8. Simulation by replicating a calculation

Make random number generation repeatable

```
set.seed(seed), for integer seed, sets starting point of (pseudo-)random number generation. e.g.
a = rnorm(1); b = rnorm(1); a == b
set.seed(0); a = rnorm(1); set.seed(0); b = rnorm(1); a == b
Repeat a calculation n times
```

```
replicate(n, expr) returns a vector (or matrix or array) of n evaluations of expr. e.g.
```

```
x = replicate(n=4, expr=rnorm(1))  # 4 random samples of size 1
y = replicate(n=4, expr=rnorm(3))  # 4 random samples of size 3
z = replicate(n=4, expr=mean(rnorm(3))) # 4 means of samples of size 3
expr can be compound in curly braces, { ... }; its value is that of its last expression. e.g.
w = replicate(n=4, expr={ mu=7; sigma=3; x=rnorm(n=3, mean=mu, sd=sigma); mean(x) })
```

Distributions

Check ?distributions. (Recall prefixes d, p, q, r for density, probability, quantile, random.)

Let's simulate a few distributions.

• $N(\mu, \sigma)$: First, confirm that \bar{x} is close to μ and that s is close to σ :

mu = 7; sigma = 3; mean(x <- rnorm(n=1000, mean=mu, sd=sigma)); sd(x)

Second, the Central Limit Theorem (CLT) says that for a large sample from (almost) any distribution with finite μ and σ , $\bar{X} \approx N(\mu, \frac{\sigma}{\sqrt{n}})$.

e.g. Consider U(0,1), which has $\mu = \frac{\text{max-min}}{2} = \frac{1}{2}$ and $\sigma = \sqrt{\frac{(\text{max-min})^2}{12}} = \sqrt{\frac{1}{12}}$. Simulate CLT by finding many sample means from samples from U(0,1):

```
curve(dunif(x, min=0, max=1), from=-0.1, to=1.1, ylim=c(0,8), lty=2) # U(0,1)
n = 30 # sample size (also try n=1 to see CLT fail)
N = 100 # number of samples
x.bars = replicate(n=N, expr=mean(runif(n=n, min=0, max=1))) # vector of sample means
mean(x.bars) # should be near 1/2
sd(x.bars) # should be near sqrt(1/12)/sqrt(n), about .0527
curve(dnorm(x, mean=1/2, sd=sqrt(1/12)/sqrt(n)), from=0, to=1, lty=3, add=TRUE) # CLT
lines(density(x.bars), lty=1) # sampling distribution of bar(x)
rug(x.bars)
legend(x="topright", legend=c("U(0,1)", "CLT", expression(bar(X))), lty=c(2,3,1))
```

• t_{n-1} : For a random sample X_1, \ldots, X_n from $N(\mu, \sigma)$, the quantity $T = \frac{\bar{X} - \mu}{s/\sqrt{n}}$ follows the *Student's t* distribution with n-1 degrees of freedom, denoted t_{n-1} . e.g. Simulate t_{n-1} for n=6:

- χ_n^2 : If Z_1, \dots, Z_n are independent, N(0,1) random variables, then $X^2 = \sum_{i=1}^n Z_i^2 \sim \chi_n^2$
- F_{n_1,n_2} : If $X \sim \chi^2_{n_1}$ and $Y \sim \chi^2_{n_2}$ are independent, then $\frac{X/n_1}{Y/n_2} \sim F(n_1,n_2)$

What is a *P*-value?

A P-value is the probability, assuming H_0 is true, of getting data, as summarized by the test statistic, more extreme than the sample data. e.g. Guinness says pouring a glass should take 119.5 seconds. Here's a random sample of times from a server:

```
x = c(118, 121, 113, 116, 117, 112, 113)

Is this server pouring correctly? Test H_0: \mu = 119.5 vs. H_1: \mu \neq 119.5: (out = t.test(x, mu=119.5))

Simulate P-value by seeing how often t, from random samples, is greater than out$statistic:

mu = 119.5

sigma = sd(x)

n = length(x) # sample size

N = 1000 # number of replicates

t = replicate(N, { x=rnorm(n, mean=mu, sd=sigma); (mean(x) - mu)/(sd(x)/sqrt(n)) })

more.extreme = (abs(t) > abs(out$statistic))

(simulated.p.value = sum(more.extreme) / N)

out$p.value

plot(density(t), main=bquote(.(N) * " Simulated t statistics")) # visualize P-value rug(t)

points(x=out$statistic, y=0, pch=19, col="red")

text(x=out$statistic, y=.02, labels="out$statistic")
```