

MT Summer Term 2021 Ex10: Intro to NNs via Logistic Regression - Andrew Ng

1. In your own words, what is the difference between a loss function \mathcal{L}



$$\mathcal{L}(\hat{y}, y)$$

and a cost function $\mathfrak{J}(\mathbf{w}, b)$

$$\mathfrak{J}(\mathbf{w}, b) = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

What are y and \hat{y} and what does the index variable i in the cost function range over?

2. If your loss function \mathcal{L} was the sum of squared errors



$$\sum_{j=1}^n \frac{1}{2} (y_j - \hat{y}_j)^2$$

for, say, an FFNN with n output neurons, what would the total cost function \mathfrak{J} be? Explain the resulting cost function in your own words. Btw. why do we have the $\frac{1}{2}$ in the sum of the squared errors?



3. In your own words, what is the relationship between logistic regression and a single artificial neuron?



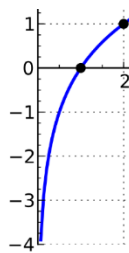
4. If you use logistic regression as a classifier, what is a popular loss function for it?



5. In your own words, explain how log/cross-entropy loss

$$\mathcal{L}(\hat{y}, y) = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))$$

works. To do this, consider the case where the true class $y = 1$ and the case where $y = 0$. The following graph of the \log may be useful:



6. Please complete the following:

$$\frac{d}{dx} \log_e x = \frac{d}{dx} \ln x = \dots$$

7. Please draw the computation graph of the following function

$$f(x, y, z) = 2(x^3 - 3(y + z))$$

using a suitable labelling of the sub-formulas in $f(x, y, z)$.

8. Please compute the forward pass on the computation graph for

$$f(x, y, z) = 2(x^3 - 3(y + z))$$

where $x = 2$, $y = -1$ and $z = 3$.



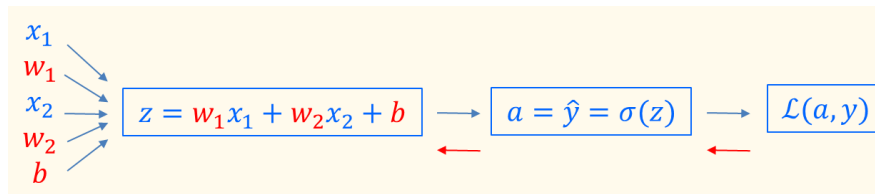
9. Please work out

$$\frac{\partial}{\partial x} 2(x^3 - 3(y + z)), \quad \frac{\partial}{\partial y} 2(x^3 - 3(y + z)), \quad \frac{\partial}{\partial z} 2(x^3 - 3(y + z))$$

using the chain rule (and others, as required).

10. Please do the same as in (9), but this time use the computation graph and your sub-formula labelling from (7) above.

11. Given the following computation graph for logistic regression (a simple artificial neuron with sigmoid activation function):



please compute $\frac{\partial}{\partial a} \mathcal{L}(a, y)$, $\frac{\partial}{\partial z} \mathcal{L}(a, y)$, $\frac{\partial}{\partial w_2} \mathcal{L}(a, y)$ and $\frac{\partial}{\partial b} \mathcal{L}(a, y)$ using the computation graph.



12. Given the partial derivatives of the loss function with respect to weights in (11) above, in your own words please explain what the following does:

$$w_1 := w_1 - \alpha \frac{\partial}{\partial w_1} \mathcal{L}(a, y)$$

$$w_2 := w_2 - \alpha \frac{\partial}{\partial w_2} \mathcal{L}(a, y)$$

$$w_b := w_b - \alpha \frac{\partial}{\partial w_b} \mathcal{L}(a, y)$$

13. Given the following definition of the **softmax** and **sigmoid**:

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{i=1}^n e^{x_i}}$$

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}$$

and the following (row) vector of four real numbers:

$$\langle 2.41, -1.71, -0.16, 2.83 \rangle$$

please compute

- elementwise **sigmoid** of the vector and
- a new vector where each element is the **softmax** of each of the elements in the original vector.



What does the **softmax** do to the original vector? What does the **sigmoid** do to each of the elements in the vector?

What do you think: is the **softmax** differentiable? I.e. can you backprop through a **softmax**?