Master Program in Data Science and Business Informatics Statistics for Data Science Lesson 12 - Simulation

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Simulation

- Not all problems can be solved with calculus!
- Complex interactions among random variables can be simulated
- Generated random values are called *realizations*
- Basic issue: how to generate realizations?
 - ► The Galton Board



Simulation

- Not all problems can be solved with calculus!
- Complex interactions among random variables can be simulated
- Generated random values are called *realizations*
- Basic issue: how to generate realizations?
 - ▶ in R: *rnorm*(5), *rexp*(2), *rbinom*(...), ...
- Ok, but how do they work?
- Assumption: we are only given runif()!
- **Problem**: derive all the other random generators

Simulation: discrete distributions

Bernoulli random variables

Suppose U has a U(0, 1) distribution. To construct a Ber(p) random variable for some 0 , we define

$$X = \begin{cases} 1 & \text{if } U < p, \\ 0 & \text{if } U \ge p \end{cases}$$

so that

$$P(X = 1) = P(U < p) = p,$$

 $P(X = 0) = P(U \ge p) = 1 - p.$

This random variable X has a Bernoulli distribution with parameter p.

$X \sim Cat(\mathbf{p})$

DEFINITION. A discrete random variable X has a *Bernoulli distribution* with parameter p, where $0 \le p \le 1$, if its probability mass function is given by

 $p_X(1) = P(X = 1) = p$ and $p_X(0) = P(X = 0) = 1 - p$.

We denote this distribution by Ber(p).

- Alternative definition: $p_X(a) = p^a \cdot (1-p)^{1-a}$ for $a \in \{0,1\}$
- Categorical distribution generalizes to $n_C \ge 2$ possible values

Categorical distribution

A discrete random variable X has a Categorical distribution with parameters p_0, \ldots, p_{n_c-1} where $\sum_i p_i = 1$ and $p_i \in [0, 1]$ if its p.m.f. is given by:

$$p_X(i) = P(X = i) = p_i$$
 for $i = 0, ..., n_C - 1$

• Alternative definition: $p_X(a) = \prod_i p_i^{\mathbb{I}_{a=i}}$ for $a = 0, \dots, n_C - 1$

$X \sim Mult(n, \mathbf{p})$

- $X \sim Bin(n, p)$ models the number of successes in *n* Bernoulli trials
- Intuition: for X_1, X_2, \ldots, X_n i.i.d. $X_i \sim Ber(p)$: $X = \sum_{i=1}^n X_i \sim Bin(n, p)$
- X ~ Mult(n, **p**) models the number of categories in n Categorical trials
- Intuition: for X_1, X_2, \ldots, X_n such that $X_i \sim Cat(\mathbf{p})$ and independent (i.i.d.), define:

$$Y_{1} = \sum_{i=1}^{n} \mathbb{1}_{X_{i}=0} \sim Bin(n, p_{0}) \quad \dots \quad Y_{n_{c}} = \sum_{i=1}^{n} \mathbb{1}_{X_{i}=n_{c}-1} \sim Bin(n, p_{n_{c}-1})$$
$$X = (Y_{1}, \dots, Y_{n_{c}}) \sim Mult(n, \mathbf{p})$$

Multinomial distribution

A discrete random variable $X = (Y_1, \ldots, Y_{n_c})$ has a Multinomial distribution with parameters p_0, \ldots, p_{n_c-1} where $\sum_i p_i = 1$ and $p_i \in [0, 1]$ if its p.m.f. is given by:

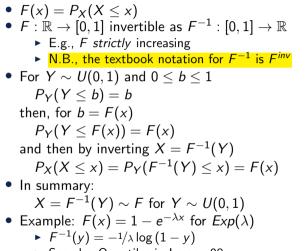
$$p_X(i_0,\ldots,i_{n_C-1}) = P(X = (i_0,\ldots,i_{n_C-1})) = \frac{n!}{i_0!i_1!\ldots i_{n_C-1}!} p_0^{i_0} p_1^{i_1} \ldots p_{(n_C-1)}^{i_{(n_C-1)}}$$

$X \sim Mult(n, \mathbf{p})$

- Example: student selection from a population with $n_C = 3$:
 - $p_0 = 60\%$ undergraduates
 - $p_1 = 30\%$ graduate
 - $p_2 = 10\%$ PhD students
- Assume n = 20 students are randomly selected
- $X \sim (Y_1, Y_2, Y_3)$ where:
 - ► Y₁ number of undergraduate students selected
 - ► Y₂ number of graduate students selected
 - ► Y₃ number of PhD students selected
- $P(X = (10, 6, 4)) = \frac{20!}{10!6!4!} (0.6)^{10} (0.3)^6 (0.1)^4 = 9.6\%$

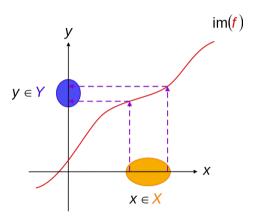
See R script

Simulation: continuous distributions



See also Quantiles in Lesson 08

See R script



 $f: X \to Y$ y = f(x)

William H. Press, Saul A. Teukolsky, William T. Vetterling, Brian P. Flannery (2007) Numerical Recipes - The Art of Scientific Computing Chapter 7: Random Numbers online book