Assignment 1 Bonus - DD2424 - One Layer Network

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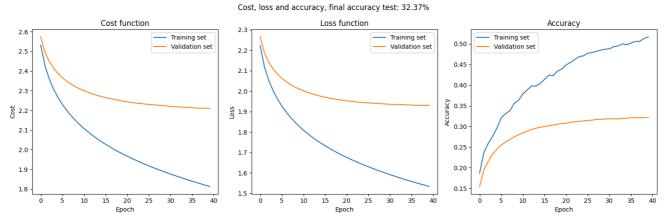
Exercise 2 - Optional for Bonus Points

Improve performance of the network

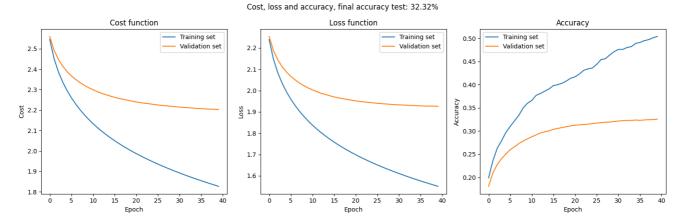
The goal now is to improve the model by adding some techniques.

At first, I retrieve all the data and I normalize it after that I split it into a training, validation and test set. I also implement a grid search to see which parameters are the best for the model. This is the best result I obtained:

• With old hyperparameters: lambda=0.1, n_epochs=40, n_batch=100, eta=.001



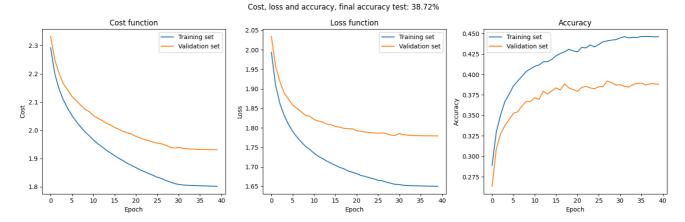
• With best hyperparameters: lambda=0.5, n_epochs=80, n_batch=100, eta=.001



Unfortunately, we see here not much improvement by selecting all the data! Indeed, it's important to have in mind that we try to classify RGB images with a single layer network! The capacity to memorize and well classify images for a single layer neural network is not enough. A more complex model is needed to have better results, like a convolutional neural network. However, the grid search is a good way to find the best hyperparameters for the model, it's just a bit long to compute.

After that, I implement the **step decay** and I only used the one batch that we used before. I re used the best parameters but with more epochs to see if the step decay is helping. I obtained the following results:

• With lambda=0.1, n_epochs=1000, n_batch=100, eta=.1



Unfortunately, the step decay is not helping, the cost is not decreasing and the accuracy is not increasing compared to the best previous model.

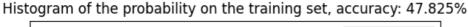
Train network - multiple binary cross-entropy losses

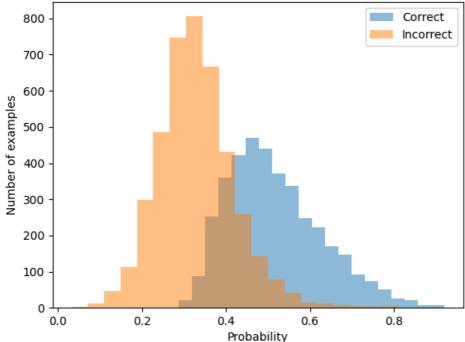
After that, I implement the multiple binary cross-entropy losses with sigmoid activation function.

$$\sigma(s) = \frac{1}{1+e^{-s}}l_{multiple\ bce} = -\frac{1}{K}\sum_{i=1}^K y_i\log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)z = Wx + b\hat{y} = \sigma(z)$$

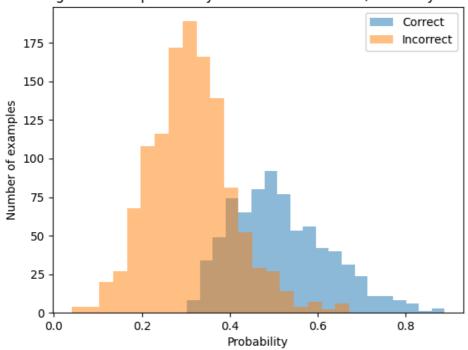
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And this is the result I obtained with the hyperparameters: lambda=0.1, n_epochs=50, n_batch=100, eta=.0001:

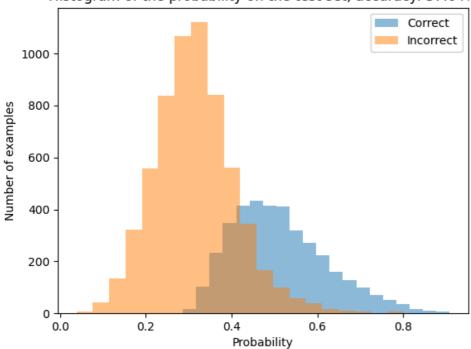




Histogram of the probability fon the validation set, accuracy: 38.25%



Histogram of the probability on the test set, accuracy: 37.64%



Here we have not a huge improvement on the accuracy compared to the previous model. The model is not overfitting but we could have a better accuracy by using a more complex model, more adapted to the problem.