MASSACHUSETTS INSTITUTE OF TECHNOLOGY

6.s077

Spring 2018

Problem Set 3

due Tuesday 3/6, in class

Problem 1.

$$\mathbb{P}(\Theta = 1|X = x) = \frac{f_{X|\Theta}(x|1)\mathbb{P}(\Theta = 1)}{f_{X}(x)}$$

$$= \frac{e^{-x} \cdot \frac{1}{2}}{e^{-x} \cdot \frac{1}{2} + 2e^{-2x} \cdot \frac{1}{2}}$$

$$= \frac{1}{1 + 2e^{-x}} \qquad x \ge 0$$

Since Θ can only take two values, to get the MAP estimate we note that $\mathbb{P}(\Theta=1|X=x)\geq \frac{1}{2}$ when $2e^{-x}\leq 1\Rightarrow x\geq \log 2$. Therefore

$$\hat{\Theta}_{MAP} = \begin{cases} 1, & \text{if } X \ge \log 2, \\ 2, & \text{if } X < \log 2. \end{cases}$$

Problem 2. Bayesian estimation with a prior that favors a zero value.

(a) We retain the terms which depend on θ .

$$f_{\Theta|Y}(\theta|y) = \frac{f_{Y|\Theta}(y|\theta) \cdot f_{\Theta}(\theta)}{f_{Y}(y)}$$
$$\propto \exp(-(y-\theta)^{2}/2 - \theta^{2}/2)$$

We maximize the posterior to get the MAP estimate. Taking derivatives yields

$$(y-\theta)-\theta=0 \Rightarrow \theta=\frac{y}{2} \Rightarrow \hat{\Theta}_{MAP}=\frac{Y}{2}$$

For an alternative derivation, note that the posterior is a normal distribution, and its peak is the same as its mean; i.e., the MAP and LMS estimatoes coincide. Furthermore, from the symmetry of $Y = \Theta + W$, we have $\mathbb{E}[\Theta|Y] = \mathbb{E}[W|Y]$. Therefore,

$$Y = \mathbb{E}[Y|Y] = \mathbb{E}[\Theta|Y] + \mathbb{E}[W|Y] = 2\mathbb{E}[\Theta|Y].$$

See also p. 448 of [BT]: Problem 13 and its solution (which is also given in the text) contains a more general version of this idea, extending it to the case of unequal variances.

(b)

$$f_{\Theta|Y}(\theta|y) = \frac{f_{Y|\Theta}(y|\theta) \cdot f_{\Theta}(\theta)}{f_{Y}(y)}$$
$$\propto \exp(-(y-\theta)^{2}/2 - |\theta|)$$

We first consider the possibility that the optimum satisfies $\theta \geq 0$. Taking derivatives yields

$$(y-\theta)-1=0 \Rightarrow \theta=y-1$$

However for $\theta \geq 0$ to hold, this condition can be satisfied only if $y \geq 1$. By a symmetrical argument, a negative optimal θ can be found by setting the derivative to zero only if $y \leq -1$.

If -1 < y < 1, we notice that the function $(y - \theta)^2/2 + |\theta|$ has a positive left derivative and a negative right derivative at $\theta = 0$, and so $\theta = 0$ is optimal.

Putting this all together yields

$$\hat{\Theta}_{MAP} = \begin{cases} Y + 1, & \text{if } Y < -1, \\ 0, & \text{if } -1 \le Y \le 1, \\ Y - 1, & \text{if } Y > 1. \end{cases}$$

Problem 3.

We have from repeated substitution

$$V_{1} = A_{1}$$

$$V_{2} = \frac{2}{3}A_{1} + A_{2}$$

$$V_{3} = \frac{4}{9}A_{1} + \frac{2}{3}A_{2} + A_{3}$$

$$X_{1} = V_{1}$$

$$= A_{1}$$

$$\Rightarrow Y_{1} = A_{1} + W_{1}$$

$$X_{2} = X_{1} + V_{2}$$

$$= \frac{5}{3}A_{1} + A_{2}$$

$$\Rightarrow Y_{2} = \frac{5}{3}A_{1} + A_{2} + W_{2}$$

$$X_3 = X_2 + V_3$$

$$= \frac{19}{9}A_1 + \frac{5}{3}A_2 + A_3$$

$$\Rightarrow Y_3 = \frac{19}{9}A_1 + \frac{5}{3}A_2 + A_3 + W_3$$

Letting $y = (y_1, y_2, y_3)$ and $\theta = (a_1, a_2, a_3)$ we get

$$f_{\Theta|Y}(\theta|y) \propto f_{Y|\Theta}(y|\theta) f_{\Theta}(\theta)$$

$$\propto \exp\left(-\frac{(y_1 - a_1)^2}{2} - \frac{(y_2 - \frac{5}{3}a_1 - a_2)^2}{2} - \frac{(y_3 - \frac{19}{9}a_1 - \frac{5}{3}a_2 - a_3)^2}{2}\right)$$
$$\times \exp\left(-\frac{a_1^2}{2} - \frac{a_2^2}{2} - \frac{a_3^2}{2}\right)$$

Problem 4.

$$\mathbb{E}[(Z-\hat{Z})^2] = \operatorname{var}[Z-\hat{Z}] + \mathbb{E}[(Z-\hat{Z})]^2$$

$$= \operatorname{var}[Z] + \operatorname{var}[\hat{Z}] - 2\operatorname{cov}[Z,\hat{Z}] + a_2^2$$

$$= 1 + \operatorname{var}[a_2Y_2 + a_3Y_3] - 2a_2\operatorname{cov}(Z,Y_2) - 2a_3\operatorname{cov}(Z,Y_3) + a_2^2$$

$$= 1 + 10a_2^2 + 16a_3^2 + 2a_2a_3\operatorname{cov}(Y_2,Y_3) - 2a_2\operatorname{cov}(Z,Y_2) - 2a_3\operatorname{cov}(Z,Y_3)$$

$$= 1 + 10a_2^2 + 16a_3^2 + 2a_2a_3\operatorname{cov}(Z^2,Z^3) - 2a_2\operatorname{cov}(Z,Z^2) - 2a_3\operatorname{cov}(Z,Z^3)$$

$$= 1 + 10a_2^2 + 16a_3^2 - 6a_3$$

So we should set $a_2 = 0$ and $a_3 = \frac{3}{16}$.

Problem 5.

(a) Let
$$g(Z) = \hat{Y} = \mathbb{E}[Y|Z] =$$

$$\mathbb{E}\big[\hat{Y}|Z=z\big] = \mathbb{E}\Big[\Big(\mathbb{E}[Y|Z] - Y\Big)|Z=z\Big]$$

$$= \mathbb{E}\big[g(Z)|Z=z\big] - \mathbb{E}[Y|Z=z]$$

$$= g(z) - g(z)$$

$$= 0$$

(b)
$$\mathbb{E}[\tilde{Y}] = \mathbb{E}\Big[\mathbb{E}[\tilde{Y}|Z]\Big]$$

$$= \mathbb{E}[0]$$

$$= 0$$

(c) Since \hat{Y} is a function of Z,

$$\mathbb{E}[\tilde{Y}\hat{Y}|Z=z] = \hat{Y}\mathbb{E}[\tilde{Y}|Z=z] = 0,$$

where the last equality follows from part (a).

- (d) Same logic as in part (b).
- (e) Substituting $Y = \hat{Y} \tilde{Y}$ yields

$$\begin{split} \mathbb{E}[Y^2] &= \mathbb{E}[\hat{Y}^2] - 2\mathbb{E}[\hat{Y}\tilde{Y}] + \mathbb{E}[\tilde{Y}]^2 \\ &= \mathbb{E}[\hat{Y}^2] + \mathbb{E}[\tilde{Y}]^2 \end{split}$$