

# CS 486/686 Introduction to Artificial Intelligence Spring 2015, Assignment 4 Solution

## 1 Question 1 (15 pts)

5 pts for each part:

$$\begin{aligned}\sigma(-a) &= \frac{1}{1+e^a} \\ &= \frac{e^{-a}}{e^{-a}+1} \\ &= \frac{1+e^{-a}-1}{e^{-a}+1} \\ &= \frac{1+e^{-a}}{1+e^{-a}} - \frac{1}{1+e^{-a}} \\ &= 1 - \sigma(a)\end{aligned}$$

$$\begin{aligned}\sigma^{-1}(a) &= \ln(a/(1-a)) \\ a &= \sigma(\ln(a/(1-a))) \\ &= \frac{1}{1+e^{-\ln(a/(1-a))}} \\ &= \frac{1}{1+(1-a)/a} \\ &= \frac{1}{1/a} \\ &= a\end{aligned}$$

$$\begin{aligned}\frac{\partial \sigma}{\partial a} &= \frac{-1}{(1+e^{-a})^2}(-e^{-a}) \\ &= \frac{1}{1+e^{-a}} \frac{e^{-a}}{1+e^{-a}} \\ &= \frac{1}{1+e^{-a}} \frac{1}{1+e^a} \\ &= \sigma(a)(1-\sigma(a))\end{aligned}$$

## 2 Question 2 (15 pts)

7 pts for showing the relation between  $\tanh(a)$  and  $\sigma(a)$ :

$$\begin{aligned}\tanh(a) &= \frac{e^a - e^{-a}}{e^a + e^{-a}} \\ &= \frac{1 - e^{-2a}}{1 + e^{-2a}} \\ &= 2\sigma(2a) - 1 \\ \sigma(a) &= \frac{1}{2}\tanh\left(\frac{a}{2}\right) + \frac{1}{2}\end{aligned}$$

8 pts for showing the equivalent neural network and linear transformation of weights, now rewrite  $y_i(x, W)$  in terms of  $\tanh()$ :

$$\begin{aligned}y_i(x, W) &= \sigma\left(\sum_j W_{ji}^{(2)} \sigma\left(\sum_k W_{kj}^{(1)} x_k + W_{0j}^{(1)}\right) + W_{0i}^{(2)}\right) \\ &= \sigma\left(\sum_j W_{ji}^{(2)} \left[\frac{1}{2}\tanh\left(\frac{1}{2}\sum_k W_{kj}^{(1)} x_k + \frac{1}{2}W_{0j}^{(1)}\right) + \frac{1}{2}\right] + W_{0i}^{(2)}\right) \\ &= \sigma\left(\sum_j \frac{1}{2}W_{ji}^{(2)} \tanh\left(\sum_k \frac{1}{2}W_{kj}^{(1)} x_k + \frac{1}{2}W_{0j}^{(1)}\right) + \sum_j \frac{1}{2}W_{ji}^{(2)} + W_{0i}^{(2)}\right) \\ &= \sigma\left(\sum_j V_{ji}^{(2)} \tanh\left(\sum_k V_{kj}^{(1)} x_k + V_{0j}^{(1)}\right) + V_{0i}^{(2)}\right)\end{aligned}$$

where  $V$  is obtained by a linear transformation of  $W$ :

$$V_{ji}^{(2)} = \frac{1}{2}W_{ji}^{(2)}$$

$$V_{0i}^{(2)} = \sum_j \frac{1}{2} W_{ji}^{(2)} + W_{0i}^{(2)}$$

$$V_{kj}^{(1)} = \frac{1}{2} W_{kj}^{(1)}$$

$$V_{0j}^{(1)} = \frac{1}{2} W_{0j}^{(1)}$$

### 3 Question 3 (30 pts)

- Is the dataset linearly separable? Explain briefly. (10 pts) Yes, the dataset is linearly separable as the perceptron finds a linear separator and the training accuracy converges to 100%.
- Train and test accuracy of the threshold perceptron. (10 pts) The accuracy is 100% for training and 90% for testing (your numbers might be slightly different).
- A printout of the final weights of the threshold perceptron. (10 pts) Here is a set of valid final weights: 99, 187, -270, -147, -81, -406, -125, 84, 153, -180, -128, 40, -339, -507, -353, -96, 13, -185, -112, -65, -187, -23, -160, -106, -234, -66, 87, -186, -231, -272, 4, -252, 112, -128, 63, 3, 231, 17, -128, 42, 158, 25, 724, 312, 235, -93, 389, -210, -329, -192, 174, 541, -142, 207, 264, 81, -114, -353, -262, -167, 205, 429, 46, 107, -33, you will get marks for weights in a similar range that makes sense.

### 4 Question 4

- Graph of train and test accuracy. (20 pts)
- Brief discussion of the results in the graph. (10 pts)
  - Training accuracy improves slightly with the number of hidden nodes, but it is not clear that this translates into better generalization, i.e. better test accuracy.
- Which algorithm performs best? Why? (10 pts)
  - Neural network works better because it produces a non-linear separator while the perceptron produces a linear separator.

