Dividable Configuration Performance Learning

Jingzhi Gong, Tao Chen, Rami Bahsoon

Abstract—Machine/deep learning models have been widely adopted for predicting the configuration performance of software systems. However, a crucial yet unaddressed challenge is how to cater for the sparsity inherited from the configuration landscape: the influence of configuration options (features) and the distribution of data samples are highly sparse. In this paper, we propose a model-agnostic and sparsity-robust framework for predicting configuration performance, dubbed DaL, based on the new paradigm of dividable learning that builds a model via "divide-and-learn". To handle sample sparsity, the samples from the configuration landscape are divided into distant divisions, for each of which we build a sparse local model, e.g., regularized Hierarchical Interaction Neural Network, to deal with the feature sparsity. A newly given configuration would then be assigned to the right model of division for the final prediction. Further, DaL adaptively determines the optimal number of divisions required for a system and sample size without any extra training or profiling. Experiment results from 12 real-world systems and five sets of training data reveal that, compared with the state-of-the-art approaches, DaL performs no worse than the best counterpart on 44 out of 60 cases (within which 31 cases are significantly better) with up to $1.61\times$ improvement on accuracy; requires fewer samples to reach the same/better accuracy; and producing acceptable training overhead. In particular, the mechanism that adapted the parameter d can reach the optimal value for 76.43% of the individual runs. The result also confirms that the paradigm of dividable learning is more suitable than other similar paradigms such as ensemble learning for predicting configuration performance. Practically, DaL considerably improves different global models when using them as the underlying local models, which further strengthens its flexibility. To promote open science, all the data, code, and supplementary materials of this work can be accessed at our repository: https://github.com/ideas-labo/DaL-ext.

Index Terms—performance engineering, configurable software systems, configuration learning, performance modeling, performance prediction, software configuration.

1 Introduction

Almost every modern software system is configurable, hence configuration management has become one of the most important phases in software engineering, especially when considering its drastic impact on software performance, such as latency, runtime, and energy consumption [15], [18], [20], [82]. Indeed, while highly configurable software systems provide great flexibility, they also introduce potential risks that can hinder their performance due to the daunting number of configuration options. For example, x264, which is a video encoder, comes with 16 options to tune which can significantly influence its runtime. As such, understanding what performance can be obtained under a given configuration before the deployment is essential for satisfying performance requirements. Practically, the knowledge of configuration performance not only enables better decisions on configuration tuning [17], [19] but also reduces the efforts of configuration testing [10] as well as renders runtime self-adaptation plausible [12], [13], [16].

To understand configuration performance, one naive solution is to directly profile the software system for all possible configurations when needed. This, however, is impractical, because (1) there might be simply too many configurations to measure [17], [37], [46], [86]. For example, HIPA^{cc} (a compiler for image processing) has more than 10,000 possible configurations. (2) Even when such a number is small, measuring a single configuration can still be extremely expensive and time-consuming [17], [46], [57], [58]: Wang *et al.* [98] report that it could take weeks of running time to benchmark and profile even a simple system. Therefore, an accurate performance model that can cheaply predict the expected performance of a newly given configuration is in high demand.

Modeling the correlation between configurations and performance is, nevertheless, not an easy task. This is because as the complexity of modern software systems increases, the number of configurable options continues to expand and the interactions between options become more complicated, leading to significant difficulty in building an accurate model [14], [87]. The problem, namely configuration performance learning, fits well with the strength of machine learning in the Artificial Intelligence (AI) paradigm. Indeed, in the past decade, machine learning models have demonstrated more promising results for learning configuration performance compared with the analytical performance models, as they are capable of modeling the complex interplay between a large number of variables by observing hidden patterns from data [37], [40], [85], [86], [88], [96], [100].

However, since machine learning modeling is data-driven, the characteristics and properties of the measured data for configurable software systems pose non-trivial challenges to the learning, primarily because it is known that the configuration landscapes of the systems do not follow a "smooth" shape [46]. For example, adjusting be-

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tween different cache strategies can drastically influence the performance, but they are often represented as a single-digit change on the landscape [17]. This leads to the notion of sparsity in two aspects:

- Only a small number of configuration options can significantly influence the performance, hence there is a clear ***feature sparsity*** involved [37], [45], [86], [96].
- The samples from the configuration landscape tend to form different divisions with diverse values of performance and configuration options, especially when the training data is limited due to expensive measurement—a typical case of ***sample sparsity*** [41], [61], [84]. This is particularly true when not all configurations are valid [86].

While prior work can handle feature sparsity through tree-liked model [35], feature selection [14], [33], [56], or regularizing deep learning [22], [29], [37], [85], the sample sparsity has almost been ignored, which causes a major obstacle to the effectiveness of the machine learning-based performance model. For example, it is known that sparse data samples can easily force the model to focus and memorize too much on a particular region in the landscape of configuration data, leading to a serious issue of overfitting[1] [41].

To address the above gap, in this paper, we propose `DaL`, a framework for configuration performance learning via the concept of "divide-and-learn". `DaL` comes under a newly proposed paradigm termed *dividable learning*—the key that enables it to be naturally model-agnostic and can improve any existing models that learn configuration performance. The basic idea is that, to handle sample sparsity, we divide the samples (configurations and their performance) into different divisions, each of which is independently learned by a local model of any kind. In this way, the highly sparse configuration data can be separated into different regions of samples, which are locally smooth, and hence their patterns and feature sparsity can be more easily captured.

In a nutshell, our main contributions are:

1) We formulate, on top of the regression problem of learning configuration performance, a new classification problem without explicit labels.
2) We modify Classification and Regression Tree (`CART`) [64] as a clustering algorithm to "divide" the samples into different divisions with similar characteristics, for each of which we build a local model of any choice.
3) Newly given configurations would be assigned into a division inferred by a Random Forest classifier [43], which is trained using the pseudo-labeled data from the `CART`. The local model of the assigned division would be used for the final prediction thereafter.
4) Under 12 systems with diverse performance attributes, scale, and domains, as well as five different training sizes, we evaluate `DaL` against the common state-of-the-art approaches, different underlying local models, and a number of its variants.

1. Overfitting means a learned model fits well with the training data but works poorly on new data.

1.1 New Extensions

It is worth noting that this work is a significant extension of our work published at FSE'23 [31], for which we make the following key additional contributions:

- We provide a more systematic qualitative study to analyze the sparsity characteristics of configuration data, including both a literature review and an empirical study, hence better motivating our needs (Section 2).
- The contribution in our FSE'23 work requires manually tuning a crucial parameter d, which controls the number of divisions. This work proposes a novel adaptive mechanism that dynamically adapts the d value to an appropriate level without additional training or profiling (Section 3.1.3).
- To determine the optimal d value in the adaptation, we proposed a new indicator μHV, extending from the standard HV that is widely used for multi-objective evaluation, which can better reflect the goodness and balance between the ability to handle sample sparsity and the amount of data for learning in the divided configuration data (Section 3.1.3).
- We evaluate four additional systems that are of different characteristics and additionally compare `DaL` with the most recent work from TOSEM'23 [22], which reports on a new state-of-the-art approach after our FSE'23 work and has shown compelling results, together with three extra research questions (**RQ3**, **RQ4**, and partial **RQ5**) that help to more thoroughly assess our contributions (Section 5).

The experiment results are encouraging: compared with the best state-of-the-art approach, we demonstrate that `DaL`

- achieves no worse accuracy on 44 out of 60 cases with 31 of them being significantly better. The improvements can be up to $1.61\times$ against the best counterpart;
- uses fewer samples to reach the same/better accuracy.
- incurs acceptable training time considering the improvements in accuracy while the adaptation of d has negligible overhead without requiring extra training.

Interestingly, we also reveal that:

- `DaL` is model-agnostic, significantly improving the accuracy of a given local model for each division compared with using the model alone as a global model (which is used to learn the entire training dataset). However, `DaL` using the hierarchical deep learning-based approach published at TOSEM'23 [22] as the local model produces the most accurate results.
- Compared with ensemble learning, which is the other similar paradigm that shares information between local models, `DaL`, which follows the paradigm of dividable learning that completely isolates the local model, performs considerably better in dealing with the sample sparsity for configuration data with up to $28.50\times$ accuracy improvement over the second-best approach depending on the local model used.

- The tailored CART, the mechanism that adapts d, and the proposed μHV indicators can indeed individually contribute to the effectiveness of DaL.
- DaL's error tends to correlate upward and quadratically with its only parameter d that sets the number of divisions. Yet, the optimal d value indeed varies depending on the actual systems and training/testing data. Despite such, DaL can adapt to the optimal d value in 76.43% of the individual runs while even when it misses hit, a promising d value, which leads to generally marginal accuracy degradations to that of the optimal d, can still be selected.

1.2 Organization

This paper is organized as follows: Section 2 introduces the problem formulation and the notions of sparsity in software performance learning. Section 3 delineates the tailored problem formulation and our detailed designs of DaL. Section 4 presents the research questions and the experiment design, followed by the analysis of results in Section 5. The reasons that DaL works, its strengths, limitations, and threats to validity are discussed in Section 6. Section 7 and 8 present the related work and conclude the paper, respectively.

2 Problem Formulation and Methodology

In this section, we introduce the essential problem formulation and the research methodology which leads to the key observations that motivate this work.

2.1 Problem Formulation

In the software engineering community, configuration performance learning has been most commonly tackled by using various machine learning models (or at least partially) [16], [39], [73], [91], [106]. Such a data-driven process relies on observing the software's actual behaviors and builds a statistical model to predict the configuration performance without heavy human intervention [3].

Formally, modeling the performance of software with n configuration options is a regression problem that builds:

$$\mathcal{P} = f(\boldsymbol{\mathcal{S}}), \mathcal{P} \in \mathbb{R} \tag{1}$$

whereby $\boldsymbol{\mathcal{S}}$ denotes the training samples of configuration-performance pairs, such that $\overline{\mathbf{x}} \in \boldsymbol{\mathcal{S}}$. $\overline{\mathbf{x}}$ is a configuration and $\overline{\mathbf{x}} = (x_1, x_2, \cdots, x_n)$, where each configuration option x_i is either binary or categorical/numerical. The corresponding performance is denoted as $\mathcal{P}$.

The goal of machine learning-based modeling is to learn a regression function f using all training data samples such that for newly given configurations, the predicted performance is as close to the actual performance as possible.

2.2 Sparsity in Configuration Data: A Qualitative Study

2.2.1 Literature review

To confirm the known characteristics of configuration data with respect to sparsity and how it is tackled, we first conducted a literature review for papers related to the performance of software configuration[2] published during the last decade, i.e., from 2013 to 2024. Specifically, we performed an automatic search over six highly influential indexing services, i.e., ACM Library, IEEE Xplore, Google Scholar, ScienceDirect, SpringerLink, and Wiley Online, by using the search string below:

> *("software" OR "system" OR "software product lines") AND ("configuration" OR "configurable") AND ("performance prediction" OR "performance modeling" OR "performance learning" OR "configuration tuning") AND "machine learning"*

The search result consists of 5,920 studies with duplication except for non-English documents. Next, we filtered out the duplication by examining the titles and also eliminated clearly irrelevant documents, e.g., those about students' learning performance. This has resulted in 422 highly relevant candidate studies. Through a detailed review of the candidate studies, we then applied various criteria to further extract a set of more representative works. In particular, a study is temporarily selected as a primary study if it meets all of the following inclusion criteria:

- The paper presents machine learning algorithm(s) for modeling configuration performance[3]; This can also include search algorithm(s) for tuning the configurations to reach better performance in which some models need to be learned, e.g., different variants of Bayesian Optimization [7], [73].
- The paper presents a study or claims, either explicitly or implicitly, related to the sparsity of configuration data in the domain studied.
- The goal of the paper is to predict, optimize, or analyze the performance of a software system.
- The paper has at least one section that explicitly specifies the algorithm(s) used.
- The paper contains quantitative evaluation with details about how the results were obtained.

Subsequently, we applied the following exclusion criteria on the previously included studies, which would be removed if they meet any below:

- The paper is not software or system-related.
- The paper is not published in a peer-reviewed venue.
- The paper is a survey, review, or tutorial.
- The paper reports a work-in-progress research, i.e., shorter than 8 double-column or 15 single-column pages.

We obtained 71 highly related candidate studies from the above procedures. Next, a snowballing systematic search was performed using Google Scholar. This involved a backward snowballing exploration of the references cited within the identified candidate studies, enabling us to uncover

2. Notably, the main purpose of the review is not to exhaustively extract much different information from existing work on configuration performance learning, but to find the general ideas about how sparsity in configuration data is defined and considered when building a model.

3. There have been diverse kinds of research related to configurable systems, including but not limited to, configuration performance learning, configuration debugging, and configuration tuning. We chose to include only papers that involve machine learning algorithms in learning configuration because our scope is to propose a new approach to better handle the data sparsity inherited in the configuration data; our literature review aims to solely serve the purpose of confirming how sparsity is currently handled in such a context. Otherwise, we might include works that do consider sparsity but from an optimization/search/tuning perspective, e.g., how to overcome the local optima caused by sparsity instead of learning it [113].

TABLE 1: Selected papers that contain domain knowledge and explicit statements related to the characteristics of sparsity in configuration data (sorted by the citation count from Google Scholar at the time of collecting paper metadata, i.e., Apr 2024). The key phrases are highlighted in bold. The completed list of reviewed papers can be found at: https://github.com/ideas-labo/DaL-ext/blob/main/supplementary_materials/SLR_full_list.xlsb

Authors/Reference	Year	Venue	#Citation	Description and/or definition related to sparsity	What is sparse?
Aken *et al.* [2]	2017	SIGMOD	640	*"DBMSs can have hundreds of knobs, but **only a subset actually affect** the DBMS's performance."*	Configuration knobs
Siegmund *et al.* [86]	2015	ESEC/FSE	305	*"The ratio over all subject systems for OW with Plackett-Burman sampling is 0.31, indicating that **one third of the options significantly contribute** to the performance of a system."*	Configuration options
Sarkar *et al.* [81]	2015	ASE	180	*"As a consequence, the performance of the system may vary substantially depending on whether **a certain feature** is selected or not."*	Features
Oh *et al.* [75]	2017	FSE	155	*"Stairs arise from discrete feature decisions; **some features are highly-influential** in performance while others have little or no impact."*	Features
Thrane *et al.* [92]	2020	IEEE Access	155	*"The satellite images offer much information, and the entirety is not necessarily relevant for radio performance prediction, especially at lower frequencies. The use of such images results ultimately in a model that is harder to train since the **latent features obtained by the CNN might be sparse**."*	Features
Jamshidi and Casale [46]	2016	MASCOTS	142	*"More specifically, this means low-order interactions among **a few dominating factors** can explain the main changes in the response function observed in the experiments."*	Factors
Nair *et al.* [73]	2020	TSE	141	*"We know of many software options where **a small change can lead to radically different** software performance."*	Configuration options
Marcus and Papaemmanoui [68]	2019	VLDB	138	*"The problem with this solution is **sparsity**: if one has many different operator types, the vectors used to represent them will have an increasingly **larger proportion of zeros**."*	Vectors of variables
Jamshidi *et al.* [47]	2017	ASE	128	*"**Only a subset of options is influential** which is largely preserved across all environment changes."*	Configuration options
Chen and Bahsoon [14]	2017	TSE	100	*"Too limited inputs may not provide enough information of relevance to the QoS (i.e., the information that drives the changes in QoS), which restricts the model accuracy and applicability. On the other hand, too many inputs can generate noise in the modeling, because it introduces **irrelevant information and large redundancy** in the inputs (i.e., the same information has been provided by more than one selected primitives, thus it becomes noise), this will downgrade the model accuracy and generate unnecessary overhead."*	Configuration primitives and inputs
Ha and Zhang [37]	2019	ICSE	93	*"It has been observed that the software **performance functions are usually very sparse** (i.e. only a small number of configuration variables and their interactions have significant impact on system performance)."*	Variables of performance function
Zhou *et al.* [112]	2020	VLDB	68	*"The **performance-related features are sparsely scattered** in the graph (e.g., for a matrix of 1000×1000, many rows only have two 1s, meaning that the corresponding operator only has 2 directly related operators)."*	Performance features
Kanellis *et al.* [50]	2020	HotStorage	49	*"Surprisingly, we find that with YCSB workload-A on Cassandra, tuning **just five knobs can achieve 99% of the performance** achieved by the best configuration that is obtained by tuning many knobs."*	Configuration knobs
Fekry *et al.* [27]	2020	KDD	39	*"However, we have observed that for each workload **only a small subset of those parameters has a significant impact** on overall performance."*	Configuration parameters
Chen *et al.* [7]	2021	ICSE	38	*"**Only a small number of optimization flags**, referred to as impactful optimizations, can have **noticeable impact** on the runtime performance of a specific program."*	Configuration flag
Zhang *et al.* [109]	2022	VLDB	36	*"Given a limited tuning budget, tuning over the configuration space with all the knobs is inefficient. It is recommended to **preselect important knobs** to prune the configuration space."*	Configuration knobs
Grohmann *et al.* [34]	2019	Middleware	35	*"We collect 1,040 platform metrics using the PCP monitoring tool as described in Section 3.1. 952 of these platform metrics consider the host, 88 are specific to service instances (i.e., containers) running on the host. As expected, **not all the metrics are relevant** for the machine learning model and in many cases metric preprocessing is required such that they can be useful or leveraged by the algorithm."*	Measured configuration metrics
Zhang [110]	2022	SIGMOD	34	*"Modern DBMSs have hundreds of plan operators, encoding the plan operators could cause the "dimensionality issue" when augmenting the **sparse and high-dimensional variables** to GP kernel."*	GP kernel
Ha and Zhang [38]	2019	ICSME	29	*"For software performance functions, their **Fourier coefficients are always very sparse**, i.e. most of Fourier coefficients are zeros. The reason is that only a small number of configurations have significant impact on system performance."*	Configuration coefficients
Kanellis *et al.* [51]	2022	VLDB	22	*"However, recent studies have shown that **tuning a handful of knobs can be sufficient** to achieve near-optimal performance and significantly reducing the number of knobs can accelerate the tuning process."*	Configuration knobs
Zhang *et al.* [108]	2018	JSA	18	*"**Not all the features have impact** on the performance evaluation result, we can find a way to confirm the real effective features and remove the redundancy ones."*	Configuration features
Gong and Chen [30]	2022	MSR	12	*"Unlike other domains, software configuration is often highly sparse, leading to unusual data distributions. Specifically, **a few configuration options could have large influence** on the software performance, while the others are trivial."*	Configuration options
Marker [69]	2014	ASE	12	*"The (implementation × performance) space of DLA is stair-stepped. Each stair is a set of implementations with very similar performance and (surprisingly) share **key design decision(s)**."*	Design decisions
Shu *et al.* [85]	2020	ESEM	12	*"This means that only a small number of parameters have significant impact on the model. In other words, the **parameters of the neural network could be sparse**."*	Configuration parameters
Cheng *et al.* [22]	2021	TOSEM	9	*"One important prior knowledge is that **only a small number of configuration options and their interactions have a significant impact** on system performance, implying sparsity on the parameters of the performance model (i.e., making parameters of many insignificant options and interactions equal to zero)."*	Configuration options
Acher *et al.* [1]	2022	SPLC	9	*"Given these results, we can say that out of the thousands of options of Linux kernel, **only a few hundreds actually influence** its binary size."*	Configuration options
Xie *et al.* [103]	2019	PDSW	8	*"Our analysis shows that the write behaviors of the GPFS system are **dominated by the metadata load and load skew** within the supercomputer and the resources used in its filesystem."* (The metadata load and load skew here are configuration options.)	Configuration options
Malik *et al.* [66]	2013	WORKS	7	*"**Not all the features actually have considerable impact** on the execution time, therefore the collected provenance data needs to be filtered and reduced."*	Configuration features
Gong and Chen [31]	2024	FSE	6	*"The division of samples and the trained local model handles the **sample sparsity** while the rDNN deals with the **feature sparsity**. "*	Feature & sample distribution
Trajkovic *et al.* [93]	2022	TECS	5	*"To be able to generate a prediction model with high accuracy, we need to select features with a significant impact on the values of the targets. Including the **features that have little or no impact on the targets may result in overfitting**."*	Parameter features
Chen *et al.* [8]	2024	TSE	5	*"They have been specifically tailored to cater for the key properties of the tuning problem, e.g., **high sparsity** and expensive measurements."*	Configuration options
Gong and Chen [32]	2024	FSE	2	*"Noteworthy, SeMPL does not achieve the highest rank for Storm, which can be attributed to a combination of factors including the **sparsity of samples** (due to the nature of the system) and the presence of more diverse environments, primarily limited to hardware changes."*	Sample distribution

additional sources that are related to sparsity. Additionally, we systematically examined the studies that cited these candidate studies in a forward snowballing search to identify recent publications that mention the sparsity in configuration data. The results are then further filtered subject to the inclusion and exclusion criteria above. Throughout the reviewing process, the first author took the primary responsibility for conducting the search and the second author served as a quality checker of the outcomes. This has led to five additional studies, resulting in a total of 76 primary studies for data collection.

All authors are part of the data collection process, which involves three iterations, as commonly used by the literature reviews in Software Engineering [59], [115]:

- In the first iteration, each of the authors conducted initial data collection independently, read carefully throughout the 76 primary studies, extracted sentences that describe sparsity and subjects that are observed to be sparse (e.g., features, vectors, and GP kernel), and summarized the data into a table.

Notably, there were situations where an author was not sure how a statement was related to sparsity (e.g., statements about sparse matrix). In these cases, the corresponding data were marked for further investigation in the next iteration.
- In the second iteration, the authors reviewed and cross-checked each other's data summary tables, ultimately integrating them into a unified table. The unclear data that were marked in the previous iteration were rechecked and we arranged meetings to reach a common agreement for each item of which the collected data from the authors were different. This is achieved through discussions; further investigations from the existing literature; or consultation with external experts.
- Finally, the goals for the third iteration are to summarize the statistics of the integrated table from the second iteration; count the number of studies for each type of sparsity; and aggregate similar sparsity definitions.

The selected results have been shown in Table 1. Albeit with diverse terminologies (e.g., knobs, metrics, or parameters), we see that almost all papers have identified evident sparse patterns in software features related to configuration options, therefore, existing work reveals high ***feature sparsity***, which refers to the fact that only a small number of configuration options are prominent to the performance. This is inevitable as the configuration space for software systems is generally rugged with respect to the configuration options [17], [47].

2.2.2 Empirical study

Although the literature review has revealed evidence of sparsity in configuration data, it is difficult to ensure that all the major aspects/characteristics of sparsity in configuration data have been covered. As such, to better understand the sparse nature of configurable software systems, we empirically analyzed the data collected from the real-world systems studied in prior work. We do so by reviewing the systems used in the work identified from the literature review stage and selecting the ones according to the following criteria:

- The system is used by more than one paper.
- There are clear articulations on how the data is collected under the systems, e.g., how many repeated measurements.
- The data contains neither missing nor invalid measurements, such as "NaN" or other suspicious values like "-1" or "9999".
- The data should express a full spectrum of all the valid configurations for the system.

The above criteria could still lead to many systems that are of similar categories and characteristics, but it would be unrealistic to study them all and hence further representatives need to be extracted. To that end, for each category of the software systems, (e.g., a video encoder or a compiler), we select the one(s) that have been overwhelmingly studied across most of the papers identified.

The extraction has led to 12 real-world configurable software systems in our analysis (their details will be discussed in Section 4).

Since it is unrealistic to visualize the configuration landscape consisting of multi-dimensional configuration options, we process the configuration data using t-distributed Stochastic Neighbor Embedding (t-SNE) [42], which processes all options and produces two new, but reduced dimensions in the visualization. In a nutshell, t-SNE is an unsupervised algorithm wherein similar configurations are modeled by nearby points and dissimilar configurations are modeled by distant points with high probability. Note that t-SNE is often used for dimensionality reduction, where only the information of the most important features is preserved.

In Figure 1, we demonstrated the t-SNE processed results. Notably, we see that the systems all exhibit a consistent pattern—Our key discovery is therefore:

Key Discovery

Even with the key options that are the most influential to the performance (as represented in the reduced dimensions by t-SNE), the samples still do not exhibit a "smooth" distribution over the configuration landscape. Instead, those with similar characteristics can condense into local divisions, but globally, those from different local divisions might be spread sparsely.

This is a typical case of high ***sample sparsity*** [41], [61], [84]. Indeed, it is difficult for precisely defining to what extent the sparsity is considered as high, but with the visualized results from our empirical study, there is strong evidence that the configuration data is certainly non-smooth and hence raising concerns of "high sparsity smells".

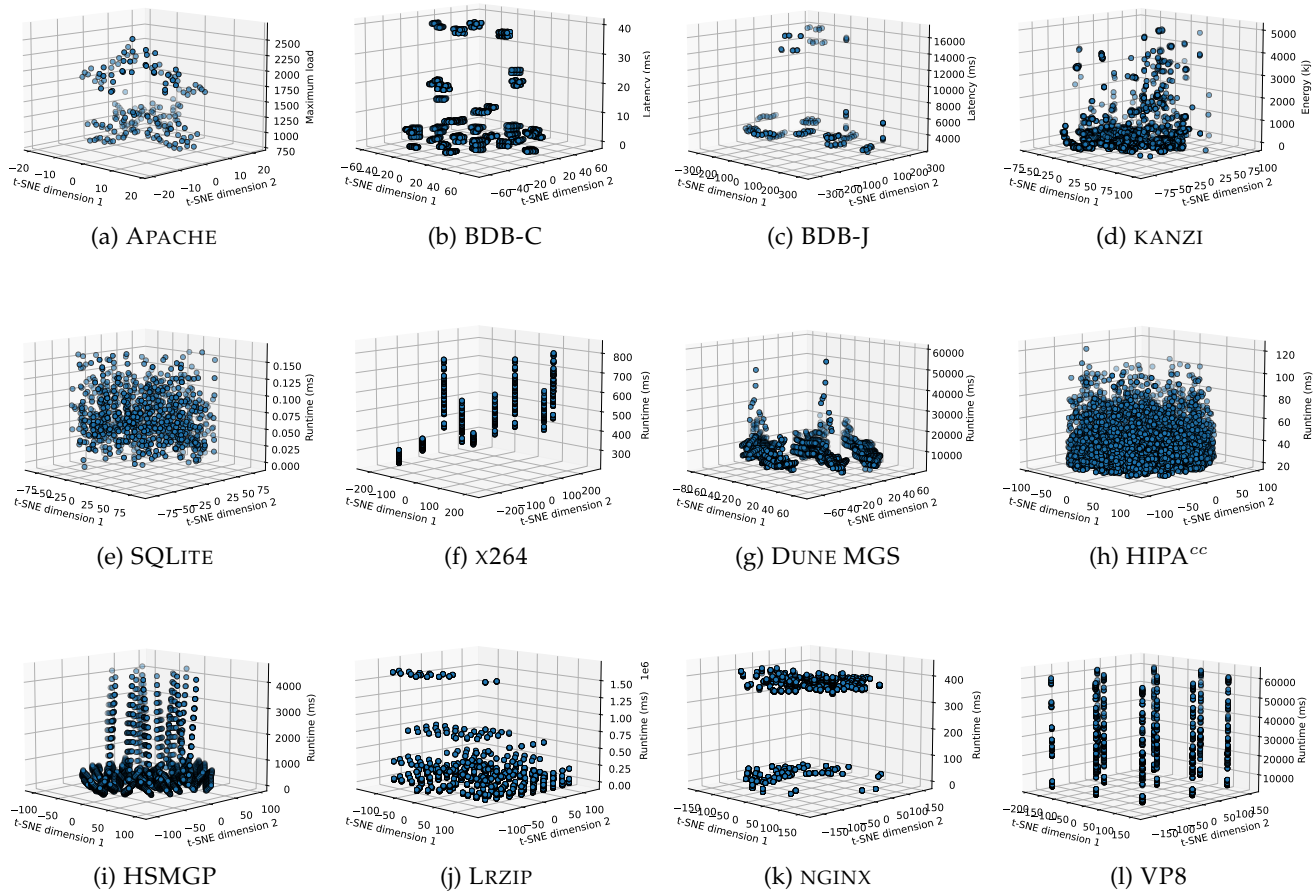
In general, such a high sample sparsity is caused by the following reasons:

- the inherited consequence of high feature sparsity.
- the complex and nonlinear interaction between configuration options, especially those categorical ones that can sharply influence the performance, e.g., adjusting between different cache strategies can drastically influence the performance, but they are often represented as a single-digit change on the landscape [17]. This leads to a highly rugged configuration landscape that leads to sparsity [17], [47].
- the fact that not all configurations are valid because of the constraints (e.g., an option can be used only if another option has been turned on) [86], thereby there are many "empty areas" in the configuration landscape.

2.2.3 Discussion

The above findings reveal the key factors to consider for our problem: when using machine learning models to learn concepts from the configuration data, we need a model that:

1) handles the complex interactions between the configuration options with high feature sparsity while;
2) captures the diverse characteristics of configuration samples over all divisions caused by the high sample sparsity, e.g., in Figure 1, where samples in different divisions have diverged performance ranges.



(a) APACHE (b) BDB-C (c) BDB-J (d) KANZI

(e) SQLITE (f) X264 (g) DUNE MGS (h) HIPA^{cc}

(i) HSMGP (j) LRZIP (k) NGINX (l) VP8

Fig. 1: Projection of configurations in the landscape using t-SNE (Note that the t-SNE dimensions are extracted and newly emerged features that do not correspond to any actual configuration options of the systems).

For the former challenge, there have been some proposed approaches previously, such as `DeepPerf` [37], `Perf-AL` [85], and `HINNPerf` [22]. The latter, unfortunately, is often ignored in existing work for configuration performance learning as we observed from our literature review and Table 1, causing a major obstacle for a model to learn and generalize the data for predicting the performance of the newly-given configuration. This is because those highly sparse samples increase the risk for models to overfit the training data, for instance by memorizing and biasing values in certain respective divisions [41], especially considering that we can often have limited samples from the configuration landscape due to the expensive measurement of configurable systems.

The above is the main motivation of this work, for which we ask: how can we improve the accuracy of predicting software configuration performance under such a high sample sparsity?

3 DIVIDE-AND-LEARN: DIVIDABLE LEARNING FOR CONFIGURATION PERFORMANCE

Drawing on our observations of the configuration data, we propose `DaL`—a framework of dividable learning that enables better prediction of the software configuration performance via "divide-and-learn". To mitigate the sample sparsity issue, the key idea of `DaL` is that, since different divisions of configurations show drastically diverse characteristics, i.e., rather different performance values with distant values of key configuration options, we seek to independently learn a local model for each of those divisions that contain *locally smooth* samples, thereby the learning can be more focused on the particular characteristics exhibited from the divisions and handle the feature sparsity. Yet, this requires us to formulate, on top of the original regression problem of predicting the performance value, a new classification problem without explicit labels. As such, we modify the original problem formulation (Equation 1) as below:

$$\boldsymbol{\mathcal{D}} = g(\boldsymbol{\mathcal{S}}) \tag{2}$$

$$\forall D_i \in \boldsymbol{\mathcal{D}}\colon \mathcal{P} = f(D_i), \mathcal{P} \in \mathbb{R} \tag{3}$$

Overall, we aim to achieve three goals:

- **Goal 1:** dividing the data samples into diverse yet more focused divisions $\boldsymbol{\mathcal{D}}$ (building function g) and;
- **Goal 2:** training a dedicated local model for each division D_i (building function f) while;

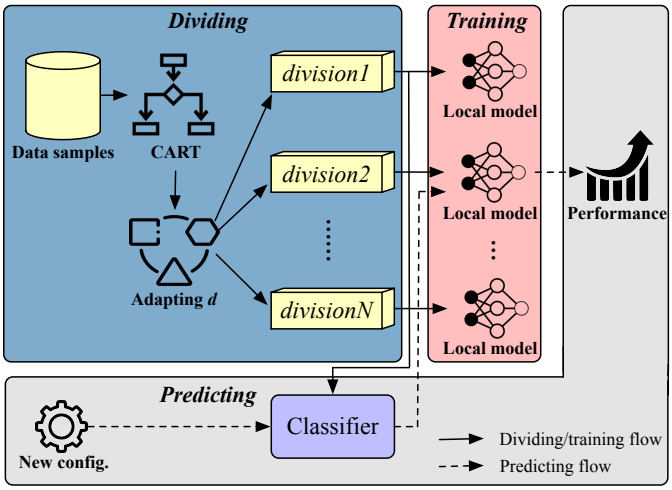


Fig. 2: The architecture of DaL.

- **Goal 3:** assigning a newly coming configuration into the right model for prediction (using functions g and f).

Figure 2 illustrates the overall architecture of DaL, in which there are three core phases, namely *Dividing*, *Training*, and *Predicting*. A pseudo-code can also be found in Algorithm 1. In particular, the options' interactions at the *Division* are handled by CART and a parameter d, i.e., only the top options are considered in the process of dividing the data samples. In the *Training*, the interaction between all options is considered by the local model. Yet, since the local model is only responsible for one division of the data, the full interactions are split, each of which is handled separately and independently.

3.1 Dividing

The very first phase in DaL is to appropriately divide the data into more focused divisions while doing so by considering both the configuration options and performance values. To that end, the key question we seek to address is: how to effectively cluster the configuration data with similar sample characteristics (**Goal 1**)?

3.1.1 Modifying CART for Generating Divisions

Indeed, for dividing data samples, it makes sense to consider various unsupervised clustering algorithms, such as kMeans [65], Agglomerative clustering [99] or DBSCAN [25]. However, we found that they are ill-suited for our problem, because:

- the distance metrics are highly system-dependent. For example, depending on the number of configuration options and whether they are binary/numeric options;
- it is difficult to combine the configuration options and performance value with appropriate discrimination;
- and clustering algorithms are often non-interpretable.

As a result, in DaL, we extend Classification and Regression Tree (CART) as the clustering algorithm (lines 3-12 in Algorithm 1) since (1) it is simple with interpretable/analyzable structure; (2) it ranks the important options as part of training (good for dealing with the feature sparsity issue), and (3) it does not suffer the issues above [11], [14], [35], [36], [72], [73], [81]. In Section 5.4, we will experimentally demonstrate that CART allows DaL to obtain much more superior results than the state-of-the-art clustering algorithms in dividing our configuration data.

Algorithm 1: Pseudo code of DaL

```
   Input: A new configuration c̄ to be predicted
   Output: The predicted performance of c̄
1  if 𝓜 = ∅ then
2      /* dividing phase.                                          */
3      𝓢 ← randomly sample a set of configurations and their
         performance
4      𝒯 ← TRAINCART(𝓢)
5      d =ADAPTINGDEPTH(𝒯)
6      d′ = 1
7      while d′ ≤ d do
8          if d′ < d then
9              𝓓 ← extract all the leaf divisions of samples from
                 𝒯 at the d′th depth
10         else
11             𝓓 ← extract all divisions of samples from 𝒯 at the
                 d′th depth
12         d′ = d′ + 1
13     /* training phase.                                          */
14     for ∀D_i ∈ 𝓓 do
15         𝓜 ← TRAINLOCALMODEL(D_i)
16 /* predicting phase.                                           */
17 if ℱ has not been trained then
18     𝓤 ← Removing performance data and labeling the
         configurations based on their divisions in 𝓓
19     𝓤′ ← SMOTE(𝓤)
20     ℱ ← TRAINRANDOMFOREST(𝓤′)
21 D_i = PREDICT(ℱ,c̄)
22 ℳ = get the model from 𝓜 that corresponds to the predicted
     division D_i
23 return PREDICT(ℳ,c̄)
```

As illustrated in Figure 3, CART is originally a supervised and binary tree-structured model, which recursively splits some, if not all, configuration options and the corresponding data samples based on tuned thresholds. A split would result in two divisions, each of which can be further split. In this work, we at first train the CART on the available samples of configurations and performance values, during which we use the most common mean performance of all samples for each division D_i as the prediction [35], [36]:

$$\overline{y}_{D_i} = \frac{1}{|D_i|} \sum_{y_j \in D_i} y_j \tag{4}$$

in which y_j is a performance value. For example, Figure 3 shows a projected example, in which the configuration that satisfies "rtQuality=true" and "threads=3" would lead to an inferred runtime of 122 seconds, which is calculated over all the 5 samples involved using Equation 4.

By choosing/ranking options that serve as the splits and tuning their thresholds, in DaL, we seek to minimize the following overall loss function during the CART training:

$$\mathcal{L} = \frac{1}{|D_l|} \sum_{y_j \in D_l} (y_j - \overline{y}_{D_l})^2 + \frac{1}{|D_r|} \sum_{y_j \in D_r} (y_j - \overline{y}_{D_r})^2 \tag{5}$$

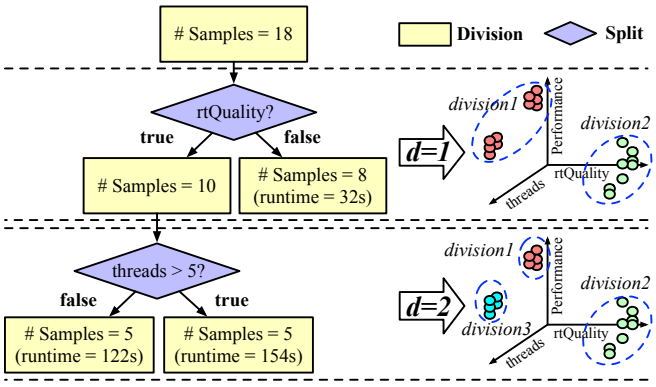


Fig. 3: Projection of CART for VP8 showing the possible divisions with different colors under alternative depth d.

where D_l and D_r denote the left and right division from a split, respectively. This ensures that the divisions would contain data samples with similar performance values while they are formed with respect to the similar values of the key configuration options as determined by the splits/thresholds (i.e., as from the *Key Discovery* in Section 2.2.2), i.e., the more important options would appear on the higher level of the tree with excessive splitting.

However, here we do not use CART to generalize prediction directly on new data once it is trained as it has been shown that the splits and simple average of performance values in the division alone can still fail to handle the complex interactions between the options, leading to insufficient accuracy [37]. Further, with our loss function in Equation 5, CART is prone to be overfitting, especially for software quality data [53]. This exacerbates the issue of sample sparsity [41] under a small amount of data samples which is not uncommon for configurable software systems [37], [85].

Instead, what we are interested in are the (branch and/or leaf) divisions generated therein (with respect to the training data), which enable us to use further dedicated and more focused local models for better generalizing to the new data (lines 7-12 in Algorithm 1). As such, the final prediction is no longer a simple average while we do not care about the CART overfitting itself as long as it fits the training data well. This is similar to the case of unsupervised clustering for which the clustering is guided by implicit labels (via the loss function at Equation 5). Specifically, in DaL we extract the data samples according to the divisions made by the dth depth of the CART, including all the leaf divisions with depth smaller than d. An example can be seen from Figure 3, where d is a controllable parameter given by the software engineers. In this way, DaL divides the data into a range of $[d+1, 2^d]$ divisions[4] ($d \geq 0$), each of which will be captured by a local model learned thereafter[5]. Note that when the number of data samples in the division is less than the minimum amount required by a model, we merge the two divisions of the same parent node.

As a concrete example, from Figure 3, we see that there are two depths: when $d = 1$ there would be two divisions (one branch and one leaf) with 10 and 8 samples respectively; similarly, when $d = 2$ there would be three leaf divisions: two of each have 5 samples and one is the division with 8 samples from $d = 1$ as it is a leaf. In this case, CART has detected that the rtQuality is a more important (binary) option to impact the performance, and hence it should be considered at a higher level in the tree. Note that for numeric options, e.g., threads, the threshold of splitting (threads > 5) is also tuned as part of the training process of CART.

It is intuitive to understand that d is such a critical parameter for DaL, thereby manually setting the right value for it can be time-consuming and error-prone. In what follows, we will delineate what role the d plays in DaL and propose an adaptive mechanism in DaL that allows dynamic adaptation of the d value during training.

3.1.2 The Role of Depth d in DaL

Since more divisions mean that the sample space is separated into more loosely related regions for dealing with the sample sparsity, one may expect that the accuracy will be improved, or at least, stay similar, thereby we should use the maximum possible d from CART in the *Dividing* phase. This, however, only exists in the "utopia case" where there is an infinite set of configuration data samples.

In essence, with the design of DaL, the depth d will manage two conflicting objectives that influence its accuracy:

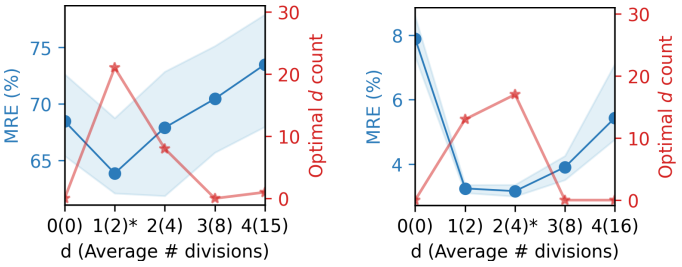
1) greater ability to handle sample sparsity by separating the distant samples into divisions, each of which is learned by an isolated local model;
2) and a larger amount of data samples in each division for the local model to be able to generalize.

Clearly, a larger d may benefit the ability to handle sample sparsity but it will inevitably reduce the data size per division for a local model to generalize since it is possible for CART to generate divisions with imbalanced sample sizes. From this perspective, we see d as a value that controls the trade-off between the two objectives, and neither a too small nor too large d would be ideal, as the former would lose the ability to deal with sample sparsity while the latter would leave too little data for a local model to learn, hence produce negative noises that harm the overall prediction. This is the key reason that setting d for a given system is crucial when using DaL.

Unfortunately, finding the appropriate d value is not straightforward, as it often requires repeatedly profiling different values following in a trial-and-error manner, which can be rather expensive, especially when the optimal d, which leads to the best mean relative error (MRE), varies depending on the system and even the training/testing data. For example, Figure 4 illustrates the optimal d for DaL on two real-world software systems (the full coverage will be discussed in Section 5.5), from which it is clear that the $d = 1$ would lead to the best overall MRE for SQLITE, but this becomes $d = 2$ for LRZIP. If we consider the individual runs that involve different training and testing configuration data, the optimal d could also differ (red lines). Notably,

4. At depth d, there can be a minimum of d+1 divisions (where only one parent node at the $d-1$ depth is further divided into two nodes), and a maximum of 2^d divisions (where all parent nodes at the $d-1$ depth are further divided into two nodes). Hence, the range of the number of divisions is [d+1, 2^d].

5. When $d = 0$, DaL is basically equivalent to a single local model.



(a) SQLITE (b) LRZIP

Fig. 4: The changing optimal d on DaL depending on the software systems being modeled and the training/testing data across 30 runs.

we see that some d values, e.g., $d = 4$ for SQLITE, can be dramatically harmful to the accuracy, leading to a result that is even worse than the case when DaL is absent (i.e., $d = 0$).

3.1.3 Adapting the Depth d

To overcome the above, in DaL, we design an adaptive mechanism as part of the *Dividing* phase that is able to dynamically find the d such that the two aforementioned objectives can be optimized and balanced (line 5 in Algorithm 1).

Specifically, we use the following functions h and z to measure the ability to handle sample sparsity and the amount of information for a division D_i, respectively:

$$\begin{cases} h(D_i) = \frac{1}{|D_i|}\sum_{y_j \in D_i} (y_j - \overline{y}_{D_i})^2 \\ z(D_i) = -n_{D_i} \end{cases} \tag{6}$$

whereby z is the additive inverse of the assigned sample size, denoted as n_{D_i}. h is basically the mean square error (or performance variance of the samples in a division) taken from the loss function (Equation 5) that splits the divisions with respect to the important configuration options. As such, the samples in a division that are generally closer to each other in terms of the performance value, after being divided according to the importance of key configuration options, will more likely to be beneficial for a local model to learn. Intuitively, both h and z need to be minimized. Given a maximum number of d_{max} divisions generated by CART under the training data, our purpose is to find the d value ($0 \leq d \leq d_{max}$) that leads to the overall best and most balanced divisions (a.k.a. knee points) in the objective space of h and z from those generated by all possible d values. In essence, from a multi-objective optimization perspective, knee points represent the solutions that, when changed, can only marginally improve one objective by largely comprising the other [16], [105], hence achieving a well-balanced trade-off.

To this end, we gain inspiration from a widely used quality indicator for evaluating multi-objective solution sets, namely Hypervolume (HV) [114]. In a nutshell, HV measures the volume between all nondominated points[6] in the objective space and a reference point (usually a nadir point); the larger the volume, the better convergence and diversity that the set achieves. The HV for a solution set $\boldsymbol{\mathcal{A}}$ can be computed as:

$$\text{HV}(\boldsymbol{\mathcal{A}}, \overline{\mathbf{r}}) = \lambda\Big(\bigcup_{\overline{\mathbf{a}} \in \boldsymbol{\mathcal{A}}} \{\overline{\mathbf{x}} | \overline{\mathbf{a}} \prec \overline{\mathbf{x}} \prec \overline{\mathbf{r}}\}\Big) \tag{7}$$

where λ is the Lebesgue measure, which takes into account the trade-offs between the objectives and the spread of the non-dominated solutions in the objective space. It is a default metric in HV used to calculate the volume of the region covered by a set of non-dominated solutions therein. More details can be found in the work of Zitzler and Thiele [114]; $\overline{\mathbf{r}}$ is the reference nadir point, which is often defined as 1.1 times the range of the nondominated set [60]. Li *et al.* [60] show that, with an appropriate setting of the reference point, HV can well reflect the preference for balanced/knee solutions, which fits precisely with our needs. However, we cannot directly adopt the original HV due to the fact that it can completely omit the contributions of divisions based on their relative domination relations, i.e., a division does not contribute to the HV value at all if it is dominated by the other division under a certain d. Indeed, this makes sense in conventional multi-objective evaluation scenarios, but in our case of dividable learning for configuration performance with DaL, the contribution of each division counts, even if it has been dominated, since the local model under such a division could still impact the result when the newly given configuration falls therein. As a result, the original HV might misjudge the true effectiveness of a d value.

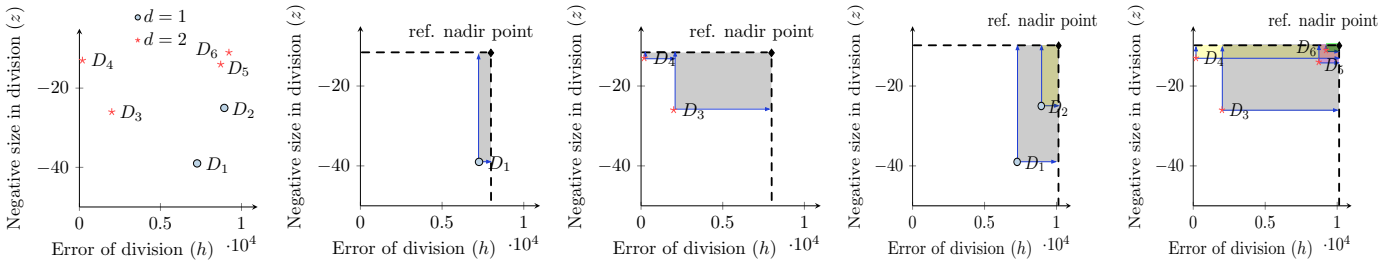
Instead of leveraging the original HV, in this work, we propose a modified HV, dubbed averaging HV (μHV), that evaluates the average quality of the HV value that takes each division into account with respect to h and z regardless of the domination relations—a typical specialization of a generic concept to cater for our needs. Formally, the μHV for all the divisions in a set $\boldsymbol{\mathcal{D}}$ under a particular d value is calculated as below:

$$\begin{aligned} &\mu\text{HV}(\boldsymbol{\mathcal{D}}, \overline{\mathbf{r}}) = \frac{1}{|\boldsymbol{\mathcal{D}}|}\sum_{D_i \in \boldsymbol{\mathcal{D}}} (|h_r - h(D_i)|) \times (|z_r - z(D_i)|) \\ &\text{s.t. } \overline{\mathbf{r}} = \langle h_r, z_r \rangle \end{aligned} \tag{8}$$

whereby h_r and z_r are the objective values for mean square error and data size of the reference nadir point $\overline{\mathbf{r}}$, respectively. Since there are only two objectives to consider in our case, each individual HV value within the μHV is essentially the area between the corresponding division and the reference nadir point in the objective space. With the above, we realize the following specializations to the original generic HV:

- **Specialization 1:** Through averaging the HV value for each individual division's objectives, μHV would take into account the contribution made by a division that is dominated by the other. This, conversely, is not the case in the original HV as it works only on the nondominated ones.
- **Specialization 2:** Unlike the original HV that uses 1.1 times the range of the nondominated divisions as the reference nadir point, μHV takes 1.1 times

6. A solution $\overline{\mathbf{a}}$ is dominated by $\overline{\mathbf{b}}$ if all objectives of $\overline{\mathbf{b}}$ are better or equivalent to those of $\overline{\mathbf{a}}$ while there is at least one objective of $\overline{\mathbf{b}}$ performs better than that of $\overline{\mathbf{a}}$. A solution is said nondominated if it cannot be dominated by any other solutions in the set.



(a) All divisions (b) HV for $d = 1$ (c) HV for $d = 2$ (d) μHV for $d = 1$ (e) μHV for $d = 2$

Fig. 5: Comparing the differences between HV and μHV for divisions with $d = 1$ and $d = 2$ under system x264. The distinctly colored area indicates the individual HV value calculated based on one (for μHV) or more divisions (for HV). (a) shows that D_1 is the nondominated division for $d = 1$ while D_3 and D_4 are the nondominated ones for $d = 2$. In (b), the original HV value equals the area between D_1 alone and the reference nadir point, i.e., HV$= 19825.43$. In (c), the original HV value equals the non-overlapped area from D_3 and D_4 to the reference nadir point, i.e., HV$= 88025.51$. In (d), μHV is the mean over the HV value of the area between D_1 and the reference nadir point together with that of the area between D_2 and the reference nadir point, i.e., μHV$= (83951.55 + 18216.65)/2 = 51084.10$. In (e), μHV is the mean over the HV value for the area of each of the divisions D_3, D_4, D_5, and D_6, i.e., μHV$= (131212.91 + 30873.60 + 5862.67 + 1014.70)/4 = 42240.97$. With the original HV, $d = 2$ would be chosen while using our proposed μHV, $d = 1$ would be chosen. In fact, here $d = 1$ tends to be better in general considering all the possible divisions in terms of h and z. The actual validation also confirms that $d = 1$ leads to $2.28\times$ more accurate result than that of $d = 2$.

the range of each of the worst objective values[7]. This is necessary to account for the divisions being dominated by others.

Considering the example illustrated in Figure 5, in which it is possible to use $d = 1$ or $d = 2$ for x264 (Figure 5a). From Figures 5b and 5c, if the original HV is used directly, then we would have $\text{HV}_1 = 19825.43$ and $\text{HV}_2 = 88025.51$ for $d = 1$ and $d = 2$, respectively. Clearly, $d = 2$ would be chosen here since $\text{HV}_1 < \text{HV}_2$. When using μHV, in Figures 5d and 5e, there are $\mu\text{HV}_1 = 51084.10$ and $\mu\text{HV}_2 = 42240.97$ for $d = 1$ and $d = 2$, respectively. As such, $d = 1$ would be chosen since $\mu\text{HV}_1 > \mu\text{HV}_2$. In fact, $d = 1$ is a better setting than $d = 2$ as the latter contains D_5 and D_6, which are two much more inferior/less balanced divisions than those in $d = 1$, leading to a higher probability of more severe negative impacts on the accuracy. Hence, $d = 1$ tends to be more desired in general considering all the possible divisions in terms of h and z. Indeed, the experiment validation confirms that it leads to $2.28\times$ more accurate results than that of $d = 2$.

The above demonstrates the limitation of the original HV for adapting d in dividable learning for configuration performance: because of the way it is computed, those divisions that are dominated by the others, e.g., D_2 for $d = 1$ and D_5 for $d = 2$, would have no contribution to the final value. This is a serious issue for our case given that the local model trained on those divisions is still important since `DaL` naturally allows any local model to be used in isolation. For example, if upon prediction, there are newly given configurations belonging to the local models for D_2 or D_5, then these models would be used for predicting the performance independently. However, the original HV would have not been able to take that into account since the contributions of the corresponding divisions were ruled out, providing likely misleading guidance. μHV addresses such a shortcoming by averaging the individual HV value for all divisions under a d value, hence taking the contribution of those being dominated by the other into account (**Specialization 1**). In this way, μHV can better assist in identifying the overall better d value and its corresponding divisions with respect to h and z. Yet, this requires changing the reference nadir point to consider not only the nondominated divisions (as in the original HV) but also anyone in the space (**Specialization 2**).

Algorithm 2 illustrates the proposed adaptive mechanism with the following key steps:

1) Compute the objective values of h_i and z_i for all division D_i under the possible d. The set of divisions $\boldsymbol{\mathcal{D}}_j$ and its corresponding d_j are kept as a vector $\langle \boldsymbol{\mathcal{D}}_j, d_j \rangle$.
2) Calculate the μHV value for all the divisions under each d up to the maximum d possible as determined by `CART`. Here, $d = 0$ is omitted since in such a case `DaL` is essentially the same as the single local model.
3) Return the d with the largest μHV value.

With such an adaptive mechanism of d, we strike more balanced results for the aforementioned objectives while requiring neither additional training nor profiling. The computational overhead of computing μHV is also ignorable, as we will show in Section 5.6.

3.2 Training

Given the divisions generated by the *Dividing* phase, we train a local model for the samples from each division identified as part of **Goal 2** (lines 13-15 in Algorithm 1). Theoretically, we can pair them with any model given the generic concept of dividable learning. However, we adopt the state-of-the-art regularized Hierarchical Interaction Neural Network [22] (namely `HINNPerf`) to serve as the default in this work, as Cheng *et al.* provide compelling empirical evidence

7. This would be 0.9 times for the objective z as it is always a negative number.

Algorithm 2: Pseudo code of ADAPTINGDEPTH

```
   Input: A trained CART model T
   Output: The most balanced d value
1  d_j = 1
2  /* step 1.                                                    */
3  while d_j ≤ d_max from T do
4      d' = 1
5      D_j ← ∅
6      while d' ≤ d_j from T do
7          if d' < d_j then
8              D_j ← extract all the leaf divisions of samples
                 from T at the d'th depth
9          else
10             D_j ← extract all divisions of samples from T at
                 the d'th depth
11         d' = d' + 1
12     for ∀D_i ∈ D_j do
13         if ⟨h_i, z_i⟩ ∉ ⟨h̄, z̄⟩ then
14             ⟨h̄, z̄⟩ ← calculate h_i and z_i for D_i according to
                 Equation 6
15     N ← ⟨D_j, d_j⟩
16     d_j = d_j + 1
17 /* step 2.                                                    */
18 r̄ = ⟨h_r, z_r⟩ ← find the nadir reference point from ⟨h̄, z̄⟩
19 for ∀⟨D_j, d_j⟩ ∈ N do
20     v_j = μHV(D_j, r̄) according to Equation 8
21     F ← ⟨v_j, d_j⟩
22 /* step 3.                                                    */
23 return the d_j with the largest v_j such that ⟨v_j, d_j⟩ ∈ F
```

on its effectiveness for handling feature sparsity and the interaction therein well for configurable software, even with very small training sample size. Section 5 reports on our use and observation of pairing DaL with HINNPerf.

In this work, we adopt exactly the same structure and training procedure as those used by Cheng *et al.* [22], hence we kindly refer interested readers to their work for the training details. Since the local models of the divisions are independent, we utilize parallel training as part of DaL.

It is worth stressing that, as we will show in Section 5.2, DaL is a model-agnostic framework and can improve a wide range of local models compared with the case when they are used to learn the entire configuration data space.

3.3 Predicting

When a new configuration arrives for prediction, DaL chooses a local model of division trained previously to infer its performance. Therefore, the question is: how to assign the new configuration to the right model (**Goal 3**)? A naive solution is to directly feed the configuration into the CART from the *Dividing* phase and check which divisions it associates with. Yet, since the performance of the new configuration is unforeseen from the CART's training data, this solution requires CART to generalize accurately, which, as mentioned, can easily lead to poor results because CART is overfitting-prone when directly working on new data [53].

Instead, by using the divided samples from the *Dividing* phase (which serves as pseudo labeled data), we train a Random Forest—a widely used classifier and is resilient to overfitting [7], [77], [94]—to generalize the decision boundary and predict which division that the new configuration should be better assigned to (lines 16-22 in Algorithm 1). Again, in this way, we are less concerned about the overfitting issue of CART as long as it matches the patterns of training data well. This now becomes a typical classification problem but there are only pseudo labels to be used in the training. Using the example from Figure 3 again, if $d = 1$ is chosen as the best value then the configurations in the 10 sample set would have a label *"division1"*; similarly, those in the 8 sample set would result in a label *"division2"*.

However, one issue we experienced is that, even with $d = 1$, the sample size of the two divisions can be rather imbalanced, which severely harms the quality of the classifier trained. For example, when training BDB-C with 18 samples, the first split in CART can lead to two divisions with 14 and 4 samples, respectively. Therefore, before training the classifier we use Synthetic Minority Oversampling Technique (SMOTE) [4] to pre-process the pseudo label data, hence the division(s) with much fewer data (minority) can be more repeatedly sampled.

Finally, the classifier predicts a division whose local model would infer the performance of the new configuration.

4 EXPERIMENT SETUP

Here, we delineate the settings of our evaluation. In this work, DaL is implemented based on Tensorflow and scikit-learn. All experiments were carried out on a server with 64-core Intel Xeon 2.6GHz and 256G DDR RAM.

4.1 Research Questions

In this work, we comprehensively assess DaL by answering the following research questions (RQ):

- **RQ1:** How accurate is DaL compared with the state-of-the-art approaches (i.e., HINNPerf, DeepPerf, Perf-AL, DECART, and SPLConqueror), and other models from the machine learning community that share a similar concept (i.e., IBMB, M5, PILOT, and MOB), for configuration performance learning?
- **RQ2:** To what extent DaL can improve different generic models (i.e., HINNPerf, regularized Deep Neural Network, CART, Linear Regression, and Support Vector Regression) when they are used locally therein for predicting configuration performance?
- **RQ3:** How do DaL perform compared with the existing ensemble approaches such as Bagging and Boosting?
- **RQ4:** What is the benefit of the components in DaL? This consists of three sub-questions:
  - **RQ4.1:** What is the benefit of using CART for dividing in DaL over the standard clustering algorithms?
  - **RQ4.2:** What is the benefit of the mechanism that adapts d compared with the variant that relies on pre-tuned fixed d as what was used in our previous FSE work?
  - **RQ4.3:** What is the benefit of μHV over the original HV in adapting d?
- **RQ5:** What is the sensitivity of DaL to a fixed d and how well does the adaptive mechanism perform in finding the optimal d for each individual run?

- **RQ6:** What is the model building time for DaL?

We ask **RQ1** to assess the effectiveness of DaL under different sample sizes against the state-of-the-art approaches and other models that share a similar concept. Since DaL is naturally model-agnostic and can be paired with different local models, we study **RQ2** to examine how the concept of dividable learning can benefit any given local model. Since DaL is similar to the ensemble approaches, e.g., Bagging [5] and Boosting [83], with **RQ3**, we seek to examine how it performs against those. **RQ4** is mainly an ablation analysis of DaL, consisting of confirming the necessity of using CART to determine the divisions over unsupervised clustering algorithms; verifying the effectiveness of adapting d compared with its counterpart under a fixed best d value obtained via trial-and-error; and assessing the benefit of using the newly proposed μHV in quantifying the usefulness of the divisions in a d value. In **RQ5**, we examine, under an extensively increased training sample size, how the depth of division (d) can impact the performance of DaL and how well the mechanism that adapts d can locate the optimal setting in individual runs, which is the ground truth. Finally, we examine the overall overhead of DaL in **RQ6**.

4.2 Subject Systems and Sample Sizes

Leveraging the criteria and procedure mentioned in Section 2.2.2, we use the same datasets of all valid configurations from real-world systems as widely used in the literature [36], [37], [76], [85], [86]. The 12 configurable software systems studied in this work are specified in Table 2. As can be seen, these software systems come with diverse domains, scales, and performance concerns. Some of them contain only binary configuration options (e.g., X264) while the others involve mixed options (binary and numeric), e.g., HSMGP, leading to configuration data that can be more difficult to model and generalize [37]. Note that the key performance-related configuration options have been identified in existing studies, hence although some systems have mixed options (e.g., APACHE), they are still binary in the dataset as those are key options that can influence the performance.

The configuration data of all the systems are collected by prior studies using the standard benchmarks with repeated measurements [36], [37], [76], [85], [86]. For example, the configurations of APACHE—a popular Web server—are benchmarked using the tools Autobench and Httperf, where workloads are generated and increased until reaching the point before the server crashes, and then the maximum load is marked as the performance value [36]. The process repeats a few times for each configuration to ensure reliability. When there exist multiple measured datasets for the same software system, we use the one with the largest size.

To ensure the generalizability of the results, for each system, we follow the protocol used by existing work [37], [85], [88] to obtain five sets of training sample size in the evaluation:

- **Binary systems:** We randomly sample n, $2n$, $3n$, $4n$, and $5n$ configurations and their measurements, where n is the number of configuration options [37], [85].

TABLE 2: Details of the subject systems. ($|\mathcal{B}|/|\mathcal{N}|$) denotes the number of binary/numerical options, and $|\mathcal{C}|$ denotes the number of valid configurations (full sample size).

System	$\lvert\mathcal{B}\rvert/\lvert\mathcal{N}\rvert$	Performance	Description	$\lvert\mathcal{C}\rvert$	Used by
APACHE	9/0	Maximum load	Web server	192	[36], [37], [85]
BDB-C	16/0	Latency (ms)	Database (C)	2560	[36], [37], [85]
BDB-J	26/0	Latency (ms)	Database (Java)	180	[36], [37], [85]
KANZI	31/0	Energy (kj)	Compression tool	3202	[71], [101]
SQLITE	14/0	Runtime (ms)	Database	1000	[6], [37], [55]
X264	16/0	Runtime (ms)	Video encoder	1152	[36], [37], [85]
DUNE	8/3	Runtime (ms)	Multi-grid solver	2304	[36], [37], [85]
HIPA^{cc}	31/2	Runtime (ms)	Image processing	13485	[37], [86]
HSMGP	11/3	Runtime (ms)	Stencil-grid solver	3456	[37], [86]
LRZIP	9/3	Runtime (ms)	Compression tool	5184	[71], [76], [101]
NGINX	12/2	Runtime (ms)	Web server	4416	[97], [101]
VP8	9/4	Runtime (ms)	Video encoder	2736	[76], [101]

TABLE 3: The training sample sizes used. n denotes the number of configuration options in a binary system.

System	Size 1 (S_1)	Size 2 (S_2)	Size 3 (S_3)	Size 4 (S_4)	Size 5 (S_5)
APACHE	n	$2n$	$3n$	$4n$	$5n$
BDB-C	n	$2n$	$3n$	$4n$	$5n$
BDB-J	n	$2n$	$3n$	$4n$	$5n$
KANZI	n	$2n$	$3n$	$4n$	$5n$
SQLITE	n	$2n$	$3n$	$4n$	$5n$
X264	n	$2n$	$3n$	$4n$	$5n$
DUNE	224	692	1000	1365	1612
HIPA^{cc}	261	528	736	1281	2631
HSMGP	77	173	384	480	864
LRZIP	127	295	386	485	907
NGINX	228	468	814	1012	1352
VP8	121	273	356	467	830

- **Mixed systems:** We leverage the sizes suggested by SPLConqueror [88] (a state-of-the-art approach) depending on the amount of budget.

The results have been illustrated in Table 3. All the remaining samples in the dataset are used for testing.

4.3 Metric and Statistical Validation

4.3.1 Accuracy

For all the experiments, mean relative error (MRE) is used as the evaluation metric for prediction accuracy, since it provides an intuitive indication of the error and has been widely used in the domain of software performance prediction [36], [37], [85]. Formally, the MRE is computed as:

$$MRE = \frac{1}{k} \times \sum_{t=1}^{k} \frac{|A_t - P_t|}{A_t} \times 100\% \tag{9}$$

whereby A_t and P_t denote the tth actual and predicted performance, respectively. To mitigate bias, all experiments are repeated for 30 runs via bootstrapping without replacement.

4.3.2 Statistical Test

Since our evaluation commonly involves comparing more than two approaches, we apply Scott-Knott test [70] to evaluate their statistical significance on the difference of MRE over 30 runs, as recommended by Mittas and Angelis [70]. In a nutshell, Scott-Knott sorts the list of treatments (the approaches that model the system) by their median values of the MRE. Next, it splits the list into two sub-lists with the largest expected difference [102]. For example, suppose that we compare A, B, and C, a possible split could be $\{A, B\}$, $\{C\}$, with the rank (r) of 1 and 2, respectively. This means

that, in the statistical sense, A and B perform similarly, but they are significantly better than C. Formally, Scott-Knott test aims to find the best split by maximizing the difference Δ in the expected mean before and after each split:

$$\Delta = \frac{|l_1|}{|l|}(\overline{l_1} - \bar{l})^2 + \frac{|l_2|}{|l|}(\overline{l_2} - \bar{l})^2 \quad (10)$$

whereby $|l_1|$ and $|l_2|$ are the sizes of two sub-lists (l_1 and l_2) from list l with a size $|l|$. $\overline{l_1}$, $\overline{l_2}$, and $\bar{l}$ denote their mean MRE.

During the splitting, we apply a statistical hypothesis test H to check if l_1 and l_2 are significantly different. This is done by using bootstrapping and $\hat{A}_{12}$ [95]. If that is the case, Scott-Knott recurses on the splits. In other words, we divide the approaches into different sub-lists if both bootstrap sampling and effect size test suggest that a split is statistically significant (with a confidence level of 99%) and with a good effect $\hat{A}_{12} \geq 0.6$. The sub-lists are then ranked based on their mean MRE.

5 Evaluation

We now present and discuss the experimental results.

5.1 Comparing with the State-of-the-art Approaches

5.1.1 Method

To understand how DaL performs compared with the state-of-the-art approaches, we assess its accuracy against both the standard works for configuration performance learning that rely on statistical learning together with recent deep learning-based ones:

- SPLConqueror [88]: linear regression with joint terms.
- DECART [36]: an improved CART with hyperparameter tuning.
- DeepPerf [37]: a single global regularized deep neural network.
- Perf-AL [85]: an adversarial learning method.
- HINNPerf [22]: a hierarchical deep neural network with embedding.

Additionally, we examine four approaches from the machine learning community that share a similar basic concept to DaL:

- IBMB [79]: a model that combines predictions from instance-based learning and model-based learning techniques.
- M5 [78]: a tree that divides to minimize the variance of each subset and trains a linear model for each leaf node.
- MOB [107]: a model that divides based on parametric models and parameter instability tests.
- PILOT [80]: a model divides similarly to CART but without pruning and trains linear models at the leaf nodes.

All approaches can be used for any type of system except for DECART, which works on binary systems only. The same randomly generated training and testing samples are used for all models, which are selected by using random sampling. Since there are 12 systems and 5 sets of sample sizes each, we obtained 60 cases to compare in total. The MREs and ranks from the Scott-Knott test are reported for all cases. To ensure consistency, we use the implementations published by their authors with the same parameter settings. We use the systems, training sizes, and statistical tests from Section 4. All experiments are repeated for 30 runs.

5.1.2 Results

The results have been illustrated in Table 4, from which we see that, remarkably, DaL achieves the best median MRE on 41 out of 60 cases. In particular, DaL considerably improves the accuracy, i.e., by up to $1.61\times$ better than the second-best one on S_4 of LRZIP (5.95 vs. 15.55). The above still holds when looking into the results of the statistical test: DaL is ranked first for 44 out of the 60 cases, in which DaL obtain the sole best rank for 31 cases. In particular, among the 19 cases where DaL does not achieve the best MRE, the inferiority to the best on 6 of them is actually insignificant since it is still equally ranked as the best together with the others. That is to say DaL is, in 44 cases, similar to (13 cases) or significantly better (31 cases) than the best state-of-the-art approaches for each specific case (which could be a different approach). Overall, DaL obtain an average rank of 1.47—the smallest among those of the others—indicating that it is much more likely to be ranked the best in terms of MRE. It is also worth noting that, the general model from the machine learning community (e.g., PILOT), although sharing a similar concept to DaL, are even inferior to some state-of-the-art models for configuration performance learning such as DeepPerf. This is because they have not been designed to handle the specific sparsity in configuration data.

When considering different training sample sizes, we see that DaL performs generally more inferior than the others when the size is too limited, i.e., S_1 and S_2 for the binary systems. This is expected as when there are too few samples, each local model would have a limited chance to observe the right pattern after the splitting, hence blurring its effectiveness in handling sample sparsity. However, in the other cases (especially for mixed systems that have more data even for S_1), DaL needs far fewer samples to achieve the same accuracy as the best state-of-the-art. For example, on LRZIP, DaL only needs 295 samples (S_2) to achieve an accuracy better than the accuracy of the second best model DeepPerf with 907 samples (S_5), saving 67% effort of data measurements. This is a beneficial outcome of properly handling the sample sparsity. That is, when a global model learns all the configuration data, it is often that case that more data is needed in order to correctly learn the full distribution of the data, as the sparsity causes the data points to spread in the landscape. In contrast, with DaL where the data can be properly divided, each local model can quickly learn the distribution of data in its local division, since the data is much more condensed to each other.

Another observation is that the improvements of DaL is much more obvious in mixed systems than those for binary systems. This is because: (1) the binary systems have fewer training samples as they have a smaller configuration space. Therefore, the data learned by each local model is more restricted. (2) The issue of sample sparsity is more severe

TABLE 4: The median and interquartile range of MRE, denoted as Med-IQR, for DaL and the state-of-the-art approaches for all the subject systems and training sizes over 30 runs. For each case, green cells mean DaL has the best median MRE; or red cells otherwise. The one(s) with the best rank (r) from the Scott-Knott test is highlighted in bold.

System	Size	DaL		HINNPerf		DeepPerf		Perf-AL		DECART		SPLConqueror		IBMB		M5		PILOT		MOB	
		r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)
APACHE	S_1	3	21.86 (7.36)	3	19.44 (10.53)	2	20.19 (6.34)	8	33.57 (11.34)	**1**	**19.44 (6.48)**	7	28.50 (11.14)	4	25.09 (4.77)	5	26.14 (4.51)	7	28.50 (11.14)	6	27.92 (8.28)
	S_2	6	12.89 (7.87)	**1**	**8.93 (3.89)**	2	9.79 (4.56)	8	32.97 (6.24)	3	9.77 (5.36)	5	18.33 (2.96)	6	25.62 (2.37)	6	23.91 (3.24)	4	17.61 (2.41)	7	28.88 (3.88)
	S_3	**1**	**6.56 (1.92)**	**1**	**7.01 (1.74)**	2	7.98 (1.91)	7	31.73 (4.66)	2	8.07 (1.05)	3	16.16 (1.41)	5	25.92 (2.57)	4	23.53 (2.09)	3	16.16 (1.41)	6	30.11 (3.62)
	S_4	2	6.87 (1.95)	**1**	**6.58 (1.04)**	2	6.85 (1.60)	7	30.67 (6.84)	3	7.47 (0.72)	4	16.12 (0.78)	6	25.90 (3.04)	5	23.14 (0.81)	4	16.12 (0.78)	7	30.30 (4.08)
	S_5	**1**	**5.78 (1.08)**	**1**	**5.85 (0.99)**	2	6.66 (1.61)	7	30.45 (4.91)	3	7.14 (0.89)	4	16.12 (1.37)	6	26.55 (2.26)	5	23.04 (0.82)	4	16.12 (1.37)	7	30.79 (3.13)
BDB-C	S_1	4	83.60 (208.75)	4	167.55 (144.47)	**1**	**43.66 (42.88)**	3	82.38 (57.27)	2	51.88 (45.91)	7	772.44 (576.45)	5	389.74 (289.18)	6	505.90 (163.69)	7	772.44 (579.59)	6	539.31 (358.57)
	S_2	3	21.92 (17.91)	2	21.45 (13.61)	2	18.17 (8.11)	4	73.99 (22.51)	**1**	**13.37 (7.25)**	6	526.69 (131.89)	5	438.62 (165.58)	6	541.59 (179.45)	6	526.69 (131.89)	7	626.96 (187.51)
	S_3	2	8.31 (7.52)	**1**	**6.50 (9.20)**	3	12.47 (4.08)	3	69.74 (4.33)	**1**	**7.56 (5.07)**	5	465.51 (88.42)	4	437.64 (109.19)	6	498.86 (126.41)	5	465.51 (89.84)	7	632.90 (112.44)
	S_4	2	3.60 (4.50)	**1**	**4.86 (2.18)**	2	9.06 (9.76)	3	69.50 (2.49)	**1**	**5.17 (5.07)**	5	438.47 (85.57)	4	399.19 (152.10)	6	503.49 (109.97)	5	443.62 (86.20)	7	594.25 (164.09)
	S_5	**1**	**1.88 (1.24)**	3	4.04 (1.24)	4	7.08 (8.03)	5	69.29 (0.69)	2	3.54 (1.92)	7	461.53 (85.82)	6	418.43 (143.13)	8	486.14 (76.71)	7	457.33 (85.98)	9	618.53 (147.33)
BDB-J	S_1	3	5.37 (4.74)	2	3.58 (1.74)	3	2.98 (3.34)	5	37.45 (2.45)	**1**	**2.36 (0.75)**	5	43.23 (5.84)	4	33.26 (3.52)	4	33.71 (7.73)	5	43.23 (6.80)	6	51.89 (16.34)
	S_2	**1**	**1.83 (0.45)**	**1**	**1.96 (0.36)**	2	1.91 (0.68)	5	37.90 (1.67)	**1**	**1.84 (0.17)**	5	38.30 (5.35)	4	32.86 (3.31)	3	32.51 (5.51)	5	38.35 (6.13)	6	49.16 (10.89)
	S_3	**1**	**1.58 (0.26)**	2	1.75 (0.41)	3	2.01 (1.10)	6	37.19 (1.70)	**1**	**1.64 (0.24)**	7	38.16 (3.88)	4	32.04 (1.20)	5	32.27 (3.41)	7	38.20 (3.75)	8	49.72 (5.45)
	S_4	**1**	**1.45 (0.22)**	2	1.52 (0.24)	3	1.70 (0.37)	6	37.74 (2.59)	**1**	**1.47 (0.12)**	6	36.88 (2.95)	4	31.83 (2.75)	5	31.73 (4.46)	6	37.00 (3.58)	7	50.87 (6.77)
	S_5	**1**	**1.40 (0.34)**	2	1.48 (0.32)	3	1.69 (0.48)	6	35.76 (4.47)	**1**	**1.37 (0.26)**	7	37.23 (3.13)	4	32.07 (3.14)	5	31.81 (4.87)	7	37.14 (2.97)	8	51.11 (5.46)
KANZI	S_1	**1**	**196.15 (213.73)**	2	262.27 (175.07)	**1**	**196.36 (122.61)**	5	1434.70 (1328.18)	2	276.50 (272.43)	6	2528.40 (662.30)	2	216.42 (270.56)	3	718.11 (341.73)	7	3106.10 (1285.5)	4	898.25 (391.69)
	S_2	2	95.31 (51.34)	**1**	**80.53 (51.36)**	3	107.12 (43.75)	7	961.11 (877.82)	3	126.50 (142.62)	8	1197.63 (349.62)	4	243.08 (214.68)	5	700.77 (211.53)	8	1198.90 (354.37)	6	970.59 (585.52)
	S_3	2	59.30 (38.47)	**1**	**62.20 (14.07)**	2	68.62 (30.41)	5	280.93 (147.45)	3	74.08 (32.14)	7	1059.46 (166.51)	4	208.36 (88.01)	6	782.13 (180.76)	7	1059.46 (166.90)	7	1002.12 (392.28)
	S_4	**1**	**42.93 (18.75)**	**1**	**46.48 (19.58)**	2	62.65 (26.54)	5	266.53 (179.59)	3	67.83 (15.79)	7	1030.40 (166.98)	4	160.99 (57.60)	6	762.99 (208.45)	7	1030.62 (163.83)	7	1028.27 (269.47)
	S_5	**1**	**35.29 (17.13)**	**1**	**34.27 (11.87)**	2	49.42 (9.99)	4	169.12 (64.60)	3	67.27 (17.95)	7	1012.03 (261.66)	5	211.48 (104.22)	6	749.61 (119.62)	7	1011.45 (264.24)	7	942.95 (295.12)
SQLITE	S_1	**1**	**73.52 (20.40)**	**1**	**70.76 (27.86)**	2	79.49 (25.36)	6	573.26 (340.38)	**1**	**74.14 (17.98)**	5	157.09 (70.92)	6	199.96 (242.69)	3	101.24 (26.56)	4	151.86 (65.00)	2	87.23 (2.08)
	S_2	**1**	**76.41 (16.66)**	2	76.69 (23.32)	3	77.75 (22.47)	6	386.74 (323.30)	2	76.20 (22.74)	4	84.41 (23.00)	4	81.65 (21.46)	5	115.69 (29.35)	4	84.41 (23.67)	3	86.26 (1.95)
	S_3	**1**	**71.63 (11.58)**	**1**	**71.02 (17.30)**	**1**	**75.01 (15.58)**	5	424.32 (311.00)	**1**	**74.16 (20.12)**	2	75.72 (24.82)	2	72.53 (21.01)	4	116.19 (29.50)	2	75.72 (24.83)	3	85.79 (1.46)
	S_4	**1**	**66.94 (10.61)**	2	70.84 (10.38)	3	72.45 (12.11)	6	363.18 (415.63)	2	71.57 (14.72)	3	69.61 (13.23)	2	68.25 (13.72)	5	120.45 (23.67)	3	69.61 (13.80)	4	85.61 (1.13)
	S_5	**1**	**64.20 (13.91)**	2	70.15 (9.71)	3	72.87 (8.86)	6	212.19 (295.12)	2	68.51 (8.54)	2	67.78 (9.68)	2	66.01 (10.76)	5	122.04 (17.73)	2	67.78 (9.68)	4	85.43 (1.26)
X264	S_1	3	10.21 (4.35)	2	8.44 (2.69)	**1**	**8.04 (3.06)**	7	37.00 (9.43)	2	9.27 (2.11)	4	12.70 (4.19)	5	32.14 (0.49)	5	32.21 (0.36)	4	12.70 (4.19)	6	34.59 (3.08)
	S_2	2	2.72 (1.52)	**1**	**2.77 (1.07)**	2	3.17 (1.00)	8	34.98 (7.81)	3	6.29 (1.72)	4	8.01 (1.19)	6	32.06 (0.76)	5	31.67 (0.26)	4	7.98 (1.32)	7	34.43 (2.82)
	S_3	2	1.57 (1.52)	**1**	**1.37 (0.46)**	2	2.23 (0.90)	8	36.25 (7.73)	3	4.57 (1.03)	4	7.61 (0.81)	6	32.06 (0.40)	5	31.54 (0.13)	4	7.61 (0.88)	7	34.57 (2.06)
	S_4	2	1.30 (1.17)	**1**	**0.81 (0.28)**	3	1.74 (0.98)	8	36.41 (6.47)	4	3.66 (1.42)	5	7.31 (0.49)	7	32.10 (0.36)	6	31.51 (0.16)	5	7.34 (0.45)	8	34.67 (1.64)
	S_5	2	0.96 (0.79)	**1**	**0.58 (0.15)**	3	1.44 (0.90)	8	36.20 (3.75)	4	2.15 (1.05)	5	7.11 (0.60)	7	32.04 (0.30)	6	31.50 (0.11)	5	7.11 (0.60)	8	34.37 (1.63)
DUNE	S_1	3	9.37 (1.15)	2	7.98 (0.98)	**1**	**7.86 (0.93)**	8	55.73 (0.12)	9	×	4	13.03 (1.74)	6	20.42 (2.38)	7	22.71 (0.85)	4	13.12 (1.91)	5	18.39 (0.70)
	S_2	**1**	**5.95 (0.54)**	2	6.15 (0.40)	**1**	**6.01 (0.21)**	7	55.72 (0.53)	8	×	3	13.09 (1.02)	5	22.39 (2.06)	6	22.89 (0.97)	3	13.09 (0.99)	4	18.52 (0.58)
	S_3	**1**	**4.81 (0.48)**	2	5.48 (0.39)	2	5.52 (0.34)	6	55.53 (1.69)	7	×	3	13.17 (0.57)	5	22.91 (2.02)	5	22.95 (0.85)	3	13.18 (0.59)	4	18.48 (0.59)
	S_4	**1**	**4.23 (0.35)**	2	5.12 (0.38)	3	5.26 (0.31)	8	54.58 (1.48)	9	×	4	13.15 (0.61)	7	24.04 (1.39)	6	22.85 (0.82)	4	13.16 (0.61)	5	18.75 (0.64)
	S_5	**1**	**3.98 (0.19)**	2	4.98 (0.64)	3	5.15 (0.34)	8	34.53 (21.14)	9	×	4	13.17 (0.55)	7	23.86 (1.77)	6	22.96 (0.78)	4	13.19 (0.52)	5	18.49 (0.47)
HIPAcc	S_1	**1**	**7.50 (1.42)**	**1**	**7.40 (1.05)**	2	9.70 (1.28)	7	31.99 (0.06)	8	×	3	20.43 (1.64)	5	26.18 (0.68)	4	25.01 (0.19)	3	20.57 (1.85)	6	33.07 (2.31)
	S_2	**1**	**4.48 (0.38)**	2	4.53 (0.48)	3	6.89 (1.44)	7	31.98 (0.06)	9	×	4	19.73 (0.89)	6	26.12 (0.49)	5	24.97 (0.07)	4	19.76 (0.86)	8	33.79 (1.24)
	S_3	**1**	**3.43 (0.34)**	2	3.67 (0.28)	3	4.68 (0.90)	7	31.99 (0.06)	9	×	4	19.33 (0.70)	6	26.00 (0.46)	5	24.95 (0.05)	4	19.32 (0.85)	8	33.73 (0.87)
	S_4	**1**	**2.60 (0.15)**	2	2.70 (0.18)	3	3.58 (1.00)	7	31.98 (0.06)	9	×	4	18.99 (0.61)	6	25.90 (0.32)	5	24.92 (0.06)	4	18.99 (0.60)	8	33.66 (0.79)
	S_5	**1**	**2.11 (0.08)**	2	2.23 (0.23)	3	2.82 (0.57)	7	31.97 (0.14)	9	×	4	18.79 (0.42)	6	25.73 (0.22)	5	24.91 (0.12)	4	18.79 (0.35)	8	33.58 (0.66)
HSMGP	S_1	**1**	**4.14 (1.44)**	2	5.03 (2.56)	3	7.09 (3.04)	8	66.70 (1294.05)	9	×	4	56.76 (18.43)	5	65.36 (30.25)	6	95.18 (11.51)	4	56.76 (18.02)	7	124.61 (36.63)
	S_2	**1**	**2.06 (0.19)**	2	3.13 (0.49)	3	3.69 (0.61)	8	66.67 (0.11)	9	×	4	50.74 (12.37)	5	67.20 (15.34)	6	89.54 (8.16)	4	50.85 (10.53)	7	121.43 (23.60)
	S_3	**1**	**1.42 (0.13)**	2	2.34 (0.38)	2	2.28 (0.37)	6	66.63 (0.18)	7	×	3	51.10 (8.01)	4	62.29 (11.54)	5	84.97 (4.24)	3	51.73 (8.30)	6	119.16 (16.57)
	S_4	**1**	**1.33 (0.08)**	2	2.19 (0.23)	3	2.23 (0.39)	6	66.63 (0.14)	9	×	4	49.45 (9.49)	5	62.38 (9.96)	7	84.76 (5.45)	4	50.41 (8.05)	8	117.78 (15.89)
	S_5	**1**	**1.19 (0.08)**	2	2.09 (0.25)	3	1.94 (0.63)	6	66.59 (0.20)	9	×	4	49.57 (3.15)	5	58.63 (4.99)	7	83.34 (3.06)	4	49.58 (3.25)	8	118.10 (7.24)
LRZIP	S_1	**1**	**31.88 (10.96)**	3	41.97 (12.02)	2	35.40 (16.59)	4	58.45 (0.12)	9	×	6	353.37 (126.02)	5	198.33 (88.16)	7	416.66 (119.43)	6	369.45 (117.97)	8	556.01 (110.73)
	S_2	**1**	**10.51 (4.39)**	3	24.10 (19.98)	2	21.46 (4.53)	4	58.46 (0.18)	9	×	6	309.08 (60.71)	5	144.88 (72.46)	7	403.42 (63.75)	6	315.26 (62.54)	8	517.67 (80.56)
	S_3	**1**	**8.04 (2.37)**	3	23.71 (16.49)	2	18.68 (3.20)	4	58.44 (0.21)	9	×	6	317.52 (47.97)	5	152.06 (92.00)	7	389.89 (44.37)	6	319.07 (50.92)	8	531.18 (104.18)
	S_4	**1**	**5.95 (0.99)**	3	19.82 (16.76)	2	15.55 (1.71)	4	58.48 (0.21)	9	×	6	318.37 (54.99)	5	151.04 (54.46)	7	385.47 (29.42)	6	325.49 (47.06)	8	531.05 (73.06)
	S_5	**1**	**4.03 (0.26)**	3	10.39 (2.92)	2	10.17 (0.91)	4	58.39 (0.21)	9	×	6	325.68 (31.40)	5	150.17 (20.91)	7	383.70 (27.71)	6	325.68 (30.81)	8	531.16 (36.15)
NGINX	S_1	**1**	**4.11 (1.45)**	2	8.08 (2.89)	3	8.76 (4.10)	7	1553.44 (965.63)	8	×	4	574.23 (25.74)	6	1218.33 (58.83)	5	1042.65 (46.12)	4	574.23 (25.74)	7	1406.58 (65.16)
	S_2	**1**	**2.60 (1.14)**	2	6.95 (1.74)	2	6.15 (4.17)	7	1637.60 (430.94)	8	×	3	566.48 (20.63)	5	1200.34 (76.00)	4	1046.84 (41.65)	3	568.39 (20.34)	6	1379.87 (80.17)
	S_3	**1**	**2.14 (0.40)**	3	6.46 (1.41)	2	4.42 (1.44)	8	1692.49 (305.78)	9	×	4	567.42 (18.59)	6	1206.44 (53.10)	5	1045.37 (32.55)	4	569.35 (15.63)	7	1379.17 (61.17)
	S_4	**1**	**1.99 (0.47)**	3	6.01 (1.68)	2	4.09 (2.27)	8	1784.76 (274.62)	9	×	4	568.66 (19.43)	6	1203.30 (54.38)	5	1046.87 (29.85)	4	571.25 (18.43)	7	1376.25 (59.62)
	S_5	**1**	**1.98 (0.21)**	3	7.27 (2.31)	2	3.17 (1.72)	8	1579.37 (515.54)	9	×	4	564.37 (24.70)	6	1199.31 (52.15)	5	1039.58 (28.93)	4	564.62 (23.57)	7	1367.38 (60.70)
VP8	S_1	**1**	**1.56 (0.18)**	**1**	**1.72 (0.25)**	2	4.68 (3.27)	4	60.05 (2.03)	8	×	3	44.06 (4.85)	6	92.98 (4.52)	5	85.03 (4.01)	3	44.06 (4.20)	7	110.78 (6.00)
	S_2	**1**	**1.15 (0.05)**	2	1.27 (0.15)	3	2.39 (1.21)	5	60.04 (0.24)	9	×	4	42.10 (3.17)	7	91.46 (5.56)	6	85.68 (4.11)	4	42.36 (3.42)	8	108.46 (6.09)
	S_3	**1**	**1.08 (0.04)**	2	1.25 (0.14)	3	1.93 (0.72)	5	60.02 (0.29)	9	×	4	42.94 (2.82)	7	91.76 (3.49)	6	84.88 (2.66)	4	43.02 (2.62)	8	108.23 (5.29)
	S_4	**1**	**0.98 (0.05)**	2	1.15 (0.11)	3	1.54 (0.40)	5	59.99 (0.27)	9	×	4	42.05 (3.59)	7	91.99 (3.14)	6	84.78 (1.95)	4	41.99 (3.12)	8	108.47 (4.25)
	S_5	**1**	**0.90 (0.06)**	2	1.12 (0.11)	3	1.45 (0.23)	5	59.95 (0.68)	9	×	4	42.87 (2.39)	7	92.21 (3.02)	6	84.53 (2.44)	4	42.66 (2.11)	8	108.43 (3.71)
Average r		1.47		1.88		2.37		6.1		5.38		4.67		5.13		5.45		4.65		6.62	

on mixed systems, as their configuration landscape is more complex and comes with finer granularity.

As a result, we anticipate that the benefit of DaL can be amplified under more complex configurable systems and/or when the size of the training data sample increases.

To summarize, we can answer **RQ1** as:

> ***RQ1:*** *For modeling configuration performance, DaL performs similar or significantly more accurate than the best state-of-the-art approach in 44 out of 60 cases (73%), in which 31 cases obtain the sole best results with up to 1.61× improvements. It also needs fewer samples to achieve the same accuracy and the benefits can be amplified with complex systems/more training samples.*

5.2 DaL under Different Local Models

5.2.1 Method

Since the paradigm of dividable learning is naturally agnostic to the underlying local models, we seek to understand how well DaL performs with different local models against their global model counterparts (i.e., using them directly to learn the entire training dataset without dividing). To that end, we run experiments on a set of global models available in `scikit-learn` that are widely used in software engineering tasks to make predictions directly [30], such as regularized Deep Neural Network (DNN), Decision Tree (CART), Random Forest (RF), Linear Regression (LR), and Support Vector Regression (SVR). We used the same settings as those for **RQ1**. Similarly, we show the ranks r produced by the Scott-Knott test and the median MRE (IQR) of the evaluation results.

5.2.2 Result

From Table 5, it is clear that when examining each pair of the counterparts in terms of the average rank, i.e., DaL$_X$ and X, DaL can indeed improve the accuracy of the local model via the concept of "divide-and-learn". Such an improvement is particularly obvious on some simple models, such as LR, which might lead to 26.08× better MRE on NGINX under S_1. This confirms the generality and flexibility of DaL: for example, when LR needs to be used as the local model for the sake of training overhead, DaL can still significantly improve the results compared with its global counterpart. Interestingly, when pairing DaL with CART as the local model, it remains slightly better than using CART as the global model alone, even though their learning procedures are similar. This is possible as the actual result of the computed loss can be different in CART when it is presented with different proportions of the data samples. Yet, the resulting MREs do not differ much as can be seen.

TABLE 5: DaL under different local models against using them as the global models. The format is the same as Table 4.

System	Size	DaL		HINNPerf		DaL_{DNN}		DNN		DaL_{CART}		CART		DaL_{LR}		LR		DaL_{SVR}		SVR	
		r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)
APACHE	S_1	2	21.86 (7.36)	3	19.44 (10.53)	**1**	**21.02 (6.64)**	2	20.19 (6.34)	2	21.61 (6.69)	2	20.85 (12.99)	**1**	**19.71 (6.80)**	4	27.72 (4.98)	3	23.30 (4.08)	3	22.67 (3.66)
	S_2	4	12.89 (7.87)	**1**	**8.93 (3.89)**	3	9.82 (6.00)	2	9.79 (4.56)	3	10.12 (5.05)	2	10.06 (3.05)	3	10.77 (7.55)	4	17.61 (2.41)	4	17.59 (3.76)	4	20.31 (3.18)
	S_3	**1**	**6.56 (1.92)**	**1**	**7.01 (1.74)**	2	7.17 (2.67)	3	7.98 (1.91)	4	9.10 (1.31)	4	9.03 (1.13)	2	7.42 (2.14)	6	16.16 (1.41)	5	15.92 (2.45)	7	18.50 (1.54)
	S_4	3	6.87 (1.95)	2	6.58 (1.04)	3	6.59 (1.77)	3	6.85 (1.60)	5	7.97 (1.35)	4	7.81 (1.35)	**1**	**6.39 (1.16)**	7	16.12 (0.78)	6	13.89 (2.35)	8	18.57 (1.58)
	S_5	3	5.78 (1.08)	3	5.85 (0.99)	2	5.96 (2.07)	4	6.66 (1.61)	5	7.63 (1.00)	5	7.71 (1.03)	**1**	**5.75 (0.55)**	7	16.12 (1.37)	6	12.63 (1.76)	8	17.82 (1.78)
BDB-C	S_1	4	83.60 (208.75)	4	167.55 (144.47)	2	41.77 (32.54)	2	43.66 (42.88)	**1**	**47.20 (19.75)**	**1**	**36.17 (9.11)**	3	65.09 (37.30)	5	698.12 (713.51)	3	65.38 (22.26)	4	154.71 (52.45)
	S_2	2	21.92 (17.91)	**1**	**21.45 (13.61)**	2	17.22 (15.67)	**1**	**18.17 (8.11)**	**1**	**16.81 (8.59)**	**1**	**19.61 (7.19)**	3	49.04 (47.11)	4	545.48 (149.70)	3	70.56 (64.18)	3	117.87 (49.95)
	S_3	3	8.31 (7.52)	2	6.50 (9.20)	2	5.74 (6.84)	4	12.47 (4.08)	3	6.72 (5.82)	**1**	**7.44 (3.70)**	5	29.00 (78.81)	7	465.51 (91.79)	6	65.69 (155.89)	5	97.22 (52.60)
	S_4	3	3.60 (4.50)	**1**	**4.86 (2.18)**	**1**	**3.68 (2.78)**	3	9.06 (9.76)	**1**	**4.15 (2.78)**	2	5.74 (3.97)	4	24.55 (4.18)	6	441.04 (85.57)	5	51.04 (29.64)	5	93.39 (41.17)
	S_5	**1**	**1.88 (1.24)**	3	4.04 (1.24)	2	2.15 (1.52)	4	7.08 (8.03)	2	3.24 (3.09)	2	3.32 (2.50)	5	22.88 (3.78)	8	456.02 (78.01)	6	46.18 (19.08)	7	105.14 (56.61)
BDB-J	S_1	2	5.37 (4.74)	2	3.58 (1.74)	2	3.14 (2.90)	2	2.98 (3.34)	**1**	**2.98 (0.81)**	**1**	**3.03 (0.99)**	3	5.31 (2.96)	5	43.23 (6.15)	4	22.77 (17.72)	3	12.93 (3.37)
	S_2	**1**	**1.83 (0.45)**	**1**	**1.96 (0.36)**	4	1.90 (0.37)	3	1.91 (0.68)	2	2.05 (0.33)	**1**	**1.99 (0.29)**	4	3.77 (0.49)	7	37.85 (6.27)	6	15.28 (12.28)	5	10.54 (0.97)
	S_3	**1**	**1.58 (0.26)**	2	1.75 (0.41)	2	1.61 (0.31)	3	2.01 (1.10)	2	1.92 (0.27)	2	1.87 (0.35)	3	3.41 (0.46)	6	37.61 (3.49)	5	15.03 (10.36)	4	11.03 (0.89)
	S_4	**1**	**1.45 (0.22)**	2	1.52 (0.24)	3	1.61 (0.29)	5	1.70 (0.37)	4	1.67 (0.29)	4	1.69 (0.36)	6	3.57 (0.66)	8	37.57 (3.48)	7	9.20 (5.36)	7	11.25 (1.35)
	S_5	**1**	**1.40 (0.34)**	2	1.48 (0.32)	2	1.46 (0.26)	4	1.69 (0.48)	3	1.67 (0.43)	3	1.68 (0.39)	5	3.23 (0.65)	8	37.48 (2.86)	6	8.21 (3.87)	7	11.51 (2.21)
KANZI	S_1	2	196.15 (213.73)	4	262.27 (175.07)	2	166.22 (122.05)	2	196.36 (122.61)	2	178.67 (123.16)	2	163.60 (121.50)	5	551.03 (1244.41)	6	3106.09 (1514.60)	3	253.06 (150.61)	**1**	**129.01 (61.27)**
	S_2	3	95.31 (51.34)	**1**	**80.53 (51.36)**	2	90.27 (63.53)	4	107.12 (43.75)	**1**	**86.55 (35.63)**	**1**	**91.65 (38.71)**	6	383.06 (493.33)	7	1191.03 (348.39)	5	190.01 (134.20)	2	105.79 (34.34)
	S_3	2	59.30 (38.47)	**1**	**62.20 (14.07)**	3	64.56 (62.71)	2	68.62 (30.41)	2	62.50 (21.15)	2	60.13 (21.42)	6	177.35 (384.90)	5	1058.91 (166.05)	4	198.38 (146.32)	3	99.24 (33.82)
	S_4	**1**	**42.93 (18.75)**	**1**	**46.48 (19.58)**	**1**	**41.83 (15.47)**	2	62.65 (26.54)	**1**	**48.69 (10.31)**	**1**	**49.06 (14.98)**	6	134.99 (522.74)	5	1030.25 (180.09)	4	186.29 (80.16)	3	89.93 (27.29)
	S_5	**1**	**35.29 (17.13)**	**1**	**34.27 (11.87)**	4	38.57 (20.46)	3	49.42 (9.99)	2	44.15 (8.53)	2	43.96 (10.22)	7	605.42 (1213.79)	7	1010.78 (264.34)	6	152.57 (97.14)	5	87.82 (16.52)
SQLITE	S_1	3	73.52 (20.40)	2	70.76 (27.86)	**1**	**73.62 (16.43)**	3	79.49 (25.36)	4	82.77 (20.99)	4	83.67 (21.57)	5	105.75 (83.62)	6	151.86 (65.00)	2	79.85 (19.78)	**1**	**74.80 (19.37)**
	S_2	**1**	**76.41 (16.66)**	2	76.69 (23.32)	3	77.81 (24.37)	3	77.75 (22.47)	4	86.76 (20.84)	4	89.07 (18.89)	5	161.86 (135.45)	4	84.41 (23.67)	2	79.52 (21.38)	2	77.78 (11.49)
	S_3	**1**	**71.63 (11.58)**	**1**	**71.02 (17.30)**	2	74.86 (15.95)	**1**	**75.01 (15.58)**	3	87.65 (24.29)	3	89.12 (23.09)	4	103.75 (29.66)	2	75.72 (24.83)	2	80.75 (14.40)	2	79.66 (10.31)
	S_4	**1**	**66.94 (10.61)**	2	70.84 (10.38)	2	70.41 (12.22)	3	72.45 (12.11)	6	86.47 (20.30)	6	87.46 (19.46)	6	82.25 (23.16)	2	69.61 (13.80)	4	77.23 (10.08)	5	79.11 (10.34)
	S_5	**1**	**64.20 (13.91)**	2	70.15 (9.71)	2	69.72 (12.48)	3	72.87 (8.86)	6	84.43 (12.41)	6	84.51 (14.40)	4	76.06 (16.27)	2	67.78 (9.68)	4	76.28 (13.41)	5	79.69 (11.05)
X264	S_1	3	10.21 (4.35)	2	8.44 (2.69)	**1**	**8.04 (1.30)**	**1**	**8.04 (3.06)**	3	10.40 (2.15)	2	8.77 (2.89)	3	10.43 (3.40)	4	14.36 (4.34)	4	14.39 (2.64)	5	25.72 (2.91)
	S_2	2	2.72 (1.52)	**1**	**2.77 (1.07)**	3	3.34 (1.90)	2	3.17 (1.00)	5	6.57 (1.67)	5	6.50 (1.63)	4	3.51 (0.98)	6	8.01 (1.23)	7	9.32 (2.16)	8	18.83 (5.32)
	S_3	2	1.57 (1.52)	**1**	**1.37 (0.46)**	2	1.97 (1.47)	2	2.23 (0.90)	4	5.01 (1.42)	4	4.72 (0.73)	3	2.84 (0.52)	5	7.61 (0.76)	5	8.25 (2.68)	6	13.66 (2.32)
	S_4	2	1.30 (1.17)	**1**	**0.81 (0.28)**	2	1.39 (0.56)	3	1.74 (0.98)	5	3.52 (1.33)	5	3.65 (1.03)	4	2.60 (0.52)	7	7.34 (0.39)	6	7.05 (4.00)	8	10.24 (1.41)
	S_5	2	0.96 (0.79)	**1**	**0.58 (0.15)**	2	1.05 (0.55)	3	1.44 (0.90)	6	2.54 (1.04)	5	2.37 (1.11)	4	2.10 (1.04)	8	7.17 (0.60)	7	7.72 (4.47)	9	9.19 (0.76)
DUNE	S_1	4	9.37 (1.15)	2	7.98 (0.98)	3	8.40 (1.61)	**1**	**7.86 (0.93)**	4	9.04 (1.13)	4	9.13 (0.99)	5	11.21 (0.88)	6	13.06 (1.90)	7	14.46 (0.51)	8	14.76 (0.64)
	S_2	**1**	**5.95 (0.54)**	2	6.15 (0.40)	**1**	**5.78 (0.41)**	**1**	**6.01 (0.21)**	3	6.25 (0.42)	3	6.26 (0.40)	4	11.13 (0.57)	5	13.02 (1.06)	5	13.37 (0.25)	6	13.47 (0.32)
	S_3	**1**	**4.81 (0.48)**	3	5.48 (0.39)	2	5.21 (0.39)	3	5.52 (0.34)	3	5.48 (0.42)	3	5.49 (0.37)	4	11.09 (0.54)	6	13.13 (0.66)	5	12.95 (0.32)	6	13.15 (0.41)
	S_4	**1**	**4.23 (0.35)**	4	5.12 (0.38)	2	4.79 (0.49)	5	5.26 (0.31)	3	5.06 (0.32)	3	5.01 (0.32)	6	11.04 (0.43)	9	13.14 (0.55)	7	12.57 (0.47)	8	12.80 (0.52)
	S_5	**1**	**3.98 (0.19)**	3	4.98 (0.64)	2	4.69 (0.50)	4	5.15 (0.34)	2	4.69 (0.35)	2	4.66 (0.36)	5	10.93 (0.48)	8	13.21 (0.57)	6	12.30 (0.46)	7	12.58 (0.69)
HIPA^{cc}	S_1	**1**	**7.50 (1.42)**	**1**	**7.40 (1.05)**	2	9.07 (1.18)	3	9.70 (1.28)	4	12.03 (0.93)	4	12.07 (1.06)	8	12.70 (1.22)	7	20.49 (1.61)	5	13.06 (0.51)	6	14.84 (0.62)
	S_2	**1**	**4.48 (0.38)**	2	4.53 (0.48)	3	5.55 (0.60)	4	6.89 (1.44)	5	8.47 (1.10)	5	8.20 (1.00)	9	11.64 (0.35)	8	19.67 (0.83)	6	11.27 (0.44)	7	14.52 (0.54)
	S_3	**1**	**3.43 (0.34)**	2	3.67 (0.28)	3	4.39 (0.41)	4	4.68 (0.90)	5	6.62 (0.80)	5	6.60 (0.75)	7	11.43 (0.34)	9	19.35 (0.72)	6	10.78 (0.28)	8	14.48 (0.57)
	S_4	**1**	**2.60 (0.15)**	2	2.70 (0.18)	3	3.22 (0.35)	4	3.58 (1.00)	5	4.42 (0.22)	5	4.31 (0.44)	7	11.13 (0.25)	9	18.97 (0.46)	6	10.31 (0.14)	8	12.06 (0.25)
	S_5	**1**	**2.11 (0.08)**	2	2.23 (0.23)	3	2.39 (0.22)	5	2.82 (0.57)	4	2.69 (0.15)	4	2.70 (0.17)	8	11.01 (0.15)	9	18.81 (0.37)	6	10.04 (0.09)	7	10.52 (0.24)
HSMGP	S_1	**1**	**4.14 (1.44)**	2	5.03 (2.56)	**1**	**4.66 (1.32)**	6	7.09 (3.04)	6	21.65 (2.31)	6	21.34 (2.41)	3	7.72 (0.80)	7	55.91 (19.98)	4	16.00 (2.48)	5	16.63 (1.38)
	S_2	**1**	**2.06 (0.19)**	3	3.13 (0.49)	2	2.66 (0.68)	4	3.69 (0.61)	7	15.59 (1.41)	7	16.43 (1.52)	5	7.35 (0.47)	8	52.54 (10.70)	6	15.24 (1.32)	7	16.30 (2.16)
	S_3	**1**	**1.42 (0.13)**	3	2.34 (0.38)	2	1.56 (0.20)	3	2.28 (0.37)	6	11.35 (0.63)	6	11.26 (0.98)	4	7.14 (0.35)	8	51.38 (9.85)	5	10.05 (0.86)	7	15.03 (0.66)
	S_4	**1**	**1.33 (0.08)**	3	2.19 (0.23)	2	1.49 (0.15)	4	2.23 (0.39)	7	10.13 (0.57)	8	10.14 (0.72)	5	7.16 (0.17)	10	49.63 (9.43)	6	8.95 (0.90)	9	15.07 (0.56)
	S_5	**1**	**1.19 (0.08)**	2	2.09 (0.25)	**1**	**1.16 (0.08)**	3	1.94 (0.63)	7	7.46 (0.46)	6	7.43 (0.34)	5	7.15 (0.20)	9	49.05 (3.00)	4	5.87 (0.52)	8	8.60 (0.38)
LRZIP	S_1	4	31.88 (10.96)	6	41.97 (12.02)	3	26.40 (6.94)	5	35.40 (16.59)	**1**	**17.95 (10.85)**	2	23.50 (10.09)	8	117.37 (24.65)	9	369.45 (116.78)	7	59.16 (13.29)	7	63.04 (23.36)
	S_2	2	10.51 (4.39)	5	24.10 (19.98)	3	15.37 (6.04)	4	21.46 (4.53)	**1**	**9.09 (2.56)**	2	10.47 (4.94)	7	109.11 (20.26)	8	315.34 (66.07)	6	63.84 (11.18)	6	61.82 (34.55)
	S_3	2	8.04 (2.37)	5	23.71 (16.49)	3	11.83 (4.53)	4	18.68 (3.20)	**1**	**7.77 (2.09)**	2	8.62 (4.75)	8	104.20 (17.55)	9	322.55 (50.28)	7	63.91 (13.58)	6	66.09 (41.44)
	S_4	**1**	**5.95 (0.99)**	5	19.82 (16.76)	3	10.10 (3.23)	4	15.55 (1.71)	**1**	**6.38 (2.72)**	2	7.09 (2.76)	7	103.74 (14.29)	8	323.59 (56.77)	6	65.19 (12.53)	6	69.07 (5.93)
	S_5	2	4.03 (0.26)	6	10.39 (2.92)	4	6.60 (1.34)	5	10.17 (0.91)	**1**	**3.58 (0.97)**	3	4.47 (1.90)	9	105.83 (7.06)	10	327.20 (27.08)	7	48.80 (2.86)	8	51.27 (2.21)
NGINX	S_1	**1**	**4.11 (1.45)**	3	8.08 (2.89)	2	4.95 (2.94)	4	8.76 (4.10)	5	14.44 (2.41)	5	14.44 (2.41)	6	22.02 (2.11)	8	574.23 (25.93)	7	456.24 (15.91)	9	1603.42 (66.06)
	S_2	**1**	**2.60 (1.14)**	2	6.95 (1.74)	**1**	**3.07 (0.94)**	2	6.15 (4.17)	3	7.44 (3.14)	3	7.44 (3.14)	4	20.25 (1.60)	6	568.09 (19.68)	5	430.40 (22.39)	7	1337.93 (148.42)
	S_3	**1**	**2.14 (0.40)**	4	6.46 (1.41)	2	2.31 (1.29)	3	4.42 (1.44)	3	4.81 (0.81)	3	4.81 (0.81)	5	19.66 (0.75)	7	568.45 (16.13)	6	389.40 (30.26)	8	942.81 (108.67)
	S_4	**1**	**1.99 (0.47)**	5	6.01 (1.68)	2	2.16 (0.88)	4	4.09 (2.27)	3	4.16 (1.01)	3	4.16 (1.01)	6	19.74 (0.82)	8	571.30 (19.18)	7	364.98 (32.75)	9	690.54 (133.59)
	S_5	**1**	**1.98 (0.21)**	4	7.27 (2.31)	**1**	**1.97 (0.52)**	3	3.17 (1.72)	2	3.33 (1.00)	2	3.33 (1.00)	5	19.17 (1.07)	8	564.69 (23.96)	6	327.92 (28.40)	7	450.48 (87.27)
VP8	S_1	**1**	**1.56 (0.18)**	**1**	**1.72 (0.25)**	2	1.59 (0.36)	5	4.68 (3.27)	3	2.57 (0.70)	4	2.47 (0.70)	6	12.72 (0.84)	9	43.69 (5.81)	7	13.84 (0.76)	8	22.37 (3.68)
	S_2	**1**	**1.15 (0.05)**	2	1.27 (0.15)	4	1.21 (0.09)	5	2.39 (1.21)	2	1.24 (0.24)	3	1.30 (0.22)	7	12.42 (0.44)	9	42.04 (3.16)	6	10.30 (0.49)	8	23.53 (1.46)
	S_3	**1**	**1.08 (0.04)**	5	1.25 (0.14)	2	1.12 (0.08)	6	1.93 (0.72)	3	1.15 (0.12)	4	1.18 (0.21)	8	12.41 (0.34)	10	42.65 (2.99)	7	10.11 (0.56)	9	25.02 (1.93)
	S_4	**1**	**0.98 (0.05)**	4	1.15 (0.11)	3	1.10 (0.06)	5	1.54 (0.40)	2	1.07 (0.08)	3	1.09 (0.08)	7	12.35 (0.31)	9	42.08 (2.79)	6	9.81 (0.36)	8	26.13 (1.14)
	S_5	**1**	**0.90 (0.06)**	5	1.12 (0.11)	4	1.07 (0.05)	6	1.45 (0.23)	2	0.94 (0.04)	3	0.94 (0.05)	8	12.41 (0.27)	10	42.69 (1.94)	7	9.71 (0.21)	9	15.54 (0.77)
Average r		1.63		2.52		2.27		3.35		3.28		3.37		5.12		6.9		5.35		6.12	

It is worth noting that, the default of DaL, which uses the HINNPerf as the local model, still performs significantly better than the others: out of the 60 cases, 33 of them come with the best MRE and there are 37 cases with the best rank, leading to an average rank of 1.63 which is again the best of amongst the others. This aligns with the previous findings that HINNPerf handles the feature sparsity better [22].

Therefore, for **RQ2**, we say:

> ***RQ2:*** *Thanks to the paradigm of dividable learning, DaL is model-agnostic, being able to significantly improve a range of global models when using them as the underlying local model in configuration performance learning. We also reveal that pairing with DaL with HINNPerf can lead to considerably better accuracy in this work.*

5.3 Comparing with Other Ensemble Approaches

5.3.1 Method

Since DaL works with multiple local models, it could naturally be compared with the ensemble learning approaches that also involve a set of local models. Here, we compare DaL with the most common ensemble learning approaches such as Bagging and Boosting. For the local model, we employ HINNPerf (the default for DaL) as well as two commonly used machine learning models LR and CART.

Specifically, we examine Bagging_{HINN} [5] (an aggregated ensemble of HINNPerf based on random data projection) and $\text{AdaBoosting}_{HINN}$ [28] (a sequentially learned ensemble of HINNPerf based on majrotiy voting). We follow similar settings for LR and CART. Yet, since CART is a tree-like structure, there exist more diverse variants of ensembles. Therefore, in this work, we examine DaL that uses CART (denoted as DaL_{CART}) against RF (a bagging version that trains multiple CART models), XGBoost [21] (a boosting version that builds multiple gbtree booster [62], which is a variant of CART), and $\text{AdaBoosting}_{CART}$ (another boosting version of CART that does not rely on optimization of a loss function).

Again, we leverage the scikit-learn package. We use the default parameter settings for all these ensemble approaches, which tends to be ideal for most scenarios. The

other experiment settings are the same as **RQ1** and **RQ2**.

5.3.2 Results

The results can be seen in Table 6, in which we compare the approaches within each type of local model, e.g., only comparing those use HINNPerf as the local model. Clearly, when using HINNPerf as the local model, DaL has the best median MRE in 56 out of 60 cases, and is ranked the first in 58 out of all the cases. Moreover, comparing the second best model ensembling method, DaL achieves up to $9.89\times$ improvements (2.14 vs. 23.32 for S_3 of NGINX). This leads to a remarkable 1.03 average Scott-Knott rank.

When using LR as the local model, $\texttt{DaL}_{LR}$ achieves considerably better accuracy than the other ensemble learning approaches, leading to the best MRE in 55 out of 60 cases with up to $28.50\times$ improvement with respect to the second best counterpart (19.17 vs. 565.62 for S_5 of NGINX). In particular, it obtains the best Scott-Knott ranks on 51 out of 60 cases, within which only 2 cases $\texttt{DaL}_{LR}$ does not achieve the sole best rank. This has resulted in the best average rank among the counterparts, i.e., 1.2.

Since DaL leverages CART to divide the data samples, one can easily expect that it would benefit less when using CART again as the local model. As a result, the relative improvement of $\texttt{DaL}_{CART}$ over the counterparts becomes blurred compared with that of $\texttt{DaL}_{LR}$. However, in Table 6, we see that $\texttt{DaL}_{CART}$ still achieve highly competitive outcomes in relation to the others: amongst the 60 cases, it is ranked as the best for 28 cases, which is higher than the 24, 17, and 10 cases for RF, XGBoost, and $\texttt{AdaBoosting}_{CART}$, respectively. Notably, $\texttt{DaL}_{CART}$ also more frequently achieves the best MRE. All the above has led to its best average rank of 1.85. Looking at the detailed MRE differences, compared with RF, the largest improvement and degradation of $\texttt{DaL}_{CART}$ is $4.83\times$ (14.44 vs. 84.12 for S_1 of NGINX) and $0.50\times$ (11.35 vs. 7.58 for S_3 of HSMGP), respectively; compared with XGBoost it is $4.20\times$ (0.94 vs. 4.89 for S_5 of VP8) and $1.13\times$ (14.44 vs. 6.78 for S_1 of NGINX), respectively; in contrast to $\texttt{AdaBoost}_{CART}$, it is respectively $5.54\times$ (6.72 vs. 43.94 for S_3 of BDB-C) and $2.43\times$ (7.44 vs. 2.17 for S_2 of NGINX). All the above reveals the superior benefit of DaL against the others.

With different local models including HINNPerf, LR and CART, we see that the benefit of DaL is more obvious for mixed systems: this is again due to the fact that those systems often come with a more sparse and complex configuration landscape, which is precisely what DaL can cope with.

In conclusion, we can state the following for **RQ3**:

> ***RQ3:*** *Compared with existing ensemble learning approaches, DaL generally has a better ability to utilize the local models for predicting configuration performance. The benefits are particularly obvious under complex local models and systems.*

5.4 The Effectiveness of Components in DaL

5.4.1 The Benefits of CART

As discussed in Section 3.1.1, we modify CART to divide the configuration data samples since its training procedure naturally fits our needs better. To confirm this point, here we experimentally examine its effectiveness over several alternative clustering algorithms that can serve as the replacement of CART in the *dividing* phase of DaL, namely: DBSCAN [25] (a density-based clustering algorithm), Agglomerative clustering [99] (a hierarchical clustering algorithm), and kMeans [63] (a centroid-based clustering algorithm). We use the most common Euclidean distance while both the configuration options and performance values are combined as the features of clustering.

Again, we directly use the implementations from the scikit-learn package while the other experiment settings are the same as the previous RQs. Among these, DBSCAN adaptively determines the best number of divisions, while for Agglomerative clustering and kMeans, we tuned the division numbers for each case and use the overall best setting throughout the runs. The other parameters are set as the default values.

As can be seen from Table 7 (left), the original design of DaL that extends CART achieves significantly and overwhelmingly better results: among the 60 cases, there are 56 cases of the solely best rank and 57 cases of the best MRE with up to $5.41\times$ improvement over the second-best counterpart. The main reason is that, while the clustering algorithms do divide the configuration data, they often fail to take the prediction loss into account—a key feature within the training procedure of CART.

5.4.2 The Necessity of Adapting d

To investigate the necessity of adapting d, we compare DaL with the version from our previous FSE work [31] where an overall best d value for each system-size pair is pre-defined via profiling, denoted as DaL-FSE. Pragmatically, the procedure that one would need to perform without d adaptation is as below:

1) Choose a system and a training size considered.
2) Pick a $d = k$ where $k \in \{1, 2, .., d_{max}\}$ and train DaL-FSE using the corresponding training size, where d_{max} is the largest depth that the CART can ever reach under a training size of the system.
3) Repeat the experiment for 30 runs under $d = k$.
4) Calculate the MREs of DaL-FSE under $d = k$ using all the remaining data as the testing set.
5) Repeat from (2) if not all possible d value has been examined.
6) Calculate the Scott-Knott ranks for MRE of DaL-FSE under different d values.
7) The d value with the best rank is used; if there are multiple d values that lead to the best rank, we select the one with the best average MRE therein.
8) Repeat from (1) if not all system and size pairs have been covered.

All other settings are the same as the previous RQs.

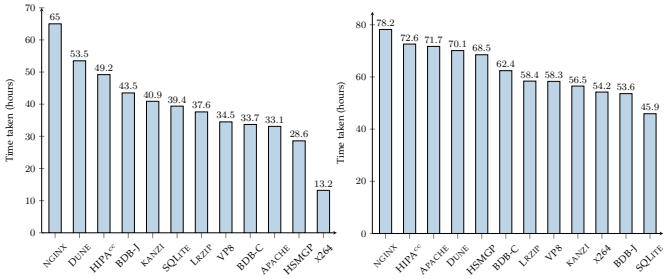
The comparisons between DaL-FSE and the proposed DaL are illustrated in Table 7 (middle). Clearly, both approaches perform very similarly across the cases. In particular, DaL reaches identical results to that of DaL-FSE, which is pre-tuned, in 54 out of 60 cases. Interestingly, it is even possible for DaL to achieve better accuracy, e.g., in S_2 of x264. This is because DaL adapts d for each individual

TABLE 6: DaL against the other ensemble approaches. The format is the same as Table 4.

System	Size	DaL		Bagging_{HINN}		AdaBoost_{HINN}		DaL_{LR}		Bagging_{LR}		AdaBoost_{LR}		DaL_{CART}		RF		XGBoost		AdaBoost_{CART}	
		r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)
APACHE	S_1	**1**	**21.86 (7.36)**	3	24.64 (9.80)	2	24.78 (6.66)	**1**	**19.71 (6.80)**	2	20.81 (4.47)	2	20.44 (5.03)	2	21.61 (6.69)	3	21.20 (7.72)	**1**	**19.03 (7.50)**	4	24.06 (7.47)
	S_2	**1**	**12.89 (7.87)**	**1**	**14.84 (6.31)**	**1**	**15.61 (5.39)**	**1**	**10.77 (7.55)**	3	17.64 (2.12)	2	16.69 (2.45)	2	10.12 (5.05)	2	12.02 (6.58)	**1**	**10.70 (3.76)**	3	13.82 (4.42)
	S_3	**1**	**6.56 (1.92)**	2	11.20 (5.52)	3	12.19 (10.08)	**1**	**7.42 (2.14)**	2	16.11 (1.34)	2	16.25 (1.68)	2	9.10 (1.31)	**1**	**7.65 (1.46)**	2	9.37 (1.36)	2	9.04 (1.70)
	S_4	**1**	**6.87 (1.95)**	3	9.17 (23.67)	2	9.86 (2.32)	**1**	**6.39 (1.16)**	2	16.20 (0.82)	2	15.96 (1.40)	3	7.97 (1.35)	**1**	**6.63 (1.19)**	4	8.70 (1.14)	2	7.64 (0.99)
	S_5	**1**	**5.78 (1.08)**	3	7.81 (24.03)	2	8.90 (3.19)	**1**	**5.75 (0.55)**	2	16.04 (1.37)	2	16.18 (1.80)	3	7.63 (1.00)	**1**	**6.43 (1.11)**	4	8.17 (1.69)	2	7.22 (0.97)
BDB-C	S_1	**1**	**83.60 (208.75)**	**1**	**158.49 (97.21)**	2	239.27 (165.36)	**1**	**65.09 (37.30)**	3	485.41 (235.62)	2	453.92 (139.97)	**1**	**47.20 (19.75)**	4	253.78 (93.63)	2	40.05 (54.70)	3	211.60 (191.00)
	S_2	**1**	**21.92 (17.91)**	2	87.45 (64.92)	3	175.89 (62.71)	**1**	**49.04 (47.11)**	3	529.58 (158.69)	2	565.28 (157.43)	2	16.81 (8.59)	3	73.41 (118.30)	**1**	**16.30 (4.99)**	3	95.94 (19.68)
	S_3	**1**	**8.31 (7.52)**	2	52.55 (22.07)	3	100.26 (43.36)	**1**	**29.00 (78.81)**	2	460.89 (90.55)	3	496.74 (56.61)	2	6.72 (5.82)	3	18.64 (19.42)	**1**	**10.23 (1.63)**	4	43.94 (7.78)
	S_4	**1**	**3.60 (4.50)**	2	35.88 (17.56)	3	77.71 (33.23)	**1**	**24.55 (4.18)**	2	440.07 (77.70)	3	475.09 (43.17)	**1**	**4.15 (2.78)**	3	11.32 (6.77)	2	8.51 (0.97)	3	21.47 (5.45)
	S_5	**1**	**1.88 (1.24)**	2	31.49 (17.12)	3	58.63 (19.41)	**1**	**22.88 (3.78)**	2	460.51 (88.56)	3	473.16 (64.47)	**1**	**3.24 (3.09)**	3	6.64 (3.35)	2	7.50 (1.11)	3	11.07 (2.28)
BDB-J	S_1	**1**	**5.37 (4.74)**	2	11.23 (6.65)	2	14.06 (7.13)	**1**	**5.31 (2.96)**	3	43.30 (6.44)	2	40.89 (6.68)	**1**	**2.98 (0.81)**	3	8.36 (10.48)	2	7.39 (1.07)	**1**	**3.61 (2.31)**
	S_2	**1**	**1.83 (0.45)**	3	5.24 (33.48)	2	5.17 (3.19)	**1**	**3.77 (0.49)**	2	37.75 (5.70)	3	39.84 (6.41)	2	2.05 (0.33)	**1**	**1.82 (0.29)**	3	6.10 (0.51)	**1**	**1.85 (0.20)**
	S_3	**1**	**1.58 (0.26)**	3	3.29 (1.29)	2	3.75 (0.62)	**1**	**3.41 (0.46)**	2	37.72 (3.80)	2	38.85 (4.51)	3	1.92 (0.27)	**1**	**1.57 (0.21)**	4	5.71 (0.61)	2	1.78 (0.25)
	S_4	**1**	**1.45 (0.22)**	3	2.93 (0.80)	2	2.70 (0.59)	**1**	**3.57 (0.66)**	3	37.07 (3.03)	2	36.17 (4.46)	3	1.67 (0.29)	**1**	**1.43 (0.21)**	4	5.48 (0.55)	2	1.66 (0.21)
	S_5	**1**	**1.40 (0.34)**	3	2.48 (0.56)	2	2.39 (0.38)	**1**	**3.23 (0.65)**	3	37.27 (3.01)	2	36.52 (5.25)	3	1.67 (0.43)	**1**	**1.40 (0.23)**	4	5.34 (0.42)	2	1.55 (0.29)
KANZI	S_1	**1**	**196.15 (213.73)**	2	256.87 (151.84)	3	410.20 (187.36)	**1**	**551.03 (1244.41)**	**1**	**1158.20 (365.64)**	**1**	**1087.10 (248.90)**	**1**	**178.67 (123.16)**	2	359.19 (147.95)	**1**	**190.78 (98.22)**	2	426.88 (221.92)
	S_2	**1**	**95.31 (51.34)**	2	184.70 (53.30)	3	285.91 (71.88)	**1**	**383.06 (493.33)**	3	1224.60 (377.56)	2	1259.43 (331.27)	**1**	**86.55 (35.63)**	2	155.50 (51.71)	**1**	**84.19 (30.01)**	3	253.92 (74.19)
	S_3	**1**	**59.30 (38.47)**	2	138.52 (75.87)	3	233.73 (39.89)	2	177.35 (384.90)	3	1194.11 (1403.01)	**1**	**1368.20 (250.10)**	**1**	**62.50 (21.15)**	2	87.44 (21.38)	**1**	**65.34 (21.07)**	3	199.28 (45.12)
	S_4	**1**	**42.93 (18.75)**	2	129.60 (73.04)	3	191.77 (38.43)	2	134.99 (522.74)	3	1041.55 (230.02)	**1**	**1396.16 (189.09)**	**1**	**48.69 (10.31)**	3	65.20 (18.86)	2	54.19 (10.26)	4	158.05 (37.81)
	S_5	**1**	**35.29 (17.13)**	2	114.69 (48.99)	3	172.70 (46.58)	**1**	**605.42 (1213.79)**	3	1014.62 (255.48)	2	1266.23 (184.09)	**1**	**44.15 (8.53)**	3	52.53 (9.96)	2	48.74 (9.81)	4	132.03 (25.97)
SQLITE	S_1	2	73.52 (20.40)	**1**	**68.63 (16.67)**	3	65.45 (19.46)	2	105.75 (83.62)	**1**	**74.67 (20.68)**	**1**	**76.22 (21.29)**	3	82.77 (20.99)	**1**	**65.16 (12.06)**	**1**	**62.32 (11.64)**	2	70.76 (20.26)
	S_2	2	76.41 (16.66)	**1**	**70.36 (14.36)**	**1**	**70.52 (24.47)**	3	161.86 (135.45)	2	95.26 (36.34)	**1**	**89.04 (34.14)**	3	86.76 (20.84)	**1**	**69.64 (10.76)**	**1**	**64.04 (13.07)**	2	75.59 (24.63)
	S_3	**1**	**71.63 (11.58)**	2	67.30 (12.50)	**1**	**69.51 (14.85)**	3	103.75 (29.66)	**1**	**76.20 (21.41)**	2	84.61 (35.20)	3	87.65 (24.29)	**1**	**69.77 (13.75)**	**1**	**64.25 (11.83)**	2	70.77 (18.66)
	S_4	**1**	**66.94 (10.61)**	2	69.71 (10.60)	2	70.93 (11.85)	2	82.25 (23.16)	**1**	**68.94 (13.83)**	2	82.27 (27.41)	3	86.47 (20.30)	2	69.29 (9.25)	**1**	**62.19 (11.78)**	2	70.01 (16.80)
	S_5	**1**	**64.20 (13.91)**	2	69.41 (10.96)	2	71.51 (14.27)	2	76.06 (16.27)	**1**	**68.03 (10.38)**	3	80.61 (23.78)	3	84.43 (12.41)	2	70.42 (9.55)	**1**	**63.59 (12.77)**	2	71.19 (13.68)
X264	S_1	**1**	**10.21 (4.35)**	3	13.65 (14.17)	2	15.17 (5.23)	**1**	**10.43 (3.40)**	**1**	**10.90 (2.21)**	**1**	**11.58 (2.30)**	2	10.40 (2.15)	**1**	**8.18 (2.78)**	3	11.19 (2.06)	4	12.22 (5.95)
	S_2	**1**	**2.72 (1.52)**	3	8.44 (24.28)	2	8.68 (2.80)	**1**	**3.51 (0.98)**	2	8.11 (1.06)	3	8.74 (1.21)	**1**	**6.57 (1.67)**	**1**	**6.42 (1.20)**	3	8.53 (0.86)	2	6.82 (1.28)
	S_3	**1**	**1.57 (1.52)**	2	5.06 (48.28)	2	6.73 (57.61)	**1**	**2.84 (0.52)**	2	7.57 (0.81)	3	7.91 (0.80)	**1**	**5.01 (1.42)**	**1**	**4.95 (0.85)**	3	7.45 (0.85)	2	5.59 (0.64)
	S_4	**1**	**1.30 (1.17)**	2	4.04 (45.08)	2	4.86 (39.30)	**1**	**2.60 (0.52)**	2	7.27 (0.45)	3	7.44 (0.37)	**1**	**3.52 (1.33)**	2	4.04 (0.86)	4	6.61 (0.73)	3	4.53 (0.67)
	S_5	**1**	**0.96 (0.79)**	2	3.80 (28.85)	2	3.98 (3.19)	**1**	**2.10 (1.04)**	2	7.12 (0.67)	3	7.19 (0.46)	**1**	**2.54 (1.04)**	2	2.98 (0.77)	4	6.26 (0.58)	3	3.55 (0.53)
DUNE	S_1	**1**	**9.37 (1.15)**	3	13.64 (1.55)	2	12.26 (0.86)	**1**	**11.21 (0.88)**	2	13.01 (1.78)	3	13.76 (5.73)	**1**	**9.04 (1.13)**	**1**	**9.27 (0.56)**	2	10.12 (0.71)	**1**	**9.29 (0.65)**
	S_2	**1**	**5.95 (0.54)**	2	8.72 (2.48)	3	9.66 (1.10)	**1**	**11.13 (0.57)**	2	12.94 (1.04)	3	27.72 (8.04)	**1**	**6.25 (0.42)**	3	7.27 (0.40)	4	8.39 (0.26)	2	6.62 (0.36)
	S_3	**1**	**4.81 (0.48)**	2	7.87 (1.49)	3	8.77 (1.21)	**1**	**11.09 (0.54)**	2	13.10 (0.50)	3	29.45 (5.73)	**1**	**5.48 (0.42)**	3	6.63 (0.33)	4	8.07 (0.24)	2	5.79 (0.24)
	S_4	**1**	**4.23 (0.35)**	2	7.22 (0.99)	3	8.58 (0.97)	**1**	**11.04 (0.43)**	2	13.15 (0.47)	3	29.21 (5.15)	**1**	**5.06 (0.32)**	3	5.97 (0.45)	4	7.85 (0.26)	2	5.26 (0.19)
	S_5	**1**	**3.98 (0.19)**	3	9.57 (2.40)	2	9.36 (0.92)	**1**	**10.93 (0.48)**	2	13.15 (0.61)	3	29.14 (3.85)	**1**	**4.69 (0.35)**	3	5.68 (0.35)	4	7.66 (0.17)	2	4.90 (0.23)
HIPA^{cc}	S_1	**1**	**7.50 (1.42)**	2	10.21 (0.86)	2	10.19 (0.66)	2	12.70 (1.22)	3	20.95 (699.46)	**1**	**23.50 (2.17)**	2	12.03 (0.93)	**1**	**11.08 (0.66)**	**1**	**11.19 (0.60)**	3	14.24 (0.61)
	S_2	**1**	**4.48 (0.38)**	2	7.41 (1.03)	3	7.87 (0.86)	3	11.64 (0.35)	**1**	**19.70 (0.89)**	2	21.82 (0.68)	**1**	**8.47 (1.10)**	**1**	**8.46 (0.70)**	2	9.88 (0.37)	3	10.48 (0.63)
	S_3	**1**	**3.43 (0.34)**	2	6.14 (0.96)	2	6.55 (0.68)	**1**	**11.43 (0.34)**	2	19.34 (0.88)	3	21.82 (0.42)	**1**	**6.62 (0.80)**	**1**	**6.69 (0.51)**	3	9.41 (0.33)	2	8.21 (0.47)
	S_4	**1**	**2.60 (0.15)**	2	4.31 (0.77)	3	5.07 (0.74)	**1**	**11.13 (0.25)**	2	18.94 (0.58)	3	21.75 (0.81)	**1**	**4.42 (0.22)**	2	4.47 (0.32)	4	8.81 (0.20)	3	5.37 (0.24)
	S_5	**1**	**2.11 (0.08)**	2	3.04 (0.81)	3	3.86 (0.58)	**1**	**11.01 (0.15)**	2	18.79 (0.35)	3	21.88 (0.76)	**1**	**2.69 (0.15)**	**1**	**2.69 (0.13)**	3	8.30 (0.20)	2	3.10 (0.13)
HSMGP	S_1	**1**	**4.14 (1.44)**	2	7.01 (1.39)	2	8.63 (1.77)	**1**	**7.72 (0.80)**	2	55.90 (20.70)	3	80.26 (38.86)	3	21.65 (2.31)	2	16.63 (2.10)	**1**	**14.63 (1.92)**	4	25.42 (5.90)
	S_2	**1**	**2.06 (0.19)**	3	4.85 (4.52)	2	5.61 (1.17)	**1**	**7.35 (0.47)**	2	51.49 (11.94)	3	81.46 (17.14)	3	15.59 (1.41)	2	11.46 (1.78)	**1**	**10.59 (0.88)**	4	18.59 (1.67)
	S_3	**1**	**1.42 (0.13)**	2	3.60 (0.69)	3	3.87 (0.75)	**1**	**7.14 (0.35)**	2	51.65 (8.15)	3	80.54 (19.98)	2	11.35 (0.63)	**1**	**7.58 (0.67)**	**1**	**7.52 (0.46)**	3	12.10 (0.67)
	S_4	**1**	**1.33 (0.08)**	2	3.57 (0.95)	2	3.91 (0.73)	**1**	**7.16 (0.17)**	2	49.96 (10.24)	3	66.32 (36.72)	3	10.13 (0.57)	**1**	**6.88 (0.61)**	2	7.10 (0.38)	4	10.47 (0.65)
	S_5	**1**	**1.19 (0.08)**	2	3.02 (1.31)	2	3.58 (0.78)	**1**	**7.15 (0.20)**	2	49.18 (3.13)	3	85.14 (39.24)	4	7.46 (0.46)	**1**	**5.15 (0.28)**	2	6.11 (0.26)	3	7.04 (0.28)
LRZIP	S_1	**1**	**31.88 (10.96)**	2	31.78 (29.81)	3	70.36 (28.67)	**1**	**117.37 (24.65)**	2	363.17 (114.48)	3	475.86 (188.56)	2	17.95 (10.85)	3	21.71 (7.45)	**1**	**16.71 (4.27)**	4	76.46 (23.85)
	S_2	**1**	**10.51 (4.39)**	2	46.26 (25.10)	3	74.19 (33.01)	**1**	**109.11 (20.26)**	2	315.54 (57.21)	3	474.88 (196.54)	**1**	**9.09 (2.56)**	2	10.18 (2.12)	**1**	**10.19 (1.79)**	3	36.47 (12.40)
	S_3	**1**	**8.04 (2.37)**	2	30.06 (17.51)	3	59.65 (24.60)	**1**	**104.20 (17.55)**	2	321.82 (49.06)	3	360.11 (241.44)	**1**	**7.77 (2.09)**	**1**	**7.90 (1.27)**	2	8.43 (0.69)	3	26.46 (7.48)
	S_4	**1**	**5.95 (0.99)**	2	31.16 (20.54)	3	71.33 (22.86)	**1**	**103.74 (14.29)**	2	325.19 (51.13)	3	346.60 (131.69)	**1**	**6.38 (2.72)**	**1**	**6.51 (0.69)**	2	7.59 (0.91)	3	19.77 (2.80)
	S_5	**1**	**4.03 (0.26)**	2	23.74 (4.27)	3	58.48 (34.30)	**1**	**105.83 (7.06)**	2	324.82 (32.57)	3	457.93 (299.67)	**1**	**3.58 (0.97)**	2	3.67 (1.31)	2	6.17 (0.43)	3	9.37 (1.21)
NGINX	S_1	**1**	**4.11 (1.45)**	2	24.02 (12.20)	3	34.82 (21.61)	**1**	**22.02 (2.11)**	3	576.17 (24.71)	2	550.28 (66.10)	3	14.44 (2.41)	4	84.12 (150.39)	2	6.78 (1.92)	**1**	**4.23 (1.21)**
	S_2	**1**	**2.60 (1.14)**	2	22.99 (9.15)	3	28.21 (2.89)	**1**	**20.25 (1.60)**	2	568.78 (17.19)	2	564.04 (37.05)	3	7.44 (3.14)	4	11.09 (3.33)	2	4.90 (0.44)	**1**	**2.17 (0.48)**
	S_3	**1**	**2.14 (0.40)**	2	23.32 (8.65)	3	27.64 (5.37)	**1**	**19.66 (0.75)**	2	567.70 (19.05)	2	570.41 (23.98)	2	4.81 (0.81)	3	5.68 (1.43)	2	4.56 (0.09)	**1**	**1.85 (0.43)**
	S_4	**1**	**1.99 (0.47)**	2	14.92 (9.09)	3	24.84 (4.19)	**1**	**19.74 (0.82)**	2	566.35 (18.53)	2	566.60 (22.75)	2	4.16 (1.01)	4	4.87 (0.63)	3	4.49 (0.05)	**1**	**1.59 (0.28)**
	S_5	**1**	**1.98 (0.21)**	2	6.11 (6.87)	3	11.91 (11.63)	**1**	**19.17 (1.07)**	2	565.62 (23.39)	2	567.96 (18.51)	2	3.33 (1.00)	3	4.49 (0.56)	3	4.44 (0.06)	**1**	**1.64 (0.30)**
VP8	S_1	**1**	**1.56 (0.18)**	3	6.05 (1.14)	2	8.31 (0.68)	**1**	**12.72 (0.84)**	3	45.51 (7.20)	2	44.69 (5.11)	**1**	**2.57 (0.70)**	3	3.32 (0.79)	3	5.99 (0.31)	2	4.42 (0.46)
	S_2	**1**	**1.15 (0.05)**	3	3.34 (1.09)	2	3.56 (0.43)	**1**	**12.42 (0.44)**	2	42.04 (3.29)	2	42.06 (2.51)	**1**	**1.24 (0.24)**	2	1.45 (0.16)	3	5.25 (0.20)	2	1.44 (0.21)
	S_3	**1**	**1.08 (0.04)**	3	2.91 (0.32)	2	2.66 (0.35)	**1**	**12.41 (0.34)**	2	42.55 (2.55)	3	44.06 (2.66)	2	1.15 (0.12)	2	1.16 (0.16)	3	5.15 (0.15)	**1**	**1.11 (0.09)**
	S_4	**1**	**0.98 (0.05)**	3	2.48 (0.39)	2	2.22 (0.33)	**1**	**12.35 (0.31)**	2	41.90 (3.11)	3	42.98 (2.47)	3	1.07 (0.08)	2	1.03 (0.11)	4	5.07 (0.10)	**1**	**1.02 (0.05)**
	S_5	**1**	**0.90 (0.06)**	3	2.20 (0.33)	2	1.66 (0.16)	**1**	**12.41 (0.27)**	2	42.79 (1.80)	3	43.19 (2.36)	3	0.94 (0.04)	**1**	**0.85 (0.03)**	4	4.89 (0.09)	2	0.88 (0.04)
Average r		1.03		2.22		2.42		1.2		2.1		2.38		1.85		2		2.35		2.43	

run while DaL-FSE uses an overall best setting, as such DaL will be able to control the d in a finer granularity, hence further pushing the full potential of the dividable learning paradigm.

While in general DaL performs very similar to DaL-FSE, it is worth noting that it does so without incurring the large overhead that would otherwise be required to find the optimal d under DaL-FSE. Figure 6 illustrates the time taken of DaL-FSE to find the best d setting (where $d \in [1, 4]$) beforehand for a given system, under the samples and largest training data size considered in this work. Clearly, across the systems, finding the optimal d between 1 and 4 (with 30 repeats) needs at least 13.2 hours up to 65 hours for the smallest training size; this can turn into between 45.9 and 78.2 hours under the biggest training size, respectively. In contrast, since the newly proposed d adaptation does not involve any additional training process, it only takes the magnitude of seconds as we will show in Section 5.6. We believe such a resource-saving is remarkable.



(a) Total overhead using S_1 (b) Total overhead using S_5

Fig. 6: The total overhead to select the optimal d (from $d = 1$ to $d = 4$) for 30 runs under the smallest (S_1) and biggest (S_5) training data size considered.

5.4.3 The Usefulness of μHV

Recall from Section 3.1.3, we have theoretically analyzed why the newly proposed indicator μHV is needed for adapting d. Here, to confirm its usefulness, we compare the results of DaL with its variant where the standard HV is used instead, which is denoted as DaL^{HV}. To that end, we leverage the HV implementation from the Python library pymoo. All other settings are the same as the previous RQs.

From Table 7 (right), we see that using μHV clearly achieves considerably better accuracy than using the standard HV: the former is overwhelmingly ranked better (47 cases) or similar (12 cases) out of the 60 cases, which is a remarkable result.

TABLE 7: Ablation study of DaL with respect to the effectiveness of using CART for dividing samples, adapting d, and μHV. The format is the same as Table 4.

System	Size	DaL		DBSCAN		Agglomerative		kMeans		DaL		DaL-FSE		DaL		DaL^{HV}	
		r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)	r	Med (IQR)
APACHE	S_1	**1**	**21.86 (7.36)**	2	26.29 (15.23)	3	30.99 (20.01)	3	40.02 (22.13)	**1**	**21.86 (7.36)**	**1**	**21.86 (7.36)**	**1**	**21.86 (7.36)**	**1**	**21.86 (7.36)**
	S_2	2	12.89 (7.87)	2	16.24 (10.00)	**1**	**15.45 (5.76)**	**1**	**14.85 (5.21)**	**1**	**12.89 (7.87)**	**1**	**11.87 (9.22)**	**1**	**12.89 (7.87)**	**1**	**12.89 (7.87)**
	S_3	**1**	**6.56 (1.92)**	3	13.24 (9.29)	2	10.62 (3.24)	2	10.60 (6.77)	**1**	**6.56 (1.92)**	**1**	**6.56 (1.92)**	**1**	**6.56 (1.92)**	2	7.00 (2.29)
	S_4	**1**	**6.87 (1.95)**	4	10.44 (4.15)	3	8.63 (2.49)	2	7.39 (2.84)	**1**	**6.87 (1.95)**	**1**	**6.87 (1.95)**	**1**	**6.87 (1.95)**	2	6.87 (1.95)
	S_5	**1**	**5.78 (1.08)**	4	9.18 (3.33)	3	7.82 (2.20)	2	6.08 (2.53)	**1**	**5.78 (1.08)**	**1**	**5.78 (1.08)**	**1**	**5.78 (1.08)**	**1**	**5.82 (1.77)**
BDB-C	S_1	**1**	**83.60 (208.75)**	2	438.69 (291.46)	2	361.68 (382.62)	2	309.58 (359.65)	**1**	**83.60 (208.75)**	**1**	**83.60 (208.75)**	**1**	**83.60 (208.75)**	**1**	**83.60 (208.75)**
	S_2	**1**	**21.92 (17.91)**	3	170.67 (133.10)	2	117.38 (99.35)	3	145.13 (135.06)	**1**	**21.92 (17.91)**	**1**	**21.92 (17.91)**	**1**	**21.92 (17.91)**	**1**	**22.67 (35.19)**
	S_3	**1**	**8.31 (7.52)**	2	43.57 (70.53)	2	39.10 (72.34)	3	38.29 (56.01)	**1**	**8.31 (7.52)**	**1**	**8.31 (7.52)**	**1**	**8.31 (7.52)**	2	12.82 (25.48)
	S_4	**1**	**3.60 (4.50)**	2	29.43 (29.08)	2	25.32 (26.66)	3	23.07 (43.38)	**1**	**3.60 (4.50)**	**1**	**3.60 (4.50)**	**1**	**3.60 (4.50)**	2	10.45 (23.90)
	S_5	**1**	**1.88 (1.24)**	3	33.50 (18.42)	2	11.67 (13.49)	4	19.27 (22.25)	**1**	**1.88 (1.24)**	**1**	**1.88 (1.24)**	**1**	**1.88 (1.24)**	2	3.81 (7.39)
BDB-J	S_1	**1**	**5.37 (4.74)**	2	14.51 (9.69)	3	14.57 (22.68)	3	11.03 (13.62)	**1**	**5.37 (4.74)**	**1**	**5.37 (4.74)**	**1**	**5.37 (4.74)**	**1**	**6.21 (5.94)**
	S_2	**1**	**1.83 (0.45)**	2	6.58 (6.33)	3	7.12 (20.32)	2	3.08 (4.46)	**1**	**1.83 (0.45)**	**1**	**1.83 (0.45)**	**1**	**1.83 (0.45)**	2	2.23 (1.59)
	S_3	**1**	**1.58 (0.26)**	2	3.48 (0.94)	3	2.24 (4.85)	2	2.05 (0.47)	**1**	**1.58 (0.26)**	**1**	**1.58 (0.26)**	**1**	**1.58 (0.26)**	2	1.60 (0.32)
	S_4	**1**	**1.45 (0.22)**	3	2.53 (0.87)	4	1.82 (0.68)	2	1.76 (0.34)	**1**	**1.45 (0.22)**	**1**	**1.45 (0.22)**	**1**	**1.45 (0.22)**	2	1.53 (0.26)
	S_5	**1**	**1.40 (0.34)**	3	2.61 (0.58)	2	1.68 (0.26)	2	1.62 (0.39)	**1**	**1.40 (0.34)**	**1**	**1.40 (0.34)**	**1**	**1.40 (0.34)**	2	1.41 (0.35)
KANZI	S_1	**1**	**196.15 (213.73)**	3	545.20 (418.67)	3	553.75 (502.84)	2	531.18 (334.99)	**1**	**196.15 (213.73)**	**1**	**196.15 (213.73)**	**1**	**196.15 (213.73)**	2	292.60 (385.37)
	S_2	**1**	**95.31 (51.34)**	2	204.18 (138.71)	3	196.73 (275.40)	2	190.64 (148.79)	**1**	**95.31 (51.34)**	**1**	**95.31 (51.34)**	**1**	**95.31 (51.34)**	2	216.02 (346.90)
	S_3	**1**	**59.30 (38.47)**	2	160.72 (82.07)	2	118.26 (106.12)	2	119.90 (76.87)	**1**	**59.30 (38.47)**	**1**	**59.30 (38.47)**	**1**	**59.30 (38.47)**	2	94.25 (64.94)
	S_4	**1**	**42.93 (18.75)**	3	103.18 (113.16)	2	81.27 (28.15)	2	81.88 (26.24)	**1**	**42.93 (18.75)**	**1**	**42.93 (18.75)**	**1**	**42.93 (18.75)**	2	134.47 (149.91)
	S_5	**1**	**35.29 (17.13)**	4	91.90 (48.67)	2	60.45 (19.99)	3	65.93 (25.27)	**1**	**35.29 (17.13)**	**1**	**35.29 (17.13)**	**1**	**35.29 (17.13)**	2	78.13 (86.63)
SQLITE	S_1	**1**	**73.52 (20.40)**	2	87.19 (30.88)	2	90.37 (22.58)	2	98.63 (64.82)	**1**	**73.52 (20.40)**	**1**	**73.52 (20.40)**	**1**	**73.52 (20.40)**	**1**	**73.52 (20.40)**
	S_2	**1**	**76.41 (16.66)**	3	84.27 (33.49)	2	81.43 (21.75)	3	83.39 (34.67)	**1**	**76.41 (16.66)**	**1**	**76.41 (16.66)**	**1**	**76.41 (16.66)**	2	79.72 (19.44)
	S_3	**1**	**71.63 (11.58)**	3	86.71 (25.06)	2	75.22 (13.79)	2	73.63 (18.36)	**1**	**71.63 (11.58)**	**1**	**71.63 (11.58)**	**1**	**71.63 (11.58)**	2	72.29 (11.70)
	S_4	**1**	**66.94 (10.61)**	3	81.04 (15.76)	2	71.66 (12.67)	2	75.77 (19.71)	**1**	**66.94 (10.61)**	**1**	**66.94 (10.61)**	**1**	**66.94 (10.61)**	2	70.51 (16.58)
	S_5	**1**	**64.20 (13.91)**	4	77.13 (17.36)	2	71.44 (12.01)	3	72.32 (13.70)	**1**	**64.20 (13.91)**	**1**	**64.20 (13.91)**	**1**	**64.20 (13.91)**	2	67.09 (16.08)
X264	S_1	**1**	**10.21 (4.35)**	2	15.09 (9.65)	2	13.36 (12.90)	3	15.72 (26.44)	**1**	**10.21 (4.35)**	**1**	**10.21 (4.35)**	**1**	**10.21 (4.35)**	**1**	**10.49 (5.06)**
	S_2	**1**	**2.72 (1.52)**	3	8.49 (6.80)	2	5.44 (3.96)	3	4.48 (3.51)	**1**	**2.72 (1.52)**	**1**	**2.74 (1.36)**	**1**	**2.72 (1.52)**	**1**	**2.64 (1.51)**
	S_3	**1**	**1.57 (1.52)**	3	6.71 (4.70)	2	2.15 (0.75)	2	1.91 (1.69)	2	1.57 (1.52)	**1**	**1.56 (0.70)**	**1**	**1.57 (1.52)**	**1**	**1.93 (2.10)**
	S_4	**1**	**1.30 (1.17)**	2	7.28 (6.34)	**1**	**1.29 (0.80)**	**1**	**1.05 (0.86)**	2	1.30 (1.17)	**1**	**1.00 (0.56)**	**1**	**1.30 (1.17)**	**1**	**1.41 (1.13)**
	S_5	3	0.96 (0.79)	4	4.46 (4.53)	2	0.83 (0.49)	**1**	**0.61 (0.33)**	2	0.96 (0.79)	**1**	**0.60 (0.36)**	**1**	**0.96 (0.79)**	**1**	**0.98 (0.77)**
DUNE	S_1	**1**	**9.37 (1.15)**	3	12.87 (3.21)	**1**	**9.21 (1.43)**	2	9.42 (1.44)	**1**	**9.37 (1.15)**	**1**	**9.19 (0.89)**	**1**	**9.37 (1.15)**	2	9.39 (1.15)
	S_2	**1**	**5.95 (0.54)**	4	13.56 (3.20)	2	6.60 (0.64)	3	6.92 (0.61)	**1**	**5.95 (0.54)**	**1**	**5.95 (0.54)**	**1**	**5.95 (0.54)**	**1**	**5.98 (0.58)**
	S_3	**1**	**4.81 (0.48)**	3	15.17 (3.61)	2	6.14 (0.46)	2	6.09 (0.56)	**1**	**4.81 (0.48)**	**1**	**4.81 (0.48)**	**1**	**4.81 (0.48)**	2	4.82 (0.48)
	S_4	**1**	**4.23 (0.35)**	3	20.52 (3.50)	2	5.61 (0.63)	2	5.52 (0.51)	**1**	**4.23 (0.35)**	**1**	**4.23 (0.35)**	**1**	**4.23 (0.35)**	**1**	**4.23 (0.35)**
	S_5	**1**	**3.98 (0.19)**	4	26.16 (4.58)	2	4.98 (0.25)	3	5.00 (0.31)	**1**	**3.98 (0.19)**	**1**	**3.98 (0.19)**	**1**	**3.98 (0.19)**	**1**	**3.98 (0.19)**
HIPA^{cc}	S_1	**1**	**7.50 (1.42)**	3	14.44 (7.83)	2	9.95 (1.94)	2	9.46 (1.37)	**1**	**7.50 (1.42)**	**1**	**7.50 (1.42)**	**1**	**7.50 (1.42)**	**1**	**7.50 (1.42)**
	S_2	**1**	**4.48 (0.38)**	4	14.76 (3.76)	3	5.61 (0.72)	2	5.50 (0.63)	**1**	**4.48 (0.38)**	**1**	**4.48 (0.38)**	**1**	**4.48 (0.38)**	2	4.48 (0.57)
	S_3	**1**	**3.43 (0.34)**	4	10.33 (1.09)	3	4.26 (0.44)	2	4.18 (0.41)	**1**	**3.43 (0.34)**	**1**	**3.43 (0.34)**	**1**	**3.43 (0.34)**	2	3.65 (1.43)
	S_4	**1**	**2.60 (0.15)**	4	7.31 (0.65)	3	2.95 (0.36)	2	2.96 (0.18)	**1**	**2.60 (0.15)**	**1**	**2.60 (0.15)**	**1**	**2.60 (0.15)**	2	4.06 (2.09)
	S_5	**1**	**2.11 (0.08)**	4	6.92 (0.60)	3	2.27 (0.14)	2	2.20 (0.09)	**1**	**2.11 (0.08)**	**1**	**2.11 (0.08)**	**1**	**2.11 (0.08)**	2	2.64 (0.56)
HSMGP	S_1	**1**	**4.14 (1.44)**	4	21.00 (94.17)	2	10.21 (14.94)	3	12.27 (47.67)	**1**	**4.14 (1.44)**	**1**	**4.14 (1.44)**	**1**	**4.14 (1.44)**	2	7.80 (10.46)
	S_2	**1**	**2.06 (0.19)**	4	26.68 (25.59)	2	3.42 (3.02)	3	5.47 (17.62)	**1**	**2.06 (0.19)**	**1**	**2.06 (0.19)**	**1**	**2.06 (0.19)**	2	2.49 (4.01)
	S_3	**1**	**1.42 (0.13)**	4	99.71 (84.77)	2	2.31 (0.41)	3	2.59 (0.72)	**1**	**1.42 (0.13)**	**1**	**1.42 (0.13)**	**1**	**1.42 (0.13)**	2	1.48 (0.48)
	S_4	**1**	**1.33 (0.08)**	4	144.33 (83.45)	2	2.15 (0.51)	3	2.30 (0.37)	**1**	**1.33 (0.08)**	**1**	**1.33 (0.08)**	**1**	**1.33 (0.08)**	2	1.40 (0.35)
	S_5	**1**	**1.19 (0.08)**	4	51.04 (24.94)	2	1.80 (0.29)	3	1.89 (0.22)	**1**	**1.19 (0.08)**	**1**	**1.19 (0.08)**	**1**	**1.19 (0.08)**	2	1.20 (0.15)
LRZIP	S_1	**1**	**31.88 (10.96)**	3	72.91 (33.63)	2	38.43 (19.53)	3	66.44 (35.18)	**1**	**31.88 (10.96)**	**1**	**31.88 (10.96)**	**1**	**31.88 (10.96)**	2	32.32 (12.02)
	S_2	**1**	**10.51 (4.39)**	3	209.93 (186.42)	2	23.70 (17.77)	3	48.56 (93.35)	**1**	**10.51 (4.39)**	**1**	**10.51 (4.39)**	**1**	**10.51 (4.39)**	2	16.23 (4.19)
	S_3	**1**	**8.04 (2.37)**	4	288.22 (299.90)	2	14.75 (16.26)	3	32.91 (20.58)	**1**	**8.04 (2.37)**	**1**	**8.04 (2.37)**	**1**	**8.04 (2.37)**	2	13.28 (6.10)
	S_4	**1**	**5.95 (0.99)**	3	124.12 (186.64)	2	12.59 (7.86)	3	34.68 (46.30)	**1**	**5.95 (0.99)**	**1**	**5.95 (0.99)**	**1**	**5.95 (0.99)**	2	10.15 (3.76)
	S_5	**1**	**4.03 (0.26)**	3	110.41 (46.00)	2	5.56 (4.32)	4	22.75 (136.13)	**1**	**4.03 (0.26)**	**1**	**4.03 (0.26)**	**1**	**4.03 (0.26)**	2	6.31 (1.86)
NGINX	S_1	**1**	**4.11 (1.45)**	3	15.18 (10.27)	2	7.30 (3.27)	2	7.89 (4.12)	**1**	**4.11 (1.45)**	**1**	**4.11 (1.45)**	**1**	**4.11 (1.45)**	2	9.44 (5.40)
	S_2	**1**	**2.60 (1.14)**	3	7.83 (4.25)	2	5.87 (1.00)	2	5.52 (1.26)	**1**	**2.60 (1.14)**	**1**	**2.60 (1.14)**	**1**	**2.60 (1.14)**	2	3.15 (1.94)
	S_3	**1**	**2.14 (0.40)**	3	4.94 (3.79)	2	5.23 (1.55)	2	4.49 (1.57)	**1**	**2.14 (0.40)**	**1**	**2.14 (0.40)**	**1**	**2.14 (0.40)**	2	2.34 (0.79)
	S_4	**1**	**1.99 (0.47)**	2	3.75 (3.14)	3	4.95 (1.01)	3	4.19 (1.15)	**1**	**1.99 (0.47)**	**1**	**1.99 (0.47)**	**1**	**1.99 (0.47)**	2	2.00 (0.77)
	S_5	**1**	**1.98 (0.21)**	4	5.83 (2.09)	2	4.10 (1.83)	3	4.32 (1.20)	**1**	**1.98 (0.21)**	**1**	**1.98 (0.21)**	**1**	**1.98 (0.21)**	2	2.10 (0.96)
VP8	S_1	**1**	**1.56 (0.18)**	4	7.58 (2.89)	2	2.16 (1.08)	3	2.86 (1.04)	**1**	**1.56 (0.18)**	**1**	**1.56 (0.18)**	**1**	**1.56 (0.18)**	**1**	**1.56 (0.18)**
	S_2	**1**	**1.15 (0.05)**	4	7.39 (2.36)	3	1.45 (0.54)	2	1.40 (0.16)	**1**	**1.15 (0.05)**	**1**	**1.15 (0.05)**	**1**	**1.15 (0.05)**	**1**	**1.15 (0.05)**
	S_3	**1**	**1.08 (0.04)**	4	9.02 (3.35)	3	1.32 (0.32)	2	1.25 (0.13)	**1**	**1.08 (0.04)**	**1**	**1.08 (0.04)**	**1**	**1.08 (0.04)**	**1**	**1.08 (0.04)**
	S_4	**1**	**0.98 (0.05)**	4	9.65 (3.27)	3	1.31 (0.31)	2	1.17 (0.09)	**1**	**0.98 (0.05)**	**1**	**0.98 (0.05)**	**1**	**0.98 (0.05)**	**1**	**0.98 (0.05)**
	S_5	**1**	**0.90 (0.06)**	4	10.23 (5.77)	2	1.03 (0.12)	3	1.05 (0.10)	**1**	**0.90 (0.06)**	**1**	**0.90 (0.06)**	**1**	**0.90 (0.06)**	**1**	**0.90 (0.06)**
Average r		1.05		3.15		2.25		2.43		1.05		1		1		1.65	

Overall, for **RQ4**, we conclude that:

> ***RQ4:*** The designed components in DaL is effective:
>
> 1) **RQ4.1:** CART is ranked the solely best for 93.3% (56/60) of the cases amongst the other clustering counterparts with up to 5.41× MRE improvement over the second-best.
> 2) **RQ4.2:** Adapting d achieves almost identical result to the version of DaL that relies on a pre-tuned d value while saving an extensive amount of effort.
> 3) **RQ4.3:** μHV is more suitable than the standard HV for determining the optimal and most balanced d value on the configuration data, leading to 98% (59/60) cases of better (47/60=78%) or similar (12/60=20%) accuracy.

5.5 Sensitivity and Adaptivity to the Depth d

5.5.1 Method

To understand the sensitivity of DaL to the depth, we examine different d values. Since the number of divisions (and hence the possible depth) is sample size-dependent, for each system, we use 80% of the full dataset for training and the remaining for testing. This has allowed us to achieve up to $d = 4$ with 16 divisions as the maximum possible bound for all systems studied. For different d values, we report on the median MRE together over 30 runs, as well as counting the number of times that a d value leads to the best MRE.

Recall that in **RQ4**, we examine DaL-FSE which serves as the variant that takes a generally optimal d (over all repeated runs) obtained via pre-tuning. Yet, while DaL-FSE mimics the practical scenario, it does not cater to the optimal d for each individual run in which the training/testing data differ. Therefore, here we further examine to what extent DaL can indeed reach the optimal d, considering individual

run under each system-size pair, which serves as the ground truth.

All other settings are the same as the previous RQs.

5.5.2 Results

In Figure 7, the best d of each subject system is marked as $*$, which has the best Scott-Knott rank, and if more than one d are ranked first, we mark the one with the smallest median MRE.

As can be seen from Figure 7, we see that the correlation between the MRE (blue axis) of DaL and d value is close to quadratic: DaL reaches its best MRE with $d = 1$ (2 divisions) or $d = 2$ (4 divisions). Since d controls the trade-off between the ability to handle sample sparsity and ensuring sufficient data samples to train all local models, $d = 1$ or $d = 2$ tends to be the "sweet points" that reach a balance for the systems studied. After the point of $d = 1$ or $d = 2$, the MRE will worsen, as the local models' training size often drops dramatically. This is a clear sign that, from that point, the side-effect of having too less samples to train a local model has started to surpass the benefit that could have been brought by dealing with sample sparsity using more local models. When $d = 0$, which means only one division and hence DaL is reduced to HINNPerf that ignores sample sparsity, the resulted MRE is the worst on 6 out of 12 systems; a similar result can be observed for the cases when $d = 4$. This suggests that neither too small d (e.g., $d = 0$ with only one division) nor too large d (e.g., $d = 4$ with up to 16 divisions, i.e., too many divisions) are ideal, which matches our theoretical analysis in Section 3.1.3.

Clearly, another important observation is that there is not a single optimal d that can be applied to all systems: four of them favor $d = 2$ in general while the remaining reveal that $d = 1$ is the overall optimal setting. This becomes even more obvious when we take a closer look at each individual run with different training/testing data: as from the count of optimal d (red axis), for the case where $d = 1$ leads to the generally best MRE, there are a considerable number of runs under which $d = 2$ is the optimal, even occasionally $d = 3$, e.g., for system KANZI. The above suggests that DaL is highly sensitive to d, depending on the systems and training/testing data—the key motivation to the extension of adapting d in this work.

To compare the ability of DaL on adapting d against the ground truth for each individual run, we plot the hit/miss hit counts in Figure 8. As can be seen, in the majority of the cases, DaL can accurately adapt to the optimal d of a run. There are a good amount of cases where the hit count is 100% and only in 5 out of 60 cases, the miss hit counts are more than 50% of the runs. We also observe a clear pattern where the hit count often increases as the training size expands, e.g., for systems BDB-J and DUNE: this is as expected as the conflicts between the ability to handle sample sparsity and the necessary amount of data to learn are relieved when the amount of data increases.

Overall, the average hit count for all the cases is 22.93 out of 30, which means in 76.43% of the runs, DaL can indeed adapt to the optimal d. For mixed systems, DaL generally reaches the optimal d more frequently, as the average hit count for all the mixed systems is 25.13 against the 20.73 for binary systems. This is because the complex configuration landscape for mixed systems can provide more information when assessing the d values during its adaptation process. To understand the severity of miss hitting the optimal d in a run, we also report on the MRE difference between the results of the optimal d and what is achieved by DaL under an adapted d. It is clear that, from Figure 9, the MRE difference is marginal in most of the cases according to their distributions: only very occasionally there are one or two extreme cases of more than 50% MRE difference, the majority of them are within 10%. This implies that, even for the cases/runs where DaL does miss hit, a promising d value can still be chosen, leading to minimal accuracy loss.

Therefore, for **RQ5**, we conclude that:

> ***RQ5:*** *The error of DaL has a (upward) quadratic correlation to d, the optimal value of which varies depending on the actual systems and training/testing data. DaL can adapt to the optimal d in 76.43% of the individual runs while even when it misses hit, a promising d value that leads to generally marginal MRE degradation can still be selected.*

5.6 Overhead of Model Building

5.6.1 Method

To study **RQ6**, we examine the overall time required for training and building the models, including those state-of-the-art configuration performance learning approaches compared in **RQ1**, and ensemble learning methods with different local models compared in **RQ3**.

5.6.2 Result

From Table 8, which shows the range of training time required across all 60 cases, DaL incurs an overall overhead from 4 to 56 minutes. Yet, from the breakdown, we see that the majority of the overhead comes from the *training phase* that trains the local models, especially when a deep learning model like the HINNPerf is used (which is the default in DaL). We also note that the entire adaptation process of adapting d is lightweight and it is independent of the local model; the only computation overhead lies in the calculation of the two functions in Equation (6), as well as the μHV. The time cost for adaptation ranges only from 10^{-6} to 0.02 minutes, which is marginal considering that it is an offline process.

Compared the default of DaL (using HINNPerf as the local model) with other state-of-the-art configuration performance learning approaches, i.e., HINNPerf (3 to 54 minutes) and DeepPerf (3 to 48 minutes), DaL have slightly higher training overhead, but the difference is merely in a matter of a few minutes, even though it trains multiple local models. This is because (1) each local model has less data to train and (2) those local models can be trained in parallel which speeds up the process. However, it is worth noting that, from **RQ1**, DaL leads to considerably better accuracy than those two. In contrast to Perf-AL (a few seconds to two minutes), DaL appears to be rather slow as the former does not use hyperparameter tuning but fixed-parameter values [85]. Yet, as we have shown for **RQ1**, DaL achieves up to a few magnitudes of accuracy improvement. Although SPLConqueror and DECART have an overhead of less than

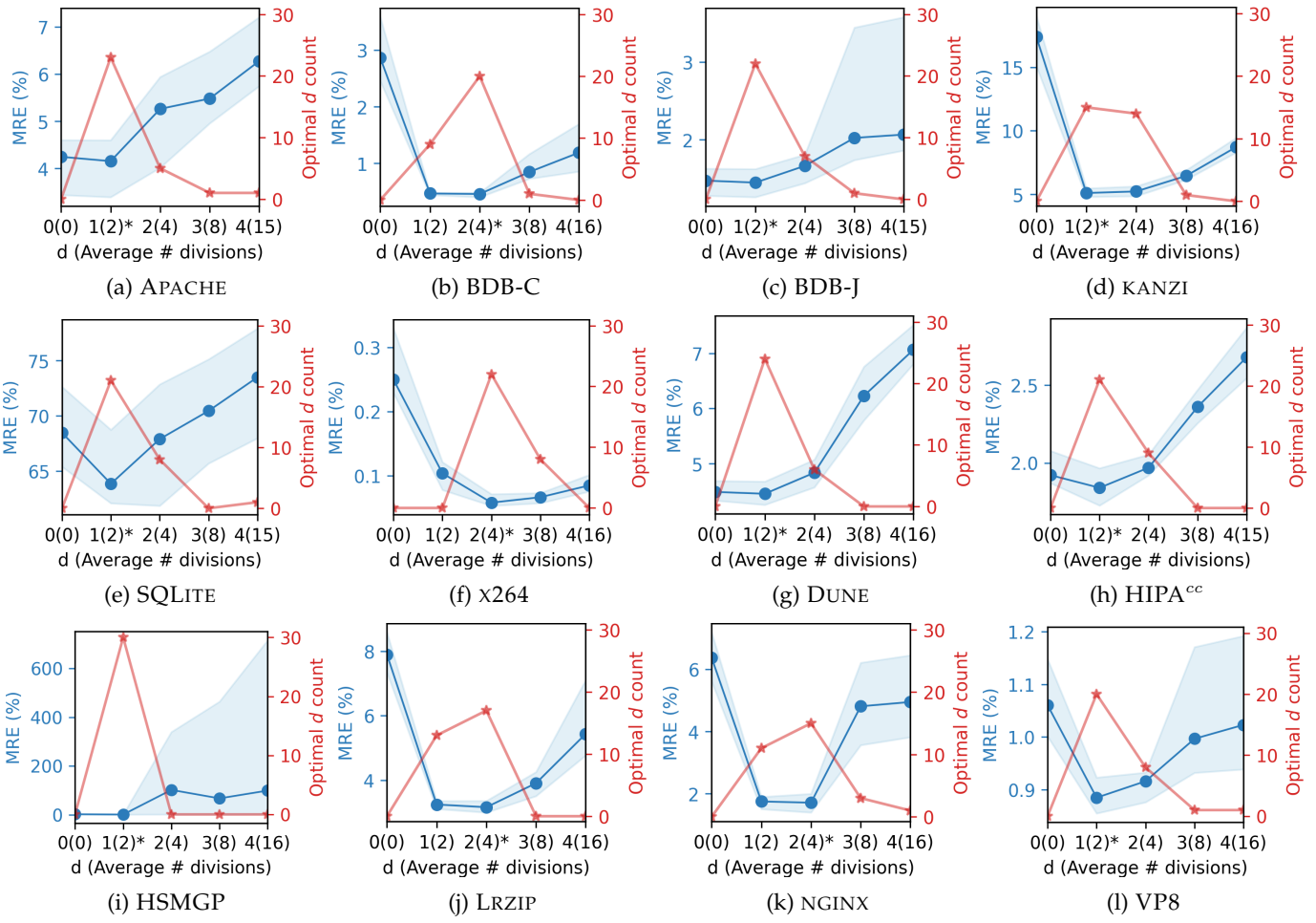


Fig. 7: The median MRE (—●—), its IQR (area), and the number of runs that a d value leads to the best MRE (—★—) over all systems and 30 runs. The better or worse is identified by the Scott-Knott test and average MRE. The generally optimal d, in terms of the overall MRE, is marked as $*$.

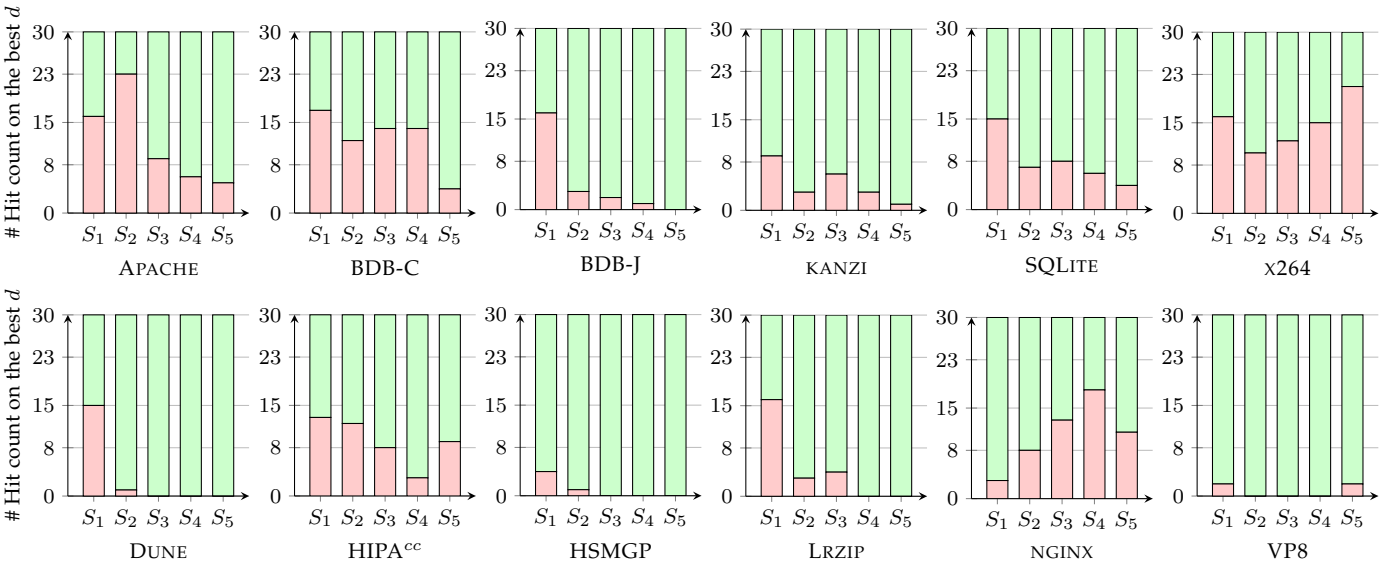


Fig. 8: Hit count of reaching the optimal d at each run (which leads to the best MRE) by the adaptive mechanism in DaL. The red bars and green bars show the miss hit counts and correct hit counts, respectively.

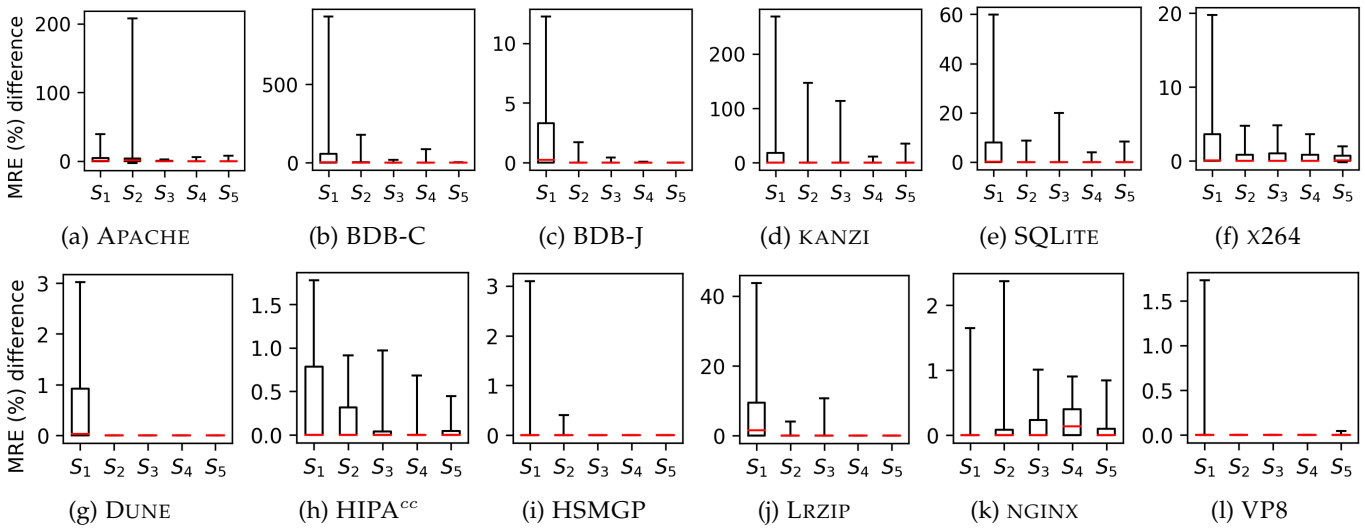


Fig. 9: MRE difference between the d adapted by DaL and the optimal d for each of the 30 runs.

TABLE 8: The overhead ranges across all systems and sizes.

Approach	Overhead (minutes)	Approach	Overhead (minutes)
DaL$_{LR}$	2×10^{-4} to 0.32	SPLConqueror	4×10^{-4} to 5×10^{-3}
— DaL (*adapting d*)	1×10^{-6} to 0.02	AdaBoost$_{LR}$	5×10^{-6} to 8×10^{-3}
— DaL (*dividing*)	9×10^{-4} to 0.18	RF	1×10^{-4} to 8×10^{-3}
— DaL (*training*)	$3\times10^{-}4$ to 0.21	XGBoost	3×10^{-4} to 8×10^{-3}
— DaL (*predicting*)	$4\times10^{-}5$ to 0.09	Adaboost$_{CART}$	5×10^{-5} to 0.02
DaL$_{CART}$	1×10^{-3} to 0.55	Bagging$_{LR}$	1×10^{-3} to 0.02
— DaL (*adapting d*)	1×10^{-6} to 0.02	DECART	0.07 to 0.5
— DaL (*dividing*)	9×10^{-4} to 0.18	Perf-AL	0.08 to 2.4
— DaL (*training*)	2×10^{-4} to 0.31	DeepPerf	3 to 48
— DaL (*predicting*)	5×10^{-4} to 0.18	HINNPerf	3 to 54
DaL	4 to 56	AdaBoost$_{HINN}$	2.28 to 92.51
— DaL (*adapting d*)	1×10^{-6} to 0.02	Bagging$_{HINN}$	2.43 to 92.63
— DaL (*dividing*)	9×10^{-4} to 0.18		
— DaL (*training*)	3 to 53		
— DaL (*predicting*)	0.3 to 3		

a minute, again their accuracy is much inferior. Further, DECART does not work on mixed systems. It is also worth noting that, when using with cheaper model like LR in DaL, the overhead can be greatly reduced.

Compared with other ensemble learning methods, it can be seen that: (1) when using HINNPerf as the local model, DaL has significantly lower overhead compared with AdaBoost$_{HINN}$ and Bagging$_{HINN}$, as these ensemble learning methods rely on training a large number of local models to get better results, whereas DaL only trains a handful number of local models in most of the cases; (2) meanwhile, with LR and CART as the local model, DaL is slightly slower than Bagging and AdaBoost. For example, DaL$_{CART}$ can take up to 0.32 minutes compared with the maximum overhead of 0.02 minutes for AdaBoost$_{CART}$. This is as expected, considering the time required for adapting depth and dividing, which could take up to 0.2 minutes.

In summary, we say that:

> ***RQ6:*** *DaL, when using HINNPerf as the local model, has competitive model building time with respect to HINNPerf and DeepPerf, and has higher overhead than the other state-of-the-art approaches, but this can be acceptable considering its improvement in accuracy. When using other cheaper local models such as LR, the overhead is marginal.*

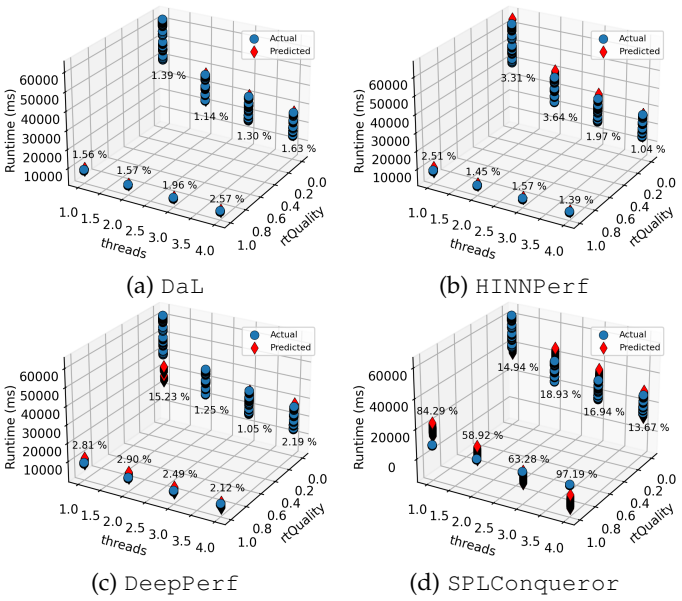
6 DISCUSSION

Here, we discuss a few insights and pointers observed from the experiment results.

6.1 Why Does DaL Work?

To provide a more detailed understanding of why DaL performs better than the state-of-the-art approaches, in Figure 10, we showcase the most common run of the predicted performance by DaL, HINNPerf, DeepPerf and SPLConqueror against the actual performance. Clearly, we note that the sample sparsity is rather obvious where there are two distant divisions.

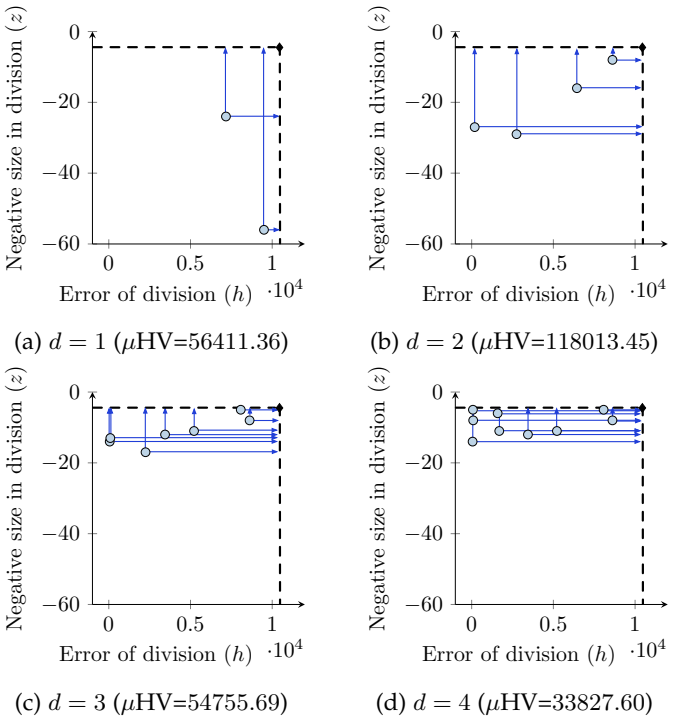
Those approaches that rely on a single local model have been severely affected by such highly sparse samples: we see that the models try to cover points in both divisions, but fail to do so as they tend to overfit/memorize the points in one or the other. For example, on DeepPerf (Figure 10c), its predictions on some configurations, which should result in high runtime, tend to have much lower values (e.g., when rtQuality=0 and threads=1) since it overfits the points with some drastically lower runtime, i.e., when rtQuality=1. Conversely, HINNPerf (Figure 10b) and SPLConqueror (Figure 10d) estimate high runtime on some configurations that should lead to excellent performance (e.g., rtQuality=1 and threads=1), which is, again, due to the fact that it memorizes those points with much higher runtime (rtQuality=0). Further, it also creates additional noises that make the predictions too high against what they should be, e.g., when rtQuality=0



(a) DaL (b) HINNPerf

(c) DeepPerf (d) SPLConqueror

Fig. 10: Example run of the actual and predicted performance by DaL, HINNPerf, DeepPerf, and SPLConqueror for S_1 of VP8. The numbers are the fine-grained MRE over each chunk of the samples.



(a) $d = 1$ (μHV=56411.36) (b) $d = 2$ (μHV=118013.45)

(c) $d = 3$ (μHV=54755.69) (d) $d = 4$ (μHV=33827.60)

Fig. 11: The snapshot of the objective values of h and z on divisions when adapting d for a run under system X264. The black diamond denotes the reference point. The testing MRE for $d = 1$, $d = 2$, $d = 3$, and $d = 4$ are 0.9676, 0.7876, 1.7858, and 3.1285, respectively.

and `threads=2`. DaL, in contrast, handles such a sample sparsity well as it contains different local models that particularly cater to each division identified, hence leading to high accuracy (Figure 10a).

6.2 Why Adapting d Helps?

We have showcased that the proposed adaptive mechanism is effective in dynamically setting the suitable d in DaL. In order to take a deeper look at why it helps, Figure 11 illustrates the process of selecting the d value at a run under X264. Here, we observed clear traces of how the sample size and mean square error in the divisions change along different d values:

- The overall sample size of the divisions (z) decreases as the d value increases since more divisions are created to divide the configuration data. This implies that there is less chance for a local model to learn and generalize.
- The overall mean square error of the divisions (h) tends to decrease with larger d, as the additionally created divisions contain some much-reduced errors. This means that the overall ability to handle sample sparsity is improved, which is expected because the larger d, the smaller the sample size, hence it is more likely to have more dense points in a division, leading to lower mean square error.

The above observations match with our theoretical analysis in Section 3.1.3, and therefore adapting the d value requires finding a good trade-off between h and z. For the example in Figure 11, the proposed μHV reflects the collective contributions of all possible divisions on both objectives, including those that are dominated, by calculating the average area that each d value covers with respect to the reference point. In this way, we identify that $d = 2$ is the best and most balanced value, which is subsequently confirmed to be indeed the case when validating their MRE.

6.3 Strengths and Limitations

The first strength of DaL is that the concept of "divide-and-learn" under the paradigm of dividable learning, paired with an appropriately chosen local model, can handle both sample sparsity and feature sparsity well. As from Section 5.1 for **RQ1**, this has led to better accuracy and better utilization of the sample data than the state-of-the-art approaches.

The second strength is that while using HINNPerf has been shown to be the best option for accuracy in our cases, one can also easily replace it with others such as LR for faster training and better interoperability, hence offering great flexibility. As such, DaL permits software engineers to make trade-offs based on different concerns depending on the practical scenarios. In particular, as from Section 5.2 for **RQ2**, DaL can additionally improve different local models compared with when they are used alone as a global model. Further, when compared with other model-agnostic frameworks from the paradigm of ensemble learning, DaL also produces more effective and accurate predictions, as demonstrated at **RQ3**.

The third strength of DaL is that it is now less parameter-dependent (apart from those of the local model) given the mechanism that adapts d. This, as from **RQ5**, is necessary and the adaptation leads to a high hit rate with effective

results. More importantly, adapting d would have saved a great amount of effort to tailor and understand the approach together with its customized parameters, which is not uncommon for a model-agnostic framework [28]. Meanwhile, at **RQ4**, we illustrate that each proposed component in DaL can individually contribute to its superiority.

From **RQ6**, a limitation of DaL is that it can incur slightly larger computational overhead when paired with a deep leanring model: it could take a longer time to build the model than some state-of-the-art approaches. Using a typical server with a CPU of 2.6GHz and 256GB RAM, DaL requires between 4 minutes and 56 minutes for systems with up to 33 configuration options and more than 2,000 samples. While this time effort might be relieved by implementing parallel training of the local models, the computational resources consumed are unavoidable. However, if efficiency is more important than accuracy, one could opt for a cheaper local model such as linear regression, which has trivial overhead as we have shown.

The other factor of DaL is that it needs to be paired with a sampling method and in this work we use random sampling. This would work if we randomly sample configurations from the valid configuration space, which has already been measured by datasets from previous runs. This is also a widely used evaluation method in the field of configuration performance learning [22], [30], [37], [85]. In practice, the vast majority of the dependency/constraints analysis tools [9], [104] that are based on taint analysis would also be able to provide such information for sampling when there is a new system without any previously measured data. We see sampling as a complementary technique to the model building. As such, DaL is certainly not random sampling-dependent; in fact, similar to SPLConqueror, it can be seamlessly paired with any sampling method, such as option-wise/pair-wise sampling, depending on the cases.

6.4 How would Invalid Configurations Affect DaL?

While applying datasets from existing studies as shown in Table 2, we only randomly sample configurations from the valid configuration space. However, it does not affect the effectiveness of DaL even if those datasets are not available in advance. This is because, when collecting the configuration data via profiling/measuring, there are two major consequences related to the invalid configurations as demonstrated by a recent study [9]:

- **Case 1:** The system crashes or throws runtime exceptions.
- **Case 2:** The system runs as usual but the violated dependency/constraint is automatically corrected by the system via some internal mechanisms or the relevant settings of the invalid options are simply ignored by some system-level checkers.

For **Case 1**, one can simply filter out those configurations that lead to invalid measurements, and hence all the remaining data contain the valid configurations only; this is similar to the data cleaning step in the common machine learning pipeline. **Case 2** is difficult to be certain about, but it is one of the typical causes of the sparsity issue (as those options that cause dependency/constraint violation would simply be non-influential to the performance), which is the exact challenge that we design DaL for.

As a result, even when collecting data for a new system for which we do not have any information about the dependency/constraint, we would still be able to easily deal with **Case 1** during the data collection process and the models in DaL would be able to handle the sparsity caused by **Case 2**. Therefore, we believe that DaL would not be weakened in such a circumstance.

6.5 How Many Options Can DaL Handle?

DaL can adapt well to any new subject systems with a large number of options, thanks to a unique structure that operates at two levels—the *Dividing* and *Training*:

- **Dividing:** Here the goal is to divide the data into divisions using CART.
- **Training:** Here is where the actual learning and modeling happens, using a paired local model for each individual division.

The CART at the *Dividing* would build a tree that partitions the data based on the sorted importance of the options. In the meantime, the parameter d determines at which option we start to identify the divisions, e.g., $d = n$ basically means that we divide the data according to the top n options produced by CART (please see Figure 3). As such, the most important options are jointly determined by CART and d and, given the characteristics of the learning procedure in CART, DaL can handle a high number of options at the *Dividing*.

Since the actual learning at the *Training* is achieved by a local model, the extent to which it can handle the number of options entirely depends on the local model used. In our work, by default, we use HINNPerf in which the high dimensionality issue is handled by the hierarchical regularization (it is also its mechanism to deal with feature sparsity).

Therefore, DaL can handle a large number of options if an appropriate local model has been chosen. Since the above has made no assumption about the system's characteristics, DaL can work on new systems too.

6.6 What is the Typical and Best Size of Divisions?

As shown in Figure 7, DaL often performs the best commonly when $d = 1$ (2 divisions) or $d = 2$ (3-4 divisions), or sometimes, $d = 3$ (4-8 divisions). However, this can vary depending on the systems and sample sizes, which motivates this extension work.

As for what division size is most appropriate, our observation indicates that the accuracy does improve with more data used for training, i.e., S_5 in our case. It is difficult to confirm the best training size required as this is system/case dependent and the fundamental question itself is still an open problem in the machine learning community. However, if there is a given preferred level of accuracy for learning configuration performance for a system, then our results can provide some insights. For example, if we expect the average of MRE to be 2% or better for NGINX, then we know that a training data size of S_4 (1,012 samples) or more is needed when using DaL.

6.7 Threats to Validity

Internal Threats. Internal threats to validity are related to the parameter values used. In this work, we set the same settings as used in state-of-the-art approaches [35], [37], [85], [88]. Automated and adaptive mechanisms are enabled for those approaches that come with parameter tuning capability, e.g., `DeepPerf` and `DBSCAN`, or the best settings are profiled in a trail-and-error manner before the experiments, e.g., for the k value in k`Means` clustering. If no parameter values are specified, we use the default settings. To mitigate stochastic error, we repeat the experiments for 30 runs and use Scott-Knott test for multiple comparisons. Indeed, although we have carefully ensured the fairness of comparisons, it is hard to guarantee that all compared models are in their best possible status.

Construct Threats. Threats to construct validity may lie in the metric used. In this study, MRE is chosen for two reasons: (1) it is a relative metric and hence is insensitive to the scale of the performance; (2) MRE has been recommended for performance prediction by many latest studies [36], [37], [85]. To assess the cost of the modeling and training process, we measure the time taken to build the models. We also compare `DaL` against state-of-the-art approaches, other ensemble learning models, and different variants thereof that are paired with different local models and come with alternative components. To confirm that adapting d is indeed effective, we verify the sensitivity of `DaL` to d value while examining the adapted d against the optimal d on both the overall results and each individual run. However, programming errors or other small implementation defects are always possible.

External Threats. External validity could be raised from the subject systems and training samples used. To mitigate such, we evaluate 12 commonly used subject software systems, which are of diverse domains, scales, and performance metrics, selected from the latest studies [6], [37], [55], [71], [86]. We have also examined different training sample sizes as determined by the number of configuration options and `SPLConqueror` [88]—a typical method. Nevertheless, we agree that using more subject systems and data sizes may be fruitful, especially for examining the adaptive mechanism for d.

7 Related Work

We now discuss the related work in light of the key contributions in `DaL`.

7.1 Analytical Models

Predicting software performance can be done by analyzing the code structure and architecture of the systems [23], [96]. For example, Marco and Inverardi [23] apply queuing network to model the latency of requests processed by the software. Velez *et al.* [96] use local measurements and dynamic taint analysis to build a model that can predict performance for part of the configuration code. However, analytical models require full understanding and access to the software's internal states, which may not always be possible/feasible. Further, due to the theoretical assumption or limitations of the measurement tool, analytical models are often restricted to certain performance metrics, most commonly time-related ones such as runtime and latency. `DaL` is not restricted to those scenarios as it is a data-driven approach while still being designed to cater to the unique sparse nature of configuration data.

7.2 Statistical Learning-based Models

Data-driven learning has relied on various statistical models, such as linear regressions [52], [86], [88], [90], tree-like models [44], [73], [81], fourier-learning models [38], [111], and even transfer learning [47], [48], [55], *etc*. Among others, `SPLConqueror` [88] utilizes linear regression combined with different sampling methods and a step-wise feature selection to capture the interactions between configuration options. `DECART` [36] is an improved CART with an efficient sampling method [111]. Jamshidi and Casale [46] use Gaussian Process (GP) to model configuration performance, which is also gradually updated via Bayesian Optimization. However, recent work reveals that those approaches do not work well with small datasets [37], which is rather common for configurable software systems due to their expensive measurements. This is a consequence of not fully handling the sparsity in configuration data. Further, they come with various restrictions and prerequisites, e.g., `DECART` does not work on mixed systems while `SPLConqueror` needs an extensive selection of the right sampling method(s); GP has also been proved to struggle in modeling the sparse configuration data [73].

In contrast, we showed that `DaL` produces significantly more accurate results while not limited to those restrictions. In addition, the paradigm of dividable learning underpins `DaL` prevent it from suffering the particular pitfalls of a single machine learning algorithm, as it can be paired with different local models.

7.3 Deep Learning-based Models

A variety of studies apply deep neural networks with multiple layers to predict configuration performance [26], [37], [49], [54], [67], [74], [85], [89], [108]. Among others, `HINNPerf` uses embedding to encodes the configuration into a latent space after which a deep neural network, combined with the hierarchical regularization, is applied to handle feature sparsity. `DeepPerf` [37] is a state-of-the-art DNN model with L_1 regularization to mitigate feature sparsity for any configurable systems, and it can be more accurate than many other existing approaches. The most recently proposed `Perf-AL` [85] relied on adversarial learning that consists of a generative network to predict the performance and a discriminator network to distinguish the predictions and the actual labels. Nevertheless, existing deep learning approaches capture only the feature sparsity while ignoring the sample sparsity, causing severe risks of overfitting even with regularization in place.

Compared with those, we have demonstrated that, by additionally capturing sample sparsity, `DaL` is able to improve the accuracy considerably with better efficiency and acceptable overhead.

7.4 Ensemble Models

Similar to the paradigm of dividable learning, ensemble learning also leads to different frameworks that can be paired with different local models, some of which have already been adopted for configuration performance learning. For example, Chen and Bahsoon [14] propose an ensemble approach, paired with feature selection for mitigating feature sparsity, to model software performance. Other ensemble learning such as Bagging [5] and Boosting [83] can also be similarly applied. However, those ensemble learning approaches allow different local models to share information at one or more phases of the learning pipeline:

- Local models can be trained on the same data [14]; or data that has been processed sequentially [83].
- Local models can make predictions collectively as opposed to individually [5].

While information sharing may be useful when different models learn data with high similarity; they might not be effective in coping with highly sparse data. DaL, in contrast, produces isolated local models without sharing knowledge at all phases, including training and prediction. This has been shown to be more suitable for dealing with the sample sparsity exhibited in configuration data, preventing overfitting and memorizing largely spread data samples.

7.5 Hybrid Models

The analytical models can be combined with data-driven ones to form a hybrid model [24], [40], [100]. Among others, Didona *et al.* [24] use linear regression and kNN to learn certain components of a queuing network. Conversely, Weber *et al.* [100] propose to learn the performance of systems based on the parsed source codes from the system to the function level.

We see DaL as being complementary to those hybrid models due to its flexibility in selecting the local model: when needed, the local models can be replaced with hybrid ones, making itself a hybrid variant. In case the internal structure of the system is unknown, DaL can also work in its default as a purely data-driven approach.

7.6 Data Splitting Models

From the machine learning community, there are also studies that have explored tree-based learning paradigms to split the training dataset. For example, IBMB [79] combines predictions from both instance-based learning and model-based learning techniques, i.e., model trees. Especially, during the construction of a model tree, the recursive algorithm partitions the data based on attribute tests until certain stopping criteria are met (e.g., reaching a maximum tree depth or a minimum number of instances per leaf). At each leaf node, a linear regression model is fitted using the samples that reach that leaf. M5 [78] splits the original dataset to minimize the variance within each subset, and subsequently trains a linear model for each leaf node. PILOT [80] divides samples in a similar manner to CART but without pruning. Additionally, it improves the efficiency of CART by utilizing linear models at the leaf nodes. Moreover, MOB [107] improves the dividing method of CART by fitting the dataset using a parametric model and performing recursive partitioning by splitting the samples based on the partitioning variable that exhibits the highest parameter instability.

However, these models are demonstrated to be ill-suited to some extent for configuration performance prediction, as they are not specifically designed for complex and non-linear regression tasks, especially given the fact that most of them utilize linear models at the leaf nodes. Moreover, one of the differences between DaL and those tree-based data splitting methods is that we allow DaL to pair with any local model depending on the preferences.

8 Conclusion

This paper proposes a model-agnostic framework dubbed DaL that effectively handles the issues of both feature and sample sparsity in configuration performance learning. The key novelty of DaL is that it follows a new paradigm of dividable learning, in which the branches/leaves are extracted from a CART that divides the samples of configuration into a number of distant divisions, which is adaptively adjusted, and trains a dedicated local model for each division thereafter. Prediction of the new configuration is then made by the local model of division inferred based on a Random Forest classifier. Such a theory of "divide-and-learn" handles the sample sparsity while the local model used (e.g., one with regularization) deals with the feature sparsity, hence collectively addressing the overall sparsity issue in configuration data.

By means of extensive experiments, we comprehensively evaluate DaL on 12 real-world systems that are of diverse domains and scales, together with five sets of training data. The results show that DaL is:

- **effective** as it is competitive to the best state-of-the-art approach on 44 out of 60 cases, in which 31 of them are significantly better with up to $1.61\times$ MRE improvement; the paradigm of dividable learning is also more suitable than the classic ensemble learning to handle the sample sparsity in configuration data;
- **efficient** since it often requires fewer samples to reach the same/better accuracy compared with the others; the adaptation of d also leads to negligible overhead as no additional training is required;
- **flexible** given that it considerably improves various global models when they are used as the local model therein;
- **robust** because the mechanism that adapted the parameter d can reach the optimal value for 76.43% of the individual runs while a similarly promising d value can be chosen even when the optimal d is missed.

Mitigating the issues caused by sparsity is only one step towards more advanced configuration performance learning, hence the possible future work based on DaL is vast, including multi-task prediction of configuration performance under different environments and merging diverse local models as part of the dividable learning paradigm.

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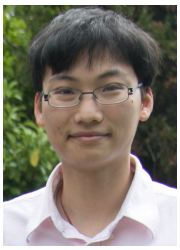

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