Spotify: The Machine Learning Approach to Discover Weekly Playlists

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***Abstract*—With over 422 million active listeners streaming millions of songs each day, Spotify has become the world's most popular on-demand music streaming service. Personalization and discovery are a huge part of the Spotify's subscriber experience, and it is critical to consumer satisfaction. Because of this, one of the most successful features Spotify offers is Discover Weekly- a music recommendation system which helps users to discover new songs every week. Discover Weekly enhances the user experience by recommending songs that coincide with the user's taste in music. To understand why Discover Weekly works so well, we will discuss the recommendation system behind Discover Weekly, and the machine learning techniques which power this system.**

I. Introduction

Before the internet boom, finding new music to listen to wasn't easy. For many people, the only way they discovered new music was from their local radio stations. Now, with the wide-spread dependency on the Internet, and music streaming services such as Spotify or Apple Music, the availability of new music is so vast that it has become increasingly daunting to attempt to find new music or "hidden gems" that are worth listening to. For Spotify, the answer was simple: give users a weekly playlist of songs recommended just for them. Now, this recommendation system is known as Spotify's Discover Weekly.

Spotify's Discover Weekly is a music recommendation system that curates a unique playlist of 30 songs tailored to a user's taste in music. Discover Weekly was Spotify's first recommendation system, and it was officially introduced in July 2015. Since its introduction, Discover Weekly has become a feature loved and used by over 422 million active users [1]. Thanks to Discover Weekly, Spotify has become known for its helpful song recommendations, which gives it an edge on its competitors (Apple Music, Pandora, YouTube Premium, etc.).

Fig. 1. How Discover Weekly is created in Spotify's Recommendation Pipeline [8]

So, now we know what Discover Weekly is, but how does it find songs to recommend? As we can see in figure 1, Discover Weekly is based on three Machine Learning techniques: Collaborative Filtering, Natural Language Processing (NLP), and Raw Audio Modeling.

In the following sections, I will go more into detail about these three Machine Learning techniques behind Discover Weekly, as well as the advantages or disadvantages they pose.

II. The ML Techniques Behind Spotify's Discover Weekly

A. *Collaborative Filtering*

As we have learned, Spotify offers a Discover Weekly playlist, which is a recommendation system for curating music to users. One of the most common techniques the recommender system uses is Collaborative filtering. Collaborative Filtering is a Machine Learning technique which builds a model to analyzes the behavior of an individual user (aka, the way the user *interacts* with the system) and then uses this data to predict another similar user's behavior. This data consists of measurable metrics that are saved through implicit feedback. These metrics are then collected and used to be compared to another user's behavior in order to determine the recommendations which best suit them.

In the context of Spotify, it's recommender system would collect metrics such as *stream count* (the number of times a song was played by the user), *saves* (when the user saves a song), *shares* (when the user shares a link to the song), *skip rate* (how long a song was listened to before it was skipped), and so on [3].

For instance, if there are two users, user A and user B, who save / share a lot of the same songs and interact with these songs in a similar manner, then it is likely that their music tastes are similar as well. This information can then be used to recommend user A the music that user B has saved, but user A has not listened to yet, and vice versa.

In Machine Learning context, the Collaborative Learning technique uses the K-Nearest Neighbors (KNN) approach. Say we have a target user in which Spotify would like to curate a Discover Weekly playlist for. The KNN algorithm will then be used to calculate the distance of "neighbor" users to the target user. In particular, KNN is searching for the neighbors who are similar to the target user based on their data metrics (saves, shares, etc.) [4]. We can then say that KNN is being used to predict a user's music preferences by finding a user-song relationship within the data.

Spotify's usage of Collaborative Filtering can be further divided into memory-based filtering and item-based filtering [4]. Memory-based filtering uses user ratings, user preferences, and item-based filtering, to successfully find a group of users who are similar to the target user.

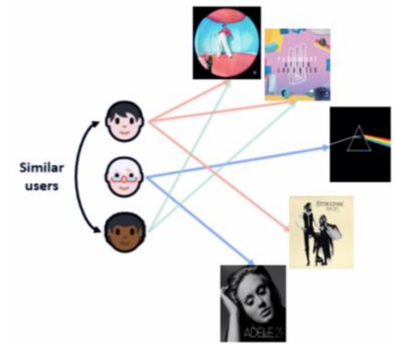

Fig. 2. Memory-Based Collaborative Filtering Method

In figure 2, we can see a simple example of what it is like to use memory-based filtering. Here, we have found users who have similar preferences and group these users accordingly. Then, from these groups of users, we can use item-based filtering to then recommend new songs to our target user based on the song preferences found in the group of similar users [5].

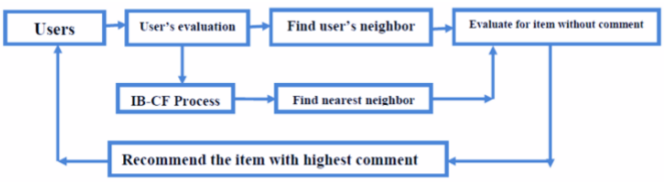

Fig. 3. Collaborative Filtering in the Spotify Recommendation System [6]

In figure 3, we see a flowchart which details the steps of the collaborative filtering method used by Spotify. The flowchart is showcasing a loop, where the user gets recommended a song that has the highest "comment", which is basically a score of how much the user is predicted to enjoy a song. This flow will loop continuously, searching through the data on both the neighbors and the target user preferences, until it finds a song from the neighbor's listening profile that has a high enough score. After around 30 songs are found, a Spotify Discover Weekly playlist will then be shared with the target user that is filled with song recommendations that the user is predicted to enjoy.

Collaborative filtering does a pretty decent job at music recommendation, but since there are some downsides, it cannot be used alone. Collaborative filtering is content-agnostic, meaning it only uses the consumption data associated with an item, and not data on the item itself. This makes collaborative filtering great for wide-spread use amongst multiple different applications, but this is also a disadvantage. Because it is content-agonistic, popular items (i.e., songs) get recommended the most as compared to unpopular items. When you think about it, this is the opposite of what we want in a music recommendation system. As discussed before, the goal is to find "hidden gems" for the user to listen to, we don't want to recommend songs just because they are well-liked or well-known [2].

If our goal is to find "hidden gems" for the user based on their preferences, what happens when we don't have any preferences to work with? This question raises the awareness to a bigger issue known as the "cold-start problem". The cold-start problem is where we have a user which is new to Spotify and has no preferences yet, and therefore it becomes increasing difficult to recommend new and unpopular songs to them.

Because of the issues raised by collaborative filtering, Spotify's recommendation system needed a second approach: Natural Language Processing.

B. *Natural Language Processing with Spotify's 'The Echo Nest' Technology*

The second method used in the Spotify recommendation system is Natural Language Processing (NLP). NLP is a machine learning / artificial intelligence technique which combines computational linguistics and machine learning models to allow a system to process human language data (either in text of voice form) and understand the full meaning of this language data [7].

In 2014, Spotify acquired The Echo Nest. The Echo Nest is a music intelligence platform which implements NLP technology to mine music blogs online and determine which artists are considered "unknown hits" and "hidden gems" but don't yet have the streaming numbers to be considered popular. Spotify's recommendation system implements The Echo Nest's services to constantly search the web for blog posts / tweets / reviews about music to find which artists and songs are generating buzz- specifically, it is finding the adjectives and language frequently used in reference to these artists or songs, and it is finding out which other artists are being discussed along with them [9]. For instance, a blogger may be the first to write a review on a new up-and-coming artist from San Antonio that has a "90s D.I.Y. grunge sound". If this artist continues making music, and writers continue to write about them, eventually the NLP bots will pick up that this is a new "hidden gem" type of artist to recommend to users who are known for liking the "90s grunge sound".

More specifically, The Echo Nest technology would bucket the data collected using NLP into "top terms". Each song or artist has hundreds of top terms associated with it. Each term has an associated weight, which is a parameter representing its performance. This weight is the probability that a user will describe the song or artist with that term.

n2 Term	Score	np Term	Score	adj Term	Score
dancing queen	0.0707	dancing queen	0.0875	perky	0.8157
mamma mia	0.0622	mamma mia	0.0553	nonviolent	0.7178
disco era	0.0346	benny	0.0399	swedish	0.2991
winner takes	0.0307	chess	0.0390	international	0.2010
chance on	0.0297	its chorus	0.0389	inner	0.1776
swedish pop	0.0296	vous	0.0382	consistent	0.1508
my my	0.0290	the invitations	0.0377	bitter	0.0871
s enduring	0.0287	voulez	0.0377	classified	0.0735
and gimme	0.0280	something's	0.0374	junior	0.0664
enduring appeal	0.0280	priscilla	0.0369	produced	0.0616

Fig. 4. The Echo Nest's top terms for a song [9]

As we can see from figure 4, we have an example of the top terms for a specific song, which have various weights (scores) associated with them. As we can see from this figure, "perky" and "nonviolent" are the two terms most relevant to the song.

Furthermore, these "top terms" found from using NLP are then used to recognize the similarities between artists or songs. This data is then used in combination with Collaborative Filtering to determine if two pieces of music are similar, and from there we can successfully recommend similar (but unknown) music to a user in their Discover Weekly Playlist.

C. Audio Analysis Models

As we have stated previously, it is important that Spotify's recommendation system is able to find "hidden gem" type of songs or artists. The Echo Nest technology was able to solve this problem using NLP, however, NLP models will fail to find unpopular music if the online coverage / social media coverage is very low. This means that our models will fail to find new songs to recommend to a target user. For example, say we uploaded a new song with only 10 streams so far. Because it has so little streams, Collaborative Filtering would not pick up on it. Also, because our song hasn't been mentioned online, the NLP models will fail to find it as well. One way to solve this issue would be to implement Audio Analysis Models, which will take new songs into account when recommending music. That way, our new song with only 10 streams will still be able to end up on a user's Discover Weekly playlist.

Audio Analysis Modeling (also known as MIR) is a deep learning technique used to analyze audio signals from sound data recorded on digital devices. On Spotify, Audio Models are used to analyze uploaded raw audio songs in order to categorize it. The process of the actual analysis is done by using Convolutional Neural Networks.

Convolutional Neural Networks (CNN) is an ANN architecture which is used to solve difficult image-driven pattern recognition tasks, such as facial recognition [10]. However, in Spotify's case, CNN is used to evaluate audio signals instead of image pixels.

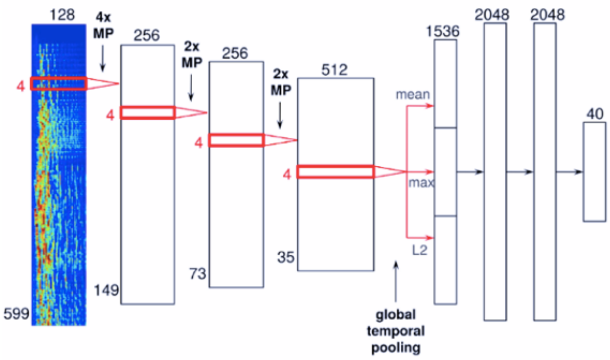

Fig. 5. CNN Architecture used in Audio Analysis Modeling [2]

In figure 5, we can see an example of the CNN architecture. Here, the network has four convolutional layers (left side) and three dense layers (right side). The audio signal input is concatenated together to form a spectrogram (far left). Then, the audio signals go through the four convolutional layers, after which they will pass through a global temporal pooling layer, which will compute the statistics of the features learned across the time of the song [9].

After the processing of the song was complete, the CNN architecture will determine certain estimations on the song's features, such as: key signature, time signature, dynamics, tempo, loudness, pitch, and more.

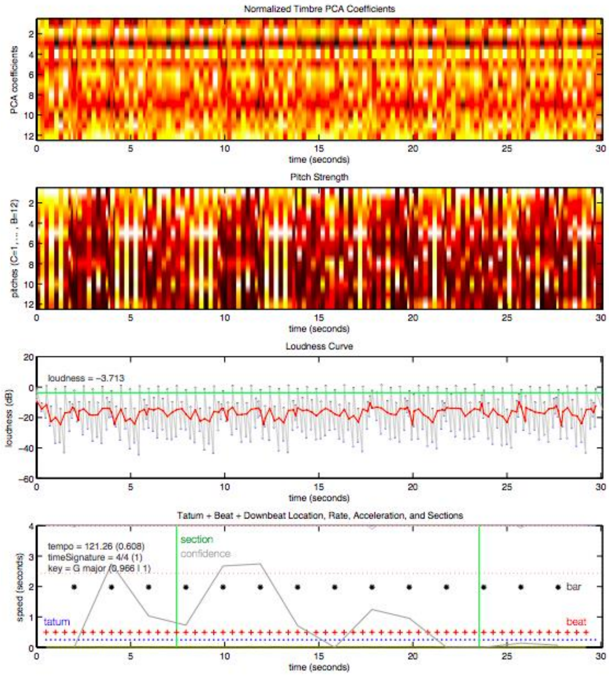

Fig. 6. Plot of key features found in song snippet [9]

In figure 10, we can see the plot of the data found for key features in the 30 second song snippet of "Around the World" by the artist Daft Punk. In these plots, we see that our Audio Analysis Model was able to use CNN to find data on the song's loudness, pitch strength, beat, and more key features. Once our Audio Model has found data on a song's key features, it allows the recommendation system to automatically find the similarities between songs found in a target user's listening history and songs which are within Spotify's database, but the user has not listened to yet. From there, the recommendation system can add songs (especially new songs or unpopular songs) into the target user's Discover Weekly playlist for their enjoyment.

Also, Audio Analysis Modeling is used beyond the scope of Discover Weekly playlists. Spotify also uses Audio Modeling to group together songs of a similar mood, aesthetic, or activity into a playlist. For example, Spotify has several pre-made playlists for users to enjoy, such as: "Dinner with Friends", "Bachelorette Party", "Sleepy Piano Music", "Sad Acoustic Instrumentals", and more. These pre-made playlists are another way for a user to find new music to listen to, or simply enjoy the playlists for its pre-defined event or mood.

III. CONCLUSION

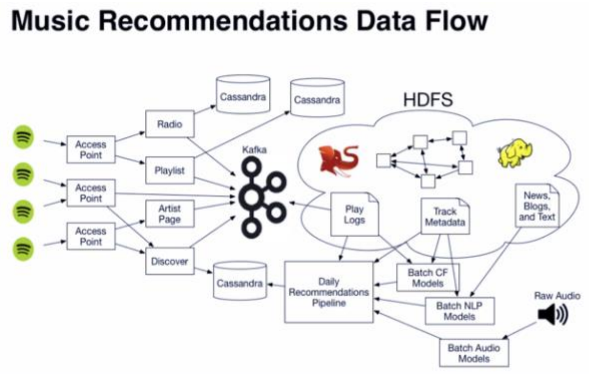

Fig. 7. Spotify's Recommendation Ecosystem [11]

Throughout this paper, we have covered the three machine learning techniques behind Spotify's Recommendation System / Discover Weekly playlists. We learned that the Collaborative Filtering technique is great for recommending songs based on similar users, but not so great at recommending *unpopular songs* with a small number of streams. The Echo Nest's implementation of the Natural Language Processing technique solves this issue by finding what songs / artists are generating "buzz" on the internet, and therefore it is able to find songs that people are enjoying but are considered *unpopular songs*. The issue here, however, is that both Collaborative Filtering and NLP fail to find *new songs* to recommend that don't have any "buzz" yet. So, we use Audio Analysis Modeling as the final technique to analyze the songs, find data on their key features, and then recommend these songs to a target user who's listening profile is most similar to the recommended song's key features. When Spotify's Recommendation system implements all three techniques, it is able to successfully create a Discover Weekly playlist that will recommend new songs, popular songs, and unpopular songs which all cater to a user's musical interests.

We can see from figure 7, that these 3 machine learning techniques are all connected within a larger music recommendation ecosystem. This ecosystem consists of the large amounts of data these techniques learn from, such as: endless music articles, blog posts, social media engagement, and an enormous amount of audio tracks- which are all scaled by using several Hadoop clusters [9]. We mainly focused on Discover Weekly playlists in this paper, but as we can see from figure 7, the machine learning techniques used to create Discover Weekly are also being used for Spotify radio stations, pre-made playlists, and the "similar to" section of an artist page.

In all, we have learned that the Machine Learning techniques used in Spotify's recommendation system is the reason why Spotify has an edge over its competitors, and I fully believe it is what makes Spotify the most popular music streaming service in the world. So, the next time you stream music on Spotify, check out your Discover Weekly playlist for this week, and take note of just how well Spotify knows you.

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