

Econ 240A: Problem Set 3

Solutions to Selected Problems from Chapter 3

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16.

Note that c is a *median* of a random variable X iff $P(X \leq c) \geq \frac{1}{2}, P(X \geq c) \geq \frac{1}{2}$. Note the following two facts:

- The definition of a median is equivalent to the statement that c is a median of X iff $P(X < c) \leq \frac{1}{2}$ and $P(X > c) \leq \frac{1}{2}$.
- It can be shown that the set of all medians $med(X)$ of X is a closed interval (or generalized rectangle): that is, there exist medians c_0, c_1 such that for every median c , $c_0 \leq c \leq c_1$.¹

We use the above two facts to show that $E|X - c|$ is minimized by requiring $c \in med(X)$:

Let $d > c_1$. Let c be a median of X . Therefore $c_0 \leq c \leq c_1$. We have

$$\begin{aligned}
 E|X - d| - E|X - c| &= \int_{x>d} (x - d)dP(x) - \int_{x<d} (x - d)dP(x) \\
 &\quad - \int_{x>c} (x - c)dP(x) + \int_{x<c} (x - c)dP(x) \\
 &= \int_{x<d} (d - x)dP(x) + \int_{x\leq c} (x - d + d - c)dP(x) \\
 &\quad + \int_{x>d} (x - d)dP(x) - \int_{x>c} (x - d + d - c)dP(x) \\
 &= \int_{c<x<d} (d - x)dP(x) + (d - c)P(X \leq c)
 \end{aligned}$$

¹It is clear that $med(X)$ contains a maximal and a minimal element (it's easy to construct a proof by contradiction). It remains to show that $med(X)$ doesn't contain any "holes" or gaps. Let $c_0 \leq c_1$ be medians. Then $P(X \leq c_0) \geq \frac{1}{2}, P(X \geq c_1) \geq \frac{1}{2}$. It follows that for any c such that $c_0 \leq c \leq c_1$, $P(X \leq c) \geq \frac{1}{2}, P(X \geq c) \geq \frac{1}{2}$. Therefore c is also a median, which shows that $med(X)$ is a closed interval (if X is scalar-valued) or a closed rectangle if X is multidimensional.

$$\begin{aligned}
& - \int_{x \geq d} (d-x)dP(x) + \int_{x > c} (d-x)dP(x) \\
& - (d-c)P(X > c) \\
= & \int_{c < x < d} (d-x)dP(x) + (d-c)[P(X \leq c) - P(X > c)] \\
& + \int_{c < x < d} (d-x)dP(x) \\
= & (d-c)[P(X \leq c) - P(X > c)] + 2 \int_{c < x < d} (d-x)dP(x) \\
\geq & 0.
\end{aligned}$$

Similarly, we can show

$$E|X-f| - E|X-c| = 2 \int_{f < x < c} (x-f)dP(x) + (c-f)[P(X \geq c) - P(X < c)] \geq 0$$

for any $f < c_0$.

22.

We have $E(X+aZ)^2 = EX^2 + 2aE[XZ] + a^2EZ^2 \geq 0 \forall a \in \Re$. If $E[Z^2] = 0$ then $E[X^2] = E[XZ] = 0$ and the Cauchy-Schwarz inequality holds with equality. Now assume $E[Z^2] > 0$. Note that if $E(X+aZ)^2 > 0$, the roots of $E(X+aZ)^2$ are nonreal² and are given by

$$a = \frac{-2E[XZ] \pm \sqrt{4(E[XZ])^2 - 4E[Z^2]E[X^2]}}{2E[Z^2]}.$$

Complexity requires $(E[XZ])^2 < E[Z^2]E[X^2]$.

Now $\forall \epsilon > 0$ we have by Markov's inequality that

$$P[|X+aZ| > \epsilon] \leq \frac{E(X+aZ)^2}{\epsilon^2}.$$

If $E(X+aZ)^2 = 0$ it follows that for any scalar a , $P(X = -aZ) = 1$, so $(E[XZ])^2 = E[Z^2]E[X^2]$.

25.

We assume that $Cov(X, Z) = 2\rho$ for $-1 \leq \rho \leq 1$. Let

$$\Sigma \equiv \begin{bmatrix} 1 & 2\rho \\ 2\rho & 4 \end{bmatrix},$$

²Recall that if $a > 0$ and $b^2 - 4ac \geq 0$, $x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$ will solve $ax^2 + bx + c = 0$; otherwise $ax^2 + bx + c > 0 \Leftrightarrow (\sqrt{a}x + \frac{b}{2\sqrt{a}})^2 + \frac{4ac - b^2}{4a} > 0 \Rightarrow 4ac - b^2 > 0$.

which implies that

$$\Sigma^{-1} = \begin{bmatrix} \frac{1}{1-\rho^2} & -\frac{\rho}{2-2\rho^2} \\ -\frac{\rho}{2-2\rho^2} & \frac{1}{4-4\rho^2} \end{bmatrix}.$$

Also, let $Y \equiv \begin{bmatrix} X \\ Z \end{bmatrix}$, $\mu \equiv \begin{bmatrix} 1 \\ 2 \end{bmatrix}$. Note that

$$\begin{aligned} (y - \mu)' \Sigma^{-1} (y - \mu) &= \frac{(x-1)^2}{1-\rho^2} + 2(x-1)(z-2) \left(-\frac{2\rho}{4-4\rho^2}\right) + \frac{(z-2)^2}{4-4\rho^2} \\ &= \frac{1}{1-\rho^2} \left((x-1) - \frac{\rho}{2}(z-2) \right)^2 - \frac{\rho^2(z-2)^2}{4(1-\rho^2)} + \frac{(z-2)^2}{4-4\rho^2} \\ &= \frac{1}{1-\rho^2} \left(x-1 - \frac{\rho}{2}(z-2) \right)^2 + \frac{(z-2)^2}{4}. \end{aligned}$$

Therefore $p(x, z) = p(x|z)p(z) \propto \frac{1}{\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2} \frac{(x-1-\frac{\rho}{2}(z-2))^2}{1-\rho^2}\right] \cdot \frac{1}{2} \exp\left[-\frac{1}{2} \frac{(z-2)^2}{4}\right]$.

It follows that $X|Z = z \sim N\left(1 + \frac{\rho}{2}(z-2), 1-\rho^2\right)$.

Bayes' theorem states that $p(Z|X) = \frac{P(X|Z)P(Z)}{\int p(X|z)p(z)dz}$. We have

$$\begin{aligned} (y - \mu)' \Sigma^{-1} (y - \mu) &= \frac{(x-1)^2}{1-\rho^2} + 2(x-1)(z-2) \left(-\frac{2\rho}{4-4\rho^2}\right) + \frac{(z-2)^2}{4-4\rho^2} \\ &= \frac{(x-1)^2}{1-\rho^2} (1-\rho^2) + \frac{1}{4-4\rho^2} (z-2-2\rho(x-1))^2 \\ &= (x-1)^2 + \frac{1}{4-4\rho^2} (z-2-2\rho(x-1))^2, \end{aligned}$$

so $p(x, z) \propto \exp\left[-\frac{1}{2}(x-1)^2\right] \cdot \frac{1}{2\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2} \frac{(z-2-2\rho(x-1))^2}{4-4\rho^2}\right]$.

We have $\int p(x|z)p(z)dz = \int p(z|x)p(x)dx = p(x) \propto \exp\left[-\frac{1}{2}(x-1)^2\right]$. Therefore $p(z|x) \propto \frac{1}{2\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2} \frac{z-2-2\rho(x-1))^2}{4-4\rho^2}\right]$, so $Z|X = x \sim N(2 + 2\rho(x-1), 4 - 4\rho^2)$.

34.

Note that the moment-generating function of $X - Y$ is given by $M_{X-Y}(t) = M_X(t)M_Y(-t)$. We show that $M_{X-Y}(t)$ is in fact the mgf of a member of the class of logistic distributions.

If X is distributed as an extreme value (or *Gumbel*) random variable with parameters a and b we have that

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} \cdot \frac{1}{b} \exp\left[-\frac{x-a}{b} - e^{-\frac{x-a}{b}}\right] dx.$$

Let $y = \exp[-\frac{x-a}{b}]$. Changing the variable of integration gives us

$$M_X(t) = e^{at} \int_0^\infty y^{-bt} e^{-y} dy = e^{at} \Gamma(1 - bt),$$

assuming that $t < \frac{1}{b}$.

Now if Z is a logistic random variable with parameters a and b we have

$$M_Z(t) = \int_{-\infty}^\infty e^{tz} \cdot \frac{1}{b} \frac{\exp(\frac{a-z}{b})}{(1 + \exp(\frac{a-z}{b}))^2} dz.$$

Let $y = \frac{1}{1 + \exp[\frac{a-z}{b}]}$. Changing variables allows us to write

$$M_Z(t) = e^{at} \int_0^1 y^{bt} (1-y)^{-bt} dy = e^{at} B(1+bt, 1-bt) = e^{at} \Gamma(1+bt) \Gamma(1-bt).$$

Therefore $L = X - Y$ is distributed as a logistic random variable with density $\frac{1}{b} \cdot \frac{\exp[\frac{z-t}{b}]}{(1 + \exp[\frac{z-t}{b}])^2}$. As expected, L has mean 0 and variance equal to twice the variance of X and Y , namely $\frac{(\pi b)^2}{6}$.

37.

Let $Z = \log Y$. We have that $Z \sim N(\mu, \sigma^2)$. One should check that Y does not in fact have a mgf. However one can in fact derive an expression for $E[Y^t]$:

Proceed by noting that the density of Y is given by transforming from the density of a normal (μ, σ^2) distribution:

$$p(y|\mu, \sigma^2) \propto \frac{1}{\sigma} \exp[-\frac{1}{2\sigma^2}(\log y - \mu)^2] \frac{1}{y}.$$

Therefore

$$\begin{aligned} E[Y^t] &= \int_0^\infty \frac{1}{\sigma} \exp[-\frac{1}{2\sigma^2}(\log y - \mu)^2] y^{t-1} dy \\ &= \int_{-\infty}^\infty e^{z(t-1)+z} \frac{1}{\sigma} \phi\left(\frac{z-\mu}{\sigma}\right) dz, \end{aligned}$$

where $\phi(x) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{x^2}{2})$.³ It follows that $E[Y^t] = M_Z(t) = \exp[\mu t + \frac{1}{2}\sigma^2 t^2]$ (i.e., the mgf for a $N(\mu, \sigma^2)$ random variable). Therefore

$$\begin{aligned} E[Y] &= e^{\mu + \frac{1}{2}\sigma^2} \\ \text{Var}[Y] &= e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2} = e^{2\mu + \sigma^2} (e^{\sigma^2} - 1). \end{aligned}$$

³This is standard notation for the pdf of a $N(0, 1)$ random variable.

40.

Suppose

$$\begin{bmatrix} X \\ Y \end{bmatrix} \sim N \left(\begin{bmatrix} \mu_X \\ \mu_Y \end{bmatrix}, \begin{bmatrix} \sigma_X^2 & \rho\sigma_X\sigma_Y \\ \rho\sigma_Y\sigma_X & \sigma_Y^2 \end{bmatrix} \right),$$

where $-1 < \rho < 1$. Proceeding as in Problem 25 above, one can show that

$$\begin{aligned} E[X|Y = y] &= \mu_X + \rho \frac{\sigma_X}{\sigma_Y} (y - \mu_Y), \\ \text{Var}[X|Y = y] &= \sigma_X^2 (1 - \rho^2), \\ E[Y|X = x] &= \mu_Y + \rho \frac{\sigma_Y}{\sigma_X} (x - \mu_X), \\ \text{Var}[Y|X = x] &= \sigma_Y^2 (1 - \rho^2). \end{aligned}$$

So if $\mu_X = 1, \mu_Y = 3$ and $\sigma_X^2 = 4, \sigma_Y^2 = 9, \rho = \frac{5}{6}$, we have

$$X|Y = y \sim N\left(1 + \frac{5}{9}(y - 3), \frac{11}{9}\right)$$

and

$$Y|X = x \sim N\left(3 + \frac{25}{4}(x - 1), \frac{11}{4}\right).$$

Therefore

(a)

$$\begin{aligned} E[2X - Y] &= E(E[2X - Y|Y]) \\ &= E(2E[X|Y] - Y) \\ &= E\left(2\left[1 + \frac{5}{9}Y - 3\right] - Y\right) \\ &= -\frac{11}{3}; \end{aligned}$$

(b)

$$\begin{aligned} \text{Var}[2X - Y] &= \text{Var}(E[2X - Y|Y]) + E(\text{Var}[2X - Y|Y]) \\ &= \text{Var}\left(2 + \frac{10}{9}Y - 6 - Y\right) + E\left(4 \cdot \frac{11}{9} - Y\right) \\ &= 2; \end{aligned}$$

(c)

$$\begin{aligned} E[2X - Y|X = 5] &= 10 - E[Y|X = 5] \\ &= 10 - 3 - \frac{25}{4} \cdot 4 \\ &= -18; \end{aligned}$$

(d)

$$\begin{aligned} \text{Var}[2X - Y|X = 5] &= \text{Var}[Y|X = 5] \\ &= \frac{11}{4}. \end{aligned}$$