

# Ch 10.2: Multi-Layer Neural Nets

## Lecture 30 - CMSE 381

Michigan State University

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Dept of Computational Mathematics, Science & Engineering

Wed, Apr 8, 2026

# Announcements

## Last time:

- Single Layer Neural Nets

## This lecture:

- Multi-layer Neural Nets
- Application to MNIST

## Announcements:

- Hw 6 Due Sunday 4/12
- Exam 3 4/20
- Project Due 4/24

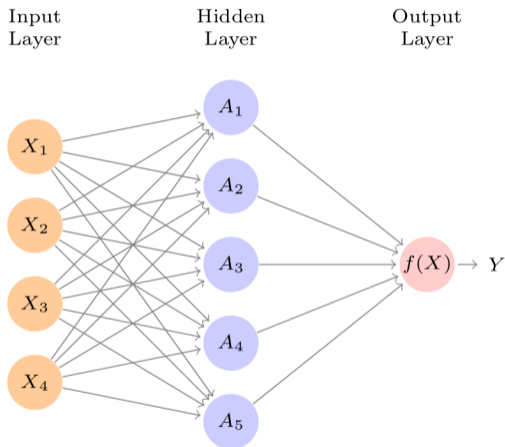
## The end is near!

27	W	4/1	SVC	9.2		Q8
28	F	4/3	SVM	9.3, 9.4		
29	M	4/6	Single Layer NN	10.1		
30	W	4/8	Multi Layer NN	10.2		Q9
31	F	4/10	CNN	10.3	HW #6 Due Sun 4/12	
32	M	4/13	Unsupervised learning / clustering	12.1, 12.4		
33	W	4/15	Virtual: Project Office Hours			
	F	4/17	<b>Review</b>			
	M	4/20	<b>Midterm #3</b>			
	W	4/22				
	F	4/24			<b>Project Due</b>	

# Section 1

Previously...

# Feed Forward Neural Network: The cartoon



$$A_k = h_k(X) = g(w_{k0} + \sum_{j=1}^p w_{kj} X_j),$$

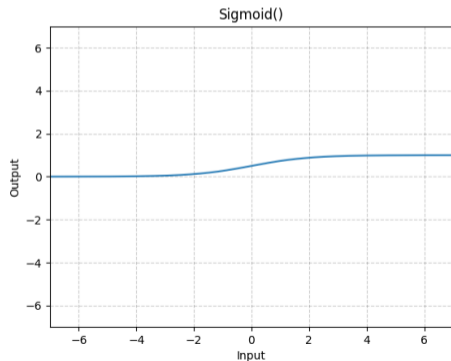
$$f(X) = \beta_0 + \sum_{k=1}^K \beta_k A_k$$

Test your understanding: [PollEv](#)

# Choices for activation function

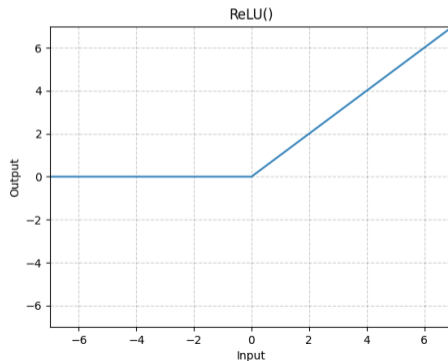
Sigmoid:

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

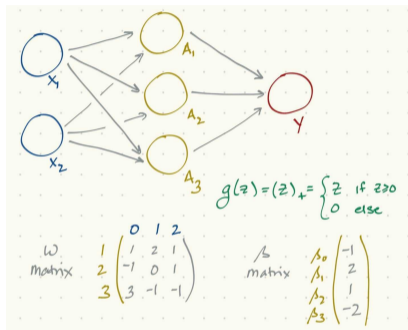


ReLU: Rectified linear unit

$$g(z) = (z)_+ = \begin{cases} 0 & \text{if } z < 0 \\ z & \text{else.} \end{cases}$$



# Matrix version



$$A_k = h_k(X) = g(w_{k0} + \sum_{j=1}^p w_{kj} X_j),$$

$$A = g(\mathbf{W} \cdot \mathbf{X}) \quad \mathbf{X}^T = (1 \ X_1 \ X_2 \ \cdots \ X_p)$$



$$f(X) = \beta_0 + \sum_{k=1}^K \beta_k A_k$$

$$Y = \beta \cdot \mathbf{A} \quad \mathbf{A}^T = (1 \ A_1 \ A_2 \ \cdots \ A_K)$$

# Training the model

Choose parameters by minimizing RSS,  $\sum_{i=1}^n (y_i - f(x_i))^2$  (or other loss function)

**Chosen in advance:**

**Tuned by the model:**

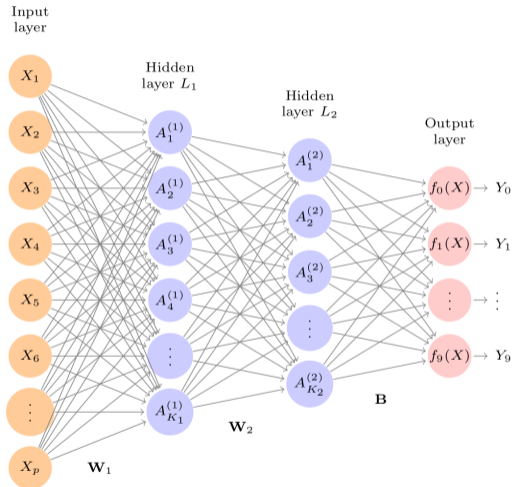
# What will you learn today?

- What is the architecture of multilayer neural networks?
  - ▶ You should be able to describe what happens at each layer mathematically for a typical classification problem.
  - ▶ You should be able to calculate class probability for the output layer using softmax.
- How to classify images using multilayer neural networks in Python?

## Section 2

# Multilayer Neural Networks

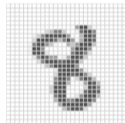
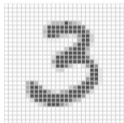
# Multiple layers



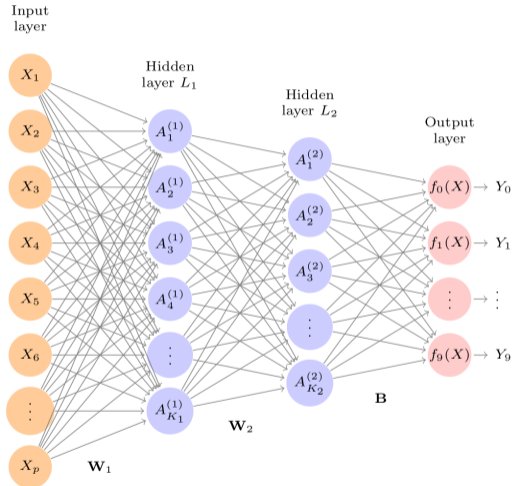
# More typical for image classification

Example: MNIST

0 1 2 3 4 5 6 7 8 9  
0 1 2 3 4 5 6 7 8 9  
0 1 2 3 4 5 6 7 8 9  
0 1 2 3 4 5 6 7 8 9



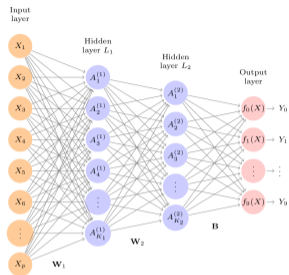
# Hidden layers



$$\begin{aligned} A_k^{(1)} &= h_k^{(1)}(X) \\ &= g(w_{k0}^{(1)} + \sum_{j=1}^p w_{kj}^{(1)} X_j) \end{aligned}$$

$$\begin{aligned} A_\ell^{(2)} &= h_\ell^{(2)}(X) \\ &= g(w_{\ell 0}^{(2)} + \sum_{k=1}^{K_1} w_{\ell k}^{(2)} A_k^{(1)}) \end{aligned}$$

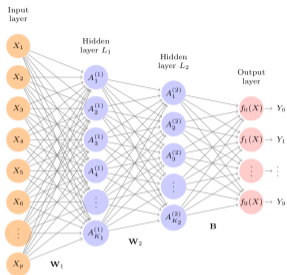
# More on that architecture



$$\begin{aligned} A_k^{(1)} &= h_k^{(1)}(X) \\ &= g(w_{k0}^{(1)} + \sum_{j=1}^p w_{kj}^{(1)} X_j) \end{aligned}$$

$$\begin{aligned} A_\ell^{(2)} &= h_\ell^{(2)}(X) \\ &= g(w_{\ell 0}^{(2)} + \sum_{k=1}^{K_1} w_{\ell k}^{(2)} A_k^{(1)}) \end{aligned}$$

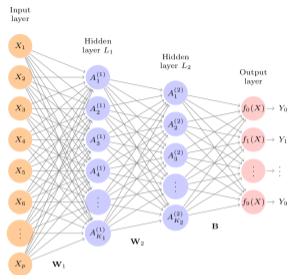
# Matrix version: First layer



$$\begin{aligned} A_k^{(1)} &= h_k^{(1)}(X) \\ &= g(w_{k0}^{(1)} + \sum_{j=1}^p w_{kj}^{(1)} X_j) \end{aligned}$$

$$A^{(1)} = g(\mathbf{W}^{(1)} \cdot \mathbf{X}) \quad \mathbf{X}^T = (1 \ X_1 \ X_2 \ \dots \ X_p)$$

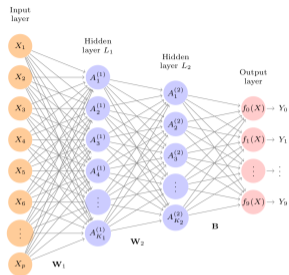
# Matrix version: Second layer



$$\begin{aligned} A_\ell^{(2)} &= h_\ell^{(2)}(X) \\ &= g(w_{\ell 0}^{(2)} + \sum_{k=1}^{K_1} w_{\ell k}^{(2)} A_k^{(1)}) \end{aligned}$$

$$A^{(2)} = g(\mathbf{W}^{(2)} \cdot \mathbf{A}^{(1)}) \quad (\mathbf{A}^{(1)})^T = (1 \ A_1^{(1)} \ A_2^{(1)} \ \dots \ A_{K_1}^{(1)})$$

# Matrix version: Last layer, first step



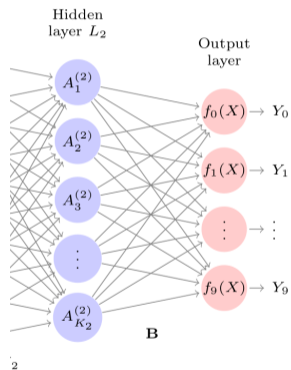
$$Z_m = \beta_{m0} + \sum_{\ell=1}^{K_2} \beta_{m\ell} h_{\ell}^{(2)}(X)$$

$$= \beta_{m0} + \sum_{\ell=1}^{K_2} \beta_{m\ell} A_{\ell}^{(2)},$$

$$\mathbf{Z} = \beta \cdot \mathbf{A}^{(2)}$$

$$\beta \text{ is } M \times (K_2 + 1) \text{ matrix} \quad (\mathbf{A}^{(2)})^T = (1 \ A_1^{(2)} \ A_2^{(2)} \ \dots \ A_{K_2}^{(2)})$$

# The last column for classification: Softmax



$$f_m(X) = \Pr(Y = m|X) = \frac{e^{Z_m}}{\sum_{l=0}^9 e^{Z_l}},$$

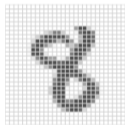
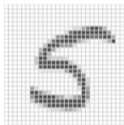
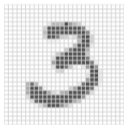
## An example

$$f_m(X) = \Pr(Y = m|X) = \frac{e^{Z_m}}{\sum_{\ell=0}^9 e^{Z_\ell}},$$

$$Z = (1 \quad 3 \quad -1 \quad 2 \quad 5)$$

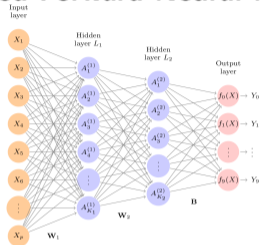
# MNIST

0 1 2 3 4 5 6 7 8 9  
0 1 2 3 4 5 6 7 8 9  
0 1 2 3 4 5 6 7 8 9  
0 1 2 3 4 5 6 7 8 9



# Coding

## Feed Forward Neural Net



$$A_k = h_k(X) = g(w_{k0} + \sum_{j=1}^p w_{kj} X_j),$$

- Combines input data using learned weights
- Linear combo of those to get output
- Sometimes softmax to get probability of classification

# Next time

21	W	3/18	Polynomial & Step Functions	7.1-7.2		
22	F	3/20	Step Functions; Basis functions; Start Splines	7.2-7.4		
23	M	3/23	Regression Splines	7.4		
24	W	3/25	Decision Trees	8.1		Q7
25	F	3/27	Random Forests	8.2.1, 8.2.2	HW #5 Due Sun 3/29	
26	M	3/30	Maximal Margin Classifier	9.1		
27	W	4/1	SVC	9.2		Q8
28	F	4/3	SVM	9.3, 9.4		
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