

Q 2.6.1

$$y_i \in \{c_1, c_2, \dots, c_{j_3}\}$$

we have to classify y_i such that posterior is max.
or c_i here.

$$y_i^* = \arg \max P(c_i | w_i)$$

$$y_i^* = \arg \max_{c_i} P(w_i | c_i) \cdot \text{Prior}$$

\downarrow Bernoulli \downarrow Beta (c_i)

$$\text{Bernoulli}(w | c_i) = c_i^w (1 - c_i)^{(1-w)}$$

$$\text{Beta}(c_i) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} \cdot c_i^{\alpha-1} (1 - c_i)^{\beta-1}$$

$$\text{Likelihood} = \arg \max_{c_i} \prod_{i=1}^n [c_i^w (1 - c_i)^{(1-w)}] \cdot \frac{\Gamma(\alpha + \beta) \cdot c_i^{\alpha-1} (1 - c_i)^{\beta-1}}{\Gamma(\alpha) \Gamma(\beta)}$$

taking log to convert $\prod \rightarrow \sum$

$$LL = \sum \ln(c_i^w (1 - c_i)^{(1-w)}) + \ln\left(\frac{\Gamma(\alpha + \beta) \cdot c_i^{\alpha-1} (1 - c_i)^{\beta-1}}{\Gamma(\alpha) \Gamma(\beta)}\right)$$

taking derivative & putting equal to zero

$$\sum \frac{\partial \ln(c_i^w (1 - c_i)^{(1-w)})}{\partial c_i} = \frac{1}{c_i} \sum w_i - \frac{1}{1 - c_i} \sum (1 - w_i)$$

Q2.6.1
Contd

$$\frac{\partial}{\partial c_i} \log \left(\frac{\Gamma(\alpha + \beta) \cdot c_i^{\alpha-1} (1-c_i)^{\beta-1}}{\Gamma(\alpha) \cdot \Gamma(\beta)} \right)$$

$$= \frac{\partial}{\partial c_i} \log \left(\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \cdot \Gamma(\beta)} \right) + \frac{\partial}{\partial c_i} \log c_i^{\alpha-1} \cdot (1-c_i)^{\beta-1}$$

$$= 0 + \frac{\alpha-1}{c_i} - \frac{\beta-1}{1-c_i}$$

now we put $\frac{\partial L}{\partial c_i} = 0$

$$0 = \frac{1}{c_i} \sum w_i - \frac{1}{1-c_i} \sum (1-w_i) + \frac{\alpha-1}{c_i} - \frac{\beta-1}{(1-c_i)}$$

$$c_i \left[\sum (1-w_i) + \beta-1 \right] = (1-c_i) \left[\sum w_i + \alpha-1 \right]$$

$$C_i \left[\sum (1 - \frac{w_i}{N}) + \sum w_i + \beta - 1 + \alpha - 1 \right] = \sum_{i=1}^N w_i + \alpha - 1$$

$$C_i \Rightarrow \left[\sum_{\substack{\downarrow \\ N \rightarrow \text{total } N}} 1 + \beta + \alpha - 2 \right] = \sum w_i + \alpha - 1$$

$\therefore \sum w_i$ denote word to be found
we can say N^f

$$C_i = \frac{N^f + \alpha - 1}{N + \beta + \alpha - 2} \rightarrow \text{smoothing}$$

Q2.6.3. Problem with ML estimators

① ML estimator does not incorporate any prior knowledge and thus don't generate estimate of certainty of results.

② ML estimator just represent proportions.
i.e. μ .

~~MAP~~

MAP.

~~we have prior beliefs, without seeing the data~~

→ we have prior beliefs about μ , even before observing the data.

→ with Bayes law we convert these prior beliefs to posterior Prob probability. $P(\mu/x)$

→ MAP estimates are ~~relative~~ produced by maximizing the ~~posterior~~ ~~log~~ likelihood func.

and hence we can inject our prior beliefs into new estimation.