

This is Problem 6.15.10 of Navidi, *Statistics for Engineers and Scientists, 2nd ed.*, Mc Graw Hill, 2008. We wish to compare two t -tests for the equality of population means. For two samples, we consider the paired t -test with the pooled t -test.

Assume that X_1, X_2, \dots, X_n and Y_1, Y_2, \dots, Y_n are two samples with means μ_X and μ_Y , respectively. In case the readings X_i and Y_i are paired, such as those taken from different treatments from the same n individuals, we consider differences $D_i = X_i - Y_i$ and do a t test on the D_i 's. In this case, under the null hypothesis $\mathcal{H}_0 : \mu_X = \mu_Y$, the statistic is

$$T_P = \frac{\bar{D}}{s_D/\sqrt{n}}$$

where \bar{D} is the sample mean and s_D is the sample standard deviation of the D_i 's. The variables X and Y may be dependent, but by considering the differences D_i we eliminate the variability due to individual differences. Assuming that $D_i \sim N(\mu_D, \sigma_D)$ are a sample taken from a normal distribution, the statistic T_P satisfies a t -distribution with $n - 1$ degrees of freedom. Thus, at a significance of α , we reject the null hypothesis in favor of the alternative hypothesis $\mathcal{H}_a : \mu_X \neq \mu_Y$ if $|T_P| > t_{\alpha/2}$. The critical value is such that $P(T > t_{\alpha/2}) = \alpha/2$ where T is distributed according to the t -distribution with $n - 1$ degrees of freedom.

Assume on the other hand that $X_1, X_2, \dots, X_n \sim N(\mu_X, \sigma_X)$ and $Y_1, Y_2, \dots, Y_n \sim N(\mu_Y, \sigma_Y)$ are two independent normal samples such that $\sigma_X = \sigma_Y$. In this case, the data may be pooled to get a better estimator for $\sigma_X = \sigma_Y$

$$s_P^2 = \sqrt{\frac{(n-1)s_X^2 + (n-1)s_Y^2}{n+n-2}} = \sqrt{\frac{s_X^2 + s_Y^2}{2}}$$

where s_x^2 and s_y^2 are the variances of the two samples. This time, under the null hypothesis $\mathcal{H}_0 : \mu_X = \mu_Y$, the statistic is

$$T_U = \frac{\bar{X} - \bar{Y}}{s_P \sqrt{\frac{1}{n} + \frac{1}{n}}} = \frac{\sqrt{n}(\bar{X} - \bar{Y})}{\sqrt{s_X^2 + s_Y^2}}$$

which satisfies the t -distribution with $n + n - 2$ degrees of freedom. Thus, at a significance of α , we reject the null hypothesis in favor of the alternative hypothesis $\mathcal{H}_a : \mu_X \neq \mu_Y$ if $|T_U| > t_{\alpha/2}$. Now the critical value is such that $P(T > t_{\alpha/2}) = \alpha/2$ where T is distributed according to the t -distribution with $2n - 2$ degrees of freedom.

Assume now that \mathcal{H}_0 fails. We shall suppose that $n = 8$ and that $\mu_X = 0$ and $\mu_1 = 1$. The power of the test is the probability that the test rejects the null hypothesis given that \mathcal{H}_0 is false, specifically $\mu_X - \mu_Y = -1$. So one minus the power is the probability of a type II error. There is a trade-off. The paired test has smaller degrees of freedom, thus $t_{\alpha/2}$ is larger and the null hypothesis is harder to reject. For $\alpha = .05$ for the paired test $t_{\alpha/2} = 2.364624$ and for the pooled test, $t_{\alpha/2} = 2.144787$. But if the variables X and Y are correlated, then s_P underestimates the standard deviation whereas the differences are smaller. it turns out T_U has less variability but \mathcal{H}_0 is harder to reject.

We consider $B = 10,000$ samples taken from both independent and correlated X_i and Y_j . For each we do the paired test and the pooled test. The independent samples X is taken from $N(0, 1)$ and Y is taken from $N(1, 1)$. To simulate dependent samples, we take independent samples X from $N(0, 1)$ and Y from $N(0, 1)$ and consider $Z = 1 + .8X + .6Y$. The correlation is

$$\rho_{XZ} = \frac{\text{Cov}(X, Z)}{\sqrt{V(Z)}\sqrt{V(Z)}}$$

The mean is

$$E(Z) = E(1 + .8X + .6Y) = E(1) + .8E(X) + .6E(Y) = 1 + 0 + 0.$$

Since X and Y are independent, the variance is

$$V(Z) = V(1 + .8X + .6Y) = (.8)^2V(X) + (.6)^2V(Y) = .64 + .36 = 1.$$

The covariance is

$$\begin{aligned} \text{Cov}(X, Z) &= E(XZ) - E(X)E(Z) \\ &= E(X + .8X^2 + .6XY) - E(X)E(Z) \\ &= E(X) + .8E(X^2) + .6E(XY) - E(X)E(Z) \\ &= E(X) + .8(V(X) + E(X)^2) + .6E(X)E(Y) - E(X)E(Z) \\ &= 0 + .8(1 + 0) + 0 - 0 \\ &= .8. \end{aligned}$$

Thus $\rho_{XZ} = .8$.

To estimate the power, we generate B samples of size n , compute the statistic and count the number of times the test rejects the null hypothesis. Then the estimate for the power is count/B . Here is a table of our power estimates:

Power	Paired t -test	Pooled t -test
Independent Samples	0.4097	0.4723
Correlated Samples	0.9662	0.4487

It worked out that for fixed $\mu_X - \mu_Y = -1$, for correlated data, the paired test had greater power and for independent data, the pooled t -test had better power.

R Session:

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

```
> ##### t-TEST STATISTIC FOR PAIRED DATA #####

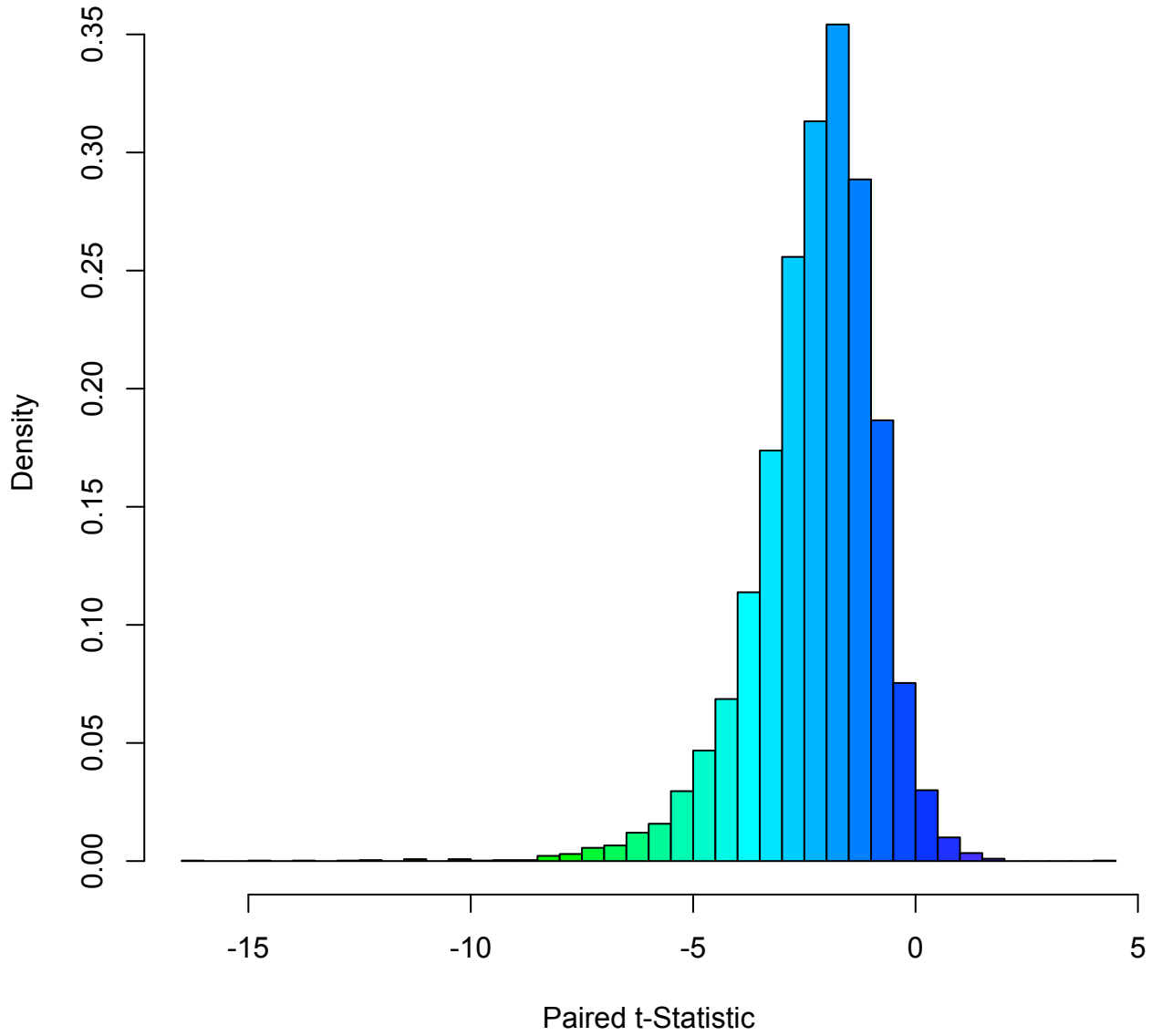
> s8 <- sqrt(8)
> tp <- function(x,y){s8* mean(x-y)/sd(x-y)}
> B <- 10000
> alpha <- .05
> ta2 <- qt(alpha/2,7,lower.tail=F); ta2
[1] 2.364624

> # Estimate power for independent data and paired t-test
> t<-replicate(B, tp(rnorm(8, 0, 1), rnorm(8, 1, 1)))
> sum(abs(t)>ta2)/B
[1] 0.4097
>
> hist(t, breaks = 40, col = rainbow(50), freq = F, main = paste(
+ "Simulate B=", B, " Uncorrelated Samples of size 8\n for Paired t-Test"),
+ xlab = "Paired t-Statistic")
> # M3074PowerPairing1.pdf
>
> ##### SAME TEST FOR CORRELATED DATA #####
> cp <- function(x,y){tp(x,1+.8*x+.6*y)}
> t<-replicate(B, cp(rnorm(8, 0, 1), rnorm(8, 0, 1)))
>
> # Estimate power for correlated data and paired t-test
> sum(abs(t)>ta2)/B
[1] 0.9662
>
> hist(t, breaks = 40, col = rainbow(50), freq = F, main = paste(
+ "Simulate B=", B, " 0.8 - Correlated Samples of size 8\n for
+ Paired t-Test"), xlab = "Paired t-Statistic")
> # M3074PowerPairing2.pdf
>
> ##### POOLED TEST FOR INDEPENDENT DATA #####
> tst <- 2*sqrt(2)
> tu <- function(x,y){tst*(mean(x)-mean(y))/sqrt(var(x)+var(y))}
> t <- replicate(B, tu(rnorm(8, 0, 1), rnorm(8, 1, 1)))
>
> tap2 <- qt(alpha/2,14,lower.tail=F); tap2
[1] 2.144787
> # Estimate power for independent data and pooled t-test
> sum(abs(t)>tap2)/B
[1] 0.4723

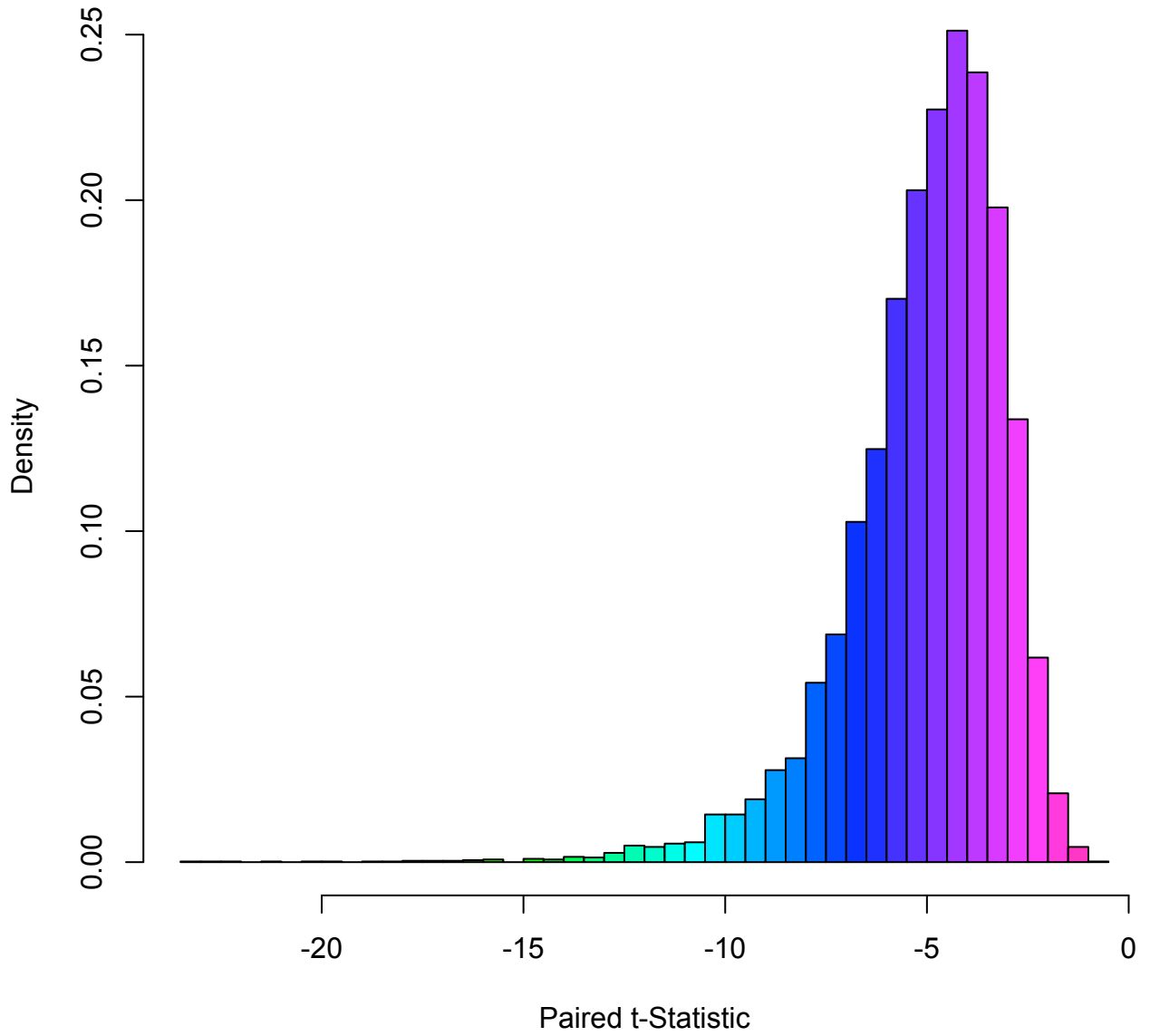
> hist(t, breaks = 40, col = rainbow(50), freq = F, main = paste(
+ "Simulate B=", B, " Uncorrelated Samples of size 8\n for Pooled Two-Sample
+ t-Test"), xlab = "Pooled Two Sample t-Statistic")
> # M3074PowerPairing3.pdf
```

```
>
>
> ##### SAME TEST FOR CORRELATED DATA #####
> cup <- function(x,y){tu(x, 1+.8*x+.6*y)}
> t<-replicate(B, cup(rnorm(8, 0, 1), rnorm(8, 0, 1)))
>
> # Estimate power for dependent data and pooled t-test
> sum(abs(t)>tap2)/B
[1] 0.4487
>
> hist(t, breaks = 40, col = rainbow(50), freq = F, main = paste(
+ "Simulate B=", B, " 0.8 - Correlated Samples of size 8\n for Pooled
+ Two-Sample t-Test"), xlab = "Pooled Two-Sample t-Statistic")
> # M3074PowerPairing4.pdf
```

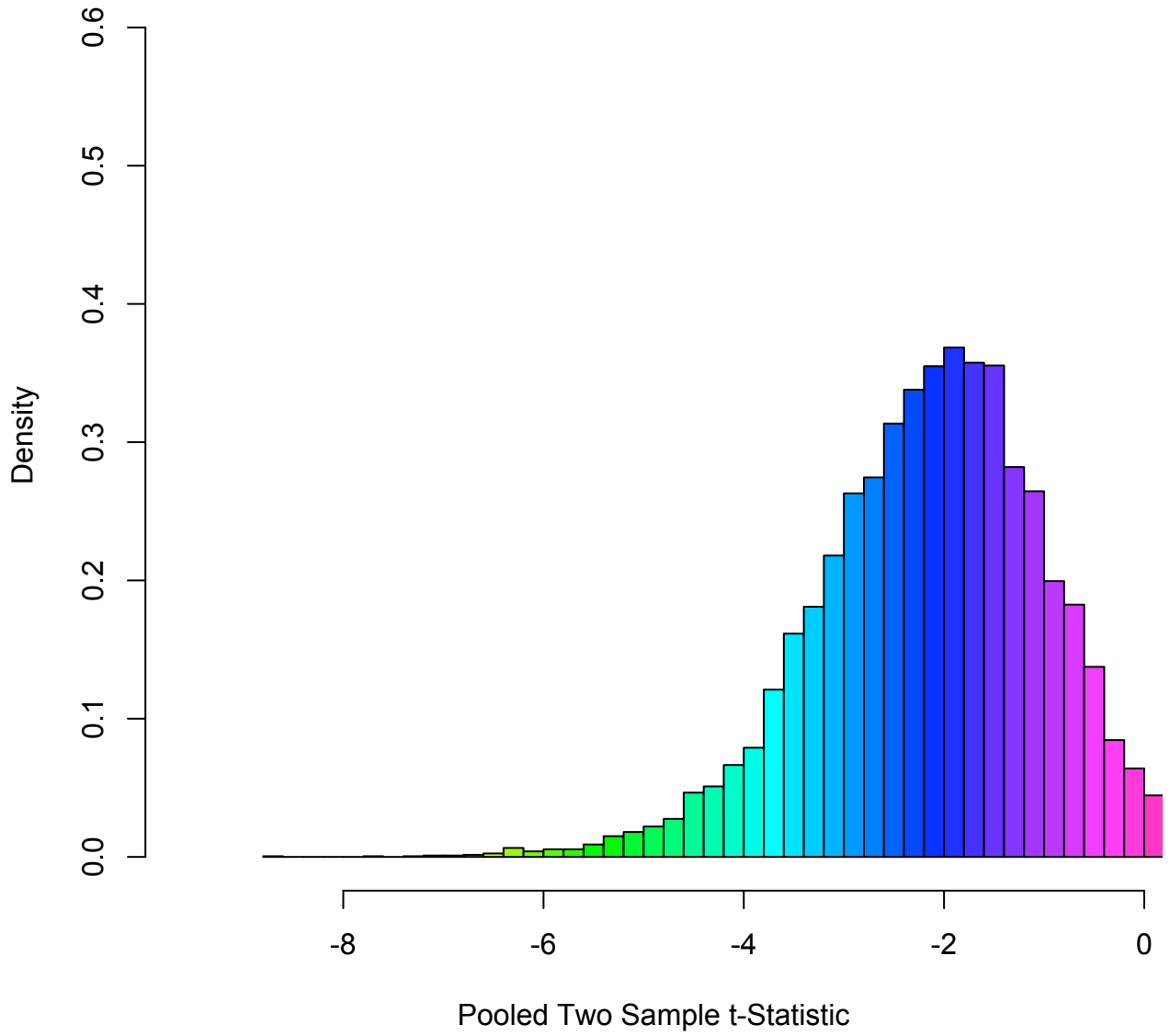
Simulate B= 10000 Uncorrelated Samples of size 8 for Paired t-Test



**Simulate B= 10000 0.8 - Correlated Samples of size 8
for Paired t-Test**



**Simulate B= 10000 Uncorrelated Samples of size 8
for Pooled Two-Sample t-Test**



**Simulate B= 10000 0.8 - Correlated Samples of size 8
for Pooled Two-Sample t-Test**

