1. (a) We check the rules of thumb for normality using $\hat{p}$ (no better estimate of p is available to us):

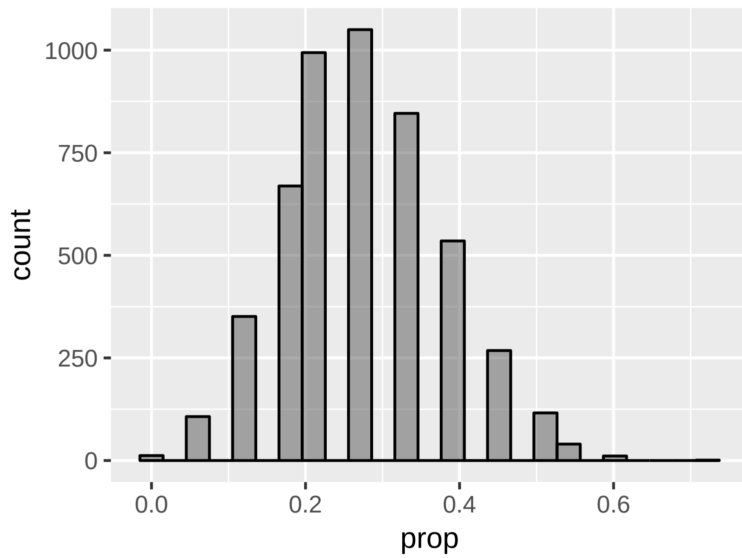
$$n\hat{p} = 18\frac{5}{18} = 5.$$

Already that is too small to assume $\hat{p}$ has a normal distribution. This means we should avoid an inference procedure which relies on such normality—which means we will *avoid* constructing a confidence interval by the method

$$\hat{p} \pm z^* \mathrm{SE}_{\hat{p}}.$$

(b) Our point estimate is $\hat{p} = 5/18 \doteq 0.278$.

(c)
```
manyRuns = do(5000) * rflip(18, prob = 5/18)
gf_histogram(~prop, data = manyRuns, bins = 25, color = "black")
```



(d) The desired confidence interval is $[0.111, 0.500]$. We have found a bootstrap percentile confidence interval using the `quantile()` function in the past. Below I've used it, and introduced two others which achieve the same purpose.

```
cdata(~prop, data = manyRuns, p = 0.95)  # bounds for centered 95% of data

      low        hi central.p
0.1111111 0.5000000 0.9500000

qdata(~prop, data = manyRuns, p = c(0.025, 0.975))  # quantiles in data

       quantile     p
2.5%  0.1111111 0.025
97.5% 0.5000000 0.975

quantile(manyRuns$prop, p = c(0.025, 0.975))  # quantiles in data

     2.5%     97.5%
0.1111111 0.5000000
```

(e) According to our formula (the one that deals with the *worst case*) from class, we want the sample size

$$n \geq \left(\frac{z^*}{2M}\right)^2 = \left(\frac{1.96}{(2)(0.006)}\right)^2 \doteq 26677.78,$$

so a sample size of $n = 26678$ should be sufficiently large. It is reasonable to think the information provided in the problem gives you a somewhat *better-than-worst-case* estimate for p. I accepted answers that took this into account, such as this one:

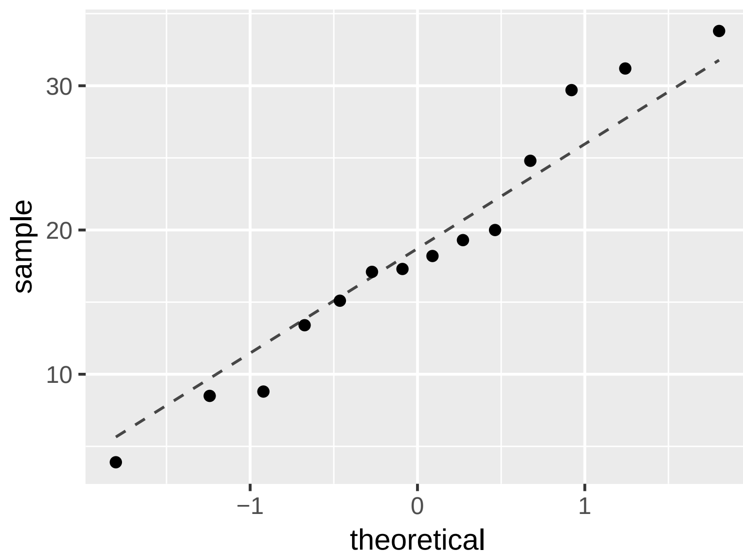
$$n \geq \left(\frac{z^*}{M}\right)^2 (p_{est})(1 - p_{est}) = \left(\frac{1.96}{(0.006)}\right)^2 (0.251)(0.749) \doteq 20061.58,$$

leading to a sample size of $n = 20062$.

2. (a) The sample size is on the small side ($n = 14$), not in the comfort range of $n \geq 30$. 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.

   More recently I have introduced a tool, the **normal quantile plot**, as a check on the normality of quantitative data. Employing this type of plot, we do not get points adhering closely to a straight line, which would (if it had been otherwise) have been evidence confirming normality.

```
gf_qq(~lbsLost, data = weightLossDat) %>% gf_qqline()
```



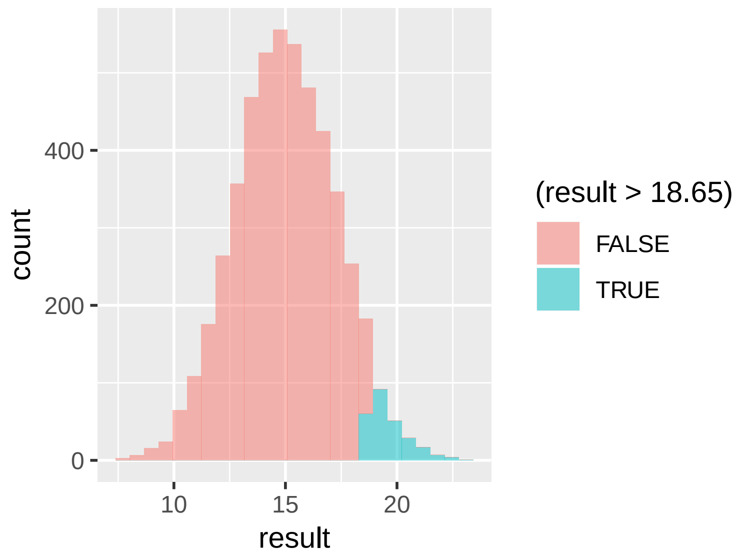
   The quantile-quantile plot is not very straight, adding to the evidence that we should *not* assume $\bar{x}$ has a normal distribution (so not use the corresponding t-procedure to find a P-value).

   (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
   0.0522
```

The evidence supports the alternate hypothesis, but is not strictly less than 0.05, so is not statistically significant at that level.