

# Introduction to Probability

## Sample Space and Probability

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \quad (\text{Venn diagram})$$

$$P(\cup_{i=1}^n A_i) \leq \sum_{i=1}^n P(A_i) \quad (\text{union bound})$$

$$P(B) = P(A_1)P(B|A_1) + \dots + P(A_n)P(B|A_n) \quad (\text{total probability})$$

$$P(\cap_{i=1}^n A_i) = P(A_1)P(A_2|A_1) \dots P(A_n|\cap_{i=1}^{n-1} A_i) \quad (\text{chain rule})$$

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{i=1}^n P(B|A_i)P(A_i)} \quad (\text{Bayes rule})$$

$$P(\cap_{i \in S} A_i) = \prod_{i \in S} P(A_i) \quad \text{for every subset } S \text{ of } \{1, 2, \dots, n\} \quad (\text{indep.})$$

$$E[X] = \sum_{x \in X} xp_x(x), \text{VAR}(X) = E[(X - E[X])^2] = E[X^2] - E[X]^2$$

$$p_x(x) = \sum_y p_{X,Y}(x, y), p_y(y) = \sum_x p_{X,Y}(x, y) \quad (\text{marginals})$$

$$p_Y(y) = \sum_{\{x|g(x)=y\}} p_X(x) \quad (\text{functions of RV})$$

$$E[X|Y=y] = \sum_x xp_{X|Y}(x|y) \quad (\text{conditional expectation})$$

$$E[X] = E[E[X|Y]] \quad (\text{iterated expectation})$$

$$\text{VAR}(X) = E[\text{VAR}(X|Y)] + \text{VAR}(E[X|Y]) \quad (\text{law of total variance})$$

$$\text{VAR}(\sum_{i=1}^n X_i) = \sum_{i=1}^n \text{VAR}(X_i) + \sum_{i \neq j} \text{COV}(X_i, X_j) \quad (\text{variance of sum})$$

## Discrete Random Variables

**Bernoulli:**  $X = \{\text{heads of a biased coin}\}$

$$p_x(x; p) = p^x(1-p)^{1-x}, x \in \{0, 1\}$$

$$E[X] = p, \text{VAR}(x) = p(1-p)$$

**Binomial:**  $X = \{\text{number of heads (successes) in } n \text{ trials}\}$

$$p_x(x; p) = \binom{n}{k} p^k (1-p)^{n-k}, k = 0, 1, \dots, n$$

$$S_n = \sum_{i=1}^n X_i \sim \text{Bin}(n, k; p), \text{ where } X_i \sim \text{Ber}(p)$$

$$E[S_n] = np, \text{VAR}(S_n) = np(1-p)$$

**Geometric:**  $X = \{\text{number of trials until the first success}\}$

$$p_x(x; k) = (1-p)^{k-1}p, k = 1, 2, \dots$$

$$E[X] = 1/p, \text{VAR}(x) = \frac{1-p}{p^2}$$

**Poisson:**  $X = \{\text{number of arrivals}\}$

$$p_x(k; \lambda) = \frac{\lambda^k}{k!} \exp(-\lambda), k = 0, 1, 2, \dots$$

$$E[X] = \lambda, \text{VAR}(x) = \lambda$$

## Continuous Random Variables

**Uniform:**  $X = \{\text{equally likely}\}$

$$f_x(x) = 1/(b-a), \quad \text{if } a \leq x \leq b$$

$$E[X] = (a+b)/2, \text{VAR}(x) = (b-a)^2/12$$

**Exponential:**  $X = \{\text{lifetime duration}\}$

$$f_x(x) = \lambda \exp\{-\lambda x\}, \quad \text{if } x \geq 0$$

$$E[X] = (a+b)/2, \text{VAR}(x) = (b-a)^2/12$$

**Poisson:**  $X = \{\text{event arrivals}\}$

$$f_x(x; \lambda, \tau) = \frac{(\lambda \tau)^k}{k!} \exp\{-\lambda \tau\}$$

$$E[X] = \lambda \tau, \text{VAR}(x) = \lambda \tau$$

**Gaussian:**  $X = \{\text{law of large numbers}\}$

$$f_x(x; \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} \exp\{-\frac{1}{2\sigma^2}(x-\mu)^2\}$$

$$f_x(x; \mu, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp\{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\}$$

$$E[X] = \mu, \text{VAR}(X) = \Sigma$$

## Further Topics on Random Variables

Let  $Y = g(X)$  a transformation of rv  $X$  then:

$$F_Y(y) = P(g(X) \leq y) = P(X \leq g^{-1}(y)) = F_X(g^{-1}(y))$$

If  $g(x)$  is one-to-one, we have:

$$f_Y(y) = f_X(x) \left| \frac{dx}{dy} \right| = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right|$$

Sum of indep. rvs  $X$  and  $Y$  is the convolution of their PDFs:

$$p_Z(z) = P(X+Y=z) = \sum_{\{(x,y):x+y=z\}} P(X=x, Y=y)$$

$$= \sum_x P(X=x, Y=z-x) = \sum_x p_X(x) p_Y(z-x)$$

Covariance and correlation:

$$\text{COV}(X, X) = \text{VAR}(X) = \sigma_X^2$$

$$\text{COV}(X, aY+b) = a\text{COV}(X, Y)$$

$$\text{COV}(X, Y+Z) = \text{COV}(X, Y) + \text{COV}(X, Z)$$

$$\text{COV}(X, Y) = E[(X-E[X])(Y-E[Y])] = E[XY] - E[X]E[Y]$$

$$\text{VAR}(X+Y) = \text{VAR}(X) + \text{VAR}(Y) + 2\text{COV}(X, Y)$$

$$\rho(X, Y) = \frac{\text{COV}(X, Y)}{\sigma_X \sigma_Y} \in [-1, 1]$$

Moment Generating Function:

$$M_X(s) = E[e^{sX}] = \sum_x p_X(x) e^{sx}; E[X^n] = \frac{d^n}{ds^n} M_X(s)|_{s=0}$$

## Further Topics on Random Variables

Sum of a random number of RVs:

Let  $Y = X_1 + \dots + X_N$ , where  $N$  is a RV

$$E[Y|N=n] = E[X_1 + \dots + X_n|N=n] = nE[X] \rightarrow E[Y|N] = NE[X]$$

$$E[Y] = E[E[Y|N]] = E[NE[X]] = E[N]E[X]$$

$$\text{VAR}(Y|N=n) = \text{VAR}(X_1 + \dots + X_n|N=n) = n\text{VAR}(X)$$

$$\text{VAR}(Y) = E[\text{VAR}(Y|N)] + \text{VAR}(E[Y|N])$$

$$= E[N\text{VAR}(X)] + \text{VAR}(NE[X]) = \text{VAR}(X)E[N] + (E[X])^2\text{VAR}(N)$$

## Inequalities and Limit Theorems

$$P(X \geq a) \leq \frac{E[X]}{a}, \quad \text{for } a > 0 \quad (\text{Markov inequality})$$

$$P(|X - \mu| \geq \epsilon) \leq \frac{\sigma^2}{\epsilon^2}, \quad \text{for } \epsilon > 0 \quad (\text{Chebyshev inequality})$$

$$P(X \geq a) = P(e^{sX} \geq e^{sa}) \leq E[e^{sX}]e^{-sa} \quad (\text{Chernoff inequality})$$

**WLLN:** Let  $M_n = \frac{1}{n}(X_1 + \dots + X_n)$ , where  $X_i$  are iid, then:

$$M_n \rightarrow \mu \text{ in prob., i.e. } \lim_{n \rightarrow \infty} P(|M_n - \mu| > \epsilon) = 0$$

**SLLN:**  $X_i$  are iid, then:  $P(\lim_{n \rightarrow \infty} (\frac{1}{n}(X_1 + \dots + X_n)) = \mu) = 1$

**CLT:** Let  $S_n = (X_1 + \dots + X_n) = nM_n$  where  $X_i$  are iid, then:

$$Z_n = \frac{S_n - n\mu}{\sigma\sqrt{n}} \sim N(0, 1), \text{ i.e. } \lim_{n \rightarrow \infty} P(Z_n \leq z) = \Phi(z)$$

Let  $\epsilon$  be accuracy and  $\delta$  be confidence level, then:

$$P(|Y_n - a| \geq \epsilon) \leq \delta \quad \forall n \geq n_0$$

## Bayesian Inference

$$\textbf{MAP: } \hat{\theta}_{MAP} = \arg \max_{\theta} p(\theta|x) = \arg \max_{\theta} p(x|\theta)p(\theta)$$

$$\textbf{LMS: } \hat{\theta}_{LMS} = E_{P(\theta|x)}[\theta|X=x] = f(x)$$

$$\text{Hypothesis Testing: } P(\theta = \theta_1|X=x) \stackrel{H_1}{\geq} P(\theta = \theta_2|X=x)$$

$$\textbf{L-LMS: } \hat{\theta} = E[\theta] + \frac{\text{COV}(\theta, X)}{\text{VAR}(X)}(X - E[X])$$

$$\text{E.g. } X_i = \theta + W_i, \theta \sim N(\mu, \sigma_0^2), W_i \sim N(0, \sigma_i^2)$$

$$\hat{\theta}_{LLMS} = \frac{\mu/\sigma_0^2 + \sum_{i=1}^n x_i/\sigma_i^2}{\sum_{i=0}^n 1/\sigma_i^2}$$

$$\text{Bias: } b(\hat{\theta}) = E[\hat{\theta}] - \theta$$

$$\text{Consistent: } \hat{\theta}_n \rightarrow \theta \text{ in prob, i.e. } \lim_{n \rightarrow \infty} P(|\hat{\theta}_n - \theta| > \epsilon) = 0$$

$$\textbf{MSE: } E[(\hat{\theta}_n - \theta)^2] = (E[\hat{\theta}] - \theta)^2 + \text{VAR}(\hat{\theta}) = \text{bias}^2 + \text{variance}$$

## Bernoulli Process

Let  $X_1, X_2, \dots$  be a sequence of iid Bernoulli( $p$ )

Then probability of  $k$  arrivals in  $n$  time-steps:

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

Let  $T_i$  be event inter-arrival times

$$T_i \sim \text{Geom}(p) = (1-p)^{k-1} p, \quad k = 1, 2, \dots$$

Let  $Y_k = T_1 + T_2 \dots + T_k$  be the total time then

$$E[Y_k] = kE[T] = \frac{k}{p}, \quad \text{VAR}(Y_k) = k\text{VAR}(T) = \frac{k(1-p)}{p^2}$$

$$P_{Y_k}(t) = \binom{t-1}{k-1} p^k (1-p)^{t-k}, \quad t = k, k+1, \dots \text{(Pascal of order } k)$$

$$P(T = t+n | T > n) = P(T = T) = (1-p)^{t-1} p \text{ (memoryless)}$$

## Poisson Process

Time-homogeneity:  $P(k, \tau)$  prob of  $k$  arrivals is the same for same  $\tau$

Independence: Number of arrivals in disjoint intervals is independent

$$P(k, \tau) \text{ satisfy : } P(0, \tau) \approx 1 - \lambda\tau, \quad P(1, \tau) \approx \lambda\tau, \quad P(> 1, \tau) \approx 0$$

$$P(k, \tau) = \frac{(\lambda\tau)^k}{k!} \exp\{-\lambda\tau\}, \text{ where } E[N_\tau] = \lambda\tau, \quad \text{VAR}(N_\tau) = \lambda\tau$$

Let  $T_i$  be event inter-arrival times  $\sim \text{Exp}(\lambda)$

$$f_T(t) = \lambda e^{-\lambda t}, t \geq 0; \quad E[T] = \frac{1}{\lambda}; \quad \text{VAR}(T) = \frac{1}{\lambda^2}$$

Let  $Y_k = T_1 + T_2 \dots + T_k$  be the total time then

$$E[Y_k] = kE[T] = \frac{k}{\lambda}, \quad \text{VAR}(Y_k) = k\text{VAR}(T) = \frac{k}{\lambda^2}$$

$$f_{Y_k}(y) = \frac{\lambda^k y^{k-1} e^{-\lambda y}}{(k-1)!}, \quad y \geq 0 \text{ (Erlang pdf of order } k)$$

## Markov Chain

$$r_{ij}(n) = P(x_n = j | x_0 = i)$$

$$r_{ij}(n) = \sum_{k=1}^m r_{ik}(n-1) p_{kj}$$

Recurrent class  $R$  is aperiodic iff there exists  $n$  s.t.

$$r_{ij}(n) > 0 \quad \forall i, j \in R$$

$\pi_j = P(X_k = j)$  when  $n$  is large (steady-state prob of  $j$ )

$$\lim_{n \rightarrow \infty} r_{ij}(n) = \pi_j \text{ regardless of where you start}$$

for recurrent, aperiodic, irreducible chain (1 class)

$$\pi = \pi P \text{ where } \pi \text{ is a row vector}$$

$$\pi_j > 0 \text{ for all recurrent states}$$

$$\pi_j = 0 \text{ for all transient states}$$