Recommender Systems and DGL

Quan Gan

AWS Shanghai AI Lab

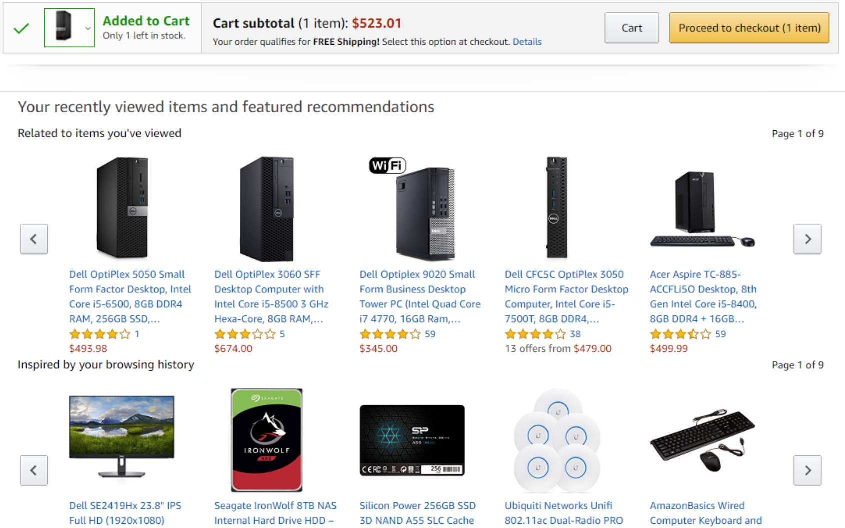
July 12, 2019

Why Recommendation

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

Why Recommendation

Good relevant recommendations make the customers adhere to us.



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Recommender System: Problem Statement

Image source: Wikipedia

Collaborative Filtering

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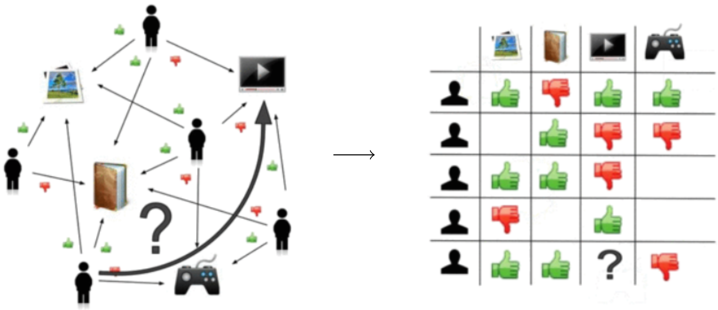

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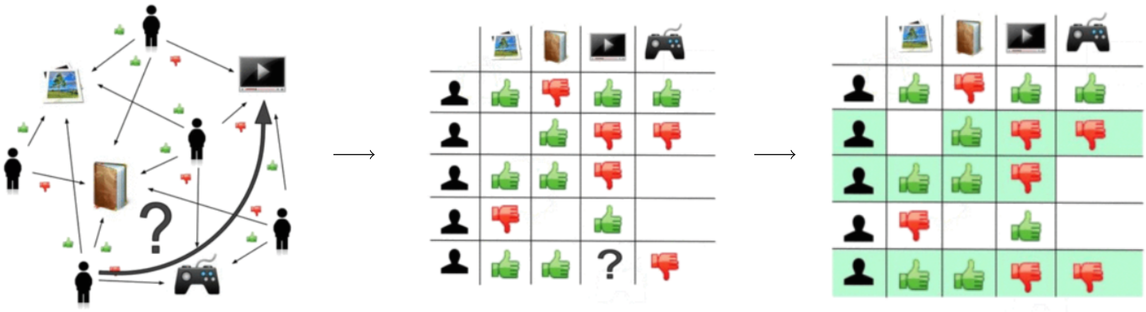

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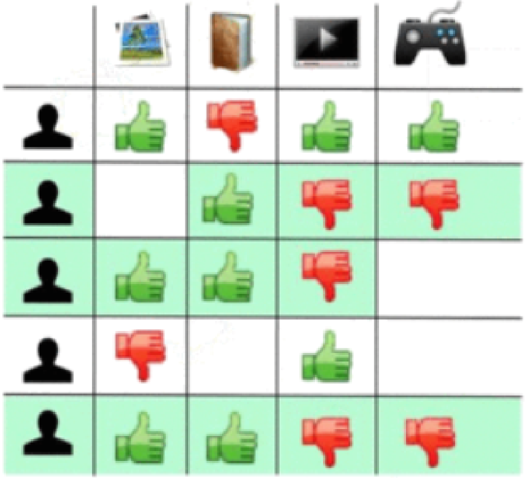
Collaborative Filtering: Classical Methods

- **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.



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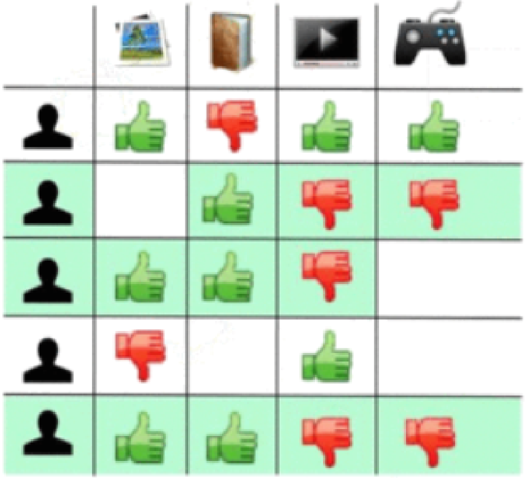
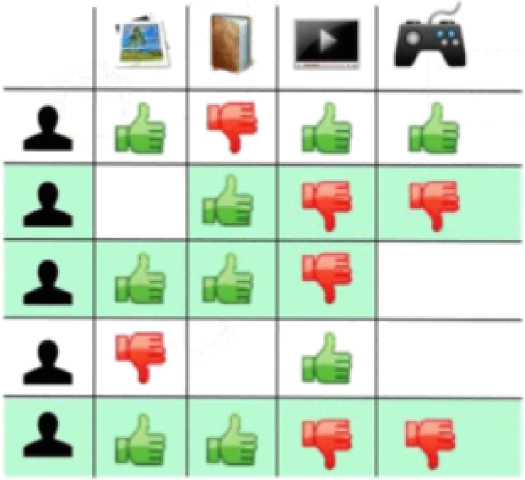


Collaborative Filtering: Classical Methods

- **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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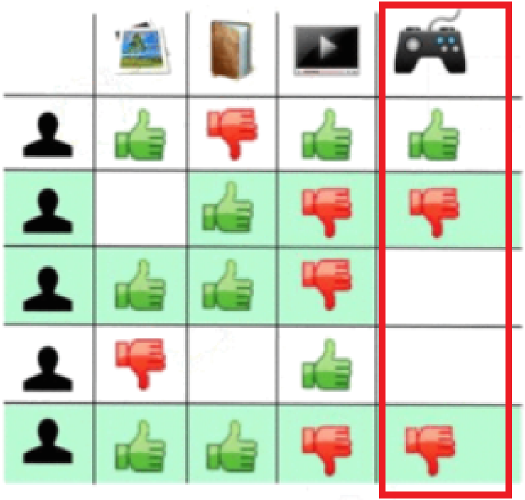

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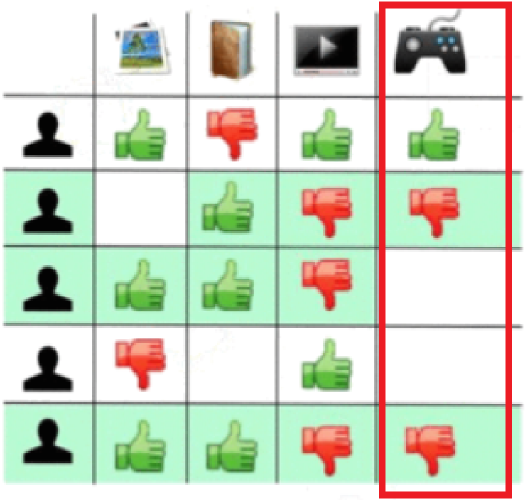
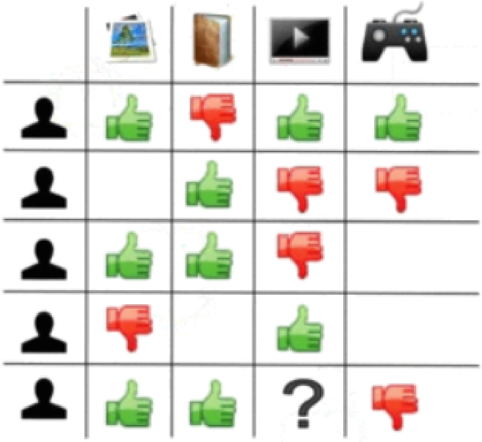


Machine Learning Kicks In



We were "representing" users and items

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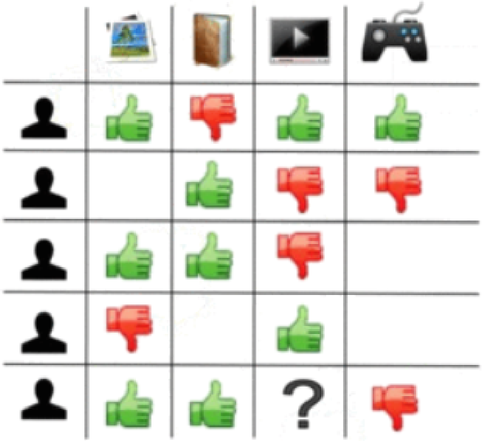

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

X

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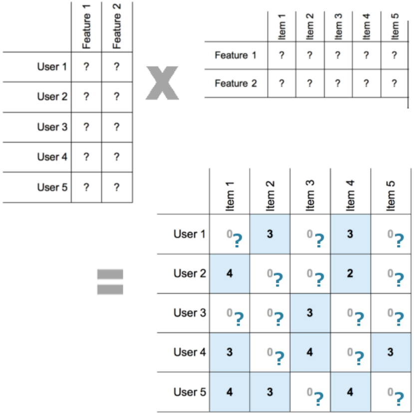
Latent Factor Model

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



Source: Kat Bailey

Latent Factor Model

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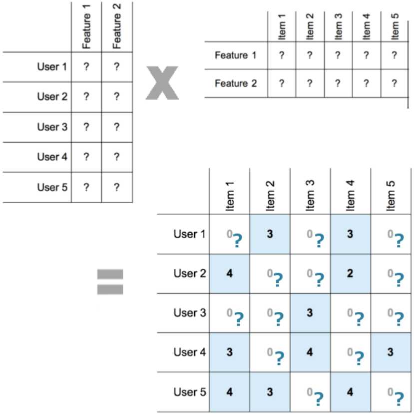

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- An item can be described with a set of features (e.g. how sweet some food is).
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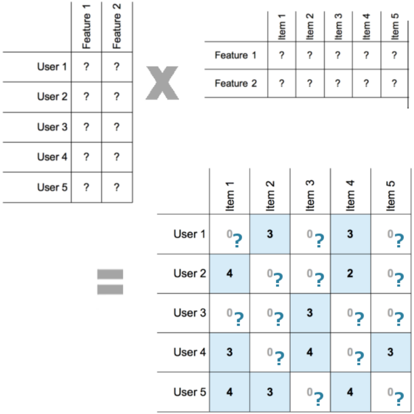

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Matrix Factorization (Explicit Feedback)

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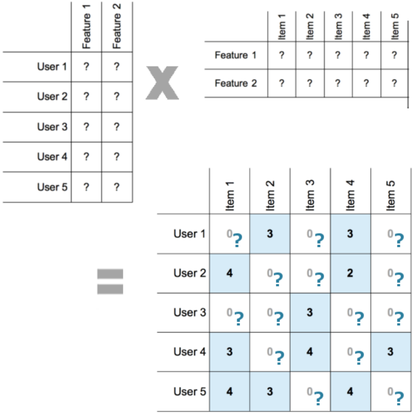

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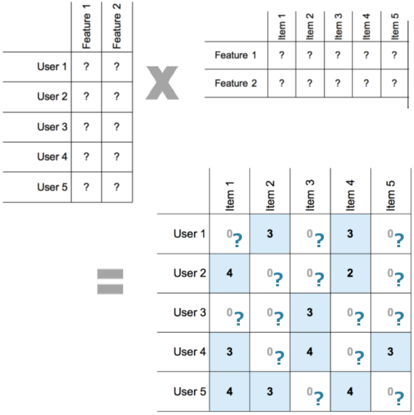

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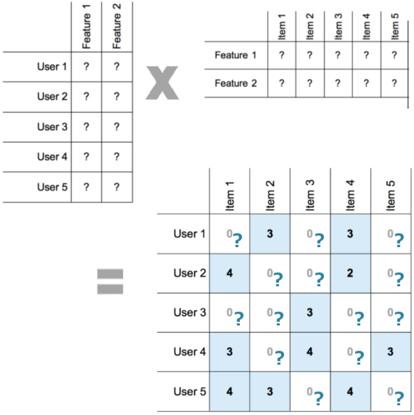

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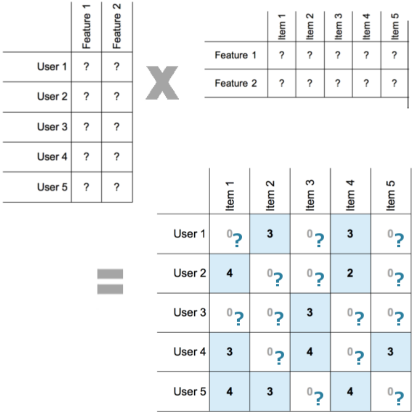

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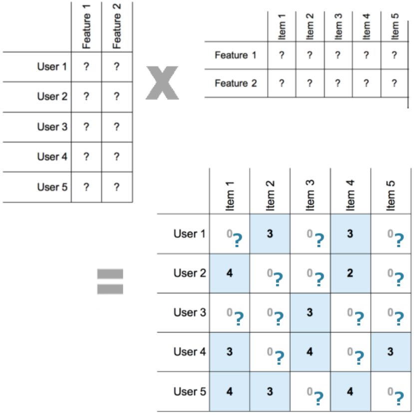

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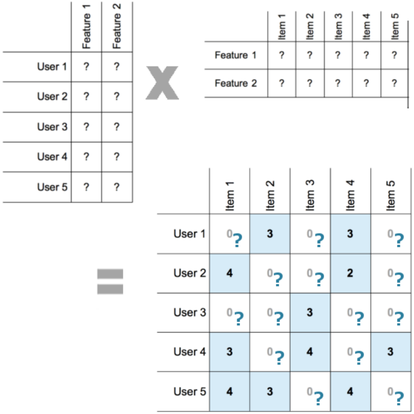

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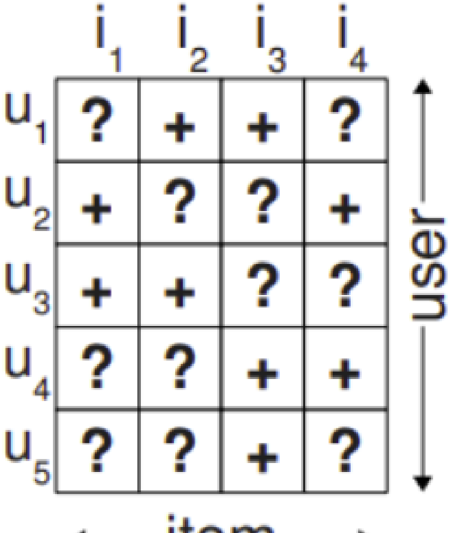
What if we don't have ratings?



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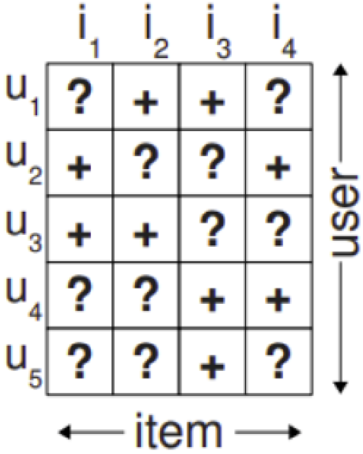

Source: *BPR: Bayesian Personalized Ranking from Implicit*

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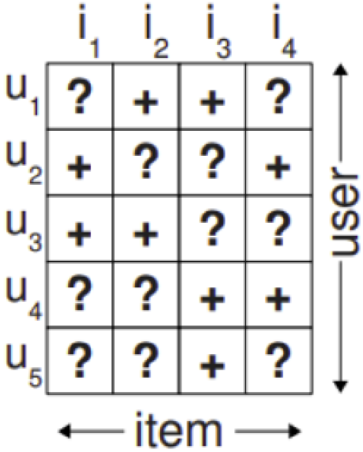

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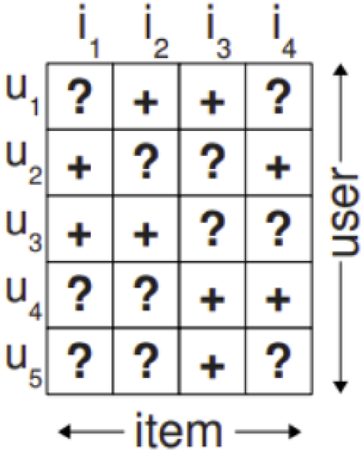
- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
  - Commonly uniformly, but adaptive sampling often helps.



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

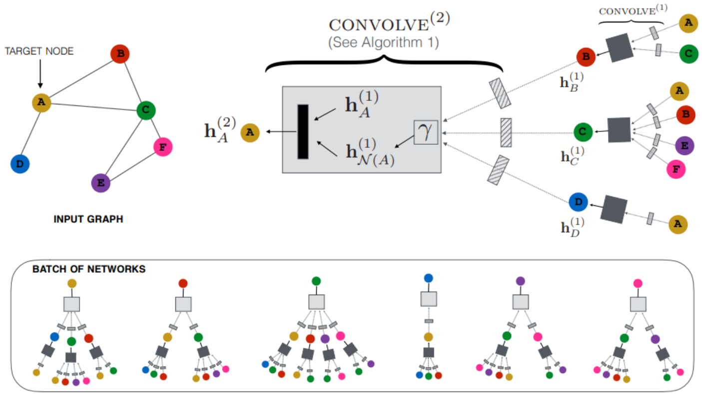
Extensions of Matrix Factorization

- 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

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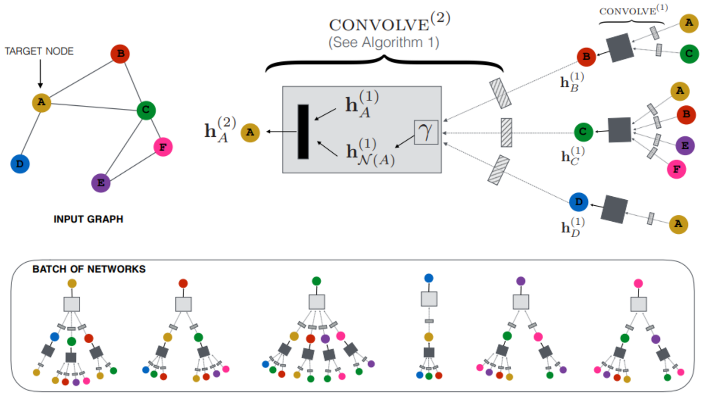

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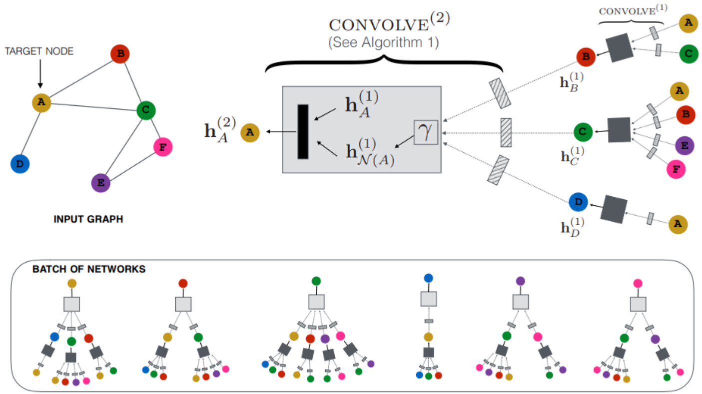

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- During inference, when new copurchases/items appear, we can just recompute the

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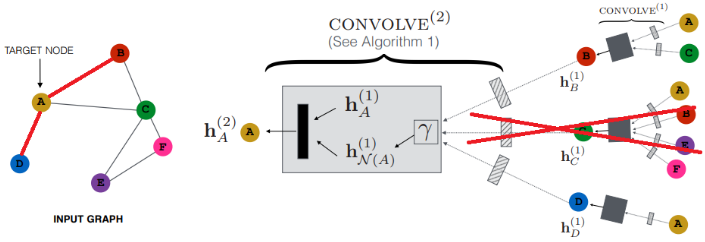
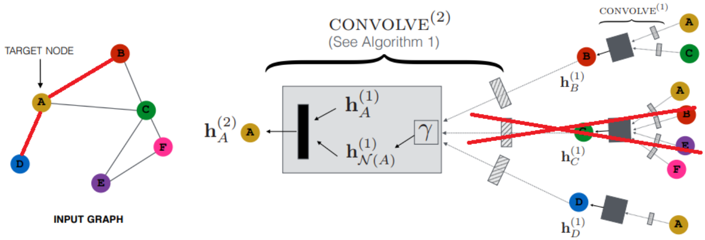


- GraphSAGE - neighbor sampling

Learning Item Representations with GCN



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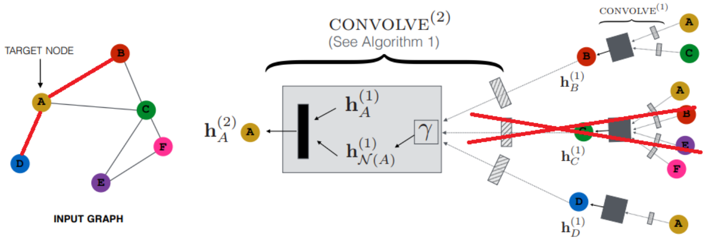

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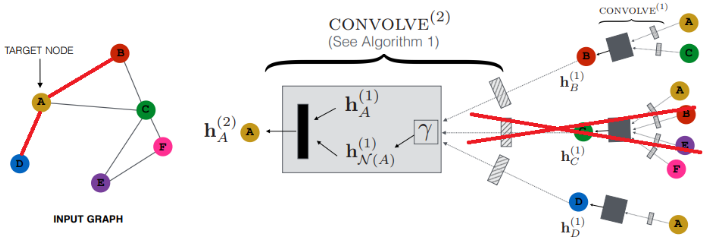

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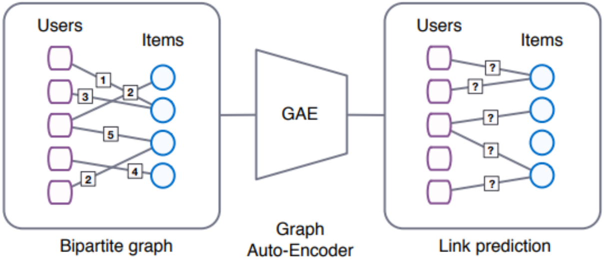
  - In the example: if $K = 2$, then B could also be a neighbor of D.
  - For concrete details of the random walk algorithm, please refer to *Pixie: A System for Recommending 3+ Billion Items to 200+ Million Users in Real-Time*, Eksombatchai et al., 2017

Learning Both User and Item Representations with GCMC



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

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

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

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

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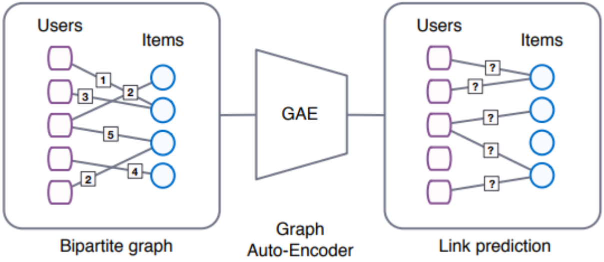

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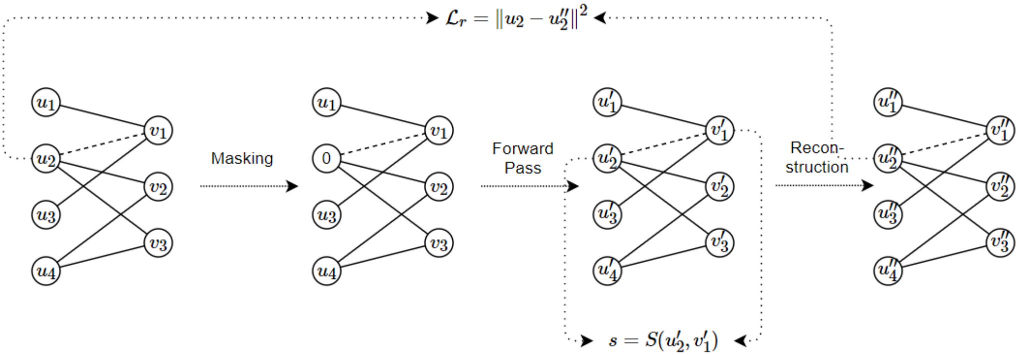
Learning Both User and Item Representations with Star-GCN



- 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.