How to GENERALize Across Many Software Projects? (with case studies on Predicting Defect and Project Health)

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ABSTRACT
Despite decades of research, SE lacks widely accepted models (that offer precise quantitative predictions) about what factors most influence software quality. This paper provides a “good news” result that such general models can be generated using a new transfer learning framework called “GENERAL”. Given a tree of recursively clustered projects (using project meta-data), GENERAL promotes a model upwards if it performs best in the lower clusters (stopping when the promoted model performs worse than the models seen at a lower level).

The number of models found by GENERAL is minimal: one for defect prediction (756 projects) and less than a dozen for project health (1628 projects). Hence, via GENERAL, it is possible to make conclusions that hold across hundreds of projects at a time. Further, the models produced in this manner offer predictions that perform as well or better than prior state-of-the-art.

To the best of our knowledge, this is the largest demonstration of the generalizability of quantitative predictions of project quality yet reported in the SE literature.

KEYWORDS
Machine Learning with and for SE, Mining Software Repositories

1 INTRODUCTION
Researchers and industry practitioners use data mining algorithms to build software quality models from project data. These quality models include many diverse tasks such as the detection of code smells, code refactoring [1–3] or the two case studies explored in this paper (for more on these case studies, see §2.2):

- Defect prediction [4–7] prioritize where to look in a codebase such that more bugs are found sooner.
- Software project health estimation [8–10] incrementally monitors open-source projects (which is a very different process to classic waterfall up-front effort estimation [11, 12] that is conducted before developers start coding).

However, what is the external validity of the conclusions reached via these data mining methods? Prior to this paper, the usual result is that such conclusions are not general to multiple projects [6, 13, 14]. When different projects result in different models, it is hard to gain general insights about (e.g.) software quality. This is troubling since, as Sawyer et al. argue, such insights are the key driver for businesses. Generating new models every time we switch to a new project exhausts users’ ability to draw insight. Hassan [15] cautions that managers lose faith in software analytics if their models keep changing since the assumptions used to make prior policy decisions may no longer hold.

An approach for transferring conclusions across multiple projects is the “bellwether” method [16–20]. It says given a community of projects, the “bellwether” is a project whose data yields the best analytic (i.e., defect prediction, effort estimation) on all others. This approach is useful since bellwethers can generate models that generalize across multiple projects. However, this method has severe limitations. Firstly, they are very slow, and secondly, they assume that only one bellwether exists amongst hundreds of projects. Keeping that in mind, this paper proposes a new algorithm called GENERAL(hierarchical transfer learning algorithm) to overcome the limitations mentioned before.

The rest of this paper answers four research questions.

RQ1: is GENERAL tractable? GENERAL runs in time $\Theta(m^2 N/m^2)$ compared to $\Theta(N^2)$ for traditional bellwether, where $N$ is the number of projects, and $m$ is the number of clusters at the leaves of the cluster tree.

RQ2: is GENERAL efficient? GENERAL’s run-time increases less-than-linearly, compared to the prior state-of-the-art in this area [16], as the project community size increases.

RQ3: is GENERAL effective? For all Github projects studied in this paper, the models generated for both case studies are better than the baseline and prior state-of-the-art(SOA) methods.

RQ4: is GENERAL parsimonious? We show that the number of models generated in this manner is very small (one for defect prediction and less than a dozen for project health).

We assert our results are novel, sound, significant and verifiable.

Novel: We offer a new algorithm to find bellwethers, which is much faster than prior methods in finding bellwether. This novel hierarchical transfer learning algorithm that uses hierarchical clustering to divide the projects, find best projects for generalization inside leaf clusters (community of projects) and finally only uses surviving projects from smaller cluster for generalization in larger

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1We call that the "bellwether" since that is the name of the leading sheep of a flock, with a bell on its neck.
cluster. We show that this approach to generating general models works for multiple SE domains (defect prediction and project health estimation). To the best of our knowledge, this is the largest demonstration of the generalizability of quantitative predictions of project quality yet reported in the SE literature.

**Sound**: Our algorithm is assessed via its computational complexity and extensive experimentation. To ensure statistical validity and to demonstrate that we avoid over-fitting, all our experiments are repeated 20 times (with different train and test sets). Our methods are compared against state-of-the-art methods (listed in §4.3) using the state-of-the-art statistical tests described in §4.4.

**Significant**: The problem we explore is important: it is hard to call SE a “scientific” discipline unless it can offer general conclusions. Our analysis is substantive: to the best of our knowledge, this is a large demonstration of the generalizability of quantitative predictions of project quality reported in the SE literature with 756 Github projects (for defect prediction) and 1628 Github projects (for project health estimation). Our methods are effective (finding general models) and significantly faster than prior work (29 times for defect prediction and 104 times for project health estimation) than prior methods.

**Verifiability and Transparency**: All our scripts and data are online at https://github.com/Anonymous633671/GENERAL.

The rest of this paper is structured as follows. Our background notes (in §2) introduce two case studies: defect prediction and effort estimation. §3 describes our new approach. §4 details the experimental rig of this paper, which is used to produce the results of §5. This is followed by some general discussion points, plus notes on our threats to validity.

Before beginning, we digress to make three points.

Firstly, here, we have demonstrated the effectiveness of GENERAL on two domains (defect prediction and project health estimation). In future work, it would be helpful to test these methods on other domains.

Secondly, while we say we build general models (that hold for many projects), it is not true that we can always generalize all projects to a single model. Indeed, as shown by the results of this paper, some domains like project health estimation require multiple models. However, even there, it is still much easier to reason about GENERAL’s dozen health models than the 1628 individual models.

Thirdly, we are often asked, “if you have (e.g.) a dozen project health models, have you won anything? How do we know which model to apply?”? We reply that our hierarchical transfer learning method is like an index that can be used to take a new project, then run it over the cluster tree to find its relevant model.

2 BACKGROUND

2.1 Why Study Generality?

In this section, we justify why it is important to seek general SE conclusions. Our concern will be with “conclusion instability” where conclusions change from one project to another. It is hard to call SE a “scientific” discipline if its conclusions change all the time.

Conclusion instability is well documented in the research community. Zimmermann et al. [6] learned defect predictors from 622 pairs of projects (project1, project2). In only 4% of pairs, predictors from project1 worked on project2. Menzies et al. [13] reported defect prediction results from 28 studies, most of which offered widely differing conclusions about what most influences software defects.

Conclusion instability is also rampant in the developer community. Multiple studies report that human beliefs in software quality may often be inconsistent and even incorrect. Devanbu et al. [21, 22] have conducted a case study among 564 Microsoft software developers to show that human beliefs on software quality can be quite varied and may not necessarily correspond with actual evidence within current projects. A more recent study by Shrikanth et al. [23] also reports such variability of human beliefs. They studied ten beliefs held by software developers about defect prediction, which were initially summarized by Wan et al. in 2018 [24]. By measuring the actual support of these beliefs within the project, Shrikanth et al. found that among over 300,000 changes seen in different open-source projects, only 24% of the projects support all ten beliefs. Curiously, beliefs held by most developers do not necessarily have the most substantial support within projects. For example, according to Shrikanth et al., a belief acknowledged by 35% of the developers have the most support. In contrast, a belief held by 76% of the developers is only ranked 7th out of ten beliefs. Worse still, as a project grows to mature, the beliefs tend to be weakened rather than strengthened.

The problem with conclusion instability is that, as Hassan [15] says, it makes managers lose trust in software analytics if the results keep changing. Such instability prevents project managers from offering clear guidelines on many issues, including (a) when a specific module should be inspected, (b) when modules should be refactored, and (c) deciding where to focus on expensive testing procedures. Bird et al. [25] notes that insights occur when users respond to software analytics models. Frequent model changes could exhaust users’ ability for confident conclusions from new data. Further, conclusion instability makes it hard to on-board novice software engineers. It is hard to design and build appropriate tools for quality assurance activities without knowing what factors most influence the local project.

To the above, we add the following comment. Conclusion instability might not be a bug in how we do analytics. Rather, conclusion instability might be inherent to SE. Moreover, perhaps it is folly to assume one model can cover something as diverse as software engineering. After all, SE is conducted on ever-changing platforms using ever-changing tools by a constantly changing and evolving developer population of varying skills.

If we cannot remove instability, perhaps another tactic is to reduce it. Maybe a better way to look at generality is to assume that:

1. From 1000’s of projects,
2. There might be a much smaller number of models,
3. So we need tools that can find and index that small set of models.

Note that indexing is important in this approach: unless we can map new projects to relevant models, then having a zoo of models will always confuse us.

Dozens of models are still more than one, so developers and managers still need to be aware of (and debate) the aspects of their project that make it distinctive. That said, if we can summarize many projects into just a handful of models, then those debates need not be extensive. Further, when training software engineers,
we could present a small range of projects to them as part of their training.

2.2 Two Case Studies

In the following, we offer a hierarchical transfer learning framework for this three-step process. After hierarchically clustering the data, it replaces many models (in a sub-tree) with a single best model (selected from that sub-tree). This process then recurses up the tree of clusters. Sometimes this will return one model (in the case of defect prediction). If that is not possible, it will return multiple models (e.g., for project health estimation, we return around a dozen models). More importantly, GENERAL indexes those models in its cluster tree. When new projects arrive, they can explore down the cluster tree in log-time to find their relevant model.

This novel approach is tested on the two case studies discussed in this section: defect prediction and project health estimation.

2.2.1 Why Defect Prediction? The perceived criticality and bugginess of the code for managing resources efficiently are often associated with the quality assurance (QA) effort. As bugs are not evenly distributed across the project [4, 26–28], it is impractical and inefficient to distribute equal effort to every component in a software system [29]. Algorithms that measure the criticality or bugginess of software using source code (product) or project history (process) are called defect prediction models. Although such defect predictors are never 100% correct, they can suggest where a defect might happen.

In a recent paper, Wan et al. [24], reported much industrial interest in these predictors since the alternative is much more time-consuming and expensive. Misirli et al. [28] and Kim et al. [30] report considerable cost savings when such predictors are used in guiding industrial quality assurance processes.

As shown in Table 1 defect prediction models might use product or process metrics to make predictions. Process metrics comment on “who” and “how” the code was written, while product metrics record “what” was written. Researchers and industry practitioners have tried many different ways to identify which features are important and why. However, there is little agreement between them. Zimmermann et al. [31] recommended complexity-based product metrics, Zhou et al. [32] suggest size-based metrics. While Matsumoto et al. [33], and Nagappan et al. [34] recommend developer-related metric and change bursts metrics, respectively. We use Table 1 metrics for both theoretical and pragmatic reasons. Our metrics include the process metrics endorsed by Devanbu et al. at ICSE’13 [35].

2.2.2 Why Project Health? Open-source software development is becoming prominent in the overall software engineering landscape. As the community matures, they become more structured with organizing foundations. Some prominent software organizations like Apache Foundation and Linux Foundation host hundreds of popular projects [36, 37]. Stakeholders of these projects make critical decisions about the future of these projects based on project status. The metrics of project health conditions are needed when they estimate the projects. On the other hand, future customers thinking about using the open-source project in their product are more likely to invest and participate in “healthy” projects.

In the past decade, many researchers [38–44] have tried to look at project health from a different perspective. For example, Jansen et al. [45] mentioned project could be estimated by the level of productivity, robustness, and niche of creation in the project history. Kikas et al. [40] reported a relationship between the dynamic and contextual features of a project and issue close time. Wang et al. [46] and Bao et al. [47] proposed different predicting models to find potential long-term contributors. Jarzycyk et al. [39] use generalized linear models for the prediction of issue closure rate. Based on multiple features (i.e., stars, commits, issues closed), they find that larger teams with more project members have lower issue closure rates than smaller teams. At the same time, increased work centralization improves issue closure rates.

From January to March 2021, Xia [48] conducted email interviews with 116 subject matter experts from 68 open-source projects. One of the questions asked was “what kind of features are the most useful to predict for?”. In those answers, certain features were marked as the most important to that community: see Table 2. Note the “Predict?” column of that table: in our experiments, we take each prediction goal, one at a time, then try to predict for it using all the other metrics for six months into the future.

### Table 1: List of metrics used in this study for defect prediction case study.

| Metric Category | Metric Name | Predict? |
|-----------------|-------------|----------|
| Activeness      | MAC: monthly number of active contributors | ✓        |
| Collaboration   | POP: monthly number of open PRs | ✓        |
| Enhancement     | MOI: monthly number of open issues | ✓        |
| Popularity      | MP: monthly increased number of forks | ✓        |

### Table 2: List of metrics used in this study for project health estimation case study.

| Metric Category | Metric Name | Predict? |
|-----------------|-------------|----------|
| ActiveDev       | activeDev   | ✓        |
| DistinctDev     | distinctDev | ✓        |
| Distribution    | distribution| ✓        |
| LinesAdded      | linesAdded  | ✓        |
| LinesDeleted    | linesDeleted| ✓        |
| MinorContributor| minor       | ✓        |
| NeighborActive  | neighborActive| ✓    |
| NumberOfModifiedDirectories | number | ✓ |
| NumberOfSubsystems | nsub | ✓   |
| UniqueChanges   | uniqueChanges| ✓      |
| OwnerContributedLines | owner | ✓ |
| DeveloperExperience | exp | ✓   |
| RecentDeveloperExperience | resp | ✓ |

From a formal perspective, GENERAL is a homogeneous, similarity-based, bellwether, transfer learning algorithm (and this section explains all the terms in italic).
The art of moving data and knowledge from one project or another is called transfer learning [49]. When there is insufficient data to apply data miners, transfer learning can be used to transfer knowledge from other source projects S to the target project. There are many reasons for using transfer learning. Transfer learning can be useful when there is insufficient local data. Clark and Madachy [50] in their study of 65 software under-development by the US Defense Department in 2015 showed developers working in an uncommon area often benefit from transferring knowledge from more common areas.

While transfer learning is widely studied and used in the software engineering domain, we warn that work mostly tries to move lessons learned from a single source project to a single target project. Hence, that research does not meet the goals of this paper (generalizations across 100s of projects). As discussed in the next section, additional engineering is required to convert current transfer learning tools into generality tools.

Transfer learning can be broadly categorized into two variants based on the similarity of features between source and target projects. Heterogeneous transfer learning is where the source and target data contain different attributes [51–55]. Homogeneous transfer learning is where the source and target data contain the same attributes [6, 16, 56, 57]. Our reproduction package for GENERAL (listed on page1) collects the same set of attributes for all projects in both (a) defect prediction or (b) project health estimation case study. Hence, GENERAL is a homogeneous transfer learner.

Another way to divide transfer learning is the approach that it follows. There are two main variants. Firstly, dimensional transformation methods manipulate the raw source data until it matches the target. An initial attempt on performing transfer learning with Dimensionality transform was undertaken by Ma et al. [58] with an algorithm called transfer naive Bayes (TNB). Since then there are many such algorithms have been proposed such as TCA [59], TCA* [60], TPRL [61], balanced distribution [62]. Here in this study, we have used the TPRL method proposed by Liu et al. [61] as the state-of-the-art (SOA) method. Note that we could only apply TPRL to defect prediction since there is no prior work on transfer learning for project health.

Apart from dimensionality transform, another commonly used transfer learning method is Similarity-Based approach. For example, the Burak filter [66] builds its training sets by finding the k = 10 nearest code modules in S for every t ∈ T. Other methods employ techniques such as recursive bi-clustering and pruning [67] or combining domain knowledge with automatic processing of features [68]. Our current implementation for GENERAL is based around the BIRCH clustering algorithm [69] that groups together projects with similar median values for their features. Hence, GENERAL is a similarity-based algorithm.

Another useful transfer learning approach is Krishna et al.’s bellwether method [70, 71]. According to Krishna et al., within a community of software projects, there is one exemplary project called the bellwether, which can define predictors for the others. This effect is called the bellwether effect. They exploit this Bellwether effect in their bellwether method that searches for such an exemplar bellwether project to construct a transfer learner with it.

The genesis of this paper was the realization that Krishna et al.’s methods had trouble scaling to the 756 and 1628 projects used in this study. Krishna et al. found their bellwether via an O(N^2) search through all pairs of projects. We found we could do much better than that by (a) applying the BIRCH clustering algorithm then (b) conducting local Bellwether tournaments just within each cluster. That said, the origins of this paper are clearly the methods of Krishna et al. Hence it is appropriate to say that GENERAL is a bellwether method.

3 GENERAL: THE DETAILS

Initially, we thought that it would be enough to just run the BIRCH clustering algorithm [69] prior to running bellwether [70]. However, as shown by Algorithm 1, we had to implement a large number of additional engineering details before anything worked, since GENERAL consists of many sub-routines:

(1) Summarize the projects via feature summarization (see §3.1) with an average-case complexity of O(N).

(2) Group all our data into sets of similar projects in a hierarchical structure. This step requires a hierarchical clustering algorithm called BIRCH (see §3.2) with a complexity of O(N) where a feature vector from step one represents each project.

(3) Select the best source project (bellwether) at each cluster at the leaves of that tree. This step needs a data mining algorithm to generate models (see §3.3) and a comparison method to select the best model (see §3.5). Here assuming an average-case scenario where N projects are divided into m clusters, the average-case complexity is O(m * (N/m)^2).

(4) Select the best source project at non-leaf levels by pushing bellwether from child nodes. Each super-group only has projects selected as bellwether from step three then steps three, four are repeated, recursively until root node. This requires a complexity of O(m^2).

(5) Use the bellwethers to predict or estimate for new projects.

The rest of this section documents our design choices made for those sub-routines:

3.1 Feature Summarization

Prior to anything else, we must summarize our project into a single vector to be used in the clustering algorithm. We follow the direction of Herbold et al. [63] and Liu et al. [61] as they have shown if data distributions between the source and target projects are close, a cross-project defect prediction (CPDP) model can achieve better prediction performance. Hence, for both case studies, we summarize using the median values of the dataset.

3.2 Hierarchical Clustering

Using the feature vectors for each project, we apply a hierarchical clustering algorithm to communities of similar projects. We use

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2This work paper out-performs many of the previous methods (i.e., TCA+ [60], TDS [63], LT [64], Dycom [65]) for homogeneous transfer learning.

3The nearest work we found was for some classical waterfall-based effort estimation from Kocagnelki et al. [11]. Waterfall estimation is done prior to developers starting to code. Hence it is very different from the incremental monitoring process used in project health. Also, waterfall estimation predicts for “total developer effort” which, as seen in Table 2, is not a metric that was not found relevant to the open-source software practitioners surveyed by Xia [48].

4According to the Oxford English Dictionary, the bellwether is the leading sheep of a flock, with a bell on its neck, that all other sheep follow.
The main requirements for that data miner framework are:

- The new bellwether analysis described above requires a working (BIRCH) algorithm from the scikit.learn \[72\] package. BIRCH is suitable for large datasets that might contain spurious outliers \[69\] and can incrementally and dynamically cluster incoming, multi-dimensional data in an attempt to maintain the best quality clustering. BIRCH also can identify data points that are not part of the underlying pattern (so it can effectively identifying and avoid outliers). For this experiment, we used defaults proposed by \[69\], a branching factor of 20, and the "new cluster creation" threshold of 0.5.

### 3.3 Data Mining

The new bellwether analysis described above requires a working data miner framework. The two different case studies in this paper need a slightly different framework as defect prediction is a classification task, while project health estimation is a regression task. The main requirements for that data miner framework are:

- **feature selector** to prune any unnecessary features (both classification and regression tasks).
- **class balancing technique** to balance the dataset (for classification tasks).
- **hyper-parameter optimizer** to tune the performance of the models (both classification and regression tasks).
- **ML learner** to generate models (both classification and regression tasks) and find answers to "what did we learn?"

### 3.4 Evaluation Criteria

We used five evaluation criteria to evaluate our defect prediction models (two effort aware and three traditional). Suppose we have a dataset with M changes and N defects. After inspecting 20% LOC, we inspected m%20 changes and found n%20 defects (m changes and n defects when inspected 100% LOC). Also, when we find the first defective change, we have inspected k changes. Using this data, we can define two effort aware evaluation criteria as follows:

- **Popt20**: is the proportion of changes inspected by reading 20% of the code, it is computed as m%20/M.
- **IFA**: is the number of initial false alarms encountered before we identify the first defective change. For the three traditional measures, they can be explained as follows:
  - **Recall**: is the proportion of inspected defective changes among all the actual defective changes, it is computed as n/N.
  - **Precision**: is the proportion of inspected defective changes among all the inspected changes, it is computed as n/m.
  - **False Alarm**: is the proportion between the non-defective changes among all the predicted defective changes.

### 3.5 Select the Best Model

The previous section listed numerous evaluation criteria (goal) that could be used to guide the learning. Combining numerous evaluation criteria is often implemented as a multi-objective optimization predicate, where one model is better than another if it satisfies a "domination predicate". We use the Zitler indicator dominance predictor \[100\] to select our bellwether (since this is known to select better models for multi-goal optimization in SE \[101, 102\]).

To fulfill these requirements, (a) for feature selector, we have used Hall’s **CFS feature selector** \[73\]. We found that without CFS, our recalls were low. Also, extensive studies have found that CFS is more useful than many other feature subset selection methods such as PCA, InfoGain, or RELIEF \[73–79\]. (b) for class balancing technique, **SMOTE** \[80\]. We used SMOTE since it is a widely used \[81–86\] class imbalance correction algorithm. We use SMOTE on the training data \(^5\) (c) for hyper-parameter optimization; we used **Differential Evolution (DE)** \[87\]. We use DE since prior work found it fast and comparatively more effective than grid search for other kinds of software analytic problems \[88–92\]. (d) for the learner, we have used **Random Forest** \[93\], **Decision Tree** \[94\] and we used these as it is widely used \[5, 7, 89, 95\] in the software engineering domain as the learner and shown to be effective in selecting important features \[96, 97\].

For both defect prediction and project health estimation case study, on the original data, we apply **CFS** \[73\]. Next, for defect prediction, we use the **SMOTE** \[80\] to balance the classes. And finally, we used **Random Forest** as the learner for defect prediction and **Decision Tree Regressor** with DE for project health estimation.
This predicate favors model $y$ over model $x$ if $x$ “losses” most:
\[
\text{worse}(x, y) = \frac{\text{loss}(x, y) > \text{loss}(y, x)}{\text{loss}(x, y) - \text{loss}(y, x) + 1} / n \quad (1)
\]

where “$n$” is the number of objectives (for us, $n = 5$) and $w_j \in (-1, 1)$ depending on whether we seek to maximize goal $x_j$.

When choosing a model based on multiple goals (defect prediction case study), model performance can be scored, and the best model can be chosen by researchers based on their choice of metrics. In this experiment, we score model performance according to the goals mentioned in §3.4. When assessing models, we chose the best model that: (a) Maximize Recall, Precision, and Popt20, and (b) Minimizes false alarm, IFA, and MRE.

4 EXPERIMENTAL METHODS

This section describes the rig used to evaluate the design choices made in the previous section.

4.1 Experimental Setup

Figure 1 illustrates our experimental rig. The following process was repeated ten times, with different random seeds used each time.

All projects are divided randomly into two groups train_1 and test_1, with a 90:10 split. The projects in train_1 were used to find bellwethers. Data from each project in test_1 is divided into “train2, test2” then (a) local models are learned from “train2”; after which time, (b) the local models from “train2” and the bellwether model from “train1” are both applied to the same data from “test2”. Note that this process is repeated ten times, with different random number seeds, to generate ten different sets of “train1, train2, test2”.

Figure 1: Experimental rig for this paper. In this rig, bellwethers are learned and tested on separate projects. Within the test set (denoted “test1”, above), the data is further divided into “train2, test2”. To assess the bellwether found from “train1” against local learning, data from each project in test1 is divided into “train2, test2” then (a) local models are learned from “train2”; after which time, (b) the local models from “train2” and the bellwether model from “train1” are both applied to the same data from “test2”. Note that this process is repeated ten times, with different random number seeds, to generate ten different sets of “train1, train2, test2”.

To filter projects, we used the standard Github “sanity checks” recommended in the literature [104, 105]:

- **Collaboration**: must have at least one pull request.
- **Commits**: must contain more than 20 commits.
- **Duration**: must contain software development activity of at least 50 weeks.
- **Issues**: must contain more than ten issues.
- **Personal**: must have at least ten contributors.
- **Software Development**: can only be a placeholder for software development source code.
- **Defective Commits**: must have at least ten defective commits with defects on Java files.
- **Forked Project**: must not be a forked project from the original repository.

Using these sanity checks from a community of 5000 Github projects, we selected 756 Github Java projects for defect prediction case study. For each project, the defect prediction data was collected in the following steps:

1. Using a modified version of Commit_Guru [106] code, we collect 21 file-level process metrics, as shown in Table 1.
2. We use Commit_Guru [106] code to identify commits that have bugs in them. This process involves identifying commits that were used to fix some bugs using a keyword-based search.

\[(\text{bug} | \text{fix} | \text{error} | \text{issue} | \text{crash} | \text{problem} | \text{fail} | \text{defect} | \text{patch})\]

For the project health estimation case study, we use the dataset collected by Xia et al. [44]. 1628 projects collected from their study passed our sanity checks. This dataset records a set of developing activities in monthly counts. Following the direction of many researchers in project health [8–10, 45, 107, 108], this dataset contains 13 features in four different categories are mentioned in Table 2. Finally, both models were then applied to the test_2 data to measure performance.

4.2 Data Collection

Github stores millions of projects. Many of these are trivially very small, not maintained, or not about software development projects.
4.3 Learners
In this study, we compare our models with reference, baseline, and state-of-the-art (SOA) learners for file-level defect prediction:

(a) Self: individual model is built using training data (train_2), which we use as the reference model in this study.

(b) Global: a single model is built by pooling all data from all projects from train_1.

(c) Bellwether: this model is built using the project data from train_1 returned by the \( \Theta(N^2) \) bellwether method proposed by Krishna et al. [17].

(d) GENERAL(\( i \)): these are the models built using the bellwether projects returned by “GENERAL” at different levels. Here “\( i \)” denotes the level at which we are trying to find a bellwether. Here except at level(0), which is the root node, all other levels will return multiple bellwethers.

Also, in the specific case of defect prediction, we ran (e) TPTL: a prior state-of-the-art transfer learning framework proposed by Liu et al. [61], which automatically chooses two source projects based on estimated highest values of F1-score and Popt20 and then leverages TCA+ [60] to build two prediction models based on the two selected projects and combine their prediction results. For more notes on TPTL and TCA+, please recall §2.3.

Note that TPTL was not used for project health since: it assumes that classification is being used as the learner and, for project health, we use a regression algorithm to obtain a numeric prediction.

4.4 Statistical Tests
When comparing the results of different models in this study, we used a statistical significance test and an effect size test:

- The significance test is useful for detecting if two populations differ merely by random noise.
- The effect sizes are useful for checking that two populations differ by more than just a trivial amount.

For the statistical test, we use the Scott-Knott test [5, 109]. This technique recursively bi-clusters a sorted set of numbers. If any two clusters are statistically indistinguishable, Scott-Knott assigns both the same “rank”. These ranks have a different interpretation, depending on whether we seek to minimize or maximize those numbers. For our purposes:

- Rank 1 is worst for recall, precision, Popt20 since we want to maximize these numbers.
- Rank 1 is best for false alarm, IFA and MRE since we want to minimize those numbers.

5 RESULTS
This section explores the research questions in detail:

5.1 RQ1: Is GENERAL tractable?
As proposed by Krishna et al., conventional bellwether compares all projects (N projects) in a given community with all others to build defect prediction models. This operation is quite expensive with, an average computational complexity of \( \Theta(N^2) \). The new bellwether method “GENERAL” proposed in this paper uses hierarchical clustering to group similar projects. GENERAL finds bellwether at leaf level clusters (m clusters) and pushes up bellwethers to parent nodes for comparisons. Algorithm 1 shows the pseudocode of the “GENERAL” algorithm, and using this, we can calculate the complexity of “GENERAL”. Assuming the BIRCH clustered N projects into m clusters at leaf level (for an average-case, we are assuming each cluster have an equal number of projects), the complexity can be calculated as:

\[
\begin{align*}
\text{feature_summarizer(line18)} : & \quad \Theta(N) \\
\text{cluster_creator(line19)} : & \quad \Theta(N) \\
\text{bellwether_finder(line23 - 25)} : & \quad \Theta(m \times (N/m)^2) \\
\text{bellwether_finder(line27 - 31)} : & \quad \Theta(m^2) \\
\text{GENERAL} : & \quad \Theta(N) + \Theta(m^2) + \\
& \quad \Theta(m \times (N/m)^2) + \Theta(m^2) = \\
& \quad \Theta(m \times (N/m)^2) \\
\end{align*}
\]

As shown in equation 2, this process reduces the computational complexity to \( \Theta(m \times (N/m)^2) \) on an average-case. Hence, by the definitions of Garey and Johnson [110], GENERAL is tractable.

5.2 RQ2: Is GENERAL efficient?
To assess the speed of GENERAL and compare it against the conventional bellwether, we ran both defect prediction and project health estimation framework of Figure 1 on a sixteen core machine running at 2.3GHz with 32GB of RAM to measure their run time.
We also measure the number of comparisons performed in conventional bellwether and our proposed model on both frameworks.

Figure 2 shows the median (over multiple runs) number of comparisons required for finding a bellwether project using conventional bellwether vs GENERAL for different community sizes ranging from 45 to 1200 projects for both case studies (for defect prediction maximum was 711 projects). The Green and the Black lines show the number of comparisons required for conventional bellwether on the defect prediction and project health estimation case study, respectively. Simultaneously, the Blue and the Red line show the number of comparisons for our GENERAL algorithm.

Here the y-axis is plotted in a log scale while the numbers shown are the actual number of comparisons performed.

Similarly, Figure 3 shows the median run time required for finding a bellwether. We can see from Figure 2 and Figure 3, with increasing community size, the number of comparisons and run-time increases rapidly for the conventional bellwether method. In contrast, GENERAL requires a relatively small number of comparisons and run-time (it increases less than linearly).

In summary, GENERAL’s run-time increases less-than-linearly as the project community size increases. GENERAL is very efficient, requiring less than an hour to terminate for both case studies (756 and 1628 Github projects for defect prediction and project health estimate). Those run-times are 29 to 104 times faster than those seen in Krishna et al.’s BELLWETHER algorithm (the prior state-of-the-art in this area [16]).

5.3 RQ3: Is GENERAL effective?

The speed improvements reported in RQ2 are only useful if this faster method can also deliver adequate predictions (i.e., predictions that are not worse than those generated by baselines and state-of-the-art).

(a) Defect prediction: Figure 4 shows the performance of all learners from §4.3 on the defect prediction case study. These results are grouped by the “rank” in the left-hand-side column (and this rank was generated using the statistical methods of §4.4).

Looking at our results, in Figure 4, we recommend GENERAL0; i.e., use the single model found at the root of the GENERAL tree. We say this since, in all performance measures, GENERAL0 performs statistically similar or better than our baseline and SOA methods while also returning the fewest models. To defend this recommendation, we note that:

- We would not recommend Krishna et al.’s Bellwether0 since its run-time is much slower $\Theta(N^2)$ and that longer run-time is not associated with an outstandingly better performance.
- Nor would we recommend TPTL since it has the outstandingly worst false alarm rate and precision).
- Nor would we recommend GENERAL1 or GENERAL2 since these never perform statistically different and better than GENERAL0. Also, these methods produce more models than GENERAL0.
- Finally, we see that our recommended model GENERAL0 performs similar to self (which is our reference model) in most cases, the only case where self beats GENERAL0 is recall. This shows that our recommended model performs similarly to the reference model, indicating our transfer learning approach is reaching respectable performance while being able to generalize conclusions.

Overall, we summarize Figure 4 results as follows: “Across multiple performance criteria, the faster GENERAL0 never performs worse than Bellwether0. Furthermore, measured in terms of recall, GENERAL0 performs statistically better. And thus suitable for transfer learning and generalization of feature importance”.

(b) Project health estimation: Figure 5 shows the results of the project health estimation case study. Here the performance criterion is Magnitude of the Relative Error (MRE), as mentioned in §3.4. Unlike defect prediction case study, project health can be estimated in many ways, as shown in Table 4. For each of the seven goals, the new algorithm GENERAL is compared against the reference model (self), global model (global), and conventional bellwether (Bellwether0)\(^{10}\).

In all cases of project health estimation goals, our recommended GENERAL1 did not beat the reference model. Our recommended model reached the reference model performance in two out of seven

\(^{10}\text{Now, one difference from defect prediction case study is that we do not compare against TPTL as it is a transfer learning approach designed explicitly for defect prediction.}\)
To answer this question, we count the number of models generated by the respective learners used in this study [111].

It is reasonable to ask what was learned from the handful of models learned above, what metrics seemed to be most important?

To determine which features are most important for prediction, we analyze both "locally important" and "globally important" features reported by the respective learners used in this study [111].

Some features are "globally important" since our analysis shows that, across many data sets, they are the ones that most predict for defects and estimate for project health. Using this information, we can create recommendations for the development process for identifying, create best practices for project management and train new developers. While "locally important" features are feature importance aggregated over all the training projects. We call these features "locally important" since results come from an analysis that is restricted to just one data set at a time.

To show the feature importance of "globally important" and "locally important" features, we use two numbers \(x/y\). Here the first number \(x\) is the aggregated feature importance for the best generalization method (GENERAL) and the second number \(y\) is feature importance from the local model (self) aggregated over all training projects. Here "globally important" features are those where \(x\) is large. Here, (a) if \(x/y\) is near one and both \(x\) and \(y\) are large, then that feature is both "globally important" and "locally important", (b) if \(x/y\) is near one and both \(x\) and \(y\) are small, then that feature is both "globally unimportant" and "locally unimportant", (c) if \(x > y\), then that feature is "globally important" but "locally unimportant", and (d) if \(x < y\), then that feature is "locally important" but "globally unimportant".

Note that the best generalization method (GENERAL) is different for defect prediction and project health estimation (in the former, it is GENERAL0, and in the latter, it is GENERAL1).

### 6.1 Defect Prediction

Table 3 shows the "globally important" features (marked in pink) in the GENERAL0 defect prediction models. We observe that only three out of 21 features are important in predicting defects. Among these three features, (a) age is an experience based metric; (b) one is change related metric. We analyzed the decisions made by our model to differentiate between a defective and non-defective entry to generate recommendations for the community of 756 Github projects studied here.\(^{11}\)

- The presence of age in the model suggests: review codes which are changed more often. The frequently a file is changed, the more problematic it can become.

- The presence of \(exp\) (experience) in our models lets us make the following recommendation: minimize the use of amateurs dabbling around the codebase in areas that are unfamiliar to them.

- \(exp\) (recent developer experience) as an important feature suggests: review codes more thoroughly when the changes are made by developers not familiar with the latest changes.

### 6.2 Project health estimation:

Table 4 shows the features which are "globally important" (marked in pink) for each of the seven project health estimation goals explored in this study. Each row in the table represents a predictor variable (13 variables as suggested by prior work (see § 4.2)), while each column represents one goal (seven goals in total). For each goal, we ask which features in practice are useful when we estimate

\(^{11}\) Note: the features which are important in predicting defects are based on the analysis of 756 studied here. So the feature generalization is applicable for these projects only.
Table 3: Distribution of feature importance using the self model and the GENERAL0 (Defect Prediction). The pink cells show important features from bellwether. Each cell consists of two numbers (like x/y): the first one (x) is the feature importance for the GENERAL0 model, and the second one (y) is feature importance for the self model. Learner is Random Forest.

| Feature | Feature Importance | Feature | Feature Importance |
|---------|--------------------|---------|--------------------|
| la      | 0.0/0.05           | avg_nadev| 0.0/0.03           |
| md      | 0.0/0.05           | avg_nadev| 0.0/0.03           |
| rt      | 0.0/0.01           | avg_ncom| 0.0/0.01           |
| age     | 0.22/0.1           | ns      | 0/0.01             |
| dev     | 0.0/0.09           | exp     | 0.21/0.03          |
| nuc     | 0.0/0.09           | srcp    | 0.0/0.02           |
| own     | 0.09/0.07          | resp    | 0.38/0.07          |
| minor   | 0.02/0.15          | sd      | 0/0.01             |
| ndev    | 0.0/0.05           | actr    | 0.0/0.07           |
| ncom    | 0.0/0.02           | nadev   | 0.0/0.01           |

Table 4: Distribution of features importance using the self model and the GENERAL1 model (project health). Each column represents one of the goals mentioned in Table 2. The pink cells show important features from bellwether derived from the underlying model (i.e., Decision Tree Regressor). Each cell consists of two numbers (like x/y): the first one (x) is the feature importance for the GENERAL1 model and the second one (y) is feature importance for the self model.

| Predictor Variables | Target Variables |
|---------------------|------------------|
| MCI                 | MAC              |
| MCP                 | MOP              | MOP              | MOP              | MCI              | MS               |
| 0.48/0.06           | 0.02/0.11        | 0.10/0.13        | 0.17/0.13        | NA               | 0.0/0.08         |
| NA                  | 0.14/0.07        | 0.09/0.09        | 0.01/0.09        | 0.09/0.05        | 0/0.1            |
| 0.28/0.09           | NA               | 0.07/0.04        | 0.04/0.04        | 0.08/0.06        | 0.0/0.07         |
| MF                  | 0.08/0.08        | 0.06/0.07        | 0.08/0.08        | 0.22/0.09        | 0.0/0.13         |
| MCI                 | 0.01/0.01        | 0.07/0.08        | 0.08/0.08        | 0.11/0.05        | 0.0/0.01         |
| 0.07/0.04           | 0.03/0.03        | 0.08/0.08        | NA               | 0.08/0.04        |
| MOP                 | 0.11/0.13        | NA               | 0.14/0.16        | 0.08/0.06        | 0.09/0.09        |
| 0.08/0.17           | 0.01/0.01        | 0.01/0.02        | 0.08/0.08        | 0.08/0.02        |
| MM                 | 0.13/0.08        | 0.11/0.01        | 0.03/0.09        | 0.01/0.01        |
| MOP                 | 0.08/0.04        | 0.05/0.06        | 0.01/0.02        | 0.07/0.08        |
| MCI                 | 0.07/0.07        | 0.06/0.06        | 0.08/0.08        |
| MS                  | 0.0/0.09         | 0.01/0.03        |
| NW                  | 0.0/0.09         | 0.01/0.02        |

7 THREATS TO VALIDITY

As with any large-scale empirical study, biases can affect the final results. Therefore, any conclusions made from this work must be considered with the following issues in mind:

(a) Evaluation Bias: While those results are accurate, the conclusion is scoped by the evaluation metrics. It is possible that using other measurements; there may well be a difference in these different kinds of projects. This is a matter that needs to be explored in future research.

(b) Construct Validity: We made many engineering decisions using advice from the literature. That said, we acknowledge that other constructs might lead to different conclusions.

(c) External Validity: The defect prediction dataset was collected using “commit_guru”. It is possible using other tools or methods may result in different outcomes. That said, the “commit_guru” is a tool that is widely used and has detailed documentation.

(d) Statistical Validity: We applied two statistical tests, bootstrap, and the a12. Hence, anytime in this paper, we reported that “X was different from Y” then that report was based on both effect size and statistical significance test.

(e) Sampling Bias: Our conclusions are based on the 756 projects (defect prediction) and 1628 projects (project health estimation). It is possible that different projects would have lead to different conclusions. That said, this sample is very large, so we have some confidence that this sample represents an interesting range of projects.

8 CONCLUSION

Software engineering suffers from the conclusion instability problem. Ideally, we should be able to generalize to a single model. However, given the diversity of SE, we warn that it is folly to assume that all projects can be represented within a single model.

We presented a method called GENERAL that recursively replaces many models (clustered into a tree) with one model per sub-tree. That model is then moved up the tree to see if it can replace any higher-level models. Sometimes, this process results in a single model (as in the case of defect prediction). On the other hand, sometimes it does not: for project health estimation, we found that GENERAL reports nine (median values) models per goal.

It should be emphasized that this approach has only been tested from predictions of defects or project health. However, within that restriction, we say that it is not necessary to always reason about each new project as a new concept that might generate a new model. Even in our worse case (project health), 1628 projects can be represented as nine exemplary models (median value).

Looking forward, based on this conclusion, we make two comments. Firstly, we think this work offers a more rational basis for SE research and SE textbooks. SE is a diverse process, but at least some aspects of that work can be captured in a handful of models. Such a small set of models could be the basis of (e.g.) a 14-week graduate class (one model per week) or a product line of software project tools (one product per model).
Secondly, we warn that much of the prior work on homogeneous transfer learning may have complicated the process with needlessly complicated methods. When building increasingly complex and expensive methods, we strongly recommend that researchers pause and compare their sophisticated methods against simpler alternatives. Going forward from this paper, we would recommend that the transfer learning community uses GENERAL as a baseline method against which they can test more complex methods.

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