

# The Statistical Sleuth in R:

## Chapter 4

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## 1 Introduction

This document is intended to help describe how to undertake analyses introduced as examples in the Second Edition of the *Statistical Sleuth* (2002) by Fred Ramsey and Dan Schafer. More information about the book can be found at <http://www.proaxis.com/~panorama/home.htm>. This file as well as the associated **knitr** reproducible analysis source file can be found at <http://www.amherst.edu/~nhorton/sleuth>.

This work leverages initiatives undertaken by Project MOSAIC (<http://www.mosaic-web.org>), an NSF-funded effort to improve the teaching of statistics, calculus, science and computing in the undergraduate curriculum. In particular, we utilize the **mosaic** package, which was written to simplify the use of R for introductory statistics courses. A short summary of the R needed to teach introductory statistics can be found in the mosaic package vignette (<http://cran.r-project.org/web/packages/mosaic/vignettes/MinimalR.pdf>).

To use a package within R, it must be installed (one time), and loaded (each session). The package can be installed using the following command:

```
> install.packages('mosaic') # note the quotation marks
```

Once this is installed, it can be loaded by running the command:

---

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```
> require(mosaic)
```

This needs to be done once per session.

In addition the data files for the *Sleuth* case studies can be accessed by installing the **Sleuth2** package.

```
> install.packages('Sleuth2') # note the quotation marks
```

```
> require(Sleuth2)
```

We also set some options to improve legibility of graphs and output.

```
> trellis.par.set(theme=col.mosaic()) # get a better color scheme for lattice
> options(digits=3, show.signif.stars=FALSE)
```

The specific goal of this document is to demonstrate how to calculate the quantities described in Chapter 4: The Rank-Sum Test using R.

## 2 Space Shuttle O-Ring Failures

Does launch temperature tend to cause O-ring incidents? This is the question being addressed by case study 4.1 in the *Sleuth*.

### 2.1 Summary statistics and graphical display

We begin by reading the data and summarizing the variables.

```
> summary(case0401)
```

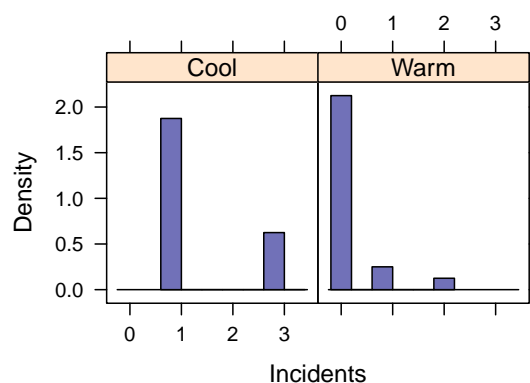
	Incidents	Launch
Min.	:0.000	Cool: 4
1st Qu.	:0.000	Warm:20
Median	:0.000	
Mean	:0.417	
3rd Qu.	:1.000	
Max.	:3.000	

```
> favstats(Incidents ~ Launch, data=case0401)
```

	Launch	min	Q1	median	Q3	max	mean	sd	n	missing
1	Cool	1	1	1	1.5	3	1.5	1.000	4	0
2	Warm	0	0	0	0.0	2	0.2	0.523	20	0

A total of 24 subjects are included in the data: 4 O-ring incidents when the temperature was cold and 20 incidents when the temperature was warm (Display 4.1, page 86).

```
> histogram(~ Incidents | Launch, data=case0401)
```



## 2.2 Permutation test on t-statistics

To replicate the permutation test performed on page 96 we use the following code, which first calculates the  $t$ -statistic of the observed outcome.

```
> t.test(Incidents ~ Launch, var.equal=TRUE, data=case0401)
```

Two Sample t-test

data: Incidents by Launch

t = 4, df = 20, p-value = 8e-04

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

0.607 1.993

sample estimates:

mean in group Cool mean in group Warm

1.5

0.2

We observe a test statistic of 3.888.

We want to get the total number of regroupings by calculating  $C_{24,4}$ .

```
> C244=factorial(24)/(factorial(4)*factorial(24-4)); C244
```

```
[1] 10626
```

There are a total of  $1.063 \times 10^4$  regroupings with 8 possible (non-equiprobable) outcomes: (0, 0, 0, 0), (0, 0, 0, 1), (0, 0, 0, 2), (0, 0, 0, 3), (0, 0, 1, 1), (0, 0, 1, 2), (0, 0, 1, 3), (0, 0, 2, 3), (0, 1, 1, 1), (0, 1, 1, 2), (0, 1, 1, 3), (0, 1, 2, 3), (1, 1, 1, 1), (1, 1, 1, 2), (1, 1, 1, 3), (1, 1, 2, 3). Because the observed cold temperature outcomes was (1, 1, 1, 3), we will only examine the same or more extreme groupings, which are (1, 1, 2, 3) and (0, 1, 2, 3).

```

> # t.test for (1, 1, 2, 3) # observations 1, 2, 4 and 24
> case0401$Incidents[c(1,2,4,24)]

[1] 1 1 3 2

> with(case0401, t.test(Incidents[c(1,2,4,24)], Incidents[-c(1,2,4,24)], var.equal=TRUE))

Two Sample t-test

data: Incidents[c(1, 2, 4, 24)] and Incidents[-c(1, 2, 4, 24)]
t = 6, df = 20, p-value = 5e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 1.04 2.16
sample estimates:
mean of x mean of y
    1.75    0.15

> # t.test for (0, 1, 2, 3) # observation 1, 4, 5 and 24
> case0401$Incidents[c(1,4,5,24)]

[1] 1 3 0 2

> with(case0401, t.test(Incidents[c(1,4,5,24)], Incidents[-c(1,4,5,24)], var.equal=TRUE))

Two Sample t-test

data: Incidents[c(1, 4, 5, 24)] and Incidents[-c(1, 4, 5, 24)]
t = 4, df = 20, p-value = 8e-04
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.607 1.993
sample estimates:
mean of x mean of y
    1.5    0.2

```

The test statistic for (1, 1, 2, 3) is 5.952 and the test statistic for (0, 1, 2, 3) is 3.888.

We already know that the total number of regroupings is  $C_{24,4}=1.063 \times 10^4$ . In order to calculate the  $p$ -value, we need to know the combinations of (1, 1, 1, 3), (2, 1, 2, 3) and (0, 1, 2, 3). There are 17 zeros, 5 ones, 1 two and 1 three.

For outcome (1, 1, 1, 3), we calculate  $C_{1113}=C_{5,3}*C_{1,1}$ :

```

> C1113 = factorial(5)/(factorial(3)*factorial(5-3))*1; C1113

[1] 10

```

For outcome (1, 1, 2, 3), we calculate  $C_{1123}=C_{5,2}*C_{1,1}*C_{1,1}$ :

```
> C1123 = factorial(5)/(factorial(2)*factorial(5-2))*1*1; C1123
[1] 10
```

For outcome (0, 1, 2, 3), we calculate  $C_{0123}=C_{17,1}*C_{5,1}*C_{1,1}*C_{1,1}$

```
> C0123 = 17*5*1*1; C0123
[1] 85
```

Now we can calculate the  $p$ -value as the proportion of the number of rearrangements that are as extreme or more extreme over the total number of rearrangements:

```
> onep = (C1113+C1123+C0123)/C244; onep
[1] 0.00988
```

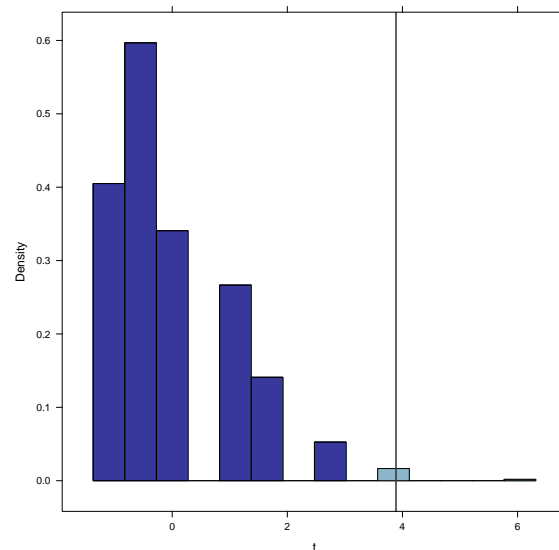
The one-sided  $p$ -value from the permutation test on the  $t$ -statistic is 0.01.

Alternatively, we can approximate the  $p$ -value using the difference of means and simulating repeatedly from the null distribution (note that the book enumerates all of the possible outcomes to get an exact result).

```
> result = t.test(Incidents ~ Launch, var.equal=TRUE, data=case0401)$statistic; result
      t
3.89

> nulldist = do(10000)*t.test(Incidents ~ shuffle(Launch), var.equal=TRUE, data=case0401)$statistic
> histogram(~ t, groups=t >= result, v=result, data=nulldist)
> tally(~ t >= result, format="proportion", data=nulldist)

t >= result
TRUE  FALSE
0.0101 0.9899
```



This simulation resulted in a  $p$ -value of 0.01.

### 3 Cognitive Load Theory in Teaching

Does use of modified instructional materials lead to quicker problem solving? That's the question being addressed by case study 4.2 in the *Sleuth*.

#### 3.1 Summary statistics and graphical display

We begin by reading the data and summarizing the variables.

```
> summary(case0402)
```

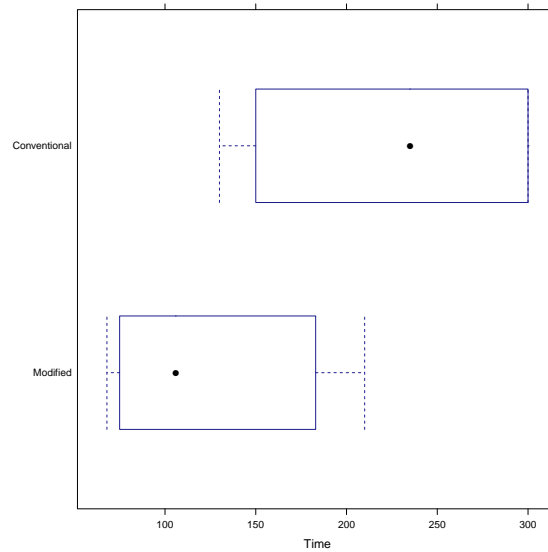
Time	Treatmt	Censor
Min. : 68	Modified :14	Min. :0.000
1st Qu.:118	Conventional:14	1st Qu.:0.000
Median :158		Median :0.000
Mean :175		Mean :0.179
3rd Qu.:232		3rd Qu.:0.000
Max. :300		Max. :1.000

```
> favstats(Time ~ Treatmt, data=case0402)
```

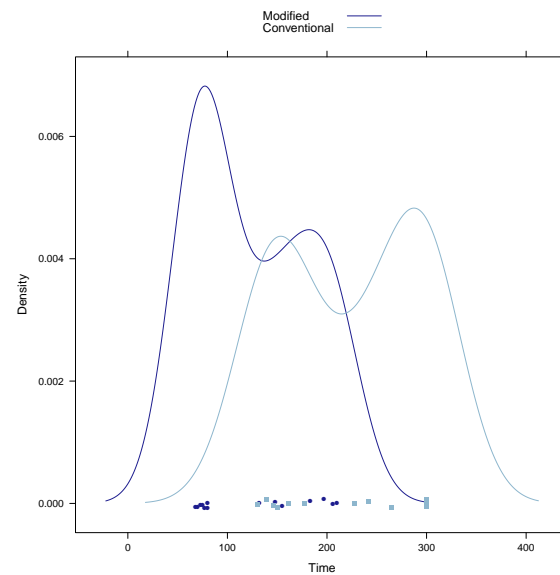
	Treatmt	min	Q1	median	Q3	max	mean	sd	n	missing
1	Modified	68	75.5	106	176	210	125	56.6	14	0
2	Conventional	130	152.8	235	300	300	224	70.5	14	0

A total of 28 subjects are included in the data: 14 students were assigned to modified instructional materials and 14 students were assigned to conventional materials.

```
> bwplot(Treatmt ~ Time, data=case0402)
```



```
> densityplot(~ Time, groups=Treatmt, auto.key=TRUE, data=case0402)
```



### 3.2 Rank-sum test

We can calculate the one-sided  $p$ -value by following rank-sum procedure. First, we try to find the statistic  $T$  (display 4.5, page 91):

```
> obsrank = rank(case0402$Time, ties.method="average"); obsrank

[1] 1.0 2.0 3.0 4.0 5.0 6.5 6.5 9.0 12.0 14.0 17.0 18.0 19.0 20.0
[15] 8.0 10.0 11.0 13.0 15.0 16.0 21.0 22.0 23.0 26.0 26.0 26.0 26.0 26.0

> mt = sum(obsrank[1:14]); mt

[1] 137
```

Next we calculate the  $p$ -value using a normal approximation (Display 4.7, page 93).

```
> average = mean(obsrank); average

[1] 14.5

> sd = sd(obsrank); sd

[1] 8.2

> n = nrow(subset(case0402, Treatmt=="Modified")); n

[1] 14

> MEANT = n * average; MEANT

[1] 203

> SDT = sd * sqrt((n^2)/(2*n)); SDT

[1] 21.7

> z = (mt-MEANT)/SDT; z

[1] -3.04

> p = pnorm(-abs(z)); p

[1] 0.00118
```

The one-sided  $p$ -value is 0.001.

Alternatively, we can use following code to calculate the Wilcoxon rank-sum test:

```
> wilcox.test(Time ~ Treatmt, conf.int=TRUE, exact=TRUE, data=case0402)

Warning in wilcox.test.default(x = c(68, 70, 73, 75, 77, 80, 80, 132, 148, : cannot
compute exact p-value with ties
Warning in wilcox.test.default(x = c(68, 70, 73, 75, 77, 80, 80, 132, 148, : cannot
compute exact confidence intervals with ties
```



```
Wilcoxon rank sum test with continuity correction

data:  Time by Treatmt
W = 30, p-value = 0.003
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 -160  -57
sample estimates:
difference in location
                -94
```

So the one-sided  $p$ -value is 0.001. The 95% confidence interval is (-160, -57). The book suggests that the 95% confidence interval should be (58, 159), which is slightly narrower than these results. Their procedure is on page 94.