

# BayesLinearRegress\_cricket

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```
library(MASS) #for mvnrm
```

## Bayesian Linear Regression. Cricket chirps example.

The basic idea of the linear regression is to understand the relationship between response  $y$  and explanatory variables  $x = (x_1, \dots, x_k)$ , based on data from experimental units index by  $i$ . In general if we assume linearity between the mean of  $y$  and the explanatory variables, independence between experimental units, and constant variance around the mean, then we have:

$$y_i \stackrel{\text{iid}}{\sim} N(\beta_1 x_{i1} + \dots + \beta_k x_{ik}, \sigma^2)$$

where  $x_{i1} = 1$  if we want to include an intercept

In matrix notation:

$$y \sim N(X\beta, \sigma^2 I)$$

where  $y = (y_1, \dots, y_n)'$ ,  $\beta = (\beta_1, \dots, \beta_k)'$ , and  $X$  is  $n \times k$  with each row being  $x_i = (x_{i1}, \dots, x_{ik})$

Bayesian Regression:

Assume the standard noninformative prior for joint distribution:

$$p(\beta, \sigma^2) \propto \frac{1}{\sigma^2}$$

then the joint distribution posterior is

$$p(\beta, \sigma^2 | y) = p(\beta | \sigma^2, y) p(\sigma^2 | y)$$

where  $p(\beta | \sigma^2, y)$  is the posterior distribution of  $\beta$  conditional to  $\sigma^2$  and  $y$ , and  $p(\sigma^2 | y)$  the marginal posterior of  $\sigma^2$ .

$$\beta | \sigma^2, y \sim N(\hat{\beta}, \sigma^2 V_{\beta})$$

$$\sigma^2 | y \sim \text{Inv-Gamma}\left(\frac{n-k}{2}, \frac{(n-k)s^2}{2}\right)$$

$$\beta | y \sim t_{n-k}(\hat{\beta}, s^2 V_{\beta})$$

Hiperparameters:

$$\hat{\beta} = (X'X)^{-1}X'y$$

$$V_{\beta} = (X'X)^{-1}$$

$$s^2 = \frac{1}{n-k}(y - X\hat{\beta})'(y - X\hat{\beta})$$

The posterior is proper if  $n > k$  and  $\text{rank}(X) = k$  at least.

For numerical stability and efficiency, the  $QR$  decomposition should be used to calculate the posterior quantities.

Def. For a  $X$ , the  $QR$  decomposition is  $X = QR$  for an orthogonal matrix  $Q$  and an upper triangular matrix  $R$ .

The quantity of interest are:

$$V_{\beta} = (X'X)^{-1} = ([QR]'QR)^{-1} = (R'Q'QR)^{-1} = (R'R)^{-1} = R^{-1}[R']^{-1}$$

$$\hat{\beta} = (X'X)^{-1}X'y = R^{-1}[R']^{-1}R'Q'y = R^{-1}Q'y =$$

$$R\hat{\beta} = Q'y$$

The last equation is useful because  $R$  is upper triangular and therefore the system of linear equations can be solved without requiring the inverse of  $R$ .

As an example, consider the relationship between the number of cricket chirps and temperature.

```
chirps<-c(20,16,19.8,18.4,17.1,15.5,14.7,17.1,15.4,16.2,15,17.2,16,17,14.1)
temp<-c(88.6,71.6,93.3,84.3,80.6,75.2,69.7,82,69.4,83.3,78.6,82.6,80.6,83.5,76.3)
```

```
X<-cbind(1,temp)
n<-nrow(X)
k<-ncol(X)
y<-matrix(chirps,n,1)

qr<-qr(X)
```

```
#check for posterior propriety
stopifnot(n>k, qr$rank==k)
```

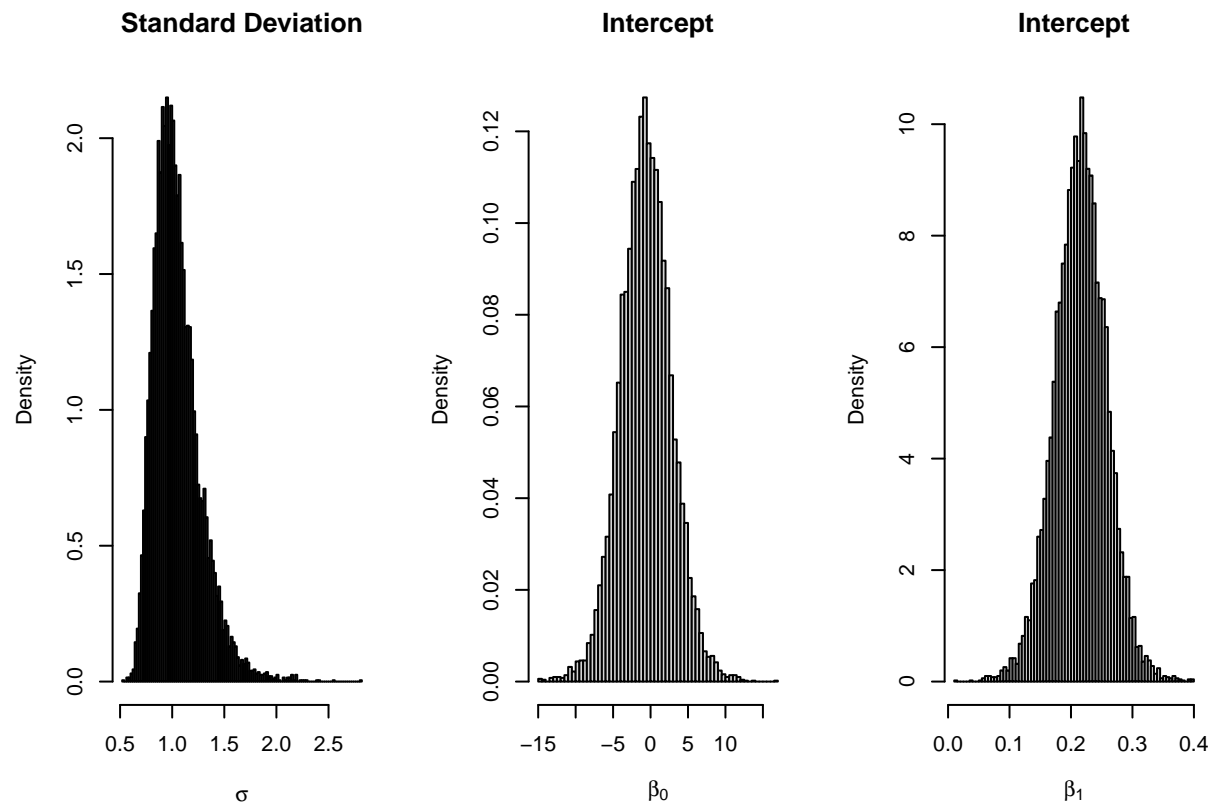
```
#Calculate posterior hyperparameters
Rinv=solve(qr.R(qr))
vbeta<-Rinv%*%t(Rinv)
betahat<-qr.solve(qr,y)
df<-n-k
e=qr.resid(qr,y)
s2<-sum(e^2)/df
```

```
#Simulte from the posterior
n.sims<-10000
sigma<-sqrt(1/rgamma(n.sims,df/2,df*s2/2))
beta<-matrix(betahat,n.sims,k,byrow=T)+sigma*mvrnorm(n.sims,rep(0,k), vbeta)
```

```

par(mfrow=c(1,3))
hist(sigma,100,freq=F,main="Standard Deviation", xlab=expression(sigma))
hist(beta[,1],100,freq=F,main="Intercept", xlab=expression(beta[0]))
hist(beta[,2],100,freq=F,main="Intercept", xlab=expression(beta[1]))

```



```

quantile(sigma, c(0.025,0.975))

```

```

##      2.5%      97.5%
## 0.7203271 1.5817162

```

```

t(apply(beta,2,quantile,probs=c(0.025,0.975)))

```

```

##      2.5%      97.5%
## -7.2777095 6.2485061
## temp 0.1299239 0.2996825

```

```

confint(lm(y~0+X))

```

```

##      2.5 %      97.5 %
## X      -7.4081577 6.1777286
## Xtemp 0.1310169 0.3003406

```