

## IMPROVED BAYESIAN FEATURE SELECTION AND CLASSIFICATION METHODS USING BOOTSTRAP PRIOR TECHNIQUES

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**ABSTRACT:** In this paper, the behavior of feature selection algorithms using the traditional t-test, Bayesian t-test using MCMC and Bayesian two-sample test using proposed bootstrap prior technique were determined. In addition, we considered some frequentist classification methods like k- Nearest Neighbor (k-NN), Logistic Discriminant (LD), Linear discriminant analysis (LDA), Quadratic discriminant analysis (QDA) and Naïve Bayes when conditional independence assumption is violated. Two new Bayesian classifiers (B-LDA and B-QDA) were developed within the frame work of LDA and QDA using the bootstrap prior technique. The model parameters were estimated using Bayesian approach via the posterior distribution that involves normalizing the prior for the attributes and the likelihood from the sample in a Monte-Carlo experiment. The bootstrap prior technique was incorporated into the Normal-Inverse-Wishart natural conjugate prior for the parameters of the multivariate normal distribution where the scale and location parameters were required. All the classifiers were implemented on the simulated data at 90:10 training-test data ratio. The efficiencies of these classifiers were assessed using the misclassification error rate, sensitivity, specificity, positive predictive value, negative predictive value and area under the ROC curve. Results from various analyses established the supremacy of the proposed Bayes classifiers (B-LDA and B-QDA) over the existing frequentists and Naïve Bayes classification methods considered. All these methods including the proposed one were implemented on a published binary response microarray data set to validate the results from the simulation study.

**KEYWORDS:** *k*-Nearest Neighbour, Bayesian Linear Discriminant Analysis, Bayesian Quadratic Discriminant Analysis, Naïve Bayes, Bootstrap prior.

### 1. INTRODUCTION

Simultaneous feature selection and classification are two main problems in data mining. The two problems are related in the sense that, when good features are identified the classification scheme or method often yields high accuracy. This implies the performance of a feature selection algorithm can be assessed using the accuracy of resulting

classification method that utilizes the identified subset features. Several studies have considered various feature selection algorithm or classifiers (classification method) that simultaneously select and classify clinical or non-clinical classification problems. In the recent time, Yahya ([Yah12]) considered feature selection algorithm using AUC (Area under the ROC Curve).

In this paper, we proposed a novel feature selection algorithm and two classification methods under the frame work of Bayesian discriminant analysis.

### 2. FEATURE SELECTION

Feature selection process is the removal of features that are irrelevant with respect to the output variable from the data set. Feature selection can be extremely useful in reducing the dimensionality of the data to be processed by the classifier, reducing execution time and improving predictive accuracy (inclusion of irrelevant features can introduce noise into the data, thus obscuring relevant features). Many feature selection methods have been proposed from the Bayesian and frequentist perspectives. Within the frequentist; p-value method (Golub [G+99]), Wilcoxon-Mann-Whitney rank sum test (Thomas [T+01]), the student-t test or its equivalent; the welch test (Nguyen & Rocke [NR02], Yahya et al. [Y+11]). Similarly within Bayesian; Cyber-T a Bayesian version of t statistic by (Baldi and Long [BL01]), among other methods based on t or ANOVA are ([WS03]), ([N+01]), ([Smy04]).

### 3. CLASSIFICATION

Predicting a qualitative response for an observation can be referred to as classifying that observation, since it involves assigning the observation to a category, or class. On the other hand, often the methods used for classification first predict the probability of each of the categories of a qualitative variable, as the basis for making the classification (Hastie et al. [H+13]). Classification can also viewed

from the Bayesian and frequentist perspective with distinction only in the incorporation of prior information to the information observed from the data. Some frequentist classification methods are Logistic Discriminant (LD),  $k$ -Nearest Neighbour ( $k$ -NN), Support Vector Machine (SVM) and Artificial Neural Network (ANN) ([D+02]; [SS05]; [Vap98]). Bayesian classifiers are, Linear and Quadratic Discriminant Analysis (LDA & QDA), Bayesian Network ([H+13]; [Bar12]).

#### 4. METHODOLOGY

##### 4.1. The proposed feature selection algorithm

We considered two class problem with  $c = c_1, c_2$  where each feature  $X_j$   $j = 1, \dots, q$  can be partition into two namely  $X_{0j}$  and  $X_{1j}$ . Often, within two samples testing paradigm assumption of independency and normality are required, that is,

$$x_{1cj}, x_{2cj}, \dots, x_{ncj} \sim N(\mu_c, \sigma_c^2)$$

The quantity really of interest is the posterior distribution of

$$\delta = \mu_{c_1} - \mu_{c_2}.$$

The hypothesis of interest under this scenario might be of the form

$$H_0: \delta = 0 \text{ against } H_1: \delta \neq 0 \quad (1)$$

Testing the above hypotheses in (1) using the Bayesian method requires computing  $p(\delta|D)$  define as the posterior distribution of  $\delta$  given data  $D$  ([Lee12]). To achieve this, we can estimate the posterior distribution of the parameters  $\mu_{c_1}$  and  $\mu_{c_2}$  separately using conjugate prior technique. The conjugate Bayes estimation procedure for estimating parameters  $\mu$  and  $\sigma^2$  of a normal random sample  $D = x_1, x_2, \dots, x_n$  requires estimation of the posterior distribution of  $\mu$  and  $\sigma^2$  given  $D$ . The posterior density following Bayes theorem is;

$$p(\mu, \sigma^2|D) = \frac{p(\mu, \sigma^2) * p(D|\mu, \sigma^2)}{\int_{\mu} \int_{\sigma^2} p(\mu, \sigma^2) * p(D|\mu, \sigma^2) d\mu d\sigma^2} \quad (2)$$

Bolstad ([Bol04]), Murphy ([Mur07]) and Lesaffre & Lawson ([LL13]) among others used the Normal-Gamma;  $NG(\mu_0, n_0, \alpha_0, \beta_0)$  natural conjugate prior for  $\mu$  and  $\lambda = \sigma^{-2}$  given as;

$$p(\mu, \lambda) = \frac{[\lambda n_0]^{1/2}}{\sqrt{2\pi}} \exp\left[-\frac{\lambda n_0}{2}(\mu - \mu_0)^2\right] \times \frac{\beta_0^{\alpha_0} \lambda^{\alpha_0-1} \exp(-\lambda \beta_0)}{\Gamma \alpha_0} \quad (3)$$

The posterior distribution is of the form  $NG(\mu_n, n_n, \alpha_n, \beta_n)$ . Where,  $\mu_n = \frac{n_0 \mu_0 + n \bar{y}}{n_0 + n}$ ;  $n_n = n_0 + n$ ;  $\alpha_n = \alpha_0 + \frac{n}{2}$  and  $\beta_n = \beta_0 + \frac{1}{2} \sum_{i=1}^n (x_i - \bar{y})^2 + \frac{n_0 n (\bar{x} - \mu_0)^2}{2(n_0 + n)}$

Thus the Bayes estimate of  $\mu$  is;

$$\hat{\mu} = \frac{n_0 \mu_0 + n \bar{x}}{n_0 + n} \quad (4)$$

Similarly, the Bayes estimate of  $\sigma^2$  is determined by;

$$\hat{\sigma}^2 = \frac{\beta_0 + \frac{1}{2} \sum_{i=1}^n (x_i - \bar{x})^2 + \frac{n_0 n (\bar{x} - \mu_0)^2}{2(n_0 + n)}}{\alpha_0 + \frac{n}{2}} \quad (5)$$

The empirical Bayes version of the above estimate involves estimating the prior parameters  $\pi = (\mu_0, n_0, \alpha_0, \beta_0)$  from the data. Thus the empirical Bayes estimate of  $\mu$  and  $\sigma^2$  are;

$$\hat{\mu}_{EB} = \frac{\hat{n}_0 \hat{\mu}_0 + n \bar{x}}{\hat{n}_0 + n} \quad (6)$$

and,

$$\hat{\sigma}_{EB}^2 = \frac{\hat{\beta}_0 + \frac{1}{2} \sum_{i=1}^n (x_i - \bar{x})^2 + \frac{\hat{n}_0 n (\bar{x} - \hat{\mu}_0)^2}{2(\hat{n}_0 + n)}}{\hat{\alpha}_0 + \frac{n}{2}} \quad (7)$$

The proposed bootstrap Bayesian version of the estimate of  $\mu$  and  $\sigma^2$  involves the following steps;

1. Generation of bootstrap samples from the original data  $B$  desired times,
2. Estimating the hyperparameters (prior parameters) each time the samples are generated using Maximum Likelihood (ML) method,
3. Updating the posterior estimates using the hyperparameters in step (2) above using (8 & 9) and
4. Then obtaining the proposed bootstrap empirical Bayesian estimates  $\hat{\mu}_{BT}$  and  $\hat{\sigma}_{BT}^2$  using;

$$\hat{\mu}_{BT} = \frac{1}{B} \sum_{j=1}^B \hat{\mu}_{EBj} \quad (8)$$

$$\hat{\sigma}_{BT}^2 = \frac{1}{B} \sum_{j=1}^B \hat{\sigma}_{EBj}^2 \quad (9)$$

$$\hat{\mu}_{BT} = \frac{1}{B} \sum_{j=1}^B \left[ \frac{n\bar{x}}{\hat{n}_{0j} + n} + \frac{\hat{n}_{0j}\hat{\mu}_{0j}}{\hat{n}_{0j} + n} \right]$$

Now fixing  $\hat{n}_{0j} = B$  and  $\hat{\mu}_{0j} = \bar{x}_{bj}$ , where  $\bar{x}_{bj}$  is the  $j$ th ML estimate based on  $j$ th  $x_b$  bootstrap sample

drawn. That is,  $\bar{x}_{bj} = \frac{\sum_{i=1}^n x_{ib}}{n}$   
Then,

$$\hat{\mu}_{BT} = \frac{1}{B} \sum_{j=1}^B \left[ \frac{n\bar{x}}{B+n} + \frac{B\bar{x}_{bj}}{B+n} \right]$$

$$\text{var}[\hat{\mu}_{BT}] = \left[ \frac{n^2 + B}{(B+n)^2} \right] \frac{\sigma^2}{n}$$

However, it can be show that the limiting form of  $\left[ \frac{n^2 + B}{(B+n)^2} \right]$  as  $B \rightarrow \infty$  is 0, this justifies the efficiency of the estimator over ML estimator. The Bootstrap samples of  $\hat{\mu}_{EB}$  represent the posterior distribution of  $\mu$ . Now moving to the two sample problem,  $p(\delta|D) = p(\mu_{c_1}^{BT}|D) - p(\mu_{c_2}^{BT}|D)$ , where  $p(\mu_{c_1}^{BT}|D)$  and  $p(\mu_{c_2}^{BT}|D)$  is the posterior distribution of  $\mu$  from class  $c_1$  and  $c_2$  respectively using the proposed bootstrap prior technique. Following central limit, the posterior distribution of  $\delta$  approaches normal distribution with mean  $\bar{\delta}$  and variance  $\sigma_{\delta}^2$ . Thus, the posterior probability of the null hypothesis  $H_0$  can then be estimated using

$$p(H_0|D) = 2 \left[ p(\delta \leq 0 | |\bar{\delta}|, \sigma_{\delta}^2) \right] \quad (10)$$

If the probability is less than chosen significance level  $\alpha$ , we reject the null hypothesis and can conclude that  $H_1$  holds. The best subsets are those features with smallest  $p(H_0|D)$  when compared with a threshold value  $\alpha$ . Furthermore, to correct for family wise error rate which often arise in multiple testing, the sidak (Abdi [Abd07]) method was adopted. The sidak method redefine the threshold  $\alpha$  as  $\alpha_o = 1 - (1 - \alpha)^{\frac{1}{q}}$ .

#### 4.2. The proposed classification methods

Classification involves classifying an observation into one of  $C$  classes, where  $C \geq 2$ . Let  $\pi_c$  represent the overall or prior probability that a randomly chosen observation comes from the  $C$ th class; also let  $f_{1C}(x) \equiv Pr(X = x | Y = c)$  denote the density function of  $X$  for an observation that comes

from the  $C$ th class. In other words,  $f_c(x)$  is relatively large if there is a high probability that an observation in the  $C$ th class has  $X \approx x$ , and  $f_c(x)$  is small if it is very unlikely that an observation in the  $C$ th class has  $X \approx x$ . Then Bayes' theorem states that;

$$Pr(Y = c | X = x) = (\pi_c f_{1C}(x)) / (\sum_{l=1}^C \pi_l f_{1l}(x)) \quad (11)$$

One can simply plug in estimates of  $\pi_c$  and  $f_c(x)$  into (11). In general, estimating  $\pi_c$  is easy if we have a random sample of  $Y$ s from the population: we simply compute the fraction of the training observations that belong to the  $c$ th class. However, estimating  $f_c(x)$  tends to be more challenging, unless we assume some simple forms for these densities. We refer to  $p_c(X)$  as the posterior probability that an observation  $X = x$  posterior belongs to the  $c$ th class. That is, it is the probability that the observation belongs to the  $c$ th class, given the predictor value for that observation. As earlier defined, the Bayes classifier, classifies an observation to the class for which  $p_c(X)$  is largest, has the lowest possible error rate out of all classifiers. (This is of course only true if the terms in (11) are all correctly specified.) Therefore, if we can find a way to estimate  $f_c(x)$ , then we can develop a classifier that approximates the Bayes classifier. Such an approach is the Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA). Hastie et al. [H+13] derived the LDA and QDA based on the assumption that  $f_c(x)$  follows the multivariate normal density function with density function given below as;

$$f(x) = \frac{1}{(2\pi)^{\frac{p}{2}} |\Sigma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu)\right) \quad (12)$$

In the case of  $p > 1$  predictors, the LDA classifier assumes that the observations in the  $c$ th class are drawn from a multivariate Gaussian distribution  $N(\mu_c, \Sigma)$ , where  $\mu_c$  is a class-specific mean vector, and  $\Sigma$  is a covariance matrix that is common to all  $C$  classes. Plugging the density function for the  $c$ th class,  $f_c(X = x)$ , into (11) and performing a little bit of algebra reveals that the Bayes classifier assigns an observation  $X = x$  to the class for which

$$\delta_c(x) = x^T \Sigma^{-1} \mu_c - \frac{1}{2} \mu_c^T \Sigma^{-1} \mu_c + \log \pi_c \quad (13)$$

is largest.

We need to estimate the unknown parameters  $\mu_1, \dots, \mu_C$ ,  $\pi_1, \dots, \pi_C$ , and  $\Sigma$ ; the formulas based

on Maximum likelihood a frequentist approach are given below.

$$\hat{\mu}_c = \frac{1}{n_c} \sum_{i: y_i=c}^{n_c} x_i$$

$$\hat{\Sigma} = \frac{n_c - 1}{n - C} \sum_{c=1}^C \hat{\Sigma}_c$$

Where  $\hat{\Sigma}$  is the pooled variance covariance matrix of all the class and  $\hat{\Sigma}_c$  is the variance covariance matrix of each class. LDA plugs these estimates into (13) and classifies to the class for which  $\hat{\delta}_c(x)$  is largest. Note that in (13)  $\delta_c(x)$  is a linear function of  $x$ ; that is, the LDA decision rule depends on  $x$  only through a linear combination of its elements. This is the reason for the word linear in LDA (Hastie et al. [H+13]). In the same manner, if the equality of variance assumption is not satisfied then individual variance covariance matrix will be used instead of the pooled variance covariance matrix. Then (13) above can be modified to yield;

$$\delta_c(x) = x^T \Sigma^{-1} \mu_c - \frac{1}{2} \mu_c^T \Sigma^{-1} \mu_c + \log \pi_c \quad (14)$$

The decision rule based on (14) is referred to as Quadratic Discriminant analysis (QDA).

The bootstrap Bayes LDA Classifier proposed here make use of the estimates derived in (8) and (9) above with their respective formulas given below; Substituting the bootstrap bayes estimates leads to;

$$\hat{\delta}_c(x) = x^T \hat{\Sigma}_{BT}^{-1} \hat{\mu}_{BTC} - \frac{1}{2} \hat{\mu}_{BTC}^T \hat{\Sigma}_{BT}^{-1} \hat{\mu}_{BTC} + \log \pi_c \quad (15)$$

Again, the bootstrap bayes assign to the class for which  $\hat{\delta}_c$  is the largest. The above formulation is the proposed bootstrap bayes denoted as B-LDA.

Modifying for unequal class variance with  $\hat{\Sigma}_{BC}$  leads to;

$$\hat{\delta}_c(x) = x^T \hat{\Sigma}_{BC}^{-1} \hat{\mu}_{BC} - \frac{1}{2} \hat{\mu}_{BC}^T \hat{\Sigma}_{BC}^{-1} \hat{\mu}_{BC} + \log \pi_c \quad (16)$$

Which we refer to as our proposed bootstrap bayes denoted as B-QDA.

## 5. SIMULATION STUDY AND ANALYSIS

To implement our newly proposed feature selection procedure and classifiers (B-LDA and B-QDA), we intend to simulate typical microarray data set with  $p > n$  i.e (the number of genes are strictly greater than the sample sizes) on which the procedure would be tested to ascertain its suitability and results' efficiencies. The performance of our method relative to some of the existing feature selection and classification methods shall be equally assessed using such simulated data. We consider two other methods under feature selection (Bayesian MCMC and Welch t - statistic). Similarly under classification, we consider Naïve bayes, LDA, QDA, K-NN and LD. The procedure we employed for simulating microarray data set here follows the method of Yahya ([Yah12]) with little modifications. We simulated  $n = 100$  observations representing the number of patients samples with two distinct biological groups  $Y = 0$  (normal patients) and  $Y = 1$  (diseased/tumour patients). On each observation, 1000 covariates,  $X = (X_1, \dots, X_{1000})$ , representing the observed gene expression profiles were simulated. The datasets  $X|Y = 0$  were simulated from multivariate normal distribution with mean  $\mu_0, \mu_0 \neq 0$  and variance-covariance matrix  $\Sigma$ . Of 1000 genes simulated on group 1 subjects, 5 of them were simulated from the mixture of two multivariate normal densities with the same covariance matrix  $\Sigma$ , and means  $\mu_1$  and  $\mu_2$ . The pdf of the dataset used can be written as;  $P(x) = N(\mu_1, \Sigma)P_1 + N(\mu_2, \Sigma)P_2$ , where  $P_1 = P_2 = 0.5$ . The remaining 995 genes for group 1 were simulated from  $N(\mu_0, \Sigma)$  distribution as those in group 0. The remaining genes that were simulated from  $N(\mu_0, \Sigma)$  densities constitute the genes with relatively low expression levels, but not necessarily zero, only that their expression levels are not as strong as those in the former group. The samples generated were in-turn partition into test and train set using the ratio (10:90). The bootstrap sample size B and number of iteration were fixed at 1000. In addition, we also used a published real life datasets on colon cancer.



**Table 1: Genes selected using the three features selection algorithm for simulated and real-life data sets**

Method	Simulated data True: X1, X2, X3, X4, X5	Real-life data (Colon Cancer)
Welch Test	X4, X5, X1, X3 (4)	X1772, X1582, X1771 (3)
MCMC	X5, X4, X1, X3 (4)	X1671, X249, X1772, X1042, X1582, X1771, X1325, X780, X515 (9)
Proposed BT Method	X5, X4, X1, X3 (4)	X138, X249, X513, X625, X780, X1582, X1771, X1772 (8)

**Table 2: Classification Performance (%) of the feature selection methods and classifiers for simulated data set with proportion of test set fixed at 0.1**

ASSESSMENT CRITERIA	Performance using Welch t-test for feature selection with (4) genes selected						
	CLASSIFIERS						
	NAIVE	LDA	B-LDA	QDA	B-QDA	LD	K-NN
MER	4.12	0.00	0.00	0.00	0.00	0.00	0.00
CCR	95.88	100.00	100.00	100.00	100.00	100.00	100.00
SENS	89.66	100.00	100.00	100.00	100.00	100.00	100.00
SPECS	100.00	100.00	100.00	100.00	100.00	100.00	100.00
PPV	100.00	100.00	100.00	100.00	100.00	100.00	100.00
NPV	94.94	100.00	100.00	100.00	100.00	100.00	100.00

**Table 3: Classification Performance (%) of the feature selection methods and classifiers for colon cancer data set with proportion of test set fixed at 0.1**

ASSESSMENT CRITERIA	Performance using Welch t-test for feature selection with (3) genes selected						
	CLASSIFIERS						
	NAIVE	LDA	B-LDA	QDA	B-QDA	LD	K-NN
MER	20.25	28.12	26.98	49.65	48.73	26.52	22.40
CCR	79.75	71.88	73.03	50.35	51.27	73.47	77.60
SENS	68.78	78.42	79.07	68.83	98.05	77.92	82.92
SPECS	90.71	65.38	66.98	90.61	4.50	69.08	72.28
PPV	91.17	73.79	74.78	50.20	50.88	76.35	79.56
NPV	78.46	79.65	80.44	59.40	70.25	80.01	85.07
ASSESSMENT CRITERIA	Performance using proposed BT method for feature selection with (8) genes selected						
	CLASSIFIERS						
	NAIVE	LDA	B-LDA	QDA	B-QDA	LD	K-NN
MER	22.12	17.48	16.27	28.30	33.17	19.05	19.93
CCR	77.88	82.53	83.72	71.70	66.83	80.95	80.08
SENS	65.18	93.36	93.31	65.23	96.25	88.91	90.86
SPECS	90.51	71.68	74.13	90.56	37.36	72.98	69.28
PPV	90.39	81.35	82.80	68.68	63.67	81.44	79.44
NPV	76.90	93.85	93.91	92.73	93.31	89.99	91.80
ASSESSMENT CRITERIA	Performance using MCMC method for feature selection with (9) genes selected						
	CLASSIFIERS						
	NAIVE	LDA	B-LDA	QDA	B-QDA	LD	K-NN
MER	17.35	17.02	16.52	29.48	37.58	20.27	16.50
CCR	82.65	82.97	83.47	70.53	62.42	79.72	83.50
SENS	74.98	93.36	92.56	74.98	95.30	85.56	85.61
SPECS	90.31	72.58	74.38	90.36	29.52	73.88	81.37
PPV	91.61	81.58	82.85	66.62	59.88	80.86	85.95
NPV	83.00	93.97	93.35	96.14	89.17	87.84	88.96

## 6. DISCUSSION OF RESULTS AND CONCLUSION

In this paper, the performance of the Bayes classifier using linear and quadratic discriminant analyses were updated with the application of bootstrap prior technique in the area of preliminary feature selection and estimation of parameters needed for adequate classification. Starting with simulated data results, the true significant genes are X1, X2, X3, X4, X5, with gene X2 having the least effect on the outcome variable. All the features selection algorithms adequately identified the most significant genes (X1, X3, X4, X5). These selected genes within the biological realm are often terms as relevant biomarkers. The genes identified were then used for classification which resulted to the classification performance (%) presented in table 2. Since the genes were perfectly identified, the 100% accuracy achieved by most of the frequentist and Bayesian method shouldn't be questioned. In addition, the failure of the Naïve Bayes classification method was as a result of the simulation scheme used, in which we incorporated some level of correlations between adjacent features. Moving to the real-life data set used, the data were on clinical results on colon cancer. The data contain 2,000 gene expression profiles of 62 tissue samples with two distinct clinical groups of tumorous (40 tissue samples) and normal (22 tissue samples) subjects. These data are freely available and can be downloaded at <http://microarray.princeton.edu/oncology/affydata/index.html>. The feature selection algorithms disagree on the subset of features selected. The algorithm based on the welch-t can be regarded as been conservative, with fewer genes selected, precisely (3) genes. Although the 3 genes selected were equally selected by the other methods. These selected genes (X1772, X1582, X1771) can be regarded as those with high biological relevance to the outcome of interest (colon cancer). The features identified by the algorithm were also used by the classification methods. The highest accuracy from most of the classifiers was observed when we used features identified by the proposed BT method. On a general note, the proposed feature selection method improved the accuracy of the classifiers. Also, the proposed classification method (B-LDA) improved classification accuracy for both simulated and real life data sets used.

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