Conditional Probability

$$P(A \mid X) = \frac{P(X \mid A)P(A)}{P(X \mid A)P(A) + P(X \mid A^{\complement})P(A^{\complement})}$$

Special Random Variables

Discrete Distributions

Bernoulli Distribution

$$X \sim Bernoulli(p), 0$$

PMF:

$$P(X = i) = p^{i}(1 - p)^{1-i}, i \in \{0, 1\}$$

Binomial Distribution

$$X \sim Binomial(n, p), 0$$

PMF:

$$P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

CDF:

$$P(X \le i) = \sum_{k=0}^{i} P(X = k)$$

$$E[X] = np, \, Var(X) = np(1-p)$$

Poisson

$$X \sim Poisson(\lambda), \lambda > 0$$

Poisson distribution is applicable:

The number of meteors greater than 1 meter diameter that strike earth in a year. The number of patients arriving in an emergency room between 10 and 11 pm PMF:

$$P(X=i) = e^{-\lambda} \frac{\lambda^i}{i!}$$

CDF:

$$P(X \le i) = e^{-\lambda} \sum_{k=0}^{i} \frac{\lambda^k}{k!}$$

$$E[X] = \lambda, Var(X) = \lambda.$$

Hypergeometric

$$X \sim Hypergeometric(N, M, n)$$

N good and M bad. Sample size n randomly chosen w/o replacement. Bin of transistors. PMF:

$$P(X = i) = \frac{\binom{N}{i} \binom{M}{n-i}}{\binom{N+M}{n}}$$

CDF:

$$P(X \le i) = \sum_{k=0}^{i} \frac{\binom{N}{i} \binom{M}{n-i}}{\binom{N+M}{n}}$$

$$E[X] = \frac{nN}{N+M}, Var(X_i) = \frac{N}{N+M} \frac{M}{N+M}$$

$$Var(X) = np(1-p)\left(1 - \frac{n-1}{N+M-1}\right)$$

PMF given two independent binomial random variables, X, Y with respective parameters (n, p) and (m, p).

$$P(X = i \mid X + Y = k) = \frac{\binom{n}{i} \binom{m}{k-i}}{\binom{n+m}{k}}$$

Continuous Distributions Uniform Distribution

$$X \sim Uniform(\alpha, \beta)$$

PDF:

$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \text{if } \alpha \le x \le \beta \\ 0 & \text{otherwise} \end{cases}$$

CDF:

$$P(a < X < b) = \frac{b - a}{\beta - \alpha}$$

$$E[X] = \frac{\alpha + \beta}{2}, Var(X) = \frac{(\beta - \alpha)^2}{12}$$

Normal Distribution

$$X \sim \mathcal{N}(\mu, \sigma^2)$$

PDF:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

$$E[X] = \mu, \, Var(X) = \sigma^2$$

$$Z = \frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$$

$$\Phi(x) = P(Z \le x) = \int_{-\infty}^{x} \frac{1}{2\pi} e^{-\frac{z^2}{2}} dz$$
$$\Phi(-x) = 1 - \Phi(x), \ x > 0$$

CDFs:

$$P(X < b) = \Phi\left(\frac{b - \mu}{\sigma}\right)$$

$$P(a < X < b) = \Phi\left(\frac{b - \mu}{\sigma}\right) - \Phi\left(\frac{a - \mu}{\sigma}\right)$$

Sums of NRVs are also normal with $\mu = \sum \mu_i$, $\sigma^2 = \sum \sigma_i^2$. Linear transformations also produce normally distributed variables.

$$a + bX \sim \mathcal{N}(a + b\mu, b^2\sigma^2)$$

Exponential Distribution

 $X \sim Exponential(\lambda), \ \lambda > 0$

PDF:

$$f(x) = \lambda e^{-\lambda x}, \ x \ge 0$$

CDF:

$$P(X \le i) = 1 - e^{-\lambda x}, \ x \ge 0$$

$$E[X] = \lambda^{-1}, \, Var(X) = \lambda^{-2}$$

Exponential distribution is memoryless, adding conditions does not change the distribution. Useful for probability you will have to wait x time for a bus that on average you have to wait y for.

Chi-Square Distribution

Z is a list of n independent standard normal variables.

$$X = \sum_{i}^{n} Z_i^2$$

$$X \sim \chi_n^2$$

$$E[X] = n, Var(X) = 2n.$$
 CDF:

$$P(X > \chi^2_{\alpha,n}) = \alpha, \ \alpha \in [0,1]$$

$$P(X \le \chi^2_{\alpha,n}) = 1 - \alpha$$

If n = 1:

$$X \sim \chi_1^2$$

$$P(X < x) = P(-\sqrt{x} < Z < \sqrt{x})$$

$$= 2\Phi(\sqrt{x}) - 1$$

If n=2:

$$X \sim \chi_2^2 \sim Exponential\left(\frac{1}{2}\right)$$

t-Distribution

Z std nrv ind to, χ_n^2

$$T_n = \frac{Z}{\sqrt{\chi_n^2/n}} \sim t_n$$

$$E[T_n] = 0, n > 1 \quad Var(T_n) = \frac{n}{n-2}, n > 2$$

$$P\{T_n > t_{\alpha,n}\} = \alpha$$

$$P\{T_n \le t_{\alpha,n}\} = 1 - \alpha$$

$$P\{T_n > -t_{\alpha,n}\} = 1 - \alpha$$

$$-t_{\alpha,n} = t_{1-\alpha,n}$$

F-Distribution

 χ_n^2 ind. of χ_m^2

$$Y = \frac{\chi_n^2/n}{\chi_m^2/m} \sim F_{n,m}$$

$$E[Y] = \frac{m}{m-2}, m > 2$$

$$Var(Y) = 2\left(\frac{m}{m-2}\right)^2 \frac{n+m-2}{n(m-4)}, m > 4$$

$$P\{Y > F_{\alpha,n,m}\} = \alpha$$

$$P\{Y \le F_{\alpha,n,m}\} = 1 - \alpha$$

$$F_{1-\alpha,m,n} = \frac{1}{F_{\alpha,n,m}}$$

Distributions of Sampling Statistics

Sample Mean

$$\bar{X} = \frac{X_1 + \dots + X_n}{n}$$

$$E[\bar{X}] = \mu, Var(\bar{X}) = \frac{\sigma^2}{n}$$

The Central Limit Theorem

 $X_1, \dots X_n$ are ind., id. dist. r.v. each with mean μ and variance $\sigma^2 R$. For n large,

$$P\left\{\frac{X_1 + \dots + X_n - n\mu}{\sigma\sqrt{n}} < x\right\} \approx P\{Z < x\}$$

where Z is a std. n.r.v.

Distribution of Sample Mean

$$\frac{\bar{X} - \mu}{\sigma / \sqrt{n}} \sim Z$$

Distribution of Sample Variance

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$$

Distribution of Sample Mean and Sample Variance

$$\sqrt{n}\frac{\bar{X} - \mu}{S} \sim t_{n-1}$$

Sampling From a Finite Population

Population of N elements. p is proportion possessing a certain trait. X_i is 1 if ith member has trait, 0 else. Assume population size much greater than sample size. Then

$$E[X] = np, Var(X) = np(1-p)$$

$$E[\bar{X}] = p, Var(\bar{X}) = p(1-p)/n$$

Parameter Estimation

Maximum Likelihood Estimators

Given sample $X_1 ... X_n$ with joint distribution f known except for some parameter θ . Define likelihood function:

$$L(\theta) = f_{\theta}(x_1, \dots x_n)$$

If X_i are independent,

$$L(\theta) = f_{\theta}(x_1) \cdots f_{\theta}(x_n).$$

To find $\hat{\theta}_{MLE}$ maximize $L(\theta)$.

Bernoulli

$$\hat{p}_{MLE} = \bar{X}$$

Binomial

$$\hat{p}_{MLE} = \bar{X}$$

Poisson

$$\hat{\lambda}_{MLE} = \bar{X}$$

Normal

When μ and σ unknown:

$$\hat{\mu}_{MLE} = \bar{X}$$

$$\hat{\sigma}_{MLE} = \sqrt{\frac{\sum (X_i - \bar{X})^2}{n}}$$

When only σ unknown:

$$\hat{\sigma^2}_{MLE} = \frac{\sum (X_i - \mu)}{n}$$

Interval Estimates

2-Sided Confidence Intervals

$$[\bar{x} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}]$$

Upper Confidence Intervals

$$[\bar{x}-z_{\alpha}\frac{\sigma}{\sqrt{n}},\infty]$$

Lower Confidence Intervals

$$[-\infty, \bar{x} + z_{\alpha} \frac{\sigma}{\sqrt{n}}]$$

Normal Mean with Unknown Variance

$$[\bar{x} \pm t_{\alpha/2,n-1} \frac{s}{\sqrt{n}}]$$