MUSIC RECOMMENDER SYSTEM

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An everyday Problem
Why a recommender system?

Music dataset is too big while life is short!!!! You need someone to teach you how to manage and give you wise suggestions according to your taste!

Music service providers need a more efficient system to attraction their clients!
Our task

Music Recommender System

Our system: off-line system
Features & Content

- **Features:**
  - Large-scale: 1,000,000 users
  - 15,000,000 songs
  - Open
  - Implicit feedback

- **Content:**
  - Triplets (user, song, count)
  - Meta-data, content-analysis
  - No users’ demographic information, timestamp

Too big dataset:
- Difficult to implement the whole dataset, so need to create a small dataset by ourselves

Format of the Dataset:
- Hdf5 files
- Need to be opened by a Python Wrapper
Four ideas

1. Popularity based model
2. Same artist greatest hits
3. Collaborative filtering
4. Content-based Model

Latent factor Model
SVD

Content based Model
Nearest Neighborhood
...
1. Popularity based model

- **Idea**
  1. Sort songs by popularity in a decreasing order
  2. For each user, recommend the songs in order of popularity, except those already in the user’s profile

- **Pros:**
  - Idea is simple
  - Easy to implement
  - Served as baseline

- **Cons:**
  - Not personalized (users and songs’ information is not taken into account)
  - Some songs will never be listened
2. Same artist greatest hits

Idea
1. Sort songs by popularity in a decreasing order
2. For each user, the ranking of songs is re-ordered to place songs by artists
3. Recommend the songs in the new order, except those already in the user’s profile

Pros:
- Idea is simple
- Easy to implement
- Minimum personalized

Cons:
- Only single-meta-data is used
- Maximally conservative: doesn’t explore the space beyond songs with which the user is likely already familiar
**3. Collaborative Filtering**

**Idea:** songs that are often listened by the same user tend to be similar and are more likely to be listened together in future by some other user.

**Idea:** users who listen to the same songs in the past tend to have similar interests and will probably listen to the same songs in future.

**Item-based**

**User-based**
e.g. user–based

Conditional probability measure of similarity between two users:
\[ W_{u,v} = P(v|u)^\alpha \cdot P(u|v)^{1-\alpha} \text{ with } \alpha \in [0,1] \]

Social recommendation:
e.g. If two users are friends, rescale \( W_{u,v} \) to give more weight to the similarity

Locality of scoring function:
It aggregates the scores obtained using individual users or items
\[ f(w) = w^q \text{ with } q \in \mathbb{N} \]
Exponential, so smaller weights drop to zero, higher ones emphasized
Stochastic aggregation of item–based and user–based ranker
4. Content-based Model

1. Based on item’s description and user’s preference profile
2. Not based on choices of other users with similar interests
3. We make recommendations by looking for music whose features are very similar to the tastes of the user

- Similarity ≠ recommendation (no notion of personalization)
- Majority of songs have too few listeners, so difficult to “collaborate”
Nearest-neighbor technique

1. Create a space of songs according to songs features. We find out neighborhood of each song.

2. We look at each user’s profile and suggest songs which are neighbors to the songs that he listens to
Idea: SVD

- Listening histories are influenced by a set of factors specific to the domain (e.g. Genre, artist).
- These factors are in general not obvious and we need to infer those so-called latent factors from the data.
- Users and songs are characterized by latent factors.

Personalized
- Meta-data is fully used, all the information is well explored
- It works well in many tested cases
### Basic notations

- **Matrix M**, a user–song play count matrix

\[
\begin{array}{cccccc}
1 & 0 & 1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 &   &   &   &   \\
... &   &   &   &   &   \\
\end{array}
\]

\[M \in \{0,1\}^{m \times n}\] where \(m\) is the number of users and \(n\) the number of songs

\[M_{u,i} = 1 \text{ if user } u \text{ listens to item } i\]

\[\text{Otherwise } 0\]
SVD (singular value decomposition)

Decomposes $M$ into a latent feature space that relates users to songs

$$M = U^T \cdot V$$

with $M \in R^{m \times n}, U \in R^{k \times m}$ and $V \in R^{k \times n}$

- $U$ is a low-rank representation of $m$ users and $k$ features containing the so-called ‘user factors’. Each row of $U$, represents user’s degree of interest in each topic.
- $V$ represents the $n$ songs containing the so-called ‘song factors’. Each row of $V$ represents the relevance of the song $v$ to each topic.
- Personalized recommendations are calculated for a user $u$ by ranking each item $i$ in descending order of the predicted feedback:

$$W_i = U_u^T \cdot V_i$$

- perform stochastic gradient descent on objective function
**Evaluation Metric**

- Off-line evaluation
- Truncated mAP (mean Average Precision)

\[
\text{precision -- at -- } k: \text{ proportion of correct recommendations within the top -- } k \text{ of the predicted ranking: } \quad P_k(u, y) = \frac{1}{k} \sum_{j=1}^{k} M_{u,y}(j) , \forall k \leq t
\]

for each user, the average precision at each recall point:

\[
AP (u, y) = \frac{1}{n_u} \sum_{j=1}^{t} P_k(u, y) \cdot M_{u,y}(k)
\]

mean average precision:

\[
mAP = \frac{1}{m} \sum AP(u, y_u)
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1. Haven’t listened to a song != dislike it. The « 0 » gives a lot confusion and little confidence.

2. We use weighted matrix factorization

3. Each entry is weighted by a confidence function so as to put more confidence on non-zero entries
Challenge 2

Non user-specific parameterization

- Represent users as a combination of item features
- User rating matrix $R$ is estimated by the factorization:

$$ R = U \sum . Q^T $$

$$ P = U \sum $$

with $P_u$ represents the user factors vector while $Q_i$ represents the item factors vector

$$ P = R . Q $$

as $U$ and $Q$ have orthonormal columns
First latent factors capture properties of the most popular items, while the additional latent factors represent more refined features related to unpopular items.

Number of latent factors influences the quality of long-tail items differently than head items.
Reference


Thank you!

Any questions or suggestions?