Automatic Playlist Continuation through a Composition of Collaborative Filters

Irene Teinemaa  
University of Tartu  
Tartu, Estonia  
irene.teinemaa@ut.ee

Nick Tax  
Eindhoven University of Technology  
Eindhoven, Netherlands  
n.tax@tue.nl

Carlos Bentes  
STACC  
Tartu, Estonia  
carlos.bentes@stacc.ee

ABSTRACT
The RecSys Challenge 2018 focused on automatic playlist continuation, i.e., the task was to recommend additional music tracks for playlists based on the playlist’s title and/or a subset of the tracks that it already contains. The challenge is based on the Spotify Million Playlist Dataset (MPD), containing the tracks and the metadata from one million real-life playlists. This paper describes the automatic playlist continuation solution of team Latte, which is based on a composition of collaborative filters that each capture different aspects of a playlist, where the optimal combination of those collaborative filters is determined using a Tree-structured Parzen Estimator (TPE). The solution obtained the 12th place out of 112 participating teams in the final leaderboard. Team Latte participated in the main track of the challenge of the RecSys Challenge 2018.

KEYWORDS
collaborative filter, hyperparameter optimization, music recommender, automatic playlist continuation

1 INTRODUCTION
With the increasing popularity of online music streaming services, the task of selecting relevant and personalized content in large music catalogs becomes important to avoid choice overload [5]. An open challenge in the area of personalization for music recommender systems is known as automatic playlist continuation (APC), where the task is to recommend tracks that are likely to be selected as additional tracks for an existing playlist. In APC it is important to recommend relevant content while, at the same time, respecting the characteristics of the original playlist [8]. For example, the recommended songs for the continuation of a playlist that consists of Christmas songs should be other Christmas songs.

To promote progress in the area of APC, the RecSys Challenge 2018 focuses on this task. The challenge was organized by Spotify, The University of Massachusetts, Amherst, and Johannes Kepler University, Linz, and was open for submissions from January to July 2018. In the competition, participants were challenged to create a recommendation system for APC using a dataset of one million playlists that have been created by Spotify users in North America.

The competition task was to generate a list of 500 tracks as playlist continuation for each of the 10000 playlists in the challenge dataset. The playlists in the challenge set were divided into ten challenge categories, based on the number of seed tracks (the tracks that are already known to be present in the playlist) and the availability of the playlist title.

This manuscript describes the solution proposed by Team Latte. The main idea behind the proposed approach is to construct several collaborative filters, based on the co-occurrence of tracks with other tracks, artists, albums, and words in the playlist title. Furthermore, the solution adopts a specialized optimization strategy, where the weights of each collaborative filter are optimized locally within each challenge category using an optimization method called Tree-structured Parzen Estimator (TPE) [4]. The final recommendation scores are produced as a weighted sum of the individual collaborative filtering components, and then post-processed using several heuristic strategies.

The remainder of this paper is organized as follows: Section 2 describes the data provided during the competition. Section 3 describes the proposed framework based on several collaborative filters and their combination. Section 4 further details the model optimization and selection procedures to combine the collaborative filters, and discusses some results on internal validation sets. Finally, in Section 5 we conclude the paper.

2 DATASET
The dataset consists of one million playlists created by Spotify users and distributed as the Million Playlist Dataset (MPD) for exclusive use in the competition. The MPD dataset includes information about the playlist (title, identification, number of artists, playlist duration) and track information (album name, identification, artist, track duration, track name) for every playlist. A complete description of the dataset can be found in [2].

In addition to the MPD dataset, the organizers provided the challenge dataset, i.e. an official test dataset that contains partial information about 10000 playlists: the playlist title and/or a number of seed tracks (a subset of tracks present in

...
We now continue with describing these stages in detail.

**Playlist Continuation Stage**

The output of every collaborative filter is combined in a final ranking model \( M_c \) using a weighted sum given by:

\[
M_c = W_a \ast M_a + W_w \ast M_w + W_d \ast M_d + W_ar \ast M_ar
\]

where \( W_a, W_w, W_d \) and \( W_ar \) are real-valued weights in range \([0,1]\).

The best configuration of weights is found using an optimization procedure, such as Tree-structured Parzen Estimator (TPE) [4]. We experiment with two types of weighting schemes: 1) global weights (optimized over all instances) and

**Collaborative Filtering Stage**

The task of collaborative filtering is to predict the utility of items (tracks) to a particular context (playlist) based on vector similarities between these entities extracted from data [6]. This context can be based on different aspects of a playlist. For example, in item-item collaborative filtering, the context is based on the tracks that are already present in the playlist. A total of four collaborative models were built in order to capture different contexts:

- **track-track model** \((M_t)\) models the relevance of a given track for a given playlist based on the set of tracks that are currently present in the playlist. This model is a traditional item-item collaborative filtering model.
- **word-track model** \((M_w)\) models the relevance of a given track for a given playlist based on the name of the playlist. This collaborative filter that models the relation between words in the playlist name and the occurrence of tracks when a playlist contains this word in the playlist title. The words are extracted from the playlist names by splitting the playlist name on the space character (i.e. ’ ’), transforming the results to lowercase, and removing punctuation marks.
- **album-track model** \((M_al)\) models the relevance of a given track for a given playlist based on the albums from the tracks that are currently present in the playlist. This collaborative filter models the relation between the set of albums of the tracks that are currently in the playlist and the occurrence of tracks when these albums are in the playlist.
- **artist-track model** \((M_ar)\) models the relevance of a given track for a given playlist based on the artists the created the tracks that are currently present in the playlist. This collaborative filter models the relation between the set of albums of the tracks that are currently in the playlist and the occurrence of tracks when these albums are in the playlist.

**Composition Stage**

The output of every collaborative filter is combined in a final ranking model \( M_c \) using a weighted sum given by:

\[
M_c = W_a \ast M_a + W_w \ast M_w + W_d \ast M_d + W_ar \ast M_ar
\]
2) local weights (optimized separately for each challenge category). We describe the procedure to determine the weights \( W_r, W_w, W_{al}, \) and \( W_{ar} \) in detail in Section 4.

**Playlist Continuation Stage**

To determine the recommended tracks for a given playlist, we filter the tracks on \( M_c > 0 \) and then sort the tracks in descending order based on their \( M_c \) value, using the \( M_c \) value that uses the weights that we found in the composition stage. However, it can be the case that fewer than 500 tracks have a value of \( M_c \) that is larger than zero, in which case the requirement of recommending 500 songs would not be satisfied. To improve the order of tracks in the recommendations ranking and to guarantee a total 500 recommended tracks for every playlist, we apply two post-processing steps.

The first post-processing step aims at completing the albums that are currently already present in the playlists. This is motivated by the fact that a reasonable number of playlists in the dataset contained exactly all the tracks of a single album, and we found the \( M_c \) to be insufficient to properly detect this scenario and complete the album for playlists that contain a high number of tracks from the same album. When the ratio of the number of tracks from the number of distinct albums that are currently in the playlist exceeds a threshold \( m \) (where \( m \) is a tunable parameter), we first recommend all the tracks from that remaining album before recommending the tracks based on \( M_c \).

As a second post-processing step, to fulfill the requirement of recommending exactly 500 tracks, we append the list of recommended tracks with the most popular tracks in the dataset in decreasing order of overall frequency until the list of recommended tracks contains exactly 500 tracks.

**4 MODEL SELECTION**

We evaluate the model instantiations using a combination of three measures R-precision, NDCG, and CLICKS, which are the same three measures that are used by the RecSys challenge organizers to score the submissions. We select the best performing model instantiation for submission.

In this section we present the evaluation measures, the procedure for optimizing the models’ parameters, the procedure and the results for selecting the best model. The framework was implemented in Python and can be found at [9] under open source license.

**Evaluation measures**

The R-precision, defined as:

\[
\text{R-precision} = \frac{|G \cap R|}{|G|}
\]

where \( G \) is the set of ground truth (holdout) tracks, and \( R \) is the set of recommended tracks. The notation \(|.|\) denotes the number of elements in the set.

The Normalized discounted cumulative gain (NDCG), defined as:

\[
\text{NDCG} = \frac{\text{DCG}}{\text{IDCG}}
\]

where:

\[
\text{DCG} = \text{rel}_1 + \sum_{i=2}^{|G|} \frac{\text{rel}_i}{\log_2(i + 1)}
\]

\[
\text{IDCG} = 1 + \sum_{i=2}^{|G|} \frac{1}{\log_2(i + 1)}
\]

The Recommended Songs CLICKS metric, that mimics a Spotify feature for track recommendation where ten tracks are presented at a certain time to the user as the suggestion to complete the playlist. This metric captures the number of refreshes needed before a relevant track is encountered, and is defined as:

\[
\text{CLICKS} = \frac{\text{argmin}_i \{R_i : R_i \in G\} - 1}{10}
\]

While NDCG and CLICKS were calculated based on the track-level agreement between the holdout tracks and the recommended tracks, R-precision was calculated on the artist-level agreement. In other words, it was considered sufficient if the artist of a recommended track matched the artist of a holdout track.

**Approaches**

We tested three instantiations of the proposed framework, namely:

- composition via global weights;
- composition via local weights, without album completion (i.e., \( m = \infty \));
- composition via local weights, where the album completion threshold \( m \) is optimized through the same procedure as optimizing the weights.

As a baseline, we compared the results to a simple popularity-based model, where the recommendation list is created based on the overall popularity of songs in a non-personalized manner.

**Model Optimization**

For each of the tested approaches, the weights for combining the collaborative filters needed to be optimized. Furthermore, in the variant with album completion, the song to album ratio \( m \) was optimized. To this end, we extracted an optimization dataset \((D_{opt})\) containing 10k playlists (playlists
980001 – 990000 from the MPD). Similarly to the original challenge dataset, we divided these playlists into 10 distinct categories that match the challenge categories (see Section 2) via random sampling. The statistics of the \( D_{opt} \) dataset can be seen in Table 2.

The optimization process was set maximizing the NDCG metric (Equation 3) and was executed using Tree-structured Parzen Estimator (TPE) [4], which is a type of a Sequential Model-Based Global Optimization (SMBO) [7] algorithm. We use the TPE implementation that is available in the Python library Hyperopt [3]. The TPE optimization process was set to run for 100 iterations and the search space of weights defined as a uniform random variable ranging from 0 to 1.

Table 3 shows the optimized best sets of weights separately for each category (used in the local weights composition) and global weights (used in the global weights composition).

### Table 3: Optimized weights

| Category       | \( W_u \) | \( W_w \) | \( W_al \) | \( W_ar \) | \( m \) |
|----------------|----------|----------|----------|----------|-------|
| title_only     | 0.000    | 1.000    | 0.000    | 0.000    | -     |
| 1_with_title   | 1.000    | 0.423    | 0.001    | 0.011    | 1     |
| 5_no_title     | 1.000    | 0.000    | 0.040    | 0.040    | 2     |
| 5_with_title   | 1.000    | 0.337    | 0.006    | 0.010    | 2     |
| 10_no_title    | 1.000    | 0.000    | 0.003    | 0.009    | 2     |
| 10_with_title  | 1.000    | 0.964    | 0.002    | 0.001    | 2     |
| 25_first       | 1.000    | 0.795    | 0.001    | 0.037    | 2     |
| 25_random      | 1.000    | 0.437    | 0.145    | 0.022    | 2     |
| 100_first      | 1.000    | 0.828    | 0.028    | 0.045    | 2     |
| 100_random     | 0.915    | 1.000    | 0.169    | 0.133    | 3     |
| global         | 1.000    | 0.517    | 0.084    | 0.056    | -     |

### Results

This subsection presents and discusses the results of our experiments.

Figure 1 shows the performance (in terms of NDCG, CLICKS, and RPREC) for the tested instantiations of the framework and the baseline popularity model. Note that in all cases, the composed collaborative model performs better than the popularity model. The model with local weights and album completion is the best performing model and was the selected strategy for our final submission.

### Model Selection

In order to select the best model from the proposed framework in an offline manner (without making an official submission), we extracted a validation dataset (\( D_{val} \)) containing 10k playlists (playlists 990001 – 1000000 from the MPD). Again, we divided these playlists into ten distinct challenge categories via random sampling. The statistics of the \( D_{val} \) dataset can be seen in Table 4. The validation set was used as a proxy to the challenge leaderboard, guiding model selection and improvements.

### Table 4: Validation Dataset Statistics

| Group | \( N_{Playlist} \) | \( H_{avg} \) | \( N_{Track} \) | \( N_{Artist} \) |
|-------|-------------------|--------------|----------------|-----------------|
| K=0   | 1000              | 38           | 0              | 0               |
| K=1   | 1000              | 37           | 943            | 737             |
| K=5   | 2000              | 33           | 7548           | 3496            |
| K=10  | 2000              | 33           | 13487          | 5127            |
| K=25  | 2000              | 32           | 27185          | 8789            |
| K=100 | 2000              | 53           | 76648          | 18242           |

### Table 5: Results of Composed Model

| Metric | Validation | Leaderboard |
|--------|------------|-------------|
| RPREC  | 0.150587   | 0.203652    |
| NDCG   | 0.288921   | 0.361175    |
| CLICKS | 5.6156     | 2.0240      |

The results of the final model on both the validation set (\( D_{val} \)) and the challenge set are presented in Table 5. The Leaderboard score is the score given by the submission website, calculated by the organizers based on the recommended tracks and the holdout tracks (the ground truth values not available to participants) in the challenge dataset.
To further analyze the performance of the final model within different challenge categories, Table 6 presents the results for the composed model in each of these categories in the validation set. We can see in this table that the model is doing considerably better in the groups where the seed tracks were selected randomly from the playlist. The performance is lowest in the category where only the playlist title was provided as input.

Table 6: Results by challenge category (model trained on 400k playlists, 100k tracks)

| Category       | NDCG  | CLICKS | RPREC |
|----------------|-------|--------|-------|
| title_only     | 0.179 | 13.990 | 0.092 |
| 1_with_title   | 0.266 | 7.252  | 0.141 |
| 5_no_title     | 0.270 | 6.373  | 0.135 |
| 5_with_title   | 0.271 | 5.943  | 0.135 |
| 10_no_title    | 0.259 | 6.740  | 0.128 |
| 10_with_title  | 0.263 | 6.565  | 0.130 |
| 25_first       | 0.258 | 6.353  | 0.122 |
| 25_random      | 0.353 | 3.307  | 0.199 |
| 100_first      | 0.219 | 6.093  | 0.108 |
| 100_random     | 0.372 | 2.782  | 0.223 |
| Overall        | 0.271 | 6.540  | 0.141 |

5 CONCLUSION

In the 2018 RecSys challenge, teams competed in the task of automatic playlist competition. To simulate different challenges in the playlist completion task, a challenge dataset was provided with ten different types of seed information (called challenge categories). Our solution was based on combining multiple different collaborative filters that each capture different aspects of a playlist, and we combined them using a Tree-structured Parzen Estimator optimization approach where we optimized the weights locally for each of the challenge categories. The solution strategy shows promising results, ranking our team in position 12 out of 112 teams in the final competition leaderboard.

REFERENCES

[1] RecSys Challenge 2018. 2018. Challenge Set Readme. https://recsys-challenge.spotify.com/challenge_readme
[2] RecSys Challenge 2018. 2018. The Million Playlist Dataset. https://recsys-challenge.spotify.com/readme
[3] James Bergstra, Dan Yamins, and David D Cox. 2013. Hyperopt: A python library for optimizing the hyperparameters of machine learning algorithms. In Proceedings of the 12th Python in Science Conference. Citeseer, 13–20.
[4] James S Bergstra, Rémi Bardenet, Yoshua Bengio, and Balázs Kégl. 2011. Algorithms for hyper-parameter optimization. In Advances in neural information processing systems. 2546–2554.
[5] Dirk Bollen, Bart P Knijnenburg, Martijn C Willemsen, and Mark Graus. 2010. Understanding choice overload in recommender systems. In Proceedings of the fourth ACM conference on Recommender systems. ACM, 63–70.
[6] John S Beese, David Heckerman, and Carl Kadie. 1998. Empirical analysis of predictive algorithms for collaborative filtering. In Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence. Morgan Kaufmann Publishers Inc., 43–52.
[7] Frank Hutter, Holger H Hoos, and Kevin Leyton-Brown. 2011. Sequential model-based optimization for general algorithm configuration. In International Conference on Learning and Intelligent Optimization. Springer, 507–523.
[8] Markus Schedl, Hamed Zamani, Ching-Wei Chen, Yashar Deldjoo, and Mehdi Elahi. 2018. Current challenges and visions in music recommender systems research. International Journal of Multimedia Information Retrieval 7, 2 (2018), 95–116.
[9] Irene Teinemaa, Niek Tax, Carlos Bentes, Maksym Semikin, Meri L Treimann, and Christian Safka. 2018. RecSys Challenge 2018 Team Latte Repository. https://github.com/irhete/recsys-challenge-2018

Note that the overall scores are slightly different than in the above, since this detailed evaluation was executed with training on 400k playlists and a total of 100k tracks only, to reduce the computations.