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Preference transfer model in collaborative filtering for implicit data

Key words: Recommender systems, Collaborative filtering, Preference transfer model, Cross domain, Implicit data

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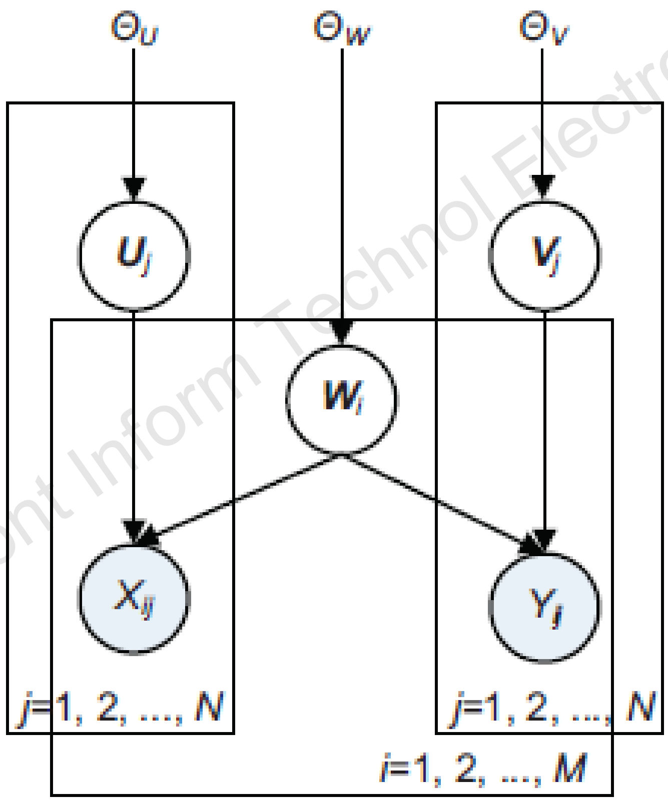
Introduction

- Predicting how much or whether an item will be liked or disliked by active users is a main task in collaborative filtering systems or recommender systems.

- We propose a novel method called the preference transfer model for effective cross-domain collaborative filtering. Based on the preference transfer model, the common basis item-factor matrix and the different user-factor matrices are factorized.

- Two factor-user matrices can be used to construct a so-called ‘preference dictionary’ which can discover in advance the consistent preference of users: from their browsing behavior to their buying behavior.

Graphical model for preference transfer modeling



Preference transfer model based on multi-task non-negative matrix factorization

$$\mathcal{L} = \min_{\boldsymbol{U},\boldsymbol{V},\boldsymbol{W}} \Bigg[\sum_{i=1}^{M}\sum_{j=1}^{N} (-X_{ij}\log(\boldsymbol{W}\boldsymbol{U})_{ij} + (\boldsymbol{W}\boldsymbol{U})_{ij})$$
$$+ \sum_{i=1}^{M}\sum_{j=1}^{N} (-Y_{ij}\log(\boldsymbol{W}\boldsymbol{V})_{ij} + (\boldsymbol{W}\boldsymbol{V})_{ij})$$
$$+ \sum_{k=1}^{K}\sum_{j=1}^{N} \left(\frac{U_{kj}}{b_u} - (a_u - 1)\log U_{kj}\right)$$
$$+ \sum_{k=1}^{K}\sum_{j=1}^{N} \left(\frac{V_{kj}}{b_v} - (a_v - 1)\log V_{kj}\right)$$
$$+ \sum_{i=1}^{M}\sum_{k=1}^{K} \left(\frac{W_{ik}}{b_w} - (a_w - 1)\log W_{ik}\right) \Bigg]$$

$$W_{ik} \leftarrow W_{ik} \frac{\sum_j U_{kj}A_{ij} + \sum_j V_{kj}B_{ij} + \dfrac{a_w - 1}{W_{ik}}}{\sum_j U_{kj} + \sum_j V_{kj} + \dfrac{1}{b_w}},$$

$$U_{kj} \leftarrow U_{kj} \frac{\sum_i W_{ik}A_{ij} + \dfrac{a_u - 1}{U_{kj}}}{\sum_i W_{ik} + \dfrac{1}{b_u}}, \ U_{kj} \leftarrow \frac{U_{kj}}{\sum_k U_{kj}},$$

$$V_{kj} \leftarrow V_{kj} \frac{\sum_i W_{ik}B_{ij} + \dfrac{a_v - 1}{V_{kj}}}{\sum_i W_{ik} + \dfrac{1}{b_v}}, \ V_{kj} \leftarrow \frac{V_{kj}}{\sum_k V_{kj}}.$$

Simulation

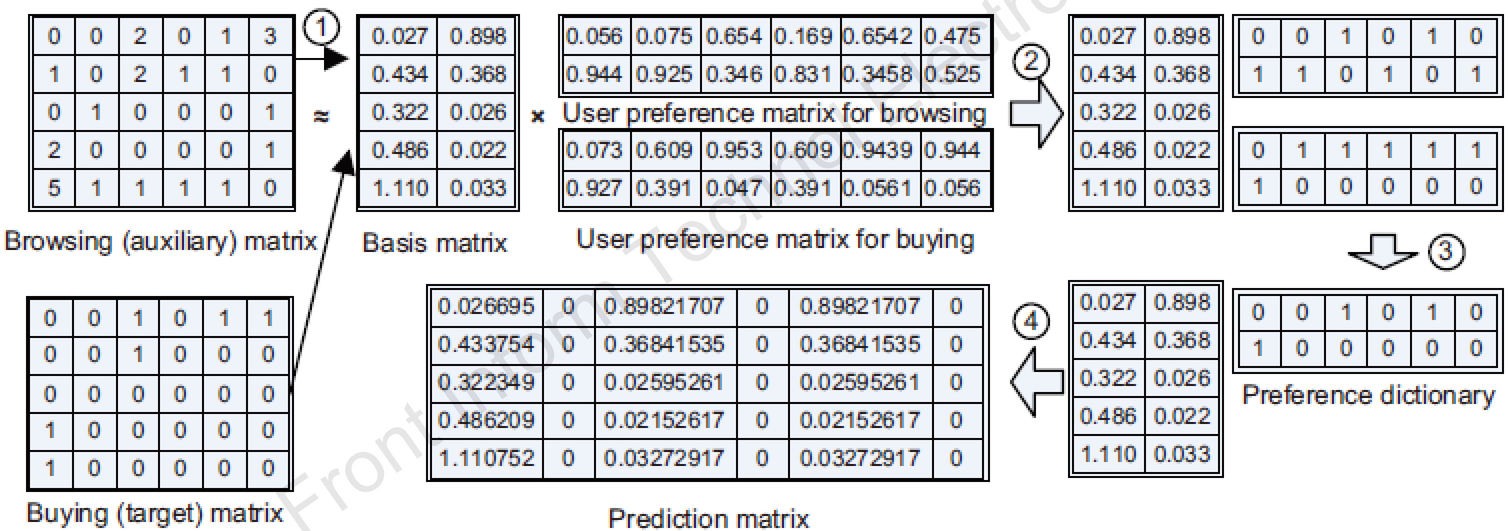


Fig. 3 Simulation of the preference transfer model for predicting user preference. By using the latent factor-user matrix, the simulation explains how to construct the consistent preference dictionary

Parameter and hyperparameter setting

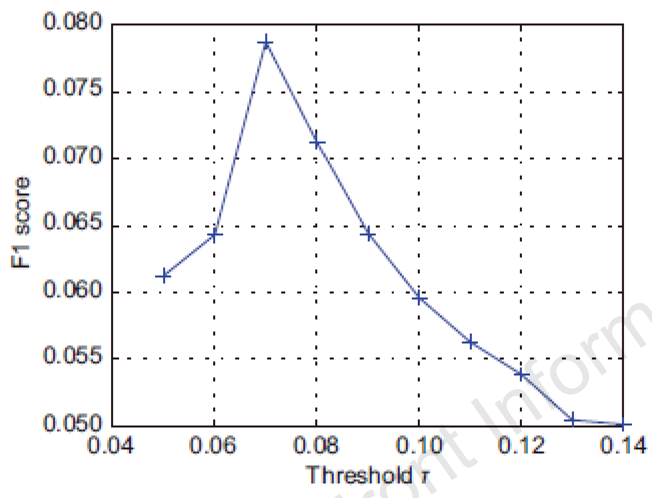


Fig. 4 F1 score influenced by different thresholds

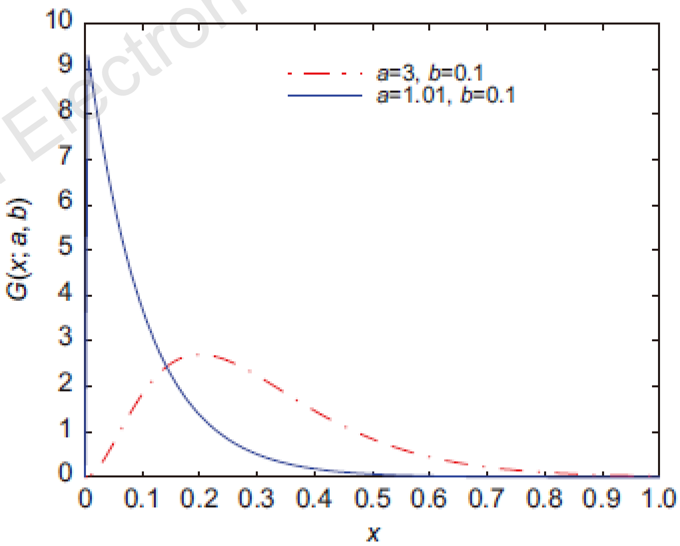
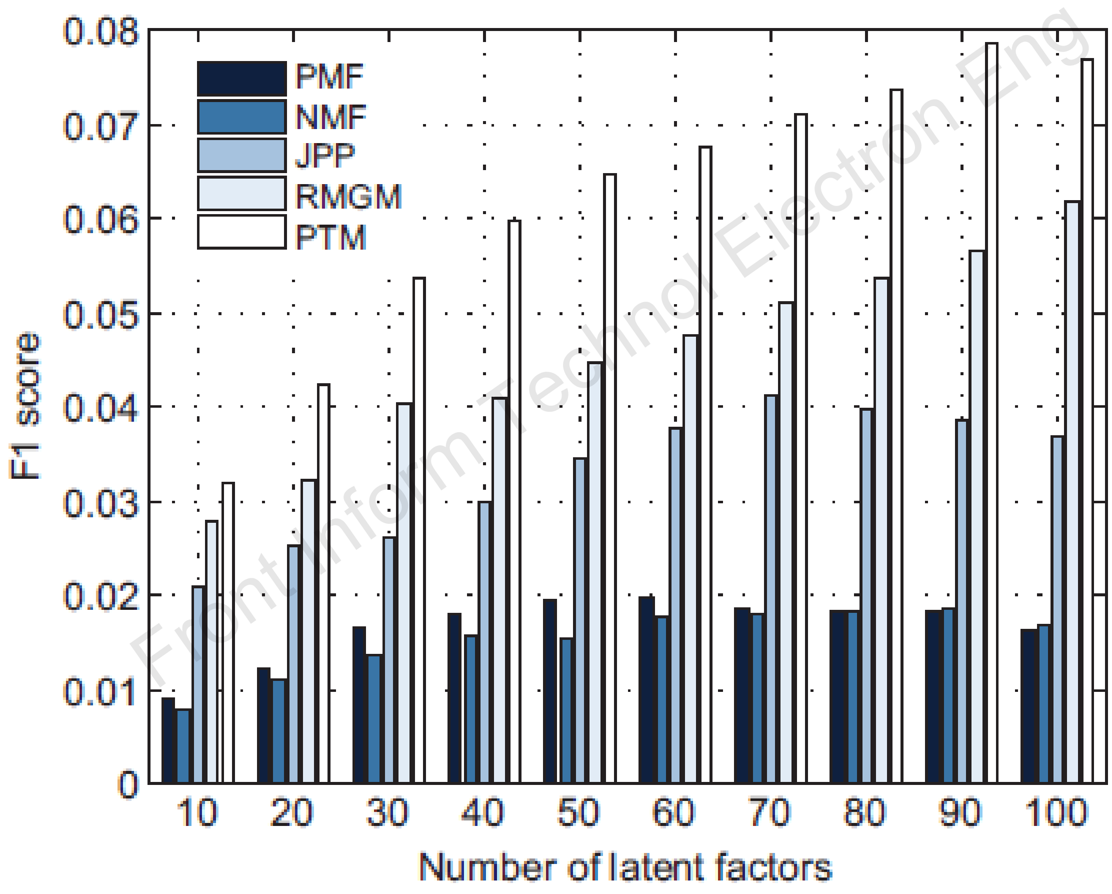


Fig. 5 Different shapes of Gamma distribution on different parameters

Performance comparison (1)



Performance comparison (2)

Table 1 Prediction performance on four weeks

Algorithm	Precision			
	Week 1	Week 2	Week 3	Week 4
PMF	0.020 [0.018, 0.021]	0.020 [0.018, 0.021]	0.019 [0.016, 0.021]	0.019 [0.016, 0.021]
NMF	0.018 [0.013, 0.021]	0.018 [0.013, 0.020]	0.015 [0.012, 0.020]	0.014 [0.012, 0.017]
JPP	0.037 [0.035, 0.039]	0.035 [0.036, 0.037]	0.036 [0.035, 0.037]	0.033 [0.031, 0.035]
RMGM	0.058 [0.052, 0.063]	**0.055** [0.052, 0.062]	**0.041** [0.038, 0.044]	**0.041** [0.038, 0.042]
PTM	**0.078** [0.076, 0.080]	0.034 [0.032, 0.370]	0.021 [0.016, 0.022]	0.014 [0.011, 0.015]

[*]: 95% confidence intervals of performance

Conclusions

- Different from other existing analogous models based on Gaussian prior, our model is based on Poisson prior for multi-task non-negative matrix factorization, which can capture the transition of the users' preferences from browsing behavior to buying behavior.

- The experimental results demonstrate that the proposed preference transfer model method can outperform the other methods on the Alibaba Tmall data.