

## HW 2 (continued)

1.3.19. a) Consider a state of nature with 2 possible values,  $\theta_1$  and  $\theta_2$ . Next consider the loss function for two actions  $a_1$  and  $a_2$ :

$l(\theta, a)$ :

	$a_1$	$a_2$
$\theta_1$	0	2
$\theta_2$	3	1

and  $X$  a RV  
with  $p(x|\theta) =$

	$x=0$	$x=1$
$\theta_1$	0.2	0.8
$\theta_2$	0.4	0.6

The non-randomized decision rules  $\delta_i(x)$  can be shown in a table:

$i =$	1	2	3	4
$x=0$	$a_1$	$a_1$	$a_2$	$a_2$
$x=1$	$a_1$	$a_2$	$a_1$	$a_2$

So, risk can be calculated (see BD pg 25) as:

$$R(\theta, \delta) = E[l(\theta, \delta(x))] = l(\theta, a_1) P[\delta(x) = a_1] + l(\theta, a_2) P[\delta(x) = a_2]$$

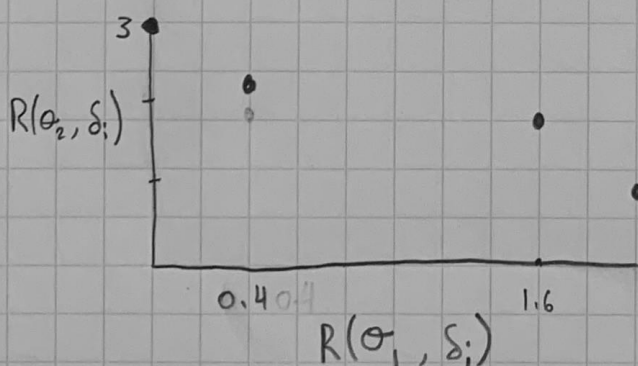
And we can construct a risk table:

$i =$	1	2	3	4
$R(\theta_1, \delta_i)$	$0(0.2) + 0(0.8)$	$0(0.2) + 2(0.8)$	$2(0.2) + 0(0.8)$	$2(0.2) + 2(0.8)$
$R(\theta_2, \delta_i)$	$3(0.4) + 3(0.6)$	$3(0.4) + 1(0.6)$	$1(0.4) + 3(0.6)$	$1(0.4) + 1(0.6)$

which equals:

$i =$	1	2	3	4
$R(\theta_1, \delta_i)$	0	1.6	0.4	2
$R(\theta_2, \delta_i)$	3	1.8	2.2	1

A plot:



The minimax rule is the one in which

$$\sup_{\theta} R(\theta, \delta^*) = \inf_{\delta} \sup_{\theta} R(\theta, \delta)$$

$$\sup_{\theta} R(\theta, \delta_{1-4}) = 3, 1.8, 2.2, 2$$

$\therefore \delta_2$  is minimax rule.

Now assume a prior distribution for  $\theta$  s.t.  $\pi(\theta_1) = 0.1$  and  $\pi(\theta_2) = 0.9$ . By BD 1.3.10, the Bayes risk is:

$$r(\delta_i) = 0.1 R(\theta_1, \delta_i) + 0.9 R(\theta_2, \delta_i)$$

Therefore our Bayes Risk table is:

$i =$	1	2	3	4
$r(\delta_i)$	$0.1(0) + 0.9(3)$	$0.1(1.6) + 0.9(1.8)$	$0.1(0.4) + 0.9(2.2)$	$0.1(2) + 0.9(1)$
$r(\delta_i) =$	2.7	1.78	2.02	1.1

So,  $\delta_4$  is the Bayes rule for this prior.

1.1.2. b) For estimation of  $\lambda$  set:

$$P_X(x|\lambda) = \frac{e^{-\lambda_1} \lambda_1^x}{x!} = \frac{e^{-\lambda_2} \lambda_2^x}{x!} = P_X(x|\lambda_2)$$

It's obvious that for any value of  $x = 0, 1, \dots$  the densities are the same if  $\lambda_1 = \lambda_2$

$$\frac{e^{-\lambda_1} \lambda_1^x}{x!} \bigg/ \frac{e^{-\lambda_2} \lambda_2^x}{x!} = \left( \frac{e^{-\lambda_1} \lambda_1}{e^{-\lambda_2} \lambda_2} \right)^x$$

The same can be said for the second part of the model:

$$P_Y(y|n) = \binom{n}{y} p^y (1-p)^{n-y} = \binom{n}{y} p_2^y (1-p_2)^{n-y} = P(y|n, p_2)$$

when  $n$  is a known integer, and therefore not a parameter,  $p_1 = p_2$  implies  $P(y|n, p_1) = P(y|n, p_2)$ . However, if  $n$  is unknown and therefore a parameter, there are combinations of  $(n, p)$  that will make  $P_Y(y|n_1, p_1) \neq P_Y(y|n_2, p_2)$ .