

Recommender Systems and DGL

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AWS Shanghai AI Lab

July 12, 2019

Why Recommendation

Why Recommendation

We don't want our customers to think (hard).

Why Recommendation

Good relevant recommendations make the customers adhere to us.



Added to Cart
Only 1 left in stock.

Cart subtotal (1 item): \$523.01
Your order qualifies for **FREE Shipping!** Select this option at checkout. [Details](#)


Cart


Proceed to checkout (1 item)

Your recently viewed items and featured recommendations

Related to items you've viewed

Page 1 of 9






Dell OptiPlex 5050 Small Form Factor Desktop, Intel Core i5-6500, 8GB DDR4 RAM, 256GB SSD,...

★★★★☆ 1


\$493.98



Dell OptiPlex 3060 SFF Desktop Computer with Intel Core i5-8500 3 GHz Hexa-Core, 8GB RAM,...

★★★★☆ 5


\$674.00



Dell Optiplex 9020 Small Form Business Desktop Tower PC (Intel Quad Core i7 4770, 16GB Ram,...

★★★★☆ 59


\$345.00



Dell CFC5C OptiPlex 3050 Micro Form Factor Desktop Computer, Intel Core i5-7500T, 8GB DDR4,...

★★★★☆ 38


13 offers from \$479.00



Acer Aspire TC-885-ACCFLI50 Desktop, 8th Gen Intel Core i5-8400, 8GB DDR4 + 16GB...

★★★★☆ 59

\$499.99



Inspired by your browsing history

Page 1 of 9





Dell SE2419Hx 23.8" IPS Full HD (1920x1080)



Seagate IronWolf 8TB NAS Internal Hard Drive HDD -



Silicon Power 256GB SSD 3D NAND A55 SLC Cache



Ubiquiti Networks Unifi 802.11ac Dual-Radio PRO




AmazonBasics Wired Computer Keyboard and



Why Recommendation



Good relevant recommendations make the customers adhere to us.

**OK GO**
256 products in account
3 reviews

**Recommended**
6.6 hrs on record

EARLY ACCESS REVIEW POSTED: 26 JANUARY, 2015

I've been waiting my entire life for this game and I didn't even know it.

Was this review helpful?  **Yes**  **No**  **Funny**

184 people found this review helpful
198 people found this review funny

3 

Recommender System: Problem Statement

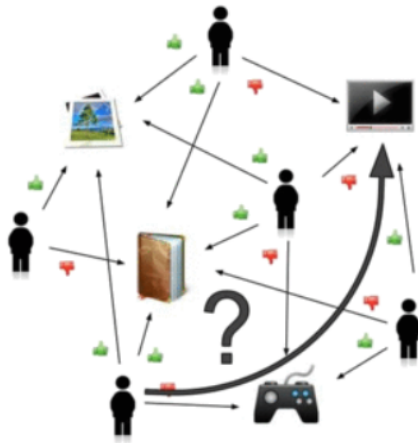
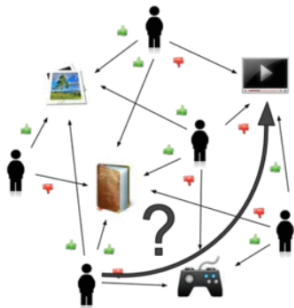
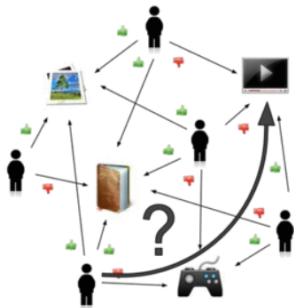


Image source: Wikipedia

Collaborative Filtering



Collaborative Filtering



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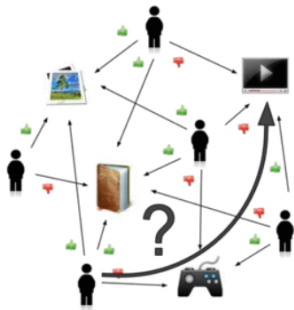




Image source: Wikipedia

Collaborative Filtering: Classical Methods

- **User-based:** Infer how a user i would act to an item j by looking at how users that have similar interactions to user i acted to item j .

Collaborative Filtering: Classical Methods

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 - We have millions of customers.


























Collaborative Filtering: Classical Methods

- **User-based:** Infer how a user i would act to an item j by looking at how users that have similar interactions to user i acted to item j .
 - We have millions of customers.
 - User profiles change constantly and quickly, requiring frequent rebuilds (which are expensive already).


























Collaborative Filtering: Classical Methods

- **Item-based**: Infer how a user i would act to an item j by looking at how **items** that have similar interactions to item j were being acted by **user i** .
 - Amazon used to have fewer items than users.

Collaborative Filtering: Classical Methods

- **Item-based:** Infer how a user i would act to an item j by looking at how items that have similar interactions to item j were being acted by user i .
 - Amazon used to have fewer items than users.
 - Now we also have millions of items.

Machine Learning Kicks In

We were "representing" users and items

Machine Learning Kicks In

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

=

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0?	3	0?	3	0?
User 2	4	0?	0?	2	0?
User 3	0?	0?	3	0?	0?
User 4	3	0?	4	0?	3
User 5	4	3	0?	4	0?

We were "representing" users and items

Latent Factor Model

- An item can be described with a set of features (e.g. how sweet some food is).

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

=

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0.?	3	0.?	3	0.?
User 2	4	0.?	0.?	2	0.?
User 3	0.?	0.?	3	0.?	0.?
User 4	3	0.?	4	0.?	3
User 5	4	3	0.?	4	0.?

Source: [Kat Bailey](#)

Latent Factor Model

- An item can be described with a set of features (e.g. how sweet some food is).
- A user can be described with preferences of the same set of features (e.g. how much a user likes sweet food).

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

=

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0.?	3	0.?	3	0.?
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User 3	0.?	0.?	3	0.?	0.?
User 4	3	0.?	4	0.?	3
User 5	4	3	0.?	4	0.?

Source: [Kat Bailey](#)

Latent Factor Model

- An item can be described with a set of features (e.g. how sweet some food is).
- A user can be described with preferences of the same set of features (e.g. how much a user likes sweet food).
- The interaction is defined by how well the item features match the user preferences.

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

=

	Item 1	Item 2	Item 3	Item 4	Item 5
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Source: [Kat Bailey](#)

Matrix Factorization (Explicit Feedback)

- An item can be described with a **vector** v_j .
- A user can be described with preferences of the same set of features (e.g. how much a user likes sweet food).
- The interaction is defined by how well the item features match the user preferences.

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

=

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0?	3	0?	3	0?
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Source: [Kat Bailey](#)

Matrix Factorization (Explicit Feedback)

- An item can be described with a vector v_j .
- A user can be described with **another vector** u_i
- The interaction is defined by how well the item features match the user preferences.

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0?	3	0?	3	0?
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User 4	3	0?	4	0?	3
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Source: [Kat Bailey](#)

Matrix Factorization (Explicit Feedback)

- An item can be described with a vector v_j .
- A user can be described with another vector u_i
- The **rating on item j by user i** is defined by $u_i^\top v_j$.

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
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=

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- A user can be described with another vector u_i
- The rating on item j by user i . is defined by $u_i^\top v_j$.
- We minimize

$$\sum_{i,j} \left(r_{i,j} - (u_i^\top v_j) \right)^2$$

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
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	Item 1	Item 2	Item 3	Item 4	Item 5
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- We minimize

$$\sum_{i,j} \left(r_{i,j} - \left(u_i^\top v_j + b_{u_i} + b_{v_j} \right) \right)^2$$

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

	Item 1	Item 2	Item 3	Item 4	Item 5
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- We minimize

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$$+ \alpha \left(\|U\|_F^2 + \|V\|_F^2 \right)$$

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

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	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
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User 4	3	0?	4	0?	3
User 5	4	3	0?	4	0?

Source: [Kat Bailey](#)

What if we don't have ratings?



	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0	3	0	0	0
User 2	4	0	0	2	0
User 3	0	0	0	0	0
User 4	0	0	4	0	3
User 5	4	3	0	4	0

	i_1	i_2	i_3	i_4	
u_1	?	+	+	?	user
u_2	+	?	?	+	
u_3	+	+	?	?	
u_4	?	?	+	+	
u_5	?	?	+	?	
	item				

Matrix Factorization (Implicit Feedback)

- For a given user i , an item being interacted j should have a higher score than another item k which was never being interacted.

	i_1	i_2	i_3	i_4
u_1	?	+	+	?
u_2	+	?	?	+
u_3	+	+	?	?
u_4	?	?	+	+
u_5	?	?	+	?

Matrix Factorization (Implicit Feedback)

- For a given user i , an item being interacted j should have a higher score than another item k which was never being interacted.
- We maximize

$$\sum_{i,j,k \in I \setminus I_{u_i}} \log \frac{1}{1 + \exp(u_i^\top v_k - u_i^\top v_j)}$$

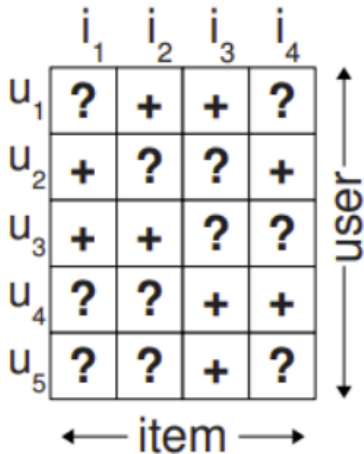
	i_1	i_2	i_3	i_4
u_1	?	+	+	?
u_2	+	?	?	+
u_3	+	+	?	?
u_4	?	?	+	+
u_5	?	?	+	?

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- For a given user i , an item being interacted j should have a higher score than another item k which was never being interacted.
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- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
 - Commonly uniformly, but adaptive sampling often helps.



Other Meaningful Aspects to Consider

- **Cold-start:** What if we have *new* users and items coming in, with few to no historical interactions?

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Other Meaningful Aspects to Consider

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- **Diversity:** Always recommending the same items (or even the same kind of item) to a user would make him/her feel *bored*.

Other Meaningful Aspects to Consider

- **Cold-start:** What if we have *new* users and items coming in, with few to no historical interactions?
- **Bias correction:** The training dataset usually comes from the result of a *previous recommender system*. How to mitigate the bias?
- **Diversity:** Always recommending the same items (or even the same kind of item) to a user would make him/her feel *bored*.
- **Fraud:** How to detect and deal with fabricated explicit feedbacks (e.g. fake ratings and reviews)?

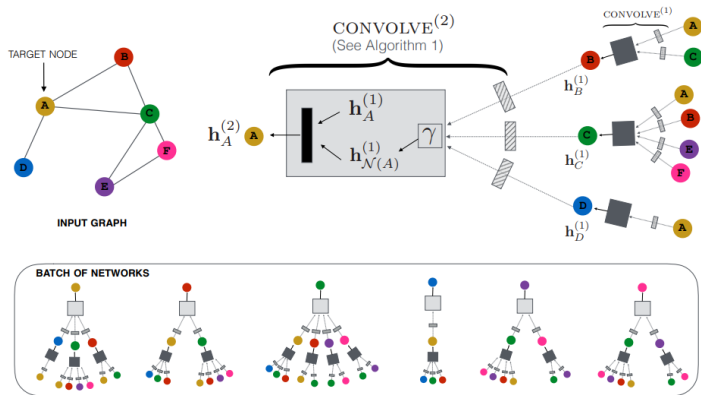
Extensions of Matrix Factorization

- The score function of vanilla MF: $u_i^\top v_j$ where user and item representations are static and independent of each other (fixing the model).
- RNN To integrate user history, $u_i = f(v_{u,1}, v_{u,2}, \dots, v_{u,n})$
 - The user representation now depends on his/her previously interacted items.
- Graph-based models to integrate neighboring items/users (in the next slide).
 - The user representation could also depend on behaviors of other users/items.
- Can combine with content-based recommendation (i.e. with user and item features).
- Can combine both explicit and implicit feedbacks.

Extensions of Matrix Factorization (with Graph-based Models)

- Graph Convolutional Networks on an item copurchase graph
 - When new interactions are added, the copurchase graph and the item representation would also change as well.
 - GCN can also be replaced with other models such as GraphSAGE or PinSAGE (*Hierarchical Temporal Convolutional Networks for Dynamic Recommender Systems*, You et al., 2019)
- GCN on the user-item bipartite graph itself
 - With one layer, becomes GCMC (van den Berg et al., 2017)
 - With neighbor sampling, becomes GraphSAGE.
 - Latest work include STAR-GCN (Zhang et al., 2019) which also deal with cold start problems.

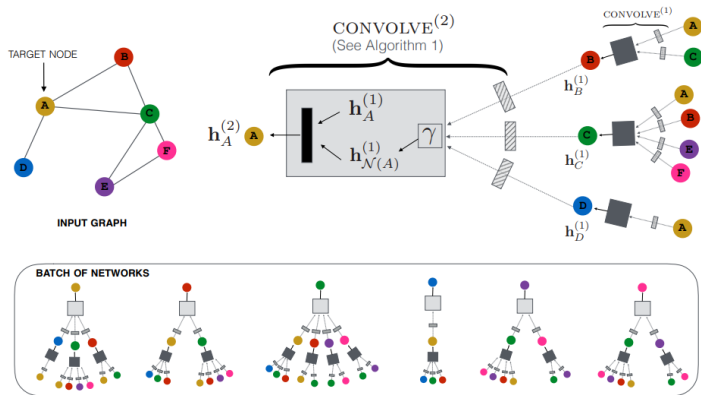
Learning Item Representations with GCN



Source: *Graph Convolutional Neural Networks for Web-Scale Recommender Systems*, Ying et al. 2018

- The graph is a copurchase graph.

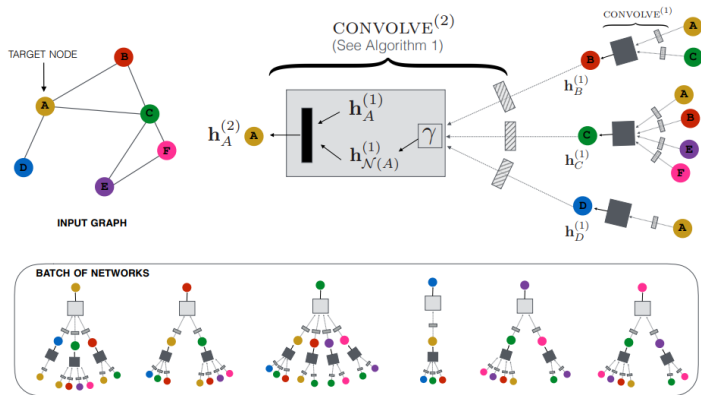
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- The graph is a copurchase graph.
- Item features can be projected before GCN.

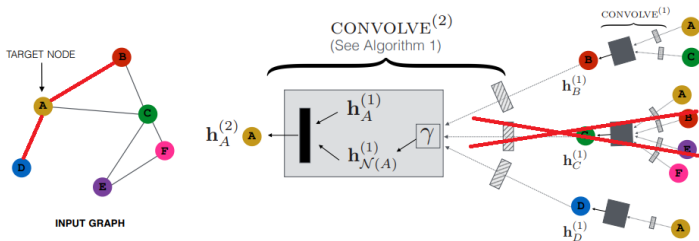
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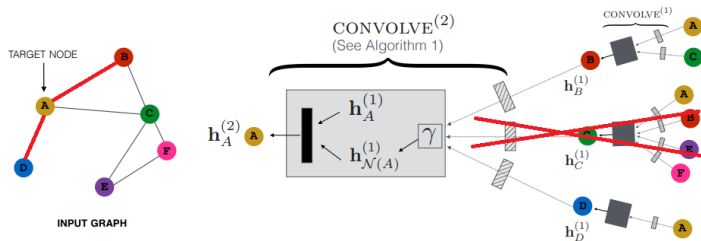
- The graph is a copurchase graph.
- Item features can be projected before GCN.
- During inference, when new copurchases/items appear, we can just recompute the

Learning Item Representations with GCN



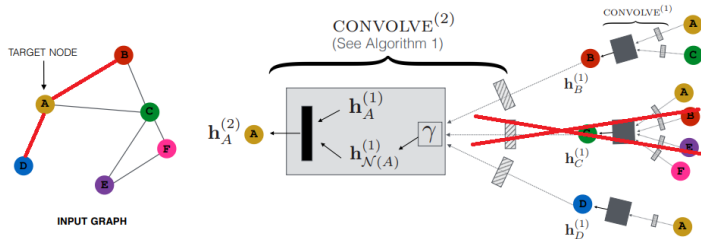
- GraphSAGE - neighbor sampling

Learning Item Representations with GCN



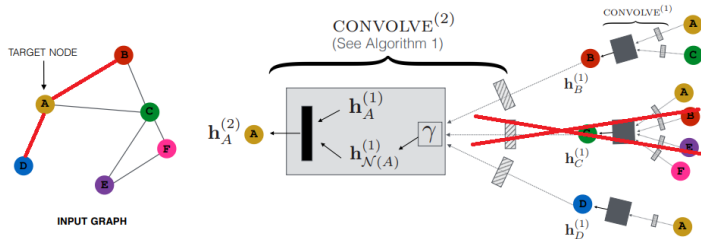
- GraphSAGE - neighbor sampling
- PinSAGE - Neighbors determined by "top-K most frequent nodes visited by random walk with restarts"

Learning Item Representations with GCN



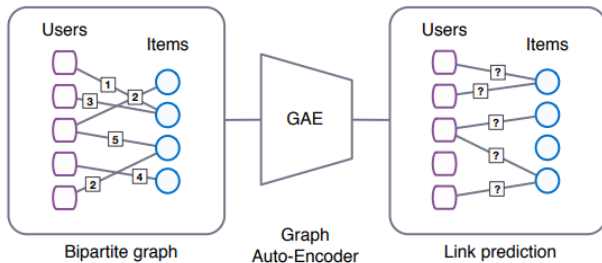
- GraphSAGE - neighbor sampling
- PinSAGE - Neighbors determined by "top-K most frequent nodes visited by random walk with restarts"
 - In the example: if $K = 2$, then B could also be a neighbor of D.

Learning Item Representations with GCN



- GraphSAGE - neighbor sampling
- PinSAGE - Neighbors determined by "top-K most frequent nodes visited by random walk with restarts"
 - In the example: if $K = 2$, then B could also be a neighbor of D.
 - For concrete details of the random walk algorithm, please refer to *Pixie: A System for Recommending 3+ Billion Items to 200+ Million Users in Real-Time*, Eksombatchai et al., 2017

Learning Both User and Item Representations with GCMC



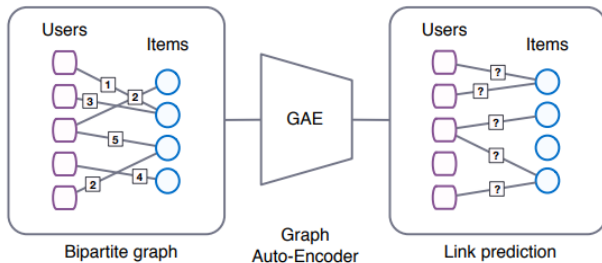
Source: *Graph Convolutional Matrix Completion*, van den Berg et al. 2017

$$\mu_{j \rightarrow i, r} = \frac{1}{C_{ij}} W_r x_j$$

$$h_i = \sigma \left[\text{accum} \left(\sum_{j \in \mathcal{N}_{i,1}} \mu_{j \rightarrow i,1}, \dots, \sum_{j \in \mathcal{N}_{i,R}} \mu_{j \rightarrow i,R} \right) \right]$$

$$u_i = \sigma(W h_i)$$

Learning Both User and Item Representations with GCMC



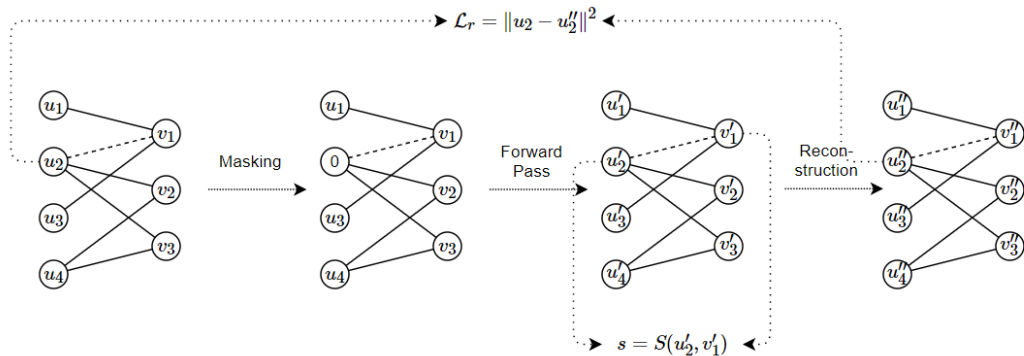
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$$\mu_{j \rightarrow i, r} = \frac{1}{C_{ij}} W_r x_j$$

$$h_i = \sigma \left[\text{accum} \left(\sum_{j \in \mathcal{S}(\mathcal{N}_{i,1})} \mu_{j \rightarrow i,1}, \dots, \sum_{j \in \mathcal{S}(\mathcal{N}_{i,R})} \mu_{j \rightarrow i,R} \right) \right]$$

$$u_i = \sigma(W h_i)$$

Learning Both User and Item Representations with Star-GCN



- Vanilla GCMC can't deal with new users/items without features and with a few interactions.
- STAR-GCN
 - "Mask" the user/item embedding to 0 as if it is new.
 - Reconstruct the embedding after the forward pass and reconstruction pass.

Coding Session

GraphSAGE on bipartite user-item graph.