What about Interpreting Features in Matrix Factorization-based Recommender Systems as Users?

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ABSTRACT

Matrix factorization (MF) is a powerful approach used in recommender systems. One main drawback of MF is the difficulty to interpret the automatically formed features. Following the intuition that the relation between users and items can be expressed through a reduced set of users, referred to as representative users, we propose a simple modification of a traditional MF algorithm, that forms a set of features corresponding to these representative users. On one state of the art dataset, we show that the proposed representative users-based non-negative matrix factorization (RU-NMF) discovers interpretable features, while slightly (in some cases insignificantly) decreasing the accuracy.

Keywords

Recommender systems, matrix factorization, features interpretation.

1. INTRODUCTION, RELATED WORKS

Recommender systems aim to estimate ratings of target users on previously non-seen items. One of the methods used for this task is matrix factorization (MF), which relies on the idea that there is a small number of latent factors (features) that underly the interactions between users and items [1]. Let M be the number of users and N the number of items. The interaction between these entities is usually represented under the form of a matrix R with element r_{mn} corresponding to the rating assigned by the user m to the item n. MF techniques decompose the original rating matrix R into two low-rank matrices U ($\dim(U) = K \times M$) and V ($\dim(V) = K \times N$) in such a way that the product of these matrices approximates the original rating matrix $R \approx R^* = U^T V$. The set of K factors can be seen as a joint latent space on which a mapping of both users and items spaces is performed [1]. Features resulting from factorization usually do not have any physical sense, what makes resulting recommendations unexplainable. Some works [2, 3] made attempts to interpret them by using non-negative matrix factorization with multiplicative update rules (for simplicity, further referred to as NMF). However, the proposed interpretation is not so easy to perform as it has to be discovered manually. Based on the assumption that the preferences between users are correlated, we assume that within the entire set of users, there is a small set of users that have a specific role or have specific preferences. These users can be considered as representative of the entire population and we intend to discover features from MF that are associated with these representative users.

2. THE PROPOSED APPROACH: RU-NMF

Let us consider 2 linear spaces L_1 and L_2 of dimensionality respectively 6 and 3, with basic vectors in canonical form $\{\vec{u}_m\}$, $m \in \overline{1,6}$ and $\{\vec{f_k}\}$, $k \in \overline{1,3}$. Let the transfer matrix from L_1 to L_2 be specified by matrix (1). Then $\vec{u}_5$, $\vec{u}_1$ and $\vec{u}_2$ are direct preimages of $\vec{f_1}$, $\vec{f_2}$ and $\vec{f_3}$ respectively, indeed, $P\vec{u}_5 = \vec{f_3}$. At the same time vectors $\vec{u}_3$, $\vec{u}_4$ and $\vec{u}_6$ will be mapped into linear combinations of basic vectors $\vec{f_1}$, $\vec{f_2}$, $\vec{f_3}$.

$$P = \begin{pmatrix} 0 & 0 & p_{13} & p_{14} & 1 & p_{16} \\ 1 & 0 & p_{23} & p_{24} & 0 & p_{26} \\ 0 & 1 & p_{33} & p_{34} & 0 & p_{36} \end{pmatrix} \quad (1)$$

Matrix U can be considered as a transfer matrix from the space of users to the space of features. Analyzing the example considered above, we can say that if matrix U has a form similar to (1), *i.e.* U has exactly K unitary columns with one non-zero and equal to 1 element on different positions, then the users corresponding to these columns are direct preimages of the K features. The features can thus be directly interpreted as users. These users will be referred to as representative users. In order to force matrix U to satisfy the imposed conditions we propose the RU-NMF approach, that consists of 6 steps, further detailed below.

Step 1. A traditional matrix factorization is performed. Following [2, 3], NMF is used.

Step 2. A normalization of each of the M column vectors of the matrix U is performed so as to result in unitary columns. The resulting normalized matrix is denoted by U_{norm} and the vector of normalization coefficients by C.

Step 3. This step is dedicated to the identification of the representative users in the U_{norm} matrix. A user u_m is considered as the best preimage candidate (representative user) for the feature f_k if the vector u_m^{norm} is the closest to the corresponding canonical vector (a vector with the only one non-zero and equal to 1 value on the position k). The notion of closeness between vectors is expressed in Euclidean distance. Once all representative users are identified, the matrix U_{norm} is modified so as to obtain a matrix in a form of (1): lines, corresponding to the representative users, are replaced with appropriate canonic vectors. The resulting modified matrix is denoted by U_{norm}^{mod}.

Step 4. Each column of the matrix U_{norm}^{mod} is multiplied by the appropriate normalization coefficient from the set C resulting in matrix U^{mod}. After this, representative users will remain preimages of the features but with scaling factors.

Step 5. In order to obtain the best model we also have to modify the matrix V. The modification of V can be performed using optimization methods with the starting value obtained during the first step. As the objective of this paper is to determine the relevance of finding preimages of the features and to quantify the decrease in the quality of the recommendations, we did not consider this step.

Step 6. The resulting recommendation model is made up of matrices U^{mod} and V ($R^* = \left(U^{mod}\right)^T V$).

3. EXPERIMENTAL RESULTS

Experiments are performed on the 100k MovieLens dataset[1], with 80% of ratings used for learning the model and 20% for testing it. The accuracy is evaluated with two classical measures: mean absolute error (MAE) and root mean square error (RMSE). The goal of the experiments is to compare the accuracies of RU-NMF and NMF. For these reasons we compute the accuracy loss $\rho = \frac{err(RU\text{-}NMF) - err(NMF)}{err(NMF)} 100\%$ for factorizations with 10, 15 and 20 features on 30 different samples. Results are presented in Table 1. A positive loss means that NMF performs better than RU-NMF. In the worst case the accuracy loss equals to 6.64%, for RMSE with 20 features, which is quite small. The lowest average accuracy loss (0.05%) is obtained with 10 features for both errors. When comparing the accuracy loss between test and learning sets, we can note that the average loss is 3 times lower on test than on learning, for both errors and for all the number of features: thus we can say that RU-NMF has a lower relative loss between learn and test compared to NMF. A thorough analysis of the losses obtained on the 30 samples has shown that the accuracy loss on the test set is lower than the one on the learning set in all cases. In some runs, RU-NMF has even a higher accuracy than NMF (Table 1, values in gray shadow).

[1]http://grouplens.org/datasets/movielens/

Table 1: Accuracy loss ρ between RU-NMF and the traditional NMF, for 10, 15 and 20 features.

	Learning set		Test set	
	MAE	RMSE	MAE	RMSE
10 features				
mean	**0.17%**	**0.19%**	**0.05%**	**0.05%**
min	0.03%	0.03%	-0.06%	-0.07%
max	0.38%	0.46%	0.18%	0.20%
15 features				
mean	**0.98%**	**1.29%**	**0.29%**	**0.33%**
min	0.49%	0.61%	-0.06%	-0.04%
max	1.71%	2.38%	0.77%	0.79%
20 features				
mean	**2.78%**	**4.08%**	**0.70%**	**0.82%**
min	1.38%	1.94%	0.13%	0.12%
max	4.27%	6.64%	1.43%	1.53%

4. DISCUSSIONS AND FUTURE WORK

The analysis of the accuracy loss between RU-NMF and traditional NMF has shown that prediction error rises slightly (in some cases insignificantly) with RU-NMF. However the features formed with this approach consistently disturb the accuracy on the test set less than on the learning one. This can be considered as a potential ability of factorization techniques with features related to reality to form better searched predictions. The proposed approach also lets us easily explain the resulting recommendations. Indeed, each user of the population is linearly mapped on the basis related to representative users (through matrix U) and the preferences of the latter ones (expressed by matrix V) are used to estimate the ratings of the whole population. In a future work, we would like to focus first of all on the verifications of the hypothesis that users associated with the features can be really considered as representative ones. We believe that this can be done while solving the new item cold-start problem with ratings of the representative users on new items used to estimate ratings of all the population on these items.

5. REFERENCES

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