A User's Guide to CARSKit

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Abstract. Context-aware recommender systems extend traditional recommenders by adapting their suggestions to users' contextual situations. CARSKit is a Javabased open-source library specifically designed for the context-aware recommendation, where the state-of-the-art context-aware recommendation algorithms have been implemented. This report provides the basic user's guide to CARSKit, including how to prepare the data set, how to configure the experimental settings, and how to evaluate the algorithms, as well as interpreting the outputs. The instructions in this guide are applicable for CARSKit v0.2.0 and v0.1.0.

Keywords: context, context-aware recommendation, CARSKit, user guide

1 Introduction

CARSKit [8] ¹ is an open-source Java-based context-aware recommendation engine, where it can be used, modified and distributed under the terms of the GNU General Public License. (Java version 1.7 or higher required). It is specifically designed for context-aware recommendations.

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1.1 Design

CARSKit provides a flexible architecture so that it is easy to expand the scope of context-aware recommendation algorithms and provides spaces to develop new algorithms in the future. The whole design can be depicted by the Figure 1.

The workflow is straightforward in our design: different recommendation algorithms are the specific implementations and extensions from the generic interfaces where the shared and common functions are defined, such as rating or score prediction for a user on one item in a specific context. Evaluations for rating predictions and top-N recommendations are embedded into the Recommender.

¹ https://github.com/irecsys/CARSKit/

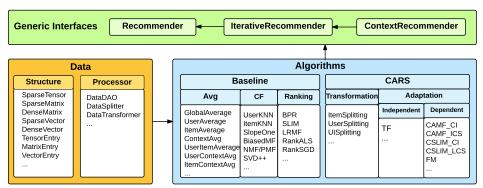


Fig. 1: CARSKit: The Architecture and Design

1.2 Algorithms

We divide the contextual algorithms into two categories in CARSKit: transformation algorithms and adaptation algorithms.

The transformation algorithms try to pre-process the data and convert the contextual data set to a 2-dimensional rating matrix which only contains users, items and ratings, so that any traditional recommendation algorithms can be applied to. One of those techniques is the context-aware splitting approaches [2,5].

The adaptation algorithms directly incorporate contexts into the prediction function. There are two subcategories involved: *independent modeling* (e.g., TF [3]) which assumes contexts are independent with users (and items), and *dependent modeling* which exploits the dependencies among users, items and contexts, such as CAMF [1] and contextual sparse linear method (CSLIM) [6,7]. Dependent modeling can be built in two ways: by modeling contextual rating deviations [1,7] and by learning context similarities [9,10]. Factorization machines (FM) [4] is a finer-grained algorithm which exploits pairwise relationships in its learning process. Among those algorithms, TF and CAMF are two popular ones which have been recognized as the standard baselines in CARS.

In addition to those state-of-the-art contextual recommendation algorithms, we also include some traditional recommendation algorithms in the package *baseline*. We did not re-compile those algorithms and directly reuse the implementations in LibRec ². There are two main purposes to include those traditional recommendation algorithms – On one hand, those algorithms can be applied after the data transformation (e.g., splitting operations), which is an essential step in the context-aware transformation algorithms. On the other hand, it is usually common to compete a contextual recommendation algorithm with non-contextual algorithms to judge whether the contextual effect is significant or a context-aware recommendation algorithm is necessary or not.

1.3 Evaluations

Most of the algorithms embedded in CARSKit are able to perform the two recommendation task: *rating prediction* and *item recommendation*, except those ones specifically

² https://github.com/guoguibing/librec/

designed for top-N recommendation, such as CSLIM. But the evaluation is different from traditional ones, since contexts are additional inputs in the evaluation process. Typically, the rating prediction can be evaluated by different prediction errors, such as mean absolute error (MAE), root mean square error (RMSE) and mean prediction error (MPE). The item recommendation can be evaluated through relevance metrics, such as precision and recall, and ranking metrics, such as mean average precision (MAP), normalized discounted cumulative gain (NDCG) and mean reciprocal rank (MMR).

2 User's Guide

In this section, the specific instructions about how to use, deploy and evaluate the context-aware recommendation algorithms by CARSKit are introduced as follows.

2.1 Data Format

Usually, the contextual rating data can be stored in two formats: *loose* format and *compact* format, as shown in tables below.

Table 1: Data Format

(a) Loose Format

UserID	ItemID	Rating	Context	Condition
U1	T1	3	Time	Weekend
U1	T1	3	Location	Work
U2	T2	4	Time	Weekday
U2	T2	4	Location	Home

(b) Compact Format

UserID	ItemID	Rating	Time	Location
U1	T1	3	Weekend	Work
U2	T2	4	Weekday	Home
U1	T1	4	Weekend	Home
U2	T2	2	Weekday	Work

Context dimension is identical to contextual variable, e.g., *Time* and *Location* as shown in the example above. Context conditions refer to specific values in a dimension, e.g. *Weekend* and *Weekday* are two conditions in the dimension *Time*. The loose format assumes that there is only one rating for each <user, item> pair in associated contexts, where the compact format allows to store multiple ratings to a same <user, item> pair in different contextual situations. Take the example shown in the two tables above, the first two rows in loose format actually represent a single rating by U1 for T1 within contexts {Weekend, Work}. In compact format, each row represents a single contextual rating profile; that is, there are only two contextual rating profiles in the loose format but four rating profiles in the compact format in this example.

UserID	ItemID	Rating	Time:Weekend	Time:Weekday	Location:Home	Location:Work
U1	T1	3	1	0	0	1
U2	T2	4	0	1	1	0
U1	T1	4	1	0	1	0
U2	T2	2	0	1	0	1

Table 2: Binary Format

Most contextual information is in shape of categorical data. Both the loose and compact format will increase storage pressure and computational costs. In CARSKit, we store contextual rating in a *binary* format as shown in Table 2, which is able to

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significantly boost the running performance. To assist the end users to prepare the rating data, we provide two methods *TransformationFromLooseToBinary* and *TransformationFromCompactToBinary* as the data transformer in our toolkit.

2.2 Data Preparation

It is better to follow the steps below to prepare your data:

- Step 1. Prepare your data set in either Loose or Compact format, and the CARSKit will automatically convert your data to the binary format. Be advised that you should add header to your data as shown in the Table . Save your file to either txt or csv format by using comma as separator.
- Step 2. Create a folder for each data set, and put the ratings.txt or ratings.csv in
 each folder. It is suggested, since the CARSKit will create a working subfolder
 under the path where your rating data is stored.
- Step 3. Assign the data path to the configuration file and run any algorithms to test the data transformation.

2.3 Experimental Configuration

You are required to create a setting.conf figure which is already included in the CARSKit repository ³. The main pieces to be configured in this file can be introduced as follows:

Data Path:

dataset.ratings.wins=C:\\Data\\DePaulMovie\\ratings.txt dataset.ratings.lins=/data/DePaulMovie/ratings.txt

Note: you may set up the data path either for windows (i.e., wins) or non-windows platforms (i.e., lins for Linus/Mac systems)

Setup Your Ratings:

ratings.setup=-threshold -1 -datatransformation 1

Note: By setting a rating threshold (e.g., -threshold 3), the ratings will be converted to binary ones (e.g., ratings larger than 3 will be 1; otherwise, 0), which is usually adopted when evaluating ranking metrics. If there is already a binary rating data under folder "CARSKit.Workspace" and you do not need data transformation, set negative value to -datatransformation; otherwise, set it as any positive value, e.g., 1

Choose An Algorithm:

recommender=xxx

Note: the list of options can be summarized as follows.

- Baseline-Avg recommender: GlobalAvg, UserAvg, ItemAvg, UserItemAvg
- Baseline-Context average recommender: ContextAvg, ItemContextAvg, UserContextAvg

³ https://github.com/irecsys/CARSKit/

- Baseline-CF recommender: ItemKNN, UserKNN, SlopeOne, PMF, BPMF, BiasedMF, NMF, SVD++
- Baseline-Top-N ranking recommender: SLIM, BPR, RankALS, RankSGD, LRMF
- CARS splitting approaches: UserSplitting, ItemSplitting, UISplitting; algorithm options: e.g., usersplitting -traditional biasedmf -minlength 2
- CARS independent models: CPTF
- CARS dependent-dev models: CAMF_CI, CAMF_CU, CAMF_CU, CAMF_CUCI, CSLIM_C, CSLIM_CI, CSLIM_CU, CSLIM_CUCI, GCSLIM_CC
- CARS dependent-sim models: CAMF_ICS, CAMF_LCS, CAMF_MCS, CSLIM_-ICS, CSLIM_LCS, CSLIM_MCS, GCSLIM_ICS, GCSLIM_LCS, GCSLIM_MCS

Setup Recommendation Task:

item.ranking=off-topN 10

Note: it will be a rating prediction task if your turn off the item.ranking; otherwise, it will run as a top-N recommendation task.

Evaluation Protocols:

evaluation.setup=cv -k 5 -p on -rand-seed 1 -test-view all -early-stop RMSE evaluation.setup=given-ratio -r 0.8

Note: You are able to choose k-fold cross validation or a simple train-testing evaluation. Once you assign a fixed value to k, the evaluation will be conducted on the same k-folds even if you examine different recommendation algorithms.

Config Your Outputs:

 $output.setup = -folder \ CARSKit.Workspace \ -verbose \ on, \ off \ -to-clipboard \ -to-file \ re-sults.txt$

Note: Basically, all the outputs will be put into the folder named as "CARSKit.Workspace" which is created under your data path. And all the evaluation results will be appended to the same file "results.txt".

Parameter Configurations:

Then you are allowed to config the algorithm parameters as shown in the setting.conf

Run The Toolkit:

java -jar CARSKit.jar -c setting.conf

java -jar CARSKit.jar -c CAMF.conf PMF.conf UserSplitting.conf

Note: You are able to run multiple algorithms or configurations by add configuration files to the command above.

2.4 Output Interpretation

Figure 2 gives an example of the running outputs.

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First of all, the outputs provide a list of simple statistics about the data, such as how many unique users, items and context dimensions or conditions, as well as rating statistics, such as the mean, mode and median in ratings.

In this example, we have results for both rating prediction task (evaluated by prediction errors) and top-N recommendation task (evaluated by precision, recall, MAP, NDCG and MRR) followed by the running parameters so that the users are able to find out the best configurations.

```
* Dataset: C:\Users\irecs\Desktop\Data\music\CARSKit.Workspace\ratings binary.txt
 * Item amount: 139
 * Rate amount: 3938
 * Context dimensions: 8 (drivingstyle, landscape, mood, naturalphenomena, roadtype,
 sleepiness, trafficconditions, weather)
 * Context conditions: 34 (drivingstyle: 3, landscape: 5, mood: 5, naturalphenomena: 5,
 roadtype: 4, sleepiness: 3, trafficconditions: 4, weather: 5)
 * Context situations: 27
 * Contextual Data density: 8.0978%
 * Scale distribution: [2.0 x 705, 4.0 x 513, 0.0 x 122, 1.0 x 1452, 5.0 x 494, 3.0 x 652]
 * Average value of all ratings: 2.447647
 * Standard deviation of all ratings: 1.474440
 * Mode of all rating values: 1.000000
 * Median of all rating values: 2.000000
 *************************
Dataset: ...ARSKit.Workspace\ratings_binary.txt
DataPath: C:\Users\irecs\Desktop\Data\music\CARSKit.Workspace\ratings_binary.txt
Rating data set has been successfully loaded.
With Setup: cv -k 5 -p on --rand-seed 1 --test-view all
Final Results by CAMF_C, MAE: 1.297121, RMSE: 1.469336, NAME: 0.259424, rMAE: 2.447637, rRMSE: 2.836681, MPE: 0.000000, numFactors: 10, numIter: 120, lrate: 2.0E-10, maxlrate: -1.0, regB: 0.001, regU: 0.001, regI: 0.001, regC: 0.001, isBoldDriver: true, Time: '00:01','00:00'
Final Results by BiasedMF. Pre5: 0.050361.Pre10: 0.025180. Rec5: 0.149967. Rec10: 0.149967.
AUC: 0.589942, MAP: 0.084189, NDCG: 0.110593, MRR: 0.122737, numFactors: 10, numIter: 100,
lrate: 2.0E-7, maxlrate: -1.0, regB: 0.001, regU: 0.001, regI: 0.001, regC: 0.001,
isBoldDriver: true, Time: '00:00','00:00'
```

Fig. 2: Sample of Running Outputs

3 Acknowledgement

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