Introduction to Artificial Intelligence

COMP307/AIML420

Neural Networks 3: Neural Engineering

Dr Andrew Lensen

Andrew.Lensen@vuw.ac.nz

Interested?

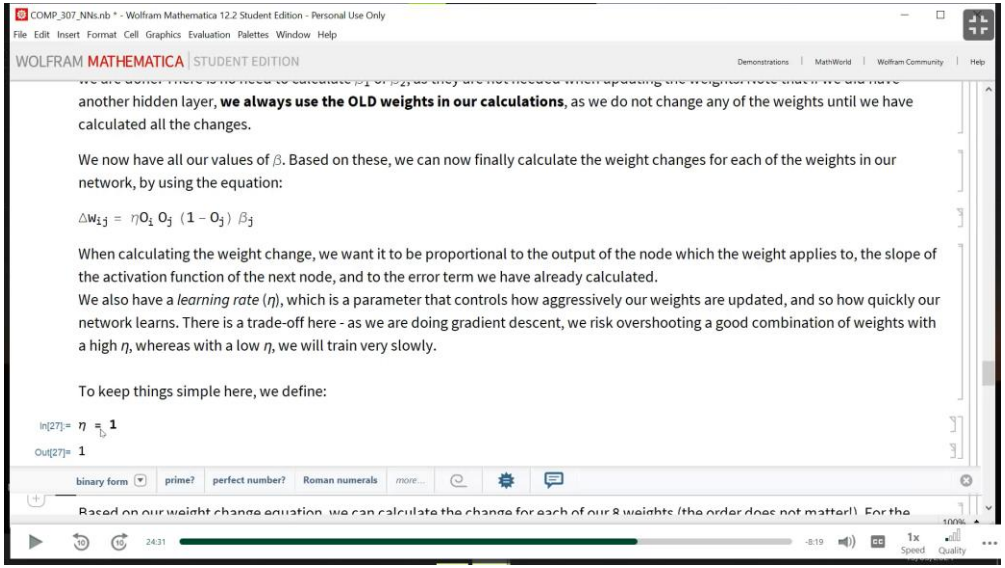
- Not too late!
- Register **now**
- Or email me if you need a team
- Andrew.Lensen@vuw.ac.nz

Assignment One

- How is it going?
  - Started?

- Double helpdesks this week
  - 3-4pm AND 5-6pm (i.e. after this lecture!)

- How are we feeling about backprop?



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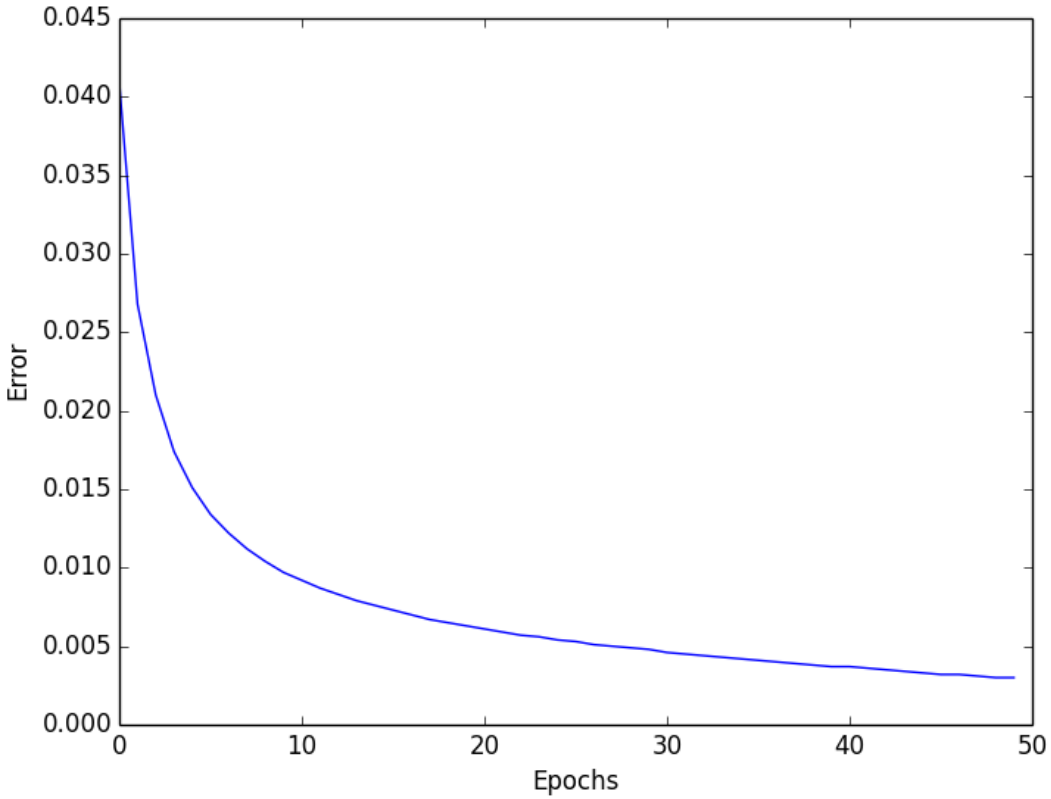
Outline

- Epochs
- Weight update frequency
- Learning rate
- Overfitting
- Stopping criteria
- Local minima
- ANN architecture
- Momentum

Notes on BP Algorithm

- *1 Epoch*: all input examples (entire training set, batch, …)
- A target of 0 or 1 cannot be reached in reasonable time. Usually interpret an output > 0.9 or > 0.8 as ‘1’
- Training may require *thousands* of epochs. A convergence curve can help to decide when to stop (overfitting?)



Weight Update Frequency

- All the weights are updated **after** one feedforward pass and one backward propagation/pass
- Frequency of weight update = Frequency of passes

- **Online learning**: a pass for each training instance
- **Batch learning**: a pass for a batch (a subset of training instances)
  - weight change is the sum of the changes for all the instances in the batch
- **Offline learning**: a pass for all the training instances
  - Weight change is the sum of the changes for all training instances

- Online and batch learning are stochastic gradient descent
- Offline learning is "true" gradient descent

在线和批量学习是随机梯度下降，
离线学习是“真”梯度下降

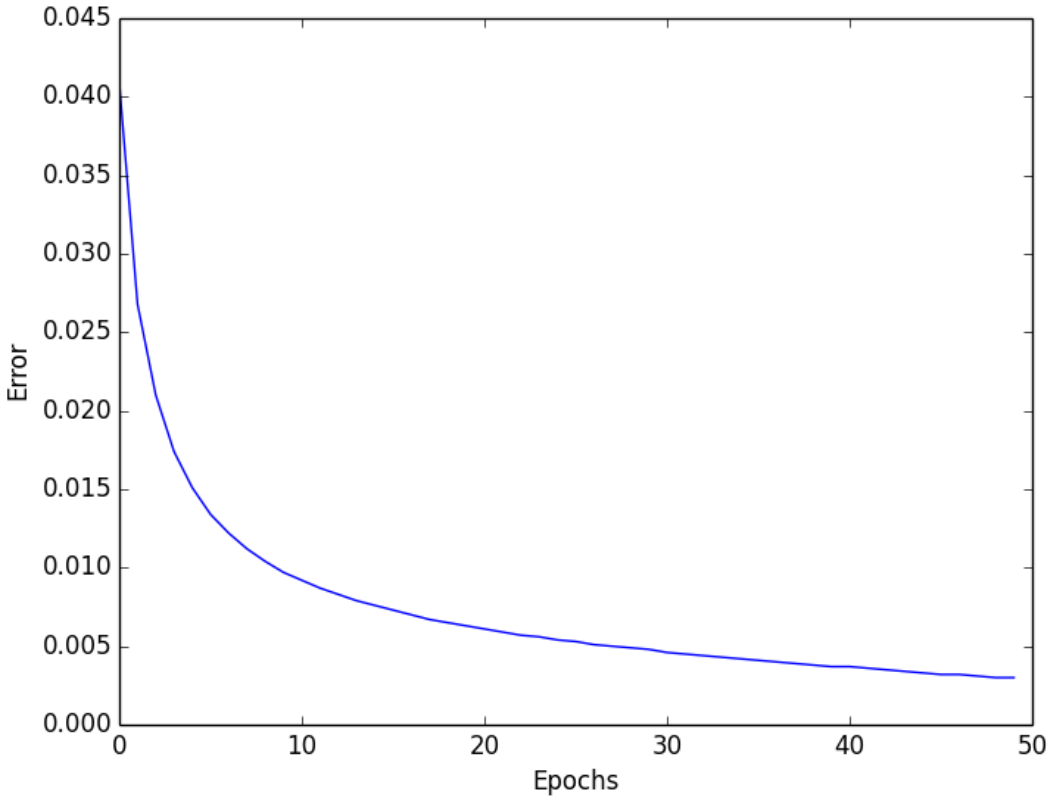
Weight Update Frequency

- Assuming a weight $w = 0.2$
- 4 training instances
- Online learning
  - Instance 1, $\Delta w = 0.1$, $w \rightarrow 0.3$
  - Instance 2, $\Delta w = 0.05$, $w \rightarrow 0.35$
  - Instance 3, $\Delta w = 0.03$, $w \rightarrow 0.38$
  - Instance 4, $\Delta w = 0.01$, $w \rightarrow 0.39$
- Offline learning
  - Instance 1, $\Delta w = 0.1$, $w = 0.2$ unchanged
  - Instance 2, $\Delta w = 0.08$, $w = 0.2$ unchanged
  - Instance 3, $\Delta w = -0.03$, $w = 0.2$ unchanged
  - Instance 4, $\Delta w = 0.05$, $w = 0.2$ unchanged
  - $w \rightarrow 0.2 + 0.1 + 0.08 - 0.03 + 0.05 = 0.4$

Weight Update Frequency

- Epoch: period when all the training instances are used once
- #Iterations = #passes

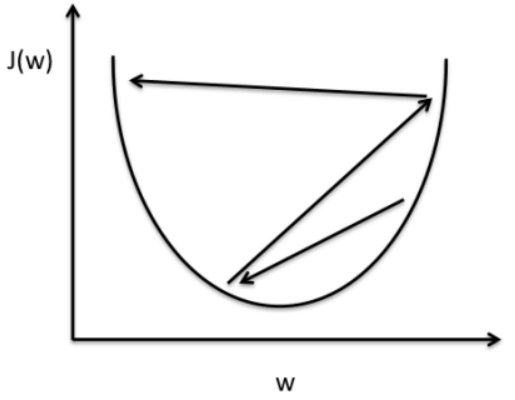
- 1000 training instances, batch size = 500, then need 2 iterations to complete **one** epoch



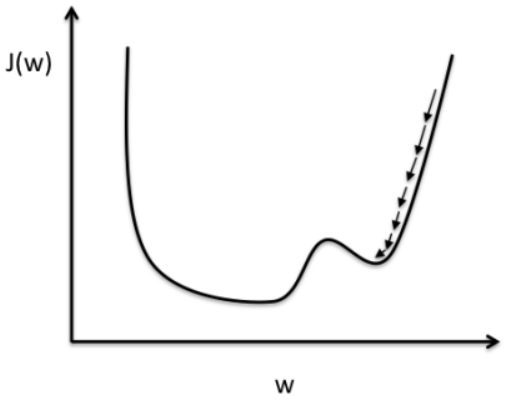
Learning Rate

- Large learning rate may cause oscillating behaviour
- Small learning rate may cause slow convergence
- 0.2 is a good starting point in practice

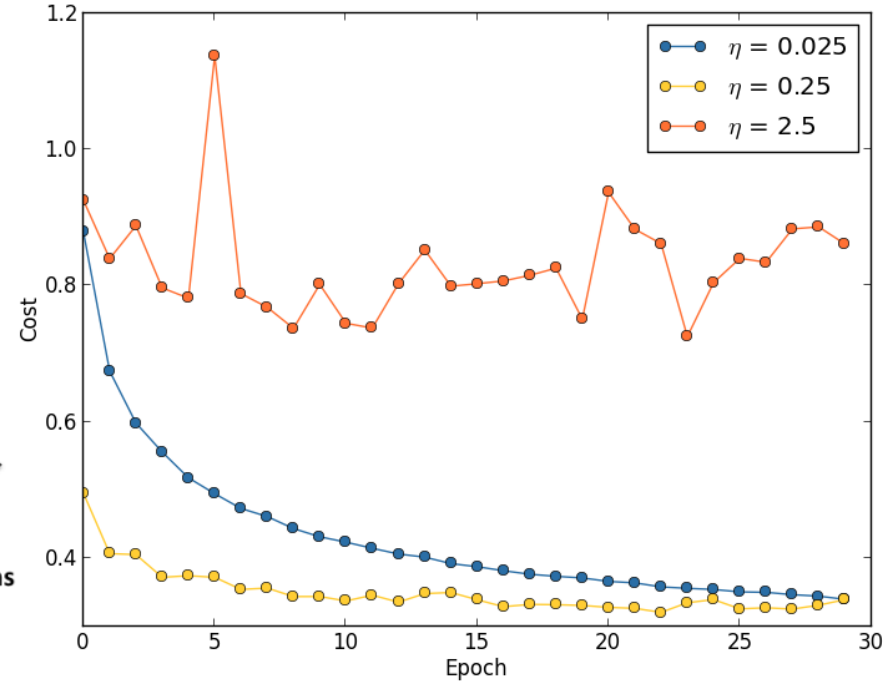
$$\Delta w_{i\to j} = \boldsymbol{\eta} o_i o_j \left(1 - o_j\right) \beta_j$$



Large learning rate: Overshooting.

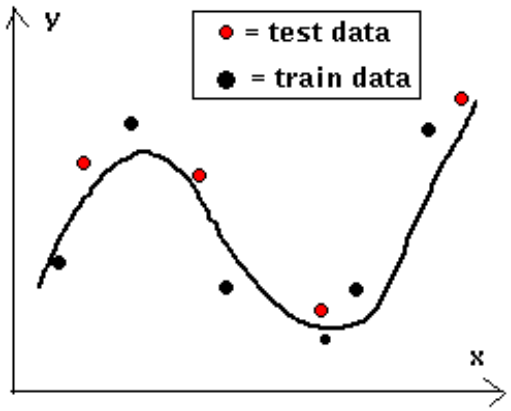


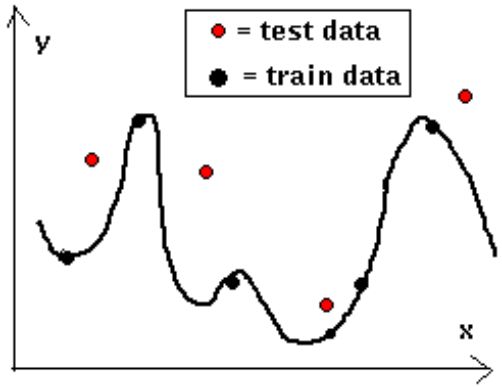
Small learning rate: Many iterations until convergence and trapping in local minima.

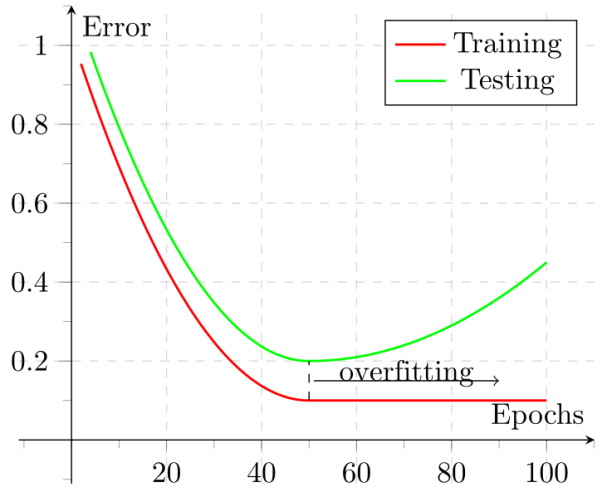


Overfitting

- Has a very high accuracy on the training set, but poor accuracy on the test set
- Caused by:
  - Training for too long
  - Too many weights (parameters) to train
  - Too few training instances
- The more parameters to train, the more data (training instances) we need to have an accurate estimation





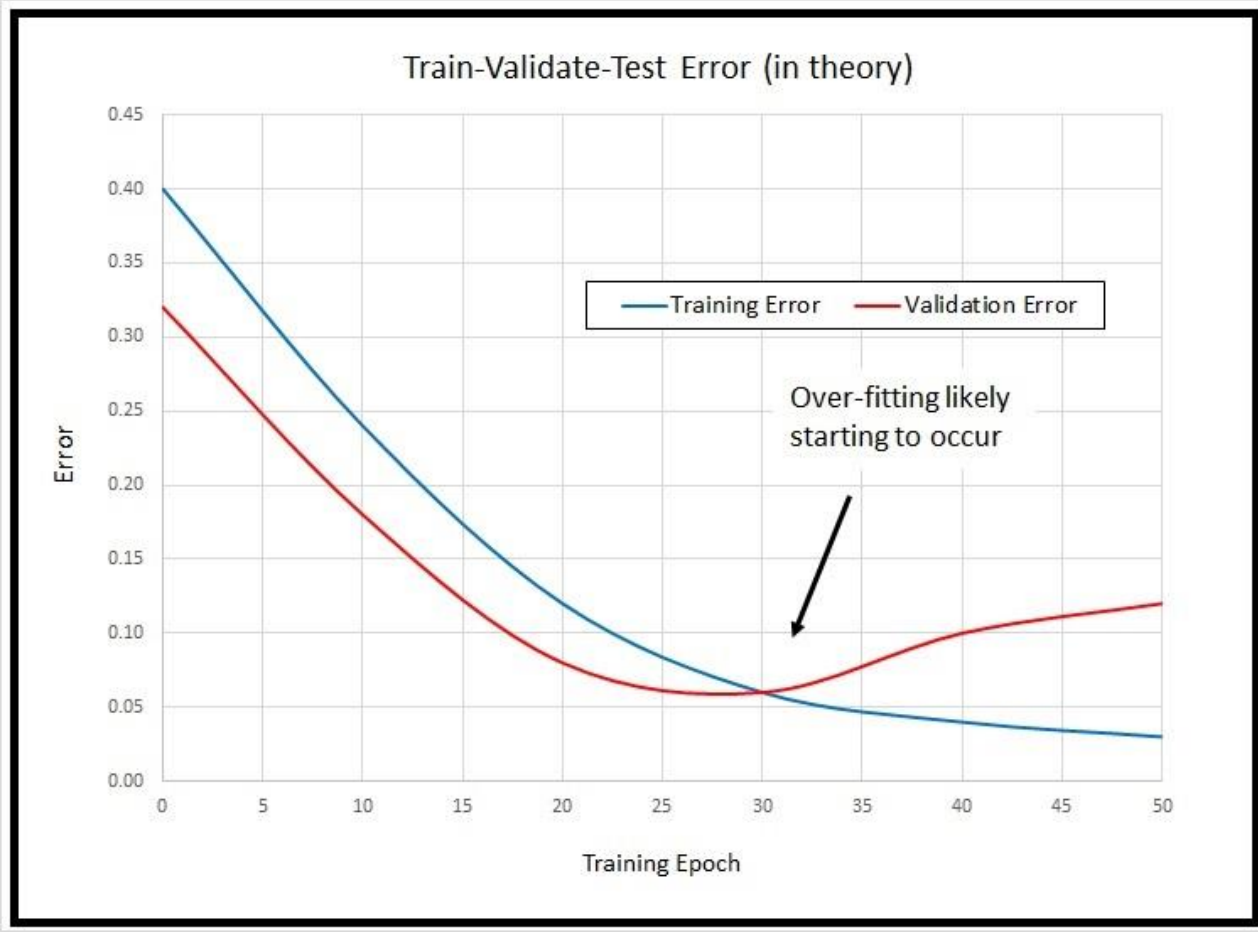


Stopping Criteria

- When a certain number of epochs is reached
- When the error (e.g. mean/total squared error) on the training set is smaller than some threshold **T**
- Proportion of correctly classified training instances (i.e. accuracy) is larger than a threshold
- Early stopping strategy
  - Validation control to **avoid overfitting**

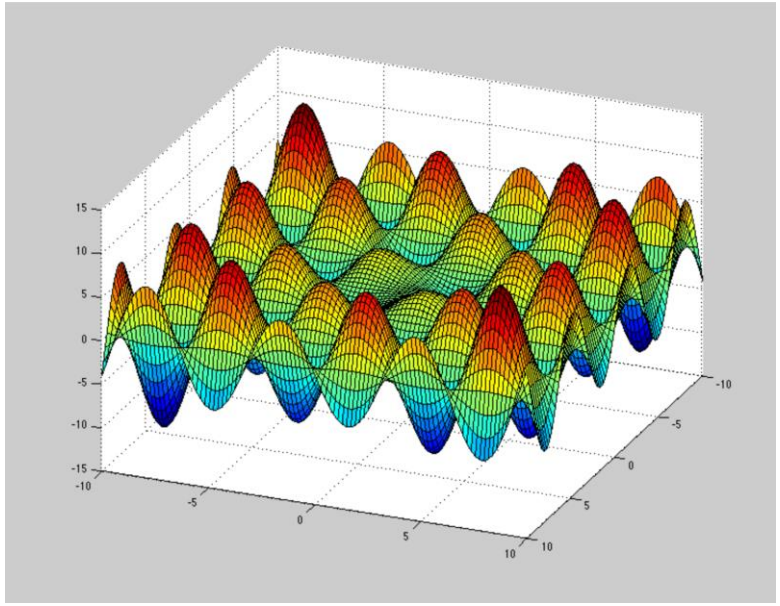
Validation Control

- Break the training set into two parts
- Use 1st part to compute the weight changes
- Every *m* (e.g. 10, 50, 100) epochs apply the current NN to the 2nd part (validation set) to calculate the validation error
- Stop when the error on the validation set is minimum

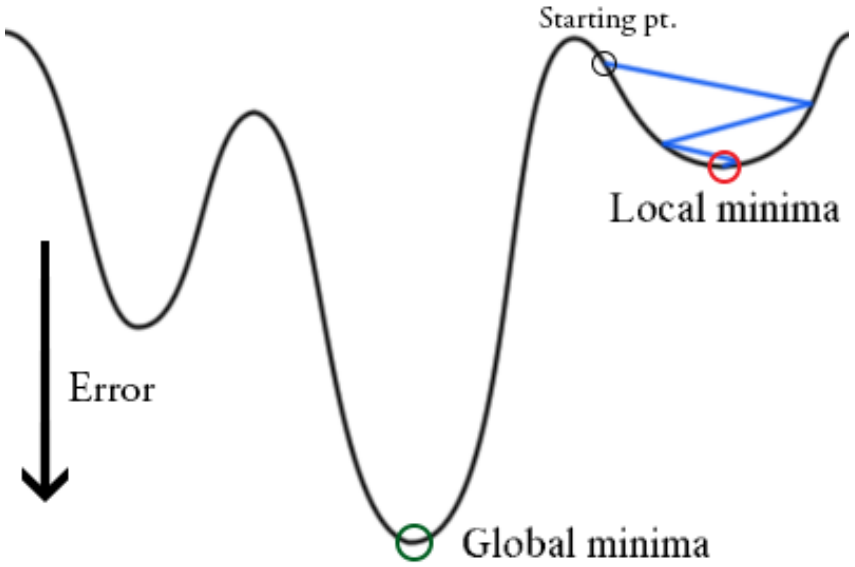


Local Minima

- For each weight vector, we can calculate the error of the NN
- The (weight vector, error) surface/landscape can be very rugged: many local minima
- Search: a trajectory of points leading to the global minima
- A bad trajectory leads to poor local minimum



Surface with 2 weights

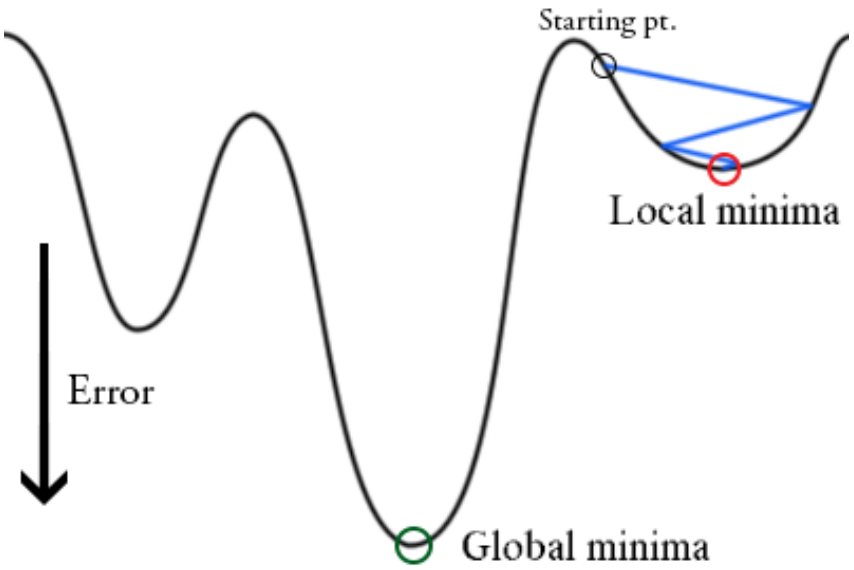


Surface with 1 weight

Local Minima

- How can you tell if a local minimum is reached?

- What to do if you reach a local minimum?



ANN Architecture

- How many input and output nodes?
  - Usually determined by the problem and data
- Number of input nodes equals the number of features
- Number of outputs
  - 1 output nodes for binary classification (true/false)
  - N output nodes for N-class classification
  - Example: (1, 0, 0) = class 1; (0, 1, 0) = class 2; (0, 0, 1) = class 3

ANN Architecture

- How many hidden layers/nodes?
  - Theorem: **one** hidden layer is enough for any problem
  - But training is significantly faster with several layers
  - Best to have as few hidden layers/nodes as possible: better *generalisation*, fewer weights to optimise (easier to solve)

  - Make the best guess you can
  - If training is unsuccessful try more hidden nodes
  - If training is successful try fewer hidden nodes
  - Observe weights after training:
    nodes with small weights can probably be eliminated

Momentum

- Normal to have huge ANNs take days/weeks/months to train
- Speeding this up is crucial!

- Momentum is a widely used approach
  - Use the gradient from last step(s)

$$\Delta w_{i \to j}(t) \leftarrow \eta o_j o_j (1 - o_j) \beta_j + \alpha \Delta w_{i \to j}(t-1)$$

- Does momentum always help?
- Have you used/seen momentum before?
- How do we choose η and α?

Design Questions

- How to properly arrange the data for network training and for measuring the results?
- Number of input/output nodes?
- How many hidden layers are needed and how many nodes in each hidden layer?
- Values for the parameters and variables for controlling the training process, for example, learning rate, initial weights, momentum and number of epochs?
- Stopping criteria (validation control)?
- How often are the weights changed (batch size)?

Summary

- Different frequencies for weight update
  - Online, offline, batch learning
- Learning rate
  - Not too large nor too small, 0.2 is a good starting point
- Overfitting
- Stopping criteria
  - Validation control to avoid overfitting
- Local minima
- ANN architecture: #input/output/hidden nodes
- Momentum to speed up training