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Spotify Artist Recommendation Engine

Introduction

Music streaming users often face a recurring issue - monotonous recommendations leading to listener boredom. Current systems struggle to adapt to temporal and dynamic user preferences, partly due to privacy constraints on essential data. Solving this issue demands both user and system involvement in refining the recommendation algorithm. Our goal is to create a recommendation system that leverages prior listening history and artist connections, incorporating elements such as genre, popularity, and collaborations. Users seek personalized yet varied recommendations and desire an engaging interaction with music streaming software.

Problem Definition

Bu and Small (2018) introduced an innovative concept - active learning in the recommendation system. It allows the system to question users about various entities in each iteration, mainly focusing on rating unlabeled entities. While this approach is a breakthrough, it has its limitations. It offers a limited number of additional data points, potentially being inefficient, and the nature of questions may not fully engage users. Our project addresses the challenge of repetitive music recommendations by actively involving users in refining their music suggestions. We aim to deliver personalized yet diverse recommendations, considering factors like genre, popularity, and collaborations. This initiative aligns with users' desire for engaging, natural interactions with music streaming software, enhancing their music exploration experience and offering artists opportunities to reach new audiences.

Literature Survey

Detecting Collaboration Profiles in Success-Based Music Genre Network detects collaboration profiles in success-based music genre networks, and introduces attributes like attractiveness, affinity, and influence. *Network Analysis of the Spotify Artist Collaboration Graph* analyzes artist collaboration networks, emphasizing popularity and genre categorization using Spotify data. The first paper examines collaboration profiles and success factors in music genre networks, and the second paper focuses on popularity & genre categorization in artist collaboration networks with Spotify data. Both face challenges due to data limitations and reliance on popularity metrics in the changing music streaming landscape.

Context-Based Music Recommendation Algorithm Evaluation evaluates six machine learning algorithms, with a focus of the Random Forest algorithm, which achieves an 84% accuracy in predicting likability by leveraging Spotify API data. *AI based Music Recommendation System Using Deep Learning Algorithms* discusses using deep learning to provide tailored music recommendations, addressing the challenge of managing a vast digital music library. Both papers focus on music recommendation systems; the first evaluates machine learning algorithms, to predict song likability using Spotify data, while the second employs deep learning with LSTM for instrument classification.

Music Individualization Recommendation System based on Big Data Analysis presents a big data-driven music individualization model that combines user behavior, context, user information, and music work data to improve recommendation accuracy, addressing issues like cold start and data sparsity. It enhances accuracy, scalability, & user satisfaction over traditional collaborative filtering models.

Factorization Meets the Neighborhood: A Multifaceted Collaborative Filtering Model employs advanced collaborative filtering techniques and a multifaceted approach, incorporating factors like genre, artist, tempo, and lyrics to enhance the accuracy and personalization of music recommendations. This is achieved through the combination of collaborative filtering and matrix factorization techniques.

Popularity and centrality in Spotify networks: critical transitions in eigenvector centrality uses Spotify data to create an artist network, highlighting a centrality shift from classical to rap artists when excluding less popular ones, introducing a social group centrality model applicable in other networks using connection & popularity data. *Music personalized recommendation system based on improved KNN algorithm* discusses common recommendation strategies, including the benefits and challenges of collaborative filtering. It introduces the KNN-Improved algorithm, which enhances precision & execution time by combining KNN with the baseline approach and standard deviation integration.

A music recommendation system based on music data grouping and user interests combines music content and user preferences, delivering personalized recommendations validated through experiments, showcasing the potential to enhance music recommendations and extend its applicability to other recommendation systems. *A Music Recommendation System Based on Music and User Grouping* groups songs by features and utilizes user access histories, offering content-based, collaborative, and statistical recommendation methods, with the statistical approach demonstrating effectiveness in song recommendations. *A Survey of Music Recommendation Systems and Future Perspectives* explores the evolving digital music landscape, emphasizing collaborative filtering, user-centric approaches and motivation-based models for an enhanced experience.

Explainability in music recommender systems offers insights into the importance of providing clear explanations for recommendations to enhance user trust and forgiveness, addressing requirements and strategies for evaluation. Meanwhile, *Music Recommendation Systems: Overview and Challenges* delves into the challenges faced by music recommendation systems, such as cold start issues, data availability, and overspecialization, highlighting the effectiveness of hybrid models combining content-based and collaborative filtering and the significance of recommendation user interfaces.

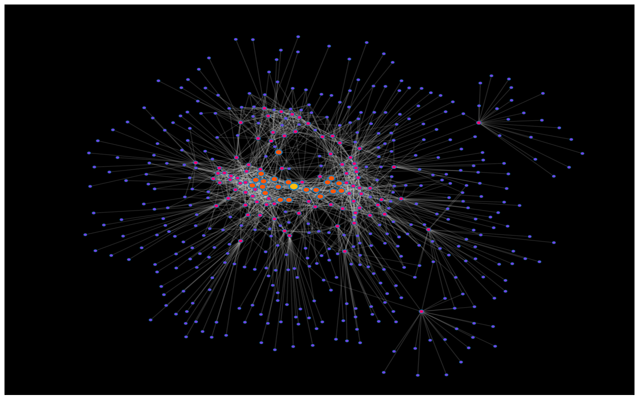
A comparative study of item space visualizations for recommender systems describes how recommendations prevent users from exploring music options in a larger context. *Interactive Visualization of Recommender systems* discusses how recommender systems help alleviate information overload by suggesting relevant items to users. Both papers focus on enhancing transparency and user perception in recommender systems. The first paper broadens recommendation context through visualizations, while the second paper prioritizes interactive visualizations for user engagement. Although the first paper's user feedback had limited impact, the second emphasizes user involvement for improved quality.

Intuitions

Our project uses a combination of collaborative filtering and content-based methods, introducing the concept of active learning to improve music recommendations. Leveraging natural language queries, we engage users, continuously updating their preferences by dynamically modifying the user-music interaction matrix based on their responses. To deliver tailored song suggestions, a content-based model scans the music database, aligning the recommendations with users' current tastes. This holistic approach aims to provide users with an interactive, diverse, and engaging music discovery experience while concurrently creating opportunities for artists to connect with new audiences, boosting their streaming numbers and listener engagement. Our primary stakeholders are users who expect relevant and enjoyable music suggestions and artists and music labels that will be connecting with new audiences. Collecting and analyzing user data may raise privacy risks and some algorithmic bias may exist. The integration of active learning into a hybrid recommendation system surpasses traditional methods by actively involving users in the recommendation process, creating a more personalized and interactive music discovery experience.

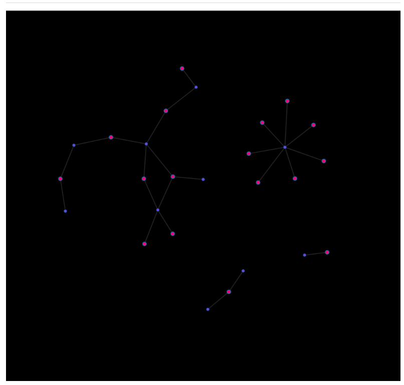
Innovations

Our team's first innovation is an artist network visualization tool that empowers users to delve into the world of music artists, discovering similar artists to their favorites. This tool is designed to provide an intuitive and engaging experience for music enthusiasts. To utilize this tool, users input a specific artist's name and specify a desired depth level. The artist serves as the central point of exploration for the network. The program then employs a breadth-first search algorithm, utilizing the Spotify API to discover related artists connected to the inputted artist. As the API identifies related artists, it establishes connections (edges) between these connected artists and assembles them into a JSON Graph object. This graph structure allows for a convenient and efficient representation of the artist network. To present this network visually, we've integrated the Alchemy.js library into an HTML website, offering users an aesthetically pleasing and interactive way to explore their artist network.



The visualization presents artists in the network as circles, with each circle's size indicating its position within the depth hierarchy. The largest circle, typically colored in yellow, represents the initially selected artist, while smaller circles, often in purple, signify artists at greater depths within the network. This visual cue makes it easy for users to identify the central artist and those further removed from the initial selection. Users can engage with the visualization in multiple ways, such as zooming in and out to focus on specific portions of the network and dragging the circles to rearrange them for a clearer view. Additionally, a hover feature provides further artist information, including the artist's name, which aids in introducing users to new artists and deepening their understanding of the network's structure. This tool combines data retrieval through the Spotify API with interactive visualization using Alchemy.js to create an engaging and informative experience for users interested in exploring artist connections and discovering new music.

Our second innovation is that users can query the network using natural language in order to only view the types of artists that they are interested in. Navigating and gaining insights from the whole network can be challenging. One scenario is that the user only wants to see a sub-network that only contains the artists that meet their interests the most. This usually leads to a smaller and less complicated network which is easier to draw insight from. For example, a user may only be interested in Irish Rock musicians. In our visualization tool, the user can input their interests by natural language and then the visualization tool will display a sub-network that contains artists that are the most related to Irish Rock bands. We achieved this using a ranking and filtering approach. We use Wikipedia API to fetch the information for each artist in the artist network. We prompt GPT-4 to extract the key highlights from each artist's wikipedia info. We store those key highlights for each artist for comparison with users' queries. Then, given a user's query, we convert it into a vector representation using Sentence-BERT (Reimer and Gurevych, 2019), a neural network that was trained to encode similar sentences into similar vectors. We encode the highlights for each artist using the same method. Then we calculate the cosine similarity between the encoded highlights of each artist and the encoded query. We rank the artists by the cosine similarity and keep the top-10 artists. We then update the artist network by only showing the top-10 artists and the artists which are directly related to the top artists. This produces a smaller network that focuses on artists that the user is interested in.



Experiments

In order to ensure the effectiveness, usability, and user satisfaction of the artists network tools, we needed to test them on various focus groups. Spotify Wrapped 2023 just came out, so we decided to use the number of artists a given user listened to create focus groups. From sampling users, we found that the three most dominant ranges for artists listened to were 0-250, 250-1000, and 1000+, and we had ten participants per focus group. There were two surveys given to all participants, one for each of the artist tools. The feedback from these surveys were important for iterations of development, allowing for adjustment of the tools to be more useful. These questions allow us to gauge the success of our recommendation algorithms in branching users out of their music bubble and allowing us to compare to existing tools.

Survey Questions on Artist Network Tool:
On a scale from 1-10, rate how easy the interface was to use?
On a scale from 1-10, rate how effective you think the interface was for recommending new artists?
On a scale from 1-10, rate how satisfied you were with the artist network tool?
On a scale from -5 to 5, how do the artist recommendations compare to artists recommended by Spotify, where -5 means the Spotify recommendations are more useful, and 5 means our tool is more useful?

Survey Questions on Natural Language Query Network Tool:
On a scale from 1-10, rate how easy the interface was to use?
On a scale from 1-10, rate how relevant artist recommendations were to the inputted artists?
On a scale from 1-10, rate how satisfied you were with the natural language query network tool?
On a scale from -5 to 5, how do the artist recommendations compare to artists recommended by Spotify where -5 means the Spotify recommendations are more useful, and 5 means our tool is more useful?

Average Survey Responses for Artist Network Tool	Users with 0-250 Streamed Artists Average Rating	Users with 250-1000 Streamed Artists Average Rating	Users with 1000+ Streamed Artists Average Rating
Ease of Use	9.6	9.3	9.6

Effectiveness	9.6	8.3	8.1
Satisfaction	9.4	8.5	8.2
Comparison to Spotify	0.3	1.2	1.6

Average Survey Responses for Natural Language Query Network Tool	Users with 0-250 Streamed Artists Average Rating	Users with 250-1000 Streamed Artists Average Rating	Users with 1000+ Streamed Artists Average Rating
Ease of Use	9.2	9.6	9.6
Relevance of Recommendations	8.4	9.6	9.8
Satisfaction	8.2	9.8	9.8
Comparison to Spotify	3.2	3.5	3.7

Evaluation

From the feedback received through user surveys, we can confidently conclude that both the artist network tool and the natural language network tool are successful visualization tools to display recommendations. The first table showcases the average survey responses for the artist network tool. Numerically, we can see that for all four survey questions, users that were in the first focus group (users that listened to between 0-200 unique artists) were more impressed by the tool, in comparison to the other focus groups that were familiar with more artists. The first question we sought to answer for this tool was how easy it was to use. Through the results, we can see that all focus groups found the artist network tool relatively easy to use, so that was a success! The next question we sought to answer was how effective the tool was at recommending new artists. Here, the user responses became more diversified, with users having listened to less artists found the tool more effective than users listening to more artists. It is also important to note that the responses between the last two focus groups, users with 250+ artists listened to, had similar survey responses to this. The reason that users in the first focus group may have found the tool more effective is because they were not as familiar with as many artists, so the artist recommendations in the earlier degrees of the network were new to them. This allowed them to more easily navigate through the network, whereas the other focus groups had to look at higher degree connections in order to find artists they were not familiar with. The next question we sought to answer for this artist network tool was how satisfied the users were with the tool. The rating distribution of this question was similar to the survey responses to the effectiveness question, implying as users used more complex networks (networks with higher degrees of connections), the less satisfied they were with the product. None of the scores received were below an 8, so overall it is still a successful tool. Finally, in comparison to Spotify, our tool seemed to be more useful in recommending artists as all average scores were above 0. This could be due to the sheer number of recommended artists shown on the graph and the ability to physically see the connections, while Spotify traditionally just recommends a few songs at the bottom of your playlist.

The second table highlights the average survey responses for the natural language query network tool. Numerically, we can see that this tool had the opposite rating trend to the artist network tool surveys, showing that users with more artists listened to were more impressed with the tool. Similarly to the artist network tool, we can see that all focus groups found the natural language query network tool relatively easy to use. In terms of relevance of recommendations, we can see that the first focus groups found the artist recommendations to be less relevant, while the second and third focus groups found them to be more effective. There are a couple explanations for this phenomenon. The first is that the first focus groups were not able to physically gauge how relevant the artist recommendations were due to their lack of knowledge of artists in the first place. Since they are not already diversified in their music taste, artists being recommended from the tool would have little significance to them, causing them to not know the relevance. Another reason for this trend in the data could be that focus groups with more artists listened to are more incentivized to listen to new artists. They have traditionally been more open to broadening their music taste, so the natural language query network tool could jog their memory on relevant artists they have heard about, but have not listened to yet. The rating distribution for the third survey question was similar to the survey responses to relevance of artist recommendations question, implying that users that were able to see the relevance of the recommendations were more satisfied with it. Finally, our tool seemed to be heavily favored for all groups in comparison to Spotify for recommending artists. On Spotify, natural language queries return a lot of results, making it difficult to find relevant information. Our tool is more concise, and solely recommends artists tailored to the users query.

There are a few more important takeaways from the experimental results. The first is that across questions that address the effectiveness/relevance of a tool, and questions that address that satisfaction of a tool, the average ratings differed by at most 0.2. This illustrates that there is a direct correlation between usefulness and satisfaction of a tool for a user. Another important takeaway is that simpler is better. Across both tools, we saw better ratings for tools that were less complex, and did not force the user to closely parse through the network to find relevant information. This is showcased by focus groups with less artists finding the artist visualization tool more useful, and by focus groups with more artists finding the natural language query network tool more useful. We predict that if focus groups with more artists were able to find new artists in lower degrees of the network, they would be more satisfied.

Discussion/Conclusion

The Spotify Artist Recommendation Engine project is a significant stride towards bursting out of the music bubble traditional recommendation systems trap users in. By integrating approaches such as natural language queries and artist network visualizations, our goal was to provide users with personalized and diverse music recommendations while actively engaging them in the recommendation process. From our experiments, we found that both tools were successful, accomplishing our goal of improving upon limited diversity of existing recommendation systems. Users with fewer artists in their listening history found the artist network tool more effective, emphasizing its role in introducing variety. In contrast, the natural language query tool resonated more with users who had a broader music taste, indicating its effectiveness in catering to diverse preferences. Additionally, simplicity emerged as a key factor, with users favoring tools that were easy to use and provided relevant recommendations. One limitation we ran into was complexity of the artist network. As the degree of connections increased, the network became more cluttered and harder to use, so future work could include branch pruning that allows the user to remove connections they do not want to see.

All team members have contributed a similar amount of effort.

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