

Probability of events

Axioms:

$$P(e) \geq 0 \quad \forall e \in \mathcal{E}$$

$$P(\Omega) = 1$$

$$P(\cup_{i=1}^n e_i) = \sum_{i=1}^n P(e_i)$$

e_i are disjoint events.

Theorems:

$$P(\{\}) = 0$$

$$e_1 \subseteq e_2 \Rightarrow P(e_1) \leq P(e_2) \quad \forall e_1, e_2 \in \mathcal{E}$$

$$P(\Omega \setminus e) = 1 - P(e) \quad \forall e \in \mathcal{E}$$

$$P(e) \in [0, 1] \quad \forall e \in \mathcal{E}$$

$$P(e_1 \cup e_2) = P(e_1) + P(e_2) - P(e_1 \cap e_2) \quad \forall e_1, e_2 \in \mathcal{E}$$

Probability density functions:

Definition: $P(e) = \int_e p(\omega) d\omega$

Requirements: $p(\omega) \geq 0 \quad \forall \omega \in \Omega$

$$\int_{\Omega} p(\omega) d\omega = 1$$

Cumulative distribution function:

Definition: $\Phi_Y(y) = P(Y < y) = \int_{-\infty}^y p_Y(\xi) d\xi$

Expected value:

$$E[Y] = \int_{\Omega_Y} y p_Y(y) dy$$

$$E \left[\sum_{i=1}^N \alpha_i Y_i \right] = \sum_{i=1}^N \alpha_i E[Y_i]$$

$$E[g(Y)] = \int_{\Omega_Y} g(y) p_Y(y) dy$$

Variance:

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

$$Var \left[\sum_{i=1}^N \alpha_i Y_i \right] = \sum_{i=1}^N \alpha_i^2 Var[Y_i] + 2 \sum_{i=1}^N \sum_{j=i+1}^N \alpha_i \alpha_j Cov(Y_i, Y_j)$$

Standard deviation: $\sigma_Y = \sqrt{Var[Y]}$

Multivariate random variables:

$$Y = (Y^1, Y^2, \dots, Y^D)$$

$$E[Y] = (E[Y^1], E[Y^2], \dots, E[Y^D])$$

$$Var[Y] = E[(Y - E[Y])^T (Y - E[Y])]$$

$$Cov[Y^i, Y^j] = \sigma_{i,j}^2 = E[(Y^i - E[Y^i])(Y^j - E[Y^j])]$$

Marginal distribution:

$$p_X(x) = \int_{\Omega_Y} p_{XY}(x, y) dy$$

Independence:

$$P(A \cap B) = P(A)P(B) \quad p_{XY}(x, y) = p_X(x)p_Y(y)$$

$$P(A|B) = P(A) \quad p_{Y|X=x}(y) = p_Y(y)$$

$$p_{X|Y=y}(x) = p_X(x)$$

Conditional probability:

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

$$p_{Y|X=x}(y) = \frac{p_{XY}(x, y)}{p_X(x)} \quad \forall y \in \Omega_Y$$

Correlation coefficient: $\rho_{XY} = \frac{Cov(X, Y)}{\sigma_X \sigma_Y}$

Bernoulli: $Y \sim \mathcal{B}(\alpha)$

$$p_Y(y) = \begin{cases} 1 - \alpha & \text{if } y = 0 \\ \alpha & \text{if } y = 1 \end{cases}$$

$$E[Y] = \alpha$$

$$Var[Y] = \alpha(1 - \alpha)$$

Exponential: $Y \sim \mathcal{E}(\lambda)$

$$p_Y(y) = \begin{cases} \lambda e^{-\lambda y} & \text{if } y \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$E[Y] = \lambda^{-1}$$

$$Var[Y] = \lambda^{-2}$$

Discrete uniform: $Y \sim \mathcal{U}(a, b)$

$$p_Y(y) = \begin{cases} \frac{1}{b-a+1} & \text{if } y \in [a, b] \\ 0 & \text{otherwise} \end{cases}$$

$$E[Y] = \frac{a+b}{2}$$

$$Var[Y] = \frac{(b-a+1)^2 - 1}{12}$$

Continuous uniform: $Y \sim \mathcal{U}(a, b)$

$$p_Y(y) = \begin{cases} \frac{1}{b-a} & \text{if } y \in [a, b] \\ 0 & \text{otherwise} \end{cases}$$

$$E[Y] = \frac{a+b}{2}$$

$$Var[Y] = \frac{(b-a)^2}{12}$$

Gaussian: $Y \sim \mathcal{N}(\mu, \sigma^2)$

$$p_Y(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \frac{(y-\mu)^2}{\sigma^2}\right)$$

$$E[Y] = \mu$$

$$Var[Y] = \sigma^2$$

Point estimators:

$$\text{Bias}[\hat{\Theta}_N] = E[\hat{\Theta}_N] - \theta$$

$$\text{Var}[\hat{\Theta}_N] = E\left[\left(\hat{\Theta}_N - E[\hat{\Theta}_N]\right)^2\right]$$

Mean squared error:

$$\text{MSE}[\hat{\Theta}_N] = E[(\hat{\Theta}_N - \theta)^2]$$

$$= \text{Var}[\hat{\Theta}_N] + (\text{Bias}[\hat{\Theta}_N])^2$$

Sample mean:

$$\bar{Y}_N = \frac{1}{N} \sum_{i=1}^N Y_i$$

Unbiased sample variance:

$$S_N^2 = \frac{1}{N-1} \sum_{i=1}^N (Y_i - \bar{Y}_N)^2$$

Biased sample variance:

$$\tilde{S}_N^2 = \frac{1}{N} \sum_{i=1}^N (Y_i - \bar{Y}_N)^2$$

Likelihood:

$$\mathcal{L}(\underline{\theta}; \mathcal{D}) = \prod_{i=1}^N p_Y(y_i; \underline{\theta})$$

Confidence intervals:

$$\rho = \frac{\sigma_Y}{\sqrt{N}} \left| \Phi_N^{-1} \left(\frac{1-\gamma}{2} \right) \right| \quad \text{or} \quad \rho = \frac{\hat{\sigma}_N}{\sqrt{N}} \left| \Phi_{t(\nu)}^{-1} \left(\frac{1-\gamma}{2} \right) \right|$$

Z and t statistics:

$$Z = \frac{\bar{Y}_N - \mu_Y}{\sigma_Y / \sqrt{N}} \quad t = \frac{\bar{Y}_N - \mu_Y}{S_N / \sqrt{N}}$$