Recommender Systems and DGL

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AWS Shanghai AI Lab

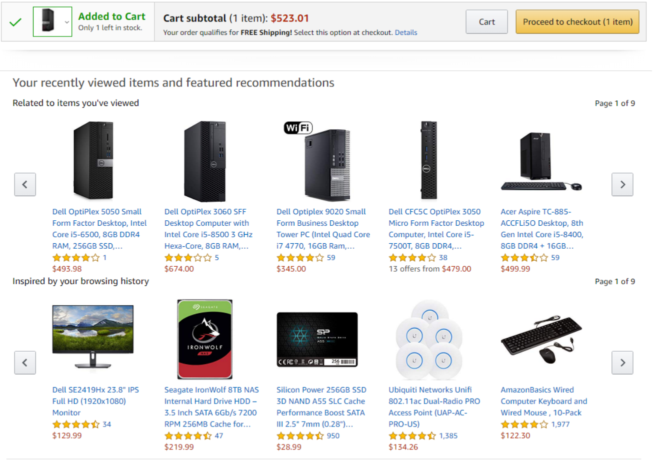
July 12, 2019

Why Recommendation

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

Why Recommendation

Good relevant recommendations make the customers adhere to us.



Why Recommendation

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Recommender System: Problem Statement

Image source: Wikipedia

Collaborative Filtering

Collaborative Filtering

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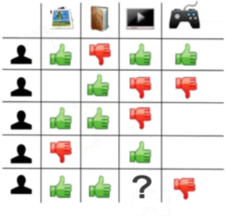


Collaborative Filtering

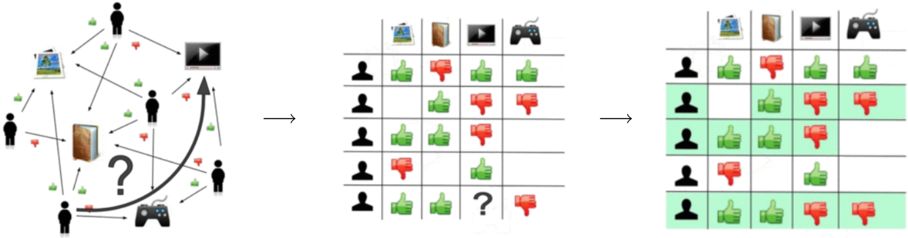
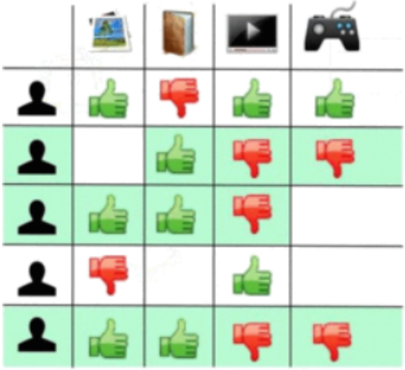


Image source: Wikipedia

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.



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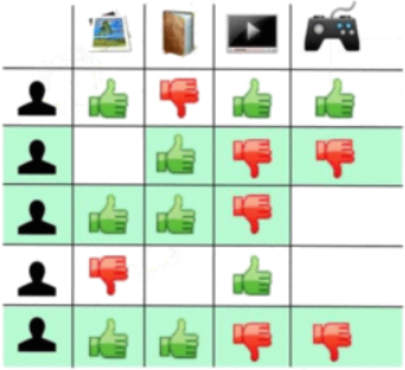
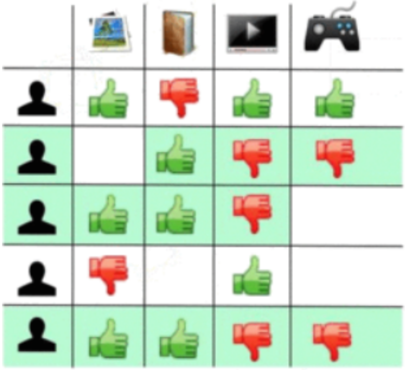


Collaborative Filtering: Classical Methods

- **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).



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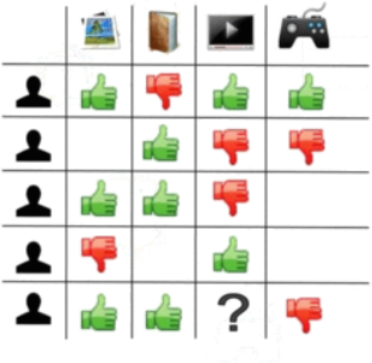
  - Amazon used to have fewer items than users.
  - Now we also have millions of items.

Machine Learning Kicks In



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

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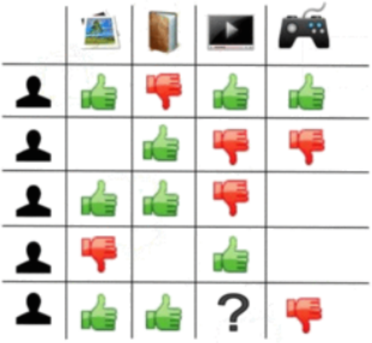

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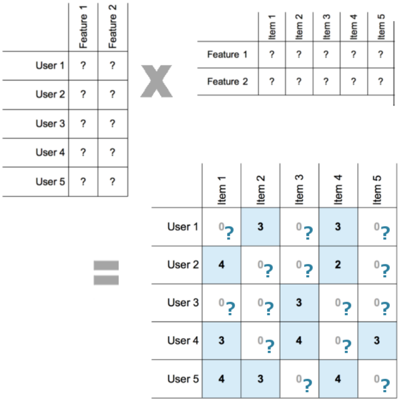
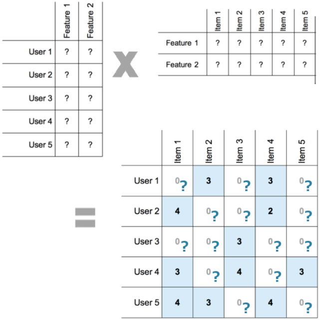


Source: Kat Bailey

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).



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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	?	?	?	?	?

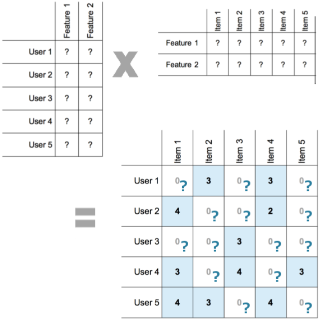
=

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0?	3	0?	3	0?
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).
- The interaction is defined by how well the item features match the user preferences.



Source: Kat Bailey

Matrix Factorization (Explicit Feedback)

- An item can be described with a vector v_j.
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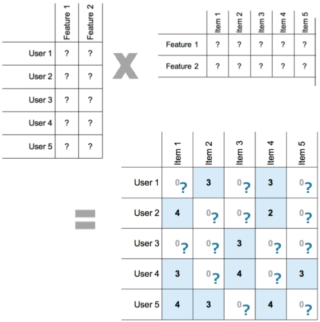

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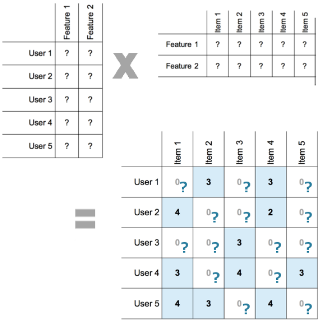

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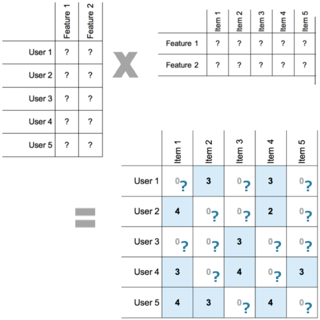

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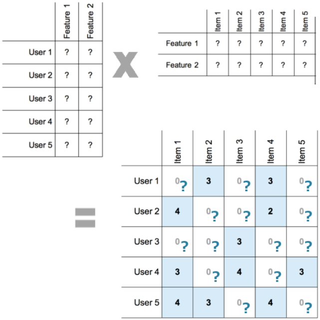
- We minimize

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



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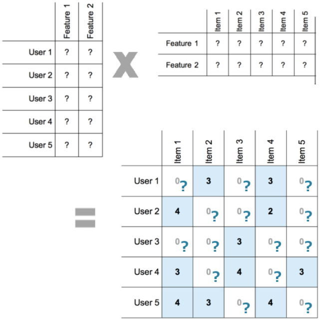

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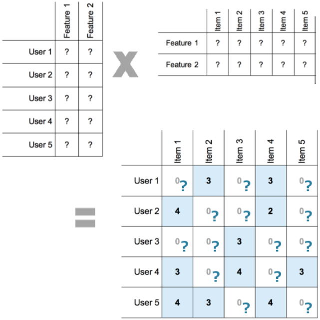
- What if the vectors are of **very** high dimensions?



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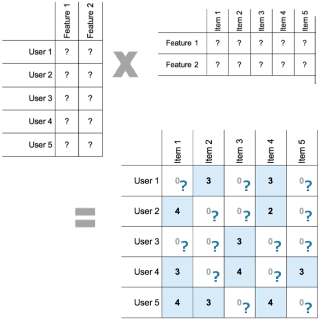

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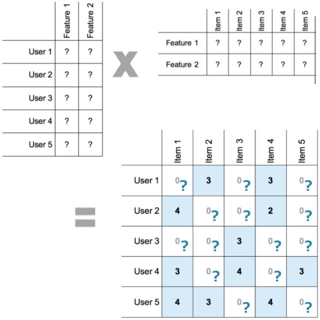

Source: Kat Bailey

- What if the vectors are of **very** high dimensions?
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- What if one product receives only one but very high rating?

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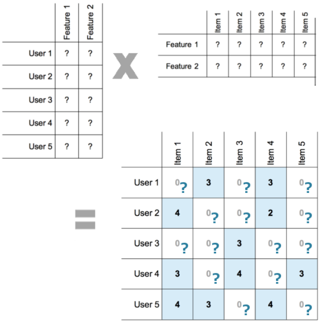
$$+\alpha \left(\|U\|_F^2 + \|V\|_F^2 \right)$$

- 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.



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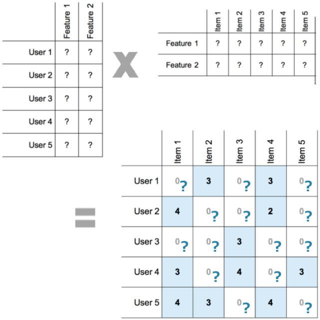

Source: Kat Bailey

Matrix Factorization (Explicit Feedback)

- We minimize

$$\sum_{(i,j)\in\mathcal{B}} \left(r_{i,j} - \left(u_i^\top v_j + b_{u_i} + b_{u_j}\right)\right)^2$$
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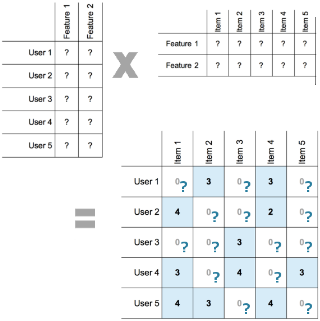
- Optimize with Stochastic Gradient Descent
  - Each time we sample a minibatch of interactions, and compute the gradient from this minibatch only.



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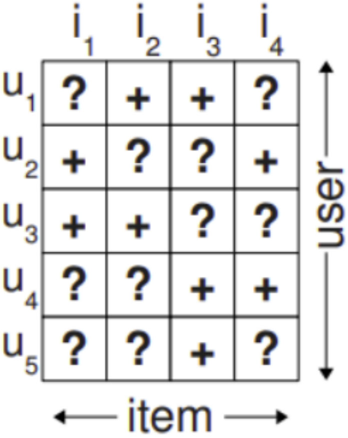
What if we don't have ratings?



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

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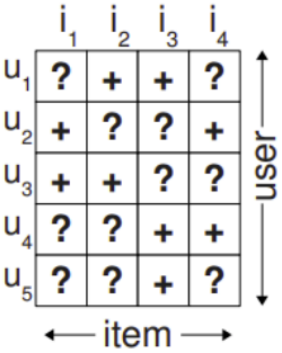
- For a given user i, an item being interacted j should have a higher score than another item k which was never being interacted.



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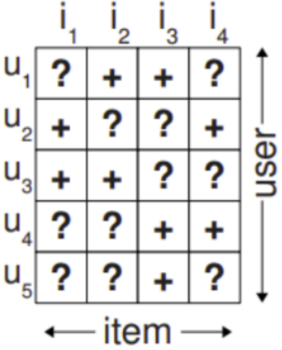

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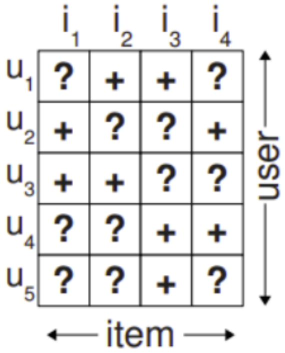
- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
    - Commonly uniformly, but adaptive sampling often helps.



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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*.
- **Fraud**: How to detect and deal with fabricated explicit feedbacks (e.g. fake ratings and reviews)?

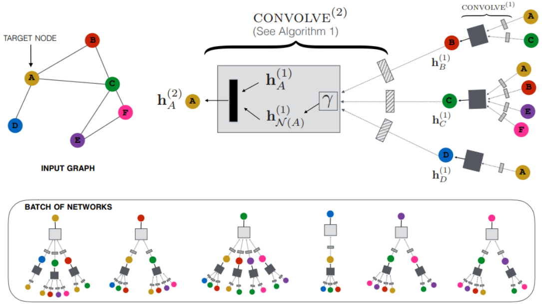
Extensions of Matrix Factorization

- 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, $u_i = f(v_{u,1}, v_{u,2}, \cdots, v_{u,n})$
  - 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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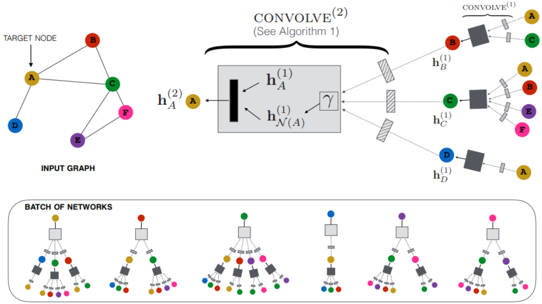

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- The graph is a copurchase graph.
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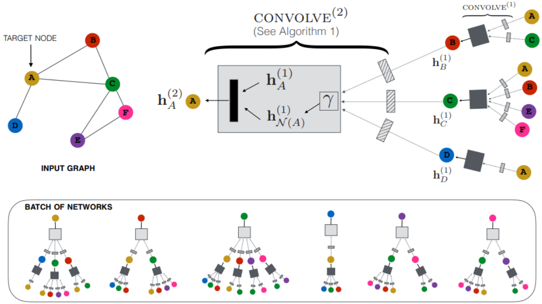

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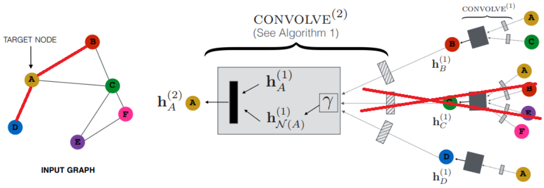
- The graph is a copurchase graph.
- Item features can be projected before GCN.
- During inference, when new copurchases/items appear, we can just recompute the embeddings on the new graph with trained parameters.

Learning Item Representations with GCN



- GraphSAGE - neighbor sampling

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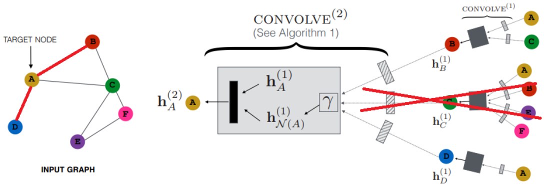

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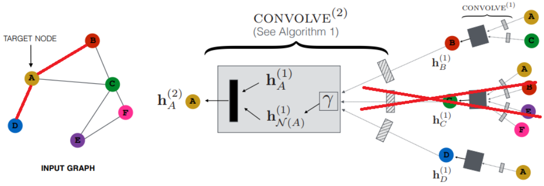

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  - In the example: if $K = 2$, then B could also be a neighbor of D.

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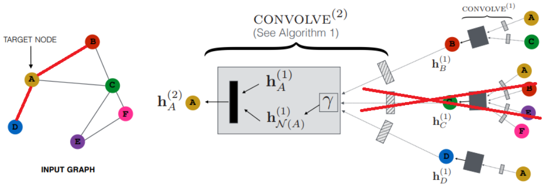

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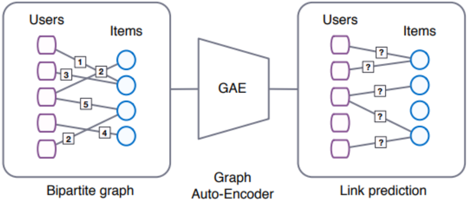
- PinSAGE - Neighbors determined by "top-K most frequent nodes visited by random walk with restarts"
  - In the example: if $K = 2$, then B could also be a neighbor of D.
  - For concrete details of the random walk algorithm, please refer to *Pixie: A System for Recommending 3+ Billion Items to 200+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

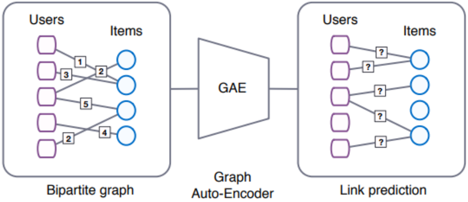
$$\mu_{j \to i, r} = \frac{1}{c_{ij}} W_r x_j$$

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

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

$$p(\hat{M}_{ij} = r) = \mathrm{softmax}(u_i^\top Q_r v_j)$$

Learning Both User and Item Representations with GCMC



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$$u_i = \sigma(Wh_i)$$

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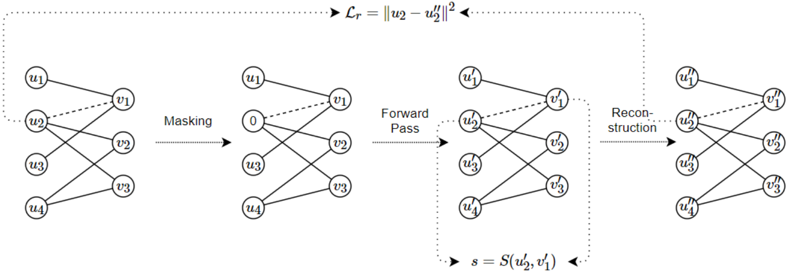
Learning Both User and Item Representations with Star-GCN



- 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.