Text Categorization and Neural Network Learning

Categorization

- Given:
  - A description of an instance, $x \in X$, where X is the *instance language* or *instance space*.
  - A fixed set of categories: $C = \{c_1, c_2, \ldots c_n\}$
- Determine:
  - The category of x: $c(x) \in C$, where $c(x)$ is a categorization function whose domain is X and whose range is C.

Learning for Categorization

- A training example is an instance $x \in X$, paired with its correct category $c(x)$: $<x, c(x)>$ for an unknown categorization function, c.
- Given a set of training examples, D.
- Find a hypothesized categorization function, $h(x)$, such that:

$$\forall < x, c(x) > \in D : h(x) = c(x)$$

Consistency

Sample Category Learning Problem

- Instance language: <size, color, shape>
  - size ∈ {small, medium, large}
  - color ∈ {red, blue, green}
  - shape ∈ {square, circle, triangle}
- C = {positive, negative}
- D:

Example	Size	Color	Shape	Category
1	small	red	circle	positive
2	large	red	circle	positive
3	small	red	triangle	negative
4	large	blue	circle	negative

General Learning Issues

- Many hypotheses are usually consistent with the training data.
- Bias
  - Any criteria other than consistency with the training data that is used to select a hypothesis.
- Classification accuracy (% of instances classified correctly).
  - Measured on independent test data.
- Training time (efficiency of training algorithm).
- Testing time (efficiency of subsequent classification).

Generalization

- Hypotheses must generalize to correctly classify instances not in the training data.
- Simply memorizing training examples is a consistent hypothesis that does not generalize.
- *Occam's razor*:
  - Finding a *simple* hypothesis helps ensure generalization.

Text Categorization

- Assigning documents to a fixed set of categories.
- Applications:
  - Web pages
    - Recommending
    - Hierarchical classification for browsing
  - Newsgroup Messages
    - Recommending
    - spam filtering
  - News articles
    - Personalized newspaper
  - Email messages
    - Routing
    - Prioritizing
    - Folderizing
    - spam filtering

Learning for Text Categorization

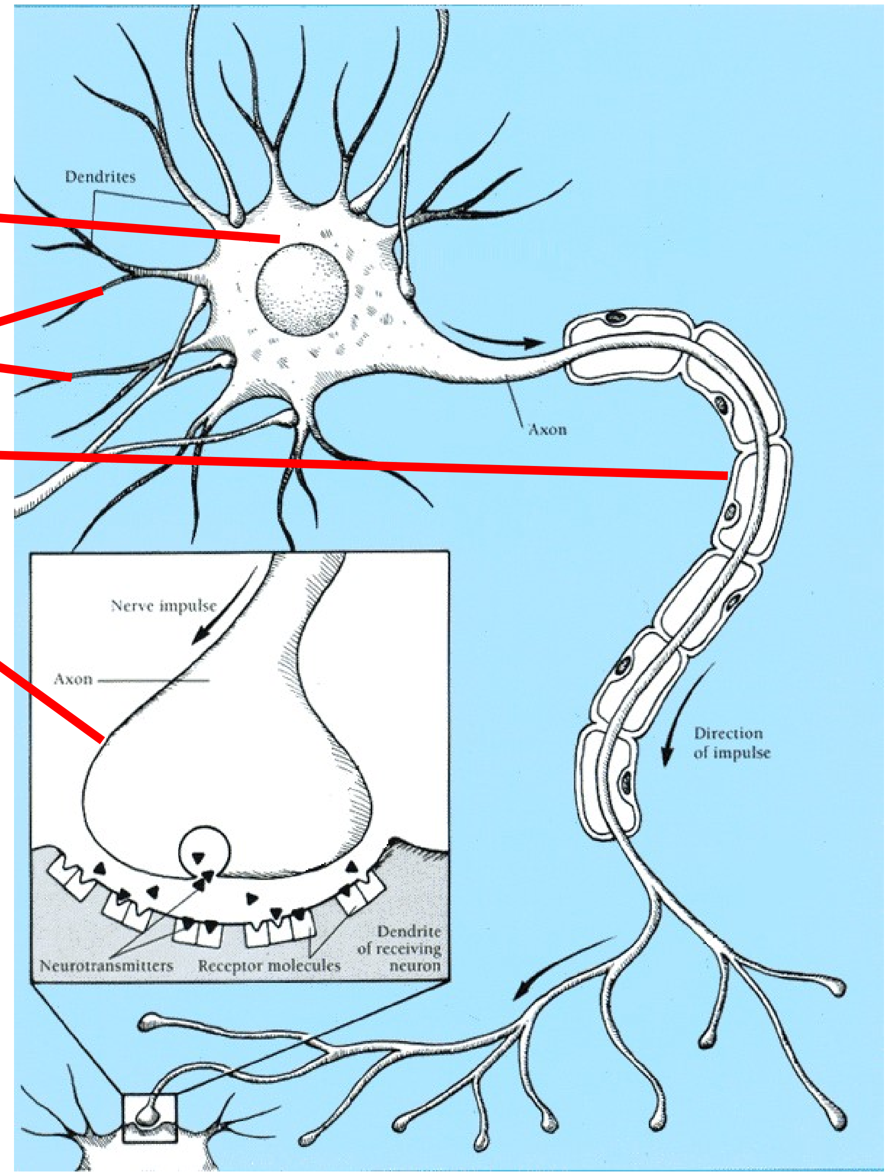
- Manual development of text categorization functions is difficult.
- Learning Algorithms:
  - **Neural network**
  - Bayesian (naïve)
  - Relevance Feedback (Rocchio classifier)
  - Rule based
  - Nearest Neighbor (case based)
  - Support Vector Machines (SVM)

Neural Network Learning

- Learning approach based on modeling adaptation in biological neural systems.
- Perceptron: Initial algorithm for learning simple neural networks (single layer) developed in the 1950's.
- Backpropagation: More complex algorithm for learning multi-layer neural networks developed in the 1980's.

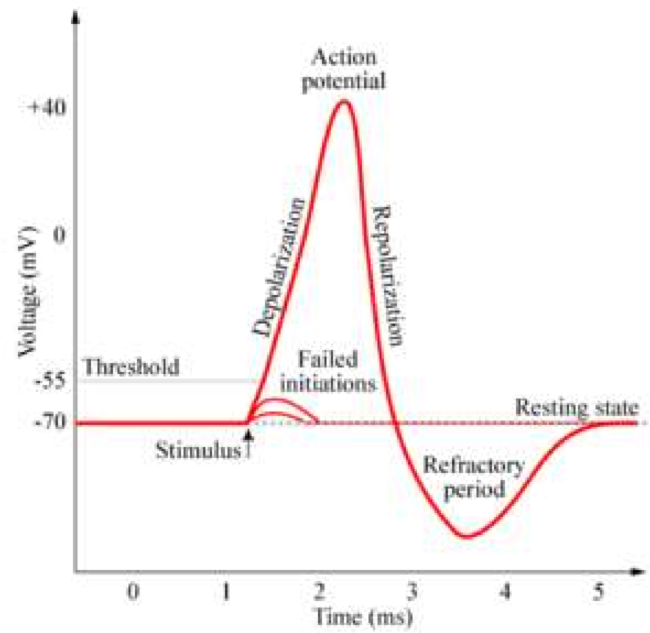
Real Neurons

- Cell structures
  - Cell body
  - Dendrites
  - Axon
  - Synaptic terminals



Neural Communication

- Electrical potential across cell membrane exhibits spikes called action potentials.
- Spike originates in cell body, travels down axon, and causes synaptic terminals to release neurotransmitters.
- Chemical diffuses across synapse to dendrites of other neurons.
- Neurotransmitters can be excititory or inhibitory.



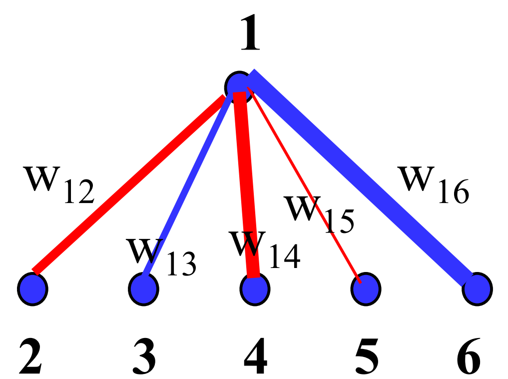
- If net input of neurotransmitters to a neuron from other neurons is excititory and exceeds some threshold, it fires an action potential.

Real Neural Learning

- Synapses change size and strength with experience.
- Hebbian learning: When two connected neurons are firing at the same time, the strength of the synapse between them increases.
- "Neurons that fire together, wire together."

Artificial Neuron Model (Linear Threshold Unit)

- Model network as a graph with cells as nodes and synaptic connections as weighted edges from node *i* to node *j*, w_{ji}



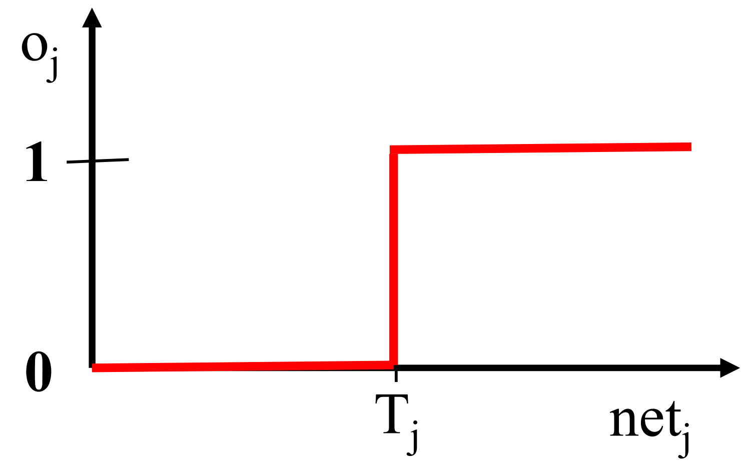
- Model net input to cell as

$$net_j = \sum_i w_{ji} o_i$$

- Cell output is:

$$o_j = \begin{cases} 0 \text{ if } net_j < T_j \\ 1 \text{ if } net_i \geq T_j \end{cases}$$

(T_j is threshold for unit j)



Neural Computation

- McCollough and Pitts (1943) showed how such model neurons could compute logical functions and be used to construct finite-state machines.
- Can be used to simulate logic gates:
  - AND: Let all w_{ji} be T_j/n, where n is the number of inputs.
  - OR: Let all w_{ji} be T_j
  - NOT: Let threshold be 0, single input with a negative weight.
- Can build arbitrary logic circuits, sequential machines, and computers with such gates.
- Given negated inputs, two layer network can compute any boolean function using a two level AND-OR network.

Perceptron Training

- Assume supervised training examples giving the desired output for a unit given a set of known input activations.
- Learn synaptic weights so that unit produces the correct output for each example.
- Perceptron uses iterative update algorithm to learn a correct set of weights.

Perceptron Learning Rule

- Update weights by:

  $$w_{ji} = w_{ji} + \eta(t_j - o_j)o_i$$

  where η is the "learning rate"

  t_j is the teacher specified output for unit j.
- Equivalent to rules:
  - If output is correct do nothing.
  - If output is high, lower weights on active inputs
  - If output is low, increase weights on active inputs
- Also adjust threshold to compensate:

  $$T_j = T_j - \eta(t_j - o_j)$$

Perceptron Learning Algorithm (Rosenblatt, 1957)

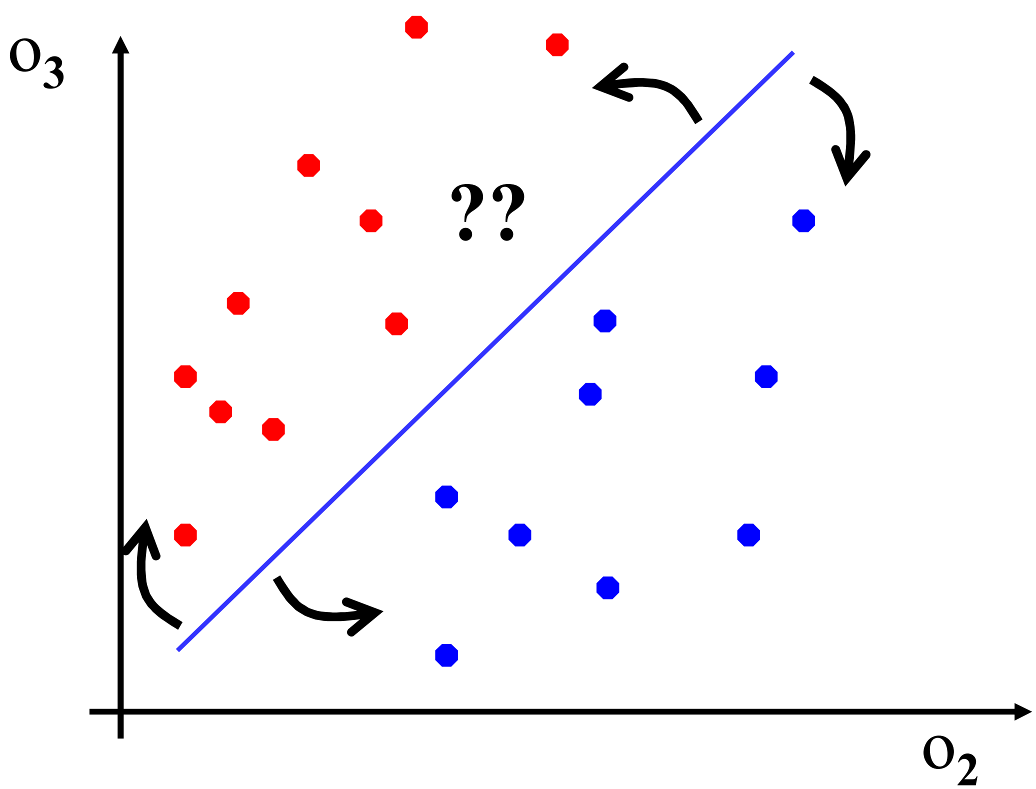
- Iteratively update weights until convergence.

Initialize weights to random values
Until outputs of all training examples are correct
    For each training pair, E, do:
        Compute current output o_j for E given its inputs
        Compare current output to target value, t_j , for E
        Update synaptic weights and threshold using learning rule

- Each execution of the outer loop is typically called an *epoch*.

Perceptron as a Linear Separator

- Since perceptron uses linear threshold function, it is searching for a linear separator that discriminates the classes.



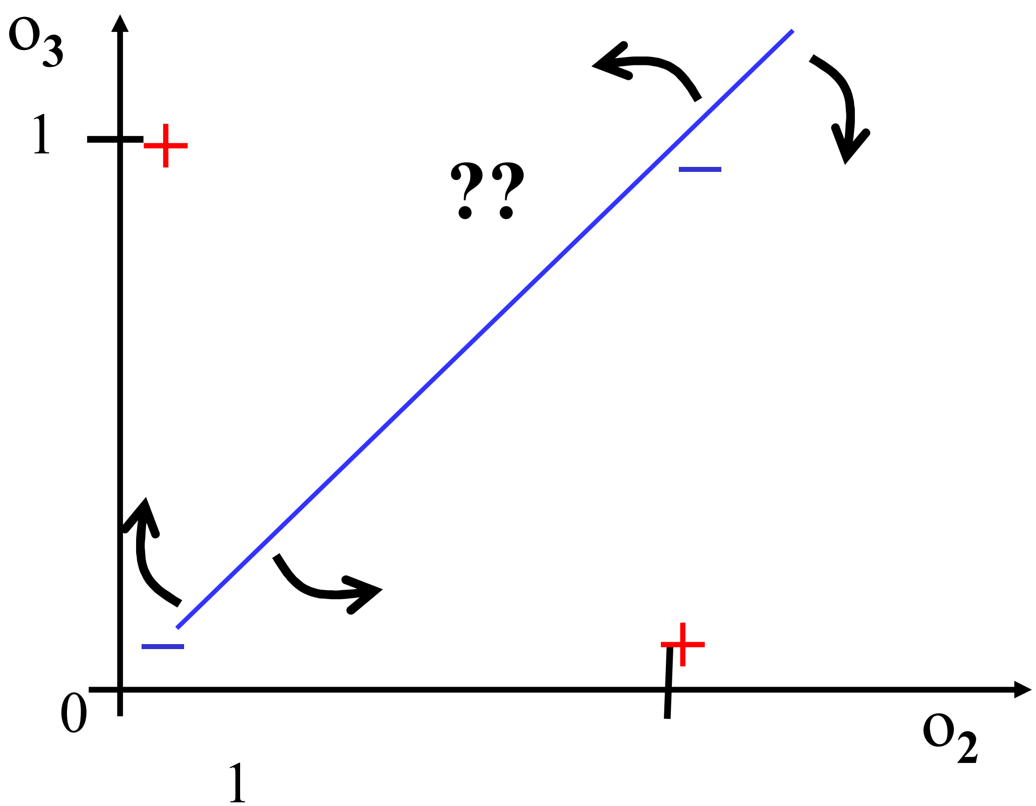
$$w_{12}o_2 + w_{13}o_3 > T_1$$

$$o_3 > -\frac{w_{12}}{w_{13}} o_2 + \frac{T_1}{w_{13}}$$

Or hyperplane in n-dimensional space

Concept Perceptron Cannot Learn

- Cannot learn exclusive-or, or parity function in general.



Perceptron Limits

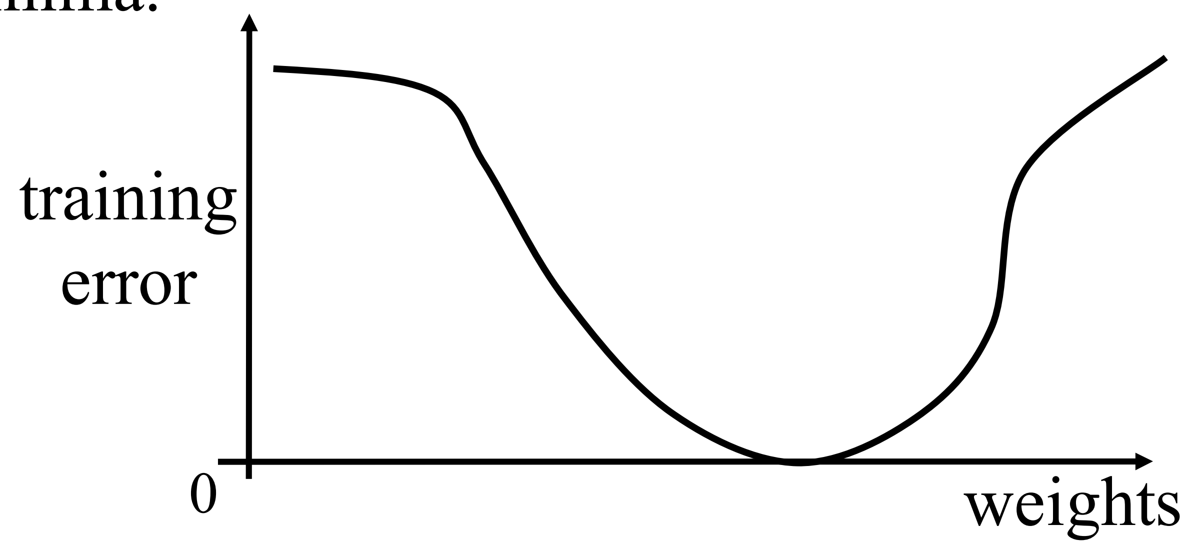
- System obviously cannot learn concepts it cannot represent.
- Minsky and Papert (1969) wrote a book analyzing the perceptron and demonstrating many functions it could not learn.
- These results discouraged further research on neural nets; and symbolic AI became the dominate paradigm.

Perceptron Convergence and Cycling Theorems

- **Perceptron convergence theorem**: If the data is linearly separable and therefore a set of weights exist that are consistent with the data, then the Perceptron algorithm will eventually converge to a consistent set of weights.
- **Perceptron cycling theorem**: If the data is not linearly separable, the Perceptron algorithm will eventually repeat a set of weights and threshold at the end of some epoch and therefore enter an infinite loop.
  - By checking for repeated weights+threshold, one can guarantee termination with either a positive or negative result.

Perceptron as Hill Climbing

- The hypothesis space being search is a set of weights and a threshold.
- Objective is to minimize classification error on the training set.
- Perceptron effectively does hill-climbing (gradient descent) in this space, changing the weights a small amount at each point to decrease training set error.
- For a single model neuron, the space is well behaved with a single minima.

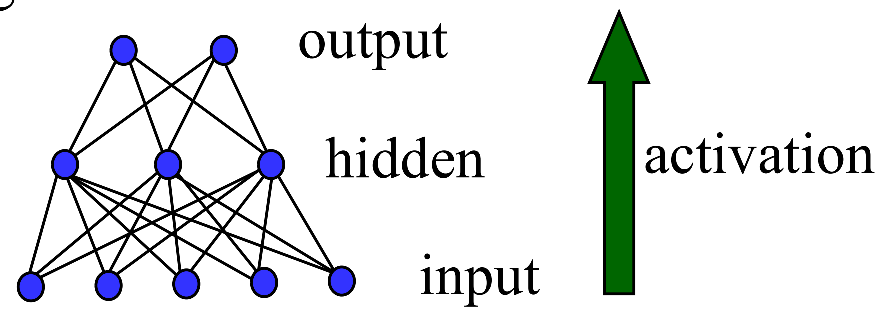


Perceptron Performance

- Linear threshold functions are restrictive (high bias) but still reasonably expressive; more general than:
  - Pure conjunctive
  - Pure disjunctive
  - M-of-N (at least M of a specified set of N features must be present)
- In practice, converges fairly quickly for linearly separable data.
- Can effectively use even incompletely converged results when only a few outliers are misclassified.
- Experimentally, Perceptron does quite well on many benchmark data sets.

Multi-Layer Networks

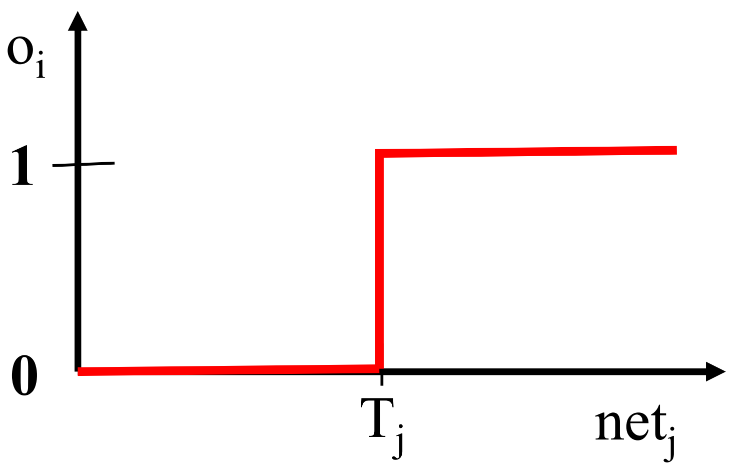
- Multi-layer networks can represent arbitrary functions, but an effective learning algorithm for such networks was thought to be difficult.
- A typical multi-layer network consists of an input, hidden and output layer, each fully connected to the next, with activation feeding forward.



- The weights determine the function computed. Given an arbitrary number of hidden units, any boolean function can be computed with a single hidden layer.

Hill-Climbing in Multi-Layer Nets

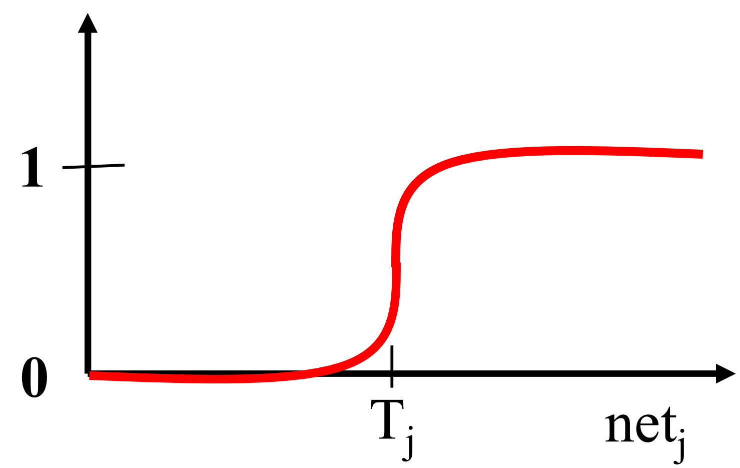
- Since "greed is good" perhaps hill-climbing can be used to learn multi-layer networks in practice although its theoretical limits are clear.
- However, to do gradient descent, we need the output of a unit to be a differentiable function of its input and weights.
- Standard linear threshold function is not differentiable at the threshold.



Differentiable Output Function

- Need non-linear output function to move beyond linear functions.
  - A multi-layer linear network is still linear.
- Standard solution is to use the non-linear, differentiable sigmoidal "logistic" function:

$$o_j = \frac{1}{1 + e^{-(net_j - T_j)}}$$



Can also use tanh or Gaussian output function

Gradient Descent

- Define objective to minimize error:

$$E(W) = \sum_{d \in D} \sum_{k \in K} (t_{kd} - o_{kd})^2$$

where D is the set of training examples, K is the set of output units, t_{kd} and o_{kd} are, respectively, the teacher and current output for unit k for example d.

- The derivative of a sigmoid unit with respect to net input is:

$$\frac{\partial o_j}{\partial net_j} = o_j(1 - o_j)$$

- Learning rule to change weights to minimize error is:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}}$$

Backpropagation Learning Rule

- Each weight changed by:

$$\Delta w_{ji} = \eta \delta_j o_i$$

$$\delta_j = o_j(1 - o_j)(t_j - o_j) \qquad \text{if } j \text{ is an output unit}$$

$$\delta_j = o_j(1 - o_j)\sum_k \delta_k w_{kj} \qquad \text{if } j \text{ is a hidden unit}$$

where η is a constant called the learning rate

t_j is the correct teacher output for unit j

δ_j is the error measure for unit j

Error Backpropagation

- First calculate error of output units and use this to change the top layer of weights.

Current output: $o_j=0.2$

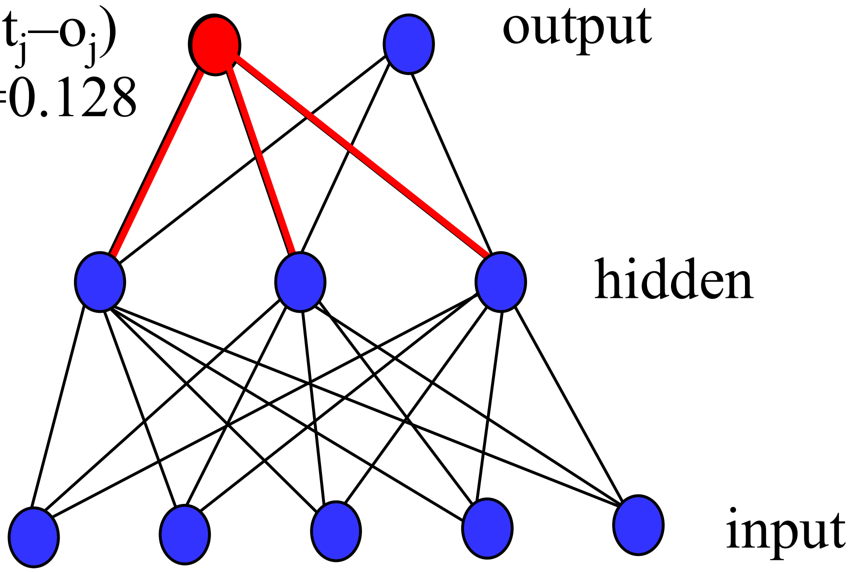
Correct output: $t_j=1.0$

Error $\delta_j = o_j(1-o_j)(t_j-o_j)$

$0.2(1-0.2)(1-0.2)=0.128$

Update weights into j

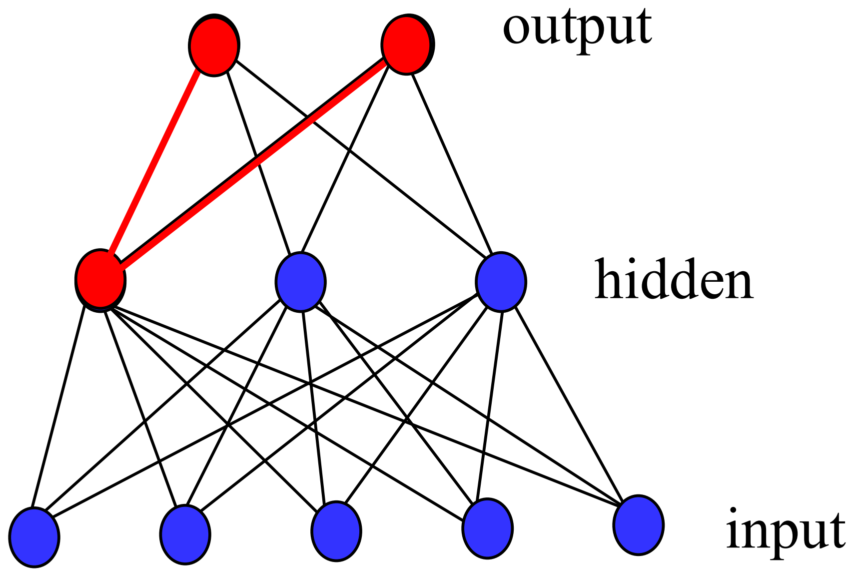
$$\Delta w_{ji} = \eta \delta_j o_i$$



Error Backpropagation

- Next calculate error for hidden units based on errors on the output units it feeds into.

$$\delta_j = o_j(1 - o_j)\sum_k \delta_k w_{kj}$$



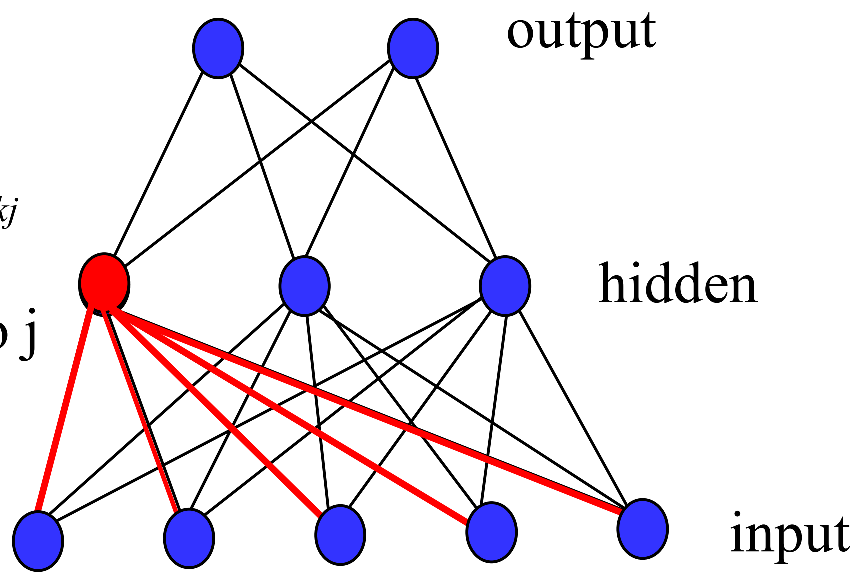
Error Backpropagation

- Finally update bottom layer of weights based on errors calculated for hidden units.

$$\delta_j = o_j(1 - o_j)\sum_k \delta_k w_{kj}$$

Update weights into j

$$\Delta w_{ji} = \eta \delta_j o_i$$



Backpropagation Training Algorithm

Create the 3-layer network with *H* hidden units with full connectivity between layers.

Set all weights to small random real values.

Until all training examples produce the correct value (within ε), or mean squared error ceases to decrease, or other termination criteria:

  Begin epoch

  For each training example, *d*, do:

    Calculate network output for *d*'s input values

    Compute error between current output and correct output for *d*

    Update weights by backpropagating error and using learning rule

  End epoch

Comments on Training Algorithm

- Not guaranteed to converge to zero training error, may converge to local optima or oscillate indefinitely.
- However, in practice, does converge to low error for many large networks on real data.
- Many epochs (thousands) may be required, hours or days of training for large networks.
- To avoid local-minima problems, run several trials starting with different random weights (*random restarts*).
  - Take results of trial with lowest training set error.
  - Build a committee of results from multiple trials (possibly weighting votes by training set accuracy).

Hidden Unit Representations

- Trained hidden units can be seen as newly constructed features that make the target concept linearly separable in the transformed space.
- On many real domains, hidden units can be interpreted as representing meaningful features such as vowel detectors or edge detectors, etc..
- However, the hidden layer can also become a distributed representation of the input in which each individual unit is not easily interpretable as a meaningful feature.

NNs for Text Categorization

- Represent documents as vectors in the standard way, using:
  - Binary word vectors
  - Bag of words normalized frequency vectors
  - TF/IDF weighted bag of words vectors
- Train a Perceptron or a multi-layer Perceptron (MLP) (typically a 3-layer backprop net) to classify these document vectors.

Summary

- Automated text categorization uses machine learning to generate a classifier function by training on labeled training data.
- There are many approaches to machine learning that incorporate various inductive biases.
- Neural networks have demonstrated recent success on many problems particularly those involving text and language.