

dame-flame: A Python Library Providing Fast Interpretable Matching for Causal Inference

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Abstract

dame-flame is a Python package for performing *matching* for *observational causal inference* on datasets containing discrete covariates. This package implements the *Dynamic Almost Matching Exactly (DAME)* and *Fast, Large-Scale Almost Matching Exactly (FLAME)* algorithms, which match treatment and control units on subsets of the covariates. The resulting matched groups are interpretable, because the matches are made on covariates (rather than, for instance, propensity scores), and high-quality, because machine learning is used to determine which covariates are important to match on. DAME solves an optimization problem that matches units on as many covariates as possible, prioritizing matches on important covariates. FLAME approximates the solution found by DAME via a much faster backward feature selection procedure. The package provides several adjustable parameters to adapt the algorithms to specific applications, and can calculate treatment effects after matching. Descriptions of these parameters, details on estimating treatment effects, and further examples, can be found in the documentation at <https://almost-matching-exactly.github.io/DAME-FLAME-Python-Package/>.

Keywords: matching, causal inference, observational data, interpretability, Python

1. Introduction

We introduce the **dame-flame** Python package for *almost exact* matching of treatment and control units in discrete observational data for causal analysis.¹ The advantage of matching is that it reduces bias of treatment effect estimates, and permits interpretable analyses that are easier to troubleshoot than other types of analysis for observational causal studies.

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1. While handling of continuous observational data is outside the scope of **dame-flame**, continuous data can be discretized before applying **dame-flame**. This is discussed in the documentation.

dame-flame produces high-quality matches for a given unit by matching it exactly on as many relevant covariates as possible. The choice of covariates to match on is aided by machine learning on a holdout training set.

Many other matching methods either produce low-quality matches (with poor treatment effect estimates), uninterpretable matches (e.g. in which matches can group units with highly dissimilar covariates values), or matches that are manually defined by an analyst. One of the most widely used algorithms is nearest neighbor propensity score matching, provided by the R package **MatchIt** (Stuart et al., 2011). Propensity score matching reduces a dataset to one dimension, and matches can contain units even at extreme ends of a covariate space; such matches are uninterpretable. Another common matching algorithm is Coarsened Exact Matching (CEM), popularly available in the R package **cem** (Iacus et al., 2009). CEM requires the user to manually pre-define a distance metric, which requires substantial human intervention to choose carefully and can be dominated by irrelevant covariates (Dieng et al., 2019). **dame-flame** has none of these disadvantages, providing interpretable matched groups, and using machine learning on a holdout training set to learn distance metrics.

dame-flame is efficient, owing to fast bit-vector computations and a combination of backwards feature elimination (for FLAME) and a type of downwards closure property (for DAME) for feature elimination. The combination of FLAME (at earlier iterations) and DAME (at later iterations) permits scalability in matching units on many dimensions in earlier iterations, and flexibility to almost-exactly match the remaining units on important covariates in later iterations.

2. Algorithm Summary

The **dame-flame** package implements the algorithms *Dynamic Almost Matching Exactly (DAME)* (Dieng et al., 2019) and *Fast Large-Scale Almost Matching Exactly (FLAME)* (Wang et al., 2019). Both algorithms iterate over two nested loops, shown in Figure 1.

The algorithms receive an input dataset with discrete observational covariates, a binary treatment indicator, and a continuous or discrete outcome column. It also receives either a separate holdout training dataset

with the same covariates as the input dataset, or it can partition the input dataset to create the holdout set. The *matching set* contains the units we aim to match and the *holdout training set* is used to determine which variables are important. Users have a variety of options for handling *missing covariate data*. They can (1) exclude rows with missing values from the procedure, (2) impute the missing data via MICE (Buuren and Groothuis-Oudshoorn, 2010), or (3) specify that matches should not occur on missing values, without dropping or imputing them.

After handling missing data, the algorithms begin by matching any units that can be matched exactly on all covariates, where both a treatment and control unit are contained

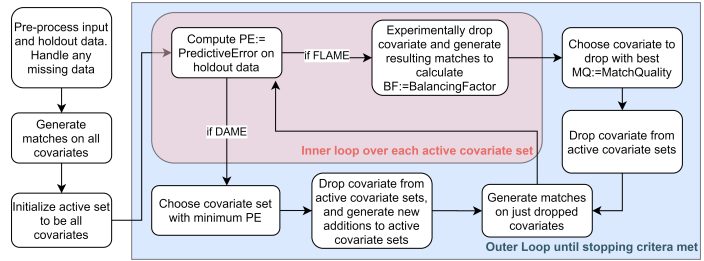


Figure 1: Flow diagram: DAME/FLAME algorithms

in each matched group. The algorithms then execute the outer loop: updating sets of covariates to match on, referred to as active covariate sets, until a stopping criterion is reached. In each iteration, the algorithms execute the inner loop, examining each covariate set to select the best one to match on. Units that have identical values in all of the covariates that are part of the chosen covariate set form a matched group, given that at least one treatment unit and at least one control unit are present in the group.

To determine the best covariate set, FLAME selects the covariates yielding the highest *match quality* MQ, defined as $MQ = C \cdot BF - PE$, where C is a user specified hyperparameter. DAME selects the covariate set minimizing PE. Here, PE denotes the *predictive error*. This term estimates how important the dropped covariates are for predicting the outcome, based on a user-chosen machine learning algorithm run on the holdout training set. The *balancing factor*, BF, measures the proportion of treatment and control units that are matched on a covariate set. DAME iterates efficiently over all covariate sets, prioritizing matching on large covariate sets if they can be used to effectively predict the outcome on the holdout training set. FLAME approximates this solution for scalability: it consistently matches on a smaller set of covariates than in the previous iteration, while still ensuring that each covariate set can be used to effectively predict the outcome on the holdout training set.

The outer loop has a number of possible stopping criteria. It must stop when all units are placed in matched groups or all covariate sets have been dropped. Additionally, users can enforce stopping based off other criteria, e.g., (1) when there are too few unmatched (treatment or control) units, (2) after a certain number of iterations, (3) when predictive error rises too much, or (4) when the balancing factor for a given round is not high enough.

Users can also choose whether units are matched with replacement; that is, whether a previously matched unit can be matched in a subsequent iteration of the algorithm.

3. Package Usage

Basic Functionality. To run DAME or FLAME, the user provides the input data as a data frame or file, which must contain an outcome column, and a treatment column. Each algorithm by default produces a table consisting of the units that were matched to at least one other unit. For each unit that was matched, the table indicates which of the covariates were used for matching, and the covariate values that each unit was matched on. The covariates that were not used to match the unit are denoted with “*” as their values. Users can find matched groups of individual units and can estimate treatment effects, including the *average treatment effect* (ATE) and *conditional average treatment effect* (CATE) of a selected unit after either algorithm has been run.

Comparison to Other Matching Packages. Many of the features previously described are unavailable in other matching packages. Table 1 compares the characteristics of `dame-flame` against popular alternatives. Most matching packages are implemented in R. R’s `cem` package was removed from CRAN in 2020, and only supports ATT treatment effects (Iacus et al., 2009). The `MatchIt` package does not support any treatment effect calculations, recommending users compute these using a separate R package, `Zelig`, which is not available on CRAN (Stuart et al., 2011). Users of any propensity score matching algorithm can adjust matched group sizes only by entering a ratio of treatment to control units, forcing all matched groups to be of the same size. Python’s `PyMatch` and `DoWhy`

Language: Package	built-in treatment-effect estimations	flexible matched group sizes	missing data handling options	provide matched groups
Python: dame-flame	ATE, ATT, CATE	✓	✓	✓
Python: DoWhy	ATT, ATE, ATC			
Python: PyMatch				✓
R: cem	ATT	✓	✓	✓
R: MatchIt Propensity Score				✓

Table 1: **Features of Matching Packages**

offer Propensity Score matching, but **DoWhy** doesn’t emphasize matched groups, favoring treatment effects and other output (Sharma et al., 2019), (Miroglio et al., 2017). A further advantage of **dame-flame** is the higher quality of the matched groups generated by DAME and FLAME relative to propensity score matching, as shown by Dieng et al. (2019).

Additional Advanced Controls of DAME-FLAME. Users are offered several ways to control the matching procedure, including early stopping criteria, and the option of placing units in matched groups with and without replacement. The default parameters for the package were chosen for their versatility and speed, so the algorithm can be relevant and easy-to-use for a range of users. Full descriptions of algorithm parameters are provided in the respective package documentations. As part of a suite of printing options, users can request that the predictive error and/or balancing factor at each iteration be returned.

4. Installation, Documentation, and Project Management

dame-flame is available for download on PyPi and on GitHub². On GitHub, users may report bugs, ask questions, and make pull requests. The documentation covers the API, installation instructions, a quick-start tutorial, several examples, and a contributing guide. The package is designed for Python 3.6 and above. **dame-flame** depends on **scikit-learn** version 0.23.2 and above, **pandas** version 0.11.0 and above, and **numpy** version 1.16.5 and above. The API consists of standard Pythonic design established by **scikit-learn**, such as the methods **fit**, where a user provides a holdout training dataset, and **predict**, where a user provides a matching dataset, and the matches of the algorithm are computed.

There is an accompanying experimental R package for the FLAME algorithm, whose development version can also be found on GitHub.³ Testing was done to ensure that **R-FLAME** and **dame-flame** yield consistent results. Furthermore, **dame-flame** offers Continuous Integration, and the extensive test suite has a code coverage of 98%.

5. Conclusion

The **dame-flame** package offers efficient, easy-to-use implementations of the DAME and FLAME algorithms, allowing users to perform fast, interpretable matching for causal inference for observational data with discrete covariates. The package is easily accessible and accompanied by detailed documentation, with concrete examples. The package is written in a highly modular manner, facilitating the introduction of new features and variations of the DAME and FLAME algorithms.

2. Code is publicly available at

<https://github.com/almost-matching-exactly/DAME-FLAME-Python-Package/>.

3. <https://github.com/almost-matching-exactly/R-FLAME>

Acknowledgments: This work was supported in part by awards NIH R01EB025021, NSF IIS-1703431, and the Duke University Energy Initiative Energy Research Seed Fund.

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