When making up data is a good idea: On the advantages of partially synthetic training sets for software analytics

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***Abstract*—The accurate prediction of where faults are likely to occur in code can help direct test effort, reduce costs and improve the quality of software. One of the approaches to tackle the problem, is based on relying on code metrics especially CK metrics. The aim of the project was to reproduce a package showing comparative study of 6 learners for defect prediction using CK metrics. We successfully made a python pip package and also found an astonishing result. Using SMOTE brought out a clear winner of which learner to use. Other users will now be able to use this package and refute our results as well as get future results in no time. There are still various improvements that can be done which we will be publishing in our next revised package.**

Keywords*—*Defects prediction, code metrics, classification.

I. Introduction

Software defect prediction has been an important research topic in the software engineering field for more than 30 years. It has generated widespread interest for a considerable period of time. The driving scenario is resource allocation: Time and manpower being finite resources, it makes sense to assign personnel and/or resources to areas of a software system with a higher probable quantity of defects. Current defect prediction work focuses on (i) estimating the number of defects remaining in software systems, (ii) discovering defect associations, and (iii) classifying the defect-proneness of software components, typically into two classes defect-prone and not defect-prone.

There have been vast amount of studies done to find the best defect prediction performing model. But literature suggests, that no single prediction technique dominates and making sense of the many prediction results is hampered by the use of different data sets, data pre-processing, validation schemes and performance statistics. We highly agree to this given so many variations available in the data and there are so many classification techniques available like Statistical, Clustering, Rule-Based, Neural Networks, Nearest Neighbour, Support Vector Machines, Decision trees, ensemble methods, to name a few.

This project deals with the third type of problem for code metrics which is classifying the defect-proneness of software components, typically into two classes defective and not defective. Ghotra et al. [7] did a comparative study on various learners for defect prediction. They found out that mainly 6 learners have been performing well namely Naive Bayes, Logistic regression, Support Vector Machines, Nearest Neighbor, decision tree and Random forest. Our project considered Ghotra et al. results as the baseline results.

For the reproduction package we generalised our datasets to be comprised of CK metrics [4]. The CK metrics aim at measuring whether a piece of code follows OO principles. It contains a check of these OO design attributes:

- **Weighted Methods for Class (WMC)** The sum of the complexities of each method in a class. If all the method complexities are considered equal and have the value of 1 (as proposed in the chidamber94), then WMC equals the number of methods in a class.
- **Depth of Inheritance Tree (DIT)** Number of classes that a particular class inherits from.
- **Number of Children (NOC)** The count of immediate subclasses of a class.
- **Response for Class (RFC)** The number of elements in the response set of a class. The response set of a class (as defined in chidamber94) is the number of methods that can potentially be executed in response to a message received by an object of that class.
- **Lack of Cohesion of Methods (LCOM)** For a class C, LCOM is the number of method pairs that have no common references to instance variables minus the number of method pairs that share references to instance variables.
- **Coupling Between Objects (CBO)** For a class C, CBO is the number of classes that are coupled to (i.e. call a function or access a variable of) C.

We created a Pip Package generalised to run any CK metrics based dataset and compare results against 6 learners. Since the classes are imbalanced (less defective class about 15 percent), we used SMOTE [3] (only on Training Data) which is a synthetic minority over-sampling technique.

The remainder of this report is organized as follows. Section II gives a brief related work on defect prediction. Since we found an astonishing results on smote, section III tells about

SMOTE. Experimental setup is provided in section IV. Then results are discussed in Section V. Final conclusion is being discussed in section VI. And section VII talks about future work.

II. Related Work

There are works on defect prediction which employs statistical approaches, capture-recapture (CR) models, and detection profile methods (DPM) [14]. The second type of work borrows association rule mining algorithms from the data mining community to reveal software defect associations [15]. A variety of approaches have been proposed to tackle the third type of problem, relying on diverse information, such as code metrics [11], [5], [8], [12], [13] (lines of code, complexity), process metrics [9] (number of changes, recent activity) or previous defects [10].

Some other research [2] indicate that it is possible to predict which components are likely locations of defect occurrence using a components development history, and dependency structure. Two key properties of software components in large systems are dependency relationships (which components depend on or are dependent on by others), and development history (who made changes to the components and how many times). Thus we can link software components to other components a) in terms of their dependencies, and also b) in terms of the developers that they have in common. Prediction models based on the topological properties of components within them have proven to be quite accurate [17].

Result by Tantithamthavorn et al. [16] also suggested that every dataset comes with different attributes. And also classification techniques often have configurable parameters that control characteristics of these classifiers that they produce. Now time has come to even think about hyperparameter optimization of these techniques and come up with an automated process [6], [1] to tune these parameters for every dataset.

And lastly we found a paper from Ghotra et al. [7] on ”Revisiting the impact of classification techniques on the performance of defect prediction models”. To compare the performance of defect prediction models, they used the Area Under the receiver operating characteristic Curve (AUC), which plots the false positive rate against the true positive rate. They ran the Scott-Knott test to group classification techniques into statistically distinct ranks

III. Case Study of SMOTE in Defect Prediction

IV. Experimental Setup

A. *Data*

We used the data sets available in promise repository[1]. Totally 14 data sets are used.

- ANT
- ARC
- CAMEL
- IVY
- JEDIT
- LOG4J
- POI
- REDAKTOR
- SYNAPSE
- TOMCAT
- VELOCITY
- XALAN
- XERCE

[1](http://openscience.us/repo/defect/ck/

B. *Preprocessing*

Most of the data is in numerals. But to generalize the package we added pre-processing component. We ignore any string columns in the data. We assume the last column in the data sets is the class label. Originally, the target class contains number of defects. We converted them into binary, i.e if target class has defect then it represents 1 otherwise its 0. The package assumes user has preprocessed the data before passing it to the learners.

C. *Classifiers*

We used six classifiers which are mentioned in the paper.

- **Support Vector Machine** (Linear Kernel) In machine learning, support vector machines (SVMs, also support vector networks[1]) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.
- **Logistic Regression** In statistics, linear regression is an approach for modeling the relationship between a scalar dependent variable y and one or more explanatory variables (or independent variables) denoted X.
- **Naive Bayes** In machine learning, naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features.
- **K Nearest Neighbours (K=8)** In pattern recognition, the k-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression.[1] In both cases, the input consists of the k closest training examples in the feature space.
- **Decision Trees (CART, Split Criteria=Entropy)** A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm.

- **Random Forest (Split Criteria=Entropy)** Random forests or random decision forests[1][2] are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

We are using K=8 for K Nearest Neighbours because it was proposed to perform better. Also for Decision trees and Random Forest we are using Entropy as split criteria. Sk Learn provides this feature of selecting the split criteria. We are using Stratified 5- Fold Cross-validation as default. The smoting can be turned on or off by passing smoting flag to the learner. We used Accuracy, Precision, Recall, F1-Measure as our performance metrics.

D. *The Package*

We implemented the package in Python 2.7 but added support for Python 3.x as well. Our package depends on scikit-learn and NLTK. It has been written in pep8 standards to ensure it can be deployed in pip. Users can import Learner module, which requires file name as mandatory parameter, folds and splits as optional parameters. The default values of folds and splits are 5, 5. The package calculates two sets of results, one with smoting and other without smoting. We are using "ball tree" algorithm for smoting. The run method accepts a list of learners to be used.

```
Sample Execution:
    import Learner
    learner = Learner("./data/ant.csv")
    learner.run()
```

The execution procedure is

- Csv file input is parsed. Converting integers to float.
- The data is now shuffled and dropped into bins using StratifiedKFold.
- The unbalanced class is smoted, depends on the user choice.
- Data is passed to each learner and its predicted value for target class is captured.
- A stats file (Scott-Knott) is used to calculate the measures using the predicted target class.
- The stats are aggregated in result object and displayed upon execution of all learners.

There are certain helper functions for user to just calculate one or more of the measures, recall, f score, accuracy, precision. A helper function to display available learners is also implemented.

The results are displayed as two tables, one with smoting and other with out smoting. Each table contain the name of the learner, median value and iqr.

E. *The Measures*

We define the measures as

- **Recall** is the fraction of relevant instances that are retrieved
- **Precision** is the fraction of retrieved instances that are relevant
- **F Score** A measure that combines precision and recall is the harmonic mean of precision and recall
- **Accuracy** is a weighted arithmetic mean of Precision and Inverse Precision (weighted by Bias) as well as a weighted arithmetic mean of Recall and Inverse Recall

F. *The Scott-Knott Test*

After the predicted values are computed, we pass the accumulated values per learner to a Scott-Knott Test which calculates the measures F-Score, Recall, Accuracy, Precision and False Alarm. The results are available to user by helper methods.

G. *The visualizations*

We have included a visualization script, when executed with a pickle file displays the pretty visualization of all the learners. Currently this is not implemented as a part of output. A user has to dump the results in a pickle file and run the script manually.

V. Results

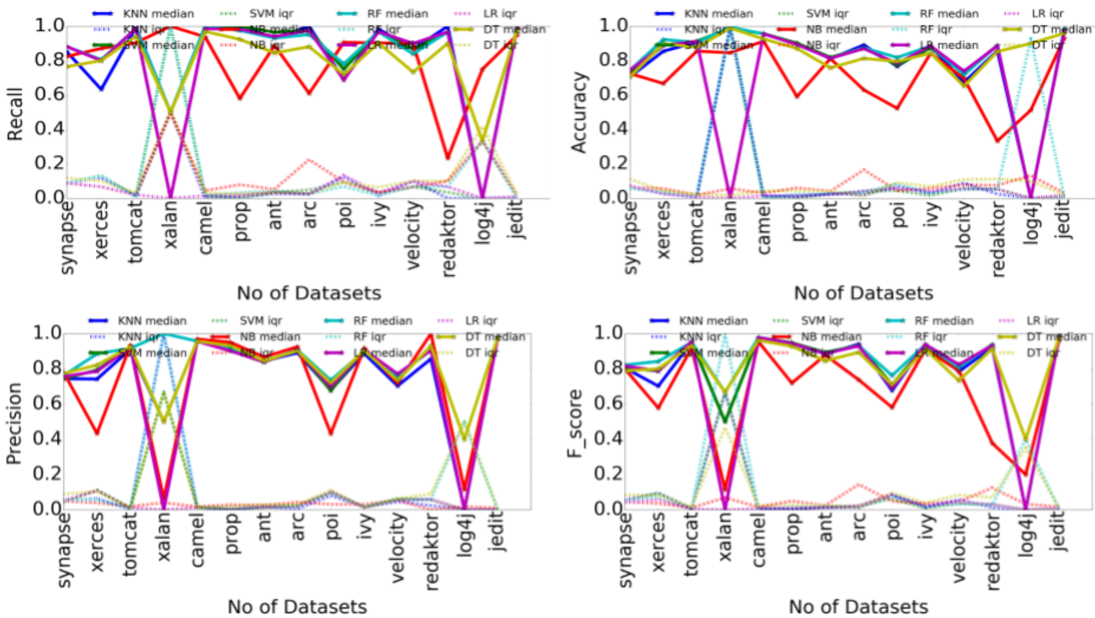
To calculate the measures, Scott-Knott is implemented. The results displayed below, show how Random Forest outperforms other learners.

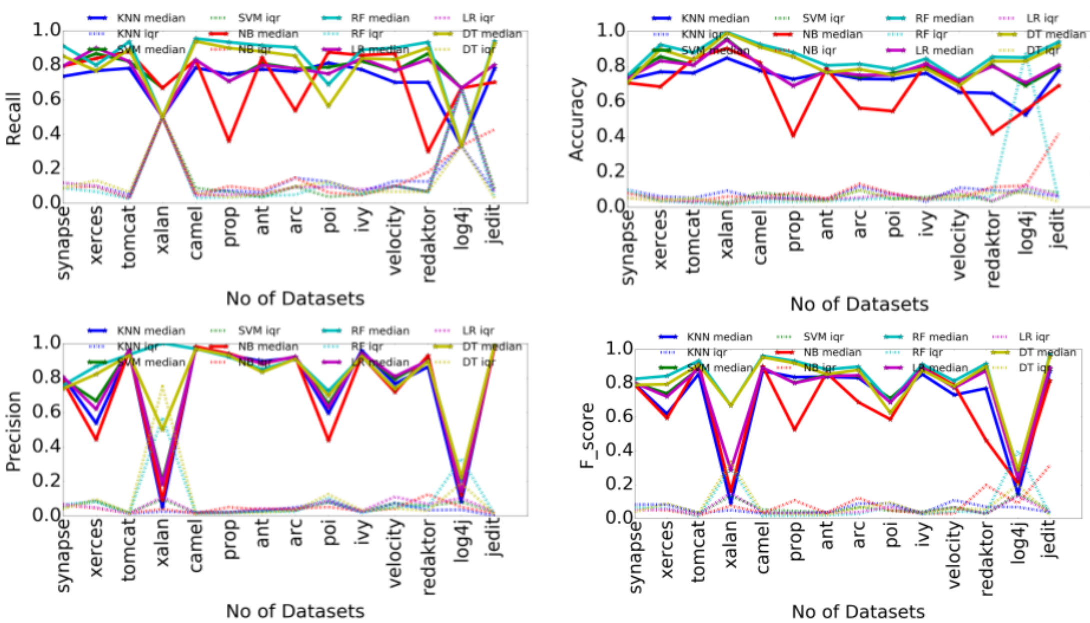
VI. Conclusion

We could reproduce the baseline paper "Revisiting the impact of classification techniques on the performance of defect prediction models". Based on the results we achieved, Random Forest outperformed every other learner. To control the high variance (iqr) and as few data sets have majority of defective class, so to reduce this bias we used smoting. Comparing the run times and performance, we suggest to use Random Forest if the data sets are not huge as it can run time overhead.

VII. Future Work

- We can implement cross project defect prediction.
- We are implementing binary classification, but this can be changed to regression model.
- The algorithm for smoting is hard-coded to "ball tree", this can be parametrized.
- The Split criteria and K value in K Nearest Neighbours are hard-coded, these can be parametrized.
- The learners currently doesn't support any tuning, which can implemented.
- Pretty visualizations can be added.





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Learners	Measures	synapse	xerces	tomcat	xalan	camel	prop	ant	arc	poi	ivy	velocity	redaktor	log4j
KNN	Recall	0.73	0.77	0.78	0.5	0.79	0.75	0.78	0.76	0.81	0.77	0.7	0.7	0.33
	Precision	**0.81**	0.54	0.95	0.05	**0.98**	0.93	**0.9**	**0.92**	0.59	**0.96**	0.77	0.86	0.08
	F_score	0.79	0.62	0.85	0.09	0.87	0.83	0.84	0.83	0.69	0.85	0.73	0.77	0.14
	Accuracy	0.72	0.77	0.76	0.85	0.78	0.73	0.77	0.73	0.73	0.76	0.65	0.65	0.52
Support Vector Machine	Recall	0.79	0.87	0.82	**0.67**	0.83	0.71	0.81	0.78	0.79	0.82	0.77	0.87	**0.67**
	Precision	0.8	0.67	**0.96**	0.2	0.97	0.93	0.89	**0.92**	0.65	0.94	0.79	0.9	0.14
	F_score	0.8	0.74	0.89	0.29	0.89	0.8	0.85	0.84	**0.71**	0.88	0.78	0.89	0.23
	Accuracy	**0.74**	0.85	0.81	0.96	0.81	0.69	0.78	0.74	0.76	0.8	**0.72**	0.81	0.69
Naive Bayes	Recall	0.79	0.84	0.88	**0.67**	0.83	0.36	0.84	0.54	**0.88**	0.86	0.87	0.3	**0.67**
	Precision	0.78	0.44	**0.96**	0.09	**0.98**	**0.94**	0.88	**0.92**	0.44	0.93	0.72	**0.93**	0.12
	F_score	0.79	0.59	0.91	0.16	0.9	0.53	0.86	0.69	0.59	0.89	0.79	0.46	0.21
	Accuracy	0.71	0.68	0.84	0.9	0.82	0.41	0.79	0.56	0.55	0.82	0.7	0.42	0.55
Random Forest	Recall	**0.91**	0.8	**0.94**	0.5	**0.95**	**0.93**	**0.91**	**0.9**	0.69	**0.89**	**0.9**	**0.93**	0.33
	Precision	0.76	**0.87**	0.94	**1**	0.97	0.92	0.85	0.91	**0.72**	0.92	0.74	0.9	0.2
	F_score	**0.82**	**0.84**	**0.93**	**0.67**	**0.96**	**0.93**	**0.88**	**0.9**	0.69	**0.91**	**0.81**	**0.92**	0.25
	Accuracy	**0.74**	**0.92**	**0.88**	**0.99**	**0.93**	**0.88**	**0.81**	**0.81**	**0.78**	**0.84**	**0.72**	**0.85**	**0.85**
Logistic Regression	Recall	0.79	**0.9**	0.82	0.5	0.83	0.71	0.8	0.78	0.75	0.84	0.77	0.83	**0.67**
	Precision	**0.81**	0.62	**0.96**	0.18	0.97	0.93	0.89	**0.92**	0.63	0.94	**0.81**	0.9	0.14
	F_score	0.8	0.72	0.89	0.29	0.89	0.8	0.84	0.85	0.69	0.89	0.77	0.87	0.23
	Accuracy	0.73	0.83	0.81	0.95	0.81	0.69	0.77	0.75	0.75	0.81	**0.72**	0.8	0.71
Decision Trees	Recall	0.85	0.77	0.89	0.5	0.94	0.9	0.88	0.85	0.56	0.84	0.83	0.9	0.33
	Precision	0.74	0.82	0.93	0.5	0.97	0.93	0.83	0.91	0.7	0.93	0.73	0.9	**0.22**
	F_score	0.79	0.79	0.91	**0.67**	0.95	0.92	0.85	0.88	0.62	0.88	0.78	0.9	**0.29**
	Accuracy	0.71	0.9	0.84	**0.99**	0.91	0.85	0.77	0.78	0.75	0.79	0.69	0.83	0.83

Learners	Measures	synapse	xerces	tomcat	xalan	camel	prop	ant	arc	poi	ivy	velocity	redaktor	log4j
KNN	Recall	0.85	0.63	**0.99**	0.5	**1**	**1**	0.93	**1**	0.69	**0.98**	0.87	**1**	0
	Precision	0.74	0.74	0.91	0.5	0.96	0.9	0.84	0.89	0.68	0.89	0.7	0.86	0
	F_score	0.81	0.7	**0.95**	0.5	**0.98**	**0.95**	0.88	**0.94**	0.68	**0.94**	0.78	0.92	0
	Accuracy	0.71	0.85	**0.91**	**0.99**	**0.96**	**0.9**	0.81	**0.89**	0.77	**0.89**	0.67	0.86	0
Support Vector Machine	Recall	**0.88**	0.8	**0.99**	0.5	**1**	**1**	**0.96**	0.98	0.75	0.97	0.87	0.97	0
	Precision	0.74	0.79	0.92	0.5	0.96	0.9	0.84	0.91	0.68	0.91	0.76	0.91	0
	F_score	0.81	0.79	**0.95**	0.5	**0.98**	**0.95**	**0.89**	0.93	0.71	0.93	0.81	**0.94**	0
	Accuracy	0.72	0.89	**0.91**	**0.99**	**0.96**	**0.9**	**0.82**	0.88	0.77	0.87	0.73	**0.89**	0
Naive Bayes	Recall	0.82	**0.87**	0.9	**1**	0.94	0.58	0.89	0.61	**0.91**	0.9	**0.9**	0.23	**0.75**
	Precision	**0.78**	0.43	**0.93**	0.06	**0.97**	**0.95**	**0.87**	**0.93**	0.43	**0.92**	0.72	**1**	0.12
	F_score	0.8	0.58	0.92	0.11	0.95	0.72	0.88	0.74	0.58	0.91	0.79	0.38	0.2
	Accuracy	0.72	0.67	0.85	0.85	0.91	0.59	0.81	0.63	0.52	0.84	0.7	0.33	0.51
Random Forest	Recall	**0.88**	0.81	**0.99**	0.5	**1**	0.97	0.93	0.95	0.78	0.97	0.84	0.97	0
	Precision	0.76	**0.89**	0.92	**1**	0.96	0.91	0.84	0.91	**0.73**	0.9	0.76	0.91	0
	F_score	**0.82**	**0.84**	**0.95**	**0.67**	**0.98**	0.94	**0.89**	0.93	**0.76**	0.94	0.81	**0.94**	0
	Accuracy	**0.74**	**0.92**	**0.91**	**0.99**	**0.96**	0.89	0.81	0.88	**0.82**	**0.89**	0.72	**0.89**	0
Logistic Regression	Recall	**0.88**	0.8	**0.99**	0	0.98	0.98	0.94	0.98	0.69	0.97	**0.9**	0.97	0
	Precision	0.76	0.79	0.92	0	0.96	0.9	0.84	0.91	0.7	0.91	**0.77**	0.91	0
	F_score	**0.82**	0.79	**0.95**	0	**0.98**	0.94	**0.89**	0.93	0.69	**0.94**	**0.82**	0.93	0
	Accuracy	**0.74**	0.89	**0.91**	0	0.95	0.89	0.81	0.87	0.78	**0.89**	**0.74**	**0.89**	0
Decision Trees	Recall	0.77	0.8	0.94	0.5	0.97	0.92	0.84	0.88	0.72	0.9	0.73	0.9	0.33
	Precision	0.77	0.82	**0.93**	0.5	0.96	0.93	0.84	0.9	0.72	0.91	0.73	0.93	**0.4**
	F_score	0.79	0.8	0.93	**0.67**	0.96	0.93	0.84	0.89	0.71	0.91	0.73	0.92	**0.4**
	Accuracy	0.71	0.9	0.88	**0.99**	0.93	0.87	0.76	0.81	0.8	0.84	0.65	0.85	**0.9**

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