Learning and Reasoning on Graph for Recommendation

Slides in https://next-nus.github.io/

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Tutorial @CIKM 2019

OUTLINE

- Introduction
- Part I: Preliminary of Recommendation (~40mins)
- Part II: Random Walk for Recommendation (~20mins)
- Part III: Network Embedding for Recommendation (~20 mins)
- Part III: Graph Neural Networks for Recommendation (~100 mins)

Slides in https://next-nus.github.io/

Age of Information Explosion

Serious Issue of Information Overloading

- Weibo： >500M posts/day
- Flickr： >300M images/day
- Kuaishou: >20M microvideos/day

… …

Ubiquitous Personalized Recommendation

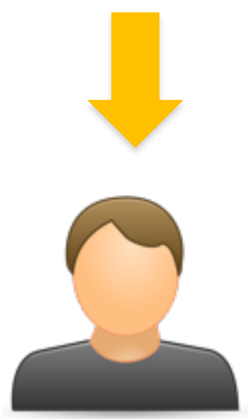
Recommendation has been widely applied in online services:

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

amazon

淘宝网 Taobao

ebay



Ad & Product Recommendation

Search results of Taobao

Ubiquitous Personalized Recommendation

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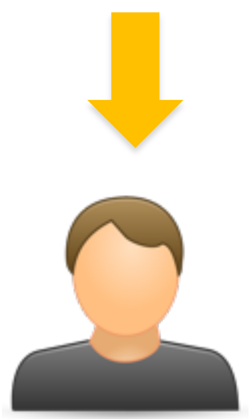

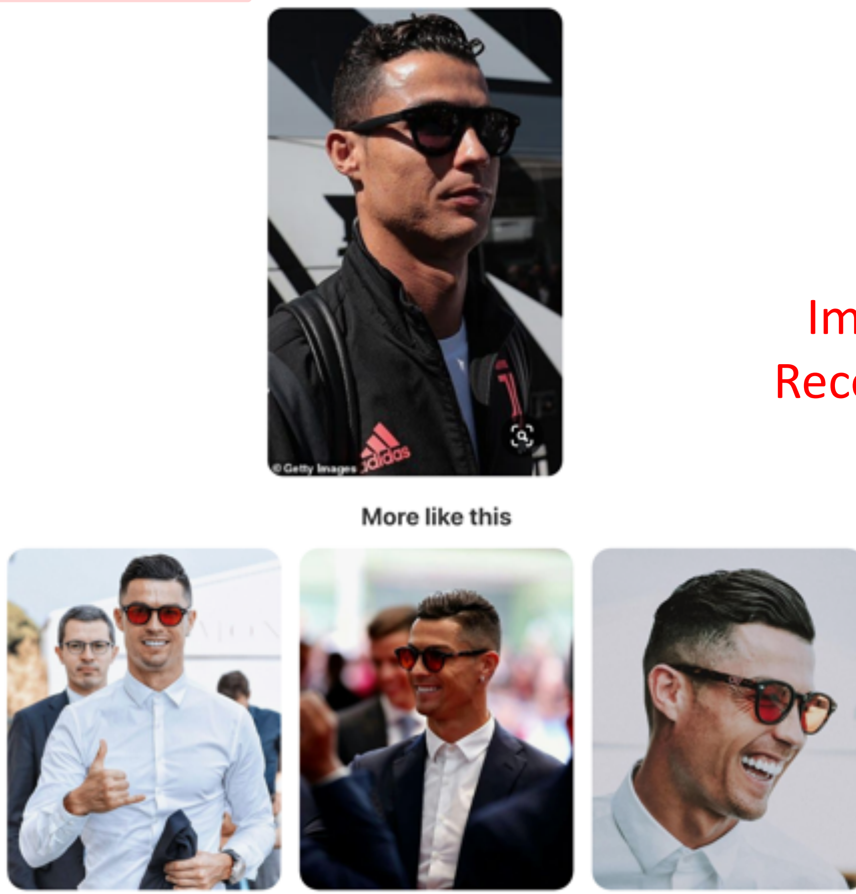

Image & Video Recommendation

Search results of Pinterest

Ubiquitous Personalized Recommendation

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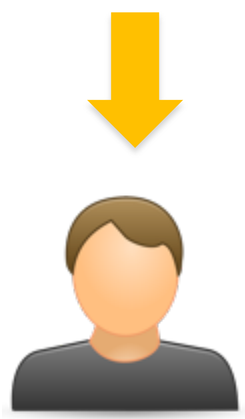
- E-commerce, Content Sharing, **Social Networking**, Forum …



Screenshot of Facebook

Friend Recommendation

Ubiquitous Personalized Recommendation

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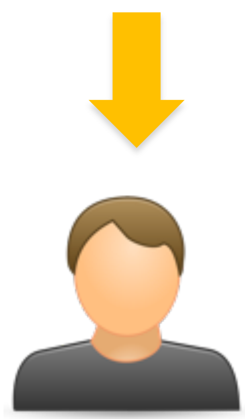
- E-commerce, Content Sharing, Social Networking, **Forum** …

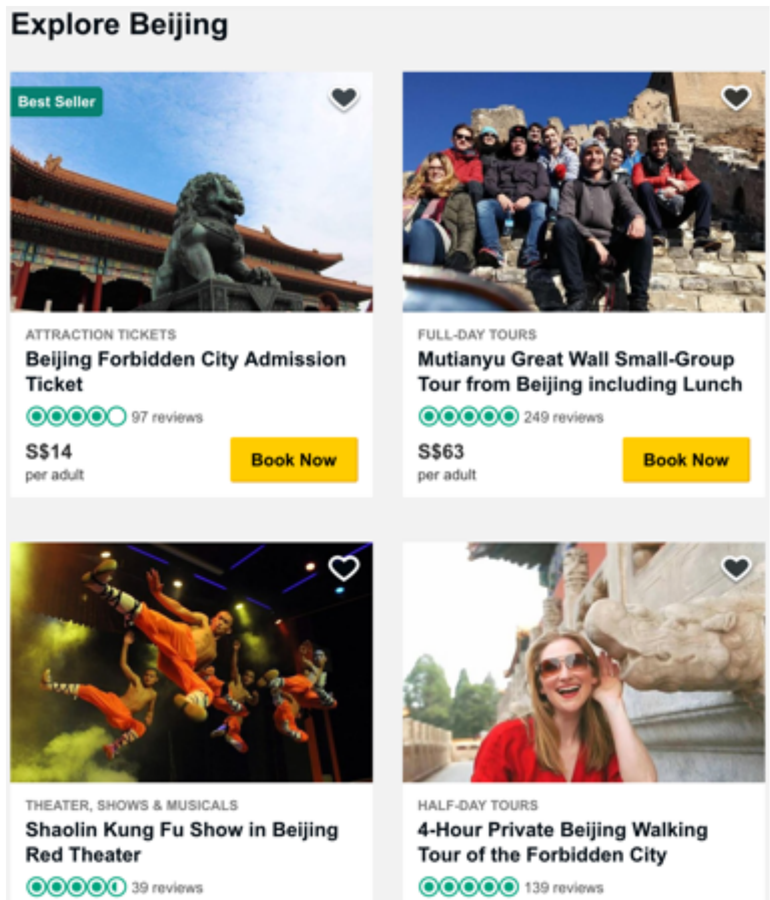
知乎

reddit

IMDb

tripadvisor





Screenshot of TripAdvisor

POI & Post Recommendation

Values of Recommender System (RecSys)

RecSys has become a major **monetization** tool for customer-oriented online services:

- E-commerce, Content Sharing, Social Networking, Forum …

Ad systems are technically supported by recommendation solutions:

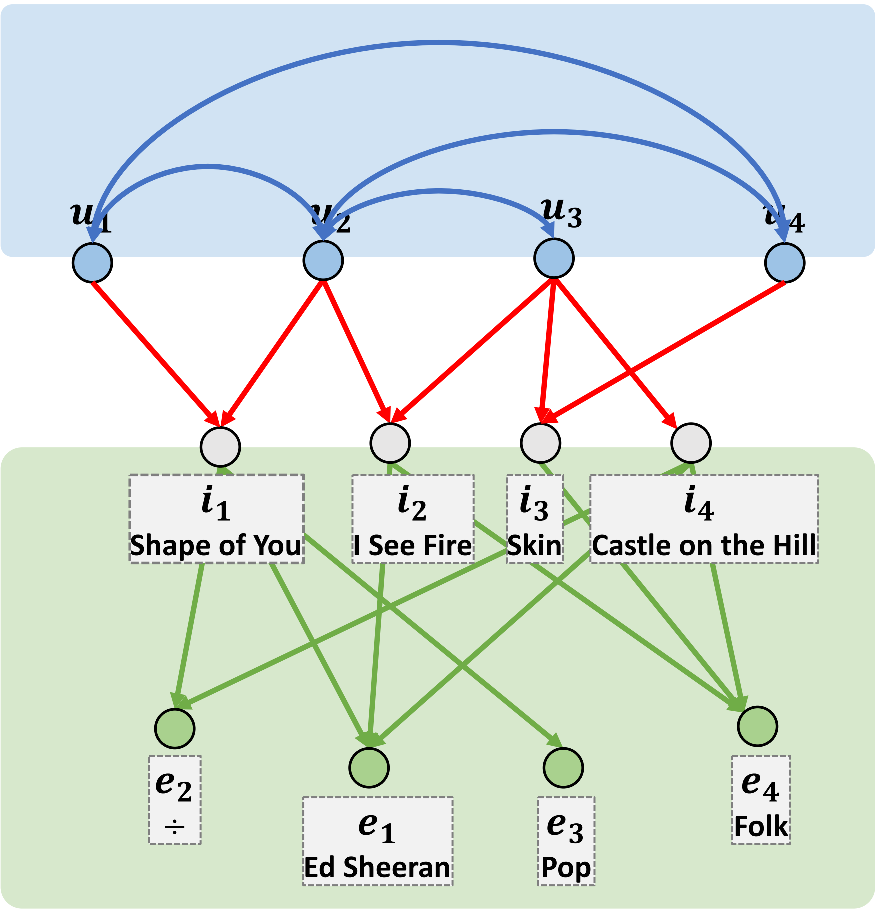
- The key is Click-Through Rate (CTR) prediction.

Some Statistics:

- YouTube Homepage: 60%+ clicks [Davidson et al. 2010]
- Netflix: 80%+ movie watches [Gomze-Uribe et al 2016]
- Amazon: 30%+ page views [Smith and Linden, 2017]

The Era of Connected World

The world is more **closely connected** than you might think!



User-User Connections
- Social Relations
- Same Profiles …

User-Item Interactions
- Implicit Feedback
- Explicit Feedback …

Item-Item Connections
- Same Attributes
- External Knowledge …

OUTLINE

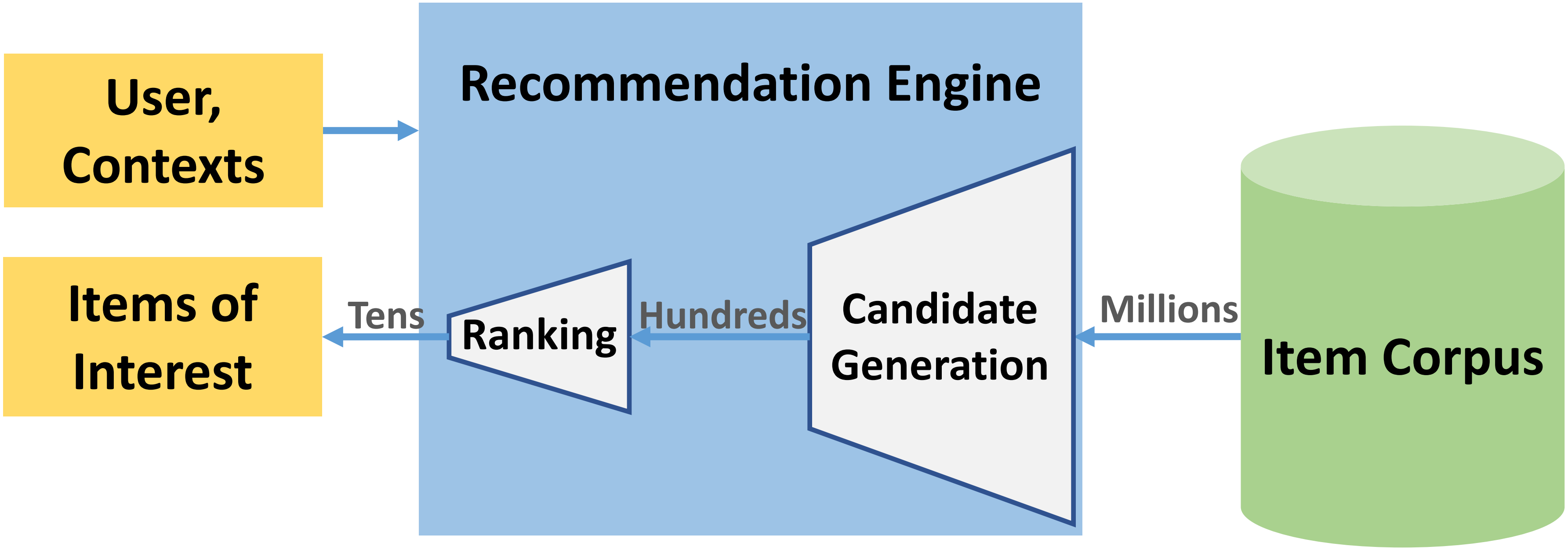
- Introduction
- **Part I: Preliminary of Recommendation**
  - **Problem Formulation**
  - **Unified View for Recommendation Paradigm**
  - **Limitations of Previous Works**
- Part II: Random Walk for Recommendation
- Part III: Network Embedding for Recommendation
- Part III: Graph Neural Networks for Recommendation

Slides in https://next-nus.github.io/

Overview of Recommendation Engine

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

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

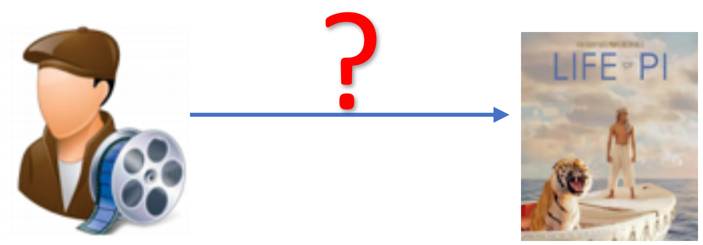


Key challenge: **user-item semantic gap**
- user and item are two **different types of entities** and are represented by different features.

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 Models

2016~2018

Deep Learning-based
- NeuMF [He]
- ONCF [He]
- DeepMF [Xue]
- ACF [Chen]
- NAIS [He]
- DeepICF [Xue]

2008~2013

Model-based (Item CF)
- FISM [Kabbur]
- SLIM [Ning]
- SVD++ [Yehuda]

2009

Model-based (User CF)
- MF [Koren]
- BPR-MF [Rendle]

1994~2004

Memory-based
- User Similarity [Thomas]
- Item Similarity [Greg Linden]
- Cosine Similarity[Stuart]
- Pearson Correlation [Paul]

Generic Feature-based Models

2016~2019

Deep Learning-based
- NFM [He]
- DeepCross [Shan]
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- FM [Rendle]
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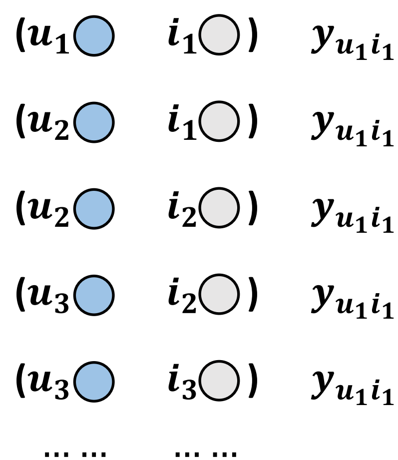
Input Data:

- User-Item Interaction Data
  - Explicit Feedback (e.g., rating)
  - Implicit Feedback (e.g., clicks)



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.

(u_1, i_1) 5
(u_2, i_1) 3
(u_2, i_2) 4
(u_3, i_2) 1
(u_3, i_3) 2
(u_3, i_4) 4
… … … …

item

user	1	2	3	4	
1	5	?	?	?	…
2	3	4	?	?	…
3	?	1	2	4	…
	…	…	…	…	…

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.

Memory-based CF

user \ item	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.

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.

item

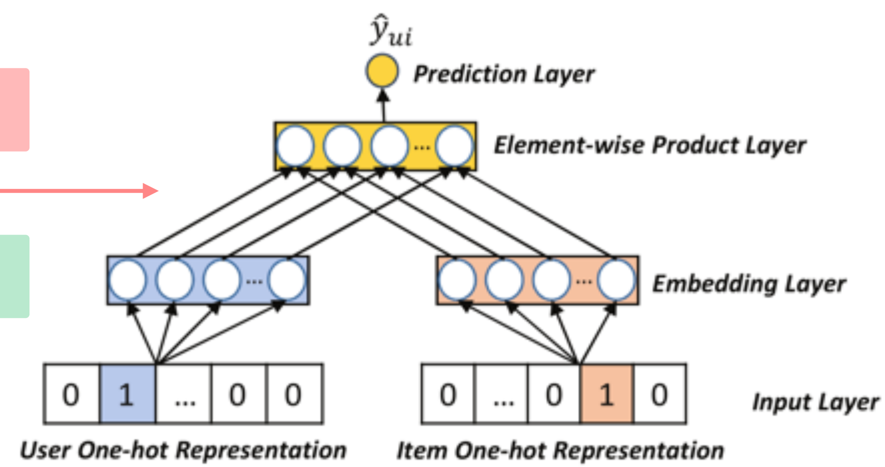
user	1	2	3	4	
1	5	?	?	?	…
2	3	4	?	?	…
3	?	1	2	4	…
	…	…	…	…	…

Interaction Matrix

User latent vector u

$$\hat{y}_{ui} = <\vec{u}, \vec{i}>$$

Item latent vector $\vec{i}$



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

Item-based CF

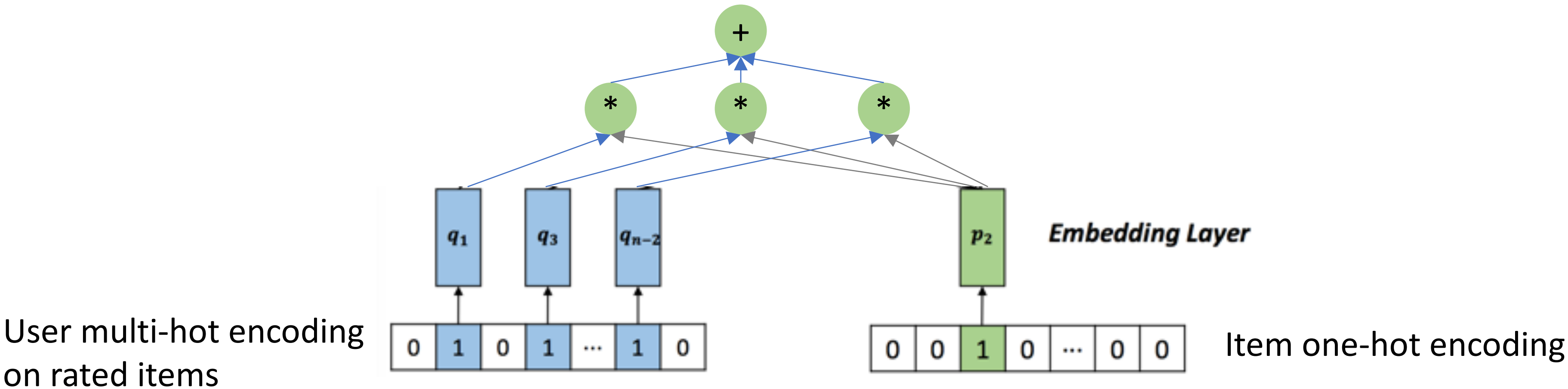
Instead of only using an ID to encode a user, we can make the encoding more meaningful by using the user's rated items.

- This can be interpreted as an item-based CF model.

$$\hat{y}_{ui} = \sum_{i' \in S_i(i)} sim(i, i') \cdot y_{ui'} \approx \sum_{j \in \mathcal{R}_u} \mathbf{q}_j^T \mathbf{p}_i$$

Use all items as neighbors

Factorize item similarity in the latent space



- E.g., FISM [Kabbur], SLIM [Ning]

Fusing User-based & Item-based CF

- MF (user-based CF) represents a user as her ID.
  - Directly projecting the ID into latent space
- FISM (item-based CF) represents a user as her interacted items.
  - Projecting interacted items into latent space

- SVD++ fuses the two types of models in the latent space:

$$\hat{y}_{ui} = (\underbrace{\mathbf{v}_u + \sum_{j \in \mathcal{R}_u} \mathbf{q}_j}_{\text{User representation in latent space}})^T \mathbf{p}_i$$

  - This is the best single model for rating prediction in the Netflix challenge [Koren, KDD '08].

Two Widely-Used Loss

Pointwise loss → e.g., log loss

- Cast the recommendation task as a classification problem
- Rating Prediction, CTR Prediction …

$$\mathcal{L} = \sum_{(u,i,\mathbf{x})\in O} -y_{ui} \log \sigma(\hat{y}_{ui}) - (1 - y_{ui}) \log (1 - \sigma(\hat{y}_{ui}))$$

Force the prediction scores to be close to the target scores

Pairwise loss → e.g., Bayesian Personalized Ranking (BPR) loss

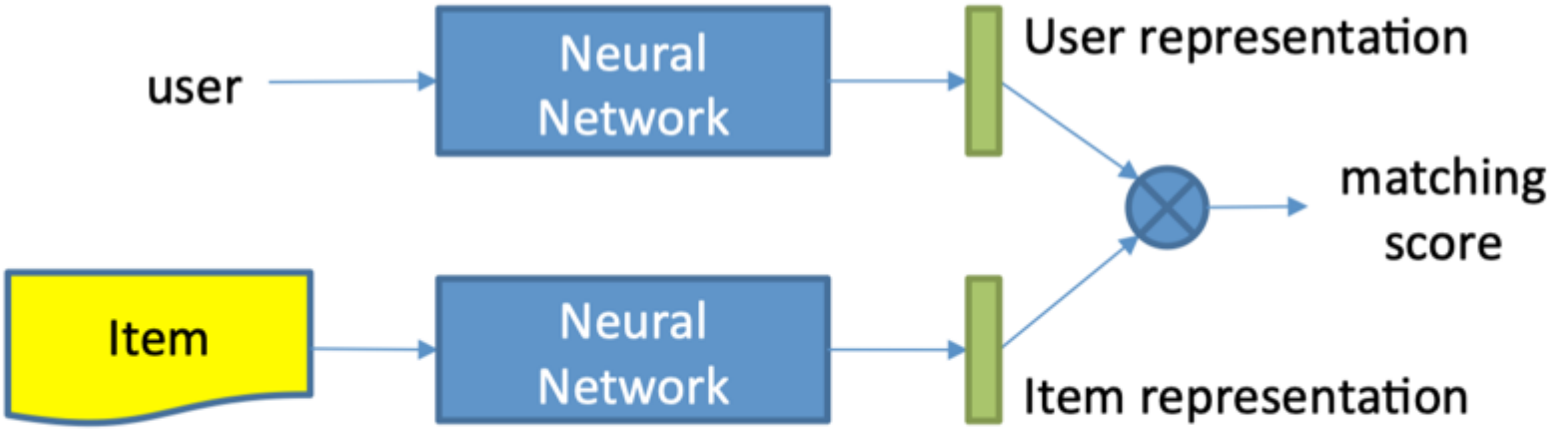
- Cast the recommendation task as a ranking problem
- Top-N Recommendation, Preference Ranking …

$$Loss = \sum_{(u,i,j)\in O} - \ln \sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda \left\| \Theta \right\|_2^2$$

Relative order between observed & unobserved interactions

Deep Learning Meets CF (1)

- **Methods of representation learning**
  - Enhance representation ability/expressiveness of models

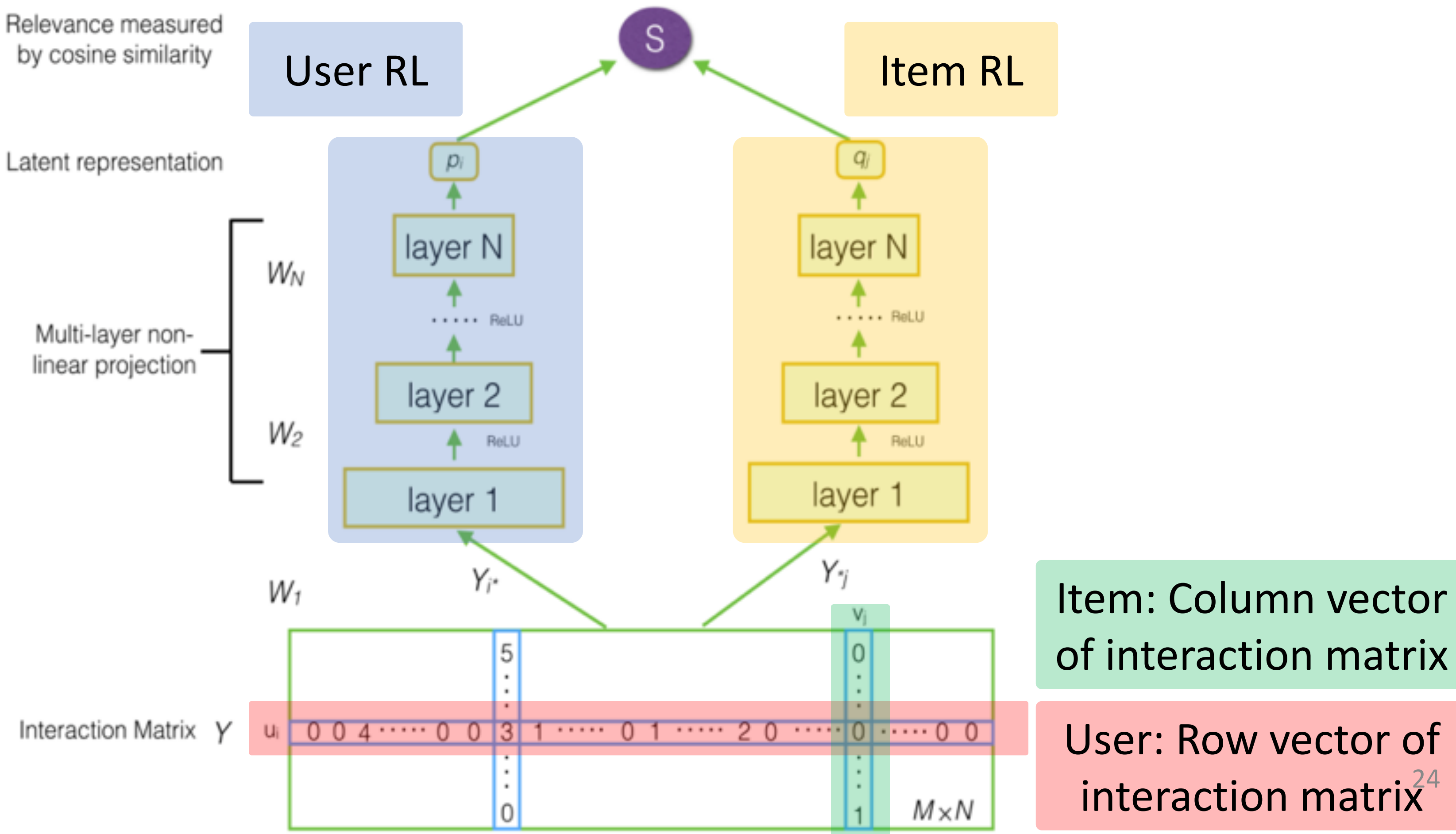


Model	Input Data	Representation Learning	Interaction Learning
DeepMF [Xue, IJCAI'17]	User: Historical items Item: User group	Multi-Layer Perceptron	Inner product
AutoRec [Sedhain, WWW'15]	User: Historical items Item: ID	Multi-Layer Perceptron	Inner Product
CDAE [Wu, WSDM'16]	User: Historical items + ID Item: ID	Multi-Layer Perceptron	Inner Product

Deep Matrix Factorization (Xue, IJCAI'17)

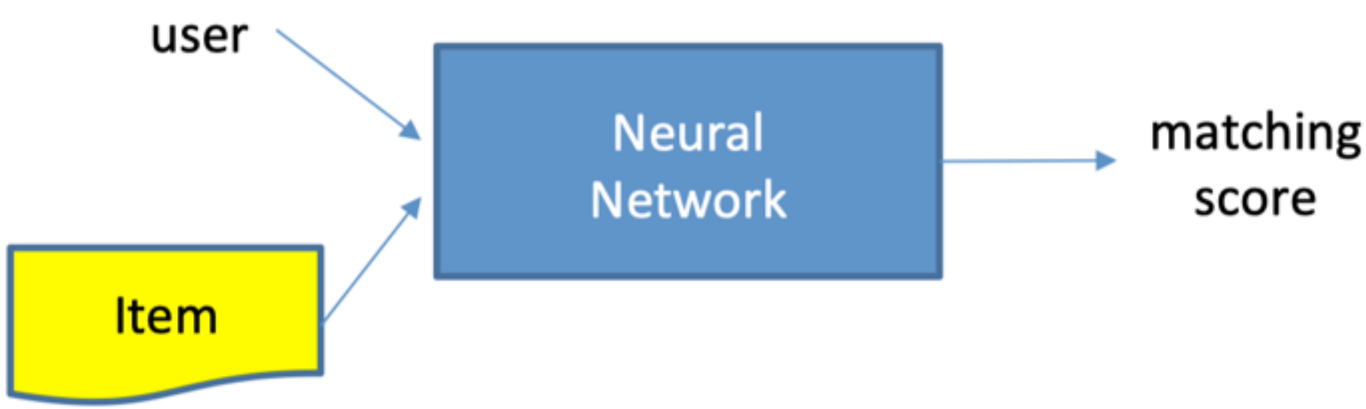
Representation Learning → Multi-layer perceptron

- Deep Neural Networks are adopted to learn representations of users & items



Deep Learning Meets CF (2)

- **Methods of interaction function learning**
  - Capture complex patterns of user-item relationships

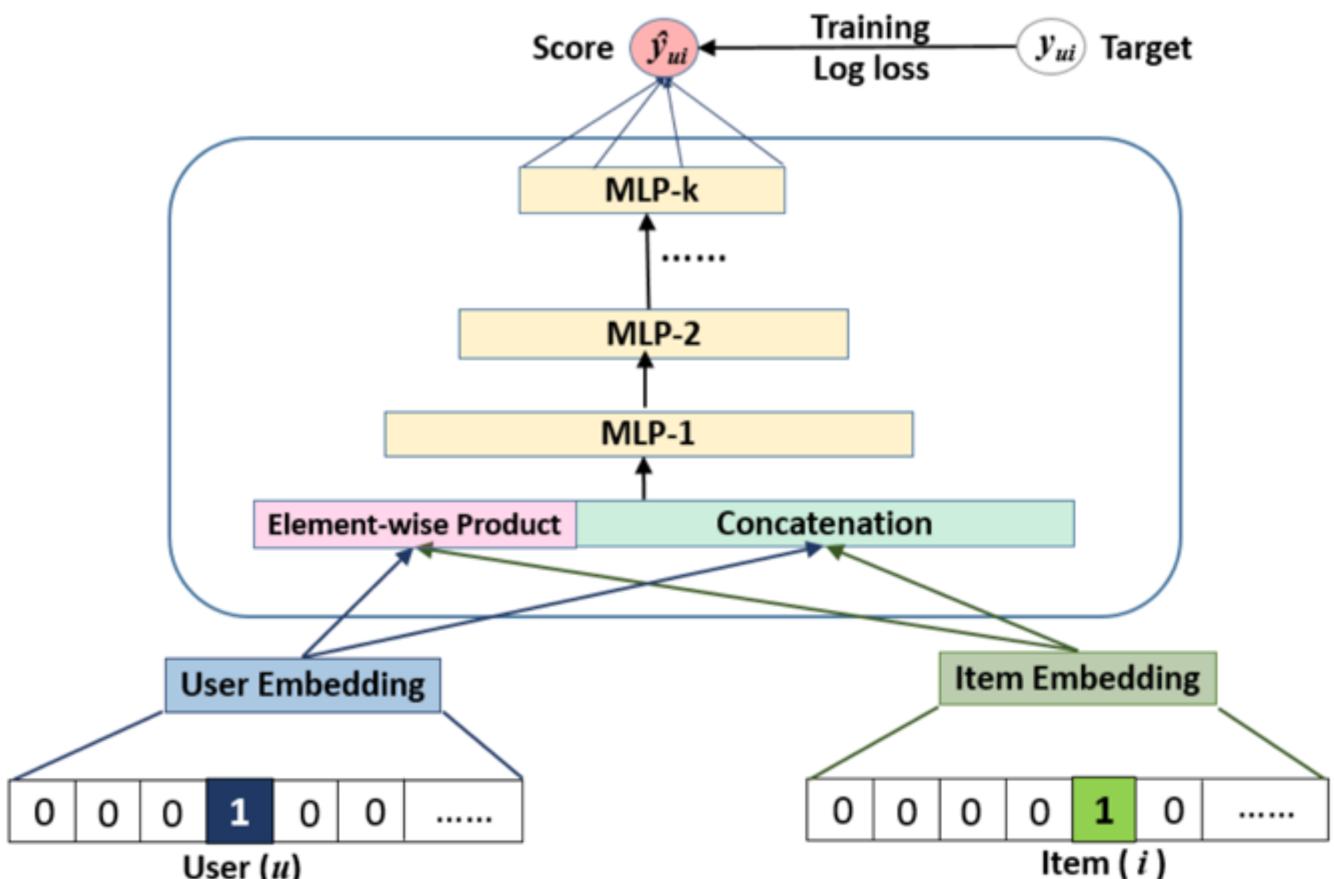


Model	Input Data	Representation Learning	Interaction Learning
NCF [He, WWW'17]	User: ID Item: ID	ID embedding	Multi-Layer Perceptron
NNCF [Bai, CIKM'17]	User: User neighbors Item: Item neighbors	Embeddings	Multi-Layer Perceptron
ONCF [He, IJCAI'28]	User: ID Item: ID	ID embedding	Convolutional Neural Network

Neural Matrix Factorization (He, WWW'17)

Interaction Modeling → MF + MLP over users and items

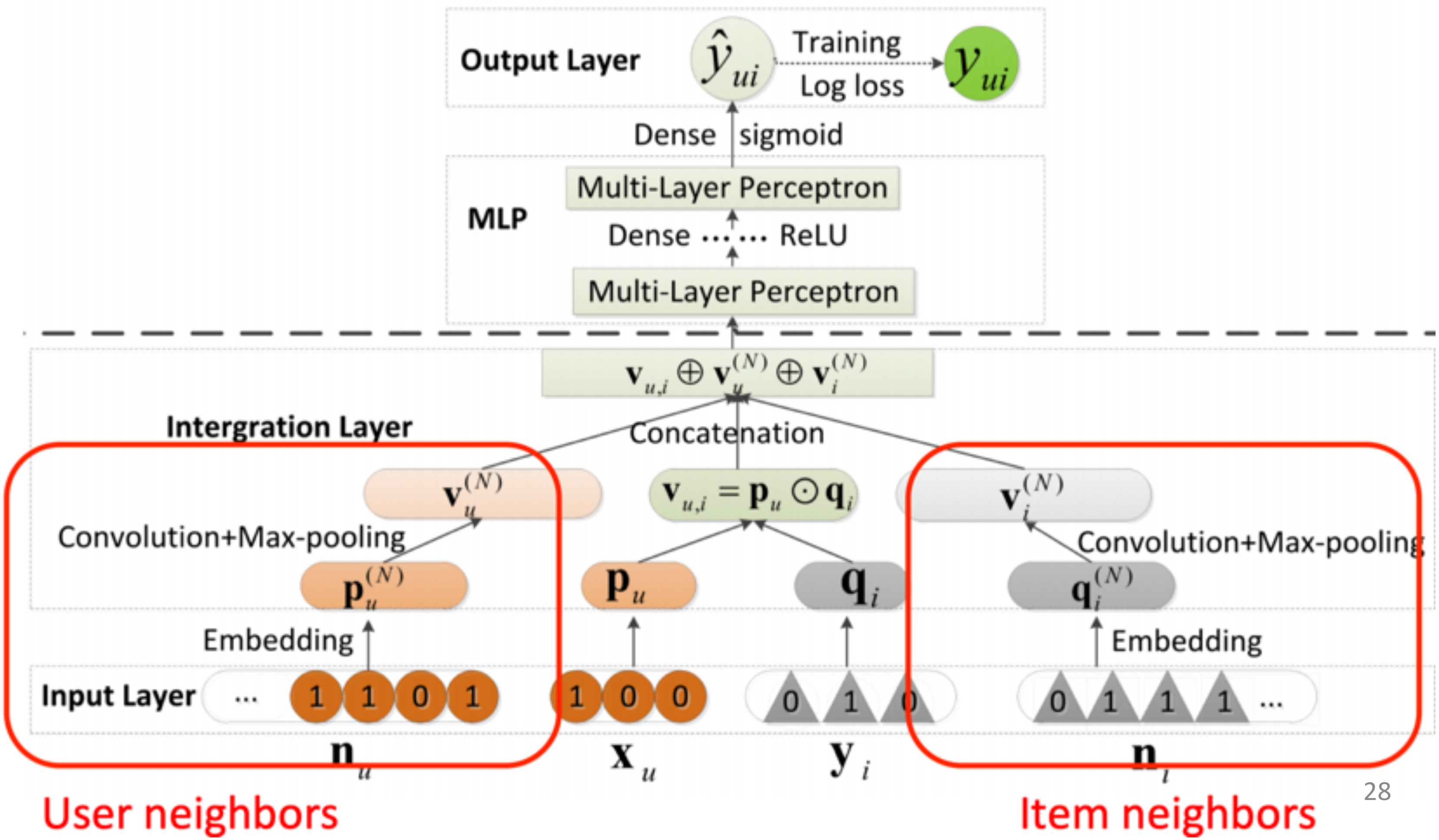
- MF uses inner product to capture the low-rank relation
- MLP is more flexible in using DNN to learn the matching function.



NNCF: Neighbor-based NCF (Bai, CIKM'17)

Interaction Modeling → MF + MLP over user and item neighbors

- Feeding user and item neighbors into the NCF framework



Research on Feature-based Models

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2010~2016

Factorization Machines
- FM [Rendle]
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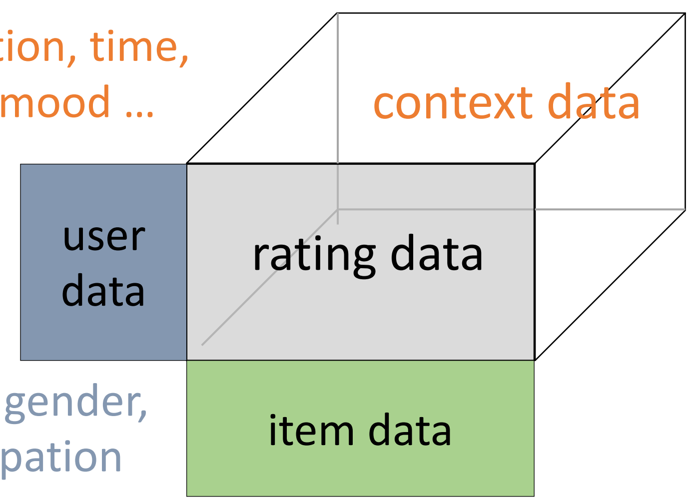
Input Data:
- User-Item Interaction Data
- Other Information
  - User Data
  - Item Data
  - Context Data

E.g., location, time, weather, mood …

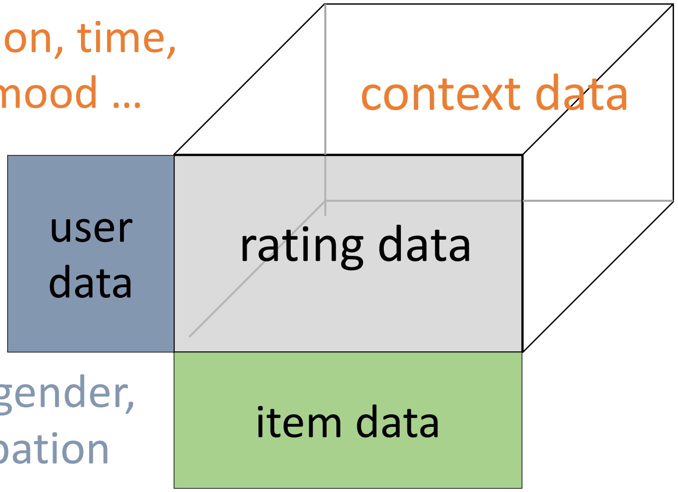


E.g., user gender, age, occupation personality …

E.g., item category, description, image …

Feature-based Models

E.g., location, time, weather, mood …



E.g., user gender, age, occupation personality …

E.g., item category, description, image …

Feature vector x

	User: A	B	C	...	Movie: TI	NH	SW	ST	...	Other Movies rated: TI	NH	SW	ST	...	Target y
$x^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	5 $y^{(1)}$
$x^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	3 $y^{(2)}$
$x^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	1 $y^{(3)}$
$x^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	4 $y^{(4)}$
$x^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	5 $y^{(5)}$
$x^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	1 $y^{(6)}$
$x^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	5 $y^{(7)}$

Raw Features:

- Categorical Features:
  - One-hot encoding on ID features
- Continuous Features:
  - E.g., time, frequency. Need feature normalization

Transformed Features:

- Categorical Features:
  - Cross Features are important (e.g., AND(A=True, B=True))
- Continuous Features:
  - E.g., outputs of other models like visual embeddings.

Factorization Machine (FM)

- FM is inspired from previous factorization models
- It represents each feature as a latent vector (embedding), and models the second-order feature interactions:

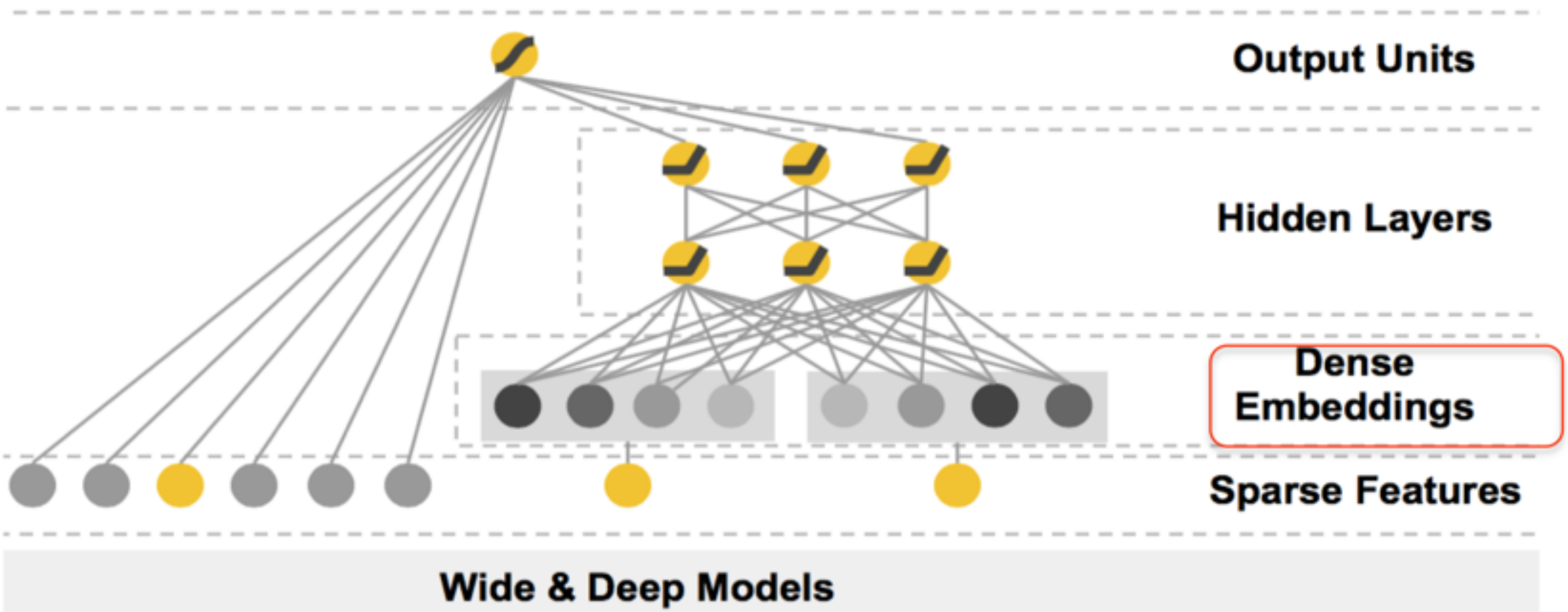
$$\hat{y}(\mathbf{x}) = w_0 + \sum_{i=1}^{p} w_i x_i + \sum_{i=1}^{p} \sum_{j>i}^{p} < \mathbf{v}_i, \mathbf{v}_j > x_i x_j$$

First-order:
Linear Regression

Second-order:
Pair-wise interactions between features

- FM allows easy feature engineering for recommendation, and can mimic many existing models (that are designed for a specific task) by inputting different features.
  - E.g., MF, SVD++, timeSVD [Koren, KDD'09], PIFT [Rendle, WSDM'10] etc.

Wide&Deep (Cheng et al, RecSys'16)

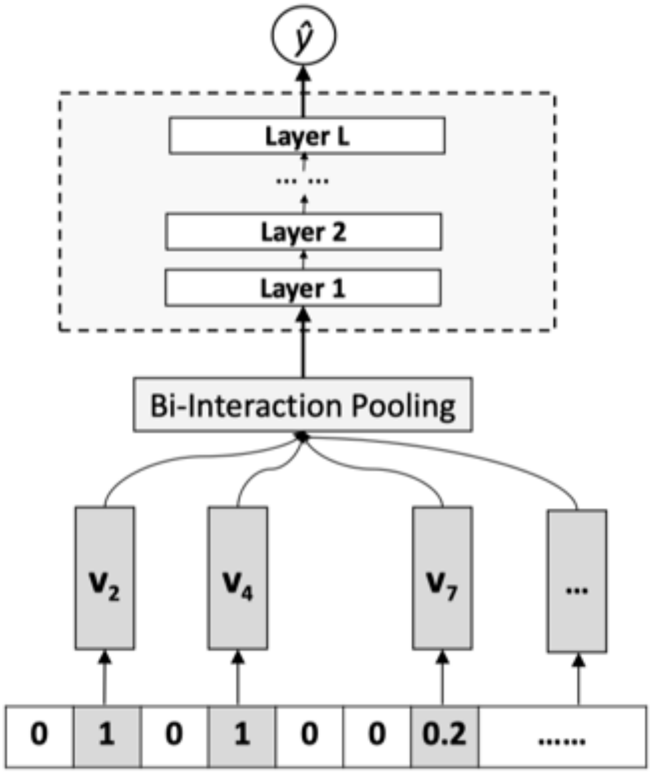


- The wide part is linear regression for memorizing seen feature interactions, which requires careful engineering on cross features.
  - E.g., AND(gender=female, language=en) is 1 if both single features are 1

- The deep part is DNN for generalizing to unseen feature interactions.
  - Cross feature effects are captured in an implicit way.

Neural Factorization Machine (He et al, SIGIR'17)

- Inspired by FM, NFM models pairwise interactions between feature embeddings with multiplication.



Prediction Score

Hidden Layers — Capture higher-order feature interactions

B-Interaction Layer

$$f_{BI}(\mathcal{V}_x) = \sum_{i=1}^{n} \sum_{j=i+1}^{n} x_i \mathbf{v}_i \odot x_j \mathbf{v}_j,$$

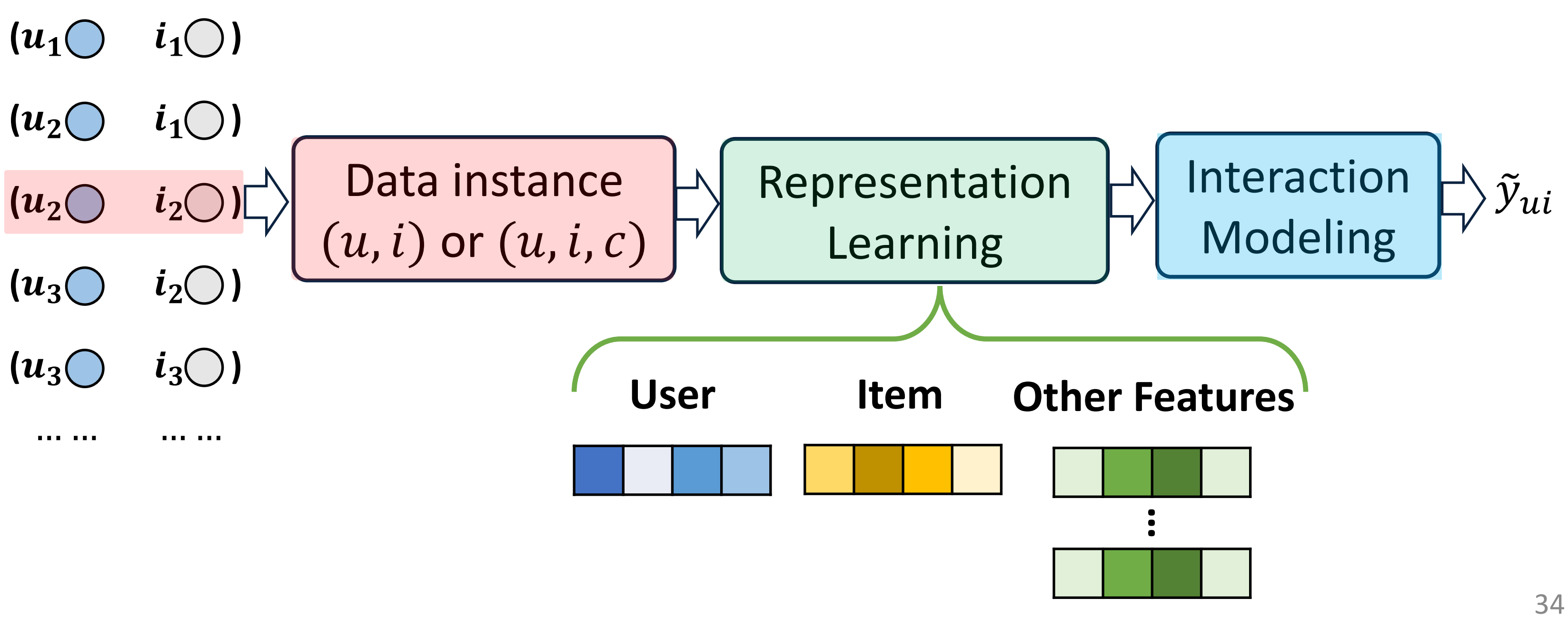
Embedding Layer — Capture bilinear interaction

Input Feature Vector (sparse)

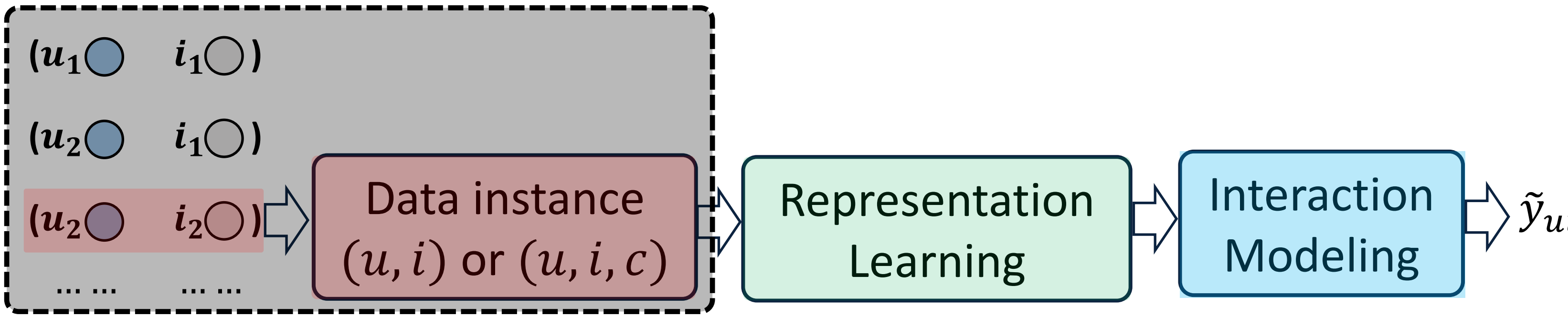
A General Paradigm

Transform each observation, a user-item pair (u, i) or with side information (u, i, c), into a separate data instance

- Initiate representations for each feature → Representation Learning
  - Design whatever features as you want
- Perform predictions based on interactions → Interaction Modeling
  - Design whatever networks as you like

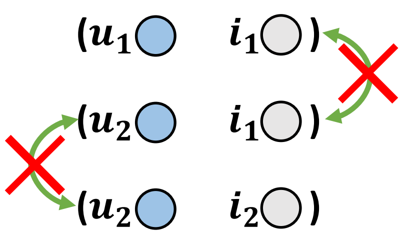


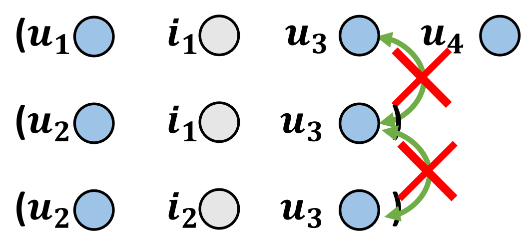
Information Isolated Island Issue (1)



Treating each observation as an independent instance

- Forgoing relationships among instances





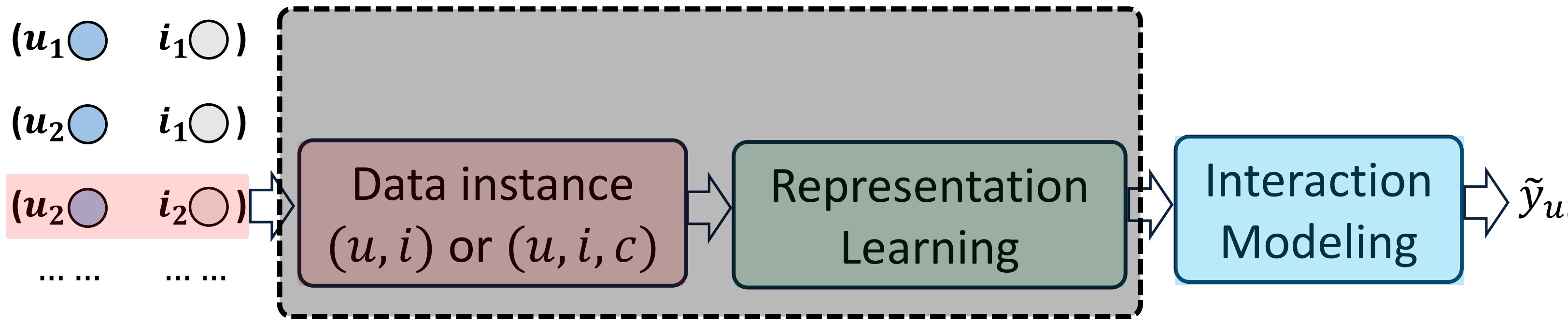
User-Item Interactions

- Behavior similarity among users
- Audience similarity among items

User-Item Interactions + Social Ties

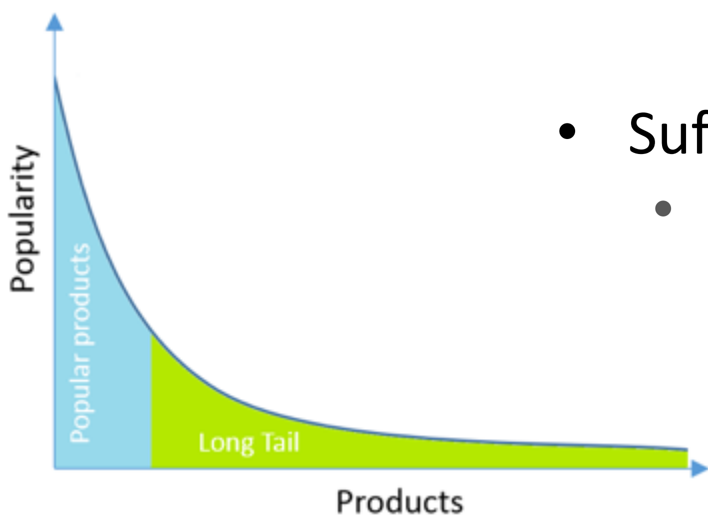
- Shared friends as bridge among users
  → mouth marketing

Information Isolated Island Issue (2)



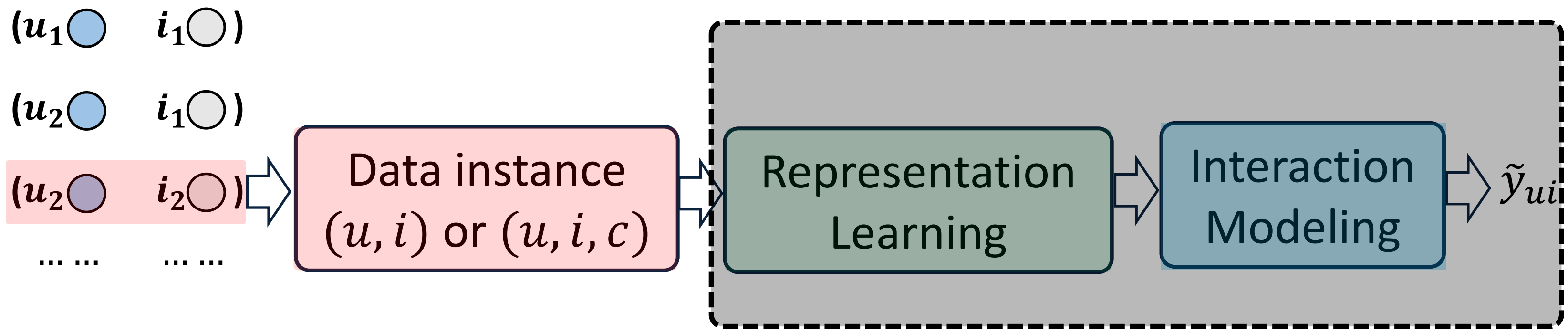
Treating each observation as an independent instance

- Limited Representation Ability
  - Instance representation is dependent on its own features merely
    - SVD++, NAIS: CF with neighbors as input are more expressive



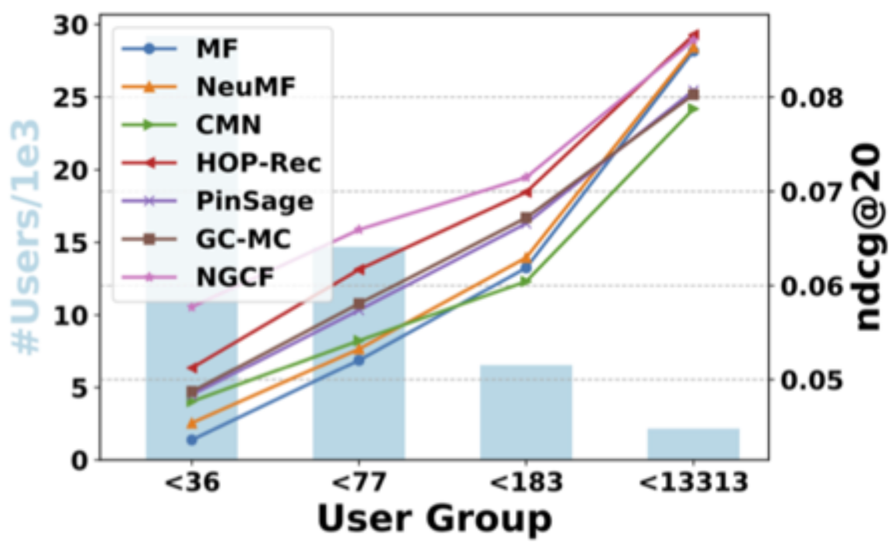
- Suffer from sparsity issue
  - inactive users, unpopular items, infrequent features → insufficient information to learn optimal representation

Information Isolated Island Issue (3)



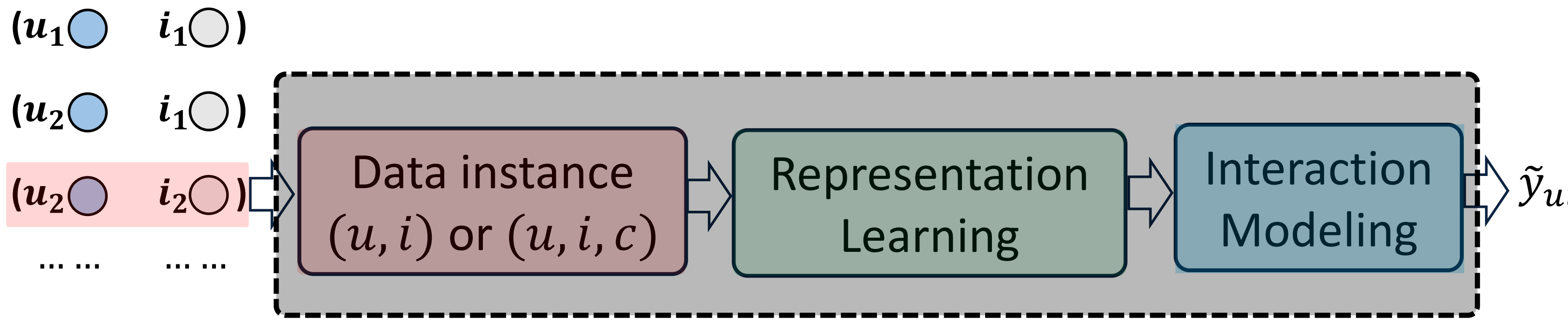
Treating each observation as an independent instance

- Suboptimal Model Capacity
  - Suboptimal representations lead to unsatisfactory interaction model, especially for unseen (user-item or feature) interactions



The methods have to rely on complex interaction function to make up for the deficiency of suboptimal embeddings

Information Isolated Island Issue (4)



Treating each observation as an independent instance

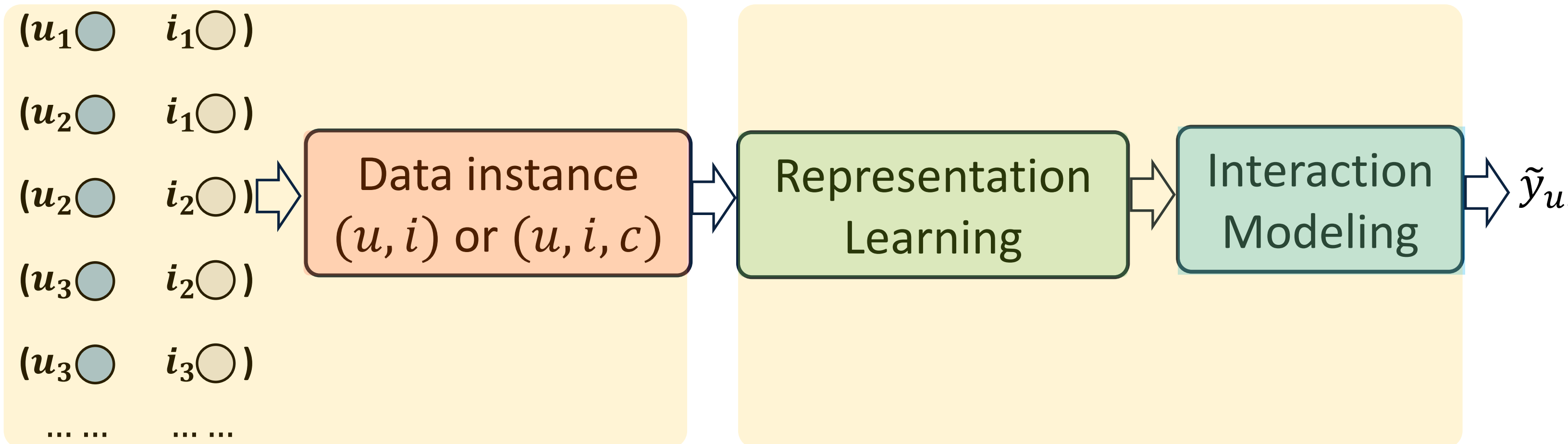
- Components work as a black-box
  - hardly exhibit the reasons behind a recommendation
  - Make the decision-making process opaque to understand

(u_1 i_1)

Why $\boldsymbol{i_1}$ is recommended to $\boldsymbol{u_1}$? Which one is more important?

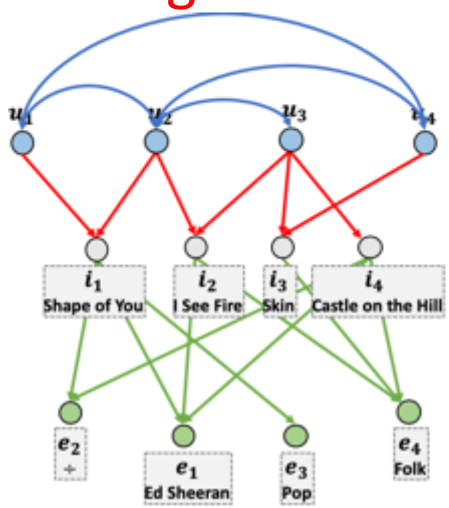
- Collaborative Signals?
- Mouth Marketing?
- Item Knowledge?

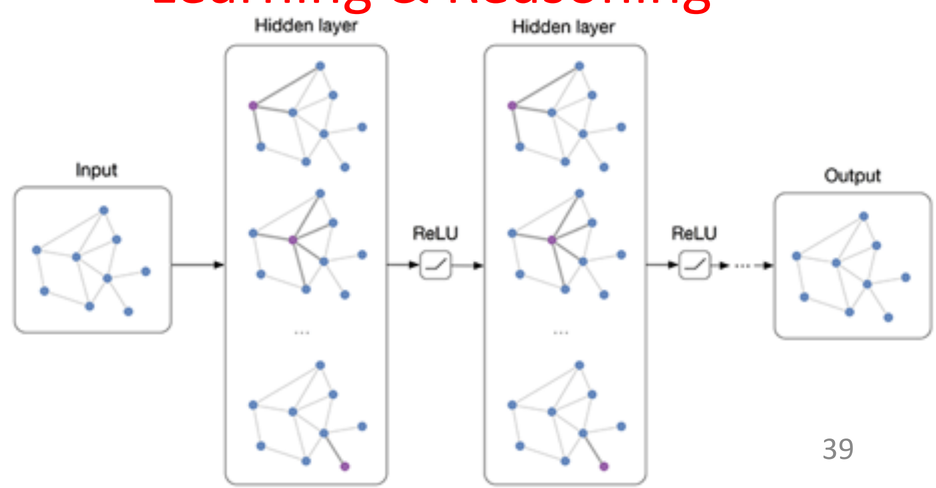
How to Solve Such Issue?



Explore & Exploit Relations among Instances

Apply Techniques of Graph Learning & Reasoning





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OUTLINE

- Introduction
- Part I: Preliminary of Recommendation
- **Part II: Random Walk for Recommendation**
  - **Random Walk**
  - **Absorption, ItemRank, TriRank, Pixie, RecWalk**
- Part III: Network Embedding for Recommendation
- Part III: Graph Neural Networks for Recommendation

Slides in https://next-nus.github.io/

Random Walk

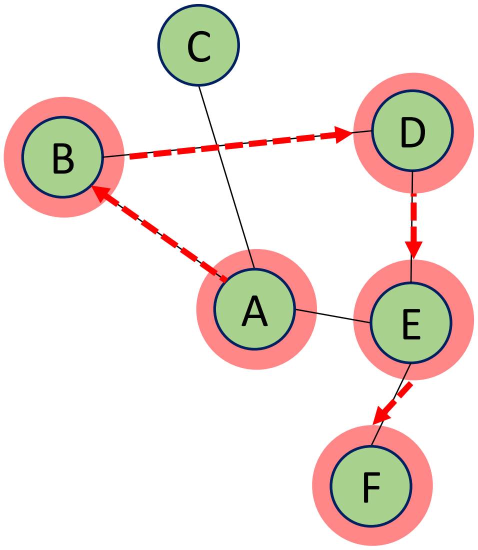
Graph Data G:

- V is the vertex set
- $E = V \times V$ is the edge set

$$p_{ij} = \mathrm{P}(v_{k+1} = j | v_k = i) = \begin{cases} \frac{1}{|N_i|}, \text{if } (i,j) \in E \\ 0, \text{otherwise} \end{cases}$$

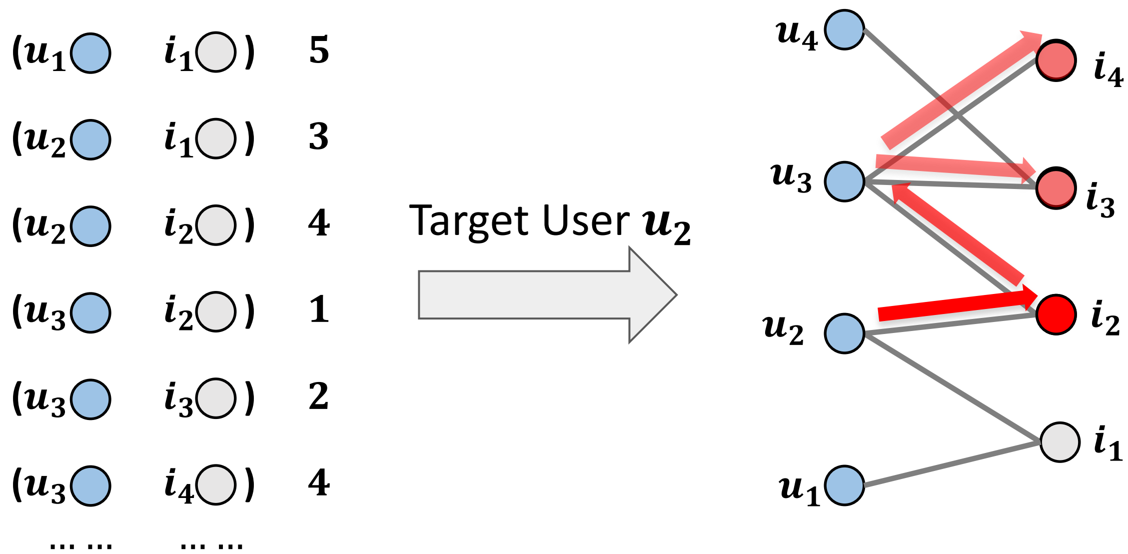
Random Walk → exhibit high-order proximity among nodes

1. Given an initial vertex (node) v_0, select randomly an adjacent node v_1;
2. Move to this neighbor v_1 and treat v_1 as the starting node;
3. Repeat Steps 1& 2.



A → B → D → E → F

Motivation —— Preference Propagation



Interaction Data

Interaction Graph

Item ranking $i_2 > i_3 \approx i_4$

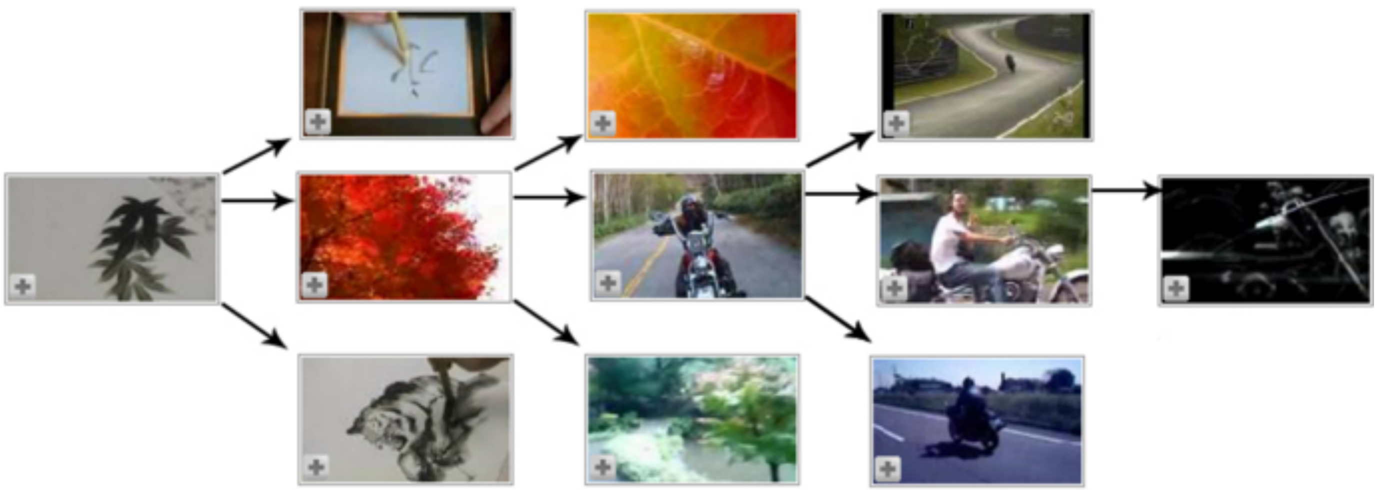
High-order Proximity→ Label Propagation → Preference Distribution

- Label (preference) propagation from the target user's historical item nodes assigns unseen items with expected labels.

Absorption: Random Walk Through View Graph

Absorption from [Baluja et al, WWW'2008]:

- Interactions → **item-item co-viewed graph** or **user-item graph**
  - Edges → two video items are often co-viewed



Take a starting node $\boldsymbol{v}$ for a random walk & output a label distribution

$$L_v(\ell) = \sum_w \sum_u N_v(u) N_u(w) L_w(\ell)$$

The probability of reaching $\boldsymbol{u}$ from $\boldsymbol{v}$ in one random walk step

The probability of picking a neighbor $\boldsymbol{w}$ of $\boldsymbol{u}$

Bakuja et al, Video Suggestion and Discovery for YouTube: Taking Random Walks Through the View Graph. WWW'2008:

ItemRank: A Random-Walk Scoring Algorithm

ItemRank from [Gori et al, IJCAI'2007]:

- Interactions → **item-item correlation graph**
  - Edges → the shared user groups

- Inspired by Classic **PageRank** [Kamvar et al., 2003a]:

Importance score for every node

$$\mathbf{PR} = \alpha \cdot \mathbf{C} \cdot \mathbf{PR} + (1-\alpha) \cdot \frac{1}{|\mathcal{V}|} \cdot \mathbf{1}_{|\mathcal{V}|}$$

Normalized connectivity matrix for graph

Restart

- **ItemRank**

Preference score for an item node & user profile

$$\mathbf{IR}_{u_i} = \alpha \cdot \mathcal{C} \cdot \mathbf{IR}_{u_i} + (1-\alpha) \cdot \mathbf{d}_{u_i}$$

User preference recorded in training set → bias

Gori et al, ItemRank: A Random-Walk Based Scoring Algorithm for Recommender Engines. IJCAI'2017

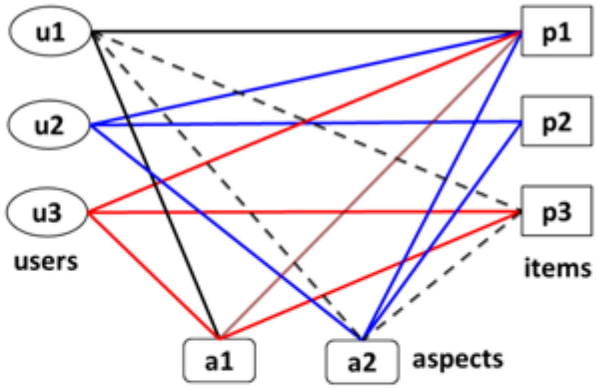
TriRank: Ranking over Tripartite Graph

TriRank from [He et al, CIKM’2015]:

- User-Item Interactions + **Item Aspects** → **Tripartite Graph**
  - User $\boldsymbol{u}$ previously rated item $\boldsymbol{p}$ with mentioning aspect $\boldsymbol{a}$

- **Ranking score** for all nodes of a node
  - User-User → user similarity;
  - User-Aspect → interests on aspects
  - User-Item → preference on items

Inputs:
<u1, p1, a1>
<u2, p1, a2>
<u2, p2, a2>
<u3, p1, a1>
<u3, p3, a1>



- **Smoothness Constrain**

$$Q_{UP}(f) = \sum_{i=1}^{|U|}\sum_{j=1}^{|P|} r_{ij}\left(\frac{f(u_i)}{\sqrt{d_i^u}} - \frac{f(p_j)}{\sqrt{d_j^p}}\right)^2$$

Local consistency → ranking scores of nearby nodes should not vary too much

- **Fitting Constrain**

$$Q_P(f) = \sum_{j=1}^{|P|}\left(f(p_j) - p_j^0\right)^2$$

Ranking scores should adhere to the observations (i.e., initial values).

He et al, TriRank: Review-aware Explainable Recommendation by Modeling Aspects. CIKM’2015

Pixie Random Walk

Pixie from [Eksombatchai et al, WWW'2018]:

- **Undirected Pin-Board Graph**
  - An edge between a pin $\boldsymbol{p}$ and a board $\boldsymbol{b}$ if a user saved $\boldsymbol{p}$ to $\boldsymbol{b}$

- **Input**: a user-specific input query pin q
- **Output**: relevant pin p

Basic Random Walk:

- Simulate many random walks on G, starting from q
- record visit count for each candidate pin p
- The more often p is visited → More related it is to q

Pixie Random Walk:

- Bias the random walk towards user-specific pins (q, U) → personalized results for even the same query set
- Perform queries based on multiple pins $(q \in Q, U)$ each with a different importance → consider the history of users

Eksombatchai et al, Pixie: A System for Recommending 3+ Billion Items to 200+ Million Users in Real-Time. WWW'2018

RecWalk: Nearly Uncoupled Random Walks

RecWalk from [Nikolakopoulos et al, WSDM'2019]:

- **Interactions → User-Item Bipartite Graph**

Adjacency matrix $\mathbf{A}_{\mathcal{G}} \triangleq \begin{pmatrix} \mathbf{0} & \mathbf{R} \\ \mathbf{R}^{\top} & \mathbf{0} \end{pmatrix}$ Interaction matrix

Transition probability matrix to govern the random sampler

$$\mathbf{P} \triangleq \alpha \mathbf{H} + (1-\alpha)\mathbf{M}$$

1. **One based on bipartite graph**

$$\mathbf{H} \triangleq \mathrm{Diag}(\mathbf{A}_{\mathcal{G}}\mathbf{1})^{-1}\mathbf{A}_{\mathcal{G}}.$$

2. **The other designed to capture item relations**

$$\mathbf{M} \triangleq \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{M}_{\mathcal{I}} \end{pmatrix}$$

Recommendation Strategies

$$\boldsymbol{\pi}_u^{\top} \triangleq \mathbf{e}_u^{\top}\mathbf{P}^K$$

- the probability the random walker lands on nodes after steps.

Nikolakopoulos et al, RecWalk: Nearly Uncoupled Random Walks for Top-N Recommendation. WSDM'2019

Summary: Random Walk for Recommendation

	Graph Data	Random Walk
Absorption	Item-item co-viewed graph	Basic
ItemRank	Item-item correlation graph	User-specific transition probability
TriRank	User-item-aspect tripartite graph	Smoothness & fitting constrains
Pixie	Pin-board graph	User-specific multi-pin transition probability
RecWalk	User-item bipartite graph	Basic + item relation-guided transition probability

Limitations

- **Efficiency Issue**:
  - for every user, generate ranking scores on all items each step → hard to apply large-scale graphs
- **Lack model parameters to optimize recommendation objective**
  - heuristic-based, rather than learning-based paradigm

OUTLINE

- Introduction
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- **Part III: Network Embedding for Recommendation**
  - **Network Embedding**
  - **HPE, HOP-Rec, CES**
- Part III: Graph Neural Networks for Recommendation

Slides in https://next-nus.github.io/

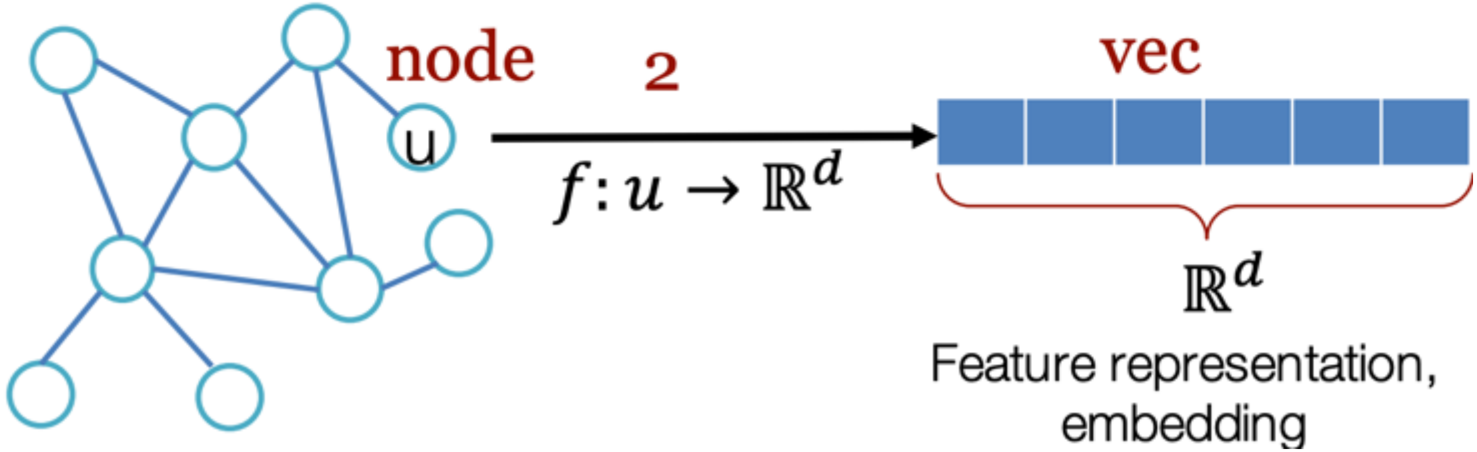
Network Embedding

Also well known as graph representation learning, node embedding, graph embedding.

Input: graph Data G

- V is the vertex set
- $E = V \times V$ is the edge set

Output: $Z \in R^{|V| \times d}$ latent feature representation matrix



Snips from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018

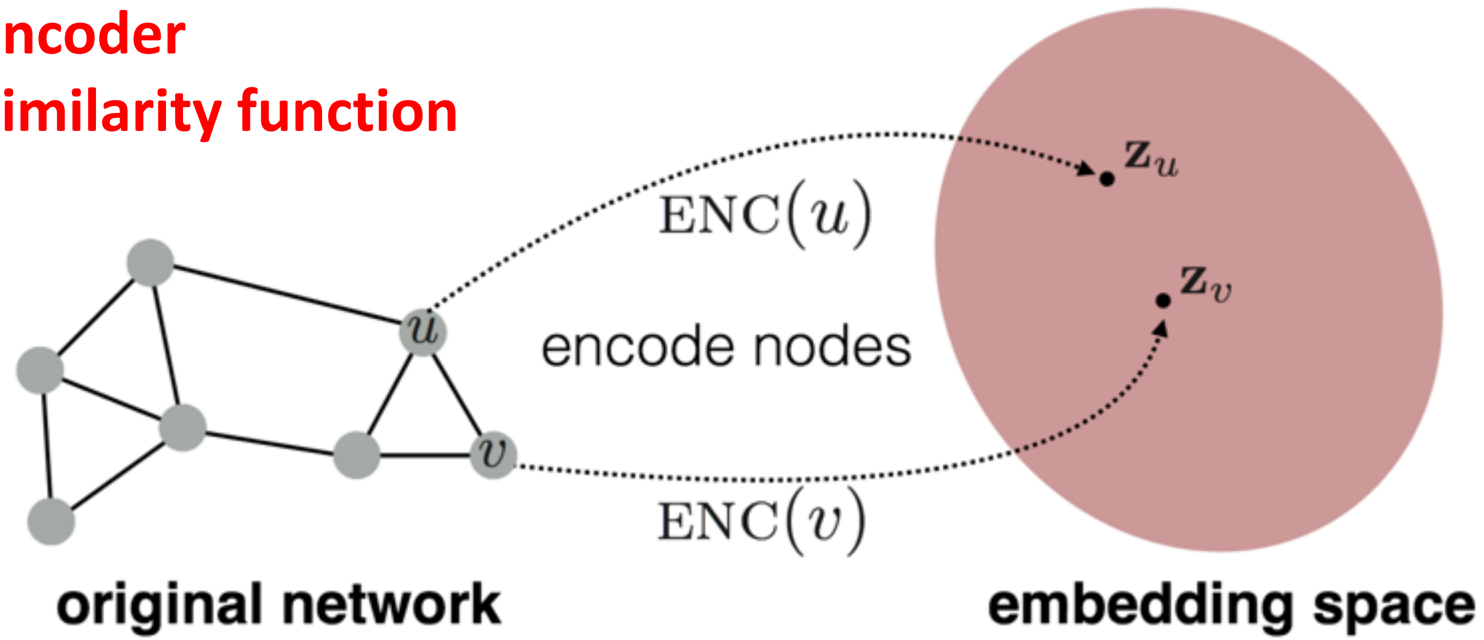
Intuition

Goal:

- Find embedding of nodes to d–dimensions
- **Similarity in the embedding space** approximates **similarity in the original network**

Need to define:

- **Encoder**
- **Similarity function**



Slides from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018

Two Main Components

- **Encoder**
  - To embed each node to a low-dimension vector representation

$$\mathrm{ENC}(v) = z_v$$

Node in input graph

- **Similarity Function**
  - To specify how relationships in the embedding space map to relationships in the original network.

$$\mathrm{similarity}(v, u) = z_u^{\mathrm{T}} z_v$$

Similarity in the original network
- Are connected?
- Share neighbors?
- Have similar structural roles?

Similarity in the embedding space

Slides from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018

One- & Multi-hop Similarity

Similarity Function

- the edge weight between v and u in the original network.

- **One-hop Similarity** → Adjacency Similarity
  - e.g., [Ahmed et al. WWW'2013]

$$\mathcal{L} = \sum_{(u,v) \in E \times E} ||z_u^{\mathrm{T}} z_v - A_{uv}||^2$$

All node pairs

(Weighted) adjacency matrix for input graph
- Only consider the existence of **direct connections**

- **Multi-hop Similarity** → overlap between node multi-hop neighbors
  - e.g., [Cao et al. CIKM'2015], [Ou et al. KDD'2016]

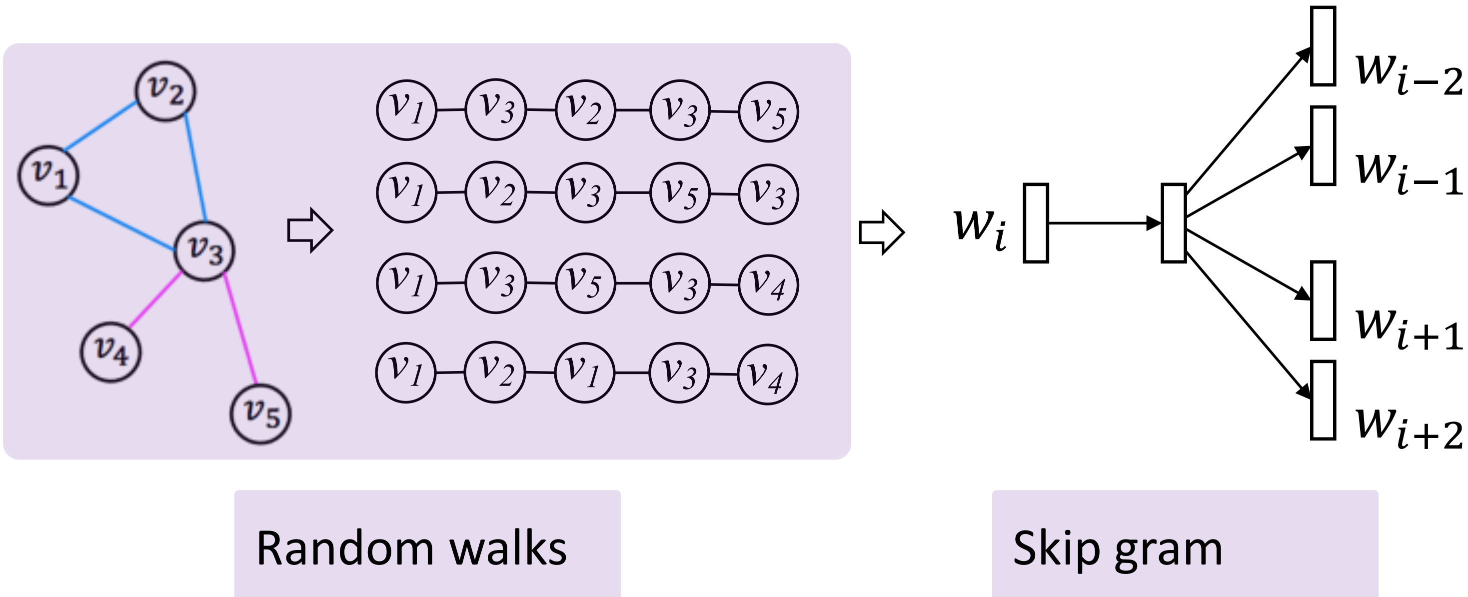
$$\mathcal{L} = \sum_{(u,v) \in E \times E} ||z_u^{\mathrm{T}} z_v - S_{uv}||^2$$

Neighborhood overlap between nodes

Random Walk-based Similarity

Similarity Function

- **Probability that** u and v co-occur on a random walk over the graph
- E.g., DeepWalk, node2vec …

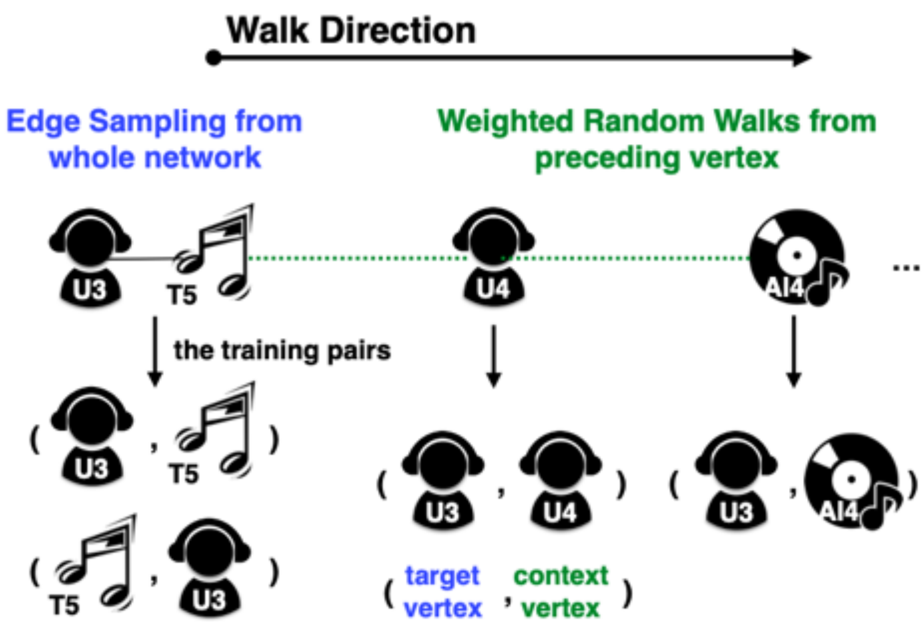


Slides from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018
Slide from: Tang Jie et al. Representation Learning on Networks, Tutorial@WWW2019

Heterogeneous Preference Embedding (HPE)

HPE from [Yang et al, RecSys'2016]

- Interactions + Side information → heterogeneous graph
- **Random walk similarity**
  - treat indirect user-item interactions as user context



$$Pr(v_j|\Phi(v_i)) = \begin{cases} 1 & \text{if } v_j \in Context(v_i) \\ 0 & \text{otherwise} \end{cases}$$

Indirect connected nodes as the contextual information of ego node

$$-\sum_{(i,j)\in S} w_{i,j} \log p(v_j|\Phi(v_i)) + \lambda \sum_i \|\Phi(v_i)\|^2$$

Random walk steps

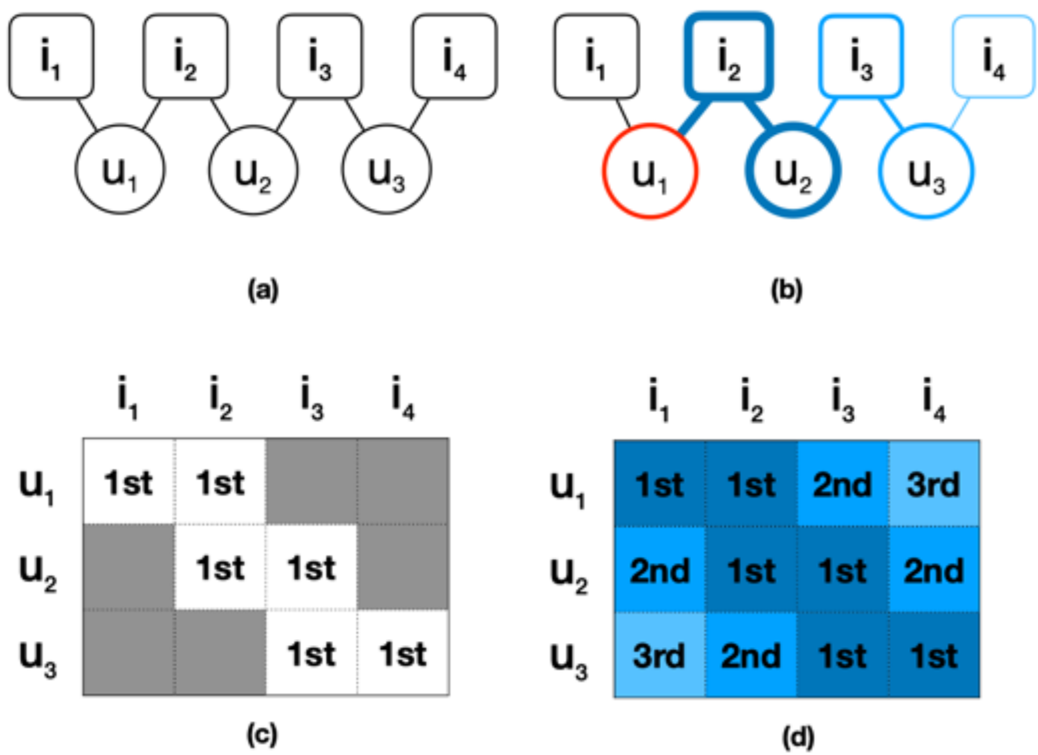
Learn the preference embeddings via contextual nodes

Yang et al, Query-based Music Recommendations via Preference Embedding. RecSys'2016

HOP-Rec: High-Order Proximity for Recommendation

HOP-Rec from [Yang et al, RecSys'2018]

- Interactions → user-item bipartite graph
- **Random walk similarity**
  - In a path, nodes with different orders → different confidence
  - Involve indirect user-item interactions into user preference



Yang et al, HOP-Rec: High-Order Proximity for Implicit Recommendation. RecSys'2018

HOP-Rec: High-Order Proximity for Recommendation

HOP-Rec from [Yang et al, RecSys'2018]

$$\mathcal{L}_{HOP} = \sum_{\substack{1 \le k \le K \\ u,(i,i')}} \overbrace{C(k)\, \mathbb{E}_{\substack{i \sim P_u^k \\ i' \sim P_N}}}^{\text{graph model}} \overbrace{\left[\mathcal{F}\left(\theta_u^\top \theta_{i'}, \theta_u^\top \theta_i\right)\right]}^{\text{factorization model}} + \lambda_\Theta \left\|\Theta\right\|_2^2$$

A random walk with a decay factor for **confidence weighting $C(k)$**

- For a given walk sequence, item with order k that the user potential prefers → **treated as positive instances**

Matrix Factorization with BPR loss

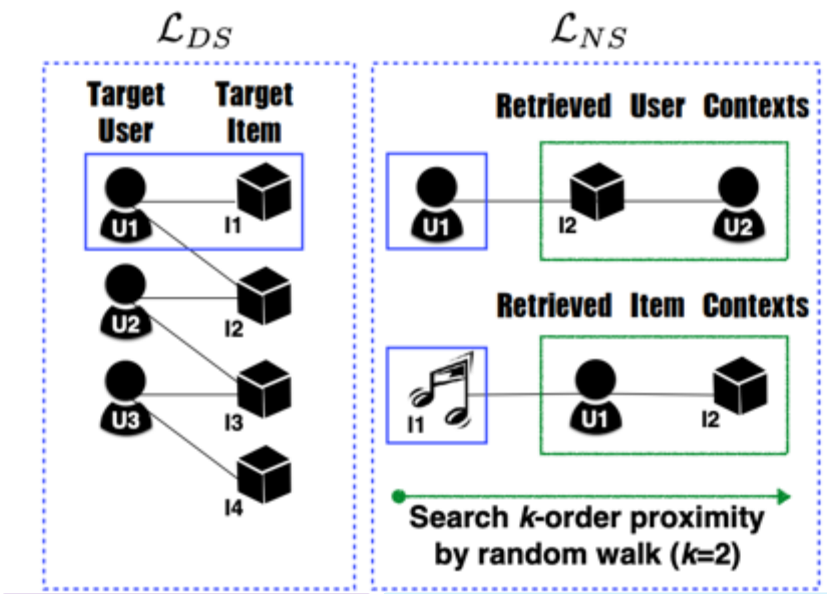
- Random walk **enriches the positive observations**

Yang et al, HOP-Rec: High-Order Proximity for Implicit Recommendation. RecSys'2018

Collaborative Similarity Embedding (CES)

CES from [Chen et al, WWW'2019]

- Interactions → user-item bipartite graph



Direct Similarity Embedding (DSEmbed)

Neighborhood Similarity Embedding (NSEmbed)

$$\arg\max_{\Phi} \sum_{(v_i, v_j) \in E} \log p(v_i, v_j | \Phi)$$

Maximize the likelihood of observed pairs

$$\arg \max_{\Phi, \Phi^{UC}, \Phi^{IC}} \prod_{(v_i,v_j)\in S_U} p(v_j | v_i; \Phi; \Phi^{UC}) + \prod_{(v_i,v_j)\in S_I} p(v_j | v_i; \Phi; \Phi^{IC})$$

- Conduct k-step random walk
- Get neighborhoods of a user (or item) pair
- Neighborhood proximity → user (or item) similarity

Chen et al, Collaborative Similarity Embedding for Recommender Systems. WWW'2019.

Summary: Network Embedding for Recommendation

	Graph Data	Connectivity/Proximity
HPE	Heterogeneous graph	Indirect connections
HOP-Rec	User-item bipartite graph	• Direct connections • Indirect connections
CES	User-item bipartite graph	• Direct similarity • Neighborhood proximity similarity

Limitations

- **Not end-to-end Learning**:
  - Random walk is conducted first to get multi-hop neighbors
- **Not fully explore high-order connectivity**
  - Multi-hop neighbors are used to enrich the training data, rather than directly contributing to the representation learning

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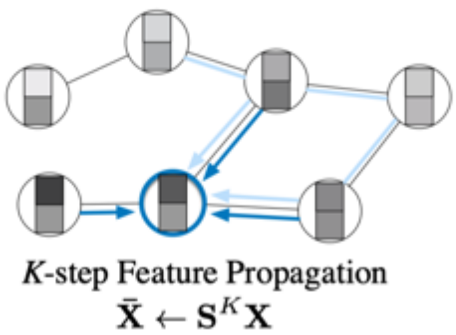
- **Part III: Graph Neural Networks for Recommendation**
  - **Graph Neural Networks**

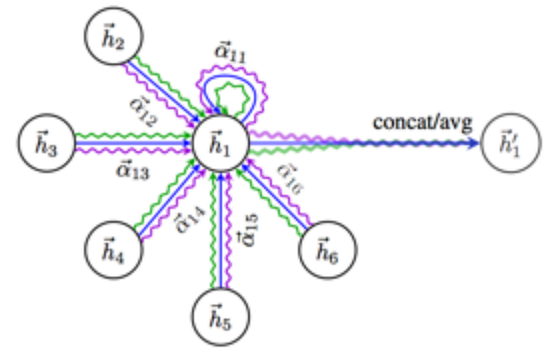
Slides in https://next-nus.github.io/

Recent Graph Neural Network (GNN) Research

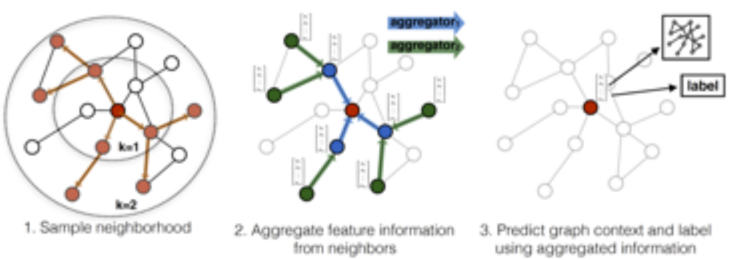
2018 SGC



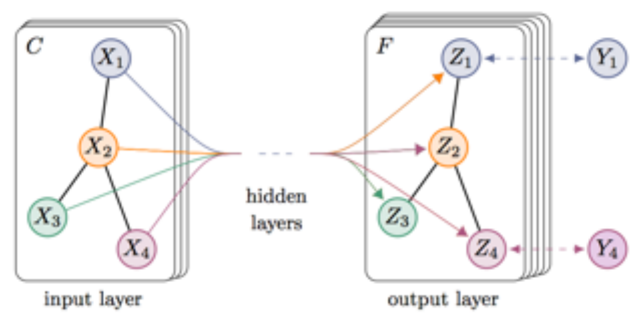
2018 GAT



2017 GraphSage

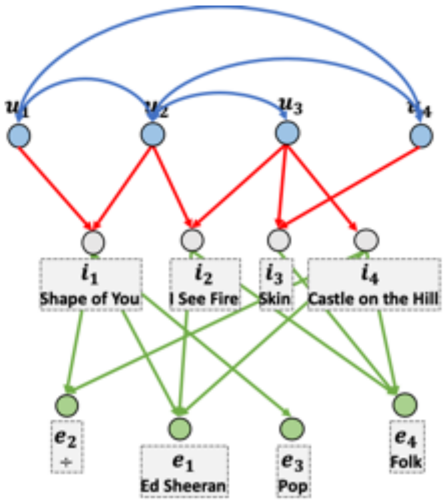


2017 GCN



Graph Data G

- V is the vertex set
- $E = V \times V$ is the edge set
  - Undirected: social relations, user-item interactions …
  - Directed: triplets in knowledge graph



- $A \in R^{|V| \times |V|}$ is the adjacency matrix
  - $A_{i,j} = \begin{cases} a_{i,j} > 0 & (i,j) \in E \\ 0 & (i,j) \notin E \end{cases}$
- $X \in R^{d \times |V|}$ is a matrix of node features
  - Categorical attributes, text, image data
  - Node degrees, clustering coefficient, …
  - Indicator vectors (i.e., one-hot encoding of each node)
- $X' \in R^{d' \times |E|}$ is a matrix of edge features
  - Relations

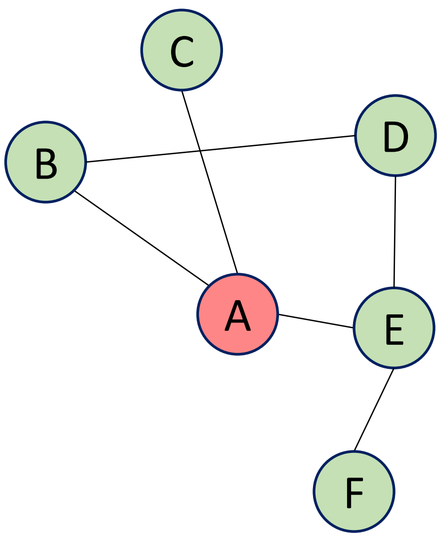
Graph Convolution Network (GCN)

- At the core of GCN
  1. Model a local structural information (neighborhood) of a node as the receptive field
  2. Apply the **graph convolution** operation
     - Spectral domain:
       - Laplacian eigen-decomposition [Bruna et al. ICLR'2014]
       - Chebyshev polynomials [Defferrard et al, NeurIPS'2016]
       - However, computationally expensive
     - Spatial domain:
       - Node (Neighborhood) aggregation [William et al, NeurIPS'2017]
  3. Update its representation.
     - $Z \in R^{d \times |V|}$ latent feature representation matrix

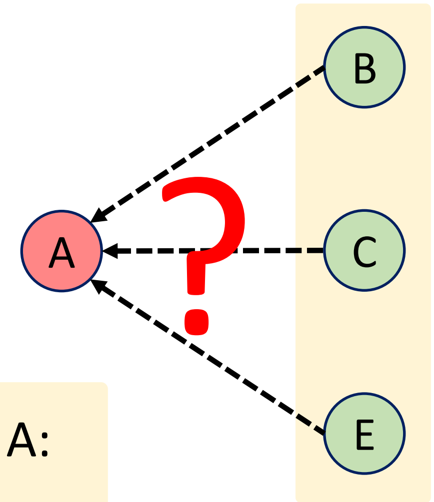
Neighborhood Aggregation (1)

Key Idea:

- Generate node embeddings based on local neighbors
- Neighborhood defines a computation graph.



Computation Graph of node A



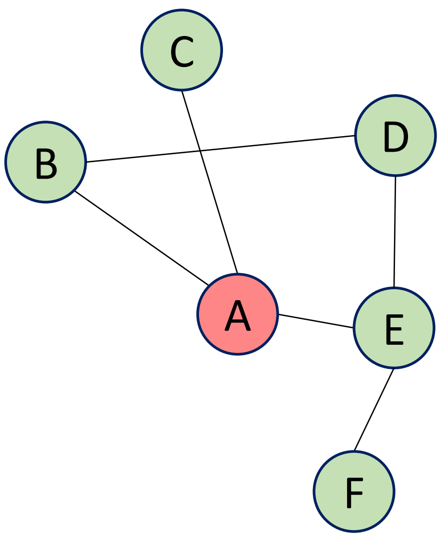
One-hop Neighborhood of node A:

$$\boldsymbol{N}_A = \{B, C, E\}$$

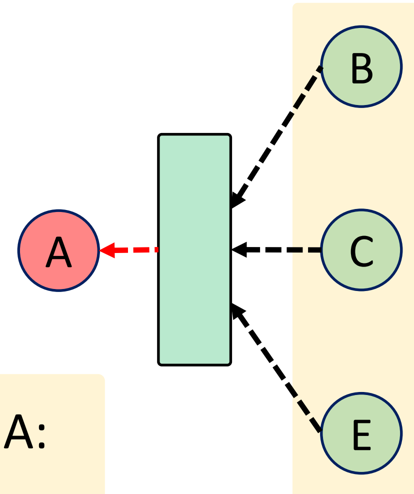
Neighborhood Aggregation (2)

Message Passing/ Information Propagation:

- A node aggregates information from their neighbors via neural networks



Computation Graph of node A



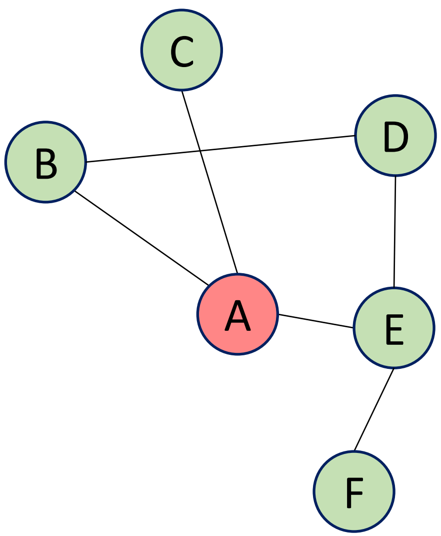
One-hop Neighborhood of node A:
$$\boldsymbol{N}_A = \{B, C, E\}$$

One-hop Neighborhood Aggregation:
$$\boldsymbol{h}'_A = f(\boldsymbol{h}_B, \boldsymbol{h}_C, \boldsymbol{h}_E)$$

Neighborhood Aggregation (3)

Moreover:

- Every neighboring node has its won computation graph!

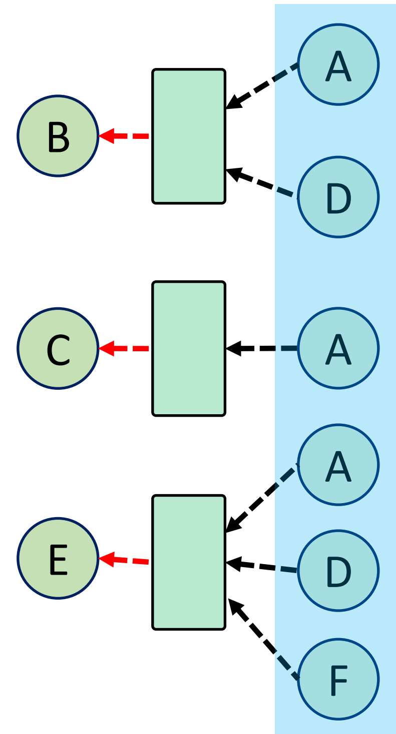


Computation Graph of each node

Two-hop Neighborhood of node A:

$$\boldsymbol{N}_A = \{\boxed{D, F}\}$$

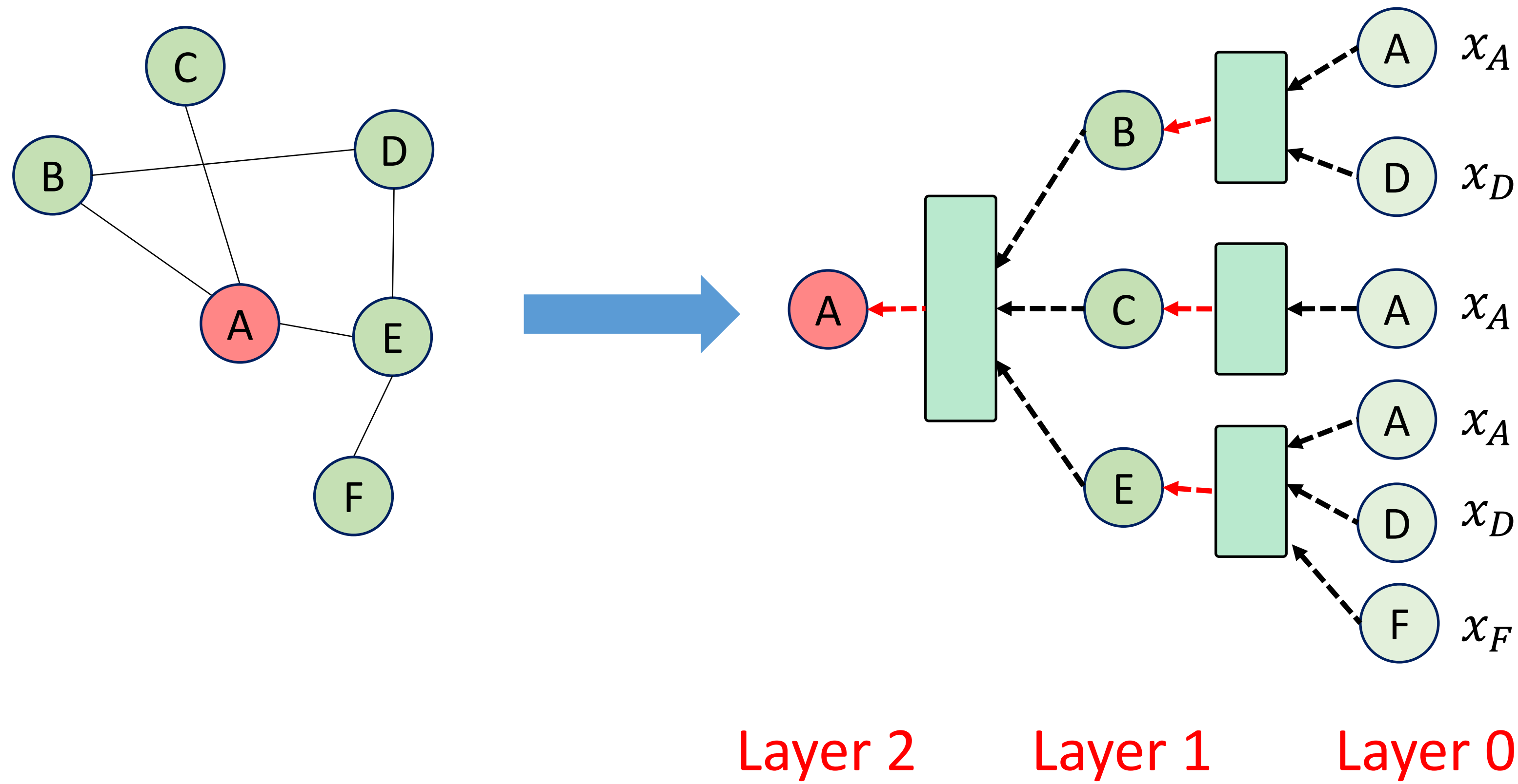
Unseen in one-hop neighborhood



Neighborhood Aggregation (4)

Stacking more neighborhood aggregation layers

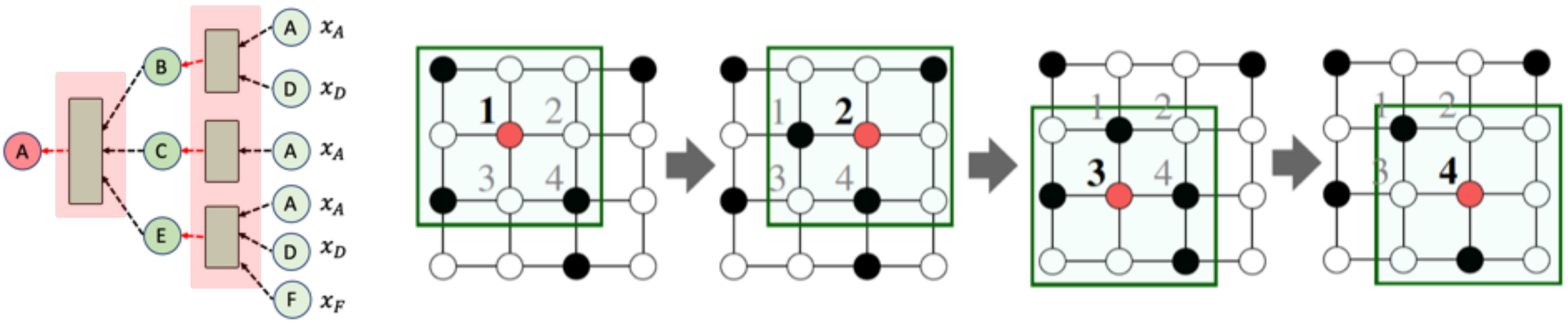
- Nodes have embeddings at each layer
- Model can be arbitrary depth
- At Layer 0, embedding of node $v \in V$ is its input feature, i.e., x_v.



Slide from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018

Graph Convolution

Neighborhood aggregation can be viewed as a center-surround filter in convolutional neural network (CNN).



Mathematically related to **spectral graph convolutions** (Bronstein et al., 2017)

Now

- How to aggregate information across layers!
- i.e., how to design the neural networks!

Slide from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018

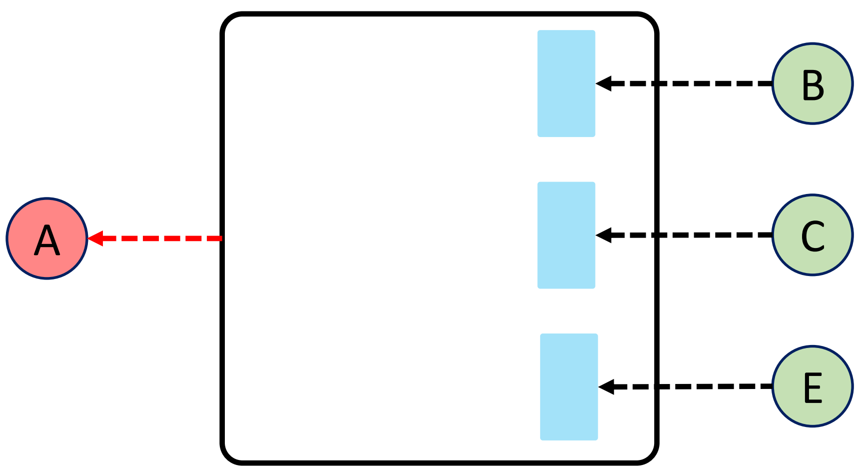
Component 1: Information Construction

Generally speaking, the first main component:

1. **Information Construction**
   Construct the information being propagated from one neighboring node to the target node.

$$m_{v\to u}^{(k-1)} = f_1^{(k-1)}\left(h_v^{(k-1)}, h_u^{(k-1)}, p_{vu}^{(k-1)}\right)$$

The information being propagated from node v to the target u	Neural network	Nodes' previous layer embeddings	Decay factor or normalization term



Component 2: Neighborhood Aggregation

Generally speaking, the second main component:

2. Neighborhood Aggregation

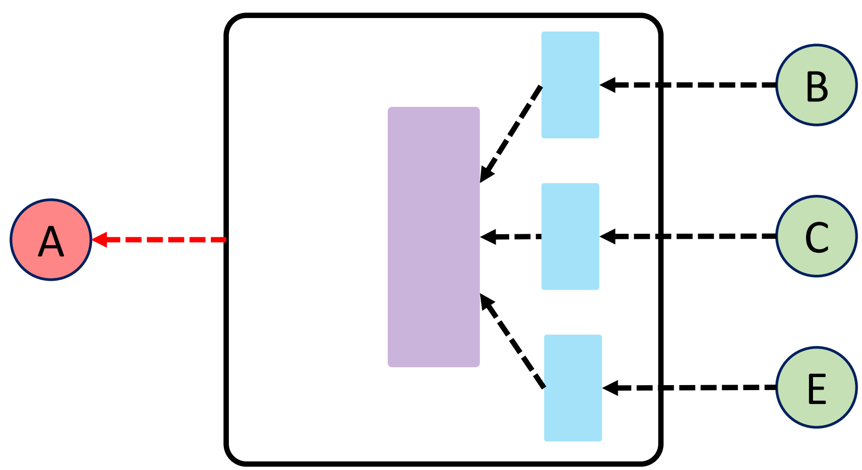
Aggregate the information from the whole neighborhood.

$$h_{\mathcal{N}_u}^{(k-1)} = f_2^{(k-1)}\left(\left\{ h_v^{(k-1)} \right\}, \text{for } v \in \mathcal{N}_u\right)$$

The information combining neighbors' information

Aggregation Function

The information obtained from the first component



Component 3: Representation Update

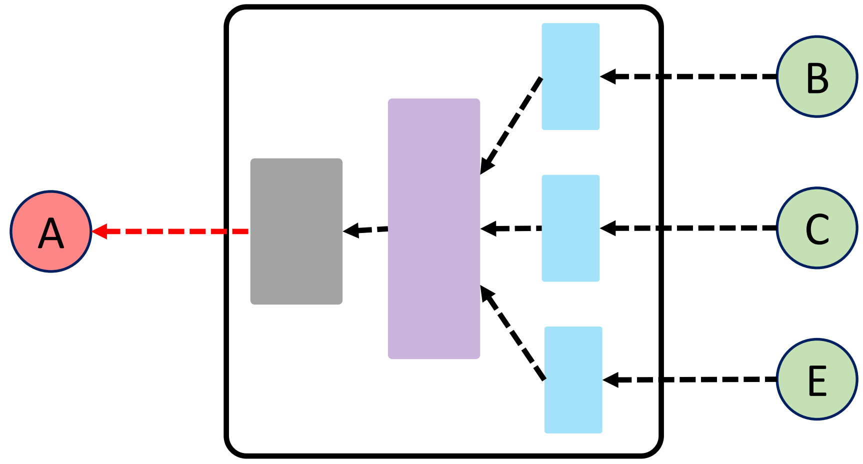
Generally speaking, the third main component:

3. Representation Update

Integrate the neighborhood information with its own representation.

$$h_u^{(k)} = f_3^{(k-1)}\left(h_{\mathcal{N}_u}^{(k-1)}, h_u^{(k-1)}\right)$$

The updated representation of u at the k-th layer	Integration Function	The representation of the target node u at the $(k-1)$-th layer



Graph Convolutional Network (GCN)

GCN from [Kipf et al., ICLR'2017]:

Nonlinear activation function

$$h_u^{(k)} = \sigma\left(W_k \sum_{v \in \mathcal{N}_u \cup u} \frac{h_v^{(k-1)}}{\sqrt{|\mathcal{N}_u||\mathcal{N}_v|}} \right)$$

The same neural network for self and neighbor embeddings in Comp.3

- More parameter sharing

Weighted sum: Aggregation in Comp. 2

per-neighbor normalization: $p_{uv}^{(k-1)}$ in Comp. 1

- Normalization varies across neighbors
- Down-weights high degree neighbors

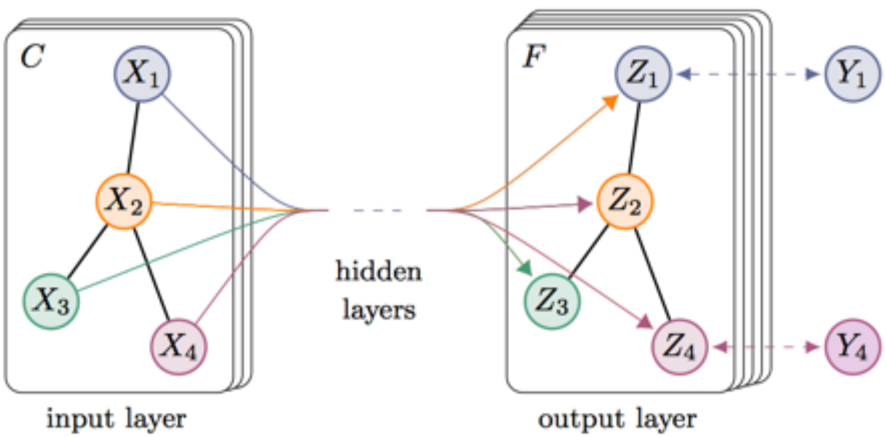
Kipf et al., ICLR'2017: Semisupervised Classification with Graph Convolutional Network.

GCN in Matrix Form

Can be rewritten in the matrix form

- Which is efficiently implemented using sparse batch operations

- Time complexity is $O(|E|)$



Representation Matrix at the k-th layer

$$H^{(k)} = \sigma\left(D^{-\frac{1}{2}}(A+I)D^{-\frac{1}{2}}H^{(k-1)}W_k\right) \Rightarrow Z = H^{(K)}$$

Laplacian Matrix for Graph G

Final representation matrix

Kipf et al., ICLR'2017: Semisupervised Classification with Graph Convolutional Network.

GraphSage

GraphSage from [Hamilton et al., NeurIPS’2017]:

- The most distinction is the **generalized aggregation**

$$h_{\mathcal{N}_u}^{(k-1)} = \boxed{f_2^{(k-1)}}\left(\left\{ h_v^{(k-1)} \right\}, \text{for } v \in \mathcal{N}_u\right)$$

Generalized Aggregation Function in Comp. 2
→ **Any differentiable function that maps a set of vectors to a single vector.**

$$h_u^{(k)} = \sigma\left(\left[W_1^{(k)} \cdot \boxed{\mathrm{AGG}\left(\left\{h_v^{(k-1)}, \forall v \in \mathcal{N}_u\right\}\right)}, W_2^{(k)} h_u^{(k-1)} \right]\right)$$

Integration Function in Comp.3 → concatenate neighbors & self embeddings, instead of sum

Hamilton et al., NeurIPS’2017. Inductive Representation Learning on Large Graphs.

Generalized Aggregation in GraphSage

- Mean

$$\text{AGG} = \sum_{\forall v \in \mathcal{N}_u} \frac{h_v^{(k-1)}}{|\mathcal{N}_v|}$$

- Pool
  - Transform neighbor vectors and apply symmetric vector function.

$$\text{AGG} = \gamma(\{Q h_v^{(k-1)}, \forall v \in \mathcal{N}_u\})$$

Element-wise mean/max

- LSTM
  - Apply LSTM to random permutation of neighbors.

$$\text{AGG} = \text{LSTM}([h_v^{(k-1)}, \forall v \in \mathcal{N}_u])$$

Hamilton et al., NeurIPS'2017. Inductive Representation Learning on Large Graphs.
Slide from: Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018

Graph Attention Network (GAT)

GAT from [Velickovic et al., ICLR'2018]:

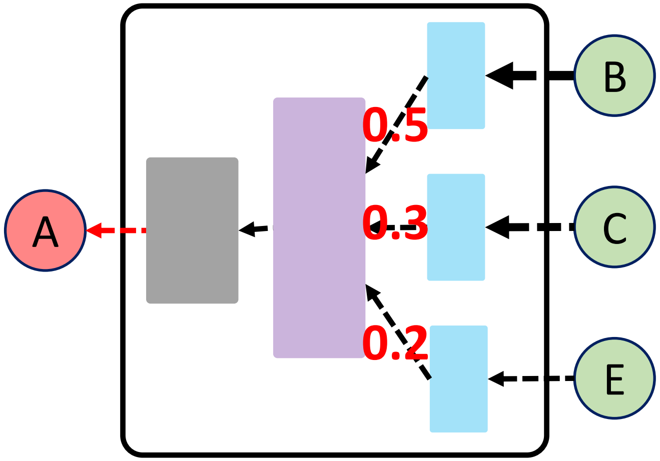
- The most distinction is the **attentive neighborhood aggregation**

$$h_{\mathcal{N}_u}^{(k-1)} = f_2^{(k-1)}\left(\left\{ h_v^{(k-1)} \right\}, \text{for } v \in \mathcal{N}_u\right)$$

Attentive Aggregation Function in Comp. 1&2

→ **Different neighbors have varying contributions when propagating information.**

→ **Instead of fixed heuristic-based decay factor like GCN, GraphSage**



$$h_u^{(k)} = \sigma\left(\sum_{v \in \mathcal{N}_u} \alpha_{u,v} W^{(k)} h_v^{(k-1)}\right)$$

Learned attentive weights

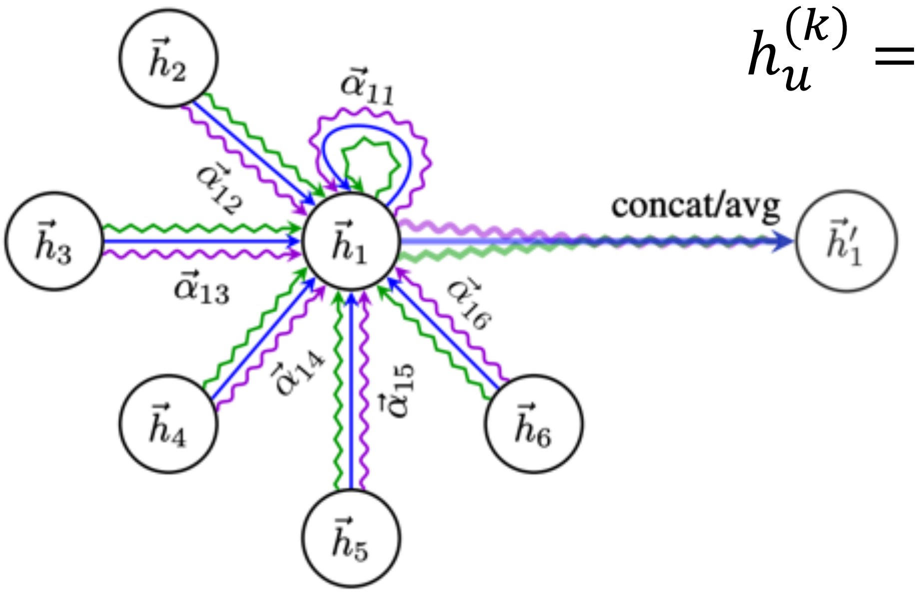
Velickovic et al. Graph Attention Networks. ICLR 2018

Attention Weights in GAT

- Attention Network

$$\alpha_{v,u} = \frac{\exp\left(\text{LeakyReLU}\left(\mathbf{a}^\top[\mathbf{Q}\mathbf{h}_v, \mathbf{Q}\mathbf{h}_u]\right)\right)}{\sum_{u' \in N(v) \cup \{v\}} \exp\left(\text{LeakyReLU}\left(\mathbf{a}^\top[\mathbf{Q}\mathbf{h}_v, \mathbf{Q}\mathbf{h}_{u'}]\right)\right)}$$

- Multi-head Attention



$$h_u^{(k)} = \sigma\left(\boxed{\frac{1}{L}\sum_{l=1}^{L}} \sum_{v \in \mathcal{N}_u} \alpha_{u,v}^{(l)} W^{(l,k)} h_v^{(k-1)}\right)$$

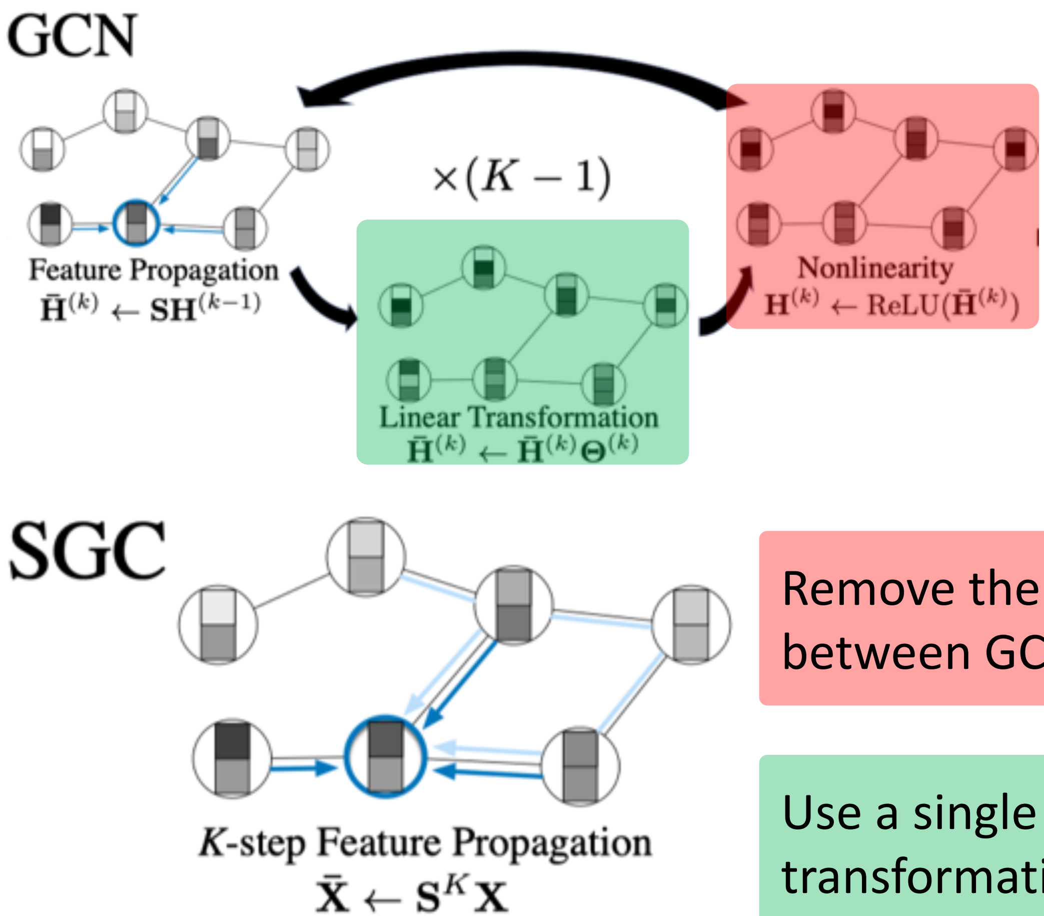
With L Heads

Velickovic et al. Graph Attention Networks. ICLR 2018

Simple Graph Convolution (SGC)

SGC from [Wu et al., ICML'2019]:

- **Unnecessary** complexity & redundant computation of GCN



Remove the nonlinearities between GCN layers

Use a single linear transformation

Wu et al. Simplifying Graph Convolutional Networks. ICML 2019

SGC in Matrix Form

- SGC improves the **efficiency** of GCN largely **without sacrificing accuracy**, & even outperforms GCN on some tasks.

GCN: $H^{(k)} = \sigma\left(D^{-\frac{1}{2}}(A+I)D^{-\frac{1}{2}}H^{(k-1)}W_k\right) \Rightarrow Z = H^{(K)}$

SGC: $H^{(k)} = D^{-\frac{1}{2}}(A+I)D^{-\frac{1}{2}}H^{(k-1)} \Rightarrow Z = H^{(K)}$

Only linear feature propagation is remained

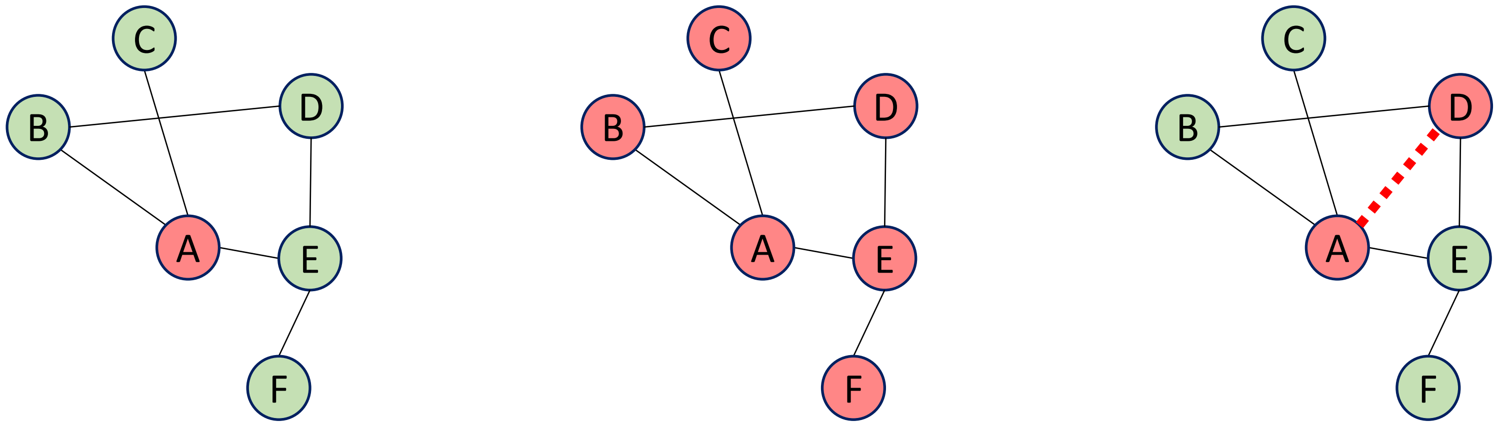
Wu et al. Simplifying Graph Convolutional Networks. ICML 2019

Training

- After K graph convolution layers (e.g., GCN, GraphSage, GAT, SGC), we get output embeddings for each node.

$$Z = H^{(K)}$$

- Upon these embeddings, we can define a loss function for a specific task:



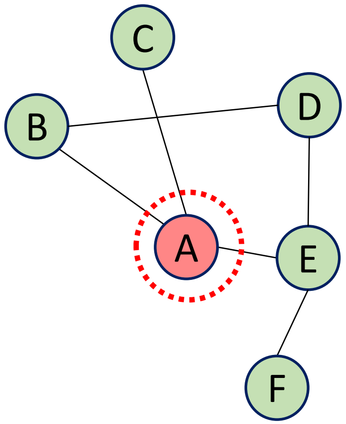
Node classification $\mathcal{L}(Z_u)$

Graph classification $\mathcal{L}(Z_G)$

Link prediction $\mathcal{L}(Z_u, Z_v)$

- Run stochastic gradient descent to train the aggregation parameters

e.g., Node Classification Task



Estimate the label of the target node:

- positive or negative?
- Belonging to one of C classes

$$\mathcal{L} = \sum_{v \in V} y_v \log\left(\sigma\left(z_v^{\mathrm{T}} \theta\right)\right) + (1 - y_v) \log\left(1 - \sigma\left(z_v^{\mathrm{T}} \theta\right)\right)$$

Ground-truth label

Trainable weights in the classifier

GNN embeddings can be plug-and-play & serve other semi-supervised & unsupervised & supervised tasks.

Recent Research on GNN

- More Details in **Previous Tutorials**:
  - Jure Leskovec et al. Representation Learning on Networks, Tutorial@WWW2018
  - Hamiltion & Jie Tang. Graph Representation Learning, Tutorial@AAAI2019
  - Jie Tang et al. Representation Learning on Networks, Tutorial@WWW2019

- More Details in **Survey Papers**:
  - Zhou et al., Graph Neural Networks: A Review of Methods and Applications
  - Zhang et al., Deep Learning on Graphs: A Survey
  - Wu et al., A Comprehensive Survey on Graph Neural Networks

- More **Paper Collections** in Github:
  - https://github.com/thunlp/GNNPapers#survey-papers
  - https://github.com/naganandy/graph-based-deep-learning-literature

OUTLINE

- Introduction
- Part I: Preliminary of Recommendation
- Part II: Random Walk for Recommendation
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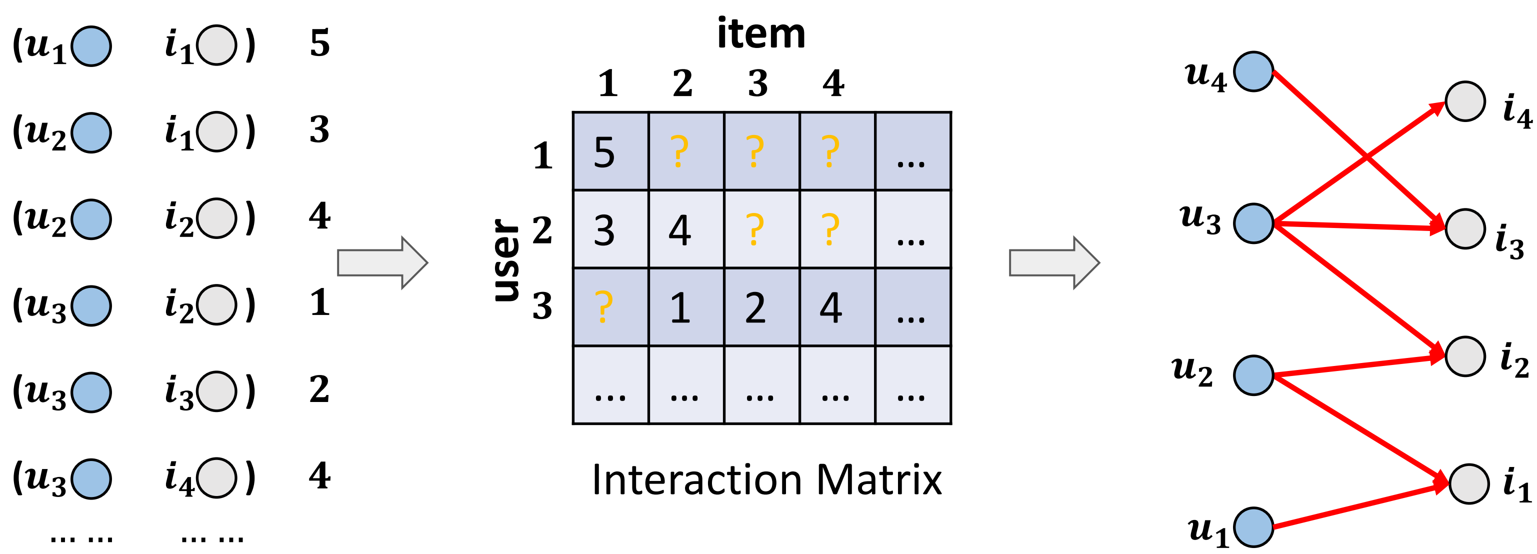
- **Part III: Graph Neural Networks for Recommendation**
    - **Collaborative Filtering: GC-MC, SpectralCF, NGCF**

Slides in https://next-nus.github.io/

Recap Collaborative Filtering (CF)

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

- User-Item Interaction Data → User-Item Bipartite Graph
  - Edges indicate the user behaviors.



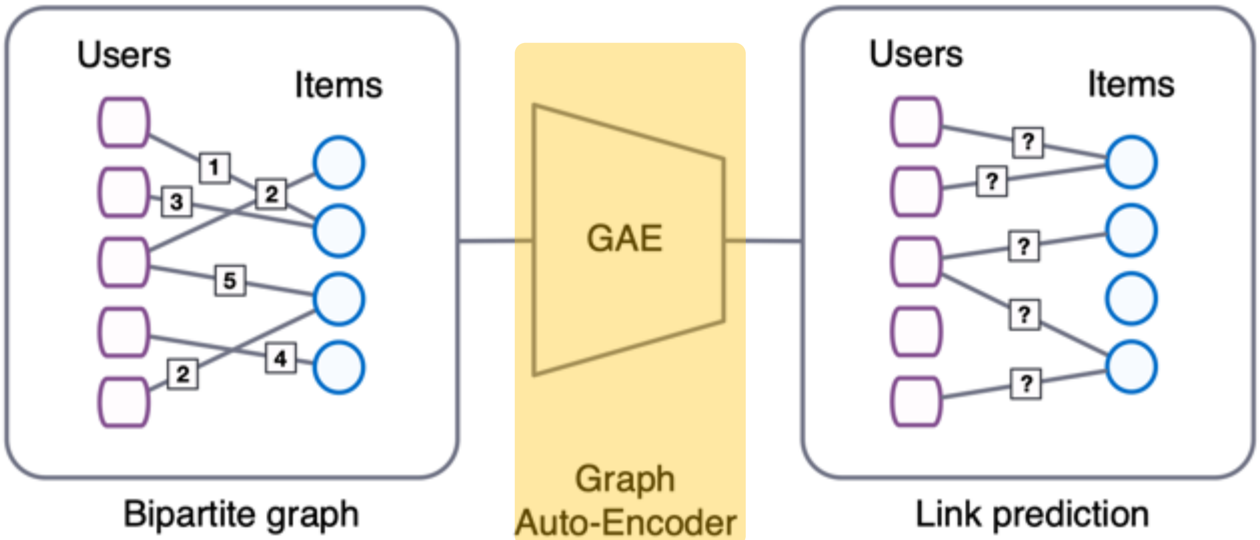
Interaction Matrix

Interaction Graph

Graph Convolutional Matrix Completion (GC-MC)

GC-MC from [Rianne et al., KDD’2018]

- View matrix completion as link prediction on interaction graph
  - Rating Prediction → predict links in bipartite user-item graph

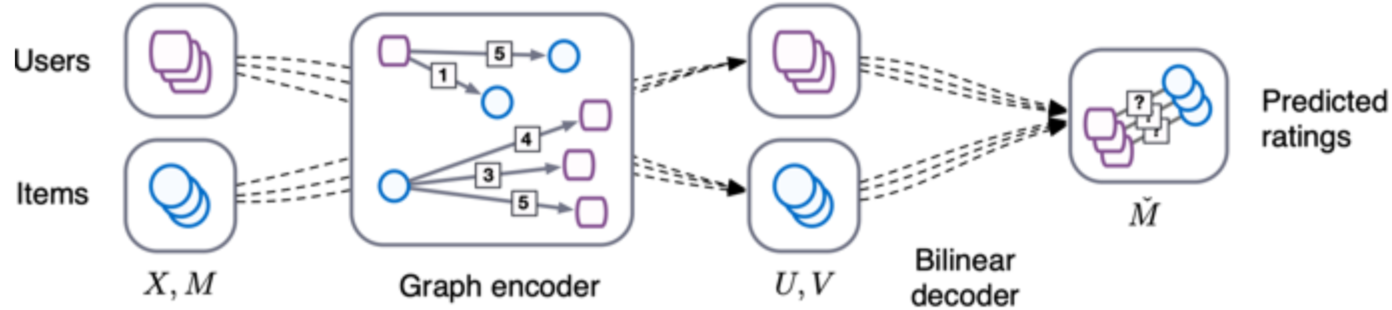


Generate high-quality embeddings of users and items on the graph in an end-to-end fashion

- Previous solutions separate the graph feature model and link prediction model

Rianne et al. Graph Convolutional Matrix Completion. KDD 2018

Graph Convolutional Encoder in GC-MC



- Comp.1: Information Construction:

$$\mu_{j \to i, r} = \frac{1}{c_{ij}} W_r x_j^v$$

Different W_r are assigned to different rating level r.

- Comp.2: Neighborhood Aggregation:

$$h_i^u = \sigma\left[\text{accum}\left(\sum_{j \in \mathcal{N}_i(u_i)} \mu_{j \to i, 1}, \ldots, \sum_{j \in \mathcal{N}_R(u_i)} \mu_{j \to i, R}\right)\right]$$

Accumulation operation over neighbors at all rating levels

- Comp.3: Representation Update:

$$z_i^u = \sigma(W h_i^u)$$

Rianne et al. Graph Convolutional Matrix Completion. KDD 2018

Rating Prediction in GC-MC

- Rating Prediction

$$p(\check{M}_{ij} = r) = \frac{e^{(z_i^u)^T Q_r z_j^v}}{\sum_{s=1}^{R} e^{(z_i^u)^T Q_s v_j}}$$

Trainable weights for different rating levels

$$\check{M}_{ij} = g(u_i, v_j) = \mathbb{E}_{p(\check{M}_{ij}=r)}[r] = \sum_{r \in R} r\, p(\check{M}_{ij} = r)$$

- Model Training

$$\mathcal{L} = -\sum_{i,j;\Omega_{ij}=1} \sum_{r=1}^{R} I[M_{ij} = r] \log p(\check{M}_{ij} = r)$$

Negative log likelihood

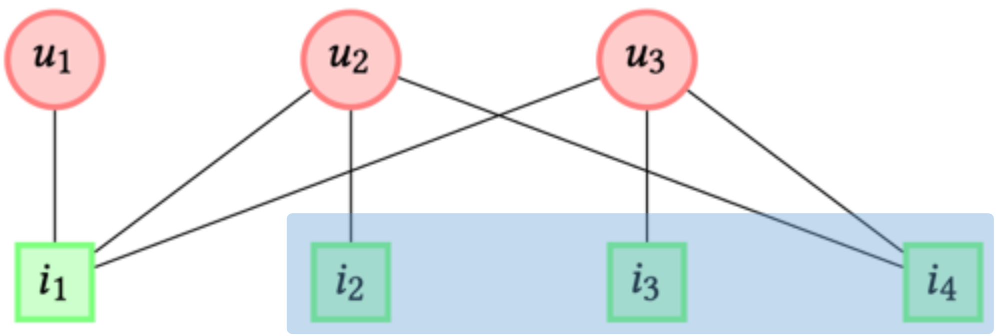
- Others:
  - One graph convolution layer achieved the best performance.
  - Structural information can be combined with interaction graph
    - Social networks, knowledge graphs, …

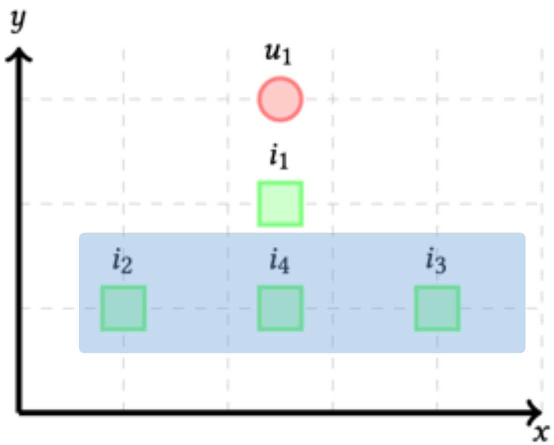
Rianne et al. Graph Convolutional Matrix Completion. KDD 2018

Spectral Collaborative Filtering

SpectralCF from [Zheng et al., RecSys'2018]

- User-Item Interaction Graph
  - GC-MC: use existing connectivity
  - SpectralCF: discover hidden connectivity in the spectral domain

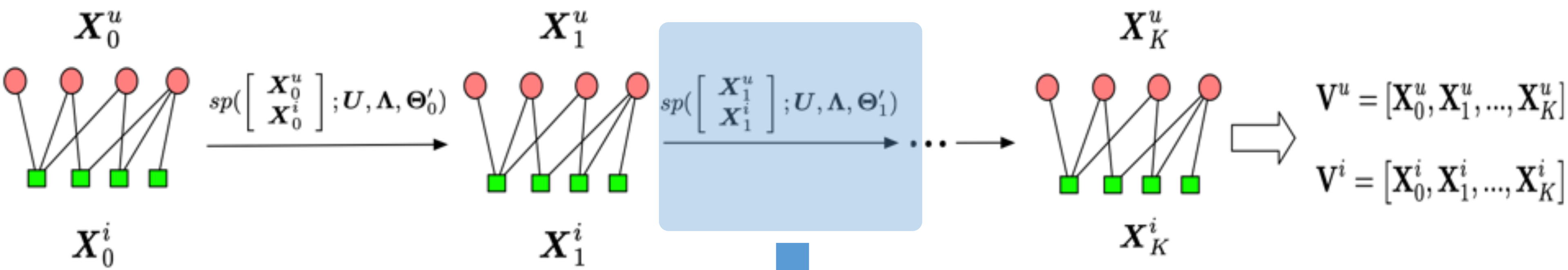




The connectivity between u_1 and i_2, i_3, i_4
- Uncovered in the frequency domain
- Discovered in the spectral domain

Zheng et al. Spectral Collaborative Filtering. RecSys 2018

Spectral Convolution Filtering in SpectralCF



Spectral Convolution Filtering

$$\begin{bmatrix} x_{new}^u \\ x_{new}^i \end{bmatrix} = U g_\theta(\Lambda) \begin{bmatrix} \hat{x}^u \\ \hat{x}^i \end{bmatrix} = U g_\theta(\Lambda) U^\top \begin{bmatrix} x^u \\ x^i \end{bmatrix}$$

Polynomial Approximation

$$\begin{bmatrix} x_{new}^u \\ x_{new}^i \end{bmatrix} = \theta'(UU^\top + U\Lambda U^\top) \begin{bmatrix} x^u \\ x^i \end{bmatrix}$$

However, eigen-decomposition of graph adjacency matrix is required

- A rather high complexity
- Difficult to support large-scale graphs

Zheng et al. Spectral Collaborative Filtering. RecSys 2018

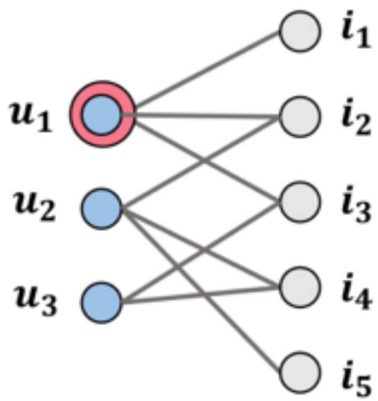
Neural Graph Collaborative Filtering (NGCF)

NGCF from [Wang et al., SIGIR'2019]

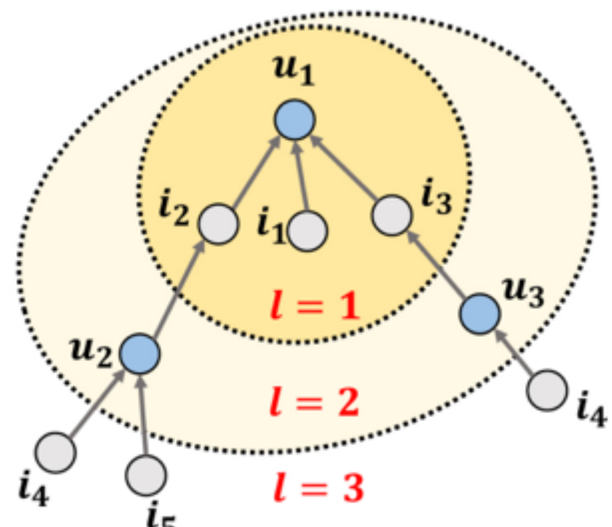
- Revisit CF via **high-order connectivity**
  - The paths that reach u_1 from any node with the path length l larger than 1 → unseen connectivity argued in SpectralCF!
  - A natural way to encode collaborative signal in the interaction graph structure

Why u_1 may like i_4?

- $u_1 \leftarrow i_2 \leftarrow u_2 \leftarrow i_4$
- $u_1 \leftarrow i_3 \leftarrow u_3 \leftarrow i_4$



User-Item Interaction Graph



High-order Connectivity for u_1

Wang et al. Neural Graph Collaborative Filtering. SIGIR 2019

First-order Connectivity Modeling

Inspired by GNNs

1. Propagate embeddings recursively on the user-item graph
2. Construct information flows in the embedding space

- Comp.1: Information Construction:

message passed from i to u

$$\mathbf{m}_{u\leftarrow i} = \frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}}\Big(\mathbf{W}_1\mathbf{e}_i + \mathbf{W}_2(\mathbf{e}_i \odot \mathbf{e}_u)\Big)$$

discount factor

- message dependent on the affinity, distinct from GCN, GraphSage, etc.
- Pass more information to similar nodes

- Comp.2 & 3: Neighbor Aggregation & Representation Update:

$$\mathbf{e}_u^{(1)} = \text{LeakyReLU}\Big(\mathbf{m}_{u\leftarrow u} + \sum_{i\in\mathcal{N}_u}\mathbf{m}_{u\leftarrow i}\Big)$$

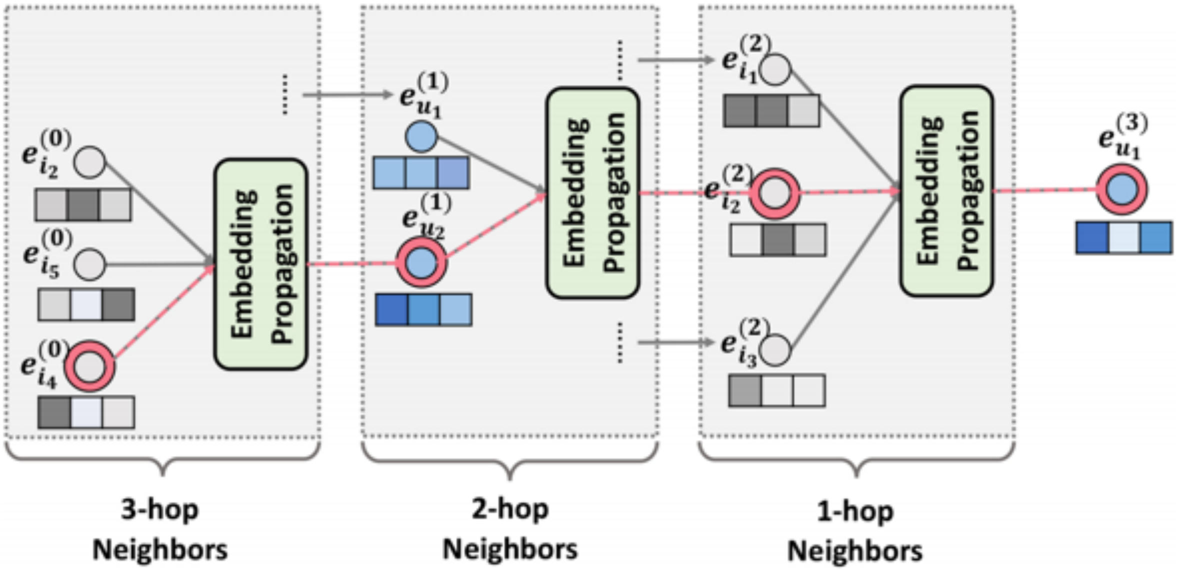
self-connections

all neighbors of u

Wang et al. Neural Graph Collaborative Filtering. SIGIR 2019

High-order Connectivity Modeling

- Stack more embedding propagation layers to explore the high-order connectivity

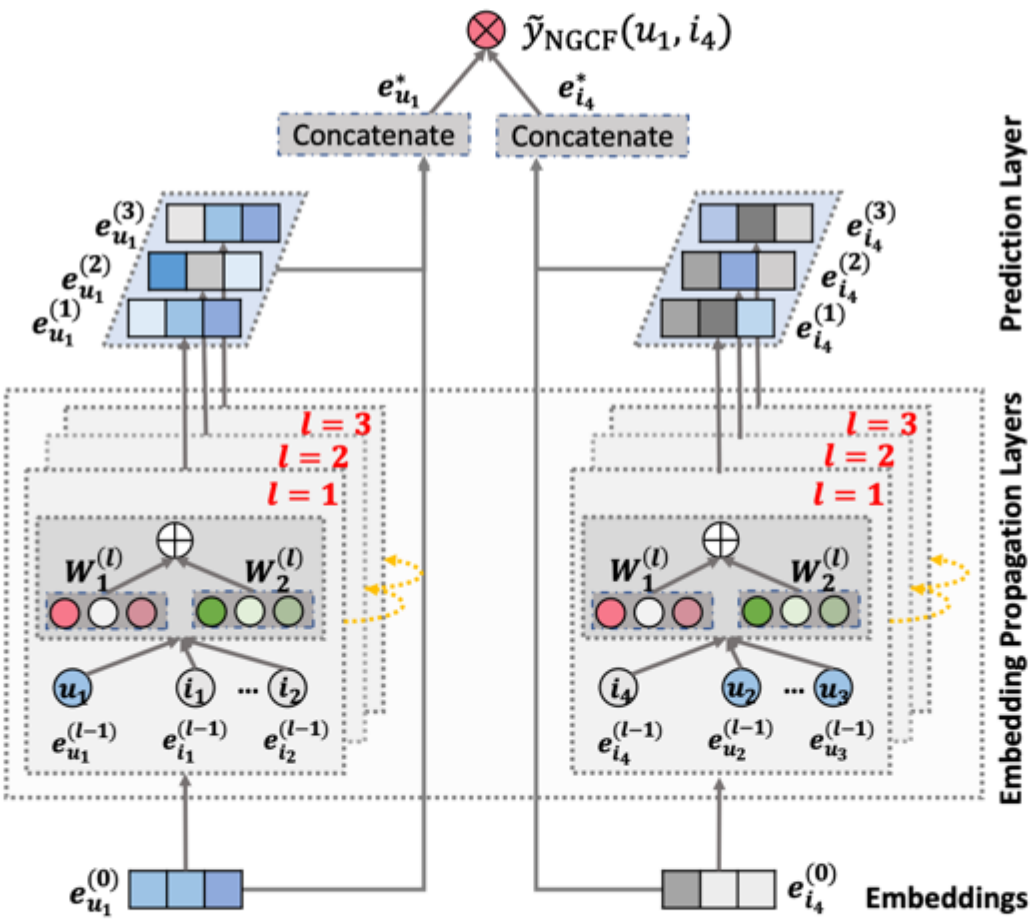


- The collaborative signal like u1 ← i2 ← u2 ← i4 can be captured in the embedding propagation process.

- **Collaborative signal can be injected into the representation learning process.**

Wang et al. Neural Graph Collaborative Filtering. SIGIR 2019

Overall Framework



$$\mathbf{e}_u^* = \boxed{\mathbf{e}_u^{(0)} \| \cdots \| \mathbf{e}_u^{(L)}}$$

$$\mathbf{e}_i^* = \mathbf{e}_i^{(0)} \| \cdots \| \mathbf{e}_i^{(L)}$$

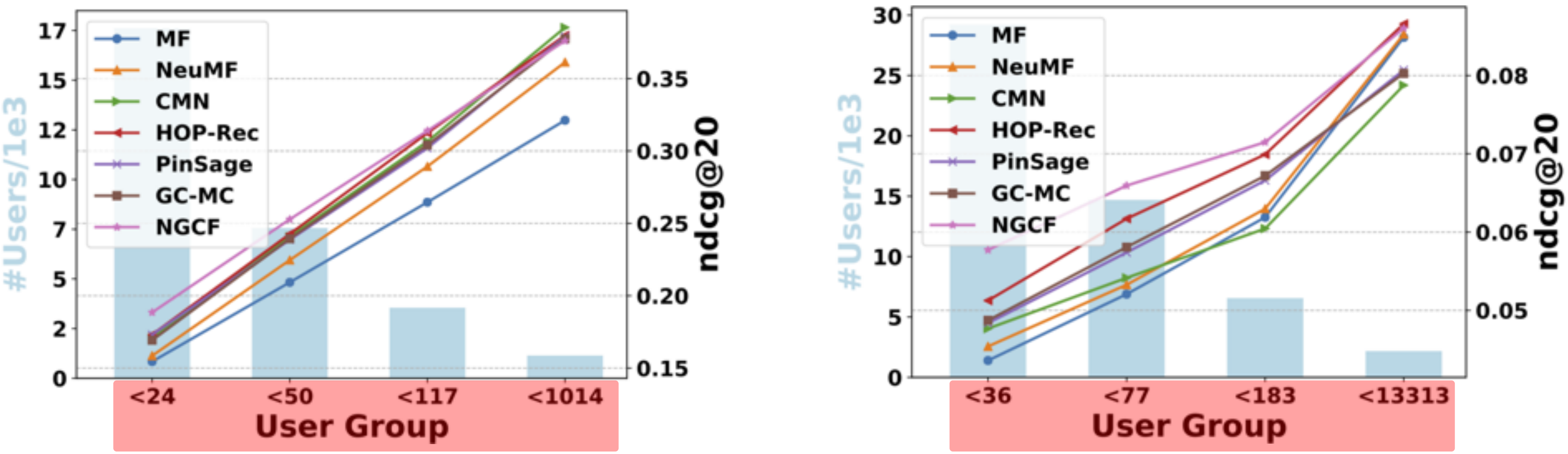
$$\hat{y}_{\mathrm{NGCF}}(u, i) = {\mathbf{e}_u^*}^\top \mathbf{e}_i^*$$

The representations at different layers

- emphasize the messages passed over different connections
- have different contributions in reflecting user preference

Wang et al. Neural Graph Collaborative Filtering. SIGIR 2019

Experiment Results —— Sparsity Issue



user groups with different group sparsity levels

- NGCF consistently outperforms all other baselines on most user groups.
- Exploiting high-order connectivity **facilitates the representation learning for inactive users.**
- **It might be promising to solve the sparsity issue in recommender systems**

Wang et al. Neural Graph Collaborative Filtering. SIGIR 2019

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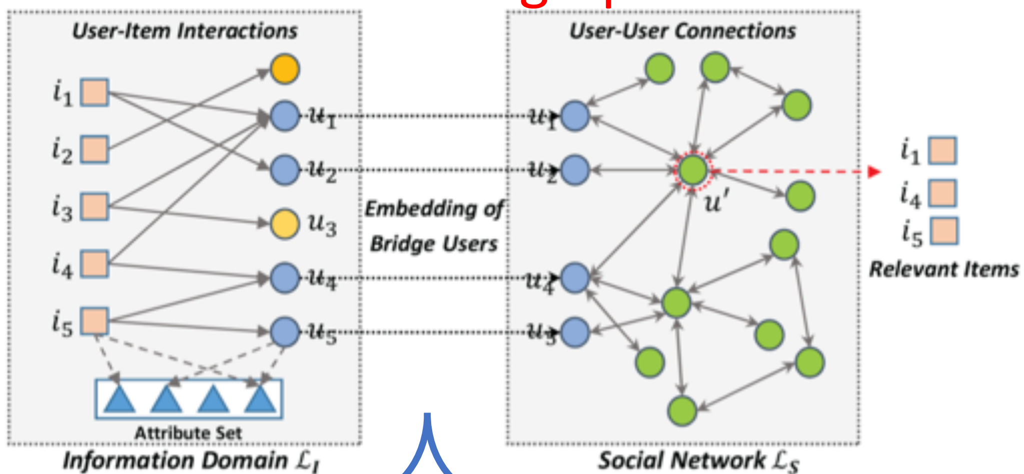
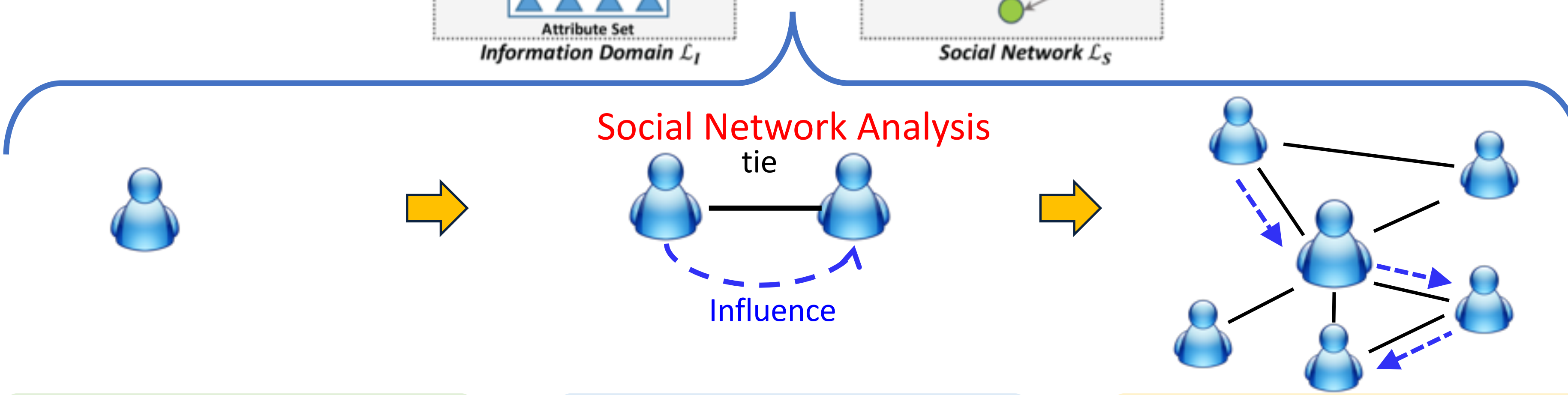
Slides in https://next-nus.github.io/

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

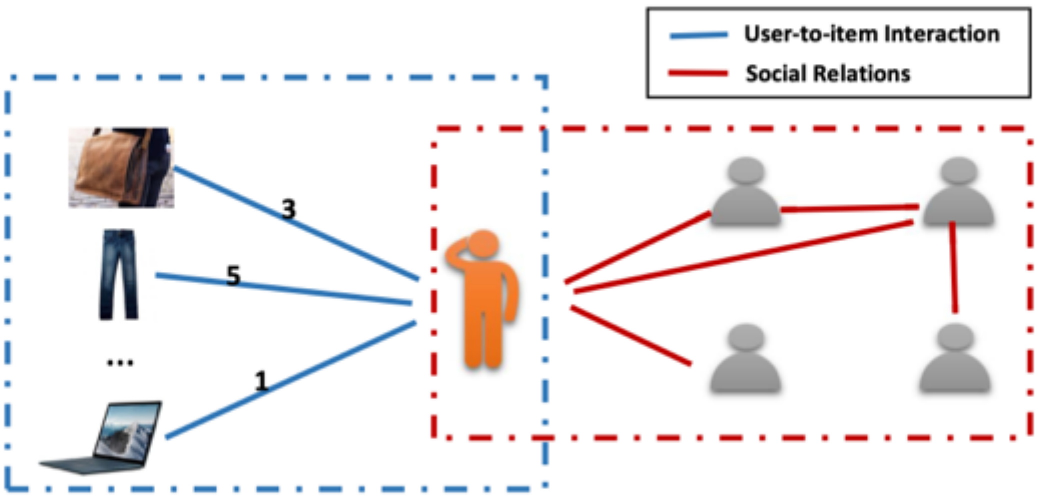
- Triad & Group Formation
- Information Diffusion

Snips from: Tang Jie et al. Representation Learning on Networks, Tutorial@WWW2019

Graph Neural Networks for Social Recommendation (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.



Fan et al. Graph Neural Networks for Social Recommendation. WWW 2019

User Modeling in GraphRec

These two graphs provide user information from different angles

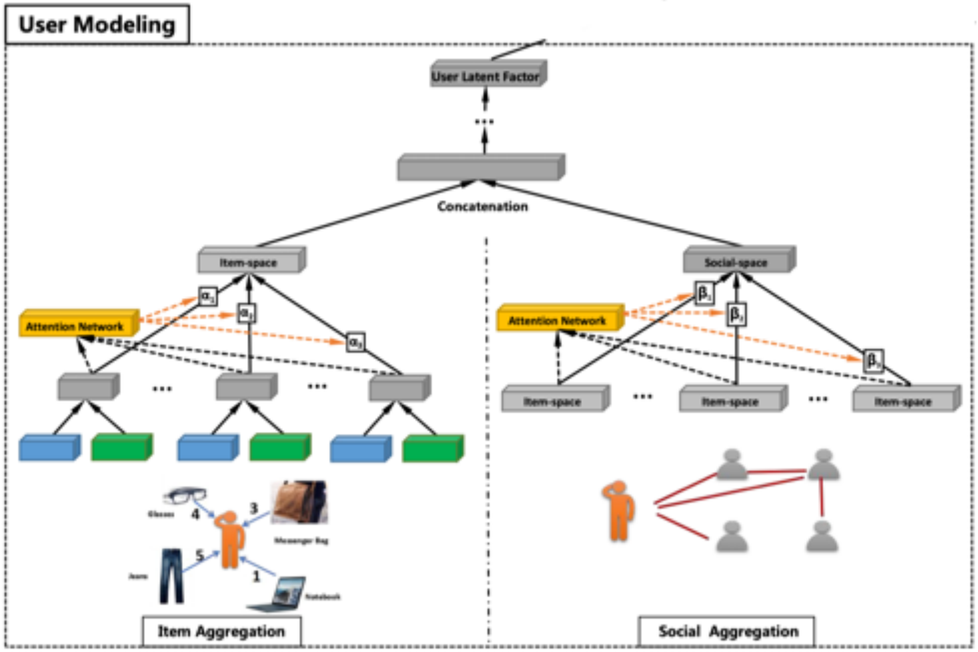
- **Item Aggregation**
  - Item space: leverage user-item interactions to get user representations

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

Opinion-aware representation of an interaction

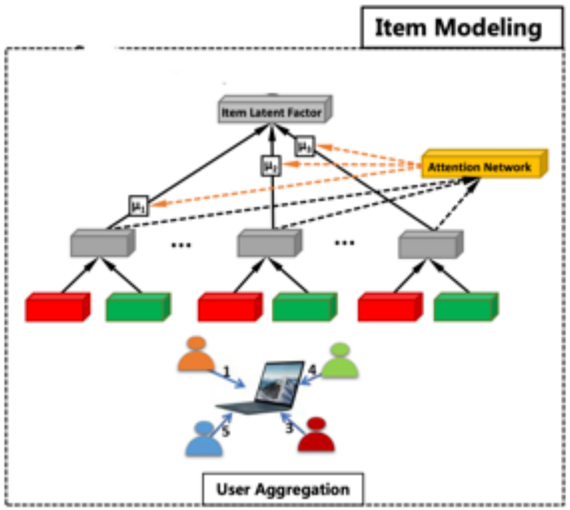
- **Social Aggregation**
  - Social space: use social relationships to get user representations

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



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

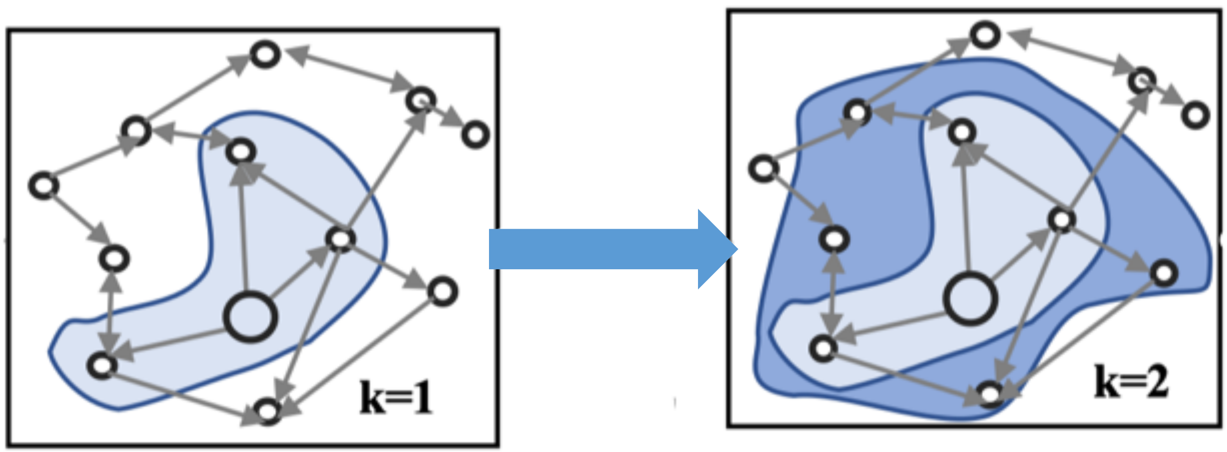
- **Rating Prediction**
  - Feed the concatenation of user & item representation into a neural network (MLP) to get predictions.

Neural Influence Diffusion Model (DiffNet)

DiffNet from [Wu et al, SIGIR’2019]

- **Social Influence** in Social Recommendation
  - A user’s preference is influenced by her trusted users, with these trusted users are influenced by their own social connections → **high-order connectivity**

  - **Social influence recursively propagates & diffuses in social network!**

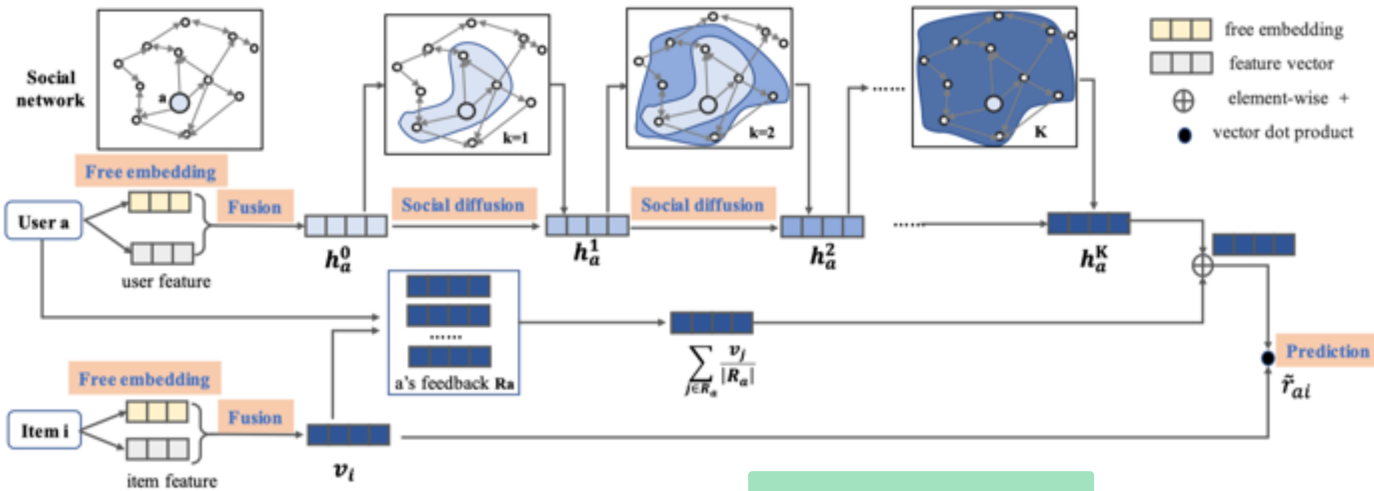


One-hop trusted users

Two-hop trusted users

Wu et al. A Neural Influence Diffusion Model for Social Recommendation. SIGIR 2019

Diffusion Influence Aggregation in DiffNet



- Comp.1: Information Construction

User features

$$\mathbf{h}_a^0 = g(\mathbf{W}^0 \times [\mathbf{x}_a, \mathbf{p}_a]),$$

User ID Embeddings

- Comp.2: Diffusion Influence Aggregation

$$\mathbf{h}_{S_a}^{k+1} = Pool(\mathbf{h}_b^k | b \in S_a)$$

Ego social network

- Comp.3: Representation Update

$$\mathbf{h}_a^{k+1} = s^{(k+1)}(\mathbf{W}^k \times [\mathbf{h}_{S_a}^{k+1}, \mathbf{h}_a^k]),$$

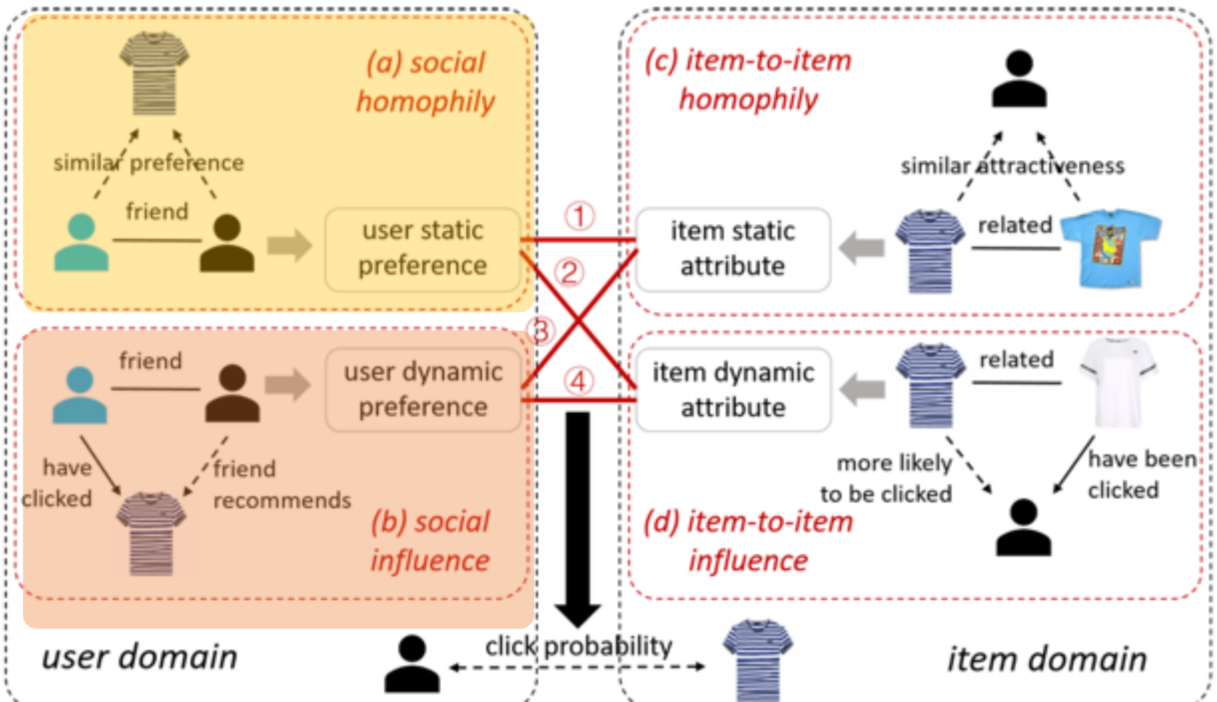
Wu et al. A Neural Influence Diffusion Model for Social Recommendation. SIGIR 2019

DANSER

DANSER from [Wu et al, WWW'2019]

Social homophily
- User static preference
- Unchanged & independent of external contexts

Social influence
- User dynamic preference
- Change dynamically with specific contexts



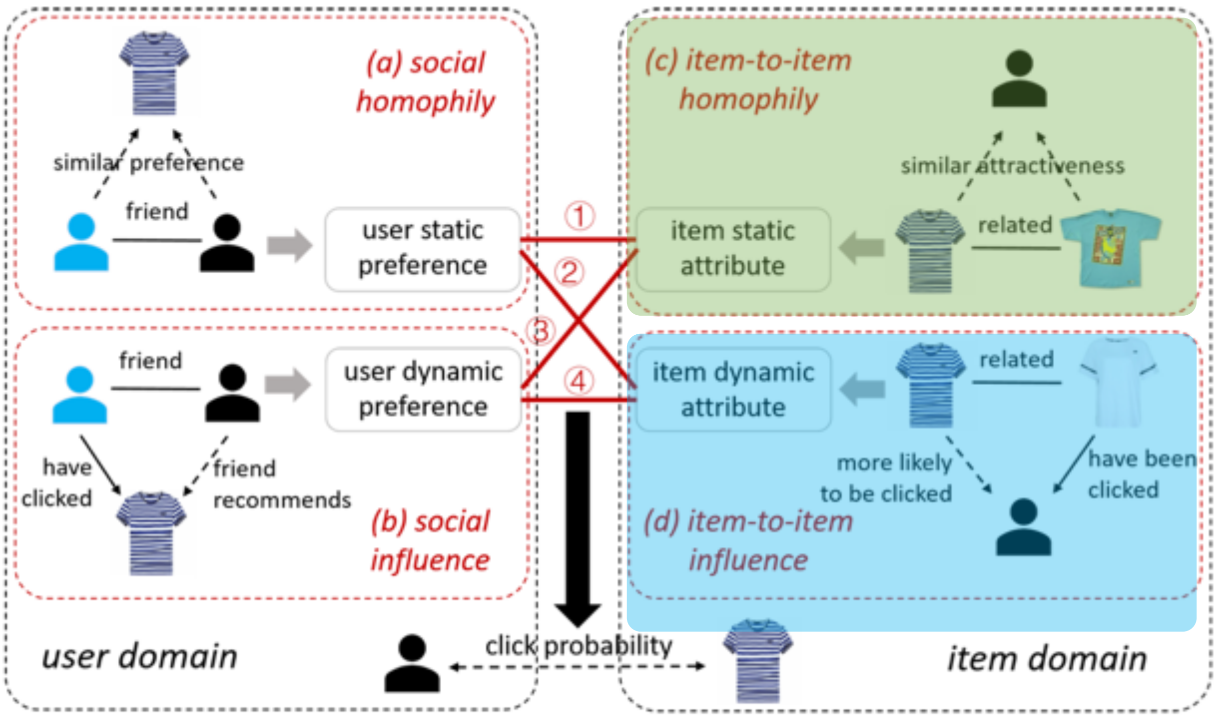
Wu et al. Dual Graph Attention Networks for Deep Latent Representation of Multifaceted Social Effects in Recommender Systems. WWW 2019

DANSER

DANSER from [Wu et al, WWW'2019]

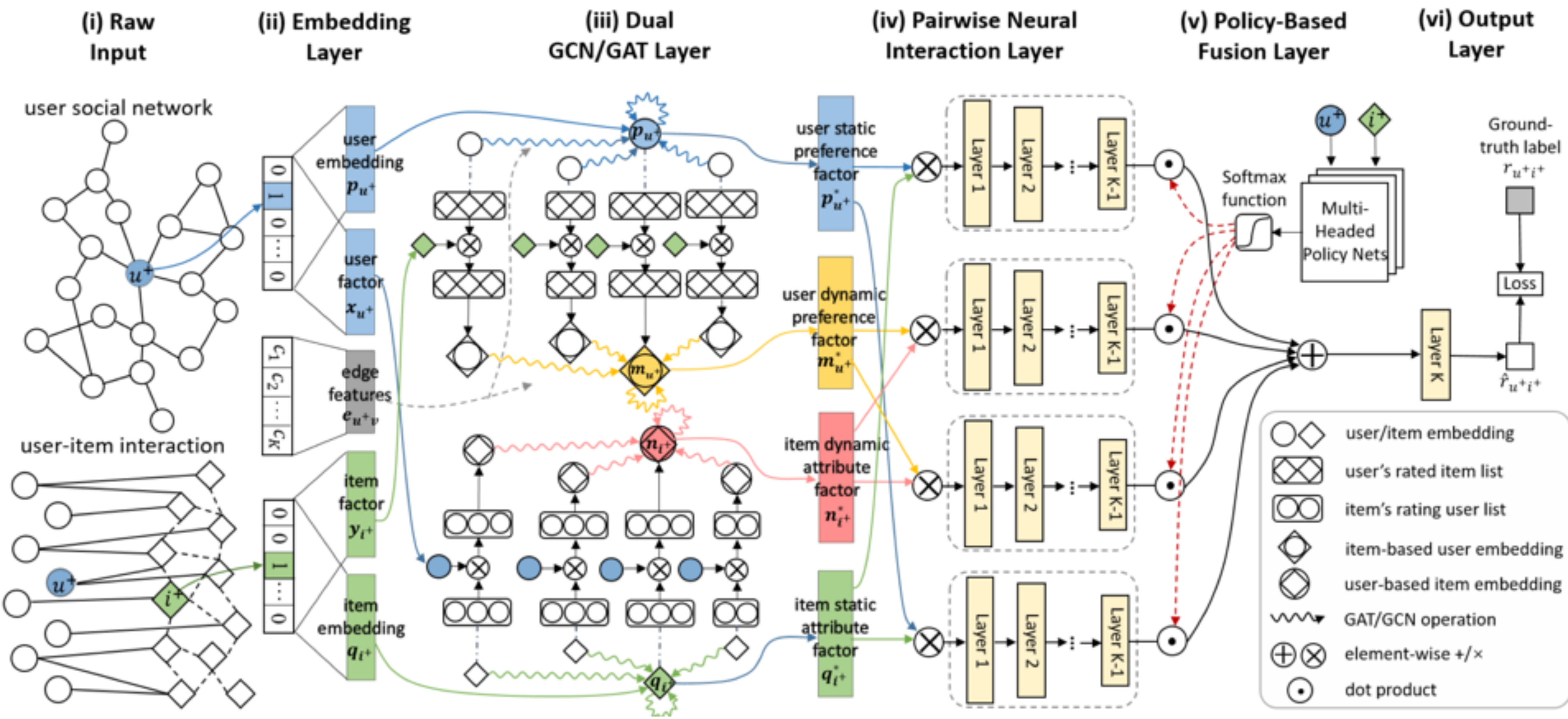
Item-to-item homophily
- Item static attribute

Item-to-item influence
- Item dynamic attribute
- Depends on a specific context



Wu et al. Dual Graph Attention Networks for Deep Latent Representation of Multifaceted Social Effects in Recommender Systems. WWW 2019

Dual GAT in User & Item Domains



Wu et al. Dual Graph Attention Networks for Deep Latent Representation of Multifaceted Social Effects in Recommender Systems. WWW 2019

Summary: GNN for Social Recommendation

	Graph Data	User Modeling	Item Modeling
GraphRec	• Interaction Graph • Social Network	First-order Connectivity • historical items • social relations	First-order Connectivity • user feedback
DiffNet	• Social Network	High-order Connectivity • social influence	First-order Connectivity • user feedback
DANSER	• Interaction Graph • Social Network	First-order Connectivity • social homophily (static) • social influence (dynamic)	First-order connectivity • item homophily (static) • item influence (dynamic)

Social recommendation needs more guides from social network analysis:

- Behavior modeling, social influence, group formation, information diffusion → from micro to macro!

OUTLINE

- Introduction
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- **Part III: Graph Neural Networks for Recommendation**
  - **Sequential Recommendation: SR-GNN, DGRec**

Slides in https://next-nus.github.io/

Sequential Recommendation

Sequential (Session-based) recommendation

- Given historical interactions, to predict the successive items that a user is likely to interact with → sequential needs of users

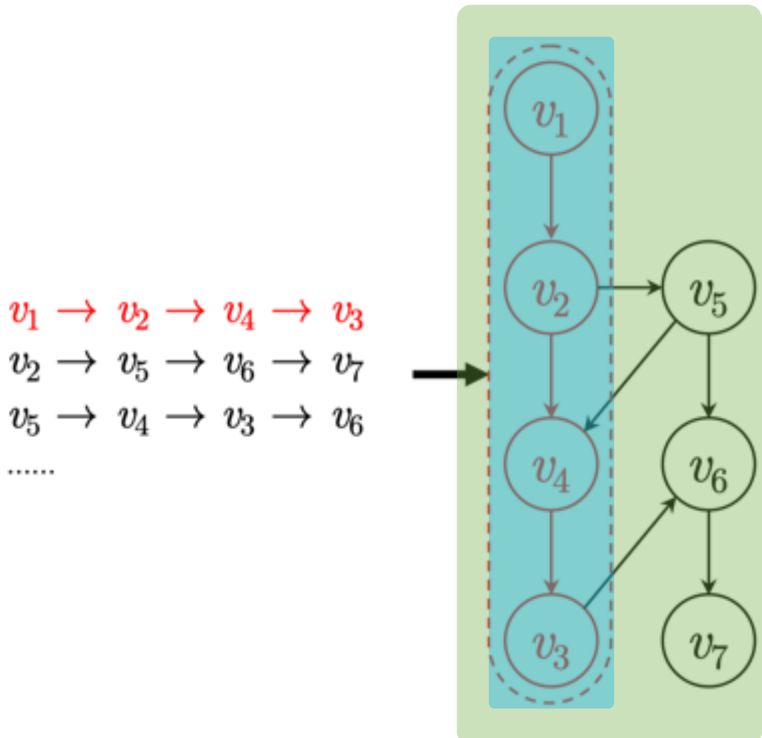
Listen To Your Heart   Dreaming Alone   The Oak Tree   Follow Your Heart

- User interests are dynamic in sessions.
- Sequential pattern is of crucial importance.

Session-based Recommendation with GNNs (SR-GNN)

SR-GNN from [Wu et al, AAAI'2019]

- Sequential pattern of a transition → one session sequence
- Complex patterns of item transitions → all session sequences



Reorganize all session sequences into graph structured data → session graph

- A directed graph G_s over items
- Each edge $(v_{s,i-1}, v_{s,i})$ means a user clicks item $v_{s,i}$ after $v_{s,i-1}$ in session s

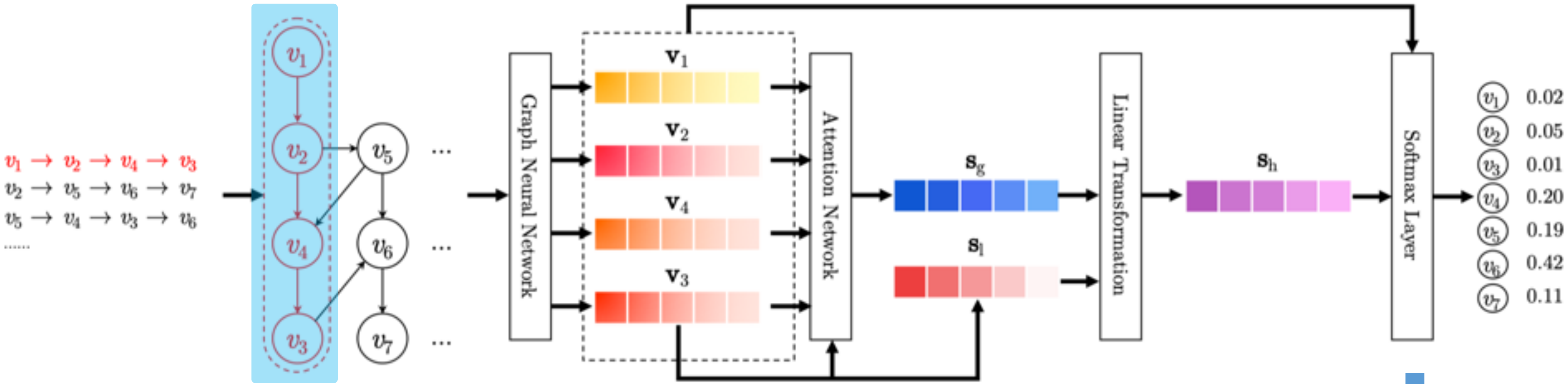
➢ Present the global preference in session s

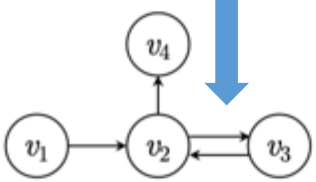
treating a session sequences as a session subgraph

➢ Present the **current interest & sequential needs** of the user in session s

Wu et al. Session-based Recommendation with Graph Neural Networks. AAAI 2019

Session Graphs with GNNs





	Outgoing edges				Incoming edges			
	1	2	3	4	1	2	3	4
1	0	1	0	0	0	0	0	0
2	0	0	1/2	1/2	1/2	0	1/2	0
3	0	1	0	0	0	1	0	0
4	0	0	0	0	0	1	0	0

$$A_s = [A_s^{(out)}, A_s^{(in)}]$$

$$\mathbf{a}_{s,i}^t = \mathbf{A}_{s,i:}^\top \left[\mathbf{v}_1^{t-1}, \ldots, \mathbf{v}_n^{t-1}\right]^\top + \mathbf{b},$$
$$\mathbf{z}_{s,i}^t = \sigma\left(\mathbf{W}_z \mathbf{a}_{s,i}^t + \mathbf{U}_z \mathbf{v}_i^{t-1}\right),$$
$$\mathbf{r}_{s,i}^t = \sigma\left(\mathbf{W}_r \mathbf{a}_{s,i}^t + \mathbf{U}_r \mathbf{v}_i^{t-1}\right),$$
$$\widetilde{\mathbf{v}_i^t} = \tanh\left(\mathbf{W}_o \mathbf{a}_{s,i}^t + \mathbf{U}_o \left(\mathbf{r}_{s,i}^t \odot \mathbf{v}_i^{t-1}\right)\right)$$
$$\mathbf{v}_i^t = \left(1 - \mathbf{z}_{s,i}^t\right) \odot \mathbf{v}_i^{t-1} + \mathbf{z}_{s,i}^t \odot \widetilde{\mathbf{v}_i^t},$$

RNN Aggregator over subgraphs

$$y_i = \mathrm{MLP}(\mathrm{Att}(v_n, v_i))$$

Prediction conducted by a MLP + Attention network

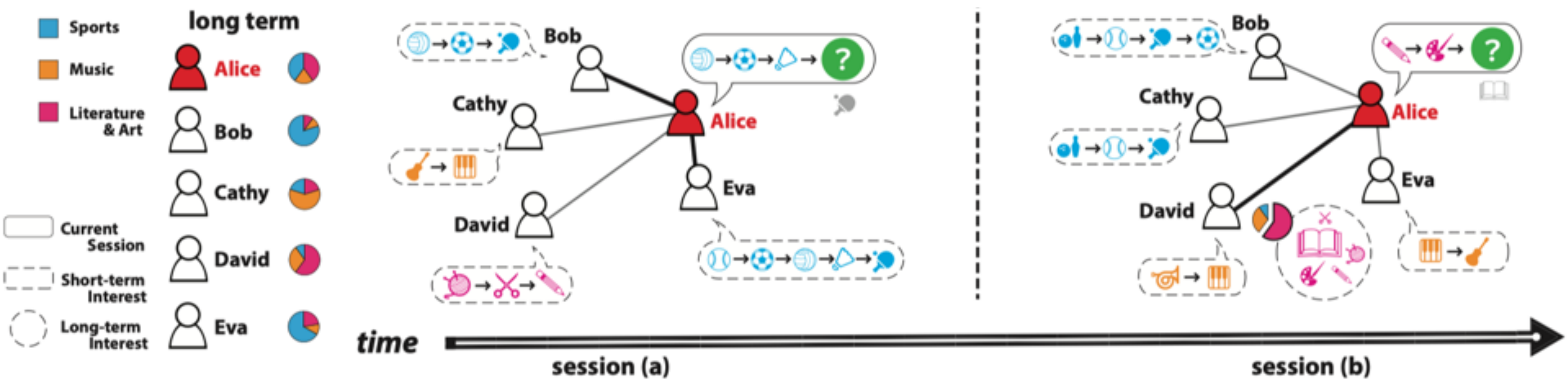
Wu et al. Session-based Recommendation with Graph Neural Networks. AAAI 2019

Dynamic Graph Attention Network for Session-based Social Recommendation (DGRec)

DGRec from [Song et al, WSDM'2019]

- Session + Social Recommendation → **social networks**

- User interests change across sessions, due to:
  - **Short-term** preferences of user friends
  - **Long-term** preferences of user friends



Song et al. Session-based Social Recommendation via Dynamic Graph Attention Networks. WSDM 2019

Dynamic Social Recommendation

- Dynamic individual interest in current session → RNN

$$h_n = f(i^u_{T+1,n}, h_{n-1}), \qquad \vec{S}^u_{T+1} = \{i^u_{T+1,1}, \ldots, i^u_{T+1,n}\}$$

User session representation

LSTM adopted on the session sequence

Session sequence of the user

- Friends' interest
  - **Short-term** preferences → a friend's latest online session

$$s^s_k = r_{N_{k,T}} = f(i^k_{T,N_{k,T}}, r_{N_{k,T-1}})$$

  - **Long-term** preferences → a friend's average interests, which is no item-sensitive

$$s^l_k = \mathbf{W}_u[k,:],$$

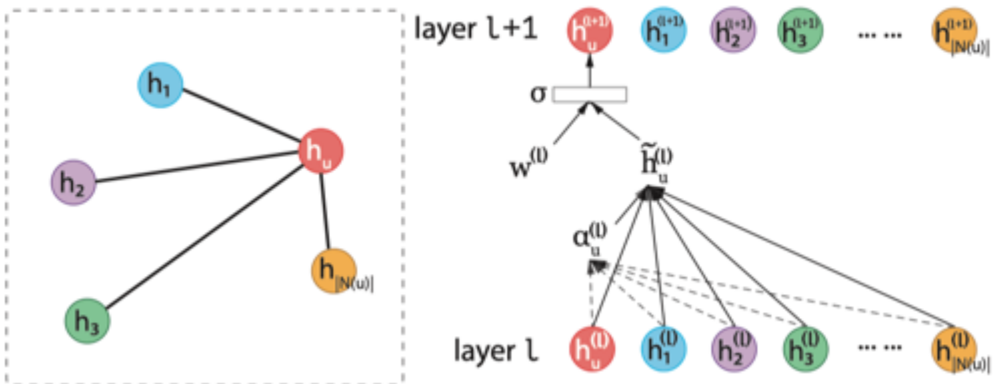
User ID embedding

  - **Unified representation**

$$s_k = ReLU(\mathbf{W}_1[s^s_k; s^l_k])$$

Song et al. Session-based Social Recommendation via Dynamic Graph Attention Networks. WSDM 2019

Dynamic Graph Attention Network



- **Dynamic feature graph**
  - User + Friends graph
  - Dynamic features → updated whenever a user consumed a new item.

- **Attentive social aggregation**

Level of influence or importance of a friend to the target user

$$\alpha_{uk}^{(l)} = \frac{exp(f(h_u^{(l)}, h_k^{(l)}))}{\sum_{j \in N(u) \cup \{u\}} exp(f(h_u^{(l)}, h_j^{(l)}))}$$

$$\tilde{h}_u^{(l)} = \sum_{k \in N(u) \cup \{u\}} \alpha_{uk}^{(l)} h_k^{(l)}$$

Final representation combining user session interests & social influence

Song et al. Session-based Social Recommendation via Dynamic Graph Attention Networks. WSDM 2019

Summary: GNN for Sequential Recommendation

	Graph Data	User Modeling	Item Modeling
SR-GNN	Directed Session Graph	• Global preference in all session sequences • Local preference in a session sequence • Without ID information	Graph representations
DGRec	Social Network	• Short-term preference in the latest session (sequential pattern) • Long-term preference in all sessions (ID Information) • Social influence (graph)	ID embeddings

Sequential recommendation needs new & reasonable angles to organize sequence data in the form of graph.

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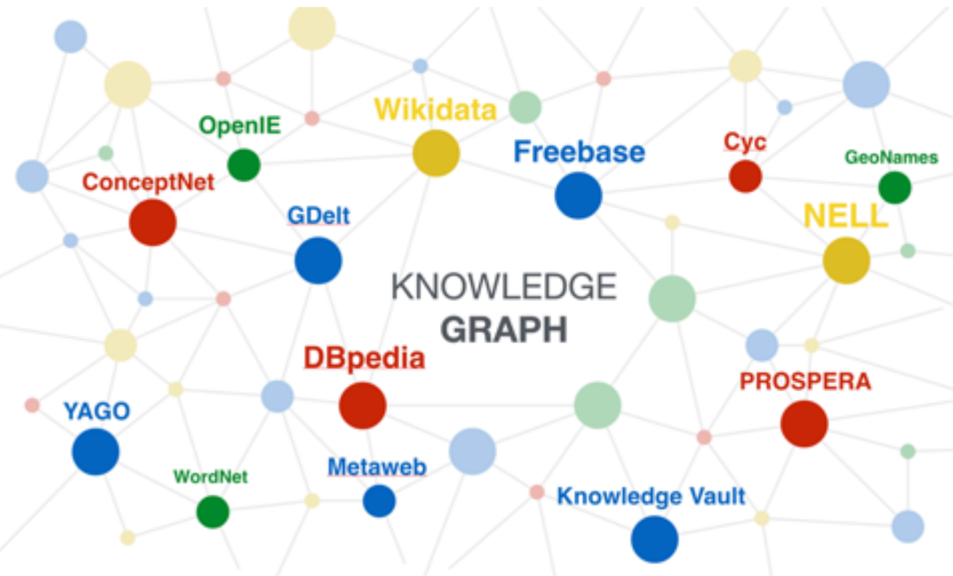
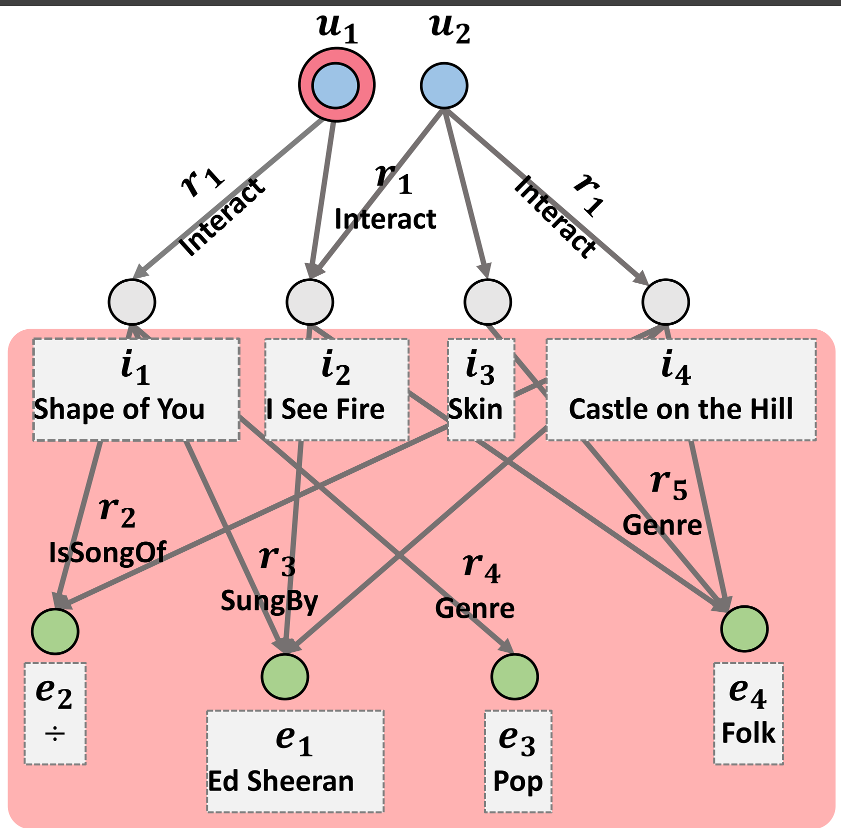
  - **Knowledge Graph-based Recommendation: KGCN, KGNN-LS, KGAT**

Slides in https://next-nus.github.io/

Knowledge Graph-based Recommendation





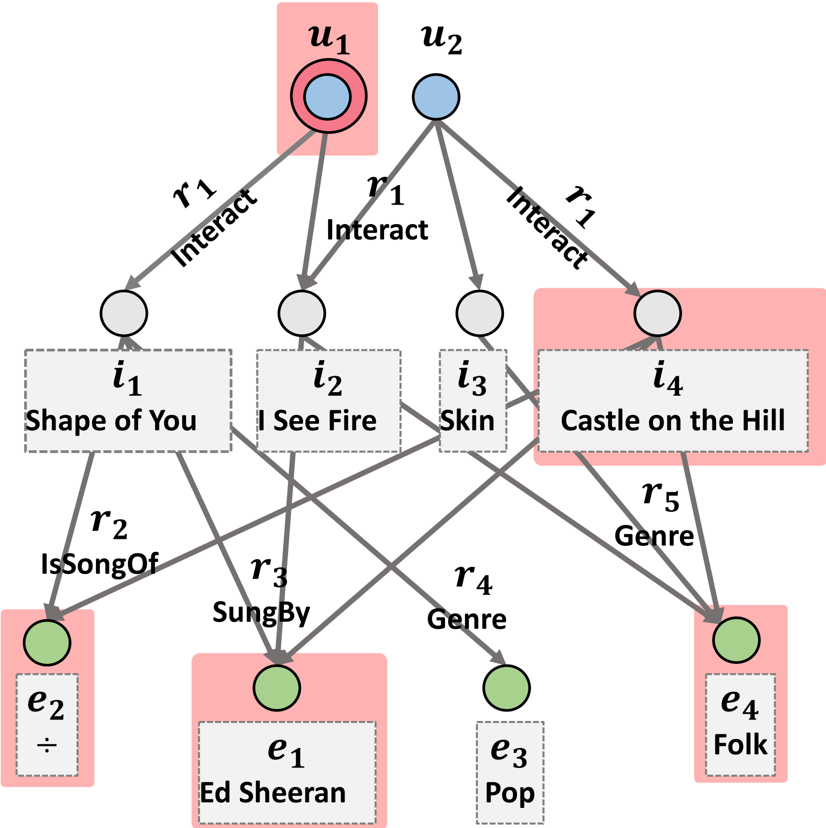
Knowledge Graph (KG):

- Background knowledge on items
- Rich semantics & Relations
- Structural information

Benefit for Recommendation

- Narrow down search space
- Explore user interests reasonably
- Offer explanations

Prior Works: Supervised Learning-based



To estimate u_1's preference on i_2

Feature Engineering

- u_1- i_4 interaction as an data instance
- transfer item knowledge into a feature vector is $\vec{x}$=<u_1, i_4, e_1, e_2, e_4>

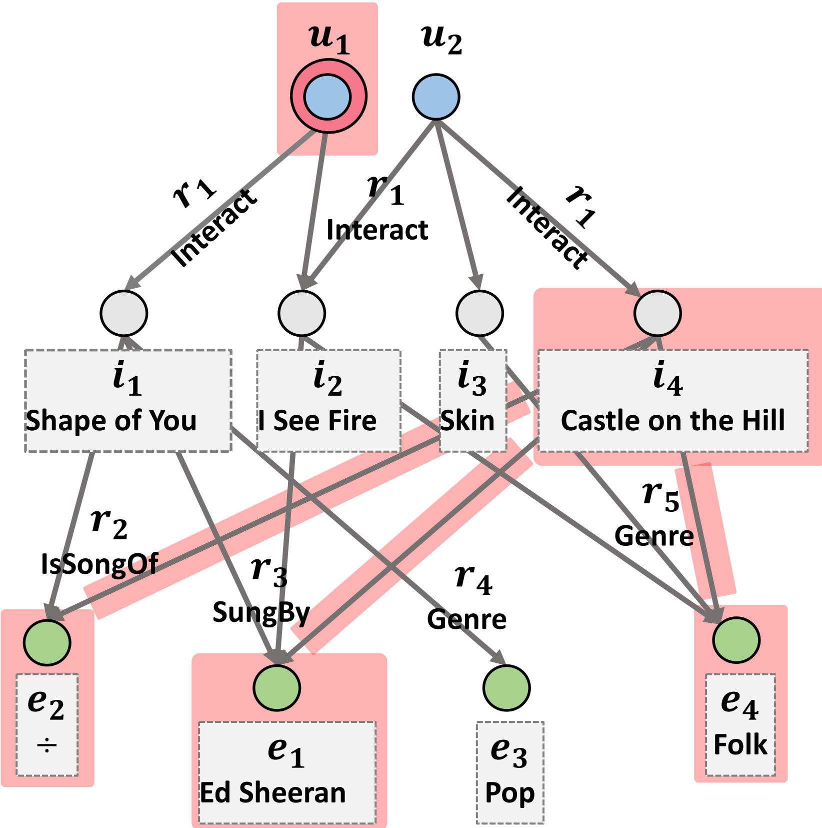
Prediction Modeling

- A supervised learning model
- e.g., FM, NFM, Wide&Deep ……

Limitations

- Semantic relations are ignored
- Graph structure is ignored
- CF signals are captured in an implicit fashion
- **High-order connectivity/relation are ignored**

Prior Works: Regularized-based



To estimate u_1's preference on i_2

Representation Learning

- i_4-related KG triplets **regularize** the learning of its representation
- Translational Principle
  - Head + Relation ≈ Tail

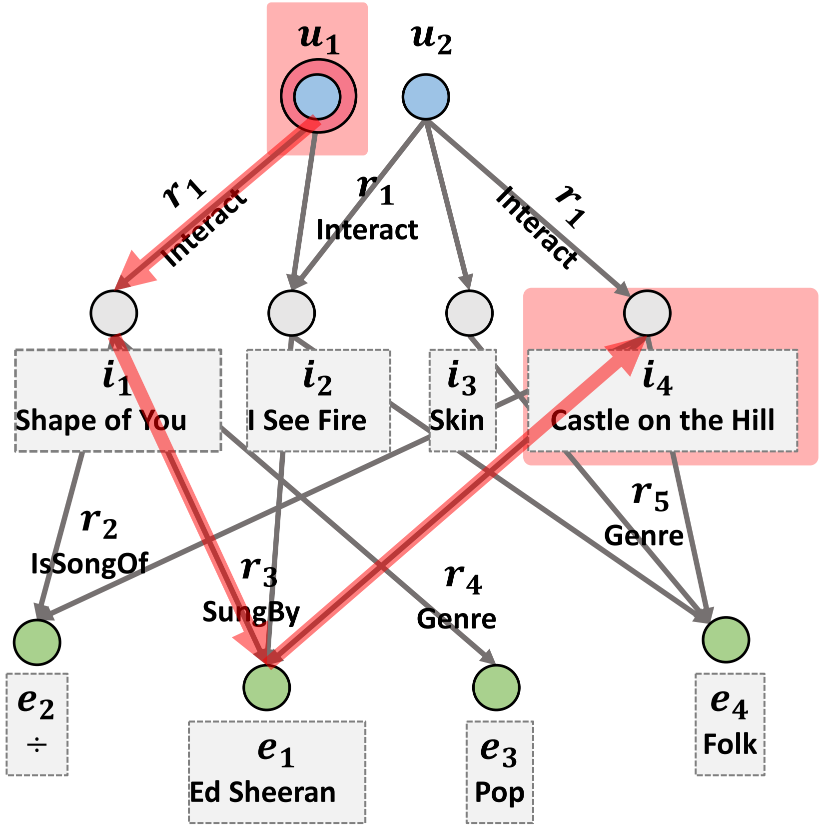
Interaction Modeling

- Reconstruct direct user-item interactions
- e.g., NCF, MF, …

Limitations

- **High-order connectivity** between user and item nodes are modeled **in an implicit fashion**
- **It fails to synthesize high-order relations.**

Prior Works: Path-based



To estimate u_1's preference on i_2

Representation Learning

- Paths connecting u_1 and i_4 to represent their connectivity
- $u_1 \rightarrow i_1 \rightarrow e_1 \rightarrow i_2.$

Interaction Modeling

- Information fusion of multiple paths
- A supervised learning model

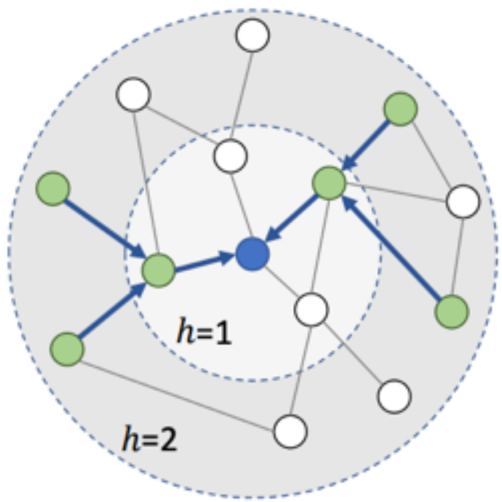
Limitations

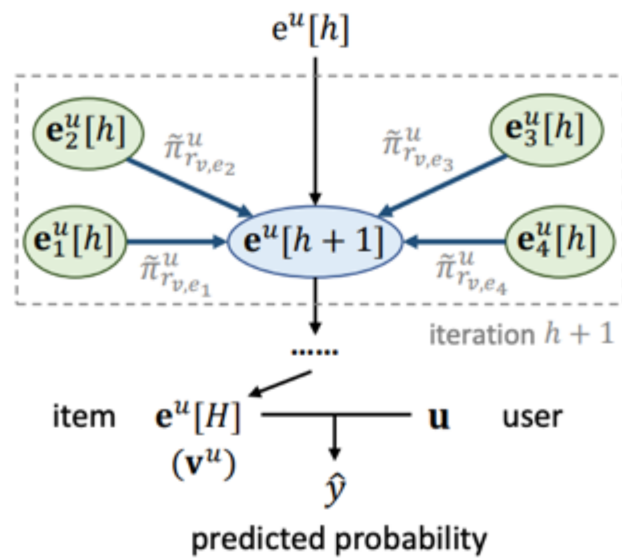
- Require **domain knowledge** to define meta-paths
- Require **labor-intensive feature engineering** to extract qualified paths
- Have rather high complexity

Knowledge Graph Convolution Network (KGCN)

KGCN from [Wang et al, WWW'2019]

- Item graph → KG entities are used to enrich item representation





Comp.1 & 2

$$\mathbf{v}^u_{\mathcal{N}(v)} = \sum_{e\in\mathcal{N}(v)} \tilde{\pi}^u_{r_{v,e}} \mathbf{e}$$

Attention score of user-relation

KG entities connected with the target item

Comp.3

$$agg_{sum} = \sigma\left(\mathbf{W}\cdot(\mathbf{v}+\mathbf{v}^u_{\mathcal{S}(v)})+\mathbf{b}\right)$$

Prediction

$$\hat{y}_{uv} = f(\mathbf{u}, \mathbf{v}^u)$$

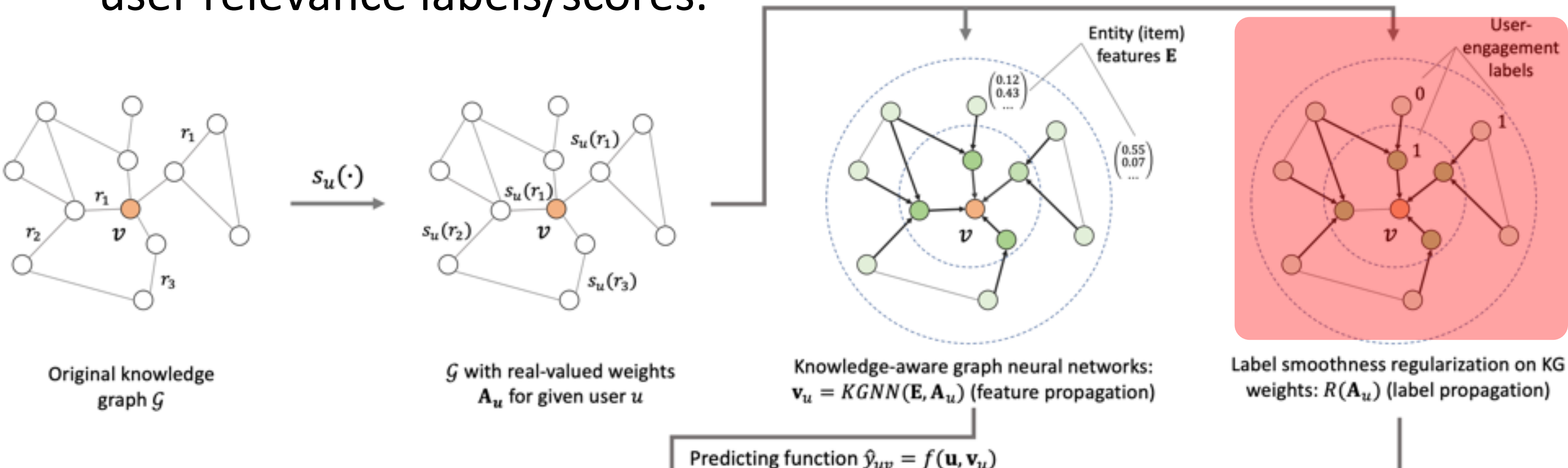
User ID embeddings → users are excluded from the propagation.

Wang et al. Knowledge Graph Convolutional Networks for Recommender Systems. WWW 2019

Knowledge Graph Neural Networks with Label Smoothness Regularization (KGNN-LS)

KGNN-LS is an extension of KGCN from [Wang et al, KDD’2019]

- Label smoothness → adjacent items in KG are likely to have similar user relevance labels/scores.



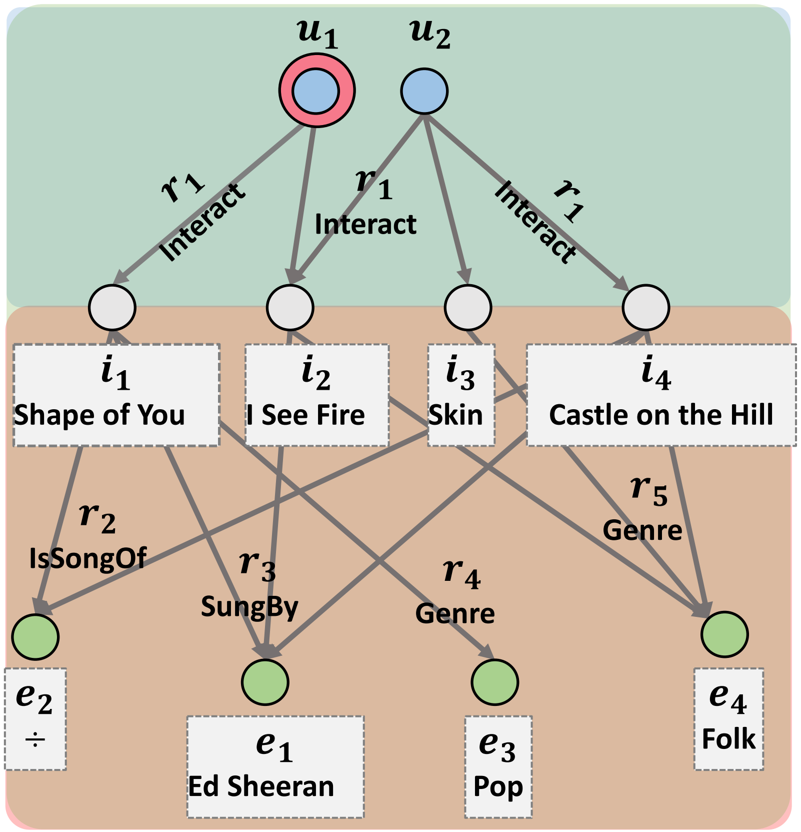
$$\mathcal{L} = J(\hat{y}_{uv}, y_{uv}) + \lambda R(\mathbf{A}_u)$$

$$E(l_u, \mathbf{A}_u) = \frac{1}{2} \sum_{e_i \in \mathcal{E}, e_j \in \mathcal{E}} A_u^{ij} \left(l_u(e_i) - l_u(e_j)\right)^2.$$

Wang et al. Knowledge-aware Graph Neural Networks with Label Smoothness Regularization for Recommender Systems. KDD 2019

Knowledge Graph Attention Network (KGAT)

KGAT from [Wang et al, KDD'2019]



User-Item Bipartite Graph

- User-Item Direct Interactions

$$u_1 \xrightarrow{r_1} i_1$$

➕

Knowledge Graph

- Item-Item External Connections

$$i_1 \xrightarrow{r_2} e_1$$

=

Collaborative Knowledge Graph

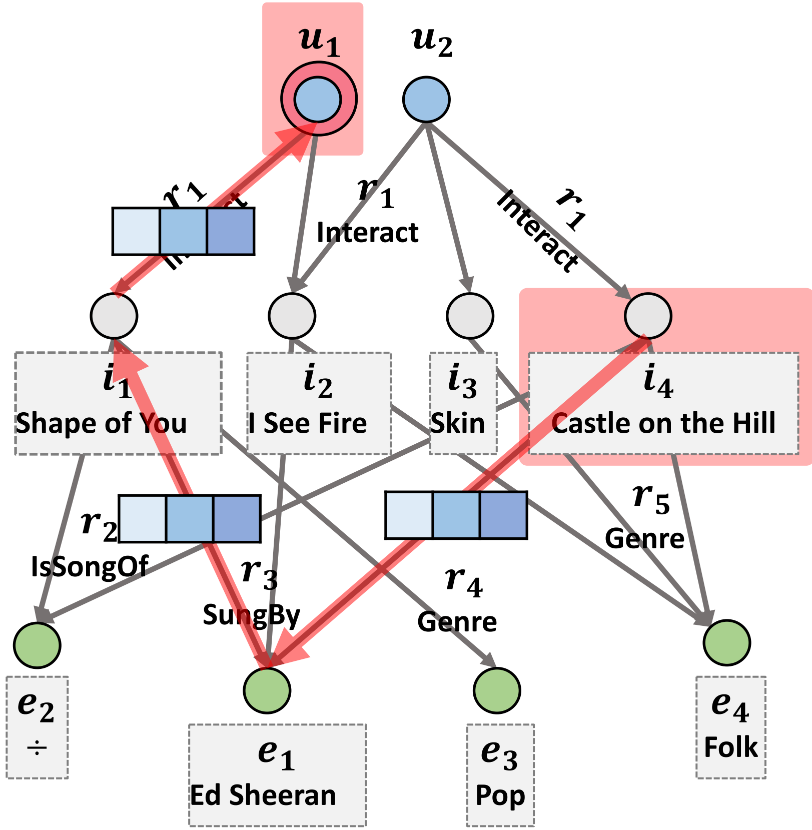
- High-order connectivity between users and items

$$u_1 \xrightarrow{r_1} i_1 \xrightarrow{r_2} e_1 \xrightarrow{-r_2} i_2 \Rightarrow u_1 \xrightarrow{r_1} i_2$$

- Reasoning ability & Explainability

Wang et al. KGAT: Knowledge Attention Network for Recommendation. KDD 2019

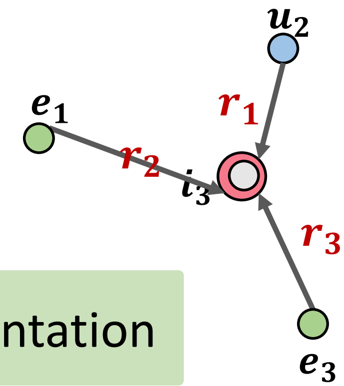
Attentive Embedding Propagation in KGAT



Attentive Embedding Propagation, inspired by GNNs

- Propagate embeddings recursively on the graph
- Reveal the importance of a high-order connectivity via relation-aware attentions
- Construct information flows in the embedding space

Attentive Embedding Propagation in KGAT



- Comp.1: Information Propagation

The messages accounting for first-order connectivity

The set of triples, where the target node is the head entity

$$\mathbf{e}_{\mathcal{N}_h} = \sum_{(h,r,t)\in\mathcal{N}_h} \pi(h,r,t)\mathbf{e}_t$$

Tail representation

- Comp.2: Knowledge-aware Attention Aggregation

decay factor on each propagation

$$\pi(h,r,t) = (\mathbf{W}_r\mathbf{e}_t)^\top \tanh\Big((\mathbf{W}_r\mathbf{e}_h + \mathbf{e}_r)\Big)$$

the attention score is dependent on the distance of e_t and e_h in r's space

- Comp.3: Representation Update

$$f_{\text{Bi-Interaction}} = \text{LeakyReLU}\Big(\mathbf{W}_1(\mathbf{e}_h + \mathbf{e}_{\mathcal{N}_h})\Big) + \text{LeakyReLU}\Big(\mathbf{W}_2(\mathbf{e}_h \odot \mathbf{e}_{\mathcal{N}_h})\Big),$$

Similar to NGCF

Model Training

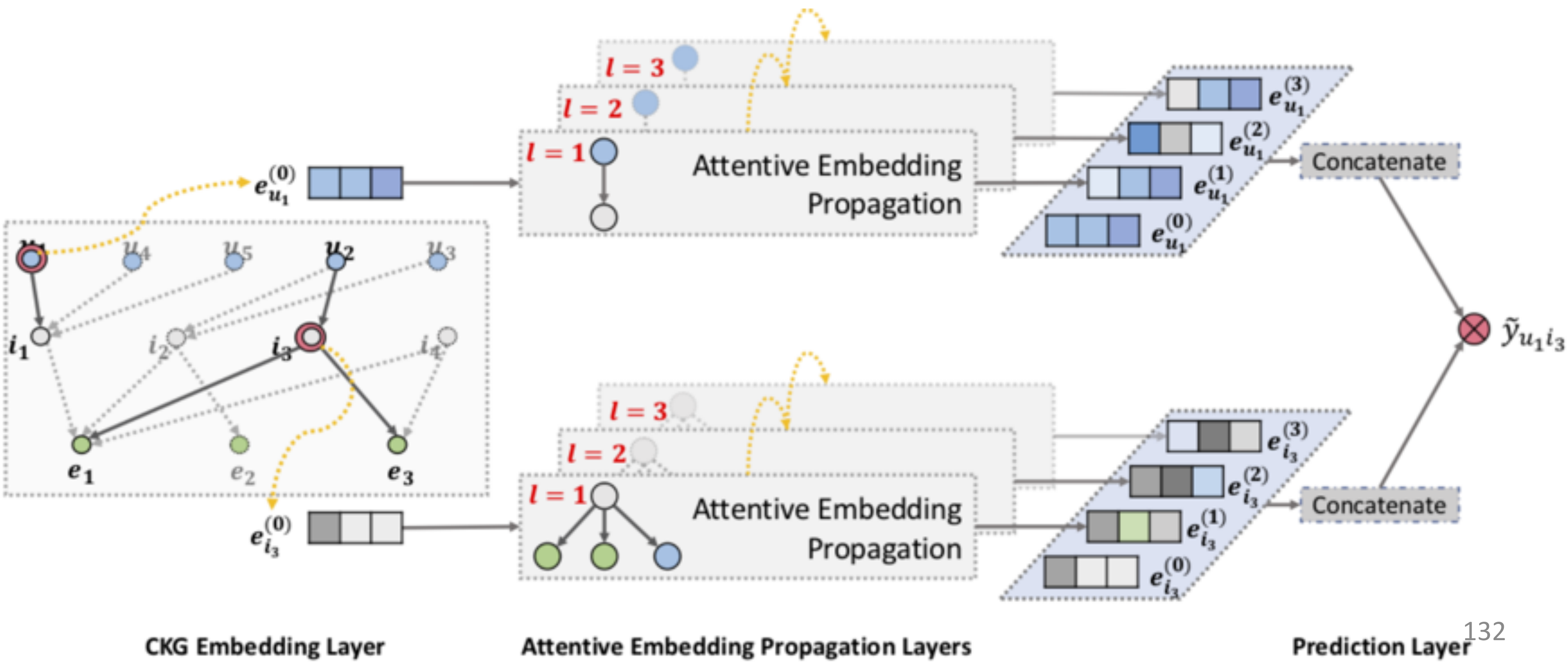
$$\mathbf{e}_u^* = \boxed{\mathbf{e}_u^{(0)} \| \cdots \| \mathbf{e}_u^{(L)}}$$

$$\mathbf{e}_i^* = \mathbf{e}_i^{(0)} \| \cdots \| \mathbf{e}_i^{(L)}$$

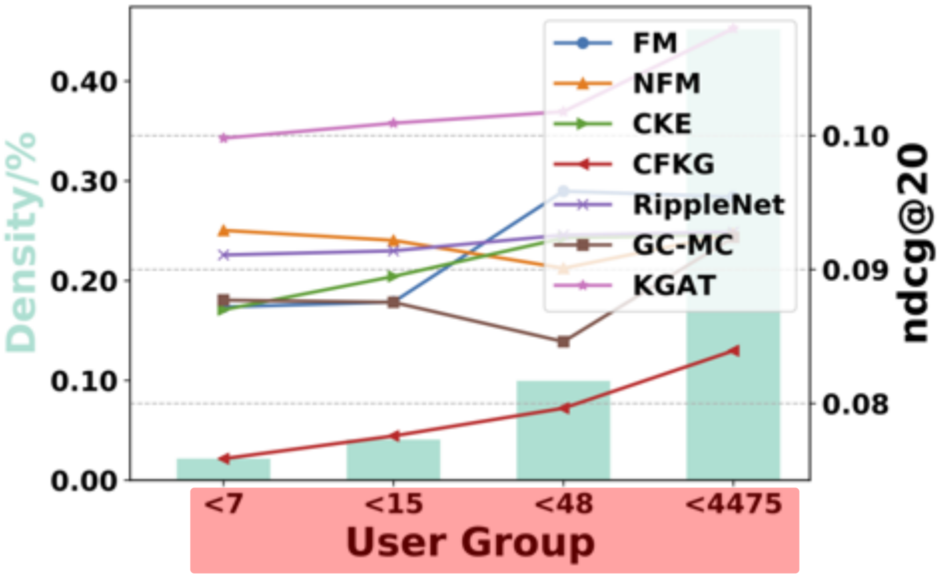
$$\hat{y}(u, i) = {\mathbf{e}_u^*}^\top \mathbf{e}_i^*$$

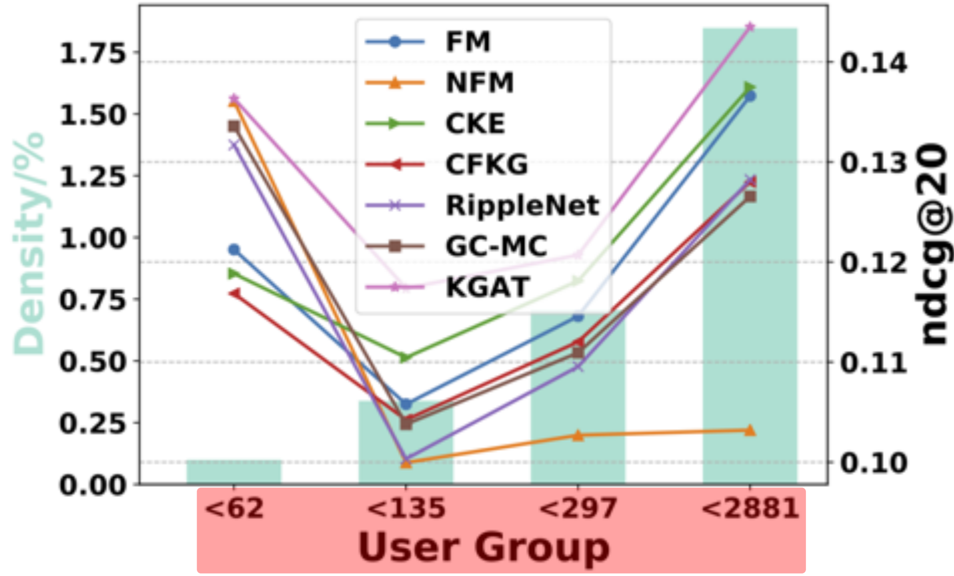
Similar to NGCF, the representations at different layers

- emphasize the messages passed over different connections
- have different contributions in reflecting user preference



Experiment Results —— Sparsity Issue





user groups with different group sparsity levels

- KGAT outperforms the other models in most cases, especially on the two sparsest user groups in Amazon-Book and Yelp2018.
- It again verifies the significance of high-order connectivity modeling:
  - contains the lower-order connectivity
  - enriches the representations of inactive users via recursive embedding propagation

Case Study for Explainable Recommendation

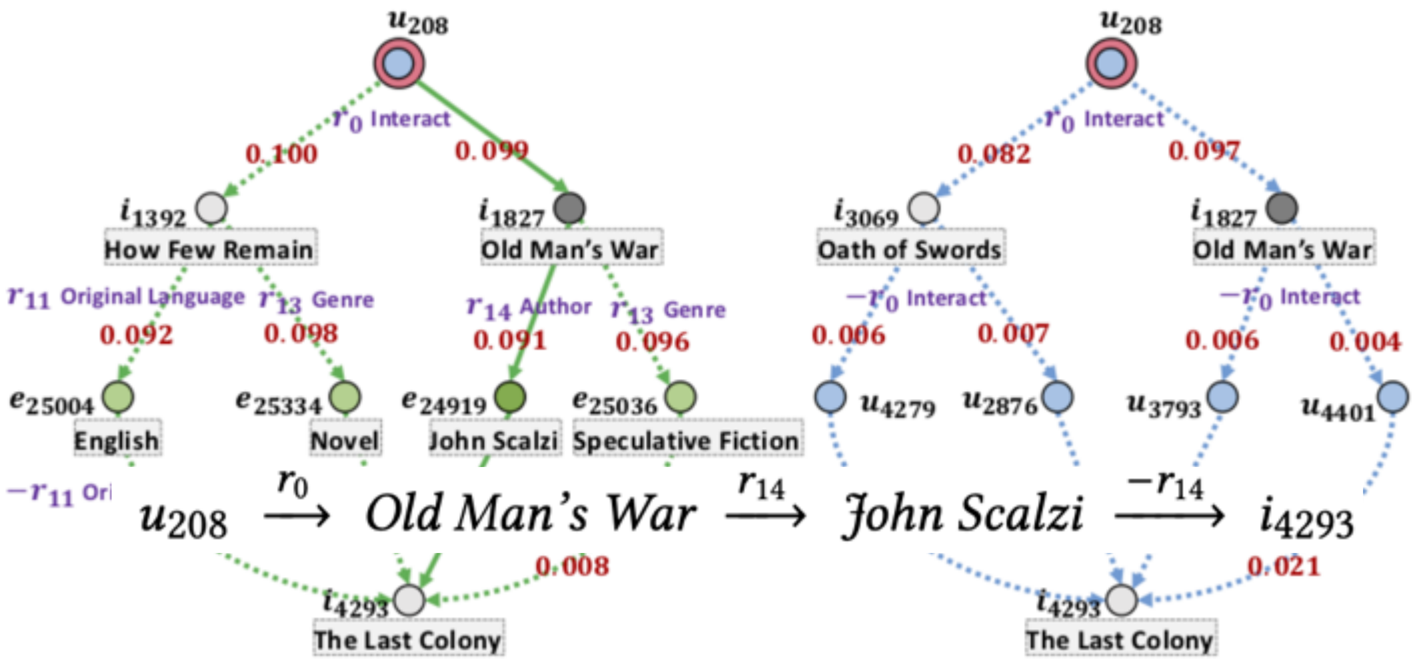


Figure 4: Real Example from Amazon-Book.

- KGAT captures the behavior-based and attribute-based high-order connectivity, which play a key role to infer user preferences.

$$u_{208} \xrightarrow{r_0} \textit{Old Man's War} \xrightarrow{r_{14}} \textit{John Scalzi} \xrightarrow{-r_{14}} i_{4293}$$

- The explanation can be "*The Last Colony is recommended since you have watched Old Man's War written by the same author John Scalzi*."

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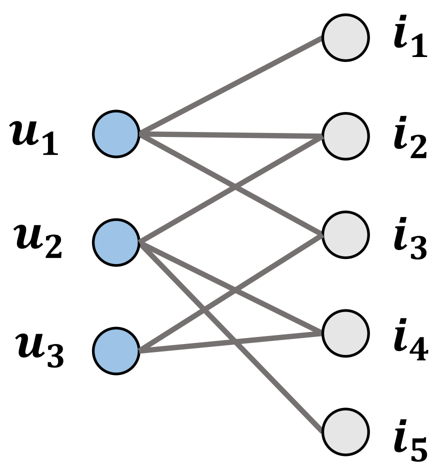
- **Summary & Future Directions**

Slides in https://next-nus.github.io/

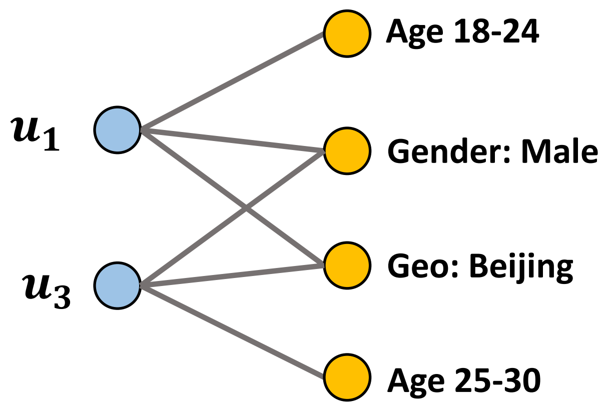
Summary

The data is more **closely connected** that we might think!

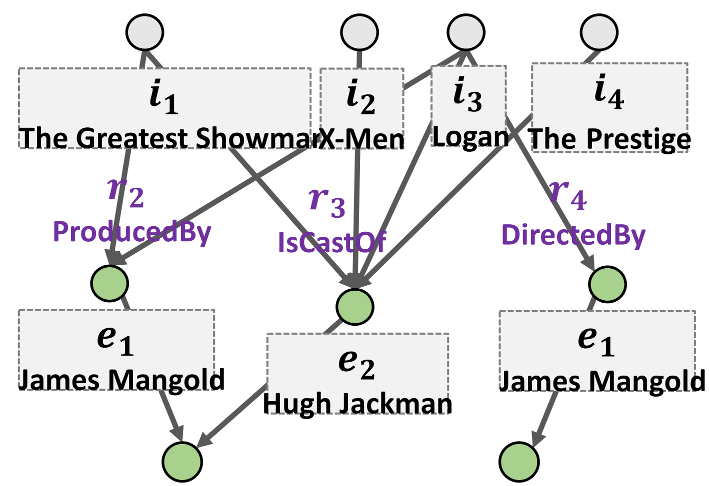
User-Item Interactions



User/Item Profiles



Knowledge Graph



Limited Representation Ability ⇨ **Information Propagation along with the connections**

Suboptimal Model Capacity ⇨ **High-order connectivity complementary to user-item interactions**

Limited Reasoning Ability ⇨ **High-order connectivity interpreting user intents**

Future Direction (1)

- Dynamic Graphs
  - Graph for recommendation evolves over time
    - Online User-Item Interactions, Trending of (fashion) items, CTR prediction …
  - Challenges:
    - How to efficiently & incrementally update representations?
    - How to incorporate edge timing?
    - How to forget old/irrelevant information? …
- Adversarial Learning
  - Attack & Defense
    - Node Features + Edge Features + Graph Structure
  - Applications:
    - Malicious detection, Fraud detection …

Future Direction (2)

- Casual Inference
  - Get intents behind user behaviors
    - What contexts → what behaviors are reasonable
  - Towards explainable recommendation

- Neural Symbolic Reasoning
  - Mimic Human reasoning
  - Study & Understand user behaviors

THANK YOU!