

RecBole 2.0: Towards a More Up-to-Date Recommendation Library

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ABSTRACT

In order to support the study of recent advances in recommender systems, this paper presents an extended recommendation library consisting of eight packages for up-to-date topics and architectures. First of all, from a data perspective, we consider three important topics related to data issues (*i.e.*, *sparsity*, *bias* and *distribution shift*), and develop five packages accordingly: meta-learning, data augmentation, debiasing, fairness and cross-domain recommendation. Furthermore, from a model perspective, we develop two benchmarking packages for Transformer-based and graph neural network (GNN)-based models, respectively. All the packages (consisting of 65 new models) are developed based on a popular recommendation framework RecBole, ensuring that both the implementation and interface are unified. For each package, we provide complete implementations from data loading, experimental setup, evaluation and algorithm implementation. This library provides a valuable resource to facilitate the up-to-date research in recommender systems. The project is released at the link: <https://github.com/RUCAIBox/RecBole2.0>.

KEYWORDS

Recommendation library; Reproducibility; Evaluation

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1 INTRODUCTION

Nowadays, recommender systems have deeply revolutionized people's daily life, bringing a huge amount of business value and great convenience for information seeking. In the literature, various recommendation algorithms have been proposed based on different architectures or approaches [85]. Despite the great progress in recommender systems, there are increasing concerns on the reproducibility of the recommendation algorithms [1, 87]. Facing with this issue, a number of open-sourced recommendation libraries have been released to facilitate the reproducible implementation of the proposed recommendation algorithms [1, 2, 4, 10, 28, 46, 58, 61, 87, 92]. These libraries largely enhance the reproducibility of recommendation algorithms for the research purpose.

However, existing recommendation libraries mainly focus on classical models, lacking consideration of the recent advances in the recommendation field, including both new models (*e.g.*, graph neural networks [73]) and new topics (*e.g.*, debiasing [6] and fairness [51]). Due to the rapid progress in recommender systems, we argue that a more up-to-date recommendation library is needed for supporting the research on new advances. It is particularly important to standardize these ongoing studies at an early stage, preventing non-standard implementation or unreliable evaluation.

Inspired by this motivation, this paper presents a significant extension of a previously released recommendation library RecBole [87]¹ (receiving extensive attention of 1.9K stars on GitHub), by incorporating a series of benchmarking packages for up-to-date advances in recommender systems. In particular, our extension is conducted in two major aspects, namely *data* and *model*. First of all, there is an increasing attention to the issues from the interaction data itself [7], and we focus on three important research topics related to data issues, namely *data sparsity*, *data bias* and *data distribution shift*. Considering the three data issues, we develop five benchmarking packages corresponding to meta-learning, data augmentation, debiasing, fairness and cross-domain recommendation. Furthermore, from a model perspective, we consider providing more support for recommendation algorithms based on emerging model architectures, and develop two benchmarking packages for Transformer based and graph neural network (GNN) based models. It is worth noting that these packages (except the Transformer package) provide complete implementations from data loading, experimental setup, evaluation and algorithm implementation, and researchers can quickly produce benchmarking results of a package according to their requirements with little effort.

¹<https://recbole.io/>

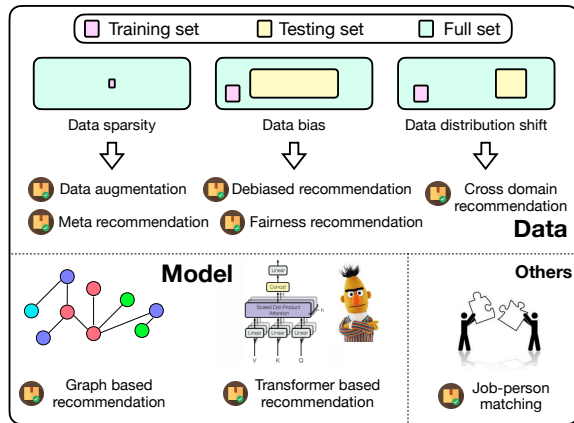


Figure 1: Overview of the implemented packages, which are grouped into the data and model parts.

The merits of this extended library are threefold. First, it is *unified* in implementation and interface: all the packages are developed fully based on the recommendation framework RecBole, reusing existing functions or modules from the main code repository as much as possible. Second, it is a *significant* extension with 65 newly implemented algorithms or models, having a good coverage of recent advances in recommender system. With this extension, RecBole has become the most comprehensive recommendation library in terms of both algorithms (130+ models) and tasks (11 tasks or topics), among the public research projects in recommender systems on GitHub. Third, it is *flexible* and *reliable* to use: we implement the complete evaluation pipeline for each package and carefully conduct the code reviewing and testing.

In the following sections, we first overview the implemented packages, then detail each one to illustrate our design principles and show the usage examples, and finally discuss the extensions of our library as compared with RecBole.

2 OVERVIEW

We present the overall introduction of the extended library in Figure 1. As we can see, our extensions consist of eight packages, grouped into two major parts concerning *data* and *model*. For the data packages, we focus on three key issues, that is, data sparsity, data bias and data distribution shift. To solve the data sparsity issue, we develop two packages, namely data augmentation (generating additional data samples for optimizing recommendation models) and meta-learning based recommendation (approaching the cold-start issue with meta-learning methods). To alleviate the data bias, we develop two packages, namely debaised (reducing the data bias) and fairness recommendation (enforcing the fairness of the recommendations). To overcome the data distribution shift problem, we implement a cross-domain recommendation package. Note that cross-domain recommendation is not a new research topic, while our focus is to include the most up-to-date cross-domain recommendation models. For the model packages, we would like to collect and implement the most up-to-date recommender models. Specially, we focus on graph neural network and Transformer based models.

Besides, we also implement an application package for the task of person-job fit [12], which has received much attention from

the research community. In our library, the optimal configurations (obtained by grid search in predefined parameter ranges) for all the models have been provided, based on which one can easily produce the benchmarking results for each package. In the following, we introduce the above packages in detail.

3 PACKAGE DETAILS AND USAGE

We organize the packages in two groups, namely data-oriented and model-oriented packages, which are detailed below.

3.1 Data-oriented Packages

Data augmentation (RecBole-DA). To alleviate the data sparsity problem, a recently proposed technique is to generate additional samples to densify the original user-item interactions [64, 75]. Following [3, 44, 64], we implement three types of models based on different data augmentation strategies, including heuristic methods (CL4SRec [75] and DuoRec [54]), model based methods (MMInfoRec [53] and CauseRec [84]) and hybrid methods (CASR [64], CCL [3] and CoSeRec [44]). Besides providing model implementations, we also provide easy-to-use APIs to configure and combine different data augmentation strategies.

Meta recommendation (RecBole-MetaRec). Originated from computer vision and machine learning, meta-learning [14, 24, 29, 48] is a principled approach to dealing with few-shot learning tasks. We implement three types of meta-learning recommendation models, for prediction (MeLU [37] and MAMO [11]), parameterization (LWA [59], NLBA [59] and TaNP [40]) and embedding (MetaEmb [49] and MWUF [93]). These models are implemented by a series of general modules (MetaDataset, MetaDataLoader, MetaRecommender, MetaTrainer, MetaCollector and MetaUtils), which are flexible to be extended with new models.

Fairness recommendation (RecBole-FairRec). The second package related to data bias is targeted at fairness recommendation [83], considering the data bias from user perspective (debaised recommendation package mainly focuses on the bias from item side). Specifically, we implement four models in this package including FOCF [78], PFCN [39], FairGo [70] and NFCF [30]. Besides models, we implement a series of fairness metrics, which are particularly important for fairness recommendation, including Gini Index [18], Popularity Rate [18], Differential Fairness [30], Value Unfairness, Absolute Unfairness, Underestimation Unfairness, Overestimation Unfairness [78] and Non-Parity Unfairness [32].

Debaised recommendation (RecBole-Debias). Data bias ubiquitously exists in the observed user-item interaction data in recommender systems [7]. To correct these biases, we implement six debaised models considering selection bias (MF-IPS [56]), popularity bias (PDA [86], MACR [65], DICE [88] and CausE [5]) and exposure bias (Rel-MF [55]). Besides, we also implement specific dataloaders for three major debiasing datasets (Yahoo!R3 [56], ML-100k [56] and KuaiRec [16]) for conveniently reproducing the experiments.

Cross-domain recommendation (RecBole-CDR). Data distribution shift often occurs in cross-domain recommendation. To conduct effective cross-domain models, we consider three representative categories of methods, including collective matrix factorization (CMF [57] and CLFM [17]), representation sharing or combination (DTCDR [90], DeepAPF [77] and NATR [15]) and knowledge

Table 1: The included packages and the implemented models in each package.

Module	Package	Models
Data	Data augmentation (RecBole-DA)	CL4SRec [75], DuoRec [54], MMInfoRe [53], CauseRec [84], CASR [64], CCL [3], CoSeRec [44]
	Meta recommendation (RecBole-MetaRec)	MeLU [37], MAMO [11], LWA [59], NLBA [59], TaNP [40], MetaEmb [49], MWUF [93]
	Debiased recommendation (RecBole-Debias)	MF-IPS [56], PDA [86], MACR [65], DICE [88], CausE [5], Rel-MF [55]
	Fairness recommendation (RecBole-FairRec)	FOCF [78], PFCN [39], FairGo [70], NFCF [30].
	Cross-domain recommendation (RecBole-CDR)	CMF [57], CLFM [17], DTCDR [90], DeepAPF [77], NATR [15], CoNet [27], BiTGCF [43], EMCDR [45], SSCDR [33] and DCDCSR [91]
Model	Graph based recommendation (RecBole-GNN)	NGCF [62], LightGCN [22], SGL [69], HMLET [35], NCL [41], SimGCL [82], SR-GNN [74], GC-SAN [76], NISER [19], LESSR [9], TAGNN [79], GCE-GNN [63], SGNN-HN [50], DiffNet [72], MHCN [81], SEPT [80]
	Transformer based recommendation (RecBole-TRM)	TiSASRec [38], SSE-PT [71], LightSANs [13], gMLP [42], CORE [25], NRMS [68], NAML [66], NPA [67]
Others	Person-job fit (RecBole-PJF)	PJFNN [89], APJFNN [52], BPJFNN [52], IPJF [36], PJFFF [31], SHPJF [26], LFRR [47]

transfer or mapping (CoNet [27], BiTGCF [43], EMCDR [45], SS-CDR [33] and DCDCSR [91]). Cross-domain recommendation is actually not a new topic, but few packages have a good coverage of various representative methods in this research line.

3.2 Model-oriented Packages

GNN based recommendation (RecBole-GNN). In recent years, graph neural networks (GNNs) [20, 34, 60] have shown to be effective to model graph structures of various data types, *e.g.*, recommender systems [73]. We implement three types of GNN models tailored to different tasks, including general recommendation (NGCF [62], LightGCN [22], SGL [69], HMLET [35], NCL [41] and SimGCL [82]), sequential recommendation (SR-GNN [74], GC-SAN [76], NISER [19], LESSR [9], TAGNN [79], GCE-GNN [63] and SGNN-HN [50]) and social recommendation (DiffNet [72], MHCN [81] and SEPT [80]). Following the original data mechanism, we design a new kind of atomic file with suffix `.net` for structured data (*e.g.*, social network) modeling.

Transformer based recommendation (RecBole-TRM). Another major model architecture we implement is the widely used Transformer and its variants [21]. We implement this package by considering two major tasks, namely sequential recommendation (TiSASRec [38], SSE-PT [71], LightSANs [13], gMLP [42] and CORE [25]) and news recommendation (NRMS [68], NAML [66] and NPA [67]). Although the basic Transformer architectures used in these tasks are similar, the inputs of them are different, which makes Transformer play different roles in sequence modeling. Specifically, in sequential recommendation, Transformer is utilized to capture user behavior correlations; while, in news recommendation, Transformer is utilized to extract text semantics.

Person-job recommendation (RecBole-PJF). Besides, we also include a package tailored for the task of *person-job fit* [12]. This task is an important application and draws much attention from both research and industry communities. This package includes three categories of models, including collaborative filtering models (NeuMF [23], LightGCN [22]) and LFRR [47]), content-based models (PJFNN [89], APJFNN [52], BPJFNN [52]) and a twin towers

BERT model) and hybrid models (IPJF [36], PJFFF [31] and SH-PJF [26]). This package designs special data mechanism to support the incorporation of additional data types.

Package summary. Note that each package can be run as an individual project (including the entire pipeline to produce comparison results) but with unified implementation based on RecBole. For clearly understanding our library, we summarize the above implemented packages and models in Table 1.

4 PACKAGE USAGE

In this section, we introduce how to use our library by showing the example codes for each package separately.

Data augmentation. In our library, the data augmentation package is provided through a series of augmentation interfaces or commands. For invoking the data augmentation package, one needs to follow two steps, that is, (1) indicating the configuration file, and (2) running the augmentation command based on existing or customized model. Figure 2(a) presents an example on how to run SASRec with a data augmentation strategy called “`item_crop`”.

Meta recommendation. For running a meta learning based recommender, one can use the quick start wrapper (see Figure 2(b)), which will automatically conduct model configuration, trainer configuration, dataset preparation, model training and model evaluation. To implement a new meta learning model, the users can follow three steps: (1) indicate the configuration file, (2) extend the `MetaRecommender` to implement the model details, and (3) extend the `MetaTrainer` to customize the training process.

Fairness recommendation. For running an implemented fairness model, one should (1) indicate the parameters about the environment, data, trainer, evaluation and model by a YAML file, and (2) specify the model and dataset, and (3) launch the program with the quick-start script. An example to train and evaluate FOCF [78] is shown in Figure 2(c). In order to implement a new fairness-aware recommender model, there are three steps: (1) extend the `Trainer` to indicate the specific training process, (2) extend the `FairRecommender` to implement the model, and (3) extend the `AbstractMetric` to implement the fairness metrics.

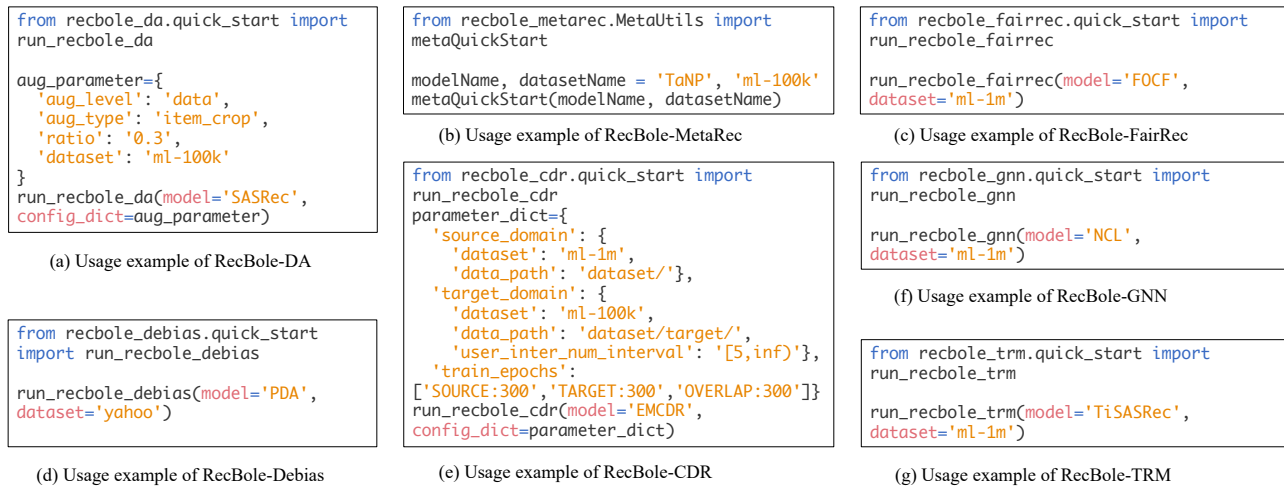


Figure 2: Example usage of the newly added packages in the RecBole library, where each subfigure corresponds to a package.

Debiased recommendation. To run an implemented debiased recommender model, one needs to follow two steps: (1) specify the setting of the model, dataset, training and evaluation processes via a YAML file, and (2) launch the program by indicating the model and dataset. An example of running PDA based on *Yahoo!R3* is shown in Figure 2(d). For implementing a model, one can implement the model architecture by extending the `DebiasedRecommender` class, and implement the trainer and sampler.

Cross-domain recommendation. To run a cross-domain recommender model, the users can set the formatted dataset as either source domain or target domain by configurations and run the model with simple commands. We present an example of how to run EMCDR [45] in our library in Figure 2(e), where we can set the source and target domain datasets, indicate the training modes and so on. For implementing a new algorithm, one can firstly extend the `CrossdomainRecommender` class and then specify the training modes with simple configurations.

GNN based recommendation. For running the implemented GNN models, there are two major steps to prepare: (1) indicate the customized configuration values and store them in an additional YAML file; (2) specify the model and dataset and launch with the quick-start script. An example to train and evaluate NCL [41] on *Movielens-1M* dataset with customized configuration is shown in Figure 2(f). For implementing new GNN-based recommendation models, one can reuse or adapt GNN layers for fast reproduction. For example, we can reuse `LightGCNConv` layer in RecBole-GNN to reproduce GNN-based collaborative filtering models, or replace the graph convolutional layer to new GNN components (e.g., `GCN2Conv` [8]) for further exploration.

Transformer based recommendation. To run an implemented Transformer-based model, one can follow three steps: (1) specify the configuration via a YAML file; (2) indicate the dataset and model; (3) run the model with the quick-start script. An example for running TiSASRec [38] based on *Movielens-1M* dataset is shown in Figure 2(g). To implement a new Transformer-based recommendation model, the users can reuse Transformer layers implemented by RecBole, or add new implementations in Transformer layers.

Person-job recommendation. This package mostly follows the use of the overall RecBole library, with several adaptations or new interfaces. The steps for developing new models are as follows: create a new model file (e.g., `PJFNN.py`), implement corresponding functions and save the hyper parameters to the configuration file. Specially, we introduced a new parameter *multi-direction* to control whether the evaluation is for bilateral or not. If it is set to true, the evaluation will be conducted at both candidate and employer sides on the same interaction records.

Above, we have briefly introduced the usage of the implemented packages. For more detailed descriptions, one can refer to our project at the link: <https://github.com/RUCAIBox/RecBole2.0>.

5 DISCUSSION AND CONCLUSIONS

The included extensions are developed based on a popular recommendation library RecBole, which originally contains more than 70 recommendation models covering the tasks of general recommendation, context-aware recommendation, sequential recommendation and knowledge-based recommendation. Since 2020, RecBole has received extension attention and use on GitHub, about 1.9K stars and 352 forks till June 1, 2022. In original RecBole, we focus on the design of underlying data structures, general evaluation pipeline and classical recommendation models.

With the rapid progress of recommender systems, we receive increasing requests from RecBole users on the support for up-to-date advances (e.g., debiased, fairness and GNNs). Meanwhile, our team members are also conducting research on these emerging topics or models. Therefore, we develop and release this extended library for enhancing RecBole by incorporating the support on recent advances of recommender systems. Specifically, in this extension, we release eight packages consisting of 65 newly implemented models, and also provide corresponding interfaces for data preparation, model running (with the well-tuned parameters) and evaluation. We believe this extension is a significant contribution to RecBole, which is a valuable resource to the research community. The RecBole team will continually improve this project, making it *up-to-date*, *comprehensive*, and *flexible* for research.

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