

Theoretical distributions of probability

Combinatorial analysis

Problem - oligomers

- How many oligomers contain exactly a single occurrence of each monomer, for oligonucleotides and oligopeptides, respectively ?

Permutations within a set - the factorial

- How many distinct permutations can be made from a set of x elements ?
 - $x = 2$ 2
 - $x = 3$ $3*2 = 6$
 - $x = 4$ $4*3*2 = 24$
 - *any* x $x*(x-1)*...1 = x!$
- The **factorial** $x!$ represents the number of possible permutations between x objects.
- Solution to the problem of oligomers
 - There are $4!=24$ distinct oligonucleotides with a single occurrence of each nucleotide (A, C, G, T)
 - There are $20!=2.4*10^{18}$ distinct oligopeptides with a single occurrence of each amino acid.

Problem - Selection of a subset of elements

- A genome contains $n=6000$ genes.
- We select a series of genes in the following way :
 - Once a gene has been selected once, it cannot be selected anymore (**no replacement**)
 - We are not interested in the order of the selection: if A and B were selected, we do not consider whether A came out in first or in second position.
- How many possibilities do we have to select
 - 1 gene ?
 - 2 genes ?
 - 3 genes ?
 - x genes ?

Selection of a subset of elements

Selection	Possible outcomes		Possible orderings		Distinct outcomes (orderless)
	calculation	value	calculation	value	
1	6000	6.00E+03	1	1	6.00E+03
2	6000*5999	3.54E+07	2*1	2	1.77E+07
3	6000*5999*5998	2.16E+11	3*2*1	6	3.60E+10
...
10	6000*5999*...*5991	6.00E+37	10*9*...*1	3628800	1.65E+31

- Number of possible outcomes
 - n size of the set
 - x size of the subset
- Possible permutations among the elements of a subset
- Number of distinct selections (orderless).
- The coefficient C_x^n represents the number of distinct choices of x elements among n . For this reason, it is called "**Choose x among n** ". It is also called **binomial coefficient** (we will see later why).

$$n(n-1)(n-2)\dots(n-x+1) = \frac{n!}{(n-x)!}$$

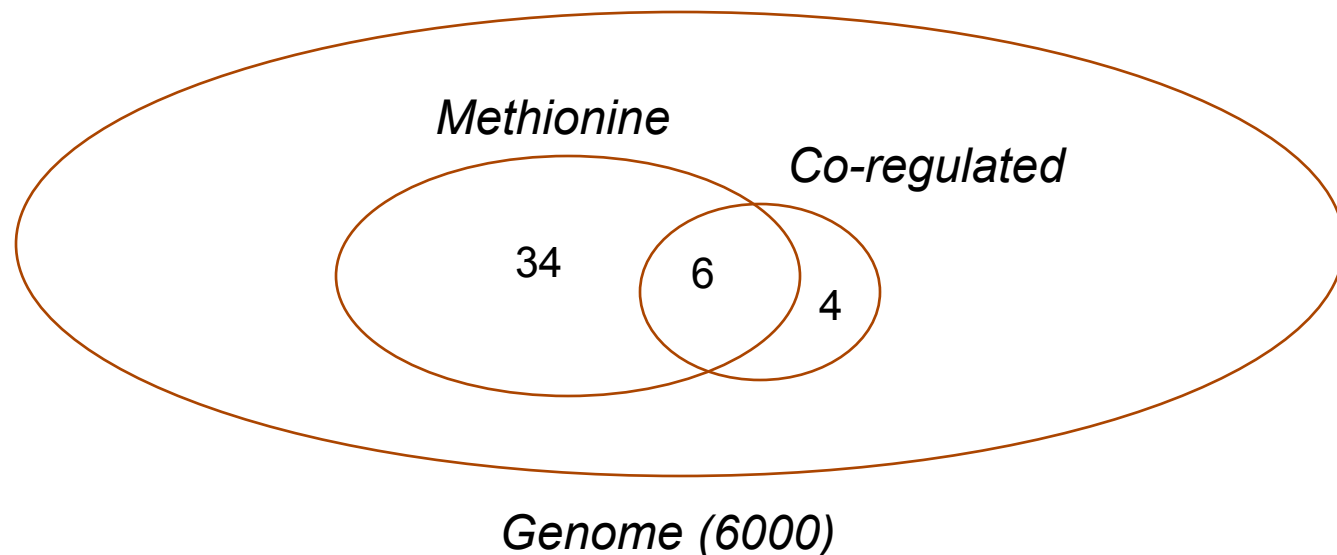
$$x!$$

$$C_n^x = \binom{n}{x} = \frac{n!}{x!(n-x)!}$$

Set comparisons

Problem - selection within a set with classes

- A given organism has 6,000 genes, 40 of which are involved in methionine metabolism.
- A set of 10 genes were reported as co-regulated in a microarray experiment. Among them, 6 are related to methionine metabolism.
- How significant is this observation ? More precisely, what would be the probability to observe such a correspondence by chance alone ?



Selection within a set with classes

- Let us define
 - $g = 6000$ number of genes
 - $m = 40$ genes involved in methionine metabolism
 - $n = 5960$ genes not involved in methionine metabolism
 - $k = 10$ number of genes in the cluster
 - $x = 6$ number of methionine genes in the cluster

- We calculate the number of possibilities for the following selections

- **C1**: 10 distinct genes among 6,000
- **C2**: 6 distinct genes among the 40 involved in methionine
- **C3**: 4 genes among the 5960 which are not involved in methionine
- **C4**: 6 methionine and 4 non-methionine genes

$$C1 = C_{m+n}^k = \frac{6000!}{10!5990!} = 1.65e^{31}$$

$$C2 = C_m^x = \frac{40!}{6!34!} = 3.8e^6$$

$$C3 = C_n^{k-x} = \frac{5960!}{4!5956!} = 5.2e^{13}$$

$$C4 = C_m^x C_n^{k-x} = 2.0e^{20}$$

- Probability to have exactly 6 methionine genes within a selection of 10

$$P(X = 6) = \frac{C_m^x C_n^{k-x}}{C_{m+n}^k} = 1.219e^{-11}$$

- Probability to have at least 6 methionine genes within a selection of 10

$$P(X \geq 6) = \sum_{i=x}^k \frac{C_m^i C_n^{k-i}}{C_{m+n}^k} = 1.222e^{-11}$$

The hypergeometric distribution

- The hypergeometric distribution represents the probability to observe x successes in a sampling without replacement

- m number of marked elements in the set
- n number of non-marked elements in the set
- k sample size
- x number of marked elements in the sample

$$P(X = x) = \frac{C_m^x C_n^{k-x}}{C_{m+n}^k}$$

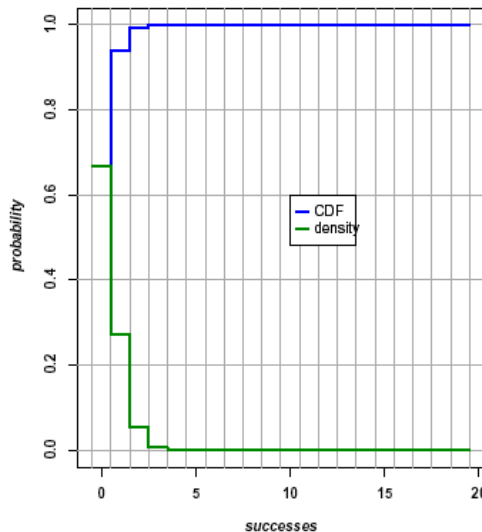
- The shape of the distribution depends on the ratio between m and n

- $m \ll n$ *i-shaped*
- $m \sim n$ *bell-shaped*
- $m \gg n$ *j-shaped*

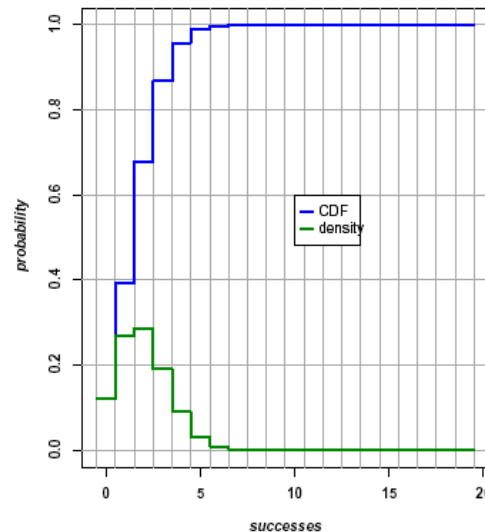
- The distribution is bounded on both sides ($0 \leq x \leq k$).
- Statistical parameters

$$\begin{aligned} \min(x) &= 0 \\ \max(x) &= \min(k, m) \\ \mu &= km / (m + n) \\ \sigma^2 &= \end{aligned}$$

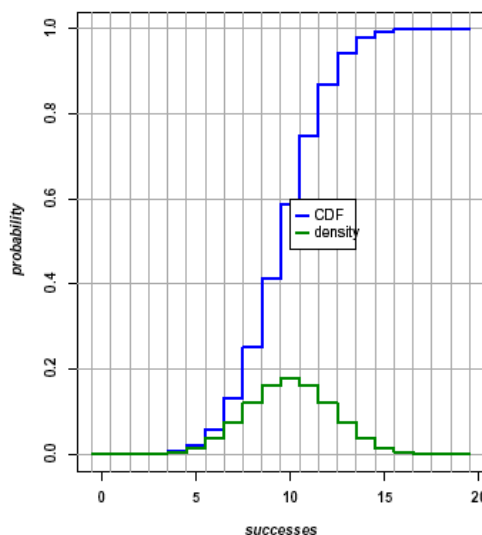
Hypergeometric ($m=120, n=5880, k=20$)



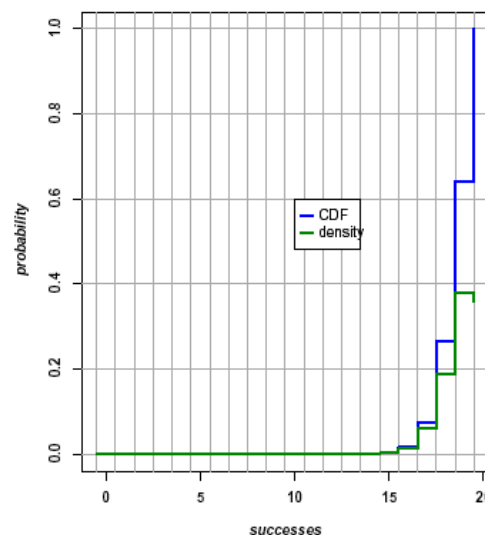
Hypergeometric ($m=600, n=5400, k=20$)



Hypergeometric ($m=3000, n=3000, k=20$)



Hypergeometric ($m=5700, n=300, k=20$)



Bernoulli Schemas

Bernoulli trial

- A Bernoulli trial is an experiment whose outcome is random and can lead to either of two possible outcomes, called **success** and **failure**, respectively.
- Examples :
 - Selection of a random nucleotide. Success if the nucleotide is a G.
 - Looking at a position from an alignment of two sequences. Success if this position corresponds to a match.
 - Selection of one gene from the yeast genome; success if the gene belongs to a specific functional class (e.g. Methionine biosynthesis).

Bernoulli schema

- A Bernoulli schema is a succession of n trials, each of which can lead or not to the realization of an event A.
 - Trials must be independent from each other
 - The probability of success is constant during the n trials
 - p is the probability of success at each trial
 - $q = 1 - p$ is the probability of failure at each trial
- Examples :
 - generation of a random sequence of length n ; event X is the addition of a purine

Extreme cases - all successes or all failures

- What is the probability to observe n successes during the n trials ?
 - We can apply the joint probability for stochastically independent events :

$$P(A_1, A_2, \dots, A_n) = P(A_1)P(A_2) \dots P(A_n)$$

- And since the probability of success is constant during the trials

$$P(A_1, A_2, \dots, A_n) = P(A)^n = p^n$$

- What is the probability to observe n failures during the n trials ?

$$P(\neg A_1, \neg A_2, \dots, \neg A_n) = P(\neg A)^n = (1 - p)^n = q^n$$

Problems - series of successes/failures

- In a random gapless alignment of two DNA sequences, what is the probability to observe a succession of exactly 10 matches at a given position ?

ATTAGTACCGTAGTAA

| | | | | | | | - | - - | |

ATTAGTACCGCACAAA

- In a random sequence with equiprobable nucleotides, what is the probability to observe the first G at the 30th position ?

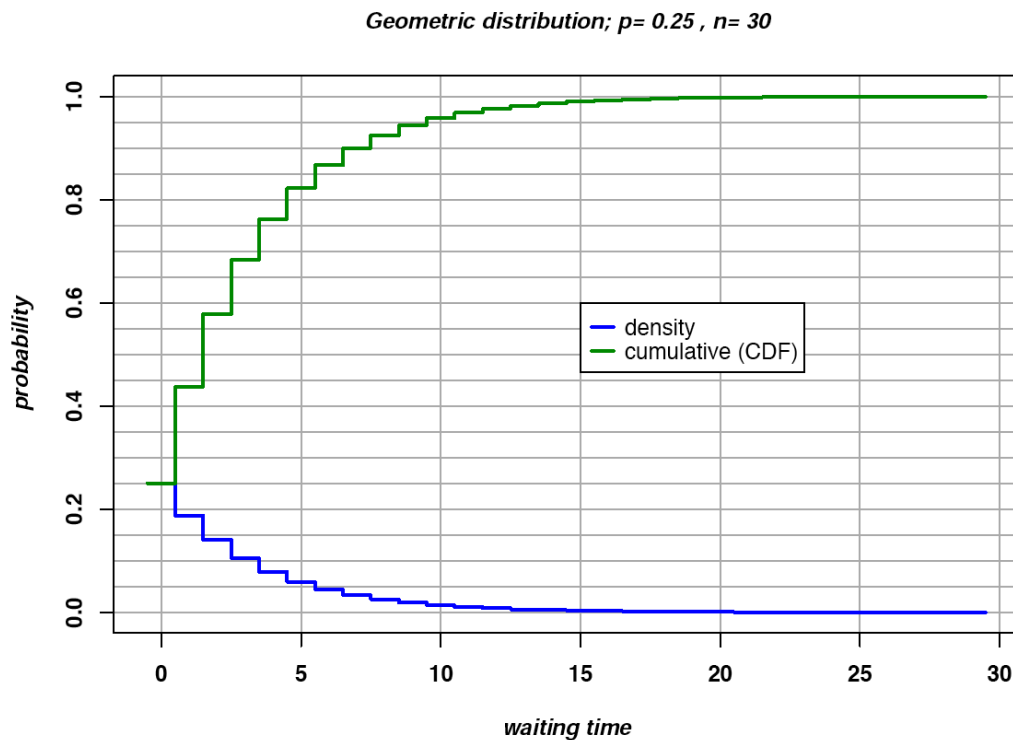
123456789012345678901234567890

ATTACTCTTACTCTCATCTATCTTTTCATCG

Series of successes/failures

- In a random gapless alignment of two DNA sequences, what is the probability to observe a succession of exactly 10 matches at a given position ?
 - $P(\text{match}) = p = 0.25$
 - $P(10 \text{ matches}) = p^{10} = 9.54e^{-7}$
 - $P(\text{mismatch}) = 1 - p = 0.75$
 - $P(10 \text{ matches and 1 mismatch}) = p^{10}(1 - p) = 7.15e^{-7}$
- In a random sequence with equiprobable nucleotides, what is the probability to observe the first G at position 30 ?
 - $P(G) = p = 0.25$
 - $P(\text{not } G) = 1 - p = 0.75$
 - $P(\text{no } G \text{ between positions 1 and 29}) = (1 - p)^{29} = 2.38e^{-4}$
 - $P(\text{first } G \text{ at position 30}) = (1 - p)^{29}p = 5.95e^{-5}$

The geometric distribution



- The geometric distribution is used to calculate the probability to observe
 - x consecutive successes followed by a failure

$$P(X = x) = p^x (1 - p)$$

- x consecutive failures followed by a success

$$P(X = x) = (1 - p)^x p$$

Defined succession of successes and failures

- What is the probability to first observe s consecutive successes, followed by $n-s$ consecutive failures ?

$$P(A_1, A_2, \dots, A_s) = p^s$$

$$P(\neg A_{s+1}, \neg A_{s+2}, \dots, \neg A_n) = q^{n-s}$$

$$P(A_1, A_2, \dots, A_s, \neg A_{s+1}, \dots, \neg A_n) = p^s q^{n-s}$$

Permutations of successes and failures

- How many ways are there to permute s successes and $n-s$ failures ?
- The number of permutations of x **distinct** objects is given by the factorial

$$\begin{aligned}0! &= 1 & 1! &= 1 \\x! &= x(x-1)! \\x! &= x(x-1)(x-2)\dots 2 \text{ when } x \text{ is large}\end{aligned}$$

- However
 - The s successes are not distinct from each other
 - The $n-s$ failures are not distinct from each other
- The number of permutations of s objects of one type and $n-s$ objects of the other type is given by the *binomial coefficient*

$$C_n^s = \binom{n}{s} = \frac{n!}{s!(n-s)!}$$

The binomial distribution (Bernoulli distribution)

- What is the probability to observe x successes during the n trials (irrespective of the particular order of succession) ?

$$P(X = x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x} = C_n^x p^x (1-p)^{n-x}$$

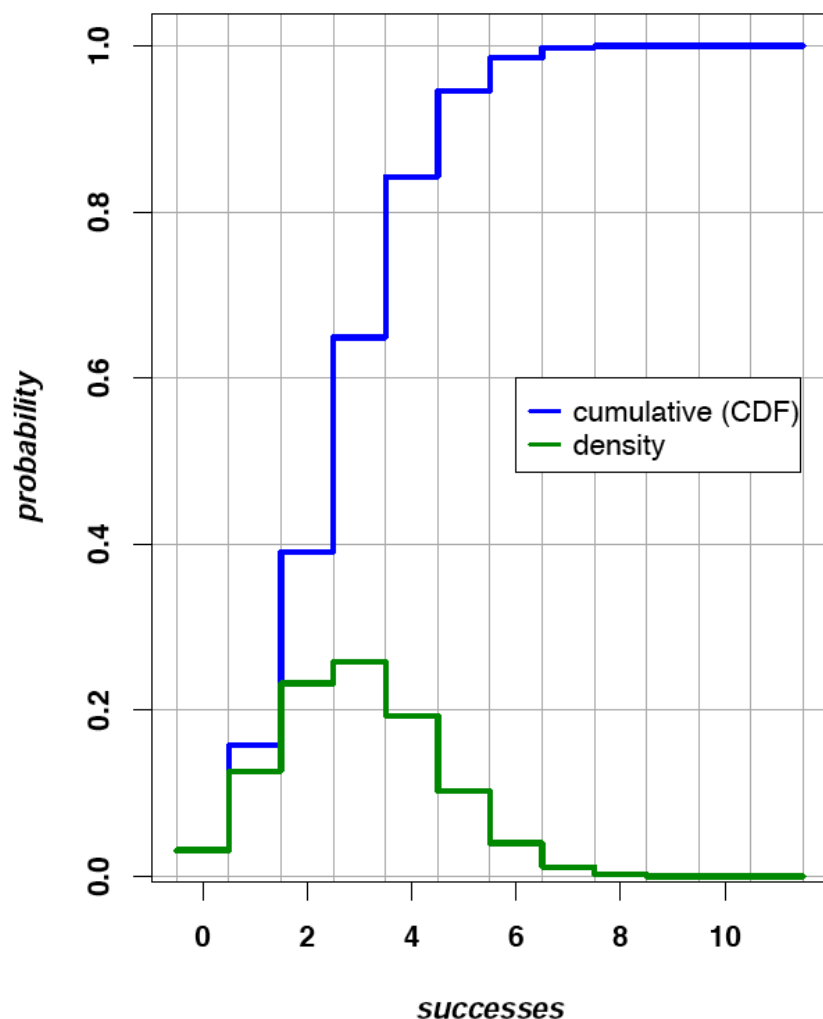
- This is the **binomial probability**.
- In this formula, the term C_n^x (*choose x among n*) is called the **binomial coefficient**.
- What is the probability to observe **up to** x successes during the n trials (irrespective of the particular order of succession) ?

$$P(X \leq x) = \sum_{i=0}^x \frac{n!}{i!(n-i)!} p^i (1-p)^{n-i}$$

- This is the **binomial cumulative distribution function (CDF)**.

The binomial distribution

Binomial ($p=0.25$, $n=12$)



- The binomial distribution represents the probability to observe x successes in a Bernoulli trial (such as a sampling **with replacement**).

- Parameters

- p the probability of success at each trial
- n number of trials
- x number of successes in the sample

- Values (X axis) are

- always positive
- comprised between 0 and n

- Probabilities (Y axis) are comprised between 0 and 1

- In R

- `dbinom(x,n,p)` ## Density function
- `pbinom(x,n,p)` ## CDF, left tail, inclusive
- `pbinom(x,n,p,lower.tail=F)` ## CDF, right tail, exclusive
- `pbinom(x-1,n,p,lower.tail=F)` ## CDF, right tail, inclusive

$$\min(s) = 0$$

$$\max(s) = n$$

$$\mu = np$$

$$\sigma^2 = np(1 - p) = npq$$

Binomial : efficient computation

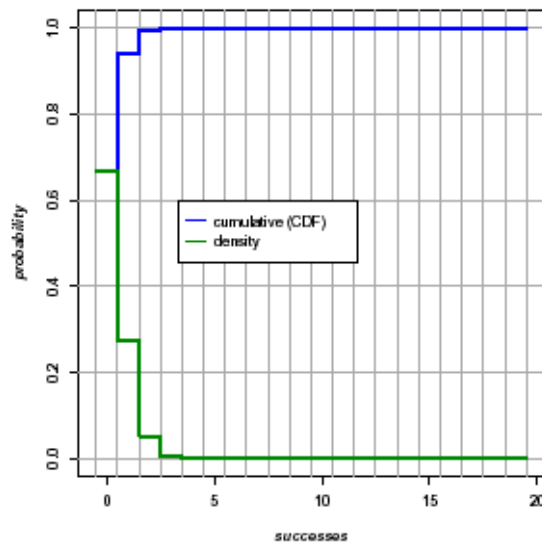
- The binomial probability can be computed efficiently by using a recursive formula.
- This drastically reduces the computation time.

$$P(X = 0) = (1 - p)^n$$

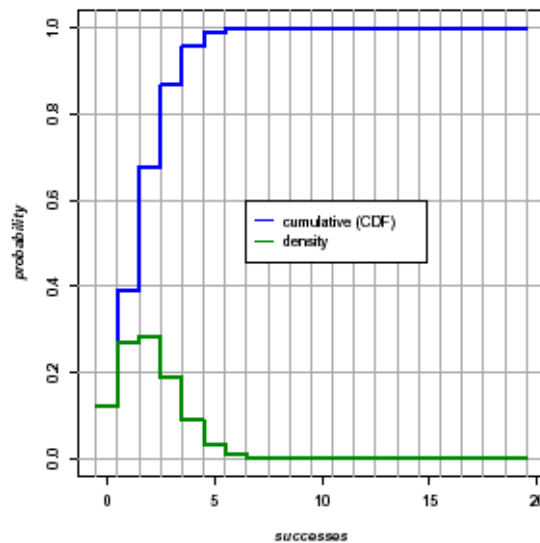
$$P(X = x + 1) = P(X = x) \frac{p(n - x)}{(1 - p)(x + 1)}$$

Binomial - effect of p (probability of success)

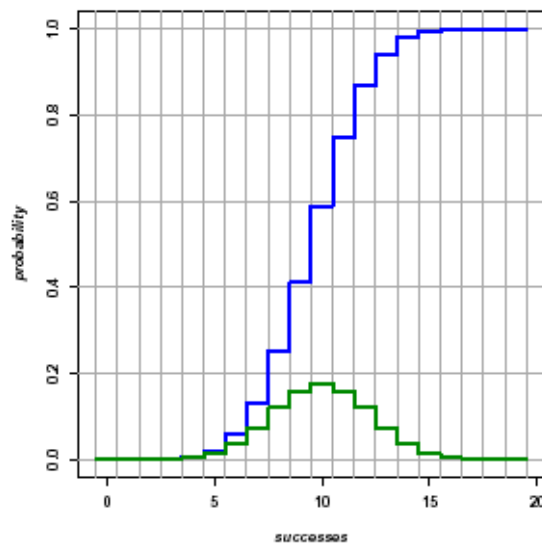
Binomial ($p=0.02$, $n=20$)



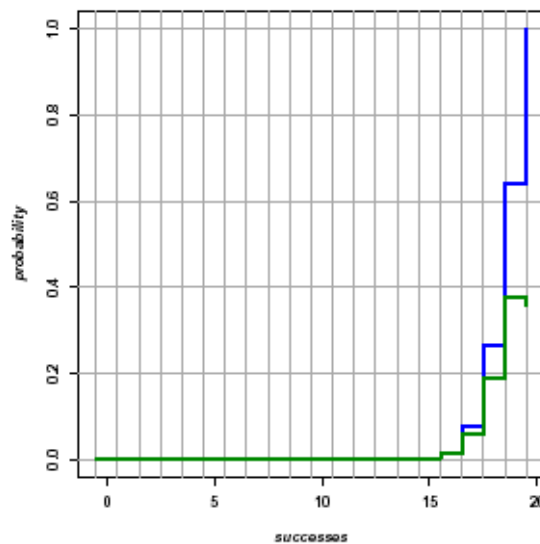
Binomial ($p=0.1$, $n=20$)



Binomial ($p=0.5$, $n=20$)



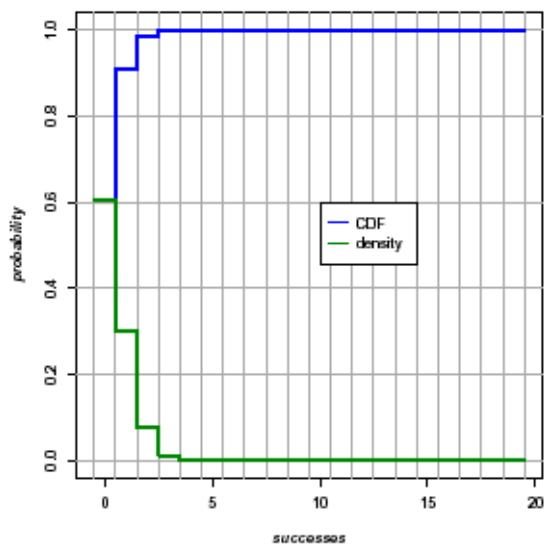
Binomial ($p=0.95$, $n=20$)



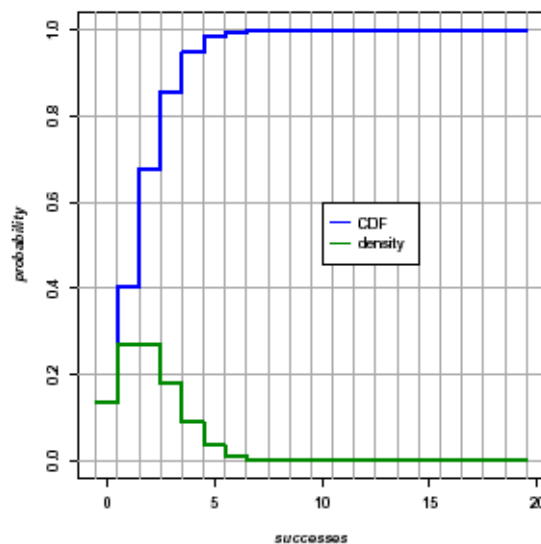
- The curve can take different shapes
 - i-shaped (small p)
 - bell-shaped (intermediate p)
 - j-shaped (high p)
- The curve is asymmetric, except when $p=0.5$
- The curve is bounded on both sides ($0 \leq s \leq n$)

Poisson distribution

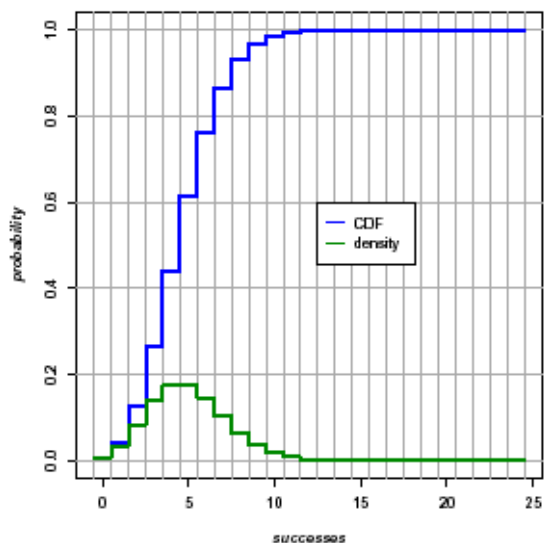
Poisson (lambda= 0.5)



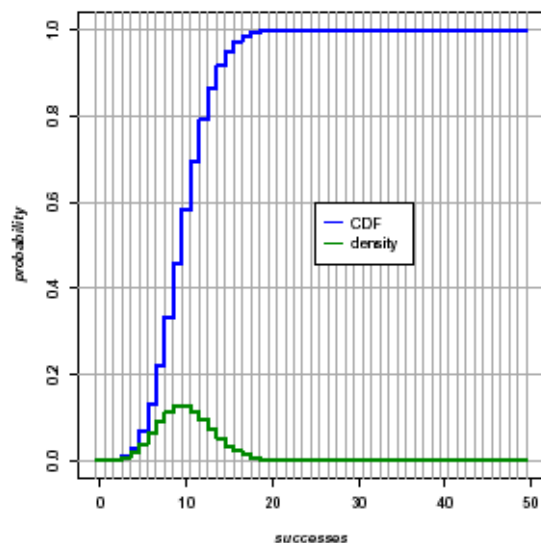
Poisson (lambda= 2)



Poisson (lambda= 5)



Poisson (lambda=10)



$$P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

$$\min(X) = 0 \quad \max(X) = \infty$$
$$\mu = \lambda \quad \sigma^2 = \lambda$$

- The Poisson distribution is characterized by a single parameter, λ , which is the mean of the distribution.
- The Poisson distribution can be used as an approximation of the binomial when
 - $n \rightarrow \infty$
 - $p \rightarrow 0$
 - $\lambda = p \cdot n$ is small (e.g. < 5)
- The curve is bounded on the left ($\min=0$).

Poisson - efficient computation

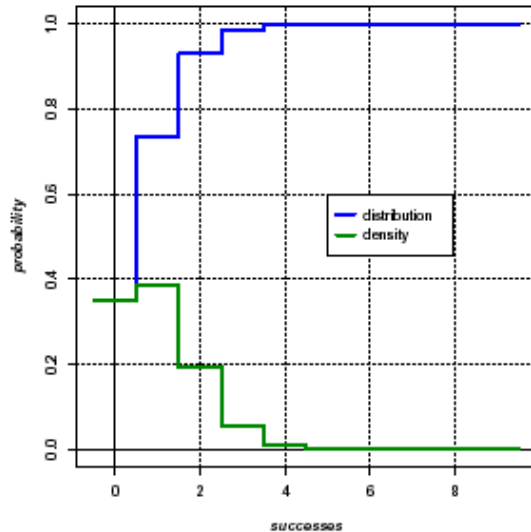
- The Poisson probability can be calculated efficiently with a recursive formula

$$P(X = 0) = e^{-E_w}$$

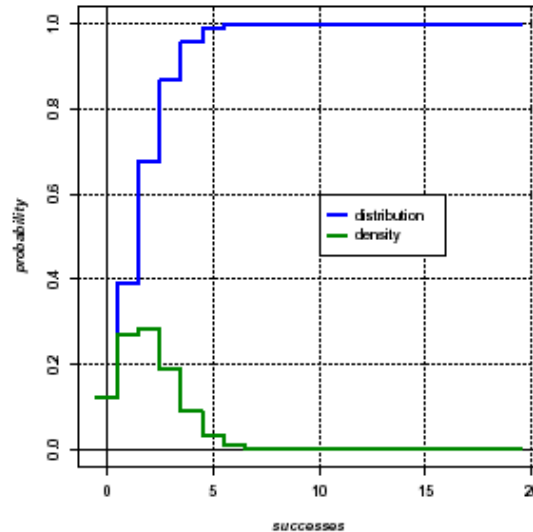
$$P(X = C_w + 1) = P(X = C_w) \frac{E_w}{(z + 1)}$$

Binomial - effect of n (number of trials)

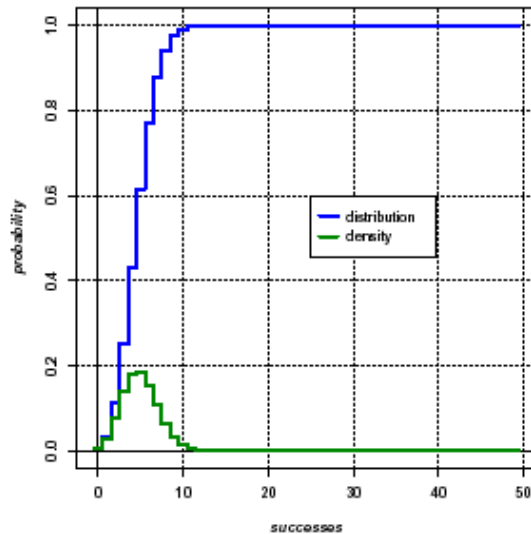
Binomial density and distribution : 10 trials



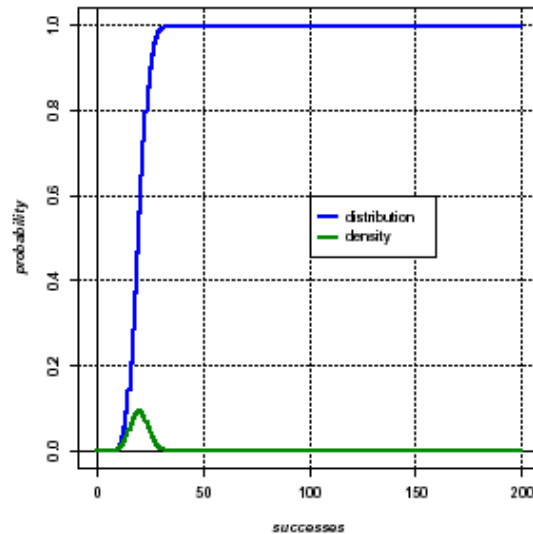
Binomial density and distribution : 20 trials



Binomial density and distribution : 50 trials

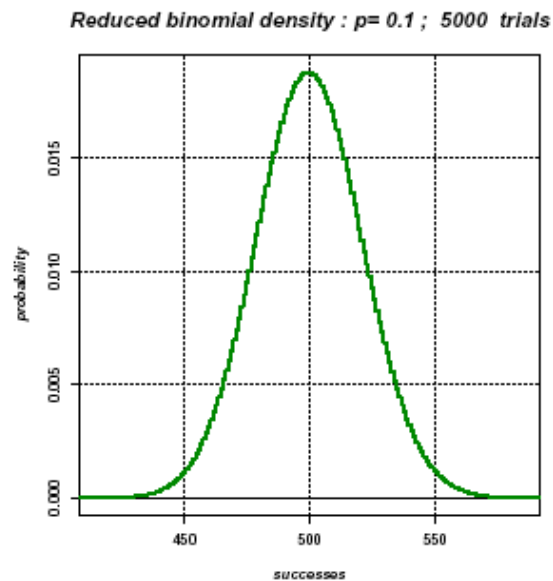
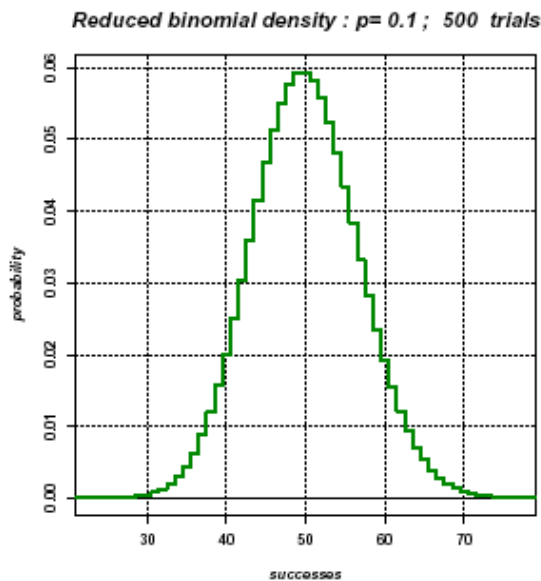
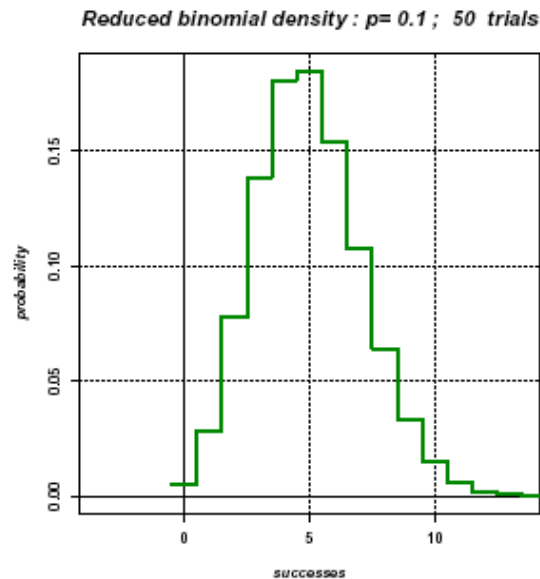
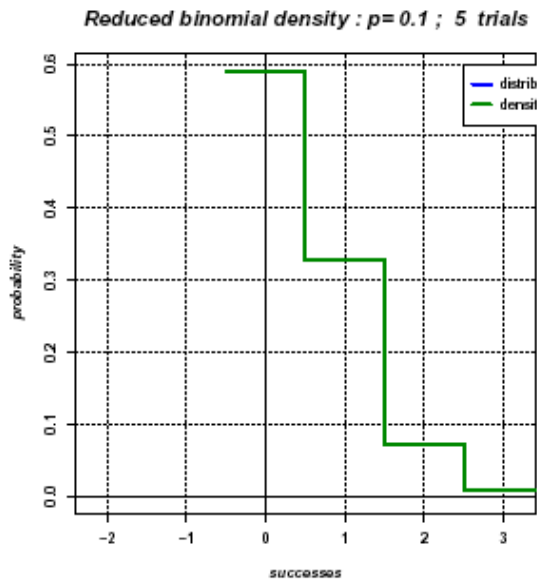


Binomial density and distribution : 200 trials



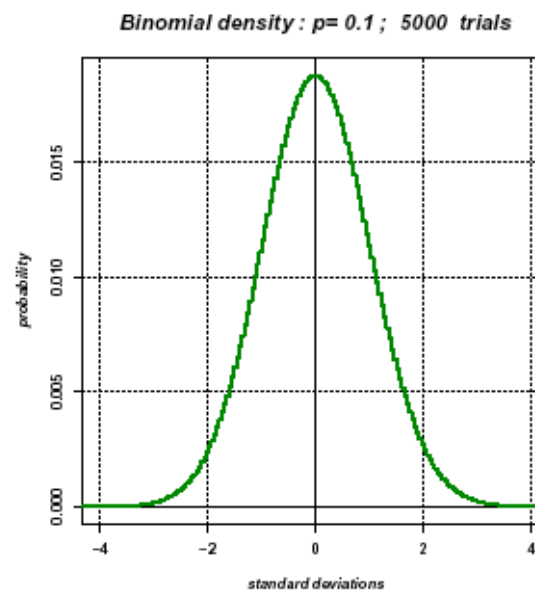
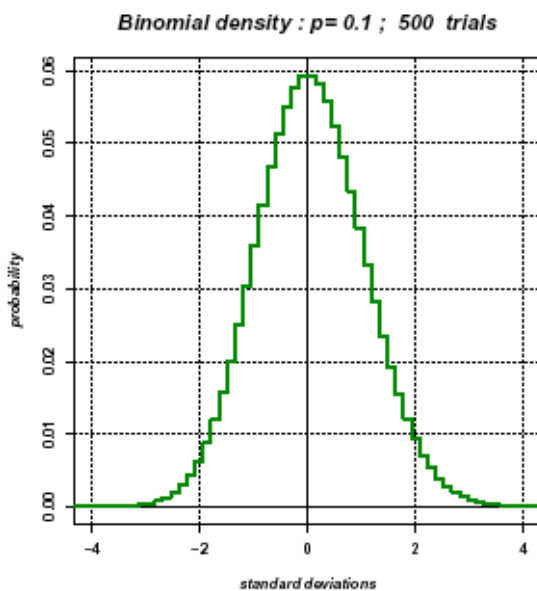
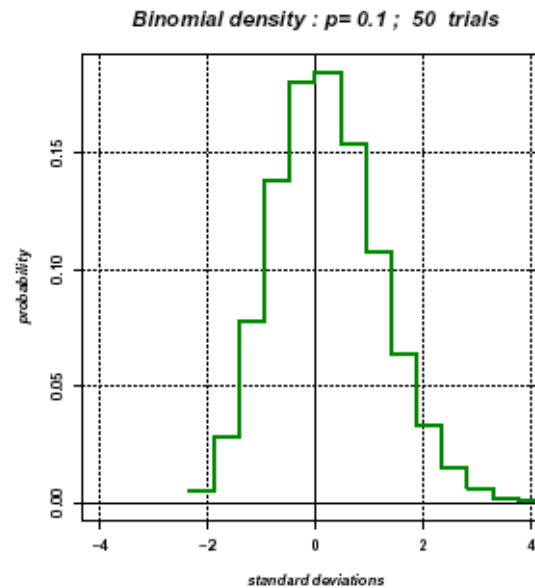
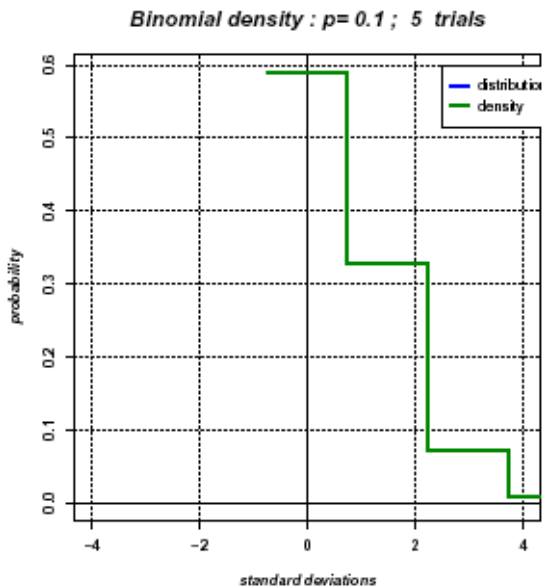
- When the number of trials increases
 - The number of distinct values for s increases
 - The probability of each value decreases
 - The binomial tends towards a bell-shaped curve

Binomial - effect of n (number of trials)



- On this figure, the density is displayed around the mean of the binomial ($\mu=np$).
- When n increases :
 - The number of distinct values for s increases.
 - The probability of each value decreases.
 - The binomial tends towards a bell-shaped curve.
- When $n \rightarrow \infty$
 - The binomial tends towards a continuous density function

Reduced binomial distribution -> Normal



- Starting from a binomial distribution, let $n \rightarrow \infty$
- Let us replace x by the *reduced variable* U

$$U = \frac{x - \mu}{\sigma} = \frac{x - np}{\sqrt{np(1-p)}} = \frac{x - np}{\sqrt{npq}}$$

- When $n \rightarrow \infty$, the binomial tends towards the **standard normal density function**

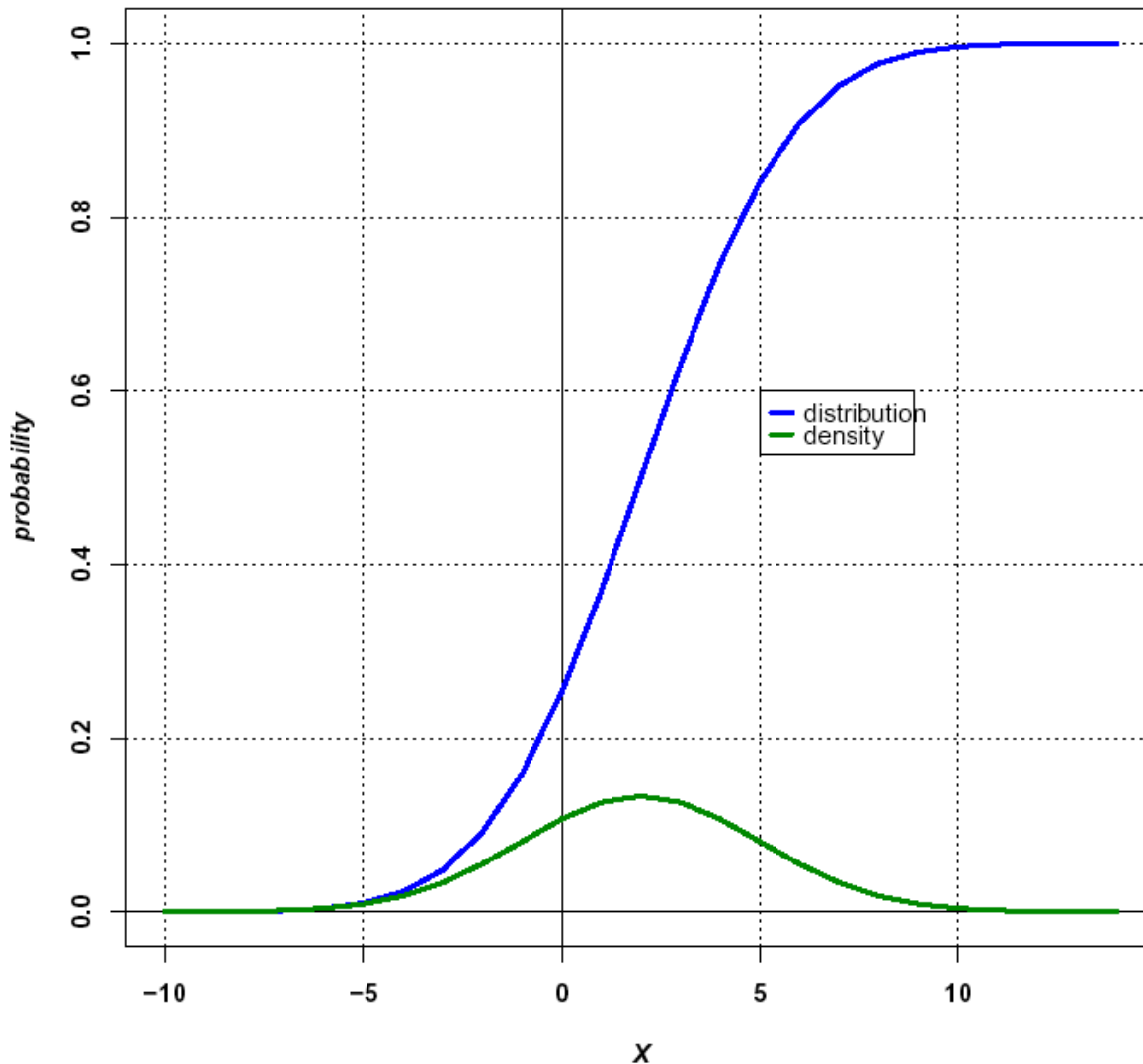
$$f_N(u) = \frac{1}{\sqrt{2\pi}} e^{-u^2/2}$$

- The **cumulative density function (CDF)** is obtained by integrating the density function

$$F_N(u) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^u e^{-u^2/2} du$$

Normal distribution

Normal density and distribution ; $m=2$; $s=3$



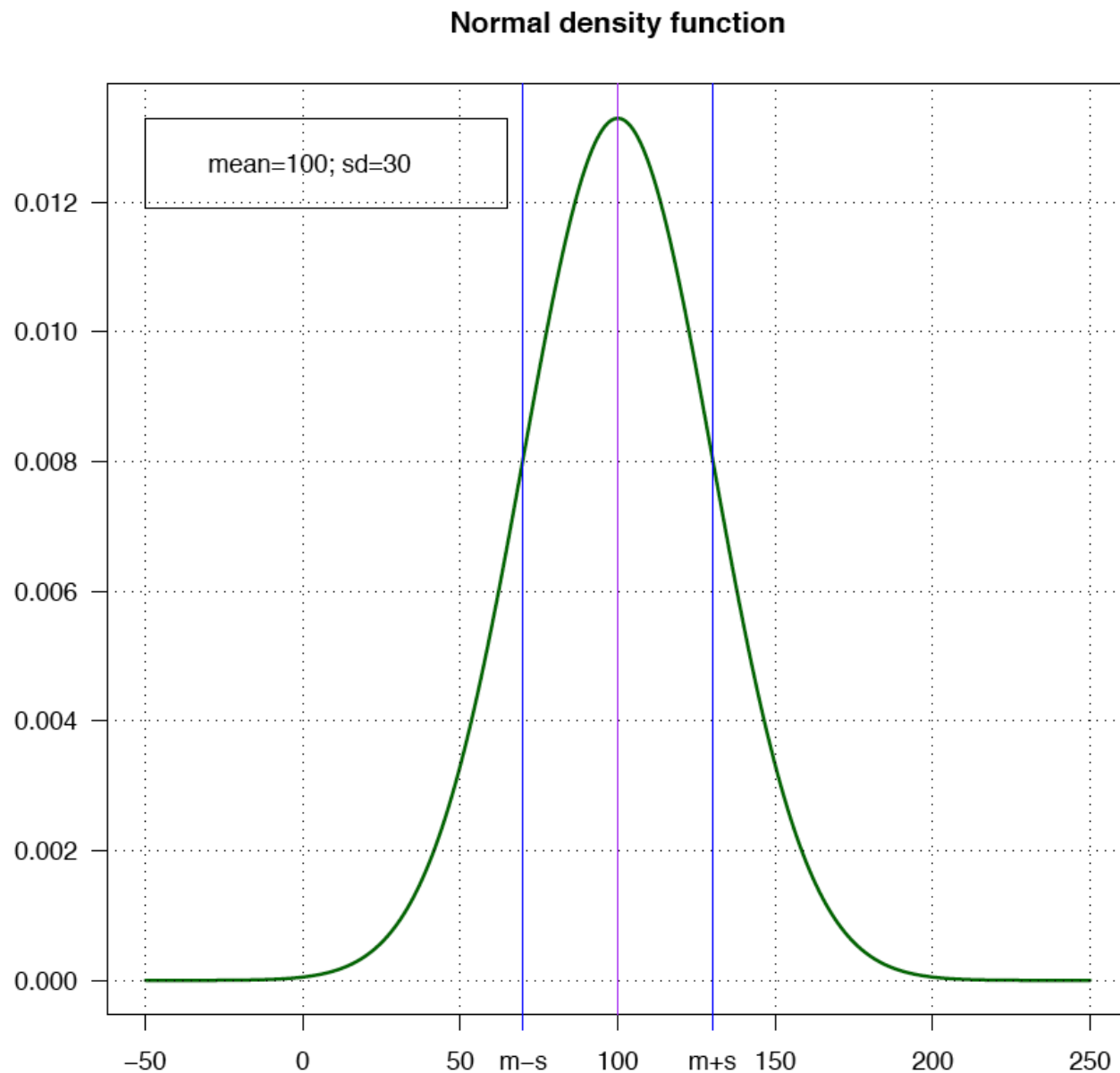
- A normal distribution with mean μ and a variance σ^2 is defined by the density function

$$f_N(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

- The distribution function is obtained by integrating the density function from $-\infty$ to x

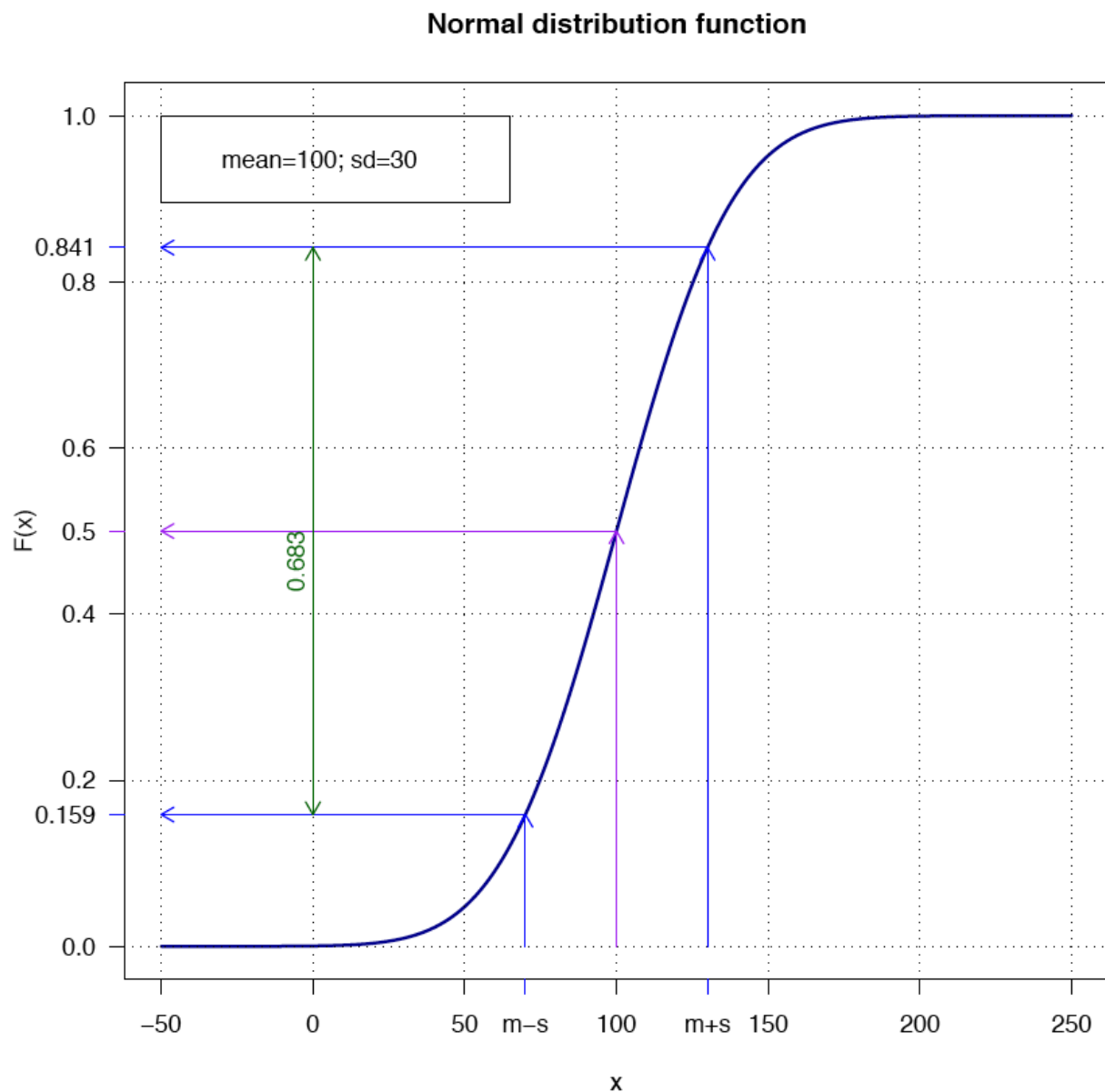
$$F_N(x) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^x e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx$$

The density function



- For continuous probability distributions, the density represents the limit of the probability per interval, when the range of this interval tends towards 0.
- The normal density function is continuous.
- It is defined from $-\infty$ to $+\infty$
- In R, the normal density function is
 - `dnorm(x,m,s)`

The distribution function

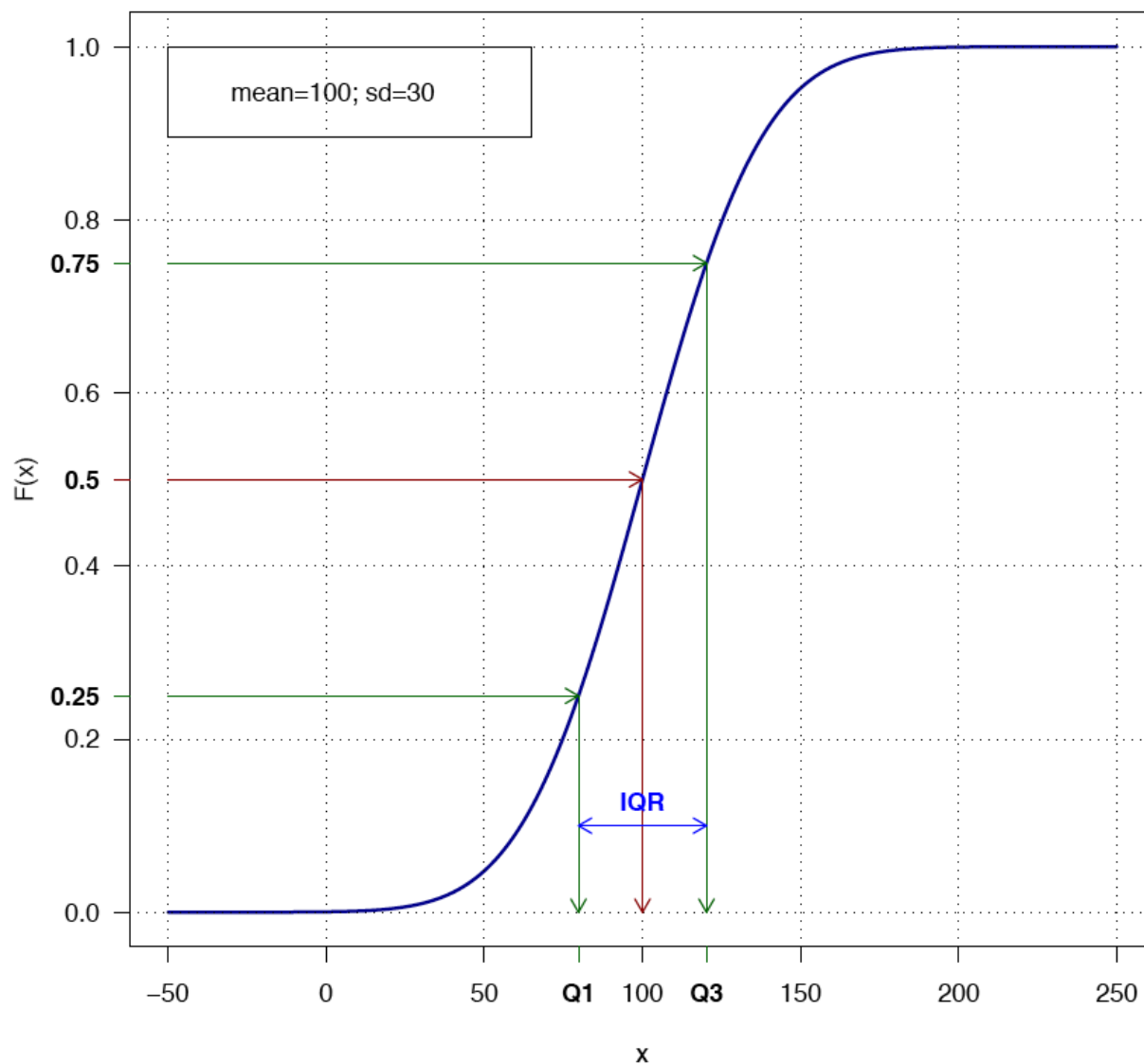


- The distribution function $F(x)$ allows to easily calculate the probability of an interval.
- $F(x)$ gives the probability to observe a value smaller than x .
- The probability to observe a value $x_1 \leq x \leq x_2$, is the difference $F(x_2) - F(x_1)$
- In R, the normal distribution function is
 - `pnorm(x,m,s)`

$$\begin{aligned} P(x_1 \leq X \leq x_2) &= \int_{x_1}^{x_2} f(x) dx \\ &= \int_{-\infty}^{x_2} f(x) dx - \int_{-\infty}^{x_1} f(x) dx \\ &= F(x_2) - F(x_1) \end{aligned}$$

Quartiles on a distribution function

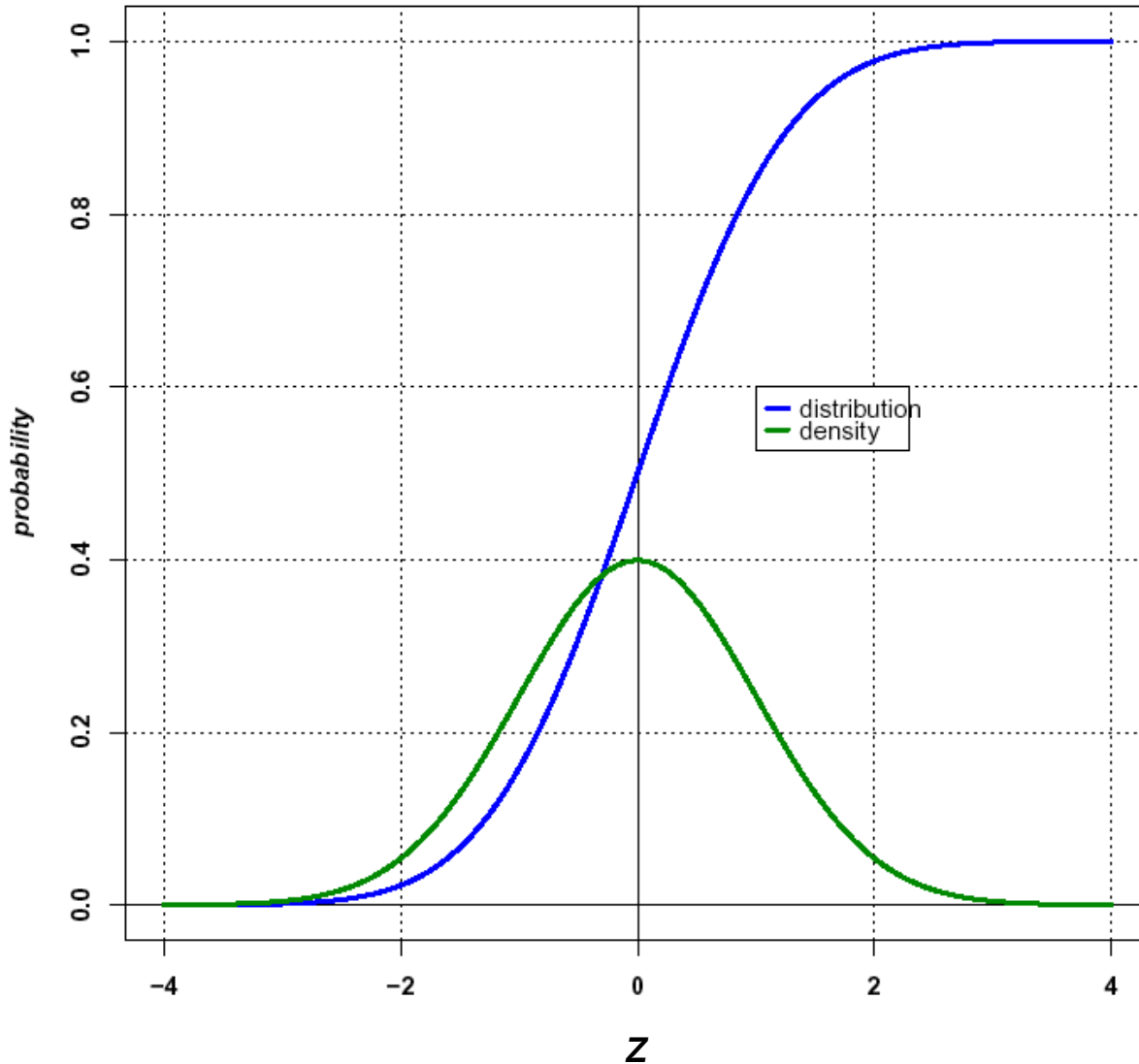
Quartiles on the normal distribution



- The first quartile $Q1$ is the x which leaves 25% of the observations on its left. It is thus the x value such that
 - $F(Q1)=0.25$.
- The third quartile $Q3$ is the x which leaves 75% of the observations on its left. It is thus the x value such that
 - $F(Q3)=0.75$.
- The inter-quartile range IQR is the difference between the third and the first quartiles.
 - $IQR=Q3-Q1$

Standard normal distribution

Normal density and distribution ; $m=0$; $s=1$



- The standard normal is obtained by the transformation

$$z = \left(\frac{x - \mu}{\sigma} \right)$$

- This distribution has
 - mean $\mu = 0$
 - variance $\sigma^2 = 1$

$$f_N(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2}$$

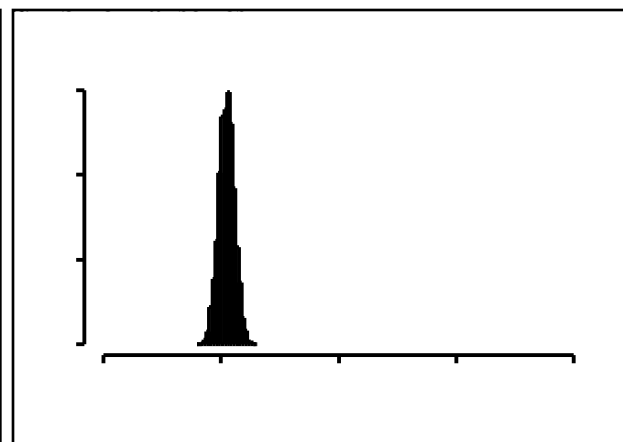
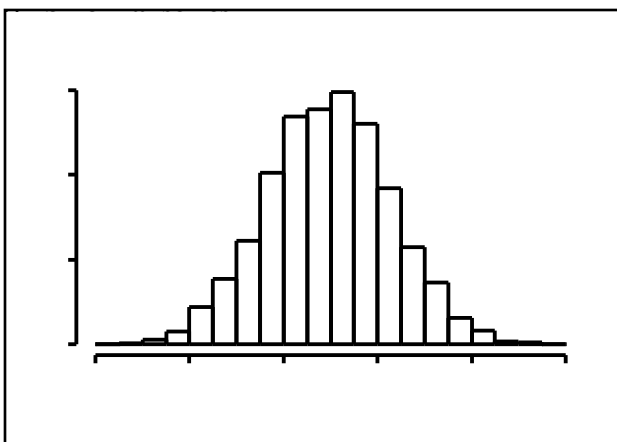
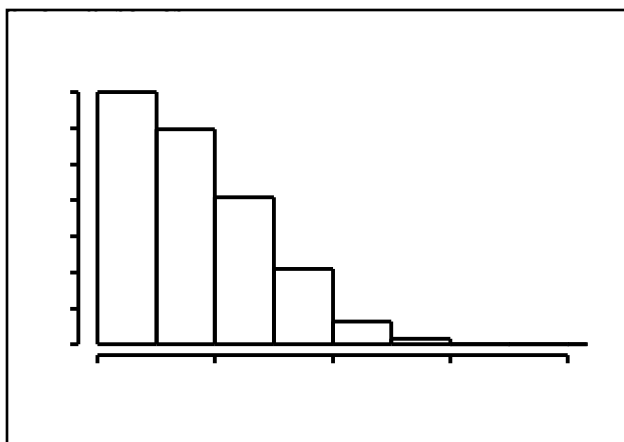
$$F_N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{1}{2}z^2} dx$$

Standard normal distribution - some landmarks

- Parameters of the reduced normal distribution
 - $m = 0$ the **standard** normal distribution is centered around 0
 - $\sigma^2 = 1$ the **standard** normal distribution has a unit variance
 - $\beta_3 = 0$ the normal distribution is symmetric
 - $\gamma_2 = 0$ the normal distribution is mesokurtic
- Some landmarks
 - $P(-\sigma < u < \sigma) = 68.3\%$
 - $P(-2\sigma < u < 2\sigma) = 95.4\%$
 - $P(-3\sigma < u < 3\sigma) = 99.7\%$

Central limit theorem

- Laplace-Liapounoff theorem
 - Any sum of n independent random variables X_1, X_2, \dots, X_n is asymptotically normal
- This naturally extends to the mean of n independent variables, since the mean is the sum divided by a constant.
- Mean of a series of binomial variables
 - Let us take a set of 100 random binomial variables, each with a small mean (e.g. $n \cdot p = 2.1$).
 - Each individual variable is far from normal : it is strongly asymmetric and has an inferior boundary at 0 (there can be no negative values).
 - The sum of these variables however fits a normal distribution.



The chi-squared (χ^2) distribution

- If we have N standard normal random variables

- X_1, \dots, X_N

- The variable

has a χ^2_n distribution with n degrees of freedom

$$S_n = \sum_{i=1}^n X_i^2$$

- Density

- Expectation

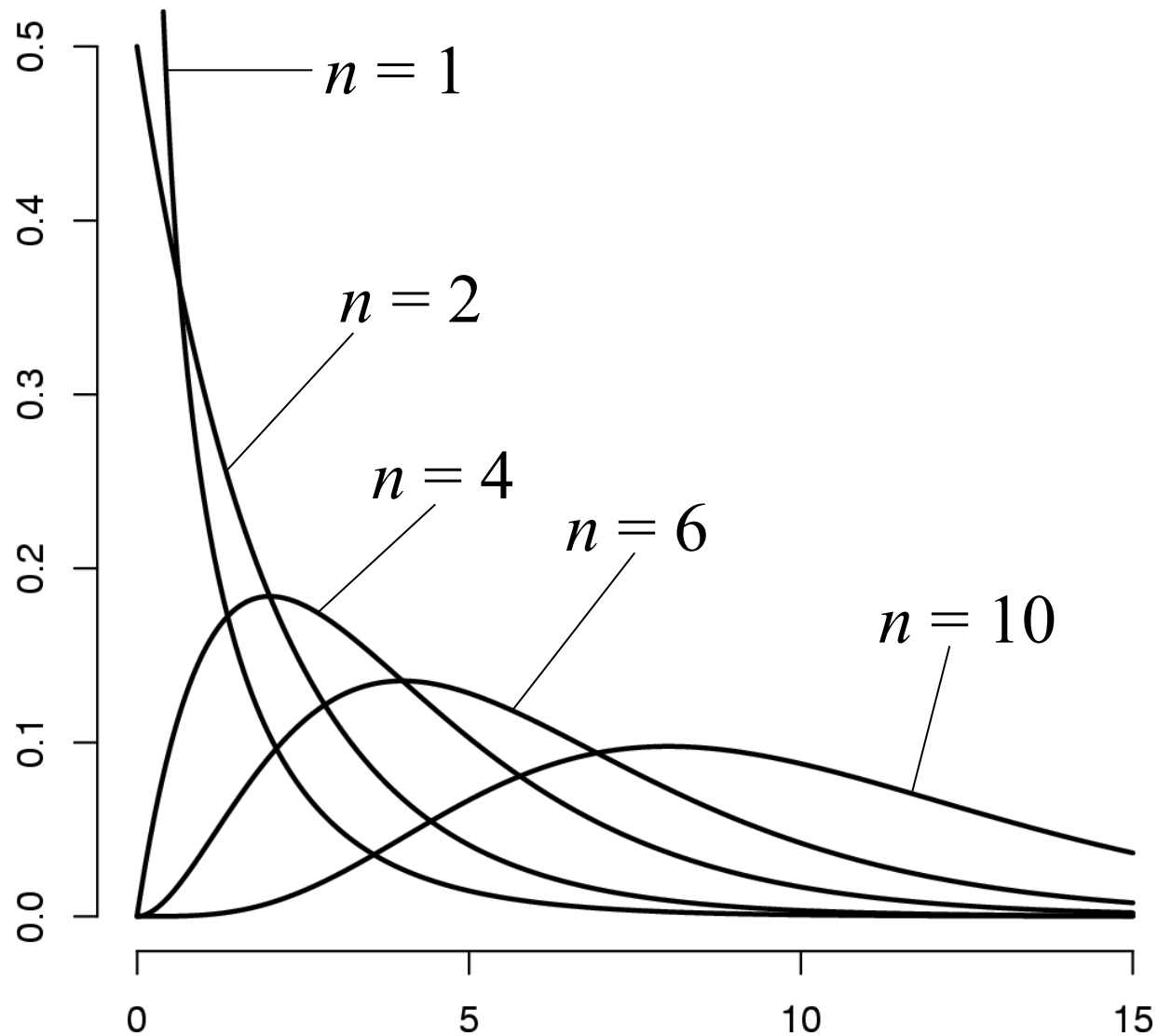
- Variance

$$f_n(x) = \frac{1}{2^{n/2} \Gamma(n/2)} x^{n/2-1} e^{-x/2}$$

$$E[S_n] = n$$

$$V[S_n] = 2n$$

Shapes of χ^2 distributions



Student (t) *distribution*

- $Z \sim N(0,1)$ independent of $U \sim \chi_n^2$
- then

$$S = \frac{Z}{\sqrt{U/n}}$$

has a t distribution with n degrees of freedom

- density

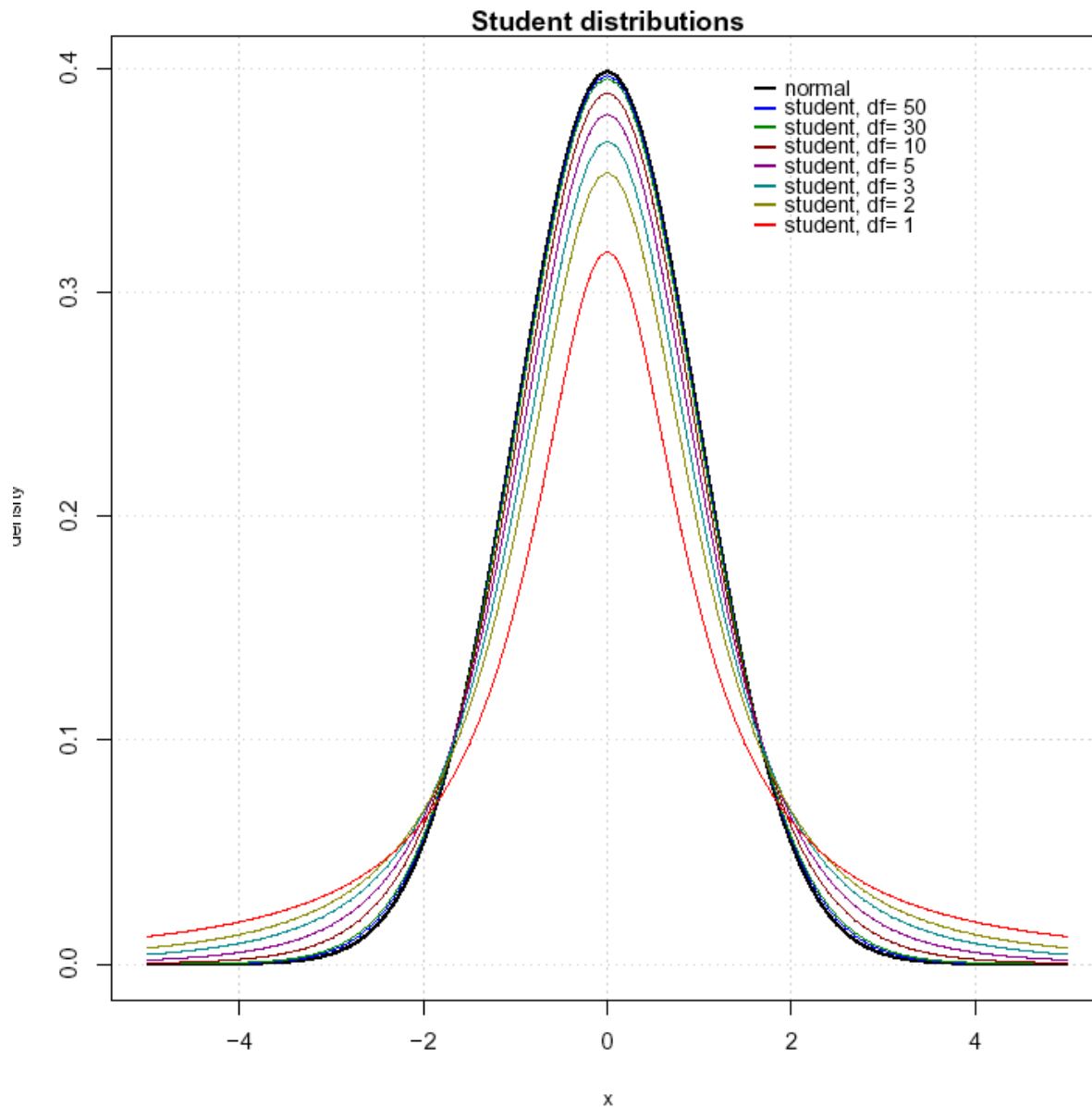
`pt(x, n)`

`dt(x, n)`

`rt(num, x, n)`

$$f_n(x) = \frac{\Gamma(n + 1/2)}{\sqrt{n\pi} \Gamma(n/2)} \left(1 + \frac{x^2}{n}\right)^{-(n+1)/2}$$

Shape of Student t distributions



- There is a family of Student distributions, defined by a degree of freedom (n).
- Platykurtic. The degree of kurtosis (flatness) decreases with the degrees of freedom.
- Approaches the normal $N(0,1)$ distribution for large n ($n > 30$)

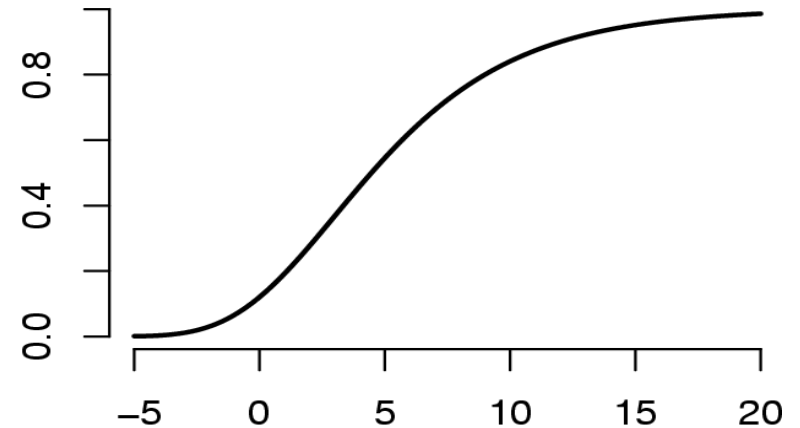
Extreme value distribution

- Cumulative distribution CDF

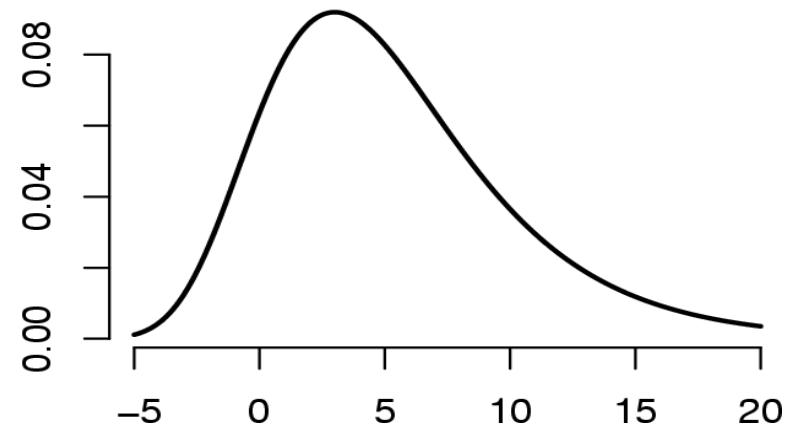
$$\Pr[X < x] = \exp\left(-e^{-(x-\mu)/\sigma}\right)$$

- Probability density PDF

$$f_{EV}(x; \mu, \sigma) = \frac{1}{\sigma} e^{-(x-\mu)/\sigma} \exp\left(-e^{-(x-\mu)/\sigma}\right)$$

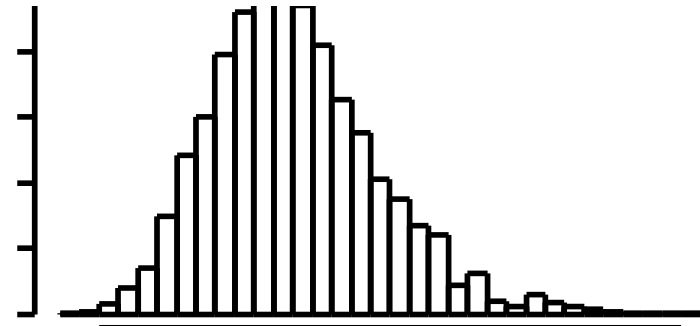


Extreme Value
 $\mu = 3, \sigma = 4$



Extreme value distributions - random example

- Generate 100 random numbers
 - with standard normal random generator ($m=0, \sigma=1$)
- Take the maximum
- Repeat 1000 times
- The distribution of maxima is
 - Asymmetrical (right-skewed)
 - Bell-shaped
 - Centered around 2.5
 - Less dispersed than the normal populations from which it originated.
- Note that this is different from the central limit theorem :
 - Extreme value distributions are obtained by taking the min or the max of several variables.
 - The central limit theorem applies to the sum or mean of several variables.



Extreme value distribution - applications

- The extreme value distribution has a particular importance in bioinformatics, for its role in BLAST
 - Aligning two sequences consists in searching the alignment with maximum score
 - Aligning a sequence against a whole database amounts to get, for each database entry, the maximum alignment score
 - BLAST scores have thus an extreme value distribution
 - (more details in the course on sequence analysis)

Other distributions not (yet) covered here

- Compound Poisson
- Snedecor (F)
- Beta function
- Gamma function

Exercises - theoretical distributions

Exercises - theoretical distributions

- In which cases is it appropriate to apply a hypergeometric or a binomial distribution, respectively ?
- Does the hypergeometric distribution correspond to a Bernoulli schema ?
- What are the relationships between binomial, Poisson and normal distributions ?

Exercise - Word occurrences in a sequence

- A sequence of length 10,000 has the following residue frequencies
 - ▣ $F(A) = F(T) = 0.325$
 - ▣ $F(C) = F(G) = 0.175$
- What is the probability to observe the word GATAAG at a given position of a sequence (assuming a Bernoulli model).
- What would be the probability to observe, in the whole sequence
 - ▣ 0 occurrences
 - ▣ at least one occurrence
 - ▣ exactly one occurrence
 - ▣ exactly 15 occurrences
 - ▣ at least 15 occurrences
 - ▣ less than 15 occurrences

Exercise - substitutions of a word

- A sequence is generated with equiprobable nucleotides. What is the probability to observe the word GATAAG or a single-base substitution of it, at the first position ?
- Same question with at most 3 substitutions.