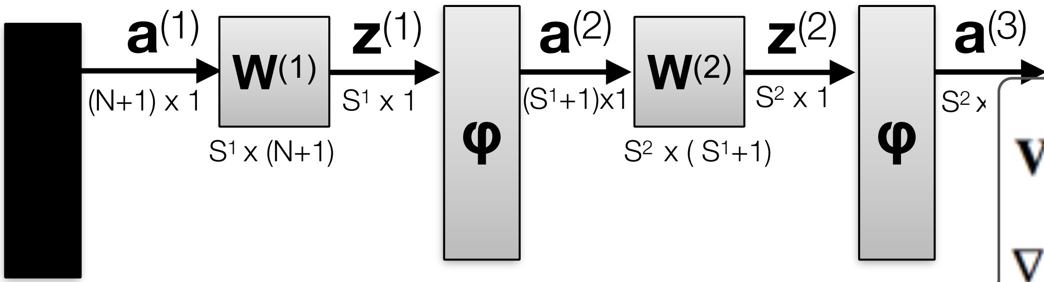
Lecture Notes for

Machine Learning in Python

Professor Eric Larson

Town Hall + MLP History

Changing the Objective Function



$$\mathbf{V}^{(2)} = -2(\mathbf{Y} - \mathbf{A}^{(3)}) * \mathbf{A}^{(3)} * (1 - \mathbf{A}^{(3)})$$

$$\nabla^{(2)} = \mathbf{V}^{(2)} \cdot [\mathbf{A}^{(2)}]^T$$

$$\mathbf{V}^{(1)} = \mathbf{A}^{(2)} * (1 - \mathbf{A}^{(2)}) * [\mathbf{W}^{(2)}]^T \cdot \mathbf{V}^{(2)}$$

$$\nabla^{(1)} = \mathbf{V}^{(1)} \cdot [\mathbf{A}^{(1)}]^T$$

$$\mathbf{W}^{(l)} \leftarrow \mathbf{W}^{(l)} - \eta \nabla^{(l)}$$

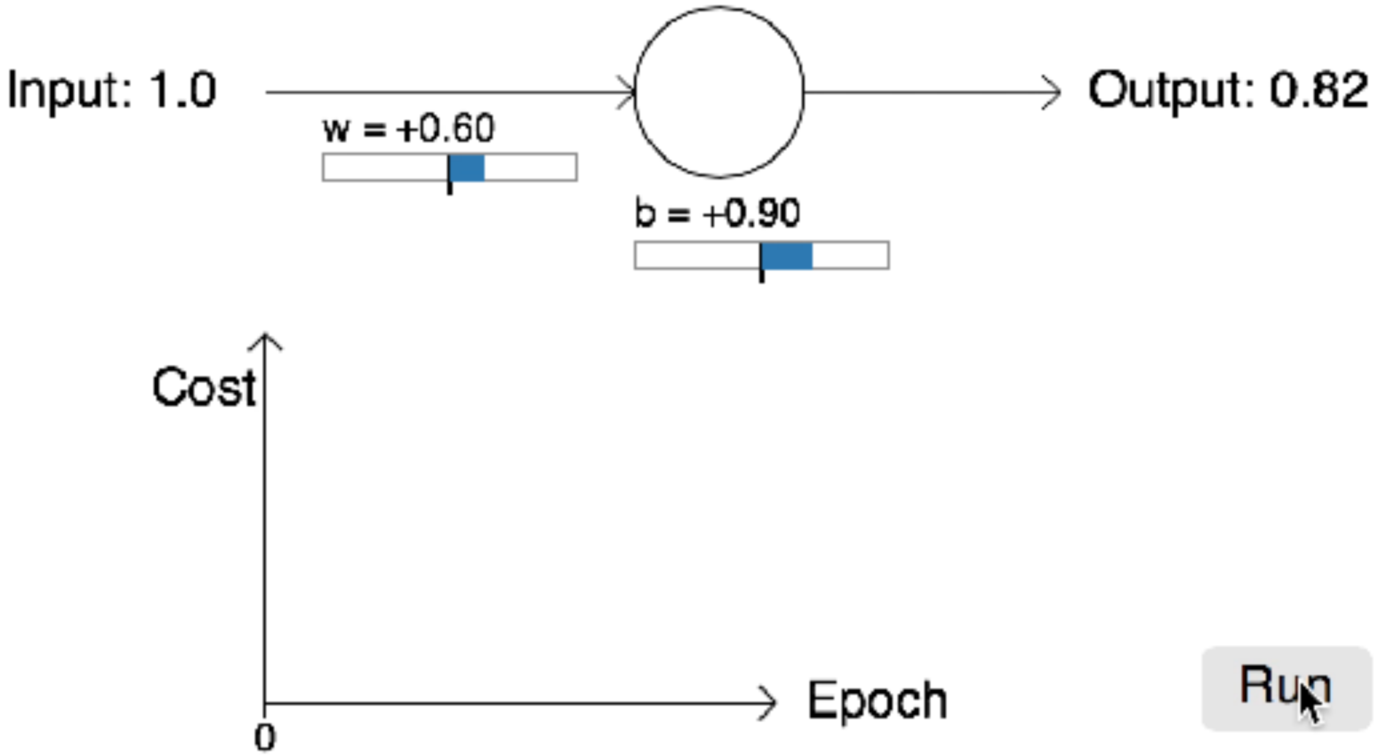
1. Forward propagate to get **Z, A**
2. Get final layer gradient
3. Back propagate sensitivities
4. Update each $\mathbf{W}^{(l)}$

- **Self Test**:
  True or False: If we change the cost function, $J(\mathbf{W})$, we only need to update the final layer sensitivity calculation, $\mathbf{V}^{(2)}$, of the back propagation steps. The remainder of the algorithm is unchanged.
  - A. True
  - B. False

- MSE

$$J(\mathbf{W}) = \sum_{k}^{M} (\mathbf{y}^{(k)} - \mathbf{a}^{(L)})^2$$

least squares objective,
tends to slow training initially



Neural Networks and Deep Learning, Michael Nielson, 2015

Practical Implementation of Architectures

- MSE

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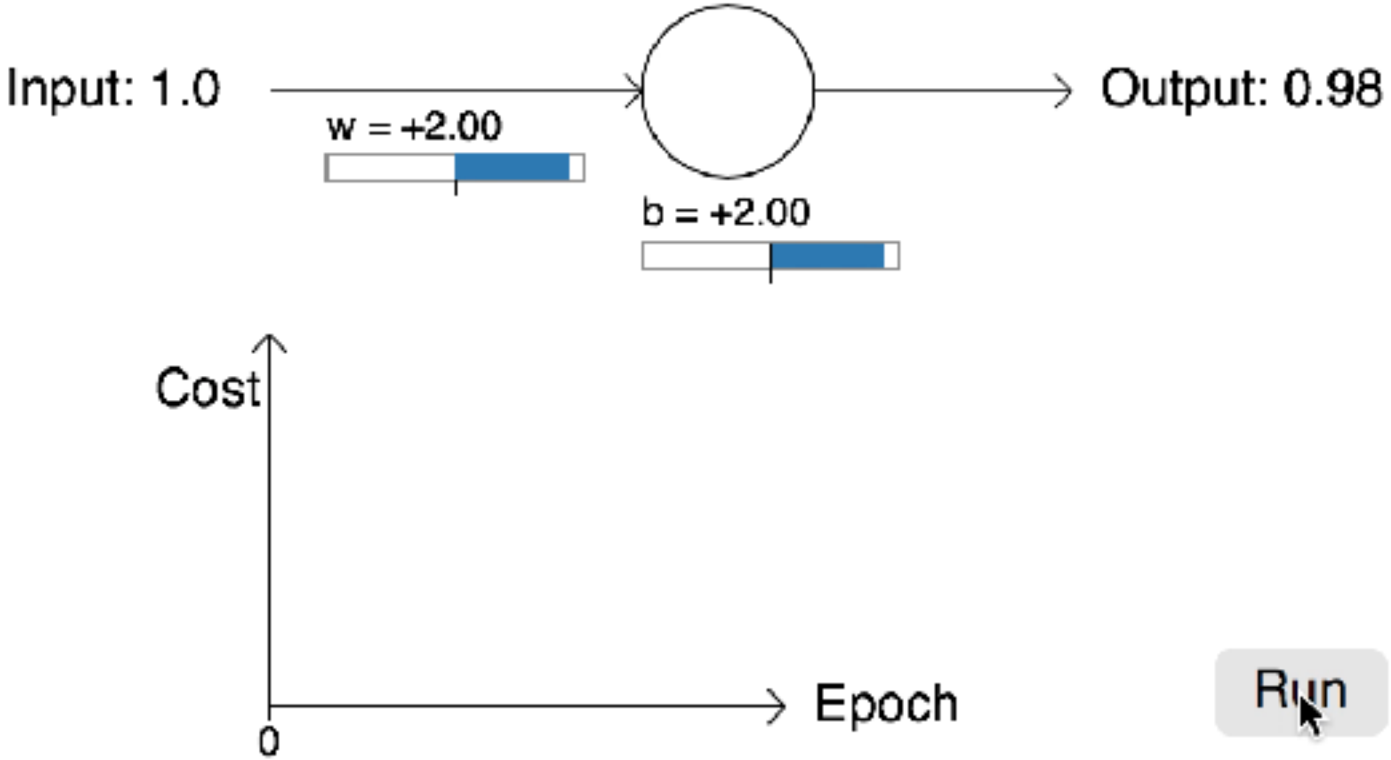


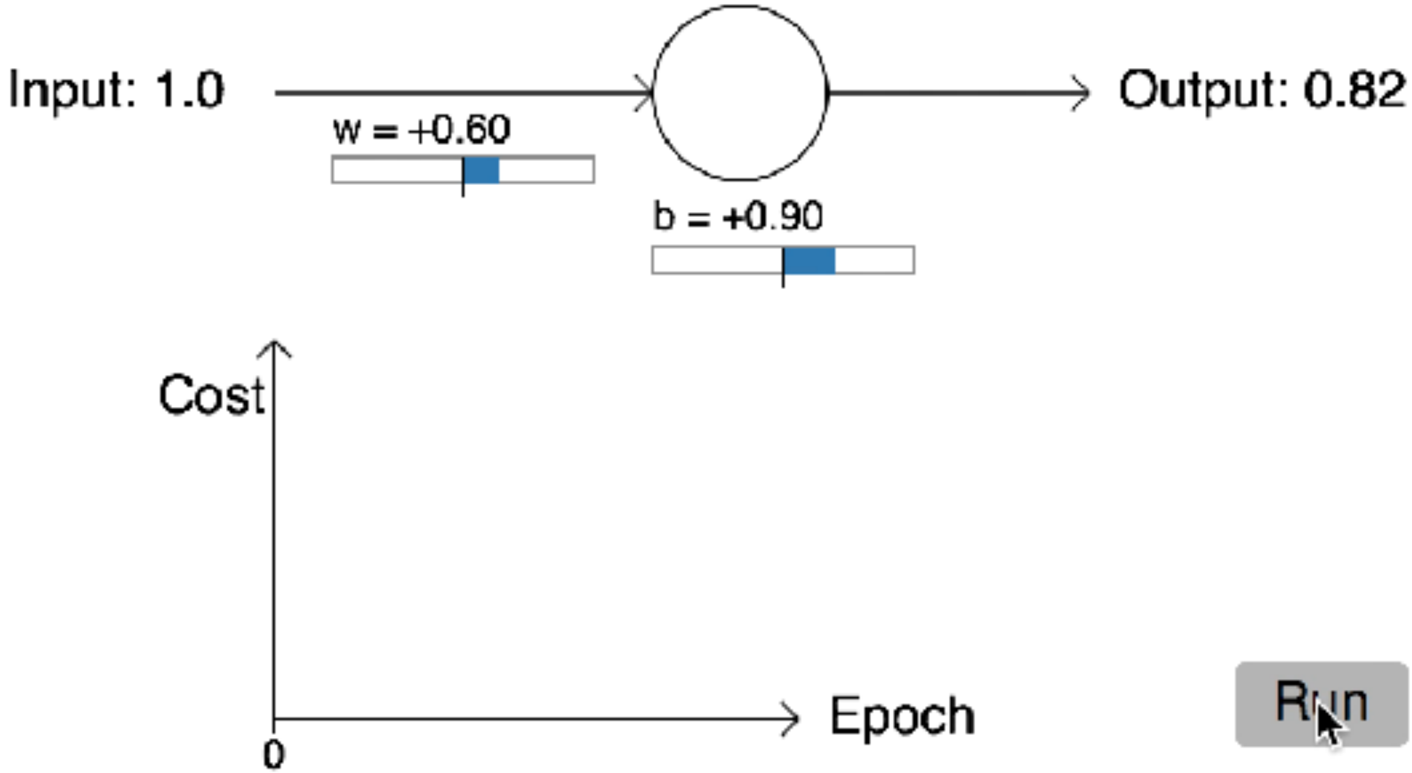
Neural Networks and Deep Learning, Michael Nielson, 2015

Practical Implementation of Architectures

- Negative of MLE: **Binary Cross entropy**

$$J(\mathbf{W}) = -\left[\mathbf{y}^{(i)} \ln([\mathbf{a}^{(L+1)}]^{(i)}) + (1-\mathbf{y}^{(i)})\ln(1-[\mathbf{a}^{(L+1)}]^{(i)})\right]$$

speeds up initial training



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Practical Implementation of Architectures

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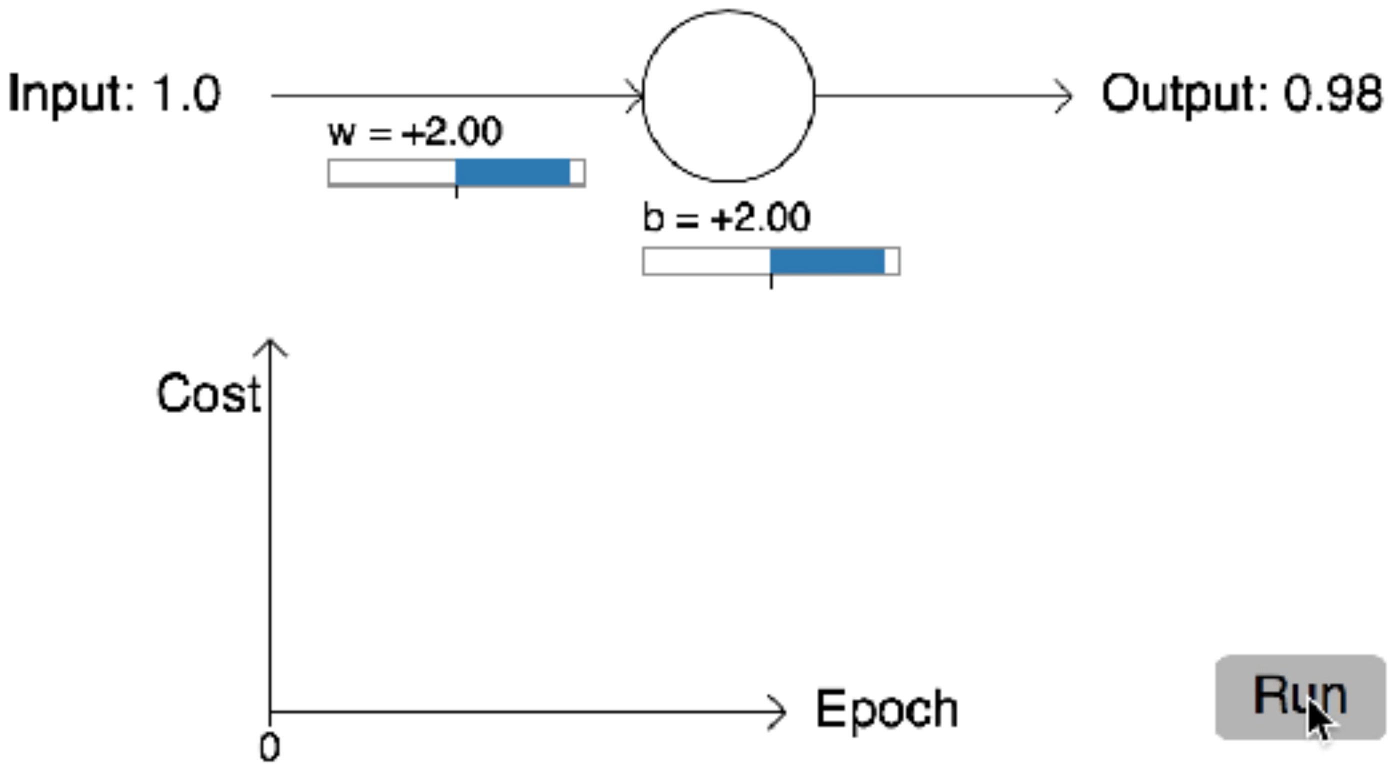

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Practical Implementation of Architectures

- Negative of MLE: **Binary Cross entropy**

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speeds up initial training

$$\left[\frac{\partial J(\mathbf{W})}{\mathbf{z}^{(L)}}\right]^{(i)}$$

$$\mathbf{V}^{(2)} = -2(\mathbf{Y}-\mathbf{A}^{(3)}) * \mathbf{A}^{(3)} * (1-\mathbf{A}^{(3)})$$ old update

Practical Implementation of Architectures

- Back to our old friend: **Cross entropy**

$$J(\mathbf{W}) = -\left[\mathbf{y}^{(i)}\ln([\mathbf{a}^{(L+1)}]^{(i)}) + (1-\mathbf{y}^{(i)})\ln(1-[\mathbf{a}^{(L+1)}]^{(i)})\right]$$

speeds up
initial training

$$\left[\frac{\partial J(\mathbf{W})}{\mathbf{z}^{(L)}}\right]^{(i)} = ([\mathbf{a}^{(L+1)}]^{(i)} - \mathbf{y}^{(i)})$$

$$\left[\frac{\partial J(\mathbf{W})}{\mathbf{z}^{(2)}}\right]^{(i)} = ([\mathbf{a}^{(3)}]^{(i)} - \mathbf{y}^{(i)})$$

```
# vectorized backpropagation
V2 = (A3-Y_enc) # <- this is only line t
V1 = A2*(1-A2)*(W2.T @ V2)

grad2 = V2 @ A2.T
grad1 = V1[1:,:] @ A1.T
```

$$\mathbf{V}^{(2)} = \mathbf{A}^{(3)} - \mathbf{Y}$$

new update

bp-5

$$\mathbf{V}^{(2)} = -2(\mathbf{Y} - \mathbf{A}^{(3)}) * \mathbf{A}^{(3)} * (1 - \mathbf{A}^{(3)})$$ old update

08. Practical_NeuralNets.ipynb

Demo

cross entropy

Practical Implementation of Architectures

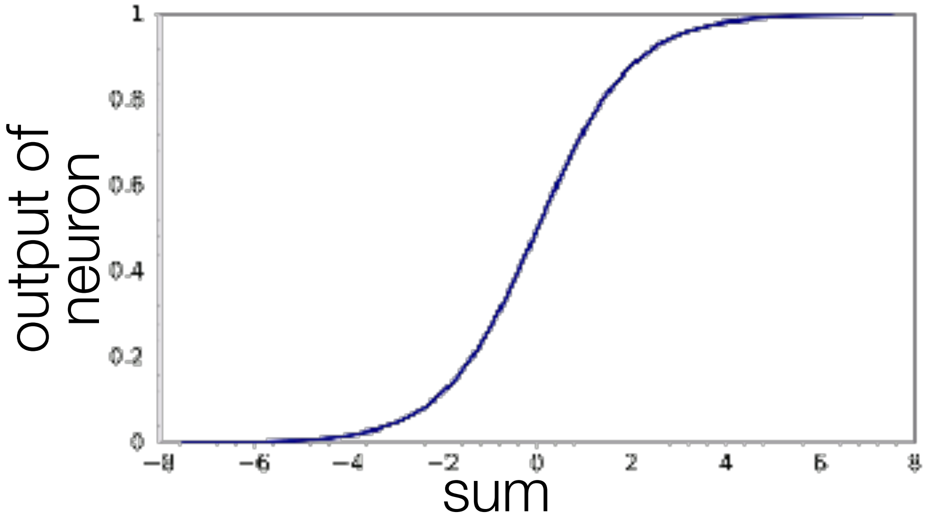
Gradient when using cosine annealing with warm restarts learning rate scheduler

Formative Self Test

- for adding Gaussian distributions, variances add together

$$\mathbf{a}^{(L+1)}=\phi(\mathbf{W}^{(L)}\mathbf{a}^{(L)})$$ assume each element of $\mathbf{a}$ is Gaussian

- If you initialized the weights, **W**, with too large variance, you would expect the output of the neuron, $\mathbf{a}^{(L+1)}$, to be:
  - A. saturated to “1”
  - B. saturated to “0”
  - C. could either be saturated to “0” or “1”
  - D. would not be saturated

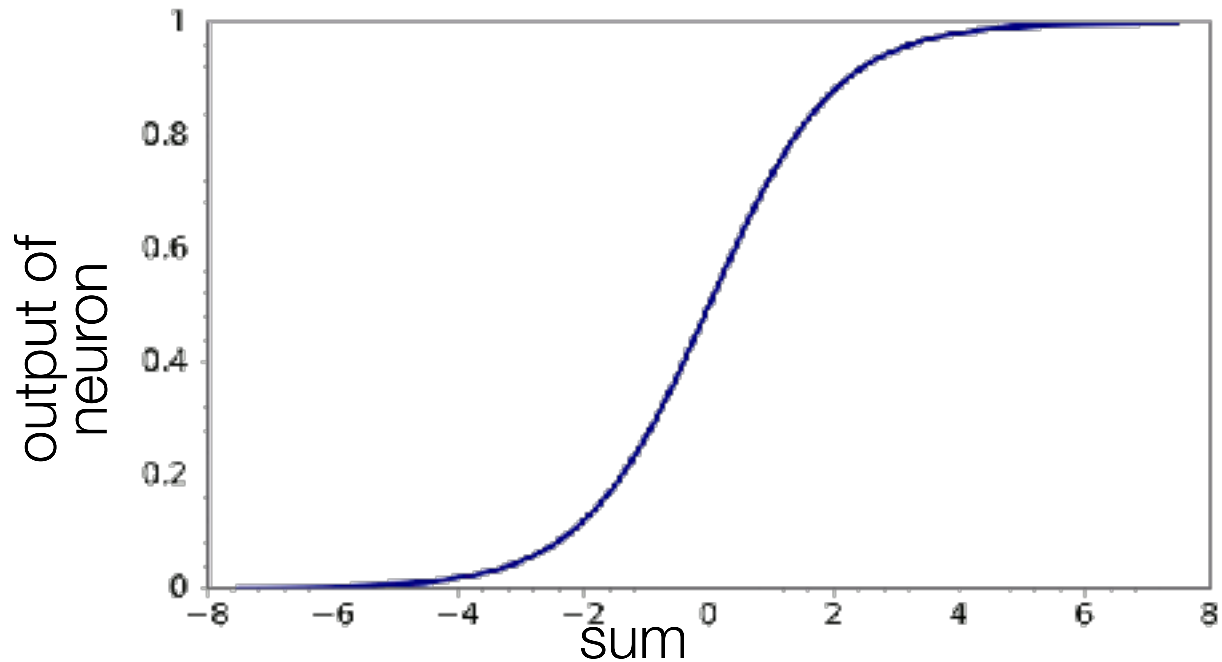


Formative Self Test

- for adding Gaussian distributions, variances add together

$\mathbf{a}^{(L+1)}=\phi(\mathbf{W}^{(L)}\mathbf{a}^{(L)})$ assume each element of $\mathbf{a}$ is Gaussian

- What is the derivative of a saturated sigmoid neuron?
  - A. zero
  - B. one
  - C. a * (1-a)
  - D. it depends

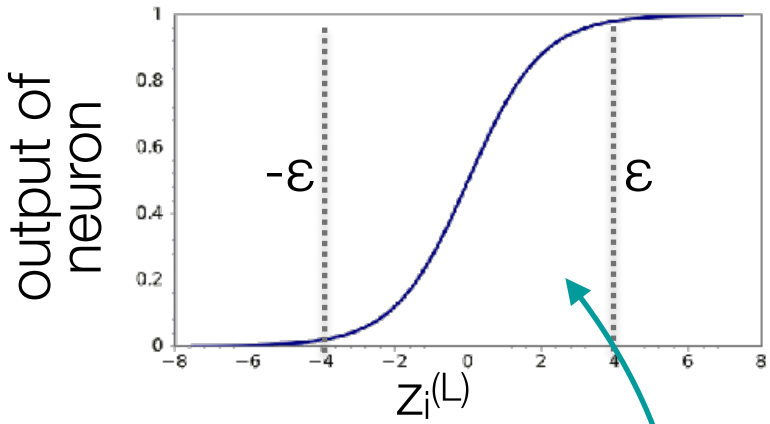


Practical Implementation of Architectures

- **Weight initialization**
  - try not to **saturate** your neurons right away!

$$\mathbf{a}^{(L+1)} = \phi(\mathbf{z}^{(L)})$$
$$\mathbf{z}^{(L)} = \mathbf{W}^{(L)}\mathbf{a}^{(L)}$$

each row is summed before sigmoid



want each $z^{(L)}$ to be between $-\varepsilon<\Sigma<\varepsilon$ for no saturation

solution: squash initial weights magnitude

- one choice: each element of **W** selected from a Gaussian with **zero mean** and **specific standard deviation**

$$w_{ij}^{(L)} \leftarrow \mathcal{N}\left(0, \sqrt{\frac{1}{n^{(L)}}}\right)$$

For a sigmoid, want $-\varepsilon<z_i^{(L)}<\varepsilon$

$\varepsilon=4$

More Weight Initialization

Understanding the difficulty of training deep feedforward neural networks

Xavier Glorot   JMLR 2010   Yoshua Bengio
DIRO, Université de Montréal, Montréal, Québec, Canada

Goal: We should not saturate **feedforward** or **back propagated** variance

Relate variance of current layer to variance in z, so $\sigma(z_i^{(L)})$ isn't saturated

try not to saturate z

$$z_i^{(L)} = \sum_j^{n^{(L)}} w_{ij} a_j^{(L)}$$

break down feed forward by each multiply

$$\text{Var}[z_i^{(L)}] = \sum_j^{n^{(L)}} \underbrace{E[w_{ij}]^2 \text{Var}[a_j^{(L)}] + \text{Var}[w_{ij}] E[a_j^{(L)}]^2}_{\text{0, if uncorrelated}} + \underbrace{\text{Var}[w_{ij}]\text{Var}[a_j^{(L)}]}_{\approx 1}$$

Want to keep Var[] ~1

assume i.i.d.
expand variance calc

$$\text{Var}[z_i^{(L)}] = 4 = n^{(L)} \text{Var}[w_{ij}] \text{Var}[a_j^{(L)}]$$

Similar for back prop.

$$\text{Var}[v_i^{(L)}] = n^{(L+1)} \text{Var}[w_{ij}] \text{Var}[v_j^{(L+1)}]$$

$$w_{ij}^{(L)} \approx \mathcal{N}\left(0,\ 4 \cdot \sqrt{\frac{1}{n^{(L)}}}\right)$$

forward
from data

$$w_{ij}^{(L)} \approx \mathcal{N}\left(0,\ 4 \cdot \sqrt{\frac{1}{n^{(L+1)}}}\right)$$

backward
from sensitivity

$$w_{ij}^{(L)} \approx \mathcal{N}\left(0,\ 4 \cdot \sqrt{\frac{2}{n^{(L)} + n^{(L+1)}}}\right)$$

compromise

More Weight Initialization

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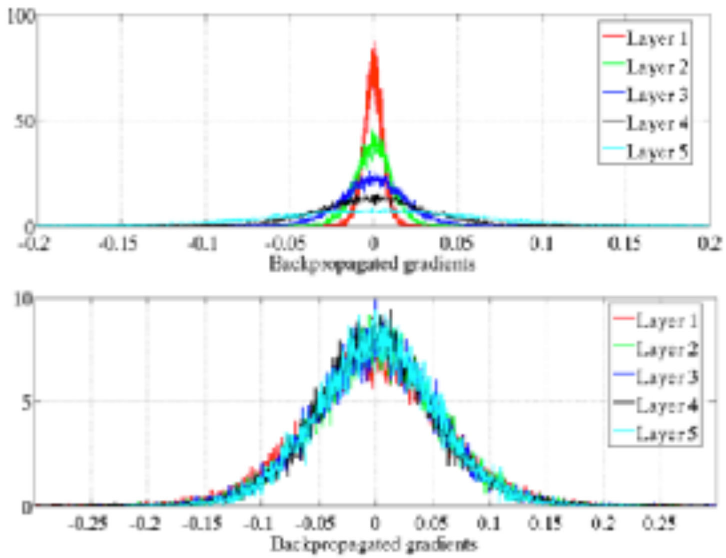


Figure 7: *Back-propagated gradients normalized histograms with hyperbolic tangent activation, with standard (top) vs normalized (bottom) initialization. Top: 0-peak decreases for higher layers.*

Starting gradient histograms per layer
standard normalization

Starting gradient histograms per layer
Glorot normalization

Glorot and He Initialization

We have solved this assuming the activation output is in the range -4 to 4 (for a sigmoid) and assuming that x is distributed Gaussian

This range, epsilon, is different depending on the activation and assuming Gaussian or Uniform

	Uniform	Gaussian
Tanh	$w_{ij}^{(L)} = \sqrt{\frac{6}{n^{(L)} + n^{(L+1)}}}$	$w_{ij}^{(L)} = \sqrt{\frac{2}{n^{(L)} + n^{(L+1)}}}$
Sigmoid	$w_{ij}^{(L)} = 4\sqrt{\frac{6}{n^{(L)} + n^{(L+1)}}}$	$w_{ij}^{(L)} = 4\sqrt{\frac{2}{n^{(L)} + n^{(L+1)}}}$
ReLU	$w_{ij}^{(L)} = \sqrt{2}\sqrt{\frac{6}{n^{(L)} + n^{(L+1)}}}$	$w_{ij}^{(L)} = \sqrt{2}\sqrt{\frac{2}{n^{(L)} + n^{(L+1)}}}$

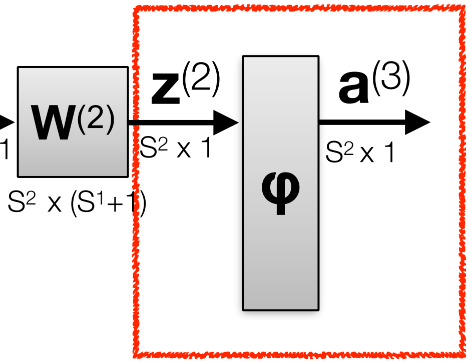
Summarized by Glorot and He

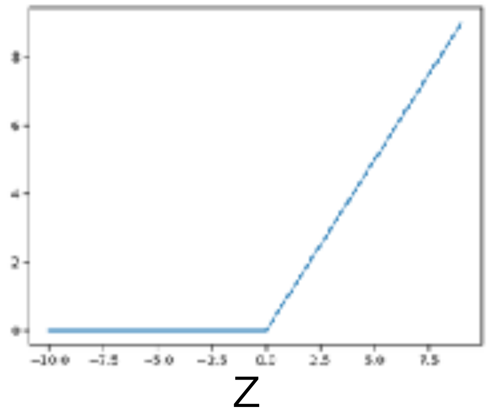
08. Practical_NeuralNets.ipynb **Demo**

Smarter Weight Initialization

Practical Implementation of Architectures

- A new nonlinearity: **recitifed linear units**





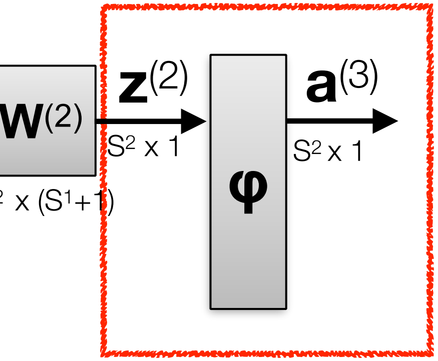
$$\phi(z) = \begin{cases} z, \text{ if } z > 0 \\ 0, \text{ else} \end{cases}$$

it has the advantage of **large gradients** and **extremely simple** derivative

$$\nabla \phi(z) = \begin{cases} 1, \text{ if } z > 0 \\ 0, \text{ else} \end{cases}$$

ReLU Nonlinearities
Important for deep networks

Other Activation Functions



- Sigmoid Weighted Linear Unit **SiLU**
  - also called Swish
- Mixing of sigmoid, σ, and ReLU

Ramachandran P, Zoph B, Le QV. Swish: a Self-Gated Activation Function. arXiv preprint arXiv:1710.05941. 2017 Oct 16

Elfwing, Stefan, Eiji Uchibe, and Kenji Doya. "Sigmoid-weighted linear units for neural network function approximation in reinforcement learning." Neural Networks (2018).

$$\varphi(z) = z \cdot \sigma(z)$$

$$\frac{\partial \varphi(z)}{\partial z} = \varphi(z) + \sigma(z)[1 - \varphi(z)]$$

$$= a^{(l+1)} + \sigma(z^{(l)}) \cdot [1 - a^{(l+1)}]$$

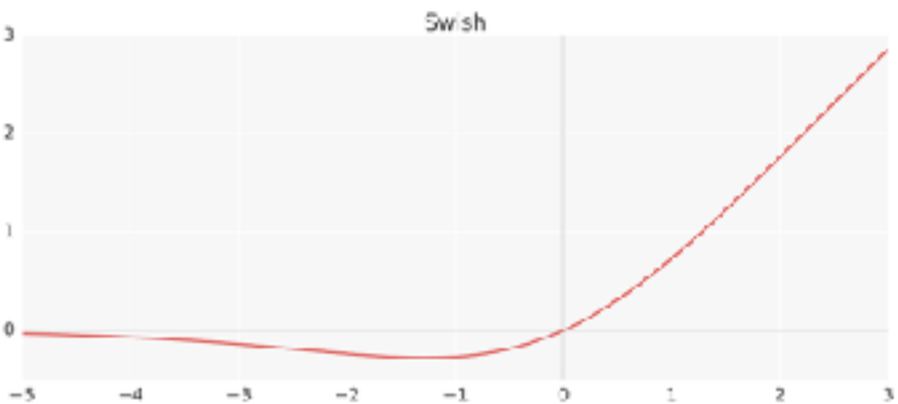
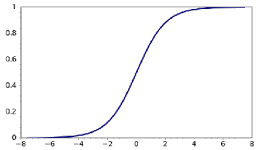
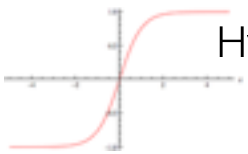
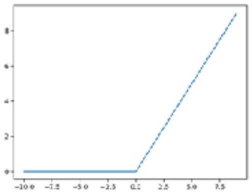
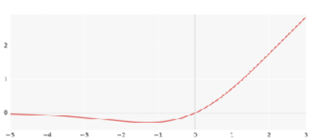


Figure 1: The Swish activation function.

Derivative Calculation:

$$= \sigma(x) + x \cdot \sigma(x)(1 - \sigma(x))$$
$$= \sigma(x) + x \cdot \sigma(x) - x \cdot \sigma(x)^2$$
$$= x \cdot \sigma(x) + \sigma(x)(1 - x \cdot \sigma(x))$$

Activations Summary

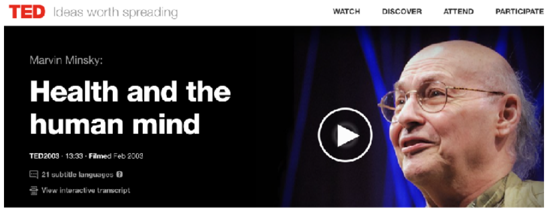
	Definition	Derivative	**Weight Init** *(Uniform Bounds)*
 Sigmoid	$\phi(z) = \frac{1}{1+e^{-z}}$	$\nabla\phi(z) = a(1-a)$	$w_{ij}^{(L)} = 4\sqrt{\frac{6}{n^{(L)}+n^{(L+1)}}}$
 Hyperbolic Tangent	$\phi(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$	$\nabla\phi(z) = \frac{4}{(e^{z}+e^{-z})^2}$	$w_{ij}^{(L)} = \sqrt{\frac{6}{n^{(L)}+n^{(L+1)}}}$
 ReLU	$\phi(z) = \begin{cases} z, \text{ if } z > 0 \\ 0, \text{ else} \end{cases}$	$\nabla\phi(z) = \begin{cases} 1, \text{ if } z > 0 \\ 0, \text{ else} \end{cases}$	$w_{ij}^{(L)} = \sqrt{2}\sqrt{\frac{6}{n^{(L)}+n^{(L+1)}}}$
 SiLU	$\phi(z) = \frac{z}{1+e^{-z}}$	$\nabla\phi(z) = a + \frac{(1-a)}{1+e^{-z}}$	$w_{ij}^{(L)} = \sqrt{2}\sqrt{\frac{6}{n^{(L)}+n^{(L+1)}}}$

Practical Details

- Neural networks can separate any data through multiple layers. The true realization of Rosenblatt:

"Given an elementary α-perceptron, a stimulus world W, and any classification C(W) for which a solution exists; let all stimuli in W occur in any sequence, provided that each stimulus must reoccur in finite time; then beginning from an arbitrary initial state, an error correction procedure will always yield a solution to C(W) in finite time…"

- **Universality**: No matter what function we want to compute, we know that there is a neural network which can do the job.



- One nonlinear hidden layer with an output layer can perfectly train any problem with enough data, but might just be memorizing…
  - … it might be better to have even more layers for decreased computation and generalizability

End of Session

- Next Time: Final Flipped Module!
- Then: Deep Learning in Keras

Back Up Slides