# Why Deep Learning?

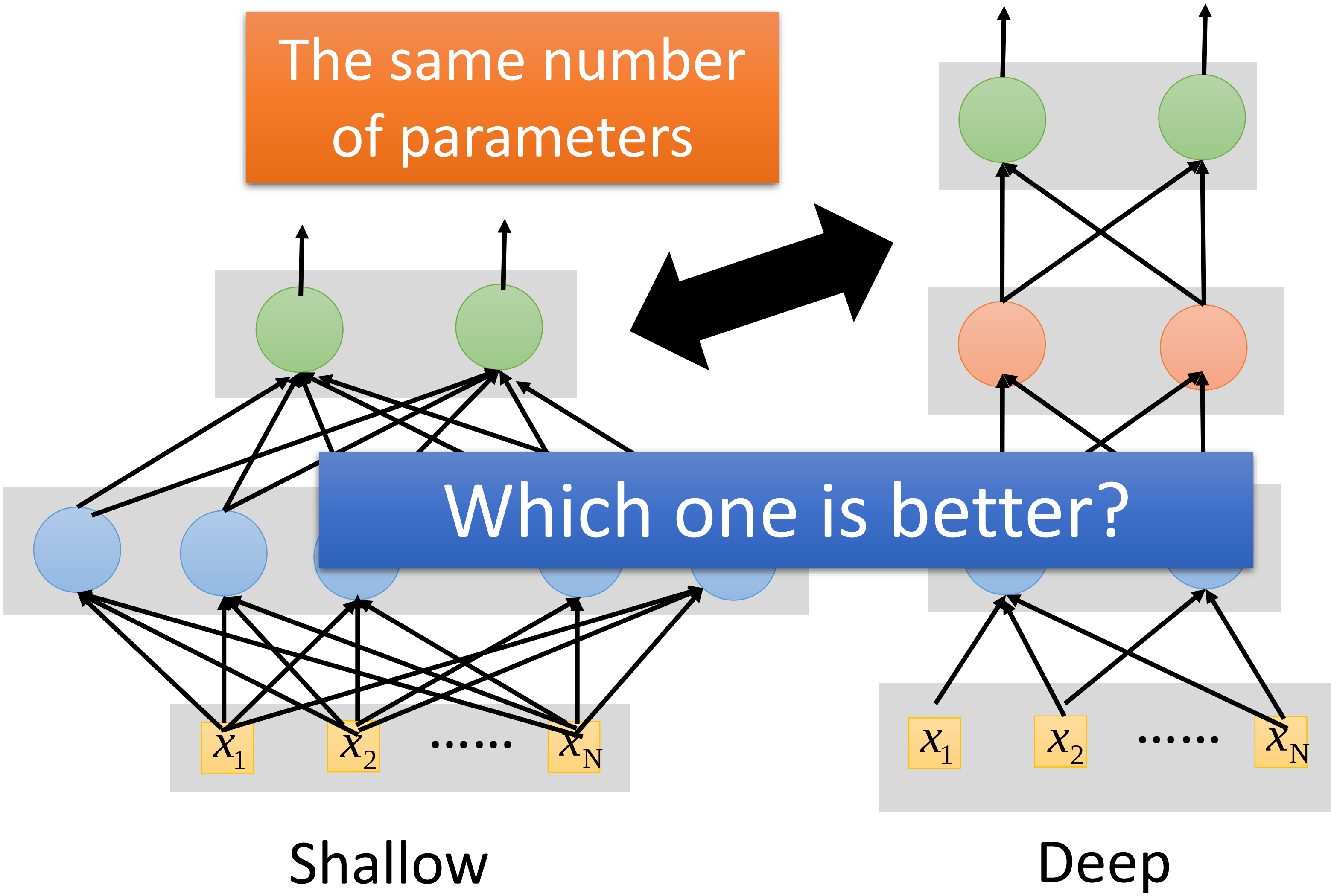
# Deeper is Better?

| 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



# Fat + Short v.s. Thin + Tall

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| 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 |

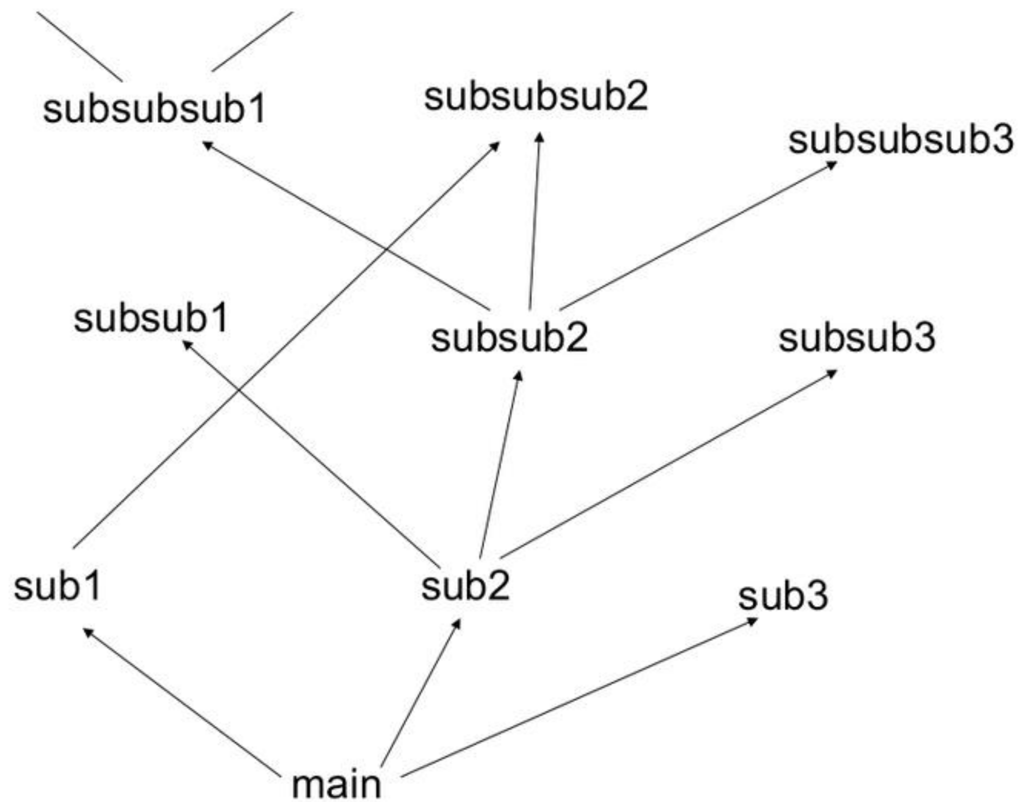
Why?

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

# Modularization

- Deep → Modularization

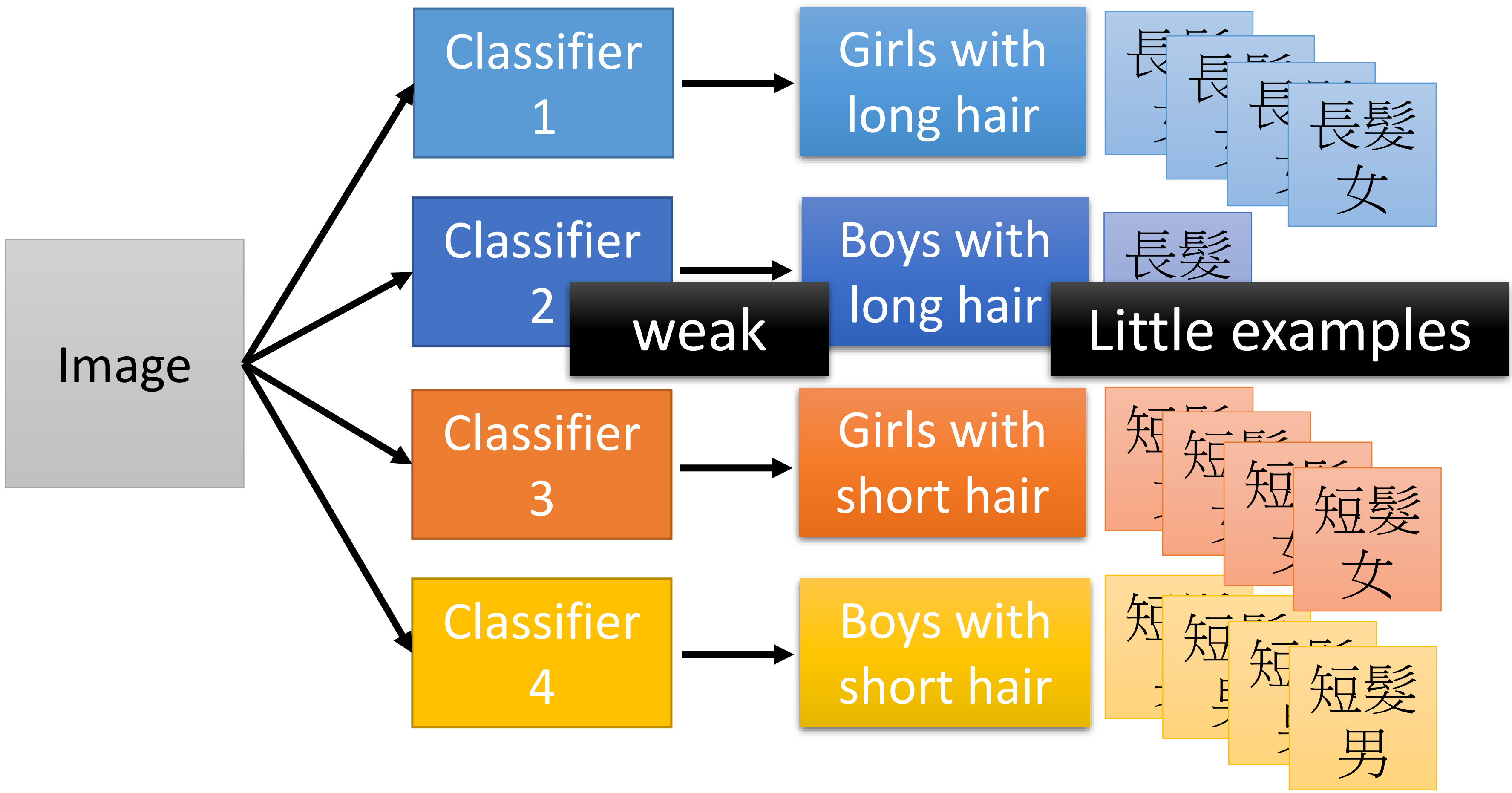
Don't put everything in your main function.




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

# Modularization

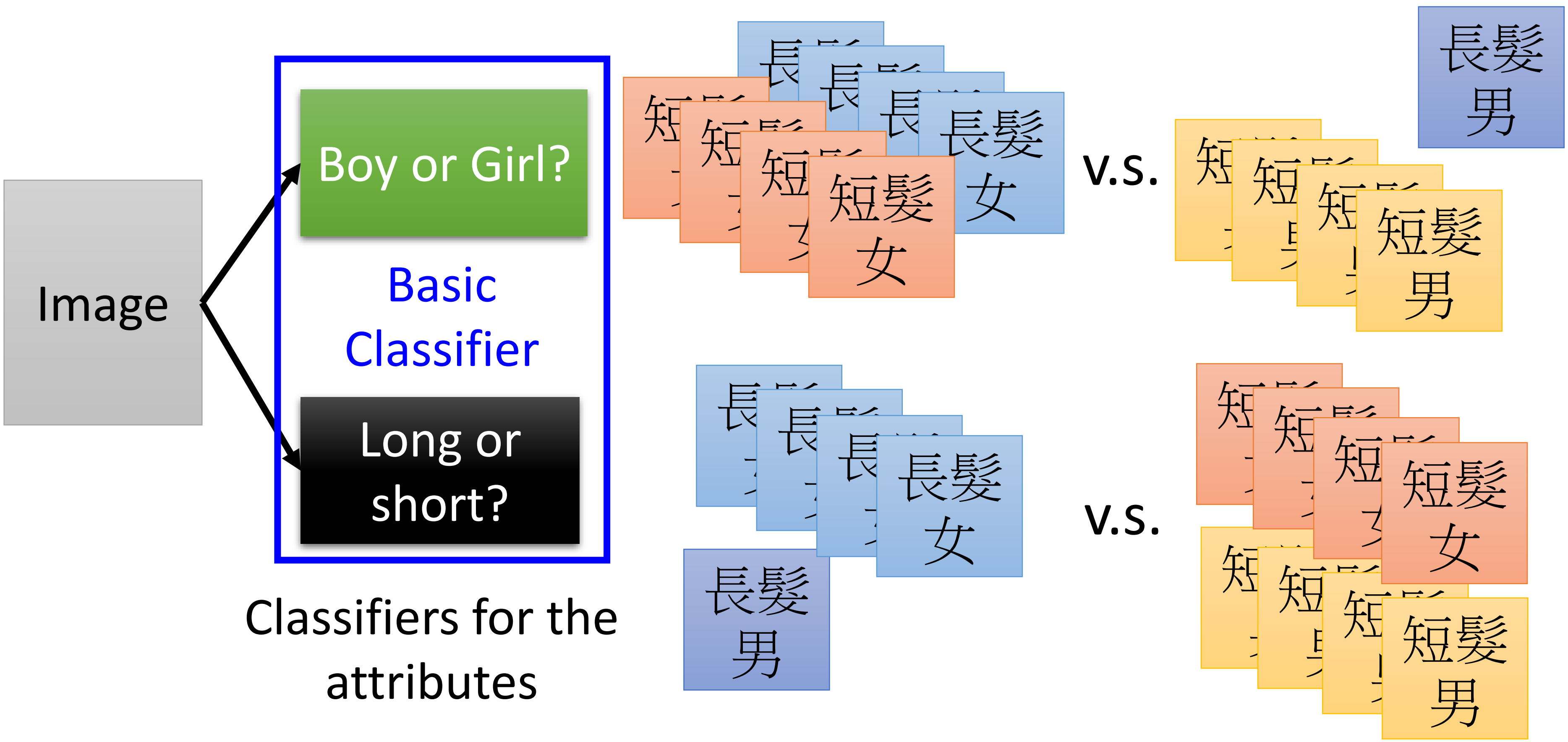
- Deep → Modularization



# Modularization

**Each basic classifier can have sufficient training examples.**

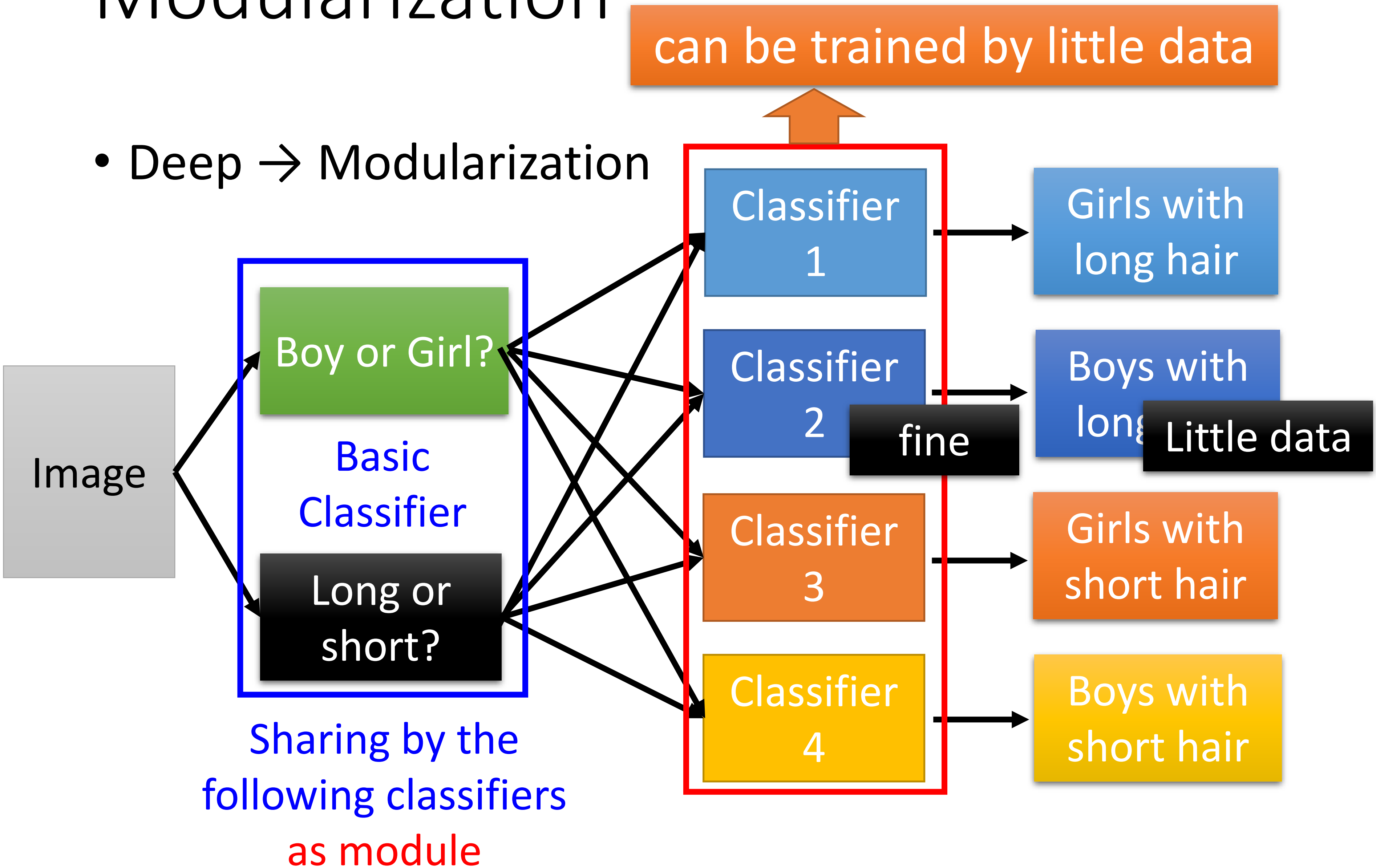
- Deep → Modularization




Classifiers for the attributes

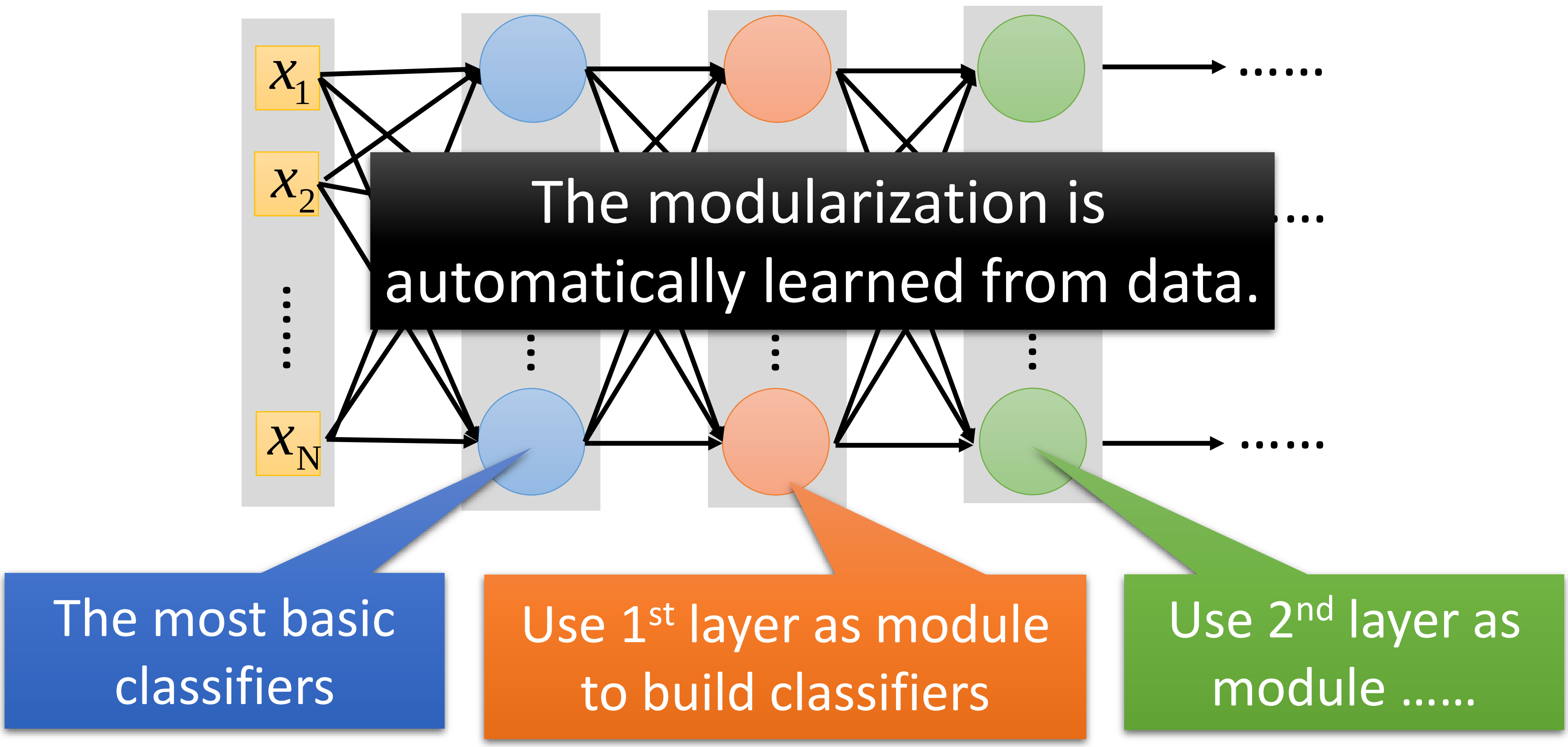
# Modularization

- Deep → Modularization



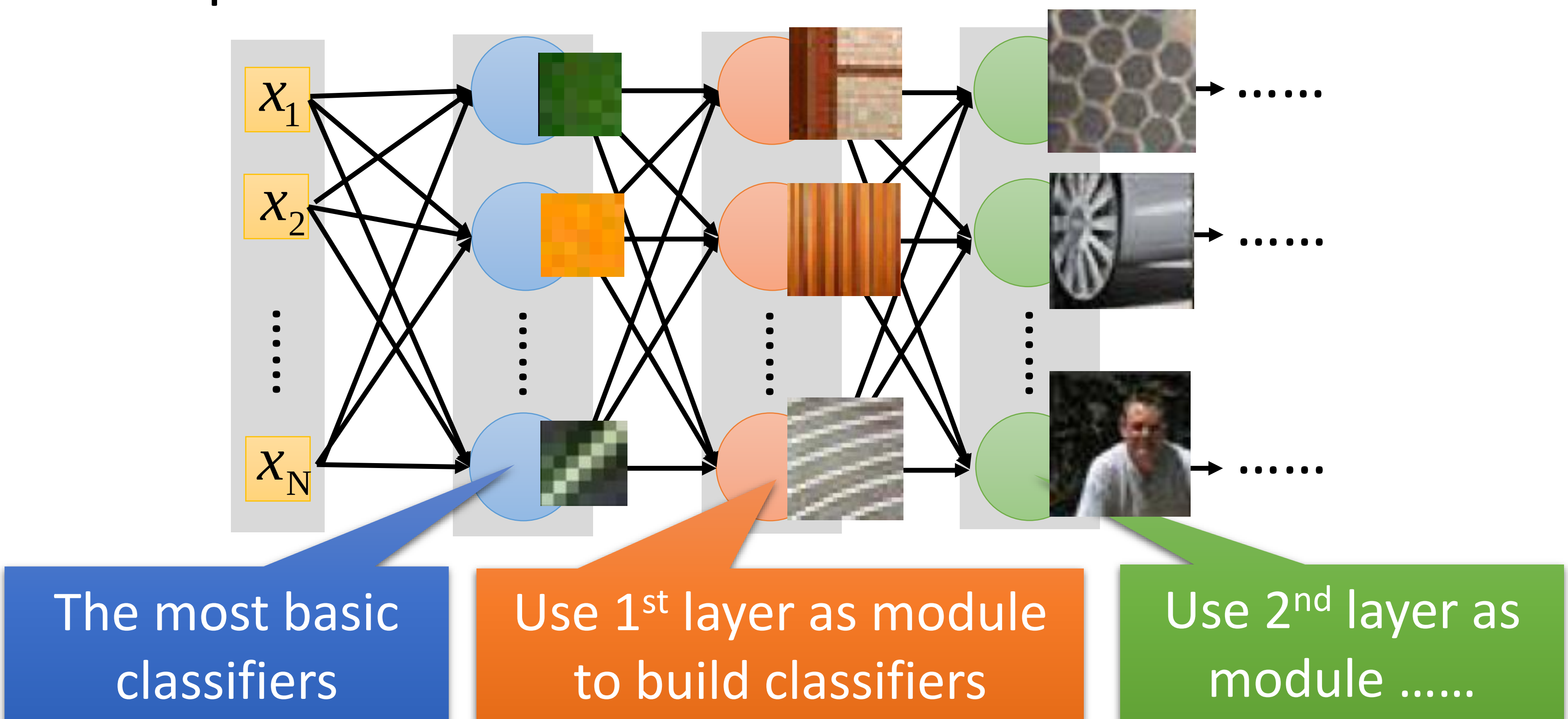
# Modularization

- 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:***

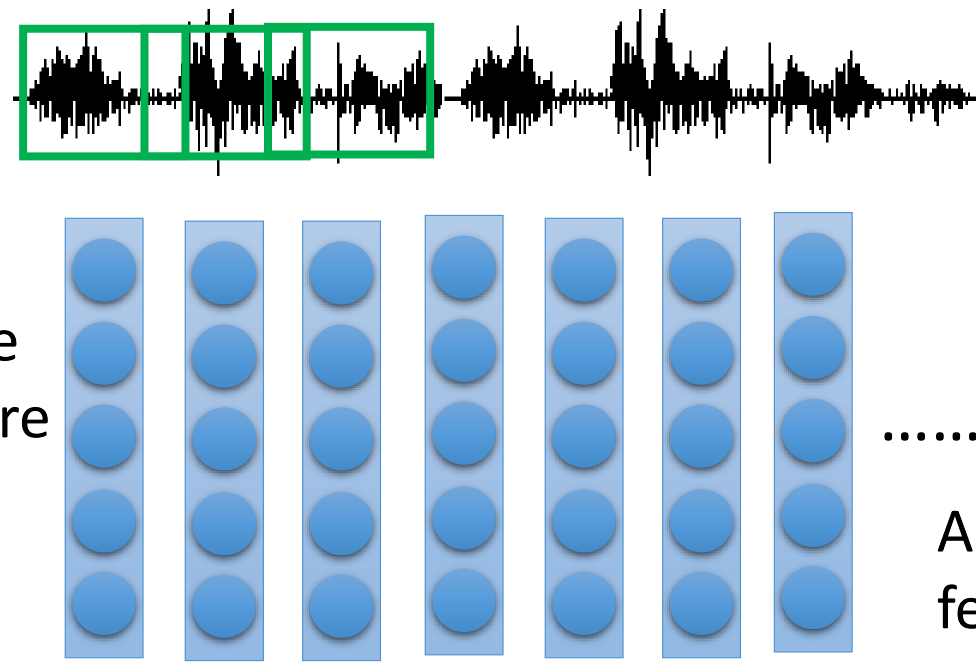
…… t-d+uw d-uw+y    uw-y+uw y-uw+th  ……

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

***State:***

# Modularization - Speech

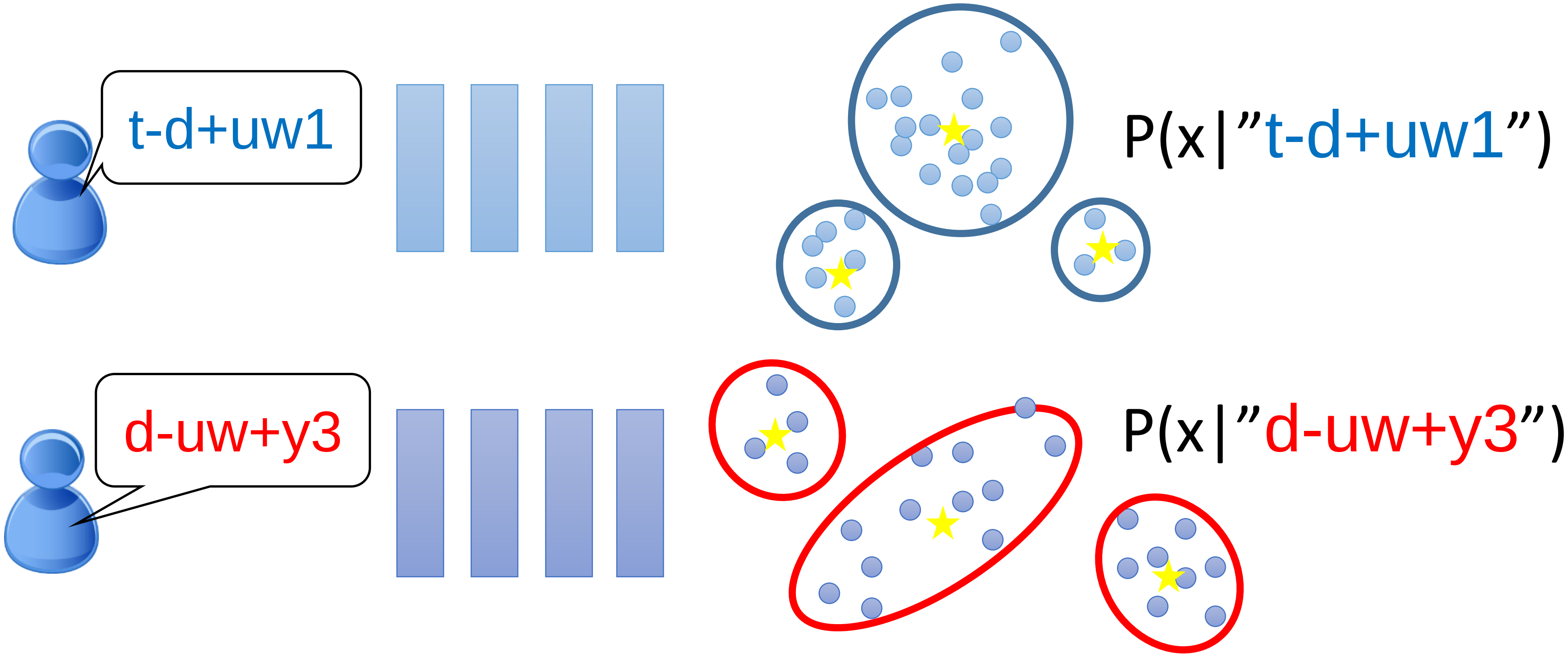
- The first stage of speech recognition
  - Classification: input → acoustic feature, output → state



# 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

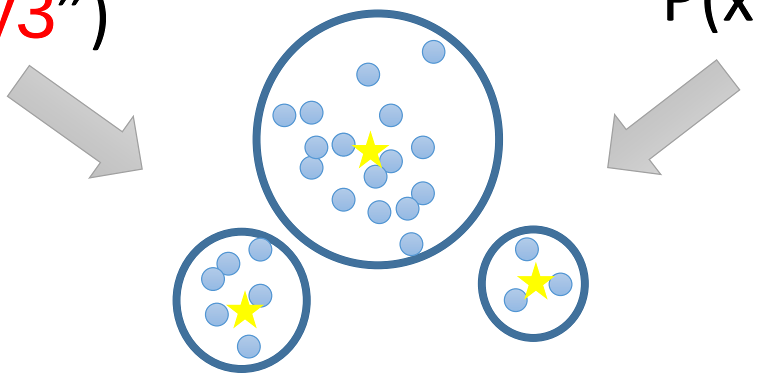
***<u>Tied-state</u>***

pointer

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

pointer

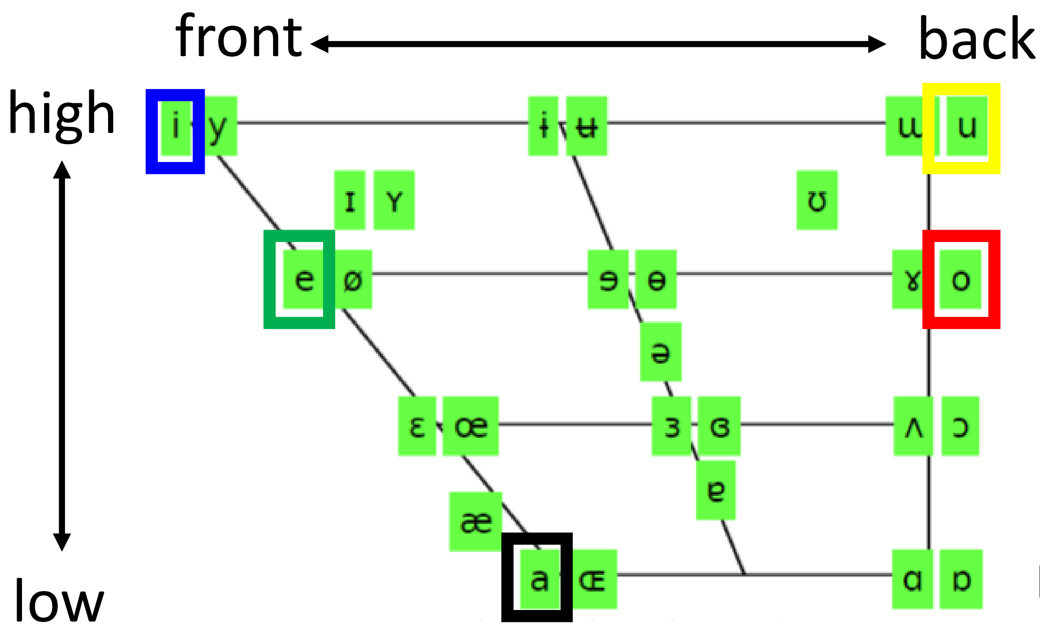
P(x|"y-uw+th3")



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/

# Modularization - Speech

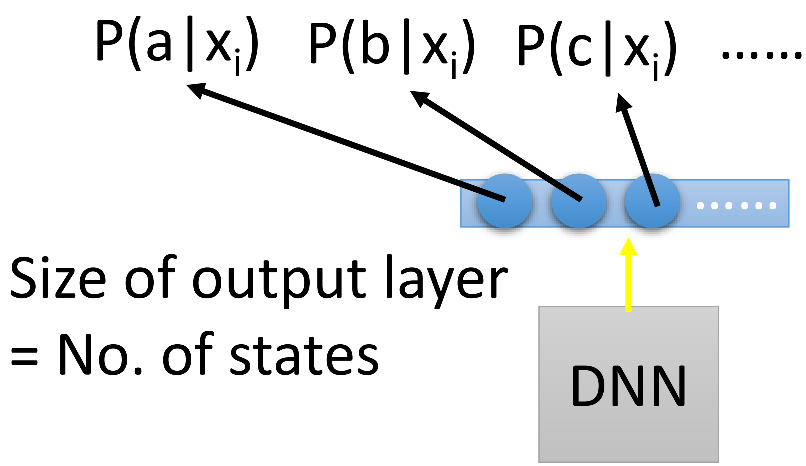
- DNN input:

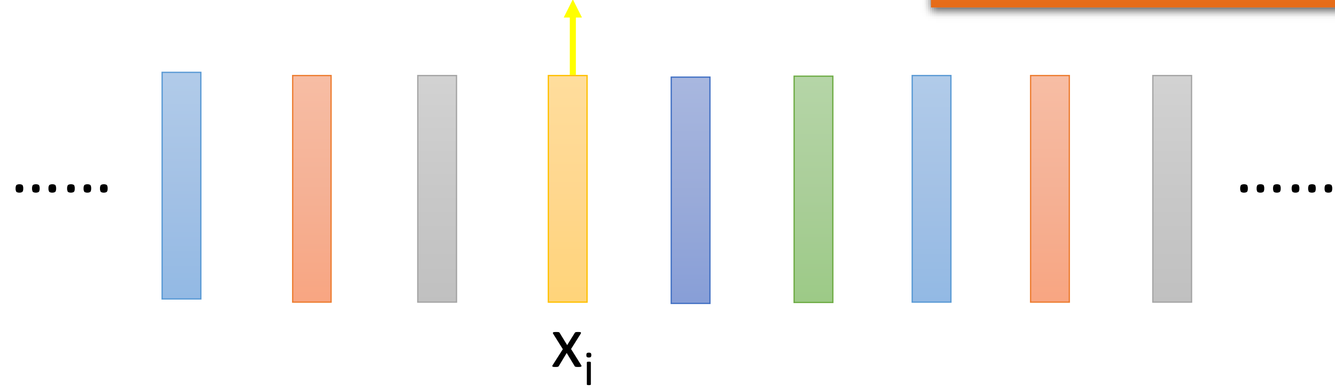
  One acoustic feature

- DNN output:

  Probability of each state

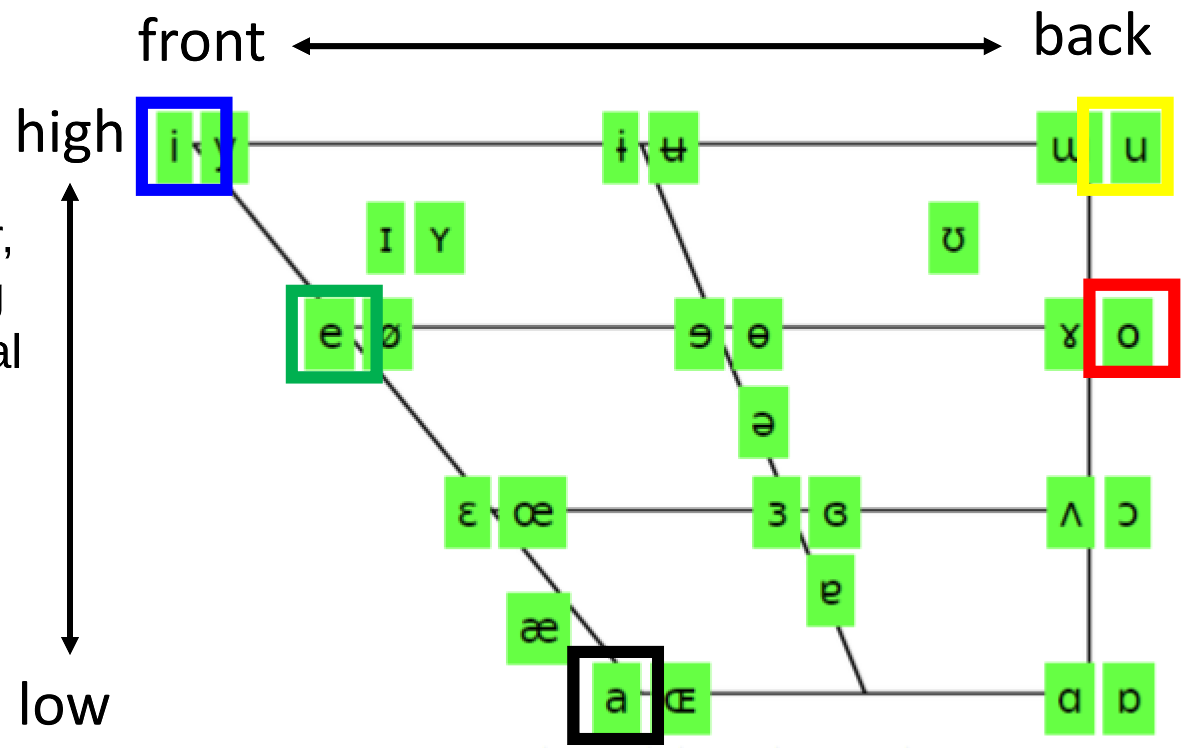
All the states use the same DNN



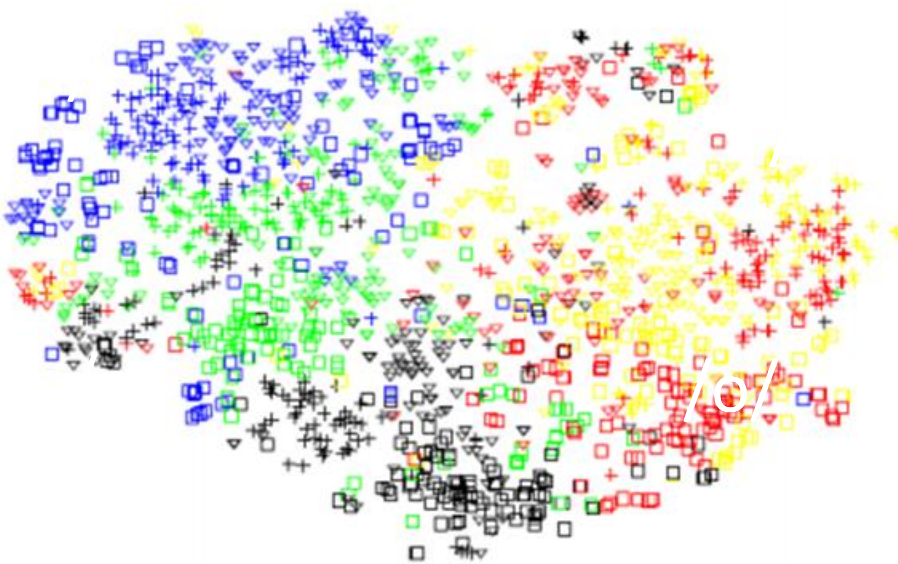



# ***Modularization***

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

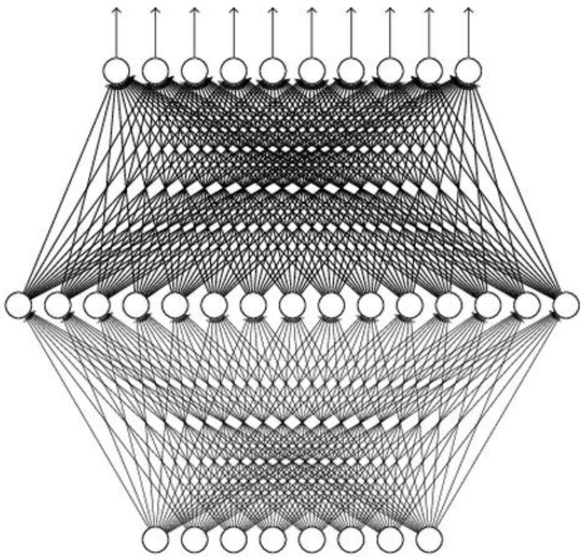
# Universality Theorem

Any continuous function f

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

Can be realized by a network with one hidden layer

(given **enough** hidden neurons)

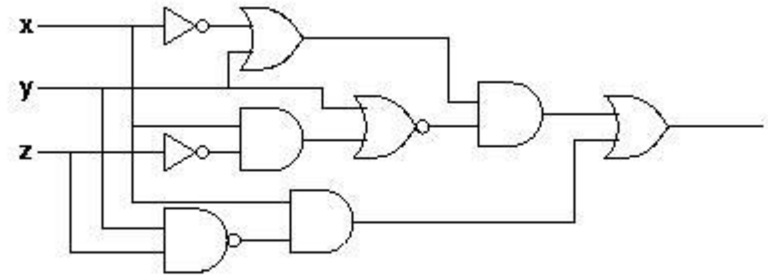


Reference for the reason: http://neuralnetworksanddeeplearning.com/chap4.html

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

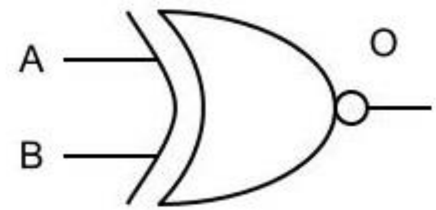
**Neural network**

- 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?

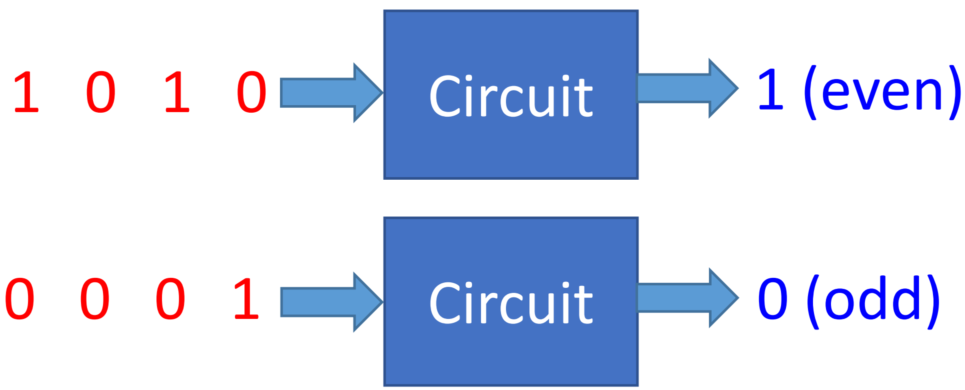
This page is for EE background.

# Analogy



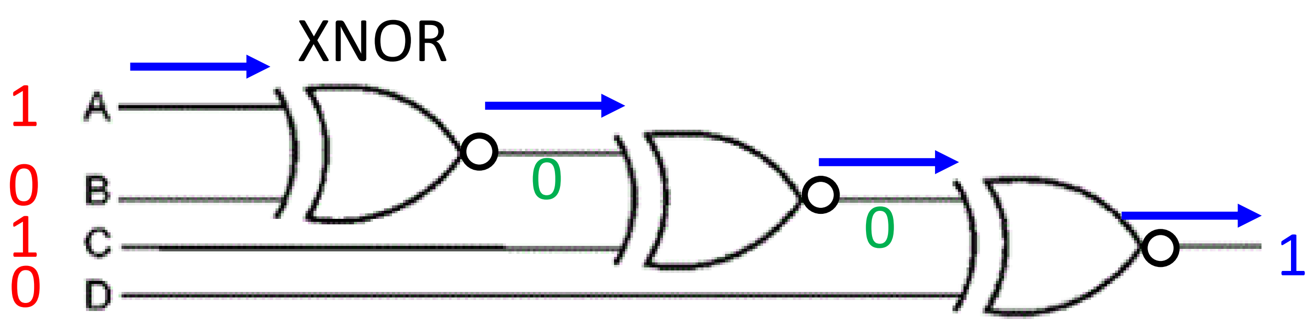

| A | B | O |
|---|---|---|
| 0 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 1 | 1 | 1 |

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



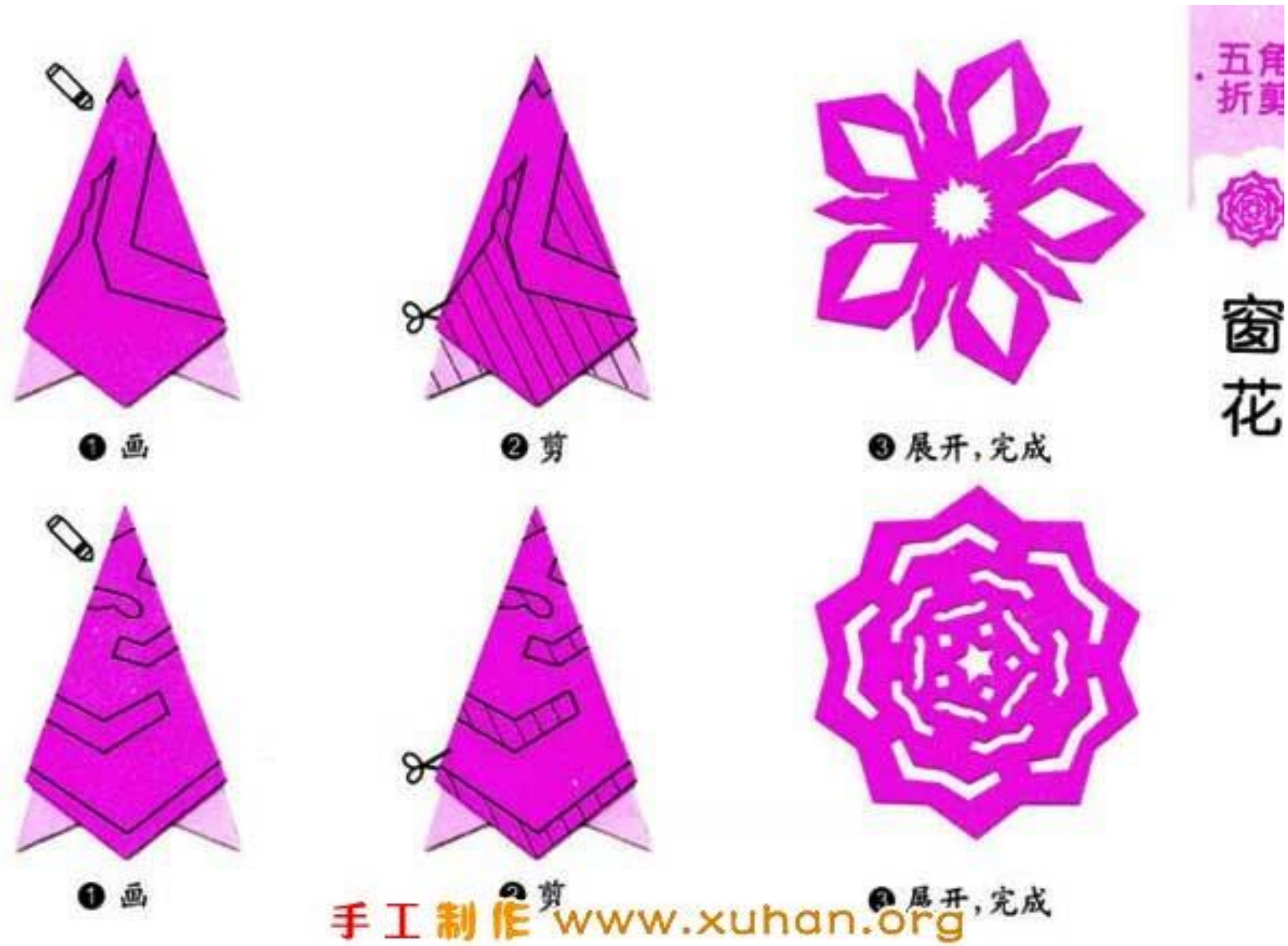

For input sequence with d bits,

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

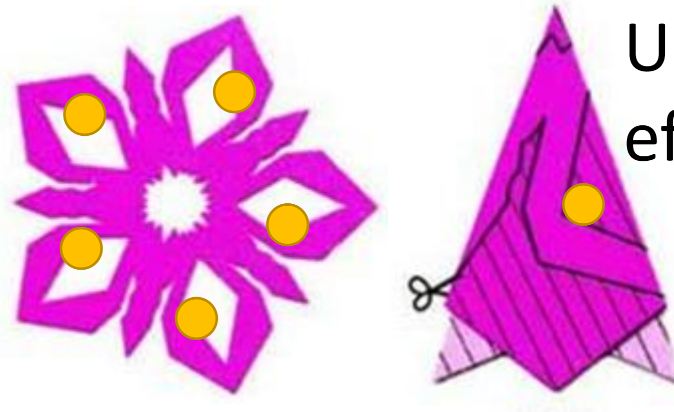



With multiple layers, we need only O(d) gates.

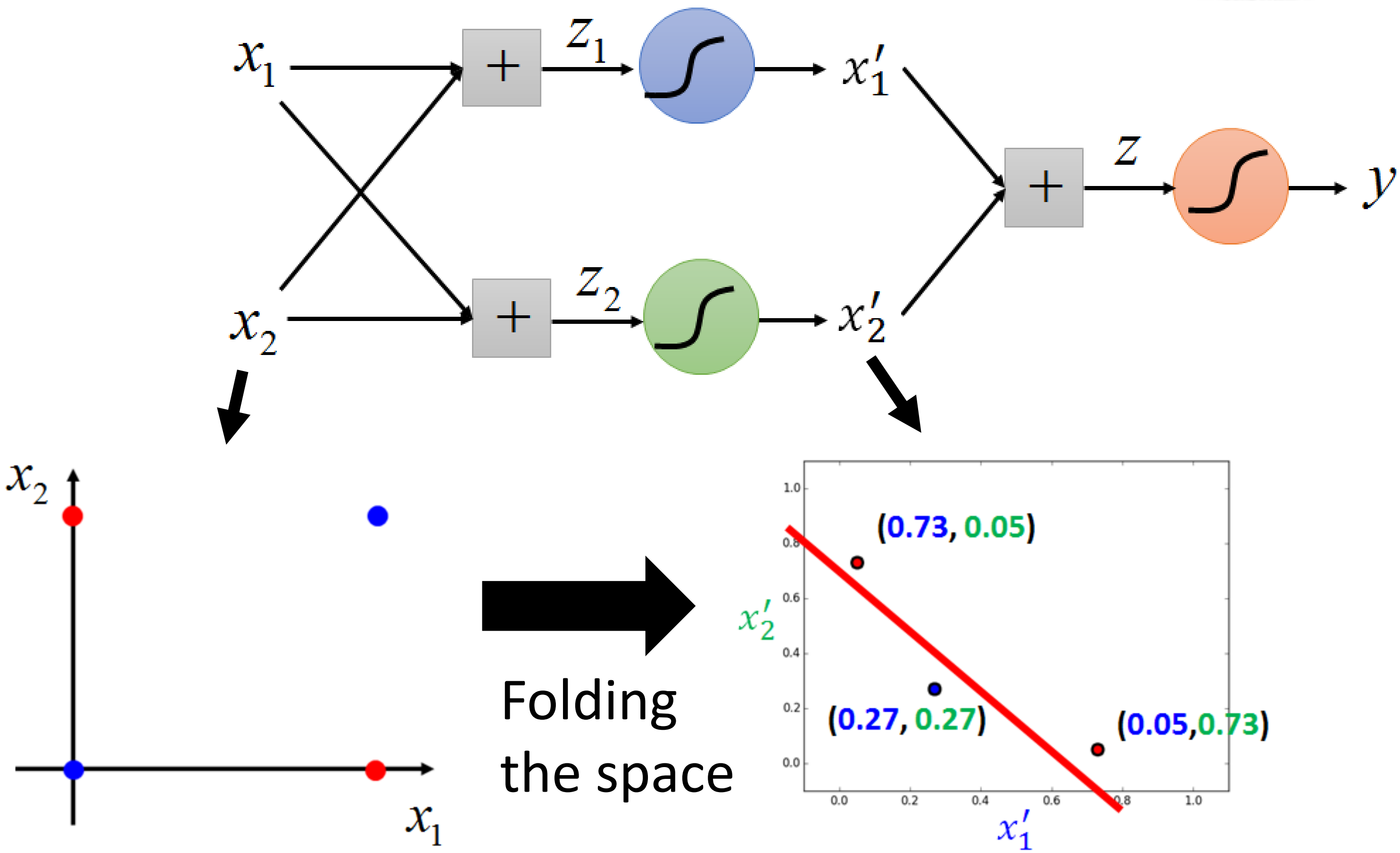
# More Analogy



# More Analogy



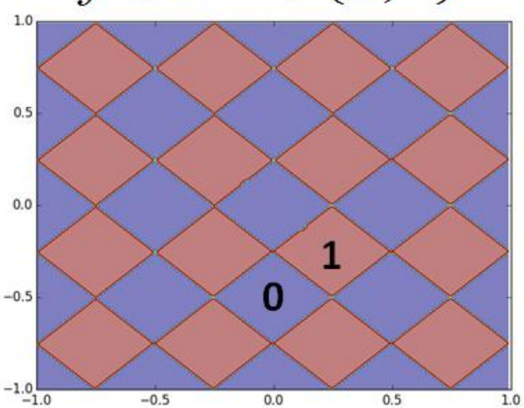
Use data effectively




Folding the space

# More Analogy - Experiment

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

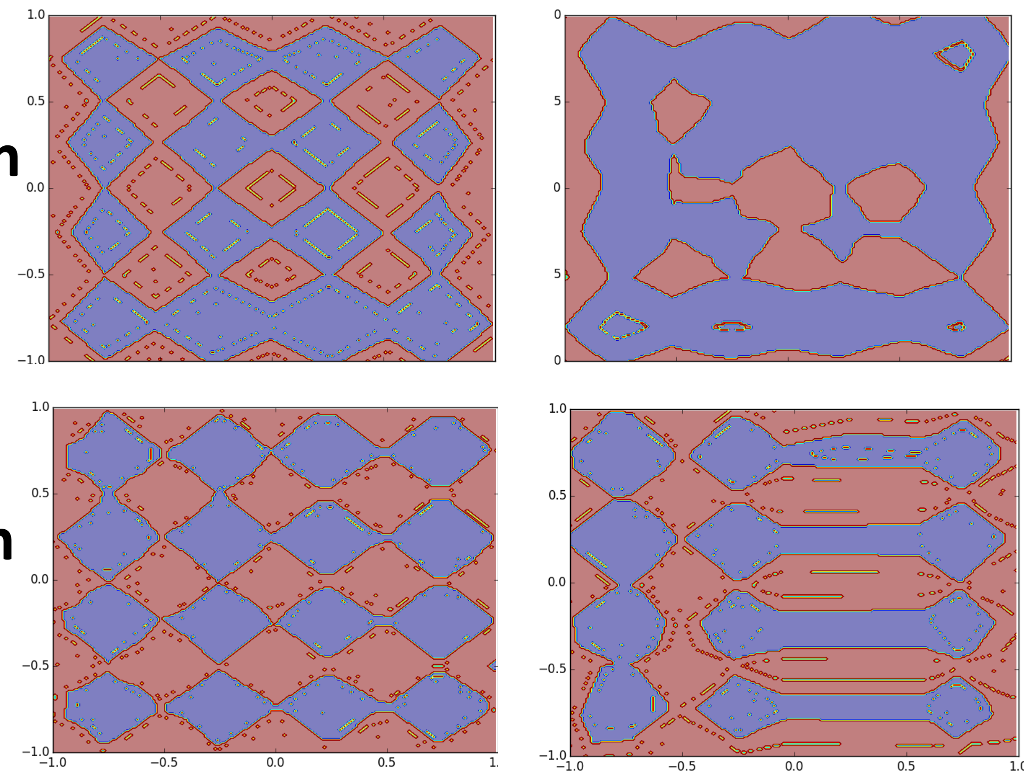



**Different numbers of training examples**

10,0000 2,0000

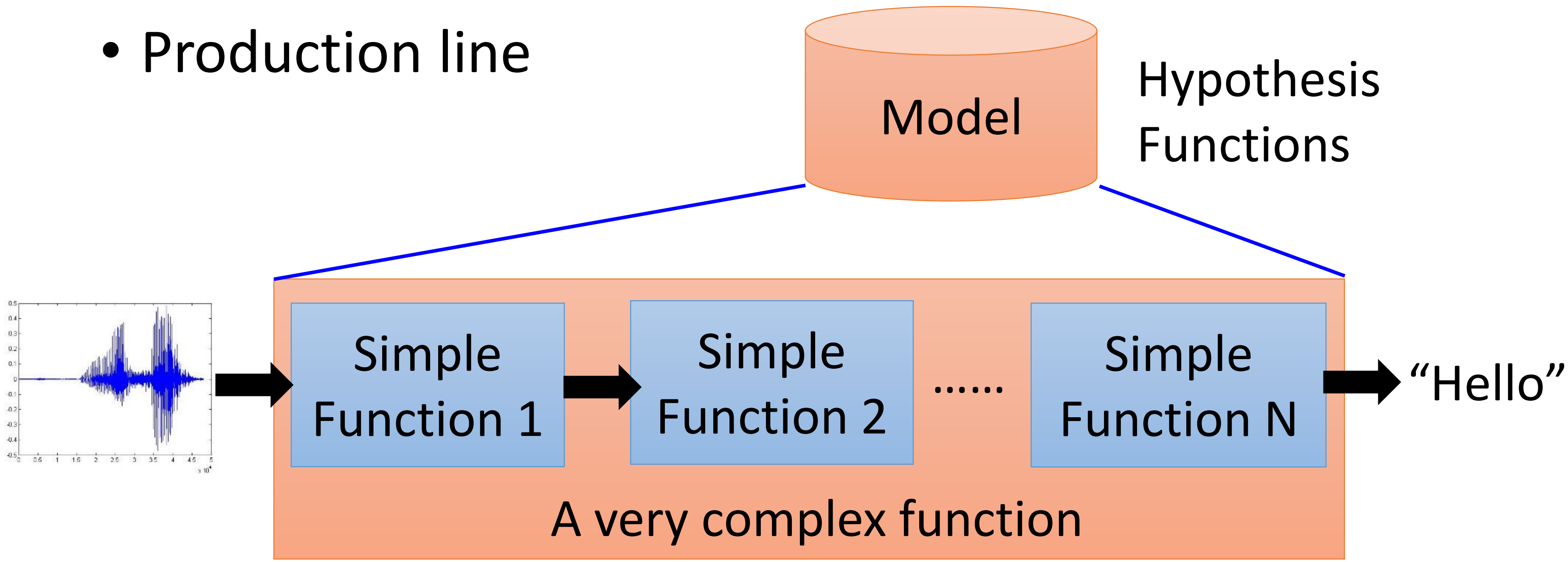
**1 hidden layer**

**3 hidden layers**



# End-to-end Learning

- Production line

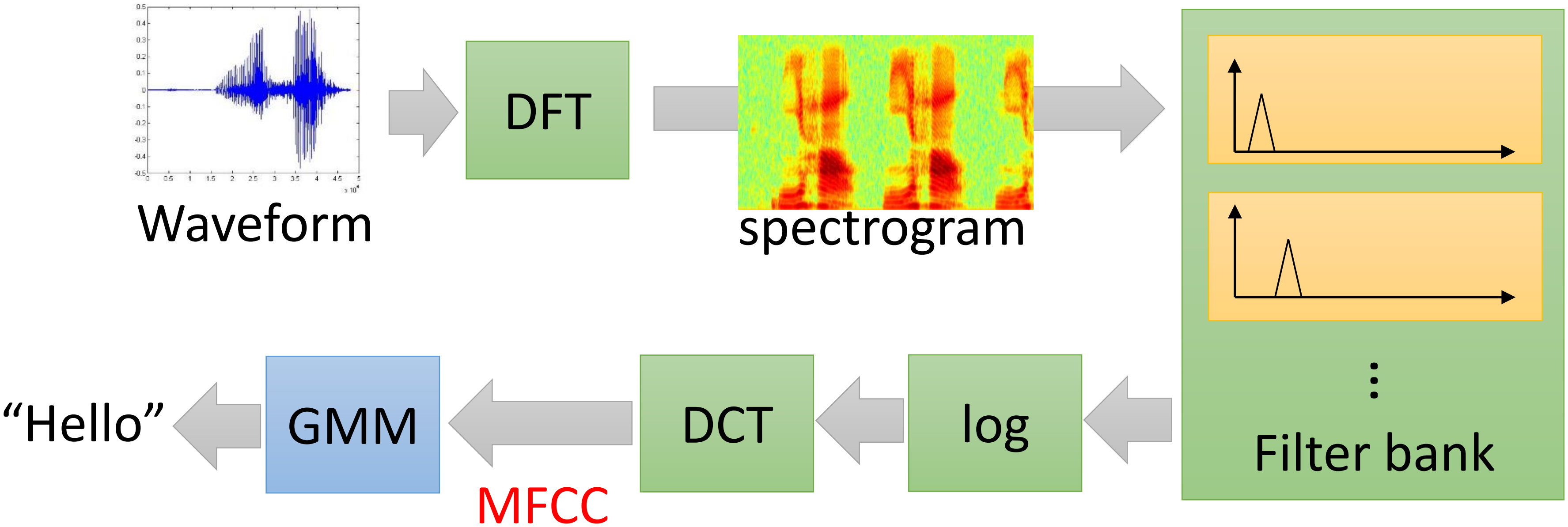



End-to-end training:

What each function should do is learned automatically

# End-to-end Learning
# - Speech Recognition

- Shallow Approach

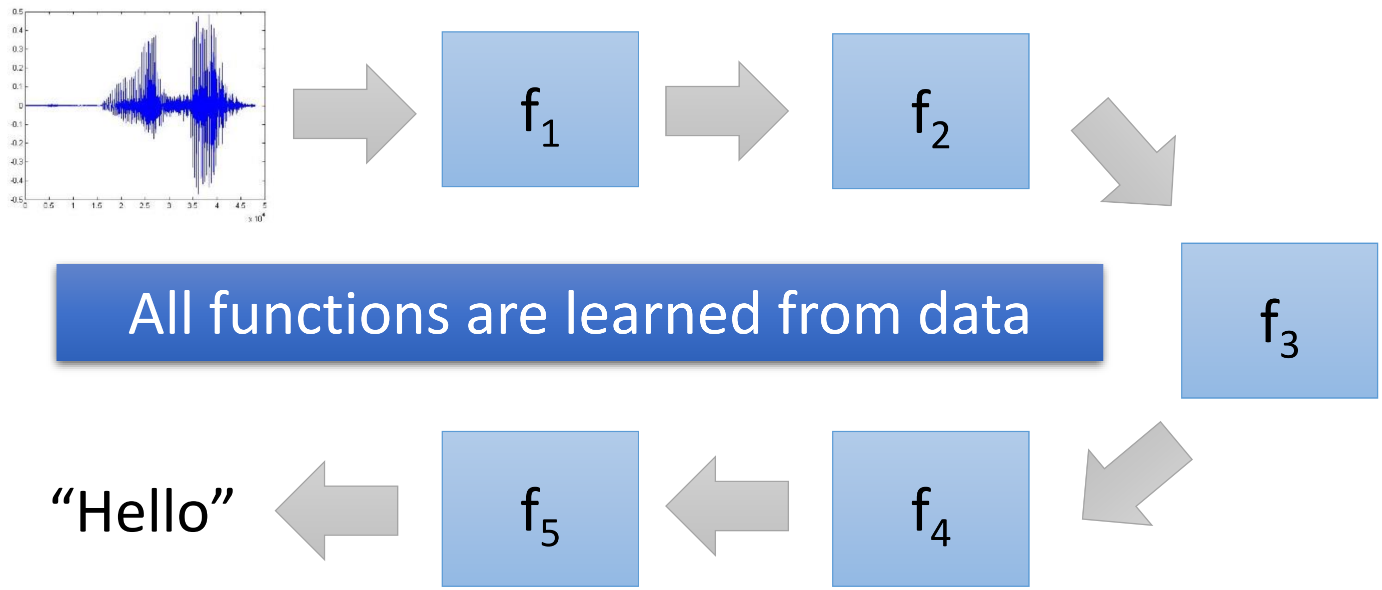



Each box is a simple function in the production line:

:hand-crafted :learned from data

# End-to-end Learning
# - Speech Recognition

- Deep Learning

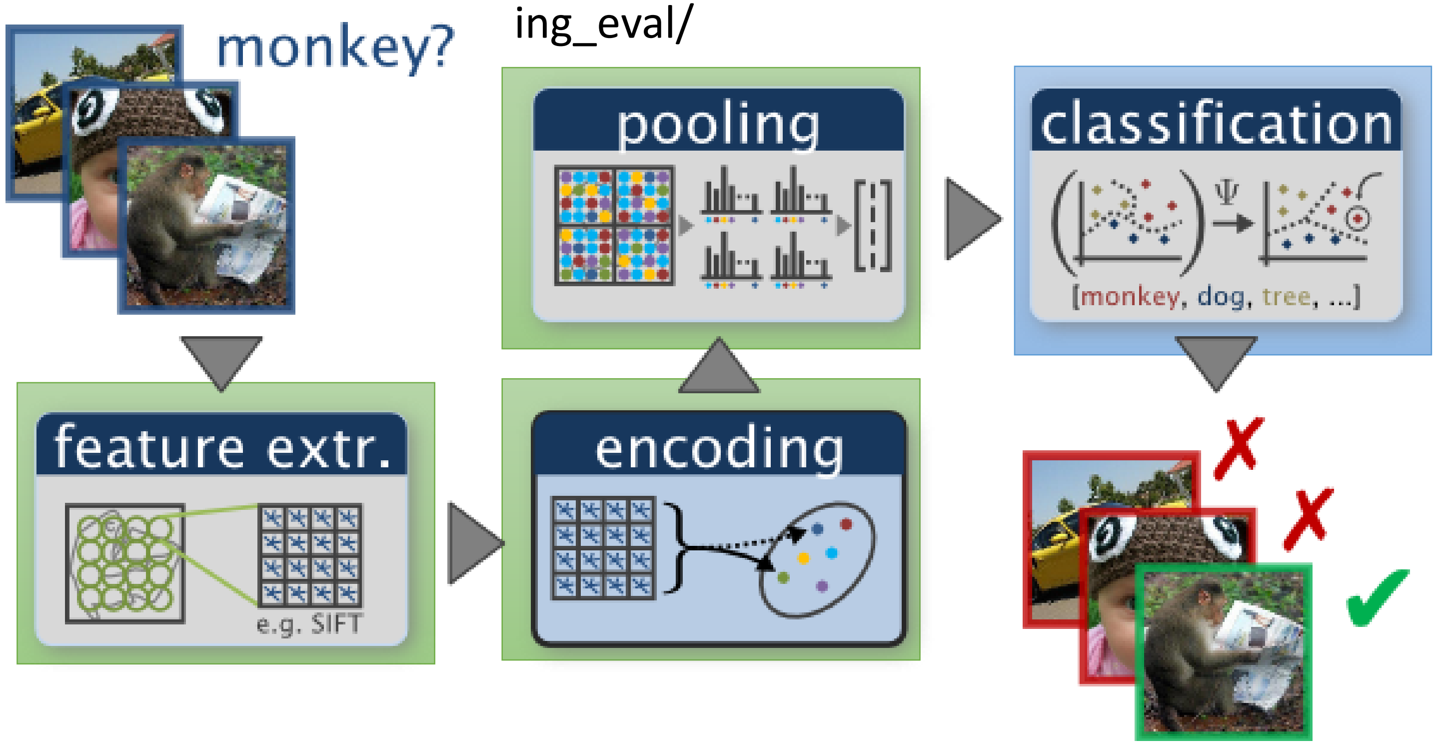



Less engineering labor, but machine learns more

# End-to-end Learning
# - Image Recognition

- Shallow Approach

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

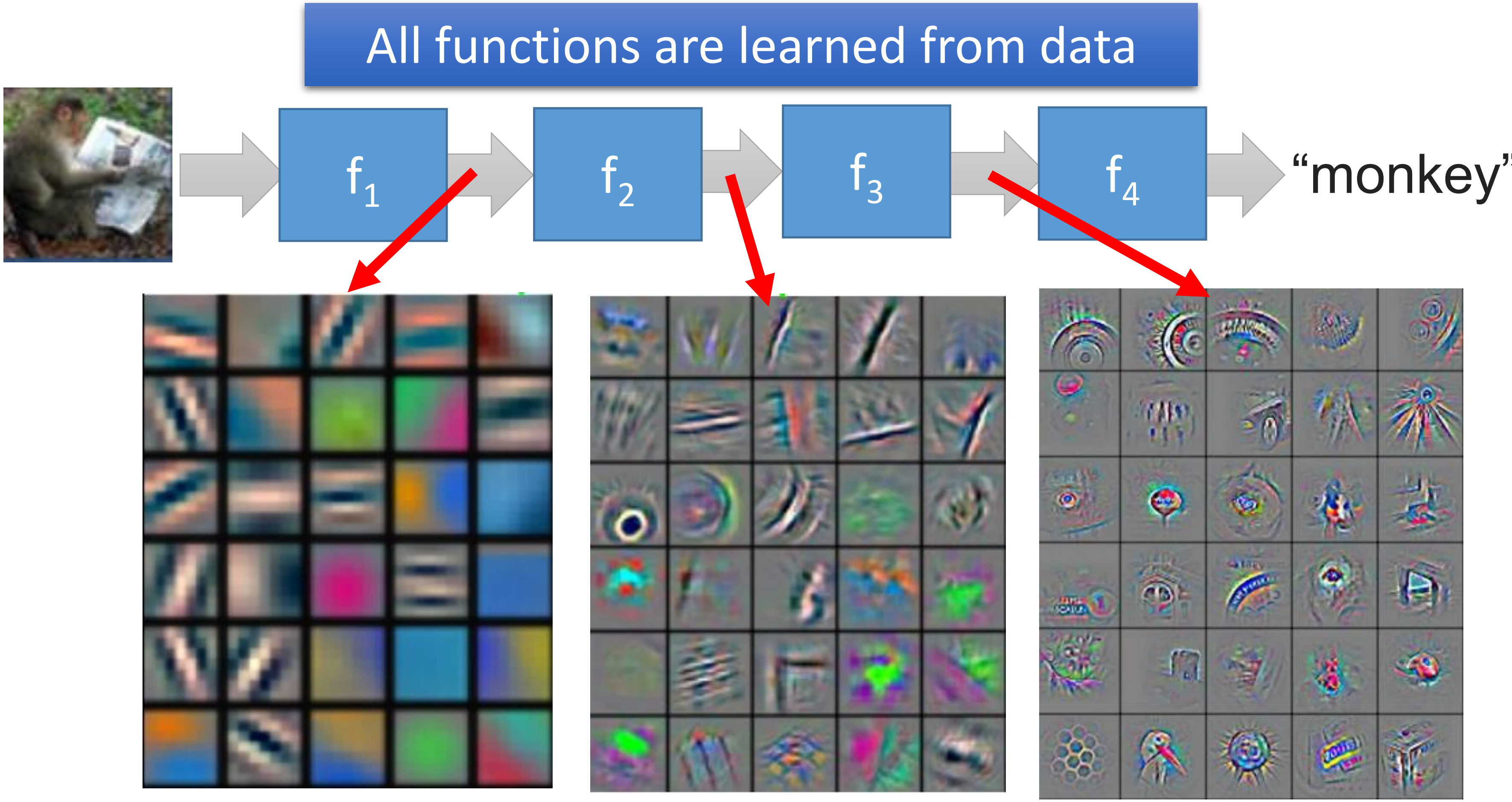



:hand-crafted :learned from data

# End-to-end Learning - Image Recognition

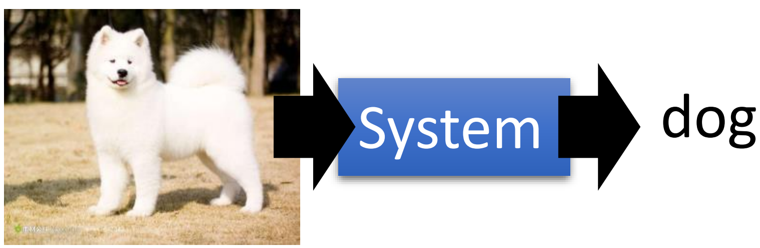
Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)

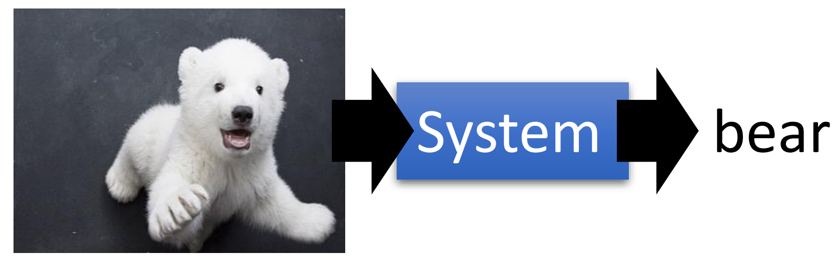
- Deep Learning



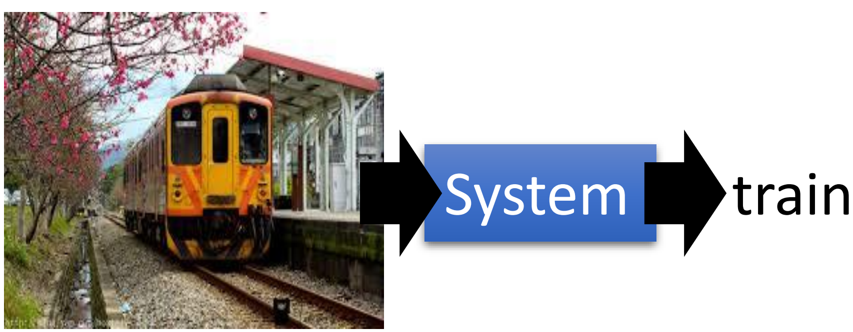
# Complex Task …

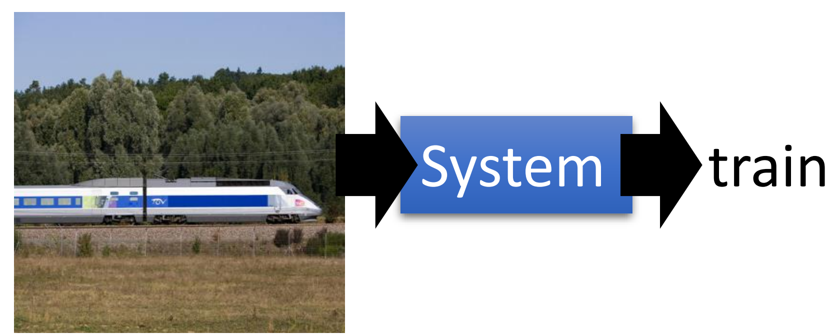
- Very similar input, different output




- Very different input, similar output

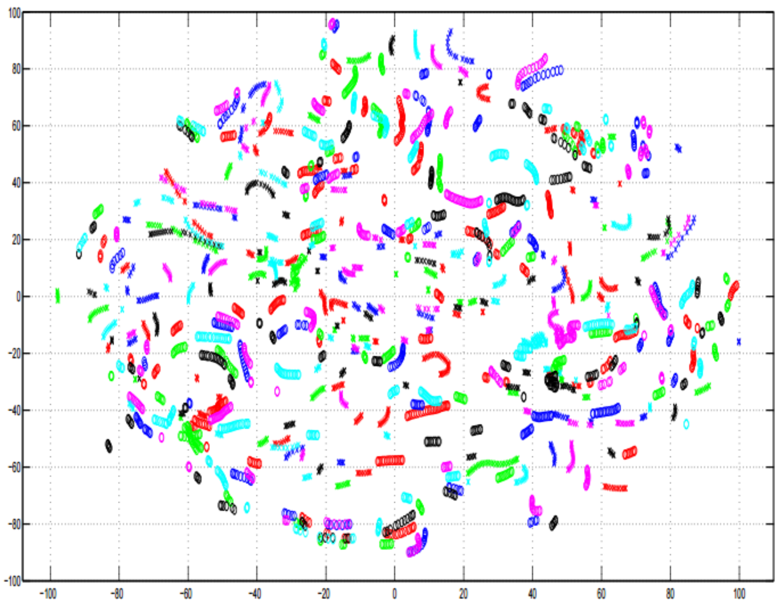


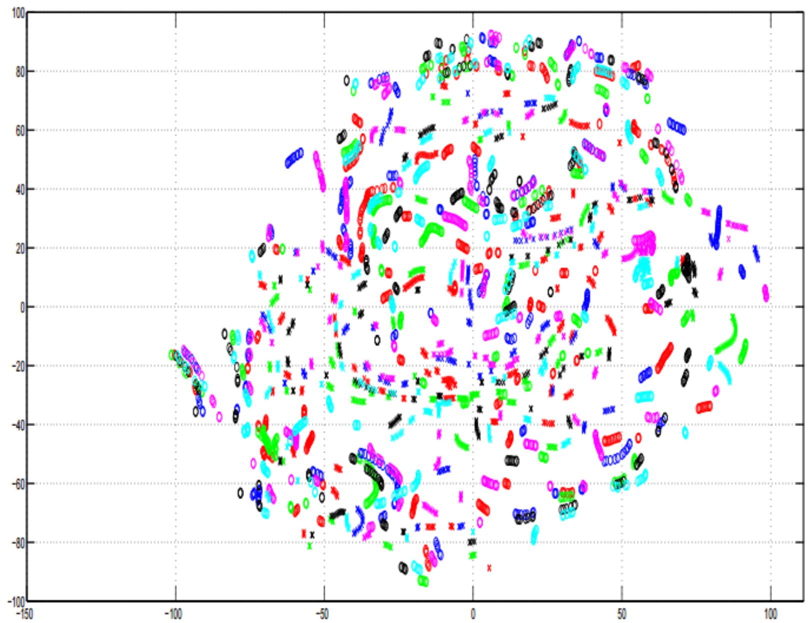
# Complex Task …

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

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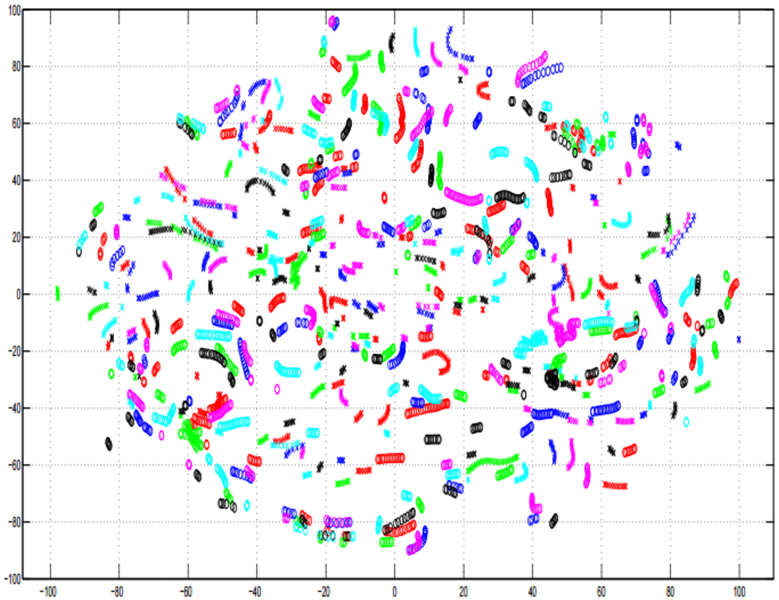

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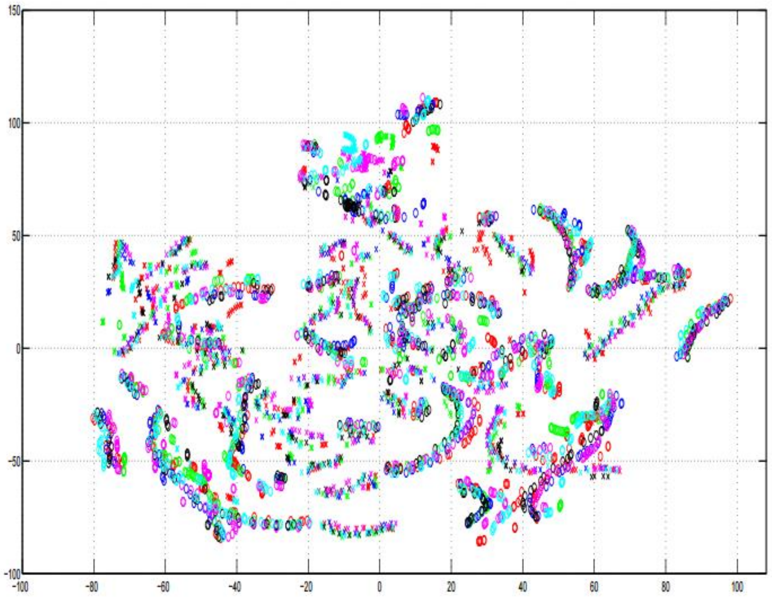
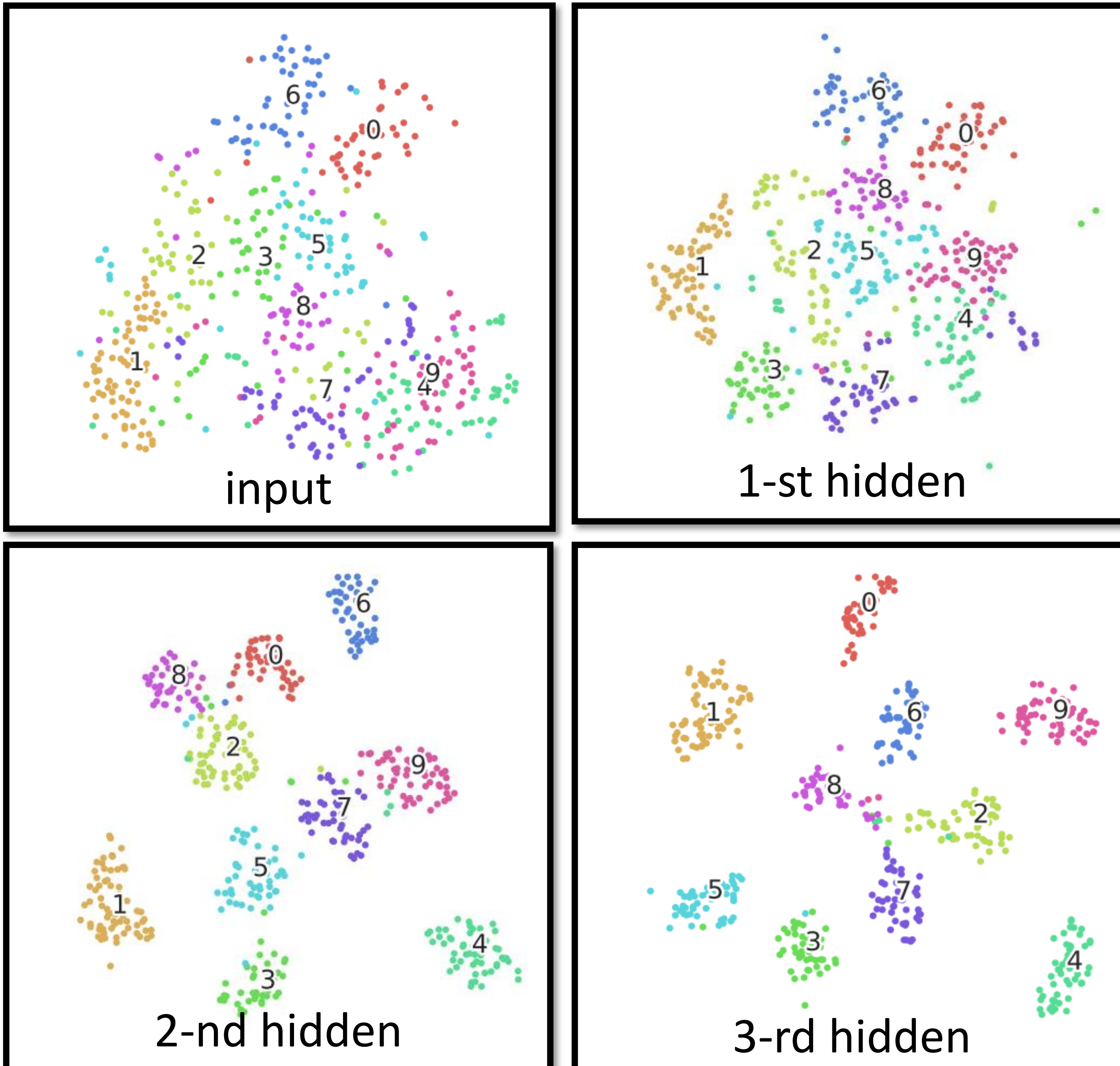


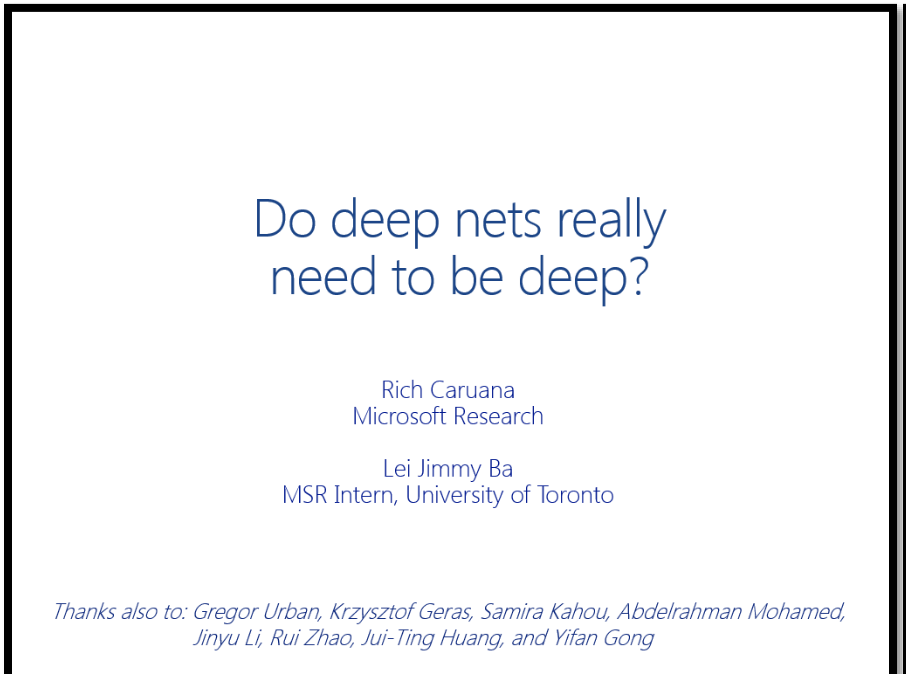
8-th Hidden Layer

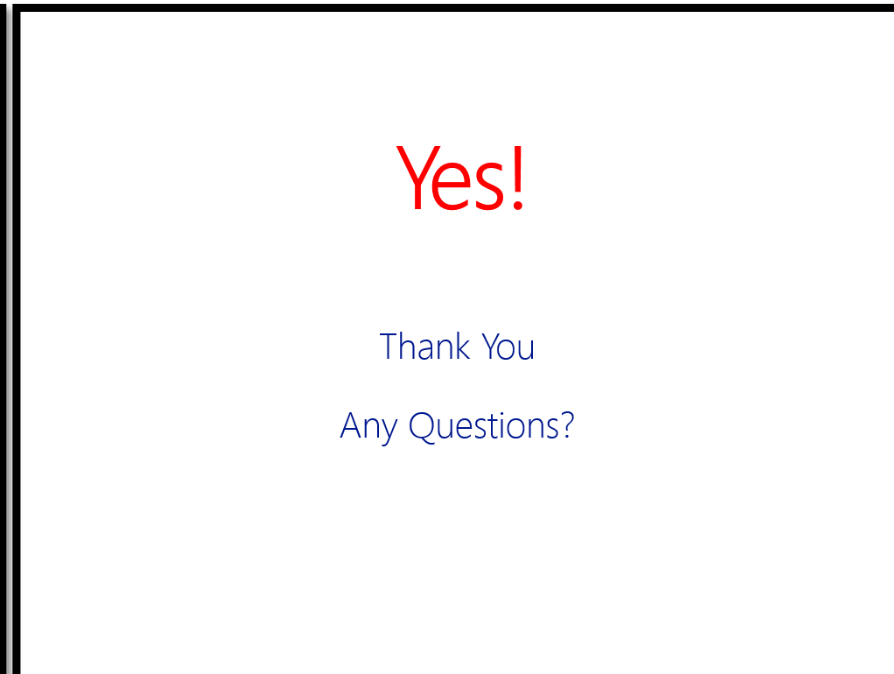
MNIST



# To learn more …

- 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