


$$P_{k,n} = \frac{n!}{(n-k)!} \quad \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

Uniform dist: 

f ← not val → z ← normal probability plot

$U_x = E(X) = \int_{-\infty}^{\infty} x f(x) dx$ } in general
 $\sigma_x^2 = \int_{-\infty}^{\infty} (x-\mu)^2 f(x) dx$ }
or $h(x)$ for some function

Lognormal $f(x, \mu, \sigma)$ (parameters are of $\ln(x)$)

- pdf = $\frac{e^{-(\ln(x)-\mu)^2/(2\sigma^2)}}{\sigma x \sqrt{2\pi}}$ when $x \geq 0$

- cdf = $\Phi((\ln(x)-\mu)/\sigma)$

- $E(X) = e^{\mu + \sigma^2/2}$, $V(X) = e^{2\mu + \sigma^2}(e^{\sigma^2} - 1)$

$$\int u dv = uv - \int v du$$

integrate \rightarrow
 $\ln(a) a^x \rightarrow a^x \rightarrow a^x / \ln(a)$

Beta $f(x, \alpha, \beta, A, B)$

- $\frac{1}{B-A} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\frac{x-A}{B-A}\right)^{\alpha-1} \left(\frac{B-x}{B-A}\right)^{\beta-1}$ if $A \leq x \leq B$

- for standard beta, $A=0, B=1$

- $\mu = A + (B-A)\alpha/(\alpha+\beta)$, $\sigma^2 = \frac{(B-A)^2 \alpha \beta}{(\alpha+\beta)^2 (\alpha+\beta+1)}$

MVUE - minimum variance unbiased estimator

$P_{\bar{x}}(5) = P(\bar{X}=5) = \text{ways } \bar{X}=5 / \text{total ways}$ ("sampling distribution")

$V(X) = E(X^2) - E(X)^2$, $E(X) = \sum x p(x)$

Distribution of Sample Mean:

- $E(\bar{x}) = E(x)$, $\sigma_{\bar{x}}^2 = \sigma_x^2/n$; $\sigma_{\bar{x}} = \sigma_x/\sqrt{n}$

- (for total T), $E(T) = n\mu$, $V(T) = \sigma^2 n$

- for large n , \bar{x} is normally distributed ($n > 30$)

if $Y = X_1, X_2, X_3, \dots$ for large n , Y is lognormal

Linear Combination $Y = a_1 X_1 + \dots + a_n X_n$

- $E(Y) = a_1 \mu_1 + \dots + a_n \mu_n$

- $V(Y) = \sum \sum a_i a_j \text{Cov}(X_i, X_j)$

- if independence: $V(Y) = a_1^2 \sigma_1^2 + \dots + a_n^2 \sigma_n^2$

Chi-Squared: $f(x, \nu) = \text{gamma}(x, \nu/2, 2)$

Weibull Distribution (generalized exponential)

- pdf $f(x, \alpha, \beta) = \frac{\alpha}{\beta^\alpha} x^{\alpha-1} e^{-(x/\beta)^\alpha}$, $x \geq 0$ mean

- cdf $F(x, \alpha, \beta) = 1 - e^{-(x/\beta)^\alpha}$ median

- $\mu = \beta \Gamma(1 + 1/\alpha)$, $\sigma^2 = \beta^2 (\Gamma(1 + 2/\alpha) - \Gamma(1 + 1/\alpha)^2)$ variance

Central limit theorem $\rightarrow \bar{X}$ is normal for large n s.d.

point estimate has value $E(X)$ and error σ
 bias = $E(\hat{\theta}) - \theta$
 If θ binomial, $\hat{\theta} = X/n$
 $\hat{\mu} = \bar{x}$

$$\hat{\sigma}^2 = \frac{\sum (X - \bar{X})^2}{n-1}$$

$$\hat{\mu} = \bar{x}$$

$\hat{\theta} = \text{estimate } \frac{\sum}{N}$

sample	pop
\bar{X}	μ
\tilde{X}	$\tilde{\mu}$
S^2	σ^2
S	σ

$$\text{cov}(X, Y) = E((X - \mu_X)(Y - \mu_Y))$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) p(x, y)$$

Binomial $b(x, n, p)$

- odds of x wins in n tests with p chance of win
- $\binom{n}{x} p^x (1-p)^{n-x}$
- $E(x) = np, V(x) = np(1-p)$

Hypergeometric $h(x, n, M, N)$

- odds of selecting x wins in n samples, with a population N containing M wins
- $\binom{M}{x} \binom{N-M}{n-x} / \binom{N}{n}$
- $E(x) = n \left(\frac{M}{N}\right), V(x) = \frac{(N-n)}{(N-1)} n \left(\frac{M}{N}\right) \left(1 - \frac{M}{N}\right)$

Negative Binomial $nb(x, r, p)$

- odds of x failures before r wins with p chance of win
- $\binom{x+r-1}{r-1} p^r (1-p)^x$
- $E(x) = r(1-p)/p, V(x) = r(1-p)p^{-2}$

Poisson $p(x, \lambda)$

- odds of x events in a time period with λ expected events
- $e^{-\lambda} \lambda^x / x!$; approximates binomial $b(x, n, p) \rightarrow p(x, np)$
- $E(x) = V(x) = \lambda$ \hookrightarrow if $n > 50, np < 5$

Normal $f(x, \mu, \sigma)$ (mean, s.d. given) ($\mu=0, \sigma=1$ for standard normal)

- pdf is $\frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/(2\sigma^2)}$
- $Z = \frac{x-\mu}{\sigma}$... table lookup result $\Phi(Z) = \Phi(z)$
- binomial $b(x, n, p) \approx \Phi\left(\frac{x+0.5-np}{\sqrt{npq}}\right)$ [$np \geq 10, nq \geq 10$]

Exponential $f(x, \lambda)$

- pdf is $\lambda e^{-\lambda x}$ (or 0 if $x < 0$)
- odds the time until event is x ; expected wait is $1/\lambda$ [memoryless]
- $E(x) = 1/\lambda, \sigma^2 = 1/\lambda^2$
- $F(x) = \text{cdf} = 1 - e^{-\lambda x}$ if $x \geq 0$ else 0

Gamma $\Gamma(\alpha)$ function

- $\int_0^{\infty} x^{\alpha-1} e^{-x} dx$
- $\Gamma(n) = (n-1)!, \Gamma(1/2) = \sqrt{\pi}$

Gamma Distribution $f(x, \alpha, \beta)$, generalized exponential dist

- $f(x, \alpha, \beta) = \begin{cases} \frac{x^{\alpha-1} e^{-x/\beta}}{\beta^\alpha \Gamma(\alpha)} & \text{if } x \geq 0 \\ 0 & \text{else } 0 \end{cases}$
- standard gamma $\Rightarrow \beta = 1$
- exponential: $\alpha = 1, \beta = 1/\lambda$

cdf = $F(x, \alpha, \beta)$
 $= F\left(\frac{x}{\beta}, \alpha\right)$
 (use tables)

$E(x) = \alpha\beta \rightarrow$
 $V(x) = \alpha\beta^2$