Predicting Fault-proneness of Object-Oriented System Developed with Agile Process using Learned Bayesian Network

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Abstract: In the prediction of fault-proneness in object-oriented (OO) systems, it is essential to have a good prediction method and a set of informative predictive factors. Although logistic regression (LR) and naïve Bayes (NB) have been used successfully for prediction of fault-proneness, they have some shortcomings. In this paper, we proposed the Bayesian network (BN) with data mining techniques as a predictive model. Based on the Chidamber and Kemerer's (C-K) metric suite and the cyclomatic complexity metrics, we examine the difference in the performance of LR, NB and BN models for the fault-proneness prediction at the class level in continual releases (five versions) of Rhino, an open-source implementation of JavaScript written in Java. From the viewpoint of modern software development, Rhino uses a highly iterative or agile development methodology. Our study demonstrates that the proposed BN can achieve a better prediction than LR and NB for the agile software.

1 INTRODUCTION

In the prediction of fault-proneness (the probability a software component contains at least one fault) as a critical indicator of software quality in object-oriented systems, it is essential to have informative predictive factors (D'Ambros et al., 2012) and a good prediction model. There are many choices for predictive factors, including product metrics, processing and external metrics, and other combinations of factors (Pai and Dugan, 2007). There are also many choices for the prediction model which is as important as the predictive factors in determining the accuracy of the fault-proneness prediction (Menzies et al., 2007).

Logistic regression has been extendedly used for the fault-proneness prediction as a benchmark method. Recently other learners such as decision tree (Singh et al., 2009), random forest (Guo et al., 2004), naive Bayes (NB) (Menzies et al., 2007), neural network (Singh et al., 2008) and support vector machine (Singh et al., 2009) have been successfully used to predict fault-proneness.

These prediction methods have some shortcomings. For example, logistic regression (Hosmer and Lemeshow, 2000) assumes a linear and addictive relationship between predictors and the dependent variable (fault-proneness) on a logistic scale. This assumption is simplistic and presents a critical constraint on the model (Gokhale and Lyn, 1997). Further, the form of logistic regression also makes it difficult to combine qualitative predictors such as processing or external factors with numeric product metrics. NB has the constraints of assuming the conditional independence of predictors and the normal distribution of continuous product metrics as predictors (John and Langley, 1995). Recently, Pai and Dugan (Pai and Dugan, 2007) used LR to construct and parameterize their BN model which did not avoid the typical constraints associated with LR. Other approaches such as random forest and neural network were black-box models and less interpretable although having a good prediction performance.

In this paper, we present a Bayesian network as a learning model. In this model, we examine the performance of BN against the LR and NB using the continual versions of the open-source JavaScript tool, Rhino which has been developed using the agile software development processes. Our study shows that the learned BN was mostly better than the LR and NB from the cross-validation test and from the validation of the continual Rhino versions. The results suggest that our proposed BN is valuable as a

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prediction model of fault-proneness.

The agile software development strategy is an iterative and incremental approach to software development which is performed in a highly collaborative manner that is cost effective and meets the changing needs of its stakeholders (Ambler and R., 2002; Cohn, 2006; Herbsleb, 2001). Agile Alliance defined 12 principles for the agile development process (Cohn, 2006). Olague *et al.* argued that Rhino was a typical software product using the agile development strategy (Olague et al., 2007). Also, their study showed that product metrics (e.g. C-K metrics) at the class level were useful for the fault-proneness prediction of the agile OO systems. Therefore, our case study uses the C-K metrics and the cyclomatic complexity metrics to examine the difference in performance of the prediction methods (LR, NB and our proposed BN) for fault-proneness.

This paper makes the following contributions. First, we present the BN with data mining techniques for learning and optimization and demonstrate its distinguishing features and advantages (more flexible network topology for including quantitative and qualitative predictors, and wide choices of optimal learning algorithms) in comparison to the LR and NB models. Second, based on the cross-validation and the validation of the continual versions of Rhino, we show the superior performance of the learned BN. Third, our study adds to the body of empirical knowledge about the prediction models of fault-proneness.

The rest of this paper is organized as follows. In section 2, we introduce the metrics used, the system under study and the collection of predictors. In section 3, we describe the modelling techniques of LR, NB and BN and compare them. Section 4 presents data analysis procedures and methods employed. The experimental results are reported and discussed in section 5. In section 6, we draw conclusions and suggest some future work.

2 BACKGROUND

2.1 Metrics used

We use the Chidamber and Kemerer's (C-K) metric suite and the cyclomatic complexity metrics at the class level as predictors. The C-K metric suite has been empirically validated to be useful for the fault-proneness prediction in many studies (Basili et al., 1996; Briand et al., 2000; Olague et al., 2007) and so are the cyclomatic complexity metrics (Cardoso, 2006). It is assumed that the higher the metric value, the more fault-prone is the class.

In the C-K metrics implemented for our research (Chidamber and Kemerer, 1994), LCOM represents a later variation of the original LCOM that has been shown to have a better predictability (Harrison et al., 1998). These metrics are listed below:

- WMC (Weighted Methods per Class): The number of methods implemented in a class.
- DIT (Depth of Inheritance Tree): Maximum number of edges between a given class and a root class in an inheritance graph (0 for a class which has no base class).
- NOC (Num. Children): A count of the number of direct children of a given class.
- CBO (Coupling Between Objects): Counts other classes whose attributes or methods are used by the given class plus those that use the attributes or methods of the given class.
- RFC (Response For a Class): A count of all local methods of a class plus all methods of other classes directly called by any of the methods of the class.
- LCOM (Lack of Cohesion of Methods): Number of disjoint sets of local methods, no two sets intersect, and any two methods on the same set share at least one local variable (1998 definition).

The cyclomatic complexity can be extracted from each of the methods (McCabe, 1976).

- CCMIN: Minimum of all cyclomatic complexity values of the methods for a class.
- CCMAX: Maximum of all cyclomatic complexity values of the methods for a class.
- CCMEAN: Arithmetic average of all cyclomatic complexity values of the methods for a class.
- CCSUM: Sum of all cyclomatic complexity values of the methods for a class.

2.2 System under Study

Mozilla's Rhino (Boyd, 2007) was used in our study. Rhino is an open-source implementation of JavaScript completely written in Java. This system has been developed by three programmers, all in separate locations worldwide, following an iterative cycle from 2 to 16 months. The core components and their related bug data of versions 1.5R3, 1.5R4, 1.5R5, 1.6R1, and 1.6R2 of Rhino were analyzed in our study. Fault reports of Rhino exist in the online Bugzilla repository (Bugzilla, 2005). We examined the change logs of each version of Rhino which listed the post-release bugs that were resolved for

the next version. Bug fixes were cross-referenced with classes affected by each bug/fix.

2.3 Collection of Metrics

In our study, we mainly used the open-source Java metric toolkits for extracting the product metrics from Rhino. Spinellis's CKJM (Spinellis, 2006) has been integrated in our program to collect the C-K metrics, and CYVIS, a software complexity visualiser (CYVIS, 2007) has been adapted to extract the cyclomatic complexity metrics (CCMAX, CCMEAN, CCSUM and CCMIN) at the class level from the Java class files.

Table 1: Descriptive Statistics of Predictive Factors Used.

Version	Items	WMC	DIT	NOC	CBO	RFC	LCOM	CCMAX
1.5R3	Mean	14.79	0.81	0.35	6.04	37.29	228.27	20.75
	STDEV	19.55	0.84	1.29	7.24	47.13	811.40	43.88
1.5R4	Mean	14.76	0.85	0.32	6.08	26.91	236.45	21.58
	STDEV	20.06	0.81	1.28	7.61	48.13	851.95	47.72
1.5R5	Mean	14.85	0.86	0.34	5.96	36.86	234.21	19.24
	STDEV	19.93	0.85	1.34	6.84	47.68	914.97	42.29
1.6R1	Mean	15.53	0.82	0.33	6.12	38.87	300.16	20.50
	STDEV	22.84	0.82	1.56	7.54	53.70	1475.65	44.82
1.6R2	Mean	15.84	0.73	0.34	6.33	39.64	303.44	20.77
	STDEV	22.82	0.65	1.58	7.64	54.24	1482.48	46.25

Note that our initial analysis shows that, among the complexity metrics, CCMIN has little contribution to the fault-proneness prediction and hence it is removed from the set of predictors. Also, there is a large correlation between CCMAX, CCMEAN and CCSUM. This leads to the problem of multicollinearity (Olague et al., 2007). After comparing their correlation with the C-K metrics, we select the complexity metric with a good predictability and less redundancy of information. Consequently, CCMAX is chosen in our case study, as shown in Table 1.

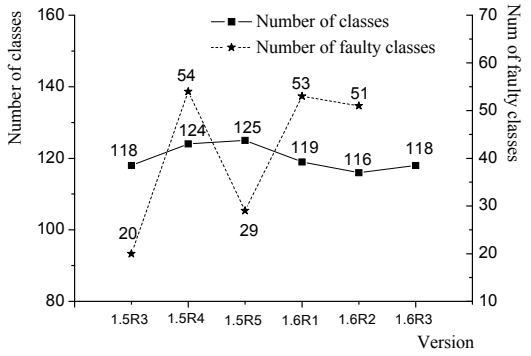


Figure 1: Number of classes and number of faulty classes for core components of the chosen Rhino versions.

As we mainly focus on the fault data of Rhino's core components, the metric data were generated from the same core components only. Table 1 presents the descriptive statistics of predictive factors and Fig. 1 shows the number of classes and the number of faulty classes reported for the core components of the chosen Rhino's versions.

3 MODELING TECHNIQUES

3.1 Logistic Regression

Logistic regression is a technique of probability estimation based on maximum likelihood estimation. In this model, let Y be the fault-proneness of a class as the dependent variable (Y=1 indicating "faulty" and Y=0 "fault-free") and X_i (i=1, 2, …, n) be the predictive factors. LR assumes that Y follows a Bernnouli distribution and the link function relating X_i and Y is the *logit* or log-odds:

$$p(Y=1 \mid \mathrm{X}, \beta) = \mu = \frac{1}{1+e^{-\mathrm{X}\beta}} \quad (1)$$

where X=(1, X_1, X_2, …, X_n), β=(β_0, β_1, β_2, …, β_n)^T and β can be estimated by the maximum likelihood estimator that would make the observed data most likely (Hosmer and Lemeshow, 2000).

The LR curve between p and X_i takes on an S shape. When X_i is not significant, the curve approximates a horizontal line; conversely, the curve presents a steep rise. This S shape is consistent with the assumption about the empirical relationship between predictors and the dependent variable (Briand et al., 2000).

As shown in equation (1), LR assumes that the predictive factors, X, are linearly and addictively related to Y on a logistic scale. This may be too simplistic and can introduce bias (Gokhale and Lyn, 1997). Further, LR uses only quantitative factors for the prediction and constrains the inclusion of other factors such as processing or external factors.

3.2 Naïve Bayes

The Bayes theorem is the theoretic foundation of the naïve Bayes (NB) and also the Bayesian network:

$$P(C \mid X) = \frac{P(X \mid C)P(C)}{P(X)} \quad (2)$$

here C refers to the hypothesis (for the fault-proneness prediction of a class, it denotes the "faulty" or "fault-free" state of the class), X is the evidence, i.e. the predictive factors. $P(X)$ and $P(C)$ respectively refer to a prior probability of X and C.

$P(X|C)$ is the likelihood of X given C, and $P(C|X)$ is the posterior probability of C conditional to any evidence, X.

Naïve Bayes is the simplest BN with a single structure of a target node and multiple evidence nodes (as shown in Figure 2) with the simplistic assumption that the predictive factors are conditionally independent given the class attribute (C="fault-free" or "faulty", see the modeling equation (3)).

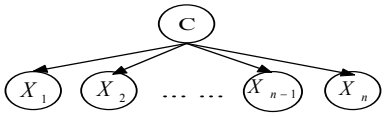


Figure 2: Naïve Bayes: the simplest BN.

$$P(C \mid X_1, \cdots, X_n) = \frac{p(C)}{P(X)} \prod_i P(X_i \mid C) \quad (3)$$

If a predictive factor is continuous, the naïve Bayes approach often assumes that within each class, the numeric predictors are normally distributed (Menzies et al., 2007). Such a distribution can be represented in terms of its mean (μ) and standard deviation (σ). Thus, we can estimate the probability of an observed value from such estimates:

$$p(X = x \mid C = c) = g(x; \mu_x, \sigma_c) \quad (4)$$

$$\text{where} \quad g(x; \mu, \sigma) = (1/(\sqrt{2\pi}\sigma))e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (5)$$

Equation 5 denotes the probability density function (pdf) for a normal (Gaussian) distribution. For the parameters (μ, σ) of the distribution of the continuous metric predictor, we can use the maximum likelihood estimates of the mean and standard deviation (the sample average and the sample standard deviation of the predictor within each class).

The two assumptions of naïve Bayes, namely, the conditional independence and the normal distribution of continuous predictors, may not hold for some domains (predictive metrics) (John and Langley, 1995), thus affecting its prediction performance.

3.3 Learned Bayesian Network

Different from the LR and NB models, Bayesian network (BN) has a flexible network topology. We can use techniques of data mining and optimization to search for an optimal network and parameters to generate a better model. Further, we can use optimal discretization techniques to convert continuous metrics into discrete inputs for the BN.

3.3.1 Basic Model

***Definition* 1.** *A Bayesian Network B* over the set of variables, V, is an ordered pair (B_S, B_P) such that

1. B_S=G(V, E) is a directed acyclic graph, called *the network structure* of B ($E \in V \times V$ is the set of directed edges, representing the probabilistically conditional dependence relationship between random variable (rv) nodes that satisfies the *Markov property*, i.e. there are no direct dependency in B_S which are not already explicitly shown via edges, E) and
2. B_P=$\{\gamma_u : \Omega_u \times \Omega_{\pi_u} \rightarrow [0...1] \mid u \in V\}$ is a set of *assessment functions*, where the state space Ω_u is the finite set of values for the variable u; π_u is the set of parent nodes of variables for u, indicated by B_S; if X is a set of variable, Ω_X is the Cartesian product of all state spaces of the variables in X; γ_u uniquely defines the joint probability distribution $P(u|\pi_u)$ of u conditional on its parent set, π_u.

Let c be the "FAULT" rv of a class and its state space Ω_c be binary, then Ω_c={"faulty", "faultless"}. In a specified BN, if some evidences are given, we can get the posterior probability or belief of c="faulty" as the fault-proneness by calculating the marginal probability:

$$Bel(c = \text{"faulty"}) = \sum_{u_i \in V, u_i \neq c} p(u_1, u_2, ..., c, ..., u_n) \quad (6)$$

where $p(u_1,...,u_n) = \prod_{u_i \in V} p(u_i \mid \pi_{u_i})$ is the joint probability over V.

In practice, we often use the efficient algorithm of exact inference or approximate inference rather than the marginalization of the joint probability to compute *Bel*.

3.3.2 Optimal Discretization by Learning

According to Definition 1, we need to generate the discrete state space Ω_u of u as inputs to the BN when the predictor u is continuous. As the predictive factors used in our study are quantitative metrics, discretization is necessary. There are two classes of discretization methods: supervised and unsupervised. Supervised methods can often achieve a better result than unsupervised methods. Since we have training instances with fault data, we use a supervised method, the optimal multi-splits algorithm proposed by Elomaa and Rousu (Elomaa and Rousu, 1996), which is based on the information theory. This algorithm finds the optimal cut-points of a continuous predictor based on the

discretization's contribution to the classification prediction ("faulty" or "fault-free"). This algorithm can achieve good splits with the optimal number of numeric intervals adaptively adjusted, although we need to set the maximum number of intervals (Elomaa and Rousu, 1996).

The algorithm uses the following as the goodness criterion:

$$Impurity(k,1,i) = \min_{1 \le j < i} (impurity(k-1,1,j) + impurity(1,j+1,i)) \quad (7)$$

where *impurity*(*k*, *j*, *i*) denotes the minimum impurity that results when the training instances *j* through *i* are partitioned into *k* intervals. The best *k*-split is the one that minimizes impurity(*k*,1, *N*), where *N* is the cardinality of the set of values of the continuous predictor. The measure impurity (1, *j*+1, *i*) is the average class entropy of the partition (the conditional entropy given the partition). The minimization of impurity makes minimum the number of bits to encode the splits for the class prediction, thus satisfying Occam's MDL principle of the information theory (Elomaa and Rousu, 1996). The algorithm is recursively run to identify the optimal splits.

3.3.3 GA Learning of the Network Structure

There are two kinds of learning methods for a BN structure: the conditional independence test and the search of the scoring space. Since our goal is to obtain a BN with the best performance, we prefer the latter because it can generate a BN satisfying the Markov property and has an optimal prediction performance. In learning of an optimal BN, a quality score is required to measure the network's quality. There are three kinds of score measures that bear a close resemblance (Bouckaert, 1995): Bayesian approach, information criterion approach, and minimum description length approach. We used the Bayesian approach that uses the posterior probability of the learned network structure given the training instances as a measure of the structure's quality.

There are different algorithms for searching the optimal Bayesian network. In our study, we used the genetic algorithm (GA) because it can better explore the search space and therefore has a lower chance of getting stuck in local optima (Kabli et al., 2007). It is more likely to find the globally optimal solution.

GA is based on the mechanics of natural selection and genetics ("survival of the fittest") and it aims to find the optimum with structured yet randomized information exchange among encoded string structures. It evolves by repeating the following steps: initialization or re-formation of the population, evaluation and selection of individuals, crossover and mutation for generation of offspring until the maximum quality score is obtained or the maximum evolution time is used up. To learn an optimal BN, a connectivity matrix $C=(c_{ij})_{i,j=1,\ldots,n}$ is used to encode the BN: if *j* is a parent node of *i* and *i*>j, c_{ij}=1; otherwise, c_{ij}=0. Then the BN can be represented by the string that consists of the elements of *C* (Larranaga et al., 1996). The inequality *i*>*j* ensures the assumed ancestral order between the variables. Using the general GA for the strings that encode the network structures, we can find the optimal BN. For details of the algorithm, see (Kabli et al., 2007; Larranaga et al., 1996).

In our study, the GA parameters were set as follows: descendant population size=100, population size=20, crossover probability=1, mutation probability=0.1, random seed=1, and run time=50.

3.3.4 Learning of the Network Parameters

After the network structure is found, the conditional probability table (CPT), i.e. implementation of assessment functions in B_P of the BN (Definition 1) needs to be estimated from the database of instances. We used the Bayesian estimator which assumes that the conditional probability of each rv node corresponding to its parent instantiation conforms to the Dirichlet distribution (Korb and Nicholson, 2004) with local parameter independence: $D(\alpha_1,\cdots,\alpha_i,\cdots,\alpha_\tau)$ with α_i being the hyperparameter for state *i*.

The Dirichlet-based parameter estimator assumes independence of local parameters which may not be true in practice. This can result in biased parameters. We can use the classification tree to improve the learning while avoiding this assumption (Korb and Nicholson, 2004).

3.3.5 Probabilistic Inference

The constructed BN model can be used to make an inference of the probability prediction of the query (target) variable ("faulty" or "fault-free"), given the nodes of predictors. There are two kinds of inference: exact inference and approximate inference. Exact inference uses all the information of nodes in the BN to make the probability inference. It has a higher prediction accuracy than the approximate inference, which makes the inference through sampling (Korb and Nicholson, 2004). For a large-scale connected BN, the exact inference is a NP problem and the approximate inference is preferred. But, in our study, as the learned network

is relatively simple (with less than 8 nodes), the exact inference of the BN's polytree (Korb and Nicholson, 2004) is used, partly because it is more efficient than the marginalization of the joint probability.

4 DATA ANALYSIS

The data analysis mainly consists of four steps: feature selection, multicollinearity analysis, modeling and prediction, and evaluation.

4.1 Feature Selection

This step selects the correlative and informative features (factors) for learning and prediction. As Pearson's correlation only measures the linear correlation and may omit nonlinear information, we use the information-based feature selector defined by Quinlan (Quinlan, 1993): Information Gain Ratio (GR). GR takes into account the information that each feature contains and measures the gain ratio given the feature to be assessed.

$$GR(c, f) = (H(f) - H(c \mid f)) / H(f) \quad (8)$$

where $H(c|f)$ is the conditional entropy of the target class c given the feature f (MacKay, 2003).

If a predictor is continuous, it is necessary to discretize the predictor. We used the algorithm presented in section 3.3.2 to discretize the continuous predictor before computing its GR according to equation (8). Table 2 shows the GR of the metrics used for each of the chosen Rhino versions. CCMIN with GR of 0 will be removed from the set of predictors.

Table 2: GR of C-K and Cyclomatic Complexity.

Metrics	1.5R3	1.5R4	1.5R5	1.6R1	1.6R2
WMC	0.23	0.21	0.14	0.23	0.26
DIT	0	0.09	0	0.18	0.12
CBO	0.36	0.24	0.13	0.22	0.20
RFC	0.49	0.24	0.22	0.30	0.26
LCOM	0.28	0.29	0.26	0.20	0.13
NOC	0	0.18	0	0	0
CCMIN	0	0	0	0	0
CCMAX	0.51	0.21	0.12	0.18	0.16
CCMEAN	0.29	0.18	0.12	0.17	0.12
CCSUM	0.11	0.22	0	0.16	0.13

4.2 Multicollinearity Analysis

For multicollinearity analysis, we can use the combination of predictive factors with less redundancy information for a better learning and prediction for LR and NB. The variance inflation factor (VIF) is often used to diagnose the multicollinearity and weaken it (Dirk and Bart, 2004). If multicollinearity exists, by comparing the Pearson's correlation and removing one of the strongly correlative independent variables, or removing the predictor with the maximum VIF value, the multicollinearity can be gradually weakened until VIFs of all the predictors are equal to or smaller than 3. We directly used the result of multicollinearity analysis in (Olague et al., 2007) since it analyzed the same system (Rhino) and similar versions (1.5R3, 1.5R4 and 1.5R5) as ours. Thus, two combinations of C-K metrics were chosen as sets of predictive factors (with VIF<3):

- C-K model 1: CBO, DIT, LCOM, NOC, and WMC;
- C-K model 2: CBO, DIT, LCOM, NOC, and RFC.

For the cyclomatic complexity metrics, Table 2 shows that CCMAX has a larger GR for almost all the Rhino versions, which indicates its higher contribution to the prediction. Further, there are large correlations between CCMAX, CCSUM and CCMEAN (CCMIN is removed as its GR is 0). Since we only need to select the one with a better GR value as the predictor of complexity, we chose CCMAX which also had a weak correlation with the C-K metrics (as shown in Table 3). Thus, CCMAX will be combined with those metrics in C-K model 1 and model 2 to generate new sets of predictors.

Table 3: CCMAX's Correlation with CK-Metrics.

Version	WMC	DIT	CBO	RFC	LCOM	NOC
1.5R3	0.45*	-0.21*	0.47*	0.56*	0.25*	0.22*
1.5R4	0.46*	-0.09*	0.44*	0.57*	0.25*	0.04*
1.5R5	0.50*	-0.07*	0.36*	0.55*	0.29*	0.023
1.6R1	0.46*	-0.05	0.37*	0.53*	0.21*	0.072
1.6R2	0.47*	0	0.38*	0.54*	0.22*	0.074
*: Correlation is significant at the 0.01 level (2-tailed).						

4.3 Modeling and Prediction

For LR and NB, we chose informative combinations (Table 4) of predictive factors with less redundancy information according to Table 2 and the above multicollinearity analysis. As BN can model the complex probabilistic dependent (conditional) relationships between predictors with its flexible network topology, we do not consider the multicollinearity issue and choose all the predictors with nonzero GR values.

The procedure of modeling and predictio

n follows the techniques described earlier in section 3. For the LR, the continuous product metrics are directly used as inputs since its model (equation 1) is based on continuous attributes; for the NB, we use the pdf of a normal (Gaussian) distribution (equation 5) for estimation (equation 3). But for the BN, the algorithm of section 3.3.2 is first used to discretize the continuous predictors and then the modeling is based on the discretized predictors and fault data.

Table 4: Combinations of predictors.

Version	Method	Combination of predictive factors
1.5R3	LR/NB	Model 1: CBO, LCOM, WMC, CCMAX Model 2: CBO, LCOM, RFC, CCMAX
	BN	WMC, CBO, LCOM, RFC, CCMX
1.5R4	LR/NB	Model 1: CBO, DIT, LCOM, NOC, WMC, CCMAX Model 2: CBO, DIT, LCOM, NOC, RFC, CCMAX
	BN	WMC, CBO, DIT, LCOM, NOC, RFC, CCMAX
1.5R5	LR/NB	Model 1: CBO, LCOM, WMC, CCMAX Model 2: CBO, LCOM, RFC, CCMAX
	BN	WMC, CBO, LCOM, RFC, CCMX
1.6R1	LR/NB	Model 1: CBO, DIT, LCOM, WMC, CCMAX Model 2: CBO, DIT, LCOM, RFC, CCMAX
	BN	WMC, CBO, DIT, LCOM, RFC, CCMAX
1.6R2	LR/NB	Model 1: CBO, DIT, LCOM, WMC, CCMAX Model 2: CBO, DIT, LCOM, RFC, CCMAX
	BN	WMC, CBO, DIT, LCOM, RFC, CCMAX

We evaluate the performance of these prediction methods in two ways. The first method applied the usual 10x10 cross-folder validation. In this validation, the dataset was randomly divided into 10 buckets of equal size. 9 buckets were used for training and the last bucket was used for the test. The procedure was iterated 10 times and the final result was averaged. For the construction of model, we used all the instances for learning. The second method used the prediction model of one version to predict the fault-proneness of the relevant classes of the next version (i.e. 1.5R3 for 1.5R4, 1.5R4 for 1.5R5, 1.5R5 for 1.6R1, and 1.6R1 for 1.6R2).

4.4 Evaluation Methods

We use the receiver operative characteristic (ROC) as the evaluation method. ROC was originated from the signal detection theory and statistical decision theory. It assumes that the binary signal is corrupted by Gaussian noise and the recognition accuracy depends on the strength of signal, noise variance, and desired hit rate or false alarm rate. We can set different discrimination thresholds (p_0) to test the sensitivity of the recognition performance of the learner for lowering the effect of noise variance. ROC has been widely used in evaluation of binary classifications as a relatively objective measure.

In a ROC graph, the horizontal axis represents 1-specificity and the vertical axis the sensitivity. If we register whether an artifact is fault-prone as the signal (0 regarded as "fault-free" and 1 as "faulty"), the 1-specificity refers to the ratio of the instances detected as "faulty" among all the fault-free instances (a.k.a. probability of false alarms, *pf*) and the sensitivity refers to the ratio of the instances also detected as "faulty" among all the faulty instances (a.k.a. probability of fault detection, *pd*). *Precision* (*p*) is the proportion of the correctly predicted cases.

Table 5: A Confusion Matrix.

		Predicted	
		fault-free	faulty
Actual	fault-free	*a*	*b*
	faulty	*c*	*d*

pd, *pf*, and *precision* can be calculated from the confusion matrix (Table 5). The *confusion matrix* contains information about actual and predicted classifications from a learner. Each column of this matrix represents the instances in a predicted class, while each row represents the instances in an actual class. From Table 5, we have:

$$pd=d/(c+d),\ pf= b/(a+b),\ p=d/(b+d)$$

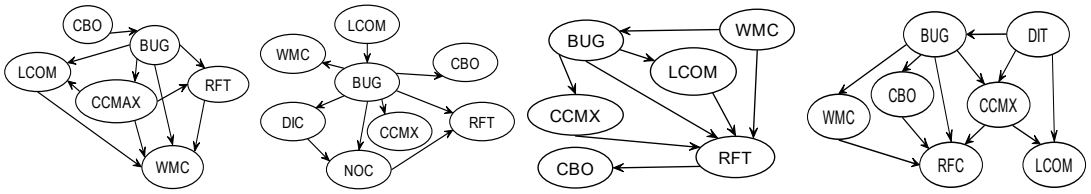
As *p* is an unstable index for measuring the prediction performance (Menzies et al., 2007b), we regard it as a secondary reference.

According to the definition of *pd* and *pf*, their range must be within the interval [0, 1]. A larger *pd* with a lower *pf* indicates a good prediction performance. When the ROC point (*pf*, *pd*) is closer to the upper-left corner (0, 1), called "sweet spot" where *pf*=0 and *pd*=1, the prediction model has a better performance. Often we cannot simultaneously achieve a high *pd* and low *pf*. The balance is based on the Euclidean distance from the sweet spot (0,1) to a pair of (*pf*, *pd*):

$$balance = 1-\sqrt{((pf-0)^2+(pd-1)^2)/2} \qquad (9)$$

A higher balance indicates being closer to the sweet spot and a better prediction performance.

ROC curve corresponds to a sensitivity analysis. We can set different values of the threshold of the fault-proneness, p_0, from 0 to 1, to calculate the value pairs (*pf*, *pd*) for each threshold. Then we use these pairs to construct a curve with *pf* varying from 0 to 1. If the curve is closer to the sweet spot and more convex than another curve, then its performance is better; if the curve is close to the diagonal line from (0, 0) to (1, 1), its prediction performance is no better than a random guess (Heeger, 1998).



1.5R3 1.5R4 1.5R5 1.6R1

Figure 3: Network topologies of the learned BN for the chosen Rhino versions.

ROC area represents the area between the horizontal axis and the ROC curve and it reflects the precision of sensitivity analysis. Its value should be between 0.5 and 1. A value close to 0.5 indicates completely invaluable, a value between 0.5 and 0.7 means lowly valuable, a value between 0.7 and 0.9 means moderately valuable, and a value above 0.9 indicates highly precise (Heeger, 1998).

5 RESULTS AND DISCUSSION

5.1 Learned Models

Table 6 lists the coefficients of model 1 and 2 learned by the LR. Our result shows that model 2 of NB had a better performance than model 1. Thus, it will be used for comparison against the LR and BN models. Table 7 presents the parameters (mean and standard deviation) of pdf for the "faulty" classes (marked with 1) and "fault-free" classes (marked with 0) of model 2 of the NB.

Figure 3 shows the network topology of the learned BN for each of the four test versions (1.5R3, 1.5R4, 1.5R5, 1.6R1).

Table 6: Coefficients (β) Learned by LR.

Version	Model	WMC	DIT	NOC	CBO	RFC	LCOM	CCMAX	Intercept
1.5R3	1	0.02	-	-	0.05	-	0.000	0.02	-3.08
	2	-	-	-	0.10	-0.01	0.002	0.02	-2.93
1.5R4	1	0.02	0.08	1.45	0.26	-	0.002	0.006	-2.4
	2	-	0.04	1.46	0.22	0.02	-0.000	0.004	-2.32
1.5R5	1	0.06	-	-	0.10	-	-0.001	-0.004	-2.63
	2	-	-	-	0.03	0.03	-0.001	-0.005	-2.40
1.6R1	1	0.03	-0.25	-	0.24	-	-0.001	0.001	-1.67
	2	-	-0.26	-	0.20	0.02	-0.001	0	-1.00
1.6R2	1	0.03	-1.0	-	0.17	-	-0.000	0.004	-1.57
	2	-	-1.09	-	0.09	0.03	-0.001	-0.00	-0.91

5.2 Comparison by Cross Validation

Table 8 gives the comparison of the prediction models (LR, NB and BN) from the 10x10 cross-folder validation. The BN achieves a better *pd* (0.55-0.792) than the NB, LR-model 1 and LR-model 2 for the chosen Rhino versions (1.5R3, 1.5R4, 1.5R5, 1.6R1 and 1.6R2). Further, for each version, the proposed BN keeps its *pd* above 0.5 which demonstrates a high stability of prediction performance.

Table 7: Pdf's Parameters for NB-Model 2.

Version	DIT		NOC		CBO		RFC		LCOM		CCMAX	
	1	0	1	0	1	0	1	0	1	0	1	0
1.5R3	-	-	-	-	13.44	4.48	90.58	25.9	1032.5	61.28	69.30	10.78
	-	-	-	-	12.13	4.62	73.65	29.23	1701.0	179.9	83.52	17.74
1.5R4	0.61	1.03	0.48	0.03	10.56	2.52	65.49	14.89	519.26	14.19	36.97	9.40
	0.78	0.77	1.84	0.33	9.33	3.25	58.80	15.98	1232.1	58.78	58.82	32.11
1.5R5	-	-	-	-	11.42	4.15	78.78	23.80	751.4	69.84	35.18	13.76
	-	-	-	-	9.93	4.59	67.24	29.80	1739.2	257.9	53.93	36.94
1.6R1	0.58	1.02	-	-	9.75	2.90	63.67	19.13	599.43	40.11	30.68	12.26
	0.90	0.69	-	-	9.53	3.08	66.43	26.95	2154.1	239.1	51.81	36.60
1.6R2	0.49	0.92	-	-	9.98	3.32	65.32	18.77	601.83	49.51	32.32	11.47
	0.61	0.62	-	-	9.83	3.34	68.33	25.29	2176.3	250.2	54.7	35.51

□:mean; □:standard deviation

Table 8: Comparison of the Models by Cross Validation.

Version	Model	*pd*	*pf*	*precision*	ROC Area	*balance*
1.5R3	LR-model1	0.4	0.031	0.727	0.784	0.399
	LR-model2	0.4	0.031	0.727	0.755	0.399
	NB-model2	0.55	0.061	0.647	0.778	0.546
	BN	0.55	0.061	0.647	0.867	0.546
1.5R4	LR-model1	0.63	0.157	0.756	0.834	0.598
	LR-model2	0.648	0.143	0.778	0.832	0.620
	NB-model2	0.519	0.071	0.848	0.803	0.514
	BN	0.722	0.129	0.813	0.89	0.694
1.5R5	LR-model1	0.276	0.052	0.615	0.756	0.274
	LR-model2	0.31	0.052	0.643	0.767	0.308
	NB-model2	0.345	0.063	0.625	0.697	0.342
	BN	0.552	0.042	0.8	0.806	0.550
1.6R1	LR-model1	0.623	0.152	0.767	0.785	0.594
	LR-model2	0.642	0.182	0.739	0.79	0.598
	NB-model2	0.377	0.061	0.833	0.785	0.374
	BN	0.792	0.242	0.724	0.84	0.681
1.5R2	LR-model1	0.627	0.231	0.681	0.796	0.561
	LR-model2	0.609	0.185	0.721	0.804	0.567
	NB-model2	0.392	0.046	0.87	0.77	0.390
	BN	0.784	0.323	0.656	0.824	0.611

Relatively, for the test versions, both LR and NB have a lower and unstable *pd* value (the LR's *pd* ranges from 0.31 to 0.648 and the NB's *pd* ranges from 0.345 to 0.519). Also, the BN's *balance* is better and more stable than that of both LR and NB although its precision is slightly lower than theirs.

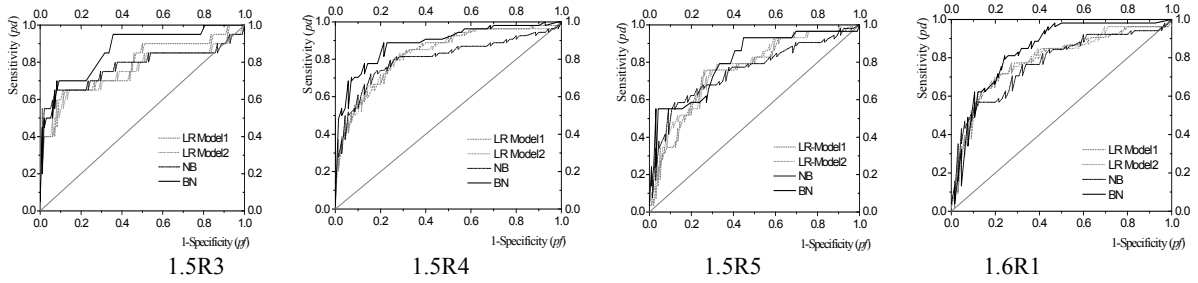


Figure 4: ROC curves of the prediction models (LR, NB and BN) for the chosen Rhino versions.

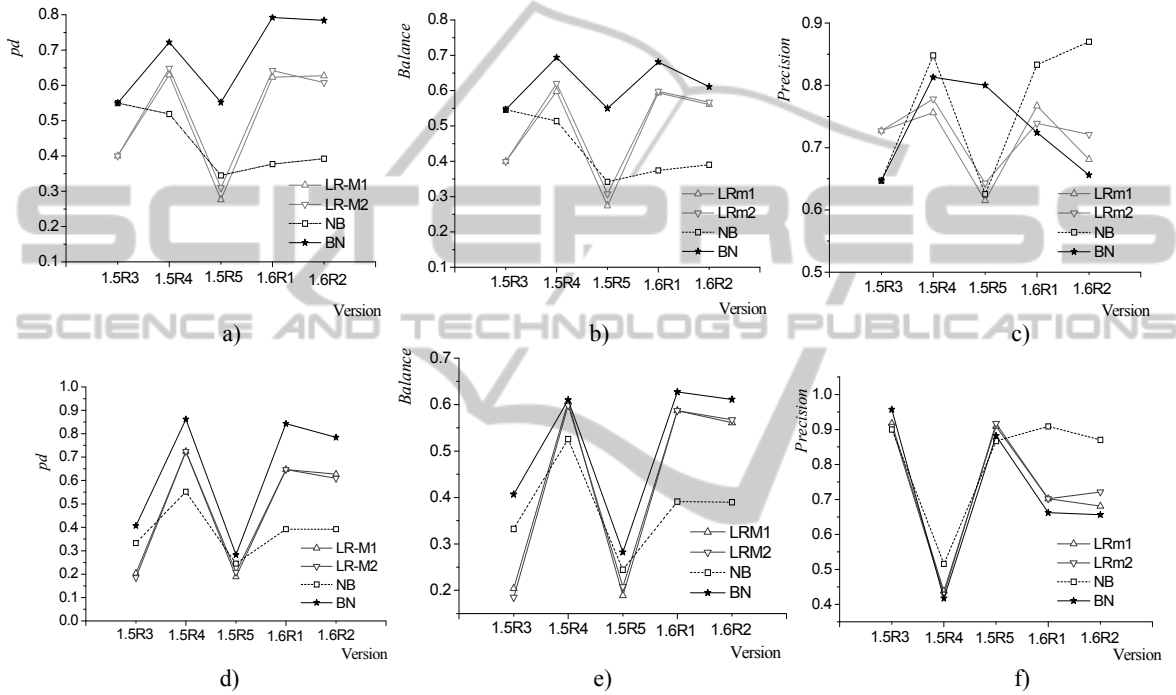


Figure 5: Changes of *pd*, *balance* and *precision* by the cross-validation (a, b, c) and the validations of continual versions (d, e, f).

Figure 4 shows ROC curves of the prediction models for the chosen Rhino versions. The ROC of the BN is mostly closer to the sweet spot and more convex than those of the LR or NB, which further indicates its better performance.

5.3 Validation by Continual Versions

For the fault-proneness prediction, a better method of validation is to use the prediction model learned from one version to test the next version. This validation by continual versions is more useful for testing software developed with a highly-iterative or agile evolutional strategy (Olague et al., 2007). We used the models of LR-model 1, LR-model 2, NB-model 2 and BN learned with the class instances of the core components of one version to test those of the next version with the same predictors (1.5R3 for 1.5R4, 1.5R4 for 1.5R5, 1.5R5 for 1.6R1 and 1.6R1 for 1.6R2). Table 9 shows the results.

For Rhino versions 1.5R3 and 1.5R5, all LR, NB and BN models present a low *pd* and *balance*. However, for these two versions, the BN has a higher *pd* and *balance* than those of LR and NB. For the other versions (1.5R4 and 1.6R1), the BN achieves a much better *pd* and *balance*. The ROC areas of all the models are above 0.7, indicating moderate to high precision.

Figure 5 shows changes of *pd*, *balance* and *precision* of the prediction models in the cross-folder validation (a, b and c) and the validation of continual versions (d, e and f). As seen in Figure 5a vs. 5d, 5b vs. 5e, the *pd* and *balance* curves of the models keep the same shape (two linked "V") and trend. The

Table 9: Validation of the Models by Continual Versions.

Version	Model	*pd*	*pf*	*precision*	ROC Area	*balance*
1.5R3	LR-model1	0.204	0.014	0.917	0.842	0.204
	LR-model2	0.185	0.014	0.909	0.847	0.185
	NB-model2	0.333	0.029	0.9	0.779	0.332
	BN	0.407	0.014	0.957	0.79	0.407
1.5R4	LR-model1	0.724	0.281	0.438	0.795	0.606
	LR-model2	0.724	0.292	0.429	0.795	0.598
	NB-model2	0.552	0.156	0.516	0.745	0.526
	BN	0.862	0.365	0.417	0.806	0.610
1.5R5	LR-model1	0.189	0.015	0.909	0.822	0.189
	LR-model2	0.208	0.015	0.917	0.825	0.208
	NB-model2	0.245	0.03	0.867	0.78	0.244
	BN	0.283	0.03	0.882	0.758	0.282
1.6R1	LR-model1	0.647	0.215	0.702	0.816	0.587
	LR-model2	0.647	0.215	0.702	0.827	0.587
	NB-model2	0.392	0.031	0.909	0.818	0.391
	BN	0.843	0.338	0.662	0.832	0.627

difference in shape between the *pd* and *balance* curves is not large. Further, the core components of Rhino version 1.5R5 have the worst prediction performance either by the cross-folder validation or the validation of continual versions. According to the change log of Rhino (Bugzilla, 2005), since version 1.6R1, there was a major revision (to support ECMAScript for XML (E4X) as specified by ECMA 357 standard) which represents a large change from the earlier versions. This additional functionality (non-fault cause) may result in the low *pd* and *balance* of the models for this version 1.5R5 when making prediction for the next version, 1.6R1 (Figure 5d and 5e).

As can be seen in Figure 5 (5a vs. 5d, 5b vs. 5e), the performance of the prediction models (LR-model 1, LR-model 2, NB-model 2 and BN) by the cross-folder validation is similar to that by the validation of continual versions. Overall, the performance by the cross-folder validation is slightly better than that by the continual validation but for the BN model, this is not the case for version 1.5R4 and 1.6R1. Further, the difference in performance of the prediction models between the cross-folder validation and the validation of continual versions is similar. The BN has achieved a better prediction performance (a larger *pd* and *balance*) for each of the chosen Rhino versions either by the cross-folder validation or by the validation of continual versions. The performance of the NB and LR models is inconsistent (for version 1.5R3 and 1.5R5, NB is better than LR; but for version 1.5R4 and 1.6R1, LR is better than NB).

On the other hand, the *precision* curves of the prediction models present an unstable trend either by the cross-folder validation (Figure 5c) or by the validation of continual versions (Figure 5f). There is no one model whose precision always keeps a better value across the releases of the continual versions. Our analysis suggests that precision is not a good measure for evaluation of the prediction models due to its large standard deviations (unstablility) (Menzies et al., 2007b). Although the BN's precision is sometimes not as good as the LR or NB, it's larger and more stable *pd* and *balance* show that it is valuable for fault-proneness prediction.

6 CONCLUSIONS

This paper presents a learned BN that is based on the data mining techniques (i.e. the optimal discretization and the genetic algorithm) for the prediction of fault-proneness of the agile OO systems. D'Ambros et al. (D'Ambros et al., 2012) illustrated the importance of predictors and Menzies et. al. (Menzies et al., 2007) showed the importance of learners such as naïve Bayes. We extended the previous work by illustrating the improvement of fault-proneness prediction by learning algorithms for feature selection and flexible network structure. Using the continual versions of the open-source system Rhino, we empirically validated the proposed prediction model and compare its performance with LR and NB.

The BN has the advantages of a flexible network structure and wide choices of the learning and optimization algorithms. It also avoids the constraints of LR (logistical-scale linear and addictive relationships between predictors and the dependent variable (fault-proneness)), and the assumptions of NB (the conditional independence and the normal distributions of predictors). Based on the 10x10 cross-validation and the validation of continual versions of the test system, the prediction results of the BN learned by the GA are *positively encouraging*: compared with the NB and LR, the BN has a better and stable *pd* and *balance*. The comparison between the ROC curves (Figure 4) of the prediction models also strengthened this conclusion.

In the previous studies on using BN for fault-proneness, Liu et al. (Liu et al., 2008) used spanning tree to construct their BN, Fenton et al. (Fenton et al., 2008) constructed the network based on the domain knowledge, and Pai and Dugan (Pai and Dugan, 2007) used LR to construct and parameterize their BN model. Compared with the previous studies, we adopted optimal discretization and genetic algorithm (GA) to improve the network (avoiding missing of domain knowledge for

construction of network and local optimization since GA is a globally optimal solution).

By the validation of continual versions, the learned BN method is particularly valuable for the quality evaluation of the OO systems developed with the highly-iterative or agile strategy.

There are several threats to validity. The first threat is that only version series of one software product (Rhino) were used to train and test the model. But the paper's focus is on examination of the learners in agile process software (not generalization of the method to general software modules). We have examined our models across other different software products and statistically demonstrated our approach's advantages in a previous study (Li and Leung, 2011). The second threat is that selection of different predictive factors for different models may damage the validity of the models. But learning was conducted to get the optimal prediction performance. Using the same methods of feature selection and optimal learning algorithms for different models, the prediction performance of the models could be comparable no matter what different predictors were used.

In the future, we will explore the following aspects:

- Using additional benchmark datasets (Basili et al., 1996; Menzies et al., 2007; Pai and Dugan, 2007) from public domain, we will conduct more empirical validation of the BN in comparison with other models for the fault-proneness prediction. This can determine the superiority and stability of BN for the quality assessment of agile software.
- Given the many data mining and optimization algorithms, we will explore the effects of different algorithms on the prediction.
- We will investigate the applicability of BN for the prediction of other aspects (e.g. reliability) of software quality, using additional metrics (e.g. slice-based cohesion and coupling) and qualitative factors.

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