unknown entries. After performing tensor decomposition, we can predict the unknown entries by low-rank approximations. (3) User/Item based collaborative filtering [8, 11, 18]. The original user-item matrix is extended by including tag information so that we can apply user/item based collaborative filtering methods.

Besides annotation behaviors, user space, tag space and item space have also been explored. [9] has studied trust networks and proposed a factor analysis approach based on probabilistic matrix factorization. [6] incorporates social network for item recommendation, but fails to improve the performance significantly. [14] links social tags from Flickr into WordNet. [7] introduces item taxonomies into recommender systems.

This paper is mainly inspired by two recent work on graph-based learning [1] and semi-supervised learning [3]. [1] proposes supervised random walks to learn the edge weights for link prediction in homogenous graph. This paper extends [1] with multi-type edges and nodes. [3] has proposed similar idea to learn edge weights and node weights with an inductive learning framework in homogenous graph. Since a recommender should have the ability to predict for future events, our framework is different from [3] in that ours belongs to transductive learning.

7. CONCLUSION AND FUTURE WORK

In this paper, we propose an optimization-based graph method for personalized tag recommendation. To alleviate data sparsity, different sources of information are incorporated into the optimization framework. There are some problems unsolved for future work: (1) Reducing the graph size. Since the random walker frequently restarts at u and i, nodes that are far away from u and i may be cut without influencing the final ranking. (2) Comparing with tensor factorization methods under a suitable experiment setting. (3) More features can be explored to further improve the results, such as the temporal factors.

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APPENDIX

We prove the convergence of Equations 26 and 33. Both the equations can be rewritten to a more general form:

$$\mathbf{p}^{(t+1)} = \lambda\overline{\mathbf{A}}\mathbf{p}^{(t)} + \mu\mathbf{q}$$

where $0 \leq \lambda, \mu \leq 1$, $\overline{\mathbf{A}}$ is a transition matrix with each column summing to 1 and $\mathbf{q}$ can be any vector with the same dimension of $\mathbf{p}$. Suppose $\mathbf{p}^{(0)} = \boldsymbol{\pi}$, we have $\mathbf{p}^{(1)} = \lambda\overline{\mathbf{A}}\boldsymbol{\pi} + \mu\mathbf{q}$, $\mathbf{p}^{(2)} = (\lambda\overline{\mathbf{A}})^2\boldsymbol{\pi} + \lambda\overline{\mathbf{A}}\mu\mathbf{q} + \mu\mathbf{q}$, ..., $\mathbf{p}^{(n)} = (\lambda\overline{\mathbf{A}})^n\boldsymbol{\pi} + \sum_{k=0}^{n-1}(\lambda\overline{\mathbf{A}})^k\mu\mathbf{q}$. Since $0 \leq \lambda, \mu \leq 1$ and the eigenvalues of the transition matrix $\overline{\mathbf{A}}$ are in [-1, 1], we have $\lim_{n\to\infty}(\lambda\overline{\mathbf{A}})^n = \mathbf{0}$ and $\lim_{n\to\infty}\sum_{k=0}^{n-1}(\lambda\overline{\mathbf{A}})^k = (\mathbf{I} - \lambda\overline{\mathbf{A}})^{-1}$. So $\mathbf{p}^{(n)}$ finally converges to $\mathbf{p}^* = (\mathbf{I} - \lambda\overline{\mathbf{A}})^{-1}\mu\mathbf{q}$.