Final Report

PROJECT:	CAPSTONE PROJECT: MUSIC RECOMMENDATION SYSTEM
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01. EXECUTIVE SUMMARY

KEY FINDINGS AND FINAL MODEL SPECIFICATIONS

The analysis conducted in Milestone revealed compelling insights regarding the performance of various recommendation models. Among these findings, the Singular Value Decomposition (SVD) model appeared as the top-performing solution, surpassing alternative models such as user-user, item-item, and co-clustering. Across key evaluation metrics: precision, recall, and F1 score, the SVD model consistently demonstrated superior performance. Precision, which measures the relevance of recommended songs to the user, along with recall, indicating the proportion of relevant songs recommended, showcased notable improvements with the SVD model. Additionally, the SVD model exhibited the lowest Root Mean Square Error (RMSE), highlighting its adeptness in accurately predicting play counts for songs. These findings collectively underscore the efficacy of the SVD model in providing personalized and accurate song recommendations tailored to user preferences. Based on the current findings, the implementation of the SVD model is expected to enhance user satisfaction and retention on the platform. With more relevant recommendations, users are likely to spend more

time engaging with the platform, leading to increased user loyalty and potentially higher subscription or ad revenue. Therefore, adopting the SVD model as the final solution aligns with the objective of improving user experience and driving business growth.

02. PROBLEM AND SOLUTION SUMMARY

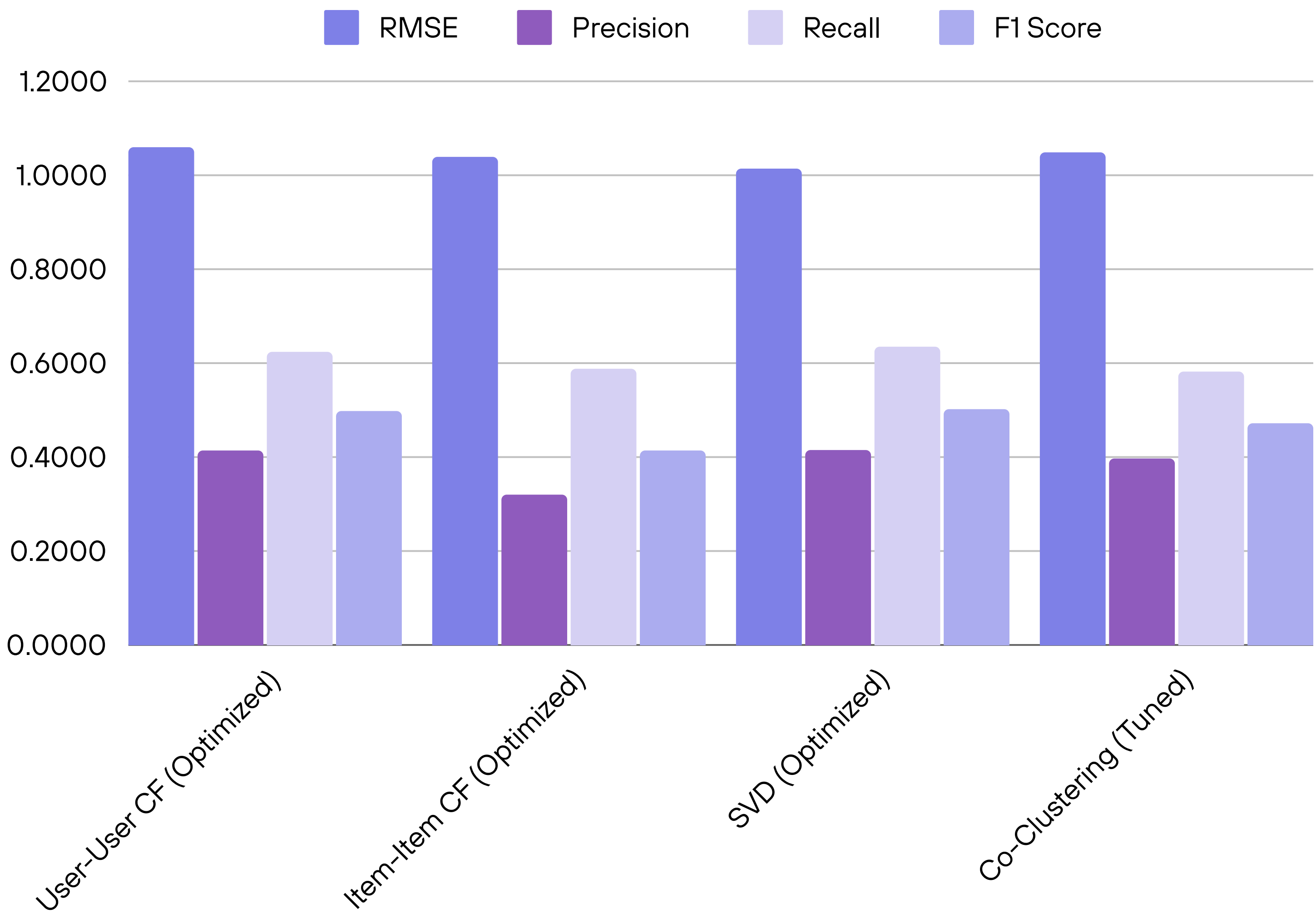
PROBLEM OVERVIEW

The problem at hand is to devise a recommendation system tailored to individual users' music preferences in order to increase user satisfaction and retention on the platform. In the today’s digital world, where user engagement and loyalty are crucial factors for profits and business models, providing personalized recommendations has become essential for platforms like Spotify to stand out amidst fierce competition. By accurately predicting and suggesting songs that resonate with users, the platform aims to foster a deeper connection with its customers, thereby increasing the customer retention and loyalty.

The main objective is to offer users a selection of songs that align with their tastes and preferences, thereby enhancing their overall listening experience. This entails leveraging user data and behavioral patterns to discern their musical inclinations and predict the songs they are likely to enjoy. The ultimate goal is to present users with recommendations that not only meet but exceed their expectations, encouraging them to explore and engage with the platform further.

PROPOSED SOLUTION DESIGN

The proposed solution design is to choose the Singular Value Decomposition (SVD) model as the primary recommendation engine. This decision stems from a comprehensive evaluation of various recommendation models, wherein the SVD model consistently outperformed its counterparts in terms of precision, recall, F1 score, as well as RMSE. These metrics are crucial indicators of the model's ability to accurately predict user preferences and recommend relevant songs tailored to individual tastes, as well as the accuracy in predicting play counts for songs by users.



The reason behind choosing the SVD model lies in its capacity to provide highly personalized recommendations, thereby enhancing user satisfaction and retention on the platform. By leveraging latent factors extracted from user-song interaction data, the SVD model can identify intricate patterns and similarities among users and songs, leading to more accurate predictions of user preferences. As a result, users are more likely to discover songs that resonate with their interests, fostering a deeper engagement with the platform.

Moreover, the adoption of the SVD model aligns with the overarching goal of the recommendation system, which is to optimize user experience and drive business growth. By recommending songs that users are more inclined to enjoy, the platform can prolong user sessions, increase user loyalty, and potentially boost subscription or ad revenue. This approach not only enhances the business' competitive advantage but also contributes to long-term sustainability and success in the music streaming industry.

In addition to the SVD model, a popularity-based method is used to address the cold start problem for new users. This ensures that even users with limited interaction history receive relevant song recommendations based on the overall popularity of songs. **Table 1** below shows the top 10 songs based on their popularity.

Song Ranking	Song Title
1	Victoria (LP Version)
2	The Big Gundown
3	Brave The Elements
4	Greece 2000
5	Secrets
6	Transparency
7	Video Killed The Radio Star
8	Sehr kosmisch
9	Luvstruck
10	You're The One

Table 1: Top 10 Songs based on Popularity

Furthermore, content-based recommendation model is considered to leverage song metadata such as title, artist name, and release, enriching the recommendation process with contextual information.

In summary, the selection of the SVD model is underpinned by its performance metrics and its ability to deliver personalized recommendations. By prioritizing user satisfaction and retention, the proposed solution aims to create an enjoyable music streaming experience for users while driving business growth and competitiveness.

03. RECOMMENDATIONS FOR IMPLEMENTATION

KEY RECOMMENDATIONS

Refine the model further: Continuous monitoring and optimization of the SVD model are crucial for ensuring its effectiveness over time. Despite that the SVD model currently proposed has already gone through hyper parameter tuning, it’s recommended to conduct the tuning further, which could potentially improve the model's accuracy and predictive power. In addition, regularly evaluating the model's performance metrics, such as precision, recall, and F1 score, and adjusting its parameters accordingly is essential. As the time goes by, we might get more and more data to test and refine the algorithm. Additionally, conducting thorough testing and validation on different datasets can provide insights into the model's generalizability and robustness.

Implement Hybrid Models: While SVD has shown relevant promising results, exploring hybrid models combining multiple recommendation techniques can further enhance the quality and the ability to personalize the recommended results to the users. For example, content-based filtering can capture semantic similarities between songs based on features like title, artist name, and release, while SVD can identify latent user preferences based on historical interaction data. By combining these approaches, the system can provide more diverse and accurate recommendations tailored to each user's preferences.

Enhance Data Collection and Preprocessing: High-quality and diverse data are essential for training accurate recommendation models. It's important to ensure robust data collection mechanisms to capture various aspects of user interactions and song metadata. For instance, the current song data only contains features like title, artist name, and release. It’s recommended to consider aggregating data from other sources to get information, like genre or lyrics, to further assist the improvement of content-based filtering. The more diverse the data sources become, the more important role data preprocessing plays. Steps like cleaning and normalization are crucial when making the data from different sources and with different scales to be consistent and comparable. In addition, feature engineering is also a critical step for preparing the data for model training. By enriching song metadata with additional features and ensuring data quality, the system can improve its ability to capture nuanced user preferences and recommend relevant content.

Collect User Feedbacks: By collecting user feedback, such as ratings, likes/dislikes, or explicit feedback forms, we can gather valuable insights into user preferences and satisfaction. Analyzing this feedback allows us to identify areas for improvement, refine recommendation algorithms, and adapt to change in user preferences over time. Moreover, actively as for user feedback may foster user engagement and trust, as users feel more involved in shaping their personalized recommendations.

KEY ACTIONABLE FOR STAKEHOLDERS

Invest in Cloud Platforms: Cloud platforms offer a cost-effective solution for the computational infrastructure for deploying and scaling the recommendation system. By operating on a pay-as-you-go pricing model, cloud platforms allows businesses to pay only for the resources and services they use, eliminating upfront capital investment in hardware. Below are the advantages of using a cloud platform:

- **Scalability:** The auto-scaling feature provides elastic computing resources that can be easily scaled up or down based on demand, enabling recommendation systems to handle fluctuations in user traffic and workload without manual intervention.
- **Managed Services:** The managed services specifically designed for machine learning and analytics workloads can take care of the complex infrastructure management by providing services like pre-configured environments and tools for training and deploying machine learning models at scale, allowing our organization to focus on building and optimizing their recommendation algorithms .
- **Data Storage:** The scalable storage solution is required to store the large volume of data required for recommendation systems, providing cost-effective and durable storage for user data, song metadata, and training datasets.
- **GPU Resources:** The available access to GPU resources is particularly useful for recommendation systems that leverage complex algorithms for personalized recommendations.

Collaborate among Stakeholders: Collaboration between data scientists, engineers, and domain experts is essential to develop and deploy a robust recommendation system. This collaboration involves the following:

- **Establish Cross-functional Teams:** Form cross-functional teams consisting of data scientists, engineers, designers, product managers, and business stakeholders to facilitate communication, collaboration, and knowledge sharing, ensuring that the solution aligns with business goals and user needs.

- **Establish Open Communication:** Organize regular meetings, workshops, or knowledge-sharing sessions where team members can exchange ideas, report current implementation obstacles, and track the project plan to make sure the timeliness and the effectiveness of the project.

EXPECTED BENEFITS

Enhanced User Retention and Satisfaction: By optimizing the recommendation system, we aim to improve user engagement and satisfaction, leading to increased user retention. As evidenced by Spotify's success, a robust recommendation system can drive a significant increase in user base, as seen by the 33% increase of Spotify's user base even among its tough competition with rivals like Apple Music (Underwood, 2020).

Revenue Growth: Similar to Spotify, with revenue model centered around the result of the music recommendation system, our business will also heavily rely on Monthly Active Users (MAUs) and Premium Subscribers. By optimizing the recommendation system, we anticipate driving higher user engagement, which can lead to increased subscription and ad revenue. Spotify's success in Q4 2023, with MAUs expanding by 23% and Premium Subscribers increasing by 15% year-over-year, serves as a promising indicator of the revenue growth potential through an enhanced user experience.

Competitive Advantage: Improving the recommendation system will be essential in establishing a competitive position in the market. In 2006, Netflix launched the Netflix Prize, a competition aimed at improving its recommendation algorithm. Ultimately, a winning team claimed a $1 million prize by surpassing Netflix's algorithm's performance by 10% (Faggella, 2021). This historical example underscores the substantial impact that even a modest 10% enhancement in recommendation system effectiveness can have on user engagement, satisfaction, and ultimately, business outcomes. Therefore, by offering users personalized and relevant content recommendations, we can differentiate ourselves from competitors and attract new users while retaining existing ones.

EXPECTED COSTS

The development cost for the music streaming app for the measure platform is as follows (Niketan Sharma is the CTO of Nimble AppGenie, 2024):

Music Streaming App	Development Cost Range
Spotify	$100,000 - $500,000+
SoundCloud	$60,000 - $300,000+
Pandora	$50,000 - $300,000+
YouTube Music	$70,000 - $500,000+
Apple Music	$100,000 - $500,000+

We can see that for high complexity music recommendation system, the cost can range from $50,000 to $500,000+.

The following provides a step-wise breakdown of the procedure and associated costs for developing an on-demand music app which can be a good estimation and baseline for our expected costs in building a music recommendation system (Niketan Sharma is the CTO of Nimble AppGenie, 2024):

Planning and Research:

- Market Analysis and Research: Estimated cost ranges from $1000 to $5000, depending on factors like market trends and competition. Time needed: 3 weeks.
- Gathering Potential Requirements: Estimated cost ranges from $500 to $2000, including meetings with stakeholders.
- Planning for the Project: Estimated cost ranges from $1000 to $3000, involving resource allocation and objective definition.

Design:

- UI/UX Design: Estimated cost ranges from $3000 to $10,000, dependent on app design complexity. Time needed: 4 weeks.
- Graphic Designing: Estimated cost ranges from $500 to $2000, covering virtual assets.

Development:

- Frontend Development: Estimated cost ranges from $10,000 to $30,000, covering media playback and authentication features. Time needed: 12 weeks.

- Backend Development: Estimated cost ranges from $15,000 to $40,000, including server-side logic and third-party integration.
- API Development: Estimated cost ranges from $5000 to $15,000, covering data exchange within the app and external systems.

Testing & Quality Assurance:

- Mutual Testing: Estimated cost ranges from $2000 to $5000, identifying bugs, usability, and compatibility. Time needed: 4 weeks.
- Automated Testing: Estimated cost ranges from $3000 to $8000, setting up automated frameworks and scripts.

Launch & Deployment:

- App Store Deployment: Estimated cost ranges from $500 to $1000, for publishing on platforms like Google Play and Apple App Store. Time needed: 2 weeks.
- Marketing & Promotion: Estimated cost ranges from $5000 to $20,000, varying based on selected marketing channels.

Maintaining and Updating the App:

- Regular Updates & Maintenance: Estimated cost ranges from $2000 to $5000 per month for bug fixes and technology updates. This process is ongoing.

POTENTIAL RISKS OR CHALLENGES

To implement a music recommendation system, several potential risks and challenges need to be addressed to ensure success and effectiveness:

Privacy Concerns: Given the collection and analysis of user data for recommendation purposes, it is essential to prioritize user privacy and ensure compliance with data protection regulations. Robust privacy safeguards must be implemented to protect user data and maintain trust among users.

Algorithmic Bias: Recommendation algorithms may exhibit bias or discrimination against certain user groups or content types. A famous case is that researchers found Google Ads displayed job ads for higher-paying positions more often to men than women (2015). One main reason might be that Google Ads personalizes ad delivery based on user data, such as browsing history and search queries. If men tend to search for higher-paying jobs more than women, the algorithm might prioritize showing them such ads. Thus, regular monitoring of the recommendation system is necessary to identify and address any bias issues

Technical Complexity: As implementing and maintaining a recommendation system involves dealing with large volumes of data, complex algorithms, and infrastructure challenges, stakeholders must be prepared to address technical complexities and allocate resources for ongoing maintenance and support to ensure the system's reliability and performance.

FURTHER ANALYSIS AND OTHER ASSOCIATED PROBLEMS

In addition to implementing the music recommendation system, there are several further analyses and problem-solving steps that can enhance the effectiveness and address potential challenges:

A/B testing: Conducting A/B testing on the experimentation of different recommendation algorithms or different combination of recommendation techniques allows for evaluation of the performance every combination of algorithms and the selection of the most effective approach.

User Engagement Metrics: Incorporating user engagement metrics, such as click-through rates, session duration, and playlist creation into analysis provides insights into how users interact with the recommendation system. Metrics, such as user retention rates, churn rates, and lifetime value, can provide insights into the long-term effectiveness and impact of the recommendation system. By analyzing these metrics, stakeholders can assess the impact of the recommendation system on user behavior and preferences, identifying areas for improvement and optimization.

Contextual Information: User location, time of day, device type, and browsing history can improve the relevance and accuracy of recommendations, ensuring that recommendations are tailored to the user's current situation and preferences, enhancing the overall user experience.

Cross-Domain: Exploring cross-domain recommendations, including other media types such as movies and books, allows for leveraging user preferences across different domains, providing more personalized and diverse recommendations, enhancing the overall user experience.

By proactively addressing these issues, stakeholders can optimize the performance of the music recommendation system and deliver a more personalized and engaging user experience, ultimately driving increased user satisfaction, retention, and business success.

04. REFERENCE

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