Part 1 CS6375 HW2 Sennan Liu

1.1 -

$$\frac{\partial o}{\partial w_0} = 1$$

$$\frac{\partial o}{\partial w_i} = x_i + x_i^2 \quad \text{where } i = 1, 2, \dots, n$$

update:

$$w_0 := w_0 - \eta \frac{\partial o}{\partial w_0} = w_0 - \eta$$

$$w_i := w_i - \eta \frac{\partial o}{\partial i} = w_i - \eta(x_i + x_i^2)$$

1.2

a. $y = h(w_{53}(h(w_{31} \cdot x_1 + w_{32} \cdot x_2)) + w_{54}(h(w_{41} \cdot x_1 + w_{42} \cdot x_2)))$

b. $y = w^{(2)} w^{(1)} X$

c. $h_s(x) = \dfrac{1}{\frac{e^x+1}{e^x}} = \dfrac{e^x}{e^x+1}$;

$$h_t(x) = \frac{\frac{e^{2x}-1}{e^x}}{\frac{e^{2x}+1}{e^x}} = \frac{e^{2x}-1}{e^{2x}+1} = \frac{e^{2x}}{e^{2x}+1} - \frac{1}{e^{2x}+1}$$

which is the originate structure in a neural net.

$$= h_s(2x) - h(-2x)$$

$$\because h_s(x) + h_s(-x) = \frac{e^x}{e^x+1} + \frac{1}{e^x+1} = 1 \quad \therefore h_s(-x) = 1 - h_s(x)$$

$$\therefore h_t(x) = h_s(2x) - (1 - h_s(2x)) = 2h_s(2x) - 1 = 2h_s(t) - 1$$

assume $t = 2x$

Then we know $h_t(x)$ is only a linear transformation of $h_s(x)$ with a constant bias. These differences can be easily matched with w and b,