1. (a) One way to produce a data frame directly in R:

```
treeSpecies <- data.frame(</pre>
    plotType = c( rep("Unlogged", 12), rep("Logged", 9) ),
    speciesCount = c(22, 18, 22, 20, 15, 21, 13, 13, 19, 13, 19, 15,
                      17, 4, 18, 14, 18, 15, 15, 10, 12)
 head(treeSpecies)
 plotType speciesCount
1 Unlogged
                     22
2 Unlogged
                     18
3 Unlogged
                     22
4 Unlogged
                     20
5 Unlogged
                     15
6 Unlogged
                     21
```

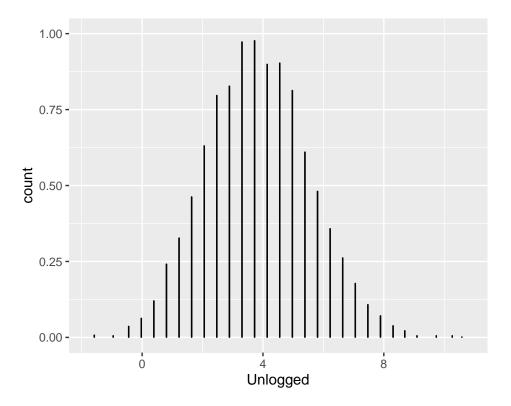
We get the observed difference in group sample means with command

```
diff( mean(speciesCount ~ plotType, data=treeSpecies) )
Unlogged
3.833333
```

To get one bootstrap statistic like it:

```
diff( mean(speciesCount ~ plotType, data=resample( treeSpecies, group = plotType )))
Unlogged
4.444444
```

The "group = plotType" switch ensures the number of "Unlogged" and "Logged" plots in the randomization sample is always 12 and 9, respectively. This command we repeat many times. I plot the results as a dotplot so you can see how to reduce the size of dots.



```
(b) sd <- sd(~ Unlogged, data=manyBstrapDiffs)
   sd
[1] 1.711551</pre>
```

Bootstrap distributions change from one run to the next, and this standard error changes as a result. Yours should be in the same ballpark: 1.712. The resulting 95% confidence, using the point estimate $\bar{x}_U - \bar{x}_L = 3$ found above, is

```
3.833 + c(-1,1) * 1.96 * sd

[1] 0.4783603 7.1876397
```

or (0.478, 7.188).

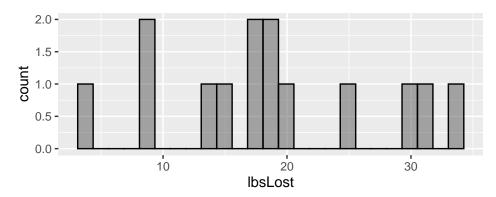
- (c) Taking μ_U to be the mean count of tree species on unlogged plots of rain forest, and μ_L the mean count of tree species on plots of rain forest that had been logged 8 years earlier, ours is a confidence interval for $\mu_U \mu_L$.
- (d) There is a nice command in R for doing this:

```
qdata(~Unlogged, data=manyBstrapDiffs, c(0.025, 0.975))
          quantile     p
2.5%  0.6388889  0.025
97.5%  7.2777778  0.975
```

Without learning about this command, there are various trial-and-error ways to find these quantiles, or one can turn to StatKey. At any rate, the interval extending from the 0.025-quantile to the 0.975-quantile (which also varies rrom one bootstrap distribution to the next) is (0.639,7.278). Both of these numbers are higher than the corresponding endpoints of the confidence interval found in part (b). This is possibly explainable by the non-pure normality of the bootstrap distribution found in part (a).

2. (a) The sample size is on the small side (n = 14), not in the comfort range of $n \ge 30$. But if the data comes from a *normal* population, any sample size would be large enough. An histogram of the data does little to suggest much of a bell shape but, again, perhaps 14 data points is not enough to bring out any distinct shape. The safe bet is to **not** assume normality.

```
weightLossDat = read.csv("http://scofield.site/teaching/data/csv/navMonk/wtLost.csv")
gf_histogram(~ lbsLost, data = weightLossDat, color="black")
```

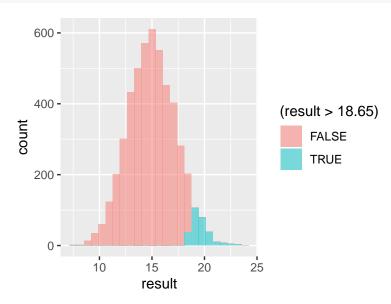


(b) The test statistic is \bar{x} , computed below using the mean() command to be 18.65.

```
mean(~lbsLost, data=weightLossDat)
```

(c) We do this in a manner similar to bootstrapping, taking care to center the distribution at 15 instead of 18.65:

```
manyXBars = do(5000) * (mean(~lbsLost, data=resample(weightLossDat)) - 3.65)
gf_histogram(~result, data=manyXBars, fill=~(result>18.65), bins=25)
```



(d) One command (different, but no better, than using subset() to select out the results which are as extreme as ours, counting the number we selected, and then dividing by the total number of rows) which gives us the approximate *P*-value

```
prop(~(result >= 18.65), data=manyXBars)
prop_TRUE
    0.0584
```

The evidence supports the alternate hypothesis, but is not strictly less than 0.05, so is not statisti-

cally significant at that level.