Pattern Recognition

and having it deep and structured

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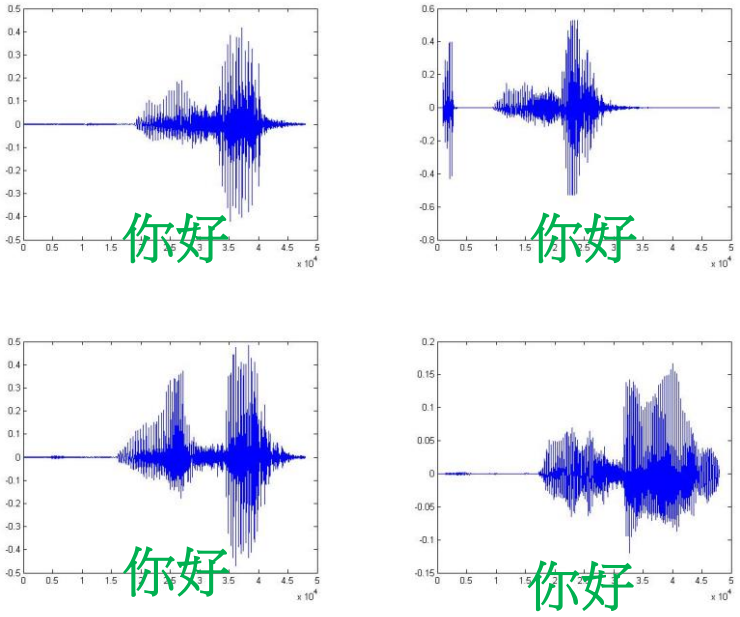
What is Machine Learning?

You know how to program …

- You can ask computers to do lots of things for you.
- However, computer can only do what you ask it to do.
- Computer can never solve the problem you can’t solve.

Some tasks are very complex

- One day, you are asked to write a program for speech recognition.

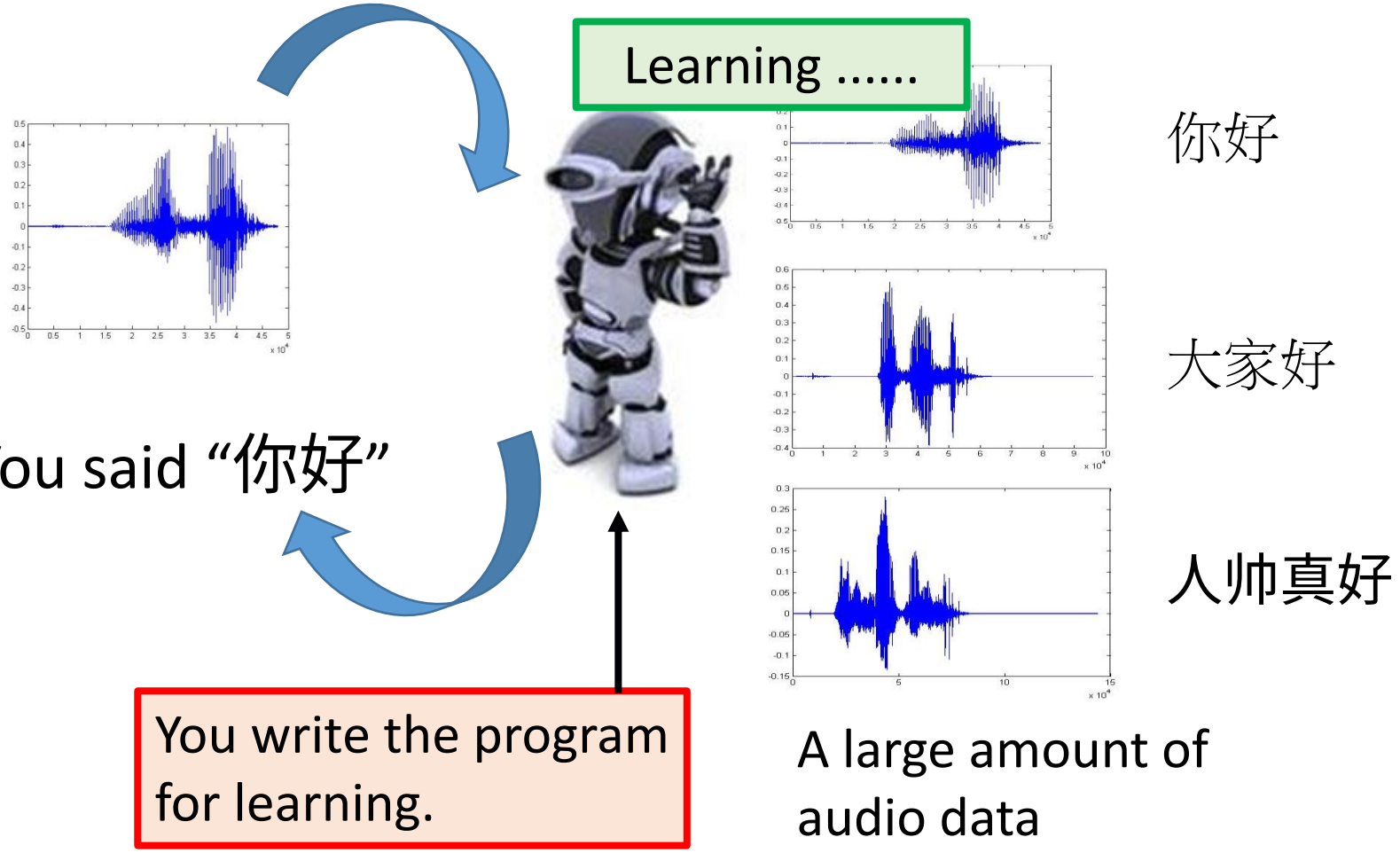


Find the common patterns from the left waveforms.

You quickly get lost in the exceptions and special cases.

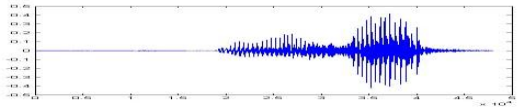
It seems impossible to write a program for speech recognition.

Let the machine learn by itself



Learning ≈ Looking for a Function

- Speech Recognition

$f($  $)=$ “你好”

- Handwritten Recognition

$f($  $)=$ “2”

- Weather forecast

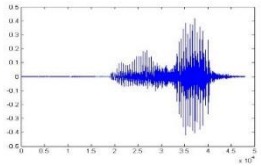
$f($ weather today $)=$ “sunny tomorrow”

- Play video games

$f($ Positions and number of enemies $)=$ “fire”

Framework

x:



$\hat{y}$: “你好” “2”

label

Model

Hypothesis Function Set

$f_1, f_2 \cdots$

Training: Pick the best Function f*

“Best” Function

f^*

Testing:

$f^*(x') = y'$

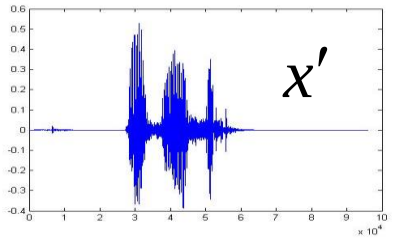
$y' =$ 大家好

Training Data

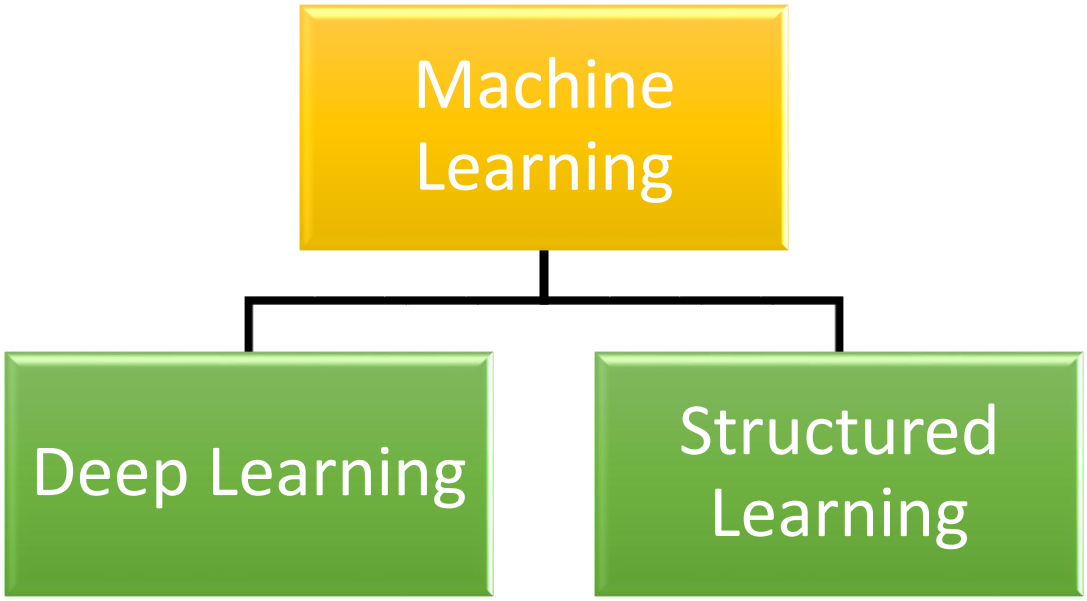
x :function input

$\hat{y}$:function output

$\{(x^1, \hat{y}^1), (x^2, \hat{y}^2), \ldots\}$



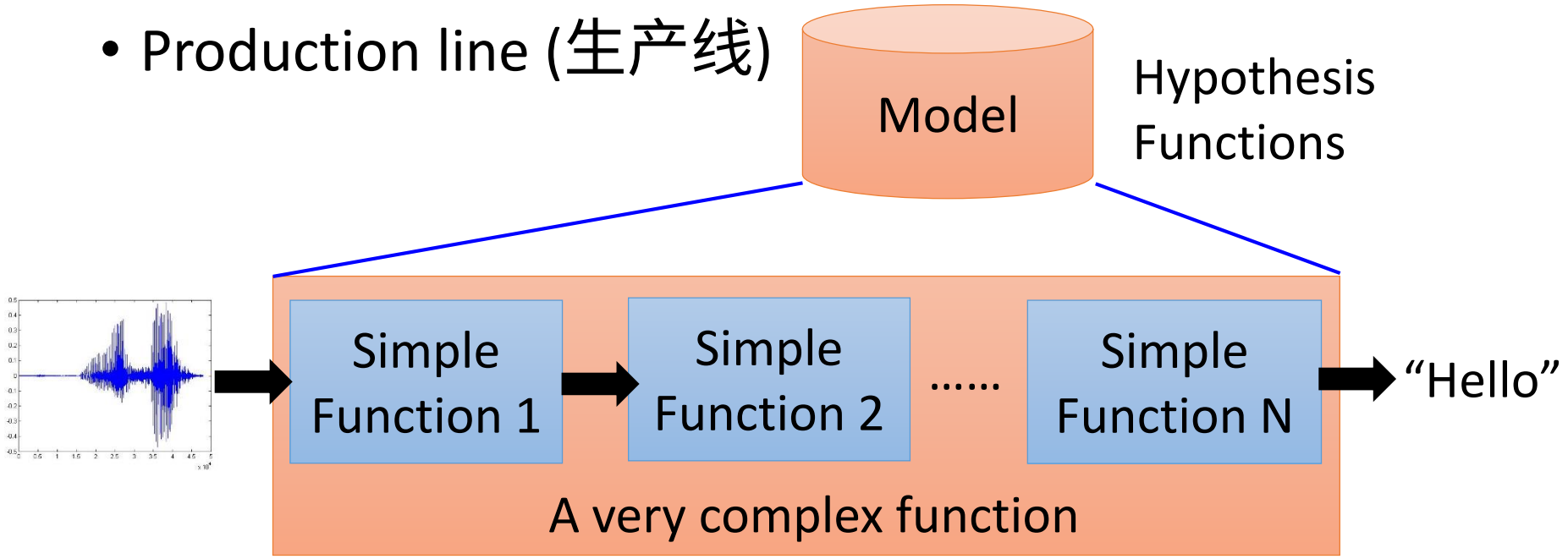
This Course



Deep Learning

What is Deep Learning?

- Production line (生产线)

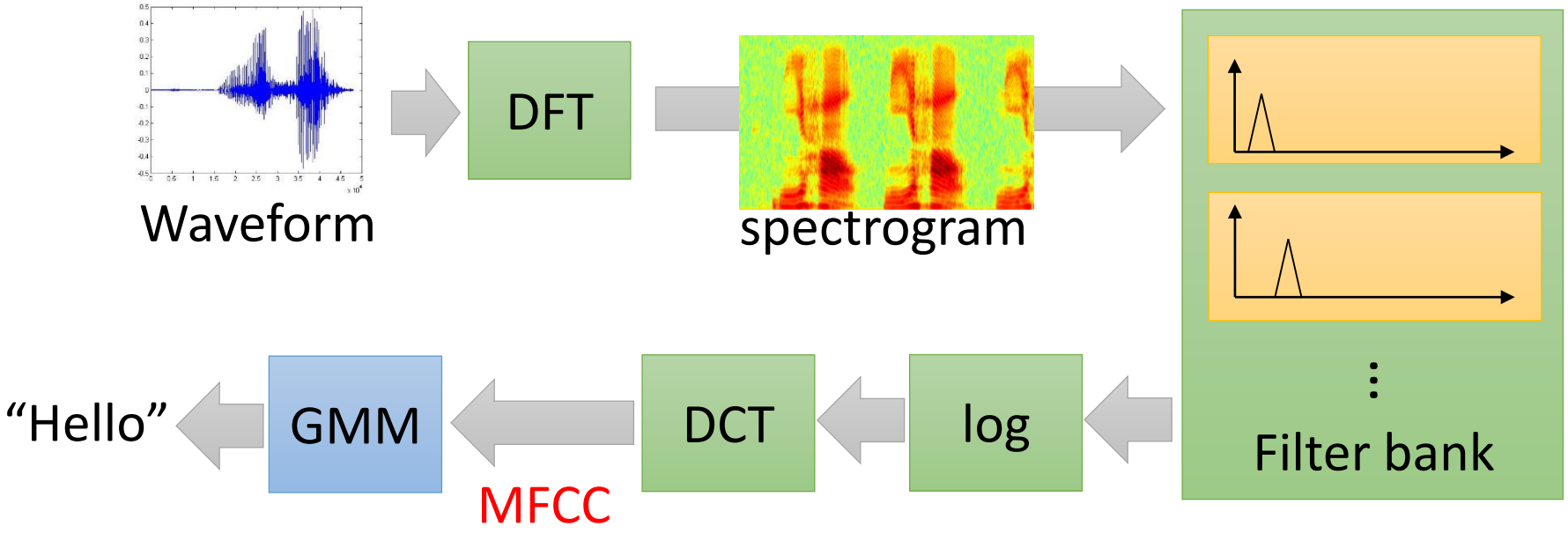


End-to-end training:

What each function should do is learned automatically

Deep v.s. Shallow - Speech Recognition

- Shallow Approach



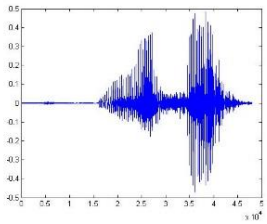
Each box is a simple function in the production line:

:hand-crafted :learned from data

Deep v.s. Shallow - Speech Recognition

- Deep Learning

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



f_1 → f_2 → f_3 → f_4 → f_5 → "Hello"

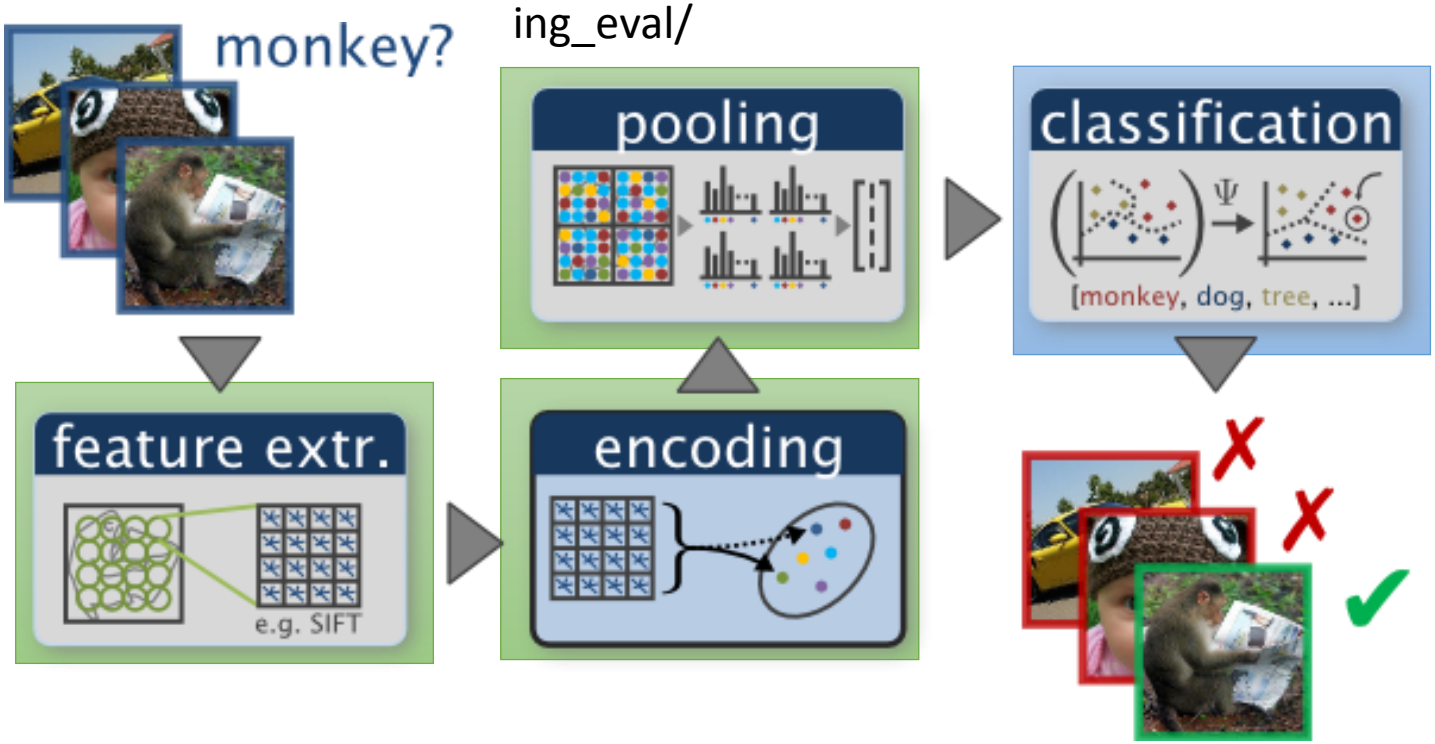
All functions are learned from data

Less engineering labor, but machine learns more

Deep v.s. Shallow
- Image Recognition

- Shallow Approach

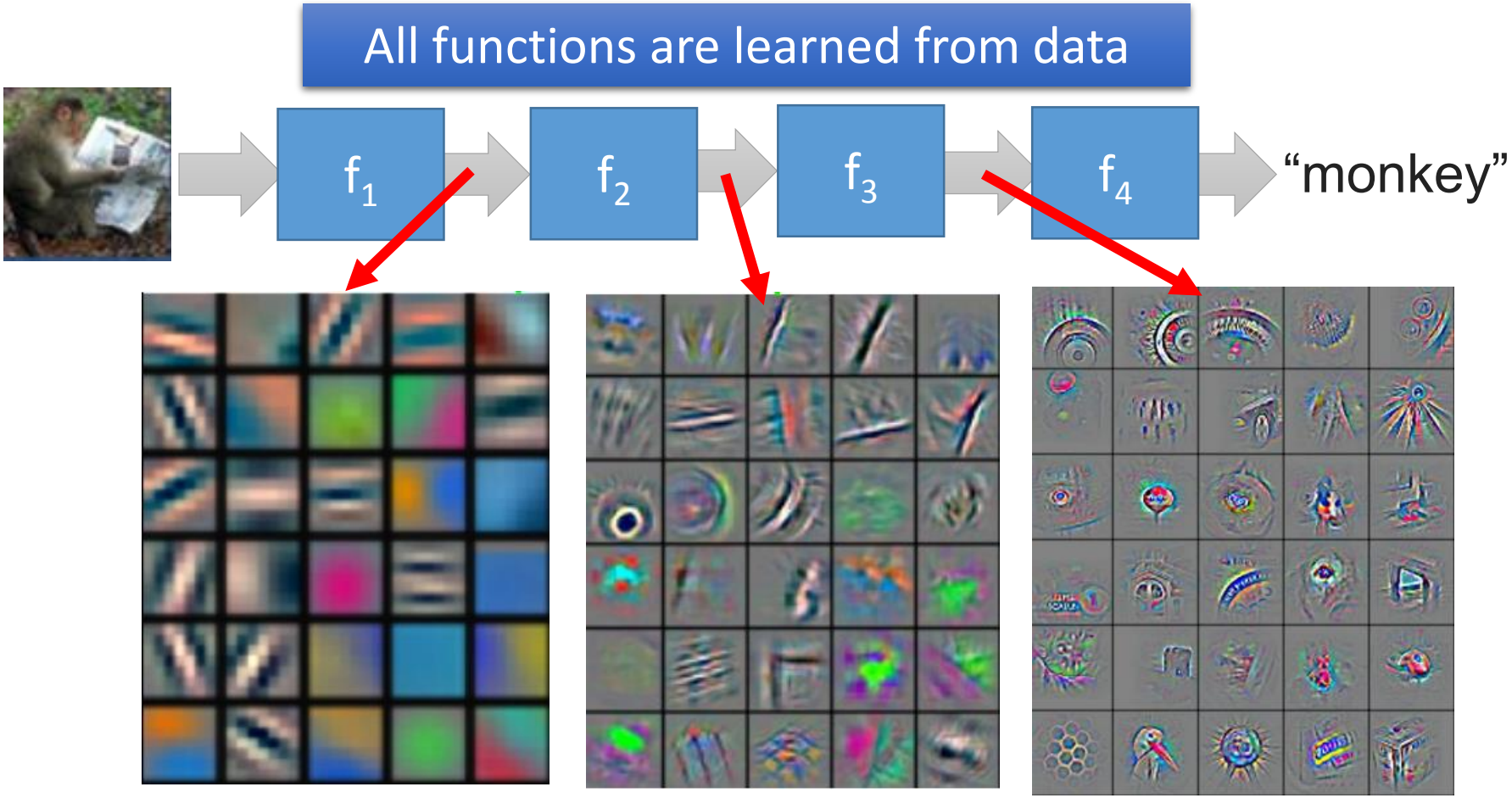
http://www.robots.ox.ac.uk/~vgg/research/encoding_eval/



Deep v.s. Shallow - Image Recognition

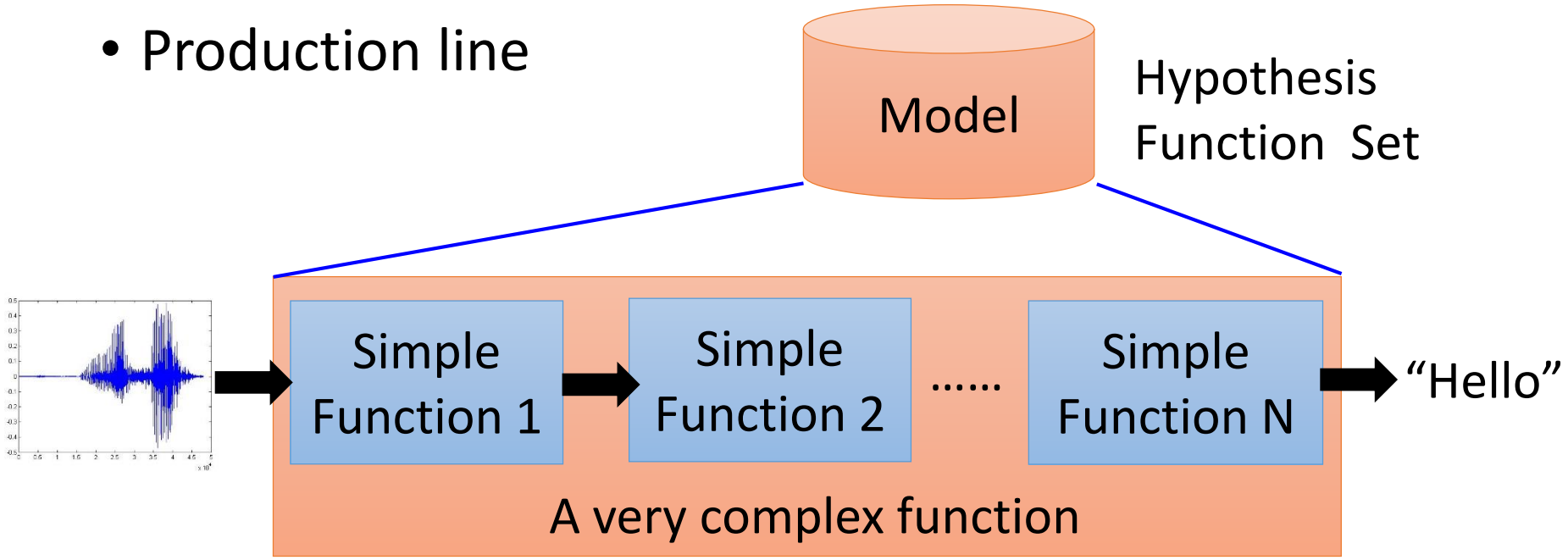
Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)

- Deep Learning



What is Deep Learning?

- Production line

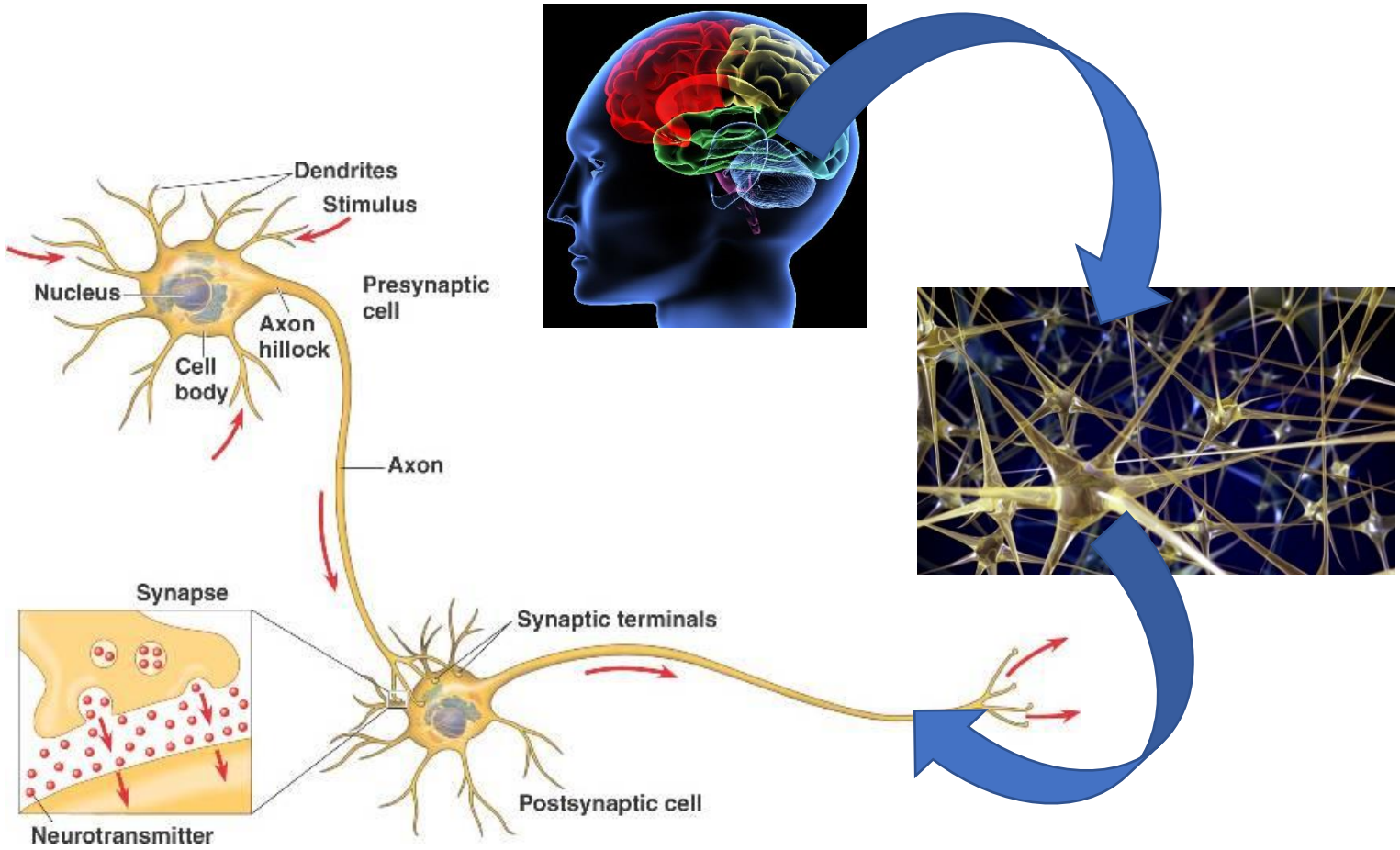


End-to-end training:

What each function should do is learned automatically

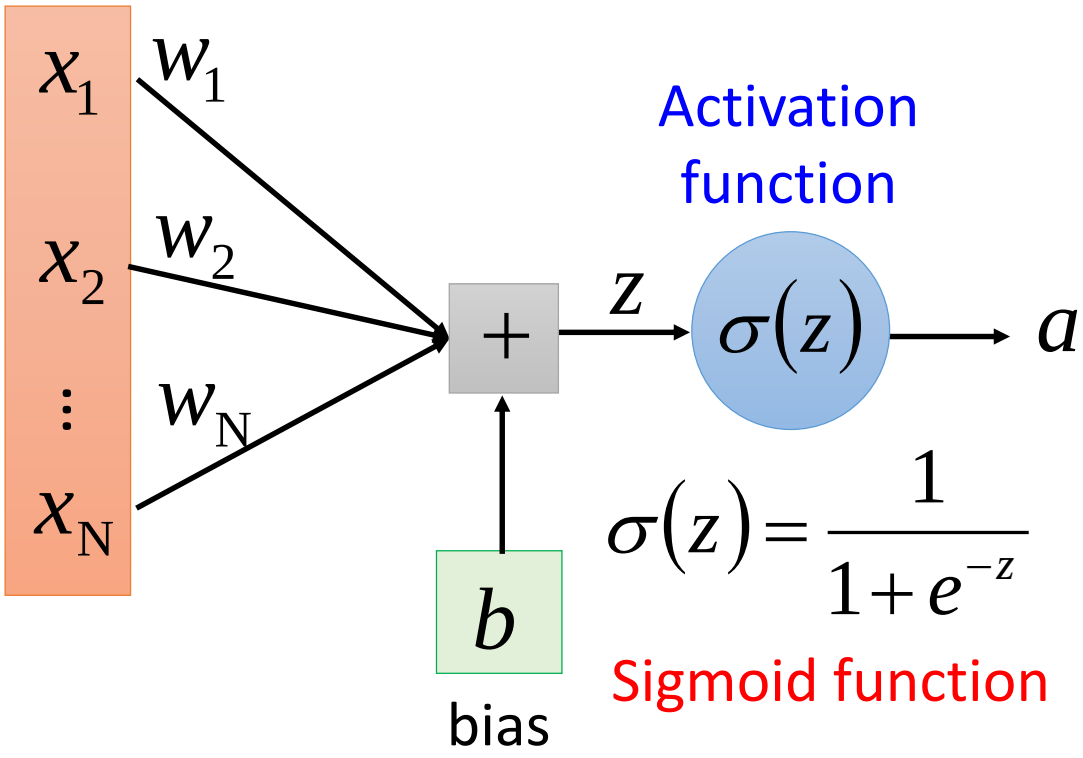
- Deep learning usually referred to neural network based approach

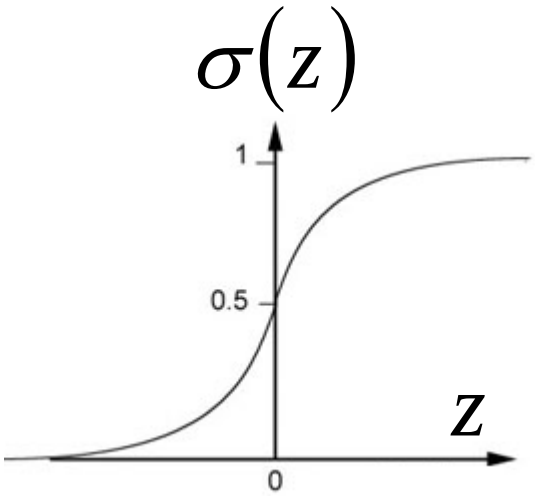
Inspired from Human Brains



A Neuron for Machine

Each neuron is a very simple function





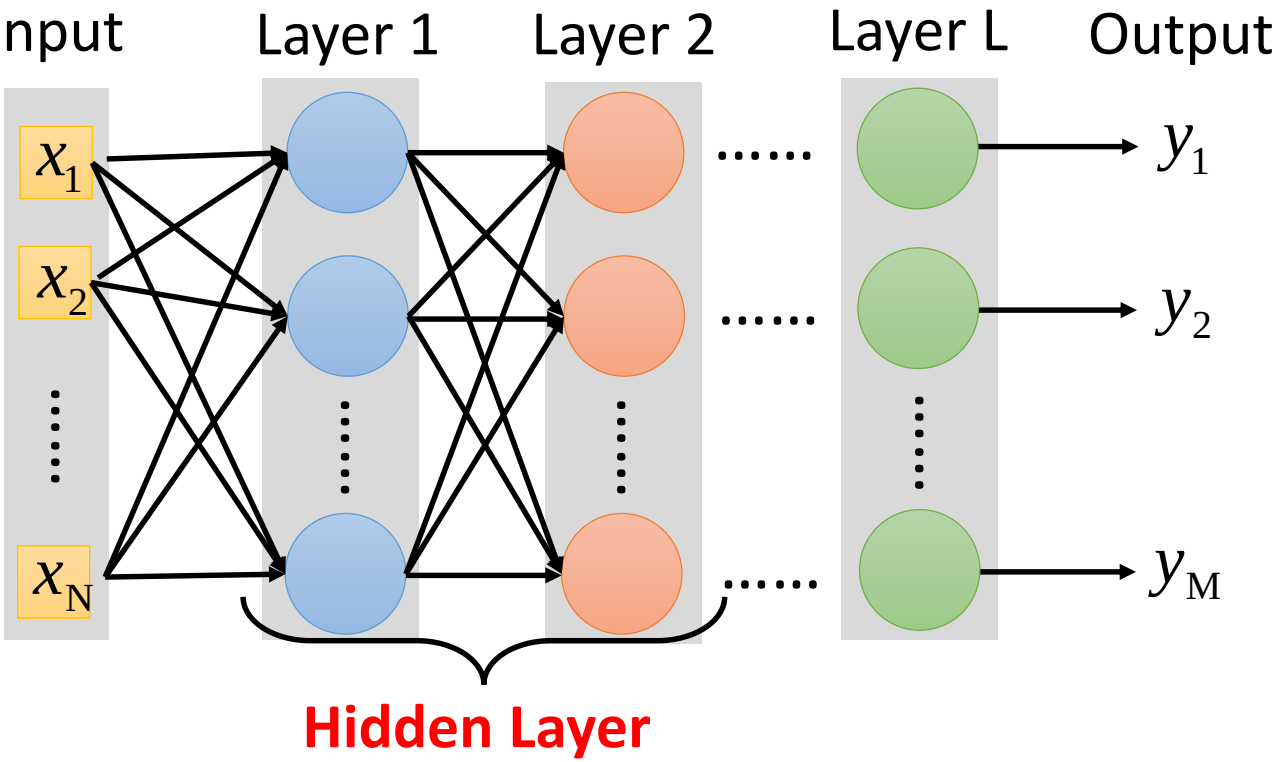
Deep Learning

A neural network is a complex function:

$$f : R^N \rightarrow R^M$$

- Cascading the neurons to form a neural network.

  Each layer is a simple function in the production line.



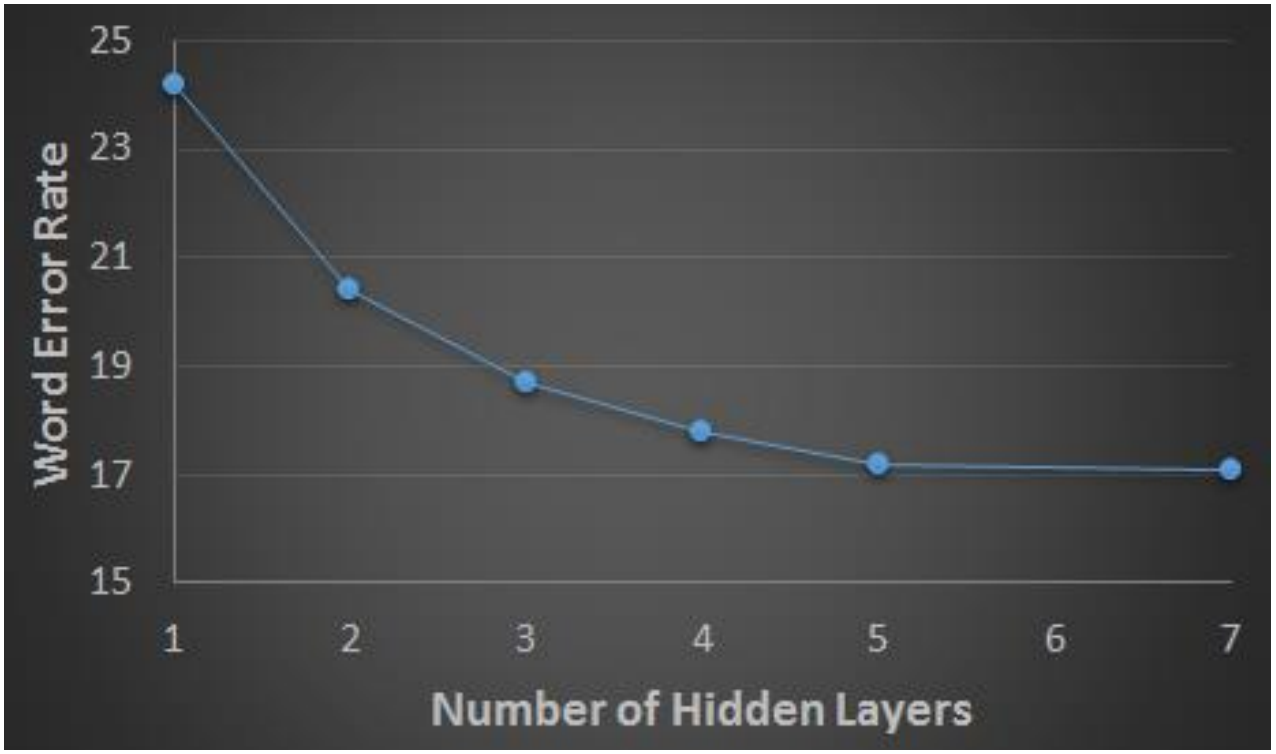
Ups and downs of Deep Learning

- 1960s: Perceptron (single layer neural network)
- 1969: Perceptron has limitation
- 1980s: Multi-layer perceptron
  - Do not have significant difference from DNN today
- 1986: Backpropagation
  - Usually more than 3 hidden layers is not helpful
- 1989: 1 hidden layer is "good enough", why deep?
- 2006: RBM initialization (breakthrough)
- 2009: GPU
- 2011: Start to be popular in speech recognition
- 2012: win ILSVRC competition (image)

Why Deep Learning?

Deeper is Better.

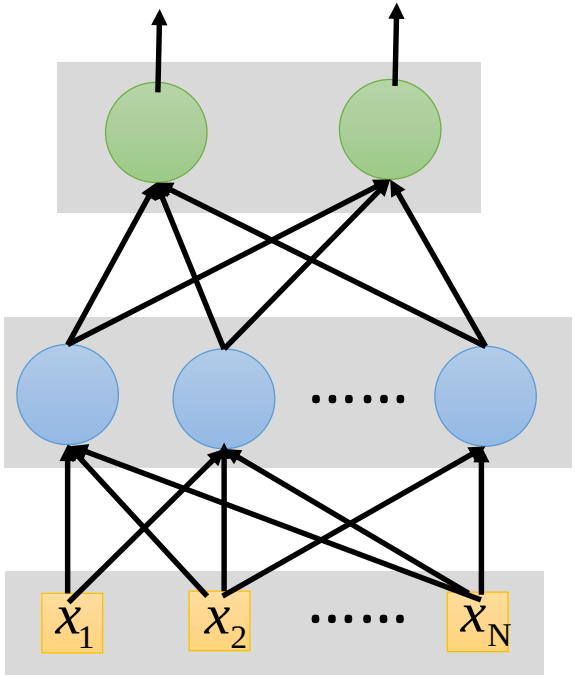
- Speech recognition



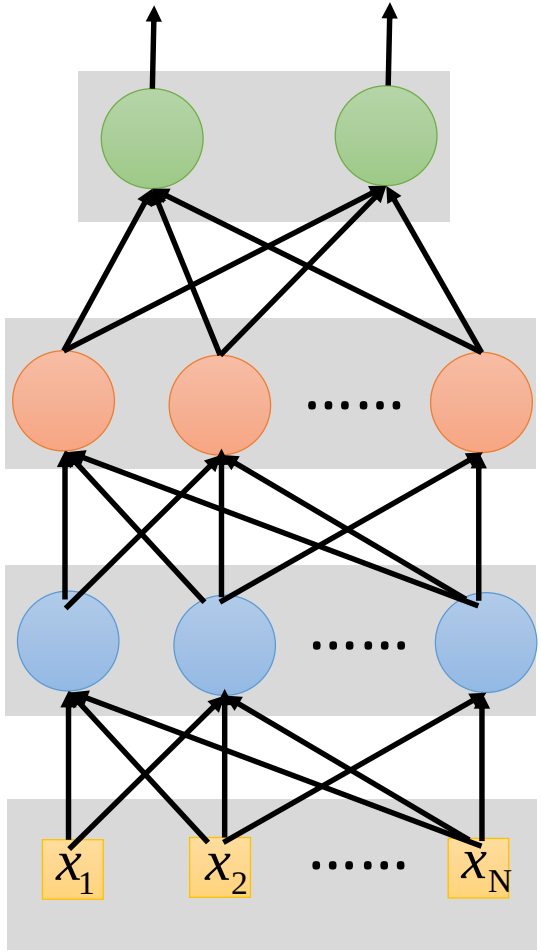
Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Why Deeper is Better?

Deep works better simply because it uses more parameters.



Shallow



Deep

Universality Theorem

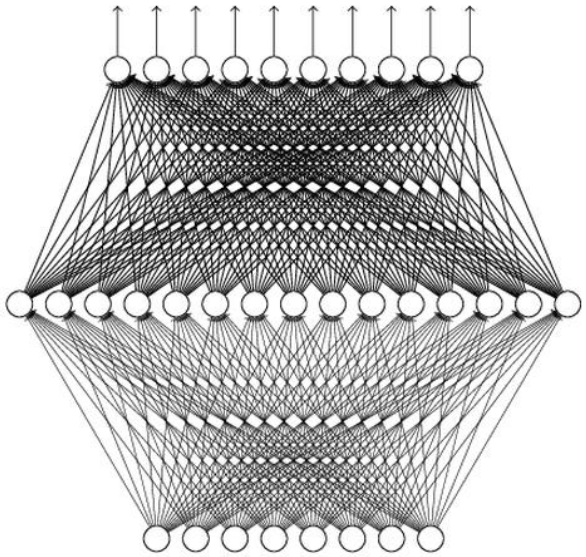
Any continuous function f

$$f : R^N \rightarrow R^M$$

Can be realized by a network with one hidden layer

(given **enough** hidden neurons)

What is the reason to be deep?



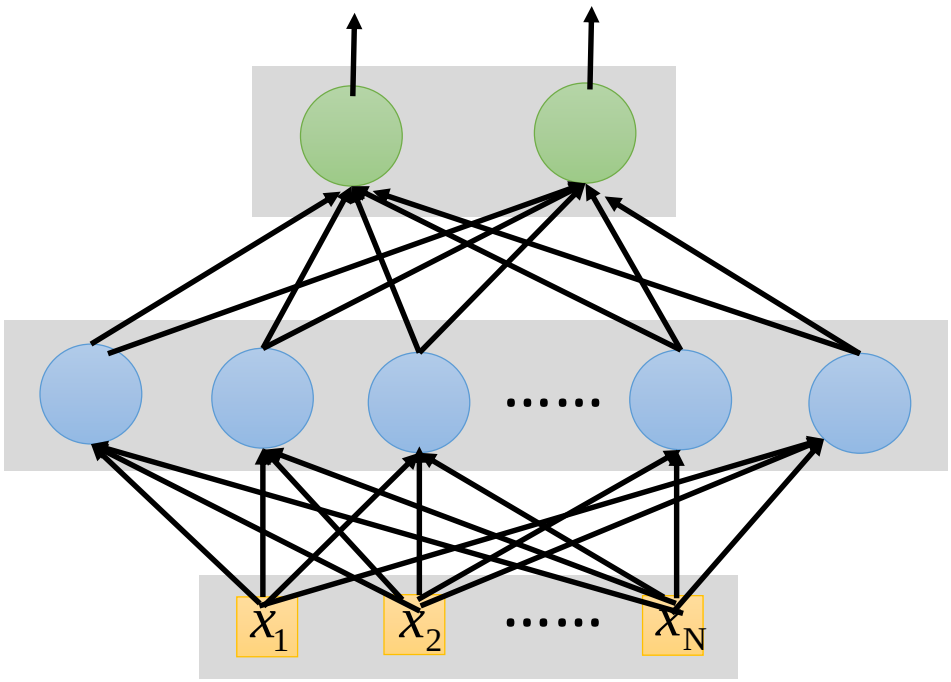
Reference:
http://neuralnetworksanddeeplearning.com/chap4.html

Why “Deep” neural network not “Fat” neural network?

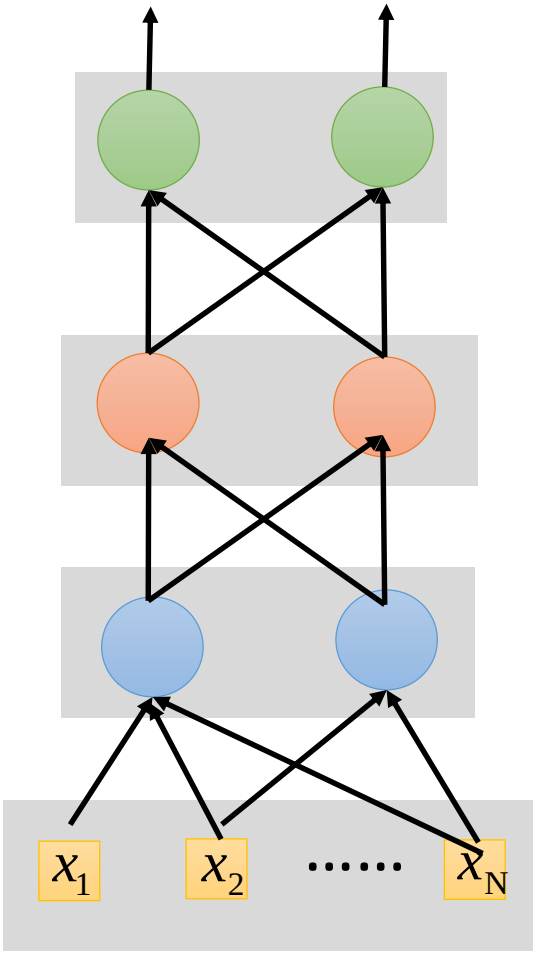
Fat + Short v.s. Thin + Tall

If they have the same parameters,

Which one is better?



Shallow

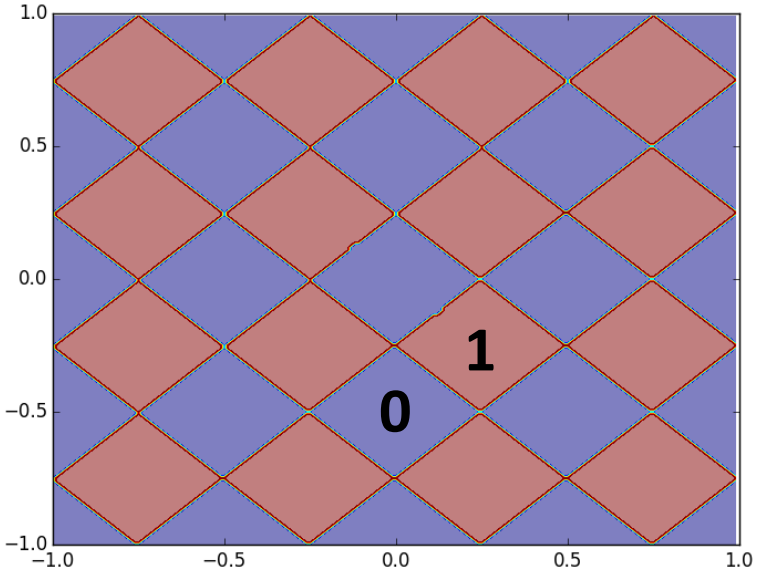


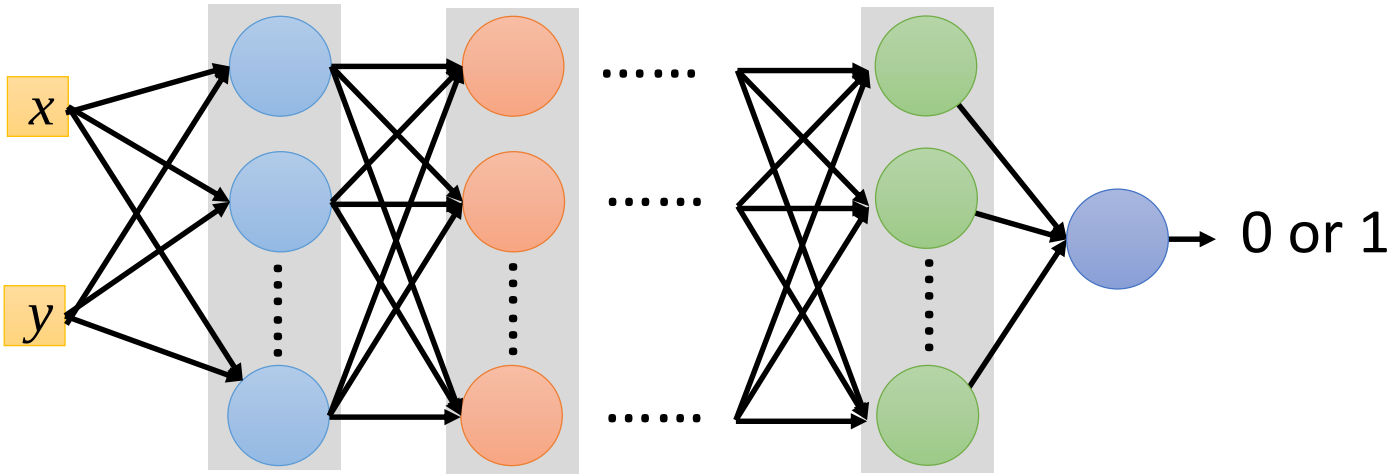
Deep

Fat + Short v.s. Thin + Tall Toy Example

$f : R^2 \rightarrow \{0,1\}$

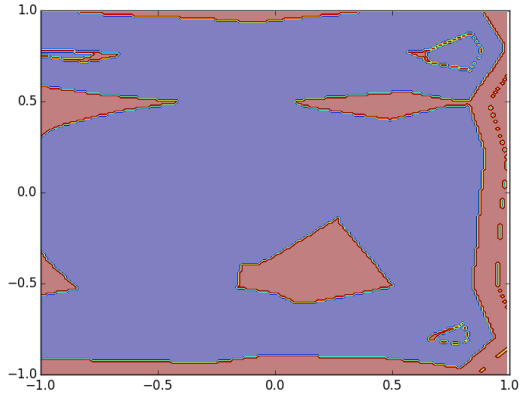
Sample 10,0000 points as training data



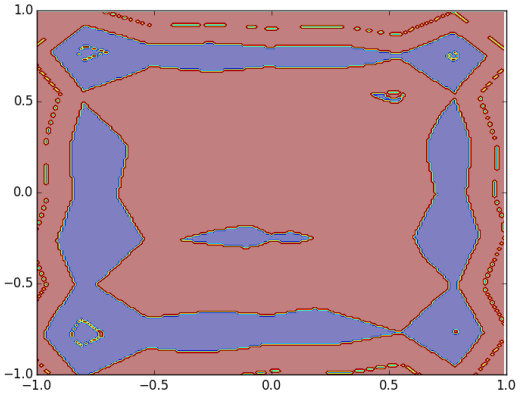


Fat + Short v.s. Thin + Tall
Toy Example

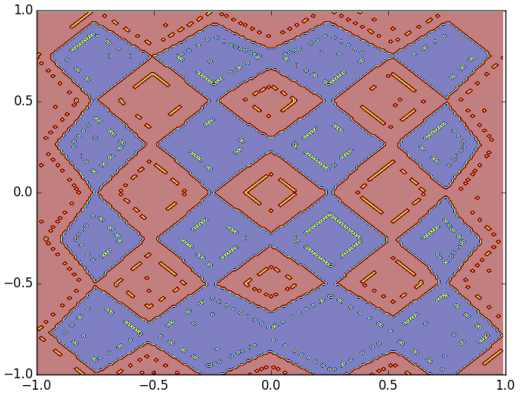
1 hidden layer:



(A) 125 neurons

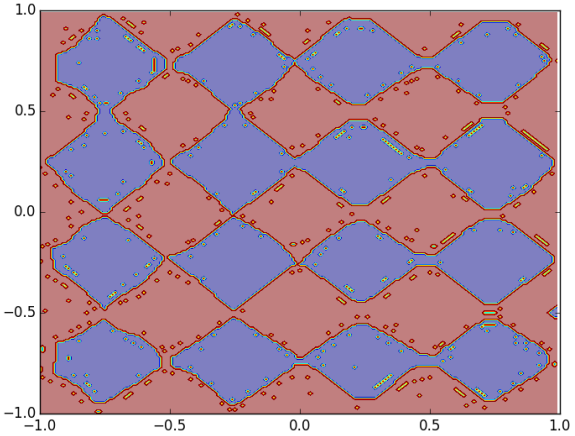


(B) 500 neurons



(C) 2500 neurons

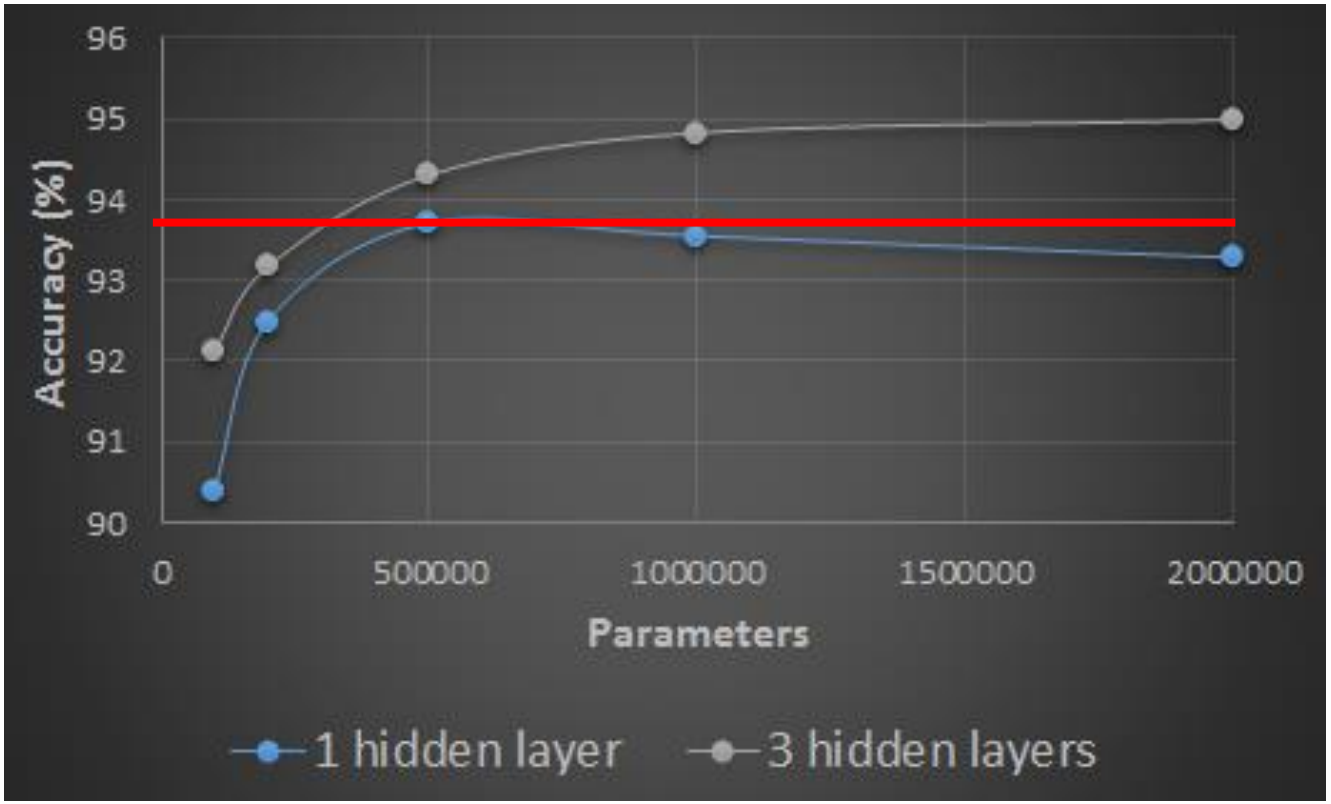
3 hidden layers:



Q: the number of parameters close to (A), (B) or (C)?

Fat + Short v.s. Thin + Tall Hand-writing digit classification

- Same parameters



Deeper: Using less parameters to achieve the same performance

Fat + Short v.s. Thin + Tall Speech Recognition

- Word error rate (WER)

Multiple layers

LxN	DBN-PT (%)
1×2k	24.2
2×2k	20.4
3×2k	18.4
4×2k	17.8
5×2k	17.2
7×2k	17.1

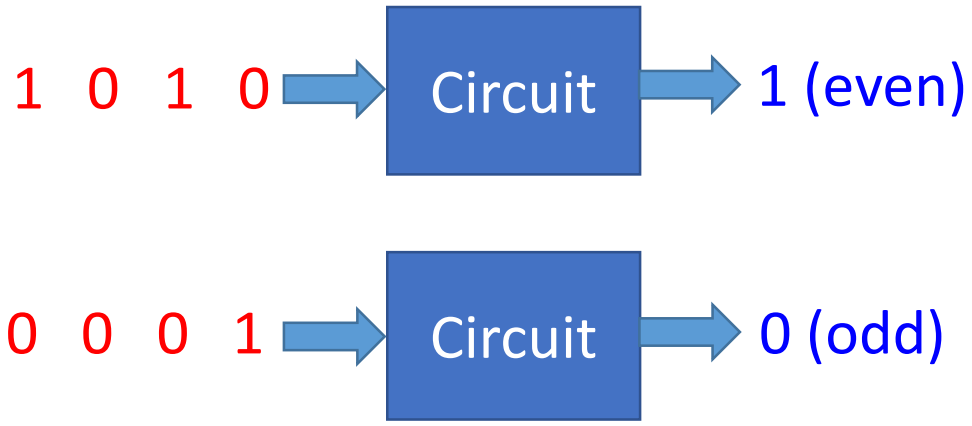
1 hidden layer

1xN	DBN-PT (%)
1×3,772	22.5
1×4,634	22.6
1×16K	22.1

Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Think about Logic Circuits ……

- A two-layer circuit of logic gates can represent any Boolean function.
- Using multiple layers of logic gates to build some functions are much simpler (less gates needed).
- E.g. ***parity check***

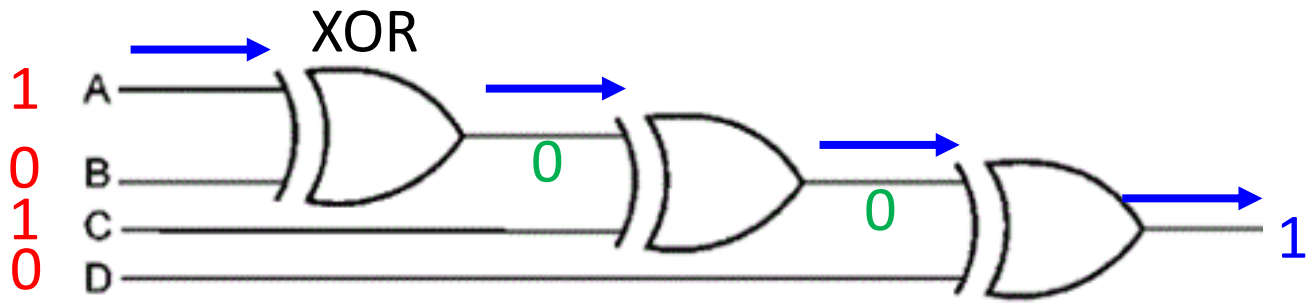


For input sequence with d bits,

Two-layer circuit need $O(2^d)$ gates.

Think about Logic Circuits ……

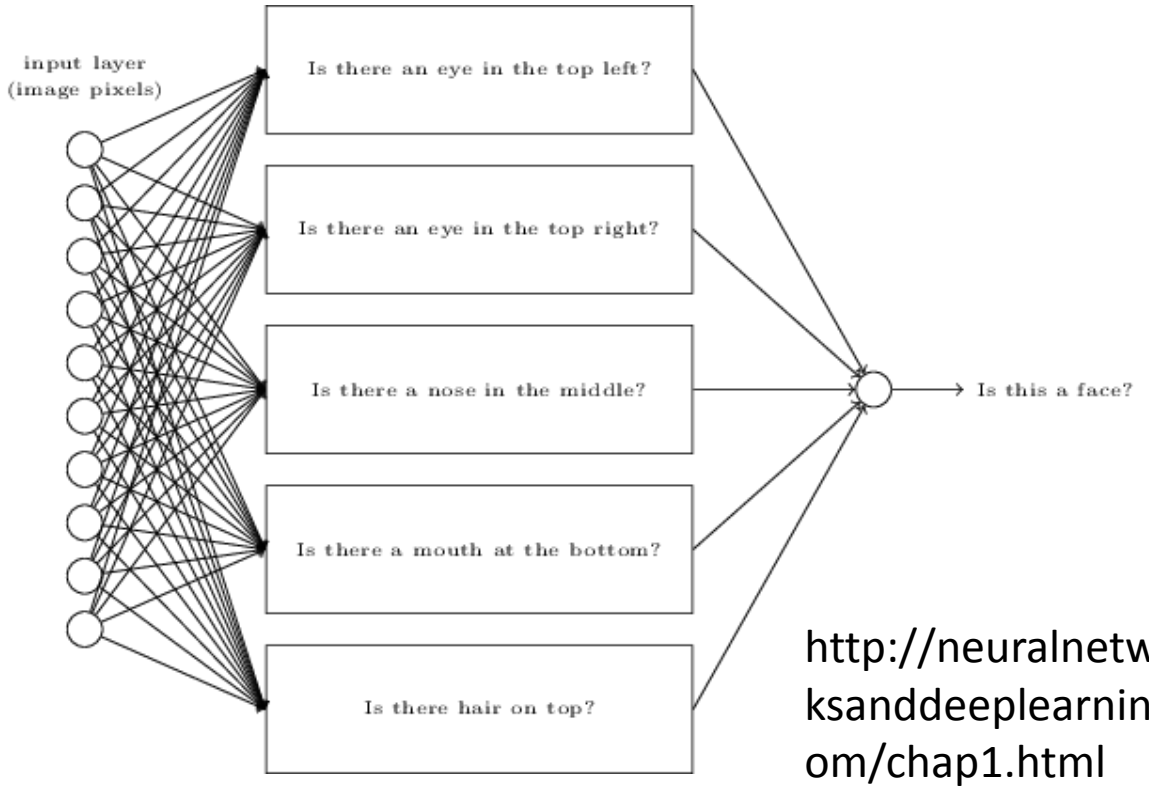
- A two-layer circuit of logic gates can represent any Boolean function.
- Using multiple layers of logic gates to build some functions are much simpler (less gates needed).
- E.g. ***parity check***



With multiple layers, we need only O(d) gates.

Back to Deep Learning

- *Some functions* can be easily represented by deep structure
  - Perhaps the functions that can be naturally decomposed into several steps
  - E.g. image



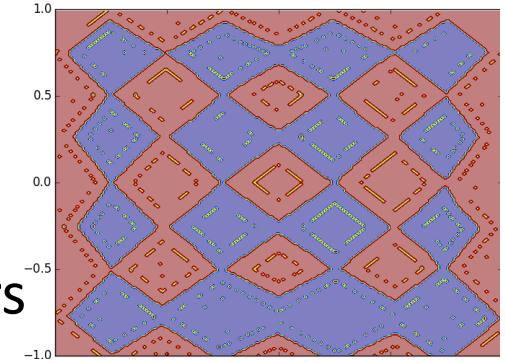
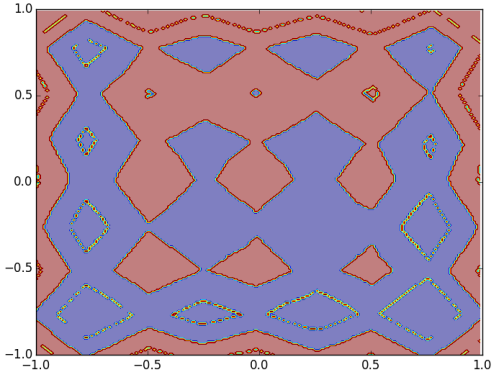
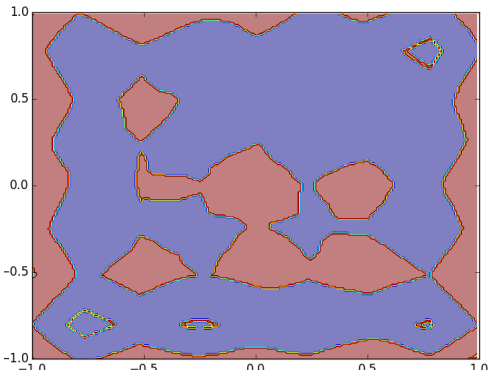
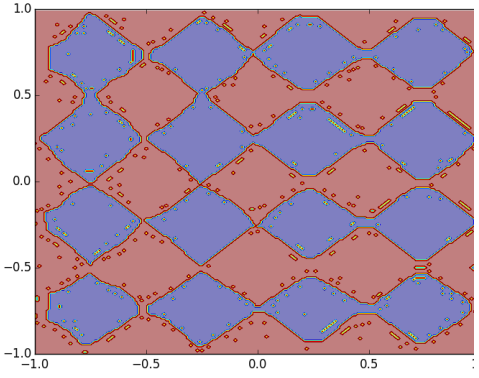
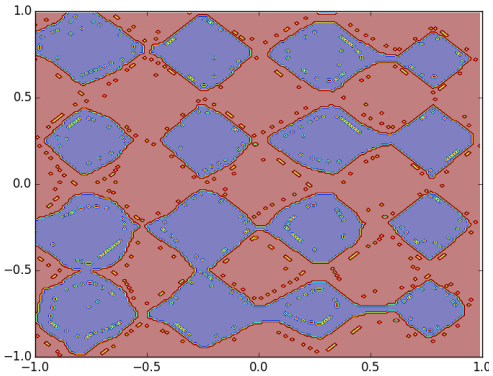
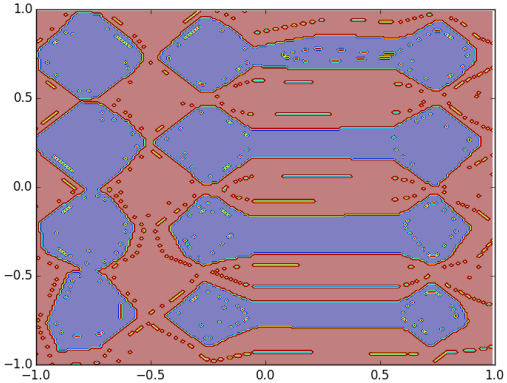
http://neuralnetworksanddeeplearning.com/chap1.html

Back to Deep Learning

- *Some functions* can be easily represented by deep structure
  - Perhaps the functions that can be naturally decomposed into several steps
  - E.g. image
- To represent the functions with shallow structure needs much more parameters
  - More parameters imply more training data needed
- To achieve the same performance, deep learning needs less training data
- With the same amount of data, deep learning can achieve better performance.

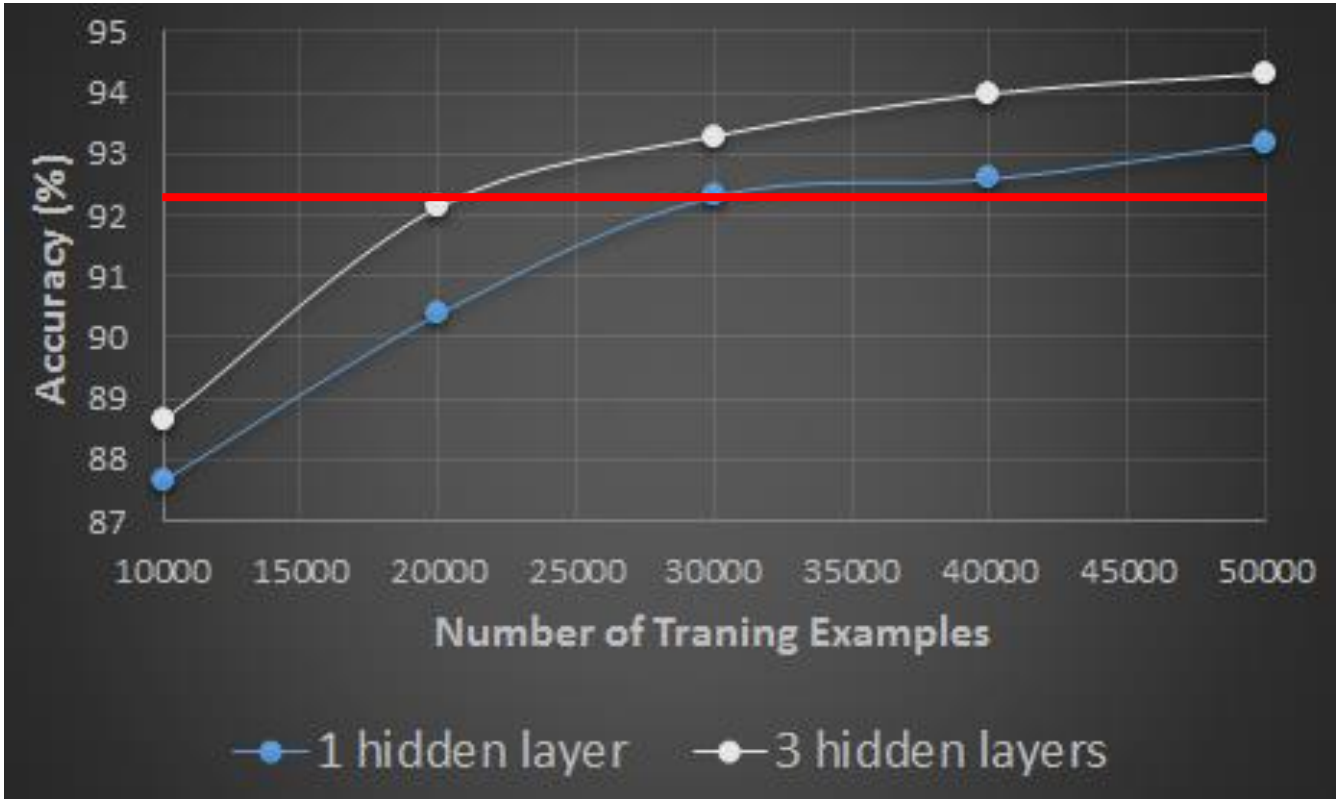
Size of Training Data

- Different numbers of training examples

	10,0000	5,0000	2,0000
1 hidden layer More parameters			
3 hidden layers Less parameters			

Size of Training Data

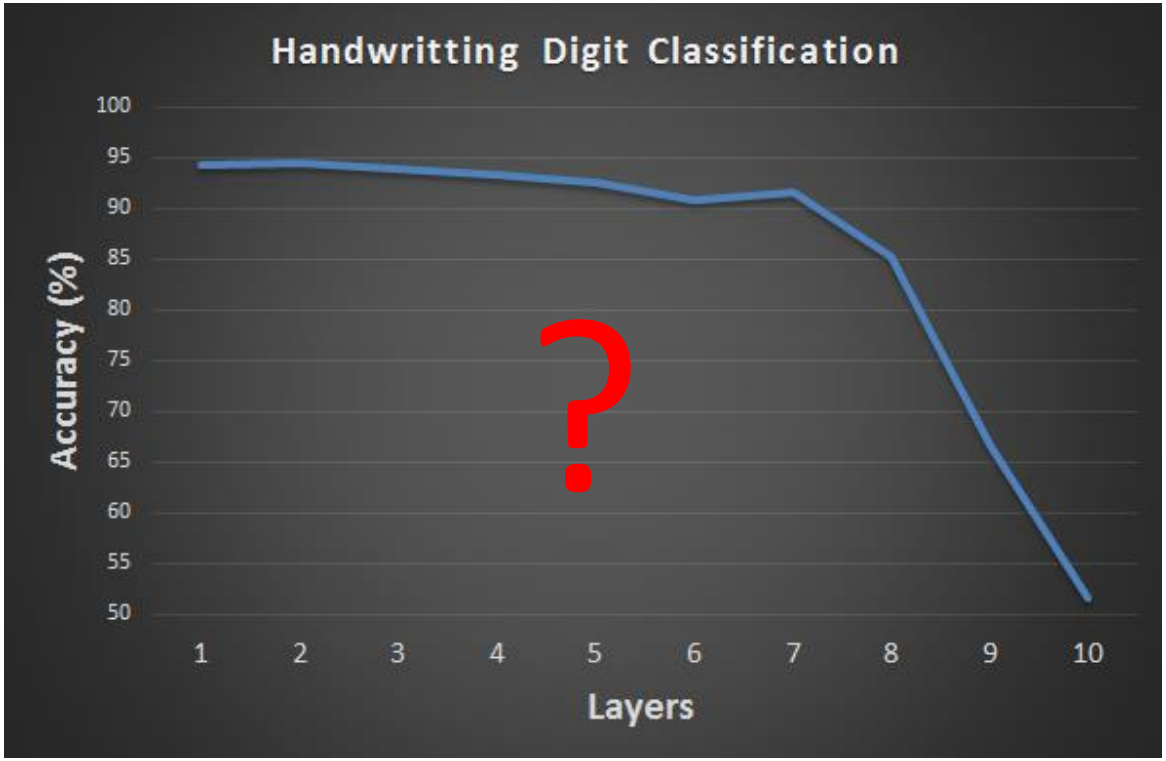
- Hand-writing digit classification



Deeper: Using less training data to achieve the same performance

Why deep is not popular before?

- In the past, usually deep does not work ……



We will go back to this issue in the following lectures.

What is Structured Learning?

In the real world ……

***X* (Input domain)**:
Sequence, graph structure, tree structure ……

***Y* (Output domain)**:
Sequence, graph structure, tree structure ……

Retrieval

“Machine learning”

(keyword)

A list of web pages (Search Result)

Translation

$$f : X \rightarrow Y$$

X :

“Machine learning and having it deep and structured”

(One kind of sequence)

Y :

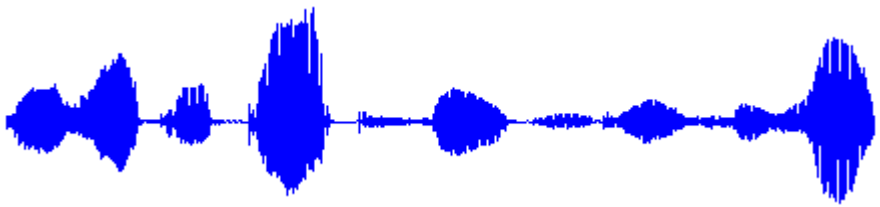
“机器学习及其深层结构化”

(Another kind of sequence)

Speech Recognition

$$f : X \rightarrow Y$$

X :



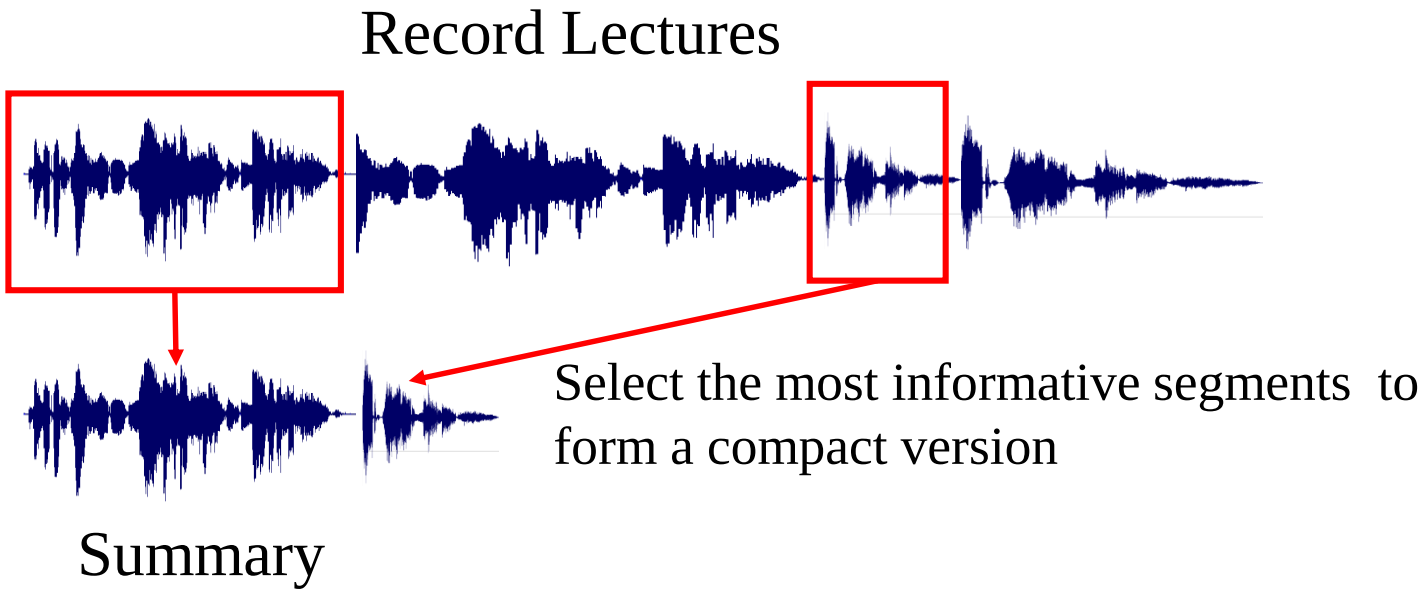
(One kind of sequence)

Y :

“大家好，欢迎来选修模式识别课程”

(Another kind of sequence)

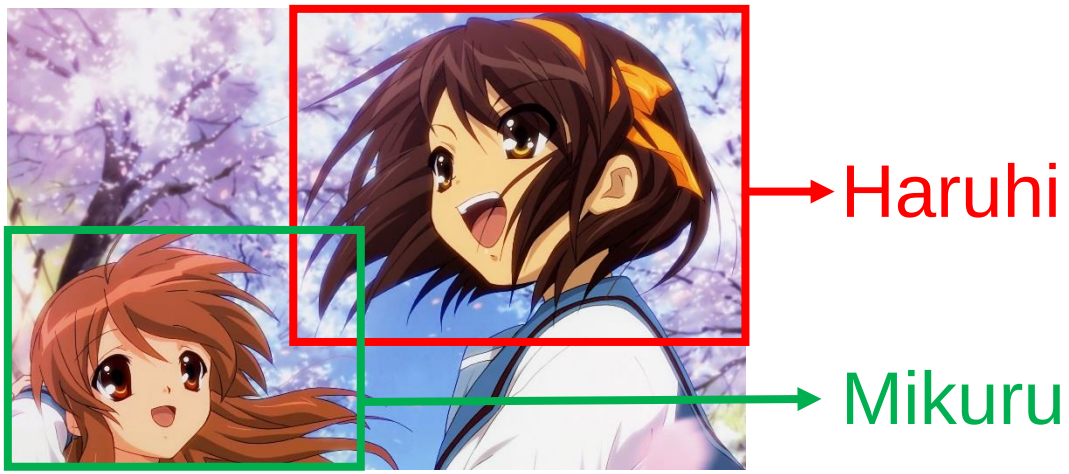
Speech Summarization



Object Detection

Image

Object Positions

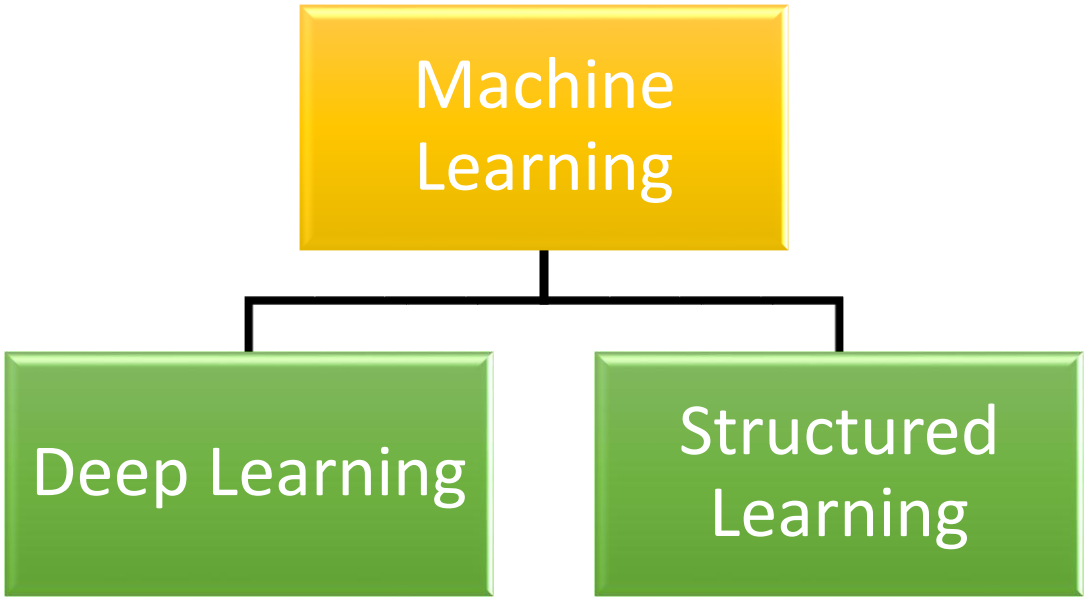


Pose Estimation

Image Pose

Source of images: http://groups.inf.ed.ac.uk/calvin/Publications/eichner-techreport10.pdf

Concluding Remarks



Reference

- No Textbook
- Deep Learning
  - “Neural Networks and Deep Learning”
    - written by Michael Nielsen
    - http://neuralnetworksanddeeplearning.com/
  - “Deep Learning” (not finished yet)
    - Written by Yoshua Bengio, Ian J. Goodfellow and Aaron Courville
    - http://www.iro.umontreal.ca/~bengioy/dlbook/
- Structured Learning
  - No suggested reference

Thank you!

Human Brains are Deep