

Automatic problem-specific hyperparameter optimization and model selection for supervised machine learning

MASTER THESIS

by

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Oct. 2013 - Apr. 2014

ETH Zurich

Zurich, 2014

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inf | Informatik
Computer Science

Acknowledgements

Many people contributed directly and indirectly to the realization of this work. I wish to express my deepest gratitude to Dr. Kevin Smith for his direct guidance and remarkable mentorship during the entire project, and to Professor Dr. Gaston Gonnet for his supervision and valuable discussions.

The statistical consulting services of the Seminar for Statistics at ETH Zurich helped validate the proposed statistical approach, and the Scientific Center for Optical and Electron Microscopy provided the infrastructure, workplace, and room for fruitful discussions.

I also want to thank my colleagues from the Computational Biology and Bioinformatics Master Program for their academical and personal support during different stages of the program, including this master thesis. Special thanks to Stefan Ganscha, Stephanie Fingerhuth, Anita Sathyanarayanan, and Eirini Arvaniti.

Finally, I wish to thank my family and friends overseas for their continuous encouragement and invaluable support.

Zurich, April 15th, 2014

R.B.C.

Abstract

The use of machine learning techniques has become increasingly widespread in commercial applications and academic research. Machine learning algorithms learn a model from data that allows computers to make and improve predictions or behaviors. Despite their popularity and usefulness, most machine learning techniques require expert knowledge to guide the decisions about the most appropriate model and settings for a particular problem. In many cases, expert knowledge is not readily available. When it is, the complexity of the problem and subjectivity of the expert can often lead to sub-optimal choices in the machine learning strategy.

Since different machine learning techniques are suitable for different problems, choosing the right technique and fine-tuning its particular settings are crucial tasks that will directly impact the quality of the predictions. However, deciding which machine learning technique is most well suited for processing specific data is not an easy task, as the number of choices is usually very large.

In this work, we present a method that automatically selects the best machine learning algorithm for a particular set of data, and optimizes its parameter settings. Our approach is flexible and customizable, enabling the user to specify their needs in terms of predictive power, sensitivity, specificity, consistency of the predictions, and speed, among other criteria.

The results obtained show that using the machine learning technique and configuration suggested by our automated approach yields predictions of a much higher quality than selecting the technique with the best results under its default settings. We also present a method to efficiently guide the search for optimal parameter settings by identifying ranges of values for each setting that produce good results for most problems. By transferring this knowledge to new problems, it is possible to find the optimal configuration of the algorithm more quickly.

Keywords: Model selection, hyperparameter optimization, Supervised Machine Learning

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CHAPTER 1

Introduction

Automatic data processing and analysis is essential in many scientific disciplines and commercial applications. The ever-increasing availability of computational resources experienced in recent years has stimulated the establishment of new disciplines that strongly depend on analysis of massive amounts of data. The complexity and scale of the data means that analysis by hand is often impractical or even impossible. Therefore automatic processing by computational methods are of paramount importance.

A clear example of this is found in biology. Methods to automate data acquisition have given rise to powerful new techniques such as *genome-wide association studies*, *high-content screening*, and *gene expression profiling*. These techniques collect vast amounts of data that must be carefully analyzed – a task which would have been impossible to do by hand, just a few years ago.

Recently, machine learning has become an essential step in the analysis process of many such techniques. Machine learning is a popular approach to automatic data processing and pattern recognition that learns a predictive model from example data. Later, the predictive model can be applied to new data for recognition or to make predictions. It is now common practice to use machine learning to perform the analysis of many biological data sets because it is faster, more accurate, and less biased than manual analysis.

Machine learning methods can be broadly categorized as either *supervised* or *unsupervised*. Supervised methods are more widely used. They infer a predictive model by detecting patterns in a set of labeled example data provided to the algorithm. Unsupervised methods are designed to work without any training information. Clustering methods are a typical example of unsupervised learning.

In this work, we focus on supervised machine learning (SML) methods, which are designed to address two families of problems: classification and regression. In the **classification** problem, instances of data (or objects) are said to belong to one class from a given set of classes. The task is to assign unseen instances to the appropriate class. The **regression** problem attempts to fit a model to observed data in order to quantify the relationship between two groups of

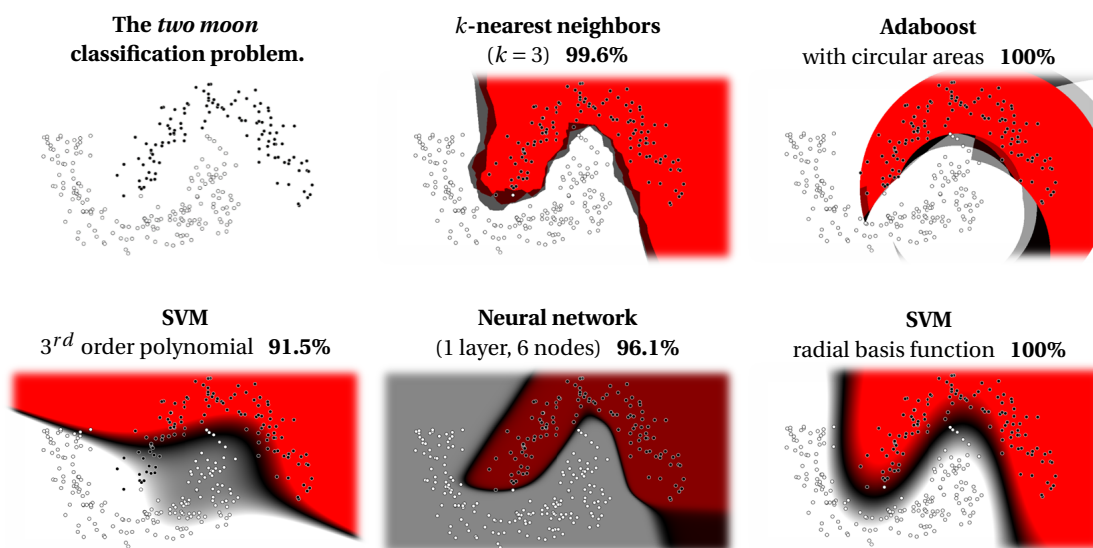


Figure 1.1: Decision boundaries for several different supervised machine learning algorithms applied to the *two moon* dataset. Inherent differences among the various models are reflected in their performance and by the shape of the decision boundaries.

variables, *predictors* and *responses*. The fitted model can be used to describe the relationship between the two groups, or to predict new response values based on the predictor values.

Model selection

Although many SML methods exist, it is usually not obvious which one to use. Choosing the best algorithm for a particular problem can be difficult, even for an expert. There are several reasons for this. First, the models underlying various machine learning algorithms are very different from one another. In a simple example using toy data depicted in Figure 1.1, the differences among various machine learning methods are obvious. Some methods misclassify entire regions of the data, some perform well but generalize poorly (they overfit the data), and for some the decision boundary is not smooth leading to ambiguity in certain regions.

Unfortunately, there is no “silver bullet” machine learning algorithm that always performs well. The choice of the method to use is tied to the structure of the data that they are to predict. Some methods make assumptions on the structure of the data, and do not give accurate predictions when such assumptions are violated. Therefore, it is important to choose the most appropriate model for the data, otherwise performance will suffer.

Hyperparameter optimization

Hyperparameters present a further complication to the problem. Most machine learning algorithms contain hyperparameters, external settings left to be tuned by the user (as opposed to parameters, which are optimized internally within the algorithm). These hyperparameter

settings, such as the cost of a support vector machine (SVM) or the number of neighbors k in k -nearest neighbors (KNN), control the SMLs internal behavior and can affect its ability to learn patterns for prediction. Finding the right combination of values may be as critical to good prediction as selecting the right machine learning method.

The space of possible hyperparameters can be quite large. One common implementation of an SVM requires the user to choose among 64 distinct categories of models, and then to set between 2 to 4 numeric values for each category. In many cases, an exhaustive evaluation of all possible hyperparameter combinations is not practical, and it is often not even possible. In practice, hyperparameter tuning is more of an art than a science, and even machine learning experts often carry out the tuning in an arbitrary or subjective way.

Our approach

We present an automatic solution to the combined model selection and hyperparameter optimization problem. Model selection is the problem of determining which among a set of machine learning algorithms is the most well suited to the data, while hyperparameter optimization searches for candidate hyperparameter values expected to most improve the prediction of the SML algorithm.

Our approach is to organize the various machine learning algorithms and their hyperparameters into a large hierarchical space. At the lowest level of the hierarchy are the numeric hyperparameters which contain values that must be set appropriately. Up the hierarchy we model conditional and categorical choices, which all belong to a single family of machine learning algorithms (support vector machines, for example). We use numeric optimization methods at the lowest level to choose the best numeric hyperparameter values for a given categorical configuration. The candidate models compete against each other using statistical tests. The best candidates are promoted to the next level of the hierarchy. The process is repeated until ultimately a single model remains, chosen among the families of classifiers or regressors.

Our approach substantially improves the performance of machine learning algorithms over their default settings, as we demonstrate on classic machine learning datasets as well as biological data. Our analysis also recognizes that, in some cases, the difference between one or more candidate models is statistically insignificant. When this occurs, the user can specify alternative criteria to choose the best model such as ranking the model's speed, simplicity, or interpretability.

CHAPTER 2

Problem description

This work aims to propose a solution for a two-fold problem: find the SML algorithm that works best for a given set of data, and find which particular choice of configuration settings for that algorithm yields the best results.

Although both sides of the problem correspond conceptually to different ideas (general approach the former, fine-tuning the latter), they are intrinsically linked and should not be treated as separate problems. This is especially true for the present work, since a poor choice of settings for an otherwise well-suited SML algorithm may be easily outperformed by another, less appropriated SML method, applied on the same data.

The formal description of the problem presented here is given in terms of the classification problem, but this description extends naturally to the regression problem.

2.1 Formal definition

The following terms and notation will be used for the rest of this document:

- An **instance** is data representing a single example, often an object. It is encoded as a pair (\mathbf{x}, y) , with \mathbf{x} a vector of values for attributes (also called *features*) related to the object, and y a mapping of the object to its corresponding class.
- A **dataset** $\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)\}$ is a set of instances on which SML is to be applied.
- An **algorithm** A is a specific implementation of any function that uses known instances (\mathbf{x}, y) (also known as *examples*) to learn patterns or rules to associate the feature values \mathbf{x} to their class y , and uses this information to predict the class y' of unseen instances from their feature values \mathbf{x}' .

$$A: (\{(\mathbf{x}, y)\}, \{\mathbf{x}'\}) \mapsto \{y'\} \quad (2.1)$$

- $\mathcal{A} = \{A^1, \dots, A^k\}$ represents the set of all algorithms to evaluate.
- An algorithm A accepts a set of **hyperparameters** \mathcal{P}_A that modify its behavior.
- λ_a is the value of a **hyperparameter** $a \in \mathcal{P}_A$ for some algorithm A .
- $\lambda^i = (\lambda_a^i, \lambda_b^i, \lambda_c^i, \dots)$ denotes a set of hyperparameter values (or **configuration**) for the i -th algorithm in \mathcal{A} .
- Λ^i represents the set of all possible values that λ^i can take (i.e. the **hyperparameter space** of the i -th algorithm).
- A realization of algorithm A under a specific configuration λ is called a **model**, and represented as A_λ .
- The **scoring** function S measures the predictive performance of a model A_λ on unseen instances drawn from the dataset \mathcal{D} .

$$S: A^i \in \mathcal{A}, \lambda^i \in \Lambda^i, \mathcal{D} \mapsto \mathbb{R} \quad (2.2)$$

The scoring function should be designed in such a way that the better the agreement between class prediction and true class assignment is, the higher the score.

It is assumed that the feature values of the examples \mathbf{x} used for training an algorithm and the feature values to predict labeling \mathbf{x}' are drawn from the same underlying distribution, and that instances with similar feature values tend to belong to the same class.

Under the described context, the model selection and hyperparameter optimization problem can be defined as:

$$A_{\lambda^*}^* = \underset{A^i \in \mathcal{A}, \lambda^i \in \Lambda^i}{\operatorname{argmax}} S(A_{\lambda^i}^i, \mathcal{D}) \quad (2.3)$$

The above equation can be simply stated as "find the algorithm and its parameter values that obtain the best score at predicting labels on the given dataset". It is worth noticing that equation 2.3 is the general form of the optimization process, and as such, only defines the structure and general behavior of the different components of the optimization. In practice, additional details such as the implementation of the scoring function, and the actual exploration of the hyperparameter spaces, must be considered.

Furthermore, the assumption that a single model $A_{\lambda^*}^*$ will be *significantly* better than the rest is not guaranteed, and hence returning multiple models as the result of the optimization process should also be considered under certain circumstances.

2.2 Related work

Few initiatives to address the model selection and hyperparameter optimization of SML algorithms have been proposed.

For hyperparameter optimization, the *de facto* method, known as *grid search*, is the exhaustive evaluation of a discretization of the hyperparameter space on a regularly-spaced grid. This approach is affected by the *curse of dimensionality* when a large number of hyperparameters needs to be analyzed. Furthermore, the step size for discretization is often decided arbitrarily.

Alternative methods to avoid these shortcomings have been proposed. The simplest of all consists on randomly retrieving and evaluating values for the hyperparameters (*random search*), and is studied in the context of SML optimization in [Bergstra and Bengio, 2012]. This method is obviously very slow as it relies only on chance to find good configurations. It does, however, allow for a uniform exploration of the hyperparameter space.

A method based on hierarchical density estimation, and another method based on hierarchical Gaussian processes, are proposed in [Bergstra et al., 2011]. These methods are limited to the optimization of hyperparameter values from a single SML algorithm, and do not consider a systematic selection of a model. Furthermore, the work lacks a statistical analysis of the optimized hyperparameters, and does not properly consider the generalization of the selected configuration to unseen data.

The very recent approach implemented in Auto-WEKA ([Thornton et al., 2013]) does consider model selection and hyperparameter optimization simultaneously. Their work models the hyperparameter space in a hierarchical way. Auto-WEKA considers generalization as the only criterion for both optimization and model selection.

Statistical frameworks for model selection on SML are described in [Pizarro et al., 2002] and [Demšar, 2006], and some of their ideas have been implemented in the present work.

CHAPTER 3

Methodology

The specific implemented approach to find solutions for equation 2.3 is explained in detail in this chapter. Important components of the solution described here include the modeling of the hyperparameter space, how to sample from the hyperparameter space, the choice of the numerical optimization method, and the definition of the target function to optimize, among others.

The general strategy followed here is summarized in figure 3.1:

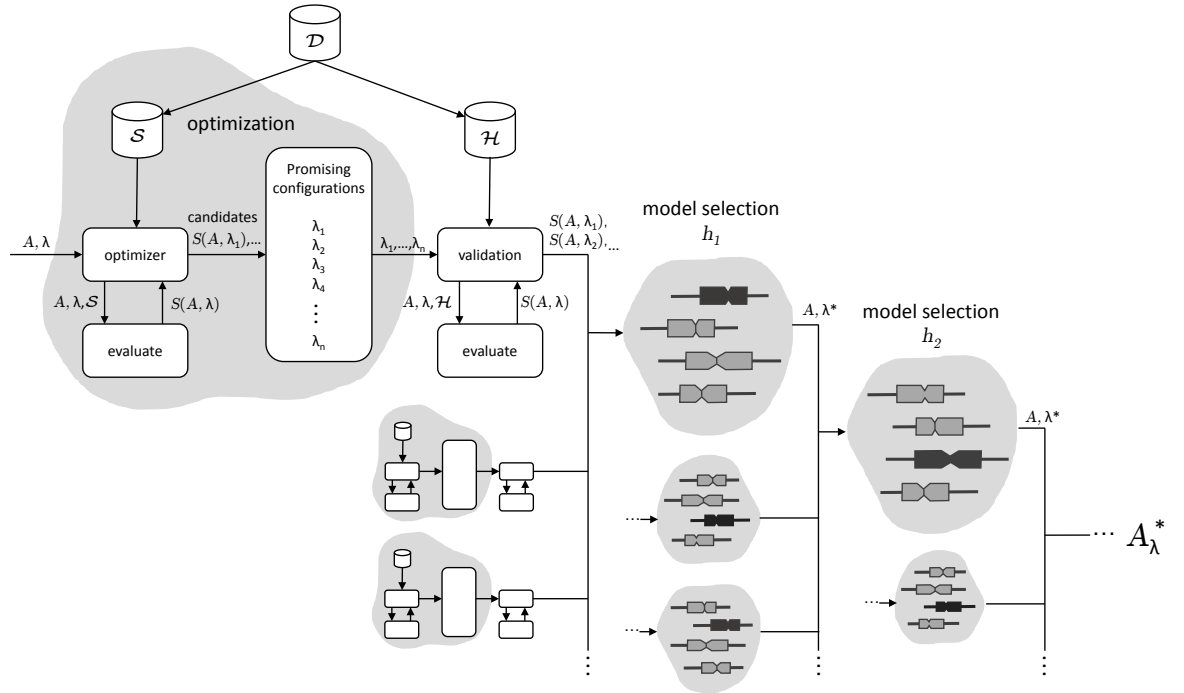


Figure 3.1: Interaction between different components of the implemented hyperparameter optimization and model selection approach.

The entire process is divided in two stages. The instances contained in the dataset \mathcal{D} are divided into two subsets \mathcal{S} and \mathcal{H} . The **hyperparameter optimization stage** explores and

evaluates a large number of models (SML algorithm under a given configuration) on the subset \mathcal{S} , in order to find the ones that exhibit the best predictive performance. The **model selection stage** analyzes the most promising models obtained from the hyperparameter optimization stage (candidates) under the subset \mathcal{H} (data unseen to the optimization process). To assess generalization, it uses that information, along with other desirable properties of the models, to systematically rule out suboptimal models and finally return the best.

3.1 Hyperparameter space modeling

Most SML algorithms contain configuration options that control different aspects of their internal behavior, which can be further adjusted to fit specific needs. For example, algorithms that make use of the distance between examples in feature space might accept a distance metric to be specified, or algorithms that internally create trees might allow the user to specify a branching factor (maximum number of branches per node), and so on. Since the configuration options control the behavior of the algorithm, they are regarded to as *hyperparameters* of the SML algorithm. The choice of hyperparameter values for a SML algorithm can heavily impact its predictive power.

Different types of hyperparameters exist. Nominal hyperparameters take values from a fixed list of categories that usually correspond to a decision of *how* the SML algorithm performs the predictions. Such **categorical hyperparameters** include, for instance, which kernel to use to compute support vectors in a support vector machine classifier, or whether to consider the distance between neighboring points or not on the prediction of a k-nearest neighbors classifier. Once all these decisions have been made, **numerical hyperparameters** control the values to use for the specific implementation of internal formulas needed for prediction, such as the number of neighbors for k-neighbors classification, or the cost parameter used by a support vector machine as a trade-off between allowing training errors and rigidly fitting the support vectors to the training set.

Other considerations such as restricting the value of a numerical hyperparameter to a fixed range (addressed here by assigning validation rules for each numerical hyperparameter), or encoding dependencies between categorical and numerical or other categorical hyperparameters (implemented here as explained in detail in subsection 3.1.2) must be taken into account when modeling the strategy to explore the hyperparameters of a SML algorithm.

3.1.1 Hyperparameter distributions

Since one of the main objectives of this work is to learn the behavior of SML algorithms under different settings, a systematic way of obtaining valid candidate configurations for performance evaluation is required. In order to achieve this, each hyperparameter is regarded as a random variable and an appropriate distribution modeling the likelihood of obtaining good performance for a given value is assigned to it.

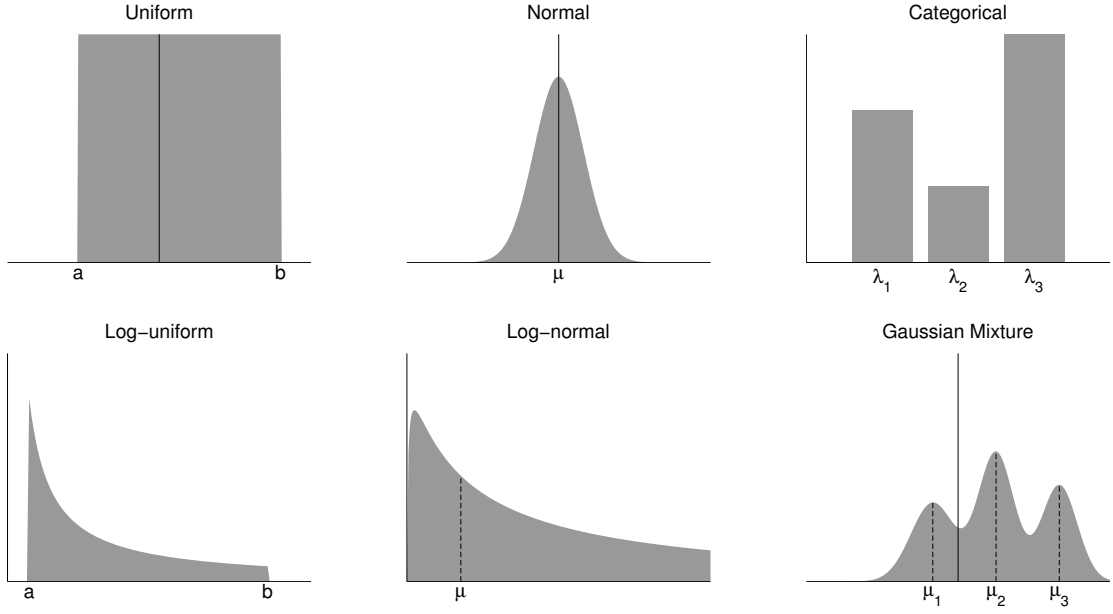


Figure 3.2: Distributions used to model hyperparameters.

A one-dimensional distribution is used to sample values for each hyperparameter independently. Section 3.1.2 describes in detail how dependencies between hyperparameters are handled. Drawing values for a hyperparameter from a distribution (other than a Uniform one) will favor some regions of the hyperparameter space over others, which can be useful when there is a good knowledge of what values for the hyperparameter produce good predictions. It is possible that the choice of specific values for the *categorical* hyperparameters affects what values for a numerical hyperparameter yield good results. Because of this, the same numerical hyperparameter is modeled with different distributions for different combinations of the categorical hyperparameters.

The choice of the distribution depends on the nature of each hyperparameter and the knowledge of the range and expected values that the hyperparameter might take. The implemented types of prior distributions, depicted in figure 3.2, are:

- **Categorical** distributions assigned to hyperparameters that can take nominal values from a list of k fixed categories, or to discrete numerical hyperparameters.

$$p(x) = p_1^{[x=1]} \cdot \dots \cdot p_k^{[x=k]}, \quad x \in \{1, \dots, k\} \quad (3.1)$$

($[x = i]$ is the *Iverson bracket*: $[P] = 1$ if statement P is true, 0 otherwise)

- **Uniform** distributions assigned to continuous numerical parameters within a bounded range $[a, b]$.

$$p(x) = \frac{1}{b-a}, \quad a \leq x \leq b \quad (3.2)$$

- **Normal** distributions assigned to continuous unbounded numerical parameters, when a specific value μ and mean variation σ is expected.

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} = \mathcal{N}(\mu, \sigma) \quad (3.3)$$

- **Log-uniform** distributions for hyperparameters that might span over different orders of magnitude.

$$p(x) = \frac{1}{x(\ln b - \ln a)} \quad (3.4)$$

- **Log-normal** distributions assigned to hyperparameters that can not have negative values, and for which a specific value and variability is expected.

$$p(x) = \frac{1}{x\sqrt{2\pi}\sigma} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} \quad (3.5)$$

- **Gaussian Mixture Models** (GMMs) are used for more complicated continuous hyperparameters that are known to be multimodal.

$$p(x) = \sum_{i=1}^N \pi_i \mathcal{N}(\mu_i, \sigma_i), \quad \sum_{i=1}^N \pi_i = 1 \quad (3.6)$$

GMMs have many parameters and thus should be used when there is solid knowledge of the shape of the hyperparameter distribution. GMMs are learned by analyzing the distribution of each hyperparameter on a large number of datasets and infer promising and harmful regions of the hyperparameter space, as explained in detail in chapter 4.

The values for the category weights, means, variances, and bounds, depend on how each specific hyperparameter is used by the SML algorithm. By default, handcrafted distributions have been designed led by interpretation of the documentation of each SML algorithm, but can be modified by the user. For instance, a hyperparameter that, according to the documentation, is used by the implementation of the SML algorithm as a relative weight, will be assigned a Uniform(0,1) distribution by default, but if the documentation suggests that values around 0.5 often yield good results, a gaussian distribution centered at 0.5 is assigned instead. The parameters for all distributions for all hyperparameters are stored as plain text in a configuration file, and can be manually edited if desired.

3.1.2 Hyperparameter hierarchy

For most SML algorithm implementations, choosing specific values for some hyperparameters may change which other hyperparameters are also used or ignored, and how they are used by the algorithm. For instance, the SVM family of algorithms can use linear, polynomial, sigmoid, or RBF kernels. If a polynomial kernel is chosen, it is possible to specify its polynomial degree;

such option has no effect when a linear kernel is used. Likewise, it is possible to specify the independent term for the polynomial and sigmoid functions used as kernels, and such value may have a different impact and different extrema depending on which kernel they operate on. The popular SVM implementation libSVM accepts a single hyperparameter `coef0` for this setting. Disregarding the duality of this hyperparameter and its dependence on the context (selected kernel in this case) when modeling and optimizing it might lead to unwanted results.

What the above example implies is that it is mandatory to consider each hyperparameter for optimization within a context given by the values of other hyperparameters (the **hyperparameter context**). We have chosen a hierarchical design, based on two observations:

1. Hyperparameter contexts can be nested. The use and semantics of a hyperparameter may depend on the value of other hyperparameters, which may in turn depend on others.
2. The hyperparameter context is always defined by a set of *categorical*, rather than numerical, hyperparameters. Since the decision of whether or not to use a hyperparameter is a discrete (boolean) value, it does not make sense to consider continuous numerical variables when defining a hyperparameter context.

A specific situation where observation 2 may be violated is when a numerical hyperparameter depends on a *rule* applied on another numerical hyperparameter, rather than on its actual value. For example, if hyperparameter *b* is only used by the SML algorithm when hyperparameter *a* adopts values within a given interval, and invalid otherwise. A *virtual* hyperparameter *b_valid* with such rule (which would be a categorical hyperparameter with categories `{True, False}`) can be added to the hyperparameter hierarchy. Hyperparameter *b* would exist in the hyperparameter context given by *b_valid=True* and would not exist in the hyperparameter context given by *b_valid=False*. Virtual hyperparameters are used only to guide the hierarchical hyperparameter sampling and validation, and should be removed from the configuration before passing it to the SML algorithm.

Following these observations, it is possible to encode the entire hyperparameter space for a SML algorithm into a tree structure that models the hierarchical dependences between sets of hyperparameters. The top nodes of the tree refer to categorical hyperparameters that do not depend on the values of others, and each category creates a new hyperparameter context (branch) under which its depending categorical hyperparameters will be represented.

The leaves of the tree correspond to the numerical hyperparameters that are valid for the deepest branching to which they belong. The branching of categorical hyperparameters corresponds to a series of decisions on what values the categorical hyperparameters take, and is referred to as the **signature** of the numerical hyperparameter context. Figure 3.3 provides an example of a hyperparameter hierarchy.

The whole model selection process can be viewed as the top level of the hyperparameter

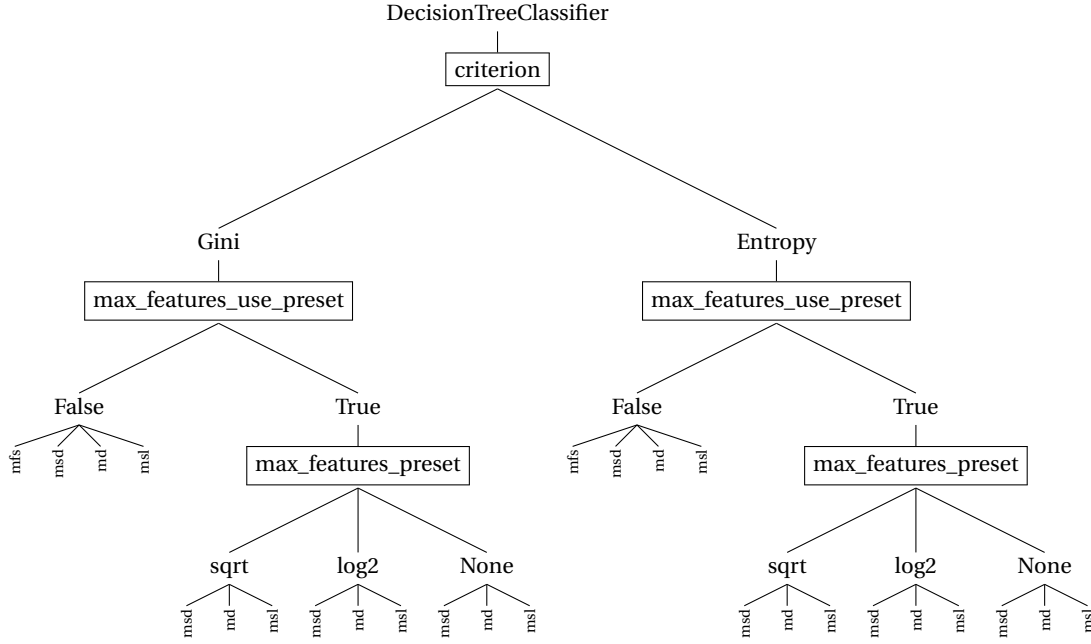


Figure 3.3: Hyperparameter hierarchy for a decision tree classifier. Numerical hyperparameters correspond to the leaves. Categorical hyperparameters (enclosed in a box) create branches for each category that they contain.

hierarchy, where the set of all SML algorithms \mathcal{A} to analyze corresponds to a categorical hyperparameter of the model selection. Each top-level branch contains the hierarchy (subtree) for all the different configurations for a specific type of algorithm (the **algorithm family**).

For simplicity, the solution has been designed under the assumption that numerical hyperparameters are independent of each other. Modeling dependences between numerical hyperparameters is outside the scope of this work, as it would require to model all the hyperparameters belonging to the same signature in the hierarchy as a single multidimensional distribution.

3.1.3 Sampling the hyperparameter space

As stated in subsection 3.1.1, a probability distribution models the parameter space of each hyperparameter, depending on their type and any prior knowledge available. These distributions are used by an optimization method to sample hyperparameter values and evaluate them.

Recall that a SML algorithm accepts a configuration $\lambda = (\lambda_a, \lambda_b, \lambda_c, \dots)$, i.e. a set of values or realizations of the hyperparameters a, b, c, \dots . Sampling the hyperparameter space means obtaining such realizations by sampling the distributions describing each hyperparameter.

Since all the information about the categorical dependencies is encoded into the tree structure, and numerical hyperparameters from the same context are assumed independent from each

other, each numerical hyperparameter is sampled independently.

Generating valid samples of the hyperparameter space of a SML algorithm reduces then to getting a valid signature (by recursively sampling the distributions of the categorical hyperparameters in the tree) and sampling each numerical hyperparameter in the context given by the signature independently. The SML algorithm under the configuration resulting from joining all these values together is the *model* to be evaluated over the data.

3.2 Model performance measurement

Once the strategy for generating models for evaluation has been established, the definition of a model performance metric is required. To measure the performance of a model means to quantify how well the prediction of it on unseen data is, and hence the quality of the labeling obtained on the prediction step of the model is the criterion to be measured.

Because the performance measurements between different algorithms must be comparable, a method that is agnostic to the algorithm should be defined. The labeling returned by the prediction step of the model can be either a single class for each instance in the prediction set, or, for some classification algorithms, a vector describing the probabilities for each instance to be assigned to a specific class.

Predictions consisting of specific classes are transformed into probability vectors with a value of 1 for the position corresponding to the assigned class, and 0 elsewhere. This step provides a consistent representation for the output of all classification algorithms. For regression, the single (possibly multidimensional) predicted value is used without further transformation.

Many metrics comparing the expected and the predicted classes exist, and different metrics allow for evaluation of different properties of the prediction. Table 3.1 summarizes some of the most widely used.

The output of these various metrics may take different ranges of values, and the interpretation of the actual values might also differ from metric to metric. As an example, the accuracy of a prediction is measured in the range between 0 and 1, and a *greater* value means a better prediction. The mean squared error is measured as a positive value, and a *lower* value means a better prediction in this case. In order to homogenize the metrics, upper and lower bounds are defined for each metric, and the relative position of the original value with respect to the bounded interval is used instead of the original value.

The upper bound is straightforward to specify, as all metrics have an ideal value that would be achieved if the prediction agrees exactly with the true classes. To define the lower bound, the values for each of the metrics are calculated by using a virtual prediction that assigns the relative frequencies of each class in the dataset as the probabilities of any instance belonging to that class (this is equivalent to weighted-randomly assigning classes to the instances). The metrics obtained by this prediction are used as a **baseline** that defines the lower bound of

Chapter 3. Methodology

Metric	Formula	Description
Accuracy	$\frac{tp + tn}{fp + fn + tp + tn}$	Ratio of correctly labeled instances
F_β score	$\frac{(1 + \beta^2)tp}{1 + \beta^2 tp + \beta^2 fn + fp}$	Weighted average of precision and recall. β is the relative importance of the recall with respect to the precision
Brier score	$\frac{1}{N} \sum_{t=1}^N \sum_{i=1}^R (p_{ti} - o_{ti})^2$	Squared difference of probabilities returned by the prediction p_{ti} and true probabilities of the labeling o_{ti} .
Matthews correlation coefficient	$\frac{tp\,tn - fp\,fn}{\sqrt{(tp + fp)(tp + fn)(tn + fn)(tn + fp)}}$	Balanced measure of true and false positives and negatives, suitable for data having classes with very different frequencies.
Coefficient of determination (R^2)	$1 - \frac{\sum_i (f_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2}$	Measure of fitness of the predictions to the expected classes.
Area under ROC curve	$\int_{-\infty}^{\infty} TPR(y)P_0(y)dy$	Probability to obtain a better score with a randomly chosen correctly-classified instance than with a randomly chosen misclassified one.
Mean absolute error	$\frac{1}{n} \sum_{i=1}^n f_i - y_i $	Absolute difference between predictions f_i and true values y_i
Mean squared error	$\frac{1}{n} \sum_{i=1}^n (f_i - y_i)^2$	Squared difference between predictions f_i and true values y_i

Table 3.1: Components of the Performance Index. tp, tn, fp, and fn correspond to the *true positive*, *true negative*, *false positive*, and *false negative* count, respectively. P_0 is the probability of an instance *not* belonging to a class.

the interval for homogenization. It is possible that some homogenized metrics lie below the baseline, when the quality of the classification is worse than the baseline.

The selected metrics are combined into a single **performance index** to be used as the target function that the optimization method will aim to maximize. The performance index S (also referred to as the **score**) is defined on a set of metrics $\mathcal{M} = \{m_1, m_2, \dots, m_z\}$ as:

$$S = \sum_{i=1}^z w_i m_i(\mathbf{y}, \hat{\mathbf{y}}), \quad \sum_{i=1}^z w_i = 1 \quad (3.7)$$

The weights w_i control the relative importance of each metric and can be tuned to suit specific needs. For instance, if it is known that none of the SML algorithms to evaluate returns probability estimates of the labeling, the Brier scores will coincide with the reported accuracy, and is therefore safe to disable it by setting its weight to zero. All metrics are weighted uniformly by default.

By default, the performance index used here combines the accuracy, the F_β score, the Brier score, and the Matthews correlation coefficient. These metrics have some properties that make them suitable for a wide range of situations. The accuracy offers a very intuitive evaluation of the quality of the prediction. The F_β score allows for tuning of the relative importance of the recall with respect to the precision, which might be useful depending on the needs of the user. The Brier score takes the probability estimates into account and therefore deals with ambiguity in the classification in a more fair way. The Matthews correlation coefficient is a balanced metric suitable for classes with very different relative frequency.

While encoding metrics into a one-dimensional performance index may hide important details of the individual metrics, and yields values that are not straightforward to interpret, it is much more convenient to use it to represent the overall performance than dealing with a multidimensional score directly. The performance index described is thus the chosen approach for defining the optimization target function.

3.3 Model validation

Using a model validation protocol is important because it reduces the risk of overfitting a model to the particularities of the training set, and hence is a first step to promote generalization of the model to unseen data. The performance index calculated by equation 3.7 maps each model to a single numerical value that represents its ability to correctly predict classes on a specific set of training and testing instances. In order to assess the predictive quality of the model in a more general setup, repeated rounds of *stratified k-fold cross-validation* are carried out.

Each *repetition* corresponds to a different random shuffling of the data. The k -fold cross-validation splits the data into k equally-sized portions (or folds), and uses one fold at a time for prediction (and the remaining $k - 1$ folds for training the model). *Stratified* cross-validation means here that the folds are enforced to all have the same proportion of examples for each class.

In most applications, a single repetition of 10-fold cross-validation is used, the scores obtained for each fold are averaged out and used as a single score. This means that, for each fold, the model is trained with 90% of the data and tested against the remaining 10%. The analysis by Kohavi ([Kohavi et al., 1995]) justifies the choice of $k = 10$ as the smallest number of folds with "acceptable" bias. The actual number of repetitions and folds used in this work is exposed as a parameter that can be customized at will.

For the optimization stage, the standard 10-fold cross-validation is used by default. For the model selection stage, since a more limited number of candidate configurations will be evaluated, and because a statistical analysis is to be performed on the distribution of results, a larger number of evaluations for each model can and should be obtained. Normality of the distribution of scores is assumed. Performing 3 repetitions of 10-fold cross-validation is suggested, to comply with the rule of thumb (derived from the central limit theorem) of using a sample size of at least 30 samples to estimate a normal distribution.

3.4 Optimization

The optimization stage retrieves configurations, evaluates their performance, and uses the performance measurements to guide the retrieval of new configurations towards regions of the hyperparameter space expected to show predictive improvement.

Since the aim of this work is to provide the framework for hyperparameter optimization and model selection, rather than to study different optimization techniques, only a couple of optimization methods have been implemented. More sophisticated optimization methods such as simulated annealing and genetic algorithms could also be used. The framework described here assumes only that the optimization method returns candidate configurations, and can be fed with their evaluation results in order to train itself if needed.

The optimization methods work on the numerical dimensions of the hyperparameter space only. This is particularly convenient because most current optimization methods are not capable of handling hierarchical, conditional and categorical spaces. Since the proposed strategy does not impose any further restrictions or special handling of the non-numerical dimensions, there is no need for specially designed optimization methods.

The optimization stage is restricted by a fixed time budget, shared across all the SML algorithms.

3.4.1 Random search

The easiest way to generate candidate configurations is to simply draw values at random for each hyperparameter.

The considerations stated in subsection [3.1.3](#) must be respected, namely the hyperparameter sampling must start from the root of the hyperparameter hierarchy, obtain a realization of the top-level hyperparameter (randomly in this case), and use its value to decide what other hyperparameters to sample. The categorical and numerical values retrieved are the components of the configuration.

Random search does not need to keep track of the evaluated model history or the retrieved scores, since every draw of hyperparameter values is independent of all the previous ones. As

a consequence, random search is a very slow and expensive optimization method. Random search is, however, useful when a more thorough exploration of the hyperparameter space is required, as it gives any possible configuration the same chance to be drawn.

A very important application of random search is presented in chapter 4, where it is used as a meta-optimizer for inferring hyperparameter distributions to train a parametric density estimation optimizer.

3.4.2 Shrinking hypercube

Unlike the random search, the shrinking hypercube method described in [Gonnet et al., 2010] does make use of the scores returned by previous optimization rounds to guide the search to a local maximum.

The shrinking hypercube algorithm works by defining a region of the multidimensional parameter space for exploration, delimited by a hypercube centered about the configuration that produces the best result of all the tested configurations. The hypercube will shrink when no improvement is found, to localize the search, and expanded when a new best is found, to stimulate exploration.

The pseudocode of the shrinking hypercube approach is presented in algorithm 1

Algorithm 1 Shrinking hypercube optimization

```

Sample and evaluate a random point from the numerical hyperparameter space.
Define a hypercube of arbitrary length centered about the sampled point.
while the size of the hypercube is larger than a threshold do
    Sample and evaluate another point randomly from within the hypercube.
    if the evaluation of the new point is better than the previous point then
        Duplicate the length of the hypercube on all dimensions.
        Center the hypercube about the new point.
    else
        Reduce the length of the hypercube on all dimensions by a small factor.
        Keep the hypercube centered about the current best point.
    end if
end while

```

Duplicating the length of the hypercube on each dimension favors exploration of the hyperparameter space since new configurations arbitrarily far from the current best can be reached. Shrinking the hypercube slowly when no improvement is achieved helps localize the search for a local maximum around the current best configuration while not significantly restricting the exploration.

The implementation used in this work considers each numerical hyperparameter space (each leaf in the hyperparameter tree) as a single, independent hypercube, and finds local maxima for each one independently. When the hypercubes are shrunk below a threshold, they are

reset to a different starting point and default hypercube side length. Multiple hypercubes can also be used in parallel with different starting points and side lengths for a better coverage of the hyperparameter space.

3.4.3 Parametric density optimization

A simple optimization approach that makes use of clues about generally high and low-scoring regions in the hyperparameter space is presented in detail in chapter 4.

The distributions for all hyperparameters are estimated automatically, by running the optimization process on a large set of standard datasets using random search to explore the hyperparameter space. The results of all the datasets are used to fit Gaussian mixtures that encode the high and low-scoring regions for each hyperparameter. The Gaussian mixtures returned by this process will replace the default distributions that represent each hyperparameter.

3.5 Model evaluation and selection

The optimization stage explores the hyperparameter space and finds candidate configurations that return a high performance index when evaluated on the *optimization data set*. The selected model will be chosen from one of such candidates according to their predictive performances on a *hold out dataset*, and other desirable criteria.

A very large number of candidate configurations might be proposed by the optimization process, and hence a strategy to efficiently discard or promote configurations must be designed. The tree structure chosen to represent the hyperparameters of a SML algorithm can be exploited to this end.

The chosen strategy analyzes the local optima found by the optimization process on the leaves of the hyperparameter tree (which only contain numerical hyperparameters), selects the ones that are significantly better, evaluates them and ranks them according to other desirable properties to narrow down the model selection even further. When a handful of very good models are selected at the numerical level, they are used to represent their branching in the tree at the deepest categorical level, and compete with representative models of the other categories in the exact same way. The selected models among all categories are promoted upwards to represent the category one level higher in the hyperparameter tree. The process is repeated until the root branching of the tree is reached, i.e., when models from different SML algorithms are compared. A schematic of the process is shown in figure 3.4.

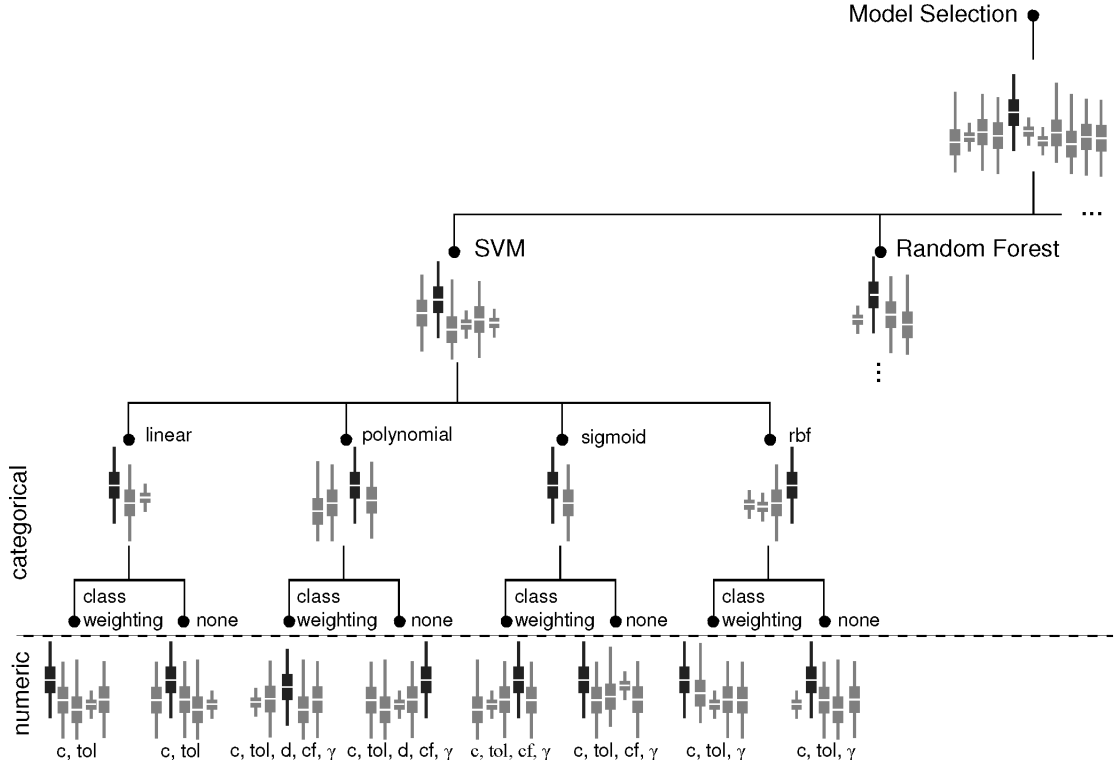


Figure 3.4: Hierarchical model selection. Each box plot represents the distribution of scores for a specific model. Distributions shown in black are promoted upwards to subsequently compete against models from the same local hierarchy.

3.5.1 Candidate model filtering

The optimization stage will mostly retrieve models with good scores because optimization techniques try to find local optima. As a consequence, they might end up testing a large number of configurations close to each optimum. This means that the distribution of hyperparameter values sampled and evaluated by the optimization stage will tend to have more density around the different local maxima found. A clustering approach is used to remove redundant configurations and only retrieve high-scoring configurations from different local maxima. This avoids overrepresentation of configurations from a single hill in the score landscape and returns a small number of configurations that represent the regions that yield good scores more homogeneously.

We apply clustering on the evaluated configurations with the *k-means* algorithm to retrieve *k* clusters of configurations, and choose the configuration with the highest score from each cluster as one of the candidate configurations that will represent a specific numerical hyperparameter space. The number of means has been arbitrarily chosen to $k = 10$ by default but can be modified via a parameter setting if needed.

3.5.2 Statistical analysis

Given a set of models, the distribution of their scores on different samples drawn from the hold out dataset is studied to determine which model offers enough evidence to be considered the best one.

The hierarchical structure of the hyperparameter space groups models that share the same signature together, at different levels. A statistical analysis is performed at all levels of the hyperparameter space, starting from the configurations that differ only on their numerical hyperparameters, and promoting good models to be compared to others at the immediately broader level of aggregation (the category immediately above in the tree) repeatedly up to the highest level in the hierarchy.

The aim of the statistical analysis in the context of this work is to compare the distributions of performance indices for all candidate models with respect to the highest-scoring one, and discard all the candidate models with strong statistical evidence that they perform worse. The models kept are **statistically indistinguishable** from the best one. The overall procedure is based on [Pizarro et al., 2002] and [Demšar, 2006] for significance testing.

Each model is used for prediction on the hold out dataset several times by using m repetitions of k -fold cross-validation ($m = 3$, $k = 10$ by default). A multiple comparison statistical test (MCT) is applied on the distributions of $m \cdot k$ scores obtained for each model.

Parametric MCTs make use of direct measurements of the data (such as the mean and variance), whereas non-parametric MCTs rely on comparisons of other properties of the data (e.g. the ranking of the groups according to some criteria) which makes them more general and applicable to a wider range of distributions, at the expense of statistical power [Sheskin, 2003]. Parametric comparison tests are more statistically powerful and are thus preferred over non-parametric alternatives. Parametric tests, however, are only valid under certain specific conditions, and when such conditions are not met, non-parametric comparison tests must be used instead.

The MCTs determine, up to a certain probability α , whether there are significant differences between a group of distributions or not, but do not tell the actual distributions that show differences. A *post-hoc* test is required in order to find which distributions differ. Both parametric and non-parametric post-hoc tests exist.

The chosen *parametric* MCT is the **one-way ANOVA test** [Fisher, 1925], which is a generalization of the t -test that corrects for accumulated errors when performing comparisons between more than two distributions, by comparing a statistic against a F -distribution that considers the specific number of distributions to compare as a parameter.

The one-way ANOVA test can be used when:

1. The observations for all the distributions are independent.

2. The distributions are approximately normal. This is tested by applying the **Kolmogorov-Smirnov test** (K-S test, validates that a sample comes from a given distribution) on the sample (after standardization) against a standard normal distribution $\mathcal{N}(0, 1)$
3. The distributions have homogeneous variances (homoscedasticity). This is tested by applying the **Bartlett's test** [Bartlett, 1937] on the different distributions of scores.

As stated above, a post-hoc test is required when the ANOVA test determines that there are significant differences between groups of scores. The **Tukey's honest significance test** compares simultaneously all the groups of scores and informs what groups are significantly different. The Tukey's test is then used to find the sets of performance indices that are not significantly different from the the highest-scoring one. Here it is assumed safe to discard models that do not pass the Tukey's test, and keep the rest for further analysis.

When the conditions to apply the parametric MCT are not met, the **Kruskal-Wallis test** is applied instead to decide if significant differences exist, and the **Nemenyi test** is used as the post-hoc test to find the actual significantly different groups in the same way as for the parametric case.

All the statistical tests make use of a critical value to reject hypotheses with a level of certainty α . The choice of α for model selection affects what models are deemed statistically indistinguishable from the best. A larger α will generally reject more models than a smaller one. Since most of the models to compare may be very similar at the family level, it is left up to the user to decide what α values to use, to manually control the number of significantly indistinguishable models to select.

3.5.3 Ranking criteria

The statistical analysis reduces the number of candidate models to those that statistically perform as good as the best, according to their performance indices. Other criteria are evaluated on the selected models in order to compare them and decide which one is the best.

The criteria used here are described in table 3.2. Each criterion is evaluated for each candidate model, and used for ranking them. Fractional rankings (to account for ties) are weighted by a user-defined relative importance value and combined into a compound ranking. The top model according to this compound ranking is selected.

The statistical test applied to the model scores compares the mean and spread of the scores obtained by a single model against all other candidate models. The test is summarized in Algorithm 2.

It is worth noticing that the proportion of data to be used for optimization and for model selection is defined by the user (a default of 50% of the data for optimization and 50% for model selection is suggested). When dealing with small datasets, the choice of this ratio will

Algorithm 2 Statistical analysis and multiple comparison procedure

Input $\mathcal{A} = \{A^1, \dots, A^k\}$ a list of algorithms
 $\{\mathbf{s}_{A^1}, \dots, \mathbf{s}_{A^k}\}$ corresponding sets of c.v. test score records
 α the desired significance level

Output $\mathcal{A}^r = (A_{\lambda^*}^*, A_{\lambda^*}^{r_2}, \dots, A_{\lambda^*}^{r_k})$ a ranked list of optimized algorithms from \mathcal{A}
 $\bar{\mathbf{s}} = (\bar{s}^*, \bar{s}^{r_2}, \dots, \bar{s}^{r_k})$ sorted c.v. performance scores
 $\mathbf{g} = (g^*, g^{r_2}, \dots, g^{r_k})$ sorted generalization scores
 $\mathbf{p} = (\cdot, p^{r_2}, \dots, p^{r_k})$ significance (p -values) between $A_{\lambda^*}^*$ and others
 $\mathbf{t} = (t^*, t^{r_2}, \dots, t^{r_k})$ sorted model simplicity estimates (time)
 $\boldsymbol{\rho} = (\rho^*, \rho^{r_2}, \dots, \rho^{r_k})$ sorted overfitting risk estimates

```

1: function MULTICOMP( $\{A^1, \dots, A^k\}, \{s_{A^1}, \dots, s_{A^k}\}, \alpha$ )
2:   for every  $A^i \in \mathcal{A}$  do
3:      $\mathbf{s}'_{A^i} \leftarrow \text{cluster}(s_{A_1^i}, s_{A_2^i}, \dots, s_{A_m^i})$  ▷ Remove very similar configurations.
4:      $\{\bar{s}_{A_1^i}, \dots, \bar{s}_{A_m^i}\} \leftarrow \text{compute means for scores in } \mathbf{s}_{A^i}$ 
5:   end for
6:    $\mathcal{S} \leftarrow \{\mathbf{s}'_{A^1}, \dots, \mathbf{s}'_{A^k}\}$  ▷ Collect all score sets into  $\mathcal{S}$ .
7:    $A_{\lambda}^{(*)} \leftarrow A_{\lambda} \mid \bar{s}_{A_{\lambda}^i} = \max(\bar{s}_{A_1^1}, \dots, \bar{s}_{A_m^1}, \dots, \bar{s}_{A_1^k}, \dots, \bar{s}_{A_m^k})$  ▷  $A_{\lambda}$  with highest mean.
8:    $D \leftarrow \text{normality}(\mathcal{S}, \alpha)$ 
9:    $T \leftarrow \text{homoscedasticity}(\mathcal{S}, \alpha)$ 
10:  if  $Tq \geq \chi_{1-\alpha, k-1}^2$  and  $D \geq D_{1-\alpha, n}^*$  use Analysis of variance (ANOVA) then
11:     $F_{\text{value}} \leftarrow \text{ANOVA}(\mathcal{S})$ 
12:    if  $F_{\text{value}} \geq F_{\alpha, k-1, N-k}$ , significant differences exist then
13:      for every  $A^i \in \mathcal{A} \setminus A_{\lambda}^{(*)}$  do
14:         $p = \text{Tukey}(A_{\lambda}^i, A_{\lambda}^{(*)})$ 
15:      end for
16:    end if
17:  else use Kruskal-Wallis H-test
18:     $K \leftarrow \text{Kruskal-Wallis}(\mathcal{S})$ 
19:    if  $K \geq \chi_{1-\alpha, k-1}^2$ , significant differences exist then
20:      for every  $A^i \in \mathcal{A} \setminus A_{\lambda}^{(*)}$  do
21:         $p = \text{Nemenyi}(A_{\lambda}^i, A_{\lambda}^{(*)})$  ▷ Probability  $\bar{s}_{A_{\lambda}^i}$  and  $\bar{s}_{A_{\lambda}^{(*)}}$  from same distribution.
22:      end for
23:    end if
24:  end if
25:   $(r_*, r_2, \dots, r_k) \leftarrow \text{rank combinations of } A \text{ and } \lambda \text{ by } \bar{s}, t, \rho$ 
26: end function

```

Criterion	Description
Generalization	Average score of the model on the hold out dataset. Models with greater values are preferred.
Speed	Average measured runtime on the hold out dataset. Models with lower values are preferred.
Stability	Measure of variability of the scores for a model (standard deviation). Models with lower values are preferred.
Simplicity	Measures the complexity of the model. Models with less terms or lower dimensionality are preferred.
Interpretability	Measures how easily the model can be understood by a human. Higher values are preferred.

Table 3.2: Alternative ranking criteria for statistically indistinguishable from the best. The values for Simplicity and Interpretability are subjective: each SML family and category are assigned predetermined values which can be modified by the user.

affect the reliability of both optimization and model selection results. Alternative approaches such as bootstrapping, or overlapping of the optimization set and the model selection set may be helpful to some extent, but should be used cautiously.

Making use of the tree structure for model selection not only provides a very efficient way to discriminate between model performances, but also has the advantage that it compares models with similar characteristics, and selects a small but representative subset of the models to compete against other sets of models.

3.5.4 The model selection algorithm

The process described above can be summarized as shown in algorithm 3

Algorithm 3 Model selection algorithm

```

function SELECT_MODELS(hyperparameter_tree, top_n,  $\alpha$ , k)
  candidates  $\leftarrow \emptyset$ 
  if hyperparameter_tree is numerical then
    candidates  $\leftarrow$  GET_ $k$ -MEANS(hyperparameter_tree, k)
  else
    for category in hyperparameter_tree do
      candidates  $\leftarrow$  candidates  $\cup$  SELECT_MODELS(category, top_n,  $\alpha$ , k)
    end for
  end if
  candidates  $\leftarrow$  FIND_SCOREWISE_EQUIVALENTS(candidates,  $\alpha$ )
  candidates  $\leftarrow$  GET_TOP_ $n$ (candidates, ranking_criteria, top_n)
  return candidates
end function

```

The function obtains the best models at each level of the hyperparameter hierarchy, by recursively filtering and selecting the best models from the lower branches of the hierarchy and

passing them to the level immediately above. At the top level, the ranked list of best models will be reported as the result of the model selection stage.

3.6 Implementation details

The actual implementation of all the components described in this chapter was developed as a program that reads datasets from different text formats, and applies a set of different SML algorithms on the read data.

The program is implemented in python 2.7.5, and it makes use of the SML algorithms implemented in the scikit-learn library [[Pedregosa et al., 2011](#)]. Most of the numerical handling and statistical tests uses the implementations available in the numpy and scipy libraries [[Jones et al., 2001](#)], and the matplotlib library [[Hunter, 2007](#)] is used for visualization of the results.

Parallelization of the execution is supported, and has been tested on the Amazon EC2 cloud computing platform, and LSF clusters such as the Brutus Cluster.

CHAPTER 4

Hyperparameter distribution learning

Applying a SML algorithm on different sets of data usually requires that the hyperparameters adopt different values to achieve the best performance. However, there are certain ranges of values that are harmful in all but some pathological cases, and likewise, some regions of the hyperparameter space produce configurations that consistently perform well when applied on different types of data, and hence are worth trying when searching for good models.

This suggests that it might be helpful to guide the hyperparameter optimization by making use of some description of the hyperparameter space that gives hints about what values a given hyperparameter should and should not take. Starting the sampling of hyperparameter values from a hyperparameter-specific **general prior distribution** that has high density around regions of the hyperparameter space known to perform well, and low or no density around regions known to harm the prediction of the SML algorithm, will help the optimization process to discover more quickly where the local optima might be, and what regions of the hyperparameter space it is safe to avoid.

The implemented approach evaluates a large number of configurations on a group of datasets with different properties, and uses the performance indices obtained to learn the general prior distribution for each numerical hyperparameter individually. Using a large number of datasets reduces the risk of overfitting the general prior learned to particularities in the evaluation of a single dataset.

Parametric vs non-parametric modeling of the general prior distribution

Due to the large number of configurations and dimensions to test, a compact representation of the general prior distributions is preferred. Estimation of parametric distributions is convenient because it allows for this compactness and because usually closed-form solutions for maximum likelihood fitting of their parameters exist.

Non-parametric techniques to estimate the general prior distribution, like Kernel Density Estimation [Rosenblatt et al., 1956], [Parzen et al., 1962] keep too much information in memory, are cumbersome to encode and store for later use, and depend on heuristics and rules

of thumb to decide parameter values such as the kernel bandwidth, and are therefore not suitable for the automatic approach presented in this work.

4.1 Learning the general prior distribution

The chosen representation for the general prior distribution is a Gaussian Mixture Model, which is convenient for encoding multimodal distributions and to which it is not very expensive to fit data. Since the true probability of a hyperparameter value being the optimal is not known, the performance index of models containing such values is used as a surrogate for the estimation of this probability, as it measures the quality of the prediction. The implementation of the learning process is a Monte Carlo method that accepts or rejects values of the hyperparameters according to their performance indices, summarized in Algorithm 4.

Algorithm 4 General prior distribution learning

```
function LEARN_GENERAL_PRIOR(training_datasets, threshold)
    general_prior  $\leftarrow$  initial GMM
    for dataset  $D$  in training_datasets do
        while convergence criterion not met do
            Sample a value  $\lambda$  for the hyperparameter from a uniform distribution
            score  $\leftarrow$  performance_index( $\lambda, D$ )
            if random(0, 1)  $\leq$  score then
                COMBINE(general_prior,  $\lambda$ )
                SIMPLIFY(general_prior, threshold)
            end if
        end while
    end for
    return general_prior
end function
```

The algorithm evaluates at each iteration if a more complex GMM (more Gaussian components) fits the data significantly better than the current GMM. In order to find a trade-off between the GMM complexity and predictive power, the proposed idea is to measure the *fidelity* of the mixture model (i.e. a quantitative estimate of its ability to describe the associated data, as described in [Declercq and Piater, 2007, Declercq and Piater, 2008] for the *uncertain Gaussian model*), and to define a fidelity threshold below which a mixture model is considered overly simplistic. Mixture models are updated upon arrival of new observations and simplified if the above condition holds.

Learned model update

Everytime a hyperparameter value is sampled and evaluated, its evaluation is added as a new component to the mixture model, by trivially combining the existing distributions with the new one.

If at any given point in time t the mixture model is expressed as a set of N weighted Gaussian distributions:

$$p^{(t)}(x) = \frac{\sum_{i=1}^N \pi_i^{(t)} g(x; \mu_i^{(t)}, \sigma_i^{(t)})}{\sum_{i=1}^N \pi_i^{(t)}} \quad (4.1)$$

Then the new mixture model for $t + 1$ is given by:

$$p^{(t+1)}(x) = \frac{\left(\sum_{i=1}^N \pi_i^{(t)} g(x; \mu_i^{(t)}, \sigma_i^{(t)}) \right) + \pi^{(t+1)} g(x; \mu^{(t+1)}, \sigma^{(t+1)})}{\left(\sum_{i=1}^N \pi_i^{(t)} \right) + \pi^{(t+1)}} \quad (4.2)$$

Learned model simplification

Adding new components to the GMM everytime a new observation arrives hinders all the advantages of using parametric estimation. If possible, merging similar components of the GMM into one should be done, in order to simplify the mixture model.

As proposed in [Declercq and Piater, 2008], two Gaussian distributions (two components of the GMM in this case) can be merged without significant loss of predictive power if the merged distribution has a *fidelity* λ close to 1, otherwise, both components must be kept to properly describe the distribution of the data.

The distance between the distribution to test, and the data to which it should fit, is given by:

$$D = \frac{1}{|I|} \int_I |\hat{F}(x) - F_n(x)| dx \quad (4.3)$$

Declercq and Piater assume such distances as Gaussian distributed, and define the *fidelity* λ as:

$$\lambda = e^{\frac{-D^2}{T_D^2}} \quad (4.4)$$

With T_D^2 a parameter that controls how much deviation from the observations is allowed and hence how relaxed the computation is about considering the merged Gaussian as an acceptable representation of the two merged components.

Two Gaussian components G_i and G_j can be merged into one by applying the following procedure:

$$\pi = \pi_i + \pi_j \quad (4.5)$$

$$\mu = \frac{1}{\pi} (\pi_i \mu_i + \pi_j \mu_j) \quad (4.6)$$

$$\sigma = \frac{\pi_i}{\pi} (\sigma_i + (\mu_i - \mu)^2) + \frac{\pi_j}{\pi} (\sigma_j + (\mu_j - \mu)^2) \quad (4.7)$$

$$G(x) = \mathcal{N}(\mu, \sigma) \quad (4.8)$$

4.2 Using the general prior for hyperparameter optimization

The distribution returned by Algorithm 4 is a rough description of the quality of the hyperparameter in different regions of the hyperparameter space. It can be used as a prior distribution for sampling candidate hyperparameter values to evaluate on a specific dataset.

Since the general prior contains hints of where, in general, high and low-scoring regions of the hyperparameter space are, but is not guaranteed to fit the true distribution of scores for the specific data set, further exploration of other regions of the hyperparameter space not favored by the general prior might be necessary.

The ideal case would be that the general prior already fits the true underlying distribution of scores for the specific dataset, in which case it would suffice to sample values from the general prior, and assume that high-scoring values will be retrieved often. As this is seldom the case, the implementation continuously assesses the goodness of fit of the evaluations to the general prior, and starts to draw samples from an alternative uniform distribution when the fitting to the general prior drops below a threshold.

CHAPTER 5

Evaluation of results

The hyperparameter optimization and model selection process was run on a number of datasets that include 29 standard datasets commonly used in the machine learning community, and 8 datasets taken from biological experiments. The performance of the SML algorithms under default settings was also computed for each dataset.

The SML algorithms applied on the datasets were:

PassiveAggressive	RadiusNeighbors	GaussianNB
ExtraTreeEnsemble	SVM	LinearDiscriminant
KNN	RandomForest	StochasticGradientDescent
LogisticRegression	NearestCentroid	LinearSVM
NuSVM	DecisionTree	Ridge
QuadraticDiscriminant	GradientBoosting	

The optimization stage for each of the datasets was run during 8 hours as distributed tasks on the Brutus Cluster.

A comparison between the performance indices obtained by using default and optimized hyperparameters is show in table [5.1](#).

In general, the performance indices of the optimized models are significantly higher than the performance indices under the default configurations. A few datasets did not show improvement over the default settings. In these cases, the best classification performance was obtained by using the LinearDiscriminant classifier, which does not expose any hyperparameters to configure.

The table shows that the SML algorithm that performs best and improvement over the default settings strictly depends on the dataset.

Standard ML datasets	default		Optimized		
	Worst	Best	Score	Boost	Family
balance-scale	0.0961	0.7452	0.8385	12.52%	LinearSVM
blood-transfusion	0.0553	0.2760	0.3307	19.80%	NearestCentroid
cmc	-0.0607	0.1995	0.2458	23.23%	KNN
dermatology	0.3414	0.9292	0.9378	0.93%	LinearSVM
diabetes	-0.0582	0.4449	0.4454	0.11%	Ridge
haberman	-0.0599	0.1523	0.2746	80.37%	LinearSVM
heart-statlog	-0.0300	0.6894	0.7036	2.05%	Ridge
ionosphere	0.5490	0.7839	0.8373	6.82%	GradientBoosting
iris	0.4250	0.9696	0.9841	1.50%	KNN
kdd_synthetic_control	0.0210	0.9987	1.0000	0.13%	KNN
letter	0.0920	0.8851	0.8851	0.00%	KNN
liver-disorders	-0.1600	0.3198	0.3333	4.25%	Ridge
mfeat-factors	-0.0002	0.9700	0.9700	0.00%	LinearDiscriminant
mfeat-fourier	0.0700	0.8143	0.8154	0.14%	KNN
mfeat-karhunen	0.4696	0.9431	0.9544	1.20%	KNN
mfeat-morphological	-0.0230	0.6719	0.6719	0.00%	LinearDiscriminant
mfeat-pixel	0.6710	0.9522	0.9570	0.51%	KNN
mfeat-zernike	-0.0000	0.7994	0.7994	0.00%	LinearDiscriminant
optdigits	0.1663	0.9743	0.9803	0.61%	QuadraticDiscriminant
page-blocks	-1.8119	0.7864	0.7992	1.64%	GradientBoosting
pendigits	0.0063	0.9825	0.9877	0.53%	KNN
segment-test	0.0180	0.9073	0.9152	0.87%	GradientBoosting
sonar	-0.0775	0.5563	0.5890	5.88%	LinearSVM
spambase	0.0444	0.7786	0.8613	10.63%	GradientBoosting
tae	-0.0165	0.3070	0.3385	10.28%	LinearSVM
vehicle	-0.0484	0.6952	0.6978	0.37%	QuadraticDiscriminant
vowel	0.1243	0.6708	0.8250	22.98%	KNN
waveform-5000	0.4915	0.7971	0.8025	0.68%	Ridge
wine	-0.1486	0.9544	0.9544	0.01%	Ridge
Biological datasets					
HK2_Standardized	0.5895	0.8060	0.8060	0.00%	LinearSVM
Huotari500_Standardized	0.2347	0.5238	0.5867	12.01%	LinearSVM
Meier500_Standardized	0.0499	0.8692	0.8748	0.66%	GradientBoosting
so	-0.0444	0.8745	0.8987	2.77%	LinearSVM
WildMain500_Standardized	0.3048	0.8020	0.8269	3.11%	LinearSVM
yeast	0.0006	0.3758	0.4093	8.90%	KNN
colonTumor	0.2198	0.7760	0.8540	10.05%	Ridge

Table 5.1: Comparison of optimized and default performance indices for all datasets.

5.1 Results on standard Machine Learning datasets

Standard datasets are commonly used for testing and evaluating machine learning approaches. Some of the datasets used here are inherently difficult to classify, and hence most SML algo-

rithms consistently obtain a very low performance index; other datasets are simple to classify and hence good performance indices are expected. Since good predictions may also be obtained by using the default values, little relative improvement (of the best model over the default values) is also expected.

Figure 5.1 shows an example of the distribution of performance indices for different models, and their shift with respect to the performance indices obtained by the default models, for a specific standard dataset. Each row in the plot corresponds to a different algorithm under the default and optimized settings (thin and thick boxplots, respectively). Distributions that are not significantly different from the best, up to a confidence level α shown on the title of the plot, are highlighted in blue. The p-values reported by the statistical test are displayed on the right side of the plot. Models with p-values above the α level are considered statistically indistinguishable from one another.

The baseline is shown as a vertical dotted line. It is possible for some models to score lower than the baseline, as explained in section 3.2. In cases where algorithms do not work at all on a given dataset, their performance indices are reported as a single point over the baseline.

5.2 Results on biological data

Similar results are obtained when the method is applied on biological datasets. Figure 5.2 shows the distribution of performance indices for different SML algorithms applied on a small dataset (62 instances), and a larger dataset (500 instances). A large spread of the scores is due precisely to the dataset size, as can be immediately noticed when comparing both plots. The variance of the candidate models is in general smaller than the variance of the performance indices from the default configuration. In particular, the models statistically indistinguishable from the best exhibit a smaller variance than the rest, since the stability of the performance index is one of the criteria considered for model selection.

5.3 General prior learning

The 29 standard machine learning datasets were used to learn general priors for all numerical hyperparameters on all SML algorithms, as explained in 4.1.

The learned distributions present more density in the regions of the hyperparameter space that consistently produce good results over different datasets. In many cases there is no clear agreement on the regions where useful values of the hyperparameter lay, and hence the learned distribution assigns relatively similar density to the whole hyperparameter domain. Using such a learned prior is roughly equivalent to using a uniform distribution.

Since different combinations of categorical variables define different contexts that might change the semantics of the numerical hyperparameter, general prior distributions are learned

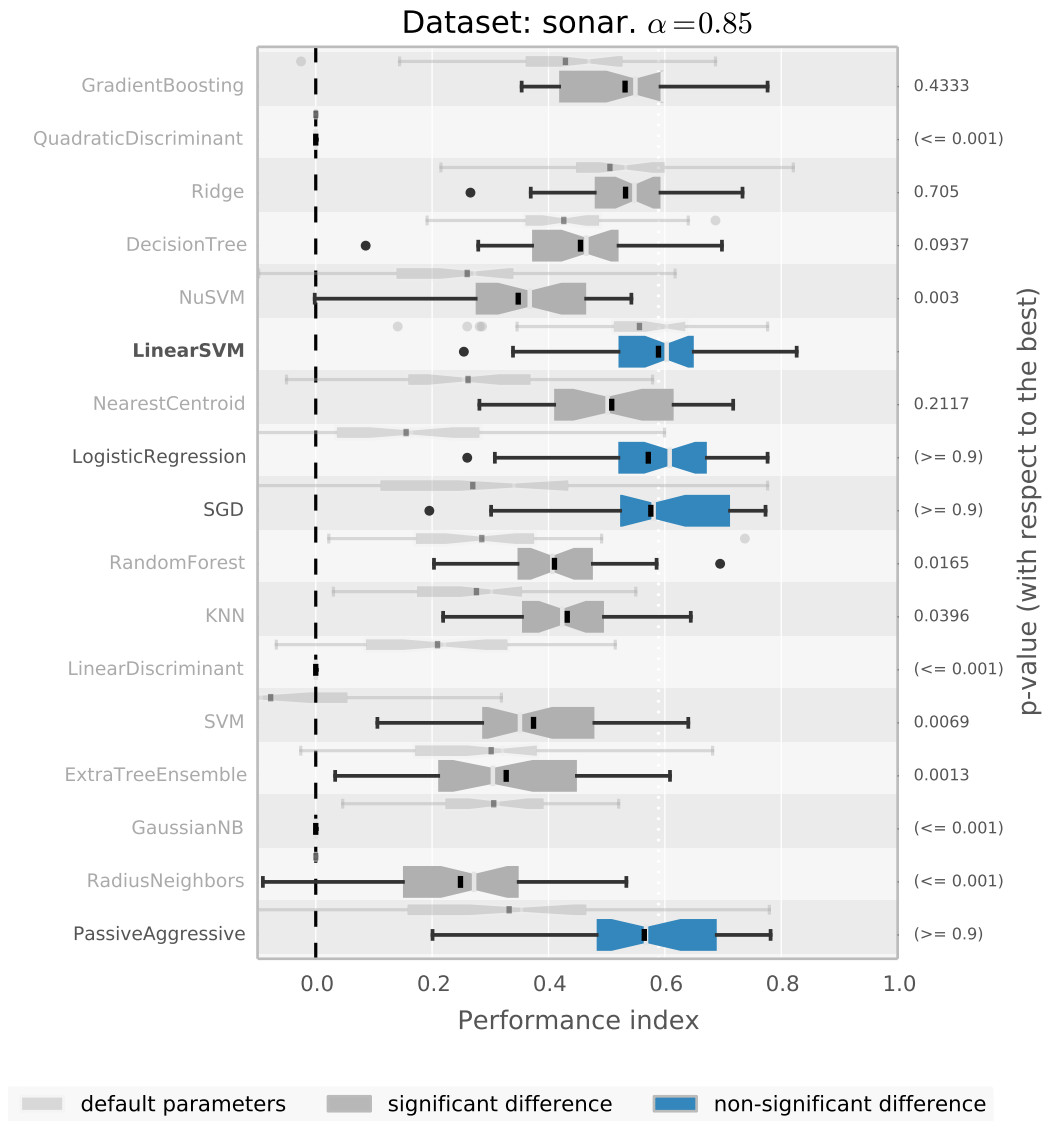


Figure 5.1: Optimized vs default values for a standard machine learning dataset

independently for each categorical context.

As an example, we present the learned distributions of the hyperparameter γ for two different kernels used by a support vector machine classifier. Plots of the learned distributions are shown in Figure 5.3

As evidenced in the plots, some categorical hyperparameters may or may not influence the distribution of the numerical hyperparameters. The value of the *shrinking* hyperparameter in this case does not significantly alter the distribution of γ .

The distributions learned by analyzing the values of γ for a *polynomial* kernel, shown in the

5.3. General prior learning

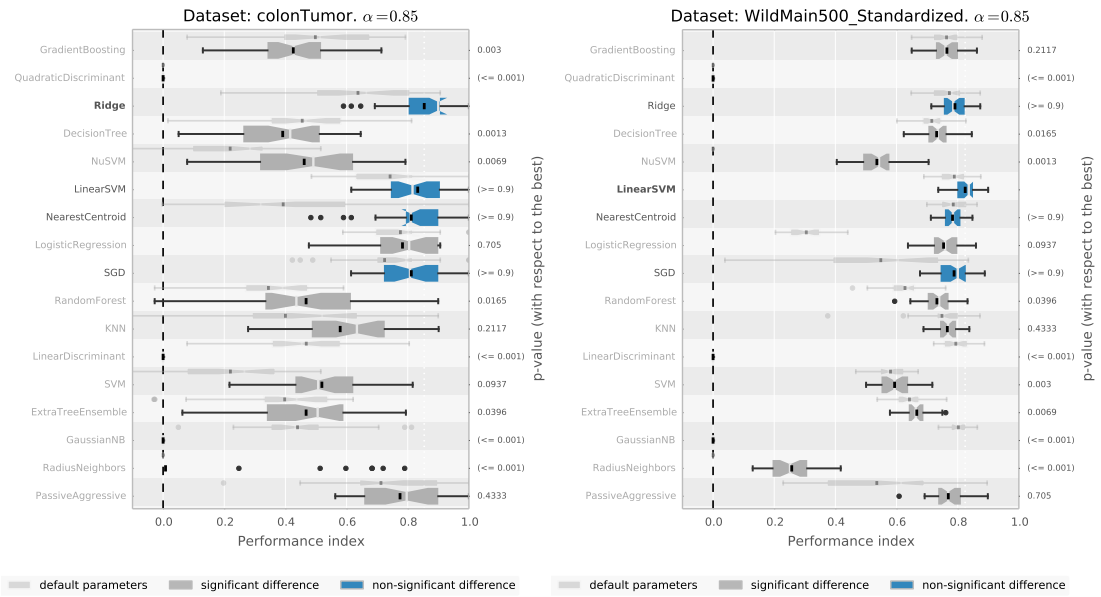


Figure 5.2: Optimized vs default values for biological datasets of different sizes. The colonTumor dataset contains 62 instances, whereas the WildMain500_Standardized dataset contains 500 instances.

top row of Figure 5.3, look similar, regardless of the value of other categorical hyperparameters. Both distributions assign a rather uniform density over the entire (0,1) domain. No important improvement in the optimization process should be expected when such distribution is used as a general prior.

The bottom row of Figure 5.3 shows the learned general prior for the same numerical hyperparameter γ when used in combination with a *sigmoid* kernel. In this case, the evaluation of the hyperparameter on the large group of datasets seems to achieve better performance when small values (close to zero) are used, although the assignment of values away from zero is also allowed. This skewness of the learned distribution, when using a sigmoid kernel, may be exploited when looking for optimal values of γ on other datasets, as a suggestion of where to look first.

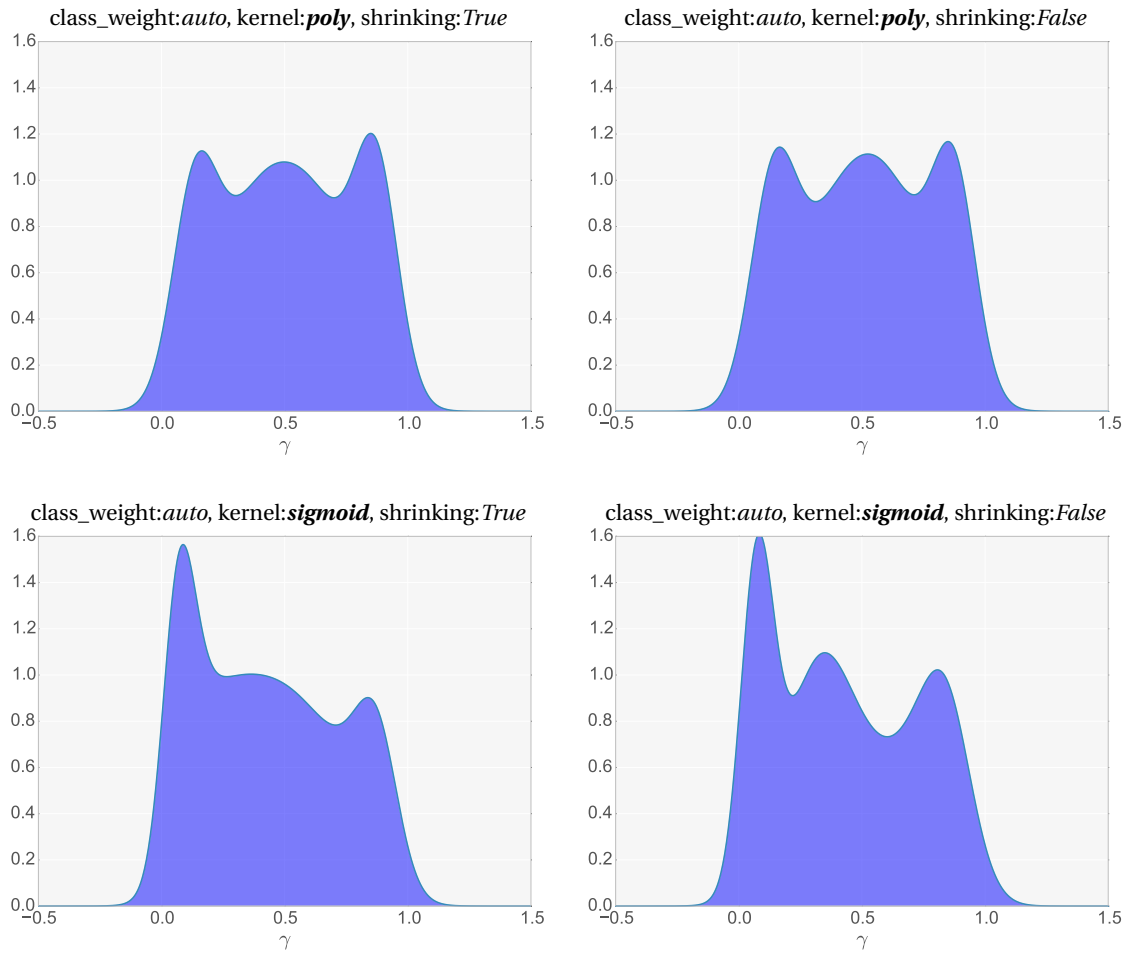


Figure 5.3: Distributions of the γ hyperparameter learned from the performance indices over a large group of datasets. The title over each plot indicates the signature of the categorical context (i.e., the values of the categorical hyperparameters).

CHAPTER 6

Conclusion

This work shows that an automatic approach to hyperparameter optimization and model selection is very valuable, especially when little knowledge of the internal function and configuration options of the SML algorithms is available. The optimized configurations retrieved by our approach significantly boosted the predictive power of most SML algorithms over their defaults. Moreover, the models optimized and selected by our method consider other preferable criteria such as the runtime, stability of the scores, and predictive generalization to unseen instances.

Furthermore, the automated procedure described here is very convenient for non-experts, as using this method requires training in machine learning that does not go beyond the general concepts. Our method is already a valuable tool that brings SML algorithms closer to the untrained user, and narrows the gap between the purely-technical machine learning community and the vast range of other disciplines that might benefit from SML techniques.

An important consideration regarding the optimization process is that, since the optimization happens simultaneously on a large group of numerical hyperparameters, finding good combinations of hyperparameters may be a slow process. The choice of an optimization method that makes use of the optimization history and other hints to guide the sampling of candidate configurations is critical when time is a concern.

6.1 Future work

Many possibilities to extend this work are considered, and planned. The most important ones are described next.

Optimization methods

Implementing more sophisticated optimization methods is the obvious next step. Optimization methods such as simulated annealing or genetic algorithms may speed up the hyperparameter optimization. Other methods such as may be implemented in the future.

Data preprocessing

In most real-world applications, the raw data obtained from experiments is not immediately suitable for training SML algorithms. Data with high dimensionality (many features) usually requires lots of computational resources, and the large number of dimensions can make a very informative signal (i.e., a dimension or group of dimensions that correlate well with the labeling) difficult to detect among all the rest of non-informative dimensions.

Feature selection and dimensionality reduction techniques should be included as a preprocessing step. The decision on which dimensionality reduction to use can also be regarded as a categorical hyperparameter of the model selection process, and included as part of the final suggestion of a best model.

Dataset classification

Having a framework that automatically finds the best model for specific data might be used on a larger scale to infer patterns between dataset-wide features and the SML algorithms that best predict on them. Approaches such as the one presented in [Tatti, 2007], where a distance metric between two datasets is suggested, can be further investigated. Finding dataset-wide features that follow patterns according to the SML algorithms best suited for them might also be used as a first clue of what SML algorithms could work well on a specific dataset.

Custom penalization of misclassifications

Some misclassifications may be more tolerable than others, for data of a certain nature. Penalization of misclassifications can be modified by using a custom confusion matrix that weights misclassifications accordingly. All the metrics that evaluate the quality of the prediction in terms of the true or false positives and negatives should use those weights in their internal computations.

APPENDIX A

Supervised machine learning algorithms

The following SML algorithms are used in this work:

Name	Description
KNN	<i>k</i> -nearest neighbors classifier.
RadiusNeighbors	Votes among neighbors within a certain radius.
NearestCentroid	Assigns the class of the centroid of the nearest cluster.
StochasticGradientDescent	Stochastic Gradient Descent classifier.
LogisticRegression	Logistic function applied on a linear combination of features.
SVM	Support Vector Machine (libSVM implementation).
LinearSVM	Linear SVM (libLinear implementation).
NuSVM	Nu-Support Vector Machine.
DecisionTree	Decision tree classification.
RandomForest	Average of multiple decision trees on subsets of the data.
ExtraTreeEnsemble	Random forest with randomized decision trees.
Ridge	Least squares regression with L2 loss.
LinearDiscriminant	Linear discriminant analysis.
QuadraticDiscriminant	Quadratic discriminant analysis.
GradientBoosting	An ensemble of regression tree classifiers.
PassiveAggressive	Passive Aggressive classifier.
GaussianNB	Gaussian Naïve Bayes classifier

APPENDIX B

Datasets

Standard datasets	Instances	Features	Classes
balance-scale	625	4	3
blood-transfusion 748	4	2	
cmc	1473	9	3
dermatology	366	34	6
diabetes	768	8	2
haberman	306	4	2
heart-statlog	270	13	2
ionosphere	351	34	2
iris	150	4	3
kdd_synthetic_control	600	60	6
letter	20000	16	26
liver-disorders	345	7	2
mfeat-factors	2000	649	10
mfeat-fourier	2000	649	10
mfeat-karhunen	2000	649	10
mfeat-morphological	2000	649	10
mfeat-pixel	2000	649	10
mfeat-zernike	2000	649	10
optdigits	3823	64	10
page-blocks	5473	10	5
pendigits	7494	16	10
segment-test	2100	19	7
sonar	208	60	2
spambase	4601	57	2
tae	151	5	3
vehicle	946	18	4
vowel	990	14	11
waveform-5000	5000	21	3
wine	178	13	3

Appendix B. Datasets

Biological datasets	Instances	Features	Classes
HK2_Standardized	1441	25	6
Huotari500_Standardized	502	25	4
Meier500_Standardized	500	27	5
so	721	160	6
WildMain500_Standardized	500	25	5
yeast	1484	8	10
colonTumor	62	2000	2

These datasets are available at <http://repository.seasr.org/Datasets/>.

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This sheet must be signed and enclosed with every piece of written work submitted at ETH.

I hereby declare that the written work I have submitted entitled

Automatic problem-specific hyperparameter optimization and model selection for supervised machine learning

is original work which I alone have authored and which is written in my own words.*

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