DGL on Real World Applications

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April 19, 2020

Various GNN Business Applications

- Recommender Systems: find the most relevant items for a given user.
- Product Search: find the most relevant items given a set of keywords.
- Fraud Detection: detect anomaly of entities in a supervised/unsupervised manner.
- Community Detection: cluster entities in a supervised/unsupervised manner.

Recommender System: Problem Statement

Image source: Wikipedia

Collaborative Filtering

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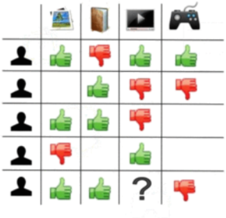

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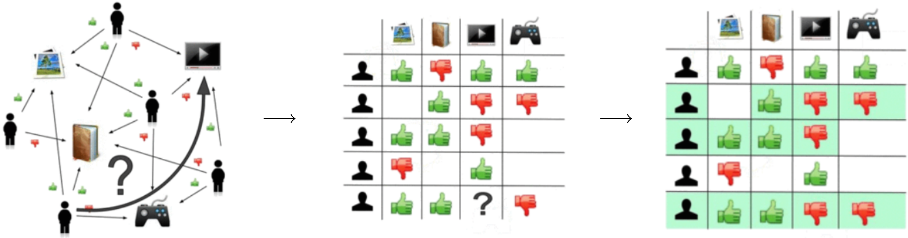

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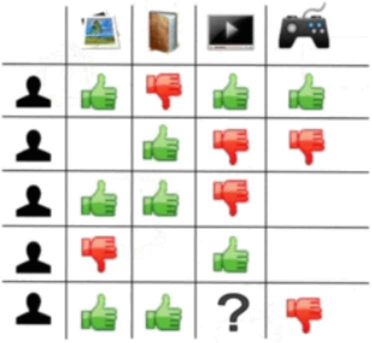
Collaborative Filtering with Machine Learning



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

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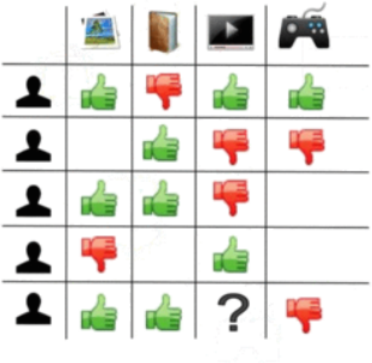

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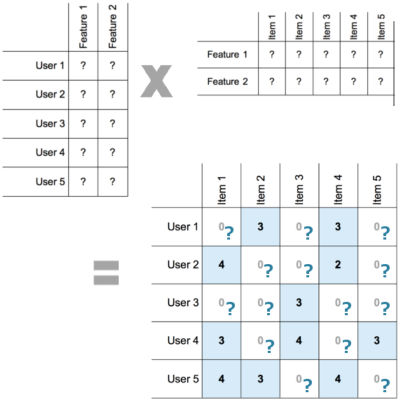
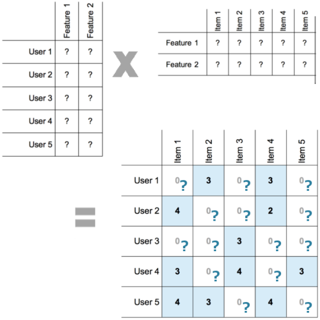


Source: Kat Bailey

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

Latent User/Item Representations

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



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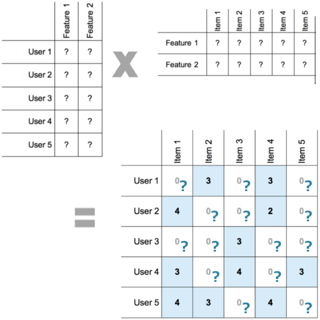

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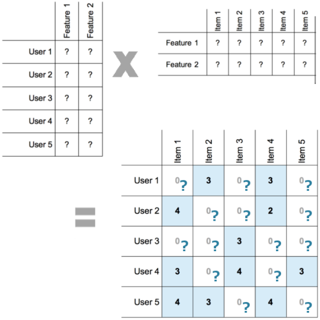

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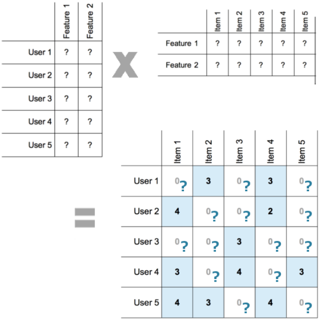

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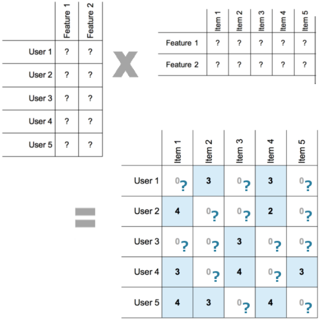

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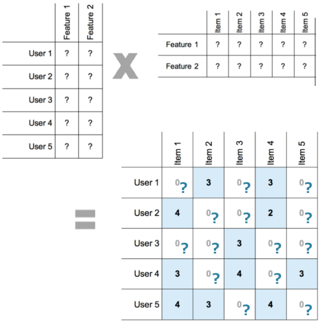

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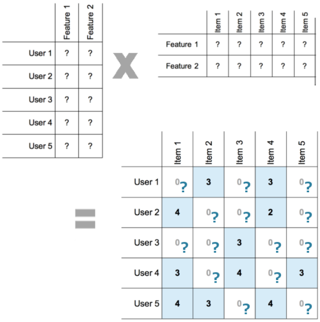

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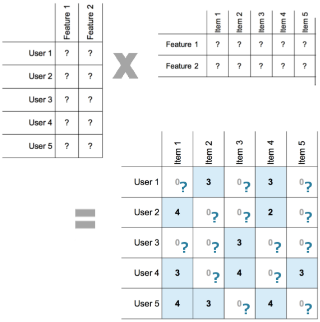

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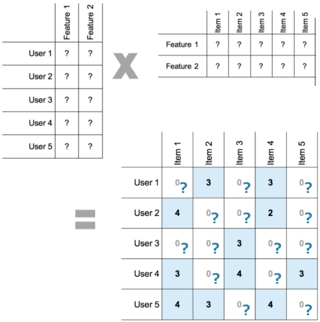

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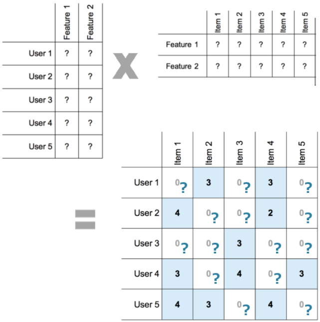

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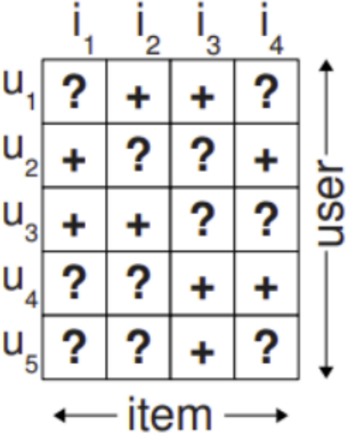
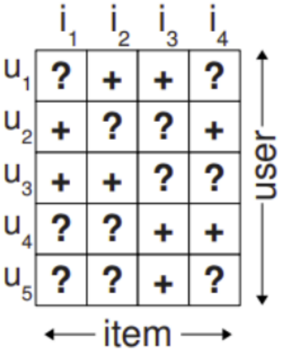
What if we don't have ratings?



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

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.



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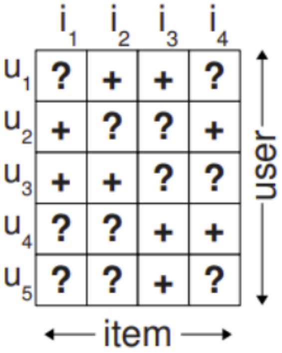

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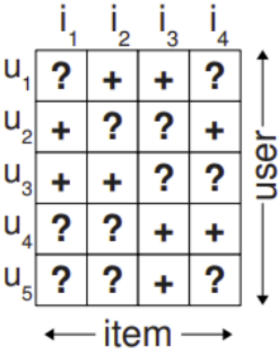
- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
  - Commonly uniformly, but adaptive sampling often helps.



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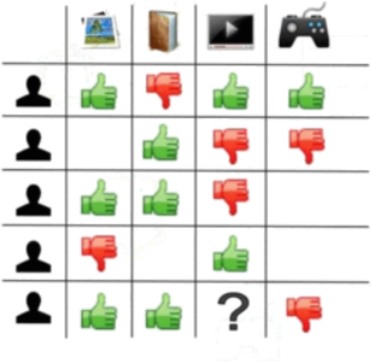
Formulating Recommender Systems as Graph Learning



- Explicit Feedback
- Implicit Feedback

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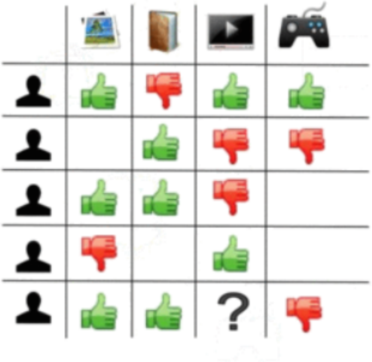
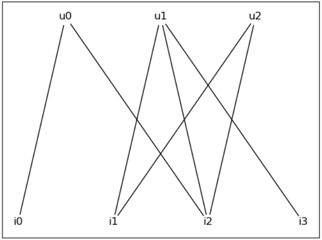
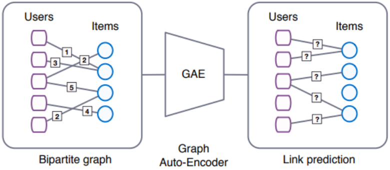




- Explicit Feedback
- Implicit Feedback

- Edge Classification/Regression
- Link Prediction

GCMC: Learning u_i and v_j from User-Item Graph



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

1. $\mu_{v_j \to u_i, r} = \frac{1}{c_{u_i v_j}} W_r x_{v_j}$

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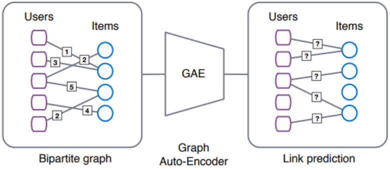

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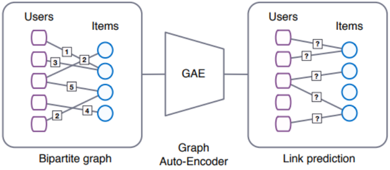

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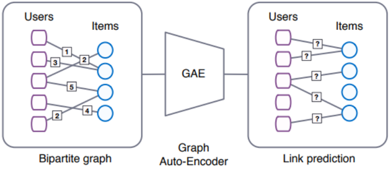

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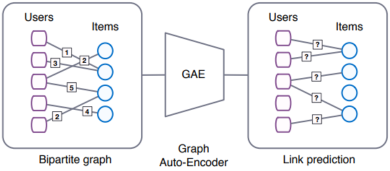

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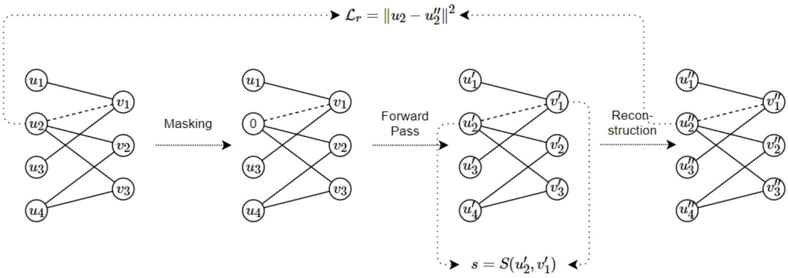
5. When new interactions are added, just re-run the forward pass on the new graph to get new u_i and v_j.

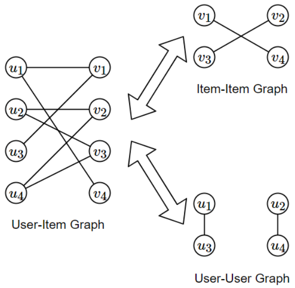
Learning u_i and v_j with Star-GCN



- Vanilla GCMC can't deal with new users/items without features (but 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.

Learning v_j and u_i from Item-Item and User-User Graph

- Decompose the user-item graph into user-user graph and item-item graph.



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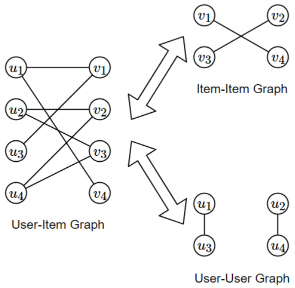

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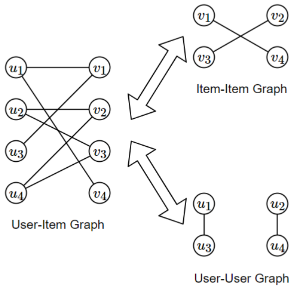

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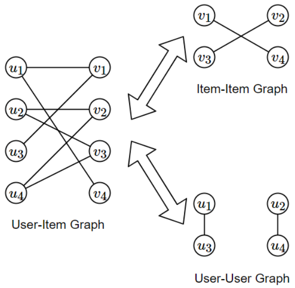

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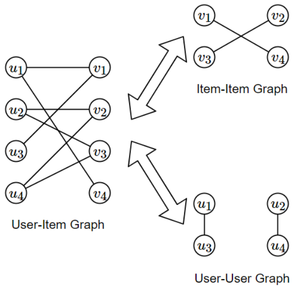

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- **Diversity**: Always recommending the same items (or even the same kind of item) to a user would make him/her feel *bored*.
- **Fraud**: How to detect and deal with fabricated explicit feedbacks (e.g. fake ratings and reviews)?

Hands-on Session

Miniature GCMC on bipartite user-item graph.