

# A Collective Variational Autoencoder for Top- $N$ Recommendation with Side Information

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- ③ Method
- ④ Experiment
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# Introduction

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# Recommendation with side information

The screenshot shows the Amazon product page for an Adidas Finland NHL White 2016 World Cup of Hockey Z.N.E. Full Zip Hoodie for Men. The page features a navigation bar at the top with the Amazon logo, search bar, and various account and shopping options. The main content area includes a product image of the hoodie, a price of \$49.99, and a promotional banner for \$10 and under with free shipping. The right sidebar contains a share section, a price breakdown, shipping information, and an 'Add to Cart' button.

amazon try Prime

Sports & Outdoors ▾ Z.N.E

Introducing Fire TV Stick 4K

Deliver to Germany

Departments ▾ Your Amazon.com Today's Deals Gift Cards Registry Sell

EN Hello, Sign in Account & Lists ▾ Orders Try Prime ▾ Cart

Sports & Outdoors Sports & Fitness Outdoor Recreation Sports Fan Shop Sports Deals Outdoor Deals

**\$10 & under with FREE shipping**

◀ Back to search results for "Z.N.E"





adidas Finland NHL White 2016 World Cup of Hockey Z.N.E. Full Zip Hoodie for Men

by adidas

Be the first to review this item

Price: **\$49.99** + \$19.46 Shipping & Import Fees Deposit to Germany [Details](#)

Size: **Medium**

- Apparel
- White
- Men
- 100% Authentic
- Licensed Products

[New \(1\) from \\$49.99 & FREE shipping. Details](#)

 Introducing: The Celebrity Store  
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Share    

**\$49.99**

+ \$19.46 Shipping & Import Fees Deposit to Germany [Details](#) ▾

This item ships to **Germany**. **Want it Tuesday, Oct. 9?** Order within **17 hrs 5 mins** and choose **AmazonGlobal Priority Shipping** at checkout. [Learn more](#)

**Only 1 left in stock - order soon.**

Sold by [retro2heritage](#) and Fulfilled by Amazon. Gift-wrap available.

 **Add to Cart**

[Turn on 1-Click ordering for this.](#)

## Side information

- information associated with users or **items**
  - item-side information are more often utilized

## Recommendation with side information

- increasingly **availability** of side information
- provide additional **information**
- overcome user rating **sparsity**

## Related work

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## Existing methods

- linear methods
- non-linear methods
  - **deep autoencoder**: using deep neural network to **extract item representation** from side information

## Denoise Autoencoder

- Collaborative Deep Learning (CDL) Wang et al. [2015]
- marginalized Denoising Autoencoder (mDA) Li et al. [2015]

## Variational Autoencoder

- collaborative filtering Variational Autoencoder (cfVAE) Li and She [2017]
  - show state-of-the-art performance



## Suffer from high-dimensionality

- determine the input scale of network
- dominate the overall size of the model

## Solution

- **collective Variational Autoencoder (cVAE)**
  - overcome the impact from **high-dimensionality**
  - take the advantage of deep learning

## Method

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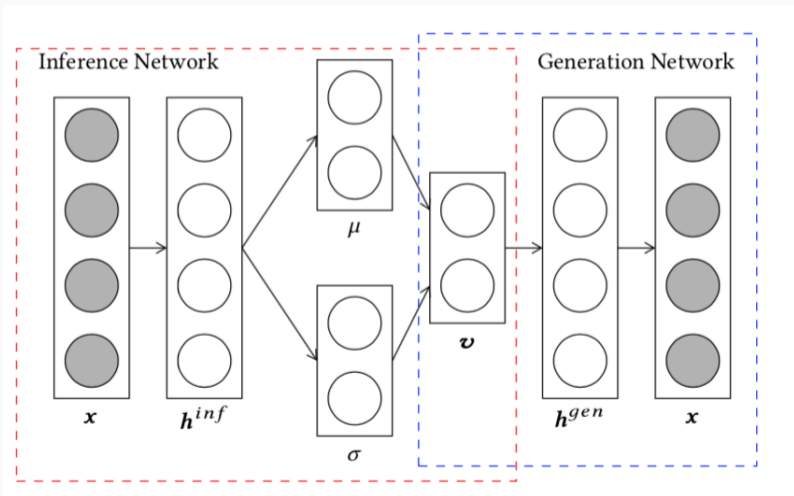
## Notation

- suppose we have  $m$  users,  $n$  items and  $d$  dimensions for side information
- user rating:  $Y \in \mathbb{R}^{m \times n}$
- item feature:  $X \in \mathbb{R}^{d \times n}$

## Assumption

- ① do not distinguish item feature with side information
- ② assume item feature is a vector with **numerical values**
- ③ side information is high-dimensional:  $d \geq n$
- ④ assume user rating is **binarized** (typical assumption for implicit feedback)

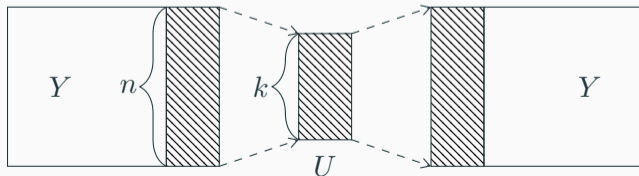
## Variational Autoencoder (VAE) Kingma and Welling [2013]



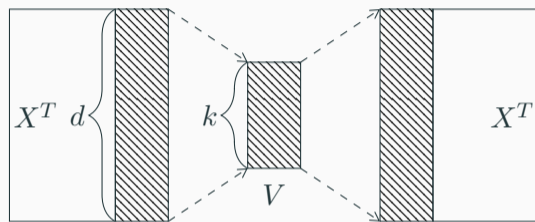
## Sparse Linear Method (SLIM) Ning and Karypis [2011]

$$\begin{aligned} \min_S \quad & \|Y - YS\|_F^2 + \frac{\beta}{2}\|S\|_F^2 + \lambda\|S\|_1 \\ \text{s.t.} \quad & S \geq 0, \text{diag}(S) = 0 \end{aligned}$$

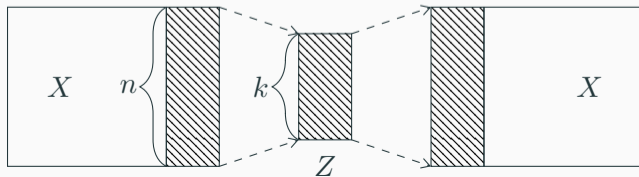
- reproduce the rating matrix:  $Y \sim YS$ , which works similarly as User-side Autoencoder (UAE)



## Item-side Autoencoder (IAE)



## Feature-side Autoencoder (FAE)



**collective Sparse Linear Method (cSLIM)** Ning and Karypis [2012]

$$\begin{aligned} \min_S \quad & \|Y - YS\|_F^2 + \alpha \|X - XS\|_F^2 + \frac{\beta}{2} \|S\|_F^2 + \lambda \|S\|_1 \\ \text{s.t.} \quad & S \geq 0, \text{diag } S = 0 \end{aligned}$$

- $\|Y - YS\|_F^2$ : works similarly as IAE
- $\|X - XS\|_F^2$ : works similarly as FAE
- collective learning: both  $X$  and  $Y$  are recovered by learning  $S$

We are inspired to propose **collective Variational Autoencoder (cVAE)**

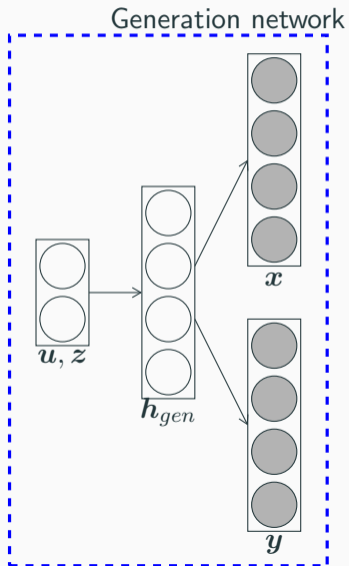
## Generation network

for each user  $j = 1, \dots, m$ :

- 1 draw  $\mathbf{u}_j \sim \mathcal{N}(0, I)$ ;
- 2 draw  $\mathbf{y}_j \sim \text{Bernoulli}(\varsigma(f_\theta(\mathbf{u}_j)))$

for each dimension of side information  
 $j = 1, \dots, d$ :

- 1 draw  $z_j \sim \mathcal{N}(0, I)$ ;
- 2 draw  $\mathbf{x}_j \sim \mathcal{N}(f_\theta(\mathbf{z}_u), I)$ .





## Inference network

for each user  $j = 1, \dots, m$

①  $\mu_j = \mu(f_\phi(\mathbf{y}_j))$

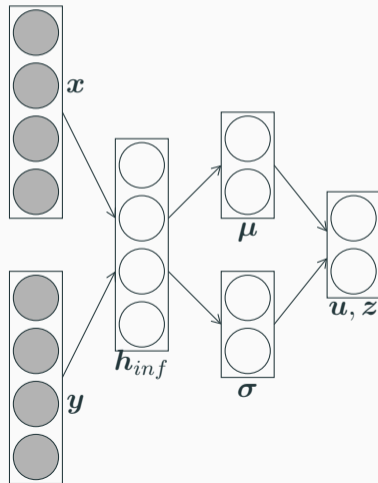
②  $\sigma_j = \sigma(f_\phi(\mathbf{y}_j))$

for each dimension of side information  $j = 1, \dots, d$

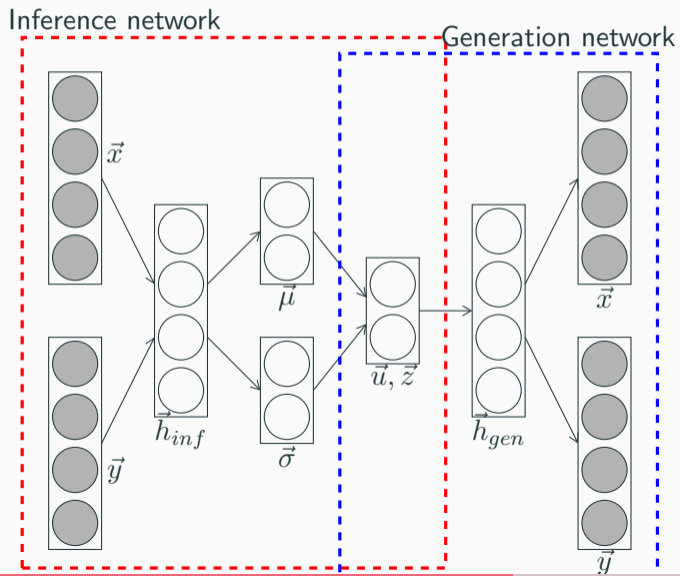
①  $\mu_{m+j} = \mu(f_\phi(\mathbf{x}_j))$

②  $\sigma_{m+j} = \sigma(f_\phi(\mathbf{x}_j))$

## Inference network



# collective Variational Autoencoder (cVAE)



## Summarization

- **collective** learning: only one VAE
- **heterogeneous** input: utilize both user rating and side information
- overcome **high-dimensionality** of side information

**Training:** pre-train is important for DNN

- **pre-train** the network with item feature
- **fine-tune** the network with user rating

# Experiment

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**Table 1:** Statistics of the datasets used.

<b>Dataset</b>	<b>#User</b>	<b>#Item</b>	<b>#Rating</b>	<b>#Dimension</b>	<b>#Feature</b>
Games	5,195	7,163	96,316	20,609	5,151,174
Sports	5,653	11,944	86,149	31,282	3,631,243

### Linear method

- cSLIM (Ning and Karypis [2012]): collective Sparse Linear Method

### Non-linear methods

- cfVAE (Li and She [2017]): collaborative Variational Autoencoder, UAE+IAE;
- rVAE (Liang et al. [2018]): Variational Autoencoder using ratings only, UAE;
- fVAE (Our): Variational Autoencoder using side information only, FAE;
- cVAE (Our): collective Variational Autoencoder, UAE+FAE.

**Table 2:** Results on Games dataset

<b>Method</b>	Rec@5	Rec@10	Rec@15	Rec@20	MAP@5	MAP@10	MAP@15	MAP@20
cSLIM	0.0761	0.1162	0.1474	0.1734	0.0590	0.0337	0.0240	0.0188
cfVAE	0.0685	0.1065	0.1359	0.1608	0.0519	0.0298	0.0212	0.0165
rVAE	0.0137	0.0206	0.0270	0.0375	0.0106	0.0060	0.0043	0.0034
fVAE	0.0495	0.0796	0.1072	0.1276	0.0390	0.0230	0.0167	0.0131
cVAE	<b>0.0858*</b>	<b>0.1376**</b>	<b>0.1731**</b>	<b>0.2081**</b>	<b>0.0668*</b>	<b>0.0394**</b>	<b>0.0279**</b>	<b>0.0218**</b>

## Conclusion

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## What have we done?

- ① we propose a **collective Variational Autoencoder (cVAE)** to utilize high-dimensional side information to address rating sparsity for top- $N$  recommendation
- ② cVAE is the combination of a UAE and a FAE
- ③ cVAE can be regarded as the non-linear generalization of cSLIM

## What should we do next?

- ① utilize side information associated with user;
- ② relax required assumption that side information is in accordance with user ratings for measuring item similarities
  - currently, cVAE performs poorly without this assumption
- ③ cVAE actually has two VAEs but they share the network parameters
  - $p_{\theta}(\mathbf{x} | \mathbf{z}), \quad p_{\theta}(\mathbf{y} | \mathbf{u})$
  - can we directly assume  $p_{\theta}(\mathbf{y} | \mathbf{u}, \mathbf{x})$ ?

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**Source code.** Source code to reproduce the experiments in this paper is available at <https://github.com/shikamaruChen/cVAE>.

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