Simpler Hyperparameter Optimization for Software Analytics: Why, How, When?

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Abstract—How to make software analytics simpler and faster? One method is to match the complexity of analysis to the intrinsic complexity of the data being explored. For example, hyperparameter optimizers find the control settings for data miners that improve for improving the predictions generated via software analytics. Sometimes, very fast hyperparameter optimization can be achieved by just DODGE-ing away from things tried before. But when is it wise to use DODGE and when must we use more complex (and much slower) optimizers? To answer this, we applied hyperparameter optimization to 120 SE data sets that explored bad smell detection, predicting Github issue close time, bug report analysis, defect prediction, and dozens of other non-SE problems. We find that DODGE works best for data sets with low “intrinsic dimensionality” ($\mu_D \approx 3$) and very poorly for higher-dimensional data ($\mu_D > 8$). Nearly all the SE data seen here was intrinsically low-dimensional, indicating that DODGE is applicable for many SE analytics tasks.

Index Terms—software, analytics, hyperparameter optimization, defect prediction, bad smell detection, issue close time, bug reports

1 INTRODUCTION

When problems are intrinsically simple, the solutions to such problems can be dramatically simplified by matching (a) the complexity of analysis to (b) the intrinsic complexity of the problem under study. For example, consider hyperparameter optimization for software analytics. Industrial practitioners (and researchers) use data mining and software analytics for many tasks [1], [2], [3], [4], [5], [6] such as learning how long it will take to integrate new code [7], where bugs are most likely [8], [9]; or how long it will take to develop this code [10], [11]. Even simple design decisions such as the color of a link are chosen by analytics [12]. In industrial settings, software analytics can be remarkable cost-effective [13], [14]. Also, such analytics performs competitively with seemingly more rigorous approaches like static code analysis [15].

Hyperparameter optimizers find better control settings for data miners used in software analytics. Such optimization can dramatically improve the quality predictions generated by software analytics [7], [8], [9], [10], [11], [12], [15], [16], [17], [18], [19], [20]. For example, Tantithamthavorn et al. [21] showed that such optimizers can convert very bad learners into outstandingly good ones (see the gains observed in Figure 1).

Hyperparameter optimization can be very slow. Table 1 shows hyperparameter options seen in recent SE papers [22]. Assuming that the numerics of that table divide into ten bins, then Table 1 lists billions of possibilities.

Recently, we achieved success using a surprisingly simple hyperparameter optimizer called DODGE [22] that “dodges” away from (i) options tried before and which have (ii) resulted in similar performance scores. DODGE ran orders of magnitude faster than prior methods since its search terminated after 30 evaluations (while other methods used thousands to millions of options). Also, its results were as good, or better, than prior state-of-the-art results.

A deficiency in those prior results is that it only gave examples where DODGE worked, but not when it failed. No optimizer works best on all data [23]. Accordingly, this paper asks when is it wise to use DODGE or when should we use more complex (and much slower) methods?

This research is structured about three issues: why, how, and when. The next section motivate why it is so important to seek simpler software analytics. After that, we look into how to simplify the computational cost of hyperparameter optimization in software analytics. Algorithms for hyperparameter optimization are discussed. These are tested on 120 data sets from five domains: four from SE and one “miscellaneous set” of non-SE data taken from the UCI machine learning repository [29]. Finally, we check when simplification is possible. Our 120 data sets can be characterized by their “intrinsic dimensionality” which measures $D$, the number of underlying dimensions in a data set. DODGE performs best for data sets with low dimensionality ($\mu_D \approx 3$) and very poorly for higher-dimensional data ($\mu_D > 8$). Nearly all the SE data explored here were low-dimensional, indicating that DODGE’s simple analysis is applicable for many SE analytics tasks.

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TABLE 1
Hyperparameter options seen in recent SE papers \[24, 25, 26, 27\] and in the documentation of a widely-used data mining library (Scikit-learn \[28\]).

| Learners: | Pre-processors for defect prediction, Issue lifetime, Bad Smells and Non-SE: |
|----------|---------------------------------------------------------------|
| • DecisionTreeClassifier(criterion=b, splitter=c, min_samples_split=a) | • StandardScaler, MinMaxScaler, MaxAbsScaler |
| – a, b, c = randuniform(0,1), randchoice(['gini', 'entropy']), randchoice(['best', 'random']) | • RobustScaler(quantile_range=(a, b)) |
| • RandomForestClassifier(n_estimators=a, criterion=b, min_samples_split=c) | • KernelCenterer |
| – a, b, c = randint(50, 150), randchoice(['gini', 'entropy']), randuniform(0, 1.0) | • QuantileTransformer(n_quantiles=a, output_distribution=c, subsample=b) |
| • LogisticRegression(penalty=a, tol=b, C=sample(c)) | • Normalizer(norm=a) = randchoice(['l1', 'l2','max']) |
| – a, b, c = randint(2, 25), randchoice(['uniform', 'distance']), randchoice(['minkowski','chebyshev']) | • Binarizer(threshold=a) = randuniform(0,100) |
| – if c=='minkowski': d= randint(1,15) else: d=2 | • SMOTE(n_neighbors=a, n_synthetic=b, Minowski_exponent=c) |

Pre-Processors for Text mining:
• CountVectorizer(max_df=a, min_df=b) = randint(100, 1000), randint(1,10)
• TfidfVectorizer(max_df=a, min_df=b, norm=c) = randint(100, 1000), randint(1,10)
• HashingVectorizer(n_features=a, norm=b) = randint(100, 1000), randint(1,10)
• LatentDirichletAllocation(n_components=a, doc_topic_prior=b, topic_word_prior=c, learning_decay=d, learning_offset=e, batch_size=f) = randint(100,200), randint(10,200)

1.1 Connection to Prior Work
This paper is a significant extension to prior work, in two ways. Here, we explore more data from more SE domains than prior studies. Previously \[22\], DODGE was assessed using 16 data sets from just two domains: 1) 10 SE defect prediction data sets; 2) 6 SE issue tracking data sets. This study repeats that analysis while also studying 3) 63 SE data sets exploring Github issue close time; 4) 4 SE data sets exploring bad smell detection. 5) 37 non-SE problems from the UCI repository.

But more importantly, here we show that intrinsic dimensionality can predict when DODGE will \emph{not} work. This is a useful result since intrinsic dimensionality can be applied to data before starting an analysis. That is, now we can determine when to use DODGE, or some other method, before analysts waste any time applying the wrong optimizer.

1.2 Reproduction Package
To encourage reproduction of this work, all our code and scripts are available on-line at \[http://tiny.cc/dodge2020\].

2 Why?
To motivate this work, we must first explain why it is so important to seek simpler software analytics. Fisher et al. \[30\] characterizes software analytics as a workflow that distills large quantities of low-value data down to smaller sets of higher-value data. Hyperparameter optimization improves the predictions generated by software analytics, but it also increases the computational cost of software analytics. Fisher et al. \[30\] warn against any such increase. They say:

\textbf{Further advances in advanced software analytics will be stunted unless we can tame our associated CPU costs.}

They note that due to the complexities and computational cost of SE analytics, “the luxuries of interactivity, direct manipulation, and fast system response are gone” \[30\]. They characterize modern cloud-based analytics as a throwback to the 1960s batch processing mainframes where jobs are submitted and then analysts wait and wait for results with “little insight into what’s really going on behind the scenes, how long it will take, or how much it’s going to cost” \[30\].

Fisher et al. document the issues seen by 16 industrial data scientists, one of whom remarks “Fast iteration is key, but incompatible with the say jobs are submitted and processed in the cloud. It’s frustrating to wait for hours, only to realize you need a slight tweak to your feature set.”

To understand the CPU problem consider the standard validation loop for a data miner shown in Figure 2. Note the problem with this loop—it must call a data miner (at line 8) \(D \times R \times F \times 3\) times. This is a problem since:

- \(D\) is an ever increasing number. 10 years ago, a paper on software analytics could be published if it used \(D < 10^3\) data sets. Now, as shown in this paper, it is common to see papers with \(D > 10^3\) data sets. In the future, as more data is extracted from open source projects (e.g. those found in Github), we expect that using \(D > 10^4\) data sets will be common.
- It is usual for \(R \times B > 20\) since, for statistical validity, it is common to repeat this loop more than 20 times.
- \(F\) comes from Table 1. Assuming that the numbers of Table 1 are divided into ten bins, then \(F > 10^3\). Since this number is too large to be explored, it is common practice to use “engineering judgement” (a.k.a. guessing) to reduce \(F\) to \(10^6\) or \(10^3\).

Even after imposing engineering judgement, the inner loop of Figure 2 must call a learner millions to billions of times. This is troubling since while some data miners are very fast (e.g. Naive Bayes), some are not (e.g. deep learning). Worse still, several “local learning” results \[31\] report that software analytics results are specific to the data set being
processed—which means that analysts may need to rerun the above loop anytime new data comes to hand.

As a result, learning good control settings for a learner can take days to weeks to years of CPU time \cite{21, 25, 32}. For example, Lam et al. needed weeks of CPU time to combine deep learning and text mining to localize buggy files from bug reports \cite{33}. Also, Hall & Holmes \cite{34} reported that the best way to find useful features is the WRAPPER algorithm that calls a data miner to assess a large number of feature subsets. This is a slow process, particularly for large data sets, since $N$ attributes would have $2^N$ subsets.

Note that this CPU problem is not solvable by (1) parallelization or (2) waiting for faster CPU. Parallelization requires the kinds of environments that Fisher et al. discuss; i.e. environments where it is frustrating to wait for hours, only to realize you need a slight tweak to your feature setting. Also, these Fisher-style large scale CPU facilities must be paid for. Cloud computing environments are extensively monetized so the total financial cost of tuning can be prohibitive, particularly for very expensive tasks; e.g. the 15 years of CPU to learn the tuning parameters of software clone detectors \cite{32}. As to waiting for faster CPUs, it is not clear that we can rely on Moore’s Law \cite{35} to double our computational power every 18 months. Power consumption and heat dissipation issues effectively block further exponential increases to CPU clock frequencies \cite{36}.

Before going on, we note that in our own lab, there are many cases where research papers were not completed by some required due date since the Figure 2 loops had yet to terminate. In that context, it becomes very tempting for researchers to “cut corners” and compromise their experimental methods. Certainly, if some result is too computationally expensive to repeat, then makes reproducibility difficult. Tools like DODGE remove that temptation–an effect we summarize as “less CPU means more science”.

3 How?
This section discusses how to simplify the computational cost of hyperparameter optimization in software analytics. But before discussing optimizers, we first have to discuss the learners that they control.

3.1 Data mining tools
Hyperparameter optimizers adjust the control parameters of data miners. This section reviews the data mining tools used in this study: SVM, Random Forests, decision tree learners, logistic regression, Naive Bayes, LDA, and EM.

Before doing that, it is reasonable to ask “why did we select these tools, and not some other set?” This paper does not compare DODGE against all other learners and all other hyperparameter optimizers (since such a comparison would not fit into a single paper). Instead, we use baselines as found in the SE literature for bad smell detection, predicting Github issue close time, bug report analysis, and defect prediction.

For example, for defect prediction, our classifiers come from a study by Ghutra et al. \cite{24}. They found that the performance of dozens of data miners (applied to defect prediction) can be clustered into just a few groups. By sampling a few algorithms from each group, we can explore the range of data miners seen in defect prediction.

Clustering algorithms like EM \cite{37} divide the data into related groups, then check the properties of each group. Another clustering method used in text mining, is Latent Dirichlet Allocation \cite{38} that infers “topics” (commonly associated words). After documents are scored according to how often they use some topic, a secondary classifier can then be used to distinguish the different topics.

Clustering algorithms like EM and LDA do not make use of any class variable. Naive Bayes classifiers \cite{39}, on the other hand, always divide the data on the class. New examples are then classified according to which class it is most similar to. Also, logistic regression fits the data to a particular parametric form (the logistic function).

Another learner that uses class variables are decision tree algorithms \cite{40, 41}. These learners divide data on attributes whose values most separate the classes. The learner then recurses on each division. Random Forests \cite{42} build a “committee” of multiple decision trees, using different subsamples of the data. Conclusions then come from a voting procedure across all the trees in the forest.

Standard clustering and decision tree algorithms base their analysis using the raw problem data. But what if some extra derived attribute is best at separating the classes? To address that issue, SVMs use a “kernel” to infer that extra dimension \cite{43}.

3.2 Hyperparameter Optimizers
In this paper, we do not compare against all hyperparameter optimization methods (since any such comparison would take too long to read). Instead, we use hyperparameter optimization methods widely seen in the SE literature.

For example, for text mining SE data, Panichella et al. \cite{44} used genetic algorithm \cite{45} (GA) to “evolve” a set of randomly generated control settings for SE text miners by repeating the following procedure, across many “generations”: (a) mutate a large population of alternate settings; (b) prune the worse performing settings; (c) combine pairs of the better, mutated options.

An alternative hyperparameter optimization strategy is the differential evolution \cite{46} used by Wu et al. \cite{25} and others \cite{25}. DE generates mutants by interpolating between the better-ranked settings. These better settings are kept in a “frontier list”. Differential evolution iterates over the frontier, checking each candidate against a new mutant. If the new mutant is better, it replaces the frontier item, thus improving the space of examples used for subsequent mutant interpolation.

Tantithamthavorn et al. \cite{21} used a grid search for their hyperparameter optimization study. Grid search runs nested “for-loops” over the range of each control option. Fu et al. \cite{47} found that for defect prediction, grid search ran 100 to 1000 times slower than DE.

3.2.1 Optimizing with DODGE
DODGE is a hyperparameter optimizer proposed by Agrawal et al. \cite{22}. DODGE was designed around the following observation. Given an ever-evolving set of tools, languages, platforms, tasks, user expectations, development
population, development practices, etc., we might expect that any prediction about an SE project will only ever be approximately accurate, i.e., within $\epsilon$ of the true value. Agrawal et al. reasoned that $\epsilon$ is not a problem to be solved, but a resource that could be exploited, as follows:

The RELAX heuristic: Ignore anything less than $\epsilon$.

DODGE applies this RELAX heuristic to do hyperparameter optimization. To illustrate this process, consider the following example:

- Suppose we are exploring the hyperparameter space of Table 1.
- Suppose further we are scoring each hyperparameter setting by applying it to a learner, then recording the performance goals of recall and false alarm seen after applying those settings to a learner.

Given performance goals with the range $0 \leq g \leq 1$, $\epsilon$ divides the performance output space into $(1/\epsilon)^2$ cells. For example, consider the $g = 2$ goals of recall and false alarm. These have minimum and maximum values of zero and one. Hence, if $\epsilon = 0.2$, then these scores divide into five regions (at 0.2, 0.4, 0.6, 0.8). As shown in Figure 3, these divided scores separate a two-dimensional plot of recall vs false alarm scores into $(1/0.2)^2 = 25$ cells. In those cells, green denotes good performance (high recall, low false alarm) and red denotes cells with relatively worse performance.

When billions of inputs (in Table 1) are mapped into the 25 cells of Figure 3, then many inputs are redundant, i.e., lead to the same outputs. The faster we can “dodge” redundant options, the faster we can move on to explore the other $(1/\epsilon)^2$ possible outputs.

To implement “dodging”, DODGE models Table 1 as a tree where all nodes have initial weights $w = 0$. Next, $N_1$ times, DODGE selects branches at random. We evaluate the options in a branch and if the resulting scores are within $\epsilon$ of any previous scores, then DODGE deprecates those options via $w = w - 1$, else $w = w + 1$.

After that, DODGE freezes the selected branches found so far. $N_2$ times, DODGE then makes random selection to restrict any numeric ranges. When a range is initially evaluated, a random number $r = \text{random}(\text{lo}, \text{hi})$ is selected and its weight $w(r)$ is set to zero. Subsequently, this weight is adjusted (as described above). When a new value is required (i.e., when the branch is evaluated again) then if the best, worst scores seen so far (in this range) are $x, y$ (respectively) then we reset $\text{lo}, \text{hi}$ to:

$$\text{IF } x \leq y \text{ THEN } \text{lo}, \text{hi} = x, (x + y)/2 \text{ ELSE } \text{lo}, \text{hi} = (x + y)/2, x$$

When $\epsilon$ is large, a few samples should suffice to find good results. Hence, Agrawal et al. \cite{22} recommends $\epsilon = 0.2$ and $N_1 = N_2 = 15$.

DODGE can be recommended for two reasons. Firstly, for SE problems, DODGE’s optimizations are better than the prior state-of-the-art (evidence: see \cite{22}, and the rest of this paper).

Secondly, DODGE achieves those results very quickly. Based on the default parameters suggested by Goldberg \cite{45}, Storn \cite{46}, and using some empirical results from Fu et al. \cite{25}, we can compute the number of times a hyperparameter optimizer would have to call a data miner. Assuming that, 25 times\cite{25} we are analyzing 10 data sets, then hyperparameter optimization with grid search or genetic algorithms or differential evolution would need to call a data miner thousands to millions of times (respectively).

### 3.3 Data Used to Assess DODGE

As stated in the introduction, previously \cite{22} was assessed using 16 data sets from two domains:

1. 10 SE defect prediction data sets;
2. 6 SE issue tracking data sets.

This study repeats that analysis while also studying

3. 63 SE data sets exploring Github issue close time;
4. 4 SE data sets exploring bad smell detection.
5. Finally, we also explore 37 miscellaneous non-SE problems from the UCI repository.

We will find that DODGE works very well for SE case studies and very badly for non-SE case studies. Later in this paper, we precisely characterize the kinds of data for which DODGE is not recommended.

The rest of this section describes the data from these five different categories.

#### 3.3.1 Defect Prediction

Software developers are smart, but sometimes make mistakes. Hence, it is essential to test the software before the deployment \cite{49, 50, 51, 52}. Software bugs are not evenly distributed across the project \cite{13, 53, 54, 55}. Hence, a useful way to perform software testing is to allocate most assessment budgets to the more defect-prone parts in software projects. Data miners can learn a predictor for defect proneness using, e.g., the static code metrics of Table 2.

Table 3 shows the static code data used in this paper. All these projects have multiple versions and we use older versions to predict the properties of the latest version. Note the fluctuating frequencies of the target class in the training and testing data (sometimes increasing, sometimes decreasing), e.g., xerces has target frequency changes between 16 to 74% while in jedit it changes from 23 to 2%. One of the challenges of doing data mining in such domains is finding learner settings that can cope with some wide fluctuations.

#### 3.3.2 Text Mining Issue Reports

Many SE project artifacts come in the form of unstructured text such as word processing files, slide presentations, comments, Github issue reports, etc. In practice, text documents require tens of thousands of attributes (one for each word). For example, Table 4 shows the number of unique words

1. Why 25? In a 5x5 cross-val experiment, the data set order is randomized five times. Each time, the data is divided into five bins.
2. For decades, this UCI repository has been the standard source of data used by the machine learning community in their research papers \cite{48}. 

TABLE 2
Static code metrics for defect prediction. For details, see [56].

| Metric | Description |
|--------|-------------|
| amc    | average method complexity |
| avg cc | average McCabe |
| ca     | afferent couplings |
| cam    | cohesion amongst classes |
| cbb    | coupling between methods |
| cbo    | coupling between objects |
| ce     | efferent couplings |
| dam    | data access |
| dit    | depth of inheritance tree |
| ioc    | inheritance coupling |
| loc    | lines of code |
| max cc | maximum McCabe |
| mfa    | functional abstraction |
| mna    | aggregation |
| noc    | number of children |
| npm    | number of public methods |
| rc     | response for a class |
| wmc    | weighted methods per class |
| defects| Boolean: where defects found in bug-tracking |

TABLE 3
Defect prediction data from [http://tiny.cc/seacraft](http://tiny.cc/seacraft) Uses metrics from Table 2.

| Project | Training Data | Testing Data |
|---------|---------------|--------------|
|            | Versions | % of Defects | Versions | % of Defects |
| Poi | 1.5, 2.0, 2.5 | 426/936 = 46% | 3.0 | 281/442 = 64% |
| Lucene | 2.0, 2.2 | 235/442 = 53% | 2.4 | 203/442 = 60% |
| Camel | 1.0, 1.2, 1.4 | 347/1819 = 21% | 1.6 | 188/965 = 19% |
| Log4j | 1.0, 1.1 | 71/248 = 29% | 1.2 | 189/205 = 92% |
| Arches | 1.2, 1.3 | 14/492 = 11% | 1.4 | 437/588 = 74% |
| Velocity | 1.4, 1.5 | 289/410 = 71% | 1.6 | 78/229 = 34% |
| Xalan | 2.3, 2.5, 2.6 | 908/2411 = 38% | 2.7 | 896/909 = 99% |
| Ivy | 1.1, 1.4 | 79/352 = 22% | 2.0 | 40/352 = 11% |
| Synapse | 1.0, 1.1 | 76/379 = 20% | 1.2 | 86/226 = 38% |
| Jedit | 2.4, 4.1, 4.2 | 292/1257 = 23% | 4.3 | 111/492 = 2% |

TABLE 4
Issue tracking data (from [http://tiny.cc/seacraft](http://tiny.cc/seacraft)).

| Dataset | No. of Documents | No. of Unique Words | Severe % |
|---------|------------------|---------------------|----------|
| PitsA   | 965              | 155,165             | 39       |
| PitsB   | 1650             | 104,052             | 40       |
| PitsC   | 323              | 23,799              | 56       |
| PitsD   | 182              | 15,517              | 92       |
| PitsE   | 825              | 93,750              | 63       |
| PitsF   | 744              | 28,620              | 64       |

found in the issue tracking system for six NASA projects PitsA, PitsB, PitsC, etc. [57], [58]. Our PITS dataset contains tens to hundreds of thousands of words (even when reduced to unique words, there are still 10,000+ unique words). One other thing to note in Table 4 is that the target class frequencies are much higher than with defect prediction (median=60%).

For large vocabulary problems, text miners apply dimensionality reduction. (see Table 1 for the list of dimensionality reduction pre-processing methods used here). After pre-processing, one of the learners from Table 1 was applied to predict for issue severity.

While these data mention five classes of severity, two of them comprise nearly all the examples. Hence, for this study, we use the most common class and combine all the others into “other”. Agrawal et al. [22] showed that using Table 1, they could auto-configure classifiers to better predict for this binary severity problem.

3.3.3 Issue Lifetime Estimation

Issue tracking systems collect information about system failures, feature requests, and system improvements. Based on this information and actual project planning, developers select the issues to be fixed.

Predicting the time it may take to close an issue has multiple benefits for the developers, managers, and stakeholders involved in a software project. Such predictions help software developers to better prioritize work. For an issue close time prediction generated at issue creation time can be used, for example, to auto-categorize the issue or send a notification if it is predicted to be an easy fix. Also, such predictions help managers to effectively allocate resources and improve the consistency of release cycles. Lastly, such predictions help project stakeholders understand changes in project timelines.

Such predictions can be generated via data mining. Rees-Jones et al. [59] analyzed the Giger et al. [60] data using Hall’s CFS feature selector [34] and the C4.5 decision tree learner [40]. They found that the attributes of Table 3 could be used to generate very accurate predictions for issue lifetime. Table 5 shows information about the nine projects used in the Rees-Jones study. Note here that the target class frequencies vary greatly from 2 to 42%.

3.3.4 Bad Code Smell Detection

According to Fowler [62], bad smells (i.e., code smells) are “a surface indication that usually corresponds to a deeper problem”. Studies suggest a relationship between code smells and poor maintainability or defect proneness [63], [64], [65]. Research on software refactoring endorses the use of code-smells as a guide for improving the quality of code as a preventative maintenance [66], [67], [68], [69].

Recently, Fontana et al. [61] considered 74 systems in data mining analysis. Table 7 shows the data used in that analysis. This corpus comes from 11 systems written in Java, characterized by different sizes and belonging to different application domains. The authors computed a large set of object-oriented metrics belonging at a class, method, package, and project level. A detailed list of metrics is available in appendices of [61]. Note in Table 7 how the target class frequencies are all around 43%.

3.3.5 Non-SE Problems

The UCI machine learning repository [29], [48], [70] was created in 1987 to foster experimental research in machine learning. To say the least, this repository is commonly used

TABLE 5
Metrics used in issue lifetime data

| # Comments | Comment |
|------------|--------|
| ByActors   | meanCommentSize |
| ByCreator  | nComments |
| ByUniqueActorsT | ByCreator |
| InProject  | ByCreatorClosed |
| Project    | CreatedInProject |
| Misc.      | CreatedInProjectClosed |
|            | CreatedProject |
by industrial and academic researchers (evidence: the 2007, 2010, and 2017 version of the repository are cited 4020, 3179 and 4179 times respectively [29], [48], [70]). Many of machine learning tools used in SE were certified using data from UCI. This repository holds 100s of data mining problems from many problem areas including engineering, molecular biology, medicine, finance, and politics. Using a recent state-of-the-art machine learning paper [71] we identified 37 UCI data sets that machine learning researchers often used in their analysis (see Table 6).

One issue with comparing Table 8 to the SE problems is that the former often have \( N > 2 \) classes whereas the SE problems use binary classification. Also, sometimes, the SE data exhibits large class imbalances (where the target is less than 25% of the total). Such imbalances are acute in the issue lifetime data in Table 6 but it also appears sometimes in the test data of Table 3.

We considered various ways to remove the above threat to validity including (a) clustering and sub-sampling each cluster; (b) some biased sampling of the UCI data. In the end, we adopted a very simple method (lest anything more complex introduced its own biases). For each UCI dataset, we selected:

- The UCI rows from the most frequent and rarest class;
- And declared that the UCI rarest class is the target class.

### Table 6

| Project | Dataset | # of instances | # metrics (see Table 4) |
|---------|---------|----------------|------------------------|
| camel   | 1 day   | 698 (14.0)     | 18                     |
|         | 7 days  | 497 (9.0)      |                        |
|         | 14 days | 148 (3.0)      |                        |
|         | 30 days | 167 (3.0)      |                        |
|         | 90 days | 298 (6.0)      |                        |
|         | 180 days| 657 (13.0)     |                        |
|         | 365 days| 3072 (41.0)    |                        |
| cloudstack | 1 day  | 658 (42.0)     | 18                     |
|          | 7 days  | 457 (29.0)     |                        |
|          | 14 days | 101 (7.0)      |                        |
|          | 30 days | 107 (7.0)      |                        |
|          | 90 days | 133 (9.0)      |                        |
|          | 180 days| 65 (4.0)       |                        |
|          | 365 days| 23 (2.0)       |                        |
| cocoon  | 1 day   | 125 (6.0)      | 18                     |
|          | 7 days  | 92 (4.0)       |                        |
|          | 14 days | 32 (2.0)       |                        |
|          | 30 days | 45 (2.0)       |                        |
|          | 90 days | 86 (4.0)       |                        |
|          | 180 days| 51 (3.0)       |                        |
|          | 365 days| 73 (3.5)       |                        |
| node    | 1 day   | 2425 (39.0)    | 18                     |
|          | 7 days  | 1800 (29.0)    |                        |
|          | 14 days | 521 (8.0)      |                        |
|          | 30 days | 453 (7.0)      |                        |
|          | 90 days | 552 (9.0)      |                        |
|          | 180 days| 254 (4.0)      |                        |
|          | 365 days| 180 (3.0)      |                        |
| deeplearn | 1 day  | 931 (65.0)     | 18                     |
|          | 7 days  | 214 (15.0)     |                        |
|          | 14 days | 76 (5.0)       |                        |
|          | 30 days | 72 (5.0)       |                        |
|          | 90 days | 69 (5.0)       |                        |
|          | 180 days| 39 (3.0)       |                        |
|          | 365 days| 52 (3.0)       |                        |
| hadoop  | 1 day   | 40 (0.0)       | 18                     |
|          | 7 days  | 65 (1.0)       |                        |
|          | 14 days | 107 (1.0)      |                        |
|          | 30 days | 396 (3.0)      |                        |
|          | 90 days | 1743 (14.0)    |                        |
|          | 180 days| 2182 (18.0)    |                        |
|          | 365 days| 2133 (17.5)    |                        |
| hive    | 1 day   | 18 (0.0)       | 18                     |
|          | 7 days  | 22 (0.0)       |                        |
|          | 14 days | 58 (1.0)       |                        |
|          | 30 days | 178 (3.0)      |                        |
|          | 90 days | 1050 (19.0)    |                        |
|          | 180 days| 1336 (24.0)    |                        |
|          | 365 days| 1440 (25.0)    |                        |
| ofbiz   | 1 day   | 1515 (25.0)    | 18                     |
|          | 7 days  | 1169 (19.0)    |                        |
|          | 14 days | 467 (8.0)      |                        |
|          | 30 days | 477 (8.0)      |                        |
|          | 90 days | 574 (9.0)      |                        |
|          | 180 days| 469 (7.5)      |                        |
|          | 365 days| 402 (6.5)      |                        |
| qpid    | 1 day   | 203 (4.0)      | 18                     |
|          | 7 days  | 188 (3.0)      |                        |
|          | 14 days | 84 (2.0)       |                        |
|          | 30 days | 178 (3.0)      |                        |
|          | 90 days | 558 (10.0)     |                        |
|          | 180 days| 860 (16.0)     |                        |
|          | 365 days| 531 (10.0)     |                        |

### Table 7

| Nature    | Dataset | # of instances | # of attributes | Smelly |
|-----------|---------|----------------|-----------------|--------|
| Method    | Feature Envy | 109 | 82 | 45 |
| Method    | Long Method | 109 | 82 | 43.1 |
| Class     | C1 Class   | 139 | 61 | 43.9 |
| Class     | Data Class | 119 | 61 | 42 |

# metrics (see Table 5).

### Table 8

| Area          | Dataset | # of instances | # of attributes | Class % |
|---------------|---------|----------------|-----------------|---------|
| Computer      | optdigits | 1143 | 64 | 50 |
| Physical      | satellite | 2159 | 36 | 28 |
| Physical      | climate-sim | 540 | 18 | 91 |
| Financial     | credit-approval | 653 | 15 | 45 |
| Medicine      | cancer | 569 | 30 | 37 |
| Business      | shop-intention | 12330 | 17 | 15 |
| Computer Vision | image | 660 | 19 | 50 |
| Life          | covtype | 12240 | 54 | 22 |
| Computer      | hand | 29876 | 15 | 47 |
| Social        | drug-consumption | 1885 | 30 | 23 |
| Environment   | biodegrade | 1055 | 41 | 34 |
| Social        | adult | 45222 | 14 | 25 |
| Physical      | crowsource | 1887 | 28 | 24 |
| Medicine      | blood-transfusion | 748 | 4 | 24 |
| Financial     | credit-default | 30000 | 23 | 22 |
| Medicine      | cervical-cancer | 668 | 33 | 7 |
| Social        | autism | 609 | 19 | 30 |
| Marketing     | bank | 3090 | 20 | 12 |
| Financial     | bankrupt | 4769 | 64 | 3 |
| Financial     | audit | 775 | 25 | 39 |
| Life          | contraceptive | 1473 | 9 | 56 |
| Life          | mushroom | 5644 | 22 | 38 |
| Computer      | pendigits | 2298 | 16 | 50 |
| Physical      | heapmass | 2000 | 27 | 50 |
| Physical      | hitox | 17898 | 8 | 9 |
| Computer      | kddcup | 3203 | 41 | 69 |
| Automobile    | sensorless-drive | 10638 | 48 | 50 |
| Physical      | waveform | 3304 | 21 | 50 |
| Physical      | anneal | 716 | 10 | 13 |
| Medicine      | cardiotoography | 2126 | 40 | 22 |
| Physical      | shuttle | 54489 | 9 | 16 |
| Electrical    | electric-stable | 10000 | 12 | 36 |
| Physical      | gamma | 1920 | 10 | 35 |
| Medicine      | liver | 579 | 10 | 72 |
3.4 Experimental Methods

3.4.1 Performance Measures

D2h, or “distance to heaven”, shows how close a classifier comes to “heaven” (recall=1 and false alarms (FPR)=0 [22]:

\[
\text{Recall} = \frac{\text{TruePositives}}{(\text{TruePositives} + \text{FalseNegatives})} \quad (1)
\]
\[
\text{FPR} = \frac{\text{FalsePositives}}{(\text{FalsePositives} + \text{TruePositives})} \quad (2)
\]
\[
d2h = \left(\sqrt{(1 - \text{Recall})^2 + (0 - \text{FPR})^2}\right) / \sqrt{2} \quad (3)
\]

Here, the \(\sqrt{2}\) term normalizes \(d2h\) to the range zero to one. The \(d2h\) metric is a “classic” metric that comments on issues widely discussed in the machine learning literature (recall and false alarm). Another “classic” metric, that we do not use here, is precision. Menzies et al. [73] show that the second derivative of this measure can be highly unstable, especially in the presence of imbalanced class distributions. Hence, we report our performance using other measures.

Apart from “classic” metrics, another important class of metrics are those that reflect the concerns of commercial practitioners. In the case of defect prediction, the standard use case is that developers want defect predictors to focus them on the small sections of the code that probably contain most bugs [55], [74]. For that purpose, \(Popt(20)\) comments on the inspection effort required after a defect predictor is triggered. \(Popt(20) = 1 - \Delta_{opt}\), where \(\Delta_{opt}\) is the area between the effort (code-churn-based) cumulative lift charts of the optimal learner and the proposed learner. To calculate \(Popt(20)\), we divide all the code modules into those predicted to be defective (\(D\)) or not (\(N\)). Both sets are then sorted in ascending order of lines of code. The two sorted sets are then laid out across the \(x\)-axis, with \(D\) before \(N\). On such a chart, the \(y\)-axis shows what percent of the defects would be recalled if we traverse the code sorted that \(x\)-axis order. Following from Ostrand et al. [55], \(Popt\) is reported at the 20% point. Further, following Kamei, Yang et al. [75], [76], [77], we normalize \(Popt\) using:

\[P_{opt}(m) = 1 - \frac{S_{\text{optimal}} - S_{\text{better}}}{S_{\text{optimal}} - S_{\text{worst}}},\]

where \(S_{\text{optimal}}\), \(S_{\text{better}}\) and \(S_{\text{worst}}\) represent the area of the curve under the optimal learner, proposed learner, and worst learner. Note that the worst model is built by sorting all the changes according to the actual defect density in ascending order.

After normalization, \(Popt(20)\) (like \(d2h\)) has the range zero to one. Note that larger values of \(Popt(20)\) are better; but smaller values of \(d2h\) are better.

3.4.2 Control Rig

Jimenez et al. [78] recommended that train/test data be labeled in their natural temporal sequence; i.e. apply training and hyperparameter optimization to the prior versions, then tested on latter version. We will call this RIG0.

When temporal markers are missing, we use a cross-val method (which is also standard in literature [75]). Given one data set and \(N\) possible treatments, then \(2^N\) times we use 80% of the data (selected at random) for training and hyperparameter optimization, then the remaining 20% for testing. We will call this RIG1.

3.4.3 Statistical Tests

When comparing results from two samples, we need a statistical significance test (to certify that the distributions are indeed different) and an effect size test (to check that the differences are more than a “small effect”). Here, we used tests that have been past peer-reviewed in the literature [25], [26]. Specifically, we use Efron’s 95% confidence bootstrap procedure [79] and the A12 effect test endorsed by Acuri & Briand in their ICSE paper [80].

3.5 Results

In the following, when we say “DODGE”, that is shorthand for DODGE using Table 1 with \(N_1 + N_2 = 30\), \(\epsilon = 0.2\). Also, when we say “DODGE performed better”, we mean that, according to a 95% confidence bootstrap and the A12 test, DODGE performed significantly better by more than a small effect.

3.5.1 Defect Prediction Results

Table 9 shows which tools found best predictors for defects, using the data of 3.3.1.

When the target class is not common (as in camel, ivy, jedit and to a lesser extent velocity and synapse), it can be difficult for a data mining algorithm to generate a model that can locate it. Researchers have used class balancing techniques such as SMOTE to address this problem [24].

Table 9 compares DODGE versus methods selected from prior state-of-the-art SE papers. An ICSE’18 paper [26] reported that hyperparameter tuning (using DE) of SMOTE usually produces the best results (across multiple learners). We used SMOTE tuning (for data-processing) plus learners taken from Ghotra et al. [24] (who found that the performance of dozens of data miners can be clustered into just a few groups). We used learners sampled across those clusters (Random Forests, CART, SVM, KNN \((k = 5)\), Naive Bayes, Logistic Regression).

Table 9 results were generated using RIG0 with \(d2h\) and \(Popt(20)\) as the performance goal. DODGE performed statistically better than the prior state-of-the-art in sixteen out of twenty results for 10 data sets.

3.5.2 Text Mining Results

Table 10 shows which techniques found best predictors for the data of 3.3.2. In this study, all data were preprocessed using the usual text mining filters [81]. We implemented stop words removal using NLTK toolkit [82] (to ignore very common stop words such as “and” or “the”). Next, Porter’s stemming filter [83] was used to delete uninformative word

| Data      | D2h      | Smote+   | Popt     | Smote+   |
|-----------|----------|----------|----------|----------|
| Pot       | 0.25     | 0.31     | 0.65     | 0.72     |
| Lucene    | 0.31     | 0.34     | 0.77     | 0.60     |
| Camel     | 0.14     | 0.36     | 0.51     | 0.40     |
| Log4j     | 0.55     | 0.45     | 0.96     | 0.51     |
| Xeres     | 0.48     | 0.43     | 0.90     | 0.78     |
| Velocity  | 0.38     | 0.42     | 0.61     | 0.51     |
| Xalan     | 0.60     | 0.45     | 0.98     | 0.90     |
| Ivy       | 0.08     | 0.39     | 0.30     | 0.21     |
| Synapse   | 0.24     | 0.34     | 0.47     | 0.40     |
| Jedit     | 0.60     | 0.40     | 0.43     | 0.32     |
endings (e.g., after performing stemming, all the following words would be rewritten to “connect”, “connection”, “connective”, “connected”, “connecting”).

Table 10 compares DODGE versus methods seen in prior state-of-the-art SE papers: specifically, SVM plus Latent Dirichlet allocation [38] with hyperparameter optimization via differential evolution [27] or genetic algorithms [44].

Table 10 results were generated using RIG1 with d2h as the performance goal. In these results, DODGE performed better than the prior state-of-the-art (in 5/6 data sets).

3.5.3 Issue Lifetime Estimation

Table 11 shows what techniques found the best predictors for the data of 3.3.3. The table compares DODGE versus the methods in a recent study on issue lifetime estimation (feature selection with the Correlation Feature Selection [34] followed by classification via Random Forests).

Table 11 was generated using RIG1 with d2h as the performance goal. In these results, DODGE performed statistically better than prior work (in 47/63~75% of the datasets).

3.5.4 Bad Code Smell Results

Figure 3 shows best predictors, using the data of 3.3.3. The figure compares DODGE versus bad smell detectors from a TSE’18 paper [84] that studied bad smells. The TSE article used Decision Trees (CART), Random Forests, Logistic Regression and KNN(\(k = 5\)). To the best of our knowledge, there has not been any prior case study that applied hyperparameter optimizer to bad smell prediction.

Figure 4 results were generated using RIG1 with d2h as the performance goal. In those results, DODGE has the same median performance as prior work for two data sets (FeatureEnvy and GodClass) and performed statistically better that the prior state-of-the-art (for DataClass and LongMethod). That is, compared to the other algorithms used in this study, DODGE statistically performs as well or better than anything else.

TABLE 11
Sixty three issue lifetime prediction results. DODGE loses to random forests in colored cells. The red cells show where DODGE failed.

| Data | 3.605 | < 1.80 | < 0.90 | < 0.30 | < 14 | < 7 | < 1 |
|------|-------|--------|--------|--------|------|-----|-----|
| cloudstack | Dodge | Dodge | Dodge | RF | RF | Dodge | Dodge |
| node | Dodge | Dodge | Dodge | RF | RF | Dodge | Dodge |
| deseplearn | Dodge | RF | RF | Dodge | RF | Dodge | Dodge |
| cocoon | RF | RF | RF | Dodge | RF | Dodge | Dodge |
| obfiz | Dodge | Dodge | Dopge | RF | RF | Dodge | Dodge |
| camel | RF | RF | RF | Dodge | RF | Dodge | Dodge |
| hadoop | Dodge | RF | RF | Dodge | RF | Dodge | Dodge |
| apid | Dodge | RF | RF | Dodge | RF | Dodge | Dodge |
| hive | RF | RF | RF | Dodge | RF | Dodge | Dodge |
| DODGE wins | 6/9 | 7/9 | 9/9 | 6/9 | 5/9 | 9/9 | 6/9 |

3.5.5 Results from Non SE-Problems

All the above problems come from the SE domain. Table 12 shows which techniques found best predictors for the 37 non-SE problems from 3.3.5.

In Table 12, DODGE was compared against standard data miners (CART, Random Forests, Logistic Regression and KNN(\(k = 5\))). Table 12 results were generated using RIG1 with d2h as the performance goal. Each cell of that table lists the best performing learner. Note that despite its use of hyperparameter optimization (which should have given some advantage) DODGE performs very badly (only succeeds in 6/31 problems).

TABLE 12
37 results from non-SE problems. Red cells mark DODGE’s failures.

| Data | Best tool | Data | Best tool |
|------|-----------|------|-----------|
| optdigits | RF | satellite | RF |
| climate-sim | SVM | credit-approval | Dodge |
| cancer | SVM | shop-intention | RF |
| image | RF | covyte | RF |
| hand | RF | drug-consumption | Dodge |
| biodegrade | RF | adult | RF |
| crowdsourcing | RF | blood-transfusion | Dodge |
| credit-default | SVM | cervical-cancer | Dodge |
| autism | RF | bank | SVM |
| bankrupt | Dodge | audit | RF |
| contraceptive | SVM | mushroom | RF |
| pendigits | RF | phishing | RF |
| car | RF | diabetic | SVM |
| hepatitis | RF | hiru2 | SVM |
| kddcup | RF | sensorless-drive | RF |
| waveform | SVM | annealing | RF |
| cardiotocography | RF | shuttle | RF |
| electric-stable | RF | gamma | RF |
| liver | Dodge | | |
4 WHEN?

Looking at the red cells of the results tables in [3.3], there is a very clear pattern:

- The UCI data results of Table 12 are nearly all red; i.e. DODGE performs very badly for these non-SE data;
- While elsewhere across the SE domains, DODGE usually performs very well.

What general lesson can be learned from that pattern? To answer that question, this section seeks a predictor that can say when DODGE will perform best. Specifically, we explore the following conjecture:

**CONJECTURE1**: DODGE works well for SE data, and fails elsewhere, since the other data is more complex.

One measure of inherent data complexity is Levina et al. [85]’s “intrinsic dimensionality” calculator. Levina et al. comment that many data sets embedded in high-dimensional format actually can be converted into a more compressed space without major information loss. While a traditional way to compute these intrinsic dimensions is PCA (Principal Component Analysis), Levina et al. caution that, as data in real-world becomes increasingly sophisticated and non-linearly decomposable, PCA methods tend to overestimate the intrinsic dimensions [85]. Hence, they propose an alternate fractal-based method for calculating intrinsic dimensionality (and that method is now a standard technique in other fields such as astrophysics). The intrinsic dimension of a dataset with $N$ items is found by computing the number of items found at distance within radius $r$ (where $r$ is the distance between two configurations) while varying $r$. This measures the intrinsic dimensionality since:

- If the items spread out in only one $r = 1$ dimensions, then we will only find linearly more items as $r$ increases.
- But the items spread out in, say, $r > 1$ dimensions, then we will find polynomially more items as $r$ increases.

As shown in Equation 4, Levina et al. normalize the number of items found according to the number of $N$ items being compared. They recommend reporting the number of intrinsic dimensions as the maximum value of the slope between $ln(r)$ vs $ln(C(r))$ value computed as follows.

$$C(r) = \frac{2}{N(N - 1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} I(||x_i, x_j|| < r)$$ (4)

$$\text{where : } I(||x_i, x_j|| < r) = \begin{cases} 
1, & ||x_i, x_j|| < r \\
0, & ||x_i, x_j|| \geq r 
\end{cases}$$

For example, in Figure 5, the intrinsic dimensionality of blue curve is its maximum slope of 1.6 (see orange line).

(Technical aside: Note that equation [3] use the L1-norm to calculate distance rather than the Euclidean L2-norm.  Courtney et al. [87] advise that for data with many columns, L1 performs better than L2.)

Algorithm 1 shows a calculator for intrinsic dimensionality. Table 13 shows a small study checking if that calculator can infer the number of underlying independent dimensions. In summary, Table 13 says that the calculator is approximately accurate up to 10 dimensions (but we do not recommend for data sets with an intrinsic dimensionality over 20).

Using the Levina, calculator, we can test CONJECTURE1. Figure 6 shows the dimensionality of the 100+ data sets studied in the rest of this paper. The horizontal/vertical axis shows that the number of data columns/intrinsic dimensions in our data.

Figure 6b shows that the intrinsic dimensionality of our SE and non-SE data is usually very different. Figure 6c summarizes that effect: the SE data usually has half the intrinsic dimensions of the non-SE data (the mean values for SE and non-SE are $D = 3.1$ and $D = 6.8$, respectively).

**Algorithm 1 Calculating intrinsic dimensionality. From [86].**

```
Import data from Testdata.py
Input: sample_num = n, sample_dim = d
Rs = \exp(n) / \exp(n)
for R in Rs do
    # Calculated by L1 Distance
    I = 0
    # count for pairwise samples within R
    for i, j in combinations(data, 2) do
        d = distance(i, j)
        # L1 distance
        if d < R then
            I += 1
        end if
    end for
    # return the intrinsic dimensionality
    Cr = 2 * 1 / (n * (n - 1))
end for
Crs = append(Cr)
for i in step do
    gradient = (Crs[i] - Crs[i - 1]) / (R[i] - R[i - 1])
    G = append(gradient)
end for
Smooth(G) # smooth the curve
intrinsicD = \max(G) # return the intrinsic dimensionality
```

**TABLE 13**

Checking that the Levina calculator can recognize the number of independent dimensions in a data set.

In Levina et al at study, data sets with $d$ independent columns were artificially generated with 10,000 rows and 5,10,20 or 40 columns. Each cell was filled with a random number selected uniformly 0 ≤ $X$ ≤ 1. When Equation [4] was applied to that data, it is observed that:

- The $d = 5$ column data scored 6.0;
- The $d = 10$ column data scored 10.3;
- The $d = 20$ column data scored 16.0;
- The $d = 40$ column scored 23.1.

Equation [4] comes close to the total value of $d$ for $d < 20$. Above that point, the algorithm underestimate the number of columns – an effect they attribute to the “shotgun correlation effect” reported by Courtney et al. [88] in 1993. They reported that, due to randomly generated spurious correlations, the correlation between $d$ random variables will increase with $d$. Hence it is not surprising that in the (e.g.) $d = 40$ example, we find less than 40 dimensions.

Fig. 5. Intrinsic dimensionality is the maximum slope of the smoothed blue curve of $ln(r)$ vs $ln(C(r))$ (the orange line).
Figure 6d summarizes how often DODGE succeeds for intrinsic dimensionality up to some threshold dimension $D$. In that plot, the y-axis values $y = n/N$ are calculated as follows: within the $N$ data sets with intrinsic dimensionality up to some value of $D$, there are $n$ data sets where DODGE defeated other methods. From Figure 6d, we see that:

- Figure 6d is not optimistic about the value of DODGE for large values of $D$: specifically, above $D = 8$, DODGE fails nearly half the time.
- That said, Figure 6d offers strong evidence for CONJECTURE1; i.e., that DODGE succeeds for SE data since that data is simple. Recall from Figure 6c our SE data has a mean intrinsic dimensionality of $D = 3.1$. As shown in Figure 6d, $D \approx 3.1$, is a region where DODGE succeeds at least 80% of the time.

5 DISCUSSION AND FUTURE WORK

Between $D = 3.1$ and $D = 8$, Figure 6d exhibits a strange performance plateau, which we explain via the distribution of our examples. Returning to Figure 6a, we observe that most of our examples have an intrinsic dimensionality of less than 5. Hence, we say that the plateau in Figure 6d from 3.1 to 8 is just the result of a sparsely populated region in our data.

From the last paragraph, it follows that future work should explore the sparser regions of the data sets used in this paper. Figure 6d offers a clear predictor DODGE’s success (our sample of SE data had $\mu_D = 3.1$ and in that region, DODGE usually succeeds). However, more work is needed to collect data at higher dimensionality. Currently, we have set ourselves the goal of creating a much larger version of Figure 6d with 1000 data sets from the SE literature. This goal will take some time to achieve (since for each such data set, we have to reproduce the prior state of the art).

Currently, we have only explored classification tasks. DODGE needs to be applied for other tasks such as regression tasks. Another useful extension to the above would be to explore problems with three or more goals (e.g., reduce false alarms while at the same time improving precision and recall).

Right now, DODGE only deprecate tunings that lead to similar results. Another approach would be to also depreciate tunings that lead to similar and worse results (perhaps to rule out larger parts of the output space, sooner).

Further, for pragmatic reasons, it would be useful if the Table 1 list could be reduced to a smaller, faster to run, set of learners. That is, here we would select learners that run fastest while generating the most variable kinds of models.

6 THREATS TO VALIDITY

External validity: The above results suggest that DODGE is useful for data sets with an intrinsic dimensionality of ($\mu_D \approx 3$) and perhaps not so useful for higher-dimensional data ($\mu_D > 8$). To date, most of the data sets we have measured from SE are low dimensional, hence DODGE should have wide applicability in SE. That said, before using DODGE, we recommend using Algorithm 1 to check the suitability of the data from DODGE.
Sampling bias threatens any classification experiment since what matters for some data sets may or may not hold for others. That said, in our case, sampling bias may be mitigated since we applied our frameworks to many data sets. In fact, our reading of the literature is that the above study uses much more data than most other publications. Also, we assert we did not “cherry pick” our data sets. All the non-SE data from [71] were applied here. As to the SE data, we used everything we could access in the time frame of this production of this paper. But, as said in future work, it would be important to check the results of this paper against yet more data sets from yet more problems from SE and elsewhere.

Learner Bias: When comparing DODGE against other tools, we did not explore all other tools. As stated above, such a comparison would not fit into a single paper. Instead, we use baselines taken from SE literature about bad smell detection, predicting Github issue close time, bug report analysis, and defect prediction. From that work we used tools that have some pedigree in the literature [21], [24], [26], [44].

Evaluation Bias: This paper used two performance measures, i.e., $P_{opt}$ and $dist2heaven$ and many others exist [89], [90], [91]. Note that just because other papers use a particular evaluation bias, then it need not follow that it must be applied in all other papers. For example, precision is a widely used evaluation method even though it is known to perform badly when data sets have rare target classes [73].

Order Bias: For the performance evaluation part, the order that the data trained and predicted can affects the results. To mitigate for order bias, we used a cross-validation procedure that (multiple times) randomizes the order of the data.

Construct Validity: At various stages of data collection by different researchers, they must have made engineering decisions about what attributes to be extracted from Github for issue lifetime data sets, or what object-oriented metrics need to be extracted. While this can inject issues of construct validity, we note that the data sets used here have also appeared in other SE publications, i.e., the class labels used here have verified by other researchers. So at the very least, using this data, we have no more construct validity bias than other researchers.

Statistical Validity: To increase the validity of our results, we applied two statistical tests, bootstrap and the a12 effect size test. Both of these are nonparametric tests so the above results are not susceptible to issues of parametric bias.

7 Conclusion

For data set with larger dimensionality (say, $\mu_D > 8$), it may be necessary to deploy complex hyperparameter optimizers that require much CPU to find their solutions. In this paper, we do not comment on effective methods for such higher-dimensional problems but for the interested reader, we refer them to the work of Apel [92], Nair [93], Krishna [94] and Chen [95].

For data sets with low intrinsic dimensionality (say, $\mu_D \leq 3$), simple stochastic sampling methods like DODGE can be very effective for software analytics hyperparameter optimization. As shown here, such stochastic sampling can run very fast (e.g. DODGE terminates in 30 evaluations) and be just as effective (or better) than more complex algorithms.

Of course, not all SE data is intrinsically simple. For example, some researchers characterize summarizing software code snippets as a translation task between source code to English. After extensive experimentation, researchers in that area now agree that deep learning methods work better [96] than older models that used simple Markov chains [97]. For our paper, this result is significant since deep learners work best on intrinsically complex data. Hence, we would not recommend using DODGE for hyperparameter optimisation for source code translators.

That said, as shown above,

- Multiple SE domains are intrinsically simple since they can be characterized by just $\mu_D = 3.1$ dimensions
- Such simple data can be detected using Equation [4].
- For such simple data, very simple methods like DODGE can be both fast and effective;
- So it is possible to glance at data to determine if DODGE or something more complicated (like deep learning) is needed.

More generally, we argue that it is useful to match the complexity of analysis to the intrinsic complexity of the data under study. Once that is done, software analytics becomes easier to implement and deploy, faster to run; scalable to larger problems; and simpler to understand, debug & extend.

Acknowledgements

This work was partially funded by a NSF Grant #1703487.

References

[1] Z. Wan, X. Xia, A. E. Hassan, D. Lo, J. Yin, and X. Yang, “Perceptions, expectations, and challenges in defect prediction,” IEEE Transactions on Software Engineering, pp. 1–1, 2018.
[2] A. Begel and T. Zimmermann, “Analyze this! 145 questions for data scientists in software engineering,” in ICSE’14. ACM, 2014.
[3] C. Theisen, K. Herzig, P. Morrison, B. Murphy, and L. Williams, “Approximating attack surfaces with stack traces,” in ICSE’15, 2015.
[4] T. Menzies, L. Williams, and T. Zimmermann, Perspectives on data science for software engineering. Morgan Kaufmann, 2016.
[5] H. Gall, T. Menzies, L. Williams, and T. Zimmermann, “Software development analytics (dagstuhl seminar 14261),” in Dagstuhl Reports, vol. 4, no. 6. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2014.
[6] C. Bird, T. Menzies, and T. Zimmermann, The art and science of analyzing software data. Elsevier, 2015.
[7] J. Czerwonka, R. Das, N. Nagappan, A. Tarvo, and A. Teterev, “Crane: Failure prediction, change analysis and test prioritization in practice – experiences from windows,” in IEEE Fourth International Conference on Software Testing, Verification and Validation, 2011.
[8] T. J. Ostrand, E. J. Weyuker, and R. M. Bell, “Where the bugs are,” in ISSSTA ’04: Proceedings of the 2004 ACM SIGSOFT international symposium on Software testing and analysis, New York, USA, 2004.
[9] T. Menzies, A. Dekhtyar, J. Distefano, and J. Greenwald, “Problems with precision,” IEEE Transactions on Software Engineering, 2007.
[10] E. Kocaguneli, T. Menzies, and J. W. Keung, “On the value of ensemble effort estimation,” IEEE TSE’12, vol. 38, no. 6, 2012.
[11] E. Kocaguneli, T. Menzies, A. Bener, and J. Keung, “Exploiting the essential assumptions of analogy-based effort estimation,” IEEE TSE’12, vol. 28, pp. 425–438, 2012.
[12] M. Linares-Vásquez, G. Bavota, C. Bernal-Cárdenas, R. Olivotto, M. Di Penta, and D. Peshyvanych, “Mining energy-greedy api usage patterns in android apps: an empirical study,” in Proceedings of the 11th Working Conference on Mining Software Repositories. ACM, 2014.
C. Kaltenecker, A. Grebhahn, N. Siegmund, and S. Apel, “The
T. Menzies, D. Port, Z. Chen, and J. Hihn, “Simple software cost
C. C. Aggarwal, A. Hinneburg, and D. A. Keim, “On the surprising
P. Campbell and S. Abhyankar, “Fractals, form, chance and dimen-
E. Levina and P. J. Bickel, “Maximum likelihood estimation of
R. Krishna and T. Menzies, “Bellwethers: A baseline method for
S. Bird, “NLTK: the natural language toolkit,” in
B. Efron and R. J. Tibshirani, An Introduction to the Bootstrap
M. Jorgensen, “Realism in assessment of effort estimation uncer-
P. Campbell and S. Abhyankar, “Fractals, form, chance and dimen-
R. Krishna and V. Nair, P. Jamshidi, and T. Menzies, “Whence to learn?
R.-S. Feldman, An Introduction to the Bootstrap. Chapman & Hall, 1993.
A. Ærcur and L. Briand, “A practical guide for using statistical tests to assess randomized algorithms in software engineering,” in ICSE’11, 2011.
R.-S. Feldman, J, The Text Mining Handbook. Cambridge University Press, 2006.
S. Bird, “NLTK: the natural language toolkit,” in Proceedings of the COLING/ACL on Interactive presentation sessions, 2006.
M. Porter, “The Porter Stemming Algorithm,” pp. 130–137, 1980. [Online]. Available: http://tartarus.org/martin/PorterStemmer/
R. Krishna and T. Menzies, “Bellwethers: A baseline method for transfer learning,” IEEE Transactions on Software Engineering, 2018.
E. Levina and P. J. Bickel, “Maximum likelihood estimation of intrinsic dimension,” in Advances in neural information processing systems, 2005, pp. 777–784.
P. Campbell and S. Abhyankar, “Fractals, form, chance and dimension,” 1978.
C. C. Aggarwal, A. Hinneburg, and D. A. Keim, “On the surprising behavior of distance metrics in high dimensional spaces,” in Proceedings of the 8th International Conference on Database Theory, ser. ICDT’01. Berlin, Heidelberg: Springer-Verlag, 2001, p. 420434.
R. Courtney and D. Gustafson, “Shotgun correlations in software measures,” Software Engineering Journal, vol. 8, 1993.
T. Menzies, A. Dekhtyar, J. Distefano, and J. Greenwald, “Problems with precision: A response to comments on ‘data mining static code attributes to learn defect predictors’,” IEEE TSE, 2013.
M. Jimenez, R. Rwemalika, M. Papadakis, F. Sarro, Y. Le Traon, and M. Harman, “The importance of accounting for real-world labelling when predicting software vulnerabilities,” in FSE’19, 2019.
B. Efron and R. J. Tibshirani, An Introduction to the Bootstrap. Chapman & Hall, 1993.
A. Ærcur and L. Briand, “A practical guide for using statistical tests to assess randomized algorithms in software engineering,” in ICSE’11, 2011.
R.-S. Feldman, J, The Text Mining Handbook. Cambridge University Press, 2006.
S. Bird, “NLTK: the natural language toolkit,” in Proceedings of the COLING/ACL on Interactive presentation sessions, 2006.
M. Porter, “The Porter Stemming Algorithm,” pp. 130–137, 1980. [Online]. Available: http://tartarus.org/martin/PorterStemmer/
R. Krishna and T. Menzies, “Bellwethers: A baseline method for transfer learning,” IEEE Transactions on Software Engineering, 2018.
E. Levina and P. J. Bickel, “Maximum likelihood estimation of intrinsic dimension,” in Advances in neural information processing systems, 2005, pp. 777–784.
P. Campbell and S. Abhyankar, “Fractals, form, chance and dimension,” 1978.
C. C. Aggarwal, A. Hinneburg, and D. A. Keim, “On the surprising behavior of distance metrics in high dimensional spaces,” in Proceedings of the 8th International Conference on Database Theory, ser. ICDT’01. Berlin, Heidelberg: Springer-Verlag, 2001, p. 420434.
R. Courtney and D. Gustafson, “Shotgun correlations in software measures,” Software Engineering Journal, vol. 8, 1993.
T. Menzies, A. Dekhtyar, J. Distefano, and J. Greenwald, “Problems with precision: A response to comments on ‘data mining static code attributes to learn defect predictors’,” IEEE TSE, vol. 33, no. 9, 2007.
T. Menzies, D. Port, Z. Chen, and J. Hihn, “Simple software cost analysis: safe or unsafe?” in ACM SIGSOFT Software Engineering Notes. ACM, 2005.
M. Jorgensen, “Realism in assessment of effort estimation uncertainty: It matters how you ask,” IEEE TSE’04, 2004.
C. Kaltenemecker, A. Grebhahn, N. Siegmund, and S. Apel, “The interplay of sampling and machine learning for software performance prediction,” IEEE Software, vol. 37, no. 4, pp. 58–66, 2020.
V. Nair, Z. Yu, T. Menzies, N. Siegmund, and S. Apel, “Finding faster configurations using flash,” IEEE Transactions on Software Engineering, 2018.
R. Krishna, V. Nair, P. Jamshidi, and T. Menzies, “Whence to learn? transferring knowledge in configurable systems using beetle,” IEEE Transactions on Software Engineering, pp. 1–1, 2020.
I. Chen and T. Menzies, “Riot: A stochastic-based method for workflow scheduling in the cloud,” in IEEE CLOUD’18, 2018.
R.-M. Karampatsis, H. Babii, R. Robbes, C. Sutton, and A. Janes, “Big code != big vocabulary: Open-vocabulary models for source code,” in ICSE’20, 2020.
V. J. Hellendoorn and P. Devanbu, “Are deep neural networks the best choice for modeling source code?” in FSE’17, 2017.

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