$\bar{x} = \frac{\Sigma_{i=1}^{n} x_i}{n}$ $s^2 = \frac{\Sigma_{i=1}^{n}(x_i - \bar{x})}{n-1}$

$P(A^c) = 1 - P(A)$ $P(A \cup B) = P(A) + P(B) - P(A \cap B)$

$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A^c)P(A^c)}$

Discrete Random Variables

Let X be a discrete random variable with a pmf of $p(x)$ then

$E[X] = \sum_x xp(x)$

Let X be a random variable, then

$Var(X) = E[X^2] - E[X]^2$

Linear combination of random variables X and Y and fixed numbers a and b:

$E[aX + bY] = aE[X] + bE[Y]$
$Var(aX + bY) = a^2 Var(X) + b^2 Var(Y)$

Distribution	**pmf**	$E(X)$	$Var(X)$
Binomial	$\binom{n}{k} p^k (1-p)^{n-k}$	np	$np(1-p)$
Geometric	$(1-p)^{n-1} p$	$\frac{1}{p}$	$\frac{1-p}{p^2}$
Discrete Uniform	$\frac{1}{n}$	$\frac{a+b}{2}$	$\frac{(b-a+1)^2 - 1}{12}$
Poisson	$\frac{\lambda^k}{k!} e^{-\lambda}$	λ	λ

Continuous Random Variables

$E[X] = \int_{x \in \Omega_x} x f(x)\, dx$

Distribution	**pmf**	$E(X)$	$Var(X)$
Continous Uniform	$\frac{1}{b-a}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$
Exponential	$\lambda e^{-\lambda x}$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$
Normal	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	μ	σ^2

Central Limit Theorem

Under certain conditions:

$\bar{x} \sim N(\mu, \frac{\sigma^2}{n})$

$(\bar{x}_1 - \bar{x}_2) \sim N(\mu_1 - \mu_2, \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2})$

$\hat{p} \sim N(p, \frac{p(1-p)}{n})$

$(\hat{p}_1 - \hat{p}_2) \sim N((p_1 - p_2), \frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2})$

Also note that

$\hat{p}_{pooled} = \frac{\hat{p}_1 n_1 + \hat{p}_2 n_2}{n_1 + n_2}$

Linear Regression

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \epsilon$

$b_1 = \frac{s_y}{s_x} R$
$b_0 = \bar{y} - b_1 \bar{x}$

Maximum Likelihood

The likelihood function

$L(\bar{\theta}) = f_1(x_1, \bar{\theta}) \times ....f_n(x_n, \bar{\theta})$

MLE estimator of $\bar{\theta}$ is

$\hat{\bar{\theta}} = \text{argmax}_{\bar{\theta}}\, L(\bar{\theta}) = \text{argmax}_{\bar{\theta}}\, lnL(\bar{\theta})$