

Data, Environment and Society:

Lecture 25: Neural Networks

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November 26, 2019

Announcements

- HW10 due today
- Next today and tuesday: neural nets
 - ▶ Feel free to use on projects – but no HW here.
- Course evaluations available online; I will make time next Tuesday
- Thursday: Career panel
 - ▶ JP Dolphin, manager of Strategic Data Science at PG&E
 - ▶ Tanner Burke, senior data engineer, Streetlight Data
 - ▶ Jason Harville, assistant executive director of the Energy Data and Analytics Office, California Energy Commission

Today's outline

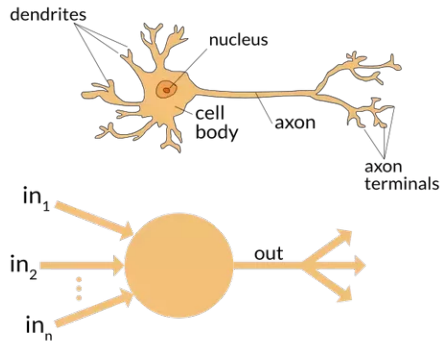
① Neural networks (NN)

- ▶ Brief introduction
- ▶ Experiment with tensorflow playground – try fitting different classification problems
- ▶ Objective: Understand the role of key parameters, what the hyperparameters are, and the model fitting process

② Exam handout and discussion

Neural networks: Origins

- The name is due to analogy with brains
- First developed in 1943
- Inspired the development of the perceptron (see HW10) in the '50s
 - ▶ Here the purpose was just to remove noise on phone lines
 - ▶ Not to reproduce thought...
- Little research activity ~1960-1990's due to computing limitations
 - ▶ Major exception: Werbos developed back-propagation in 1974. First effort to get NN to "learn" parameters
- Computing advances made "deep" NN possible in the last 20 years



Mathematics for a single "neuron"

In words, each neuron...

- Takes a vector of values as inputs
- Creates a scalar from a linear combination of the vector entries
- Passes the resulting scalar through an "activation function"
- Outputs a single value from that activation function

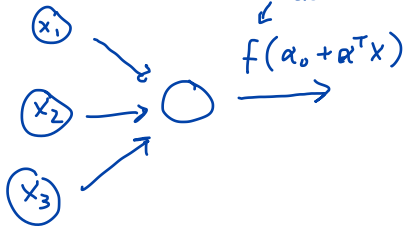
Terminology analogies:

- Electrical signal from other cells \rightleftharpoons input
- Neuron \rightleftharpoons Activation function
- Electrical signal to other cells \rightleftharpoons output

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix}$$

$$v = \alpha_0 + \alpha^T X \quad \leftarrow \text{Scalar value.}$$
$$= \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3$$

"activation function"



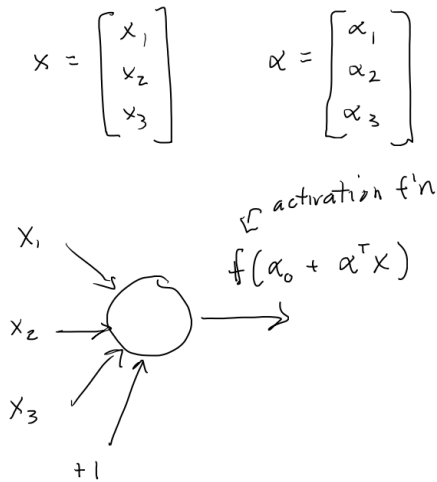
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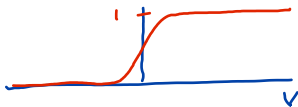
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What's f , the activation function?

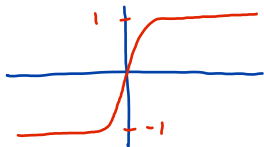
$$v = \alpha_0 + \alpha^T x$$

① sigmoid



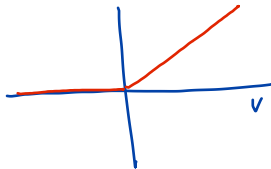
$$f(v) = \frac{1}{1 + e^{-v}}$$

② tanh



$$f(v) = \frac{e^v - e^{-v}}{e^v + e^{-v}}$$

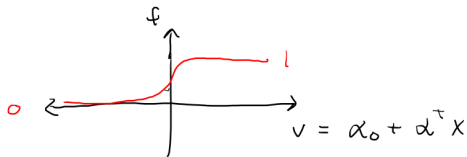
③ rectified linear (ReLU)



$$v = \max(0, v)$$

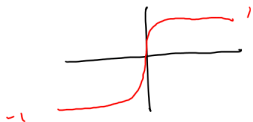
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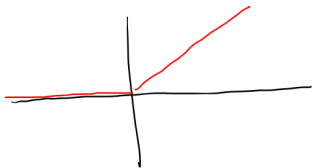
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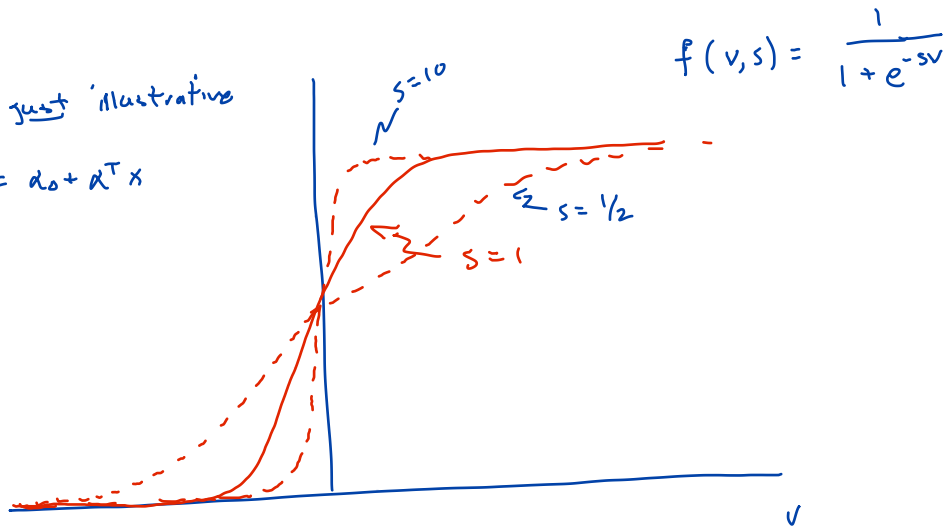
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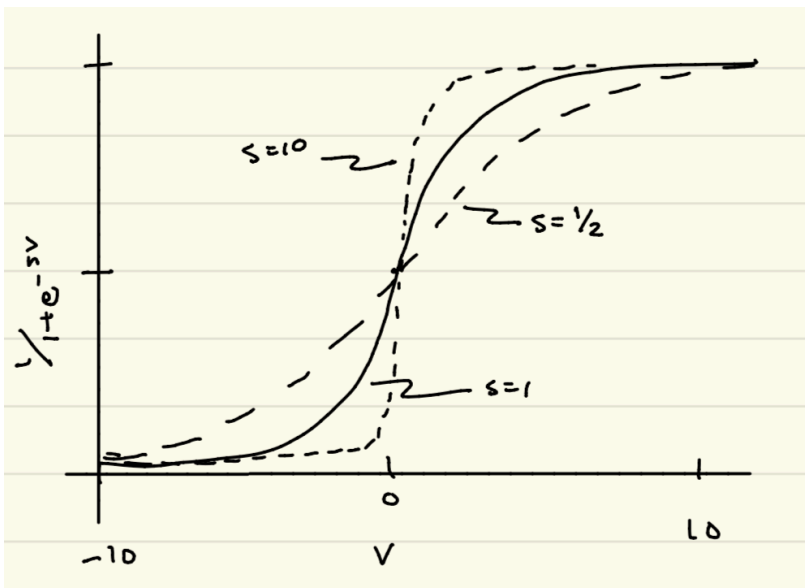
$$\max(0, v)$$

How the sigmoid function works

s here is just illustrative
In fact $v = w_0 + w^T x$

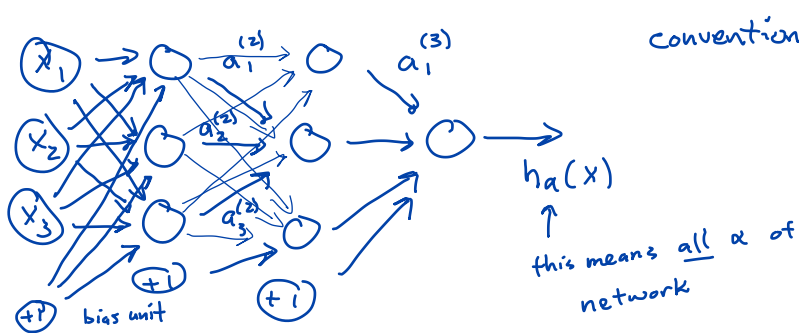


How the sigmoid function works



Remember: $v = \alpha_0 + \alpha^T \mathbf{x}$

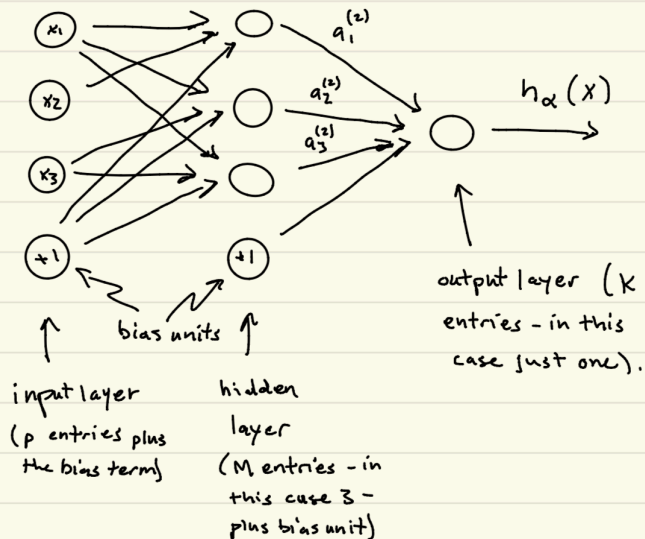
Neural network: just gang the neurons together



convention: $a_i^{(l)}$ output from node i in layer l .

$$v = \alpha_0 + \alpha^T x$$

Neural network: just gang the neurons together



Convention: $a_i^{(l)}$ is the output of the i^{th} neuron in the l^{th} layer.

Mathematical merging of neurons

Convention:

- $\alpha_{ij}^{(l)}$ \rightarrow weight from node j in layer l to node i in $l + 1$ layer.
- $a_i^{(l)}$ \rightarrow output of node i in layer l .

$$a_1^{(2)} = f\left(\alpha_{10}^{(1)} + \alpha_{11}^{(1)} x_1 + \alpha_{12}^{(1)} x_2 + \alpha_{13}^{(1)} x_3\right)$$

$$a_1^{(3)} = f\left(\alpha_{10}^{(2)} + \sum_{j=1}^{M_2} \alpha_{1j}^{(2)} a_j^{(2)}\right)$$

Note that I used x in the first equation because I'm calling the features (inputs to the model) the first "layer" of the network

Question: What are the parameters of a neural network model?

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Question: What are the parameters of a neural network model?

Just the α values. a values are outputs from internal nodes or neurons. We call these "hidden states" because they depend on the input values x .

Thinking about the features and target

Let's watch this video. It uses graphics in a nice way to explain what NNs are doing.

<https://www.youtube.com/watch?v=aircAruvnKk>

Start the video at 2:05. We'll stop watching around 5:30.

Compact notation motivates a name...

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$$a_i^{(2)} = f(\alpha_{i0}^{(1)} + \alpha_{i1}^{(1)} x_1^{(1)} + \alpha_{i2}^{(1)} x_2^{(1)} + \alpha_{i3}^{(1)} x_3^{(1)})$$

$$a_i^{(3)} = f(\alpha_{i0}^{(2)} + \sum_{j=1}^{M_2} \alpha_{ij}^{(2)} a_j^{(2)}) \quad (M_j \text{ is the number of neurons in layer } j)$$

$$a_i^{(4)} = f(\alpha_{i0}^{(3)} + \sum_{j=1}^{M_3} \alpha_{ij}^{(3)} a_j^{(3)})$$

\vdots

$$h_\alpha(x) = f(a^{(\ell)}, \alpha^{(\ell)}) \quad \text{Final output of NN. } \ell \text{ is the number of layers}$$

- The α subscript means h is a function of ALL the α values of the network
- We dropped subscripts on a , meaning a is a vector of inputs to the final layer

Because each layer informs the next, we call this a **feedforward** neural network.

Fitting the model - regression

Training data: $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$

$$h_{\alpha}(x)$$

$x \in \mathbb{R}^p$ (p features), single output, y

Objective function:

$$J(\alpha, x, y) = \sum_{i=1}^n \left(h_{\alpha}(x_i) - y_i \right)^2 + \lambda \sum_{l=1}^{n_L} \sum_{i=1}^{S_{l+1}} \sum_{j=1}^{S_l} \left(\alpha_{ij}^{(l)} \right)^2$$

layers
↓
nodes in $l+1$ layer

↑
can also use
 L_0, L_1 norm.

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Handwritten annotations:
- n_l : # layers
- s_{l+1} : nodes in $l+1$ layer
- s_l : nodes in l

Quick notes on objective function and finding parameters

- Form is amenable to classification, just one-hot encode the output and use classification error rate as your objective
- For regression, be sure to scale the *output* variables to lie in the range of the activation function.
 - ▶ For sigmoid, scale to: $[0, 1]$

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 - ▶ For sigmoid, scale to: $[0, 1]$
 - ▶ Tanh: $[-1, 1]$
 - ▶ (I *believe* ReLU requires shifting output to be non-negative; textbook does not address.)
- Solving the objective function involves a form of gradient search
 - ▶ The partial derivatives are found via a technique called backpropagation



Tensorflow playground

On **this website** you'll find a cool interactive tool that allows you to play with NN for classification.

- ① What are the hyperparameters of the model? Can you explain what each one does?
- ② Try fitting the “exclusive or” (choose on top left) data set.
- ③ Also try fitting the “Spiral” data set.
- ④ Possible spiral solution:

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 - ① Learning rate 0.03
 - ② Two hidden layers, six and four neurons each
 - ③ Tanh activation
 - ④ Include all but X_1X_2 features.
 - ⑤ L1 regularization, regularization rate = 0.001

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 - ⑤ L1 regularization, regularization rate = 0.001
- ⑤ You got close by trial and error. What's another way?
 - ▶ Cross validation! Grid search, randomized search
 - ▶ But everything is computationally intense.

What's going on in the hidden layers?

Hover over the hidden layers in the tensorflow playground.

Q: What are we looking at?

What's going on in the hidden layers?

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Q: What are we looking at?

Ans: The scalar output of that neuron's activation function at each point in the feature space.

These can have interesting (but sometimes dubious) interpretations. More next time!