# Applied Deep Learning



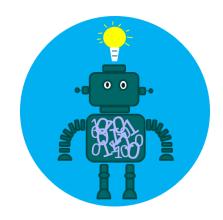
## Introduction



September 7th, 2023 <a href="http://adl.miulab.tw">http://adl.miulab.tw</a>



National Taiwan University



# What is Machine Learning?

什麼是機器學習?

白話文讓你了解!

## 3 — AI & ML

**Artificial intelligence (AI)** is intelligence—perceiving, synthesizing, and inferring information—demonstrated by machines, as opposed to intelligence displayed by animals and humans.

**Machine learning (ML)** is a field of inquiry devoted to understanding and building methods that "learn", that is, methods that leverage data to improve performance on some set of tasks.

It is seen as a part of <u>artificial intelligence</u>.

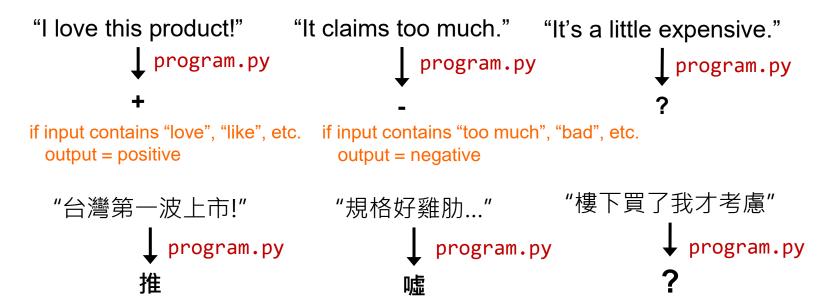
#### What Computers Can Do?



→ Programs can do the things you ask them to do

#### **Program for Solving Tasks**

Task: predicting positive or negative given a product review



Some tasks are complex, and we don't know how to write a program to solve them.

#### **Learning** ≈ **Looking for a Function**

Task: predicting positive or negative given a product review



Given a large amount of data, the machine learns what the function f should be.

#### **Learning** ≈ **Looking for a Function**

Speech Recognition

 $\bigcirc$  Handwritten Recognition f(



Weather forecast



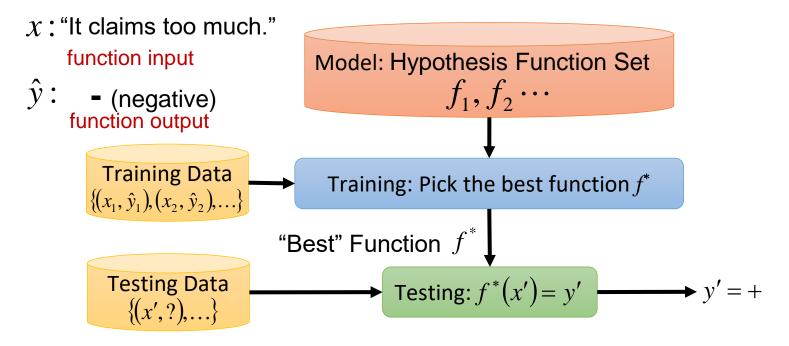
f( Thursday )= " Saturday"

Play video games

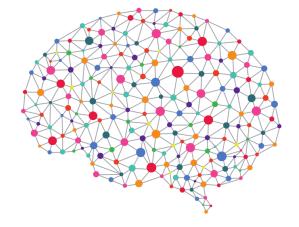


)= "move left"

#### **Machine Learning Framework**



Training is to pick the best function given the observed data Testing is to predict the label using the learned function



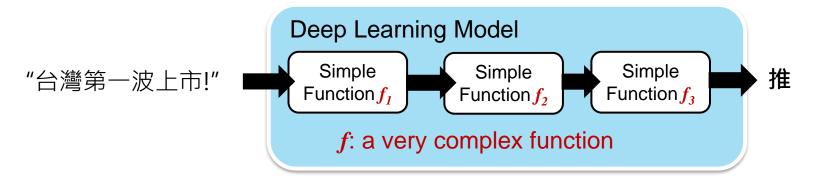
# What is Deep Learning?

什麼是深度學習?

A subfield of machine learning

#### Stacked Functions Learned by Machine

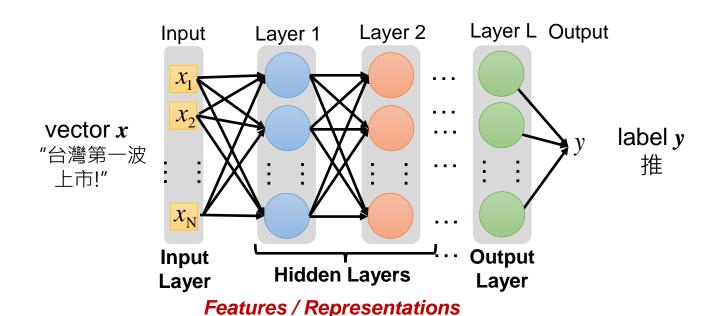
● Production line (生產線)



End-to-end training: what each function should do is learned automatically

Deep learning usually refers to neural network based model

#### Stacked Functions Learned by Machine

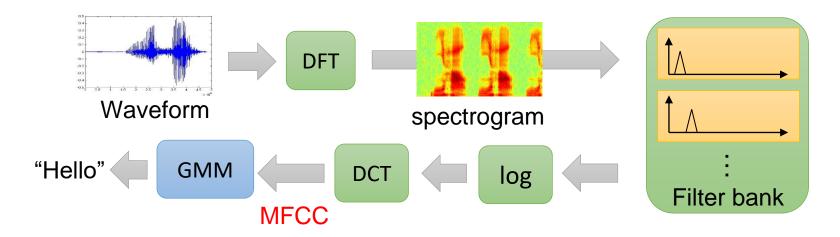


Representation Learning attempts to learn good features/representations

Deep Learning attempts to learn (multiple levels of) representations and an output

#### Deep v.s. Shallow – Speech Recognition

#### Shallow Model



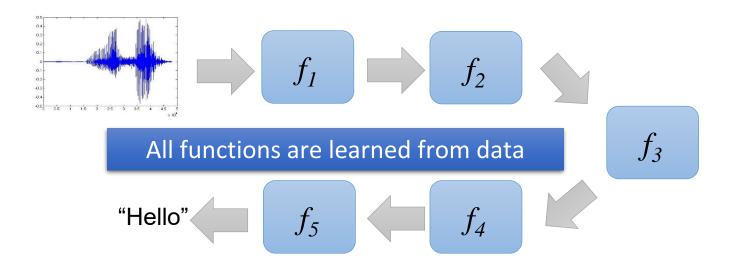
Each box is a simple function in the production line:



#### Deep v.s. Shallow – Speech Recognition

"Bye bye, MFCC" - Deng Li in Interspeech 2014

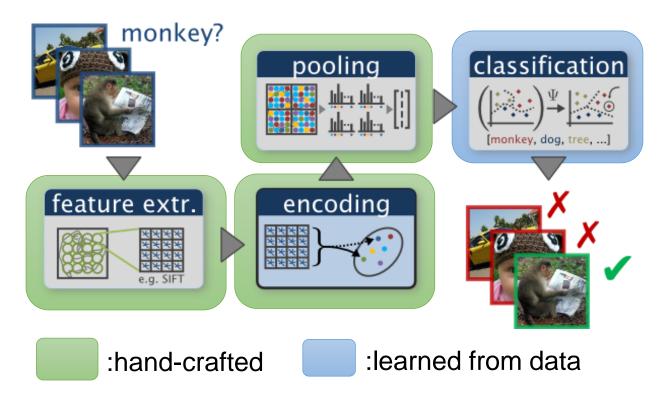
#### Deep Model



Less engineering labor, but machine learns more

#### Deep v.s. Shallow – Image Recognition

Shallow Model

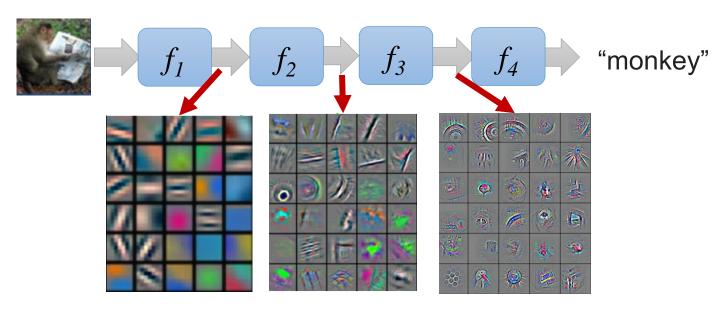


#### Deep v.s. Shallow – Image Recognition

Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In Computer Vision–ECCV 2014 (pp. 818-833)

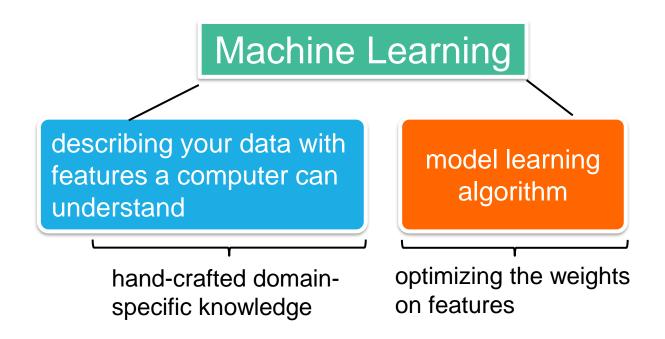
#### Deep Model

#### All functions are learned from data

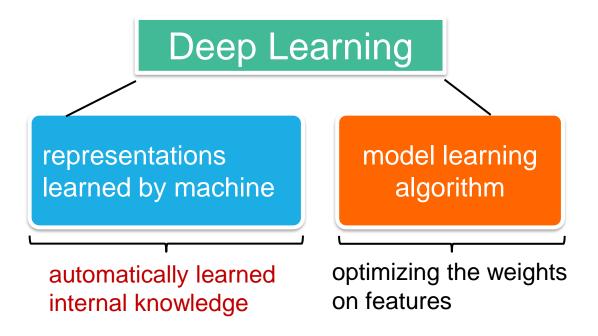


Features / Representations

#### Machine Learning v.s. Deep Learning



#### Machine Learning v.s. Deep Learning

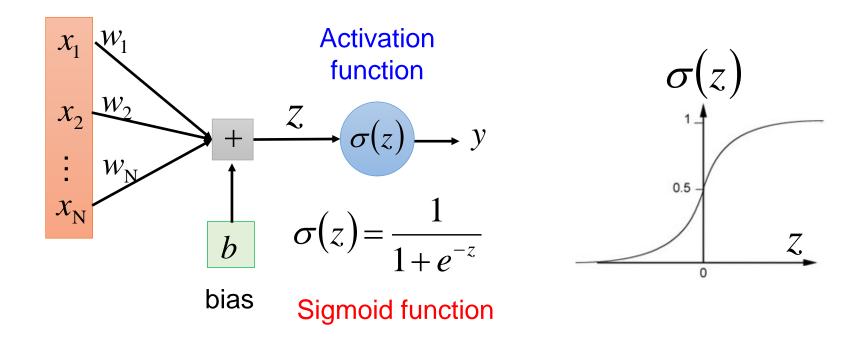


Deep learning usually refers to *neural network* based model

**Inspired by Human Brain** 18 Cell body Telodendria Axon Nucleus Axon hillock Synaptic terminals Golgi apparatus Endoplasmic reticulum Mitochondrion Dendrite

Dendritic branches

#### **A Single Neuron**

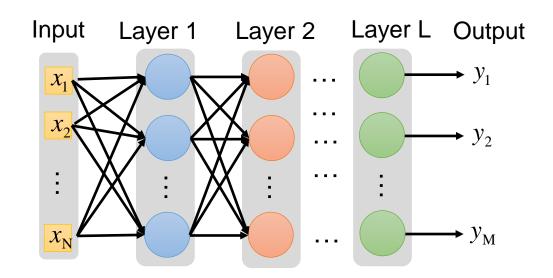


Each neuron is a very simple function

#### **Deep Neural Network**

A neural network is a complex function:  $f: \mathbb{R}^N \longrightarrow \mathbb{R}^M$ 

Cascading the neurons to form a neural network



Each layer is a simple function in the production line

#### **History of Deep Learning**

- 1960s: Perceptron (single layer neural network)
- 1969: Perceptron has limitation
- 1980s: Multi-layer perceptron
- 1986: Backpropagation
- 1989: 1 hidden layer is "good enough", why deep?
- 2006: RBM initialization (breakthrough)
- 2009: GPU
- 2010: breakthrough in Speech Recognition (Dahl et al., 2010)
- 2012: breakthrough in ImageNet (Krizhevsky et al. 2012)
- 2015: "superhuman" results in Image and Speech Recognition
- 2016: AlphaGo "superhuman" results in Go playing
- 2022: ChatGPT "human-level" results in diverse domains



#### **Deep Learning Breakthrough**

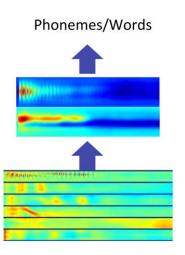
First: Speech Recognition

<b>Acoustic Model</b>	WER on RT03S FSH	WER on Hub5 SWB
Traditional Features	27.4%	23.6%
Deep Learning	18.5% (-33%)	16.1% (-32%)

Second: Computer Vision







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Why does deep learning show breakthrough in applications after 2010?



## **Why Deep Learning Works**

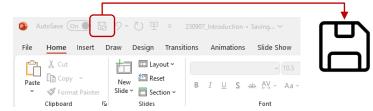


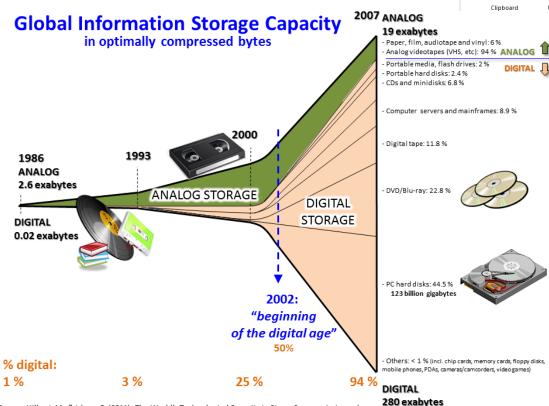


**Big Data** 

**GPU** 

#### **Data Storage**







#### **GPU for Efficient AI Training**

Searching for: 為什麼訓練AI需要很多GPU的資源

為什麼訓練AI需要很多GPU的資源

Generating answers for you...

訓練AI需要很多GPU的資源,主要是因為AI的一種方法叫做深度學習,它使用了大量的神經網絡來處理數 據1。神經網絡是一種高度並行的計算任務,也就是說,它可以把一個大的任務分成很多小的任務,同 時在不同的處理器上執行<sup>1</sup>。GPU是一種專門用於並行計算的處理器,它有很多個核心(core),每個 核心都可以執行一個小任務<sup>12</sup>。相比之下,CPU是一種用於串行計算的處理器,它有較少的核心,但 每個核心都可以執行較複雜的任務<sup>2</sup>。因此,GPU比CPU更適合人工智能計算,尤其是當數據量和計算 量都很大時 3 2。

Learn more: 1. zhuanlan.zhihu.com

2. zhihu.com

3. zhuanlan.zhihu.com

#### **GPU Companies**

Searching for: 有提供GPU的公司有甚麼

有提供GPU的公司有甚麼?

Generating answers for you...

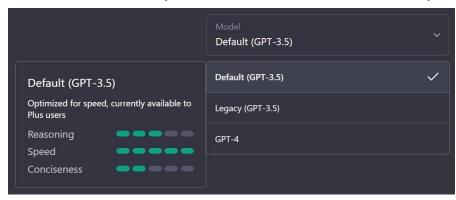
有提供GPU的公司有很多,其中最知名的是**英偉達**(NVIDIA)和AMD,它們分別生產了GeForce和 Radeon系列的GPU 1。這兩家公司的GPU主要用於遊戲和專業市場,也適合訓練AI 2 1。除此之外,還 有一些國内的公司也在開發自己的GPU,例如長沙景嘉微電子股份有限公司,它擁有完全自主知識產權的 GPU產品<sup>2</sup>。另外,一些大型科技公司也在研發自己的GPU或類似產品,例如谷歌的TPU(Tensor Processing Unit) ,蘋果的M1芯片等 1。

**Learn more:** 1. sohu.com 2. thepaper.cn

3. gigabyte.com

#### Why Speed Matters?

- Training time
  - Big data increases the training time
  - Too long training time is not practical
- Inference time
  - Users are not patient to wait for the responses

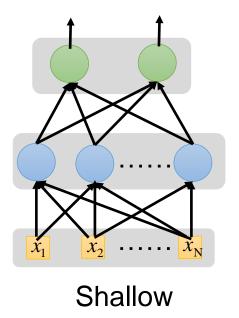




GPU enables the real-world applications using the computational power

### Why Deeper is Better?

Open → More parameters



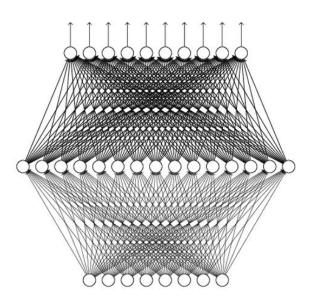
Deep

#### **Universality Theorem**

 $\bigcirc$  Any continuous function f

$$f: \mathbb{R}^N \to \mathbb{R}^M$$

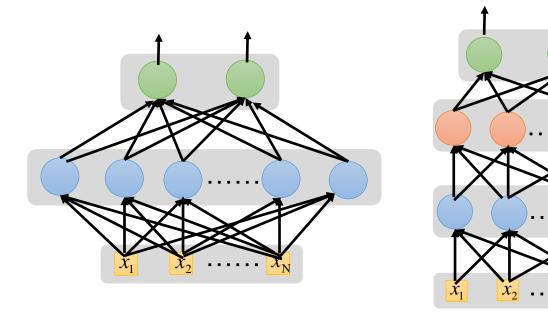
o can be realized by a network with only hidden layer



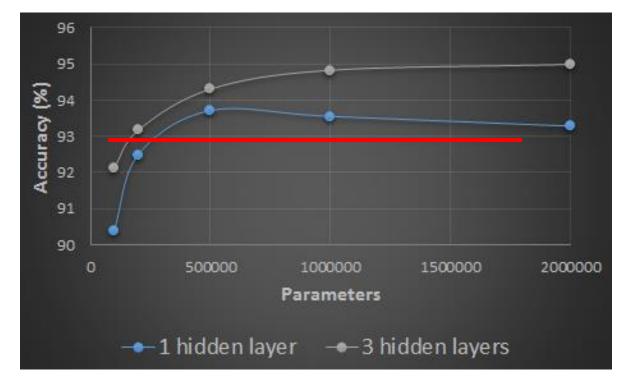
Why "deep" not "fat"?

#### Fat + Shallow vs. Thin + Deep

Two networks with the same number of parameters



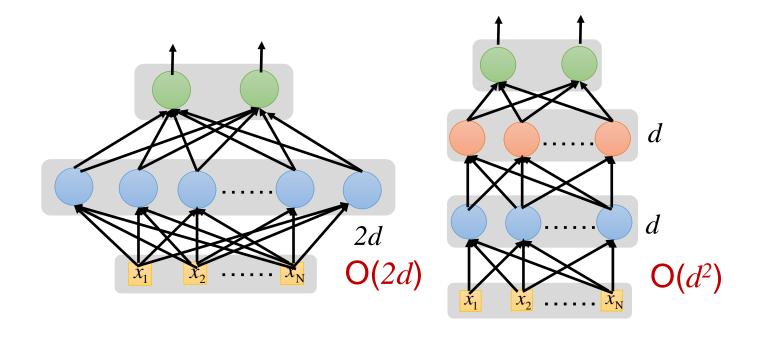
# Fat + Shallow vs. Thin + Deep Hand-Written Digit Classification



The deeper model uses less parameters to achieve the same performance

#### Fat + Shallow vs. Thin + Deep

Two networks with the same number of parameters





# How to Apply?

如何應用深度學習?

#### **How to Frame the Learning Problem?**

 $\bigcirc$  The learning algorithm f is to map the input domain X into the output domain Y

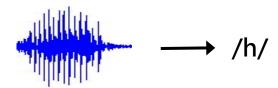
$$f: X \to Y$$

- Input domain: word, word sequence, audio signal, click logs
- Output domain: single label, sequence tags, tree structure, probability distribution

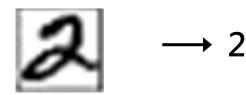
#### **Output Domain – Classification**

Sentiment Analysis

Speech Phoneme Recognition



Handwritten Recognition



#### **Output Domain – Sequence Prediction**

POS Tagging

"推薦我台大後門的餐廳"

→ 推薦/VV 我/PN 台大/NR 後門/NN 的/DEG 餐廳/NN

Speech Recognition



Machine Translation

"How are you doing today?" → "你好嗎?"

Learning tasks are decided by the output domains

#### **Input Domain** – How to Aggregate Information

- Input: word sequence, image pixels, audio signal, click logs
- Property: continuity, temporal, importance distribution
- Example
  - CNN (convolutional neural network): local connections, shared weights, pooling
    AlexNet, VGGNet, etc.
  - RNN (recurrent neural network): temporal information
  - Transformer: multiple inputs with interaction

Network architectures should consider the input domain properties

#### **How to Frame the Learning Problem?**

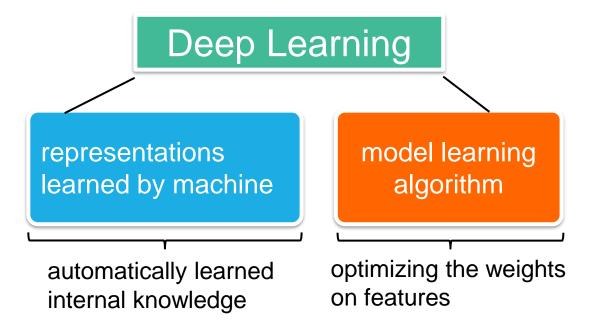
lacktriangle The learning algorithm f is to map the input domain X into the output domain Y

$$f: X \to Y$$

- Input domain: word, word sequence, audio signal, click logs
- Output domain: single label, sequence tags, tree structure, probability distribution

Network design should leverage input and output domain properties

#### "Applied" Deep Learning



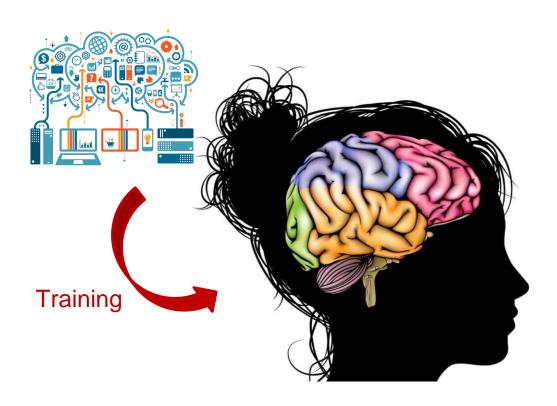
How to frame a task into a learning problem and design the corresponding model

#### **Core Factors for Applied Deep Learning**

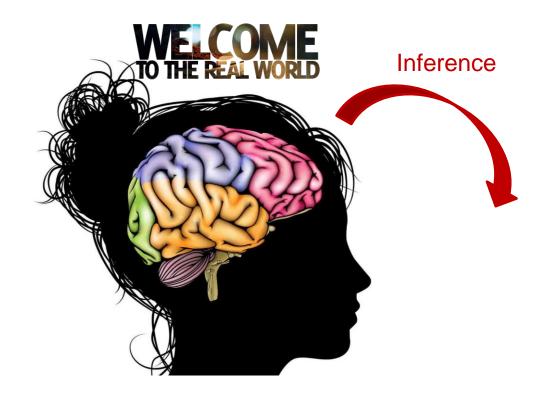
- 1. Data: big data
- 2. Hardware: GPU computing
- 3. Talent: design algorithms to allow networks to work for the specific problems



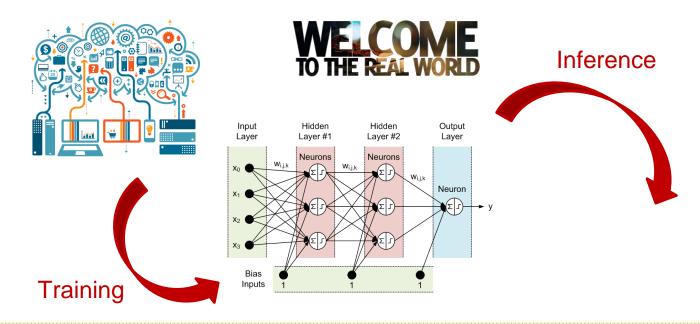
## **Concluding Remarks**



### **Concluding Remarks**



#### **Concluding Remarks**



Main focus: how to apply deep learning to the real-world problems

#### Reference

- Reading Materials
  - Referenced academic papers can be found in the slides
- Open Deep Learning
  - Goodfellow, Bengio, and Courville, "Deep Learning," 2016.
    <a href="http://www.deeplearningbook.org">http://www.deeplearningbook.org</a>
  - Michael Nielsen, "Neural Networks and Deep Learning" <a href="http://neuralnetworksanddeeplearning.com">http://neuralnetworksanddeeplearning.com</a>



# • Thanks!

# Any questions?

You can find the course information at

- http://adl.miulab.tw
- <u>adl-ta@csie.ntu.edu.tw</u>
- slido: #ADL2023
- YouTube: Vivian NTU MiuLab