VICTORIA UNIVERSITY OF WELLINGTON
Te Whare Wananga o te Upoko o te Ika a Maui

School of Engineering and Computer Science

COMP 307 — Lecture 09

Machine Learning 6

Neural Networks and Neural Engineering

Dr Bing Xue (Prof. Mengjie Zhang)

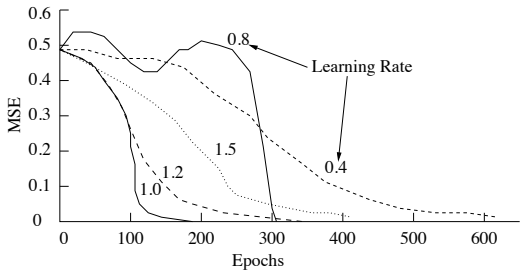
bing.xue@ecs.vuw.ac.nz

Outline

- Learning rate
- Overfitting
- Stopping criteria
- Local minima/optima
- Network architecture
- Momentum
- Parameters
- Other types of neural networks
- Problems

Learning Rate

- Which learning rate appears best for this problem ?
- Usually exists an optimal learning rate, but problem dependent
- In practice $\eta = 0.2$ is good starting point



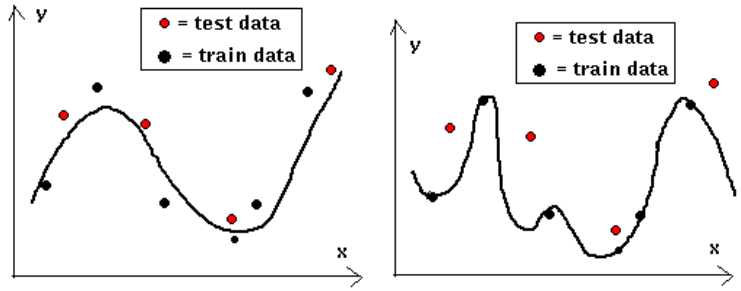
$$\Delta w_{i \to j} = \eta \, o_i \, o_j \left(1 - o_j\right) \beta_j$$

Epoch: one single complete pass through the whole training set

Overfitting

- The network has high accuracy on the data from which it was developed (training), but low accuracy on new data (test)
- *Caused by*
  - Training for too long
  - Having a network with too many nodes and weights
    - Each weight (and bias) is a parameter that needs to be estimated
    - The more parameters we have the *more data* we need for accurate estimates
  - Too few training examples
    - How many examples do you need to learn properly
    - Given that we have *n* examples, how well can we expect to learn ?

Overfitting (Continued)

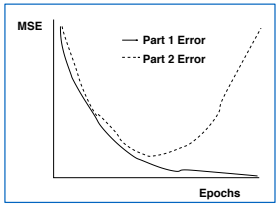


Small networks
Simple curve

Large networks
Complex curve

When to Stop Training

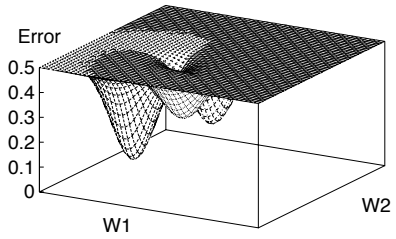
- The *epoch/cycle control* strategy
- The *error control* strategy: TSS, MSE, RMSE can be used.
- The *proportion control* strategy: accuracy.
- The *user control* strategy.



- The *early stopping* strategy:
  Validation control
  - Break the TRAINING set into 2 parts
  - Use *part 1* to compute the weight changes
  - Every m (Typical values 10, 50, 100) epochs apply the partially trained network to *part 2* (the validation set) and save the weights
  - Goal: avoid overfitting

Local Minima (Optima)

- Suppose we are training a network with two weights w_1, w_2
- For any given values of w_2 and w_2 we can work out the error.
- Plotting error vs weights might give such a surface/landscape
  - Note in general we can't do this because there are too many dimensions
- What we desire is a trajectory of points which leads us to the global minimum (optimum)
- A bad trajectory or starting point will take us to a local minimum
- Oscillating trajectory



Local Minima (Optima)

- How can you tell if a local minimum has been reached?
  - A number of runs with different starting points end with (very) different TSS errors
- What to do about a local minimum?
  - Nothing, if training is 'good enough'
  - Increase the value of the learning rate η
- Oscillation
  - The error graph is very 'jerky' without an overall downward trend.
  - Decrease the learning rate.
- Sometimes decreasing the learning rate as training proceeds works well.

Network Size/Architecture

- Usually the numbers of inputs and outputs is determined by the problem
- How many hidden layers? Hidden nodes?
- Theorem: One hidden layer is enough for any problem
- But, training might be faster with several layers
- Best is to have as few hidden layers/nodes as possible
  - Forces better generalisation
  - Fewer weights to be found
- Determining the number of hidden layers/nodes
  - Make the best guess you can
  - If training is unsuccessful try more hidden nodes
  - If training is successful try fewer hidden nodes
  - Inspect weights after training. Nodes which have small weights can probably be eliminated

Momentum

- Momentum: When updating a weight, add a contribution from time $t-1$
- Weight update rule becomes:

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

- Momentum is controversial
  - One view: It is hopeless, don't ever use it
  - Opposite view: It's always better with momentum. You just have to get the right values for η and α

Online Learning vs Offline Learning

- Online learning: A variation of BP learning
  - At what stage are the network weights updated when training patterns are presented?
  - In general, two possibilities.
  - Online learning (or called the *stochastic gradient procedure*), where the weight changes are applied to the network after each training pattern.
  - off-line learning (or called the *true gradient procedure*) in which the weight changes are accumulated for all training patterns and the sum of all changes is applied after one full epoch. (The standard BP uses this)

Main Parameters for Network Training

- Random range (r): The random range ([-r, r]) of the initial weights.
- Learning rate (η): The constant in *true gradient descent*. The bigger the learning rate, the larger the changes in the weights.
- Momentum (α): A constant which determines the effect of past weight changes on the current direction of movement in weight space.
- Critical error (ce): The desired error (TSS, MSE or RMSE) for stopping network training. If the actual error is equal to or less than this error, the training will be terminated.

Tackling a Problem with NNs

Given a neural network package:

• How to properly arrange the data for network training and for measuring the results?

- What is the number of output nodes?
- How many input nodes are needed?
- How many hidden layers are needed and how many nodes in each hidden layer?
- What values can be given for the parameters and variables for controlling the training process, for example, *learning rate, range of initial weights, momentum and number of epochs*?
- What termination strategies need to be applied during network training and how many runs do we perform for the problem?
- At what stage are the network weights updated when training patterns are presented? i.e. online or off-line

Neural Networks as Nonlinear Regression

- Very powerful, general function fitting mechanisms
  - can represent any function
  - (with enough hidden nodes)
- Output units represent "smoothed" hyperplane
- Hidden nodes transform space arbitrarily, black box
- Useful in huge variety of domains

Other Neural Networks

- Multilayer, feed forward, back propagation
  - the "standard", for learning to classify or predict
- Recurrent/feedback networks
  - Cycles in networks, with or without time delay
  - Sequence prediction — can remember recent inputs
- Network for remembering patterns
  - Hopfield networks: "Content addressable memory"
  - Given part of or distorted pattern, find best matching pattern
- Networks for automatic clustering
  - Kohonen networks
  - Self organising maps (SOMs)

Summary

- Feed forward networks and neural engineering
  - Back propagation example
  - Learning rate
  - Overfitting
  - Stopping criteria
  - Local minima/optima
  - Network architecture
  - Momentum
  - Parameters
- Other types of neural networks
- Problems and directions
- Next week: Evolutionary Learning/Computing