

Continuous Random Variables

STAT 211 - 509

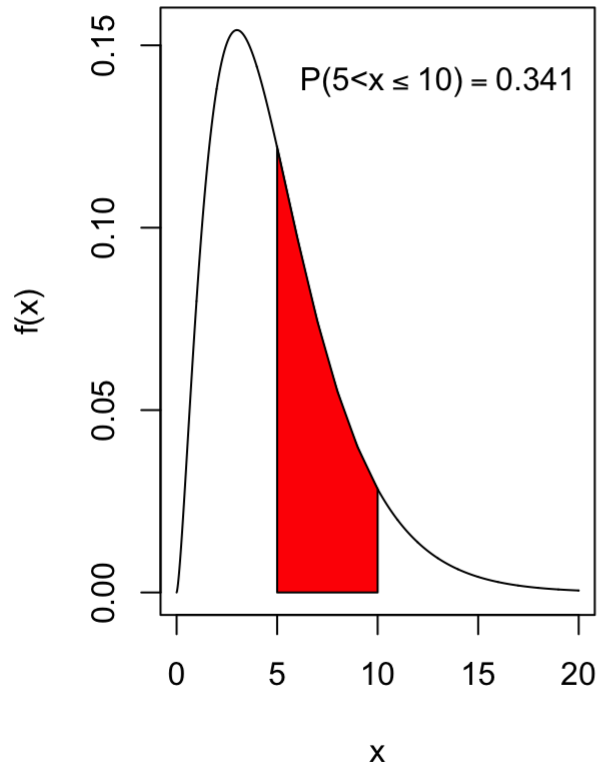
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Continuous Random Variables

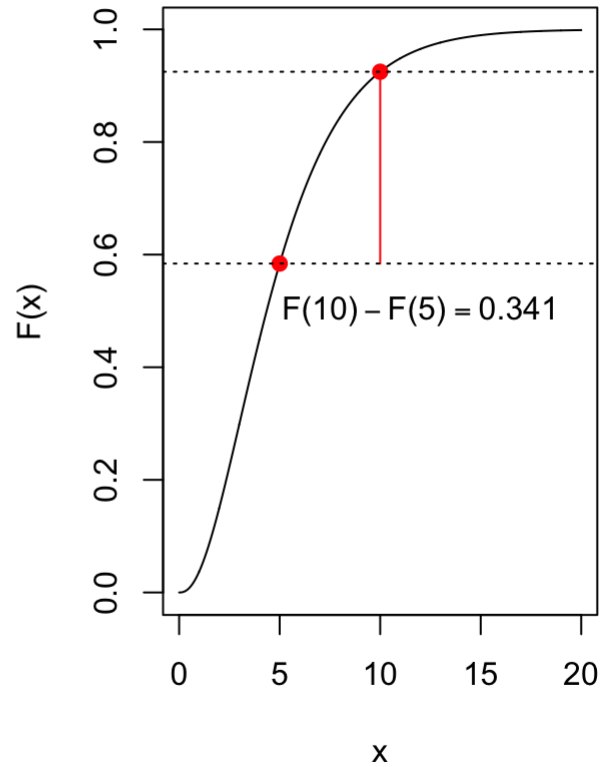
Let X be a continuous random variable:

- The **probability density function (pdf)** $f(x)$ is defined as
- The **cumulative distribution function (cdf)** $F(x)$ is defined as
- At every point x at which $f(x)$ is continuous,


PDF of chi-square with df = 5

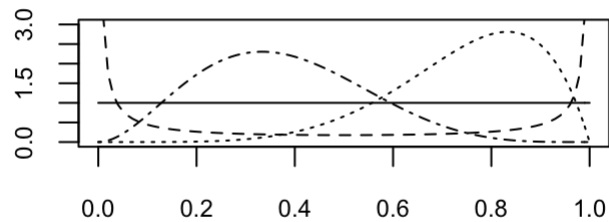


CDF of chi-square with df = 5

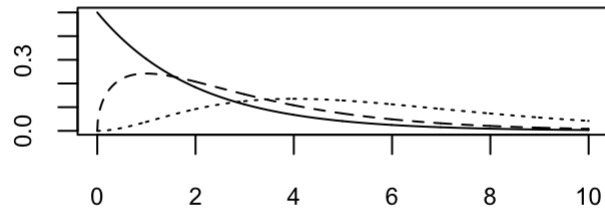


- Beta

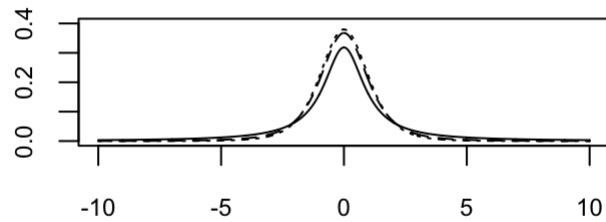
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- conjugate prior for binomial distribution parameter
- In R: `(d|p|q|r)beta`



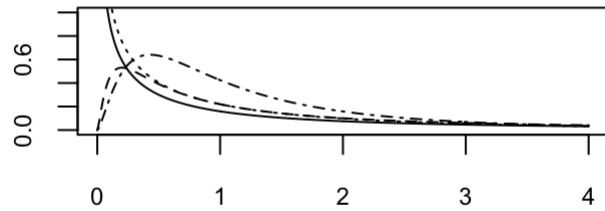
- Chi-square
 -
 - Chi-square test for goodness of fit
 - In R: `(d | p | q | r)chisq`



- t
 -
 - t-test for difference in means
 - In R: `(d|p|q|r)t`



- F
 -
 - F-test for equality of means in ANOVA
 - In R: `(d|p|q|r)f`



Continuous distributions in R

Suppose $X \sim \text{Chisq}(3, 2)$.

:

```
pchisq(3, 2) - pchisq(1, 2)
```

```
## [1] 0.3834005
```

:

```
dchisq(3, 2)
```

```
## [1] 0.1115651
```

Sample 10 numbers from X :

```
rchisq(10, 2)
```

```
## [1] 0.3102827 3.7648032 3.6090250 1.6723553 2.4450873 2.3167105 1.9800399  
## [8] 0.6147466 0.1892382 0.3144031
```


Expected Values With Continuous RVs

Let X be a continuous random variable:

- The expected value (*mean*) of X is $E[X] = \int_{-\infty}^{\infty} x f(x) dx$
- The expected value of X^2 is $E[X^2] = \int_{-\infty}^{\infty} x^2 f(x) dx$
- The variance of X is $\text{Var}[X] = E[X^2] - (E[X])^2$
- The moment generating function of X is $M_X(t) = E[e^{tX}] = \int_{-\infty}^{\infty} e^{tx} f(x) dx$

Joint and Conditional Distributions

Let X and Y be continuous random variables with marginal pdfs f_X and f_Y and **joint probability density function** $f_{X,Y}$:

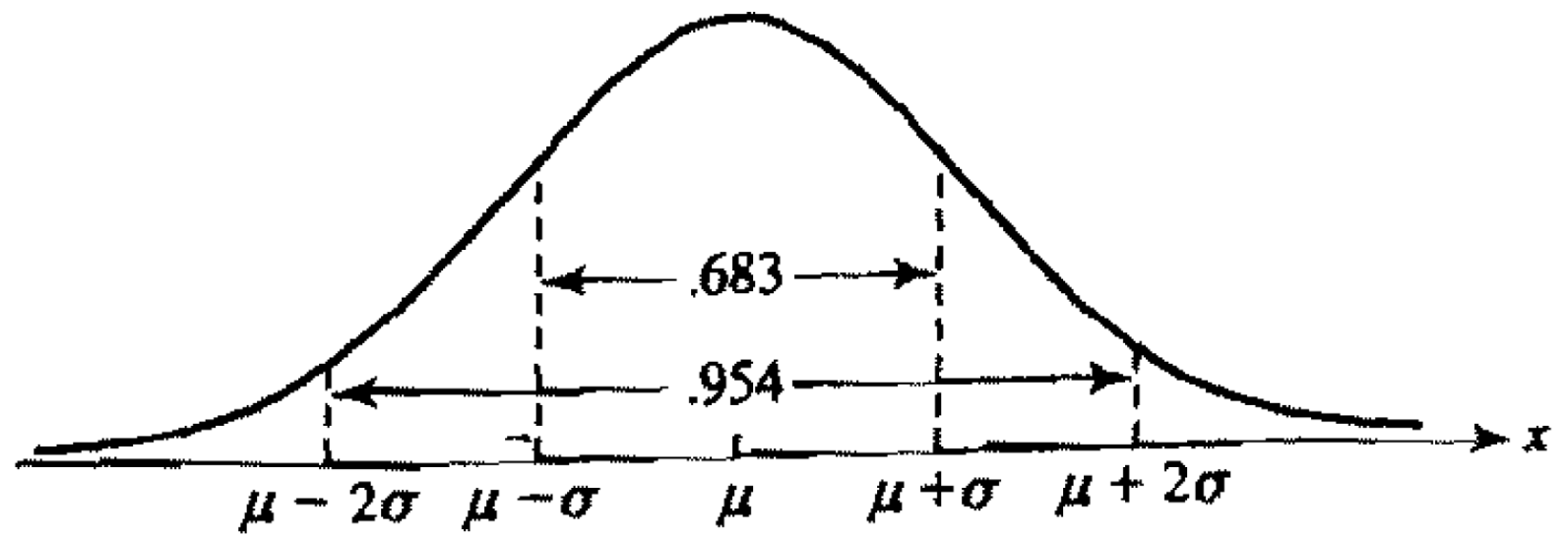
- Joint probabilities are double integrals of the joint pdf:
- The **conditional probability density function** $f_{Y|X}$ of Y given that $X=x$ is:
$$f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)}$$
- X and Y are **independent** if

The Normal Distribution

The random variable X has a Normal distribution with parameters μ and σ (written $X \sim N(\mu, \sigma)$) if its pdf is

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

- μ is the mean, σ is the standard deviation.
- Let $Z = \frac{X - \mu}{\sigma}$. Then $Z \sim N(0, 1)$.
- The 68 / 95 / 99.7 rule:
 - 68% of the data lies within 1 standard deviation of the mean.
 - 95% of the data lies within 2 standard deviations of the mean.
 - 99.7% of the data lies within 3 standard deviations of the mean.



Bivariate normal

If X and Y are bivariate normal, then:

$$\frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_X)^2}{\sigma_X^2}-2\rho\frac{(x-\mu_X)(y-\mu_Y)}{\sigma_X\sigma_Y}+\frac{(y-\mu_Y)^2}{\sigma_Y^2}\right]\right\}$$

where μ_X, μ_Y are the means of X and Y , σ_X^2, σ_Y^2 are the variances, and ρ is the correlation between X and Y .

Sums of Independent Normal RVs

Let X_1, \dots, X_n be iid Normal random variables with μ_i and σ_i^2 , $i = 1, \dots, n$. Let a_1, \dots, a_n be arbitrary constants. Then

Special case: let $\mu_i = \mu$ and $\sigma_i^2 = \sigma^2$. Then sample mean

—

Central Limit Theorem

Let X_1, X_2, \dots, X_n be an IID sample from a distribution with mean μ and variance σ^2 . This is not necessarily a Normal distribution. Assume that $\mu < \infty$ and $\sigma^2 < \infty$.

- As $n \rightarrow \infty$, the (sampling) distribution of \bar{X}_n converges to the Normal distribution with mean μ and variance $\frac{\sigma^2}{n}$, regardless of the distribution from which the sample was drawn.
- If we have a “large enough” sample size, we can use a Normal distribution to approximate the sampling distribution of \bar{X}_n , regardless of the form of the population distribution.
 - This facilitates mean-based statistical inference.
 - Common rule of thumb for “large enough” is 30, although the required sample size varies depending on the situation.