

Stat 543

1-19-05

A bit more about decision Thy

Example $X \sim N(\theta, 1)$ $\Theta = \mathcal{A} = \mathbb{R}$

$$L(\theta, a) = (\theta - a)^2$$

$$\delta_c = cX \quad c \in [0, 1]$$

~~$$R(\theta, \delta_c) = (1-c)^2 \theta^2 + c^2$$~~

consider comparing these risk functions
(comparing δ_c 's)

From a minimax point of view

$$\max_{\theta} R(\theta, \delta_c) = \infty \text{ unless } c=1$$

$$R(\theta, \delta_1) = 1$$

Since $1 < \infty$, δ_1 is "minimax" among $\{\delta_c \mid 0 \leq c \leq 1\}$

From a Bayes point of view... one possible prior distn for θ is $N(0, \gamma^2)$ (prior G is $N(0, \gamma^2)$)

The average of $R(\theta, \delta_c)$ against this (prior) ASN for θ is

$$\begin{aligned} R(G, \delta_c) &= \int R(\theta, \delta_c) g(\theta) d\theta \\ &= (1-c)^2 \gamma^2 + c^2 \\ &= (1+\gamma^2)c^2 - 2\gamma^2 c + \gamma^2 \end{aligned}$$

This is minimized over choices of c if

$$\begin{aligned} 2(1+\gamma^2)c &= 2\gamma^2 \\ c &= \frac{\gamma^2}{1+\gamma^2} \end{aligned}$$

So for this prior dsn

$$\frac{\delta_{r^2}}{1+r^2}$$

is "Bayes" among $\{\delta_c \mid 0 \leq c \leq 1\}$

Sufficiency (Data Reduction w/o loss of Important Information)

Example X_1, X_2, \dots, X_n iid $N(\mu, \sigma^2)$
 we "automatically" reduce $X = (X_1, \dots, X_n)$
 to (\bar{X}, S^2)

Example X_1, X_2, \dots, X_5 iid $\text{Ber}(p)$

we "automatically" reduce $X = (X_1, \dots, X_5)$ to $\sum X_i$

Is this reasonable? How can it be justified?
What is the corresponding rationale in other models?

Def We'll call a function of the observable X , $T(X)$, a statistic - usually T will take values in \mathbb{R}^k and we can

Then think of the statistic as being
 "k-dimensional"

Example iid $N(\mu, \sigma^2)$

$$T((X_1, \dots, X_n)) = (\bar{X}, S^2)$$

Example iid $\text{Ber}(p)$

$$T((X_1, \dots, X_5)) = \sum_{i=1}^5 X_i$$

"Clearly" knowing $T(X)$ I know no
 more about θ than I do if I know
 X itself

Q: When do I really "lose nothing" in going from X to $T(X)$?

Example X_1, X_2, \dots, X_5 iid $\text{Ber}(p)$

$$T(X) = \sum X_i$$

$$f(x|p) = \mathbb{I} \left[\begin{array}{l} \text{all } x_i \\ \text{are 0 or 1} \end{array} \right] p^{\sum x_i} (1-p)^{5-\sum x_i}$$

$$P_p \left[\overset{\parallel}{X} = x \right]$$

Consider $P_p [X=x | T(X)=t]$

$$= \frac{P_p [X=x \text{ and } T(X)=t]}{P_p [T(X)=t]}$$

$$= \begin{cases} 0 & \text{if } \sum x_i \neq t \\ \frac{p^t (1-p)^{5-t}}{\binom{5}{t} p^t (1-p)^{5-t}} & \text{if } \sum x_i = t \end{cases}$$

$$= \begin{cases} 0 & \text{if } \sum x_i \neq t \\ \frac{1}{\binom{5}{t}} & \text{if } \sum x_i = t \end{cases}$$

this prescription
doesn't depend
on p !!!

in some sense, this says that if I know $T(X)$ I don't really need to know X itself - this conditional dsu (that is uniform over x with $\sum x_i = t$) doesn't provide any information about p beyond what is in $T(X)$

In fact, if you give me $T(X)$ I can use the value of $T(X)$ plus some randomization that doesn't depend on p to invent X^* with the same dsn as X — how?

$$X^* \sim \text{uniform on } \{(x_1, \dots, x_5) \mid \sum x_i = T(X)\}$$

This motivates

Def In the statistical model for X $\mathcal{P} = \{P_\theta\}$
 we'll say that the statistic $T(X)$ is sufficient

for θ (or for the family/model \mathcal{P})
 provided for each t the conditional distn of

$$X \mid T(X) = t$$

is the same for all $\theta \in \Theta$ (is free of
 dependence upon θ)

How to recognize a sufficient statistic?

Example X_1, \dots, X_n Bernoulli (p)

$T(X) = \sum X_i$ is sufficient for p

Theorem 1 (Fisher/Neyman/Halmos/Savage)

(Factorization Theorem) If $f(z|\theta)$ is either a pdf for X on \mathbb{R}^k or a pmf for X

Then $T(X)$ is sufficient for θ

\Leftrightarrow

There are nonnegative functions $g(t, \theta)$ and $h(z)$ such that

$$f(z|\theta) = g(T(z), \theta) h(z)$$

Interpretation: Shape of the log likelihood depends on X only through $T(X)$