

ddop: A python package for data-driven operations management

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Summary

In today's fast-paced world, companies face considerable uncertainty when making important decisions in operations management, for example, when deciding upon capacity, inventory levels, transportation, and production schedules. However, with the rise of digitization, companies have gained unprecedented access to data related to their particular decision problem, offering the opportunity to reduce the degree of uncertainty. For example, in inventory management the decision maker may have access to historical demand data as well as additional side information, such as social media data, customer behaviour, weather forecasts or calendar data. Driven by the availability of such rich data sources there has recently emerged a stream of literature in operations management research called "data-driven operations management" (DDOM). The focus of DDOM is to combine machine learning and traditional optimization techniques to prescribe cost optimal decisions directly from data. Various models have been developed and shown great performance on the dataset used. However, what is missing is efficient access to open-source code and datasets. With *ddop*, we provide a Python library that integrates well-established algorithms from the field of data-driven operations management, as well as standard benchmark datasets. Thus, *ddop* helps researchers in two ways:

- Researchers can efficiently apply and compare well-established DDOM models.
- Researchers can test new developed models on benchmark datasets provided in the package.

The application programming interface (API) of *ddop* is designed to be consistent, easy-to-use, and accessible even for non-experts. With only a few lines of code, one can build and compare various models. In *ddop* all models are offered as objects implementing the estimator interface from scikit-learn ([Buitinck et al., 2013](#)). We thus not only provide a uniform API for our models, but also ensure that they safely interact with scikit-learn pipelines, model evaluation and selection tools.

The library is distributed under the 3-Clause BSD license, encouraging its use in both academic and commercial settings. The full source code is available at <https://github.com/opimwue/ddop>. The package can be installed via the Python Package Index using `pip install ddop`. A detailed documentation providing all information required to work with the API can be found at <https://opimwue.github.io/ddop/>.

Statement of need

With the growing number of publications in the field of data-driven operations management, comparability is becoming increasingly difficult. The reasons for this are twofold: One, most

39 scientists work with proprietary company data which cannot be shared. Two, it is not yet
40 standard that researchers share code used to implement their models. Consequently, results
41 are not directly reproducible and models have to be re-implemented every time a researcher
42 wants to benchmark a new approach. This not only takes a lot of time but can also be a
43 demanding process since such complex models are often challenging to implement. Against
44 this background, there has recently been a call to take inspiration from the machine learn-
45 ing community, where great APIs like scikit-learn (Buitinck et al., 2013), fastai (Howard &
46 Gugger, 2020), or Hugging Face (Wolf et al., 2019) have been developed that allow previous
47 developed ML models to be effectively applied on different dataset. Following up on this, *ddop*
48 is the first of its kind to integrate well-established data-driven models for operations manage-
49 ment tasks. At the current state, this includes various approaches to solve the data-driven
50 newsvendor problem, such as weighted sample average approximation (Bertsimas & Kallus,
51 2020), empirical risk minimization (Ban & Rudin, 2019), and a deep learning based approach
52 (Oroojlooyjadid et al., 2020). In addition, the library provides different real-world datasets
53 that can be used to quickly illustrate the behaviour of the available models or as a benchmark
54 for testing new models. *ddop*'s aim is to make data-driven operations management accessible
55 and reproducible.

56 Usage

57 Since all models in *ddop* implement the estimator interface from *scikit-learn* consisting of a *fit*,
58 *predict*, and *score* method, usage follows the standard procedure of an *scikit-learn* regressor.
59 First, a model is initialized by calling the class constructor from a given set of constant hyper-
60 parameter values, each describing the model or the optimisation problem the estimator tries
61 to solve. Note that for ease of use, all estimators use reasonable default values. It is therefore
62 not necessary to pass any parameter to the constructor. However, it is recommended to tune
63 them for the respective application, since this can often improve decision quality. After the
64 model has been initialized, the *fit* method is used to learn a decision model from the training
65 data (X_{train} , y_{train}). Once the training process is completed, the function returns the
66 fitted model, which can then be used to make decisions for new data (X_{test}) by using the
67 *predict* method. Finally, the *score* method can be used to access the decision quality of a
68 model. The method takes as input X_{test} as well as the corresponding true values y_{test}
69 and computes the average costs between y_{test} and $predict(X_{test})$. Because all estimators
70 follow the same interface, using a different model is as simple as replacing the constructor.

71 Future Work

72 There are several directions that the *ddop* project aims to focus on in future development.
73 While at the current state there are only algorithms available to solve the newsvendor problem,
74 the goal is to include models to solve other operations management task like multi-period
75 inventory management or capacity management. In addition, we aim to extend the library in
76 terms of available datasets and tutorials.

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