# **MNIST Digits Classification with MLP**

#### Introduction

Ignoring setups used to select hyperparameters, I have looked at the required 2 activations \* 2 layers \* 2 loss functions = 8 different setups (see **Results Summary**). Additionally, I have also looked at Model5 which differs from Model4 only in the number of neurons in its layers. Altogether, there are 10 different setups.

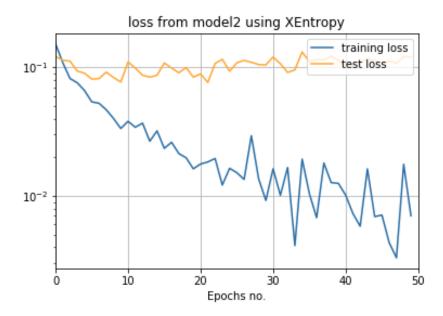
## **Hyperparameter Selection**

In theory, to select the right hyperparameters, a full exhaustive search that iterates through every combination should be done with a **validation dataset**. However, for simplicity's sake, this is done mainly on an ad hoc basis, where the parameters work well enough in combination.

Hyperparameters of interests are reproduced below.

| Hyperparameter | Value                               |
|----------------|-------------------------------------|
| Batch size     | 100                                 |
| Weight decay   | 0                                   |
| Momentum       | 0.9                                 |
| Max epoch      | 50/100 depending on convergence     |
| Learning rate  | 0.01/0.001 depending on convergence |

Particularly, a learning rate of 0.01 generally works well on all models in 50 epochs. This is not the case for models with ReLU and XEntropy loss though. As can be seen from this plot of a bad example below, learning rate of 0.01 is too high, producing the zigzag shape of training loss.



Learning rate is thus reduced to 0.001 and max epoch increased to 100 to produce better convergence.

## **Results Summary**

Here, convergence refers to the convergence of loss on test dataset. Convergence tends to be ill defined when we try to compare different loss functions – it therefore only indicates an approximate epoch no. here.

| Model  | Activation | Layers | Loss      | Learning | Convergence  | Accuracy | Loss |
|--------|------------|--------|-----------|----------|--------------|----------|------|
| no.    |            |        | function  | rate     | at epoch no. |          |      |
| Model1 | Sigmoid    | 1      | Euclidian | 0.01     | 50           | 97.5%    | 10-2 |
| Model1 | Sigmoid    | 1      | XEntropy  | 0.01     | 30           | 98.0%    | 10-1 |
| Model2 | ReLU       | 1      | Euclidian | 0.01     | 30           | 98.1%    | 10-2 |
| Model2 | ReLU       | 1      | XEntropy  | 0.001    | 70           | 96.9%    | 10-1 |
| Model3 | Sigmoid    | 2      | Euclidian | 0.01     | 30           | 97.3%    | 10-2 |
| Model3 | Sigmoid    | 2      | XEntropy  | 0.01     | 30           | 98.1%    | 10-1 |
| Model4 | ReLU       | 2      | Euclidian | 0.01     | 50           | 98.2%    | 10-2 |
| Model4 | ReLU       | 2      | XEntropy  | 0.001    | 30           | 96.6%    | 10-1 |
| Model5 | ReLU       | 2      | Euclidian | 0.01     | 30           | 98.4%    | 10-2 |
| Model5 | ReLU       | 2      | XEntropy  | 0.001    | 30           | 97.2%    | 10-1 |

Architecture of Model4 & Model5:

Model4: (784 x 512) -> (512 x 128) -> (128 x 10) Model5: (784 x 392) -> (392 x 196) -> (196 x 10)

#### **Comments and Discussion on Results**

Sigmoid vs. ReLU:

Generally, ReLU is preferred over sigmoid.

Model 4 & model 5 of **2 hidden layers** of **ReLU** activation and **Euclidian** loss function perform the best out of the setups.

#### 1 hidden layer vs. 2 hidden layers:

Prediction accuracy does not always improve when we add a layer. This depends on the activation function and loss function. Notably, model & model (2 layers) do have improvements over model (1 layer).

Generally, models with 2 layers tend to converge faster, as the plots show (see **Plots** *model1\_Euclidean\_accuracy* & *model3\_Euclidean\_accuracy*).

Euclidian vs. Cross-Entropy Loss:

Between the two, cross-entropy loss introduces more overfitting (see **Plots** *model3\_Xentropy\_loss*).

#### Architecture:

Not much difference between Model4 & Model5.

## Overfitting:

From the **Plots**, it is fairly obvious that overfitting plagues each model to various degrees. To improve accuracy, we could include regularization in our training process.

### **Plots**

The loss (training & test) and accuracy (training & test) of each setup are plotted below.

