

*

General Theories of Software Defect Prediction: A Preliminary Report

William Mensah
WVU, Morgantown, WV
wmensah@csee.wvu.edu

Adam Nelson
WVU, Morgantown, WV
anelson8@csee.wvu.edu

Tomi Prifti
WVU, Morgantown, WV
tprifti@csee.wvu.edu

ABSTRACT

This paper presents a preliminary work on defect prediction data using a combination of preprocessing tools. This can yield beneficial results for organizations that want to know how their software will perform *before* it is released. Through this work, and later research, it is hoped that a general theory of software defect prediction will be the outcome, and that the current methods will be more empirically defined as stable or unstable.

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

*A full version of this paper is available as *Author's Guide to Preparing ACM SIG Proceedings Using L^AT_EX₂ ϵ and BibT_EX* at www.acm.org/eaddress.htm

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

Copyright 200X ACM X-XXXXX-XX-X/XX/XX ...\$10.00.

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 PROMISE¹ 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

¹<http://promisedata.org/>

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 of CC data.

3. THE EXPERIMENT

3.1 Preparing the Data

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

- Logging
Replacing all number values N with $\log(N)$ when $N > 0.0001$ or with 0.0001 if otherwise.
- Binning
Splitting each data set into 10 bins (by default) and then building train data from 90% of the data and 10% from what is left.
- Feature Subset Selection
Sample bias via *InfoGain* 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 and why is time wasted generating them before the learner is applied? 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, that is, be missing some attributes or attribute values or it could simply consist of only aggregated values. In addition to that, the data could be inconsistent, and could also contain errors and outliers.

3.2 Discretization techniques

Two discretization method were used for performing the experiments: Equal Interval Width (10 bins) and K-Means. Both methods fall under the unsupervised discretization methods class. Equal bin length is a global technique 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 supplied by the user. It makes no use of the instance class and is thus an unsupervised discretization method. Equal Bin Length is a global discretization method since it produces a mesh over the entire n -dimensional instance space [2]. The k -means on the other hand is a local discretization tool which groups the data into a number of clusters based on some similarity measure. Local discretization methods are applied to local regions of the data. K-Means is grouping the rows in k different clusters using the Euclidean distance as a measure of similarity between the instances. At the beginning the centroids (means) for each cluster are picked at random and then the instances are assigned to the group with the closest centroids to that particular instance.

K-Means will stop iteration through the instance set when the centroids for all the clusters do not change anymore or when a stopping criteria is reached. In both cases of discretization the data is preprocessed by taking the log of each numeric value. Since these two methods do not take into consideration class labels there might be some loss of classification information as a result of grouping instances that are strongly related but belong to different classes. Since our main learning algorithm is Naive-Bayes, both discretization methods greatly improve the performance of the learner. Naive-Bayes is used with both k -means clustering and equal interval width bins on each of the datasets.

3.3 Tools

3.3.1 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 comprising 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 (break ties by choosing the condition with the largest p) 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.

3.3.2 B-SQUARED

In addition to InfoGain, we added one more feature subset selector to our pool of irrelevant-column-pruners to assist us better model our learners. The algorithm for B-squared is pretty simple:

- Replace each class symbol with a utility score: True = 1, False = 0.
- Sort instances by that score and divide them using $N=20\%$ -chops.

- Label all the rows in bin=1 (20%) "best" and the remaining (80%) "rest".
- Collect the frequencies of ranges in best/rest.
- Sort each range (r) by $br/(b+r)$ where
-
- $b = \text{freq}(r \text{ in Best}) / \text{SizeOfBest?}$
-
- $r = \text{freq}(r \text{ in Rest}) / \text{SizeOfRest?}$
- Sort each attribute by the median score of $b2/(b+r)$.
- Reject attributes with less than X% of the max. median score.

Whenever $b < r$, we simply set $b = 0$.

3.4 Experiment 1: InfoGain and Learners

The experiments conducted in this project primarily aim at building software defect prediction models given a number of datasets to train on and to determine which turn out to be better defect predictors. To be able to effectively mine the raw data to be used in our experimentation we had to run a number of preprocessing techniques on them. Specifically, our experiments involved applying different combinations of preprocessing algorithms on the datasets available to us and then reducing the dataset by applying feature subset selections on them, particularly InfoGain. As a result, our experiments can be categorized into 3 groups. The first group being deliberately omitting discretization of the data, clustering and applying Naive-Bayes learner on it. The second group involved discretizing the data, applying InfoGain on the dataset and then applying Naive-Bayes on it. And finally the third group involved feature subset selection via InfoGain, clustering the data and applying Naive-Bayes. It should be noted that for every experiment, a fresh set of data was used. That is, no altered dataset from one experiment was passed on as input to another. Each experiment produced fascinating results which will be discussed later in section 4.

3.5 Experiment 2: InfoGain, B-Squared and Learners

Equipped with 2 features subset selectors: InfoGain and B-squared and 2 learners: NaiveBayes classifier and Prism, we decided to run a number of experiments based on different combinations of these tools. We came up with a total of x combinations in all:

- InfoGain x NaiveBayes
- B-Squared x NaiveBayes
- InfoGain x Prism
- B-Squared x Prism

For each of these combinations, we experimented on an increasing number of attributes ranging from 2 through 12. And finally for each of these combinations generated, we experimented by sub-sampling the datasets using K-nearest neighbor or doing without it; adding 2 more parameters to our combinations. A few of such combinations, for instance, would look like this:

- - InfoGain x NaiveBayes x 2-attributes x 10-nearest-neighbors
- - B-Squared x Prism x 8-attributes x 10-nearest-neighbors

Each of these unique combinations were run 10 times and after compiling the results, the median of each outcome was taken and accepted as the best combination. It is important to note that in each case, or combination for that matter, the number of nearest neighbors selected was set to 10 and remained constant.

4. RESULTS

The following table represents the top 12 attributes selected by the best treatment.

Table 1: Top Features selected by InfoGain and B-Squared

Feat.	Attribute (Shared)	Attributes (Turkish)
1	LOCOMMENT	EXECUTABLE LOC
2	EV	UNIQUE-OPERATORS
3	V	TOTAL-OPERANDS
4	D	TOTAL-OPERATORS
5	I	HALSTEAD-LENGTH
6	E	HALSTEAD-VOLUME
7	B	HALSTEAD-DIFFICULTY
8	T	HALSTEAD-ERROR
9	LOCODE	BRANCH-COUNT
10	UNQ-OPND	DECISION-COUNT
11	TOTAL-OP	CONDITION-COUNT
12	TOTAL-OPND	CYCLOMATIC-COMPLEXITY

5. RELATED WORK

This project is inspired by the Cross-project Defect Prediction 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 transitive. 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.

6. CONCLUSIONS

The study undertaken and discussed in this paper involves investigating a criteria for predicting default-prone modules in both small and large-scale software systems. From the experiments performed on each of the data sets we obtained from NASA and SoftLab, we learned that within-company software defect prediction works when the data accumulated for prior versions of the software in question is available. The results from our self-test experiments validates this conclusion. In other words, creating train and test data from the same data set allows us to successfully build models for software defect prediction. This is especially feasible in cases where the company (whose datasets are being used in the experiment) has been around for years, for example NASA, Microsoft or the Mozilla Foundation; or older versions of its software have already been in use for years. The data generated from such older versions can be analyzed, learned on and used to build defect prediction models in order to predict defects in newer versions of the software.

Some researchers indicate that collecting data from case studies and subjecting it to isolated analysis is not enough because statistics on its own does not provide scientific explanations; and that “we need compelling and sophisticated theories that have the power to explain the empirical observations”[3]. However, in our experiments, we ran 10 tests on 10 datasets, each time with a different number of nearest-neighbors and number of columns to be selected via infogain, and despite the fact that these experiments were conducted on randomly selected objects from the different data sets and resulted in inconsistencies in the accuracy of defect predictions, the average probability of detection was relatively high while the probability of false alarm was relatively low. Of course, these values were obtained after intensive analysis on the results from applying learners on our datasets which we pre-processed using a number of machine learning / data mining methods as mentioned in section 3.1.

7. FUTURE WORK

The experiments for this project were conducted using data obtained from NASA and SoftLab for this project simply because they are 2 complete different companies that operate and function in different ways.

Analyzing the results of the experiments conducted, we are able to determine the number of attributes that matter the most, or in other words, are the most relevant with regards to defect prediction. However, at this stage, we are unable to determine exactly what these attributes are. Although this information can easily be fetched from our feature subset selectors, we weren’t permitted by the constraint of time to explore that path.

In future, similar attributes identified by both InfoGain and B-Squared majority of the time, if not always, can be singled out and used to rebuild the datasets to be used in future experiments when attempting to detect defects in cross-company data.

Another experiment worth considering would involve reducing the size of the training set using both row pruners and column pruners concurrently. This would mean having combinations such as: InfoGain x B-Squared x Prism x 8-attributes x 10-nearest-neighbors. This is technically known as micro-sampling. Other methods for reducing the number of rows within the dataset include the Burak filter

and super-Burak filter, and for reducing the columns: the Greedy Forward Select and Greedy Back Select; but their results will have to be compared to the results we have presented in this document to see how well they rank.

We believe that for better results and much better success rates at predicting software defects, regression algorithms could be applied to the datasets to model the data with the least error. That is, apply the learners to the datasets a number of times and discard arguments to algorithms such as k-nearest neighbor and infogain that germinated less desirable results. Also, the learning algorithms used could be altered to analyze additional data instances added to the data already learned on and determine whether the new data would be beneficial to predicting defects or not. Furthermore, this work could be extended to exploit datasets that comprised of more than 2 classes (TRUE, FALSE) and with multiple class columns (at least 2). Also, for any cross-company software defect prediction to be done, datasets from 2 or more different sources but with similar columns will be required. In the case of our study, the data from SoftLab contained more metrics than that from NASA. This rendered it difficult to build models by learning on the 2 datasets thus experiment on only within-company.

Nonetheless, a number of other rule-based learners could be used rather than *NaiveBayes* as was used for this project. These include, but are not limited to, the *PRISM* algorithm which aims at inducing modular classification rules directly from the training set; *OneR*, *TwoR*, *RIPPER*, and even *HyperPipes*. Due to the constraint on time, we were unable to experiment on such learners but the outcome of applying each of them on the same datasets we used would be of great value to software engineers / data miners.

Finally, because all the data sets we used were complete, the algorithms used in our experiments didn’t account for missing values but in future implementations, this will have to be addressed since ignoring this problem can introduce bias into the models being evaluated and lead to inaccurate data mining conclusions. This can easily be done by either ignoring the entire record, filling in with a global constant (not recommended since most data mining algorithms will regard it as a normal value), filling in with the attribute’s mean or median, filling in with the most likely value (using regression, decision trees, most similar records, etc) or using other attributes to predict the value of the missing data [6].

8. REFERENCES

- [1] Cross-project defect prediction: A large scale experiment on data vs. domain vs. process.
- [2] J. Dougherty, R. Kohavi, and M. Sahami. Supervised and unsupervised discretization of continuous features. *Morgan Kaufmann*, 1995.
- [3] N. E. Fenton and M. Neil. A critique of software defect prediction models. In *IEEE Transactions On Software Engineering*, pages 675–687, October 1999.
- [4] E. Frank, M. Hall, and B. Pfahringer. Locally weighted naive bayes. In *Proceedings of the Conference on Uncertainty in Artificial Intelligence*, pages 249–256. Morgan Kaufmann, 2003.
- [5] G. Gay, T. Menzies, and B. Cukic. How to build repeatable experiments. In *PROMISE ’09: Proceedings of the 5th International Conference on Predictor Models in Software Engineering*, pages 1–9, New York, NY, USA, 2009. ACM.

- [6] J. F. K. Marvin L., Brown. Data mining and the impact of missing data. In *Industrial Management Data Sysyms*, pages 611–621. MCB UP Ltd, October 2003.
- [7] B. Turhan, T. Menzies, A. Bener, and J. Distefano. On the relative value of cross-company and within-company data for defect prediction. *Empirical Software Engineering*, November 2009.