### Advanced Scientific Computing with R 5. Simulating Data

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## Introduction

Simulated ("random") data is used in many areas:

- gambling
- statistical sampling
- computer simulation
- cryptography
- simulations (Monte Carlo experiments)

### Sampling

- Univariate Distributions
- 3 Identifying Distributions
- 4 Multivariate Distributions
- 5 Examples



# Sampling

'sample' takes a sample of the specified size from the elements of 'x' using either with or without replacement.

```
R> sample(1:100, size=10)
[1] 12 62 60 61 83 97 1 22 99 47
R> sample(1:10, size=100, replace=TRUE)
[1] 7 6 3 10 3 9 3 3 2 3 4 4 2 1 3 9 6 10
[19] 9 1 5 3 4 6 2 8 3 3 10 9 6 7 4 7 4 6
[37] 7 5 3 8 1 4 8 6 2 6 5 8 2 9 9 1 4 1
[55] 3 8 4 6 1 6 2 9 1 8 1 6 4 1 4 7 10 5
[73] 2 6 2 9 4 4 2 9 2 10 2 2 2 6 4 1 4 8
[91] 1 6 3 3 2 4 2 2 5 1
```

sample can be used to sample from data.frames and matrices.

```
R> data(iris)
R> dim(iris)
[1] 150   5
R> s <- iris[sample(1:nrow(iris), size=50), ]
R> dim(s)
[1] 50   5
```

## Simple Coin Tossing

We can specify the probability for each outcome.

```
R> x <- sample(c(TRUE, FALSE), 100, replace=TRUE,</pre>
prob=c(0.2,0.8))
R > x
  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE
                                                    TRUE
 [10] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 [19] FALSE FALSE FALSE FALSE FALSE FALSE
                                        TRUE FALSE
                                                    TRUE
 [28] FALSE FALSE FALSE FALSE TRUE FALSE TRUE TRUE
                                                   TRUE
 [37] TRUE FALSE TRUE FALSE FALSE FALSE FALSE FALSE
 [46] FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE
 [55] FALSE TRUE FALSE FALSE FALSE TRUE FALSE FALSE FALSE
 [64] FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE
 [73] FALSE TRUE FALSE FALSE FALSE FALSE TRUE FALSE
 [82] FALSE FALSE FALSE TRUE FALSE FALSE FALSE TRUE FALSE
 [91] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[100] FALSE
R> table(x)
```

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FALSE TRUE

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### Simple Coin Tossing II

R> barplot(table(x))



#### Sampling



- Identifying Distributions
- 4 Multivariate Distributions





### Distributions

Functions for all distributions in R come in 4 variants. For example for the normal distribution we have:

```
dnorm(x, mean = 0, sd = 1, log = FALSE)
pnorm(q, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)
qnorm(p, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)
rnorm(n, mean = 0, sd = 1)
```

Probability density function (d), distribution function (p), quantile function (q) and random deviates (r).

# Probability density function (pdf)

Probability of a random variable taking certain values: f(x)

```
R> x <- seq(-5,5, by=.1)
R> plot(x, dnorm(x))
```



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# (Cumulative) distribution function (cdf)

Probability that a real-valued random variable X with a given probability distribution will be found at a value less than or equal to x:  $F_X(x) = P(X \le x)$ 

R> plot(x, dnorm(x), "1")
R> abline(v=2, col="red")

R> plot(x, pnorm(x), "1")





## Quantile function

$$Q(p) = \inf\{x \in R : p \le F(x)\}$$





#### Random deviates

R> x <- rnorm(100)
R> head(x)
[1] 1.014 0.253 -1.172 0.669 -1.650 -0.366
R> plot(x)



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### Random deviates II

R> hist(x)



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Histogram of x

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## Some useful distributions

- rnorm
- Inorm
- runif
- rpois
- rexp
- rbinom
- rnbinom
- rmultinom
- rchisq
- rt
- rbeta
- rweibull

Sampling

- Univariate Distributions
- Identifying Distributions
- 4 Multivariate Distributions





## Histogram

Compare empirical distribution with a fitted theoretical distribution.







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### Quantile-Quantile plot

R> qqplot(x, rnorm(100, mean=mu, sd=sd))
R> # use qqnorm for normal distribution
R> abline(0,1, col="red")



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- Sampling
- 2 Univariate Distributions
- 3 Identifying Distributions
- 4 Multivariate Distributions





#### Multivariate Distributions

```
R> library(MASS)
R> Sigma <- rbind(c(1,0), c(0,1)) ## covariance matrix
R> x <- mvrnorm(100, c(1,1), Sigma=Sigma)
R> head(x)
       [,1] [,2]
[1,] 2.189 0.767
[2,] 2.060 1.156
[3,] 2.337 0.396
[4,] 0.633 1.629
[5,] 0.696 1.714
[6,] 0.650 2.076
R> plot(x)
```



#### Multivariate Distributions

```
R> Sigma <- rbind(c(1,.9), c(-.9,1)) ## strong correlation
R> x <- mvrnorm(100, c(1,1), Sigma=Sigma)
R> plot(x)
```



More about multivariate data can be found in the Task View "Multivariate"

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#### Sampling

- 2 Univariate Distributions
- 3 Identifying Distributions
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# Mixture of two univariate Gaussian

Measurement of height (in centimeters) for subjects from two groups (female/male).





Histogram of x

Height (cm)

#### Multivariate data

Create a dataset for clustering with two clusters and uniform noise.

R> head(data) x y class 51 4.68 4.625 c2 164 5.49 -0.898 noise 86 4.97 4.373 c2 79 5.68 7.728 c2 167 3.91 5.375 noise 71 5.68 1.813 c2

### Multivariate data II

R> plot(data)



### Multivariate data III

R> cl <- kmeans(data[-3],2)
R> plot(data, col= cl\$cluster)



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#### Exercises

- You use two dice for a party. The first die is fair while the second one has a 10% higher chance of rolling a 6 and a 5% each lower chance to role a 1 or a 4. Each time a player chooses randomly one die and rolls it. Display the distribution of the numbers rolled after 100 times. Hint: use sample for the dice.
- Create a variable with 100 random values following a Poisson distribution with parameters of your choice. Use a histogram and a Q-Q plot to compare the distribution to a normal distribution and to a Poisson distribution.