Lecture Notes on
Pattern Recognition

Module 09(A): Deep Learning Overview

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Road map

- Deep Learning Overview
  - Deep Learning
    - Why
    - End-to-End Learning
  - FFN
    - Matrix Operation
    - Learning FFN
  - BP
    - Forward Pass
    - Backward Pass

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Deep Learning

- Deep Learning
- Why Deep Learning?
  - Modularization
  - End-to-End Learning

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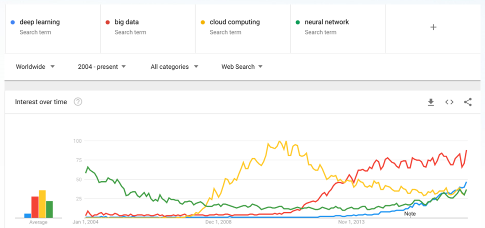
Google Trends



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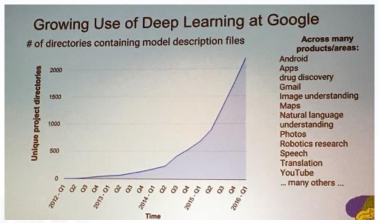
Deep learning trends at Google

- SIGMOD 2016, Jeff Dean



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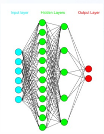
What is Deep Learning?

- Fast answer:
  - Fast answer: multilayer perceptron (aka deep neural networks) of the 1980s rebranded in 2006.
  - But early nets go stuck at 1-2 hidden layers.



- Slow answer:
  - distributed representation, multiple steps of computation, modelling the compositionality of the world, a better prior, advances in compute, data & optimization, neural architectures, etc.

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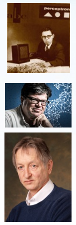
From ANN to Deep Learning

- 1958: Perceptron (linear model)
- 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?



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From ANN to Deep Learning

- 2006: RBM initialization
- 2009: GPU
- 2012: win ILSVRC image competition
- 2015.2:
  - Image recognition surpassing human-level performance
- 2016.3: Alpha GO beats Lee Sedol
- 2016.10:
  - Many system as good as humans

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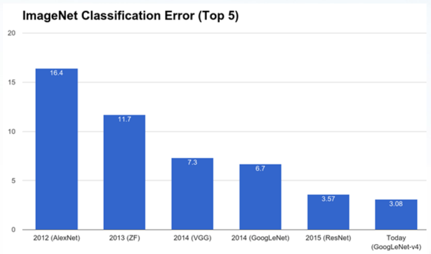
Deep Works



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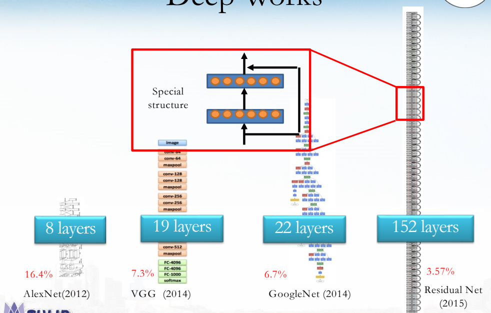
Deep Works



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The Best of Machine Learning

- Strong/flexible priors:
  - Good features: Feature engineering
  - Data structure: HMM, CRF, MRF, Bayesian nets
  - Model structure, VC-dimension, regularization, sparsity:
    - SVM, compressed sensing
  - Manifold assumption, class/region separation:
    - Metric + semi-supervised learning
  - Factors of variation: PCA, ICA, FA
- Uncertainty quantification:
  - Bayesian, ensemble: RF, GBM
- Sharing statistical strength:
  - model reuse: transfer learning, domain adaption, multitask learning, lifelong learning

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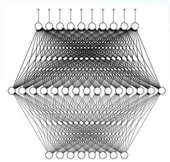
Universality Theorem

- Shallow network can represent any function.
- Given **enough** hidden neurons, Any continuous function $f: R^N \rightarrow R^M$ can be realized by a network with one hidden layer
- However, using deep structure is more effective.



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

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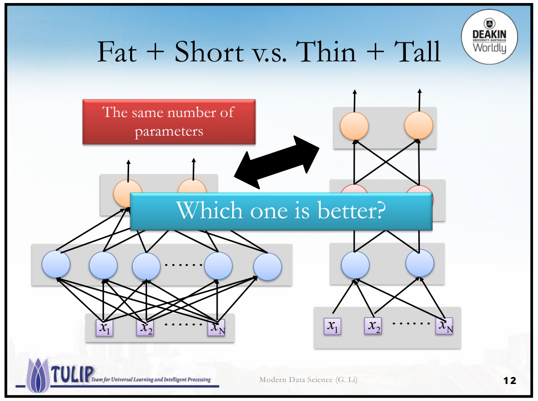

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Fat + Short v.s. Thin + Tall

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4	Why?	
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

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

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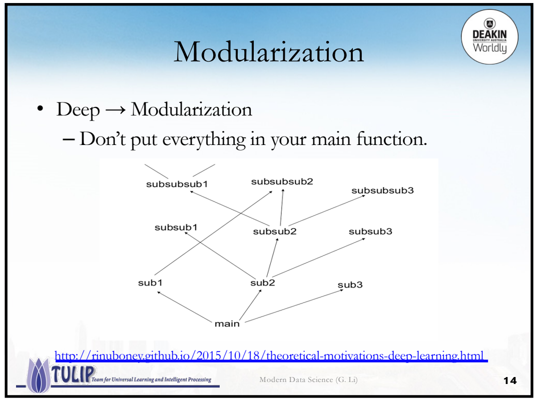

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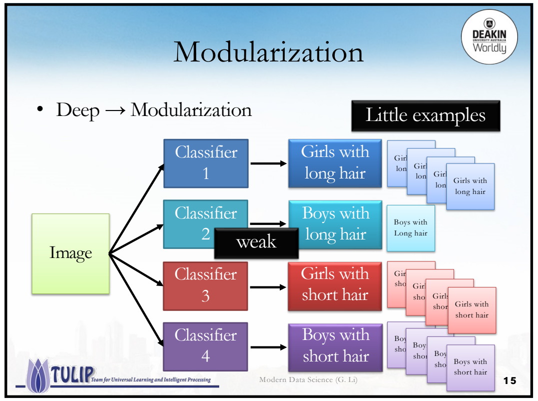

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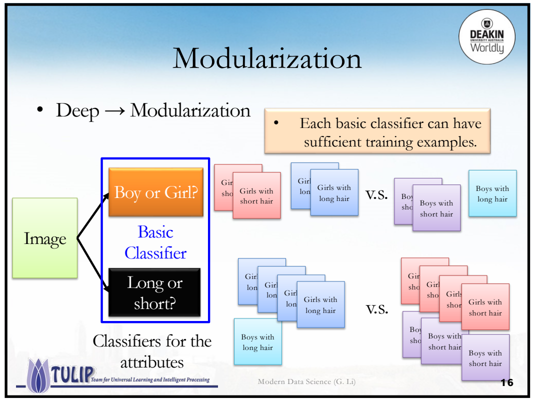

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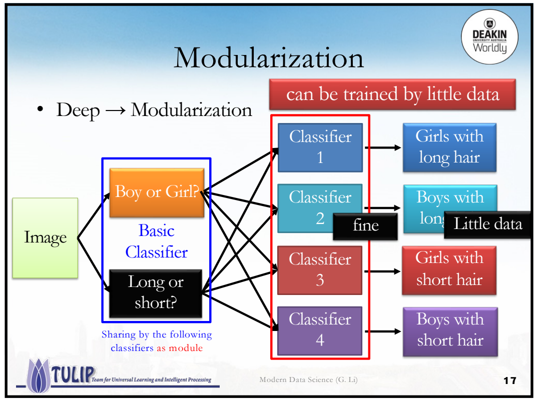

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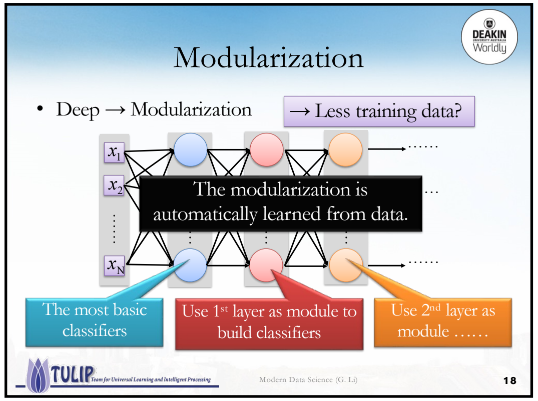

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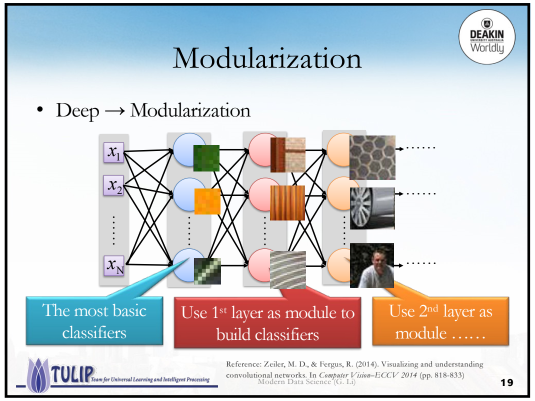

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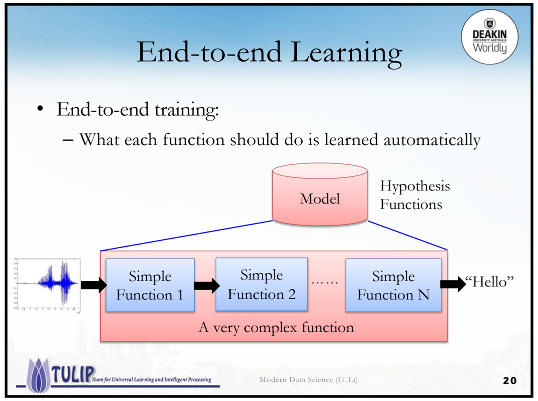

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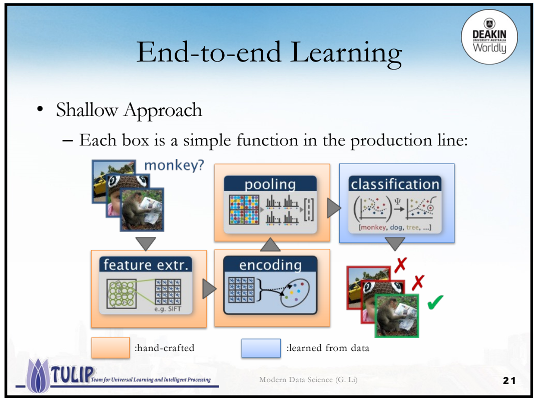

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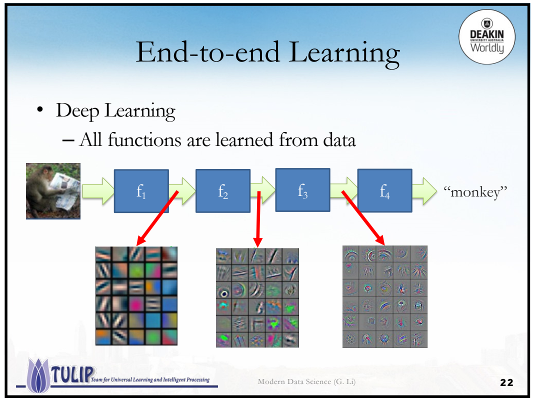

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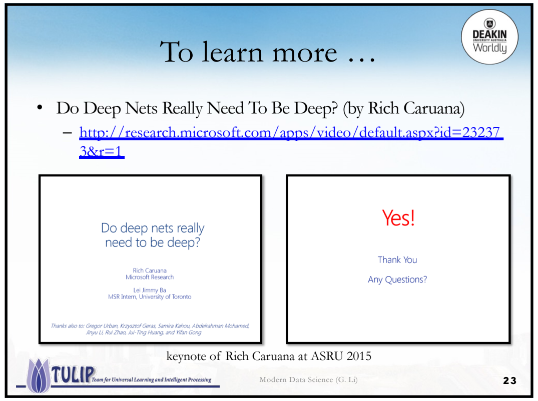

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Tensorflow or MXNet?

Tensorflow vs. MXNET

	Languages	MultiGPU	Distributed	Mobile	Runtime Engine
Tensorflow	Python	Yes	No	Yes	?
MXNET	Python, R, Julia, Go	Yes	Yes	Yes	Yes
(Googlenet) E5-1650/980	Tensor flow	Torch7	Caffe	MXNET	
Time	940ms	172ms	170ms	180ms	
Memory	all (OOM after 24)	2.1GB	2.2GB	1.6GB	

Marianas Labs Carnegie Mellon University

K + TensorFlow

K mxnet

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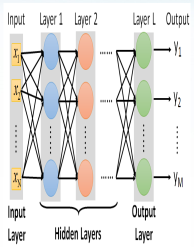
FFN



- FFN
- Matrix Operation
- Learning

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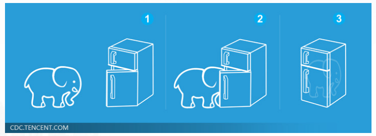
Deep Learning is so simple ……

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function



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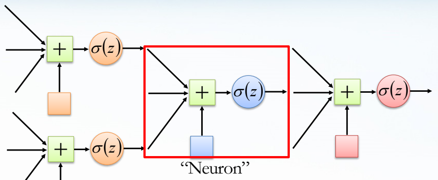
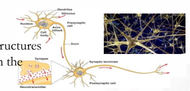
Neural Network



Neural Network:
- Different connection leads to different network structures
- Network parameter θ: all the weights and biases in the "neurons"



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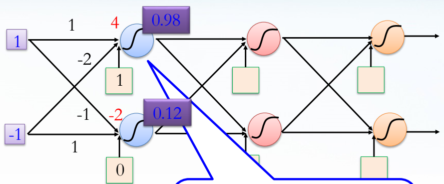
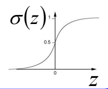
Fully Connected Feedforward Network



Sigmoid Function

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



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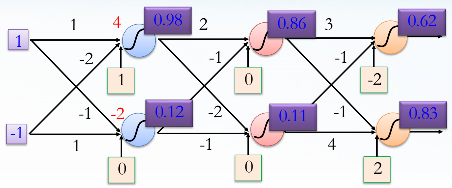
Fully Connected Feedforward Network



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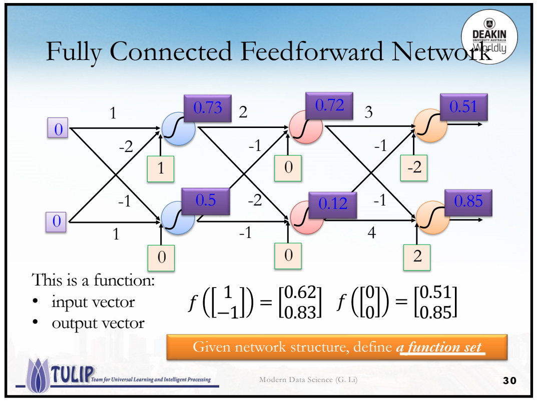

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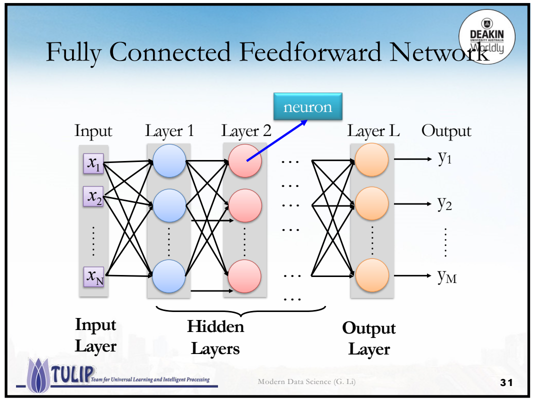

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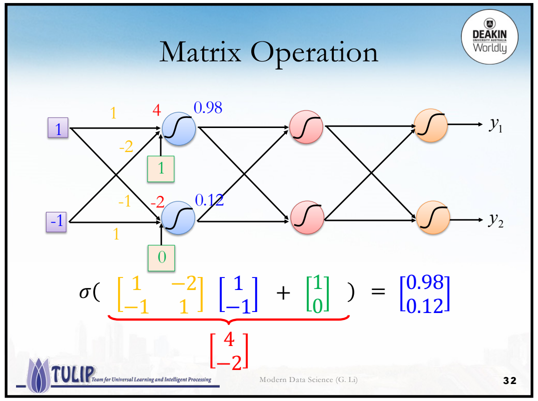

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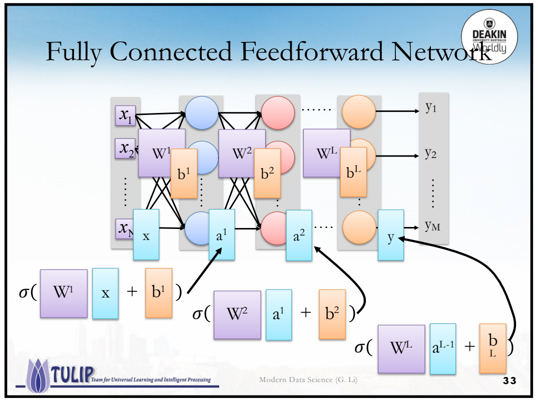

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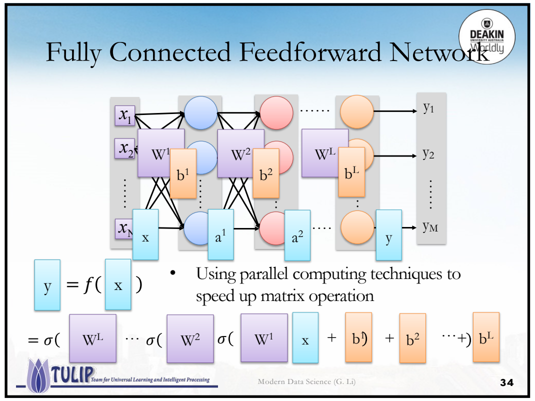

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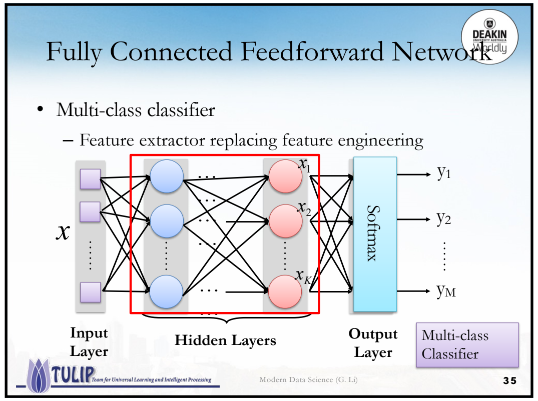

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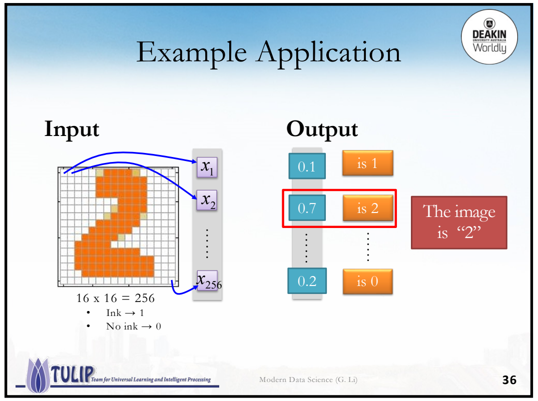

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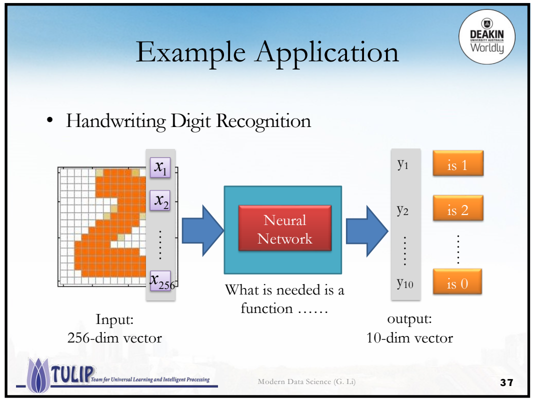

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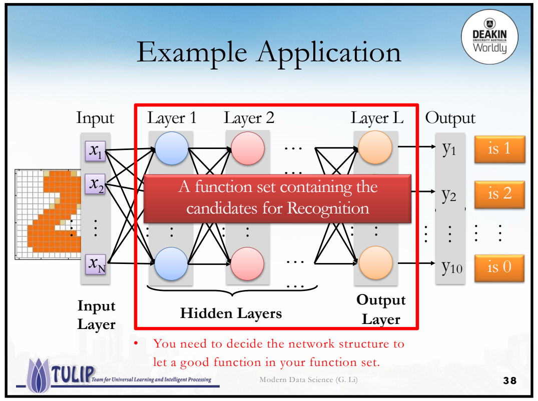

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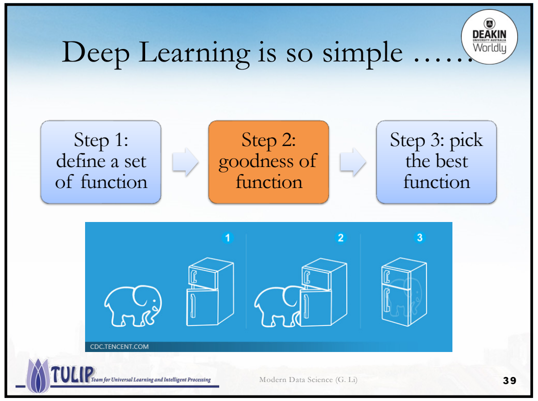

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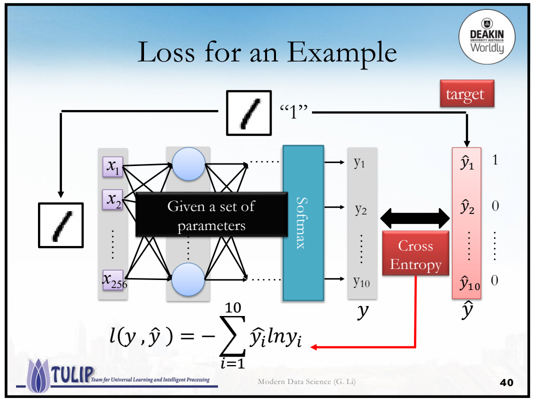

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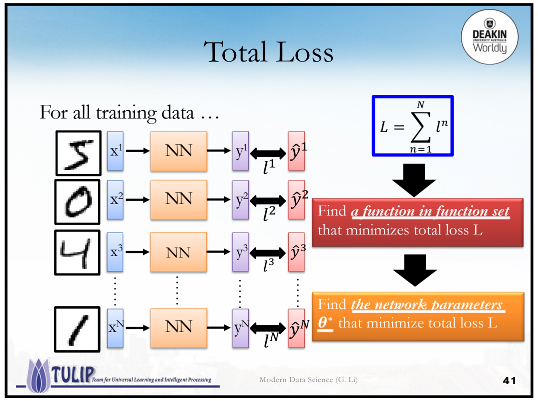

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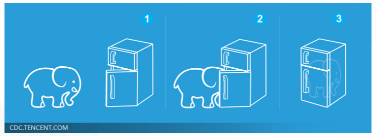
Deep Learning is so simple ……

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function



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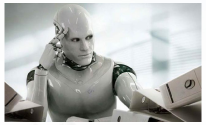
Gradient Descent

- Gradient Descent is the "learning" of machines in deep learning ……
  - Even alpha go using this approach.



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Gradient Descent

θ

w_1: 0.2 $\xrightarrow[-\mu\,\partial L/\partial w_1]{\text{Compute } \partial L/\partial w_1}$ 0.15

w_2: -0.1 $\xrightarrow[-\mu\,\partial L/\partial w_2]{\text{Compute } \partial L/\partial w_2}$ 0.05

⋮

b_1: 0.3 $\xrightarrow[-\mu\,\partial L/\partial b_1]{\text{Compute } \partial L/\partial b_1}$ 0.2

⋮

$$\nabla L = \begin{bmatrix} \frac{\partial L}{\partial w_1} \\ \frac{\partial L}{\partial w_2} \\ \vdots \\ \frac{\partial L}{\partial b_1} \\ \vdots \end{bmatrix}$$

gradient

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Gradient Descent

θ

w_1: 0.2 $\xrightarrow[-\mu\,\partial L/\partial w_1]{\text{Compute } \partial L/\partial w_1}$ 0.15 $\xrightarrow[-\mu\,\partial L/\partial w_1]{\text{Compute } \partial L/\partial w_1}$ 0.09 ……

w_2: -0.1 $\xrightarrow[-\mu\,\partial L/\partial w_2]{\text{Compute } \partial L/\partial w_2}$ 0.05 $\xrightarrow[-\mu\,\partial L/\partial w_2]{\text{Compute } \partial L/\partial w_2}$ 0.15 ……

⋮

b_1: 0.3 $\xrightarrow[-\mu\,\partial L/\partial b_1]{\text{Compute } \partial L/\partial b_1}$ 0.2 $\xrightarrow[-\mu\,\partial L/\partial b_1]{\text{Compute } \partial L/\partial b_1}$ 0.10 ……

⋮

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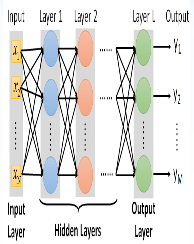
Back Propagation



- Forward Pass
- Backward Pass

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Gradient Descent

Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

Starting Parameters $\theta^0 \longrightarrow \theta^1 \longrightarrow \theta^2 \longrightarrow \cdots\cdots$

$$\nabla L(\theta) = \begin{bmatrix} \partial L(\theta)/\partial w_1 \\ \partial L(\theta)/\partial w_2 \\ \vdots \\ \partial L(\theta)/\partial b_1 \\ \partial L(\theta)/\partial b_2 \\ \vdots \end{bmatrix}$$

Compute $\nabla L(\theta^0)$ $\quad \theta^1 = \theta^0 - \eta \nabla L(\theta^0)$

Compute $\nabla L(\theta^1)$ $\quad \theta^2 = \theta^1 - \eta \nabla L(\theta^1)$

Millions of parameters ……

To compute the gradients efficiently, we use ***backpropagation***.

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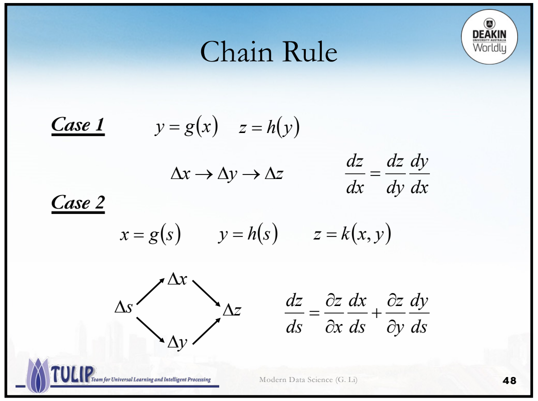

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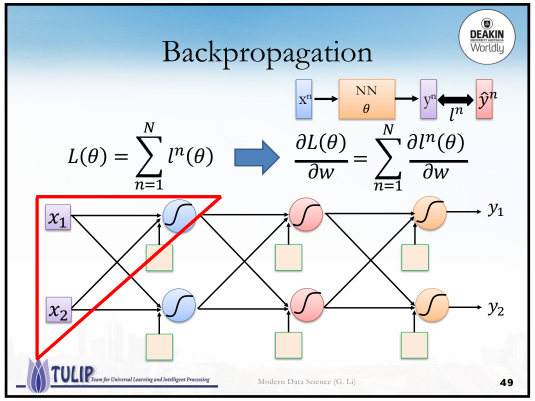

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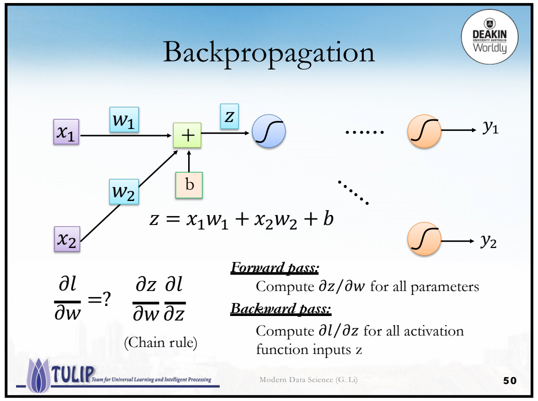

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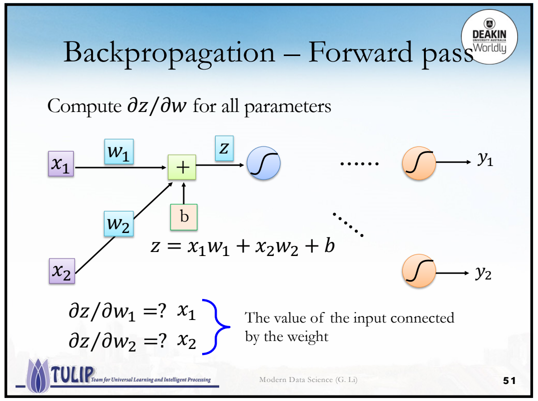

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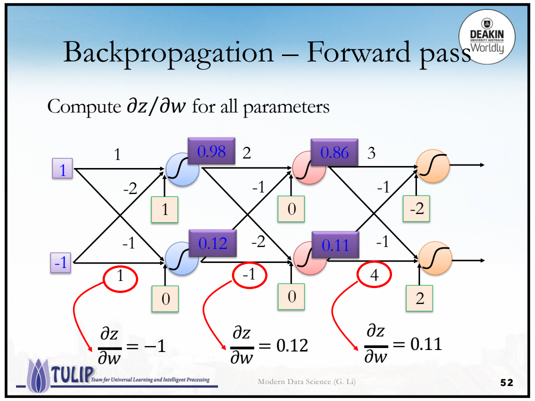

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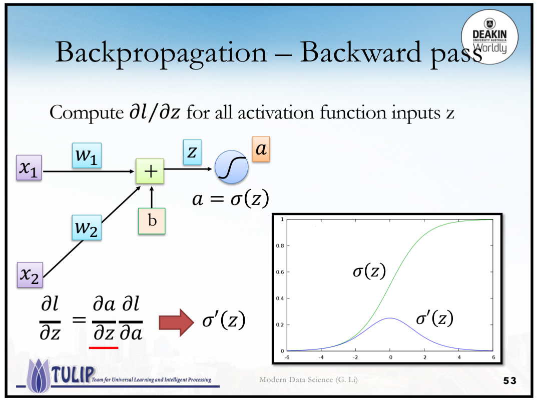

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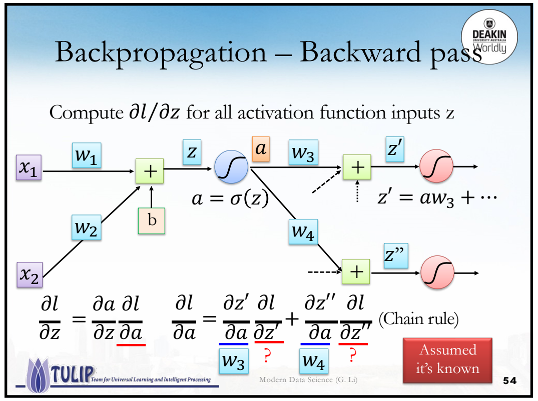

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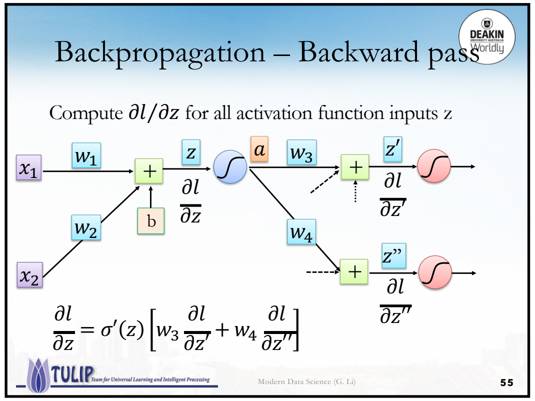

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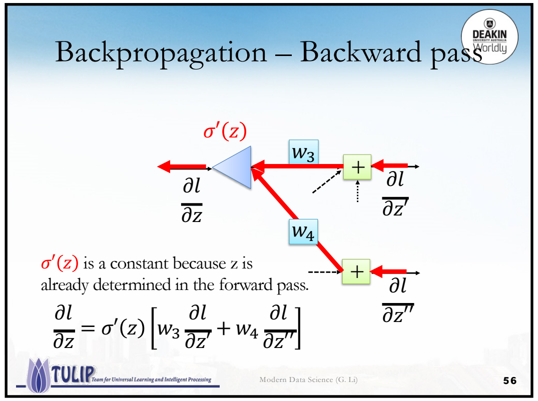

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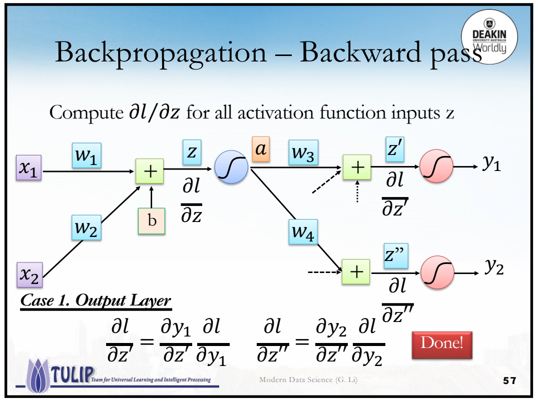

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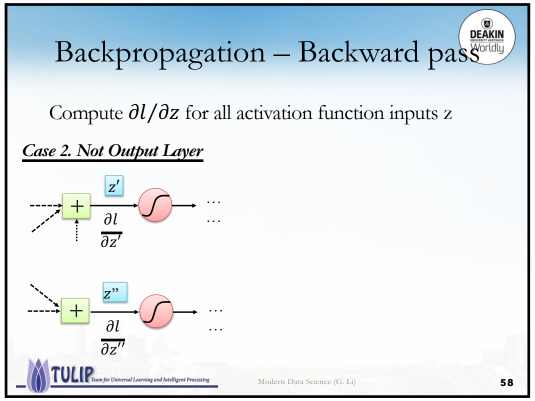

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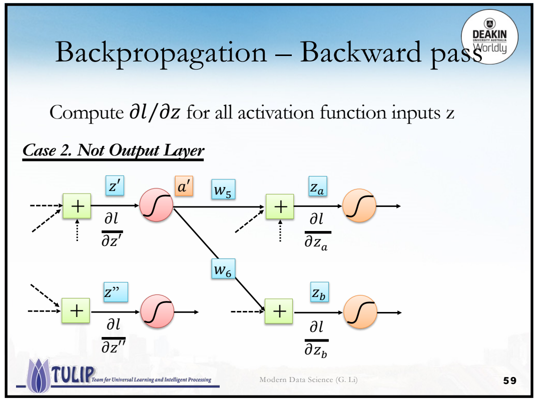

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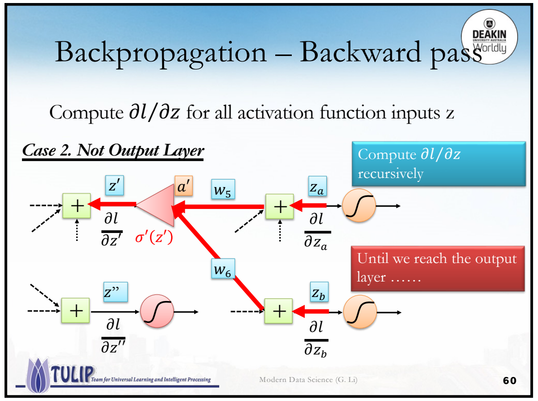

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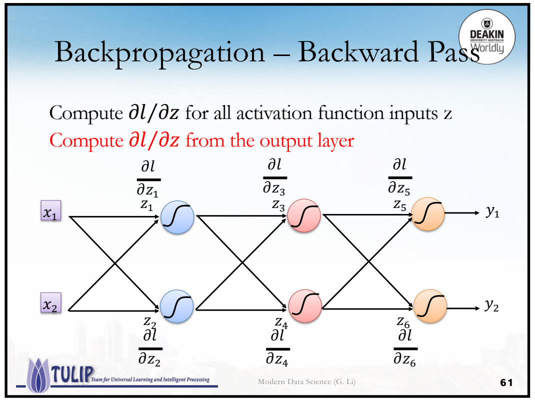

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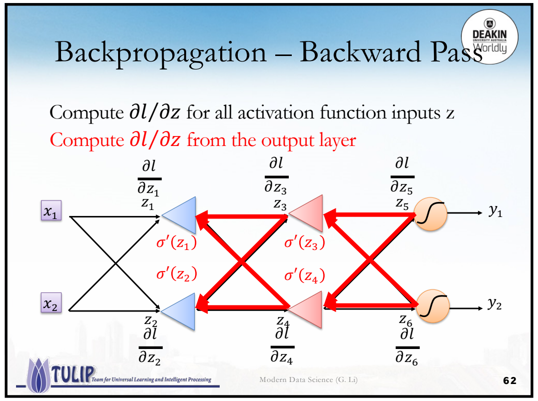

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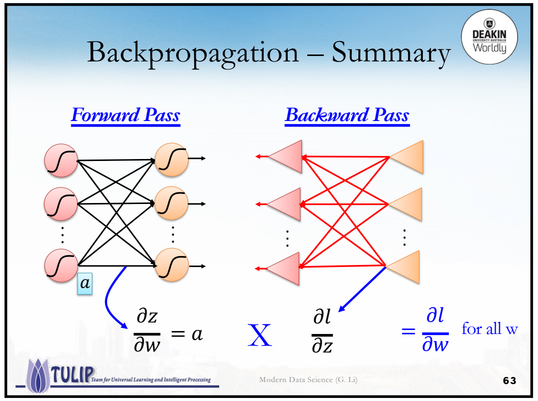
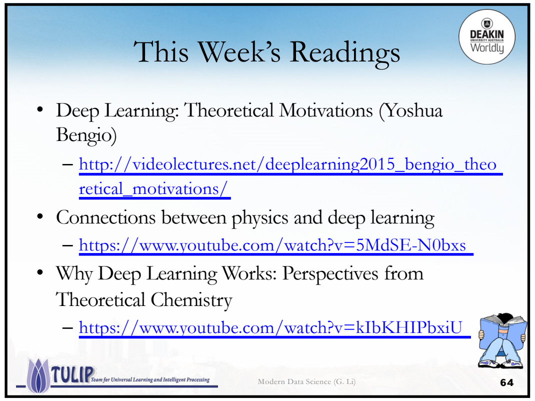


63



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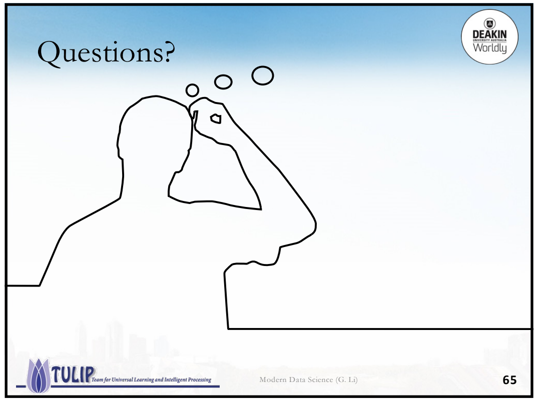

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