

Q2(a)

MSE

Let k be the number of x_i in R_{jm}

$$r_{jm} = \underset{r}{\operatorname{argmin}} \sum_{x_i \in R_{jm}} (y_i - f_{m-1}(x_i) - r)^2$$

$$0 = \frac{\partial}{\partial r} \sum_{x_i \in R_{jm}} (y_i - f_{m-1}(x_i) - r)^2$$

$$0 = \sum_{x_i \in R_{jm}} 2(y_i - f_{m-1}(x_i) - r)$$

$$0 = \sum_{x_i \in R_{jm}} 2y_i - 2f_{m-1}(x_i) - 2r$$

$$0 = \sum_{x_i \in R_{jm}} 2y_i - 2f_{m-1}(x_i) - \sum_{x_i \in R_{jm}} 2r$$

$$0 = \sum_{x_i \in R_{jm}} 2y_i - 2f_{m-1}(x_i) - 2kr$$

$$2kr = \sum_{x_i \in R_{jm}} 2y_i - 2f_{m-1}(x_i)$$

$$r_{jm}^* = \frac{1}{2k} \sum_{x_i \in R_{jm}} 2y_i - 2f_{m-1}(x_i)$$

$$r_{jm}^* = \frac{1}{k} \sum_{x_i \in R_{jm}} y_i - f_{m-1}(x_i)$$

2(a) Binomial deviance

$$\text{odds} = \frac{p}{1-p}$$

$$\begin{aligned} D &= -2 [y_i \cdot \log(p) + (1-y_i) \cdot \log(1-p)] \\ &= -2 [y_i \log(p) + \log(1-p) - y_i \log(1-p)] \\ &= -2 [y_i (\log(p) - \log(1-p)) + \log(1-p)] \\ &= -2 [y_i \log\left(\frac{p}{1-p}\right) + \log(1-p)] \\ &= -2 [y_i \log(\text{odds}) - \log(1-p)] \\ &= -2 [y_i \log(\text{odds}) - \log(1 + e^{\log(\text{odds})})] \end{aligned}$$

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$$\begin{aligned} \log(1-p) &= \log\left(1 - \frac{e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}}\right) = \log\left(\frac{1 + e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}} - \frac{e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}}\right) \\ &= \log\left(\frac{1}{1 + e^{\log(\text{odds})}}\right) \\ &= \log(1) - \log(1 + e^{\log(\text{odds})}) \\ &= -\log(1 + e^{\log(\text{odds})}) \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial \log(\text{odds})} &-2 [y_i \log(\text{odds}) - \log(1 + e^{\log(\text{odds})})] \\ &= -2 \left[y_i - \frac{e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}} \right] \\ &= -2 [y_i - p] \end{aligned}$$

$$\begin{aligned}
& \frac{\partial^2}{\partial^2 \log(\text{odds})} - 2 [y_i \log(\text{odds}) - \log(1 + e^{\log(\text{odds})})] \\
&= 2 \frac{\partial}{\partial^2 \log(\text{odds})} \left[-y_i + \frac{e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}} \right] \\
&= 2 \left[-\log(\text{odds})^{-2} e^{\log(\text{odds})} \cdot e^{\log(\text{odds})} + (1 + e^{\log(\text{odds})})^{-1} e^{\log(\text{odds})} \right] \\
&= 2 \left[\frac{-e^{2\log(\text{odds})}}{(1 + e^{\log(\text{odds})})^2} + \frac{e^{\log(\text{odds})}}{(1 + e^{\log(\text{odds})})} \right] \\
&= 2 \left[\frac{-e^{2\log(\text{odds})}}{(1 + e^{\log(\text{odds})})^2} + \frac{e^{\log(\text{odds})} + e^{2\log(\text{odds})}}{(1 + e^{\log(\text{odds})})^2} \right] \\
&= 2 \left[\frac{-e^{2\log(\text{odds})} + e^{\log(\text{odds})} + e^{2\log(\text{odds})}}{(1 + e^{\log(\text{odds})})^2} \right] \\
&= 2 \frac{e^{\log(\text{odds})} \times 1}{(1 + e^{\log(\text{odds})}) (1 + e^{\log(\text{odds})})} \\
&= 2 \cdot \frac{e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}} \cdot \frac{1}{1 + e^{\log(\text{odds})}} \\
&= 2 p(1-p)
\end{aligned}$$

Taylor expansion

$$\begin{aligned}
L(y_i, F_{m-1}(x_i) + r) &\approx L(y_i, F_{m-1}(x_i) + r) + \frac{\partial}{\partial F} L(y_i, F_{m-1}(x_i)) r \\
&\quad + \frac{1}{2} \frac{\partial^2}{\partial^2 F} L(y_i, F_{m-1}(x_i)) r^2
\end{aligned}$$

$$\therefore r_{jm} = \arg \min_r \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + r)$$

$$0 = \frac{\partial}{\partial r} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + r)$$

$$\begin{aligned}
0 &= \frac{\partial}{\partial r} \sum_{x_i \in R_{jm}} \left\{ L(y_i, F_{m-1}(x_i) + r) + \frac{\partial}{\partial F} L(y_i, F_{m-1}(x_i)) r \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2}{\partial^2 F} L(y_i, F_{m-1}(x_i)) r^2 \right\}
\end{aligned}$$

$$\sum_{x_i \in R_{jm}} \left[\frac{\partial}{\partial F} L(y_i, F_{m-1}(x_i)) + \frac{\partial^2}{\partial F^2} L(y_i, F_{m-1}(x_i)) r \right] = 0$$

$$r = \frac{-\sum_{x_i \in R_{jm}} \frac{\partial}{\partial F} L(y_i, F_{m-1}(x_i))}{\sum_{x_i \in R_{jm}} \frac{\partial^2}{\partial F^2} L(y_i, F_{m-1}(x_i))}$$

$$= \frac{\sum_{x_i \in R_{jm}} 2(y_i - p)}{\sum_{x_i \in R_{jm}} 2p(1-p)}$$

$$= \frac{\sum_{x_i \in R_{jm}} (y_i - p)}{\sum_{x_i \in R_{jm}} p(1-p)}$$

$$\therefore L(y_i, F_{m-1}(x_i)) = -2 [y_i F_{m-1}(x_i) - \log(1 + e^{F_{m-1}(x_i)})]$$

$$\therefore \frac{\partial}{\partial F} L(y_i, F_{m-1}(x_i)) = -2(y_i - p)$$

$$\frac{\partial^2}{\partial F^2} L(y_i, F_{m-1}(x_i)) = 2p(1-p)$$

$$\log\left(\frac{p}{1-p}\right) = \log(\text{odds}) = F_{m-1}(x_i)$$

$$e^{\log\left(\frac{p}{1-p}\right)} = e^{F_{m-1}(x_i)}$$

$$\frac{p}{1-p} = e^{F_{m-1}(x_i)}$$

$$p = e^{F_{m-1}(x_i)} - e^{F_{m-1}(x_i)} p$$

$$(1 + e^{F_{m-1}(x_i)}) p = e^{F_{m-1}(x_i)}$$

$$p = \frac{e^{F_{m-1}(x_i)}}{1 + e^{F_{m-1}(x_i)}}$$

$$r_{jm}^* = \frac{\sum_{x_i \in R_{jm}} (y_i - p)}{\sum_{x_i \in R_{jm}} p(1-p)} \quad \text{where} \quad p = \frac{e^{F_{m-1}(x_i)}}{1 + e^{F_{m-1}(x_i)}}$$

$$2(b) \quad \text{Obj}(\theta)^t = \sum_{i=1}^n \mathcal{L}(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \mathcal{R}(f_t) + \text{constant}$$

$$\text{where } \mathcal{R}(f_t) = rT + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2$$

$$\text{Let } g_i = \frac{\partial}{\partial \hat{y}^{(t-1)}} \mathcal{L}(y_i, \hat{y}^{(t-1)}) \quad h_i = \frac{\partial^2}{\partial \hat{y}^{(t-1)^2}} \mathcal{L}(y_i, \hat{y}^{(t-1)})$$

Using Taylor approximation:

$$\begin{aligned} \text{Obj}(\theta)^t &\approx \sum_{i=1}^n \left[\mathcal{L}(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \mathcal{R}(f_t) + \text{constant} \\ &\propto \sum_{i=1}^n \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \mathcal{R}(f_t) \\ &= \sum_{i=1}^n \left[g_i w_{L(x_i)} + \frac{1}{2} h_i w_{L(x_i)}^2 \right] + rT + \lambda \frac{1}{2} \sum_{j=1}^T w_j^2 \\ &= \sum_{j=1}^T \left[\left(\sum_{i \in \mathcal{I}_j} g_i \right) w_j + \frac{1}{2} \left(\sum_{i \in \mathcal{I}_j} h_i + \lambda \right) w_j^2 \right] + rT \end{aligned}$$

$$\begin{aligned} &\sum_{j=1}^T \left(\sum_{i \in \mathcal{I}_j} h_i + \lambda \right) w_j^2 \\ &= \sum_{j=1}^T \frac{1}{2} \left(\sum_{i \in \mathcal{I}_j} h_i \right) w_j^2 + \frac{1}{2} \lambda w_j^2 \\ &= \sum_{j=1}^T \frac{1}{2} \left(\sum_{i \in \mathcal{I}_j} h_i + \lambda \right) w_j^2 \end{aligned}$$

$$\begin{aligned} \text{Let } G_j &= \sum_{i \in \mathcal{I}_j} g_i \\ H_j &= \sum_{i \in \mathcal{I}_j} h_i \end{aligned}$$

$$\therefore \hat{\text{Obj}}(\theta)^t = \sum_{j=1}^T \left[G_j w_j + \frac{1}{2} (H_j + \lambda) w_j^2 \right] + rT$$

$$\frac{\partial \hat{\text{Obj}}(\theta)^t}{\partial w_j} = G_j + (H_j + \lambda) w_j = 0$$

$$w_j = - \frac{G_j}{H_j + \lambda}$$

- MSE :

$$g_i = \frac{\partial}{\partial \hat{y}^{(t-1)}} (y_i - \hat{y}^{(t-1)})^2$$

$$= -2 (y_i - \hat{y}^{(t-1)})$$

$$h_i = \frac{\partial^2}{\partial^2 \hat{y}^{(t-1)}} (y_i - \hat{y}^{(t-1)})^2$$

$$= \frac{\partial}{\partial \hat{y}^{(t-1)}} -2 y_i + 2 \hat{y}^{(t-1)}$$

$$= 2$$

$$G_j = \sum_{i \in I_j} -2 (y_i - \hat{y}^{(t-1)})$$

$$H_j = \sum_{i \in I_j} 2$$

$$w_j = - \frac{\sum_{i \in I_j} -2 (y_i - \hat{y}^{(t-1)})}{\sum_{i \in I_j} 2 + \lambda}$$

- Binomial deviance :

$$g_i = -2 (y_i - p)$$

$$h_i = 2 p (1 - p)$$

$$G_j = \sum_{i \in I_j} -2 (y_i - p)$$

$$H_j = \sum_{i \in I_j} 2 p (1 - p)$$

$$\log\left(\frac{p}{1-p}\right) = \log(\text{odds}) = \hat{y}^{(t-1)}$$

$$p = \frac{e^{\hat{y}^{(t-1)}}}{1 + e^{\hat{y}^{(t-1)}}}$$

$$w_j = - \frac{\sum_{i \in I_j} -2 (y_i - p)}{\sum_{i \in I_j} 2 p (1 - p) + \lambda} \quad \text{where } p = \frac{e^{\hat{y}^{(t-1)}}}{1 + e^{\hat{y}^{(t-1)}}}$$