When to Use Data from Other Projects for Effort Estimation

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ABSTRACT

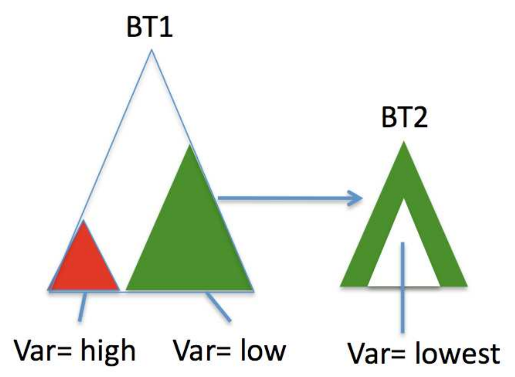
Collecting the data required for quality prediction *within* a development team is time-consuming and expensive. An alternative to make predictions using data that *crosses* from other projects or even other companies. We show that with/without *relevancy filtering*, imported data performs the same/worse (respectively) than using local data. Therefore, we recommend the use of relevancy filtering whenever generating estimates using data from another project.

INTRODUCTION

When data is scarce *within* one project, it is tempting to use data imported from other projects. Such *cross*-project data exist; for example the PROMISE repository [?] offers a dozen effort estimation data sets for public access.
A recent survey paper has evaluated *within* or *cross* data for effort estimation [?]. They concluded that they could not make a conclusion; that the current findings are contradictory about the relative merits of *within* or *cross* data.
In other work [?], we have shown that it is acceptable to use *cross* data sources for defect prediction, providing that data has been pre-processed by some sort of *relevancy filtering*. Given a large training set, such relevancy filters select a small subset relevant to the current test case. Such filtering removes training instances that create noise in the estimation process, leaving a body of data that, in theory, follows the principle of locality.
The success of relevancy filtering for defect prediction prompts us to apply it to effort estimation. To the best of our knowledge, this is the first exploration in the effort estimation community of the effects of relevancy filtering when applied to *cross* and *within* project data. We show that *cross* data can usually attain estimation accuracies just as high as those of *within* data, provided that a relevancy filter is applied to the data, prior to making estimates.

TWO PASS RELEVANCY FILTERING

Each tree BT1 and BT2 are binary cluster trees. The red subtree is pruned in pass one due to high variance. The remaining subtrees (shown in green) form the right-hand tree.



In pass two, test instances start at the root of this tree and traverse to the nearest child (and so on, recursively). While the sub-tree variance continues to decrease, the traversal continues. Estimates are generated from the median of the instances of the right-hand-side sub-tree with lowest variance.

DETAILS OF RELEVANCY FILTERING

Our relevancy filter extends standard analogy-based estimation methods (which we call ABE0). ABE0 generates estimates for a test project by gathering evidence from the effort values of similar projects in some training set. By analyzing the previous research of experts like Shepperd et. al.[?], Mendes et. al.[?] and Li et. al.[?] on the field of analogy-based estimation, we can come up with a baseline technique:

- Build a training data from rows of past projects;
- The columns of this set are composed of *independent* variables (the features that define projects) and a *dependent* variable (the recorded effort value).
- Decide on how many similar projects (*analogies*) to use when examining a new test instance , i.e. *k*-values.
- For each test instance, select *k* analogies from training.
  - While selecting analogies, use a similarity measure (such as the Euclidean distance of features).
  - Before calculating similarity, apply a scaling measure on independent features to equalize their influence on this similarity measure.
- Use the effort values of the *k* nearest analogies to calculate an effort estimate.

We can refer to this baseline framework as ABE0. For the similarity measure, we use Euclidean distance:

$$Distance = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (1)$$

ABE0 returns the median of the efforts in the *k* nearest analogies.

The leaves of the remaining sub-trees are the *survivors* of pass one. These move to pass 2 where the survivors are used to build a second binary tree (called BT2). BT2 is generated and traversed by test instances in the same fashion as BT1. This time, while traversing the tree, instead of storing the variances of sub-trees, we use the variance as a decision criterion. If the variance of the current tree is larger than its sub-trees, then continue to move down the subtree; otherwise, stop moving and select the instances in the current tree as the relevant instances and adapt them for estimation.

This filter is similar to the NN-filter used by Turhan et.al.[?], except that there is no need to pre-specify the number of analogies k to be used for estimation. Each test instance selects its own relevant analogies by traversing to different sub-trees of BT2. For a detailed discussion on the rationale behind this filter, see [?]. All we need to say here is that this filter is known to generate low errors for ABE0-style effort estimation [?]. Hence, it is a suitable tool for the rest of this study.

METHODOLOGY

In our research, we have used subsets of three commonly-used datasets in software effort estimation research: Nasa93, the original Cocomo81 [?], and Desharnais[?]. We will denote the subsets of

Nasa93 as Nasa93c1, Nasa93c2 and Nasa93c5 that contain projects from development centers 1, 2 and 5 respectively. In a similar fashion, subsets of Cocomo81 will be denoted as Coc81o, Coc81e and Coc81s (for organic, embedded, and semidetached). Finally, the Desharnais dataset is split into three different subsets: DesL1, DesL2 and DesL3 (languages 1, 2 and 3 respectively). Since each of these subsets have certain common criteria (the development center, development mode, or development language), each subset will be treated as a separate *within* dataset. All of the datasets used in this research are available in PROMISE data repository [?]. For each of the three main datasets

(Nasa93, Cocomo81 and Desharnais) in our research, we have conducted *within* and *cross* experiments. Each subset became a *within* dataset that contains projects sharing the particular characteristics of a single development firm. To understand the *within* and *cross* data

formation, assume that a dataset X with its three subsets X_1, X_2 and X_3 is under consideration. For *within* experiments, relevancy filtering described is applied on each one of X_1, X_2 and X_3 separately and the median of the filtered project instances in the training set is stored as the effort estimate for the test instance. For the separation of training and testing sets, the leave-one-out method is used. Leave-one-out selects one instance out of a dataset of n instances as the test instance and uses the remaining $n-1$ instances as the training set.
For the *cross* experiments, one of X_1, X_2 or X_3 is chosen as the test set and the combination of the remaining two forms the *cross* dataset for training. This time, the relevancy filtering is applied on the *cross* dataset, and the estimations for projects in the test set are stored. Each

of the *within* and *cross* experiments are repeated twenty times in order to remove any bias that would otherwise be brought by a particular test and training set combination. In order to compare the perfor-

mance of *within* and *cross* datasets, we have used two measures: the magnitude of relative error (MRE) and win-tie-loss values generated by a statistical rank-sum test.

$$MRE = \frac{|actual_i - predicted_i|}{actual_i} \qquad (2)$$

Using a Mann-Whitney test (95%), we checked how often one treatment won/lost/tied with the others. Here, a "tie" means that they are not statistically significant different. If statistically different, then the method with a lower median MRE score gets one more "win" and the other method gets one more "loss".

RESULTS-Without Relevancy Filtering

Every odd and even line is a pair of experiments. In each pair, there is a *within* and a *cross* experiment.

Data set	Train Set	Test Set	Method	Win	Tie	Loss
Nasa93	Nasa93c1	Leave-one-out test instance	*Within*	1		
	Nasa93c2 and Nasa93c5	Nasa93c1	*Cross*			1
	Nasa93c2	Leave-one-out test instance	*Within*	1		
	Nasa93c1 and Nasa93c5	Nasa93c2	*Cross*			1
	Nasa93c5	Leave-one-out test instance	*Within*		1	
	Nasa93c1 and Nasa93c2	Nasa93c5	*Cross*		1	
Cocomo81	Coc81o	Leave-one-out test instance	*Within*	1		
	Coc81e and Coc81s	Coc81o	*Cross*			1
	Coc81e	Leave-one-out test instance	*Within*		1	
	Coc81o and Coc81s	Coc81e	*Cross*		1	
	Coc81s	Leave-one-out test instance	*Within*		1	
	Coc81o and Coc81e	Coc81s	*Cross*		1	
Desharnais	DesL1	Leave-one-out test instance	*Within*	1		
	DesL2 and DesL3	DesL1	*Cross*			1
	DesL2	Leave-one-out test instance	*Within*		1	
	DesL1 and DesL3	DesL2	*Cross*		1	
	DesL3	Leave-one-out test instance	*Within*	1		
	DesL1 and DesL2	DesL3	*Cross*			1

In *cross* experiment, a linear regression model is built on *cross* data and tested on the

within data. In *within* experiment, the test instance is selected with leave-one-out, and a linear regression model is built on the remaining instances and tested on the selected test instance. A "1" denotes which item in the pair won, lost or tied.

RESULTS-With Relevancy Filtering

Cocomo81 Results

Dataset	Method	Win	Tie	Loss
Coc81o	within	13	7	0
Coc81e and Coc81s	cross	0	7	13
Coc81e	within	1	19	0
Coc81o and Coc81s	cross	0	19	1
Coc81s	within	0	20	0
Coc81o and Coc81e	cross	0	20	0

Nasa93 Results

Dataset	Method	Win	Tie	Loss
Nasa93c1	within	3	15	2
Nasa93c2 and Nasa93c5	cross	2	15	3
Nasa93c2	within	3	17	0
Nasa93c1 and Nasa93c5	cross	0	17	3
Nasa93c5	within	1	19	0
Nasa93c1 and Nasa93c2	cross	0	19	1

Desharnais Results

Dataset	Method	Win	Tie	Loss
DesL1	within	1	19	0
DesL2 and DesL3	cross	0	19	1
DesL2	within	1	19	0
DesL1 and DesL3	cross	0	19	1
DesL3	within	16	4	0
DesL1 and DesL2	cross	0	4	16

This section shows that for each data set, the application of relevancy filtering reverses the conclusion of the previous section; i.e. the *cross* data becomes useful for estimating the local project. Figure **??**, shows the the win-tie-loss values for the subsets of Nasa93. The greedy clustering algorithm of the two pass relevancy filtering uses some non-determinism (when breaking ties between instances of similar distances), so we repeat these experiments twenty times. This results shows us that, in all three treatments, the *tie* values are quite high. This indicates that, for at least 75% of the tests, there is no statistical difference between filtered *cross* and *within* results. In short, for Nasa93, the performance of *cross* data (filtered for relevancy) is indistinguishable from the performance of *within* data.

Figure **??** shows the win-tie-loss values for the subsets of Cocomo81. In two out of the three treatments the *tie* values are 19, which tells us that for these treatments, *within* and *cross* performance are almost identical. However, the first treatment shows a preference for *within* data on thirteen of the twenty tests.
The win-tie-loss values for subsets of Desharnais are given in Figure **??**. The derived results for the Desharnais subsets are similar to those of Cocomo81 treatments: Two out of the three treatments show identical *tie* values of 19, which again suggests that the performance of filtered *cross* datasets is statistically identical to *within* datasets. However, in one of the treatments, *within* outperforms *cross* on sixteen of the twenty trials.
WIn summary, with relevancy filtering, in the majority case ($\frac{7}{9}$ treatments) the *cross* data performs as well as the *within* data for effort estimation. There are only two treatments, DesL3 and Coc81o, where *within* performance was significantly better than *cross* performance. A possible explanation for those two scenarios may be hidden in the dataset size or in the quality of the *within* datasets, but the currently-available information makes it difficult to suggest any conclusive reason for the situation.

FOR MORE INFORMATION

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