

$(x_1 + \dots + x_k)^n = \sum_{(n_1, \dots, n_k) : n_1 + \dots + n_k = n} \frac{n!}{n_1! \dots n_k!} x_1^{n_1} \dots x_k^{n_k}$		
$\begin{cases} P(S) = 1 \\ P(E) \geq 0, \forall E \subseteq S \\ P\left(\bigcup_{i=1}^{\infty} E_i\right) = \sum_{i=1}^{\infty} P(E_i) \end{cases}$	$P(\cdot B) = \frac{P(\cdot \cap B)}{P(B)}$ $P(B_k A) = \frac{P(A \cap B_k)}{\sum_{i=1}^n P(A \cap B_i)}$	
$P\left(\bigcap_{i=1}^k A_i\right) = P(A_1)P(A_2 A_1)P(A_3 A_1 \cap A_2) \dots P(A_k \bigcap_{j=1}^{k-1} A_j)$		

Discrete rv	Parameters	$p_X(x)$	$Ran(X)$	$E(X)$	$Var(X)$
$X \sim Bin(n, p)$	$n = 1, 2, 3, \dots$ $p \in (0, 1)$	$\binom{n}{x} p^x (1-p)^{n-x}$	$x = 0, 1, 2, \dots$	np	$np(1-p)$
$X \sim Bernoulli(p) = Bin(n=1, p)$					
$X \sim Poisson(\lambda)$	$\lambda \in (0, \infty)$	$\frac{\lambda^x e^{-\lambda}}{x!}$	$x = 0, 1, 2, \dots$	λ	λ
$Binomial(n, p) \approx Poisson(np)$					
$X \sim N.Bin(k, p)$	$k = 1, 2, 3, \dots$ $p \in (0, 1)$	$\binom{x-1}{k-1} p^k (1-p)^{x-k}$	$x = k, k+1, k+2, \dots$	$\frac{k}{p}$	$\frac{k(1-p)}{p^2}$
$X \sim Geometric(p) = N.Bin(k=1, p)$ $f_X(x) = (1-p)^{x-1} p$ $P(X > s+t X > t) = P(X > s)$, memorylessness (unique) $N.Bin = \text{count}(\text{total trials until } k \text{ successes})$					
$X \sim N.Bin(k, p), P(X \leq s) \Leftrightarrow k \text{ successes, } s-k \text{ failures, complete before } s-k+1 \text{ failures}$ $P(E \text{ precedes } F) = \frac{P(E)}{P(E) + P(F)}$, disjoint competing events E, F					
$P(X \leq s) = P(Y \geq k)$, connecting $X \sim N.Bin(k, p), Y \sim Bin(s, p)$					
$X \sim Hypergeo(n, m, N)$	$\{m \cdot A, (N-m) \cdot B\}$, n draws	$\frac{\binom{m}{x} \binom{N-m}{n-x}}{\binom{N}{n}}$	$x \in [\max(0, n+m-N), \min(m, n)]$	$\frac{nm}{N}$	$\frac{N-n}{N-1} np(1-p)$, $p = \frac{m}{N}$
$\text{binomial without replacement, hence varying } p$ $Hypergeo(n, m, N) \approx Bin\left(n, p = \frac{m}{N}\right) \text{ or } Poisson\left(\lambda = \frac{nm}{N}\right) \text{ as } (n, m, N) \rightarrow \infty$					
$E[g(X)] \equiv E[Y]$ $= \sum_{y \in \mathcal{X}_Y} y p_Y(y) = \sum_{y \in \mathcal{X}_Y} y \left[\sum_{x \in \mathcal{X}_{X(y)}} p_X(x) \right] = \sum_{y \in \mathcal{X}_Y} \sum_{x \in \mathcal{X}_{X(y)}} g(x) p_X(x)$ $= \sum_{x \in \bigcup_{y \in \mathcal{X}_Y} \mathcal{X}_{X(y)} = \mathcal{X}_X} g(x) p_X(x)$					
$E[X] = \sum_{x \in \mathcal{X}} P(X \geq x)$, tail sum					
$1 = \sum_{x \in \mathcal{X}} p_X(x)$, "freedom"					
$Var[X] = E[(X - E(X))^2] = \sum_{x \in \mathcal{X}} (x - E(X))^2 p_X(x) = E[X^2] - E[X]^2$					

<i>Continuous rv</i>	<i>Parameters</i>	$f_X(x)$	$Ran(X)$	$E(X)$	$Var(X)$
$X \sim N(\mu, \sigma^2)$	$\mu \in \mathbb{R}$ $\sigma \in (0, \infty)$	$\frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	$x = \mathbb{R}$	μ	σ^2
$Z = \frac{X - \mu}{\sigma} \sim N(0,1)$ $\Phi(a) := P(Z \leq a) = 1 - \Phi(-a)$					
<p><i>normal approximation</i> $X \approx Z \sim N(\mu_X, \sigma_X^2)$ for $X \sim \text{distr}$, dynamically find μ_X, σ_X^2</p> $P(X = k) = P(X \leq k) - P(X < k) \approx P\left(Z \leq \frac{k + 0.5 - \mu}{\sigma}\right) - P\left(Z \leq \frac{k - 0.5 - \mu}{\sigma}\right)$ $P(X \geq k) \approx P\left(Z \geq \frac{k - 0.5 - \mu}{\sigma}\right), \quad P(X > k) \approx P\left(Z \geq \frac{k + 0.5 - \mu}{\sigma}\right)$ $P(a \leq X \leq b), P(a < X < b), \dots$					
$X \sim \text{Gamma}(\alpha, \beta)$	$\alpha, \beta \in (0, \infty)$	$\frac{\beta^\alpha x^{\alpha-1}}{\Gamma(\alpha)} e^{-\beta x}$	$x \geq 0$	$\frac{\alpha}{\beta}$	$\frac{\alpha}{\beta^2}$
$\Gamma(t) := \int_0^\infty x^{t-1} e^{-x} dx$ $\Gamma(t) = (t-1)\Gamma(t-1); \Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$ <p><i>Gamma = count(time interval between random events)</i></p>					
$X \sim \text{Chisq}(\theta) = \text{Gamma}\left(\frac{\theta}{2}, \frac{1}{2}\right), \text{ as in } \frac{(n-1)s_{n-1}^2}{\sigma^2} \sim \text{Chisq}(n-1)$					
$X \sim \text{Exp}(\lambda) = \text{Gamma}(1, \beta), \quad \text{Exponential}$ $f_X(x) = \beta e^{-\beta x}, Ran(X) = \{x > 0\}$ $P(X > s+t) = P(X > t)P(X > s), \quad \text{memorylessness(unique)}$					
$Y \sim \text{Exp}(\lambda) \xrightarrow{X= Y +1} X \sim \text{Geometric}(p = 1 - e^{-\lambda}) \text{ connecting Exp, Geometric}$					
$P(Y \leq t) = P(N(t) \geq \alpha), \quad \text{connecting } Y \sim \text{Gamma}(\alpha, \lambda), N(t) \sim \text{Poisson}(\lambda t)$ $\text{count(arrivals in } [0, t]) \Leftrightarrow \text{duration}(\alpha^{\text{th}} \text{ arrival})$					
$X \sim \text{Beta}(a, b)$	$a, b \in (0, \infty)$	$\frac{x^{a-1}(1-x)^{b-1}}{B(a, b)}$	$x \in (0,1)$	$\frac{a}{a+b}$	$\frac{ab}{(a+b)^2(a+b+1)}$
$B(a, b) := \int_0^1 x^{a-1}(1-x)^{b-1} dx$ $B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)} = \frac{a+b}{a} B(a+1, b) = \frac{a+b}{b} B(a, b+1)$ $\text{Beta} = \mathbb{P}(\mathbb{P} \text{ event})$					
$X \sim U_{[a,b]}, \quad \text{Uniform } (a < b)$ <p><i>originates from Beta(a = 1, b = 1), $f_X(x) = \frac{1}{\text{Beta}(1,1)} = 1, Ran(X) = (0,1)$</i></p> $f_X(x) = \frac{1}{k_2 - k_1}, Ran(X) = (k_1, k_2) \text{ or } [k_1, k_2] \text{ or } \dots$					
$f_{Y=g(X)}(y) = f_X(g^{-1}(y)) \left \frac{d}{dy} g^{-1}(y) \right , \quad \text{distr of transformation}$ <p><i>for strictly increasing and differentiatble $g(\cdot)$</i></p>					

$(X_1, \dots, X_{r-1}) \sim \text{Multinomial}(n, p_1, \dots, p_{r-1})$ $X_r = n - \sum_{i=1}^{r-1} X_i, p = 1 - \sum_{i=1}^{r-1} p_i$	$\sum_{i=1}^r x_i = n$	$\frac{n!}{x_1! \dots x_r!} p_1^{x_1} \dots p_r^{x_r} = \frac{n!}{\prod_{i=1}^r x_i!} \prod_{i=1}^r p_i^{x_i}$
$(X_1, \dots, X_n) \sim N_n(\vec{\mu}, \Sigma)$	$\text{spd } \Sigma \in \mathbb{R}^{n \times n}$ $\vec{\mu} \in \mathbb{R}^n$	$\frac{1}{(2\pi)^{\frac{n}{2}} \Sigma ^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)}$

Joint cdf, $F_{\vec{X}}(\vec{t})$	$\sum_{x_n \leq t_n} \dots \sum_{x_1 \leq t_1} p_{\vec{X}}(\vec{x})$	$\int_{-\infty}^{t_n} \dots \int_{-\infty}^{t_1} f_{\vec{X}}(\vec{x}) d\vec{x}$
Marginal cdf, $F_{X_i}(t)$	$\lim_{x_n \rightarrow \infty} (\setminus x_k) \dots \lim_{x_1 \rightarrow \infty} F_{\vec{X}}(\vec{x}, x_i = t)$ $= \sum_{k \leq t} p_{X_i}(k)$	$\int_{-\infty}^{t_1} f_{X_i}(x_i) dx_i$
Joint		$f_{\vec{X}}(\vec{x}) = \frac{\partial^n}{\partial t_n \dots \partial t_1} F_{\vec{X}}(\vec{t})$
Marginal (Joint Marginal)	$p_{X_i}(x_i)$ $= \sum_{x_n} \dots (\setminus x_i) \sum_{x_1} p_{\vec{X}}(\vec{x}, x_i)$	$f_{X_i}(x_i)$ $= \int_{-\infty}^{\infty} \dots (\setminus x_i) \int_{-\infty}^{\infty} f_{\vec{X}}(\vec{x}, x_i) d\vec{x}$
Conditional (Conditional Joint)	$p_{X Y}(x y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$ $= \frac{p_{X,Y}(x,y)}{\sum_x p_{X,Y}(x,y)}$	$f_{X Y}(x y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$ $= \frac{f_{X,Y}(x,y)}{\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx}$
$\iint_R 1 dA = \iint_{(x,y): \text{graph}} 1 dx dy \text{ or } dy dx$		

$X \perp Y \Leftrightarrow p_{X,Y}(x,y) = p_X(x)p_Y(y) \text{ or } f_{X,Y}(x,y) = f_X(x)f_Y(y)$
$f_X(x) = \int_{-\infty}^{\infty} f_{X Y}(x y) f_Y(y) dy, \quad \text{when } X \sim \text{distr}' \text{ given fixed } y$

$p_{g(X,Y)}(k) = \sum_{(x,y): g(x,y)=k} p_{X,Y}(x,y), \text{ for } g = +, -, \times, \div$
$f_{g(X,Y)}(k) = \frac{d}{dk} \iint_{(x,y): g(x,y) \leq k} f_{X,Y}(x,y) dx dy, \text{ for } g = +, -, \times, \div$
$f_{X+Y}(a) = \int_{-\infty}^{\infty} f_{X,Y}(x, a-x) dx, \quad \text{put } y = a-x$ $f_{X-Y}(a) = \int_{-\infty}^{\infty} f_{X,Y}(x, x-a) dx, \quad \text{put } y = x-a$ $f_{XY}(a) = \int_{-\infty}^{\infty} \frac{1}{ x } f_{X,Y}\left(x, \frac{a}{x}\right) dx, \quad \text{put } y = \frac{a}{x}$ $f_{\frac{X}{Y}}(a) = \int_{-\infty}^{\infty} y f_{X,Y}(ay, y) dy, \quad \text{put } x = ay$
CLT: $\{iid X_i \mid \text{finite common } \mu, \sigma^2\}, \frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n}\sigma} = \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \sim N(0,1), \text{ as } n \rightarrow \infty$
$\text{Bin}(\sum_{i=1}^n m_i, p) \quad \text{Possion}(\sum_{i=1}^n \lambda_i) \quad N.\text{Bin}(\sum_{i=1}^n 1, p) \quad N(\sum_{i=1}^n \mu_i, \sigma^2) \quad \text{Gamma}(\sum_{i=1}^n \alpha_i, \beta)$

$\mathcal{X} = \{(x_1, x_2): p_{X_1, X_2}(x_1, x_2) > 0 \text{ (noniid)}\} = \cup_{(y_1, y_2) \in \mathcal{D}} \mathcal{X}_{y_1, y_2},$ Define $\mathcal{D} = \{y_1 = g_1(x_1, x_2), y_2 = g_2(x_1, x_2): (x_1, x_2) \in \mathcal{X}\},$ $\mathcal{X}_{y_1, y_2} = \{(x_1, x_2) \in \mathcal{X}: y_1 = g_1(x_1, x_2), y_2 = g_2(x_1, x_2)\}$
$p_{Y_1=g_1(X_1, X_2), Y_2=g_2(X_1, X_2)}(y_1, y_2) = \sum_{(x_1, x_2) \in \mathcal{X}_{y_1, y_2}} p_{X_1, X_2}(x_1, x_2), \quad \text{for } (y_1, y_2) \in \mathcal{D}$
Singleton counting: outer summation varies, inner summation \equiv for sub

$\mathcal{X} = \{(x_1, x_2): f_{X_1, X_2}(x_1, x_2) > 0 \text{ (noniid)}\}, \quad \text{Define } \mathcal{D} = \{y_1 = g_1(x_1, x_2), y_2 = g_2(x_1, x_2)(aux)\}$
(1) $\mathcal{X} \xrightarrow{g_1, g_2 \text{ bij}} \mathcal{D}, \quad (2) g_1^{-1}, g_2^{-1} \in C^1, \quad (3) J = \left \frac{\partial(x_1 = g_1^{-1}(y_1, y_2), x_2 = g_2^{-1}(y_1, y_2))}{\partial(y_1, y_2)} \right \neq 0$
$f_{Y_1, Y_2}(y_1, y_2) = J f_{X_1, X_2}(x_1 = g_1^{-1}(y_1, y_2), x_2 = g_2^{-1}(y_1, y_2)), \quad (y_1, y_2) \in \mathcal{D}$

$E[g(X_1, \dots, X_n)] = \sum_{x_n} \dots \sum_{x_1} g(x_1, \dots, x_n) p_{X_1, \dots, X_n}(x_1, \dots, x_n), \text{ or } E[Y = g(X_1, \dots, X_n)] = \sum_{y \in \mathcal{X}_Y} y p_Y(y)$ $E[g(X_1, \dots, X_n)] = \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} g(x_1, \dots, x_n) f_{X_1, \dots, X_n}(x_1, \dots, x_n) dx_1 \dots dx_n, \text{ or } E[Y] = \int_{-\infty}^{\infty} y f_Y(y) dy$	
$E[\sum_{i=1}^n X_i] = \sum_{i=1}^n E[X_i], \text{ further put } X_i = c_i g_i(X_i), \text{ for generic } \{X_i\}$ $E[\sum_{i=1}^n X_i] = \sum_{i=1}^n E[X_i], \text{ further put } X_i = c_i g_i(X_i) \text{ for independent } \{X_i\}$	
$Cov(X, Y) := E[(X - E(X))(Y - E(Y))], \quad \text{Covariance}$ $Cov(X, Y) = E(XY) - E(X)E(Y)$ $X \perp Y \xrightarrow{E(XY)=E(X)E(Y)} Cov(X, Y) = 0$ $X \perp Y \xleftarrow{(X,Y) \sim N_2(\vec{\mu}, \Sigma)} Cov(X, Y) = 0, \quad \text{counter examples}$	
$Cov(X, Y) = Cov(Y, X); \quad Cov(X, X) = Var(X); \quad Cov(aX, bY) = abCov(X, Y)$ $Cov(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j) = \sum_{i=1}^n \sum_{j=1}^m Cov(X_i, Y_j)$	
$Var(\sum_{i=1}^n X_i) = \sum_{i=1}^n Var(X_i) + 2 \sum_{1 \leq i < j \leq n} \sum Cov(X_i, X_j) \xrightarrow{ind, Cov(X_i, Y_j)=0} \sum_{i=1}^n Var(X_i)$	
$-1 \leq \rho(X, Y) := \frac{Cov(X, Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}} \leq 1, \text{ if } Var(X), Var(Y) > 0, \quad \text{Correlation (linearity)}$ $Var\left(W = \frac{X}{\sigma_X} - \frac{Y}{\sigma_Y}\right) \geq 0 \Leftrightarrow Cov(X, Y) \leq \sqrt{Var(X)}\sqrt{Var(Y)},$ $\rho(X, Y) = 1, Var(W) = 0, W = E(W) \text{ with } p = 1, Y = [-\sigma_Y E(W)] + \left(\frac{\sigma_Y}{\sigma_X}\right)X$	
$E(X Y = y) = \sum_k k p_{X Y}(k y) \text{ or } \int_{-\infty}^{\infty} k f_{X Y}(k y) dk, \quad \text{Conditional Expectation}$ $\text{is rv function of fixed } Y, \quad E(X Y) \text{ has distribution}$ $E[E(X Y)] = E(X), \quad \text{Double Expectation Formula}$	

$M_X(t) = E(e^{tX})$	$\sum_{g(x)} [e^{tg(x)} p_X(x)] \text{ or } \int_{-\infty}^{\infty} [e^{tg(x)} f_X(x)]$
$M_{aX+b}(t) = e^{tb} M_X(at), \quad \text{rv transform}$	$M_{X+Y}(t) = M_X(t) M_Y(t) \text{ for } X \perp Y$
$E(X) = M_X^{(1)}(0), \quad E(X^k) = M_X^{(k)}(0)$	$Var(X) = E(X^2) - E(X)^2$
$E(X^3), \quad \text{Skewness}$	$E(X^4), \quad \text{Kurtosis}$

$X \sim \text{Poisson}(\lambda)$	$M_X(t) = e^{\lambda(e^t - 1)}$
$X \sim \text{Bin}(n, p)$	$M_X(t) = (pe^t + 1 - p)^n$
$X \sim N. \text{Bin}(k, p)$	$M_X(t) = \left[\frac{pe^t}{1 - (1 - p)e^t} \right]^k$

$Z \sim N(0, 1)$ $X \sim N(a, b)$	$M_Z(t) = e^{\frac{t^2}{2}}, \quad \text{hence } M_{X=a+\sqrt{b}Z}(t) = e^{at + \frac{bt^2}{2}}$
$X \sim \text{Exp}(\lambda)$	$M_X(t) = \frac{\lambda}{\lambda - t}, \quad \text{for } t < \lambda$
$X \sim \text{Gamma}(\alpha, \beta)$	$M_X(t) = \left(\frac{\beta}{\beta - t} \right)^\alpha, \quad \text{for } t < \beta$
$X \sim U_{[a, b]}$	$M_X(t) = \frac{e^{bt} - e^{at}}{(b - a)t}$

$\text{mgf uniquely determines distribution} \Rightarrow \text{exploit change of parameters}$
