ADAM MICKIEWICZ UNIVERSITY POZNAŃ

Part 7: WRMF: Weighted Regularized Matrix Factorization

Robert Kwieciński

OLX Group and Adam Mickiewicz University

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Idea

Matrix factorization model was designed for explicit data and gives really good results. In learning procedure only items that user interacted with are used.

Of course for implicit feedback we can assume all unspecified ratings to be zeros and learn our model, but:

- in case of RMSE loss function mistakes in estimating zeros (which we assumed) are then as important as mistakes in estimating ones (which we know),
- optimization through gradient descent might be really slow in case of sparse datasets.

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But the idea of replacing missing entries with zeros is not so bad.
We will see that both problems can be overcome by Weighted Regularized Matrix Factorization (WRMF) model introduced in [1].

WRMF model

Denote by r_{ui} the "rating" of user u of item i. It might be the real rating in case of explicit feedback dataset or number of times user visited the given page in implicit feedback. In case of no interactions we assume $r_{ui} = 0$. As in the original paper we will call r_{ui} values **observations**.

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Then our cost function is:

$$\min_{x_*, y_*} \sum_{u,i} c_{ui}(p_{ui} - x_u^T y_i)^2 + \lambda(\sum_u ||x_u||^2 + \sum_i ||y_i||^2),$$

where x_u is user's u f-dimensional embedding and y_i is item's i f-dimensional embedding.

ALS

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In this case our loss function becomes quadratic and for example for each user u, vector latent representation x_u minimizing the loss function is:

$$x_u = (Y^T C^u Y + \lambda I)^{-1} Y^T C^u p(u),$$

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where C^u is a diagonal matrix with $C^u_{ii} = c_{ui}$. Note that

$$Y^T C^u Y = Y^T Y + Y^T (C^u - I) Y,$$

and $Y^T Y$ is independent of u.

It leads to the fact ALS procedure is fast and scales linearly with the size of the data.

Python implementation

To do (especially for absent students):

- Go through - *P7. WRMF (Implicit ALS)* notebook to:
  - check implementation of WRMF model using Implicit library - Implicit library is really fast,
  - compare the results using different loss functions,
  - check the impact of some hyperparameters on evaluation measures.

Project tasks

- project task 1: implement TopRated
- project task 2: implement self-made BaselineIU
- project task 3: implement some other evaluation measure
- project task 4: use a version of your choice of Surprise KNN algorithm
- project task 5: implement SVD on top baseline (as it is in Surprise library)
- project task 6: generate recommendations of RP3Beta for hiperparameters found to optimize recall
- project task 7 (optional): implement graph-based model of your choice (for example change length of paths in RP3beta)

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References I

[1] Y. Hu, Y. Koren, and C. Volinsky, "Collaborative filtering for implicit feedback datasets," *Proceedings - IEEE International Conference on Data Mining, ICDM*, pp. 263–272, Dec. 2008. DOI: 10.1109/ICDM.2008.22.