Matrix Factorization For Implicit Ratings

If we have a matrix of implicit ratings, this leads to its own set of concerns:

- There is no negative feedback.
- The feedback that does exist may be very noisy.
- The numerical value does not indicate preference.

For example, if we are using # of plays as an implicit rating for songs:

- The user may leave a playlist / album / randomized list to play out. Not all these songs share the same preference
- Long songs have less opportunity to be played many times than short songs.
- A zero rating does not necessarily mean no preference.

Preferences and Confidence

To recover a measure of preference from implicit feedback data, we take a catagorization approach:

$$p_{ij} = \begin{cases} 1 & \text{if } r_{ij} > 0 \Leftarrow \text{User likes this item} \\ 0 & \text{if } r_{ij} = 0 \Leftarrow \text{user does not like this item.} \end{cases}$$

Our factorization is built to recover these preferences:

$$p_{ij} \approx \sum_{k} u_{ik} v_{jk} \quad \text{or} \quad P = UV^t$$

The second novelty with implicit ratings is that these preferences are associated with varying levels of confidence. Our model assumes these confidences are related to the implicit ratings

$$c_{ij} = 1 + \alpha r_{ij}$$

— A new parameter. $\alpha = 0 \Rightarrow$ We believe all the preferences equally.

There is a minimal level of confidence in a preference. We are more confident in non-zero ratings than zero ratings.

Our confidence in a preference increases linearly with the implicit rating.

We want our model to put more effort into correctly predicting the preferences with high confidence. To accomplish this, we optimize the weighted loss:

$$\hat{U}, \hat{V} = \underset{U,V}{\operatorname{argmin}} \left\{ \sum_{i,j} c_{ij} \underbrace{\left(p_{ij} - \vec{u}_i \cdot \vec{v}_j \right)}^2 + \lambda \left(\sum_{i,k} u_{ik}^2 + \sum_{j,k} v_{jk}^2 \right) \right\}$$

Confidences are used as weights

Model attempts to recover the preferences.

This is the implicit feedback matrix factorization model.