DESlib: A Dynamic ensemble selection library in Python

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Abstract

DESlib is an open-source python library providing the implementation of several dynamic selection techniques. The library is divided into three modules: (i) *dcs*, containing the implementation of dynamic classifier selection methods (DCS); (ii) *des*, containing the implementation of dynamic ensemble selection methods (DES); (iii) *static*, with the implementation of static ensemble techniques. The library is fully documented (documentation available online on Read the Docs), with a high test coverage (cover.io) as well as code quality (Landscape). Documentation, code and examples can be found on its GitHub page: https://github.com/Menelau/DESlib.

Keywords: Multiple classifier systems, Ensemble of Classifiers, Dynamic classifier selection, Dynamic ensemble selection, Machine learning, Python

1. Introduction

Dynamic selection (DS) has become an active research topic in the multiple classifier systems literature in recent years. In this paradigm, one or more base classifiers[1] are selected for each query instance to be classified. Such techniques have demonstrated improvements over traditional (static) combination approaches, such as majority voting and Boosting (Britto et al., 2014; Cruz et al., 2018). DS techniques work by estimating the competence level of each classifier from a pool of classifiers. Only the most competent, or an ensemble containing the most competent classifiers is selected to predict the label of a specific test sample. The rationale for such techniques is that not every classifier in the pool is an expert in classifying all unknown samples; rather, each base classifier is an expert in a different local region of the feature space.

In this paper, we introduce a library for dynamic ensembles in python: DESlib. The library contains the implementation of the key dynamic selection techniques in the literature. It also provides dynamic weighting implementation of such methods, as well as static ensemble techniques which are often used as baseline comparisons for dynamic ensembles. The following sections present the project organization, the API design, currently implemented methods and future directions for the API.

1. The term base classifier refers to a single classifier belonging to an ensemble or a pool of classifiers.

2. Project management

DESlib was developed with two objectives in mind: to make it easy to integrate Dynamic Selection algorithms to machine learning projects, and to facilitate research on this topic, by providing implementations of the main DES and DCS methods, as well as the commonly used baseline methods. Each algorithm implements the main methods in the scikit-learn API (Pedregosa et al., 2011): **fit**(X, y), **predict**(X), **predict_proba**(X) and **score**(X, y). Any classifier from scikit-learn (or from other libraries that follow this API) can be used as base classifiers, making the library easy to use and to integrate in other projects.

The implementation of the DS methods is modular, following a taxonomy defined in Cruz et al. (2018). This taxonomy considers the main characteristics of DS methods, that are centered in three components: (1) the methodology used to define the local region, in which the competence level of the base classifiers are estimated (region of competence); (2) the source of information used to estimate the competence and (3) the selection approach to define the best classifier (for DCS) or the best set of classifiers (for DES). This modular approach makes it easy for researchers to implement new DS methods, in many cases requiring only the implementation of methods `estimate_competence` and `select`.

The library is written in pure python, working on any platform, and depends on the following python packages: scikit-learn, numpy and scipy. The project follows these guidelines:

- **Development:** All development is performed collaboratively using GitHub, which facilitates code integration, communication between collaborators and issue tracking. External contributions are encouraged.

- **Code quality:** The code was written following the PEP 8 standards. We use Landscape[2] to measure and track code quality. The library is also covered by unit tests (py.test), using Travis CI. The first release of the library has a code coverage of 98%. Moreover, Landscape and Travis CI are used to automatically check each new contribution according to the code quality and test coverage. Thus, we can assert the code quality over time.

- **Documentation:** The code of DESlib is fully documented, including detailed instructions and examples for using the API. The documentation is provided based using numpydoc and sphinx, being automatically updated with new developments. It is available online at `http://deslib.readthedocs.io/en/latest/`

- **Bugs and new features:** Bugs and new feature requests are tracked through the project's GitHub page: `https://github.com/Menelau/DESlib/issues`. This environment allows a discussion between the collaborators to find the best solution for the problem. New users can check whether the problems they found or new requests are already being addressed.

3. Implemented techniques

The library is divided into three modules:

2. https://landscape.io/

Table 1: Implemented DES and DCS methods

DES	DCS
META-DES (Cruz et al., 2015)	Modified Rank (Sabourin et al., 1993)
KNORA-E (Ko et al., 2008)	OLA (Woods et al., 1997)
KNORA-U (Ko et al., 2008)	LCA (Woods et al., 1997)
DES-P (Woloszynski et al., 2012)	MLA (Smits, 2002)
KNOP (Cavalin et al., 2013)	MCB (Giacinto and Roli, 2001)
DES-RRC (Woloszynski and Kurzynski, 2011)	A Priori (Didaci et al., 2005)
DES-KL (Woloszynski et al., 2012)	A Posteriori (Didaci et al., 2005)
DES-Exponential (Woloszynski and Kurzynski, 2009)	
DES-Logarithmic (Woloszynski and Kurzynski, 2009)	
DES-Minimum Difference (Antosik and Kurzynski, 2011)	
DES-Clustering (Souto et al., 2008)	
DES-KNN (Souto et al., 2008)	

Table 2: Implemented baseline methods

Static
Oracle (Kuncheva, 2002)
Single Best (Britto et al., 2014)
Static Selection (Ruta and Gabrys, 2005)

Dynamic Classifier Selection (DCS): This module contains the implementation of techniques in which only the base classifier that attained the highest competence level is selected for the classification of the query.

Dynamic Ensemble Selection (DES): Dynamic ensemble selection strategies refers to techniques that selects an ensemble of classifier rather than a single one. All base classifiers that attain a minimum competence level are selected to compose the ensemble of classifiers.

Static Ensembles: This module provides the implementation of static ensemble techniques that are usually used as baseline for the comparison of DS methods: Single Best (SB), Static Selection (SS) and Oracle.

Tables 1 and 2 list the implemented DS and baseline methods, respectively.

4. Installation and Usage

The latest stable version of the library can be installed using pip (Python package manager): `pip install deslib`. Alternativelly, the master branch, which contains features that will be included in future releases, can be installed directly from the GitHub address: `pip install git+https://github.com/menelau/deslib`. We note that new features are only merged to the master branch after code review and the creation of unit tests.

4.1 Usage

Each implemented method receives as an input a list of classifiers, which can be either from the same type (homogeneous pool) or containing different type classifier models (heterogeneous pool). The library supports any type of base classifiers from scikit-learn. After instantiation, the method **fit**(X, y) is used to fit the Dynamic Selection dataset (DSEL). Predictions for new examples can then be obtained with **predict**(X) and **predict_proba**(X). In the example below, we show how to use the library, with a given Training, DSEL and Testing datasets. We use Multiple Classifier Behaviour (MCB) (Giacinto and Roli, 2001) and META-DES (Cruz et al., 2015) in this example.

```
from sklearn.ensemble import RandomForestClassifier
from deslib.dcs.mcb import MCB
from deslib.des.meta_des import METADES

# Train a pool of 10 classifiers
pool_classifiers = RandomForestClassifier(n_estimators=10)
pool_classifiers.fit(X_train, y_train)

# Initialize the DS model
metades = METADES(pool_classifiers)
mcb = MCB(pool_classifiers)

# Preprocess the Dynamic Selection dataset (DSEL)
metades.fit(X_dsel, y_dsel)
mcb.fit(X_dsel, y_dsel)

# Predict new examples:
metades.predict(X_test)
mcb.predict(X_test)
```

The library also offers the implementation of methods which are used in conjunction with DS techniques to achieve higher classification performance: The Dynamic Frienemy Pruning (DFP) proposed in (Oliveira et al., 2017) can be easily done just by setting the DFP in the argument to the constructor:

```
metades = METADES(pool_classifiers, DFP=True)
mcb = MCB(pool_classifier, DFP=True)
```

5. Conclusion and future plans

In this paper we introduced the first version of DESlib that implements a wide variety of dynamic classifier and ensemble selection techniques, with an API based on scikit-learn. Future work on this library includes the implementation of dynamic selection methods in different contexts, such as One-Class-Classification (OCC) and regression.

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