Item Silk Road: Recommending Items from Information Domains to Social Users

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Online Platforms

≈

Forums & E-commerce sites

amazon
tripadvisor
IMDb
foursquare

Ample User-Item Interactions

→ **Information-oriented Domains**

+

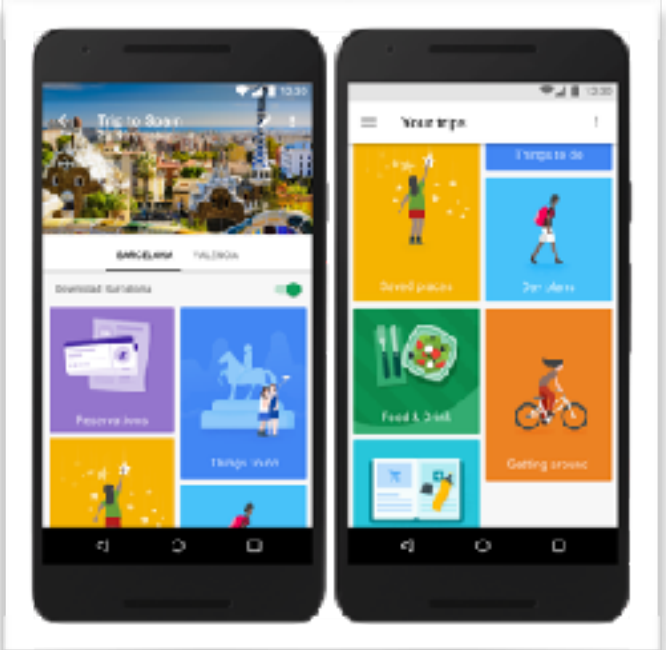
Social Networking Services

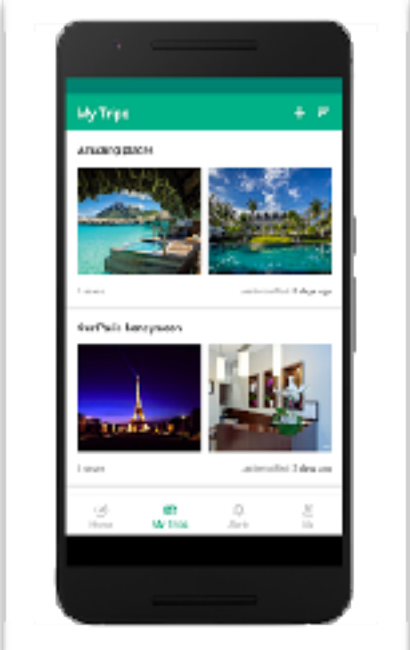
twitter
facebook
LinkedIn

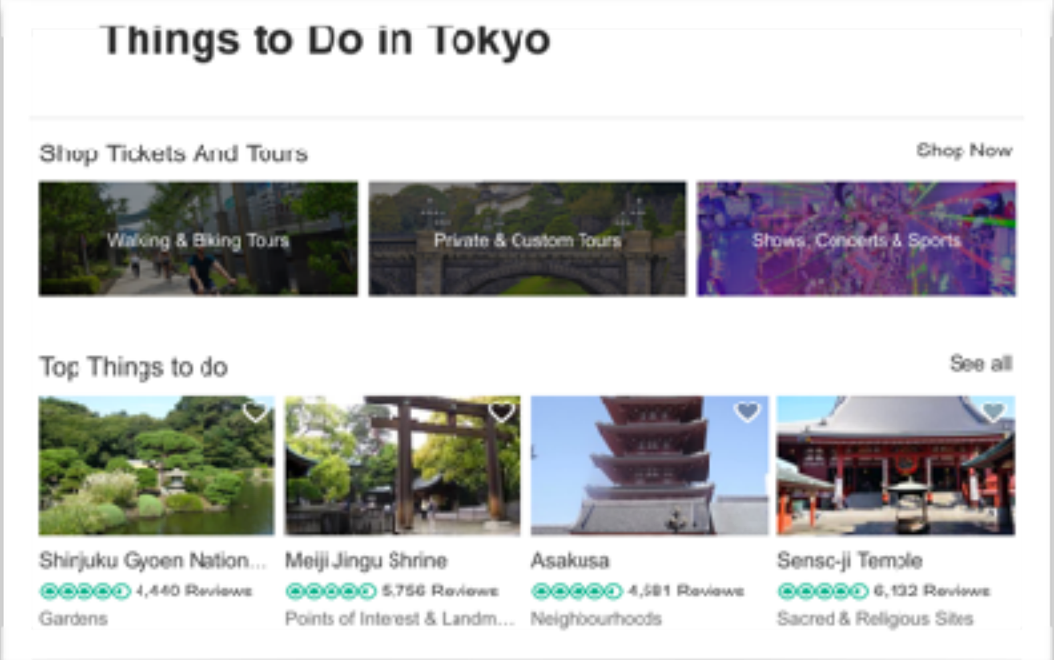
Rich User-User Social Relations

→ **Social-oriented Domains**

Recommendation





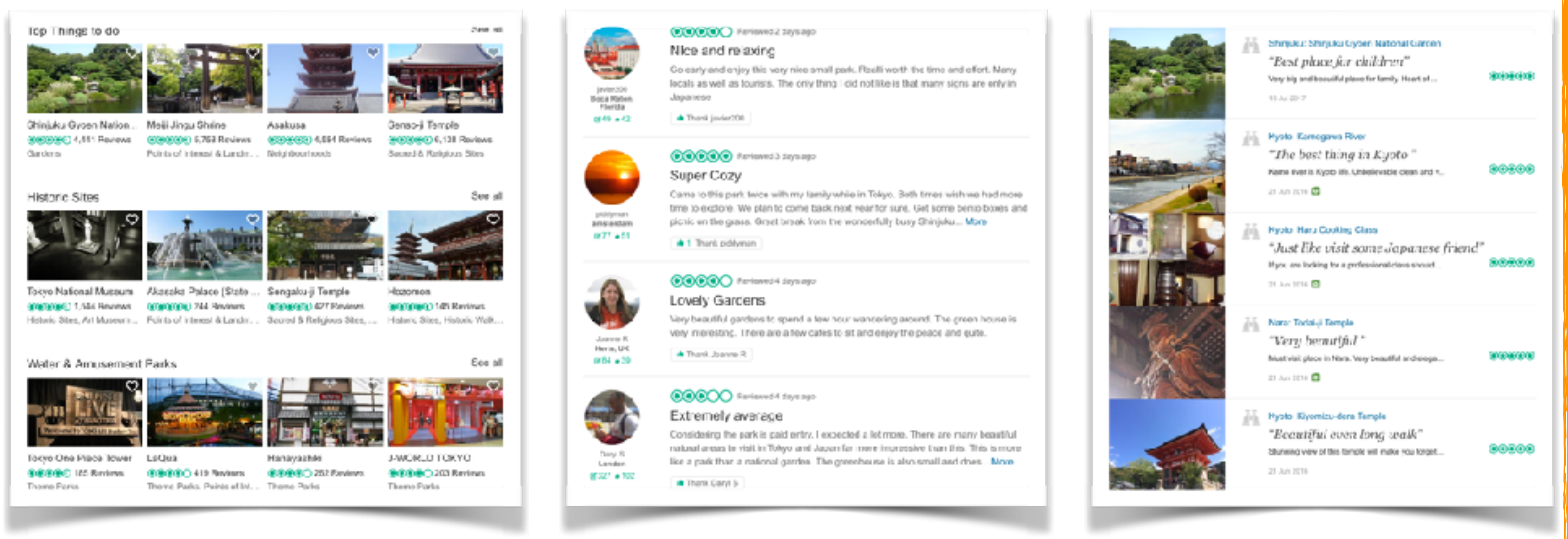


Consulting the information sites

Gathering information from experienced friends

Information-oriented Domains

As a user of information sites



Item set | Others' Reviews | Personal Reviews

Ample User-Item Interactions

- Real valued explicit ratings
- Binary 0/1 implicit feedbacks

Feature Matrix X | **Target Y**

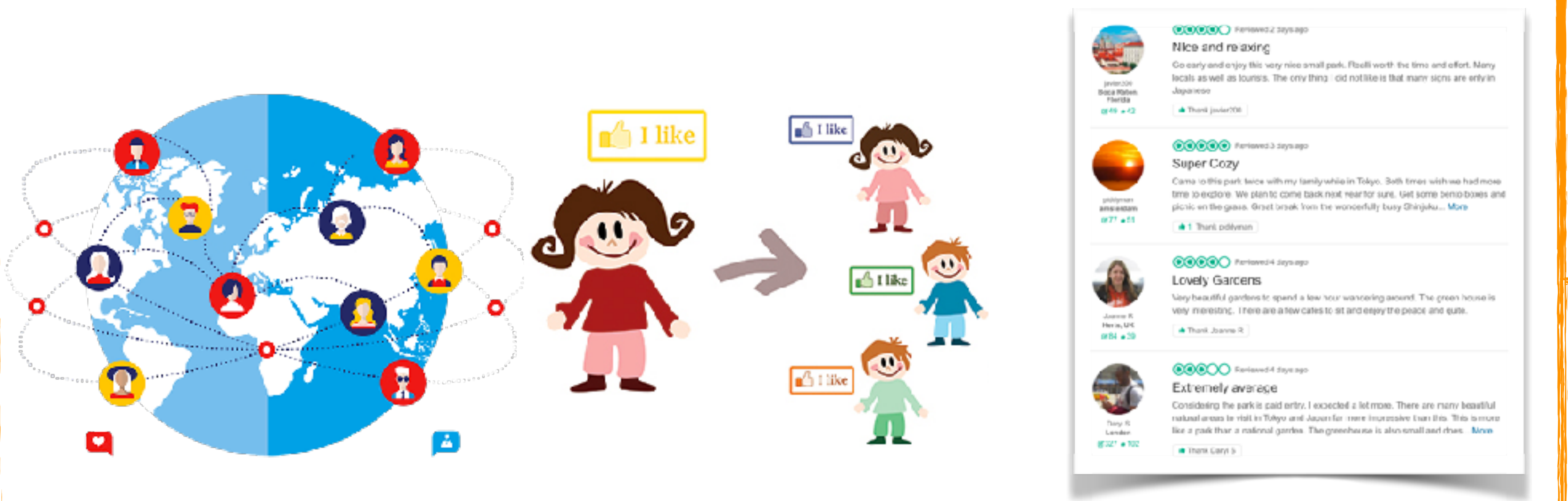
	1	0	...	1	1	...		1
Item	1	0	...	0	?	...		1
	0	1	...	1	0	...		0
	0	1	...	0	1	...		1
					User			

Traditional Recommendation Methods!

- Collaborative Filtering
  - Matrix Factorization
  - Factorization Machines
  - ...

Social-oriented Domains

As a user on social networks



Social Relations　　Info Propagation　　User Preference

Rich User-User Social Relations

- Friendship
- Following/Follower
- Weighted Similarity

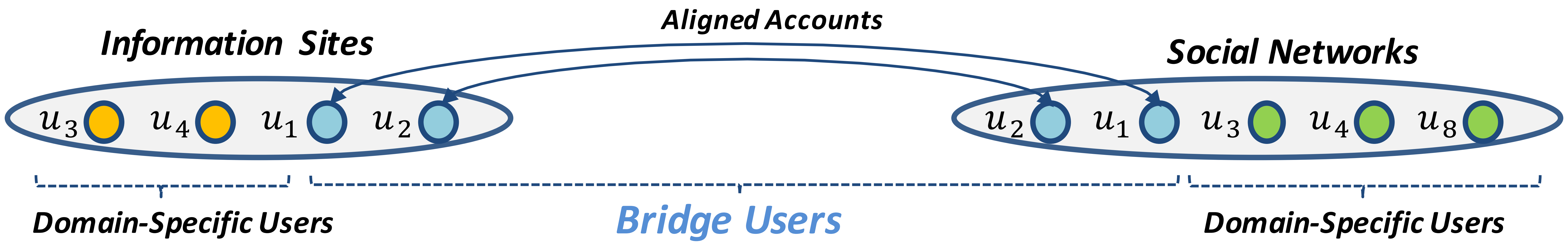
Feature Vector *X*

	1	0	...	1	1	...
Item	1	0	...	0	?	...
	0	1	...	1	0	...
	0	1	...	0	1	...
					User	

Scarcity of User-Item Interactions

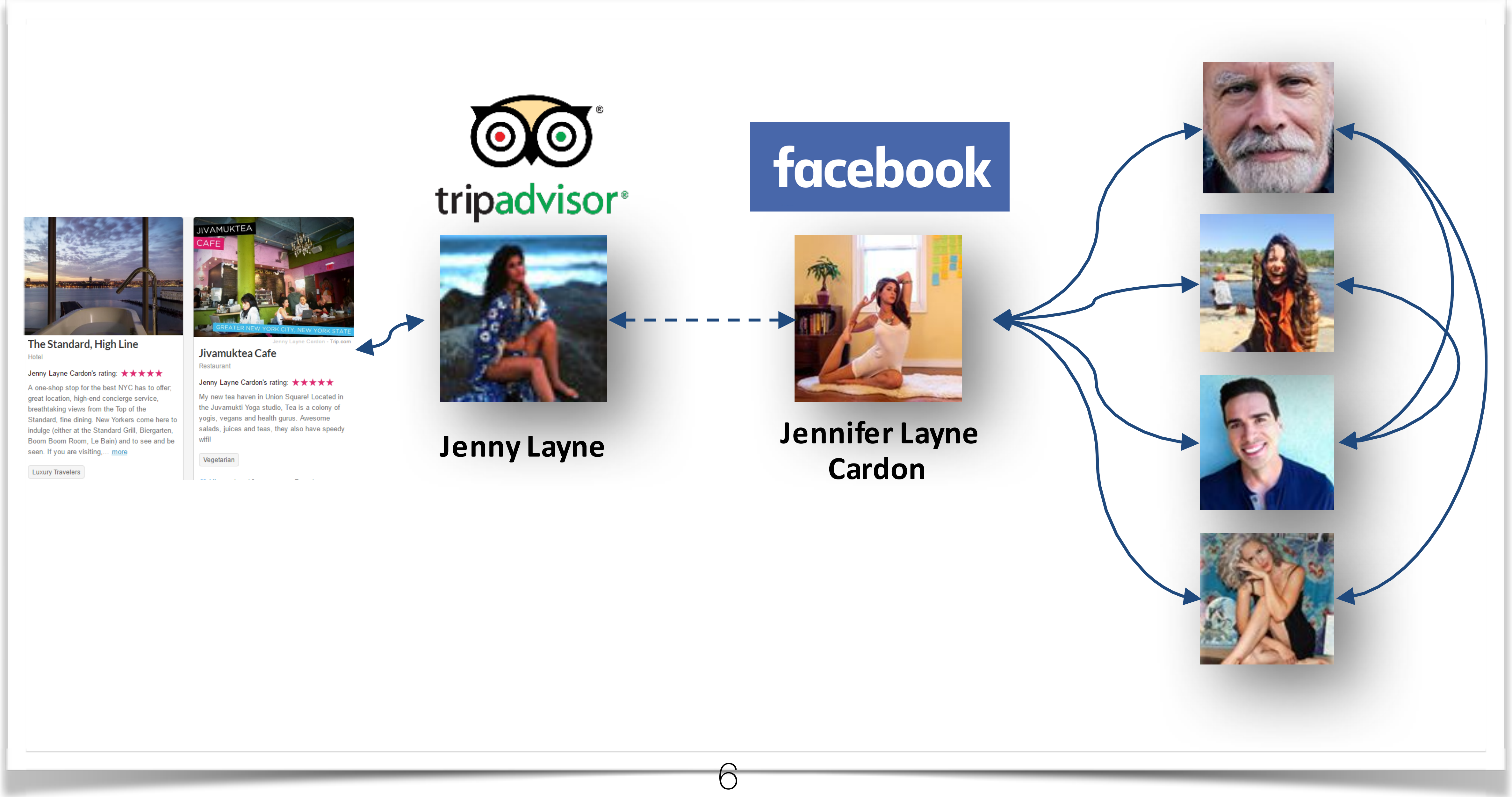
- Not focus on seeking options regarding items
- Only item names & BRIEF info/opinion

Bridge Users

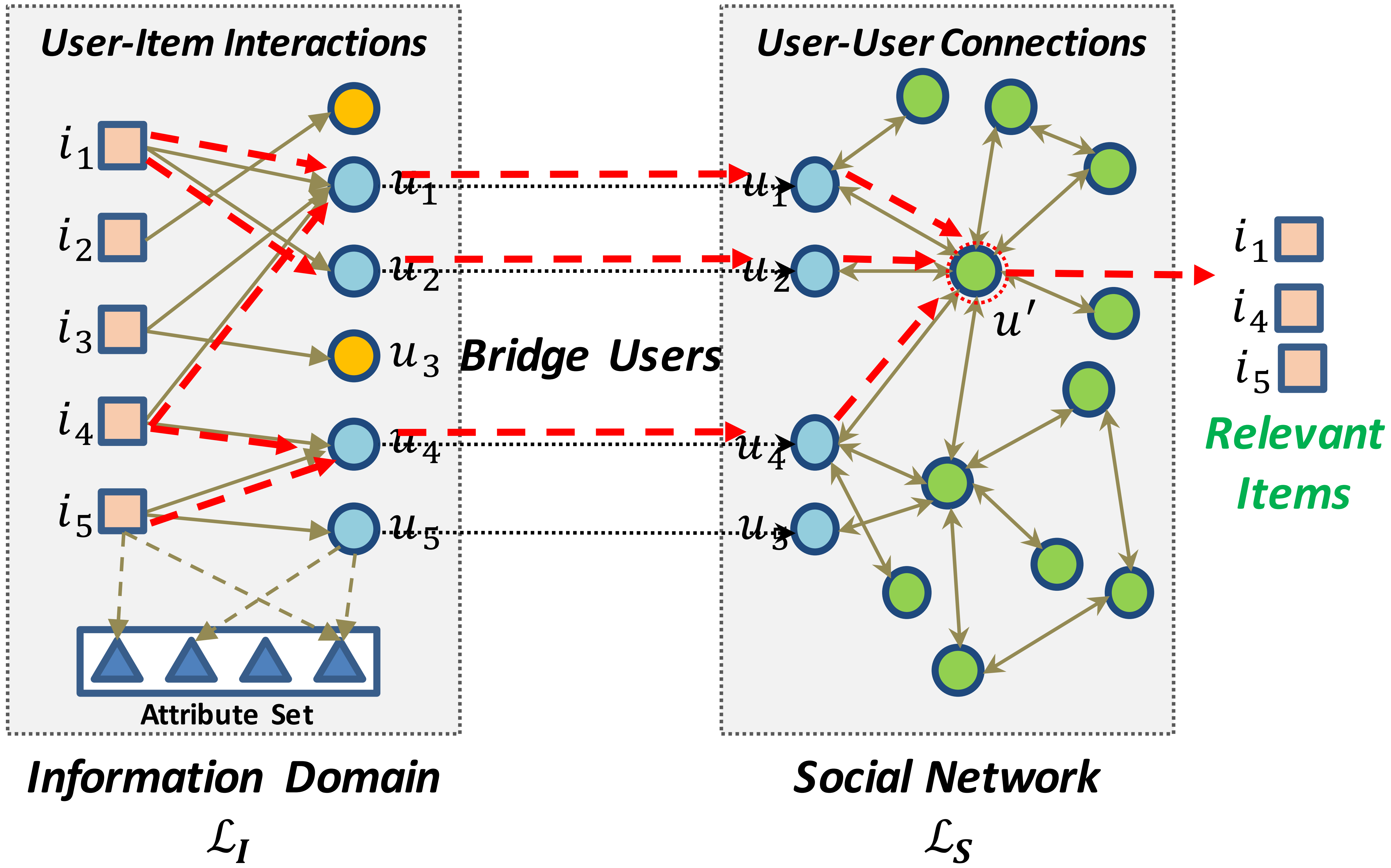


Simultaneously Involved Two Domains

Acting as a bridge to propagate user-item interaction across domains



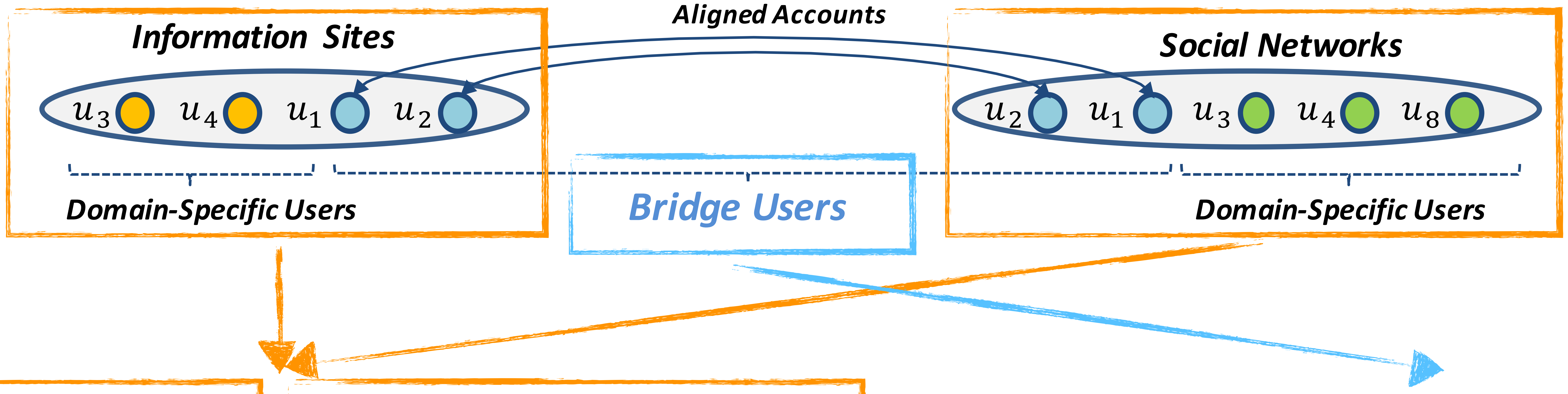
Cross-Domain Social Recommendation

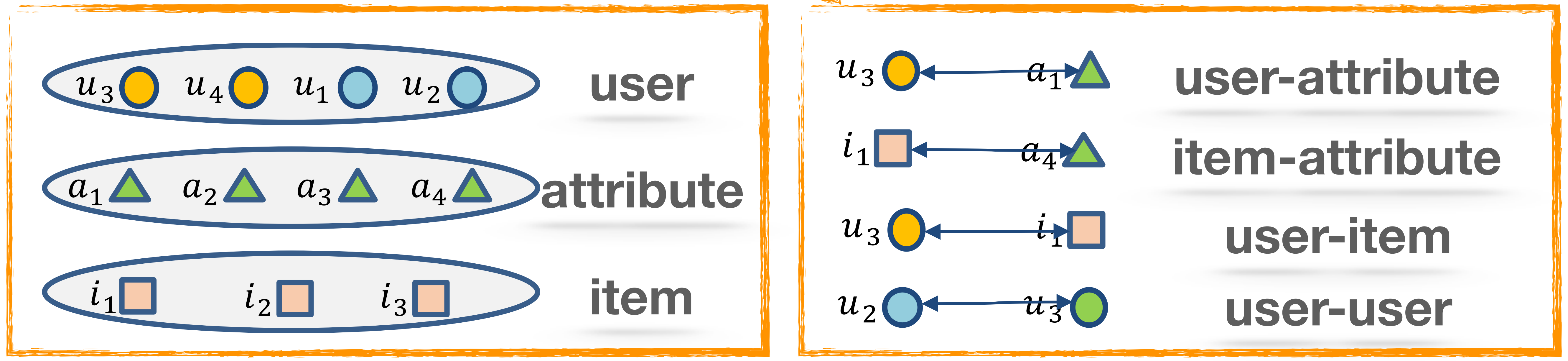


Cross-Domain Social Recommendation

- Recommend relevant items of information domains to the users of social domains
- Work as Item Silk Road

Why Challenging?





	Facebook-Trip	Twitter-Trip
Percentage of Bridge Users	10.468%	5,420%

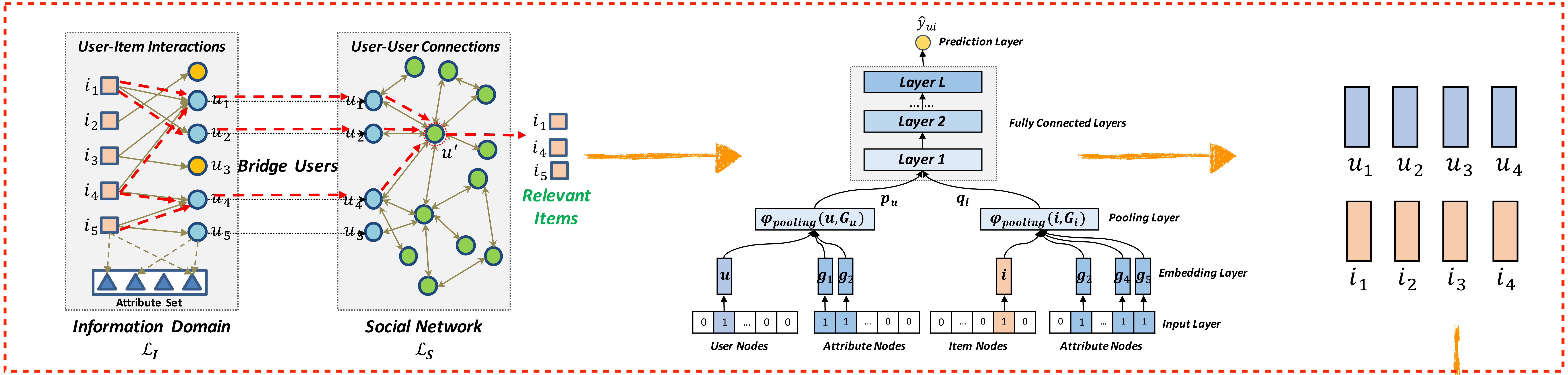
Heterogeneous Domains

- Various entities
- Various relations
  - *jerry {luxury travel, art lover}*
  - *marina bay sands {luxury travel, nightlife}*

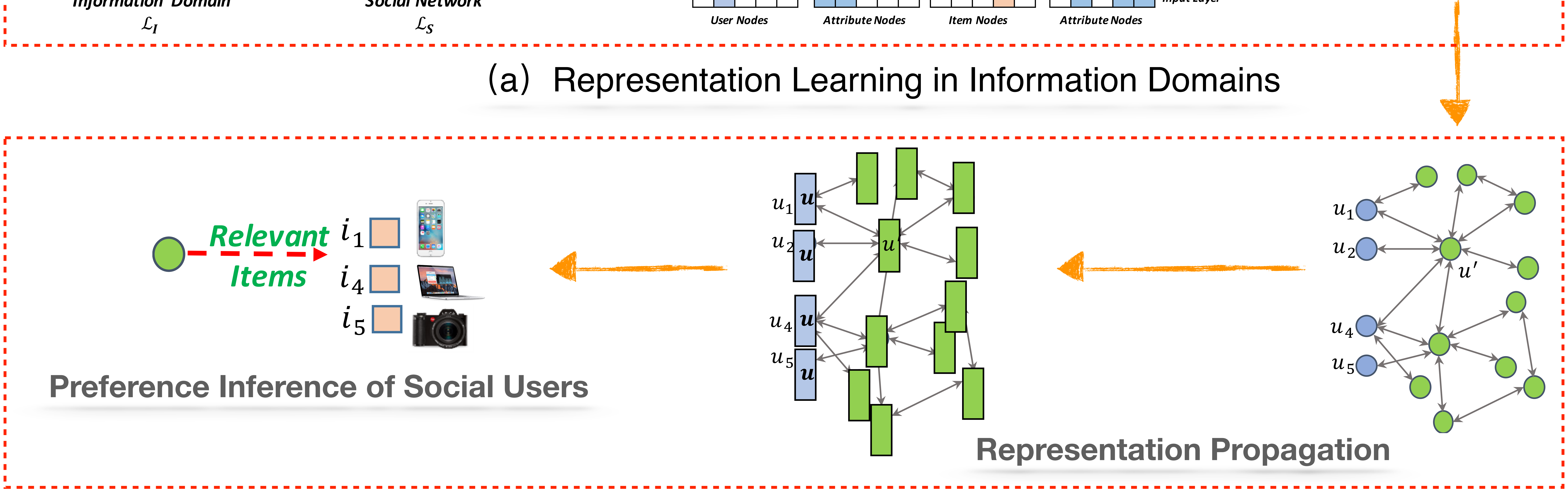
Weak Connection

- Partially overlapped
- Insufficient Bridge Users

Our Framework

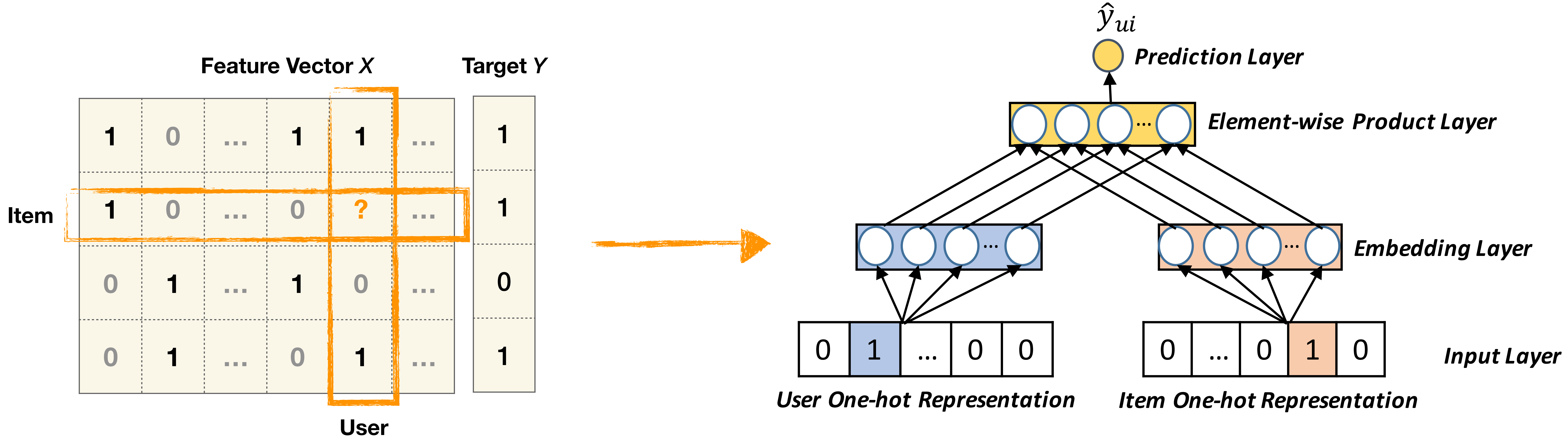


(a) Representation Learning in Information Domains



(a) Representation Propagation & Preference Inference in Social Domains

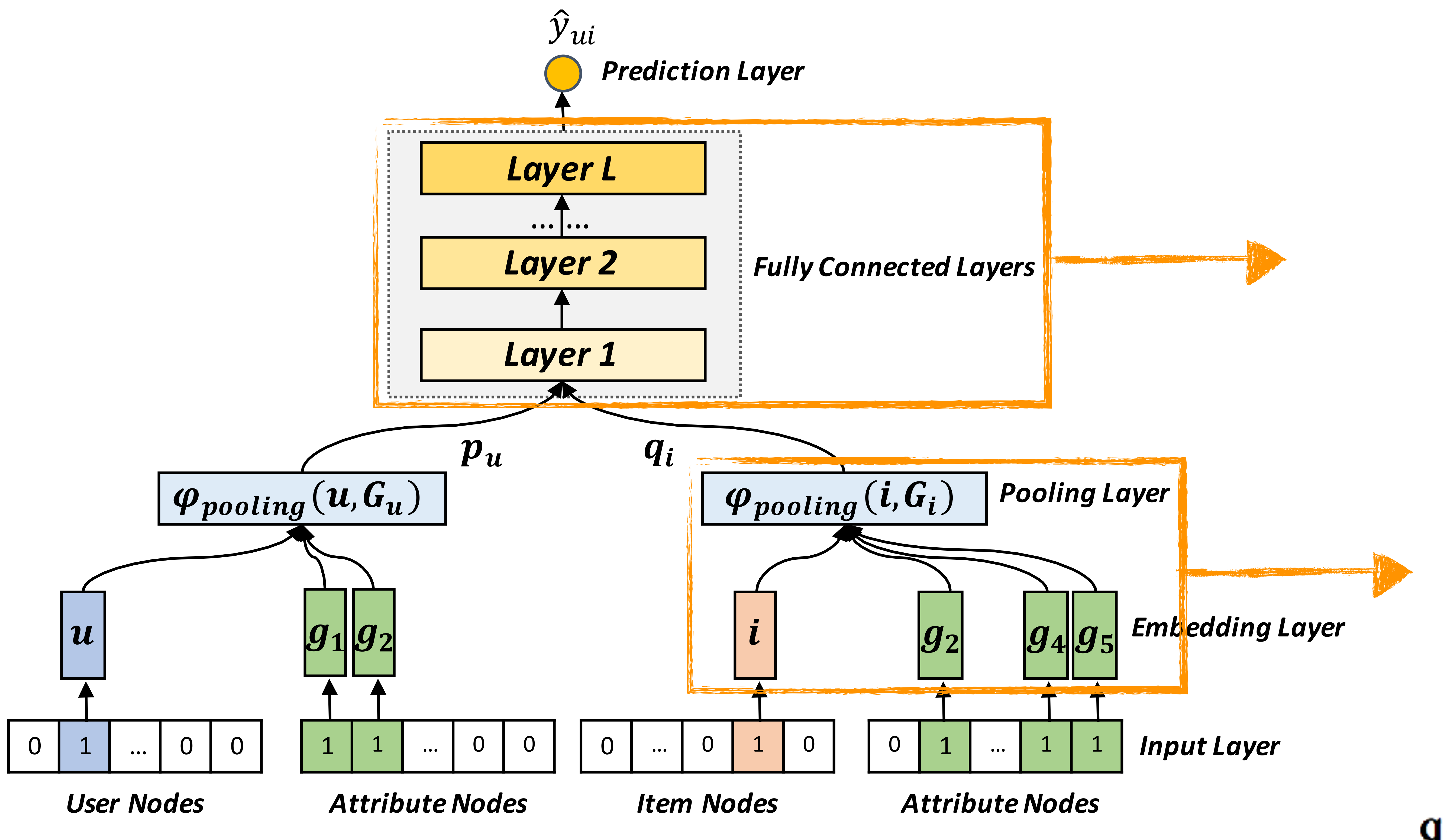
Collaborative Filtering



Collaborative Filtering (CF)

- **Assumption**
  - Similar users would have similar preference on items.
- **Matrix Factorization (MF):**
  - It characterises a user or an item with a latent vector;
  - It then model a user-item interaction as the inner product of their latent vectors.

Attribute-aware Neural CF



"Deep Layers"

- capture the nonlinear & higher-order correlations among users, items, & attributes

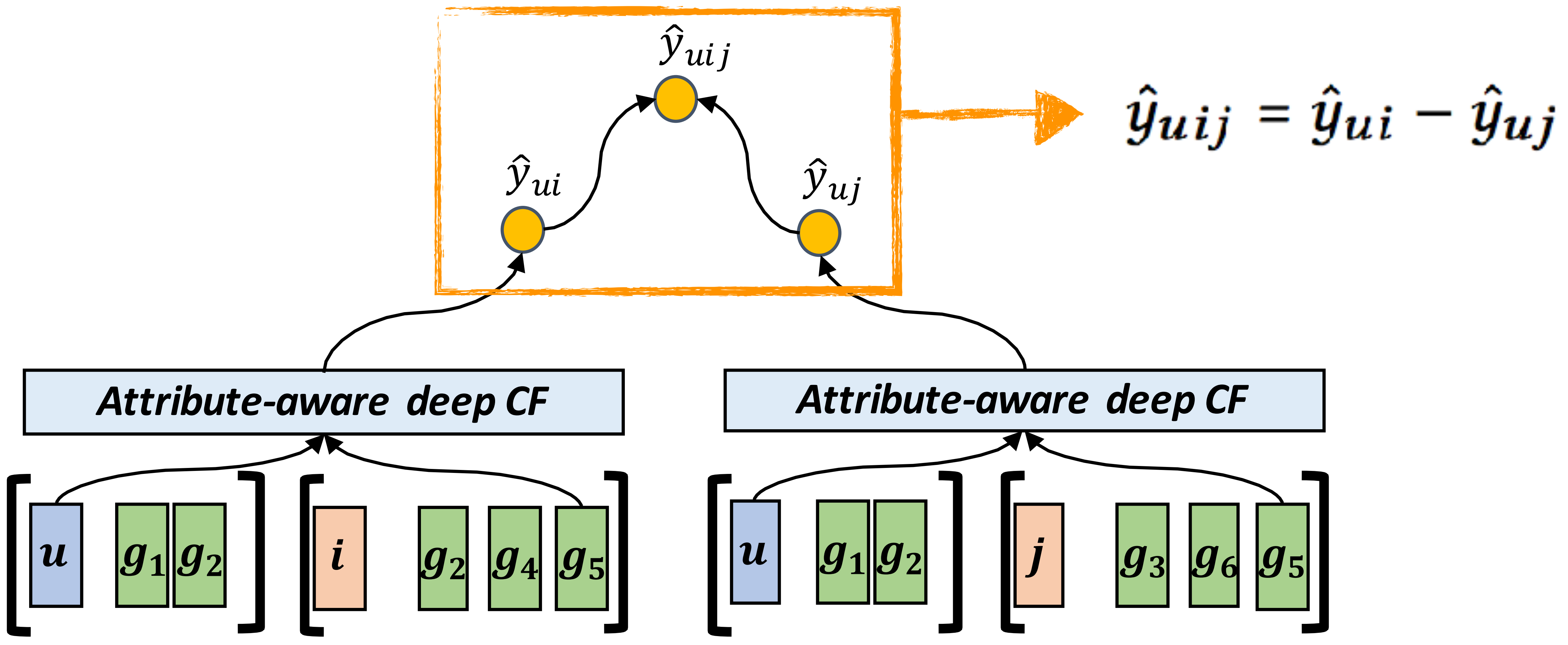
Pairwise Pooling

- model the pairwise correlation between a user (or item) & her attributes, and all nested correlations among attributes.

$$\mathbf{q}_i = \varphi_{pairwise}(\mathbf{i}, \{\mathbf{g}_t^i\}) = \sum_{t=1}^{V_i} \mathbf{i} \odot \mathbf{g}_t^i + \sum_{t=1}^{V_i} \sum_{t'=t+1}^{V_i} \mathbf{g}_t^i \odot \mathbf{g}_{t'}^i$$

$$\mathbf{p}_u = \varphi_{pairwise}(\mathbf{u}, \{\mathbf{g}_t^u\}) = \sum_{t=1}^{V_u} \mathbf{u} \odot \mathbf{g}_t^u + \sum_{t=1}^{V_u} \sum_{t'=t+1}^{V_u} \mathbf{g}_t^u \odot \mathbf{g}_{t'}^u$$

Pairwise Loss Function



Pairwise Objective Function

- concerns the relative order between the pairs of observed & unobserved interactions.

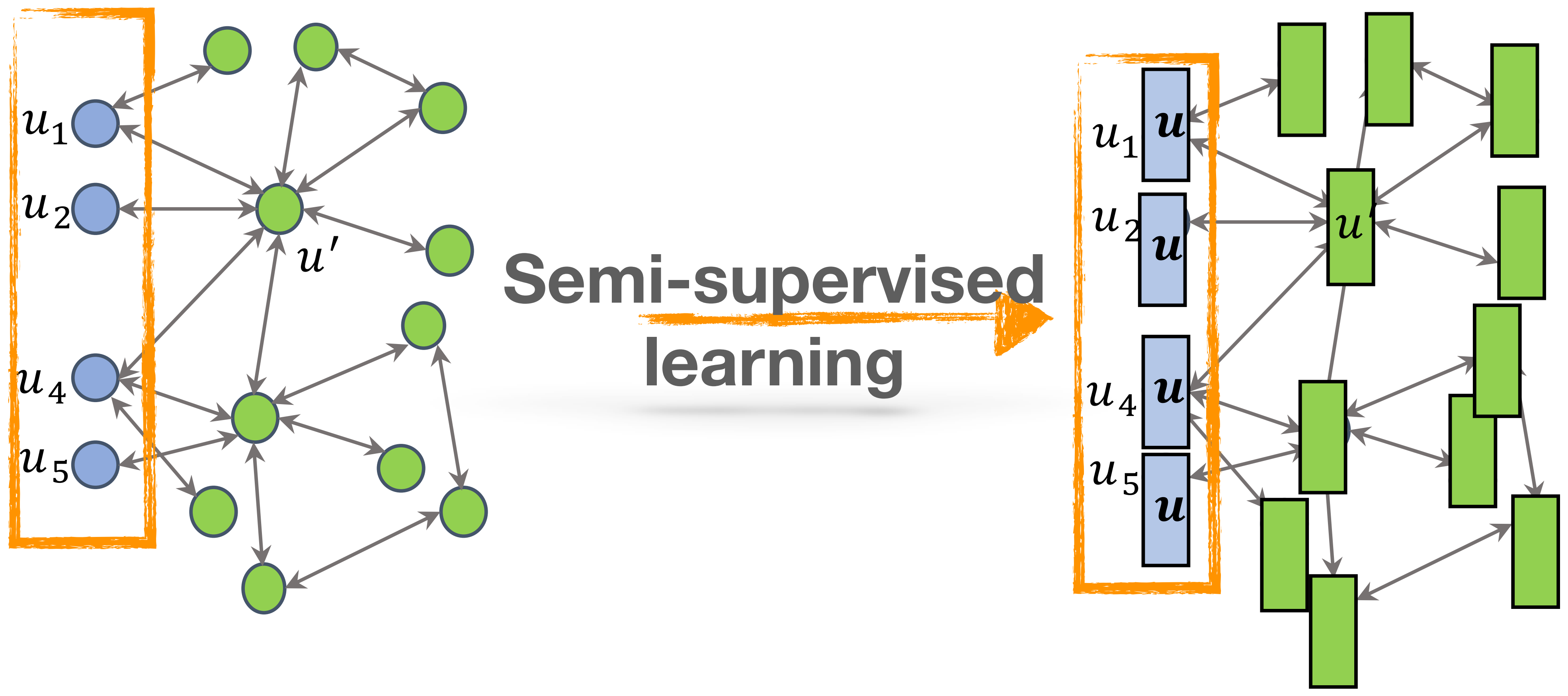
$$\mathcal{L}_I = \sum_{(u,i,j)\in O} \mathcal{L}(y_{uij}, \hat{y}_{uij})$$

Regression-based Ranking Loss

- other pairwise ranking functions can also be applied, such as BPR.

$$\mathcal{L}_I = \sum_{(u,i,j)\in O} (y_{uij} - \hat{y}_{uij})^2 = \sum_{(u,i,j)\in O} (\hat{y}_{ui} - \hat{y}_{uj} - 1)^2$$

Representation Propagation



$$
\begin{cases}
\mathbf{e}_1 = \sigma_1(\mathbf{W}_1(\mathbf{p}_{u'} \odot \mathbf{q}_i) + \mathbf{b}_1) \\
\cdots\cdots \\
\mathbf{e}_L = \sigma_L(\mathbf{W}_L \mathbf{e}_{L-1} + \mathbf{b}_L) \\
\widehat{y}_{u'i} = \mathbf{w}^\top \mathbf{e}_L
\end{cases}
$$

Smoothness

- Structural consistency:
  - the nearby vertices of a graph should not vary much in their representations.

$$\theta(\mathcal{U}_2) = \frac{1}{2} \sum_{u', u'' \in \mathcal{U}_2} s_{u'u''} \left\| \frac{\mathbf{p}_{u'}}{\sqrt{d_{u'}}} - \frac{\mathbf{p}_{u''}}{\sqrt{d_{u''}}} \right\|^2$$

Fitting

- Latent space consistency:
  - the representations of bridge users should be invariant & act as ***anchors*** across domains.

$$\theta(\mathcal{U}) = \frac{1}{2} \sum_{u' \in \mathcal{U}} \left\| \mathbf{p}_{u'} - \mathbf{p}_{u'}^{(0)} \right\|^2$$

Dataset

Information-oriented Domains

Social-oriented Domains

Trip.com

- attractions as items
- tags (attraction mode & travel preference) as attributes

Facebook & Twitter

- friendship & following/follower as social relations

Information Domain	User#	Item#	Interaction#
Trip.com	6,532	2,952	93,998
SNSs	**Bridge User#**	**Social User#**	**Social Connection#**
Twitter	502	7,233	42,494
Facebook	858	8,196	49,156

Experiments

RQ1: Cross-Domain Social Recommendation

RQ2: Effect of Different Parameter Settings

RQ3: Effect of Deep Layers

Data Split based on Bridge Users

- 60% bridge users + all non-bridge users for training
- 20% bridge users for validation and testing, respectively

Evaluation Metrics

- AUC & Recall@5 (larger score, better performance)

Baselines

- Item Popularity (ItemPop)
- Matrix Factorization (MF)
- Factorization Machine (FM)
- Social Recommendation (SR)
- Neural Social Collaborative Ranking (NSCR)

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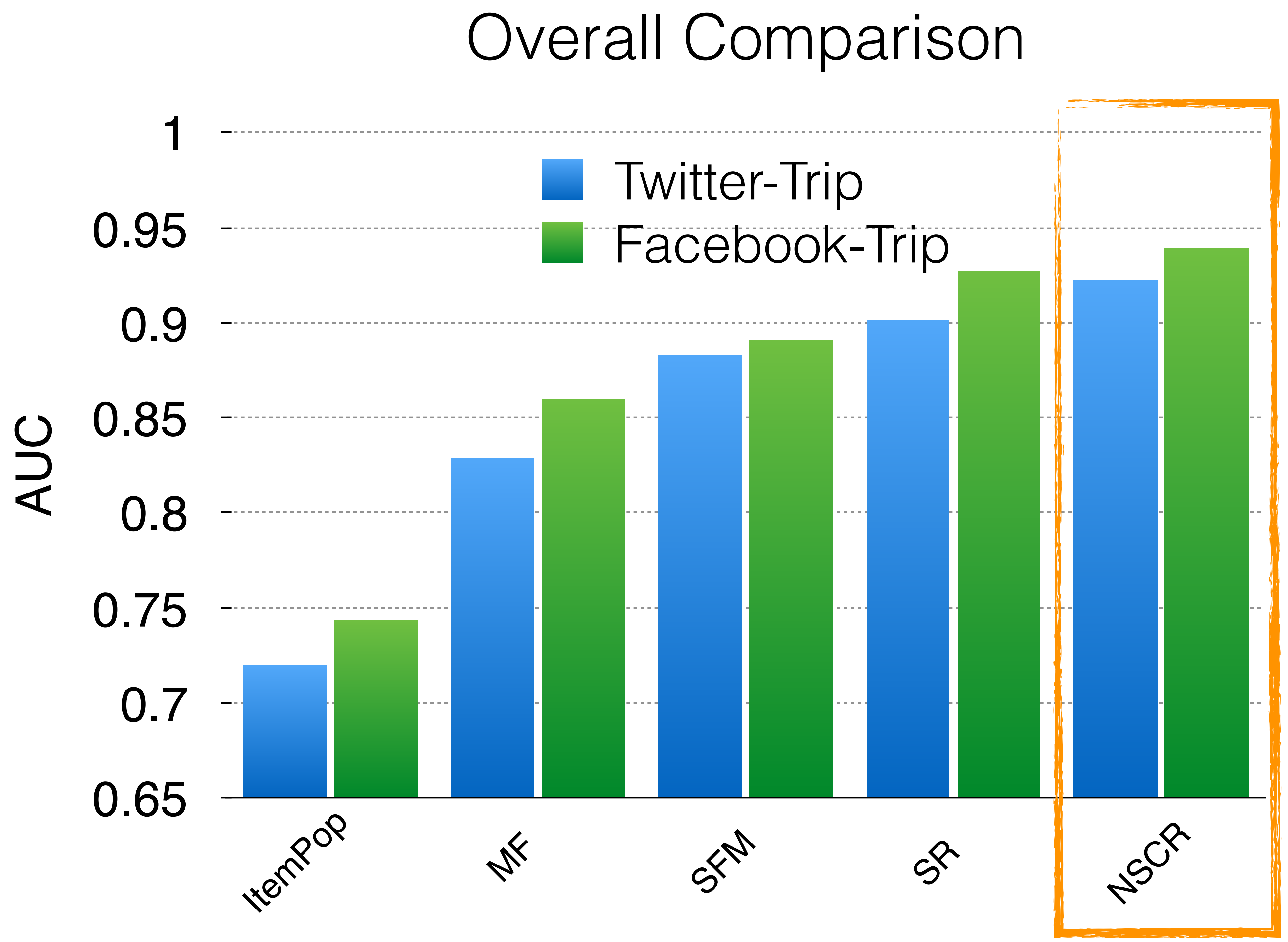
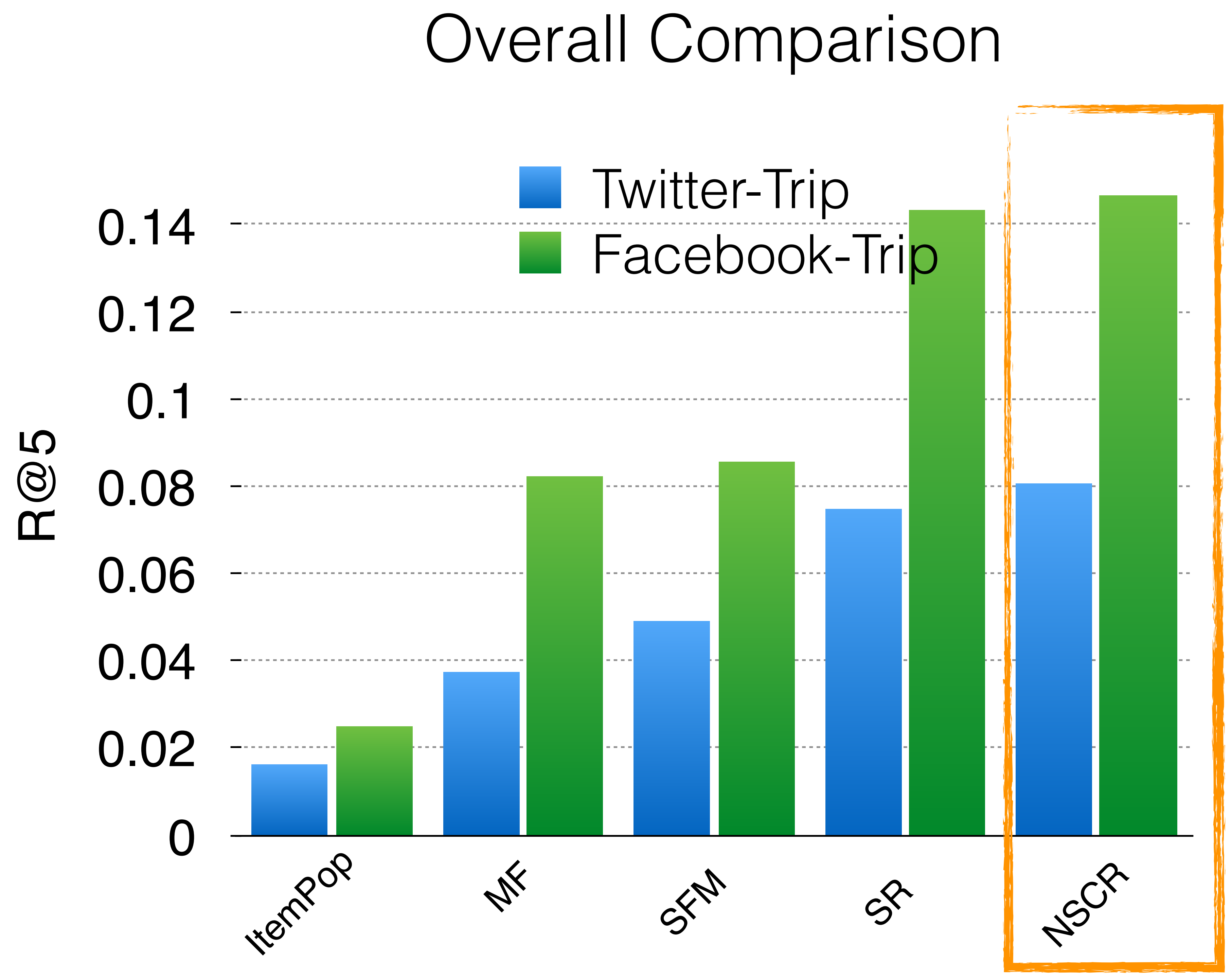
I. Personalised Travel Recommendation

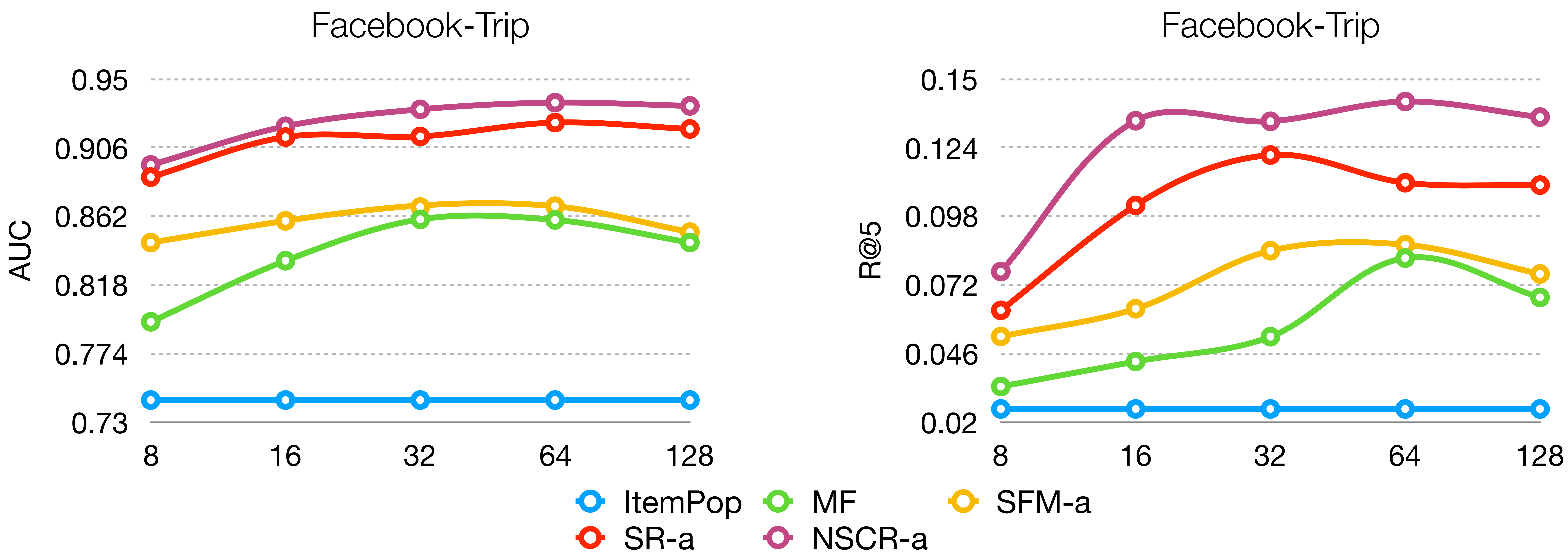




Insights

- **the necessity of personalised preference & attributes**
  - **ItemPop & MF are the worst.**
- **the significance of bridge users**
  - **Facebook-Trip > Twitter-Trip**

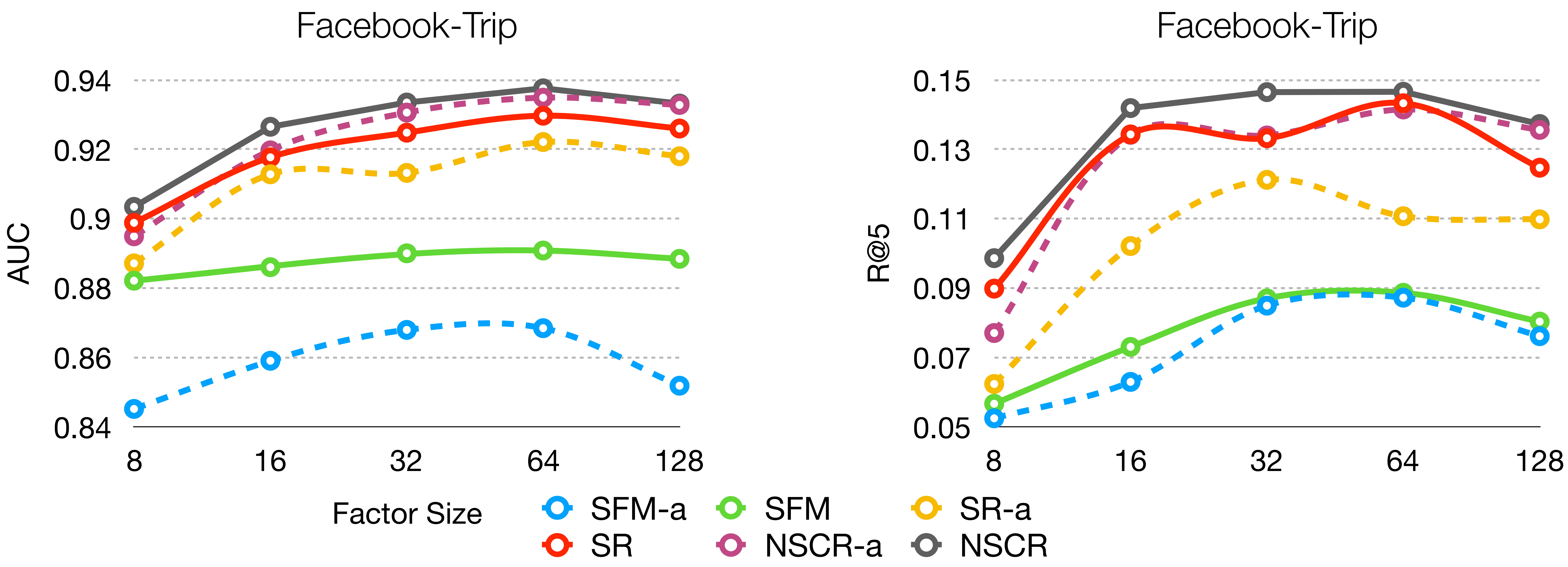
II. Effect of Social Modelling



Insights on social modelling

- **SFM-a overlooks the exclusive features of social networks.**
  - SR-a > SFM-a
- **the significance of normalised graph Laplacian**
  - NSCR-a > SR-a

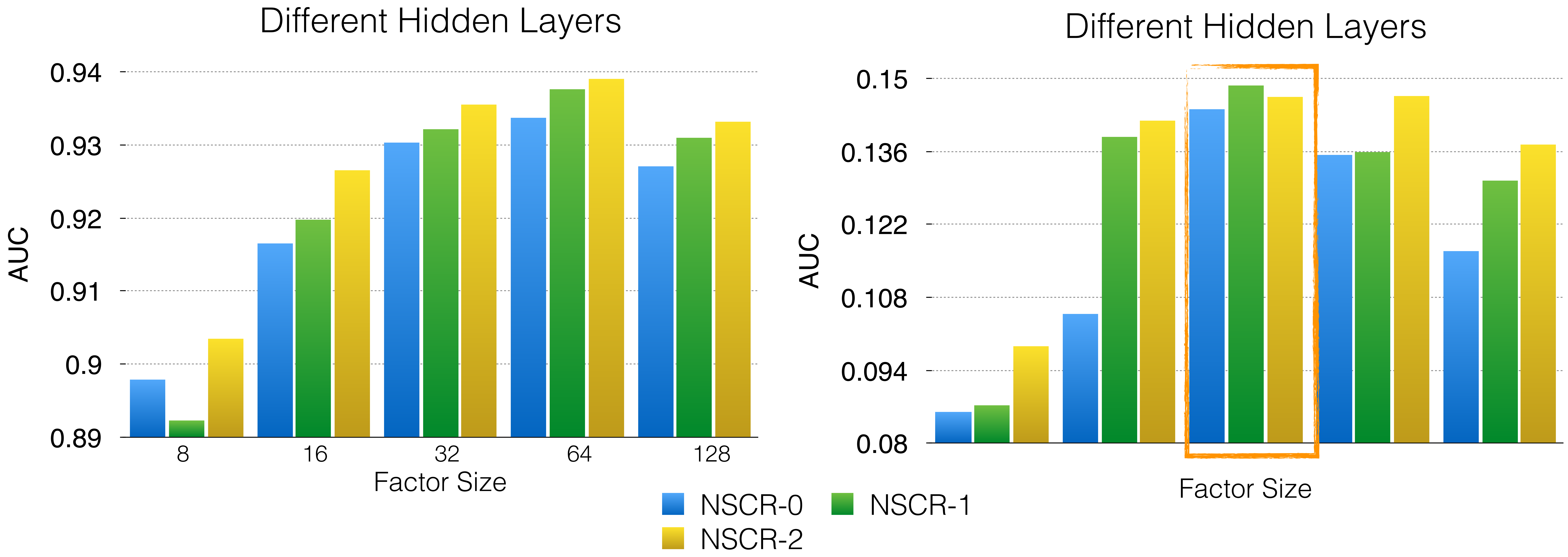
III. Effect of Attribute Modelling



Insights on attribute modelling

- **All models can achieve improvements.**
- **Large embedding size may cause overfitting. (64 for AUC, 32 for R@5)**

IV. Effect of Deep Layers



Insights on deep layers

- **Stacking hidden layers is helpful & has a strong capability.**
- **Using a large number of embedding size has powerful representation ability.**

Conclusion

Contribution-1

What have done

Cross-domain social recommendation

* bridge users
* recommendation across domains

Future Work

consider weak connections (*e.g.*, contextual signals) across domains.

Contribution-2

What have done

Neural social collaborative ranking

* attribute-aware deep CF
* representation propagation

Future Work

involve attributes of social users (demographics & personality).

Contribution-3

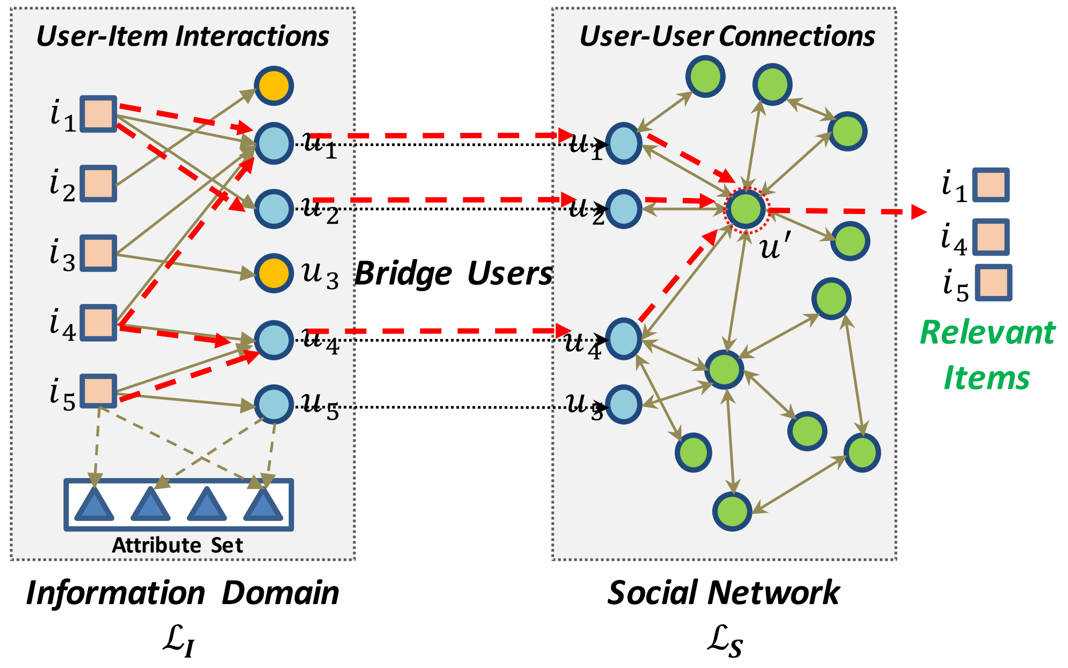
What have done

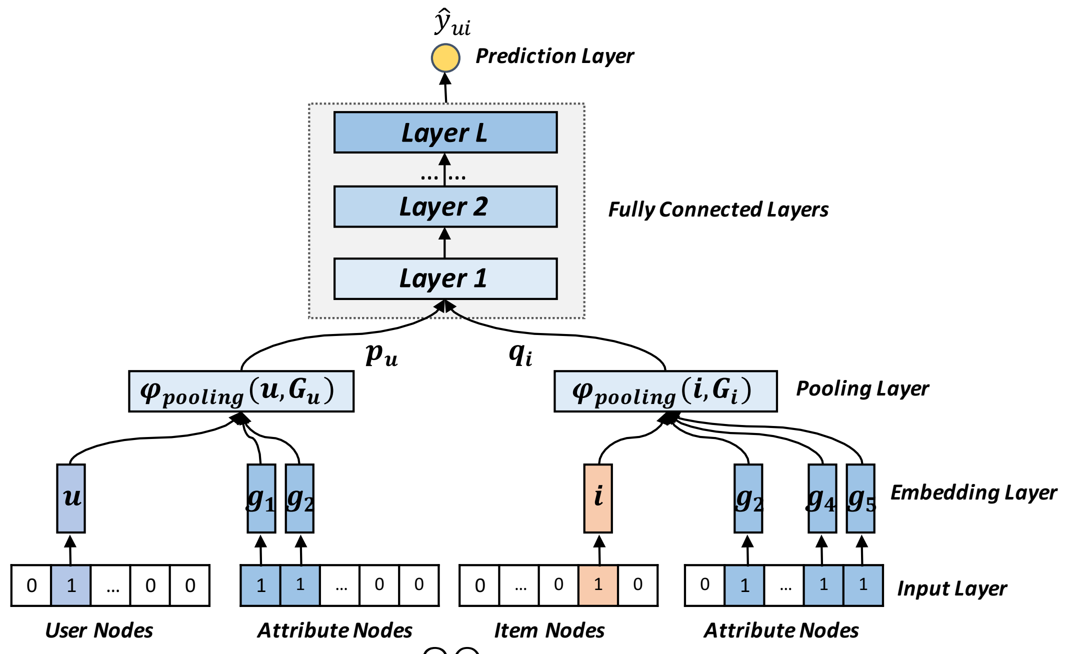
Dataset

* Trip.com
* Facebook/Twitter

Future Work

enlarge the datasets & evaluate on non-bridge users





Q&A