

Probability theory

Justifying inference in regression settings

Possibilities:

Assumptions about distribution of error terms

- ▶ Normal distribution
- ▶ t distribution

Asymptotic results - when number of observations go to infinity

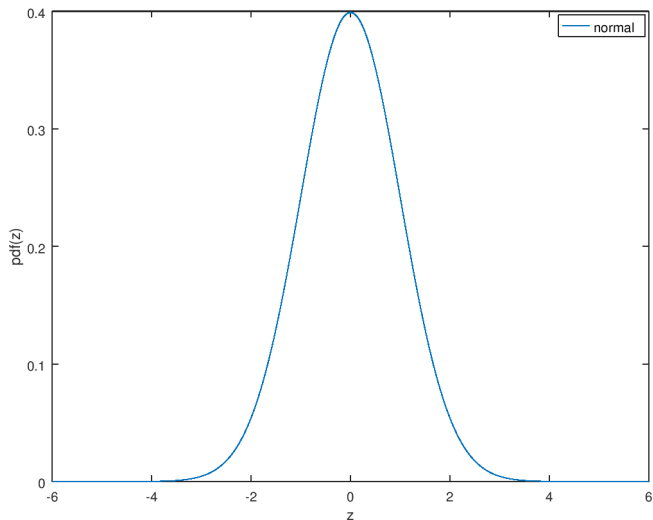
- ▶ Asymptotic normality

Probability distributions important for statistics

- ▶ Normal
- ▶ t-distribution
- ▶ The χ^2 distribution
- ▶ The F distribution

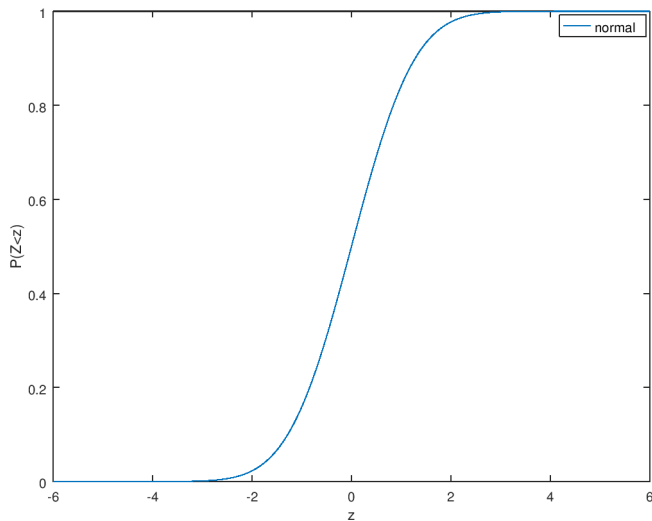
The unit normal distribution

Is defined over $(-\infty, \infty)$, but most of the probability mass centered at zero



The unit normal distribution

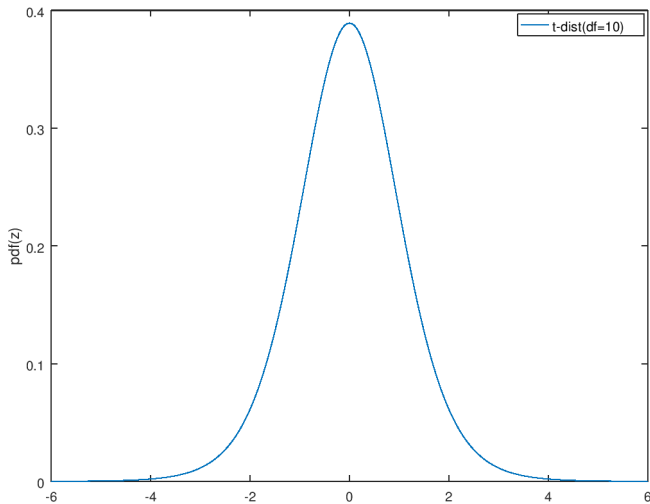
The cumulative probability function of a normal distribution



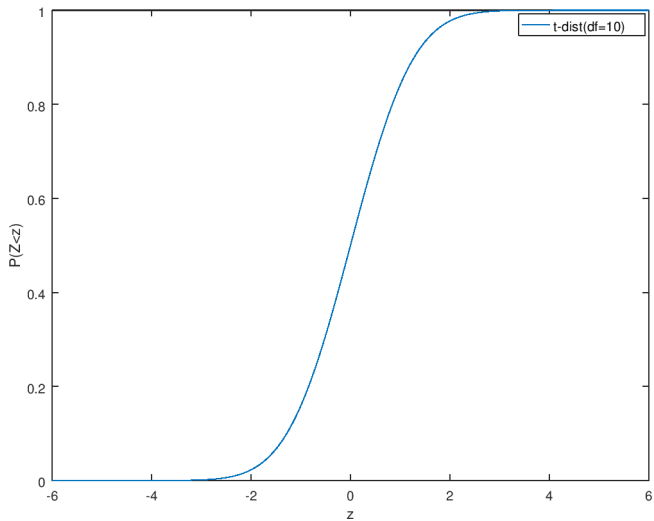
The T distribution

Is similar to the normal, defined over $(-\infty, \infty)$, but most of the probability mass centered at zero

The probability density function of a t-distribution (df=10)

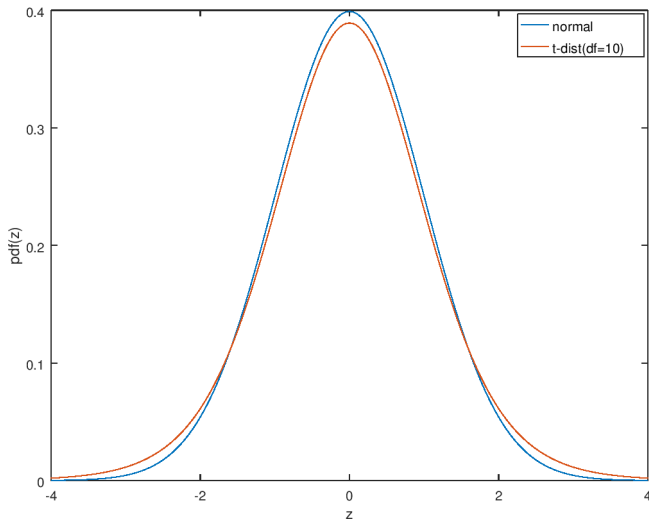


The cumulative probability function of a t-distribution (df=10)

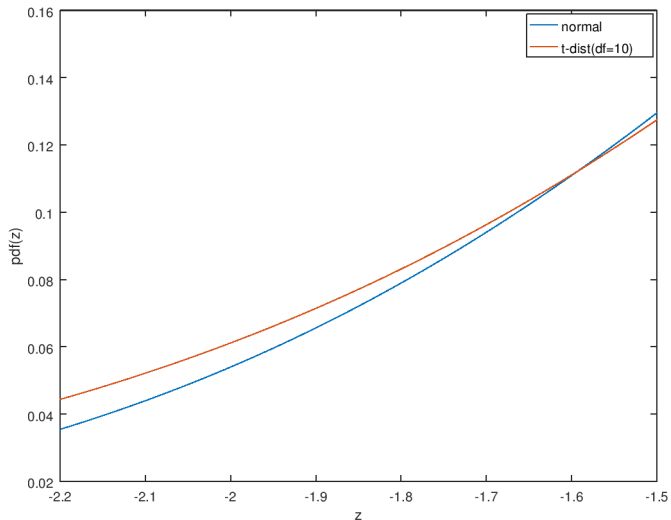


Comparing normal distribution and t distribution

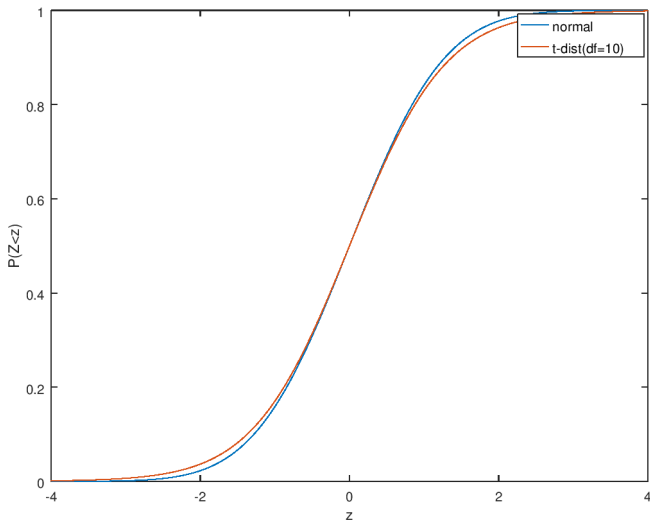
Comparing probability density functions of a normal distribution and a t-distribution (df=10)



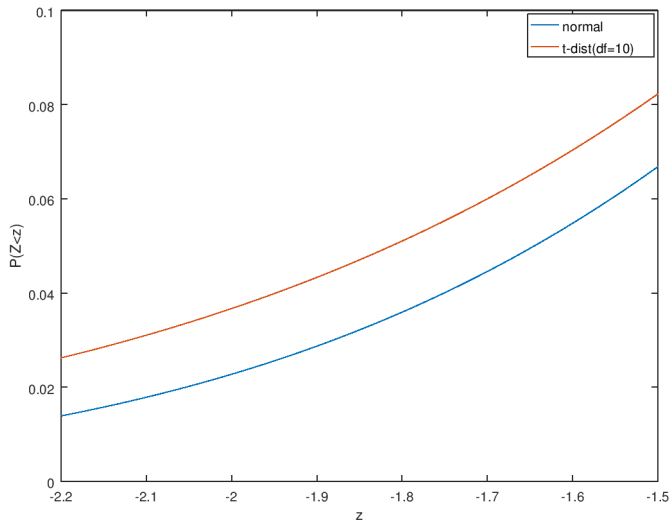
Comparing probability density functions of a normal distribution and a t-distribution (df=10) - Detail



Comparing cumulative probability functions of a normal distribution and a t-distribution (df=10)

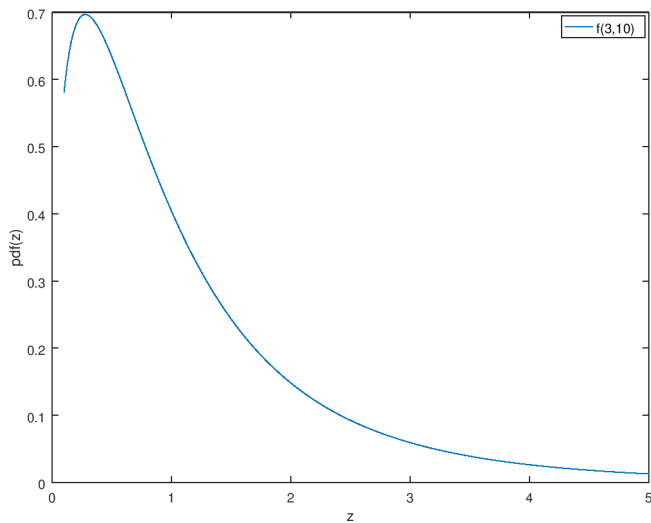


Comparing cumulative probability functions of a normal distribution and a t-distribution (df=10) - Detail



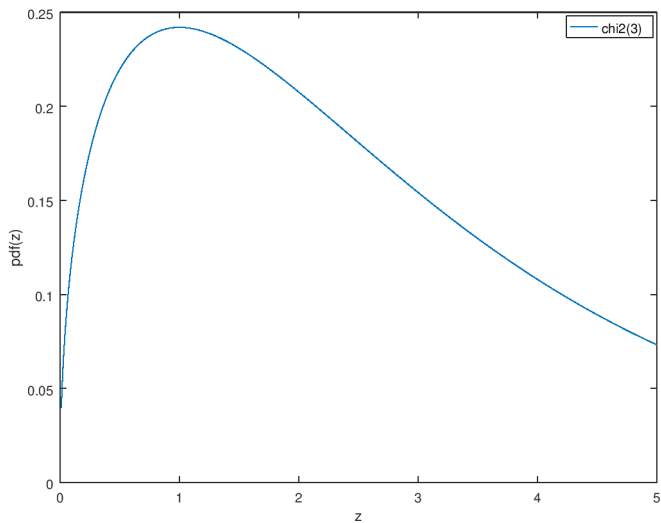
F dist

The probability density function of a F-distribution (df=3,10)



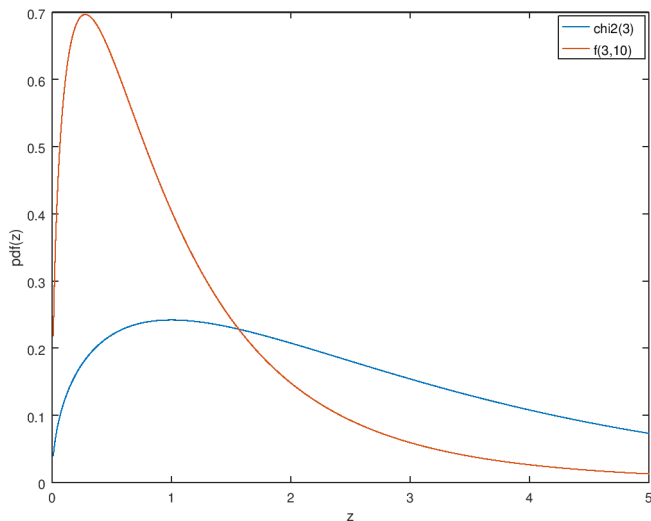
χ^2 dist

The probability density function of a χ^2 -distribution (df=3)

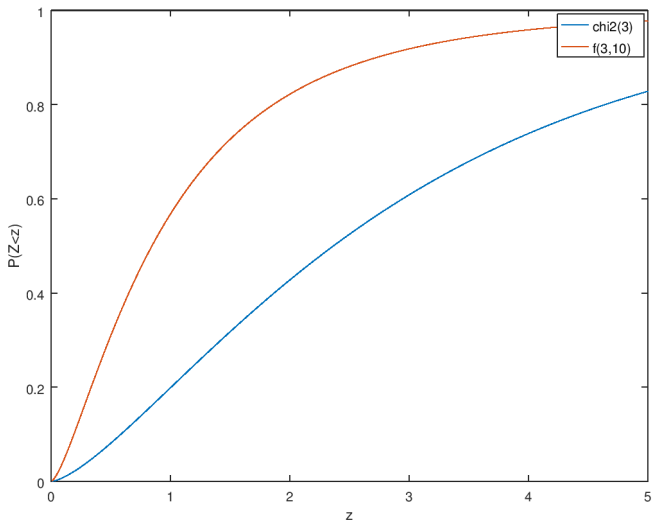


Comparing F and χ^2 distributions

The probability density functions of a F and χ^2 -distribution ($df=3$)



The cumulative probability functions of a F and χ^2 -distribution (df=3)



Motivating the concept of convergence in probability.

$$\tilde{x}_i \sim N(0, 1)$$

Consider drawing T samples of x_i , and take the average

$$X_T = \sum_{t=1}^T x_t$$

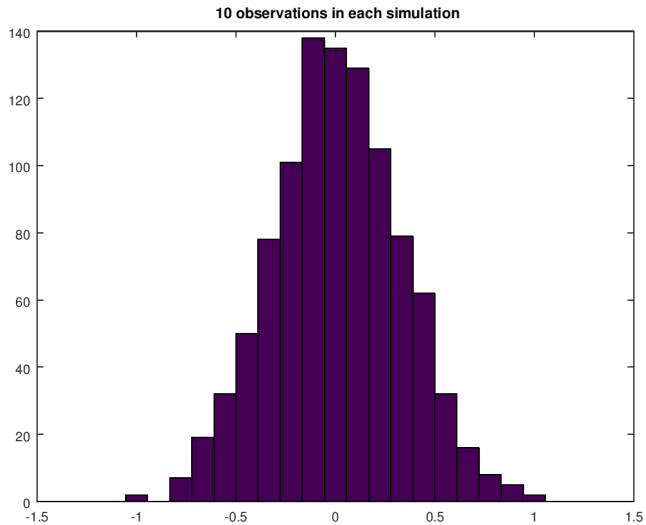
Do this as a simulation, where in each simulation we draw T \tilde{x}_i observations.

Make a histogram of the resulting averages for values of T of 10, 100 and 1000

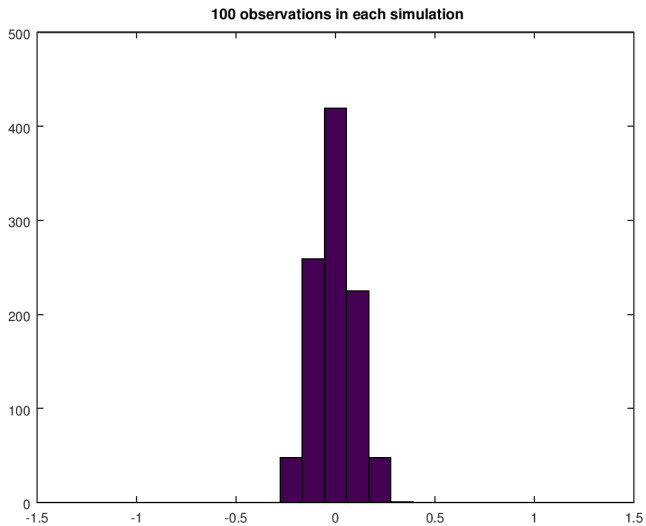
Using matlab to do simulation of convergence in probability

```
function con_prob(n, no_sims)
    X = randn(n,no_sims);
    bins = linspace(-1,1,19);
    m = mean(X);
    hist(m,bins);
endfunction;
```

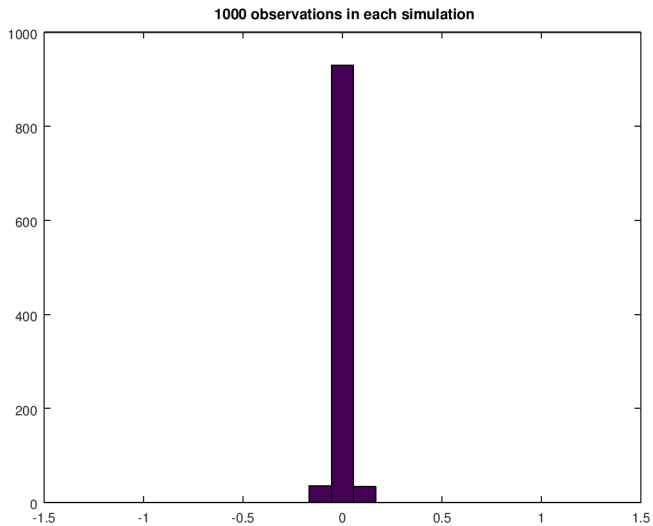
$T = 10$



$T = 100$



$T = 1000$



Convergence to a constant

We have just illustrated the concept of

- ▶ Convergence in probability

Used to justify estimation: In large sample, the sample mean will converge to its true value.

Motivating the concept of convergence in distribution.

$$\tilde{x}_i \sim N(0, 1)$$

Consider drawing T samples of x_i , and take the average

$$X_T = \sum_{t=1}^T x_t$$

Multiply this average with \sqrt{T} :

$$\sqrt{T}X_T$$

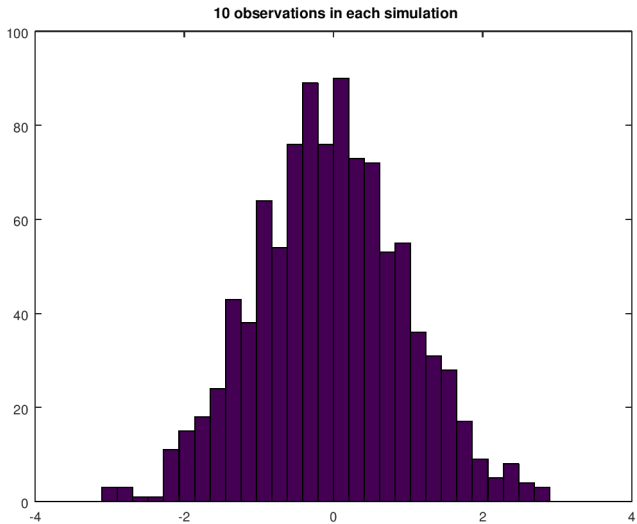
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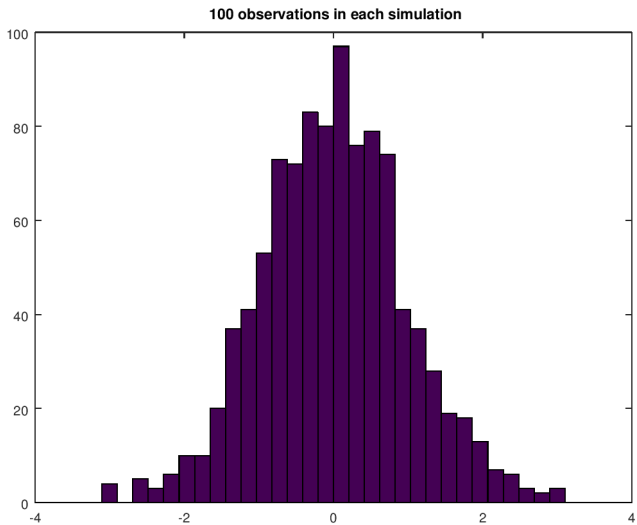
Using matlab to do simulation of convergence in distribution

```
function con_dist(n, no_sims)
    X = randn(n,no_sims);
    bins = linspace(-3,3,30);
    m = sqrt(n)*mean(X);
    hist(m,bins);
endfunction;
```

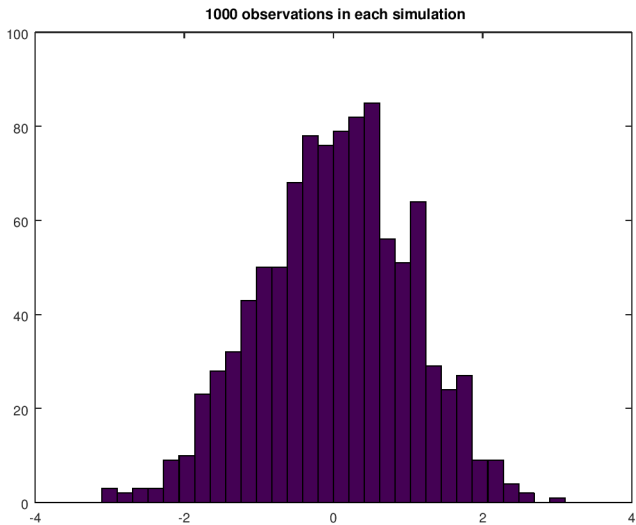
$T = 10$



$T = 100$



$T = 1000$



Convergence to a distribution

We have just illustrated the concept of

- ▶ Convergence in distribution

Used to justify probability statements: In large samples, a sample mean multiplied with the square root of the number of observations will not converge to a constant, it will have a distribution.

This is what one uses to evaluate the quality of an estimate: How sure are we of it – Quantified as a probability using this probability distribution.