If $X \sim \text{Bin}(n, p)$ then for large enough n, $\quad X \dot{\sim} \mathcal{N}(np, np(1-p))$.

Moment Generating Function of $X \sim \text{Pois}(\lambda)$

PMF: $P_X(x) = \frac{e^{-\lambda}\lambda^x}{x!}$

MGF;

$$\begin{aligned}
M_X(t) = \mathbb{E}[e^{tx}] &= \sum_{x=0}^{\infty} e^{tx} \frac{e^{-\lambda}\lambda^x}{x!} \\
&= \sum_{x=0}^{\infty} e^{-\lambda} \frac{e^t \lambda}{x!} \\
&= \sum_{x=0}^{\infty} \frac{e^{-\lambda}(e^t\lambda)^x e^{-e^t\lambda} e^{e^t\lambda}}{x!} \cdots (1) \\
&= e^{e^t\lambda - \lambda} = e^{(e^t-1)\lambda}
\end{aligned}$$

where the above holds since (1); $\sum_{x=0}^{\infty} \frac{e^{-e^t\lambda}(e^t\lambda)^x}{x!} = 1$

So If $X_1, X_2, X_3, \ldots, X_n$ are *iid* Pois(1) then the Distribution of $X_1 + X_2 + \cdots + X_n$ is ?

when Random Variables are independent;

$$\begin{aligned}
M_{X_1+X_2+\ldots X_n}(t) &= M_{X_1}(t) M_{X_2}(t) \ldots M_{X_n}(t) \\
&= (M_{X_1}(t))^n \\
&= \left(e^{\left(e^t-1\right)}\right)^n
\end{aligned}$$

$$so, X_1 + X_2 + \cdots + X_n \sim Pois(n)$$

and for n longe enough; $X_1 + X_2 + \cdots + X_n \dot{\sim} N(n, n)$ So By Central Limit Theorem; If $X \sim \text{Pois}(n)$ then $X \dot{\sim} \mathcal{N}(n, n)$ for large enough n. {Use Continuity Correction}

$\rightarrow$ Gamma convergence to Normal; (Excercise) (1) MGF of Gamma (n, λ) (2) Show that the MGF of $X_1 + X_2 + \cdots + X_n$ is same as MGF of Gamma (n, λ) where $X_1, X_n, \ldots, X_n$ are *iid* Expo(λ). (3) Then by CLT for n large enough; $X_1 + X_2 + \cdots + X_n \dot{\sim} \mathcal{N}\left(\frac{n}{\lambda}, \frac{n}{\lambda^2}\right)$

Suppose $Z_1, Z_2, \ldots, Z_n$ are ind $\mathcal{N}(0,1)$ then $\bar{Z}_n = \frac{Z_1 + Z_n + \cdots + Z_n}{n}$ will have $\bar{Z}_n \sim N\left(0, \frac{1}{n}\right)$. Note that $\bar{Z}_n$ and $\sum_{j=1}^{n}\left(Z_j - \bar{Z}_n\right)^2$ are independent and $\sum_{j=1}^{n}\left(Z_j - \bar{Z}_n\right)^2 \sim \chi^2_{n-1}$

For $n=2$; $\quad \bar{Z}_n = \frac{Z_1+Z_2}{2}$ and $\sum_{j=1}^{2}\left(Z_j-\bar{Z}_2\right)^2 = \left(Z_1-\bar{Z}_2^2\right)+\left(Z_2-\bar{Z}_2\right)^2$

$$
\begin{aligned}
&= \left(Z_1 - \frac{Z_1+Z_2}{2}\right)^2 + \left(Z_2 - \frac{Z_1+Z_2}{2}\right)^2 \\
&= \left(\frac{Z_1-Z_2}{2}\right)^2 + \left(\frac{Z_2-Z_1}{2}\right)^2 = 2\left(\frac{Z_1-Z_2}{2}\right)^2 = \left(\frac{Z_1-Z_2}{\sqrt{2}}\right)^2
\end{aligned}
$$

Note

$$
\begin{aligned}
Z_1 - Z_2 &\sim N(0,2) \\
\frac{Z_1-Z_2}{\sqrt{2}} &\sim N(0,1) \\
\Rightarrow \left(\frac{Z_1-Z_2}{\sqrt{2}}\right)^2 &\sim \chi_1^2(1)
\end{aligned}
$$

Now to show that $\bar{Z}_2$ and $\sum_{j=1}^{2}\left(Zj-Z_n\right)^2$ are independent, we reed to show that Z_1+Z_2 and Z_1-Z_2, are independent since $\sum_{j=1}^{2}(Zj-Zn)^2 = \left(\frac{Z_1-Z_2}{\sqrt{2}}\right)^2$ is some function of Z_1 and Z_2 same as $\bar{Z}_2 = \frac{Z_1+Z_2}{2}$ is a function of Z_1 and Z_2.

Now If,$\bar{Z}_n \sim \mathcal{N}\left(0,\frac{1}{n}\right)$ then $\sqrt{n}\bar{Z}_n \sim \mathcal{N}(0,1)$ and it is independent of $\sum_{j=1}^{n}\left(Z_j-Z_n\right)^2$ too.

Now, $T = \frac{Z}{\sqrt{\frac{X}{n}}}$ where $Z \sim \mathcal{N}(0,1)$ and $X \sim \chi_n^2$ and,

$\Rightarrow \frac{\sqrt{n}\bar{Z}_n}{\sqrt{\frac{\Sigma\left(Z_j-Z_n\right)^2}{n-1}}} \sim t_{n-1}$ distribution with $n-1$ deg of freedom.

Now suppose $X_1, X_2, \ldots, X_n \overset{iid}{\sim} \mathcal{N}\left(\mu,\sigma^2\right)$, then

$$
S_n^2 = \frac{\sum_{i=1}^{n}\left(X_i-\bar{X}_n\right)^2}{n-1}
$$

is the sample variance, when $\bar{X}_n$ is the sample mean, and the distribution of $\frac{(n-1)S_n^2}{\sigma^2} = \frac{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)^2}{\sigma_2} \sim \chi_{n-1}^2$.

Note that,

$$\begin{aligned}\frac{(n-1)S_n^2}{\sigma^2} &= \sum_{i=1}^{n}\left(\frac{X_i-\bar{X}}{\sigma}\right)^2 \\ &= \sum_{i=1}^{n}\left(\frac{X_i-\mu}{\sigma}-\frac{\bar{X}_n-\mu}{\sigma}\right)^2 \\ &= \sum_{i=1}^{n}\left(Z_i-\bar{Z}_n\right)\sim\chi^2_{n-1}\end{aligned}$$

and

$$\begin{aligned}Z_i &= \frac{X_i-\mu}{\sigma}\sim\mathcal{N}(0,1) \\ \bar{Z}_n &= \frac{\sum\frac{X_i}{n}-\mu}{\sigma}=\frac{\sum\frac{(X_i-\mu)}{\sigma}}{n}=\bar{Z}_n\end{aligned}$$

$$\begin{aligned}&\bar{Z}_n=\frac{\sum_{i=1}^{n}\left(\frac{x_i-\mu}{\sigma}\right)}{n}\text{ and }\frac{(n-1)s_n^2}{\sigma^2} \\ &\text{are independent by }\cdots(1) \\ &\bar{Z}_n=\frac{\bar{X}_n-\mu}{\sigma}\sim N\left(0,\frac{1}{n}\right) \\ &\text{then }\sqrt{n}\bar{Z}_n=\sqrt{n}\left(\frac{\bar{X}_n-\mu}{\sigma}\right)\sim\mathcal{N}(0,1) \\ &\implies\frac{\sqrt{n}\left(\frac{\bar{X}_n-\mu}{\sigma}\right)}{\sqrt{\frac{(n-1)S_n^2}{\sigma^2(n-1)}}}=\frac{\sqrt{n}\left(\frac{\bar{X}_n-\mu}{\sigma}\right)}{\sqrt{\frac{(S_n)^2}{\sigma^2}}}\sim t_{n-1}\end{aligned}$$

Now, $\frac{\sqrt{n}(\bar{x}_n-\mu)}{\sigma}\sim N(0,1)$ in this we can replace σ by S_n which will then give us t_{n-1} distribution and will have a fatter tail than $\mathcal{N}(0,1)$.

Statistics

Point Estimation

When we are trying to estimate a finite number of points or parameter; e.g; trying to estimate the average height ofthe class of some tudents, where average height $=\mu$ So population μ in the unknown parameter of interest. Say distribution of the whole Class's average height is $\mathcal{N}(\mu,1)$ then we draw a sample $X_1,X_2,X_3,\ldots,X_n\overset{iid}{\sim}\mathcal{N}(\mu,1)$ then we find a reasonable function $h(X_1,X_2,\ldots,X_n)$ which will be equal to the estimator of μ.

one good estimator of μ is $\frac{X_1+X_2+\cdots+X_n}{n}$, the sample mean, and it is good estimator because by law of large numbers as $n \to \infty$ $\frac{X_1+X_2+\ldots X_n}{n}$ converges to μ in probability.

Biased and Unbiased Estimators

(1) $\hat{H}_1 = X_1$ (is unbiased but not a very good estimator, since variance does not tend to 0)

(2) $\hat{H}_2 = \frac{\sum_{i=1}^{n} X_i}{n}$ (is unbiased and also a good estimator)

(3) $\hat{H}_3 = \frac{\sum_{i=1}^{n} X_i}{n} + \frac{1}{n}$ is a biased estimator.