Data Characterization for Meta-Learning

Prof. Adriano Rivolli
rivolli@utfpr.edu.br

Departamento de Computação (DACOM)
Universidade Tecnológica Federal do Paraná (UTFPR)

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Outline

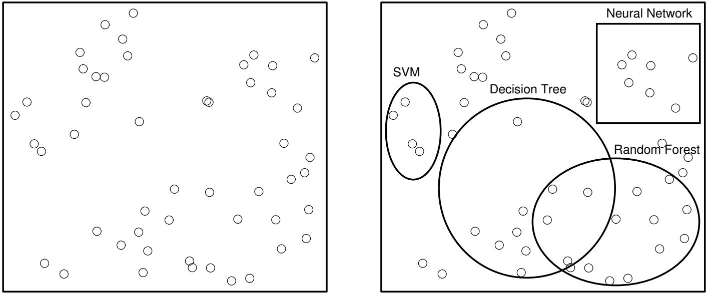
1. Introduction
2. Meta-Learning
3. Meta-Feature Extractor (MFE)
4. Standard Analysis
5. Prospective work

Introduction

Bias Definition

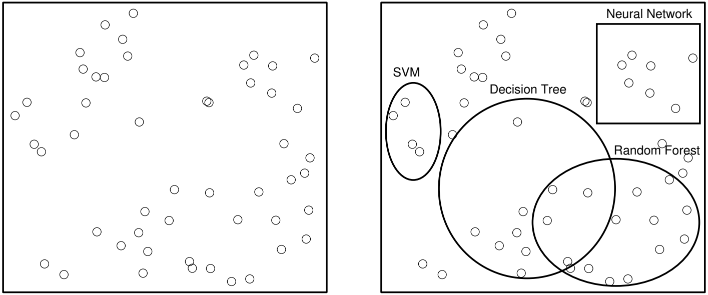
Bias has been defined as the choice of a specific generalization **hypothesis** over others, restricting the **search space** and model representation, making learning from data possible [Mitchell, 1997].

Hypothesis and search space



(a) Search space. (b) Preference bias of ML algorithms.

Hypothesis and search space

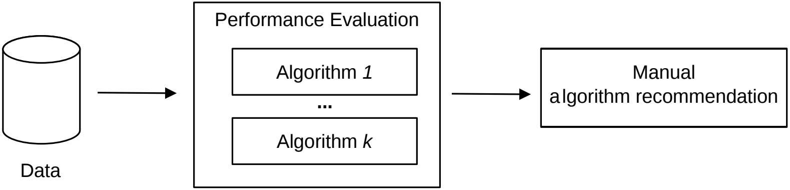


(c) Search space.

(d) Preference bias of ML algorithms.

The effect of bias for Data Science is that several algorithms are usually tried. This is called **trial-and-error approach.**

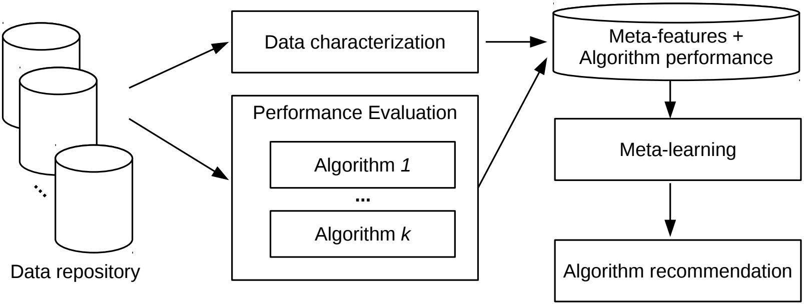
Trial-and-error approach



Trial-and-error approach

- Laborious and subjective;
- Increase the training time;
- Can cause overfitting;
- Decrease the experimental reproducible.

Meta-Learning (MtL) approach



Meta-Learning (MtL) approach

- Laborious but objective;
- Remove the training time;
- Can avoid overfitting;
- Towards the experimental reproducible.

Open gaps

- Increase the reproducible in MtL;
- Improve data characterization with new meta-features;
- Improve the MtL performance;
- Management of bias.

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Meta-learning

MtL Definition

Study of methods that explore **metaknowledge** in order to improve or to obtain more efficient ML solutions [Brazdil et al., 2009].

Algorithm Selection Applications:

- Optimization [Kanda et al., 2011];
- Time series analysis [Rossi et al., 2014];
- Gene expression tissue classification [de Souza et al., 2010];
- SVM parameter tuning [Mantovani et al., 2015].

Algorithm Selection Framework

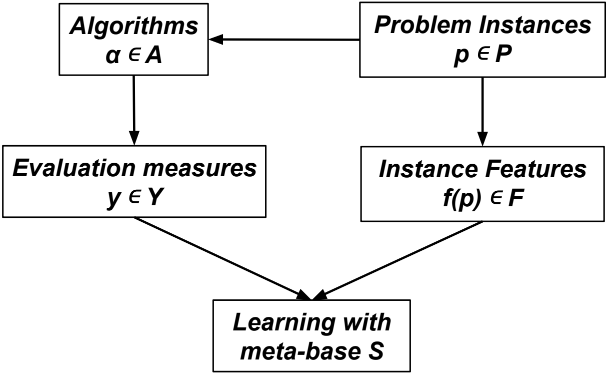

Figure: Algorithm selection framework. (Adapted from [Smith-Miles, 2008])

Problem Instances (P)

The problem instances P are datasets p that will be used to generate the meta-base. They can be collected from:

- UCI [Lichman, 2013];
- Keel [Alcalá-Fdez et al., 2011];
- OpenML [Vanschoren et al., 2013];
- Artificial datasets [Vanschoren and Blockeel, 2006];
- Datasetoids [Prudêncio et al., 2011].

Instance Features (F)

The meta-features F are designed to extract general properties of datasets $f(p)$. They are able to provide evidence about the future performance of the investigated techniques [Soares et al., 2001].

Instance Features (F)

The main groups of meta-features are:

- **General:** Extract simple and basic information;
- **Statistical:** Capture data distribution indicators;
- **Information-theoretic:** Capture the amount of information in the data and their complexity;
- **Model-based:** Extract characteristics like the shape and size of a Decision Tree (DT) model induced from a dataset.
- **Landmarking:** Represents the performance of simple and efficient learning algorithms.

Instance Features (F)

The **general meta-features** are basic information directly extracted from the dataset:

- number of attributes, instances and classes;
- frequency of instances in each class.

Instance Features (F)

The **statistical meta-features** extract information about the data distribution:

- correlation and covariance matrix;
- skewness and kurtosis.

Instance Features (F)

The **information-theoretic meta-features** capture the amount of information in the datasets:

- entropy;
- mutual information;
- noise signal ratio.

Instance Features (F)

The **model-based meta-features** are information extracted from a DT model:

- tree depth;
- distribution of the leaves in the tree;
- number of nodes.

Instance Features (F)

The **landmarking meta-features** are the performance of a set of fast and simple learners:

- Linear Discriminant;
- Elite-Nearest Neighbor;
- One node DT-models.

Algorithms (A)

They represent a set of the algorithms α that will be applied to the datasets $\alpha(p)$ in the algorithm selection process.

- Classifiers, regressors and clustering algorithms [Garcia et al., 2018, Pimentel and de Carvalho, 2019]
- Pre-processing algorithms [Garcia et al., 2016]
- Hyperparameters [Mantovani et al., 2015]
- Optimization [Kanda et al., 2011]
- ...

Evaluation Measures (Y)

The models induced by the algorithm α can be evaluated by different measures to the datasets $y(\alpha(p))$. They are mainly:

- Accuracy, F_β, AUC and kappa for classification;
- MSE, RMSE for regression problems;
- ...

Meta-base (S)

The meta-base S is a collection of meta-examples. A meta-example is the characterization measures from the datasets $f(p)$ plus the evaluation of the algorithms $y(\alpha(p))$ for these dataset.

Meta-base (S)

Meta-{classification, regression and ranking}:

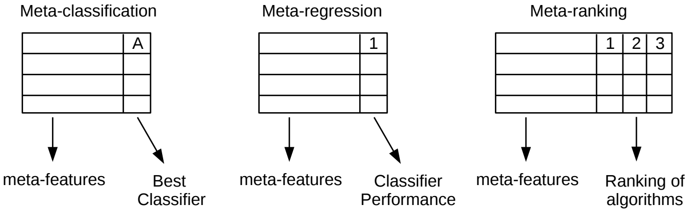

Figure: Example of meta-bases.

Recommendation System based on MtL

Predicting the classifier performance:

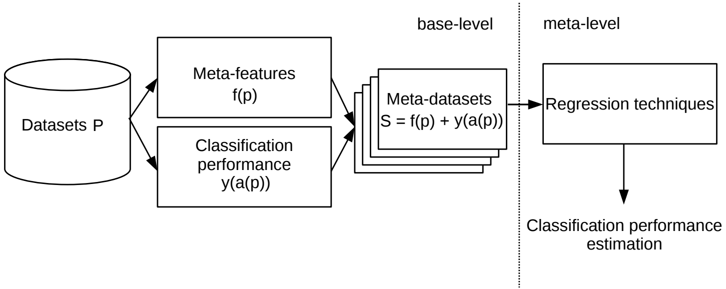

Figure: Example of MtL system to predict classifiers performance.

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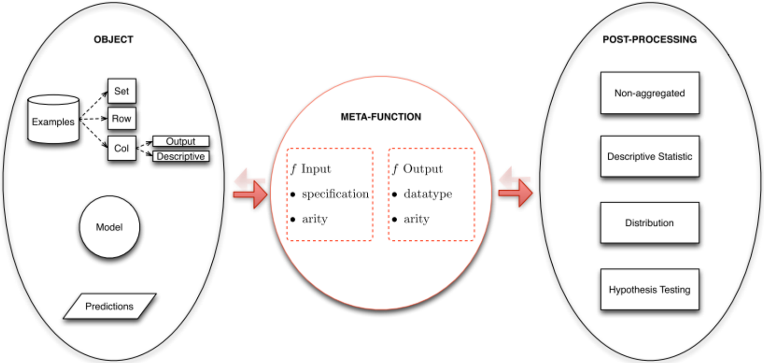
Introduction

- An R (MFE) and Python (PyMFE) package for dataset characterization
- Contains the implementation of the main characterization measures available
- It also can be used for analyzing of machine learning algorithms' performance

Software Architecture



PyMFE

https://pymfe.readthedocs.io/en/latest/

Open Issues

- Development of new characterization measures
- Understanding the behavior/semantic of current measures
- Development of techniques for features reduction and summarization
- Development of tools
- Creation of synthetic datasets based on specific features values range

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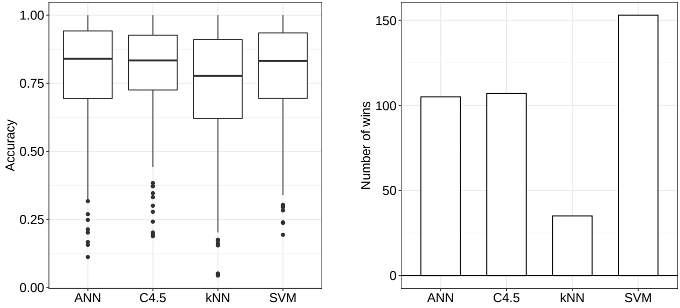
Standard Analysis

Evaluating the MtL to predict the classifier performance:

- **Meta-base Analysis:** Distribution of the algorithms in the meta-base and etc...
- **Meta-level Analysis:** Error of the meta-regressors to predict the performance of each classifier.
- **Base-level Analysis:** Performance of the meta-regressors to predict the best classifier for a dataset.
- **Execution time:** Difference of execution time between trial-and-error and MtL approach.

Meta-base Analysis



(a) Distribution of accuracies. (b) Winning classifiers.

Figure: Performance of the base-classifiers.

Meta-level Analysis

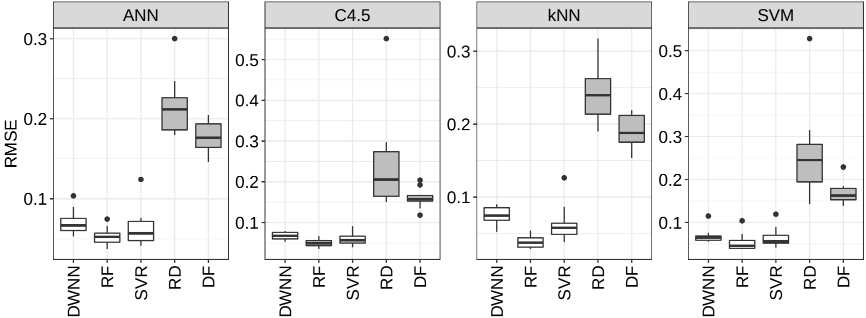


Figure: RMSE of each meta-regressor for each classifier.

Base-level Analysis

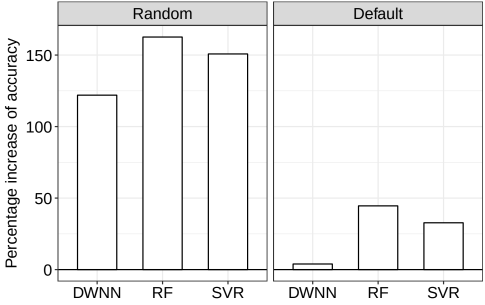
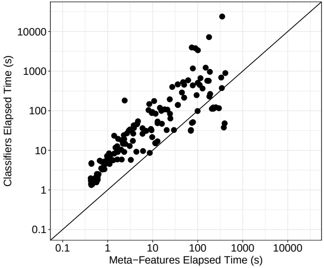
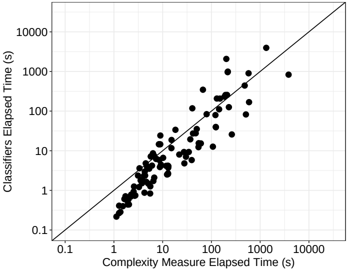


Figure: Improvement of base-classifier accuracies over baselines.

Execution time



(a) Average time elapsed to compute the meta-features and classifiers.



(b) Average time elapsed to compute the complexity measures and classifiers.

Meta-features Importance

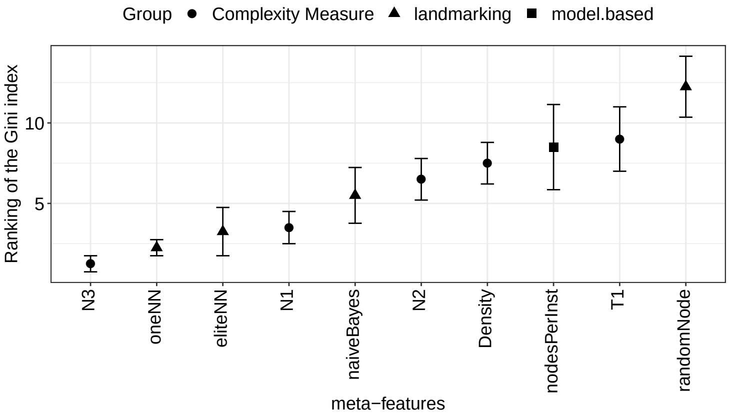


Figure: Top-ranked meta-features selected by the RF meta-regressor

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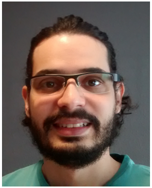
Prospective work

Main interests:

- Proposing a framework to extract meta-features;
- Simulating the Complexity Measures;
- Investigating new measures like Clustering Indexes and types of model-based
- Constructing meta-models for AutoML;
- Solving real problems with MtL.

Collaborations


Andre (USP)


Luís Paulo (UNB)


Davi (USP)


Carlos (FEUP)

MtL for AutoML

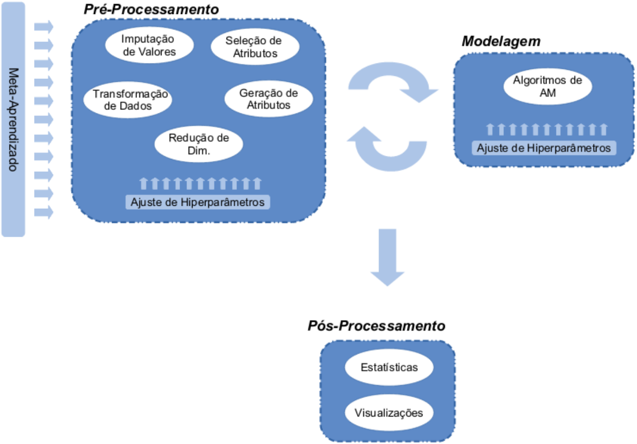


Figure: Defining AutoML pipelines with MtL.

Prospective work

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- Garcia, L. P. F., Campelo, F., Ramos, G. N., Rivolli, A., Carvalho, A. C. P. L. F. (2021) Evaluating Clustering Meta-features for Classifier Recommendation. Brazilian Conference on Intelligent Systems
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Prospective work

Packages

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