

Reccomandation system

The idea is to match consumers with the most appropriate products/services is key to enhancing user satisfaction and loyalty.

R.S. formalism

- Set of users $U = \{u_1 \dots u_m\}$
- Set of items $I = \{i_1 \dots i_n\}$
- Utility function (user-item matrix) $r : U \times I \rightarrow R$
- $R \subseteq \mathbb{R}$, it defines the set of **ratings**, R is made by either discrete ratings (i.e. from 1 to 5 stars) or continuous values.

The utility functions

You create a matrix made by **m rows (number of users)** and **n cols (number of items)**, each matrix's entries represent the rating given to a specific item by a specific user. However, this matrix tends to be very sparse, there are a lot of missing data, not every user rates every item.

The 3 Key problems for a r.s.

- **1. Data collection**, how to populate the matrix
- **2. Rating prediction**, fill the gap w.r.t the missing rating
- **3. R.S. eval**, measure the performance of recommender methods

1. Data collection

Two ways to do it:

- **Explicit**, ask people to rate items;
- **Implicit**, find out using user's behaviour i.e. the user queries and the click etc..., but the user doesn't explicitly give a value to the item

2. Rating prediction

Two main issues:

- The matrix is very sparse;
- Cold start, the new users cannot have a history, and the system cannot have any specific

information about him to give a recommendation.

3. R.S. eval

- RMSE
- Precision, Recall at K
- Personalization
- Serendipity

Recommendation strategies

- 1. Content-based filtering
- 2. Collaborative filtering
- 3. Hybrid filtering

1. Content based filtering

Recommend items to user u similar to previous items rated highly by u .

Given the **item profiles**, the description of an item, we want to be able to create a **user profiles**, it says what the users likes.

After do that we want combine **user profiles** with the item through all catalog.

- **item profiles**, for each item i create a profile, i.e. a set of features, that's better represent the specific item, this is a f.e. tags.

Let's take an item as article, the possible profile could be an array of word for each article, and this array contains the a score for every word in the arrays.

User profiles strategies

For each user create a user profile.

- **the simplest solution** is to take the average through all items rated by the user, this approach is not fair, all items are treated equally

Suppose user u has watched (and rated) **5** movies

	0		-2		-1		2		1
1	0	0	1	0	1	1	0	0	1
actor ₁	actor ₂	actor ₁	actor ₂	actor ₁	actor ₂	actor ₁	actor ₂	actor ₁	actor ₂

Normalize ratings by subtracting user's mean rating before



The slides above shows a list of item profiles, which are represented using features actor₁, actor₂, up to every cell there's the scaled rating for that movie.

The user profile is the green rectangle, which is the mean of the rating across the 5 items profile previously chosen.

Building predictions, content-based filtering

- Given user profile u we can estimate the missing entries of the utility matrix for u ;
- For each item **unrated** by u , compute the cosine sim (or another) between u and the corresponding item profile vectors;
- Finally, we pick the top- k items with **the highest similarity score**, and we recommend those to u .

$$\begin{aligned}
 A^0 &= \emptyset \\
 A^1 &= \operatorname{argmax}_i \{ \operatorname{sim}(u, i) : i \in I - I_u - A^0 \} \\
 A^2 &= \operatorname{argmax}_i \{ \operatorname{sim}(u, i) : i \in I - I_u - A^0 - A^1 \} \\
 R_{u,k} &= \bigcup_{j=1}^k A^j
 \end{aligned}$$

PROs

- No need for data on other users: only the user and the items rated by her/him are needed;
- no **item cold start** problem, when the item is new or unpopular, it can still be recommended to users with highest profile similarity;
- you have to perform a sort of feature engineering strategies, and it's very human understandable.

CONs

- Find the best features which express well the items;
- unable to find the quality judgments of other users;
- **user cold start**, for new users, if the user hasn't rated any items, then there's no user profile;
- overspecialization, never recommends items outside user's profile;

2. Collaborative filtering

Recommend items to user u based on preferences of other users similar to u

Here we aren't using any sort of f.e. techniques, we don't need any effort in order to extract information

Three main approaches

- 2.1. Neighbourhood-based

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Compute the relationship between users or items, the first one evaluates a user's preference for an item based on ratings of "neighboring" users for that item; whereas item-based evaluate preference on rating of "neighboring" items by the same user

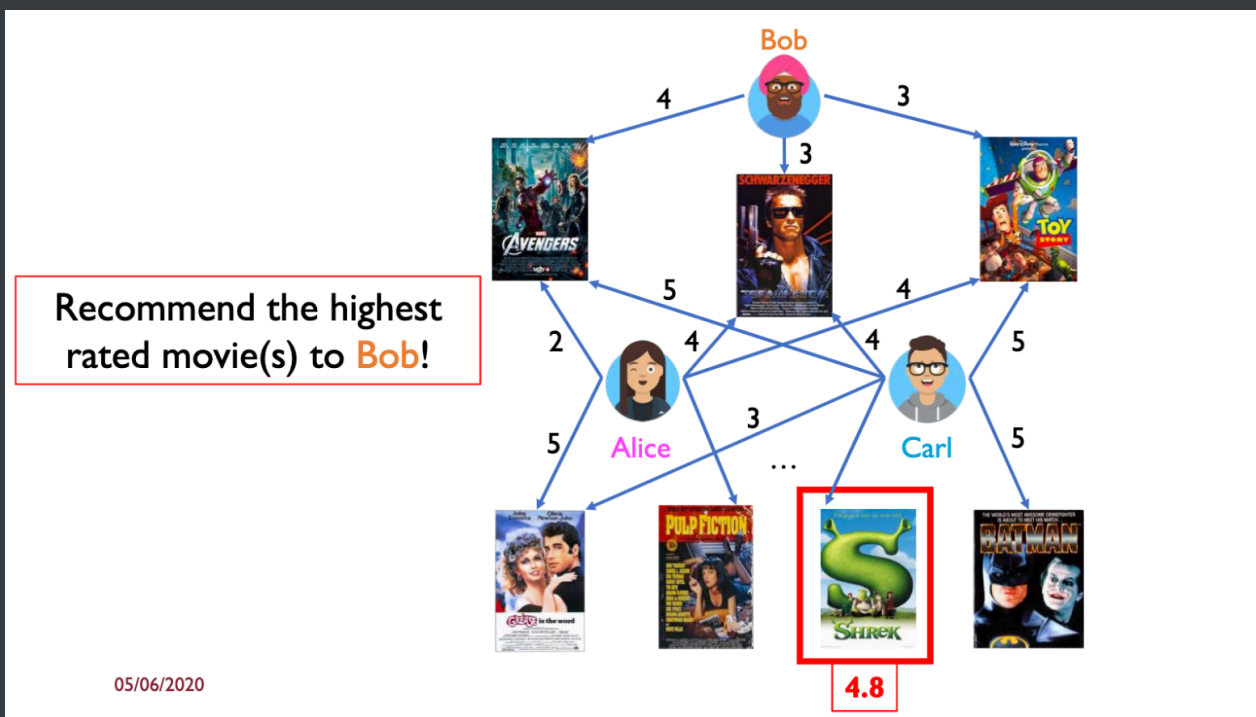
2.1.1. User based Neigh.

Given a user u and an item i not rated by u , we want estimate $r(u,i)$, takes the set $\{u' : u' \neq u\}$, who have already rated the item i , extract a subset of k neighbours of u

K -neigh of u is found on the basis of the similarity between user ratings without the need of explicit user profiles

In theory, rating prediction $r(u,i)$ could be defined on any i not rated by u , in practice we are interested only in estimating $r(u,i)$ for those i which have been rated by the u 's k -neigh.

Hint: if a user v is not in the k -n of u then very likely u will not be interested in any item that only v has rated.



Bob has Alice and Carl as your neigh., according to the mean compute through all moovies watched by Alice and Carl **user-based neigh.** recommend Sherek which is the highest.