Balancing the trade-off between accuracy and interpretability in software defect prediction, ESE 2019

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ABSTRACT

Can we build accurate ML systems that are also interpretable? This poster summarizes the method described in [5]: a novel classification model is proposed that is both accurate and interpretable. It extends the standard Naive Bayes model to create an ensemble, and then creates a linear approximation. The method, superposed Naive Bayes (SNB) produces a balanced output that is both interpretable and accurate, and its results are discussed in the context of software datasets.

1 INTRODUCTION

Software engineering is one of the domains where machine learning could potentially be useful. Among other use cases, machine learning techniques have been extensively applied in software defect prediction [4]. This paper outlines a novel classification model that first builds an ensemble of Naive Bayes classifiers and then creates a linear approximation, with the intention that the first step improves accuracy, and the second step improves interpretability.

We aim to answer the following research questions:

(1) **How accurate are the current predictors?**
(2) **How do we assess the interpretability of classifiers?**
(3) **How can we balance the trade-off between accuracy and interpretability?**

2 METHOD

We focus on binary classification problems, since multi-class classification problems can be converted to binary classification problems by schemes such as one-vs-rest.

2.1 Naive Bayes

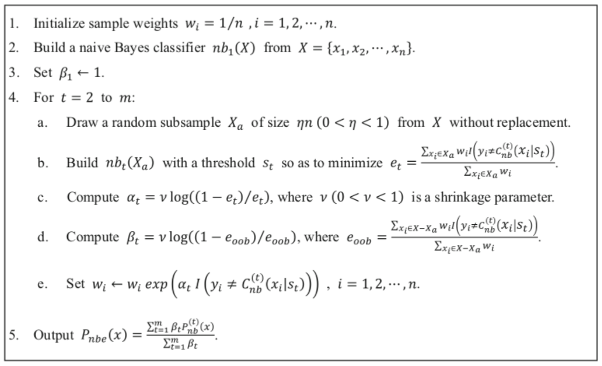
Naive Bayes is a special case of Gaussian Discriminant Analysis with the stronger assumption that the predictor variables are conditionally independent given the target variable. We then use Bayes' rule to compute posterior likelihoods:

$$p(y=1|x_1,\ldots,x_d) \propto p(y=1)\prod_{i=1}^{d} p(x_i|y=1) \tag{1}$$

From this, we compute the log-odds ratio:

$$\frac{\log p(y=1|x_1,\ldots,x_d)}{\log p(y=0|x_1,\ldots,x_d)} = \log\frac{p(y=1)}{p(y=0)} + \sum_{i=1}^{d}\log\frac{p(x_i|y=1)}{p(x_i|y=0)} \tag{2}$$

which can be expressed as



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1. Initialize sample weights $w_i = 1/n$ , $i = 1, 2, \cdots, n$.
2. Build a naive Bayes classifier $nb_1(X)$ from $X = \{x_1, x_2, \cdots, x_n\}$.
3. Set $\beta_1 \leftarrow 1$.
4. For $t = 2$ to $m$:
   a. Draw a random subsample $X_a$ of size $\eta n$ $(0 < \eta < 1)$ from $X$ without replacement.
   b. Build $nb_t(X_a)$ with a threshold $s_t$ so as to minimize $e_t = \frac{\sum_{x_i \in X_a} w_i I\left(y_i \neq C_{nb}^{(t)}(x_i|s_t)\right)}{\sum_{x_i \in X_a} w_i}$.
   c. Compute $\alpha_t = \nu \log((1-e_t)/e_t)$, where $\nu$ $(0 < \nu < 1)$ is a shrinkage parameter.
   d. Compute $\beta_t = \nu \log((1-e_{oob})/e_{oob})$, where $e_{oob} = \frac{\sum_{x_i \in X-X_a} w_i I\left(y_i \neq C_{nb}^{(t)}(x_i|s_t)\right)}{\sum_{x_i \in X-X_a} w_i}$.
   e. Set $w_i \leftarrow w_i\, exp\left(\alpha_t\, I\left(y_i \neq C_{nb}^{(t)}(x_i|s_t)\right)\right)$ , $i = 1, 2, \cdots, n$.
5. Output $P_{nbe}(x) = \frac{\sum_{t=1}^{m} \beta_t P_{nb}^{(t)}(x)}{\sum_{t=1}^{m} \beta_t}$.
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Figure 1: Naive Bayes ensemble algorithm

$$W(X) = W_0 + \sum W_i(x_i) \tag{3}$$

Each term here is called a weight of evidence. A positive $W_i(x_i)$ indicates that the state of x_i is evidence in favor of the hypothesis that $y = 1$. The total sum of the weights of evidence gives a raw score $W(X)$, a higher value indicating a higher posterior likelihood that $y = 1$.

There are some issues with the standard Naive Bayes. One major issue is with post-processing of the raw score. Class membership probability estimates can be obtained by sigmoid calibration of the raw scores:

$$p_{nb}(X) = \sigma(c_0 + c_1 W(X)) = \frac{1}{1+\exp(-(c_0 + c_1 W(X)))} \tag{4}$$

Given a discrimination threshold t, we predict $C_{nb}(X|t) = 1$ if $p_{nb}(X) \geq t$.

2.2 Naive Bayes ensemble

Creating ensembles can be done in several ways involving random selection of feature subsets to train different models. Boosting is one such technique that incrementally builds an ensemble by reweighting each training sample; correctly classified samples are given a lower weight, and incorrectly classified samples are given a higher weight. AdaBoost [1] uses a multiplicative weight update rule. An extension of this called stochastic gradient boosting uses a gradient descent approach at each iteration.

Figure 1 shows the algorithm to create a Naive Bayes ensemble.

2.3 Superposed Naive Bayes

We then create a single Naive Bayes model by superposing the different models, weighted by the weights of evidence.

[0] Toshiki Mori and Naoshi Uchihira. Balancing the trade-off between accuracy and interpretability in software defect prediction. Empirical Software Engineering, 24(2):779–825, 2019.

From (3) and (4), the output of the Naive Bayes ensemble is

$$p_{nbe}(X) = \frac{\sum_{t=1}^{m} \beta_t p_{nb}^{(t)}(X)}{\sum_{t=1}^{m} \beta_t} = \frac{\sum_{t=1}^{m} \beta_t \sigma \left(c_0^{(t)} + c_1^{(t)} \sum_{i=0}^{d} W_i^{(t)}(x_i) \right)}{\sum_{t=1}^{m} \beta_t} \quad (5)$$

We now approximate the sigmoid function by its first order Taylor series approximation about c_0:

$$\begin{aligned} \sigma\left(c_0^{(t)} + c_1^{(t)} W^{(t)}(X)\right) &= \sum_{n=0}^{\infty} \frac{\sigma^{(n)}(c_0^{(t)})}{n!} \left(c_1^{(t)} W^{(t)}(X)\right) \\ &\approx \sigma(c_0^{(t)}) + \left(c_1^{(t)} \sigma(c_0^{(t)}) \left(1 - \sigma(c_0^{(t)})\right)\right) W^{(t)}(X) \end{aligned} \quad (6)$$

which is of the form $a_t + b_t W^{(t)}(X)$.

3 EXPERIMENTAL SETTINGS

We use 13 datasets from two sources: a cleaned version of the NASA MDP datasets provided by [6], and the JIT datasets provided by [3]. From the first source, 11 datasets that were initially from various NASA systems, are collected. We use 2 datasets from the second source: Bugzilla and Columba.

We evaluate predictive accuracy using 5-fold cross-validation. The entire 5-fold cross-validation is repeated 5 times with different random subsets. We use the area under receiver operating characteristics (AUC-ROC) as the performance measure, and use the Scott-Knott test [2] to partition the predictors into statistically distinct ranks at a significance level of 5%. We rank predictors using a double Scott-Knott test. At the first level, the Scott-Knott test is performed on each dataset. At the second level, we run the test on the results of the first level to find the statistically distinct ranks of the predictors.

To evaluate interpretability, we use Lipton's criteria: model transparency (can a user understand the model?), component transparency (can a user understand each component?), and algorithmic transparency (is the algorithm deterministic?).

4 RESULTS

4.1 How accurate are current defect predictors?

The AUC-ROC values vary considerably among classifiers and datasets, and even among different subsets in 5-fold cross-validation.

Figure 2 gives the result of the second Scott-Knott test on the reversed fractional ranks (RFRs) of the first Scott-Knott tests. Classifiers are sorted in descending order of mean RFR.

4.2 How can we assess the interpretability of classifiers?

We assume the interpretability of the classifiers is ranked by the number of "Yes" counts to the qualitative indicators discussed, and an RFR is calculated based on this. Rule-based classifiers score the highest. Naive Bayes tree-based models get a Yes on the first and third questions, and SNB gets a Yes on the first two.

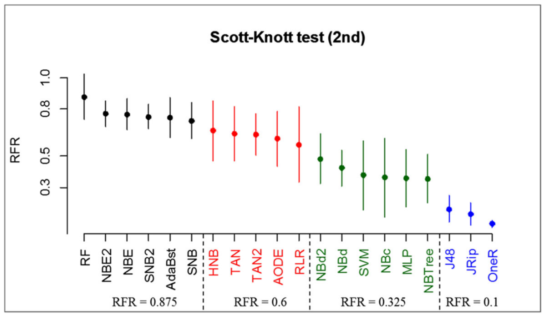

Figure 2: Result of second Scott-Knott test on RFRs of the first Scott-Knott tests

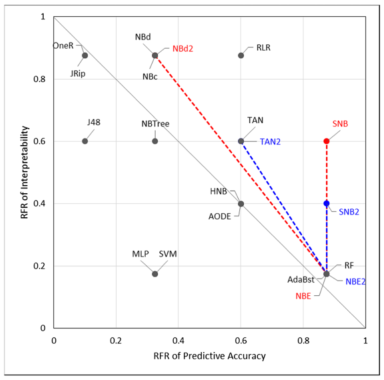

Figure 3: Scatterplot of RFRs of accuracy and interpretability

4.3 How can we balance the trade-off between accuracy and interpretability?

We combine the results of the first two with a scatter plot of the RFRs. The diagonal line $y = 1 - x$ is the typical belief of the trade-off between accuracy and interpretability.

Clearly, from Figure 3, SNB being in the top-right, achieves a high interpretability as well as accuracy.

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