Introduction to Deep Learning

1. Neural Networks 101

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| 8:30-9:00 | Continental Breakfast | | |
|-------------|---|--|--|
| 9:00-9:45 | Introduction and Setup | | |
| 9:45-10:30 | Neural Networks 101 | | |
| 10:30-10:45 | Break | | |
| 10:45-11:15 | Machine Learning Basics | | |
| 11:15-11:45 | Context-free Representations for Language | | |
| 11:45-12:15 | Convolutional Neural Networks | | |
| 12:15-13:15 | Lunch Break | | |
| 13:15-14:00 | Recurrent Neural Networks | | |
| 14:00-14:45 | Attention Mechanism and Transformer | | |
| 14:45-15:00 | Coffee Break | | |
| 15:00-16:15 | Contextual Representations for Language | | |
| 16:15-17:00 | Language Generation | | |



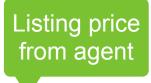
Outline

- Linear Model
 - Single layer network
 - XOR is hard
- Multilayer Perceptron
 - Layers
 - Nonlinearities
 - Computational Cost



House Buying 101

- Pick a house, take a tour, and read facts
- Estimate its price, bid



\$5,498,000 7 5 4,865 Sq. Ft. Price Beds Baths \$1130 / Sq. Ft.

Redfin Estimate: \$5,390,037 On Redfin: 15 days

Predicted sale price







Virtual Tour

- Branded Virtual Tour
- Virtual Tour (External Link)

Parking Information

- Garage (Minimum): 2
- Garage (Maximum): 2
- Parking Description: Attached Garage, On Street
- Garage Spaces: 2

Multi-Unit Information

of Stories: 2

School Information

- Elementary School: El Carmelo El
- Elementary School District: Palo
- Middle School: Jane Lathrop Stan
- High School: Palo Alto High
- · High School District: Palo Alto Un

Interior Features

Bedroom Information

- # of Bedrooms (Minimum): 7
- # of Rodrooms (Maximum) 7

 Kitchen Description: Countertop Dishwasher, Garbage Disposal, Ho Island with Sink, Microwave, Over

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A Simplified Model



Assumption 1

The key factors impacting the prices are #Beds, #Baths, Living sqft, denoted by x_1, x_2, x_3

Assumption 2

The sale price is a weighted sum over the key factors

$$y = w_1 x_1 + w_2 x_2 + w_3 x_3 + b$$

Weights and bias are determined later



Linear Model

$$\mathbf{x} = [x_1, x_2, \dots, x_n]^T$$

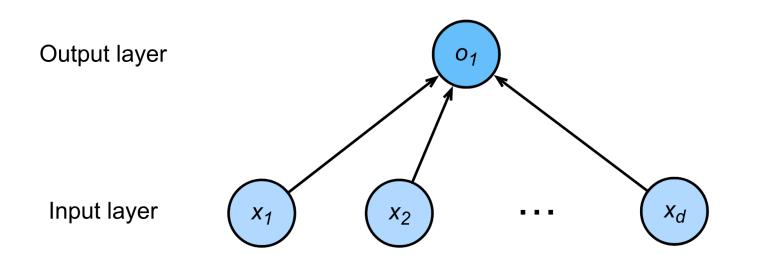
$$\mathbf{w} = [w_1, w_2, ..., w_n]^T, b$$

$$y = w_1 x_1 + w_2 x_2 + \dots + w_n x_n + b$$

$$y = \langle \mathbf{w}, \mathbf{x} \rangle + b$$



Linear Model as a Single-layer Neural Network

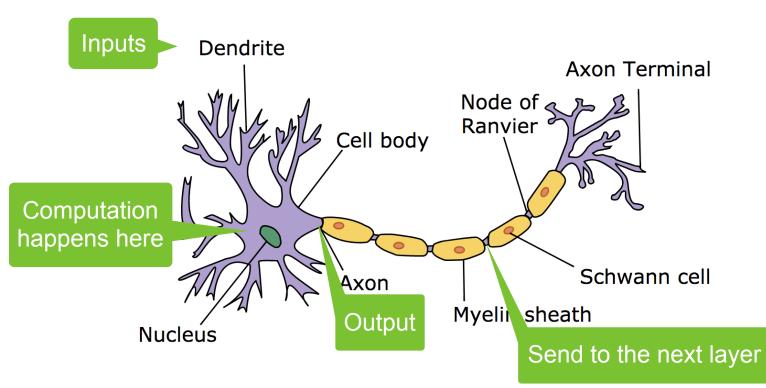


We can stack multiple layers to get deep neural networks



Neural Networks Derive from Neuroscience

The real neuron





Measure Estimation Quality

- Compare the true value vs the estimated value Real sale price vs estimated house price
- Let y the true value, and \hat{y} the estimated value, we can compare the **squared loss**

$$\mathscr{E}(y,\hat{y}) = \left(y - \hat{y}\right)^2$$



Learn Parameters

Training loss

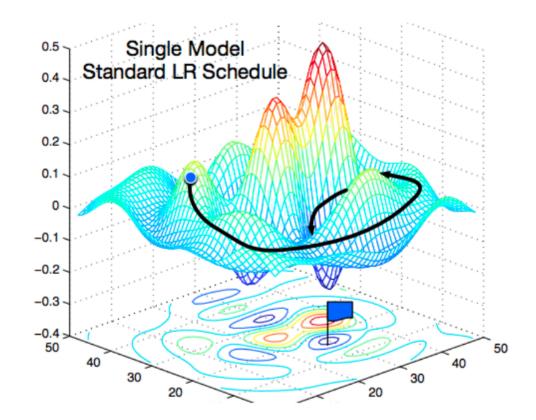
$$\mathscr{E}(\mathbf{X}, \mathbf{y}, \mathbf{w}, b) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \langle \mathbf{x}_i, \mathbf{w} \rangle - b)^2 = \frac{1}{n} \| \mathbf{y} - \mathbf{X}\mathbf{w} - b \|^2$$

Minimize loss to learn parameters

$$\mathbf{w}^*, \mathbf{b}^* = \arg\min_{\mathbf{w}, b} \mathcal{E}(\mathbf{X}, \mathbf{y}, \mathbf{w}, b)$$



Basic Optimization

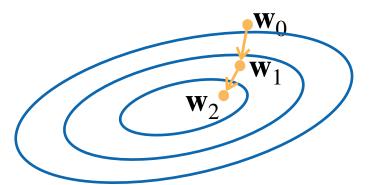




Gradient Descent

- Choose a staring point w₀
- Repeat to update the weight t=1,2,3

$$\mathbf{w}_{t} = \mathbf{w}_{t-1} - \eta \frac{\partial \mathcal{E}}{\partial \mathbf{w}_{t-1}}$$



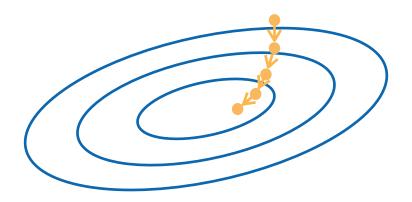
- Gradient: a direction that increases the value
- Learning rate: a hyper-parameter specifies the step length

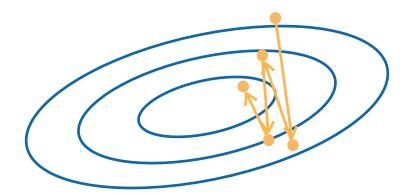


Choose a Learning Rate

Not too small

Not too big







Mini-batch Stochastic Gradient Descent (SGD)

- Computing the gradient over the whole training data is too expensive
 - Takes minutes to hours for DNN models
- Randomly sample b examples $i_1, i_2, ..., i_b$ to approximate the loss

$$\frac{1}{b} \sum_{i \in I_b} \mathcal{E}(\mathbf{x}_i, y_i, \mathbf{w})$$

 b is the batch size, another important hyperparameters



Choose a Batch Size

Not too small

Not too big

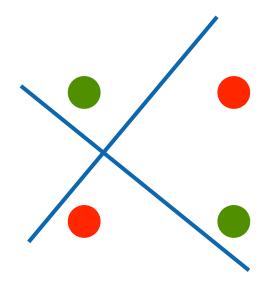
Workload is too small, hard to fully utilize computation resources

Memory issue Waste computation, e.g. when all x_i are identical



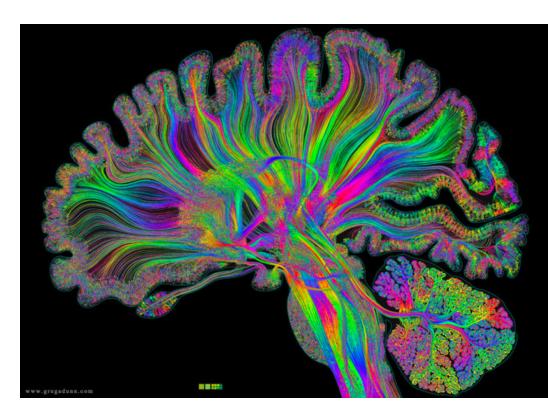
XOR Problem (Minsky & Papert, 1969)

The perceptron cannot learn an XOR function (neurons can only generate linear separators)



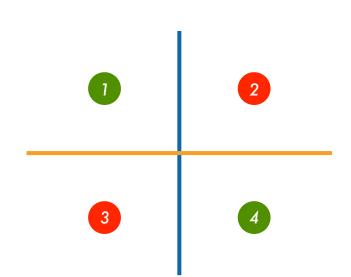


Multilayer Perceptron

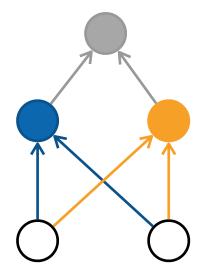




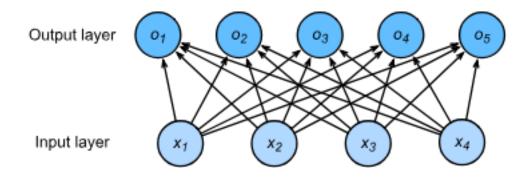
Learning XOR



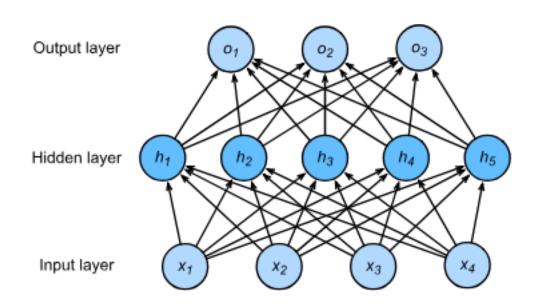
| | 1 | 2 | 3 | 4 |
|---------|---|---|---|---|
| | + | - | + | - |
| | + | + | - | - |
| product | + | - | - | + |











Hyperparameter - size m of hidden layer



- Input $\mathbf{x} \in \mathbb{R}^n$
- Hidden $\mathbf{W}_1 \in \mathbb{R}^{m \times n}, \mathbf{b}_1 \in \mathbb{R}^m$
- Output $\mathbf{w}_2 \in \mathbb{R}^m, b_2 \in \mathbb{R}$

$$\mathbf{h} = \sigma(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1)$$

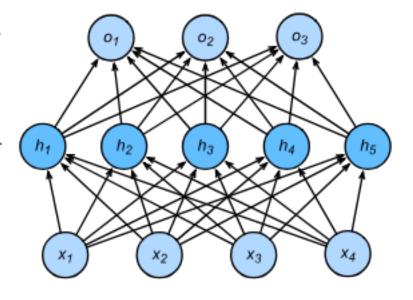
$$\mathbf{o} = \mathbf{w}_2^T \mathbf{h} + b_2$$

 σ is an element-wise activation function

Output layer

Hidden layer

Input layer





Why do we need an a nonlinear activation?

Output layer

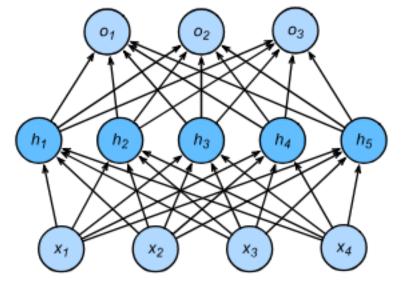
 $\mathbf{h} = \sigma(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1)$

 $\mathbf{o} = \mathbf{w}_2^T \mathbf{h} + b_2$

 σ is an element-wise activation function

Hidden layer

Input layer





Why do we need an a nonlinear activation?

Output layer

 $\mathbf{h} = \mathbf{W}_1 \mathbf{x} + \mathbf{b}_1$

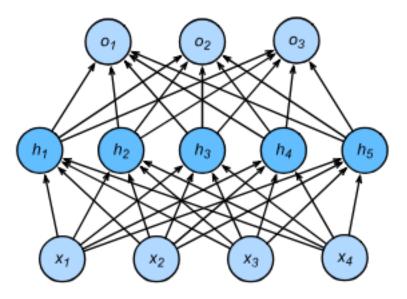
 $\mathbf{o} = \mathbf{w}_2^T \mathbf{h} + b_2$

hence $o = \mathbf{w}_2^\mathsf{T} \mathbf{W}_1 \mathbf{x} + b'$

Hidden layer

Input layer

Linear ...





From Regression to Multi-class Classification

Calibrated Scale

• Output matches probabilities (nonnegative, sums to 1)

$$p(y | o) = \operatorname{softmax}(o)$$
$$= \frac{\exp(o_y)}{\sum_{i} \exp(o_i)}$$

Negative log-likelihood

$$-\log p(y | y) = \log \sum_{i} \exp(o_i) - o_y$$

Classification

- Multiple classes, typically multiple outputs
- Score *should* reflect confidence ...

