Machine Learning Review
Neural Network Training

COSC 7336: Advanced Natural Language Processing
Fall 2017

Some content in these slides has been adapted from Jurafsky & Martin 3rd edition, and lecture slides from Rada Mihalcea, Ray Mooney and the deep learning course by Manning and Socher.

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Today's Lecture

- Machine learning review
  - The learning problem
  - Learning and optimization
  - Generalization
- Neural network training
  - Perceptron training
  - Backpropagation
  - In-class assignment

What is machine learning?

★ Artificial intelligence
★ Pattern recognition
★ Computational learning theory
★ Data mining, predictive analytics, data science
★ Statistics, statistical learning

What is a pattern?

★ Data regularities
★ Data relationships
★ Redundancy
★ Generative model

Learning a boolean function

x_1	x_2	f_1	f_2	...	f_{16}
0	0	0	0	...	1
0	1	0	0	...	1
1	0	0	0	...	1
1	1	0	1	...	1

How many Boolean functions of n variables are?

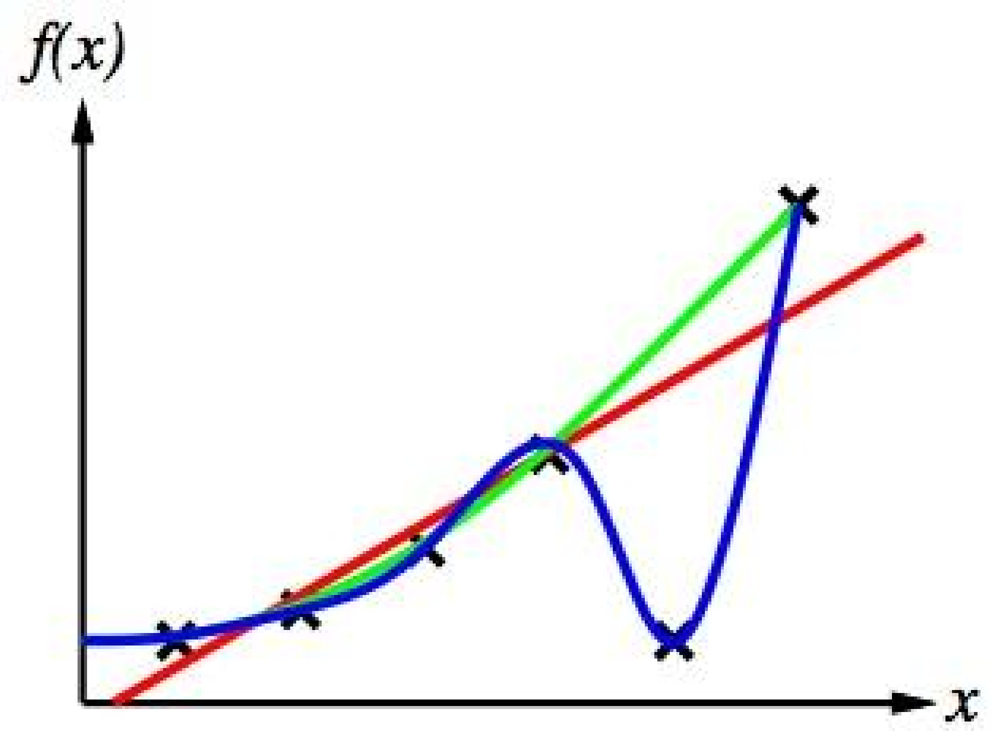
How many candidate functions are removed by a sample?

Is it possible to generalize from examples?

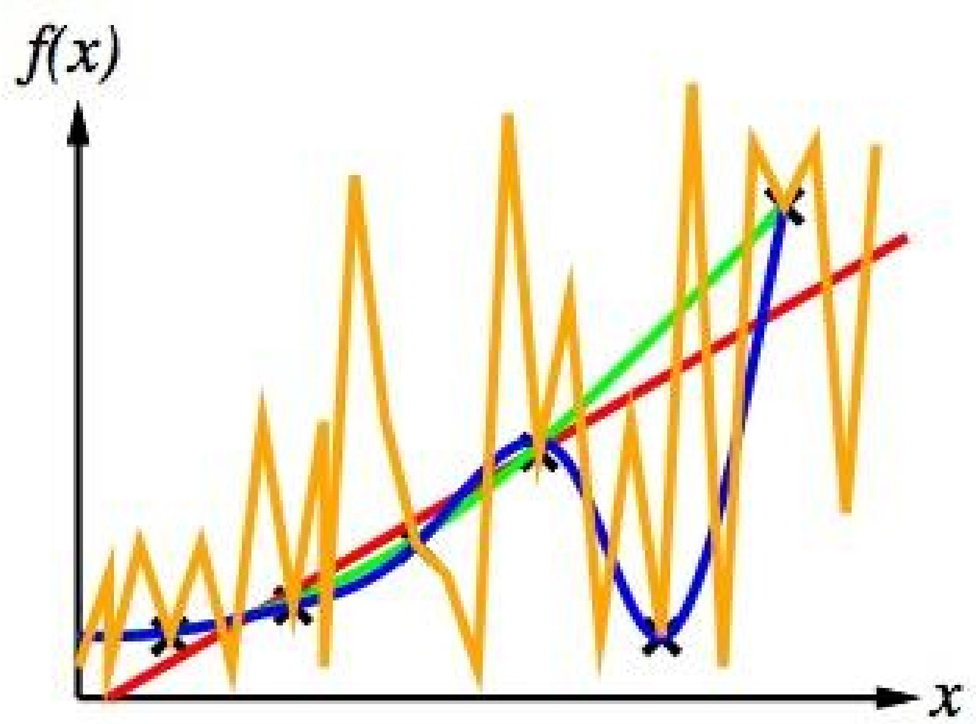
Inductive bias

- ★ In general, the learning problem is ill-posed (more than one possible solution for the same particular problem, solutions are sensitive to small changes on the problem)
- ★ It is necessary to make additional assumptions about the kind of pattern we want to learn
- ★ **Hypothesis space**: set of valid patterns that can be learnt by the algorithm

What is a good pattern?



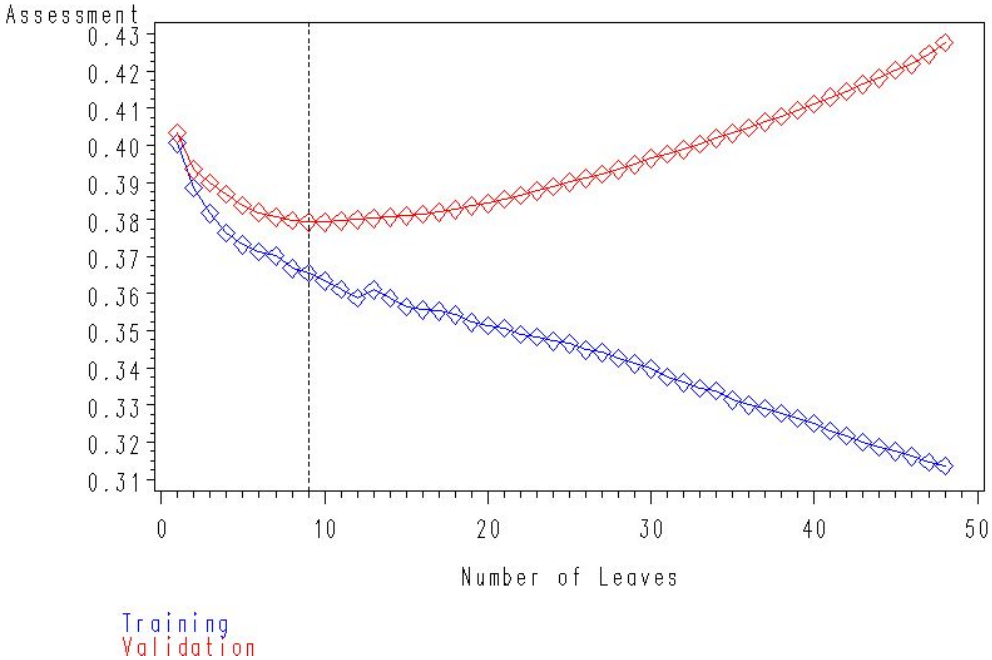
What is a good pattern?



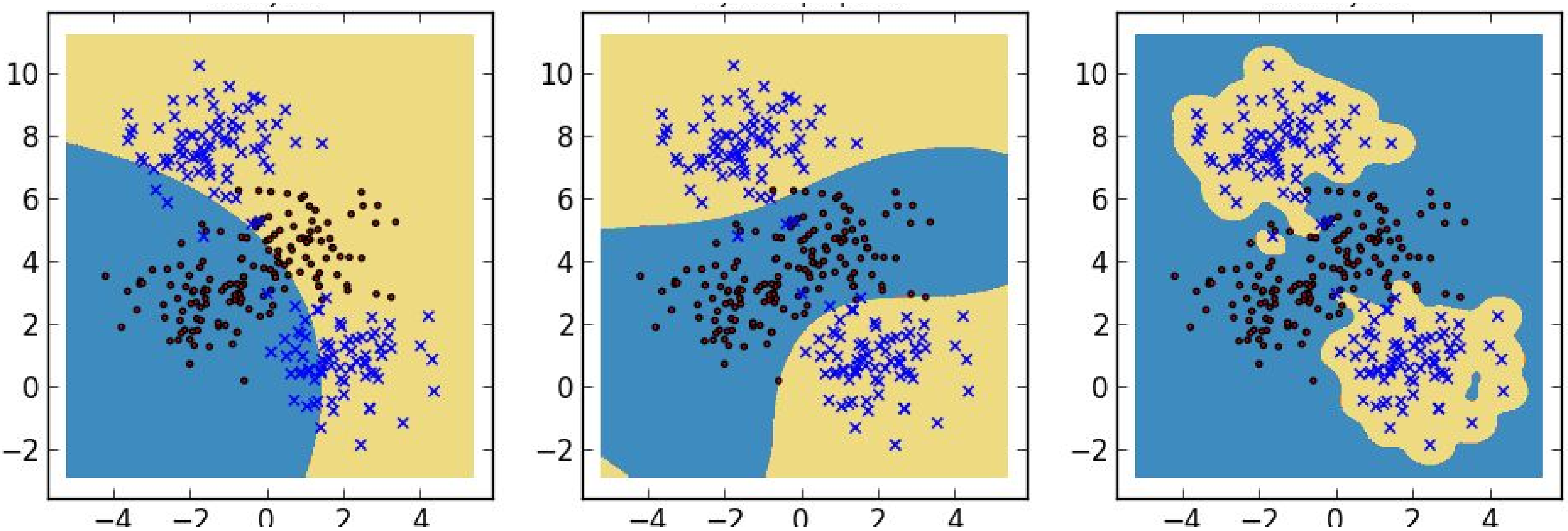
Generalization

★ The loss function measures the error in the training set
★ Is this a good measure of the quality of the solution?

Average Square Error (Gini index)



Over-fitting and under-fitting



Generalization error

- Generalization error:

$$E[(L(f_w, D)$$

- How to control the generalization error during training?
    - Cross validation
    - Regularization

Regularization

Vapnik (1995):

Expected loss

$$R(\alpha) = \int \frac{1}{2}|y - f(\mathbf{x}, \alpha)|dP(\mathbf{x}, y)$$

Empirical loss

$$R_{emp}(\alpha) = \frac{1}{2l}\sum_{i=1}^{l}|y_i - f(\mathbf{x}_i, \alpha)|.$$

Model complexity

$$R(\alpha) \leq R_{emp}(\alpha) + \sqrt{\left(\frac{h(\log(2l/h) + 1) - \log(\eta/4)}{l}\right)}$$

Number of samples

Types of learning problems

- ★ Supervised learning
- ★ Non-supervised learning
- ★ Semi-supervised learning
- ★ Active/reinforcement learning

Methods

★ There are many!

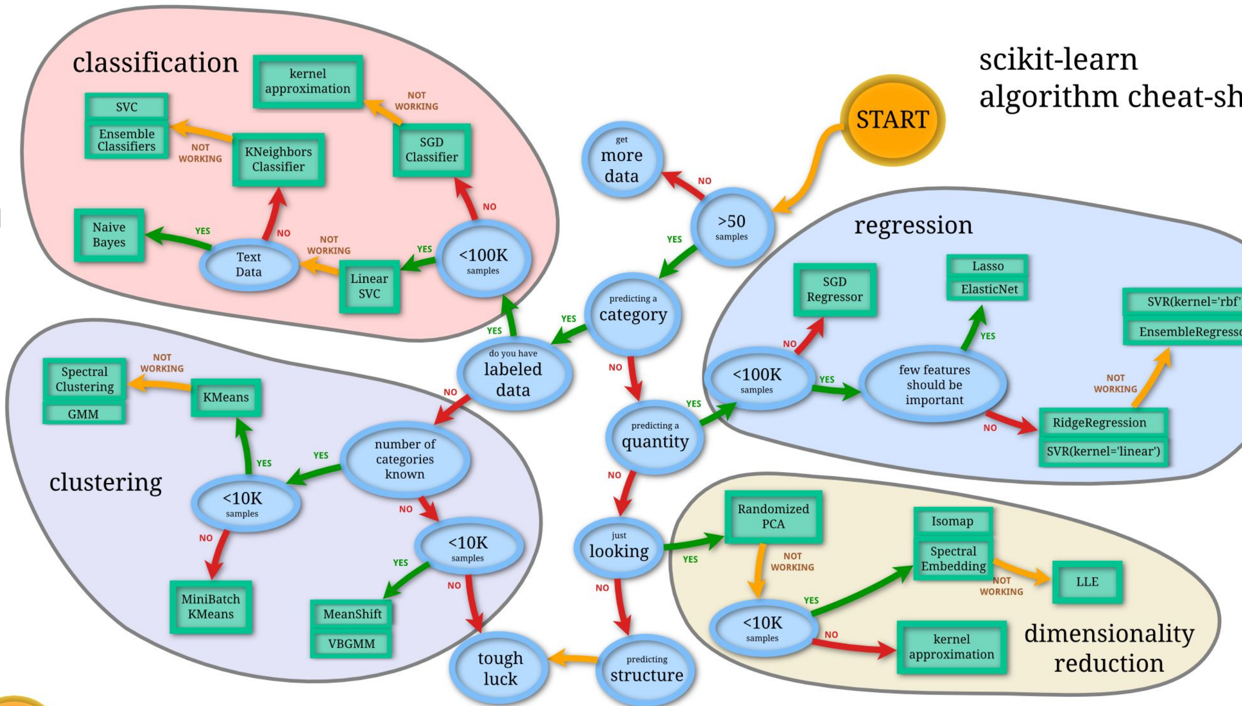
★ Depend on the problem to solve and underline strategy

★ Trends change through time.

★ Now:

- NNs
- SVMs

★ Used to be the other way around



Back

Perceptron Training Demo

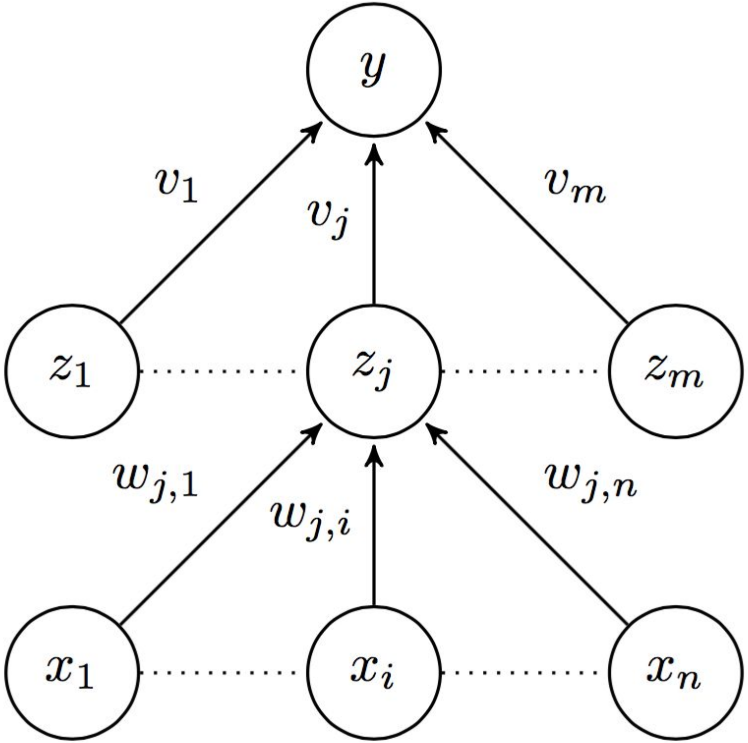
Neural Network Training

Training multilayer networks

- ★ We will use gradient descent as well.
- ★ We need to calculate

$$\frac{\partial E_\ell}{\partial w_{ji}}$$

- ★ An analytical solution gets very complicated even for a small NN
- ★ Backpropagation is an efficient strategy for gradient calculation



Rumelhart, D.; Hinton, G.; Williams, R. (1986). "Learning representations by back-propagating errors". *Nature*. **323** (6088): 533–536.

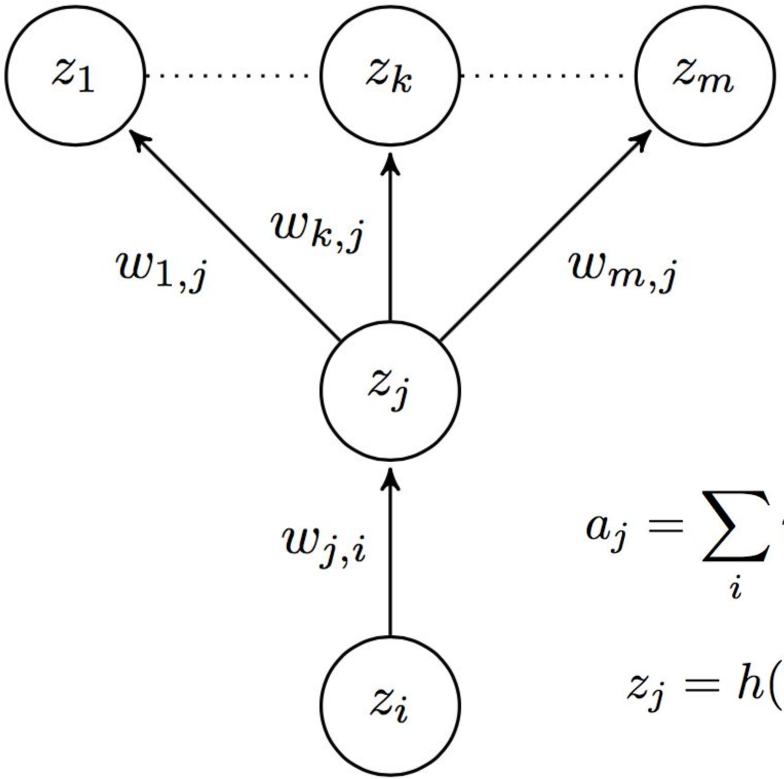
Gradient calculation

- ★ General case for a neuron z_j and z_i in layers n and n-1 respectively
- ★ We want to calculate the gradient:

$$\frac{\partial E_\ell}{\partial w_{ji}}$$

- ★ General strategy: re-express the gradient as a function of two values

$$\frac{\partial E_\ell}{\partial w_{ji}} = \delta_j z_i$$



$$a_j = \sum_i w_{ji} z_i$$

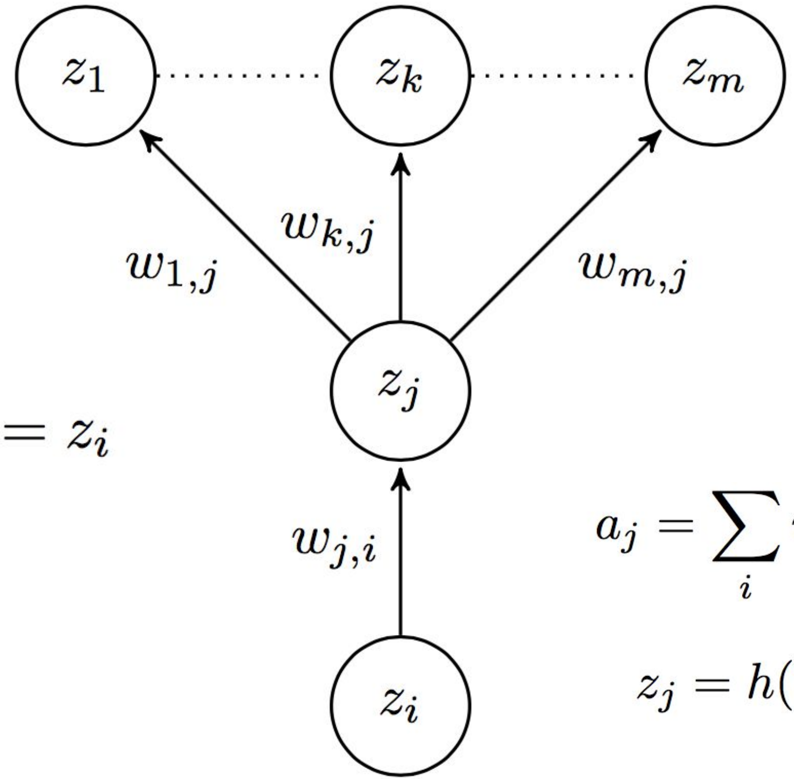
$$z_j = h(a_j)$$

Gradient decomposition

$$\frac{\partial E_\ell}{\partial w_{ji}} = \frac{\partial E_\ell}{\partial a_j}\frac{\partial a_j}{\partial w_{ji}}$$ (chain rule)

$$\delta_j = \frac{\partial E_\ell}{\partial a_j} \qquad \frac{\partial a_j}{\partial w_{ji}} = \frac{\partial \sum_i w_{ji} z_i}{\partial w_{ji}} = z_i$$

$$\frac{\partial E_\ell}{\partial w_{ji}} = \delta_j z_i$$



$$a_j = \sum_i w_{ji} z_i$$

$$z_j = h(a_j)$$

Generalized (multidimensional) chain rule (GCR)

$$y = f(u_1, \ldots, u_m)$$

$$\mathbf{u} = g(x_1, \ldots, x_n)$$

$$\frac{\partial y}{\partial x_i} = \sum_{\ell=1}^{m} \frac{\partial y}{\partial u_\ell} \frac{\partial u_l}{\partial x_i}$$

δ_j recursive calculation

$$\delta_j = \frac{\partial E_\ell}{\partial a_j} = \sum_{k=1}^{m} \frac{\partial E_\ell}{\partial a_k}\frac{\partial a_k}{\partial a_j}$$

Applying GCR since $E_\ell = f(a_1, \dots, a_k)$

$$= \sum_{k=1}^{m} \delta_k \frac{\partial a_k}{\partial a_j}$$

Definition of δ_j

$$= \sum_{k=1}^{m} \delta_k \frac{\partial a_k}{\partial z_j}\frac{\partial z_j}{\partial a_j}$$

Chain rule

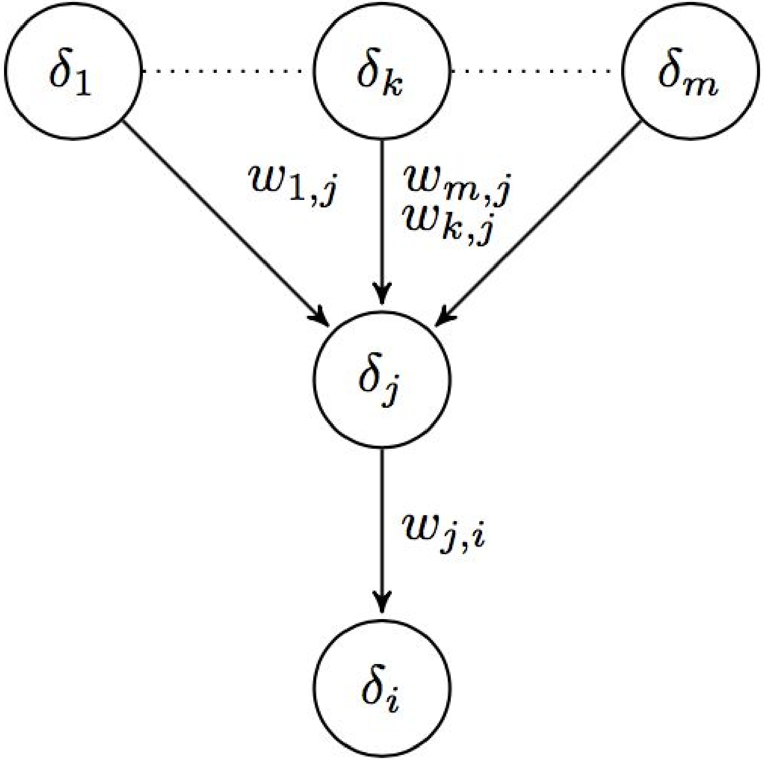
$$= \sum_{k=1}^{m} \delta_k w_{kj} h'(a_j)$$

$$= h'(a_j) \sum_{k=1}^{m} \delta_k w_{kj}$$

δ_j backpropagation

Deltas in layer *n* are calculated from deltas in layer *n + 1*:

$$\delta_j = h'(a_j) \sum_{k=1}^{m} \delta_k w_{kj}$$



Backpropagation algorithm

```
1: Initialize w
2: for n = 1 to num epochs
3:     for all x^ℓ ∈ D
4:         Forward propagate x^ℓ through the network
           to calculate the a_j and z_j values
5:         Calculate δ_o = ∂E_ℓ/∂a_o
           for all the output neurons
6:         Backward propagate δ_j values
           δ_j = h'(a_j) Σ_{k=1}^{m} δ_k w_kj
7:         for all w_ji ∈ w
8:             Δw_ji ← δ_j z_i
9:             w_ji ← w_ji − η_n Δw_ji
```

1: Initialize $\mathbf{w}$

2: for n = 1 to num epochs

3: for all $x^\ell \in D$

4: Forward propagate x^ℓ through the network to calculate the a_j and z_j values

5: Calculate $\delta_o = \frac{\partial E_\ell}{\partial a_o}$ for all the output neurons

6: Backward propagate δ_j values $\delta_j = h'(a_j) \sum_{k=1}^{m} \delta_k w_{kj}$

7: for all $w_{ji} \in \mathbf{w}$

8: $\Delta w_{ji} \leftarrow \delta_j z_i$

9: $w_{ji} \leftarrow w_{ji} - \eta_n \Delta w_{ji}$

Two layers NN with sigmoid activation

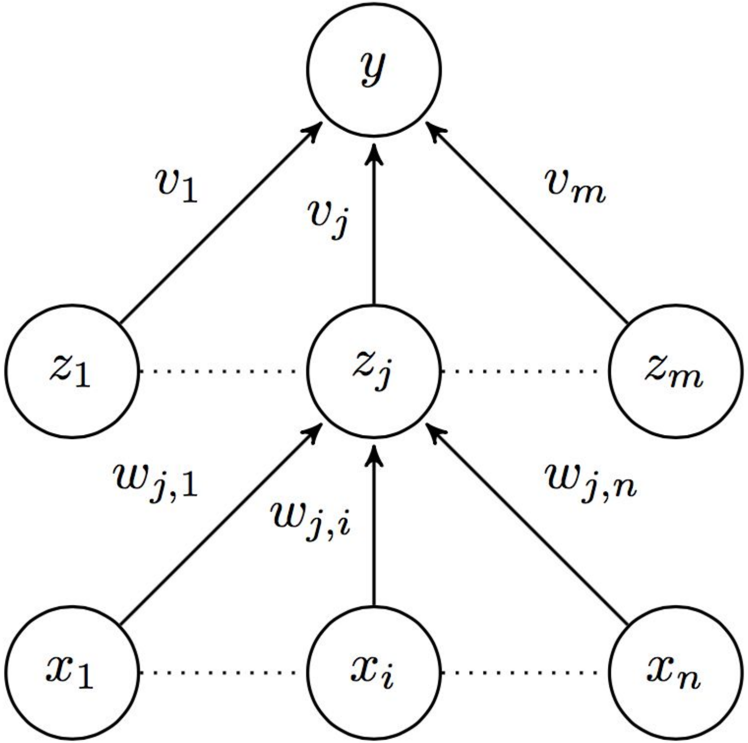
$$a_j = \sum_i w_{ji} x_i$$

$$z_j = \sigma(a_j)$$

$$a_y = \sum_j v_j z_j$$

$$y = \sigma(a_y)$$

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



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Two layers NN with sigmoid activation

$$E_\ell(w) = -r^\ell \log y^t - (1 - r^\ell)\log(1 - y^t)$$

$$\delta_y = \frac{\partial E_\ell}{\partial a_y} = \sigma(a_y) - r^\ell = z_j - r^\ell$$

$$\delta_j = \sigma'(a_j)\delta_y v_j = \sigma(a_j)(1 - \sigma(a_j))\delta_y v_j = z_j(1 - z_j)\delta_y$$