Learning Personalized Itemset Mapping for Cross-Domain Recommendation

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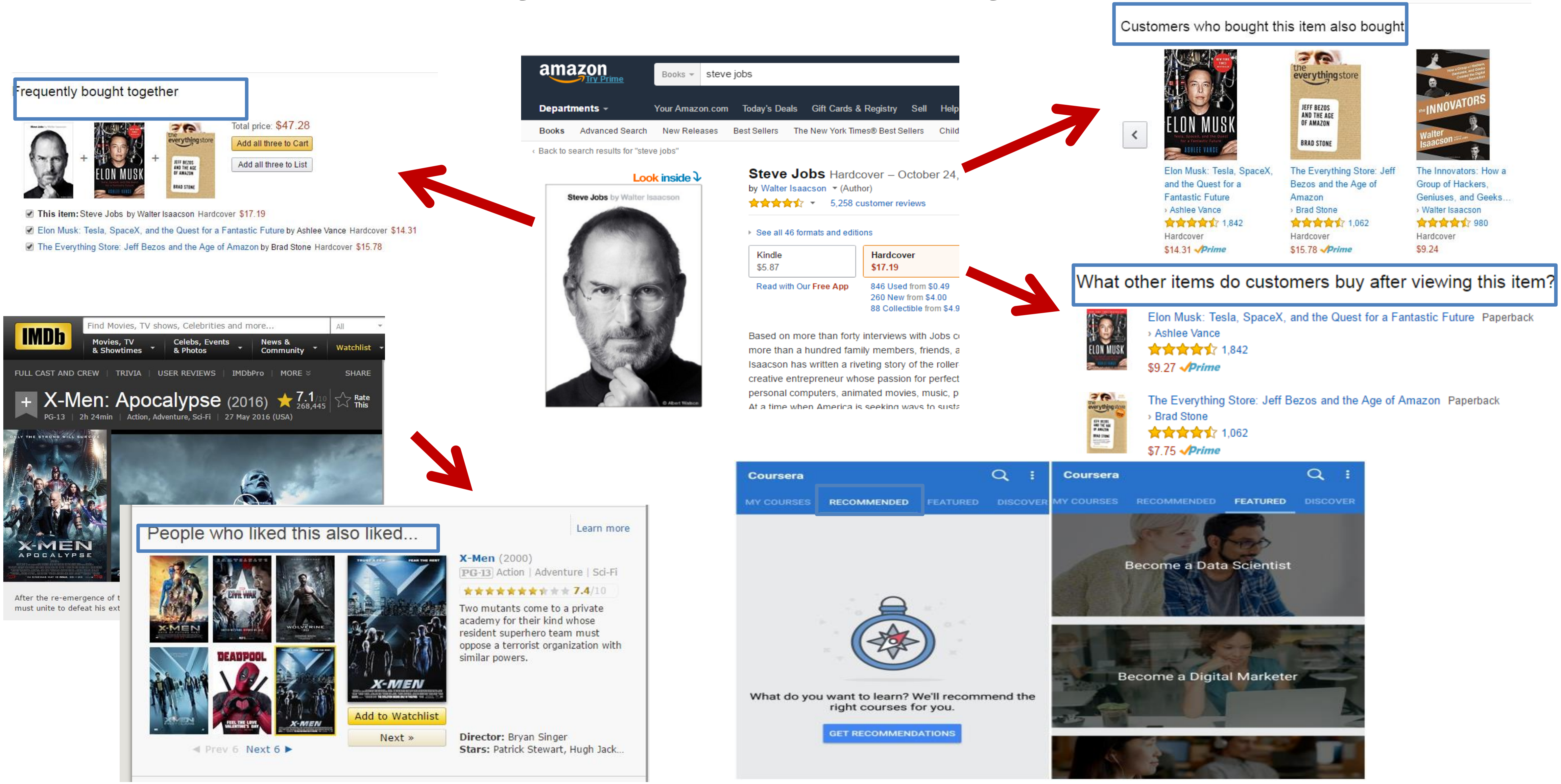
Agenda

- Background
- CGN Model
- Experimental Results
- Conclusion

Recommendation Systems in Our daily life



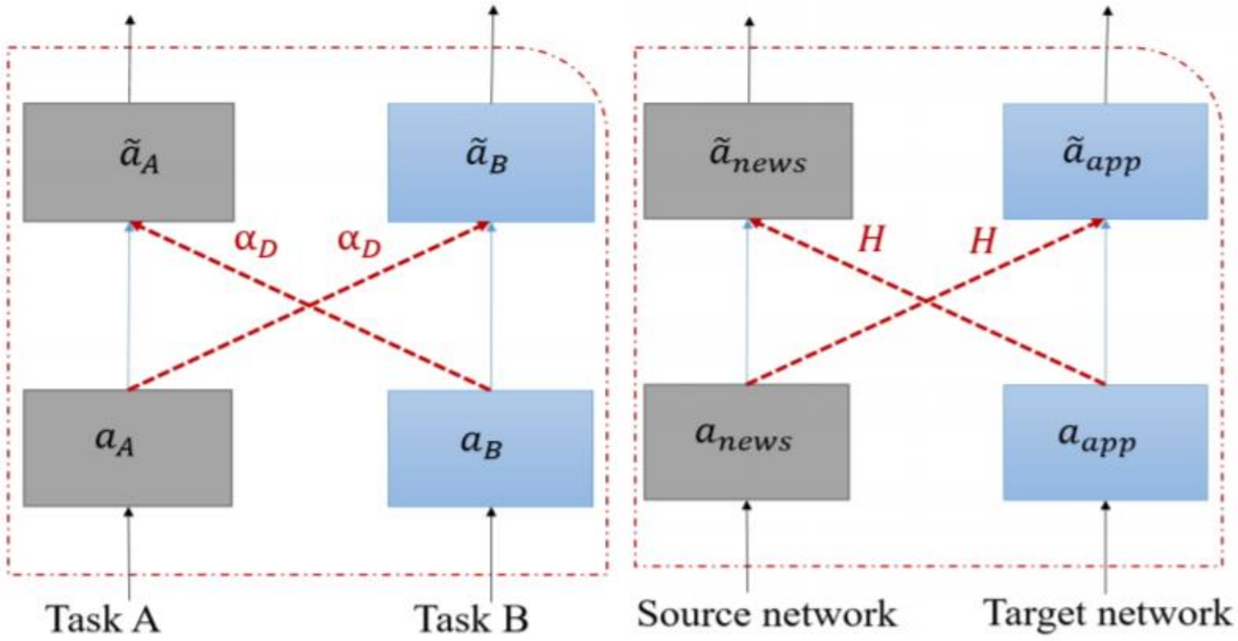
Cross-Domain Recommendation Systems

✓ Transfer Learning

Existing methods usually transfer knowledge across different domains implicitly.

➢ In practice, users' interests and states may vary over time.

➢ Users usually interact with items in multiple domains.

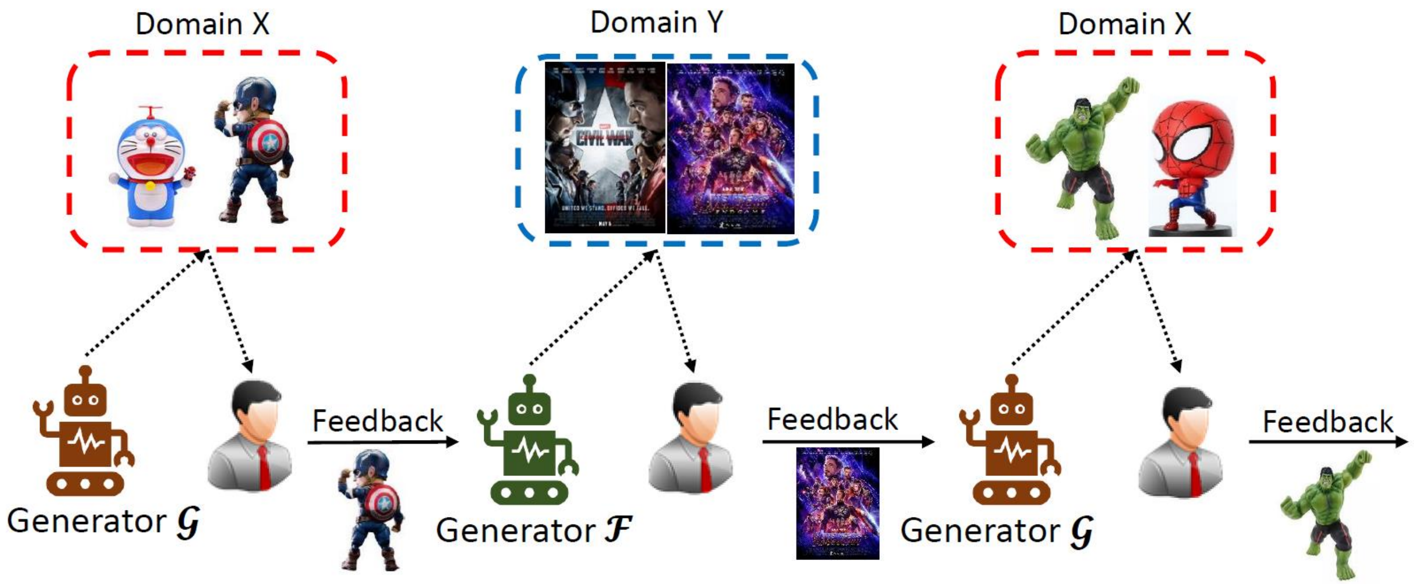


(a) Cross-stitch unit (b) Cross connection unit

CoNet: Collaborative Cross Networks for Cross-Domain Recommendation, CIKM'18

Problem Formulation

- In this work, we aim to exploit a user's behavior data in one domain to generate her item recommendation for the same time period in another domain.
- We proposed Cycle Generation Networks (CGN).



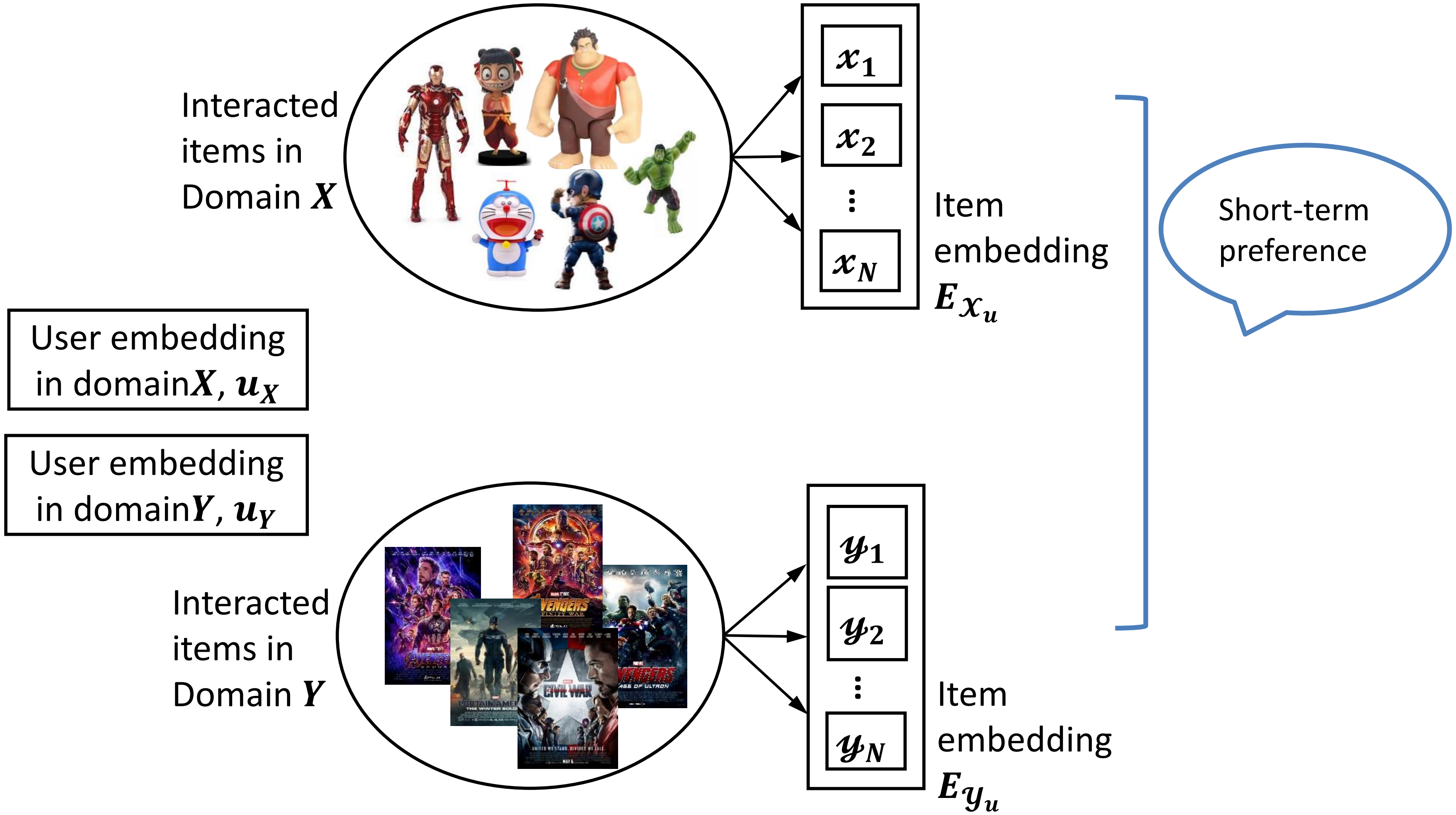
Cycle Generation Networks

Long-term preference

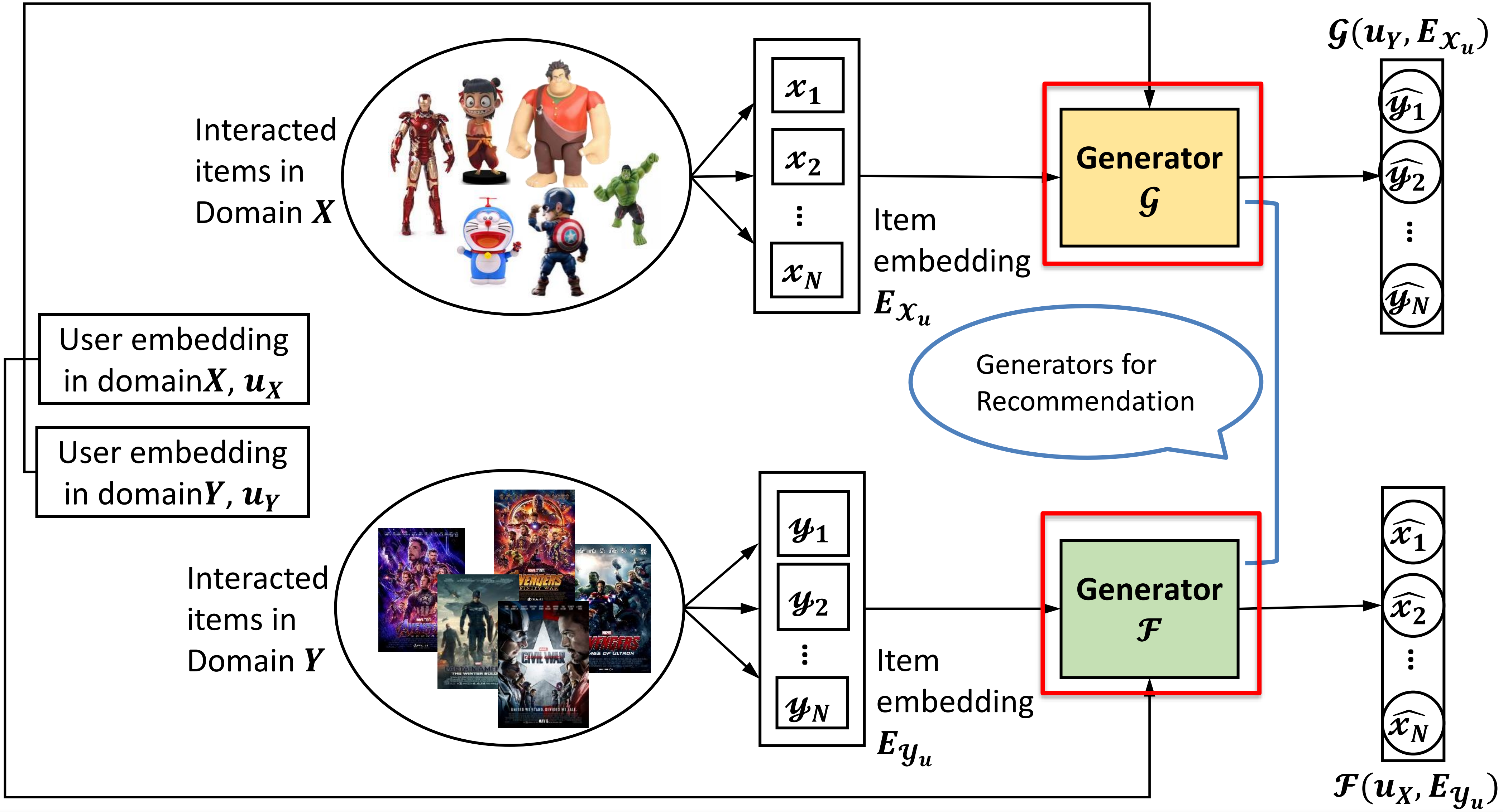
User embedding in domain $\boldsymbol{X}$, $\boldsymbol{u_X}$

User embedding in domain $\boldsymbol{Y}$, $\boldsymbol{u_Y}$

Cycle Generation Networks

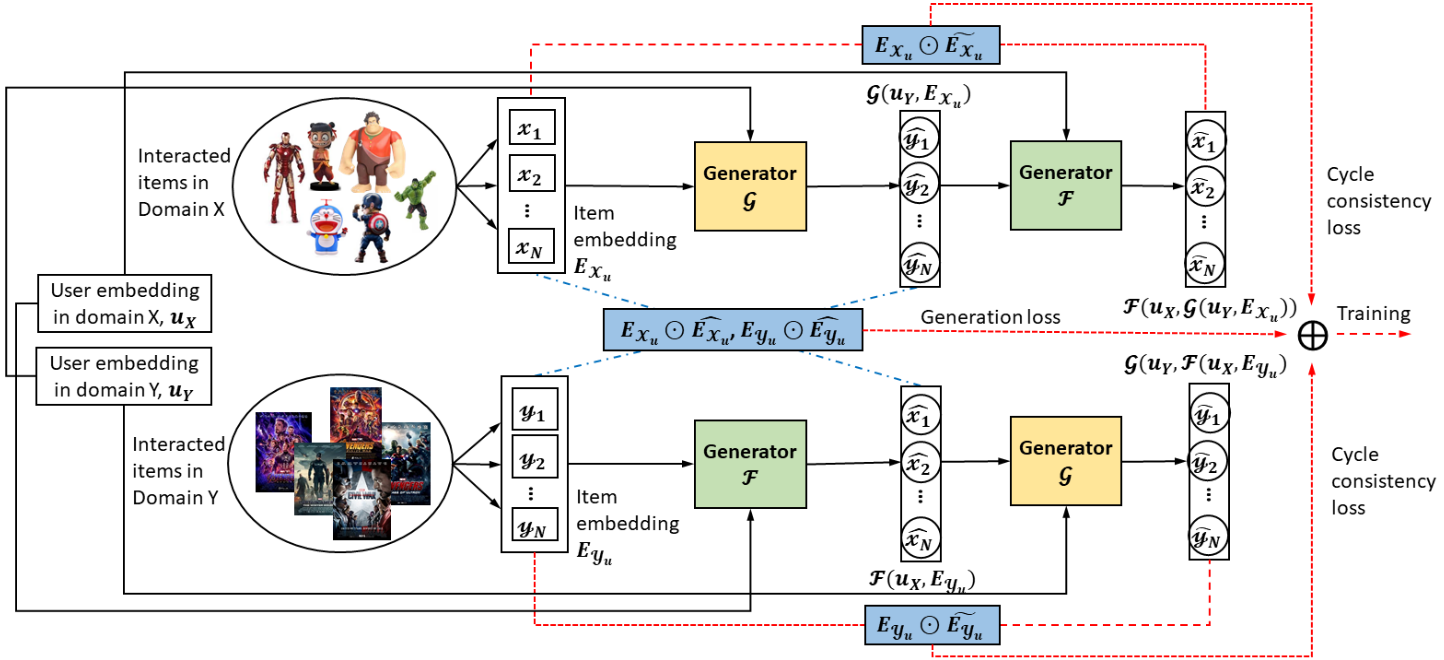


Cycle Generation Networks

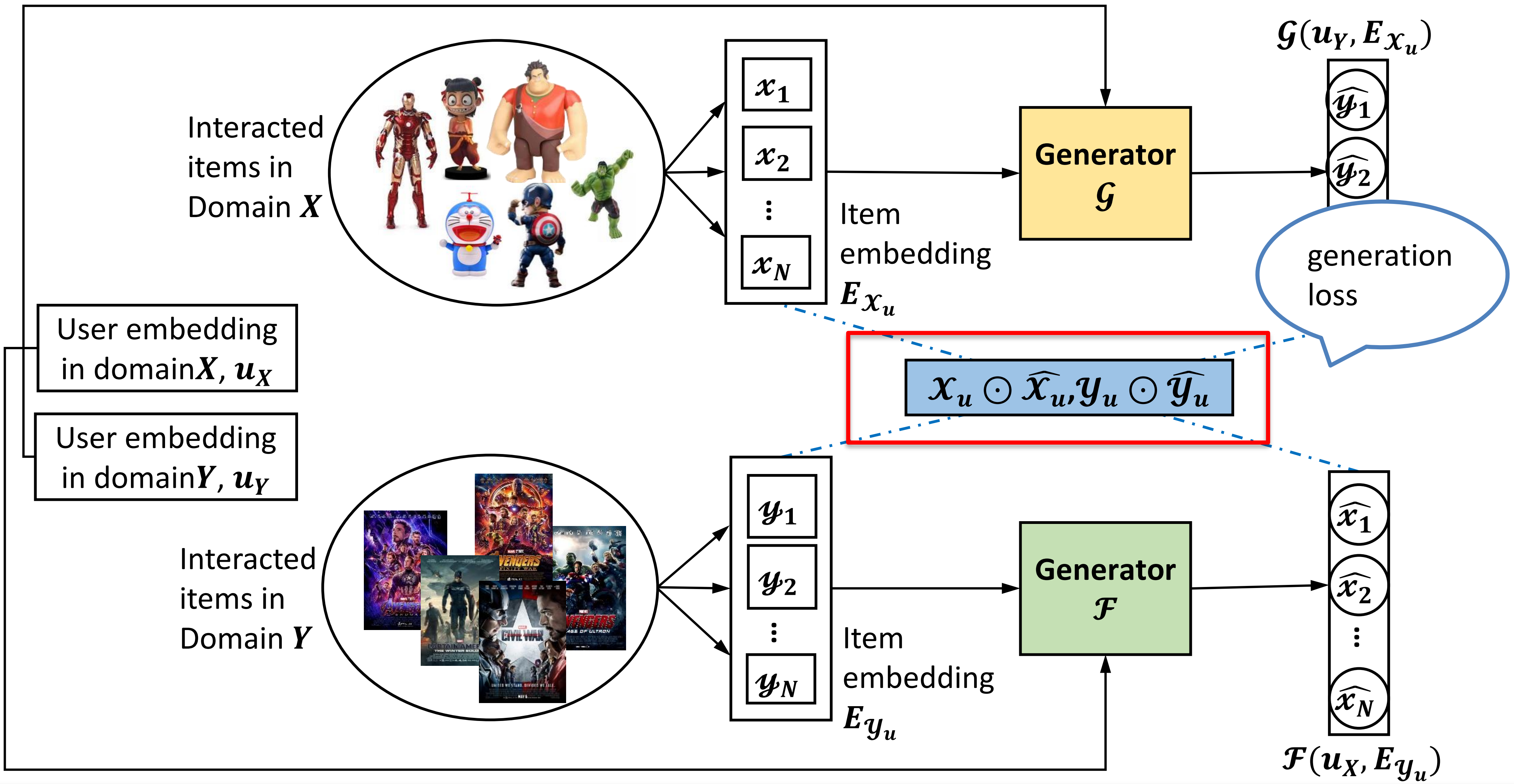


Cycle Generation Networks

- Loss Functions
  - generation loss
  - cycle consistency loss



Cycle Generation Networks



Cycle Generation Networks

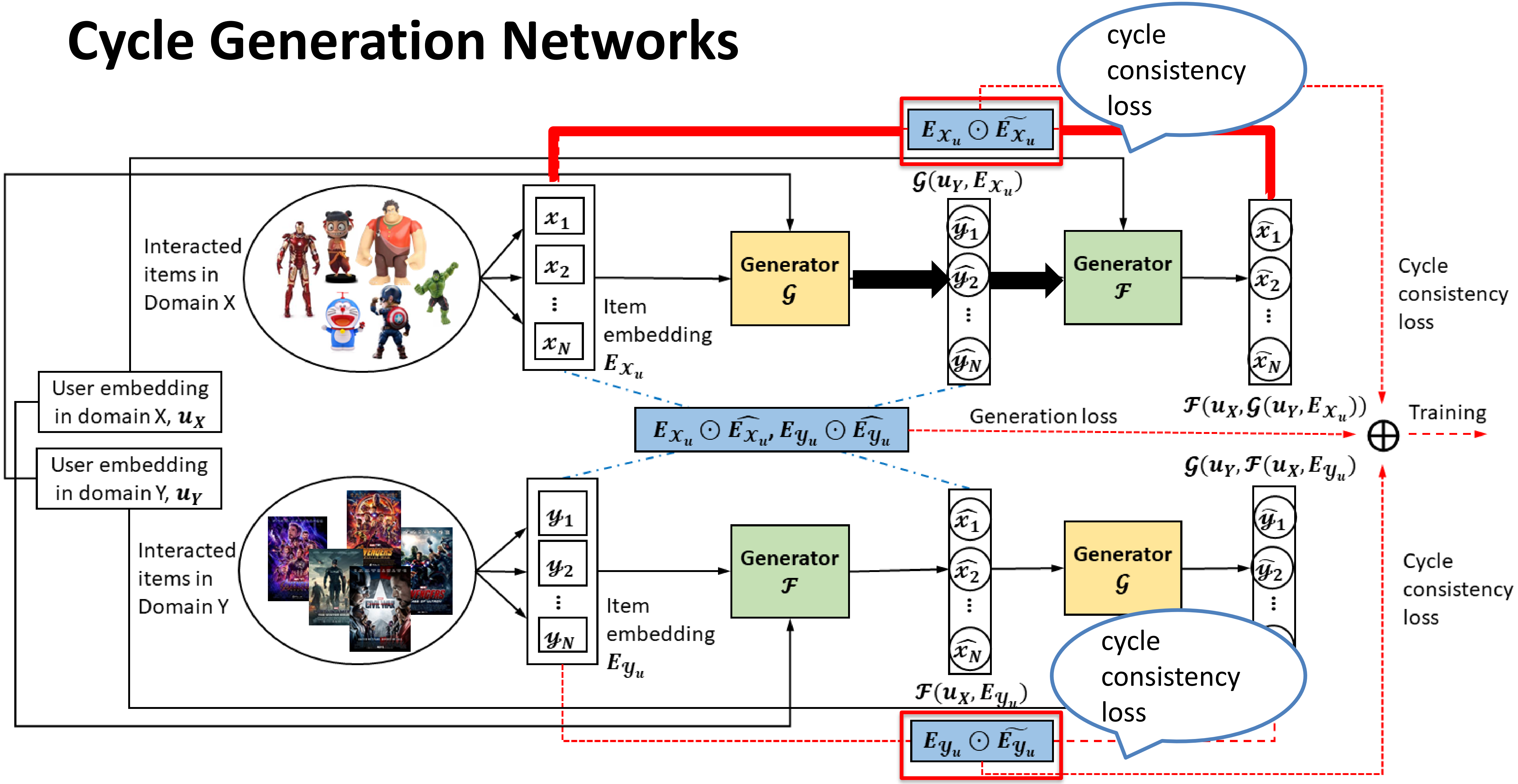
- generation loss
  - maximum mean discrepancy (MMD)

$$MMD(\boldsymbol{M}, \boldsymbol{E}) = \frac{1}{m^2}\sum_{i}^{m}\sum_{i'}^{m} k(\boldsymbol{M}_i, \boldsymbol{M}_{i'}) + \frac{1}{n^2}\sum_{j}^{n}\sum_{j'}^{n} k(\boldsymbol{E}_j, \boldsymbol{E}_{j'}) - \frac{2}{mn}\sum_{i}^{m}\sum_{j}^{n} k(\boldsymbol{M}_i, \boldsymbol{E}_j), \quad (1)$$

  - generation loss

$$\ell_{gen}(\boldsymbol{u}_X, \boldsymbol{u}_Y, \mathcal{X}_u, \mathcal{Y}_u) = MMD\Big(\mathcal{G}(\boldsymbol{u}_Y, \boldsymbol{E}_{\mathcal{X}_u}), \boldsymbol{E}_{\mathcal{Y}_u}\Big) + MMD\Big(\mathcal{F}(\boldsymbol{u}_X, \boldsymbol{E}_{\mathcal{Y}_u}), \boldsymbol{E}_{\mathcal{X}_u}\Big). \quad (2)$$

Cycle Generation Networks



Cycle Generation Networks

- cycle consistency loss
  - cycle consistency pattern

$$\mathcal{G}(\boldsymbol{u}_Y, \hat{\boldsymbol{E}}_{\mathcal{X}_u}) \rightarrow \mathcal{F}(\boldsymbol{u}_X, \mathcal{G}(\boldsymbol{u}_Y, \hat{\boldsymbol{E}}_{\mathcal{X}_u})) \approx \boldsymbol{E}_{\mathcal{X}_u}$$

$$\mathcal{F}(\boldsymbol{u}_X, \boldsymbol{E}_{\mathcal{Y}_u}) \rightarrow \mathcal{G}(\boldsymbol{u}_Y, \mathcal{F}(\boldsymbol{u}_X, \mathcal{Y}_u)) \approx \boldsymbol{E}_{\mathcal{Y}_u}$$

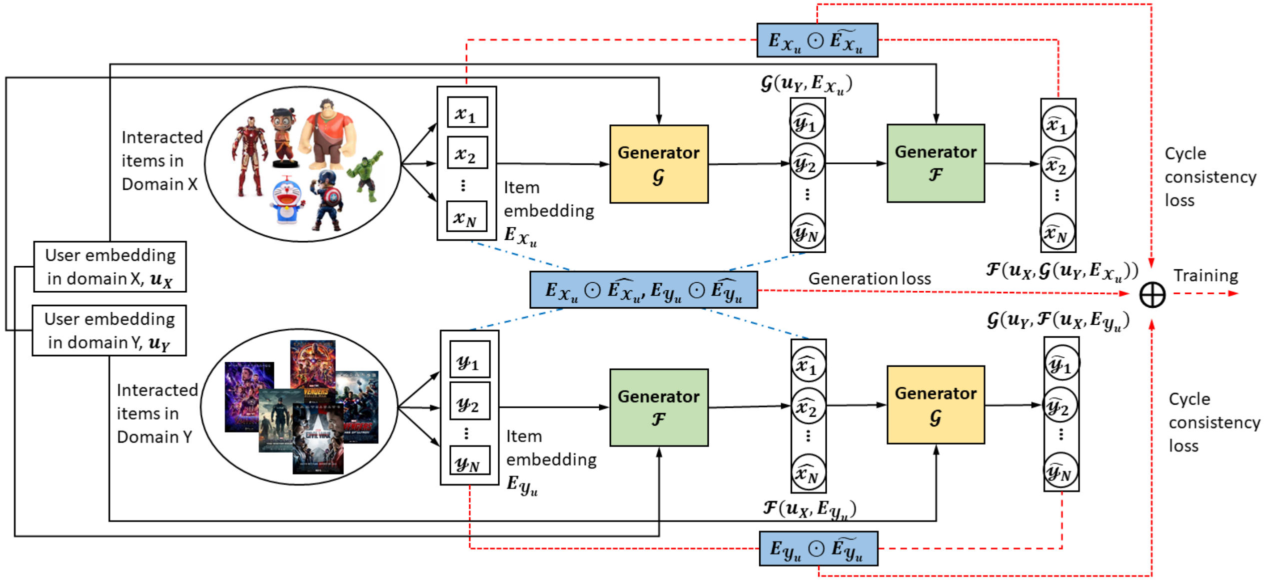
  - cycle consistency loss

$$\ell_{cyc}(\boldsymbol{u}_X, \boldsymbol{u}_Y, \mathcal{X}_u, \mathcal{Y}_u) = \left\| \mathcal{F}(\boldsymbol{u}_X, \mathcal{G}(\boldsymbol{u}_Y, \boldsymbol{E}_{\mathcal{X}_u})) - \boldsymbol{E}_{\mathcal{X}_u} \right\|_F^2 + \left\| \mathcal{G}(\boldsymbol{u}_Y, \mathcal{F}(\boldsymbol{u}_X, \boldsymbol{E}_{\mathcal{Y}_u})) - \boldsymbol{E}_{\mathcal{Y}_u} \right\|_F^2, \qquad (3)$$

Cycle Generation Networks

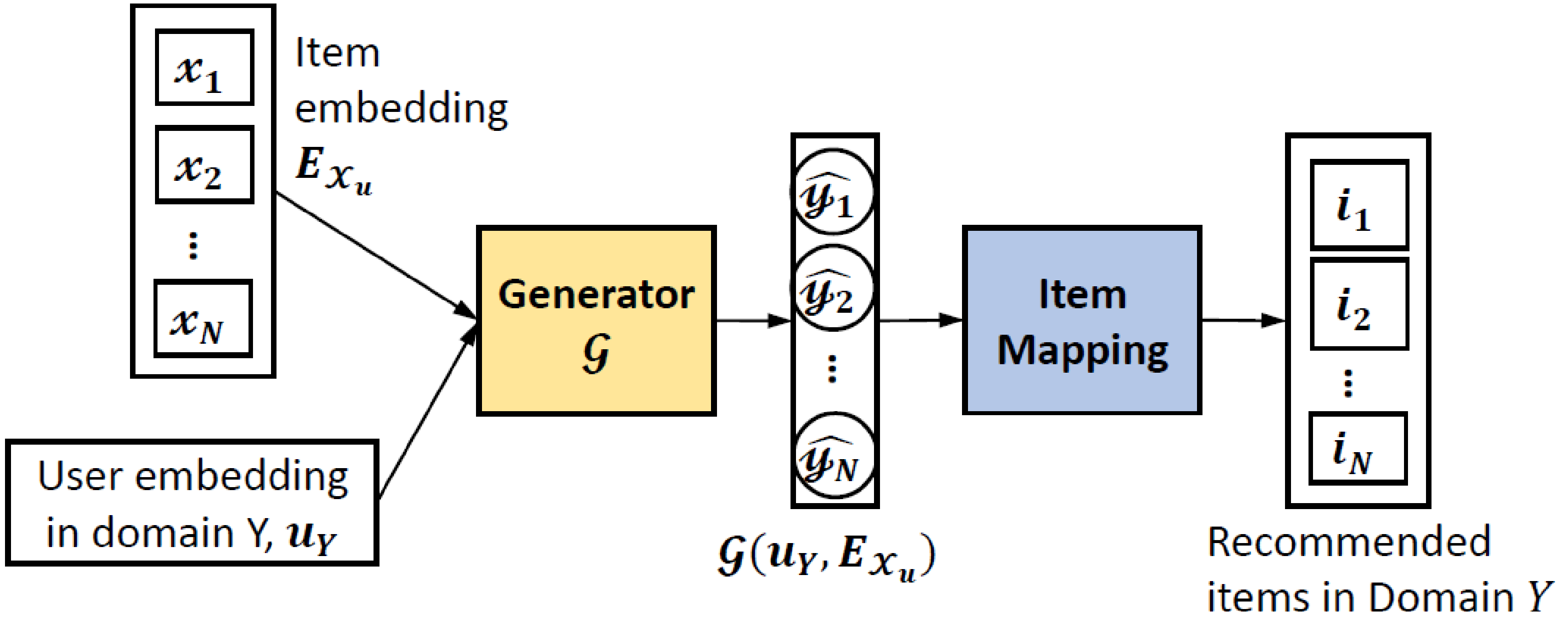
- Final loss function

$$\ell_{gen}(\boldsymbol{u}_X, \boldsymbol{u}_Y, \mathcal{X}_u, \mathcal{Y}_u) + \lambda \ell_{cyc}(\boldsymbol{u}_X, \boldsymbol{u}_Y, \mathcal{X}_u, \mathcal{Y}_u).$$



Cycle Generation Networks

- Recommendation Process



Experimental Settings

- Experimental datasets

Datasets	#Initial Users	#Initial Items	#Valid Users	#Valid Items	#Valid Inter.
Home	2,512 K	410 K	206	4,793	6,637
Clothing	3,117 K	1,136 K		6,159	6,525
Books	8,026 K	2,330 K	800	37,533	159,735
Movies	2,089 K	201 K		22,662	114,808

- Evaluation metrics
  - Hit Ratio (HR)
  - Precision
  - Recall

Experimental Results

Datasets	Metrics	BPRMF	Caser	CMF	CoNet	CGN$_{w/o\ UE}$	CGN$_{w/o\ Cycle}$	CGN
Source Domain: Clothing; Target Domain: Home	HR@5	0.1582	0.2260*	0.0113*	0.0622*	0.1695	0.1582	**0.2316**
	HR@10	0.2316	0.2486*	0.0226*	0.0735*	0.2316	0.2316	**0.2700**
	HR@20	**0.3277**	0.2768*	0.0339*	0.1469*	0.2825	0.3107	0.3220
	Precision@5	0.0757	0.0678*	0.0023*	0.0147*	0.1209	**0.1232**	0.1100
	Precision@10	0.0723	0.0514*	0.0023*	0.0090*	0.1113	0.1215	**0.1249**
	Precision@20	0.0715	0.0412*	0.0017*	0.0102*	0.0760	0.0783	**0.0900**
	Recall@5	0.0312*	0.0301*	0.0021*	0.0070*	**0.0655**	0.0651	0.0612
	Recall@10	0.0613*	0.0418*	0.0068*	0.0091*	0.1141	0.1203	**0.1267**
	Recall@20	0.1194	0.0600*	0.0110*	0.0297*	0.1339	0.1428	**0.1606**
Source Domain: Movies; Target Domain: Books	HR@5	0.0405	0.0544	0.0038*	0.0139*	0.0126	0.0708	**0.0777**
	HR@10	0.0683	0.0822	0.0101*	0.0405*	0.0240	0.0936	**0.1113**
	HR@20	0.0910	0.1113	0.0177*	0.0797*	0.0202	0.0961	**0.1290**
	Precision@5	0.0162	0.0134	0.0008*	0.0038*	0.0028	**0.0245**	0.0238
	Precision@10	0.0182	0.0124*	0.0010*	0.0051*	0.0028	0.0214	**0.0230**
	Precision@20	**0.0197**	0.0104	0.0010*	0.0051*	0.0013	0.0130	0.0181
	Recall@5	0.0017	0.0042	0.0003*	0.0009*	0.0005	0.0050	**0.0064**
	Recall@10	0.0045*	0.0081	0.0007*	0.0037	0.0013	0.0092	**0.0140**
	Recall@20	0.0088	0.0120*	0.0018*	0.0079*	0.0025	0.0071	**0.0165**

- Overall, these results indicate that CGN usually achieves superior performance in terms of most evaluation metrics, comparing with all baselines.
- Both users' personalized preferences and the cycle consistency loss can help improve recommendation.

Experimental Results

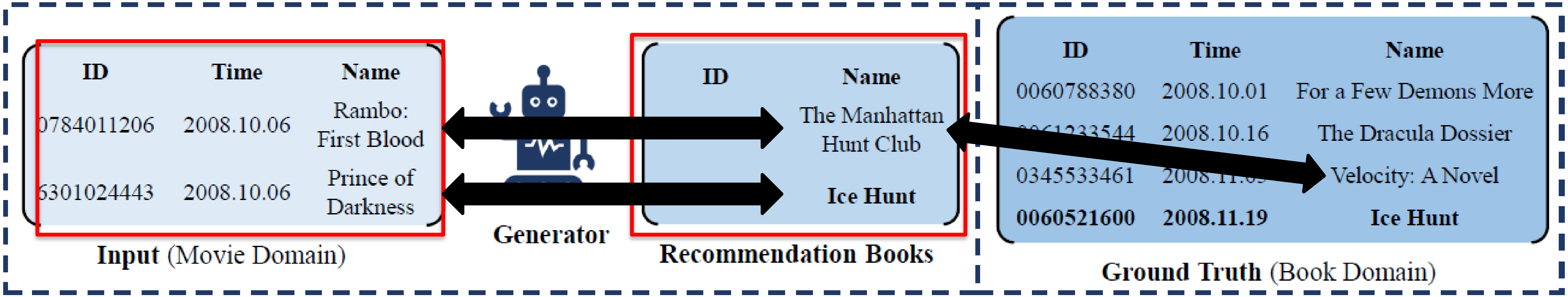


Figure 5: A case study of cross-domain recommendation showing the effectiveness of the proposed CGN model.

- Both "Rambo: First Blood" and "The Manhattan Hunt Club" talk about crime.
- Both "Prince of Darkness" and "Ice Hunt" are about the doomsday theme.

Experimental Results

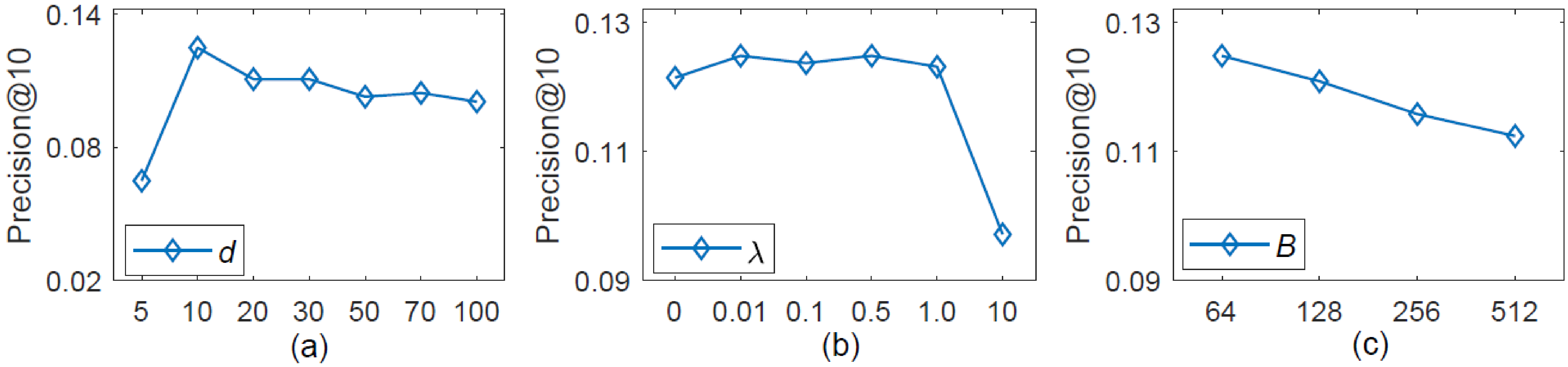


Figure 4: The recommendation accuracy of CGN with respect to different settings of d, λ, and B, measured by Precision@10.

- The best performance is achieved when dimension d is set to 10.
- The recommendation accuracy can be improved by incorporating cycle consistency loss in training the generator networks.
- Better results can be usually achieved by using a smaller batch size (e.g., B=64).

Conclusion

- We propose a novel cross-domain recommendation model(CGN), which learns a user's personalized mapping between her interaction itemsets in different domains at the same temporal period.

- We perform extensive experiments on four real-world datasets to demonstrate the effectiveness of CGN. CGN usually outperforms baseline methods in terms of all metrics.


Thank you!