

Exercise 5

2 LDA-Derivation from the Least Squares Error (16 points)

$$\begin{aligned}\frac{\partial}{\partial \beta} \sum_{i=1}^N (y^* - X_i \beta)^2 &= \sum_{i=1}^N \left(-2X_i^\top (y^* - X_i \beta) \right) \\ &= \sum_{i=1}^N (-2X_i^\top y^* + 2X_i^\top X_i \beta) \\ &= -2 \left(\sum_{i:y_i^*=1} X_i^\top - \sum_{i:y_i^*=-1} X_i^\top \right) + 2\beta \sum_{i=1}^N X_i^\top X_i\end{aligned}$$

$$\because N_1 = N_{-1} = N/2$$

$$\because \sum_{i:y_i^*=1} X_i^\top = N_1 \mu_1 = \frac{N}{2} \mu_1, \sum_{i:y_i^*=-1} X_i^\top = N_{-1} \mu_{-1} = \frac{N}{2} \mu_{-1}$$

$$\because \mathbb{E}(X^2) = \frac{\sum_{i=1}^N X_i^2}{N}$$

$$\because \sum_{i=1}^N X_i^\top X_i = N \cdot \mathbb{E}(X^2)$$

$$\begin{aligned}\therefore \frac{\partial}{\partial \beta} \sum_{i=1}^N (y^* - X_i \beta)^2 &= -2 \left(\frac{N}{2} \mu_1 - \frac{N}{2} \mu_{-1} \right)^\top + 2\beta N \mathbb{E}(X^2) \\ &= -N(\mu_1 - \mu_{-1})^\top + 2\beta N \mathbb{E}(X^2)\end{aligned}$$

Next, we infer the relationship between $\mathbb{V}(X)$ and Σ .

Frist we need some intermediate result.

$$\because \sum_{i=1}^N X_i = 0$$

$$\therefore \mathbb{V}(X) = \frac{1}{N} \sum_{i=1}^N (X_i - 0)^2 = \frac{1}{N} \sum_{i=1}^N X_i^2$$

Notice that under our assumption, $\mu_{-1} + \mu_1 = 0$.

$$\begin{aligned}\Sigma &= \frac{1}{N} \left(\sum_{i:y_i^*=-1} (X_i - \mu_{-1})^2 + \sum_{i:y_i^*=1} (X_i - \mu_1)^2 \right) \\ &= \frac{1}{N} \left(\sum_{i=1}^N (X_i - 0)^2 + 2 \sum_{i:y_i^*=-1} X_i \mu_{-1} - \sum_{i:y_i^*=-1} \mu_{-1}^2 + 2 \sum_{i:y_i^*=1} X_i \mu_1 - \sum_{i:y_i^*=1} \mu_1^2 \right) \\ &= \mathbb{V}(X) + \frac{1}{N} (2\mu_{-1} \sum_{i:y_i^*=-1} X_i + 2\mu_1 \sum_{i:y_i^*=1} X_i - \sum_{i=1}^N \mu_i^2) \\ &= \mathbb{V}(X) + \frac{1}{N} (2\mu_{-1} \cdot \frac{N}{2} \mu_{-1} + 2\mu_1 \cdot \frac{N}{2} \mu_1 - N \cdot \mu_1^2) \\ &= \mathbb{V}(X) + \mu_{-1}^2 + \mu_1^2 - \mu_1^2 \\ &= \mathbb{V}(X) + \mu_{-1}^2\end{aligned}$$

$$\because \mathbb{V}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2$$

$$\text{also } \because \mathbb{E}(X) = 0$$

$$\begin{aligned}
\mathbb{E}(X^2) &= \mathbb{V}(X) + \mathbb{E}(X)^2 \\
\therefore &= \mathbb{V}(X) \\
&= \Sigma - \mu_{-1}^2
\end{aligned}$$

$$\begin{aligned}
\frac{\partial}{\partial \beta} \sum_{i=1}^N (y^* - X_i \beta)^2 &= -N(\mu_1 - \mu_{-1})^\top + 2\beta N \mathbb{E}(X^2) \\
&= -N(\mu_1 - \mu_{-1})^\top + 2\beta N(\Sigma - \mu_{-1}^2) \\
&= -N(\mu_1 - \mu_{-1})^\top + 2\beta N \Sigma - 2\beta N \mu_{-1}^2
\end{aligned}$$

Now we only need to obtain the $(\mu_1 - \mu_{-1})^\top (\mu_1 - \mu_{-1}) = (\mu_1 - \mu_{-1})^2$ part.

$$\begin{aligned}
(\mu_1 - \mu_{-1})^2 &= \mu_1^2 + \mu_{-1}^2 - 2\mu_1 \mu_{-1} \\
&= \mu_1^2 + \mu_{-1}^2 - 2\mu_1(-\mu_1) \\
&= 4\mu_1^2
\end{aligned}$$

$$\begin{aligned}
\frac{\partial}{\partial \beta} \sum_{i=1}^N (y^* - X_i \beta)^2 &= -N(\mu_1 - \mu_{-1})^\top + 2\beta N \Sigma - 2\beta N \mu_{-1}^2 \\
&= -N(\mu_1 - \mu_{-1})^\top + 2\beta N \Sigma - \frac{1}{2} \beta N (4\mu_1^2) \\
&= -N(\mu_1 - \mu_{-1})^\top + 2\beta N \Sigma - \frac{1}{2} \beta N (\mu_1 - \mu_{-1})^2 \stackrel{!}{=} 0
\end{aligned}$$

Dividing by $2N$

$$\begin{aligned}
&\Rightarrow -\frac{1}{2}(\mu_1 - \mu_{-1})^\top + \beta \Sigma - \frac{1}{4} \beta (\mu_1 - \mu_{-1})^2 = 0 \\
&\Rightarrow \beta \Sigma - \frac{1}{4} \beta (\mu_1 - \mu_{-1})^2 = \frac{1}{2}(\mu_1 - \mu_{-1})^\top
\end{aligned}$$