

Recommender Systems and DGL

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AWS Shanghai AI Lab

July 8, 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.

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

★★★★☆ 1


\$493.98



Dell OptiPlex 9020 Small Form Factor Desktop, Intel Core i5-8500 3 GHz Hexa-Core, 8GB RAM,...

★★★★☆ 5


\$674.00



Dell OptiPlex 9020 Small Form Factor Desktop, 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-ACCFLU50 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) Monitor

★★★★☆ 34


\$129.99



Seagate IronWolf 8TB NAS Internal Hard Drive HDD - 3.5 inch SATA 6Gb/s 7200 RPM 256MB Cache for...

★★★★☆ 47


\$219.99



Silicon Power 256GB SSD 3D NAND A55 SLC Cache Performance Boost SATA III 2.5" 7mm (0.28")...

★★★★☆ 950


\$28.99



Ubiquiti Networks Unifi 802.11ac Dual-Radio PRO Access Point (UAP-AC-PRO-US)

★★★★☆ 1,385


\$134.26



AmazonBasics Wired Computer Keyboard and Mouse, 10-Pack

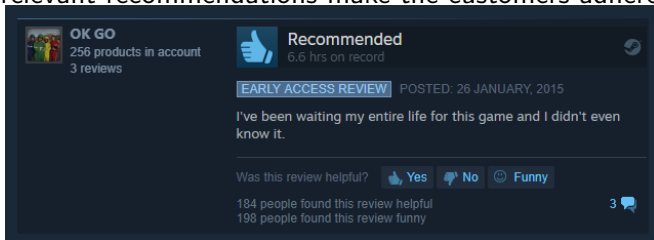
★★★★☆ 1,977

\$122.30



Why Recommendation

Good relevant recommendations make the customers adhere to us.



Recommender System: Problem Statement



Image source: Wikipedia

Collaborative Filtering



Collaborative Filtering



Collaborative Filtering





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.

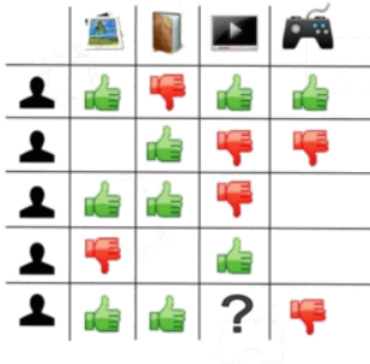
				
				
				
				
				
				

Machine Learning Kicks In

We were "representing" users and items with the items/users that had interactions with them.

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 with the items/users that had interactions with them.

Source: [Kat Bailey](#)

Can we represent users and items as a set of features?

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

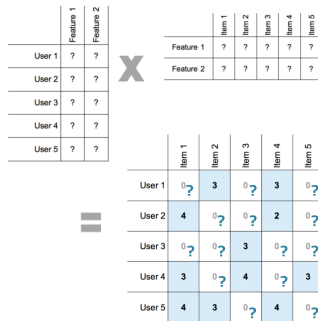
	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

	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).



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
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](#)

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?
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](#)

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	?	?

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](#)

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	?	?	?	?	?
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](#)

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 $u_i^\top v_j$.
- We minimize

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

	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
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](#)

Matrix Factorization (Explicit Feedback)

- We minimize

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

	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
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)

- We minimize

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

- We actually don't handpick which set of features we want the model to learn; we solve it as a normal optimization problem.

	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](#)

Matrix Factorization (Explicit Feedback)

- We minimize

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

- We actually don't handpick which set of features we want the model to learn; we solve it as a normal optimization problem.
- Additionally learn a per-user and per-item bias to make it easier.

	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](#)

Matrix Factorization (Explicit Feedback)

- We minimize

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

- What if the vectors are of **very** high dimensions?

	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
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Source: [Kat Bailey](#)

Matrix Factorization (Explicit Feedback)

- We minimize

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

- What if the vectors are of **very** high dimensions?
 - Use low-dimensional u_i and 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	?	?	?	?	?
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?
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Source: [Kat Bailey](#)

Matrix Factorization (Explicit Feedback)

- We minimize

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

- What if the vectors are of **very** high dimensions?
 - Use low-dimensional u_i and v_j .
- What if one product receives only one but very high rating?

	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](#)

Matrix Factorization (Explicit Feedback)

- We minimize

$$\sum_{i,j} \left(r_{i,j} - \left(u_i^\top v_j + b_{u_i} + b_{u_j} \right) \right)^2 + \alpha \left(\|U\|_F^2 + \|V\|_F^2 \right)$$

- What if the vectors are of **very** high dimensions?
 - Use low-dimensional u_i and v_j .
- What if one product receives only one but very high rating?
 - Penalize the magnitude of parameters.

	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.?
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Source: [Kat Bailey](#)

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- We minimize

$$\sum_{i,j} \left(r_{i,j} - \left(u_i^\top v_j + b_{u_i} + b_{u_j} \right) \right)^2 + \alpha \left(\|U\|_F^2 + \|V\|_F^2 \right)$$

	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	?	?	?	?	?

	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](#)

Matrix Factorization (Explicit Feedback)

- We minimize

$$\sum_{(i,j) \in \mathcal{B}} \left(r_{i,j} - \left(u_i^\top v_j + b_{u_i} + b_{u_j} \right) \right)^2 + \alpha \left(\|U\|_F^2 + \|V\|_F^2 \right)$$

- Optimize with Stochastic Gradient Descent
 - Each time we sample a minibatch of interactions, and compute the gradient from this minibatch only.

	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](#)

What if we don't have ratings?



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

Source: BPR: Bayesian Personalized Ranking from

Implicit Feedback, Rendle et al. 2012

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	?	+	+	?	user ↑ ↓
u_2	+	?	?	+	
u_3	+	+	?	?	
u_4	?	?	+	+	
u_5	?	?	+	?	
	← item →				

Source: *BPR: Bayesian Personalized Ranking*
from *Implicit Feedback*, Rendle et al. 2012

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	?	+	+	?	user ↑ ↓
u_2	+	?	?	+	
u_3	+	+	?	?	
u_4	?	?	+	+	
u_5	?	?	+	?	
	← item →				

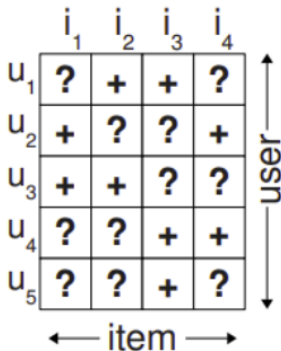
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from *Implicit Feedback*, Rendle et al. 2012

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

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

- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
 - Commonly uniformly, but adaptive sampling often helps.



Source: *BPR: Bayesian Personalized Ranking from Implicit Feedback*, Rendle et al. 2012

Other Meaningful Aspects to Consider

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

Other Meaningful Aspects to Consider

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- **Bias correction:** The training dataset usually comes from the result of a *previous recommender system*. How to mitigate the bias?

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*.

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)?

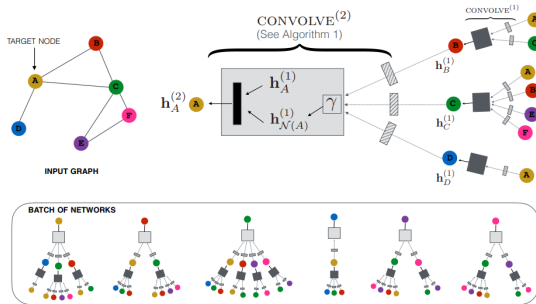
Extensions of Matrix Factorization

- 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.

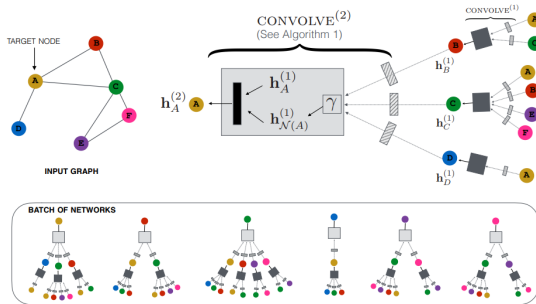
Learning Item Representations with GCN



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

- The graph is a copurchase graph.

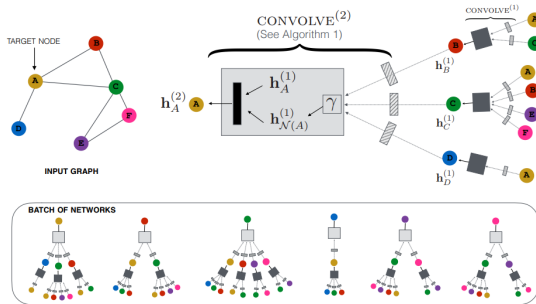
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- The graph is a copurchase graph.
- Item features can be projected before GCN.

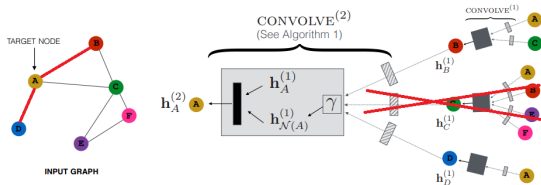
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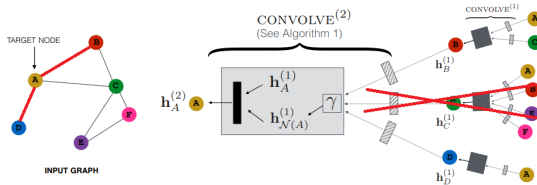
- The graph is a copurchase graph.
- Item features can be projected before GCN.
- During inference, when new copurchases/items appear, we can just recompute the embeddings on the new graph with trained parameters.

Learning Item Representations with GCN



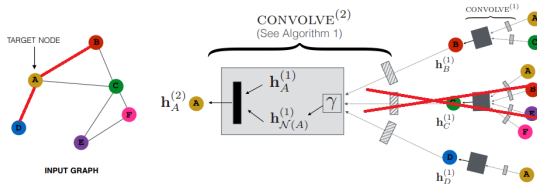
- GraphSAGE - neighbor sampling

Learning Item Representations with GCN



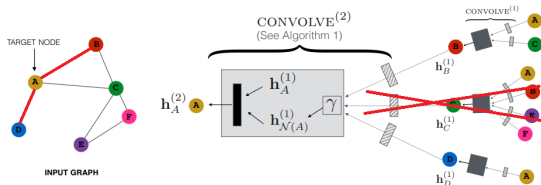
- GraphSAGE - neighbor sampling
- PinSAGE - Neighbors determined by "top-K most frequent nodes visited by random walk with restarts"

Learning Item Representations with GCN



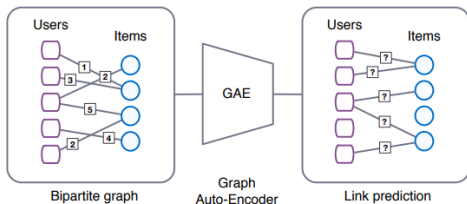
- GraphSAGE - neighbor sampling
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 - In the example: if $K = 2$, then **B** could also be a neighbor of **D**.

Learning Item Representations with GCN



- GraphSAGE - neighbor sampling
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 - 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

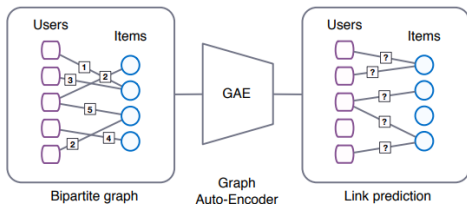
Learning Both User and Item Representations with GCMC



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

$$\mu_{j \rightarrow i, r} = \frac{1}{c_{ij}} W_r x_j$$
$$h_i = \sigma \left[\text{accum} \left(\sum_{j \in \mathcal{N}_{i,1}} \mu_{j \rightarrow i,1}, \dots, \sum_{j \in \mathcal{N}_{i,R}} \mu_{j \rightarrow i,R} \right) \right]$$
$$u_i = \sigma(W h_i)$$
$$p(\hat{M}_{ij} = r) = \text{softmax}(u_i^\top Q_r v_j)$$

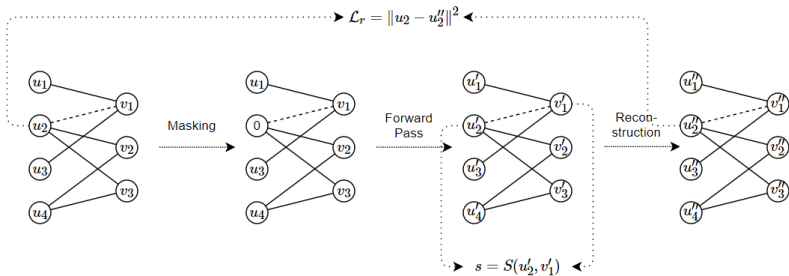
Learning Both User and Item Representations with GCMC



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$$\mu_{j \rightarrow i, r} = \frac{1}{c_{ij}} W_r x_j$$
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$$u_i = \sigma(W h_i)$$
$$p(\hat{M}_{ij} = r) = \text{softmax}(u_i^\top Q_r v_j)$$

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.