Question 2.1

The summary statistic of the data:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Variance.
8.920	9.995	10.690	10.916	11.977	12.900	1.257

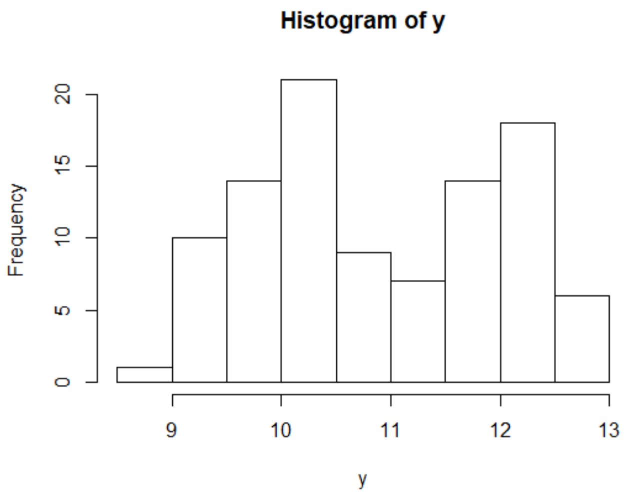

Figure 1: Histogram of sample of daily sales amount, $\underline{y}$

Assuming that when the super discount was announced on that day, the amounts of sales will increase. We know that the mean of the sample of daily sales amount, $\mu_i = \alpha + \gamma d_i$. Therefore, we can say that **α is the base amounts of sales for the store and γ is the extra amounts of sales when super discount was announced on that day**.

In Figure 1, we can see that the highest frequency of the amounts of sales is around 10 indicates that the base amounts of sales should be around 10. Then, the second highest frequency of the amounts of sales is around 12 indicates that these might be the amounts of sales when super discount was announced on that day since the amounts of sales are slightly higher. Hence, we can say that **the approximate value of α is 10 and the approximate value of γ is 2**.

Question 2.2

Let A be the amounts of sales when super discount was announced on that day (corresponding to $d_i = 1$) and B be the amounts of sales without announcement of super discount (corresponding to $d_i = 0$).

Since $y_i \sim N(\mu_i, \psi)$, therefore A and B are both follow normal distribution where A~$N(\alpha + \gamma, \psi)$ and $B \sim N(\alpha, \psi)$. Hence,

$$f_A(y_i; \alpha, \gamma, \psi) = \frac{1}{\sqrt{2\pi}} \psi^{\frac{1}{2}} \exp\{-\frac{(y_i - \alpha - \gamma)^2}{2} \psi\}$$

$$f_B(y_i; \alpha, \psi) = \frac{1}{\sqrt{2\pi}} \psi^{\frac{1}{2}} \exp\{-\frac{(y_i - \alpha)^2}{2} \psi\}$$

The mixture distribution corresponding to y_i for each $i = 1,2,\dots,n$ is

$$g(y_i; p, \alpha, \gamma, \psi) = p f_A(y_i; \alpha, \gamma, \psi) + (1-p) f_B(y_i; \alpha, \psi)$$

$$g(y_i; p, \alpha, \gamma, \psi) = p \frac{1}{\sqrt{2\pi}} \psi^{\frac{1}{2}} \exp\{-\frac{(y_i - \alpha - \gamma)^2}{2} \psi\} + (1-p) \frac{1}{\sqrt{2\pi}} \psi^{\frac{1}{2}} \exp\{-\frac{(y_i - \alpha)^2}{2} \psi\}$$

The likelihood of the observed data $\underline{y}$, given α, γ, ψ and p is

$$L\left(\underline{d}, \underline{y}; p, \alpha, \gamma, \psi\right)$$

$$= \prod_{i=1}^{n} [p f_A(y_i; \alpha, \gamma, \psi)]^{I\{d_i = A\}} [(1-p) f_B(y_i; \alpha, \psi)]^{I\{d_i = B\}}$$

$$= p^{n_A(d)} * (1-p)^{n_B(d)} * \left[\prod_{i=1}^{n_A(d)} f_A(y_i; \alpha, \gamma, \psi)\right] * \left[\prod_{i=1}^{n_B(d)} f_B(y_i; \alpha, \psi)\right]$$

$$= p^{n_A(d)} (1-p)^{n_B(d)} \left[\left(\frac{\psi}{2\pi}\right)^{\frac{n_A(d)}{2}} \exp\left\{-\frac{\sum_{i=1}^{n_A(d)} (y_i - \alpha - \gamma)^2}{2} \psi\right\}\right] \left[\left(\frac{\psi}{2\pi}\right)^{\frac{n_B(d)}{2}} \exp\{-\frac{\sum_{i=1}^{n_B(d)} (y_i - \alpha)^2}{2} \psi\}\right]$$

Where $n_A(d)$ is the number of d_i for d equalling A, and similarly $n_B(d)$

Question 2.3

For each $\theta \in \{\alpha, \gamma\}$, the prior specification on θ given by $\mu_\theta = 0$ and $\sigma_\theta^2 = 100$ is $\theta \sim N(0,100)$. This is because we want to have small mean and big variance to draw out a vague prior PDF (probability density function) on θ.

$Given\ p \sim Beta(\alpha_p, \beta_p)$. The prior mean for p is 0.4 and the prior variance for p is 0.12.

The mean for Beta:

$$\frac{\alpha_p}{\alpha_p + \beta_p} = 0.4$$

$$1.5\alpha_p = \beta_p$$

The variance for Beta:

$$\frac{\alpha_p \beta_p}{\left(\alpha_p + \beta_p\right)^2 (\alpha_p + \beta_p + 1)} = 0.12 \qquad (1)$$

Substitute $1.5\alpha_p = \beta_p$ into the equation (1), we get

$$\frac{1.5\alpha_p^2}{\left(2.5\alpha_p\right)^2 (2.5\alpha_p + 1)} = 0.12$$

$$\boldsymbol{\alpha_p = 0.4}$$

Substitute $\alpha_p = 0.4$ into $1.5\alpha_p = \beta_p$, we get

$$\boldsymbol{\beta_p = 0.6}$$

Prior specification for $\boldsymbol{p}$ is $\boldsymbol{p \sim Beta(0.4, 0.6)}$.

Given $\psi \sim Gamma(\alpha_\psi, \beta_\psi)$. The prior mean for ψ is 1 and the prior variance for ψ is 100.

Mean for Gamma:

$$\frac{\alpha_\psi}{\beta_\psi} = 1$$

$$\alpha_\psi = \beta_\psi$$

Variance for Gamma:

$$\frac{\alpha_\psi}{\beta_\psi^2} = 100$$

Substitute $\alpha_\psi = \beta_\psi$ into $\frac{\alpha_\psi}{\beta_\psi^2} = 100$,

$$\alpha_\psi = 0.01,\ \beta_\psi = 0.01$$

Prior specification for $\boldsymbol{\psi}$ is $\boldsymbol{\psi \sim Gamma(0.01, 0.01)}$.

<u>Question 2.4</u>

To use the technique of Gibbs sampling, we need to find the conditional posterior PDF of p, α, γ and ψ.

First, we find the full posterior $\pi(p, \alpha, \gamma, \psi |\ \underline{d}, \underline{y})$.

$$\pi(p, \alpha, \gamma, \psi |\ \underline{d}, \underline{y}) = \pi(p)\pi(\alpha)\pi(\gamma)\pi(\psi)p^{n_A(d)}(1-p)^{n_B(d)} * \left[\prod_{i=1}^{n_A(d)} f_A(y_i; \alpha, \gamma, \psi)\right] * \left[\prod_{i=1}^{n_B(d)} f_B(y_i; \alpha, \psi)\right]$$

Then we view the full posterior $\pi(p, \alpha, \gamma, \psi |\ \underline{d}, \underline{y})$ as a function of each variable while keeping the others fixed.

For conditional posterior PDF of p, consider only the terms that depend on p only:

$\pi(p|\alpha, \gamma, \psi, \underline{d}, \underline{y})$

$\propto \pi(p)p^{n_A(d)}(1-p)^{n_B(d)}$

$\propto p^{\alpha_p - 1}(1-p)^{\beta_p - 1}p^{n_A(d)}(1-p)^{n_B(d)}$

$\propto p^{0.4-1}(1-p)^{0.6-1}p^{n_A(d)}(1-p)^{n_B(d)}$

$= \pi(p|\underline{d}, \underline{y})$ since the last expression doesn't depends on α, γ and ψ

$$\boldsymbol{\pi(p|\underline{d}, \underline{y}) \sim Beta(n_A(d) + 0.4, n_B(d) + 0.6)}$$

For conditional posterior PDF of α, consider only the terms that depend on α only:

$\pi(\alpha|p, \gamma, \psi, \underline{d}, \underline{y})$

$$\propto\ \pi(\alpha)\left[\prod_{i=1}^{n_A(d)} f_A(y_i; \alpha, \gamma, \psi)\right] * \left[\prod_{i=1}^{n_B(d)} f_B(y_i; \alpha, \psi)\right]$$

$$\propto \exp\left\{-\frac{(\alpha - \mu_\theta)^2}{2\sigma_\theta^2}\right\} \exp\left\{-\frac{\sum_{i=1}^{n_A(d)}(y_i - \alpha - \gamma)^2}{2}\psi\right\} \exp\left\{-\frac{\sum_{i=1}^{n_B(d)}(y_i - \alpha)^2}{2}\psi\right\}$$

$$= \exp -\{\frac{\alpha^2}{200} + \frac{\psi}{2}\left[\sum_{i=1}^{n_A(d)}(y_i - \alpha - \gamma)^2 + \sum_{i=1}^{n_B(d)}(y_i - \alpha)^2\right]\}$$

$$= \exp -\{\left(\frac{1}{200}+\frac{n}{2}\psi\right)\alpha^2+\frac{\psi}{2}\left[\sum_{i=1}^{n_A(d)}[(y_i-\gamma)^2+(2\alpha\gamma-2\alpha y_i)]+\sum_{i=1}^{n_B(d)}(y_i^2-2\alpha y_i)\right]\}$$

$$= exp -\left\{\frac{1}{2}\left(\frac{1}{100}+n\psi\right)\alpha^2-\alpha\psi\left(\sum_{i=1}^{n}y_i-n_A(d)\,\gamma\right)+\frac{\psi}{2}\left(\sum_{i=1}^{n}y_i^2-2n_A(d)\,\overline{y_A}\gamma+n_A\gamma^2\right)\right\}$$

$$= \exp\left\{-\frac{1}{2}\left(\frac{1}{100}+n\psi\right)\left[\alpha^2-\frac{2\alpha\psi(\sum_{i=1}^{n}y_i-n_A(d)\,\gamma)}{\frac{1}{100}+n\psi}+\frac{\psi(\sum_{i=1}^{n}y_i^2-2n_A(d)\,\overline{y_A}\gamma+n_A\gamma^2)}{\frac{1}{100}+n\psi}\right]\right\}$$

$$\propto \exp\left\{-\frac{1}{2}\left(\frac{1}{100}+n\psi\right)\left[\alpha-\frac{\psi(\sum_{i=1}^{n}y_i-n_A(d)\,\gamma)}{\frac{1}{100}+n\psi}\right]^2\right\}$$

$$= \exp\left\{-\frac{(\alpha-\alpha^*)^2}{2(\sigma_\alpha^*)^2}\right\}$$

$= \pi(\alpha|\gamma,\psi,\underline{d},\underline{y})$ since the last expression doesn't depend on p

Where $\alpha^* = \frac{\psi(\sum_{i=1}^{n}y_i-n_A(d)\,\gamma)}{\frac{1}{100}+n\psi}$ and $(\sigma_\alpha^*)^2 = \left(\frac{1}{100}+n\psi\right)^{-1}$

$$\boldsymbol{\pi(\alpha|\gamma,\psi,\underline{d},\underline{y}) \sim N(\alpha^*,(\sigma_\alpha^*)^2)}$$

For conditional posterior PDF of γ, consider only the terms that depend on γ only:

$\pi(\gamma|p,\alpha,\psi,\underline{d},\underline{y})$

$$\propto \pi(\gamma)\left[\prod_{i=1}^{n_A(d)}f_A(y_i;\alpha,\gamma,\psi)\right]$$

$$\propto \exp\left\{-\frac{(\gamma-\mu_\theta)^2}{2\sigma_\theta^2}\right\}\exp\left\{-\frac{\sum_{i=1}^{n_A(d)}(y_i-\alpha-\gamma)^2}{2}\psi\right\}$$

$$= \exp\left\{-\frac{\gamma^2}{200}-\frac{\sum_{i=1}^{n_A(d)}(y_i-\alpha-\gamma)^2}{2}\psi\right\}$$

Define $y_i^* = y_i-\alpha$ for each i, Then the expression above becomes

$$= \exp\left\{-\frac{\gamma^2}{200}-\frac{\sum_{i=1}^{n_A(d)}(y_i^*-\gamma)^2}{2}\psi\right\}$$

$$\propto \exp\left\{-\frac{(\gamma-\gamma^*)^2}{2\left(\sigma_\gamma^*\right)^2}\right\}$$

$= \pi(\gamma|\,\psi,\underline{d},\underline{y})$ since the last expression doesn't depend on p and α

Where $\gamma^* = \frac{\overline{y}_{A,i}^*(n_A(d)\psi)}{n_A(d)\psi+\frac{1}{100}}$, $\left(\sigma_\gamma^*\right)^2 = \left(\frac{1}{100}+n_A(d)\psi\right)^{-1}$ and $\overline{y}_{A,i}^* = \frac{\sum_{i;d_i=A}^{N}(y_i^*)}{n_A(d)}$

$$\boldsymbol{\pi(\gamma|\,\psi,\underline{d},\underline{y}) \sim N\left(\gamma^*,\left(\sigma_\gamma^*\right)^2\right)}$$

For conditional posterior PDF of ψ, consider only the terms that depend on ψ only:

$\pi(\psi|p,\alpha,\gamma,\underline{d},\underline{y})$

$\propto \pi(\psi)\left[\prod_{i=1}^{n_A(d)} f_A(y_i;\alpha,\gamma,\psi)\right] * \left[\prod_{i=1}^{n_B(d)} f_B(y_i;\alpha,\psi)\right]$

$\propto \psi^{\alpha_\psi - 1}\exp\{-\psi\beta_\psi\}\,\psi^{\frac{n_A(d)}{2}}\psi^{\frac{n_B(d)}{2}}\exp\left\{-\frac{\sum_{i=1}^{n_A(d)}(y_i-\alpha-\gamma)^2}{2}\psi\right\}\exp\left\{-\frac{\sum_{i=1}^{n_B(d)}(y_i-\alpha)^2}{2}\psi\right\}$

$= \psi^{\frac{n}{2}+0.01-1}\exp\left\{-\psi\left(0.01+\frac{\sum_{i=1}^{n_A(d)}(y_i-\alpha-\gamma)^2}{2}+\frac{\sum_{i=1}^{n_B(d)}(y_i-\alpha)^2}{2}\right)\right\}$

$= \pi(\psi|\alpha,\gamma,\underline{d},\underline{y})$ since the last expression doesn't depend on p

$$\boldsymbol{\pi(\psi|\alpha,\gamma,\underline{d},\underline{y}) \sim Gamma\left(\frac{n}{2}+0.01, 0.01+\frac{\sum_{i=1}^{n_A(d)}(y_i-\alpha-\gamma)^2}{2}+\frac{\sum_{i=1}^{n_B(d)}(y_i-\alpha)^2}{2}\right)}$$

We know that the priors p,α,γ and ψ are independent of each other. Hence, the conditional posterior PDFs of p,α,γ and ψ are independent of each other given s and can be updated parallelly based on information on $(\underline{d},\underline{y})$ only.

For the conditional posterior PMF (probability mass function) of $\underline{d}$, consider only the terms that depends on $\underline{d}$ only:

$p(\underline{d}|p,\alpha,\gamma,\psi,\underline{y})$

$\propto p^{n_A(d)}(1-p)^{n_B(d)}\left[\prod_{i=1}^{n_A(d)} f_A(y_i;\alpha,\gamma,\psi)\right]\left[\prod_{i=1}^{n_B(d)} f_B(y_i;\alpha,\psi)\right]$

$= \prod_{i=1}^{n}[pf_A(y_i;\alpha,\gamma,\psi)]^{I\{d_i=A\}}[(1-p)f_B(y_i;\alpha,\psi)]^{I\{d_i=B\}}$

$\propto \prod_{i=1}^{n}\pi(d_i|p,\alpha,\gamma,\psi,y_i)$

where

$$\pi(d_i|p,\alpha,\gamma,\psi,y_i) = \begin{cases} \dfrac{pf_A(y_i;\alpha,\gamma,\psi)}{pf_A(y_i;\alpha,\gamma,\psi)+(1-p)f_B(y_i;\alpha,\psi)} & if\ d_i = A, and \\ \dfrac{(1-p)f_B(y_i;\alpha,\psi)}{pf_A(y_i;\alpha,\gamma,\psi)+(1-p)f_B(y_i;\alpha,\psi)} & if\ d_i = B. \end{cases}$$

$p(\underline{d}|p,\alpha,\gamma,\psi,\underline{y}) = \prod_{i=1}^{n}\pi(d_i|p,\alpha,\gamma,\psi,y_i)$

Implies that each d_i can be updated independently of each other.

Each $\pi(d_i|p,\alpha,\gamma,\psi,y_i)$ is a PMF on two points, A and B, with probabilities

$$\frac{pf_A(y_i;\alpha,\gamma,\psi)}{pf_A(y_i;\alpha,\gamma,\psi)+(1-p)f_B(y_i;\alpha,\psi)} \text{ and } \frac{(1-p)f_B(y_i;\alpha,\psi)}{pf_A(y_i;\alpha,\gamma,\psi)+(1-p)f_B(y_i;\alpha,\psi)}$$

respectively, which can be simulated using the inverse cumulative density function method.

Developing the Gibbs sampler for the model:

Step 1: Let the initial states be $\left(\alpha^0, \gamma^0, \psi^0, p^0, \underline{d}^0\right)$ and we initialize the parameters in the region of support of $\pi\left(p, \alpha, \gamma, \psi, \underline{d} \middle| \underline{y}\right)$.

Step 2: Let the current state (after k iterations) be $\left(\alpha^k, \gamma^k, \psi^k, p^k, \underline{d}^k\right)$. Then we obtain the new state $\left(\alpha^{k+1}, \gamma^{k+1}, \psi^{k+1}, p^{k+1}, \underline{d}^{k+1}\right)$ as follows:

i. Draw $\alpha^{k+1} \sim \pi(\alpha | \gamma^k, \psi^k, \underline{d}^k, \underline{y})$

ii. Draw $\gamma^{k+1} \sim \pi\left(\gamma \,\middle|\, \psi^k, \underline{d}^k, \underline{y}\right)$

iii. Draw $\psi^{k+1} \sim \pi\left(\psi \middle| \alpha^{k+1}, \gamma^{k+1}, \underline{d}^k, \underline{y}\right)$

iv. Draw $p^{k+1} \sim \pi\left(p \,\middle|\underline{d}^k, \underline{y}\right)$

v. Draw $d_i^{k+1} \sim \pi(\, d_i | p^{k+1}, \alpha^{k+1}, \gamma^{k+1}, \psi^{k+1}, y_i)$

$$= \begin{cases} \dfrac{p^{k+1} f_A(y_i; \alpha^{k+1}, \gamma^{k+1}, \psi^{k+1})}{p^{k+1} f_A(y_i; \alpha^{k+1}, \gamma^{k+1}, \psi^{k+1}) + (1 - p^{k+1}) f_B(y_i; \alpha^{k+1}, \psi^{k+1})} & if\ d_i = A, and \\ \dfrac{(1 - p^{k+1}) f_B(y_i; \alpha^{k+1}, \psi^{k+1})}{p^{k+1} f_A(y_i; \alpha^{k+1}, \gamma^{k+1}, \psi^{k+1}) + (1 - p^{k+1}) f_B(y_i; \alpha^{k+1}, \psi^{k+1})} & if\ d_i = B. \end{cases}$$

vi. $\underline{d}^{k+1} = (d_1^{k+1}, d_2^{k+1}, \dots, d_N^{k+1})$

Step 3: Proceed from $i+1$ and repeat the steps above, run the sampler until it converges.

Question 2.5

From Question 2.1, we have the approximate values of α and γ as 10 and 2 respectively. Hence, we choose the initial value $\boldsymbol{\alpha^0 = 10}$ and $\boldsymbol{\gamma^0 = 2}$. In Question 2.3, we have the prior specification for p with prior mean 0.4 and the prior specification for ψ with prior mean 1. Hence, we choose the initial value $\boldsymbol{p^0 = 0.4}$ and $\boldsymbol{\psi^0}$**=1**. To choose the initial value for $\underline{d}^0$, we separate the samples, $\underline{y}$ to group A and group B. **For every $\boldsymbol{y_i > 10}$, we put in group A. For every $\boldsymbol{y_i \le 10}$, we put in group B.**

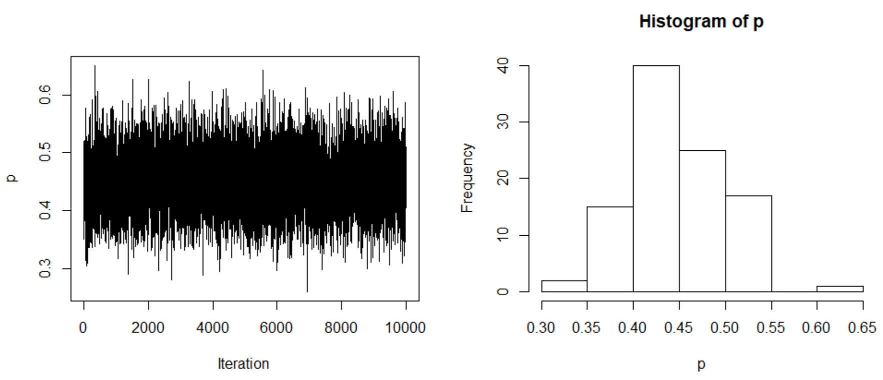

Figure 2: Trace plot and histogram of p

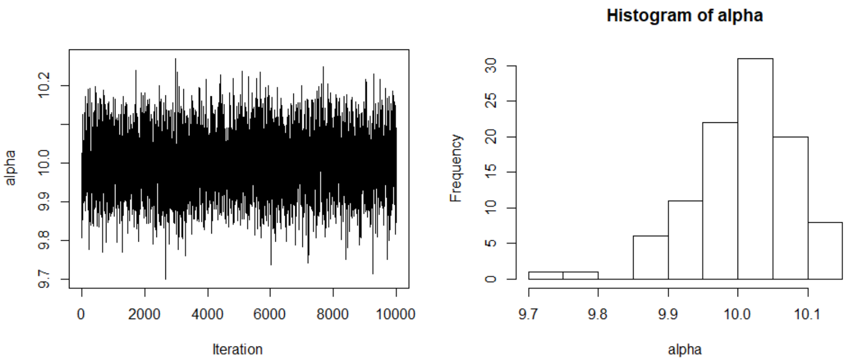

Figure 3: Trace plot and histogram of α

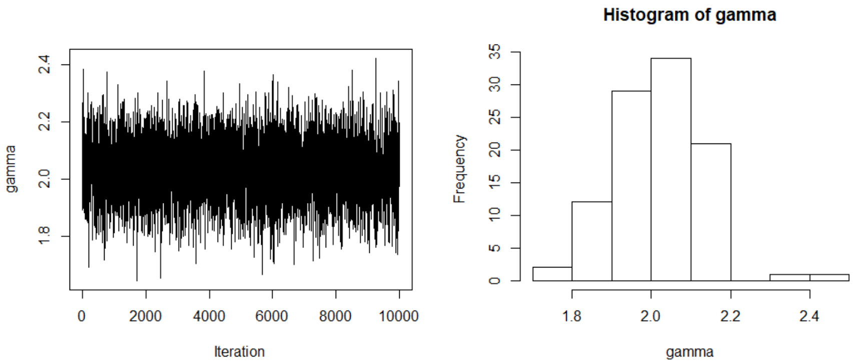

Figure 4: Trace plot and histogram of γ

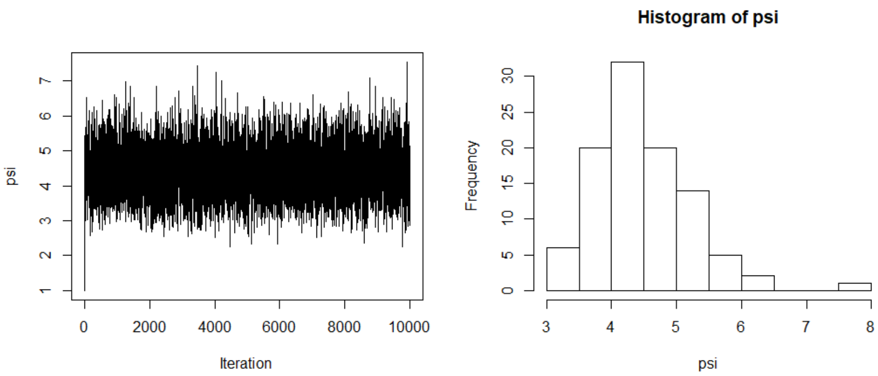

Figure 5: Trace plot and histogram of ψ

In Figure 2,3,4 and 5, we can see that all the trace plots converge without any trend indicates that the Markov Chain has mixed satisfactorily.

	Posterior Mean	Posterior Variance
α	10.0000	0.0049
γ	2.0306	0.0096
ψ	4.3778	0.4707
p	0.4512	0.0026

Table 1: Posterior mean and variance for each parameter

The conclusions for the daily sales problem are the daily sales of a store are affected when the store has announced super discounts on that day. The amounts of daily sales will increase around 2 when the store has announced super discounts on that day. The super discounts days are held on 45.12% of days in a year, independently of each other.

Appendix

```
y <- c(
  12.21, 9.57, 12.50, 10.55, 10.22, 10.67, 10.24, 11.43, 9.86, 12.25,
  11.95, 9.41, 9.48, 9.48, 10.83, 11.84, 12.60, 10.04, 11.97, 10.87,
  12.58, 12.01, 9.31, 10.38, 11.49, 12.32, 9.62, 12.42, 10.19, 11.78,
  10.02, 12.40, 11.59, 10.05, 12.15, 10.76, 8.92, 9.75, 12.53, 9.41,
  10.13, 10.24, 10.85, 12.05, 9.95, 12.00, 9.80, 11.41, 10.01, 11.88,
  9.92, 11.50, 9.31, 12.22, 12.17, 11.40, 11.87, 10.47, 12.43, 10.37,
  11.76, 10.58, 10.29, 9.02, 10.68, 10.29, 10.04, 12.20, 9.30, 12.13,
  12.73, 11.68, 10.43, 9.78, 10.70, 12.33, 11.52, 10.42, 10.16, 9.64,
  12.33, 11.97, 11.34, 12.78, 9.59, 9.19, 11.07, 12.24, 12.90, 9.61,
  9.80, 9.45, 10.14, 9.66, 10.44, 12.09, 9.78, 11.94, 11.86, 10.15
)
y_df <- data.frame(y)
###Question 1###
summary(y) #summary statistic of the data
var(y) #variance of the data
hist(y,xlab="y") #histogram of y
###Question 5###
N_iter <- 10000 #Number of iterations to run #Burn in
n <- 100 #Number of data
m <- 10 #thinning

alpha <- vector("numeric",N_iter) #create vector for alpha
gam <- vector("numeric",N_iter) #create vector for gamma
psi <- vector("numeric",N_iter) #create vector for psi
p <- vector("numeric",N_iter) #create vector for p
variance <- 100 #variance of theta
alpP <- 0.4 #alpha for p
betP <- 0.6 #beta for p
alpPsi <- 0.01 #alpha for psi
betPsi <- 0.01 #beta for psi
d <- 1*(y > 10) + 0* (y <=10) #separate the data to A=1 and B=0

alpha[1] = 10 #initial value for alpha
gam[1] = 2 #initial value for gamma
psi[1] = 1 #initial value for psi
```

```
p[1] = 0.4 #initial value for p

for(iter in 1:(N_iter-1)){
  #update alpha
  meanalp <- (psi[iter]*(sum(y)-sum(d==1)*gam[iter]))/((n*psi[iter])+(1/variance))
  varalp <- 1/(n*psi[iter]+(1/variance))
  alpha[iter+1] <- rnorm(1,meanalp, sqrt(varalp))

  #update gamma
  R1 <- mean(y[d==1]-alpha[iter+1])
  meangam <- (R1*sum(d==1)*psi[iter])/(sum(d==1)*psi[iter]+(1/variance))
  vargam <- 1/(sum(d==1)*psi[iter]+(1/variance))
  gam[iter+1] <- rnorm(1, meangam, sqrt(vargam))

  #update psi
  psi[iter+1] <- rgamma(1,n/2+alpPsi,betPsi+(sum((y[d==1]-alpha[iter+1]-gam[iter+1])^2)+
                                   sum((y[d==0]-alpha[iter+1])^2))/2)

  #update p
  p[iter+1] <- rbeta(1,sum(d==1) + alpP,sum(d==0) + betP)

  #Update labels given parameters
  probsA <- p[iter+1]*dnorm(y,alpha[iter+1]+gam[iter+1],sqrt(1/psi[iter+1]))
  probsB <- (1-p[iter+1])*dnorm(y,alpha[iter+1],sqrt(1/psi[iter+1]))
  probs <- probsA/(probsA+probsB)
  u <- runif(n,0,1)
  d <- 1*(u<probs) + 0*(u>=probs)
}
#trace plot and histogram
par(mfrow=c(1,2))
plot(seq(1,N_iter,1), p, type="l",xlab="Iteration")
hist(p[seq(N_iter-(m*n)+1,N_iter,m)],main="Histogram of p",xlab="p")
plot(seq(1,N_iter,1), alpha, type="l",xlab="Iteration")
hist(alpha[seq(N_iter-(m*n)+1,N_iter,m)],main="Histogram of alpha",xlab="alpha")
plot(seq(1,N_iter,1), gam, type="l",xlab="Iteration",ylab="gamma")
hist(gam[seq(N_iter-(m*n)+1,N_iter,m)],main="Histogram of gamma",xlab="gamma")
plot(seq(1,N_iter,1), psi, type="l",xlab="Iteration")
```

```
hist(psi[seq(N_iter-(m*n)+1,N_iter,m)],main="Histogram of psi",xlab="psi")
#posterior mean and posterior variance
mean(p); var(p)
mean(alpha) ;var(alpha)
mean(gam) ; var(gam)
mean(psi) ; var(psi)
```