T-RECSYS: A Novel Music Recommendation System Using Deep Learning

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***Abstract*—A recommendation system is a program that utilizes techniques to suggest to a user items that they would likely prefer. This paper focuses on an approach to improving music recommendation systems, although the proposed solution could be applied to many different platforms and domains, including Youtube (videos), Netflix (movies), Amazon (shopping), etc. Current systems lack adequate efficiency once more variables are introduced. Our algorithm, Tunes Recommendation System (T-RECSYS), uses a hybrid of content-based and collaborative filtering as input to a deep learning classification model to produce an accurate recommendation system with real-time prediction. We apply our approach to data obtained from the Spotify Recsys Challenge, attaining precision scores as high as 88% at a balanced discrimination threshold.**

***Index Terms*—music recommendation; deep learning; content-based filtering; collaborative filtering;**

I. Introduction

Recommendation systems are algorithms used to make accurate suggestions based off user preferences or needs [1]. They are an often underappreciated aspect of our daily lives, influencing the way we browse videos, listening to music, and shop online. Given the wide array of applications, there are a number of decisions and approaches surrounding the design of such systems. Historically, two main approaches to recommendation existed. Content-based filtering recommends based on similarities in properties of the items [2]. If a user likes A, and B is similar to A, then a user might like B. Alternatively, collaborative filtering uses similarities between users (listening, playing, or purchasing the same/similar items) for recommendations [3]. If a user A is similar to user B, then user A might like what user B likes. Another important issue involves whether a recommender system can operate in real time, which is defined as involving pre-processing methods which are performed while data is being collected [4].

In this paper, we create a novel algorithm for recommending music to users in the form of k recommendations. Our system, Tunes Recommendation System (T-RECSYS), scores each song in a database according to user preference by utilizing a learned hybridization of content-based and collaborative filtering [5][6], returning the top-k scoring songs. The algorithm incorporates input from users utilizing historical data and preferences [7], extracting multiple key metadata variables such as genre, mood, and tempo. These variables serve as the input for our recommendation system, enabling fast and responsive recommendation. The exact mechanism for scoring ranks confidences obtained from a deep learning classification model which infers whether or not a certain song would be enjoyed by a user given the aforementioned inputs [8][9]. This approach is similar to services such as Spotify's Discover Weekly Playlist, a weekly collection of songs that Spotify recommends based on recent listening habits [10].

T-RECSYS can also be applied to the related task of playlist continuation, in which songs are recommended to the user to ”continue” a current playlist. Incidentally, this is the challenge put forth by Spotify in their RecSys Challenge 2018 [10], affirming a continuing demand for such research even while major recommendation systems are deployed on the web.

The rest of this paper is organized as follows. Section II describes the motivations behind our decision to create this algorithm, followed by Section III, which gives an overview of related work in recommendation systems. Section IV covers the methodology behind T-RECSYS. Section V illustrates and interprets experimental results obtained from an evaluation of our algorithm. Section VI discusses limitations and directions for future work, and Section VII concludes the paper.

II. Motivation

Our initial interest in recommendation systems stems from a research gap, namely the lack of multiple variable algorithms that can produce accurate recommendations with real-time updates. During our research, we found that the foundation of most algorithms for recommendation systems took into account a singular variable type [8]. The algorithms that did include more than one variable type did not include real-time updates [11]. Instead, these systems' recommendations were suggested to users based on historical data from the day before. This problem is prevalent in even well-known platforms such as Youtube and Netflix. Our interest was fueled further when we discovered the challenge issued by Spotify, the Spotify RecSys Challenge 2018, which asks teams of academic and non-academic participants to improve their already in-place recommendation system [10]. This challenge provided our dataset and allowed us to focus our broad topic of recommendation systems to specifically music recommendation systems.

III. Related Work

Articles that recognized similar problems from the lack of real-time updates or multiple variable types in recommendation systems have suggested solutions. A proposal by Fang et al. advocates a solution that first uses a questionnaire to create a user profile [11]. They state, “the information obtained from the questionnaire is compared with musical features to prune the initial 384,500 songs to 1000 songs the user is more likely to enjoy" [11]. Clustering, a class of machine learning that separates data into clusters of similar data points, is applied to the questionnaire to assign users into groups with similar musical tastes [11][12]. Through the intended use of collaborative filtering, the program combines user profiles, creating group profiles to find recommendations that are likely to be acceptable and appropriate for the whole group [11]. These recommendations focus on activities such as group physical therapies, Zumba, yoga, or pilates. Reinforcement Learning (RL) is then used to refine initial results provided by the User Profiling (UP) recommendation system [11]. The questionnaire [11] allows users to input tempo, loudness, energetic, positive, familiarity of the music, and prominence of the rhythm on a five-point scale. This allows users to adhere to strict preferences that are possibly needed during choice exercises. Although this paper includes multiple variables, collaborative, and content-based filtering, it applies specifically to exercise music, which is not suitable for everyday recommendations.

In 2017, Jiang et al. "applied a recurrent neural networks model (RNN) to make comparisons of different songs by similarity, which helps recommendation systems give ranking scores based on a combination of factors in music" [13]. RNN models are mentioned in other systems [14], but this paper measured the similarity between songs, unlike previous approaches. Although this program took into account musical factors, there was no mention of real-time updates.

Hayashi et al. proposed a fast content-based music information retrieval (CBMIR) framework called indirect matching [15]. This framework used representative queries from offline searches. They [15] integrated these offline searches as a base for providing fast similarity approximations from online sources. Similar to [13] and [16], their research included elements of content-based filtering. However, collaborative filtering and real-time updates were not elements present in the algorithm.

In 2017, Sunny et al. suggested processing real-time data streams that could provide accurate recommendations on the fly [9]. In their work, they implemented real-time updates in recommendation systems through the use of Spark and machine learning libraries, choosing to study TV channel recommendations in particular. This is similar to work from Mwinyi et al., who proposed a predictive self-learning recommendation system for multimedia content that takes into account users' preferences before and after selections are made [17]. Although both approaches implement real-time updates and multiple variable types, neither incorporated collaborative filtering into their programs. Other research from the Big Data Hub includes [18-100],

IV. ALGORITHM

The algorithm utilizes an input vector carrying information useful for both content-based and collaborative filtering. This input is fed into a deep neural network, and through a training process, the network learns to recognize patterns in a user's listening history, ultimately recommending songs it has confidence the user will enjoy.

A. Overview

T-RECSYS can be broadly described as follows. A deep learning model takes as input information representing 9 songs that are enjoyed by the listener, as well as a 10th song that represents a song that the listener may or may not like. It returns a score from 0 to 1, inclusive, that signifies the likelihood that the listener would like that 10th song based on the first 9. T-RECSYS identifies the k highest-scoring songs and recommends those to the user.

B. Content-Based Filtering

Content-based filtering in T-RECSYS is enabled by obtaining song metadata. T-RECSYS considers six categories of metadata: genre, artist type, artist era, mood, tempo, and release year. Table I illustrates an example 10-song playlist with values for each metadata field. This data can be obtained using various online APIs; in our specific experimental implementation, we accessed the Gracenote API by way of the pygn Python library. This information is instantaneous to obtain and represents a lightweight encoding of the content of a song. When provided as input into the deep neural network as described below, a content-based filtering approach can be learned by the model.

Of the six metadata categories, three are unorderable (genre, artist type, and mood) while the remaining three (artist era, tempo, and release year) are orderable. Therefore, for the purposes of the input vector for the deep learning model (which only accepts numeric values), the unorderable data are one-hot encoded – a machine learning technique where a categorical variable is converted into multiple boolean variables. Table II illustrates an example of one-hot encoding for genre, artist type, and mood, demonstrating that there is a unique one-hot encoding for each metadata class.

C. Collaborative Filtering

Collaborative filtering is also present in T-RECSYS. In particular, it manifests itself as a measure of the pair similarity between each of the nine songs enjoyed by the user and the tenth song. That similarity is defined as the frequency with which the two songs appear together in a dataset of playlists. Intuitively, if the songs frequently appear in playlists together, one is a likely recommendation for the other. T-RECSYS incorporates this similarity score in two slightly different ways. One is a volume measure, in which simply the total number of playlists where each pair of songs appear

TABLE I: Example playlist when defined by song metadata

Playlist 1	**Song 1**	**Song 2**	**Song 3**	**Song 4**	**Song 5**	**Song 6**	**Song 7**	**Song 8**	**Song 9**	**Song 10**
Genre	Urban	Rock	Country	Pop	Rap	Pop	Classical	Hip-Hop	Pop	Country
Artist Type	Female Group	Female Solo	Male Duo	Female Solo	Male Duo	Male Solo	Male Duo	Female Duo	Male Group	Female Group
Artist Era	2000's	1950's	1930's	2010's	1940's	1990's	1970's	1930's	1960's	1990's
Mood	Happy	Angry	Sad	Party	Sad	Energetic	Dance	Sad	Energetic	Happy
Tempo	Fast	Fast	Medium	Slow	Medium	Fast	Medium	Medium	Medium	Fast
Release Year	2001	1962	1930	2009	1949	1986	1977	1932	1966	2010

TABLE II: Example of one-hot encoding for different song metadata

Genre	Binary	Artist Type	Binary	Mood	Binary
Hip-Hop	0000001000	Female Duos	0000100000	Sad	0010000000
Country	0010000000	Male Duos	0010000000	Sad	0010000000
Pop	1000000000	Female Group	1000000000	Happy	1000000000
Rap	0000100000	Male Group	0001000000	Sad	0010000000
Rock	0100000000	Female Solo	0100000000	Angry	0100000000
Urban	0001000000	Female Solo	0100000000	Party	0001000000

is recorded. However, this measure does not take into account how often each song appears independently. Two songs may appear together many times, but perhaps they appear without each other far more often. To accomodate for this, T-RECSYS also measures the Sorenson index for each pair:

$$\frac{2|X \cap Y|}{|X| + |Y|},$$

where X and Y represent the set of playlists that the first song and second song in the pair appear in respectively. Altogether, two measures for nine song pairs results in 18 values representing the portion of the input vector dedicated to collaborative filtering.

D. Deep Learning Model

The input vector is assembled by combining the content-based and collaborative filtering information as described above. The intention is for this data to be used first to train a deep neural network to learn the concept of song recommendation, and then to actually give accurate song recommendations.

Experimentation with different hyperparameter configurations resulted in the network structure specification described in Table III. We utilized Google's Tensorflow together with the Python deep learning library Keras to build, train, and deploy our model. For the training process, we modified the playlist dataset provided by Spotify [10] to obtain a training set. Each playlist containing ten or more songs was used to build two training instances. In the first instance, the first nine songs in the playlist were used to evaluate whether or not the user would like the tenth, and corresponded to a positive recommendation (since the user who built the playlist liked all ten songs). In the second instance, the first nine songs were used to evaluate whether or not the user would like a random song, and corresponded to a negative recommendation. There is no way of knowing whether the user would actually like the randomly selected song, but probability favors the negative case. Once all training instances were built in this manner, 20% of the training set was separated at random to construct a testing set for evaluation purposes.

TABLE III: Neural network configuration

Layer	**Parameters**
Fully Connected	Nodes: 70, Activation: ReLU
Dropout	Dropout: 80%
Fully Connected	Nodes: 20, Activation: ReLU
Dropout	Dropout: 40%
Fully Connected	Nodes: 7, Activation: ReLU
Dropout	Dropout: 20%
Fully Connected	Nodes: 3, Activation: ReLU
Output	Nodes: 1, Activation: Sigmoid

V. Results

To evaluate the model, we chose to use precision as the chief metric, defined as

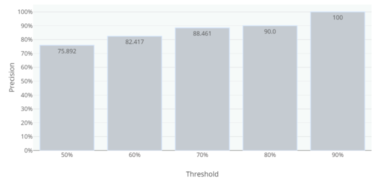
$$precision = \frac{t_p}{t_p + f_p},$$

where t_p indicates true positives and f_p indicates false positives. Specifically in the context of song recommendations, precision can be described as how often a song that was recommended was actually enjoyed. This aligns with our intuitive notion of how recommendation systems should work. Another configurable variable of note is the discrimination threshold. The discrimination threshold determines how high of a confidence score (as predicted by the deep neural network) should be obtained before a recommendation is made. By default, a recommendation might be made when the confidence score exceeds 50% since it is predicted that the listener would more likely than not like the song, but the threshold can be raised so that only songs with high confidence (i.e., high probability of being liked) are recommended.

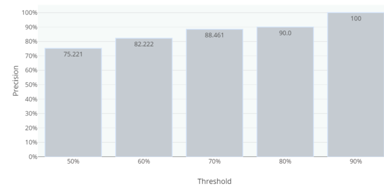
Figures 1a to 1d illustrate 4 separate test trials, depicting precision obtained at various discrimination thresholds. As can be observed, by utilizing a 90% threshold, perfect precision was achieved in 3 out of 4 trials, meaning every single song that was recommended was enjoyed. Even when using the default 50% threshold, impressive precision scores can be obtained, with Trial 3 scoring over 88% precision. The sample standard deviation between the 4 trials was 8.58%, indicating that the procedure is fairly consistent.

VI. Discussion

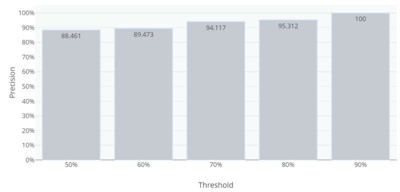
Overall, we were certainly impressed with the precision scores we were able to achieve. There are a few limitations with our setup worth noting. One concern was the lack of ground truth on negative recommendations. Utilizing solely a collection of playlists, there is no way of knowing the songs that a user would not like. However, this is a dataset limitation rather than a inherent issue with T-RECSYS as this could be



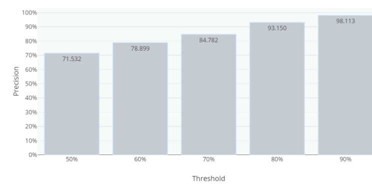
(a) Trial 1



(b) Trial 2



(c) Trial 3



(d) Trial 4

Fig. 1: Precision vs. Discrimination Threshold

easily remedied with user data about disliked songs, which is most certainly collected by Spotify and any other music service. Another drawback with the approach is the way that collaborative filtering data is obtained. Calculating both values requires global information about every song and playlist, which can be expensive to maintain. However, if deployed at a large scale, the utilization of industry-standard indexing techniques should make this drawback negligible.

Avenues for future research are clear to see. Within the domain of music recommendation, more songs (rather than the 9 used in this paper) could be used to establish the user preferences baseline. For each song, more types of metadata could be used, or even intrinsic musical features of the song itself perhaps. Parallelization via Spark could be performed to increase training and recommendation efficiency. Extensions of the T-RECSYS framework to videos, movies, shopping, and any other domain could be performed as well. Like songs, each item has numerically representable features that can be encoded as described in the paper.

VII. Conclusion

Recommendation systems are an overlooked part of our daily lives that frequently dictate the music we listen to on Spotify and the videos we watch on YouTube. Research continues to advance the sophistication and precision of these systems. In our paper, we describe one such recommendation system, T-RECSYS, that takes into account both content-based and collaborative filtering as input into a deep learning model that learns user music preferences to create song recommendations, similar to the systems employed by Spotify, Pandora, and iTunes. In the development of our algorithm, we sought to overcome recurring problems in existing algorithms from the literature, such as the lack of real-time updates and multiple variable input types. The result is a system capable of achieving high recommendation precision and readily extensible to different market services such as Amazon or Netflix.

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