

# Lecture 1 How random number generators

(don't) work.

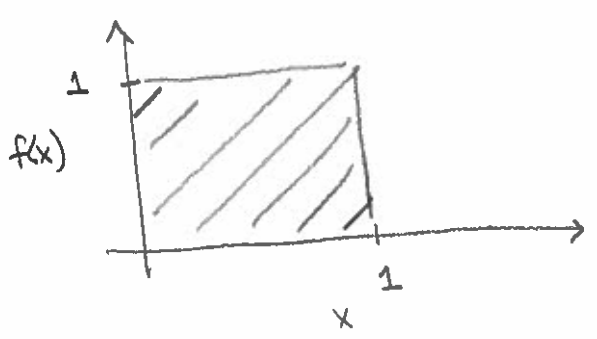
## Plan

1. Review syllabus
2. Quantile functions
3. Box Muller
4. Rejection sampling
5. Importance sampling.

Quantile functions: We can generate a lot of random variables using  $Unif(0,1)$  random variables.

- Running assumption that we can generate as many  $Unif(0,1)$  r.v.s as we want.

$Unif(0,1)$



pdf  $f(x) = 1, 0 < x < 1$   
 "probability density function"

$$\begin{aligned}
 \text{cdf } F(x) &= P\{U \leq x\} \\
 &= \int_0^x f(u) du \\
 &= \int_0^x 1 du \\
 &= x, 0 < x < 1
 \end{aligned}$$

"cumulative distribution function"

- Exercise: given just ONE  $Unif(0,1)$  random variable, we can generate INFINITELY MANY ind.  $Unif(0,1)$  r.v.s

- Hint: Use binary notation.
- Caveat: This is NOT how computers work.
- The cdf of a random variable  $X$  is  $F(x) = P\{X \leq x\}$ .
- The quantile function is  $Q = F^{-1}$  if  $X \mapsto F(x)$  is strictly increasing, continuous
- More generally,  $Q(p) = \inf \{y \in \mathbb{R} : F(y) \geq p\}$

Proposition (Random number generation), IF

$U \sim \text{Unif}(0,1)$ , then  $Q(U)$  has cdf  $F$ .

PF 1. First, check the Galois inequalities  
 $p \leq F(x) \iff x, p \in \mathbb{R}$ .

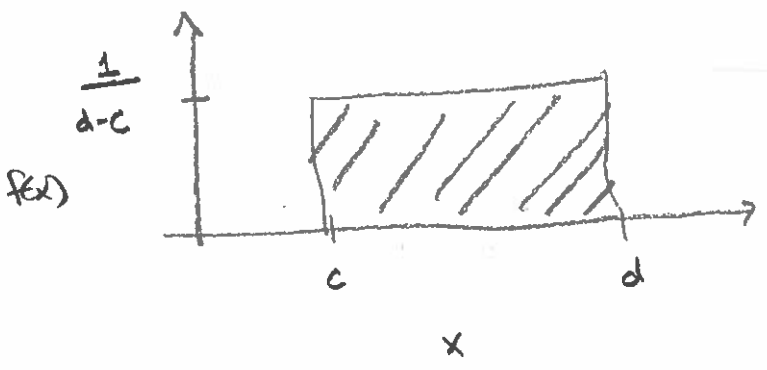
2. Next,  $P\{Q(U) \leq x\} = P\{U \leq F(x)\} = F(x)$ .  $\square$

Examples:

1.  $\text{Unif}(c,d)$

$$F(x) = \frac{x-c}{d-c}, \quad c < x < d$$

$$Q(p) = c + (d-c)p, \quad 0 < p < 1$$

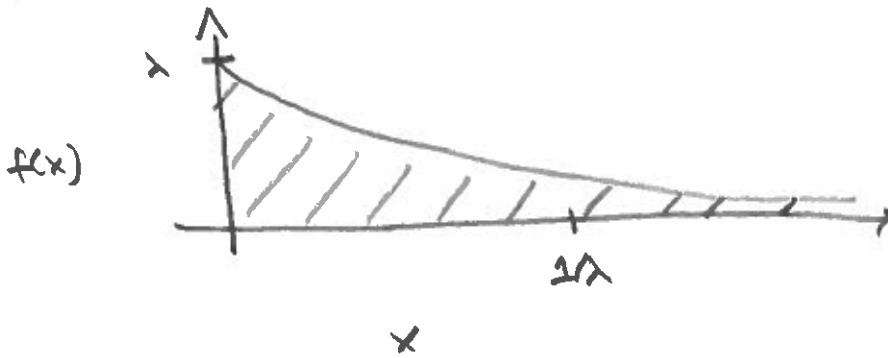


$$\Rightarrow c + (d-c)U \sim \text{Unif}(c,d)$$

2.  $\exp(\lambda)$

$$F(x) = 1 - e^{-\lambda x}, \quad x > 0 \quad (3)$$

$$Q(p) = \frac{-\log(1-p)}{\lambda}$$



$$\Rightarrow \frac{-\log(1-u)}{\lambda} \sim \exp(\lambda)$$

Using  $1-u \sim \text{Unif}(0,1)$ , there is a simpler

formula

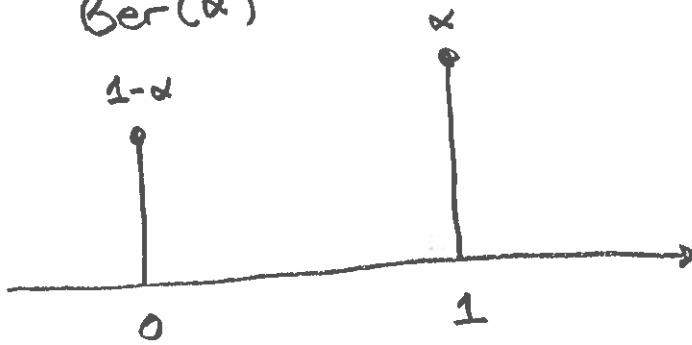
$$\boxed{\frac{-\log u}{\lambda} \sim \exp(\lambda)}$$

3.

$\text{Ber}(\alpha)$

$$F(x) = \begin{cases} 0, & x < 0 \\ 1-\alpha, & 0 < x < 1 \\ 1, & x > 1 \end{cases}$$

$p(x)$



$$Q(p) = \mathbb{1}\{p \geq 1-\alpha\}$$

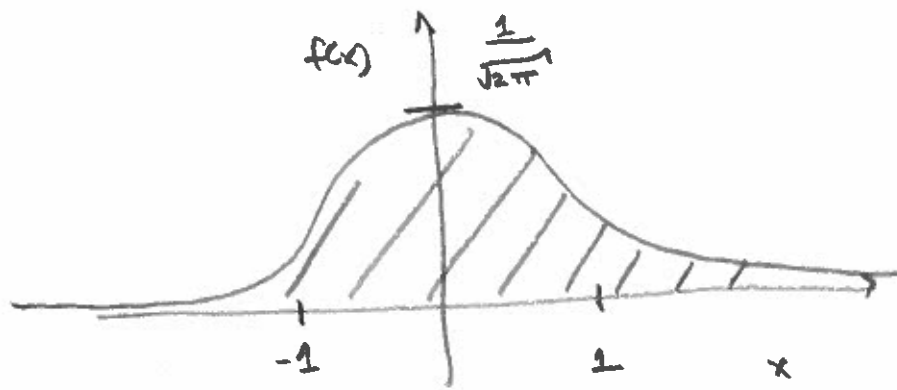
$$\Rightarrow \mathbb{1}\{u \geq 1-\alpha\} \sim \text{Ber}(\alpha) \quad \text{OR} \quad \boxed{\mathbb{1}\{u \leq \alpha\} \sim \text{Ber}(\alpha)}$$

Q: How do we generate a vector of independent r.v.s  $\vec{X} = (X_1, \dots, X_n)$  with  $X_i \sim \text{Ber}(\alpha_i)$ ?

A: Generate  $\vec{U} = (U_1, \dots, U_n)$ ,  $\vec{\alpha} = (\alpha_1, \dots, \alpha_n)$ ,  $\vec{X} = \mathbb{1}\{\vec{U} \leq \vec{\alpha}\}$

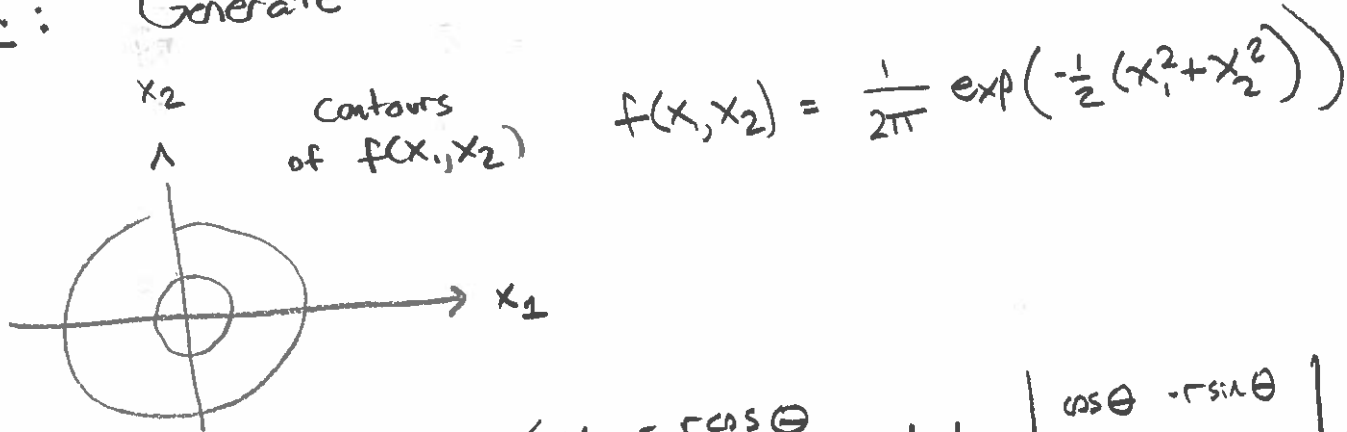
Q: We've got  $\text{Unif}(c,d)$ ,  $\exp(\lambda)$ ,  $\text{Ber}(a)$ . (4)  
 what else can we do?

Box Muller: How can we generate  $X \sim \mathcal{N}(0,1)$ ?



$$f(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}x^2\right)$$

- Idea: Generate TWO indep. Gaussians  $x_1, x_2 \sim \mathcal{N}(0,1)$



$$f(x_1, x_2) = \frac{1}{2\pi} \exp\left(-\frac{1}{2}(x_1^2 + x_2^2)\right)$$

1. Change of variables  $\begin{cases} x_1 = r \cos \theta \\ x_2 = r \sin \theta \end{cases} \Rightarrow |J| = \begin{vmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{vmatrix} = r$

2. change of density  $f(x_1, x_2) dx_1 dx_2 = \frac{1}{2\pi} \exp\left(-\frac{1}{2}r^2\right) r d\theta dr = f(\theta, r) d\theta dr$

3. Change of variables  $S = \frac{1}{2}r^2 \Rightarrow |J| = |r| = r$

4. Change of density  $f(\theta, r) d\theta dr = \frac{1}{2\pi} \exp(-s) d\theta ds = f(\theta, s) d\theta ds$

5. pdf  $f(\theta, s) = \frac{1}{2\pi} \exp(-s) \Rightarrow \theta, s$  indep. r.v.'s with  $\theta \sim \text{Unif}(0, 2\pi)$ ,  $S \sim \exp(1)$

$$\Rightarrow \begin{cases} X_1 = \sqrt{-2 \log U_1} \cos(2\pi U_2) \sim \mathcal{N}(0, 1) \\ X_2 = \sqrt{-2 \log U_2} \sin(2\pi U_2) \sim \mathcal{N}(0, 1) \end{cases}$$

and  $X_1, X_2$  are indep.

Q: How can we generate a  $\mathcal{N}(\vec{M}, \Sigma)$  random vector?

A: Generate independent  $Z_1, \dots, Z_N \sim \mathcal{N}(0, 1)$  and

set  $\vec{X} = \vec{M} + \Sigma^{1/2} \vec{Z}$ .

- Summary: we can generate lots of r.v.s using

$\text{Unif}(0, 1)$  r.v.s

- Caution: your computer builds on these foundations and uses even faster algorithms, e.g.

"Ziggurat" (Marsaglia & Tsang, 1984).

Rejection sampling: Want to sample from pdf

$f$ , only know how to sample from pdf  $g$ .

a) Sample  $X \sim g$ , compute  $r = \frac{f(x)}{g(x)M} (\leq 1)$ .

b) Sample  $U \sim \text{Unif}(0, 1)$ . If  $U \leq r$ , accept  $X$ .

Otherwise, try again.

Q: what is the best  $M$ ?

$$\underline{A}: M = \sup_{x \in \mathbb{R}} \frac{f(x)}{g(x)} \quad (6)$$

Proposition (Rejection works): Random variable  $X$  from rejection sampling has pdf  $f$ , waiting time to success is  $\text{Geo}(\frac{1}{M})$ .

Pf 1. Calculate  $P(X \in dx, \text{success}) = P(X \in dx) P(\text{success} | X=x)$

$$= g(x) \frac{f(x)}{g(x) M} = \frac{f(x)}{M}$$

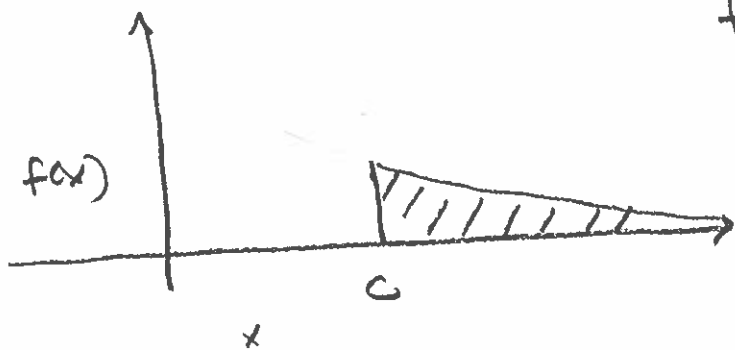
2. Integrate  $P(\text{success}) = \int P(X \in dx, \text{success}) dx = \frac{1}{M}$

3. Apply Bayes rule  $P(X \in dx | \text{success}) = \frac{P(X \in dx, \text{success})}{P(\text{success})}$

$$= \frac{f(x)/M}{1/M} = f(x). \quad \square$$

Ex: we want to sample  $z | z > c$  where  $z \sim \mathcal{N}(0, 1)$

$$f(x) = \frac{\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}x^2)}{P(Z > c)}, \quad x > c$$



Idea: Let's try sampling  $X \sim \mathcal{N}(c, 1)$



$$g(x) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}(x-c)^2)$$

$$\frac{f(x)}{g(x)M} = \frac{\exp(-xc + \frac{1}{2}c^2)}{P(Z=c)M}, \quad x > c$$

(7)

Need to make this  $\leq 1$

Sample  $X \sim \mathcal{N}(c, 1)$ , compute  $r = \exp(-c(x-c)) \mathbb{1}\{x > c\}$ ,  
 accept w/ prob  $r$

Exercise: What is the success probability for generating a truncated Gaussian?

Hint: It's  $\frac{1}{M} \geq \frac{1}{\sqrt{2\pi}} \frac{c}{c^2+1}$ . Prove it using

"Mills' ratio".

Q: Is this better than generating a bunch of Gaussians  $Z_1, \dots, Z_N \sim \mathcal{N}(0, 1)$  and selecting the ones larger than  $c$ ?

Importance sampling: Want to sample from pdf  $f$ , only know how to sample from pdf  $g$ .

a) Sample  $X_1, \dots, X_N \sim g$ .

b) Set  $w_i = \frac{f(x_i)}{g(x_i)M}$  for  $1 \leq i \leq N$ .

c) Approximate any average  $\mu_h = \int f(x)h(x) dx$  as

$$\hat{h}_{imp} = \frac{w_1 h(x_1) + \dots + w_N h(x_N)}{w_1 + \dots + w_N}$$

Q: what is the best  $M$ ? (8)

A: whatever makes the computation of  $w_i$  simplest

Proposition (Importance sampling works): Random variable  $w_i h(x_i)$  from importance sampling has expected value  $\frac{1}{M} \mu_h$  (hence  $E w_i = \frac{1}{M}$ ).

Pf  $E [w_i h(x_i)] = \int g(x) \frac{f(x)}{g(x)M} h(x) dx = \frac{1}{M} \mu_h. \quad \square$

Ex We want to sample  $Z | Z > c$  where  $Z \sim \mathcal{N}(0, 1)$

Let's try sampling  $X_i \sim \mathcal{N}(c, 1)$  for  $1 \leq i \leq N$ .

$$w_i = \frac{f(x_i)}{g(x_i)M} = \frac{\exp(-x_i c + \frac{1}{2} c^2)}{P(Z > c) M}, \quad x_i > c$$

Need to make this simple.

Sample  $X_1, \dots, X_N \sim \mathcal{N}(c, 1)$ , compute  $w_i = e^{-cX_i} \mathbb{1}\{X_i > c\}$   
(or maybe  $w_i = e^{-c(X_i - c)} \mathbb{1}\{X_i > c\}$ ), use  $(w_i, X_i)_{1 \leq i \leq N}$

for computations

Proposition (Importance beats rejection): For a fn  $h$ ,

$$\hat{h}_{\text{rej}} = \frac{\mathbb{1}\{U_1 \leq r_1\} h(X_1) + \dots + \mathbb{1}\{U_N \leq r_N\} h(X_N)}{\mathbb{1}\{U_1 \leq r_1\} + \dots + \mathbb{1}\{U_N \leq r_N\}}$$

be the estimate of  $\mu_h = \int f(x) h(x)$  from rejection sampling.



$$\text{Let } \hat{h}_{\text{imp}} = \frac{w_1 h(x_1) + \dots + w_N h(x_N)}{w_1 + \dots + w_N} \quad (9)$$

be the estimate of  $\mu_h$  from importance sampling. Then as  $N \rightarrow \infty$

$$\sqrt{N} (\hat{h}_{\text{rej}} - \mu_h) \rightarrow \mathcal{N}(0, V_{\text{rej}}) \quad \text{"} \hat{h}_{\text{rej}} = \mu_h \pm \frac{1}{\sqrt{N}} V_{\text{rej}}^{1/2} \text{"}$$

$$\sqrt{N} (\hat{h}_{\text{imp}} - \mu_h) \rightarrow \mathcal{N}(0, V_{\text{imp}}) \quad \text{"} \hat{h}_{\text{imp}} = \mu_h \pm \frac{1}{\sqrt{N}} V_{\text{imp}}^{1/2} \text{"}$$

where

$$V_{\text{imp}} = \int \frac{f^2(x)}{g(x)} |h(x) - \mu_h|^2 dx \leq V_{\text{rej}} = M \int f(x) |h(x) - \mu_h|^2 dx.$$

True because  $M = \frac{f(x)}{g(x)} \quad \forall x \in \mathbb{R}$

Pf Exercise using the "delta method". □