Affiliation Recommendation using Auxiliary Networks

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RecSys, 2010

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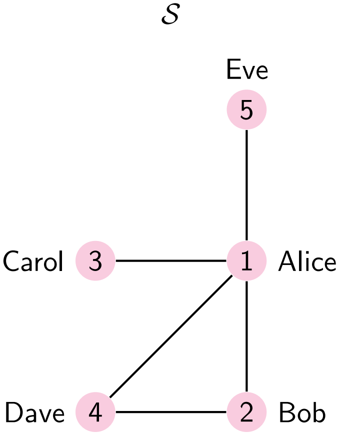
- Conclusions.

Social and Affiliation networks

Social network $\mathcal{S}$: An undirected graph.



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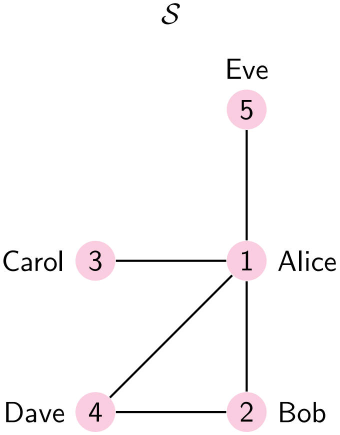
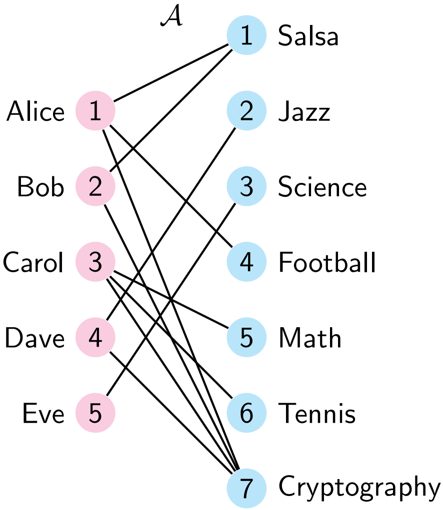


- S: users $\times$ users .

Affiliation network $\mathcal{A}$: A bipartite graph.



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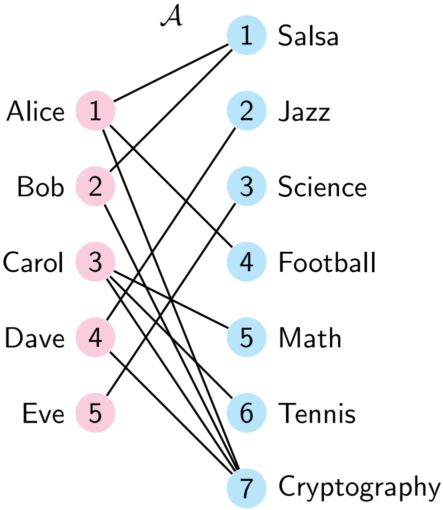

- A: users $\times$ groups/affiliations .

Affiliation networks

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- Communities in social networks.

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Affiliation networks

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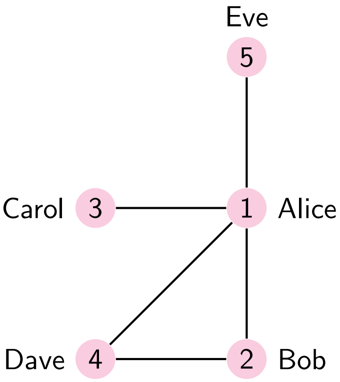
- Not necessarily among people — gene-disease network.

Social network analysis.

$\mathcal{S}$



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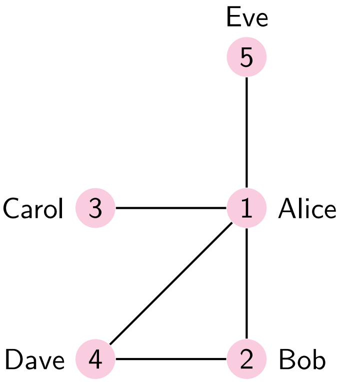

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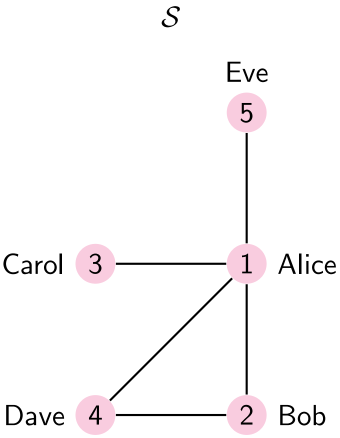

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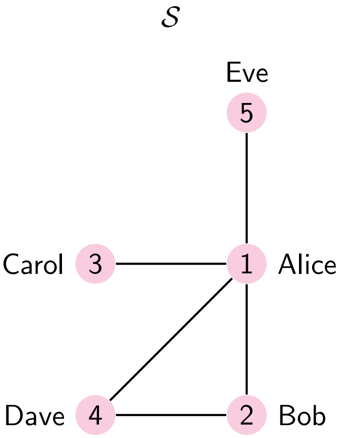

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- Link prediction.
- Community identification.

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- Can we exploit auxiliary networks (like the friendship network)?

Modeling user-affiliation affinity

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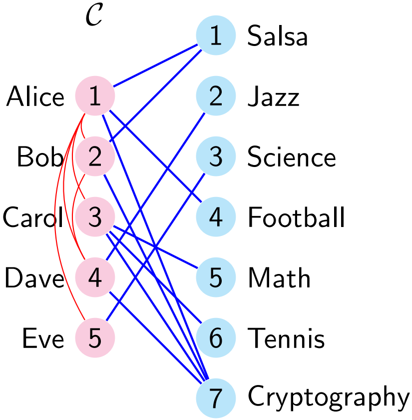
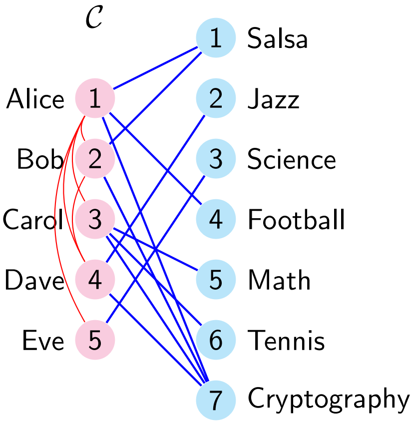


The combined network $\mathcal{C}$

$$\mathbf{C}(\lambda, \mathbf{D}) = \begin{bmatrix} \lambda S & A \\ A^T & \mathbf{D} \end{bmatrix}$$



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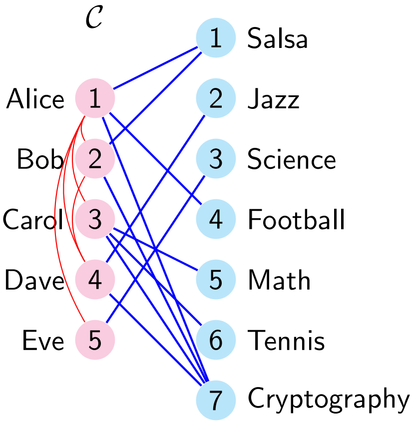

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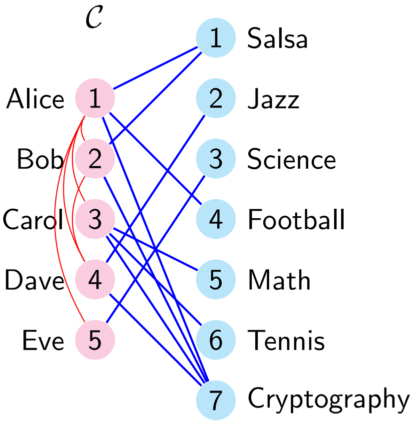

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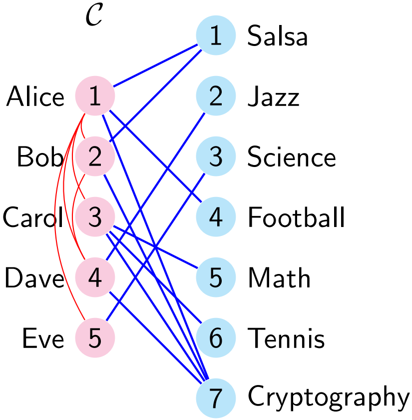

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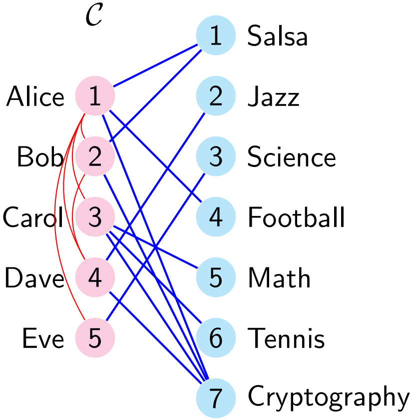

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- λ: relative weight associated with information in S.
- $\mathbf{D}$: unobserved (choices: $A^T A, \ldots$).

Latent factors model

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- User-group affinity as product of low dimensional vectors: $A_{i,j} \approx \langle \mathbf{U}(i,:), \mathbf{G}(i,:) \rangle$.

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  U - User preferences; **G** - Affiliation characteristics.

- For user u, recommend affiliations with high affinity.

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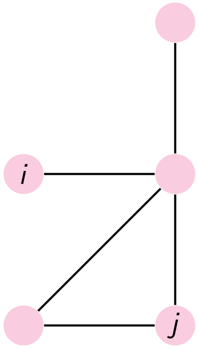
- $\mathbf{V}_1 \Lambda \mathbf{V}_2^T$ is a similarity score matrix for ranking potential affiliations.

Graph proximity model

Proximity between users in a social network



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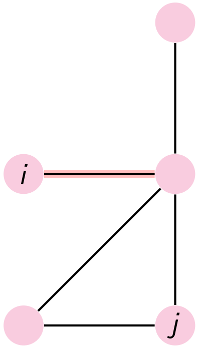

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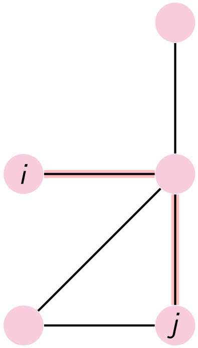

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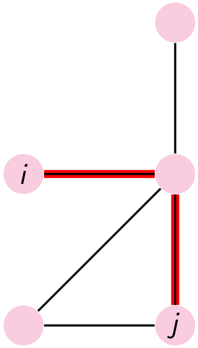

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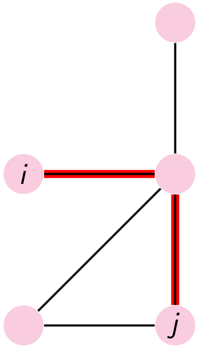

$(\mathbf{C}^2)_{i,j}$: Number of paths of length 2 between i and j.

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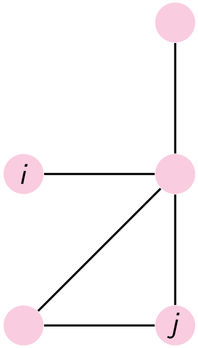

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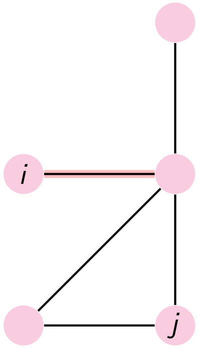

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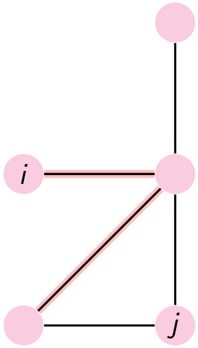

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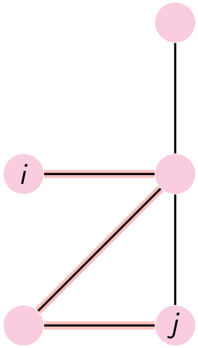

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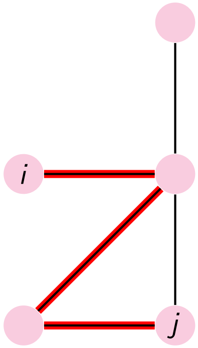

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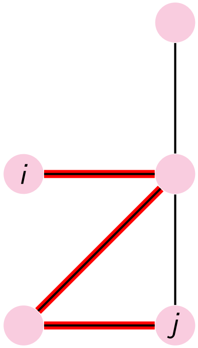

$(\mathbf{C}^3)_{i,j}$: Number of paths of length 3 between i and j.

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- Recommend affiliations based on proximity in $\mathbf{C}$.

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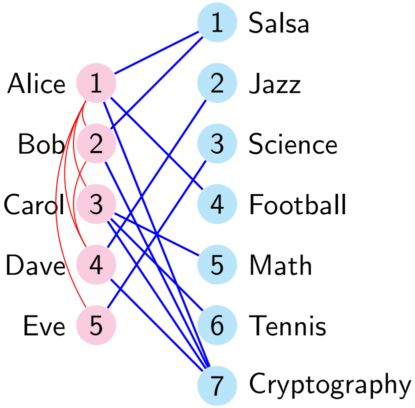

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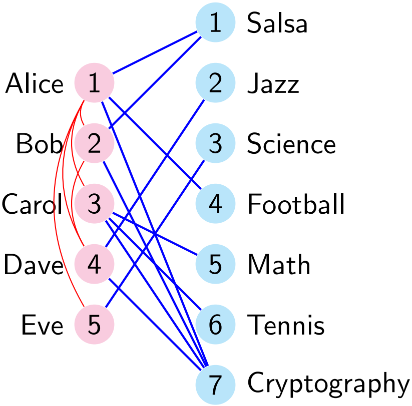

Eve $\xrightarrow{S}$ Alice $\xrightarrow{A}$ Cryptography (in $\mathbf{C}^2$)

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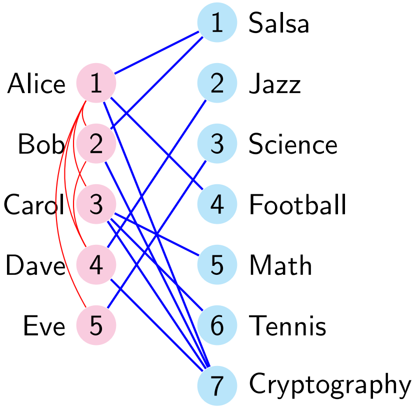

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Scalability

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- Recall tKatz$(\mathbf{C}, \beta, k) = \sum_{i=1}^{k} \beta^i \mathbf{C}^i$.
- $\mathbf{C}^i$ gets denser — prohibitively expensive computations and memory usage.

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- Use low rank approximations — $\mathbf{C} \approx \mathbf{V}\Lambda\mathbf{V}^T$.
- Then, $\mathbf{C}^i \approx \mathbf{V}\Lambda^i\mathbf{V}^T$. [Submitted]

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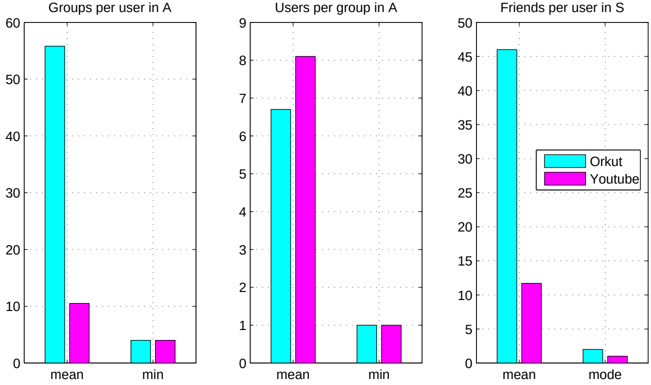
- Clustered low-rank approximations [Submitted].

Evaluation of the algorithms

Data sets

Extracted social and affiliation networks: *Orkut* and *Youtube* data sets [Mislove,2007]; Orkut: $N_u = 9123, N_g = 75546$. Youtube: $N_u = 16575, N_g = 21326$.



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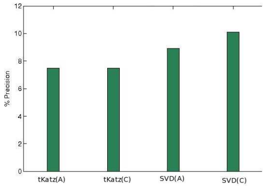
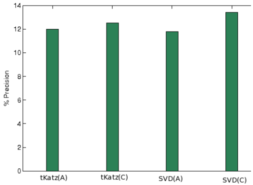


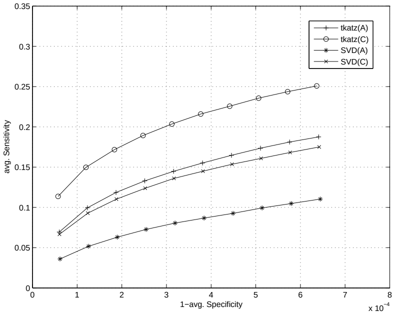
(i) Orkut dataset



(j) Youtube dataset

Results: “Per-user” sensitivity

Consider the top k recommendations made for a user for $k = 5, 10, \ldots, 50$.



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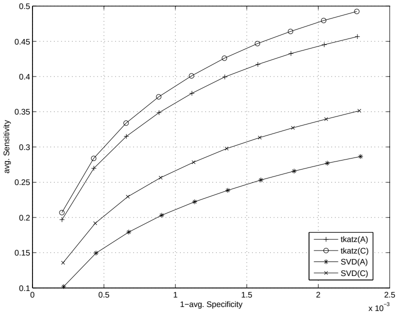

(l) Youtube dataset

Similarity between affiliations in the combined network?

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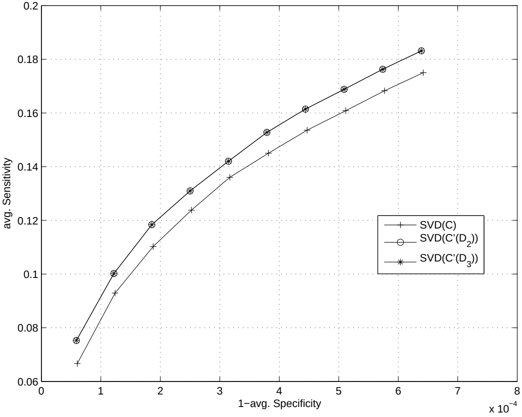
$$\text{Recall } \mathbf{C} = \begin{bmatrix} \lambda S & A \\ A^T & \mathbf{D} \end{bmatrix}$$



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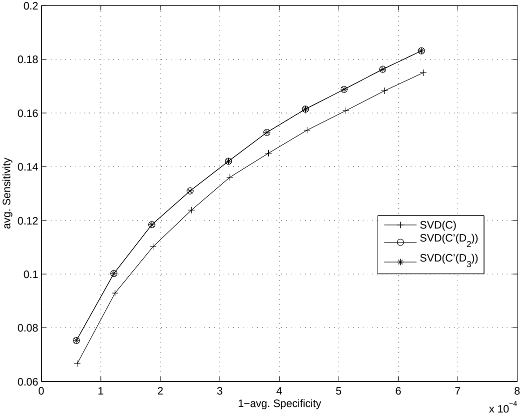

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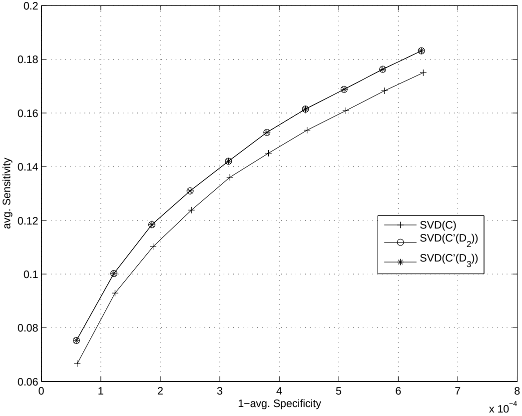

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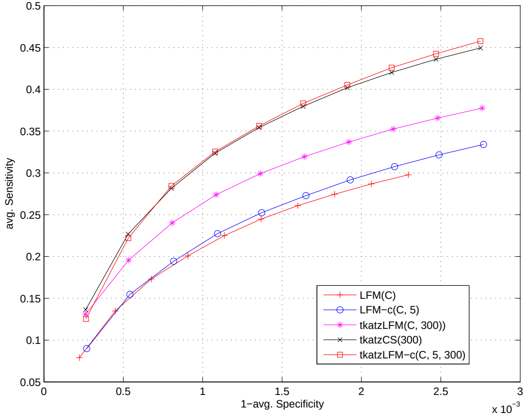
Information from **D** may be redundant!

Scalable approximations: Youtube



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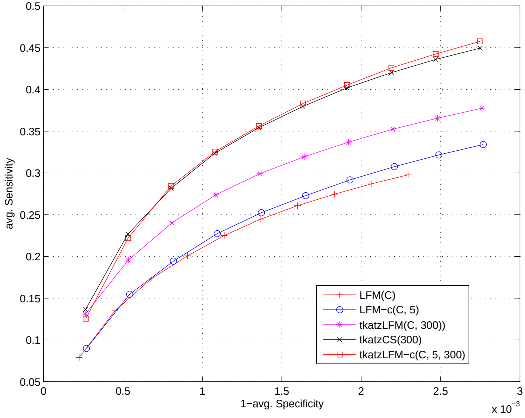

tKatzLFM: tKatz on low-rank approximation.

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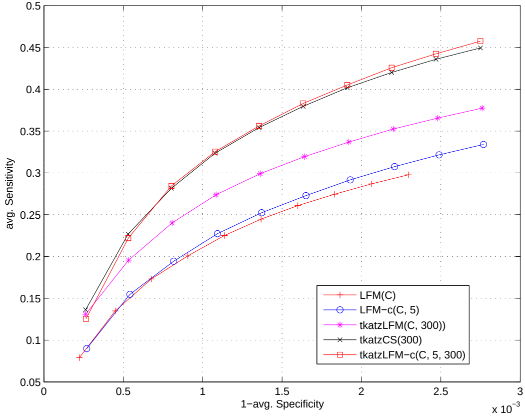

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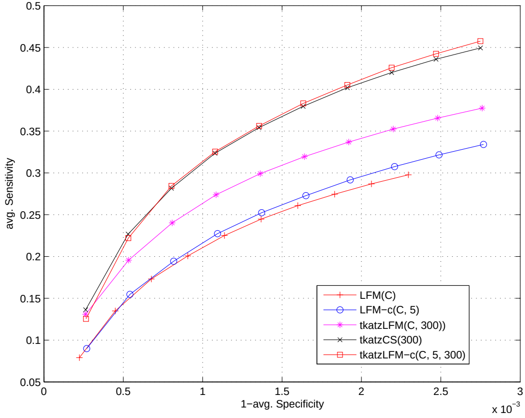

tKatzLFM: tKatz on low-rank approximation.

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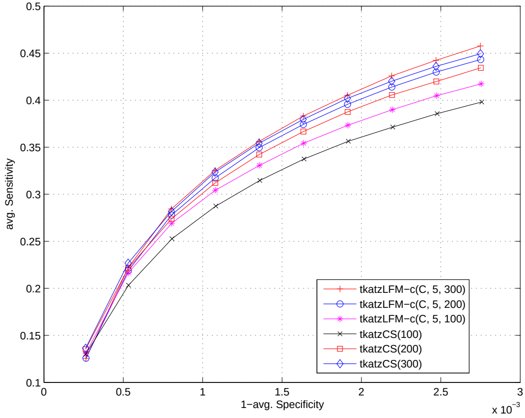
and other clustered approximation variants...

Quality of approximations



Conclusions

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- Community recommendation – link prediction perspective.

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- Community recommendation – link prediction perspective.
- Two ways of modeling the information from auxiliary networks — Latent Factor and Graph Proximity models.

Future work

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- More sources of information – How do you use them all?
- More scalable models.

References

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- Vishvas Vasuki, Nagarajan Natarajan, Zhengdong Lu, Berkant Savas, Inderjit Dhillon. Scalable affiliation recommendations using auxiliary networks. Submitted to Transactions on Intelligent Systems and Technology, 2010.
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Thank you!