TTT4275 Summary for February 1th Spring 2019

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Maximum Likelihood Estimator (MLE)

- The LSE estimator (linear model approximation) and BLUE did not need knowledge of $p(x,\theta)$. Thus CRLB can not be found, and the estimator quality is generally unknown.
- ullet The MLE requires knowledge of $p(x,\theta)$, thus CRLB can be found
- The term likelihood means $L(\theta/x) = p(x,\theta)$ where x is known and θ is unknown/variable
- MLE is generally not efficient, but is always asymptoticallt efficient, i.e.

$$\lim_{N \to \infty} E\{\widehat{\theta}\} = \theta \tag{1}$$

$$\lim_{N\to\infty} var(\widehat{\theta}) = CRLB$$

As the name MLE indicates the estimator is found by

$$\hat{\theta} = argmax_{\theta} L(\theta/x) \tag{2}$$



Bayesian estimation -1

- Classical estimation (LSE, BLUE, MLE) : θ is unknown but deterministic, i.e. $p(x,\theta) = p(x/\theta)p(\theta) = p(x/\theta)$
- Bayesian estimation (BMSE, MAP): θ is unknown and a stochastic variable with prior density $p(\theta)$
- Bayesian MSE is given by

$$BMSE(\theta) = E\{(\theta - \theta)^2\} = \int \int (\theta - \theta)^2 p(x, \theta) d\theta dx$$
 (3)

• Utilizing $p(x,\theta) = p(\theta/x)p(x)$

$$BMSE(\acute{ heta}) = \int F(\acute{ heta}, x) p(x) dx$$
 where
$$F(\acute{ heta}, x) = \int (\theta - \acute{ heta})^2 p(\theta/x) d\theta$$



Bayesian estimation -2

- Minimizing $BMSE(\theta)$ is eqivalent to minimizing the integrand $F(\theta,x)$ as all variables inside the integrals are positive
- Minimizing $F(\hat{\theta},x)$ by setting the derivative wrt. $\hat{\theta}$ equal to zero results in $\hat{\theta} = E\{\theta/x\} = \int \theta p(\theta/x) dx \tag{4}$
- ullet The strategy then is first to find the posterior density $p(\theta/x)$ from

$$p(\theta/x) = \frac{p(x/\theta)p(\theta)}{p(x)}$$

and then calculate the integral in eq. 4.

• In practice it is seldom easy to calculate the integral. Thus a (suboptimal) strategy is to use the maximum value of the posterior (MAP)

$$\hat{\theta} = argmax_{\theta} \ p(\theta/x) = argmax_{\theta} \ \frac{p(x/\theta)p(\theta)}{p(x)} = argmax_{\theta} \ p(x/\theta)p(\theta)$$
 (5)

• If the posterior is symmetric MAP and minimum BMSE are identical

