4.1 4.2 Joint, Marginal, Conditional

$$f_X(x) = \sum_{y \in \mathbf{R}} f_{X,Y}(x,y) = \int_{-\infty}^{\infty} f(x,y) dy \ 4.1.6/10 \ f(x|y) = P(X = x|Y = y) = \frac{f(x,y)}{f_Y(y)} \ 4.2.1$$

Indep $f(x,y) = f_X(x)f_Y(y)$ 4.2.5 = g(x)h(y) 4.2.7 X, Y indep r.v. g(X),h(Y) indep 4.3.5

 $F(x,y) = P(X \le x, Y \le y) = \int_{-\infty}^{y} \int_{-\infty}^{x} f(s,t) ds dt$ — Indep $F_{X,Y}(x,y) = F_X(x) F_Y(y)$ $M_Z(t) = M_X(t)M_Y(t)$ 4.2.12 — $M_Z(t) = (M_X(t))^n$ 4.6.7 — $M_{\bar{X}}(t) = [M_X(\frac{t}{n})]^n$ 5.2.7

 $M_W(t) = M_X(t)M_V(t) = e^{\mu_1(e^t - 1)}e^{\mu_2(e^t - 1)} = e^{(\mu_1 + \mu_2)(e^t - 1)}$ Use 4.2.12 proof 4.3.2

 $U \sim Geom(\frac{1}{2}), u = 1, 2... V \sim NBin(2, \frac{1}{2}), v = 2, 3... \{(u, v) : u = 1, 2, ...; v = u + 1, u + 2, ...\}$ not indep

Expectations

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx = E[E(X|Y)] \text{ 4.4.3 } E[g(x)] = \sum_{x \in D} h(x) p(x) = \int_{-\infty}^{\infty} g(x) f(x) dx$$

$$E[(X - \mu)^n] = \mu_n = \sum (x - \mu)^n p(x) = \int (x - \mu)^n f(x) dx - E(aX + b) = aE(X) + b$$

 $E[g(\vec{X})] = \sum \cdots \sum_{\substack{all\vec{x} \\ N}} \overline{g(\vec{x})} p(\vec{x}) = \int \cdots \int g(\vec{x}) f(\vec{x}) d\vec{x}$ $E[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f(x,y) dx dy \ 4.1.10$

$$E[g(X)|y] = \sum_{n=0}^{\infty} g(x)f(x|y) = \int_{-\infty}^{\infty} g(x)f(x|y)dx \text{ r.v.(y) } 4.2.3 \ E[g(X)h(Y)|y] = h(Y)E[g(X)|y]$$

 $E[XY] = E[X]E[Y] = E[g(x)]E[h(y)] \ P(X \le x, Y \le y) = P(X \le x)P(Y \le y) \ \text{indep } 4.2.10$ $E[g_1(X_1)\cdots g_n(X_n)] = E[g_1(X_1)]\cdots E[g_n(X_n)] X_1,...,X_n \text{ indep } 4.6.6 \ E[g(X)|y] = E[g(X)] \text{ indep}$

$$\begin{array}{l} V[X] = \sigma_x^2 = E(X^2) - [E(X)]^2 = E[V(X|Y)] + V[E(X|Y)] \ 4.4.7 - V[aX+b] = a^2\sigma^2 \\ V[X|Y] = E[(X-E[X|Y])^2|Y] = \sum\limits_{\alpha} [x-E[X|Y]^2 f(x|y) = E[X^2|y] - (E[X|y])^2 \ 4.2.4 - (E[X|Y])^2 f(x|y) \end{array}$$

$$V[aX \pm bY] = a^2VX + b^2VY \pm 2abCov(X,Y) - V[X \pm Y] = VX + VY \text{ Indep } 4.5.6$$

$$E[\sum_{i=1}^n g(X_i)] = nE(g(X_1)) - V[\sum_{i=1}^n g(X_i)] = nVar(g(X_1)) \text{ r.s. } 5.25$$

4.5 Covariance and Correlation

$$\begin{array}{l} Cov(X,Y) = E[(X-\mu_X)(Y-\mu_Y)] = E(XY) - E(X)E(Y) = E[XY] - \mu_X\mu_Y = \sigma_{XY} \ 4.5.1/3 \\ Cov(aX,bY) = abCov(X,Y) \ Cov(X,Y+Z) = Cov(X,Y) + Cov(X,Z) \ Cov(X,c) = 0 \\ \rho_{XY} = \frac{\sigma_{XY}}{\sigma_X\sigma_Y} \ Corr(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} \ 4.5.2 \end{array}$$

4.3 Transform

$$f_{U,V}(u,v) = f_{X,Y}(h_1(u,v), h_2(u,v))|J| \ 4.3.2 = \sum_{i=1}^k f_{X,Y}(h_{1i}(u,v), h_{2i}(u,v))|J_i| \ 4.3.5$$

$$\begin{aligned} f_{U,V}(u,v) &= f_{X,Y}(h_1(u,v),h_2(u,v))|J| \ 4.3.2 = \sum_{i=1}^k f_{X,Y}(h_{1i}(u,v),\ h_{2i}(u,v))|J_i| \ 4.3.5 \\ \left| \begin{matrix} u = g_1(x,y) & x = h_1(u,v) \\ v = g_2(x,y) & y = h_2(u,v) \end{matrix} \right| \ J &= \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{matrix} = \frac{\partial x}{\partial u} \frac{\partial y}{\partial v} - \frac{\partial y}{\partial u} \frac{\partial x}{\partial v} \end{aligned}$$

 $f_Z(z) = \int_{-\infty}^{\infty} f_X(w) f_Y(z-w) dw \ Z = X + Y \ 5.2.9$ Convolution

Distribution

 $X \sim n(\mu, \sigma^2), Y \sim n(\gamma, \tau^2) - X + Y \sim n(\mu + \gamma, \sigma^2 + \tau^2)$ indep 4.2.14

 $X, Y \sim n(0,1) - X + Y, X - Y \sim n(0,2), X/Y \sim cauchy(0,1)$ indep 4.3.4/6

 $X \sim Poisson(\theta), Y \sim Poisson(\lambda) - X + Y \sim Poisson(\theta + \lambda)$ indep 4.3.2

 $X \sim Beta(\alpha, \beta), Y \sim Beta(\alpha + \beta, \gamma) \longrightarrow XY \sim n(\alpha, \beta + \gamma) \text{ indep } 4.3.3$

 $X|Y \sim Bin(Y,p), Y|\Lambda \sim Pois(\Lambda), \Lambda \sim Expo(\beta) \text{ or } X|Y \sim Bin(Y,p), Y \sim NBin(1,\frac{1}{1+\beta})$ 4.4.5

 $Y|\Lambda \sim Pois(\Lambda), \Lambda \sim Gamma(\alpha, \beta)$ then $Y \sim NBin(\alpha, \frac{1}{1+p\beta})$ Pois-Gamma

 $X|P \sim Bin(n,P), P \sim Gamma(\alpha,\beta)$ $EX = E[E(X|P)] = E[nP] = n \frac{\alpha}{\alpha+\beta}$ Beta-Bin 4.4.6

 $V[X] = V[E(X|P)] + E[V(X|P)] = \frac{n^2 \alpha \beta}{(\alpha+\beta)^2(\alpha+\beta+1)} + \frac{n\alpha\beta}{(\alpha+\beta)(\alpha+\beta+1)} = \frac{n\alpha\beta(\alpha+\beta+n)}{(\alpha+\beta)^2(\alpha+\beta+1)}$ Beta-Bin 4.4.8

bivarialte normal $f_X(x) \sim n(\mu_X, \sigma_X^2)$ — $f_{X|Y}(x|y) \sim n\left(\mu_X + \rho \frac{\sigma_X}{\sigma_Y}(y - \mu_Y), \sigma_X^2(1 - \rho^2)\right)$

 $4.5.10 \ \rho_{XY} = \rho \ f_Y(y) \sim n(\mu_Y, \sigma_Y^2) - aX + bY \sim n(a\mu_X + b\mu_Y, a^2\mu_X^2 + b^2\mu_Y^2 + 2ab\rho\sigma_X\sigma_Y^2)$

 $X_1,...X_n \sim Gamma(\alpha,\beta), X_1 + ...X_n \sim Gamma(\alpha_1 + ...\alpha_n,\beta) \bar{X} \sim Gamma(n\alpha,\beta/n)$ indep 4.6.8

 $X \sim Cauchy(0, \sigma), Y \sim Cauchy(0, \tau) - X + Y \sim Cauchy(0, \sigma + \tau)$ 5.2.10 $X_1,..,X_n \sim Cauchy(0,\sigma) - \bar{X} \sim Cauchy(0,\sigma), \sum_{i=1}^n X \sim Cauchy(0,n\sigma)$

5.3 Sampling from N

$$\bar{X} = \frac{X_{1} + \ldots + X_{n}}{n} = \frac{1}{n} \sum_{i=1}^{n} X_{i} \ 5.2.2 \ \bar{X}_{n+1} = \frac{\sum_{i=1}^{n+1} X_{i}}{n+1} = \frac{\sum_{i=1}^{n} X_{i} + X_{n+1}}{n+1} = \frac{n\bar{X}_{n} + X_{n+1}}{n+1} \ 5.3.1$$

$$S^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (X_{i} - \bar{X})^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (X_{i}^{2} - n\bar{X}^{2}) \ 5.2.3 \ nS_{n+1}^{2} = (n-1)S_{n}^{2} + (\frac{n}{n+1})(X_{n+1} - \bar{X}_{n})^{2}$$

$$\frac{5.2.6 \quad X_{1}, \ldots, X_{n} \ \text{iid} \quad E[\bar{X}] = \mu \qquad E[S^{2}] = \sigma^{2} \qquad V[\bar{X}] = \frac{\sigma^{2}}{n} \qquad \text{W/o Normal}$$

$$\frac{5.3.1 \quad \sim n(\mu, \sigma^{2}) \qquad \bar{X}, S^{2} \ \text{indep} \qquad \bar{X} \sim N(\mu, \frac{\sigma^{2}}{n}) \qquad \frac{(n-1)S^{2}}{\sigma^{2}} \sim \chi_{n-1}^{2} \qquad \text{W Normal}$$

$$X \sim n(\mu, \sigma^2), \ \frac{x - \mu}{\sigma}, \frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \sim n(0, 1), \ \frac{\bar{X} - \mu}{S/\sqrt{n}} = \frac{\frac{\bar{x} - \mu}{\sigma/\sqrt{n}}}{\sqrt{S^2/\sigma^2}} = \frac{U}{\sqrt{\frac{\chi_{n-1}^2}{\eta_{n-1}}}} \sim t_{n-1} \ 5.3.4 - t_1 = Cauchy(0, 1)$$

 $x_i \sim n(0,1), \sum_{i=1}^n x_i^2 \sim \chi_n^2 - x_i \sim n(0,\sigma^2), \sum_{i=1}^n x_i^2 \sim \sigma^2 \chi_n^2, \sum_{i=1}^n (x_i - \bar{x})^2 \sim \sigma^2 \chi_{n-1}^2$

 $\chi_2^2 \Leftrightarrow Expo(2) \ \chi_2^2 \sim Gamma(\frac{p}{2}, 2) \ 4.6.8$

 $X_1,..X_n \sim \chi^2_{p_i}, X_1 + ..X_n \sim \tilde{\chi}^2_{p_1 + ..p_n} \ 5.3.2 \ U \sim \chi^2_m, V \sim \chi^2_n, \ U + V \sim \chi^2_{m+n}$

$$X_i \sim n(\mu_X, \sigma_X^2) Y_j \sim n(\mu_Y, \sigma_Y^2), X_1..X_n, Y_1..Y_m \text{ indep}, \frac{S_X^2}{\sigma_X^2} \sim \chi^2 - \frac{S_X^2/\sigma_X^2}{S_Y^2/\sigma_Y^2} \sim F 5.3.5$$

$$X \sim F_{p,q}, \ \frac{1}{X} \sim F_{q,p} - X \sim T_q, \ X^2 \sim F_{1,q} - X \sim F_{p,q}, \ \frac{\frac{p}{q}X}{\frac{1+\frac{p}{q}X}{2}} \sim Beta(\frac{p}{2}, \frac{q}{2})$$

$$V\chi_{n-1}^2 = V[\frac{(n-1)S^2}{\sigma^2}] = \frac{(n-1)^2}{\sigma^4} Var[S^2] = 2(n-1) \implies Var[S^2] = \frac{2\sigma^4}{n-1}$$

5.4 Order statistics

$$5.4.4 f_K(x) = K\binom{n}{k} [F_X(x)]^{k-1} [1 - F_X(x)]^{n-k} f(x) \text{ or } \frac{n!}{(k-1)!(n-k)!} \text{ 1-29p9}$$

$$5.4.6 \ f_{X_{(1)},...,X_{(n)}}(x_1,...,x_n) = \begin{cases} n! f_X(x_1) \cdot ... \cdot f_X(x_n) & -\infty < x_1 < ... < x_n < \infty \\ 0 & \text{otherwise} \end{cases}$$

$$f_{X_{(i)},X_{(j)}}(u,v) = \frac{n!}{(i-1)!(j-1-i)!(n-j)!} f_X(u) f_X(v) [F_X(u)]^{i-1} [F_X(v) - F_X(u)]^{j-1-i} [1 - F_X(v)]^{n-j}$$

1 from N to T to Chi to F

Given some function of these, find the distribution.

2 Transformation of pairs of r.v.s

Given 2 r.v.s, f(x,y), and a function of them, find its distribution. 1-10p1

$$f(x,y) = \frac{1}{4}e^{-\frac{x+y}{2}}, 0 < x < \infty, 0 < y < \infty, u = \frac{X-Y}{2}$$

1.
$$\begin{vmatrix} U = \frac{x - y}{2} & X = 2u + v \\ V = y & Y = v \end{vmatrix}$$
 2.
$$J = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} 2 & 1 \\ 0 & 1 \end{vmatrix} = 2$$

3.
$$q(u,v) = f(x,y)|J| = \frac{1}{4}e^{-\frac{x+y}{2}} = \frac{1}{2}e^{-\frac{2u+v+v}{2}} = \frac{1}{2}e^{-(u+v)}$$

3.
$$g(u,v) = f(x,y)|J| = \frac{1}{4}e^{-\frac{x+y}{2}}2 = \frac{1}{2}e^{-\frac{2u+v+v}{2}} = \frac{1}{2}e^{-(u+v)}$$

4. $0 < x < \infty, 0 < y < \infty \implies 0 < 2u + v < \infty, 0 < v < \infty \implies v > -2u$

5. Double Exponential(Laplace)

$$g_{U}(u) = \begin{vmatrix} \int_{-2u}^{\infty} \frac{1}{2} e^{-(u+v)} dv = \frac{1}{2} e^{-u} \int_{-2u}^{\infty} e^{-v} dv = \frac{1}{2} e^{-u} \left[-e^{-v} \right]_{-2u}^{\infty} = \frac{1}{2} e^{-u} \left[0 + e^{2u} \right] & u < 0 \\ = \frac{1}{2} e^{|u|} & \int_{0}^{\infty} \frac{1}{2} e^{-(u+v)} dv = \frac{1}{2} e^{-u} \int_{0}^{\infty} e^{-v} dv = \frac{1}{2} e^{-u} \left[-e^{-v} \right]_{0}^{\infty} = \frac{1}{2} e^{-u} \left[0 + 1 \right] & u \ge 0 \end{vmatrix}$$

Given f(x, y), find the

$$f_X(x) = -E[X] = -V[X] =$$

$$f_Y(y) = --E[Y] = --V[Y] =$$

$$f(x,y) = -E[XY] =$$

$$Cov(x, y) = E[XY] - EXEY =$$

$$f(X|Y) = --E[X|Y] = --V[X|Y] =$$

$$\rho = Cov(x,y)/\sqrt{V[X]V[Y]} =$$

$$4.5.7 \ E[Y|X] = a + bx, \ E[Y] = E[E[Y|X]] = E[a + bX] = a + bE[X]$$
 by $4.4.3$,

 $E[XE[Y|X]] = E[X(a+bX)] = aE[X] + bE[X^2], E[XE[Y|X]] = \int_{-\infty}^{\infty} xE[Y|x]f_X(x)dx$ by 2.2.1,

$$= \int_{-\infty}^{\infty} x \left[\int_{-\infty}^{\infty} y f_Y(y|x) dy \right] f_X(x) dx \text{ by } 4.2.3, = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x y f(x,y) dy dx = E[XY] \text{ by } 4.1.10,$$

$$\sigma_{XY} = E[XY] - \mu_X \mu_Y = a\mu_X + bE[X^2] - \mu_X \mu_Y = a\mu_X + b(\sigma_X^2 + \mu_X^2) - \mu_X(a + b\mu_X) = b\sigma_X^2$$

$$\rho_{XY} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} = \frac{b\sigma_X^2}{\sigma_X \sigma_Y} = b\frac{\sigma_X}{\sigma_Y}$$

4 Order statistics

Find the distribution of X(k) or $X_{(i)}, X_{(k)}$

joint pmf 1-31p2-3

5.4.5 uniform order pdf 1-31p4-8

pdf/pmf

CDF:
$$F(x) = P(X \le x) = \sum_{y:y \le x} p(y) = \int_{-\infty}^{x} f(y)dy$$

probabilities: a < b:

PMF:
$$p(x) = P(X = x) = P(\forall w \in \mathcal{W} : X(w) = x)$$

$$P(a \le X \le b) = F(b) - F(a^-); P(a \le X \le b) = F(b) - F(a); P(a \le X \le a) = p(a);$$

 $P(a < X < b) = F(b^{-}) - F(a)$; (where a^{-} is the largest possible X value strictly less than a); Taking a = b yields P(X = a) = F(a) - F(a - 1) as desired.

PDF:
$$P(\forall w \in \mathcal{W} : a \leq X(w) \leq b) = \int_a^b f(x) dx$$

$$P(a \le X \le b) = P(a \le X \le b) = P(a \le X \le b); P(X > a) = 1 - F(a); P(a \le X \le b) = F(b) - F(a)$$

CDF

Condition:
$$f(x) \ge 0 \forall x \text{ pmf } \sum_{x} f_X(x) = 1, pdf \int_{-\infty}^{\infty} f(x) dx = 1$$

$$\begin{split} E(e^{tx}) &= \int e^{tx} f(x) dx = \sum e^{tx} f(x); \ M_{aX+b}(t) = e^{tb} M_{aX}(t) \\ M_X(t) &= E(e^{tx}) & M_X(0) = 1 \\ M_X'(t) &= E(xe^{tx}) & M_X'(0) = E(X) \\ M_X''(t) &= E(x^2 e^{tx}) & M_X''(0) = E(X^2) \\ M_X^n(t) &= E(x^n e^{tx}) & M_X^n(0) = E(X^n) \end{split}$$

transform

$$\begin{array}{c|c} g(x) \uparrow & F_Y(y) = F_X(g^{-1}(y)) \\ g(x) \downarrow & F_Y(y) = 1 - F_X(g^{-1}(y)) \\ \textbf{not monotone} \because X \leq 0 \ is \ \emptyset \therefore P(X \leq -\sqrt{y}) = 0 \\ F_Y(y) = P(Y \leq y) = P(X^2 \leq y) = P(-\sqrt{y} \leq X \leq \sqrt{y}) = P(X \leq \sqrt{y}) - P(X \leq -\sqrt{y}) = F_X(\sqrt{y}) = \sqrt{y}, \ 0 < \sqrt{y} < 1 \end{array}$$

monotone:
$$f_Y(y) = f_X(g^{-1}(y)) |\frac{d(g^{-1}(y))}{dy}|$$

Series

Integrals+c

Substitution
$$u = g(x)$$
 $du = g'(x)dx$ $\int_a^b f(g(x))g'(x)dx = \int_{g(a)}^{g(b)} f(u)du$ $du = 3x^2dx$ $\int_1^2 5x^2\cos(x^3)dx = \int_1^8 \frac{5}{3}\cos(u)du$

Integreation by parts
$$\begin{pmatrix} u & du & dv & v \\ x & dx & e^{-x} & -e^{-x} \end{pmatrix} \int_a^b u dv \int_a^b x e^{-x} dx$$

$$\begin{cases} \ln x & \frac{1}{2} dx & dx & x \end{cases} \int_b^5 x \ln x dx$$

$$= uv|_a^b - \int_a^b v du$$

$$= -xe^{-x} + \int xe^{-x} dx = -xe^{-x} - e^{-x} + c$$

$$= xlnx|_3^5 - \int_3^5 dx = (xlnx - x)|_3^5 = 5ln5 - 3ln3 - 2$$

$$\int_a^b f(x) dx = F(b) - F(a) = -\int_b^a f(x) dx = \int_a^c f(x) dx + \int_c^b f(x) dx;$$

$$\frac{d}{dx} \int_{v(x)}^{u(x)} f(t) dt = u'(x) f[u(x)] - v'(x) f[v(x)]$$

Derivatives

Derivatives
$$(cf)' = cf'(x) \qquad (fg)' = f'g + fg' \qquad (f \pm g)' = f'(x) \pm g'(x)$$

$$\frac{dx}{dx} = 1 \qquad (\frac{f}{g})' = \frac{(f'g - fg')}{g^2} \qquad (f(g(x)))' = f'(g(x))g'(x)$$

$$\frac{de^x}{dx} = e^x \qquad \frac{d(x^n)}{dx} = nx^{n-1} \qquad \frac{d\ln(x)}{dx} = \frac{1}{x}, x > 0$$

$$\frac{d\cos x}{dx} = -\sin x \qquad \frac{d\tan^n x}{dx} = \frac{1}{1+x^2} \qquad \frac{d\log_a(x)}{dx} = \frac{1}{x\ln a}, x > 0$$

$$\frac{d\cos x}{dx} = -\sin x \qquad \frac{d\tan x}{dx} = \sec^2 x \qquad \text{No Replace}$$

HGeom Fixed # trials (n)Binomial (Bern if n = 1) Draw until r success NBin NHGeom (Geom if r=1)

 $\overline{U} \sim Geom(\frac{1}{2}), u = 1, 2.. \#$ of trials needed to get the first head.

 $V \sim NBin(2, \frac{1}{2}r), v = 2, 3.. \#$ of trials needed to get two heads in repeated tosses of a fair coin.

Distribution	CDF	P(X=x),f(x)	μ	EX^2	Var	MGF	M'(t)	M"(t)	$M^n(t)$
$\frac{\operatorname{Bern}(p)}{\operatorname{Bin}(p,p)}$	I (m m m + 1)	$p^{x}q^{1-x}, x \in \{1, 0\}$ $\binom{n}{x}p^{x}q^{n-x}; x \in \{0, 1n\}$	<i>p</i>	<i>p</i>	pq	$\frac{pe^t + q}{(pe^t + q)^n}$			
Bin(n,p)	$I_{1-p}(n-x,x+1)$	N.C.	$\frac{np}{1}$	$\mu(\mu+q)$	μq				
Geom(p)	$1 - q^x$	$pq^{x-1}, x \in 1, 2, \dots$	$\frac{1}{p}$	$\frac{p+2q}{p^2}$	$\frac{q}{p^2}$	$\frac{pe^t}{1 - qe^t}, t < -\ln q$	4	_	
	$1 - q^{x+1}$	$pq^x, x \in 0, 1, \dots$	$\frac{q}{p}$	$\frac{p+2q}{p^2}$ $\frac{q^2+q}{p^2}$	$\frac{q}{p^2}$	$\frac{p}{1-qe^t}, qe^t < 1$	$\frac{pqe^t}{(1-qe^t)^2}$	$\frac{2pqe^t}{(1-qe^t)^3} - M'(t)$	
NBin(r, p)		$\binom{x-1}{r-1} p^r q^{x-r}, x \in r, r+1$	$\frac{r}{p}$	F		$\left(\frac{pe^t}{1-qe^t}\right)^r$	(- 4-)	(- 4-)	
(· , _F)		$\binom{r-1}{r-1} p^r q^x, x \in 0, 1$	$\frac{p}{rq}$		$\frac{rq}{p^2}$ $\frac{rq}{p^2}$	$\left(\frac{1-qe^t}{1-qe^t}\right)^r, qe^t < 1$			
		$ \frac{\binom{r-1}{k}\binom{N-m}{k-x}}{\binom{m}{k}\binom{N-m}{k-x}} $			1	$(1-qe^t)$, $q = -1$			
$\mathrm{HGeom}(N,m,k)$		$\frac{\left(\begin{array}{c} x \end{array}\right)\left(\begin{array}{c} k-x \end{array}\right)}{\left(\begin{array}{c} N \\ k \end{array}\right)}$	$\frac{km}{N}$		$\mu \frac{(N-m)(N-k)}{N(N-1)}$				
		$\binom{k}{w}\binom{k}{b}$							
$\mathrm{HGeom}(w,b,k)$		$\frac{\binom{w}{x}\binom{b}{k-x}}{\binom{w+b}{k}}$	$\frac{kw}{w+b}$		$\mu_{\frac{b(w+b-k)}{(w+b)(w+b-1)}}$				
				2		$e^{\mu(e^t-1)}$	+ = = (·)	+ / · · · + > = / · ·	
$Pois(\mu)$	$e^{-\mu} \sum_{i=0}^{x} \frac{\mu^{i}}{i!}$	$\frac{\mu^x}{x!}e^{-\mu}, x \in 0, 1$	μ	$\mu^2 + \mu$	μ		$\mu e^t M(t)$	$\mu e^t (1 + \mu e^t) M(t)$	
$\mathrm{Unif}(n)$		$\frac{1}{n}, x \in 1, 2n$	$\frac{n+1}{2}$	$\frac{(n+1)(2n+1)}{6}$	$\frac{(n^2-1)}{12}$	$\frac{\sum_{i=1}^{n} e^{ti}}{n}$			
$\mathrm{Unif}(a,b)$	$\frac{x-a}{b-a}$	$\frac{1}{b-a}, x \in (a,b)$	$\frac{a+b}{2}$		$\frac{(b-a)^2}{12}$	$\frac{e^{tb} - e^{ta}}{t(b-a)}$			
	b-a	$\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	2			$e^{\mu t + \frac{\sigma^2 t^2}{2}}$			
$\mathcal{N}(\mu,\sigma^2)$		$\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2\sigma^2}}$	μ	$\mu^2 + \sigma^2$	σ^2		$(\mu+\sigma^2t)M(t)$	$[(\mu+\sigma^2t)^2+\sigma^2]M(t)$	
$\mathcal{N}(0,1)$		$1 e^{-\frac{x}{2}}$	0	1	1	$e^{\frac{t^2}{2}}$			
		$\sqrt{2\pi}$ $-(\ln x - \mu)^2$	σ^2	2	2				
$\mathcal{LN}(\mu, \sigma^2)$		$\frac{1}{x\sigma\sqrt{2\pi}}e^{-2}$ $\frac{1}{x\sigma\sqrt{2\pi}}e^{-(\ln x - \mu)^2}$ 1 1	$e^{\mu + \frac{\sigma^2}{2}}$	$e^{2\mu+2\sigma^2}$	$\theta^2(e^{\sigma^2}-1)$	×			
$Cauchy(\theta, \sigma^2)$		$\frac{1}{\pi\sigma} \frac{1}{1 + (\frac{x-\theta}{\sigma})^2}$	×	×	×				
D Expo (μ, σ^2)		$\frac{1}{2\pi\sigma}e^{-\left \frac{\sigma}{x-\mu}\right }$	μ	$\mu^2 + 2\sigma^2$	$2\sigma^2$	$e^{\mu t}$			
$\frac{\text{Expo}(\lambda)}{\text{Expo}(\lambda)}$	$1 - e^{-\lambda x}$	$\lambda e^{-\lambda x}, x \in (0, \infty)$	$\frac{1}{\lambda}$	μ + 20	$\frac{1}{\lambda^2}$	$\frac{\frac{\varepsilon}{1-\sigma^2 t^2}}{\frac{\lambda}{\lambda-t}, t < \lambda}$			
$\operatorname{Expo}(\beta)$	1 0	$\frac{1}{\beta}e^{-\frac{x}{\beta}}$	eta eta		$\frac{\lambda^2}{\beta^2}$	$\lambda - t$, $t < \lambda$	$\beta(1-\beta t)^{-2}$	$2\beta^2(1-\beta t)^{-3}$	
		$\frac{\overline{\beta}e^{-\beta}}{\overline{\beta}e^{-\beta}}$			r	$\frac{1}{1-\beta t}$	$\beta(1-\beta t)$	$2\beta^{2}(1-\beta t)^{-3}$	
$\operatorname{Gamma}(a,\lambda)$		$\frac{\lambda^a}{\Gamma(a)} x^{a-1} e^{-\lambda x}, x \in (0, \infty)$	$\frac{a}{\lambda}$	$\frac{a}{\lambda^2}$	$\left(\frac{\lambda}{\lambda - t}\right)^a, t < \lambda$				
$\operatorname{Gamma}(\alpha,\beta)$		$\frac{1}{\Gamma(a)\beta^{\alpha}}x^{a-1}e^{-x/\beta}$	$\alpha\beta$	$\alpha \beta^2$	$\left(\frac{1}{1-\beta t}\right)^a, t < \frac{1}{\beta}$				
Beta(a,b)		$\frac{\Gamma(a)\beta^{-1}}{\Gamma(a)\Gamma(b)} x^{a-1} (1-x)^{b-1}$ $\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}, x \in (0,1)$	$\frac{a}{a+b}$		$\frac{\mu(1-\mu)}{(a+b+1)}$				$\frac{\Gamma(\alpha+n)\Gamma(\alpha+\beta)}{\Gamma(\alpha+\beta+n)\Gamma(\alpha)}$
$B(\alpha, \beta) =$		$\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha)\Gamma(\beta)} x \in (0, 1)$	a+b	$\frac{a(a+1)}{(a+b)(a+b+1)}$	ab				$1(\alpha+\beta+n)1(\alpha)$
		$\Gamma(\alpha+\beta)$, $x \in (0,1)$			$(a+b)^2(a+b+1)$				
χ_p^2		$\frac{x^{\frac{p}{2}-1}}{\Gamma^{\frac{p}{2}}2^{\frac{p}{2}}}e^{-\frac{x}{2}}$	p	$2p + p^2$	2p	$(1-2t)^{-p/2}, t < \frac{1}{2}$			
		$\Gamma(\frac{p+1}{2})$ (r^2) $-\frac{p+1}{2}$			n -				
t_p		$\frac{\Gamma(\frac{p+1}{2})}{\Gamma(\frac{p}{2})\sqrt{p\pi}} \left(1 + \frac{x^2}{p}\right)^{-\frac{p+1}{2}}$	0, p > 1		$\frac{p}{p-2}, p > 2$	×			
\overline{F}	x > 0	$\frac{\Gamma(\frac{p+q}{2})}{\Gamma(\frac{p}{2})\Gamma(\frac{q}{2})} {(\frac{p}{q})}^{\frac{p}{2}} \frac{x^{\frac{p}{2}-1}}{(1+\frac{p}{2}x)^{\frac{p+q}{2}}}$	$\frac{q}{q-2}$	q > 2	$2\left(\frac{q}{q-2}\right)^2 \frac{p+q-2}{p(q-4)}$	q > 4			
			q-2	*	\q-2' p(q-4)	•			
Arcsine	$\frac{1}{\pi \arcsin \sqrt{x}}$	$\frac{1}{\pi\sqrt{x(1-x)}}, x \in [0,1]$	$\frac{1}{2}$		$\frac{1}{8}$				$\operatorname{Beta}(\frac{1}{2},\frac{1}{2})$
Dirichlet	$B(a) = \frac{\prod_{i=1}^{k} \Gamma(a_i)}{\Gamma(\sum_{i=1}^{k} a_i)}$	$\frac{1}{B(a)} \prod_{i=1}^{k} x_i^{a_i - 1}, x \in (0, 1)$	$\frac{a_i}{\sum_k a_k}$	$\sum_{i=1}^{k} x_i = 1$	$\frac{a_i(a_0\!-\!a_i)}{a_0^2(a_0\!+\!1)}$	$Cov(X_i, X_j) =$	$\frac{-a_i a_j}{a_0^2 (a_0 + 1)}$	$a_0 = \sum_{i=1}^k a_i$	