Recommender Systems and DGL

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AWS Shanghai AI Lab

July 12, 2019

Why Recommendation

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

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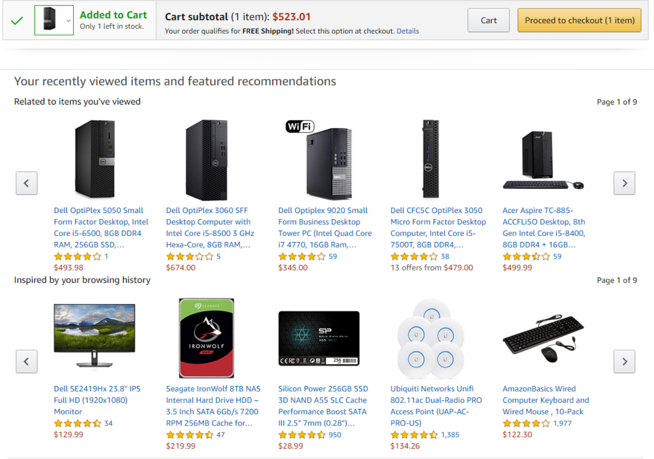
Good relevant recommendations make the customers adhere to us.



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Recommender System: Problem Statement

Image source: Wikipedia

Collaborative Filtering

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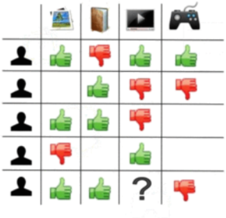
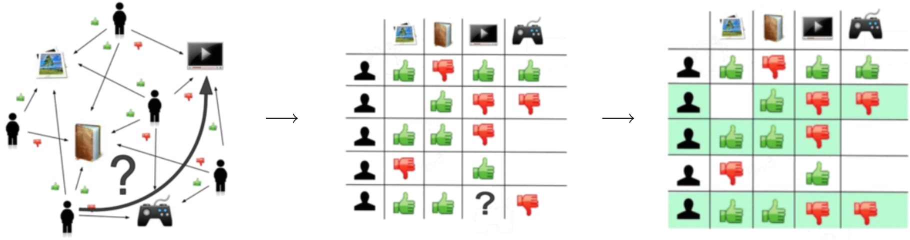


Collaborative Filtering



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Collaborative Filtering: Classical Methods

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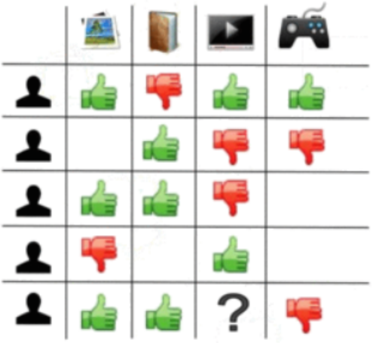
  - We have millions of customers.
  - User profiles change constantly and quickly, requiring frequent rebuilds (which are expensive already).
  - Not interpretable (can't answer why a user prefers this).

Machine Learning Kicks In



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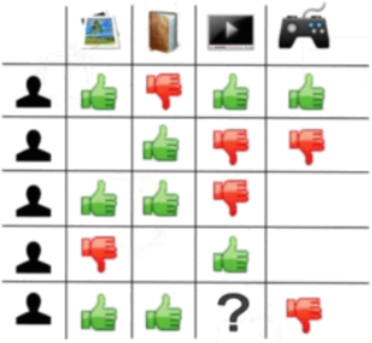

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	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

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

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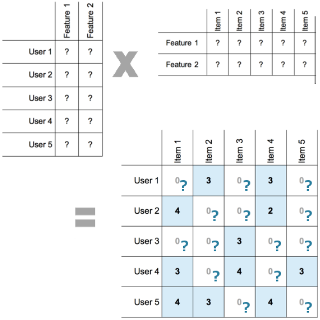
	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0 ?	3	0 ?	3	0 ?
User 2	4	0 ?	0 ?	2	0 ?
User 3	0 ?	0 ?	3	0 ?	0 ?
User 4	3	0 ?	4	0 ?	3
User 5	4	3	0 ?	4	0 ?

Source: Kat Bailey

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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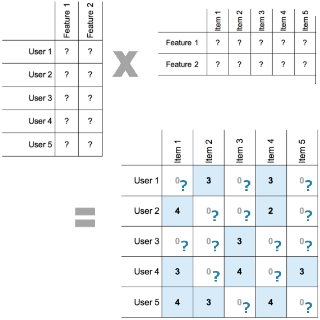

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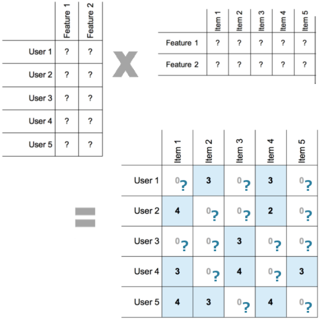

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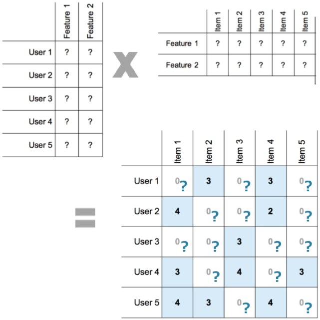

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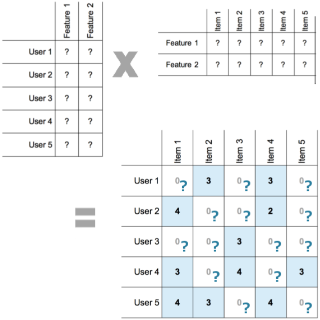

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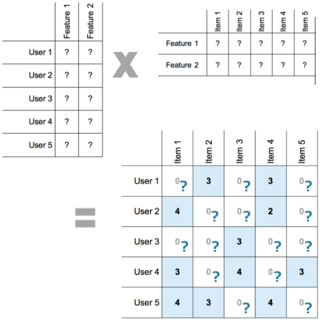

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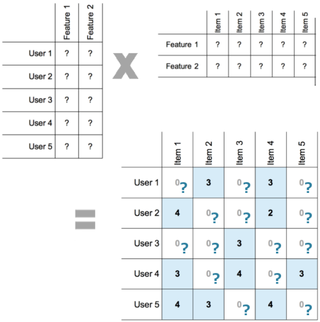

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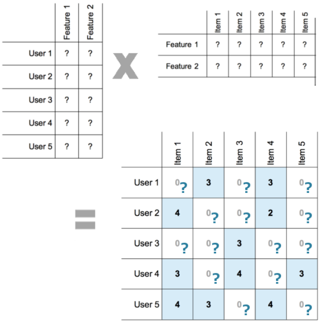

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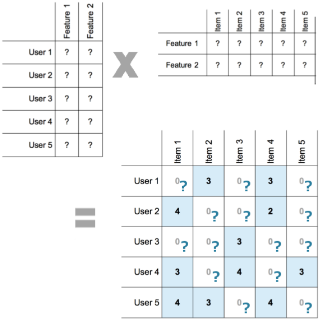

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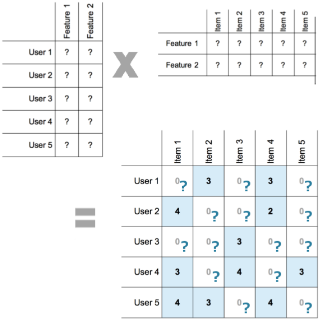

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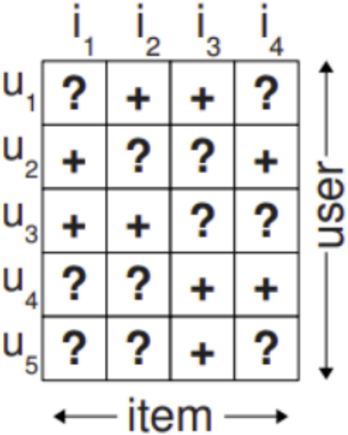
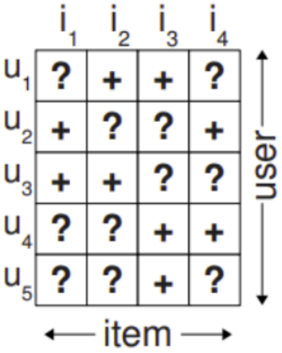
What if we don't have ratings?



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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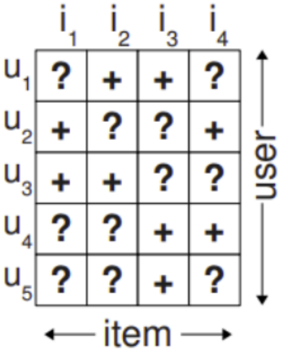

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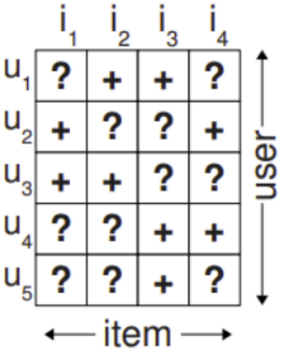
- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
    - Commonly uniformly, but adaptive sampling often helps.



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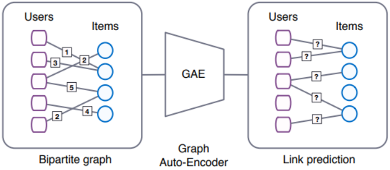
- Scoring function can also change (e.g. to bilinear $u_i^\top Q v_j$)

GCMC: Learning u_i and v_j from User-Item Graph



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

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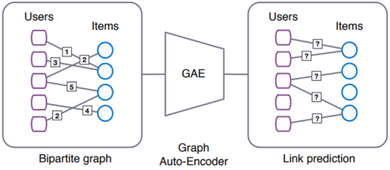

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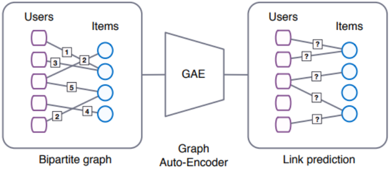

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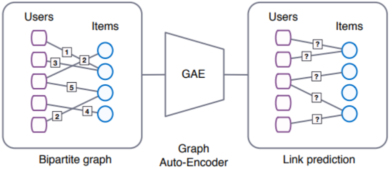

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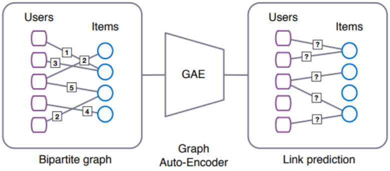

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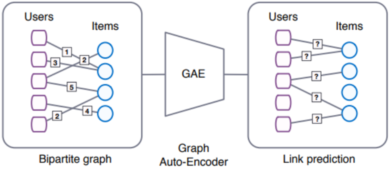
Simplifying GCMC to GraphSAGE



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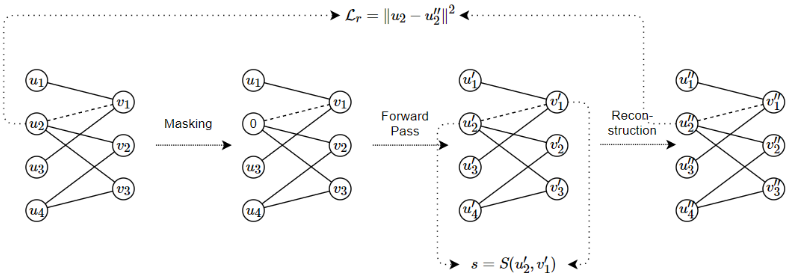
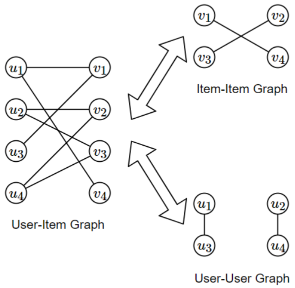
Learning u_i and v_j with Star-GCN



- 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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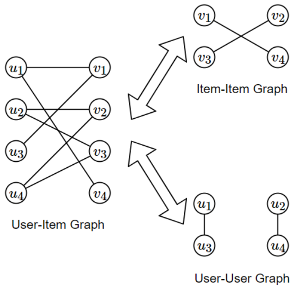

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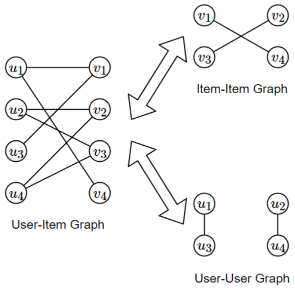

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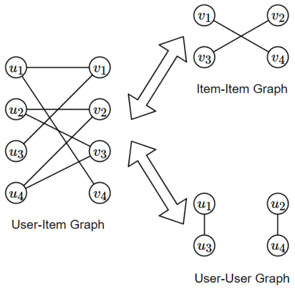

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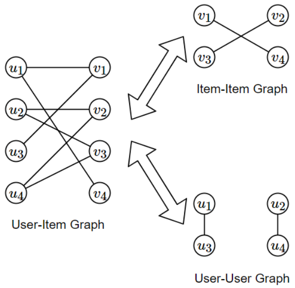

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- **Bias correction**: The training dataset usually comes from the result of a *previous recommender system*. How to mitigate the bias?
- **Diversity**: Always recommending the same items (or even the same kind of item) to a user would make him/her feel *bored*.
- **Fraud**: How to detect and deal with fabricated explicit feedbacks (e.g. fake ratings and reviews)?

Coding Session

GraphSAGE on bipartite user-item graph.