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distribution relation: without proof:

Geometric / Negative binomial
 $f(x) = p(1-p)^{x-1}$ $f(x) = \binom{n+x-1}{x} p^n (1-p)^x$ // no. of failure before n success.
 clearly when, when $n=1$ // means 1st success, then
 Negative binomial \Rightarrow Geometric
 Again, sum of n geometric $x_i \Rightarrow$ Neg binomial with (n, p)

Negative Binomial / Poisson
 $\exp(-\lambda) \frac{\lambda^x}{x!} \leftarrow \binom{n+x-1}{x} p^n (1-p)^x$
 n should be large, $p \rightarrow 1$ and $\{n(1-p) = \lambda\}$ then CDF $f_x \approx f_y$;
 poisson random with $\lambda = n(1-p)$

Beta Binomial / Discrete uniform
 $\frac{\binom{n}{x} B(\alpha+x, \beta-n+x)}{B(\alpha, \beta)}$ $f(x) = \frac{1}{n}$ if $x=1, \dots, n$
 $\alpha=1, \beta=1$; $n=n$ then, Beta binomial \Rightarrow Discrete uniform

Hypogeometric / geometric
 $\frac{\binom{m}{x} \binom{N-m}{k-x}}{\binom{N}{k}}$ $p(1-p)^x$
 Has to do with ~~geometric~~ sample size, & bootstrapping. When
 population size increases relative to sample size,

Binomial / Poisson

$$\left\{ \begin{array}{l} \binom{n}{x} p^x (1-p)^{n-x} \quad \exp(-\lambda) \frac{\lambda^x}{x!} \\ \text{For binomial } P(X=x) \approx P(Y=x) \text{ ; when } np \text{ is large } \& \ np \text{ is small.} \end{array} \right.$$

\nearrow Poisson (np)

Binomial / Bernoulli

$$\left\{ \begin{array}{l} \binom{n}{x} p^x (1-p)^{n-x} \quad p \\ n=1 \& \ p \text{ is Bernoulli prob } \Rightarrow \text{Bernoulli} \end{array} \right.$$

Bernoulli / Binomial

sum of n Bernoulli(p) r.v. is Binomial(n, p)

Poisson / Normal

$$\left\{ \begin{array}{l} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right) \\ P(j \leq X \leq k) \approx P(j - \frac{1}{2} \leq Y \leq k + \frac{1}{2}) \\ \begin{array}{l} X \text{ poisson with} \\ \text{large mean} \end{array} \quad \parallel \quad \begin{array}{l} Y \text{ is normal same } m, \sigma^2 \\ \text{as } X. \end{array} \end{array} \right.$$

Binomial / normal

$$\left\{ \begin{array}{l} P(j \leq X \leq k) \approx P(j - \frac{1}{2} \leq Y \leq k + \frac{1}{2}) \\ \begin{array}{l} Y \text{ normal with mean } np \& \text{ var } np(1-p) \\ \text{better result with } p = \frac{1}{2} \end{array} \end{array} \right.$$

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Beta/Uniform

$$\frac{x^{\alpha-1} (1-x)^{\beta-1}}{\int_0^1 u^{\alpha-1} (1-u)^{\beta-1} du} ; \alpha=1 \& \beta=1 ; \text{easy}$$

standard Normal/chi-square

by definition sum of K standard Normal R.V. $\rightarrow \chi_K^2$
 \downarrow
 Degree of freedom

Gamma/chi-square

$$\frac{\beta^\alpha x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)} \quad n \sim \text{Normal } N(\mu, \sigma)$$

if $\alpha = \frac{\nu}{2} \& \beta = 1$; Gamma $\sim \nu$ degree of χ_ν^2

cauchy/Normal - standard $(\mu, \sigma^2) = (0, 1)$

$$\frac{\sigma}{\pi ((x-\mu)^2 + \sigma^2)}$$

\downarrow location \nwarrow scale

$\sim \frac{1}{\sqrt{\pi \sigma^2}} \exp\left(-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}\right)$
 \uparrow
 $\frac{x}{y} \sim \text{cauchy}(0, 1)$

student-t/standard Normal

$$f(x) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi} \Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{x^2}{\nu}\right)^{-\frac{\nu+1}{2}} \quad f_x \propto f_y \rightarrow \text{standard Normal}$$

\downarrow
Large No. of Degree of freedom ν

$\frac{\bar{x} - \mu}{s/\sqrt{n}} \rightarrow t\text{-distribution with } n-1 \text{ degree of freedom}$

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Normal / Log Normal

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)$$

$$f(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\log(y) - \mu)^2}{2\sigma^2}\right) / y$$

the $\log(x)$ is normal (μ, σ^2) r.v.

← easily

Beta / Normal

$f_x = f_y$ where x, y is normal with $\mu = \frac{\alpha}{\alpha + \beta}$

↙

reparamit.

$$f(y) = \frac{y^{\alpha-1} (1-y)^{\beta-1}}{\int_0^1 u^{\alpha-1} (1-u)^{\beta-1} du}$$

$$f' = \frac{\alpha\beta}{(\beta+\alpha)^2 (\alpha+\beta+1)}$$

Gamma / Beta

$\Gamma(\alpha, \beta)$

↓

k shape

$\frac{1}{\theta}$ scale

$\frac{x^{\alpha-1} (1-x)^{\beta-1}}{n \cdot \text{constant}}$

$$f(x; \alpha, \beta) = \frac{\beta^\alpha x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)}$$

↙

$(\alpha-1)! / \alpha$ per unit.

$$x_1 \sim \text{gamma}(\alpha_1, \beta)$$

$$x_2 \sim \text{gamma}(\alpha_2, \beta)$$

the $\frac{x_1 \beta_2}{\beta x_1 + x_2 \beta_2} \sim \text{Beta}(\alpha_1, \alpha_2)$

Chi-Square / Exponential

$$\frac{1}{\mu} \exp\left(-\frac{x}{\mu}\right)$$

$$\chi^2_2 \rightarrow \frac{1}{2} \exp\left(-\frac{x}{2}\right); \text{avg}; \mu=2 \quad \hookrightarrow \text{vice versa.}$$

Gamma / Exponential :

$$\frac{\beta^\alpha x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)}$$

$$\frac{1}{\mu} \exp\left(-\frac{x}{\mu}\right); x \geq 0$$

$$\Rightarrow \text{If } \alpha = 1 \text{ then } \text{Gamma}(\alpha, \beta) = \exp(\beta)$$

$$\text{sum of } n \text{ exp}(\beta) \text{ p.v.} \rightarrow \chi^2(n, \beta)$$

student-t / cauchy

$$\frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi} \Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{t^2}{v}\right)^{-\frac{v+1}{2}} / \frac{\sigma}{\pi \left((x-\mu)^2 + \sigma^2\right)} \approx \left[\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}\right]$$

"if $v=1$ // 1 degree of freedom \rightarrow student-t \rightarrow cauchy(0,1)