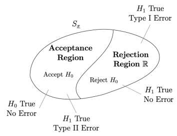
Notation: $P_{X|Y}(x \mid y) = P[X = x \mid Y = y]$
*Subscript indicates the RV, and the value indicates the realization.
Intro:
Random Experiment: An outcome for each run.
Sample Space Ω: Set of all possible outcomes.
Event: Measurable subsets of Ω.
Prob. of Event A: $P(A) = \frac{\text{Number of outcomes in A}}{\text{Number of outcomes in } \Omega}$
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 $H_1, H_2, \ldots, H_n$ form a partition of Ω, 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): $P_X(x_j) = P[X = x_j]\ j = 1, 2, \ldots$
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 | $E[Y|X]$ w.r.t. Y.
Estimation: Estimate unknown parameter θ from n i.i.d. measurements $X_1, X_2, \ldots, X_n$, $\hat{\Theta}(\underline{X}) = g(X_1, X_2, \ldots, X_n)$
Estimation Error: $\hat{\Theta}(\underline{X}) - \theta$.
Unbiased: $\hat{\Theta}(\underline{X})$ is unbiased if $E[\hat{\Theta}(\underline{X})] = \theta$.
***Asymptotically unbiased:** $\lim_{n \to \infty} E[\hat{\Theta}(\underline{X})] = \theta$.
Consistent: $\hat{\Theta}(\underline{X})$ is consistent if $\hat{\Theta}(\underline{X}) \to \theta$ as $n \to \infty$ or $\forall \epsilon > 0, \lim_{n \to \infty} P[|\hat{\Theta}(\underline{X}) - \theta| < \epsilon] \to 1$.
Sufficient: A statistic is sufficient if the expression depends only on the statistic, it should be made up of $x_1, x_2, \ldots, x_n$.
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, $X_1, X_2, \ldots, X_n$, 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, $X_1, X_2, \ldots, X_n$, 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: $\lim_{n \to \infty} P[|M_n - \mu| < \epsilon] = 1\ \forall \epsilon > 0$.
ML Estimation: Choose θ that is most likely to generate the obs. $x_1, x_2, \ldots, x_n$.
*Disc: $\hat{\Theta} = \arg\max_\theta P_{\underline{X}}(\underline{x}|\theta) \overset{\log}{\to} \hat{\theta} = \arg\max_\theta \sum_{i=1}^{n} \log P_X(x_i|\theta)$
*Cont: $\hat{\Theta} = \arg\max_\theta f_{\underline{X}}(\underline{x}|\theta) \overset{\log}{\to} \hat{\theta} = \arg\max_\theta \sum_{i=1}^{n} \log f_X(x_i|\theta)$
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: $P_{\Theta|\underline{X}}(\theta|\underline{x}) = \begin{cases} \frac{P_{\underline{X}|\Theta}(\underline{x}|\theta) P_\Theta(\theta)}{P_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ disc.} \\ \frac{f_{\underline{X}|\Theta}(\underline{x}|\theta) P_\Theta(\theta)}{f_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ cont.} \end{cases}$
$f_{\Theta|\underline{X}}(\theta|\underline{x}) = \begin{cases} \frac{P_{\underline{X}|\Theta}(\underline{x}|\theta) f_\Theta(\theta)}{P_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ disc.} \\ \frac{f_{\underline{X}|\Theta}(\underline{x}|\theta) f_\Theta(\theta)}{f_{\underline{X}}(\underline{x})} & \text{if } \underline{X} \text{ cont.} \end{cases}$
*Independent of θ: $f_{\underline{X}}(\underline{x}) = \int_{-\infty}^{\infty} f_{\underline{X}|\Theta}(\underline{x}|\theta) f_\Theta(\theta)\, d\theta$

Least Mean Squares (LMS) Estimation: Assume prior $P_\Theta(\theta)$ or $f_\Theta(\theta)$ w/ obs. $\underline{X} = \underline{x}$.
*$\hat{\theta} = g(\underline{x}) = \mathbb{E}[\Theta|\underline{X} = \underline{x}]$ | $\hat{\Theta} = g(\underline{X}) = \mathbb{E}[\Theta|\underline{X}]$

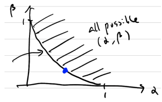
Conditional Exp. $E[X|Y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y)\, dx$
Binary Hyp. Testing: H_0: Null Hyp., H_1: Alt. Hyp.
$\Omega_{\underline{X}}$: Set of all possible obs. $\underline{x}$.



TI Err. (False Rejection): Reject H_0 when H_0 is true.
*$\alpha(R) = P[\underline{X} \in R \mid H_0]$ (false alarm)
TII 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: $\forall \underline{x}\ L(\underline{x}) = \dfrac{P_{\underline{X}}(\underline{x}|H_1)}{P_{\underline{X}}(\underline{x}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} 1$ or ξ

***Max. Likelihood Test:** 1, **Likelihood Ratio Test:** ξ
Neyman-Pearson Lemma: Given a false rejection prob. (α), the LRT offers the smallest possible false accept. prob. (β), and vice versa.
*LRT produces (α, β) pairs that lie on the efficient frontier.



Bayesian Hyp. Testing:

MAP Rule: $L(\underline{x}) = \dfrac{p_{\underline{X}}(\underline{x}|H_1)}{p_{\underline{X}}(\underline{x}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \dfrac{P[H_0]}{P[H_1]}$

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 $A_j(\underline{x}) = \sum_{i=0}^{1} C_{ij}\, P[H_i|\underline{X} = \underline{x}]$.

Min. Cost Dec. Rule: $L(\underline{x}) = \dfrac{P_{\underline{X}}(\underline{x}|H_1)}{P_{\underline{X}}(\underline{x}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \dfrac{(C_{01}-C_{00})P[H_0]}{(C_{10}-C_{11})P[H_1]}$.

*C_{01}: False accept. cost, C_{10}: False reject. cost.
Naive Bayes Assumption: Assume $X_1 \ldots, X_n$ (features) are ind., then $p_{\underline{X}|\Theta}(\underline{x} \mid \theta) = \Pi_{i=1}^{n} p_{X_i|\Theta}(x_i \mid \theta)$.
Notation: $P_{\underline{X}|\Theta}(\underline{x}|\theta)$, only put RVs in subscript, not values.
$P_{\underline{X}}(\underline{x}|H_i)$, didn't put H in subscript b/c it's not a RV.
Binomial # of successes in n trials, each w/ prob. p
$b(x \mid n, p) = \binom{n}{x} p^x (1-p)^{n-x}, x = 0, 1, 2, \ldots$
*$E[X] = \mu = np \ \mid\ Var(X) = \sigma^2 = np(1-p)$
Multinomial # of x_i successes in n trials, each w/ prob. p_i
$f(x_i \mid p_i \forall i, n) = \frac{n!}{x_1! \ldots x_m!} p_1^{x_1} \ldots p_m^{x_m}$
*$\sum_i x_i = n$, and $\sum_{i=1}^{m} p_i = 1$
*$E[X_i] = \mu_i = np_i \ \mid\ Var(X_i) = \sigma_i^2 = np_i(1-p_i)$
Hypergeometric # of successes in n draws from N items, k of which are successes
$h(x \mid N, n, k) = \dfrac{\binom{k}{x}\binom{N-k}{n-x}}{\binom{N}{n}}$
*$\max\{0, n-(N-k)\} \leq x \leq \min\{n, k\}$
*$E[X] = \mu = \frac{nk}{N} \ \mid\ Var(X) = \sigma^2 = \frac{N-n}{N-1} \cdot n \cdot \frac{k}{N} \cdot \left(1 - \frac{k}{N}\right)$
Negative Binomial # of trials until k successes, each w/ prob. p
$b^*(x \mid k, p) = \binom{x-1}{k-1} p^k (1-p)^{x-k}$
*$x \geq k, x = k, k+1, \ldots$
*$E[X] = \mu = \frac{k}{p} \ \mid\ Var(X) = \sigma^2 = \frac{k(1-p)}{p^2}$
Geometric # of trials until 1st success, each w/ prob. p
$g(x \mid p) = p(1-p)^{x-1}$
*$x \geq 1, x = 1, 2, 3, \ldots$
*$E[X] = \mu = \frac{1}{p} \ \mid\ Var(X) = \sigma^2 = \frac{1-p}{p^2}$
Poisson # of events in a fixed interval w/ rate λ
$p(x \mid \lambda t) = \frac{e^{-\lambda t}(\lambda t)^x}{x!}$
*$x \geq 0, x = 0, 1, 2, \ldots$
*$E[X] = \mu = \lambda t \ \mid\ Var(X) = \sigma^2 = \lambda t$
Beta Prior Θ 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 α and β: $\alpha = \beta = 1$ (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: $\underline{X} = (X_1, \ldots, X_n) = \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} = [X_1 \quad \cdots \quad X_n]^T$

Mean Vector: $\underline{m}_{\underline{X}} = E[\underline{X}] = [\mu_1, \ldots, \mu_n]^T$

Corr. Mat.: $R_{\underline{X}} = \begin{bmatrix} E[X_1^2] & \cdots & E[X_1 X_n] \\ E[X_2 X_1] & \cdots & E[X_2 X_n] \\ \vdots & \ddots & \vdots \\ E[X_n X_1] & \cdots & E[X_n^2] \end{bmatrix}$
*Real, symmetric ($R = R^T$), and PSD ($\forall \underline{a}$, $\underline{a}^T R \underline{a} \geq 0$).
Covar. Mat.: $K_{\underline{X}} = \begin{bmatrix} \text{Var}[X_1] & \cdots & \text{Cov}[X_1, X_n] \\ \text{Cov}[X_2, X_1] & \cdots & \text{Cov}[X_2, X_n] \\ \vdots & \ddots & \vdots \\ \text{Cov}[X_n, X_1] & \cdots & \text{Var}[X_n] \end{bmatrix}$
*$K_{\underline{X}} = R_{\underline{X} - \underline{m}_{\underline{X}}} = R_{\underline{X}} - \underline{m}\underline{m}^T$
*Diagonal $K_{\underline{X}} \iff X_1, \ldots, X_n$ are (mutually) uncorrelated.

Lin. Trans. $\underline{Y} = A\underline{X}$ (A rotates and stretches $\underline{X}$)
Mean: $E[\underline{Y}] = A\underline{m}_{\underline{X}}$

Covar. Mat.: $K_{\underline{Y}} = AK_{\underline{X}}A^T$
Diagonalization of Covar. Mat. (Uncorrelated):
$\forall \underline{X}$, set $P = [\underline{e}_1, \ldots, \underline{e}_n]$ of $K_{\underline{X}}$, if $\underline{Y} = P^T\underline{X}$, then
$K_{\underline{Y}} = P^T K_{\underline{X}} P = \Lambda$
*$\underline{Y}$: Uncorrelated RVs, $K_{\underline{X}} = P\Lambda P^T$
Find an Uncorrelated $K_{\underline{Y}}$
1. Find eigenvalues, normalized eigenvectors of $K_{\underline{X}}$.
2. Set $K_{\underline{Y}} = \Lambda$, where $\underline{Y} = P^T\underline{X}$
PDF of L.T. If $\underline{Y} = A\underline{X}$ w/ A not singular, then
$f_{\underline{Y}}(\underline{y}) = \frac{f_{\underline{X}}(\underline{x})}{|\det A|}\Big|_{\underline{x}=A^{-1}\underline{y}}$
Find $f_{\underline{Y}}(\underline{y})$ 1. Given $f_{\underline{X}}(\underline{x})$ and RV relations, define A
2. Determine $|\det A|$, A^{-1}, then $f_{\underline{Y}}(\underline{y})$.
Gaussian RVs: $\underline{X} \sim \mathcal{N}(\underline{\mu}, \Sigma)$
PDF of jointly Gaus. $X_1, \ldots, X_n \equiv$ Guas. vector:
$f_{\underline{X}}(\underline{x}) = \frac{1}{(2\pi)^{n/2}|\det\Sigma|^{1/2}} e^{-\frac{1}{2}(\underline{x}-\underline{\mu})^T\Sigma^{-1}(\underline{x}-\underline{\mu})}$

*1D: $f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$
*$\underline{\mu} = \underline{m}_{\underline{X}}$, $\Sigma = K_{\underline{X}}$ (Σ not singular)

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

*IID: $f_{\underline{X}}(\underline{x}) = \frac{1}{(2\pi)^{n/2}\sigma^n} e^{-\frac{1}{2\sigma^2}\sum_{i=1}^n(x_i-\mu)^2}$
*Cond. PDF: $f_{\underline{X}|\underline{Y}}(\underline{x}|\underline{y}) = \mathcal{N}(\underline{\mu}_{\underline{X}|\underline{Y}}, \Sigma_{\underline{X}|\underline{Y}})$
Properties of Guassian Vector:
1. PDF is completely determined by $\underline{\mu}$, Σ.
2. $\underline{X}$ uncorrelated $\iff$ $\underline{X}$ independent.
3. Any L.T. $\underline{Y} = A\underline{X}$ is Gaus. vector w/ $\underline{\mu}_{\underline{Y}}=A\underline{\mu}_{\underline{X}}$, $\Sigma_{\underline{Y}}=A\Sigma_{\underline{X}}A^T$.
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 $P = [\underline{e}_1, \ldots, \underline{e}_n]$ of $\Sigma_{\underline{X}}$, if $\underline{Y} = P^T\underline{X}$, then
$\Sigma_{\underline{Y}} = P^T\Sigma_{\underline{X}}P = \Lambda$
*$\underline{Y}$: Indep. Gaussian RVs, $\Sigma_{\underline{X}} = P\Lambda P^T$
How to go from Y to X? 1. Given, $\underline{X} \sim \mathcal{N}(\underline{\mu}, \Sigma)$
2. $\underline{V} \sim \mathcal{N}(\underline{0}, I)$ 3. $\underline{W} = \sqrt{\Lambda}\underline{V}$ 4. $\underline{Y} = P\underline{W}$ 4. $\underline{X} = \underline{Y} + \underline{\mu}$
Guassian Discriminant Analysis:
Obs: $\underline{X} = \underline{x} = (x_1, \ldots, x_D)$
Hyp: $\underline{x}$ is generated by $\mathcal{N}(\underline{\mu}_c, \Sigma_c)$, $c \in C$
Dec: Which "Guassian bump" generated $\underline{x}$?
Prior: $P[C = c] = \pi_c$ (Gaussian Mixture Model)
MAP: $\hat{c} = \arg\max_c P_C[c|\underline{X} = \underline{x}] = \arg\max_c f_{\underline{X}|C}(\underline{x} \mid c)\pi_c$
LGD: Given $\Sigma_c = \Sigma\ \forall c$, find c w/ best $\underline{\mu}_c$
$\hat{c} = \arg\max_c \underline{\beta}_c^T\underline{x} + \gamma_c$
*$\underline{\beta}_c^T = \underline{\mu}_c^T\Sigma^{-1}$ | $\gamma_c = \log\pi_c - \frac{1}{2}\underline{\mu}_c^T\Sigma^{-1}\underline{\mu}_c$

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 Σ_c are diff., find c w/ best $\underline{\mu}_c$, Σ_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 $\pi_c, \underline{\mu}_c, \Sigma_c$: Given n points gen. by GMM, then
n_c points $\{\underline{x}_1^c, \ldots, \underline{x}_{n_c}^c\}$ come from $\mathcal{N}(\underline{\mu}_c, \Sigma_c)$
$\hat{\pi}_c = \frac{n_c}{n}$ (categorical RV)
$\hat{\mu}_c = \frac{1}{n_c}\sum_{i=1}^n \underline{x}_i^c$, (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.)
Guassian Estimation:
MAP Estimator for $\underline{X}$ Given $\underline{Y}$ When $\underline{W}=(\underline{X}, \underline{Y}) \sim \mathcal{N}(\underline{\mu}, \Sigma)$
Given $\underline{X} = \{X_1, \ldots, X_n\}$, $\underline{Y} = \{Y_1, \ldots, Y_m\}$
$\hat{\underline{x}}_{\text{MAP}}(\underline{y}) = \hat{\underline{x}}_{\text{LMS}}(\underline{y}) = \underline{\mu}_{\underline{X}|\underline{Y}} = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{XY}}\Sigma_{\underline{YY}}^{-1}(\underline{y} - \underline{\mu}_Y)$
*$\hat{\underline{x}}_{\text{MAP/LMS}}$: Linear fcn of $\underline{y}$

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

*$\Sigma_{\underline{XX}} = \Sigma_{\underline{X}} = E\left[(\underline{X} - \underline{\mu}_{\underline{X}})(\underline{X} - \underline{\mu}_{\underline{X}})^T\right]$ | $\Sigma_{\underline{YY}} = \Sigma_{\underline{Y}}$

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

Prec. Matrices: $\Lambda = \Sigma^{-1}$
Mean and Covar. Mat. of $\underline{X}$ Given $\underline{Y}$:
*$\underline{\mu}_{\underline{X}|\underline{Y}} = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{XY}}\Sigma_{\underline{YY}}^{-1}(\underline{y} - \underline{\mu}_Y)$
*$\Sigma_{\underline{X}|\underline{Y}} = \Sigma_{\underline{X}} - \Sigma_{\underline{XY}}\Sigma_{\underline{YY}}^{-1}\Sigma_{\underline{YX}}$
***Reducing Uncertainty:** 2nd term is PSD, so given $\underline{Y} = \underline{y}$, always reducing uncertainty in $\underline{X}$.
ML Estimator for θ w/ Indep. Guas:

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

*$X_i=\theta + Z_i$: Measurement | $Z_i \sim \mathcal{N}(0, \sigma_i^2)$: 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 θ w/ Indep. Gaus., Gaus. Prior:
Given $\underline{X}=\{X_1, \ldots, X_n\}$, prior $\Theta \sim \mathcal{N}(x_0, \sigma_0^2)$

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

*$X_i=\theta + Z_i$: Measurement | $Z_i \sim \mathcal{N}(0, \sigma_i^2)$: Noise (indep.)
*f_Θ: Gaussian prior $\equiv$ prior meas. x_0 w/ σ_0^2.
***SC:** As $n \to \infty$, $\hat{\theta}_{\text{MAP}} \to \hat{\theta}_{\text{ML}}$. As $\sigma_0^2 \to \infty$, $\hat{\theta}_{\text{MAP}} \to \hat{\theta}_{\text{ML}}$
LMMSE Estimator for $\underline{X}$ Given $\underline{Y}$ w/ non-Guas. $\underline{X}$, $\underline{Y}$:
$\hat{\underline{x}}_{\text{LMMSE}}(\underline{y}) = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{XY}}\Sigma_{\underline{YY}}^{-1}(\underline{y} - \underline{\mu}_Y)$
Linear Guassian System: Given $\underline{Y} = A\underline{X} + \underline{b} + \underline{Z}$
*$\underline{X} \sim \mathcal{N}(\underline{\mu}_{\underline{X}}, \Sigma_{\underline{X}})$, $\underline{Z} \sim \mathcal{N}(\underline{0}, \Sigma_{\underline{Z}})$: 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 $\underline{W} = \begin{bmatrix} \underline{X} \\ A\underline{X} + \underline{b} + \underline{Z} \end{bmatrix} = \begin{bmatrix} I & 0 \\ A & I \end{bmatrix} \begin{bmatrix} \underline{X} \\ \underline{Z} \end{bmatrix} + \begin{bmatrix} \underline{0} \\ \underline{b} \end{bmatrix}$

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

*$\Sigma_{\underline{XY}} = \Sigma_{\underline{X}} A^T$, $\Sigma_{\underline{YY}} = A\Sigma_{\underline{X}} A^T + \Sigma_{\underline{Z}}$

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

***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. $\{(\underline{x}_1, y_1), \ldots, (\underline{x}_n, y_n)\}$ (MLE/MAP)

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

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

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

*Assume $X^T X$ has full rank (i.e. invertible) since $n \gg D$
*n: # of obs., D: # of features.
*$\underline{x} = \{x_1, \ldots, x_D\}$: Input features
*$\underline{w} = \{w_1, \ldots, w_D\}$: Weights (parameter)
*$Z \sim \mathcal{N}(0, \sigma^2)$: Noise (i.i.d.)
*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: $\hat{y} = \underline{w}^T \underline{\phi}(\underline{x}) + Z$ w/ same assumptions, then $\hat{\underline{w}}_{\text{ML}} = (XX^T)^{-1} X^T \underline{y}$

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

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

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

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

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
*X: Can be linear or non-linear transformation of $\underline{x}$
*$\underline{x} = \{x_1, \ldots, x_D\}$: Input features
*$\underline{w} = \{w_1, \ldots, w_D\}$: Weights (parameter)
*$Z \sim \mathcal{N}(0, \sigma^2)$: Noise (i.i.d.)
*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.

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

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

*$\underline{w} \sim \mathcal{N}(\underline{0}, \tau^2 I)$, $\underline{Z} \sim \mathcal{N}(\underline{0}, \sigma^2 I)$
*$E[\hat{\underline{w}}(\underline{Y})] \to \underline{w}$ as $n \to \infty$
*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 $f_{\underline{w}|\underline{Y}}(\underline{w} \mid \underline{y}) = \mathcal{N}(\mu_{\underline{w}|\underline{Y}}, \Sigma_{\underline{w}|\underline{Y}})$ to return $f_{Y'}(y' \mid \mathcal{D})$ where Y' is Gaussian given $\mathcal{D}$ w/

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

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

Linear Classification (Hyp. Test):

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

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

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

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

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

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

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

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

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

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

*Note: Measures the distance between 2 distributions.
*Dropped the subscripts.

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

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

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

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

Multiclass Logistic Regression: $Y \in \{1, 2, \ldots, C\}$, then use softmax fn $P_Y(k \mid \underline{x}, \underline{w}_1, \ldots, \underline{w}_C) = \dfrac{e^{\underline{w}_k^T \underline{x}}}{\sum_{c=1}^C e^{\underline{w}_c^T \underline{x}}}$

*$W = [\underline{w}_1, \ldots, \underline{w}_C] \in \mathbb{R}^{D \times C}$: Weights matrix

ML Estimator: Given $\mathcal{D} = \{(\underline{x}_i, y_i)\}, i = 1, \ldots, n$, then $\hat{W}_{\text{ML}} = \arg\min_W - \sum_{i=1}^n \log P(y_i \mid \underline{x}_i, W)$

MAP Estimator: Given $\mathcal{D} = \{(\underline{x}_i, y_i)\}, i = 1, \ldots, n$, then $\hat{W}_{\text{MAP}} = \arg\min_W - \sum_{i=1}^n \log P(y_i \mid \underline{x}_i, W) + \sum_{c=1}^C \lambda_c ||\underline{w}_c||^2$

Markov:

Notation:

*$P[X_n = x_n, \ldots, X_0 = x_0] = P(x_n, \ldots, x_0)$

*Index the possible values of X_n w/ integers $0, 1, 2, \ldots$

Markov Chain (Memoryless/Markovian Property): A sequence of discrete-valued RVs $X_0, X_1, \ldots$ is a (discrete-time) Markov chain if

$$P[\underbrace{X_{k+1} = x_{k+1}}_{\text{Future}} \mid \underbrace{X_k = x_k}_{\text{Present}}, \underbrace{X_{k-1} = x_{k-1}, \ldots, X_0 = x_0}_{\text{Past}}] =$$

$P[X_{k+1} = x_{k+1} \mid X_k = x_k] \ \forall k, x_1, \ldots, x_{k+1}$

***Markovian:** $P(x_n, \ldots, x_0) = P(x_n \mid x_{n-1}) \cdots P(x_1 \mid x_0) P(x_0)$

***Equiv. Form:** $k+1 \to n_{k+1}$, $k \to n_k$ and so on for any $n_{k+1} > n_k > \cdots > n_0$ (i.e. farther in future/past)

State Distribution: State distribution of the MC at time n is $P_j(n) \equiv P[X_n = j], j = 0, 1, \ldots \ \mid \ \underline{P}(n) \equiv [P_0(n), P_1(n), \ldots]$

*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 $n+m$: $\underline{P}(n+m) = \underline{P}(m)P^n \ \forall n, m$

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 $\underline{P}(0)$

$\underline{P}(\infty) \equiv \lim_{n\to\infty} \underline{P}(n) = \underline{q}$ or

$\underline{P}(0)P^\infty \equiv \underline{P}(0) \lim_{n\to\infty} P^n = \underline{q}$

Theorem: A MC has a limiting distribution $\underline{q}$ iff $q_i = \lim_{n\to\infty} P_{ij}^{(n)} \ \forall i, j$

*i.e. every row of P^∞ equals $\underline{q}$ (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. $\underline{q} = \lim_{n\to\infty} \underline{P}(n)$ exists and $q_j = \lim_{n\to\infty} P_{ij}^{(n)} \ \forall i, j$

(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 $U \equiv [\underline{\pi}^T, \underline{u}_2, \ldots, \underline{u}_D]$ and eigenvalues $\Lambda \equiv \text{diag}[1, \lambda_2, \ldots, \lambda_D]$, 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, $\Lambda^n = \text{diag}[1, \lambda_2^n, \ldots, \lambda_D^n]$

(3) For ergodic MC, $P^n \to [\underline{\pi}, \ldots, \underline{\pi}]^T$ (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. $\Lambda^n = \text{diag}[1, 0, \ldots, 0]$

Rate of Convergence: Depends on the 2nd largest eigenvalue of P^T i.e. $(\lambda_2)^n$ is the rate of convergence.