

Intro: Random Experiment: An outcome for each run.

Sample Space Ω : Set of all possible outcomes.

Event: Subsets of Ω .

Prob. of Event A : $P(A) = \frac{\text{Number of outcomes in } A}{\text{Number of outcomes in } \Omega}$

Axioms: $P(A) \geq 0 \forall A \in \Omega$, $P(\Omega) = 1$,

If $A \cap B = \emptyset$, then $P(A \cup B) = P(A) + P(B) \forall A, B \in \Omega$

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

* $P(A \cap B) = P(A|B)P(B) = P(B|A)P(A)$

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 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: CDF: $F_X(x) = P[X \leq x]$

PMF: $P_X(x_j) = P[X = x_j] \ j = 1, 2, \dots$

PDF: $f_X(x) = \frac{d}{dx} F_X(x)$

* $P[a \leq X \leq b] = \int_a^b f_X(x) dx$ IS THIS CORRECT?

Cond. PMF: $P_X(x|A) = P[X = x|A] = \frac{P[X=x, A]}{P[A]}$ IS THIS CORRECT?

Cond. PDF: $f_X(x|A) = \frac{f_{X,A}(x,a)}{f_A(a)}$ IS THIS CORRECT?

Exp.: $E[h(X)] = \int_{-\infty}^{\infty} h(x) f_X(x) dx \mid \sum_{k=-\infty}^{\infty} h(k) P_X(x_i=k)$

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 (Corr.): $E[XY]$

Covar.: $\text{Cov}[X, Y] = E[(X - \mu_X)(Y - \mu_Y)] = E[XY] - E[X]E[Y]$

Corr. Coeff.: $\rho_{X,Y} = E\left[\left(\frac{X - \mu_X}{\sigma_X}\right)\left(\frac{Y - \mu_Y}{\sigma_Y}\right)\right] = \frac{\text{Cov}[X,Y]}{\sigma_X \sigma_Y}$

Marginal PMF: $P_X(x) = \sum_{j=1}^{\infty} P_{X,Y}(x, y_j)$

Marginal PDF: $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy$

Cond. PMF: $P_{X|Y}(x|Y) = P[X = x|Y = y] = \frac{P_{X,Y}(x, y)}{P_Y(y)}$

Cond. PDF: $f_{X|Y}(x|y) = \frac{f_{X,Y}(x, y)}{f_Y(y)}$

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.: $f_{X|Y}(x|y) = f_X(x) \ \forall y \Leftrightarrow f_{X,Y}(x, y) = f_X(x) f_Y(y)$

* If independent, then uncorrelated.

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 θ 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 $\forall \epsilon > 0, \lim_{n \rightarrow \infty} P[|\hat{\Theta}(\underline{X}) - \theta| < \epsilon] \rightarrow 1$.

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.

Chebychev's Inequality: $P[|X - E[X]| \geq \epsilon] \leq \frac{\text{Var}[X]}{\epsilon^2}$

Weak Law of Large #s: $\lim_{n \rightarrow \infty} P[|M_n - \mu| < \epsilon] = 1 \ \forall \epsilon > 0$.

ML Estimation: Choose parameter θ that is most likely to generate the obs. x_1, x_2, \dots, x_n .

* Disc: $\hat{\Theta} = \arg \max_{\theta} P_{\underline{X}|\Theta}(\underline{x}|\theta) \xrightarrow{\log} \hat{\theta} = \arg \max_{\theta} \sum_{i=1}^n \log P_X(x_i|\theta)$

* Cont: $\hat{\Theta} = \arg \max_{\theta} f_{\underline{X}|\Theta}(\underline{x}|\theta) \xrightarrow{\log} \hat{\theta} = \arg \max_{\theta} \sum_{i=1}^n \log f_X(x_i|\theta)$

Maximum A Posteriori (MAP) Estimation:

* Disc: $\hat{\theta} = \arg \max_{\theta} P_{\Theta|\underline{X}}(\theta|\underline{x}) = \arg \max_{\theta} \frac{P_{\underline{X}|\Theta}(\underline{x}|\theta) P_{\Theta}(\theta)}{P_{\underline{X}}(\underline{x})}$

* Cont: $\hat{\theta} = \arg \max_{\theta} f_{\Theta|\underline{X}}(\theta|\underline{x}) = \arg \max_{\theta} \frac{f_{\underline{X}|\Theta}(\underline{x}|\theta) f_{\Theta}(\theta)}{f_{\underline{X}}(\underline{x})}$

* $f_{\Theta|\underline{X}}(\theta|\underline{x})$: 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 θ : $f_{\underline{X}}(\underline{x}) = \int_{-\infty}^{\infty} f_{\underline{X}|\Theta}(\underline{x}|\theta) f_{\Theta}(\theta) d\theta$

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).

Least Mean Squares (LMS) Estimation: Assume prior $P_{\Theta}(\theta)$ or $f_{\Theta}(\theta)$ w/ obs. $\underline{X} = \underline{x}$.

* $\hat{\theta} = g(\underline{x}) = E[\Theta|\underline{X} = \underline{x}] \mid \hat{\Theta} = g(\underline{X}) = E[\Theta|\underline{X}]$

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

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

Conditional Exp. $E[X|Y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx$

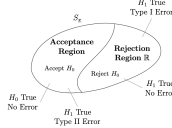
Binary Hyp. Testing: H_0 : Null Hyp., H_1 : Alt. Hyp.

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

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

TII Err. (False Accept.): Accept H_0 when H_1 is true.

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



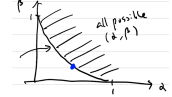
Likelihood Ratio Test: For each value of \underline{x} ,

* $L(\underline{x}) = \frac{P_{\underline{X}}(\underline{x} \mid H_1)}{P_{\underline{X}}(\underline{x} \mid H_0)} \geq 1$ or ξ

*MLT: 1, LRT: 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:

$L(\underline{x}) = \frac{p_{\underline{X}}(\underline{x} \mid H_1)}{p_{\underline{X}}(\underline{x} \mid H_0)} \geq \frac{P[H_0]}{P[H_1]}$

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 exp. 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: $L(\underline{x}) = \frac{P_{\underline{X}}(\underline{x} \mid H_1)}{P_{\underline{X}}(\underline{x} \mid H_0)} \geq \frac{(C_{01} - C_{00})P[H_0]}{(C_{10} - C_{11})P[H_1]}$.

* 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

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

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

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 $\sum_{i=1}^m p_i = 1$

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

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

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

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

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

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

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

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

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

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

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

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

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

Poisson # of events in a fixed interval w/ rate λ

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

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

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

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 $x \geq 0$.

Random Vector: $\underline{X} = [X_1, \dots, X_n]^T$

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

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

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

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

* $K_{\underline{X}} = R_{\underline{X}} - \underline{m}_X \underline{m}_X^T = R_{\underline{X}} - \underline{m} \underline{m}^T$

*Diagonal $K_{\underline{X}} \iff X_1, \dots, X_n$ 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.: $K_{\underline{Y}} = A K_{\underline{X}} A^T$

Diag. Covar. Mat.: For any \underline{X} , if $\underline{Y} = P^T \underline{X}$, then

$K_{\underline{Y}} = P^T K_{\underline{X}} P = \Lambda$ (i.e. \underline{Y} is uncorrelated)

* $K_{\underline{X}} = P \Lambda P^T$ | $P = [\underline{e}_1, \dots, \underline{e}_n]$ of $K_{\underline{X}}$

Find $K_{\underline{Y}}$ 1. Find eigenvalues, norm. eigenvectors of $K_{\underline{X}}$.

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

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 $f_{\underline{X}}(\underline{x})$, define transformation A

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

Gaussian RVs: Analytic Tractability: PDF of jointly Gaussian X_1, \dots, X_n is Gaussian vector.

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

* $\underline{\mu} = \underline{m}_{\underline{X}}$, $\Sigma = K_{\underline{X}}$ (if Σ is not singular) *Independent:
 $f_{\underline{X}}(\underline{x}) = \prod_{i=1}^n f_{X_i}(x_i) = \frac{1}{(2\pi)^{n/2} \prod_{i=1}^n \sigma_i} e^{-\frac{1}{2} \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i}\right)^2}$
*Indep. Gaus. $\xrightarrow{\text{Indep.}} \text{Jointly Guas.}$ $\xrightarrow{\text{L.T}} \text{Jointly Guas.}$ W6 L1
*Conditional PDF of Gaus. RVs is Gaussian. W6 L1
*IID: $f_{\underline{X}}(\underline{x}) = \frac{1}{(2\pi)^{n/2} \sigma^n} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$

Properties of Gaussian Vector: $\underline{X} \sim \mathcal{N}(\underline{\mu}, \Sigma)$
1. PDF is completely determined by $\underline{\mu}, \Sigma$.
2. \underline{X} uncorrelated $\iff \underline{X}$ independent.
3. Any L.T. $\underline{Y} = A\underline{X} + \underline{b}$ is Gaussian 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 Gaussian.
5. Any cond. PDF of a subset of $\{X_i\}$ given the other elements is Gaussian.

Diag. of Gaussian Covar. Eigen decomp. of $\Sigma_{\underline{X}}: \{\lambda_i\}, \{e_i\}$
 $A = [\underline{e}_1, \dots, \underline{e}_n]^T$, then $\underline{Y} = A\underline{X}$ has $\Sigma_{\underline{Y}} = \Lambda$.
* \underline{Y} : Vector of indep. Gaussian RVs.
How to go from \underline{Y} to \underline{X} ? 1. Given, $\underline{X} \sim \mathcal{N}(\underline{\mu}, \Sigma)$, then find $\Sigma = P\Lambda P^T$.
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 gen. 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 Rule: $\hat{c} = \arg \max_c P_C[c|\underline{X} = \underline{x}] = \arg \max_c f_{\underline{X}|C}(\underline{x} | c)\pi_c$

LGD: $\Sigma_c = \Sigma \forall c$, find c w/ best $\underline{\mu}_c$
 $\hat{c} = \arg \max_c \underline{\beta}_c^T \underline{x} + \gamma_c$
* $\underline{\beta}_c^T = \underline{\mu}_c^T \Sigma^{-1} \underline{x} \mid \gamma_c = \log \pi_c - \frac{1}{2} \underline{\mu}_c^T \Sigma^{-1} \underline{\mu}_c$
*Bin. hyp. dec. boundary: $\underline{\beta}_0^T \underline{x} + \gamma_0 = \underline{\beta}_1^T \underline{x} + \gamma_1$ (lin. in space of \underline{x})
QGD: Σ_c are diff., find c w/ best $\underline{\mu}_c, \Sigma_c$
*Bin. hyp. dec. boundary: Quadratic in space of \underline{x}
How to find $\underline{\mu}_c, \underline{\mu}_c, \Sigma_c$: Given n points gen. by GMM, then n_c points $\{\underline{x}_1^c, \dots, \underline{x}_{n_c}^c\}$ come from $\mathcal{N}(\underline{\mu}_c, \Sigma_c)$
 $\hat{\pi}_c = \frac{n_c}{n}, \hat{\mu}_c = \frac{1}{n_c} \sum_{i=1}^{n_c} \underline{x}_i^c$,
 $\Sigma_c = \frac{1}{n_c} \sum_{i=1}^{n_c} (x_i^c - \hat{\mu}_c)(x_i^c - \hat{\mu}_c)^T$

Gaussian Estimation: ML Estimator for θ 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
* $Z_i \sim \mathcal{N}(0, \sigma_i^2)$: Noise (indep. not iid)
* $\frac{1}{\sigma_i^2}$: 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 $\underline{X} = \{X_1, \dots, X_n\}$, prior $\Theta \sim \mathcal{N}(x_0, \sigma_0^2)$
 $\hat{\theta}_{\text{MAP}} = \frac{\sum_{i=0}^n \frac{x_i}{\sigma_i^2}}{\sum_{i=1}^n \frac{1}{\sigma_i^2}} = \frac{\frac{1}{\sigma_0^2}}{\frac{1}{\sigma_0^2} + \sum_{i=1}^n \frac{1}{\sigma_i^2}} x_0 + \frac{\sum_{i=1}^n \frac{1}{\sigma_i^2}}{\frac{1}{\sigma_0^2} + \sum_{i=1}^n \frac{1}{\sigma_i^2}} \hat{\theta}_{\text{ML}}$

* $X_i = \theta + Z_i$: Measurement
* $Z_i \sim \mathcal{N}(0, \sigma_i^2)$: Noise (indep. not iid)
* f_{Θ} : Gaussian prior \equiv prior meas. x_0 w/ σ_0^2 .
***SC:** As $n \rightarrow \infty, \hat{\theta}_{\text{MAP}} \rightarrow \hat{\theta}_{\text{ML}}$. As $\sigma_0^2 \rightarrow \infty, \hat{\theta}_{\text{MAP}} \rightarrow \hat{\theta}_{\text{ML}}$
MAP Estimator for \underline{X} Given \underline{Y} When $\underline{W} = (\underline{X}, \underline{Y}) \sim \mathcal{N}(\underline{\mu}, \Sigma)$
Given $\underline{X} = \{X_1, \dots, X_n\}, \underline{Y} = \{Y_1, \dots, Y_m\}$
 $\hat{\underline{x}}_{\text{MAP}}(\underline{y}) = \hat{\underline{x}}_{\text{LMS}}(\underline{y}) = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{X}\underline{Y}} \Sigma_{\underline{Y}\underline{Y}}^{-1} (\underline{y} - \underline{\mu}_{\underline{Y}})$
* $\hat{\underline{x}}_{\text{MAP/LMS}}$: Linear fcn of \underline{y}

Covar. Matrices: $\Sigma = \begin{bmatrix} \Sigma_{\underline{X}\underline{X}} & \Sigma_{\underline{X}\underline{Y}} \\ \Sigma_{\underline{Y}\underline{X}} & \Sigma_{\underline{Y}\underline{Y}} \end{bmatrix}$
* $\Sigma_{\underline{X}\underline{X}} = \Sigma_{\underline{X}} = E \left[(\underline{X} - \underline{\mu}_{\underline{X}})(\underline{X} - \underline{\mu}_{\underline{X}})^T \right] \mid \Sigma_{\underline{Y}\underline{Y}} = \Sigma_{\underline{Y}}$
* $\Sigma_{\underline{X}\underline{Y}} = E \left[(\underline{X} - \underline{\mu}_{\underline{X}})(\underline{Y} - \underline{\mu}_{\underline{Y}})^T \right] \mid \Sigma_{\underline{Y}\underline{X}} = \Sigma_{\underline{X}\underline{Y}}^T$
Mean and Covar. Mat. of \underline{X} Given \underline{Y} :
* $\underline{\mu}_{\underline{X}|\underline{Y}} = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{X}\underline{Y}} \Sigma_{\underline{Y}\underline{Y}}^{-1} (\underline{y} - \underline{\mu}_{\underline{Y}})$
* $\Sigma_{\underline{X}|\underline{Y}} = \Sigma_{\underline{X}} - \Sigma_{\underline{X}\underline{Y}} \Sigma_{\underline{Y}\underline{Y}}^{-1} \Sigma_{\underline{Y}\underline{X}}$
***Reducing Uncertainty:** 2nd term is PSD, so given $\underline{Y} = \underline{y}$, always reducing uncertainty in \underline{X} .

LMMSE Estimator for \underline{X} Given \underline{Y} w/ non-Guas. $\underline{X}, \underline{Y}$:
 $\hat{\underline{x}}_{\text{LMMSE}}(\underline{y}) = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{X}\underline{Y}} \Sigma_{\underline{Y}\underline{Y}}^{-1} (\underline{y} - \underline{\mu}_{\underline{Y}})$
Linear Gaussian 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 $\underline{W} = \begin{bmatrix} \underline{X} \\ A\underline{X} + \underline{b} + \underline{Z} \end{bmatrix} = \begin{bmatrix} I & 0 \\ A & I \end{bmatrix} \begin{bmatrix} \underline{X} \\ \underline{Z} \end{bmatrix} + \begin{bmatrix} 0 \\ \underline{b} \end{bmatrix}$
 $\hat{\underline{x}}_{\text{MAP/LMS}} = \underline{\mu}_{\underline{X}} + \Sigma_{\underline{X}} A^T (A \Sigma_{\underline{X}} A^T + \Sigma_{\underline{Z}})^{-1} (\underline{y} - A \underline{\mu}_{\underline{X}} - \underline{b})$
* $\Sigma_{\underline{X}\underline{Y}} = \Sigma_{\underline{X}} A^T, \Sigma_{\underline{Y}\underline{Y}} = A \Sigma_{\underline{X}} A^T + \Sigma_{\underline{Z}}$
 $\hat{\underline{x}}_{\text{MAP/LMS}} = \left(\Sigma_{\underline{X}}^{-1} + A^T \Sigma_{\underline{Z}}^{-1} A \right)^{-1} \left(A^T \Sigma_{\underline{Z}}^{-1} (\underline{y} - \underline{b}) + \Sigma_{\underline{X}}^{-1} \underline{\mu}_{\underline{X}} \right)$
***Use:** Good to use when \underline{Z} is indep.
Covar. Mat of \underline{X} Given $\underline{Y} = \underline{y}$: $\Sigma_{\underline{X}|\underline{y}} = \left(\Sigma_{\underline{X}}^{-1} + A^T \Sigma_{\underline{Z}}^{-1} A \right)^{-1}$