

$$1. E_0(w) = \frac{1}{2} \sum_{n=1}^N r_n (t_n - w^T \phi(x_n))^2$$

$$i) \frac{d}{dw} E_0(w) = \sum_{n=1}^N r_n \{t_n - w^T \phi(x_n)\} \phi(x_n)^T = 0$$

$$\sum_{n=1}^N r_n t_n \phi(x_n)^T = \sum_{n=1}^N r_n \phi(x_n) \phi(x_n)^T w$$

$$w = \frac{\sum_{n=1}^N r_n t_n \phi(x_n)^T}{\sum_{n=1}^N r_n \phi(x_n) \phi(x_n)^T}$$

$$ii) E_0(w) = \frac{1}{2} \sum_{n=1}^N r_n (t_n - w^T \phi(x_n))^2$$

$$\text{Rewrite as } = \frac{1}{2} (\phi w - t)^T R (\phi w - t)$$

$$= \frac{1}{2} (w^T \phi^T R \phi w - w^T \phi^T R t + t^T R \phi w + t^T R t)$$

$$= \frac{1}{2} (w^T \phi^T R \phi w - 2t^T R \phi w + t^T R t)$$

where $R = \text{diag}(r_1, \dots, r_N)$

$$\Delta E_0(w) = \phi^T R \phi w - t^T R \phi$$

$$w = (\phi^T R \phi)^{-1} t^T R \phi$$

$$= \phi^T R \phi^{-1} \phi^T R t.$$

$$2. p(w, \beta) = \mathcal{N}(w | m_0, \beta^{-1} S_0) \text{Gam}(\beta | a_0, b_0)$$

$$\propto \left(\frac{\beta}{|S_0|}\right)^{\frac{1}{2}} \exp\left(-\frac{1}{2}(w - m_0)^T \beta S_0^{-1} (w - m_0)\right) b_0^{a_0} \beta^{a_0-1} \exp(-b_0 \beta)$$

$$p(t|w, \beta) = \prod_{n=1}^N \mathcal{N}(t_n | w^T \phi(x_n), \beta^{-1})$$

$$\propto \prod_{n=1}^N \beta^{\frac{1}{2}} \exp\left[-\frac{\beta}{2} (t_n - w^T \phi(x_n))^2\right]$$

Since $p(w, \beta | t) \propto p(t | x, w, \beta) \times p(w, \beta)$

$$\begin{aligned} \text{We have quadratic term} &= -\frac{\beta}{2} w^T S_0^{-1} w + \sum_{n=1}^N -\frac{\beta}{2} w^T \phi(x_n) \phi(x_n)^T w \\ &= -\frac{\beta}{2} w^T \left(S_0^{-1} + \underbrace{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T}_{S_N^{-1}} \right) w \end{aligned}$$

$$S_N = \left[S_0^{-1} + \sum_{n=1}^N \phi(x_n) \phi(x_n)^T \right]^{-1}$$

$$\begin{aligned} \text{linear term} &= \beta m_0^T S_0^{-1} w + \sum_{n=1}^N \beta t_n \phi(x_n)^T w \\ &= \beta \left[m_0^T S_0^{-1} + \sum_{n=1}^N t_n \phi(x_n)^T \right] w \\ &\quad \underbrace{m_N^T S_N^{-1}} \end{aligned}$$

$$\text{Then } m_N = S_N \left[S_0^{-1} m_0 + \sum_{n=1}^N t_n \phi(x_n) \right]$$

$$\begin{aligned} \text{Constant term} &= \left(-\frac{\beta}{2} m_0^T S_0^{-1} m_0 - b_0 \beta \right) - \frac{\beta}{2} \sum_{n=1}^N t_n^2 \\ &= -\beta \left(\frac{1}{2} m_0^T S_0^{-1} m_0 + b_0 + \frac{1}{2} \sum_{n=1}^N t_n^2 \right) \end{aligned}$$

$$\text{Then } \frac{1}{2} m_N^T S_N^{-1} m_N + b_N = \frac{1}{2} m_0^T S_0^{-1} m_0 + b_0 + \frac{1}{2} \sum_{n=1}^N t_n^2$$

$$b_N = \frac{1}{2} m_0^T S_0^{-1} m_0 + b_0 + \frac{1}{2} \sum_{n=1}^N t_n^2 - \frac{1}{2} m_N^T S_N^{-1} m_N$$

$$\text{exp term} = (2 + a_0 - 1) + \frac{N}{2}$$

$$2 + a_{N-1} = (2 + a_0 - 1) + \frac{N}{2}$$

$$\underline{a_N = a_0 + \frac{N}{2}}$$

3. let $w^T \phi(x_n) > 0$ and let $w^T \phi(x_m) < 0$,

$$\text{Show } P(C_1 | \phi) = \gamma(\phi) = \sigma(w^T \phi)$$

when $|w| \rightarrow \infty$

$$P(C_1 | \phi(x_n)) = \sigma(w^T \phi(x_n)) \rightarrow 1$$

$$P(C_2 | \phi(x_m)) = 1 - P(C_1 | \phi(x_m)) = 1 - \sigma(w^T \phi(x_m)) \rightarrow 1$$

4. Since y_n is the output of logistic regression model

$$\text{Then } 0 < y_n < 1 \Rightarrow y_n(1-y_n) > 0$$

$$\text{By } H = \nabla \nabla E(w) = \sum_{n=1}^N y_n(1-y_n) \phi_n \phi_n^T = \Phi^T R \Phi \quad (4.97)$$

for an vector $a \neq 0$

$$a^T H a = a^T \left[\sum_{n=1}^N y_n(1-y_n) \phi_n \phi_n^T \right] a$$

$$= \sum_{n=1}^N y_n(1-y_n) (\phi_n^T a)^T (\phi_n^T a)$$

$$= \sum_{n=1}^N y_n(1-y_n) b_n^2 \quad \text{where denote } b_n = \phi_n^T a$$

Then There $\exists b_n \in \{b_1, \dots, b_N\} \neq 0$.

Then $a^T H a > 0$, H is positive definite.

$$5. a) f(x; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$$

$$= \frac{\beta^\alpha}{\Gamma(\alpha)} \exp\{-\beta x + (\alpha-1)\ln x\}$$

$$\eta = \begin{bmatrix} -\beta \\ \alpha-1 \end{bmatrix}, \quad u(x) = \begin{bmatrix} x \\ \ln x \end{bmatrix}, \quad h(x) = 1 \quad g(\eta) = \ln \frac{\beta^\alpha}{\Gamma(\alpha)}$$

$$b) \stackrel{L(u)}{=} f(t_k | x_k) = \frac{1}{\Gamma(u)} \left(\frac{v t_k}{y_k} \right)^u \frac{1}{y_k} e^{-\frac{v t_k}{y_k}}$$

$$\text{Then } \ln f(t_k | x_k) = v \ln(v t_k) - v \ln(y_k) - \frac{v t_k}{y_k} - \ln(\Gamma(u)) - \ln(y_k)$$

$$= v \ln(v t_k) - \ln(\Gamma(u)) - v(w_0 + w_1 x_k) - \frac{v t_k}{w_0 + w_1 x_k} - (w_0 + w_1 x_k)$$

$$\frac{\partial \ln f(t_k | x_k)}{\partial w_0} = -v - \frac{v t_k}{(w_0 + w_1 x_k)^2} - 1$$

$$\frac{\partial^2 \ln f(t_k | x_k)}{\partial^2 w_0} = \frac{2v t_k}{(w_0 + w_1 x_k)^3} \geq 0$$

$$\frac{\partial \ln f(t_k | x_k)}{\partial w_1} = v x_k - \frac{v t_k x_k}{(w_0 + w_1 x_k)^2} - x_k$$

$$\frac{\partial^2 \ln f(t_k | x_k)}{\partial^2 w_1} = \frac{2v t_k x_k (1 + x_k)}{(w_0 + w_1 x_k)^3} \geq 0$$

Then the likelihood function is a convex function.

$$b) \quad p(w) = \frac{1}{2b} \exp\left(-\frac{|w|}{b}\right)$$

$$L(w) = \prod_{i=1}^n \frac{1}{2b} \exp\left(-\frac{|w_i|}{b}\right)$$

$$= \left(\frac{1}{2b}\right)^n \prod_{i=1}^n \exp\left(-\frac{|w_i|}{b}\right)$$

$$\log L(w) = -n \log(2b) - \frac{1}{b} \sum_{i=1}^n |w_i|$$

The Method of moments is

$$E_n(x) = x^{n-1} r(1-n, x), \text{ which is a Lasso regression.}$$

hw2

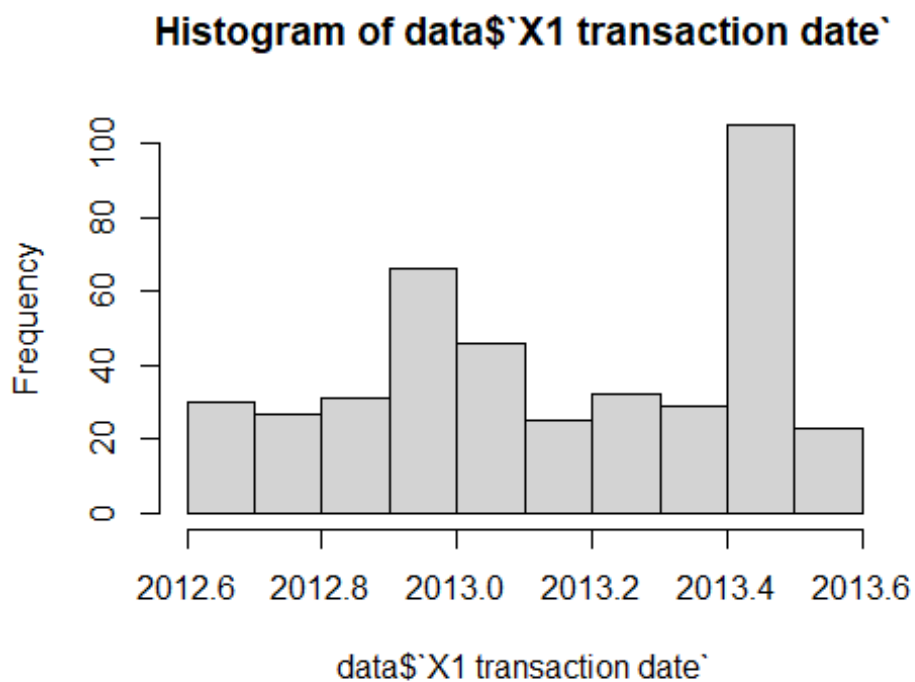
Enbo Tian

2/14/2022

Linear Regression Problem

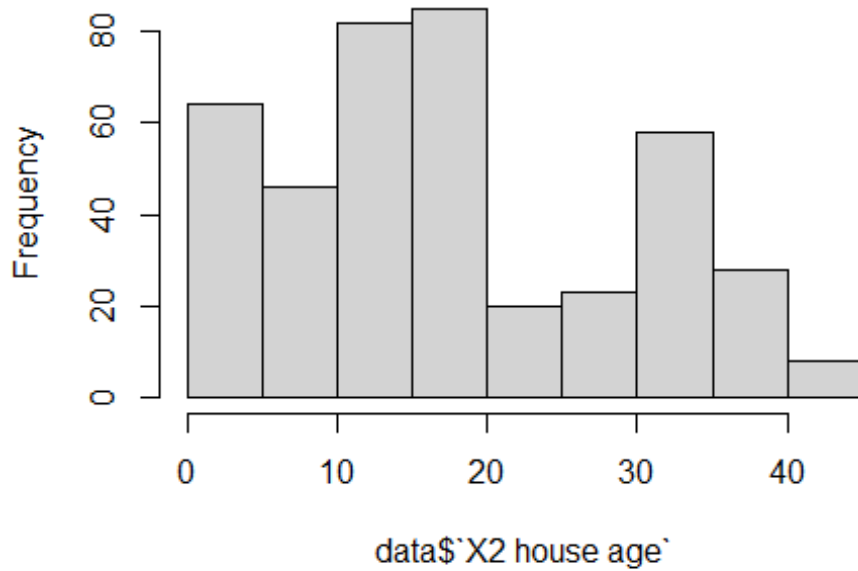
1)

```
rm(list=ls())  
library("readxl")  
data<-read_excel("Real estate valuation data set.xlsx")  
## a  
hist(data$`X1 transaction date`)
```



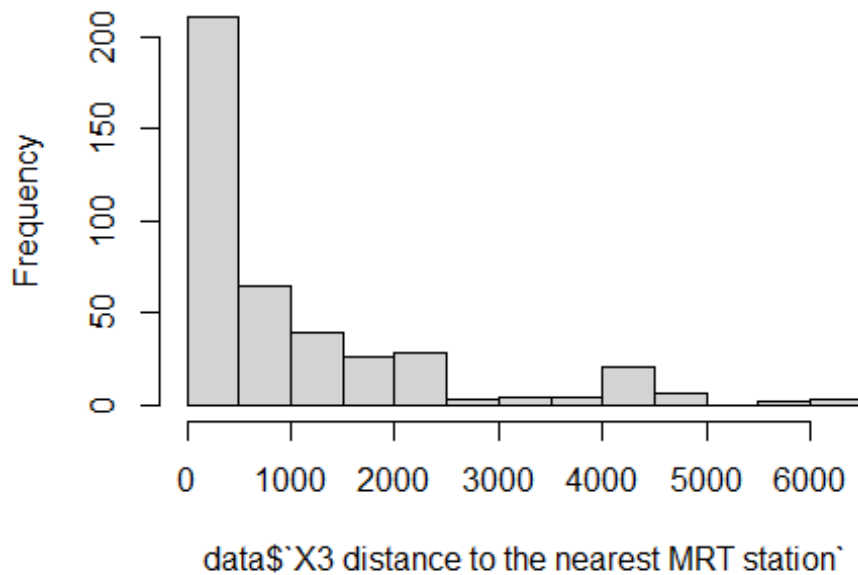
```
hist(data$`X2 house age`)
```

Histogram of data\$`X2 house age`



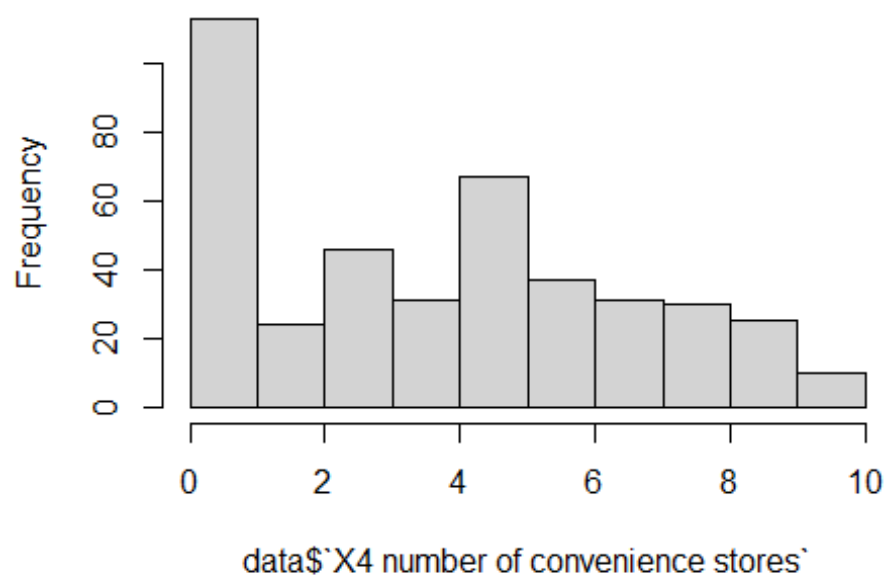
```
hist(data$`X3 distance to the nearest MRT station`)
```

istogram of data\$`X3 distance to the nearest MRT station`



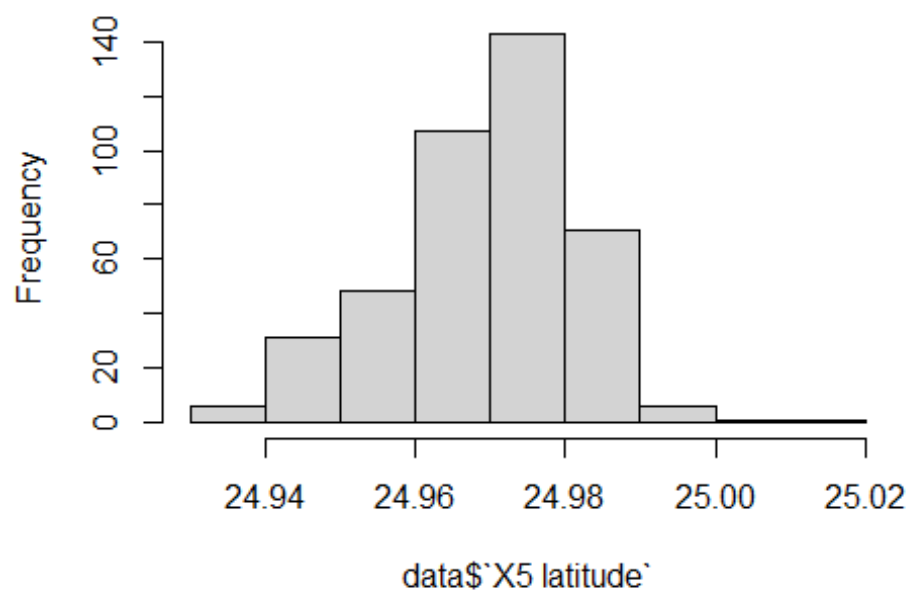
```
hist(data$`X4 number of convenience stores`)
```

Histogram of data\$`X4 number of convenience stor



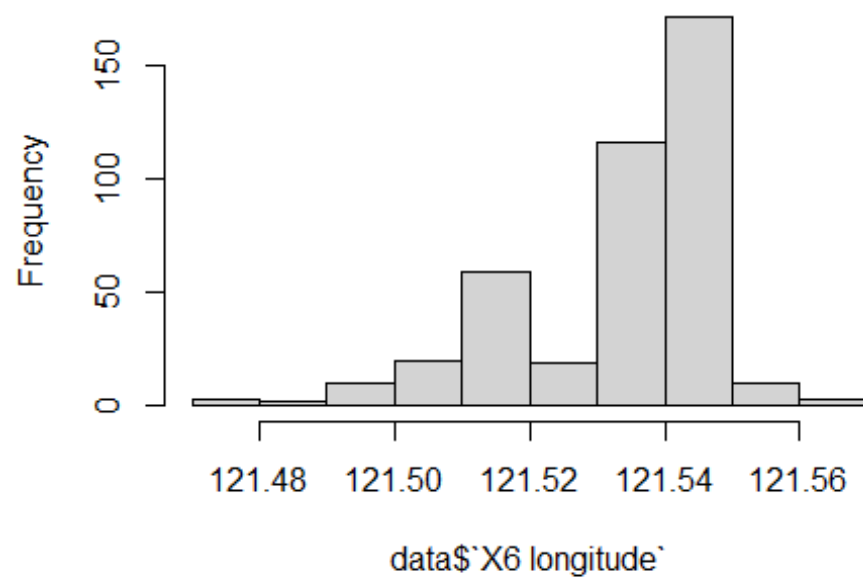
```
hist(data$`X5 latitude`)
```

Histogram of data\$`X5 latitude`



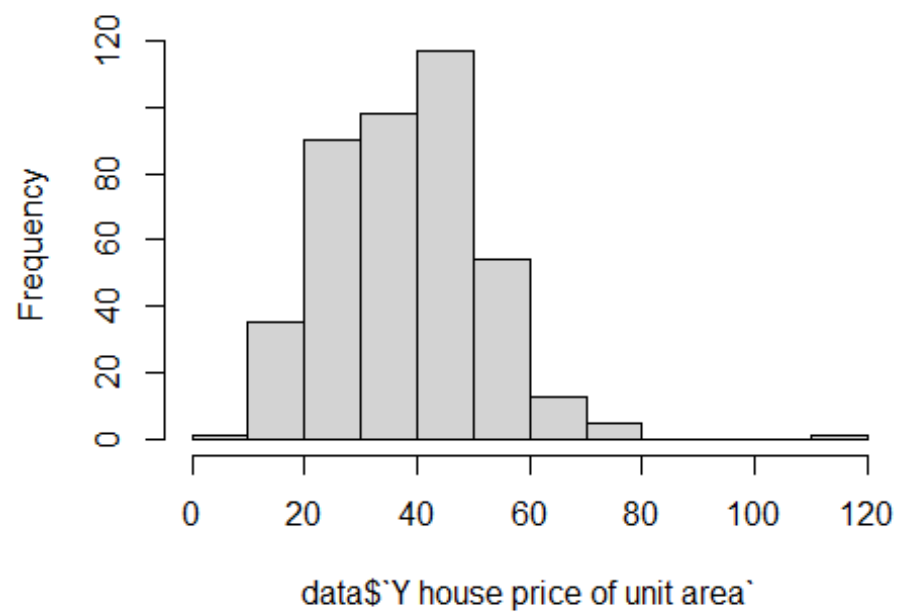
```
hist(data$`X6 longitude`)
```


Histogram of data\$`X6 longitude`

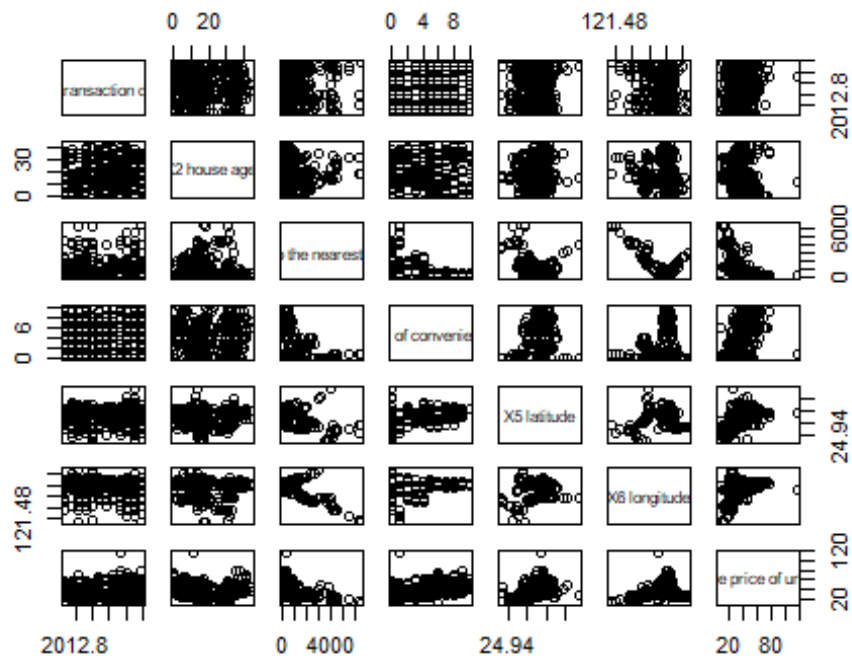


```
hist(data$`Y house price of unit area`)
```

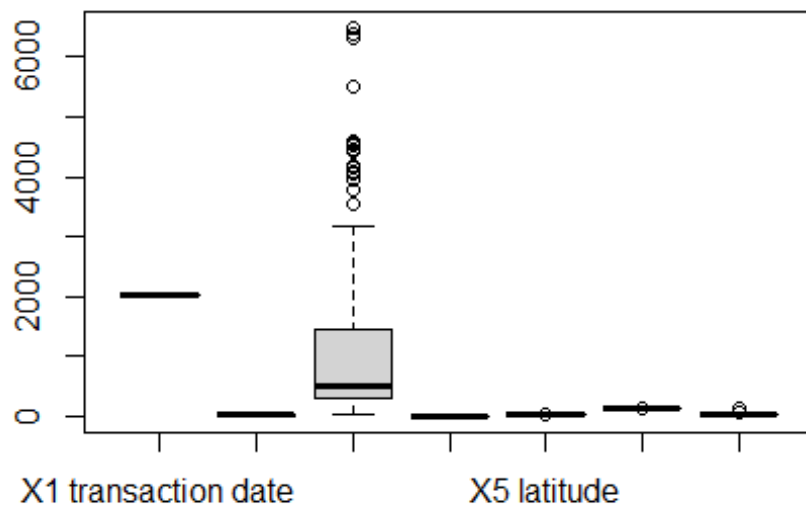
Histogram of data\$`Y house price of unit area`



```
## b
plot(data[,2:8])
```



```
boxplot(data[,2:8])
```



There is significant outlier for X3: distance to the nearest MRT station

```
cor(data[,2:8])
```

	X1 transaction date	X2 house age
## X1 transaction date	1.000000000	0.01754
234		
## X2 house age	0.017542341	1.00000
000		
## X3 distance to the nearest MRT station	0.060880095	0.02562
205		
## X4 number of convenience stores	0.009544199	0.04959
251		
## X5 latitude	0.035016305	0.05441
990		
## X6 longitude	-0.041065078	-0.04852
005		
## Y house price of unit area	0.087529272	-0.21056
705		
##		
	X3 distance to the nearest MR	
T station		
## X1 transaction date		0.
06088009		
## X2 house age		0.
02562205		
## X3 distance to the nearest MRT station		1.

```

00000000
## X4 number of convenience stores -0.
60251914
## X5 latitude -0.
59106657
## X6 longitude -0.
80631677
## Y house price of unit area -0.
67361286
## X4 number of convenience stor
es
## X1 transaction date 0.0095441
99
## X2 house age 0.0495925
13
## X3 distance to the nearest MRT station -0.6025191
45
## X4 number of convenience stores 1.0000000
00
## X5 latitude 0.4441433
06
## X6 longitude 0.4490990
07
## Y house price of unit area 0.5710049
11
## X5 latitude X6 longitude
## X1 transaction date 0.03501631 -0.04106508
## X2 house age 0.05441990 -0.04852005
## X3 distance to the nearest MRT station -0.59106657 -0.80631677
## X4 number of convenience stores 0.44414331 0.44909901
## X5 latitude 1.00000000 0.41292394
## X6 longitude 0.41292394 1.00000000
## Y house price of unit area 0.54630665 0.52328651
## Y house price of unit area
## X1 transaction date 0.08752927
## X2 house age -0.21056705
## X3 distance to the nearest MRT station -0.67361286
## X4 number of convenience stores 0.57100491
## X5 latitude 0.54630665
## X6 longitude 0.52328651
## Y house price of unit area 1.00000000

```

2

```

df <- data.frame(data[2:8])
LR<-lm(data$`Y house price of unit area`~data$`X1 transaction date`
+data$`X2 house age`
+data$`X3 distance to the nearest MRT station`
+data$`X4 number of convenience stores`
+data$`X5 latitude`+data$`X6 longitude`)
summary(LR)

```

```
## Call:
## lm(formula = data$`Y house price of unit area` ~ data$`X1 transaction date` +
##      data$`X2 house age` + data$`X3 distance to the nearest MRT station` +
##      data$`X4 number of convenience stores` + data$`X5 latitude` +
##      data$`X6 longitude`)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -35.667  -5.412  -0.967   4.217  75.190
##
## Coefficients:
##                                Estimate Std. Error
## t value
## (Intercept)                   -1.444e+04  6.775e+03
##                                -2.132
## data$`X1 transaction date`      5.149e+00  1.557e+00
##                                3.307
## data$`X2 house age`            -2.697e-01  3.853e-02
##                                -7.000
## data$`X3 distance to the nearest MRT station` -4.488e-03  7.180e-04
##                                -6.250
## data$`X4 number of convenience stores`  1.133e+00  1.882e-01
##                                6.023
## data$`X5 latitude`             2.255e+02  4.457e+01
##                                5.059
## data$`X6 longitude`            -1.243e+01  4.858e+01
##                                -0.256
##
##                                Pr(>|t|)
## (Intercept)                   0.03364 *
## data$`X1 transaction date`      0.00103 **
## data$`X2 house age`            1.06e-11 ***
## data$`X3 distance to the nearest MRT station` 1.04e-09 ***
## data$`X4 number of convenience stores`  3.83e-09 ***
## data$`X5 latitude`             6.38e-07 ***
## data$`X6 longitude`            0.79820
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.858 on 407 degrees of freedom
## Multiple R-squared:  0.5824, Adjusted R-squared:  0.5762
## F-statistic: 94.6 on 6 and 407 DF, p-value: < 2.2e-16

# predicted weights
summary(LR)$coefficients

##                                Estimate Std. E
```

```
## (Intercept) -1.444198e+04 6.775386
e+03
## data$`X1 transaction date` 5.149017e+00 1.556876
e+00
## data$`X2 house age` -2.696967e-01 3.852998
e-02
## data$`X3 distance to the nearest MRT station` -4.487508e-03 7.180118
e-04
## data$`X4 number of convenience stores` 1.133325e+00 1.881597
e-01
## data$`X5 latitude` 2.254701e+02 4.456578
e+01
## data$`X6 longitude` -1.242906e+01 4.858117
e+01
##
## t value Pr(>|t|)
## (Intercept) -2.1315365 3.364344e-0
2
## data$`X1 transaction date` 3.3072743 1.025782e-0
3
## data$`X2 house age` -6.9996591 1.063915e-1
1
## data$`X3 distance to the nearest MRT station` -6.2499086 1.037344e-0
9
## data$`X4 number of convenience stores` 6.0232088 3.826895e-0
9
## data$`X5 latitude` 5.0592667 6.382166e-0
7
## data$`X6 longitude` -0.2558411 7.982028e-0
1

# price as a function of time(X1)
## increase in 5.149
# RMSE
summary(LR)$sigma
## [1] 8.857515
```

3

```
library(rstanarm)

## Loading required package: Rcpp

## This is rstanarm version 2.21.1

## - See https://mc-stan.org/rstanarm/articles/priors for changes to de
fault priors!

## - Default priors may change, so it's safest to specify priors, even
if equivalent to the defaults.
```

```

## - For execution on a local, multicore CPU with excess RAM we recommen
d calling

## options(mc.cores = parallel::detectCores())

# lambda = 1
bayesm<- stan_glm(df$Y.house.price.of.unit.area~.,data=df,prior_aux = e
xponential(1))

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition wou
ld take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.086 seconds (Warm-up)
## Chain 1:                0.117 seconds (Sampling)
## Chain 1:                0.203 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition wou
ld take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%] (Warmup)

```

```
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.085 seconds (Warm-up)
## Chain 2: 0.111 seconds (Sampling)
## Chain 2: 0.196 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.095 seconds (Warm-up)
## Chain 3: 0.106 seconds (Sampling)
## Chain 3: 0.201 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%] (Warmup)
```



```

## Chain 4: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.079 seconds (Warm-up)
## Chain 4: 0.108 seconds (Sampling)
## Chain 4: 0.187 seconds (Total)
## Chain 4:

summary(bayesm)

##
## Model Info:
## function:      stan_glm
## family:        gaussian [identity]
## formula:       df$Y.house.price.of.unit.area ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  414
## predictors:    7
##
## Estimates:
##
##              mean      sd      10%
50%
## (Intercept)      -14500.0  6527.6 -22783.2 -1
4402.5
## X1.transaction.date      5.2      1.5      3.2
5.2
## X2.house.age      -0.3      0.0      -0.3
-0.3
## X3.distance.to.the.nearest.MRT.station      0.0      0.0      0.0
0.0
## X4.number.of.convenience.stores      1.1      0.2      0.9
1.1
## X5.latitude      225.5      44.7      168.5
225.4
## X6.longitude      -12.0      47.4      -72.0
-12.7
## sigma      8.8      0.3      8.4
8.8
##
##              90%
## (Intercept)      -6201.9
## X1.transaction.date      7.1
## X2.house.age      -0.2

```

```

## X3.distance.to.the.nearest.MRT.station      0.0
## X4.number.of.convenience.stores             1.4
## X5.latitude                                283.6
## X6.longitude                               48.5
## sigma                                       9.2
##
## Fit Diagnostics:
##           mean    sd   10%   50%   90%
## mean_PPD 38.0    0.6 37.2  38.0  38.8
##
## The mean_ppd is the sample average posterior predictive distribution
## of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##
##           mcse  Rhat  n_eff
## (Intercept) 103.8   1.0 3956
## X1.transaction.date      0.0   1.0 5469
## X2.house.age             0.0   1.0 6011
## X3.distance.to.the.nearest.MRT.station 0.0   1.0 3093
## X4.number.of.convenience.stores      0.0   1.0 5193
## X5.latitude              0.7   1.0 4665
## X6.longitude             0.8   1.0 3712
## sigma                  0.0   1.0 5577
## mean_PPD              0.0   1.0 4534
## log-posterior          0.0   1.0 1698
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
## rude measure of effective sample size, and Rhat is the potential scale
## reduction factor on split chains (at convergence Rhat=1).

# Lambda = 10
bayesm2<- stan_glm(df$Y.house.price.of.unit.area~.,data=df,prior_aux =
exponential(10))

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
## take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [ 0%] (Warmup)
## Chain 1: Iteration:  200 / 2000 [10%] (Warmup)
## Chain 1: Iteration:  400 / 2000 [20%] (Warmup)
## Chain 1: Iteration:  600 / 2000 [30%] (Warmup)
## Chain 1: Iteration:  800 / 2000 [40%] (Warmup)
## Chain 1: Iteration: 1000 / 2000 [50%] (Warmup)
## Chain 1: Iteration: 1001 / 2000 [50%] (Sampling)

```

```

## Chain 1: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.1 seconds (Warm-up)
## Chain 1: 0.113 seconds (Sampling)
## Chain 1: 0.213 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 2: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.102 seconds (Warm-up)
## Chain 2: 0.113 seconds (Sampling)
## Chain 2: 0.215 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)

```

```

## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.09 seconds (Warm-up)
## Chain 3:          0.107 seconds (Sampling)
## Chain 3:          0.197 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 4: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.09 seconds (Warm-up)
## Chain 4:          0.117 seconds (Sampling)
## Chain 4:          0.207 seconds (Total)
## Chain 4:

summary(bayesm2)

##
## Model Info:
## function:      stan_glm
## family:        gaussian [identity]
## formula:       df$Y.house.price.of.unit.area ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  414

```

```

## predictors: 7
##
## Estimates:
##               mean      sd      10%
50%
## (Intercept) -14463.2  6122.8 -22280.7 -1
4436.5
## X1.transaction.date      5.1      1.4      3.3
5.1
## X2.house.age      -0.3      0.0      -0.3
-0.3
## X3.distance.to.the.nearest.MRT.station      0.0      0.0      0.0
0.0
## X4.number.of.convenience.stores      1.1      0.2      0.9
1.1
## X5.latitude      224.8      41.2      172.7
225.3
## X6.longitude      -12.1      43.8      -68.1
-12.8
## sigma      8.1      0.3      7.8
8.1
##
##               90%
## (Intercept) -6690.0
## X1.transaction.date      7.0
## X2.house.age      -0.2
## X3.distance.to.the.nearest.MRT.station      0.0
## X4.number.of.convenience.stores      1.4
## X5.latitude      276.8
## X6.longitude      43.5
## sigma      8.4
##
## Fit Diagnostics:
##               mean      sd      10%      50%      90%
## mean_PPD 38.0      0.6 37.3  38.0  38.7
##
## The mean_ppd is the sample average posterior predictive distribution
  of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##               mcse  Rhat  n_eff
## (Intercept) 100.4   1.0 3717
## X1.transaction.date      0.0   1.0 5862
## X2.house.age      0.0   1.0 5400
## X3.distance.to.the.nearest.MRT.station      0.0   1.0 2896
## X4.number.of.convenience.stores      0.0   1.0 4984
## X5.latitude      0.6   1.0 4421
## X6.longitude      0.8   1.0 3384
## sigma      0.0   1.0 4929
## mean_PPD      0.0   1.0 4577
## log-posterior      0.0   1.0 1847

```

```
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
rude measure of effective sample size, and Rhat is the potential scale
reduction factor on split chains (at convergence Rhat=1).

# Lambda = 100
bayesm3<- stan_glm(df$Y.house.price.of.unit.area~.,data=df,prior_aux =
exponential(100))

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition wou
ld take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 1: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.116 seconds (Warm-up)
## Chain 1:           0.106 seconds (Sampling)
## Chain 1:           0.222 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition wou
ld take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 2: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration:  1000 / 2000 [ 50%] (Warmup)
```

```
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.107 seconds (Warm-up)
## Chain 2: 0.108 seconds (Sampling)
## Chain 2: 0.215 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.099 seconds (Warm-up)
## Chain 3: 0.106 seconds (Sampling)
## Chain 3: 0.205 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%] (Warmup)
```

```

## Chain 4: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.077 seconds (Warm-up)
## Chain 4: 0.106 seconds (Sampling)
## Chain 4: 0.183 seconds (Total)
## Chain 4:

summary(bayesm3)

##
## Model Info:
## function:      stan_glm
## family:        gaussian [identity]
## formula:       df$Y.house.price.of.unit.area ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  414
## predictors:    7
##
## Estimates:
##
##              mean      sd      10%
50%
## (Intercept)      -14593.4  4374.2 -20304.7 -1
4576.4
## X1.transaction.date      5.2      1.0      3.9
5.2
## X2.house.age      -0.3      0.0      -0.3
-0.3
## X3.distance.to.the.nearest.MRT.station      0.0      0.0      0.0
0.0
## X4.number.of.convenience.stores      1.1      0.1      1.0
1.1
## X5.latitude      225.4      28.8      188.3
225.2
## X6.longitude      -11.4      31.6      -51.0
-12.3
## sigma      5.7      0.1      5.6
5.7
##
##              90%
## (Intercept)      -9008.1
## X1.transaction.date      6.4
## X2.house.age      -0.2

```



```
## X3.distance.to.the.nearest.MRT.station      0.0
## X4.number.of.convenience.stores             1.3
## X5.latitude                                262.5
## X6.longitude                                30.0
## sigma                                       5.9
##
## Fit Diagnostics:
##           mean    sd   10%   50%   90%
## mean_PPD 38.0    0.4  37.5  38.0  38.5
##
## The mean_ppd is the sample average posterior predictive distribution
## of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##                                     mcse Rhat n_eff
## (Intercept)                      71.7  1.0  3718
## X1.transaction.date                0.0  1.0  5307
## X2.house.age                       0.0  1.0  5596
## X3.distance.to.the.nearest.MRT.station 0.0  1.0  3286
## X4.number.of.convenience.stores     0.0  1.0  3709
## X5.latitude                         0.4  1.0  4599
## X6.longitude                         0.5  1.0  3575
## sigma                              0.0  1.0  4994
## mean_PPD                           0.0  1.0  4572
## log-posterior                      0.0  1.0  1887
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
## rude measure of effective sample size, and Rhat is the potential scale
## reduction factor on split chains (at convergence Rhat=1).
```

4

```
library(robustHD)

## Loading required package: ggplot2

## Loading required package: perry

## Loading required package: parallel

## Loading required package: robustbase

x2 <- data$`X2 house age`
x3 <- data$`X3 distance to the nearest MRT station`

s2<-standardize(x2)
s3<-standardize(x3)

bayesm4<- stan_glm(data$`Y house price of unit area`~s2+s3,data=data)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
```

```
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [ 0%] (Warmup)
## Chain 1: Iteration:  200 / 2000 [10%] (Warmup)
## Chain 1: Iteration:  400 / 2000 [20%] (Warmup)
## Chain 1: Iteration:  600 / 2000 [30%] (Warmup)
## Chain 1: Iteration:  800 / 2000 [40%] (Warmup)
## Chain 1: Iteration: 1000 / 2000 [50%] (Warmup)
## Chain 1: Iteration: 1001 / 2000 [50%] (Sampling)
## Chain 1: Iteration: 1200 / 2000 [60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.057 seconds (Warm-up)
## Chain 1:                0.073 seconds (Sampling)
## Chain 1:                0.13 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [ 0%] (Warmup)
## Chain 2: Iteration:  200 / 2000 [10%] (Warmup)
## Chain 2: Iteration:  400 / 2000 [20%] (Warmup)
## Chain 2: Iteration:  600 / 2000 [30%] (Warmup)
## Chain 2: Iteration:  800 / 2000 [40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.059 seconds (Warm-up)
## Chain 2:                0.078 seconds (Sampling)
## Chain 2:                0.137 seconds (Total)
## Chain 2:
```

```

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 3: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.044 seconds (Warm-up)
## Chain 3:                0.067 seconds (Sampling)
## Chain 3:                0.111 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 4: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.048 seconds (Warm-up)
## Chain 4:                0.077 seconds (Sampling)

```

```
## Chain 4:                0.125 seconds (Total)
## Chain 4:

summary(bayesm4)

##
## Model Info:
## function:      stan_glm
## family:        gaussian [identity]
## formula:       data$`Y house price of unit area` ~ s2 + s3
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  414
## predictors:    3
##
## Estimates:
##           mean    sd   10%   50%   90%
## (Intercept) 38.0    0.5  37.4  38.0  38.6
## s2          -2.6    0.5  -3.3  -2.6  -2.0
## s3          -9.1    0.5  -9.7  -9.1  -8.5
## sigma       9.7     0.3   9.3   9.7  10.2
##
## Fit Diagnostics:
##           mean    sd   10%   50%   90%
## mean_PPD 38.0     0.7  37.1  38.0  38.8
##
## The mean_ppd is the sample average posterior predictive distribution
  of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##           mcse Rhat n_eff
## (Intercept)  0.0  1.0  5171
## s2           0.0  1.0  4699
## s3           0.0  1.0  4916
## sigma        0.0  1.0  5197
## mean_PPD     0.0  1.0  4663
## log-posterior 0.0  1.0  1580
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
  rude measure of effective sample size, and Rhat is the potential scale
  reduction factor on split chains (at convergence Rhat=1).
```

5

```
library(bayestestR)
map_estimate(bayesm)

## MAP Estimate
##
## Parameter | MAP_Estimate
```

```
## -----
## (Intercept) | -13565.89
## X1.transaction.date | 5.16
## X2.house.age | -0.28
## X3.distance.to.the.nearest.MRT.station | -4.41e-03
## X4.number.of.convenience.stores | 1.15
## X5.latitude | 223.37
## X6.longitude | -18.29

map_estimate(bayesm4)

## MAP Estimate
##
## Parameter | MAP_Estimate
## -----
## (Intercept) | 38.03
## s2 | -2.60
## s3 | -9.16

M = 7
N = 414

lnp1 <- 1727 - 1/2*7*log(414)
lnp2 <- 1747 - 1/2*7*log(414)
lnp1
## [1] 1705.909

lnp2
## [1] 1725.909
```

7 Gaussian basis model have a high evidence

6

```
#kfold1<-kfold(bayesm,K = 10)
#kfold2 <- kfold(bayesm4,K=10)
#loo_compare(kfold1,kfold2)
```

bayes model too large to run k fold cv.

Classification Problem

1

```
rm(list=ls())
data<-read_excel("ENB2012_data.xlsx")

diff <- rep(0,768)

for( i in 1: 768){
```

```

if(data$Y1[i]-data$Y2[i]>0){
  diff[i] <- 1
}
}

```

1

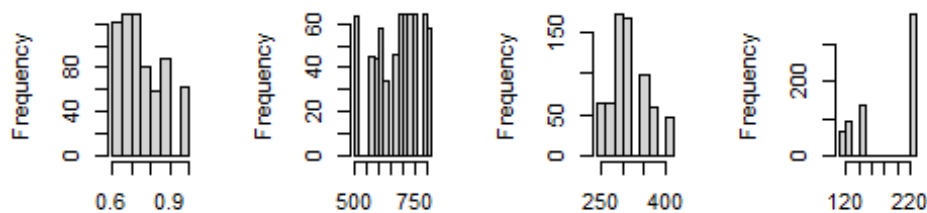
Label 0

```

par(mfrow=c(2,4))
hist(data$X1[which(diff==0)])
hist(data$X2[which(diff==0)])
hist(data$X3[which(diff==0)])
hist(data$X4[which(diff==0)])
hist(data$X5[which(diff==0)])
hist(data$X6[which(diff==0)])
hist(data$X7[which(diff==0)])
hist(data$X8[which(diff==0)])

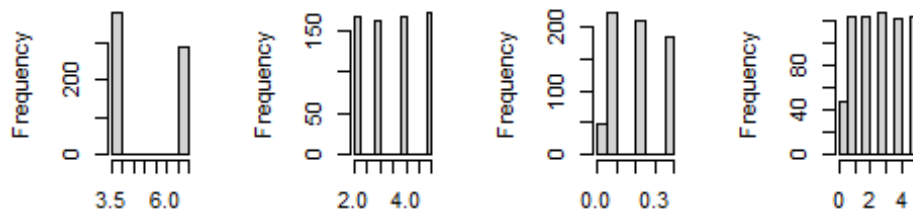
```

am of data\$X1[whiam of data\$X2[whiam of data\$X3[whiam of data\$X4[whic



data\$X1[which(diff == data\$X2[which(diff == data\$X3[which(diff == data\$X4[which(diff ==

am of data\$X5[whiam of data\$X6[whiam of data\$X7[whiam of data\$X8[whic



data\$X5[which(diff == data\$X6[which(diff == data\$X7[which(diff == data\$X8[which(diff ==

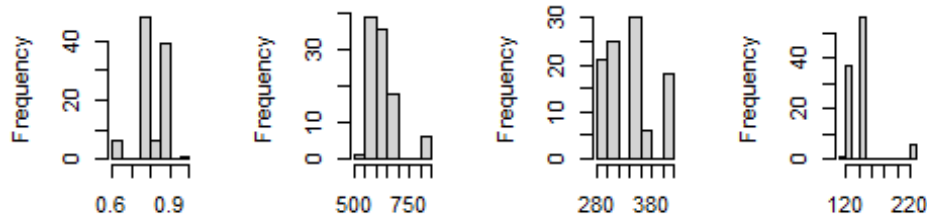
Label 1

```

hist(data$X1[which(diff==1)])
hist(data$X2[which(diff==1)])
hist(data$X3[which(diff==1)])
hist(data$X4[which(diff==1)])
hist(data$X5[which(diff==1)])
hist(data$X6[which(diff==1)])
hist(data$X7[which(diff==1)])
hist(data$X8[which(diff==1)])

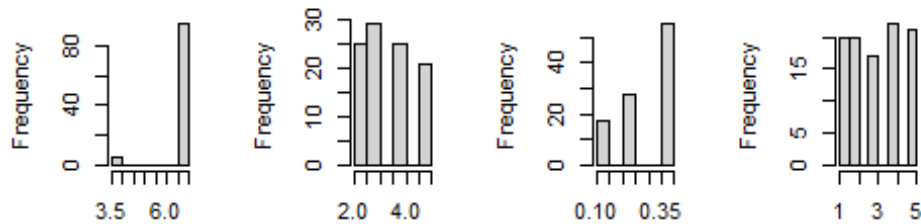
```

am of data\$X1[whiam of data\$X2[whiam of data\$X3[whiam of data\$X4[whic



data\$X1[which(diff == data\$X2[which(diff == data\$X3[which(diff == data\$X4[which(diff ==

am of data\$X5[whiam of data\$X6[whiam of data\$X7[whiam of data\$X8[whic



data\$X5[which(diff == data\$X6[which(diff == data\$X7[which(diff == data\$X8[which(diff ==

```
df<-data.frame(data[,1:8],diff)
cor(df)
```

```
##           X1           X2           X3           X4           X5
## X1  1.000000e+00 -9.919015e-01 -0.2037817 -8.688234e-01  0.8277473
## X2 -9.919015e-01  1.000000e+00  0.1955016  8.807195e-01 -0.8581477
## X3 -2.037817e-01  1.955016e-01  1.0000000 -2.923165e-01  0.2809757
## X4 -8.688234e-01  8.807195e-01 -0.2923165  1.000000e+00 -0.9725122
## X5  8.277473e-01 -8.581477e-01  0.2809757 -9.725122e-01  1.0000000
## X6  0.000000e+00  0.000000e+00  0.0000000  0.000000e+00  0.0000000
## X7  7.617400e-20  4.664140e-20  0.0000000 -1.197187e-19  0.0000000
## X8  0.000000e+00  0.000000e+00  0.0000000  0.000000e+00  0.0000000
## diff 1.787384e-01 -2.042417e-01  0.2022058 -2.968207e-01  0.3404822
##           X6           X7           X8           diff
## X1  0.00000000  7.617400e-20  0.00000000  0.17873840
## X2  0.00000000  4.664140e-20  0.00000000 -0.20424166
## X3  0.00000000  0.000000e+00  0.00000000  0.20220577
## X4  0.00000000 -1.197187e-19  0.00000000 -0.29682073
## X5  0.00000000  0.000000e+00  0.00000000  0.34048222
## X6  1.00000000  0.000000e+00  0.00000000 -0.02768514
## X7  0.00000000  1.000000e+00  0.21296422  0.21106177
## X8  0.00000000  2.129642e-01  1.00000000  0.05679049
## diff -0.02768514  2.110618e-01  0.05679049  1.00000000
```

x5 have the highest predictive power

2

```
model <- glm(diff~.,data = df, family=binomial)
summary(model)

##
## Call:
## glm(formula = diff ~ ., family = binomial, data = df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.54464  -0.49154  -0.09946  -0.00436   2.53343
##
## Coefficients: (1 not defined because of singularities)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.212e+02  9.823e+01  -3.270 0.001074 **
## X1           1.520e+02  4.982e+01   3.052 0.002273 **
## X2           2.651e-01  8.074e-02   3.283 0.001027 **
## X3          -3.370e-02  9.573e-03  -3.520 0.000431 ***
## X4              NA          NA      NA      NA
## X5           6.019e+00  1.508e+00   3.992 6.54e-05 ***
## X6          -1.001e-01  1.121e-01  -0.893 0.371862
## X7           6.340e+00  1.058e+00   5.995 2.04e-09 ***
## X8           6.424e-02  8.584e-02   0.748 0.454258
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 594.10  on 767  degrees of freedom
## Residual deviance: 400.32  on 760  degrees of freedom
## AIC: 416.32
##
## Number of Fisher Scoring iterations: 9

## predicted weights: estimate
## classifier accuracy: AIC
```

3

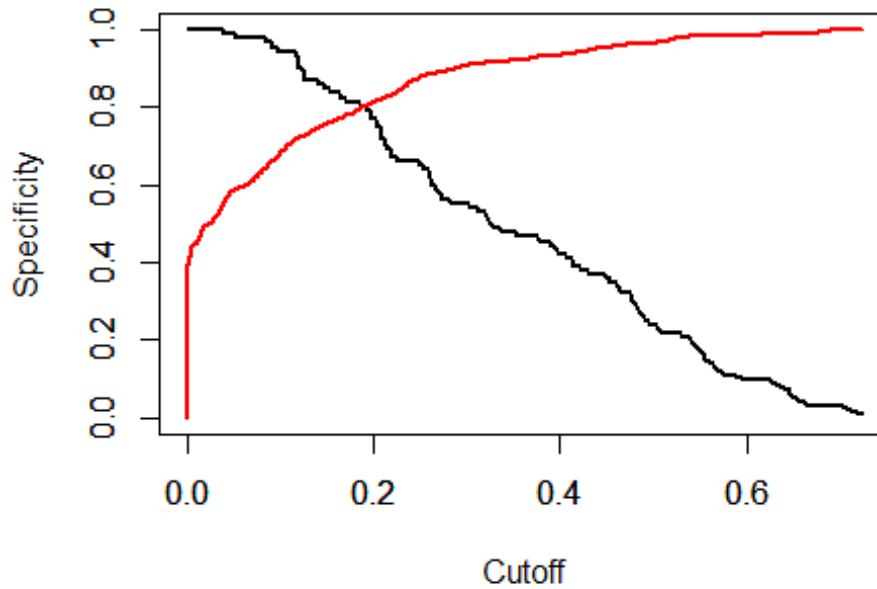
```
library(ROCR)
pred = predict(model, newdata=df, type="response")

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if
## (type == :
## prediction from a rank-deficient fit may be misleading

predictions = prediction(pred, diff, label.ordering = NULL)
plot(unlist(performance(predictions, "sens")@x.values), unlist(performa
nce(predictions, "sens")@y.values),
     type="l", lwd=2, ylab="Specificity", xlab="Cutoff")
par(new=TRUE)
```



```
plot(unlist(performance(predictions, "spec")@x.values), unlist(performance(predictions, "spec")@y.values),
     type="l", lwd=2, col='red', ylab="", xlab="")
```



4

```
library(rstanarm)
bayes<- stan_glm(diff~.,data=df,prior = normal(location = 0, scale = 0.1, autoscale = FALSE) )
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 1: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration:  1600 / 2000 [ 80%] (Sampling)
```

```
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.052 seconds (Warm-up)
## Chain 1: 0.133 seconds (Sampling)
## Chain 1: 0.185 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 2: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.072 seconds (Warm-up)
## Chain 2: 0.14 seconds (Sampling)
## Chain 2: 0.212 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
```

```

## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.059 seconds (Warm-up)
## Chain 3: 0.104 seconds (Sampling)
## Chain 3: 0.163 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.057 seconds (Warm-up)
## Chain 4: 0.1 seconds (Sampling)
## Chain 4: 0.157 seconds (Total)
## Chain 4:

## Warning: There were 57 divergent transitions after warmup. See
## https://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## to find out why this is a problem and how to eliminate them.

## Warning: There were 4 chains where the estimated Bayesian Fraction of Missing Information was low. See
## https://mc-stan.org/misc/warnings.html#bfmi-low

## Warning: Examine the pairs() plot to diagnose sampling problems

## Warning: The largest R-hat is 4.55, indicating chains have not mixed.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#r-hat

```

```

## Warning: Bulk Effective Samples Size (ESS) is too low, indicating po
sterior means and medians may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#bulk-ess

## Warning: Tail Effective Samples Size (ESS) is too low, indicating po
sterior variances and tail quantiles may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#tail-ess

## Warning: Markov chains did not converge! Do not analyze results!

summary(bayes)

##
## Model Info:
## function:      stan_glm
## family:        gaussian [identity]
## formula:       diff ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  768
## predictors:    9
##
## Estimates:
##           mean    sd   10%   50%   90%
## (Intercept) 115.6  19.0  93.2 113.7 141.8
## X1           0.1   0.1  -0.1   0.2   0.2
## X2          -0.1   0.0  -0.2  -0.1  -0.1
## X3          -0.1   0.1  -0.2  -0.1   0.0
## X4          -0.1   0.1  -0.2  -0.1   0.1
## X5           0.0   0.1  -0.1  -0.1   0.2
## X6           0.0   0.1  -0.1   0.0   0.1
## X7           0.1   0.1  -0.1   0.1   0.2
## X8           0.0   0.1  -0.2   0.0   0.1
## sigma       0.3   0.3   0.1   0.1   0.9
##
## Fit Diagnostics:
##           mean    sd   10%   50%   90%
## mean_PPD  0.2    0.9  -1.3   0.7   0.9
##
## The mean_ppd is the sample average posterior predictive distribution
of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##           mcse           Rhat           n_eff
## (Intercept) 1.340000e+01 9.655939e+07 2
## X1          1.000000e-01 6.003400e+08 2
## X2          0.000000e+00 1.147783e+08 2
## X3          0.000000e+00 2.500334e+08 2

```

```

## X4          1.000000e-01 4.303424e+08 2
## X5          1.000000e-01 5.977296e+08 2
## X6          1.000000e-01 5.491989e+08 2
## X7          1.000000e-01 4.648210e+08 2
## X8          1.000000e-01 4.433299e+08 2
## sigma       2.000000e-01 4.957460e+04 2
## mean_PPD    6.000000e-01 5.830000e+01 2
## log-posterior 1.202593e+12 9.599700e+03 2
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
rude measure of effective sample size, and Rhat is the potential scale
reduction factor on split chains (at convergence Rhat=1).

bayes2<- stan_glm(diff~.,data=df,prior = normal(location = 0, scale = 1,
autoscale = FALSE) )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition wou
ld take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [ 0%] (Warmup)
## Chain 1: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.054 seconds (Warm-up)
## Chain 1:           0.124 seconds (Sampling)
## Chain 1:           0.178 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition wou
ld take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:

```

```

## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 2: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.104 seconds (Warm-up)
## Chain 2:                0.087 seconds (Sampling)
## Chain 2:                0.191 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 3: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.042 seconds (Warm-up)
## Chain 3:                0.097 seconds (Sampling)
## Chain 3:                0.139 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.

```

```

## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 4: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.064 seconds (Warm-up)
## Chain 4:           0.11 seconds (Sampling)
## Chain 4:           0.174 seconds (Total)
## Chain 4:

## Warning: There were 195 divergent transitions after warmup. See
## https://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## to find out why this is a problem and how to eliminate them.

## Warning: There were 4 chains where the estimated Bayesian Fraction of Missing Information was low. See
## https://mc-stan.org/misc/warnings.html#bfmi-low

## Warning: Examine the pairs() plot to diagnose sampling problems

## Warning: The largest R-hat is 4.55, indicating chains have not mixed.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#r-hat

## Warning: Bulk Effective Samples Size (ESS) is too low, indicating posterior means and medians may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#bulk-ess

## Warning: Tail Effective Samples Size (ESS) is too low, indicating posterior variances and tail quantiles may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#tail-ess

## Warning: Markov chains did not converge! Do not analyze results!

summary(bayes2)

##
## Model Info:

```

```

## function:      stan_glm
## family:       gaussian [identity]
## formula:      diff ~ .
## algorithm:    sampling
## sample:       4000 (posterior sample size)
## priors:       see help('prior_summary')
## observations: 768
## predictors:   9
##
## Estimates:
##           mean    sd    10%    50%    90%
## (Intercept) 1014.7 729.0 -219.6 1301.8 1674.7
## X1          -0.8   1.3   -1.9   -1.4    1.4
## X2          -0.7   1.4   -1.5   -1.4    1.7
## X3          -1.2   0.8   -1.9   -1.3    0.0
## X4          -1.1   0.7   -1.6   -1.5    0.2
## X5           1.3   0.8    0.0    1.6    1.9
## X6           0.7   0.6   -0.2    0.8    1.4
## X7           0.2   1.7   -1.7    0.2    2.0
## X8          -0.1   1.3   -1.5   -0.2    1.5
## sigma        0.6   0.3    0.0    0.6    1.0
##
## Fit Diagnostics:
##           mean    sd    10%    50%    90%
## mean_PPD -0.3    1.2  -1.5   -0.7    1.7
##
## The mean_ppd is the sample average posterior predictive distribution
## of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##           mcse          Rhat          n_eff
## (Intercept) 5.153000e+02 4.483715e+07 2
## X1          9.000000e-01 4.209010e+07 2
## X2          1.000000e+00 8.960885e+07 2
## X3          5.000000e-01 2.450304e+07 2
## X4          5.000000e-01 3.358717e+07 2
## X5          5.000000e-01 2.795428e+07 2
## X6          4.000000e-01 1.984754e+07 2
## X7          1.200000e+00 6.895481e+07 2
## X8          1.000000e+00 5.535733e+07 2
## sigma       2.000000e-01 3.310300e+03 2
## mean_PPD    8.000000e-01 5.250000e+01 2
## log-posterior 7.388089e+12 4.910890e+04 2
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
## rude measure of effective sample size, and Rhat is the potential scale
## reduction factor on split chains (at convergence Rhat=1).

bayes3<- stan_glm(diff~.,data=df,prior = normal(location = 0, scale = 1
0, autoscale = FALSE) )

```



```

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:      1 / 2000 [ 0%] (Warmup)
## Chain 1: Iteration:    200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:    400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:    600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:    800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration:   1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration:   1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration:   1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration:   1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration:   1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration:   2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.064 seconds (Warm-up)
## Chain 1:                0.101 seconds (Sampling)
## Chain 1:                0.165 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:      1 / 2000 [ 0%] (Warmup)
## Chain 2: Iteration:    200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration:    400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration:    600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration:    800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration:   1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration:  1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration:   1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration:   1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration:   1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration:   1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration:   2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.072 seconds (Warm-up)
## Chain 2:                0.097 seconds (Sampling)

```

```
## Chain 2:                0.169 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 3: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 3: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 67.563 seconds (Warm-up)
## Chain 3:                0.316 seconds (Sampling)
## Chain 3:                67.879 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 4: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration:  1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration:  1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration:  1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration:  1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration:  1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration:  2000 / 2000 [100%] (Sampling)
## Chain 4:
```

```

## Chain 4: Elapsed Time: 0.063 seconds (Warm-up)
## Chain 4: 0.117 seconds (Sampling)
## Chain 4: 0.18 seconds (Total)
## Chain 4:

## Warning: There were 139 divergent transitions after warmup. See
## https://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## to find out why this is a problem and how to eliminate them.

## Warning: There were 4 chains where the estimated Bayesian Fraction of Missing Information was low. See
## https://mc-stan.org/misc/warnings.html#bfmi-low

## Warning: Examine the pairs() plot to diagnose sampling problems

## Warning: The largest R-hat is 4.55, indicating chains have not mixed.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#r-hat

## Warning: Bulk Effective Samples Size (ESS) is too low, indicating posterior means and medians may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#bulk-ess

## Warning: Tail Effective Samples Size (ESS) is too low, indicating posterior variances and tail quantiles may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#tail-ess

## Warning: Markov chains did not converge! Do not analyze results!

summary(bayes3)

##
## Model Info:
## function: stan_glm
## family: gaussian [identity]
## formula: diff ~ .
## algorithm: sampling
## sample: 4000 (posterior sample size)
## priors: see help('prior_summary')
## observations: 768
## predictors: 9
##
## Estimates:
##
```

	mean	sd	10%	50%	90%
## (Intercept)	5607.5	7702.2	-3809.9	4305.7	17628.6
## X1	3.4	15.6	-17.1	5.9	18.9
## X2	-2.5	6.6	-13.7	0.4	3.0
## X3	-9.8	8.0	-18.3	-12.2	3.2
## X4	-4.4	12.2	-18.5	-4.9	10.8

```

## X5          -2.3    5.3    -7.9    -3.4    5.4
## X6           0.5   14.3   -19.2     1.3   18.5
## X7           2.5   16.1   -19.2     5.0   19.1
## X8          -10.1    5.7   -19.9    -7.1   -6.4
## sigma        1.1    0.7     0.1     1.0    2.1
##
## Fit Diagnostics:
##           mean    sd   10%   50%   90%
## mean_PPD  0.0    1.2  -1.2    0.0    1.4
##
## The mean_ppd is the sample average posterior predictive distribution
## of the outcome variable (for details see help('summary.stanreg')).
##
## MCMC diagnostics
##           mcse           Rhat           n_eff
## (Intercept) 5.444900e+03 2.513220e+08 2
## X1          1.100000e+01 3.055833e+08 2
## X2          4.600000e+00 1.939928e+08 2
## X3          5.600000e+00 2.206221e+08 2
## X4          8.700000e+00 1.782411e+08 2
## X5          3.700000e+00 1.062473e+08 2
## X6          1.010000e+01 2.989405e+08 2
## X7          1.140000e+01 4.211788e+08 2
## X8          4.000000e+00 7.816572e+07 2
## sigma       5.000000e-01 1.790955e+05 2
## mean_PPD     8.000000e-01 2.660000e+01 2
## log-posterior 1.112754e+12 3.129959e+06 2
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
## rude measure of effective sample size, and Rhat is the potential scale
## reduction factor on split chains (at convergence Rhat=1).

bayes4<- stan_glm(diff~.,data=df,prior = normal(location = 0, scale = 1
0, autoscale = FALSE) )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
## take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%] (Warmup)
## Chain 1: Iteration:   200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration:   400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration:   600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration:   800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration:  1000 / 2000 [ 50%] (Warmup)

```

```

## Chain 1: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.216 seconds (Warm-up)
## Chain 1: 0.145 seconds (Sampling)
## Chain 1: 0.361 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 2: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 2: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 2: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 2: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.655 seconds (Warm-up)
## Chain 2: 0.137 seconds (Sampling)
## Chain 2: 0.792 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%] (Warmup)

```

```

## Chain 3: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.064 seconds (Warm-up)
## Chain 3: 0.117 seconds (Sampling)
## Chain 3: 0.181 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 4: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 4:
## Chain 4: Elapsed Time: 0.106 seconds (Warm-up)
## Chain 4: 0.102 seconds (Sampling)
## Chain 4: 0.208 seconds (Total)
## Chain 4:

## Warning: There were 137 divergent transitions after warmup. See
## https://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## to find out why this is a problem and how to eliminate them.

## Warning: There were 4 chains where the estimated Bayesian Fraction of Missing Information was low. See
## https://mc-stan.org/misc/warnings.html#bfmi-low

## Warning: Examine the pairs() plot to diagnose sampling problems

```

```
## Warning: The largest R-hat is 4.55, indicating chains have not mixed.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#r-hat
```

```
## Warning: Bulk Effective Samples Size (ESS) is too low, indicating po
sterior means and medians may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#bulk-ess
```

```
## Warning: Tail Effective Samples Size (ESS) is too low, indicating po
sterior variances and tail quantiles may be unreliable.
## Running the chains for more iterations may help. See
## https://mc-stan.org/misc/warnings.html#tail-ess
```

```
## Warning: Markov chains did not converge! Do not analyze results!
```

```
summary(bayes4)
```

```
##
```

```
## Model Info:
```

```
## function:      stan_glm
## family:        gaussian [identity]
## formula:       diff ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  768
## predictors:    9
```

```
##
```

```
## Estimates:
```

	mean	sd	10%	50%	90%
## (Intercept)	5159.1	4495.1	-834.9	5079.5	11312.2
## X1	-0.7	11.5	-17.8	1.1	12.7
## X2	-6.4	6.1	-16.7	-4.3	-0.4
## X3	-1.8	12.2	-19.6	-1.1	14.7
## X4	-1.6	2.2	-4.9	-1.4	1.1
## X5	-0.9	10.7	-16.0	-0.4	13.2
## X6	-5.1	10.5	-19.8	-4.5	8.3
## X7	-0.6	8.3	-13.4	1.1	8.5
## X8	9.2	4.9	0.8	11.9	12.2
## sigma	0.5	0.3	0.1	0.4	0.9

```
##
```

```
## Fit Diagnostics:
```

	mean	sd	10%	50%	90%
## mean_PPD	-1.6	0.3	-1.9	-1.8	-1.2

```
##
```

```
## The mean_ppd is the sample average posterior predictive distribution
of the outcome variable (for details see help('summary.stanreg')).
```

```
##
```

```
## MCMC diagnostics
```

	mcse	Rhat	n_eff
--	------	------	-------

```
## (Intercept) 3.177700e+03 4.838164e+08 2
## X1          8.100000e+00 1.067856e+09 2
## X2          4.300000e+00 5.144333e+08 2
## X3          8.600000e+00 8.271686e+08 2
## X4          1.500000e+00 1.615384e+08 2
## X5          7.600000e+00 9.842748e+08 2
## X6          7.500000e+00 7.890844e+08 2
## X7          5.900000e+00 7.882981e+08 2
## X8          3.400000e+00 4.095371e+08 2
## sigma       2.000000e-01 1.133206e+06 2
## mean_PPD    2.000000e-01 1.420000e+01 2
## log-posterior 1.210984e+12 1.549200e+04 2
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a c
rude measure of effective sample size, and Rhat is the potential scale
reduction factor on split chains (at convergence Rhat=1).
```

5

```
#kfold1<-kfold(bayes,K = 10)
#kfold2<-kfold(bayes2,K=10)
#kfold3<-kfold(bayes3,K = 10)
#kfold4<-kfold(bayes4,K = 10)
#loo_compare(kfold1, kfold2, kfold3,kfold4)
```

The code above should be correct, but since I have 1.5MB for each bayes model, It is not able to run the code.

6

```
X1 = c(0.8,600.0,286.0,138.1,5,4,0.25)
X2 = c(0.67,630.0,296.0,238.1,2,6,0.5)
```