Collaborative Deep Learning for Recommender Systems

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- Motivation
- Stacked Denoising Autoencoders
- Probabilistic Matrix Factorization
- Collaborative Deep Learning
- Experiments
- Summary

Recommender Systems

Rating matrix:

movie \ user	1	2	3	4	5
1	✓	?	?	?	?
2	✓	?	?	✓	?
3	?	?	✓	?	?
4	?	✓	?	?	✓
5	✓	?	?	?	?

Matrix completion ⇒ Observed preferences: ✓

To predict: ?

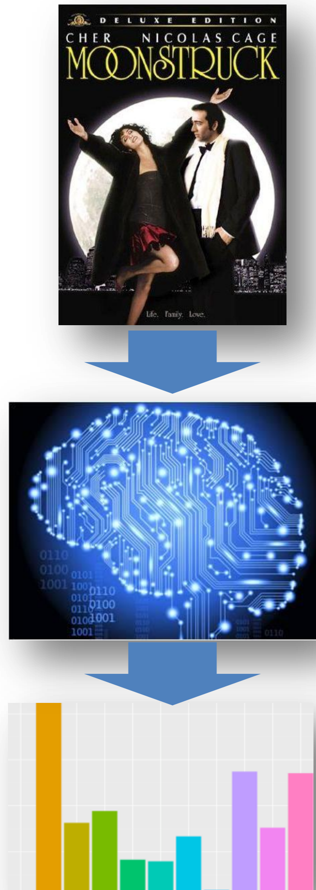
Recommender Systems with Content

movie \ user	1	2	3	4	5
1	✓	?	?	?	?
2	✓	?	?	✓	?
3	?	?	✓	?	?
4	?	✓	?	?	✓
5	✓	?	?	?	?

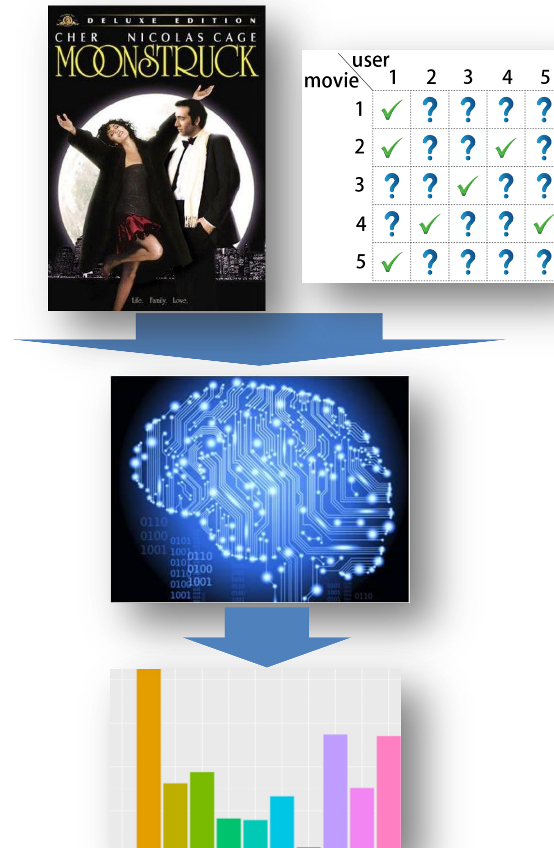
Content information:
Plots, directors, actors, etc.

Modeling the Content Information

Handcrafted features



Automatically learn features



movie \ user	1	2	3	4	5
1	✓	?	?	?	?
2	✓	?	?	✓	?
3	?	?	✓	?	?
4	?	✓	?	?	✓
5	✓	?	?	?	?

Automatically learn features and **adapt for ratings**

Modeling the Content Information

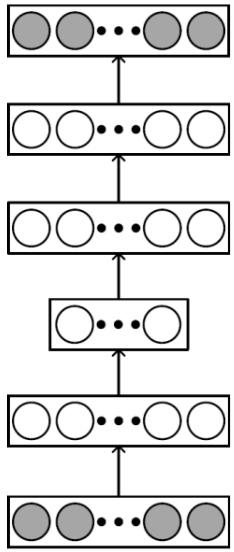
1. Powerful features for content information

Deep learning

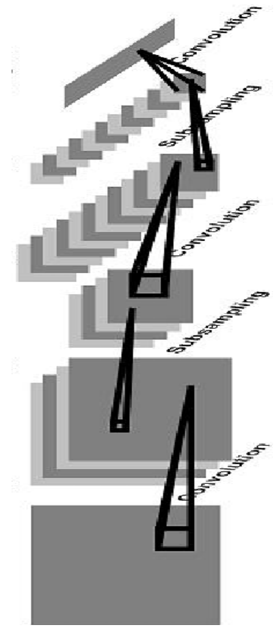
2. Feedback from rating information ➡ Non-i.i.d.

Collaborative deep learning

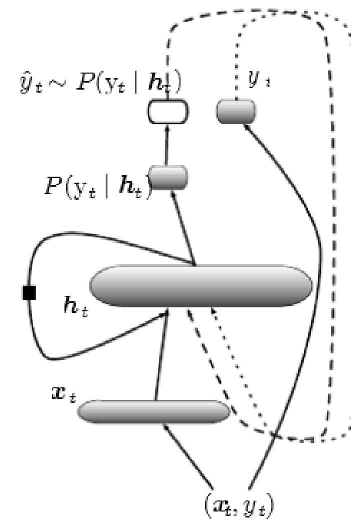
Deep Learning



Stacked denoising autoencoders



Convolutional neural networks

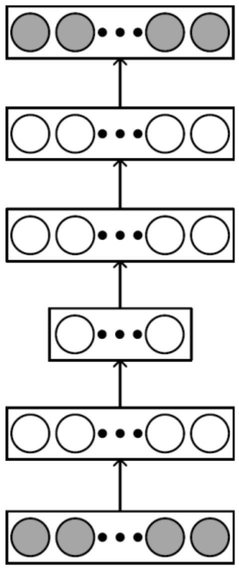


Recurrent neural networks

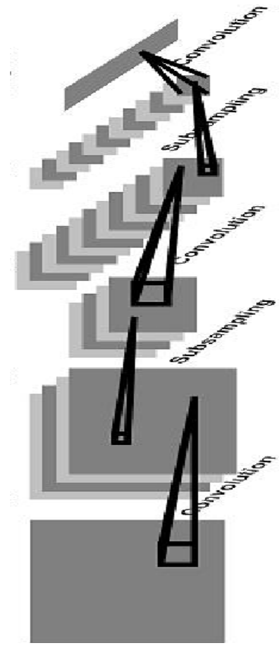
Deep learning allows **computational models** that are composed of **multiple processing layers** to learn representations of data with **multiple levels of abstraction**.

Bengio et al. 2015

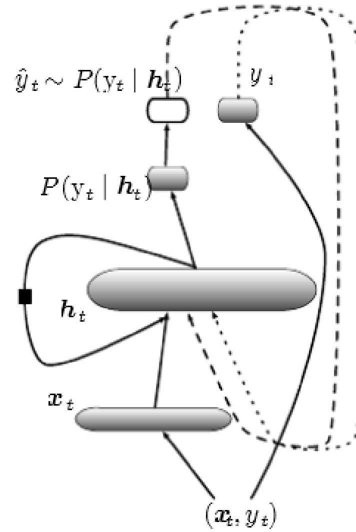
Deep Learning



Stacked denoising autoencoders



Convolutional neural networks



Recurrent neural networks

Typically for i.i.d. data

Modeling the Content Information

1. Powerful features for content information

Deep learning

2. Feedback from rating information → Non-i.i.d.

Collaborative deep learning (CDL)

Contribution

- **Collaborative deep learning:**

  *** deep learning for non-i.i.d. data**

  *** joint representation learning and collaborative filtering**

Contribution

- Collaborative deep learning
- Complex target:
  - * beyond targets like classification and regression
  - * to complete a low-rank matrix

Contribution

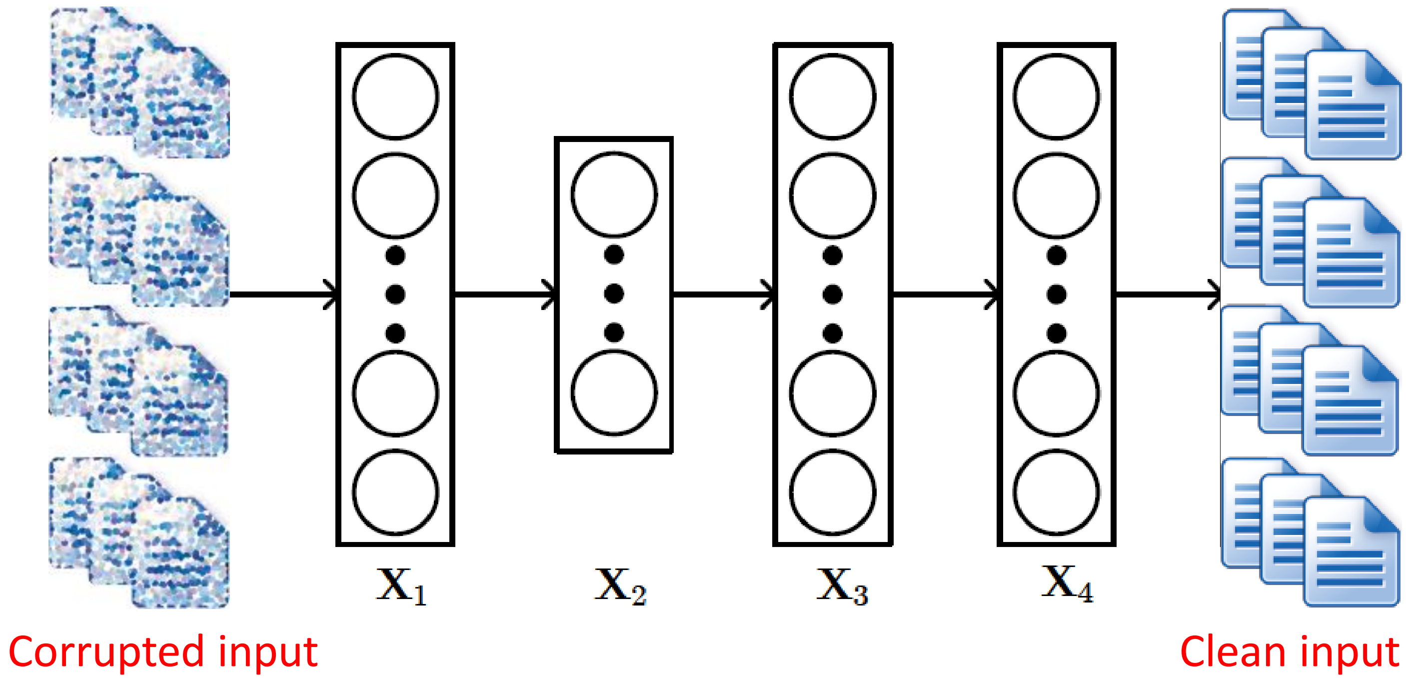
- Collaborative deep learning
- Complex target
- First hierarchical Bayesian models for hybrid deep recommender system

Contribution

- Collaborative deep learning
- Complex target
- First hierarchical Bayesian models for hybrid deep recommender system
- Significantly advance the state of the art

- **Motivation**
- **Stacked Denoising Autoencoders**
- **Probabilistic Matrix Factorization**
- **Collaborative Deep Learning**
- **Experiments**
- **Summary**

Stacked Denoising Autoencoders (SDAE)



SDAE solves the following optimization problem:

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

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

Vincent et al. 2010

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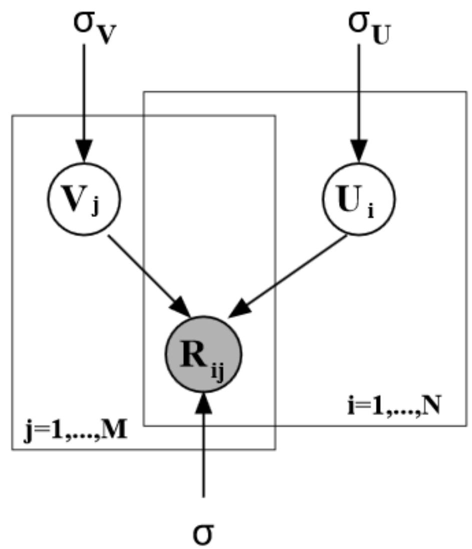
Probabilistic Matrix Factorization (PMF)

Graphical model:



Notation:

- V_j latent vector of item j
- U_i latent vector of user i
- R_{ij} rating of item j from user i

Generative process:

$$p(U|\sigma_U^2) = \prod_{i=1}^{N} \mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I}) \qquad p(V|\sigma_V^2) = \prod_{j=1}^{M} \mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})$$

$$p(R|U, V, \sigma^2) = \prod_{i=1}^{N} \prod_{j=1}^{M} \left[\mathcal{N}(R_{ij}|U_i^T V_j, \sigma^2) \right]^{I_{ij}}$$

Objective function if using MAP:

$$E = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} I_{ij} (R_{ij} - U_i^T V_j)^2 + \frac{\lambda_U}{2} \sum_{i=1}^{N} \| U_i \|_{Fro}^2 + \frac{\lambda_V}{2} \sum_{j=1}^{M} \| V_j \|_{Fro}^2$$

Salakhutdinov et al. 2008

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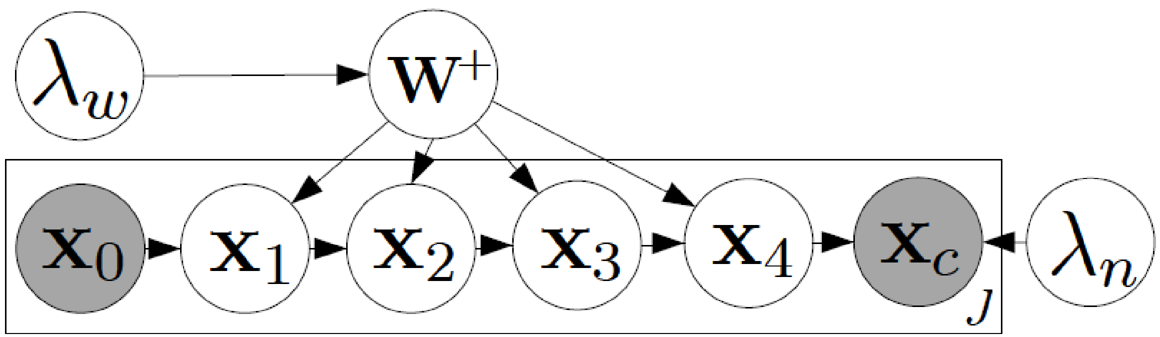
Probabilistic SDAE

Graphical model:



Generative process:

$$\mathbf{W}_{l,*n} \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$$

$$\mathbf{b}_l \sim \mathcal{N}(0, \lambda_w^{-1}\mathbf{I}_{K_l})$$

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

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

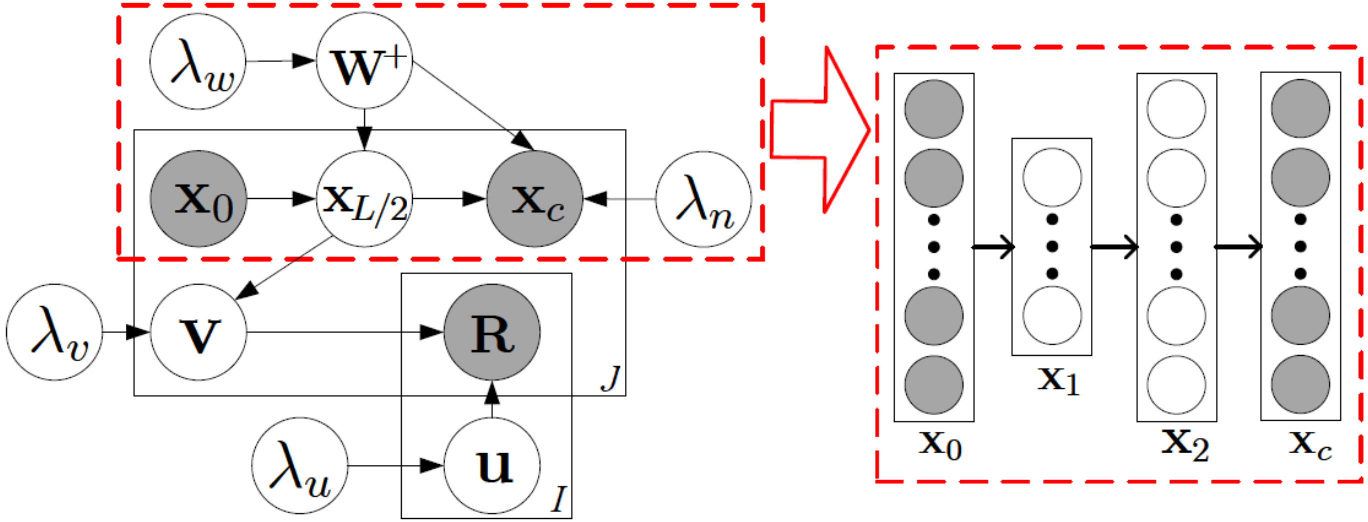
Generalized SDAE

Notation:

- $\mathbf{x}_0$ corrupted input
- $\mathbf{x}_c$ clean input
- $\mathbf{W}^+$ weights and biases

Collaborative Deep Learning

Graphical model:



Collaborative deep learning **SDAE**

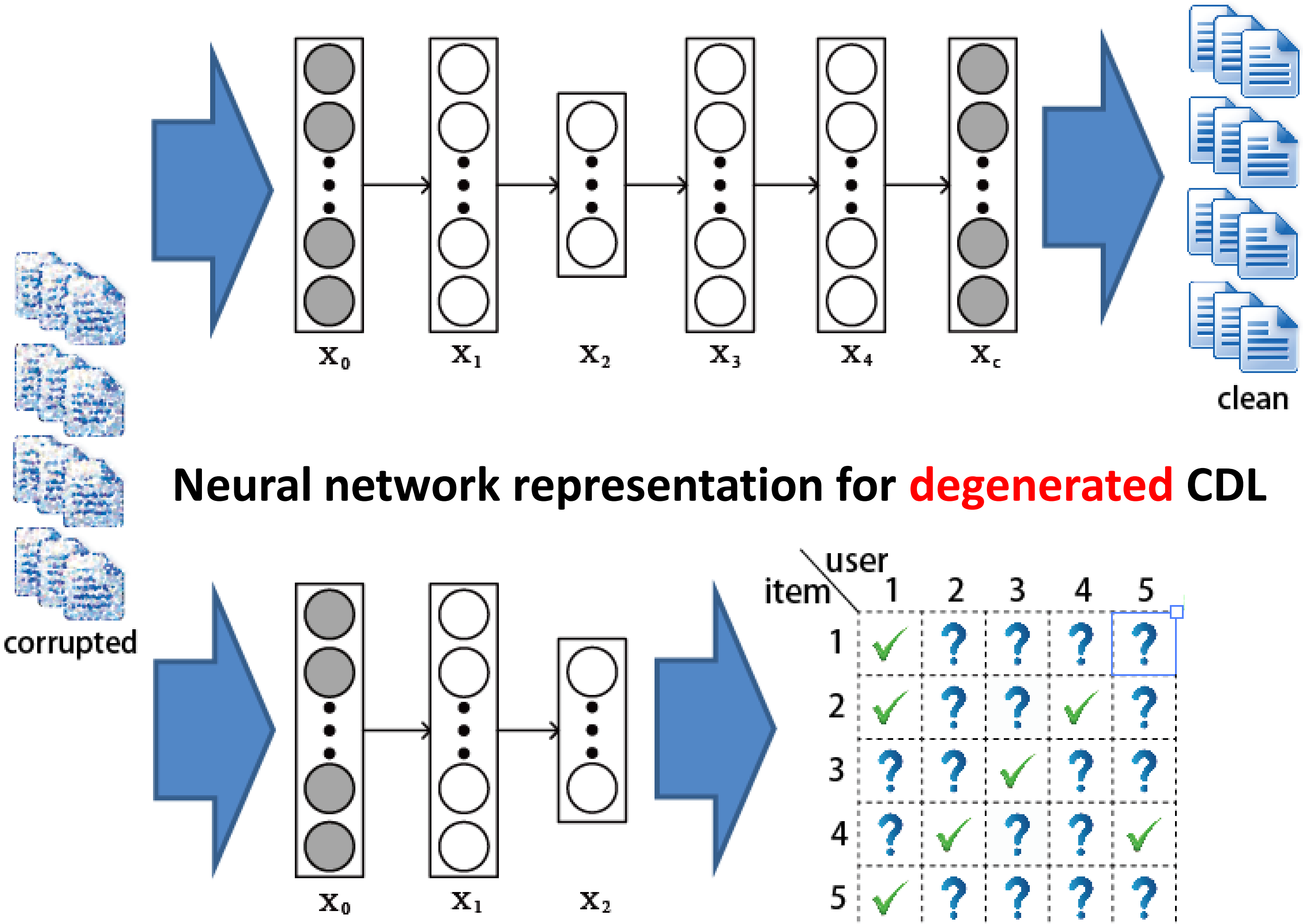
Two-way interaction

- More powerful representation
- Infer missing ratings from content
- Infer missing content from ratings

Notation:

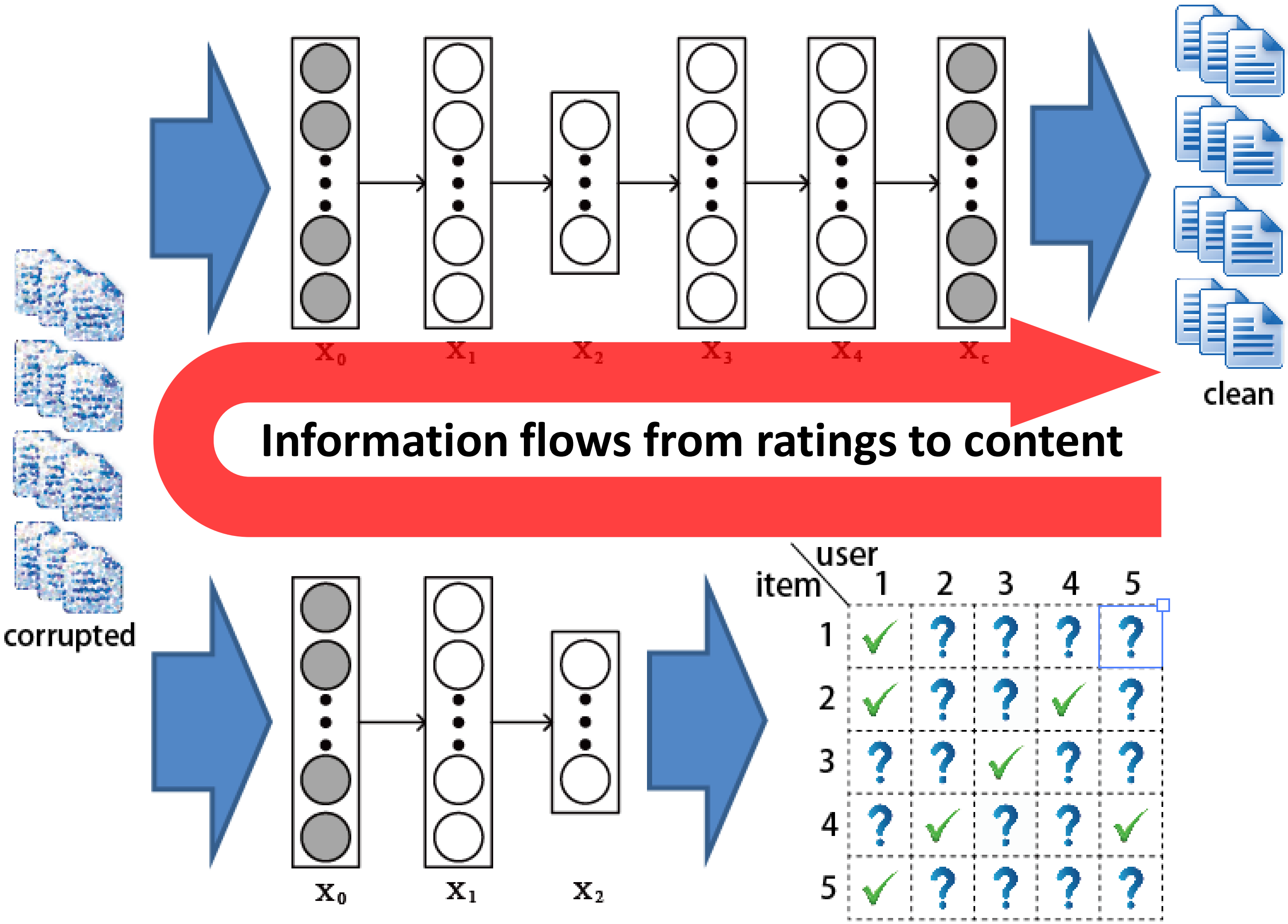
- R rating of item j from user i
- v latent vector of item j
- u latent vector of user i
- $\mathbf{x}_0$ corrupted input
- $\mathbf{x}_c$ clean input
- $\mathbf{W}^+$ weights and biases
- $\mathbf{x}_{L/2}$ content representation

Collaborative Deep Learning

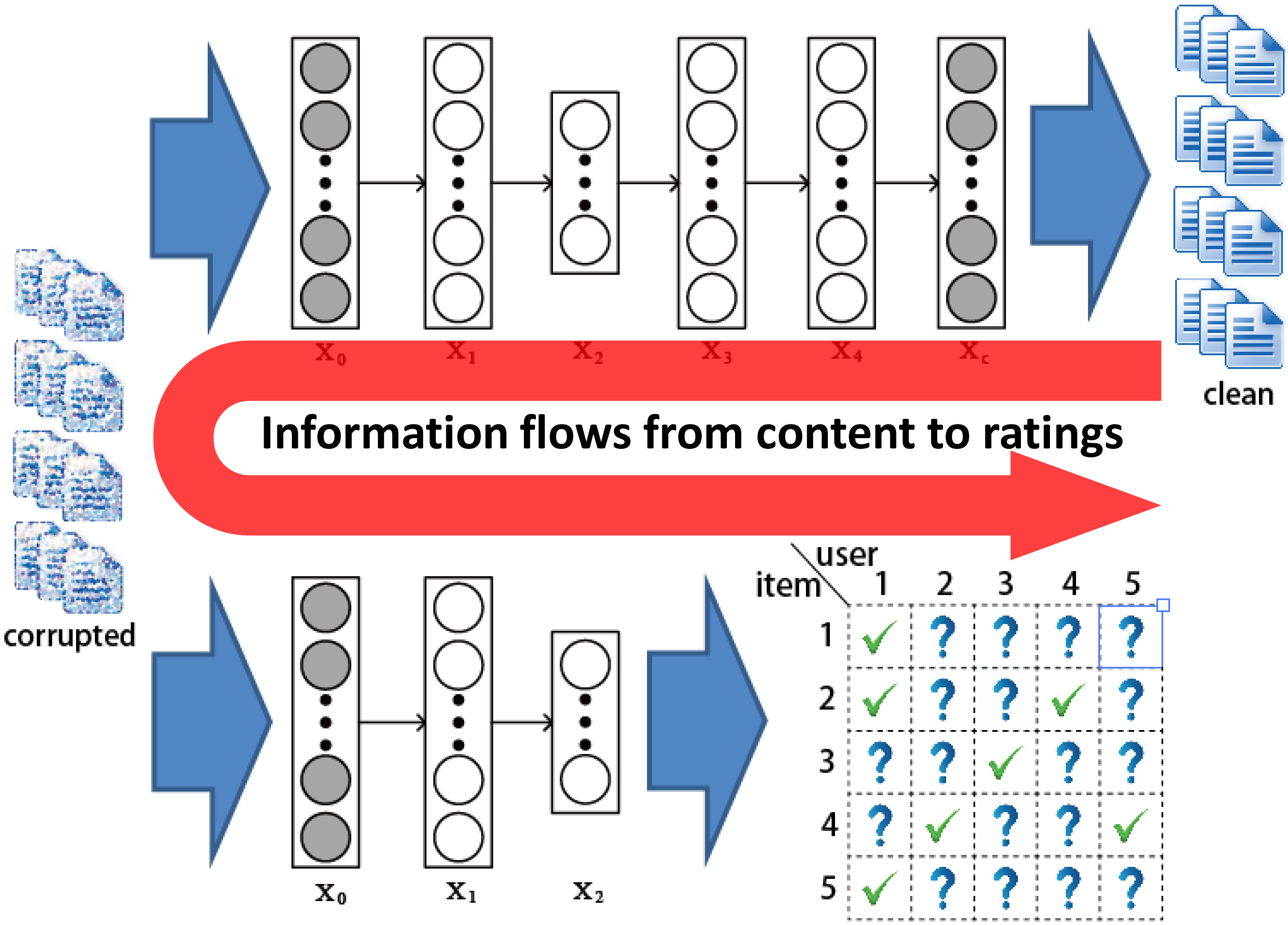


Neural network representation for degenerated CDL

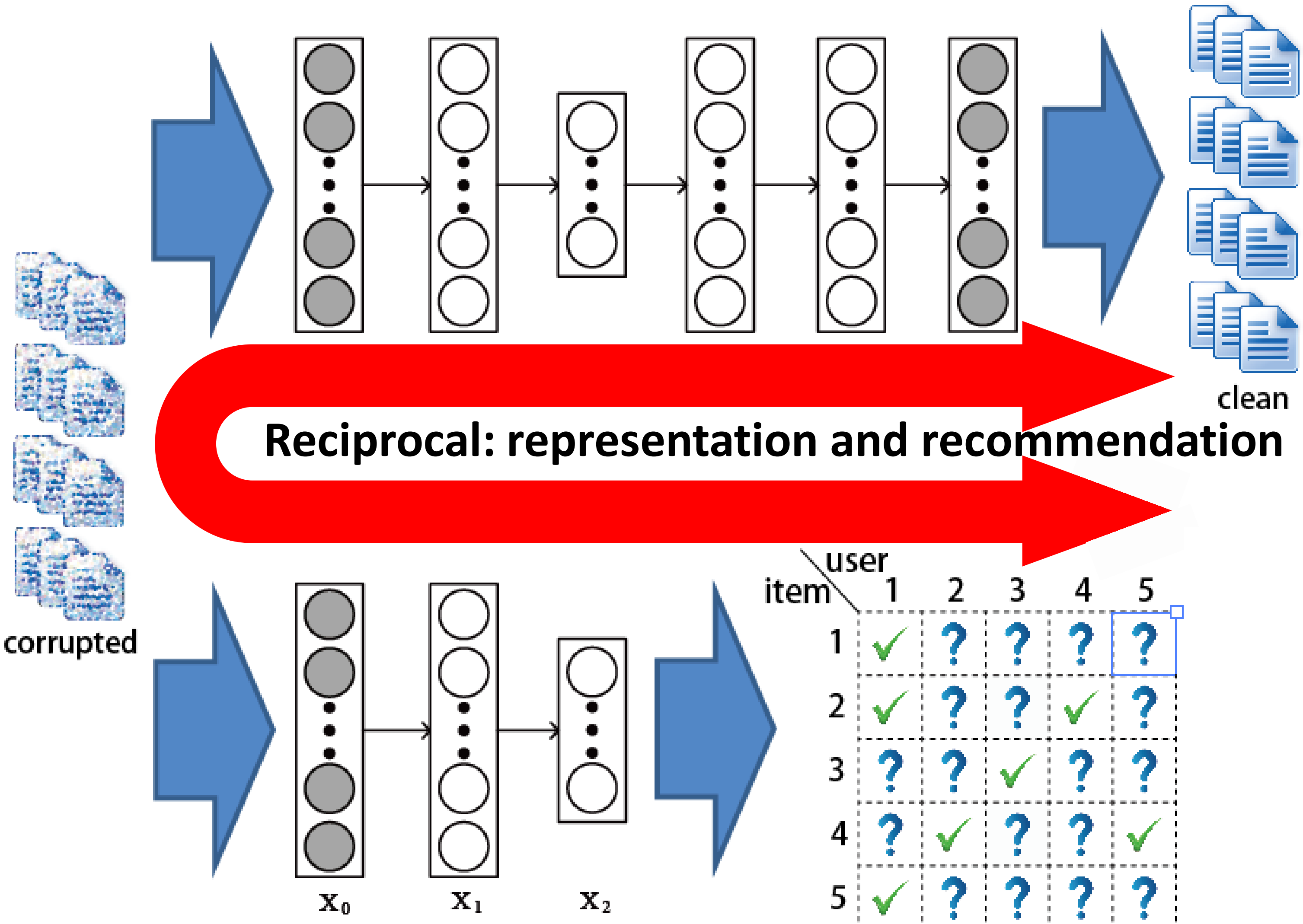
Collaborative Deep Learning



Collaborative Deep Learning



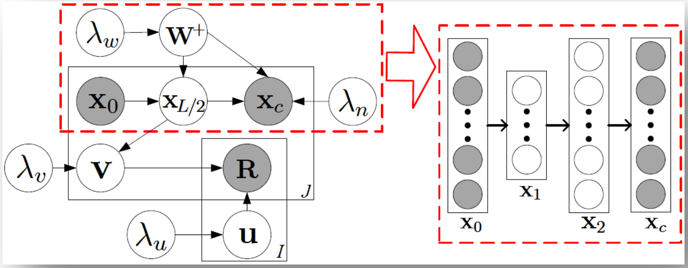
Collaborative Deep Learning



Learning

maximizing the posterior probability is equivalent to maximizing the joint log-likelihood

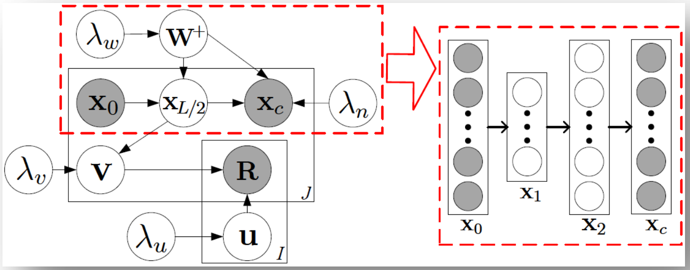
$$
\begin{aligned}
\mathscr{L} = &-\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l (\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2) \\
&- \frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}^T_{\frac{L}{2},j*}\|_2^2 - \frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2 \\
&- \frac{\lambda_s}{2}\sum_l\sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2 \\
&- \sum_{i,j}\frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2.
\end{aligned}
$$



Learning

Prior (regularization) for user latent vectors, weights, and biases

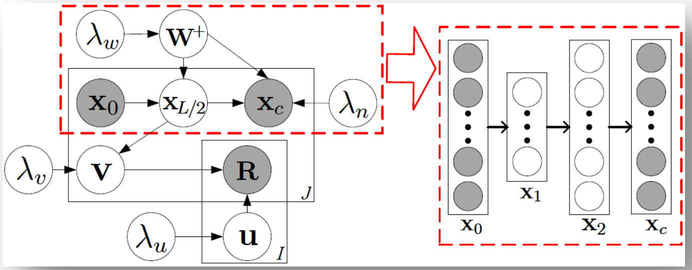
$$
\begin{aligned}
\mathscr{L} = & \boxed{-\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l (\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2)} \\
& -\frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}_{\frac{L}{2},j*}^T\|_2^2 - \frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2 \\
& -\frac{\lambda_s}{2}\sum_l \sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2 \\
& -\sum_{i,j} \frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2.
\end{aligned}
$$



Learning

Generating item latent vectors from content representation with Gaussian offset

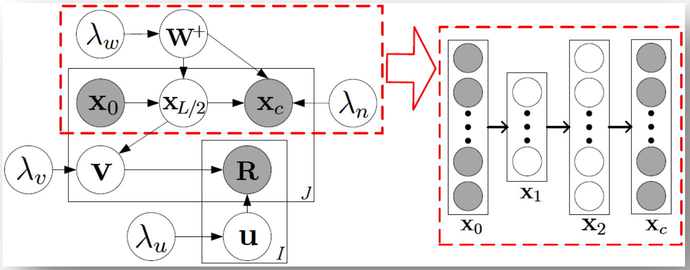
$$
\begin{aligned}
\mathscr{L} = & -\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l (\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2) \\
& \boxed{-\frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}_{\frac{L}{2},j*}^T\|_2^2} - \frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2 \\
& -\frac{\lambda_s}{2}\sum_l \sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2 \\
& -\sum_{i,j} \frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T \mathbf{v}_j)^2.
\end{aligned}
$$



Learning

'Generating' clean input from the output of probabilistic SDAE with Gaussian offset

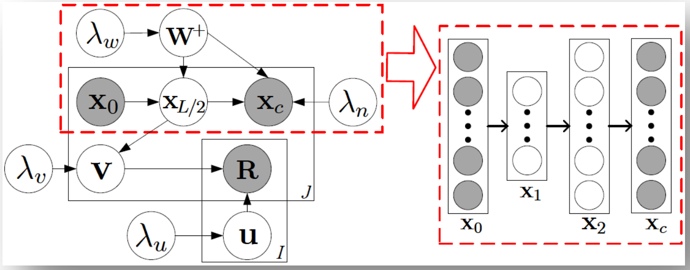
$$
\begin{aligned}
\mathscr{L} = & -\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l (\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2) \\
& -\frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}_{\frac{L}{2},j*}^T\|_2^2 - \boxed{\frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2} \\
& -\frac{\lambda_s}{2}\sum_l \sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2 \\
& -\sum_{i,j}\frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2.
\end{aligned}
$$



Learning

Generating the input of Layer l from the output of Layer l-1 with Gaussian offset

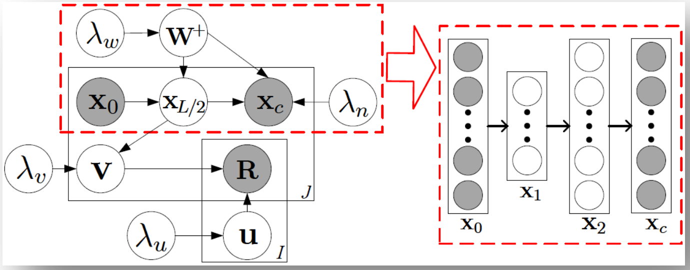
$$
\begin{aligned}
\mathscr{L} = &-\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l(\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2) \\
&- \frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}^T_{\frac{L}{2},j*}\|_2^2 - \frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2 \\
&\boxed{-\frac{\lambda_s}{2}\sum_l\sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2} \\
&- \sum_{i,j}\frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2.
\end{aligned}
$$



Learning

measures the error of predicted ratings

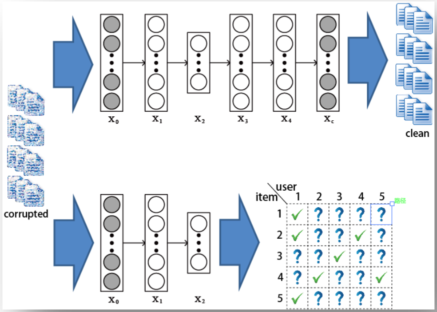
$$\mathscr{L} = -\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l (\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2)$$
$$-\frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - \mathbf{X}_{\frac{L}{2},j*}^T\|_2^2 - \frac{\lambda_n}{2}\sum_j \|\mathbf{X}_{L,j*} - \mathbf{X}_{c,j*}\|_2^2$$
$$-\frac{\lambda_s}{2}\sum_l \sum_j \|\sigma(\mathbf{X}_{l-1,j*}\mathbf{W}_l + \mathbf{b}_l) - \mathbf{X}_{l,j*}\|_2^2$$
$$\boxed{-\sum_{i,j}\frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2}.$$



Learning

If λ_s goes to infinity, the likelihood becomes

$$\mathscr{L} = -\frac{\lambda_u}{2}\sum_i \|\mathbf{u}_i\|_2^2 - \frac{\lambda_w}{2}\sum_l (\|\mathbf{W}_l\|_F^2 + \|\mathbf{b}_l\|_2^2)$$
$$-\frac{\lambda_v}{2}\sum_j \|\mathbf{v}_j - f_e(\mathbf{X}_{0,j*}, \mathbf{W}^+)^T\|_2^2$$
$$-\frac{\lambda_n}{2}\sum_j \|f_r(\mathbf{X}_{0,j*}, \mathbf{W}^+) - \mathbf{X}_{c,j*}\|_2^2$$
$$-\sum_{i,j}\frac{\mathbf{C}_{ij}}{2}(\mathbf{R}_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2,$$



Update Rules

For U and V, use block coordinate descent:

$$\mathbf{u}_i \leftarrow (\mathbf{V}\mathbf{C}_i\mathbf{V}^T + \lambda_u \mathbf{I}_K)^{-1}\mathbf{V}\mathbf{C}_i\mathbf{R}_i$$

$$\mathbf{v}_j \leftarrow (\mathbf{U}\mathbf{C}_i\mathbf{U}^T + \lambda_v \mathbf{I}_K)^{-1}(\mathbf{U}\mathbf{C}_j\mathbf{R}_j + \lambda_v f_e(\mathbf{X}_{0,j*}, \mathbf{W}^+)^T)$$

For W and b, use a modified version of backpropagation:

$$\begin{aligned}
\nabla_{\mathbf{W}_l}\mathscr{L} &= -\lambda_w \mathbf{W}_l \\
&- \lambda_v \sum_j \nabla_{\mathbf{W}_l} f_e(\mathbf{X}_{0,j*}, \mathbf{W}^+)^T (f_e(\mathbf{X}_{0,j*}, \mathbf{W}^+)^T - \mathbf{v}_j) \\
&- \lambda_n \sum_j \nabla_{\mathbf{W}_l} f_r(\mathbf{X}_{0,j*}, \mathbf{W}^+)(f_r(\mathbf{X}_{0,j*}, \mathbf{W}^+) - \mathbf{X}_{c,j*}) \\
\nabla_{\mathbf{b}_l}\mathscr{L} &= -\lambda_w \mathbf{b}_l \\
&- \lambda_v \sum_j \nabla_{\mathbf{b}_l} f_e(\mathbf{X}_{0,j*}, \mathbf{W}^+)^T (f_e(\mathbf{X}_{0,j*}, \mathbf{W}^+)^T - \mathbf{v}_j) \\
&- \lambda_n \sum_j \nabla_{\mathbf{b}_l} f_r(\mathbf{X}_{0,j*}, \mathbf{W}^+)(f_r(\mathbf{X}_{0,j*}, \mathbf{W}^+) - \mathbf{X}_{c,j*})
\end{aligned}$$

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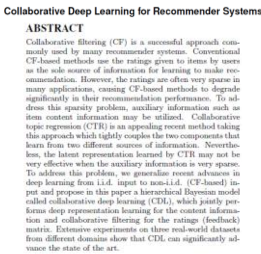
Datasets

	citeulike-a	citeulike-t	Netflix
#users	5551	7947	407261
#items	16980	25975	9228
#ratings	204987	134860	15348808

Content information



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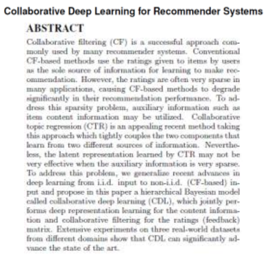
ABSTRACT

Collaborative filtering (CF) is a successful approach commonly used by many recommender systems. Conventional CF-based methods use the ratings given to items by users as the sole source of information for learning to make recommendation. However, the ratings are often very sparse in many applications, causing CF-based methods to degrade significantly in their recommendation performance. To address this sparsity problem, auxiliary information such as item content information may be utilized. Collaborative topic regression (CTR) is an appealing recent method taking this approach which tightly couples the two components that learn from two different sources of information. Nevertheless, the latent representation learned by CTR may not be very effective when the auxiliary information is very sparse. To address this problem, we generalize recent advances in deep learning from i.i.d. input to non-i.i.d. (CF-based) input and propose in this paper a hierarchical Bayesian model called collaborative deep learning (CDL), which jointly performs deep representation learning for the content information and collaborative filtering for the ratings (feedback) matrix. Extensive experiments on three real-world datasets from different domains show that CDL can significantly advance the state of the art.



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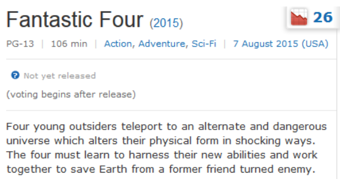


Titles and abstracts | Titles and abstracts | Movie plots

Wang et al. 2011
Wang et al. 2013

Evaluation Metrics

Recall:

$$\text{recall@}M = \frac{\text{number of items that the user likes among the top } M}{\text{total number of items that the user likes}}$$

Mean Average Precision (mAP):

$$mAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q}$$

$$AveP = \frac{\sum_{k=1}^{n} (P(k) \times rel(k))}{\text{number of relevant items}}$$

Higher recall and mAP indicate better recommendation performance

Comparing Methods

- **CMF**: Collective Matrix Factorization (Singh et al. 2008) is a model incorporating different sources of information by simultaneously factorizing multiple matrices.
- **SVDFeature**: SVDFeature (Chen et al. 2012) is a model for feature-based collaborative filtering.

Hybrid methods using BOW and ratings

- **DeepMusic**: DeepMusic (Oord et al. 2013) is a model for music recommendation.

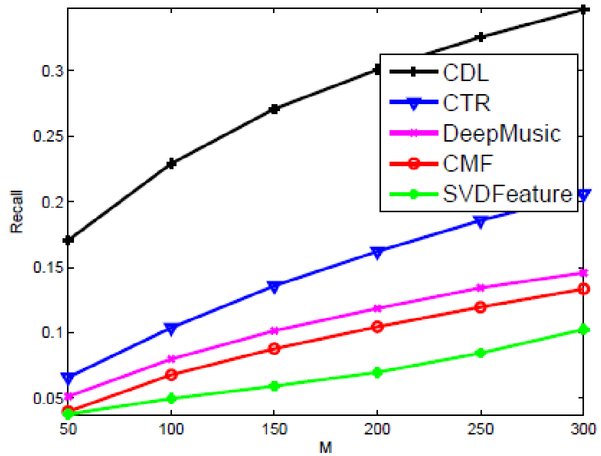
Loosely coupled; interaction is not two-way

- **CTR**: Collaborative Topic Regression (Wang et al. 2011) is a model performing topic modeling and collaborative filtering simultaneously.

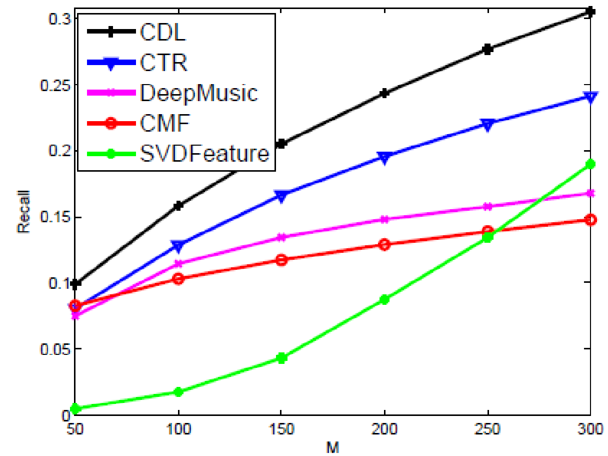
PMF+LDA

Recall@M

When the ratings are **very sparse**:

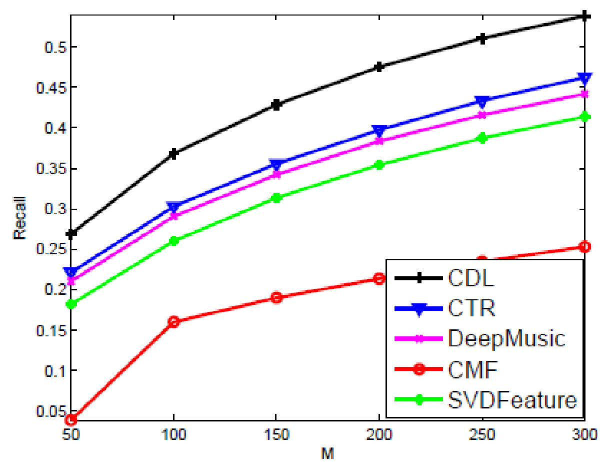


***citeulike-t*, sparse setting**

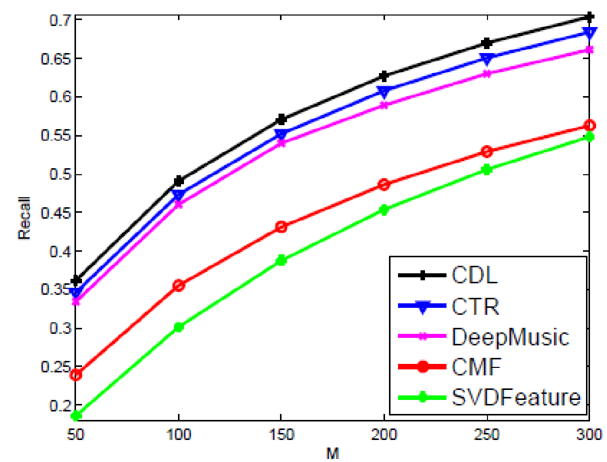


***Netflix*, sparse setting**

When the ratings are **dense**:



***citeulike-t*, dense setting**



***Netflix*, dense setting**

Mean Average Precision (mAP)

	citeulike-a	*citeulike-t*	*Netflix*
CDL	**0.0514**	**0.0453**	**0.0312**
CTR	0.0236	0.0175	0.0223
DeepMusic	0.0159	0.0118	0.0167
CMF	0.0164	0.0104	0.0158
SVDFeature	0.0152	0.0103	0.0187

Exactly the same as Oord et al. 2013, we set the cutoff point at 500 for each user.

A relative performance boost of about 50%

Number of Layers

Sparse Setting

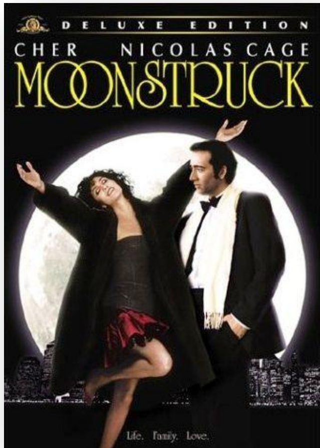
#layers	1	2	3
citeulike-a	27.89	**31.06**	30.70
citeulike-t	32.58	34.67	**35.48**
Netflix	29.20	30.50	**31.01**

Dense Setting

#layers	1	2	3
citeulike-a	58.35	**59.43**	59.31
citeulike-t	52.68	53.81	**54.48**
Netflix	69.26	70.40	**70.42**

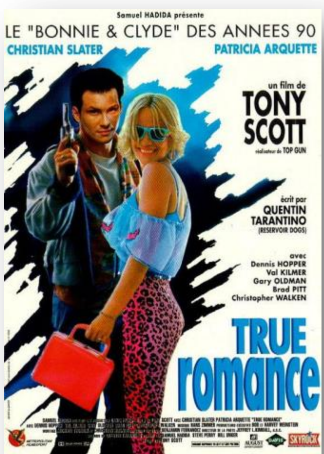
The best performance is achieved when the number of layers is **2 or 3** (**4 or 6** layers of generalized neural networks).

Example User



Moonstruck

Romance Movies



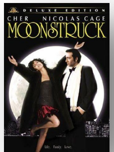
True Romance

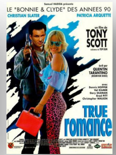
# training samples	2
Top 10 recommended movies by **CTR**	Swordfish
	A Fish Called Wanda
	Terminator 2
	A Clockwork Orange
	Sling Blade
	Bridget Jones's Diary
	Raising Arizona
	A Streetcar Named Desire
	The Untouchables
	The Full Monty

# training samples	2
Top 10 recommended movies by **CDL**	Snatch
	The Big Lebowski
	Pulp Fiction
	Kill Bill
	Raising Arizona
	The Big Chill
	Tootsie
	Sense and Sensibility
	Sling Blade
	Swinger

Precision: 30% VS 20%

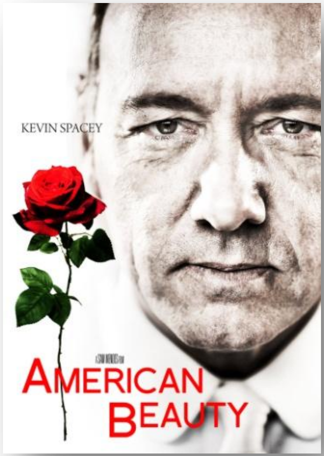
Example User





Johnny English

Action & Drama Movies



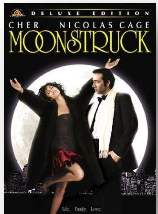
American Beauty

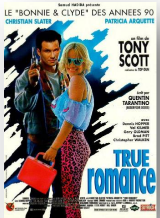
# training samples	4
Top 10 recommended movies by **CTR**	**Pulp Fiction**
	A Clockwork Orange
	Being John Malkovich
	Raising Arizona
	Sling Blade
	Swordfish
	A Fish Called Wanda
	Saving Grace
	The Graduate
	Monster's Ball

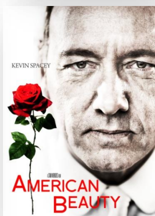
# training samples	4
Top 10 recommended movies by **CDL**	**Pulp Fiction**
	Snatch
	The Usual Suspect
	Kill Bill
	Momento
	The Big Lebowski
	One Flew Over the Cuckoo's Nest
	As Good as It Gets
	Goodfellas
	The Matrix

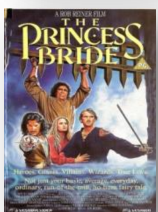
Precision: 50% VS 20%

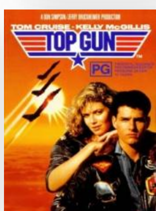
Example User

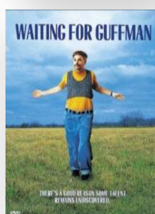


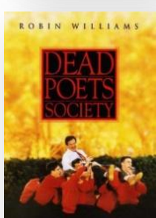












# training samples	10
Top 10 recommended movies by **CTR**	**Best in Snow**
	Chocolat
	Good Will Hunting
	Monty Python and the Holy Grail
	Being John Malkovich
	Raising Arizona
	The Graduate
	Swordfish
	Tootsie
	Saving Private Ryan

# training samples	10
Top 10 recommended movies by **CDL**	**Good Will Hunting**
	Best in Show
	The Big Lebowski
	A Few Good Men
	Monty Python and the Holy Grail
	Pulp Fiction
	The Matrix
	Chocolat
	The Usual Suspect
	CaddyShack

Precision: 90% VS 50%

- **Motivation**
- **Stacked Denoising Autoencoders**
- **Probabilistic Matrix Factorization**
- **Collaborative Deep Learning**
- **Experiments**
- **Summary**

Summary

- Non-i.i.d (collaborative) deep learning
- With a complex target
- First hierarchical Bayesian models for hybrid deep recommender system
- Significantly advance the state of the art

Summary

- Word2vec, tf-idf
- Sampling-based, variational inference
- Tagging information, networks

Thank you!

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More results, code, and datasets:
http://www.wanghao.in