

One of the new topics added to our text in this edition, Devore's "Probability & Statistics for Engineering and the Sciences, 8th ed." is a discussion of the sampling distribution of the p -value, in section 8.4. The main point is that the p -value is a random variable. By simulating many t -tests, we can plot the histogram to appreciate the sampling distribution of the p -value.

Assume one selects random sample $X_1, X_2, \dots, X_n \sim N(\mu, \sigma)$ from a normal distribution. To test the hypothesis $H_0 : \mu = \mu_0$ vs. the alternative $H_a : \mu > \mu_0$, one computes the T statistic,

$$T = \frac{\bar{X} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

which is also a random variable which is distributed according to the t -distribution with $n - 1$ degrees of freedom. In particular, any function of this is also a random variable, for example, the p -value

$$P = 1 - F(T) = \text{pt}(T, n - 1, \text{lower.tail} = \text{FALSE}),$$

where $F(x) = P(T \leq x)$ is the cdf for T with $n - 1$ degrees of freedom. If the background distribution has $\mu = \mu_0$, then the type I errors occur when P is small. The probability of a type I error is $P(P \leq \alpha)$ for a significance level α test, namely, that the test shows that the mean is significantly above μ_0 (*i.e.*, we reject H_0), even though the sample was drawn from data satisfying the null hypothesis $X_i \sim N(\mu_0, \sigma)$.

It turns out that the p -value is a uniform rv in $[0, 1]$ when $\mu = \mu_0$. This is simply a consequence of definitions. Indeed, the cdf for P is

$$\begin{aligned} P(P \leq \alpha) &= P(1 - F(T) \leq \alpha) \\ &= P(F(T) \geq 1 - \alpha) \\ &= P(T \geq F^{-1}(1 - \alpha)) \\ &= 1 - P(T < F^{-1}(1 - \alpha)) \\ &= 1 - F(F^{-1}(1 - \alpha)) \\ &= 1 - (1 - \alpha) \\ &= \alpha, \end{aligned}$$

which is the cdf for a uniform rv and so $P \sim U(0, 1)$.

I ran examples with $\mu_0 = 0$, $\sigma = 1$, samples of size $n = 10$ and $m = 10,000$ trials for various $\mu = \mu_1$'s. In our histograms the bar from 0 to .05 is drawn red. For example, when $\mu_1 = \mu_0$, and so $P \sim U(0, 1)$, the bars have nearly the same height and type I errors occurred 515 times or 5.15% of the time. If $\mu_1 > 0$, then the test is more likely to show that the mean is significantly greater than μ_0 . As μ_1 increases, then the test is more and more likely to indicate that $\mu > \mu_0$ significantly. Note that if $\mu_1 < 0$, then the test is even less likely to make a type I error.

We start our **R** study by recalling Student's actual 1908 data to demonstrate his one-tailed t -test.

R Session:

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[R.app GUI 1.31 (5538) powerpc-apple-darwin8.11.1]

[Workspace restored from /Users/andrejstreibergs/.RData]

```
> ##### STUDENT'S ONE-DAMPLE T-TEST DATA #####
> # From M.G.Bulmer, "Principles of Statistics," Dover, 1979.
> # Student's 1908 Data:
> # Additional hrs sleep gained after administering Hyoscene
> # to ten patients
> #
> x <- scan()
1: 1.9 .8 1.1 .1 -.1 4.4 5.5 1.6 4.6 3.4
11:
Read 10 items
> x
 [1] 1.9 0.8 1.1 0.1 -0.1 4.4 5.5 1.6 4.6 3.4

> t.test(x,alternative="greater")
```

One Sample t-test

```
data: x
t = 3.6799, df = 9, p-value = 0.002538
alternative hypothesis: true mean is greater than 0
95 percent confidence interval:
 1.169334      Inf
sample estimates:
mean of x
 2.33

> # Strong evidence that mu>0: Hyocene is soporific
```

```

> ##### ANALYZE THE DATA BY HAND #####
> xbar <- mean(x); xbar
[1] 2.33
> s <- sd(x); s
[1] 2.002249
> n <- length(x); n
[1] 10
> t <- xbar/(s/sqrt(n)); t
[1] 3.679916
> # crit value for upper tailed test
> alpha <- .05
> qalpha <- qt(alpha, df = n-1, lower.tail = FALSE); qalpha
[1] 1.833113
> # T exceeds this so at 1-alpha conf., mu signif. greater than 0
> PV <- pt(t, n-1, lower.tail = FALSE); PV
[1] 0.002538066
> # same numbers as from canned test.

> ##### SAMPLING DISTRIBUTION OF P-VALUE #####
> # simulate p-values.
> # mu1 = mean of normal variable, 1 = sd of normal variable.
> # m = number of trials
> m <- 10000
> # n = sample size
> n <- 10
> # to make sure these computations are done outside the loop.
> c <- sqrt(n)
> nu <- n-1
> # Vector of nice colors.
> cl <- c(2,rep(rainbow(12,alpha=.4)[6],19))
> xl <- "p - Value"
>
> # The sapply(v,f) does the function "f" to each element of vector "v"
> # In our case, f generates a p-value from a random sample every time
> # it's called.
> # In a vector oriented language, vectorwise computations replace loops
> # and do it faster.
>
> mu1 <- 0
> # Save the title.
> mn <- paste("Histogram of t-Test p-Values, Sample from N(",mu1,",1),
+ \n Samp.Size=", n,", No.Trials=", m)
> # Each call to pv gives p-value for a simulated upper-tail t-test
> # for size n. Z is a random N(mu1,sigma) sample of size n
> pv <- function(j){Z<- rnorm(n,mu1,1);pt(c*mean(Z)/sd(Z),nu,lower.tail=F)}
> hist(sapply(1:m,pv),breaks=20,col=cl,labels=T,main=mn,xlab=xl)
> # M3074RVpValue1.pdf

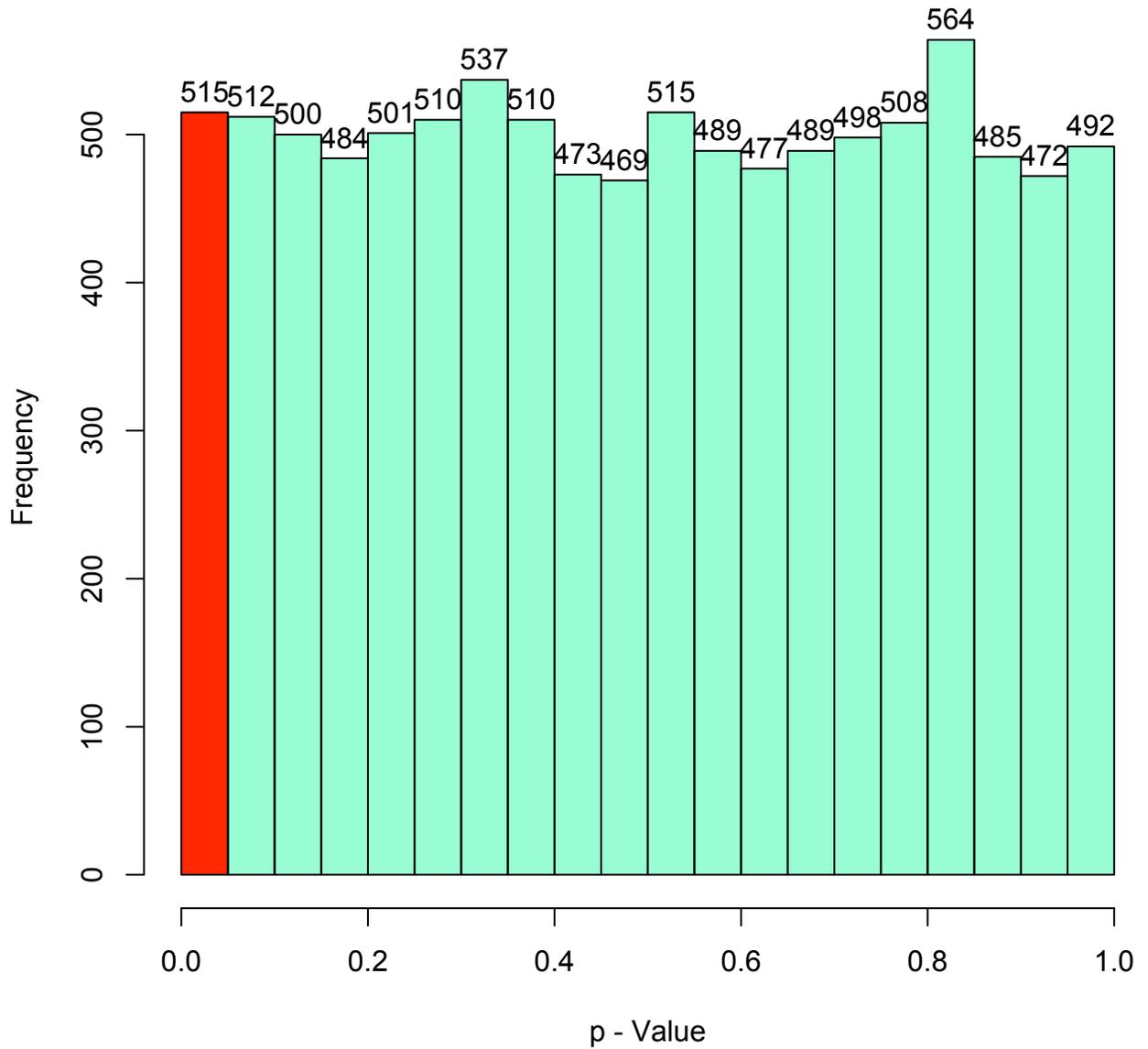
```

```

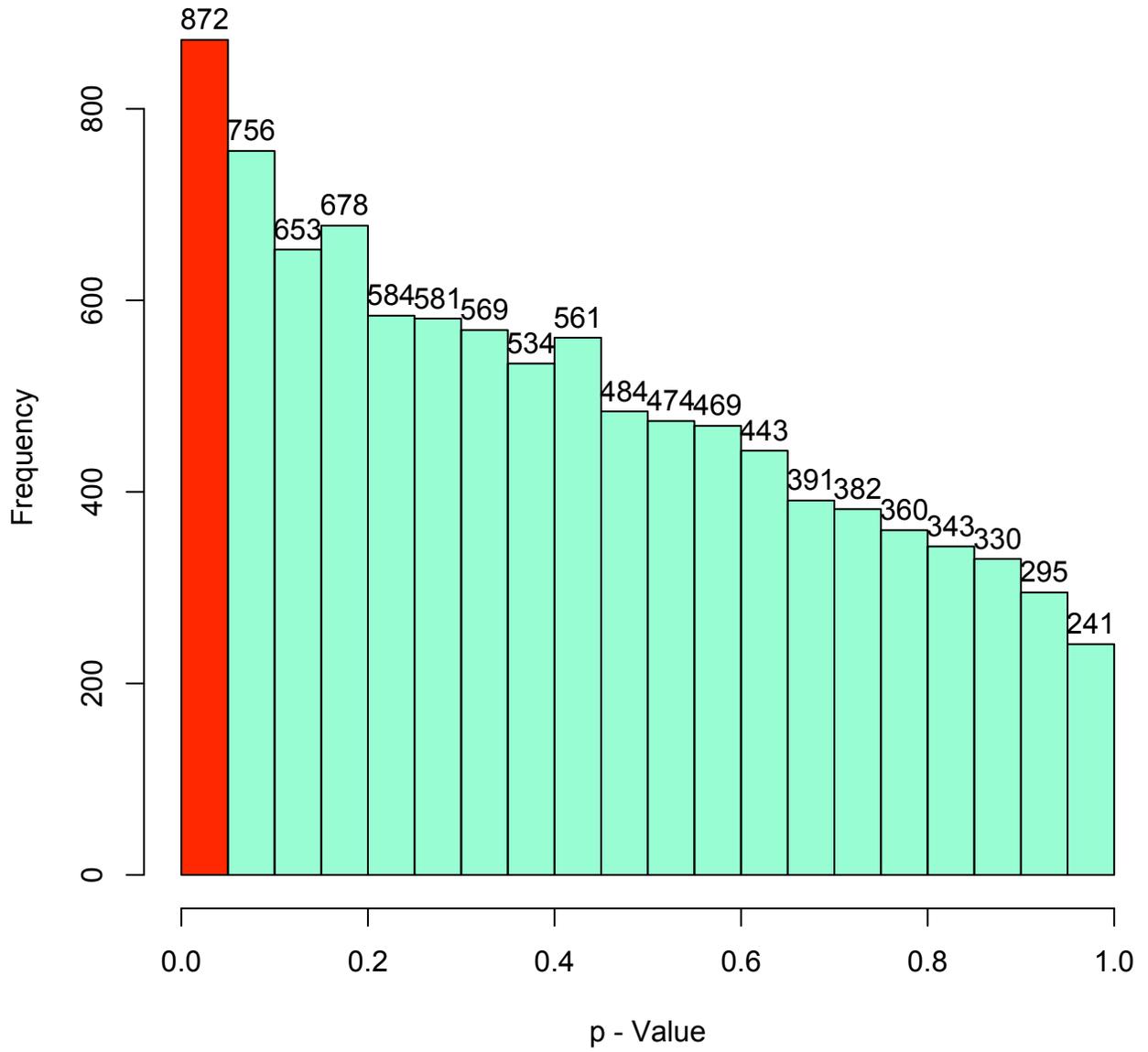
> mu1 <- 0.1
> mn <- paste("Histogram of t-Test p-Values, Sample from N(",mu1,",1),
+ \n Samp.Size=", n, ", No.Trials=", m)
> pv <- function(j){Z<- rnorm(n,mu1,1);pt(c*mean(Z)/sd(Z),nu,lower.tail=F)}
> hist(sapply(1:m,pv),breaks=20,col=c1,labels=T,main=mn,xlab=x1)
> # M3074RVpValue2.pdf
>
>
> mu1 <- 0.2
> mn <- paste("Histogram of t-Test p-Values, Sample from N(",mu1,",1),
+ \n Samp.Size=", n, ", No.Trials=", m)
> pv <- function(j){Z<- rnorm(n,mu1,1);pt(c*mean(Z)/sd(Z),nu,lower.tail=F)}
> hist(sapply(1:m,pv),breaks=20,col=c1,labels=T,main=mn,xlab=x1)
> # M3074RVpValue3.pdf
>
>
> mu1 <- 0.5
> mn <- paste("Histogram of t-Test p-Values, Sample from N(",mu1,",1),
+ \n Samp.Size=", n, ", No.Trials=", m)
> pv <- function(j){Z<- rnorm(n,mu1,1);pt(c*mean(Z)/sd(Z),nu,lower.tail=F)}
> hist(sapply(1:m,pv),breaks=20,col=c1,labels=T,main=mn,xlab=x1)
> # M3074RVpValue4.pdf
>
>
> mu1 <- 1
> mn <- paste("Histogram of t-Test p-Values, Sample from N(",mu1,",1),
+ \n Samp.Size=", n, ", No.Trials=",m)
> pv <- function(j){Z<- rnorm(n,mu1,1);pt(c*mean(Z)/sd(Z),nu,lower.tail=F)}
> hist(sapply(1:m,pv),breaks=20,col=c1,labels=T,main=mn,xlab=x1)
> # M3074RVpValue5.pdf
>
>
> mu1 <- -.5
> mn <- paste("Histogram of t-Test p-Values, Sample from N(",mu1,",1),
+ \n Samp.Size=", n, ", No.Trials=", m)
> hist(sapply(1:m,pv),breaks=20,col=c1,labels=T,main=mn,xlab=x1)
> # M3074RVpValue6.pdf

```

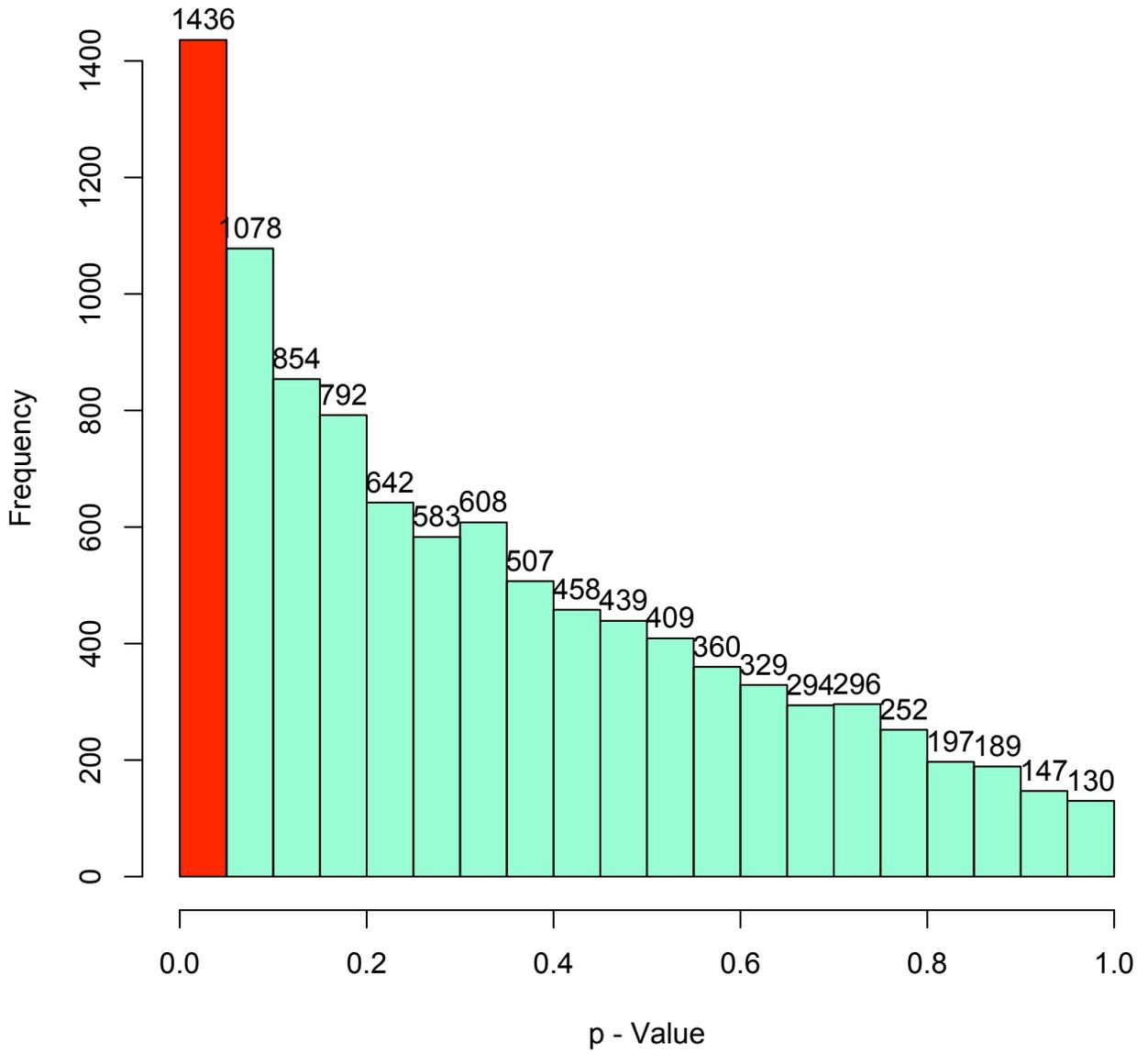
**Histogram of t-Test p-Values, Sample from $N(0,1)$,
Samp.Size= 10 , No.Trials= 10000**



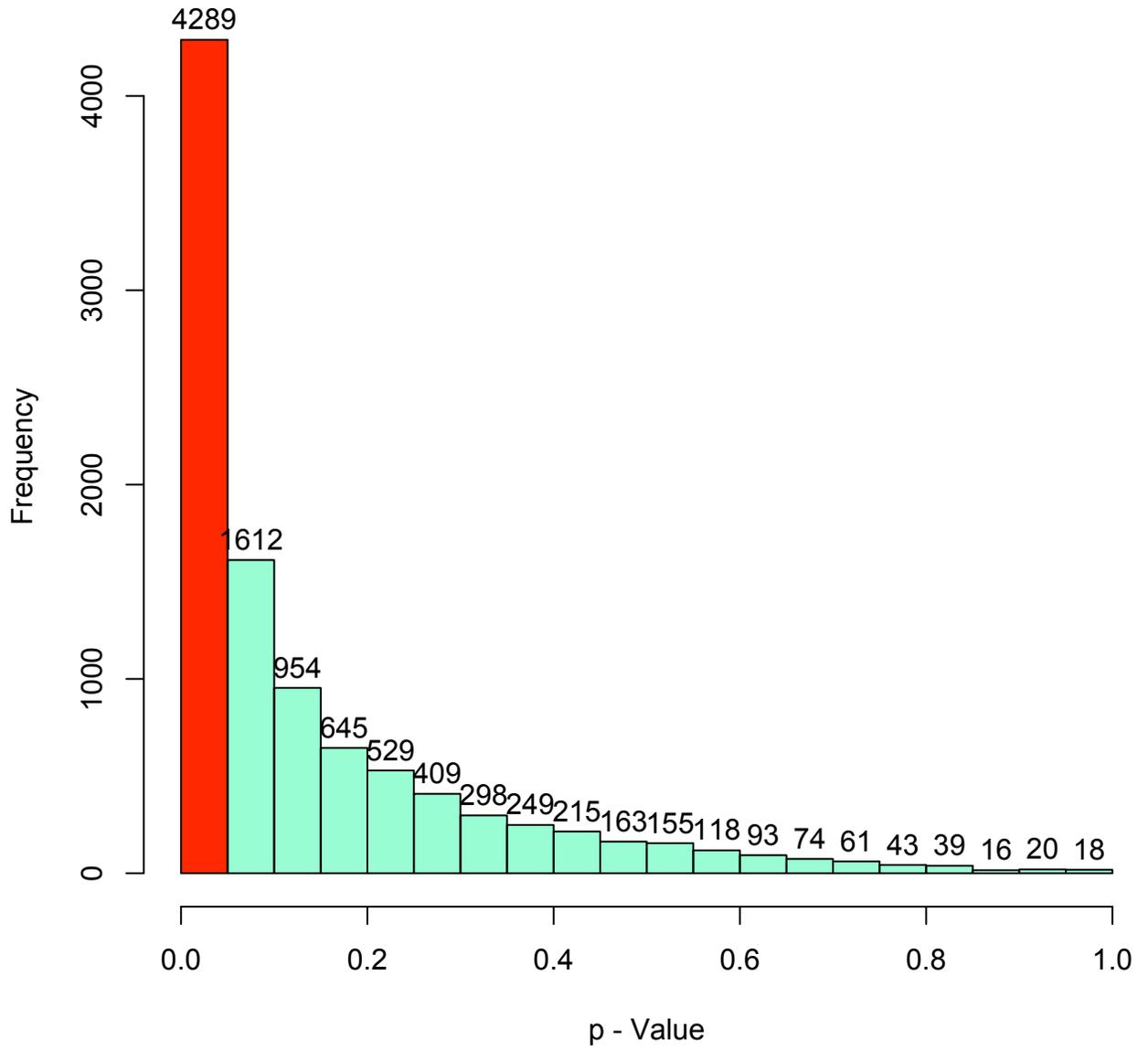
**Histogram of t-Test p-Values, Sample from $N(0.1, 1)$,
Samp.Size= 10 , No.Trials= 10000**



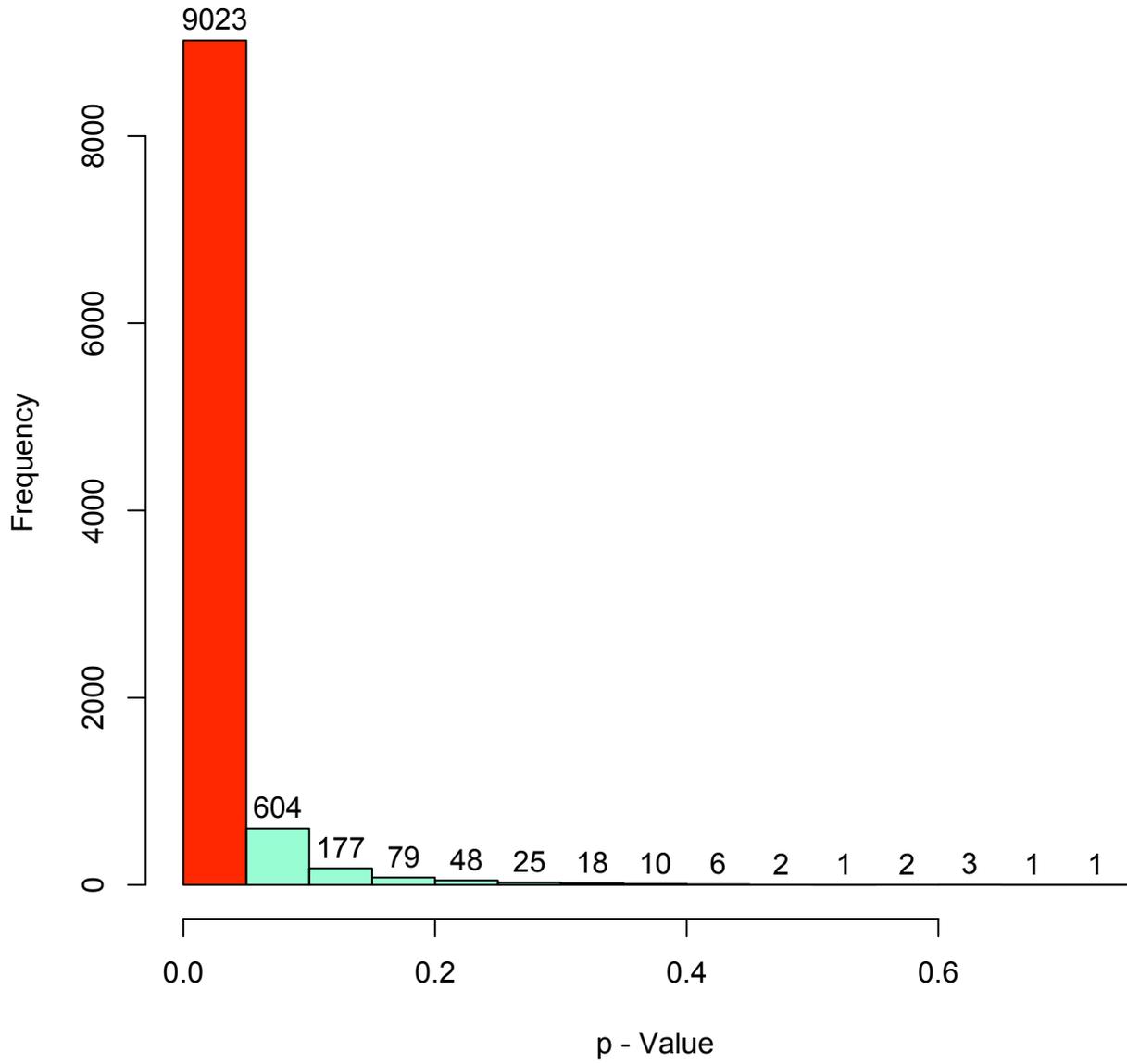
**Histogram of t-Test p-Values, Sample from $N(0.2, 1)$,
Samp.Size= 10 , No.Trials= 10000**



**Histogram of t-Test p-Values, Sample from $N(0.5, 1)$,
Samp.Size= 10 , No.Trials= 10000**



**Histogram of t-Test p-Values, Sample from $N(1,1)$,
Samp.Size= 10 , No.Trials= 10000**



**Histogram of t-Test p-Values, Sample from $N(-0.5, 1)$,
Samp.Size= 10 , No.Trials= 10000**

