Pseudorandom Number Generation

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Computational Methods in Statistics and Data Science (Stats 406)

Random Number Generation

Example from First Lecture: Sample Maximum Magnitude

What is the distribution of the sample maximum magnitude?

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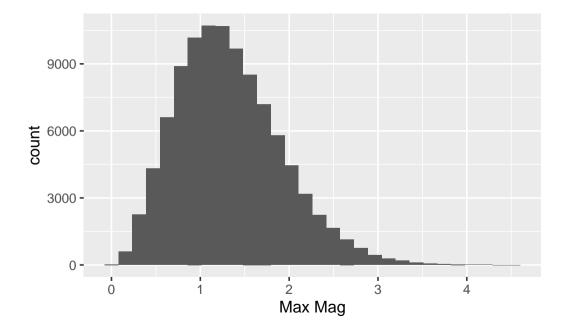
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In R, the random number generator for standard Normal variables is rnorm:



Question: Aren't our data random enough? Why do we need to generate RVs?

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- Non-deterministic optimization

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We will use **pseudorandom numbers** that are "close enough" to true random numbers.

Aside: Getting true random numbers in R

```
Using random.org:
```

```
> library(random) # you need to install this with `install.packages`
```

> system.time(rand.org <- randomNumbers(10, 0, 255))</pre>

```
user system elapsed 0.030 0.012 1.667
```

```
> system.time(devrand <- replicate(10,
   as.integer(packBits(rawToBits(charToRaw(
   system("dd if=/dev/random bs=1 count=1 status=none", TRUE))))))
        system elapsed
  user
 0.056 0.042 0.104
> system.time(pseudo.randoms <- runif(5, 0, 255))
        system elapsed
  user
 0.000
        0.001 0.001
```

Pseudrandom Number Generators

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A pseudorandom number generator (PRNG) is a function that takes a seed and produces a (pseudo)random number and a new seed:

```
> prng <- function(seed) {
+  # do something
+  c(random_number, new_seed)
+ }</pre>
```

A very simple PRNG

```
> lcg <- function(seed) {
+  a <- 5 ; c <- 1 ; m <- 8
+  new_number <- (a * seed + c) %% m
+  c(new_number, new_number) # using the new number as the seed
+ }
> lcg(7)
[1] 4 4
```

Using the lcg

```
> rngs <- numeric(length = 16)
> seed <- 7
> for (i in 1:16) {
+    rs <- lcg(seed)
+    rngs[i] <- rs[1] # pull out the first item in the vector
+    seed <- rs[2]
+ }</pre>
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+ }
 [1] 4 5 2 3 0 1 6 7 4 5 2 3 0 1 6 7
> rngs / 7 # scale to [0, 1]
 [1] 0.5714 0.7143 0.2857 0.4286 0.0000 0.1429 0.8571 1.0000
 [9] 0.5714 0.7143 0.2857 0.4286 0.0000 0.1429 0.8571 1.0000
```

Evaluating PRNGs



Figure 1: ©2001 Scott Adams

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But you can reject with high confidence hypothesis tests.

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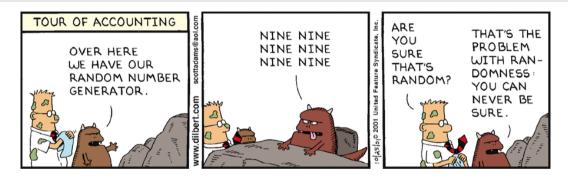


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Test suites exist that implement these tests (TestU01 and diehard).

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The default ("Marsenne-Twister") has a period of $2^{19937} - 1$ (compared to our example of 2^8) and it maps multiple seeds to the same values. It is reasonably fast as well.

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You can set the random seed with

> set.seed(3949392)

The full seed

In fact, for the default MT the real seed is composed of 624 integers!

- > length(.Random.seed) # first two items are book keeping
- [1] 626
- > .Random.seed[3:6] # just a few elements
- [1] 1173446700 -1537720515 1428012250 1749109907

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We will develop tools for turning uniform (0,1) RVs into other distributions.