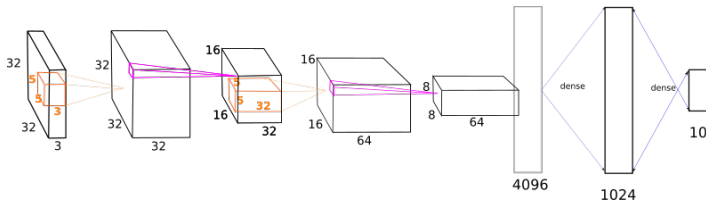# COMSM0045: Lab3 Practical

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October 20, 2021

Hyperparameters in this practical

- In this practical, we will NOT revisit the architecture - will stick to it
- We will though think about the critical parameters to change, for a given architecture

Selecting hyperparameter values

▶ For each hyperparameters, one must understand the relationship between its value and each of the following:

  ▶ Training error/loss
  ▶ Testing error/loss (generalisation)
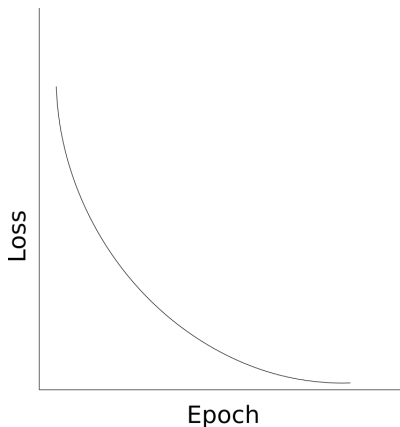 ▶ Computational resources (memory and runtime)

Evaluation Metrics

- Let's look again at the curves you are getting during training
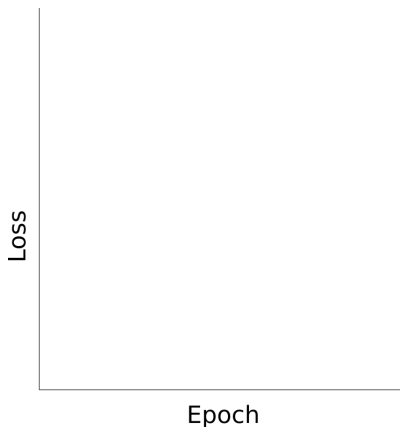
Evaluation Metrics
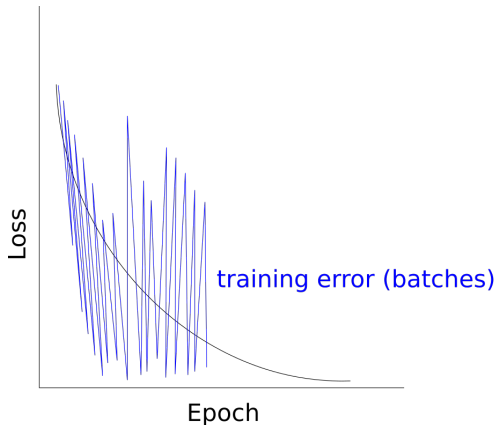
▶ Optimally, the loss decreases after each iteration

Evaluation Metrics - What if??

▶ Training Error starts to go up?!

Evaluation Metrics - What if??
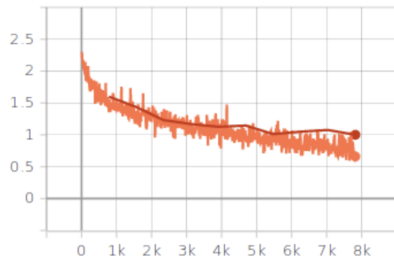
▶ Training error wiggles A LOT?!

Evaluation Metrics

▶ Practically, due to mini-batch optimisation, you see this wiggly curve
▶ The test curve (over the full test set) is smoother, and is not calculated at every step
▶ Always look at both the "loss" (what you're optimising) and the evaluation metric (e.g. accuracy)
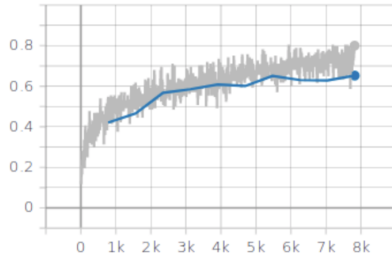
Evaluation Metrics

▶ Observe overfitting
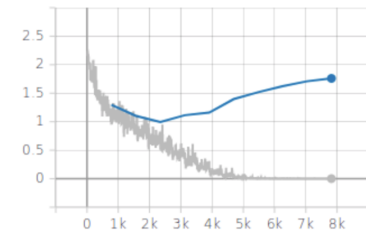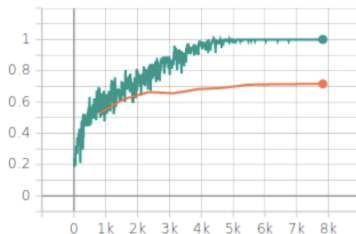
1. Learning Rate

▶ The learning rate is the **most important hyperparameter** to set

"If you have time to tune only one parameter, tune the learning rate"[1]

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[1] Goodfellow et al, p 424

1. Learning Rate
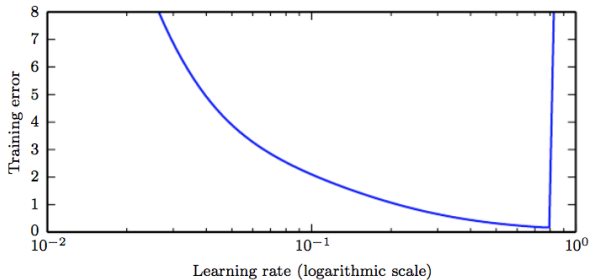
Figure 11.1: Typical relationship between the learning rate and the training error.

1. Learning Rate

1. Learning Rate

- ▶ You have learnt about decaying the learning rate
- ▶ Remind yourself about gradient descent with momentum optimiser from the lectures to use it in the Lab work

2. Batch-size Training

- ▶ Recall from lecture on optimisation, that there are two extremes when performing gradient descent
    - ▶ Calculating the gradient from a single example
    - ▶ Calculating the gradient for the whole dataset
- ▶ Neither is ideal, thus we typically calculate the gradient from a number of data points
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▶ To correctly approximate the loss from a batch, it is crucial that samples are selected randomly
▶ However, there are approaches that sample data for a purpose **(read about hard mining)**

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    - ▶ To make the most of the GPU architectures, batches that are a power of 2 provide the best runtime - 128, 256, ...
    - ▶ For small-sized data samples, batches between 32 and 256 are typical
    - ▶ For large-sized data samples, batches of 8 or 16 are common

3. Parameter initialisation

On the importance of initialization and momentum in deep learning

Ilya Sutskever[1]   ILYASU@GOOGLE.COM
James Martens   JMARTENS@CS.TORONTO.EDU
George Dahl   GDAHL@CS.TORONTO.EDU
Geoffrey Hinton   HINTON@CS.TORONTO.EDU

ICML 2013

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Abstract

Deep and recurrent neural networks (DNNs and RNNs respectively) are powerful models that were considered to be almost impossible to train using stochastic gradient descent with momentum. In this paper, we show that when stochastic gradient descent with momentum uses a well-designed random initialization and a particular type of slowly increasing schedule for the momentum parameter, it can train both DNNs and RNNs (on datasets with long-term dependencies) to levels of performance that were previously achievable only with Hessian-Free optimization. We find that both the initialization and the momentum are crucial since poorly initialized networks cannot be trained with momentum and well-initialized networks perform markedly worse when the momentum is absent or poorly tuned.

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- ▶ However, more practically, it's best to start from some pre-trained model on a relevant problem with larger datasets
- ▶ In images for example, it's customary to start from a model pre-trained on ImageNet
- ▶ This gives an informative initial set of parameters to train CNNs when images are targeted

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- ▶ The distribution of $\hat{\mathbf{x}}$ would then be zero-meaned with a standard deviation of 1
- ▶ When training using $\hat{\mathbf{x}}$ instead of $\mathbf{x}$, the training converges faster.
- ▶ You can compensate for that effect on the output by learnt variables

$$y = \boldsymbol{\lambda}\hat{\mathbf{x}} + \boldsymbol{\beta}$$

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▶ Important: Do not add batch normalisation to your last output for classification.

▶ Using batch normalisation, higher learning rates can be used.

And now....

READY....

STEADY....

GO...