

Ch 4 Probability Models for Continuous Random Variables

Some Models Introduced in this Chapter (after the tools to describe them are covered).
Uniform, Normal, Gamma, Exponential, Chi-squared, Weibull, Lognormal

Sections 1 and 2 – Tools to describe continuous RVs

Continuous RV – takes values over an interval (p 148)

Density function of RV X is $f(x)$ defined by

$$P(a \leq X \leq b) = \int_a^b f(x)dx$$

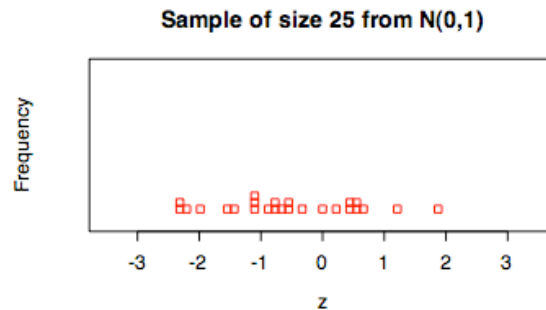
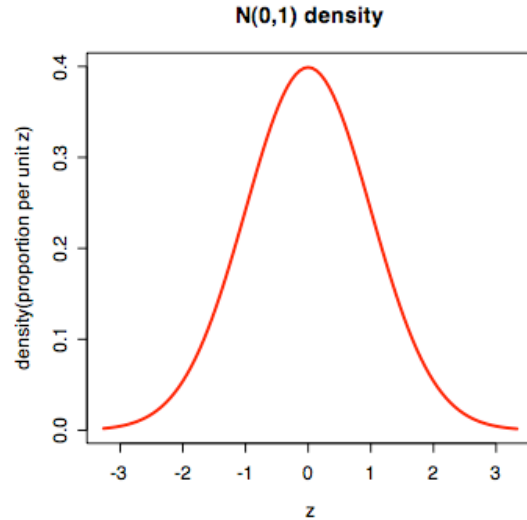
If this seems mysterious, note that for a discrete RV Y,

$$P(a \leq X \leq b) = \sum_a^b P(X = x)$$

So $f(x)dx$ is a bit like $P(X=x)$. But $f(x)dx$ is a limiting value of $f(x)\Delta x$, where $f(x)\Delta x$ is the area in the rectangle with base Δx and height $f(x)$. So $f(x)$ gives the *relative* probabilities for random values x , even though $f(x)dx = 0 = P(X=x)$. Now look at the graph of $f(x)$ at the bottom of page 147. The area between a and b (approximated by all those thin rectangles over Δx in (a,b)) is the probability that X lies in (a,b) . The heights of $f(x)$ gives the relative frequencies of X .

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If the function $f(x)$ gives the relative frequencies of X , what would a random sample of $n=25$ points look like? Would you expect the intervals with big $f(x)$ to have the greater proportion of the 25 sample values? YES.



$f(x)$ is called the density of X , and sometimes the notation is $f_X(x)$ to allow specification of the related random variable.

Note the connection between the cumulative distribution function and the density function:

$$P(X \leq x) = F(x) = \int_{-\infty}^x f(x) dx$$

Check the definitions of $E(X)$ and $V(X)$ for continuous RVs pp157-158

The Uniform Distribution on $[0,1]$ denoted $U(0,1)$ usually, U the RV

This is the distribution that attributes equal relative frequency to every value in the interval $[0,1]$ of the real line. $f(x) = 1$ as long as $0 \leq x \leq 1$. What about $x \leq 0$ or $x \geq 1$?

$$\text{so } P(X \leq x) = F(x) = \int_0^x 1 dx = x \text{ for } 0 \leq x \leq 1 \text{ in this case.}$$

Check, by thinking of the graph of $f_U(x)$, that this result $P(X \leq x) = x$, is reasonable.

The Normal Distribution (section 4.3 pp 160ff).

The normal density function (p 161) looks complex but is essentially just e^{-x^2} . In this function, as you move away from 0 x^2 gets bigger and e^{-x^2} gets smaller. Or, think of e^{x^2} as x moves away from 0, and then think of the reciprocal. You get the well-known "bell curve". The rest of the functional form has parameters that

1. ensure the integral is 1
2. allows the mean to be different from 0
3. allows the spread to be controlled by an SD parameter.

Now look at the box on p 162. This is sometimes denoted the $N(0,1)$ distribution – the standard normal distribution.

Note that the integral for the normal distribution is not tractable – this is a pity! It would be nice to have a closed expression for $P(Z \leq z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz$. However this function is tabulated – see p 740, Table A.3. So, for example, $P(Z < 0) = .5000$ (but you knew this already from the symmetry, and also $P(Z < 1) = 0.8413$ which you could not guess.

So this tells you how to look up $P(a < Z < b)$ also, as long as Z has $N(0,1)$ distribution.

For example $P(-1 < Z < 2) =$
 (tabulated value for 2) – (tabulated value for -1) = .9772 - .1587 = 0.8185

In other words, 81.85% of the distribution falls between -1 and +2.

But what if we have a normal RV X with $(\mu, \sigma) \neq (0,1)$? How do we compute $P(X < x)$?

Suppose $(\mu, \sigma) = (100, 15)$. What is the $P(X < 130)$?

It turns out we can look this up in the $N(0,1)$ Table with a little trickery.

Since X has mean 100 and sd 15, $X-100$ has mean 0, and $(X-100)/15$ has sd = 1. (p 115-116)

So if we define $Z = (X-100)/15$. what expression in Z is equivalent to $X < 130$?

Note that $X < 130$ if and only if $(X-100)/15$ is less than 2. (How did I get 2? just plug in 130 into the expression for Z .) And from the $N(0,1)$ table $P(Z < 2) = .9772$.

Why is the normal distribution important in stats? Most averages have a normal distribution. No matter what the distribution of the population, sample averages tend to have a normal distribution. There is also a technical reason. The Binomial, Poisson, Negative Binomial, Geometric, Exponential and Gamma distributions all have a special relationship to the normal distribution. We will explore these ideas in detail