This is a review of machine learning designed as a memory refresher; f not all concepts have been discussed in class. Feel free to consult any reference materials.

## 1. [10 pts] Understanding Entropy

This problem reviews Shannon's informational entropy. Please use  $log_2$  for all computations.

(a) Compute the entropy of the following distribution.

$$X = \begin{cases} 1 & \text{w.p. } 0.3 \\ 0 & \text{w.p. } 0.7 \end{cases}$$

(b) Compute the entropy of the following distribution.

$$X = \begin{cases} 1 & \text{w.p. } 0.6 \\ 0 & \text{w.p. } 0.4 \end{cases}$$

(c) Compute the entropy of the following distribution.

$$X = \begin{cases} 1 & \text{w.p. } 0.998 \\ 0 & \text{w.p. } 0.002 \end{cases}$$

- (d) Note that increasing Pr[X = 1] monotonically from 0.3 to 0.6 to 0.998 does not increase entropy monotonically. Assuming two outcomes, what distribution of X maximizes entropy?
- (e) In your own words, relate entropy to the concept of surprise (aka information content).

## 2. [10 pts] Understanding Cross-Entropy

Suppose we have a true distribution of

$$P = \begin{cases} 10 & \text{w.p. } 0.65 \\ 11 & \text{w.p. } 0.25 \\ 12 & \text{w.p. } 0.1 \end{cases}$$

and an estimated distribution of

$$Q = \begin{cases} 10 & \text{w.p. } 0.1 \\ 11 & \text{w.p. } 0.4 \\ 12 & \text{w.p. } 0.5 \end{cases}$$

- (a) Compute the cross-entropy H(P,Q).
- (b) Suppose we obtain a better estimate Q' s.t.

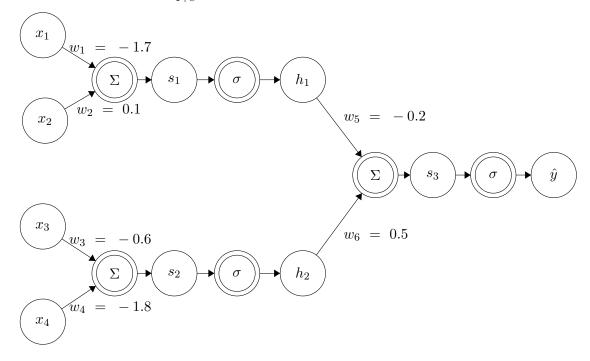
$$Q' = \begin{cases} 10 & \text{w.p. } 0.6 \\ 11 & \text{w.p. } 0.3 \\ 12 & \text{w.p. } 0.1 \end{cases}$$

Compute the cross-entropy H(P, Q').

- (c) Is cross-entropy symmetric? i.e. if we reverse the distributions for P, Q, will we get the same cross-entropy?
- (d) Suppose we have a true label y = [1, 0, 0], and a logistic regression model computes estimated probabilities  $\hat{y} = [0.91, 0.08, 0.01]$ . Compute the cross-entropy loss.
- (e) What would happen to the cross-entropy loss if any of the estimated probabilities were zero? Is this possible in a logistic regression?

## 3. [10 pts] Backpropagation by Hand

Consider the following neural network. Single-circled nodes denote variables (e.g.  $x_1$  is an input variable,  $h_1$  is an intermediate variable,  $\hat{y}$  is an output variable), and double-circled nodes denote functions (e.g.  $\Sigma$  takes the sum of its inputs, and  $\sigma$  denotes the logistic function  $\sigma(x) = \frac{1}{1+e^{-x}}$ . In the network below,  $h_1 = \frac{1}{1+e^{-x_1w_1-x_2w_2}}$ .



Suppose we have an L2 loss  $L(y,\hat{y}) = ||y - \hat{y}||_2^2$ . We are given a data point  $(x_1, x_2, x_3, x_4) = (-0.7, 1.2, 1.1, -2)$  with true label 0.5. Use the backpropagation algorithm to compute the partial derivative  $\frac{\partial L}{w_1}$ .

(Hint: the gradient of an L2 loss function  $||\hat{y}-y||_2^2$  is  $2||\hat{y}-y||.)$ 

## 4. [10 pts] Other Definitions

Define the following terms.

- (a) Leave-one-out cross validation
- (b) Bayes error
- (c) Supervised leraning
- (d) AUC
- (e) bias-variance decomposition
- (f) confusion matrix
- (g) sparse feature
- (h) PCA
- (i) epoch
- (j) L1 regularization