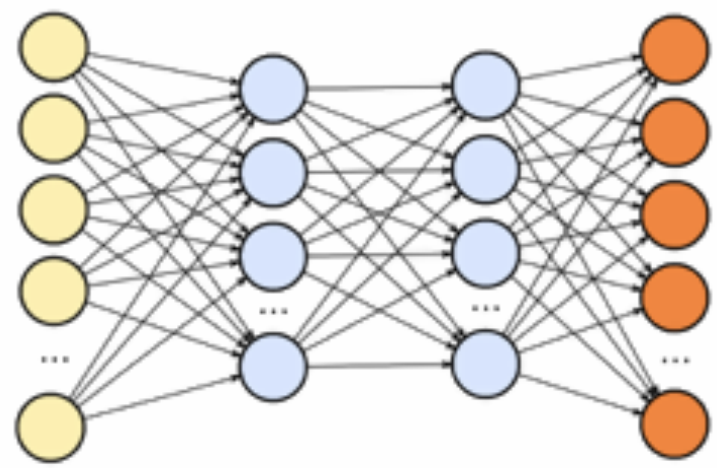
# CSE 543

Simon Du



# CSE543: Deep Learning

Instructor: Simon Du

Teaching Assistant: Ruoqi Shen, Yifang Chen

Course Website (contains all logistic information): https://courses.cs.washington.edu/courses/cse543/23wi/

Piazza: https://piazza.com/class/lbsxy7e01whdd

Announcements: Canvas

Homework: Canvas

# CSE543: Deep Learning

## What this class is:

- **Fundamentals of DL:** Neural network architecture, approximation properties, optimization, generalization, generative models, representation learning
- **Preparation for further learning / research:** the field is fast-moving, you will be able to apply the fundamentals and teach yourself the latest

## What this class is not:

- **An easy course:** mathematically easy
- **A survey course:** laundry list of algorithms
- **An application course**: implementation of different architectures on different datasets

# Prerequisites

- Working knowledge of:
    - Linear algebra
    - Vector calculus
    - Probability and statistics
    - Algorithms
    - Machine leanring (CSE 446/546)
- Mathematical maturity
- “Can I learn these topics concurrently?”

# Lecture

- Time: Tuesday and Thursday 9:00 - 10:20AM
- MUE 153 or Zoom (see website for the schedule)
- Slides + handwritten notes (e.g., proofs)
- Please ask questions
- *Recordings on Canvas
- Tentative schedule on course website

# Homework (40%)

- 2 homework (20%+20%)
  - Each contains both theoretical questions and will have programming
  - Related to course materials
  - Collaboration okay but must write who you collaborated with. You must write, submit, and understand your answers and code.
  - Submit on Canvas
  - Must be **typed**
  - **Two** late days
  - Tentative timeline:
    - HW 1 due: 1/27
    - HW 2 due: 2/10

# Course Project (60%)

- Group of 1 - 2.
- Topic: literature review (state-of-the-art) or original research.
- Some potential topics are in listed on Canvas. OK to do a project on listed.
- You can work on a project related to your research.
- Proposal (due: 1/13): **5%**
  - Format: NeurIPS Latex format, ~1 - 1.5 pages
- Presentations on (3/7 and 3/9 on Zoom): **20%**
- Final report (due: 3/17): **35%**
  - Format: NeurIPS Latex format, ~8 pages
- Submit on Canvas

# Possible Topics

- Approximation properties
- Advanced optimization methods
- Optimization theory for deep learning
- Generalization theory for deep learning
- Deep reinforcement learning
- Implicit regularization
- Meta-learning algorithm / theory
- Robustness
- Lottery ticket hypothesis
- Deep learning application
- …

# Communication Chanels

- **Announcements**
  - Canvas
- **questions about class, homework help**
  - Piazza
  - Office hours:
    - Simon Du: Tu 10:30 - 11:30 AM (in person Gates 312 and/or Zoom)
    - Ruoqi Shen:
    - Yifang Chen:
  - **Regrade requests / Personal concerns:**
    - Email to instructor or TAs

# Addcodes

- Email: Elle Brown (elleean@cs.washington.edu) for addcodes

# Topic 1: Review (Today)

- ML Review: training, generalization
- Neural network basics: fully-connected neural network, gradient descent

# Topic 2: Approximation Theory

- Why neural networks can express the (regression, classification, …) function you want?
- Construction of such desired neural networks
- Universal approximation theorem

# Topic 3: Optimization

- Review: Back-propagation
- Auto-differentiation
- Advanced optimizers: momentum (Nesterov acceleration), adaptive method (AdaGrad, Adam)
- Techniques for improving optimization: batch-norm, layer-norm, ..
- Theory: global convergence of gradient of over-parameterized neural networks
- Neural Tangent Kernel

# Topic 4: Generalization

- Measures of generalization
- Double descent
- Techniques for improving generalization
- Generalization theory beyond VC-dimension
- Implicit regularization
- Why NN outperforms kernel

# Topic 5: Architecture

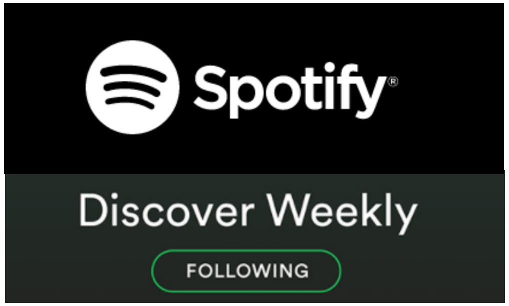
- Convolutional neural network
- Recurrent neural network
    - LSTM
- Attention-based neural network
    - Transformer
- General framework

# Topic 6: Representation Learning

- Multi-task representation learning
- Transfer learning
- Contrastive learning
- Domain adaptation
- Meta-learning
- Theory

# Topic 7: Generative Models

- Generative adversarial network
- Variational Auto-Encoder
- Energy-based models
- Normalizing flows


## ML uses past data to make predictions



# Supervised Learning Process

Collect a **dataset**

Decide on a **model**

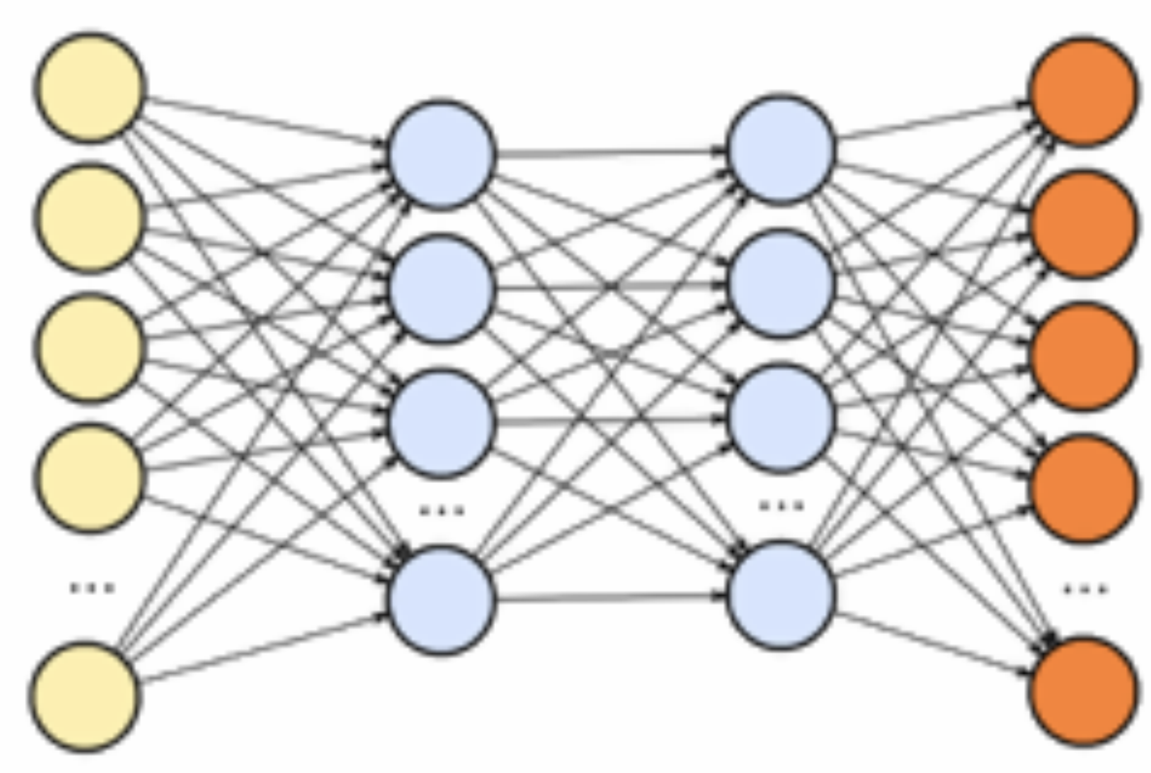
Find the function which fits the data best

- **Choose a loss function**
- **Pick the function which minimizes loss on data**

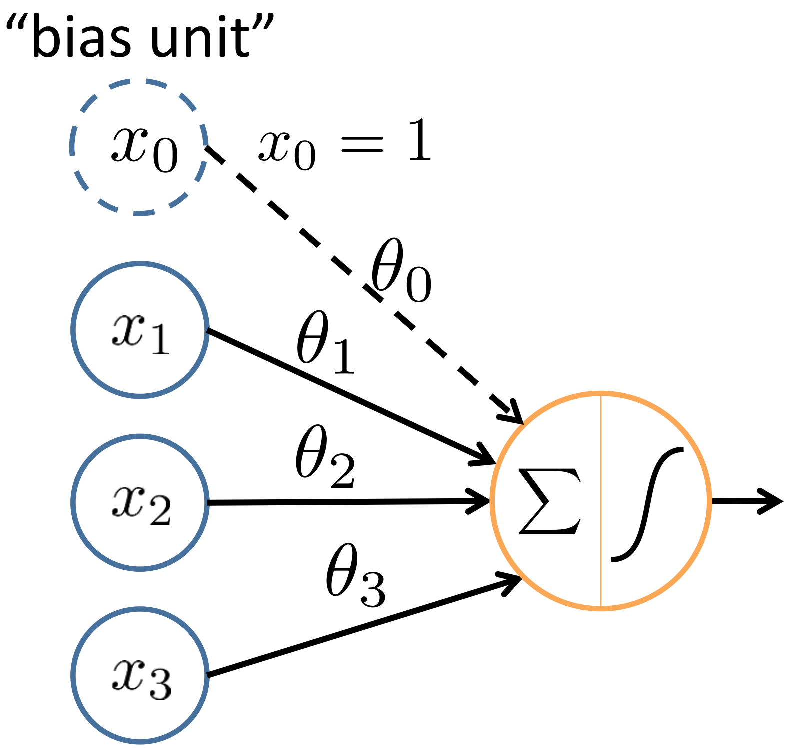
Use function to make prediction on new examples

# Framework

# Neural Networks



# Single Node



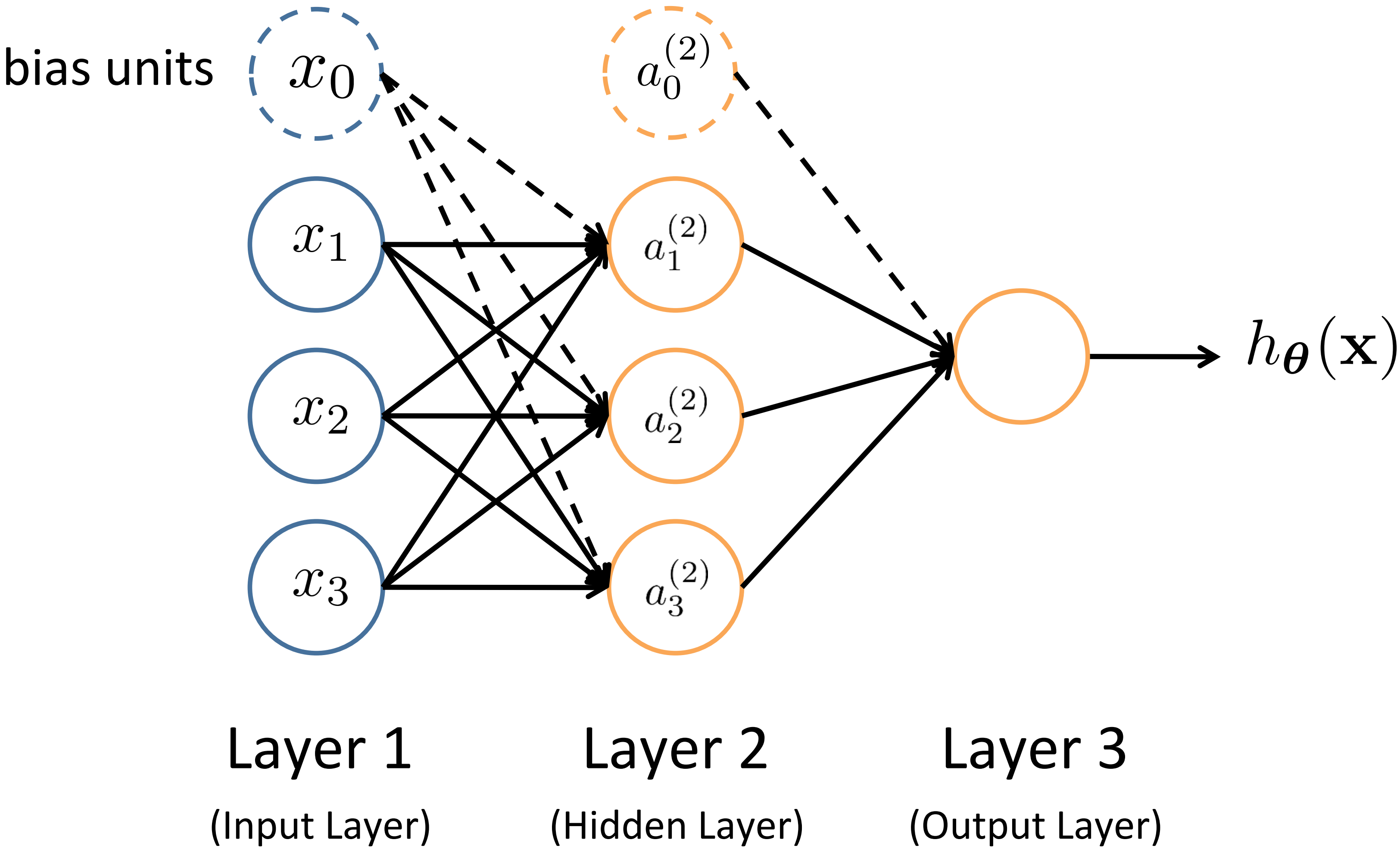

$$\mathbf{x} = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad \boldsymbol{\theta} = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

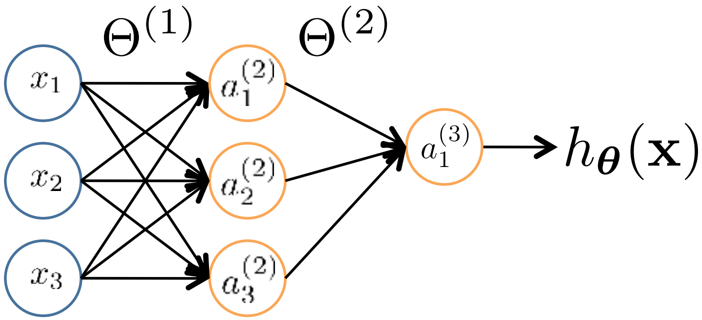
$$h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(\boldsymbol{\theta}^{\intercal}\mathbf{x}\right) = \frac{1}{1 + e^{-\boldsymbol{\theta}^{\intercal}\mathbf{x}}}$$

Binary Logistic Regression

Sigmoid (logistic) activation function: $g(z) = \dfrac{1}{1 + e^{-z}}$

# Neural Network






$a_i^{(j)}$ = "activation" of unit $i$ in layer $j$

$\Theta^{(j)}$ = weight matrix stores parameters from layer $j$ to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)} x_0 + \Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3)$$
$$a_2^{(2)} = g(\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3)$$
$$a_3^{(2)} = g(\Theta_{30}^{(1)} x_0 + \Theta_{31}^{(1)} x_1 + \Theta_{32}^{(1)} x_2 + \Theta_{33}^{(1)} x_3)$$
$$h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)} + \Theta_{13}^{(2)} a_3^{(2)})$$

If network has $s_j$ units in layer $j$ *and* $s_{j+1}$ units in layer $j+1$, then $\Theta^{(j)}$ has dimension $s_{j+1} \times (s_j+1)$ .

$$\Theta^{(1)} \in \mathbb{R}^{3\times 4} \qquad \Theta^{(2)} \in \mathbb{R}^{1\times 4}$$

# Multi-layer Neural Network - Binary Classification

$$a^{(1)} = x$$

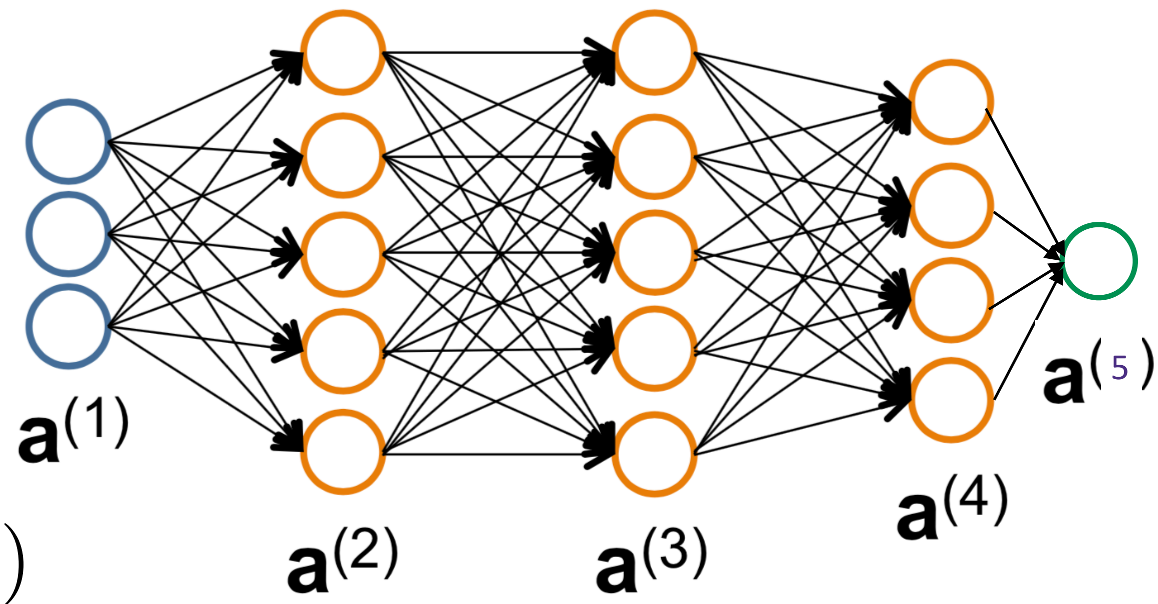
$$a^{(2)} = g(\Theta^{(1)} a^{(1)})$$

$$\vdots$$

$$a^{(l+1)} = g(\Theta^{(l)} a^{(l)})$$

$$\vdots$$

$$\widehat{y} = g(\Theta^{(L)} a^{(L)})$$




$$L(y, \hat{y}) = y\log(\hat{y}) + (1-y)\log(1-\hat{y})$$

$$g(z) = \frac{1}{1+e^{-z}}$$

Binary
Logistic
Regression

# Multi-layer Neural Network - Binary Classification

$$a^{(1)} = x$$

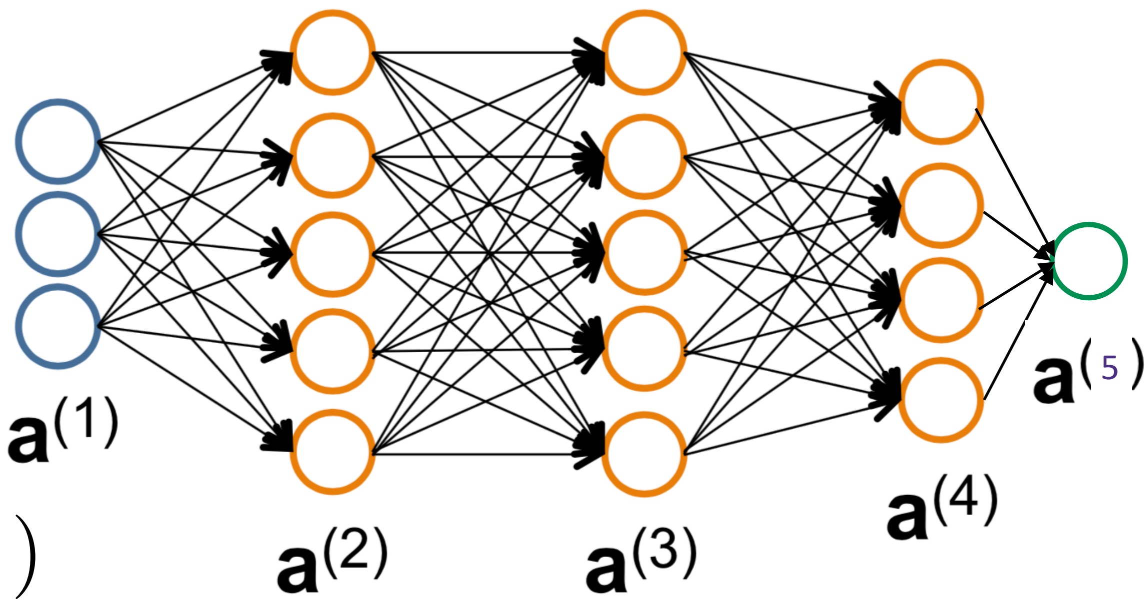
$$a^{(2)} = \sigma(\Theta^{(1)} a^{(1)})$$

$$\vdots$$

$$a^{(l+1)} = \sigma(\Theta^{(l)} a^{(l)})$$

$$\vdots$$

$$\widehat{y} = g(\Theta^{(L)} a^{(L)})$$




$$L(y, \widehat{y}) = y \log(\widehat{y}) + (1-y)\log(1-\widehat{y})$$

$$\sigma(z) = \max\{0, z\} \quad g(z) = \frac{1}{1+e^{-z}}$$

Binary
Logistic
Regression

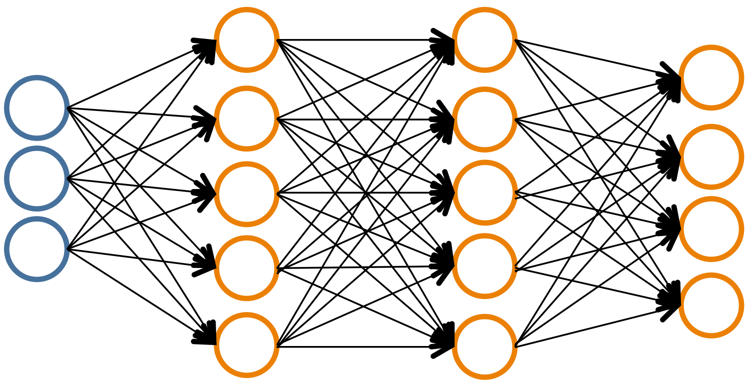
# Multiple Output Units: One-vs-Rest

Pedestrian

Car

Motorcycle

Truck



$$h_\Theta(\mathbf{x}) \in \mathbb{R}^K$$

Multi-class Logistic Regression

We want:

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

when pedestrian

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

when car

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

when motorcycle

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

when truck

# Multi-layer Neural Network - Regression

$$a^{(1)} = x$$

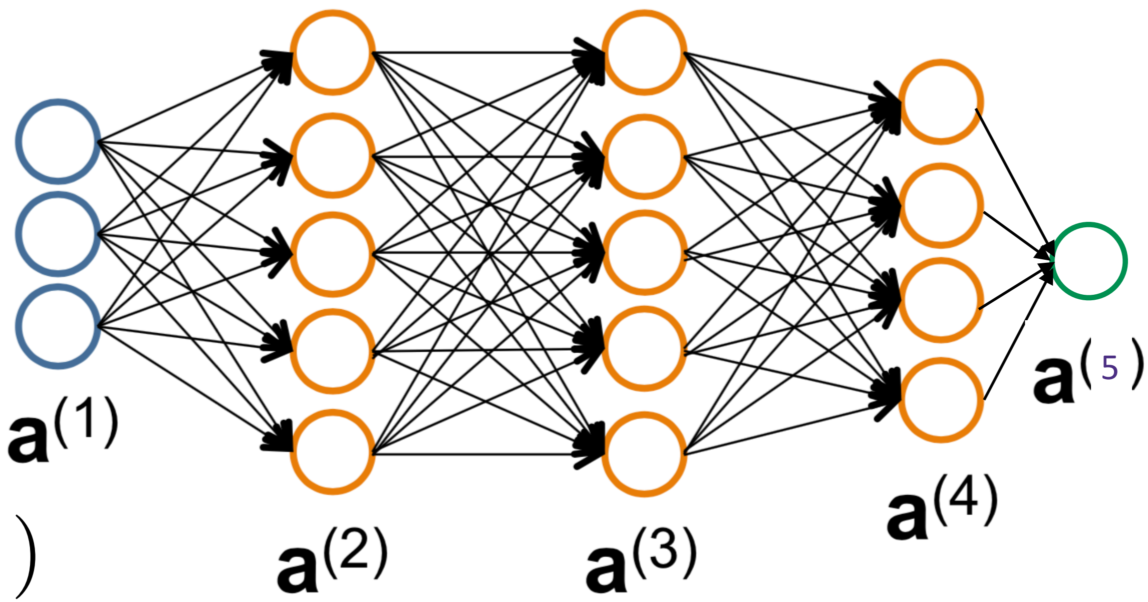
$$a^{(2)} = \sigma(\Theta^{(1)} a^{(1)})$$

$$\vdots$$

$$a^{(l+1)} = \sigma(\Theta^{(l)} a^{(l)})$$

$$\vdots$$

$$\widehat{y} = \Theta^{(L)} a^{(L)}$$




$$L(y, \widehat{y}) = (y - \widehat{y})^2$$

$$\sigma(z) = \max\{0, z\}$$

Regression

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

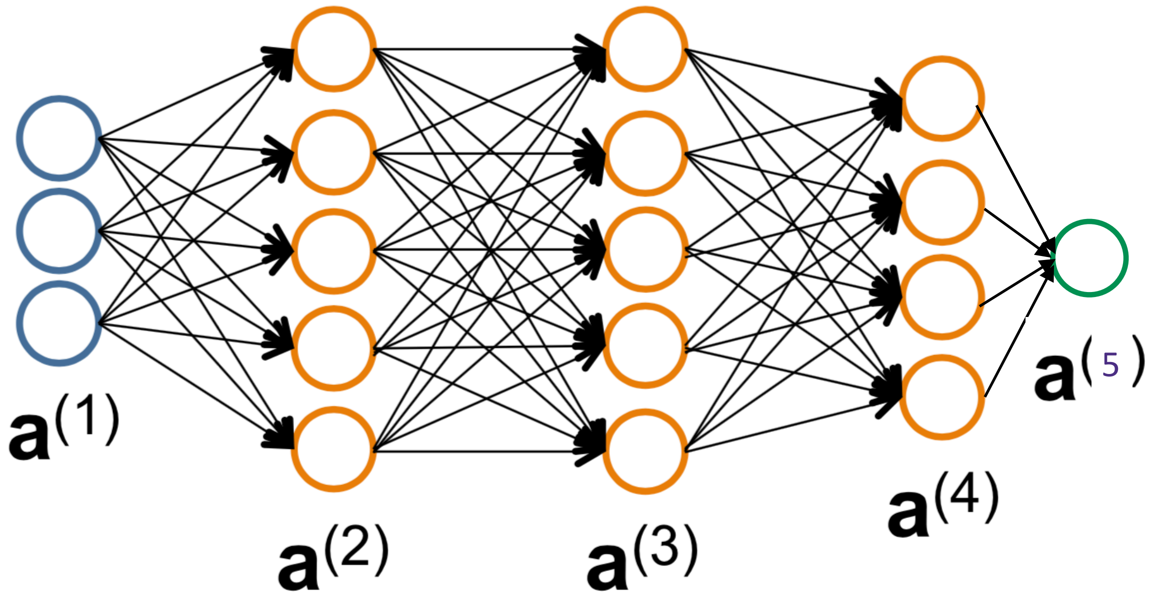
$$\vdots$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\widehat{y} = g(\Theta^{(L)} a^{(L)})$$




$$L(y, \widehat{y}) = y \log(\widehat{y}) + (1 - y)\log(1 - \widehat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

Gradient Descent: $\Theta^{(l)} \leftarrow \Theta^{(l)} - \eta \nabla_{\Theta^{(l)}} L(y, \widehat{y}) \qquad \forall l$

Gradient Descent: $\Theta^{(l)} \leftarrow \Theta^{(l)} - \eta \nabla_{\Theta^{(l)}} L(y, \widehat{y}) \qquad \forall l$

Seems simple enough, why are packages like PyTorch, Tensorflow, Theano, Cafe, MxNet synonymous with deep learning?

1. Automatic differentiation

2. Convenient libraries

3. GPU support

## Gradient Descent:

Seems simple enough,
Theano, Cafe, MxNet s

1. Automatic differ

2. Convenient libra

```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 3x3 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 3)
        self.conv2 = nn.Conv2d(6, 16, 3)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 6 * 6, 120)  # 6*6 from image dimension
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

```
# create your optimizer
optimizer = optim.SGD(net.parameters(), lr=0.01)

# in your training loop:
optimizer.zero_grad()   # zero the gradient buffers
output = net(input)
loss = criterion(output, target)
loss.backward()
optimizer.step()    # Does the update
```