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Tuesday, February 2, 2021 9:13 PM

QDA. 4.9

Point Estimation:

Suppose a measurement y is recorded with a $N(\theta, \sigma^2)$

here σ^2 known and $\theta \in [0, 1]$

Consider two point estimation for θ :

(i) MLE

(ii) the posterior mean based on the assumption of a uniform prior distribution on θ .

(i) First let us find MLE of θ .

Given $y \sim N(\theta, \sigma^2)$ $\theta \in [0, 1]$, σ^2 known

Then likelihood function is.

$$f(y|\theta) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{1}{2\sigma^2}(y-\theta)^2\right\}$$

Since we want to maximize $f(y|\theta)$.

hence it is sufficient to say $\min (y-\theta)^2$

discuss: if $y < 0$. then choose $\hat{\theta}_{MLE} = 0$

if $y \in [0, 1]$. then choose $\hat{\theta}_{MLE} = y$

if $y > 1$ then choose $\hat{\theta}_{MLE} = 1$

because θ has restriction $[0, 1]$

Then, putting everything together.

$$\hat{\theta}_{MLE} = \begin{cases} 0 & \text{if } y < 0 \\ y & \text{if } y \in [0, 1] \\ 1 & \text{if } y > 1 \end{cases}$$

(ii) Next, let us find the posterior.

Assume prior: $\theta \sim \text{uniform}([0, 1])$

$y|\theta \sim \text{normal}(\theta, \sigma^2)$

Then the posterior is

$$\begin{aligned}
P(\theta|y) &\propto P(\theta) \cdot P(y|\theta) \\
&= \exp\left(-\frac{1}{2\sigma^2}(y-\theta)^2\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}(y^2 - 2y\theta + \theta^2)\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}y^2 + \frac{1}{\sigma^2}y\theta - \frac{1}{2\sigma^2}\theta^2\right) \\
&\propto \exp\left(\frac{1}{\sigma^2}y\theta\right) \exp\left(-\frac{1}{2\sigma^2}\theta^2\right)
\end{aligned}$$

take $\sigma \rightarrow \infty \rightarrow \exp(0) \exp(-0) = 1$

Thus we conclude as $\sigma \rightarrow \infty$, the posterior tends to uniform dist.

So posterior mean estimator $\hat{\theta}_{\text{pos}} = \frac{1}{2}$.

(iii) let us compute MSE for both estimators.

$$\begin{aligned}
\text{MSE}(\hat{\theta}_{\text{MLE}}) &= \mathbb{E}(\hat{\theta}_{\text{MLE}} - \theta)^2 \quad \text{where } \hat{\theta}_1 \text{ as } \hat{\theta}_{\text{MLE}} \\
&= \int_0^1 (\hat{\theta}_1 - \theta)^2 d\theta \\
&= \int_0^1 \theta_1^2 - 2\hat{\theta}_1\theta + \theta^2 d\theta \\
&= \hat{\theta}_1^2 \theta - \hat{\theta}_1 \theta^2 + \frac{1}{3} \theta^3 \Big|_0^1 \\
&= \hat{\theta}_1^2 - \hat{\theta}_1 + \frac{1}{3}
\end{aligned}$$

$$\begin{aligned}
\text{MSE}(\hat{\theta}_{\text{pos}}) &= \mathbb{E}(\hat{\theta}_{\text{pos}} - \theta)^2 \\
&= \mathbb{E}\left(\frac{1}{2} - \theta\right)^2 \\
&= \int_0^1 \left(\frac{1}{2} - \theta\right)^2 d\theta \\
&= \int_0^1 \frac{1}{4} - \theta + \theta^2 d\theta \\
&= \frac{1}{4} - \frac{1}{2} \theta^2 + \frac{1}{3} \theta^3 \Big|_0^1 \\
&= \frac{1}{4} - \frac{1}{2} + \frac{1}{3} = \frac{3-6+4}{12} = \frac{1}{12}
\end{aligned}$$

$\frac{1}{12}$