The Journal of Open Source Software

Surprise: A Python library for recommender systems

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DOI: 10.21105/joss.02174

Software

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Submitted: 02 March 2020
Published: 05 August 2020

Summary

Recommender systems aim at providing users with a list of recommendations of items that a service offers. For example, a video streaming service will typically rely on a recommender system to propose a personalized list of movies or series to each of its users. A typical problem in recommendation is that of *rating prediction*: given an incomplete dataset of user-item interations which take the form of numerical ratings (e.g. on a scale from 1 to 5), the goal is to predict the missing ratings for all remaining user-item pairs.

`Surprise` is a Python library for building and analyzing rating prediction algorithms. It was designed to closely follow the `scikit-learn` API (Buitinck et al., 2013; Pedregosa et al., 2011), which should be familiar to users acquainted with the Python machine learning ecosystem.

`Surprise` provides a collection of estimators (or prediction algorithms) for rating prediction. Among others, classical algorithms are implemented such as the main similarity-based algorithms (Aggarwal & others, 2016), as well as algorithms based on matrix factorization like SVD (Koren, Bell, & Volinsky, 2009) or NMF (Lee & Seung, 2001). It also supports tools for model evaluation like cross-validation iterators and built-in metrics *à la* `scikit-learn`, as well as tools for model selection and automatic hyper-parameter search, namely grid search and randomized search. Thanks to simple primitives and a light API, users can also implement their own recommendation technique with a minimal amount of code.

Classical datasets such as the MovieLens datasets (Harper & Konstan, 2015) are directly available in the package, but user-defined datasets are also supported either by loading `csv` files, or by using `pandas` dataframes (McKinney, 2010).

`Surprise` is mainly written in Python, while the computationally intensive parts are optimized with `Cython` (Behnel et al., 2011). Internally, `Surprise` relies on built-in Python data structures (mainly dictionaries) as well as `numpy` arrays (Walt, Colbert, & Varoquaux, 2011).

`Surprise` was designed to be useful to researchers who want to quickly explore new recommendation ideas by supporting the creation of custom prediction algorithms, but can also serve as a learning resource for students and less experienced users thanks to its detailed documentation.

Other popular recommendation libraries with similar functionalities include `LibRec` (Guo, Zhang, Sun, & Yorke-Smith, n.d.) (Java) or `MyMediaLite` (Gantner, Rendle, Freudenthaler, & Schmidt-Thieme, 2011) (C#). In Python, `OpenRec` (Yang, Bagdasaryan, Gruenstein, Hsieh, & Estrin, 2018) and `Spotlight` (Kula, 2017) support neural-network inspired algorithms; `implicit`[1] is specialized in implicit feedback recommendation, and `LightFM` (Kula, 2015) implements a hybrid algorithm based on matrix factorization. To the best of our knowledge, `Surprise` is the only library to provide a `scikit-learn` like API with model selection tools, and with a focus on explicit rating prediction.

[1] https://github.com/benfred/implicit

Example

Here is a simple example showing how to (down)load a dataset, split it into five folds for cross-validation, and compute the Mean Average Error (MAE) and the Root Mean Squared Error (RMSE) of the SVD algorithm.

```
from surprise import SVD
from surprise import Dataset
from surprise.model_selection import cross_validate

# Load the movielens-100k dataset (download it if needed).
data = Dataset.load_builtin('ml-100k')

# Use the famous SVD algorithm, with default parameters.
algo = SVD()

# Run 5-fold cross-validation and print results. They can also be returned.
cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)

# printed output:
# Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
#              Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
# RMSE         0.9311  0.9370  0.9320  0.9317  0.9391  0.9342  0.0032
# MAE          0.7350  0.7375  0.7341  0.7342  0.7375  0.7357  0.0015
# Fit time     6.53    7.11    7.23    7.15    3.99    6.40    1.23
# Test time    0.26    0.26    0.25    0.15    0.13    0.21    0.06
```

Acknowledgements

We are grateful to all the people who have contributed to the software, with special thanks to Maher Malaeb and David Stevens for the hyper-parameter searches, and to Lauriane Ducasse for the logo design.

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