BLOMA: Explain Collaborative Filtering via Boosted Local Rank-One Matrix Approximation

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An Interesting Problem

Understanding the reasons behind the model can make users accept the result. Consider the following example in recommendation system: when recommending the Chinese seafood noodle to a user, instead of plainly pointing out that"people also viewed", the system makes explanation like,

"This recommendation is tailored to your tastes for Chinese cuisine (fitting 60%) and seafood (fitting 30%). Have a try?"

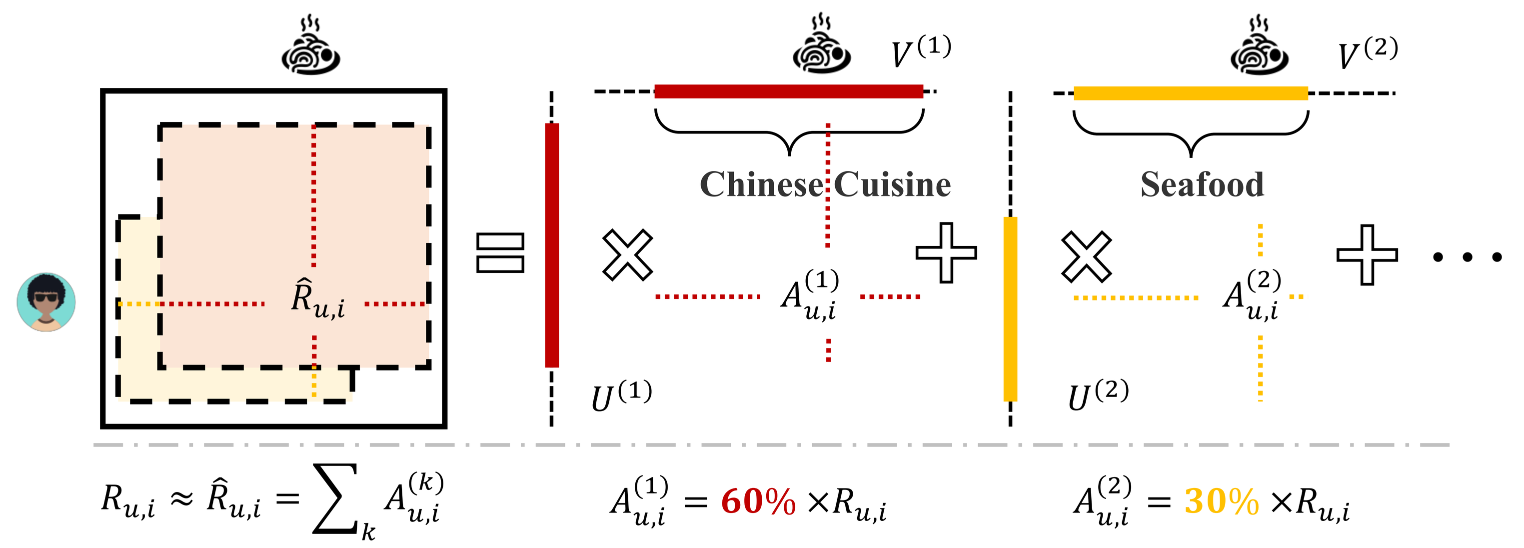

Fig. 1: Illustration of the explainable matrix approximation model.

To this end, we propose a Boosted Local rank-One Matrix Approximation (BLOMA) model, which has, compared to traditional methods, **three major differences:**

1) The rating matrix is factorized locally on the part of the users and items.
2) The factorization is applied for many times sequentially on the residue matrix.
3) Each factorization is a rank-one decomposition.

The three changes together make the topics extracted from the latent factors more distinct.

Advantages and Issues

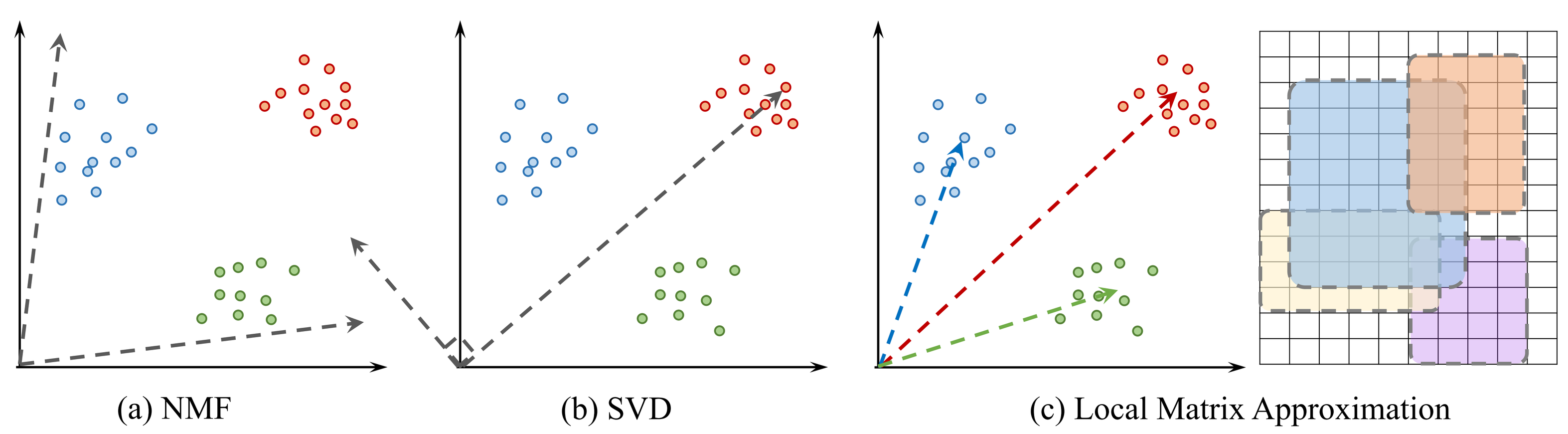

Fig. 2: Illustration of three matrix approximation methods.

We illustrate three kinds of matrix factorization models. NMF and SVD can approximate the matrix accurately, but cannot spot the three topics directly in their item factors as they just pursue the combination of latent factors closing to the ratings in the training set. Meanwhile, **since LMA models explore correlations at the first place, it can easily distinguish every topic.** However, there are still two issues to be tackled:

1) How to determine K, the number of local sub-matrices?
2) How to determine the subset of users and items to construct the sub-matrix?

Sub-matrices Construction

- **Sample Core User and Item.** To approximate the residue matrix $R^{(k)}$ which represents the unexplained part remained in last stage, a natural idea is to choose the core user u and core item i with large values in $R^{(k)}$ to approximate (the **green triangles** in Fig. 3).
- **Find Neighbors from Rating Matrix.** we choose a set of users/items that have strong correlations (small arc-cosine distance) with u and i respectively (the light yellow areas in Fig. 3), which are represented by $\mathcal{N}_u, \mathcal{N}_i$ in Fig. 4.

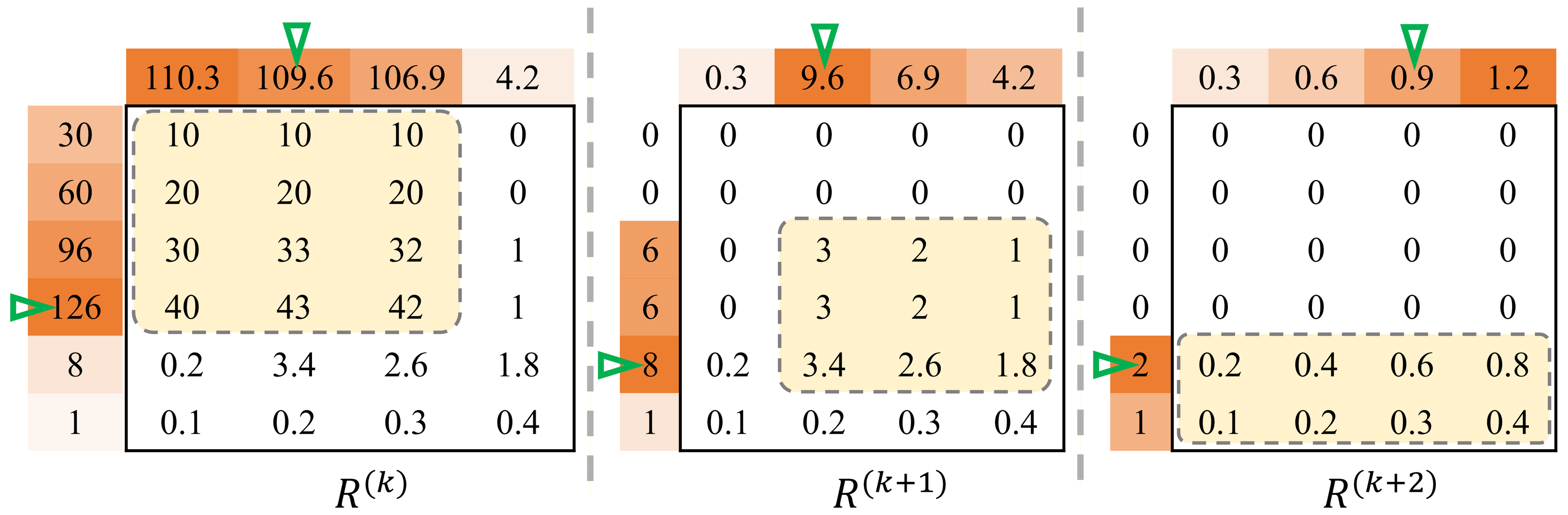

Fig. 3: Illustration of the core user/item selection and sub-matrices construction.

- **Find Neighbors from Networks.** Assume: 1) Friends of a user u could have the same interests of user u. 2) A user visits a POI i might visit other POIs near it. We define the nodes linked with core user/item u, i on the social/item network as another kinds of neighbors,$\mathcal{F}_u, \mathcal{F}_i$.

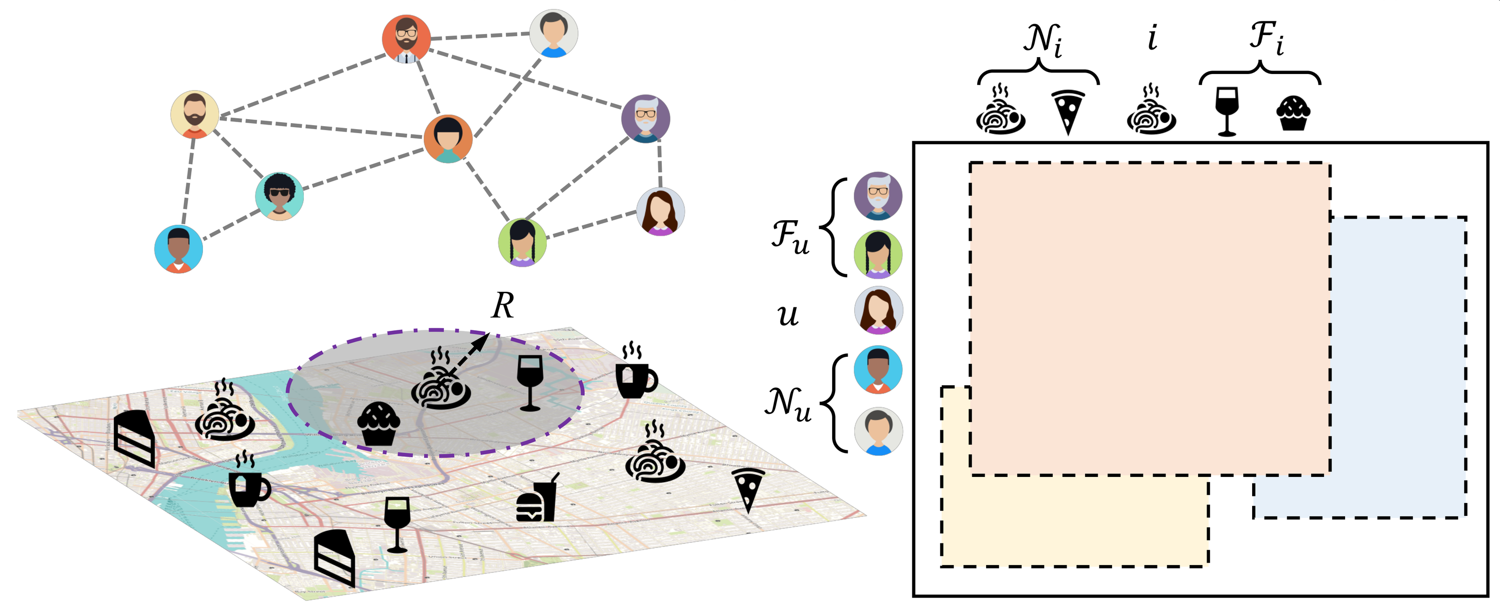

Fig. 4: Illustration of selection of the two kinds of neighbors.

Residue Matrix Updating

We iteratively add a new local model to better approximate original rating matrix R in a forwarding stagewise manner. In each stage, we are fitting the residue sub-matrix obtained from previous stage:

$$\arg\min_{U^{(k)},V^{(k)}} \left\| \mathcal{I}\left(R^{(k)} - g\left(\left(\alpha U^{(k)} + (1-\alpha)SU^{(k)}\right)\cdot\left(\beta V^{(k)} + (1-\beta)V^{(k)}T\right)\right)\right)\right\|_F^2 + \frac{\lambda_1}{2}\|U^{(k)}\|_F^2 + \frac{\lambda_2}{2}\|V^{(k)}\|_F^2, \quad (1)$$

where $R^{(k)} \in \mathbb{R}^{m\times n}$ is the selected residue rating matrix. $U^{(k)} \in \mathbb{R}^{m\times 1}, V^{(k)} \in \mathbb{R}^{1\times n}$ are vectors representing latent factors of users/items. $S \in \mathbb{R}^{m\times m}$ and $T \in \mathbb{R}^{n\times n}$ are the normalized adjacent matrices of social network and item network with $\sum_u S(\cdot,u) = 1$ and $\sum_i T(i,\cdot) = 1$. α and β are the coefficients controlling the ratios of the user/item's own factor and its neighbors' factors. $\mathcal{I}(\cdot)$ is the indicator function. $g(x) = 1/(1+e^{-x})$ is the logistic function.The residue matrix $R^{(k+1)}$ is computed in the forward stagewise manner as:

$$R^{(k+1)} = R^{(k)} - g\left(\left(\alpha U^{(k)} + (1-\alpha)SU^{(k)}\right)\cdot\left(\beta V^{(k)} + (1-\beta)V^{(k)}T\right)\right), \quad (2)$$

Experiments of Explainability

We conduct the experiments on Yelp, a well-known POI recommendation data set. We extract a POI network from the given features. We compare our BLOMA with the state-of-the-art models. To discover the meaning in the latent factors and explain the recommendation results, we compute the average Point-wise Mutual Information (PMI) of every pair of items with top-10 largest absolute values on each column of item factor matrix V.

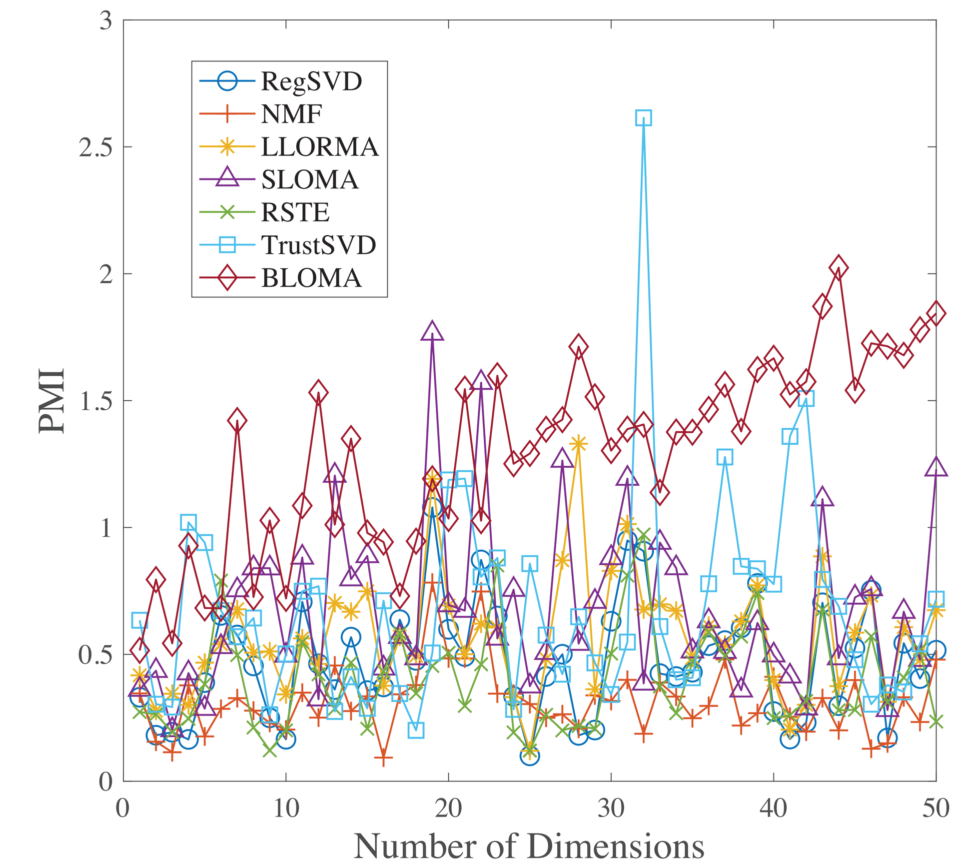

Fig. 5: Evalution of explainability on PMI metric

The result is shown in Fig. 5. We can see that BLOMA outperforms all other methods, and maintain the highest topic coherence with the dimension K increasing. This result reflects two conclusions:

1. In the beginning, the user communities and items with similar semantic categories can be discovered by carefully selecting the sub-indices and using the rank-one decomposition.
2. After iteratively subtracting a local approximation from the residue matrix, the rating remained to be approximated is more distinct and easier to be explained.

See Fig 6 for an example. In the beginning, the subset of items is composed of items of common categories, e.g., Food and Bars. When BLOMA runs after 30 stages, the subset of items starts to show different categories in the check-in data, such as Arts and Parks.

	1
1	'Korean, Chicken Wings, Hot Dogs, Resta...
2	'Coffee & Tea, Restaurants, Food, Breakfa...
3	'Lounges, Cocktail Bars, Bars, Nightlife'
4	'Bars, Breakfast & Brunch, Tex-Mex, Nigh...
5	'Breakfast & Brunch, Bubble Tea, Restaura...
6	'Nightlife, Adult Entertainment, Local Flav...
7	'Specialty Food, Grocery, Beer, Wine & Spi...
8	'"Gastropubs, American (Traditional), Am...
9	'Sandwiches, Restaurants, Coffee & Tea, ...
10	'Restaurants, Steakhouses'

	30
1	'Parks, Active Life, Hiking'
2	'Arts & Entertainment, Botanical Gardens'
3	'Restaurants, Gelato, Ice Cream & Frozen Yog...
4	'Public Services & Government, Arts & Entert...
5	'Arts & Entertainment, Active Life, Arcades, ...
6	'Baseball Fields, Active Life, Stadiums & Aren...
7	'Japanese, Tapas/Small Plates, Asian Fusion, ...
8	'Food, Poke, Restaurants, Hawaiian'
9	'Desserts, Ice Cream & Frozen Yogurt, Food'
10	'Ice Cream & Frozen Yogurt, Desserts, Food'

Fig. 6: An exemplar Illustration