

# Introduction to R\*

Lecture 5: Environments, Running R , Libraries and some probability distributions

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# 1 R Environments

under construction

# 2 Running R

under construction

# 3 R Packages

under construction

## 3.1 Installation of R packages

## 3.2 Using R packages

# 4 Probability distributions

R comes with the most important probability distributions installed. They can be classified as:

- discrete distributions
- continuous distributions

## 4.1 Discrete distributions

Let  $\mathbb{P}(X = k; \{\xi\})$  be a discrete probability mass function when the random variable  $X = k$  and which depends on the parameter set  $\{\xi\}$ .

Let **distro** be the name of the corresponding distribution. Then,

- **ddistro**( $k, \dots$ ) : calculates the probability  $\mathbb{P}(X = k)$
- **pdistro**( $k, \dots$ ) : calculates the cumulative probability function (CDF) at  $k$ :

$$F(X = k; \{\xi\}) := \sum_{j=0}^k \mathbb{P}(X = j)$$

- **qdistro**( $p, \dots$ ): calculates the value of  $k$  where  $p = F(k; \{\xi\})$  or  $k = \lceil F^{-1}(p; \{\xi\}) \rceil$
- **rdistro**( $n, \dots$ ): generates a vector of  $n$  random values sampled from the distribution **distro**.

Some common discrete probability distributions

distro	Name	$\mathbb{P}(X = k; \{\xi\})$	Parameter set ( $\{\xi\}$ )
binom	Binomial	$\binom{n}{k} p^k (1-p)^{n-k}$	$0 \leq p \leq 1$
nbinom	Negative Binomial	$\binom{k+r-1}{k} (1-p)^k p^r$	$0 \leq p \leq 1 ; r > 0$
hyper	Hypergeometric	$\frac{\binom{K}{k} \binom{N-K}{n-k}}{\binom{N}{n}}$	$N \in \{0, 1, 2, \dots\}; K, n \in \{0, 1, \dots, N\}$
pois	Poisson	$\frac{\lambda^k e^{-\lambda}}{k!}$	$0 < \lambda < \infty$

#### 4.1.1 Examples

- Let's consider the following distribution: `binom(p = 0.3, n = 5)`.

```
n <- 5
p <- 0.3
# Own code for the binom distribution
mybinom <- function(n,p){
  v <- vector(mode="double", length=(n+1))
  for(k in 0:n){
    v[k+1] <- choose(n,k)*p^k*(1-p)^(n-k)
  }
  return(v)
}
pvec <- mybinom(n,p)
```

- Value of the PMF at  $k = \{0, 1, \dots, 5\}$ :

```
for(k in 0:n){
  cat(sprintf(" P(X=%d):%8.6f and should be %8.6f\n",
    k, dbinom(k, size=n, p), pvec[k+1]))
}
```

```
P(X=0):0.168070 and should be 0.168070
P(X=1):0.360150 and should be 0.360150
P(X=2):0.308700 and should be 0.308700
P(X=3):0.132300 and should be 0.132300
P(X=4):0.028350 and should be 0.028350
P(X=5):0.002430 and should be 0.002430
```

- Value of the CDF at  $k = \{0, 1, \dots, 5\}$ :

```
for(k in 0:n){
  cat(sprintf(" F(X=%d):%8.6f and should be %8.6f\n",
    k, pbinom(k, size=n, p), sum(pvec[1:(k+1)]) ))
}
```

```
F(X=0):0.168070 and should be 0.168070
F(X=1):0.528220 and should be 0.528220
F(X=2):0.836920 and should be 0.836920
```

```

F(X=3):0.969220 and should be 0.969220
F(X=4):0.997570 and should be 0.997570
F(X=5):1.000000 and should be 1.000000

```

– The quantile function:

```

pvec <- c(0.0, 0.25, 0.50, 0.75, 1.00)
for(item in pvec){
  cat(sprintf(" P:%4.2f => k=%d\n",
    item, qbinom(item,size=n, prob=p)))
}

```

```

P:0.00 => k=0
P:0.25 => k=1
P:0.50 => k=1
P:0.75 => k=2
P:1.00 => k=5

```

– Sampling random numbers from the distribution:

```

tot <- 15
vec <- rbinom(tot,size=n, prob=p)
print(vec)

```

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

## 4.2 Continuous distributions

Let  $f(x; \{\xi\})$  be a continuous probability density function (pdf), which depends on the variable  $x$  and the parameter set  $\{\xi\}$ .

Let **distro** be the name of the corresponding distribution. Then,

- **ddistro**( $x, \dots$ ) : calculates the value of the pdf at  $x$ , i.e.  
 $f(x; \{\xi\})$
- **pdistro**( $x, \dots$ ) : calculates the cumulative probability function (cdf) at  $x$ :  
$$F(x; \{\xi\}) := \int_{-\infty}^x f(t; \{\xi\}) dt$$
- **qdistro**( $p, \dots$ ): calculates the value of  $x$  where  $p = F(x; \{\xi\})$  or  
 $x = F^{-1}(p; \{\xi\})$
- **rdistro**( $n, \dots$ ): generates a vector of  $n$  random values sampled from the distribution **distro**.

Some common continuous distributions (see e.g. (Casella & Berger, 2002)) are:

distro	Name	$f(x; \{\xi\})$	Dom( $x$ )	Parameter set ( $\{\xi\}$ )
unif	Uniform	$\frac{1}{(b-a)}$	$a \leq x \leq b$	$a, b$
norm	Normal	$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$	$-\infty < x < \infty$	$-\infty < \mu < \infty, \sigma > 0$
cauchy	Cauchy	$\frac{1}{\pi\sigma} \frac{1}{1 + \left(\frac{x-\theta}{\sigma}\right)^2}$	$-\infty < x < \infty$	$-\infty < \theta < \infty, \sigma > 0$
t	t-Student	$\frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})} \frac{1}{\nu\pi} \frac{1}{\left(1 + \frac{x^2}{\nu}\right)^{(\nu+1)/2}}$	$-\infty < x < \infty$	$\nu = 1, 2, \dots$
chisq	Chi-squared	$\frac{1}{\Gamma(\nu/2)2^{(\nu/2)}} x^{(\nu/2)-1} e^{-\frac{x}{2}}$	$0 \leq x < \infty$	$\nu = 1, 2, \dots$
f	F	$\frac{\Gamma(\frac{\nu_1+\nu_2}{2})}{\Gamma(\frac{\nu_1}{2})\Gamma(\frac{\nu_2}{2})} \frac{x^{(\nu_1-2)/2}}{\left(1 + \left(\frac{\nu_1}{\nu_2}\right)x\right)^{(\nu_1+\nu_2)/2}}$	$0 \leq x < \infty$	$\nu_1, \nu_2 = 1, 2, \dots$
exp	Exponential	$\lambda e^{-\lambda x}$	$0 \leq x < \infty$	$\lambda > 0$

where  $\Gamma(x)$  stands for the gamma function which has the following mathematical form:

$$\Gamma(x) := \int_0^\infty t^{x-1} e^{-t} dt$$

#### 4.2.1 Examples

- Let's consider the following distribution:  $N(\mu = 5.0, \sigma^2 = 4.0)$ .  
Therefore, **distro:norm**

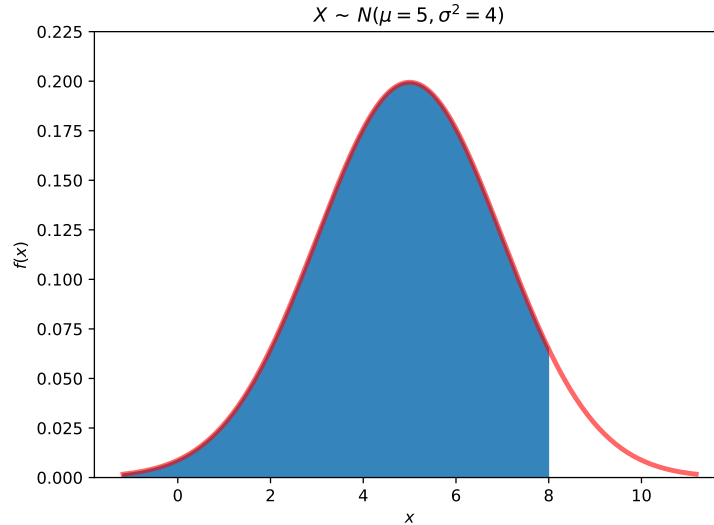


Figure 1: Plot of the normal distribution (red). The area under the curve (blue) represents the cumulative probability at  $x = 8.0$ .

```
x <- 8.0
mu <- 5.0
sigma <- 2.0
```

- Value of the PDF at  $x$ :

```
cat(sprintf("The density at %f is %12.10f\n", x, dnorm(x,mean=mu, sd=sigma)))
```

The density at 8.000000 is 0.0647587978

- Value of the CDF at  $x$ :

```
prob <- pnorm(x,mean=mu,sd=sigma)
cat(sprintf("The Cumulative Probability at %f is %12.10f", x, prob))
```

The Cumulative Probability at 8.000000 is 0.9331927987

- The quantile function:

```
cat(sprintf("The point where the Cumulative Probability is %12.10f: %8.4f",
            prob, qnorm(prob, mean=mu, sd=sigma)))
```

The point where the Cumulative Probability is 0.9331927987: 8.0000

- Sampling random numbers from the distribution:

```
vec <- rnorm(n=10, mean=mu, sd=sigma)
print(vec)
```

```
[1] 5.3621494 6.7463792 2.5564777 7.9355664 3.9496334 3.8057722 5.8507367
[8] 0.6241145 5.0169393 5.4506935
```

## Bibliography

Casella G. & Berger R.L. (2002). Statistical Inference. Duxbury Advanced Series in Statistics and Decision Sciences. Thomson Learning.