A. MODEL SUMMARY

A1. Background on you/your team

* Competition Name:
  + OTTO – Multi-Objective Recommender System
* Team Name:
  + mrkmakr
* Private Leaderboard Score:
  + 0.60503
* Private Leaderboard Place:
  + 1st
* Name:
  + mrkmakr
* Location:
  + Japan
* Email:
  + mrkmakr123@gmail.com

A2. Background on you/your team

* What is your academic/professional background?
  + ML engineer and data scientist in a web service company.
  + Especially about internet advertising recommendation
* Did you have any prior experience that helped you succeed in this competition?
  + working with data in similar formats in my real work.
* What made you decide to enter this competition?
  + The problem setting was relatively close to my actual work, and it seemed easy to make use of what I had learned.
* How much time did you spend on the competition?
  + 1month

A3. Summary

I used a two-step strategy of recall and reranking. Covisitation and Neaural network (NN) were used for recall, and LGBMRanker was used for reranking. NN was useful for clicks and carts, and covisitation was useful for orders. I used python. I used pytorch for NN.

A4. Features Selection / Engineering

* What were the most important features?
  + for clicks and carts, prediction of NN is most important
  + for orders, covisitation is most important

|  |  |
| --- | --- |
| feature name | description |
| emb\_\* | Predicted value of NN with aid series as input |
| count\_dic\_\* | Features derived from the covisitation |
| a\_\* | Features for each aid. Popularity, type ratio, etc. |
| ah\_\* | Features for each time and aid. Popularity around the end time of the Session, etc. |
| isin\_\* | Features related to aid that appeared in the session. When did you visit the aid, etc. |
| u\_\* | Features per session (user features). What type of behavior were you doing, etc. |

**recall by each top feature**

recall@20 is calculated by each feature in small local validation and sorted by recall@20 for each type and I show top20 features.

グラフィカル ユーザー インターフェイス が含まれている画像

自動的に生成された説明

For clicks, Best one is NN score and it is about 6% better than covisitation

グラフィカル ユーザー インターフェイス が含まれている画像

自動的に生成された説明

For carts, Best one is NN score and it is about 2% better than covisitation.

テキスト

自動的に生成された説明

For orders, covisitation is important and NN dosent perform well.

**gain importance at reranking**

* グラフ, 棒グラフ

  自動的に生成された説明
* グラフ, 棒グラフ

  自動的に生成された説明
* グラフ, 棒グラフ

  自動的に生成された説明

Similar to recall results. For clicks and carts NN is important. For orders covisitation is important.

Some aid popularity features also contribute to reranking.

* How did you select features?
  + gain importance by lightgbm
  + recall@20 at local validation when the features were added

A5. Training Method(s)

* What training methods did you use?

ダイアグラム

自動的に生成された説明

* + NN is used for candidate generation and interaction features for reranking.
    - NN is trained in the manner of two tower model.
  + LGBMRanker is used for reranking.
* Did you ensemble the models?
  + 8 NN predictions were used (Recall and Reranker features)
  + LGBMRankers with 9 different hyperparameters
* If you did ensemble, how did you weight the different models?
  + Regarding NN, it was used in the form of stacking by giving it as a feature value of LGBMRanker
  + The LGBMRanker ensemble was performed by simple averaging of output scores.

A6. Interesting findings

NN is more effective than the covisitation for the prediction of clicks and carts. Interaction information involving multiple aids may be important for predicting clicks and carts.

On the other hand, in predicting orders, the covisitation and revisitation information were more effective than NN. Most part of ordering accuracy may be determined systematically, such as ordering aid that has already been put into carts. If so, complex models may not be needed.

* What do you think set you apart from others in the competition?

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Private | clicks | carts | orders | total |
| my | **0.05705** | **0.13787** | 0.4101 | **0.60503** |
| [2nd](https://twitter.com/0verfit/status/1625308436690001921?cxt=HHwWgoDTta7aoI4tAAAA) | 0.05653 | 0.13749 | **0.41044** | 0.60446 |

Comparing the second-place team's accuracy by type, I win in clicks and carts but loses in orders.

An attempt that contributes to the accuracy of clicks and carts and that few other teams have tried is NN. So, I think that the improvement of clicks and carts by NN has made a difference

A7. Simple Features and Methods

I tried 1 NN, 4 covisitation, revisitation information and 1 lgbm reranker as a simple solution.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Private | clicks | carts | orders | total |
| final | 0.05705 | 0.13787 | 0.4101 | 0.60503 |
| simple | 0.05533 | 0.13384 | 0.4048 | 0.59398 |

Clicks and carts are 3% worse and orders are 1% worse. It may be that only relatively simple predictions were made regarding the orders information.

A8. Model Execution Time

The simple solution takes 2days.

The final solution takes 2weeks.

グラフィカル ユーザー インターフェイス, アプリケーション

自動的に生成された説明

グラフィカル ユーザー インターフェイス, アプリケーション, タイムライン

自動的に生成された説明

A9. References

Score of 2nd place team

https://twitter.com/0verfit/status/1625308436690001921?cxt=HHwWgoDTta7aoI4tAAAA