



How to use blasso function in R package "monomvn"? [closed]

Asked 2 years, 8 months ago Active 2 years, 7 months ago Viewed 1k times



2



I am a freshman with Bayesian lasso. I searched online and found that the only package I can use is monomvn. There's only one example about diabetes data in its R document. However, the parameters set in that example is quietly simply. Just "blasso(x,y)". I tried to follow this but when it comes to my data, all coefficients were shrunk to zeros. Should I give initial values to beta? Appreciate it if anyone could provide examples describing how to set parameters for this function? Thanks a lot.

[r](#) [bayesian](#) [lasso](#)

asked Mar 20 '17 at 21:08

[purod](#)

157 11

closed as off-topic by [Jake Westfall](#), [kjetil b halvorsen](#), [gung - Reinstate Monica](#) ♦, [Juho Kokkala](#), [Michael R. Chernick](#) Apr 5 '17 at 17:11

This question appears to be off-topic. The users who voted to close gave this specific reason:

- "This question appears to be off-topic because EITHER it is not about statistics, machine learning, data analysis, data mining, or data visualization, OR it focuses on programming, debugging, or performing routine operations within a statistical computing platform. If the latter, you could try the [support links we maintain](#)." – [Jake Westfall](#), [kjetil b halvorsen](#), [gung - Reinstate Monica](#), [Juho Kokkala](#), [Michael R. Chernick](#)

If this question can be reworded to fit the rules in the [help center](#), please [edit the question](#).

Questions about how to use software are generally off topic here, & tutorials are explicitly outside our mandate. – [gung - Reinstate Monica](#) ♦ Apr 5 '17 at 16:59

1 Answer



4



I am not an expert but I would be happy to share my experience with the monomvn package.

Should I give initial values to beta?

Given enough iterations, initial values shouldn't have any impact on any parameter (e.g. regression coefficients, error variance and penalty parameter). Please consider the R code and traceplots below:

By using our site, you acknowledge that you have read and understand our [Cookie Policy](#), [Privacy Policy](#), and our [Terms of Service](#).

```
data(diabetes); attach(diabetes)

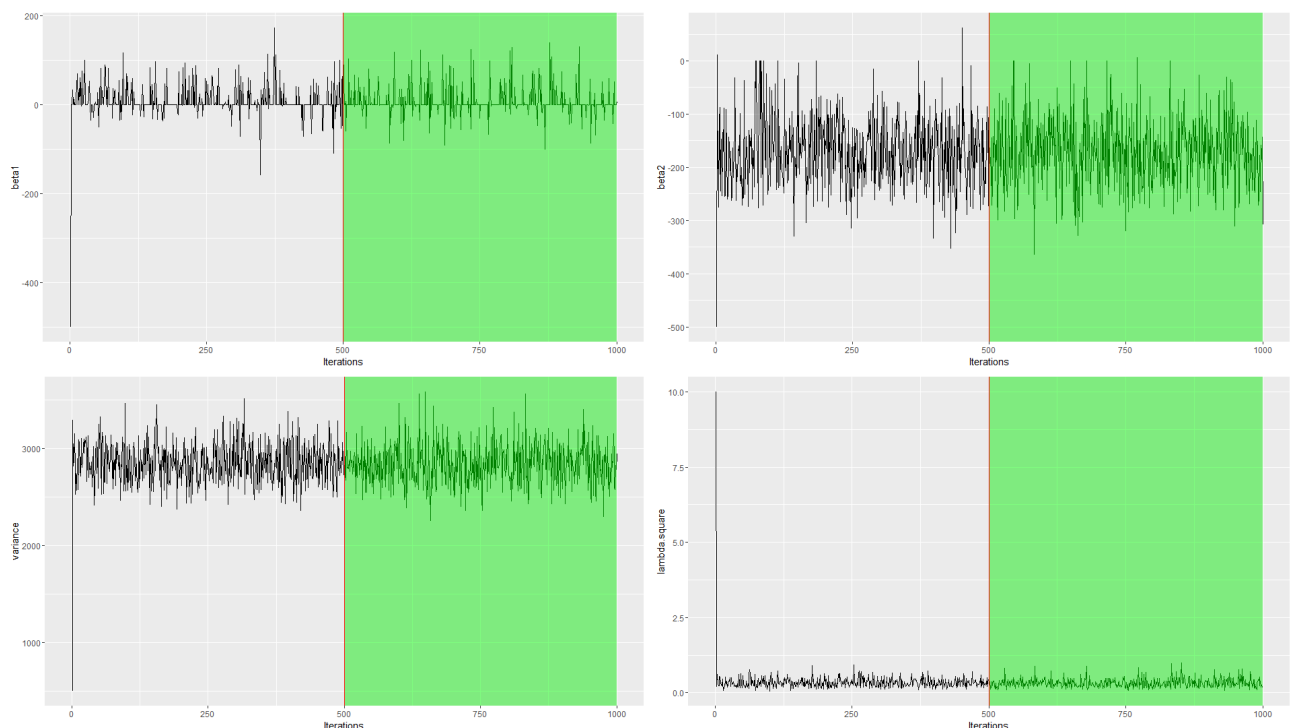
# define the burn-in period, number of mcmc samples to be drawn and initial values
burnin <- 500
iter <- 1000
initial.beta <- rep(-500, dim(x2)[2]) # assigning an extreme initial value for all betas
initial.lambda2 <- 10 # assigning an extreme initial value for lambda (penalty parameter)
initial.variance <- 500 # assigning an extreme initial value for variance parameter

# starting the Gibbs sampler here
lasso <- blasso(X = x2, # covariate matrix with dimensions 442 x 64
               y = y, # response vector with length of 442
               T = iter, # number of iterations
               beta = initial.beta,
               lambda2 = initial.lambda2,
               s2 = initial.variance)

# collecting draws for some of the parameters for visualization
coef.lasso <- as.data.frame(cbind(iter = seq(iter),
                                beta1 = lasso$beta[, "b.1"],
                                beta2 = lasso$beta[, "b.2"],
                                variance = lasso$s2,
                                lambda.square = lasso$lambda2))
```

To get the parameter estimations, I would use the posterior median as Park and Casella (2008) have done.

```
> colMedians(coef.lasso[seq(burnin), -1])
beta1      beta2      variance      lambda.square
0.0000000 -172.3840906 2841.4410472      0.3031814
```



Please consider that I have computed the coefficients after discarding first half of the draws. Since I have considered only the draws from green shaded areas, these extreme initial values I

By using our site, you acknowledge that you have read and understand our Cookie Policy, Privacy Policy, and our Terms of Service.

Let's now compare lasso (glmnet package) and Bayesian lasso (monomvn package)

```
fit.glmnet <- glmnet(as.matrix(x2), y,
                    lambda=cv.glmnet(as.matrix(x2), y)$lambda.1se)
coef.glmnet <- coef(fit.glmnet)
sum(coef.glmnet == 0)
53
```

The original lasso implementation has shrunk 53 parameters to 0. Let's now check Bayesian lasso:

```
sum(colMedians(lasso$beta[-seq(burnin), ]) == 0)
56
```

and it shrank 56 out of 64 exactly to 0.

Please also note that your estimation results might significantly differ when you specify the prior distributions. A quick example would be to change the parameters using the 'rd' argument in blasso() where 'rd' controls the gamma prior on λ^2 . (please hit ?blasso for other hyperprior specifications)

Here is an example:

```
lasso2 <- blasso(X = x2, # covariate matrix with dimensions 442 x 64
                y = y, # response vector with length of 442
                T = iter, # number of iterations
                beta = initial.beta,
                lambda2 = initial.lambda2,
                s2 = initial.variance,
                rd = c(1, 1.78)) # hyperparameters suggested by Park & Casella
(2008)

coef.lasso2 <- as.data.frame(cbind(iter = seq(iter),
                                   beta1 = lasso2$beta[, "b.1"],
                                   beta2 = lasso2$beta[, "b.2"],
                                   variance = lasso2$s2, lambda.square =
                                   lasso2$lambda2))

colMedians(coef.lasso2[-seq(burnin), -1]) # new posterior median estimations
beta1      beta2      variance      lambda.square
0.0000000   -183.7851178 2817.3811240    0.2313924
```

I hope it is now clear now that giving initial values doesn't really help. Have you tried estimating the parameters using glmnet? If the results differ a lot, then you might consider tuning the hyperpriors on parameters in blasso(). If you still get the same results, maybe the parameters are all indeed 0 :-)

Hope that helps!

edited Apr 5 '17 at 15:59

answered Apr 5 '17 at 15:45

 yahsin
71 4