

**Notation:**  $P_{X|Y}(x \mid y) = P[X = x \mid Y = y]$   
\*Subscript indicates the RV, and the value indicates the realization.  
**Intro:**  
**Random Experiment:** An outcome for each run.  
**Sample Space  $\Omega$ :** Set of all possible outcomes.  
**Event:** Measurable subsets of  $\Omega$ .  
**Prob. of Event A:**  $P(A) = \frac{\text{Number of outcomes in A}}{\text{Number of outcomes in } \Omega}$   
**Axioms:** (1)  $P(A) \geq 0 \forall A \in \Omega$ , (2)  $P(\Omega) = 1$ ,  
(3) If  $A \cap B = \emptyset$ , then  $P(A \cup B) = P(A) + P(B) \forall A, B \in \Omega$   
**Cond. Prob.**  $P(A|B) = \frac{P(A \cap B)}{P(B)}$   
\*Prob. measured on new sample space  $B$ .  
 $*P(A \cap B) = P(A|B)P(B) = P(B|A)P(A)$   
**Independence:**  $P(A|B) = P(A) \Leftrightarrow P(A \cap B) = P(A)P(B)$   
**Total Prob. Thm:** If  $H_1, H_2, \dots, H_n$  form a partition of  $\Omega$ , then  $P(A) = \sum_{i=1}^n P(A|H_i)P(H_i)$ .  
**Bayes' Rule:**  $P(H_k|A) = \frac{P(H_k \cap A)}{P(A)} = \frac{P(A|H_k)P(H_k)}{\sum_{i=1}^n P(A|H_i)P(H_i)}$   
\*Posteriori:  $P(H_k|A)$ , Likelihood:  $P(A|H_k)$ , Prior:  $P(H_k)$   
**1 RV:**  
**Cumulative Distribution Fn (CDF):**  $F_X(x) = P[X \leq x]$   
**Prob. Mass Fn (PMF):**  $P_X(x_j) = P[X = x_j] \ j = 1, 2, \dots$   
**Prob. Density Fn (PDF):**  $f_X(x) = \frac{d}{dx} F_X(x)$   
 $*P[a \leq X \leq b] = \int_a^b f_X(x) \, dx$   
**Exp.:**  $E[h(X)] = \int_{-\infty}^{\infty} h(x) f_X(x) \, dx$   
 $E[h(X)] = \sum_{k=-\infty}^{\infty} h(k) P_X(x_i = k)$   
**Variance:**  $\sigma_X^2 = \text{Var}[X] = E[(X - E[X])^2] = E[X^2] - E[X]^2$   
**Cond. Exp.:**  $E[X|A] = \int_{-\infty}^{\infty} x f_X(x|A) \, dx$   
**2 RVs:**  
**Joint PMF:**  $P_{X,Y}(x, y) = P[X = x, Y = y]$   
**Joint PDF:**  $f_{X,Y}(x, y) = \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x, y)$   
 $*P[(X, Y) \in A] = \int \int_{(x,y) \in A} f_{X,Y}(x, y) \, dx \, dy$   
**Exp.:**  $E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{X,Y}(x, y) \, dx \, dy$   
**Correlation:**  $E[XY]$   
**Covar.:**  $\text{Cov}[X, Y] = E[(X - \mu_X)(Y - \mu_Y)] = E[XY] - E[X]E[Y]$   
**Corr. Coeff.:**  $\rho_{X,Y} = E\left[\left(\frac{X - \mu_X}{\sigma_X}\right)\left(\frac{Y - \mu_Y}{\sigma_Y}\right)\right] = \frac{\text{Cov}[X,Y]}{\sigma_X \sigma_Y}$   
 $*-1 \leq \rho_{X,Y} \leq 1$   
**Marginal PMF:**  $P_X(x) = \sum_{j=1}^{\infty} P_{X,Y}(x, y_j) \mid P_Y(y)$   
**Marginal PDF:**  $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) \, dy \mid f_Y(y)$   
**Cond. PMF:**  $P_{X|Y}(x|y) = \frac{P_{X,Y}(x,y)}{P_Y(y)} \mid P_{Y|X}(y|x)$   
**Cond. PDF:**  $f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} \mid f_{Y|X}(y|x)$   
**Bayes' Rule**  
 $f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{f_{X|Y}(x|y)f_Y(y)}{\int_{-\infty}^{\infty} f_{X|Y}(x|y')f_Y(y') \, dy'}$   
 $*P_{Y|X}(y|x) = \frac{P_{X,Y}(x,y)}{P_X(x)} = \frac{P_{X|Y}(x|y)P_Y(y)}{\sum_{j=1}^{\infty} P_{X|Y}(x|y_j)P_Y(y_j)}$   
**Ind.:**  $f_{X|Y}(x|y) = f_X(x) \forall y \Leftrightarrow f_{X,Y}(x, y) = f_X(x)f_Y(y)$   
**Thm:** If independent, then uncorrelated unless Guassian.  
**Uncorrelated:**  $\text{Cov}[X, Y] = 0 \Leftrightarrow \rho_{X,Y} = 0$   
**Orthogonal:**  $E[XY] = 0$   
**Cond. Exp.:**  $E[Y] = E[E[Y|X]]$  or  $E[E[h(Y)|X]]$   
 $*E[E[Y|X]]$  w.r.t.  $X \mid E[Y|X]$  w.r.t.  $Y$ .  
**Estimation:** Estimate unknown parameter  $\theta$  from  $n$  i.i.d. measurements  $X_1, X_2, \dots, X_n$ ,  $\hat{\Theta}(\underline{X}) = g(X_1, X_2, \dots, X_n)$   
**Estimation Error:**  $\hat{\Theta}(\underline{X}) - \theta$ .  
**Unbiased:**  $\hat{\Theta}(\underline{X})$  is unbiased if  $E[\hat{\Theta}(\underline{X})] = \theta$ .  
**Asymptotically unbiased:**  $\lim_{n \rightarrow \infty} E[\hat{\Theta}(\underline{X})] = \theta$ .  
**Consistent:**  $\hat{\Theta}(\underline{X})$  is consistent if  $\hat{\Theta}(\underline{X}) \rightarrow \theta$  as  $n \rightarrow \infty$  or  $\forall \epsilon > 0, \lim_{n \rightarrow \infty} P[|\hat{\Theta}(\underline{X}) - \theta| < \epsilon] \rightarrow 1$ .  
**Sufficient:** A statistic is sufficient if the expression depends only on the statistic, it should be made up of  $x_1, x_2, \dots, x_n$ .  
**Sample Mean:**  $M_n = \frac{1}{n} S_n = \frac{1}{n} \sum_{i=1}^n X_i$ .  
\*Given a sequence of i.i.d. RVs,  $X_1, X_2, \dots, X_n$ ,  $M_n$  is unbiased and consistent.  
**Sample Variance:**  $S_n^2 = \frac{1}{n} \sum_{i=1}^n (X_i - M_n)^2$ .  
\*Given a sequence of i.i.d. RVs,  $X_1, X_2, \dots, X_n$ ,  $S_n^2$  is biased and consistent.  
\*Use  $S_n^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - M_n)^2$  for unbiased.  
**Chebychev's Inequality:**  $P[|X - E[X]| \geq \epsilon] \leq \frac{\text{Var}[X]}{\epsilon^2}$   
 $*P[|X - E[X]| < \epsilon] \geq 1 - \frac{\text{Var}[X]}{\epsilon^2}$   
**Weak Law of Large #s:**  $\lim_{n \rightarrow \infty} P[|M_n - \mu| < \epsilon] = 1 \forall \epsilon > 0$ .  
**ML Estimation:** Choose  $\theta$  that is most likely to generate the obs.  $x_1, x_2, \dots, x_n$ .  
\*Disc:  $\hat{\Theta} = \arg \max_{\theta} P_{\underline{X}}(\underline{x}|\theta) \stackrel{\log}{=} \hat{\theta} = \arg \max_{\theta} \sum_{i=1}^n \log P_X(x_i|\theta)$   
\*Cont:  $\hat{\Theta} = \arg \max_{\theta} f_{\underline{X}}(\underline{x}|\theta) \stackrel{\log}{=} \hat{\theta} = \arg \max_{\theta} \sum_{i=1}^n \log f_X(x_i|\theta)$   
**Maximum A Posteriori (MAP) Estimation:**  
\*Disc:  $\hat{\theta} = \arg \max_{\theta} P_{\Theta|\underline{X}}(\theta|\underline{x}) = \arg \max_{\theta} P_{\underline{X}|\Theta}(\underline{x}|\theta)P_{\Theta}(\theta)$   
\*Cont:  $\hat{\theta} = \arg \max_{\theta} f_{\Theta|\underline{X}}(\theta|\underline{x}) = \arg \max_{\theta} f_{\underline{X}|\Theta}(\underline{x}|\theta)f_{\Theta}(\theta)$   
 $*f_{\Theta|\underline{X}}(\theta|\underline{x})$ : Posteriori,  $f_{\underline{X}|\Theta}(\underline{x}|\theta)$ : Likelihood,  $f_{\Theta}(\theta)$ : Prior  
**Bayes' Rule:**  $P_{\Theta|\underline{X}}(\theta|\underline{x}) = \begin{cases} \frac{P_{\underline{X}|\Theta}(\underline{x}|\theta)P_{\Theta}(\theta)}{P_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ disc.} \\ \frac{f_{\underline{X}|\Theta}(\underline{x}|\theta)f_{\Theta}(\theta)}{f_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ cont.} \end{cases}$   
 $f_{\Theta|\underline{X}}(\theta|\underline{x}) = \begin{cases} \frac{P_{\underline{X}|\Theta}(\underline{x}|\theta)f_{\Theta}(\theta)}{P_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ disc.} \\ \frac{f_{\underline{X}|\Theta}(\underline{x}|\theta)f_{\Theta}(\theta)}{f_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ cont.} \end{cases}$   
\*Independent of  $\theta$ :  $f_{\underline{X}}(\underline{x}) = \int_{-\infty}^{\infty} f_{\underline{X}|\Theta}(\underline{x}|\theta)f_{\Theta}(\theta) \, d\theta$   
**Least Mean Squares (LMS) Estimation:** Assume prior  $P_{\Theta}(\theta)$  or  $f_{\Theta}(\theta)$  w/ obs.  $\underline{X} = \underline{x}$ .  
 $*\hat{\theta} = g(\underline{x}) = E[\Theta|\underline{X} = \underline{x}] \mid \hat{\Theta} = g(\underline{X}) = E[\Theta|\underline{X}]$   
**Conditional Exp.**  $E[X|Y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) \, dx$   
**Binary Hyp. Testing:**  $H_0$ : Null Hyp.,  $H_1$ : Alt. Hyp.  
 $\Omega_{\underline{X}}$ : Set of all possible obs.  $\underline{x}$ .



**TI Err. (False Rejection):** Reject  $H_0$  when  $H_0$  is true.

\* $\alpha(R) = P[\underline{X} \in R \mid H_0]$  (false alarm)

**II Err. (False Accept.):** Accept  $H_0$  when  $H_1$  is true.

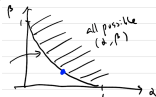
\* $\beta(R) = P[\underline{X} \in R^c \mid H_1]$  (missed detection)

**Likelihood Ratio Test:**  $\forall \underline{x} \quad L(\underline{x}) = \frac{P_{\underline{X}}(\underline{x} \mid H_1)}{P_{\underline{X}}(\underline{x} \mid H_0)} \gtrless_{H_0} 1$  or  $\xi$

\***Max. Likelihood Test:** 1, **Likelihood Ratio Test:**  $\xi$

**Neyman-Pearson Lemma:** Given a false rejection prob. ( $\alpha$ ), the LRT offers the smallest possible false accept. prob. ( $\beta$ ), and vice versa.

\*LRT produces  $(\alpha, \beta)$  pairs that lie on the efficient frontier.



**Bayesian Hyp. Testing:**

**MAP Rule:**  $L(\underline{x}) = \frac{p_{\underline{X}}(\underline{x} \mid H_1)}{p_{\underline{X}}(\underline{x} \mid H_0)} \gtrless_{H_0} \frac{P[H_0]}{P[H_1]}$

**Gaussian to Q Fcn:** 1. Find  $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$ .

2. Use table to find  $Q(x)$  for  $x \geq 0$ .

**Min. Cost Bayes' Dec. Rule:**  $C_{ij}$  is cost of choosing  $H_j$  when  $H_i$  is true. Given obs.  $\underline{X} = \underline{x}$ , the expected cost of choosing  $H_j$  is  $A_j(\underline{x}) = \sum_{i=0}^1 C_{ij} P[H_i \mid \underline{X} = \underline{x}]$ .

**Min. Cost Dec. Rule:**  $L(\underline{x}) = \frac{P_{\underline{X}}(\underline{x} \mid H_1)}{P_{\underline{X}}(\underline{x} \mid H_0)} \gtrless_{H_0} \frac{(C_{01} - C_{00})P[H_0]}{(C_{10} - C_{11})P[H_1]}$ .

\* $C_{01}$ : False accept. cost,  $C_{10}$ : False reject. cost.

**Naive Bayes Assumption:** Assume  $X_1, \dots, X_n$  (features) are ind., then  $p_{\underline{X}}(\underline{x} \mid \theta) = \prod_{i=1}^n p_{X_i}(x_i \mid \theta)$ .

**Notation:**  $P_{\underline{X}}(\underline{x} \mid \theta)$ , only put RVs in subscript, not values.

$P_{\underline{X}}(\underline{x} \mid H_i)$ , didn't put  $H$  in subscript b/c it's not a RV.

**Binomial #** of successes in  $n$  trials, each w/ prob.  $p$

$b(x \mid n, p) = \binom{n}{x} p^x (1-p)^{n-x}$ ,  $x = 0, 1, 2, \dots$

\* $E[X] = \mu = np$  |  $\text{Var}(X) = \sigma^2 = np(1-p)$

**Multinomial #** of  $x_i$  successes in  $n$  trials, each w/ prob.  $p_i$

$f(x_i \mid p_i \forall i, n) = \frac{n!}{x_1! \dots x_m!} p_1^{x_1} \dots p_m^{x_m}$

\* $\sum_i x_i = n$ , and  $\sum_{i=1}^m p_i = 1$

\* $E[X_i] = \mu_i = np_i$  |  $\text{Var}(X_i) = \sigma_i^2 = np_i(1-p_i)$

**Hypergeometric #** of successes in  $n$  draws from  $N$  items,  $k$  of which are successes

$h(x \mid N, n, k) = \frac{\binom{k}{x} \binom{N-k}{n-x}}{\binom{N}{n}}$

\* $\max\{0, n - (N - k)\} \leq x \leq \min\{n, k\}$

\* $E[X] = \mu = \frac{nk}{N}$  |  $\text{Var}(X) = \sigma^2 = \frac{N-n}{N-1} \cdot n \cdot \frac{k}{N} \cdot \left(1 - \frac{k}{N}\right)$

**Negative Binomial #** of trials until  $k$  successes, each w/ prob.  $p$

$b^*(x \mid k, p) = \binom{x-1}{k-1} p^k (1-p)^{x-k}$

\* $x \geq k$ ,  $x = k, k+1, \dots$

\* $E[X] = \mu = \frac{k}{p}$  |  $\text{Var}(X) = \sigma^2 = \frac{k(1-p)}{p^2}$

**Geometric #** of trials until 1st success, each w/ prob.  $p$

$g(x \mid p) = p(1-p)^{x-1}$

\* $x \geq 1$ ,  $x = 1, 2, 3, \dots$

\* $E[X] = \mu = \frac{1}{p}$  |  $\text{Var}(X) = \sigma^2 = \frac{1-p}{p^2}$

**Poisson #** of events in a fixed interval w/ rate  $\lambda$

$p(x \mid \lambda t) = \frac{e^{-\lambda t} (\lambda t)^x}{x!}$

\* $x \geq 0$ ,  $x = 0, 1, 2, \dots$

\* $E[X] = \mu = \lambda t$  |  $\text{Var}(X) = \sigma^2 = \lambda t$

**Beta Prior**  $\Theta$  is a Beta R.V. w/  $\alpha, \beta > 0$

$f_{\Theta}(\theta) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1} & \text{if } 0 < \theta < 1 \\ 0 & \text{otherwise} \end{cases}$

\* $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$

**Prop.:** 1.  $\Gamma(x+1) = x\Gamma(x)$ . For  $m \in \mathbb{Z}^+$ ,  $\Gamma(m+1) = m!$ .

2.  $\beta(\alpha, \beta) = \frac{(\alpha+\beta-1)!}{(\alpha-1)!(\beta-1)!} = \beta \binom{\alpha+\beta-1}{\alpha-1}$

3. Expected Value:  $E[\Theta] = \frac{\alpha}{\alpha+\beta}$  for  $\alpha, \beta > 0$

4. Mode (max of PDF):  $\frac{\alpha-1}{\alpha+\beta-2}$  for  $\alpha, \beta > 1$

**Drawing Beta Dist.** 1. Label  $x$ -axis from 0 to 1. 2. Identify mode.

3. Determine shape based on  $\alpha$  and  $\beta$ :  $\alpha = \beta = 1$  (uniform),  $\alpha = \beta > 1$  (bell-shaped, peak at 0.5),  $\alpha = \beta < 1$  (U-shaped w/ high density near 0 and 1),  $\alpha > \beta$  (left-skewed),  $\alpha < \beta$  (right-skewed).

**Uniform PDF**  $f_X(x) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$

\* $E[X] = \frac{a+b}{2}$ ,  $\text{Var}[X] = \frac{(b-a)^2}{12}$

**Random Vector:**  $\underline{X} = (X_1, \dots, X_n) = \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} = [X_1 \quad \dots \quad X_n]^T$

**Mean Vector:**  $\underline{m}_X = E[\underline{X}] = [\mu_1, \dots, \mu_n]^T$

**Corr. Mat.:**  $R_X = \begin{bmatrix} E[X_1^2] & \dots & E[X_1 X_n] \\ E[X_2 X_1] & \dots & E[X_2 X_n] \\ \vdots & \ddots & \vdots \\ E[X_n X_1] & \dots & E[X_n^2] \end{bmatrix}$

\*Real, symmetric ( $R = R^T$ ), and PSD ( $\forall \underline{a}, \underline{a}^T R \underline{a} \geq 0$ ).

**Covar. Mat.:**  $K_X = \begin{bmatrix} \text{Var}[X_1] & \dots & \text{Cov}[X_1, X_n] \\ \text{Cov}[X_2, X_1] & \dots & \text{Cov}[X_2, X_n] \\ \vdots & \ddots & \vdots \\ \text{Cov}[X_n, X_1] & \dots & \text{Var}[X_n] \end{bmatrix}$

\* $K_X = R_X - \underline{m}_X \underline{m}_X^T$

\*Diagonal  $K_X \iff X_1, \dots, X_n$  are (mutually) uncorrelated.

**Lin. Trans.**  $\underline{Y} = A\underline{X}$  (A rotates and stretches  $\underline{X}$ )

**Mean:**  $E[\underline{Y}] = A\underline{m}_X$

**Covar. Mat.:**  $K_Y = AK_XA^T$

**Diagonalization of Covar. Mat. (Uncorrelated):**

$\forall \underline{X}$ , set  $P = [\underline{e}_1, \dots, \underline{e}_n]$  of  $K_X$ , if  $\underline{Y} = P^T \underline{X}$ , then

$K_Y = P^T K_X P = \Lambda$

\* $\underline{Y}$ : Uncorrelated RVs,  $K_X = PAP^T$

**Find an Uncorrelated  $K_Y$**

1. Find eigenvalues, normalized eigenvectors of  $K_X$ .

2. Set  $K_Y = \Lambda$ , where  $\underline{Y} = P^T \underline{X}$

**PDF of L.T.** If  $\underline{Y} = A\underline{X}$  w/  $A$  not singular, then

$f_Y(\underline{y}) = \frac{f_X(\underline{x})}{|\det A|} \Big|_{\underline{x}=A^{-1}\underline{y}}$

**Find  $f_Y(\underline{y})$**  1. Given  $f_X(\underline{x})$  and RV relations, define  $A$

2. Determine  $|\det A|$ ,  $A^{-1}$ , then  $f_Y(\underline{y})$ .

**Gaussian RVs:**  $\underline{X} \sim \mathcal{N}(\underline{\mu}, \Sigma)$

PDF of jointly Gaus.  $X_1, \dots, X_n \equiv$  Guas. vector:

$f_X(\underline{x}) = \frac{1}{(2\pi)^{n/2} |\det \Sigma|^{1/2}} e^{-\frac{1}{2}(\underline{x}-\underline{\mu})^T \Sigma^{-1}(\underline{x}-\underline{\mu})}$

\*1D:  $f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$

\* $\underline{\mu} = \underline{m}_X$ ,  $\Sigma = K_X$  ( $\Sigma$  not singular)

\*Indep.:  $f_X(\underline{x}) = \frac{1}{(2\pi)^{n/2} \prod_{i=1}^n \sigma_i} e^{-\frac{1}{2} \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i}\right)^2}$

\*IID:  $f_X(\underline{x}) = \frac{1}{(2\pi)^{n/2} \sigma^n} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$

\*Cond. PDF:  $f_{X|Y}(\underline{x}|\underline{y}) = \mathcal{N}(\underline{\mu}_{X|Y}, \Sigma_{X|Y})$

**Properties of Gaussian Vector:**

1. PDF is completely determined by  $\underline{\mu}$ ,  $\Sigma$ .

2.  $\underline{X}$  uncorrelated  $\iff \underline{X}$  independent.

3. Any L.T.  $\underline{Y} = A\underline{X}$  is Gaus. vector w/  $\underline{\mu}_Y = A\underline{\mu}_X$ ,  $\Sigma_Y = A\Sigma_X A^T$ .

4. Any subset of  $\{X_i\}$  are jointly Gaus.

5. Any cond. PDF of a subset of  $\{X_i\}$  given the other elements is Gaus.

**Diagonalization of Guassian Covar. (Indep.)**

$\forall \underline{X}$ , set  $P = [\underline{e}_1, \dots, \underline{e}_n]$  of  $\Sigma_X$ , if  $\underline{Y} = P^T \underline{X}$ , then

$\Sigma_Y = P^T \Sigma_X P = \Lambda$

\* $\underline{Y}$ : Indep. Gaussian RVs,  $\Sigma_X = PAP^T$

**How to go from Y to X?** 1. Given,  $\underline{X} \sim \mathcal{N}(\underline{\mu}, \Sigma)$

2.  $\underline{Y} \sim \mathcal{N}(\underline{0}, I)$  3.  $\underline{W} = \sqrt{\Lambda} \underline{V}$  4.  $\underline{Y} = P\underline{W}$  4.  $\underline{X} = \underline{Y} + \underline{\mu}$

**Gaussian Discriminant Analysis:**

Obs:  $\underline{X} = \underline{x} = (x_1, \dots, x_D)$

Hyp:  $\underline{x}$  is generated by  $\mathcal{N}(\underline{\mu}_c, \Sigma_c)$ ,  $c \in C$

Dec: Which "Gaussian bump" generated  $\underline{x}$ ?

Prior:  $P[C = c] = \pi_c$  (Gaussian Mixture Model)

**MAP:**  $\hat{c} = \arg \max_c P_C[c|\underline{X} = \underline{x}] = \arg \max_c f_{\underline{X}|C}(\underline{x} | c) \pi_c$

**LGD:** Given  $\Sigma_c = \Sigma \forall c$ , find  $c$  w/ best  $\underline{\mu}_c$

$\hat{c} = \arg \max_c \underline{\beta}_c^T \underline{x} + \gamma_c$

\* $\underline{\beta}_c^T = \underline{\mu}_c^T \Sigma^{-1} \mid \gamma_c = \log \pi_c - \frac{1}{2} \underline{\mu}_c^T \Sigma^{-1} \underline{\mu}_c$

**Bin. Hyp. Decision Boundary**  $\underline{\beta}_0^T \underline{x} + \gamma_0 = \underline{\beta}_1^T \underline{x} + \gamma_1$

\*Linear in space of  $\underline{x}$

**QGD:** Given  $\Sigma_c$  are diff., find  $c$  w/ best  $\underline{\mu}_c$ ,  $\Sigma_c$

$\hat{c} = \arg \max_c -\frac{1}{2} \log |\Sigma_c| - \frac{1}{2} (\underline{x} - \underline{\mu}_c)^T \Sigma_c^{-1} (\underline{x} - \underline{\mu}_c) + \log \pi_c$

**Bin. Hyp. Decision Boundary** Quadratic in space of  $\underline{x}$

**How to find  $\underline{\beta}_c$ ,  $\underline{\mu}_c$ ,  $\Sigma_c$ :** Given  $n$  points gen. by GMM, then

$n_c$  points  $\{\underline{x}_1^c, \dots, \underline{x}_{n_c}^c\}$  come from  $\mathcal{N}(\underline{\mu}_c, \Sigma_c)$

$\hat{\pi}_c = \frac{n_c}{n}$  (categorical RV)

$\hat{\mu}_c = \frac{1}{n_c} \sum_{i=1}^{n_c} \underline{x}_i^c$ , (sample mean)

$\Sigma_c = \frac{1}{n_c} \sum_{i=1}^{n_c} (x_i^c - \hat{\mu}_c)(x_i^c - \hat{\mu}_c)^T$  (biased sampled var.)

**Gaussian Estimation:**

**MAP Estimator for  $\underline{X}$  Given  $\underline{Y}$  When  $\underline{W}=(\underline{X}, \underline{Y}) \sim \mathcal{N}(\underline{\mu}, \Sigma)$**

Given  $\underline{X} = \{X_1, \dots, X_n\}$ ,  $\underline{Y} = \{Y_1, \dots, Y_m\}$

$\hat{\underline{\mu}}_{\text{MAP}}(\underline{y}) = \hat{\underline{\mu}}_{\text{LMS}}(\underline{y}) = \underline{\mu}_{X|Y} = \underline{\mu}_X + \Sigma_{XY} \Sigma_{YY}^{-1} (\underline{y} - \underline{\mu}_Y)$

\* $\hat{\underline{\mu}}_{\text{MAP/LMS}}$ : Linear fcn of  $\underline{y}$

**Covar. Matrices:**  $\Sigma = \begin{bmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{bmatrix}$

\* $\Sigma_{XX} = \Sigma_X = E \left[ (\underline{X} - \underline{\mu}_X)(\underline{X} - \underline{\mu}_X)^T \right] \mid \Sigma_{YY} = \Sigma_Y$

\* $\Sigma_{XY} = E \left[ (\underline{X} - \underline{\mu}_X)(\underline{Y} - \underline{\mu}_Y)^T \right] \mid \Sigma_{YX} = \Sigma_{XY}^T$

**Prec. Matrices:**  $\Lambda = \Sigma^{-1}$

**Mean and Covar. Mat. of  $\underline{X}$  Given  $\underline{Y}$ :**

\* $\underline{\mu}_{X|Y} = \underline{\mu}_X + \Sigma_{XY} \Sigma_{YY}^{-1} (\underline{y} - \underline{\mu}_Y)$

\* $\Sigma_{X|Y} = \Sigma_X - \Sigma_{XY} \Sigma_{YY}^{-1} \Sigma_{YX}$

\***Reducing Uncertainty:** 2nd term is PSD, so given  $\underline{Y} = \underline{y}$ , always reducing uncertainty in  $\underline{X}$ .

**ML Estimator for  $\theta$  w/ Indep. Guas:**

Given  $\underline{X}=\{X_1, \dots, X_n\}$ :  $\hat{\theta}_{\text{ML}} = \frac{\sum_{i=1}^n \frac{x_i}{\sigma_i^2}}{\sum_{i=1}^n \frac{1}{\sigma_i^2}}$  (weighted avg.  $\underline{x}$ )

\* $X_i=\theta + Z_i$ : Measurement  $\mid Z_i \sim \mathcal{N}(0, \sigma_i^2)$ : Noise (indep.)

\* $\frac{1}{\sigma_i^2}$ : Precision of  $X_i$  (i.e. weight)

\*Larger  $\sigma_i^2 \implies$  less weight on  $X_i$  (less reliable measurement)

\***SC:** If  $\sigma_i^2 = \sigma^2 \forall i$  (iid), then  $\hat{\theta}_{\text{ML}} = \frac{1}{n} \sum_{i=1}^n x_i$ .

**MAP Estimator for  $\theta$  w/ Indep. Gaus., Gaus. Prior:**

Given  $\underline{X}=\{X_1, \dots, X_n\}$ , prior  $\Theta \sim \mathcal{N}(x_0, \sigma_0^2)$

$\hat{\theta}_{\text{MAP}} = \frac{\sum_{i=0}^n \frac{x_i}{\sigma_i^2}}{\sum_{i=1}^n \frac{1}{\sigma_i^2}} = \frac{1}{\sigma_0^2 + \sum_{i=1}^n \frac{1}{\sigma_i^2}} x_0 + \frac{1}{\sigma_0^2 + \sum_{i=1}^n \frac{1}{\sigma_i^2}} \hat{\theta}_{\text{ML}}$

\* $X_i=\theta + Z_i$ : Measurement  $\mid Z_i \sim \mathcal{N}(0, \sigma_i^2)$ : Noise (indep.)

\* $f_{\Theta}$ : Gaussian prior  $\equiv$  prior meas.  $x_0$  w/  $\sigma_0^2$ .

\***SC:** As  $n \rightarrow \infty$ ,  $\hat{\theta}_{\text{MAP}} \rightarrow \hat{\theta}_{\text{ML}}$ . As  $\sigma_0^2 \rightarrow \infty$ ,  $\hat{\theta}_{\text{MAP}} \rightarrow \hat{\theta}_{\text{ML}}$

**LMMSE Estimator for  $\underline{X}$  Given  $\underline{Y}$  w/ non-Guas.  $\underline{X}$ ,  $\underline{Y}$ :**

$\hat{\underline{\mu}}_{\text{LMMSE}}(\underline{y}) = \underline{\mu}_X + \Sigma_{XY} \Sigma_{YY}^{-1} (\underline{y} - \underline{\mu}_Y)$

**Linear Gaussian System:** Given  $\underline{Y} = A\underline{X} + \underline{b} + \underline{Z}$

\* $\underline{X} \sim \mathcal{N}(\underline{\mu}_X, \Sigma_X)$ ,  $\underline{Z} \sim \mathcal{N}(\underline{0}, \Sigma_Z)$ : Noise (indep. of  $\underline{x}$ )

\* $A\underline{X} + \underline{b}$ : channel distortion,  $\underline{Y}$ : Observed sig.

MAP/LMS Estimator for  $\underline{X}$  Given  $\underline{Y}$  w/  $\underline{W} = (\underline{X}, \underline{Y})$

Given  $\underline{W} = \begin{bmatrix} \underline{X} \\ A\underline{X} + \underline{b} + \underline{Z} \end{bmatrix} = \begin{bmatrix} I & 0 \\ A & I \end{bmatrix} \begin{bmatrix} \underline{X} \\ \underline{Z} \end{bmatrix} + \begin{bmatrix} 0 \\ \underline{b} \end{bmatrix}$

$\hat{\mu}_{\text{MAP/LMS}} = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{X}} A^T (A \Sigma_{\underline{X}} A^T + \Sigma_{\underline{Z}})^{-1} (\underline{y} - A \underline{\mu}_{\underline{X}} - \underline{b})$

$\Sigma_{\underline{X}\underline{Y}} = \Sigma_{\underline{X}} A^T, \Sigma_{\underline{Y}\underline{Y}} = A \Sigma_{\underline{X}} A^T + \Sigma_{\underline{Z}}$

$\hat{\mu}_{\text{MAP/LMS}} = \left( \Sigma_{\underline{X}}^{-1} + A^T \Sigma_{\underline{Z}}^{-1} A \right)^{-1} \left( A^T \Sigma_{\underline{Z}}^{-1} (\underline{y} - \underline{b}) + \Sigma_{\underline{X}}^{-1} \underline{\mu}_{\underline{X}} \right)$

\***Use:** Good to use when  $\underline{Z}$  is indep.

**Covar. Mat of  $\underline{X}$  Given  $\underline{Y} = \underline{y}$ :**  $\Sigma_{\underline{X}|\underline{y}} = \left( \Sigma_{\underline{X}}^{-1} + A^T \Sigma_{\underline{Z}}^{-1} A \right)^{-1}$

**Linear Regression:** Estimate unknown target fn  $Y = g(\underline{X})$  w/ iid obs.  $\{(\underline{x}_1, y_1), \dots, (\underline{x}_n, y_n)\}$  (MLE/MAP)

\* $\underline{y} = [y_1 \quad \dots \quad y_n]^T$

\* $\underline{X} = \begin{bmatrix} \underline{x}_1^T \\ \vdots \\ \underline{x}_n^T \end{bmatrix} \in \mathbb{R}^{n \times D}$

**ML Estimator:**  $Y = h(\underline{x}) = \underline{w}^T \underline{x} + Z \approx g(\underline{X})$ , then  $\hat{\underline{w}}_{\text{ML}} = (X X^T)^{-1} X^T \underline{y}$

\*Assume  $X^T X$  has full rank (i.e. invertible) since  $n \gg D$

\* $n$ : # of obs.,  $D$ : # of features.

\* $\underline{x} = \{x_1, \dots, x_D\}$ : Input features

\* $\underline{w} = \{w_1, \dots, w_D\}$ : Weights (parameter)

\* $Z \sim \mathcal{N}(0, \sigma^2)$ : Noise (i.i.d.)

\* $\underline{Y}$ : Target/observed output

\* $X^\dagger = (X^T X)^{-1} X^T$ : Pseudo-inverse of  $X$  (minimizes  $\|X \underline{w} - \underline{y}\|_2^2 \iff$  maximizes the likelihood of training data)

**Non-Linear Trans:**  $\hat{y} = \underline{w}^T \phi(\underline{x}) + Z$  w/ same assumptions,

then  $\hat{\underline{w}}_{\text{ML}} = (X X^T)^{-1} X^T \underline{y}$

\* $\phi(\underline{x})$ : Non-linear transformation of  $\underline{x}$

-E.g. of 1 dim  $x$ :  $\phi(x) = \begin{bmatrix} 1 \\ x \\ x^2 \\ \vdots \\ x^M \end{bmatrix}$ : Polynomial regression

\* $M$ : Degree of polynomial,  $D = 1 + M$ : # of features.

\* $\underline{X} = \begin{bmatrix} \phi(\underline{x}_1)^T \\ \vdots \\ \phi(\underline{x}_n)^T \end{bmatrix} \in \mathbb{R}^{n \times D}$

**Underfitting vs. Overfitting:**

\*Underfitting: Model too simple, high bias, low variance.

-Results in high train/test error.

\*Overfitting: Model too complex, low bias, high variance.

-Results in low train error, high test error.

**MAP Estimator (Bayesian Linear Regression):** Assume

prior  $w_i \sim \mathcal{N}(0, \tau^2)$  (i.i.d.) and  $\hat{y} = \underline{w}^T \underline{x} + Z$ , then

$\hat{\underline{w}}_{\text{MAP}} = (X^T X + \lambda I)^{-1} X^T \underline{y}$

\* $\lambda = \frac{\sigma^2}{\tau^2}$ : Regularization parameter

\* $\underline{X}$ : Can be linear or non-linear transformation of  $\underline{x}$

\* $\underline{x} = \{x_1, \dots, x_D\}$ : Input features

\* $\underline{w} = \{w_1, \dots, w_D\}$ : Weights (parameter)

\* $Z \sim \mathcal{N}(0, \sigma^2)$ : Noise (i.i.d.)

\* $\underline{Y}$ : Target/observed output

**Notes:**

1. Useful when training data set size is small i.e.  $n \ll D$ .

2. Regularization: Prevents overfitting by penalizing large weights.

\* $\tau = \infty \implies \lambda = 0$ : No regularization so  $\hat{\underline{w}}_{\text{MAP}} = \hat{\underline{w}}_{\text{ML}}$

\* $\tau = 0 \implies \lambda = \infty$ : Infinite regularization so  $\hat{\underline{w}}_{\text{MAP}} = \underline{0}$

\* $\tau \downarrow \implies \lambda \uparrow$ : More regularization, simpler model.

\* $\tau \uparrow \implies \lambda \downarrow$ : Less regularization, more complex model.

**Gaussian Linear System** Given training data  $\underline{Y} = \underline{X} \underline{w} + \underline{Z}$

$\hat{\underline{w}}_{\text{MAP}} = \underline{\mu}_{\underline{w}|\underline{Y}} = (X^T X + \lambda I)^{-1} X^T \underline{y}$

\* $\underline{w} \sim \mathcal{N}(\underline{0}, \tau^2 I)$ ,  $\underline{Z} \sim \mathcal{N}(\underline{0}, \sigma^2 I)$

\* $E[\hat{\underline{w}}(\underline{Y})] \rightarrow \underline{w}$  as  $n \rightarrow \infty$

\*Note: Matching it to canonical form.

**Covar. Mat:**  $\Sigma_{\underline{w}|\underline{y}} = \left( \frac{1}{\sigma^2} X^T X + \frac{1}{\tau^2} I \right)^{-1} \preceq \tau^2 I$

-Less uncertainty in  $\underline{w}$  w/ more data. As  $n \uparrow$ ,  $\Sigma_{\underline{w}|\underline{y}} \downarrow$

**Bayesian Prediction** Given some new  $\underline{x}'$  (test data sample), find its label  $y'$

**Plug-In Approx:**  $\hat{Y}' = \underline{x}'^T \hat{\underline{w}}_{\text{MAP}}(\mathcal{D}) + Z'$

\* $\mathcal{D}$ : Training data set,  $Z' \sim \mathcal{N}(0, \sigma^2)$ : Noise

**Bayesian Prediction:** Use  $Y' = \underline{x}'^T \underline{w} + Z'$  and

$f_{\underline{w}|\underline{Y}}(\underline{w} | \underline{y}) = \mathcal{N}(\underline{\mu}_{\underline{w}|\underline{Y}}, \Sigma_{\underline{w}|\underline{Y}})$  to return  $f_{Y'}(y' | \mathcal{D})$  where  $Y'$  is Gaussian given  $\mathcal{D}$  w/

$\mu_{Y'|\mathcal{D}} = \underline{x}'^T \underline{\mu}_{\underline{w}|\underline{Y}}$

$\sigma_{Y'|\mathcal{D}}^2 = \underline{x}'^T \Sigma_{\underline{w}|\underline{Y}} \underline{x}' + \sigma^2$

**Linear Classification (Hyp. Test):**

**Binary Logistic Regression:** Estimate  $\underline{w}$  s.t. it is a soft decision

$P_{Y|\underline{X}}(1 | \underline{x}) = \frac{P_{\underline{X}|Y}(\underline{x}|1) P_Y(1)}{P_{\underline{X}|Y}(\underline{x}|0) P_Y(0) + P_{\underline{X}|Y}(\underline{x}|1) P_Y(1)}$

$P_{Y|\underline{X}}(1 | \underline{x}) = \frac{1}{1 + e^{-\alpha}} = \sigma(\alpha)$

$P_{Y|\underline{X}}(0 | \underline{X}) = 1 - \sigma(\alpha) = \frac{1}{1 + e^{\alpha}} = \sigma(-\alpha)$

$\alpha = \log \frac{P_{\underline{X}|Y}(\underline{x}|1) P_Y(1)}{P_{\underline{X}|Y}(\underline{x}|0) P_Y(0)} = \underline{w}^T \underline{x}$

$\alpha \rightarrow \infty \implies$  more likely to be in class 1

$\alpha \rightarrow -\infty \implies$  more likely to be in class 0.

$\alpha = 0 \implies$  equally likely to be in class 0 or 1.

**Non-Linear Trans.** Use  $\sigma(\underline{w}^T \phi(\underline{x}))$

**ML Estimator:** Given  $\mathcal{D} = \{(\underline{x}_i, y_i)\}, i = 1, \dots, n$ , then  $\hat{\underline{w}}_{\text{ML}} = \arg \min_{\underline{w}} - \sum_{i=1}^n \log P_{Y|\underline{X}}(y_i | \underline{x}_i, \underline{w})$

**Cross Entropy** b/w actual  $y_i$  and  $P_{Y|\underline{X}}(\cdot | \underline{x}_i, \underline{w})$  is

$P_{Y|\underline{X}}(y_i | \underline{x}_i, \underline{w}) = \sum_{i=1}^n - (y_i \log P(1 | \underline{x}_i, \underline{w}) + (1 - y_i) \log P(0 | \underline{x}_i, \underline{w}))$

\*Note: Measures the distance between 2 distributions.

\*Dropped the subscripts.

**Gradient Descent:** No closed-form soln. so use GD.

**MAP Estimator:** Given  $\mathcal{D} = \{(\underline{x}_i, y_i)\}, i = 1, \dots, n$ , then

$\hat{\underline{w}}_{\text{MAP}} = \arg \min_{\underline{w}} - \sum_{i=1}^n \log P_{Y|\underline{X}}(y_i | \underline{x}_i, \underline{w}) + \lambda \|\underline{w}\|^2$

\* $\underline{w} \sim \mathcal{N}(\underline{\mu}, \Sigma)$ : Prior on  $\underline{w}$

\*Necessary: B/c same boundary  $\underline{w}^T \underline{x} = 0$  for any scaling of  $\underline{w}$ .

**Multiclass Logistic Regression:**  $Y \in \{1, 2, \dots, C\}$ , then use

softmax fn  $P_Y(k \mid \underline{x}, \underline{w}_1, \dots, \underline{w}_C) = \frac{e^{\underline{w}_k^T \underline{x}}}{\sum_{c=1}^C e^{\underline{w}_c^T \underline{x}}}$

\* $W = [\underline{w}_1, \dots, \underline{w}_C] \in \mathbb{R}^{D \times C}$ : Weights matrix  
**ML Estimator**: Given  $\mathcal{D} = \{(\underline{x}_i, y_i)\}, i = 1, \dots, n$ , then  $\hat{W}_{ML} = \arg \min_W - \sum_{i=1}^n \log P(y_i \mid \underline{x}_i, W)$   
**MAP Estimator**: Given  $\mathcal{D} = \{(\underline{x}_i, y_i)\}, i = 1, \dots, n$ , then  $\hat{W}_{MAP} = \arg \min_W - \sum_{i=1}^n \log P(y_i \mid \underline{x}_i, W) + \sum_{c=1}^C \lambda_c ||\underline{w}_c||^2$   
**Markov**:

**Notation**:  
 \* $P[X_n = x_n, \dots, X_0 = x_0] = P(x_n, \dots, x_0)$   
 \*Index the possible values of  $X_n$  w/ integers  $0, 1, 2, \dots$   
**Markov Chain (Memoryless/Markovian Property)**: A sequence of discrete-valued RVs  $X_0, X_1, \dots$  is a (discrete-time) Markov chain if  $P[X_{k+1} = x_{k+1} \mid \underbrace{X_k = x_k}_{\text{Present}}, \underbrace{X_{k-1} = x_{k-1}, \dots, X_0 = x_0}_{\text{Past}}] =$

$P[X_{k+1} = x_{k+1} \mid X_k = x_k] \forall k, x_1, \dots, x_{k+1}$   
**Markovian**:  $P(x_n, \dots, x_0) = P(x_n \mid x_{n-1}) \cdots P(x_1 \mid x_0) P(x_0)$

\***Equiv. Form**:  $k + 1 \rightarrow n_{k+1}, k \rightarrow n_k$  and so on  
 for any  $n_{k+1} > n_k > \dots > n_0$  (i.e. farther in future/past)  
**State Distribution**: State distribution of the MC at time  $n$  is  $P_j(n) \equiv P[X_n = j], j = 0, 1, \dots \mid \underline{P}(n) \equiv [P_0(n), P_1(n), \dots]$   
 \*Subscript: Value of  $X_n$ , Argument: Time step  
 \*Row vector NOT col vector.

**Transition Probabilities**:  
 $P_{ij}(n, n + 1) \equiv P[X_{n+1} = j \mid X_n = i] \forall i, j, n$   
**Homogeneous MC**:  $P_{ij}(n, n + 1) = P_{ij} \forall i, j, n$   
 \*Time invariant,  $P_{ij}$  does not depend on  $n$

**Transition Probability Matrix**:  $P = \begin{bmatrix} P_{00} & P_{01} & \cdots \\ P_{10} & P_{11} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}$

**Notes**: (1) **Stochastic Matrix**: (1) All entries of  $P$  are non-negative and (2) each row sums to 1:  $\sum_j P_{ij} = 1 \forall i$   
 (2) State Dist. at time  $n + 1$ :  $\underline{P}(n) = \underline{P}(n - 1)P$   
 \* $\underline{P}(n) = \underline{P}(0)P^n$  in terms of initial distribution  $\underline{P}(0)$   
 (3) State Dist. at time  $n + m$ :  $\underline{P}(n + m) = \underline{P}(n)P^m \forall n, m$   
**n-step Transition Probabilities**: Stochastic matrix  $P^n$  s.t.  $P_{ij}^{(n)} \equiv P[X_{k+n} = j \mid X_k = i]$  for  $n \geq 0$  are the entries of  $P^n$

**Limiting Distribution** A MC has a limiting distribution  $\underline{q}$  if for any initial distribution  $\underline{P}(0)$   
 $\underline{P}(\infty) \equiv \lim_{n \rightarrow \infty} \underline{P}(n) = \underline{q}$  or  
 $\underline{P}(0)P^\infty \equiv \underline{P}(0) \lim_{n \rightarrow \infty} P^n = \underline{q}$

**Theorem**: A MC has a limiting distribution  $\underline{q}$  iff

$q_i = \lim_{n \rightarrow \infty} P_{ij}^{(n)} \forall i, j$   
 \*i.e. every row of  $P^\infty$  equals  $q$  (row vector)  
**Steady State (Stationary) Distribution  $\underline{\pi}$**  is a steady state distribution of a MC if  $\underline{\pi} = \underline{\pi}P$   
 \* $1 = \sum_j \pi_j$

**Theorem**: If a limiting dist. exists  $\underline{q} = \underline{P}(\infty)$ , then it is also a steady state dist.  
**Ergodic**: For a finite-state, irreducible, and aperiodic MC, then  
 (1) Limiting dist.  $\underline{q} = \lim_{n \rightarrow \infty} \underline{P}(n)$  exists and  $q_j = \lim_{n \rightarrow \infty} P_{ij}^{(n)} \forall i, j$   
 (2) Steady state dist.  $\underline{\pi}$  is unique.  
 (3)  $\underline{\pi} = \underline{q}$

**How Fast Does  $\underline{P}(n)$  Converge to  $\underline{\pi}$ ?** (1)  $\underline{\pi}^T = \underline{\pi}^T P^T$

\* $\underline{\pi}^T$  is an eigenvector of  $P^T$  w/ eigenvalue 1  
 (2) Suppose  $P^T$  has eigenvectors  $U \equiv [\underline{\pi}^T, \underline{u}_2, \dots, \underline{u}_D]$  and eigenvalues  $\Lambda \equiv \text{diag}[1, \lambda_2, \dots, \lambda_D]$ , then  $P^T U = U \Lambda \implies P^T = U \Lambda U^{-1}$  so  $n$  times  $P^n = (P^T)^n = (U \Lambda U^{-1})^n = U \Lambda^n U^{-1}$   
 Therefore,  $\Lambda^n = \text{diag}[1, \lambda_2^n, \dots, \lambda_D^n]$

(3) For ergodic MC,  $P^n \rightarrow [\underline{\pi}, \dots, \underline{\pi}]^T$  (i.e. rank 1)  
 Therefore, # of non-zero eigenvalues is 1, so the rest of the eigenvalues must be  $|\lambda_i| < 1 \forall i \geq 2$  s.t.  $\Lambda^n = \text{diag}[1, 0, \dots, 0]$   
**Rate of Convergence**: Depends on the 2nd largest eigenvalue of  $P^T$  i.e.  $(\lambda_2)^n$  is the rate of convergence.

**Bayesian Network**: Network of RVs  $X_1, \dots, X_n$  w/ directed edges  
 \***Not State-Transition Diagram**: 1 RV w/ different values w/ different probabilities to each value.  
 \***Fully Connected Graph**: No special dependency structure, so doesn't give additional info as we can write joint dist. from defn. (true for any graph).  
 \***Non-Fully Connected Graph (Absence of Links)**: Conveys useful info about the dependency structure.  
 \***Purpose**: Clarify the dependencies among a set of RVs to simplify the calculation of joint probabilities.

**Factorization of Joint Dist.** Suppose the dependencies among RVs can be represented by a DAG, then

$P(x_1, \dots, x_n) = \prod_{i=1}^N P(x_i \mid \text{pa}\{X_i\})$   
**Topological Ordering**: Often index the RVs s.t. each child has an index greater than those of the parents.

**Fact**: Every DAG has at least one topological ordering.  
**Conditional Independence**:  $A \perp B \mid C$  if  
 (1)  $P(a, b \mid c) = P(a \mid c)P(b \mid c) \forall a, b, c$  (i.e. A and B are indep. given C)  
 (2)  $P(a \mid b, c) = P(a \mid c) \forall a, b, c$  (i.e. B gives no add. info about A given C)

**Common Cause (Tail to Tail)**:  $A \perp B \mid C$ , o.w.  $A \not\perp B$   
**Causal Chain (Head to Tail or Tail to Head)**:  $A \perp B \mid C$ , o.w.  $A \not\perp B$   
**Common Effect (Head to Head)**:  $A \perp B$ , o.w.  $A \not\perp B \mid C$  or its descendants  
 \***Explaining Away**: If  $A \rightarrow B \leftarrow C$ , then if you observe  $B$ , then the other cause  $A$  is less likely to be the cause for the effect  $B$ .

**Directed Separation (D-seperation)**: For non-overlapping subsets of RVs  $\mathcal{A}, \mathcal{B}, \mathcal{C}$ , if all undirected paths blocked, then  $\mathcal{A}$  and  $\mathcal{B}$  are **d-separated** by  $\mathcal{C}$ , i.e.  $\mathcal{A} \perp \mathcal{B} \mid \mathcal{C}$   
**Blocked Path**: An undirected path is blocked if it includes a node s.t.  
 1. The node is head-to-tail or tail-to-tail (Cases 1 and 2) and it is in set  $\mathcal{C}$   
 2. The node is head-to-head, but neither itself nor any of its descendants are in set  $\mathcal{C}$  (Case 3)  
**Markov Boundary (Blanket)**: Minimal set of RVs  $\mathcal{M}$  that isolate  $X_i$  from all the remaining RVs, i.e.  $X_i \perp \mathcal{N} \setminus (\{X_i\} \cup \mathcal{M}) \mid \mathcal{M}$   
 \* $\mathcal{N}$ : Set of all RVs  
 \* $\mathcal{M}$  = parents  $\cup$  children  $\cup$  co-parents: Blocks all paths b/w  $X_i$

and the remaining nodes.

**Markov Random Field:** Represent RVs as an undirected graph s.t. conditional independence  $\mathcal{A} \perp \mathcal{B} \mid \mathcal{C}$  hold iff all paths b/w  $\mathcal{A}$  and  $\mathcal{B}$  go through  $\mathcal{C}$ .

**\*Markov blanket of  $X_i$ :** = set of neighbours of  $X_i$

**\*No Order:** No longer a way to order the RVs.

**Factorization of Joint Dist. 2 non-neighbouring nodes (RVs)** are conditionally indep. given the set of nodes that separate them:

$P(x_i, x_j \mid C) = P(x_i \mid C)P(x_j \mid C) \forall i, j$

**\*i.e.**  $x_i$  and  $x_j$  should not appear in the same factor.

**Clique:** A set of nodes s.t. there is link b/w any pair of them

**Maximal Clique:** A clique s.t. we cannot add another node and maintain a clique.

**Hammersley-Clifford Theorem:** Let  $\underline{x}_C$  denote the values of RVs in set  $C$ . Any strictly positive dist.  $P(\underline{x})$  that satisfies a Markov random field can be factorized as

$$P(\underline{x}) = \frac{1}{Z} \prod_C \psi_C(\underline{x}_C) = \frac{1}{Z} e^{-\sum_C E(\underline{x}_C)}$$

$Z = \sum_{\underline{x}} \prod_C \psi_C(\underline{x}_C)$ : Normalization constant

$\prod_C$ : Product of all maximal cliques

$\psi_C(\underline{x}_C) = e^{-E(\underline{x}_C)}$ : Potential function over the clique  $C$  (not necessarily a prob.)

$E(\underline{x}_C)$ : Energy function over the clique  $C$

**Conversion from Bayesian Net to Markov Random Field**

Always possible, but some dependency structure will be lost

- (1) For each clique  $C$ , define a potential function  $\psi_C$
- (2) For each pair of nodes  $i, j$  that are not connected by an edge, add a clique  $C$  that contains  $i, j$  and define  $\psi_C$
- (3) For each node  $i$ , add a clique  $C$  that contains  $i$  and its parents and define  $\psi_C$