Recommender Systems

Collaborative filtering methods

Collaborative methods for recommender systems are methods that are based solely on the past interactions recorded between users and items in order to produce new recommendations. These interactions are stored in the so-called "user-item interactions matrix".

Then, the main idea that rules collaborative methods is that these past user-item interactions are sufficient to detect similar users and/or similar items and make predictions based on these estimated proximities.

User-user method: based on the search of similar users in terms of interactions with items. Every user have only interacted with a few items, it makes the method sensitive to any recorded interactions (high variance). As the final recommendation is only based on interactions recorded for users similar to our user of interest, we obtain more personalized results (low bias).

Item-item method: based on the search of similar items in terms of user-item interactions. (low variance, high bias)

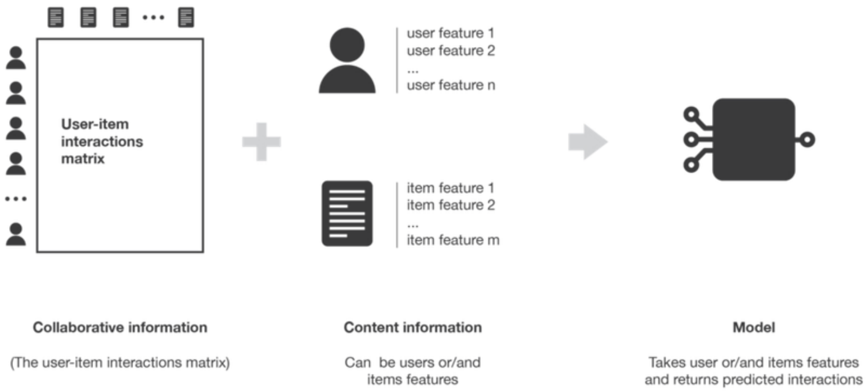
Users	User-item interactions matrix	Items
suscribers	rating given by a user to a movie (integer)	movies
readers	time spent by a reader on an article (float)	articles
buyers	product clicked or not when suggested (boolean)	products

...

Illustration of the user-item interactions matrix.

Content based methods

Unlike collaborative methods that only rely on the user-item interactions, content based approaches use additional information about users and/or items. The idea of content based methods is to try to build a model, based on the available “features”, that explain the observed user-item interactions. It suffers far less from the cold start problem



Overview of the content based methods paradigm.

Item-centred Bayesian classifier: for each item we want to train a Bayesian classifier that takes user features as inputs and output either “like” or “dislike”. To achieve the classification task, we want to compute

$$P_{\text{item}}(\text{like}|\text{user features}) = \frac{P_{\text{item}}(\text{user features}|\text{like}) \times P_{\text{item}}(\text{like})}{P_{\text{item}}(\text{user features})}$$

$$P_{\text{item}}(\text{dislike}|\text{user features}) = \frac{P_{\text{item}}(\text{user features}|\text{dislike}) \times P_{\text{item}}(\text{dislike})}{P_{\text{item}}(\text{user features})}$$

$$\frac{P_{\text{item}}(\text{like}|\text{user features})}{P_{\text{item}}(\text{dislike}|\text{user features})} = \frac{P_{\text{item}}(\text{user features}|\text{like}) \times P_{\text{item}}(\text{like})}{P_{\text{item}}(\text{user features}|\text{dislike}) \times P_{\text{item}}(\text{dislike})}$$

where

$$P_{\text{item}}(\text{like}) \text{ and } P_{\text{item}}(\text{dislike}) (= 1 - P_{\text{item}}(\text{like}))$$

are priors computed from the data whereas

$$P_{\text{item}}(.\mid\text{like}) \text{ and } P_{\text{item}}(.\mid\text{dislike})$$

are likelihoods assumed to follow Gaussian distributions with parameters to be dtermined also from data. Various hypothesis can be done about the covariance matrices of these two likelihood distributions (no assumption, equality of matrices, equality of matrices and features independence) leading to various well-known models (quadratic discriminant analysis, linear discriminant analysis, naive Bayes classifier). Here, likelihood parameters have to be estimated only based on data (interactions) related to the considered item.

User-centred linear regression: for each user we want to train a simple linear regression that takes item features as inputs and output the rating for this item.