

# Binomial Approximation

There are times when it is exceptionally hard to numerically calculate probabilities for a binomial distribution, especially when  $n$  is large. For example, say  $X \sim \text{Bin}(n = 10000, p = 0.5)$  and you want to calculate  $P(X > 5500)$ . The correct formula is:

$$\begin{aligned} P(X > 55) &= \sum_{i=5500}^{10000} P(X = i) \\ &= \sum_{i=5500}^{10000} \binom{10000}{i} p^i (1-p)^{10000-i} \end{aligned}$$

That is a difficult value to calculate. Luckily there is an easier way. For deep reasons which we will cover in our section on "uncertainty theory" it turns out that a binomial distribution can be very well approximated by both Normal distributions and Poisson distributions if  $n$  is large enough.

Use the [Poisson approximation](#) when  $n$  is large ( $>20$ ) and  $p$  is small ( $<0.05$ ). A slight dependence between results of each experiment is ok

Use the [Normal approximation](#) when  $n$  is large ( $>20$ ), and  $p$  is mid-ranged. Specifically it's considered an accurate approximation when the variance is greater than 10, in other words:  $np(1-p) > 10$ . There are situations where either a Poisson or a Normal can be used to approximate a Binomial. In that situation go with the Normal!

## Poisson Approximation

When defining the Poisson we proved that a Binomial in the limit as  $n \rightarrow \infty$  and  $p = \lambda/n$  is a Poisson. That same logic can be used to show that a Poisson is a great approximation for a Binomial when the Binomial has extreme values of  $n$  and  $p$ . A Poisson random variable approximates Binomial where  $n$  is large,  $p$  is small, and  $\lambda = np$  is "moderate". Interestingly, to calculate the things we care about (PMF, expectation, variance) we no longer need to know  $n$  and  $p$ . We only need to provide  $\lambda$  which we call the rate. When approximating a Poisson with a Binomial, always choose  $\lambda = n \cdot p$ .

There are different interpretations of "moderate". The accepted ranges are  $n > 20$  and  $p < 0.05$  or  $n > 100$  and  $p < 0.1$ .

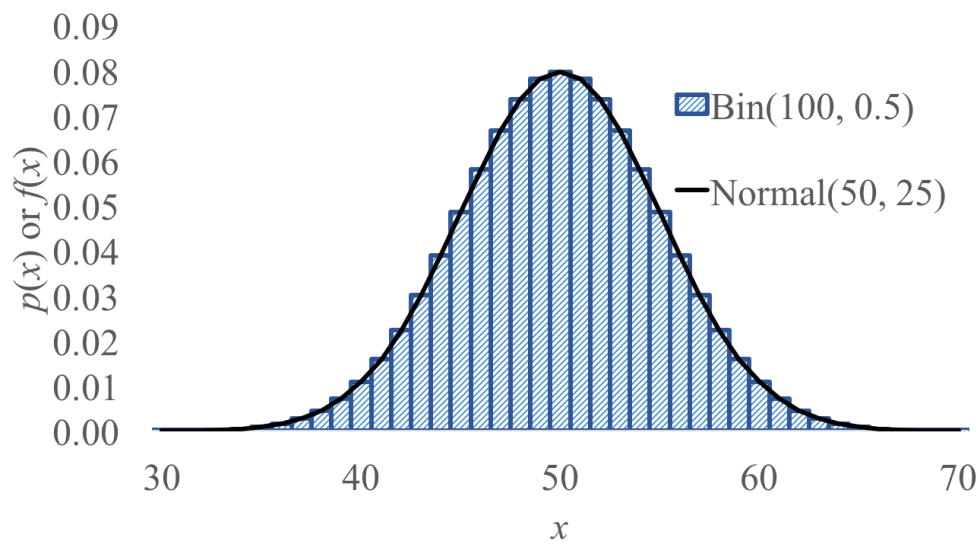
Let's say you want to send a bit string of length  $n = 10^4$  where each bit is independently corrupted with  $p = 10^{-6}$ . What is the probability that the message will arrive uncorrupted? You can solve this using a Poisson with  $\lambda = np = 10^4 10^{-6} = 0.01$ . Semantically,  $\lambda = 0.01$  means that we expect 0.01 corrupt bits per string, assuming bits are continuous. Let  $X \sim \text{Poi}(0.01)$  be the number of corrupted bits. Using the PMF for Poisson:

$$\begin{aligned} P(X = 0) &= \frac{\lambda^0}{0!} e^{-\lambda} \\ &= \frac{0.01^0}{0!} e^{-0.01} \\ &\sim 0.9900498 \end{aligned}$$

We could have also modelled  $X$  as a binomial such that  $X \sim \text{Bin}(10^4, 10^{-6})$ . That would have been impossible to calculate on a computer but would have resulted in the same number (up to the millionth decimal).

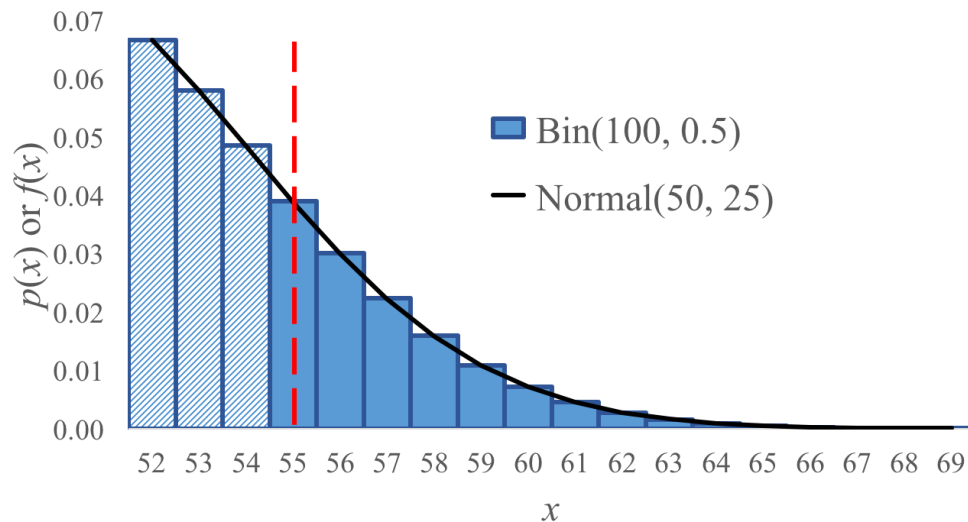
## Normal Approximation

For a Binomial where  $n$  is large and  $p$  is mid-ranged, a Normal can be used to approximate the Binomial. Let's take a side by side view of a normal and a binomial:



Lets say our binomial is a random variable  $X \sim \text{Bin}(100, 0.5)$  and we want to calculate  $P(X \geq 55)$ . We could cheat by using the closest fit normal (in this case  $Y \sim N(50, 25)$ ). How did we choose that particular Normal? Simply select one with a mean and variance that matches the Binomial expectation and variance. The binomial expectation is  $np = 100 \cdot 0.5 = 50$ . The Binomial variance is  $np(1-p) = 100 \cdot 0.5 \cdot 0.5 = 25$ .

You can use a Normal distribution to approximate a Binomial  $X \sim \text{Bin}(n, p)$ . To do so define a normal  $Y \sim (E[X], \text{Var}(X))$ . Using the Binomial formulas for expectation and variance,  $Y \sim (np, np(1-p))$ . This approximation holds for large  $n$  and moderate  $p$ . That gets you very close. However since a Normal is continuous and Binomial is discrete we have to use a continuity correction to discretize the Normal.



$$P(X = k) \sim P\left(k - \frac{1}{2} < Y < k + \frac{1}{2}\right) = \Phi\left(\frac{k - np + 0.5}{\sqrt{np(1-p)}}\right) - \Phi\left(\frac{k - np - 0.5}{\sqrt{np(1-p)}}\right)$$

You should get comfortable deciding what continuity correction to use. Here are a few examples of discrete probability questions and the continuity correction:

Discrete (Binomial) probability question	Equivalent continuous probability question
$P(X = 6)$	$P(5.5 < X < 6.5)$
$P(X \geq 6)$	$P(X > 5.5)$
$P(X > 6)$	$P(X > 6.5)$
$P(X < 6)$	$P(X < 5.5)$
$P(X \leq 6)$	$P(X < 6.5)$

**Example:** 100 visitors to your website are given a new design. Let  $X$  = # of people who were given the new design and spend more time on your website. Your CEO will endorse the new design if  $X \geq 65$ . What is  $P(\text{CEO endorses change} | \text{it has no effect})$ ?

$E[X] = np = 50$ .  $\text{Var}(X) = np(1 - p) = 25$ .  $\sigma = \sqrt{\text{Var}(X)} = 5$ . We can thus use a Normal approximation:  $Y \sim \mathcal{N}(\mu = 50, \sigma^2 = 25)$ .

$$P(X \geq 65) \approx P(Y > 64.5) = P\left(\frac{Y - 50}{5} > \frac{64.5 - 50}{5}\right) = 1 - \Phi(2.9) = 0.0019$$

**Example:** Stanford accepts 2480 students and each student has a 68% chance of attending. Let  $X$  = # students who will attend.  $X \sim \text{Bin}(2480, 0.68)$ . What is  $P(X > 1745)$ ?

$E[X] = np = 1686.4$ .  $\text{Var}(X) = np(1 - p) = 539.7$ .  $\sigma = \sqrt{\text{Var}(X)} = 23.23$ . We can thus use a Normal approximation:  $Y \sim \mathcal{N}(\mu = 1686.4, \sigma^2 = 539.7)$ .

$$\begin{aligned} P(X > 1745) &\approx P(Y > 1745.5) \\ &\approx P\left(\frac{Y - 1686.4}{23.23} > \frac{1745.5 - 1686.4}{23.23}\right) \\ &\approx 1 - \Phi(2.54) = 0.0055 \end{aligned}$$