## Assignment 4, Written Part

Please turn in the answers to this written part of assignment 4 by either

- Typesetting your answers inline with LaTeX (.tex file provided).
- Write out your answers with tablet / stylus, and submit the annotated pdf.
- Print out the assignment, write answers by hand, and scan / photograph your work. The image must be clearly legible, and all pages must be combined into one file.
- For the written response questions, clearly justify all conclusions to receive full credit. A correct answer with no supporting work will receive no credit.

1. Consider a linear model for classification in which we use a logistic activation, but instead of cross-entropy loss, we use squared error loss. Assume a 1-dimensional input x, a single weight w and an outcome  $y_i \in \{0, 1\}$ . We will ignore the intercept term.

$$a_i = wx_i$$
  
 $p_i = \text{logistic}(a_i)$   
 $l_i = (y_i - p_i)^2$ 

Recall that logistic  $(u) = \frac{1}{1+e^{-u}}$ . Calculate the following:

- a.  $\frac{dl_i}{dp_i}$
- b.  $\frac{dp_i}{da_i}$ , as a function of  $a_i$
- c.  $\frac{dp_i}{da_i}$ , rewritten as a function of  $p_i$  only
- d.  $\frac{da_i}{dw}$
- e.  $\frac{dl_i}{dw}$
- f. Assume that  $y_i = 1$ . What is  $\lim_{p\to 0} \frac{dl_i}{dw}$ ? Is this good or bad for learning? Explain why.

2. Consider a linear model for classification based on the hinge loss, with a penalty for weight magnitude. This is the basic support vector machine (don't worry if you haven't studied it). Unlike question 1, we will now assume that  $y_i \in \{-1,1\}$ . Again, assume a single input variable  $x_i$ , and ignore the intercept term.

$$a_i = wx_i$$
  
$$l_i = \max(0, 1 - y_i a_i) + w^2$$

Calculate the following:

- a.  $\frac{\partial l_i}{\partial a_i}$  [Note: This technically should be a subgradient. Only worry about the two cases of  $y_i a_i < 1$  and  $y_i a_i > 1$ . Don't worry about the non-differentiable point where  $y_i a_i = 1$ .]
- b.  $\frac{dl_i}{dw}$  [Again, there are two cases.]
- c. Assume that  $y_i = 1$ . What is update rule for w for stochastic gradient descent?
- d. Contrast this rule with the update rule for the perceptron.

$$y = x + \frac{1}{wx + b}$$

Draw the computation graph for calculating y from x, w and b, Fill in the blanks for the reverse mode AD table at x = 0.3, w = 0.5, b = 0.1

Part 1 - Computation Graph

## Forward Primal Trace

Part 2 - Reverse Adjoint Trace

$v_{-2}^{-}$	=	=
$v_{-1}^-$	=	=
$\bar{v_0}$	=	=
$\bar{v_1}$	=	=
$\bar{v_2}$	=	=
$\bar{v_3}$	=	=
$\bar{v_4}$	=	= 1