning models to better understand user preferences, using natural language processing (NLP) for analysing reviews, and exploring computer vision to analyse film content. Innovation will also include cross-media recommendations, trend prediction, and real-time adaptation based on user feedback. Additionally, improving recommendation transparency to boost user trust and optimizing system performance for scalability are priorities. Success will be measured through metrics like recommendation accuracy, user satisfaction, and system speed.

**Monetisation and Revenue Growth**: To sustain the platform, the goal is to increase premium subscriptions by offering enhanced features like advanced film analysis and ad-free viewing. For free-tier users, AI-driven targeted ads will maximize revenue without disrupting the user experience. The platform also plans to offer additional services, such as social features, professional recommendation engines, and film analytics tools, to diversify revenue streams and ensure long-term growth.

Leading Indicators

**User Satisfaction and Net Promoter Score (NPS):** This leading indicator focuses on measuring how users feel about the AI-powered film database. It aims to gauge user satisfaction through regular surveys and by tracking the Net Promoter Score. The goal is to maintain a consistently high NPS, indicating that users are not only satisfied with the service but are also likely to recommend it to others. This metric can provide early feedback on the effectiveness of new features or changes in the AI recommendation system. Success in this area suggests that the platform is meeting user needs and is likely to see growth in user base and engagement over time. Regular monitoring of user comments and feedback will also provide qualitative insights to complement the quantitative NPS data.

**Daily Active Users (DAU) and Session Duration:** This indicator measures the level of user engagement with the platform on a daily basis. By tracking the number of daily active users and the average duration of their sessions, we can gain insights into how well the AI recommendations are keeping users interested and engaged. An increase in DAU and longer session durations suggest that users find value in the platform and are likely to become habitual users. This metric can provide quick feedback on the impact of new AI features or changes in the recommendation algorithm. It's a strong indicator of future user retention and potential revenue growth. The goal is to see a steady increase in both DAU and average session duration over time.

**AI Recommendation Acceptance Rate:** This leading indicator focuses specifically on the performance of the AI recommendation system. It measures the rate at which users engage with (click on, watch, or save for later) the films recommended by the AI. A high and increasing acceptance rate indicates that the AI is successfully understanding user preferences and providing relevant recommendations. This metric directly reflects the effectiveness of the core AI technology and can provide quick feedback on algorithm updates or new features. The goal is to continuously improve this rate, which should correlate with increased user satisfaction and engagement. Additionally, tracking which types of recommendations are most often accepted can provide valuable insights for further AI development and content curation strategies.

User Outcomes

Enhanced Film Discovery and Enjoyment: This goal aims to ensure users consistently find films they genuinely enjoy through the AI recommendations. The system should not only suggest popular or highly-rated films but also uncover hidden gems that align with each user's unique tastes. Success can be measured by tracking the percentage of recommended films that users watch to completion, rate positively, or 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. This outcome directly addresses whether users are finding content they end up liking, which is crucial for a film recommendation system.

Efficient Decision-Making in Film Selection: The goal here is to reduce the time and effort users spend in choosing what to watch. The AI should provide concise, relevant information and personalized recommendations that help users make quick, satisfying decisions. This can be measured by tracking the average time between a user opening the app and starting to watch a film, as well as the frequency of users changing their minds or stopping films shortly after starting. A successful outcome would show users making faster decisions with higher satisfaction rates, indicating that the AI is effectively assisting in the decision-making process.

Expanded Film Knowledge and Appreciation: This outcome focuses on broadening users' cinematic horizons and deepening their appreciation for film. The AI should introduce users to a diverse range of genres, eras, and cultures in cinema, gradually expanding their viewing preferences. Success can be measured by tracking the diversity of genres and types of films users engage with over time, as well as through user surveys gauging their perceived growth in film knowledge. The system could also incorporate educational elements, providing interesting facts or context about recommended films, and measure user engagement with this information. A positive outcome would show users exploring a wider variety of films and reporting a greater understanding and appreciation of cinema as an art form.

Model Properties

**Recommendation Accuracy Rate**: This goal focuses on improving the accuracy of the AI model's film recommendations. The aim is to increase the percentage of recommended films that users engage with positively. This can be measured by tracking the ratio of recommended films that users watch, rate highly, or add to their watchlists compared to the total number of recommendations made. For example, we might set a target of achieving an 85% accuracy rate, where 85 out of 100 recommended films result in positive user engagement. Improving this metric directly contributes to user satisfaction and engagement, key factors in the system's overall success. However, it's important to balance this goal with other factors like recommendation diversity to avoid over-optimization that might lead to a "filter bubble" effect.

**Response Time Optimization**: This goal aims to minimize the time taken by the AI model to generate and serve personalized recommendations. Fast response times are crucial for maintaining user engagement and providing a smooth experience. The target could be to consistently deliver personalized recommendations within 200 milliseconds for 99% of requests. This goal directly impacts the user experience, as faster recommendations allow for more seamless browsing and discovery. However, it's essential to ensure that improvements in speed don't come at the cost of recommendation quality. The optimization process should focus on efficient algorithms, caching strategies, and potentially leveraging distributed computing to achieve both speed and accuracy.

**Cold Start Performance**: This goal addresses the model's ability to provide relevant recommendations for new users or for newly added films with limited data. The objective is to improve the quality of recommendations in these "cold start" scenarios. Success can be measured by the engagement rate of first-time users with their initial recommendations, and the pick-up rate of newly added films. For instance, we might aim for new users to engage with at least 3 out of their first 10 recommendations within their first session. For new films, the goal could be to have them appear in relevant recommendation lists within 24 hours of being added to the database. Improving cold start performance is crucial for quickly engaging new users and ensuring that the platform remains dynamic and up-to-date with new content.

How the Goals Relate to Each Other

User Engagement Drives Multiple Objectives: The organizational objective of maximizing user engagement directly influences leading indicators like Daily Active Users and Session Duration. Enhanced user engagement contributes to better monetization opportunities, supporting the Revenue Growth objective. Higher engagement provides more data for AI learning, improving the Recommendation Accuracy Rate model property.

AI Capabilities Underpin System Performance: The goal to enhance AI capabilities affects nearly all other goals, from improving user outcomes to boosting model properties. Advanced AI directly impacts the Recommendation Accuracy Rate and Cold Start Performance model properties. Better AI capabilities contribute to the user outcome of Efficient Decision-Making in Film Selection.

User Satisfaction Links Outcomes to Objectives: The User Satisfaction leading indicator is a direct result of successful user outcomes like Enhanced Film Discovery and Enjoyment. High user satisfaction supports the organizational objective of user retention and potentially drives revenue growth through word-of-mouth recommendations.

Model Properties Support User Outcomes: The Recommendation Accuracy Rate directly influences the user outcome of Enhanced Film Discovery and Enjoyment. Response Time Optimization contributes to Efficient Decision-Making in Film Selection. Improved Cold Start Performance helps in achieving Expanded Film Knowledge and Appreciation by introducing users to new content more effectively.

Leading Indicators Predict Organizational Success: The AI Recommendation Acceptance Rate is an early indicator of the system's ability to meet the organizational objective of enhancing AI capabilities. Daily Active Users and Session Duration metrics provide insights into potential monetization opportunities and overall user engagement.

Revenue Growth Depends on User-Centric Goals: The monetization objective is supported by positive user outcomes and high engagement metrics. Improved AI capabilities and model properties indirectly contribute to revenue growth by enhancing the overall user experience.

Feedback Loop Between Goals: User outcomes provide data that helps improve model properties. Enhanced model properties lead to better user outcomes, creating a positive feedback loop. This loop supports the continuous improvement of AI capabilities and maintains the competitive edge of the platform.

Conclusion

By aligning organizational objectives with user outcomes and refining model properties, the AI-powered film database aims to create a personalized and engaging platform that drives user satisfaction and business success.

References

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