Graph Neural Networks for social recommendation

Hoang Thi Linh

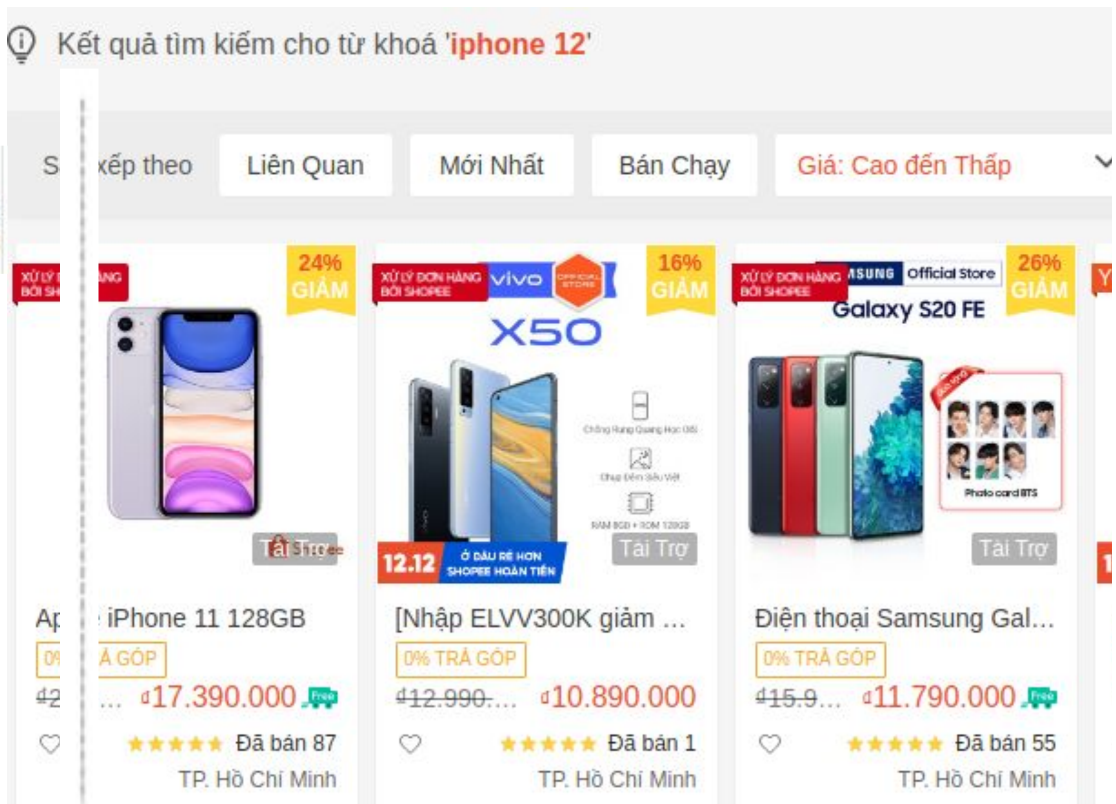
Outline

1. Introduction
2. Probabilistic Matrix Factorization (PMF)
3. Neural Matrix Factorization (NeuMF)
4. Graph Neural Networks for Social Recommendation(GraphRec)

Ubiquitous Personalized Recommendation

Recommendation has been widely applied in online services:

- **E-commerce**, Content Sharing, Social Networking, Forum,...



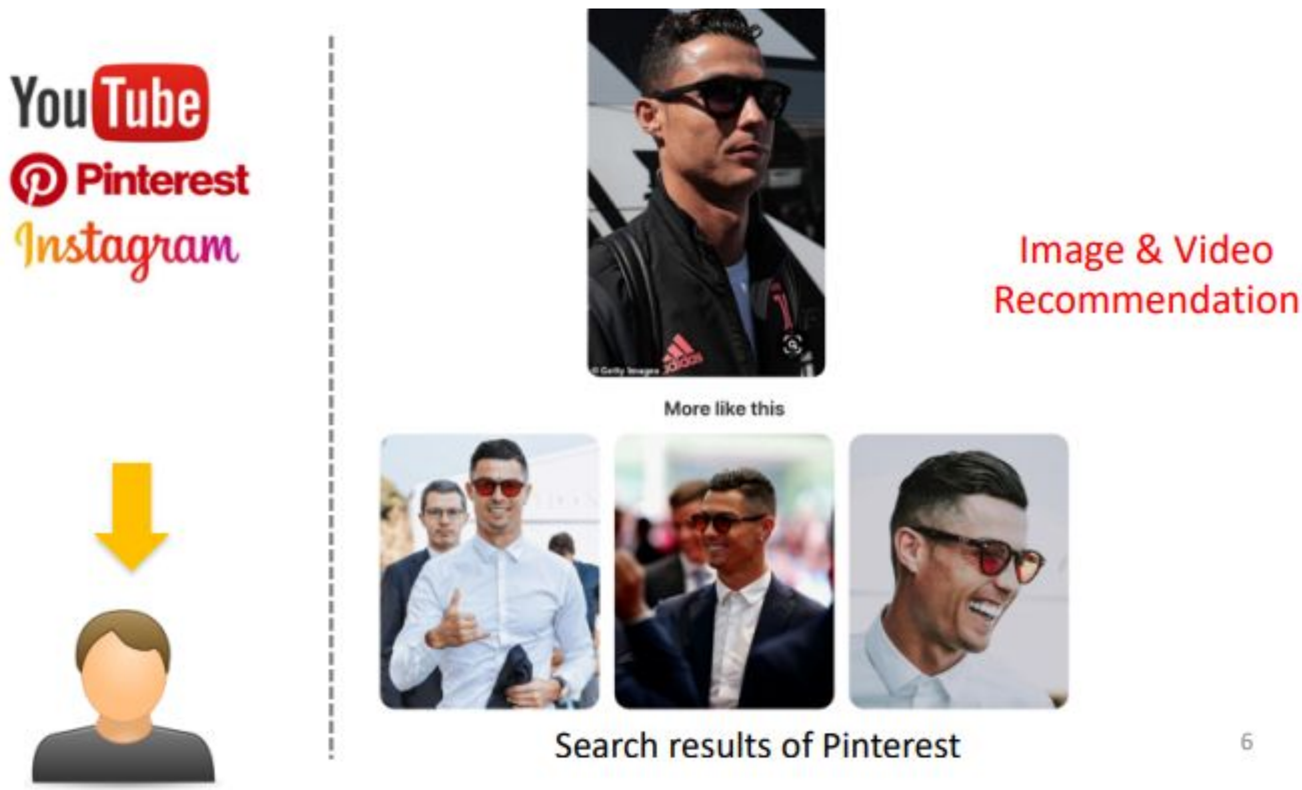
Ad & Product Recommendation

Search results of Shopee

Ubiquitous Personalized Recommendation

Recommendation has been widely applied in online services:

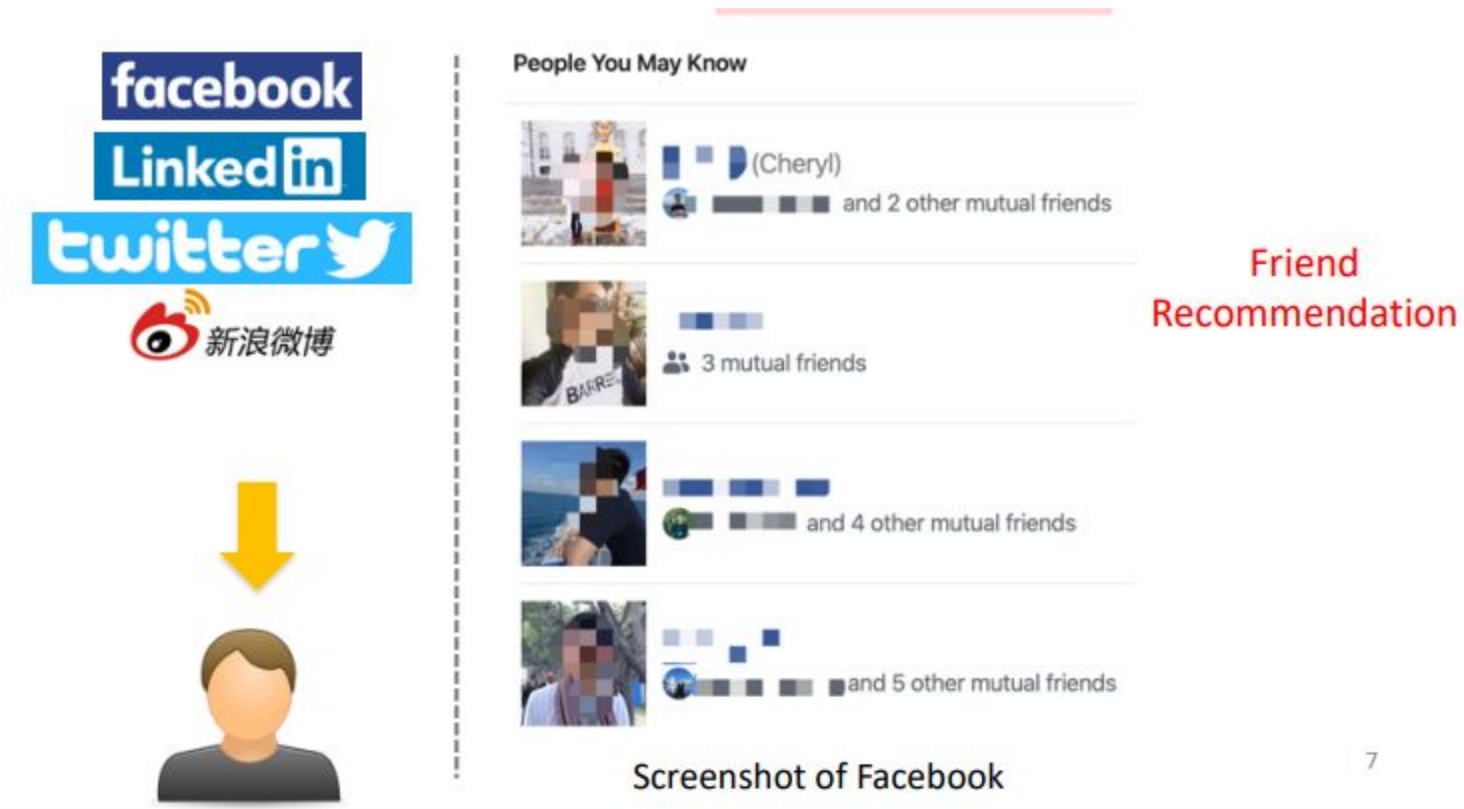
- E-commerce, **Content Sharing**, Social Networking, Forum,...



Ubiquitous Personalized Recommendation

Recommendation has been widely applied in online services:

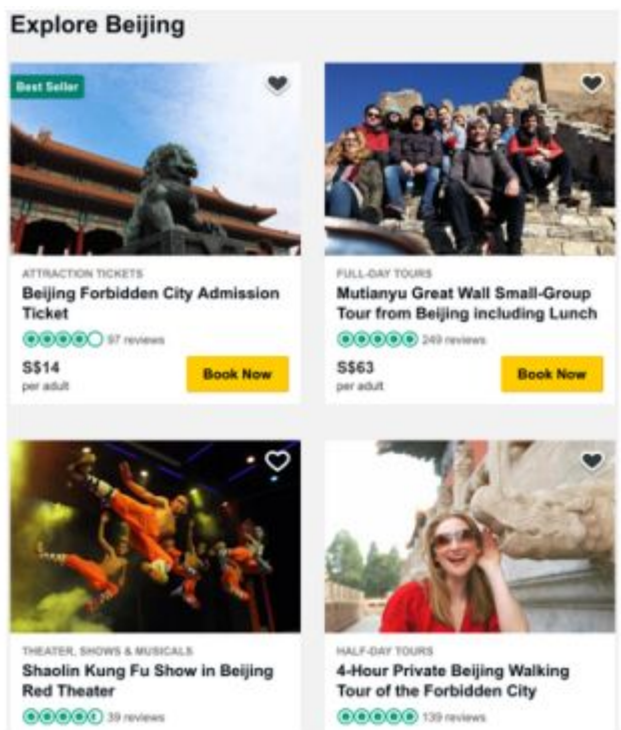
- E-commerce, Content Sharing, **Social Networking**, Forum,...



Ubiquitous Personalized Recommendation

Recommendation has been widely applied in online services:

- E-commerce, Content Sharing, Social Networking, **Forum**,...



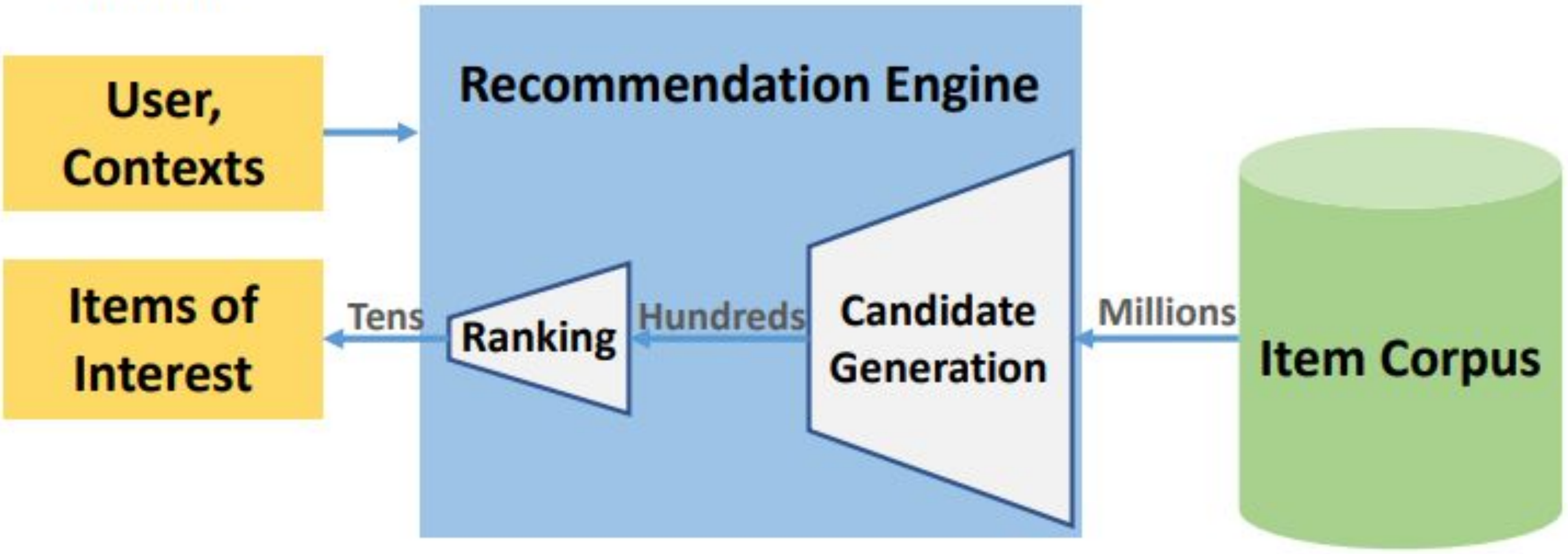
Screenshot of TripAdvisor

POI & Post Recommendation

Overview of Recommendation Engine

User Interest is implicitly reflected in:
- Interaction history
- Demographics …
- Contexts

Items can be:
Products, News, Movies, Videos, Friends …



Key challenge: **user-item semantic gap**

- user and item are two **different types of entities** and are represented by different features.

Problem Formulation

- **Input:** historical user-item interactions or additional side information (e.g., user profile, item profile)
- **Output**: given a target Item (e.g., movie, song, product), how likely a user would interact with it (e.g., click, view, or purchase)

User Profile:
- User ID
- Rating history
- Age, Gender
- Clicks
- Income level

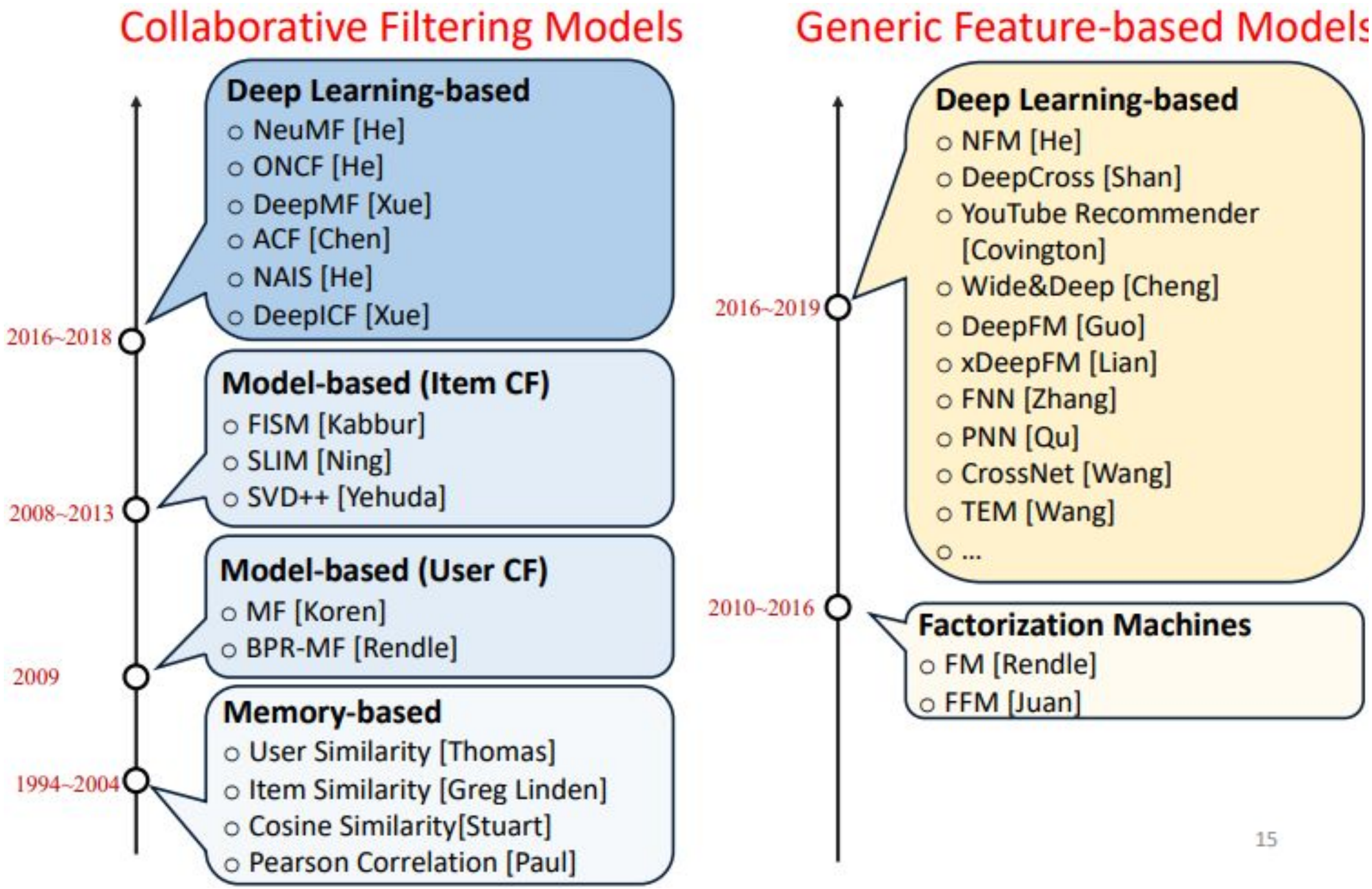
....

Item Profile:
- Item ID
- Description
- Image
- Category
- Price

....

There may be no overlap between user features and item features.

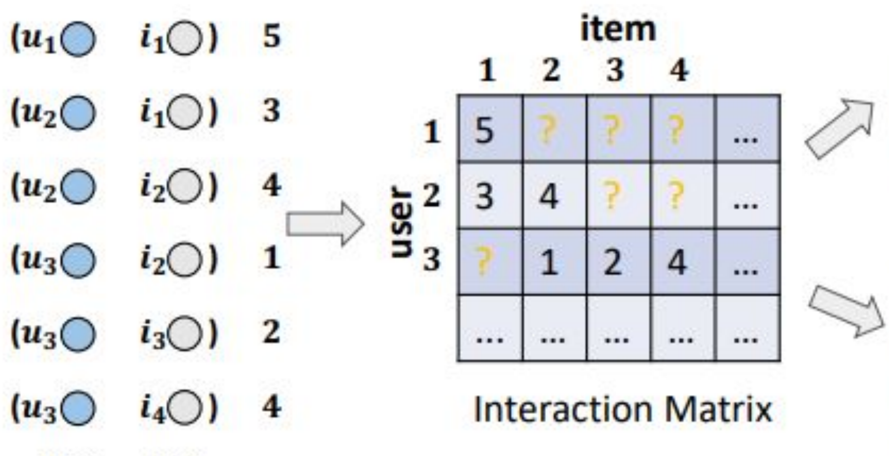
Research on Prevalent RecSys



Collaborative Filtering (CF)

- **CF** is the most well-known technique for recommendation.
  - *"CF makes predictions (**filtering**) about a user's interest by collecting preferences information from many users (**collaborating**)" ---Wikipedia*

- Collaborative Signals → Behavior Similarity of Users
  - Similar users would have similar preference on items.



Interaction Matrix

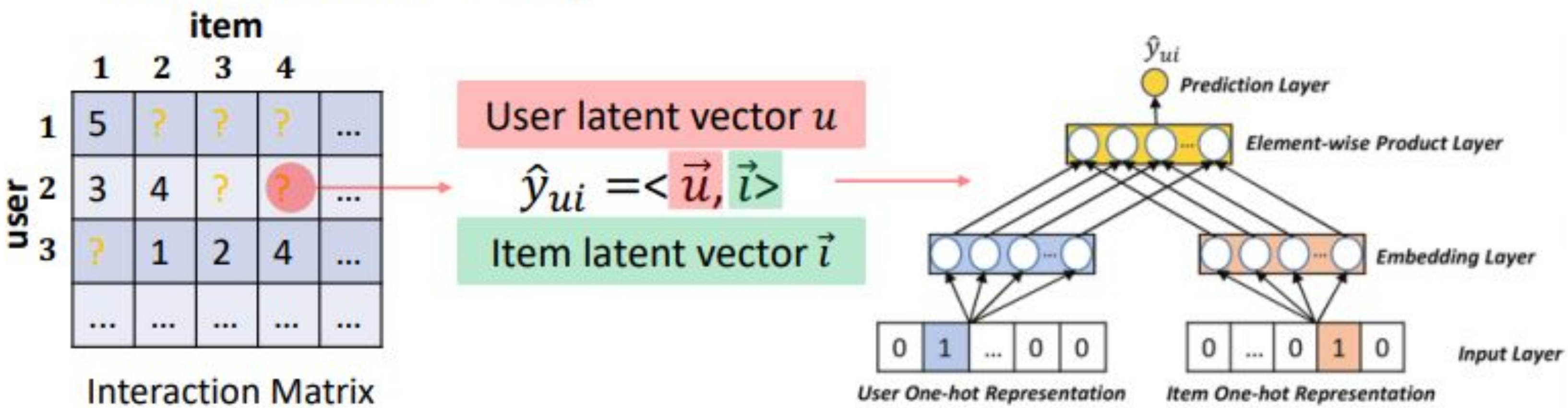
1. Memory-based CF:
Predict by **memorizing** similar users' (or items') ratings

2. Model-based CF:
Predict by **inferring** from an underlying model.

Model-based CF

Matrix Factorization (MF) is the most popular and effective model-based CF method.

- It represents a user and an item as a vector of latent factors.
- The score is estimated as the **inner product** of user latent vector and item latent vector.



- Optimizing a loss to minimize the prediction error on training data can get the latent vectors.

Memory-based CF

item

user	1	2	3	4	
1	5	?	?	?	...
2	3	4	?	?	...
3	?	1	2	4	...
	...	...	...	...	...

Interaction Matrix

Problem: predict user u's rating on item i.

- User-based CF leverages the ratings of u's **similar users** on the target item i.

$$\hat{y}_{ui} = \underbrace{\sum_{u' \in S_u(u)}}_{\text{Similar users of } u} sim(u, u') \cdot \underbrace{y_{u'i}}_{\text{Rating of a similar user on } i}$$

- Item-based CF leverages the ratings of u on other **similar items** of i.

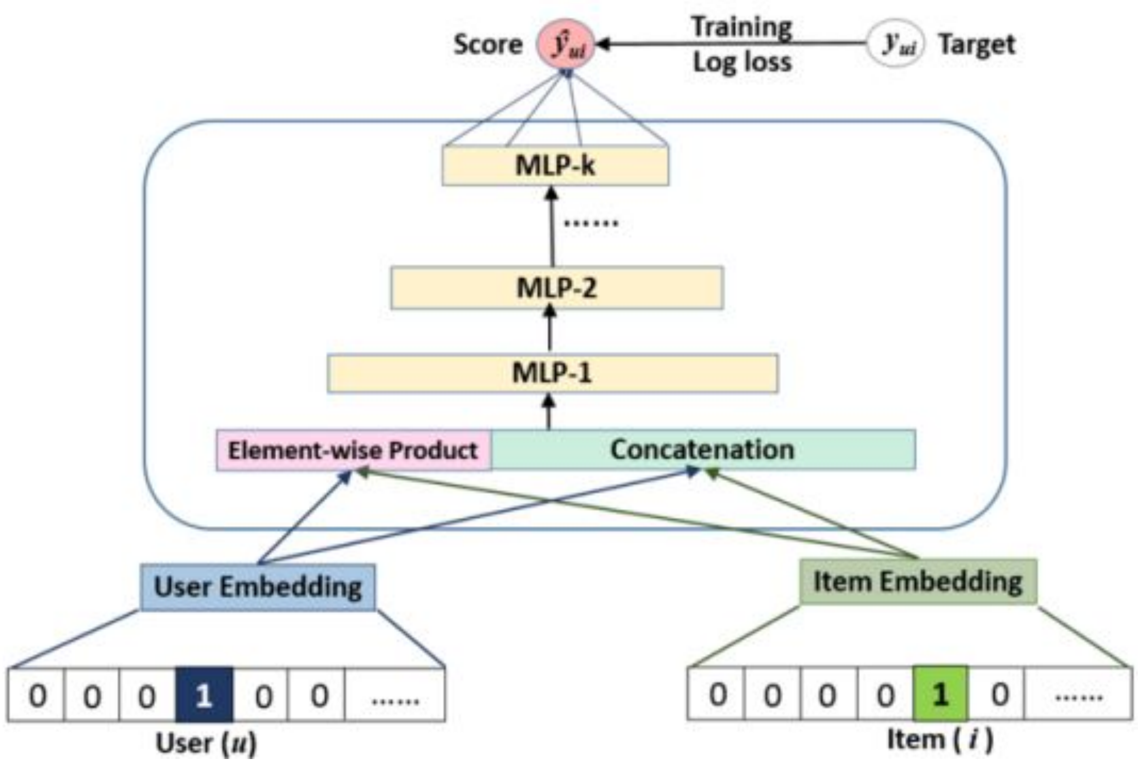
$$\hat{y}_{ui} = \underbrace{\sum_{i' \in S_i(i)}}_{\text{Similar items of } i} sim(i, i') \cdot \underbrace{y_{ui'}}_{\text{Rating of } u \text{ on a similar item}}$$

- Many similarity measures can be used, e.g., Jaccard, Cosine, Pearson Correlation. Recent advance learns the similarity from data.

Neural Matrix Factorization (NeuMF)

Interaction Modeling → MF + MLP over users and items

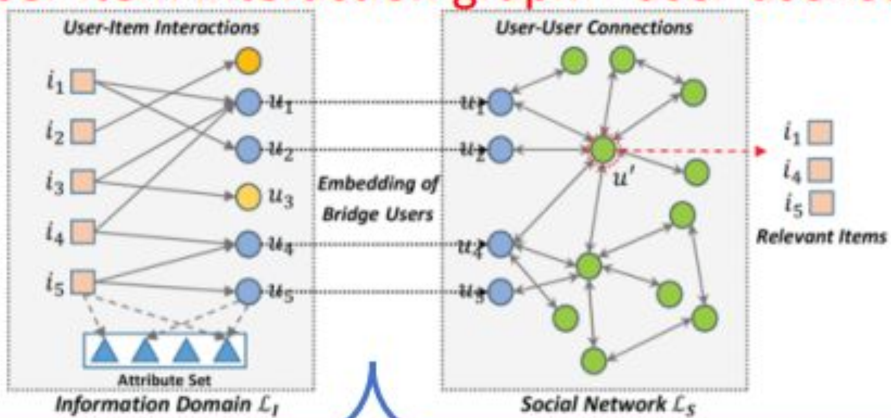
- MF uses inner product to capture the low-rank relation
- MLP is more flexible in using DNN to learn the matching function.

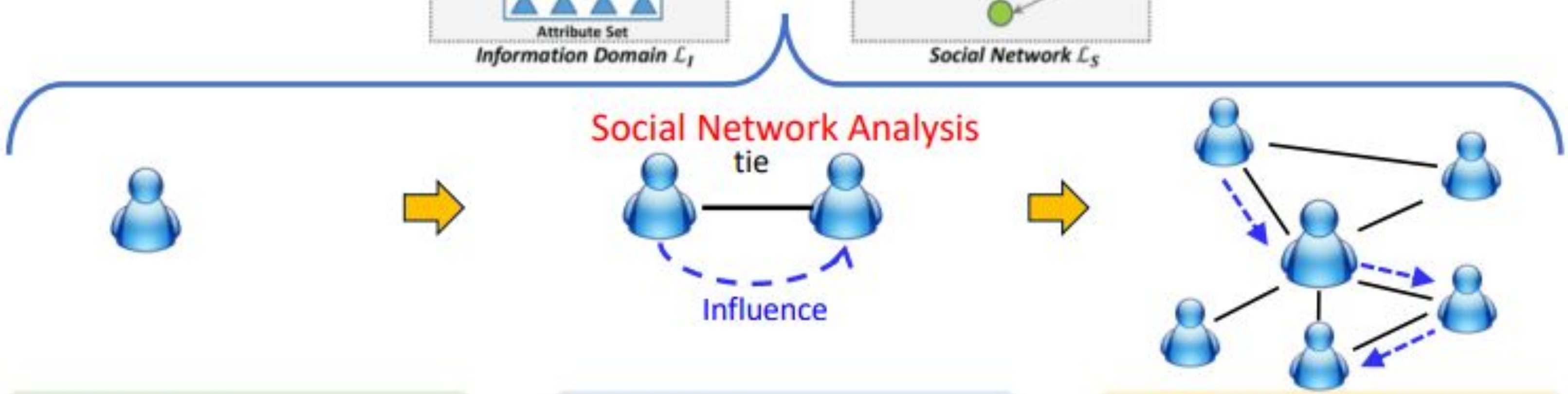


Social Recommendation

Social relation is of importance to help users filter information

- Tow graphs → user-item interaction graph + user-user social graph.





- User Profiling
- Behavior Modeling

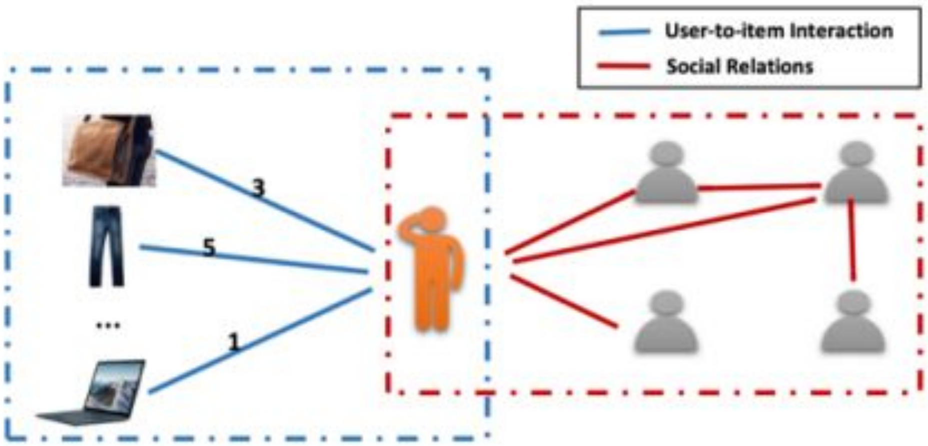
- Social Tie
- Social Influence

- Triad & Group Formation
- Information Diffusion

Graph Neural Networks for Social Recommendations (GraphRec)

GraphRec from [Fan et al, WWW'2019]

- User-Item Graph
  - Interactions between users and items
  - Users' opinions on items (i.e., explicit feedback, ratings)
- User-User Graph
  - Social relations have heterogeneous strengths
    - Strong & weak ties are mixed together
  - Users are likely to share more similar tastes with strong ties than weak ties.



User Modeling in GraphRec

These two graphs provide user information from different angles

- **Item Aggregation**
  - Item space: leverage user-item interactions to get user representations

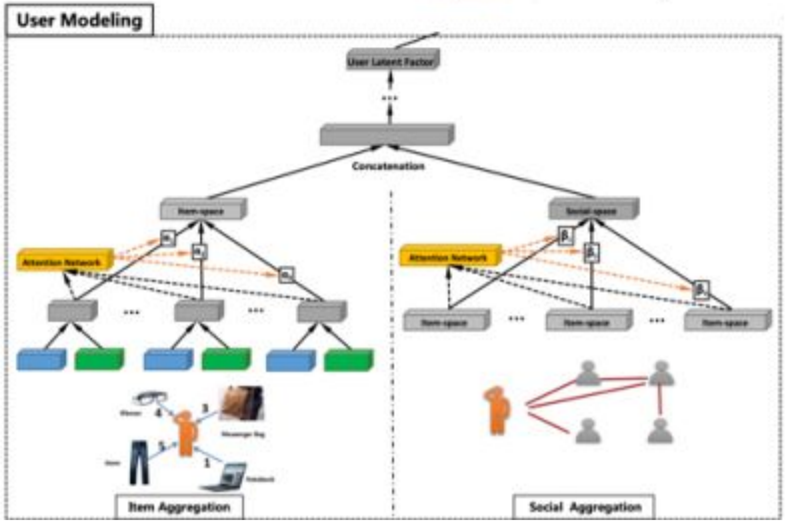
$$\boxed{\mathbf{h}_i^I} = \sigma(\mathbf{W} \cdot Aggre_{items}(\{\boxed{\mathbf{x}_{ia}}, \forall a \in C(i)\}) + \mathbf{b})$$

- **Social Aggregation**

Opinion-aware representation of an interaction

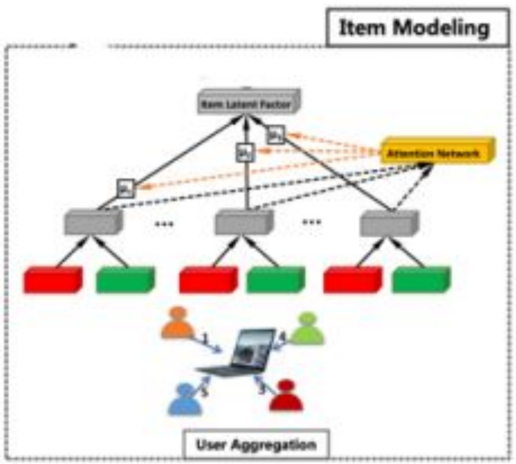
  - Social space: use social relationships to get user representations

$$\mathbf{h}_i^S = \sigma(\mathbf{W} \cdot Aggre_{neigbhors}(\{\boxed{\mathbf{h}_o^I}, \forall o \in N(i)\}) + \mathbf{b})$$



Item Modeling in GraphRec

- **User Aggregation**
  - Consider both interactions & opinions to get item representations



Attention network to differentiate the importance weight

$$\mathbf{z}_j = \sigma(\mathbf{W} \cdot Aggre_{users}(\{\mathbf{f}_{jt}, \forall t \in B(j)\}) + \mathbf{b})$$

Opinion-aware representation of an interaction

- **Rating Prediction**
  - Feed the concatenation of user & item representation into a neural network (MLP) to get predictions.

Experiment