Music Recommendation System

MIT ADSP Capstone Project

Dustin Kearns

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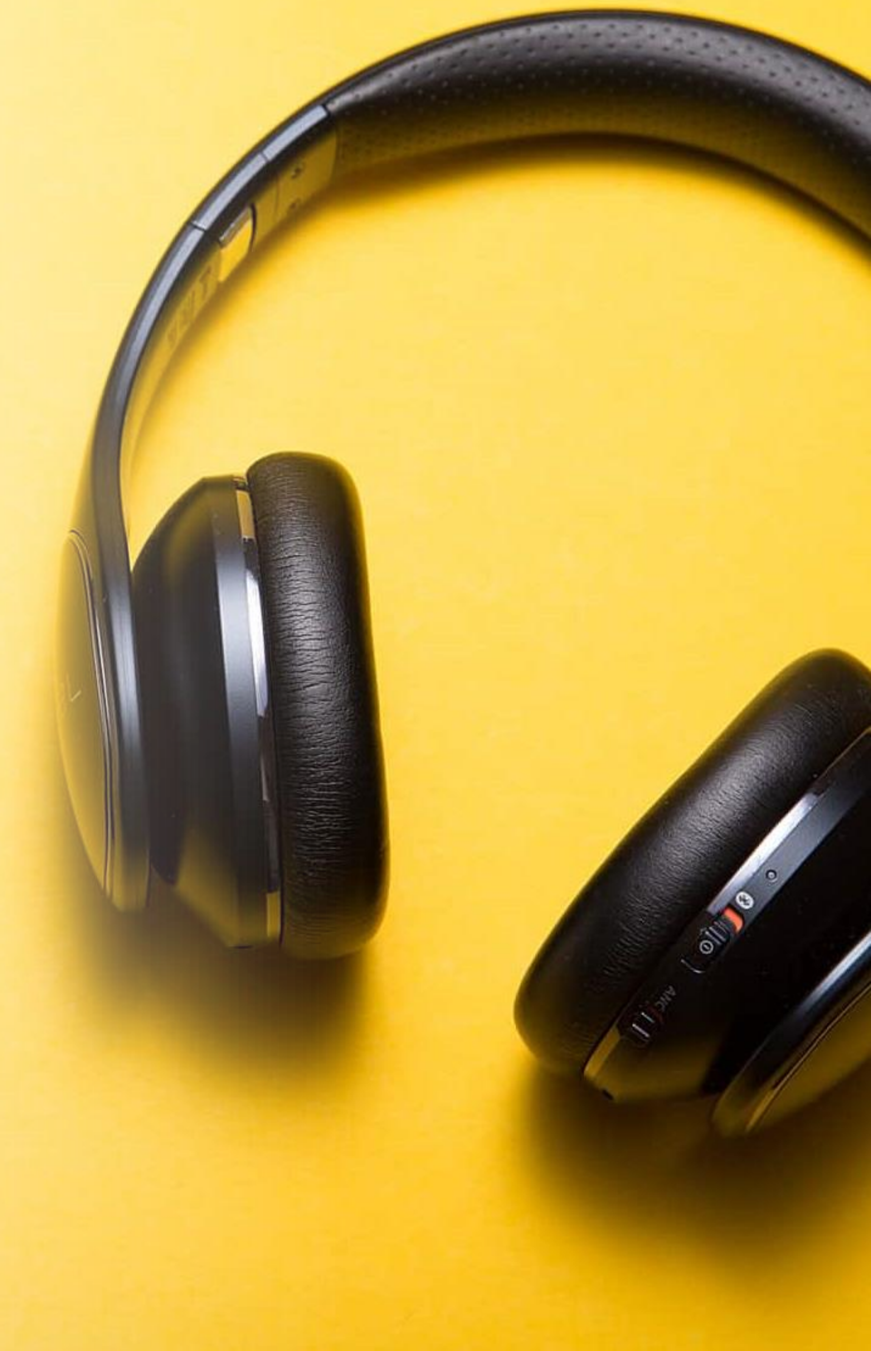
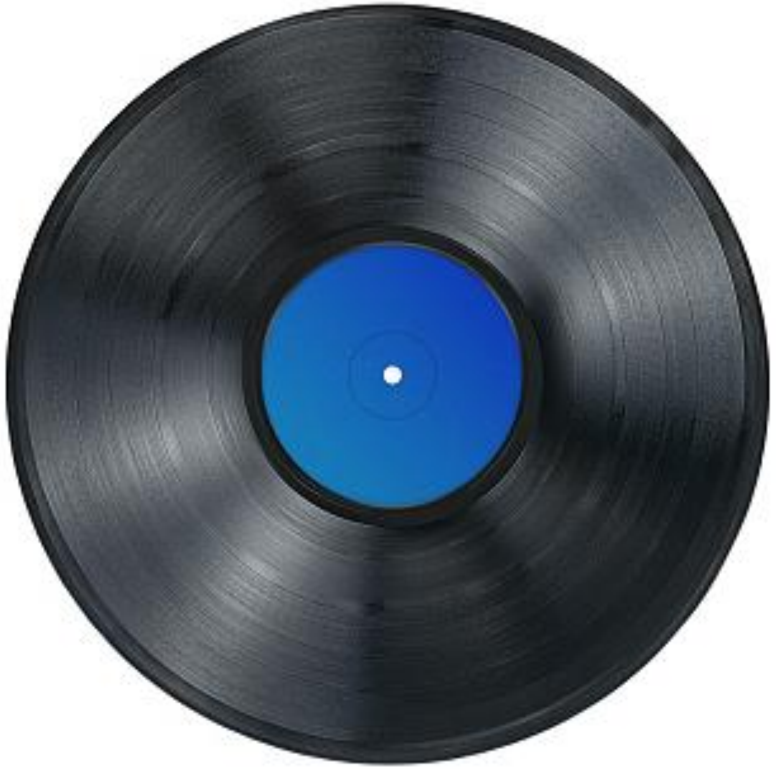


Executive Summary

- After testing various types of recommendation systems, I have determined a **User User Similarity-Based Recommendation System** to be the best fit for our platform
- Implementing this system will improve the user experience, boost user interactivity, reduce user churn, and could even improve relations with artists and the music industry as a whole
- Following implementation, we must continue to monitor the performance of our system to avoid potential deficiencies surrounding sparsity of data, cold-starts, and scalability



The Problem

To stay competitive as a major music streaming service we must create an effective music recommendation system capable of suggesting the top 10 songs a user is most likely to enjoy. The need for this is threefold:

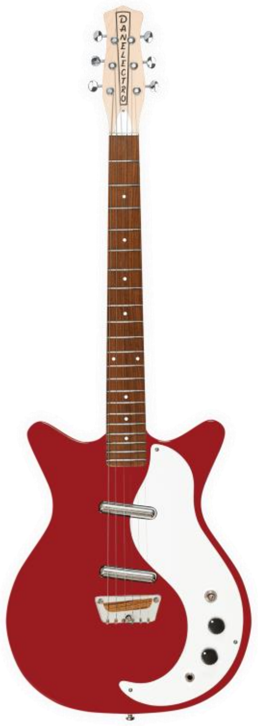
- To help our users navigate the incredible volume of music being released so they can find songs they like
- To aid artists in their search for an audience by helping them connect with potential fans
- To reduce user churn and boost our platform’s reputation as an artist-friendly destination

Methodology

I built, tuned, and evaluated 4 types of recommendation systems utilizing a subset of the Million Song Dataset released by The Echo Nest, which contains user listening activity for a set of songs released from 1922 to 2011.

The types of systems tested include:

- Rank-Based
- User-User Similarity Based
- Item-Item Similarity Based
- Model-Based



Measures of Success

I used the below metrics to assess the performance of each model on the test dataset:

- Precision - The fraction of recommended songs that are relevant to the user
- Recall - The fraction of relevant songs that are recommended to the user
- F1-Score - The harmonic mean of the Precision and Recall

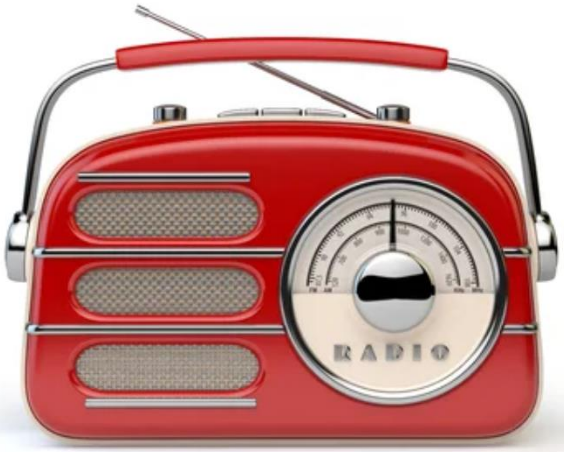
Taking the interests of all stakeholders into account it is important that we maximize both Precision and Recall. As such, I used the F1-Score as my main measure of model performance – the higher the F1-Score, the better the model.

Proposed Solution

Of these models, I have determined that a **User User Similarity-Based Recommendation System** would best fulfill the needs of our users, artists, and platform given the constraints present. This system bases its recommendations on the listening activity of other users who have similar taste to that of the target user. My tuned model achieved an F1-Score of 0.571.

The optimal parameters with which we should implement this model are:

- Similarity Measure: Pearson Baseline
- Max K: 30
- Min K: 9
- Min Support: 2



Expected Benefits and Costs

Benefits

- Improved user experience
- Increased user interactivity
- Lower user churn
- Improved artist/industry relations

Costs

- Engineering and data science talent
- Computational resources

Key Risks and Challenges

Sparsity

It will be difficult for our recommendation system to give good results if we have a highly sparse matrix (i.e. many user-song pairings with no data)

Cold-start

We will have no information on new users or songs with which to compare them to others, making personalized recommendations for them difficult

Scalability

The more users whose activity we consider in our model, the more computationally expensive it will become to run

Looking Ahead

Once implemented it is important to monitor the performance of the recommendation system and tune/adjust as needed. We should be prepared to respond to the potential challenges mentioned on the previous slide and continue to assess our options as more data is received.

Going forward we should also research ways to ethically collect more detailed data on both our users and the songs they stream. Additional datapoints will open up new opportunities for us to enhance our recommendation system and even try new models not previously tested.

Thank you!

Dustin Kearns

dustinpkearns@gmail.com

LinkedIn