

Problem 1 (Naive Bayes problem sets)

In this problem, we look at maximum likelihood parameter estimation using the naive Bayes assumption. Here, the input features $x_j, j = 1, \dots, n$ to our model are discrete, binary-valued variables, so $x_j \in \{0, 1\}$. We call $x = [x_1, x_2, \dots, x_n]^T$ to be the input vector. For each training example, our output targets are a single binary-value $y \in \{0, 1\}$. Our model is then parameterized by $\theta_{j|y=0} = p(x_j = 1|y = 0), \theta_{j|y=1} = p(x_j = 1|y = 1)$, and $\theta_y = p(y = 1)$. We model the joint distribution of (x, y) according to

$$\begin{aligned} P(y) &= (\theta_y)^y (1 - \theta_y)^{1-y} \\ p(x|y = 0) &= \prod_{j=1}^n p(x_j|y = 0) \\ p(x|y = 1) &= \prod_{j=1}^n p(x_j|y = 1) \end{aligned}$$

- (a) Find the joint likelihood function $L = \log \prod_{i=1}^m p(x^{(i)}, y^{(i)}; \theta)$ in terms of the model parameters given above. Here, θ represents the entire set of parameters $\{\theta_y, \theta_{j|y=0}, \theta_{j|y=1}, j = 1, \dots, n\}$.
- (b) Derive the parameters $\theta_y, \theta_{j|y=0}, \theta_{j|y=1}$ which maximize the likelihood function

(a)

$$\begin{aligned} L &= \log \prod_{i=1}^m p(x^{(i)}, y^{(i)}; \theta) \\ &= \log \prod_{i=1}^m p(x^{(i)}|y^{(i)}; \theta) P(y^{(i)}; \theta) \\ &= \log \prod_{i=1}^m \left(\prod_{j=1}^n p(x_j^{(i)}|y^{(i)}; \theta) \right) P(y^{(i)}; \theta) \\ &= \sum_{i=1}^m \left(\sum_{j=1}^n \log p(x_j^{(i)}|y^{(i)}; \theta) \right) + \log P(y^{(i)}; \theta) \\ &= \sum_{i=1}^m \left(\sum_{j=1}^n (x_j^{(i)} \log \theta_{j|y^{(i)}} + (1 - x_j^{(i)}) \log(1 - \theta_{j|y^{(i)}})) + y^{(i)} \log \theta_y + (1 - y^{(i)}) \log(1 - \theta_y) \right) \end{aligned}$$

(b)

$$\begin{aligned}
\nabla_{\theta_{j|y=0}} L &= \nabla_{\theta_{j|y=0}} \sum_{j=1}^m (x_j^{(i)} \log \theta_{j|y^{(i)}} + (1 - x_j^{(i)}) \log(1 - \theta_{j|y^{(i)}})) \\
&= \nabla_{\theta_{j|y=0}} \sum_{j=1}^m (x_j^{(i)} \log \theta_{j|y=0} 1\{y^{(i)} = 0\} + (1 - x_j^{(i)}) \log(1 - \theta_{j|y=0}) 1\{y^{(i)} = 0\}) \\
&= \sum_{j=1}^m \left(\frac{x_j^{(i)} 1\{y^{(i)} = 0\}}{\theta_{j|y=0}} + \frac{(1 - x_j^{(i)}) 1\{y^{(i)} = 0\}}{1 - \theta_{j|y=0}} \right) \\
0 &= \sum_{j=1}^m \left(\frac{x_j^{(i)} 1\{y^{(i)} = 0\}}{\theta_{j|y=0}} + \frac{(1 - x_j^{(i)}) 1\{y^{(i)} = 0\}}{1 - \theta_{j|y=0}} \right) \\
&= \sum_{j=1}^m (x_j^{(i)} (1 - \theta_{j|y=0}) 1\{y^{(i)} = 0\} + (1 - x_j^{(i)}) \theta_{j|y=0} 1\{y^{(i)} = 0\}) \\
&= \sum_{j=1}^m ((x_j^{(i)} - \theta_{j|y=0}) 1\{y^{(i)} = 0\}) \\
&= \sum_{j=1}^m (x_j^{(i)} 1\{y^{(i)} = 0\}) - \sum_{j=1}^m (\theta_{j|y=0}) 1\{y^{(i)} = 0\} \\
&= \sum_{j=1}^m (1\{x_j^{(i)} = 1 \wedge y^{(i)} = 0\}) - \theta_{j|y=0} \sum_{j=1}^m 1\{y^{(i)} = 0\} \\
\theta_{j|y=0} &= \frac{\sum_{j=1}^m (1\{x_j^{(i)} = 1 \wedge y^{(i)} = 0\})}{\sum_{j=1}^m 1\{y^{(i)} = 0\}}
\end{aligned}$$

Therefore,

$$\begin{aligned}
\theta_{j|y=1} &= \frac{\sum_{j=1}^m (1\{x_j^{(i)} = 1 \wedge y^{(i)} = 1\})}{\sum_{j=1}^m 1\{y^{(i)} = 1\}} \\
\nabla_{\theta_y} L &= \nabla_{\theta_y} \sum_{j=1}^m (y^{(i)} \log \theta_y + (1 - y^{(i)}) \log(1 - \theta_y)) \\
0 &= \sum_{j=1}^m (y^{(i)} (1 - \theta_y) + (1 - y^{(i)}) \theta_y) \\
&= \sum_{j=1}^m y^{(i)} - \sum_{j=1}^m \theta_y \\
\theta_y &= \frac{\sum_{j=1}^m 1\{y^{(i)} = 1\}}{m}
\end{aligned}$$