DGL on Real World Applications

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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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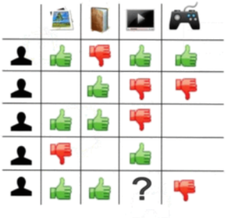
$\longrightarrow$



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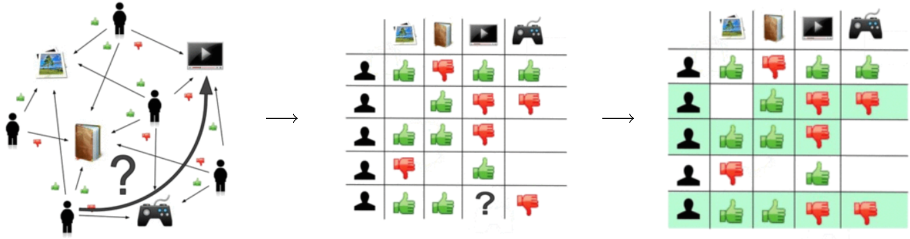

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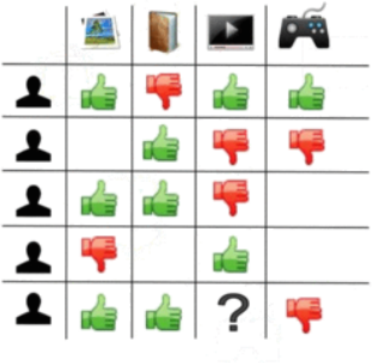
Collaborative Filtering with Machine Learning



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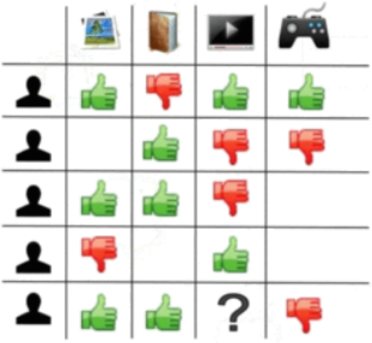

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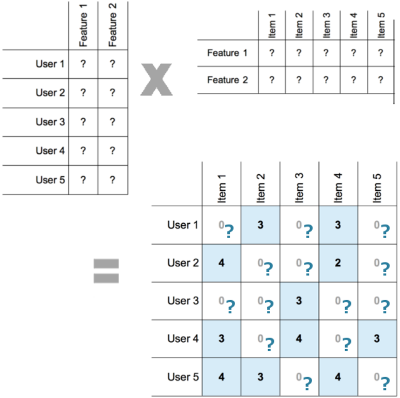
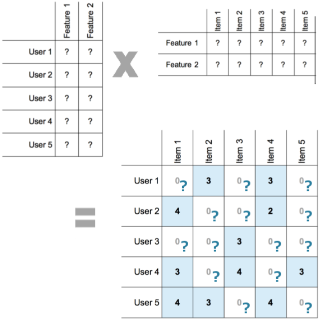


Source: Kat Bailey

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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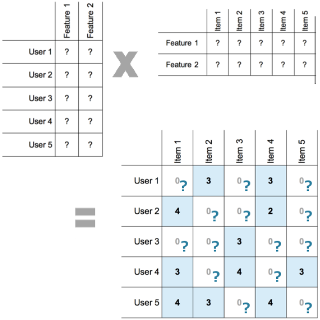

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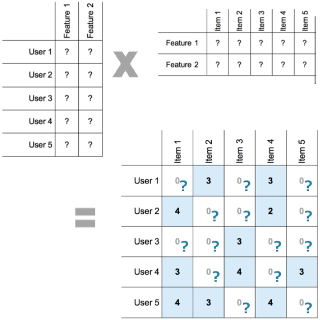

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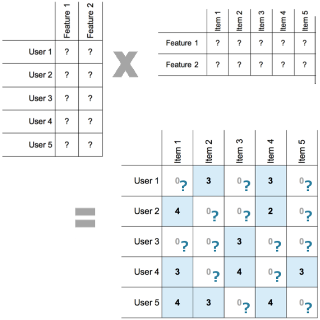

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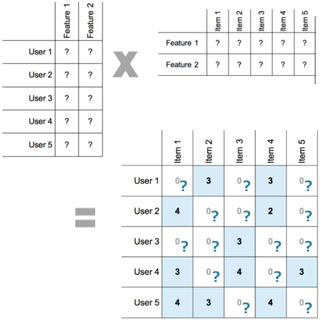

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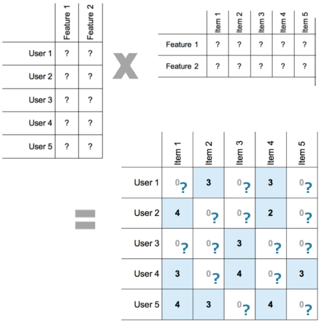

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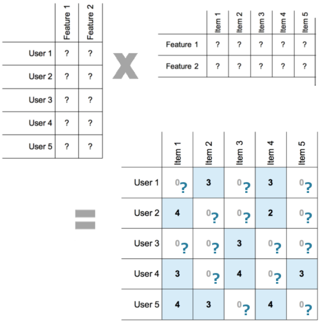

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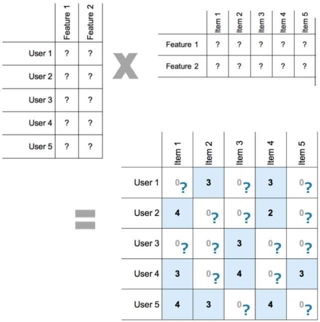

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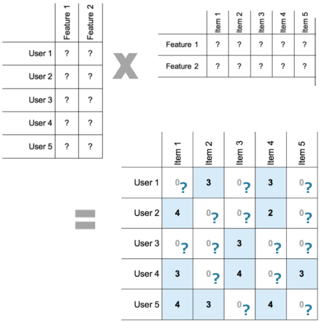

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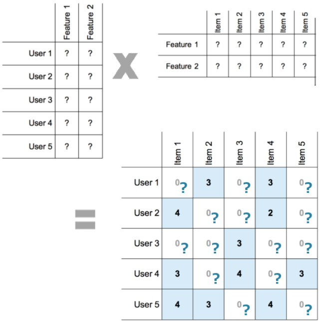

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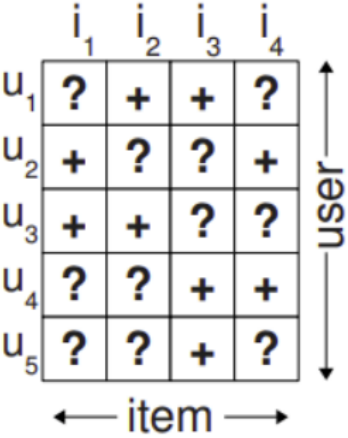
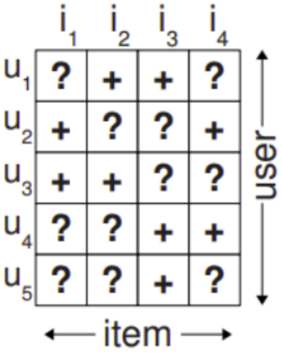
What if we don't have ratings?



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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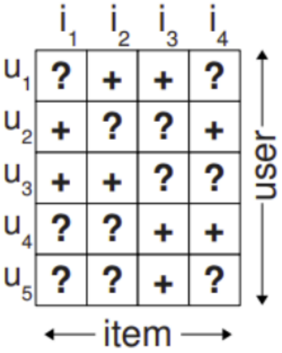

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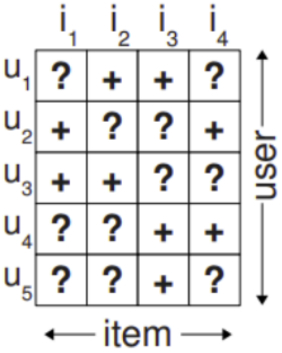
- We usually *sample* one or multiple k when computing gradients (**negative sampling**).
    - Commonly uniformly, but adaptive sampling often helps.



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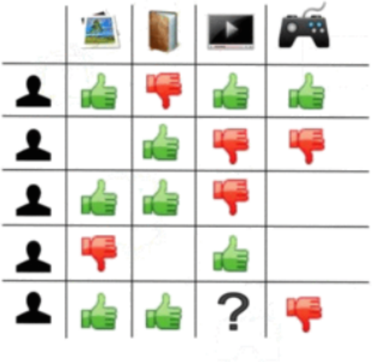
Formulating Recommender Systems as Graph Learning



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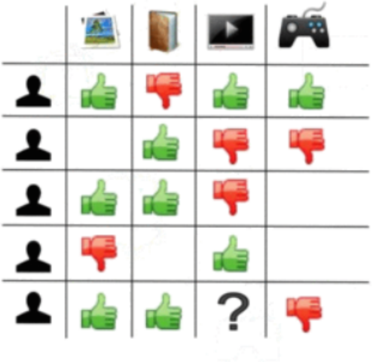

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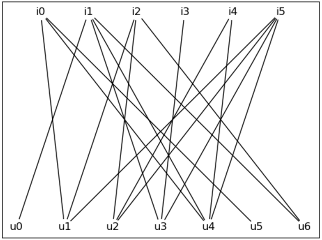
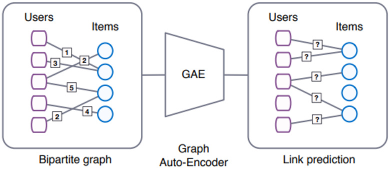


- Edge Classification/Regression
- Link Prediction

GCMC: Learning u_i and v_j from User-Item Graph



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

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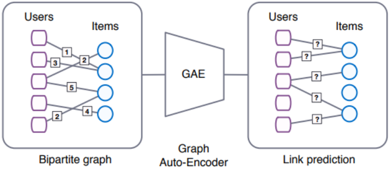

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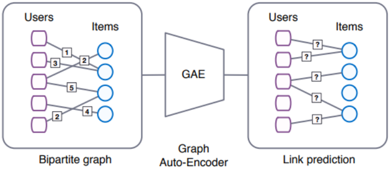

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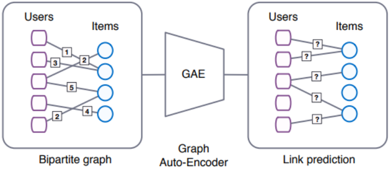

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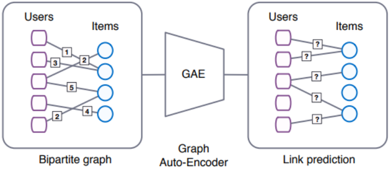

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4. $p(\hat{M}_{ij} = r) = \mathrm{softmax}(u_i^\top Q_r v_j)$
5. If users and items have no features, we make x_{v_j} and x_{u_i} themselves learnable parameters.

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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)?

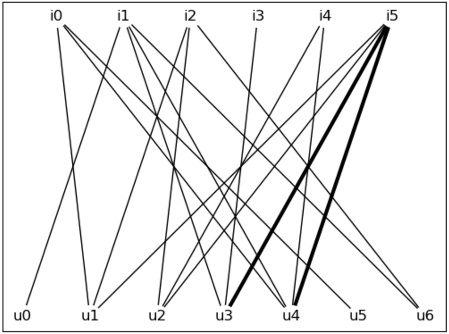
Non-exhaustive List of Recommender System Models

- PinSAGE
- STAR-GCN
- Knowledge Graph Attention Networks
- Knoledge Graph Convolutional Networks
- Inductive Matrix Completion (IGMC)
- ...

Hands-on Session

Miniature GCMC on bipartite user-item graph with DGL.

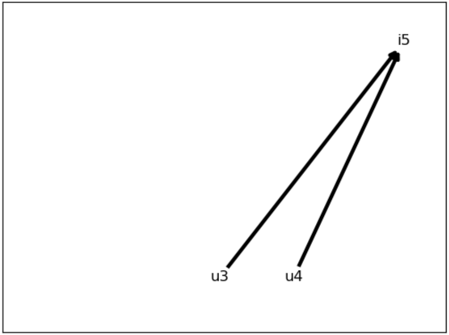
How to Train GCMC Stochastically?



- Given the graph above, we wish to predict the rating of the selected edge minibatch with a 1-layer GCMC.

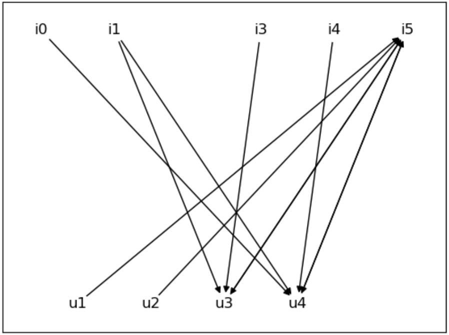
Constructing a "Pair Graph"

- DGL provides an `apply_edges` method that computes edge features in parallel based on source, destination, and other edge features.
- Construct a pair graph that consists of the edges to be trained only.



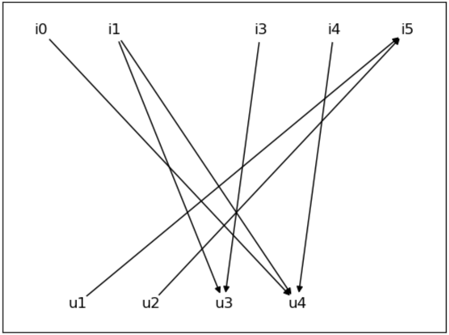
Find Necessary Neighbors

- The computation dependency can be used in message passing by transforming the dependency graph by `dgl.to_block` into a bipartite-structured graph as explained in the previous tutorial.



Removing Information Leakage

- Since we are training to predict the rating of `(u3, i5)` and `(u4, i5)`, we don't want to tell the model that these edges exist. Therefore we need to remove these edges.



The Computation Procedure (Reference to Notebook)

- Sample a minibatch of edges.
- Construct a pair graph from those edges.
- Construct the computation dependency graph.
- Transform the dependency graph with `dgl.to_block` for message passing.
- Copy features from the original graph to the blocks.
- Compute the outputs from the GNN layers on the blocks.
- Copy the output of the GNN layers to the pair graph.
- Compute the score on the edges of the pair graph with `dgl.apply_edges`.