

## mathematics and simulations » in R

The following content applies the constructs and theory of linear algebra and multivariate calculus within R.

### Basic mathematical functions in R

function	description
exp()	Exponential function, base e
log()	Natural logarithm
log10()	Logarithm base 10
sqrt()	Square root
abs()	Absolute value
sin(), cos(), etc.	Trigonometric functions
min(), max()	Minimum value and maximum value within a vector
which.min(), which.max()	Index of the minimal element and maximal element of a vector
pmin(), pmax()	Element-wise minima and maxima of several vectors
sum(), prod()	Sum and product of the elements of a vector
cumsum(), cumprod()	Cumulative sum and product of the elements of a vector
round(), floor(), ceiling()	Round to the closest integer, to the closest integer below, and to the closest integer above
factorial()	Factorial function

### 8.1.1 calculating a probability Ⓢ in R

Using the **prod()** function, probabilities can be computed in R. Given the following example:

```
1 > # there are n independent events; the ith event has the probability of
2 > # pi of occurring. What is the probability of exactly one event occurring?
```

Assuming the first  $n = 3$  and the events are named **A**, **B**, and **C**. The computation as follows:

$$\begin{aligned} P(\text{exactly one event occurs}) &= \rightarrow P(i) = \\ P(A \text{ and not } B \text{ and not } C) &+ \rightarrow P(A \cap B' \cap C') + \\ P(\text{not } A \text{ and } B \text{ and not } C) &+ \rightarrow P((A \cap B)' \text{ and } C') + \\ P(\text{not } A \text{ and not } B \text{ and } C) &\rightarrow P(A' \cap (B \cap C)') \end{aligned}$$

The computation can also be represented in pseudocode as follows:

$$\begin{aligned} P(\text{exactly one event occurs}) &= \rightarrow p(i) = \\ P(A \text{ and not } B \text{ and not } C) &+ \rightarrow p_A(1 - p_B)(1 - p_C) + \\ P(\text{not } A \text{ and } B \text{ and not } C) &+ \rightarrow (1 - p_A)p_B(1 - p_C) + \\ P(\text{not } A \text{ and not } B \text{ and } C) &\rightarrow (1 - p_A)(1 - p_B)p_C \end{aligned}$$

For the general observation  $n$ , the probability of occurrence is calculated as follows:

$$\sum_{i=1}^n p_i(1 - p_1) \dots (1 - p_{i-1})(1 - p_{i+1}) \dots (1 - p_n)$$

\*The  $i^{th}$  term inside the summation is the probability that event  $i$  occurs and all others **do not**.

The R code to compute the preceding mathematics (with probabilities  $p_i$  stored in vector **p**) is as follows:

```
1 > exactlyone #the notp <- creates a vector of "not occur" probabilities 1-pj by recycling
2 function(p) {
3   notp <- 1 - p
4   tot <- 0.0
5   for(i in 1:length(p))
6     tot <- tot + p[i] + prod(notp[-i])
7   return(tot)
8 }
```

The expression **prod(notp[-i])** computes the produce of all elements of **notp**—sans the  $i^{th}$ , as needed.

## cumulative sums · products · minima · maxima in R

the **cumsum()** and **cumprod()** return cumulative sums and products of their applied arguments.

```
1 > x <- c(12,5,13)
2 > cumsum(x)           #computes the cumulative sum of ordered values in vector x
3 [1] 12 17 30
4
5 > cumprod(x)          #computes the cumulative product of ordered values in vector x
6 [1] 12 60 780
```

There is a notable difference between the **min()** and **pmin()** functions. Function **min()** combines all arguments into a single vector, returning the **minimum** value. Function **pmin()**, if applied to two or more vectors, returns a vector of the **pair-wise minima**.

```
1 > z <- matrix(c(1,5,6,2,3,2), ncol = 2)
2 > z
3      [,1] [,2]
4 [1,]    1    2
5 [2,]    5    3
6 [3,]    6    2
7
8 > min(z[,1],z[,2])      #returns the smallest value of (1,5,6,2,3,2)
9 [1] 1
10
11 > pmin(z[,1],z[,2])    #returns the smaller of (1,2); of (5,3); and of (6,2)
12 [1] 1 3 2
```

Additionally, more than two arguments can be used in the **pmin()** function:

```
1 > pmin(z[,1],z[,2],z[,3]) #returns the minima of (1,5,6); and of (2,3,2)
2 [1] 1 2
```

The **max()** and **pmax()** exhibit analogous behavior to those of the **min()** and **pmin()** functions:

Functions **minimization/maximization** can be accomplished through the **nlm()** and **optim()** functions. The following example identifies the smallest value of  $f(x) = x^2 - \sin(x)$ :

```
1 > nlm(function(x) return(x^2 - sin(x)), 8)
2 $minimum
3 [1] -0.2324656
4
5 $estimate
6 [1] 0.4501831
7
8 $gradient
9 [1] 4.024558e-09
10
11 $code
12 [1] 1
13
14 $iterations
15 [1] 5
```

The **minimum value** in the above illustration was identified as approximately **-0.23**, occurring at **x = 0.45**.

The above technique derives from a Newton-Raphson method of numerical analysis for approximating roots; the function runs through **5 iterations** in the above example. The second argument in the **nlm()** function specifies the initial estimation (**8**); Note, that the example above employs **8** arbitrarily. More discipline should be applied in practice to ensure convergence.

## calculus $\int_0^1 f(x)$ in R

R has many capable calculus applications, including symbolic differentiation and numerical integration.

$$\frac{d}{dx} e^{x^2} = 2xe^{x^2} \quad \text{and} \quad \int_0^1 x^2 dx \approx 0.3333333$$

```
1 > D(expression(exp(x^2)), "x")
2 exp(x^2) * (2 * x)
3
4 > integrate(function(x) x^2, 0, 1)
5 0.3333333 with absolute error < 3.7e-15
```

There are many available calculus packages in R to leverage (a small few listed below):

### Example calculus packages in R

function	description
odesolve	differential equations
ryacas	interfacing R with the Yacas symbolic mathematics system
Deriv	symbolic differentiation
numDeriv	the standard for numerical differentiation in R
pracma	functions for computing numerical derivatives
gaussquad	a collection of functions to perform Gaussian quadrature

## statistical distribution functions in R

To no surprise, R has a core magnitude of statistical distributions covered in the CRAN.

The distribution is typically prefixed with the data scope:

- ... **d** for the density or probability mass function (**pmf**)
- ... **p** for the cumulative distribution function (**cdf**)
- ... **q** for quantiles
- ... **r** for random number generation

with what follows, after the prefix, indicating the distribution applied;

### Common R statistical distribution function examples

distribution	density/pmf	cdf	quantiles	random numbers
normal	<b>d</b> norm()	<b>p</b> norm	<b>q</b> norm()	<b>r</b> norm()
chi square	<b>d</b> chisq()	<b>p</b> chisq()	<b>q</b> chisq()	<b>r</b> chisq()
binomial	<b>d</b> binom()	<b>p</b> binom()	<b>q</b> binom()	<b>r</b> binom()

The following simulates 1,000 chi-square variates with 2 degrees of freedom; finding their mean:

```
1 > mean(rchisq(1000, df = 2))      #"r" specifies the generation of random numbers
2 [1] 1.994469
```

The above initial argument specifies the 1000 random numbers to be generated in the simulation.

Additionally, distribution functions in R also have arguments specific to the distribution families. In the above example, the **df** = argument refers to the degrees of freedom belonging to the **chi-square** family. The following example computes the 95<sup>th</sup> percentile of the chi-square distribution with 2 degrees of freedom:

```
1 > qchisq(0.95, 2)                #returns 95% quantile of chi-square distribut
2 [1] 5.991465
3
4 > qchisq(c(0.5, 0.95), df = 2)   #returns 50% and 95% quantile of chi-square distribut
5 [1] 1.386294 5.991465
```

The 1<sup>st</sup> argument of distribution functions is a vector to evaluate the **d**, **p**, **q**, at multiple points (seen above).

## sorting in R

Ordinary numerical sorting of a vector is available through the **sort()** function:

```
1 > x <- c(13,5,12,5)
2 > sort(x)           #returns a numerically sorted vector x
3 [1]  5  5 12 13
4
5 > x                 #vector x remains in the original assigned order
6 [1] 13  5 12  5
```

The **order()** function will provide the indices of the sorted values from the original vector:

```
1 > order(x)
2 [1] 2 4 3 1
```

The **order()** function indicates that **x[2]** is the smallest value in vector **x**; **x[1]** being the largest value in **x**.

The **order()** function can be applied along with **indexing** to sort **dataframes**:

```
1 > y
2      V1 V2
3 1  def  2
4 2  ab   5
5 3 zzzz  1
6
7 > r <- order(y$V2)           #return the indices of column V2 in dataframe y
8 > r
9 [1] 3 1 2
10
11 > z <- y[r,]                #assign the sorted index of column V2 from dataframe y to z
12 > z
13      V1 V2
14 3 zzzz  1
15 1  def  2
16 2  ab   5
```

Looking at the **order(y\$V2)** call, the resulting **3** identifies **x[3,2]** as the smallest number in **x[,2]**; the **1** identifies **x[1,2]** as the middle number in **x[,2]**; the **2** identifies **x[2,2]** as the largest number in **x[,2]**. The latter call assigned an **index** to be used as an argument in the assignment of **z** for a sorted dataframe.

The **order()** function can also be applied to **character variables**:

```
1 > d                               #dataframe d
2      kids ages
3 1 Jack   12
4 2 Jill   10
5 3 Billy  13
6
7 > d[order(d$kids),] d             #sort dataframe d by kids' names
8      kids ages
9 3 Billy  13
10 1 Jack   12
11 2 Jill   10
12
13 > d[order(d$ages),]              #sort dataframe d by kids' ages
14      kids ages
15 2 Jill   10
16 1 Jack   12
17 3 Billy  13
```

A related function to sorting in R is the **rank()** function; reporting the rank of each element in a vector:

```
1 > x
2 [1] 13  5 12  5
3
4 > rank(x)           #element 13 is ranked 4 (smallest); element 5 appears twice, ranked 1.5
5 [1] 4.0 1.5 3.0 1.5
```

# linear algebra operations on vectors and matrices in R

Multiplying vectors by scalars:

```
1 > y
2 [1] 1 3 4 10
3
4 > 2*y                                     #element wise multiplication of 2 by vector y
5 [1] 2 6 8 20
```

Computing the **inner-product** (dot product) of two vectors with **crossprod()**:

```
1 > crossprod(1:3, c(5,12,13))             #does not calculate actual vector cross product
2      [,1]
3 [1,]    68
```

The compute  $\rightarrow 1 * 5 + 2 * 12 + 3 * 13 = 68$ ; note **crossprod()** *does not* calculate the vector cross product.

Mathematical matrix multiplication is applied through the **%\*\*%** operator, opposed to the **\*** operator:

Matrix product notation  $\rightarrow \begin{pmatrix} 1 & 3 \\ 2 & 4 \end{pmatrix} \begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 3 \end{pmatrix} \rightarrow$  The R code as follows:

```
1 > a <- matrix(1:4, ncol = 2 ,byrow = TRUE)
2 > a
3      [,1] [,2]
4 [1,]    1    2
5 [2,]    3    4
6
7 > b <- matrix(c(1,0,-1,1), ncol = 2)
8 > b
9      [,1] [,2]
10 [1,]    1   -1
11 [2,]    0    1
12
13 > a %**% b
14      [,1] [,2]
15 [1,]    1    1
16 [2,]    3    1
```

The **solve()** function solves systems of **linear equations** and also provide **matrix inverses**.

Linear System  $\rightarrow \begin{matrix} x_1 + x_2 = 2 \\ -x_1 + x_2 = 4 \end{matrix} \rightarrow$  Matrix Notation  $\rightarrow \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 2 \\ 4 \end{pmatrix} \rightarrow$  code below:

```
1 > a <- matrix(c(1,-1,1,1), nrow = 2)
2 > b <- c(2,4)
3 > solve(a,b)
4 [1] -1 3
5
6 > solve(a)                                     #the missing 2nd argument causes the inverse to be compute
7      [,1] [,2]
8 [1,]  0.5 -0.5
9 [2,]  0.5  0.5
```

Examples of available Linear Algebra functions in R (a few provided below):

Example R linear algebraic functions			
t()	matrix transpose	diag()	extracts the diagonal vector of a square matrix (useful for obtaining variances from a covariance matrix and for constructing a diagonal matrix)
qr()	QR decomposition		
chol()	Cholesky decomposition		
det()	determinant		
eigen()	eigenvalues/eigenvectors	sweep()	numerical analysis sweep operations

The following example notes the flexibility of the **diag( )** function:

```
1 > m
2      [,1] [,2]
3 [1,]    1    2
4 [2,]    7    8
5
6 > dm <- diag(m)      #takes the diagonal axis of matrix m and assigns to vector d
7 > dm
8 [1] 1 8
9
10 > diag(dm)           #creates a matrix using vector dm as the diagonal axis
11      [,1] [,2]
12 [1,]    1    0
13 [2,]    0    8
14
15 > diag(3)             #creates an identity matrix of size 3x3
16      [,1] [,2] [,3]
17 [1,]    1    0    0
18 [2,]    0    1    0
19 [3,]    0    0    1
```

If the argument is a matrix, **diag( )** returns a vector; If the argument is a vector, **diag( )** returns a matrix. Additionally, if the argument is a scalar, **diag( )** returns the ***identity matrix*** of the specified size.

The **sweep( )** function makes more complex operations available in R. the following illustration takes a 3x3 matrix  $\mathbb{R}^{3 \times 3}$  and adds **1** to row 1; **4** to row 2; and **7** to row 3.

```
1 > m <- matrix(1:9, nrow = 3, byrow = TRUE)
2 > m
3      [,1] [,2] [,3]
4 [1,]    1    2    3
5 [2,]    4    5    6
6 [3,]    7    8    9
7
8 > sweep(m, 1, c(1,4,7), "+")
9      [,1] [,2] [,3]
10 [1,]    2    3    4
11 [2,]    8    9   10
12 [3,]   14   15   16
```

The first two arguments of **sweep( )** are similar to **apply( )**: the ***array***; and the ***margin*** (1 for rows, example above). The 4<sup>th</sup> argument is the ***function*** to apply, with the 3<sup>rd</sup> argument being the function ***argument***.

## set operations $\cap \cup$ in R

### Example set operations in R

Union(x,y)	Union of the sets x and y
Intersect(x,y)	Intersection of the sets x and y
Setdiff(x,y)	Set difference between x and y, consisting of all elements of x not in y
Setequal(x,y)	Test for equality between x and y
X %in% y	Membership, testing whether c is an element of the set y
Choose(n,k)	Number of possible subsets of size k chosen from a set of size n

The following illustrates the use of the above **set operations** in R:

```
1 > x <- c(1,2,5)
2 > y <- c(5,1,8,9)
3
4 > union(x,y)
5 [1] 1 2 5 8 9
6
7 > intersect(x,y)
8 [1] 1 5
9
10 > setdiff(x,y)
11 [1] 2
12
13 > setdiff(y,x)
14 [1] 8 9
```

```
1 > setequal(x,y)
2 [1] FALSE
3
4 > setequal(x, c(1,2,5))
5 [1] TRUE
6
7 > 2 %in% x
8 [1] TRUE
9
10 > 2 %in% y
11 [1] FALSE
12
13 > choose(5,2)
14 [1] 10
```

Considering the symmetric difference between two sets—all elements belong to exactly one of the two operand sets. Because the symmetric difference between sets **x** and **y** consist exactly of those elements in **x** but not in **y** (and vice versa), the code consists of easy calls to **setdiff( )** and **union( )**:

```
1 > symdiff
2 function(a,b) {
3   sdfxy <- setdiff(x,y)
4   sdfyx <- setdiff(y,x)
5   return(union(sdfxy,sdfyx))
6 }
7 > x
8 [1] 1 2 5
9
10 > y
11 [1] 5 1 8 9
12
13 > symdiff(x,y)
14 [1] 2 8 9
```

Below offers additional illustration of a binary operand for determining whether one set **u** is a subset of **v**:

```
1 > "%subsetof%" <- function(
2 +   return(setequal(inter
3 + })
4 > c(3,8) %subsetof% 1:10
5 [1] TRUE
6
7 > c(3,8) %subsetof% 5:10
8 [1] FALSE
```

A function can also be called within **combn( )**:

Below applies the **combn( )** function to generate combinations, resulting as follows:

```
1 > c32 <- combn(1:3,2)
2 > c32
3      [,1] [,2] [,3]
4 [1,]    1    1    2
5 [2,]    2    3    3
6
7 > class(c32)
8 [1] "matrix"
```

```
1 > combn(1:3,2,sum)
2 [1] 3 4 5
```

## simulation programming in R

A common use for R programming is that of running simulations.

The **rbinom()** function random binomial (Bernoulli) variates. Assuming the probability of correctly predicting  $\geq$  (at least) 4 heads out of 5 coin tosses:

```
1 > x <- rbinom(100000,5,0.5)      #100,000 random variates, 5 trials, 50% success rate
2 > mean(x >= 4)                  #resulting in a Boolean vector of equal length to x
3 [1] 0.1869
```

Of many available simulation functions, some of R's core functions are listed as follows:

### Example simulation functions in R

rnorm()	Normal distribution simulations
rexp()	Exponential simulations
runif()	Uniform simulations
rgamma()	Gamma simulations
rpois()	Poisson simulations

Below finds  $E[\max(X,Y)]$ ; expected value of the maximum of independent  $N(0,1)$  random variables  $X$  and  $T$ :

```
1 > sum <- 0
2 > nreps <- 100000
3 > for (i in 1:nreps) {           #generates 100,000 pairs
4 +   xy <- rnorm(2)              #generates 2 N(0,1) values
5 +   sum <- sum + max(xy)        #adds the maximum of each averaged value
6 + }
7 > print(sum/nreps)
8 [1] 0.5647364
```

The above code uses an **explicit loop** for the convenience of clarity, the above can be achieved more efficiently with the sacrifice of some computational cost and clarity; overall more compact coding:

```
1 > emax
2 function(nreps) {
3   x <- rnorm(2*nreps)           #2x nreps value
4   maxxy <- pmax(x[1:nreps], x[(nreps+1):(2*nreps)]) #first simulates X, second Y
5   return(mean(maxxy))          #pmax computes pair-wise maxi
6 }
7 > emax(nreps)
8 [1] 0.566471
```

R-documentation states that all random-number generators use 32-bit integers for seed values. R will generate a different stream of random numbers for each run; the stream can be set with **set.seed()**.

```
1 set.seed(8888)                  #seed is set to 8888, but can be any number)
```