

Computational statistics, lecture 3

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Simulation in Statistics

- Computer-generated random variables
- Purpose:
 - Simulate a situation where a statistical model can be assumed
 - Simulate situation repeatedly to investigate properties of estimators, confidence intervals, significance tests
 - Example: power of a test in situations where assumptions are not fulfilled
 - Perform Monte Carlo integration
- Problem: Given a density f of a target distribution, generate random draws X_1, \dots, X_n which follow the target distribution

Random variables from familiar distributions

- Computer-generated random variables are not really random but deterministic (Gentle, 2009, Ch.7.1)
- Algorithms are used such that the deterministic nature is not visible, and variables seem random
- Deterministic algorithm generates values between 0 and 1 which follow well independent draws from $\text{Unif}[0,1]$
- Then, random variables following other familiar distributions can be generated from $\text{Unif}[0,1]$ and are implemented in statistical software, see Givens and Hoeting (2013), Tab. 6.1

Generating Unif[0,1] random variables

- Linear congruential generator
 - x_0 is seed
 - $x_{k+1} = (ax_k + c) \bmod m$
 - $r_k = x_k/m$ is the generated k-th random number
- Here, a, c, and m need to be chosen carefully (m large and often a prime)
- Sequences like that have a period (they repeat after some k)
- Another type of generator works on the bit-level, shifting 0-1-sequences
- The “Mersenne twister” is a good generator used in \mathbf{R} ; it is based on shifting 0-1-sequences and twisting terms by some matrix multiplication
- The period of the Mersenne twister is $p = 2^{19937} - 1$
(both p and 19937 are primes)

The seed

- If seed is set fixed, the following generated sequence of random variables is fixed
- Therefore, the seed is determined often based on the system time by default
- For purposes of **reproducibility of results**, the user can choose a specific seed, which can be communicated to other users
- In R:

```
> set.seed(2023)
> sample(1:15, 15)
[1]  5  9  8  3 10  2  1 14 15 13  6  7  4 11 12
```
- Note that there was a change in the method used by the **sample**-function from R-version 3.6.0 (but even later versions might still use the older method if they had been updated from older versions). You can then change between versions by

```
set.seed(2023, RNGkind="Rejection") (new)
set.seed(2023, RNGkind="Rounding")  (old, use only for reproducing older results)
```

Random variables of familiar distributions in R

- In R, random variables can be generated for a number of distributions, e.g:
- `rbeta`, `rcauchy`, `rchisq`, `rexp`, `rf`, `rgamma`, `rlnorm`, `rnorm`, `rt`, `runif`, `rweibull`
- `rbinom`, `rgeom`, `rhyper`, `rmultinom`, `rnbinom`, `rpois`

```
x <- rnorm(6, mean = 1.2, sd = 2)
```

```
x
```

```
[1] 3.8839870 2.8328797 3.5344539 -2.5464309 3.2059822 0.1872261
```

```
rbinom(25, size = 3, prob = 0.25)
```

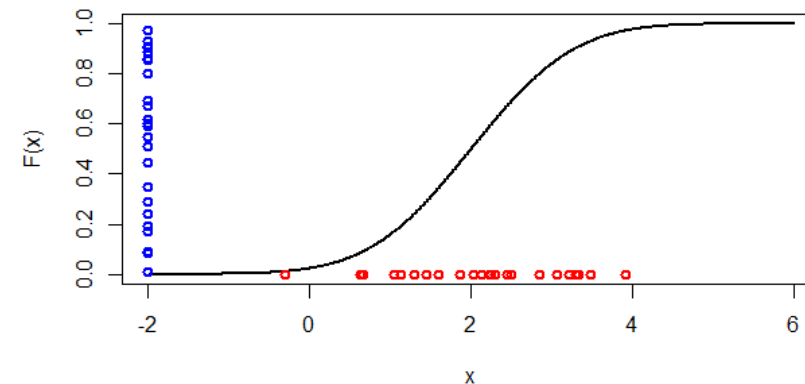
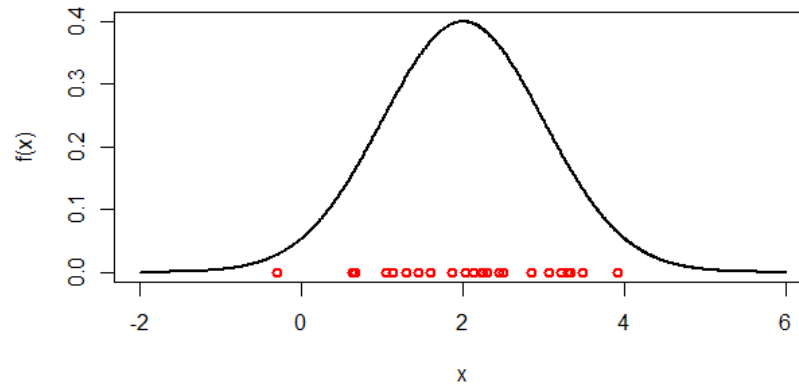
```
[1] 1 2 0 0 0 0 0 2 3 0 0 2 1 1 0 0 1 0 1 1 2 2 1 0 0
```

Random variables from non-familiar distributions

- Problem: Given a density f of a target distribution, generate random draws X_1, \dots, X_n which follow the target distribution
- Now: Density f of arbitrary form
- Methods we will consider:
 - Inverse cumulative distribution function (CDF) method
 - Rejection sampling
 - Generate normal distributed variables
 - Composition sampling (use of conditional distributions)
 - Markov chain Monte Carlo (MCMC) → Lecture 4

Inverse cumulative distribution function method

- Continuous random variable X with density f and distribution function F
- Then: $F(X)$ is uniformly distributed on $[0,1]$



- Therefore: if we can generate uniformly distributed random variables U , we can compute $X = F^{-1}(U)$ and obtain the desired sample

Inverse CDF method

- Example 1: We want to generate random variables X with triangle distribution having density

$$f(x) = \begin{cases} 2 - 2x, & \text{if } 0 \leq x \leq 1, \\ 0, & \text{otherwise} \end{cases}$$

- We compute the distribution function:

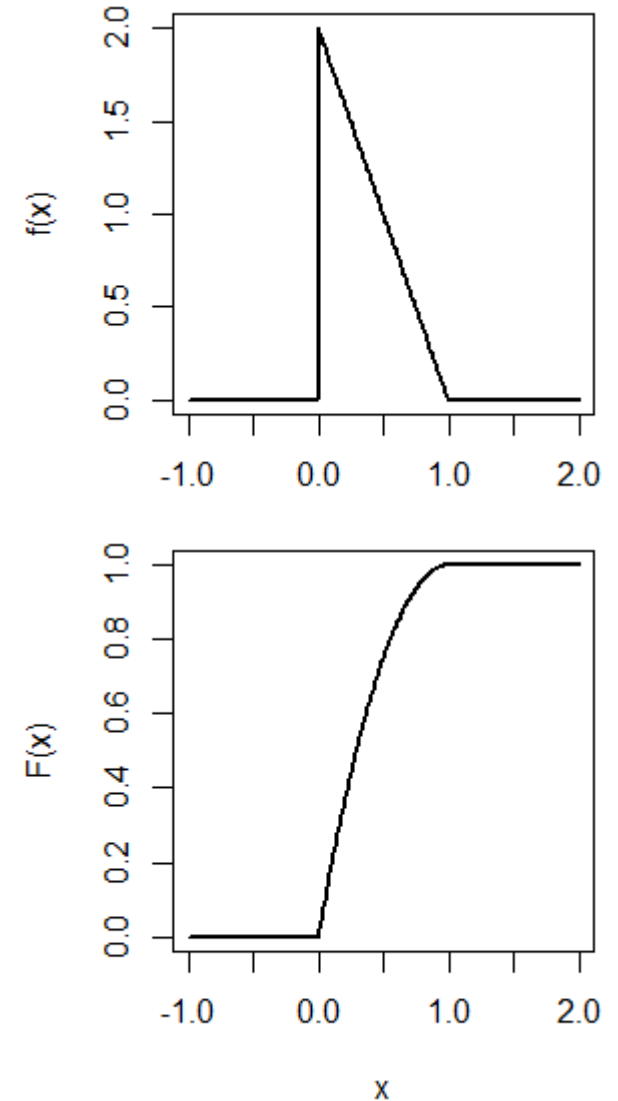
$$F(x) = \int_{-\infty}^x f(t) dt = \begin{cases} 0, & \text{if } x < 0, \\ 2x - x^2, & \text{if } 0 \leq x \leq 1, \\ 1, & \text{if } x > 1. \end{cases}$$

- The inverse distribution function is

$$F^{-1}(y) = 1 - \sqrt{1 - y}$$

$$\text{since } y = 2x - x^2 \Leftrightarrow x^2 - 2x + y = 0 \Leftrightarrow$$

$$x_{1,2} = 1 \pm \sqrt{1 - y} \Rightarrow 1 - \sqrt{1 - y}$$



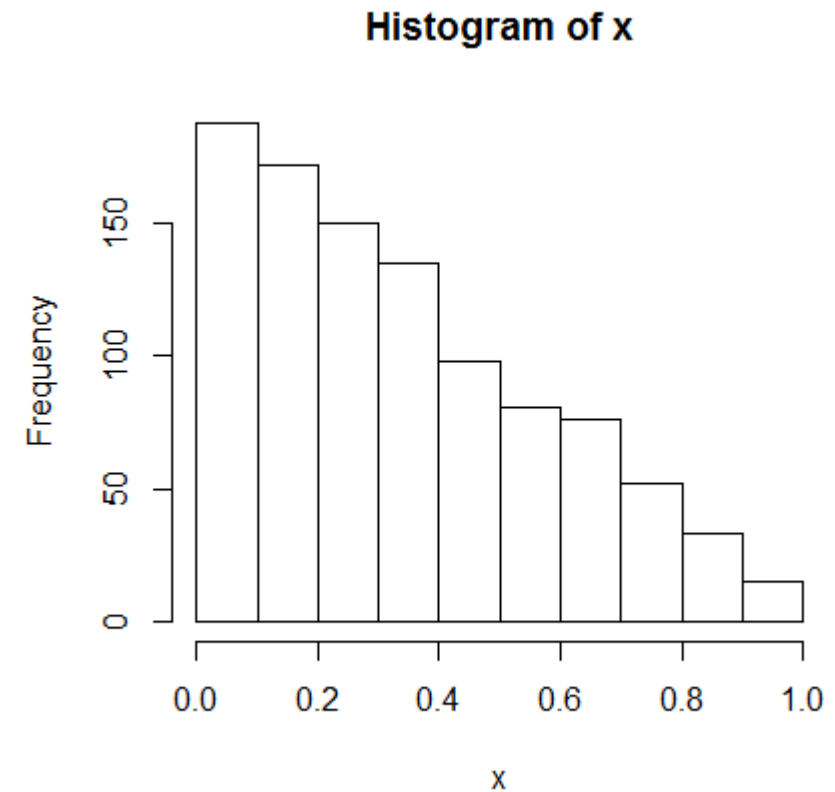
Inverse cumulative distribution function method

- 1000 random numbers for the triangle distribution can be generated by:

```
u <- runif(1000)
```

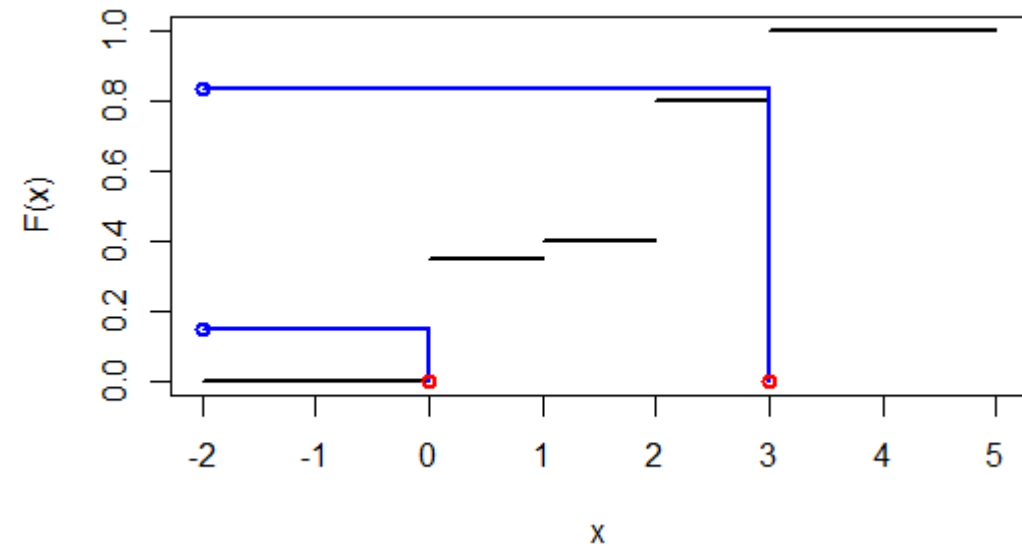
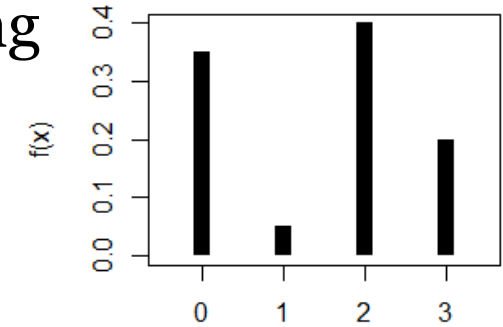
```
x <- 1-sqrt(1-u)
```

```
hist(x)
```



Inverse CDF method – discrete random variables

- Example 2: We want to generate a random variable X being 0 with probability 0.35, 1 with probability 0.05, 2 with probability 0.4, 3 with probability 0.2
- $F(x) = P(X \leq x)$; how to apply inverse cumulative distribution function method?

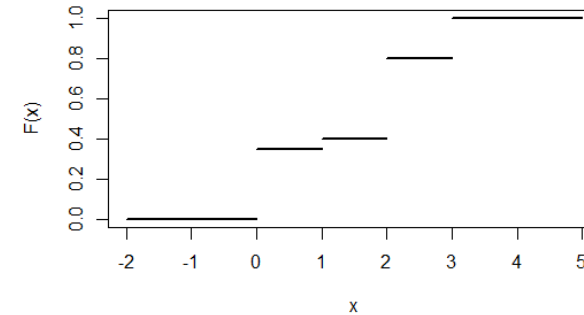


Inverse CDF method – discrete random variables

- Example 2: We want to generate a random variable X being
 - 0 with probability 0.35,
 - 1 with probability 0.05,
 - 2 with probability 0.4,
 - 3 with probability 0.2
- How to apply inverse transformation method?
- Generate $U \sim \text{Unif}[0,1]$
- If $U \leq 0.35$, then $X = 0$,
if $0.35 < U \leq 0.4$, then $X=1$,
if $0.4 < U \leq 0.8$, then $X=2$,
if $0.8 < U$, then $X=3$.

```
u <- runif(100000)
```

```
x <- (u>0.35) + (u>0.4) + (u>0.8)
```



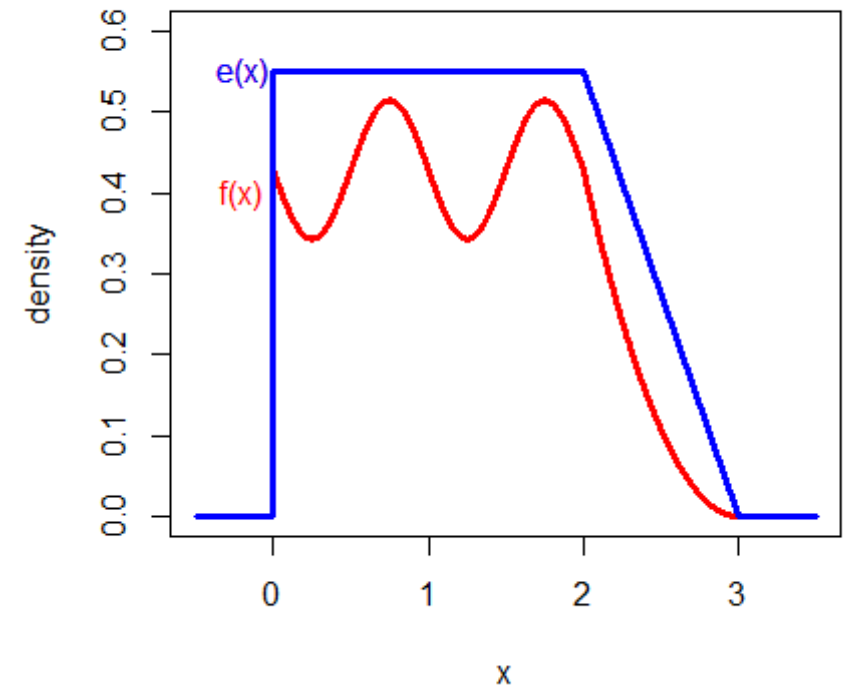
This is 1 if the condition in (...) is true, otherwise it is 0

Inverse cumulative distribution function method

- Inverse cumulative distribution function method worked well in preceding examples
- In general, drawbacks are:
 - Computation of F^{-1} might be difficult
 - Not possible to generalize to multiple dimensions
 - Often less efficient as alternatives

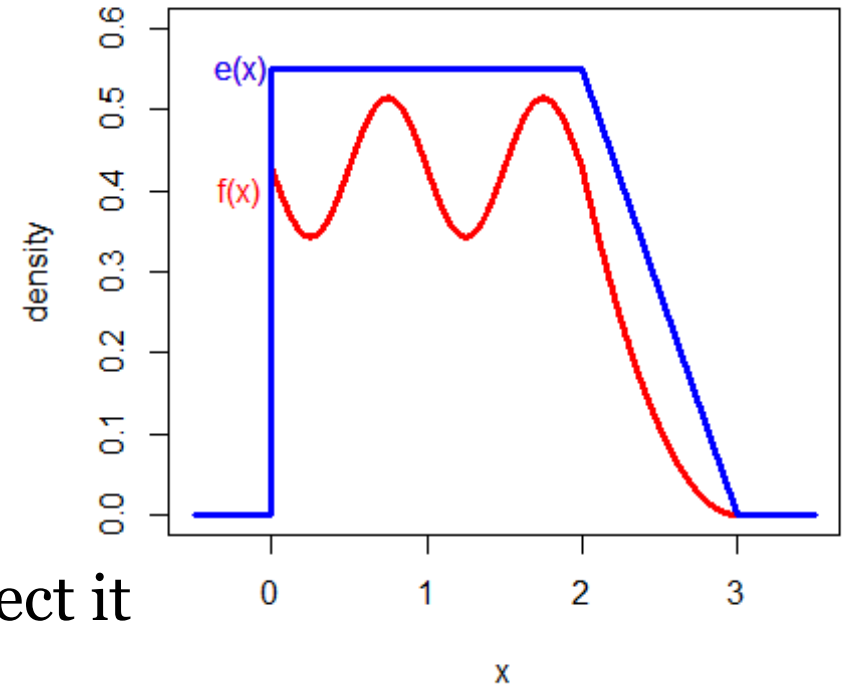
Rejection sampling

- **Problem:** Given a density f of a target distribution, generate random draws X_1, \dots, X_n which follow the target distribution
- It can be difficult to sample with respect to f
- **Situation:** There is another density g which can be sampled from and which is after scaling larger than f for all x ,
$$e(x) = g(x)/a \geq f(x)$$
for all x and some $a < 1$
- $e(x)$ is called "envelope"



Rejection sampling

- $e(x)=g(x)/a \geq f(x)$ for all x and some $a < 1$
- Rejection sampling algorithm:
 1. Sample $Y \sim g$
 2. Sample $U \sim \text{Unif}(0,1)$
 3. If $U \leq f(Y)/e(Y)$, accept Y ; set $X=Y$; otherwise reject it
 4. If more samples desired go to 1.



Example (for picture above): $Y=2.21$; $f(Y)=0.267$, $e(Y)=0.435$,
 $f(Y)/e(Y)=0.616$; sample U ; If $U \leq 0.616$, use Y , otherwise reject it

Rejection sampling

1. Sample $Y \sim g = ea$
2. Sample $U \sim \text{Unif}(0,1)$
3. If $U \leq f(Y)/e(Y)$, accept Y ; set $X=Y$; otherwise reject it
4. If more samples desired, go to 1

Example (for picture above):

$(Y_1, U_1) = (2.21, 0.492) \rightarrow U_1 < 0.616 \rightarrow \text{accept } Y_1$

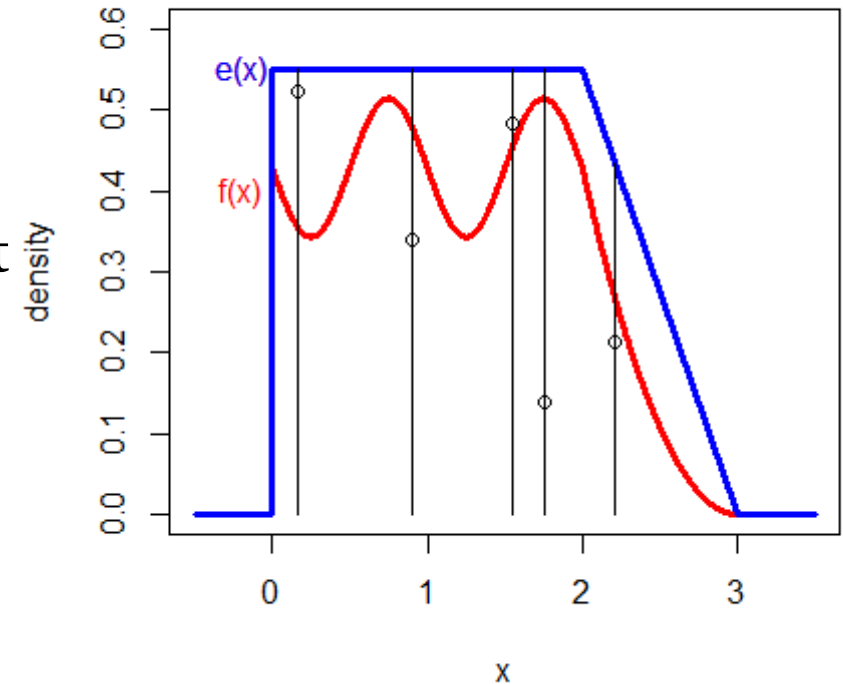
$(Y_2, U_2) = (0.17, 0.952) \rightarrow U_2 > f(0.17)/e(0.17) \rightarrow \text{reject } Y_2$

$(Y_3, U_3) = (1.76, 0.250) \rightarrow U_3 < f(1.76)/e(1.76) \rightarrow \text{accept } Y_3$

$(Y_4, U_4) = (1.55, 0.880) \rightarrow U_4 > f(1.55)/e(1.55) \rightarrow \text{reject } Y_4$

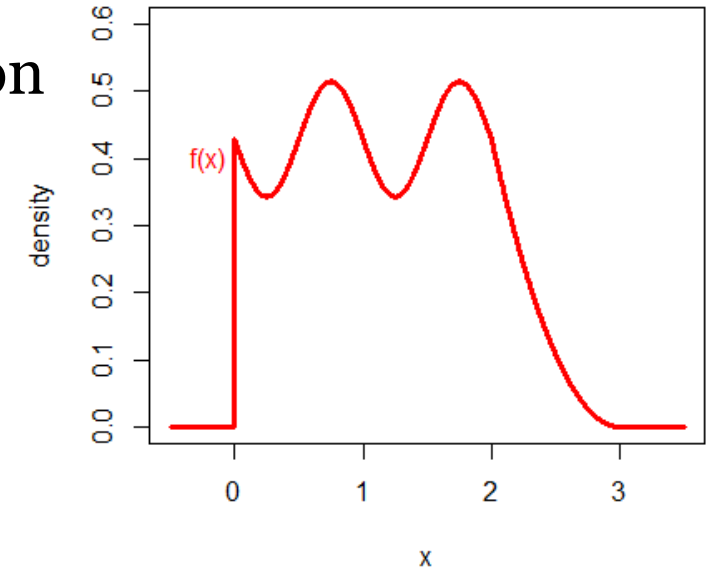
$(Y_5, U_5) = (0.90, 0.619) \rightarrow U_5 < f(0.90)/e(0.90) \rightarrow \text{accept } Y_5$

$\rightarrow \text{use } (2.21, 1.76, 0.90)$



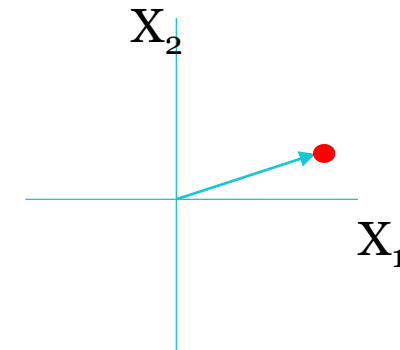
Using the generated distribution

- We have now a way to generate an arbitrary distribution
- We can use it then for different purposes
- Example 3: What is the mean and the variance?



Generate univariate standard normal variables

- **R**-function `rnorm` uses by default inverse transf. method
 - Inverse distribution function Φ^{-1} of normal distribution function used; no closed formula for Φ^{-1} exists; **R** uses approximation algorithm which is very precise
- Another method: Box-Muller (can be selected in **R**, too)
 - If (X_1, X_2) standard bivariate normally distributed (i.e., X_1 and X_2 independent standard normal), then $Y = X_1^2 + X_2^2$ has χ_2^2 -distribution; χ_2^2 equal to $\text{Exp}(1/2)$
 - Angle A uniformly distributed on $[0, 2\pi]$
 - Generate squared length Y with inverse transformation from one uniform dist. and angle A from an independent uniform dist.
 - $X_1 = \sqrt{-2 \log(Y)} \cos A$, $X_2 = \sqrt{-2 \log(Y)} \sin A$
- Box-Muller is around 40% slower as the default in **R**



Generate a multivariate normal distribution

- A multivariate normal distribution $N(\mu, \Sigma)$ with mean vector μ and covariance matrix Σ has density

$$f(x) = \frac{1}{((2\pi)^p |\Sigma|)^{1/2}} e^{-(x-\mu)^T \Sigma^{-1} (x-\mu)/2}$$

- If X is a p -dimensional vector of independent standard normal variables (i.e. X is multivariate normal $N(0, I)$), then $Y = A^T X + \mu$ has a $N(\mu, \Sigma)$ -distribution with $\Sigma = A^T A$
- To generate $Y \sim N(\mu, \Sigma)$:
 - compute A with $\Sigma = A^T A$ (e.g. Cholesky decomposition),
 - generate $X \sim N(0, I)$ (by generating p indep. $N(0, 1)$ -var),
 - compute $Y = A^T X + \mu$

Generate a multivariate normal distribution

- Example 4: Generate one random vector according to the bivariate normal distribution with mean vector 0, variance 1 of each component and correlation ρ , $-1 \leq \rho \leq 1$ (this means that the covariance matrix is $\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$)
- One can show that $\Sigma = A^T A$ with $A = \begin{pmatrix} 1 & \rho \\ 0 & \sqrt{1 - \rho^2} \end{pmatrix}$
- Therefore:
 - Simulate two independent $X_1 \sim N(0,1)$; $X_2 \sim N(0,1)$
 - Compute $Y = A^T X$, which means:
 $Y_1 = X_1$,
 $Y_2 = \rho X_1 + \sqrt{1 - \rho^2} X_2$.
 - Vectors Y generated this way have then the desired distribution

Generate multivariate normal distribution in R

- Package **mvtnorm** supplies (besides densities, probabilities, and quantile functions) random generator **rmvnorm** for multivariate normal:

$$\Sigma = \begin{pmatrix} 1 & 0.5 & 0.25 \\ 0.5 & 1 & 0.5 \\ 0.25 & 0.5 & 1 \end{pmatrix}$$

```
library(mvtnorm)
```

```
Sig <- matrix(c(1,0.5,0.25, 0.5,1,0.5, 0.25,0.5,1), nrow = 3)
```

```
rmvnorm(5, mean = c(2,-1,0), sigma = Sig)
```

```
      [,1]      [,2]      [,3]  
[1,] 2.447613 -1.7390355 -0.43272668  
[2,] 1.933296 -1.9893701  0.47161126  
[3,] 2.872344 -0.6396215  0.61383902  
[4,] 2.505797 -0.8080744 -0.51696135  
[5,] 2.614221 -1.9280517  0.04471815
```

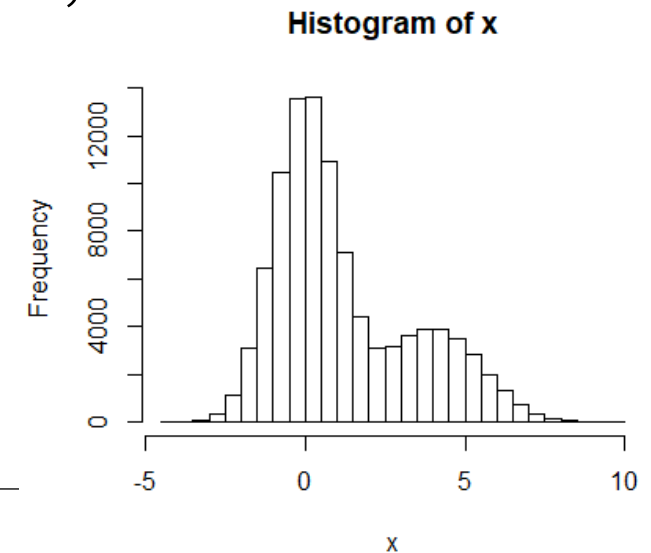
Each row is one
generated random vector

- Optionally, method of decomposition can be chosen
- Multivariate t distribution (same package): **rmvt**

Composition sampling (use of conditional distributions)

- If $f_i(x), i = 1, \dots, n$, are densities, a random variable X with density $\sum_i p_i \cdot f_i(x)$, where $\sum_i p_i = 1$, is called finite mixture; p_i =mixing parameters
- A finite mixture distribution can be generated by:
 - simulating the group-membership using the discrete distribution for mixing parameters
 - simulating the distribution of this group's distribution, i.e. the conditional distribution given the group
- Ex. 5: X normal mixture of $N(0, 1)$ and $N(4, 1.5^2)$ with mixing parameter 0.7 and 0.3, respectively

```
g <- rbinom(100000, size = 1, prob = 0.3)
x <- rnorm(100000, mean = 4*g, sd = 1+0.5*g)
hist(x, breaks = 25)
```



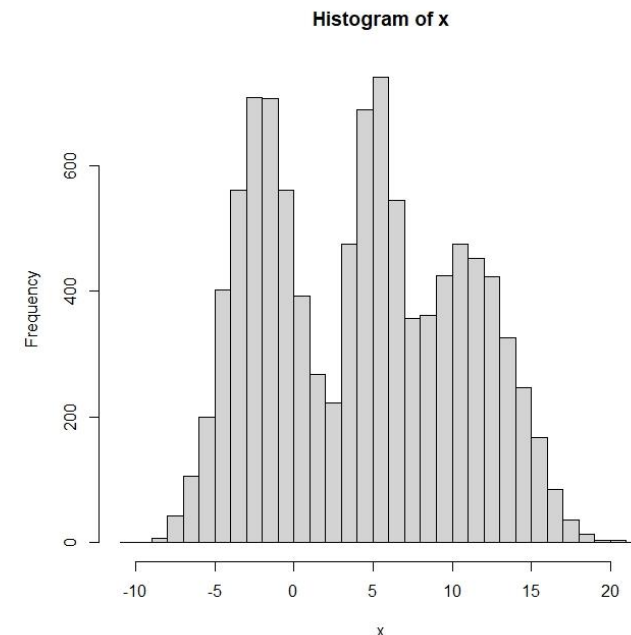
Composition sampling (use of conditional distributions)

- More flexible code for simulating a finite mixture distribution (e.g., a finite normal mixture) with composition sampling:
 - Define mean, standard deviations and mixing parameters as vector:

```
mu      <- c(-2, 5, 11)
sigma   <- c(2.2, 1.4, 2.9)
prob    <- c(0.4, 0.25, 0.35)
n       <- 10000
```

- Generate mixture by:

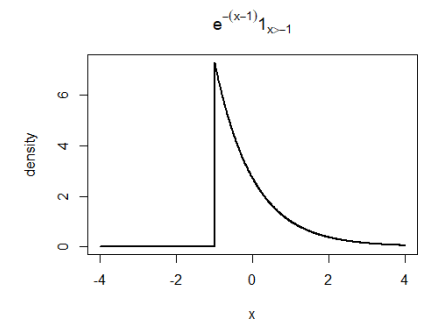
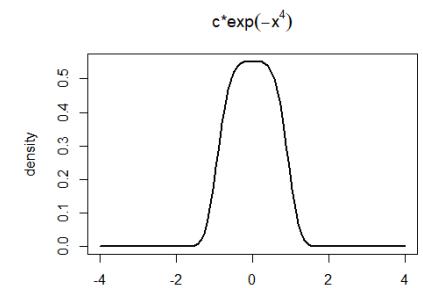
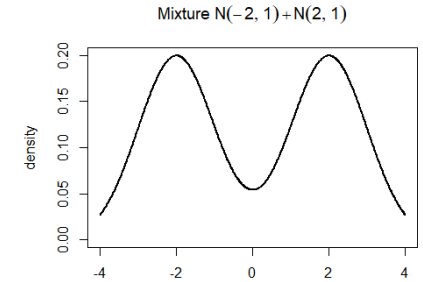
```
g <- sample(length(mu), n, replace=TRUE, p=prob)
x <- rnorm(n, mean = mu[g], sd = sigma[g])
hist(x, breaks = 25)
```



Example 6:

With which method would you generate random variables for the following distributions?

- a) An equal mixture of $N(-2,1)$ and $N(2,1)$,
- b) Distribution with density: $f(x)=c \exp(-x^4)$,
- c) Distribution with density: $f(x)=e^{-(x-1)} \mathbf{1}_{\{x>-1\}}$



Example 7:

Assume you have now generated a sample for the distribution with density: $f(x) = c \exp(-x^4)$ with an appropriate method

What is its variance and kurtosis?

