Relational Stacked Denoising Autoencoder for Tag Recommendation

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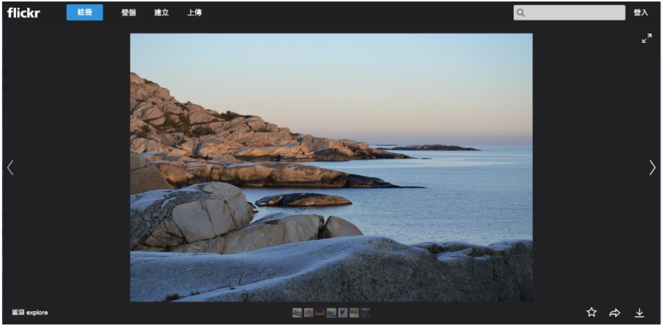
Outline

Outline

1. Background and Related Work
2. Generalized Probabilistic SDAE
3. Relational SDAE
4. Performance Evaluation
5. Case study
6. Conclusion

Tag Recommendation: Flickr



https://www.flickr.com

Tag Recommendation: CiteULike

✓ An Algorithmic Framework for Performing Collaborative Filtering
In Proceedings of the 22Nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (1999), pp.
by Jonathan L. Herlocker, Joseph A. Konstan, Al Borchers, John Riedl
posted to collaborative_filtering recommendation by wangxinxi on 2014-11-24 14:12:37 ★★ along with 32 people and 6 groups
Abstract

✓ Google News Personalization: Scalable Online Collaborative Filtering
In Proceedings of the 16th International Conference on World Wide Web (2007), pp. 271-280, doi:10.1145/1242572.1242610
by Abhinandan S. Das, Mayur Datar, Ashutosh Garg, Shyam Rajaram
posted to collaborative_filtering news recommendation by wangxinxi on 2014-11-24 14:08:35 ★★ along with 74 people and 11 groups
Abstract

✓ Probabilistic Matrix Factorization
In NIPS '08 (2008)
by Ruslan Salakhutdinov, Andriy Mnih
posted to collaborative_filtering matrix_factorization probabilistic recommendation by nguyenthaibinh on 2014-09-14 20:29:47 ✓ along with
Abstract

✓ Active Learning in Collaborative Filtering Recommender Systems
In E-Commerce and Web Technologies, Vol. 188 (2014), pp. 113-124, doi:10.1007/978-3-319-10491-1_12
by Mehdi Elahi, Francesco Ricci, Neil Rubens
edited by Martin Hepp, Yigal Hoffner
posted to active_learning collaborative_filtering matrix_factorization by wangxinxi on 2014-08-24 09:28:27 ★★★★
Abstract

Google news personalization: scalable online collaborative filtering
In Proceedings of the 16th international conference on World Wide Web (2007), pp. 271-280, doi:10.1145/1242572.1242610
by Abhinandan S. Das, Mayur Datar, Ashutosh Garg, Shyam Rajaram
posted to collaborative_filtering by eustache_diemert on 2014-06-06 07:32:15 ★★
Abstract

http://www.citeulike.org

Tag Recommendation

item \ tag	1	2	3	4	5
1	✓	?	?	?	?
2	✓	?	?	✓	?
3	?	?	✓	?	?
4	?	✓	?	?	✓
5	✓	?	?	?	?

Related Work

Content-based:

1. Chen et al., 2008
2. Chen et al., 2010
3. Shen and Fan, 2010

Co-occurrence based:

1. Garg and Weber, 2008
2. Weinberger et al., 2008
3. Rendle and Schmidt-Thieme, 2010

Hybrid:

1. Wu et al., 2009
2. Wang and Blei, 2011
3. Yang et al., 2013

Content-based

1. Chen et al., 2008
2. Chen et al., 2010
3. Shen and Fan, 2010
4. . . .

Pros:

1. Tag independence
2. Interpretability
3. No New-item problem

Cons:

1. Need domain knowledge

Co-occurrence based

1. Garg and Weber, 2008
2. Weinberger et al., 2008
3. Rendle and Schmidt-Thieme, 2010
4. . . .

Pros:

1. No domain knowledge needed

Cons:

1. Requires some form of rating feedback (co-occurrence matrix)
2. New-tag problem and new-item problem

Hybrid

1. Wu et al., 2009
2. Wang and Blei, 2011
3. Yang et al., 2013
4. ...

BEST OF BOTH WORLDS

Collaborative Topic Regression (CTR) (Wang and Blei, KDD 2011)

Maximum Likelihood from Incomplete Data via the *EM* Algorithm

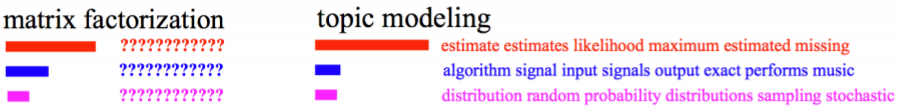
By A. P. Dempster, N. M. Laird and D. B. Rubin

Harvard University and Educational Testing Service

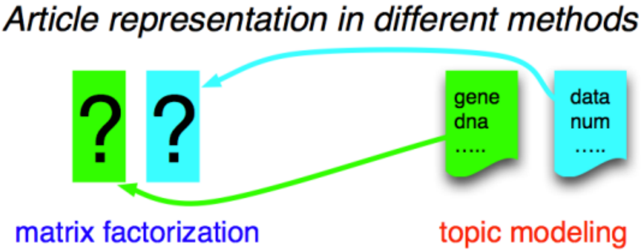
[Read before the Royal Statistical Society at a meeting organized by the Research Section on Wednesday, December 8th, 1976, Professor S. D. Silvey in the Chair]

Summary

A broadly applicable algorithm for computing maximum likelihood estimates from incomplete data is presented at various levels of generality. Theory showing the monotone behaviour of the likelihood and convergence of the algorithm is derived. Many examples are sketched, including missing value situations, applications to grouped, censored or truncated data, finite mixture models, variance component estimation, hyperparameter estimation, iteratively reweighted least squares and factor analysis.



Collaborative Topic Regression (CTR) (Wang and Blei, KDD 2011)



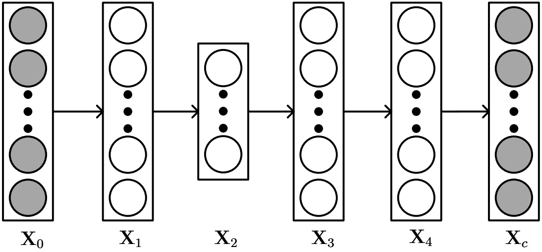
- **LDA**: sparse, relatively high dimension
- **MF**: low rank, low dimension

Problems to Explore

1. Can SDAE learn effective representation for recommendation?
2. How to incorporate relational information into SDAE?
3. How is the performance?

Outline

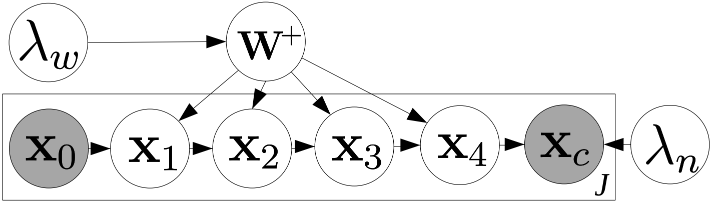
Stacked Denoising Autoencoder (Vincent et al. JMLR 2010)



$$\min_{\{\mathbf{W}_l\},\{\mathbf{b}_l\}} \|\mathbf{X}_c - \mathbf{X}_L\|_F^2 + \lambda \sum_l \|\mathbf{W}_l\|_F^2,$$

where λ is a regularization parameter and $\|\cdot\|_F$ denotes the Frobenius norm.

Generalized Probabilistic SDAE



1. For each layer l of the SDAE network,
   1. For each column n of the weight matrix $\mathbf{W}_l$, draw $\mathbf{W}_{l,*n} \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$.
   2. Draw the bias vector $\mathbf{b}_l \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$.
   3. For each row j of $\mathbf{X}_l$, draw

$$\mathbf{X}_{l,j*} \sim \mathcal{N}(\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l), \lambda_s^{-1}\mathbf{I}_{K_l}).$$

2. For each item j, draw a clean input

$$\mathbf{X}_{c,j*} \sim \mathcal{N}(\mathbf{X}_{L,j*}, \lambda_n^{-1}\mathbf{I}_B).$$

Outline

Relational SDAE: Generative Process

1. Draw the relational latent matrix $\mathbf{S}$ from a *matrix variate normal distribution*:

$$\mathbf{S} \sim \mathcal{N}_{K,J}(0, \mathbf{I}_K \otimes (\lambda_l \mathscr{L}_a)^{-1}).$$

2. For layer l of the SDAE where $l = 1, 2, \ldots, \frac{L}{2} - 1$,
    1. For each column n of the weight matrix $\mathbf{W}_l$, draw $\mathbf{W}_{l,*n} \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$.
    2. Draw the bias vector $\mathbf{b}_l \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$.
    3. For each row j of $\mathbf{X}_l$, draw

$$\mathbf{X}_{l,j*} \sim \mathcal{N}(\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l), \lambda_s^{-1}\mathbf{I}_{K_l}).$$

3. For layer $\frac{L}{2}$ of the SDAE network, draw the representation vector for item j from the product of two Gaussians (PoG):

$$\mathbf{X}_{\frac{L}{2},j*} \sim \text{PoG}(\sigma(\mathbf{X}_{\frac{L}{2}-1,j*}\mathbf{W}_l + \mathbf{b}_l), \mathbf{s}_j^T, \lambda_s^{-1}\mathbf{I}_K, \lambda_r^{-1}\mathbf{I}_K).$$

Relational SDAE: Generative Process

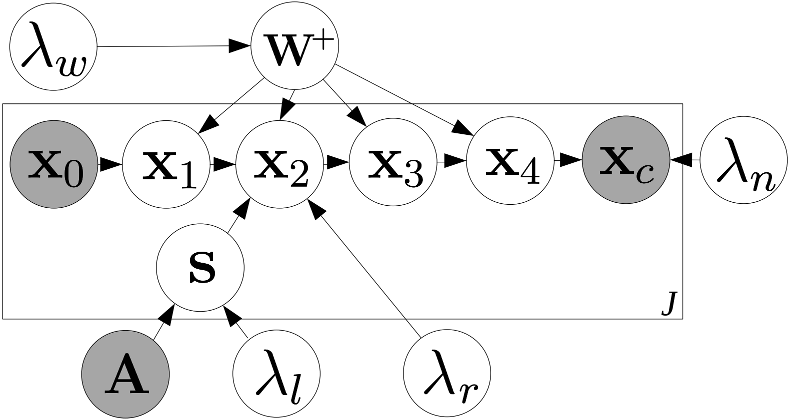
1. For layer l of the SDAE network where $l = \frac{L}{2}+1, \frac{L}{2}+2, \ldots, L$,
    1. For each column n of the weight matrix $\mathbf{W}_l$, draw $\mathbf{W}_{l,*n} \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$.
    2. Draw the bias vector $\mathbf{b}_l \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$.
    3. For each row j of $\mathbf{X}_l$, draw

$$\mathbf{X}_{l,j*} \sim \mathcal{N}(\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l), \lambda_s^{-1}\mathbf{I}_{K_l}).$$

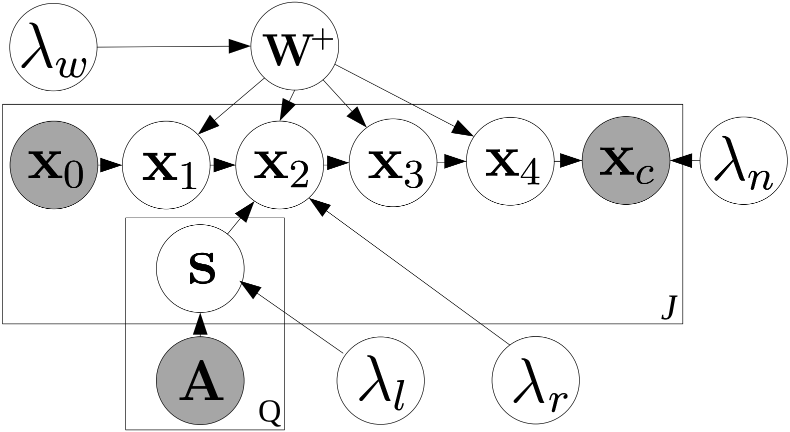
2. For each item j, draw a clean input

$$\mathbf{X}_{c,j*} \sim \mathcal{N}(\mathbf{X}_{L,j*}, \lambda_n^{-1}\mathbf{I}_B).$$

Relational SDAE: Graphical Model



Multi-Relational SDAE: Graphical Model



Relational SDAE: Objective function

The log-likelihood:

$$\begin{aligned}\mathscr{L} = &-\frac{\lambda_l}{2}\mathrm{tr}(\mathbf{S}\mathscr{L}_a\mathbf{S}^T) - \frac{\lambda_r}{2}\sum_j \|(\mathbf{s}_j^T - \mathbf{X}_{\frac{L}{2},j*})\|_2^2 \\ &- \frac{\lambda_w}{2}\sum_l(\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2) \\ &- \frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2 \\ &- \frac{\lambda_s}{2}\sum_l\sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2,\end{aligned}$$

where $\mathbf{X}_{l,j*} = \sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l)$. Similar to the generalized SDAE, taking λ_s to infinity, the last term of the joint log-likelihood will vanish.

Updating Rules

For $\mathbf{S}$:

$$\mathbf{S}_{k*}(t+1) \leftarrow \mathbf{S}_{k*}(t) + \delta(t) r(t)$$

$$r(t) \leftarrow \lambda_r \mathbf{X}^T_{\frac{L}{2},*k} - (\lambda_l \mathscr{L}_a + \lambda_r \mathbf{I}_J)\mathbf{S}_{k*}(t)$$

$$\delta(t) \leftarrow \frac{r(t)^T r(t)}{r(t)^T (\lambda_l \mathscr{L}_a + \lambda_r \mathbf{I}_J) r(t)}.$$

For $\mathbf{X}$, $\mathbf{W}$, and $\mathbf{b}$: Use Back Propagation.

From Representation to Tag Recommendation

Objective function:

$$\mathscr{L} = -\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}^T_{\frac{L}{2},j*}\|_2^2$$
$$-\sum_{i,j}\frac{c_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2,$$

where λ_u and λ_v are hyperparameters. c_{ij} is set to 1 for the existing ratings and 0.01 for the missing entries.

Algorithm

1. **Learning representation:**

   repeat

   Update $\mathbf{S}$ using the updating rules

   Update $\mathbf{X}$, $\mathbf{W}$, and $\mathbf{b}$

   until convergence

   Get resulting representation $\mathbf{X}_{\frac{L}{2},j*}$

2. **Learning $\mathbf{u}_i$ and $\mathbf{v}_j$:**

   Optimize the objective function $\mathscr{L}$

3. **Recommend tags to items according to the predicted R_{ij}:**

   $\mathbf{R}_{ij} = \mathbf{u}_i^T \mathbf{v}_j$

   Rank $\mathbf{R}_{1j}$,$\mathbf{R}_{2j}$,. . . ,$\mathbf{R}_{Ij}$

   Recommend tags with largest $\mathbf{R}_{ij}$ to item j

Problems to Explore

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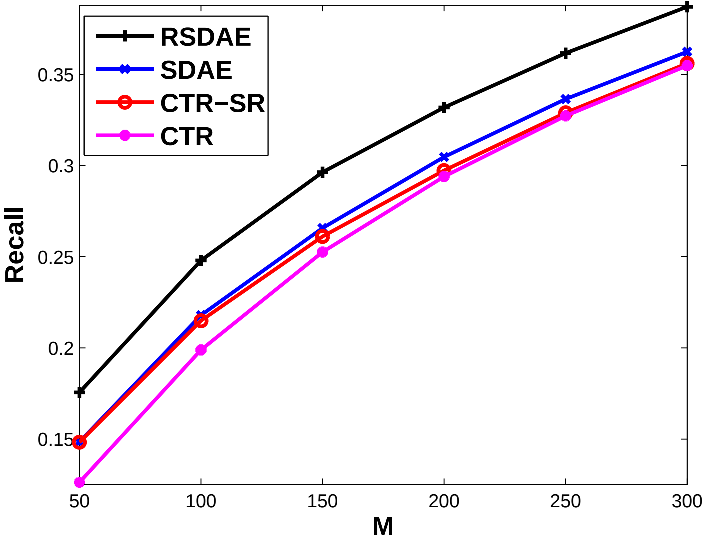
Outline

Datasets

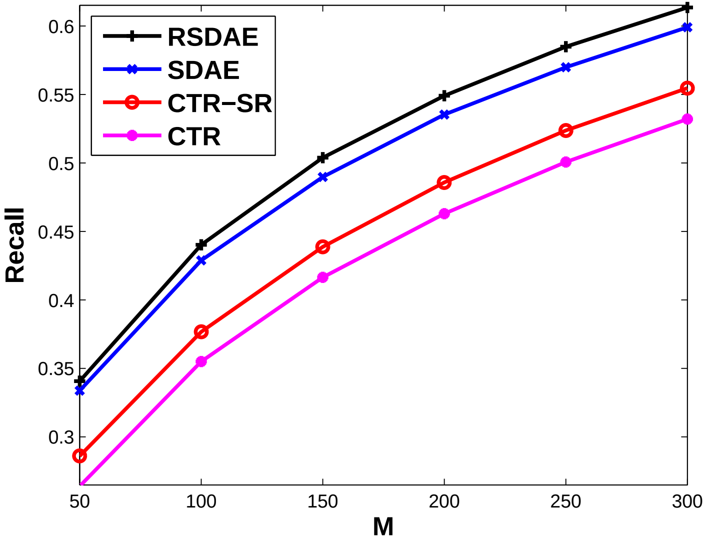
Description of datasets

	citeulike-a	citeulike-t	movielens-plot
#items	16980	25975	7261
#tags	7386	8311	2988
#tag-item paris	204987	134860	51301
#relations	44709	32665	543621

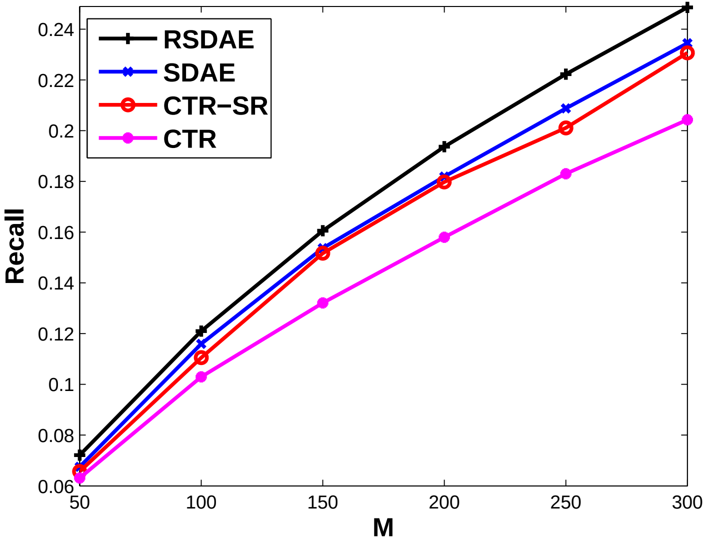
citeulike-a, Sparse Settting



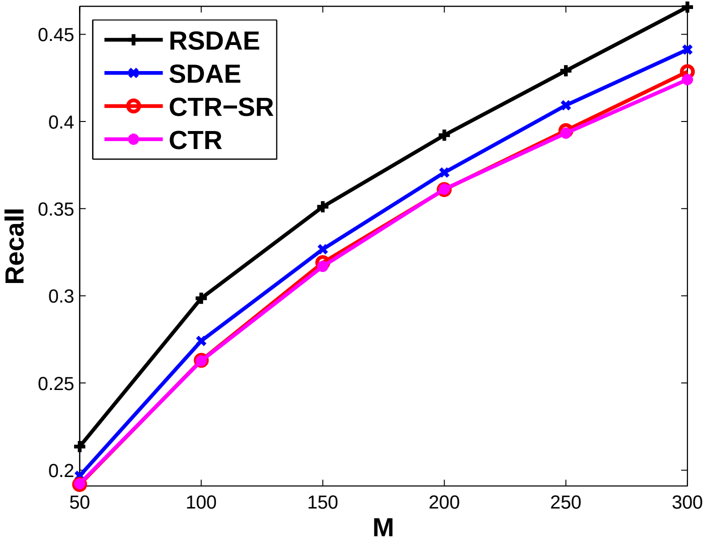
citeulike-a, Dense Settting



movielens-plot, Sparse Settting



movielens-plot, Dense Settting



Outline

Tagging Scientific Articles

An example article with recommended tags

Example Article	Title: Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews			
	Top topic 1: language, text, mining, representation, semantic, concepts, words, relations, processing, categories			
Top 10 tags	SDAE	True?	RSDAE	True?
	1. instance	no	1. sentiment_analysis	no
	2. consumer	**yes**	2. instance	no
	3. sentiment_analysis	no	**3. consumer**	**yes**
	4. summary	no	4. summary	no
	5. 31july09	no	**5. sentiment**	**yes**
	6. medline	no	**6. product_review_mining**	**yes**
	7. eit2	no	**7. sentiment_classification**	**yes**
	8. l2r	no	8. 31july09	no
	9. exploration	no	**9. opinion_mining**	**yes**
	10. biomedical	no	**10. product**	**yes**

Tagging Movies

An example movie with recommended tags

Example Movie	Title: E.T. the Extra-Terrestrial	
	Top topic 1: crew, must, on, earth, human, save, ship, rescue, by, find, scientist, planet	
Top 10 recommended tags	SDAE	True tag?
	1. Saturn Award (Best Special Effects)	**yes**
	2. Want	no
	3. Saturn Award (Best Fantasy Film)	no
	4. Saturn Award (Best Writing)	**yes**
	5. Cool but freaky	no
	6. Saturn Award (Best Director)	no
	7. Oscar (Best Editing)	no
	8. almost favorite	no
	9. Steven Spielberg	**yes**
	10. sequel better than original	no

Tagging Movies

An example movie with recommended tags

Example Movie	Title: E.T. the Extra-Terrestrial	
	Top topic 1: crew, must, on, earth, human, save, ship, rescue, by, find, scientist, planet	
Top 10 recommended tags	RSDAE	True tag?
	1. Steven Spielberg	**yes**
	2. Saturn Award (Best Special Effects)	**yes**
	3. Saturn Award (Best Writing)	**yes**
	4. Oscar (Best Editing)	no
	5. Want	no
	6. Liam Neeson	no
	7. AFI 100 (Cheers)	**yes**
	8. Oscar (Best Sound)	**yes**
	9. Saturn Award (Best Director)	no
	10. Oscar (Best Music - Original Score)	**yes**

Outline

Conclusion

Contribution:

1. Adapt SDAE for tag recommendation
2. A probabilistic relational model for relational deep learning
3. State-of-the-art performance

Take-home Message:

1. Deep models significantly boost recommendation accuracy
2. Probabilistic formulation facilitates relational deep learning
3. Incorporating relational information further boosts accuracy

Future Work

1. Applications other than tag recommendation
2. Adaption for other deep learning models
3. Integrated model instead of separate ones
4. Fully Bayesian methods

Q & A