

## STEP Support Programme

# STEP 2 Specification Probability Notes

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These notes are designed to help students in preparing for STEP 2. They cover the "bold and italic" sections of the STEP 2 specification which are not covered in the A-level single Mathematics specifications, or AS Further Maths Common Core. Many of these topics will be covered in A Level Further Mathematics, and will be covered in some AS Further Mathematics modules.

There are more notes on the various sections of the specification in the STEP 2 modules.





#### Poisson Distribution

The *Poisson distribution* measures the number of occurrences of an event in a given time interval. It was first used by Ladislaus Josephovich Bortkiewicz to model the number of deaths of Prussian cavalry-men by horse kicks in a year.

A Poisson random variable satisfies the following conditions:

- I Occurrences are independent.
- II The mean (or expected) number of occurrences during a time interval is proportional to the length of the time interval.

As well as modelling the number of occurrences in a given time interval it can be used to model the number of occurrences in a given space interval. Some applications are the number of car accidents in a mile of road, the number of people joining a queue every 5 minutes and the number of hairs in a burger.

The number of occurrences in a given time interval is given by:

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

where r is an integer, with  $r \ge 0$ ,  $\lambda$  is the mean number of occurrences in the given interval and (by convention) 0! = 1.

Note that the sum of all the probabilities is given by:

$$\sum_{r=0}^{\infty} \frac{\mathrm{e}^{-\lambda} \lambda^r}{r!} = \mathrm{e}^{-\lambda} \times \sum_{n=0}^{\infty} \frac{\lambda^n}{r!} = \mathrm{e}^{-\lambda} \times \mathrm{e}^{\lambda} = 1.$$

For the last equality, we used the exponential series expansion  $e^x = 1 + x + \frac{x^2}{2!} + \cdots$ . The fact that the probabilities sum to 1 should be reassuring!

The expectation of the Poisson distribution is given by:

$$\begin{split} \mathbf{E}(X) &= \sum_{r=0}^{\infty} \frac{\mathrm{e}^{-\lambda} \lambda^r}{r!} \times r \\ &= 0 + \left( 1 \times \mathrm{e}^{-\lambda} \lambda \right) + \left( 2 \times \frac{\mathrm{e}^{-\lambda} \lambda^2}{2!} \right) + \left( 3 \times \frac{\mathrm{e}^{-\lambda} \lambda^3}{3!} \right) + \left( 4 \times \frac{\mathrm{e}^{-\lambda} \lambda^4}{4!} \right) + \cdots \\ &= \lambda \mathrm{e}^{-\lambda} \left( 1 + \lambda + \frac{\lambda^2}{2!} + \frac{\lambda^3}{3!} + \cdots \right) \\ &= \lambda \mathrm{e}^{-\lambda} \times \mathrm{e}^{\lambda} \\ &= \lambda \end{split}$$

Similarly, it can be shown that  $Var(X) = \lambda$  (you might like to do this). If X has a Poisson distribution then we write  $X \sim Po(\lambda)$ .





The proportionality principle means that if the number of successes in a time interval can be modelled as a Poisson distribution with a mean of  $\lambda$ , then the number of successes in a time interval twice as long can be modelled as a Poisson distribution with mean  $2\lambda$ , and so on.

Example: The number of calls to "Kalculus Kids" is Poisson distributed with, on average, 8 calls an hour. Find the probabilities of:

(a) 5 calls in one hour

here 
$$X \sim Po(8)$$
 and so  $P(X = 5) = \frac{e^{-8} \times 8^5}{5!}$ 

**(b)** 10 calls in two hours

here 
$$X \sim \text{Po}(16)$$
 and so  $P(X = 10) = \frac{e^{-16} \times 16^{10}}{10!}$ 

(c) 2 calls in 30 mins

here 
$$X \sim Po(4)$$
 and so  $P(X = 2) = \frac{e^{-4} \times 4^2}{2!} = 8e^{-4}$ 

(d) Fewer than 2 calls in 15 mins

here 
$$X \sim \text{Po}(2)$$
 and so  $P(X < 2) = P(X = 0 \text{ or } 1) = \frac{e^{-2} \times 2^0}{0!} + \frac{e^{-2} \times 2^1}{1!} = 3e^{-2}$ 

Note that I have not written these as decimals, and have only simplified the expressions if it was straightforward and useful to do so.

If you have two *independent*<sup>1</sup> Poisson distributions, X with mean  $\lambda$  and Y with mean  $\mu$ , then the sum X + Y is also a Poisson distribution with mean  $\lambda + \mu$ .

Example: A company making gizmos accepts orders on-line or by phone. Both of these follow a Poisson distribution, telephone orders with a mean of 2 per day and on-line orders with a mean of 5 per day. The telephone and on-line orders are independent of each other. What is the probability that they receive 10 orders on one day?

The total number of orders per day is distributed as  $X \sim \text{Po}(7)$  and so we have  $P(X=10) = \frac{\mathrm{e}^{-7} \times 7^{10}}{10!}$ .

<sup>&</sup>lt;sup>1</sup> Independent means that the outcome of one of the events has no affect on the outcome of the other. If two events are independent then we have  $P(X = x \text{ and } Y = y) = P(X = x) \times P(Y = y)$ .





### **Approximating Distributions**

The Normal, Binomial and Poisson distributions model different situations:

- The Normal distribution models a continuous situation (such as height), and can take values in the range  $(-\infty, \infty)$ . The Normal distribution is symmetrical about the mean.
- The *Binomial* distribution is a discrete distribution which can take the values  $0, 1, 2, 3, \dots, n$ . It can be thought of as the number of "successes" out of n "trials".
- The *Poisson* distribution is also a discrete distribution, but in this case it can take the values  $0, 1, 2, 3, \cdots$  (i.e. there is no upper bound). It can be thought of as the number of "occurrences" in a given interval (which might be a time interval, space interval etc.).

Under certain situations the Binomial distribution can be approximated by a Poisson or Normal distribution, and the Poisson distribution can be approximated by a Normal distribution.

If n "is large" and p "is small" then the Binomial distribution B(n, p) can be approximated with a Poisson distribution, Po(np).

"Large" and "small" are not well defined. One rule of thumb is that we need  $np \leq 10$ , and the larger the value of n the better the approximation.

- If  $X \sim B(n, p)$  and n is "large" and/or p is "close to  $\frac{1}{2}$ " then X can be approximated by a normal distribution,  $X \sim N(np, np(1-p))$ .
- If  $X \sim \text{Po}(\lambda)$  and  $\lambda$  is "large" then X can be approximated by a normal distribution,  $X \sim \text{N}(\lambda, \lambda)$ .

If you are approximating a discrete distribution, X, (e.g. Binomial or Poisson) by a continuous Normal distribution, Y, then you will need to apply a continuity correction:

- $P(X < 3) \implies P(Y < 2.5)$
- $P(X \le 3) \implies P(Y < 3.5)$
- $P(X \ge 3) \implies P(Y > 2.5)$
- $\bullet \qquad \mathrm{P}(X > 3) \implies \mathrm{P}(Y > 3.5)$
- $P(1 < X \le 4) \implies P(1.5 < Y < 4.5)$

Note that it doesn't matter if we use strict or non-strict inequalities for Y — as Y is continuous we have  $P(Y < 2.5) = P(Y \le 2.5)$ .





### **Continuous Distributions**

The Normal distribution is one example of a continuous distribution.

A continuous distribution is defined by a probability density function (or p.d.f.) and a range of possible values. The p.d.f. for the Standard Normal distribution is  $f(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}x^2}$ .

For a continuous distribution with p.d.f. f(x) we have:

- $P(a \leqslant X \leqslant b) = \int_a^b f(x) dx$
- $\int_{-\infty}^{\infty} f(x) dx = 1$  (as the total probability must be 1). This means that the total area under the curve y = f(x) must be 1.

If f(x) is equal to 0 for some ranges of x then you will be able to change the limits accordingly. For example if f(x) = kx for  $0 \le x \le 10$ , and is equal to 0 elsewhere, then we could write  $\int_0^{10} f(x) dx = 1$  (and hence find the value of k).

• The *expectation* (or mean) is given by:

$$\mu = \int_{-\infty}^{\infty} x f(x) \, \mathrm{d}x$$

• The *variance* is given by:

$$\int_{-\infty}^{\infty} x^2 f(x) dx - \mu^2$$

• The *cumulative distribution function* is defined by:

$$F(x) = P(X \le x) = \int_{-\infty}^{x} f(t) dt$$

Here we have taken the lower limit as  $-\infty$ . It may be that f(x) = 0 for  $-\infty < x < a$  say, in which case we could write the lower limit as a. Note the use of "dummy variable" t inside the integral — we cannot use x inside the integral as it is used as a limit.

- f(x) = F'(x)
- $P(a \leqslant X \leqslant b) = F(b) F(a)$
- The median, m satisfies  $P(X \leq m) = P(X \geq m) = \frac{1}{2}$ , i.e.  $\int_{-\infty}^{m} f(x) dx = \int_{m}^{\infty} f(x) dx = \frac{1}{2}$ . Equivalently we have  $F(m) = \frac{1}{2}$ .
- The *mode* is where the probability distribution function has a maximum (there may be more than one!). With piece-wise p.d.f.s you might have to consider the boundary points separately.

Note that for a Normal distribution we have mean = median = mode.





### Continuous Uniform Distribution

The continuous uniform distribution or rectangular distribution is defined between two end points a and b has a p.d.f. which is a horizontal line segment. Since the total area under this line segment must be equal to 1 then the line is at a height of  $\frac{1}{b-a}$  and so the p.d.f. is given by:

$$f(x) = \frac{1}{b-a}, \quad x \in [a, b]$$

.

The mean of the uniform distribution is given by:

$$\int_a^b \frac{x}{b-a} dx = \left[\frac{x^2}{2(b-a)}\right]_a^b$$

$$= \frac{b^2 - a^2}{2(b-a)}$$

$$= \frac{(b+a)(b-a)}{2(b-a)}$$

$$= \frac{1}{2}(a+b)$$

This makes sense as you would expect the mean to be half way through the rectangle.

Using 
$$Var(X) = \int_a^b \frac{x^2}{b-a} dx - [E(X)]^2$$
 gives the variance as  $\frac{(b-a)^2}{12}$ .

You might like to do the integration and show that the variance is actually as given above!

