Neural Networks

Philipp Koehn

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Supervised Learning

- Examples described by attribute values (Boolean, discrete, continuous, etc.)

- E.g., situations where I will/won't wait for a table:

Example	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*WillWait*
X_1	*T*	*F*	*F*	*T*	*Some*	*$$$*	*F*	*T*	*French*	*0–10*	*T*
X_2	*T*	*F*	*F*	*T*	*Full*	*$*	*F*	*F*	*Thai*	*30–60*	*F*
X_3	*F*	*T*	*F*	*F*	*Some*	*$*	*F*	*F*	*Burger*	*0–10*	*T*
X_4	*T*	*F*	*T*	*T*	*Full*	*$*	*F*	*F*	*Thai*	*10–30*	*T*
X_5	*T*	*F*	*T*	*F*	*Full*	*$$$*	*F*	*T*	*French*	*>60*	*F*
X_6	*F*	*T*	*F*	*T*	*Some*	*$$*	*T*	*T*	*Italian*	*0–10*	*T*
X_7	*F*	*T*	*F*	*F*	*None*	*$*	*T*	*F*	*Burger*	*0–10*	*F*
X_8	*F*	*F*	*F*	*T*	*Some*	*$$*	*T*	*T*	*Thai*	*0–10*	*T*
X_9	*F*	*T*	*T*	*F*	*Full*	*$*	*T*	*F*	*Burger*	*>60*	*F*
X_{10}	*T*	*T*	*T*	*T*	*Full*	*$$$*	*F*	*T*	*Italian*	*10–30*	*F*
X_{11}	*F*	*F*	*F*	*F*	*None*	*$*	*F*	*F*	*Thai*	*0–10*	*F*
X_{12}	*T*	*T*	*T*	*T*	*Full*	*$*	*F*	*F*	*Burger*	*30–60*	*T*

- Classification of examples is positive (T) or negative (F)

Naive Bayes Models

- Bayes rule

$$p(C|\mathbf{A}) = \frac{1}{Z}\, p(\mathbf{A}|C)\; p(C)$$

- Independence assumption

$$\begin{aligned} p(\mathbf{A}|C) &= p(a_1, a_2, a_3, ..., a_n|C) \\ &\simeq \prod_i p(a_i|C) \end{aligned}$$

- Weights

$$p(\mathbf{A}|C) = \prod_i p(a_i|C)^{\lambda_i}$$

Naive Bayes Models

- Linear model

$$p(\mathbf{A}|C) = \exp \prod_i p(a_i|C)^{\lambda_i}$$

- Probability distribution as features

$$\begin{aligned} h_i(\mathbf{A}, C) &= \log p(a_i|C) \\ h_0(\mathbf{A}, C) &= \log p(C) \end{aligned}$$

- Linear model with features

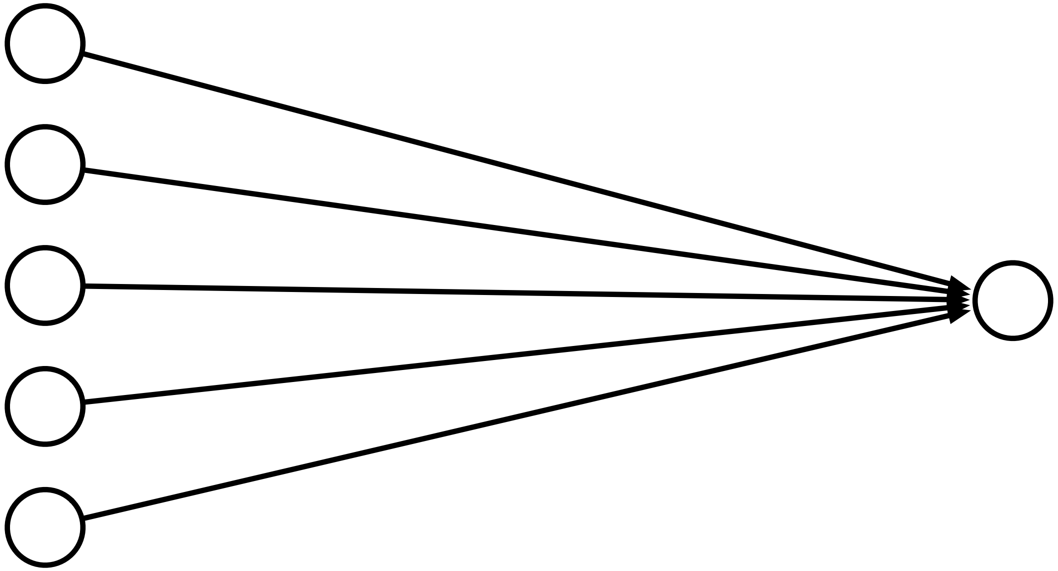
$$p(C|\mathbf{A}) \propto \sum_i \lambda_i \, h_i(\mathbf{A}, C)$$

Linear Model

- Weighted linear combination of feature values h_j and weights λ_j for example $\mathbf{d}_i$

$$\text{score}(\lambda, \mathbf{d}_i) = \sum_j \lambda_j \, h_j(\mathbf{d}_i)$$

- Such models can be illustrated as a ”network”



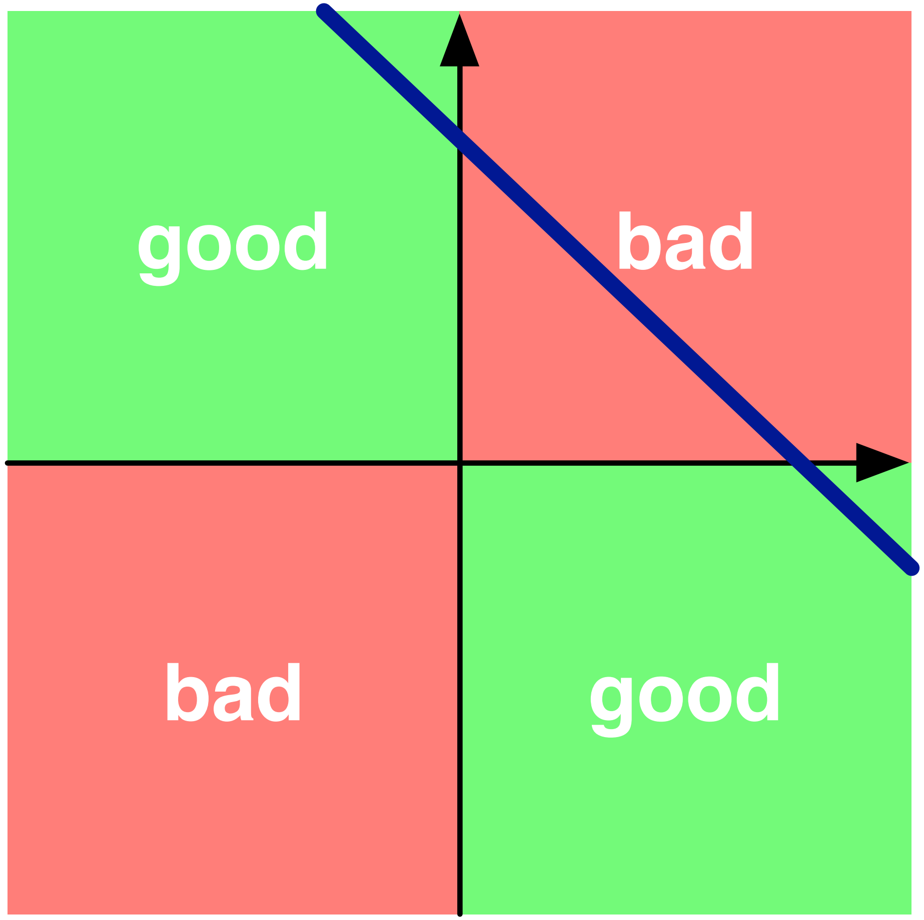
Limits of Linearity

- We can give each feature a weight

- But not more complex value relationships, e.g,
  - any value in the range [0;5] is equally good
  - values over 8 are bad
  - higher than 10 is not worse

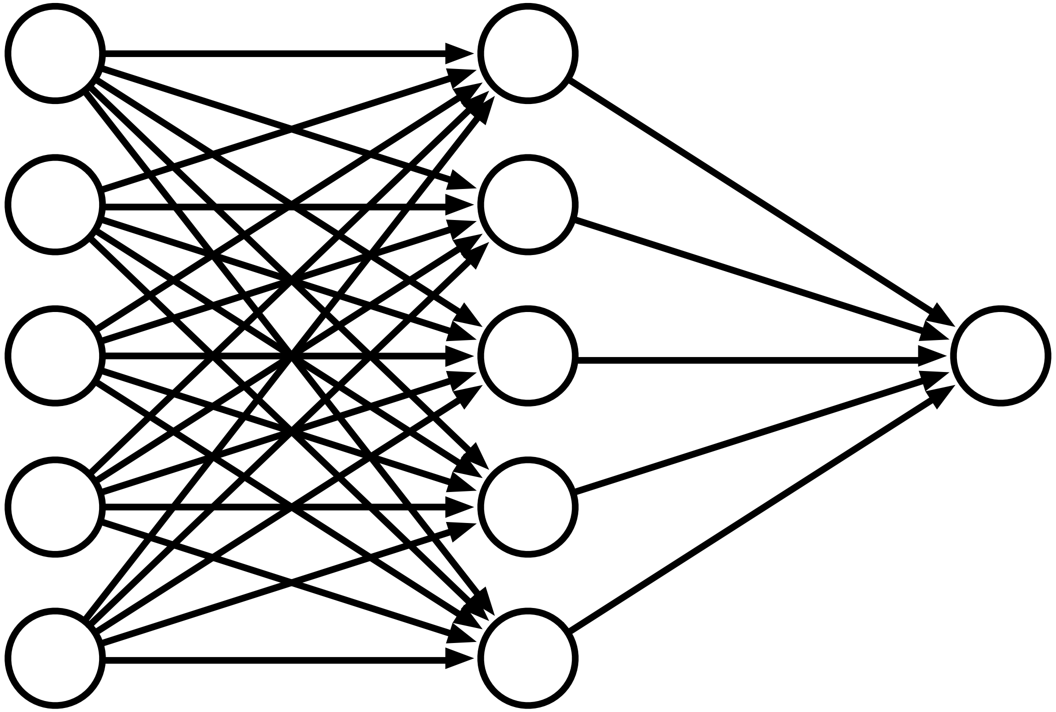
XOR

- Linear models cannot model XOR



Multiple Layers

- Add an intermediate (”hidden”) layer of processing (each arrow is a weight)



- Have we gained anything so far?

Non-Linearity

- Instead of computing a linear combination

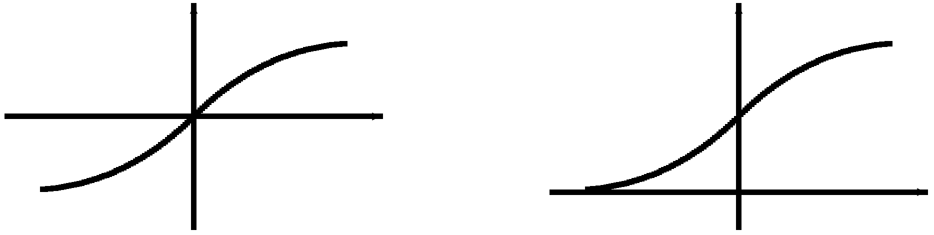
$$\text{score}(\lambda, \mathbf{d}_i) = \sum_j \lambda_j \, h_j(\mathbf{d}_i)$$

- Add a non-linear function

$$\text{score}(\lambda, \mathbf{d}_i) = f\Big(\sum_j \lambda_j \, h_j(\mathbf{d}_i) \Big)$$

- Popular choices

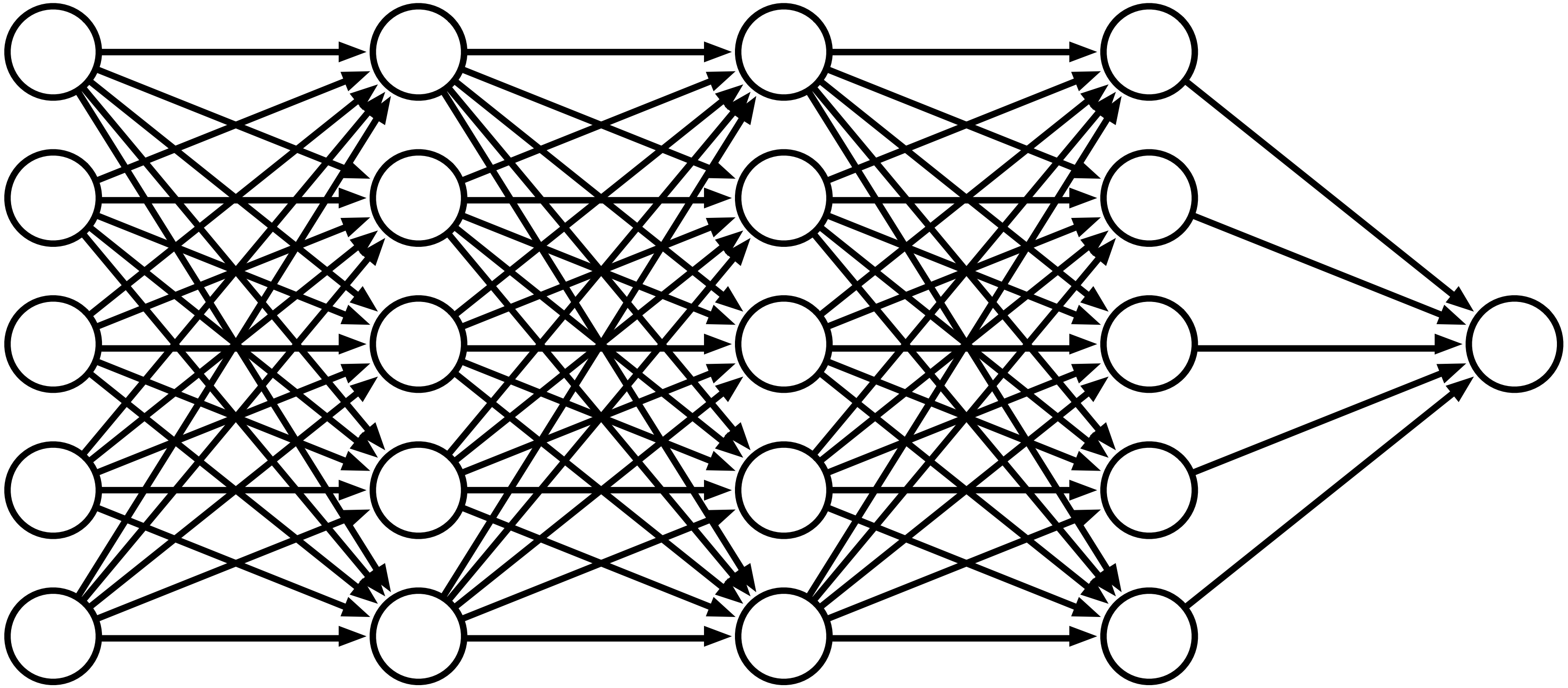
tanh(x) sigmoid(x) = $\frac{1}{1+e^{-x}}$



(sigmoid is also called the "logistic function")

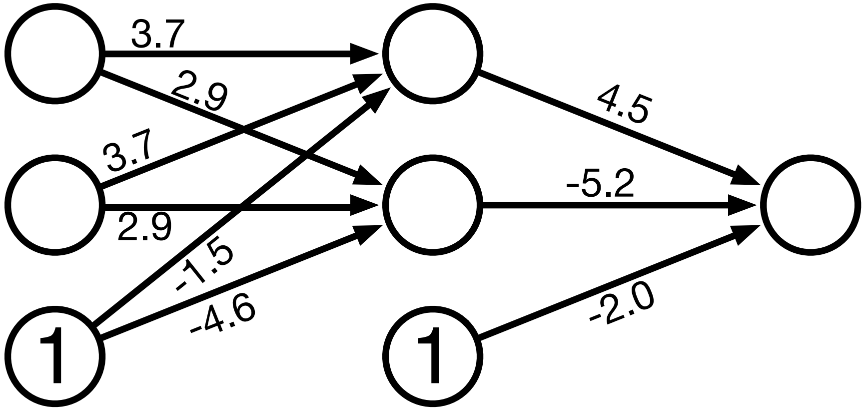
Deep Learning

- More layers = deep learning



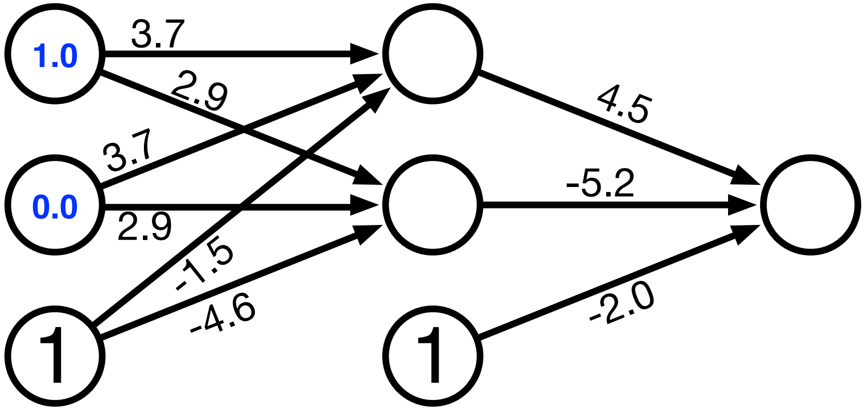
example

Simple Neural Network



- One innovation: bias units (no inputs, always value 1)

Sample Input



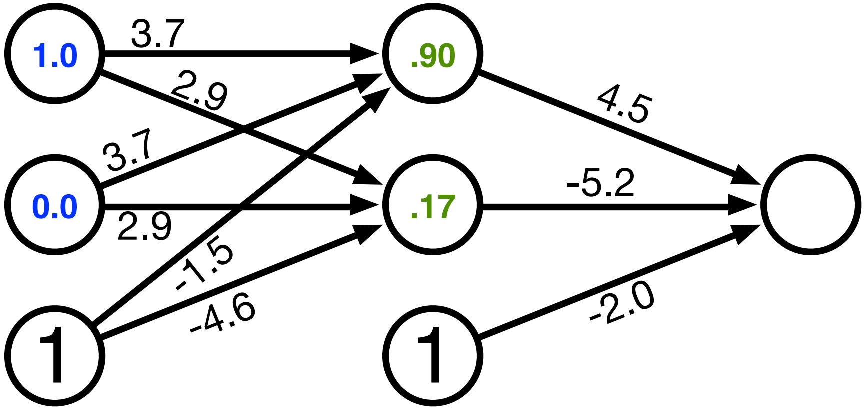
- Try out two input values

- Hidden unit computation

$$\text{sigmoid}(1.0 \times 3.7 + 0.0 \times 3.7 + 1 \times -1.5) = \text{sigmoid}(2.2) = \frac{1}{1+e^{-2.2}} = 0.90$$

$$\text{sigmoid}(1.0 \times 2.9 + 0.0 \times 2.9 + 1 \times -4.5) = \text{sigmoid}(-1.6) = \frac{1}{1+e^{1.6}} = 0.17$$

Computed Hidden



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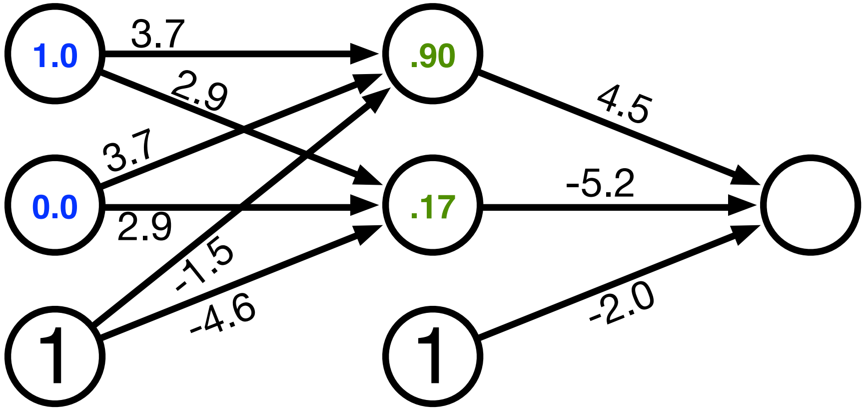
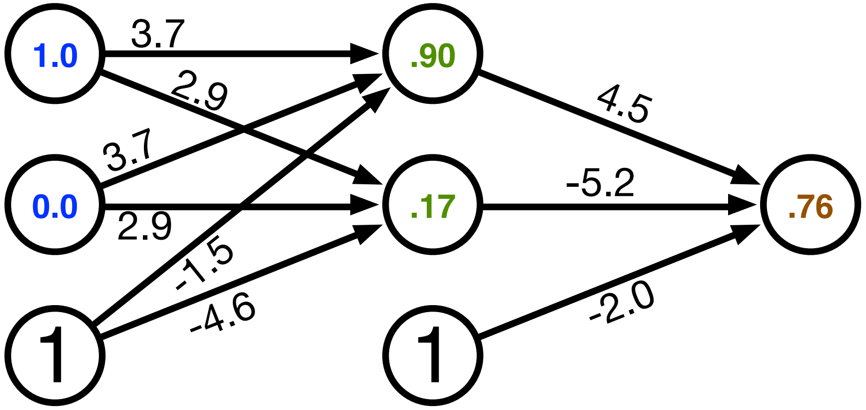
Compute Output



- Output unit computation

$$\text{sigmoid}(.90 \times 4.5 + .17 \times -5.2 + 1 \times -2.0) = \text{sigmoid}(1.17) = \frac{1}{1 + e^{-1.17}} = 0.76$$

Computed Output



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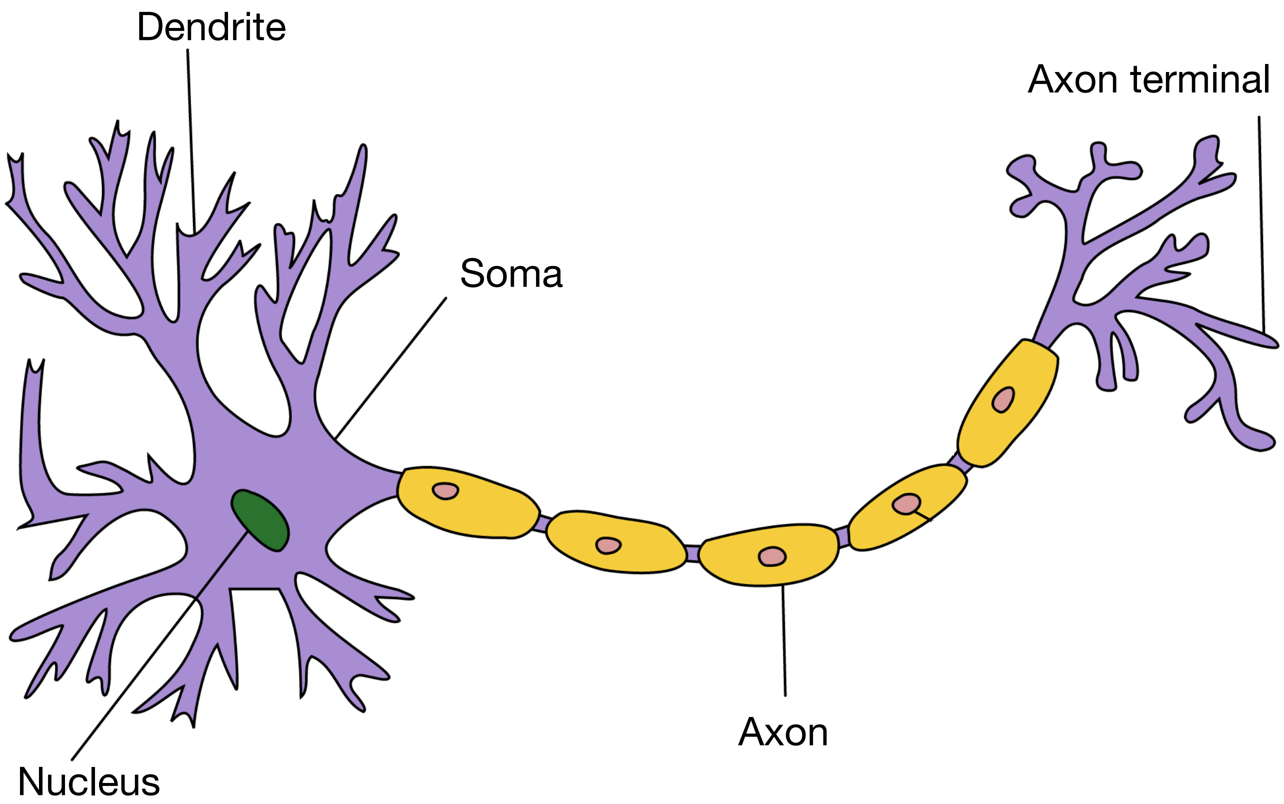
why ”neural” networks?

Neuron in the Brain

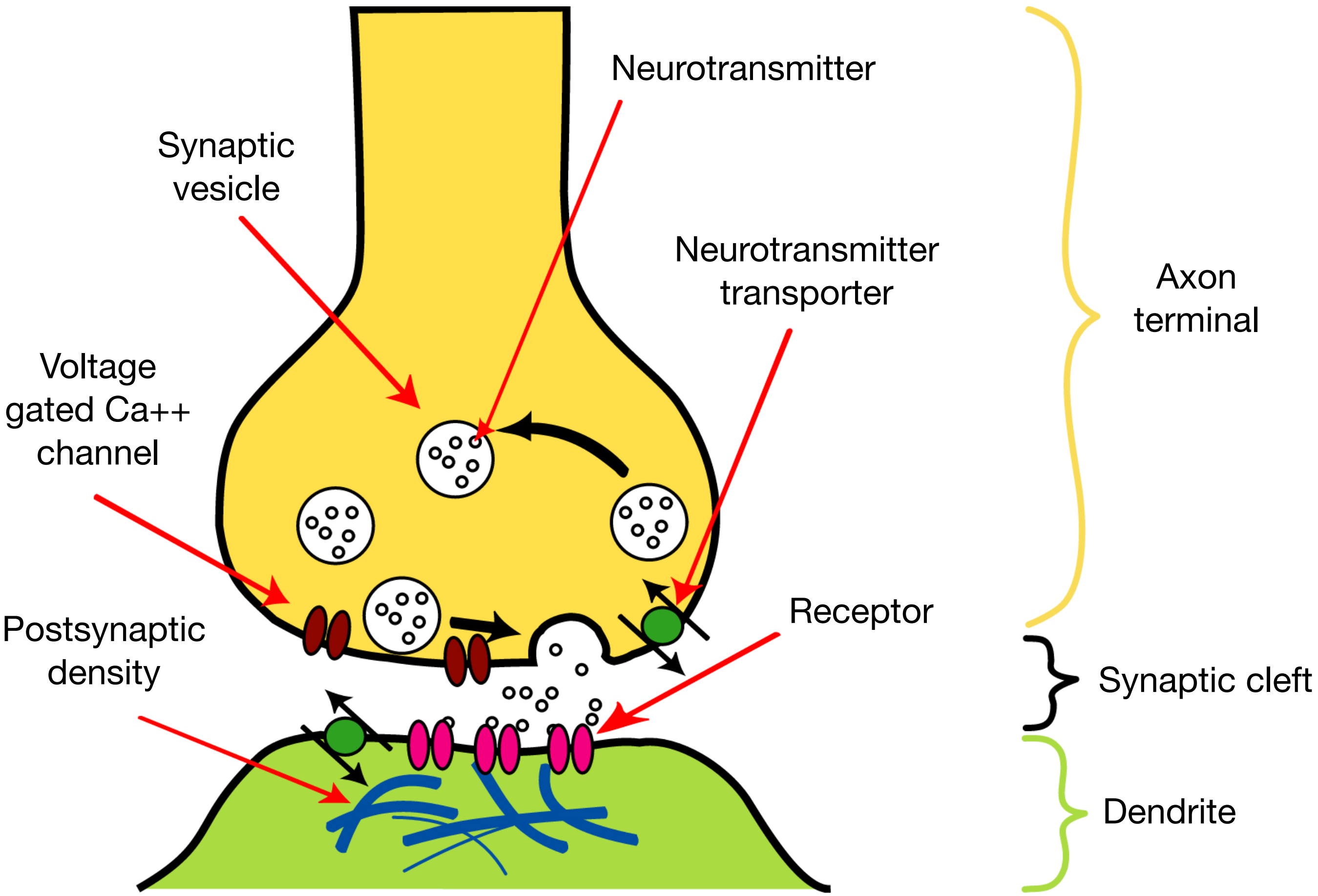
- The human brain is made up of about 100 billion neurons



- Neurons receive electric signals at the dendrites and send them to the axon

Neural Communication

- The axon of the neuron is connected to the dendrites of many other neurons



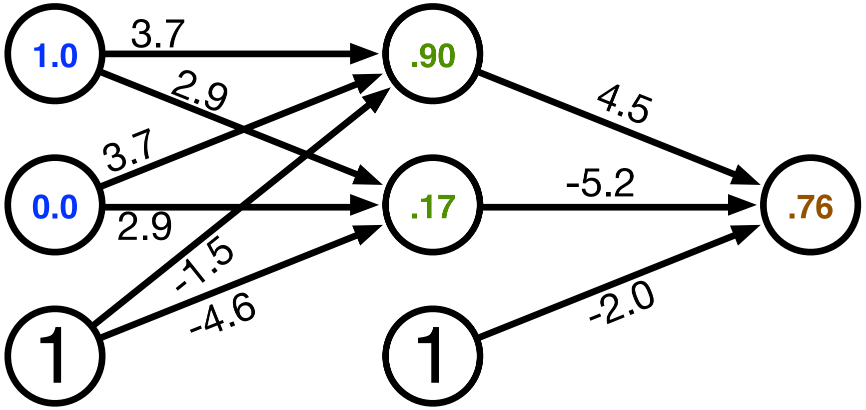
The Brain vs. Artificial Neural Networks

- Similarities
  - Neurons, connections between neurons
  - Learning = change of connections, not change of neurons
  - Massive parallel processing

- But artificial neural networks are much simpler
  - computation within neuron vastly simplified
  - discrete time steps
  - typically some form of supervised learning with massive number of stimuli

back-propagation training

Error



- Computed output: $y = .76$

- Correct output: $t = 1.0$

⇒ How do we adjust the weights?

Key Concepts

- Gradient descent
  - error is a function of the weights
  - we want to reduce the error
  - gradient descent: move towards the error minimum
  - compute gradient → get direction to the error minimum
  - adjust weights towards direction of lower error

- Back-propagation
  - first adjust last set of weights
  - propagate error back to each previous layer
  - adjust their weights

Derivative of Sigmoid

- Sigmoid

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}$$

- Reminder: quotient rule

$$\left(\frac{f(x)}{g(x)}\right)' = \frac{g(x)f'(x) - f(x)g'(x)}{g(x)^2}$$

- Derivative

$$\begin{aligned}
\frac{d\,\text{sigmoid}(x)}{dx} &= \frac{d}{dx}\frac{1}{1 + e^{-x}} \\
&= \frac{0 \times (1 - e^{-x}) - (-e^{-x})}{(1 + e^{-x})^2} \\
&= \frac{1}{1 + e^{-x}}\left(\frac{e^{-x}}{1 + e^{-x}}\right) \\
&= \frac{1}{1 + e^{-x}}\left(1 - \frac{1}{1 + e^{-x}}\right) \\
&= \text{sigmoid}(x)(1 - \text{sigmoid}(x))
\end{aligned}$$

Final Layer Update

- Linear combination of weights $s = \sum_k w_k h_k$
- Activation function $y = \text{sigmoid}(s)$
- Error (L2 norm) $E = \frac{1}{2}(t - y)^2$
- Derivative of error with regard to one weight w_k

$$\frac{dE}{dw_k} = \frac{dE}{dy}\frac{dy}{ds}\frac{ds}{dw_k}$$

Final Layer Update (1)

- Linear combination of weights $s = \sum_k w_k h_k$

- Activation function $y = \text{sigmoid}(s)$

- Error (L2 norm) $E = \frac{1}{2}(t - y)^2$

- Derivative of error with regard to one weight w_k

$$\frac{dE}{dw_k} = \frac{dE}{dy}\frac{dy}{ds}\frac{ds}{dw_k}$$

- Error E is defined with respect to y

$$\frac{dE}{dy} = \frac{d}{dy}\frac{1}{2}(t - y)^2 = -(t - y)$$

Final Layer Update (2)

- Linear combination of weights $s = \sum_k w_k h_k$
- Activation function $y = \text{sigmoid}(s)$
- Error (L2 norm) $E = \frac{1}{2}(t - y)^2$
- Derivative of error with regard to one weight w_k

$$\frac{dE}{dw_k} = \frac{dE}{dy}\frac{dy}{ds}\frac{ds}{dw_k}$$

- y with respect to x is $\text{sigmoid}(s)$

$$\frac{dy}{ds} = \frac{d\,\text{sigmoid}(s)}{ds} = \text{sigmoid}(s)(1 - \text{sigmoid}(s)) = y(1 - y)$$

Final Layer Update (3)

- Linear combination of weights $s = \sum_k w_k h_k$
- Activation function $y = \text{sigmoid}(s)$
- Error (L2 norm) $E = \frac{1}{2}(t - y)^2$
- Derivative of error with regard to one weight w_k

$$\frac{dE}{dw_k} = \frac{dE}{dy}\frac{dy}{ds}\frac{ds}{dw_k}$$

- x is weighted linear combination of hidden node values h_k

$$\frac{ds}{dw_k} = \frac{d}{dw_k}\sum_k w_k h_k = h_k$$

Putting it All Together

- Derivative of error with regard to one weight w_k

$$\begin{aligned}\frac{dE}{dw_k} &= \frac{dE}{dy}\frac{dy}{ds}\frac{ds}{dw_k} \\ &= -(t-y) \quad y(1-y) \quad h_k\end{aligned}$$

  - error
  - derivative of sigmoid: y'

- Weight adjustment will be scaled by a fixed learning rate μ

$$\Delta w_k = \mu \; (t-y) \; y' \; h_k$$

Multiple Output Nodes

- Our example only had one output node
- Typically neural networks have multiple output nodes
- Error is computed over all j output nodes

$$E = \sum_j \frac{1}{2}(t_j - y_j)^2$$

- Weights $k \to j$ are adjusted according to the node they point to

$$\Delta w_{j \leftarrow k} = \mu(t_j - y_j)\ y'_j\ h_k$$

Hidden Layer Update

- In a hidden layer, we do not have a target output value
- But we can compute how much each node contributed to downstream error
- Definition of error term of each node

$$\delta_j = (t_j - y_j)\ y'_j$$

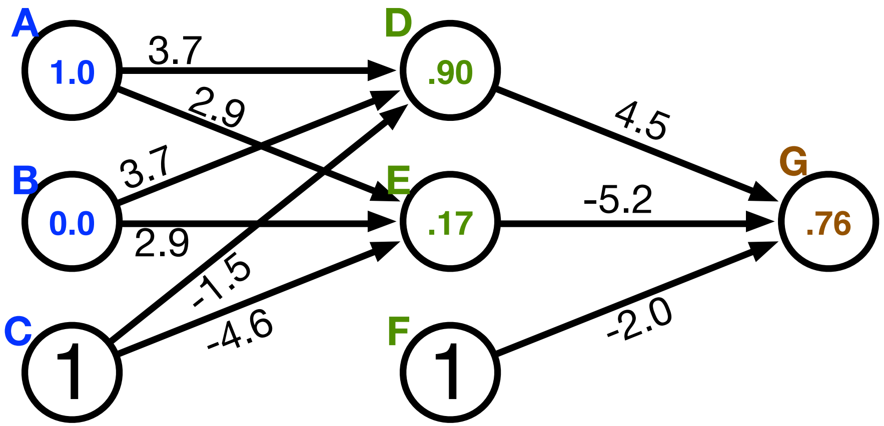
- Back-propagate the error term
  (why this way? there is math to back it up...)

$$\delta_i = \Big(\sum_j w_{j\leftarrow i}\delta_j \Big)\ y'_i$$

- Universal update formula

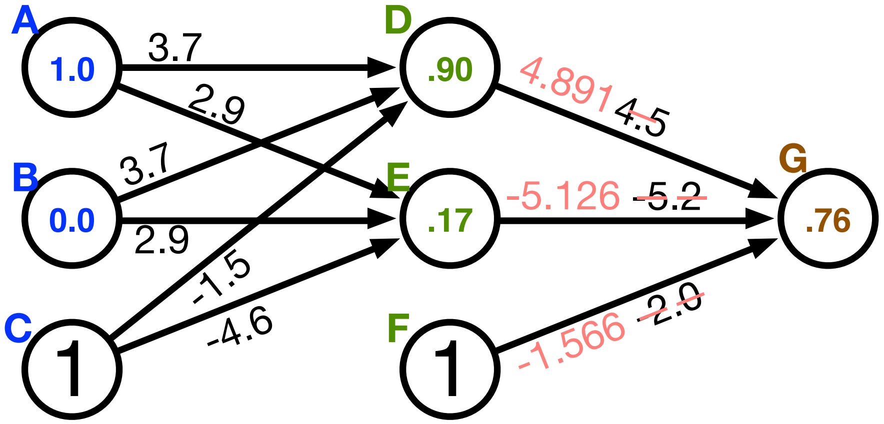
$$\Delta w_{j\leftarrow k} = \mu\ \delta_j\ h_k$$

Our Example



- Computed output: $y = .76$
- Correct output: $t = 1.0$
- Final layer weight updates (learning rate $\mu = 10$)
  - $\delta_{\text{G}} = (t - y)\ y' = (1 - .76)\ 0.181 = .0434$
  - $\Delta w_{\text{GD}} = \mu\ \delta_{\text{G}}\ h_{\text{D}} = 10 \times .0434 \times .90 = .391$
  - $\Delta w_{\text{GE}} = \mu\ \delta_{\text{G}}\ h_{\text{E}} = 10 \times .0434 \times .17 = .074$
  - $\Delta w_{\text{GF}} = \mu\ \delta_{\text{G}}\ h_{\text{F}} = 10 \times .0434 \times 1 = .434$

Our Example



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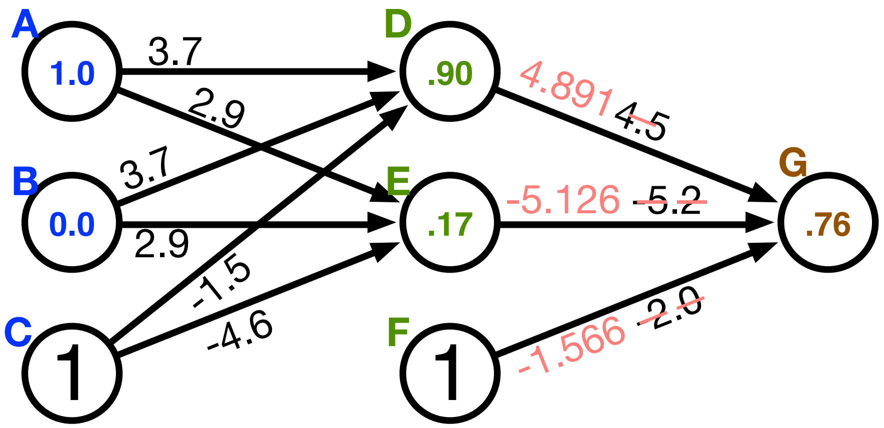
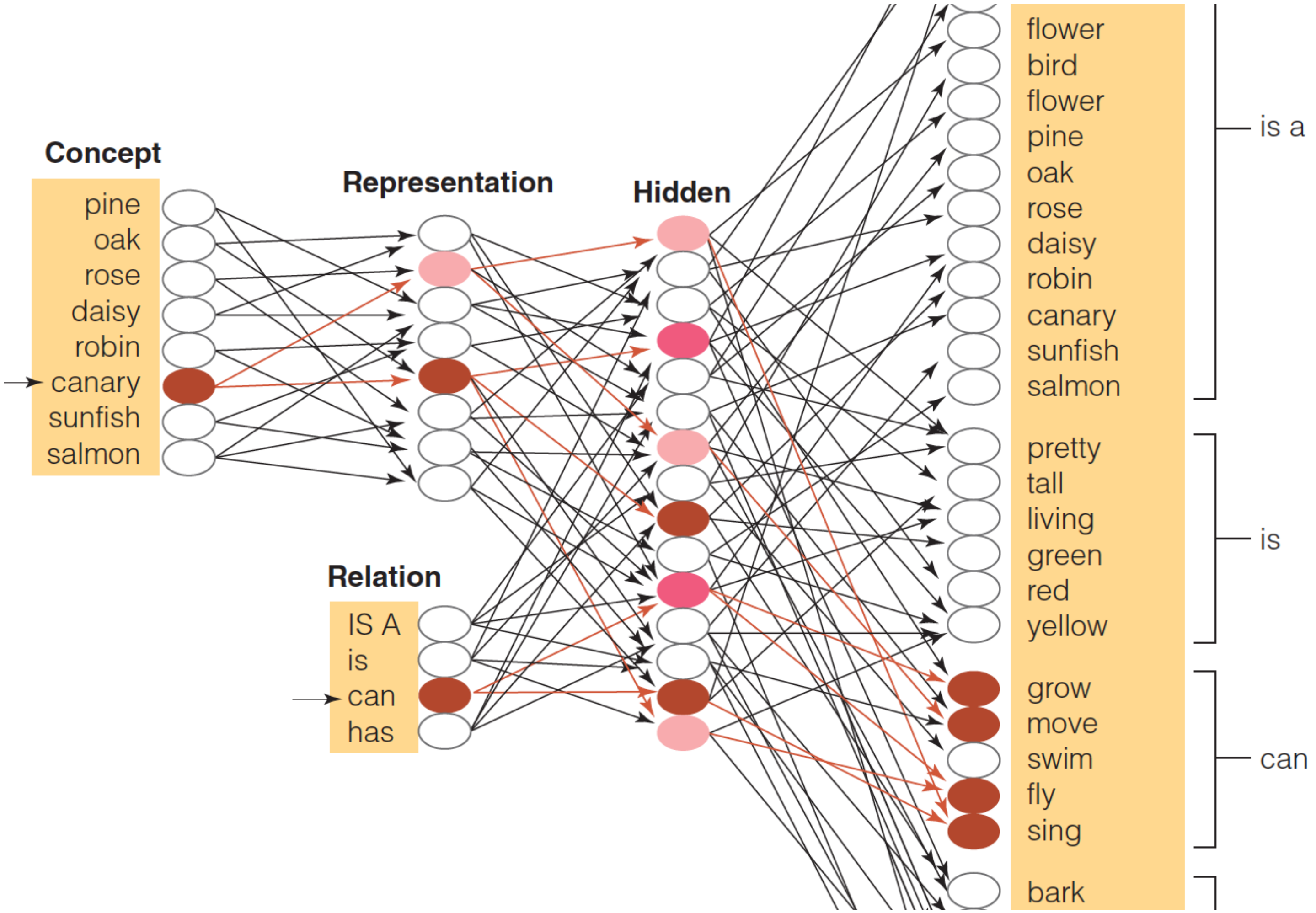
Hidden Layer Updates



- Hidden node **D**
  - $\delta_{\text{D}} = \left(\sum_j w_{j \leftarrow i} \delta_j \right) y'_{\text{D}} = w_{\text{GD}}\ \delta_{\text{G}}\ y'_{\text{D}} = 4.5 \times .0434 \times .0898 = .0175$
  - $\Delta w_{\text{DA}} = \mu\ \delta_{\text{D}}\ h_{\text{A}} = 10 \times .0175 \times 1.0 = .175$
  - $\Delta w_{\text{DB}} = \mu\ \delta_{\text{D}}\ h_{\text{B}} = 10 \times .0175 \times 0.0 = 0$
  - $\Delta w_{\text{DC}} = \mu\ \delta_{\text{D}}\ h_{\text{C}} = 10 \times .0175 \times 1 = .175$
- Hidden node **E**
  - $\delta_{\text{E}} = \left(\sum_j w_{j \leftarrow i} \delta_j \right) y'_{\text{E}} = w_{\text{GE}}\ \delta_{\text{G}}\ y'_{\text{E}} = -5.2 \times .0434 \times 0.2055 = -.0464$
  - $\Delta w_{\text{EA}} = \mu\ \delta_{\text{E}}\ h_{\text{A}} = 10 \times -.0464 \times 1.0 = -.464$
  - etc.

Connectionist Semantic Cognition



- Hidden layer representations for concepts and concept relationships

some additional aspects

Initialization of Weights

- Weights are initialized randomly
  e.g., uniformly from interval $[-0.01, 0.01]$

- Glorot and Bengio (2010) suggest
  - for shallow neural networks

$$[-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}]$$

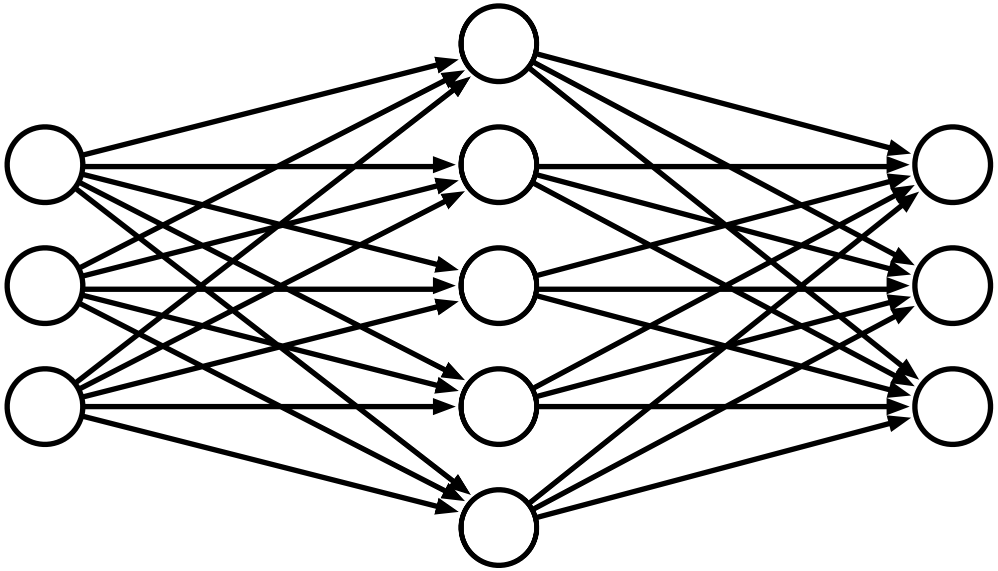
n is the size of the previous layer

  - for deep neural networks

$$[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}]$$

n_j is the size of the previous layer, n_j size of next layer

Neural Networks for Classification



- Predict class: one output node per class
- Training data output: "One-hot vector", e.g., $\vec{y} = (0, 0, 1)^T$
- Prediction
  - predicted class is output node y_i with highest value
  - obtain posterior probability distribution by soft-max

$$\text{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

Speedup: Momentum Term

- Updates may move a weight slowly in one direction
- To speed this up, we can keep a memory of prior updates

$$\Delta w_{j \leftarrow k}(n-1)$$

- ... and add these to any new updates (with decay factor ρ)

$$\Delta w_{j \leftarrow k}(n) = \mu \, \delta_j \, h_k + \rho \Delta w_{j \leftarrow k}(n-1)$$

computational aspects

Vector and Matrix Multiplications

- Forward computation: $\vec{s} = W\vec{h}$
- Activation function: $\vec{y} = \text{sigmoid}(\vec{h})$
- Error term: $\vec{\delta} = (\vec{t} - \vec{y})\ \text{sigmoid}'(\vec{s})$
- Propagation of error term: $\vec{\delta}_i = W\vec{\delta}_{i+1} \cdot \text{sigmoid}'(\vec{s})$
- Weight updates: $\Delta W = \mu\vec{\delta}\vec{h}^T$

GPU

- Neural network layers may have, say, 200 nodes

- Computations such as $W\vec{h}$ require $200 \times 200 = 40,000$ multiplications

- Graphics Processing Units (GPU) are designed for such computations
  - image rendering requires such vector and matrix operations
  - massively mulit-core but lean processing units
  - example: NVIDIA Tesla K20c GPU provides 2496 thread processors

- Extensions to C to support programming of GPUs, such as CUDA

Theano

- GPU library for Python
- Homepage: `http://deeplearning.net/software/theano/`
- See web site for sample implementation of back-propagation training
- Used to implement
    - neural network language models
    - neural machine translation (Bahdanau et al., 2015)