

## Theory Portion

I. A)  $z = w_0 + w_1x_1 + \dots + w_nx_n$  or  $\langle w, x \rangle$ ,  $\text{sigmoid}(z) = \frac{1}{1+e^{-z}}$ ,  $y = \begin{cases} 1, & \text{sigmoid}(z) \\ 0, & 1 - \text{sigmoid}(z) \end{cases}$

B)  $P(y = 1|x) = \frac{P(x|y=1) * P(x)}{P(y=1)}$ ,  $P(y = 0|x) = \frac{P(x|y=0) * P(x)}{P(y=0)}$

C)  $P(x_j|d_i) = \frac{1}{\sigma_{ji}\sqrt{2\pi}} \exp\left(-\frac{(x_j - \mu_{ji})^2}{2\sigma_{ji}^2}\right)$

D)  $P(y = 1|x) = \frac{P(x_j|d_i) * P(d_i)}{P(y=1)} \propto P(x_j|d_i) * P(d_i)$

E) huh?

II. Cross-Verification Failure:

Since we know that the  $P(y = 1) = P(y = 0) = \frac{1}{2}$  or the  $\text{loss}_D(h) = \frac{1}{2}$  is used when choosing the label, and that the learning predictor:

$$h(x) = \begin{cases} 1, & \text{if number of 1s in training set labels is odd} \\ 0, & \text{otherwise} \end{cases}$$

Let say that the number of 1s in training set labels is odd, then you leave-one-out, thus making the predictor constantly output 0, so since the output is all the same then the  $\text{loss}_S(h) = 1$ . And vice versa this is true when training set labels is even. So  $\text{loss}_S(h) - \text{loss}_D(h) = 1/2$

III. Decision Tree:

Labels =  $\{0, 1\}$ , and data points of  $x_i$   $i \in (1, \dots, d)$ . Decision tree is a recursive algorithm that build the tree based on test or question (is  $x_i = 0$ ) we recursively find best feature  $x$  and split on it, since there is  $d$  numbers of  $x$  we split on it  $d+1$  because each split we would remove the used feature.