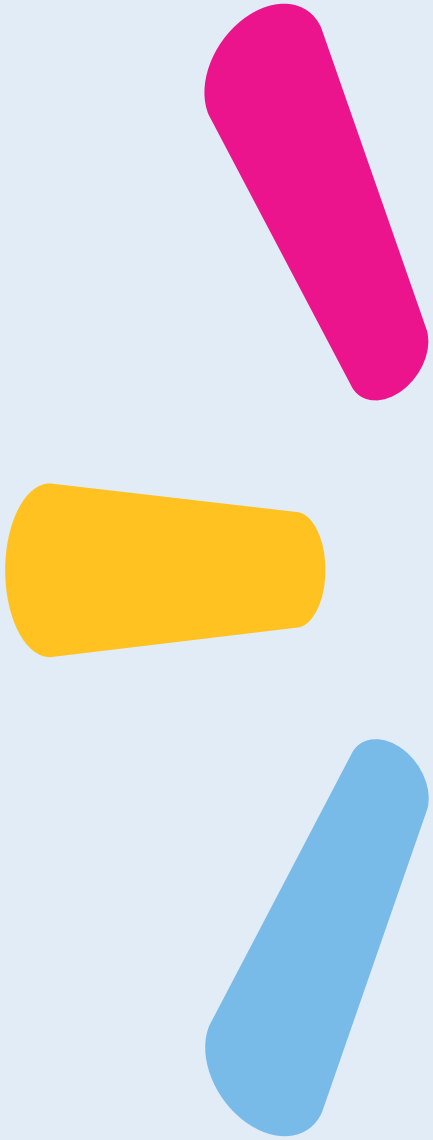
Personalized Recommender for Implicit Data

Walmart Internship Report

Zehao Guan, 2019/08/01

Agenda

- Introduction
- Project
- Future Work
- Conclusion



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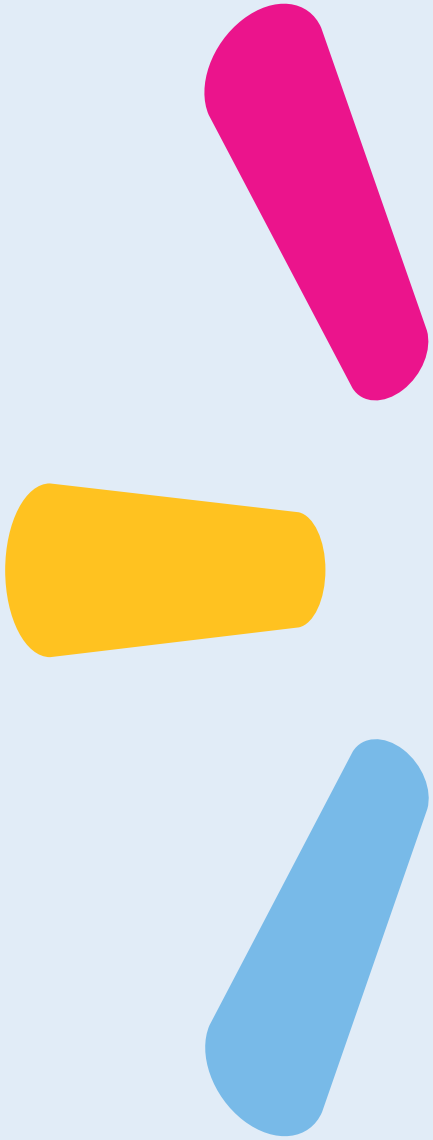


Abstract

- Target

  Design a personalized recommendation system for implicit feedback data.

- Methods

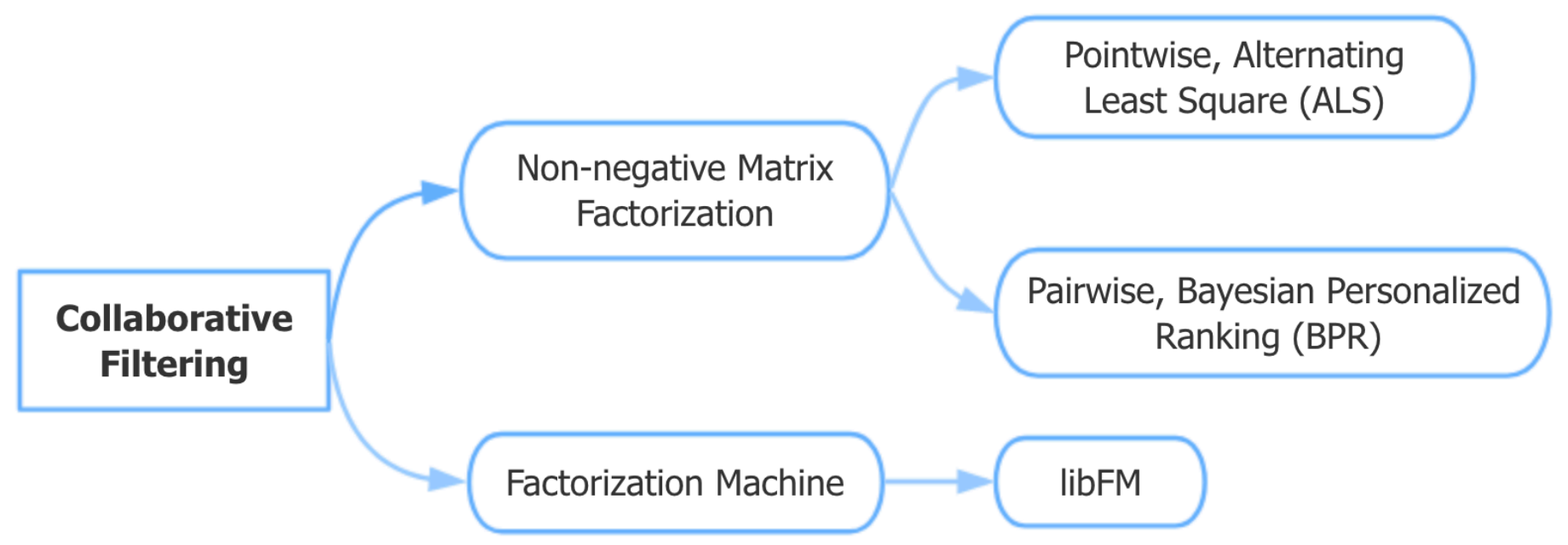
  Latent factor model based collaborative filtering, like pointwise/pairwise matrix factorization and factorization machine with libFM.

- Experiment

  Split into train/validation data in temporal manner;

  Apply ranking based metrics for model evaluation.

Sketch


Collaborative Filtering
Non-negative Matrix Factorization
Pointwise, Alternating Least Square (ALS)
Pairwise, Bayesian Personalized Ranking (BPR)
Factorization Machine
libFM

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Background

- Unlike extensively researched explicit feedback, no direct input from the users regarding their preferences.
- Treat transaction data as indication of positive and negative preference associated with varying confidence levels.
- Should design a scalable optimization procedure and explainable factor model for recommendations.
- The target is to realize top-N personalized recommendation based on users' response.

Algorithm

- Pointwise NMF, Alternating Least Square (ALS)

$$\min_{x_\star, y_\star} \sum_{u,i} c_{ui}(p_{ui} - x_u^T y_i)^2 + \lambda \left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2 \right)$$

- Pairwise NMF, Bayesian Personalized Ranking (BPR)

$$\sum_{(u,i,j) \in D_S} \ln \sigma(\hat{x}_{uij}) - \lambda_\Theta ||\Theta||^2$$

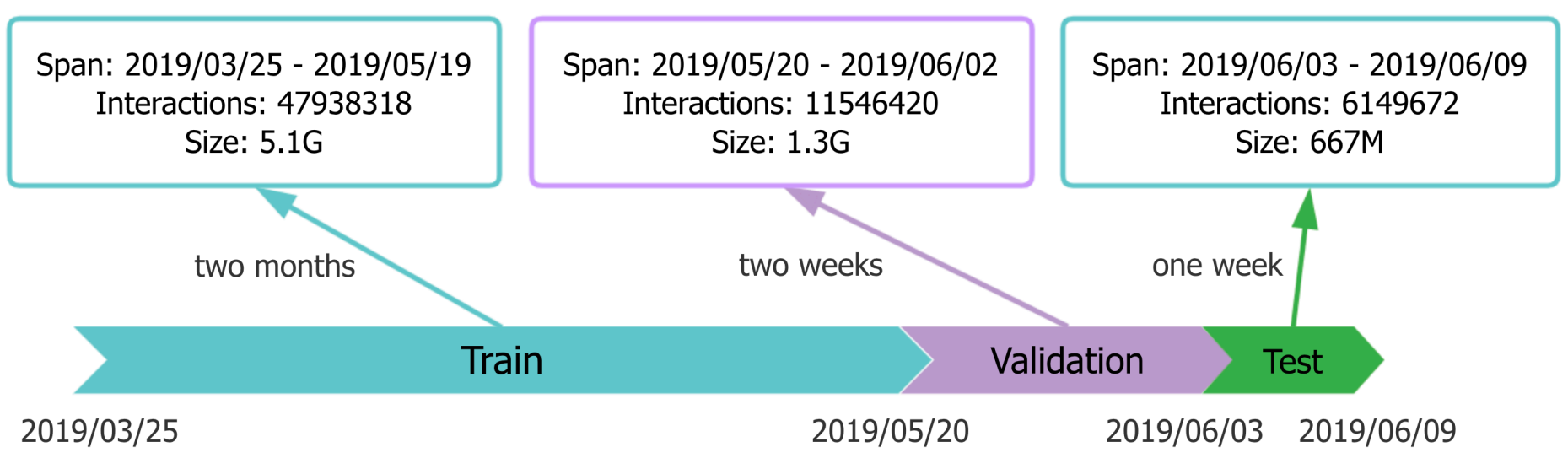
- Factorization Machines with libFM

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{j=1}^{p} w_j x_j + \sum_{j=1}^{p} \sum_{j'=j+1}^{p} x_j x_{j'} \sum_{f=1}^{k} v_{j,f} v_{j',f}$$

Experiment Design

- To capture sequential users' purchase behavior, split into train/validation data in temporal manner.
- As items ranked higher should be more preferred by users, ranking based metrics are applied.
- Start with demos on small-scale data, and then improve the scalability.

Temporal Manner



Ranking Metrics

- Hit ratio (HR)
- Normalized discounted cumulative gain (NDCG)
- Mean average precision (MAP)
- Area under curve (AUC)

Top-N recommendation !

Data

- Database: ucid
- Table: common_transaction_model
- Source: Walmart.com
- Columns: cid, catalog_item_id, purchase_date
- Features:
  - Implicit feedback
  - High sparsity
  - Imbalance

Preprocess

- Clean outliers like infrequent customers/items and resellers.
- Map user and item ids to categorical values.
- Store observed data in <userId, itemId, rating> triple format.
- Convert to sparse matrix for other operations.

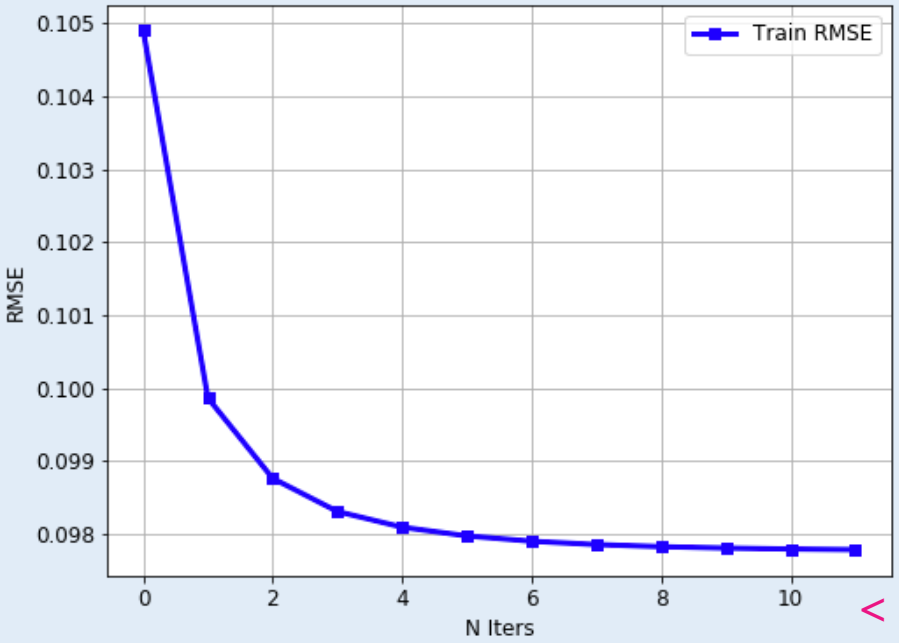
Sample data in demo:

Ignore: 14847105 * 2958922

Raw: 14929995 * 3008950 → Processed: 34209 * 47857

density: 0.0712%

Train



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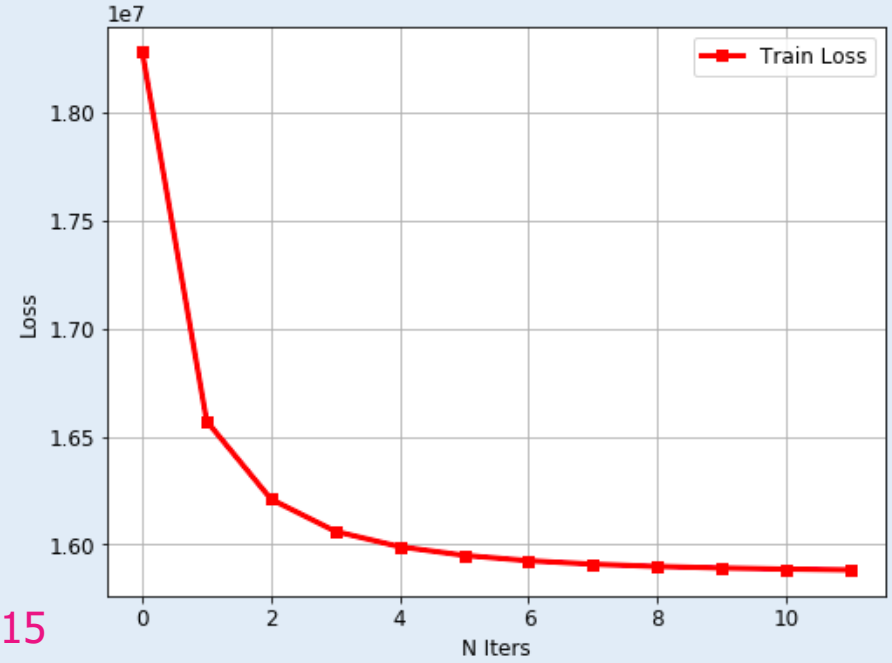
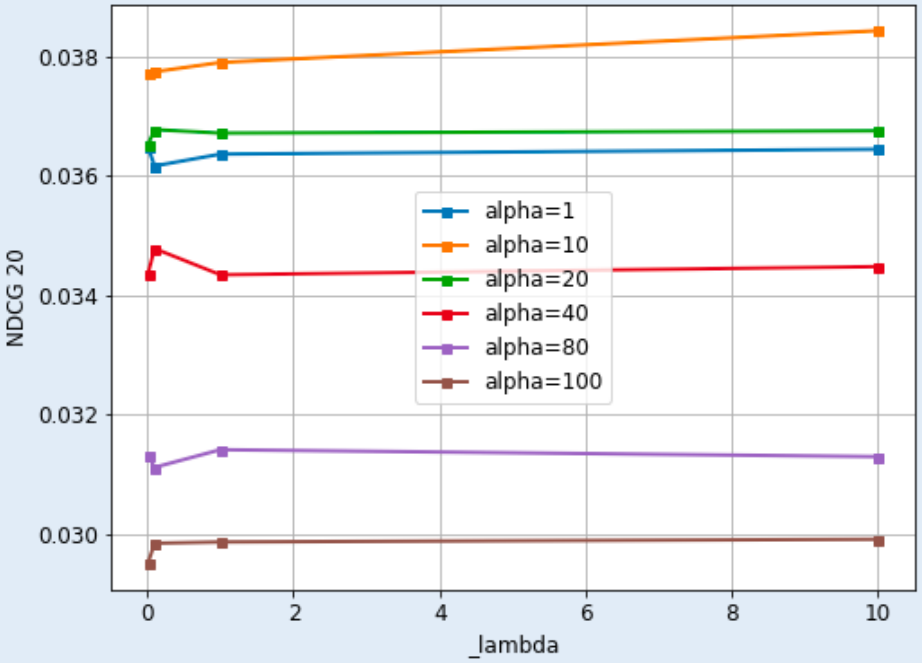
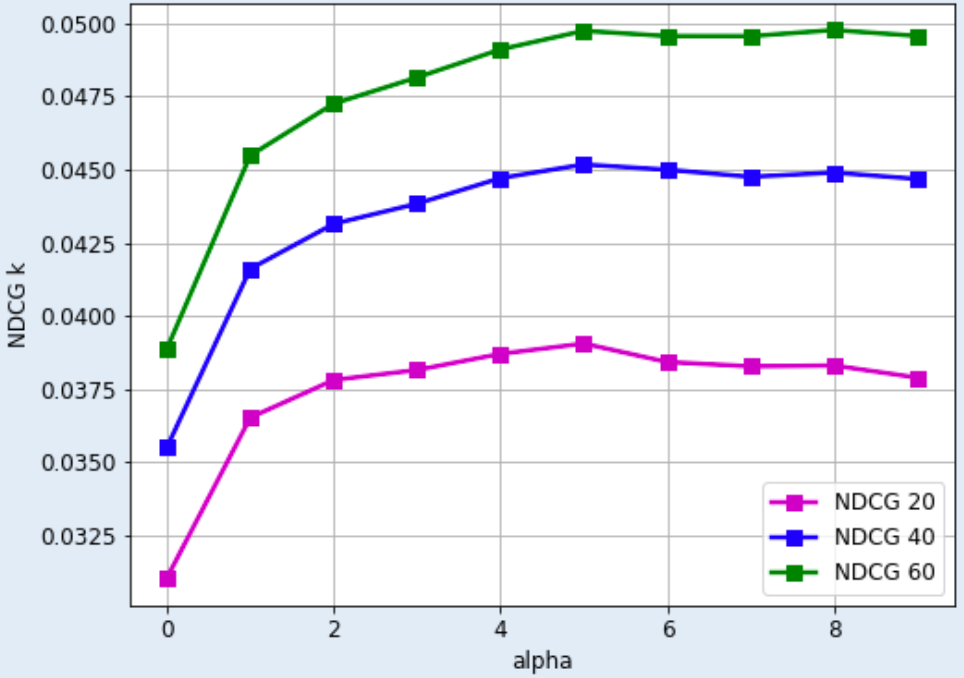


Assume n_iters that is enough for the loss to converge.

Evaluation

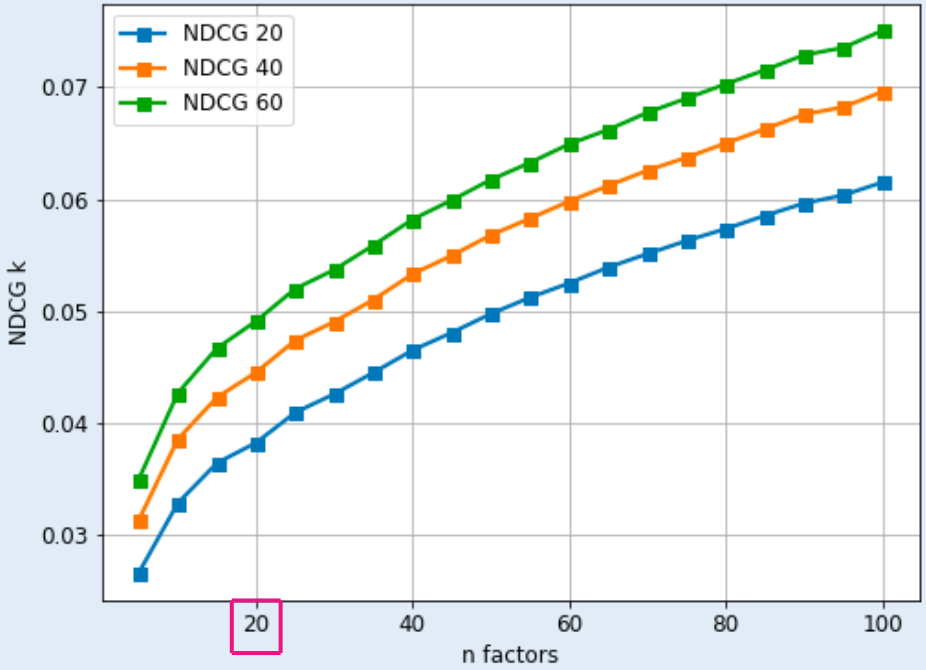


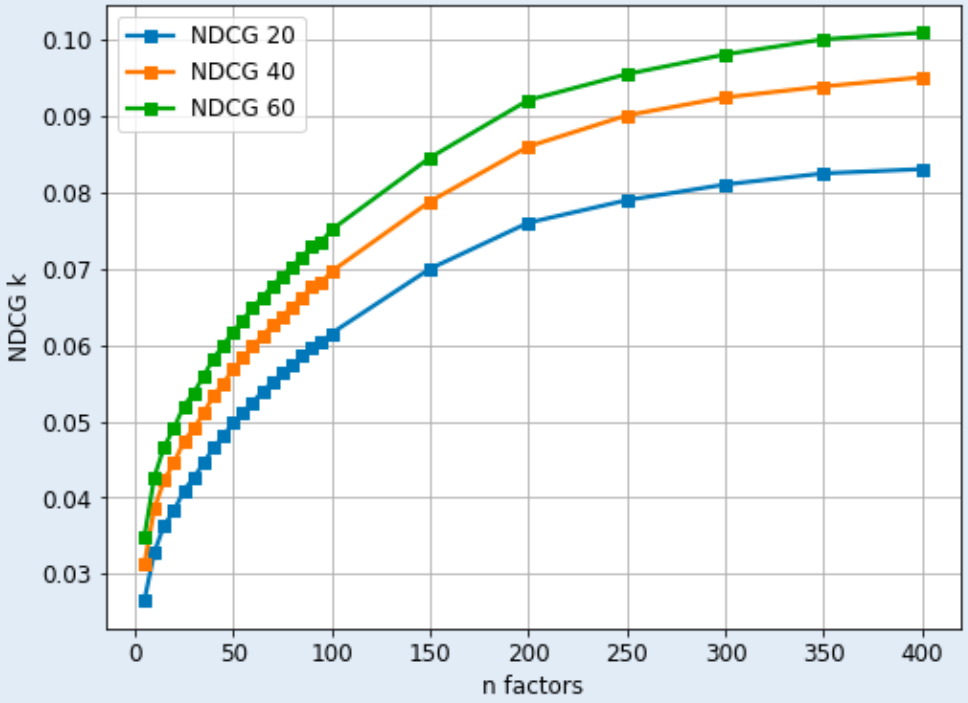


Tune on parameters like _lambda and alpha.

$$c_{ui} = 1 + \alpha r_{ui}$$

Evaluation

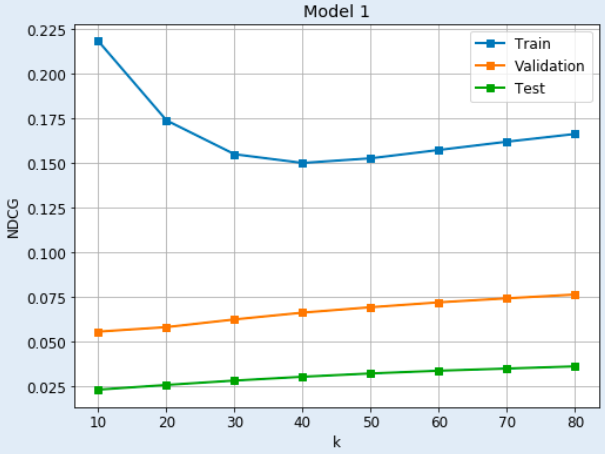


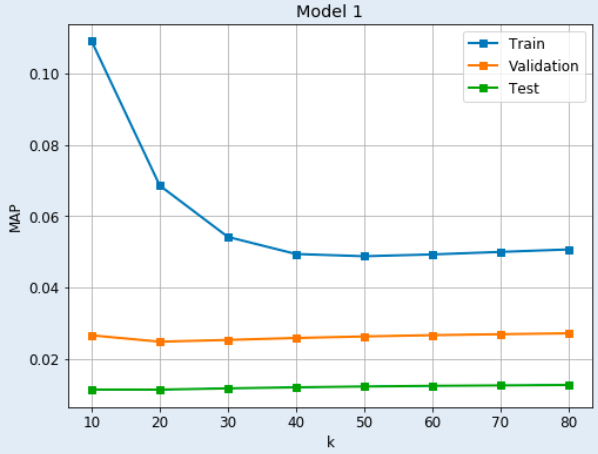


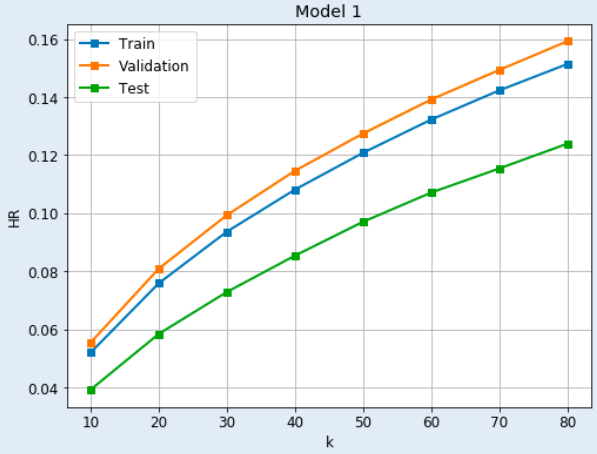
Extend scale to 0~400, and select best n_factors for test, also consider computation cost and avoid over-fitting.

Evaluation – Model selection

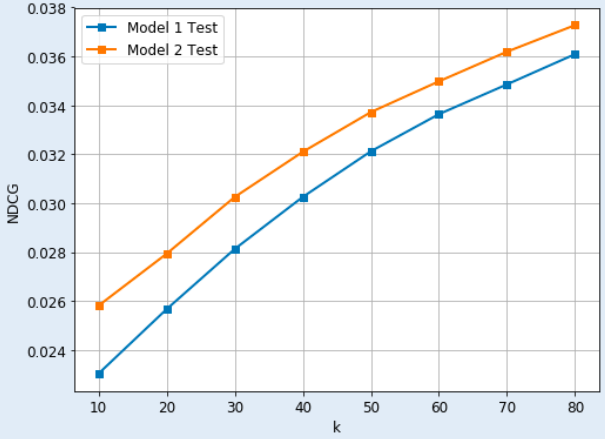
Top-k

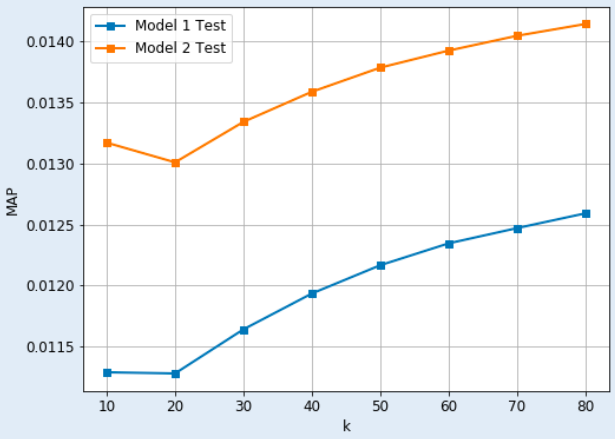


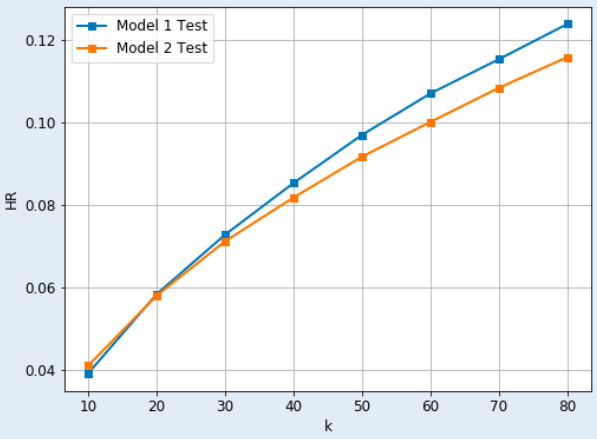




0/1 v.s. normalized frequency







Test – Recommend for users

```
1 n_samples = 5
2 sampled_users = np.random.choice(list(train_user_map.keys()), n_samples)
3 sampled_users
```

```
array(['ad082399f3c546ccb21c22ed549ca908',
       'f05077c5608c0cfee044001517f43a86',
       '7b581a751de24fd48020fe151edd3f2b',
       'c17b06ffbbfd438da3ba75e618a74eff',
       '6c80ba0e97e44015abce52d19453b1f1'], dtype='<U32')
```

cid

```
1 sampled_user_ids = list(map(lambda x:train_user_map.get(x), sampled_users))
2 sampled_user_ids
```

```
[27025, 27943, 10784, 19260, 34192]
```

user_id

```
1 best_model._recommend_user(6753, N=6)  # 'f0760cb6eeb034cce044001517f43a86
```

```
[305, 594, 386, 1062, 992, 436]
```

```
1 best_model.recommend(sampled_user_ids, N=6)  # same as the previous test
```

```
array([[  137,  1567,   714,  1467,   226,   693],
       [  309,   992,   215,   305,  2026,   273],
       [  535,  2051, 17703,  2415,   748,  1704],
       [ 2649,   215,   726,  2026,  4622,  3738],
       [ 4254,  1455,  9539,  6690,  1983,  1660]])
```

item_id

https://gecgithub01.walmart.com/z0g00mx/Intern_project/blob/master/als.ipynb

Test – Find similar items

```
1  sampled_items = np.random.choice(list(train_item_map.keys()), n_samples)
2  sampled_items
```

```
array(['16879847', '653330322', '10322221', '24797654', '53834652'],
      dtype='<U10')
```

catalog_item_id

```
1  sampled_item_ids = list(map(lambda x:train_item_map.get(x), sampled_items))
2  sampled_item_ids
```

```
[11940, 17210, 22782, 21439, 46809]
```

```
1  best_model._similar_items(sampled_item_ids, N=5)
```

```
array([[14287, 21535,  5768,  1448,  9261],
       [20512, 12668,   249,  7587,  4939],
       [42478, 47871, 33527, 22274, 44058],
       [30214, 24232, 35489,  5927, 17440],
       [19244, 34813,  5583, 40392, 26451]])
```

item_id

https://gecgithub01.walmart.com/z0g00mx/Intern_project/blob/master/als.ipynb

Test – Case study


10307700.jpeg

14018038.jpeg


14089586.jpeg


14150016.jpeg

15783126.jpeg


19635718.jpeg

20606796.jpeg

23619931.jpeg


24360609.jpeg


25065575.jpeg

27231189.jpeg

33963183.jpeg


35756520.jpeg


38453308.jpeg

45612361.jpeg


49333136.jpeg

49527355.jpeg


52459941.jpeg


55630914.jpeg

127471323.jpeg

127722938.jpeg

151835792.jpeg

162433676.jpeg


165253444.jpeg

327970267.jpeg


331157650.jpeg

610627633.jpeg

723575351.jpeg

762509212.jpeg

835076821.jpeg

User purchase history

Recommend


14504328.jpeg


23636896.jpeg

49509899.jpeg


52196241.jpeg

153202890.jpeg

401199665.jpeg

54048...44.jpeg


603122123.jpeg

Top-8 recommended items

Test – Case study

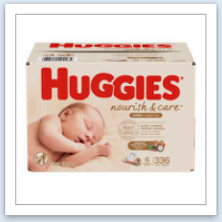
Sampled item

Similar →

10824297.jpeg

46291110.jpeg

55139724.jpeg



278392073.jpeg

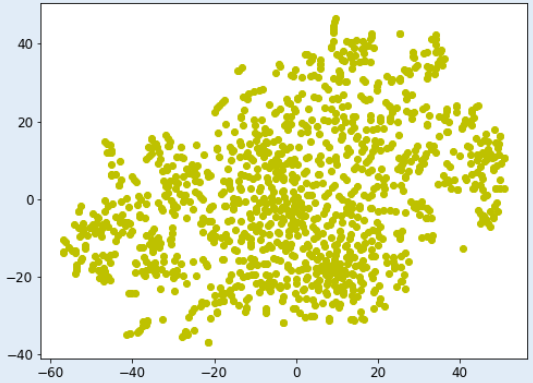
929828867.jpeg

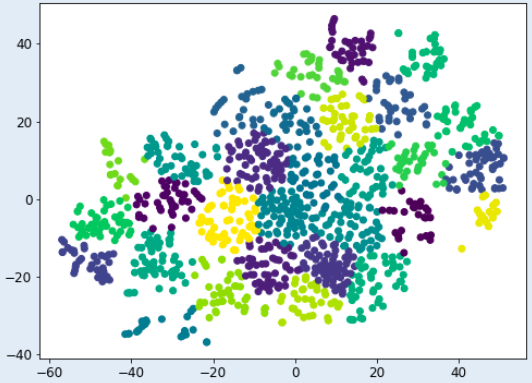
Top-5 similar items

(KNN, Euclidean metric)

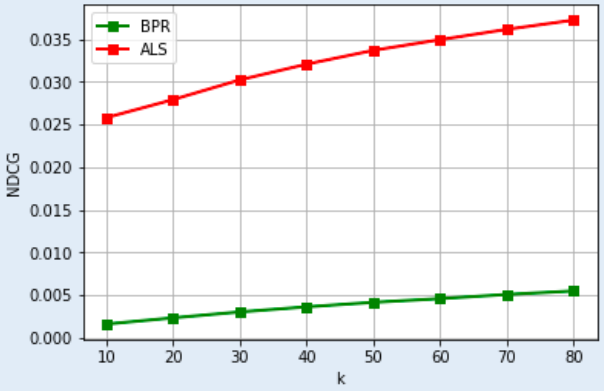
Analysis

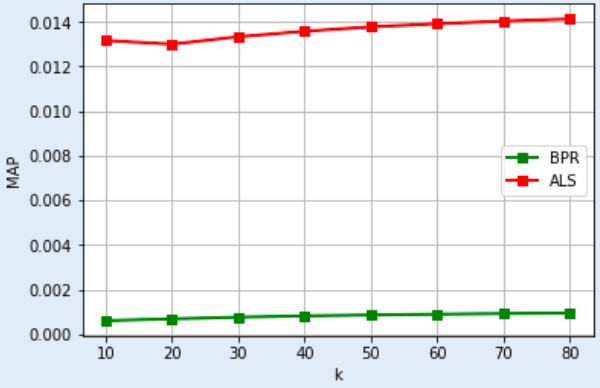
- Separability of latent factors with t-SNE, K-means

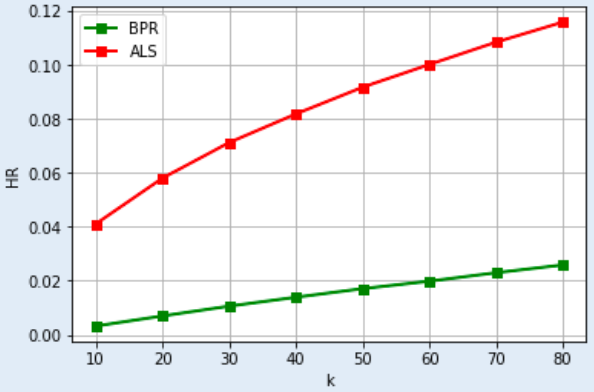




- Pointwise method performs better than BPR







Accomplishment

- Three recommender demos in same experimental procedures with Walmart.com transaction data.
- Code implementation for large-scale data. (1856520 * 831859)
  - Write bash scripts to use libFM by C++ for matrix factorization to get latent factors.
  - Python codes for preprocessing, ranking metrics evaluation and personalized recommendation.

    https://gecgithub01.walmart.com/z0g00mx/Intern_project/tree/master/CF_libFM

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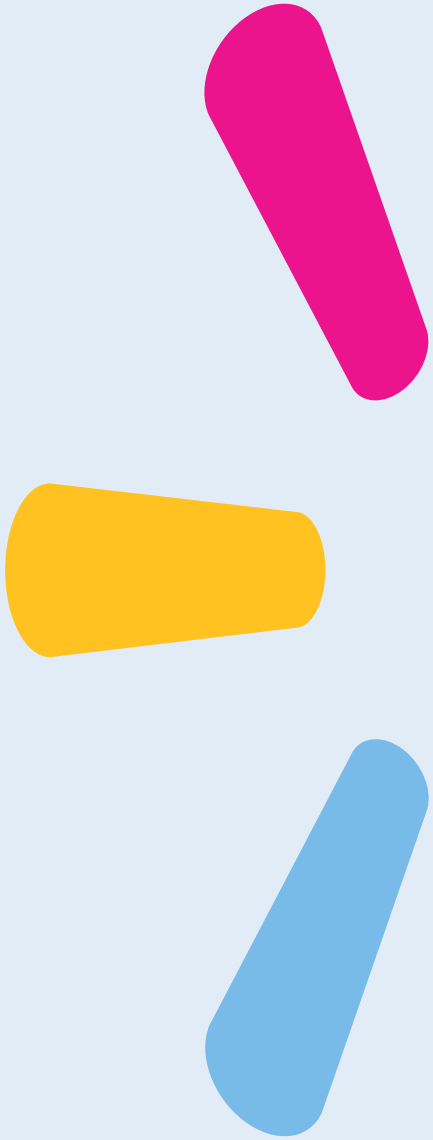

Future Work

- Realize industrial level APIs of the recommender demos.
- Evaluate the model with different sources of data.
- Besides these baseline models, explore more advanced methods for matrix factorization and optimization.

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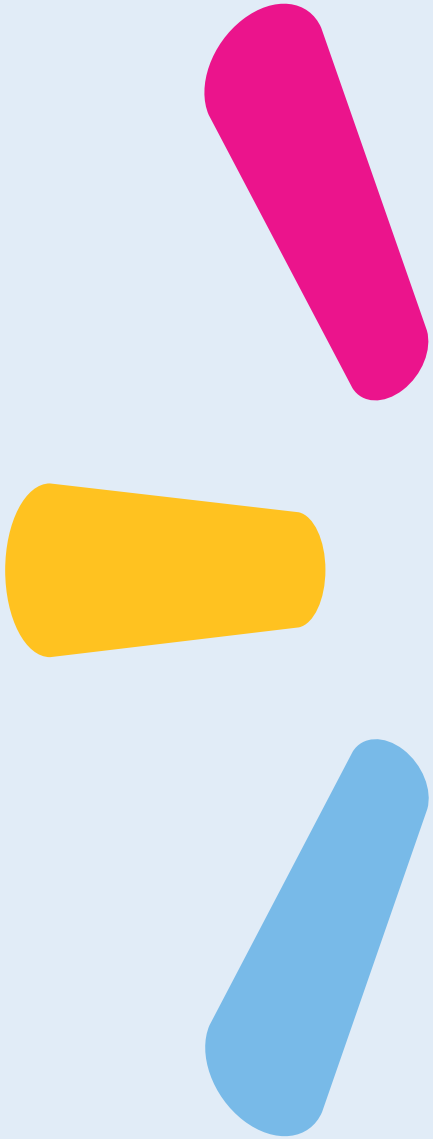


Challenge

- Inexperience with recommendation system for implicit feedback dataset.
- Lots of efforts to process highly sparse and unbalanced transaction data.
- Difficulty to apply PySpark for evaluating ranking metrics.
- Problems in face of scalability.

What I've learnt

- Tools like Hive, Spark, Kubernetes, libFM…
- More familiar with libraries like pandas, scipy, sklearn…
- Knowledge about the field of implicit recommendation, like classic models and widely-used ranking methods.
- Experience with experiments design and conduct.
- Capability to learn by doing.

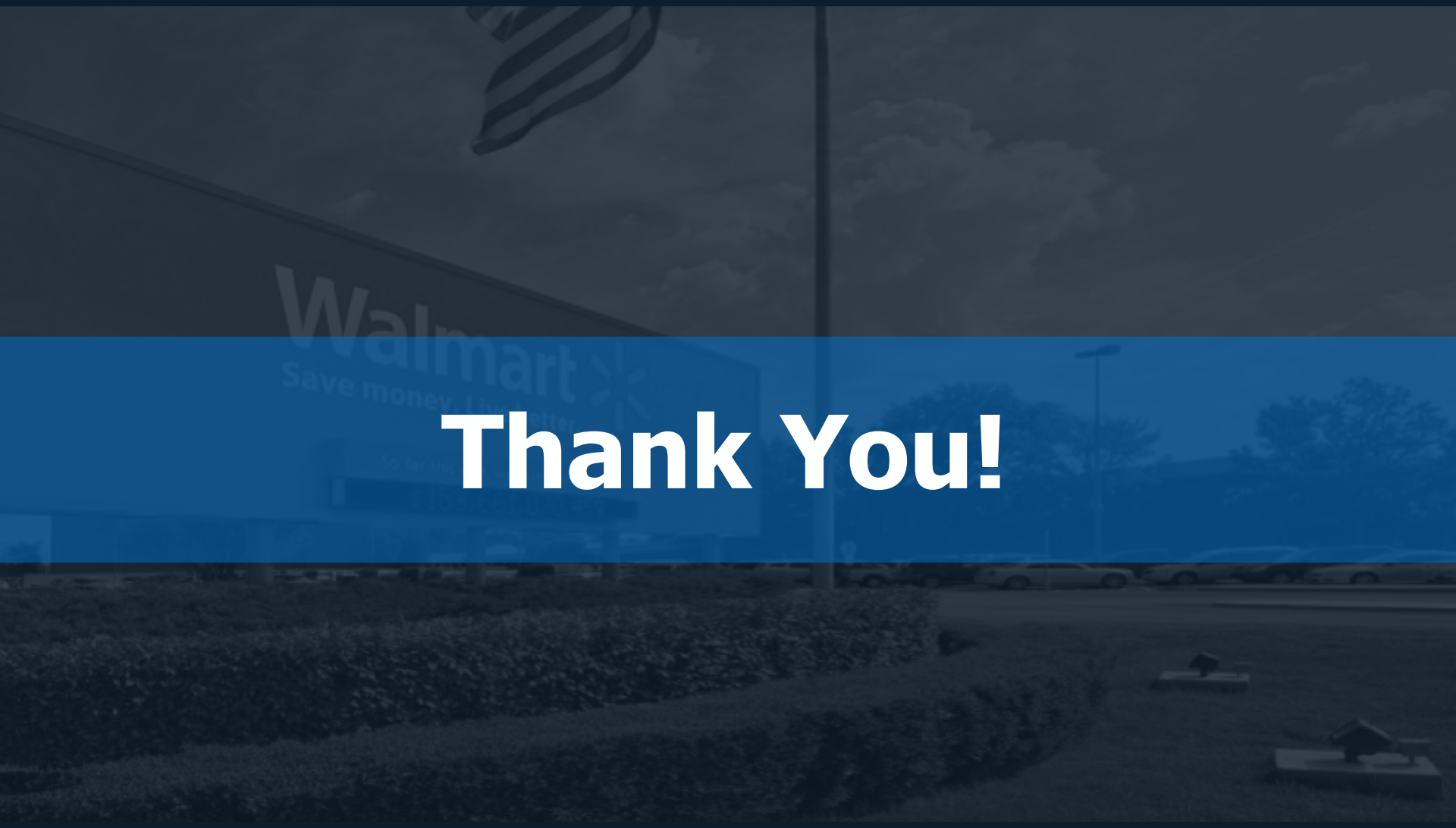
Reference

1. Hu, Yifan, Yehuda Koren, and Chris Volinsky. "Collaborative filtering for implicit feedback datasets." *2008 Eighth IEEE International Conference on Data Mining.* Ieee, 2008.
2. Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer*8 (2009): 30-37.
3. Rendle, Steffen, et al. "BPR: Bayesian personalized ranking from implicit feedback." *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence.* AUAI Press, 2009.
4. Rendle, Steffen. "Factorization machines with libfm." *ACM Transactions on Intelligent Systems and Technology* (TIST)3.3 (2012): 57.

Appendix

- GitHub link:

  https://gecgithub01.walmart.com/z0g00mx/Intern_project



Thank You!