When SIMPLE is better than complex
A case study on deep learning for predicting Bugzilla issue close time

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Abstract Is deep learning over-hyped? Where are the case studies that compare state-of-the-art deep learners with simpler options? In response to this gap in the literature, this paper offers one case study on using deep learning to predict issue close time in Bugzilla.

We report here that a SIMPLE extension to a decades-old feedforward neural network works better than the more recent, and more elaborate, “long-short term memory” deep learning (which are currently popular in the SE literature). SIMPLE is a combination of a fast feedforward network and a hyper-parameter optimizer. SIMPLE runs in 3 seconds while the newer algorithms take 6 hours to terminate. Since it runs so fast, it is more amenable to being tuned by our optimizer.

This paper reports results seen after running SIMPLE on issue close time data from 45,364 issues raised in Chromium, Eclipse, and Firefox projects from January 2010 to March 2016. In our experiments, this SIMPLEr tuning approach achieves significantly better predictors for issue close time than the more complex deep learner. These better and SIMPLEr results can be generated 2,700 times faster than if using a state-of-the-art deep learner.

From this result, we make two conclusions. Firstly, for predicting issue close time, we would recommend SIMPLE over complex deep learners. Secondly, before analysts try very sophisticated (but very slow) algorithms, they might achieve better results, much sooner, by applying hyper-parameter optimization to simple (but very fast) algorithms.

Keywords deep learning · software engineering · issue close time · feedforward networks · hyper-parameter optimization
1 Introduction

As modern infrastructure allows for cheaper processing, it has inevitably led to the exploration of more complex modeling. For example, many software engineering researchers are now using deep learning methods [14, 23, 32, 58, 58, 11, 29].

One problem with deep learning is that it can be very slow to run. For example, for the case study of this paper, we estimate that we would need 6 years of CPU time. Such long runtimes can complicate many aspects of the scientific process (e.g. initial investigations, subsequent attempts at reproduction).

Accordingly, this paper checks if anything simpler than deep learner can handle SE tasks. The particular task explored here will be **predicting the close time for issues in a code repository**. When programmers work on repositories, predicting issue close time has multiple benefits for the developers, managers, and stakeholders since it helps:

- Developers prioritize work;
- Managers allocate resources and improve consistency of release cycles;
- Stakeholders understand changes in project timelines and budgets.
- It is also useful to predict issue close time when an issue is created; e.g. to send a notification if it is predicted that the current issue is an easy fix.

We explore issue close time, for two reasons. Firstly, it is a well studied problem [30, 45, 53, 5, 13, 15, 35, 26, 20]. Secondly, recent work has proposed a state-of-the-art deep learning approach to issue close time prediction (see the DeepTriage deep learning systems from COMAD’19, described later in this paper [34]).

The experiments of this paper show that simpler methods than DeepTriage are better for predicting issue close time. Specifically, a simple extension to a 1980s-style feedforward neural network, which we call “SIMPLE”, runs much faster than DeepTriage (3 seconds versus 6 hours). Since it runs faster, SIMPLE is more amenable to automatic hyper-parameter tuning:

- Learners have hyper-parameters that are control the learning process. For example, Table 1 shows the hyperparamters of a simple neural network.
- Hyper-parameter tuners find tunings that work better for specific data sets.
- The faster the learner, the more hyper-parameters can be explored.

The value of hyper-parameter tuning for SE data has been reported previously [50, 15, 2, 3]. However, to the best of our knowledge, this paper is the first to show that hyper-parameter optimization works so well for issue close time prediction, compared to state-of-the-art deep learners. In all our experiments, SIMPLE made significantly better predictions than state-of-the-art deep learners.

The rest of this paper is structured as follows. § 2 presents the necessary background and § 2.1 discusses the SE task under consideration. § 3 discusses our proposed approach. Then, in § 4 we show our results. We discuss the threats to the validity of our study in § 5. In § 6 we conclude that before analysts try very sophisticated (but very slow) algorithms, they might achieve better results, much sooner, by applying hyper-parameter optimization to simple (but very fast) algorithms.

In order to support open science, we offer a reproduction package with all our scripts and data

1 [https://github.com/fastidiouschipmunk/simple](https://github.com/fastidiouschipmunk/simple)
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Table 1: Feedforward networks are controlled by these hyper-parameters.

| Preprocessors:                      |
|-------------------------------------|
| StandardScaler: i.e. all input data set numerics are adjusted to \((x - \mu) / \sigma\). |
|MinMaxScaler (range = (0, 1)): i.e. scale each feature to (0, 1). |
|Normalizer (norm = randchoice([‘l1’, ‘l2’, ‘max’])): i.e. normalize to a unit norm. |
|MaxAbsScaler (range = (0, 1)): scale each feature by its maximum absolute value |
|Binarizer (threshold = randuniform(0,100)), i.e., divide variables on some threshold |

| Hyper-parameters:                  |
|------------------------------------|
| Number of layers                   |
|Number of units in each layer       |
|Batch size (i.e., the number of samples processed at a time) |

2 Background

2.1 Our Test Domain: Predicting Bugzilla Issue Close Time

Most large software systems have a system to track bugs, or issues, in the product. These issues typically go through the same lifecycle, in which they transition across various states, including UNCONFIRMED and CLOSED, while also being assigned final states such as WONTFIX [56].

The estimated time to close an issue is helpful for managers to assign priorities, for developers to design and refactor code accordingly, for end-users who are directly affected by the bug, and for stakeholders who have vested interests in the product itself:

- Although bugs have an assigned severity, this is not a sufficient predictor for the lifetime of the issue. For example, the author who issued the bug may be significant, if, for example, they are a significant contributor to the project.
- Alternatively, an issue deemed more visible to end-users may be given higher priorities. It is therefore insufficient simply to consider the properties of the issue itself (i.e., the issue metrics), but also of its environment (i.e., context metrics). This is similar to recent work on how process metrics are better defect predicting measures than product metrics [33].

To find prior work on predicting issue close time, we searched for papers in the last ten years (since 2010) in Google Scholar using keywords “bug fix time”, “issue close time”, and “issue lifetime”. Then, we filtered them according to the criterion that they must be published in a top venue according to Google Scholar metrics Software Systems. Finally, using engineering judgement, we added in systems that were recommended by reviewers of a prior draft of this paper. That search found several noteworthy systems:

- Guo et al [18] use logistic regression on a large closed-source project (Microsoft Windows), to predict whether or not a bug will be fixed. Using regression analysis, they identified the factors that led to bugs being fixed or not fixed.

[https://scholar.google.com/citations?view_op=top_venues&hl=en&vq=eng__softwaresystems]
Giger et al. [15] use decision trees to predict the bug-fix time for Mozilla, Eclipse, and GNOME projects. They divided their target class into two labels: fast and slow, to get a binary classification problem, and used the area under the ROC curve (AUC) metric as their evaluation criteria.

Marks et al. [35] also used decision trees, but instead, use an ensemble method, i.e., random forests, on Eclipse and Mozilla data. Their motivation for using random forests, apart from the better performance as compared to standard decision trees, is the ability to extract the relative importance of features in the input data. They report accuracy scores of 63.8% and 67.2% on the Mozilla and Eclipse repositories respectively.

At MSR’16, Kikas, Dumas, and Pfahl [26] built time-dependent models for issue close time prediction using Random Forests with a combination of static code features, and non-code features to predict issue close time with high performance.

More recently, Habayeb et al. [20] reported in IEEE TSE’17 a prediction system based on hidden Markov chains. Like Giger et al. [15], they divided their target labels into fast and slow fix-times and experimented with different values of the number of hidden states of the hidden Markov model.

Based on the above, we assert that the two prior state-of-the-art non-neural methods in area used random forests and logistic regression. Hence we will use these two systems as part of the following study.

As to deep learning and issue close time prediction, two contenders for “state-of-the-art” are DASENet [30] and DeepTriage [34]. The DASENet paper asserts that their algorithm defeats DeepTriage but, after much effort, we could not reproduce that result. Hence, for this study, we use DeepTriage since:

- It is a state-of-the-art deep learner that performs for lifetime prediction.
- It has been very recently published (2019);
- Its reproduction package allowed us to run that code on our machines.
- It uses datasets commonly used in the literature (Technical aside: we were tempted to use the dataset provided by Vieira et al. [53] for our deep learning baseline. However, their lack of prior benchmarks meant we could not provide a comparison to demonstrate the efficacy of our approach.)

From a technical perspective, DeepTriage is Mani et al. [34]’s extension of bidirectional LSTMs with an “attention mechanism”. A Long Short-Term Memory (LSTM) [24] is a form of recurrent neural network that has additional “gate” mechanisms to allow the network to model connections between long-distance tokens in the input. Bidirectional variants of recurrent models, such as LSTMs, consider the token stream in both forward and backward directions; this allows for the network to model both the previous and the following context for each input token. Attention mechanisms [6] use learned weights to help the network “pay attention” to tokens that are more important than others in a context. Prior to running DeepTriage, its authors recommend using a standard set of preprocessing techniques: pattern matching to remove special characters and stack traces, tokenization, and and pruning the corpus to a fixed length. Beyond these steps, they rely on the deep learner to perform automated feature engineering.

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3 We found that the reproduction package published with DASENet has missing files. We tried contacting the authors of that paper, without success.
2.2 Deep Learning

2.2.1 High-Level View

To provide background for the rest of this paper, we must first introduce deep learning. For the rest of this paper, the following distinction will be important:

- DeepTriage is based on new neural network technology comprising extensive layers of reasoning, where layer $i$ organizes the inputs offered to layer $i + 1$.
- Our SIMPLE algorithm is based on old feedforward neural networks, which is a technology that dates back decades. At each node of these networks, the inputs are multiplied with weights that are learned, and then an activation function is applied. The weights are learned by the backpropagation algorithm [48].

The difference between these approaches can be understood via Figure 1. The older methods use just a few layers while the “deep” learners use many layers. Also, the older methods use a threshold function at each node, while feedforward networks typically use the ReLU function $f(x) = \max(0, x)$.

2.2.2 DL and SE

To understand how deep learning is used in SE, we performed the following steps.

- **Seed**: Our approach started with collecting relevant papers. As a seed, we collected papers from the recent literature review conducted by Watson [55].
- **Search**: To this list, we added papers added by our own searches on Google Scholar. Our search keywords included “deep learning AND software”, “deep learning AND defect prediction”, and “deep learning AND bug fix” (this last criteria was added since we found that some recent papers, such as Lee et al [30], used the term “bug fix time” rather than “issue close time”).
- **Filter**: Next, we filtered papers using the following criteria: (a) published in top venues as listed in Google Scholar metrics for Software Systems, Artificial
Intelligence, and Computational Linguistics; or, released on arXiv in the last 3 years or widely cited (> 100 cites) (b) has at least 10 cites per year, unless it was published in or after 2017 (the last three years). The distribution of papers across different venues is shown in Figure 2.

- **Backward Snowballing:** As recommended by Wohlin [57], we performed “snowballing” on our paper (i.e. we added papers cited by the papers in our list that also satisfy the criteria above). Our snowballing stopped when either (a) the list of papers cited by the current generation is a subset of the papers already in the list, or (b) there were no further papers found.

This led to a list of 99 papers, which we summarize in Figure 3. Some engineering judgement was used in assigning papers to the categories of that figure. For example, a paper on learning a latent embedding of an API [42] for various purposes, such as discovering analogous APIs among third-parties [10], was categorized as “code comprehension”. Similarly, most papers performing some variant of code translation, including API translation as in [17], were categorized into “language processing”—a bin that contains programming language processing and natural language processing. Tasks that we could not justifiably merge into an existing bin (e.g. on image processing [43, 49] were given their own special category.

Note the numbers on top of the columns of Figure 3:

- Slightly more than half (60.1%) of those papers compare their results to non-DL methods. We suggest that number should be higher—it is important to benchmark new methods against prior state-of-the-art.
- Only a minority of papers (39.4%) performed any sort of hyper-parameter optimization (HPO), i.e., used methods that tune the various “hyper-parameters”, such as the number of layers of the deep learner, to eke out the best performance of deep learning (39.4%).
- Even fewer papers (18.2%) applied hyper-parameter optimization in a non-trivial manner; i.e., not using deprecated grid search [7] and using a hold-out set to assess the tuning before going to a separate test set).
- Finally, few papers (10.1%) used both non-trivial hyper-parameter optimization and compared to results to prior non-deep learning work

![Fig. 2: The distribution of papers across venues](image-url)
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Fig. 3: A summary of our literature review of deep learning methods in SE. The blue row denotes the DeepTriage system used in this paper. **Legend:** A = attention mechanism, B = deep belief network, C = convolutional networks, E = embedding, F = feedforward networks (which includes traditional perceptrons [46] [36]), G = graph networks, M = misc (i.e. some particular architecture invented by the author, used in one paper), S = sequence, W = word2vec. N

This paper uses Figure 3 to design the experiments of this paper, as follows:

- Do not just run DL on some SE data. Rather, compare DL to some non-DL approaches.
- When comparing something other than DL to DL, try tuning that alternative.
  This is important since hyper-parameter optimization is an alternate technology that might also offer some benefit to building predictors for software analytics.
- When tuning algorithms, ensure that analysts are using a non-trivial optimizer.

### 2.2.3 Some Detailed Notes on Specific Algorithms

Feedforward neural networks [28] apply a general “activation function” at each node after performing the matrix multiplication of the weights with the inputs. These networks grew in popularity following the invention of the ReLU (rectified linear unit) function [41], $f(x) = \max(0, x)$, which significantly improved the results of neural networks. Specifically, for a layer $i$, if the weight matrix is represented in matrix form as $W^{[i]}$, the bias terms (the constants) are represented by $b^{[i]}$, and the values of the activation function are represented as $a^{[i]}$, then $a^{[0]} = X$ and $z^{[i]} = W^{[i]} a^{[i-1]} + b^{[i]}$ and $a^{[i]} = f(z^{[i]})$ where $X$ is the input matrix.

There are several activation functions; for brevity, we only discuss the ones relevant in this study. Following the advice of LeCun et al [28], for binary and multi-classification problems:

- For the last layer of the network, this study uses $\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}}$ and $\text{Softmax}(x) = \frac{\exp(x_j)}{\sum_{j=1}^{n} \exp(x_j)}$ respectively.
- For the other layers, we use $\text{ReLU}(x) = \max(0, x)$. 

| All papers | Compared to non-DL [60] | Perform same HPO [39] | Non-trivial HPO [18] | Non-trivial HPO - compare [10] |
|------------|-------------------------|-----------------------|----------------------|-------------------------------|
| code-synthesis | 5                       | 2                     | 1                    | 1                             |
| code comprehension | 1                       | 1                     | 1                    | 1                             |
| language model | 7                       | 2                     | 1                    | 2                             |
| defect prediction | 6                       | 1                     | 1                    | 2                             |
| clone detection | 1                       | 1                     | 1                    | 1                             |
| program repair | 3                       | 2                     | 1                    | 1                             |
| misuse detection | 1                       | 1                     | 1                    | 1                             |
| software configuration | 1                     | 1                     | 1                    | 1                             |
| bug localization | 1                       | 1                     | 1                    | 1                             |
| feature extraction | 3                       | 1                     | 1                    | 1                             |
| software energy metrics | 3                     | 1                     | 1                    | 1                             |
| code audit | 1                       | 1                     | 1                    | 1                             |
Since the development of feedforward networks in the 1990s, there have been numerous advances. For example, “sequence models” refer to a specific type of architecture where the nodes form a directed acyclic graph that can be unrolled. Such models are used for sequence data, such as text and audio. Other advancements in sequence models include Long Short-Term Memory (LSTM) \[24\] and Bidirectional LSTMs (Bi-LSTMs). Sequence models have been successfully used in language modeling, such as BERT \[12\] and GPT-3 \[9\].

A common factor in all deep learners is the existence of many layers of neural networks \[16\]. In deep learning terminology, an “architecture” refers to the arrangement of nodes in the network and the connections between them, which dictates how the backpropagation algorithm updates the weights. These weights are the parameters of the model. Depending on the choice of the optimization algorithm (such as Adam \[27\]) and the architecture used, the model also has several hyper-parameters, such as the number of layers, the number of nodes in each layer, and hyper-parameters of the optimization algorithm itself \[9\].

### 3 Experimental Methods

The rest of this paper comparatively evaluates different ways to do issue close time prediction. We explore three learners:

L1: DeepTriage: a state-of-the-art deep learner from COMAD’19 \[34\];
L2: Our SIMPLEr neural network learner, described in §3.2;
L3: Non-neural approaches: random forest from Marks et al \[35\], and logistic regression from Guo et al \[18\] (we present the better of the two results, where “better” is defined via the statistical methods of §3.4).

These learners will be studied twice:

S0: Once, with the default off-the-shelf settings for learners control parameters;
S1: Once again, using the settings found after some automatic tuning.

The original research plan was to present six sets of results:

\[
\text{planned} = \{L1, L2, L3\} \times \{S0, S1\}
\]

However, as noted below, the tuning times from DeepTriage were so slow that we could only report five results:

\[
\text{actual} = (\{L1\} \times \{S0\}) + (\{L2, L3\} \times \{S0, S1\})
\]

### 3.1 Data

To obtain a fair comparison with the prior state-of-the-art, we use the same data as used in the prior Lee et al \[30\] study. One reason to select this baseline is that we were able to obtain the data used in the original study (see our reproduction package) and, therefore, were able to obtain results comparable to prior work. For a summary of that data, see Table 2.

For the comparison with the Mani et al \[34\] study, the data was collected from Bugzilla for the three projects: Firefox, Chromium, and Eclipse:
Table 2: An overview of the data used in the Lee et al [30] study. Note that because of the manner of data collection, i.e., using bin-sequences for each day for each report, there are many more data samples generated from the number of reports mined.

| Project  | Observation Period  | # Reports | # Train | # Test |
|----------|----------------------|-----------|---------|--------|
| Eclipse  | Jan 2010–Mar 2016    | 16,575    | 44,545  | 25,459 |
| Chromium | Mar 2014–Aug 2015    | 15,170    | 44,801  | 25,200 |
| Firefox  | Apr 2014–May 2016    | 13,619    | 44,800  | 25,201 |

To collect that data, Mani et al [34] applied standard text mining preprocessing (pattern matching to remove special characters and stack traces, tokenization, and and pruning the corpus to a fixed length).

Next, the activities of each day were collected into “bins”, which contain metadata (such as whether the person was the reporter, days from opening, etc.), system records (such as labels added or removed, new people added to CC, etc.), and user activity such as comments.

The metadata can directly be represented in numerical form, while the user and system records are transformed from text to numerical form using the word2vec [38, 39] system. These features, along with the metadata, form the input to the DeepTriage [34] system and our feedforward learners for comparison.

In the same manner as prior work using the Bugzilla datasets, we discretize the target class into 2, 3, 5, 7, and 9 bins (so that each bin has roughly the same number of samples). This yields datasets that are near-perfectly balanced (for example, in the Firefox 2-class dataset, we observed a 48%-52% class ratio).

3.2 Optimizing the SIMPLER Algorithm

Our SIMPLER algorithm is shown in Algorithm 1. Table 1 shows the parameters that control the feedforward network used by SIMPLE.

One issue with any software analytics paper is how researchers decide on the “magic numbers” that control their learners (e.g., Table 1). In order to make this paper about simpler neural feedforward networks versus deep learning (and not about complex methods for hyper-parameter optimization), we selected the controlling hyper-parameters for the feedforward networks using hyper-parameter optimization.

For this study, we consider using two such optimizers: TPE (tree-structured Parzen estimators) from Bergstra et al. [7, 8] and DODGE from Agrawal et al. [3, 4]:

- TPE is a candidate hyper-parameter optimizer since a December 2020 Google Scholar search for “Hyper-parameter optimization” reported that papers by Bergstra et al. [7, 8] on TPE optimization have more citations (2159 citations and 4982 citations) than any other paper in this arena.

4 The nearest other work was a 2013 paper by Thornton et al. on Auto-WEKA [51] with 931 citations.
Algorithm 1: SIMPLE

1. Set random number seed;
2. for 20 times do
3. Shuffle data;
4. Set train, test = 70%, 30% splits of the data;
5. /* Learning */
   Apply a feedforward neural network; On the training data, tune the hyper-parameters of Table 1 using the methods of §3.2.
6. Take the best model found from the training data, apply it to the test data;
7. Report performance scores on the test data.
8. end

– **DODGE** is another candidate hyper-parameter since, unlike **TPE**, it has been extensively tested on SE data sets. In 2019, Agrawal et al. [3] reported that for a range of SE problems (bad small detection, defect prediction, issue severity prediction) learners tuned by DODGE out-perform prior state-of-the-art results (but a missing part of their analysis is that they did not study deep learning algorithms, hence, this paper).

How to choose between these algorithms? In 2021, Agrawal et al. [4] showed that **DODGE** is preferred over **TPE** for “intrinsically simple” data sets:

– Levina and Bickel [31] argue that many datasets embedded in high-dimensional spaces can be compressed without significant information loss.
– They go on to say that a simple linear transformation like Principal Components Analysis (PCA) [44] is insufficient, as the lower-dimensional embedding of the high-dimensional points are not merely projections.
– Instead, Levina and Bickel [31] propose a method that computes the intrinsic dimensionality by counting the number of points within a distance $r$ while varying $r$. For notes on that computation, see Table 3
– Intrinsic dimensionality (which we will denote as $D$) can be used to select an appropriate hyper-optimization strategy. Agrawal et al. [4], experiments show that **DODGE** beats **TPE** for low dimensional data (when $D < 8$) while **TPE** is the preferred algorithm for more complex data.

Using the calculation methods of Agrawal et al. [4], we find that for our data:

$$D(\text{Firefox, Chromium, Eclipse}) = \{2.1, 1.95, 1.9\}$$

From this, we make two observations:

– In a result that may not have surprised Levina et al., this data from Firefox, Chromium, Eclipse can be compressed to just a few dimensions.
– All our data can be found below the $D < 8$ threshold proposed by Agrawal et al. [4]. Hence, for this study, we use **DODGE**.

Compared to other hyper-parameter optimizers, **DODGE** is a very simple algorithm that runs in two steps:

1. During an initial random step, **DODGE** selects hyper-parameters at random from Table 1. Each such tuning is used to configure a learner. The value of that configuration is then assessed by applying that learner to a data set. If ever a NEW result has performance scores near an OLD result, then a “tabu”
Before presenting the mathematics of the Levina and Bickel [31] measure, we offer a little story to explain the intuition behind this measure. Consider a brother and sister who live in different parts of town. The sister lives alone, out-of-town, on a road running north-south with houses only on one side of the street. Note that if this sister tries to find company by walking:

- Vertically up or down;
- Or east or west

then she will meet no one else. But if she walks north or south, then she might find company. That is, the humans in that part of town live in a one-dimensional space (north-south). Meanwhile, the brother lives downtown in the middle of a large a block of flats that is also oriented north-south. The brother is ill-advised to walk east-west since then they will fall off a balcony. On the other hand, if he:

- Climbs up or down one storey
- Or walks to the neighboring flats north or south

then the brother might meet other people. That is to say, the humans in that block of flats effectively live in a two-dimensional space (north-south and up-down).

To compute Levina’s intrinsic dimensionality, we create a 2-d plot where the x-axis shows $r$; i.e. how far we have walked away from any instance and the y-axis show $C(r)$ which counts how many more people we have meet after walking some distance $r$ way from any one of $n$ instances:

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

The maximum slope of ln $C(r)$ vs. ln $r$ is then reported as the intrinsic dimensionality. Note that $I[\cdot]$ is the indicator function (i.e., $I[x] = 1$ if $x$ is true, otherwise it is 0); $x_i$ is the $i$th sample in the dataset. Note also that, as shown by Aggarwal et al [1], at higher dimensions the distance calculations should use the $L_1$ norm, i.e., $\sum|x_i|$ rather than the $L_2$ norm, i.e., $\sqrt{\sum x_i^2}$.

Table 3: Notes on intrinsic dimensionality.

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zone is created around OLD and NEW configurations that subsequent random searches avoid that region of configurations.

2. In the next step, DODGE selects configurations via a binary chop of the tuning space. Each chop moves in the bounds for numeric choices by half the distance from most distant value to the value that produced the “best” performance. For notes on what “best” means, see §3.3.

Agrawal et al. recommend less than 50 evaluations for each of DODGE’s two stages. Note that this is far less than other hyper-parameter optimizations strategies. To see that, consider another hyper-parameter optimization approach based on genetic algorithms that mutate $P$ individuals over $G$ generations (and between each generation, individuals give “birth” to new individuals by crossing-over attributes from two parents). Holland [25] recommends $P=G=100$ as useful defaults for genetic algorithms. Those default settings implies that a standard genetic algorithm optimizer would require $100 \times 100 = 10,000$ evaluations.

Note that we also considered tuning DeepTriage, but that proved impractical:

- The DeepTriage learner used in this study can take up to six CPU hours to learn one model from the issue close time data. When repeated for 20 times (for statistically validity) over our (15) data sets, that means that using DODGE (using 42 evaluations) on DeepTriage would require over 8 years of CPU time.
On the other hand, with 20 repeats over our datasets, DODGE with feed-forward networks terminated in 26 hours; i.e. nearly 2,700 times faster than tuning DeepTriage.

3.3 Performance Metrics

Since we wish to compare our approach to prior work, we take the methodological step of adopting the same performance scores as that seen in prior work. Lee et al [30] use the following two metrics in their study:

- **Accuracy** is the percentage of correctly classified samples. If TP, TN, FP, FN are the true positives, true negatives, false positives, and false negatives (respectively), then accuracy is \( \frac{TP + TN}{TP + TN + FP + FN} \).
- **Top-2 Accuracy**, for multi-class classification, is defined as the percentage of samples whose class label is among the two classes predicted by the classifier as most likely. Specifically, we predict the probabilities of a sample being in each class, and sort them in descending order. If the true label of the sample is among the top 2 classes ranked by the classifier, it is marked as “correct”.

In other software analytics work, other evaluation measures are used such as recall, false alarm, precision etc. Previously, we have critiqued those measures saying that they can have issues with data sets where one class is far more frequent than another [37]. In this dataset, those concerns do not apply since, as discussed in §3.1, the pre-processing of our data ensures that all our classes occur at equal ratios. Hence, the measures shown above (Accuracy and Top-2 Accuracy) are sufficient.

3.4 Statistics

Since it is so slow, the challenge in these results is to compare the results of a very slow system versus a very fast one (SIMPLE) where the latter can be run multiple times while it is impractical to repeatedly run the former. Hence, for our definition of “best”, we will compare one result of size \( |N_1| = 1 \) from the slower learner (DeepTriage) to a sample of \( |N_2| = 20 \) results from the other.

Statistically, our evaluation of these results requires a check if one results is less than a “small effect” different to the central tendency of the other population. For that statistical task, Rosenthal et al [47] says there are two “families” of methods: the \( r \) group that is based on the Pearson correlation coefficient; or the \( d \) family that is based on absolute differences normalized by (e.g.) the size of the standard deviation. Rosenthal et al [47] comment that “none is intrinsically better than the other”. Hence, the most direct method is utilized in our paper. Using a \( d \) family method, it can be concluded that one distribution is the same as another if their mean value differs by less than Cohen’s delta (d*standard deviation).

\[
d = \text{small effect} = 0.3 \cdot \sqrt{\frac{\sum x_i - (\sum x_i/n)^2}{n - 1}}
\]

i.e., 30% of the standard deviation of the \( N_2 \) population.
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Table 4: Results on BugZilla data used in prior deep learning state of the art. The target label is discretized into a different number of classes (columns) as in the prior work. Dark cells indicate statistically better performance.

**Key:**
- **DT** = DeepTriage [34].
- **NDL-T** = best result of untuned non-neural methods; i.e. best of logistic regression [18] and random forests [35].
- **NDL+T** = best of DODGE-tuned non-neural methods; i.e. **NDL-T** plus tuning.
- **FF** = untuned feedforward network; i.e Algorithm 1, without tuning.
- **SIMPLE** = SIMPLE i.e. **FF** plus tuning; \( T_k \) = Top-\( k \) accuracy;

| Project  | Model  | 2-class | 3-class | 5-class | 7-class | 9-class |
|----------|--------|---------|---------|---------|---------|---------|
|          |        | T_1 | T_2 | T_1 | T_2 | T_1 | T_2 | T_1 | T_2 |
| Firefox  | DT     | 66.8 | 43.6 | 78.4 | 30.7 | 57.5 | 20.7 | 39.4 | 18.6 | 34.9 |
|          | NDL-T  | 70.0 | 42.6 | 64.2 | 30.0 | 42.4 | 17.8 | 29.9 | 17.8 | 29.8 |
|          | NDL+T  | 67.7 | 46.8 | 78.8 | 34.0 | 61.3 | 24.6 | 45.2 | 21.1 | 38.5 |
|          | FF     | 70.5 | 49.4 | 81.8 | 36.7 | 62.6 | 25.6 | 47.0 | 22.5 | 41.0 |
|          | SIMPLE | 70.3 | 53.4 | 86   | 39.4 | 66.9 | 36.6 | 60.7 | 24.6 | 44.5 |
| Chromium | DT     | 62.7 | 42.6 | 75.0 | 27.2 | 51.7 | 21.9 | 38.1 | 18.2 | 32.9 |
|          | NDL-T  | 64.2 | 34.8 | 55.5 | 22.8 | 36.4 | 14.8 | 27.2 | 15.0 | 27.6 |
|          | NDL+T  | 64.1 | 49.1 | 79.2 | 30.2 | 55.6 | 25.6 | 42.1 | 23.4 | 39.5 |
|          | FF     | 65.4 | 53.1 | 82.0 | 34.7 | 59.9 | 27.4 | 45.4 | 25.5 | 41.8 |
|          | SIMPLE | 68.3 | 54.6 | 82.9 | 35.8 | 61.4 | 29.2 | 47.5 | 28.0 | 45.1 |
| Eclipse  | DT     | 61.2 | 44.1 | 73.2 | 26.6 | 51.1 | 20.1 | 36.9 | 18.5 | 34.3 |
|          | NDL-T  | 65.8 | 32.6 | 53.6 | 23.1 | 38.1 | 15.6 | 29.2 | 15.6 | 29.1 |
|          | NDL+T  | 64.6 | 51.6 | 81.1 | 30.1 | 55.7 | 27.0 | 43.9 | 27.0 | 42.1 |
|          | FF     | 66.3 | 53.9 | 81.4 | 32.4 | 59.4 | 30.1 | 47.2 | 29.6 | 45.8 |
|          | SIMPLE | 68.8 | 56.2 | 83.9 | 34.7 | 61.8 | 30.5 | 47.7 | 32.5 | 49.0 |

4 Results

In Table 4, best results are indicated by the **gray cells**. The columns of that table describe how detailed our time predictions are. A column labeled \( k \)-class means that the data was discretized into \( k \) distinct labels, as done in prior work (see Lee et al [30] for details).

Recall that cells are in gray if the are statistically significantly better. In all cases, SIMPLE’s results were (at least) as good as anything else. Further, once we start exploring more detailed time divisions (in the 3-class, 5-class, etc problems) then SIMPLE is the stand-out best algorithm.

Another thing we can say about these results is that SIMPLE is much faster than other approaches. The above results took \( \approx 90 \) hours to generate, of which 9 hours was required for SIMPLE (for 20 runs, over all 15 datasets) and 80 hours were required for the deep learner (for 1 run, over all 15 datasets). Recall that if we had also attempted to tune the deep learner, then that runtime would have exploded to six years of CPU.

5 Threats to Validity

**Sampling bias:** As with any other data mining paper, it is important to discuss sampling bias. We claim that this is mitigated by testing on 3 large SE projects over multiple discretizations, and demonstrating our results across all of them.
Further, these datasets have been used in prior work that have achieved state-of-the-art performance recently. Nevertheless, in future work, it would be useful to explore more data.

**Learner bias:** Our learner bias here corresponds to the choice of architectures we used in our deep learners. As discussed above, we chose the architectures based on our reading of “standard DL” from the literature. While newer architectures may lead to better results, the crux of this paper was on how simple networks suffice. Therefore, we maintain that the intentional usage of the simple, feedforward architecture was necessary to prove our hypothesis.

**Evaluation bias:** We compared our methods using top-1 and top-2 accuracy scores, consistent with prior work. These metrics are valid since the method the classes were discretized (as discussed in prior work) lends to equal-frequency classes. We further reduce the evaluation bias by running our experiments 20 times for each setup, and using distribution statistics, i.e., the Scott-Knott test, to check if one setup is significantly better than another.

**Order bias:** This refers to bias in the order in which data elements appear in the training and testing sets. We minimize this by running the experiment 20 times, each with a different random train-test split.

**External validity:** We tune the hyper-parameters of the neural network using DODGE, removing external biases from the approach. Our baseline results are based on the results of Montufar et al. [40], which has been evaluated by the deep learning community. We also compare our work to non-deep learning methods, both with and without tuning by DODGE, to provide a complete picture of the performance of our suggested approach in relation to prior work and other learners.

### 6 Discussion and Conclusion

In this paper, we explored the state of literature applying deep learning techniques to software engineering tasks. We discussed and explored a systemic tendency to choose fundamentally more complex models than needed. We used this as motivation to apply simpler deep learning models to one software engineering task, predicting issue close time, to achieve state-of-the-art performance. Our model is much simpler than prior state-of-the-art deep learning models, takes significantly less time to run, and achieves better results.

As to why it performs so well, we hypothesize that the power of SIMPLE came from tuning the hyper-parameters. To test this, we also ran a feedforward architecture without tuning (see FF in Table 4). We note a stark difference between the performance of the untuned and tuned versions of this architecture.

Our results present a cautionary tale about the pitfalls of using deep learners. While it is certainly tempting to use the state-of-the-art results from deep learning literature (which, as prior work has shown, certainly yields good results), we advise the reader to instead attempt the use of simpler models and apply hyper-parameter tuning to achieve better performance, faster.

It is left as future work to explore whether this same principle of using SIMPLE models for other software engineering tasks works equally well. By relying on simple architectures of deep learners, we obtain faster, simpler, and more space-efficient models. This exploration naturally lends itself to the application of modern deep learning theory to further simplify these SIMPLE models. In particular,
Han et al. [21] explored model compression techniques based on reduced-precision weights, an idea that is gaining increasing attention in the deep learning community (we refer the reader to Gupta et al. [19] and Wang et al. [51] for details, and Tung and Mori [52] for a parallel implementation of these techniques). Further, knowledge distillation [22], a method of training student learners (such as decision trees) from a parent deep learning model, has shown great promise, with the student learners outperforming the deep learners they were derived from. This would make it possible to have the accuracy of deep learning with the speed of decision tree learning.

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- **Funding:** None.
- **Conflicts of interest/Competing interests:** None.
- **Availability of data and material:** All data used in this manuscript is publicly available at [https://github.com/mkris0714/Bug-Related-Activity-Logs](https://github.com/mkris0714/Bug-Related-Activity-Logs).
- **Code availability:** All source code used is available at [https://github.com/fastidiouschipmunk/simple](https://github.com/fastidiouschipmunk/simple).

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