RecSys Challenge
MultiBeerBandits

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Our Approach

Exploration

Basic models:

- User-based filtering
- Item-based filtering
- Content-based filtering
- SVD (Content and Collaborative)
- SLIM (RMSE and BPR)
- Matrix Factorization (RMSE and BPR)
- Factorization Machine

Exploration

Hybrid models:

- ICM + URM Content Based
- CSLIM BPR
- Ranked Lists Merging
- Similarity Ensemble

What Worked

ICM + URM Content Based

ICM + URM Content Based

Rationale: the similarity between two items is strongly influenced by their attributes and by the number of users they've in common.

$$ICM_{augmented} = \begin{bmatrix} \alpha_1 \cdot ICM \\ \alpha_2 \cdot URM \end{bmatrix}$$

Here users are seen as features of an item.

ICM + URM Content Based

Succesful Preprocessing

- Feature weighing (Hyperparameters to tune)
- TFIDF + topK filtering (on tags)

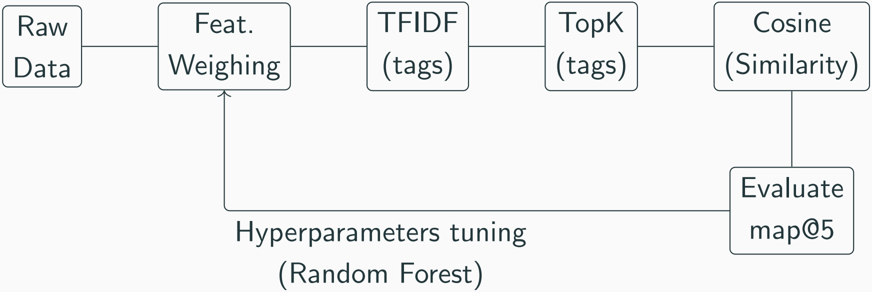
ICM + URM Content Based

Unsuccesful Preprocessing

- TFIDF on all the features
- Clustering on continuous-valued features (duration and playcount)
- Inference on missing data (album, duration and playcount)
- Aggregated features (tags) [1]

[1] Daniele Grattarola et al 2017. Content-Based approaches for Cold-Start Job Recommendations

Tuning process



CSLIM BPR

CSLIM BPR

Preprocessing

Tag aggregation:

- Select the topK most popular tags
- For each tuple T of tags compute the logical AND
- The result is a new feature, describing the items that share tags in T

CSLIM BPR

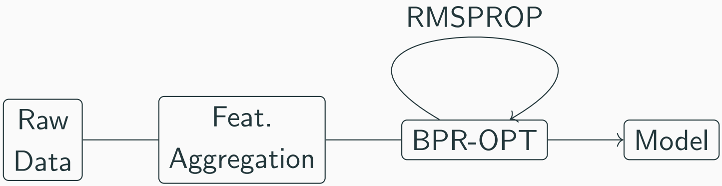
Our Improvements

- *Momentum* update rule implemented
- Samples to train the model are drawn from ICM and URM with different probabilities (in our case sampling more from ICM than URM gave better results).

Results

Even if this approach is a model-based one, we were able to achieve similar results with respect to the memory-based one: *ICM + URM Content Based*.

Training process



Similarity Ensemble

Similarity Ensemble

Rationale:

- Combining different sets of features is very hard. Some features are more present than others and stating their relative importance is even harder
- Different models capture different aspects of the similarity between items

Our approach was to optimize each model separately and combine their similarity matrices.

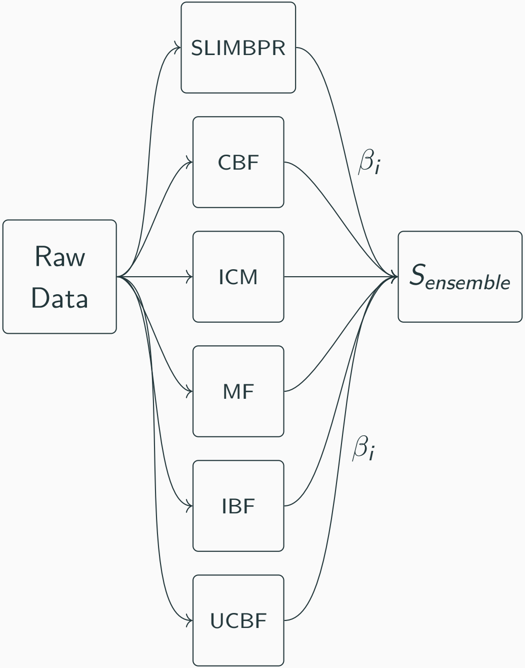
Similarity Ensemble

The model

$$S_{ensemble} = \sum_{i \in M} \beta_i S_i$$

Where M is the set of models.
The coefficients β_i are hyperparameters that we tune with Random Forest.
Properties:

- The similarity of each item with the others must be normalized
- For each item in $S_{ensemble}$ we keep only the topK similar items
- $S_{ensemble}$ is again normalized


SLIMBPR
CBF
Raw Data
ICM
$S_{ensemble}$
MF
IBF
UCBF
β_i
β_i

Similarity Ensemble with Clustering

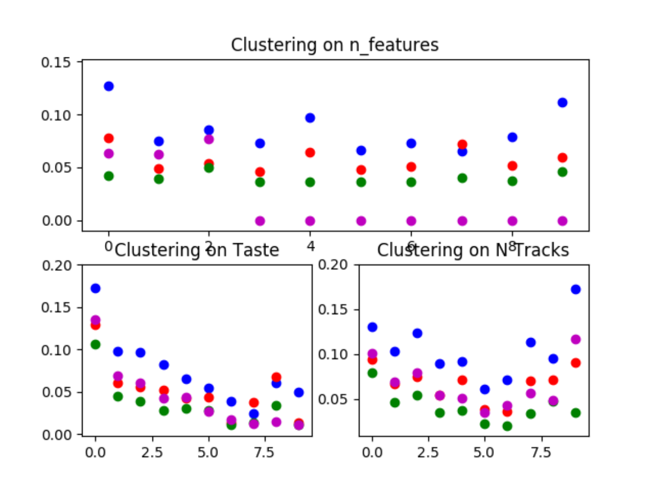


Figure 1: This figure shows the performance of some models on users clustered with respect to different features.

Similarity Ensemble with Clustering

The model

$$S_{ensemble_j} = \sum_{i \in M} \beta_{ij} S_i$$

$$\hat{r}_i^j = r_i \cdot S_{ensemble_j}$$

Let i be a user belonging to cluster j, the prediction $\hat{r}_i^j$ is computed from the ensemble similarity matrix personalized for that cluster ($S_{ensemble_j}$).

Thank you all!