Simple Random Sampling: Not So Simple

Kellie Ottoboni with Philip B. Stark and Ron Rivest

Department of Statistics, UC Berkeley Berkeley Institute for Data Science

Moore-Sloan Data Science Summit October 24, 2016





PRNGs

Pseudorandom number generator: a deterministic algorithm that produces sequences that are computationally indistinguishable from the uniform distribution

Theorem (Pigeonhole Principle)

If there are n pigeonholes and m>n pigeons, then there exists at least one pigeonhole containing more than one pigeon.



Theorem (Pigeonhole Principle)

If there are n pigeonholes and m > n pigeons, then there exists at least one pigeonhole containing more than one pigeon.



Corollary (Too few pigeons)

If $\binom{n}{k}$ is greater than the size of a PRNG's state space, then the PRNG cannot possibly generate all samples of size k from a population of n.

Does it matter in practice?

Does it matter in practice?

Period of 32-bit linear congruential generators (e.g. RANDU): $2^{32} \approx 4 \times 10^9$

Samples of size 10 from 50: $\binom{50}{10} \approx 10^{10}$

More than half of samples cannot be generated

Does it matter in practice?

Period of 32-bit linear congruential generators (e.g. RANDU): $2^{32} \approx 4 \times 10^9$

Samples of size 10 from 50: $\binom{50}{10} \approx 10^{10}$

More than half of samples cannot be generated

Period of Mersenne Twister (standard PRNG in Statistics): $2^{32 \times 624} \approx 2 \times 10^{6010}$

Permutations of 2084 objects: $2084! \approx 3 \times 10^{6013}$

Less than 0.01% of permutations can be generated

The good, the bad, and the ugly

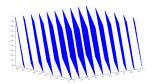
(Knuth, 1997)

"Random numbers should not be generated with a method chosen at random."

The good, the bad, and the ugly

(Knuth, 1997)

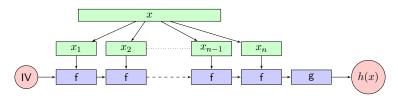
"Random numbers should not be generated with a method chosen at random."



Triples of RANDU lie on 15 planes in 3D space $x_{n+1} = (65539x_n) \mod 2^{31}$ (Wikipedia)

A better alternative

One solution: Find a class of PRNGs with infinite state space



Cryptographic hash functions:

- · computationally infeasible to invert
- difficult to find two inputs that map to the same output
- small input changes produce large, unpredictable changes to output
- · resulting bits are uniformly distributed

Choice of seed

Preliminary results: the distribution of simple random samples is less uniform if you use a stupid seed

	p-value	p-value
PRNG	(seed = 100)	(seed = 233424280)
RANDU	0	0
Super-Duper LCG	0.1798	1
Mersenne Twister*	0.0858	0.4741
Mersenne Twister	0.1996	0.6143
SHA-256 PRNG	0.1710	0.8584

^{*} using np.random.choice to sample

 Do "good" PRNGs produce all samples with equal probability? All permutations?

- Do "good" PRNGs produce all samples with equal probability? All permutations?
- Do departures from uniformity introduce bias?

- Do "good" PRNGs produce all samples with equal probability? All permutations?
- Do departures from uniformity introduce bias?
- Replace the default PRNGs in Python https://www.github.com/statlab/cryptorandom

- Do "good" PRNGs produce all samples with equal probability? All permutations?
- Do departures from uniformity introduce bias?
- Replace the default PRNGs in Python https://www.github.com/statlab/cryptorandom
- Results apply more broadly to computer simulations: permutation tests, bootstrapping, MCMC, etc.

Thanks!

https://github.com/kellieotto/msdse-summit-talk-2016

i ilaliks: