Affiliation Recommendation using Auxiliary Social Networks

August 19, 2010

Outline

What to look out for?

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- Affiliation recommendation problem.

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- Affiliation recommendation algorithms.

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Social networks

[1] TODO: Pictures of orkut, facebook, yeast network.

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Social networks

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- Not necessarily among people - Yeast gene network.

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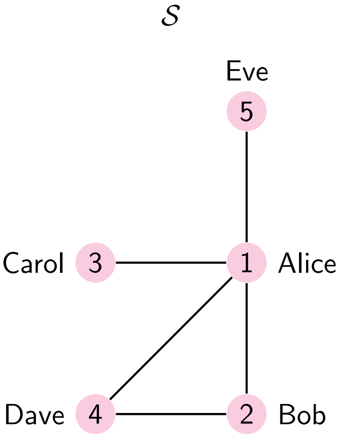
Social network S: An undirected graph.



Affiliation networks

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- Pictures of orkut and facebook communities.

Affiliation networks

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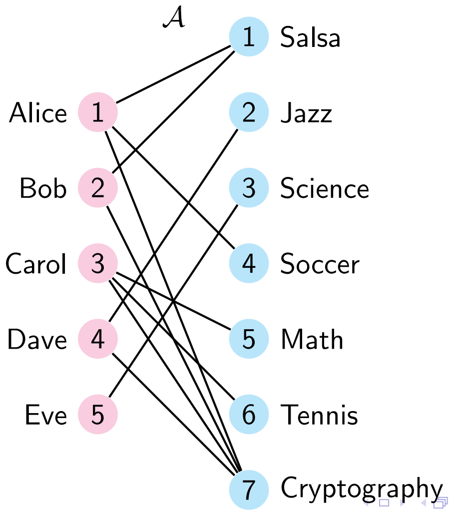
- Not necessarily among people - gene-disease network.

Affiliation network A: A bipartite graph.



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Problems in social network analysis.

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- Modelling network evolution.

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- Link prediction.

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- Community identification.

Affiliation Recommendation.

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- Exploiting social network in making affiliation recommendations.

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- Exploiting social network in making affiliation recommendations.
- Generalizable to the item recommendation problem.

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The combined network

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- λ: relative weight associated with information in S.

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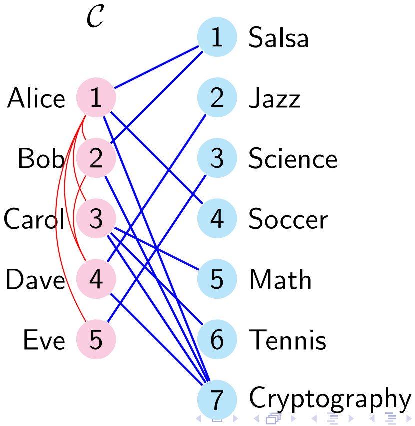
- λ: relative weight associated with information in S.
- $\mathbf{D}$: unobserved.

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



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Modelling A alone

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- For user j, recommend affiliations with high affinity.

Modelling C

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- A **good model** will account for edges in **S** too.
$\mathbf{C}(\lambda, \mathbf{D}) \approx \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \end{bmatrix} \mathbf{L} \left[\mathbf{V}_1^T \mathbf{V}_2^T \right]$, rank of $\mathbf{V}_i$ and $\mathbf{L} \leq k$.

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

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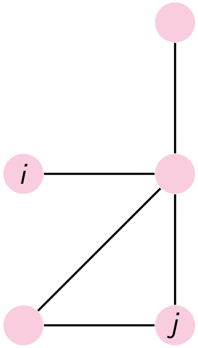
Proximity between users in a social network

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

$$\mathcal{C} \rightarrow \mathcal{C}^2$$



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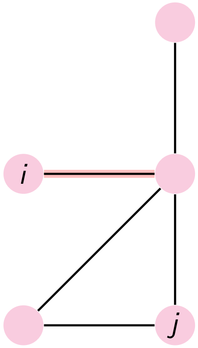

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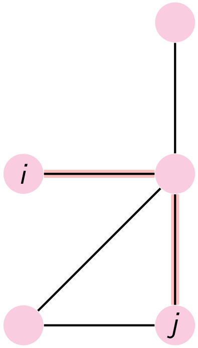

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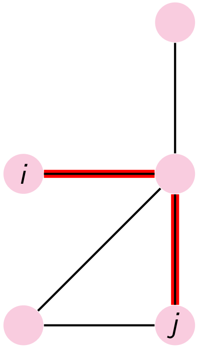

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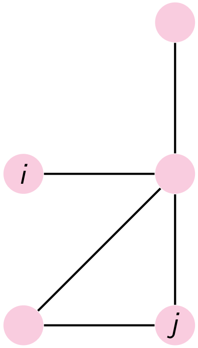

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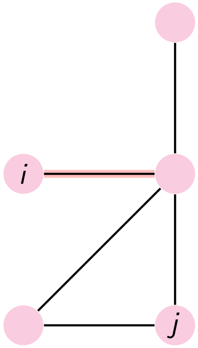

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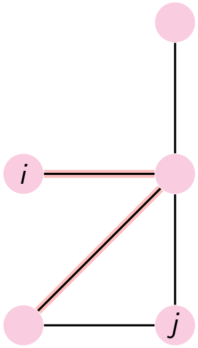

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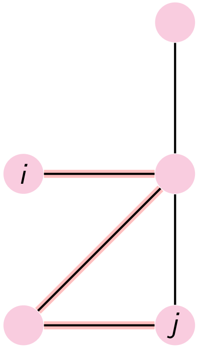

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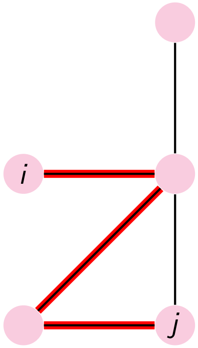

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- Recommend user-group affiliations based on proximity in $\mathbf{C}$.

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- user $i \xrightarrow{\mathbf{S}}$ user $j \xrightarrow{\mathbf{AA}^T} k \xrightarrow{\mathbf{A}}$ group n (in $\mathbf{C}^4$)

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Scalable recommenders for the graph proximity model

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- Use Low rank approximations of $\mathbf{C} \approx \mathbf{V}\Lambda^i\mathbf{V}^T$. Use $\mathbf{C}^i \approx \mathbf{V}\Lambda^i\mathbf{V}^T$. [3]

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- $\text{tKatz}(\mathbf{C}; \beta, 3)_{12} = \beta\mathbf{A} + \beta^2\lambda\mathbf{SA} + \beta^3(\lambda^2\mathbf{S}^2\mathbf{A} + \mathbf{AA}^T\mathbf{A})$.

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- Use $\mathbf{S} \approx \mathbf{Q}(\mathbf{Q}^T\mathbf{S}\mathbf{Q})\mathbf{Q}^T \equiv \mathbf{Q}\mathbf{D}_\mathbf{S}\mathbf{Q}^T, \mathbf{A} \approx \mathbf{Q}(\mathbf{Q}^T\mathbf{A}\mathbf{V})\mathbf{V}^T \equiv \mathbf{Q}\mathbf{D}_\mathbf{A}\mathbf{V}^T$.

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- Now $(\mathbf{A}\mathbf{A}^T)^i \approx \mathbf{Q}(\mathbf{D}_\mathbf{A}\mathbf{D}_\mathbf{A}^T)^i\mathbf{Q}^T$, $(\mathbf{S})^i \approx \mathbf{Q}\mathbf{D}_\mathbf{S}^i\mathbf{Q}^T$, $(\mathbf{S}\mathbf{A}\mathbf{A}^T) \approx \mathbf{Q}\mathbf{D}_\mathbf{S}(\mathbf{D}_\mathbf{A}\mathbf{D}_\mathbf{A}^T)\mathbf{Q}^T$.

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Data sets

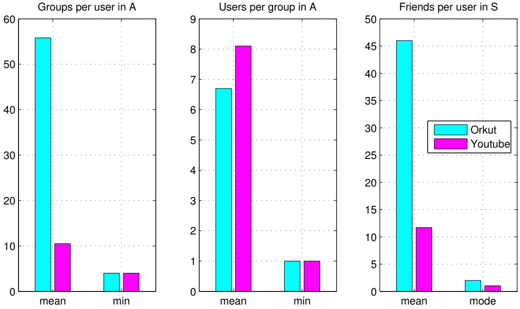

Figure: Statistics of extracted social and affiliation networks: *Orkut* and *Youtube* data sets [1]; Orkut: $N_u = 9123$, $N_g = 75546$. Youtube: $N_u = 16575$, $N_g = 21326$.

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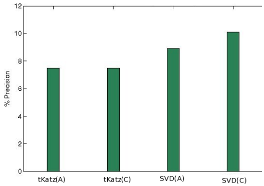
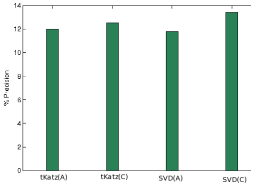


(a) Orkut dataset



(b) Youtube dataset

Figure: Comparison of recommendation algorithms using "global sensitivity".

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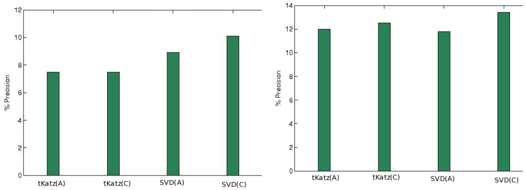

(a) Orkut dataset (b) Youtube dataset

Figure: Comparison of recommendation algorithms using "global sensitivity".

- Consider the top 50 recommendations made for a user.

Outline

Results

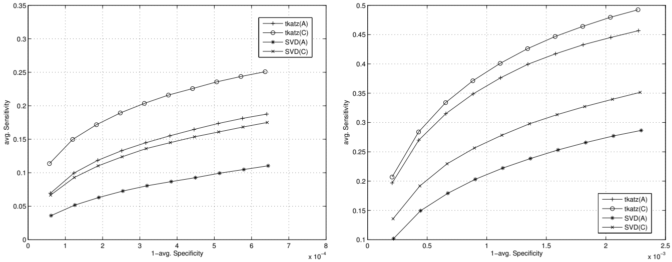

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Figure: Comparison of recommendation algorithms using "Per-user" sensitivity.

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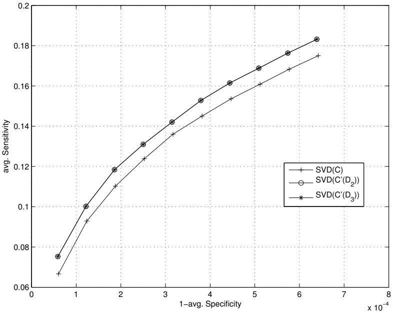

Figure: Comparison of latent factors based algorithms for various choices of $\mathbf{D}$, for the Orkut dataset: $\mathbf{D}_2 = \mathbf{A}^T\mathbf{A}, \mathbf{D}_3 = \lambda\mathbf{A}^T\mathbf{A}$.

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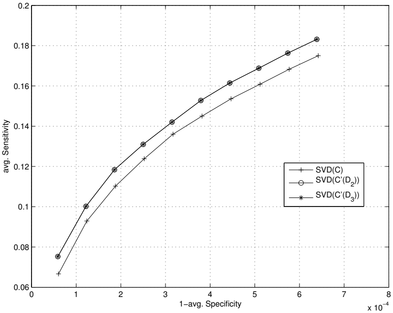

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- Choice of **D** is immaterial! (Consistent on Youtube).

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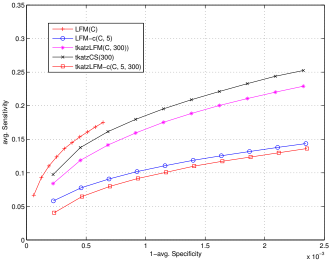
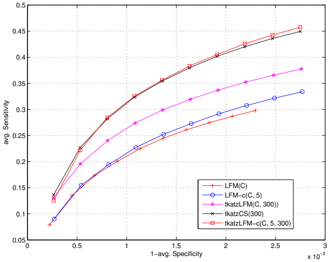


(a) Orkut-1c data set



(b) Youtube-1c data set

Figure: Scalable approximations

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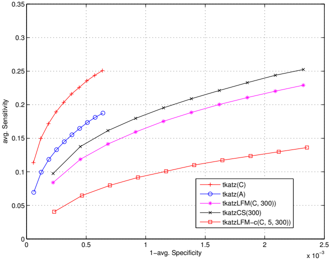

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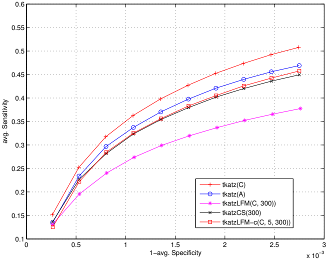

(b) Youtube-1c data set

Figure: Scalable approximations: Clustering

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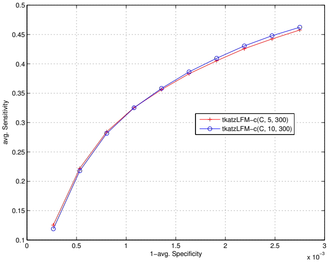
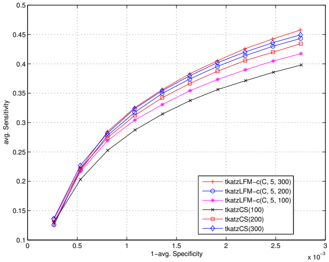


(a) Effect of changing the number of clusters.



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- Community recommendation – link prediction perspective.
- Two ways of modeling the information from auxiliary networks.
- Choice of evaluation strategy is important.

Future work

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- Huge networks – Scalability.

The take home message

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- Graph proximity on Combined user/ item network $\longrightarrow$ Good item recommendations.

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- Graph proximity on Combined user/ item network $\longrightarrow$ Good item recommendations.
- Can make this scalable.

References

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pdf, bib.