Introduction to Neural Networks

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Automatic Speech Recognition— ASR Lecture 10
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Neural networks for speech recognition

- Introduction to Neural Networks
- Training feed-forward networks
- Hybrid neural network / HMM acoustic models
- Neural network features – Tandem, posteriorgrams
- Deep neural network acoustic models
- Neural network language models

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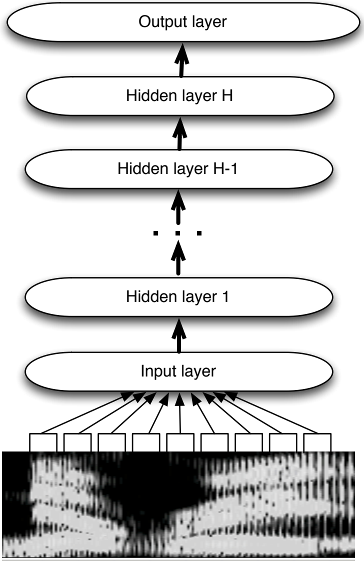
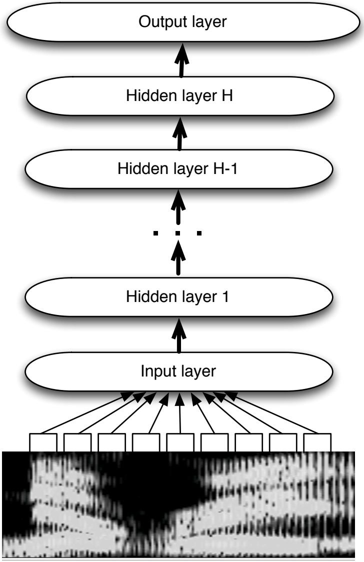
Neural network acoustic models



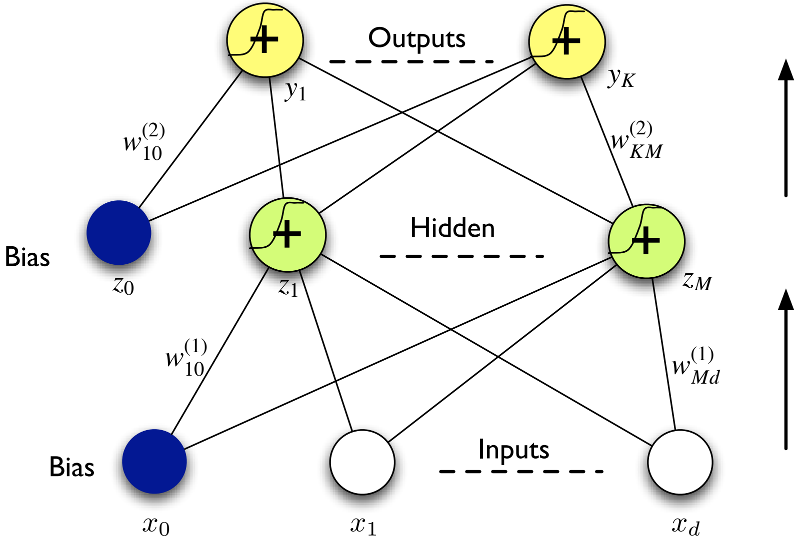
- Input layer takes several consecutive frames of acoustic features
- Output layer corresponds to classes (e.g. phones, HMM states)
- Multiple non-linear hidden layers between input and output
- Neural networks also called multi-layer perceptrons

NN vs GMM



- Potential **deep** structure through multiple hidden layers (rather than a single layer of GMMs)
- Operates on multiple frames of input (rather than a single frame)
- One big network for everything (rather than one HMM per phone)

Layered neural networks: structure (1)



Neural network with one hidden layer

Layered neural networks: structure (2)

- d input units, M hidden units, K output units
- Hidden layer: each of M units takes a linear combination of the inputs x_i:

$$b_j = \sum_{i=0}^{d} w_{ji}^{(1)} x_i$$

  - b_j: activations
  - $w_{ji}^{(1)}$: first layer of weights

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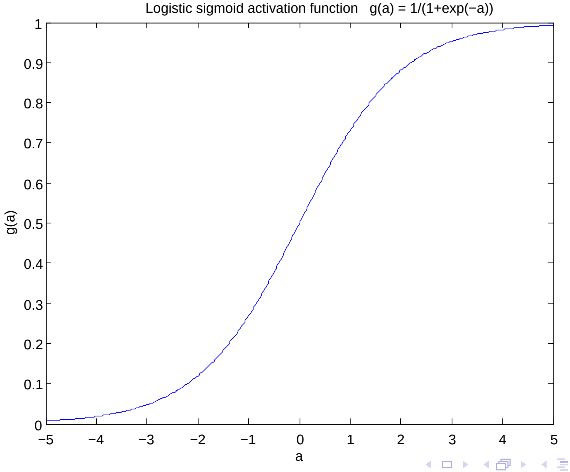
- Activations transformed by a nonlinear activation function h (e.g. a sigmoid):

$$z_j = h(b_j) = \frac{1}{1 + \exp(-b_j)}$$

  - z_j: hidden unit outputs

Logisitic sigmoid activation function

$$g(a) = \frac{1}{(1 + \exp(-a))}$$



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- Outputs of the hidden units are linearly combined to give activations of the output units:

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- If output unit k corresponds to class C_k, then interpret outputs of trained network as posterior probability estimates

$$P(C_k \mid \mathbf{x}) = y_k$$

Layered neural networks: training

- Weights w_{ji} are the trainable parameters
- Train the weights by adjusting them to minimise a cost function which measures the error the network outputs y_k^n (for the nth frame) compared with the *target* output t_k^n
  - Sum squared error

$$E^n = \frac{1}{2} \sum_{k=1}^{K} ||t_k^n - y_k^n||^2$$

  - For multiclass classification, the natural cost function is (negative) log probability of the correct class

$$E^n = -\sum_{k=1}^{K} t_k^n \log y_k^n$$

- $E = \sum_n E^n$
- Optimise the cost function using *gradient descent* (back-propagation of error — backprop)

Gradient descent

- Gradient descent can be used whenever it is possible to compute the derivatives of the error function E with respect to the parameters to be optimized $\mathbf{W}$
- Basic idea: adjust the weights to move downhill in *weight space*
- Weight space: space defined by all the trainable parameters (weights)
- Operation of gradient descent:
  1. Start with a guess for the weight matrix $\mathbf{W}$ (small random numbers)
  2. Update the weights by adjusting the weight matrix in the direction of $-\nabla_{\mathbf{W}} E$.
  3. Recompute the error, and iterate
- The update for weight w_{ki} at iteration $\tau + 1$ is:

$$w_{ki}^{\tau+1} = w_{ki}^{\tau} - \eta \frac{\partial E}{\partial w_{ki}}$$

The parameter η is the *learning rate*

Using neural networks for acoustic modelling

- **Hybrid** NN/HMM systems
  - Basic idea: in an HMM, replace the GMMs used to estimate output pdfs with the outputs of neural networks
  - Transform NN posterior probability estimates to *scaled likelihoods* by dividing by the relative frequencies in the training data of each class

$$P(\mathbf{x}_t \mid C_k) \propto \frac{P(C_k \mid \mathbf{x}_t)}{P_{\text{train}}(C_k)} = \frac{y_k}{P_{\text{train}}(C_k)}$$

  - NN outputs correspond to phone classes or HMM states
- **Tandem** features
  - Use NN probability estimates as an additional input feature stream in an HMM/GMM system (posteriograms)

End of part 1

- Next two lectures
  - Hybrid NN/HMM systems
  - Tandem features
  - Deep neural networks
  - Neural network language models
- Reading
  - N Morgan and H Bourlard (May 1995). Continuous speech recognition: An introduction to the hybrid HMM/connectionist approach, IEEE Signal Processing Magazine, 12(3), 24-42.
  - Christopher M Bishop (2006). *Pattern Recognition and Machine Learning*, Springer. Chapters 4 and 5.