

Problem Set #2

2. (a)

$$\frac{\sum_{i \in I_{a,b}} P(y^{(i)} = 1 | x^{(i)}; \theta)}{|\{i \in I_{a,b}\}|} = \frac{\sum_{i \in I_{a,b}} \mathbb{I}\{y^{(i)} = 1\}}{|\{i \in I_{a,b}\}|}$$

$$P(y=1|x, \theta) = h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

$I_{a,b} = \{i | i \in \{1, \dots, m\}, h_{\theta}(x^{(i)}) \in (a, b)\}$ ← index set of training examples

$|S|$: size of the set S .

Show that the above property holds true for the described logistic regression model over the range of $(a,b) = (0,1)$

$$\{x^{(i)}, y^{(i)}\}_{i=1}^m$$

$$\underline{x_0^{(i)} = 1} \quad x^{(i)} \in \mathbb{R}^{n+1} \quad y^{(i)} \in \{0,1\} \quad \theta \in \mathbb{R}^{n+1}$$

$$\frac{\sum_{i \in I_{a,b}} P(y^{(i)} = 1 | x^{(i)}; \theta)}{|\{i \in I_{a,b}\}|} = \frac{\sum_{i \in I_{a,b}} h_{\theta}(x)}{|\{i \in I_{a,b}\}|} = \frac{\sum_{i \in I_{a,b}} \frac{1}{1 + e^{-\theta^T x^{(i)}}}}{|\{i \in I_{a,b}\}|} \quad |\{i \in I_{a,b}\}| = |\{i \in I_{0,1}\}| = m$$

$$= \frac{\sum_{i \in I_{a,b}} \frac{1}{1 + e^{-\theta^T x^{(i)}}}}{m} = \frac{1}{m} \sum_{i \in I_{a,b}} \frac{1}{1 + e^{-\theta^T x^{(i)}}} = \frac{1}{m} \sum_{i \in I_{a,b}} \frac{1}{1 + e^{-(\theta_0 + \theta^T x^{(i)})}} = \frac{1}{m} \left\{ \sum_{i=1}^m \frac{1}{1 + e^{-(\theta_0 + \theta^T x^{(i)})}} \right\}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \quad x^{(i)} = \begin{bmatrix} x_0^{(i)} \\ x_1^{(i)} \\ \vdots \\ x_n^{(i)} \end{bmatrix} = 1 \quad \theta^T = \begin{bmatrix} \theta_1 & \dots & \theta_n \end{bmatrix} \quad x'^{(i)} = \begin{bmatrix} x_1^{(i)} \\ x_2^{(i)} \\ \vdots \\ x_n^{(i)} \end{bmatrix} \quad \theta_0 x_0^{(i)} = \theta_0 = \text{bias term}$$

$$\frac{1}{m} \left\{ \sum_{i=1}^m \frac{1}{1 + e^{-(\theta_0 + \theta^T x^{(i)})}} \right\} = \frac{\sum_{i \in I_{a,b}} \mathbb{I}\{y^{(i)} = 1\}}{|\{i \in I_{a,b}\}|} = \frac{1}{m} \sum_{i \in I_{a,b}} \mathbb{I}\{y^{(i)} = 1\}$$

$$\sum_{i=1}^m \frac{1}{1 + e^{-(\theta_0 + \theta^T x^{(i)})}} = \sum_{i=1}^m \mathbb{I}\{y^{(i)} = 1\} = \sum_{i=1}^m y^{(i)}$$

negative log likelihood

$$l(\theta) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log h_{\theta}(x^{(i)}) + (1-y^{(i)}) \log (1-h_{\theta}(x^{(i)}))]$$

$$h_{\theta}(x^{(i)}) = \frac{1}{1+e^{-(\theta^T x + \theta_0)}} = \sigma(x)$$

(i) when $j=0$

$$\frac{\partial}{\partial \theta_0} l(\theta) = \frac{\partial}{\partial \theta_0} \left[-\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log h_{\theta}(x^{(i)}) + (1-y^{(i)}) \log (1-h_{\theta}(x^{(i)}))] \right]$$

$$= -\frac{1}{m} \sum_{i=1}^m \left[y^{(i)} \times \frac{1}{h_{\theta}(x^{(i)})} \times \sigma(x) (1-\sigma(x)) \times 1 + (1-y^{(i)}) \times \frac{1}{1-h_{\theta}(x^{(i)})} \times (-\sigma(x))(1-\sigma(x)) \times 1 \right]$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} (1-\sigma(x)) + (1-y^{(i)}) (-\sigma(x))]$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} (1-h_{\theta}(x^{(i)}) - h_{\theta}(x^{(i)}) + y^{(i)} h_{\theta}(x^{(i)})]$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} - h_{\theta}(x^{(i)})] = 0$$

$$\therefore \sum_{i=1}^m y^{(i)} = \sum_{i=1}^m h_{\theta}(x^{(i)})$$

(ii) When $j \neq 0$

$$\frac{\partial}{\partial \theta_j} \ell(\theta) = \frac{\partial}{\partial \theta_j} \left[-\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log h_{\theta}(x^{(i)}) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)}))] \right] = 0$$

$$h_{\theta}(x^{(i)}) = \frac{1}{1 + e^{-(\theta^T x^{(i)} + \theta_0)}}$$

$$\begin{aligned} \frac{\partial}{\partial \theta_j} \ell(\theta) &= -\frac{1}{m} \sum_{i=1}^m \left[y^{(i)} \times \frac{1}{h_{\theta}(x^{(i)})} \times \sigma(x^{(i)}) (1 - \sigma(x^{(i)})) x_j^{(i)} + (1-y^{(i)}) \frac{1}{1-h_{\theta}(x^{(i)})} \right. \\ &\quad \left. \times (-1) \sigma(x^{(i)}) (1 - \sigma(x^{(i)})) x_j^{(i)} \right] \end{aligned}$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} (1-h_{\theta}(x^{(i)})) x_j^{(i)} + (1-y^{(i)}) (-1) \sigma(x^{(i)}) x_j^{(i)}] = 0$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} x_j^{(i)} - y^{(i)} h_{\theta}(x^{(i)}) x_j^{(i)} - (1-y^{(i)}) h_{\theta}(x^{(i)}) x_j^{(i)}] = 0$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} x_j^{(i)} - y^{(i)} h_{\theta}(x^{(i)}) x_j^{(i)} - h_{\theta}(x^{(i)}) x_j^{(i)} + y^{(i)} h_{\theta}(x^{(i)}) x_j^{(i)}] = 0$$

$$= -\frac{1}{m} \sum_{i=1}^m [y^{(i)} x_j^{(i)} - h_{\theta}(x^{(i)}) x_j^{(i)}] = 0$$

$$\sum_{i=1}^m y^{(i)} x_j^{(i)} = \sum_{i=1}^m h_{\theta}(x^{(i)}) x_j^{(i)}$$

$$y^T x_j = h_{\theta}(x)^T x_j$$

$$\therefore \sum_{i=1}^m y^{(i)} = \sum_{i=1}^m h_{\theta}(x^{(i)})$$

Therefore,

$$\frac{\sum_{i \in \mathcal{I}_{a,b}} h_{\theta}(x^{(i)})}{|\{i \in \mathcal{I}_{a,b}\}|} = \frac{\sum_{i \in \mathcal{I}_{a,b}} y^{(i)}}{|\{i \in \mathcal{I}_{a,b}\}|}$$

$$(a|b) = (0,1)$$