



Statistical Signal Processing

Lecture 5

chapter 1: parameter estimation: deterministic parameters

- some optimality properties
- Maximum Likelihood estimation, examples
- Fischer Information Matrix
- Cramer-Rao lower bound on the MSE, example
- linear model
- asymptotic (large sample) properties
- recap: estimator properties and estimators
- simplified estimators: BLUE, (W)LS, method of moments

Asymptotic (Large Sample) Properties

- asymptotic: $n \rightarrow \infty$
- *asymptotically unbiased*: $\lim_{n \rightarrow \infty} b_n(\theta) = 0$, $\forall \theta \in \Theta$
- Example (mean and variance of Gaussian i.i.d. variables):

$$E[\widehat{\sigma}_{ML}^2 | \mu, \sigma^2] = \frac{n-1}{n} \sigma^2$$

$$b_n = \frac{n-1}{n} \sigma^2 - \sigma^2 = -\frac{\sigma^2}{n} \xrightarrow{n \rightarrow \infty} 0$$

$\widehat{\sigma}_{ML}^2$: biased but asymptotically unbiased

- *consistency*: convergence of (a series of random vectors:) $\widehat{\theta}_n \rightarrow \theta$
 - convergence in probability
 - mean square convergence
 - convergence with probability one
 - convergence in distribution

Consistency

the sequence of estimates $\hat{\theta}(Y_n)$ is said to be

- *simply or weakly consistent* if

$$\lim_{n \rightarrow \infty} \Pr_{Y_n|\theta} \{ \|\hat{\theta}(Y_n) - \theta\| < \epsilon \} = 1, \quad \forall \epsilon > 0, \quad \forall \theta \in \Theta$$

- *mean-square consistent* if

$$\lim_{n \rightarrow \infty} \text{MSE}_n = \lim_{n \rightarrow \infty} E_{Y_n|\theta} \|\hat{\theta}(Y_n) - \theta\|^2 = 0, \quad \forall \theta \in \Theta$$

- *strongly consistent* if

$$\Pr_{Y_\infty|\theta} \{ \lim_{n \rightarrow \infty} \hat{\theta}(Y_n) = \theta \} = 1, \quad \forall \theta \in \Theta$$

- Any of these 3 consistencies implies asymptotic unbiasedness. E.g. for mean-square:

$$\underbrace{E_{Y_n|\theta} \|\hat{\theta}(Y_n) - \theta\|^2}_{\text{MSE}} = \underbrace{\| E_{Y_n|\theta} \hat{\theta}(Y_n) - \theta \|^2}_{\text{bias}} + \underbrace{E_{Y_n|\theta} \|\hat{\theta}(Y_n) - E_{Y_n|\theta} \hat{\theta}\|^2}_{\text{variance}} \rightarrow 0$$

$$\Rightarrow \lim_{n \rightarrow \infty} E_{Y_n|\theta} \hat{\theta}(Y_n) = \theta$$

Consistency (2)

- Strong and mean-square consistency do not imply each other in general. Either implies weak consistency (e.g. use the Chebyshev inequality to show that mean-square consistency implies weak consistency), but not conversely. Except when Θ is bounded: then weak consistency implies mean-square consistency.

- example: i.i.d. $y_i \sim \mathcal{N}(\mu, \sigma^2)$, $\theta = \mu$, σ^2 known. $\hat{\mu}_{ML} = \bar{y}$

$$\text{Var}(\hat{\mu}_{ML}) = \frac{\sigma^2}{n} \xrightarrow{n \rightarrow \infty} 0 \quad \text{mean-square consistent}$$

- example: i.i.d. $y_i \sim U[\theta - \frac{1}{2}, \theta + \frac{1}{2}]$, $\hat{\theta}_{ML} = \frac{y_{min} + y_{max}}{2}$

$$\begin{cases} y_{min} \rightarrow \theta - \frac{1}{2} & \text{in probability} \\ y_{max} \rightarrow \theta + \frac{1}{2} & \text{in probability} \end{cases} \quad \text{weak consistency}$$

$$\hat{\theta}_{ML} \rightarrow \theta \quad \text{in probability}$$

mean-square consistency can also be shown

Asymptotic Normality

- if $\widehat{\theta}_n$ consistent, then $\widetilde{\theta} \rightarrow 0$ in some sense
- introduce a magnifying glass: $d_n(\widehat{\theta}_n - \theta)$ where $0 < d_{n-1} \leq d_n \rightarrow \infty$
- *convergence in distribution*: weaker than the 3 forms of convergence of sequences of random vectors mentioned before
- if $d_n(\widehat{\theta}_n - \theta) \xrightarrow{\text{in dist.}} \xi$, some random vector, then the distribution of ξ useful as a measure for the limiting behavior of $\widehat{\theta}_n$
- usually $d_n = \sqrt{n}$
- $\widehat{\theta}_n$ *consistent asymptotically normal* (CAN) :
 if $\widehat{\theta}_n$ simply consistent and $d_n(\widehat{\theta}_n - \theta) \xrightarrow{\text{in dist.}} \mathcal{N}(0, \Xi(\theta))$
 CAN implies asympt. unbiased (which requires that bias $\rightarrow 0$ faster than $\frac{1}{d_n}$),
 Ξ = asymptotic normalized covariance of $\widehat{\theta}_n$. We say that $\widehat{\theta}_n = \theta + \mathcal{O}_p(\frac{1}{d_n})$
- distinguish $\Xi(\theta)$ from $V(\theta) = \lim_{n \rightarrow \infty} d_n^2 C_{\widehat{\theta}\widehat{\theta}}(\theta)$ which may not even exist for a CAN estimate (if $\widehat{\theta}_n$ is simply but not mean-square consistent). $V(\theta)$ exists for a mean-square consistent $\widehat{\theta}_n$, but is not necessarily $= \Xi(\theta)$.
- Hence CAN can be used to formulate *interval estimators* on the basis of *point estimators*.

Asymptotic Optimality of ML

- *asymptotic normalized information matrix* : $J_0(\theta) = \lim_{n \rightarrow \infty} \frac{1}{d_n^2} J_n(\theta)$ if it exists
 $(J_0(\theta) = \text{asymptotic average information per data sample } y_n \text{ if } d_n = \sqrt{n})$
 - *best asymptotically normal (BAN)*: CAN and $\Xi(\theta) = J_0^{-1}(\theta)$
also called *asymptotically efficient*
 - under some regularity conditions (maximum of the likelihood function unique, y_i given θ i.i.d.,...) the ML estimate is strongly consistent and BAN with $d_n = \sqrt{n}$ (\Rightarrow another use of the CRB). In particular, the ML estimate is
 - asymptotically unbiased
 - asymptotically efficient (i.i.d.: $J_n = nJ_1 \Rightarrow J_0 = J_1$)
 - asymptotically normal
 - example: i.i.d. $y_i \sim \mathcal{N}(\mu, \sigma^2)$, $\theta = \mu$, σ^2 known. $\hat{\mu}_{ML} = \bar{y}$
- $$\hat{\mu}_{ML} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right) \longrightarrow \sqrt{n}(\hat{\mu}_{ML} - \mu) \sim \mathcal{N}(0, \sigma^2), \quad J_n = \frac{n}{\sigma^2} \Rightarrow J_0^{-1} = \sigma^2 = \Xi(\theta)$$

Recap: Properties of Estimators $\hat{\theta}(Y)$

small sample (finite n):

- *bias*: $b_{\hat{\theta}}(\theta) = E_{Y|\theta} \hat{\theta}(Y) - \theta = -E_{Y|\theta} \tilde{\theta} = -m_{\tilde{\theta}} \quad (= 0, \forall \theta \in \Theta : \text{unbiased})$
- *error correlation*: $R_{\tilde{\theta}\tilde{\theta}} = E_{Y|\theta} (\hat{\theta}(Y) - \theta) (\hat{\theta}(Y) - \theta)^T = C_{\tilde{\theta}\tilde{\theta}} + b_{\hat{\theta}} b_{\hat{\theta}}^T$

Cramer-Rao Bound : $\hat{\theta}$ unbiased: $R_{\tilde{\theta}\tilde{\theta}} = C_{\tilde{\theta}\tilde{\theta}} = C_{\hat{\theta}\hat{\theta}}$

$$C_{\hat{\theta}\hat{\theta}} \geq J^{-1}(\theta) \quad , \quad J(\theta) = -E_{Y|\theta} \frac{\partial}{\partial \theta} \left(\frac{\partial \ln f(Y|\theta)}{\partial \theta} \right)^T \quad \text{information matrix}$$

efficient: $C_{\hat{\theta}\hat{\theta}} = J^{-1}(\theta) \quad , \quad \forall \theta \in \Theta \quad \Rightarrow \quad \hat{\theta}(Y) \text{ is UMVUE}$

large sample ($n \rightarrow \infty$):

- *asymptotically unbiased*: $\lim_{n \rightarrow \infty} b_{\hat{\theta}}(\theta) = 0, \forall \theta \in \Theta$
- *consistency* (weak, in mean square, strong): \Rightarrow asymptotically unbiased
- *asymptotic normality*:

$$\text{BAN} \left\{ \begin{array}{l} \diamond \text{ weakly consistent} \\ \diamond \text{ asymptotically normal} \\ \diamond \text{ asymptotically efficient} \end{array} \right\} \text{CAN}$$



Recap: Estimation Techniques

- *Uniformly Minimum Variance Unbiased Estimator* (UMVUE): complicated (via "sufficient statistics")
- *Maximum likelihood* (ML): $\hat{\theta}_{ML} = \arg \max_{\theta} f(Y|\theta)$

Qualities:

- ◇ if \exists efficient $\hat{\theta} = \hat{\theta}_{eff}$ and $\hat{\theta}_{ML}$ is obtained from $\frac{\partial \ln f(Y|\theta)}{\partial \theta} = 0$
 $\Rightarrow \hat{\theta}_{eff} = \hat{\theta}_{ML} = \hat{\theta}_{UMVUE}$
- ◇ $\hat{\theta}_{ML} = \text{BAN}$

Problems:

- ◇ what if $f(Y|\theta)$ is unknown?
- ◇ if $f(Y|\theta)$ is not concave (local maxima)
- simplified estimators:
 - ◇ *Best Linear Unbiased Estimator* (BLUE) \rightarrow linear model
 - ◇ *Method of Moments*
 - ◇ *Least-Squares* (LS) \rightarrow linear model



Best Linear Unbiased Estimator (BLUE)

- deterministic analog of LMMSE in the Bayesian case
- *linear*: $\hat{\theta}(Y) = F Y \quad (F : m \times n)$
- *unbiased*: $E_{Y|\theta} \hat{\theta} = F E(Y|\theta) = \theta$
- *best = minimum variance*: $\min C_{\tilde{\theta}\tilde{\theta}}$
- remarks:
 - BLUE inferior to UMVUE unless UMVUE is linear
 - generalizations: $X = g(Y) : \hat{\theta}(Y) = F X = F g(Y)$ (linear in X)
e.g.: linear in Y inappropriate if $\theta \neq 0$ and $E(Y|\theta) = 0$



Example of $X = g(Y)$

- $y_i \sim \mathcal{N}(0, \sigma^2)$ i.i.d., $\theta = \sigma^2$, $Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$
- linear: $\hat{\sigma}^2 = F Y \Rightarrow E_{Y|\sigma^2} \hat{\sigma}^2 = F E(Y|\sigma^2) = 0 \neq \sigma^2$
no linear unbiased estimator $\hat{\sigma}^2$ exists
- however, let $x_i = y_i^2$, $X = \begin{bmatrix} y_1^2 \\ \vdots \\ y_n^2 \end{bmatrix}$, $E X = \begin{bmatrix} E y_1^2 \\ \vdots \\ E y_n^2 \end{bmatrix} = \begin{bmatrix} \sigma^2 \\ \vdots \\ \sigma^2 \end{bmatrix} = \sigma^2 \mathbf{1}$
- $\hat{\sigma}^2 = F X \Rightarrow E_{Y|\sigma^2} \hat{\sigma}^2 = F E(X|\sigma^2) = \sigma^2 F \mathbf{1} = \sigma^2 \Rightarrow F \mathbf{1} = 1$
- for this problem: $\hat{\sigma}_{UMVUE}^2 = \frac{1}{n} \mathbf{1}^T X = \hat{\sigma}_{BLUE}^2$ ($F = \frac{1}{n} \mathbf{1}^T$)

BLUE Assumptions

- unbiased: $F E(Y|\theta) = \theta$, $\forall \theta \in \Theta$

unbiasedness and the requirement that a large class of linear unbiased estimators (many F satisfying $F E(Y|\theta) = \theta$) should exist naturally lead to:

- *assumption 1* : $E(Y|\theta) = H \theta$, $(H : n \times m)$

unbiasedness $\rightarrow F H = I_m$ ($\Rightarrow n \geq m$)

- variance:

$$\begin{aligned} C_{\tilde{\theta}\tilde{\theta}} &= C_{\hat{\theta}\hat{\theta}} = E_{Y|\theta} (\hat{\theta} - E_{Y|\theta} \hat{\theta}) (\hat{\theta} - E_{Y|\theta} \hat{\theta})^T \\ &= E_{Y|\theta} (F Y - F E(Y|\theta)) (F Y - F E(Y|\theta))^T \\ &= F E_{Y|\theta} (Y - E(Y|\theta)) (Y - E(Y|\theta))^T F^T = F C_{YY}(\theta) F^T \end{aligned}$$

- *assumption 2* : $C_{YY}(\theta) = c(\theta) C$

$c(\theta)$ (> 0 , $\forall \theta$) is a scalar function of θ , $C > 0$ is constant w.r.t. θ

BLUE Optimization Problem

- $\min_{\hat{\theta}: E_Y |_{\theta} \hat{\theta}(Y) = \theta} C_{\hat{\theta}\hat{\theta}} \rightarrow \min_{F: FH=I} F C F^T$
- introduce matrix square root B ($n \times n$) of $C = C^T > 0$ ($n \times n$): $C = B B^T$
notation: $B = C^{1/2}$, $C^{T/2} = (C^{1/2})^T$, $C = C^{1/2} C^{T/2}$, $C^{-1} = C^{-T/2} C^{-1/2}$
- Consider a vector space of matrices with n columns with matrix inner product $\langle X_1, X_2 \rangle = X_1 X_2^T$. Take $X_1 = H^T C^{-T/2}$, $X_2 = F C^{1/2}$. With $FH = I$:

$$\left\langle \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}, \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \right\rangle = \begin{bmatrix} H^T C^{-T/2} \\ F C^{1/2} \end{bmatrix} \begin{bmatrix} H^T C^{-T/2} \\ F C^{1/2} \end{bmatrix}^T = \begin{bmatrix} H^T C^{-1} H & I \\ I & F C F^T \end{bmatrix} = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix} \geq 0$$

- From the Schur Complements Lemma, $R_{22} \geq R_{21} R_{11}^{-1} R_{12}$ with equality iff $X_2 = R_{21} R_{11}^{-1} X_1$.
- Hence $\min_{F: FH=I} F C F^T = (H^T C^{-1} H)^{-1}$
for $F = (H^T C^{-1} H)^{-1} H^T C^{-1} = (H^T C_{YY}^{-1} H)^{-1} H^T C_{YY}^{-1}$.
- Or $\hat{\theta}_{BLUE} = (H^T C^{-1} H)^{-1} H^T C^{-1} Y = (H^T C_{YY}^{-1} H)^{-1} H^T C_{YY}^{-1} Y$
with $C_{\hat{\theta}\hat{\theta}} = F C_{YY} F^T = c(\theta) F C F^T = c(\theta) (H^T C^{-1} H)^{-1} = (H^T C_{YY}^{-1} H)^{-1}$

BLUE: Example Cont'd and Recap

Example Cont'd:

- $y_i \sim \mathcal{N}(0, \sigma^2)$ i.i.d., $\theta = \sigma^2$, $x_i = y_i^2$, $\widehat{\sigma^2} = F X$
- BLUE assumptions OK: $E(X|\sigma^2) = \mathbf{1} \sigma^2 = H \theta$, $C_{XX} = 2\sigma^4 I = c(\theta) C$

$$R_{x_i x_j} = E y_i^2 y_j^2 = \begin{cases} \sigma^4 & , i \neq j \\ 3\sigma^4 & , i = j \end{cases} \Rightarrow R_{XX} = 2\sigma^4 I + \sigma^4 \mathbf{1}\mathbf{1}^T, C_{XX} = R_{XX} - m_X m_X^T = 2\sigma^4 I$$

$$\widehat{\sigma^2}_{BLUE} = (H^T C^{-1} H)^{-1} H^T C^{-1} X = \frac{1}{n} \mathbf{1}^T X = \overline{y^2}$$

$$C_{\widehat{\sigma^2} \widehat{\sigma^2}}(\sigma^2) = (H^T C_{XX}^{-1} H)^{-1} = \frac{2\sigma^4}{n} \quad H = \mathbf{1}, C = I, c(\theta) = 2\sigma^4$$

- note: this example is not a linear model!

Recap: BLUE assumptions:

- $\begin{cases} (1) E(Y|\theta) = H \theta \\ (2) C_{YY}(\theta) = c(\theta) C \end{cases}$

Only need to know the first two moments of $f(Y|\theta)$ which need to satisfy these assumptions. The higher-order moments of $f(Y|\theta)$: don't need to know, can be arbitrary functions of θ . So the problem should more or less look like a linear model problem, up to the second-order moments.



BLUE: Linear Model

- $Y = H \theta + V$, $EV = 0$, $EVV^T = C_{VV}$

(EV and C_{VV} independent of θ , only first two moments of V specified)

- BLUE assumptions satisfied:

$$\begin{cases} E(Y|\theta) = H\theta \\ C_{YY}(\theta) = E_{Y|\theta}(Y - E(Y|\theta))(Y - E(Y|\theta))^T = E_V V V^T = C_{VV} = C \quad (c(\theta) = 1) \end{cases}$$

- $\hat{\theta}_{BLUE} = (H^T C_{VV}^{-1} H)^{-1} H^T C_{VV}^{-1} Y$ with $C_{\tilde{\theta}\tilde{\theta}} = (H^T C_{VV}^{-1} H)^{-1}$

- If $V \sim \mathcal{N}(0, C_{VV})$ then $\hat{\theta}_{BLUE} = \hat{\theta}_{ML} = \text{efficient} \Rightarrow \hat{\theta}_{UMVUE}$

Method of Moments

Principle:

- m unknown parameters $\theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_m \end{bmatrix}$
- $f(Y|\theta)$ depends on $\theta \Rightarrow$ its moments also
- take m moments $\mu = g(\theta) = \begin{bmatrix} g_1(\theta) \\ \vdots \\ g_m(\theta) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_m \end{bmatrix}$

such that $g(\cdot)$ is invertible, i.e. $\theta = g^{-1}(\mu)$: can determine θ from μ .

- estimate the moments: $\hat{\mu}$ (e.g. sample moments)
- method of moments: $\hat{\theta}_{MM} = g^{-1}(\hat{\mu})$

Method of Moments: Example 1

- $y_i, i = 1, \dots, n$ i.i.d., $f(y|\theta)$ mixture distribution, θ mixture parameter

$$f(y|\theta) = (1-\theta)\phi_1(y) + \theta\phi_2(y), \quad \phi_k(y) = \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{-\frac{y^2}{2\sigma_k^2}}, k = 1, 2$$

- $\mu = E(y^2|\theta) = (1-\theta)\sigma_1^2 + \theta\sigma_2^2 = g(\theta) \Rightarrow \theta = g^{-1}(\mu) = \frac{\mu - \sigma_1^2}{\sigma_2^2 - \sigma_1^2}$

- $\hat{\theta}_{MM} = g^{-1}(\hat{\mu}) = \frac{\hat{\mu} - \sigma_1^2}{\sigma_2^2 - \sigma_1^2}, \quad \hat{\mu} = \frac{1}{n} \sum_{i=1}^n y_i^2$ sample mean squared value

- bias: $E\hat{\theta} = \frac{1}{\sigma_2^2 - \sigma_1^2} E\hat{\mu} - \frac{\sigma_1^2}{\sigma_2^2 - \sigma_1^2} = \frac{1}{\sigma_2^2 - \sigma_1^2} \mu - \frac{\sigma_1^2}{\sigma_2^2 - \sigma_1^2} = \theta$: unbiased



Method of Moments: Example 1 (cont'd)

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$$\begin{aligned} \text{Var}(\hat{\theta}) &= \text{Var}\left(\frac{1}{\sigma_2^2 - \sigma_1^2} \hat{\mu} - \frac{\sigma_1^2}{\sigma_2^2 - \sigma_1^2}\right) = \frac{1}{(\sigma_2^2 - \sigma_1^2)^2} \text{Var}(\hat{\mu}) = \frac{1}{(\sigma_2^2 - \sigma_1^2)^2} \text{Var}\left(\frac{1}{n} \sum_{i=1}^n y_i^2\right) \\ &= \frac{1}{(\sigma_2^2 - \sigma_1^2)^2} \sum_{i=1}^n \text{Var}\left(\frac{1}{n} y_i^2\right) = \frac{1}{(\sigma_2^2 - \sigma_1^2)^2} \sum_{i=1}^n \frac{1}{n^2} \text{Var}(y_i^2) = \frac{1}{(\sigma_2^2 - \sigma_1^2)^2} \frac{1}{n} \text{Var}(y^2) \end{aligned}$$

$$f(y|\theta) = (1-\theta) \phi_1(y) + \theta \phi_2(y)$$

$$\begin{aligned} \bullet \text{Var}(y^2) &= Ey^4 - (Ey^2)^2, & Ey^2 &= (1-\theta) \sigma_1^2 + \theta \sigma_2^2 \\ & & Ey^4 &= (1-\theta) 3\sigma_1^4 + \theta 3\sigma_2^4 \end{aligned}$$

$$\bullet \Rightarrow \text{Var}(\hat{\theta}_{MM}) = \frac{3(1-\theta)\sigma_1^4 + 3\theta\sigma_2^4 - [(1-\theta)\sigma_1^2 + \theta\sigma_2^2]^2}{n(\sigma_1^2 - \sigma_2^2)^2} \xrightarrow{n \rightarrow \infty} 0$$

$$\Rightarrow \hat{\theta}_{MM} = \text{mean-square consistent}$$

MM Example 2: Sinusoid in White Noise

- $y_k = s_k + v_k = A \cos(\omega k + \phi) + v_k, \quad k = 1, \dots, n$

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}, S = \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix}, V = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}, \theta = \begin{bmatrix} A \\ \omega \\ \sigma_v^2 \end{bmatrix}, \Theta : A > 0, \omega \in [0, \pi], \sigma_v^2 > 0$$

- distributions: $\phi \sim \mathcal{U}[0, 2\pi]$ independent of θ, V ; $EV = 0, EVV^T = \sigma_v^2 I_n$

randomness: $f(Y, \phi | \theta) = f(\phi | \theta) f(Y | \theta, \phi) = f(\phi) f_{\mathbf{V} | \sigma_v^2}(Y - S(A, \omega, \phi) | \sigma_v^2)$

in what follows: only first and second moments of V needed

- mean: $E_{Y, \phi | \theta} y_k = AE \cos(\omega k + \phi) + Ev_k = 0$

covariance sequence:

$$\begin{aligned} r_{yy}(i) &= Ey_k y_{k+i} = A^2 E \cos(\omega k + \phi) \cos(\omega k + \phi + \omega i) \\ &\quad + AE \cos(\omega k + \phi) Ev_{k+i} + AE \cos(\omega k + \phi + \omega i) Ev_k + Ev_k v_{k+i} \\ &= \frac{A^2}{2} E \cos(2\omega k + 2\phi + \omega i) + \frac{A^2}{2} E \cos(\omega i) + \sigma_v^2 \delta_{i0} \\ &= \frac{A^2}{2} \cos(\omega i) + \sigma_v^2 \delta_{i0} \end{aligned}$$



MM Example 2: Sinusoid in White Noise (2)

- moments: $\mu = \begin{bmatrix} r_{yy}(0) \\ r_{yy}(1) \\ r_{yy}(2) \end{bmatrix} = \begin{bmatrix} \frac{A^2}{2} + \sigma_v^2 \\ \frac{A^2}{2} \cos(\omega) \\ \frac{A^2}{2} \cos(2\omega) \end{bmatrix} = g(\theta)$

- $\theta = g^{-1}(\mu)$:
$$\omega = \begin{cases} \arccos\left(\frac{r_{yy}(2) + \sqrt{r_{yy}^2(2) + 8r_{yy}^2(1)}}{4r_{yy}(1)}\right) & , r_{yy}(1) \neq 0 \\ \frac{\pi}{2} & , r_{yy}(1) = 0 \end{cases}$$

$$A = \begin{cases} \sqrt{\frac{2r_{yy}(1)}{\cos(\omega)}} & , r_{yy}(1) \neq 0 \\ \sqrt{-2r_{yy}(2)} & , r_{yy}(1) = 0 \end{cases} , \quad \sigma_v^2 = r_{yy}(0) - \frac{A^2}{2}$$

- sample moments $\hat{\mu}$: $\hat{r}_{yy}(i) = \frac{1}{n} \sum_{k=1}^{n-i} y_k y_{k+i} , \quad i = 0, 1, 2$



Method of Moments: Properties

- $\hat{\mu}$ easy to compute, $\hat{\theta}_{MM} = g^{-1}(\hat{\mu})$ straightforward if μ chosen well, hence $\hat{\theta}_{MM}$ easy to determine and easy to implement
- no optimality properties but usually consistent (since $\hat{\mu}$ consistent)
- if performance of $\hat{\theta}_{MM}$ not satisfactory, can use $\hat{\theta}_{MM}$ as initialization in an iterative optimization procedure that finds $\hat{\theta}_{ML}$