#### Theoretical part: Question 1

First denote  $f(x, w)_i = z_i$  From the chain rule we get

$$\frac{\partial L(\hat{y}, y)}{\partial w} = \sum_{i} \frac{\partial L(\hat{y}, y)}{\partial \hat{y}_{i}} \frac{\partial \hat{y}_{i}}{\partial w}$$
$$\frac{\partial \hat{y}_{i}}{\partial w} = \sum_{k} \frac{\partial \hat{y}_{i}}{\partial z_{k}} \frac{\partial z_{k}}{\partial w}$$

and since

$$\hat{y}_{i} = softmax(x)_{i} = \frac{e^{f(x,w)_{i}}}{\sum_{j} e^{f(x,w)_{j}}} = \frac{e^{z_{i}}}{\sum_{j} e^{z_{j}}}$$

we get

$$\frac{\partial \hat{y}_{i}}{\partial z_{k}} = \begin{cases} \frac{e^{z_{i}}}{\sum_{j} e^{z_{j}}} \left( 1 - \frac{e^{z_{i}}}{\sum_{j} e^{z_{j}}} \right) = \hat{y}_{i} (1 - \hat{y}_{i}) &, i = k \\ -\frac{e^{z_{i}}}{\sum_{j} e^{z_{j}}} \frac{e^{z_{k}}}{\sum_{j} e^{z_{j}}} = -\hat{y}_{i} \hat{y}_{k} &, i \neq k \end{cases}$$

$$\frac{\partial \hat{y}_{i}}{\partial w} = \sum_{k \neq i} -\hat{y}_{i} \hat{y}_{k} \frac{\partial z_{k}}{\partial w} + \hat{y}_{i} (1 - \hat{y}_{i}) \frac{\partial z_{i}}{\partial w} = \sum_{k} -\hat{y}_{i} \hat{y}_{k} \frac{\partial z_{k}}{\partial w} + \hat{y}_{i} \frac{\partial z_{i}}{\partial w}$$

$$\frac{\partial z_{i}}{\partial w} = \frac{\partial f(x, w)_{i}}{\partial w}$$

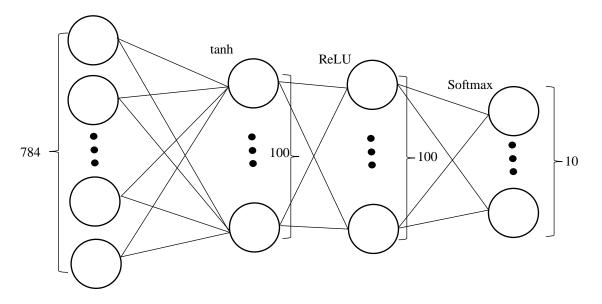
and so we get

$$\frac{\partial L(\hat{y}, y)}{\partial w} = \sum_{i} \left( \sum_{k} - \hat{y}_{i} \hat{y}_{k} \frac{\partial z_{k}}{\partial w} + \hat{y}_{i} \frac{\partial z_{i}}{\partial w} \right) \frac{\partial L(\hat{y}, y)}{\partial \hat{y}_{i}}$$

Practical part:

Question 1:

#### Network architecture:



## Hyperparameters:

In the ADAM implementation the hyperparameters were  $\beta_1=.9,\beta_2=.999,\,\varepsilon=10^{-8}$  In the training process, I set the batch\_size parameter to 100

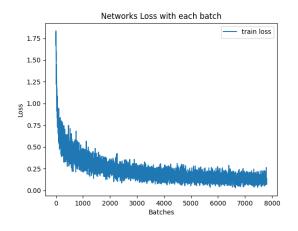
## Optimization:

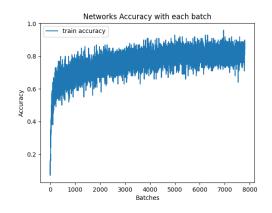
Implemented the ADAM optimizer in the backward function

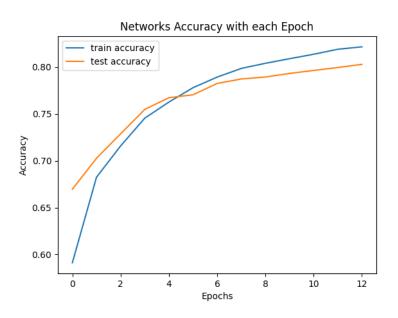
Calculated the gradients w.r.t. to each weight matrix, bias and updated the weights and biases accordingly

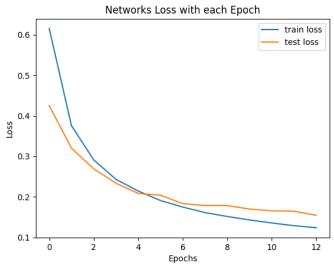
#### Short summary & conclusions:

Although I calculated the gradient of softmax in Question 1 (Theoretical part) the training process seemed to be negatively affected from the gradient of the softmax and the network loss seemed to improve better when the softmax gradient weren't multiplied

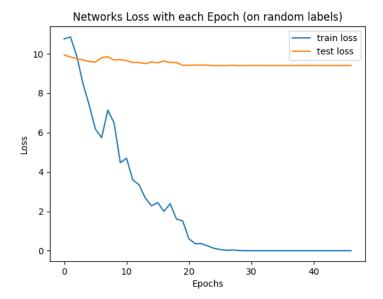








# Question 2:



although the loss on the training set is improving and almost 0, the loss on the test set is almost the same as the initial loss.

And that's due to the face that the network attempted to learn the labels that's being generated at random.

And of course we can't learn the "toss of a coin".

