

# BayesExam

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## Problem 1

### Task b

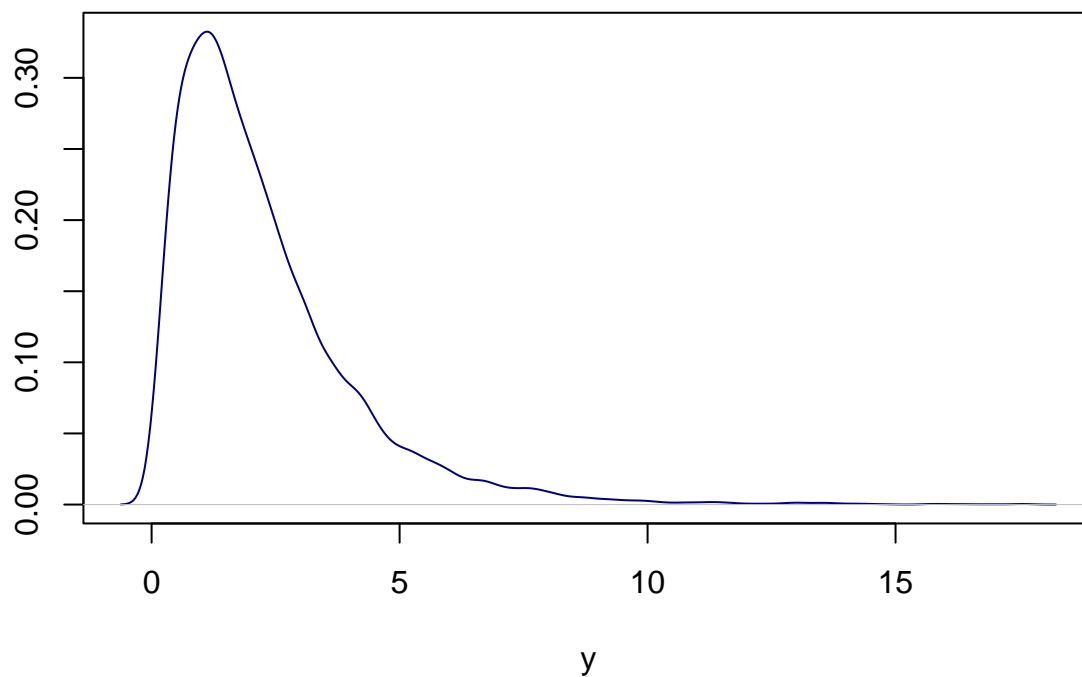
```
set.seed(12345)

nSim <- 10000
y <- c(2.32,1.82,2.4,2.08,2.13)
n <- 5

theta <- rgamma(nSim,shape = 2*n+1,rate = 0.5+sum(y))
y_values <- rgamma(nSim,shape = 2,rate = theta)

plot(density(y_values), type = "l", col = "navy",
     main = "Predictive distribution of the maximal weight",
     xlab = "y", ylab = "")
```

### Predictive distribution of the maximal weight



```
problb <- mean(y_values<1.9)
```

The  $Pr(Y_6 < 1.9|y_1, \dots, y_5)$  is 0.5285.

## Task b

```
set.seed(12345)

nWeeks <- 30
weights <- matrix(0, nrow = nSim, ncol = nWeeks)

for (i in 1:nSim) {
  theta <- rgamma(nWeeks, shape = 2*n+1, rate = 0.5+sum(y))
  weights[i,] <- rgamma(nWeeks, shape = 2, rate = theta)
}

problb <- mean(rowSums(weights > 2.4))
```

The expected number of weeks out of the future 30 weeks in which the maximal weight will exceed 2.4 thousands of kilos is approximately 10.5.

## Task c

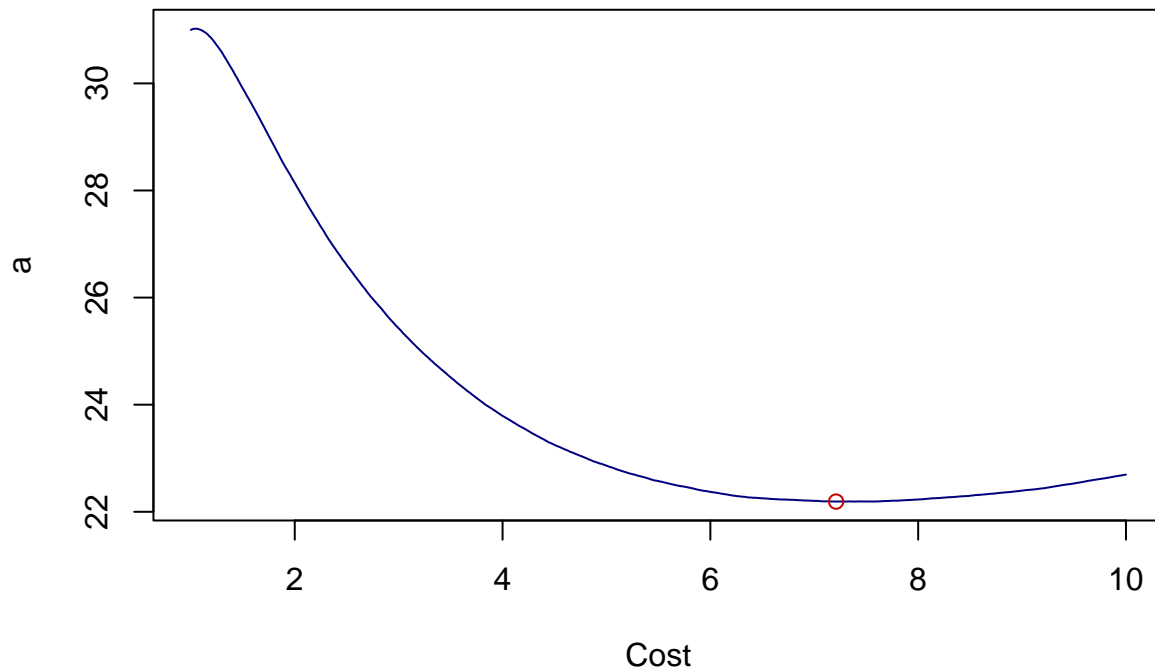
```
loss_function <- function(a,theta) {
  res <- a + mean(rowSums(weights > 0.9*log(a)))
  return(res)
}

aGrid <- seq(1,10,0.01)
cost <- matrix(0, nrow = length(aGrid), ncol = 1)

for (i in 1:length(aGrid)) {
  cost[i,] <- loss_function(aGrid[i],weights)
}

aOpt <- aGrid[which.min(cost)]

plot(aGrid,cost, type = "l", col = "navy",
      xlab = "Cost", ylab = "a")
points(aOpt,loss_function(aOpt,theta), col = "red3")
```



The optimal cost is approximately 7.52.

## Problem 2

```
source("ExamData.R")
```

### Task a

```
set.seed(12345)

library("mvtnorm")

mu_0 <- as.vector(rep(0,8))
Omega_0 <- (1/9)*diag(8)
v_0 <- 1
sigma2_0 <- 9
nIter <- 10000
X <- as.matrix(X)

PostDraws <- BayesLinReg(y, X, mu_0, Omega_0, v_0, sigma2_0, nIter)

Betas <- PostDraws$betaSample

intervalB1 <- quantile(Betas[,2], probs = c(0.005,0.995))

intervalB1 <- data.frame(lower_bound = intervalB1[1], upper_bound = intervalB1[2])
colnames(intervalB1) <- c("Lower bound", "Upper bound")
rownames(intervalB1) <- c("95% Equal Tail Credible Interval")
knitr::kable(intervalB1)
```

	Lower bound	Upper bound
95% Equal Tail Credible Interval	-0.3714471	1.825996

The 99% posterior probability that  $\beta_1$  is on the interval.

### Task b

```
mu <- Betas[,1] + Betas[,2] + Betas[,3] + Betas[,4]*0.5 + Betas[,6] + Betas[,8]

CV <- sqrt(PostDraws$sigma2Sample)/mu

MedianCV <- median(CV)
```

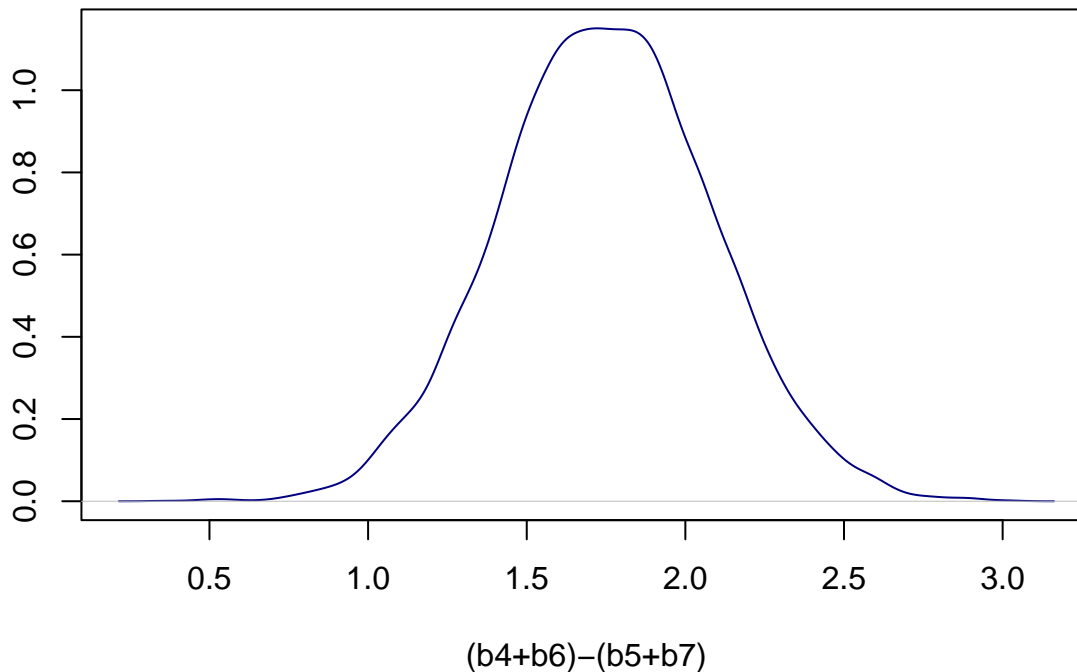
The median of the coefficient of variation is approximately 1.81.

### Task c

```
Effect_Inner <- Betas[,5] + Betas[,7]
Effect_South <- Betas[,6] + Betas[,8]
Diff <- Effect_Inner - Effect_South

plot(density(Diff), type = "l", col = "navy",
     main = "Selling price difference for apartments in the inner
city compared to apartments on the south side of the city",
     xlab = "(b4+b6)-(b5+b7)", ylab = "")
```

### Selling price difference for apartments in the inner city compared to apartments on the south side of the city



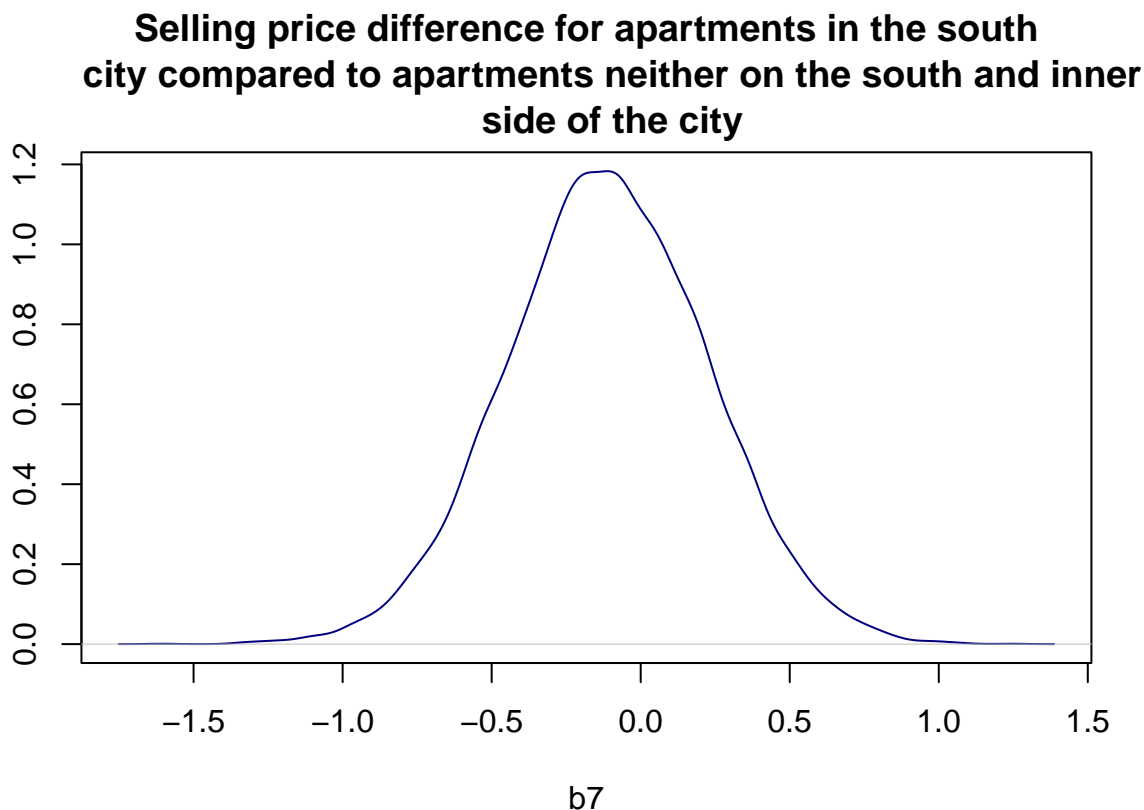
```
intervalDiff <- quantile(Diff, probs = c(0.025,0.975))

intervalDiff <- data.frame(lower_bound = intervalDiff[1], upper_bound = intervalDiff[2])
colnames(intervalDiff) <- c("Lower bound", "Upper bound")
rownames(intervalDiff) <- c("95% Equal Tail Credible Interval")
knitr::kable(intervalDiff)
```

	Lower bound	Upper bound
95% Equal Tail Credible Interval	1.094938	2.413954

There is a substantial mass probability that the expected selling price  $\mu$  is higher for apartments in the inner city compared to apartments on the south side of the city when  $x_1 = 1$ . The 95% equal tail credible interval illustrates that the difference takes positive values, which strengthens the above assumption.

```
plot(density(Betas[,8]),type = "l", col = "navy",
     main = "Selling price difference for apartments in the south
city compared to apartments neither on the south and inner
side of the city",
     xlab = "b7", ylab = "")
```



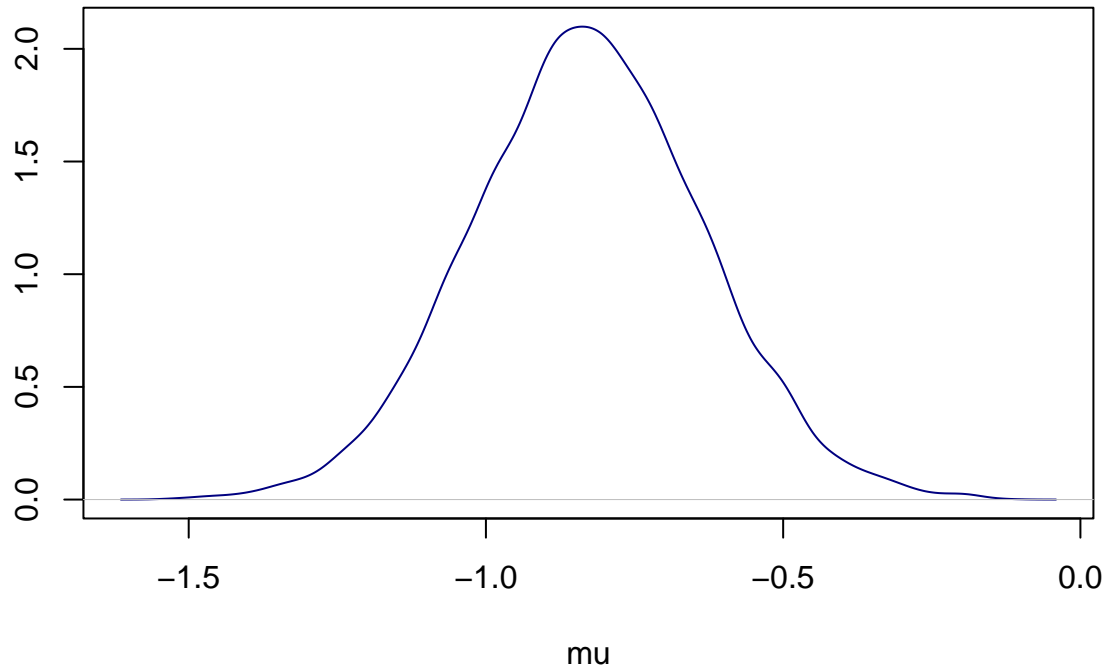
The effect on the selling price  $y$  from  $x_1$  does not differ for apartments on the south side of the city compared to apartments which are neither in the inner city nor on the south side of the city.

#### Task d

```
mu <- Betas[,1] + Betas[,2]*(-0.5) + Betas[,3]*(-0.5) + Betas[,6] + Betas[,8]*(-0.5)
```

```
plot(density(mu), type = "l", col = "navy",
     main = "Posterior Distribution of mu",
     xlab = "mu", ylab = "")
```

## Posterior Distribution of $\mu$



```
prob2d <- mean(mu>0)
```

The posterior probability that  $\mu > 0$  is 0.

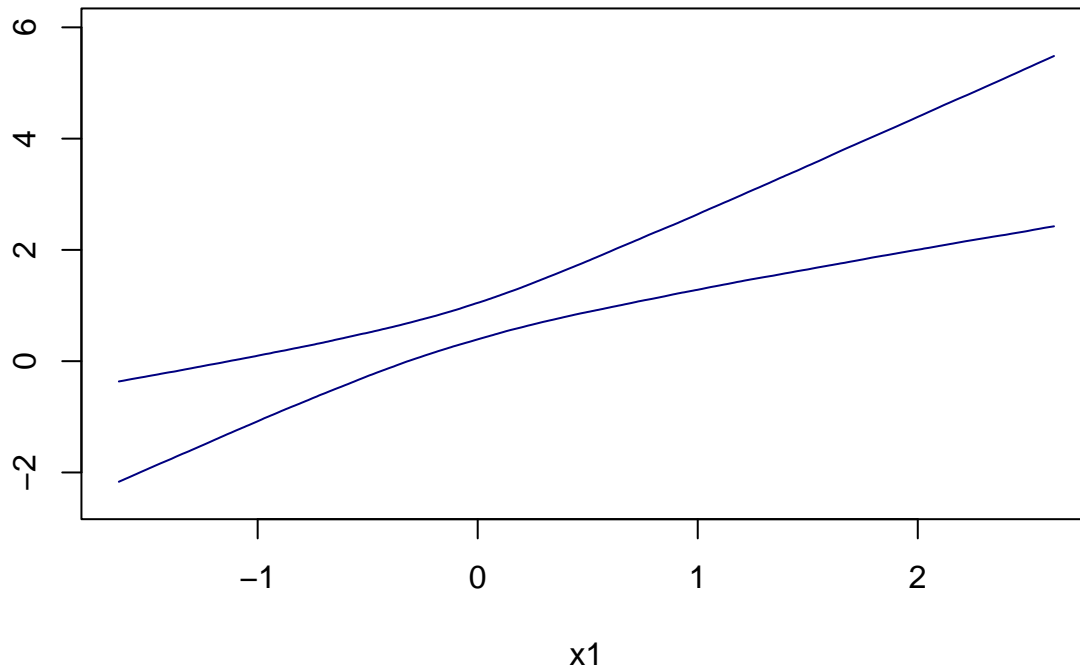
## Task e

```
x1Grid <- seq(min(X[,2]),max(X[,2]),0.01)
intervals <- matrix(0, nrow = length(x1Grid), ncol = 2)

for (i in 1:length(x1Grid)) {
  mu <- Betas[,1] + Betas[,2]*x1Grid[i] + Betas[,3]* +
    Betas[,4]*0.5 + Betas[,5] + Betas[,7]*x1Grid[i]
  intervals[i,] <- quantile(mu, probs = c(0.025,0.975))
}

plot(x1Grid,intervals[,1], type = "l", col = "navy",
     main = "95% equal tail posterior predictive
           intervals for y on a grid of values of x1",
     xlab = "x1", ylab = "", ylim = c(-2.5,6))
lines(x1Grid,intervals[,2], type = "l", col = "navy")
```

### 95% equal tail posterior predictive intervals for y on a grid of values of x1



## Problem 3

### Task d

```
LogPost <- function(theta,n,sumlnx){
  res <- 2*theta*sumlnx - n*(theta^2)
  return(res)
}

thetaGrid <- seq(-1.5,2.5,0.01)
n <- 5
sumlnx <- 2

PostDens_propto <- exp(LogPost(thetaGrid,n,sumlnx))
PostDens <- PostDens_propto/(0.01*sum(PostDens_propto))

plot(thetaGrid,PostDens,type="l", col="navy",
     main = "Posterior Distribution of theta",
     xlab = "theta", ylab = "")
```

**Posterior Distribution of theta**

