

Stat 543

2-16-05

Recall: Decision-theoretic argument for the conditional/posterior mean as a (Bayes) estimator

To minimize  $R(G, \delta)$  it suffices to for each  $x$  minimize

$$\int L(\theta, a) g(\theta|x) d\theta = \begin{array}{l} \text{conditional expected} \\ \text{loss for action } a \\ \text{given } X=x \end{array}$$

In the case that  $L(\theta, a) = (\gamma(\theta) - a)^2$  this is

"minimize

$$\int (\gamma(\theta) - a)^2 g(\theta|x) d\theta$$

by choice of  $a$ "

i.e. minimize

$$\int \gamma^2(\theta) g(\theta|x) d\theta - 2a \int \gamma(\theta) g(\theta|x) d\theta + \int a^2 g(\theta|x) d\theta = a^2$$

This is a quadratic in  $a$  with minimum where

$$-2 \int \gamma(\theta) g(\theta|x) d\theta + 2a = 0$$

i.e.

$$a = \int \gamma(\theta) g(\theta|x) d\theta$$

i.e.  $\delta(x) = \int \gamma(\theta) g(\theta|x) d\theta$  gives the Bayes estimator  $\delta(x)$

BTW if I start with a different loss function I get a different prescription for a Bayes estimator

Example  $\theta \in \mathbb{R}^1$   $L(\theta, a) = |\theta - a|$   
(absolute error loss)

$$\int |\theta - a| g(\theta|x) d\theta$$

is minimized by any  $a$  that is a median of the posterior i.e. if

$$\delta(x) = \text{median of } G(\theta|x)$$

$\delta(X)$  is a Bayes estimator of  $\theta$

How does one implement the Bayes prescription in a real/complicated problem?

Suppose  $\theta \in \mathbb{R}^k$

If  $k$  is small  $\Rightarrow$  I can understand  
 $g(\theta/x) \propto L(\theta)g(\theta)$   
 pretty easily by plotting  
 and low-dimensional  
 numerical integration

If  $k$  is big I have problems ... I may  
 not even be able to compute

using numerical analysis  
 $\int L(\theta)g(\theta) d\theta$

how then to compute things like posterior mean  $\theta_i$  given  $X=x$

$$\frac{\int \theta_i L(\theta) g(\theta) d\theta}{\int L(\theta) g(\theta) d\theta}$$



perhaps one can use simulation

Suppose we're interested in

$$Q = \int q(\theta) g(\theta|x) d\theta$$

for some  $q: \mathbb{R}^k \rightarrow \mathbb{R}^1 \dots$   $q$  could be  
 $q(\theta) = \theta_i$

or  $q(\theta) = \mathbb{I}[\theta \in \Delta]$  for  $\Delta \subset \mathbb{R}^k$

If I could generate/simulate  $\theta_1^*, \theta_2^*, \dots$   
 iid  $G(\theta|x)$  I might approximate  $Q$  by  
 by

$$\frac{1}{n} \sum_{i=1}^n q(\theta_i^*)$$

figuring that LLN says that

$$\frac{1}{n} \sum_{i=1}^n q(\theta_i^*) \xrightarrow{P} Q$$

$G(\theta|x)$   
probability

At first look, this may be no help, because  
 it's not obvious (particularly if I can't

compute  $\int L(\theta) g(\theta) d\theta$  that I'm going to be able to do the simulation — but then the situation is not so bleak — there are

- 1) The rejection algorithm
- 2) Markov Chain Monte Carlo

Rejection Algorithm (for sampling from  $g(\theta|x)$  when I only know  $L(\theta)g(\theta)$ )

Suppose that  $h(\theta)$  specifies a dsu from which I can easily sample and  $\exists$  a constant  $M > 0$  such that

$$Mh(\theta) > \underbrace{L(\theta)g(\theta)}_{\text{proportional to } g(\theta|z)}$$

To generate  $\theta^* \sim g(\theta|z)$  I can

① generate  $\theta^{**} \sim h(\theta)$

② generate  $U \sim (0,1)$

③ if  $MUh(\theta^{**}) < L(\theta^{**})g(\theta^{**})$

set  $\theta^* = \theta^{**}$

otherwise return to ①

And generating  $\theta_1^*, \theta_2^*, \dots$  in this way  
I can approximate  $Q$

"Argument" for why the rejection algorithm works - Note that

$$P[\text{algorithm stops at current iteration} \mid \theta^{**}] = \frac{L(\theta^{**})g(\theta^{**})}{M h(\theta^{**})}$$

So  $P[\text{algorithm fails to stop on a particular iteration} \mid \text{it gets to that iteration}]$

$$= 1 - \int \frac{L(\theta)g(\theta)}{M h(\theta)} h(\theta) d\theta$$

$$= 1 - \frac{\int L(\theta)g(\theta) d\theta}{M}$$

$P [ i \text{ iterations are required and } \theta^* \text{ is near } \theta ]$

$$\approx \left( 1 - \frac{\int L(\theta) g(\theta) d\theta}{M} \right)^{i-1} \left( \frac{L(\theta) g(\theta)}{M h(\theta)} \right) \times h(\theta) (\text{vol}^n \Delta \theta)$$