Software Defect Prediction on Unlabelled Datasets with Machine Learning Techniques

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Outline

Background

Machine Learning (ML) may help in various SE tasks, such as **software defects prediction and estimation** and **test code generation**.

To accomplish these tasks, **data** have to be **collected** and **properly preprocessed** before the application of machine learning techniques. These activities are **essential to manage missing values** and **inconsistencies amongst data**.

Datasets are composed of **instances** and **features** used to build learning models with Machine Learning techniques.

- *Instances*: modules, such as files, classes and functions;
- *Features:* software metrics.

In SE practice, **datasets may lack information**, such as defectiveness, mandatory for SL techniques.

Labelled dataset are related to software project whose features have been extracted over time, e.g. defect data are included.
New projects or projects with partial historical data may lack some features' data, e.g. defect data are not included.

- Their datasets are called **unlabelled datasets**.

Unlabelled datasets are the **vast majority** of software datasets.

- The extraction of the complete set of features (defectiveness included) implies effort and time.

Only in the last decade unlabelled datasets have been investigated for analysis and (defect) prediction.

Example of Labelled Dataset for Defect Prediction

	$Metric_1$	$Metric_2$	$Metric_3$	$Metric_{\ldots}$	$Metric_M$
$Instance_1$					
$Instance_2$					
$Instance_3$					
$Instance_{\ldots}$					?
$Instance_N$					?

$instance_{Unlabelled}$

				?

$instance_{Buggy-labelled}$

$Metric_{value}$

$instance_{Clean-labelled}$

Prediction models are **trained** with the **labelled instances** and **tested** with the **unlabelled instances**.

An **instance** can be e.g. a file, a class, a function.

Each cell contains a **metric value**.

Example of Unlabelled Dataset for Defect Prediction

	$Metric_1$	$Metric_2$	$Metric_3$	$Metric_{...}$	$Metric_M$
$instance_1$					?
$instance_2$					?
$instance_3$					?
$instance_{...}$					?
$instance_N$					?

$instance_{Unlabelled}$					?

$Metric_{value}$ $\boxed{}$

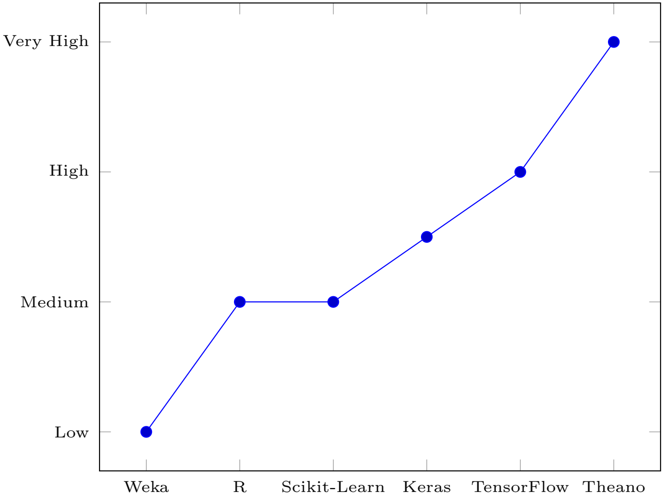
To build a prediction model, different approaches are available.

Approach	Limitation
Cross-project defect prediction	uses specific data from other projects
Expert-based defect prediction	always requires human experts
Threshold-based defect prediction	needs to decide metrics thresholds in advance
Clustering, LAbeling, Metric selection, Instance selection (CLAMI)	**claims to be independent on thresholds**

Why this study?

- Machine learning techniques employed on unlabelled datasets entail a high number of permutations to perform prediction analysis.
- This involves resource and time consumption on average systems and platforms, such as laptops and desktops.
- Cloud computing service allows researches to overcome limitations of these systems by providing large-scale computing and storage.
- Cloud computing service, by enabling time execution reductions, has also given the chance to experiment more techniques, e.g. the python-based ones.

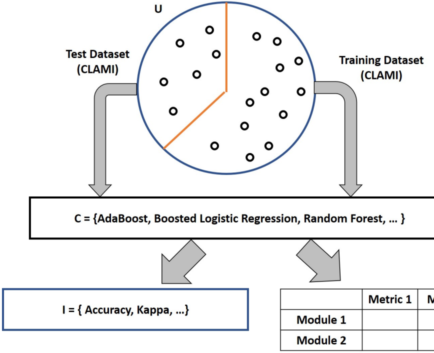
ML Framework: Learning Curve



Experimental Settings

Experimental settings

- Input:
  - U = set of unlabelled instances
  - C = set of machine learning techniques
- Process:
  1. Repeat 2-5 N times for each $u \in U$ to conduct M predictions
  2. Randomly split dataset in training (67%) dataset (with labelled defective instances) and test (33%) dataset
  3. Construct classifier by applying $c \in C$ to training dataset
  4. Assess classifier
  5. Predict test dataset
- Output:
  - Average P (P = set of performance indicators)
  - Test dataset prediction



CLAMI Approach [1]

Unlabelled Dataset ↗ Training Dataset ↘ *to build* ML Techniques

Unlabelled Dataset ↘ Test dataset

ML Techniques ↙ *to predict* Test dataset

[1] J. Nam, S. Kim, CLAMI: Defect Prediction on Unlabeled Datasets, In Proc. 30th IEEE/ACM International Conference on Automated Software Engineering

To generate TRaining (TR) dataset:	To generate Test (T) dataset:
TR1 clustering instances	**T selecting metrics**
TR2 labelling instances in clusters	
TR3 selecting metrics	
TR4 selecting instances (not applicable for this case)	T dataset has the same set of metrics specified in the Training dataset
TR1,TR2 allow to label all instances	
TR3,TR4 allow to remove noisy metrics and instances	

CLAMI: clustering and labelling instances

I = instance index, J = metric index

inst.	m_1	m_2	m_3	m_4	m_5	m_6
A	10	11	4	6	8	?
D	23	10	15	14	10	?
E	15	17	4	8	5	?
F	9	10	9	6	3	?
G	11	13	15	5	8	?
H	14	10	17	9	0	?
I	7	9	21	13	9	?

Example of cutoff threshold is Median$_j$ (cutoff threshold for each m_j)

	m_1	m_2	m_3	m_4	m_5
Median	11	10	15	8	8

Yellow cell$_{i,j}$ = j-th metric value of i-th instance greater than Median$_j$

K = Number of metrics for each instance whose values are greater than the median for each metric

instances	K
A	$K = 1$
D	$K = 3$
E	$K = 2$
F	$K = 0$
G	$K = 1$
H	$K = 3$
I	$K = 3$

Cluster$_z$ = group of instances with K=z identified by different colours [2]

Clusters divided into 2 groups:

1. Clean for K ∈ {0,1,2} (a bottom half)
2. Buggy for K=3 (a top half)

The instances that have larger value on all metrics are more likely to be defective. [2]

[2] M. D'Ambros, M. Lanza, R. Robbes, Evaluating defect prediction approaches: a benchmark and an extensive comparison, Empirical software Engineering, vol. 17, no. 4–5, pp. 531–577, 2012.

CLAMI: metric selection

Gray cell$_{i,j}$ = Metric value that violates the defect-proneness tendency [2]:

- D is Buggy, but $m_2 = 10$ is not greater than Median$_2$
- E is Clean, but $m_1 = 15$ is greater than Median$_1$

inst.	m_1	m_2	m_3	m_4	m_5	m_6
A	10	11	4	6	8	*C*
D	23	10	15	14	10	*B*
E	15	17	4	8	5	*C*
F	9	10	9	6	3	*C*
G	11	13	15	5	8	*C*
H	14	10	17	9	0	*B*
I	7	9	21	13	9	*B*

	m_1	m_2	m_3	m_4	m_5
Median	11	10	15	8	8

MVS$_j$ = the ratio between the number of violation in the j-th metric and the number of metric values in the j-th metric

	m_1	m_2	m_3	m_4	m_5
MVS	$\frac{1}{7}$	$\frac{5}{7}$	$\frac{1}{7}$	$\frac{0}{7}$	$\frac{0}{7}$

Metrics with the minimum MVS are selected for the TR dataset.

inst.	m_4	m_5	m_6
A	6	8	*C*
D	14	10	*B*
E	8	5	*C*
F	6	3	*C*
G	5	8	*C*
H	9	0	*B*
I	13	9	*B*

Each measure can be defined on the basis of the confusion matrix below.

		Prediction: Buggy	Prediction: Clean
Actual value	**Buggy**	True Positive (TP)	False Negative (FN)
	Clean	False Positive (FP)	True Negative (TN)

Kappa statistic is a metric (whose value is $\in$ [0,1]) that compares an Observed accuracy with an Expected Accuracy [3].

It determines how much better a classifier is performing over the performance of a classifier that simply guesses at random.

If **Kappa statistic** $\in$ [0.81, 0.99], then the value indicates an almost perfect agreement.

Accuracy is the percentage of instances correctly classified as either buggy or non-buggy (i.e. clean). $\frac{TP+TN}{TP+FP+TN+FN}$

[3] Landis, J.R.; Koch, G.G. (1977). The measurement of observer agreement for categorical data. Biometrics 33 (1): 159–174

Results

Testbed Description

The experimental Testbed was composed by 2 Machines.

Physical Machine:

- CPU: 2xIntel(R)E5-2640v2 @2.00GHz
- Number of Cores: 32 (HT)
- GPU: 2 x NVIDIA TeslaK40m
- Memory: 128GB RAM.
- Operating System: CentOS Linux release 7.4.1708.
- Python: 2.7.5
- Jupyter-notebook: 5.7.8

Virtual Machine:

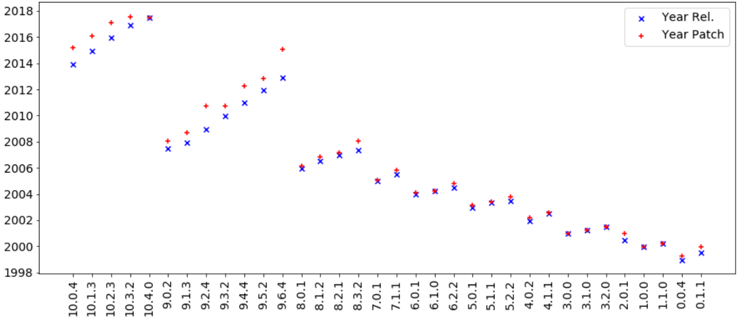
- CPU: 16 V CPU
- Disk: 40 GB
- Memory: 32 GB RAM
- Operating System: Ubuntu Linux release 18.04
- Python: 3.6.7
- R: 3.5.2
- Jupyter-notebook: 5.7.4

hosted on an hypervisor with the following characteristics:

- CPU: 2 x 12 AMD Opteron(TM) Processor 6238
- RAM: 80GB

Considered Geant4 Software Releases

Years over Geant4 software releases



Considered the last patch for each release when available.

Unlabelled Datasets

The data belongs to the **Geant4** software.

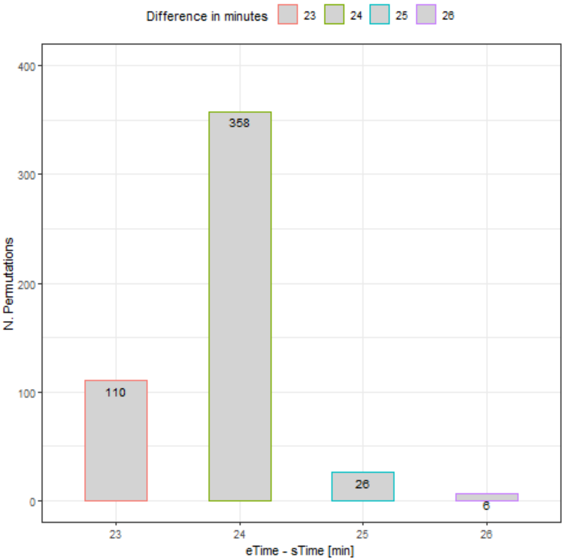
So far collected data for 34 releases by using Imagix4D tool.

Summarized some information for the major release 10 at **class** level.

For each instance the name of class is reported.

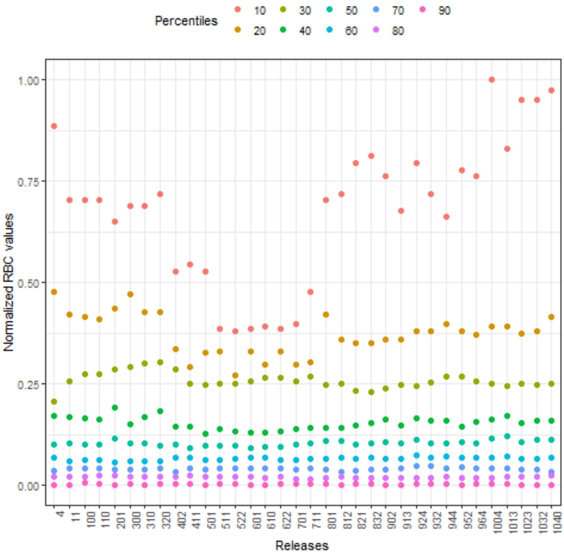
Release	#Instances	Buggy (%)	#Metrics
10.4.0	482	?	66
10.3.2	482	?	66
10.2.3	482	?	66
10.1.3	482	?	66
10.0.4	482	?	66

Preprocessing Time



N. Permutations: 500
N. Releases: 34
N. Cutoff (i.e. percentile): 10
N. Days: 8
Total Preprocessing Time: 11928 [min]
Average Time per permutation: 23.856 [min]
eTime - sTime: time requested to build training and test sets per permutation
Testbed: Virtual machine on cloud infrastructure

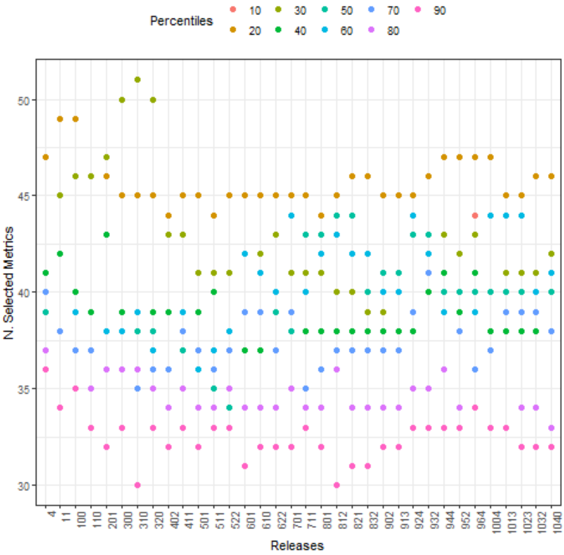
Normalized RBC per percentile



$$RBC = \frac{N.Buggies}{N.Clean}$$

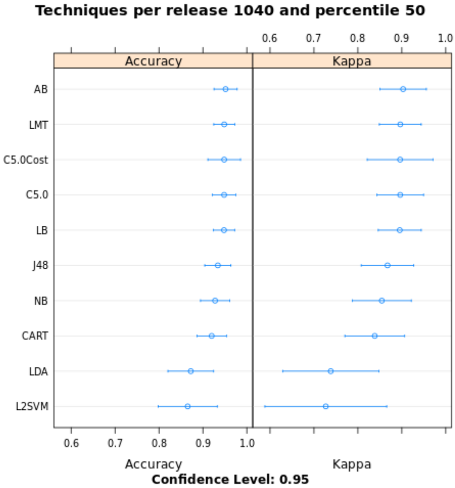
N. Releases: 34
N. Permutations: 500
N. Cutoff 9: percentile at 10, 20, ... , 90
Omitted percentile at 100
N. Training datasets per release: 4500
The greater RBC, the lower the percentile.

Selected metrics



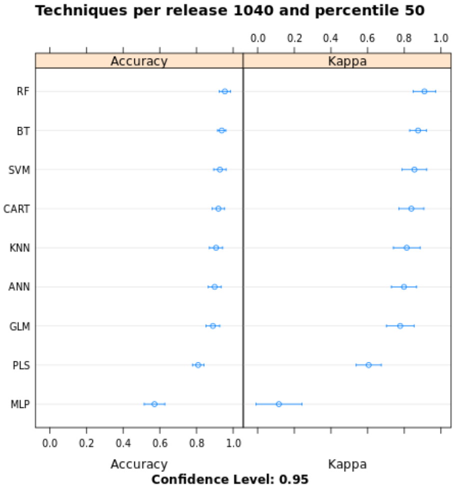
N. Selected Metrics: [45%,77%]
Average Selected Metrics: 38 out of 66
N. Releases: 34
N. Cutoff 9: percentile at 10, 20, ... , 90
Omitted percentile at 100
Metrics Categories: size, complexity, maintainability, object orientation
Class information in the dataset.
The smaller the N. of Selected Metrics, the bigger the percentile.

Comparing Metrics of Predictions



N. Release: 10.4.0
N. Percentile: 50
N. Classification Techniques: 10
Accuracy Processing Time per technique: 36 [sec]
Cross validation: 10
Best ML Technique: Ada Boost
Kappa statistic: almost perfect agreement
Testbed: Virtual machine on cloud infrastructure

Comparing Metrics of Predictions

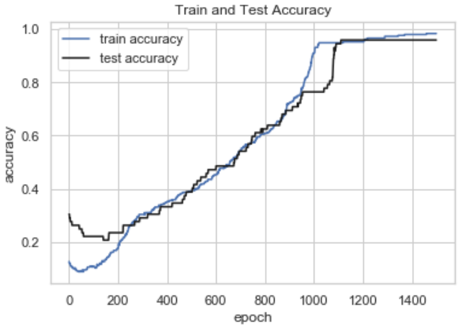


N. Release: 10.4.0
N. Percentile: 50
N. Classification & Regression Techniques: 9
Accuracy Processing Time per technique: 36 [sec]
Cross validation: 10
Best ML Technique: Random Forest
Kappa statistic: almost perfect agreement
Testbed: Virtual machine on cloud infrastructure

Best Techniques

Release	10	20	30	40	50	60	70	80	90	
10.0.4	**AB**	**AB**	C5.0 Cost	C5.0 Cost	**AB**	**LB**	**AB**	LMT	**AB**	
10.1.3	LMT	**AB**	**LB**	**LB**	**LB**	J48	C5.0 Cost	LMT	**LB**	
10.2.3	C5.0 Cost	C5.0 Cost	**LB**	**AB**	C5.0 Cost	**LB**	**LB**	**LB**	**LB**	Class.
10.3.2	**AB**	**AB**	**LB**	C5.0 Cost	**LB**	C5.0 Cost	LMT	**AB**	**LB**	
10.4.0	**AB**	LMT	**LB**	**LB**	**AB**	**AB**	**LB**	**LB**	**LB**	
10.0.4	**RF**	**RF**	**RF**	BT	BT	**RF**	**RF**	BT	**RF**	
10.1.3	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	BT	
10.2.3	PLS	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	Class. & Regr.
10.3.2	PLS	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	SVM	
10.4.0	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	**RF**	MLP	SVM	

AB (Ada Boost), LB (Boosted Logistic Regression) for class. techs.; RF (Random Forest) for class. & regr. techs.
Friedman test to rank the ML techniques.



N. Release: 10.4
N. Percentile: 50
N. Classification Techniques: 10
Accuracy Processing Time: 3 [sec]
Cross validation: 10
Technique: Logistic Regression
Testbed: physical machine with GPU
Processing Time performance improved by 10 compared to the other machine.

Discussion and Future Work

Discussion

AdaBoost, Logistic Regression and Random Forest techniques have achieved the best average accuracy.

The effectiveness of this procedure to detect likely defective instances depends on existing software documentation and datasets, such as release notes and software metrics.

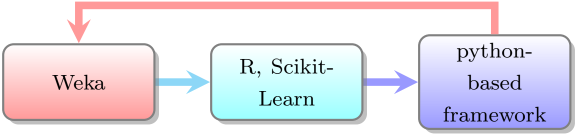
- So far it is possible to detect pieces of software that require particular attention.
- Learning techniques are complementary to existing SE tools and methodology to address SE tasks.

The CLAMI approach enables developers to build a prediction model on unlabelled datasets in an automated manner.

- Once obtained a labelled dataset, one can employ all the other supervised and semi-supervised techniques to detect defective instances.
- However, noise in data can make difference in the results.

What are the pros and cons of using the R or python-based framework?

- It depends on data, problem to be solved, hardware available, data preparation time.
- According to our experience:



Future Works

- Assessment of modules predicted as defective (in collaboration with the Geant4 team)
- Investigating Transfer Defect Learning approach in the clustering phase
- Investigating other statistical tests to detect the best ML techniques
- Exploration of other software datasets with the same features to apply cross project approach
- Adding other tests on GPU-equipped resources
- Making available software written by using the various framework (python, R and java code)

Thanks & Questions

Be curious! Have fun!

Co-authors: Marco Canaparo
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E. Ronchieri, M. Canaparo, D. Salomini, "Software Defect Prediction on Unlabelled Dataset with Machine Learning Techniques," submitted at IEEE NSS MIC 2019

E. Ronchieri, M. Canaparo, D. Salomoni, "Machine Learning Techniques for Software Analysis of Unlabelled Program Modules," under pub Proc. of ISGC 2019

E. Ronchieri, M. Canaparo, D. C. Duma, A. Costantini, "Data mining techniques for software quality prediction: a comparative study," under pub Proc. of IEEE NSS MIC 2018

M. Canaparo, E. Ronchieri, "Data mining techniques for software quality prediction in open source software: an initial assessment," under pub Proc. of CHEP 2018