Learning Changes to Software Projects

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Abstract—
BACKGROUND: Given many possible changes to a software project, which ones are recommended?
AIM: To comparatively assess different decision procedures for recommending project changes.
METHOD: We search for project recommendations within data from eight projects using various AI tools: six model-based methods and one instance-based method called \( W \& 2 \). Results were assessed by comparing effort, defects, development time values in the raw data versus the subset of the data selected by those recommendations.
RESULTS: In the majority case, significantly large reductions on effort, defects and development time were achieved. Further, \( W \& 2 \) performed as well, or better, than any other methods in this study. \( W \& 2 \) does not rely on an underlying model of software process so it does not demand that domain data be expressed in the terminology of that model. Hence, it can be quickly adapted to a new domain and easy to maintain (just add more instances).
CONCLUSION: We recommend instance-based methods such as \( W \& 2 \) for learning changes to a software project.

Index Terms—Search-based software engineering, Analogy, COCOMO

1 INTRODUCTION

There are many ways a manager might change, and hopefully improve, their software development project. Some changes require tools such as using the new generation of functional programming languages or execution and testing tools [1] or automated formal analysis [2]. Other changes use process improvement techniques such as changing the organizational hiring practices, or a continual renegotiation of the requirements as part of an agile software development cycle [3].

Endres & Rombach [4] list dozens of laws of software engineering to justify a particular change to a project. If a manager proposed using all the laws, then senior management would most likely suggest they scale back their plans to just a minimal set of most effective measures.

This paper explores different ways for finding this minimal set of most effective changes to a project. Specifically, we compare model-based vs instance-based methods. The difference between these two methods is as follows. Model-based methods develop a model via expert advice [5] or using automatic methods such as data mining [6]. Once built, the model can be used for “what-if” queries in order to assess possible changes to a project. For example:

\[
data \rightarrow model \rightarrow whatIf \rightarrow scores
\]

Here, Scores represents business concerns; for example reduce defects before release the software product. Also, the whatIf query defines a context within which a manager seeks ways to improve a project.

Instance-based methods, on the other hand, insert the “what-if” query into a \( n \)-dimensional space populated with historical project cases [7]–[11]. Unlike model-based methods, instance-based methods do not require an underlying model. Rather, the immediate neighborhood of the “what-if” is somehow scored to find summary of those neighboring cases:

\[
data + whatIf \rightarrow neighborhood \rightarrow scores
\]

In previous work [12]–[20], we tried combining model-based methods with AI tools to control thousands of “What-If” queries over COCOMO models. This paper compares those model-based methods with \( W \& 2 \), a novel instance-based method. Given a “What-If” query that selects some set of similar projects, \( W \& 2 \) seeks a treatment \( R_s \), which finds the “better” parts of those similar projects within the dataset:

\[
data + WhatIf \rightarrow neighborhood1 \rightarrow scores1
\][
\[
R_s + data + WhatIf \rightarrow neighborhood2 \rightarrow scores2
\][
\[
scores2 > scores1
\]

When compared to model-based methods:

- \( W \& 2 \) identified similar or better treatments.
- \( W \& 2 \) was faster to run: all the experiments in this paper require 10 minutes with \( W \& 2 \), but days for using models.

This research was conducted at West Virginia University, University of Southern California, and NASA Jet Propulsion Laboratory under a NASA sub-contract. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not constitute or imply its endorsement by the United States Government.

This research was funded in part by NSF/CISE, project #0810879.
• \( W2 \) was \textit{simpler to implement}: \( W2 \)'s 200 lines AWK replaces thousands of lines of the model-based LISP.
• \( W2 \) was \textit{simpler to maintain}: with instance-based methods, “maintenance” implies “adding more instances”.
• \( W2 \) was \textit{simpler to adapt to new domains}: \( W2 \) do not require an underlying model and therefore it imposes no restrictions on the data being processed. It is more efficient and it can be quickly applied to more data sets.

Hence, we now recommend the instance-based methods like \( W2 \) for identifying changes to software projects.

In summary, this study has 4 significant contributions:

1) We demonstrate that managers have many options for effectively changing and improving their projects.
2) We enhance algorithms proposed by other researchers. Prior work on instance-based methods founds ways to \textit{generate} estimates \([21]–[24]\). We show that a small modification to standard instance-based analysis allows us to determine how to \textit{change} an estimate.
3) We improve our prior results on instance-based methods. \( W2 \) outperforms our model-based methods described in \([12]–[20]\) as well as earlier versions of our instance-based reasoner in \([25]\) and \([26]\). As discussed in §3, \( W2 \) handles missing values better than \( W1 \). More significantly, this paper is the first report on extending any version of \( W \) beyond standard COCOMO data.
4) Results show simple instance-based methods can perform better than more complex model-based methods.

While the first points may be of most interest to industrial practitioners, but it is the last point that may be most interesting to researchers. There are many sophisticated methods for exploring the complexities and uncertainties of trying to control software engineering projects. Based on the results of this paper, we advise researchers to first explore simpler methods, if only for the purposes of establishing a performance baseline.

This result shows that the \( W2 \) instance-based method is superior to all the model-based methods explored in this study. This does not imply that learning changes to software projects is \textit{always} best achieved using simple instance methods. For example, the next release planning problem discussed in \([27], [28]\) is a process problem of great complexity. For that task, the Pareto frontier optimization methods employed by (e.g.) Ruhe \([27]\) is preferred to \( W2 \).

2 BACKGROUND

2.1 Software Estimation Research

Instance-based software estimation such as \textit{Case-Based Reasoning} (CBR) is a widely explored area in software engineering research \([21]–[24]\). Based on our collective experience, when a manager sees an estimate, his/her immediate question is “how can I change that?” While the effort estimation literature describes many estimation methods (both model-based and instance-based \([21]–[24], [29]–[33]\)) in order to address manager’s immediate concern, we focus on how to \textit{change} estimates.

\( W2 \) explores multiple goals such as reducing development effort and defects and the total calendar time to deliver the software. Instead, most other work in this area explores a single goal. For example, Pendharkar et al. \([29]\) demonstrate the utility of Bayes networks in software effort estimation while Fenton and Neil explore Bayes nets and software defect prediction \([34]\), neither of these teams links defect models to effort models. In addition, as mentioned above, these work focus much more on \textit{prediction}, rather than on the subsequent problem of learning how to \textit{change} those predictions.

2.2 Search-Based Software Engineering (SBSE)

Multi-goal optimization in Search-Based Software Engineering (SBSE) is well explored in the field \([35]\). SBSE employs optimization techniques from operations research and meta-heuristic search (for example in simulated annealing and genetic algorithms) in an attempt to hunt for near-optimal solutions. Harman \([35]\) distinguishes AI search-based methods from those seen in standard numeric optimizations. Such optimizers offer settings to all controllables. This may result in needlessly complex recommendations since a repeated empirical observation is that many model inputs are contaminated or correlated in similar ways to model outputs \([36]\). Such contaminated or correlated variables can be pruned to generate simpler solutions that are easier and quicker to understand. For continuous variables, there are many work on feature selection \([37]\) and techniques like principal component analysis \([38]\) to reduce the number of dimensions reported by a data analysis. Some studies report that discrete AI methods perform better at reducing the size of the reported theory \([36]\).

The SBSE approach can and has been applied successfully to many software engineering domains such as requirements engineering \([39]\), but more commonly used in software testing \([1]\). Harman’s work provides the inspiration to this study in an attempt to experiment simulated annealing for our model-based methods \([14]\) (which we subsequently found performed worse than \( W2 \)).

2.3 Model: Benefits

High-level abstraction models represent and transmit common software patterns observed in multiple specific situations \([40]\). At a keynote address at PROSIM’05 Walt Scacchi noted that merely writing a model can clarify local business processes \([41]\). Executable software process models can be used for many purposes including but not limited to reducing the inspection effort at different stages of the software life cycle \([42]\). Even if a model lacks a sophisticated execution engine, it can still be used for what-if queries that are insightful to different business processes (e.g. see Boehm et al.’s what-if studies in Chapter Three of \([43]\)).

Models can combine and summarize both expert insights \textit{and} local data. Fenton \([5]\) builds the general structure of his Bayes nets via workshops of business knowledge. The details of these structures are then tuned via local data. Elsewhere, Boehm reports the advantages of combining local data with model structures initialized via expert knowledge \([44]\).

Another subtle advantage of models is data sharing. Schulz reports that organizations that are reluctant to share specific
data, may be willing to share models (if those models do not reveal details from particular business sites) [45].

Finally, models let us extrapolate from past examples to new examples. A trend that is sampled by $N$ historical examples can be extended to offer predictions for new examples that have not been seen previously.

### 2.4 Models: Drawbacks

Extrapolation, while sometimes useful, may over fit the data. If that occurs, then a model may offer unsupported recommendations. For example, as shown in the results below, our model-based methods were ineffective since, sometimes, they proposed conclusions that applied to none of the test data.

Another drawback with model-based tools is that they only accept data that conforms to the ontology of the model (i.e. use the input values of the model). If local data does not conform to that ontology, then the tool cannot be applied. For example, Figure 1 shows the data sets used in this study. Our model-based methods can only process the two data sets that conform to the COCOMO ontology of Figure 2. On the other hand, the W2 instance-based method can process all of them.

Models need to be learned from data and collecting that data can be difficult due to the business sensitivity associated with the data as well as differences in how the metrics are determined, collected and archived. In many cases the required data is not archived at all. In our experience, for example, after two years we were only able to add 7 records to our NASA wide software cost metrics repository [14]. Alternatively, open-source code repositories are a rich source of product information, but usually lack process details such as the descriptions of the applications experience of the developers. Other researchers also have noted similar problems with collecting process data. Lowry [46] discusses the complexities involved in calibrating his software failure models. Those models require parameters that are clearly antiquated. For example, he mentions a commercial model-based cost estimation tool that requires a parameter that rates “the time it takes for a software development environment to respond to a keyboard input”. When software was written on remote time-shared computers, this was an important factor. However, today it is irrelevant but it is kept in the model for backwards compatibility and because it was measured in the software projects on which the model was calibrated.

Baker [47] discusses another serious concerns with model calibration: tuning instability. Software construction is a very human-intensive process, therefore the data collected from that

<table>
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<tr>
<th>Dataset</th>
<th>Cols</th>
<th>Rows</th>
<th>Notes</th>
<th>Measures</th>
<th>effort</th>
<th>time</th>
<th>defects</th>
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<td>total: 774</td>
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**Fig. 1.** Seven data sets from promisedata.org/?cat=14:

effort is total staff months; time is calendar time (start to stop); defects is number of delivered defects.

In summary, model-based methods can suffer from:

- Inappropriate extrapolations;
- Ontology restrictions;
- Untamed variance inside the models

Hence, in this paper, we explore alternative methods.

### 3 Instance-Based Methods

This section described three versions of the $W$ instance-based tool. Lessons learned from $W0$ [25] and $W1$ [26] will inform the description of the current version, $W2$.

Similar to all instance-based methods, $W$ assumes access to historical cases described using $P$ project descriptors (e.g. analyst capability; process maturity; etc). Note that, unlike the model-based approach, $W$ does not assume that all cases are described using the same set of $P$ descriptors. Rather, $P$ can be varied. For example, Figure 1 lists the datasets used in our analysis. If $W$ was restricted to just the COCOMO ontology, then it could only analyze two of those seven data sets: NASA93ii and COC81i. $W$’s applicability to a wide

<table>
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<th>Increases</th>
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<th>decreases</th>
<th>Measures</th>
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<th>time: required % of available CPU</th>
<th>defects: number of delivered defects</th>
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<td>docu: documentation</td>
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<td>use: required reuse</td>
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<td>stor: required % of available RAM</td>
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<td>effort: product complexity</td>
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<td></td>
<td></td>
<td>acap: analyst capability</td>
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</table>

**Fig. 2.** COCOMO II effort multipliers.

The equation presents COCOMO’s core assumption that software development effort is exponential on software size. In this equation, $a$ and $b$ control the linear and exponential inferences (respectively) on model estimates; while $pmat$ (process maturity) and $acap$ (analyst capability) are project choices articulated by managers. Equation 1 contains only two features ($acap, pmat$) and a full COCOMO model contains a set of project descriptors as shown in Figure 2.

Baker [47] learned values of $(a,b)$ for a full COCOMO model using Boehm’s local calibration method [48] from 300 random samples of 90% of the available project data. The ranges varied widely:

$$3.2 \leq a \leq 9.4 \land 0.8 \leq b \leq 1.12$$

Such large variation in model tunings not only violates standard gradient descent methods, but it also obscure any benefits observed within a particular project change. Suppose a proposed technology doubles productivity, but $a$ changed from 9.0 to 4.5, any improvement would be obscured by the tuning instability.

In summary, model-based methods can suffer from:

- Inappropriate extrapolations;
- Ontology restrictions;
- Untamed variance inside the models

Hence, in this paper, we explore alternative methods.
range of data sets is an important advantage over the AI model-based methods described above.

$\mathcal{W}$'s next assumption is that each case is described by a set of qualities such as number of defects, development time, total staff effort etc. All of these qualities are summarized into a single value by some value function like Equation 6.

Similar to our model-based methods, $\mathcal{W}$ assumes that a manager can offer us (a) a description of the context $\subseteq P$ that interests them and (b) a list of controllable options which they can change (control $\subseteq$ context). For example, once we asked a NASA software project manager for a description of the effects of assigning inexperienced people. The manager commented that, at his site, such inexperience implies low applications experience ($\text{aexp}$), low to very low platform experience ($\text{plex}$), and language and tool experience ($\text{ltex}$) that is not high. Next, we asked the manager to describe the range of projects seen at his site (using the COCOMO names of Figure 2). The resulting context1 is shown below:

c1 = $\text{apex} \in \{2\} \land \text{plex} \in \{1, 2, 3\} \land \text{ltex} \in \{1, 2, 3\} \land 
?\text{pvol} \in \{3, 4, 5\} \land \text{data} \in \{2, 3\} \land 
?\text{cplx} \in \{4, 5\} \land \text{time} \in \{4, 5\} \land \text{stor} \in \{3, 4, 5\} \land 
?pvol \in \{2, 3, 4\} \land \text{acap} \in \{3, 4, 5\} \land \text{pcap} \in \{3, 4, 5\} \land 
?\text{tool} \in \{3, 4\} \land \text{sced} \in \{2, 3\}$

Here, “?” are the controllable labels; for example, this manager is senior enough adjust factors like schedule pressure (sced).

Note that there is no requirement for managers to include all project descriptors in their context statement. As seen below, $\mathcal{W}$ can handle contexts that are a subset of the descriptors.

Another important assumption made by $\mathcal{W}$2 is that we should not reason on all the data. Rather, we need to focus on the data relevant to the context of the current problem. A mistake made by $\mathcal{W}$0 was to reason over all the data which lead to problems of learning from inappropriate examples. $\mathcal{W}$0 tended to converge on nearby projects with increased productivity, but because it had (e.g.) a lower level of complexity or required reliability, it selected for regions containing acceptable alternatives. Sometimes, this is unavoidable (e.g. if all the available examples mention lower complexity or reliability). However, as much as possible, $\mathcal{W}$'s reasoning needs to respect the context limitations offered by the user. $\mathcal{W}$2 finds a project treatment $R_x$ by studying the project similar to the context in the case repository. Formally, $\mathcal{W}$ explores the neighborhood of the context, looking for ways to select for the “best” cases. (as determined by a value functions like Equation 6). In $\mathcal{W}$2, this is a seven step procedure:

1) Divide cases randomly into train : test in the ratio 2:1.
2) Use context to find the neighborhood within train.
3) Divide neighborhood into (a) the best cases that should be emulated, and (b) the remaining cases to avoid (which we call rest).
4) Rank all differences between (a) and (b) according to how strongly they select for the best cases.
5) Use the train set again, experiment with treatments $R_x$ built from the top ranked items found in Step4. Return the treatment that selects for the cases in the train set with highest median value.
6) Test the treatment from Step6 using relevant cases from the test set; i.e. find all rows in the neighborhood of the context in test set; then find the subset of those rows that match the treatment. Assess those rows using a value function such as Equation 6.
7) Repeat above six steps $n = 20$ times with other randomly selected train : test sets. Prune unstable treatments; i.e. those not found in the majority of repeats.

Note that Step7 is a new feature of $\mathcal{W}$2 (since $\mathcal{W}$0 and $\mathcal{W}$1 neglected to test for treatment stability).

On issue encountered with Step2 (finding the neighborhood) was that the context cannot be treated as a rigid criteria. In our experiments with $\mathcal{W}$0, we found that some data sets were so small that, often, none of the cases contained all the ranges mentioned in the context. For example, Figure 3.a shows training data from NASA93ii. The gray cells in that figure show ranges that do not appear in context1. Note that all rows have at least one gray cell. That is, none of that data exactly matches context1. Consequently, $\mathcal{W}$1 used some partial match operator to compute the neighborhood. Members...
of the training set were sorted according to their Euclidean distance from the context. If a context only mentions a subset of the project descriptors $P$, then $W1$’s distance function filled in \{$P - context$\} with random values (selected from the known ranges). This was repeated 50 times to generate 50 context queries that reference all project descriptors. Next, the neighborhood was computed using the intersection of the 20 instances closest to any of those 50 queries.

This technique solves the problem of missing parts of the context. However, it creates another problem: a large variance in all the results. To rectify this issue, $W2$ ensures context became a set overlap membership function. For example, context$_1$ defines ranges for 14 project descriptors. Any training case contains ranges that overlaps with between 0 and 14 of the ranges is context$_1$. As shown in Figure 3.a, we can use the size of this overlap to sort the cases: the neighborhood cases are those with greatest overlap. Appealing to the central limit theorem, $W2$ implies that the neighborhood of a query are the $K_1 = 20$ training cases with largest overlap to the query (and for very small data sets, we use all the training examples except the $K_2 = 5$ examples discussed below).

$W2$’s set overlap operator is only defined for finite ranges. Hence, $W2$ adds a Step 0: discretization of all project descriptors (but not quality attributes) into $B$ bins. All the following experiments assume that all numbers $y$ are discretized using \(\text{round}((y - \text{min})/((\text{max} - \text{min})/B))\). We set the $B$ value after experiments with one dataset, then leaving it fixed for the rest. For all of the $W$ experiments in this paper, $B = 5$.

Step 3 (division into best and rest) is illustrated in Figure 3.b. The neighborhood is sorted by case value; the top $K_2$ cases are best; and the remaining $K_1-K_2$ examples are rest. While the ranking algorithm of Step 4 works best for larger $K_2$ values, we did not want to exceed accepted standards in the research community. After a review of the analogy-based estimation literature [22]–[24], [30], [31] we noted that no researcher proposed using more than five neighbors. Hence, we used the $K_2 = 5$ cases with highest value (in this example, value means lower development effort).

Step 4 (rank the ranges in best) is shown in Figure 3.c. $W0$ used the following simple Bayesian ranking method. Observer that nominal tool (tool = 3) occurs 5 times in best and 14 times in rest. Given that information, we can rank tool = 3 according to its ability to select best cases:

\[
E = \text{(tool } = 3) \\
\text{freq}(E|\text{best}) = 5 \\
\text{freq}(E|\text{rest}) = 14 \\
\text{ratio}(E|\text{best}) = 5/5 = 1 \\
\text{ratio}(E|\text{rest}) = 10/15 = 0.67 \\
\text{rank}(E) = \frac{\text{ratio}(E|\text{best})}{\text{ratio}(E|\text{best}) + \text{ratio}(E|\text{rest})} = 0.52
\]

$W0$ encountered problems with evidence that was infrequent, but relatively more frequent in best than rest. To avoid this problem, $W1$ and $W2$ adds a support term. Support should increase as the frequency of a range increases, i.e. $\text{ratio}(E|\text{best})$ is a valid support measure. Hence, $W2$’s range

| row | tool | pmat | metric | rank | freq | support | ratio(E|best) | ratio(E|rest) | ratio(E|best)² | ratio(E|best) + ratio(E|rest) | rank(E) * support(E) | effort | overlap |
|-----|------|------|--------|------|------|---------|-------------|-------------|---------------|------------------|------------------------|--------|--------|
| 57  | 3    | 2    | 3      | 4    | 3    | 5      | 5          | 5           | 5             | 3               | 0.52                   | 15     | 13     |
| 56  | 3    | 2    | 3      | 4    | 3    | 5      | 5          | 5           | 5             | 3               | 0.52                   | 15     | 13     |
| 55  | 3    | 2    | 3      | 4    | 3    | 5      | 5          | 5           | 5             | 3               | 0.52                   | 15     | 13     |
| 53  | 2    | 1    | 2      | 3    | 2    | 4      | 5          | 5           | 5             | 2               | 0.67                   | 12     | 13     |
| 52  | 2    | 1    | 2      | 3    | 2    | 4      | 5          | 5           | 5             | 2               | 0.67                   | 12     | 13     |
| 51  | 2    | 1    | 2      | 3    | 2    | 4      | 5          | 5           | 5             | 2               | 0.67                   | 12     | 13     |
| 26  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 25  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 24  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 23  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 22  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 21  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 20  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 19  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 18  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 17  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 16  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 15  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 14  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 13  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 12  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |
| 11  | 3    | 3    | 3      | 3    | 3    | 4      | 3          | 3           | 3             | 3               | 0.52                   | 11     | 12     |

The $x$ top-ranked items of Figure 3.c are candidate treatments:

\[
R_1 : \text{pmat } = 3 \\
R_2 : \text{pmat } = 3 \land \text{seed } = 3 \\
R_3 : \text{pmat } = 3 \land \text{seed } = 3 \land \text{tool } = 3 \\
R_4 : \text{pmat } = 3 \land \text{seed } = 3 \land \text{tool } = 3 \land \text{acap } = 3 \\
\text{etc}
\]

Step 5 (pruning the treatments) applies $R_x$ to the projects similar to the context; i.e. those found in the test set’s neighborhood. For example, Figure 4 shows the $K_1 = 20$ cases closest to context$_1$ in the train set.

Figure 5 shows the cases from this neighborhood that satisfy $R_1 : \text{pmat } = 3$. It turns out, that for cases relevant to context$_1$...
in this test set, there is some association between the ranges see in $R_1$, $R_2$ and $R_3$: all these treatments select the same rows. Only when $R_4$ is applied does Figure 5 shrink to the two rows containing acap = 3. $\forall 1$’s results exhibited large variances if we drew conclusions from less than three rows. Hence, Step5 explores $R_x$ upwards from $x = 1$ while:

- The median value of the rows selected by $R_{x+1}$ is greater than that of $R_x$.
- The number of selected rows $|R_x \land \text{neighborhood}| \geq 3$.

In the case of Figure 5, Step5 returns $R_1$ ($\text{pmat} = 3$).

Figure 6 applies $R_1$ on the test data. Its impact is reported as the median effort value of the cases. For the cases of Figure 6, this is 81 months of effort.

$\forall 2$ is not a slow algorithm. Nothing in any of these steps takes more than log-linear time, and even that is only to sort $K_1$ items (which is a very small list). Even when implemented in an interpreted language (GAWK), $\forall 2$ runs in less than half a second for up to 500 cases (on a 3MHz dual core Macintosh, OS/X 10.6, 4GB of ram).

To compare the effectiveness of different treatments, we offer the following performance measures:

- All our measures are taken from the test set.
- The asis values are from the neighborhood of the context; e.g. the effort column.
- The tobe values are from the cases selected by a treatment; e.g. the effort column.
- The median of a distribution is the 50-th percentile of the sorted values in that distribution.
- The spread of a distribution is the (75-25)th percentile of the sorted values.
- The improvement from $a = \text{asis}$ to $t = \text{tobe}$ is $100 \ast (a - t)/a$. Larger improvements are better.

For example, consider $\text{pmat} = 3$:

- Without the $\text{pmat} = 3$ restriction, the median and spread in the test set are 235 and 633 months, respectively.
- With $\text{pmat} = 3$, the median and spread of projects similar to context1 are 81 and 353 months (see Figure 5).
- The observed improvement in the median is hence 66%.
- The observed improvement in the spread is hence 44%.

### 3.1 Empirical Example

Figure 7 shows the results seen after apply $\forall 2$ to:

- Enhancements to a U.K. telecommunications product;
- Projects collected by Miyazaki et al [49];
- Finnish Information Systems projects;
- A large dataset of Chinese software projects;
- Large COBOL projects, collected by Kemerer [50].

The format of this data is highly varied and includes number of basic logical transactions, query count and number of distinct business units serviced. For these data sets, we did not have access to specific case studies like Figure 8. Hence, these results are based on contexts developed as follows:

- The first contained the entire range of possible project descriptors, representing complete freedom to recommend any change within the space.
- The other two queries were generated by randomly choosing 50% of each attribute values from either the lower, middle, or upper ranges for each project descriptor.

For these experiments, the values function was just “reduce effort” (later in this article we explore other results on COCOMO-related data, that tries to reduce effort and defects and calendar months).

There are three noteworthy aspects of the Figure 7 results:

- All the points in that figure are positive; i.e. improvements were seen in all cases.
- The dotted lines show the 50% percentile range of the results: half that results had at least 56% and 73% improvement in median and spread.
- There is no evidence that $\forall 2$ has problems with smaller data sets. The two smallest examples processed by $\forall 2$ are Kemerer and Telecom containing 15 and 18 examples each. The minimum improvements seen, even for these small data sets, are 55% (in both median and spread).

The expected value of the results in these examples is very high; e.g. a 56% median improvement in effort. The reason for these large improvements is that, in these examples, we focus only on effort. Clearly, there are many ways to cut corners in a project and some of those can have disastrous results (e.g. allocate no effort to testing will reduce the cost, but that is clearly not a recommended management action for a software project). Later in this paper we are examples where $\forall 2$ is chasing improvements to effort and defects and total calendar time to develop the software. Optimizing for $N = 3$ goals is a harder task than just the $N = 1$ goal of Figure 7. Hence, those the improvements seen in those examples will be more modest (around 20%).

### 4 Model-based Methods

This section discusses SEESAW, our best model-based method for learning changes to a software project. Subsequent sections will compare SEESAW to $\forall$. 

![Fig. 7. Effort results for five non-COCOMO datasets.](image URL)
4.1 Case Studies

Since all our model-based methods are built around the COCOMO-suite, we must use COCOMO data and contexts written in the COCOMO ontology. Figure 8 shows some real-world context and control information taken from a debrief of some NASA program managers:

- **Ground and flight** represent typical ranges for most NASA projects at the Jet Propulsion Laboratory (JPL);
- **OSP** represents the guidance, navigation, and control aspects of NASA’s 1990 Orbital Space Plane (OSP);
- **OSP2** represents a second, later version of OSP with a more limited scope of COCOMO attributes.

The uncontrolable column in Figure 8 shows project features that cannot be changed. For example in project OSP, the required reliability is fixed at rely = 5. On the other hand, the low and high ranges in that figure define the space of possible changes to that project. For instance, the reliability of flight software varies from 3 (nominal) to 5 (very high).

4.2 Handling the Models

Optimizing for a set of goals is traditionally resolved by computing partial differential equations of a model, and then exploring the surface of steepest change. A premise of this approach is tuning stability; i.e. that the gradients at any point in the model can be determined with certainty. As shown in Equation 2, this premise does not hold for the COCOMO models used in this study.

If tuning instability cannot be isolated, it must instead be managed. Our model-based methods assume that predictions are altered by project variables $P$ and tuning variables $T$:

$$ prediction = model(P, T) $$

For example, in local calibration, the tuning options $T$ are the ranges of $(a, b)$ and the project options $P$ are the $EM_i$ values.

At any local site, only part of the tunings is relevant; we denote these as $t \subseteq T$. This subset can be found in many ways including linear regression or local calibration. However, if there is insufficient data for stable tunings, then $T$ may as well be left unconstrained, so $t \subseteq T$ can be selected randomly.

Managers explore a specific context (the particulars of their project) context $\subseteq P$ and control some items of context (control $\subseteq$ context). Since it is too expensive to use all control settings, we seek minimal treatments $R_e \subseteq$ control; i.e. no smaller treatment has the same (or better) effect as $R_e$.

Models assess different treatments by running them on the model and returning the one that maximizes a model’s value:

$$ \text{AI search} \quad R_e \subseteq \text{control}, \text{median}_n \left( t \subseteq T, \text{value(model}(R_e, t)) \right) $$

$\text{median}_n$ is the median observed in $n$ repeats of the random selection and $\text{value}$ is a domain-specific function. For example, $\text{value}$ could be computed from the difference of the model estimates to zero (effort, defects, development time):

$$ value = 1 - \left( \sqrt{\text{Effort}^2 + \text{Defects}^2 + \text{Time}^2 \div \sqrt{3}} \right) $$

4.3 Six AI Model-Based Algorithms

The case studies of Figure 8 can be used to assess how well different AI algorithms can find changes to software projects. For example, a typical Simulated Annealing (SA) run explores 10,000 variants on some solution [51]. A side-effect of that run is 10,000 sets of inputs, each scored with the $value$ function.
of Equation 6. Our tool classified the outputs into the 90% rest and the 10% best seen during the run of the SA. All the ranges from all the features were then ranked according to how much more frequently they appeared in best than rest. A forward select was then called using the first 1...x ranked items. Figure 9 shows the treatment $R_x$ at any $x$ value is the conjunction of ranges observed between 1 to $x$ (see the table at the bottom of that figure). The $y$ axis scores show median results in 100 runs of COCOMO/COQUALMO, after imposing the treatment. The “pruned” range of that figure shows the results of a back select that worked backwards over the forward select ordering, deleting any item $x$ whose distribution of values was statistically insignificantly different to $x - 1$. SA's final recommendation was the treatment $1 \leq x \leq 13$. The improvement generated by that treatment can be seen by comparing the values at $x = 0$ to $x = 13$.

- Defects reduced: 350 to 75;
- Time reduced: 16 to 10 months;
- Effort reduced: 170 to 80 staff months.

SA is just one way to generate a treatment. For our AI model-based methods, we explored five others. Given a random selected treatment, MaxWalkSat tries $n$ modifications to randomly selected features [52]. Sometimes (controlled by the $\alpha$ parameter), the algorithm chooses the range that minimizes the value of the current solution. Other times (at probability $1 - \alpha$), a random range is chosen for the feature. After $N$ retries, the best solution is returned. Our implementation used $n = 50$, $\alpha = 0.5$, and $N = 10$.

SEESAW [18] augments MaxWalkSat with a search heuristic taken from simplex optimization. SEESAW ignores all ranges except the minimum and maximum values for a feature in $p$. Like MaxWalkSat, each feature is randomly selected on each iteration. However, SEESAW has the ability to delay bad decisions until the end of the algorithm (i.e. decisions where constraining the feature to either the minimum or maximum

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Defects</th>
<th>Months</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEESAW</td>
<td>4</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>BEAM</td>
<td>0</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>A-star</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>SA</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>MaxWalkSat</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>ISAMP</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig. 10. Number of times algorithms were top-ranked (largest is 4: i.e. one for each Figure 8 case study).

value results in a worse solution). Hence, SEESAW’s search was followed by the same back-select process used in SA.

This paper also explores the ISAMP, BEAM, and A-STAR algorithms described in the appendix. Initially, we planned to explore more AI algorithms but the success of $W$’s instance-based approach has decreased our motivation in that regard.

4.4 Comparisons of AI Model-based Methods

For each case study of Figure 1, each algorithm was run 20 times (guided by the value function of Equation 6). Separate statistics were collected for the defects/effort/time predictions seen at the policy point in the 20x4 trials. The top-ranked algorithm(s) of Figure 10 had statistically different and lower defects/effort/time predictions than any other algorithm(s).

Note the dramatic difference between MaxWalkSat and SEESAW results. The difference between these two algorithms is very small: SEESAW assumed that the local search state space was monotonic, so it only explored minimum and maximum values for each feature. This result underscores the power of the simplex heuristic.

From Figure 10, the worst algorithms are MaxWalkSat and ISAMP and the best algorithms are SEESAW and BEAM. The performance of these best algorithms is sometimes equivalent (e.g., in time, both algorithms achieved an equal number of top ranks). However, BEAM is not recommended:

- BEAM runs 10 times slower than SEESAW.
- SEESAW performs better than BEAM in some cases (e.g. in defects, BEAM is never top-ranked).

Since SEESAW performs best, we will use it for our subsequent comparisons with instance-based methods.

5 MODEL VS. INSTANCE-BASED METHODS

SEESAW requires models in the COCOMO format so for our comparisons, we restrict ourselves to data in that format. W2 used the historical cases from the NASA93ii and COC81ii datasets. These data sets all have the features defined by Boehm [48]; e.g. analyst capability, required software reliability, and use of software tools. Originally collected in the COCOMO-I format, JPL business experts have translated them from their original COCOMO format to COCOMOII.

Both SEESAW and W2 guided their search using Equation 6 and the four contexts of §4.1. SEESAW used those contexts to guide their “what-if” queries around its COCOMO/COQUALMO models. W2 took those contexts then applied the seven step procedure described above to NASA93ii and COC81ii. Recall that, in those steps, some $R_x$ was assessed on projects similar to the context in a test set; i.e.
all the cases in the context's neighborhood. Our comparison rig studied that same test neighborhood using SEESA and W2. We say that rows1 and rows2 are the rows selected from the neighborhood after applying SEESA’s or W2’s recommendations (and by “apply”, we mean reject any row that contradicts the ranges in the recommendation). From rows1, we applied Equation 6 to find values1.

The are shown in Figure 11, divided into the defect, effort, months changes see in GROUND, FLIGHT, OSP2 and OSP.

![Fig. 11. Changes in median and spread.](image)

In all, we show 24 comparisons:

\[
\begin{pmatrix}
\text{NASA93ii} \\
\text{COC81ii} \\
\text{defects} \\
\text{effort} \\
\text{months}
\end{pmatrix} \times
\begin{pmatrix}
\text{defects} \\
\text{effort} \\
\text{months}
\end{pmatrix} \times
\begin{pmatrix}
\text{ground} \\
\text{flight} \\
\text{OSP2}
\end{pmatrix}
\]

W2 produced larger median reductions that SEESA in 16/24 comparisons. The “Win” column of those figures indicates when any member of a comparison had a higher value and was statistically significantly different (Mann-Whitney, 95% confidence). In nearly half the comparisons (11/24), W2 results were statistically different and better than SEESA (in the remaining comparisons, SEESA’s median improvements were never better than W2).

Figure 12 shows the sorts the median and spread improvements seen from the Figure 11 results. Note that rarely were the changes to the median less than zero. In the majority of cases, W2’s median and spread improvements were positive (an expected value of 20.5; sometimes ranging over 50%).

While occasionally the spread degraded sharply (down to 50% worse), such cases were uncommon: note that in only 10% of our cases were the spread changes below -15%. Also, all the cases where W2 had poor spread results were in the COC81ii data set which, as discussed below, is a data set with certain special features.

The gray cells in Figure 11 show optimization failures; i.e., a zero or negative improvement. W2 failed less than SEESA (had fewer gray cells). W2 showed 3/24 and 7/24 failures for medians and spreads (respectively) while SEESA showed 13/24 and 7/24 failures for medians and spreads (respectively). One of SEESA’s failures was particularly dramatic: witness the increase from 98 effort months to 447 effort months in the OSP2 effort results. We conjecture that SEESA’s greater failures in median reduction are due to the over-fitting problem discussed in §2.4. SEESA’s model-based methods are free to sample increasingly narrow segments of the internal state space of a model (“flying in”, as we were, into small cracks between the training data). If that sampling is taken to extreme, and the model-based methods offer recommendations that cover a tiny part of the state space, and if the test data does not fall into that tiny region, then the model-based recommendations will fail.
Note that most of the gray cells occur in the COC81ii results. Boehm assumed that this data was to be analyzed by regression so spent much effort on the COC81ii data, applying his domain expertise to prune or trim outstanding values. Curiously, W2 performed best on the “uncleansed” data set (NASA93ii) than the cleaner data set (COC81ii). We conjecture that, sometimes, seemingly “dirty” data actually contains data that is insightful in some contexts. While such outliers confuse regression-based methods (that try to fit one model over the entire data), instance-based tools like W2 can exploit those less-common instances (since they build local models around each context).

In summary:
- W2’s performance was better than SEESA W;
- W2 was more effective at reducing the medians;
- Both instance-based and model-based methods had similar issues with reducing the spread.
- Possibly, the instance-based approach of W performs better on “dirtier”, nosier data than model-based methods.

6 DISCUSSION

6.1 Intra- and Inter-Project Stability

One of the premises of instance-based methods like W2 is that local reasoning in some specific context is best that fitting one model over an entire space. This is required if the “best” solutions in a one context do not hold in others.

To test this premise, we generated a report of what treatments were found under different conditions. Figure 13 shows the results of W2’s Step7 (prune all treatments that do appear in less than 50% of 20 repeated trials). The left-hand column of Figure 13 shows the four values function used in that study:

1) Defects aims at reducing just defects;
2) Effort aims at reducing just effort;
3) Months aims at reducing a project’s total calendar time.
4) All refers to Equation 6; i.e. try to decrease effort and development time and number of defects;

The last of these is a multi-objective function while the rest strive to optimize one objective without concern to the others. Figure 13 shows that, in any row, the conclusions reached by W2 are stable (i.e. appear at high frequency, across 20 random selections of train : test). That is, W2’s results exhibit intra-project conclusion stability (when the context and values function are held constant). For project managers, this is good news since it shows that their data contains clear signals on how to best change their particular project in order to achieve particular goals.

However, Figure 13 also shows that if the context is changed (from generalized FLIGHT systems to a specific flight system like OSP), then the recommended changes are very different. Similarly, the OSP results show that altering the values function also dramatically changes recommendations.

Menzies & Shull [55] report that many SE papers conclude that what is “best” for one project may not be “best” for another. For example, Zimmermann studied 629 pairs of software development projects [54]. In only 4% of those hundreds of pairs was a defect prediction model learned from one project useful on another. When such inter-project conclusion instability exists, then tools like W2 are essential since it is best to learn changes that are tuned to the specifics of particular projects (like OSP & OSP2) rather than on generalized descriptions of software (like FLIGHT & GROUND).

6.2 When Not to Use W2

Like any instance-based method, W2 requires historical cases. If such data is missing then W2 cannot be used.

In that circumstance, discussions about how to best change a project can use results borrowed from other sites. For example, Figure 14 show’s Boehm et al.’s [43] analysis of the effects of changing some project attribute from its minimum to maximum value. Based on data from a regression analysis of 161 projects, this figure comments that changing (e.g.) personnel/team capability can alter the effort to build software by up to 350%. Using this data, the effects of various changes can be investigated using Boehm’s delta analysis technique [55]:

- An old project with known efforts is used as a baseline.
- A change to a project is described as a new project, expressed in terms of deltas to the variables of Figure 14.
- The new estimate is then the product of the baseline times the effort multiplier deltas.

Fig. 13. Recommendation frequency across 20 runs of W2 for reducing individual goals (defects, effort, or months) as well as all goals at once (all).
Fig. 14. Relative effects on development effort. From [55].

(e.g., \(W2\)). Note how that only a third of the Figure 14 attributes appear in the “best” treatments of Figure 13. Curiously, the two attributes with greatest impact (personnel/team capability and product complexity) are absent from Figure 13.

Why is \(W2\) ignoring an attribute with such a large impact (350%)? To answer that question, we have go to the context-dependent particulars. Recall from Figure 8 that in OSP2, product complexity is fixed at \(cplx = 4\) and personnel/team capability is fixed at \(pcap = 3\). \(W2\) does not recommend treatments for things that cannot change. Hence, \(cplx\) and \(pcap\) are absent from the OSP2 results of Figure 13. Similarly, OSP allows only \(pcap = 3\) so this attribute is also absent.

The same reasoning does not explain the other absent attributes. To understand these, we must look at the data. OSP sets \(cplx \in \{5, 6\}\). This attribute is absent in the treatments since there is insufficient support in NASA93ii to justify their inclusion (there only five \(cplx = 5\) examples in NASA93ii and no examples of \(cplx = 6\)). Similar explanations can explain all the remaining absences. Examples such as these show how \(W2\) can provide recommendations that may go against common expert advice. This lack of a defined relationship between data attributes underscores the need for careful query construction. For example, if a query contains conflicting attributes, \(W2\) maintains no internal inconsistency check. Model-based approaches such as S-COST [56] can provide this sanity check, but incur the costs associated with model-based methods discussed above (ontology restrictions, untamed internal model variance, etc).

In summary, when data is absent, managers can debate changes to projects by reuseing data like Figure 14. However, the conclusions reached from a context-independent reasoning (like delta analysis) can be more specific with local information about the kinds of projects seen in the local environment and the kinds of changes the local managers are willing to accept. Therefore, where possible, we recommend collecting local data and analyzing it with \(W2\).

6.3 Scope of the Study

This study use conveniently available datasets in the PROMISE repository, the result applies within the same context of the datasets. In addition, our evaluation compares the performance of different methods across a finite number of problems, so it cannot be used to predict which method will be superior to others for some future, as yet unseen, problem. In fact, no method has been found so far that is universally superior to others in all problems; indeed, the “no-free-lunch theorem” [57] suggests that such an universal best method for all problems can never exist. In practice, for a given new learning problem, various methods need to be empirically evaluated to find the best ones, such as the ones carried out in the study.

We have shown that some treatments identified can improve the quality measures observed in historical project datasets. Our performance measures including median and spread reductions seen in “hold-out data” should not be confused with practical significance in the real world.

That being said, we note that publications from other research communities assess their models in the same manner as this paper: see the effort estimation [22]–[24], [30], [31] and defect prediction [58]–[61] literature. Ideally, researchers in effort estimation, defect prediction, or learning changes to software projects should apply their recommendations to live projects. However, hold-out tests are widely used due to the tremendous practical difficulties associated with performing such tests on multiple software projects. At the very least, studies like this paper are required to prune the space of methods to be laboriously tested on new, real-world, projects.

7 Conclusion

To attain knowledge, add things every day.
To attain wisdom, remove things every day.
– Lao-tse

Managers must make management decisions about changes to software projects. Currently, they have only very limited guidance from the SE literature on how to make the fewest number of most effective changes to their projects. Hence, we have spent several years exploring methods for guiding managers towards better choices.

Originally, our work focused on model based methods. Models have many advantages such as representing and visualizing expert domain knowledge. Also, models let us extrapolate from past observations to new situations that may not have been seen previously. As demonstrated by the recent increase in conferences devoted to the construction and exploration of models (e.g. MODELS\(^1\) and SBSE\(^2\)), there is much current interest in model-based software engineering.

Since models seemed so useful, in previous work, we have employed model-based methods to find changes for software projects. This paper reports the surprising result that a small extension to standard instance-based methods (a greedy search

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over the neighborhood of some query, divided into a best and rest region) out-performs numerous model-based methods. Specifically, when compared to model-based methods, the W2 instance-based method:

- Is faster to run.
- Is simpler to code.
- Is easier to maintain (just add more cases).
- Is faster to adapt to data sets from new domains.
- Finds equivalent or better ways to improve projects.
- Scales to large problems (since it runs in log-linear time)

Following on from this report, there many issues that could motivate future work:

- Are model-based methods worse for noisier data?
- Is “data cleansing” recommended for regression, but deprecated for instance-based methods?
- How best to reduce spread, thus increase the confidence a user has in the results?
- Why does W2 performs as well as more elaborate model-based methods?

As to this last point, we conjecture that the kinds of process data we can collect from projects are a shallow source of knowledge. With such shallow sources:

- Very simple methods can plumb their depths;
- More elaborate methods may do no better than the very simple.

As evidence for this conjecture, we note that our data sets are often very small (e.g. the 15 rows of KEMERER or the 13 rows of TELECOM). Such small data sources may only hold very limited, and very shallow, structures. If so, then sophisticated AI search algorithms may find little more than the simple greedy search of W2.

This work has focused on software process data. Nevertheless, instance-based methods (such as the W2 algorithm used in this study) can be effectively used in many other fields. For (very long) lists of application areas of instance-based reasoning, see Kolodner [10], Aamodt [62], Lenz [63], Shepperd [8] and the proceedings of the International Conference on Case-Based Reasoning[1]. While our results do not show that all instance-based methods are better than all instance-based methods, they do motivate more investigations of case-based methods. Before researchers elaborate their model-based methods, it may be both theoretically insightful (as well as pragmatically useful) to build an instance-based version of their method. Based on our experience, we predict that such an instance-based method would be simple to build and, at the very least, provide a baseline against which it is possible to demonstrate the value of more elaborate systems.

References


The nominal range \( \{n=3\} \) corresponds to an effort multiplier of 1 (i.e., no change). Hence, these ranges can be modeled as straight lines \( y = mx + b \) passing through the point \((x, y)=(3, 1)\). Such a line has a y-intercept of \( b = 1 - 3m \). Substituting this value of \( b \) into \( y = mx + b \) yields:

\[
\forall x \in \{1..6\} \quad EM_i = m_\alpha (x - 3) + 1
\]

(7)

where \( m_\alpha \) is the effect of \( \alpha \) on effort/cost. The positive effort \( EM \) features such as \( cpplx \) with slopes \( m_+ \), are positively correlated to effort/cost. The negative effort \( EM \) features such as \( acap \), with slopes \( m_- \), are negatively correlated to effort/cost. The \( m \) ranges, as seen in 161 projects [55], are:

\[
0.073 \leq m_+ \leq 0.21 \land -0.178 \leq m_- \leq -0.078
\]

(8)

To random sample the tunings, all that is required is to select \( m \) at random from the ranges of Equation 8. As shown in [16], similar equations can be derived from the COCOMO scale factors and the COQUALMO model.

**ISSAMP, BEAM, A-STAR**

**ISSAMP** is a fast stochastic iterative sampling method that extends a treatment using randomly selected ranges. The algorithm follows one solution, then resets to try other paths (our implementation resets 20 times). The algorithm has proved remarkably effective at scheduling problems, perhaps because it can rapidly explore more of the search space [64]. To avoid exploring low-value regions, our version of ISSAMP stores the worst solution observed so far. Any conjunction whose value exceeds that of the worst solution is abandoned, and the new “worst value” is retained. If a conjunction runs out of new ranges to add, then the “worst value” is slightly decreased. This ensures that consecutive failing searches do not permanently raise the “worst value” by an overly permissive value.

Our other two algorithms use some variant of tree search. Each branch of the tree is a different “what-if” query of size \( i \). If \( i \) is less than the number of input values to COCOMO/COQUALMO, the missing values were selected at random from the legal ranges of those inputs.

**BEAM search** extends search branches as follows. Each branch forks once for every new option available to that range. All the new leaves are sorted by their value and only the top \( N \) ranked branches are marked for further expansion. For this study we used \( N = 10 \) and results scored using the median values seen in the top \( N \) branches.

**A-STAR** runs like BEAM, but the sort order is determined by the sum \( f \) (the cost of reaching the current solution) plus \( g \) (a heuristic estimate of the cost to reach the final solution). Also, unlike BEAM, the list of options is not truncated so a termination criterion is needed (we stop the search if the best solution so far has not improved after \( m \) iterations). For this study, we estimated \( f \) and \( g \) as follows:

- \( f \) was estimated as the percentage of the project descriptors with ranges in the current branch;
- \( g \) was estimated using \( 1 - Equation 6 \) (i.e., distance to the utopia of no effort, no development time, and no defects).

**APPENDIX**

**Modeling Variance in COCOMO/COQUALMO**

For COCOMO effort multipliers (the features that affect effort/cost in a linear manner), the off-nominal ranges \( \{v=1, l=2, h=4, v_h=5, x_h=6\} \) change the prediction by some ratio.

\[ f \] was estimated as the percentage of the project descriptors with ranges in the current branch;

\[ g \] was estimated using \( 1 - Equation 6 \) (i.e., distance to the utopia of no effort, no development time, and no defects).
Tim Menzies is an associate professor at the Lane Department of Computer Science at West Virginia University (USA), and has been working with NASA on software quality issues since 1998. He has a CS degree and a PhD from the University of New South Wales and is the author of over 160 publications. His recent research concerns modeling and learning with a particular focus on light weight modeling methods.

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Barry Boehm received his B.A. degree from Harvard in 1957, and his M.S. and Ph.D. degrees from UCLA in 1961 and 1964, all in Mathematics. Between 1989 and 1992, he served within the U.S. Department of Defense (DoD) as Director of the DARPA Information Science and Technology Office, and as Director of the DDR&E Software and Computer Technology Office. He worked at TRW from 1973 to 1989, culminating as Chief Scientist of the Defense Systems Group, and at the Rand Corporation from 1959 to 1973, culminating as Head of the Information Sciences Department. He was a Programmer-Analyst at General Dynamics between 1955 and 1959. His current research interests include software process modeling, software requirements engineering, software architectures, software metrics and cost models, software engineering environments, and knowledge-based software engineering.