Copyright Notice

Hyperparameter tuning

Tuning process

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Hyperparameters

→ $\boxed{\alpha}$ Learning Rate

$\boxed{\beta}$ ~0.9 Momenta

$\beta_1, \beta_2, \varepsilon$ Adam

0.9 0.999 10^{-8}

$\boxed{\text{\# layers}}$

$\boxed{\text{\# hidden units}}$

$\boxed{\text{learning rate decay}}$

$\boxed{\text{mini-batch size}}$

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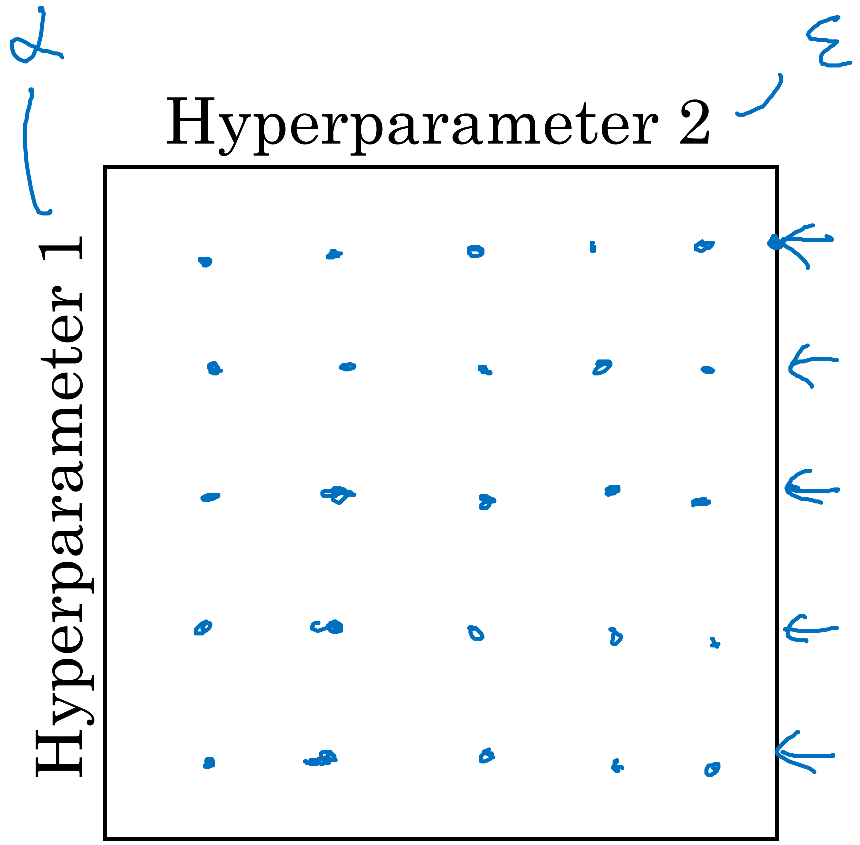
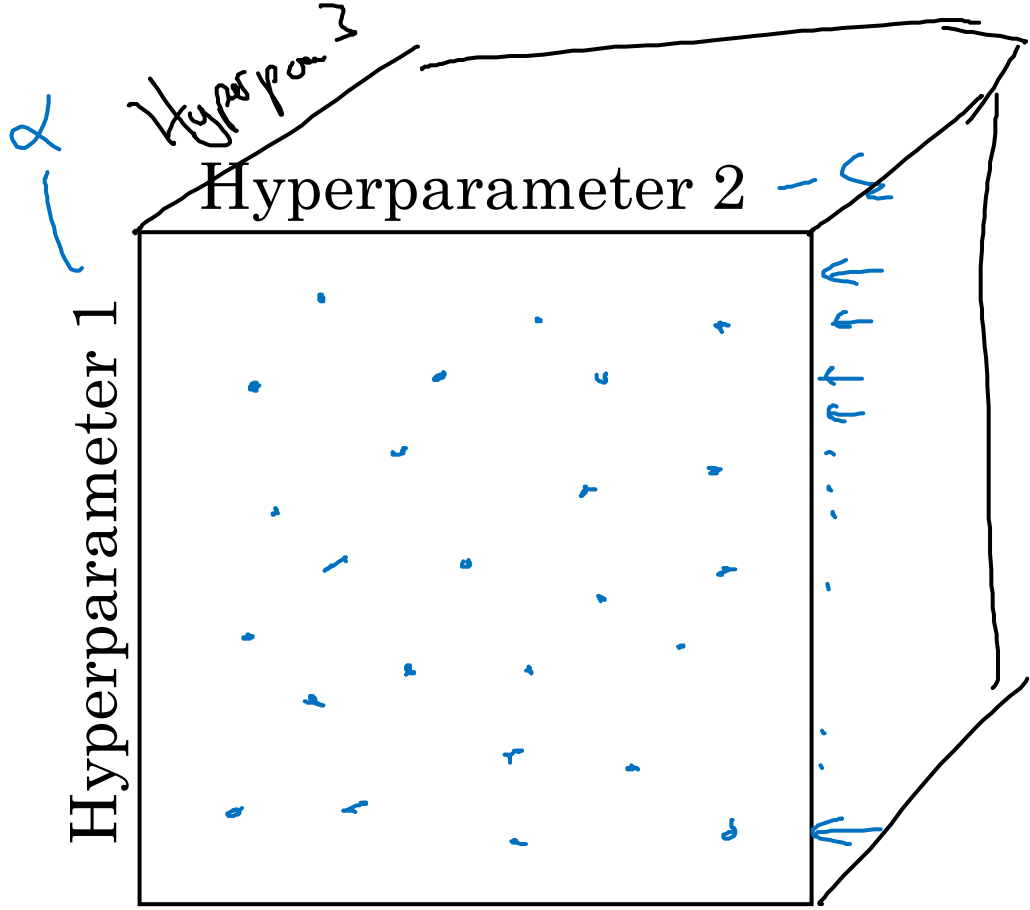
Try random values: Don't use a grid





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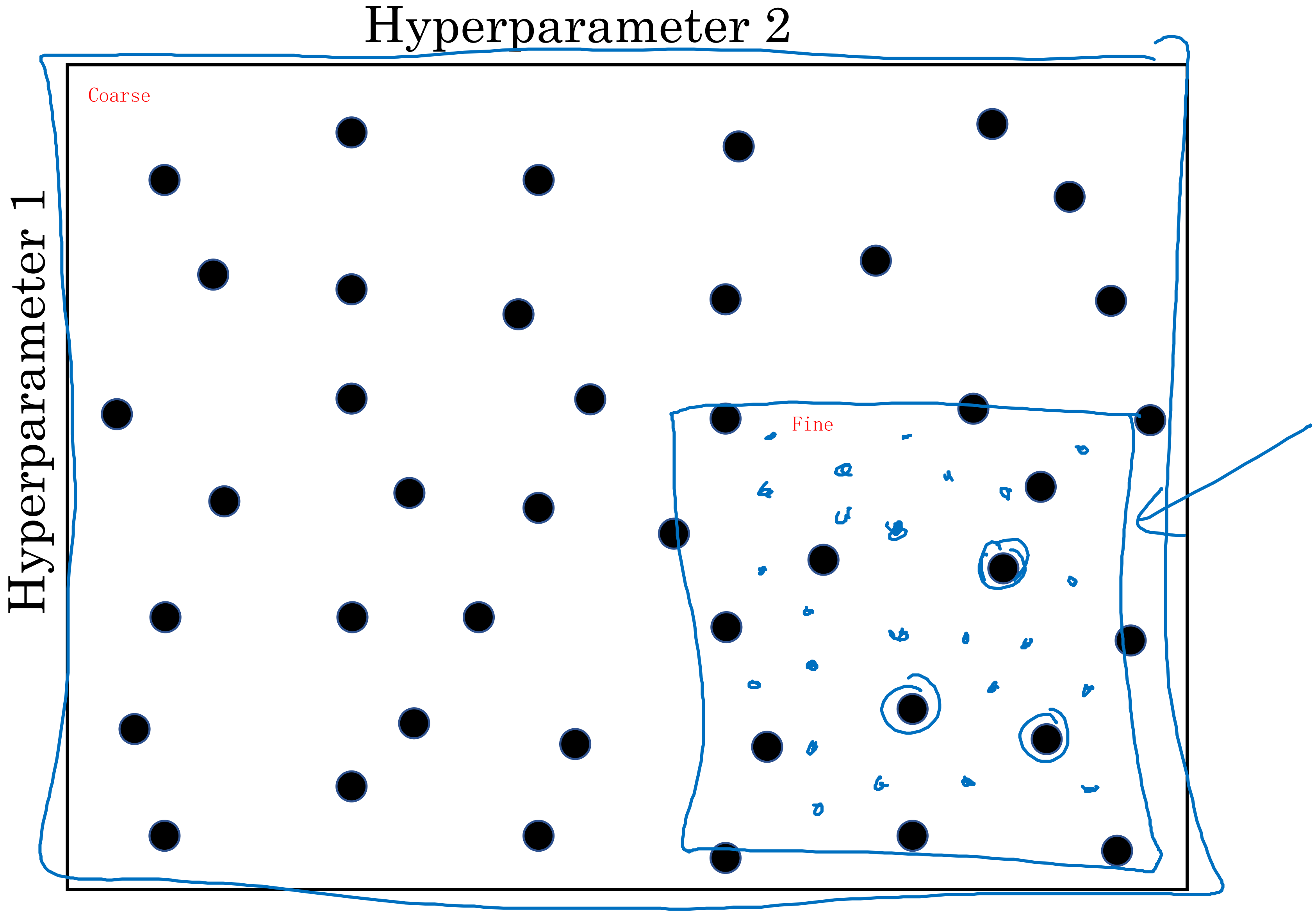
Coarse to fine



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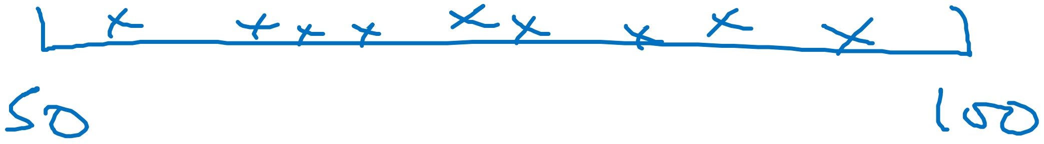
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \dots, 100$



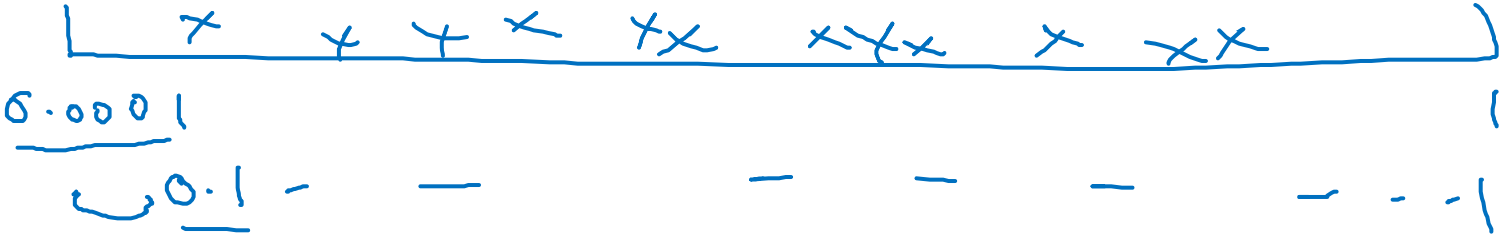
→ #layers $L: 2 - 4$

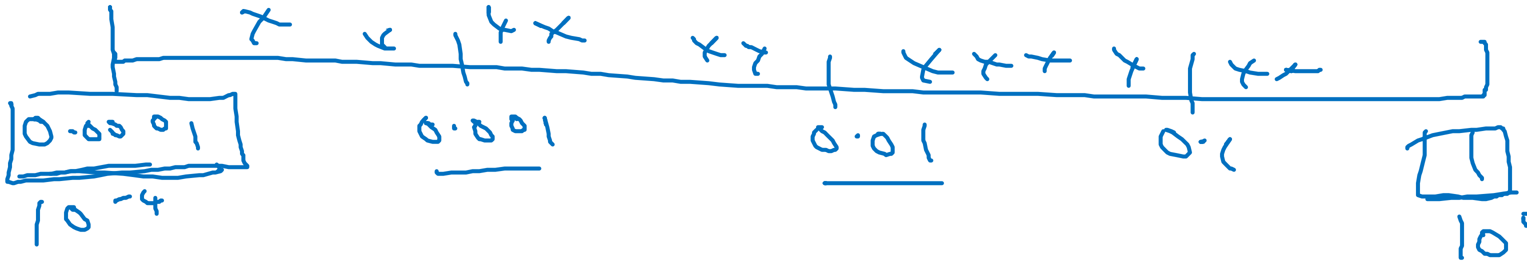
sometimes sampling
uniformly at random
might be reasonable

$2, 3, 4$

Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots\ldots, 1$





10^a $\quad$ 10^b

$a = \log_{10} 0.0001 = -4$ $\quad$ $r = -4 * \text{np.random.rand()}$ $\leftarrow$ $r \in [-4, 0]$ $\quad$ $b = \log_{10} 1 = 0$

$\alpha = 10^r$ $\leftarrow$ $10^{-4} \ldots 10^0$

$10^a \ldots 10^b$ $\qquad$ $r \in [a, b]$ $\quad$ $[-4, 0]$ $\qquad$ $\alpha = 10^r$

Hyperparameters for exponentially weighted averages

$\beta = 0.9 \quad \dots \quad 0.999$

average over last $10 \quad\quad 1000$

$1-\beta = 0.1 \quad \dots \quad 0.001$

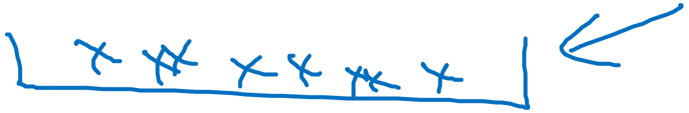
$\beta: 0.9000 \to 0.9005 \; \} \sim 10$

$\beta: 0.999 \to 0.9995$

$\sim 1000 \quad\quad \sim 2000$

become away
more sensitive

$\frac{1}{1-\beta}$



$0.9 \quad\quad 0.999$

$0.9 \quad 0.99 \quad 0.999$

$0.1 \quad 0.01 \quad 0.001$

$10^{-1} \quad\quad 10^{-3}$

$r \in [-3, -1]$

$1-\beta = 10^r$

$\beta = 1-10^r$

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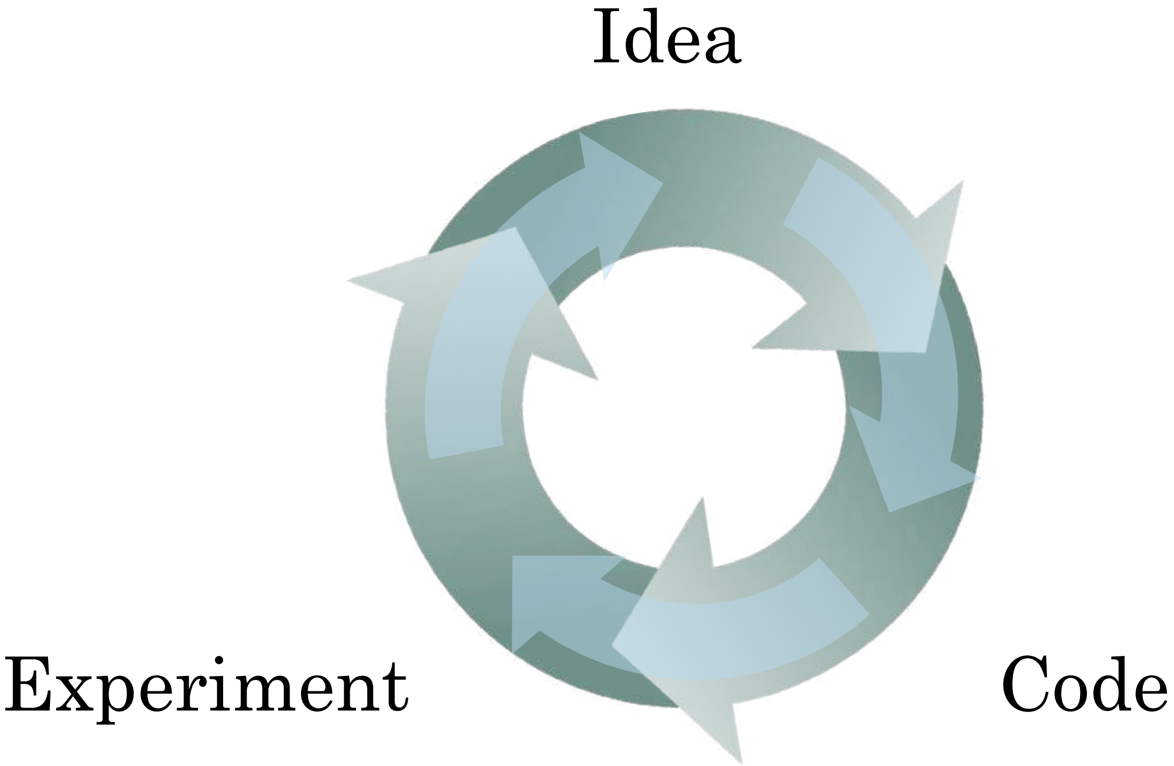
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

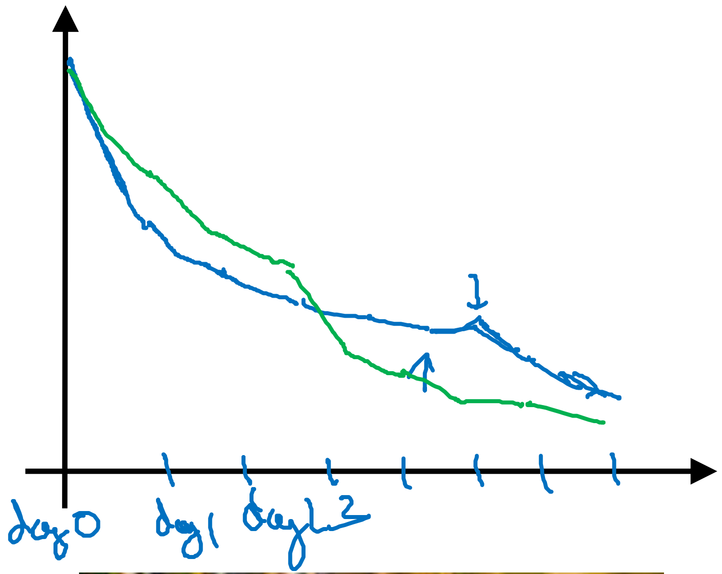
Re-test hyperparameters occasionally



- NLP, Vision, Speech, Ads, logistics, ...

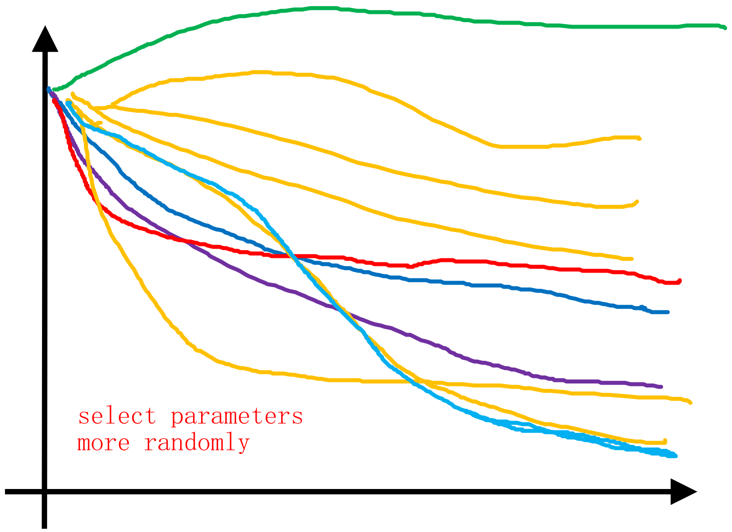
- Intuitions do get stale. Re-evaluate occasionally.

Babysitting one model



Panda

Training many models in parallel



Caviar

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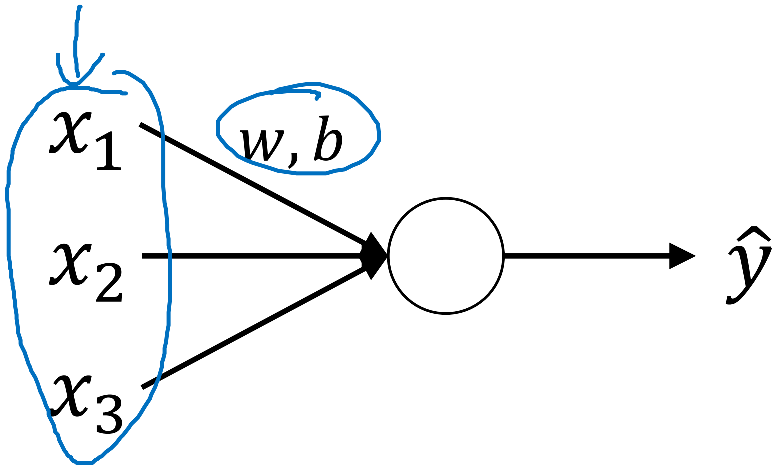
Batch Normalization

Normalizing activations in a network

make hyperparameter search much easier and the NN much more robust

Normalizing inputs to speed up learning

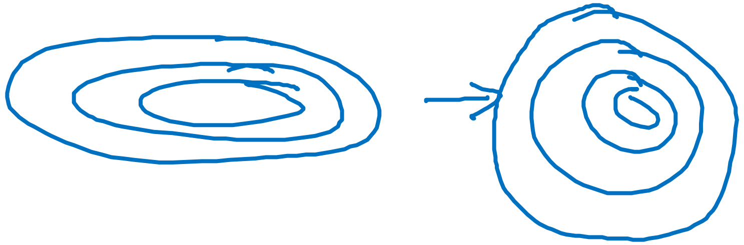


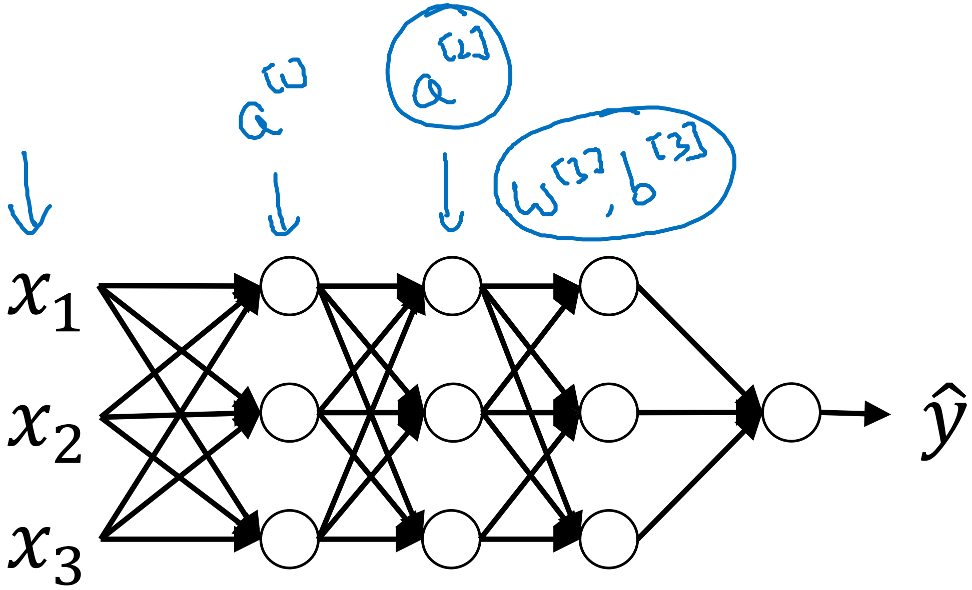
$$\mu = \frac{1}{m} \sum_i x^{(i)}$$

$$X = X - \mu$$

$$\sigma^2 = \frac{1}{m} \sum_i x^{(i)2} \quad \leftarrow \text{element-wise}$$

$$X = X / \sigma$$





Can we normalize $\underline{a^{[2]}}$ so as to train $W^{[3]}, b^{[3]}$ faster

Normalize $\underline{z^{[2]}}$ much more often

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Implementing Batch Norm

Given some intermediate values in NN $\underbrace{z^{(1)}, \ldots, z^{(m)}}_{z^{[l](i)}}$

$$\mu = \frac{1}{m} \sum_i z^{(i)}$$

$$\sigma^2 = \frac{1}{m} \sum_i (z_i - \mu)^2$$

$$z^{(i)}_{norm} = \frac{z^{(i)} - \boxed{\mu}}{\boxed{\sqrt{\sigma^2 + \varepsilon}}}$$

$$\tilde{z}^{(i)} = \gamma z^{(i)}_{norm} + \beta$$

learnable parameters of model.

If

$$\gamma = \boxed{\sqrt{\sigma^2 + \varepsilon}}$$

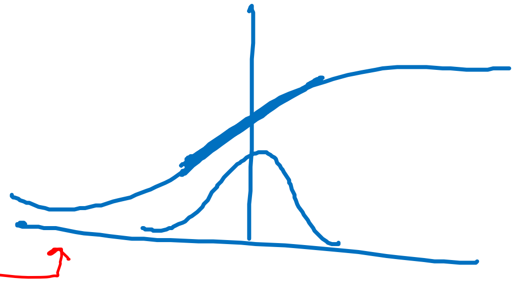
$$\beta = \boxed{\mu}$$

then $\tilde{z}^{(i)} = z^{(i)}$

X

$z^{(i)}$

not necessarily mean 0, variance 1
avoid to become linear function
like this



Use $\tilde{z}^{[l](i)}$ instead of $z^{[l](i)}$.

apply normalization
not only in the
input layer but also
in hidden layers

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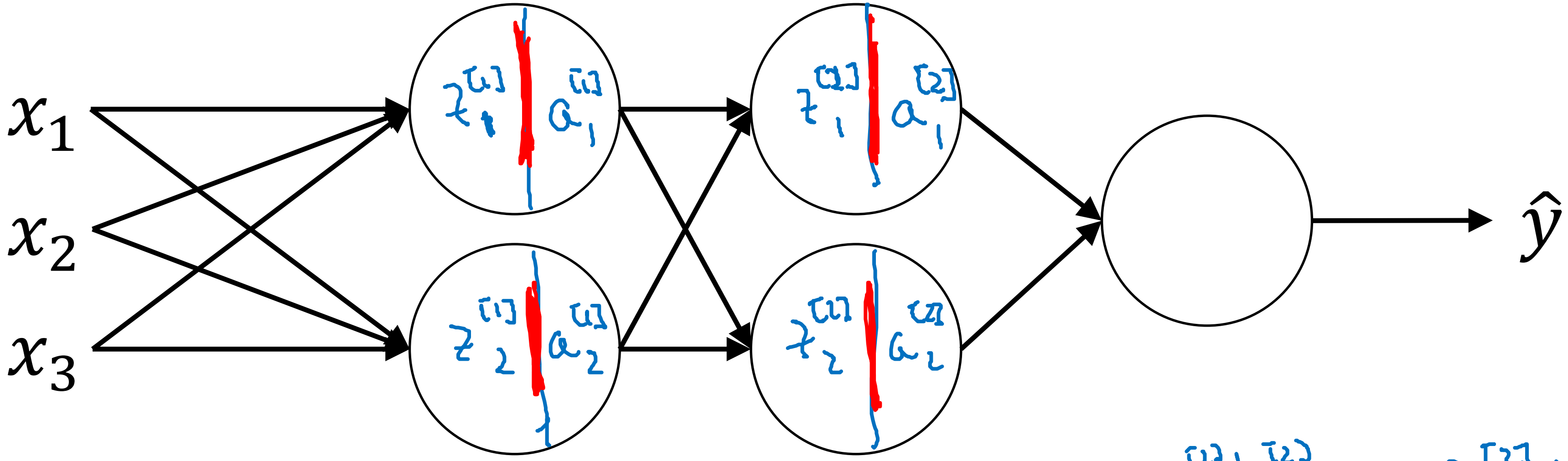
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network



$$X \xrightarrow{W^{[1]},\, b^{[1]}} z^{[1]} \xrightarrow[\text{Batch Norm (BN)}]{\beta^{[1]},\, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow a^{[1]} = g^{[1]}(\tilde{z}^{[1]}) \xrightarrow{W^{[2]},\, b^{[2]}} z^{[2]} \xrightarrow[\text{BN}]{\beta^{[2]},\, \gamma^{[2]}} \tilde{z}^{[2]} \rightarrow a^{[2]} \rightarrow \cdots$$

Parameters: $\left.\begin{array}{l} W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, \ldots, W^{[L]}, b^{[L]}, \\ \rightarrow \beta^{[1]}, \gamma^{[1]}, \beta^{[2]}, \gamma^{[2]}, \ldots, \beta^{[L]}, \gamma^{[L]} \end{array}\right]$

$d\beta^{[l]}$ $\qquad \beta^{[l]} = \beta^{[l]} - \alpha\, d\beta^{[l]}$

tf.nn.batch_normalization $\Leftarrow$

$\rightarrow \beta$ not the beta in Adam

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Working with mini-batches

$$X^{\{1\}} \xrightarrow{W^{[1]},\, b^{[1]}} z^{[1]} \xrightarrow[BN]{\beta^{[1]},\, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow g^{[1]}(\tilde{z}^{[1]}) = a^{[1]} \xrightarrow{W^{[2]},\, b^{[2]}} z^{[2]} \rightarrow \cdots$$

$$X^{\{2\}} \longrightarrow z^{[1]} \xrightarrow[BN]{\beta^{[1]},\, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow \cdots$$

$$X^{\{3\}} \longrightarrow \cdots$$

Parameters: $W^{[l]}$, $\cancel{b^{[l]}}$, $\beta^{[l]}$, $\gamma^{[l]}$.

$b^{[l]}$: $(n^{[l]}, 1)$ $\beta^{[l]}$: $(n^{[l]}, 1)$ $\gamma^{[l]}$: $(n^{[l]}, 1)$

$z^{[l]}$: $(n^{[l]}, 1)$

$$z^{[l]} = W^{[l]} a^{[l-1]} + \boxed{\cancel{b^{[l]}}}$$

canceled out by mean subtraction

$$z^{[l]} = W^{[l]} a^{[l-1]}$$

$$z^{[l]}_{norm}$$

$$\tilde{z}^{[l]} = \gamma^{[l]} z^{[l]}_{norm} + \boxed{\beta^{[l]}}$$

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Implementing gradient descent

for $t = 1 \ldots$ numMiniBatches

Compute forward prop on $X^{\{t\}}$.

In each hidden layer, use BN to replace $\underline{z^{[l]}}$ with $\underline{\tilde{z}^{[l]}}$.

Use backprop to compute $\underline{dW^{[l]}}$, $\cancel{db^{[l]}}$, $\underline{d\beta^{[l]}}$, $\underline{d\gamma^{[l]}}$

Update params

$$\left.\begin{aligned} W^{[l]} &:= W^{[l]} - \alpha \, dW^{[l]} \\ \beta^{[l]} &:= \beta^{[l]} - \alpha \, d\beta^{[l]} \\ \gamma^{[l]} &:= \ldots \end{aligned}\right\} \leftarrow$$

Works w/ momentum, RMSprop, Adam.

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Batch Normalization

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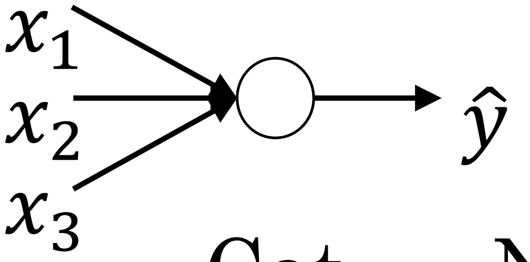
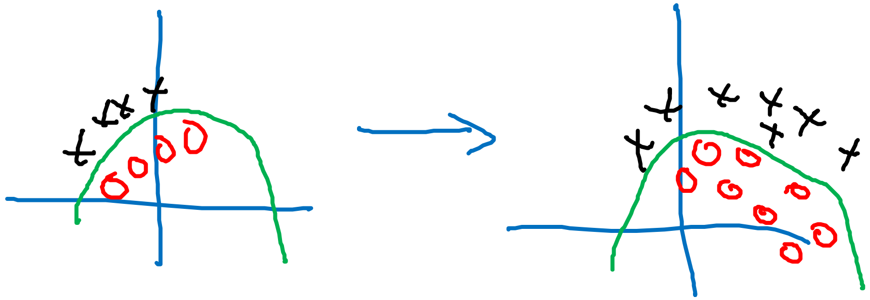
Why does Batch Norm work?

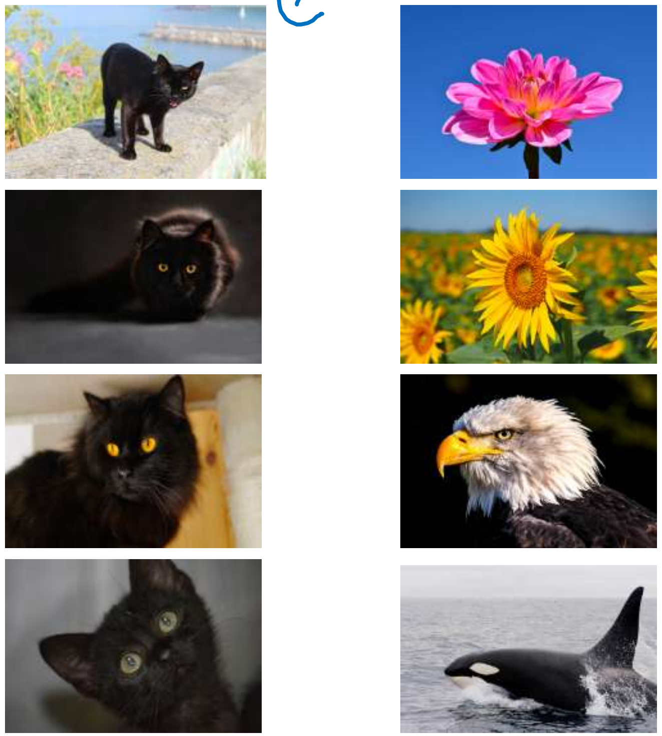
1. take a similar range of values that can speed up learning
2. other reasons are in the slides below

Learning on shifting input distribution





Cat	Non-Cat
$y = 1$	$y = 0$



$y = 1$	$y = 0$

"Covariate shift"

if the distribution of x changes, then we need to retrain the model

$X \to y$

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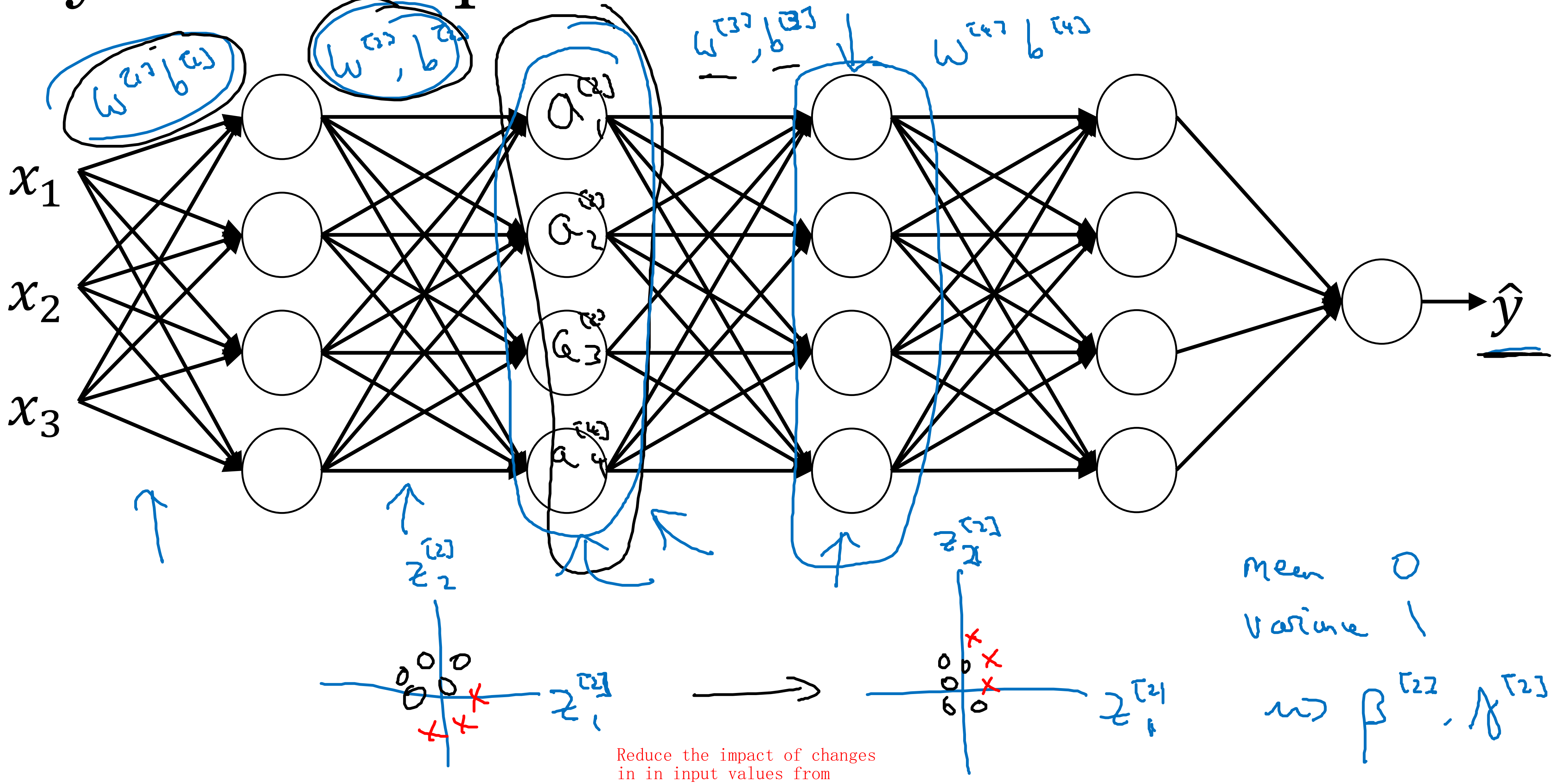
Why this is a problem with neural networks?



Reduce the impact of changes in in input values from previous layer, make them more stable, make the parameters of each layer more independent

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Batch Norm as regularization

- Each mini-batch is scaled by the mean/variance computed on just that mini-batch.
- This adds some noise to the values $z^{[l]}$ within that minibatch. So similar to dropout, it adds some noise to each hidden layer's activations.
- This has a slight regularization effect.

X

$X^{\{t\}}$

$\tilde{z}^{[l]}$

64, 128

$z^{[l]}$

μ, σ^2

mini-batch : 64 ⟶ 512

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Batch Norm at test time

might not have the whole minbatch to compute these

$$\mu = \frac{1}{m}\sum_i z^{(i)}$$

$$\sigma^2 = \frac{1}{m}\sum_i (z^{(i)}-\mu)^2$$

$$z_{\text{norm}}^{(i)} = \frac{z^{(i)}-\mu}{\sqrt{\sigma^2+\varepsilon}}$$

$$\tilde{z}^{(i)} = \gamma z_{\text{norm}}^{(i)} + \beta$$

μ, σ^2: estimate using exponentially weighted average (across mini-batches).

$X^{\{1\}}, X^{\{2\}}, X^{\{3\}}, \ldots$

$\mu^{\{1\}[l]}$, $\mu^{\{2\}[l]}$, $\mu^{\{3\}[l]}$ $\longrightarrow \mu$

θ_1, θ_2, θ_3 $\quad \sigma^2$

$\sigma^{2\{1\}[l]}$, $\sigma^{2\{2\}[l]}$, ...

$$z_{\text{norm}} = \frac{z-\mu}{\sqrt{\sigma^2+\varepsilon}} \qquad \tilde{z} = \gamma z_{\text{norm}} + \beta$$

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Multi-class classification

Softmax regression

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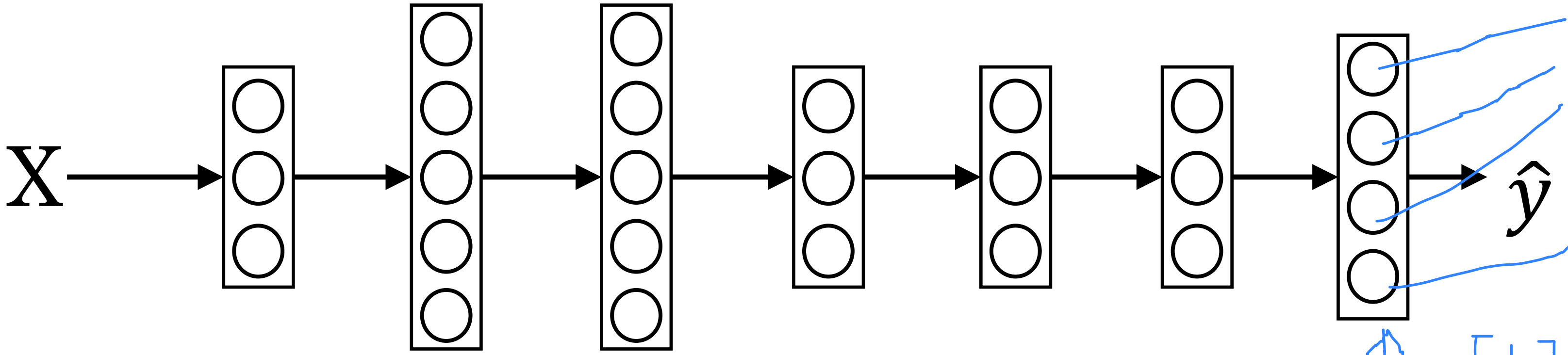
Recognizing cats, dogs, and baby chicks

3 1 2 0 3 2 0 1

$C = \#\text{classes} = 4 \quad (0, \ldots, 3)$



P(class|x)

$n^{[L]} = 4 = C$

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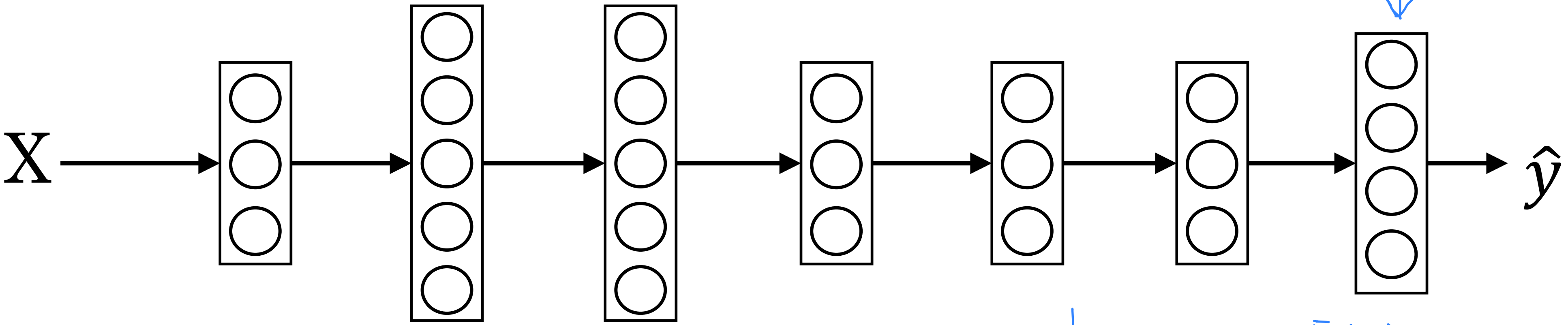
Softmax layer

$a^{[L]}$



$$z^{[L]} = W^{[L]} a^{[L-1]} + b^{[L]}$$

(4, 1)

(Softmax)

Activation Function:

→ $t = e^{(z^{[L]})}$ (4, 1)

→ $a^{[L]} = \dfrac{e^{z^{[L]}}}{\sum_{j=1}^{4} t_i}$, $a_i^{[L]} = \dfrac{t_i}{\sum_{j=1}^{4} t_i}$

(4, 1)

instead of (2,1)

$$z^{[L]} = \begin{bmatrix} 5 \\ 2 \\ -1 \\ 3 \end{bmatrix}$$

$$t = \begin{bmatrix} e^5 \\ e^2 \\ e^{-1} \\ e^3 \end{bmatrix} = \begin{bmatrix} 148.4 \\ 7.4 \\ 0.4 \\ 20.1 \end{bmatrix}$$

$$\sum_{j=1}^{4} t_j = 176.3$$

$$a^{[L]} = t / 176.3$$

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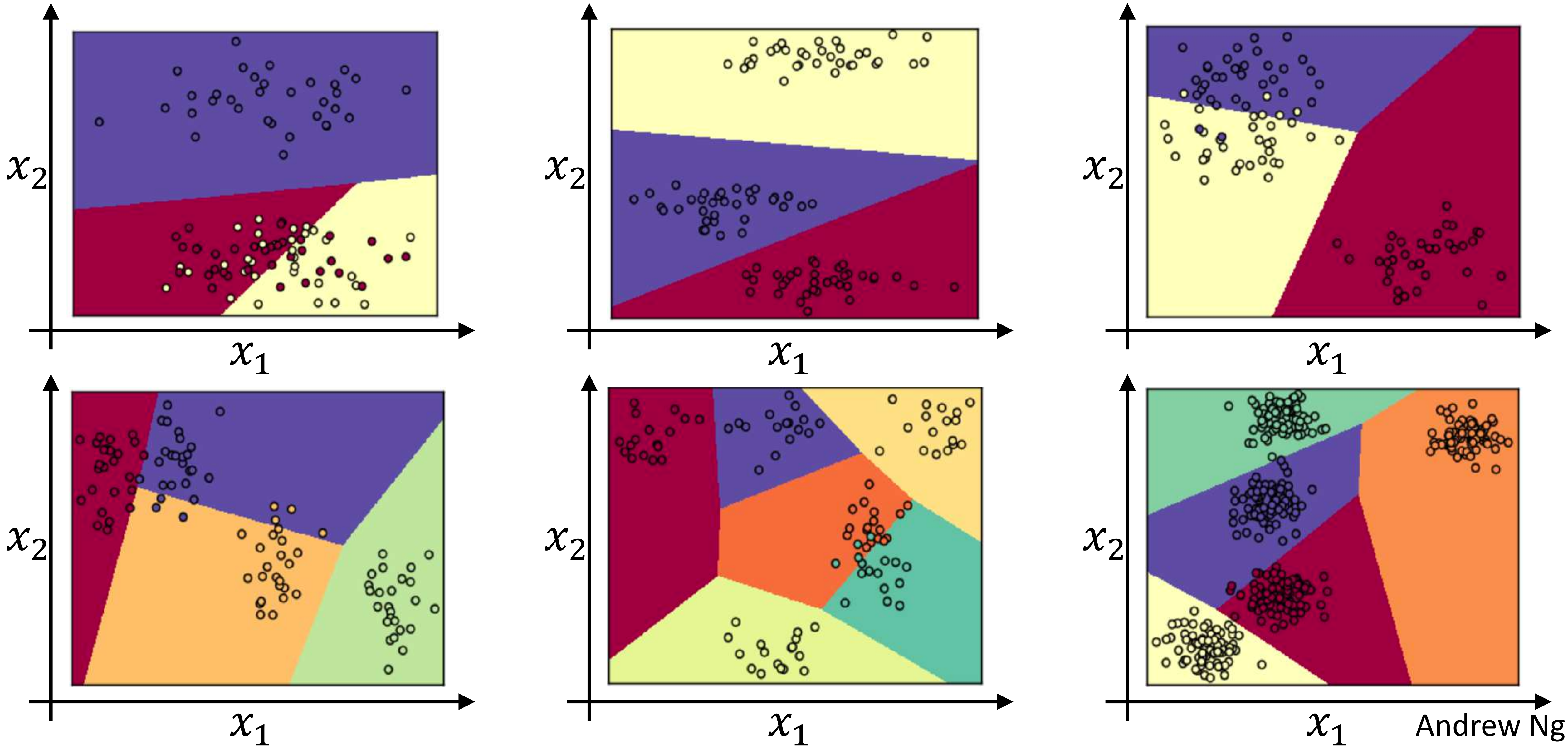
Softmax examples

$x_1 \rightarrow \boxed{\begin{matrix}\circ\\\circ\\\circ\end{matrix}} \rightarrow \hat{y}$, $x_2 \rightarrow$

$z^{[L]} = w^{[L]}x + b^{[L]}$
$a^{[L]} = \hat{y} = g(z^{[L]})$



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Understanding softmax

(4,1)

$$z^{[L]} = \begin{bmatrix} 5 \\ 2 \\ -1 \\ 3 \end{bmatrix} \qquad t = \begin{bmatrix} e^5 \\ e^2 \\ e^{-1} \\ e^3 \end{bmatrix}$$

$C = 4$ $\qquad g^{[L]}(\cdot)$

"soft max"

$$a^{[L]} = g^{[L]}(z^{[L]}) = \begin{bmatrix} e^5/(e^5+e^2+e^{-1}+e^3) \\ e^2/(e^5+e^2+e^{-1}+e^3) \\ e^{-1}/(e^5+e^2+e^{-1}+e^3) \\ e^3/(e^5+e^2+e^{-1}+e^3) \end{bmatrix} = \begin{bmatrix} 0.842 \\ 0.042 \\ 0.002 \\ 0.114 \end{bmatrix}$$

"hard max"

$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Softmax regression generalizes logistic regression to C classes.

If $\underline{C=2}$, softmax reduces to logistic regression. $a^{[L]} = \begin{bmatrix} 0.842 \\ \cancel{0.158} \end{bmatrix}$

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Loss function

$(4,1)$

$y^{(i)} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$ – cat

$y_2 = 1$

$y_1 = y_3 = y_4 = 0$

$(4,1)$

$a^{[L](i)} = \hat{y}^{(i)} = \begin{bmatrix} 0.3 \\ 0.2 \\ 0.1 \\ 0.4 \end{bmatrix}$

$C = 4$

$$\underbrace{\mathcal{L}(\hat{y}, y)}_{\text{small}} = \underbrace{-\sum_{j=1}^{4} y_j \log \hat{y}_j}$$

$$J(w^{[1]}, b^{[1]}, \dots) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

$$-y_2 \log \hat{y}_2 = -\log \hat{y}_2.$$

Make $\hat{y}_2$ big.

$$Y = [y^{(1)}\ y^{(2)} \dots, y^{(m)}]$$

$$= \begin{bmatrix} 0 & 0 & 1 & \dots \\ 1 & 0 & 0 & \\ 0 & 1 & 0 & \\ 0 & 0 & 0 & \end{bmatrix}$$

$(4, m)$

$$\hat{Y} = [\hat{y}^{(1)}, \dots, \hat{y}^{(m)}]$$

$$= \begin{bmatrix} 0.3 & \dots \\ 0.2 & \\ 0.1 & \\ 0.4 & \end{bmatrix}$$

$(4, m)$

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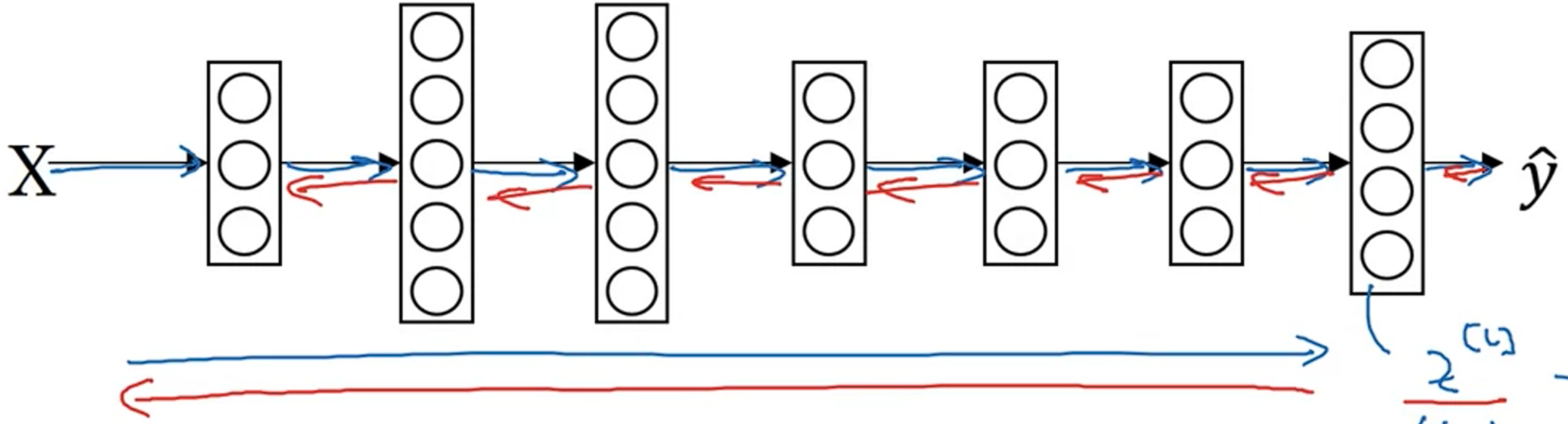
Gradient descent with softmax



$$\underset{(4,1)}{z^{[L]}} \rightarrow a^{[L]} = \hat{y} \rightarrow \mathcal{L}(\hat{y}, y)$$

Backprop: $\underset{(4,1)}{dz^{[L]}} = \hat{y} - y$

$$\frac{\partial J}{\partial z^{[L]}}$$

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Programming Frameworks

Deep Learning frameworks

Deep learning frameworks

- Caffe/Caffe2
- CNTK
- DL4J
- Keras
- Lasagne
- mxnet
- PaddlePaddle
- TensorFlow
- Theano
- Torch

Choosing deep learning frameworks

- Ease of programming (development and deployment)
- Running speed
- Truly open (open source with good governance)

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Programming Frameworks

TensorFlow

Motivating problem

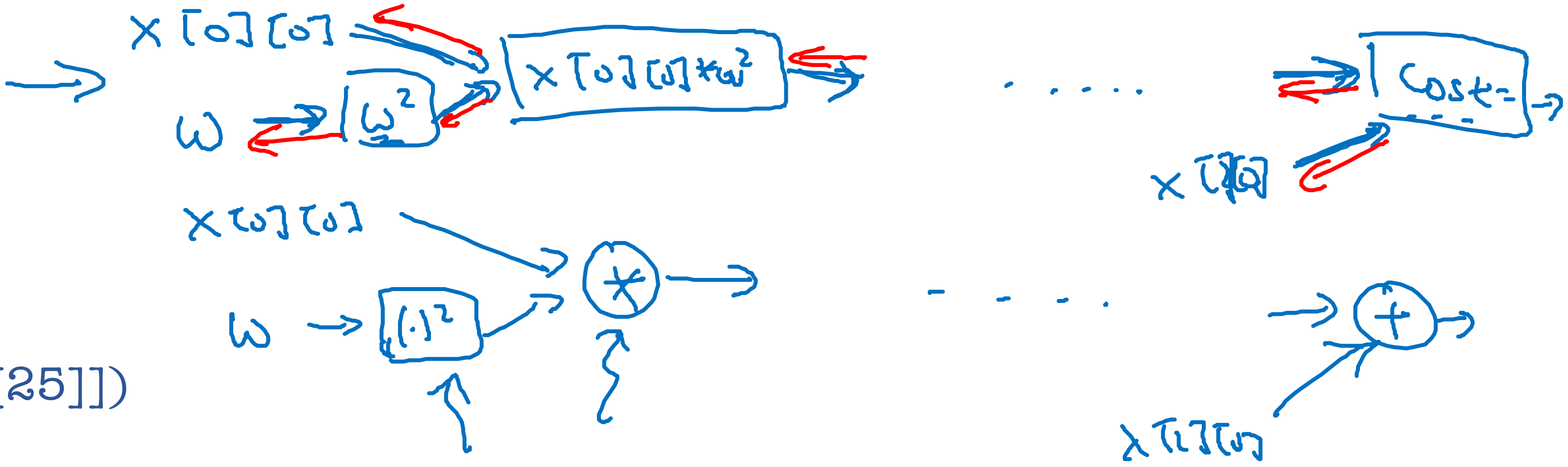
$J(w) = \boxed{w^2 - 10w + 25}$
(cost)

$(w-5)^2$

$w = 5$

$J(w, b)$

Code example




```
import numpy as np
import tensorflow as tf

coefficients = np.array([[1], [-20], [25]])

w = tf.Variable([0],dtype=tf.float32)
x = tf.placeholder(tf.float32, [3,1])
cost = x[0][0]*w**2 + x[1][0]*w + x[2][0]    # (w-5)**2
train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
init = tf.global_variables_initializer()
session = tf.Session()
session.run(init)
print(session.run(w))

for i in range(1000):
    session.run(train, feed_dict={x:coefficients})
print(session.run(w))
```

```
with tf.Session() as session:
    session.run(init)
    print(session.run(w))
```

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