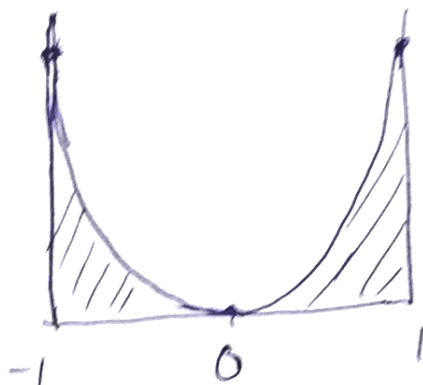


Solution Problem Set 2

1. ■



$$p(y|x) = \frac{1}{x^2} \quad 0 \leq y \leq x^2$$

$$= 0$$

$$p(x) = \frac{1}{2}$$

$$p(x, y) = \frac{1}{2x^2} \quad \left. \begin{array}{l} \text{for } -1 \leq x \leq 1 \\ 0 \leq y \leq x^2 \end{array} \right\} \text{Region R}$$

a) $E[X] = 0$ given symmetry

$(x, y) \rightarrow (-x, y)$ is a symmetry of the distribution.

$$E[X \cdot Y] = \int_R dx dy \, xy p(x, y)$$

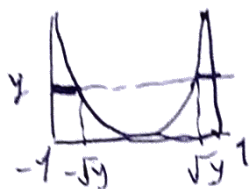
using $x \rightarrow -x$ transformation $= 0$

$$\text{So } \text{Cov}(X, Y) = E[XY] - E[X]E[Y] = 0$$

$$\Rightarrow \text{correlation} = 0$$

$$b) \quad I(x, y) = H(y) - H(y|x)$$

$$p(y) = \int_{-1}^{-\sqrt{y}} + \int_{\sqrt{y}}^1 \left[\frac{1}{2x^2} \right] dx$$



$$= 2 \left[-\frac{1}{2x} \right]_{\sqrt{y}}^1 = \frac{1}{\sqrt{y}} - 1 = \frac{1-\sqrt{y}}{\sqrt{y}}$$

$$H(y) = \int_0^1 dy \frac{1-\sqrt{y}}{\sqrt{y}} \log \frac{\sqrt{y}}{1-\sqrt{y}} = 2 \int_0^1 dt (1-t) \log \frac{t}{1-t}$$

with $y=t^2$

$$H(y|x) = \int_{-1}^1 dx \log x^2 = 2 \int_0^1 dx \log x$$

entropy
of y for fixed x

$$So \quad H(y) - H(y|x) = -2 \int_0^1 dt (1-t) \log(1-t) + 2 \int_0^1 dt (1-t) \log t - 2 \int_0^1 dx \log x$$

$$= -2 \int_0^1 dt (1-t) \log(1-t) + 2 \int_0^1 dt \log t - 2 \int_0^1 dt t \log t - 2 \int_0^1 dx \log x$$

$$= -4 \int_0^1 dt t \log t$$

$$\int_0^1 t^\alpha dt = \left[\frac{t^{2+\alpha}}{2+\alpha} \right]_0^1 = \frac{1}{2+\alpha} = \frac{1}{2} \left(1 + \frac{\alpha}{2}\right)^{-1} = \frac{1}{2} = \frac{\alpha}{4} + o(\alpha^2)$$

$$\begin{aligned} \int_0^1 t^{1+\alpha} dt &= \int_0^1 t (1 + \alpha \log t + o(\alpha^2)) dt \\ &= \frac{1}{2} + \alpha \int_0^1 dt t \log t + o(\alpha^2) \end{aligned}$$

$$\text{So } \int_0^1 dt t \log t = -\frac{1}{4}$$

$$I(X, Y) = 1 \quad \text{in nats} \\ \text{(since I use log base e)}$$

2. All of you did a fine job generating the distribution of the estimates and getting it to be peaked close to the true values.

$$3. a) P(\mathbf{x}) = \frac{e^{-\frac{\sum_{i=1}^N x_i^2}{2\sigma^2}}}{(2\pi\sigma^2)^{N/2}}$$

$$\log P = -\frac{\sum_{i=1}^N x_i^2}{2\sigma^2} - \frac{N}{2} \log 2\pi\sigma^2$$

Vary w.r.t. σ^2

$$\frac{\sum_{i=1}^N x_i^2}{2(\sigma^2)^2} - \frac{N}{2\sigma^2} = 0$$

$$\Rightarrow \hat{\sigma}^2 = \frac{\sum_{i=1}^N x_i^2}{N}$$

$$E[\hat{\sigma}^2] = \frac{N\sigma^2}{N} = \sigma^2$$

$$b) \text{Var}[\hat{\sigma}^2] = \text{Var}\left[\frac{\sum_{i=1}^N (x_i^2 - E[x_i^2])}{N}\right]$$

since $x_i^2 - E[x_i^2]$ are independent

$$\text{Var}[\hat{\sigma}^2] = \sum_{i=1}^N \text{Var}\left[\frac{x_i^2 - E[x_i^2]}{N}\right]$$

$$= \frac{1}{N^2} \sum_{i=1}^N E[(x_i^2 - \sigma^2)^2] = \frac{1}{N^2} \sum_{i=1}^N (E[x_i^4] - \sigma^4)$$

$$= \frac{1}{N^2} N (3\sigma^4 - \sigma^4) = \frac{2\sigma^4}{N}$$

c).

$$I(\sigma^2) = -E\left[\frac{\partial^2 \log P}{(\partial \sigma^2)^2}\right]$$

$$= -E\left[\frac{\partial^2}{(\partial \sigma^2)^2} \left\{ -\frac{\sum x_i^2}{2\sigma^2} - \frac{N}{2} \log(\sigma^2) \right\}\right]$$

$$= -E\left[-\frac{\sum x_i^2}{(\sigma^2)^3} + \frac{N}{2} \frac{1}{(\sigma^2)^2} \right]$$

$$= \frac{N\sigma^2}{(\sigma^2)^3} - \frac{N}{2(\sigma^2)^2}$$

$$= \frac{N}{2\sigma^4}$$

Cramer-Rao bound

$$\text{Var}(\hat{\sigma}^2) \geq \frac{2\sigma^4}{N}$$

In this case we have an equality

4.

$$P(D|\theta) = \prod_{i=1}^N \prod_{\alpha=1}^K \frac{\theta_{\alpha}^{x_{\alpha}^{(i)}}}{x_{\alpha}^{(i)}!}$$

$$\log P = \sum_{\alpha} \left(\sum_i x_{\alpha}^{(i)} \right) \log \theta_{\alpha} - \text{const}$$

depend only on data and not θ

We have the constraint $\sum_{\alpha} \theta_{\alpha} = 1$

$$\frac{\partial}{\partial \theta_{\alpha}} \left[\log P(D|\theta) - \lambda (\sum_{\alpha} \theta_{\alpha} - 1) \right]$$

$$\frac{\sum_i X_{\alpha}^{(i)}}{\hat{\theta}_{\alpha}} - \lambda = 0$$

$$\text{So } \hat{\theta}_{\alpha} = c \sum_{i=1}^N X_{\alpha}^{(i)}$$

To determine c

$$\sum_{\alpha} \hat{\theta}_{\alpha} = 1$$

$$\begin{aligned} 1 &= c \sum_{\alpha=1}^K \sum_{i=1}^N X_{\alpha}^{(i)} \\ &= c \sum_{i=1}^N \sum_{\alpha=1}^K X_{\alpha}^{(i)} \\ &= c \sum_{i=1}^N n \\ &= c N n \end{aligned}$$

$$\text{So } \hat{\theta}_{\alpha} = \frac{\sum_{i=1}^N X_{\alpha}^{(i)}}{nN}$$