

# Probability Distributions

Brendon J. Brewer

Department of Statistics  
The University of Auckland

<https://www.stat.auckland.ac.nz/~brewer/>

# Probability Distributions

Suppose a quantity  $X$  might be 1, 2, 3, 4, or 5, and we assign probabilities of  $\frac{1}{5}$  to each of those possible values. There is some terminology:

# Probability Distributions

Suppose a quantity  $X$  might be 1, 2, 3, 4, or 5, and we assign probabilities of  $\frac{1}{5}$  to each of those possible values. There is some terminology:

- $X$  is called a 'random variable' (not often by me)

# Probability Distributions

Suppose a quantity  $X$  might be 1, 2, 3, 4, or 5, and we assign probabilities of  $\frac{1}{5}$  to each of those possible values. There is some terminology:

- $X$  is called a ‘random variable’ (not often by me)
- $\{1, 2, 3, 4, 5\}$  is called the ‘sample space’, ‘hypothesis space’, or ‘parameter space’

# Probability Distributions

Suppose a quantity  $X$  might be 1, 2, 3, 4, or 5, and we assign probabilities of  $\frac{1}{5}$  to each of those possible values. There is some terminology:

- $X$  is called a ‘random variable’ (not often by me)
- $\{1, 2, 3, 4, 5\}$  is called the ‘sample space’, ‘hypothesis space’, or ‘parameter space’
- $\mathbf{p} = \{\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}\}$  is the ‘probability distribution’ for  $x$ . In this case, it is a *discrete uniform* distribution.

# Probability Distributions

Suppose a quantity  $X$  might be 1, 2, 3, 4, or 5, and we assign probabilities of  $\frac{1}{5}$  to each of those possible values. There is some terminology:

- $X$  is called a ‘random variable’ (not often by me)
- $\{1, 2, 3, 4, 5\}$  is called the ‘sample space’, ‘hypothesis space’, or ‘parameter space’
- $\mathbf{p} = \{\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}\}$  is the ‘probability distribution’ for  $x$ . In this case, it is a *discrete uniform* distribution.

The probability distribution is often written as  $P(X = x) =$  (some function of  $x$ ).

# Properties of discrete probability distributions

# Properties of discrete probability distributions

Normalisation:

$$\sum_x P(X = x) = 1.$$



# Properties of discrete probability distributions

Normalisation:

$$\sum_x P(X = x) = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \sum_x xP(X = x)$$

# Properties of discrete probability distributions

Normalisation:

$$\sum_x P(X = x) = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \sum_x xP(X = x)$$

Variance:

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \sum_x (x - \mathbb{E}(X))^2 P(X = x)$$

# Properties of discrete probability distributions

Normalisation:

$$\sum_x P(X = x) = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \sum_x xP(X = x)$$

Variance:

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \sum_x (x - \mathbb{E}(X))^2 P(X = x)$$

Standard deviation:

$$\text{sd}(X) = \sqrt{\text{Var}(X)}$$

# Properties of discrete probability distributions

Normalisation:

$$\sum_x P(X = x) = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \sum_x xP(X = x)$$

Variance:

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \sum_x (x - \mathbb{E}(X))^2 P(X = x)$$

Standard deviation:

$$\text{sd}(X) = \sqrt{\text{Var}(X)}$$

The expected value and sd describe the *center* and *width* of the distribution respectively.

# Shorthand notation

$P(X = x)$  is cumbersome.  $x$  is also just a dummy variable. Common shorthand notation: Use  $p(x)$  instead, equivocate between the quantity itself and the dummy variable. E.g.:

$$\mathbb{E}(x) = \sum xp(x) \quad (1)$$

# Numerical handling

Numerical handling of discrete probability distributions for a single quantity:

```
xs = np.arange(5, 21) # Grid of possibilities
ps = xs**2             # Not normalised
ps = ps/ps.sum()      # Normalise it
plt.bar(xs, ps)        # Plot it

# Expected value and variance
ex = np.sum(xs*ps)
variance = np.sum(ps*(xs - ex)**2)
np.sum(ps[xs >= 10]) # P(x >= 10)
```

# Common discrete distributions

Here are some common discrete distributions:

# Common discrete distributions

Here are some common discrete distributions:

- Discrete Uniform (which one is it?)



# Common discrete distributions

Here are some common discrete distributions:

- Discrete Uniform (which one is it?)
- Binomial (how many successes out of  $N$  quasi-identical trials?)

# Common discrete distributions

Here are some common discrete distributions:

- Discrete Uniform (which one is it?)
- Binomial (how many successes out of  $N$  quasi-identical trials?)
- Poisson (how many occurrences of rare event?)

# Astronomy uses for Discrete Uniform

The number of emission lines in this spectrum is somewhere from 0 to 100, and I don't know the number.

# Astronomy uses for Binomial

Suppose it is known (or hypothesised) that 30% of stars of a particular type exhibit a certain kind of oscillation signal. In a new sample of  $N = 100$  such stars, let  $x$  be the number that have the oscillation.

Then  $x \sim \text{Binomial}(100, 0.3)$ .

I set a probability equal to a frequency here. What implicit assumption am I making?

# Astronomy uses for Poisson

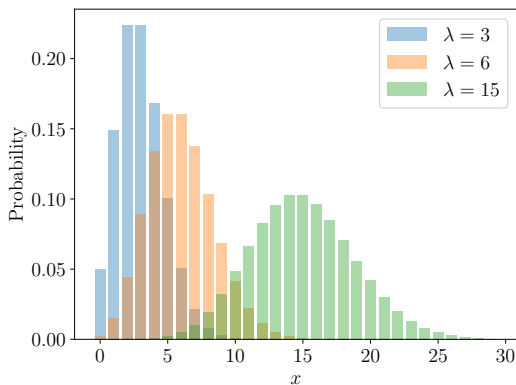
The intensity of an X-ray source is such that you would expect to detect  $\lambda$  photons per minute. Let  $x$  be the actual number of photons you observe in a minute.

$$x|\lambda \sim \text{Poisson}(\lambda) \quad (2)$$

$$p(x|\lambda) = \frac{\lambda^x e^{-\lambda}}{x!} \quad (3)$$

where  $\lambda \geq 0$  and  $x \in \{0, 1, 2, 3, \dots\}$ .

# Three Poisson Distributions



# Continuous distributions

These are characterised by a continuous hypothesis space (e.g. “all real numbers”) and a *probability density function* (PDF).

For example, normal/gaussian distributions:

$$X|\mu, \sigma \sim \text{Normal}(\mu, \sigma^2) \quad (4)$$

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(x - \mu)^2\right] \quad (5)$$

$f_X(x)$  is the full notation favoured by many statisticians. You can also just write  $f(x)$  or  $p(x)$  (and not having any upper-case  $X$ ).

# Properties of continuous probability distributions

Just like discrete, with integrals (implicitly over all  $x$ ) replacing sums!



# Properties of continuous probability distributions

Just like discrete, with integrals (implicitly over all  $x$ ) replacing sums!

Normalisation:

$$\int p(x) dx = 1.$$

# Properties of continuous probability distributions

Just like discrete, with integrals (implicitly over all  $x$ ) replacing sums!

Normalisation:

$$\int p(x) dx = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \int xp(x) dx$$

# Properties of continuous probability distributions

Just like discrete, with integrals (implicitly over all  $x$ ) replacing sums!

Normalisation:

$$\int p(x) dx = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \int xp(x) dx$$

Variance:

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \int (x - \mathbb{E}(X))^2 f(x) dx$$

# Properties of continuous probability distributions

Just like discrete, with integrals (implicitly over all  $x$ ) replacing sums!

Normalisation:

$$\int p(x) dx = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \int x p(x) dx$$

Variance:

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \int (x - \mathbb{E}(X))^2 f(x) dx$$

Standard deviation:

$$\text{sd}(X) = \sqrt{\text{Var}(X)}$$

# Properties of continuous probability distributions

Just like discrete, with integrals (implicitly over all  $x$ ) replacing sums!

Normalisation:

$$\int p(x) dx = 1.$$

Expected value:

$$\mathbb{E}(X) = \langle X \rangle = \int x p(x) dx$$

Variance:

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \int (x - \mathbb{E}(X))^2 f(x) dx$$

Standard deviation:

$$\text{sd}(X) = \sqrt{\text{Var}(X)}$$

The expected value and sd describe the *center* and *width* of the distribution respectively.

# Numerical handling

Numerical handling of continuous probability distributions for a single quantity:

```
xs = np.linspace(-10.0, 10.0, 10001) # Grid of possibilities
ps = np.exp(-0.5*((xs - 2.0)/1.5)**2) # Not normalised
ps = ps/np.trapz(ps, x=xs) # Normalise it (integral, not sum)
plt.plot(xs, ps) # Plot it

# Expected value and variance - integrals, not sums
ex = np.trapz(xs*ps, x=xs)
variance = np.trapz(ps*(xs - ex)**2, x=xs)
np.trapz(ps*(xs >= 5.0), x=xs) # P(x >= 5)
```

# Common continuous distributions

Here are some common continuous distributions:

# Common continuous distributions

Here are some common continuous distributions:

- Uniform ('lots of uncertainty')



# Common continuous distributions

Here are some common continuous distributions:

- Uniform ('lots of uncertainty')
- Normal/gaussian (commonly used for noise)

# Common continuous distributions

Here are some common continuous distributions:

- Uniform ('lots of uncertainty')
- Normal/gaussian (commonly used for noise)
- $t$  (like a normal but with fatter tails)

# Common continuous distributions

Here are some common continuous distributions:

- Uniform ('lots of uncertainty')
- Normal/gaussian (commonly used for noise)
- $t$  (like a normal but with fatter tails)
- Gamma (nice two-parameter family for a positive quantity)

# Common continuous distributions

Here are some common continuous distributions:

- Uniform ('lots of uncertainty')
- Normal/gaussian (commonly used for noise)
- $t$  (like a normal but with fatter tails)
- Gamma (nice two-parameter family for a positive quantity)
- Exponential (how long between subsequent events?)

# Common continuous distributions

Here are some common continuous distributions:

- Uniform ('lots of uncertainty')
- Normal/gaussian (commonly used for noise)
- $t$  (like a normal but with fatter tails)
- Gamma (nice two-parameter family for a positive quantity)
- Exponential (how long between subsequent events?)
- Pareto ('power law')

# Astronomy uses for Uniform

There is an asteroid somewhere in an image. Where?

# Astronomy uses for Normal/Gaussian

A very common and popular model for how far 'noise' will cause a measurement to depart from the true value of what is being measured.

# Astronomy uses for $t$

I recommend using the  $t$ -distribution instead of the gaussian distribution for noise if you think a heavier-tailed distribution might be appropriate.



# Higher dimensions

Joint probability distributions can be created using the product rule. e.g.,

$$p(x, y) = p(x)p(y|x) \quad (6)$$

The joint distribution allows you to calculate the probability of statements about the *pair*  $(x, y)$ .

$$P((x, y) \in R) = \int_R p(x, y) dx dy \quad (7)$$

# Marginalisation

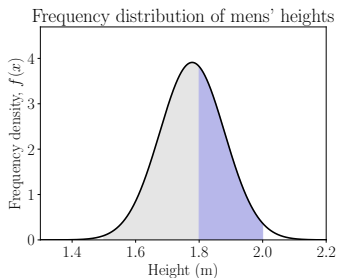
If you have a joint distribution but only care about statements about one of the quantities, you can find the *marginal distribution*:

$$p(x) = \int_{-\infty}^{\infty} p(x, y) dy \quad (8)$$

# Bayesian and frequentist uses

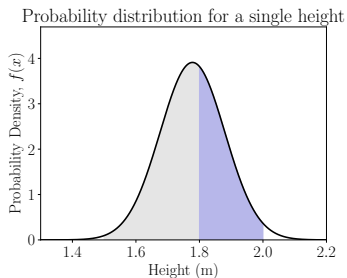
Probability distributions are used in both Bayesian and frequentist senses.

# A frequency distribution...



$$\begin{aligned}\text{Frac}(x \geq 1.8 | x \in [1.5, 2.0]) &= \frac{\text{Frac}(x \geq 1.8, x \in [1.5, 2.0])}{\text{Frac}(x \in [1.5, 2.0])} \\ &= \frac{\int_{1.8}^{2.0} f(x) dx}{\int_{1.5}^{2.0} f(x) dx}\end{aligned}$$

# A probability distribution...



$$\begin{aligned}\text{Plaus}(x \geq 1.8 | x \in [1.5, 2.0]) &= \frac{\text{Plaus}(x \geq 1.8, x \in [1.5, 2.0])}{\text{Plaus}(x \in [1.5, 2.0])} \\ &= \frac{\int_{1.8}^{2.0} f(x) dx}{\int_{1.5}^{2.0} f(x) dx}\end{aligned}$$

## Important!

The biggest source of confusion in statistics is the failure to distinguish between **frequency distributions** which describe *populations*, and **probability distributions** which describe *uncertainty about a single quantity*<sup>a</sup>.

---

<sup>a</sup>Could be a single non-scalar quantity, such as (3.2, 1.7).

See `questions2.pdf`