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Comparing the Performance of LASSO Regression and Bayesian Logistic Regression After Variable Selection: A Practical Application

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Abstract
Uncontrolled and aberrant cell proliferation in lung tissues is the cause of lung cancer, one of the most prevalent and deadly malignancies in the world. The LASSO approach was initially used in this study to find factors that might be connected to the disease's start. After that, a Bayesian logistic regression model was built, and in order to get more accurate parameter estimates, extensive posterior chains were generated using MCMC sampling.
To ascertain which variables in the Bayesian model had the greatest impact on the occurrence of disease, their relative relevance was assessed using 95% Confidence Intervals and Posterior Means. With the exception of one variable that it kept but the Bayesian analysis subsequently eliminated due to its credible interval, LASSO chose a comparable set of variables.
Overall, the two approaches yielded almost equal sets of significant variables; nevertheless, the Bayesian logistic regression model performed better. It offered more accurate explanations of the variables influencing the incidence of lung cancer as well as a clearer assessment of parameter significance.

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Keywords: Lasso Select Variables, Binary Logistic Regression, Bayesian Binary Logistic Regression, Cross-Validation, Pseudo–R^2

Introduction

I built a LASSO model for the prediction of moderate to severe dry mouth (xerostomia) in patients with head and neck cancer that has been treated with IMRT. Subsequently, I used quality-of-life data from a large cohort (206 patients – include reference here). LASSO already identified important prognostic factors associated with 3- and 12-month xerostomia. The mean parotid doses as well as age, education, smoking, T stage, and baseline dryness were all factors. In detail, the NTCP model outcome showed good calibration and discrimination indicating that logistic regression enhanced through LASSO can predict patient-rated xerostomia after IMRT reliably (Lee *et al.*, 2014) [15]. The challenges of gene selection for high-dimensional cancer classification are addressed using a new initial weight for CBPLR. The CBPLR performs better than LASSO and adaptive LASSO in different aspects like accuracy and misclassification rates while selecting less number of genes with more information across various cancer datasets. Count 2. The findings highlight the effectiveness and competitiveness of CBPLR, which has a large potential in high-dimensional gene selection. (Algamal & Lee, 2015) [1]. This study investigates an ensemble learning method for credit scoring. The technique uses LASSO-regularized logistic regression as its base classifier. The proposed Lasso-logistic ensemble with superior performance is achieved by clustering and bagging to balance and diversify largescale imbalanced data to enhance its area under the curve and F-measure compared to decision trees, LASSO-logistic regression, random forests. The approach also provides measures of variable importance to identify important credit risk predictors. Applied Bayesian LASSO regression also used to estimate key aquatic factors and their interactions influencing Fe(II), S(−II) and suspended sediment during black bloom events in Chaohu Lake, China (H. Wang *et al*., 2015) [24] Total phosphorus (TP) was the most important predictor of all three variables, including various interactions, including TN×DO and CHLA×ORP. Results emphasize TP as the key factor in black blooms, providing scientific grounding for targeted management and control and reduction of lakes. Based on well log and core data, (L. Wang *et al*., 2019) [25] used Bayesian Model Averaging (BMA) and LASSO modeling of core permeability, further predicting permeability in a sandstone well's non-cored intervals. The results show that both methods accurately estimated permeability, although LASSO performs slightly better than BMA and linear regression. The BMA and LASSO are effective integrated joint predictive models for accurate permeability prediction. According to (Al-Mudhafar, 2019), [2] the authors used group-LASSO and Bayesian networks to analyze risk factors associated with acute kidney injury (AKI) among 2395 patients with hematologic malignancy in Shanghai. Age and hemoglobin concentration and eGFR sodium potassium directly affected AKI while cancer type and treatment indirectly impacted AKI. The Bayesian network achieved good predictive performance AUC = 0.835. The findings indicate that Bayesian networks reveal relationships between predictors and help detect individual patient risk for early AKI. (Li *et al*., 2020) Compares the LASSO and the Bayesian Relevance Vector Machine (RVM) sparse logistic regression methods for identifying influential variables in knowledge-based systems to improve prediction. Both methods achieve similar prediction performance. RVM outperforms LASSO in both structure recovery and accuracy, particularly as the data dimensionality increases. LASSO competes with RVM when p > n (Zanon *et al*., 2020) Aggressive taxi speeders are classified by fuzzy C-means clustering based on speeding frequency and severity and then analysed using a random-parameters Bayesian LASSO logistic model. The research report finds that driving further away, earning more money per hour, driving at night, and driving on roads with a low speed limit increases aggressive speeding. But, the intensity of lane-changing and napping does not impact that. According to the analysis, belligerent speeders are more reactive to operational variables, emphasizing the management and countermeasures required. According to (Zhou *et al*., 2021) [27], they used ordinary and Bayesian Lasso logistic regression models to find out the factors influencing mortality in 339 patients suffering from gastric cancer in Kerman, Iran. Tumor symptoms mostly identified in adult men, with women often misdiagnosed with benign ovarian tumors, leading to a poor prognosis. The results show the great many people dying from this condition. This is especially true for people who are below the age of 45. According to a recent study (Hosseinnataj *et al*., 2020) [13], the analysis of the death ratios of COVID-19 using the Novel Multiple Logistic Regression and Linear Regression on 239 locations using supervised learning methods. Logistic regression was more accurate (96%) than linear regression (86%) and the result was statistically significant (p = 0.030). The findings results would endorse Novel Multiple Logistic Regression models for the prediction of COVID-19 death ratios.(Raju & Deepa, 2022) [19],This study used CHARLS 2018 data of 6,886 Chinese adults aged ≥60, and applied LASSO variable selection and Bayesian Networks to discover variables associated with cognitive impairment. The study found that age, education and indoor air pollution were direct determinants of CI while marital status and residence affected CI indirectly through them. The findings demonstrate that Bayesian Networks can efficiently expose complex inter-relationships of factors and develop public health measures for the prevention of CIs among older people. (Chen *et al*., 2024)[6].

1. Binary Logistic Regression Model:

Binary logistic regression is employed to model a dichotomous outcome using a set of predictors selected through the LASSO procedure. Let $Y_i \in \{0,1\}$denote the binary response for observation $i = 1, \dots, n$, with $Y_i = 1$indicating the occurrence of the event of interest and $Y_i = 0$otherwise. The corresponding vector of predictors is denoted by $\mathrm{x}_i = (x_{i2}, x_{i3}, \dots, x_{i,15})^\top$, restricted to the subset $\mathcal{S}$chosen via penalized selection. The conditional probability of event occurrence is $p_i = \Pr(Y_i = 1 \mid \mathrm{x}_i)$. Assuming a Bernoulli likelihood, the binary response model is specified as $Y_i \mid \mathrm{x}_i \sim \text{Bernoulli}(p_i)$.The logit link relates the predictors to the event probability through

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_{j\in\mathcal{S}} \beta_j\, x_{ij},$$

where $\beta_0$is the intercept and $\beta_j$are the regression coefficients. The inverse-logit function maps the linear predictor to the probability scale:

$$p_i = \frac{\exp\left(\beta_0 + \sum_{j\in\mathcal{S}} \beta_j\, x_{ij}\right)}{1+\exp\left(\beta_0 + \sum_{j\in\mathcal{S}} \beta_j\, x_{ij}\right)}.$$

The log-likelihood for the complete sample is

$$\ell(\beta) = \sum_{i=1}^{n} [y_i \log(p_i) + (1 - y_i)\log(1 - p_i)].$$

Model coefficients are estimated under the generalized linear model (GLM) framework using maximum likelihood: (Hosmer Jr *et al*., 2013)[12].

$$\hat{\beta}_{\text{MLE}} = \arg\max_{\beta}\ \ell(\beta).$$

2. LASSO-Penalized Binary Logistic Regression:

To address multicollinearity and perform variable selection, the logistic model is extended via LASSO regularization. The penalized objective solved by glmnet is

$$\hat{\beta}^{(\lambda)} = \arg\min_{\beta} \left\{-\frac{1}{n}\ell(\beta) + \lambda \sum_{j=1}^{p} |\beta_j|\right\},$$

where:

- $-\ell(\beta)$is the negative log-likelihood,
- $\lambda \geq 0$controls the degree of shrinkage,
- the intercept $\beta_0$is not penalized.

Large λvalues shrink many coefficients toward zero, effectively performing variable selection, whereas small λvalues approach the unpenalized model. (Tibshirani, 1996) [22] The optimal penalty parameter is chosen using 10-fold cross-validation:

$$\hat{\lambda}_{\min} = \arg\min_{\lambda} \left[\frac{1}{K}\sum_{k=1}^{K} D^{(k)}(\lambda)\right],$$

where $D^{(k)}(\lambda)$is the binomial deviance on the validation fold k. The 1-SE rule selects the largest λwithin one standard error of the minimum.

The final subset of predictors is. (Friedman *et al*., 2010) [7]

$$\mathcal{S} = \{j: \hat{\beta}_j^{(\hat{\lambda}_{\min})} \neq 0\}.$$

3. McFadden's Pseudo–R^2:

Model performance is evaluated using McFadden's pseudo–R^2, defined as

$$R^2_{\text{McFadden}} = 1 - \frac{L_{\text{full}}}{L_{\text{null}}},$$

where

- $L_{\text{full}}$is the log-likelihood of the fitted model,
- $L_{\text{null}}$is the log-likelihood of the intercept-only model.

Values in the range 0.2–0.4 typically indicate strong goodness-of-fit for discrete choice models. (McFadden, 1972) [17]

4. Bayesian Binary Logistic Regression (BRMS)

The Bayesian formulation retains the logistic likelihood but treats all model parameters as random variables. This framework incorporates prior beliefs and quantifies full posterior uncertainty. (Bürkner, 2017)[4].

4.1. Bayesian Likelihood

Given $p_i = \Pr(Y_i = 1 \mid x_i, \beta)$, the sampling distribution of each observation follows a Bernoulli model:

$$Y_i \mid x_i, \beta \sim \text{Bernoulli}(p_i).$$

The relationship between the predictors and the probability $p_i$is defined through the logit link function:

$$\text{logit}(p_i) = \beta_0 + \sum_{j\in S} \beta_j x_{ij}.$$

Accordingly, the likelihood of observing the full dataset $y = (y_1, \ldots, y_n)$given the parameters $\beta$and the design matrix $X$is:

$$p(y \mid \beta, X) = \prod_{i=1}^{n} p_i^{y_i}\,(1 - p_i)^{1-y_i}.$$

4.2. Priors

Weakly informative Student-t priors are assigned to stabilize estimation:

$$\beta_j \sim t_{\nu=3}(0, 2.5), j \in \mathcal{S},$$
$$\beta_0 \sim t_{\nu=3}(0, 5).$$

These heavy-tailed priors allow detection of large effects while avoiding over-shrinkage, particularly important in logistic models with imbalance or near-separation. (Gelman *et al*., 1995) [9]

4.3. Posterior Distribution:

Posterior inference follows Bayes' theorem:

$$p(\beta \mid \text{y}, X) \propto p(\text{y} \mid \beta, X) \cdot p(\beta).$$

Because no closed-form posterior exists, Hamiltonian Monte Carlo (HMC) via Stan is used to obtain samples. From these samples, posterior means, standard errors, and 95% credible intervals are computed. Predictors whose credible intervals exclude zero are interpreted as statistically important.

5. Cross-Validation Deviance (Model Selection):

For each λ, the cross-validated binomial deviance is:

$$\text{CV}(\lambda) = \frac{1}{K}\sum_{k=1}^{K} D^{(k)}(\lambda),$$

where the deviance for fold $k$is

$$D^{(k)}(\lambda) = -2\sum_{i\in I_k}\left[y_i \log \hat{p}_i^{(\lambda)} + (1 - y_i)\log(1 - \hat{p}_i^{(\lambda)})\right].$$

The CV curve displays mean deviance, error bars (±1 SE), and vertical lines marking $-\log(\hat{\lambda}_{\min})$and $-\log(\hat{\lambda}_{1SE})$, guiding optimal model selection. (Trevor *et al*., 2009)

Data description

The data was taken from the website (https://www.kaggle.com/) consisting of 16 variables and 284 views, and the description of the variables is as in Table No. (1).

Table 1: Data description

Variables	Variables Names	Description Variables	Variables	Variables Names	Description Variables
Y	Lung Cancer	YES, NO	X8	Fatigue	YES=2, NO=1
X1	Gender	M(male), F(female)	X9	Allergy	YES=2, NO=1
X2	Age	Age of the patient	X10	Wheezing	YES=2, NO=1
X3	Smoking	YES=2, NO=1	X11	Alcohol	YES=2, NO=1
X4	Yellow fingers	YES=2, NO=1	X12	Coughing	YES=2, NO=1
X%	Anxiety	YES=2, NO=1	X13	Shortness of Breath	YES=2, NO=1
X6	Peer pressure	YES=2, NO=1	X14	Swallowing Difficulty	YES=2, NO=1
X7	Chronic Disease	YES=2, NO=1	X15	Chest pain	YES=2, NO=1

McFadden's Value

McFadden's R^2 of 0.6013 indicates an exceptionally strong model fit for a binary logistic regression with a Bernoulli outcome. Considering the fifteen predictors used, this value reflects a high ability of the model to explain variation in the dependent variable.

Lasso Select Variables

The figure number (1) with the rows representing the variables that are potential candidates for inclusion in the model and the columns s_0, s_1,…, and s_71 representing various levels of λ, the matrix that is displayed shows the paths of the LASSO model coefficients for a binary logistic regression at a set of values for the contraction coefficient λ. By following the regression coefficients' changes along the contraction path, this kind of analysis is among the most effective ways to determine whether variables have a real impact on the dependent variable. The following variables have coefficients that climb clearly and consistently as λ lowers, indicating their significant significance in predicting the dependent variable, according to an examination of the routes.

The variables were selected using the Lasso regression method during several stages. In the first stage, the variables that have no effect on the equation, namely the two variables (X1), were excluded. The variables were arranged into three stages. The first stage was the variables with the most effect, which are (X12, X13, X14, X11, X10, X8) in the regression equation that will be built based on these variables. The second stage was the variables with medium effect (X7, X2, X3, X4, X10). As for the variables that will be less important (less influential) in the model, they are (X5, X6, X15). That is, the model that was built based on the variables will have the effect of the variables according to what was mentioned in the divisions mentioned in the paragraph.

Examining the trajectories reveals that the following variables exhibit clearly and consistently increasing coefficients as λ decreases, reflecting their high importance in predicting the dependent variable(x4,x6,x7,x8,x9,x10,x11,x12). These variables show smooth, progressively increasing trajectories and decouple early from the zero line, indicating a strong and stable correlation with the studied outcome. Furthermore, the consistent increase in the coefficients of these variables as λ decreases further supports their statistical stability and explanatory power within the model.

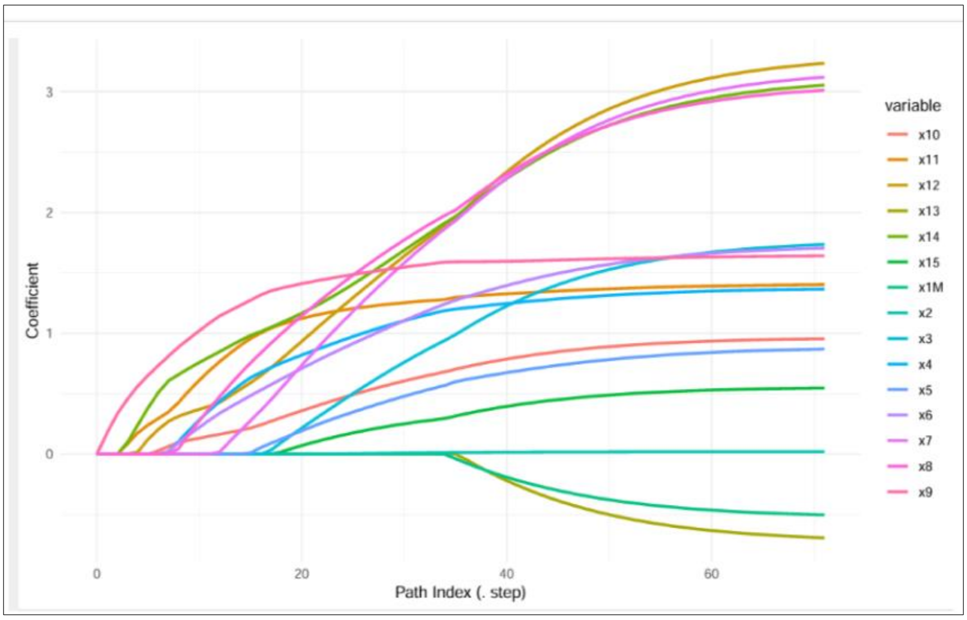

Fig 1: Lasso Coefficient Paths from (Binary Logistic)

Cross-Validation curve

The cross-validation curve of binary logistic LASSO regression is shown in figure (2). Each red dot shows how much the average deviance of the model varies between the cross-validation folds. The grey error bars show how much the estimates vary across the folds.

The curve of the model is U-shaped. Thus, model performance improves as λ increases, up to a point after which performance deteriorates with excessive regularization. Like so, increase in performance happens with low regularization. But high regularization makes the model forget all concepts.

The position of $\lambda_{\min}$, which is where the minimum deviance occurs and therefore the best predictive performance is achieved, is indicated by the left vertical dashed line while the right vertical dashed line indicates λ_{1se}, which results in a more parsimonious model as it falls within one standard error of the minimum deviance. The visualization helps to choose an adequate level of regularization where predictive accuracy and model simplicity are balanced. It depicts the basic working of the LASSO estimator in high-dimensional logistic regression settings.

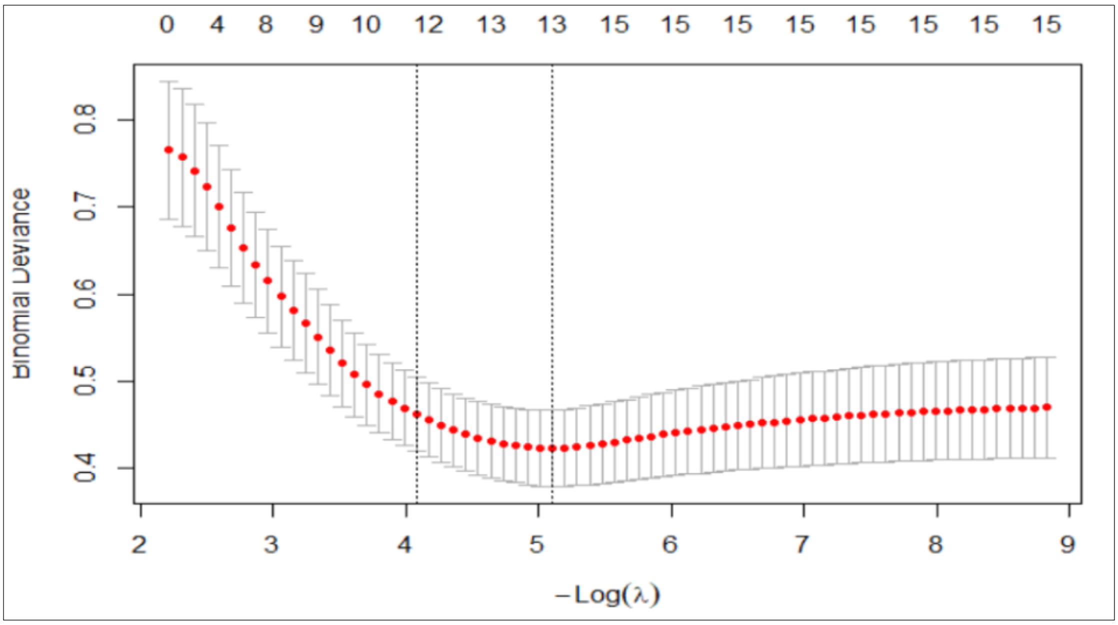

Fig 2: Binary Logistic LASSO cross-validation Curve.

Table (2) summarizes the key cross-validation statistics obtained from the binary LASSO logistic Pick different λ and see which work best with the model The table provides the mean cross-validation error, standard deviation, and upper and lower confidence bounds for each quantile of λ (minimum, 1st quartile, median, mean, 3rd quartile, and maximum).

In smaller values of λ (for example λ_min = 0.0001473) the mean cross-validation error is a smaller number, but it is ill-fitted and less regularized. Cross-validation error rises or increases with λ. This implies that the penalization is stronger. It also implies that the coefficients are being more strongly shrunken. The largest λ had the most variability and the largest error values, suggesting heavy simplification. In conclusion, for a better understanding of how the model performance stresses across the regularization path, thus allowing to choose the optimal λ which balances predictive accuracy and model sparsity.

Table 2: Binary LASSO Selection

	lambda	Cross- Validation Mean	Cross-Validation Standard Deviation	Cross-Validation Upper Bound	Cross-Validation Lower Bound
Min.	0.0001473	0.423	0.04175	0.4667	0.3791
1st Qu.	0.0007685	0.4425	0.04532	0.4895	0.3944
Median	0.0040082	0.4616	0.05218	0.5141	0.4074
Mean	0.0169964	0.4917	0.05256	0.5443	0.4392
3rd Qu.	0.0208932	0.4793	0.05661	0.5282	0.4351
Max.	0.1088477	0.7651	0.07895	0.844	0.6861

Bayesian Binary Logistic Regression

The results of Bayesian Logistic regression model, the predictors x7, x8, x12, x14, x6, x9, x4,x3 and x11 have significant and positive effect on the probability of the outcome. This conclusion came from the observation that the corresponding 95% Bayesian credible intervals do not include 0.

The Rhat indicated no autocorrelation for all parameters, and the 1 value revealed that MCMC sampling was stable and posterior estimates were reliable which showed that the model had great convergence diagnostics.

We are more confident in the model's inferences because of this convergence.

On the other hand, the predictors x2, x5, x10 and x15 were not considered to have credible effect judgments as their intervals reached through zero. As a consequence, there is not enough evidence to say that x2, x5, x10 or x15 affect the response variable. The creation of the model has excluded factors X1 and X13 from the model formation. We can see clearly in table and figure (2).

Overall, these findings suggest that the model identifies key predictors and can assess their importance in explaining the variance. In summary, the model tends to create an outcome that is rigorously and reliably inferential.

Table 3: Bayesian Binary Logistic Regression.

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	-29.02	4.88	-39.28	-20.33	1	1833	2142
x2	0.03	0.03	-0.04	0.09	1	4681	2992
x3	1.39	0.64	0.19	2.72	1	2863	2469
x4	1.54	0.7	0.23	2.98	1	3010	2633
x5	0.87	0.72	-0.56	2.27	1	3491	3008
x6	1.68	0.61	0.57	2.96	1	3203	2834
x7	2.65	0.75	1.25	4.16	1	2407	2689
x8	2.62	0.65	1.41	3.98	1	2578	2411
x9	1.91	0.7	0.55	3.33	1	3736	2806
x10	0.98	0.73	-0.44	2.37	1	3981	3070
x11	1.53	0.72	0.18	2.95	1	3533	3085
x12	2.51	0.86	0.88	4.25	1	2313	2384
x14	2.53	0.92	0.81	4.45	1	2373	1859
x15	0.47	0.63	-0.76	1.73	1	3624	2668

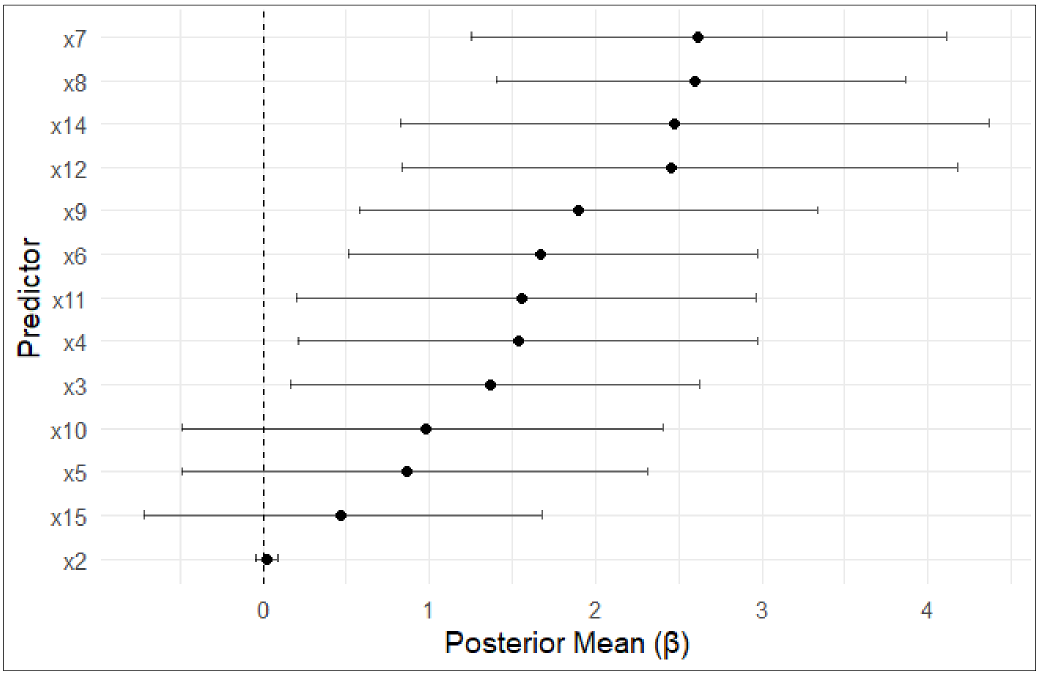

Fig 3: Bayesian Binary Logistic Regression

Comparative Paragraph

The kernel density plot shown here shows the distribution of predicted probabilities P(Y = 1) from the Bayesian BRMS and LASSO logistic regression models. The graphical patterns in the figure exhibit a clear right skew behavior for both methods, with densities increasingly rising around probability value 1.0. This steep concentration shows that the two models predict the positive class with a very high confidence for most observations.

The two curves are pretty close to one another, but there are some slight differences. The Bayesian BRMS shape is a bit smoother and slightly higher at the very top end due to posterior averaging. While posterior averaging is not just a one-curve tool, it helps account for uncertainty in coefficient estimation. Conversely, the LASSO curve shows near identical right tail concentration but a slightly more compact rise, complying with the presence of shrinkage as dictated by the LASSO penalty. This penalty stabilizes predictions after variable selection.

In the regions with lower probability (0.0−0.40), both curves show little variation, however, the Bayesian also showed more spread than LASSO. This means generation of moderate probability prediction is more flexible with the Bayesian model compared to LASSO.

As depicted in Figure (4), which represents the kernel density plot of predicted probabilities for Bayesian BRMS vs. LASSO shows that both the models are predicted highly consistent with each other. However, they are different with each other in terms of smoothing behaviour and uncertainty representation. These differences highlight how Bayesian regularization and LASSO shrinkage influence the shape of predicted probabilities. Overall, the predicted probabilities are still trending toward robust confidence in the positive outcome.

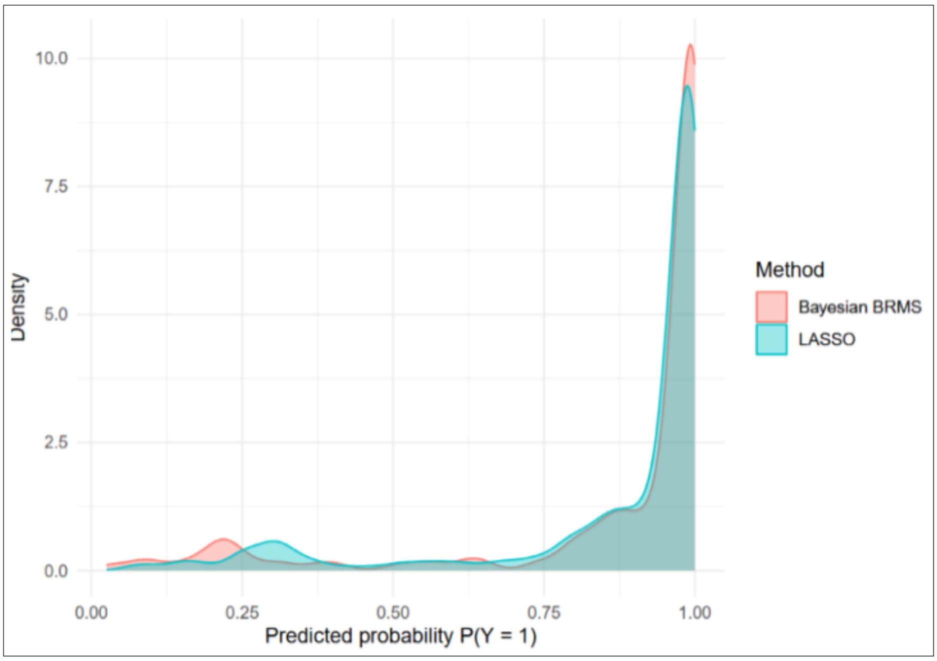

Fig 4: Predicted Probabilities -Bayesian BRMS vs LASSO.

Conclusions

The variables picked by LASSO backward selection fit those picked by Bayesian approach with regard to their content. Though the over the two approaches differ with respect to the number of variables that are left out. While the LASSO has dropped X1, the Bayesian dropped both X1 and X13. When we included X13 in the LASSO model, the performance was not affected significantly. When we exclude X13 in the Bayesian framework, the predictive performance will improve. Adding any more explanatory variables will not help regress. In fact, including a variable that shouldn't be in the regression likely does more harm than just excluding it entirely.

We can conclude that the posterior means and the credible intervals can be used as a more reliable criterion for identifying influential predictors and developing a robust and parsimonious model.

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Competing Interests

The authors declare that they have no competing interests.

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