Why Deep Learning?

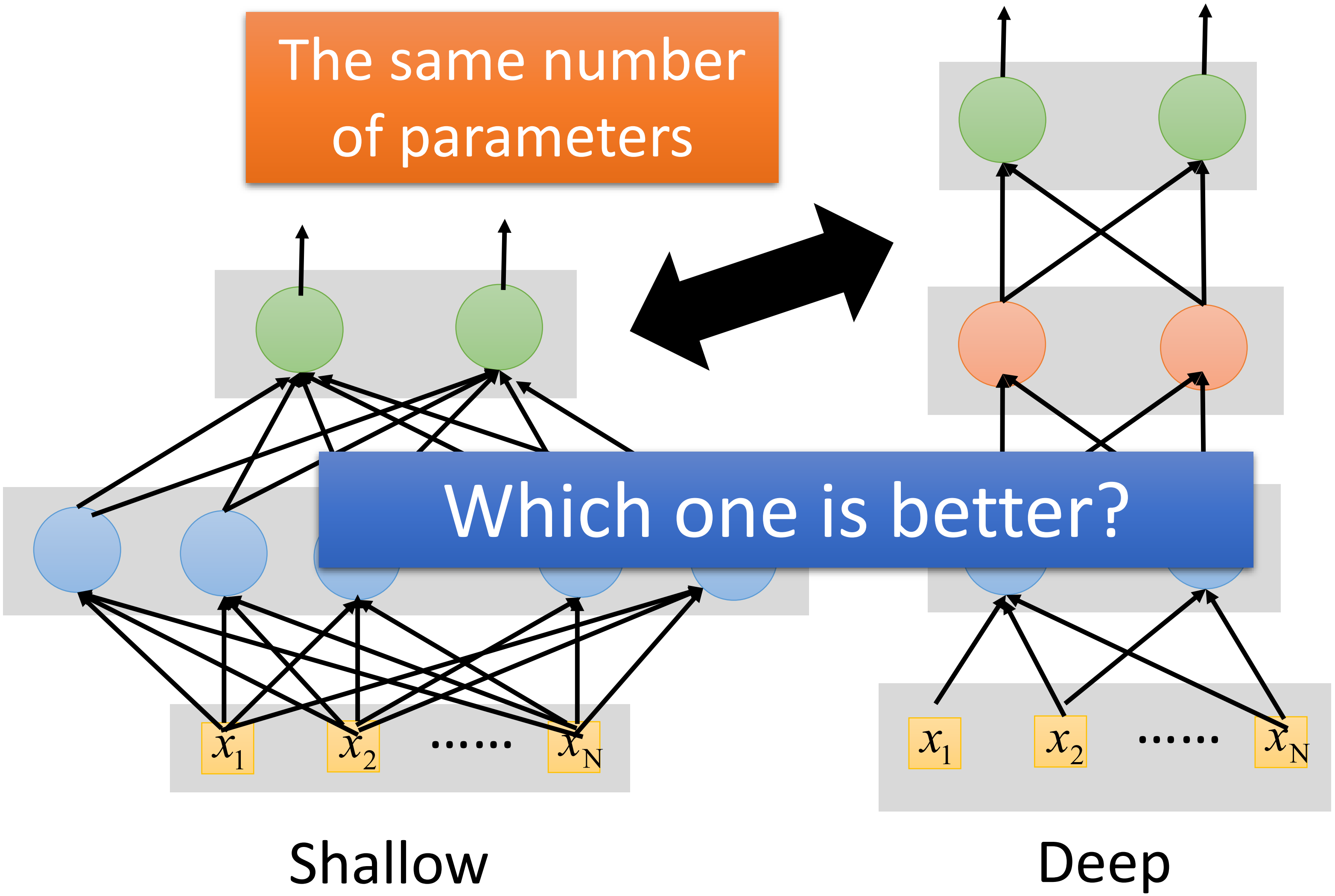
Deeper is Better?

Layer X Size	Word Error Rate (%)
1 X 2k	24.2
2 X 2k	20.4
3 X 2k	18.4
4 X 2k	17.8
5 X 2k	17.2
7 X 2k	17.1

Not surprised, more parameters, better performance

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

Fat + Short v.s. Thin + Tall



首先要先將參數調整到一樣多的情況

Fat + Short v.s. Thin + Tall

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4		
3 X 2k	18.4		
4 X 2k	17.8		
5 X 2k	17.2	1 X 3772	22.5
7 X 2k	17.1	1 X 4634	22.6
		1 X 16k	22.1

Why?

參數量是一樣多的

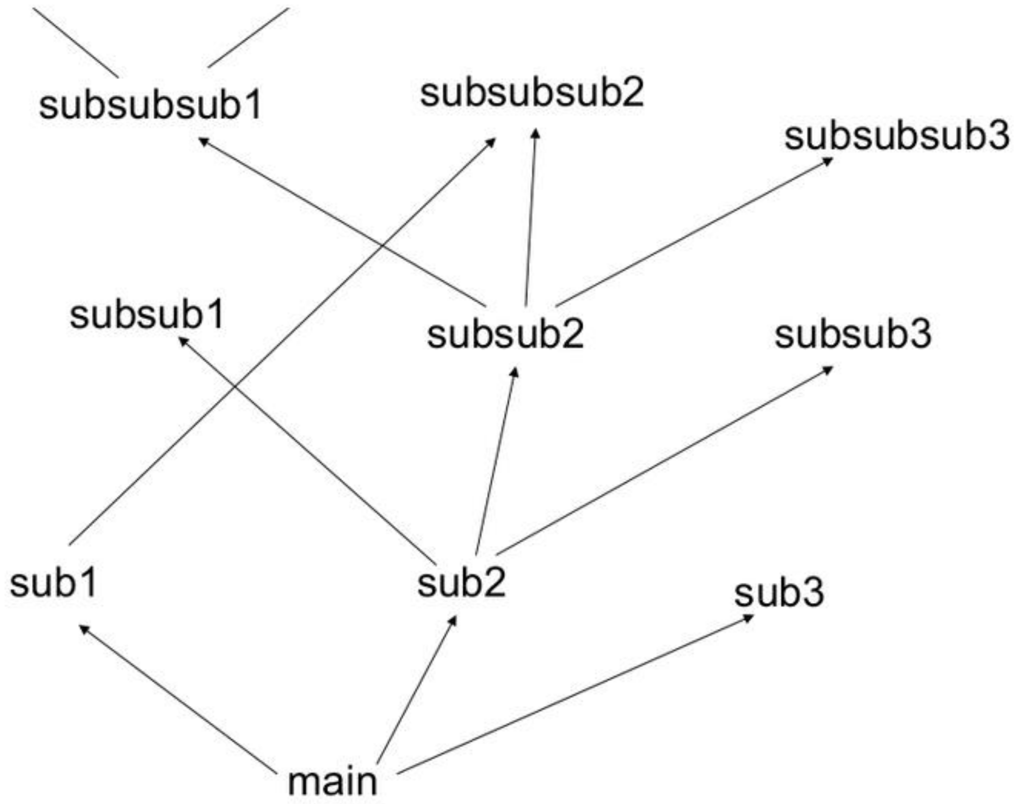
Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Modularization

- Deep → Modularization

Don't put everything in your main function.

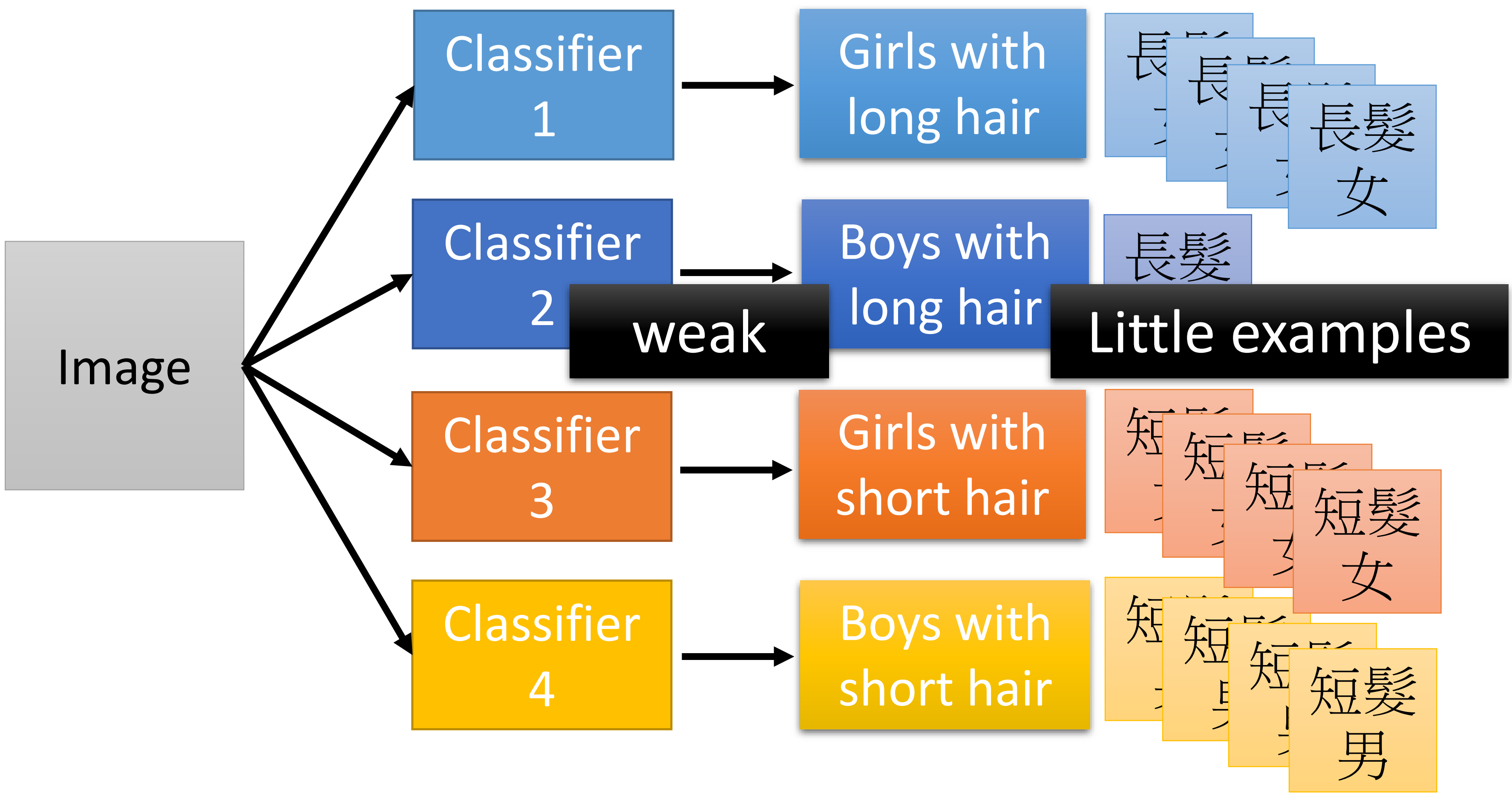
共用參數/行數



http://rinuboney.github.io/2015/10/18/theoretical-motivations-deep-learning.html

Modularization 模組化

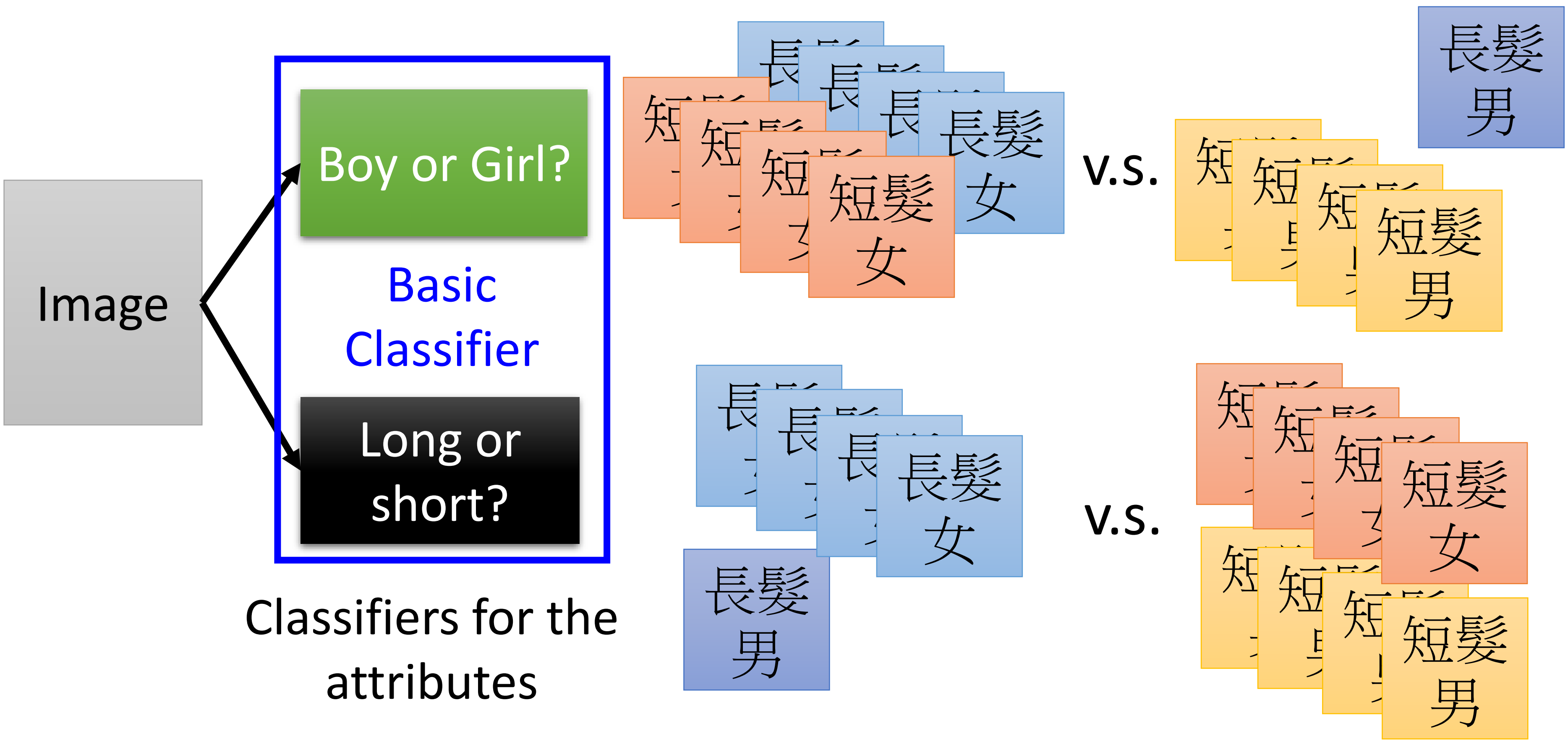
- Deep → Modularization



Modularization

Each basic classifier can have sufficient training examples.

- Deep → Modularization



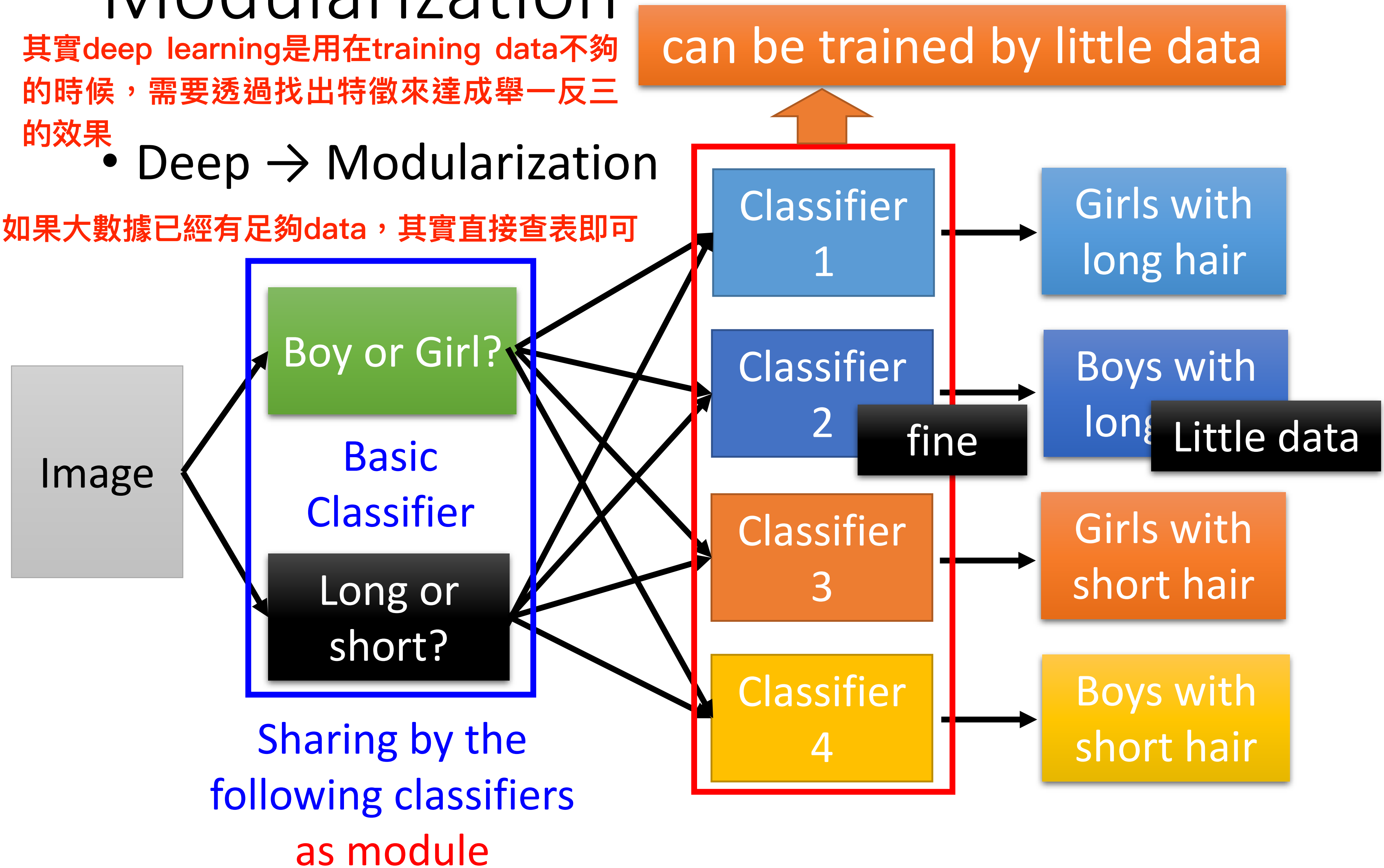
如果沒有模組化，class2需要大量的training data

Modularization

其實deep learning是用在training data不夠的時候，需要透過找出特徵來達成舉一反三的效果

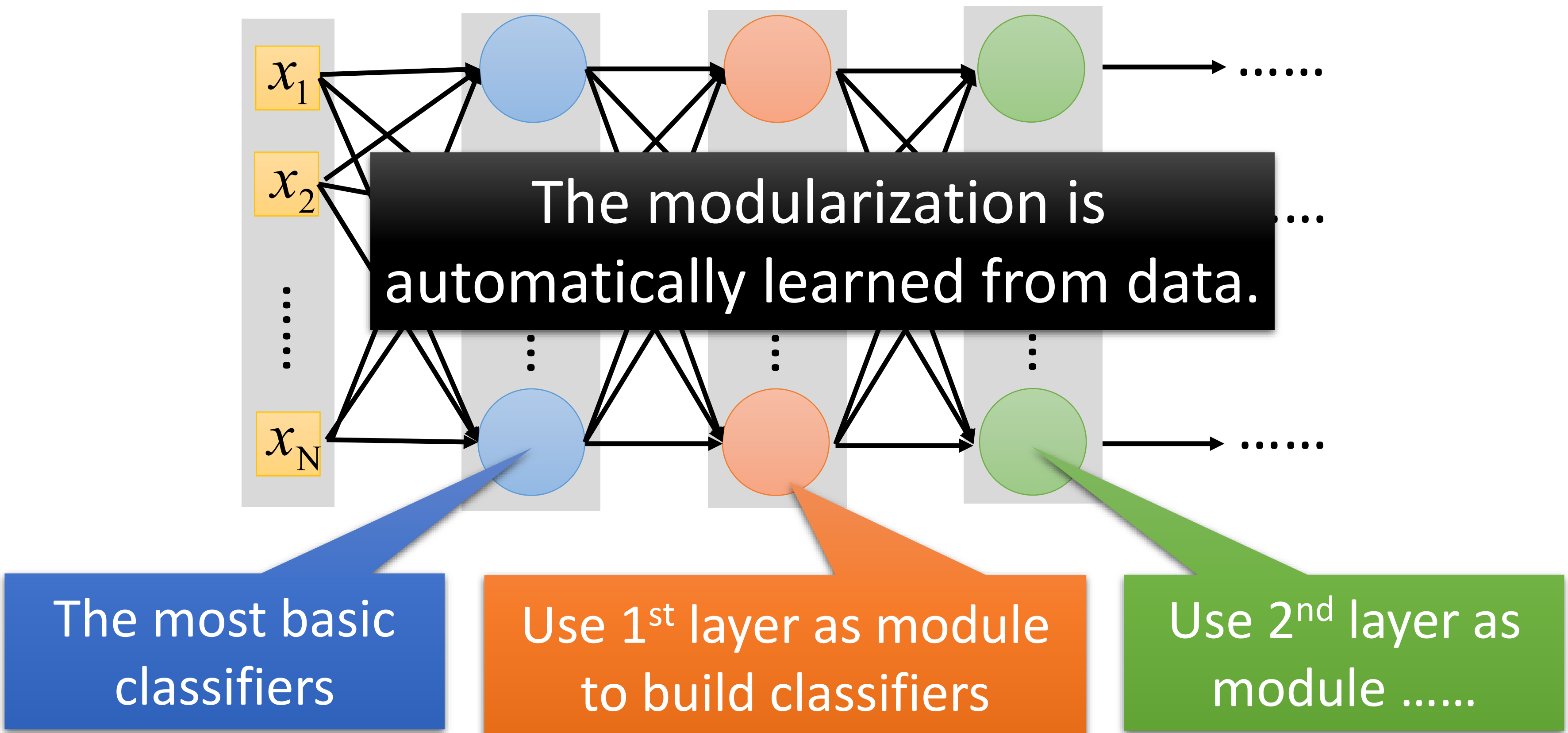
- Deep → Modularization

如果大數據已經有足夠data，其實直接查表即可



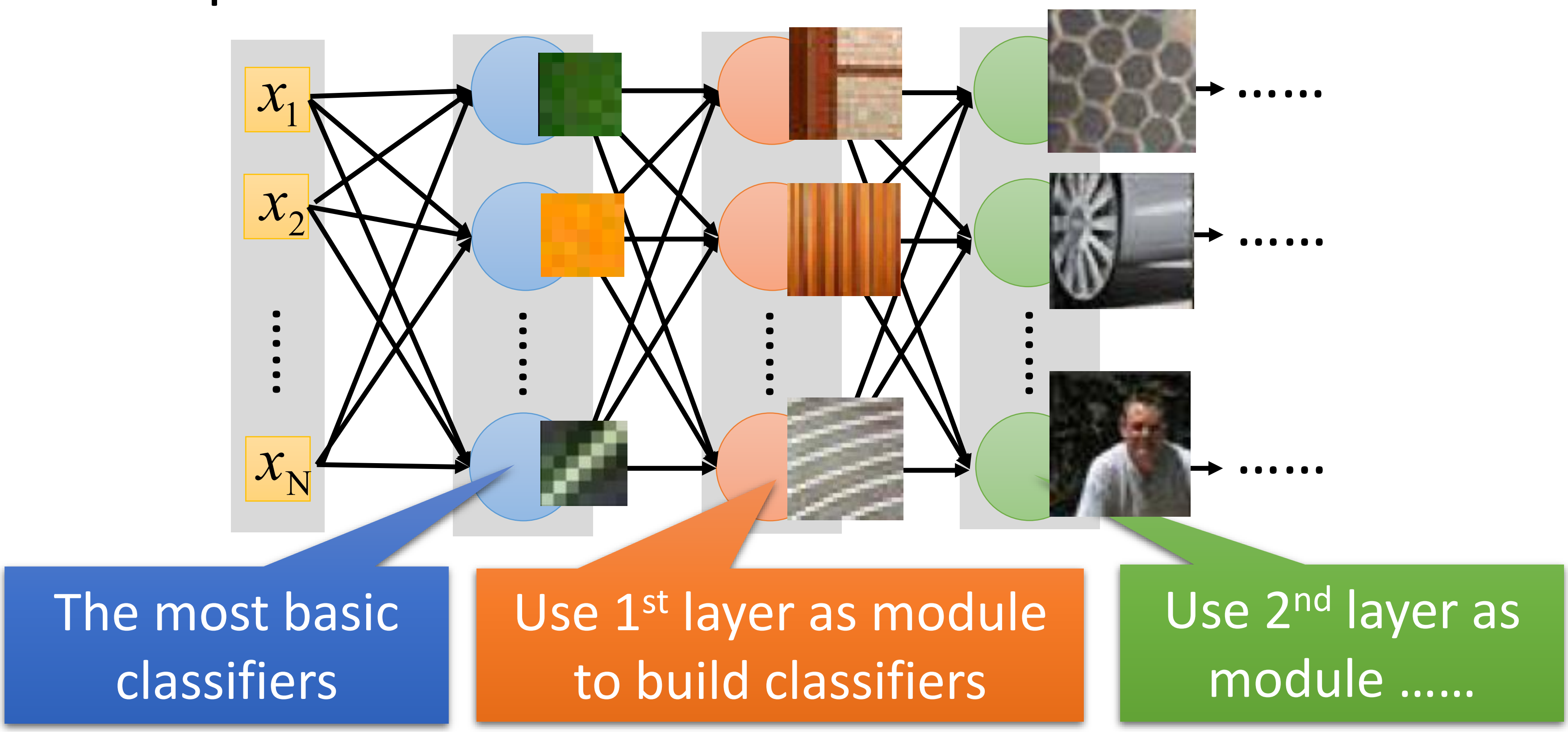
Modularization

- Deep → Modularization → Less training data?



Modularization - Image

- Deep → Modularization



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

Modularization - Speech

- The hierarchical structure of human languages

what do you think

Phoneme:

hh w aa t   d uw   y uw   th ih ng k

Tri-phone:

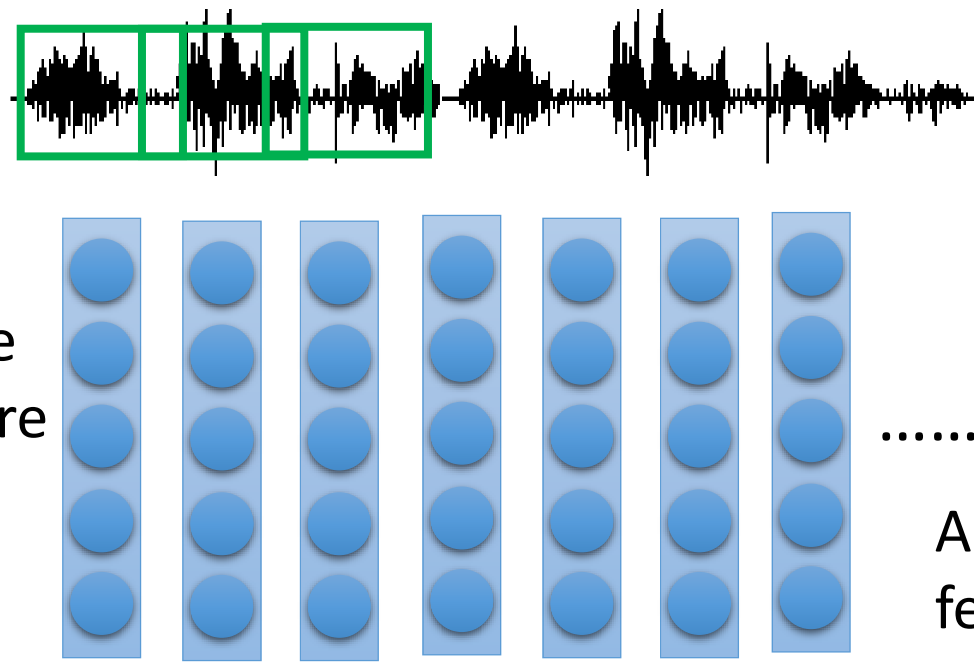
…… t-d+uw d-uw+y   uw-y+uw y-uw+th ……

t-d+uw1 t-d+uw2 t-d+uw3   d-uw+y1 d-uw+y2 d-uw+y3

State:

Modularization - Speech

- The first stage of speech recognition
  - Classification: input → acoustic feature, output → state



Determine the state each acoustic feature belongs to

......

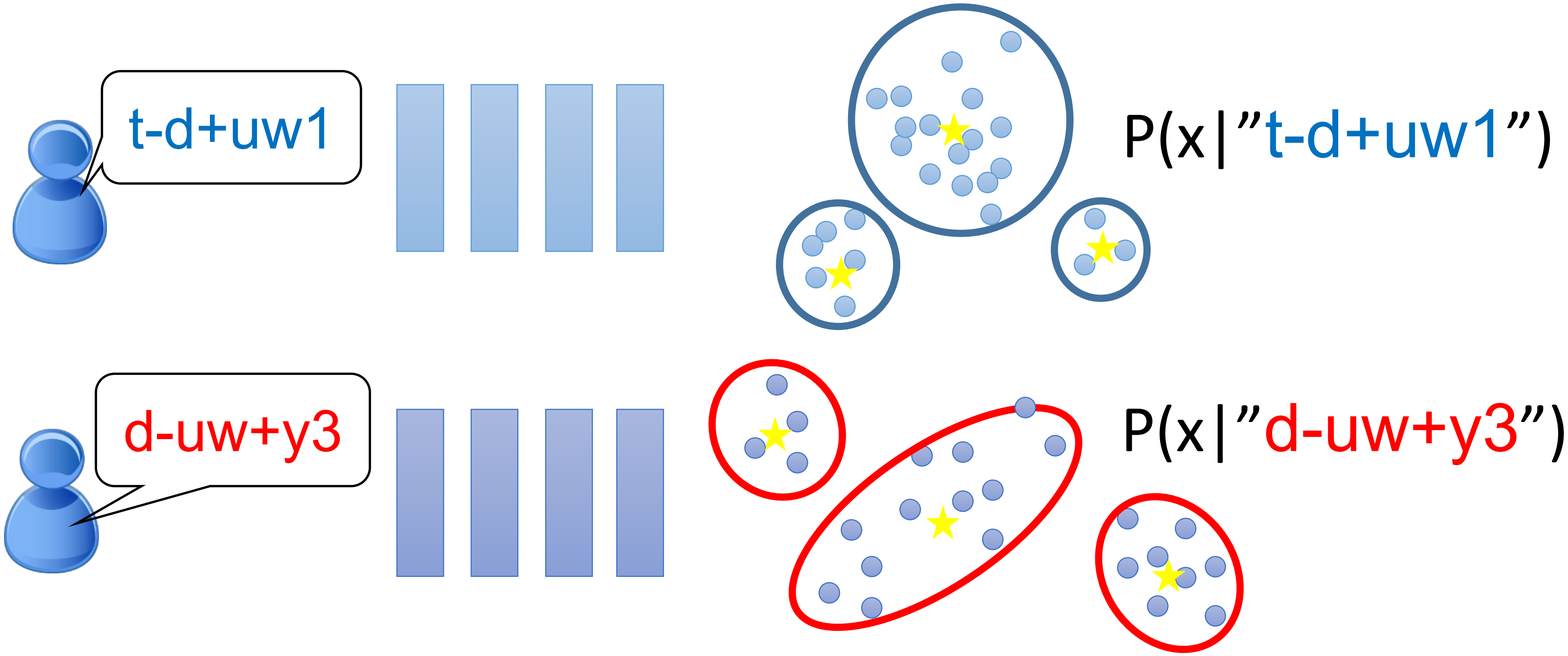
Acoustic feature

States: a a a b b c c

Modularization - Speech

- Each state has a stationary distribution for acoustic features

Gaussian Mixture Model (GMM)



Modularization - Speech

- Each state has a stationary distribution for acoustic features

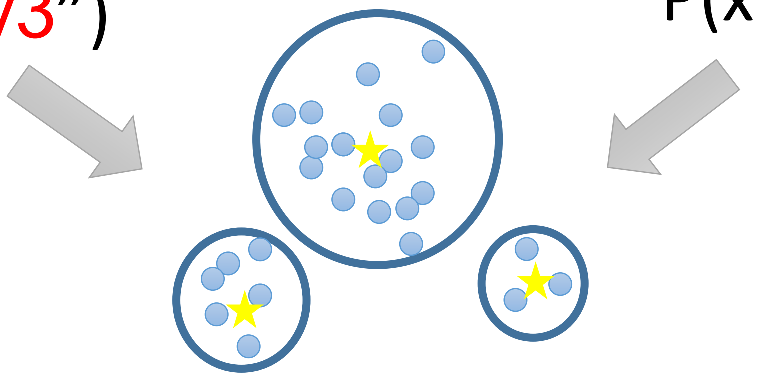
<u>Tied-state</u>

pointer

P(x|"d-uw+y3")

pointer

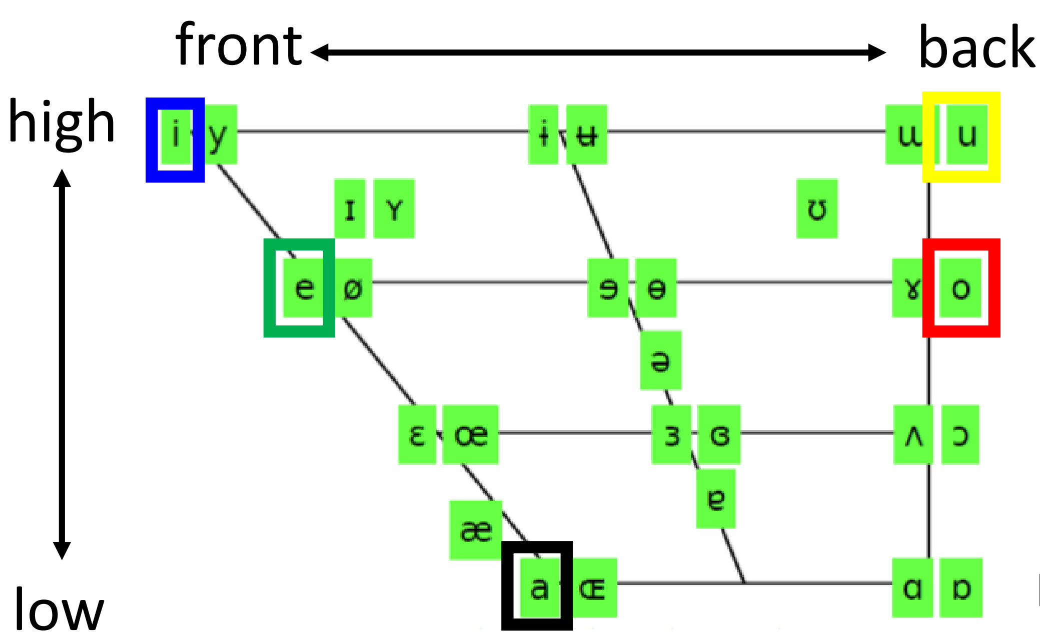
P(x|"y-uw+th3")



Same Address

Modularization - Speech

- In HMM-GMM, all the phonemes are modeled independently
  - Not an effective way to model human voice



The sound of vowel is only controlled by a few factors.

http://www.ipachart.com/

舌頭在口腔的位置

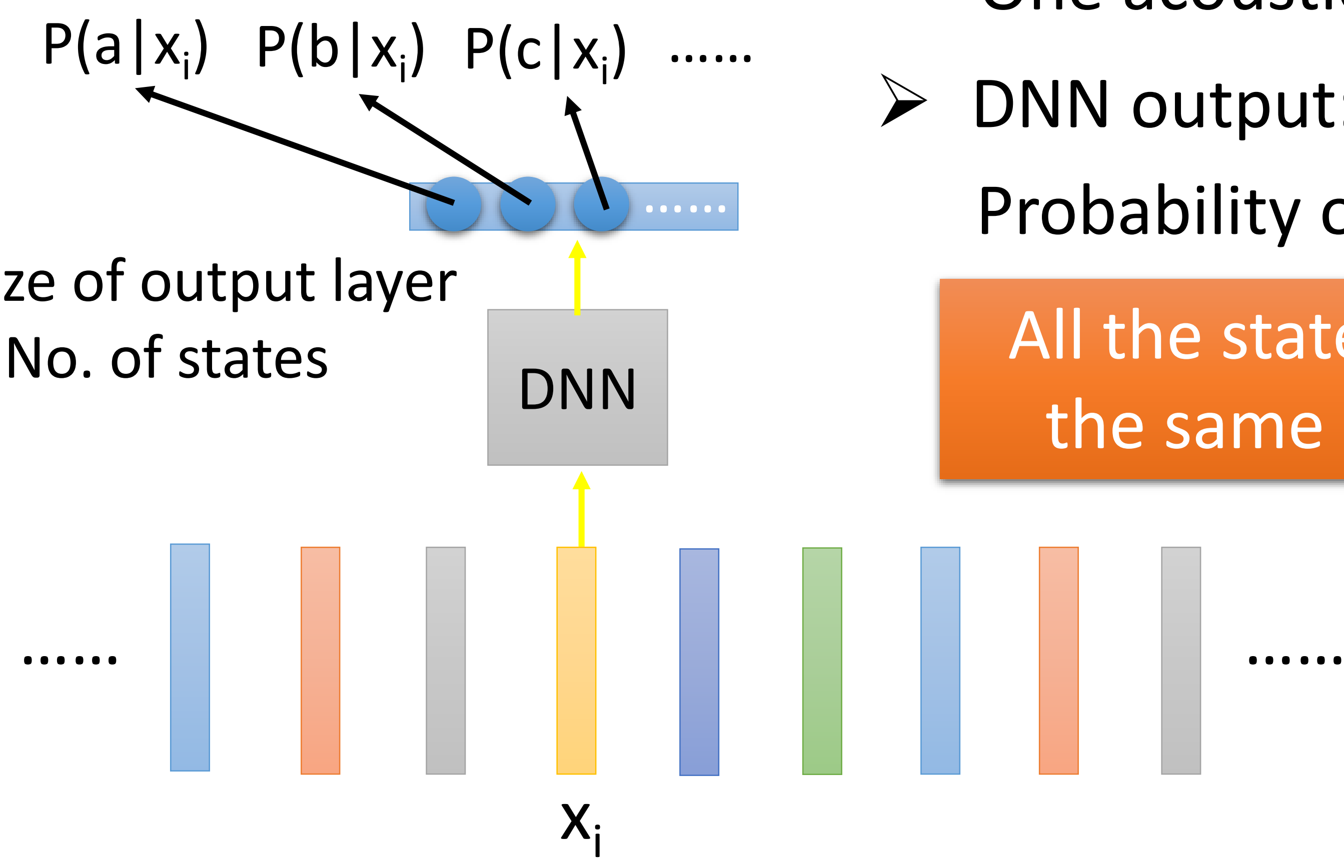
DNN(discriminative) v.s. HMM(generative)

其實HMM也可以做discriminative training，其參數也與DNN差不多

Modularization - Speech

D N N 強 在 他 將 每 個 p a r a m e t e r 視 為 dépendant，不像HMM視為indépendant

- DNN input:
  One acoustic feature
- DNN output:
  Probability of each state



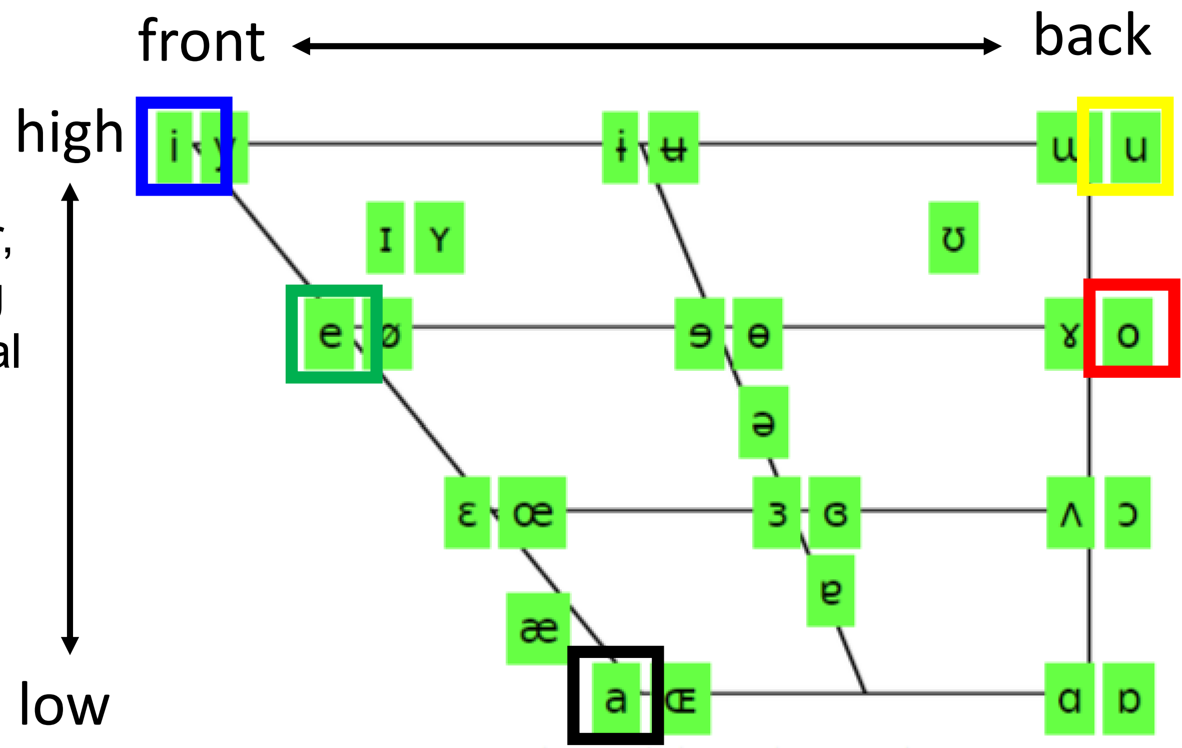
Size of output layer
= No. of states

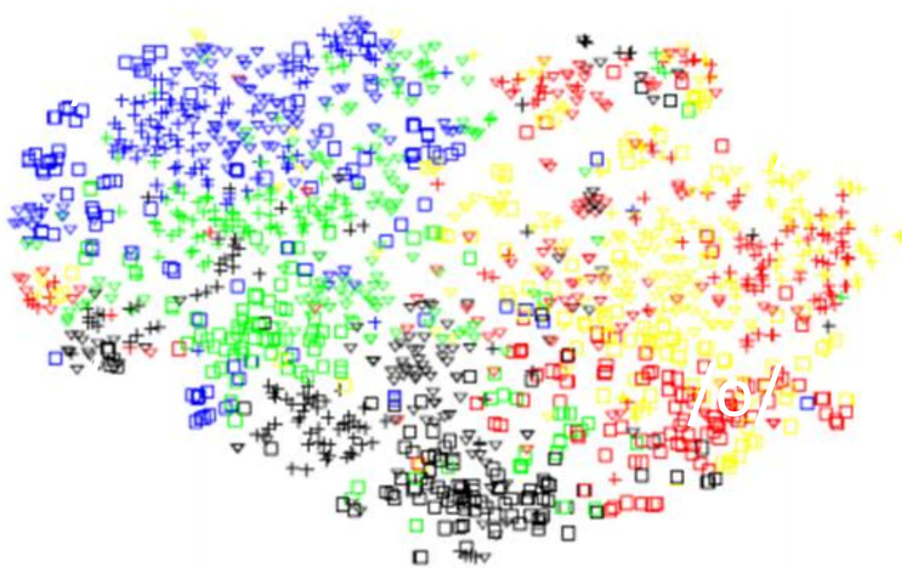
All the states use the same DNN

Modularization

Vu, Ngoc Thang, Jochen Weiner, and Tanja Schultz. "Investigating the Learning Effect of Multilingual Bottle-Neck Features for ASR." *Interspeech*. 2014.

Output of hidden layer reduce to two dimensions





- The lower layers detect the manner of articulation
- All the phonemes share the results from the same set of detectors.
- Use parameters effectively

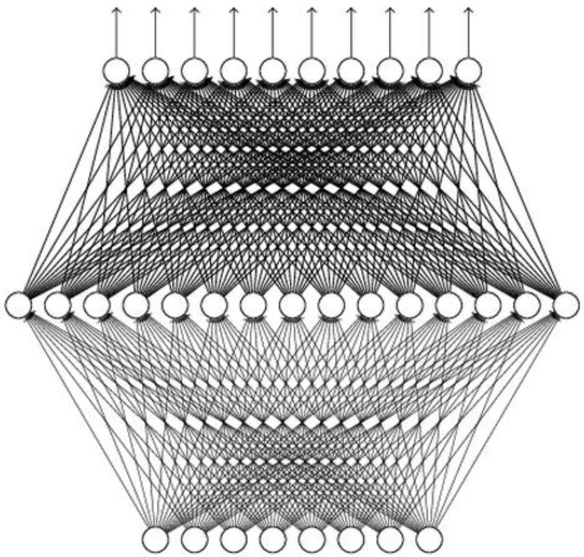
Universality Theorem

Any continuous function f

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

Can be realized by a network with one hidden layer

(given **enough** hidden neurons)



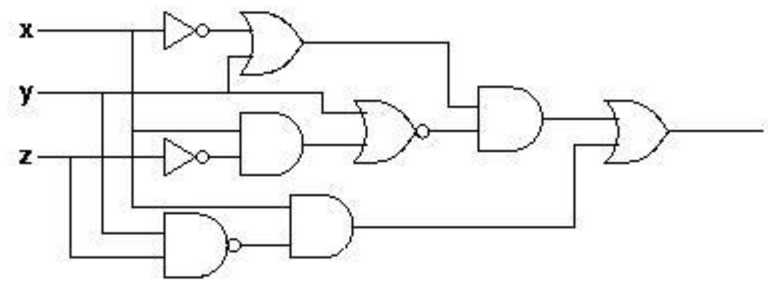
Reference for the reason: http://neuralnetworksanddeeplearning.com/chap4.html

雖然可以表示任何function，但是deep比較有架構性

Yes, shallow network can represent any function.

However, using deep structure is more effective.

Analogy



Logic circuits

- Logic circuits consists of **gates**
- **A two layers of logic gates** can represent **any Boolean function.**
- Using multiple layers of logic gates to build some functions are much simpler

→ less gates needed

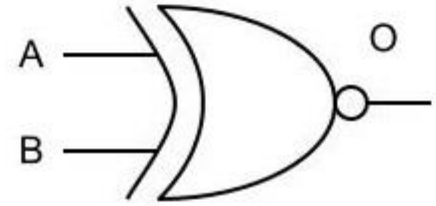
Neural network

- Neural network consists of **neurons**
- **A hidden layer network** can represent **any continuous function.**
- Using multiple layers of neurons to represent some functions are much simpler

→ less parameters → less data?

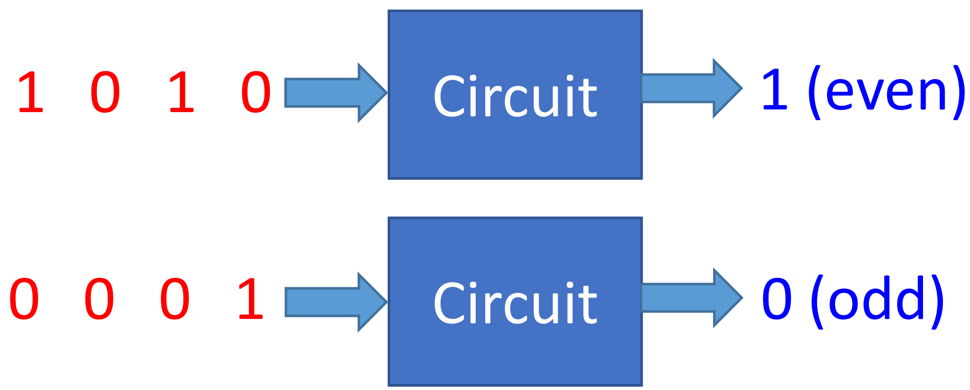
This page is for EE background.

Analogy



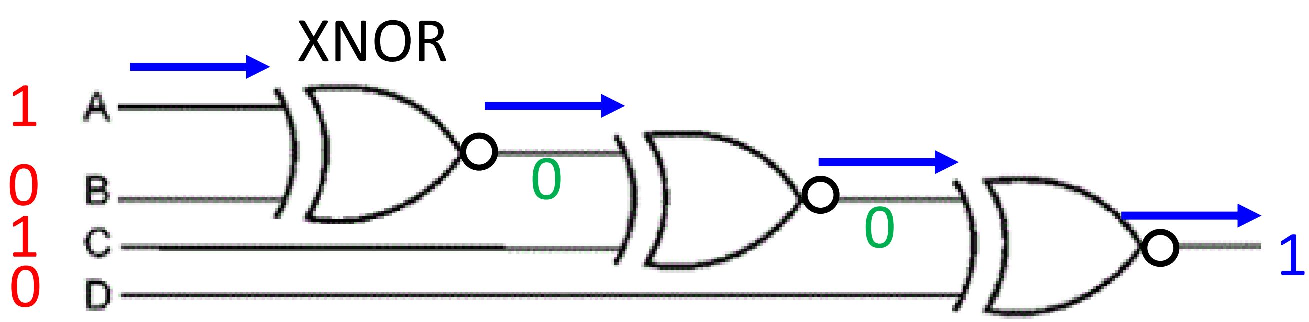
A	B	O
0	0	1
0	1	0
1	0	0
1	1	1

- E.g. ***parity check***



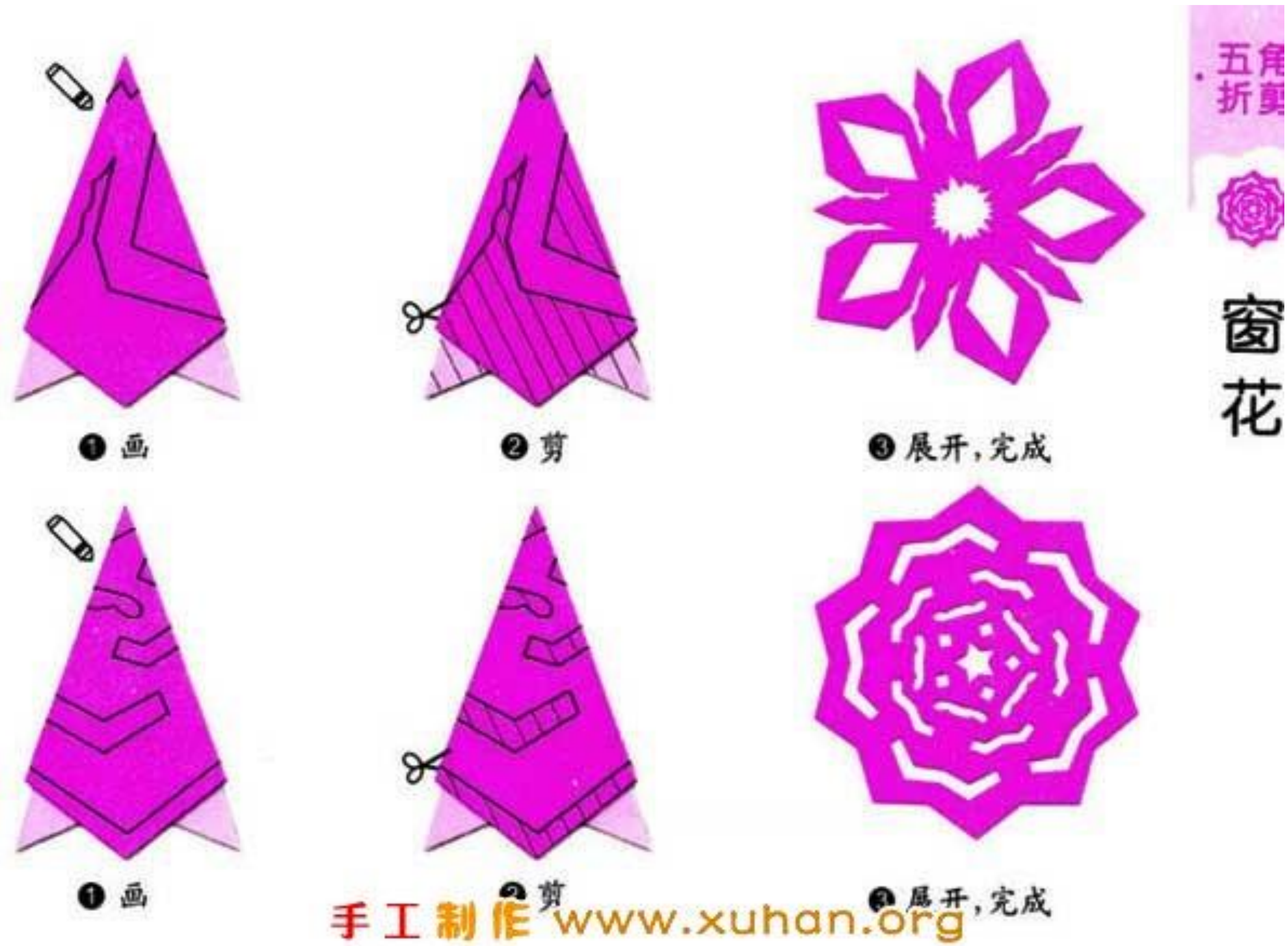
For input sequence with d bits,

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



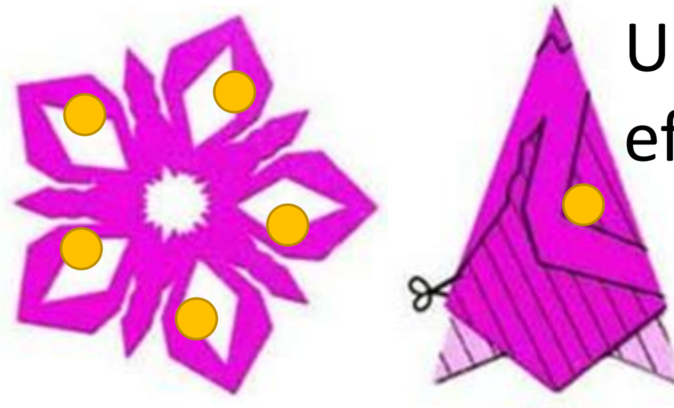
With multiple layers, we need only O(d) gates.

More Analogy

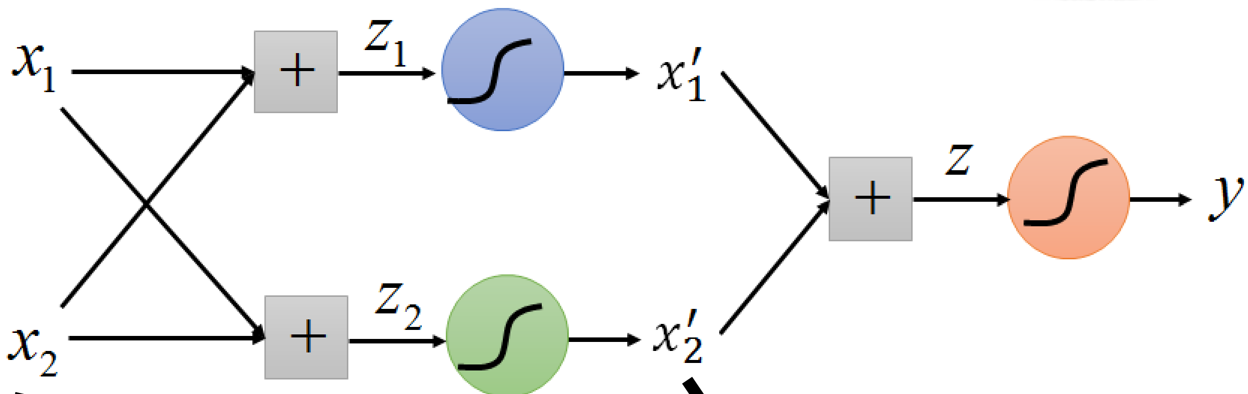


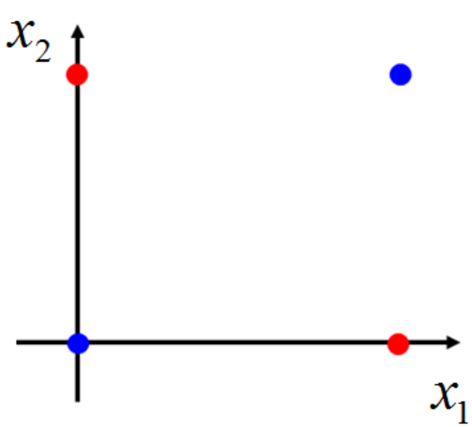
More Analogy

deep learning適合用在data少，可重複將一筆data視為很多data的情況

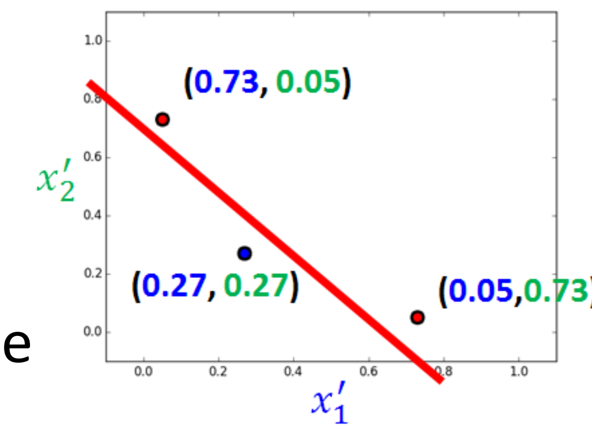


Use data effectively



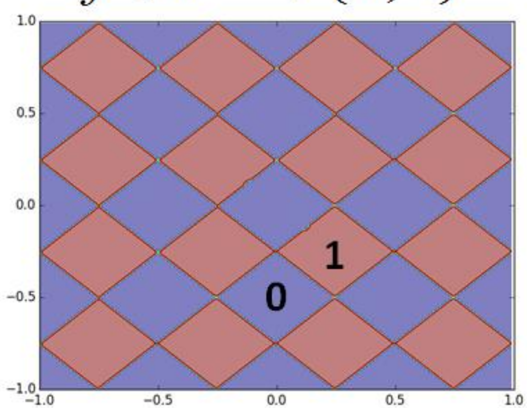


Folding the space



More Analogy - Experiment

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

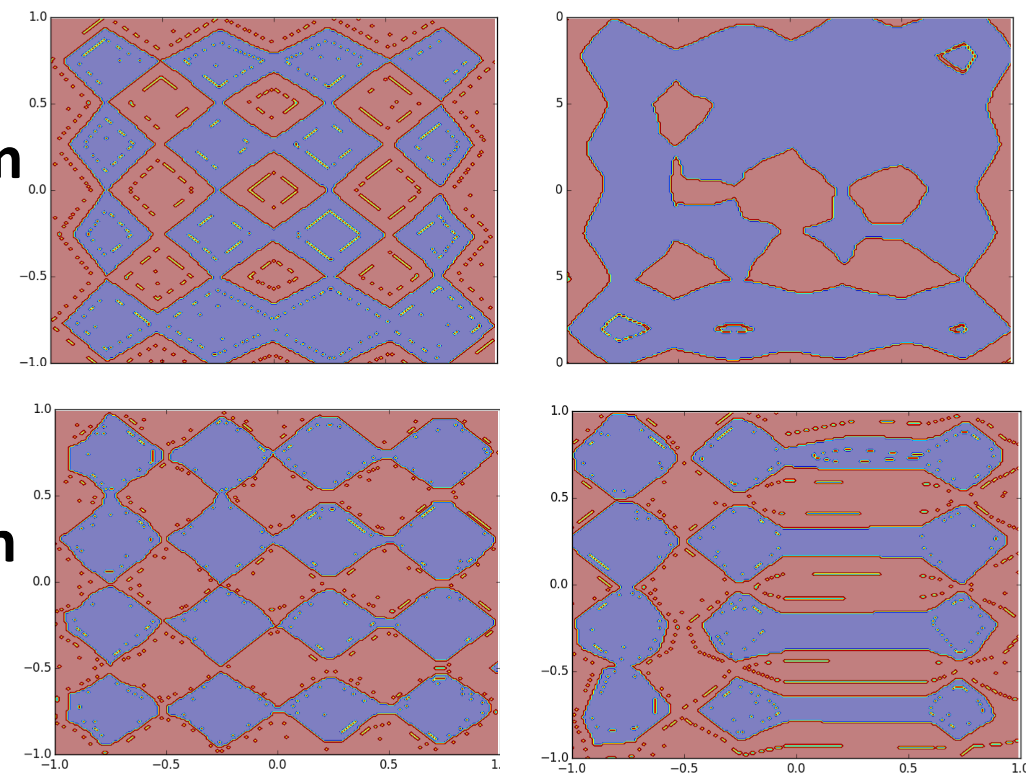


Different numbers of training examples

10,0000 2,0000

1 hidden layer

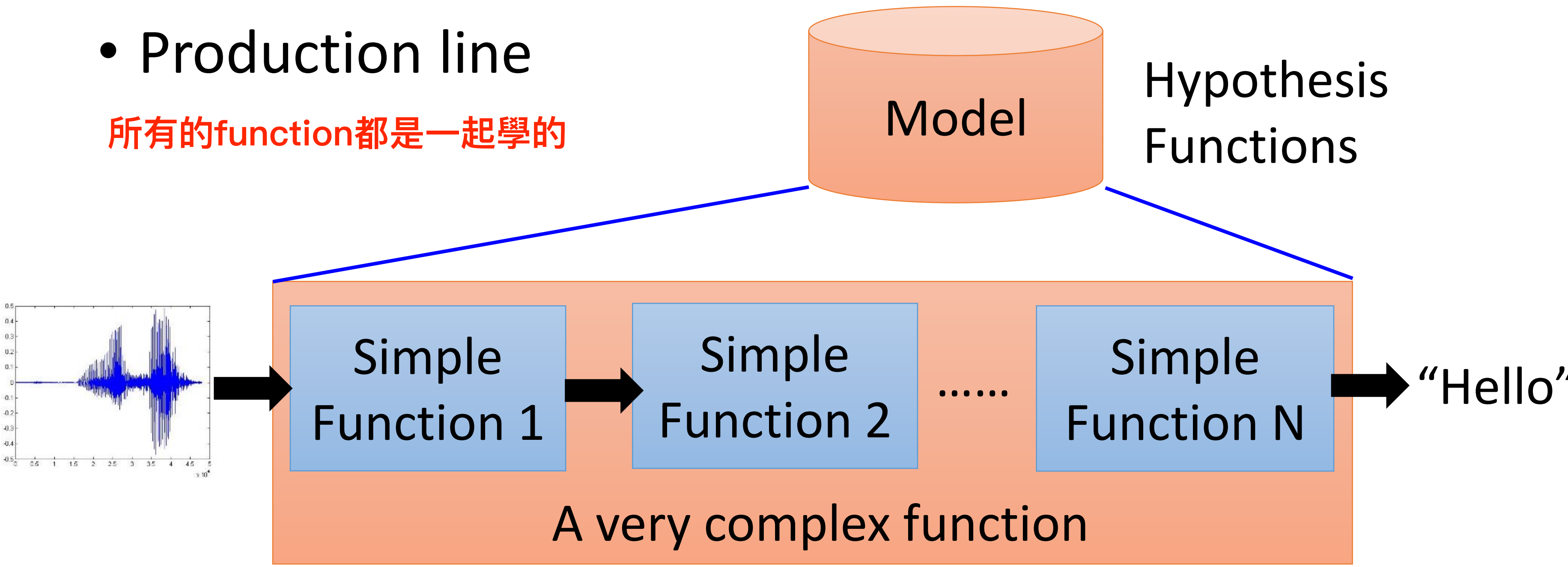
3 hidden layers



End-to-end Learning

- Production line

所有的function都是一起學的

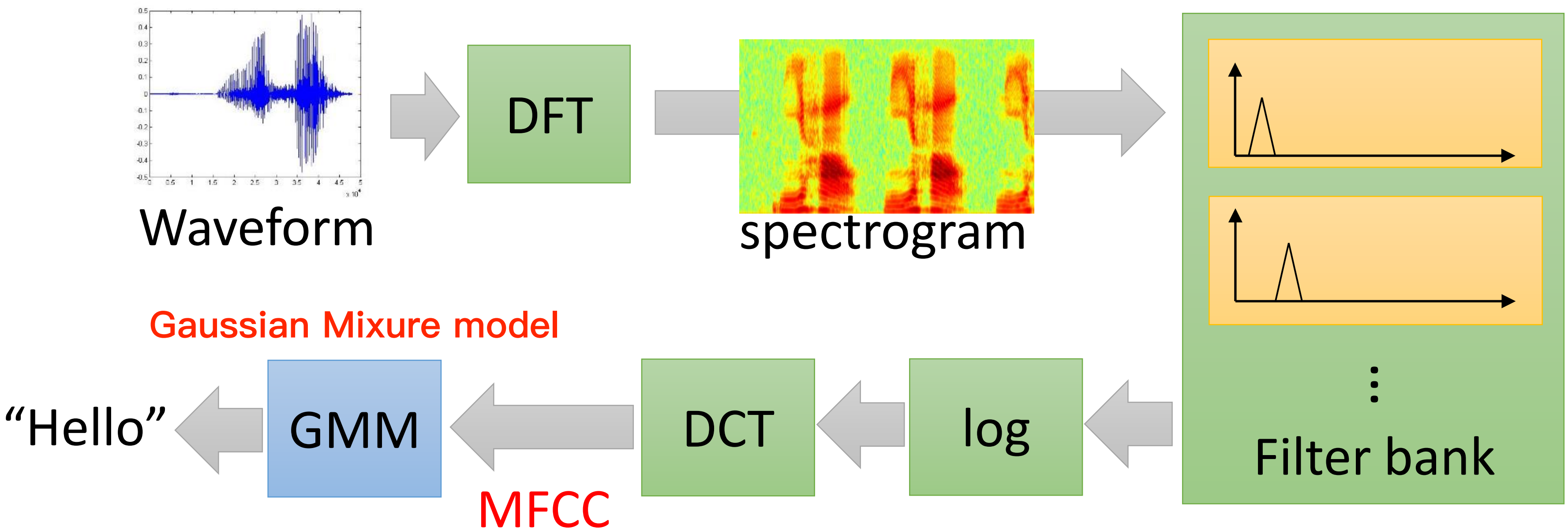


End-to-end training:

What each function should do is learned automatically

End-to-end Learning
- Speech Recognition

- Shallow Approach



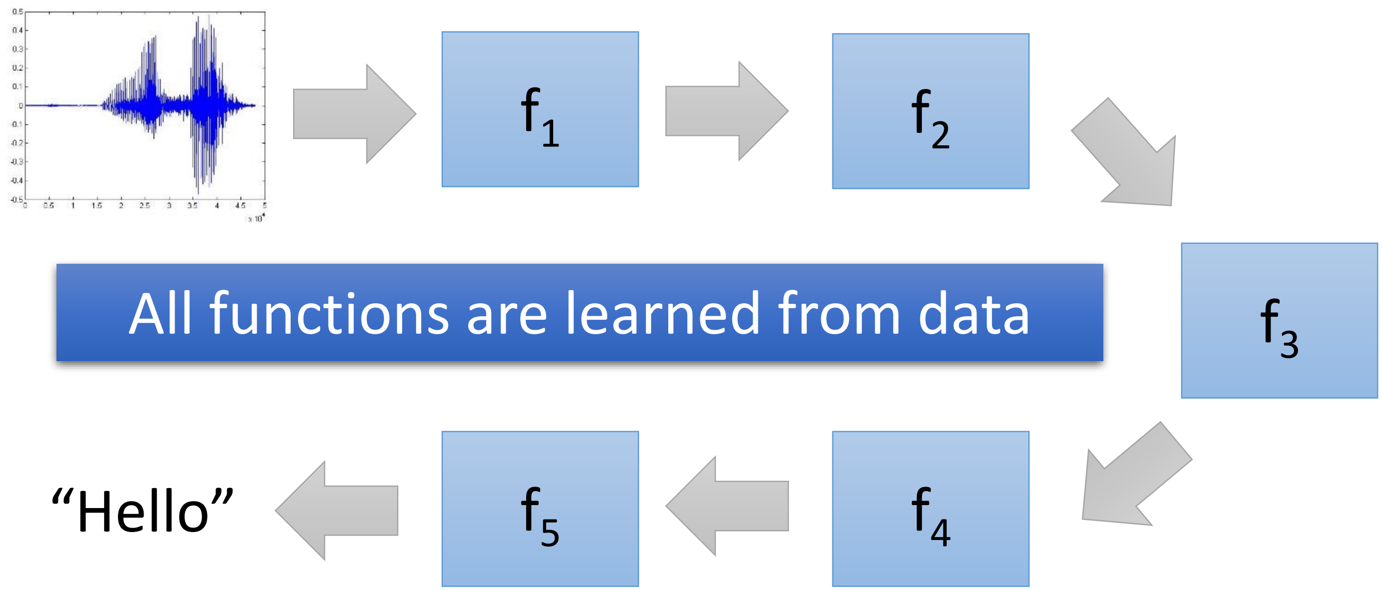
Each box is a simple function in the production line:

:hand-crafted :learned from data

End-to-end Learning
- Speech Recognition

- Deep Learning

先做Fourier transform

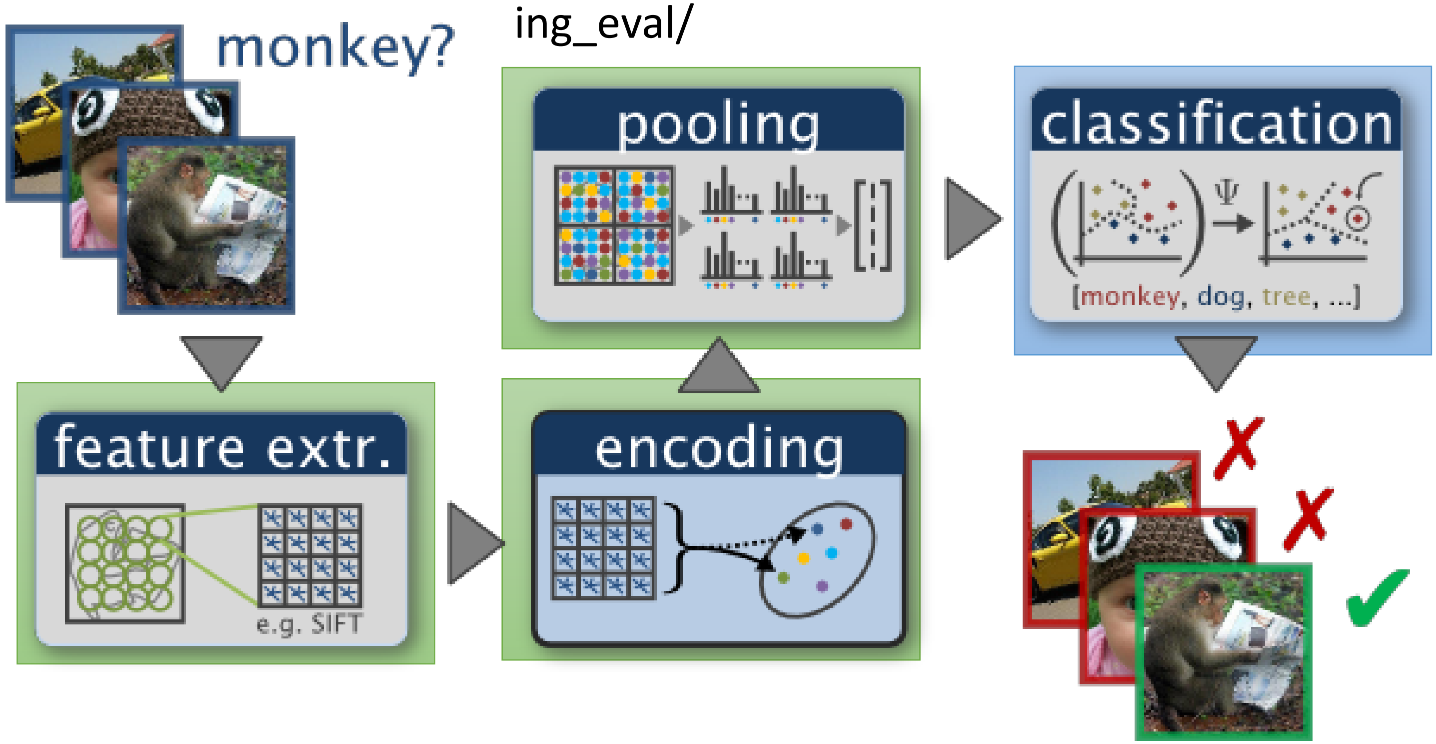


Less engineering labor, but machine learns more

End-to-end Learning
- Image Recognition

- Shallow Approach

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

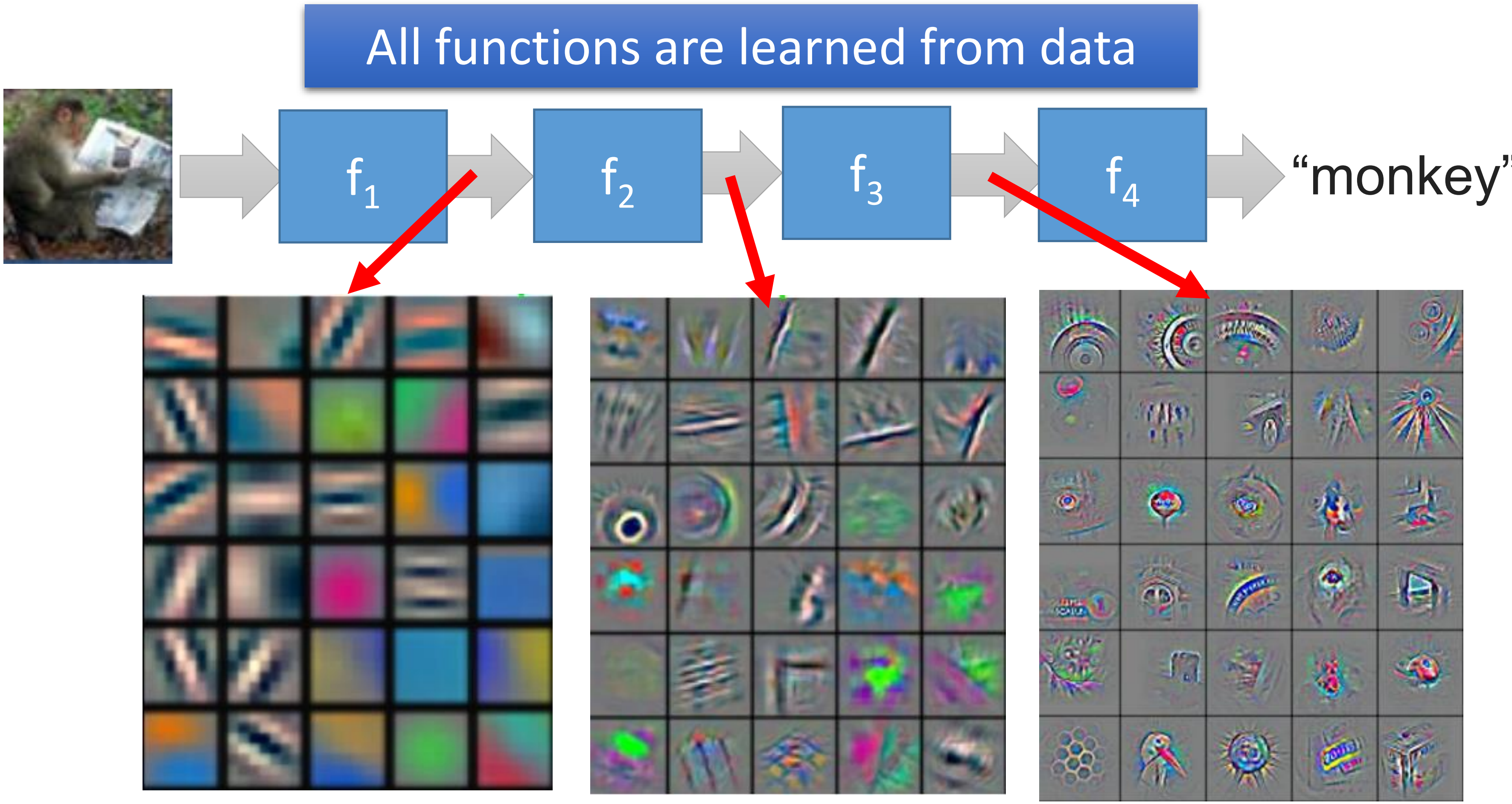


:hand-crafted :learned from data

End-to-end Learning - Image Recognition

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

- Deep Learning



Complex Task …

- Very similar input, different output 輸入很像，輸出不像

System → dog

System → bear

- Very different input, similar output 輸入不像，輸出很像

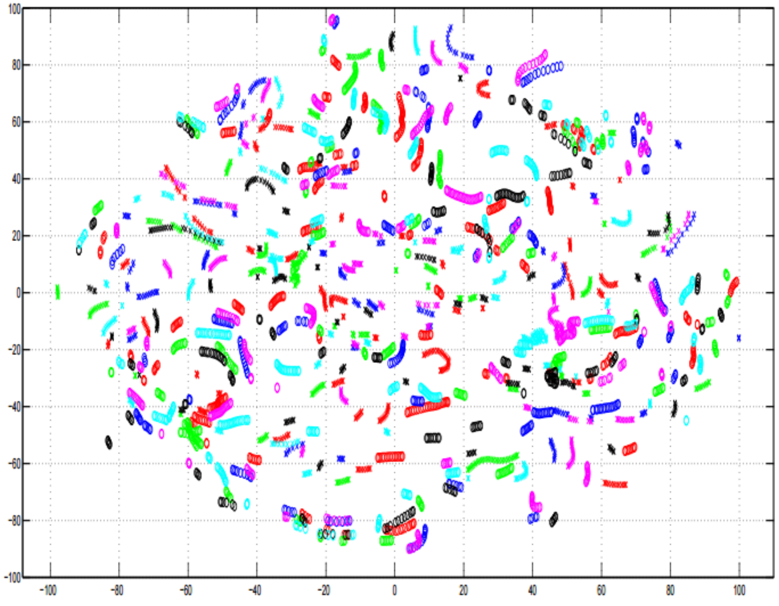
System → train

System → train

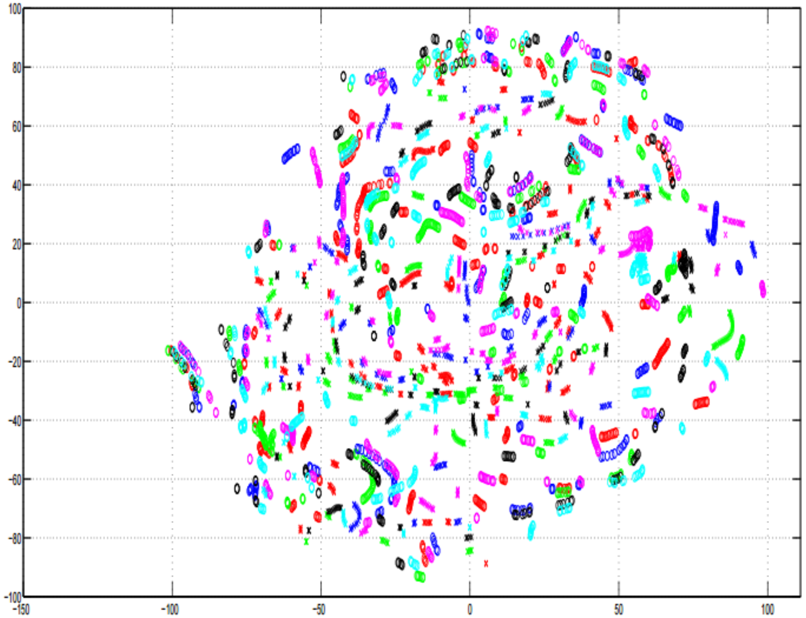
Complex Task …

A. Mohamed, G. Hinton, and G. Penn, “Understanding how Deep Belief Networks Perform Acoustic Modelling,” in ICASSP, 2012.

- Speech recognition: Speaker normalization is automatically done in DNN



Input Acoustic Feature (MFCC)

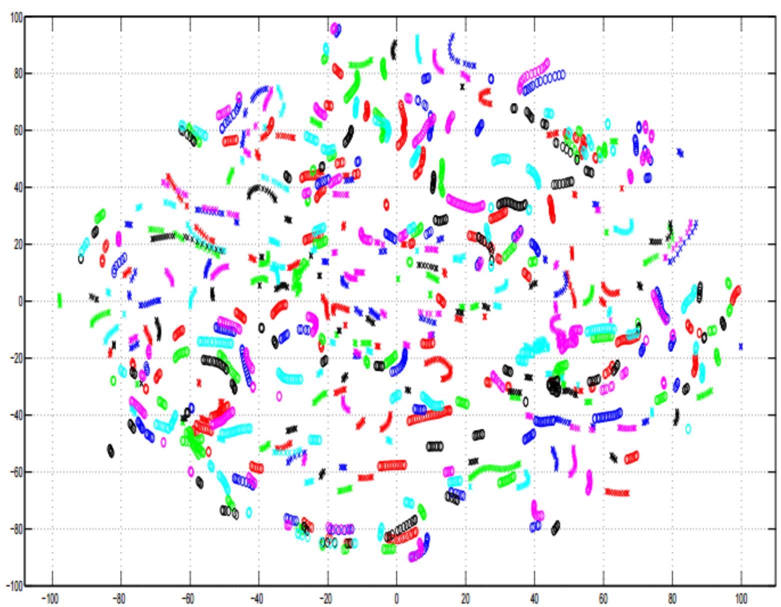


1-st Hidden Layer

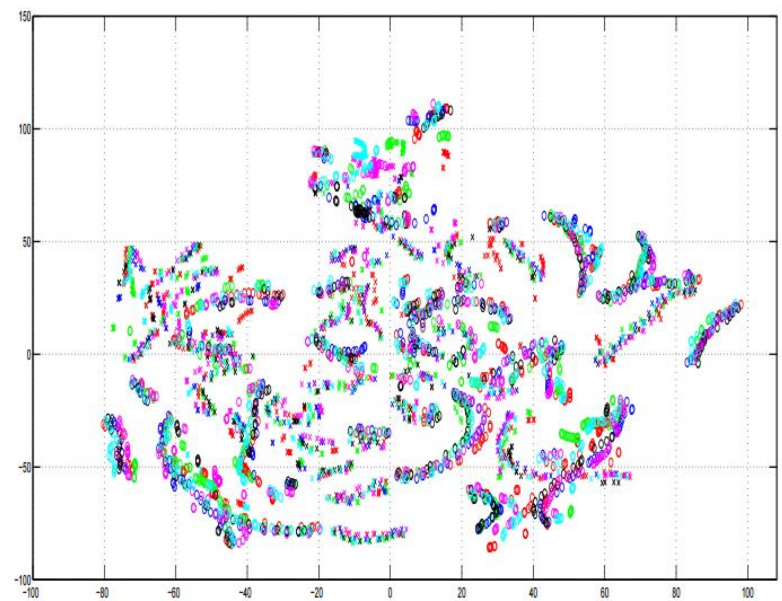
Complex Task …

A. Mohamed, G. Hinton, and G. Penn, “Understanding how Deep Belief Networks Perform Acoustic Modelling,” in ICASSP, 2012.

• Speech recognition: Speaker normalization is automatically done in DNN



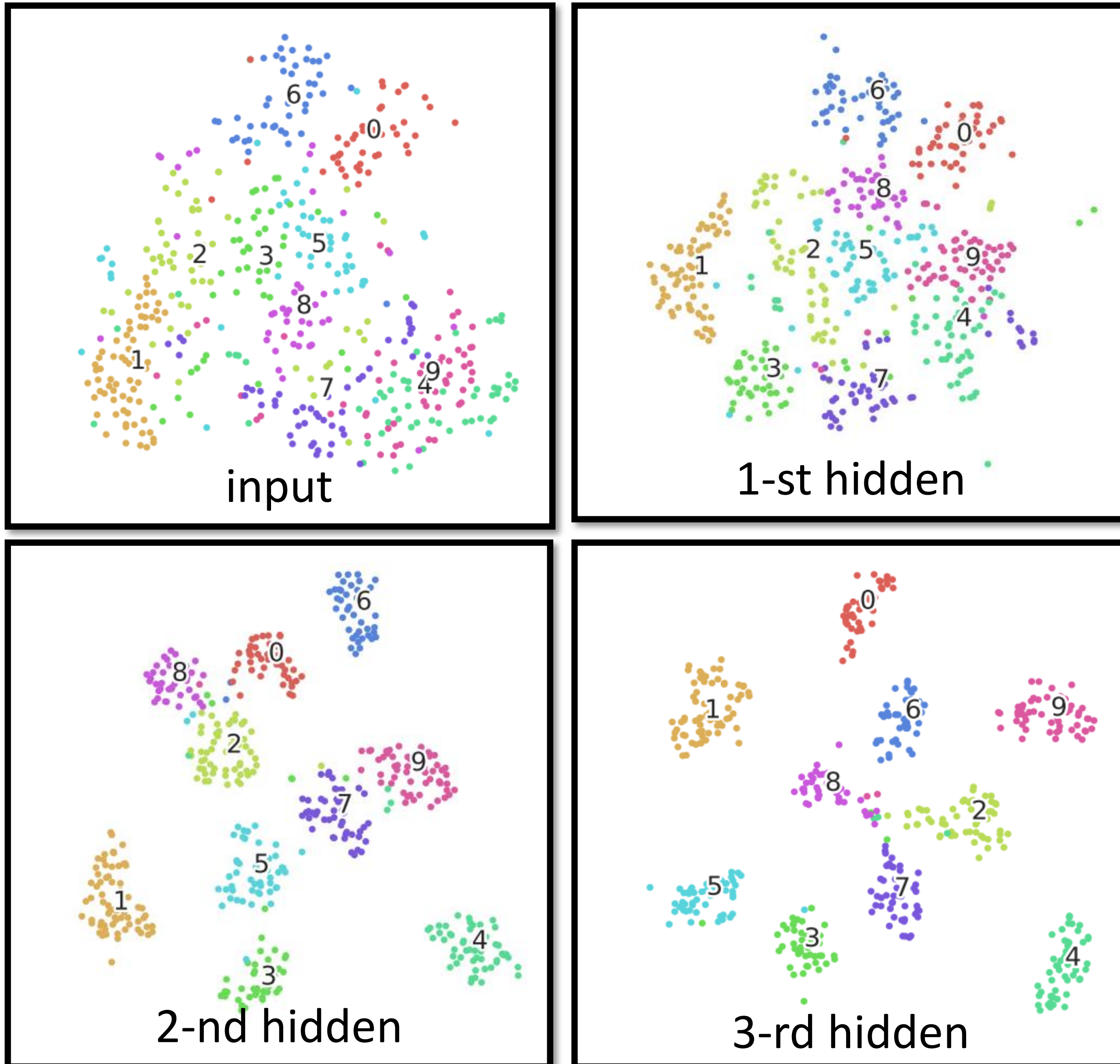
Input Acoustic Feature (MFCC)



8-th Hidden Layer

通過很多hidden　layer轉換，machine
已經將同一句不同人的話都在一起

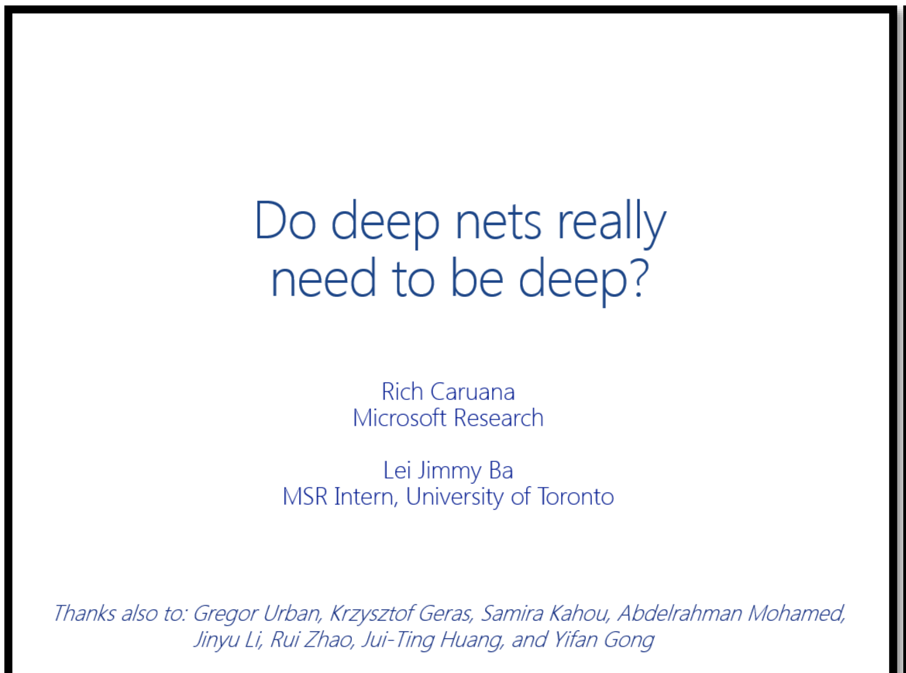
MNIST

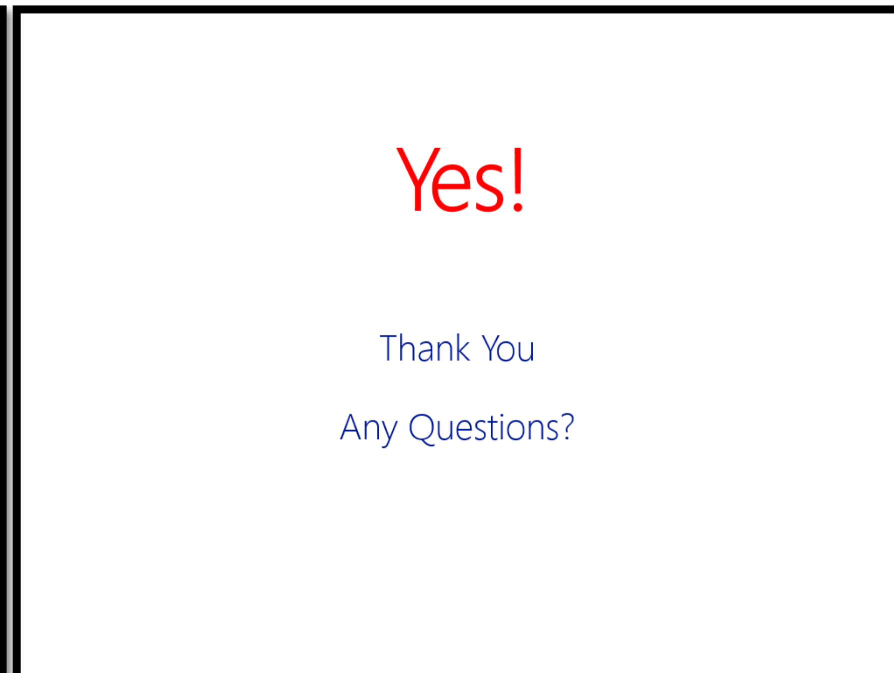


To learn more …

看一下！

- Do Deep Nets Really Need To Be Deep? (by Rich Caruana)
- http://research.microsoft.com/apps/video/default.aspx?id=232373&r=1





keynote of Rich Caruana at ASRU 2015

To learn more …

- Deep Learning: Theoretical Motivations (*Yoshua Bengio*)
  - http://videolectures.net/deeplearning2015_bengio_theoretical_motivations/
- Connections between physics and deep learning
  - https://www.youtube.com/watch?v=5MdSE-N0bxs
- Why Deep Learning Works: Perspectives from Theoretical Chemistry
  - https://www.youtube.com/watch?v=kIbKHIPbxiU