## **PART I: Derivative**

softmax(z)<sub>j</sub> = 
$$\frac{e^{zj}}{\sum_{i=1}^{K} e^{zi}}$$

L(z) = - lg(softmax(z)<sub>j</sub>)  
Let softmax(z)<sub>j</sub> = p<sub>j</sub>  
L(z) = - 
$$\sum_i$$
 y<sub>i</sub> lg(p<sub>i</sub>)

$$\frac{\partial L}{\partial zi} = -\sum_{k} y_{k} \frac{\partial \log (p_{k})}{\partial p_{k}} x \frac{\partial p_{k}}{\partial zi}$$
$$= -\sum_{k} y_{k} \frac{1}{p_{k}} x \frac{\partial p_{k}}{\partial zi}$$

$$\begin{split} \frac{\partial L}{\partial zi} &= -y_{i}(1-p_{i}) - \sum_{k \neq i} y_{k} \frac{1}{p_{k}} (-p_{k} \cdot p_{i}) \\ &= -y_{i}(1-p_{i}) + \sum_{k \neq i} y_{k} \cdot p_{i} \\ &= -y_{i} + y_{i}p_{i} + \sum_{k \neq i} y_{k} \cdot p_{i} \\ &= p_{i} (y_{i} + \sum_{k \neq i} y_{k}) - y_{i} \end{split}$$

y is an encoded vector for the labels, so  $\sum_k y_k = 1$  and  $y_i + \sum_{k \neq i} y_k = 1$ Thus,

$$\frac{\partial L}{\partial zi} = -y_i + p_i$$
$$= -\delta_{i,j} + \text{softmax}(z)_i$$

## **PART II: Implementation and Test**

## Forward and Backward pass

```
A1 = X @ W1 + b1

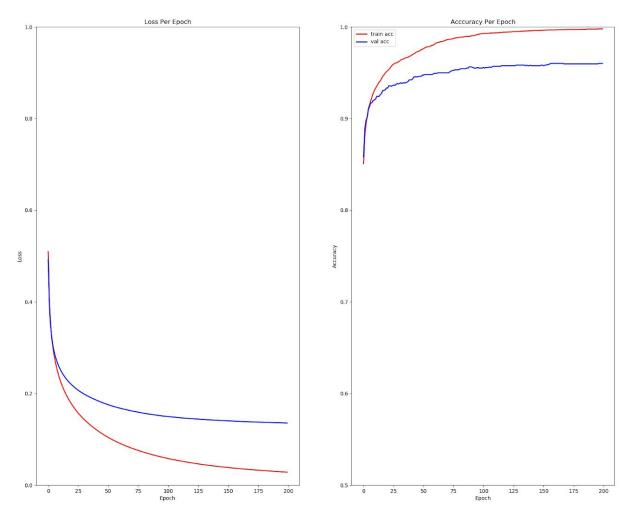
reluA1 = relu(A1)

A2 = reluA1 @ W2 + b2

log_softmax = np.log(softmax(A2))
entropy = np.sum(log_softmax * labels)
entropy = -entropy
decay = reg * (np.sum(np.square(W1)) + np.sum(np.square(W2)))

cost = entropy + decay
grad = -labels + softmax(A2)
d_b2 = grad.sum(axis=0, keepdims=True)
d_w2 = 2*reg*W2 + (reluA1.T @ grad)
d_RA1 = grad @ W2.T
d_A1 = d_RA1 * np.where(A1 > 0, 1, 0)
d_b1 = d_A1.sum(axis=0, keepdims=True)
d_w1 = X.T @ d_A1 + 2*reg*W1
```

**Test**Using the parameters of **epochs = 200**, **batch\_size = 30**, **Ir = 0.0001**, **reg = 1e-2** for the fit function, we were able to achieve an in-sample accuracy and test sample accuracy of over 95%.



in sample accuracy 0.9921965317919075 data shape, type, min, max (2580, 784) float64 -1.0 1.0 labels shape and type (2580,) int64 0 9 test sample accuracy 0.951937984496124 outputting to file epoch\_plots.png