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Baptiste Rocca Follow
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Introduction to recommender systems

Overview of some major recommendation algorithms.

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This post was co-written with Joseph Rocca.

Introduction

During the last few decades, with the rise of Youtube, Amazon, Netflix and many other such web services, recommender systems have taken more and more place in our lives. From e-commerce (suggest to buyers articles that could interest them) to online advertisement (suggest to users the right contents, matching their preferences), recommender systems are today unavoidable in our daily online

or anything else depending on industries).

Recommender systems are really critical in some industries as they can generate a huge amount of income when they are efficient or also be a way to stand out significantly from competitors. As a proof of the importance of recommender systems, we can mention that, a few years ago, Netflix organised a challenges (the "Netflix prize") where the goal was to produce a recommender system that performs better than its own algorithm with a prize of 1 million dollars to win.

In this article, we will go through different paradigms of recommender systems. For each of them, we will present how they work, describe their theoretical basis and discuss their strengths and weaknesses.

Outline

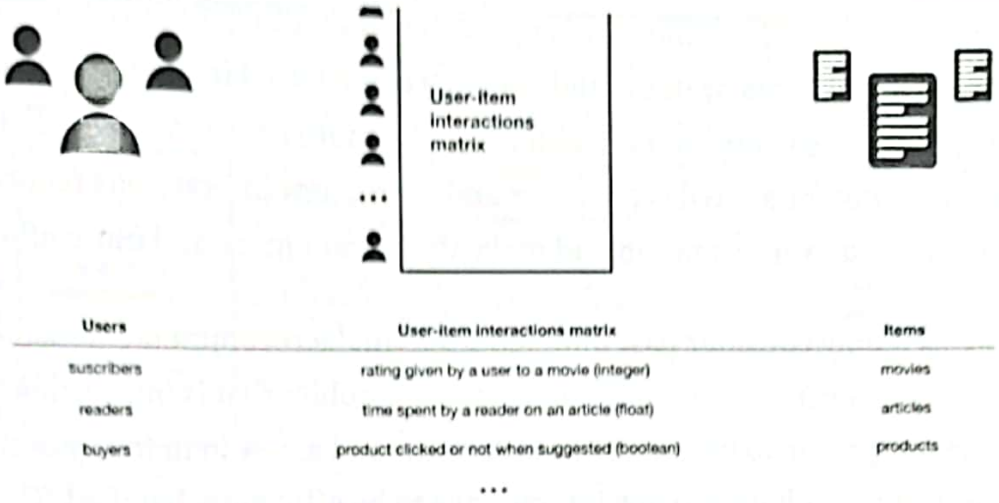
In the first section we are going to overview the two major paradigms of recommender systems : collaborative and content based methods. The next two sections will then describe various methods of collaborative filtering, such as user-user, item-item and matrix factorization. The following section will be dedicated to content based methods and how they work. Finally, we will discuss how to evaluate a recommender system.

Collaborative versus content

The purpose of a recommender system is to suggest relevant items to users. To achieve this task, there exist two major categories of methods : collaborative filtering methods and content based methods. Before digging more into details of particular algorithms, let's discuss briefly these two main paradigms.

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

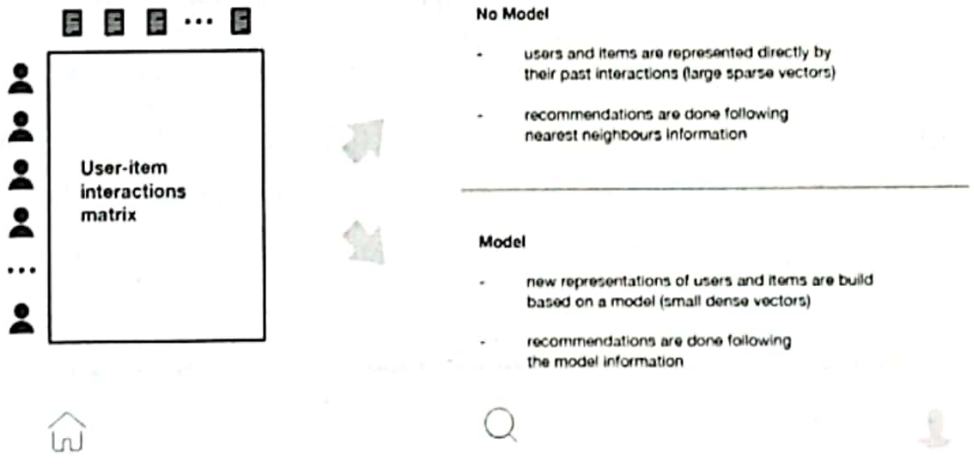


Users	User-item interactions matrix	Items
suscribers	rating given by a user to a movie (integer)	movies
readers	time spent by a reader on an article (float)	articles
buyers	product clicked or not when suggested (boolean)	products
...		

Illustration of the user-item interactions matrix.

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.

The class of collaborative filtering algorithms is divided into two sub-categories that are generally called memory based and model based approaches. Memory based approaches directly works with values of recorded interactions, assuming no model, and are essentially based on nearest neighbours search (for example, find the closest users from a user of interest and suggest the most popular items among these neighbours). Model based approaches assume an underlying "generative" model that explains the user-item interactions and try to discover it in order to make new predictions.



The main advantage of collaborative approaches is that they require no information about users or items and, so, they can be used in many situations. Moreover, the more users interact with items the more new recommendations become accurate: for a fixed set of users and items, new interactions recorded over time bring new information and make the system more and more effective.

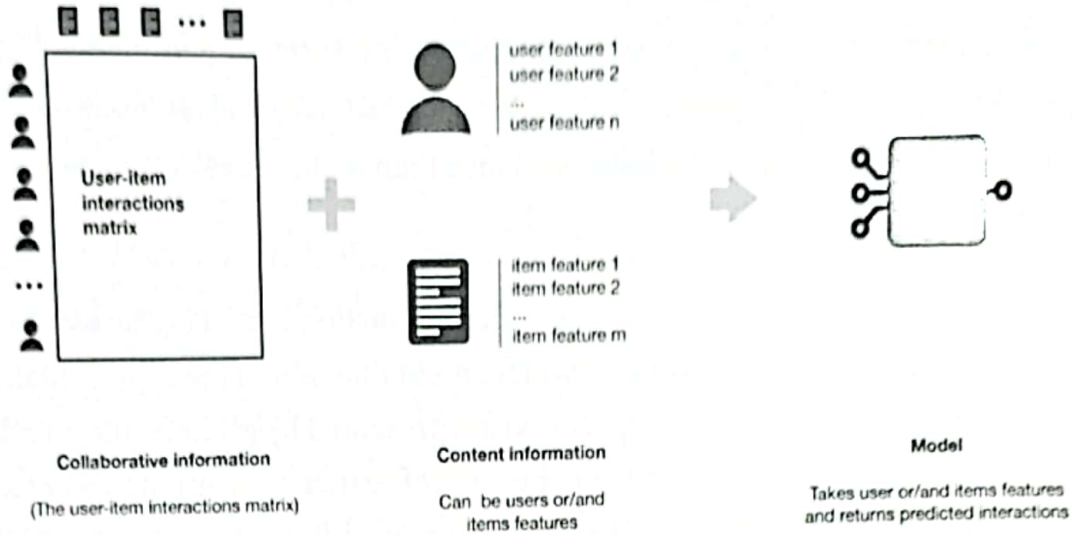
However, as it only consider past interactions to make recommendations, collaborative filtering suffer from the "cold start problem": it is impossible to recommend anything to new users or to recommend a new item to any users and many users or items have too few interactions to be efficiently handled. This drawback can be addressed in different way: recommending random items to new users or new items to random users (random strategy), recommending popular items to new users or new items to most active users (maximum expectation strategy), recommending a set of various items to new users or a new item to a set of various users (exploratory strategy) or, finally, using a non collaborative method for the early life of the user or the item.

In the following sections, we will mainly present three classical collaborative filtering approaches: two memory based methods (user-user and item-item) and one model based approach (matrix factorisation).

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. If we consider the example of a movies recommender system, this additional information can be, for example, the age, the sex, the job or any other personal information for users as well as the category, the main actors, the duration or other characteristics for the movies (items).

Then, 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. Still considering users and movies, we will try, for example, to model the fact that young women tend to rate better some movies, that young men tend to rate better some other movies and so on. If we manage to get such model, then, making new



Overview of the content based methods paradigm.

Content based methods suffer far less from the cold start problem than collaborative approaches: new users or items can be described by their characteristics (content) and so relevant suggestions can be done for these new entities. Only new users or items with previously unseen features will logically suffer from this drawback, but once the system old enough, this has few to no chance to happen.

Later in this post, we will further discuss content based approaches and see that, depending on our problem, various classification or regression models can be used, ranging from very simple to much more complex models.

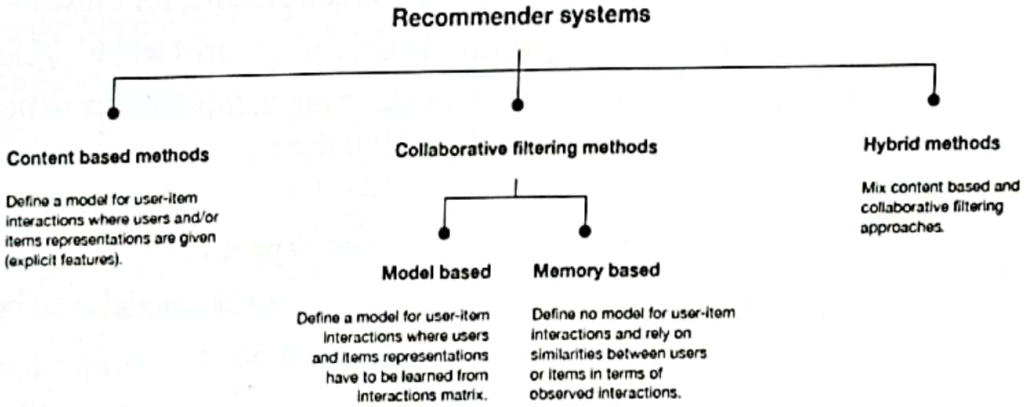
Models, bias and variance

Let's focus a bit more on the main differences between the previously mentioned methods. More especially let's see the implication that the modelling level has on the bias and the variance.

In memory based collaborative methods, no latent model is assumed. The algorithms directly works with the user-item interactions: for example, users are represented by their interactions with items and a nearest neighbours search on

representation of users and items. New suggestions can then be done based on this model. The users and items latent representations extracted by the model have a mathematical meaning that can be hard to interpret for a human being. As a (pretty free) model for user-item interactions is assumed, this methods has theoretically a higher bias but a lower variance than methods assuming no latent model.

Finally, in content based methods some latent interaction model is also assumed. However, here, the model is provided with content that define the representation of users and/or items: for example, users are represented by given features and we try to model for each item the kind of user profile that likes or not this item. Here, as for model based collaborative methods, a user-item interactions model is assumed. However, this model is more constrained (because representation of users and/or items are given) and, so, the method tends to have the highest bias but the lowest variance.



Summary of the different types of recommender systems algorithms.

Memory based collaborative approaches

The main characteristics of user-user and item-item approaches it that they use only information from the user-item interaction matrix and they assume no

tries to identify users with the most similar "interactions profile" (nearest neighbours) in order to suggest items that are the most popular among these neighbours (and that are "new" to our user). This method is said to be "user-centred" as it represent users based on their interactions with items and evaluate distances between users.

Assume that we want to make a recommendation for a given user. First, every user can be represented by its vector of interactions with the different items ("its line" in the interaction matrix). Then, we can compute some kind of "similarity" between our user of interest and every other users. That similarity measure is such that two users with similar interactions on the same items should be considered as being close. Once similarities to every users have been computed, we can keep the k-nearest-neighbours to our user and then suggest the most popular items among them (only looking at the items that our reference user has not interacted with yet).

Notice that, when computing similarity between users, the number of "common interactions" (how much items have already been considered by both users?) should be considered carefully! Indeed, most of the time, we want to avoid that someone that only have one interaction in common with our reference user could have a 100% match and be considered as being "closer" than someone having 100 common interactions and agreeing "only" on 98% of them. So, we consider that two users are similar if they have interacted with a lot of common items in the same way (similar rating, similar time hovering...).

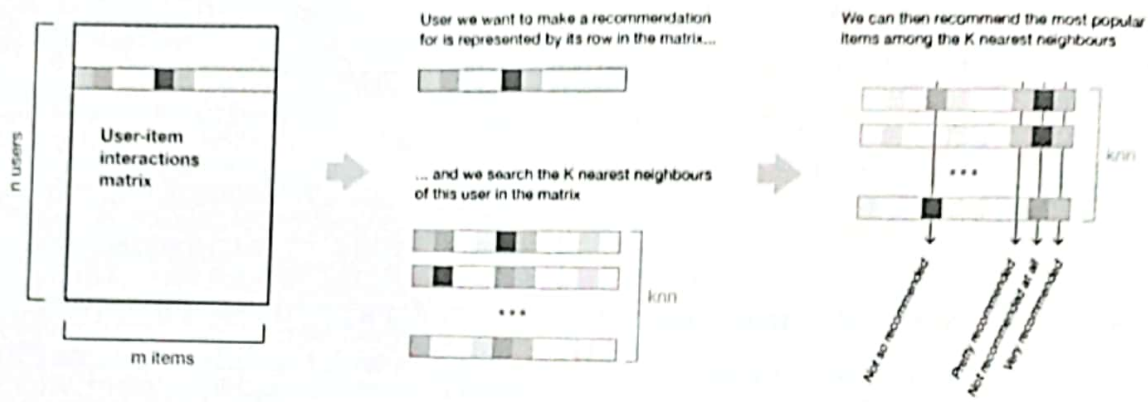


Illustration of the user-user method. The same colour code will be used in the remaining of the post.

Item-item

To make a new recommendation to a user, the idea of item-item method is to find items similar to the ones the user already "positively" interacted with. Two items are considered to be similar if most of the users that have interacted with both of them did it in a similar way. This method is said to be "item-centred" as it represent items based on interactions users had with them and evaluate distances between those items.

Assume that we want to make a recommendation for a given user. First, we consider the item this user liked the most and represent it (as all the other items) by its vector of interaction with every users ("its column" in the interaction matrix). Then, we can compute similarities between the "best item" and all the other items. Once the similarities have been computed, we can then keep the k-nearest-neighbours to the selected "best item" that are new to our user of interest and recommend these items.

Notice that in order to get more relevant recommendations, we can do this job for more than only the user's favourite item and consider the n preferred items instead. In this case, we can recommend items that are close to several of these preferred items.

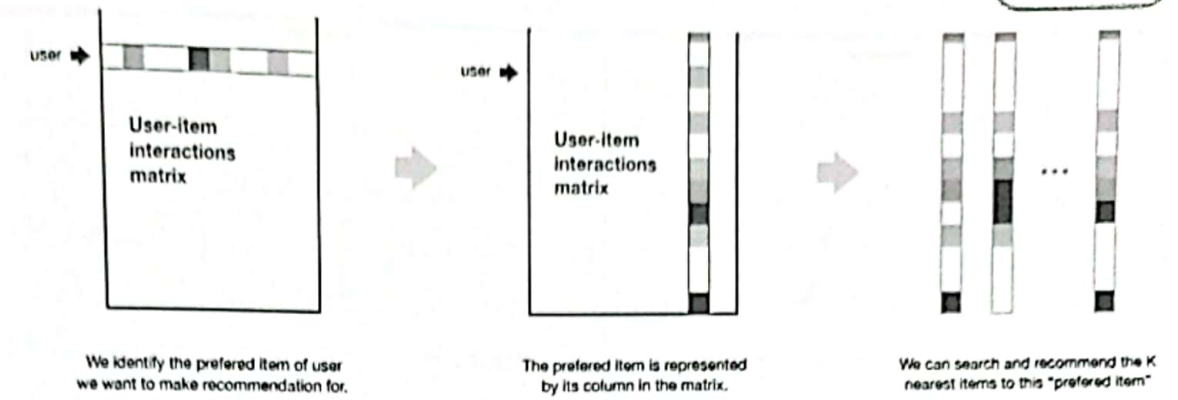


Illustration of the item-item method.

Comparing user-user and item-item

The user-user method is based on the search of similar users in terms of interactions with items. As, in general, every user have only interacted with a few items, it makes the method pretty sensitive to any recorded interactions (high variance). On the other hand, 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).

Conversely, the item-item method is based on the search of similar items in terms of user-item interactions. As, in general, a lot of users have interacted with an item, the neighbourhood search is far less sensitive to single interactions (lower variance). As a counterpart, interactions coming from every kind of users (even users very different from our reference user) are then considered in the recommendation, making the method less personalised (more biased). Thus, this approach is less personalized than the user-user approach but more robust.

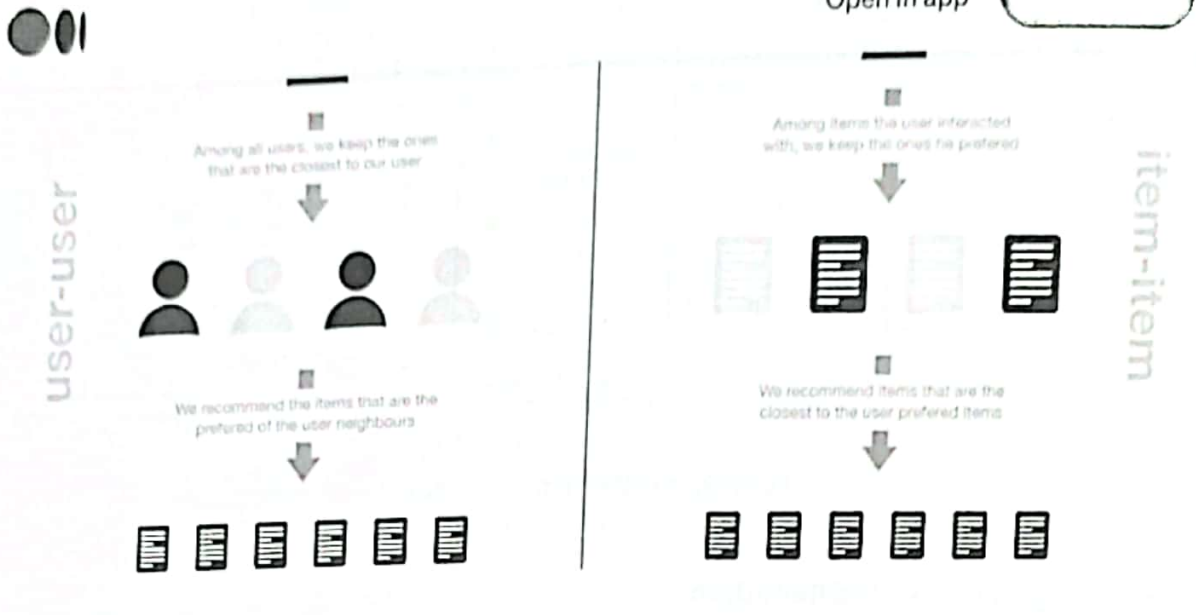


Illustration of the difference between item-item and user-user methods.

Complexity and side effect

One of the biggest flaw of memory based collaborative filtering is that they do not scale easily: generating a new recommendation can be extremely time consuming for big systems. Indeed, for systems with millions of users and millions of items, the nearest neighbours search step can become intractable if not carefully designed (KNN algorithm has a complexity of O(ndk) with n the number of users, d the number of items and k the number of considered neighbours). In order to make computations more tractable for huge systems, we can both take advantage of the sparsity of the interaction matrix when designing our algorithm or use approximate nearest neighbours methods (ANN).

In most of the recommendation algorithms, it is necessary to be extremely careful to avoid a "rich-get-richer" effect for popular items and to avoid getting users stuck into what could be called an "information confinement area". In other words, we do not want that our system tend to recommend more and more only popular items as well as we do not want that our users only receive recommendations for items extremely close to the one they already liked with no chance to get to know new items they might like too (as these items are not "close enough" to be suggested). If, as we mentioned, these problems can arise in most of the recommendation algorithms, it is especially true for memory based collaborative ones. Indeed, with the lack of model "to regularise", this kind of

Model based collaborative approaches

Model based collaborative approaches only rely on user-item interactions information and assume a latent model supposed to explain these interactions. For example, matrix factorisation algorithms consists in decomposing the huge and sparse user-item interaction matrix into a product of two smaller and dense matrices: a user-factor matrix (containing users representations) that multiplies a factor-item matrix (containing items representations).

Matrix factorisation

The main assumption behind matrix factorisation is that there exists a pretty low dimensional latent space of features in which we can represent both users and items and such that the interaction between a user and an item can be obtained by computing the dot product of corresponding dense vectors in that space.

For example, consider that we have a user-movie rating matrix. In order to model the interactions between users and movies, we can assume that:

- there exists some features describing (and telling apart) pretty well movies.
- these features can also be used to describe user preferences (high values for features the user likes, low values otherwise)

However we don't want to give explicitly these features to our model (as it could be done for content based approaches that we will describe later). Instead, we prefer to let the system discover these useful features by itself and make its own representations of both users and items. As they are learned and not given, extracted features taken individually have a mathematical meaning but no intuitive interpretation (and, so, are difficult, if not impossible, to understand as human). However, it is not unusual to ends up having structures emerging from that type of algorithm being extremely close to intuitive decomposition that human could think about. Indeed, the consequence of such factorisation is that close users in terms of preferences as well as close items in terms of characteristics ends up having close representations in the latent space.

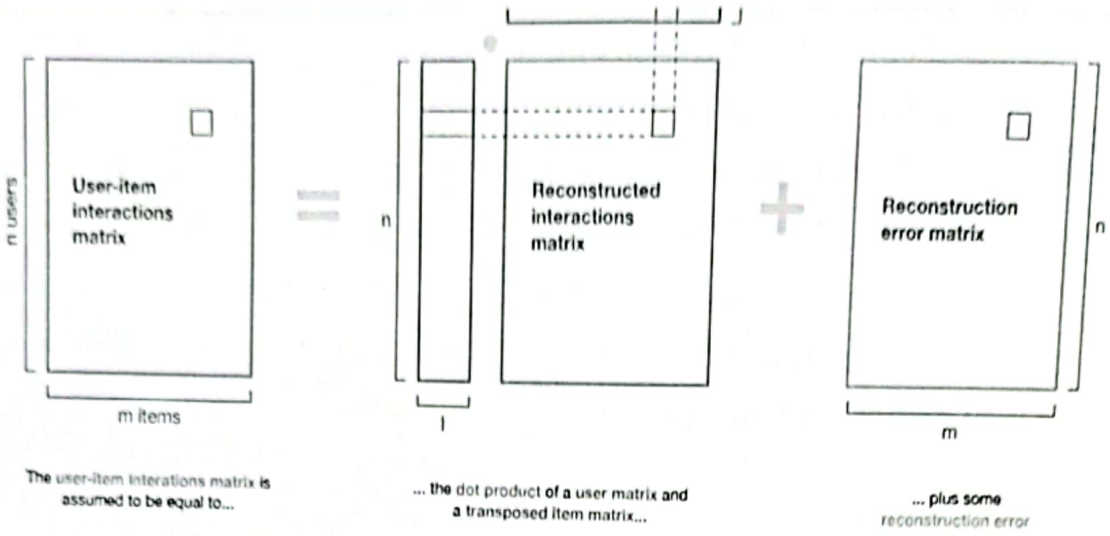


Illustration of the matrix factorization method.

Mathematics of matrix factorisation

In this subsection, we will give a simple mathematical overview of matrix factorization. More especially, we describe a classical iterative approach based on gradient descent that makes possible to obtain factorisations for very large matrices without loading all the data at the same time in computer's memory.

Let's consider an interaction matrix M (nxm) of ratings where only some items have been rated by each user (most of the interactions are set to None to express the lack of rating). We want to factorise that matrix such that

$$M \approx X.Y^T$$

where X is the "user matrix" (nxl) whose rows represent the n users and where Y is the "item matrix" (mxl) whose rows represent the m items:

$$user_i \equiv X_i \qquad \forall i \in \{1, ..., n\}$$
$$item_j \equiv Y_j \qquad \forall j \in \{1, ..., m\}$$

Here l is the dimension of the latent space in which users and item will be represented. So, we search for matrices X and Y whose dot product best approximate the existing interactions. Denoting E the ensemble of pairs (i,j) such that M_ij is set (not None), we want to find X and Y that minimise the "rating

Adding a regularisation factor and dividing by 2, we get

$$(X, Y) = \underset{X,Y}{argmin} \frac{1}{2} \sum_{(i,j) \in E} [(X_i)(Y_j)^T - M_{ij}]^2 + \frac{\lambda}{2}(\sum_{i,k}(X_{ik})^2 + \sum_{j,k}(Y_{jk})^2)$$

The matrices X and Y can then be obtained following a gradient descent optimisation process for which we can notice two things. First, the gradient do not have to be computed over all the pairs in E at each step and we can consider only a subset of these pairs so that we optimise our objective function "by batch". Second, values in X and Y do not have to be updated simultaneously and the gradient descent can be done alternatively on X and Y at each step (doing so, we consider one matrix fixed and optimise for the other before doing the opposite at the next iteration).

Once the matrix has been factorised, we have less information to manipulate in order to make a new recommendation: we can simply multiply a user vector by any item vector in order to estimate the corresponding rating. Notice that we could also use user-user and item-item methods with these new representations of users and items: (approximate) nearest neighbours searches wouldn't be done over huge sparse vectors but over small dense ones making some approximation techniques more tractable.

Extensions of matrix factorisation

We can finally notice that the concept of this basic factorisation can be extended to more complex models with, for example, more general neural network like "decomposition" (we cannot strictly speak about "factorisation" anymore). The first direct adaptation we can think of concerns boolean interactions. If we want to reconstruct boolean interactions, a simple dot product is not well adapted. If, however, we add a logistic function on top of that dot product, we get a model that takes its value in [0, 1] and, so, better fit the problem. In such case, the model to optimise is

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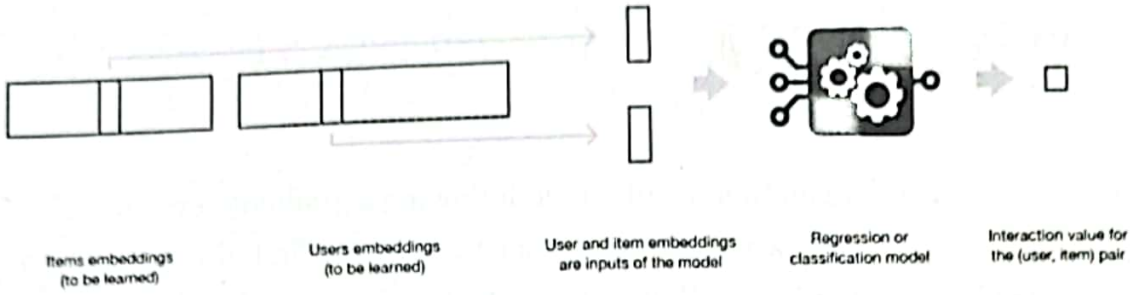

Matrix factorization can be generalized with the use of a model on top of users and items embeddings.

Content based approaches

In the previous two sections we mainly discussed user-user, item-item and matrix factorisation approaches. These methods only consider the user-item interaction matrix and, so, belong to the collaborative filtering paradigm. Let's now describe the content based paradigm.

Concept of content-based methods

In content based methods, the recommendation problem is casted into either a classification problem (predict if a user "likes" or not an item) or into a regression problem (predict the rating given by a user to an item). In both cases, we are going to set a model that will be based on the user and/or item features at our disposal (the "content" of our "content-based" method).

If our classification (or regression) is based on users features, we say the approach is item-centred: modelling, optimisations and computations can be done "by item". In this case, we build and learn one model by item based on users features trying to answer the question "what is the probability for each user to like this item?" (or "what is the rate given by each user to this item?", for regression). The model associated to each item is naturally trained on data related to this item and it leads, in general, to pretty robust models as a lot of