Constructing a Graph from User Implicit Feedback

Haozhe Zhang[1] Yan Qu[2] Shad Kirmani[2]

[1]Iowa State University, Ames, IA, USA

[2]eBay Inc, Brisbane, CA, USA

SIAM CSE 2019

Talk Overview

Introduction and motivation (4 minutes)

Construction a graph from implicit user feedback (7 minutes)

Making buy recommendations (4 minutes)

Empirical Evaluation (remaining time)

eBay is a marketplace

- eBay marketplace has about 180 million active users.
- eBay users buy and sell on eBay.
  - A number of eBay users buy but don't sell on eBay marketplace.
  - A number of eBay users sell but don't buy on eBay marketplace.
  - A number of eBay users both buy and sell on eBay marketplace.

Goal for the recommendation system

We would like all of our sellers to buy on eBay

- Encourage eBay users who sell on the marketplace to also source their inventory from eBay.
- Recommendation should take into account seller profile.
- Recommend new - System should recommend inventory that is not already being bought by the seller.
- Recommendation should be relevant.

Recommendation System using a seller graph

Suppose, we have a seller graph where each vertex is a seller on eBay marketplace, and an edge represent some kind of similarity between them.

Recommendation System using a seller graph

Suppose, we have a seller graph where each vertex is seller on eBay marketplace, and an edge represent some kind of similarity between them.

recommendation score will be a determined by

- Items sold by the seller
- Items bought by the seller
- Items sold in seller *neighborhood*
- Items bought in seller *neighborhood*

Graph based recommendation systems in industry

Similar work has been done at Amazon[1], Twitter[2], Pinterest[3] and Google[4].

[1] *Graph based recommendation engine for Amazon products*. https://towardsdatascience.com/graph-based-recommendation-engine-for-amazon-products-1a373e639263. Accessed: 2019-01-18.

[2] Pankaj Gupta et al. "Real-time Twitter Recommendation: Online Motif Detection in Large Dynamic Graphs". In: *Proc. VLDB Endow.* 7.13 (Aug. 2014), pp. 1379–1380. ISSN: 2150-8097. DOI: 10.14778/2733004.2733010. URL: http://dx.doi.org/10.14778/2733004.2733010.

[3] *Introducing Pixie an advanced graph-based recommendation system*. https://medium.com/@Pinterest_Engineering/introducing-pixie-an-advanced-graph-based-recommendation-system-e7b4229b664b. Accessed: 2019-01-18.

[4] Sujith Ravi and Qiming Diao. "Large scale distributed semi-supervised learning using streaming approximation". In: *Artificial Intelligence and Statistics*. 2016, pp. 519–528.

Our Contributions

- We develop a graph from seller data.
- We propose a graph based item recommendation system.
- We empirically evaluate the recommendation.

Relevance to the Minisymposium on Reproducibility in Network Algorithms

- We create networks from raw data. Already support multiple variants.
- Seller network is an inherently dynamic network. We make recommendations on a snapshot of data.
- Community here can provide feedback on approaches that leverage network time-series.

Building a graph from seller implicit feedback

- Any questions so far?

Data

Concentrating on sellers who run *small businesses* on the eBay marketplace

- Small businesses are a small percentage of overall sellers.
- Small businesses contribute a significant portion of the overall sales on the marketplace.
- We are not including large businesses or casual sellers in this graph because those segments have a different business model.

Data

We use historical data of small business sellers

- For each small business seller, we have a list of items sold and bought on the eBay marketplace in a given time period.
- Rows: The number of small business sellers on eBay is in the order of millions.
- Columns: The number of *item types* sold by such sellers is in ten of thousands.
  - *Two very similar items are considered as one item type.*
  - Henceforth, when we refer to an item, we mean item type.

Selling and buying matrices for small business sellers

Figure: On the left, we have the user-item **selling** matrix S and on the right we have **buying** matrix B.

Selling Matrix: S $(n \times m)$

					…
	1	0	0	0	8
	0	0	0	67	0
	2	0	0	0	1
	0	0	2	0	0
⋮	0	5	0	0	0
⋮	0	0	0	0	1

Buying Matrix: B $(n \times m)$

					…
	0	0	0	0	0
	0	0	0	10	0
	1	1	2	3	0
	5	0	0	0	1
⋮	0	2	4	0	0
⋮	0	0	0	0	0

S and B are row-sparse

Computing small business similarity based on their selling history

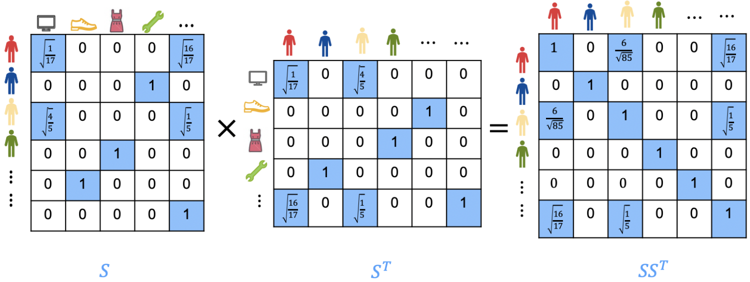
- Matrix S is the selling matrix, where each row is a small business and each column is an item.
- Sij is number of items j sold by small business i.
- Row normalizing and then we compute similarity as weighted cosine distance.
- For business reasons, we keep an item weight matrix, W.
- To keep the similarity matrix sparse, we apply a threshold.
- We try to keep some non-zeros for each row, so that we can make a recommendation.

Small business similarity on their selling history

Figure: Calculating cosine similarity for sellers' selling history matrix.

Cosine Similarity Based on Selling Record Vectors:

$$sim_{cosine}(\boldsymbol{u_i}, \boldsymbol{u_j}) = \frac{\boldsymbol{u_i'} W \boldsymbol{u_j}}{||\boldsymbol{u_i}|| * ||\boldsymbol{u_j}||} \times I\left(\frac{\boldsymbol{u_i'} W \boldsymbol{u_j}}{||\boldsymbol{u_i}|| * ||\boldsymbol{u_j}||} > \delta\right)$$



Small business similarity on their selling history

- We also tried SVD based decomposition to compute similarity. More effort and becomes difficult to explain.
- We can use a lot more features than selling history but avoided doing so for technical and business reasons.

- SVD for large-scale sparse matrices used[5].
- Cosine Similarity Based on top k Singular Vectors

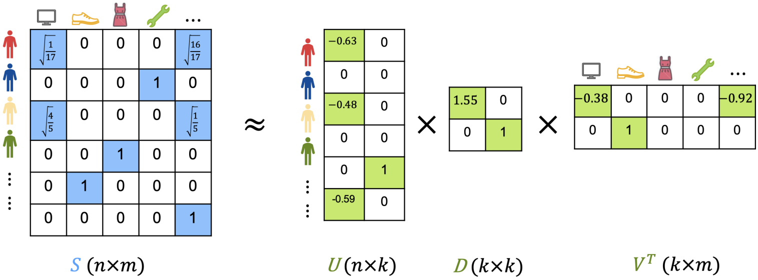


Figure: Calculating cosine similarity for sellers' singular vectors.

[5] R. B. Lehoucq, D. C. Sorensen, and C. Yang. *ARPACK Users Guide: Solution of Large Scale Eigenvalue Problems by Implicitly Restarted Arnoldi Methods.*. 1997.

Constructing a small business graph

A graph $G = (V, E)$

- V corresponds to small businesses in S.
- An edge $(u, v) \in E$ if the similarity between vectors corresponding to u and v is greater than some threshold δ.
- The neighborhood of a vertex, $\mathcal{N}(u) = \{v \mid (u, v) \in E\}$, is the set of all vertices which are directly connected to u.

Visualizing[6] small business graph

We would like your feedback on how to visualize such graphs.

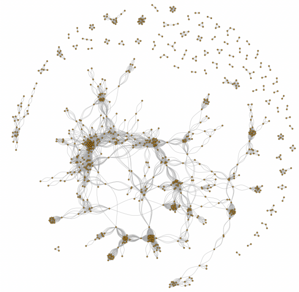


Figure: Visualization of the *sub-sampled* graph constructed on small businesses' sale history.

[6] Gabor Csardi and Tamas Nepusz. "The igraph software package for complex network research". In: *InterJournal* Complex Systems (2006), p. 1695. URL: http://igraph.org.

Making recommendations

Any questions so far?

Initial buy recommendation

- Recommend top k items the small businesses are already buying.
- Since the goal is to recommend new items, we see no improvement.
- For users who do not buy on eBay marketplace, we use the top k *sold* items as the initial recommendation.

Recommend what neighbors are buying

- Recommend top-k items bought by users $\in \mathcal{N}(u)$, weighted by edge weights.
  - Intuition is that if similar businesses are buying some items, then probably they have discovered a movement in demand that you might be late to understand.
- Recommend what neighbors of neighbors are buying.

Making recommendations

- At iteration 0: Each user has a initial recommendation vector.
- At iteration i: Edge weighted average vector of their neighboring vertices' recommendation vector.
- Stop after a few iterations.

$$rec\_vec_u^{l+1} = \frac{1}{|\mathcal{N}(u)|} \sum_{v \in \mathcal{N}(u)} sim(u, v) \times rec\_vec_v^{l} \tag{1}$$

Empirical Evaluation

- *Caveat*: This feature is not live. We did back-testing to evaluate the algorithm.
- We construct a small business graph based on their selling history in time period t.
- We recommend maximum 10 items to buy to each small business.
- A buy recommendation is successful, if the small business actually buys an item in time period $t + 1$ based on the recommendation made in time period t.
- *Evaluation Metric*: Percentage of successful recommendations out of the recommendations made.

Future Work Directions

- Coming up with scalable graph visualizations.
- Collaborate with academia to get feedback on our work.
- Community detection and visualization.