Reiew of the Paper

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Cold-start Playlist Recommendation with Multitask Learning
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Introduction/Main Goal
This paper was published in 2019. The main goal of this paper is to provide a recommended list of songs to the users, in the following three scenarios:
a) Recommended list for existing users. (cold playlists)
b) Recommended list for new users. (cold users)
c) Recommended new released songs to users. (cold songs)
The authors proposed a novel Multitask Learning method, and claim that such method could improve the performance of the recommendation.

What's New/Improvement
The conventional method, matrix factorization, cannot dealing with the "Cold Start" problem. And it is challenging for the standard supervised learning to train with users that have multiple playlists.

The authors proposed a novel way of multitask learning method, which basically optimize a bipartite ranking. Moreover, since the previously formulated bipartite ranking is a convex problem with a great amount of constraints, the authors derived an equivalent unconstrained optimization for efficiency.

Observations/Analysis
The input data is the encoded feature from the dataset with:
a) song metadata (loudness, mode, tempo)
b) raw audio data, genre, and artistic information of the song
c) the popularity of artist and the song
The output is obviously the list of recommended songs for users with three settings as mentioned previously.

The overall prediction task is basically finding the numerical optimal solution for the constructed optimization problem:

$$min_\theta \;\; R(f, D) + \Omega(\theta)$$

Where R is the risk function with affinity function f (affinity of song m in the playlist i for user u) and dataset D as parameters. Ω is the regularization term on the parameters α, β, μ in the affinity function f where $f(m, u, i) = (\alpha_u + \beta_i + \mu)^T x_m$, where α_u and β_i can be learned from the playlists of each user, and μ learned from the entire set of playlist.

Result

The multitask learning method proposed by the authors is compared with other popular recommendation algorithm, include Matrix Factorization and k-Nearest-Neighbors. The result is shown below (page 6 of the paper):

Table 2: AUC for playlist recommendation in three cold-start settings. *Higher* values indicate better performance.

Cold Playlists			Cold Users			Cold Songs		
Method	30Music	AotM-2011	Method	30Music	AotM-2011	Method	30Music	AotM-2011
PopRank	94.0	93.8	PopRank	88.3	**91.8**	PopRank	70.9	76.5
CAGH	94.8	94.2	CAGH	86.3	88.1	CAGH	68.0	77.4
SAGH	64.5	79.8	SAGH	54.5	53.7	SAGH	51.5	53.6
WMF	79.5	85.4	WMF+kNN	84.9	N/A	MF+MLP	81.4	80.8
MTC	**95.9**	**95.4**	MTC	**88.8**	**91.8**	MTC	**86.6**	**84.3**

factorisation (WMF) algorithm (Hu et al., 2008), which learns the latent factors of songs and users. In the *cold users* setting, we first learn the latent factors of songs and users using WMF, then approximate the latent factors of a new user by the average latent factors of the k (e.g., 100) nearest neighbours (in terms of cosine similarity of user attributes, e.g., age, gender and country) in the training set. We call this method WMF+kNN. [7] In the *cold songs* setting, we factorise the song-playlist matrix to learn the latent factors of songs and playlists, which are then used to train a neural network to map song content features to the corresponding latent factors (Gantner et al., 2010; Oord et al., 2013). We can then obtain the latent factors of a new song as long as its content features are available. We call this method MF+MLP.

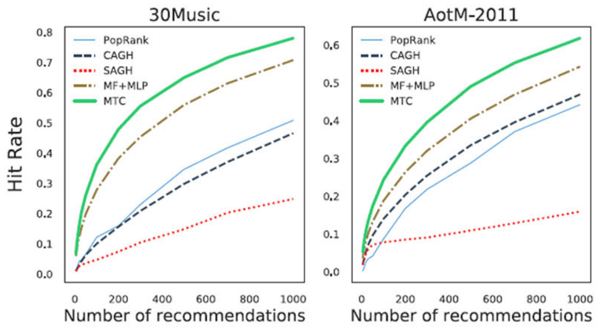

Figure 2: Hit rate of recommendation in the *cold songs* setting. *Higher* values indicate better performance.

Where both AUC and hit rate of recommendation in the cold songs setting shows that the proposed method performed better.

Extension/Follow up

The possible extension is to apply such method in other fields. For example, in the task of Student Stress Prediction, it would be a great extended application that recommend actions to student (e.g. listen songs, watch videos, etc) based on the predicted results of the mental states of students.