Table 4: Performance Comparisons (A Smaller RMSE or MAE Value Means a Better Performance)

Training Data	Metrics	PMF	SoRec	Trust	STE	LRSDP (w/o ρ)	LRSDP (w/o L)	LRSDP
80%	RMSE	1.1826	1.1530	1.2140	1.1346	1.4998	1.1502	**1.1304**
	MAE	0.8951	0.8638	0.9221	0.8594	1.1730	0.8830	**0.8557**
90%	RMSE	1.1575	1.1333	1.1959	1.1109	1.5677	1.1292	**1.1095**
	MAE	0.8676	0.8442	0.9054	0.8377	1.2219	0.8593	**0.8338**

more efficient than the STE method (Ma, King, and Lyu 2009). Specifically, LRSDP only requires no more than 7% of the training time for STE. This is because the LRSDP approach employs an efficient quasi-Newton optimization algorithm while the STE method involves with the time-consuming step to directly fuse the social trust information into the high dimensional user-item matrix. Additionally, we can see that the computational time for the presented LRSDP method increases along with the total number of ratings in the user-item matrix.

Table 5: Comparisons of time cost on Epinions dataset

STE (90%)	LRSDP (80%)	LRSDP (90%)
133min	7.5min	8.5min

6 Conclusions

It is clear that our novel low-rank semidefinite program approach to social recommendation is powerful and effective. It offers several distinct advantages over the conventional approaches. First, we introduce the graph Laplacian to effectively regularize the user-specific latent space and capture the underlying relationships among the different users. Second, the presented social recommendation with the graph Laplacian regularization problem is directly formulated into the low-rank semidefinite programming, which can be efficiently solved by the quasi-Newton algorithm. Finally, the mapping function for the normalization is carefully addressed in our formulation. Our approach has been tested on the Epinions dataset with over half million ratings. The encouraging experimental results show that our presented method is both effective and promising.

In the future, we will investigate the relationship among the items by taking into account of the category information. Moreover, we will explore the recommendation problem in the multimedia domain, in which the content information in music and videos can be used to estimate the similarity between the different items.

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