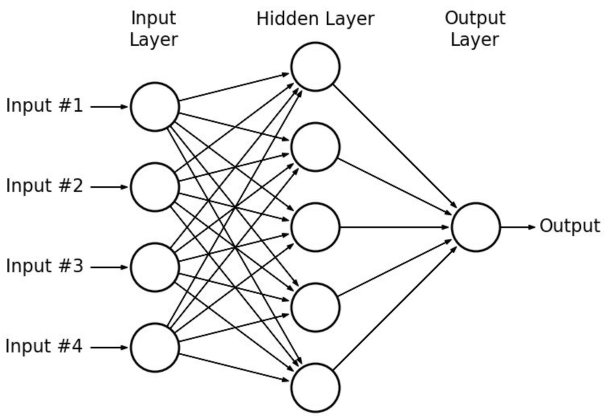
Week 7

Agenda

1. Neural Network discussion
2. Deep Learning notebook

For next week: Backpropagation discussion during next week's office hour

History



Timeline

- 40s-50s Idea emerges.
- 1962 Perceptron learning
- 1969 Minisky: XOR problem
- 1982 Multi-layer neural networks
- 1986 Backpropagation
- 1989 Universal Approximation Theorem
- 90s-00s SVMs gain favor
- 00s SGD popularized
- 2009-present Deep learning: return of neural nets

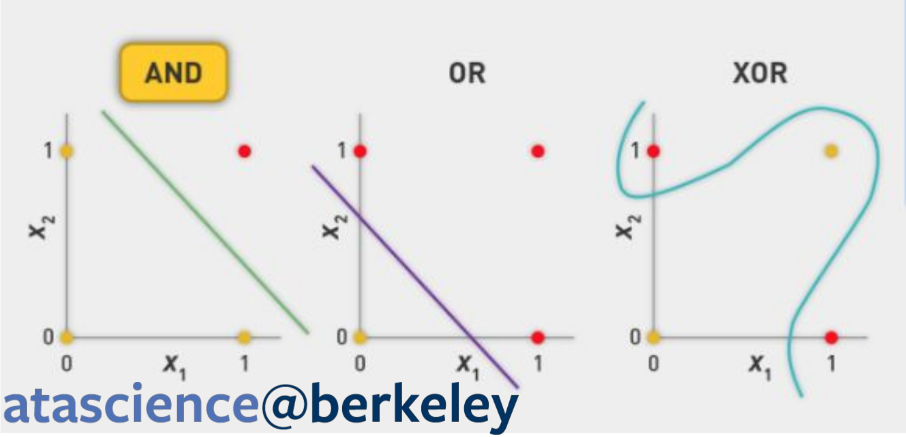
People to Know

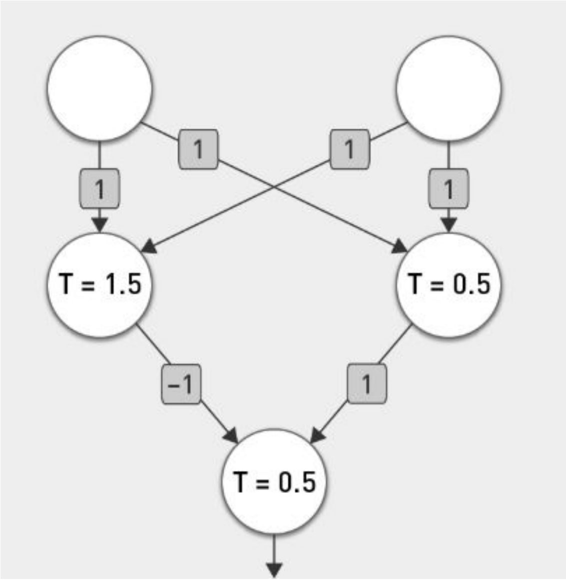
- Geoffrey Hinton. http://www.cs.toronto.edu/~hinton/ (https://www.coursera.org/learn/neural-networks)
- Yann LeCun.   http://yann.lecun.com/
- Yoshua (and Samy) Bengio. http://www.iro.umontreal.ca/~bengioy/yoshua_en/
- Leon Bottou (SGD). http://leon.bottou.org/

Conferences

- NIPS, ICML
- APPLIED: KDD, SIGIR, AAAI

1. What's the limitation of a perceptron? What differs about Neural Nets that allow them to learn non-linear function?





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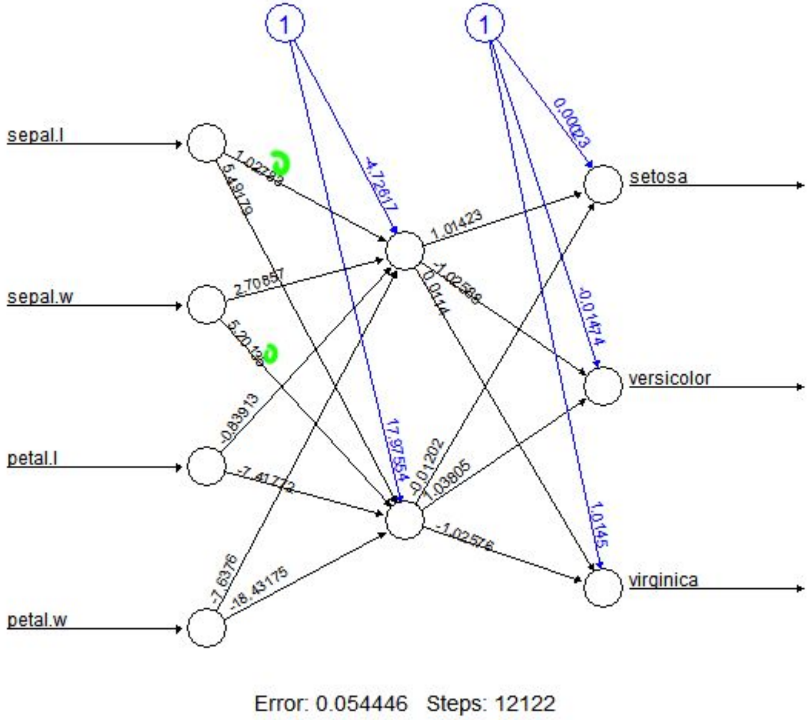
Example Trained Neural Network



1. What do you remember about Iris dataset?
2. How many parameters in this model?
3. How is multi-class handled?
4. Sparse vs dense representation. Which one will we get? Why?
5. How many layers?
6. How can we think about this network as an ensemble/stacked model?
7. How can we think about this network as a series of matrix operations?

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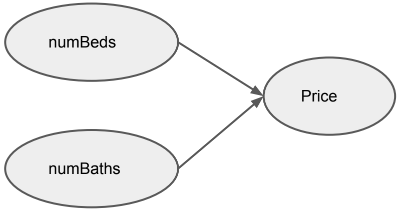
A challenge...

Describe logistic regression represented as a NN?

Price = beta * numBeds + alpha * numBaths



Accuracy on MNIST

Type	Classifier	Distortion	Preprocessing	Error rate (%)
Linear classifier	Pairwise linear classifier	None	Deskewing	7.6[9]
Non-Linear Classifier	40 PCA + quadratic classifier	None	None	3.3[9]
Neural network	2-layer 784-800-10	None	None	1.6[17]
Boosted Stumps	Product of stumps on Haar features	None	Haar features	0.87[15]
Neural network	2-layer 784-800-10	elastic distortions	None	0.7[17]
Support vector machine	Virtual SVM, deg-9 poly, 2-pixel jittered	None	Deskewing	0.56[16]
K-Nearest Neighbors	K-NN with non-linear deformation (P2DHMDM)	None	Shiftable edges	0.52[14]
Deep neural network	6-layer 784-2500-2000-1500-1000-500-10	elastic distortions	None	0.35[18]
Convolutional neural network	Committee of 35 conv. net, 1-20-P-40-P-150-10	elastic distortions	Width normalizations	0.23[8]

Universal Approximation Theorem

- Two-layer networks are universal function approximators
  - Let F be a continuous function on a bounded subset of D-dimensional space. Then there exists a two-layer neural network F' with a finite number of hidden units that approximate F arbitrarily well. Namely, for all x in the domain of F,

$$|F(x) - F'(x)| < \varepsilon$$

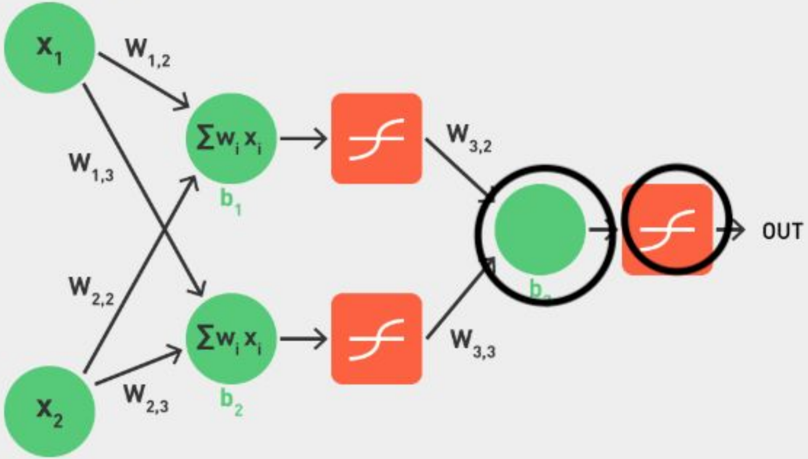
- Two-layer networks can approximate any function.
- Still may want more than two layers (fewer neurons, time to learn, time to compute, etc).

1. Why is this a theorem about representation rather than learning?

Training and Predicting

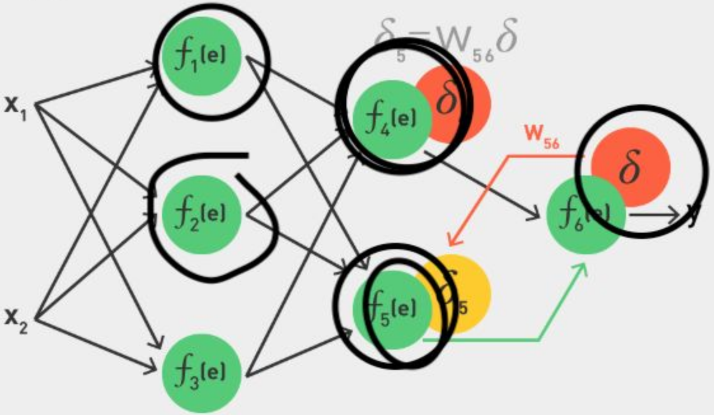
Intuition: Forward Propagation

- Given a training example (X_1, X_2) and output Y_i
- Propagate inputs/activations forward, applying sigmoid function on dot products



Intuition: Backward Propagation (cont.)

Propagate costs backward to earlier nodes:

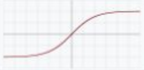
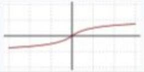


- For each hidden unit h in k^{th} layer:

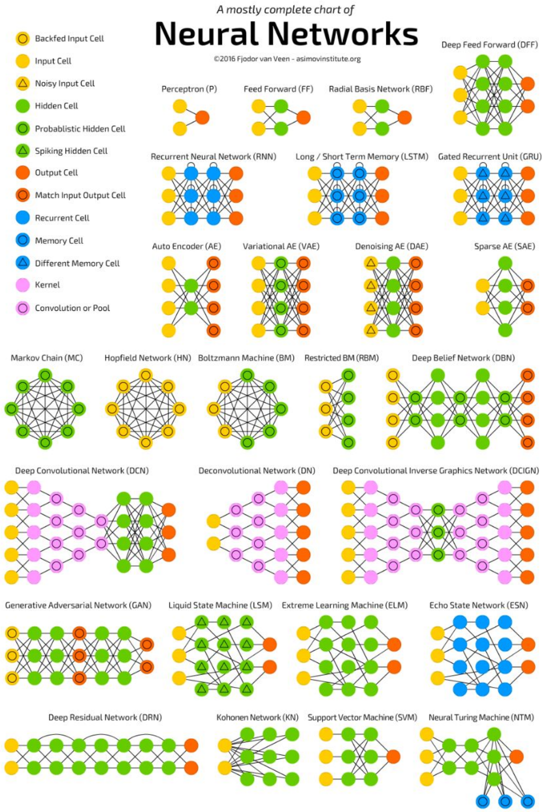
$$\delta_{hk} = Y_{hk}\left(1 - Y_{hk}\right) \sum_{j \in K} w_{hj}\delta_j$$

- Update each weight as $+\eta\delta_{hk}x_i$.
  - Daume ch. 8 for full algorithm

Activation Functions are Active Area of Research

Name	Plot	Equation	Derivative (with respect to x)	Range
Identity		$f(x) = x$	$f'(x) = 1$	$(-\infty, \infty)$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$	$\{0, 1\}$
Logistic (a.k.a. Soft step)		$f(x) = \frac{1}{1 + e^{-x}}$	$f'(x) = f(x)(1 - f(x))$	$(0, 1)$
TanH		$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$	$(-1, 1)$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2 + 1}$	$\left(-\frac{\pi}{2}, \frac{\pi}{2}\right)$
Softsign [7][8]		$f(x) = \frac{x}{1 + \lvert x \rvert}$	$f'(x) = \frac{1}{(1 + \lvert x \rvert)^2}$	$(-1, 1)$
Rectified linear unit (ReLU)[9]		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$[0, \infty)$
Leaky rectified linear unit (Leaky ReLU)[10]		$f(x) = \begin{cases} 0.01x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0.01 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$(-\infty, \infty)$
Parameteric rectified linear unit (PReLU)[11]		$f(\alpha, x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(\alpha, x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$(-\infty, \infty)$

Beyond Basic FF Networks -- Many Architectures



Output Layer

$$\frac{dE}{dw_5} = \frac{dE}{d\hat{y}} \frac{d\hat{y}}{da_3} \frac{da_3}{dw_5}$$

$\hookrightarrow z_1$

derivative of logistic

derivative of cost

$$\frac{dE}{dw_5} = (.66-1)(.66\cdot(1-.66))(.64) = -0.05$$

$$\frac{dE}{dw_6} = \text{" \quad "}(.6) = -0.046$$

$$w_5 = .5 - .2(-0.05) = .51$$

$$w_6 = .6 - .2(-0.046) = .61$$

Hidden Layer

$$\frac{dE}{dw_1} = \frac{dE}{dz_1} \frac{dz_1}{da_1} \frac{da_1}{dw_1}$$

$\hookrightarrow \emptyset$

$.64(1-.64)$

$$\frac{dE}{dz_1} = \frac{dE}{d\hat{y}} \frac{d\hat{y}}{da_3} \frac{da_3}{dz_1}$$

$\hookrightarrow .5$

$.23$

$-.37$

$$\frac{dE}{dw_1} = (-.37)(.22)(.5)(.23)(\emptyset) = \emptyset$$

$$\frac{dE}{dw_2} = \emptyset$$

$$\frac{dE}{dw_3} = \text{" \quad "}(.1) = -0.01$$

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training, (x))

this:

Final Thoughts?