

Wanted to approximate

$$X_1 \sim \text{Bin}(n_1, p_1) \quad X_2 \sim \text{Bin}(n_2, p_2) \\ \xrightarrow{\text{approx}} T = X_1 + X_2$$

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$$P(k|T) = P(X_1 = k | T = t)$$

Know this depends on p_1, p_2 only through $p = \frac{p_1 p_2}{p_1 p_2 + p_2 p_1}$

So consider $X_1 \sim \text{Bin}(n_1, p)$ $X_2 \sim \text{Bin}(n_2, p)$ $\xrightarrow{\text{approx}} T \approx X_1 + X_2$

where p_1, p_2 are the unique solution to

$$\frac{p_1 p_2}{p_1 p_2 + p_2 p_1} = p, \quad n_1 p_1 + n_2 p_2 = t$$

Then instead of looking at $P(X_1 = k | T = t)$ we can look at $P(\tilde{X}_1 = k | \tilde{T} = t)$.

Now, from the CLT we have

$$\begin{aligned} \tilde{X}_1 &\sim N(n_1 \mu_1, n_1 \sigma_1^2) \\ \tilde{X}_2 &\sim N(n_2 \mu_2, n_2 \sigma_2^2) \end{aligned} \quad \text{as } n \rightarrow \infty$$

so that

$$\begin{bmatrix} \tilde{X}_1 \\ \tilde{X}_2 \\ T \end{bmatrix} \sim N \left(\begin{bmatrix} n_1 \mu_1 \\ n_2 \mu_2 \\ n_1 \mu_1 + n_2 \mu_2 \end{bmatrix}, \begin{bmatrix} n_1 \sigma_1^2 & & \\ & n_2 \sigma_2^2 & \\ n_1 \sigma_1^2 & & n_1 \sigma_1^2 + n_2 \sigma_2^2 \end{bmatrix} \right)$$

By bivariate normal theory, we have that if

$$\begin{bmatrix} Y \\ Z \end{bmatrix} \sim N \left(\begin{bmatrix} \mu_Y \\ \mu_Z \end{bmatrix}, \begin{bmatrix} \sigma_Y^2 & \sigma_{YZ} \\ \sigma_{YZ} & \sigma_Z^2 \end{bmatrix} \right)$$

then the conditional dist'n of Y given Z is normal with

$$E[Y|Z] = \mu_Y + \frac{\sigma_{YZ}}{\sigma_Z^2} (Z - \mu_Z)$$

$$\text{Var}(Y|Z) = \sigma_Y^2 \left(1 - \frac{(\sigma_{YZ})^2}{\sigma_Z^2 \sigma_Y^2} \right)$$

Applying this to \tilde{X}_1, T we get that the conditional dist'n of \tilde{X}_1 given T is (approximately) normal with

$$\text{mean} = n_1 \mu_1 + \frac{n_1 \sigma_1^2}{n_1 \sigma_1^2 + n_2 \sigma_2^2} (T - [n_1 \mu_1 + n_2 \mu_2])$$

$$= n_1 \mu_1$$

(since we defined μ_1, μ_2 to satisfy the condition $n_1 \mu_1 + n_2 \mu_2 = T$)

$$\frac{E(n_2 - t + E)}{(t - E)(n_1 - E)} = \frac{(n_1 p_1)(n_2 p_2)}{(n_2 p_2)(n_1 p_1)} = \frac{p_1 p_2}{p_2 p_1} = 1$$

Thus we have

$n_1 p_1$	t
$n_2 p_2$	t
n_1	$n_1 + n_2 - t$
n_2	$n_1 + n_2$

with $E = n_1 p_1$. Now using $n_1 p_1 + n_2 p_2 = t$, we find that this is the same as

$n_1 - E$	E
$n_2 - t + E$	$t - E$
n_1	$n_1 + n_2 - t$
n_2	$n_1 + n_2$

written as

The approximate conditional means of all the table entries can be

$$\begin{aligned} \text{Variance} &= n_1 p_1 p_1 \left(1 - \frac{n_1 p_1 p_1}{n_1 p_1 p_1 + n_2 p_2 p_2} \right) \\ &= \frac{(n_1 p_1 p_1)(n_2 p_2 p_2)}{n_1 p_1 p_1 + n_2 p_2 p_2} \\ &= \left(\frac{1}{n_1 p_1 p_1} + \frac{1}{n_2 p_2 p_2} \right)^{-1} \end{aligned}$$

Conclusion: The conditional dist'n of X_1 given $T=t$ is approximately $N(E, V)$, where E satisfies the equation

$$\frac{E(n_2 - t + \epsilon)}{(t - \epsilon)(n_1 - \epsilon)} = \eta$$

and $V = \left(\frac{1}{n_1 p_1 \alpha_1} + \frac{1}{n_2 p_2 \alpha_2} \right)^{-1}$

where $p_1 = \frac{\epsilon}{n_1}$, $p_2 = \frac{t - \epsilon}{n_2}$.