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General Theories of Software Defect Prediction

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ABSTRACT

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

1. INTRODUCTION

By predicting defects in software systems *before* the deployment of that software, it is possible to gauge not only the probable quality upon delivery, but also the maintenance effort. Software defect prediction builds models using available company data that can then be applied in order to predict these software faults. But in order to employ these models, a company must have a data repository where information regarding defects from past projects are stored. However, according to Turhan, et. al. [7], few companies are applying this practice. Turhan, et. al. claims (and we agree), that this is most likely due to a lack of local data repositories. When this is the case, companies must use non-local data in order to build defect predictors. Thus, it is not only important to determine how well cross-company data can be used when local data is unavailable, but also to find the presence or absence of a general theory of software defect prediction. In other words, in determining the existence of an empirically-derived correlation between varying defect data sets, a statement can be made in regards to not only the stability of current defect prediction, but also the underlying similarities of cross-company software projects. On the other hand, if no correlation is found to exist, instability of those current predictors may suggest that further research should be conducted in order to provide incite into the variance between projects.

2. BACKGROUND

The ability of an organization being able to use cross-company (CC) data when within-company (WC) data is not available in order to build defect predictors would be advantageous. However, it remains unclear if this practice can yield beneficial results.

Turhan et al. conducted three experiments to rule in favor of CC data obtained from other sites, or WC data gathered locally. The conclusions of those experiments show that CC data, when applied using *relevancy filtering* via a k-nearest neighbor scheme. The idea behind the k-NN filter is simple; by building a training set that is homogeneous with the testing set, it is assumed that a bias in the model will be introduced. The filter works as follows: for each instance in the test set, the k nearest neighbors in the training set are chosen. Then, duplicates are removed and the remaining instances are used as the new training set. This relevancy filtering can lead to defect predictors almost as effective as WC data. Thus, as stated by Gay et. al. [5], "...while local data is the preferred option, it is feasible to use imported data provided that it is selected by a relevancy filter."

Gat et. al. confirmed Turhan et. al.'s results, but instead of implementing a nearest neighbor filter, a locally weighted scheme was used to filter the data via [4]. This experiment was of significance due to the fact that Gay et. al.'s results showed not only that CC data can be used when local data is not available, but also that publicly available data such as the PROMISE [1] data.

On the other hand, [1] shows that CC data cannot be used to build accurate defect predictors. For example, in one experiment conducted by Zimmerman et. al., Firefox and Internet Explorer were used due to their domain relationship (browsers) in order to determine how well one could predict for the other. It was found that while Firefox could predict for Internet Explorer at a precision of 76.47%, Firefox could *not* predict for Internet Explorer approaching the same precision (4.12%). However, this experiment did not utilize any form of relevancy filtering, so it is unknown how the two data sets would react to predicting for one another under these circumstances.

If CC data, when filtered, can be used in order to predict defects, we are left to assume that this is due to the fact that the data sets share some innate similarities of their metrics. But if it is found conclusively that CC data cannot most generally build good defect predictors, we are to conclude that other measures must be taken in either the collection of the WC data, or for more research in the further filtering

*A full version of this paper is available as *Author's Guide to Preparing ACM SIG Proceedings Using LaTeX2ε and BibTeX* at `www.acm.org/eaddress.htm`

[1] http://promisedata.org/

of CC data.

3. FINDING GENERALITY

In an ideal situation a company would have large amount of data from a software project that can be used to build models that can predict defects for future releases of the software. In practice however training data from within company is not available in most of the cases. Using data from other projects or other companies is the only option to build prediction models. An ideal model will be able to predict software defect of a project even if trained on data obtained outside the company. Zimmerman et. al in their paper try to asess the extent that cross-project data can be used to predict defects and what kind of software systems are good for cross-predictors. Their results show that simply using projects in the same domain does not work to build accurate prediction models. In our work we are trying to find generality between cross data projects following a different approach based on prism rule learner.

4. THE EXPERIMENT

The primary purpose of our study was to find generality within cross-company datasets along the lines of post-release software defect prediction. The experiment conducted generally involved basic preprocessing techniques, modeling learners by training on data from one company and testing on another and then, finally, analyzing the results obtained in order to conclude on the existence or probability of any form of generality. The subsequent sections below elaborate the steps taken in our experiment, the learners used, and the results achieved.

4.1 Preparing the Data

The data we are using for to test our is extracted from two very different companies: NASA and SoftLab (a turkish software company). The data sets are shown below.
NASA Datasets

- KC1. Storage Management for ground data
- PC1. Flight Software for each orbiting satellite
- KC2 Storage management for ground data
- CM1 Spacecraft Instrument
  Turkish Datasets
- AR4 embedded controller for dish washer
- AR3 Embedded controller for washing machine
- AR5 Embedded controller for refrigerator

We employed a number of preprocessing techniques to prepare the original data before applying our learner to it. These include:

- Discretization
  Splitting each data set randomly into *10* bins (by default)
- Feature Subset Selection
  Sample bias via *B-Square* whereby each column in the data set is ranked by some criteria and the top n columns are maintained and used for the experiment because they are more likely to have a stronger influence on the results.

Why are all these preprocessing techniques necessary? Why not use the data in its raw form? When it comes to data mining, real world data is considered by most software engineers as *dirty*. This is because the data could be incomplete in that it could be missing some attributes or attribute values or it could simply consist of only aggregated values. Moreover, the data could be inconsistent, and could also contain errors and outliers. Preprocessing transforms the data into a format that will be more easily and effectively processed.

4.1.1 Discretization technique

We discretized the data using Equal Interval Width (10 bins). This method falls under the unsupervised discretization methods class. Equal bin length is a global techinque which replaces each value by the identifier of the bin. The range of values is divided into k equally sized bins where k is a parameter manually supplied for the purpose of our experiment. For each attribute the maximum and the minimum are recorded and the range is divided into 10 equal bins. Equal in frequency is easy and straightforward to implement however does not guarantee that the instances falling in each bin will be of the same frequency. It makes no use of the instance class and is thus an unsupervized discretization method. Equal Bin Length is a global discretization method since it produces a mesh over the entire n-dimensional instance space. Other discretization techniques such as Equal Frequency Bin or Feyyad Irani could be used as a discretization technique. Research on the field shows that discretization increases the accuracy of the learner however there is no significant increase in performance in using a specific discretizer over the other [2].

4.1.2 Merging Cross-Company Data

In order to create a large, unified data set from which attributes could be selected, the data sets used in this experiment were merged. The intuition behind this was that if final rules generated from the experiment were to reflect upon the similarities (generalities) in cross-company data, those rules should thus be constructed from portions of a larger, unified pool of data. The results from the experiment should, in theory, provide the ability to predict accurately the defects in cross-company data if a general theory of software defect prediction in fact exists.

The merged data used in the experiment, as seen above, resulted in 5000 instances, on which attribute selection, row pruning and rule generation was used.

4.1.3 Feature Subset Selection via B-Square

B-Square served as the sole feature subset selection (FSS) method employed to assist us in modelling the data based on not only the most important attributes, but also to decrease the overall runtimes of experimentation using the data. The pseudocode for B-Square is outlined as follows:

1. Replace each class symbol with a utility score: True = 1, False = 0.
2. Sort instances by that score and divide them using N=20%-chops.
3. Label all the rows in bin=1 (20%) ”best” and the remaining (80%) ”rest”.
4. Collect the frequencies of ranges in best/rest.

5. Sort each range (r) by br/(b+r) where
6. b = freq(r in Best) / SizeOfBest
7. r = freq(r in Rest) / SizeOfRest
8. Sort each attribute by the median score of b2/(b+r).
9. Reject attributes with less than X% of the max. median score.

The top five attributes were selected using B-Square from the merged data set, and then this data set was reconstructed using only those attributes. This decreased the columns of the data significantly, allowing more lengthy experiments to be conducted.

4.1.4 Slice Generation

The reconstructed, attribute-reduced data was then randomly placed into 50 bins by iteratively filling each bin with randomly selected instances from the entire data set. Each bin was designated as a "slice" in our experiment.

4.1.5 Row Pruning via K-means

In order to remove potential outliers from the data, each slice was clustered using a naive K-means clustering algorithm. K-means clustering groups similar instances together iteratively by finding a cluster's center of mass. K-means works as follows:

1. Select initial *K* centroids at random;
2. Assign each incoming point to its nearest centroid;
3. Adjusts each cluster's centroid to the mean of each cluster;
4. Repeat steps 2 and 3 until the centroids in all clusters stop moving by a noteworthy amount

Twelve clusters were generated from each slice, and the largest cluster

4.2 Learners

4.2.1 PRISM

One of the learners we used in our experiment was *PRISM*. Its algorithm was first introduced by Cendrowska and its aim is to induce molecular classification rules directly from the training set.

Prism uses the '*take the first rule that fires*' conflict resolution strategy when the resulting rules are applied to unseen data. Simply speaking, it identifies a rule that covers many instances in a given class, separates out the covered instances and continues with the remainder of the data.

When working with the Prism learner, we first calculate the probability that class = i for each attribute / value pair. After that we select the pair with the largest probability and create a subset of the training set compromising all the instances with the selected attribute / value combination (for all classifications). We then repeat the previous steps for this subset until a subset is reached that contains only instances of class i. The induced rule is then the conjunction of all the attribute / value pairs selected. Finally, we remove all instances covered by this rule from the training set.

The pseudo-code for the Prism algorithm can be outlined as follows:

```
For each class C
Initialize E to the instance set
While E contains instances in class C
  Create a rule R with an empty left-hand
  side that predicts class C
  Until R is perfect
  (or there are no more attributes to use) do
For each attribute A not mentioned in R,
and each value v,
  Consider adding the condition A = v
  to the left-hand side of R
Select A and v to maximize the accuracy p/t
Add A = v to R
Remove the instances covered by R from E
```

Both the Turkish data and data from NASA comprised of True / False classes, and also had quite a number of attributes in common so we figured Prism was a good option to explore, especially when it comes to cross-project defect prediction. The effect of using Prism on our datasets is analysed and discussed in our *Results* section.

4.3 Experiment 1: Prism

The Prism learner, described in section 4.2.1, was modeled by training on the training set and applying the ruleset generated to the test set. In general, the experiment with Prism involved combining all the datasets into one gigantic datasets consisting of over 5700 instances which were later randomized into 50 slices. For each slice, K-means was applied and the cluster with the most number of instances was selected to be used in place of the slice sinceits much smaller and contains more relevant data as determined by the K-means algorithm. After K-means had been run on all 50 slices, 10% of the clusters obtained were allocated to be used as testing and the remaining 90% for training the learner.

Once preparation of the data had been completed, our experiment entailed iterating through each dataset in the training set and generating new rules, applying those rules to the test set and comparing the results of the probability of defect (pd) to that of the Rulest when applied to the test set as well. The pseudocode describing the algorithm is outlined as follows

```
for each slice s do
if Better (ruleset, s)
  continue
else
  ruleset = Rebuild (s, ruleset)
  if !Better (s, ruleset) then
    ruleset = s
    end if
end for

procedure Better (s, ruleset)
if pd(ruleset) > pd(s)
    return true
return false
```

With reference the algorithm, whenever the pd of the Ruleset is better than that of the current slice, iteration proceeds to the next slice; otherwise, a new Ruleset is generated by rebuilding or simply merging the two datasets.

Once this is done, the current slice is given another chance to obtain apd better than that of the Ruleset. If this turns out to be the case, data from the Ruleset is replaced with that of the slice and the iteration is carried on. This is done because the slice's data is much smaller than theRuleset's and is deemed a better defect predictor.

The operation described above was repeated 500 times and each time, besides the first iteration, the Ruleset from the previous iteration was maintained. While this time-expensive operation was carried out, changes in the Ruleset was tracked. A best case scenario is where theRulset never changes throughout all 500 runs and a worst case scenario is where the Ruleset changes everytime. The former would result in a consistent horizontal line when graphed whereas the latter would result in a straight diagonal line. The results of our experiment is discussed in the next section.

4.4 Experiment 2: Naive Bayes

The Bayes classifier is a simple statistical-based learning scheme. For this experiment, it was used as a secondary learner, in order to compare its results to that of Prism, our primary learner. Before the experiment could be conducted, the data had to be preprocessed as described in section 4.1 and the train and test sets were derived using the same approach described in the previous section (4.2) for Prism. In this experiment, however, the generation of rules was omitted. Naive Bayes simply trained on the training set obtained after applying K-means on the slices and then tested on. The classifier performs by combining frequency counts for different ranges of attributes within the current dataset in question. If the attribute has not been seen before, the some of those frequency counts will drop.

5. RESULTS

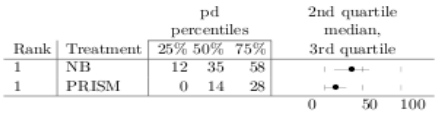
PD and PF values in Figure 1 represent results obtained by training on data set A, and attempting to predict on data set B. It can be shown that neither learner performs well predicting cross company defects.

Also, the cumulative graph in Figure 2 shows the number of times that Ruleset loses when compared to a new set of rules as we iterate through the training set. The graph shows clearly that our learner is *not* converging to an optimal set of rules that willalways win when compared to new set of rules. The best results achieved by Prism occurs approximately between 85000 and 95000 comparisons, which is roughly 8.3% of the total comparisons made - a result absolutely far from desireable.

The diagram in Figure 3 illustrates the sequence of events undertaken by the alogorithm used in training the learner as described in section 4.3. In the diagram, BP represents the backpocket rules, otherwise referred to as the Ruleset and S is the current slice whose PD, after aplying Prism, is to be compared to that of the Ruleset during each iteration. *Better* represents the procedure that accepts a Ruleset and a Slice and determines if the Ruleset's defect prediction probability is better than that of the Slice and returns a boolean value as the result. *Rebuild* represents the procedure that rebuilds the Ruleset by merging its data with data from the Slice passed to it.

6. RELATED WORK

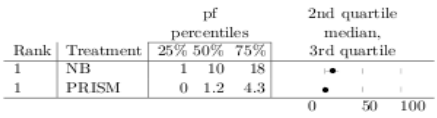
This project is inspired by the Cross-project Defect Pre-



Rank	Treatment	pd percentiles 25%	50%	75%	2nd quartile median, 3rd quartile
1	NB	12	35	58	
1	PRISM	0	14	28	

0 50 100

Figure 1: Probability of Detection (PD) results, sorted by median values.



Rank	Treatment	pf percentiles 25%	50%	75%	2nd quartile median, 3rd quartile
1	NB	1	10	18	
1	PRISM	0	1.2	4.3	

0 50 100

Figure 2: Probability of False Alarm (PF) results, sorted by median values.

Figure 1: Ranked by a Mann-Whitney test at 95% confidence, PD and PF values of prediction based on the ruleset obtained from the PRISM experiment are compared to those obtained from Naive bayes cross-project prediction. Notice that while Naive Bayes ranks higher for PDs, surprisingly PRISM's PF values are more desirable.

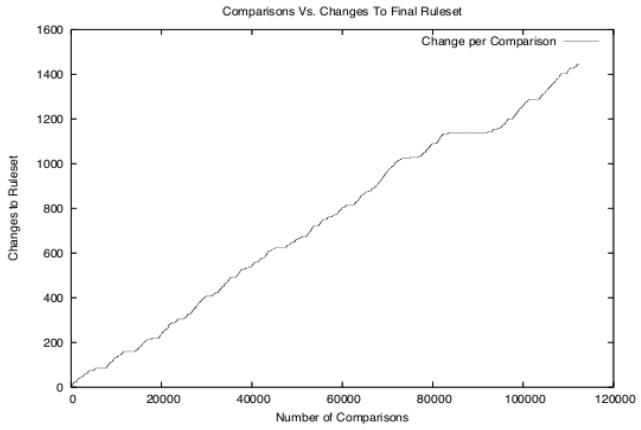


Figure 2: The almost linear line represents the lack of convergence of the experiment's ruleset, hinting at the rulesets inability to describe the entire data.

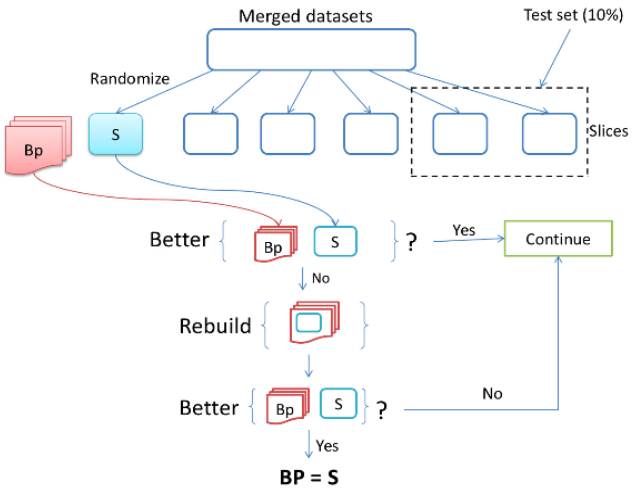


Figure 3: An illustration of the process of the experiment using the incrementally generated/pruned rulest we denote as the "back pocket", or *bp*

diction work conducted by Thomas Zimmerman et. al. who claimed that software defect prediction works well whenever there is sufficient data to train any models and that in the case where data is insufficient, cross-project defect prediction suffices[1]. In their experiment, they ran 622 cross-project predictions for 12 real-world applications including Microsoft's Internet Explorer and Mozilla Foundation's Firefox web browser, and their results indicated that simply using models from projects in the same domain or with the same process does not lead to accurate predictions. With respect to the experiments they conducted, they learned that Firefox could predict defects in Internet Explorer but not vice versa and they succumbed to the conclusion that this is so because Firefox has more files than Internet Explorer has binaries and that the probability of a software with more data is more likely to predict defects in software with relatively less amount of data or modules.

Their study led to conclusions that some attributes were less significant than others which is somewhat obvious but also lead to questions such as why defect-prediction is not transivitve. As in, with regards to the experiments they conducted, File system predicted defects in Printing and Printing predicted Clustering but File system did not predict Clustering.

7. CONCLUSIONS

The results from the experiment shows that our learner fails to find generality in the data. Prism fails to converge to a rule set that generalizes through all datasets partitions. According to our approach and experiments, the prediction methods lack evidence of generality in cross-over company data. This evidence is supported by the divergence of rules and the low probabilities of detection. Based on this results, PRISM is not a suitable learner for predicting software defects on the data of this nature. Our results are similar to those of Zimmerman et. al in that they fail to show evidence of generality in cross-company defect prediction. On the other hand existing research in the field, such as that of Turan et. al, hints at generality in cross-company data. This highlights the importance of requiring confirmation in our experimental results.

8. FUTURE WORK

An alternate approach worth exploring that could shed some light on this experiment is to split up each slice into train and test sets after clustering rather than taking the largest cluster. This method allows for the realization of generality in the case where the learner is able to predict defects for each test fairly well provided some treshhold has been given. Futhermore, unless pressed for time, more runs could be conducted, say 1000 with hopes of finding a converging graph. Moreover, different preprocessing techniques such as microsampling and other learners besides Naive Bayes and Prism could be exploitedto achieve results that could be compared to that of our experiment.

9. ACKNOWLEDGMENTS

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