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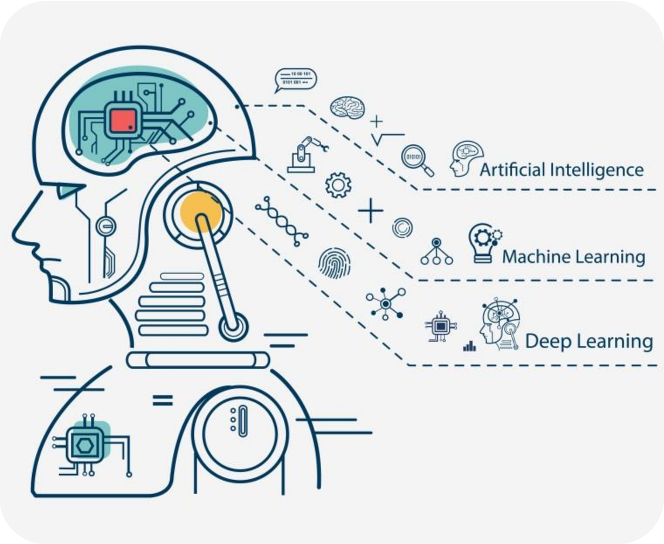
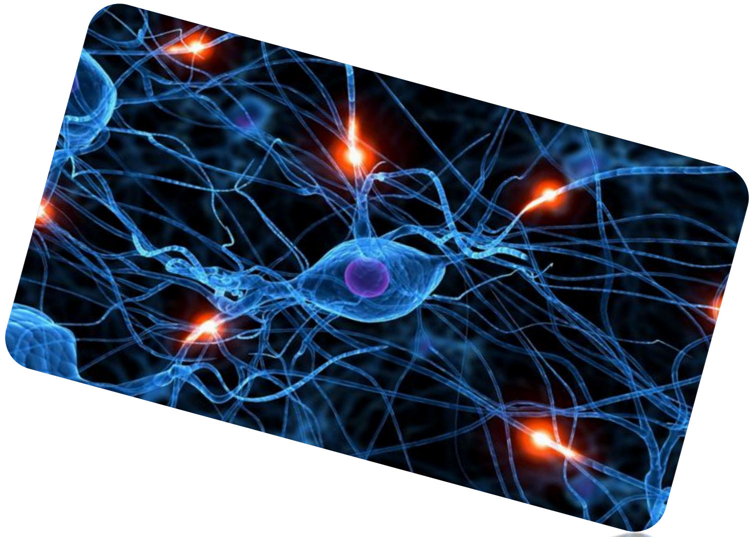
School of Computing





Introduction to Neural Networks And Deep Learning

Zhao Yunkun

AlphaGo Defeats Best Players, But…

I

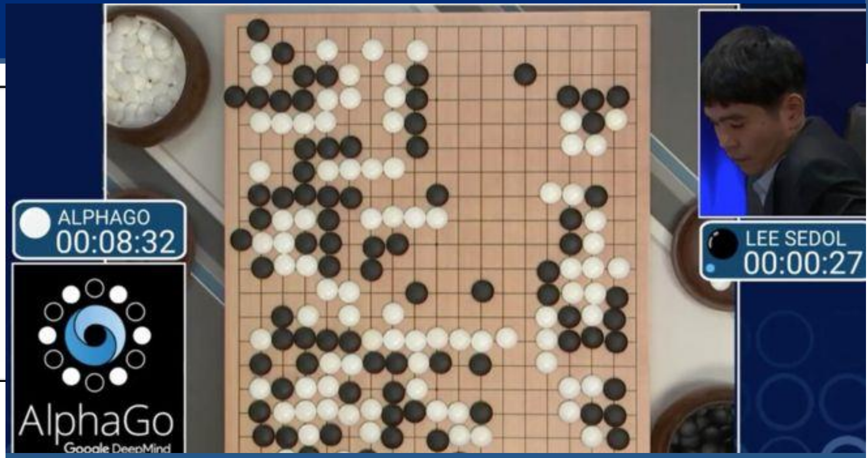
- 2016-03
- AlphaGo(1.0) **4 : 1** Lee Sedol

II

- 2017-05
- AlphaGo(2.0) **3 : 0** Ke Jie

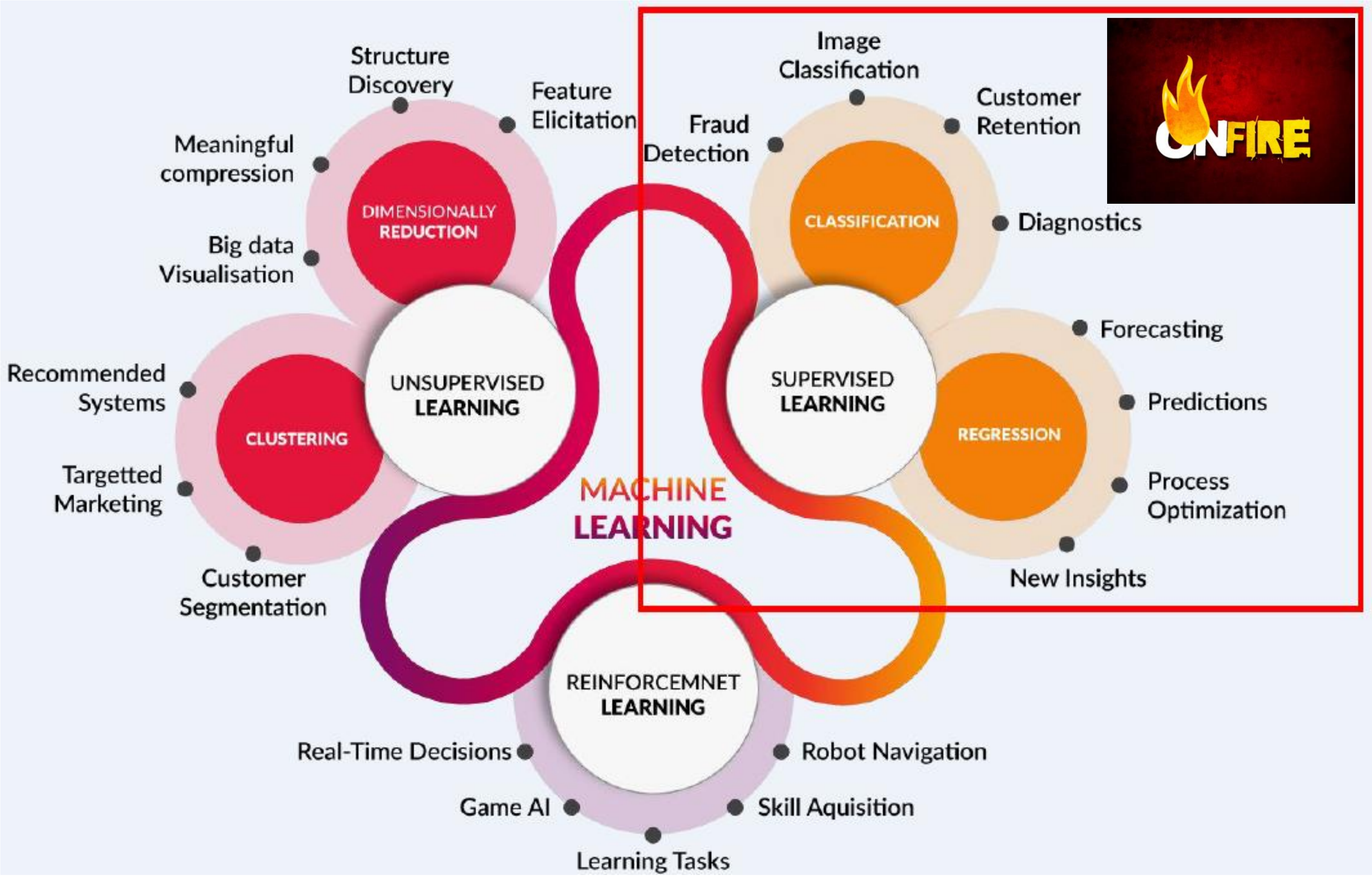
III

- 2017-10
- AlphaGo(2.0) **0 : 100** AlphaGo Zero



Baidu AI Brain Wins In Face-Recognition Competitions

Machine Learning And Deep Learning



How Does Machine Learns ?

➢ Example: Price Prediction With Regression

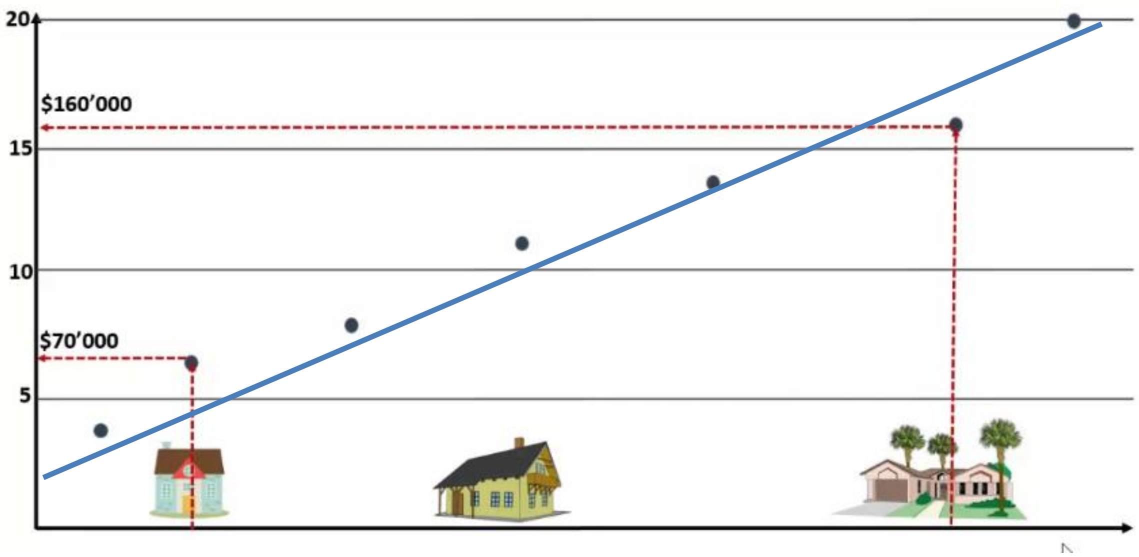
Model: $Y = f(X) + \varepsilon = X\beta + \varepsilon$

$$X = \begin{array}{c} \begin{array}{cccc} \text{Size} & \text{Bedroom} & & \text{Bathroom} \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix} \end{array}, \quad \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix}, \quad Y = \begin{array}{c} \text{Price} \\ \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{bmatrix} \end{array}$$

$$\min_{\beta} RSS(\beta) = \varepsilon^T \varepsilon = (Y - X\beta)^T (Y - X\beta)$$

$$\rightarrow \text{f.d.: } -2X^T Y + 2X^T X\beta = 0$$

$$\rightarrow \beta_{OLS} = (X^T X)^{-1} X^T Y$$



ID	Size (m²)	#Bed room	#Bath room	Price (k)
1	65	2	2	900
2	72	3	2	1200
……	……	……	……	……
n	50	1	1	500

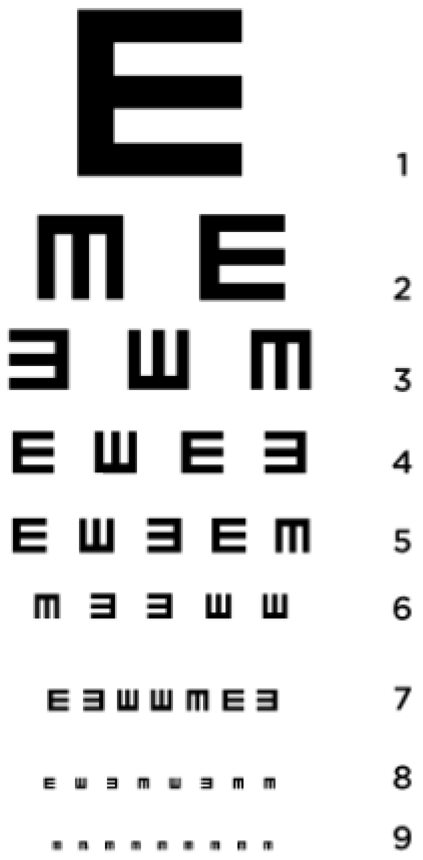
How Does Machine Learns ?

Machine

Learning (Not Memorizing)

Use algorithms to discover patterns in the data

Resource



Machine Learning: Formalization

Input: $\boldsymbol{X} \in \mathbb{R}^d$ **(Housing information, e.g., size, #room, etc.)**

Output: Regression: $y \in (-\infty, \infty)$ **(e.g., Price)**

Classification: $y \in (0,1)$

Target Function: $f : X \to y$ **(Ideal price prediction formula)**

f **is unknown**

Data: $D = \{(x_1, y_1), \ldots (x_N, y_N)\}$ **(Historical records)**

Approximation Function (or Model $\hat{f} \in F$): $\hat{f} : X \to y$ **(Min. in-sample/train error)**

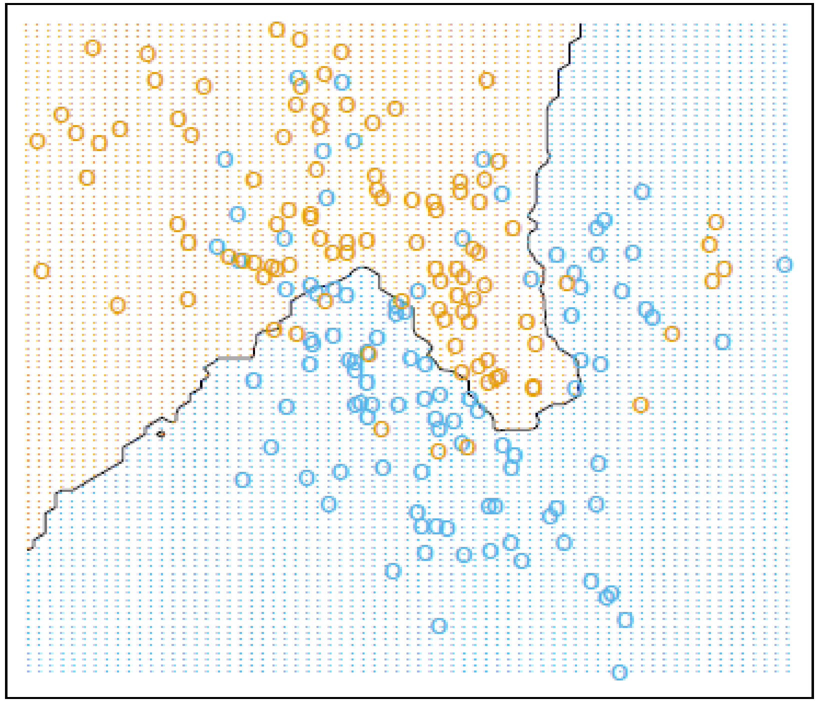
where in-sample error is $\frac{1}{N}\sum_{n=1}^{N} Loss(\hat{f}(x_n) \neq f(x_n))$

Goal of Machine Learning: $\min_{\hat{f}} E[Loss(\hat{f}(x_{new}) \neq f(x_{new}))]$ **(Min. out-of-sample/test error)**

- ➢ Example: Simple Classification With Traditional Machine Learning Methods on Nonlinear-Pattern Data

Underfit: Bias

Y

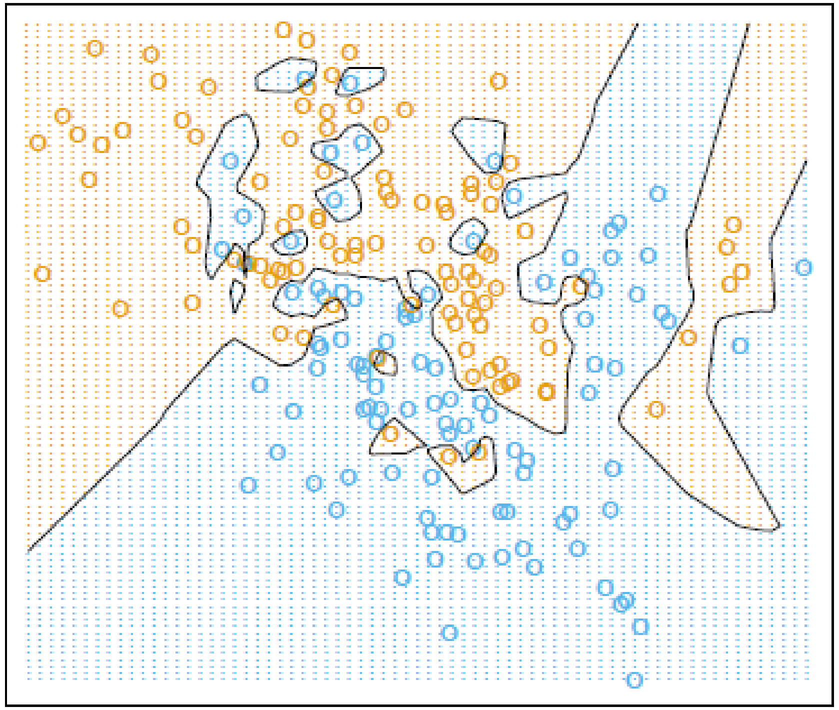


From ESL

X

Overfit: Variance

Y



From ESL

X

Traditional Machine Learning

➢ Generalization Error Bound on Test Data (i.e., Out-of-sample):

$$\Pr\{|\frac{1}{N}\sum_{n=1}^{N} Loss(\hat{f}(x_n) \neq f(x_n)) - E[Loss(\hat{f}(x_{new}) \neq f(x_{new}))]| > \varepsilon\}$$

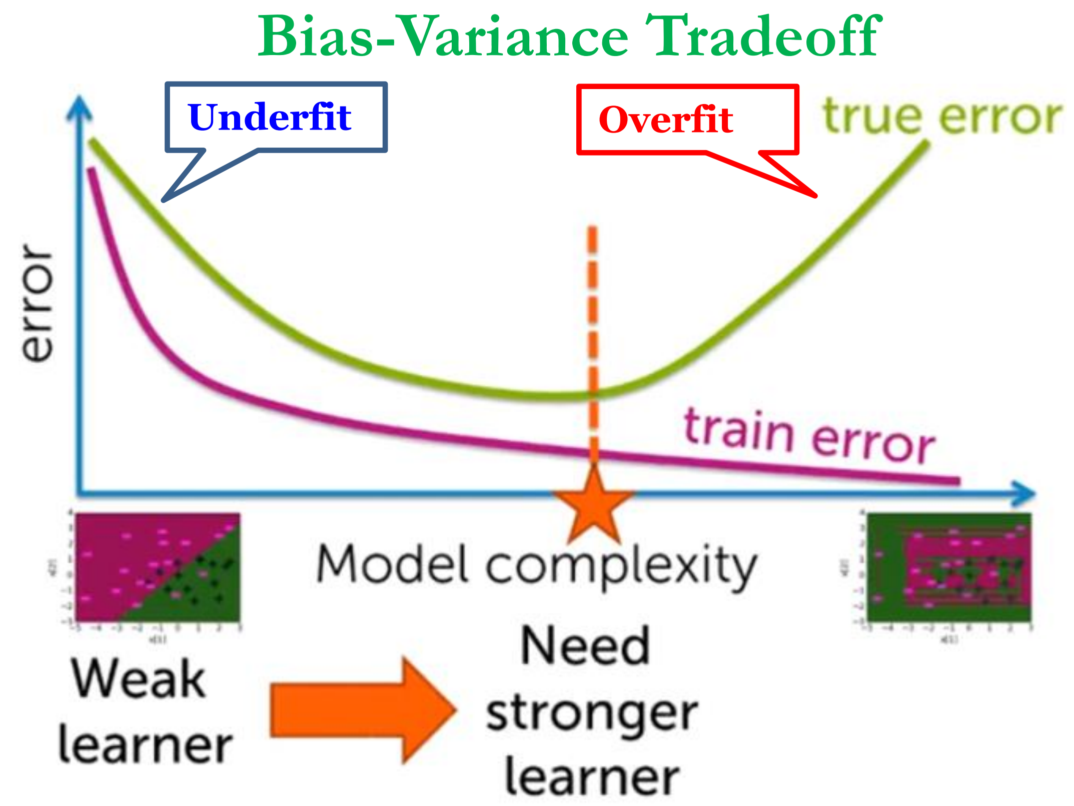
$$= \Pr\{|\text{InSampleError} - \text{OutOfSampleError}| > \varepsilon\}$$

$$\leq \frac{2M}{e^{2N\varepsilon^2}}$$

- M: reflects the complexity of model
- N: number of training samples
- ε: How much you can tolerate your
- In-sample error to be different from
- Out-of-sample error

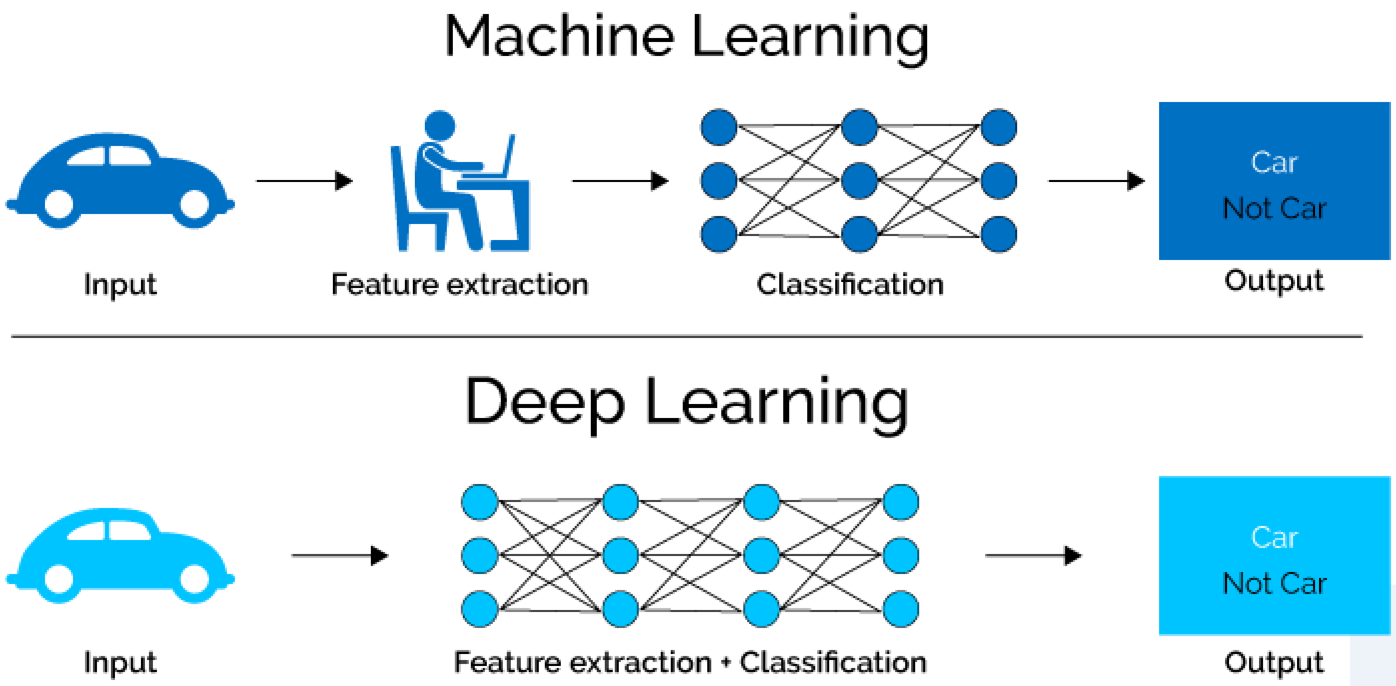
♥ $\hat{f}$: InSampleError ≈ 0

and InSampleError ≈ OutOfSampleError

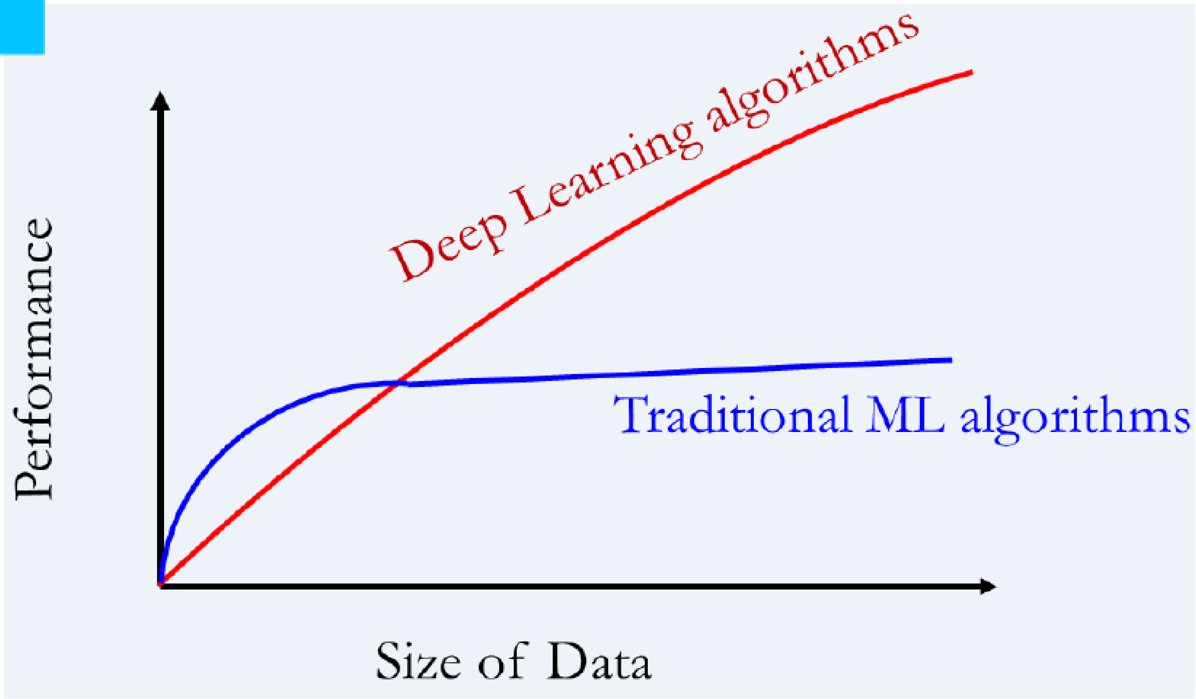


$$\mathrm{E}\left[\left(y-\hat{f}(x)\right)^2\right] = \left(\mathrm{Bias}\left[\hat{f}(x)\right]\right)^2 + \mathrm{Var}\left[\hat{f}(x)\right] + \sigma^2$$

Traditional Machine Learning



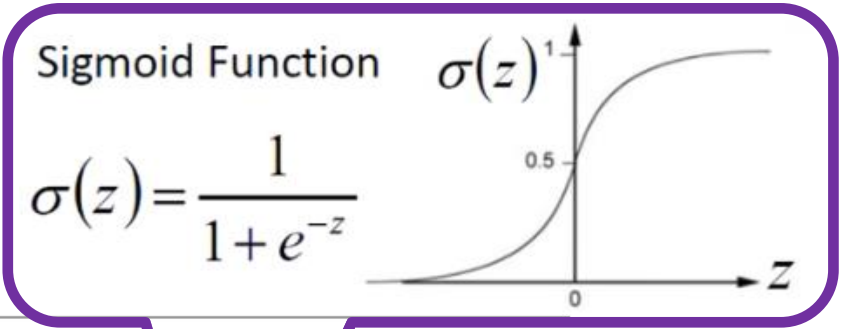
- Human brain is so great in learning, why not making machine learning **mimic human train** ?

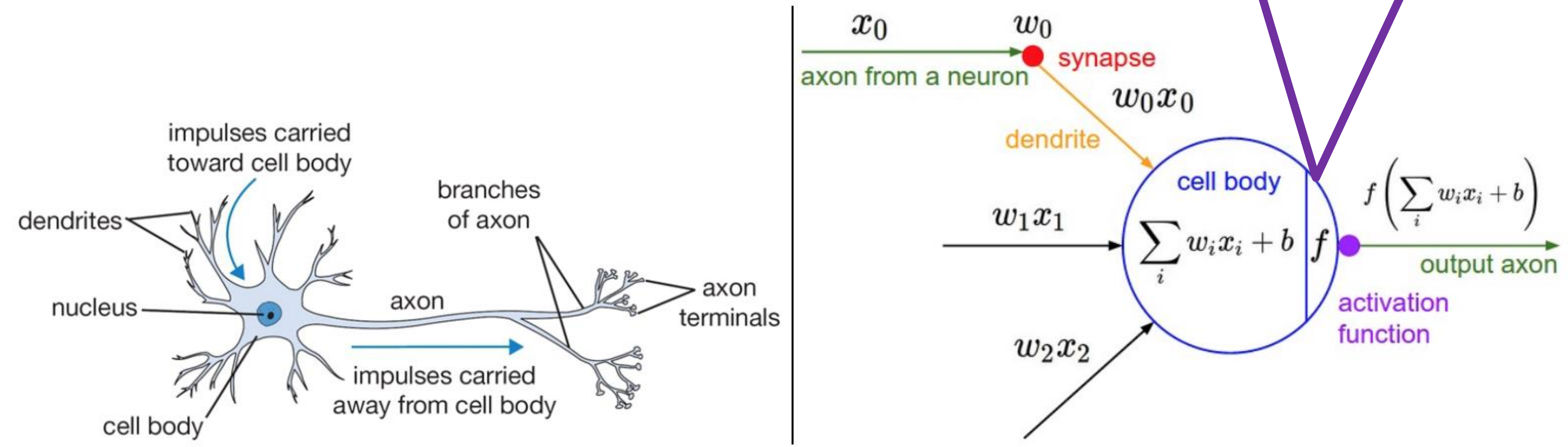


- Deep Learning doesn't do different things, **it does things differently**
- Deep Learning is self-adaptive

Deep Learning: Basics

- How to Make Machine Learning Mimic Human Brain ?
- Biological View
  - Neuron (or Perceptron): Information Reception, Process and Transfer
  - Hierarchical Structure: Multi-Layer and Multi-Level Inputs
  - **Activation Function (Nonlinear):** Nonlinear Reaction to Inputs

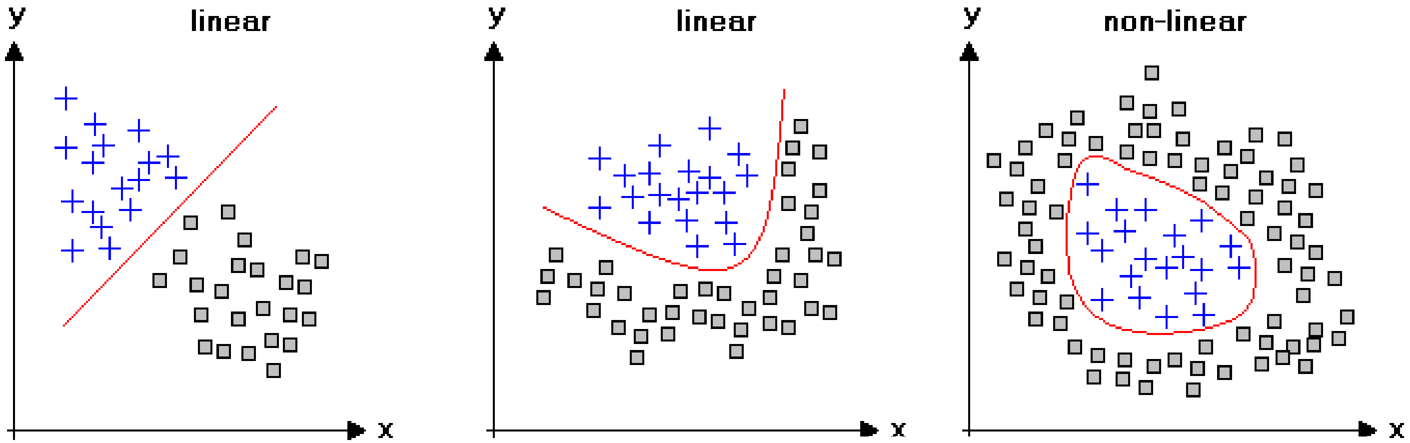




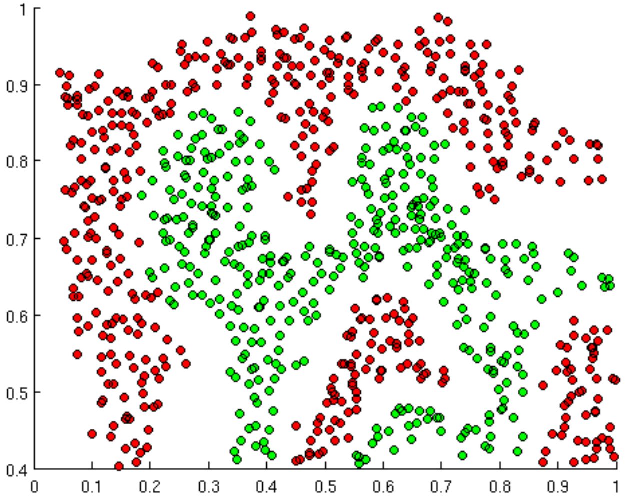
A cartoon drawing of a biological neuron (left) and its mathematical model (right).

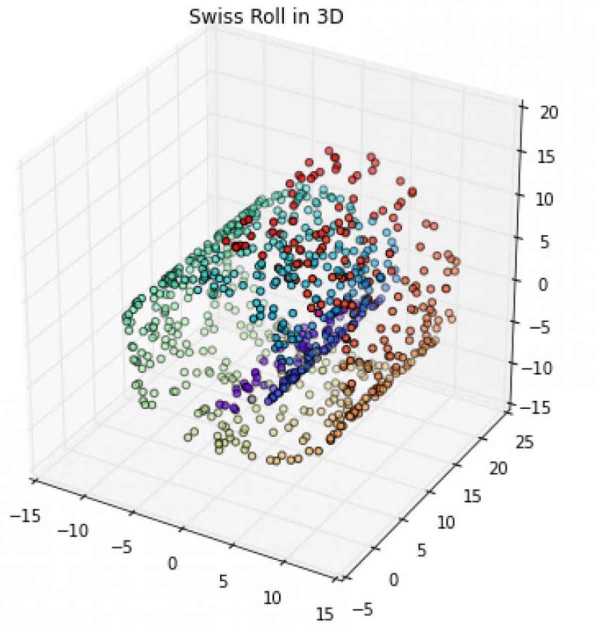
Neural Networks: Activation Function

- How do neural networks learn nonlinear data pattern better ?
- Nonlinear Activation Function



Nonlinear Activation functions are really important for NN to learn and make sense of something really **Complicated** and **Non-linear complex functional mappings between the inputs and outputs**. They introduce **non-linear properties** to our NN.

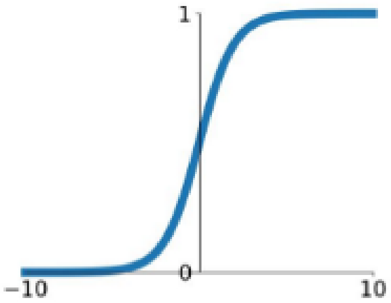




Activation Functions

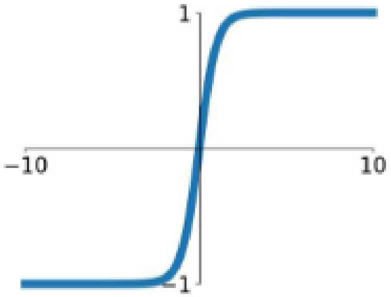
Sigmoid

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



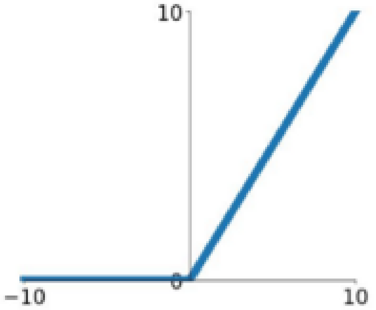
tanh

$\tanh(x)$



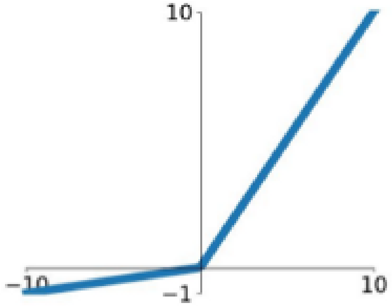
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

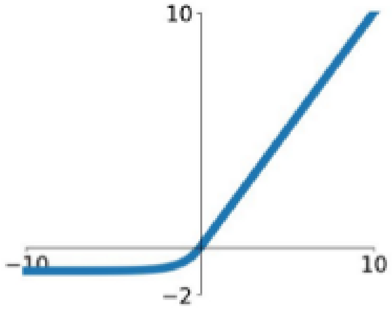


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Neural Networks: Structure

➢ Structure: Interconnecting Multi-Layers of Neurons/Perceptrons

Input Layer

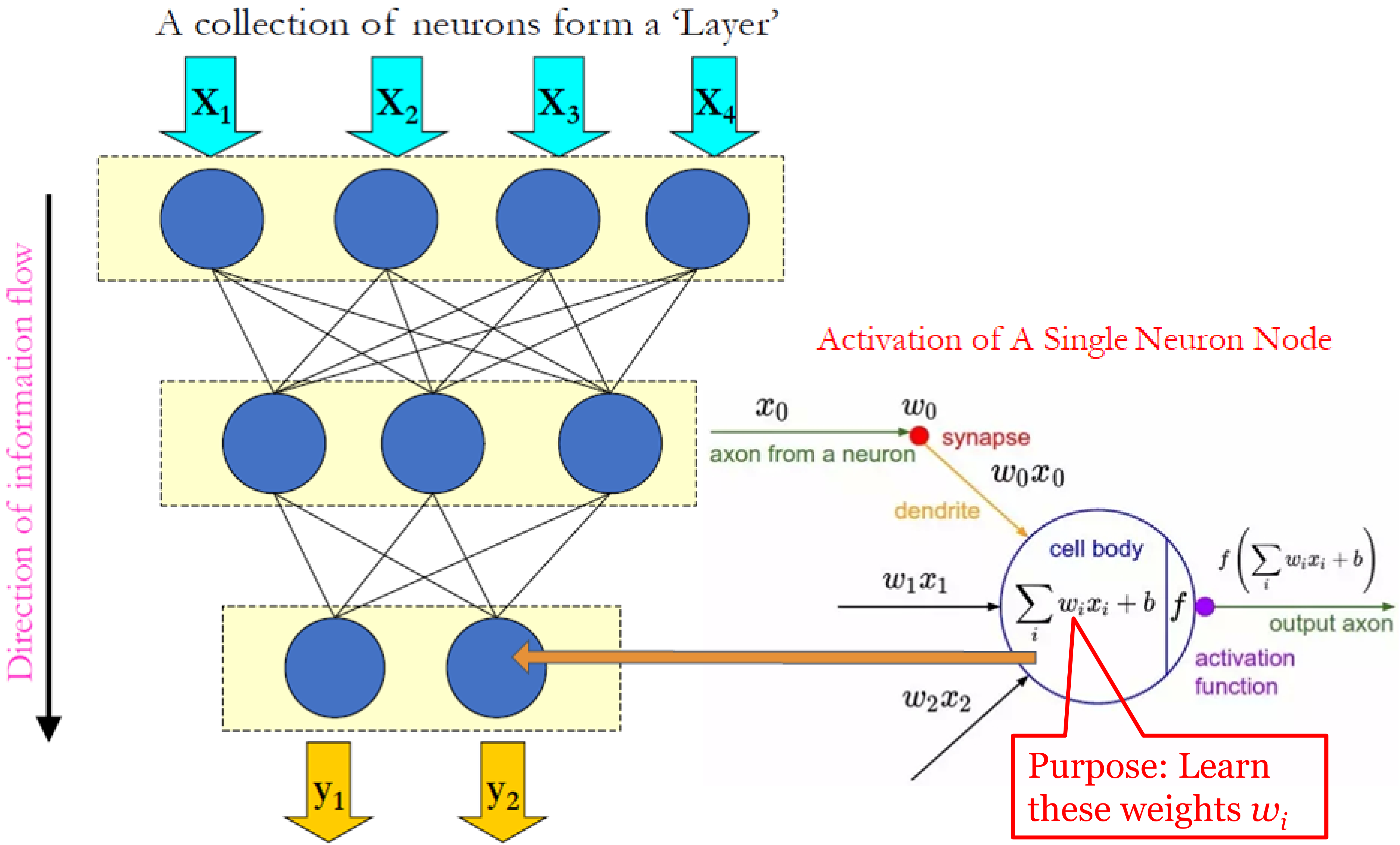
- Each neuron gets ONLY one input, directly from outside

Hidden Layer

- Connects Input and Output layers

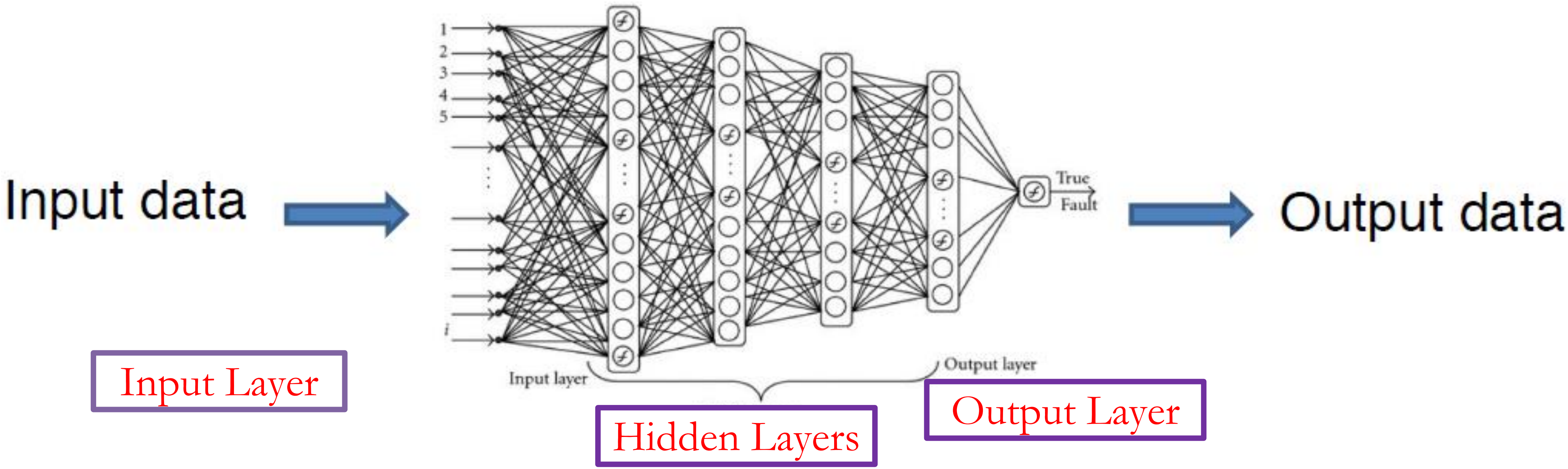
Output Layer

- Output of each neuron directly goes to outside

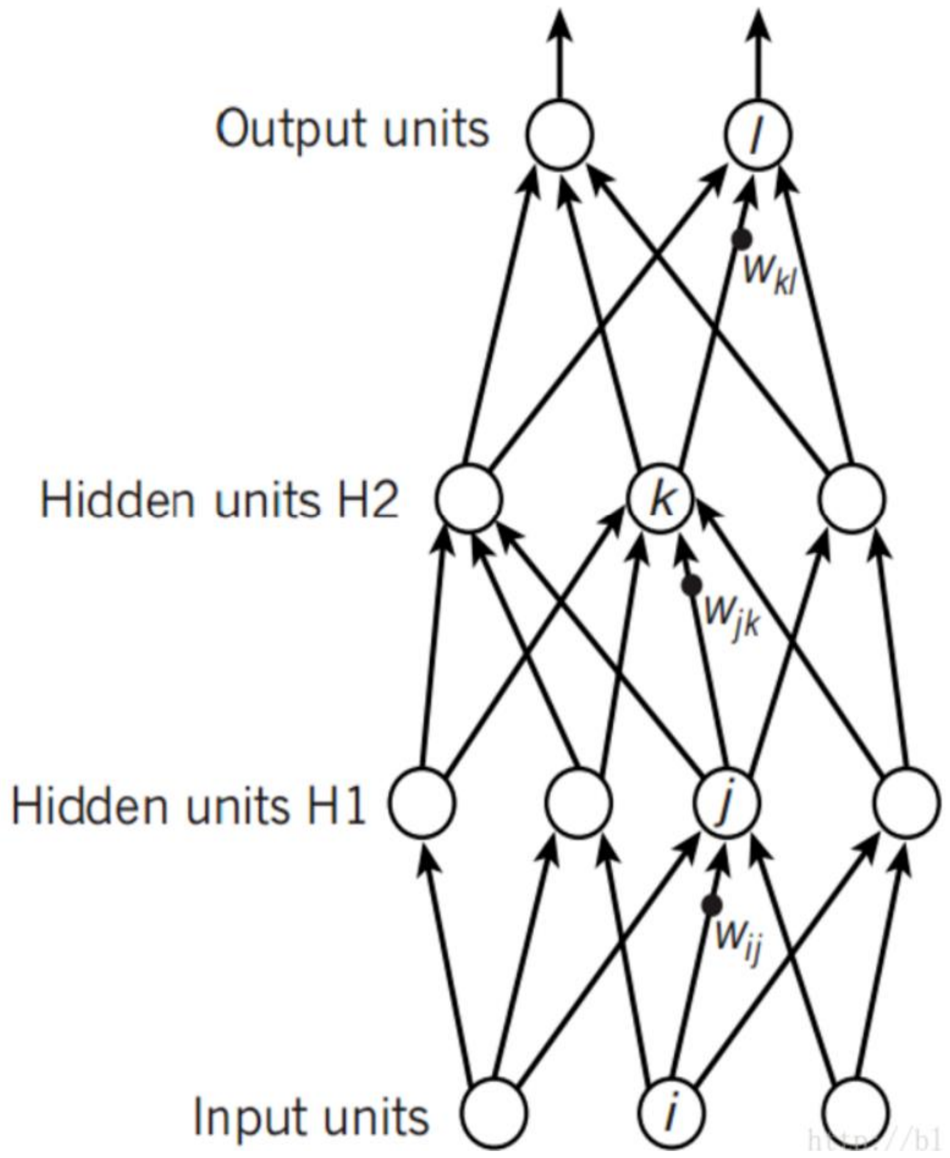


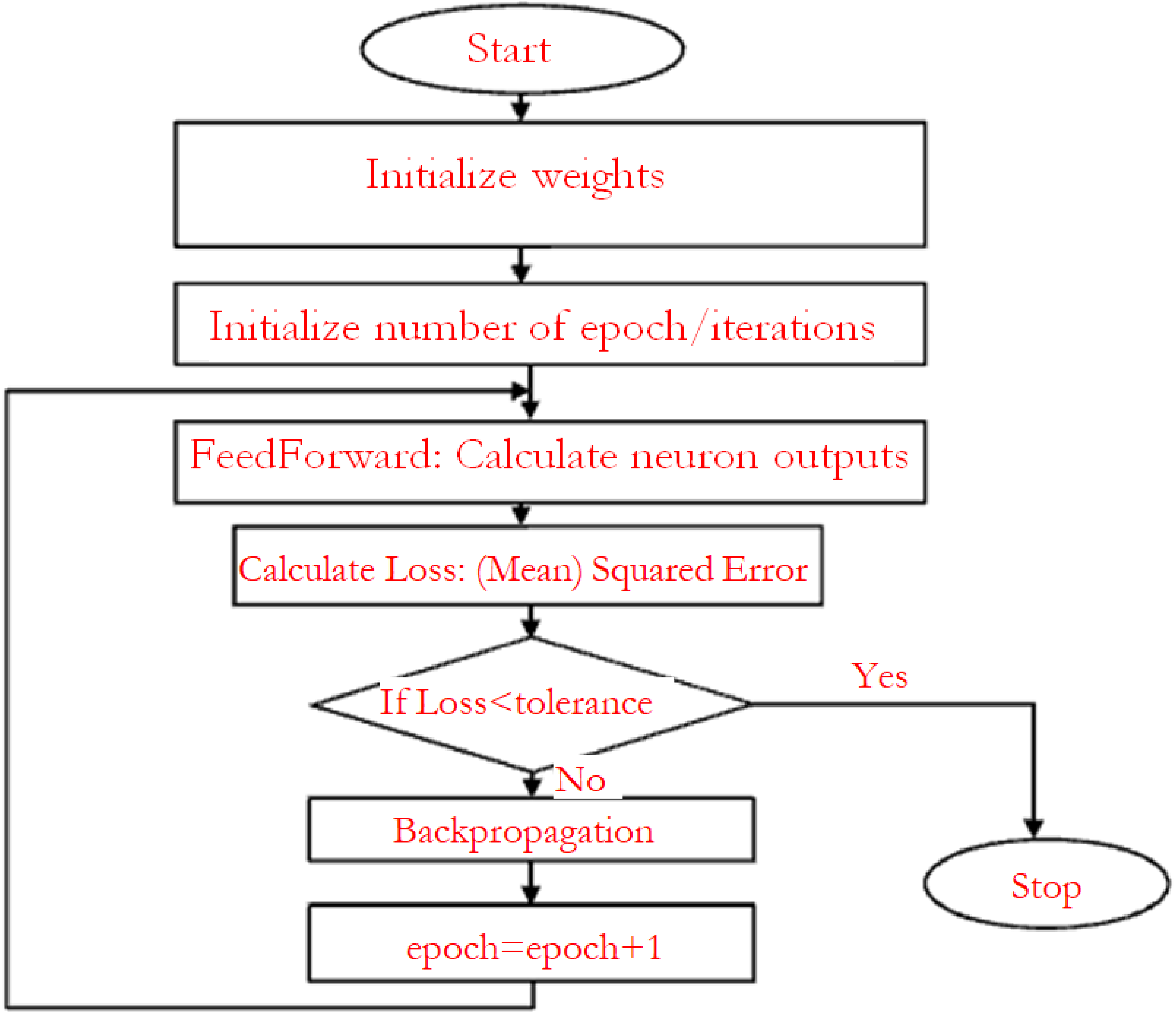
- Deep Neural Networks
  - Structure: Interconnecting Multi-Layers of Neurons/Perceptrons
  - Multiple hidden layers

NN (perceptron) consists of three layers:

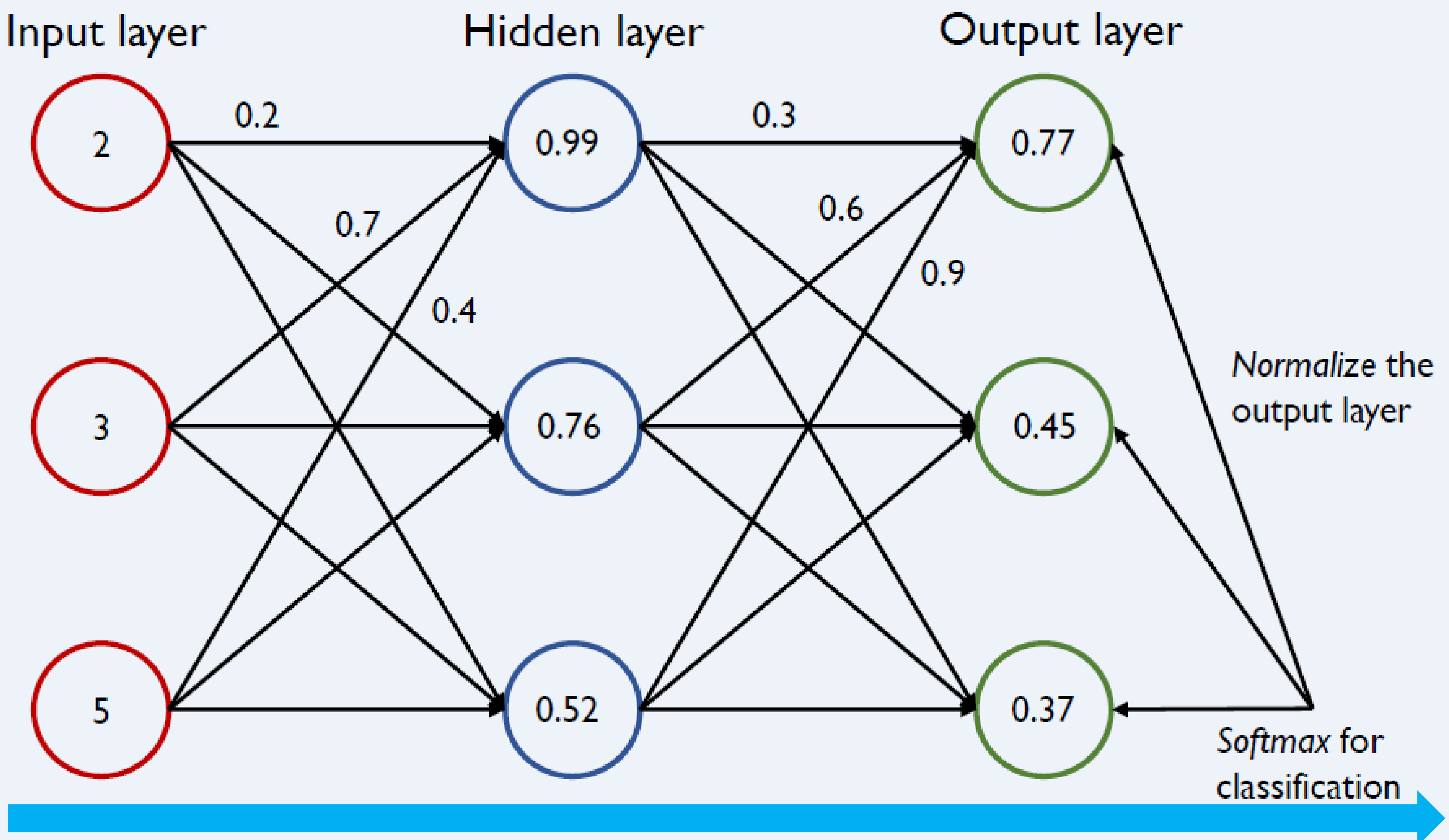


Neural Networks: Training Procedures





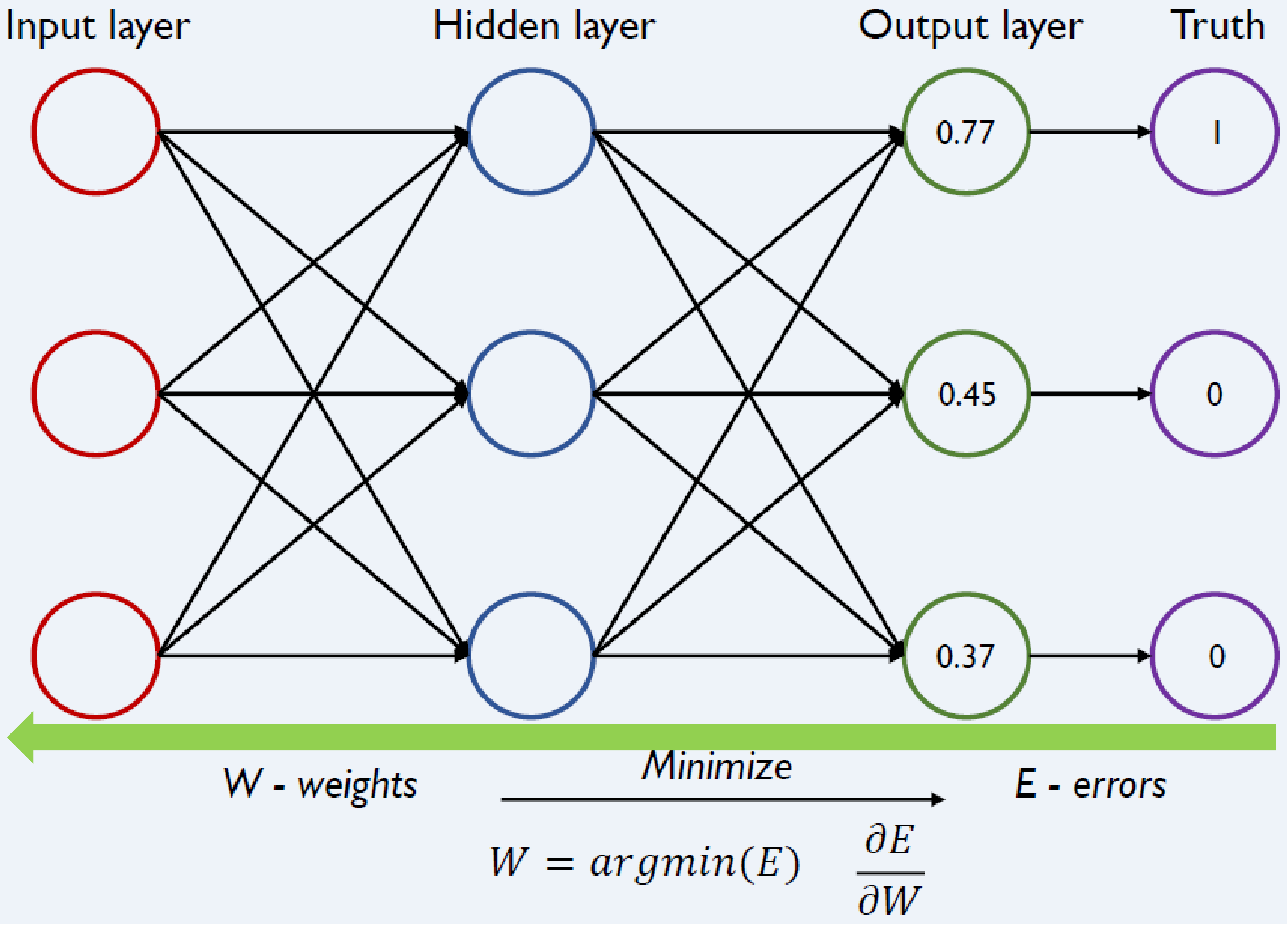
Neural Networks: FeedForward



$$2 * 0.2 + 3 * 0.7 + 4 * 0.5 = 4.5 \qquad 0.98 * 0.3 + 0.76 * 0.6 + 0.52 * 0.9 = 1.218$$

$$sigmoid(x) = \frac{1}{1+e^{-x}} = 0.99 \qquad sigmoid(x) = \frac{1}{1+e^{-x}} = 0.77$$

Neural Networks: BackPropagation



Q: Why do we need backpropagation?

- Reduce overall/total errors after updating weights

- Go back to update weights/parameters (Gradient Descent)

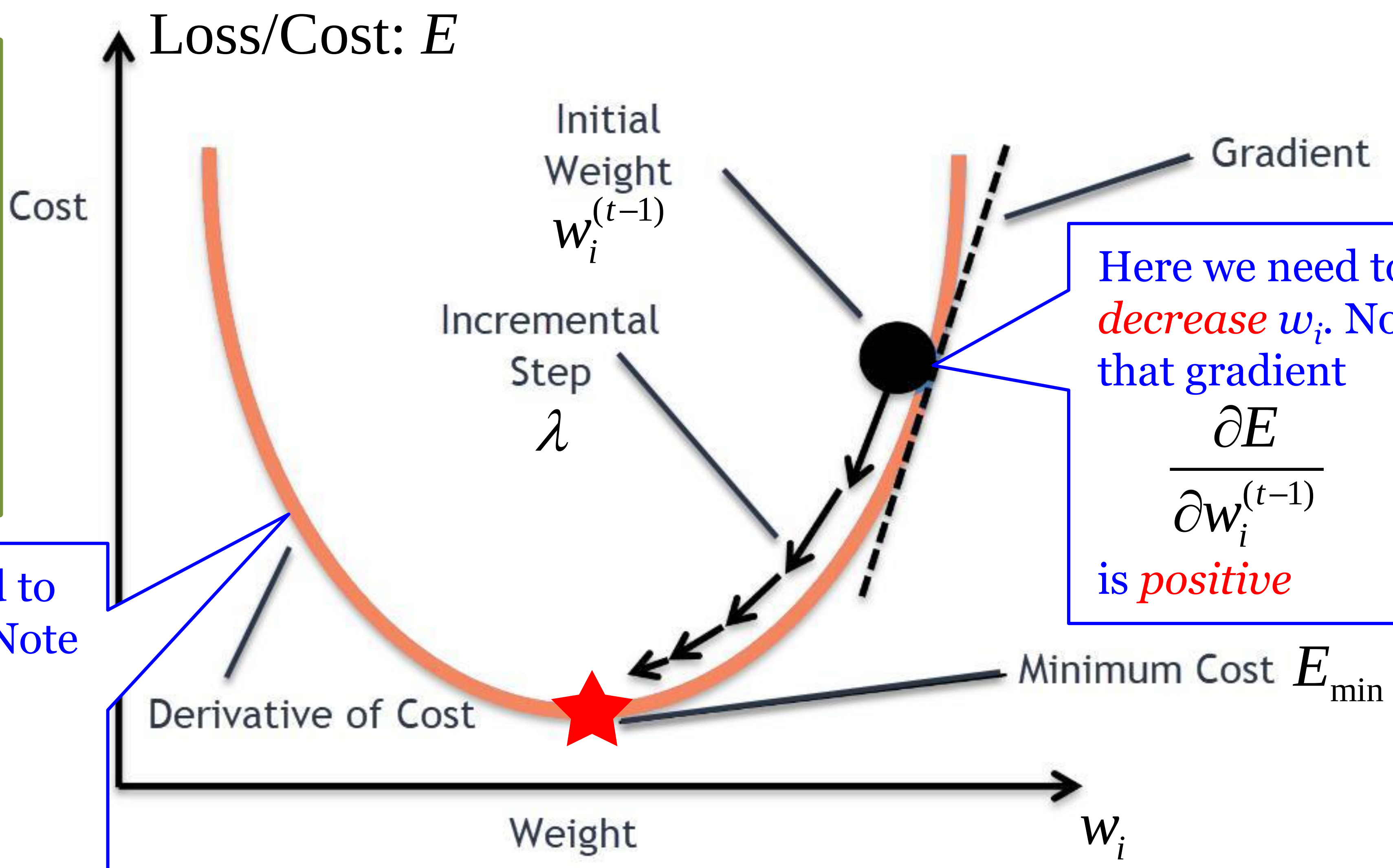
Neural Networks: BackPropagation

- Gradient Descent

Update Rule:

Move in the direction opposite to the gradient direction, by a step with rate λ :

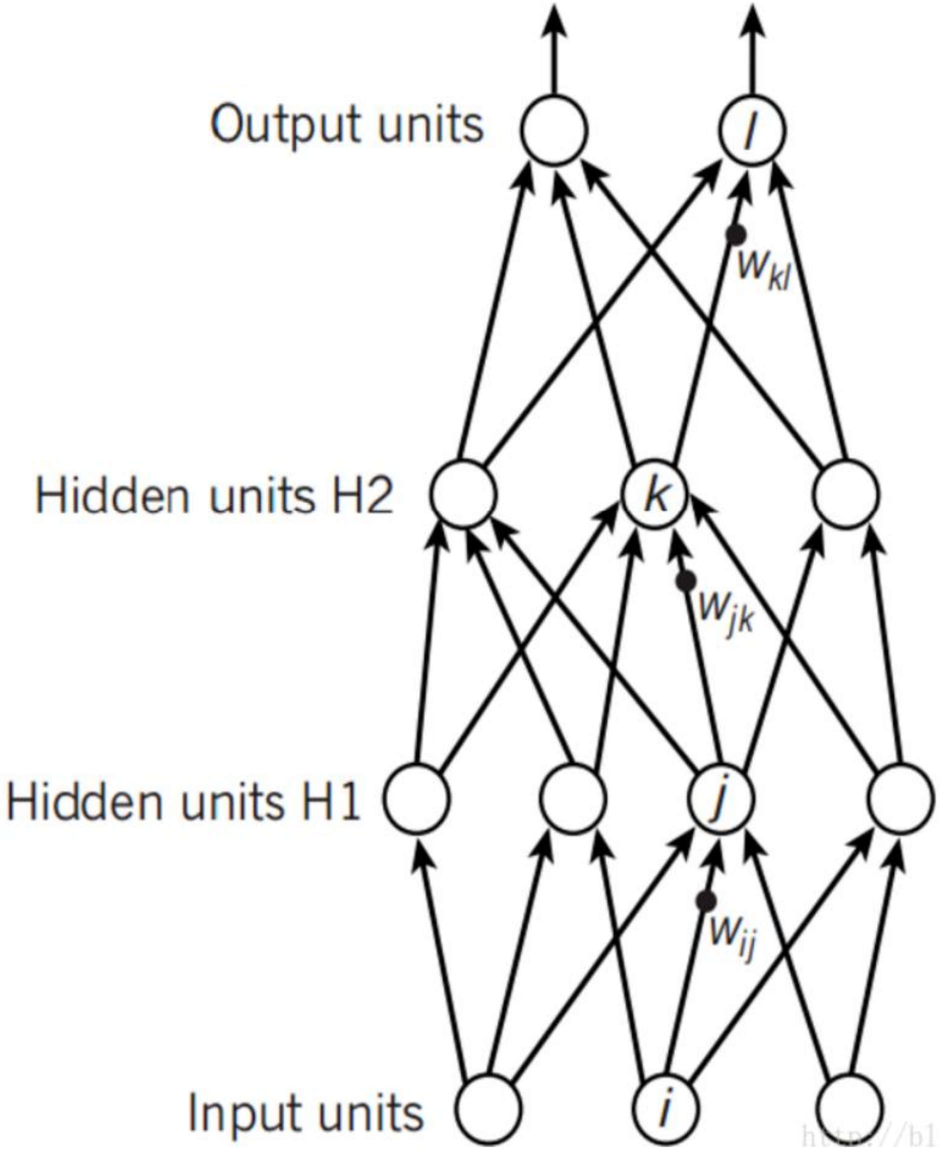
$$w_i^{(t)} \leftarrow w_i^{(t-1)} - \lambda \times \frac{\partial E}{\partial w_i^{(t-1)}}$$

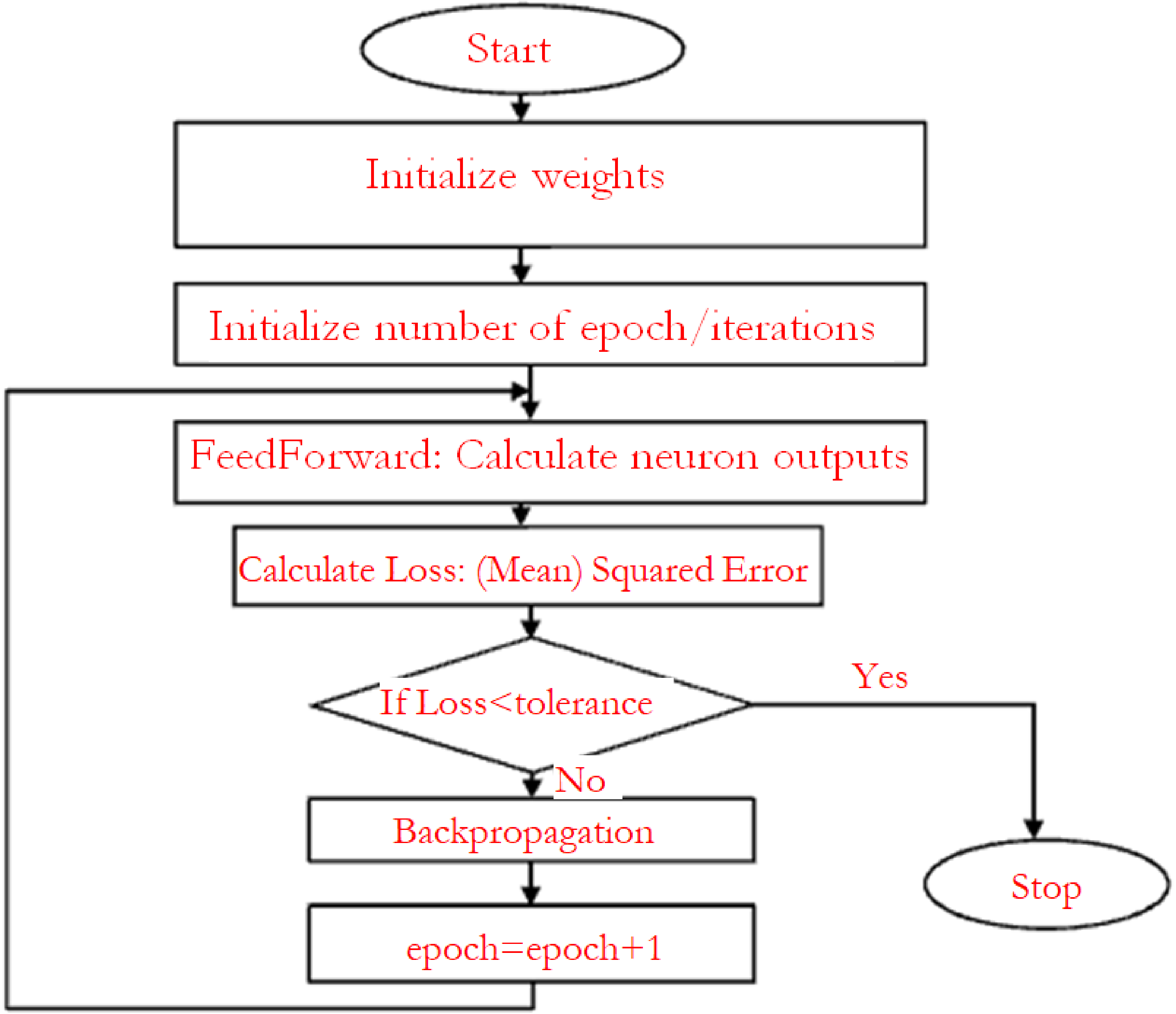


Here we need to *increase* w_i. Note that gradient $\frac{\partial E}{\partial w_i^{(t-1)}}$ is *negative*

Here we need to *decrease* w_i. Note that gradient $\frac{\partial E}{\partial w_i^{(t-1)}}$ is *positive*

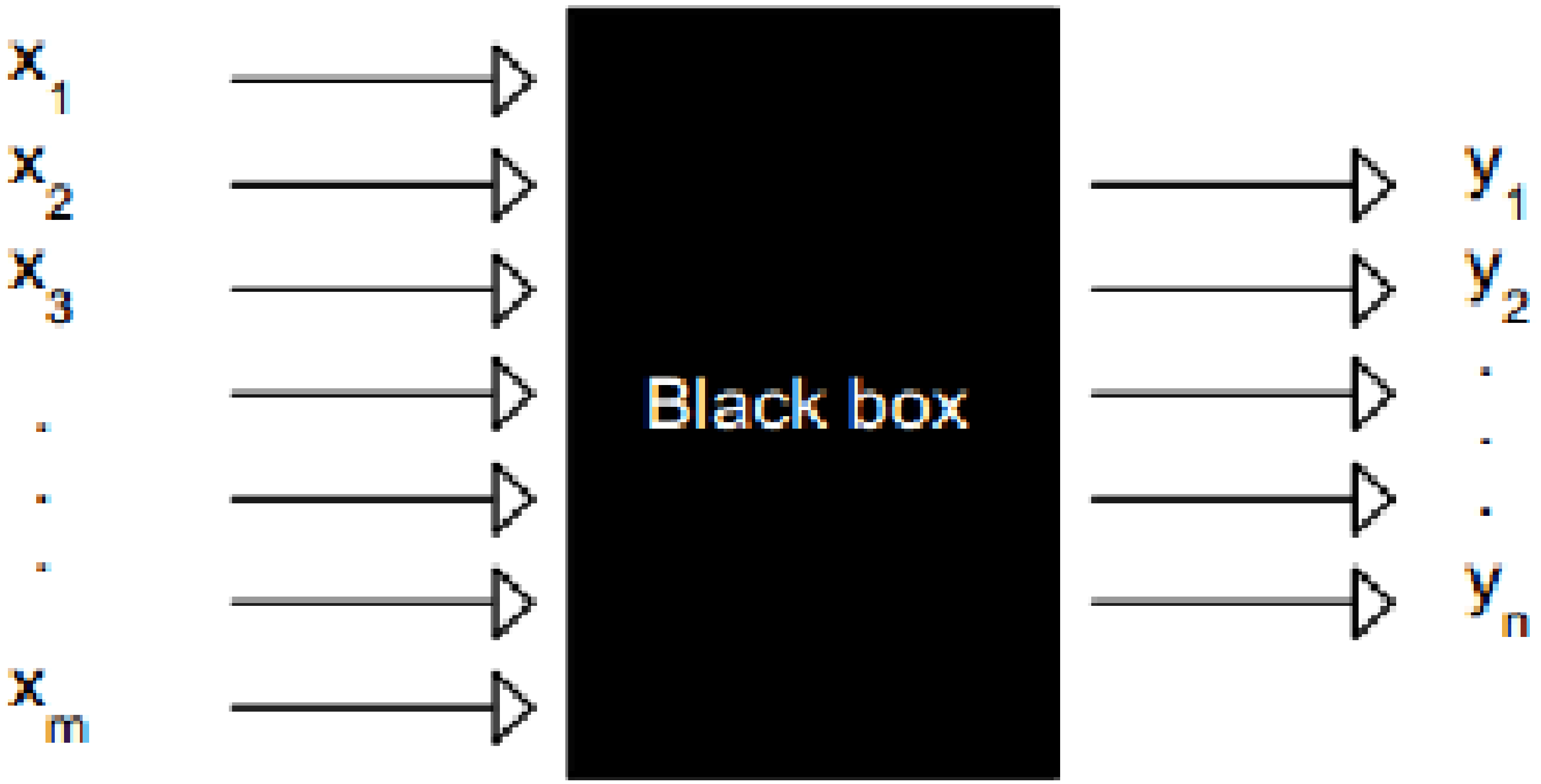
Neural Networks: Summary





Neural Networks: Limitations

Neural Networks: Limitation I



- Good at making prediction, but bad at making interpretation
- What happens in the “Black Box”? The effectiveness of features ?

Neural Networks: Limitation II

- Gradient Vanishing & Gradient Explosion

Update: $w_i^{(t)} \leftarrow w_i^{(t-1)} - \lambda \times \dfrac{\partial E}{\partial w_i^{(t-1)}}$

$$X1 \xrightarrow{\boxed{w_0}} h1 \xrightarrow{w_1} h2 \xrightarrow{w_2} \cdots\cdots hn \xrightarrow{w_n} O1 \longrightarrow E$$

- **Derivative Chain Rule**

$$\frac{\partial E}{\partial w_0} = \frac{\partial E}{\partial O_{1\_out}} \times \frac{\partial O_{1\_out}}{\partial O_{1\_in}} \times \frac{\partial O_{1\_in}}{\partial h_{n\_out}} \times \frac{\partial h_{n\_out}}{\partial h_{n\_in}} \times \cdots \times \frac{\partial h_{1\_out}}{\partial h_{1\_in}} \times \frac{\partial h_{1\_in}}{\partial w_0}$$

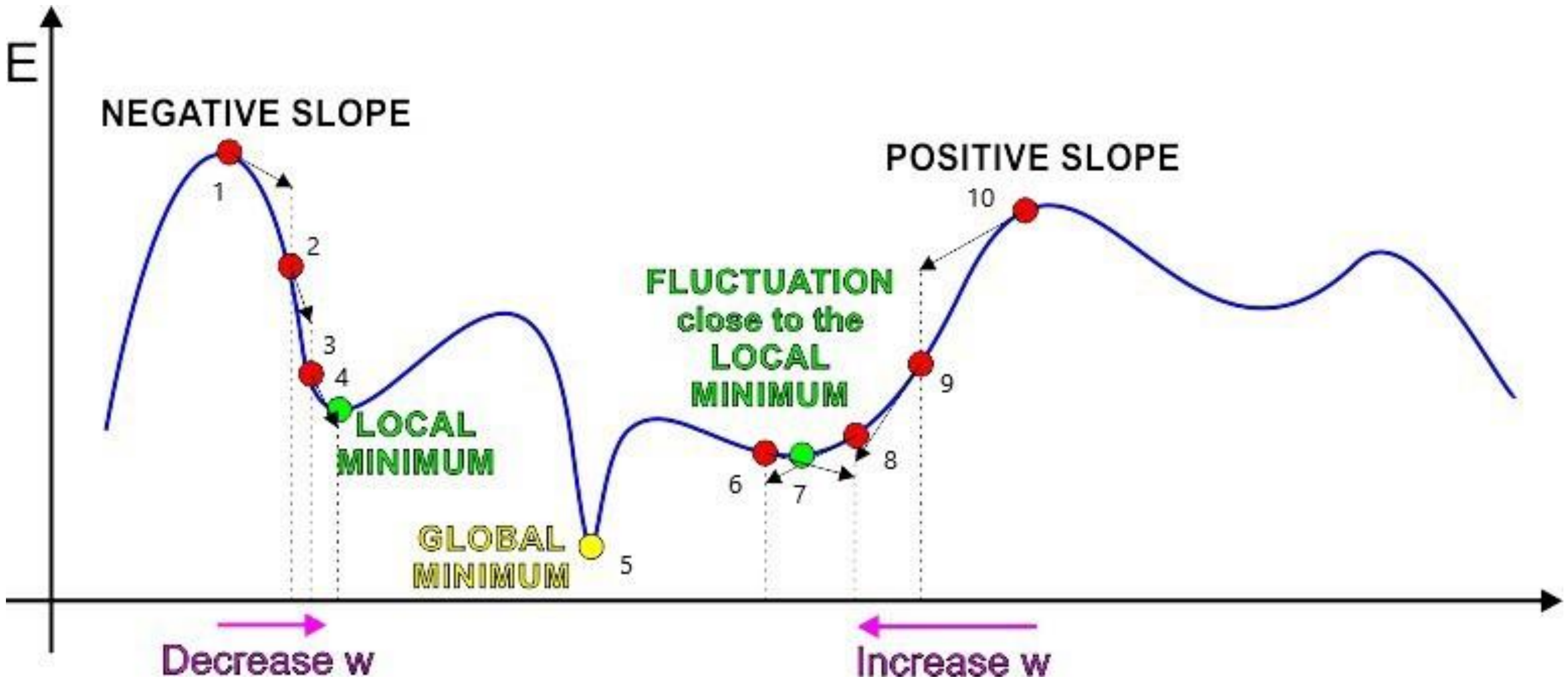
  - Calculating gradient of weights:

$$= \frac{\partial E}{\partial O_{1\_out}} \times f'(O_{1\_in}) \times w_n \times f'(h_{n\_in}) \times w_{n-1} \times \cdots \times f'(h_{1\_in}) \times x_1$$

- If we choose activation functions carelessly,
  - If gradients are lower than 1 → Gradient Vanishing : $\dfrac{\partial Sigmoid(x)}{\partial x} \in (0,1)$ so $\dfrac{\partial E}{\partial w_0} \to 0$
    - Solutions: Choose activation functions carefully
  - If gradients are greater than 1 → Gradient Explosion : $\dfrac{\partial E}{\partial w_0} \to \infty$
    - Solutions: Gradient Clipping; Regularization on weights

Neural Networks: Limitation III

- Optimization With Gradient Descent:



Remember:

Gradient Descent is a greedy algorithm

- Solutions:
  - Revised GD: Stochastic Gradient Descent (SGD), etc.
  - Alternative optimization methods: Simulated Annealing in Boltzmann Machine

Neural Networks: Limitation IV

- Generalization Error Bound on Test Data (i.e., Out-of-sample):

$$\Pr\{|\frac{1}{N}\sum_{n=1}^{N} Loss(\hat{f}(x_n) \neq f(x_n)) - E[Loss(\hat{f}(x_{new}) \neq f(x_{new}))]| > \varepsilon\}$$

$$= \Pr\{|\,\mathrm{InSampleError} - \mathrm{OutOfSampleError}\,| > \varepsilon\}$$

$$\leq \frac{2M}{e^{2N\varepsilon^2}}$$

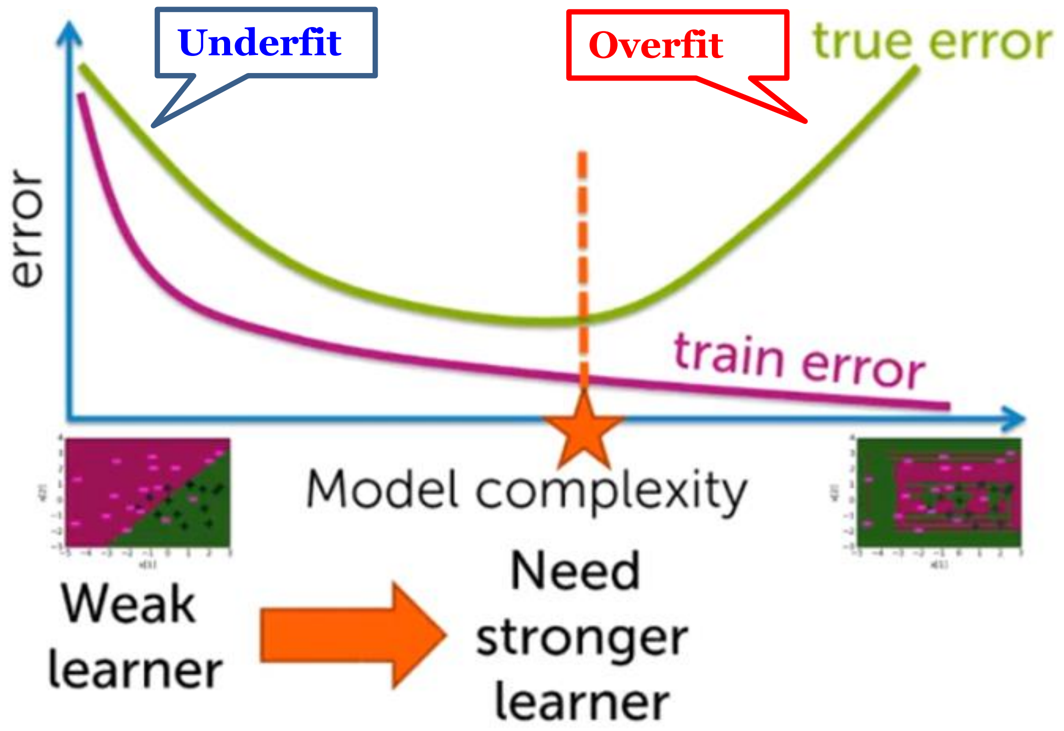
♥ $\hat{f}$: InSampleError ≈ 0

and InSampleError ≈ OutOfSampleError

- Neural Networks may still overfit !

- General Solutions:
  - Regularization on weights
  - Batch normalization
  - Dropout neurons randomly in each layer

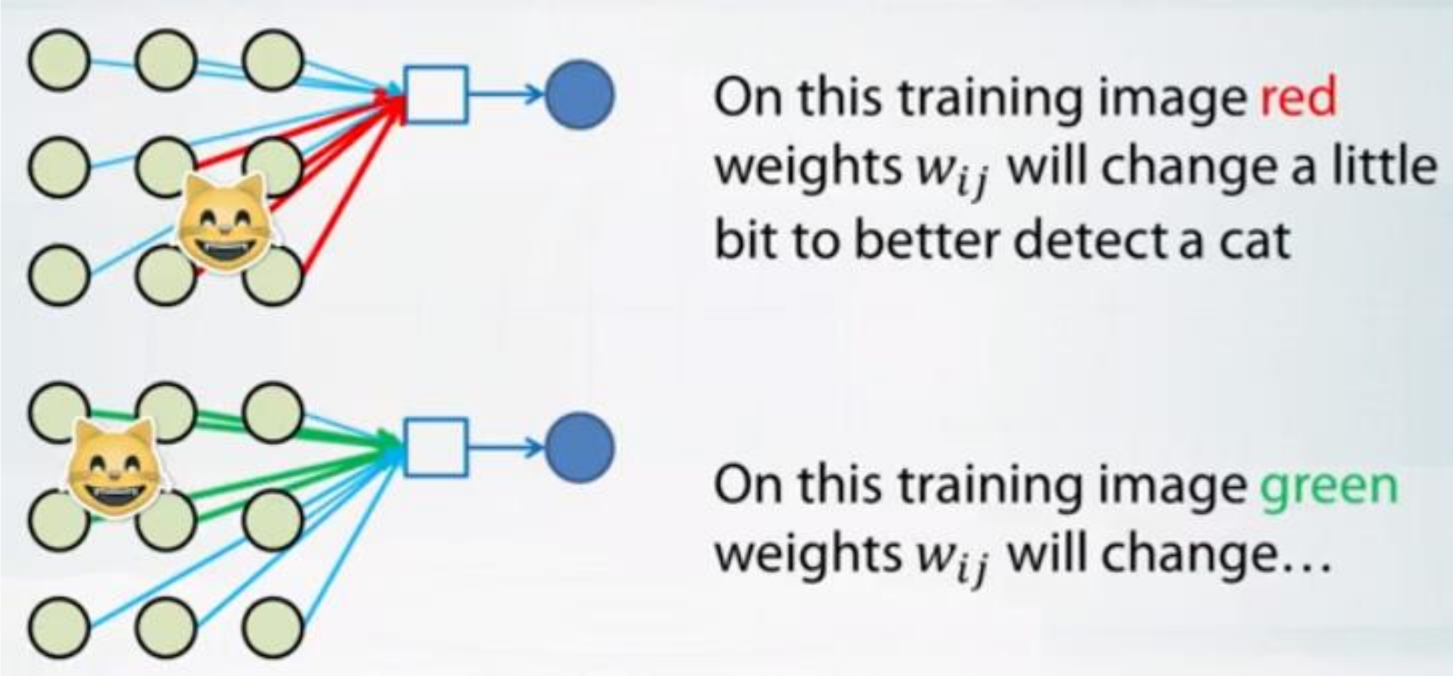
Bias-Variance Tradeoff



"No Free Lunch"

Neural Networks: Limitation IV

- Image Classification:
  - What if we use a normal full-connected neural network to do classification?
  - We split the whole image into multiple pixels. Each pixel (a value to represent darkness or brightness of color: 0 to 255) is one feature.
  - What is wrong here ?



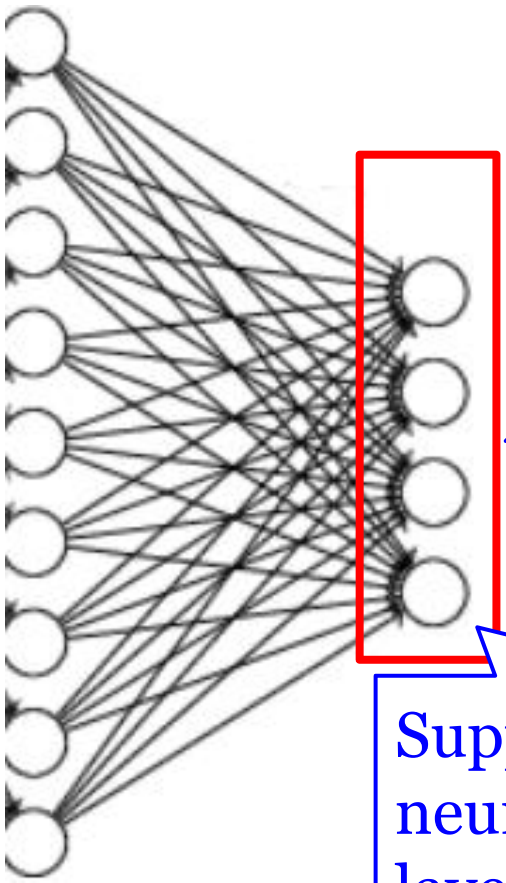
- We don't fully utilize the training data
- What if in test data, the cat is in other areas (e.g., in the centre of the image)?

Neural Networks: Limitation IV

- Image Classification:

Fully Connected Normal NN

300*300
inputs



300*300*4+1
About 360,001
weights

Suppose you have four neurons in the hidden layer

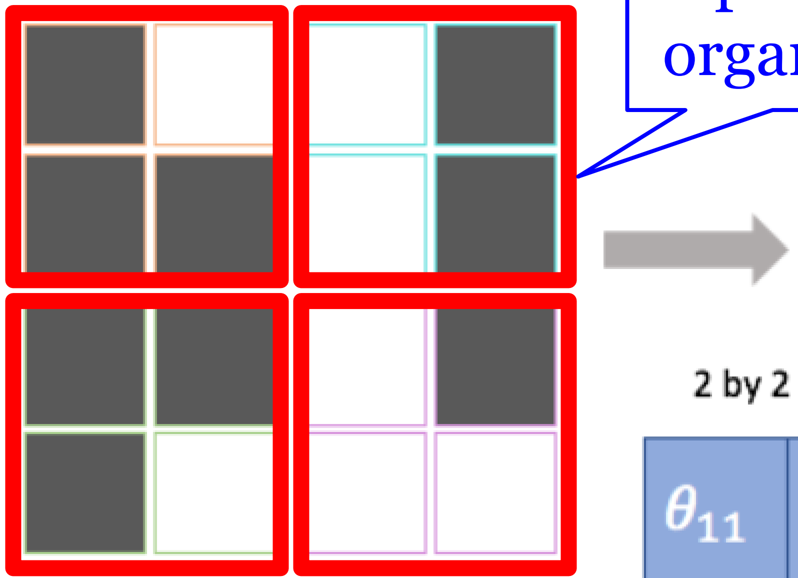
Fully-Connected Neural Network in Computer Vision:

- Slow
- Overfit

Neural Networks: CNN

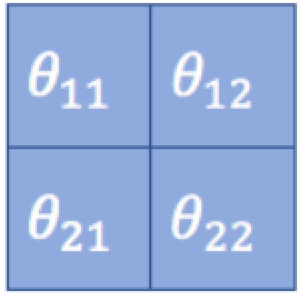
- Convolutional Neural Networks:

4 by 4 pixel image

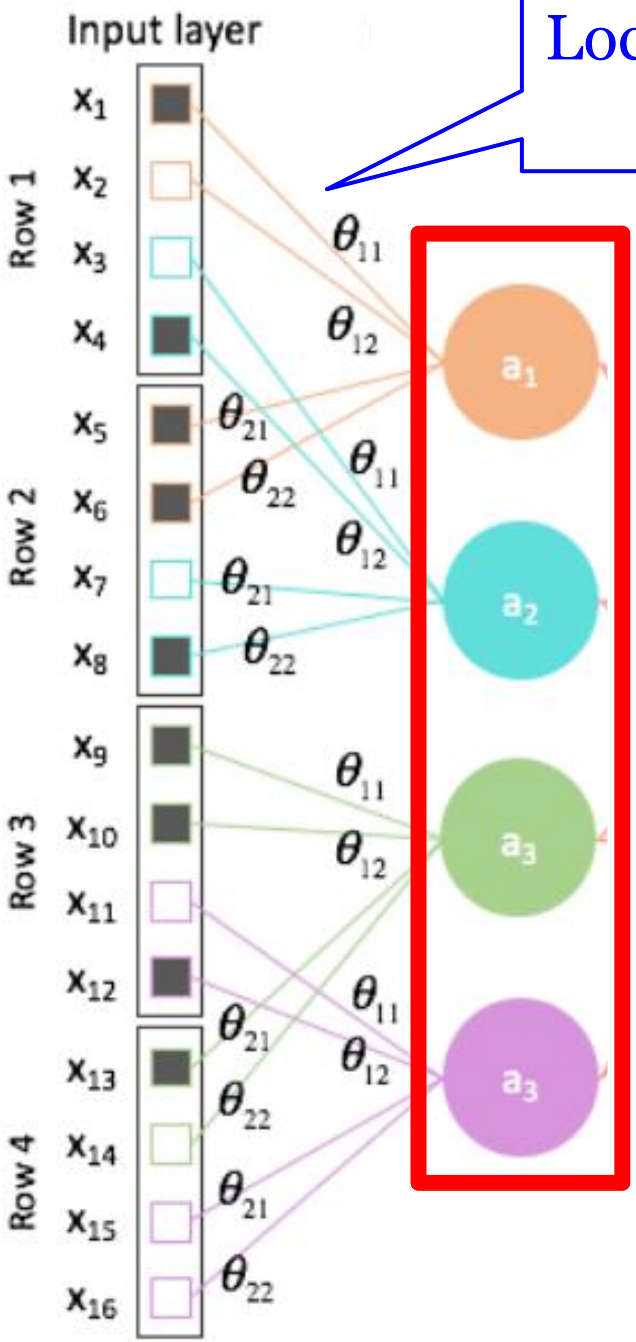


Spatially organized

2 by 2 filter



Convolution Layer (Filter/Kernel):
Suppose Slide Stride=2



Local/Sparse Connectivity:
Sharing weights

Because interesting features (edges) can happen at anywhere in the image.

=

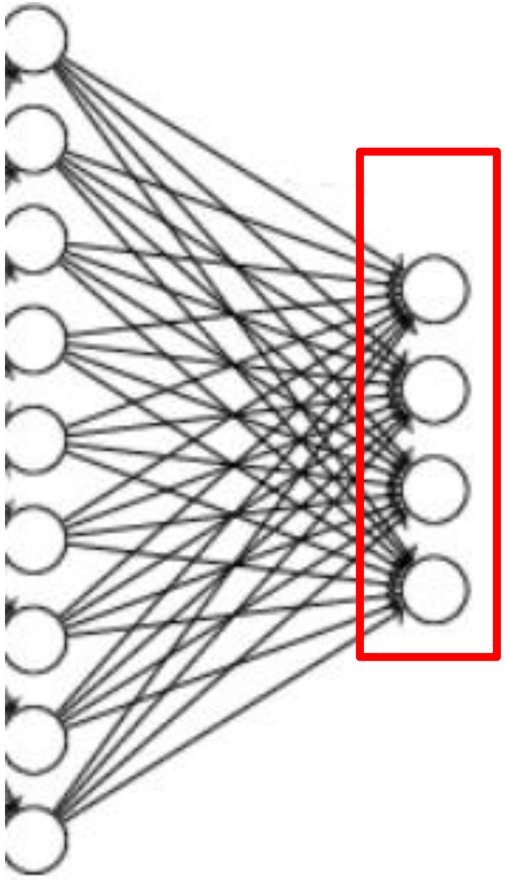
Feature Map:
with new “pixels”

Neural Networks: CNN

- ➢ Convolutional Neural Networks

Fully Connected Normal NN

300*300
inputs

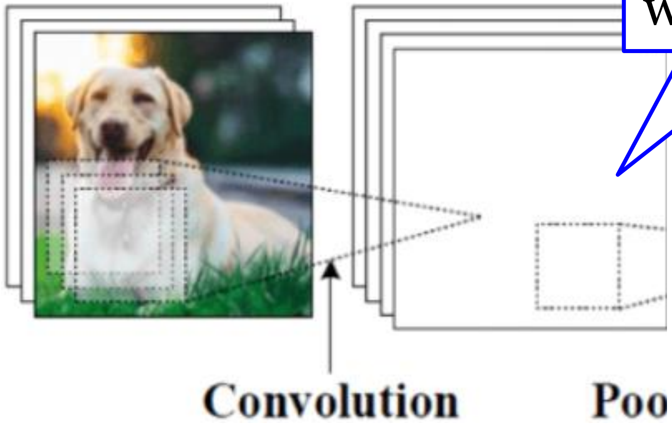


300*300*4+1
About 360,001
weights

Suppose you
have four
neurons in the
hidden layer

CNN

300*300
inputs



(5*5+1)*4
Only 104
weights

Suppose you have
four 5*5 kernels in
the convolution layer

Neural Networks: Alternative Variants

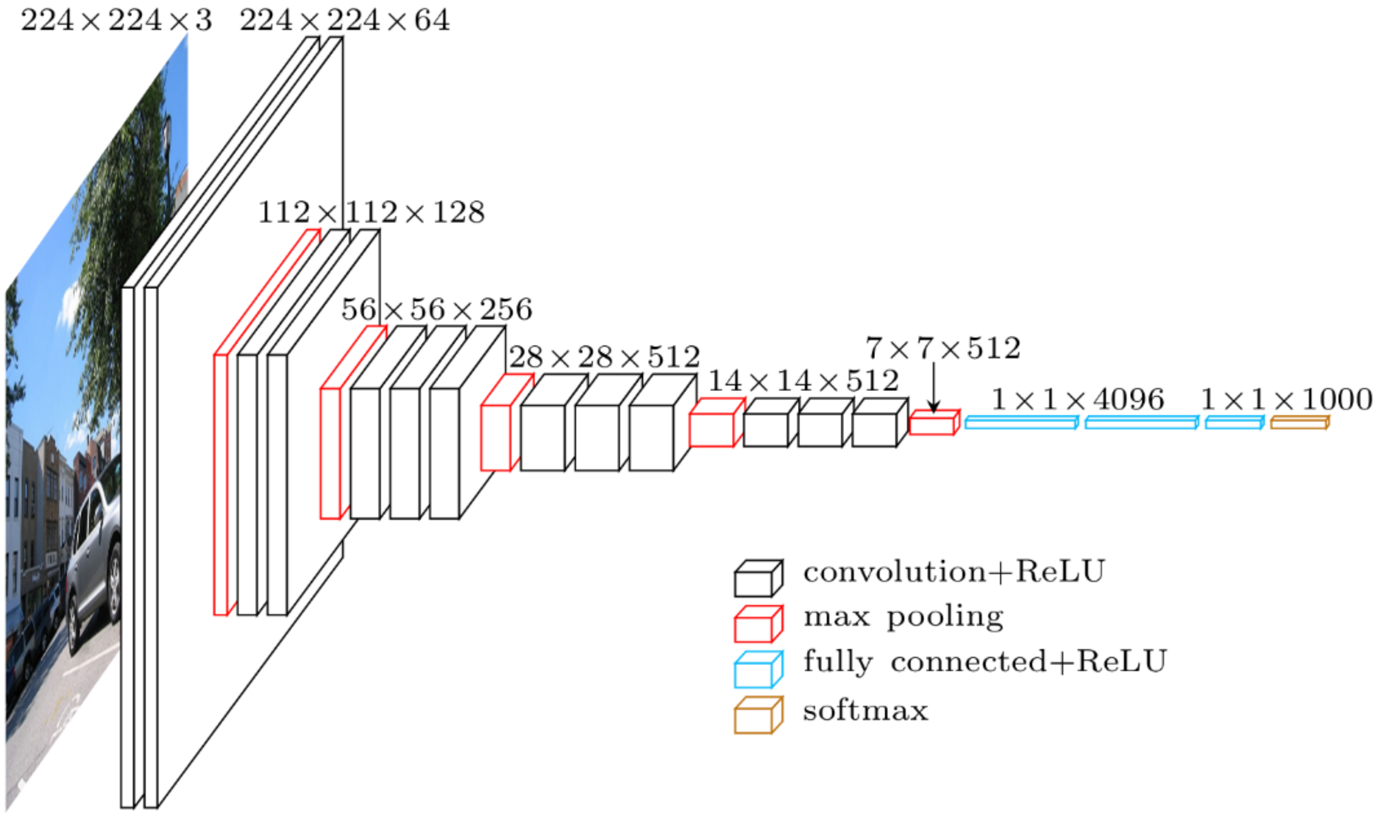
- Recurrent Neural Networks (RNN)
  - Time-dependent Neuron States
  - Long-Short-Term-Memory (LSTM)
- Restricted Boltzmann Machine (RBM)
- Deep Belief Network (DBN)
- Auto-Encoder
- More…

Neural Networks:
Applications in IS Research

Neural Networks: Applications

➤ Academic Research

- Shunyuan Zhang, Dokyun Lee, Param Vir Singh, Kannan Srinivasan. *How Much is an Image Worth? Airbnb Property Demand Analytics Leveraging A Scalable Image Classification Algorithm*. Working Paper. (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2976021)



- Question: What is the effect of joining Airbnb photography program (i.e., verified photos)?
- Training: Label image quality on Amazon Mechanical Turk
- CNN (VGG-16): Image quality and (12) interpretable image features

Neural Networks: Applications

- Computer Vision
  - Image Classification, Face Recognition, Object Detection
  - Video Mining
- Natural Language Processing
  - Textual Feature Extraction (e.g., Content features, sentiment/semantic features, etc.)
- Time Series Forecasting
- Speech Recognition
- More…

Remember:
Earn money and Buy GPUs

One Sentence for Machine Learning And Deep Learning

In God we trust, all others bring data

------William Edwards Deming (1900-1993)

From "The Elements of Statistical Learning" (ESL) by Trevor Hastie, Robert Tibshirani and Jerome Friedman

Thank You !