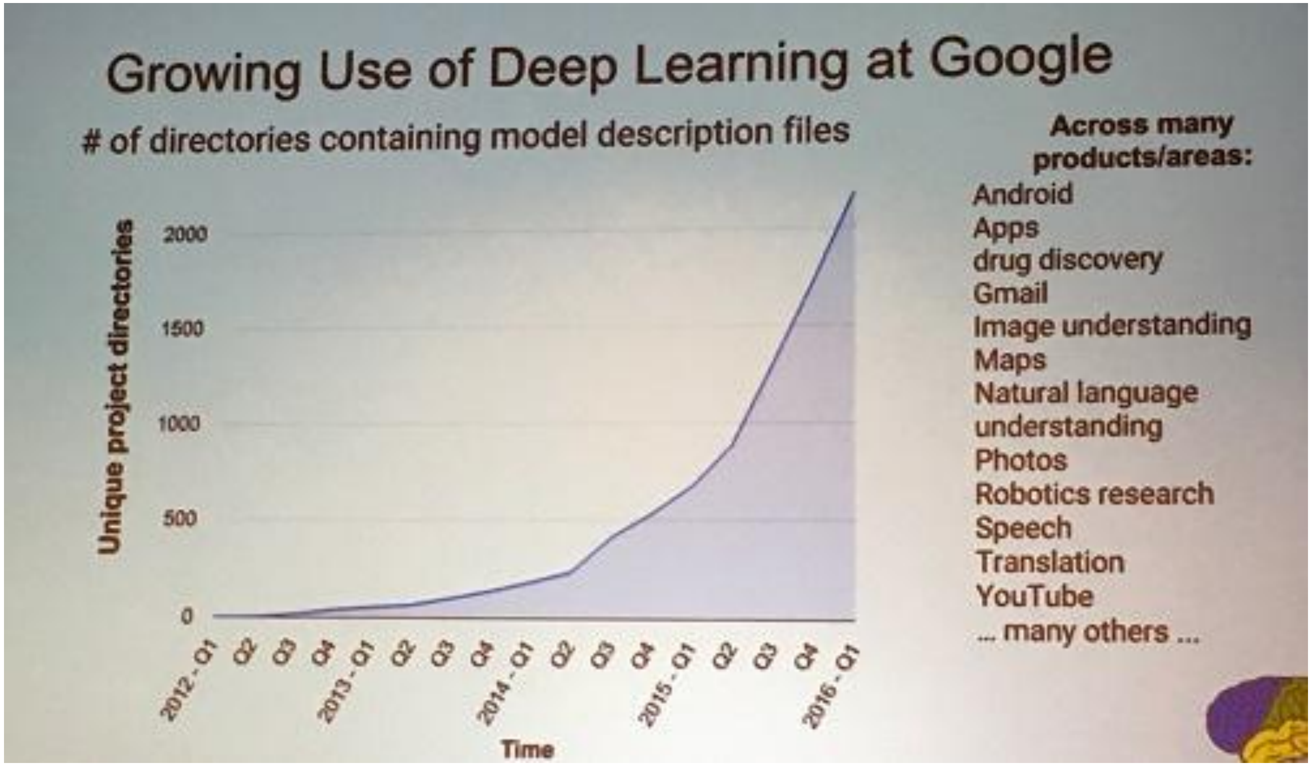
BIG DATA and AI for business

Deep Learning (1)

Decisions, Operations & Information Technologies
Robert H. Smith School of Business
Fall, 2020

Deep learning attracts lots of attention.

- I believe you have seen lots of exciting results before.



Deep learning trends at Google. Source: SIGMOD/Jeff Dean

We mainly focus on the basic techniques.

Introduction to Deep Learning

Outline

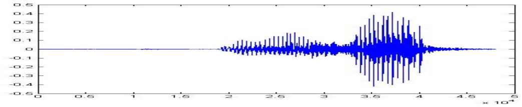
Introduction of Deep Learning

"Hello World" for Deep Learning

Tips for Deep Learning

Machine Learning
≈ Looking for a Function

- Speech Recognition

$f($  $) =$ "How are you"

- Image Recognition

$f($  $) =$ "Cat"

- Playing Go

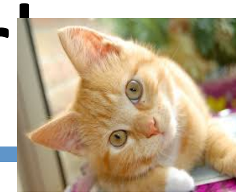
$f($  $) =$ "5-5" (next move)

- Dialogue System

$f($ "Hi" (what the user said) $) =$ "Hello" (system response)

Image Recognition:

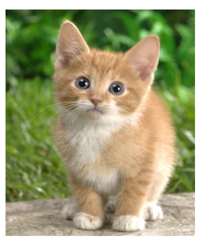
Framework

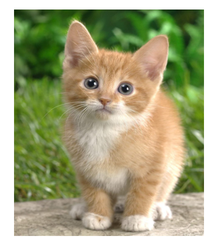
$f($  $)=$ "cat"

A set of function

Model

$f_1, f_2 \cdots$

$f_1($  $)=$ "cat"

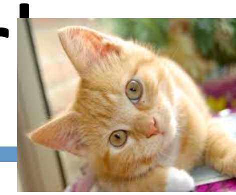
$f_2($  $)=$ "money"

$f_1($  $)=$ "dog"

$f_2($  $)=$ "snake"

Framework

Image Recognition:

$f($  $)=$ "cat"

A set of function

Model

$f_1, f_2 \cdots$

$f_1($  $)=$ "cat"

$f_2($  $)=$ "money"

Better!

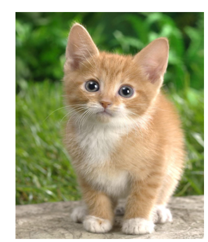
$f_1($  $)=$ "dog"

$f_2($  $)=$ "snake"

Goodness of function f

Training Data

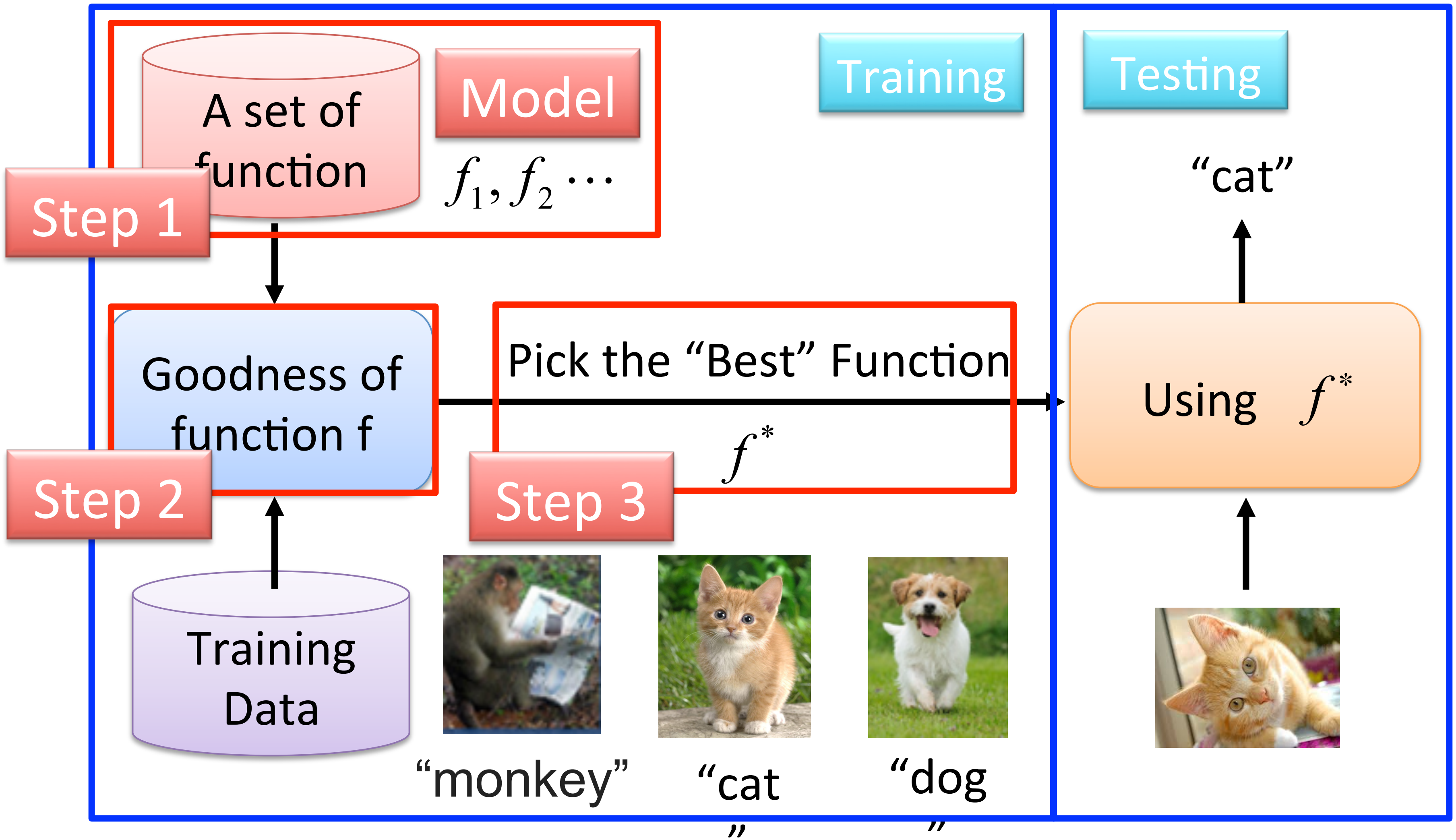
Supervised Learning

function input:   

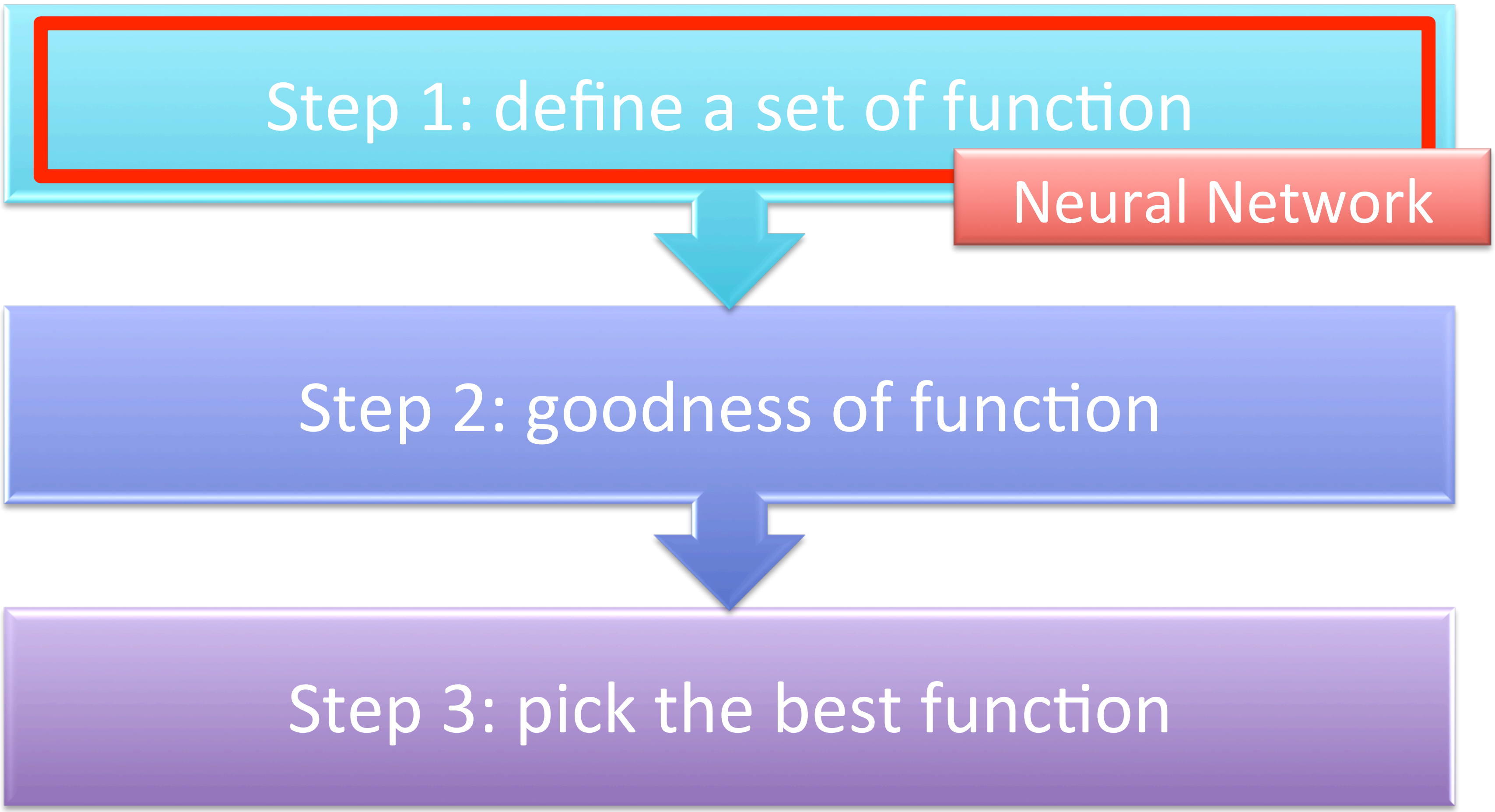
function output: "monkey" "cat" "dog"

Framework

Image Recognition:



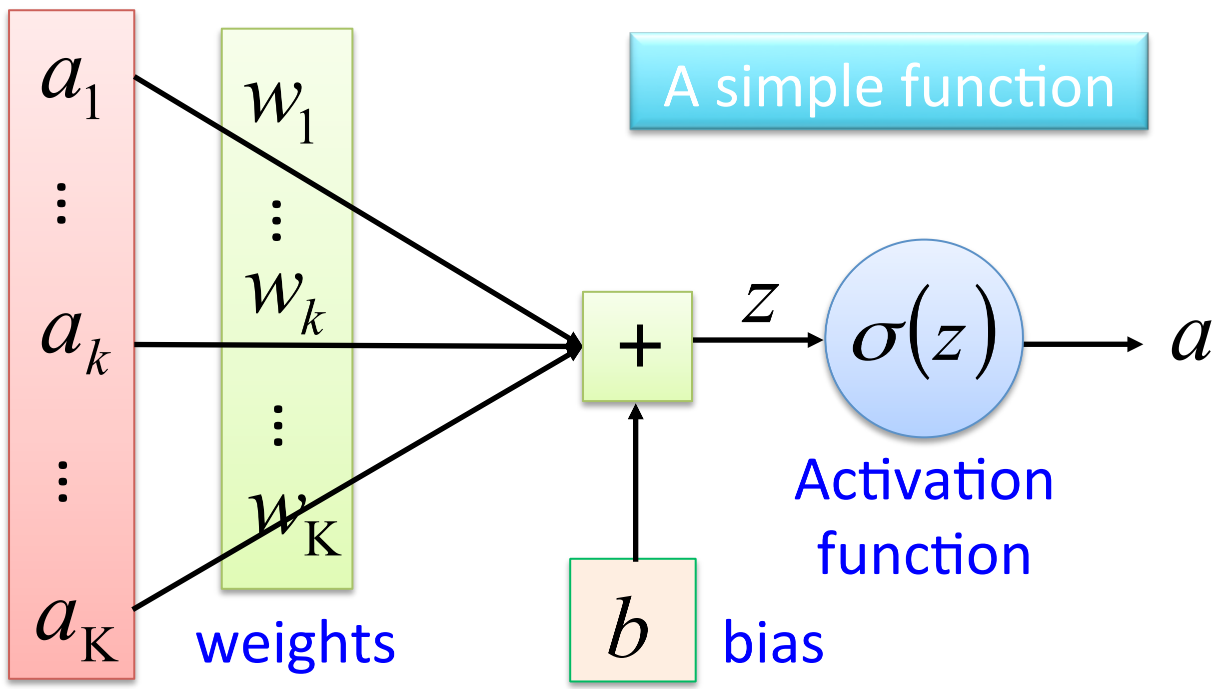
Three Steps for Deep Learning



Neural Network

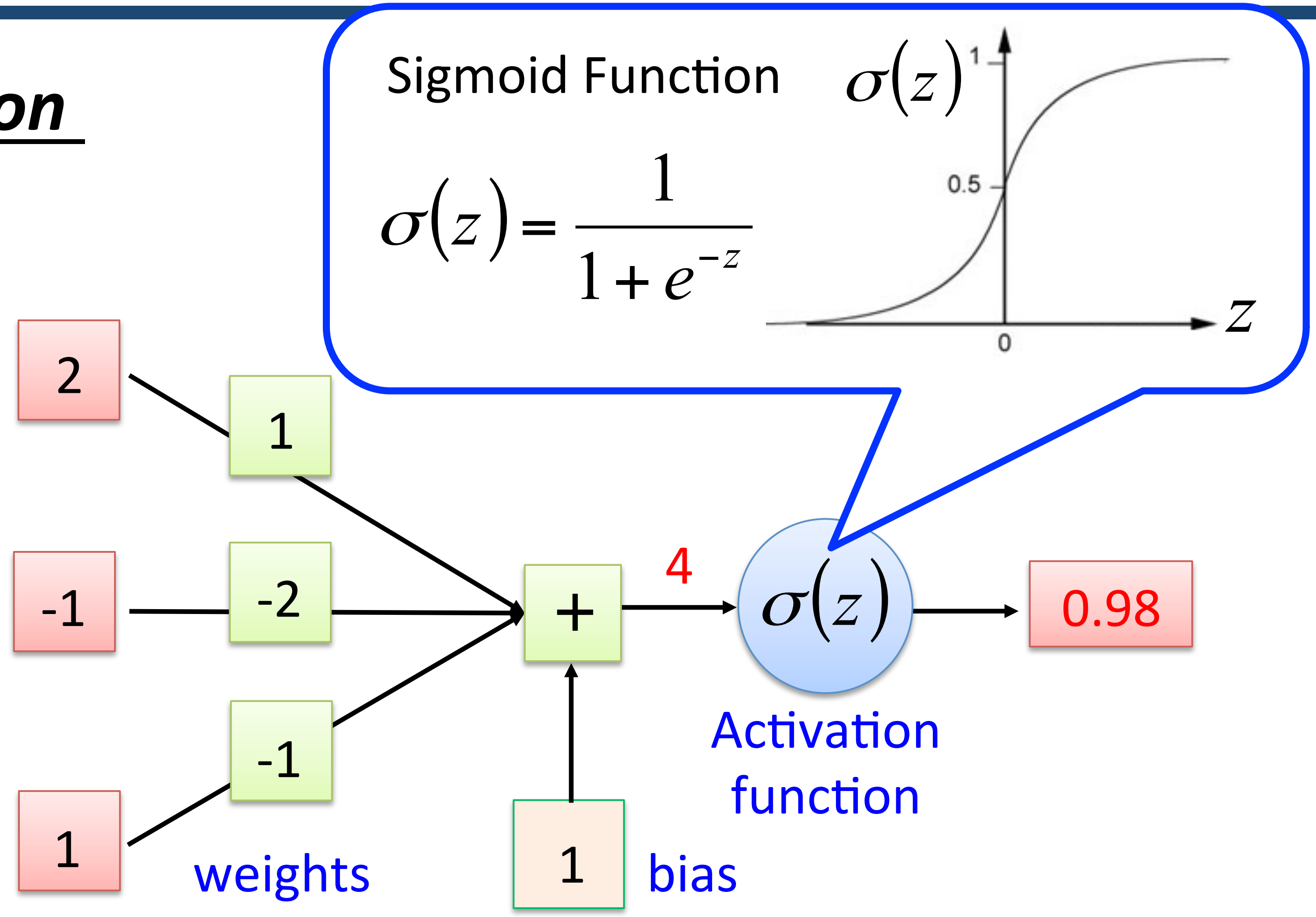
Neuron

$$z = a_1 w_1 + \cdots + a_k w_k + \cdots + a_K w_K + b$$

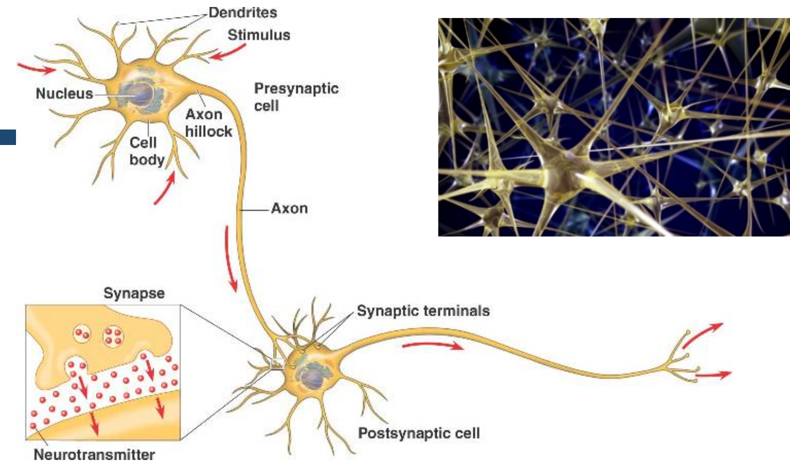


Neural Network

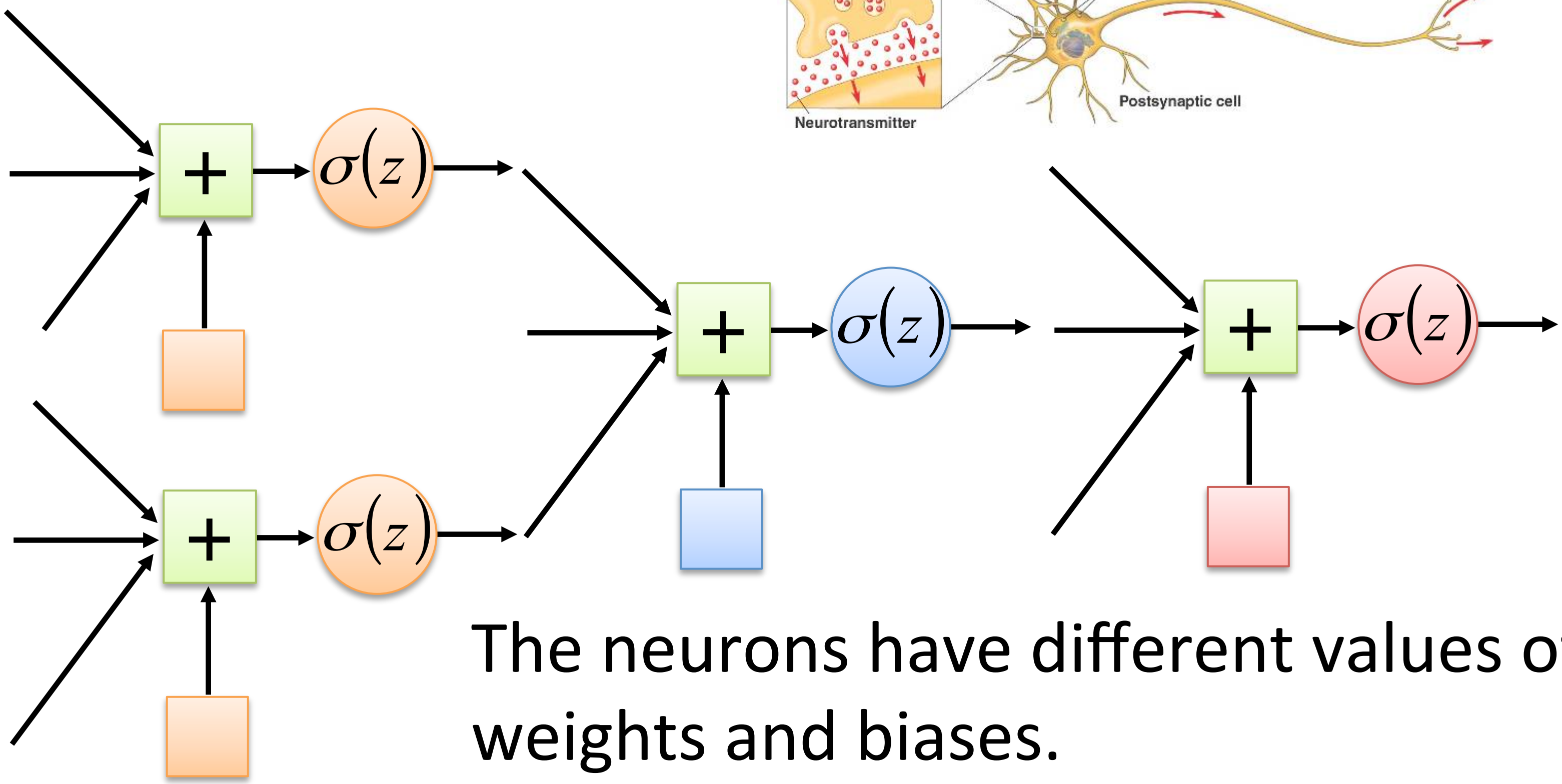
Neuron



Neural Network



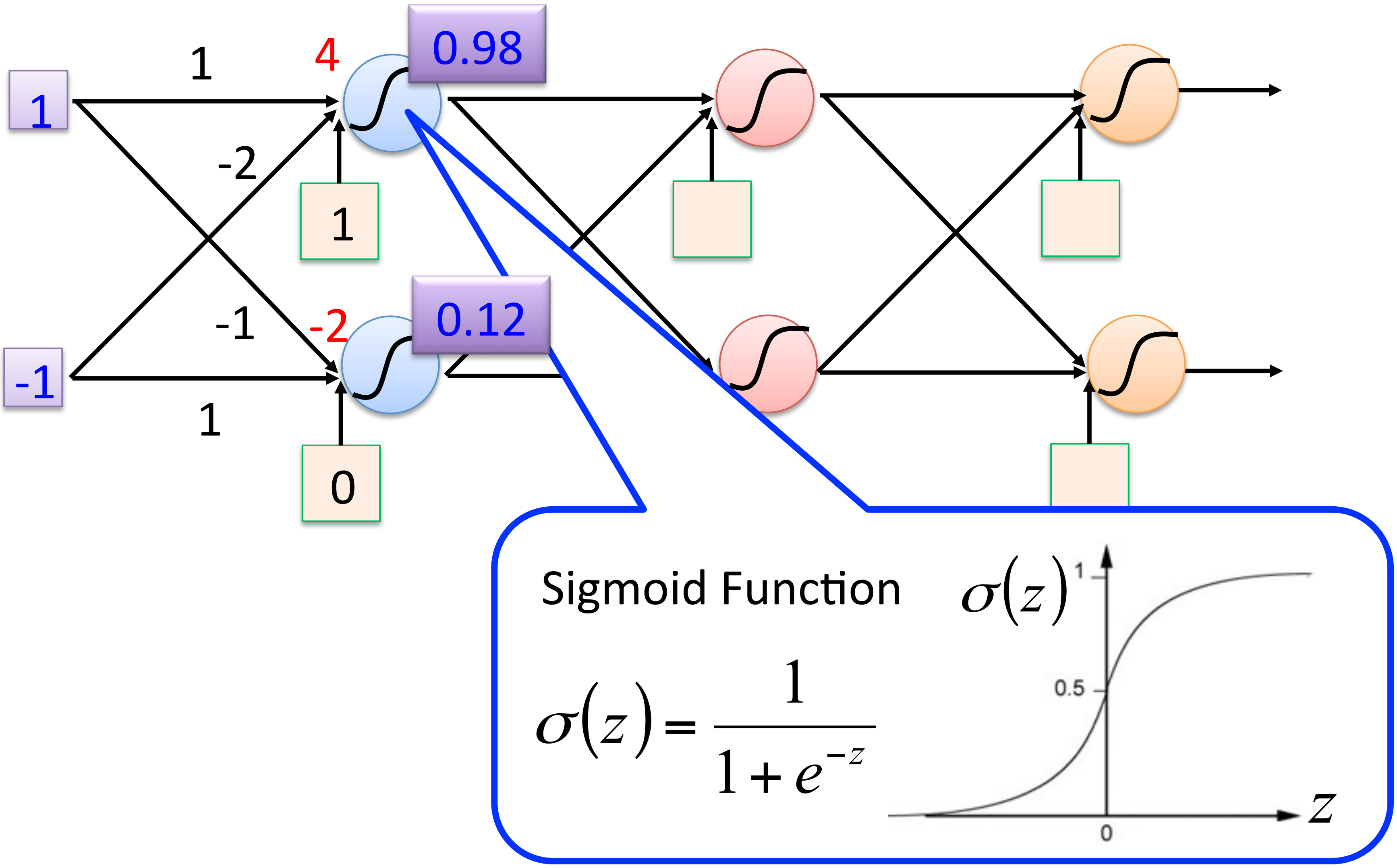
Different connections lead to different network structures



The neurons have different values of weights and biases.

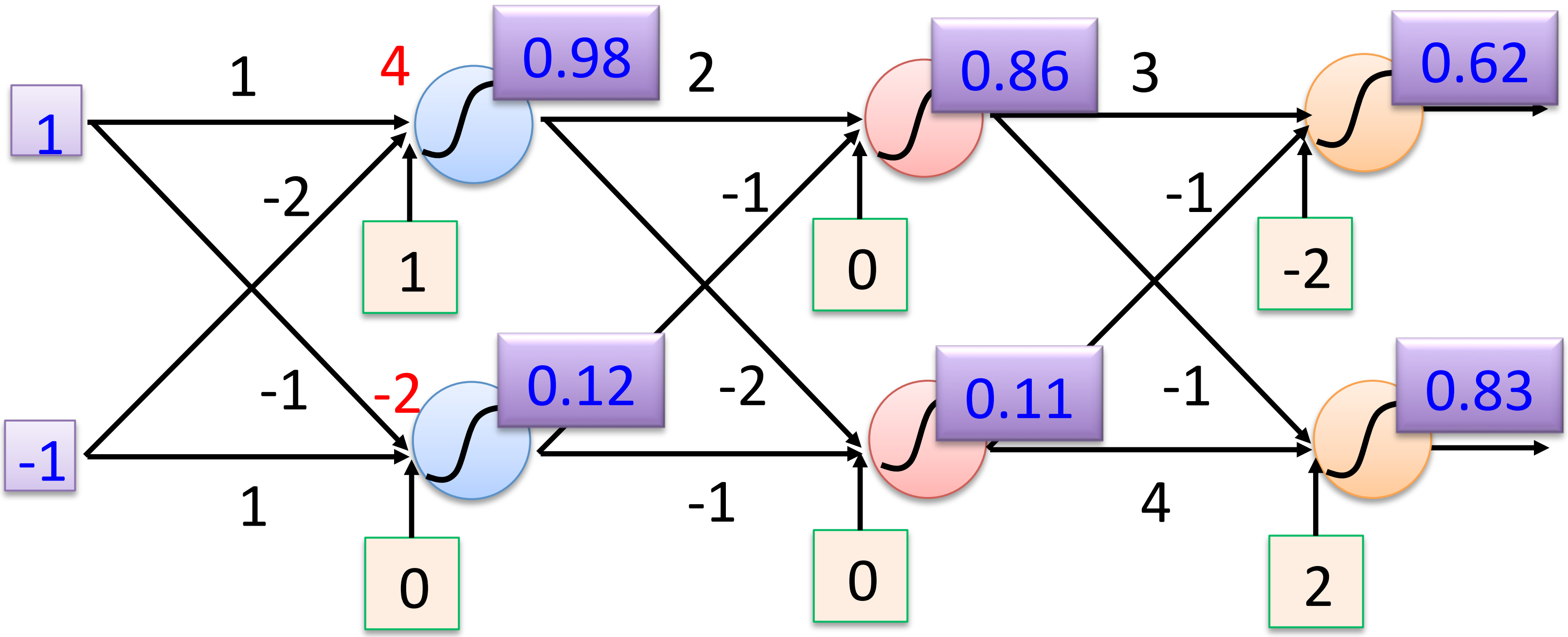
Weights and biases are network parameters θ

Fully Connect Feedforward Network

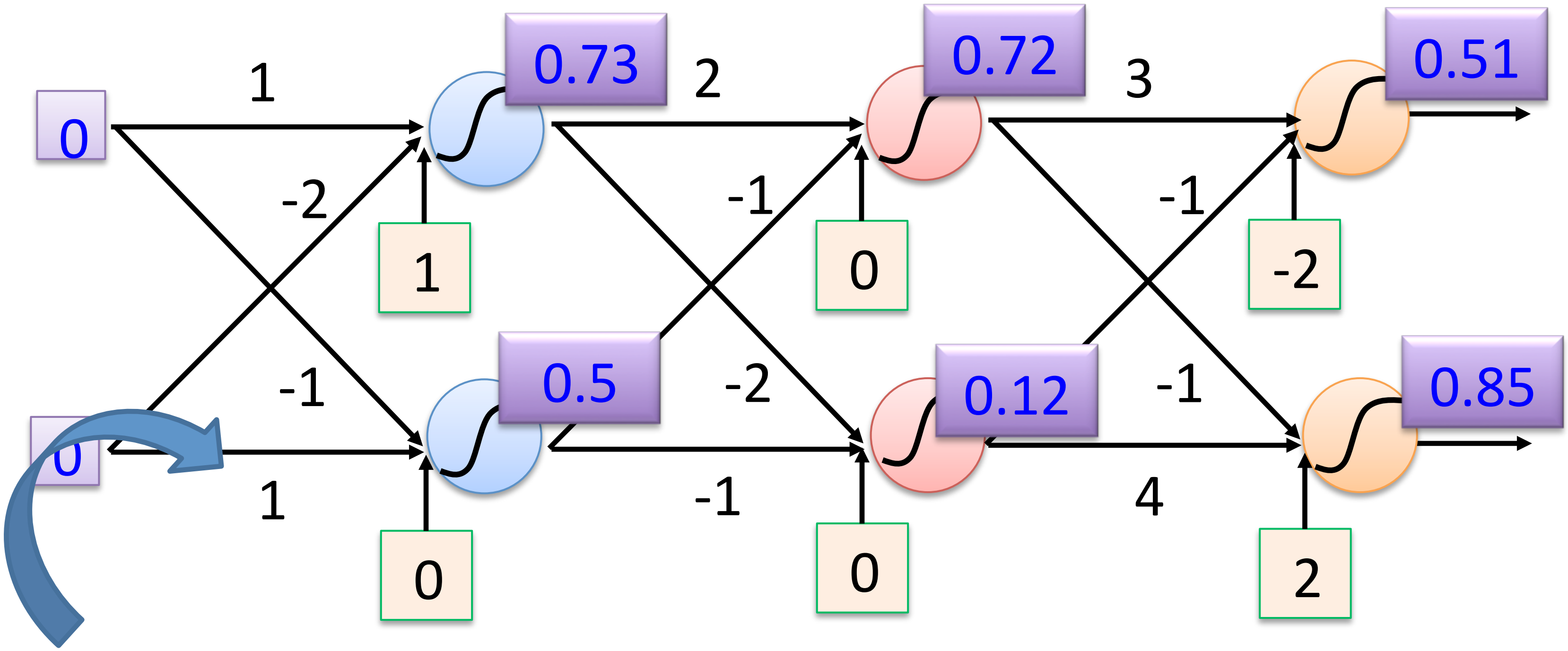


$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Fully Connect Feedforward Network



Fully Connect Feedforward Network



This is a function.

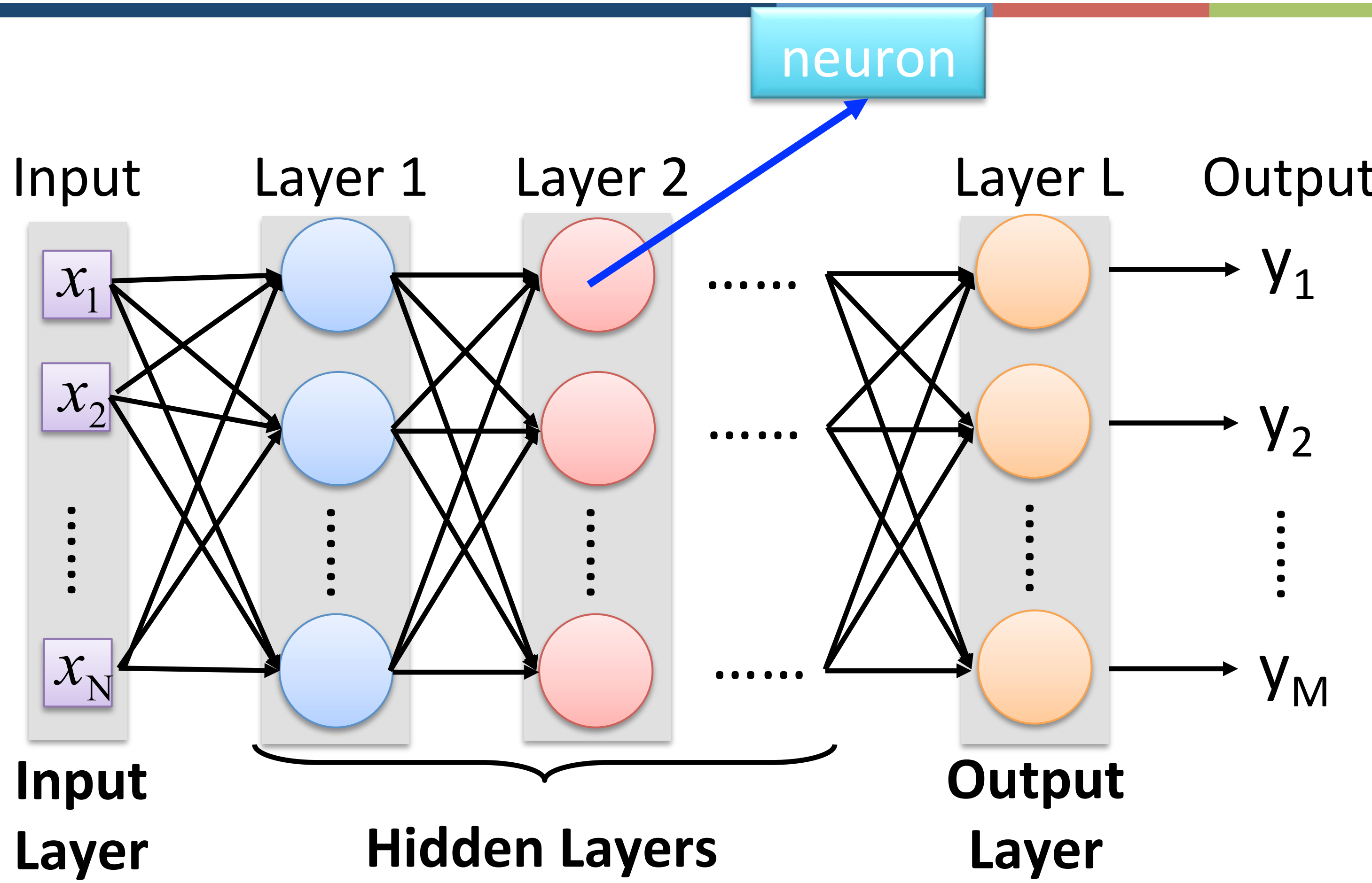
Input vector, output vector

$f\left(\begin{bmatrix}1\\-1\end{bmatrix}\right)=\begin{bmatrix}0.62\\0.83\end{bmatrix}$ $f\left(\begin{bmatrix}0\\0\end{bmatrix}\right)=\begin{bmatrix}0.51\\0.8\end{bmatrix}$

Given parameters θ, define a function

Given network structure, define ***a function set***

Fully Connect Feedforward Network



Deep means many hidden layers

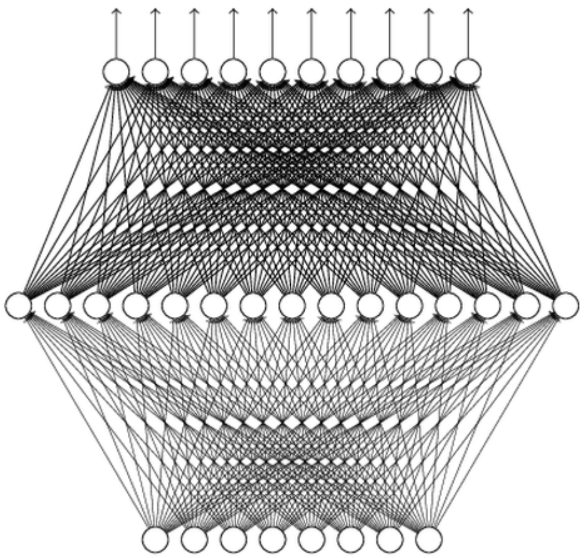
Why Deep? Universality Theorem

Any continuous function f

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

Can be realized by a network with one hidden layer

(given **enough** hidden neurons)



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

Why "Deep" neural network not "Fat" neural network?

Why Deep? Analogy

Logic circuits

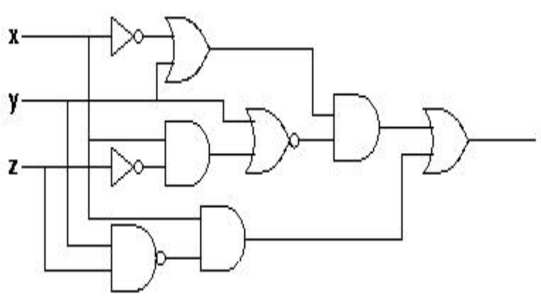
- Logic circuits consists of **gates**
- **A two layers of logic gates** can represent **any Boolean function.**
- Using multiple layers of logic gates to build some functions are much simpler

→ 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?



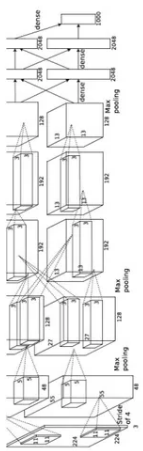
More reason: https://www.youtube.com/watch?v=XsC9byQkUH8&list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49&index=13

Deep = Many hidden layers

http://cs231n.stanford.edu/slides/winter1516_lecture8.pdf

8 layers

16.4%



AlexNet (2012)

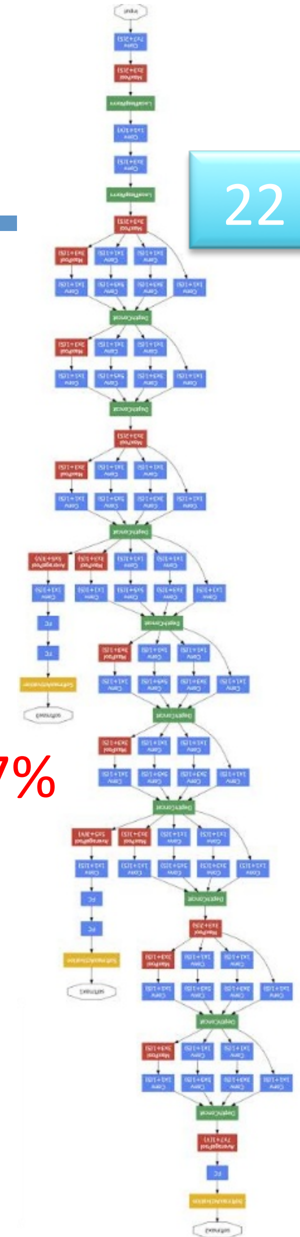
19 layers

7.3%

VGG (2014)

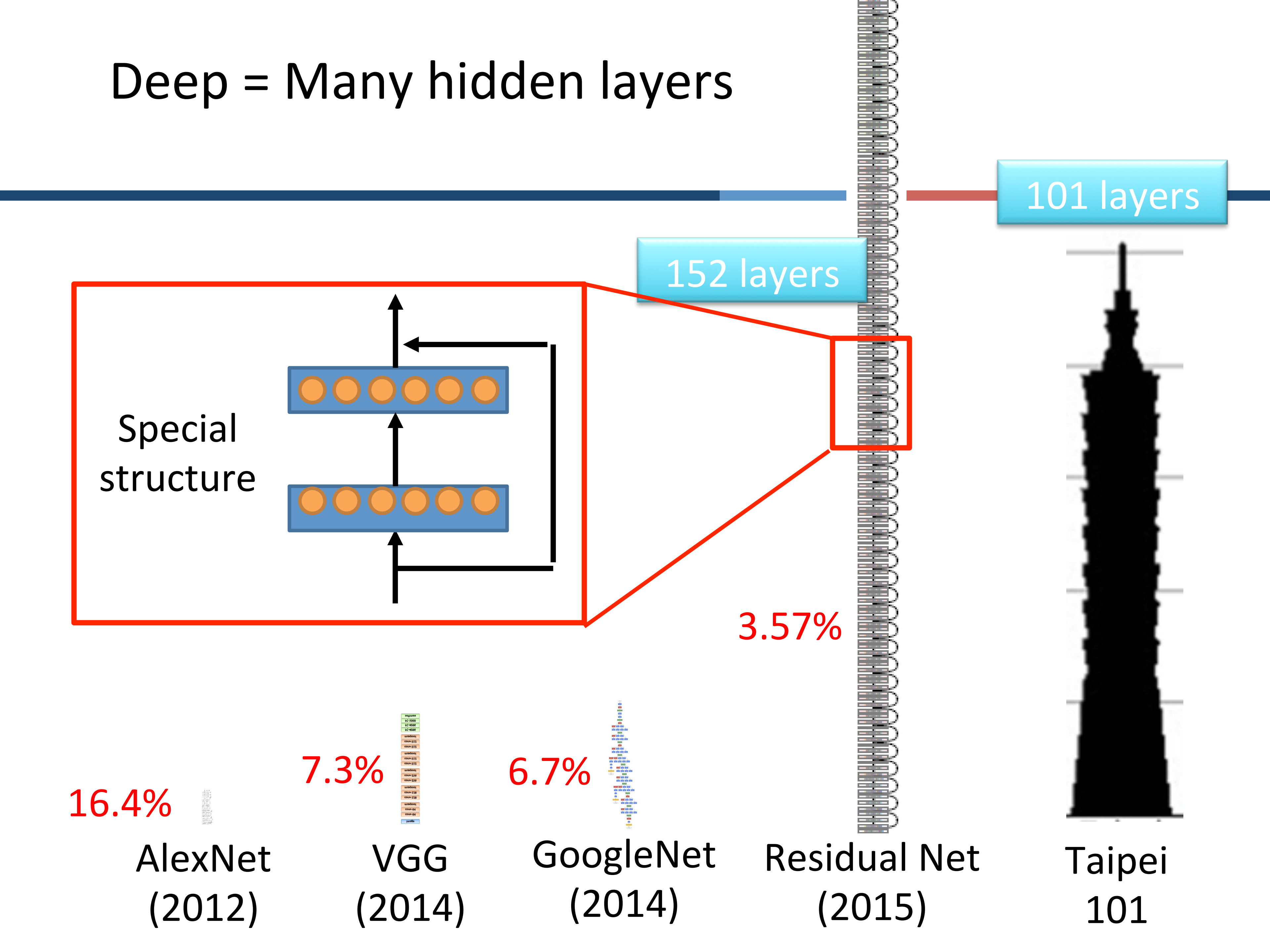
22 layers

6.7%



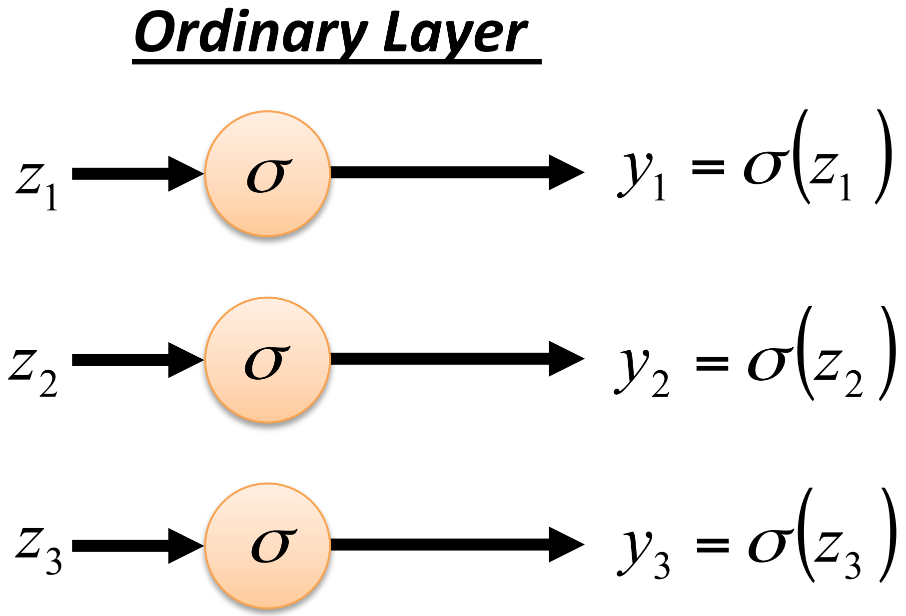
GoogleNet (2014)

Deep = Many hidden layers



Output Layer

- Softmax layer as the output layer



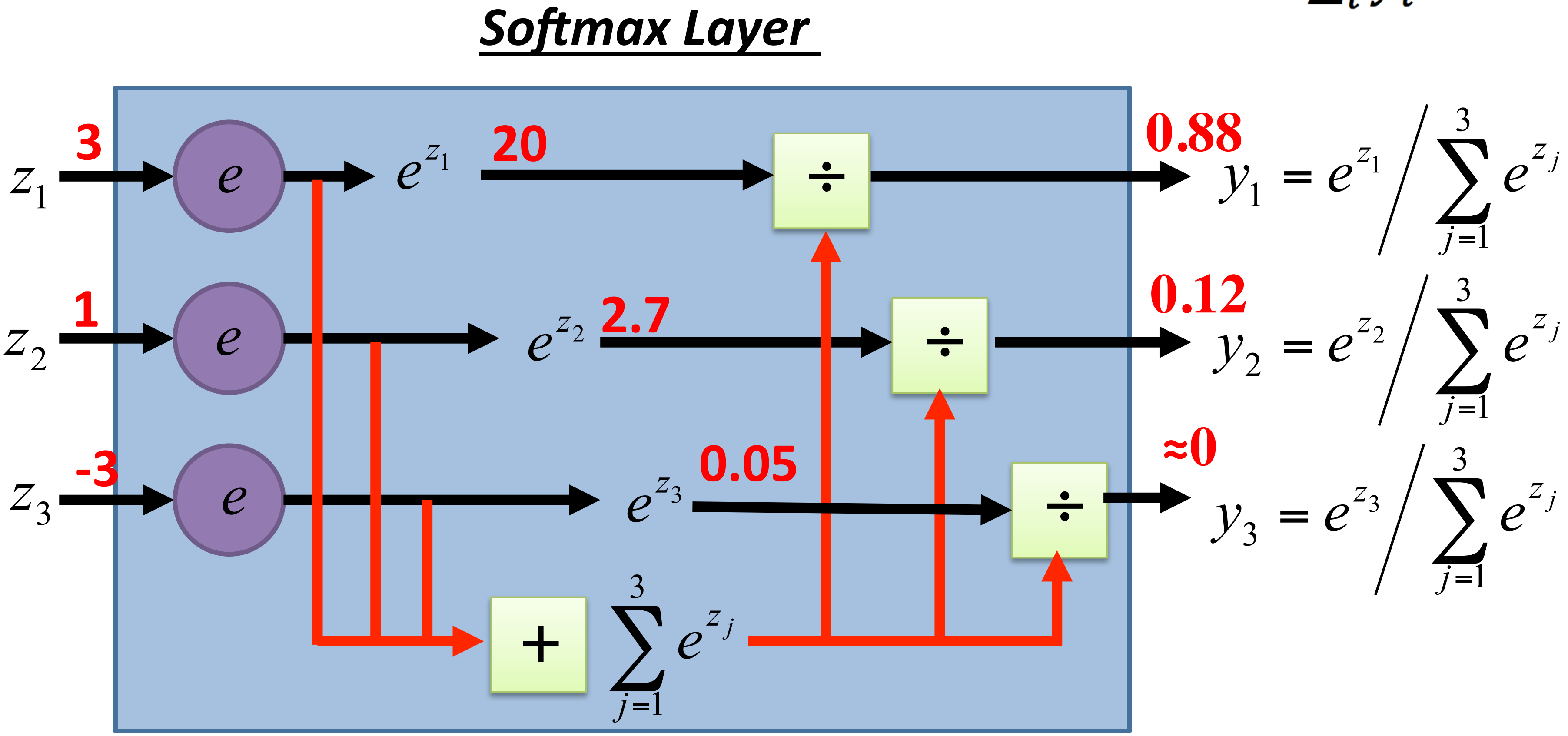
In general, the output of network can be any value.

May not be easy to interpret

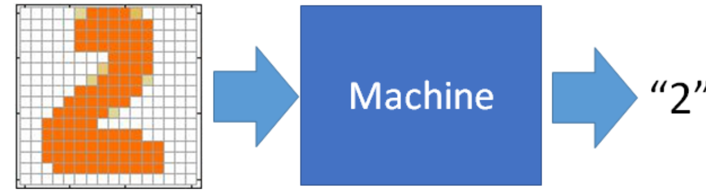
Output Layer

- Softmax layer as the output layer

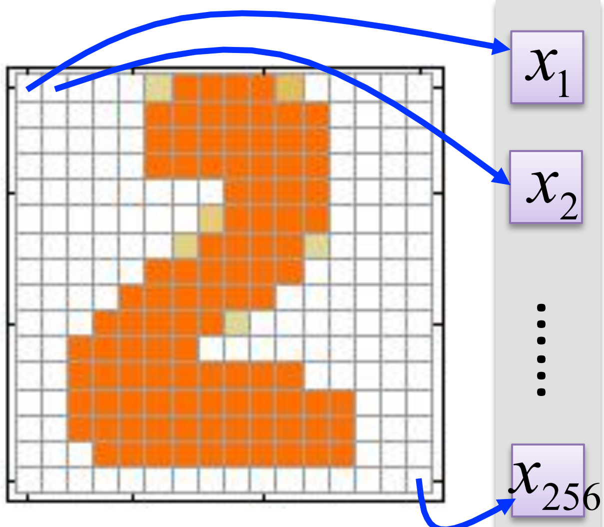
Probability:
- $1 > y_i > 0$
- $\sum_i y_i = 1$



Example Application



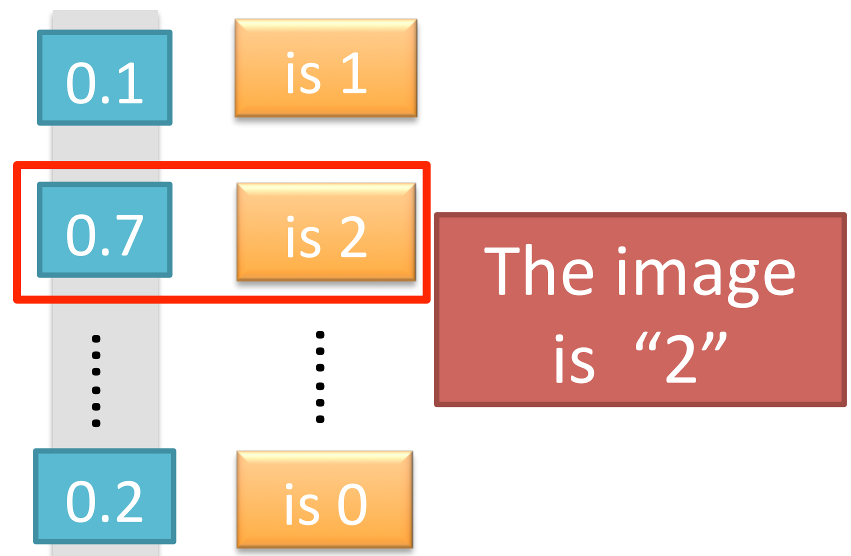
Input



16 x 16 = 256

Ink → 1
No ink → 0

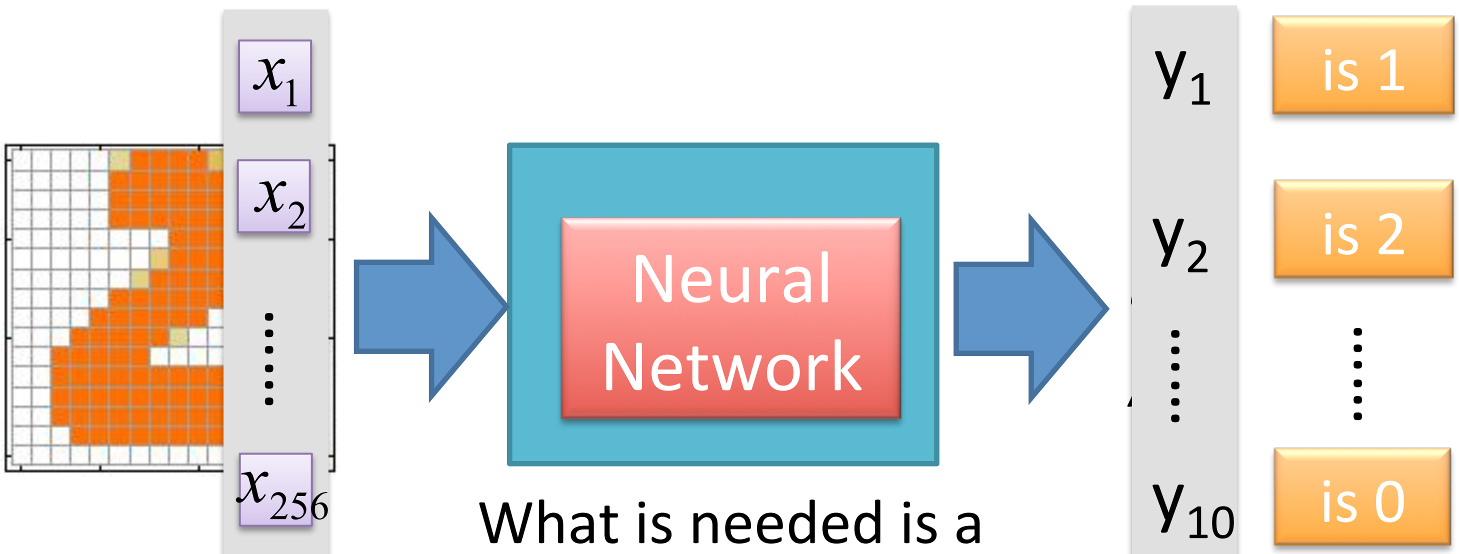
Output



Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition

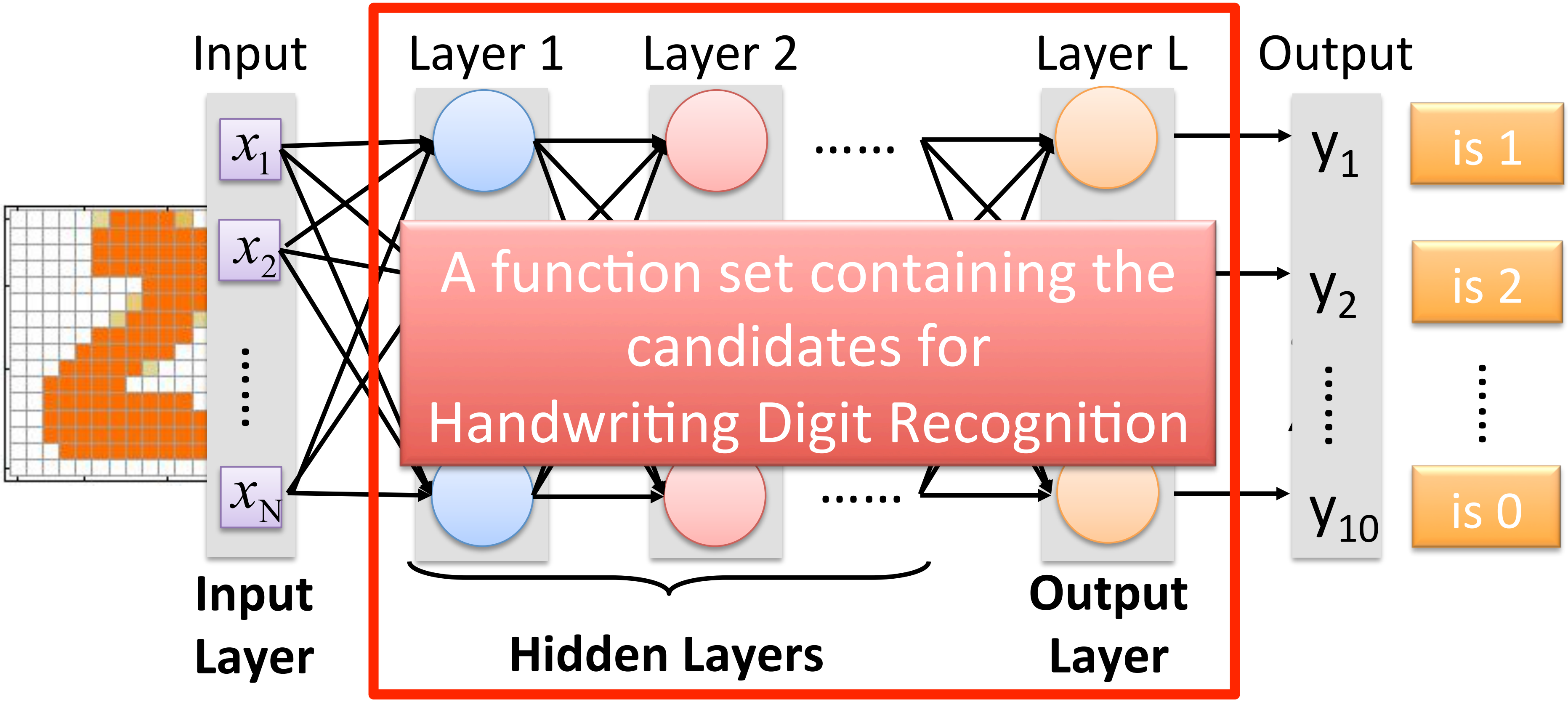


What is needed is a function ……

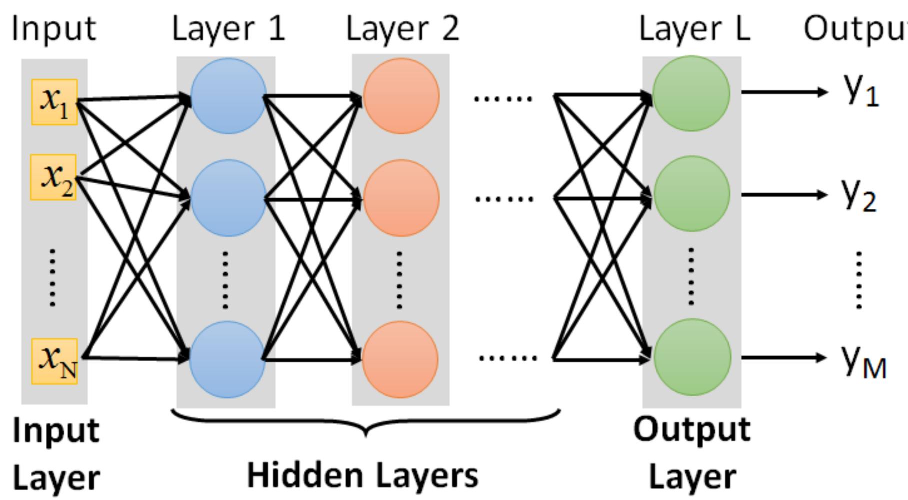
Input:
256-dim vector

output:
10-dim vector

Example Application



You need to decide the network structure to let a good function in your function set.



- Q: How many layers? How many neurons for each layer?

  Trial and Error + **Intuition**

- Q: Can we design the network structure?

  Convolutional Neural Network (CNN) in the next lecture

- Q: Can the structure be automatically determined?
  - Yes, but not widely studied yet.

Three Steps for Deep Learning

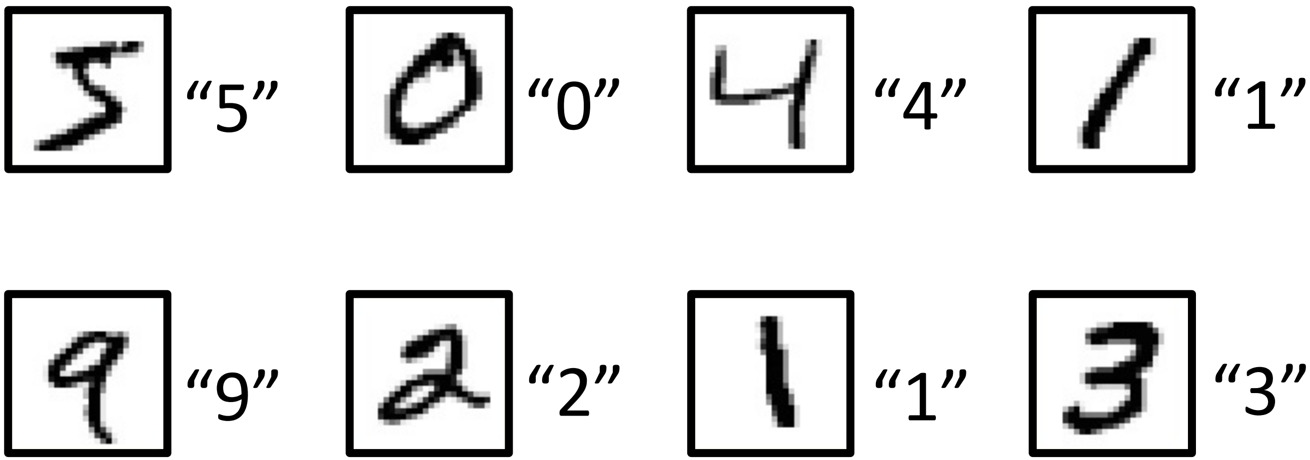
Step 1: define a set of function

Step 2: goodness of function

Step 3: pick the best function

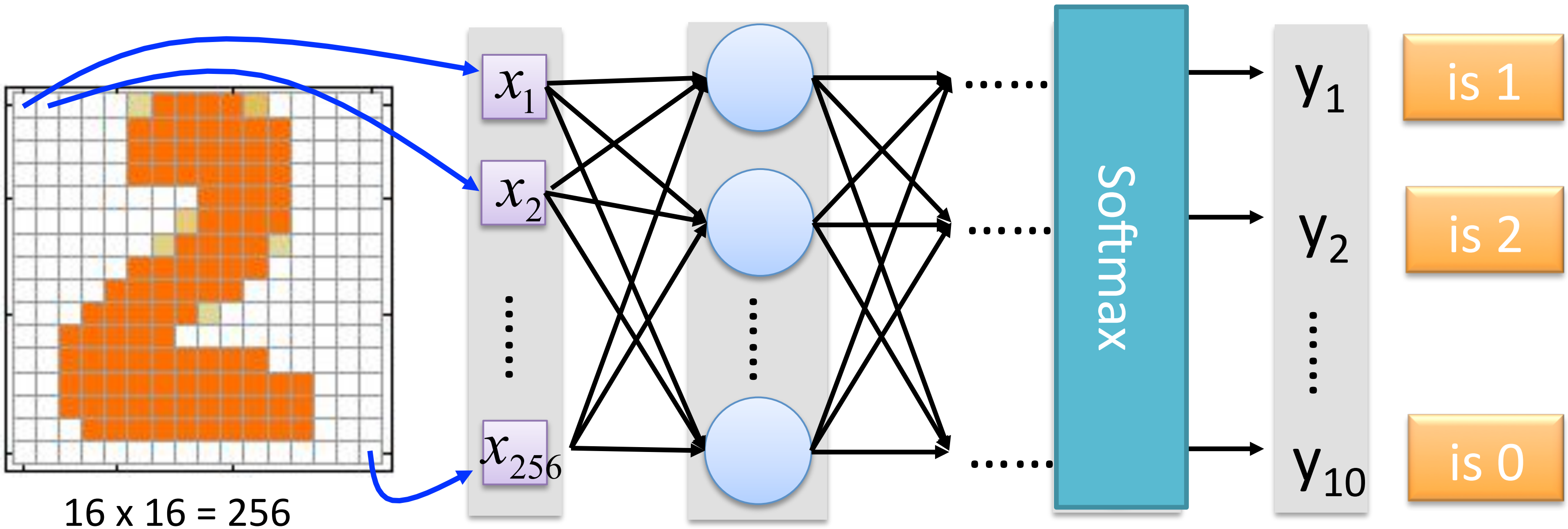
Training Data

- Preparing training data: images and their labels



The learning target is defined on the training data.

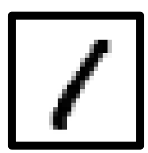
Learning Target

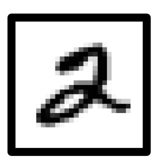


Ink → 1

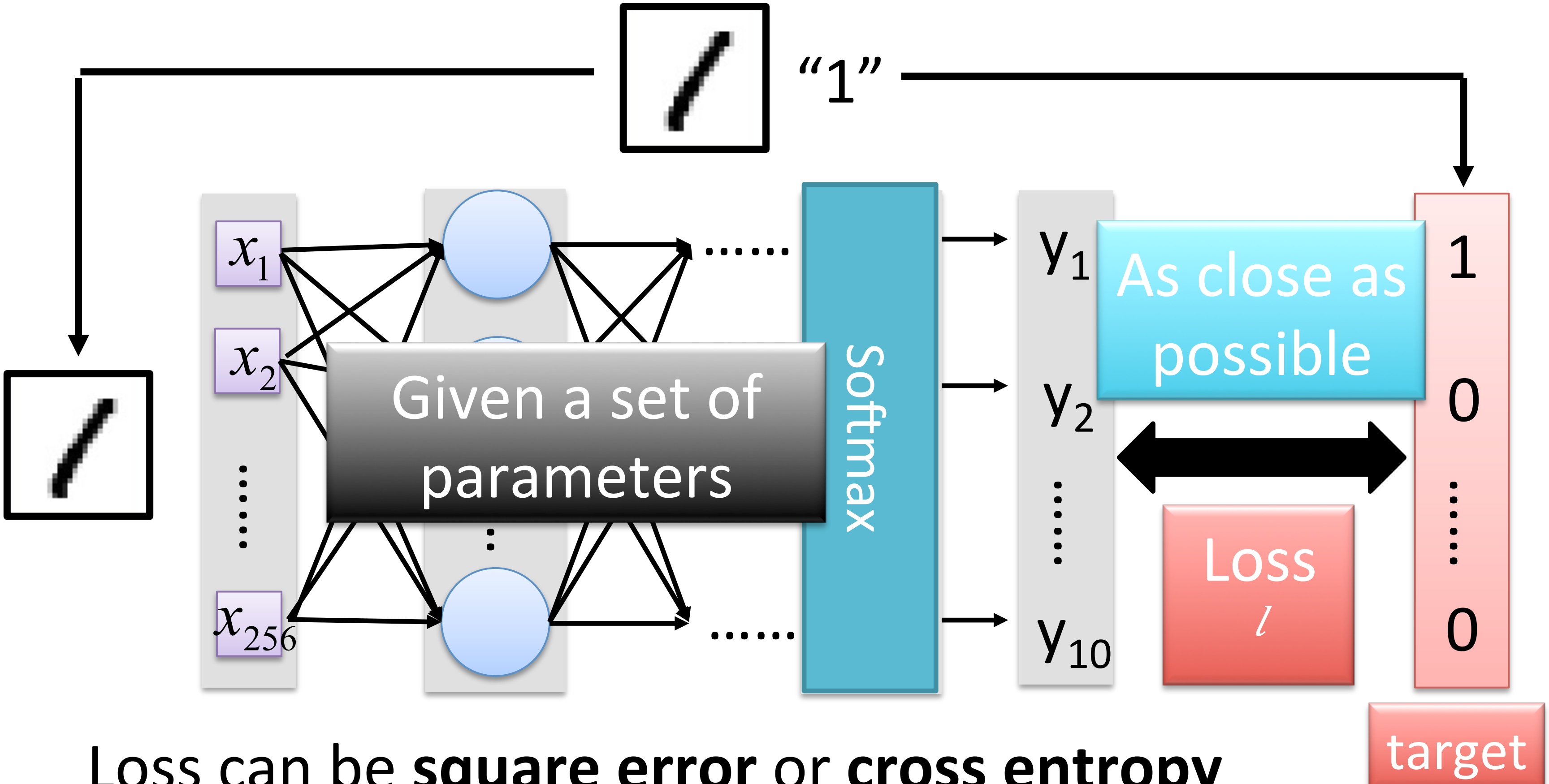
No ink → 0

The learning target is ......

Input:  → y_1 has the maximum value

Input:  → y_2 has the maximum value

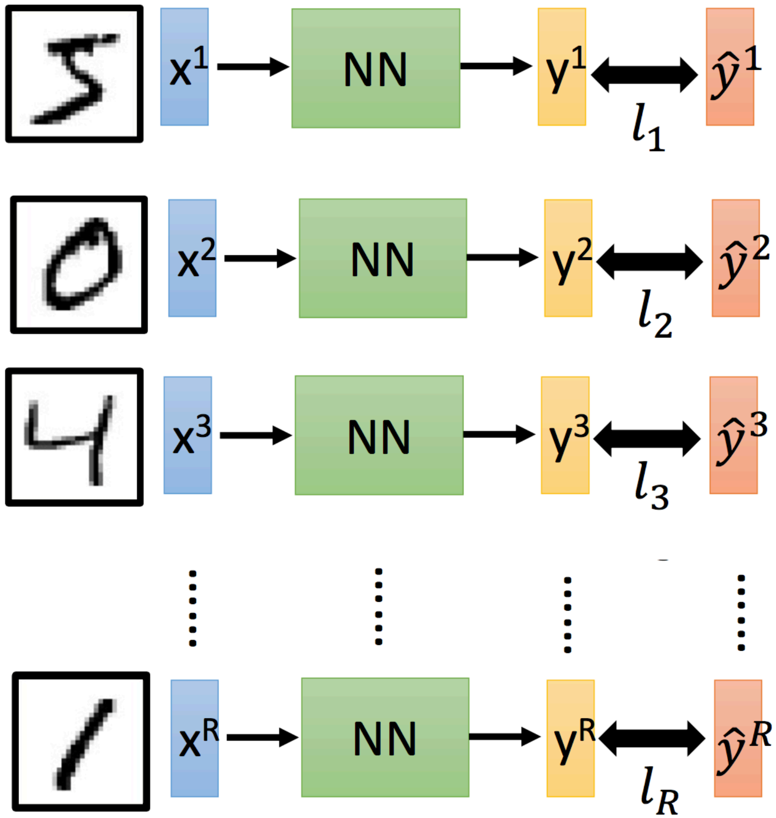
A good function should make the loss of all examples as small as possible.



Loss can be **square error** or **cross entropy** between the network output and target

Total Loss

For all training data …



Total Loss:

$$L = \sum_{r=1}^{R} l_r$$

As small as possible

Find ***a function in function set*** that minimizes total loss L

Find ***the network parameters θ^**** that minimize total loss L

Three Steps for Deep Learning

Step 1: define a set of function

Step 2: goodness of function

Step 3: pick the best function

How to pick the best function

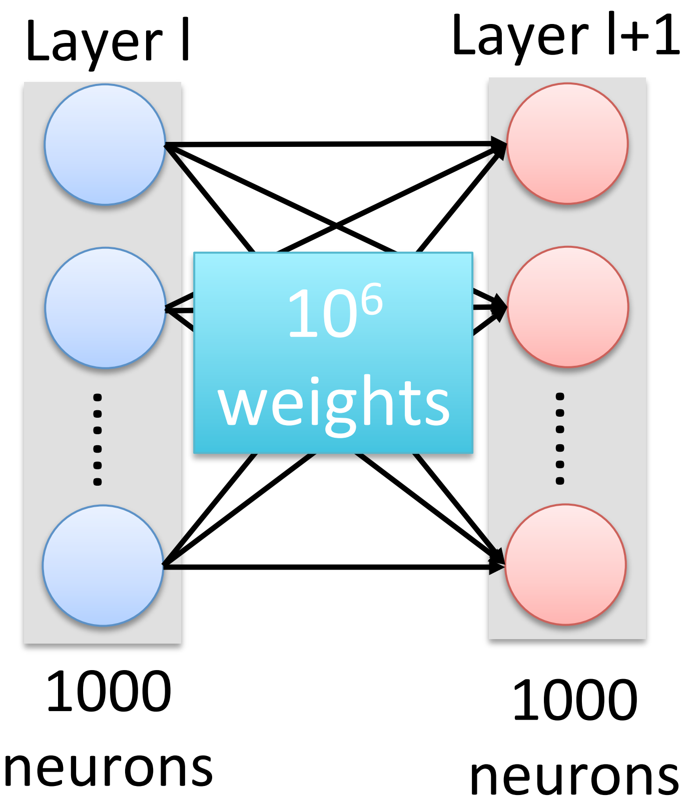
Find ***network parameters*** θ^* that minimize total loss L

Enumerate all possible values

Networ… ram… s $\theta=\{w_1, w_2, w_3, \cdots, b \ldots, \cdots\}$

Millio… of p… meters

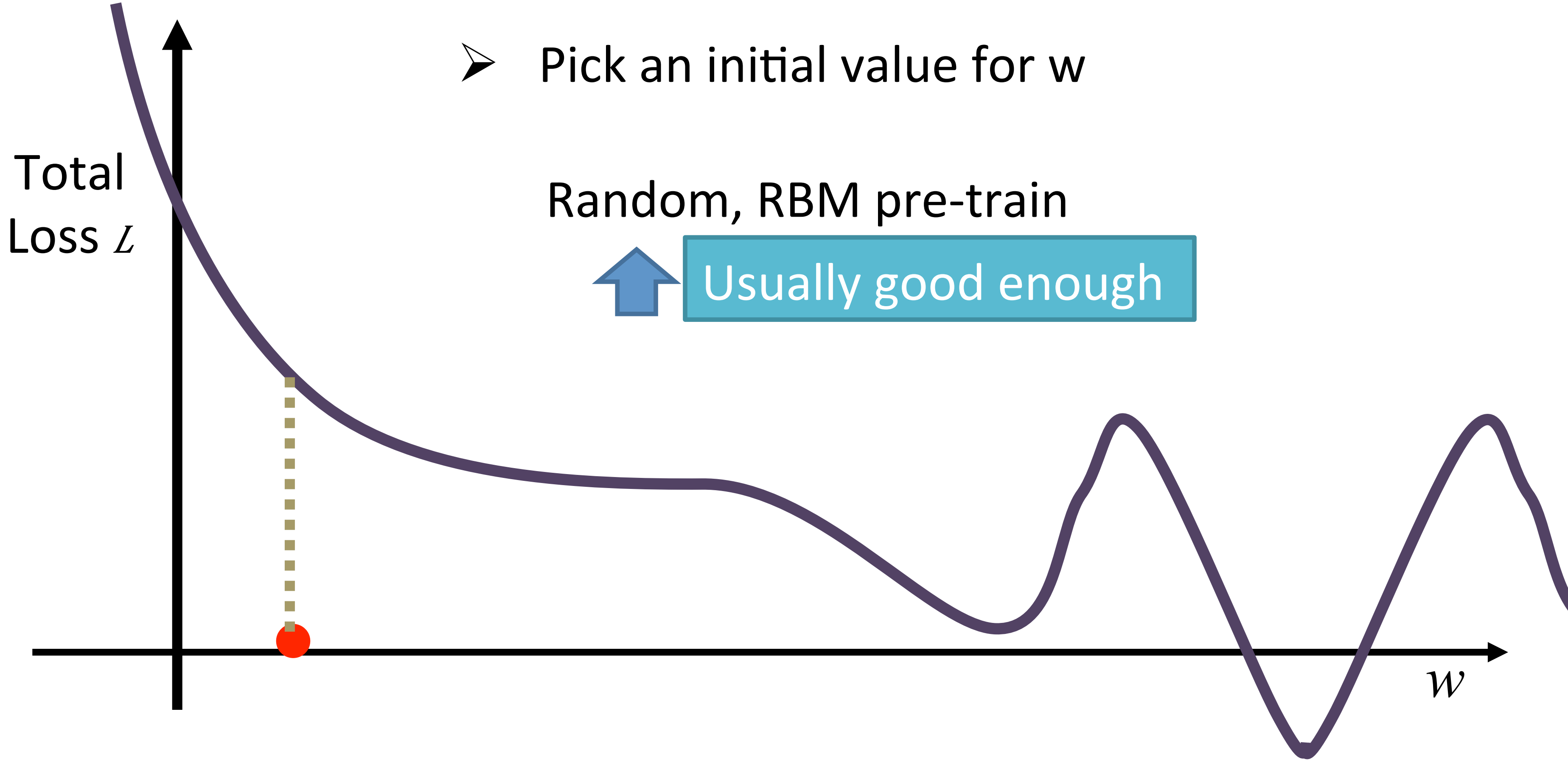
E.g. speech recognition: 8 layers and 1000 neurons each layer



Gradient Descent

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

Find ***network parameters*** $\boldsymbol{\theta^*}$ that minimize total loss L



- Pick an initial value for w

Random, RBM pre-train

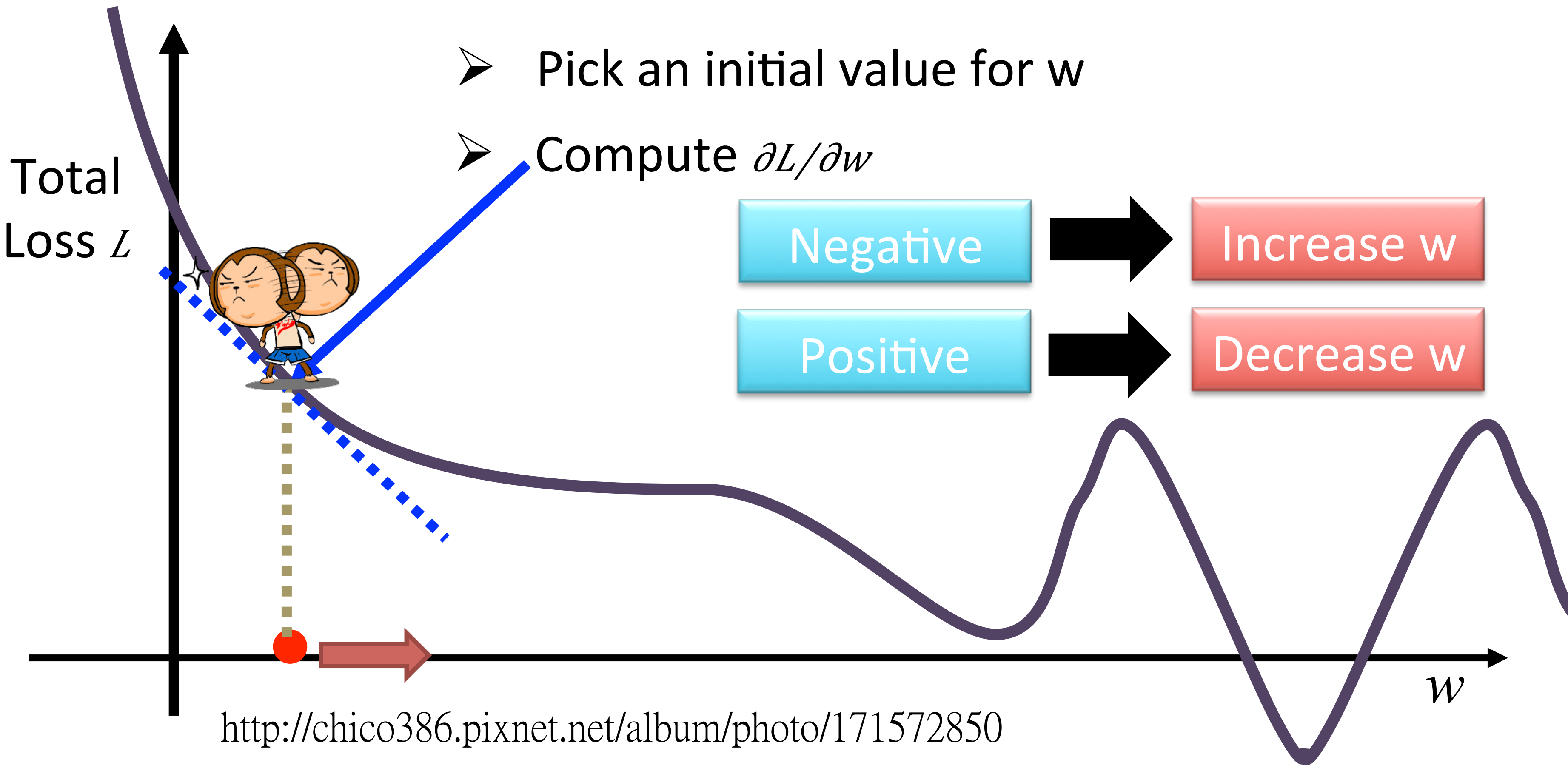
Usually good enough

Gradient Descent

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

Find ***network parameters*** θ^* that minimize total loss L

- Pick an initial value for w
- Compute $\partial L/\partial w$



Gradient Descent

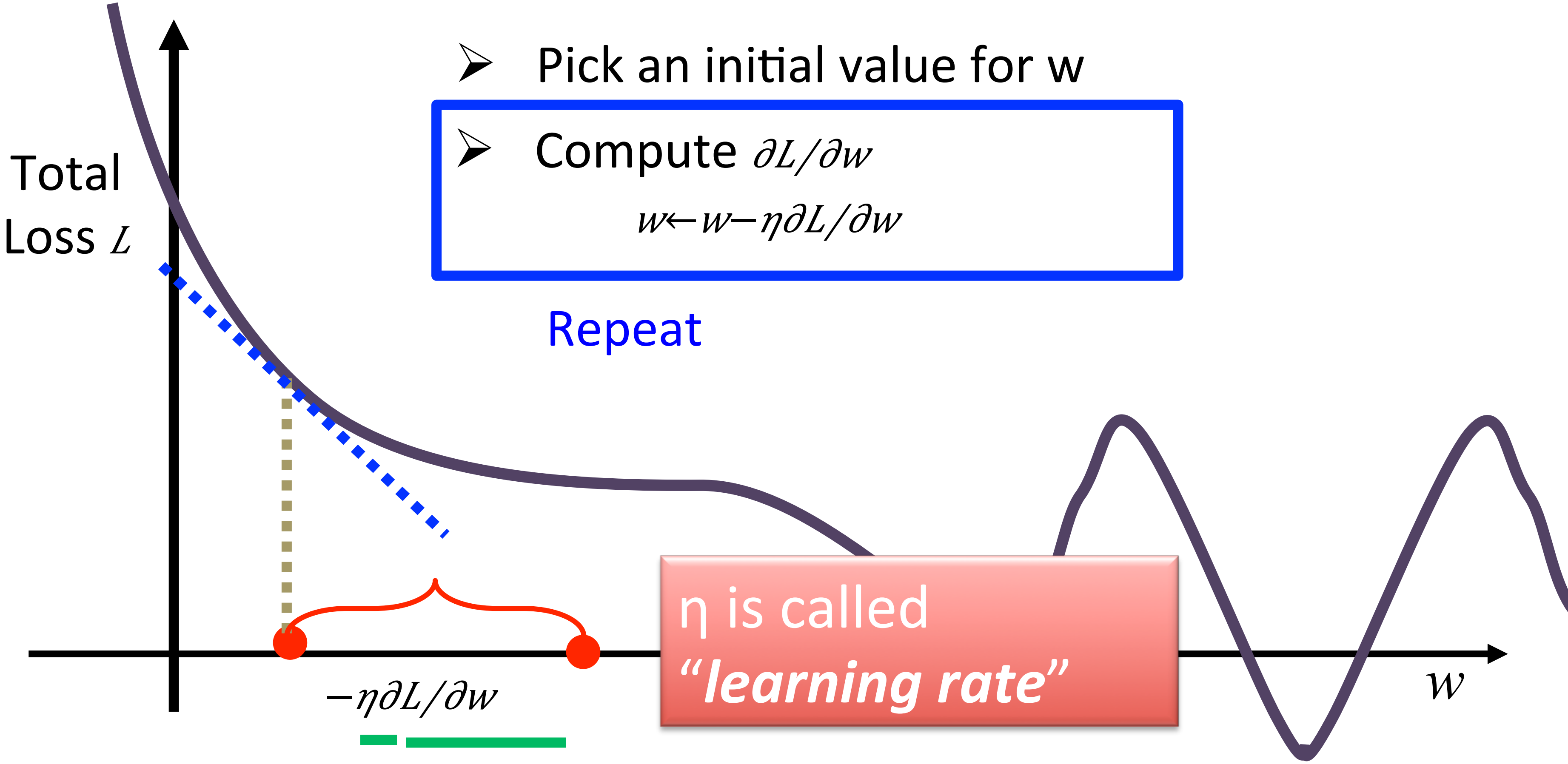
Network parameters $\theta=\{w_1, w_2, \ldots, b_1, b_2, \ldots\}$

Find ***network parameters θ^**** that minimize total loss L

- Pick an initial value for w
- Compute $\partial L / \partial w$

  $w \leftarrow w - \eta \partial L / \partial w$

Repeat



η is called ***"learning rate"***

Gradient Descent

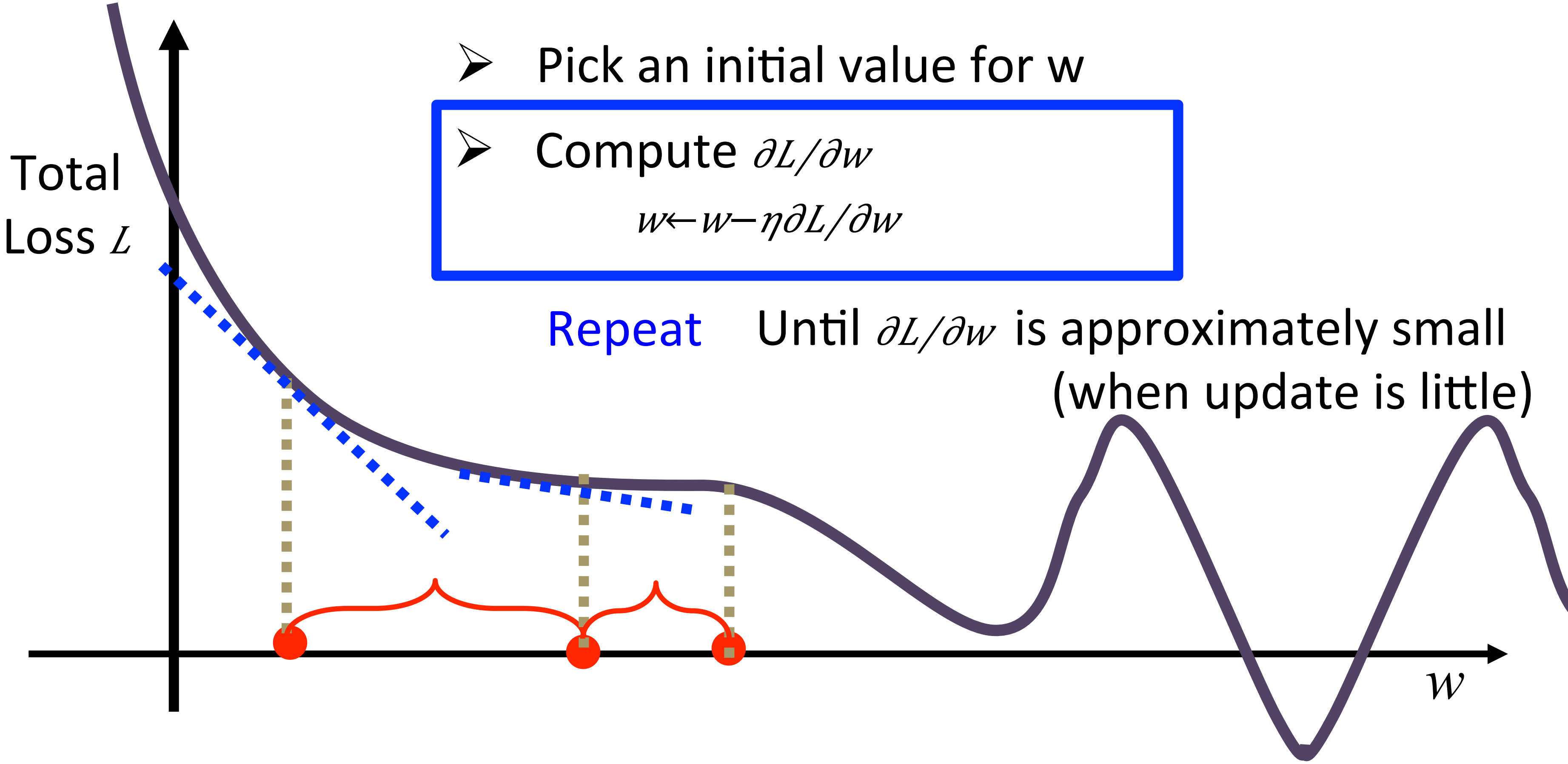
Network parameters $\theta=\{w_1, w_2, \ldots, b_1, b_2, \ldots\}$

Find ***network parameters θ^**** that minimize total loss L

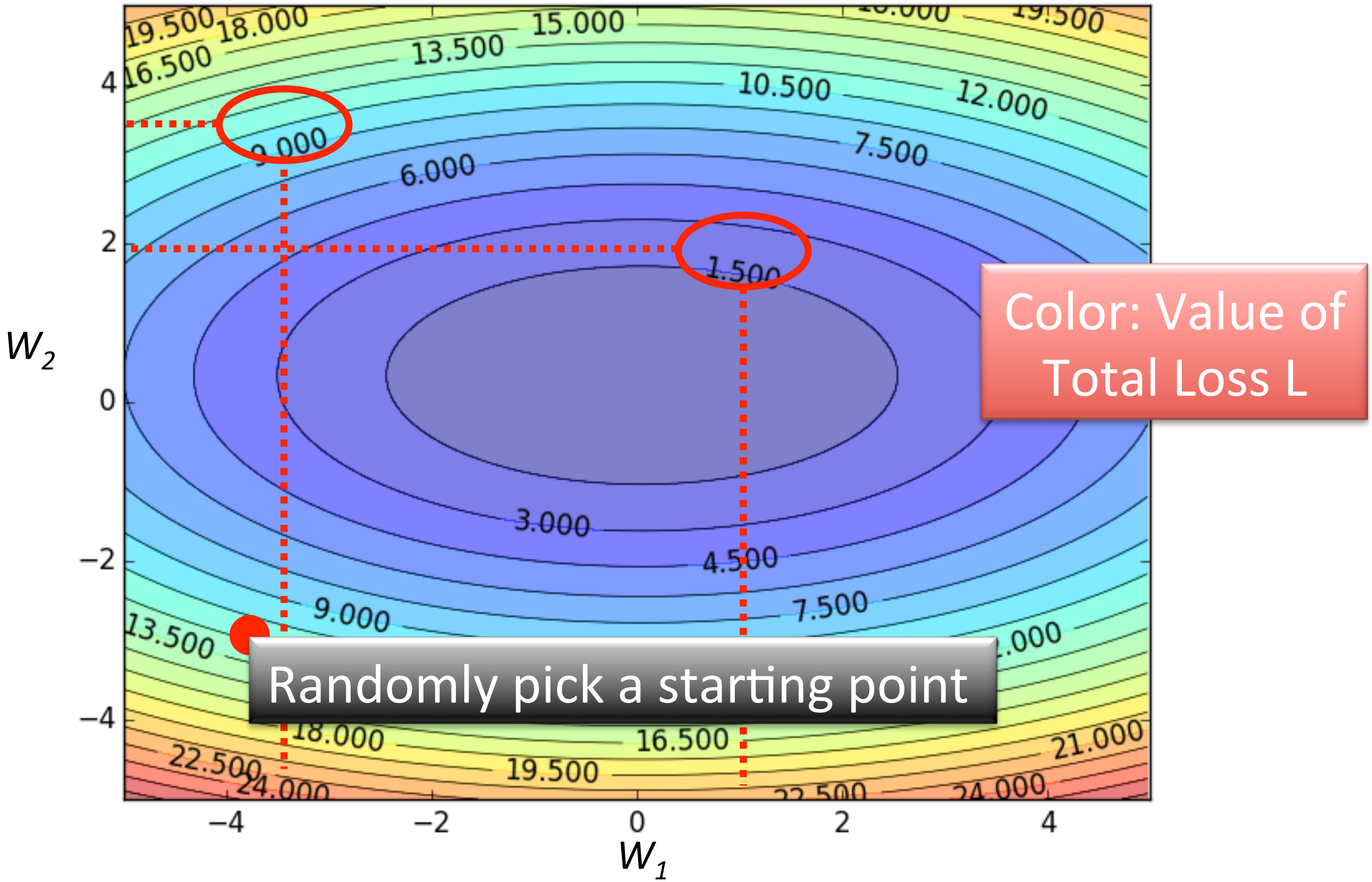
- Pick an initial value for w
- Compute $\partial L/\partial w$

  $w \leftarrow w - \eta \partial L/\partial w$

Repeat Until $\partial L/\partial w$ is approximately small (when update is little)

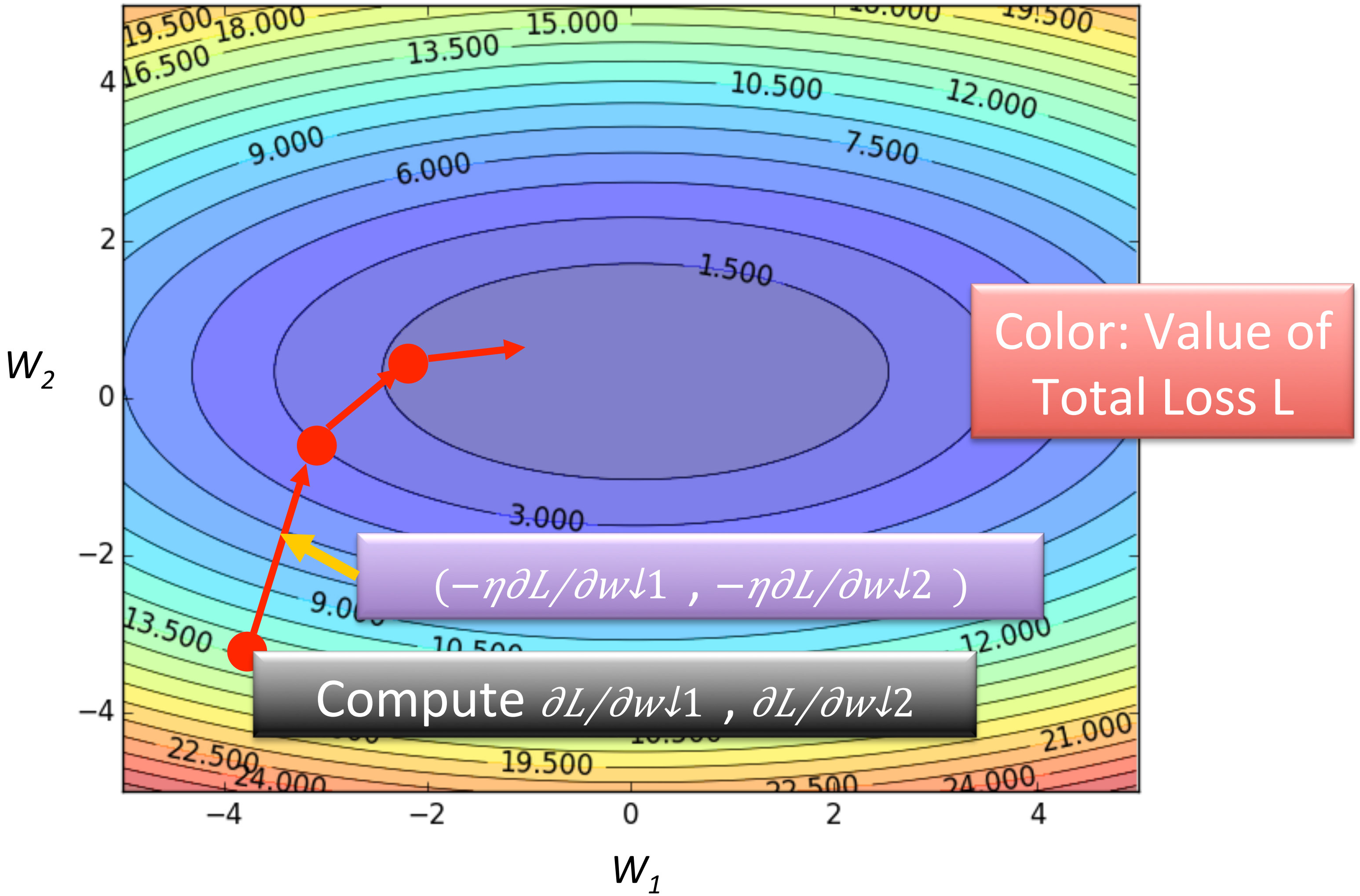


Gradient Descent

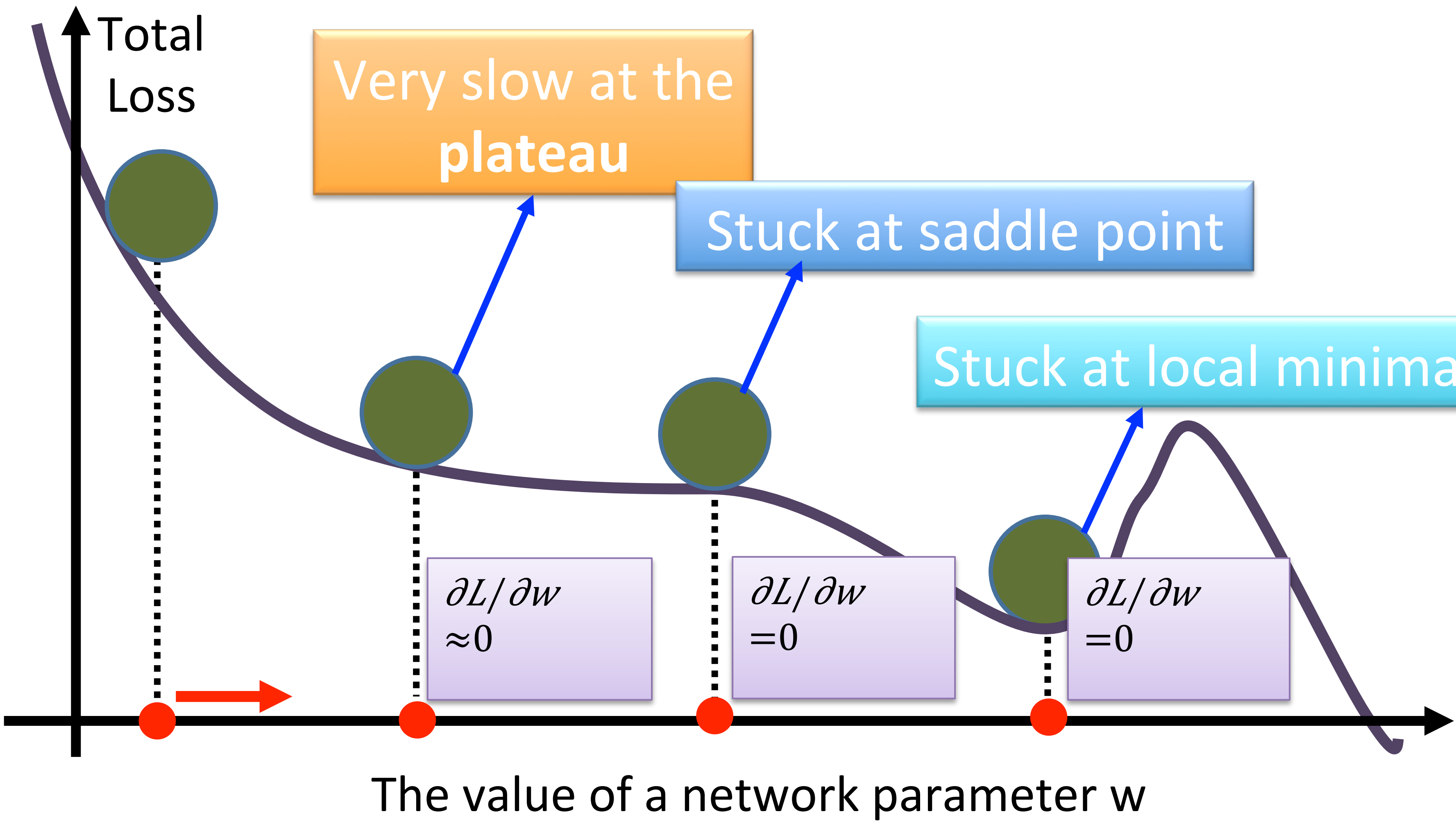


Gradient Descent

Hopfully, we would reach a minima .....

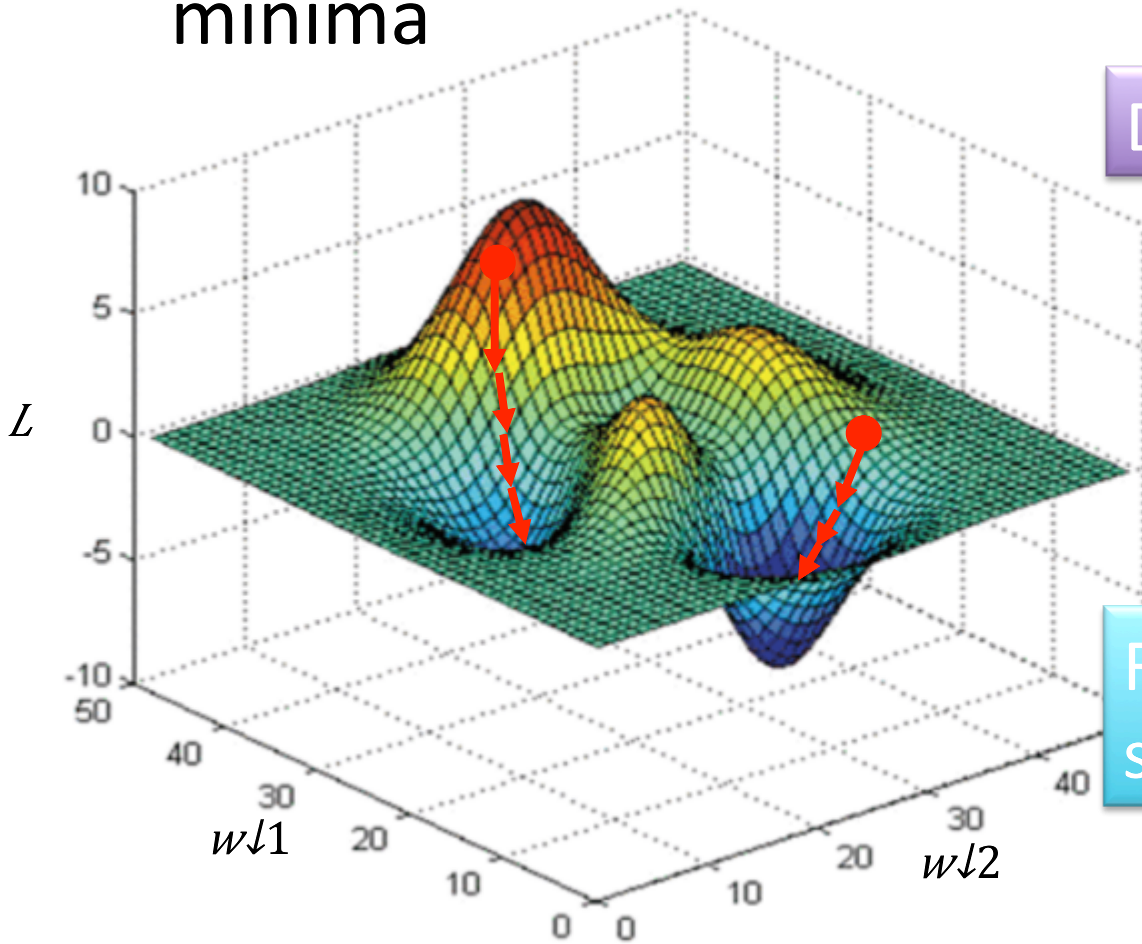


Local Minima



Local Minima

- Gradient descent never guarantee global minima



Different initial point

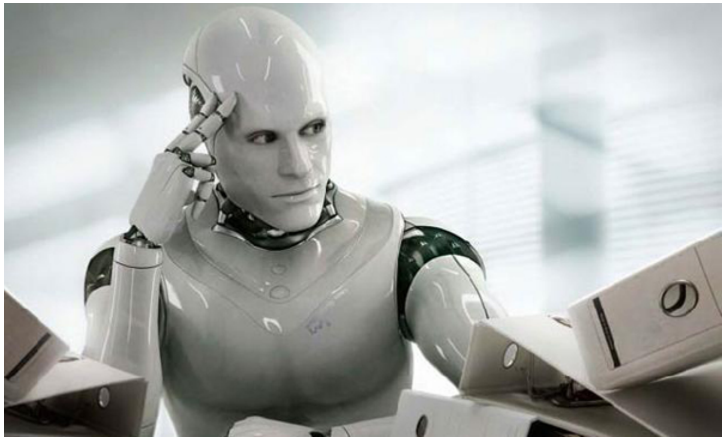
Reach different minima, so different results

Gradient Descent

This is the "learning" of machines in deep learning ……

➡ Even alpha go using this approach.

People image ……



Actually …..

I hope you are not too disappointed :p

Backpropagation

- Backpropagation: an efficient way to compute $\partial L/\partial w$ in neural network

TensorFlow

torch

theano

Caffe

Microsoft CNTK

Chainer

Deep Learning library produced by Amazon
DSSTNE

mxnet

Three Steps for Deep Learning

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

Deep Learning is so simple ……

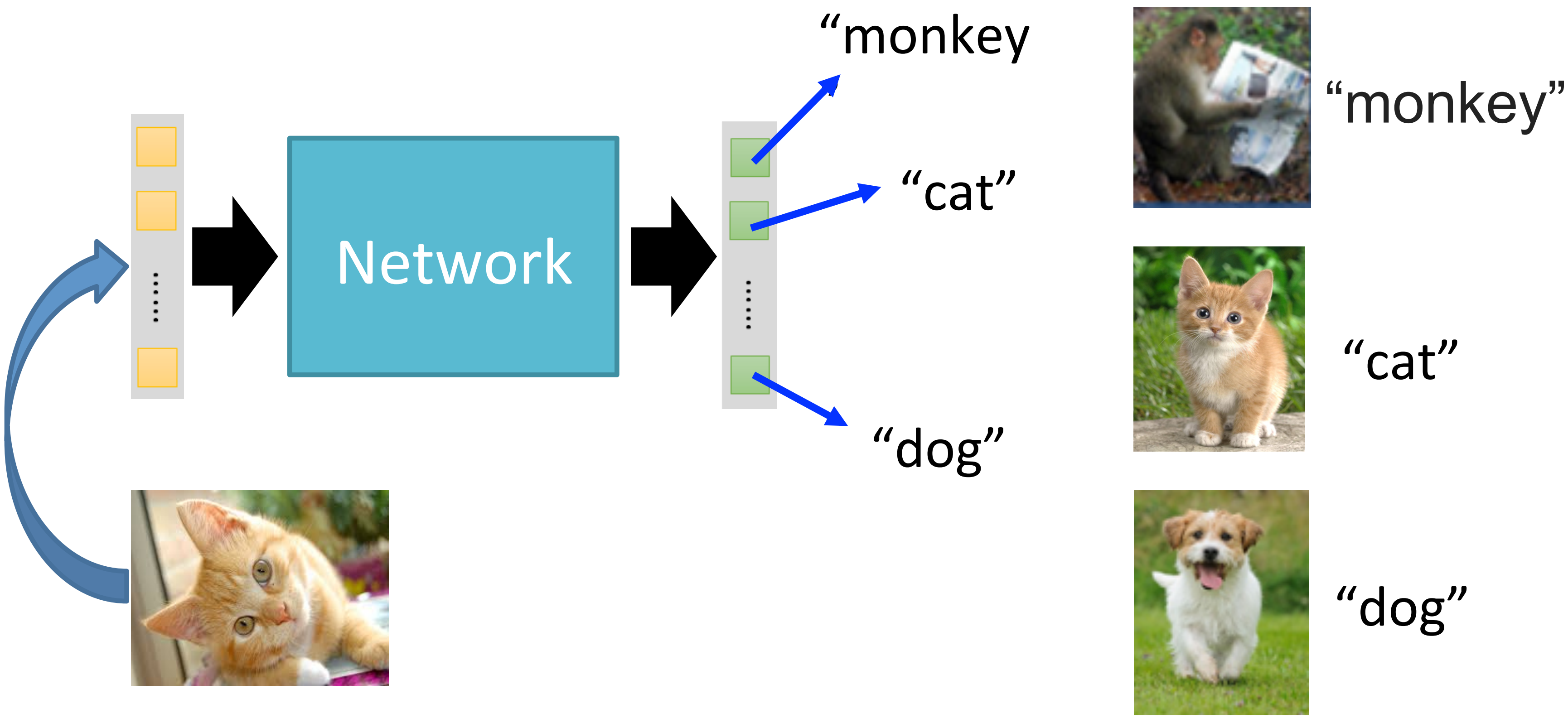
Now If you want to find a function

If you have lots of function input/output (?) as training data

→ You can use deep learning

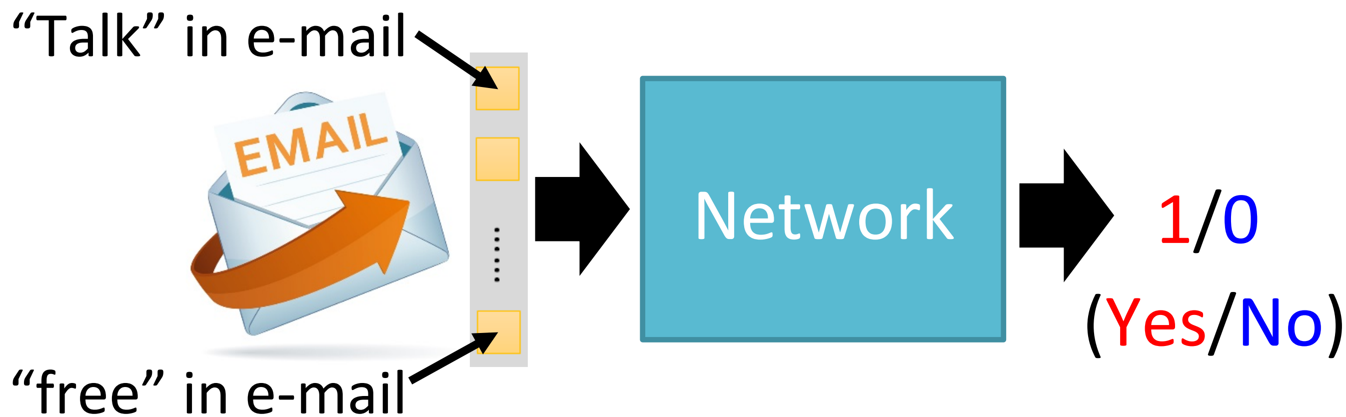
For example, you can do …….

- Image Recognition



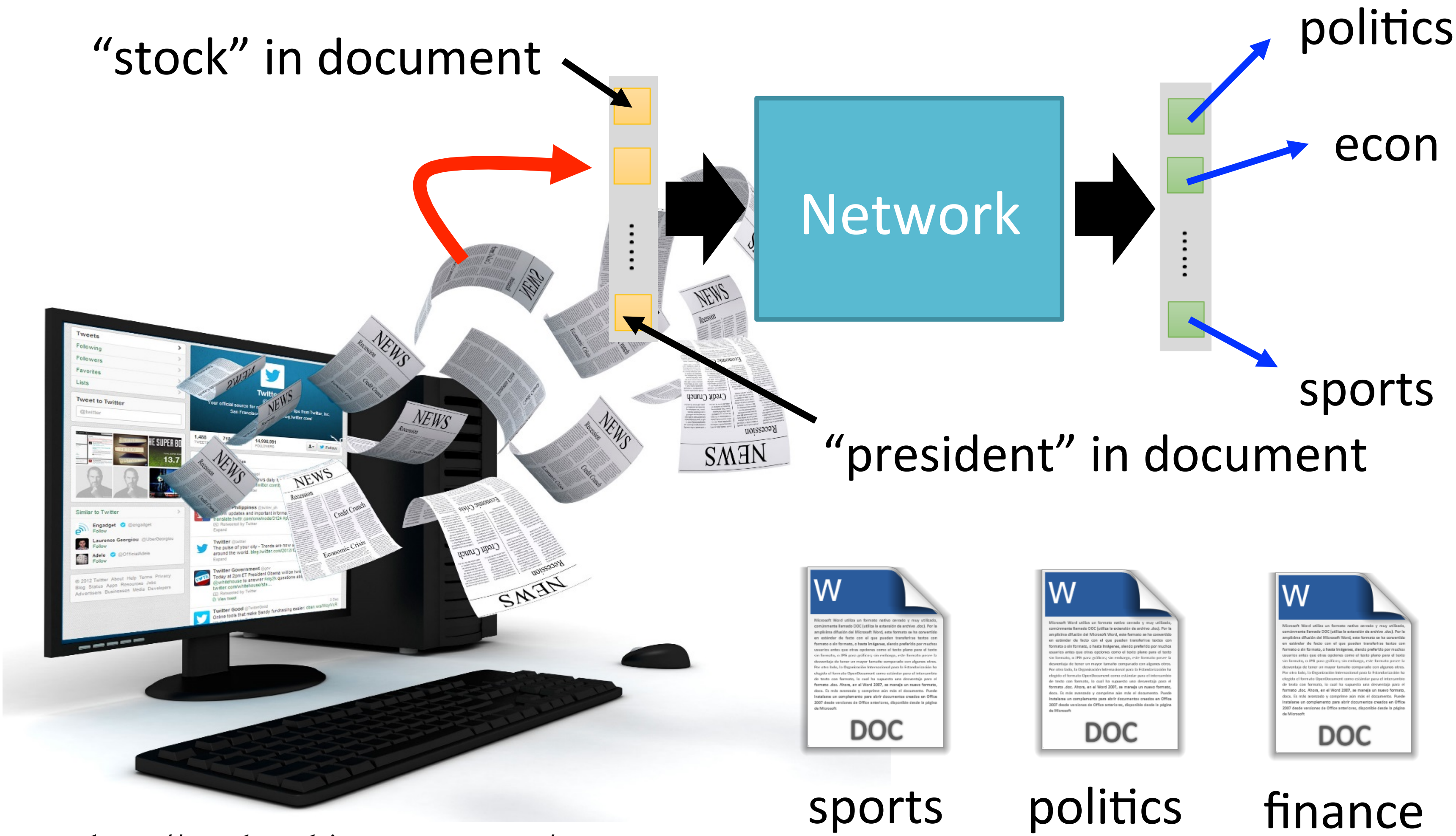
For example, you can do …….

Spam filtering



(http://spam-filter-review.toptenreviews.com/)

For example, you can do …….



http://top-breaking-news.com/

Outline

Introduction of Deep Learning

“Hello World” for Deep Learning

Tips for Deep Learning

Keras

TensorFlow or theano

Very flexible

Need some effort to learn

Interface of TensorFlow or Theano

keras

Easy to learn and use

(still have some flexibility)

You can modify it if you can write TensorFlow or Theano

Keras

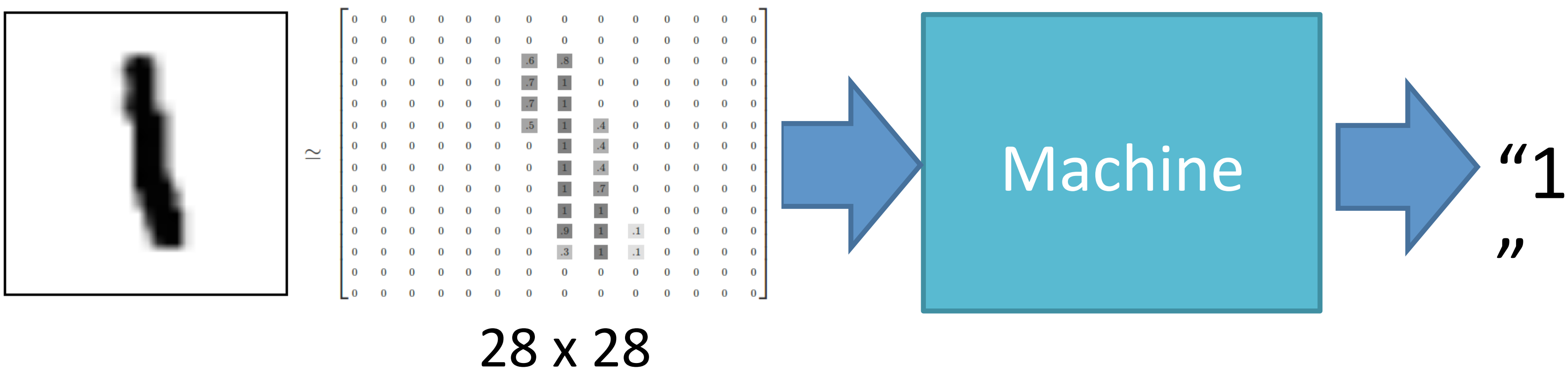
- François Chollet is the author of Keras.
- Keras means *horn* in Greek
- Documentation: http://keras.io/
- Example: https://github.com/fchollet/keras/tree/master/examples

PyTorch

- Tutorial: https://pytorch.org/tutorials

Example Application

- Handwriting Digit Recognition

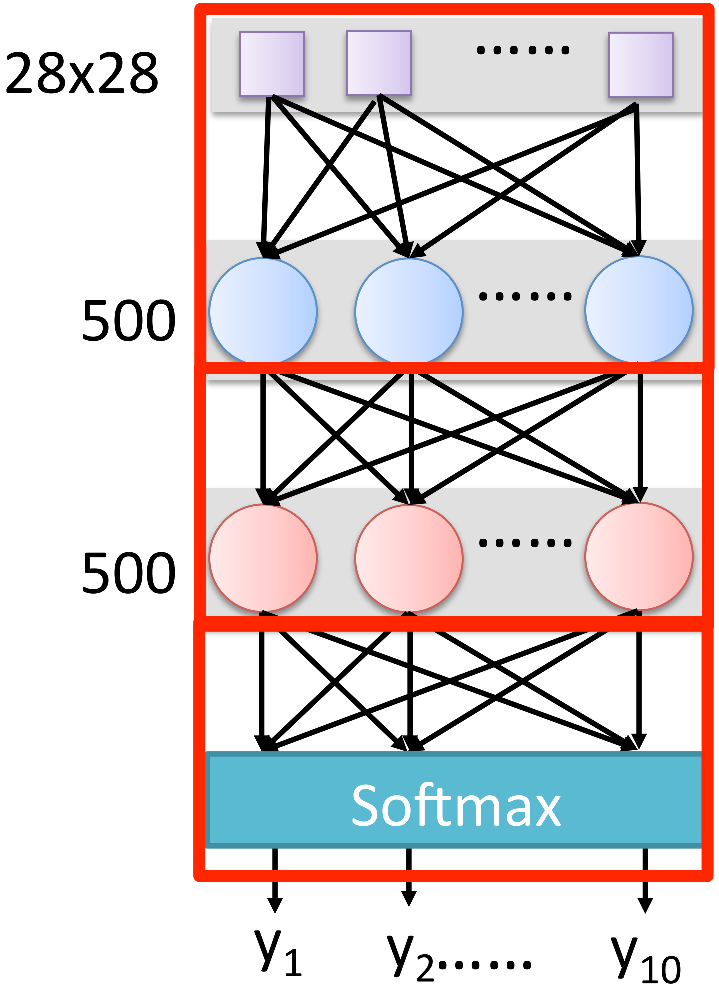


MNIST Data: http://yann.lecun.com/exdb/mnist/

“Hello world” for deep learning

Keras provides data sets loading function: http://keras.io/datasets/

Keras




```
model = Sequential()
```

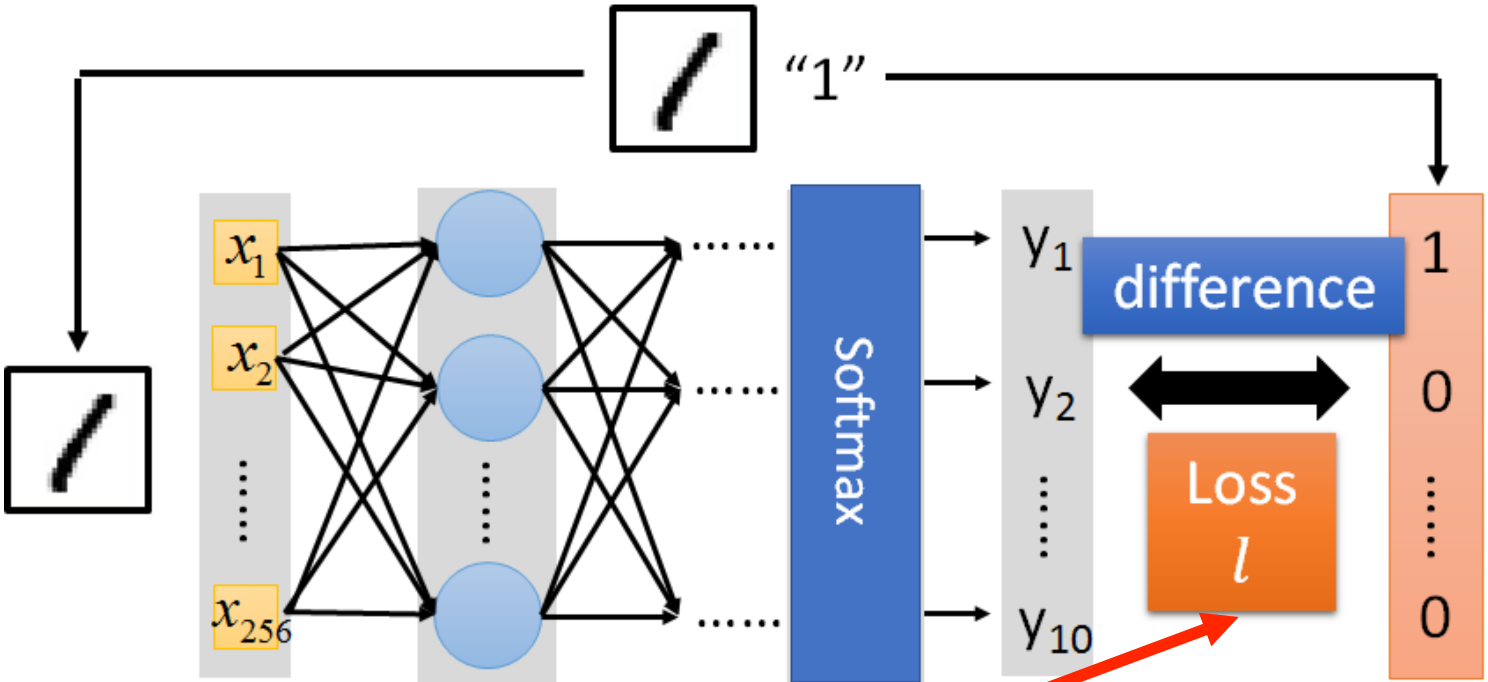
```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

```
model.add( Dense( output_dim=500 ) )
model.add( Activation('sigmoid') )
```

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

Keras

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




```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

Keras

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

Step 3.1: Configuration

```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

$w \leftarrow w - \eta \partial L / \partial w$

0.1

Step 3.2: Find the optimal network parameters

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

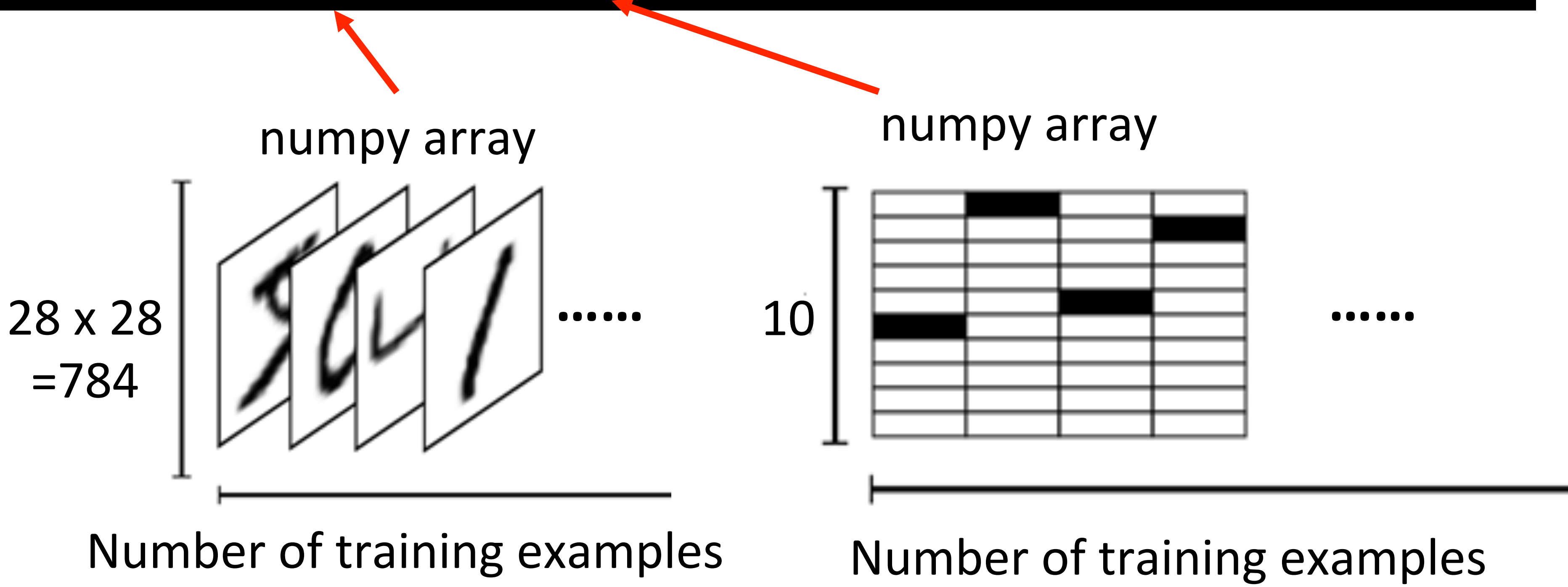
Training data (Images)

Labels (digits)

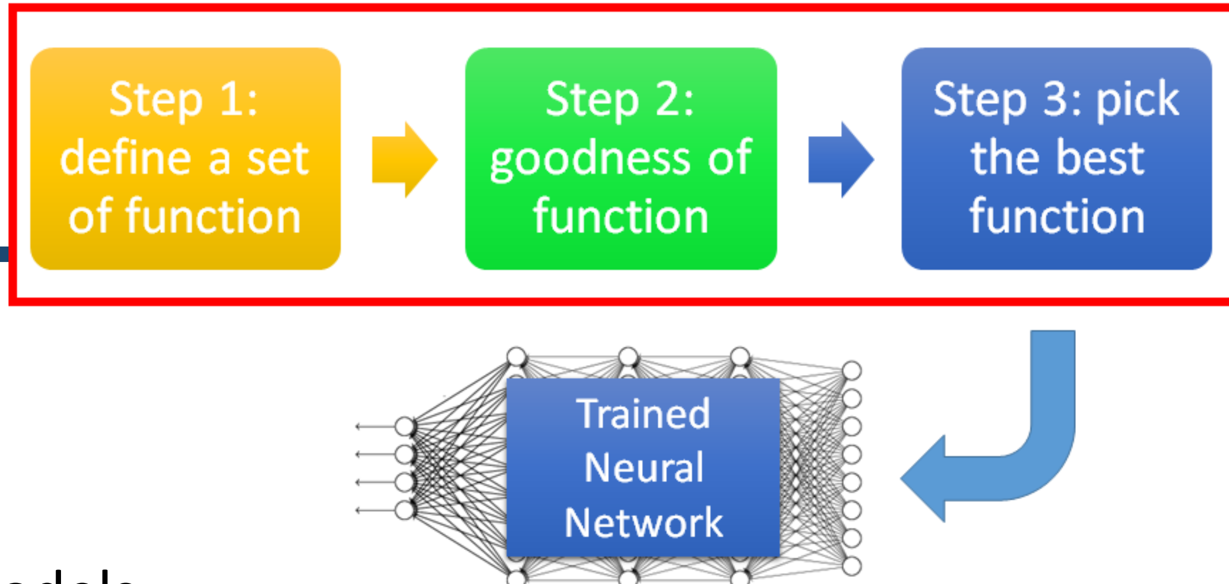
Keras

Step 3.2: Find the optimal network parameters

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```



https://www.tensorflow.org/versions/r0.8/tutorials/mnist/beginners/index.html



Save and load models

http://keras.io/getting-started/faq/#how-can-i-save-a-keras-model

How to use the neural network (testing):

case 1:

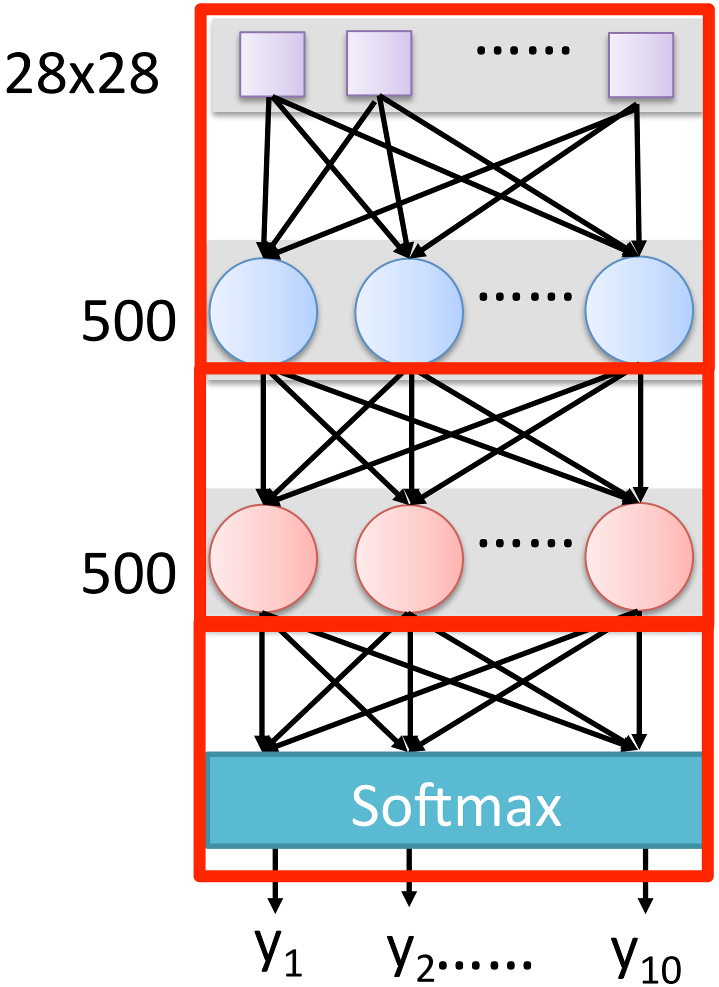
```
score = model.evaluate(x_test,y_test)
print('Total loss on Testing Set:', score[0])
print('Accuracy of Testing Set:', score[1])
```

case 2:

```
result = model.predict(x_test)
```

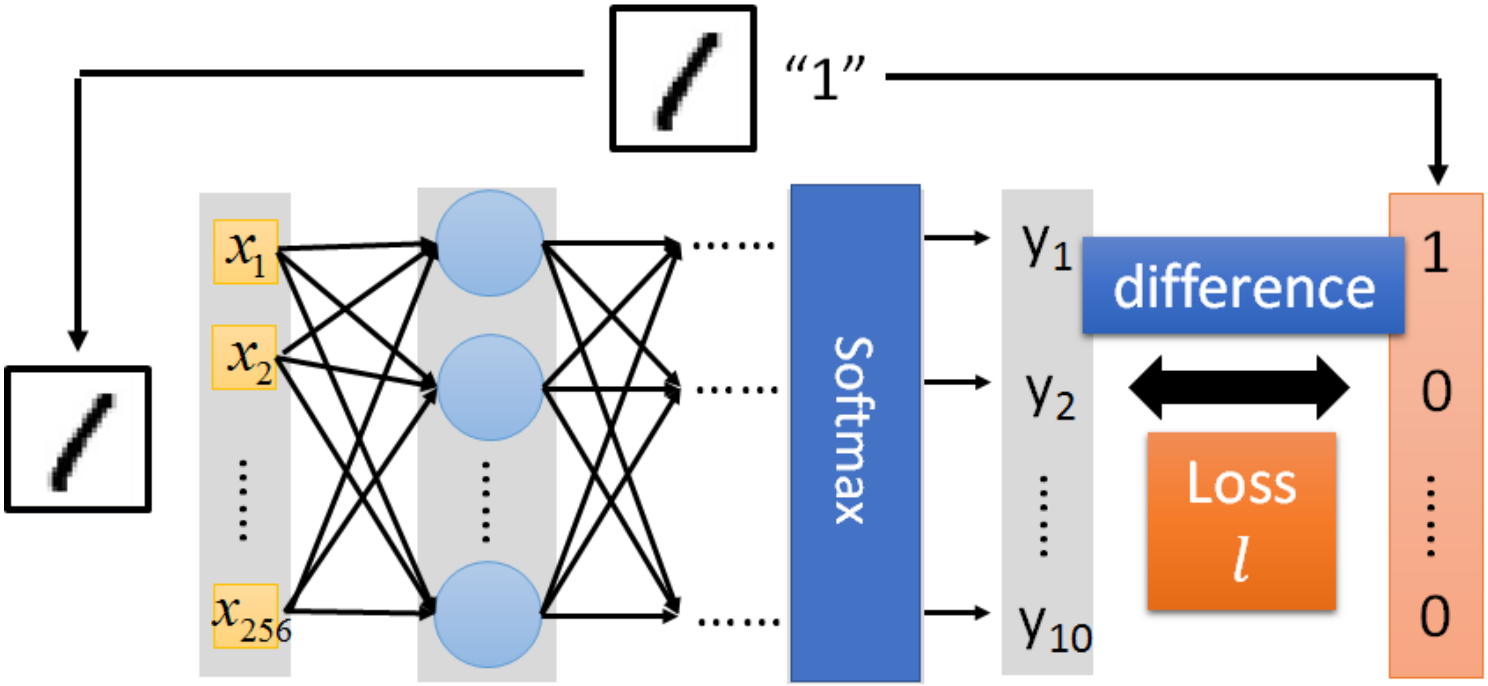
PyTorch

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




```
import torch.nn as nn
import torch.nn.functional as F

class MyNetwork(nn.Module):
    def __init__(self):
        super(MyNetwork, self).__init__()

        self.fc1 = nn.Linear(28 * 28, 500)
        self.fc2 = nn.Linear(500, 500)
        self.fc3 = nn.Linear(500, 10)

    def forward(self, x):
        x = F.sigmoid(self.fc1(x))
        x = F.sigmoid(self.fc2(x))
        x = self.fc3(x)
        return F.log_softmax(x)
```

PyTorch




```
net = MyNetwork()
optimizer = torch.optim.SGD(net.parameters(), lr=0.1, momentum=0.9)
criterion = nn.MSELoss()
```

PyTorch

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

Step 3.1: Training

```
for epoch in range(epochs):
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = Variable(data), Variable(target)
        # resize data from (batch_size, 1, 28, 28) to (batch_size, 28*28)
        data = data.view(-1, 28*28)

        optimizer.zero_grad()
        net_out = net(data)
        loss = criterion(net_out, target)
        loss.backward()
        optimizer.step()

        if batch_idx % log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                    epoch, batch_idx * len(data), len(train_loader.dataset),
                        100. * batch_idx / len(train_loader), loss.data[0]))
```

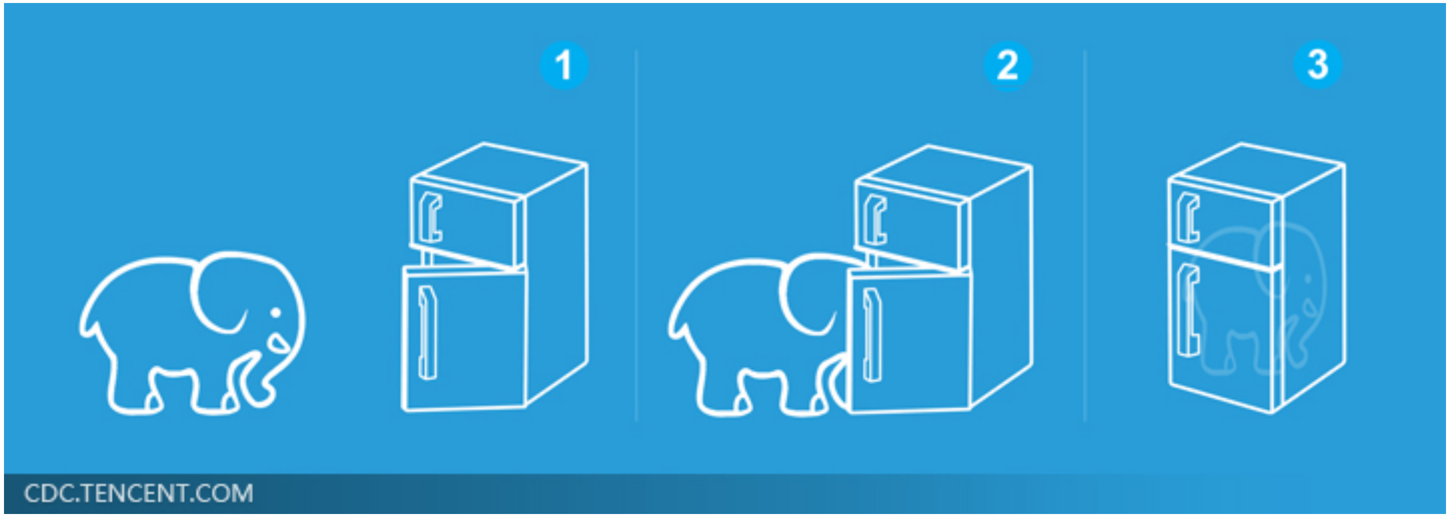
Step 3.2: Performance report


```
test_loss, correct = 0, 0
for data, target in test_loader:
    data, target = Variable(data, volatile=True), Variable(target)
    data = data.view(-1, 28 * 28)
    net_out = net(data)
    # sum up batch loss
    test_loss += criterion(net_out, target).data[0]
    pred = net_out.data.max(1)[1]  # get the index of the max log-probability
    correct += pred.eq(target.data).sum()

test_loss /= len(test_loader.dataset)
print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))
```

Three Steps for Deep Learning

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

Deep Learning is so simple ……



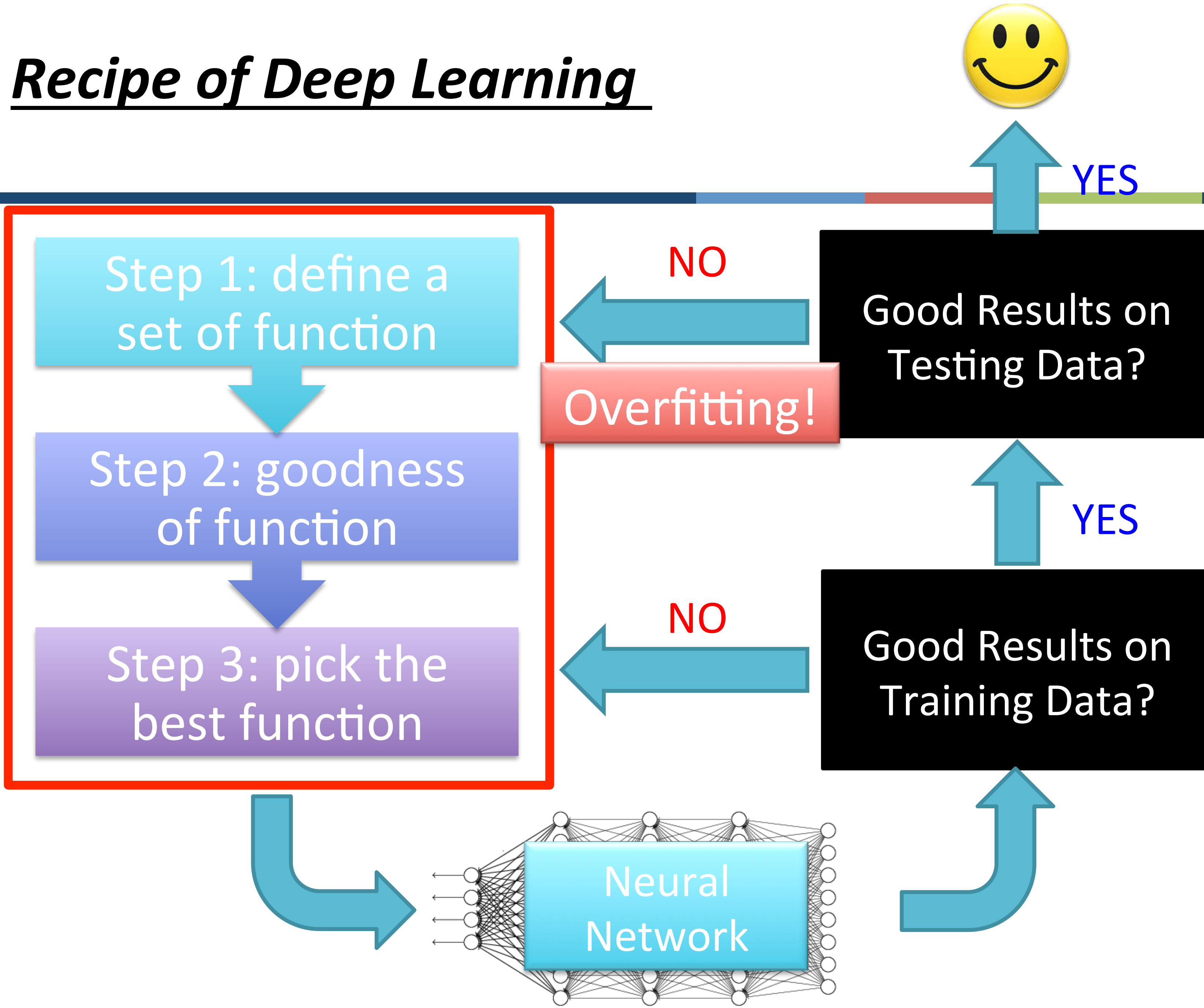
Outline

Introduction of Deep Learning

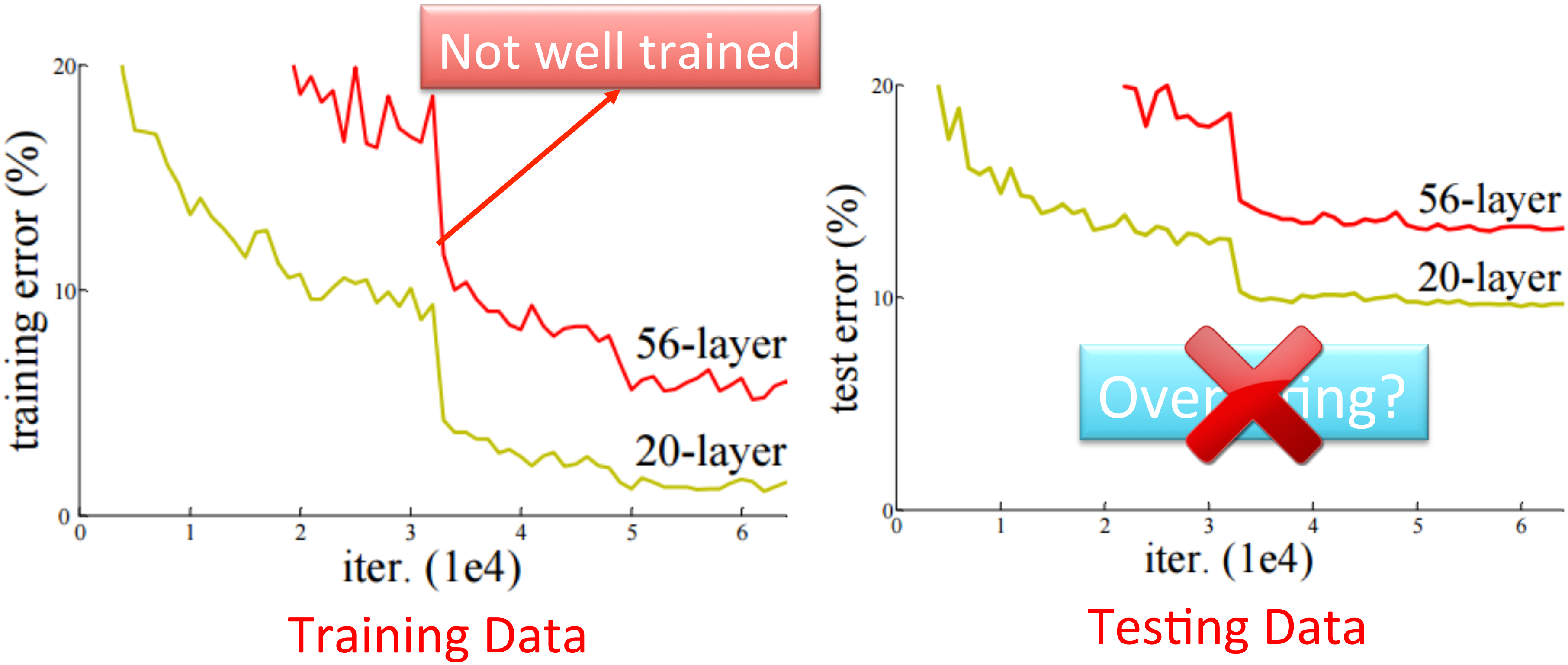
"Hello World" for Deep Learning

Tips for Deep Learning

Recipe of Deep Learning

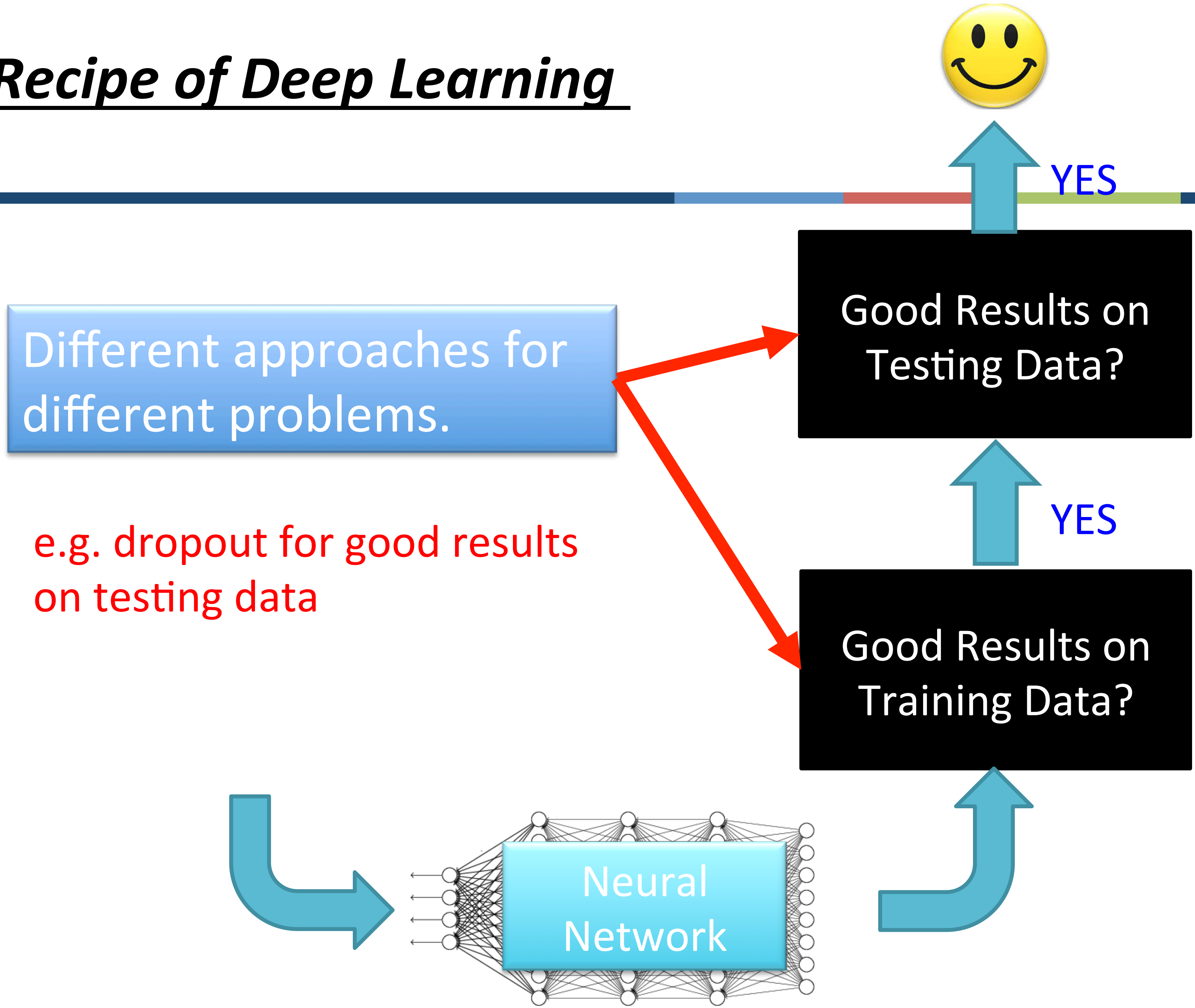


Do not always blame Overfitting



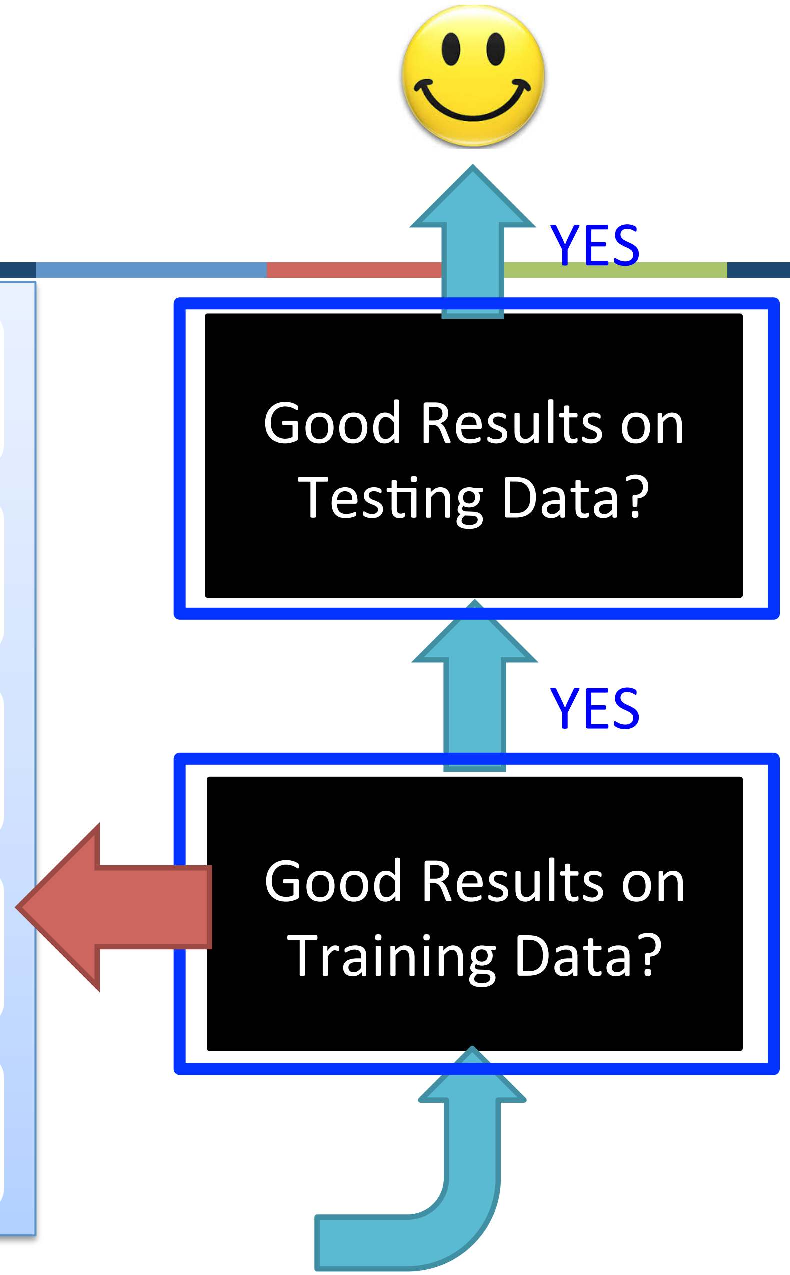
Deep Residual Learning for Image Recognition
http://arxiv.org/abs/1512.03385

Recipe of Deep Learning

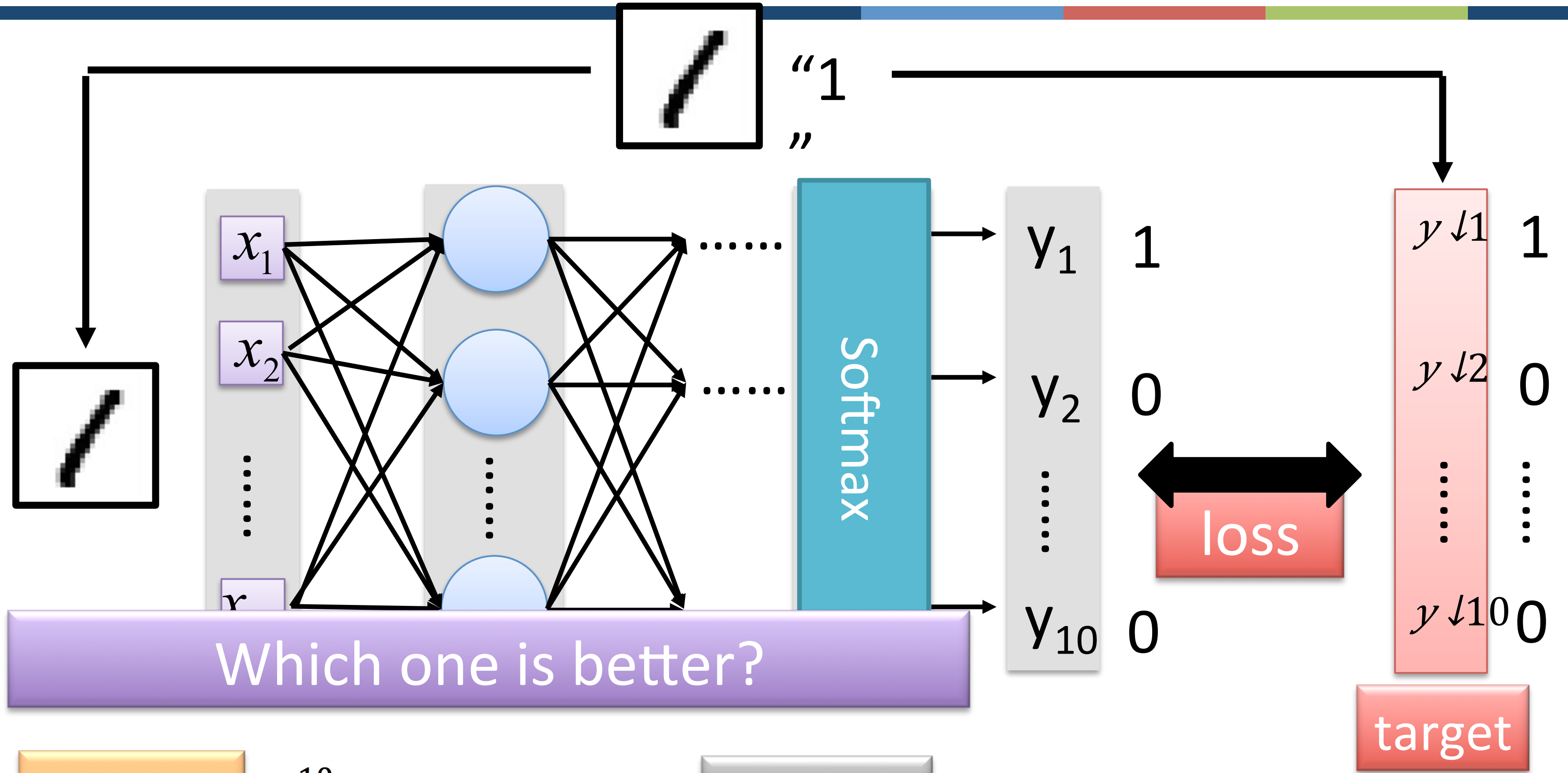


Recipe of Deep Learning

- Choosing proper loss
- Mini-batch
- New activation function
- Adaptive Learning Rate
- Momentum



Choosing Proper Loss



Square Error

$$\sum_{i=1}^{10}(y_i - \hat{y}_i)^2$$

=0

Cross Entropy

$$-\sum_{i=1}^{10}\hat{y}_i \ln y_i$$

=0

Demo

Square Error

```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

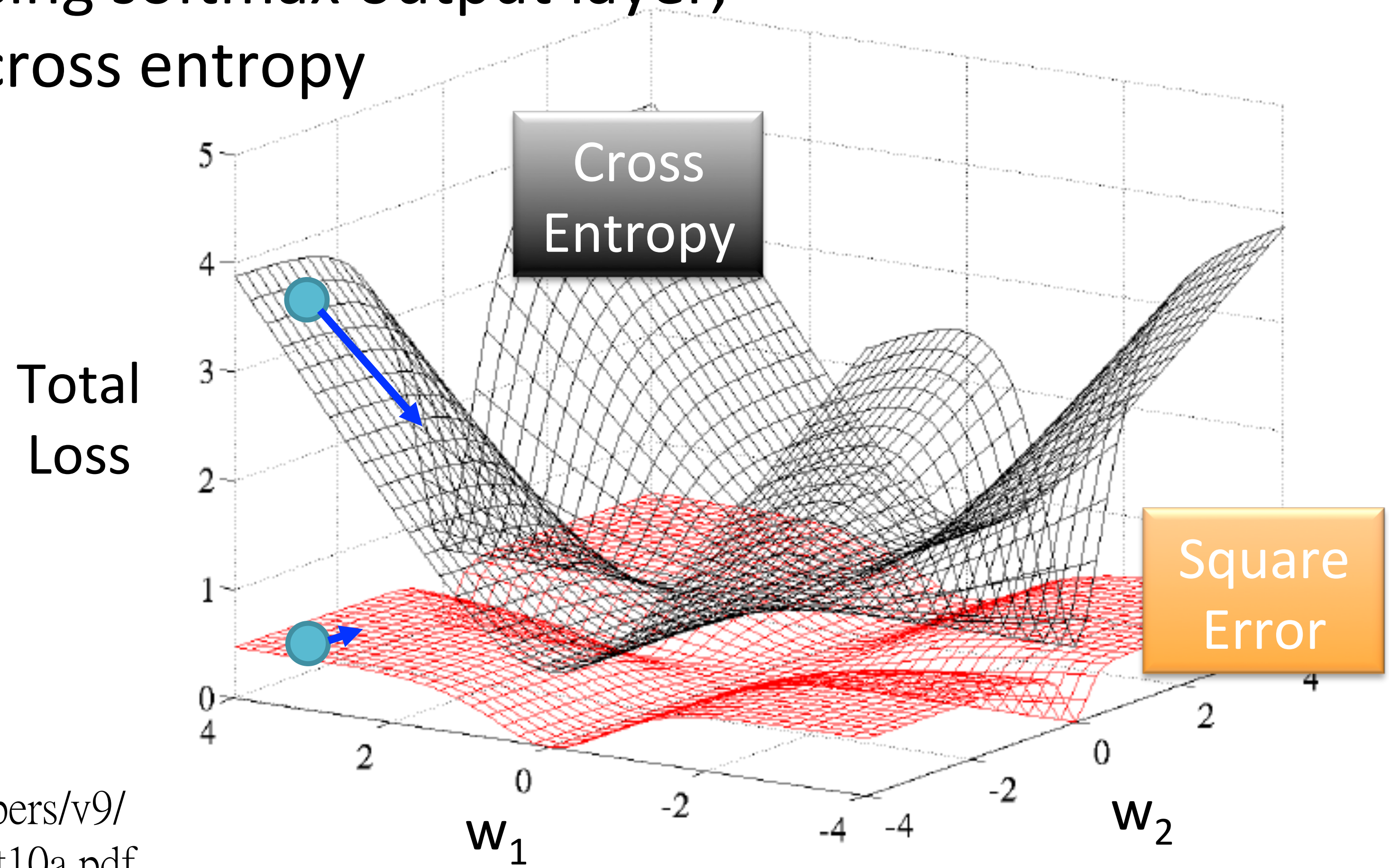
Cross Entropy

```
model.compile(loss='categorical_crossentropy',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

Several alternatives: https://keras.io/objectives/

Choosing Proper Loss

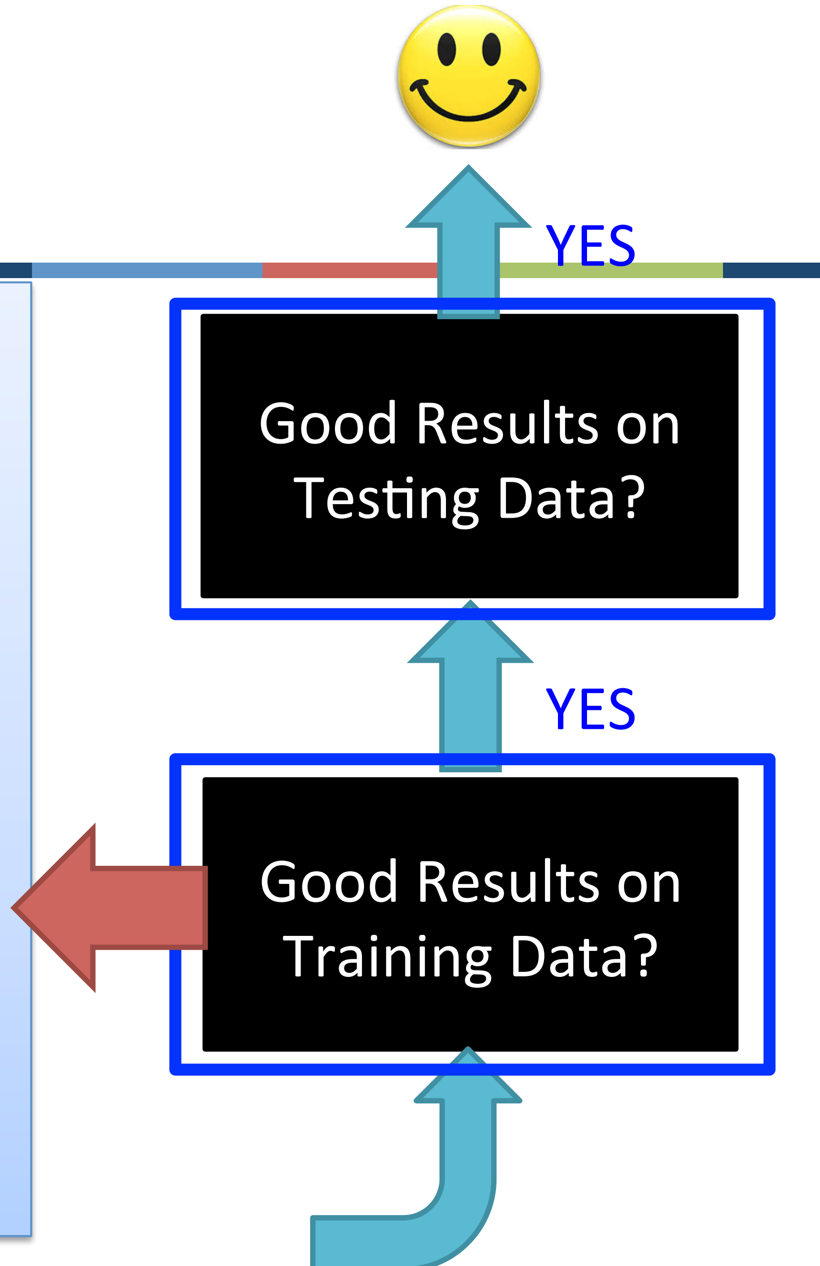
When using softmax output layer, choose cross entropy



http://jmlr.org/proceedings/papers/v9/glorot10a/glorot10a.pdf

Recipe of Deep Learning

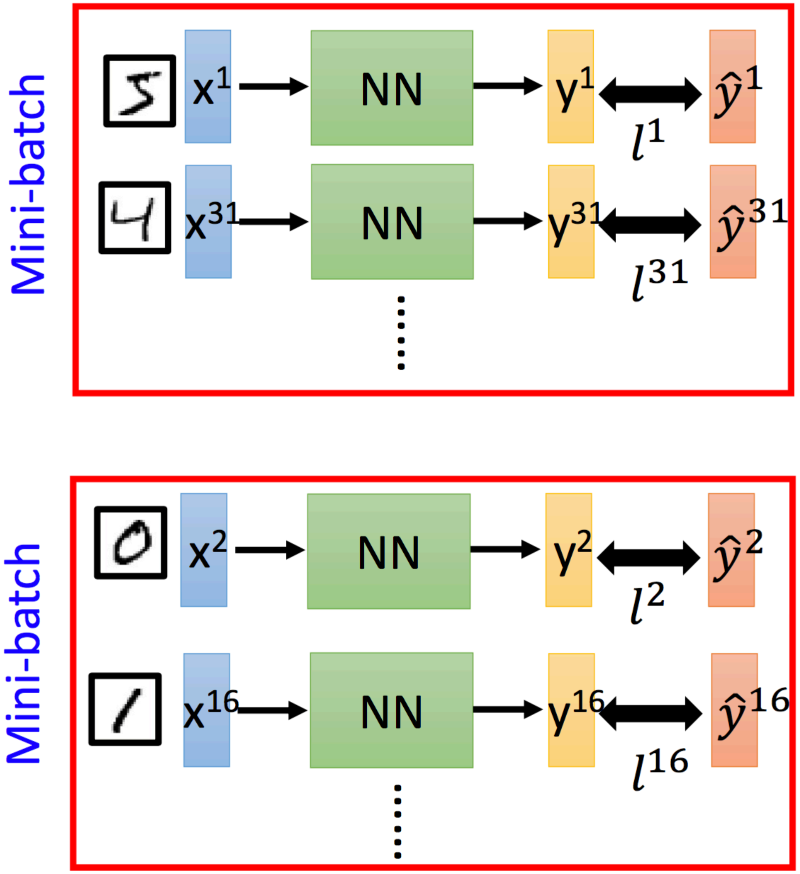
- Choosing proper loss
- Mini-batch
- New activation function
- Adaptive Learning Rate
- Momentum




```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

We do not really minimize total loss!

Mini-batch



- Randomly initialize network parameters

- Pick the 1st batch
  $L' = l^1 + l^{31} + \cdots$
  Update parameters once
- Pick the 2nd batch
  $L'' = l^2 + l^{16} + \cdots$
  Update parameters once

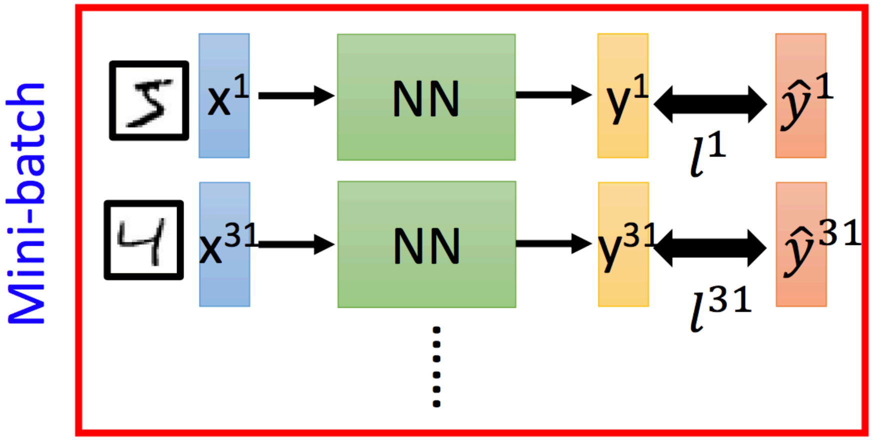
  ⋮
- Until all mini-batches have been picked

one epoch

Repeat the above process

Mini-batch

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```



100 examples in a mini-batch

- Pick the 1st batch

  $L' = l^1 + l^{31} + \cdots$

  Update parameters once

- Pick the 2nd batch

  $L'' = l^2 + l^{16} + \cdots$

  Update parameters once

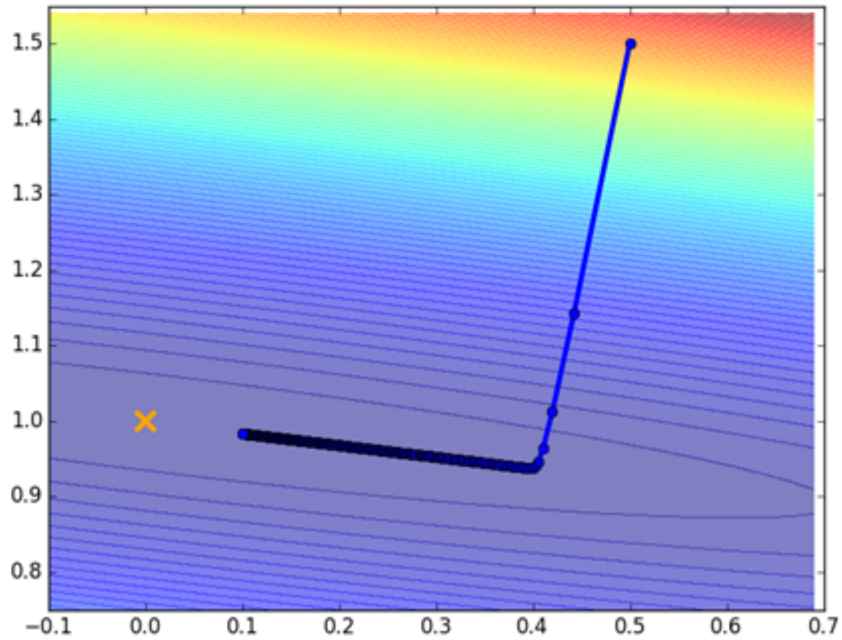
  ⋮

- Until all mini-batches have been picked

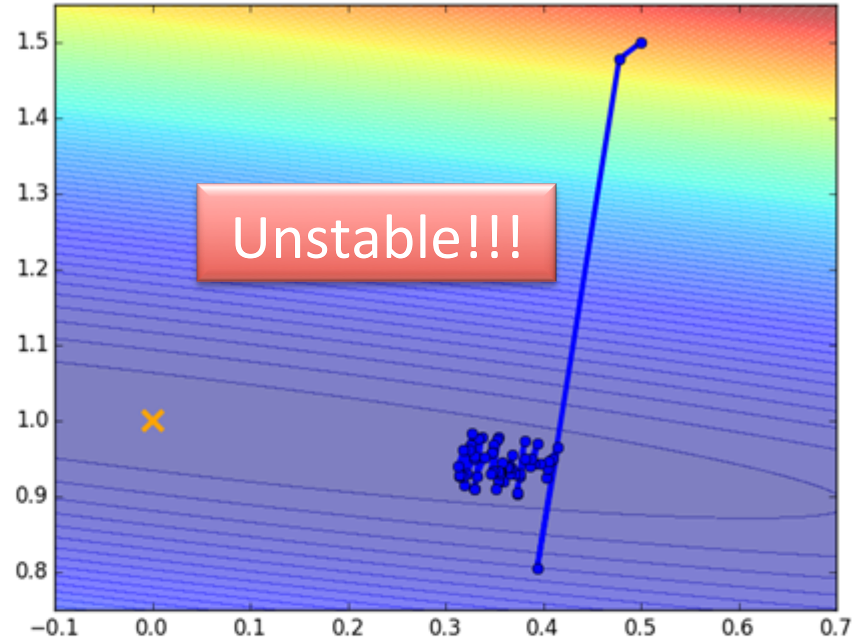
Repeat 20 times

Mini-batch

Original Gradient Descent



With Mini-batch



The colors represent the total loss.

Mini-batch is Faster

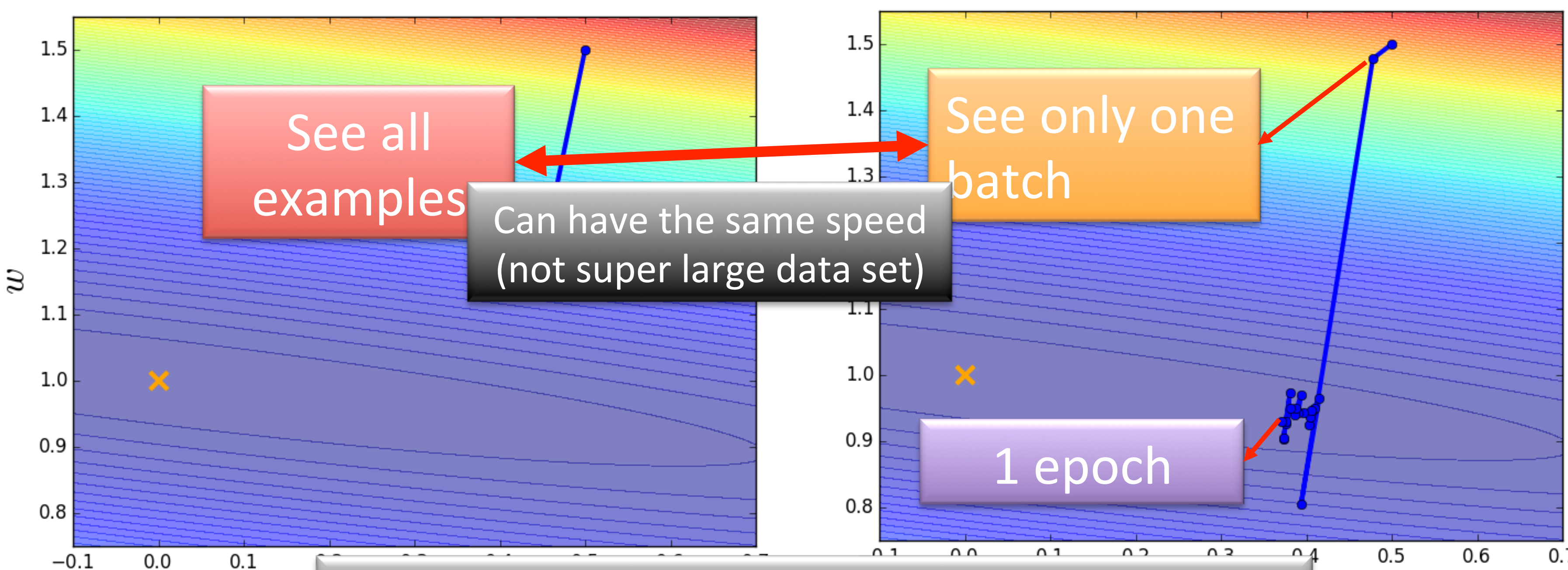
Not always true with parallel computing.

Original Gradient Descent

Update after seeing all examples

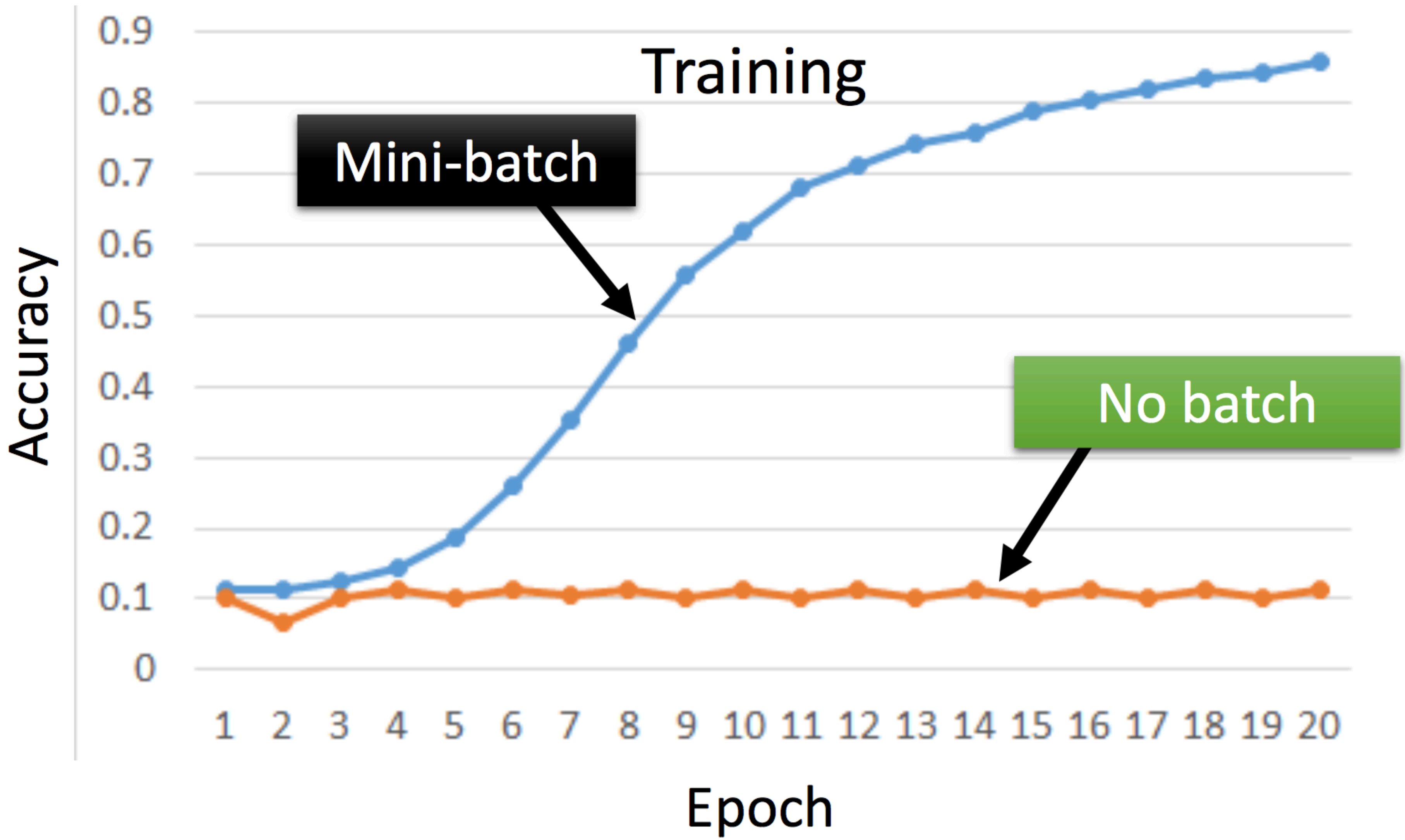
With Mini-batch

If there are 20 batches, update 20 times in one epoch.

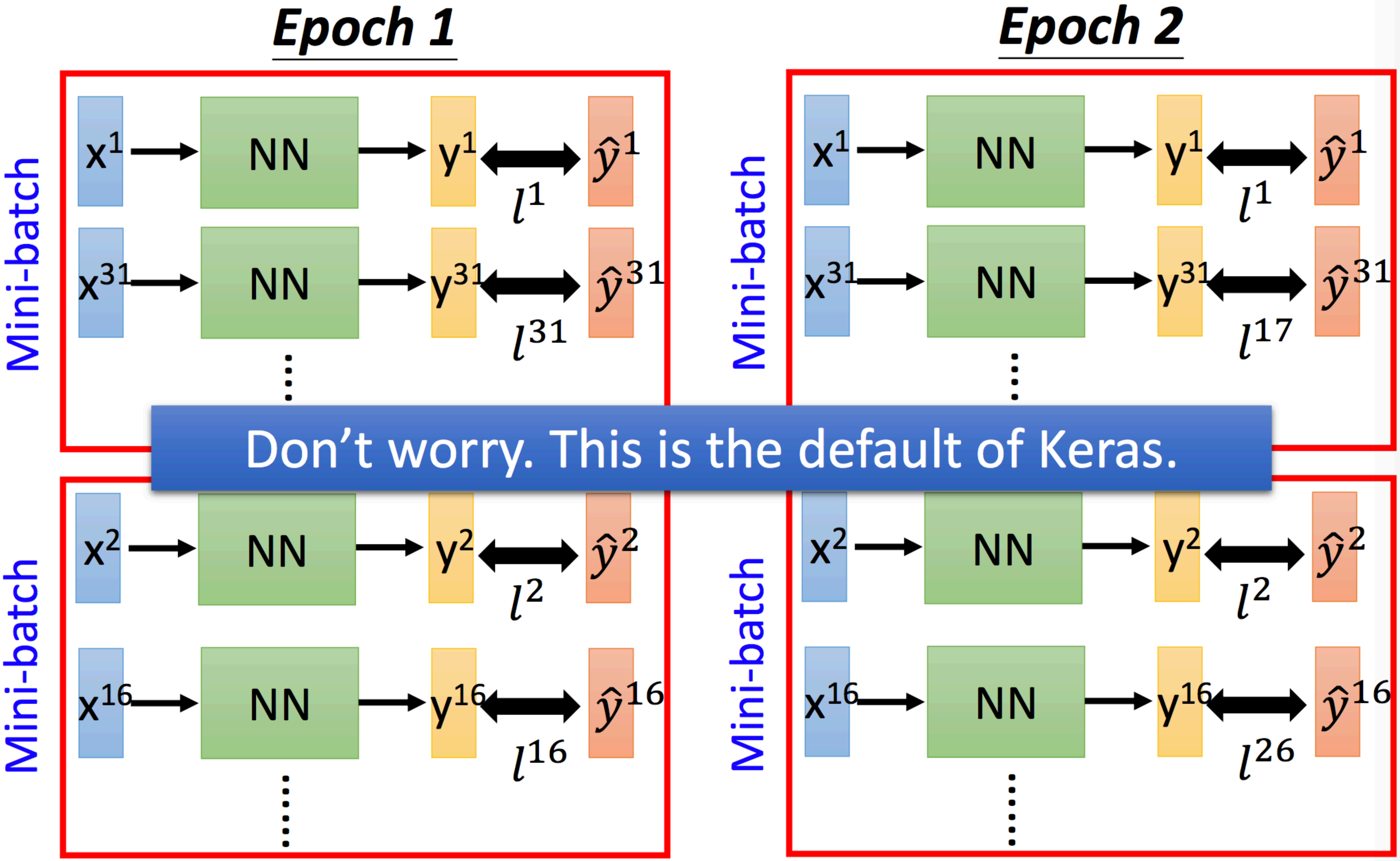


Mini-batch has better performance!

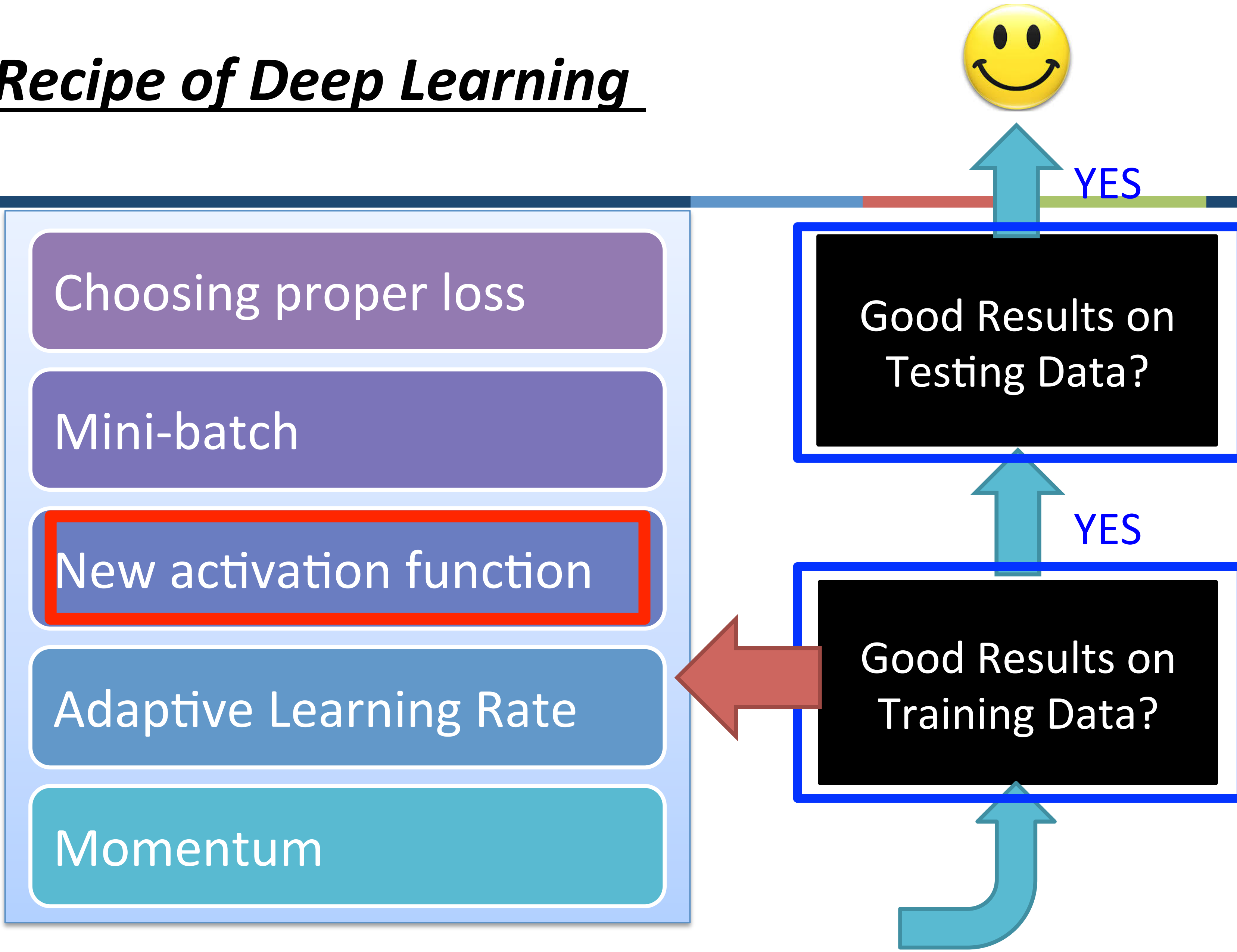
Mini-batch is Faster



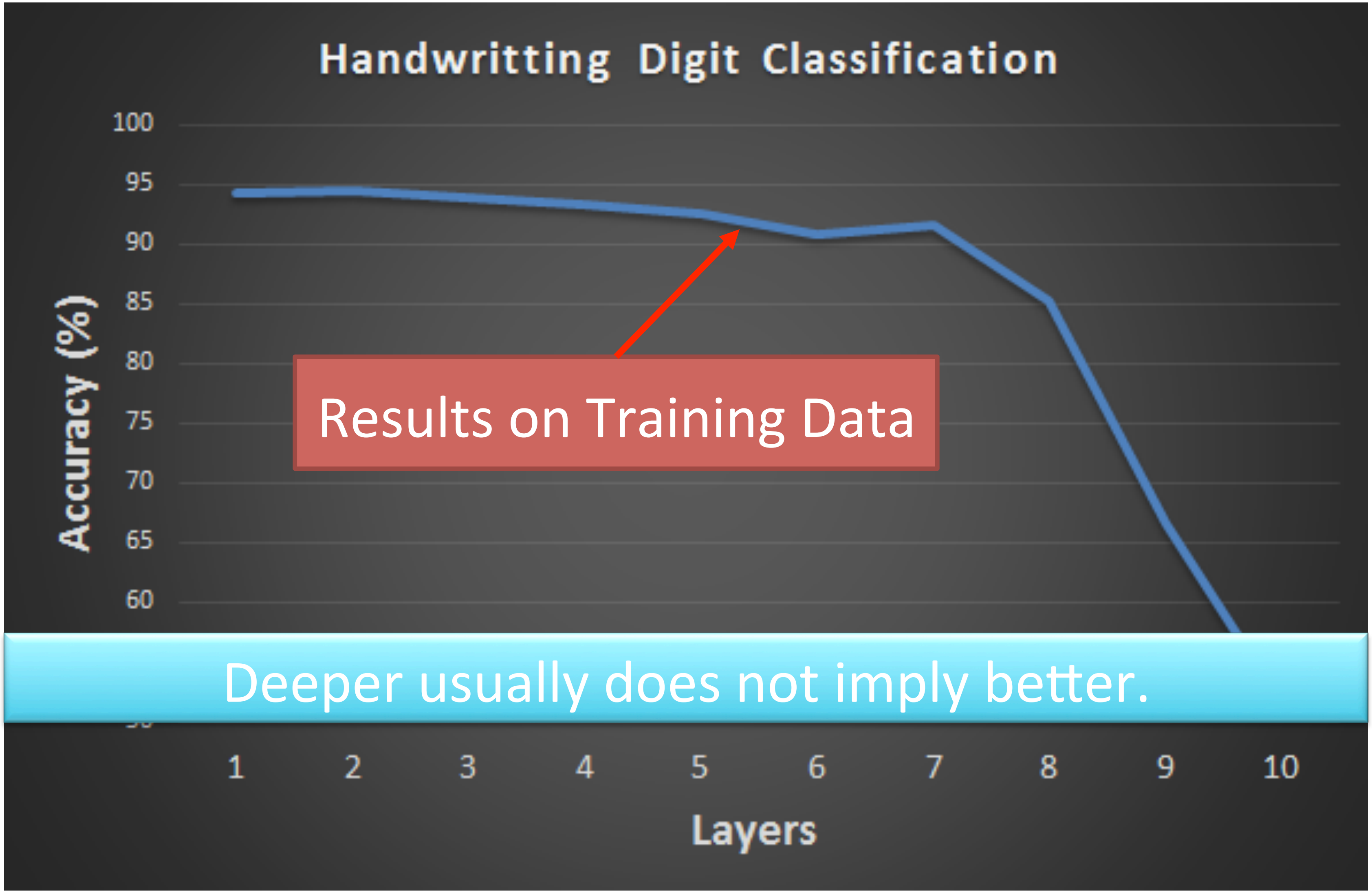
Shuffle the training examples for each epoch



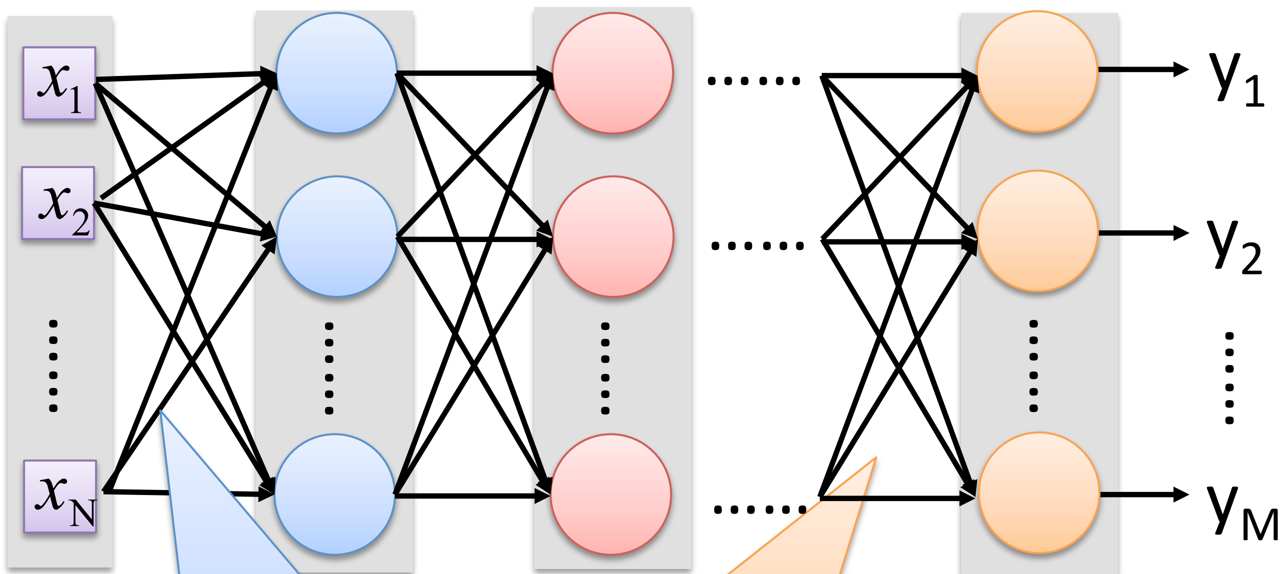
Recipe of Deep Learning



Hard to get the power of Deep …



Vanishing Gradient Problem



Smaller gradients

Learn very slow

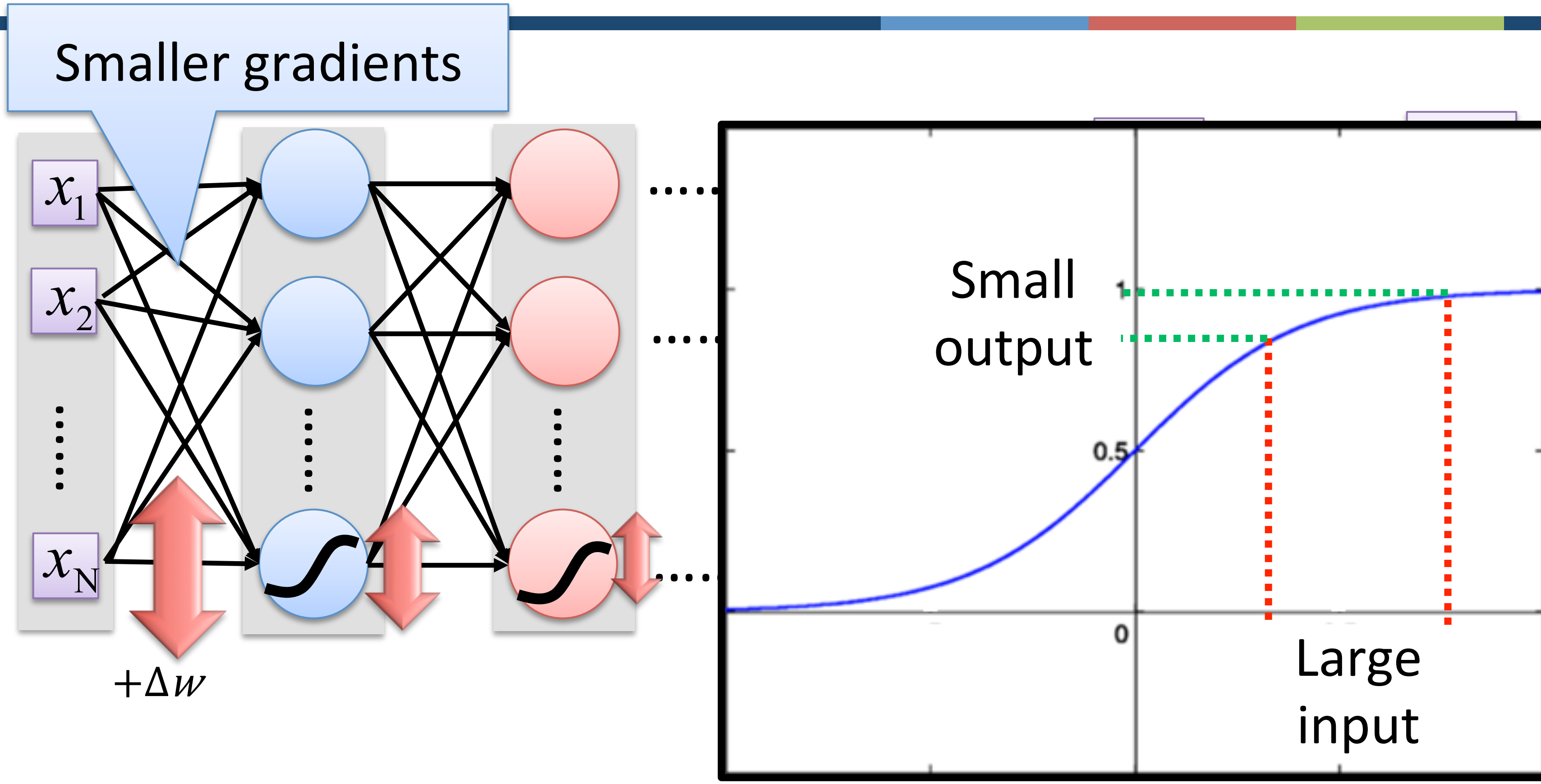
Almost random

Larger gradients

Learn very fast

Already converge

Vanishing Gradient Problem

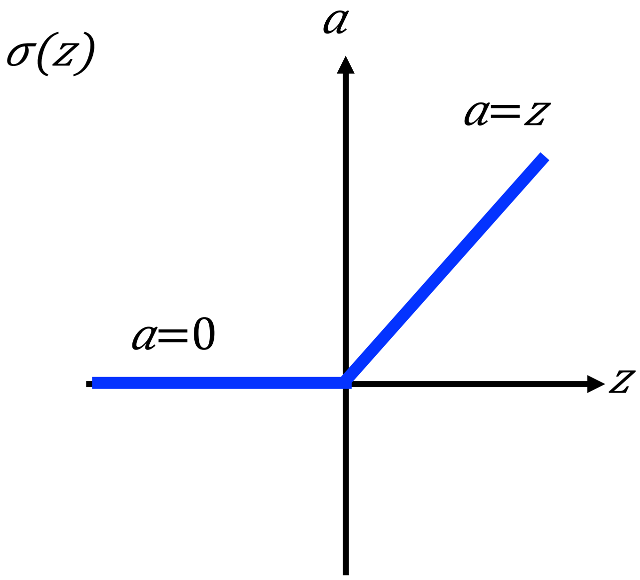


Intuitive way to compute the derivatives …

$$\partial l / \partial w = ?\ \Delta l / \Delta w$$

ReLU

- Rectified Linear Unit (ReLU)



[Xavier Glorot, AISTATS'11]
[Andrew L. Maas, ICML'13]
[Kaiming He, arXiv'15]

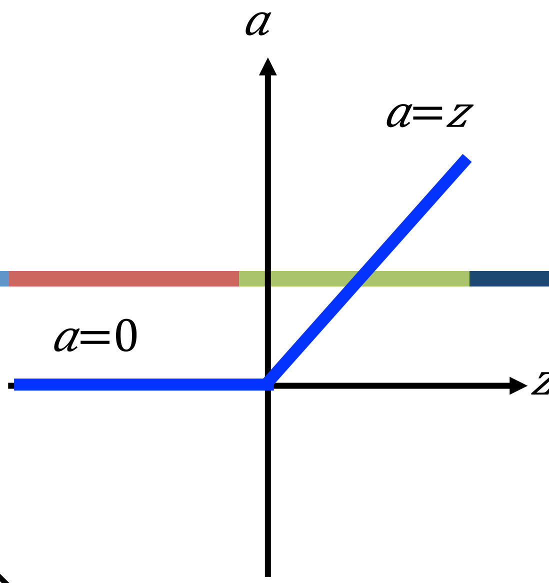
Reason:

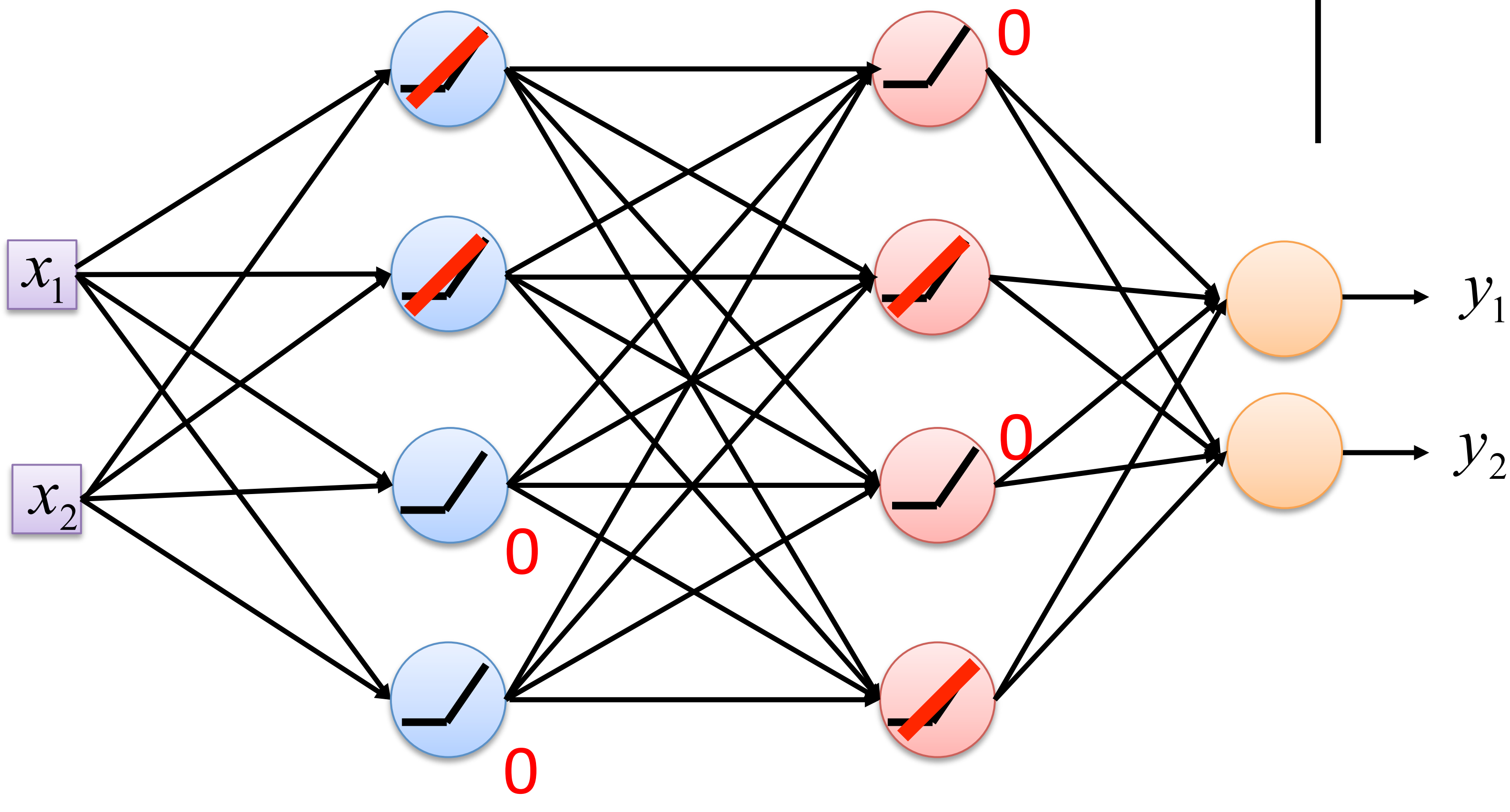
1. Fast to compute

2. Sparsity

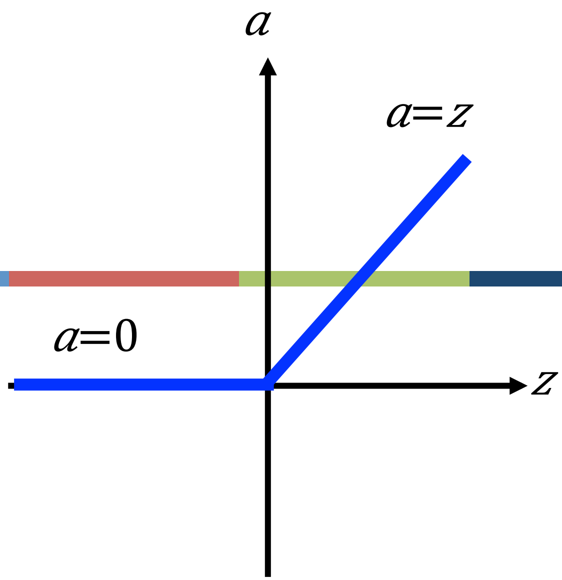
3. Vanishing gradient problem

ReLU

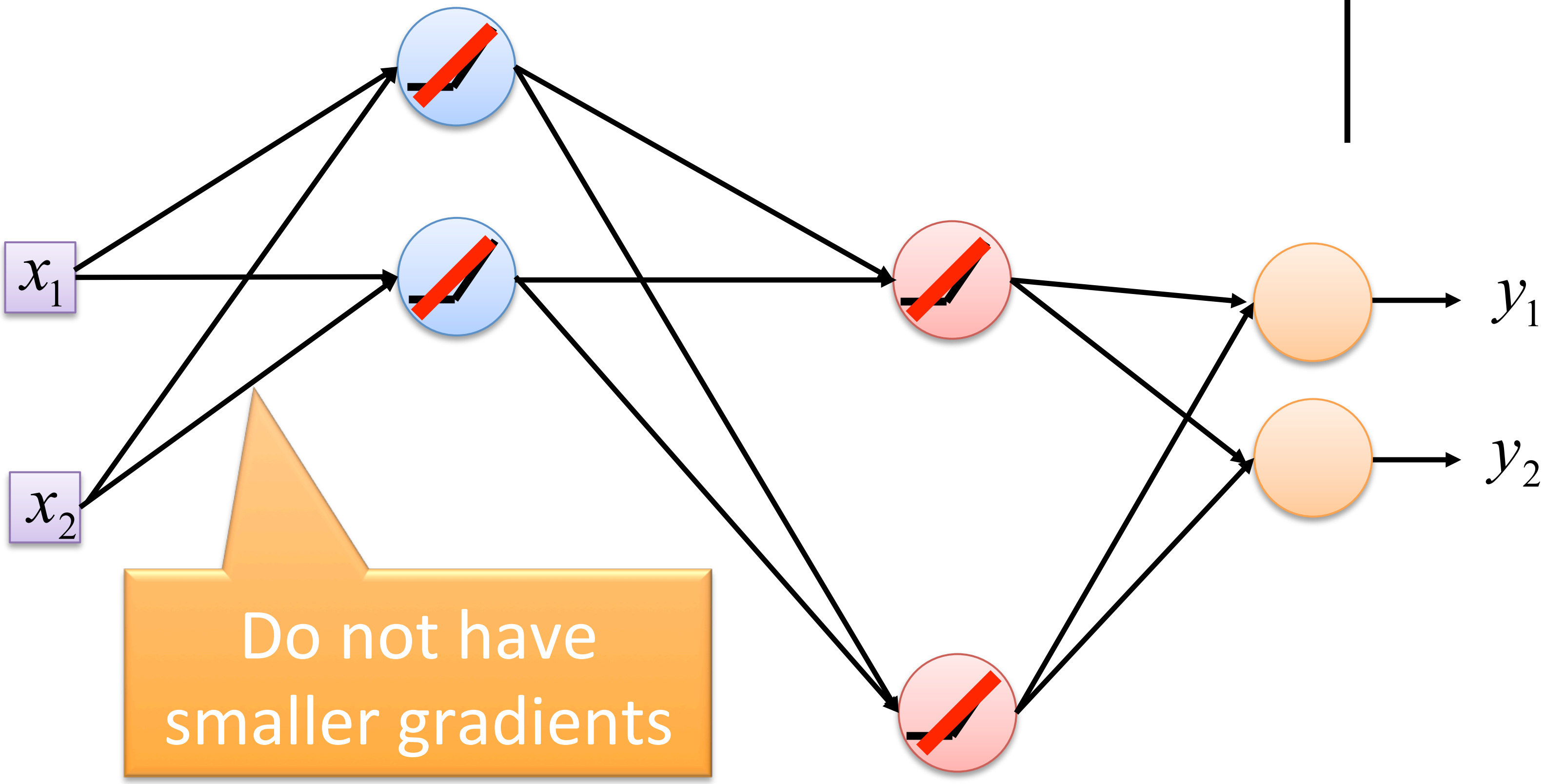




ReLU

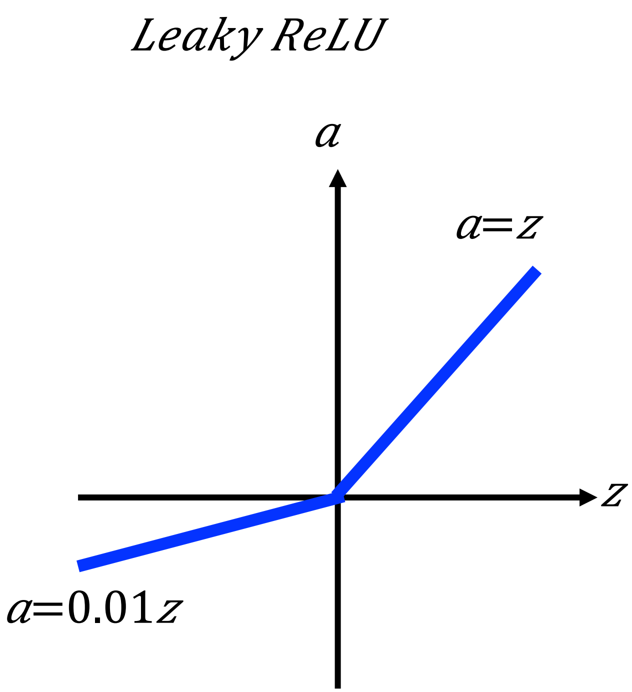


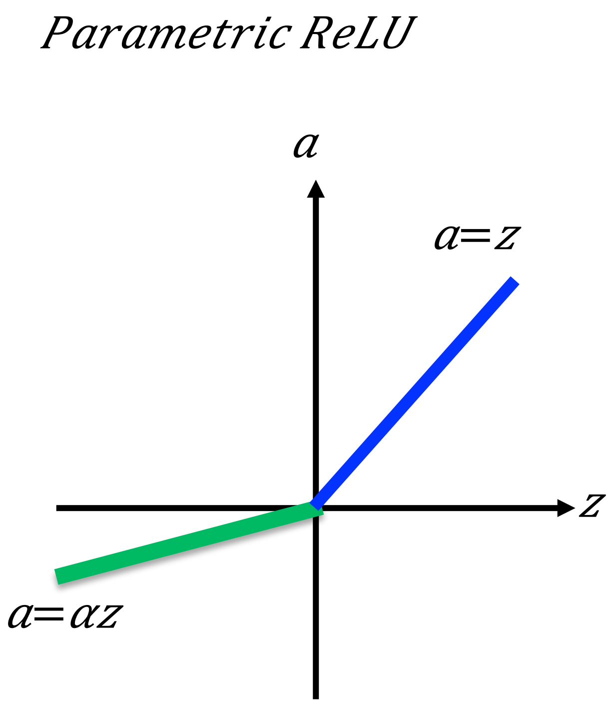
A Thinner linear network



Do not have smaller gradients

ReLU - variant



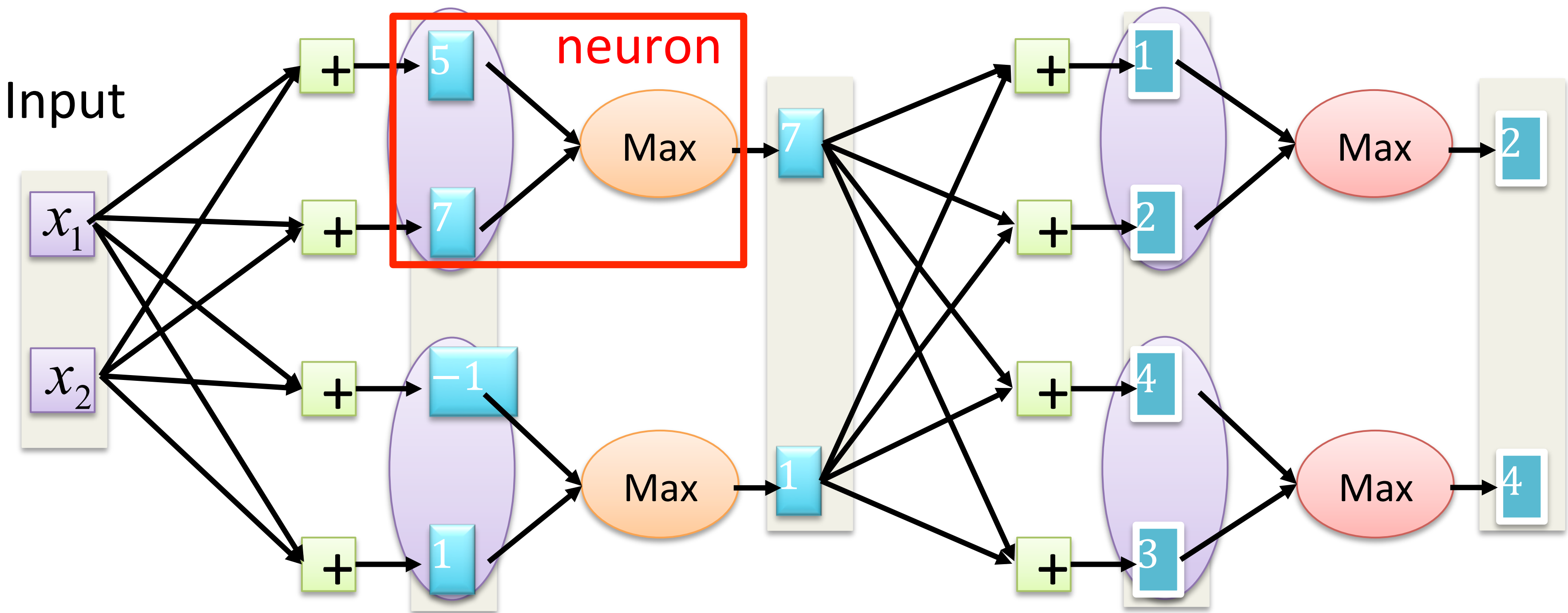


α also learned by gradient descent

Maxout

ReLU is a special cases of Maxout

- Learnable activation function [Ian J. Goodfellow, ICML'13]



You can have more than 2 elements in a group.

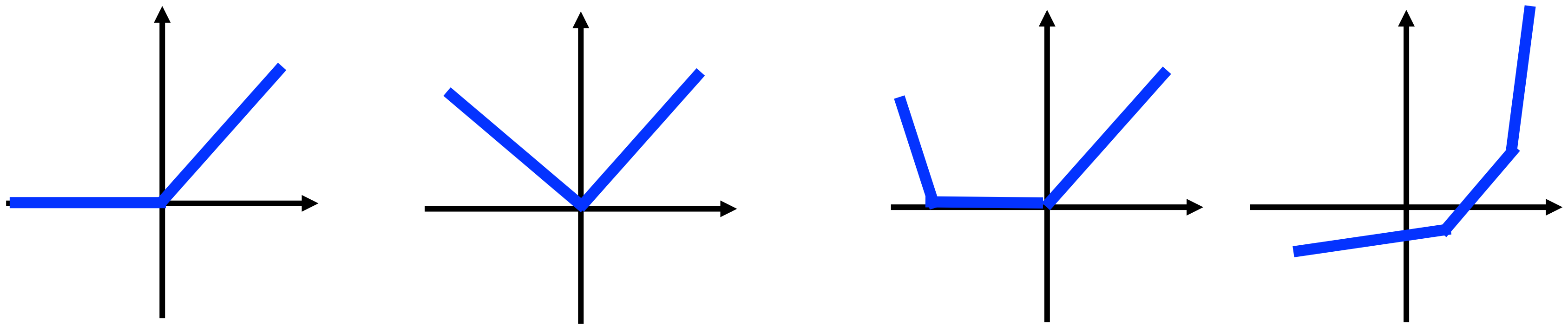
Maxout

ReLU is a special cases of Maxout

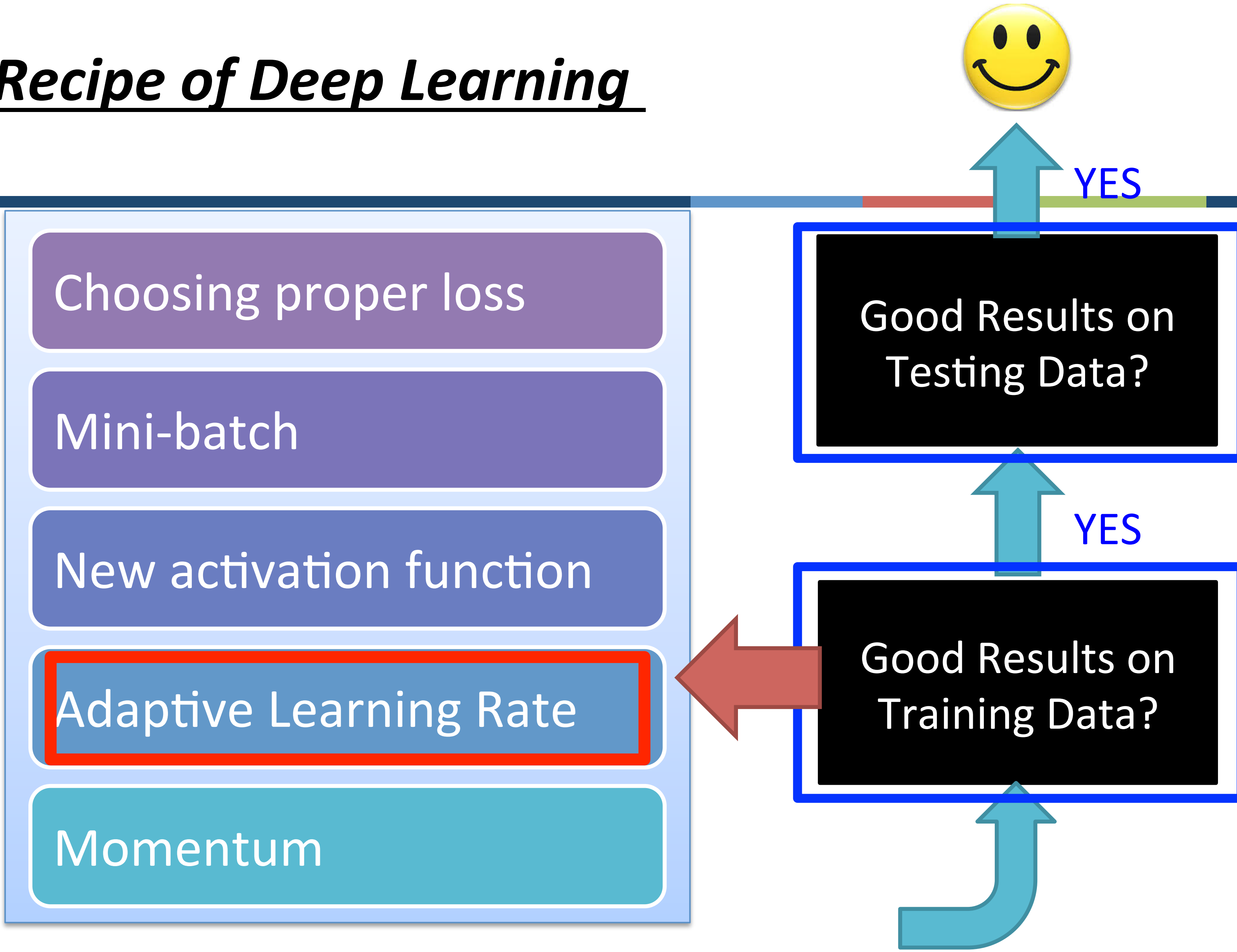
- Learnable activation function [Ian J. Goodfellow, ICML'13]
  - Activation function in maxout network can be any piecewise linear convex function
  - How many pieces depending on how many elements in a group

2 elements in a group

3 elements in a group

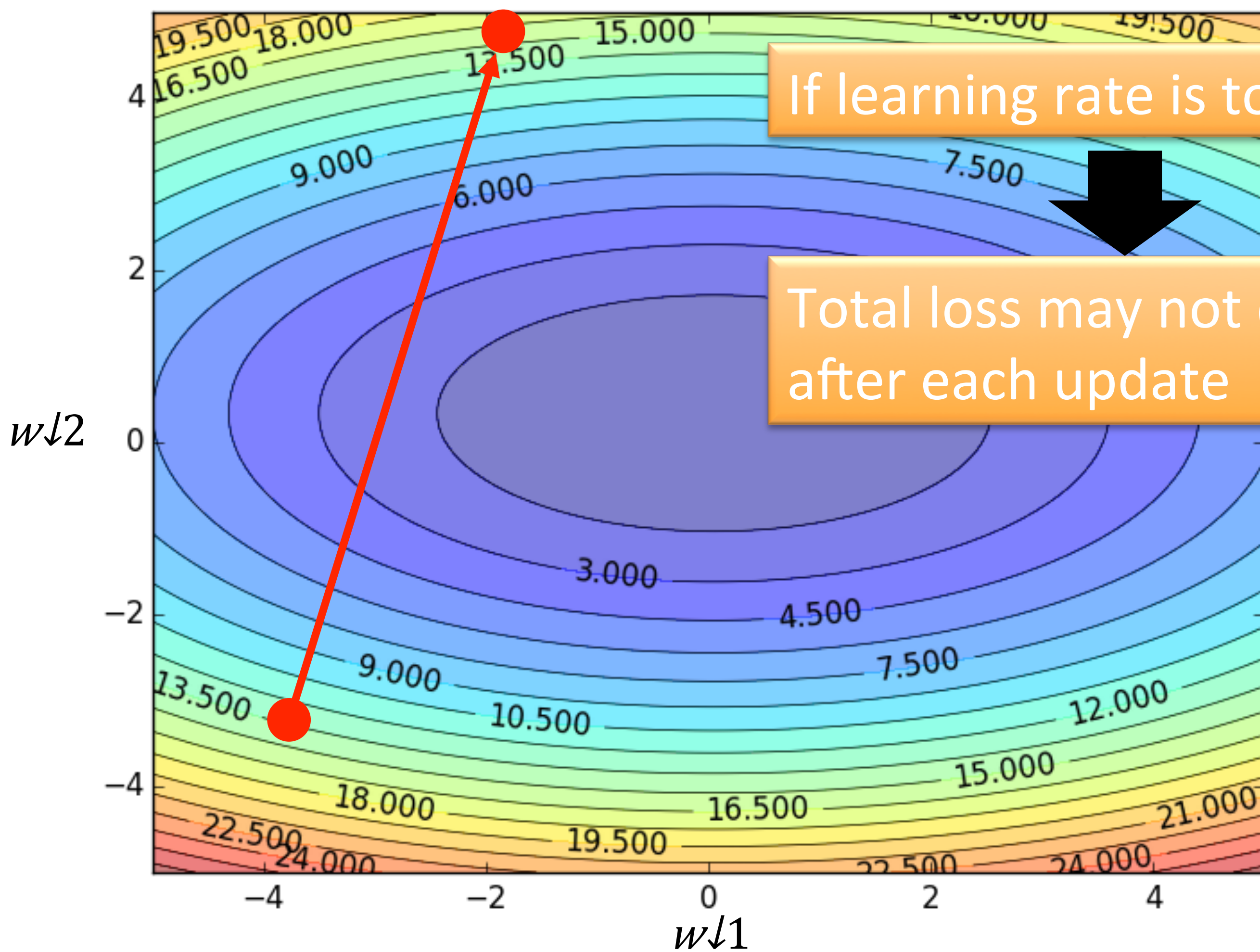


Recipe of Deep Learning



Learning Rates

Set the learning rate η carefully

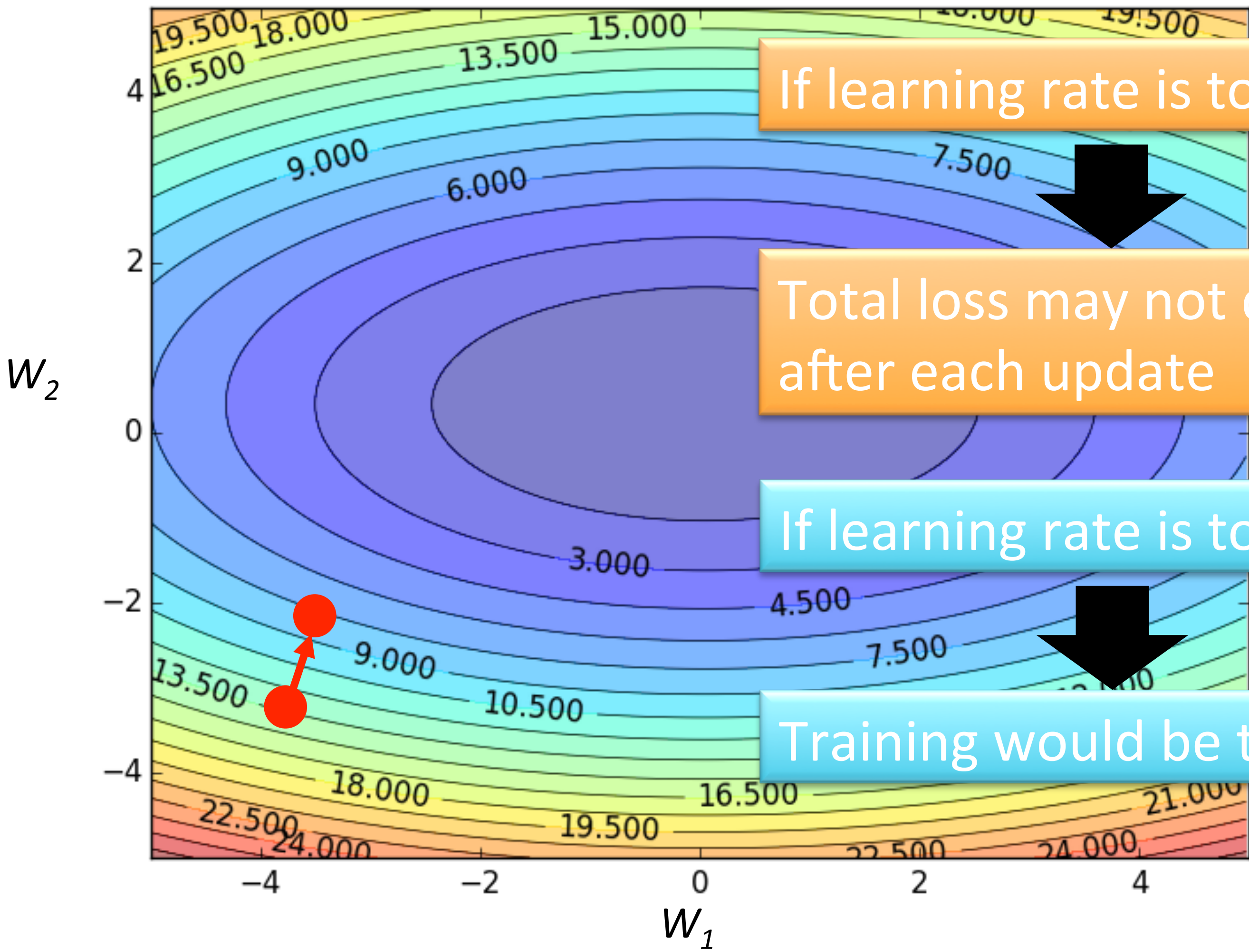


If learning rate is too large

Total loss may not decrease after each update

Learning Rates

Set the learning rate η carefully



If learning rate is too large

Total loss may not decrease after each update

If learning rate is too small

Training would be too slow

Learning Rates

- Popular & Simple Idea: Reduce the learning rate by some factor every few epochs.
  - At the beginning, we are far from the destination, so we use larger learning rate
  - After several epochs, we are close to the destination, so we reduce the learning rate
  - E.g. 1/t decay: $\eta^t = \eta / \sqrt{t+1}$
- Learning rate cannot be one-size-fits-all
  - Giving different parameters different learning rates

Adagrad

Original: $w \leftarrow w - \eta \partial L / \partial w$

Adagrad: $w \leftarrow w - \eta_w \partial L / \partial w$

Parameter dependent learning rate

$$\eta_w = \frac{\eta}{\sqrt{\sum_{i=0}^{t} (g^i)^2}}$$

constant

g^i is $\partial L / \partial w$ obtained at the i-th update

Summation of the square of the previous derivatives

Adagrad

$$\eta_w = \frac{\eta}{\sqrt{\sum_{i=0}^{t}(g^i)^2}}$$

w_1	g^0
	0.1

Learning rate:

$$\frac{\eta}{\sqrt{0.1^2}} = \frac{\eta}{0.1}$$

$$\frac{\eta}{\sqrt{0.1^2 + 0.2^2}} = \frac{\eta}{0.22}$$

w_2	g^0
	20.0

Learning rate:

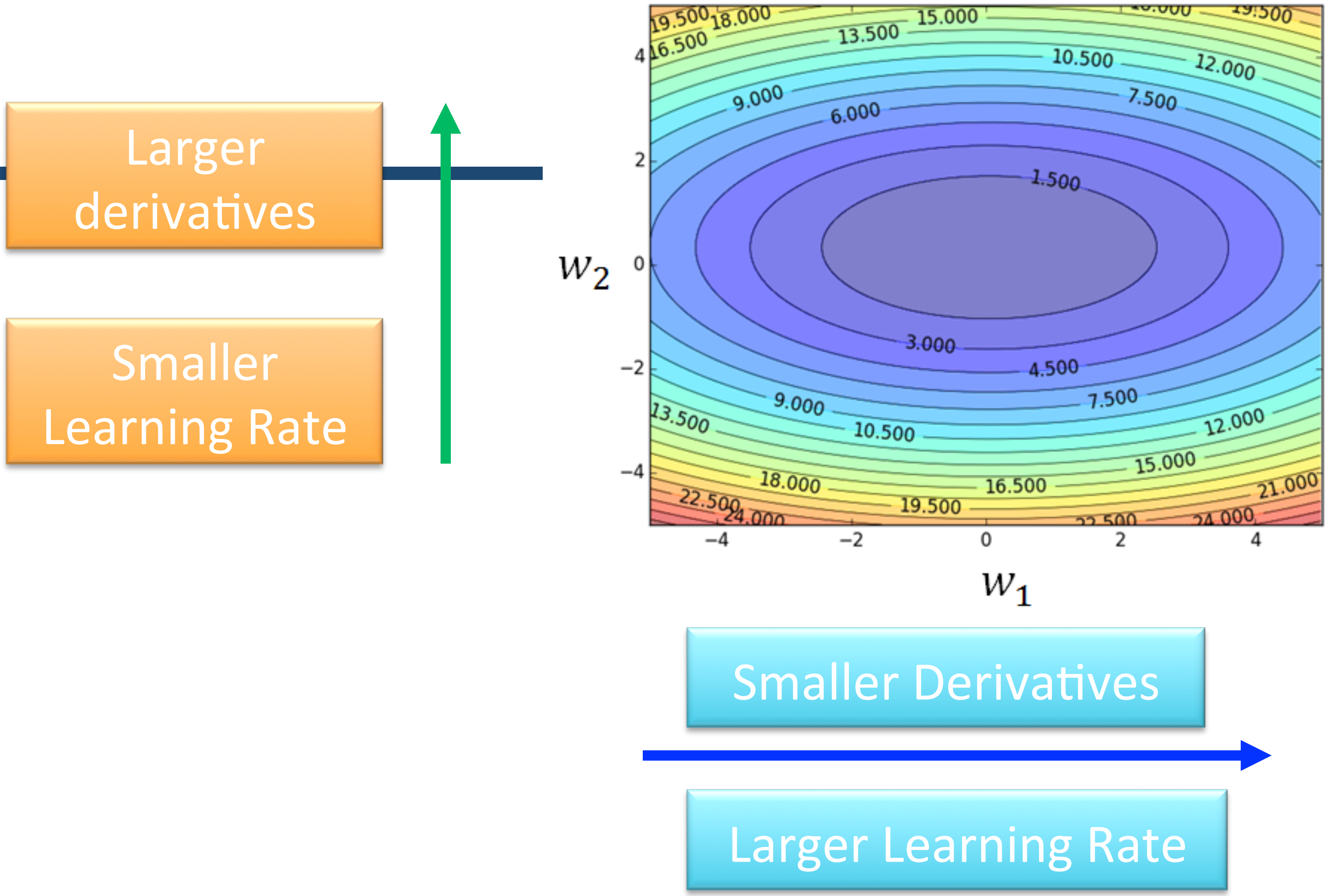
$$\frac{\eta}{\sqrt{20^2}} = \frac{\eta}{20}$$

$$\frac{\eta}{\sqrt{20^2 + 10^2}} = \frac{\eta}{22}$$

Observation: 1. Learning rate is smaller and smaller for all parameters

2. Smaller derivatives, larger learning rate, and vice versa

Why?



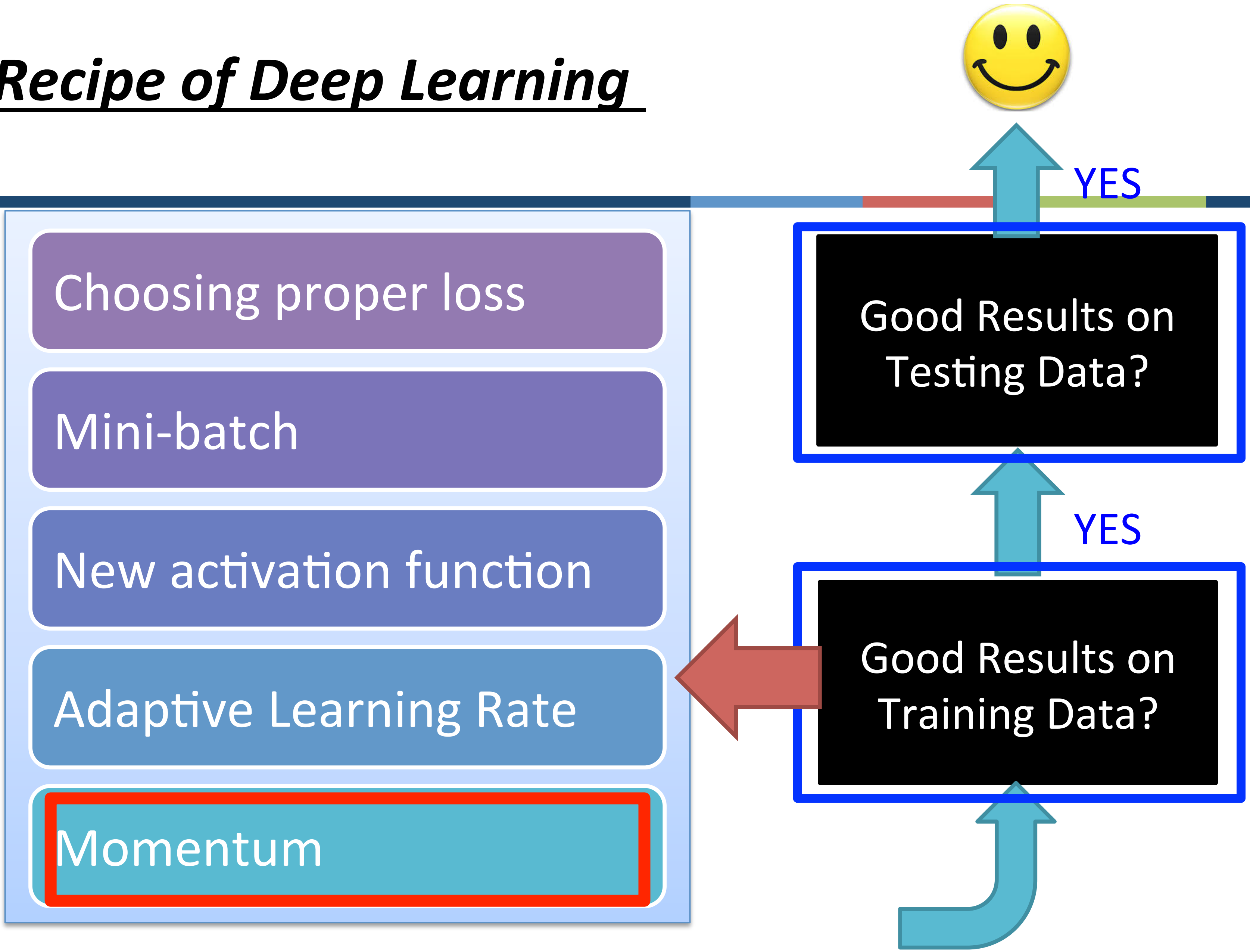
2. Smaller derivatives, larger learning rate, and vice versa

Why?

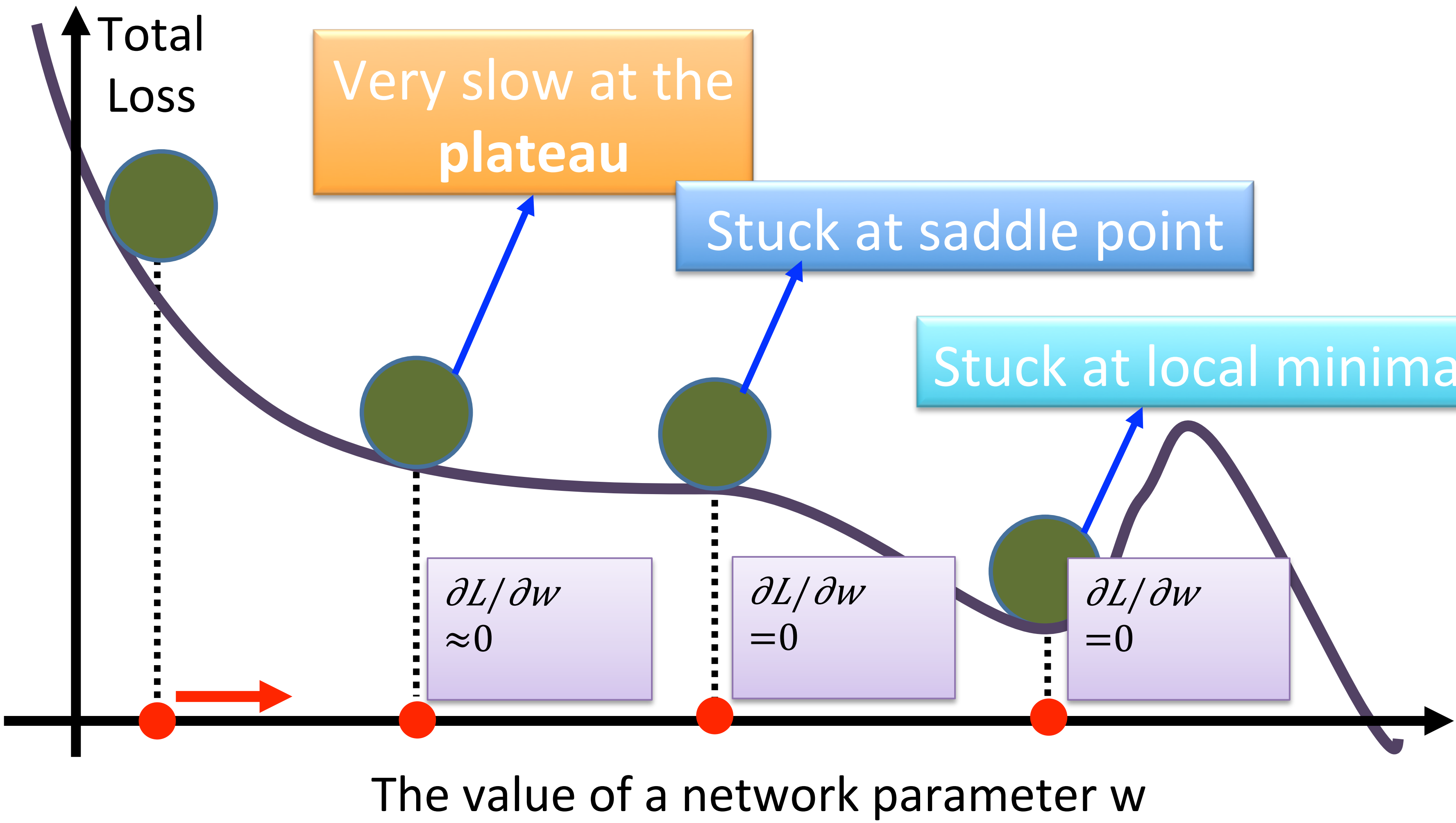
Not the whole story ……

- Adagrad [John Duchi, JMLR'11]
- RMSprop
  - https://www.youtube.com/watch?v=O3sxAc4hxZU
- Adadelta [Matthew D. Zeiler, arXiv'12]
- "No more pesky learning rates" [Tom Schaul, arXiv'12]
- AdaSecant [Caglar Gulcehre, arXiv'14]
- Adam [Diederik P. Kingma, ICLR'15]
- Nadam
  - http://cs229.stanford.edu/proj2015/054_report.pdf

Recipe of Deep Learning

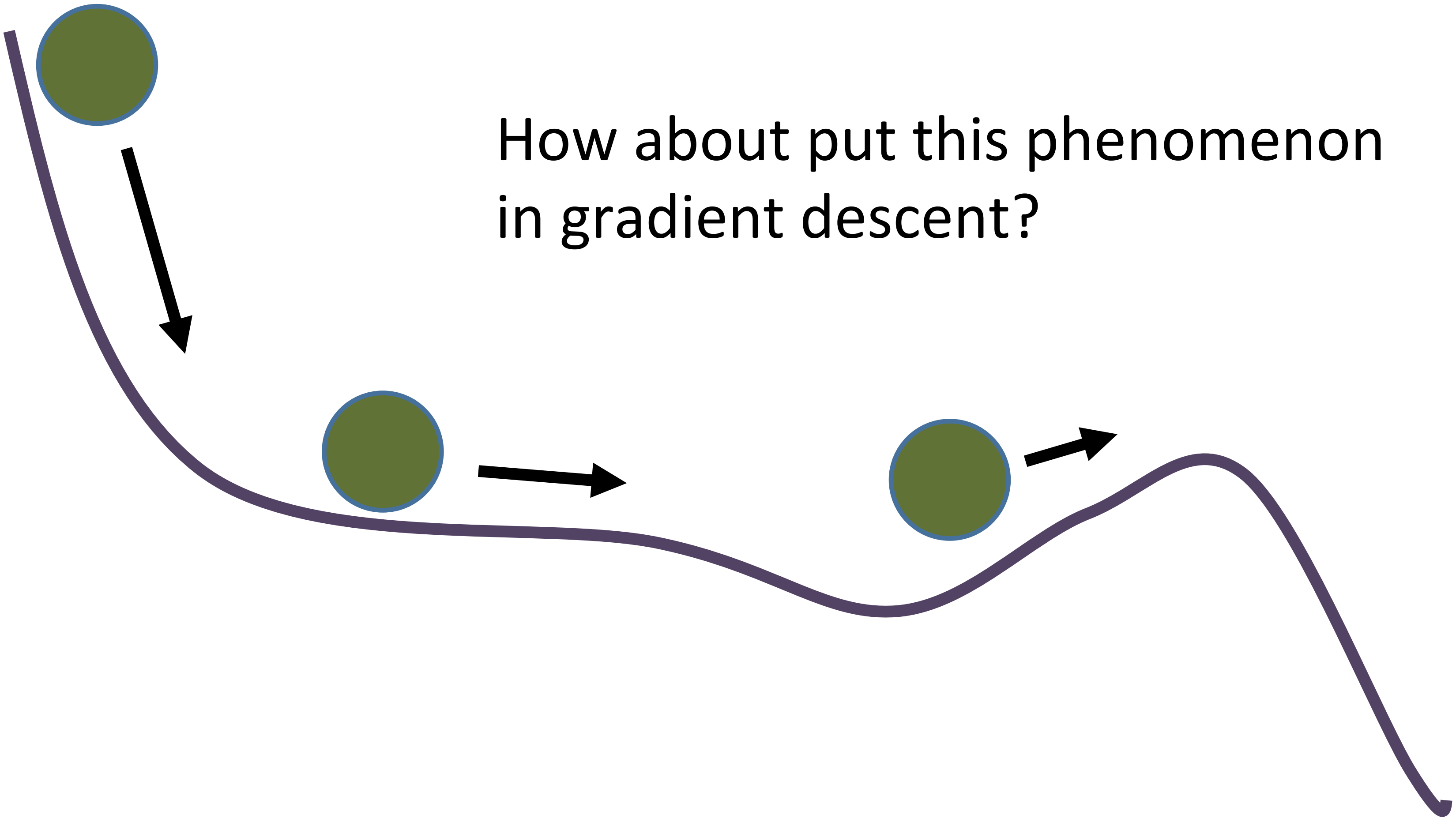


Hard to find optimal network parameters



In physical world ……

- Momentum

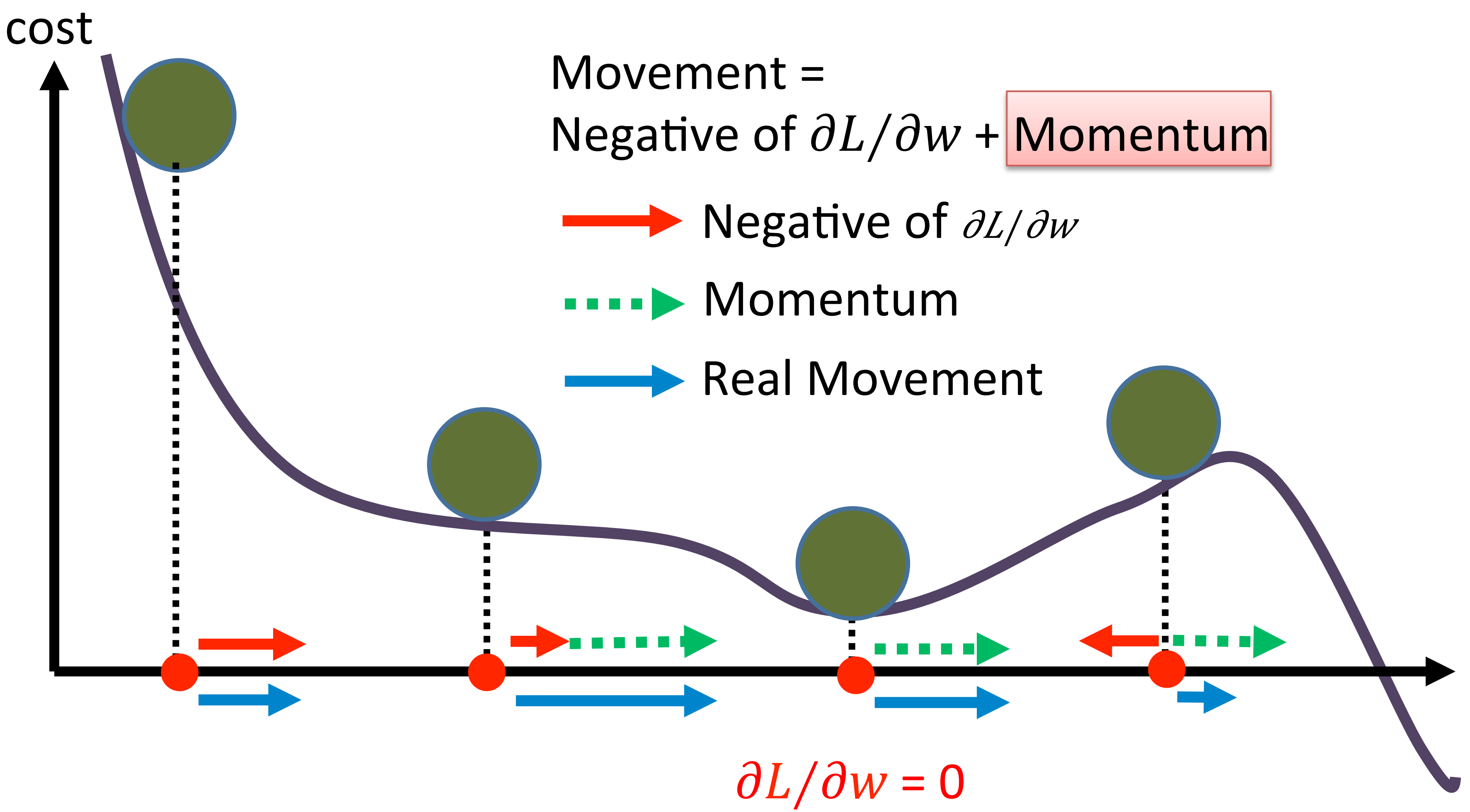


How about put this phenomenon in gradient descent?

Momentum

Still not guarantee reaching global minima, but give some hope ……

Movement = Negative of $\partial L/\partial w$ + Momentum



RMSProp (Advanced Adagrad) + Momentum

```
model.compile(loss='categorical_crossentropy',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

```
model.compile(loss='categorical_crossentropy',
              optimizer=Adam(),
              metrics=['accuracy'])
```

Algorithm 1: *Adam*, our proposed algorithm for stochastic optimization. See section 2 for details, and for a slightly more efficient (but less clear) order of computation. g_t^2 indicates the elementwise square $g_t \odot g_t$. Good default settings for the tested machine learning problems are $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$. All operations on vectors are element-wise. With β_1^t and β_2^t we denote β_1 and β_2 to the power t.

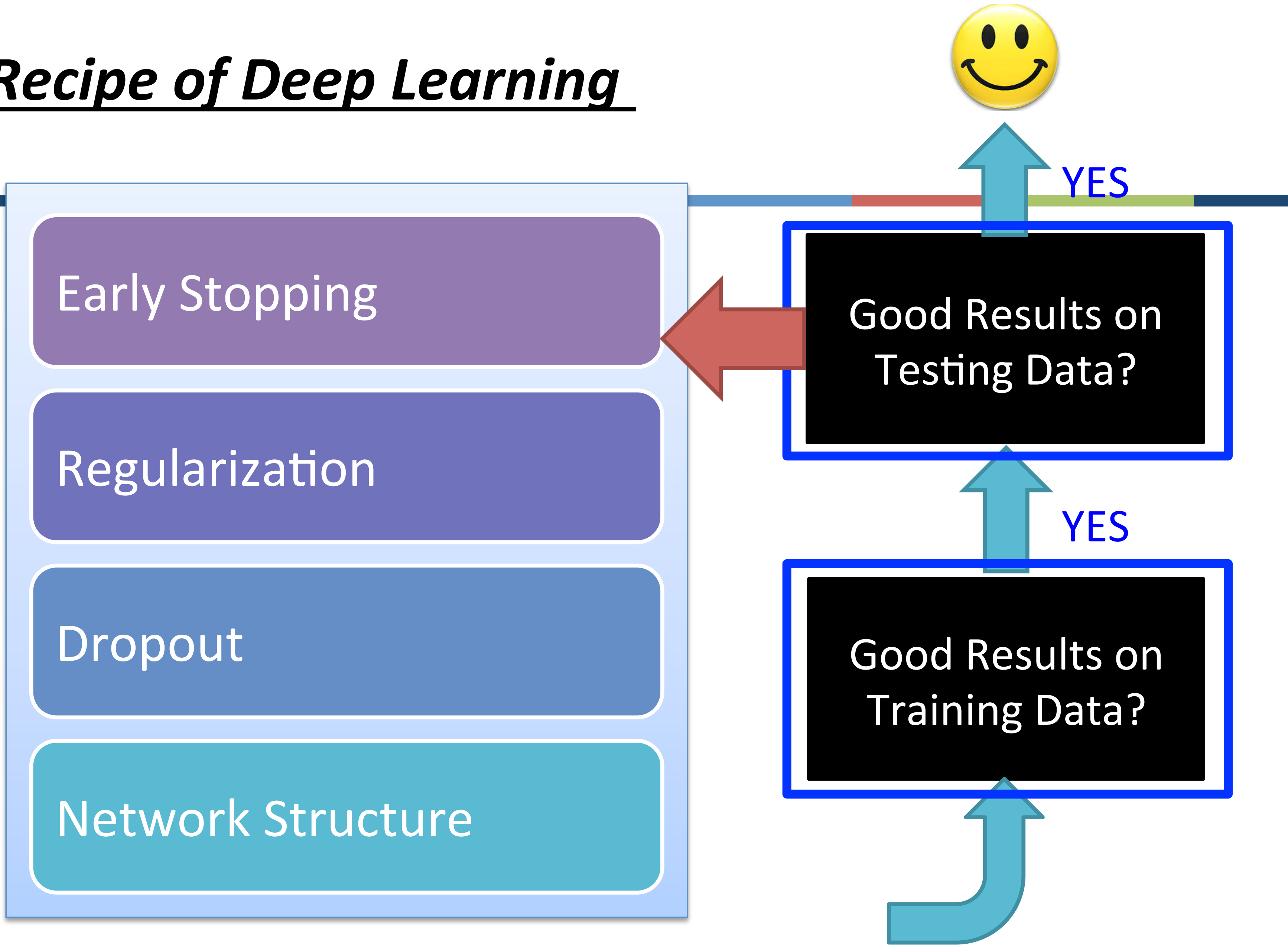
Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
$m_0 \leftarrow 0$ (Initialize 1[st] moment vector)
$v_0 \leftarrow 0$ (Initialize 2[nd] moment vector)
$t \leftarrow 0$ (Initialize timestep)

at timestep t)
ent estimate)
moment estimate)

$\widehat{m}_t \leftarrow m_t/(1-\beta_1^t)$ (Compute bias-corrected first moment estimate)
$\widehat{v}_t \leftarrow v_t/(1-\beta_2^t)$ (Compute bias-corrected second raw moment estimate)
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t/(\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)
end while
return θ_t (Resulting parameters)

```
loss = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.1)
```

Recipe of Deep Learning

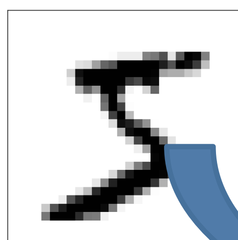


Panacea for Overfitting

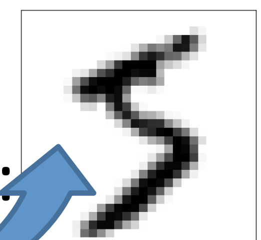
- Have more training data
- ***Create*** more training data (?)

Handwriting recognition:

Original
Training Data:

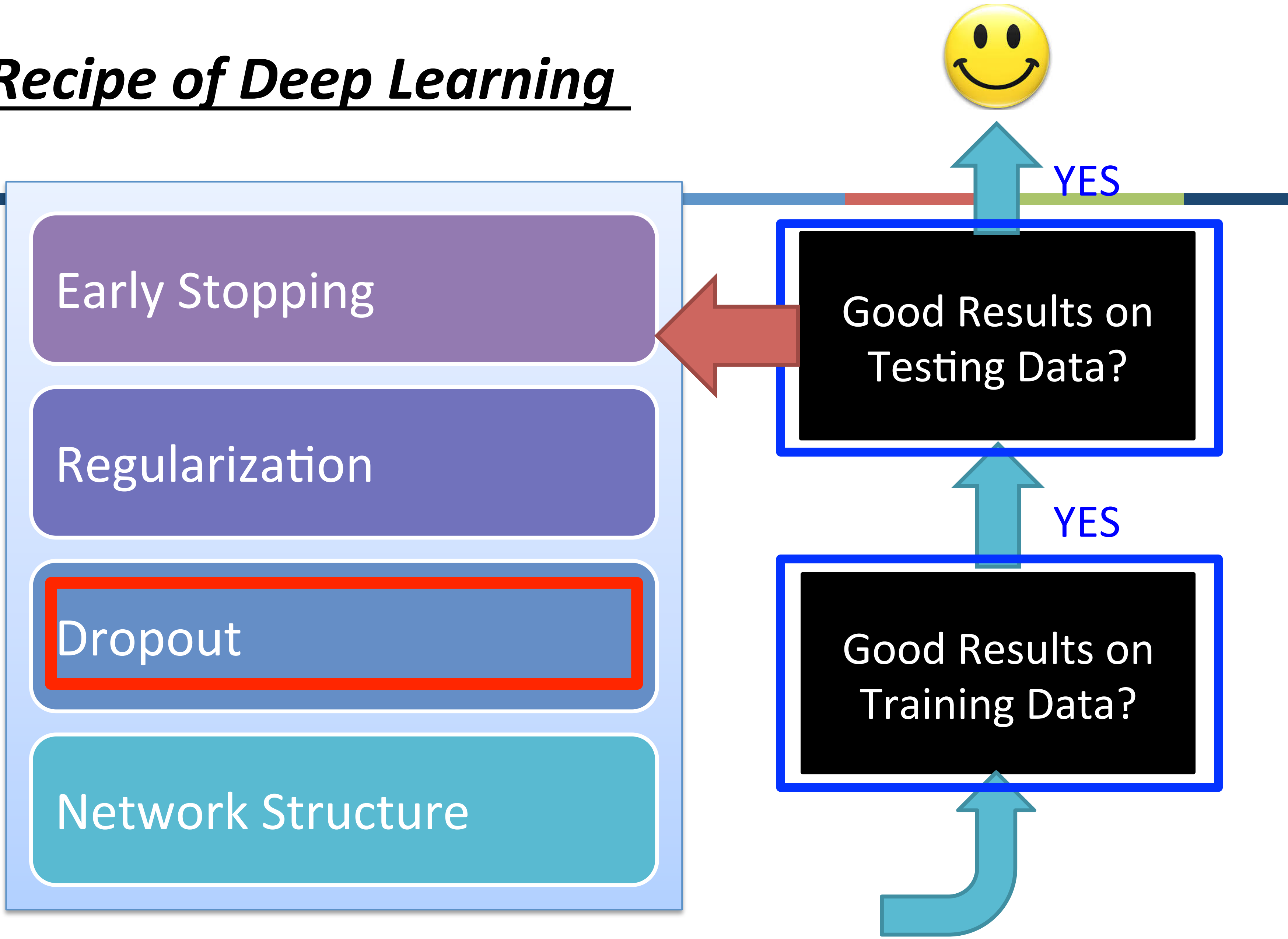


Created
Training Data:



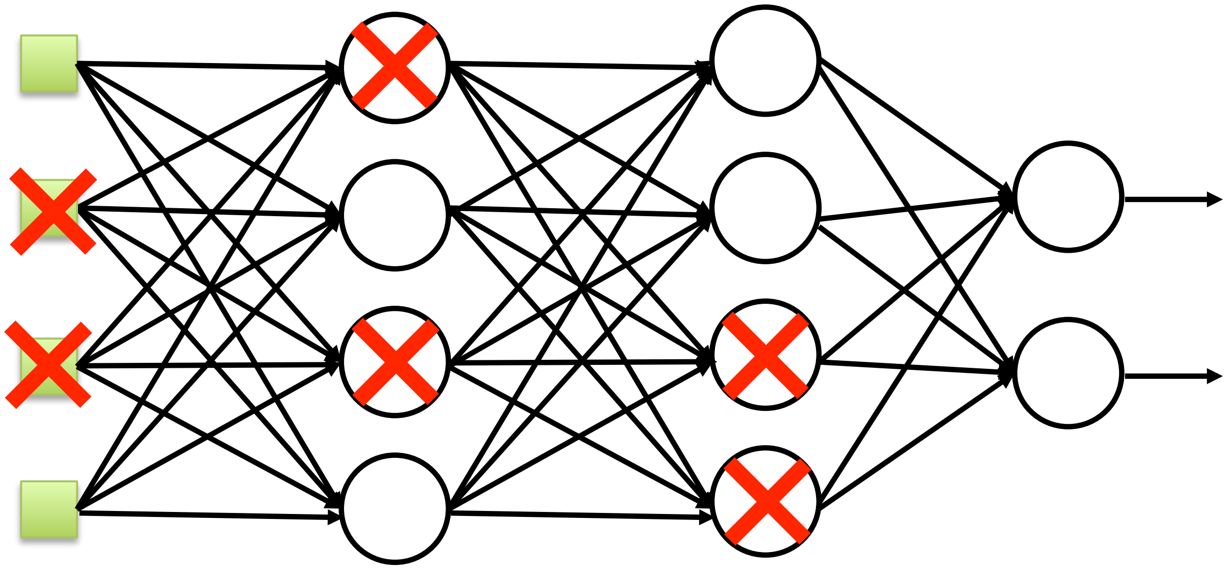
Shift 15 °

Recipe of Deep Learning



Dropout

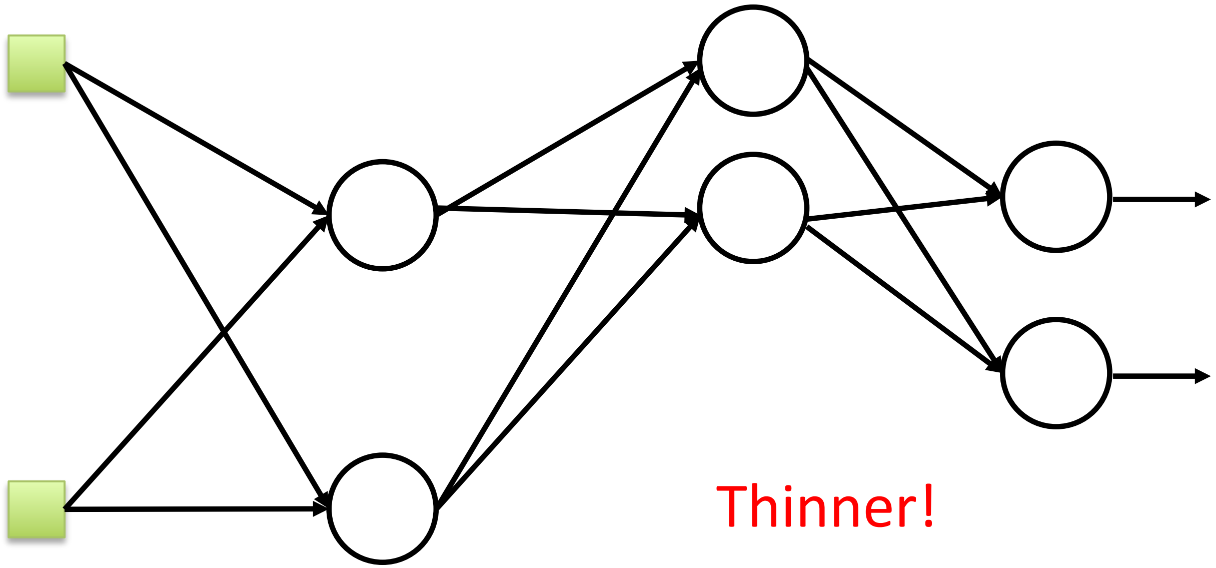
Training:



- **Each time before updating the parameters**
  - Each neuron has a probability of *p* to dropout

Dropout

Training:



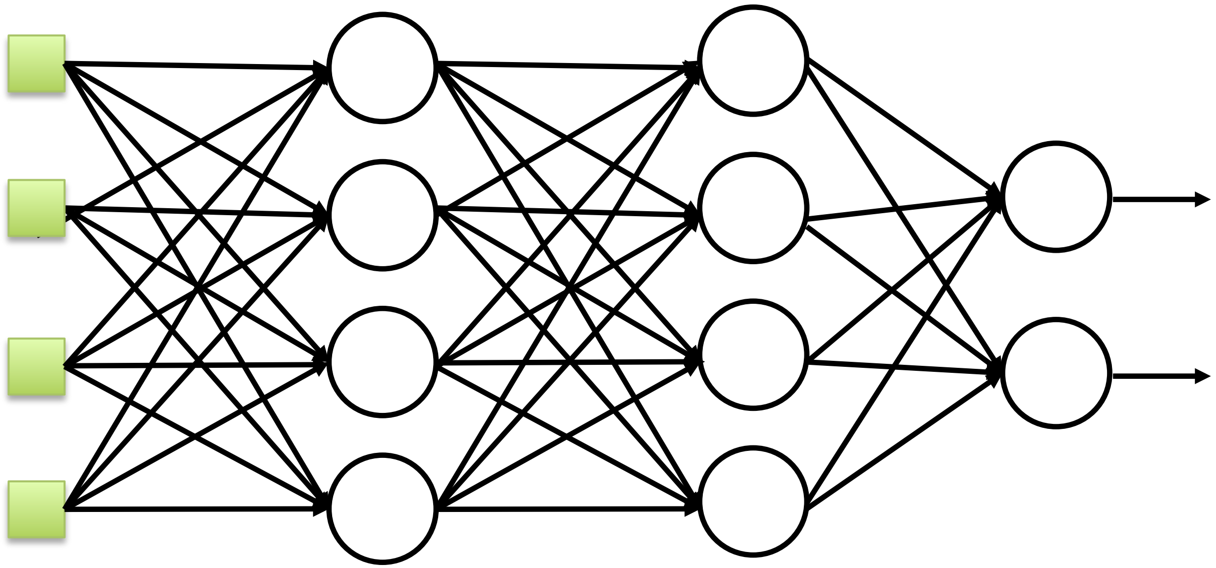
- **Each time before updating the parameters**
  - Each neuron has a probability of p to dropout

    ➡ **The structure of the network is changed.**
  - Using the new network for training

For each mini-batch, we resample the dropout neurons

Dropout

Testing:



➢ **No dropout**

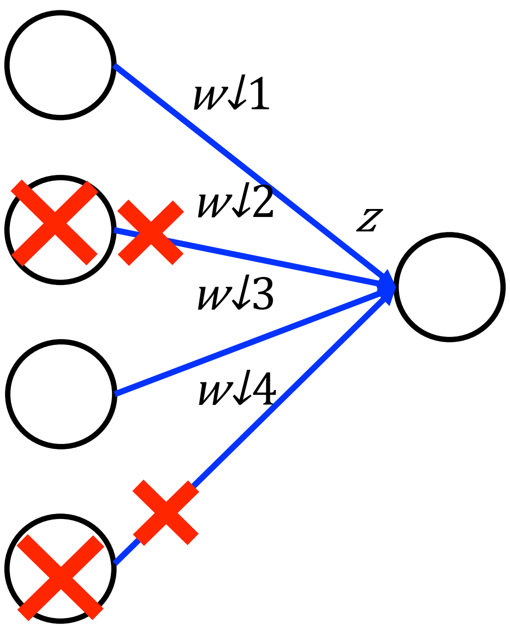
- If the dropout rate at training is p, all the weights times 1-p
- Assume that the dropout rate is 50%.
  If a weight $w=1$ by training, set $w=0.5$ for testing.

Dropout - Intuitive Reason

- Why the weights should multiply (1-p) when testing?

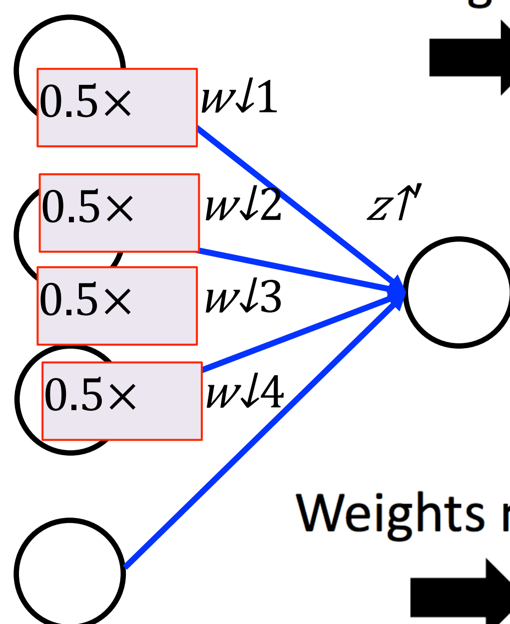
<u>Training of Dropout</u>

Assume dropout rate is 0.5



<u>Testing of Dropout</u>

No dropout



Weights from training

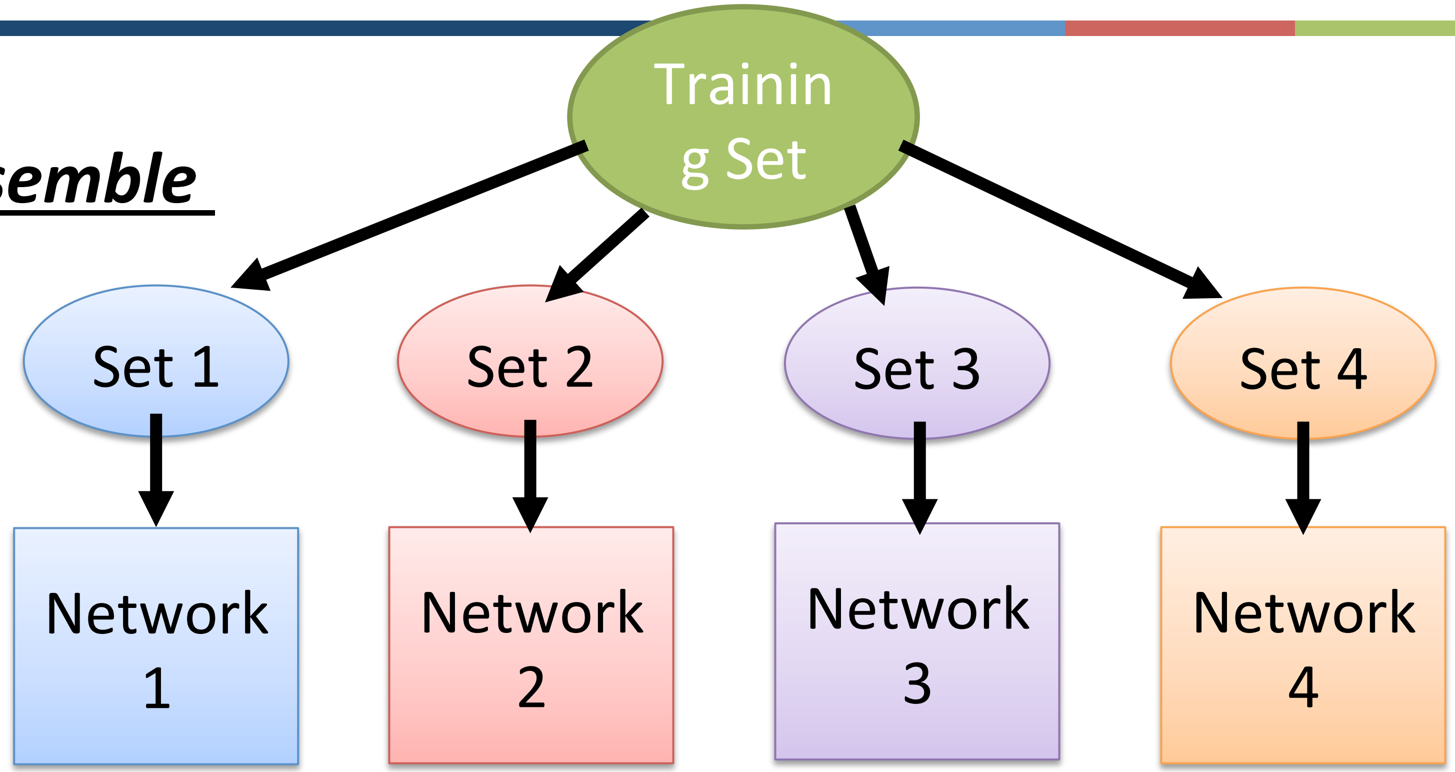
➡ $z' \approx 2z$

Weights multiply (1-p)%

➡ $z' \approx z$

Dropout is a kind of ensemble.

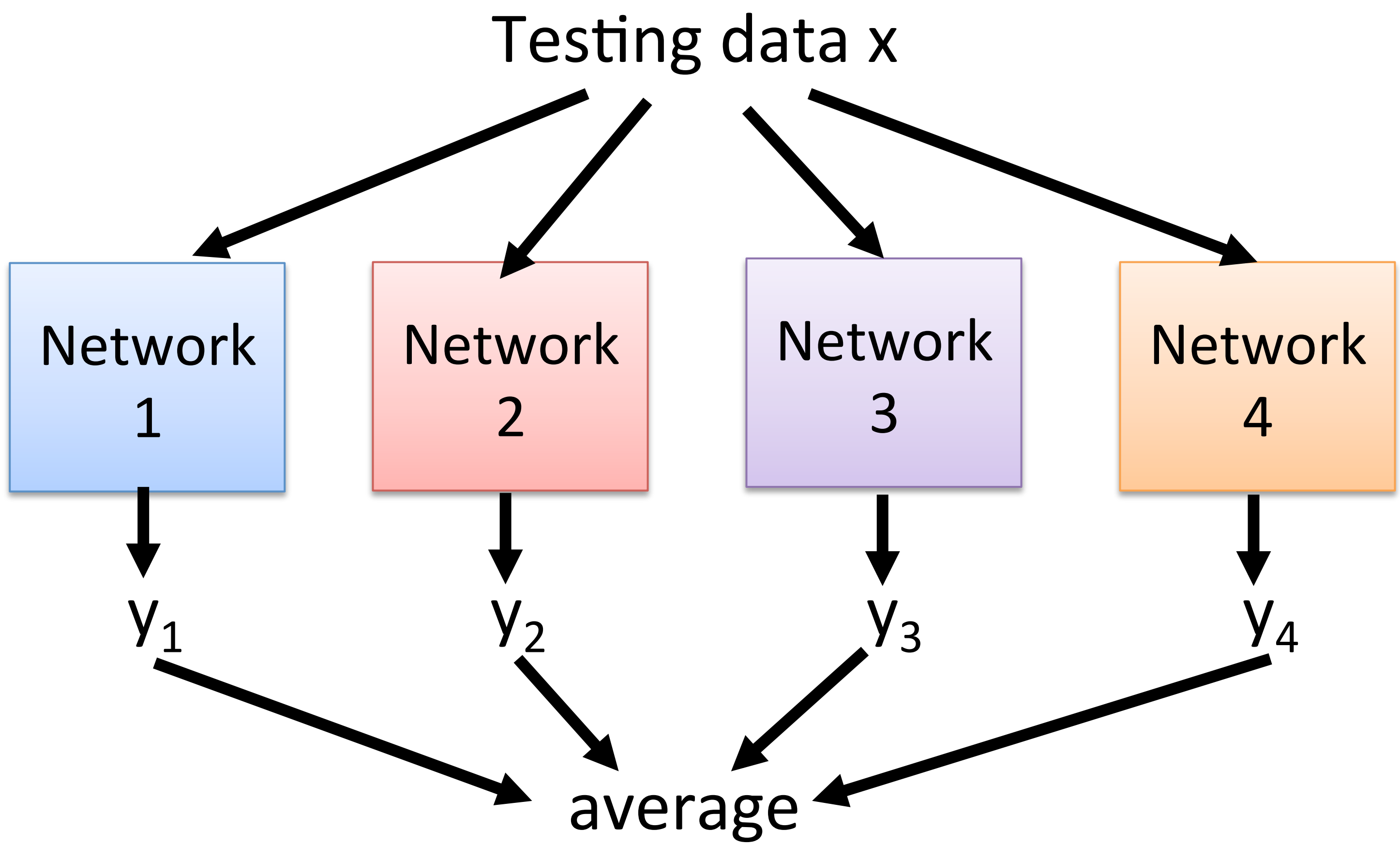
Ensemble



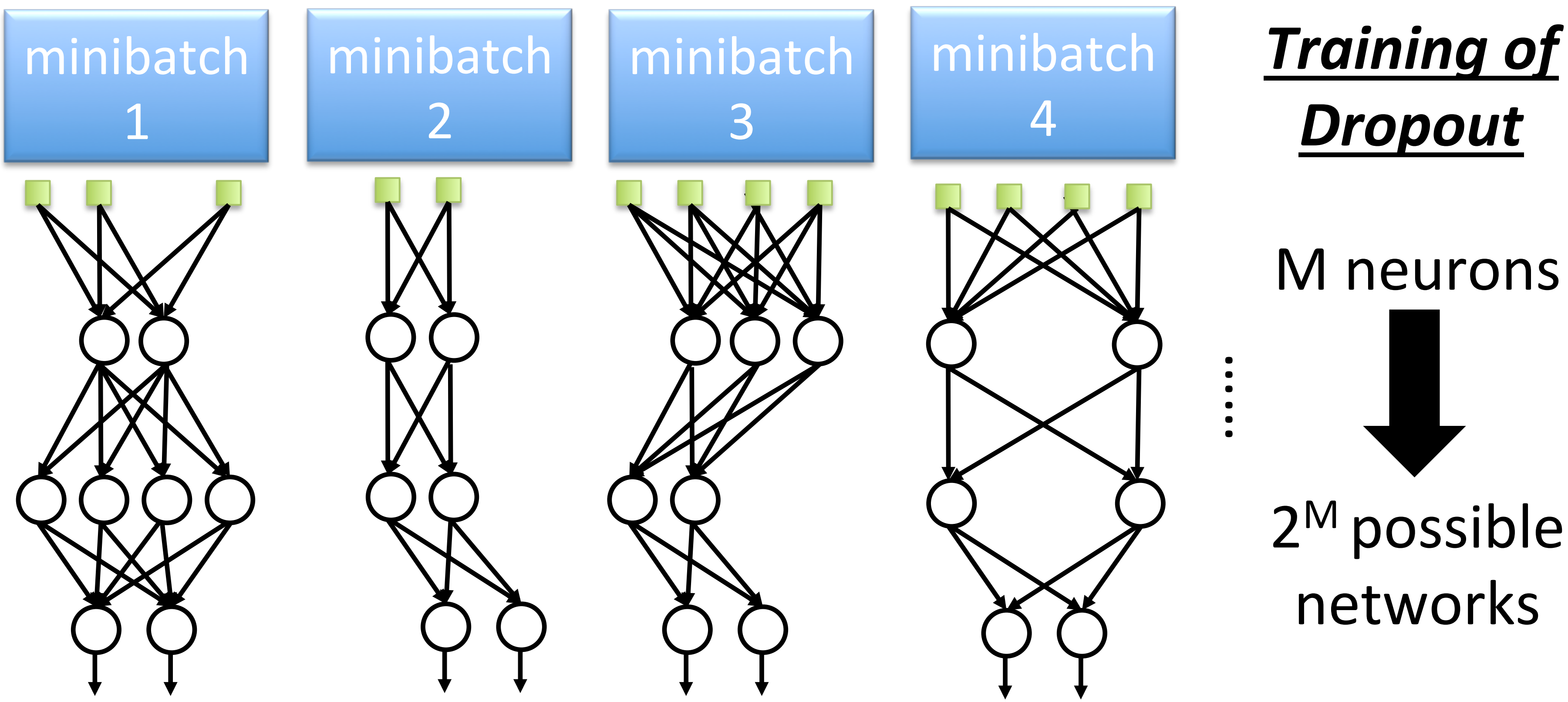
Train a bunch of networks with different structures

Dropout is a kind of ensemble.

Ensemble



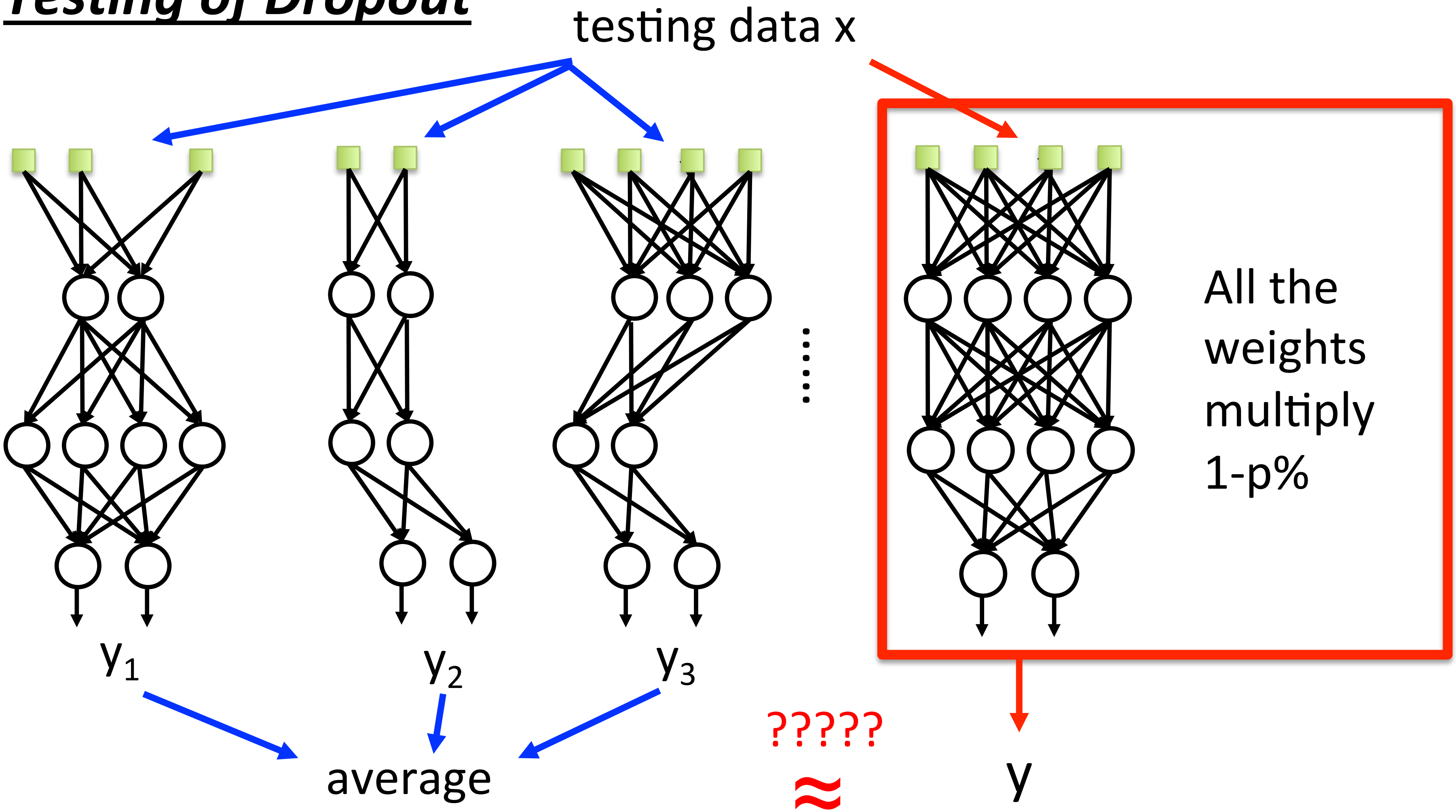
Dropout is a kind of ensemble.



- Using one mini-batch to train one network
- Some parameters in the network are shared

Dropout is a kind of ensemble.

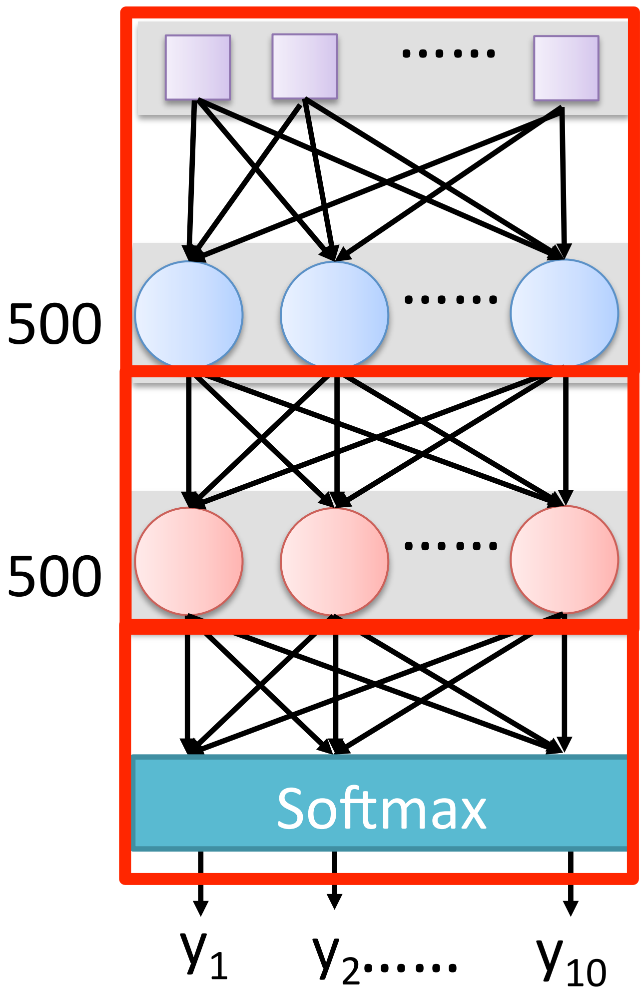
Testing of Dropout



More about dropout

- More reference for dropout [Nitish Srivastava, JMLR'14] [Pierre Baldi, NIPS'13][Geoffrey E. Hinton, arXiv'12]
- Dropout works better with Maxout [Ian J. Goodfellow, ICML'13]
- Dropconnect [Li Wan, *ICML'13*]
  - Dropout delete neurons
  - Dropconnect deletes the connection between neurons
- Annealed dropout [S.J. Rennie, SLT'14]
  - Dropout rate decreases by epochs
- Standout [J. Ba, NISP'13]
  - Each neural has different dropout rate

Demo




```
model = Sequential()
```

```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

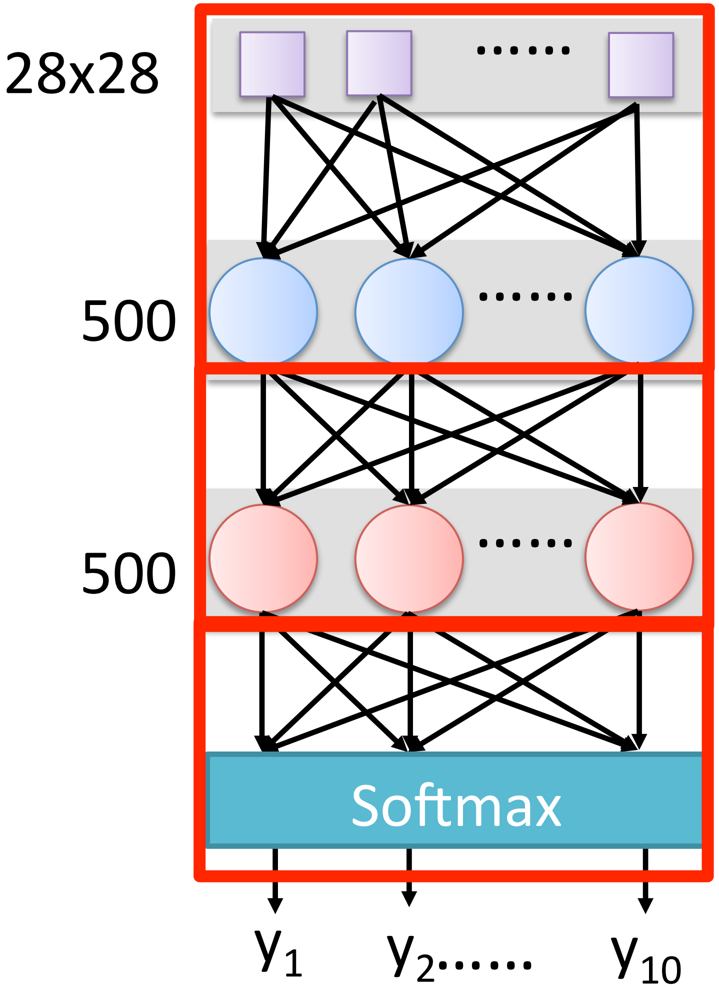
model.add(dropout(0.8))

```
model.add( Dense( output_dim=500 ) )
model.add( Activation('sigmoid') )
```

model.add(dropout(0.7))

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

PyTorch

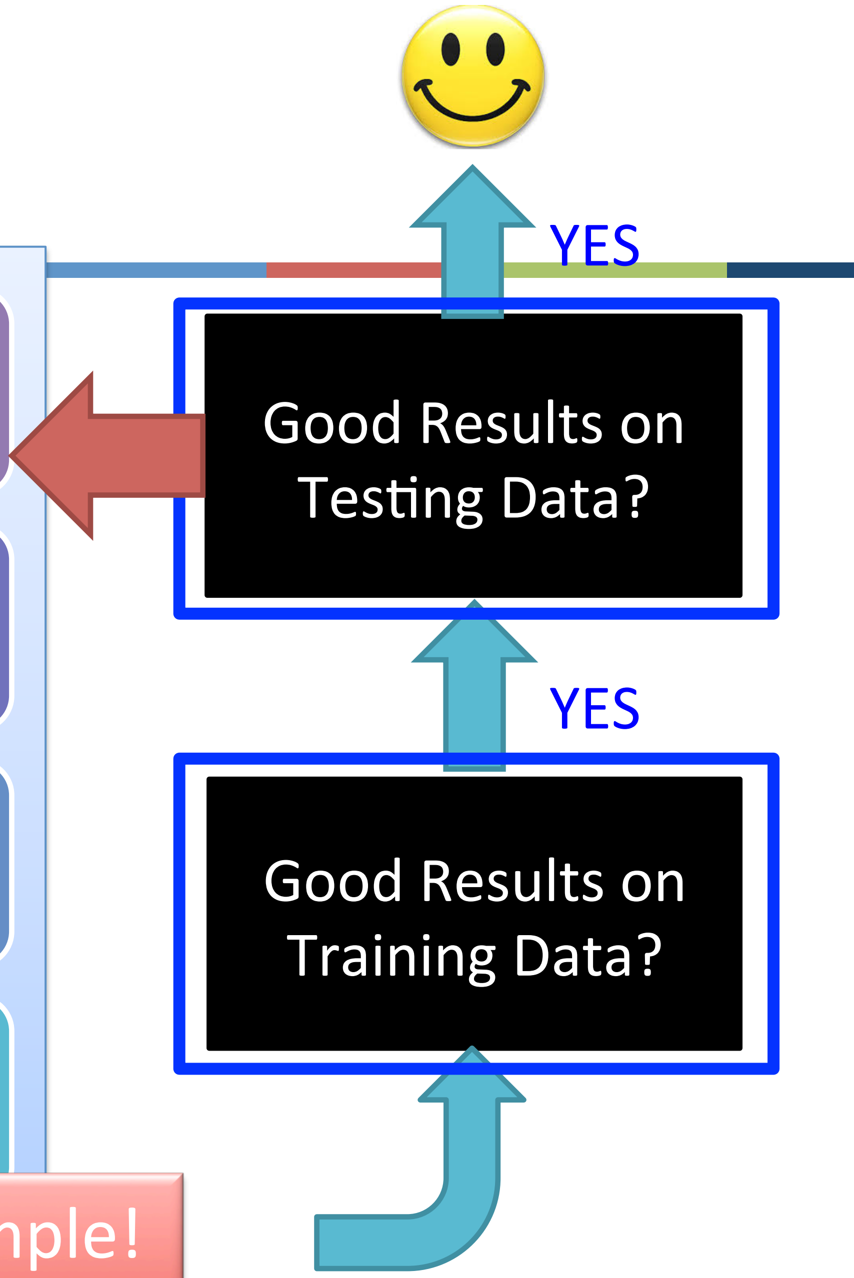



```
import torch.nn as nn
import torch.nn.functional as F

class MyNetwork(nn.Module):
    def __init__(self):
        super(MyNetwork, self).__init__()

        self.fc1 = nn.Linear(28 * 28, 500)
        self.fc2 = nn.Linear(500, 500)
        self.fc3 = nn.Linear(500, 10)
        self.do1 = nn.Dropout(0.8)
        self.do2 = nn.Dropout(0.7)

    def forward(self, x):
        x = F.sigmoid(self.fc1(x))
        x = self.do1(x)
        x = F.sigmoid(self.fc2(x))
        x = self.do2(x)
        return F.log_softmax(self.fc3(x))
```

Recipe of Deep Learning

- Early Stopping
- Regularization
- Dropout
- Network Structure

CNN is a very good example!
(next lecture)



Concluding Remarks

Recipe of Deep Learning