Improving Top-K Recommendation via Joint Collaborative Autoencoders

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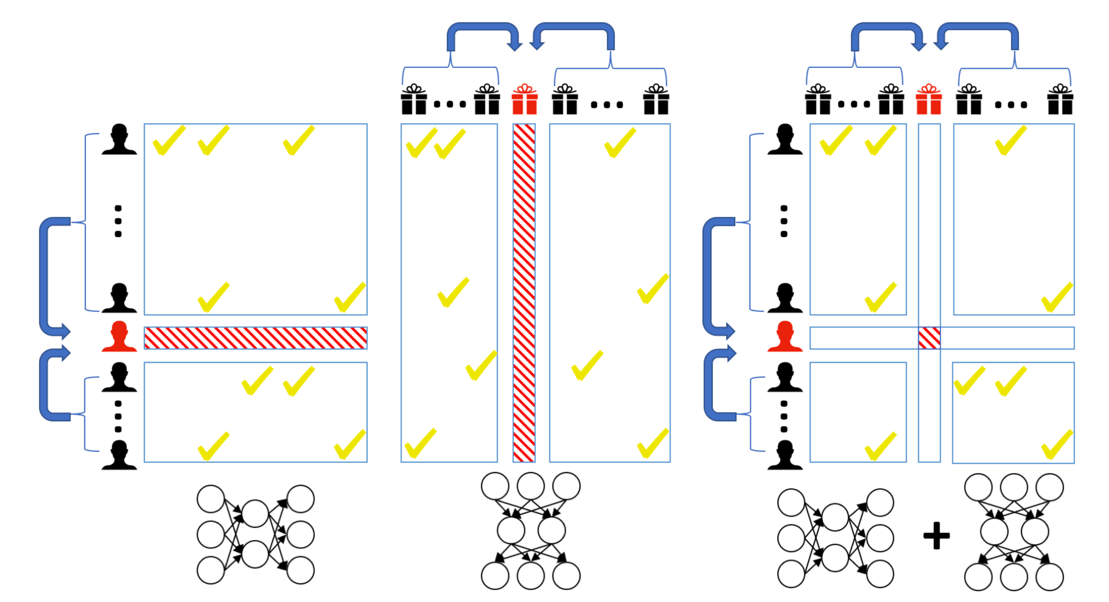
Introduction

- ***Problem & Goal***: Collaborative Autoencoders only consider **user-user** or **item-item correlations**, and the quality of recommendation may be restricted. In contrast, effective modeling of user-item interactions could lead to improved recommendation.



- **Contributions:**

(i) Propose the **Joint Collaborative Autoencoder** (JCA) that captures both user-user and item-item correlations simultaneously.

(ii) Adopt a **pairwise hinge-based objective function** to optimize **top-K precision** and **recall** directly.

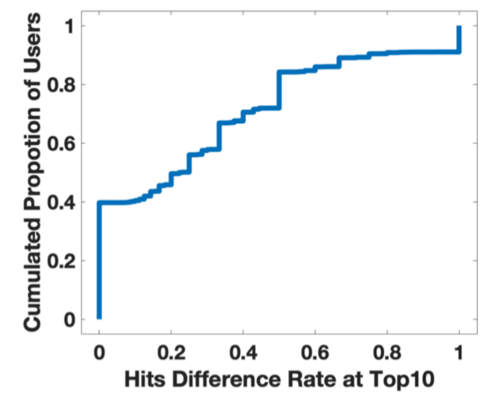
(iii) Present a **mini-batch optimization algorithm**.

(iv) Extensive **experiments** show that the JCA outperforms state-of-the-art neural and non-neural baselines.

User-based AutoRec and Item-based AutoRec Are Complementary

- **Hits Different Rate for U-AutoRec and I-AutoRec:** run U-AutoRec and I-AutoRec on the same MovieLens 1M dataset, and compare the HitsDifferenceRate of the top-10 recommendations by the two models.

$$\text{HitsDifferenceRate} = \frac{size(\mathbb{H}_U \cup \mathbb{H}_I) - size(\mathbb{H}_U \cap \mathbb{H}_I)}{size(\mathbb{H}_U \cup \mathbb{H}_I)}$$

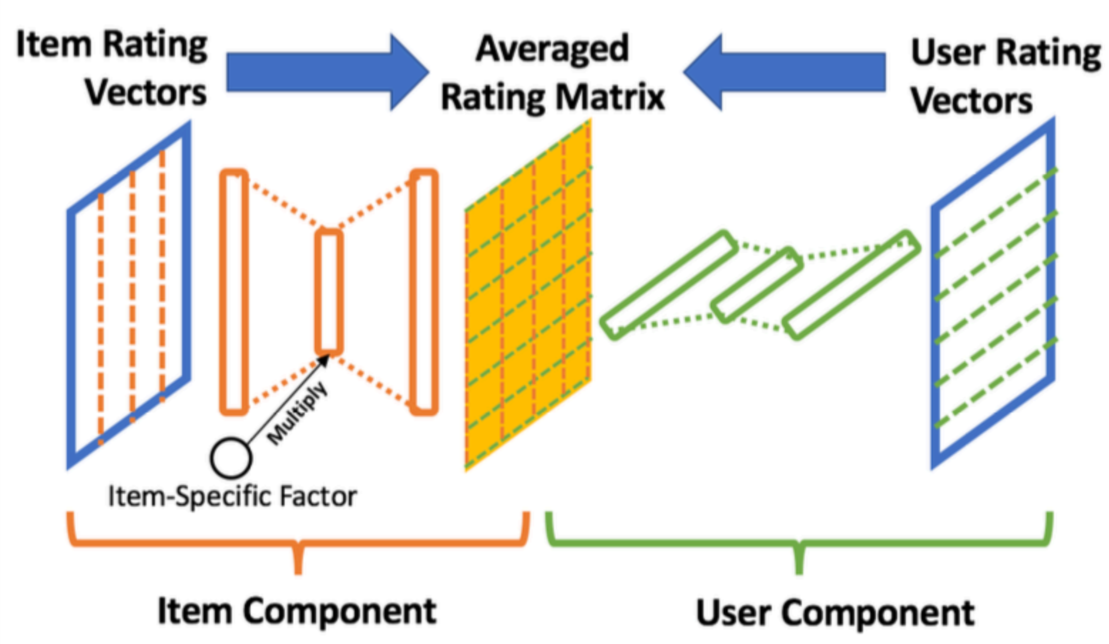


- **Recommendation by averaging U-AutoRec and I-AutoRec:** compare the recommendation quality between U-AutoRec, I-AutoRec and a simple averaging model of them.

	ML1M			Yelp			Games		
	P@10	R@10	F@10	P@10	R@10	F@10	P@10	R@10	F@10
U-AutoRec	**.2343**	.1698	.1969	.0230	.0608	.0333	.0152	.1022	.0265
I-AutoRec	.1782	.1454	.1602	.0202	.0556	.0296	.0138	.0979	.0241
UI-AutoRec	.2209	**.1801**	**.1984**	**.0240**	**.0646**	**.0350**	**.0171**	**.1192**	**.0298**

Proposed Model

- ***Framework:***



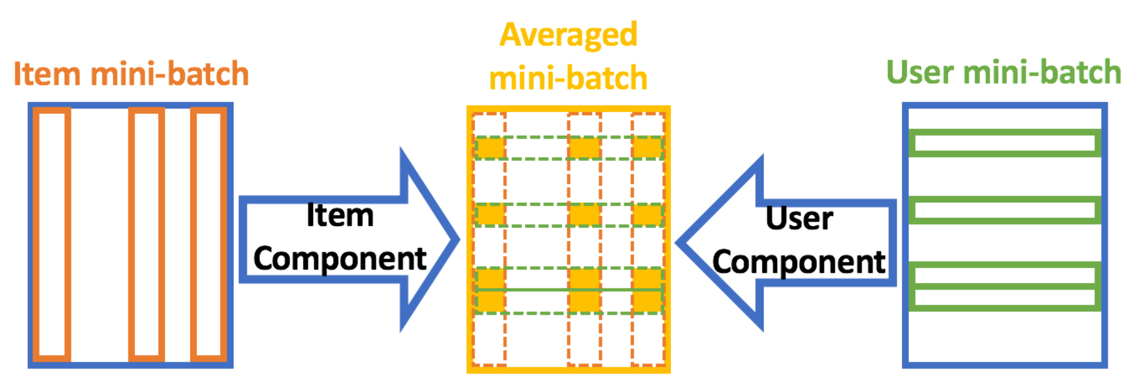
- **Joint Collaborative Autoencoder:**

$$\widehat{\mathrm{R}} = \frac{1}{2}[\sigma(\sigma(\mathbf{R}\mathbf{V}^U + \mathbf{b}_1^U)\mathbf{W}^U + \mathbf{b}_2^U) + \sigma(\sigma((\mathbf{R}^\top\mathbf{V}^I + \mathbf{b}_1^I) \circ \mathbf{f})\mathbf{W}^I + \mathbf{b}_2^I)^\top]$$

- **Hinge-based Objective Function:**

$$\underset{\Theta}{\text{minimize}} \quad \mathcal{L} = \sum_{u \in \mathbb{U}} \sum_{\substack{i \in \mathbb{O}_u^+ \\ j \in \mathbb{O}_u^-}} max(0, \widehat{r}_{u,j} - \widehat{r}_{u,i} + d) + \frac{\lambda}{2}\|\Theta\|_F^2$$

- **Mini-batch Training Process:**



Experiment Setup

- **Three Datasets:**

	Users	Items	Ratings	Sparsity(%)
MovieLens 1M (ML1M)	6,027	3,062	574,026	3.11
Yelp	12,705	9,245	318,314	0.271
Video Games (Games)	19,056	9,073	184,609	0.107

- **Evaluation Metrics:**

$P@k = |\mathbb{O}_u^k \cap \mathbb{O}_u^+|/k$

$R@k = |\mathbb{O}_u^k \cap \mathbb{O}_u^+|/|\mathbb{O}_u^+|$

$F1@k = (2 \cdot P@k \cdot R@k)/(P@k + R@k)$

- **Baselines:**

MF, BPR, CDAE, U-AutoRec, I-AutoRec, UI-AutoRec, NCF, and NPR.

- **Code and data:** https://github.com/Zziwei/Joint-Collaborative-Autoencoder

Proposed Model vs. State-of-the-art Models

- **Observations:** (i) JCA performs best for all three datasets; (ii) the performance improvement is larger for sparser datasets; (iii) the performance improvement is larger for smaller k.

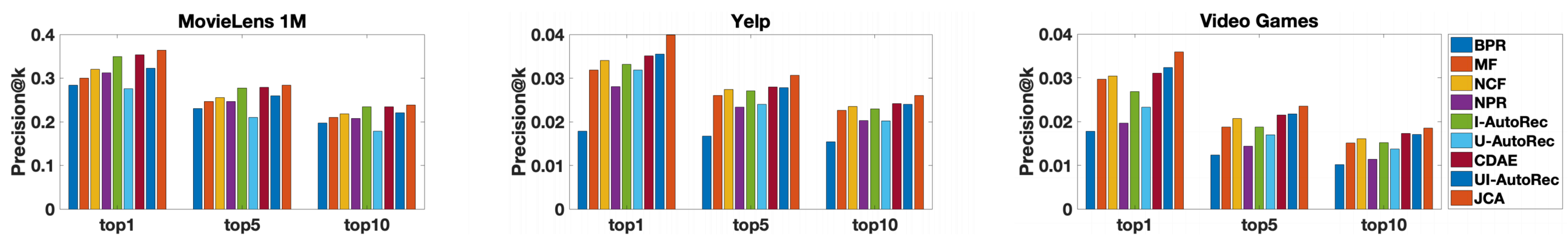


Figure 3: Precision@k results of the proposed method vs. baselines for the three datasets.

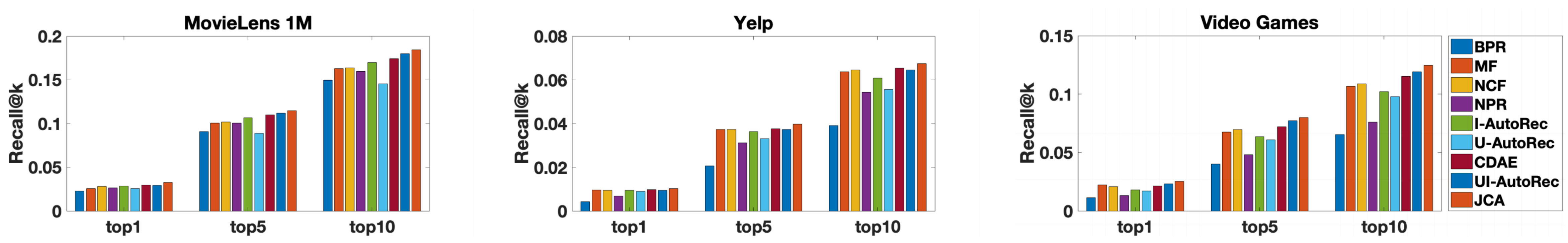


Figure 4: Recall@k results of the proposed method vs. baselines for the three datasets.

Conclusion and Future Work

- **Conclusions:**

(i) Propose the Joint Collaborative Autoencoder framework that learns both user-user and item-item correlations simultaneously.

(ii) Adopt a pairwise hinge-based objective function to optimize the top-K precision and recall.

(iii) Present a mini-batch training algorithm so that JCA can be trained on large datasets.

(iv) Extensive experiments show that the proposed framework outperforms state-of-the-art baselines.

- **Future Work:** exploring how to incorporate auxiliary information, such as textual and visual information, into the framework to further improve the recommendation quality.

Proposed Model and Objective Function

- **JCA with different objective functions vs. corresponding baselines**

	ML1M			Yelp			Games		
	P@10	R@10	F@10	P@10	R@10	F@10	P@10	R@10	F@10
JCA-MSE	**.2346**	**.1768**	**.2017**	**.0256**	**.0665**	**.0370**	**.0178**	**.1205**	**.0311**
NCF	.2182	.1637	.1870	.0235	.0636	.0343	.0161	.1089	.0281
UI-AutoRec	.2209	**.1801**	.1984	.0240	.0646	.0350	.0171	**.1192**	.0298
CDAE	**.2344**	.1743	**.1999**	**.0242**	**.0654**	**.0353**	**.0173**	.1154	**.0301**
JCA-BPR	**.2106**	**.1597**	**.1817**	**.0234**	**.0639**	**.0343**	**.0173**	**.1160**	**.0301**
NPR	**.2078**	**.1594**	**.1806**	**.0203**	**.0543**	**.0295**	**.0114**	**.0762**	**.0198**
BPR	.1975	.1498	.1704	.0154	.0391	.0221	.0101	.0655	.0175

JCA-MSE and JCA-BPR outperform SOTA baselines with MSE and BPR objective functions respectively.

- **JCA vs. JCA with different objective functions**

	ML1M			Yelp			Games		
	P@10	R@10	F@10	P@10	R@10	F@10	P@10	R@10	F@10
JCA	**.2384**	**.1845**	**.2080**	**.0261**	**.0674**	**.0376**	**.0185**	**.1247**	**.0322**
JCA-MSE	.2346	.1768	.2017	.0256	.0665	.0370	.0178	.1205	.0311
JCA-BPR	.2106	.1597	.1817	.0234	.0639	.0343	.0173	.1160	.0301

JCA outperforms other JCA variations with MSE and BPR objective functions.

- **JCA vs. JCA without item normalization factor**

	ML1M			Yelp			Games		
	P@10	R@10	F@10	P@10	R@10	F@10	P@10	R@10	F@10
JCA	**.2384**	**.1845**	**.2080**	**.0261**	**.0674**	**.0376**	**.0185**	**.1247**	**.0322**
JCA-NF	.2303	.1777	.2006	.0257	.0669	.0371	.0179	.1214	.0313

JCA outperforms JCA without item normalization factor.