Discovering Task Neighbourhoods through Landmark Learning Performances

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Abstract. Arguably, model selection is one of the major obstacles, and a key once solved, to the widespread use of machine learning/data mining technology in business. Landmarking is a novel and promising meta-learning approach to model selection. It uses accuracy estimates from simple and efficient learners to describe tasks and subsequently construct meta-classifiers that predict which one of a set of more elaborate learning algorithms is appropriate for a given problem. Experiments show that landmarking compares favourably with the traditional statistical approach to meta-learning.

1 Introduction

The menu of data mining/machine learning techniques offers an increasingly large variety of choices. And, as with food, no one selection is universally satisfactory [15]. Instead, for every learning task, an appropriate learning algorithm must be chosen. An important goal of machine learning is to find principled ways to make this choice, which has become known as the model selection problem. Meta-learning endeavours to use machine learning itself (in a kind of recursive fashion) to the problem of model selection.

Meta-learning can be done by considering similar tasks in a reference class of tasks [1, 6, 10, 11], by inducing rules about algorithm selection [7, 11] or simply by training a meta-classifier [2, 3, 9]. In any case, tasks need to be described so that relations between tasks and learning algorithms can be automatically found. A number of strategies for task description have been used, based on statistics, information-theoretic considerations and properties of induced decision trees [2, 3, 7, 10, 11, 16]. Recently, we have proposed a novel approach, called landmarking [12, 4]. We believe this approach to be simpler, more intuitive and more effective.

Consider the class of tasks on which a learning algorithm performs well under a reasonable measure of performance (e.g., predictive accuracy) and call this class the *area of expertise* of the learner. The basic idea of landmarking is that the performance of a learner on a task uncovers information about the nature of that task. Hence, a task can be described by the collection of areas of expertise to which it belongs. We call a *landmark learner*, or simply a *landmarker*, a learning mechanism whose performance is used to describe a task. Exploring

the meta-learning potential of landmarking amounts to investigating how well a landmark learner's performance hints at the location of learning tasks in the expertise space (i.e., the space of all areas of expertise). By thus locating tasks, landmarking discovers experimentally neighbouring areas of expertise. It therefore finds neighbourhoods of learning strategies and, ultimately, draws a map of the complete expertise space.

The paper is organised as follows. In section 2 we present our chosen set of landmarkers. Section 3 reports empirical results which complement those reported in [12, 4]. Finally, section 4 concludes the paper.

2 A Set of Landmarkers

In principle, every learner's performance can signpost the location of a problem with respect to other learner's expertise. In practice, however, we want landmarkers that have low time complexity.¹

Clearly, the landmarkers may change according to the *learner pool*, i.e., the set of target learners from which one must be selected. At present, our learner pools are subsets of {C5.0tree, C5.0rule, C5.0boost, MLC++'s Naive Bayes, MLC++'s IBL, Clementine's MLP, Clementine's RBF, Ripper, Linear Discriminant, Ltree}. Given such pools, we construct the following set of landmarkers. In addition to being computationally efficient, each landmarker is intended to inform about the learning task, e.g., linear separability (see [4] for details).

1. *Decision node*: A single decision node consisting of the root of a C5.0 decision tree, where the attribute to branch on is chosen so as to maximise the information gain ratio [13].
2. *Worst node*: Same as above except that the attribute to branch on is chosen so as to minimise, rather than maximise, the information gain ratio.
3. *Randomly chosen node*: Same as above except that the attribute to branch on is chosen at random.
4. *Naive Bayes*: The standard Naive Bayes classifier [8].
5. *1-Nearest Neighbour*: The standard 1-NN classifier, based on the closest training example [8].
6. *Elite 1-Nearest Neighbour*: Same as above except that the nearest neighbour is computed based on a subset of all attributes. This elite subset is composed of the most informative attributes if the information gain ratio difference between them is small. Otherwise, the elite subset is a singleton and the learner acts like a decision node learner.
7. *Linear Discriminant*: A linear approximation of the target function [14].

For each task, the error rate of a landmarker is given by the average error over the whole instance space of the learner trained on 10 different training sets of

¹ In general, the cost of running the chosen landmarkers should be smaller than the cost of running the more sophisticated learners; otherwise, it would be better to run all the learners to find out which one performs best.

Meta-learner	Landmarking	Information-based	Combined
Default Class	0.460	0.460	0.460
C5.0boost	0.248	0.360	0.295
C5.0rules	0.239	0.333	0.301
C5.0tree	0.242	0.342	0.314
MLP	0.301	0.317	0.320
RBFN	0.289	0.323	0.304
LD	0.335	0.311	0.301
Ltree	0.270	0.317	0.286
IB	0.329	0.366	0.342
NB	0.429	0.407	0.363
Ripper	0.292	0.314	0.295
Average	0.298	0.339	0.312

Table 1. Meta-learning performance for different task descriptions

equal size. Each task is then described by a vector of 7 meta-attributes (i.e., the error rates of the 7 landmarks) and labelled by the learner (from the learner pool), which gives the highest predictive accuracy based on stratified 10-fold cross-validation. We use the special label “tie” when the difference in performance between the best and worst learners is small (here, less than 10%).² Once a (meta-)dataset has thus been constructed, it can be (meta-)learned by any supervised learning technique.

3 Experiments with Landmarking

In the first experiment, we compare landmarking with the more traditional statistical/information theoretic approach to task description (e.g., see [9, 11]). We consider the following 6 widely-used meta-attributes: class entropy, average entropy of the attributes, mutual information, joint entropy, equivalent number of attributes and signal-to-noise ratio. For this comparative experiment, the learner pool includes all 10 learners. We use 320 artificially generated Boolean datasets with 5 to 12 attributes, where the classifications are partly rule-based and partly random. The 10 learning algorithms in the learner pool are also used as meta-learners. Error rates are based on stratified 10-fold cross-validation and the results are given in Table 1. The default class is “tie”.

Table 1 shows that landmarking compares favourably with the information-based task description approach. In all but 2 cases, landmarking produces lower error rates than the information-based approach. The table also suggests that adding the information-based features to describe task impairs landmarking performance. These results are further confirmed by the learning curves of the three approaches (see Fig. 1).

² When performance differences are small, meta-learning is not only harder but also less useful since there is no great advantage of the best learner over the others.

Fig. 1. Learning curves for the landmarking approach, the information-based approach and the combined approach

Note that in the above experiment three learners, namely Linear discriminant, Naive Bayes and Nearest Neighbor, are both in the set of landmarks and in the learner pool. This can be seen as making the landmarking enterprise too easy. Notice, however, that the meta-learners are not informed of this identity, nor is it easy to uncover it since the landmarking meta-attributes values are only error rates. In fact, the meta-learner has to proceed as in the general case, finding correlations between the meta-attributes and the best learners. Experiments reported in [4], for example, suggest that the presence of Naive Bayes among the landmarks does not significantly impact performance.

In the second experiment, we consider the performance of landmarking when the learner pool is smaller. Of course, if the learner pool is sufficiently small, it is more efficient to run all the learners in the pool to select the most suitable one. However, this experiment is intended to shed some light on the ability of landmarking to describe tasks and discriminate between areas of expertise. We restrict our attention to pairs of learners including C5.0boost (C5B), MLP, Ripper (RIP) and Naive Bayes (N-B). The results, reported in Table 2, show that landmarking with most meta-learners improves on the default class.

In the third experiment, we investigate whether knowledge induced from artificial tasks is valid when applied to more “real-world” applications. To this end, we train C4.5 (as a meta-learner) on the meta-dataset arising from our 320 Boolean problems and test the induced hypothesis on 16 benchmark datasets from UCI [5] and Daimler-Chrysler. Table 3 reports the error rate differences between the best and the worst learners. The figures preceded by ν are the error figures of cases where landmarking chooses the best learner. Hence, these are figures of errors that landmarking avoids. When landmarking selects “tie”, we pessimistically make the assumption that it would select the worst learner. The results show that, in most cases, landmarking’s recommendations are either right or not very damaging to the overall performance. This is to say that it selects the worst learner when the worst learner is not greatly worse than the best one.

Meta-learner	C5B vs MLP	C5B vs RIP	MLP vs RIP	N-B vs RIP	C5B vs N-B
Default Class	0.450	0.550	0.510	0.490	0.550
C5.0boost	0.328	0.308	0.366	0.176	0.193
C5.0rules	0.355	0.317	0.411	0.138	0.179
C5.0tree	0.364	0.334	0.405	0.147	0.176
MLP	0.387	0.358	0.472	0.252	0.235
RBFN	0.410	0.331	0.481	0.276	0.261
LD	0.375	0.364	0.425	0.267	0.290
Ltree	0.384	0.249	0.405	0.199	0.188
IB	0.387	0.308	0.405	0.278	0.264
NB	0.554	0.387	0.627	0.375	0.334
Ripper	0.364	0.317	0.446	0.202	0.199
Average	0.391	0.327	0.444	0.231	0.232

Table 2. Landmarking performance when selecting between pairs of learners

4 Conclusions

Landmarking is a strategy to describe tasks through the performance of simple and efficient learners. Tasks are therefore described by their position in the expertise space. The expertise space is itself a suggestive way of thinking of learners and tasks. Landmarking relies on the position of a problem in that space to represent it: “tell me what can learn you and I will tell you what you are”. Empirical results suggest that it pays off to run bare-bone, landmark learners on a number of tasks and learn how their performance relates to that of other, more fleshed-out learners. These results indicate that the information about a task given by the performance of a portfolio of simple learners is useful for meta-learning. Furthermore, they also suggest that it is safe to apply to real-world tasks, knowledge learned from artificial ones.

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Task	C5B vs MLP	C5B vs RIP	MLP vs RIP	N-B vs RIP	C5B vs N-B
mushrooms	ν 0.050	0.000	ν 0.032	ν 0.003	0.003
abalone	ν 0.500	0.033	0.088	0.047	0.015
crx	0.056	ν 0.027	0.008	0.084	ν 0.110
acetylation	ν 0.091	ν 0.357	ν 0.267	ν 0.333	ν 0.024
titanic	0.007	0.211	0.219	ν 0.216	0.004
waveform	0.040	0.176	ν 0.136	ν 0.204	0.028
yeast	0.009	0.276	ν 0.428	ν 0.422	0.004
car	0.011	ν 0.083	0.094	ν 0.021	ν 0.104
chess	ν 0.112	ν 0.380	0.269	0.195	ν 0.186
led7	ν 0.014	ν 0.042	0.028	0.038	0.004
led24	0.013	ν 0.001	0.012	0.025	0.026
tic	0.009	ν 0.005	ν 0.015	ν 0.280	ν 0.274
MONK1	ν 0.156	ν 0.256	0.000	0.218	0.245
MONK2	ν 0.141	ν 0.141	0.000	ν 0.164	ν 0.023
satimage	ν 0.431	ν 0.046	0.016	ν 0.068	ν 0.114
quiscclas	0.023	ν 0.003	0.026	ν 0.258	ν 0.261

Table 3. Error rate differences between best and worst learners

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