

Statistics 582, Problem Set 4 Solutions

Wellner; 2/2/2011

1. Let $\Theta = \{0, 1\} = \mathbf{A}$ where 0 = a patient has tuberculosis, 1 = a patient does not have tuberculosis. Let X be the number of positive reactions to two different tuberculosis tests, so that $\mathbf{X} = \{0, 1, 2\}$, and suppose that X has the following distributions

x	0	1	2
$p_0(x)$.02	.13	.85
$p_1(x)$.70	.27	.03

If the losses are given by $L(1, 1) = L(0, 0) = 0$, $L(0, 1) = 100$, $L(1, 0) = 10$, and the prior $\lambda = (\lambda_0, \lambda_1) = (.2, .8)$, find the Bayes rule d_B and the minimax rule d_M . Plot the risk set and label the non-randomized decision rules.

Solution: Let $d = (d_0, d_1, d_2)$ with $d_i = \text{prob of action 1 when } x = i \text{ is observed}$, $i = 0, 1, 2$. Then the risks are

$$\begin{aligned} R(0, d) &= 100\{d_0(.02) + d_1(.13) + d_2(.85)\} \\ R(1, d) &= 10\{(1 - d_0)(.70) + (1 - d_1)(.27) + (1 - d_2)(.03)\}, \end{aligned}$$

and, for $\underline{\lambda} = (.2, .8)$, the Bayes risk of d is

$$\begin{aligned} \mathcal{R}(\lambda, d) &= (.2)R(0, d) + (.8)R(1, d) \\ &= 8 + (.01)\{-520d_0 + 44d_1 + 1676d_2\} \end{aligned}$$

which is minimized by $d = (1, 0, 0) \equiv d_B = d_4$ (in the list of nonrandomized rules below).

To find a minimax rule, equate $R(0, d) = R(1, d)$: this yields

$$\{2d_0 + 13d_1 + 85d_2\} = 10 - 7d_0 - 2.7d_1 - .3d_2.$$

Solving for d_1 yields

$$d_1 = (100 - 90d_0 - 85.3d_2)/157,$$

and plugging this back into $R(0, d)$ yields

$$\begin{aligned} R(0, d) = R(1, d) &= 2d_0 + \frac{130}{157}(10 - 9d_0 - 85.3d_2) + 85d_2 \\ &= \frac{1300}{157} + \left(2 - \frac{13 \cdot 90}{157}\right)d_0 + \left(85 - \frac{130 \cdot 85.3}{90}\right)d_2 \end{aligned}$$

which is minimized by $d_0 = 1$, $d_2 = 0$; then $d_1 = 10/157 \doteq .0637\dots$. Hence the minimax rule is $d_M = (1, 10/157, 0)$, and the corresponding common risk is $R(0, d_M) = R(1, d_M) = 444/157 \doteq 2.8280\dots$. Note that for the Bayes rule we have $R(0, d_B) = 2$, $R(1, d_B) = 3$.

The nonrandomized rules and their risks are:

x	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8
0	0	0	0	1	1	1	0	1
1	0	0	1	0	1	0	1	1
2	0	1	0	0	0	1	1	1
$R(0, d)$	0	85	13	2	15	87	98	100
$R(1, d)$	10	9.7	7.3	3	0.3	2.7	7	0

Here is a plot of the risk body:

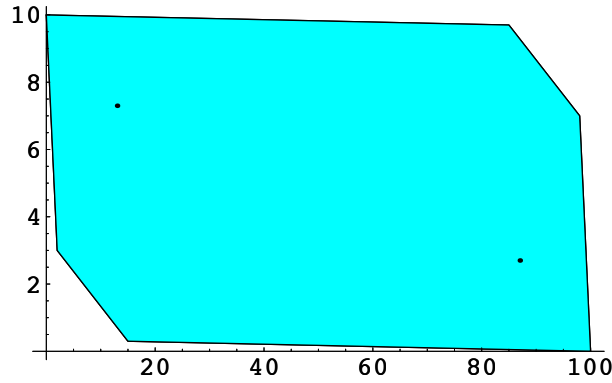


Figure 1: Risk Body.

2. Consider testing the simple hypothesis $H_0 : X \sim P_0$ versus the simple alternative $H_1 : X \sim P_1$. Let ϕ be a test of H_0 versus H_1 , and let $a \equiv E_1(1 - \phi)$, $b \equiv E_0\phi$.
- (a) Find a test ϕ which minimizes $a + Db$ where D is a fixed number.
- (b) When $D = 1$, relate the minimized total $a + b$ to the risk and to the total variation distance $d_{TV}(P_0, P_1)$ between P_0 and P_1 (or $\int p_0 \wedge p_1 d\mu$ for a dominating measure μ , e.g. $P_0 + P_1$).
- (c) Carry the computations of (b) through in the context of problem 1 when the losses are $L(0, 0) = L(1, 1) = 0$, $L(0, 1) = 10 = L(1, 0)$, and the prior distribution is $\lambda = (\lambda_0, \lambda_1) = (.5, .5)$.

Solution: (a) Let $p_i \equiv dP_i/d\mu$ where $\mu \equiv P_0 + P_1$, $i = 0, 1$. Now

$$a + Db = E_1(1 - \phi) + DE_0\phi = 1 + \int \phi(Dp_0 - p_1)d\mu = 1 - \int \phi(p_1 - Dp_0)d\mu,$$

so $a + Db$ is minimized by

$$\phi(x) = \begin{cases} 1 & \text{if } p_1(x) > Dp_0(x) \\ \gamma(x) & \text{if } p_1(x) = Dp_0(x) \\ 0 & \text{if } p_1(x) < Dp_0(x). \end{cases}$$

For any other test ϕ^* ,

$$\int (\phi - \phi^*)(p_1 - Dp_0)d\mu$$

$$\begin{aligned}
&= \int_{[p_1 > Dp_0]} (\phi - \phi^*)(p_1 - Dp_0) d\mu + \int_{[p_1 < Dp_0]} (\phi - \phi^*)(p_1 - Dp_0) d\mu \\
&= \int_{[p_1 > Dp_0]} (1 - \phi^*)(p_1 - Dp_0) d\mu + \int_{[p_1 < Dp_0]} (0 - \phi^*)(p_1 - Dp_0) d\mu \\
&\geq 0
\end{aligned}$$

so that

$$\int \phi(p_1 - Dp_0) d\mu \geq \int \phi^*(p_1 - Dp_0) d\mu.$$

This can be reformulated in a Bayesian context by writing

$$\begin{aligned}
a + Db &= (1 + D) \left\{ \frac{1}{1 + D} a + \frac{D}{1 + D} b \right\} \\
&= (1 + D) \{ (1 - \lambda) E_1(1 - \phi) + \lambda E_0 \phi \} \\
&= (1 + D) \mathcal{R}(\Lambda, \phi),
\end{aligned}$$

the Bayes risk with respect to the prior distribution Λ given by $\lambda = (\lambda, 1 - \lambda)$ with $\lambda \equiv D/(1 + D)$. Then minimizing $a + Db$ is equivalent to minimizing the Bayes risk with the prior $1 - \lambda = 1/(1 + D)$ on P_1 and $\lambda = D/(1 + D)$ on P_0 . As we saw in class on 1/30, any rule of the form

$$\phi(X) = \begin{cases} 1 & \text{if } p_1(X) > \frac{\lambda}{1-\lambda} p_0(X) \\ \gamma(X) & \text{if } p_1(X) = \frac{\lambda}{1-\lambda} p_0(X) \\ 0 & \text{if } p_1(X) < \frac{\lambda}{1-\lambda} p_0(X) \end{cases}$$

is Bayes wrt λ .

(b) When $D = 1$, the minimized total $a + b$ equals, by using by using our earlier results for total variation distance,

$$\begin{aligned}
1 + \int_{[p_0 < p_1]} (p_0 - p_1) d\mu &= 1 - d_{TV}(P_0, P_1) \\
&= 1 - \left\{ 1 - \int p_0 \wedge p_1 d\mu \right\} \\
&= \int p_0 \wedge p_1 d\mu;
\end{aligned}$$

i.e. the test which minimizes the sum of the error probabilities has total error probability equal to $\int p_0 \wedge p_1 d\mu = 1 - d_{TV}(P_0, P_1)$ (c) For the two distributions in problem 1,

$$\begin{aligned}
\rho(P_0, P_1) &= \int p_0 \wedge p_1 d\mu = .4 + .16 + .05 = .25, \\
d_{TV}(P_0, P_1) &= 1 - .25 = .75 = 2^{-1} \int |p_0 - p_d| d\mu.
\end{aligned}$$

The rule which minimizes $a + b = 2((1/2)a + (1/2)b)$ is the Bayes rule with respect to the prior $\lambda = (1/2, 1/2)$, and it is given by $\phi(X) = 1\{X \in \{0, 1\}\}$. The total risk is twice the Bayes risk for the prior $(.5, .5)$ and it equals $\rho(P_0, P_1) = .25$. Thus the Bayes risk equals $10 \times .125 = 1.25$ in this case.

3. Let $\mathcal{X} = \{0, 1\}$, $\mathcal{A} = \Theta = \{1, 2\}$, and assume that the losses are given by $L(1, 1) = L(2, 2) = 0$, $L(1, 2) = a$, $L(2, 1) = b$. Suppose that the statistician can observe either X or Y where

$$p_1(1) = P_1(X = 1) = 2/3, \quad p_2(1) = P_2(X = 1) = 1/2,$$

$$p_1^*(1) = P_1(Y = 1) = 3/4, \quad p_2^*(1) = P_2(Y = 1) = 1/2.$$

Let $\underline{\lambda} = (\lambda, 1 - \lambda)$, $\lambda \in [0, 1]$ be the prior distribution over Θ .

- (a) Find the Bayes risk when X is observed, and similarly for Y .
(b) In the case $a = b$, $\lambda = 1/2$, would the statistician prefer to observe X or Y ?
(c) For general $a \neq b$, $\lambda \in (0, 1)$ would the statistician prefer to observe X or Y ?

Solution: Let d_i = probability of action 1 given that i is observed.

- (i) The Bayes risks for observing X or Y are:

$$\mathcal{R}_X(\lambda, d) = \lambda a \left\{ (1 - d_0) \frac{1}{3} + (1 - d_1) \frac{2}{3} \right\} + (1 - \lambda) b \left\{ d_0 \frac{1}{2} + d_1 \frac{1}{2} \right\},$$

and

$$\mathcal{R}_Y(\lambda, d) = \lambda a \left\{ (1 - d_0) \frac{1}{4} + (1 - d_1) \frac{3}{4} \right\} + (1 - \lambda) b \left\{ d_0 \frac{1}{2} + d_1 \frac{1}{2} \right\}.$$

- (ii) When $a = b$ and $\lambda = 1/2$,

$$\mathcal{R}_X(\lambda, d) = a \frac{1}{2} \left\{ 1 + \frac{1}{6} d_0 - \frac{1}{6} d_1 \right\},$$

$$\mathcal{R}_Y(\lambda, d) = a \frac{1}{2} \left\{ 1 + \frac{1}{4} d_0 - \frac{1}{4} d_1 \right\},$$

and these are both minimized by choosing $d = (0, 1) \equiv d_\lambda$. Then $\mathcal{R}_X(\lambda, d_\lambda) = (5/12)a > (3/8)a = \mathcal{R}_Y(\lambda, d_\lambda)$, so we would prefer to observe Y .

- (iii) The risks are

$$R_X(1, d) = a \left\{ (1 - d_0) \frac{1}{3} + (1 - d_1) \frac{2}{3} \right\}, \quad R_X(2, d) = b \left\{ d_0 \frac{1}{2} + d_1 \frac{1}{2} \right\}$$

$$R_Y(1, d) = a \left\{ (1 - d_0) \frac{1}{4} + (1 - d_1) \frac{3}{4} \right\}, \quad R_Y(2, d) = b \left\{ d_0 \frac{1}{2} + d_1 \frac{1}{2} \right\}.$$

Plotting these for $d_1 = (1, 1)$, $d_2 = (1, 0)$, $d_3 = (0, 1)$, and $d_4 = (0, 0)$ yields the following plot of the risk bodies:

This plot makes it clear that we will always prefer to observe Y . To confirm this, let $r = a/b$, and write

$$\mathcal{R}_X = a\lambda + b \left\{ (1 - \lambda) \frac{1}{2} - r\lambda \frac{1}{3} \right\} d_0 + b \left\{ (1 - \lambda) \frac{1}{2} - r\lambda \frac{2}{3} \right\} d_1,$$

$$\mathcal{R}_Y = a\lambda + b \left\{ (1 - \lambda) \frac{1}{2} - r\lambda \frac{1}{4} \right\} d_0 + b \left\{ (1 - \lambda) \frac{1}{2} - r\lambda \frac{3}{4} \right\} d_1.$$

First consider $\mathcal{R}_X(\lambda, d)$:

For $0 \leq \lambda \leq (1 + 4r/3)^{-1}$, both coefficients are > 0 , so $d_\lambda = (0, 0)$ and $\mathcal{R}_X(\lambda, d_\lambda) = a\lambda$.

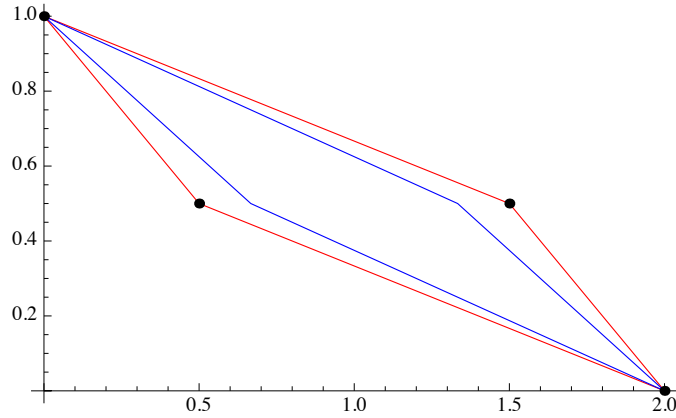


Figure 2: Comparison of the risk bodies \mathcal{R}_Y (red), \mathcal{R}_X (blue), for $a = 2$, $b = 1$

For $(1 + 4r/3)^{-1} \leq \lambda(1 + 2r/3)^{-1}$, $d_\lambda = (0, 1)$ and $\mathcal{R}_X(\lambda, d_\lambda) = a\lambda/3 + b(1 - \lambda)/2$.

For $(1 + 2r/3)^{-1} \leq \lambda \leq 1$, $d_\lambda = (1, 1)$ and $\mathcal{R}_X(\lambda, d_\lambda) = b(1 - \lambda)$.

Now consider $\mathcal{R}_Y(\lambda, d)$:

For $0 \leq \lambda \leq (1 + 2r/3)^{-1}$, both coefficients are > 0 , so $d_\lambda = (0, 0)$ and $\mathcal{R}_Y(\lambda, d_\lambda) = a\lambda$.

For $(1 + 3r/2)^{-1} \leq \lambda(1 + r/2)^{-1}$, $d_\lambda = (0, 1)$ and $\mathcal{R}_Y(\lambda, d_\lambda) = a\lambda/4 + b(1 - \lambda)/2$.

For $(1 + r/2)^{-1} \leq \lambda \leq 1$, $d_\lambda = (1, 1)$ and $\mathcal{R}_Y(\lambda, d_\lambda) = b(1 - \lambda)$.

These Bayes risks are plotted in the following figure. Thus the Bayes risk is *always* small for Y .

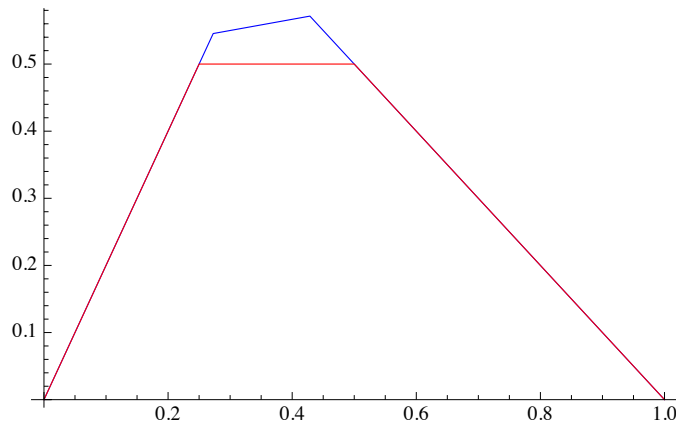


Figure 3: Comparison of the Bayes risks $\mathcal{R}_Y(\Lambda, d_\Lambda)$ (red), $\mathcal{R}_X(\Lambda, d_\Lambda)$ (blue), for $a = 2$, $b = 1$

4. Let $\Theta = \mathcal{A} = \{0, 1\}$, assume the (hypothesis testing) loss function $L(0, 0) = L(1, 1) = 0$, $L(0, 1) = L(1, 0) = 1$. Suppose that we observe the random variable X with the discrete distribution $P_\theta(X = x) = 2^{-(x+\theta)}1_{\mathbb{Z}^+ \cap [1-\theta, \infty)}(x)$.
 - (a) Describe the set of all non-randomized decision rules.
 - (b) Plot the risk set \mathcal{R} in the plane. Which non-randomized rules are admissible? Why?
 - (c) Can you find a non-randomized minimax rule?
 - (d) What decision rules result from a Neyman-Pearson approach?

Hint: every number $z \in [0, 1]$ has a diadic representation of the form $\sum_{x=1}^{\infty} d(x)2^{-x}$ where $d(x) = 0$ or 1 .

Solution: Let $d(x) =$ probability of choosing $\theta = 1$ given that $X = x$ is observed. Thus an arbitrary rule $d = (d(0), d(1), d(2), \dots)$, and the nonrandomized rules have 0 or 1 in each coordinate. Hence the nonrandomized rules consist of all infinite sequences of 0's and 1's. For any rule d

$$\begin{aligned} R(0, d) &= \sum_{x=1}^{\infty} d(x)2^{-x}, \\ R(1, d) &= \sum_{x=0}^{\infty} (1 - d(x))2^{-(x+1)} = \frac{1}{2} \sum_{x=0}^{\infty} (1 - d(x))2^{-x} \\ &= 1 - \frac{1}{2}d(0) - \frac{1}{2}R(0, d). \end{aligned}$$

Note that as d ranges over all non-randomized rules, $R(0, d) = \sum_1^{\infty} d(x)2^{-x}$ ranges over all real numbers between 0 and 1; every $z \in [0, 1]$ has a diadic expansion. Hence the non-randomized rules have risk points on the lines obtained by taking $d(0) = 0$ or $d(0) = 1$; Those with $d(0) = 0$ are inadmissible since the rule with $d(0) = 1$ is better (i.e. has strictly smaller $R(1, d)$); note that $X = 0$ is never observed when $\theta = 0$. When $d(0) = 1$, $R(1, d) = 2^{-1}(1 - R(0, d))$, and hence the minimax risk is $R(0, d) = R(1, d) = 1/3$. This risk is attained by the non-randomized rule $d_M(2x) = 1$, $d_M(2x + 1) = 0$, $x \geq 0$. In fact, there are infinitely many randomized minimax rules; e.g. $(1, 2/3, 0, \dots)$, $(1, 0, 1, 2/3, 0, \dots)$, $(1, 0, 1, 0, 1, 2/3, 0, \dots)$, and so forth.

To find a least-favorable prior, for rules d with $d(0) = 1$, write the Bayes risk as

$$\begin{aligned} \mathcal{R}(\lambda, d) &= \lambda R(0, d) + (1 - \lambda)R(1, d) = \lambda R(0, d) + (1 - \lambda)\frac{1}{2}(1 - R(0, d)) \\ &= \frac{1}{2}(1 - \lambda) + \frac{1}{2}(3\lambda - 1)R(0, d). \end{aligned}$$

For $0 \leq \lambda < 1/3$, $3\lambda - 1 < 0$, so the Bayes risk is minimized by rules d with $R(0, d) = 1$, e.g. $d = (1, 1, \dots)$, and the Bayes risk is λ , $0 \leq \lambda \leq 1/3$.

For $1/3 < \lambda \leq 1$, $3\lambda - 1 > 0$, so the Bayes risk is minimized by rules d with $R(0, d) = 0$; e.g. $d = (1, 0, 0, \dots)$, with Bayes risk $\mathcal{R}(\lambda, d_\lambda) = (1 - \lambda)/2$.

When $\lambda = 1/3$, $3\lambda - 1 = 0$, and all rules with $d(0) = 1$ are Bayes wrt λ , with Bayes risk $\mathcal{R}(\lambda, d_\lambda) = 1/3$. Hence the least favorable prior is $\lambda = (1/3, 2/3)$.

Here is another way: Note that for any minimax rule d_M , d_M is Bayes wrt $\lambda = (1/3, 2/3)$, and for this $\underline{\lambda}$ we have

$$\mathcal{R}(\lambda, d_M) = \frac{1}{3} = \sup_{\theta=0,1} R(\theta, d_M);$$

hence by Theorem 6.2, $\underline{\lambda} = (1/3, 2/3)$ is least favorable.

The Neyman - Pearson approach would be to find d so that $R(0, d) = \alpha < 1$, and so that $R(1, d) =$ probability of type 2 error is as small as possible. Thus we are lead to a rule of the form $d = (1, d_1, d_2, \dots)$ where $\alpha = \sum_1^{\infty} d_x 2^{-x} = R(0, d)$, and then $R(1, d) = 2^{-1}(1 - \alpha)$.

5. Let X be a random variable with distribution function F having finite first moment: $E|X| < \infty$.

(a) Show that $f(b) \equiv E|X - b|$ is minimized by $b =$ any median of the distribution F of X . [A median m of F is any value satisfying $F(m) = P(X \leq m) \geq 1/2$ and $1 - F(m-) = P(X \geq m) \geq 1/2$; see Lehmann and Casella, TPE, page 62, problems 1.7 and 1.8.]

(b) For $0 < \tau < 1$, let $\rho_\tau(x) = x(\tau - 1_{(-\infty, 0)}(x))$. Consider minimizing

$$M_\tau(\theta) = E\rho_\tau(X - \theta)$$

with respect to θ . Show that the solution $\theta_0 = \theta_0(F)$ is given by the τ -th quantile of F : $\theta_0(F) = F^{-1}(\tau)$.

Solution: (a) Suppose that m is a median of F . From Lehmann and Casella problem 1.7, it follows that $m_0 \leq m \leq m_1$ so that the set of medians is a closed interval.

This is easily proved as follows: suppose that \mathcal{M} is the set of medians of F . Note that \mathcal{M} is always non-empty since $m_0 \equiv \inf\{x : F(x) \geq 1/2\} \in \mathcal{M}$. If $\mathcal{M} = \{m_0\}$, then $[m_0, m_0] = \{m_0\}$ is closed. If $a, b \in \mathcal{M}$ with $a < b$, then if $c \in (a, b)$ we have $P(X \leq c) \geq P(X \geq a) \geq 1/2$ (since $a \in \mathcal{M}$), and $P(X \geq c) \geq P(X \geq b) \geq 1/2$ (since $b \in \mathcal{M}$). Thus $c \in \mathcal{M}$ and hence $(a, b) \subset \mathcal{M}$. Let $(m_0, m_1) = \cup_{a, b \in \mathcal{M}}(a, b)$ be the union of all the open intervals contained in \mathcal{M} . Then if $m \in (m_0, m_1)$

$$\begin{aligned} 1/2 \leq P(X \leq m) &= E1\{X \leq m\} \rightarrow E1\{X < m_1\} \leq E1\{X \leq m_1\} = P(X \leq m_1), \quad \text{and} \\ 1/2 \leq P(X \geq m) &= E1\{X \geq m\} \rightarrow E1\{X \geq m_1\} = P(X \geq m_1) \end{aligned}$$

as $m \nearrow m_1$ by the dominated convergence theorem. Thus $m_1 \in \mathcal{M}$. Similarly,

$$\begin{aligned} 1/2 \leq P(X \leq m) &= E1\{X \leq m\} \rightarrow E1\{X \leq m_0\} \leq P(X \leq m_0), \quad \text{and} \\ 1/2 \leq P(X \geq m) &= E1\{X \geq m\} \rightarrow E1\{X > m_0\} \leq P(X \geq m_0) \end{aligned}$$

as $m \searrow m_0$ by the dominated convergence theorem. Thus $m_0 \in \mathcal{M}$ and we conclude that $[m_0, m_1] \subset \mathcal{M}$. On the other hand $\mathcal{M} \subset [m_0, m_1]$ with $m_0 \equiv \inf\{x : F(x) \geq 1/2\}$ and $m_1 \equiv \inf\{x : F(x) > 1/2\}$.

Suppose that $c > m_1$. Then by examining the graphs of $|x - c|$ and $|x - m|$ we see that

$$\begin{aligned} |x - c| - |x - m| &= (m - c)1_{[x \geq c]} + (c - m)1_{[x \leq m]} + \{(c - x) - (x - m)\}1_{[m < x < c]} \\ &= (c - m) \{1_{[x \leq m]} - 1_{[x \leq c]}\} + (c + m - 2x)1_{[m < x < c]} \\ &= (c - m) \{1_{[x \leq m]} - 1_{[x \leq c]}\} + 2(c - x)1_{[m < x < c]} - (c - m)1_{[m < x < c]} \\ &= (c - m) \{1_{[x \leq m]} - 1_{[x > m]}\} + 2(c - x)1_{[m < x < c]}. \end{aligned}$$

Replacing x by X and taking expectations across the identity with respect to X yields

$$\begin{aligned} E|X - c| - E|X - m| &= (c - m)\{P(X \leq m) - P(X > m)\} + 2E\{(c - X)1_{[m < X < c]}\} \\ &> 0 + 0 = 0 \end{aligned}$$

since m is a median of F implies that $P(X \leq m) - P(X > m) \geq 0$ and $c > m_1 \geq m_0$ implies that $E\{(c - X)1_{[m < X < c]}\} = E\{(c - X)1_{[m_1 < X < c]}\} > 0$. Similarly, if $c < m_0$,

$$|x - c| - |x - m| = (m - c)(1_{[x \geq m]} - 1_{[x < m]}) + 2(x - c)1_{[c < x < m]},$$

and taking expectations yields

$$\begin{aligned} E|X - c| - E|X - m| &= (m - c)\{P(X \geq m) - P(X < m)\} + 2E\{(X - c)1_{[c < X < m]}\} \\ &> 0. \end{aligned}$$

Thus $E|X - b|$ is minimized by any median of the distribution F of X .

(b) First rewrite $M_\tau(\theta)$ as

$$\begin{aligned} M_\tau(\theta) &= E\rho_\tau(X - \theta) = (\tau - 1) \int_{(-\infty, \theta]} (x - \theta)dF(x) + \tau \int_{(\theta, \infty)} (x - \theta)dF(x) \\ &= (\tau - 1) \int_{(-\infty, \theta]} (x - \theta)f(x)dx + \tau \int_{(\theta, \infty)} (x - \theta)f(x)dx \end{aligned}$$

if F is absolutely continuous with density f . Thus in this case

$$\begin{aligned} M'_\tau(\theta) &= -(\tau - 1) \int_{(-\infty, \theta]} dF(x) - \tau \int_{(\theta, \infty)} dF(x) \\ &= (1 - \tau)F(\theta) - \tau(1 - F(\theta)) = F(\theta) - \tau \\ &= 0 \end{aligned}$$

if θ is a τ -quantile of F , $\theta = \theta_0(F) = F^{-1}(\tau)$. If F is an arbitrary distribution, then an argument as in (a) shows that any τ -th quantile of F minimizes $M_\tau(\theta)$.