COMSM0045: Lab3 Practical

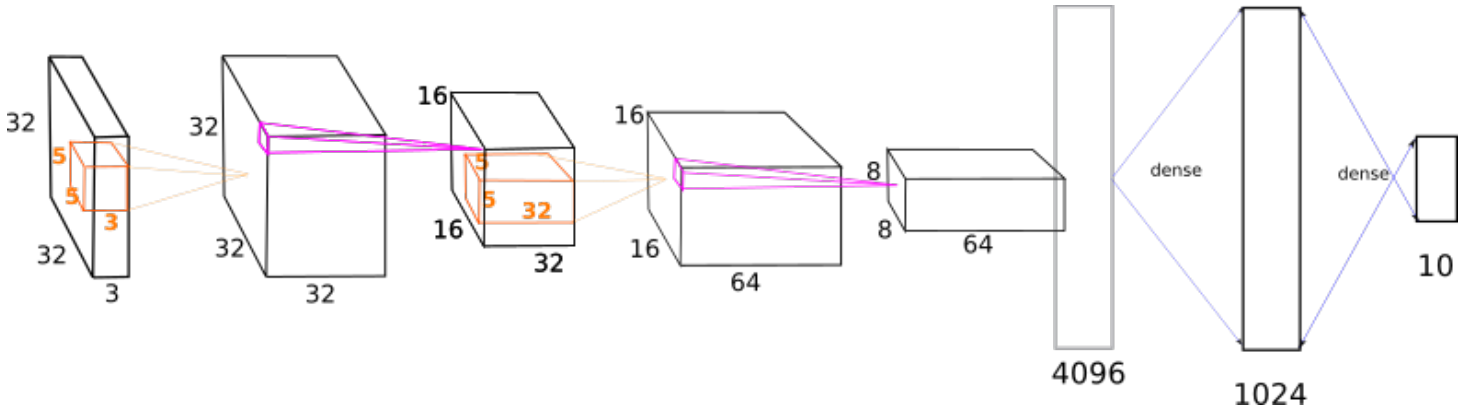
Dima Damen
Dima.Damen@bristol.ac.uk

Bristol University, Department of Computer Science
Bristol BS8 1UB, UK

October 24, 2020

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

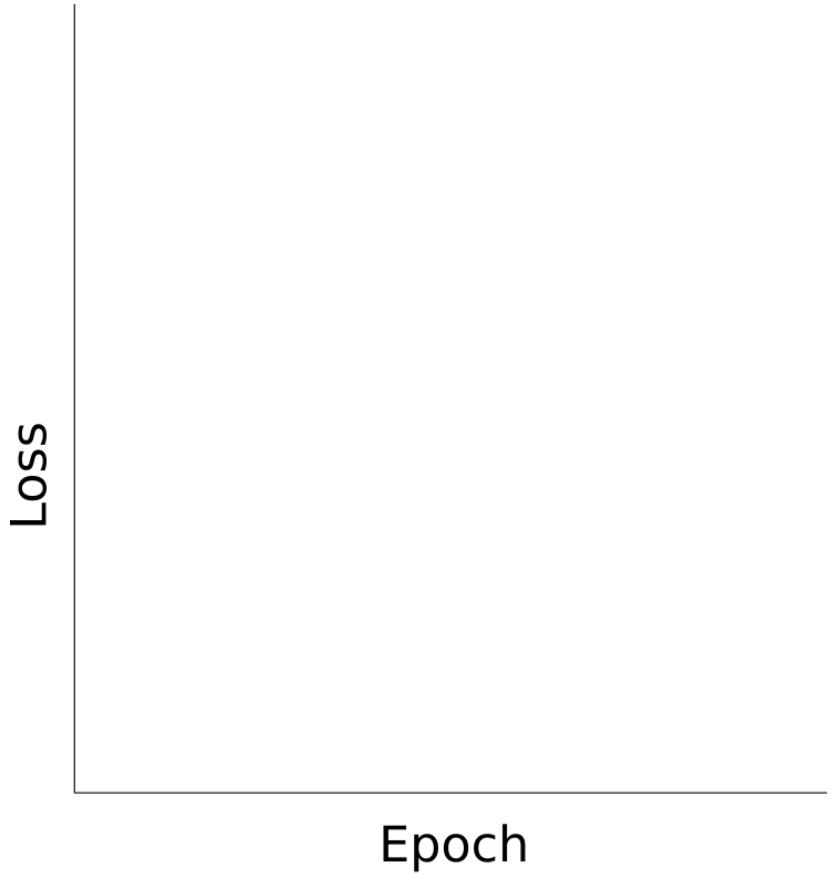


Selecting hyperparameter values

- 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)

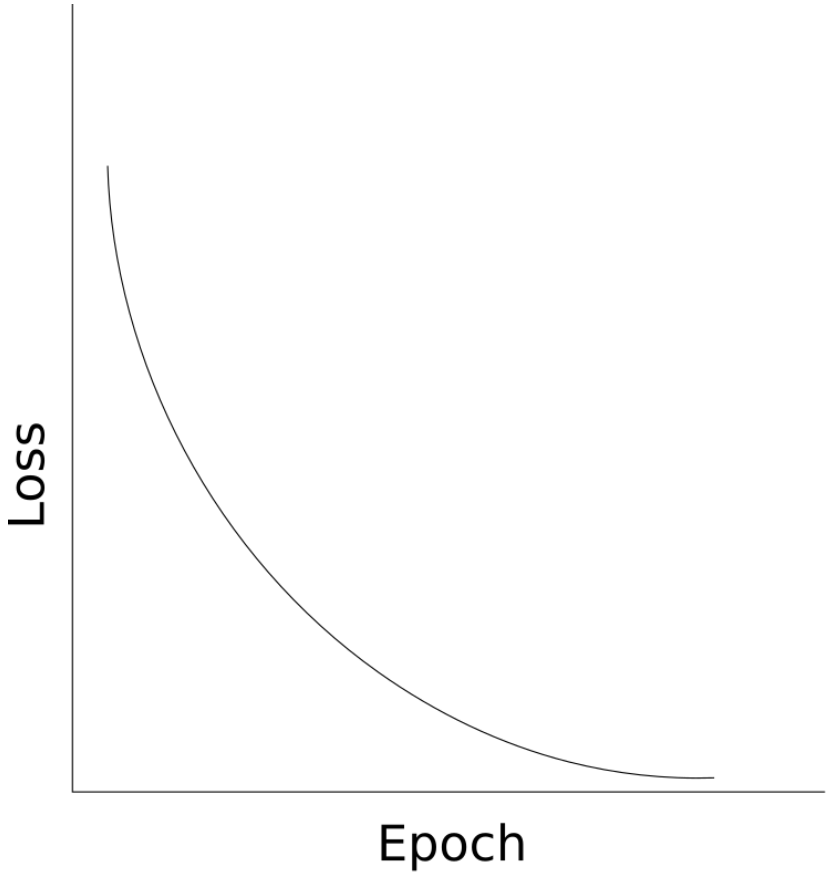
Evaluation Metrics

- Let's look again at the curves you are getting during training



Evaluation Metrics

- Optimally, the loss decreases after each iteration

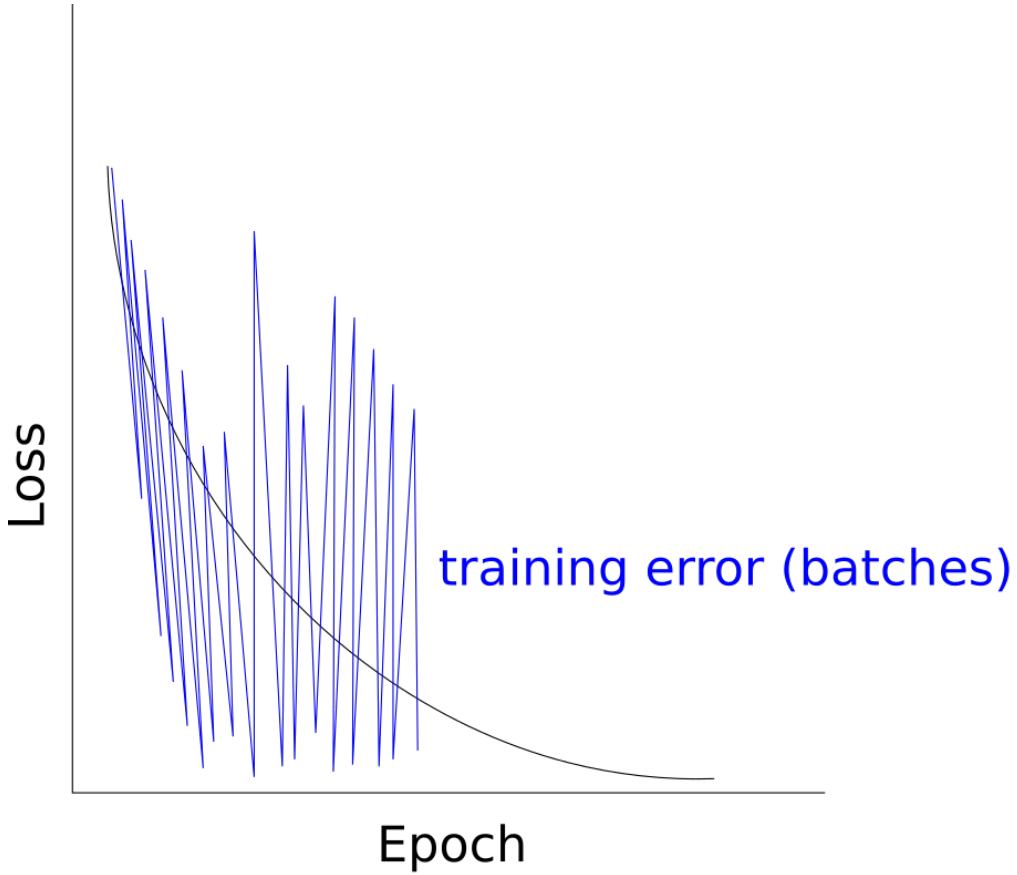


Evaluation Metrics - What if??

- Training Error starts to go up?!

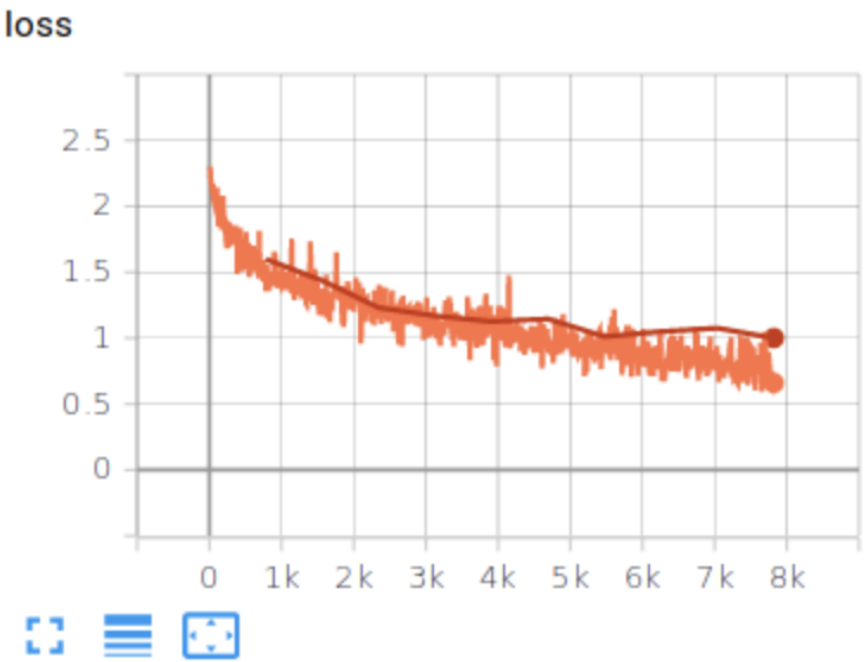
Evaluation Metrics - What if??

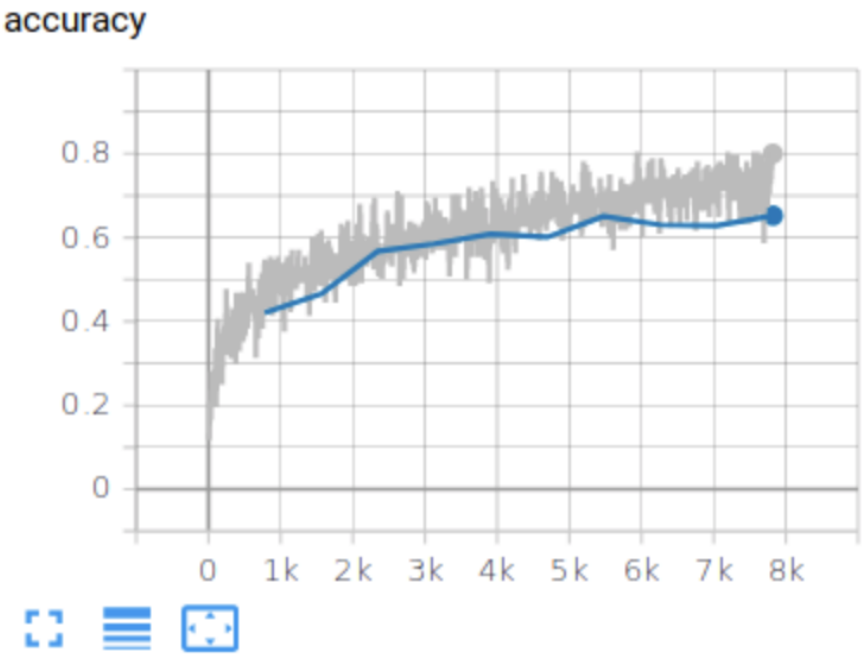
- Training error wiggles A LOT?!



Evaluation Metrics

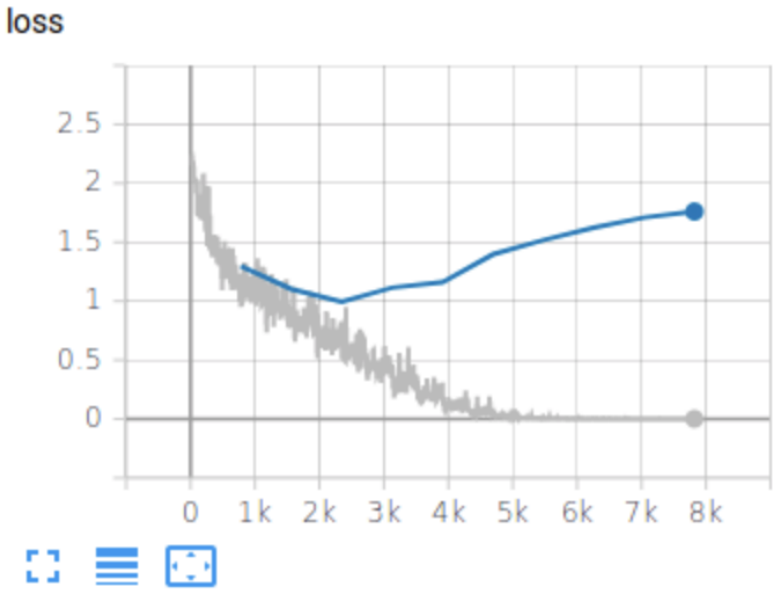
- Practically, due to mini-batch optimisation, you see this wiggly curve
- The test curve (over the full test set) is smoother, and is not calculated at every step
- Always look at both the “loss” (what you’re optimising) and the evaluation metric (e.g. accuracy)

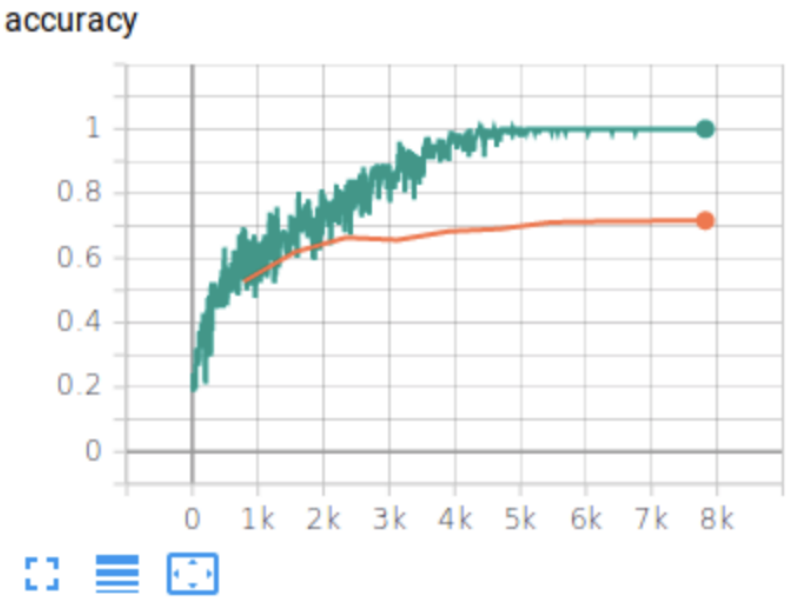




Evaluation Metrics

- 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]

[1] Goodfellow et al, p 424

1. Learning Rate

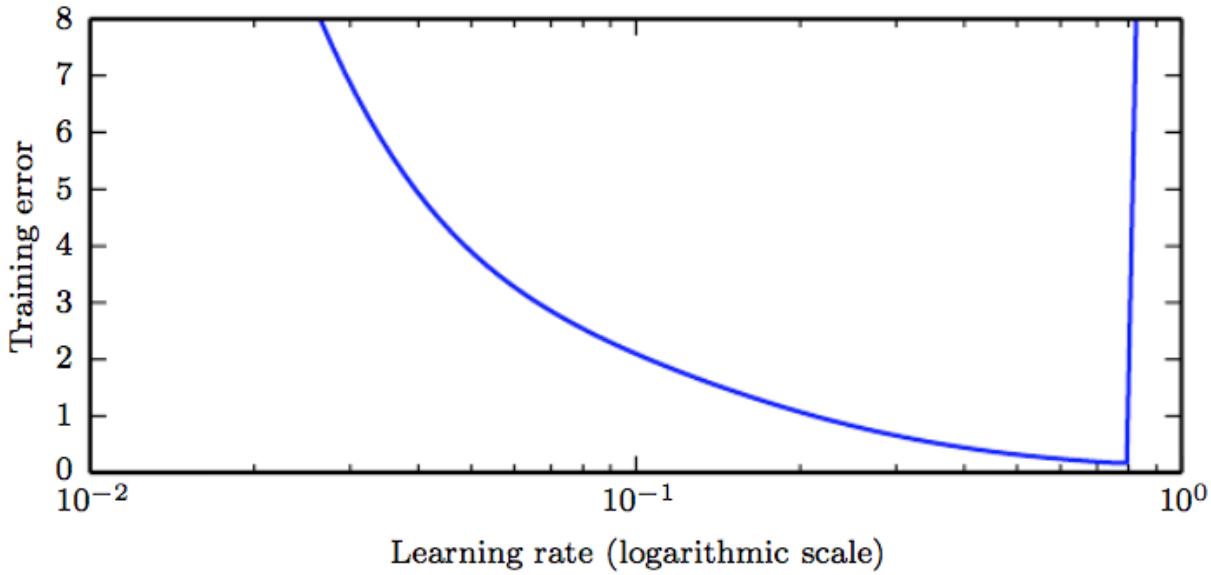
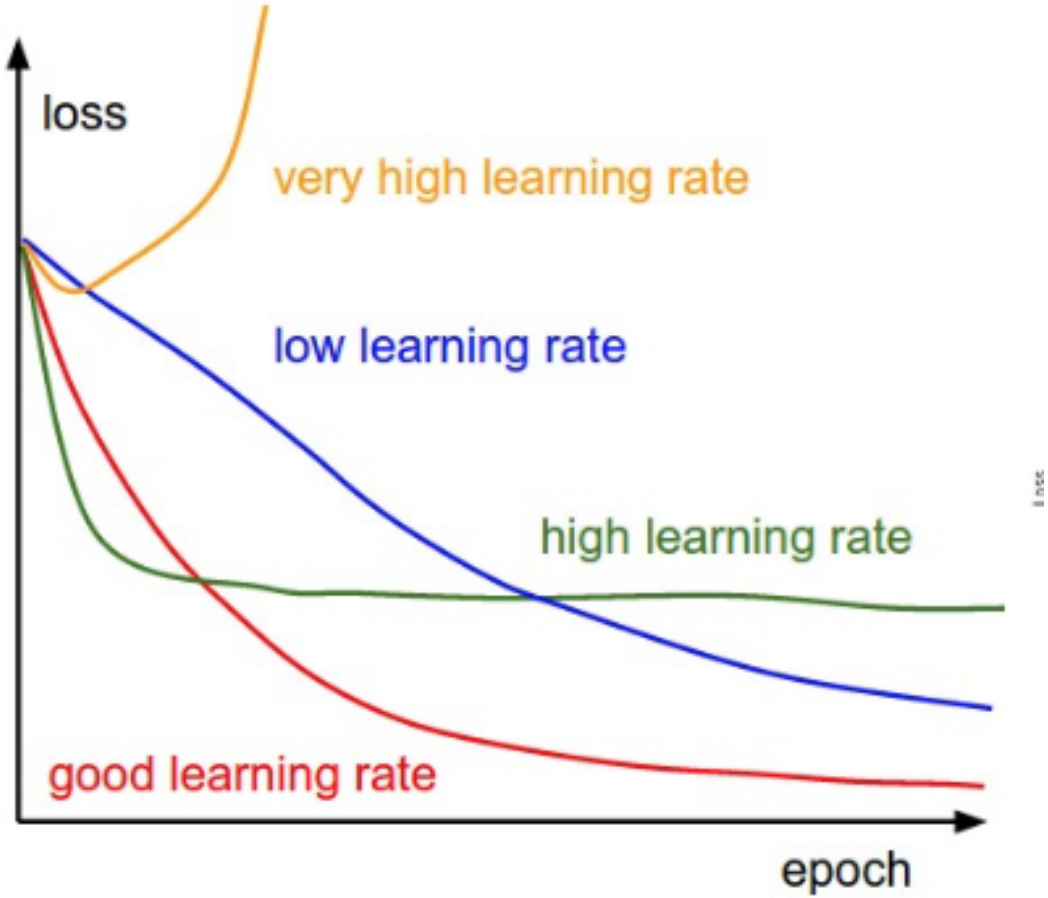


Figure 11.1: Typical relationship between the learning rate and the training error.

Goodfellow et al p 425

1. Learning Rate



http://cs231n.github.io/neural-networks-3/

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
- This number is referred to as the ‘batch size’
- 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)**

2. Batch-size Training

- The effect of changing the batch-size on the accuracy of a dataset, depends on the dataset
- The amount of wiggle in the training loss is related to the batch size.
- However there are general guidelines:
  - Larger batches indeed provide better approximation of the full-dataset gradient
  - However, as batch size increases, the increase in accuracy or the decrease in training time is NOT linear
  - Due to parallel processing, the typical limitation to batch size is the GPU memory
  - There's a minimum size below which the gradient is too noisy
  - We are always searching for this sweet spot between too small and too large
  - 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

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.

ICML 2013

3. Parameter initialisation

- The cost function in a DNN is non-convex
- Any non-convex optimisation algorithm will depend on the initial parameters
- In the lab you'll use random initialisation as a practical way to initialise the weights in a DNN
- 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

4. Batch Normalisation

- Another powerful practical modification to the baseline training algorithm is known as **batch normalisation**
- Recall the standardisation approach to data

$$\hat{\mathbf{x}} = \frac{\mathbf{x} - \bar{\mathbf{x}}}{\sigma}$$

- 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

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

4. Batch Normalisation

- When applied to **each** layer in the network, all layers are given the chance to converge faster
- In convolutional layers, you'll need BatchNorm2d, while in fully connected layers you'll use BatchNorm1d.
- 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...