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As noted earlier, these are more correctly called "psuedorandom" numbers, because they are not actually random.

Because they are used extensively, it is worth spending some time to understand how they are generated.

Most algorithms for generating psuedorandom numbers work by computing a sequence of numbers *recursively*, meaning that we always compute the next number in the sequence from its predecessor(s).

We might represent a general recursive algorithm by the *recursion formula* or *difference equation*

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The "solution" of such an equation is a sequence for which each pair of consecutive terms satisfies the recursion formula:

$$x_2 = f(x_1)$$

$$x_3 = f(x_2)$$

$$x_4 = f(x_3)$$

$$\vdots \qquad \vdots$$

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Every initial value problem has a unique solution, which is a sequence x_1, x_2, x_3, \ldots

One of the common types of psuedorandom number generators uses the following recursion formula:

$$x_{n+1} = b \cdot x_n \mod a, \quad n = 1, 2, 3, \dots$$

where $b \cdot x_n \mod a$ means "the remainder when $b \cdot x_n$ is divided by a"

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Integers that produce the same remainder on division by *a* are said to be "congruent modulo *a*". As a result, this class of psuedorandom number generators is called *congruental*.

Congruential generators are popular because they are easy to program, inexpensive to run, and produce "good" results for certain values of *a* and *b*.

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As an example of how easy they are to program, we will now write a congruental generator in R.

First start R and define the values of a and b.

We'll use a = 23 and b = 5. Enter:

a<-23 b<-5

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The recursion formula requires a starting value x_1 , which we'll assign to the first element of the x array in R.

Always pick an integer greater than 0 and less than a. Enter: x[1] < -13

Now write the R statement that implements the recursion formula

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The MOD operator in R is a double percent sign %%, and the multiplication operator is an asterisk *.

We designate the n^{th} element of x by x[n]. In the R language, the recursion formula for x_{n+1} is:

x[n+1] <- (b*x[n]) %% a

We will also make use of a construct called FOR that enables us to execute a block of statements a certain number of times, in this case 9,999.

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for(n in 1:9999) {some statement to be executed}

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In the R language, the correct syntax for this is:

for(n in 1:9999) {some statement to be executed}

This construct will execute the statements in curly brackets $\{\}$ 9,999 times, with n set to:

- 1 the first time
- 2 the second time
- 3 the third time

and so on.

Now we are ready to write the full R statement by combining the FOR construct with the recursion formula from the previous slide. The result is:

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Notice that the sequence consists of 22 positive integers repeated over and over in this sequence:

13, 19, 3, 15, 6, 7, 12, 14, 1, 5, 2, 10, 4, 20, 8, 17, 16, 11, 9, 22, 18, 21

Now generate a frequency table of the values in x by entering:

table(x)

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For certain choices of *a* and *b*, number theory guarantees that this will happen:

The sequence will contain the positive integers from 1 to a-1 in some shuffled order that repeats over and over.

One last step remains. We would like our psuedorandom number generator to produce numbers between zero and one, not integers from 1 to 22.

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We can accomplish this by dividing each element of the sequence by the value of a, 23 in this case. Enter:

z<-x/23 z[1:100]

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We can accomplish this by dividing each element of the sequence by the value of a, 23 in this case. Enter:

z<-x/23 z[1:100]

Notice that the contents of the z array resemble the output of runif().

In fact, the only thing that keeps this from being a decent random number generator is the fact that it only generates 22 values.

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The only difference between our congruential generator and the ones actually implemented in many statistical packages is that they have a much larger value of *a*.

(as well as a corresponding *b* that produces all integers from 1 to a - 1).

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If you specify the seed, the same sequence of "random" numbers will be generated every time.

This is helpful for things like debugging simulation programs.

Implementations that do not allow you to specify the seed usually determine it internally in a way that makes it somewhat random.

One way to do this is to use the low order digits of a high resolution clock, which most systems have, at the instant the "enter" key is pressed.