

HDS Exercise set 2_Post

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Problem 2 – Solution

```
library(qvalue)

# Generate 5000 p-values
m = 1000
p = 5000
pval <- c(rbeta(m, 1, 100), runif(p-m, 0, 1))

# BH
BH <- p.adjust(pval, method = "BH", n = length(pval))

# Qvalue
Qval <- qvalue(pval)
pi0 <- Qval$pi0 # overall proportion of true null hypotheses

# Linear Reg
lm.fit <- lm(Qval$qvalues ~ BH)
lm.fit$coefficients

##      (Intercept)              BH
## -8.641789e-15   8.624009e-01
```

On comparison of slope to the π_0 estimate from qval we see that they are similar to each other. To answer this why this might be so, we need to look at the definitions of the terms itself.

p-value = most extreme probability for a test statistic under the null hypothesis, not accounting for multiple comparisons.. BH p-value or p_{BH} = most extreme probability for the above, after accounting for multiple comparisons such that there is an upper-bound to the overall false positive rate at $\leq p$. And finally, q-value is a direct estimate of the FDR associated with p_{BH} .

Now, as in the examples before and other course notes we see that q-values depend also on the estimated fraction of test p-values in the chance or uniform component of the distribution at some p_{FDR} p. Here,

π_0 = estimated probability (overall) of a given result being truly null (i.e., false positive) at p_{FDR} . And then, q-value = $p_{BH} * \pi_0$ (probability that test t incorrectly rejects the null at p_{BH}).

So $q = p_{BH} * \pi_0$ as seen above in the example, and directly estimates the p_{FDR} for any given test t. In fact, going by the above regression equation and the explanation above, if π_0 is estimated as at or very near 1.0, then p_{BH} and q will be the same for any given test t.

Problem 3 – Solutions

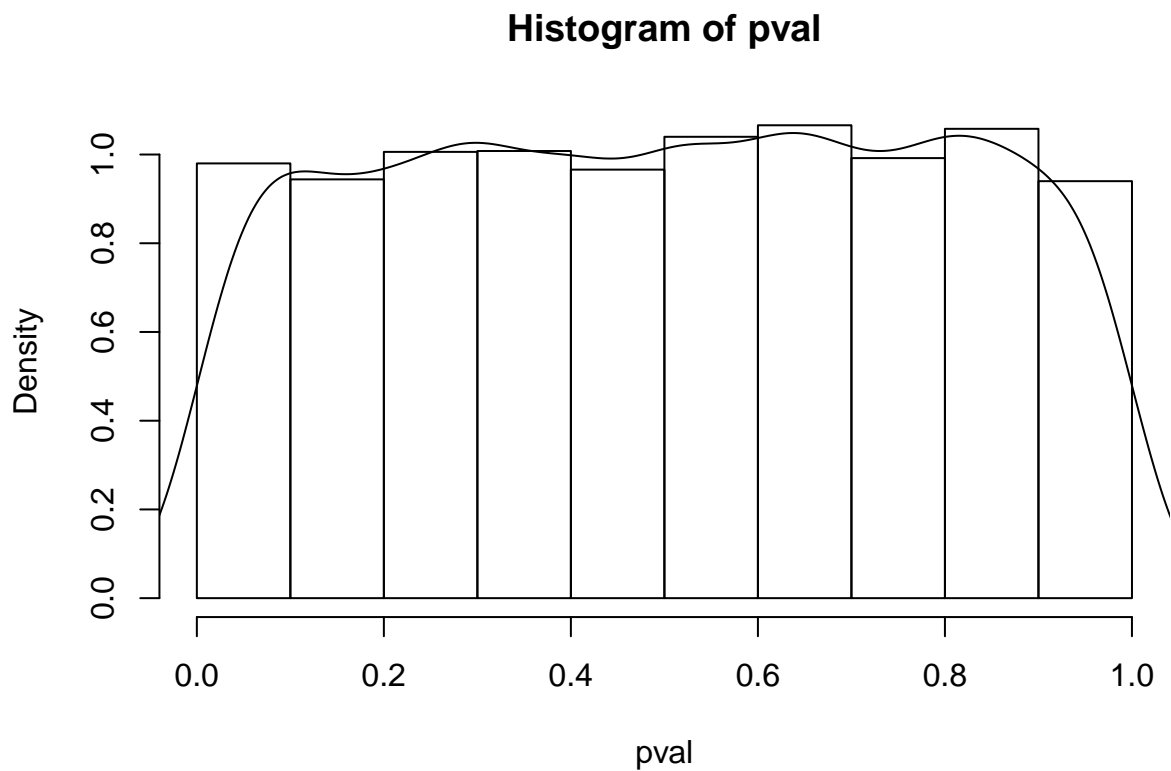
(a)

```

# Generate 5000 p-values
m = 500
p = 5000
#pval <- c(rbeta(m, b.1, b.0), runif(p-m, 0, 1))

b.1 = 1
b.0 = 1
pval <- c(rbeta(m, b.1, b.0), runif(p-m, 0, 1))
hist(pval, xlab = "pval", prob = TRUE)
lines(density(pval))

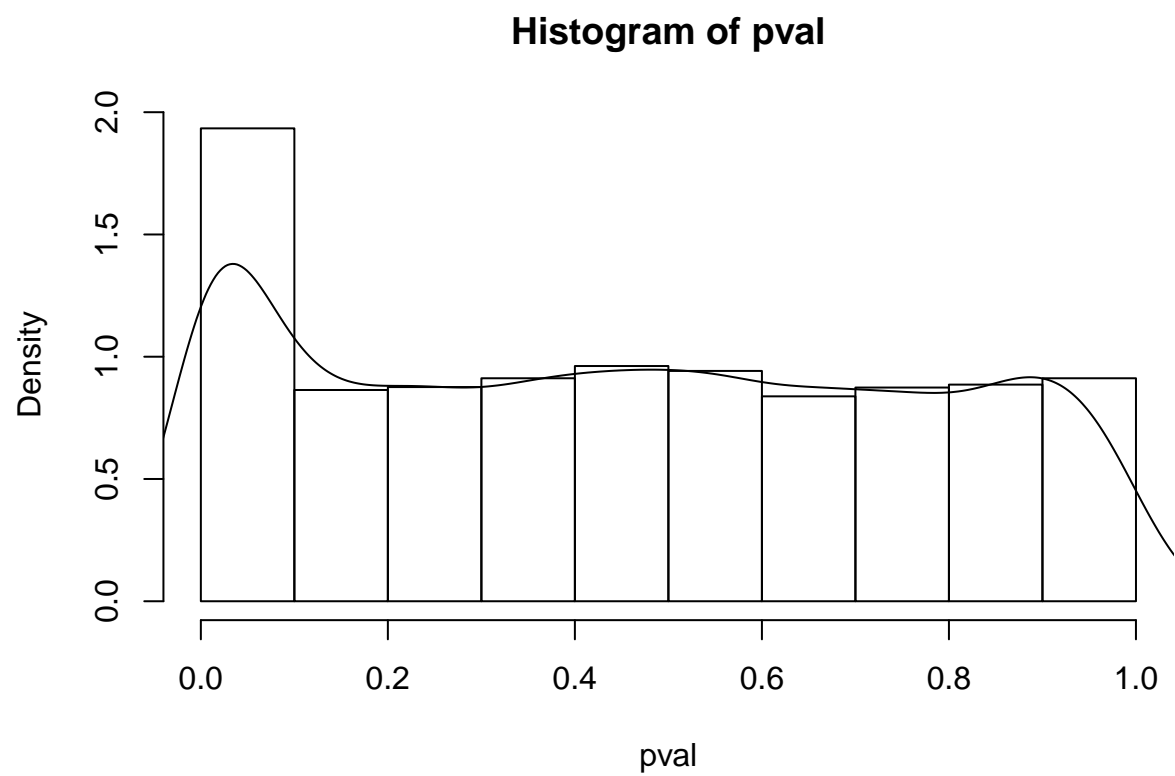
```



```

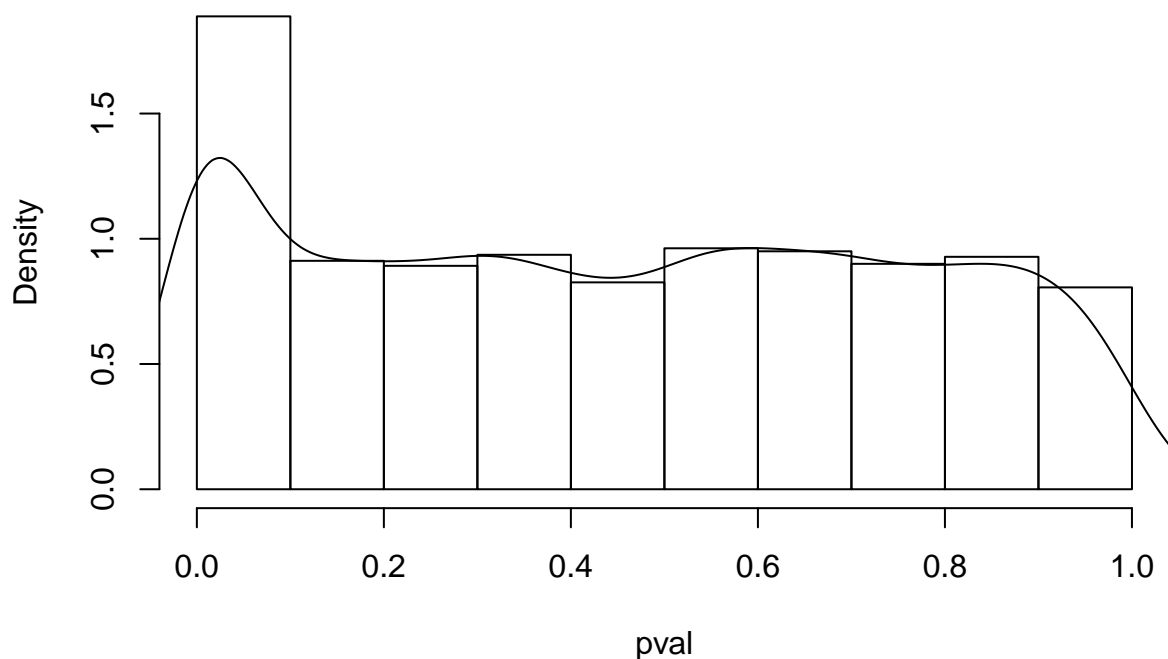
b.1 = 1
b.0 = 100
pval <- c(rbeta(m, b.1, b.0), runif(p-m, 0, 1))
hist(pval, xlab = "pval", prob = TRUE)
lines(density(pval))

```



```
b.1 = 1
b.0 = 500
pval <- c(rbeta(m, b.1, b.0), runif(p-m, 0, 1))
hist(pval, xlab = "pval", prob = TRUE)
lines(density(pval))
```

Histogram of pval



(b)

```
# Generate R = 500 replicates
R = 500
qval_fun <- function(x) {qvalue(p = x)}

#####

b.1 = 1
b.0 = 1

# Generate replicated pvalues and apply qval function over the columns
pval_new <- replicate(R, c(rbeta(m, b.1, b.0), runif(p-m, 0, 1)))
eff <- c(rep(T, m), rep(F, p - m))
qval <- lapply(1:ncol(pval_new), function(x) qvalue(pval_new[,x]))

# Extract variables/elements from the above list
qval_rep <- lapply(qval, `[`, c('qvalues'))
qval_rep_df <- data.frame(matrix(unlist(qval_rep), nrow=length(qval_rep), byrow=T))

pi0_rep <- lapply(qval, `[`, c('pi0'))
pi0_rep_df <- data.frame(matrix(unlist(pi0_rep), nrow=length(pi0_rep), byrow=T))
names(pi0_rep_df) <- names(pi0_rep[[which(lengths(pi0_rep)>0)[1]])

alpha=0.1
```

```

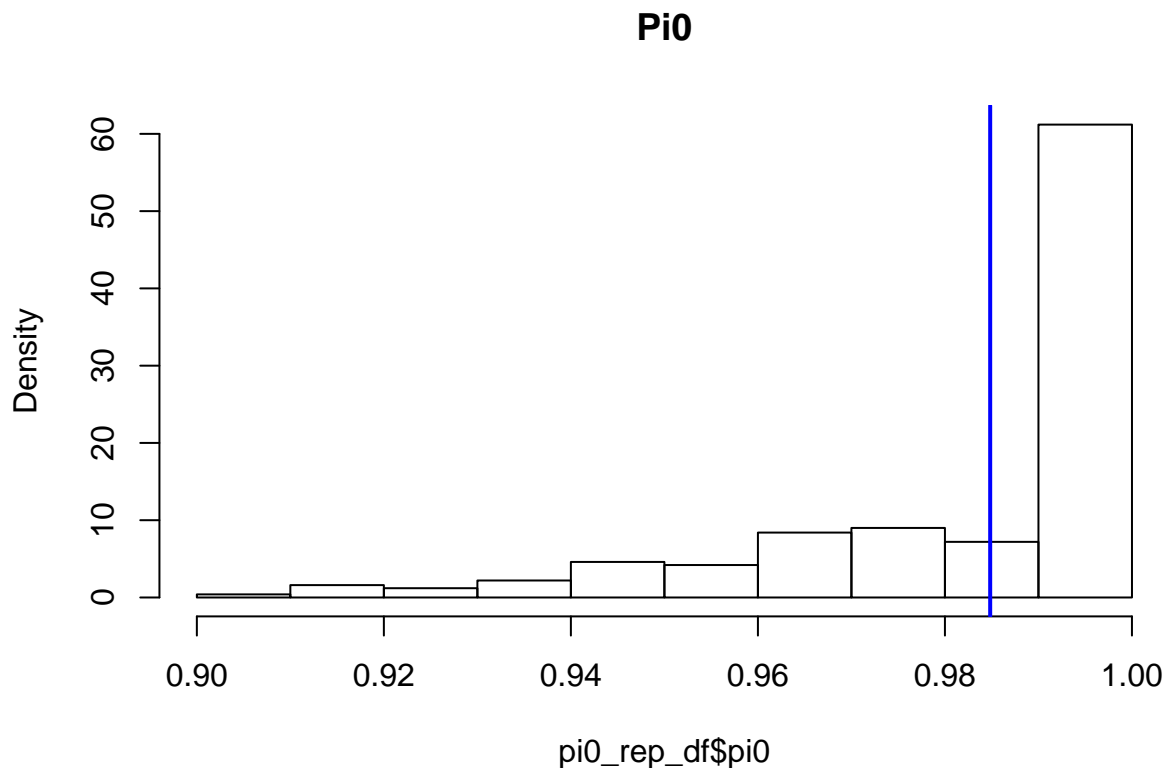
# Discoveries
D_func <- function(x) { (sum(qval_rep_df[x] < alpha)) }
Disc <- lapply(1:ncol(pval_new), D_func)
Disc_rep_df <- data.frame(matrix(unlist(Disc), nrow=length(Disc), byrow=T)) # Extract and generate df f
colnames(Disc_rep_df) <- "Discoveries"

# FDP
FD_func <- function(x) {sum(qval_rep_df[(m + 1):p] < alpha)}
FD <- lapply(1:ncol(pval_new), FD_func)
FD_rep_df <- data.frame(matrix(unlist(FD), nrow=length(FD), byrow=T))
colnames(FD_rep_df) <- "False Discoveries"
FDP <- as.data.frame(ifelse(Disc_rep_df$Discoveries == 0, 0, FD_rep_df$`False Discoveries`/Disc_rep_df$
colnames(FDP) <- "FD_Proportion"

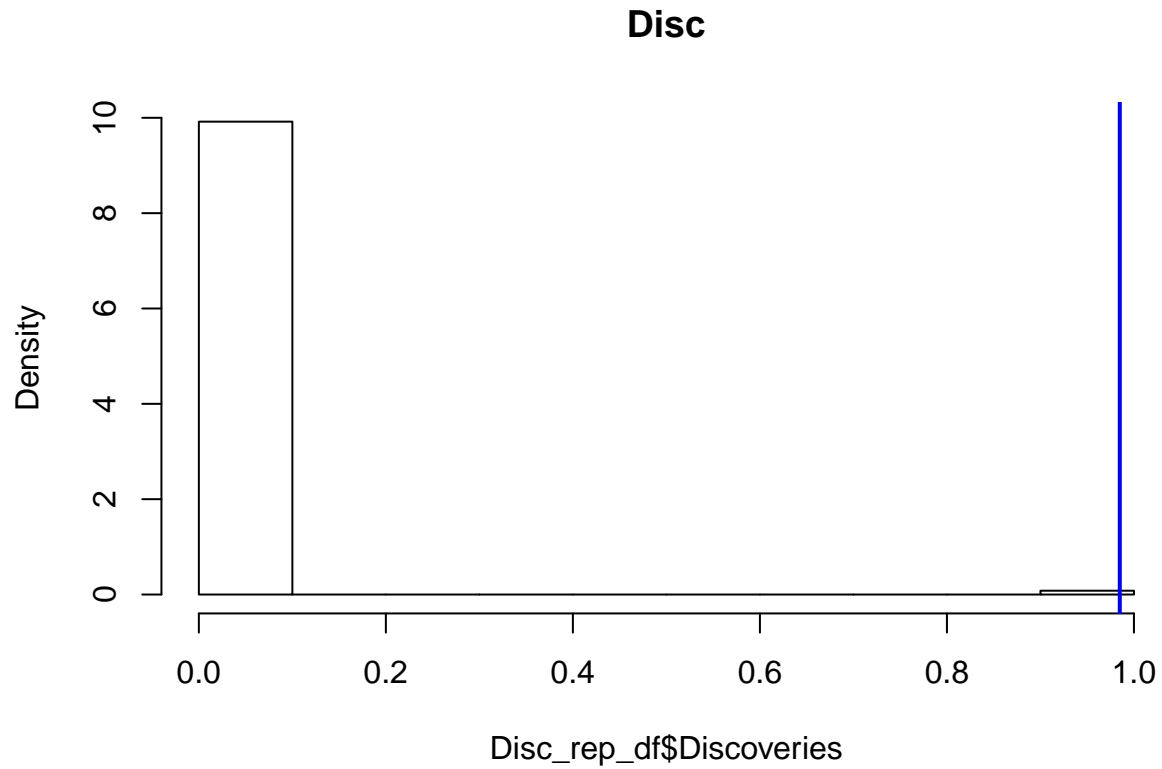
# Power
val <- which(Disc_rep_df$Discoveries < alpha)
Disc_corr <- sum(eff[val] == "TRUE")
pow <- Disc_corr/m

# Histograms
pi_mean <- mean(pi0_rep_df$pi0)
hist(pi0_rep_df$pi0, main = "Pi0", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)

```

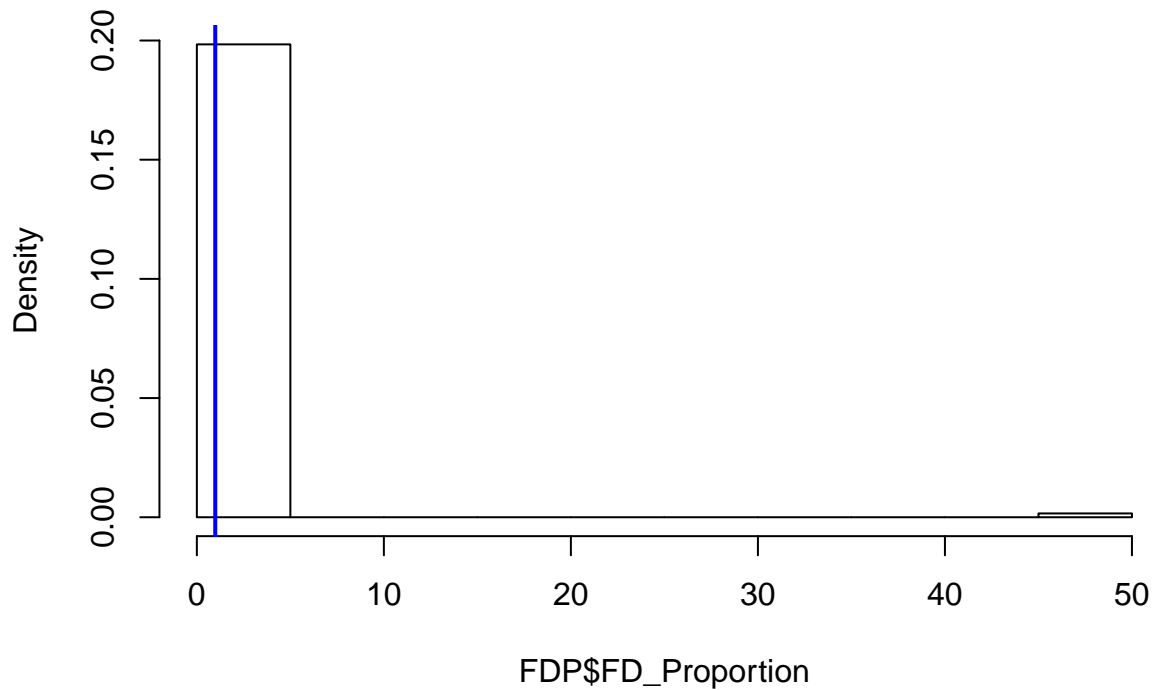


```
Disc_mean <- mean(Disc_rep_df$Discoveries)
hist(Disc_rep_df$Discoveries, main = "Disc", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)
```



```
FDP_mean <- mean(FDP$FD_Proportion)
hist(FDP$FD_Proportion, main = "FDP", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)
```

FDP



```
#####
b.1 = 1
b.0 = 100

# Generate replicated pvalues and apply qual function over the columns
pval_new <- replicate(R, c(rbeta(m, b.1, b.0), runif(p-m, 0, 1)))
eff <- c(rep(T, m), rep(F, p - m))
qval <- lapply(1:ncol(pval_new), function(x) qvalue(pval_new[,x]))

# Extract variables/elements from the above list
qval_rep <- lapply(qval, `[`, c('qvalues'))
qval_rep_df <- data.frame(matrix(unlist(qval_rep), nrow=length(qval_rep), byrow=T))

pi0_rep <- lapply(qval, `[`, c('pi0'))
pi0_rep_df <- data.frame(matrix(unlist(pi0_rep), nrow=length(pi0_rep), byrow=T))
names(pi0_rep_df) <- names(pi0_rep)[[which(lengths(pi0_rep)>0)[1]]]

alpha=0.1

# Discoveries
D_func <- function(x) { (sum(qval_rep_df[x] < alpha)) }
Disc <- lapply(1:ncol(pval_new), D_func)
Disc_rep_df <- data.frame(matrix(unlist(Disc), nrow=length(Disc), byrow=T))
colnames(Disc_rep_df) <- "Discoveries"
```

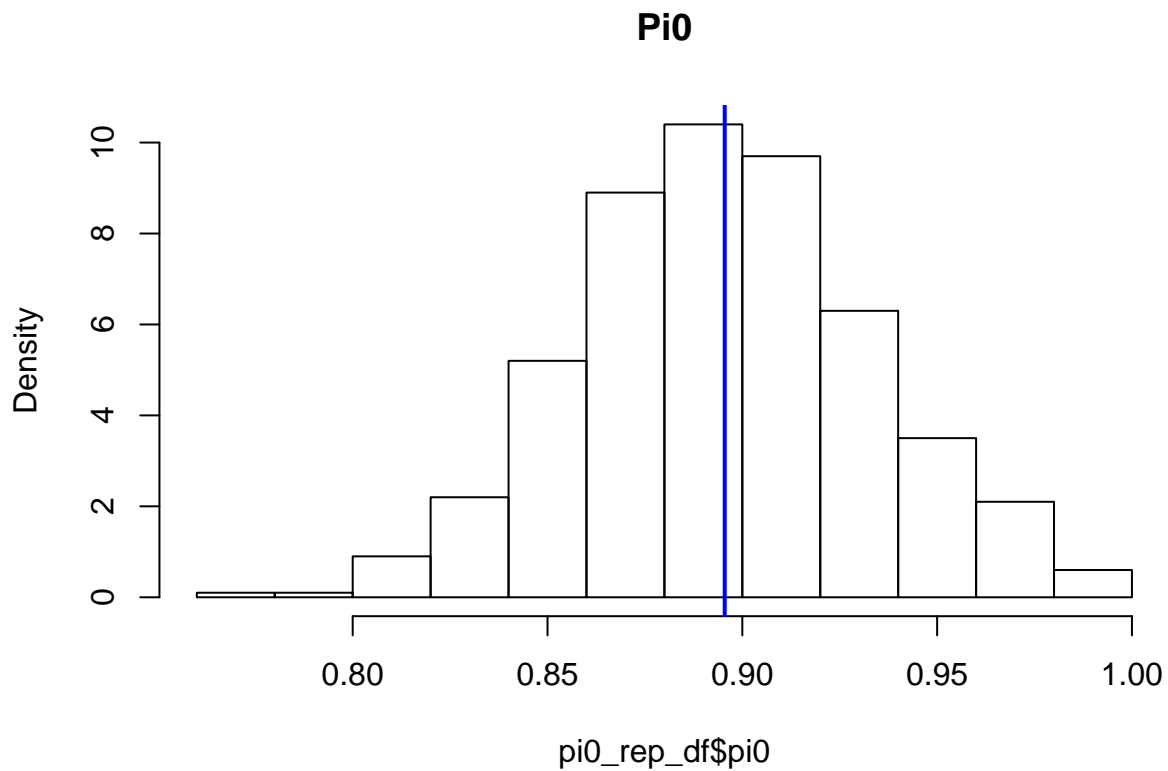
```

# FDP
FD_func <- function(x) {sum(qval_rep_df[(m + 1):p] < alpha)}
FD <- lapply(1:ncol(pval_new), FD_func)
FD_rep_df <- data.frame(matrix(unlist(FD), nrow=length(FD), byrow=T))
colnames(FD_rep_df) <- "False Discoveries"
FDP <- as.data.frame(ifelse(Disc_rep_df$Discoveries == 0, 0, FD_rep_df$`False Discoveries`/Disc_rep_df$Discoveries))
colnames(FDP) <- "FD_Proportion"

# Power
val <- which(Disc_rep_df$Discoveries < alpha)
Disc_corr <- sum(eff[val] == "TRUE")
pow <- Disc_corr/m

# Histograms
pi_mean <- mean(pi0_rep_df$pi0)
hist(pi0_rep_df$pi0, main = "Pi0", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)

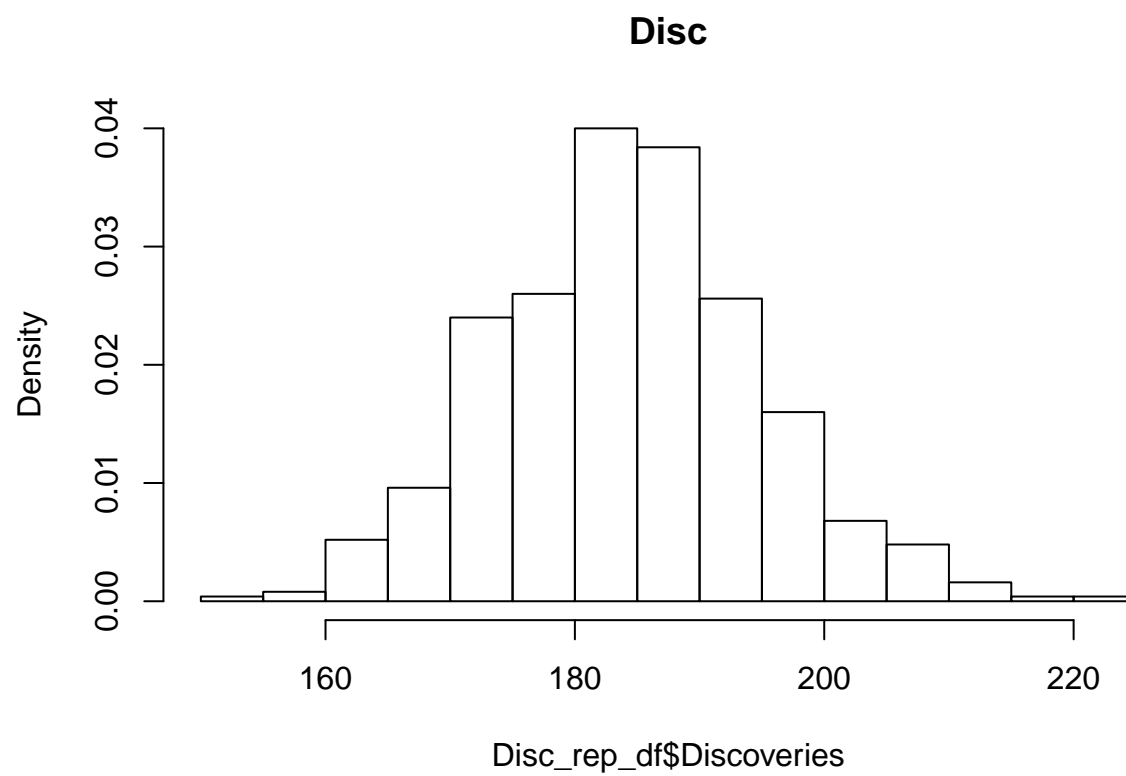
```



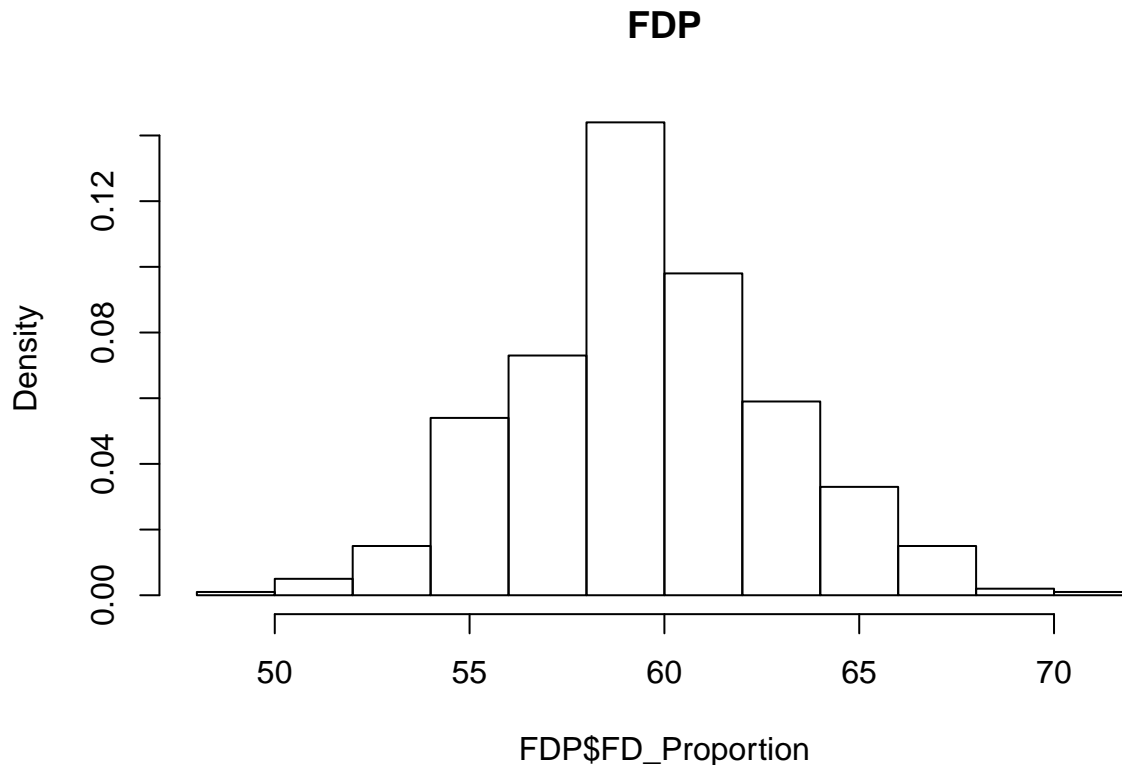
```

Disc_mean <- mean(Disc_rep_df$Discoveries)
hist(Disc_rep_df$Discoveries, main = "Disc", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)

```

```
FDP_mean <- mean(FDP$FD_Proportion)
hist(FDP$FD_Proportion, main = "FDP", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)
```



```
#####

b.1 = 1
b.0 = 500

# Generate replicated pvalues and apply qual function over the columns
pval_new <- replicate(R, c(rbeta(m, b.1, b.0), runif(p-m, 0, 1)))
eff <- c(rep(T, m), rep(F, p - m))
qval <- lapply(1:ncol(pval_new), function(x) qvalue(pval_new[,x]))

# Extract variables/elements from the above list
qval_rep <- lapply(qval, `[`, c('qvalues'))
qval_rep_df <- data.frame(matrix(unlist(qval_rep), nrow=length(qval_rep), byrow=T))

pi0_rep <- lapply(qval, `[`, c('pi0'))
pi0_rep_df <- data.frame(matrix(unlist(pi0_rep), nrow=length(pi0_rep), byrow=T))
names(pi0_rep_df) <- names(pi0_rep)[[which(lengths(pi0_rep)>0)[1]]]

alpha=0.1

# Discoveries
D_func <- function(x) { (sum(qval_rep_df[x] < alpha)) }
Disc <- lapply(1:ncol(pval_new), D_func)
Disc_rep_df <- data.frame(matrix(unlist(Disc), nrow=length(Disc), byrow=T))
colnames(Disc_rep_df) <- "Discoveries"
```

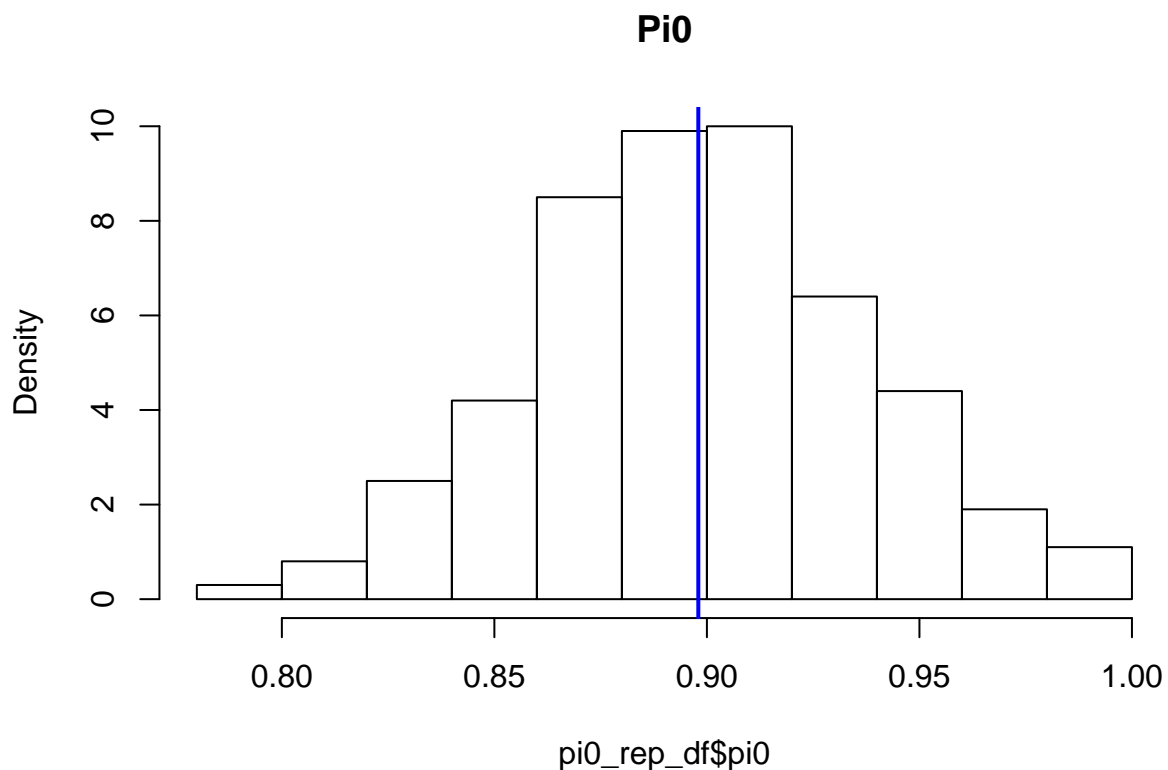
```

# FDP
FD_func <- function(x) {sum(qval_rep_df[(m + 1):p] < alpha)}
FD <- lapply(1:ncol(pval_new), FD_func)
FD_rep_df <- data.frame(matrix(unlist(FD), nrow=length(FD), byrow=T))
colnames(FD_rep_df) <- "False Discoveries"
FDP <- as.data.frame(ifelse(Disc_rep_df$Discoveries == 0, 0, FD_rep_df$`False Discoveries`/Disc_rep_df$Discoveries))
colnames(FDP) <- "FD_Proportion"

# Power
val <- which(Disc_rep_df$Discoveries < alpha)
Disc_corr <- sum(eff[val] == "TRUE")
pow <- Disc_corr/m

# Histograms
pi_mean <- mean(pi0_rep_df$pi0)
hist(pi0_rep_df$pi0, main = "Pi0", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)

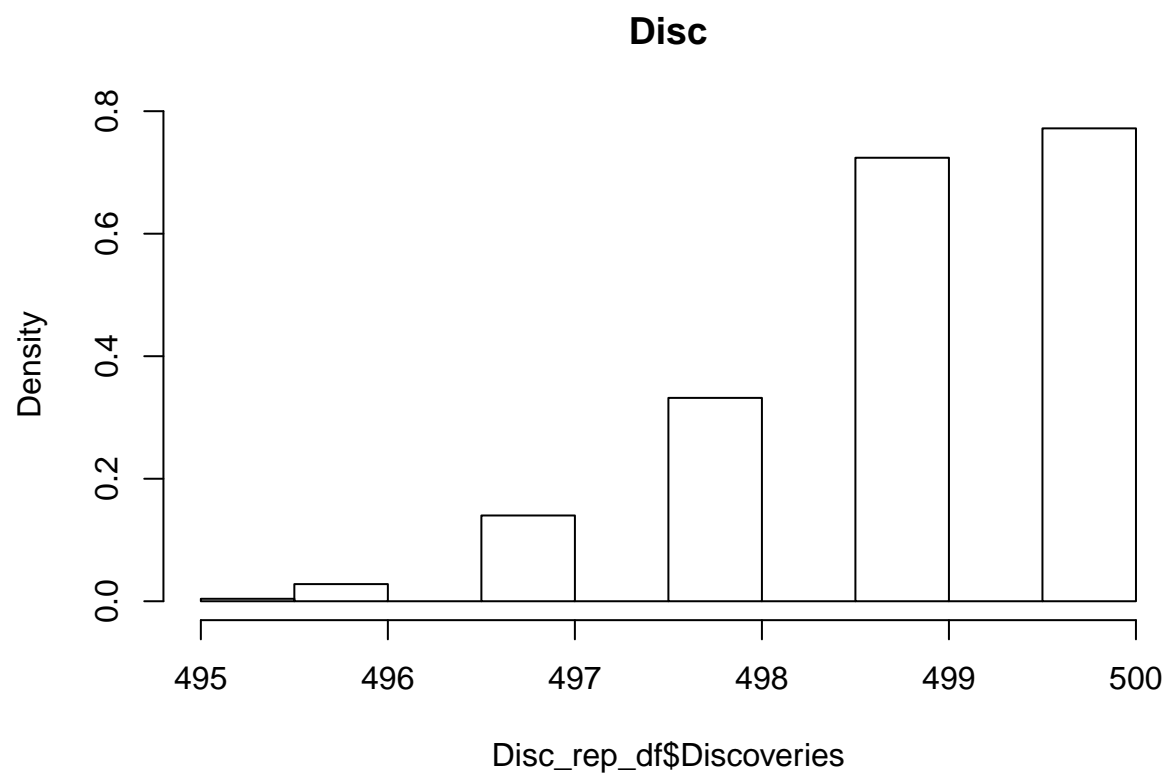
```



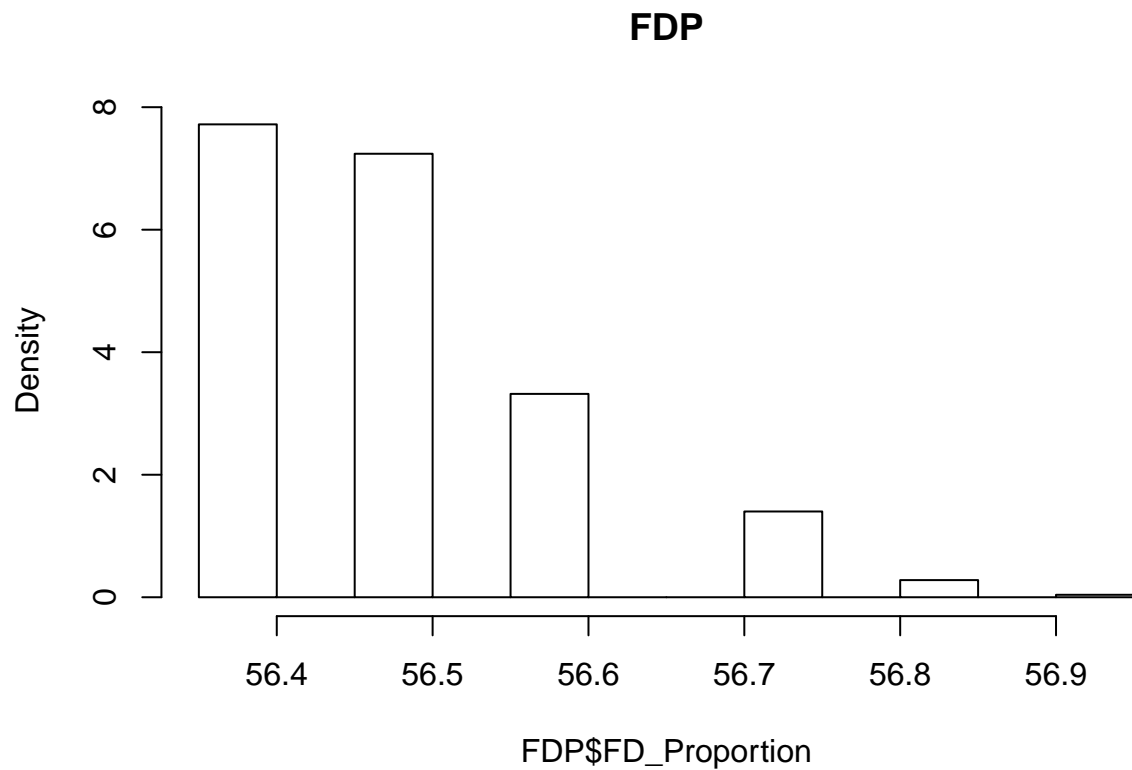
```

Disc_mean <- mean(Disc_rep_df$Discoveries)
hist(Disc_rep_df$Discoveries, main = "Disc", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)

```



```
FDP_mean <- mean(FDP$FD_Proportion)
hist(FDP$FD_Proportion, main = "FDP", prob = T)
abline(v = pi_mean, col = "blue", lwd = 2)
```



Problem 4 – Solutions

(a)

```
# For 1 coin toss
```

```
p <- 1
```

```
# Fair coin
```

```
null_prob <- 0.5
```

```
# possible number of heads after 2 tosses
```

```
y <- c(0, 1, 2)
```

```
# Null hypothesis for 3 possible outcomes aka heads in the tosses
```

```
null_prob <- dbinom(y, 2, null_prob)
```

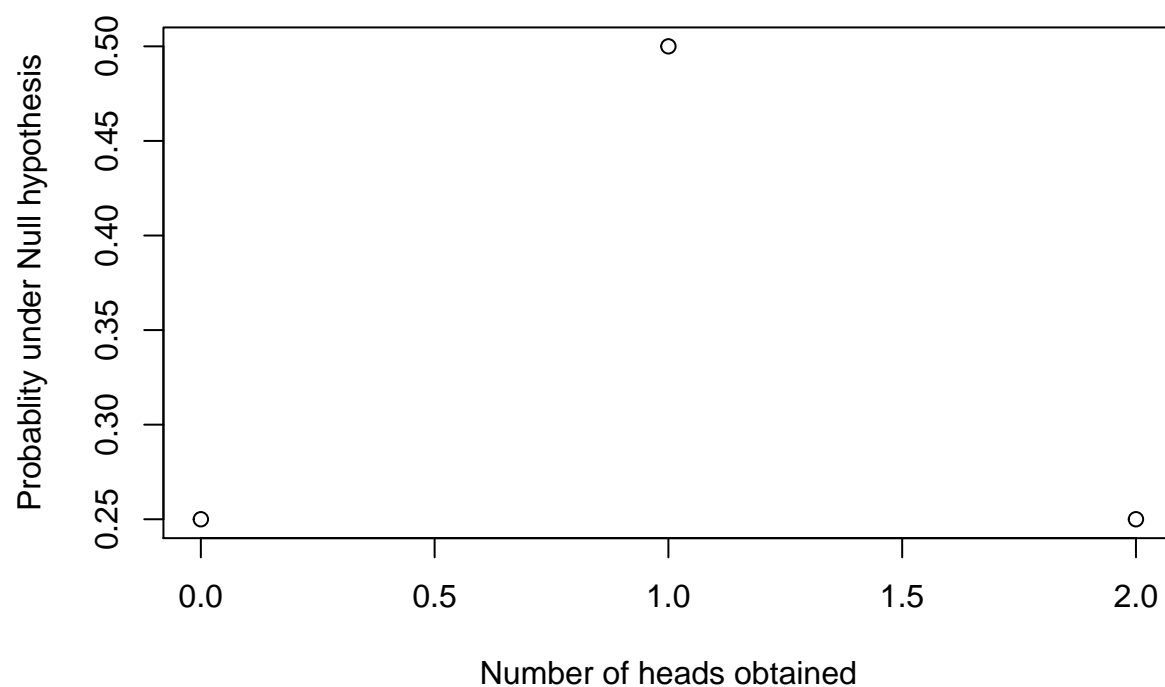
```
null_prob
```

```
## [1] 0.25 0.50 0.25
```

```
# Null distribution of outcome v/s the number of heads obtained
```

```
plot(y, null_prob, type='p', main = "Null distribution of outcome from a single coin tossed 2 times", xlab = "Number of heads", ylab = "Probability")
```

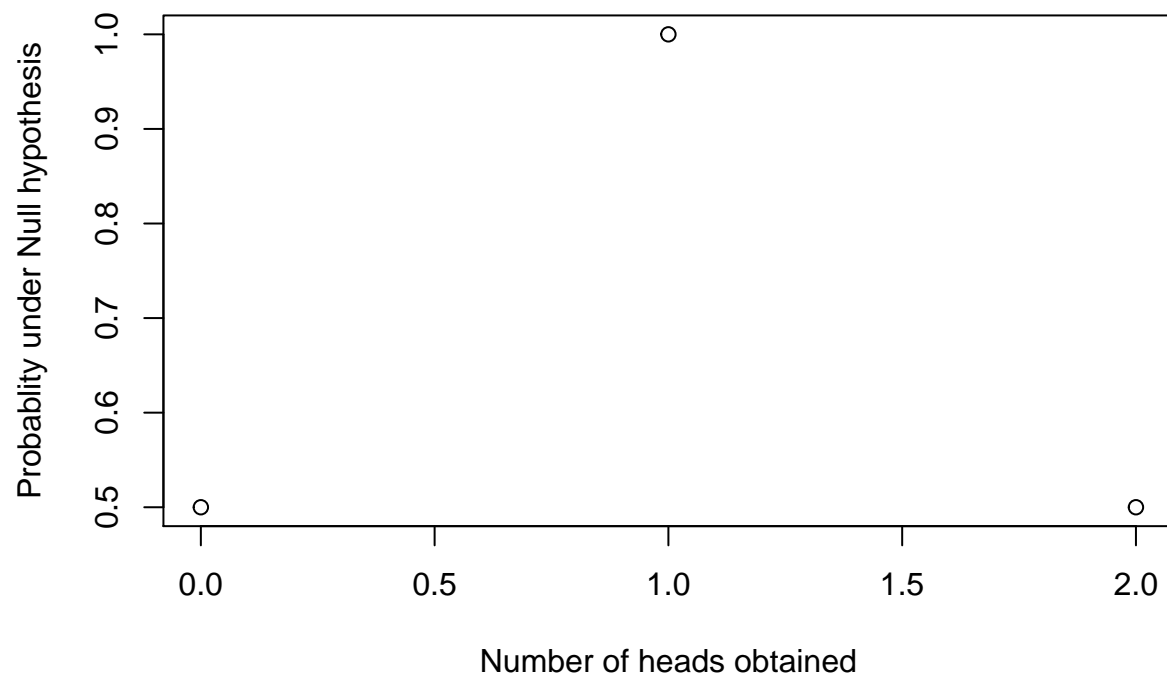
Null distribution of outcome from a single coin tossed 2 times



```
# Null distribution of p-values from tossing coin twice, assuming its a fair coin
null_p_distr <- c(0.5, 1, 0.5)

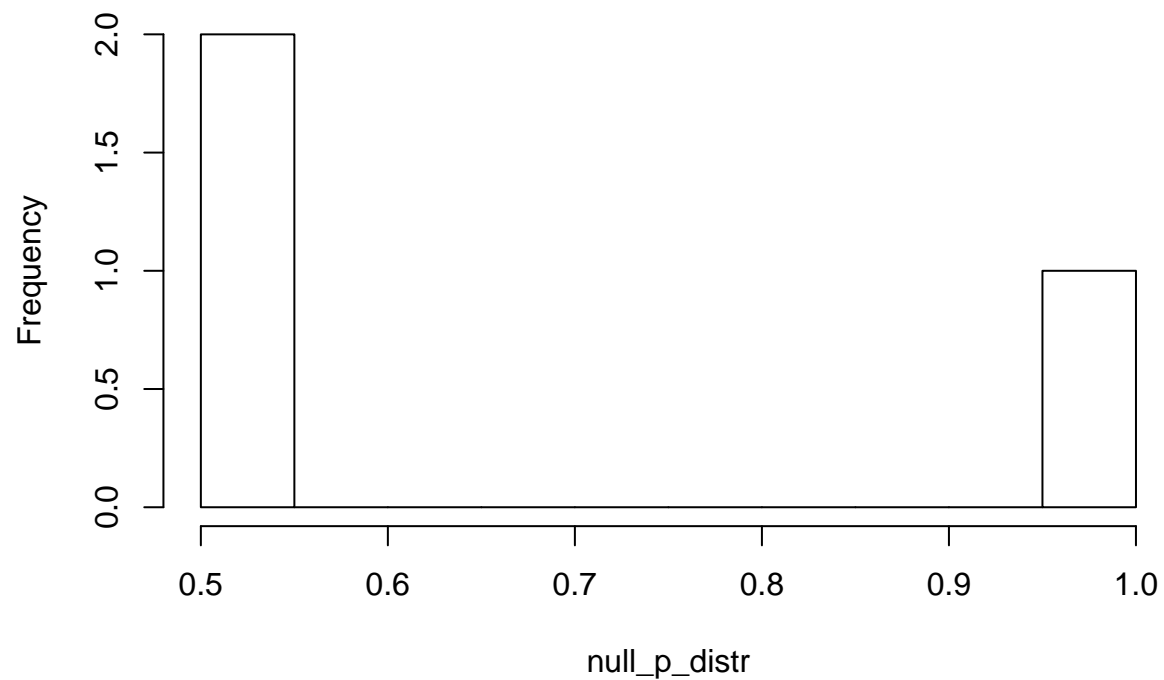
# Null distribution v/s the number of heads obtained
plot(y, null_p_distr, type='p', main = "Null distribution of p-values from tossing coin twice", xlab =
```

Null distribution of p-values from tossing coin twice



```
# Histogram of the p-values  
hist(null_p_distr, 10, main="Null distribution of p-values from tossing coin twice, assuming its a fair
```

ull distribution of p-values from tossing coin twice, assuming its a fair



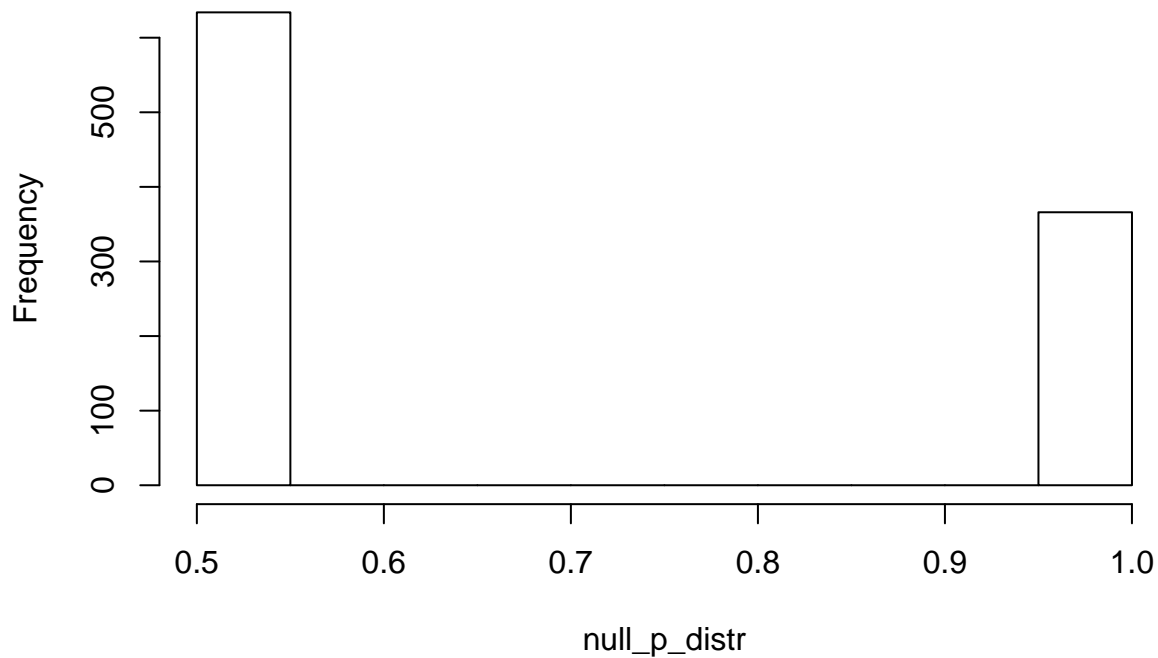
(b)

```
# For 1000 coins
p <- 1000

# Observed counts of outcomes
y <- c(180, 366, 454)

# Distribution of tp-values for the above 1000 coins
null_p_distr <- rep(c(0.5, 1, 0.5), y)
hist(null_p_distr, 10, main="Null distribution of p-values")
```


Null distribution of p-values



From the null distribution from part(a) of the question we see that the prob of 1 head is 1 as this is

*# $Pi0 = (2 * \text{Fair coins}) / \text{Total coins}$*

In the above example, estimate of $Pi0$ would be

```
Pi0_est <- (2*366)/p
Pi0_est
```

```
## [1] 0.732
```

(c)

Given values of lambda

```
lambda <- c(0.4, 0.5, 0.9)
```

Estimate of $Pi0$

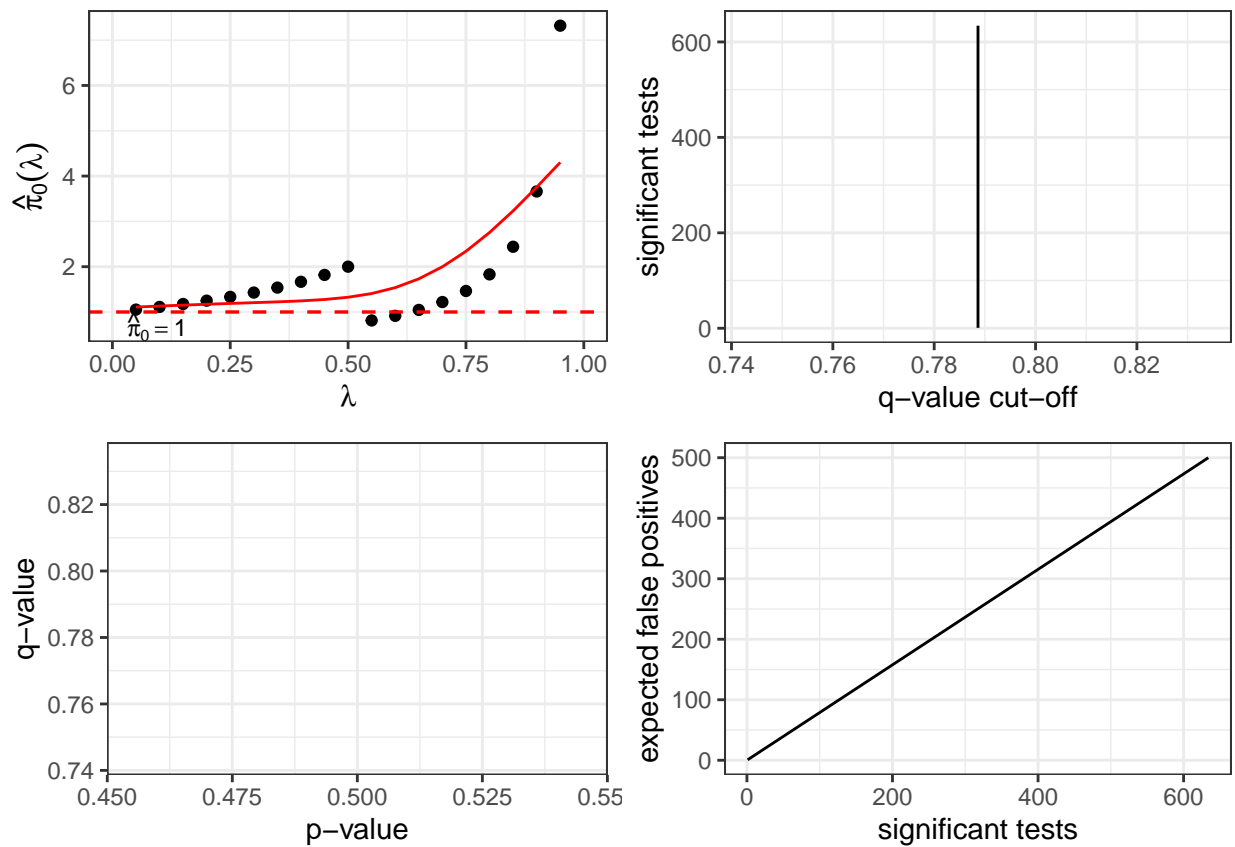
```
Pi0_est <- as.data.frame(sapply(lambda,function(x){sum(null_p_distr > x)})/p/(1 - lambda))
colnames(Pi0_est) <- "lambda"
```

```
View(Pi0_est)
```

Only for lambda = 0.5 estimate agrees with part(a).

#Q-values

```
qVal <- qvalue(null_p_distr)
plot(qVal)
```



Q-values don't seem to work with discrete data at all, as Q-value for observations whose p-value=0.5 is around 0.79. This value is higher than that we got in (b)