Taylor Swift Recommendation System

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Introduction

The rise of modern music streaming platforms, combined with accessible recording tools, has transformed the music industry by lowering the barrier of entry for new artists. Previously, artists relied on expensive studio equipment and record labels, but musicians can now produce and distribute music independently via platforms like Bandcamp, SoundCloud, and Spotify. This democratization has increased the diversity of artists and music available to listeners.

Streaming platforms have seen a surge in artists, with Spotify's artist count doubling from 200,000 to 400,000 between 2014 and 2020 (Competition and Markets Authority, 2022). These platforms allow musicians to reach global audiences directly, bypassing traditional gatekeepers and fostering a more inclusive music ecosystem.

For consumers, the abundance of music—over 615 million active users on Spotify—has shifted discovery toward personalized recommendations. Algorithms analyze user preferences and behaviors to suggest tracks, helping users navigate vast libraries while uncovering new artists and genres. These systems play a dual role, introducing artists to potential fans and enhancing the listening experience for consumers.

Recommendation systems also empower artists by connecting them with the right audiences, turning casual listeners into loyal fans. For users, these systems streamline music discovery, reducing choice paralysis and enriching their experience. This mutual reliance on algorithms is redefining how music is consumed and distributed, fostering closer connections between artists and fans while shaping the future of the industry.

Overview of Recommendation Systems

Recommendation systems use different approaches to suggest items like music, movies, or products to users. The three most common approaches are content-based filtering, collaborative filtering, and hybrid systems.

Content-based filtering recommends items based on their features and the user’s past behavior. It builds a profile of a user’s preferences and matches new items to that profile. The system uses similarity measures like cosine similarity or Euclidean distance to find items that are similar to what the user has already liked. However, content-based filtering only recommends items within the scope of the user's existing preferences, so it can't suggest things outside of those preferences (Canidate).

Collaborative filtering expands on content-based filtering by using the preferences of other users. It can be user-based (recommending items liked by similar users) or item-based (recommending items similar to ones the user has liked). There are two types of collaborative filtering: memory-based and model-based, and advanced methods, like deep learning, can also be used for more accurate predictions (Najmani et al., 2022)

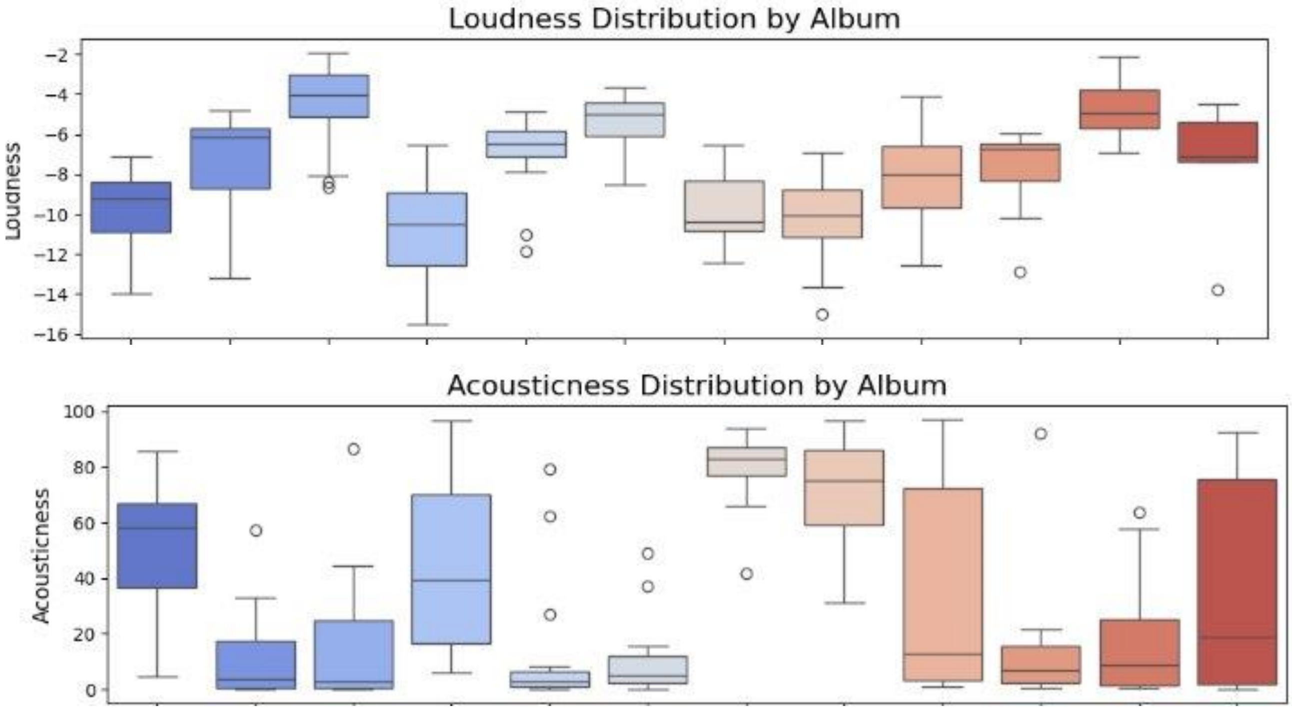
Hybrid approaches combine content-based and collaborative filtering to offer both personalized recommendations and the opportunity for users to explore new items. For example, Spotify uses a hybrid approach to recommend music based on a user's past listening while also introducing new tracks they might enjoy (McInerney, 2018).

Project Objectives

In this project, we will use a dataset consisting of Taylor Swift's songs to recommend new songs to a user based on their preferences. The dataset includes features such as song titles, album names and audio characteristics. Our goal is to recommend songs from Taylor Swift's catalog that are most likely to align with the user's preferences. We will use content-based filtering by creating a user profile and matching these preferences to Taylor Swift albums and compare two methods—cosine similarity and K-means clustering—to evaluate their effectiveness.

Data

The dataset from Kaggle is well-prepared for analysis, containing no missing values across any of its columns. All features are appropriately typed for their intended use, with numerical attributes correctly formatted to support statistical and visual analysis. We can see below that song attributes vary by attribute for some attributes, making it an interesting case to see if we can recommend certain albums to a user based on song attributes.



Building the Recommendation System

The objective of our modeling is to suggest which Taylor Swift album a person would like based on their user profile. Each of Taylor Swift's albums has a distinct sound and emotional tone, making the recommendation process crucial for introducing new listeners to her music. Recommending an album that aligns with a listener's musical tastes can make the difference between a casual listener and a new die-hard fan.

To generate recommendations, we will use two different approaches: cosine similarity and K-means clustering. Cosine Similarity measures the similarity between two vectors (in this case, album features and a user profile) by calculating the cosine of the angle between the vectors. K-means Clustering is a machine learning technique that groups similar items together. It divides songs into clusters based on their features. Songs within the same cluster are more similar to each other than to songs in other clusters.

We evaluated the effectiveness of these methods by comparing their recommendations for different user profiles.

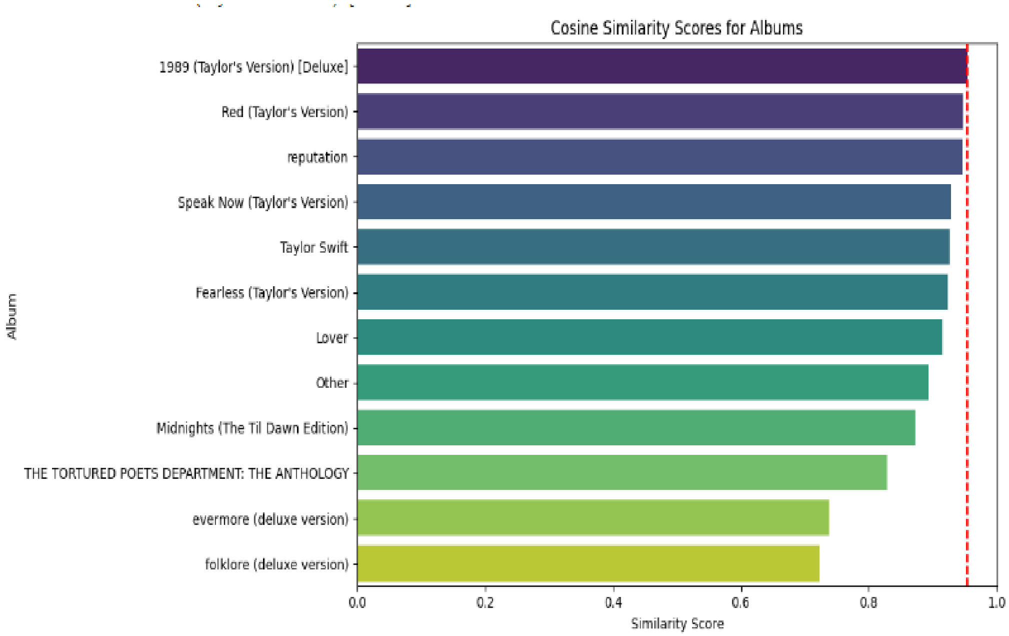
User Profile

For both methods, we created a user profile based on the mean of the normalized attributes of the user's top 5 songs. Building a user profile from multiple songs, rather than a single song, provides a more comprehensive representation of a user's preferences. By averaging the features of multiple songs, the user profile better represents overall preferences across various attributes, leading to more reliable and diverse recommendations. This approach also reduces bias from outliers or exceptional songs that might not reflect the user's usual taste.

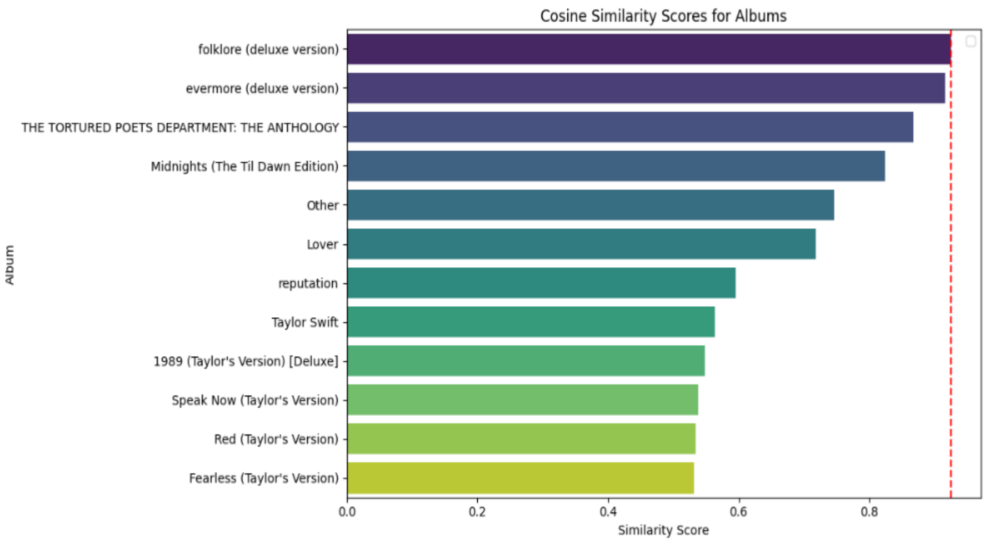
Cosine Similarity

To apply cosine similarity, we first aggregated the mean song features by album. After calculating the similarity between the user profile and each album, we returned the album with the highest similarity score.

User Profile 1 (Riya): Recommended album is *1989*, with *Red* and *reputation* as close runners-up.



User Profile 2 (Michelle): Recommended album is *folklore*, with *evermore* as a close second.



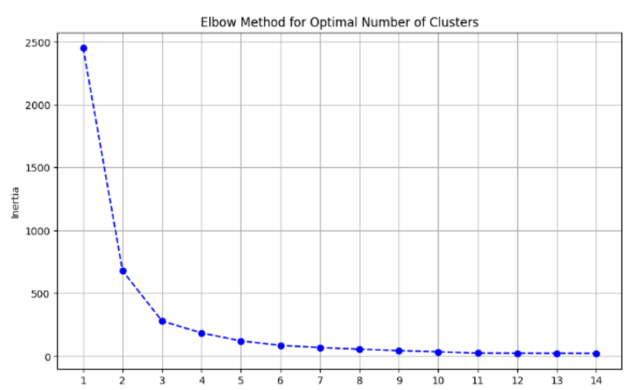
Limitations of this Method:

Aggregating the attributes of all songs in an album may not be the best representation of an album since different songs in the album may have different attributes. We saw above that if we look at the album level, some attributes vary widely between albums, but that other attributes are similar across all albums if you aggregate the songs. It may be better to look at the song-level similarity, which is what we try to do with clustering next.

<u>K-Means Clustering</u>

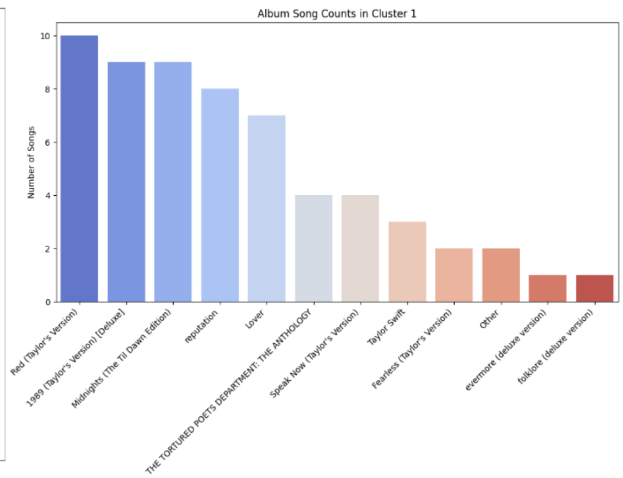
For clustering, all songs were run through K-means clustering. We matched the user profile with a cluster of songs using cosine similarity. We return a visualization for the number of songs in each album for that cluster, and we would recommend the album(s) that have a high number of songs. There are a few limitations of this method that we will highlight below.

Using the elbow method, we determined that 3 clusters represented the ideal tradeoff between simplicity and interpretability for this dataset.



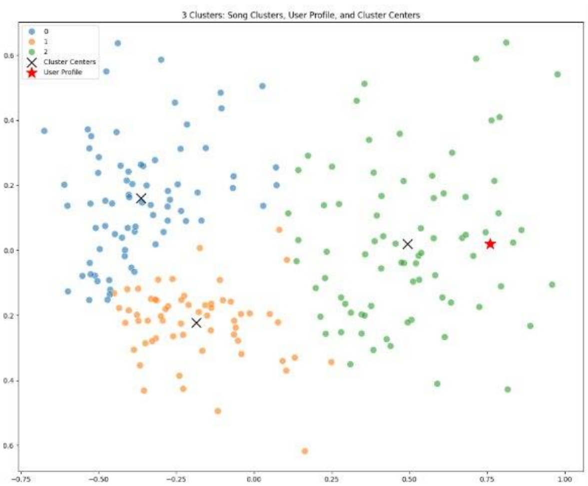
User Profile 1 (Riya) with 3 clusters:

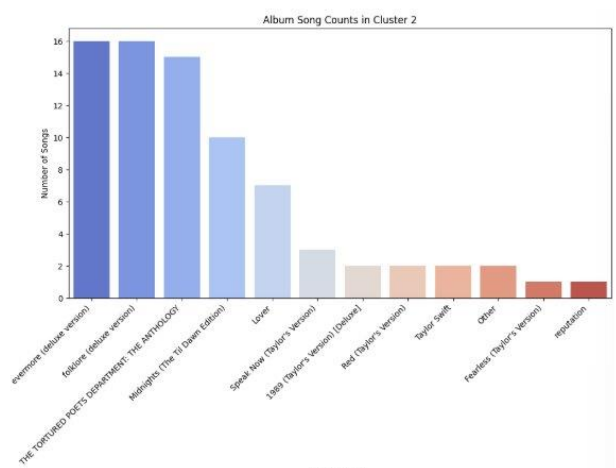
Recommended albums: Red, 1989, Midnights



User Profile 2 (Michelle) with 3 clusters:

Recommended albums: evermore, folklore, The Tortured Poets Department



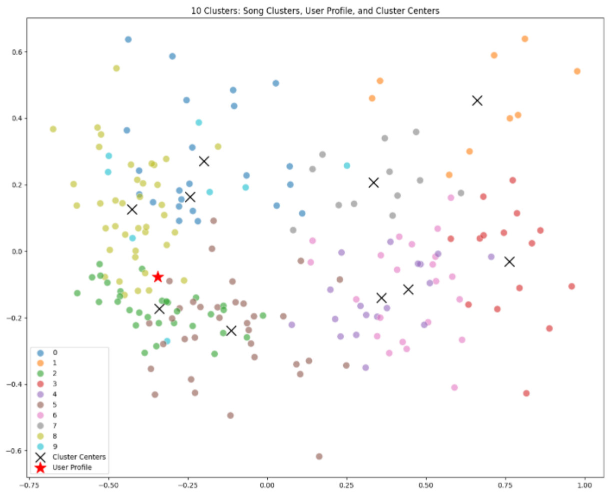


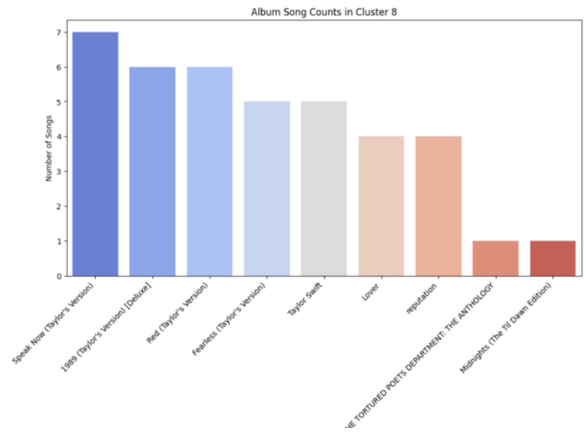
In the cluster visualizations, we can see that there's very little overlap and it's clear to see cluster boundaries. Looking at the visualization, it is clear to understand that this Michelle's musical preferences falls within cluster 2. In this 2D visualization, Riya falls between clusters 1 and 3, which is a little more difficult to see.

With only 3 clusters, however, the cluster assignments not be as personalized as they could be, so we want to try to increase the number of clusters to see if we can get more unique recommendations based on a user's profile. We tried several different cluster numbers, but settled on 10. With too many clusters, we found that recommendations were based on too few songs, and that it's difficult to differentiate recommendations in clusters where for example the album with the most songs in that cluster had 3 songs, whereas the rest of the albums had 2 songs.

User Profile 1 (Riya) with 10 clusters:

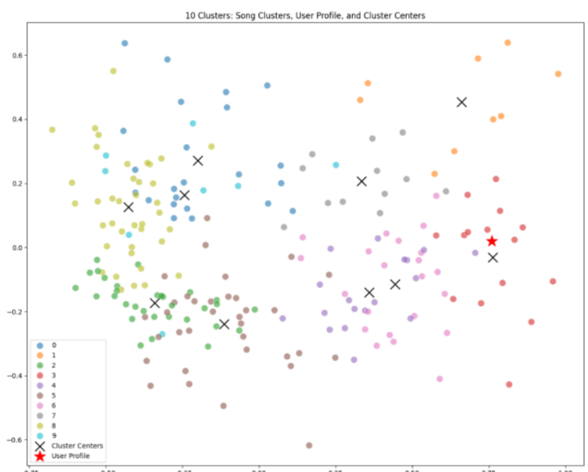
Cluster 8, Recommended albums: Speak Now, 1989, Red

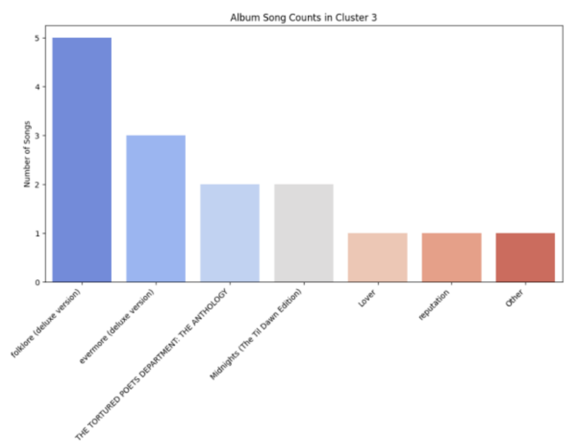




User Profile 2 (Michelle) with 10 clusters:

Cluser 3, Recommended album: folklore





We can see a similar challenge here that we saw earlier of where to cut off the album recommendation. For Michelle's profile, it's may be easier to say if there are 5 songs vs 3 songs from an album, we can recommend that album. But in Riya's case, would we recommend an album with 7, 6, 5, or 4 songs from an album in that cluster? If we want to simplify and recommend only the top album, then we are often going to be recomending one album over another by a difference of only one song, and there are some albums that would never be recommended to a user because they are not the most representative in any cluster.

Summary and Comparison of Methods

Cosine similarity is straightforward and computationally efficient. However, it may oversimplify user preferences by aggregating features at the album level. K-means clustering provides more nuanced groupings of songs, allowing for more diverse recommendations. However, there are challenges with determining thresholds and the recommended album is not as straightforward as with cosine similarity. It’s also possible that based on song attributes, a user may enjoy a few songs from a particular album, but not the rest of the songs on that album.

There are limitations on both recommendation systems. Both methods rely on audio features to define user preferences, which may not fully capture the emotional or contextual factors influencing a listener’s enjoyment of a song. Other features, such as lyrics, genre, or cultural context, could improve recommendation accuracy.

Test Cases

In order to test the effectiveness of our models, we obtained a number of test cases.

Test 1: We want to ensure that our models do indeed recommend different albums based on user song preferences, so we gathered data from our team members on their top 5 songs. After building each user profile, we found that each person was recommended different albums, given in the table below. It's expected that each model would produce a different album recommendation because of the differing ways that album recommendation was calculated.

Recommendation System	Michelle	Riya	Charlie	Claire	Ishaan
Cosine Similarity	folklore	1989	1989	Taylor Swift	Lover
Clustering	folklore	Speak Now	Reputation, Midnights	Red	Red

Test 2: Next, we want to test the effectiveness of our recommendations. This question is difficult to measure because not all users are listeners of Taylor Swift and are not able to determine whether the models recommend the best albums for them. In the future, it would be interesting to measure the effectiveness of the models by playing a song at random from the recommended album. If the user continues to listen to that song for a certain period of time (30s to 1m), then the recommendation was effective. If they skip that song, then the recommendation was not effective. We could do this several times to find the ideal cutoff point for listening time to determine if a recommendation was effective, and also determine how many times we play a song from a certain album before we determine that this album recommendation was the right one or not.

Conclusion

This project highlights the complexities of building recommendation systems, the tradeoffs between different modeling approaches, and the potential for personalized recommendations to connect listeners with albums that resonate with their unique music tastes. By analyzing Taylor Swift's discography in depth, we uncovered patterns and trends in her audio features that reflect her artistic evolution and explored how these features can be used to recommend entire albums. While cosine similarity and K-means clustering provided useful insights, the limitations in feature representation and model evaluation underscore the challenges faced by companies building robust recommendation systems.

In the future, our project could focus on enhancing the model by incorporating additional data and implementing a hybrid approach that combines collaborative filtering and content-based filtering. By including user preferences such as music genres and analyzing user behavior, including engagement patterns and implicit signals, we can build a more robust and personalized recommendation system.

Moreover, the additional data would enable us to assign different weights to various attributes, moving beyond the equal weighting approach used in our current model. These enhancements have the potential to significantly improve the accuracy of recommending Taylor Swift albums to our users, ensuring a more tailored and satisfying user experience.

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