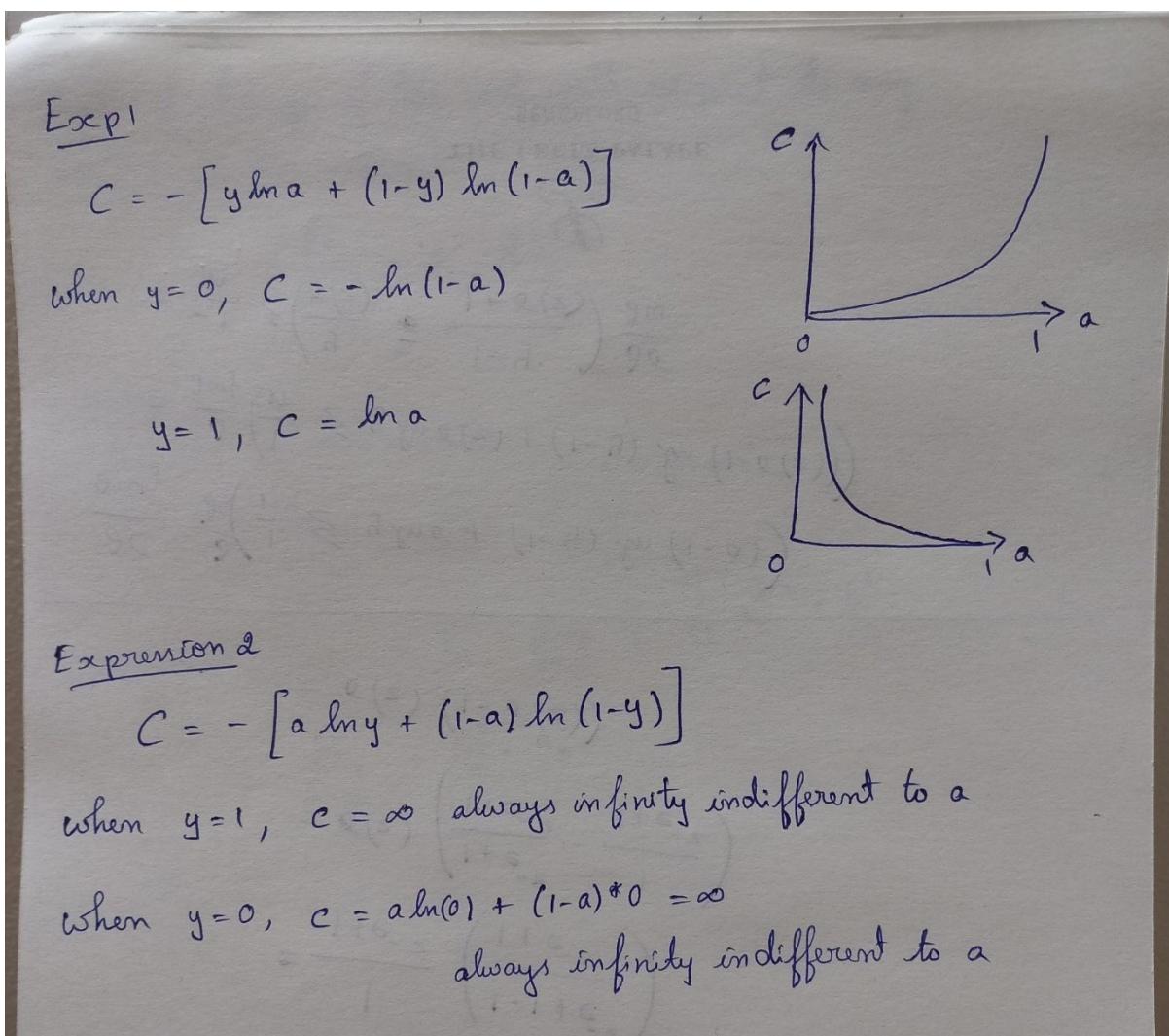


Exercise

- Verify that $\sigma'(z) = \sigma(z)(1 - \sigma(z))$.

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

- One gotcha with the cross-entropy is that it can be difficult at first to remember the respective roles of the y s and the a s. It's easy to get confused about whether the right form is $-[y \ln a + (1 - y) \ln(1 - a)]$ or $-[a \ln y + (1 - a) \ln(1 - y)]$. What happens to the second of these expressions when $y = 0$ or 1? Does this problem afflict the first expression? Why or why not?



- In the single-neuron discussion at the start of this section, I argued that the cross-entropy is small if $\sigma(z) \approx y$ for all training inputs. The argument relied on y being equal to either 0 or 1. This is usually true in classification problems, but for other problems (e.g., regression problems) y can sometimes take values intermediate between 0 and 1. Show that the cross-entropy is still minimized when $\sigma(z) = y$ for all training inputs. When this is the case the cross-entropy has the value:

$$C = -\frac{1}{n} \sum_x [y \ln y + (1-y) \ln(1-y)]. \quad (64)$$

The quantity $-[y \ln y + (1-y) \ln(1-y)]$ is sometimes known as the **binary entropy**.

$$\begin{aligned} C &= -[y \ln a + (1-y) \ln(1-a)] \\ \frac{\partial C}{\partial a} &= -\left[\frac{y}{a} + \frac{1-y}{1-a}(-1)\right] = \frac{1-y}{1-a} - \frac{y}{a} \\ &= \frac{a-ay-y+ay}{a-a^2} \\ \frac{\partial C}{\partial a} &= \frac{a-y}{a-a^2} \\ \text{At minimum, } \frac{\partial C}{\partial a} &= 0 \\ \frac{a-y}{a-a^2} &= 0 \\ \boxed{a=y} \end{aligned}$$