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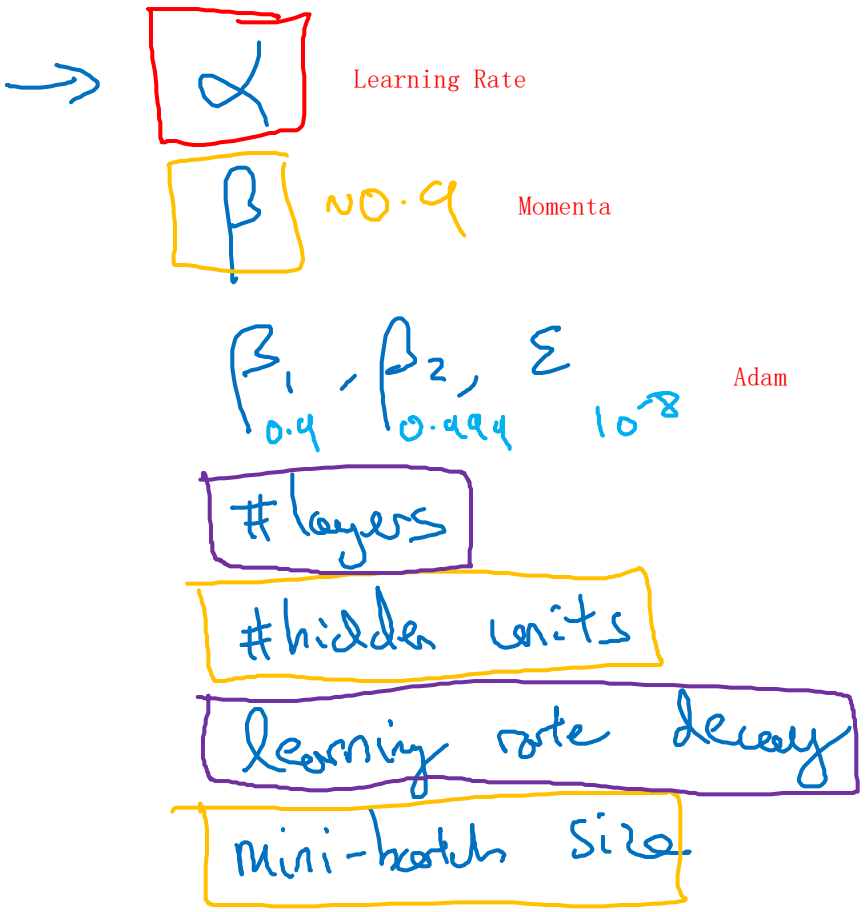
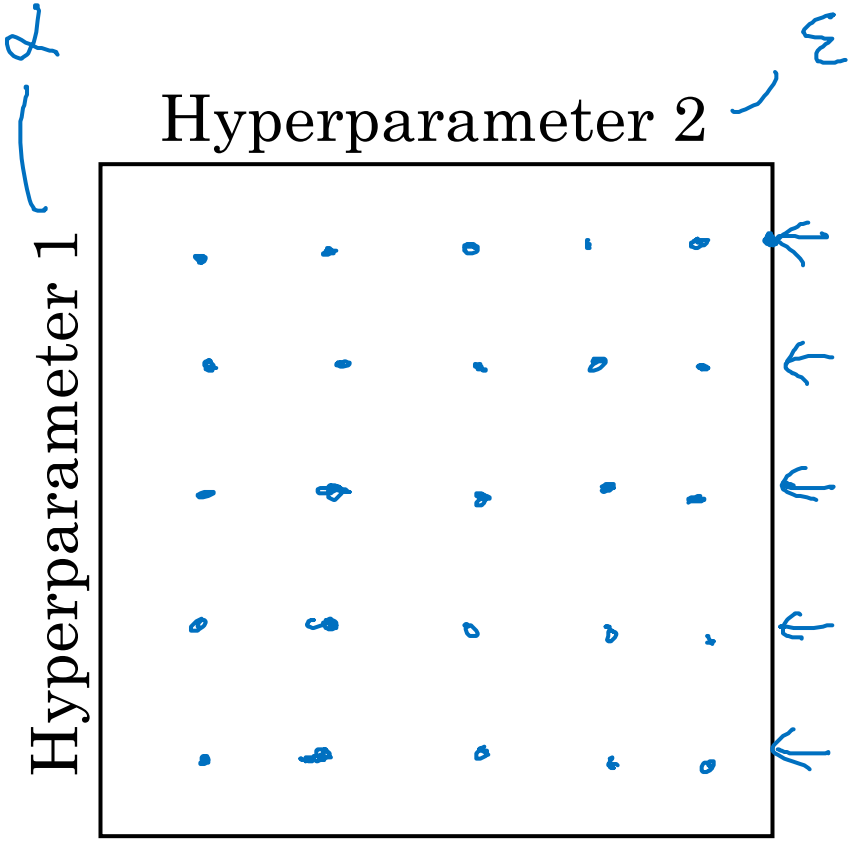
Hyperparameter tuning

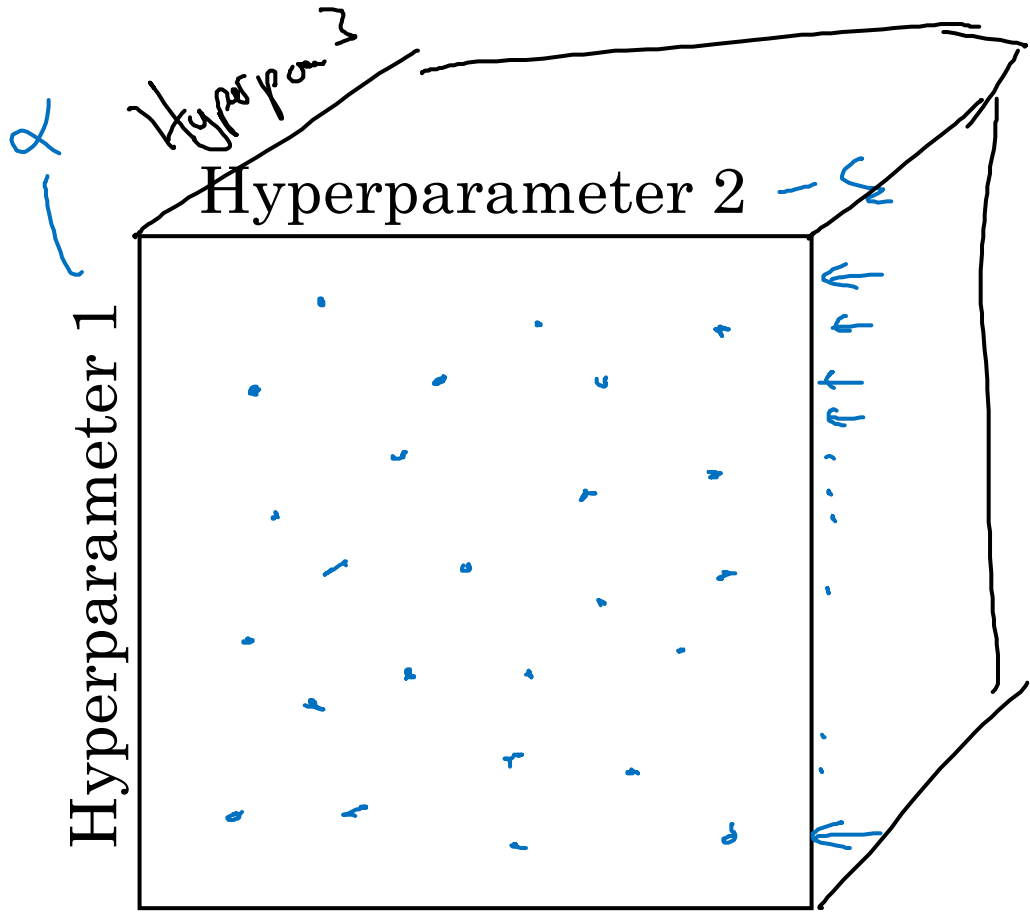
Tuning process

Hyperparameters

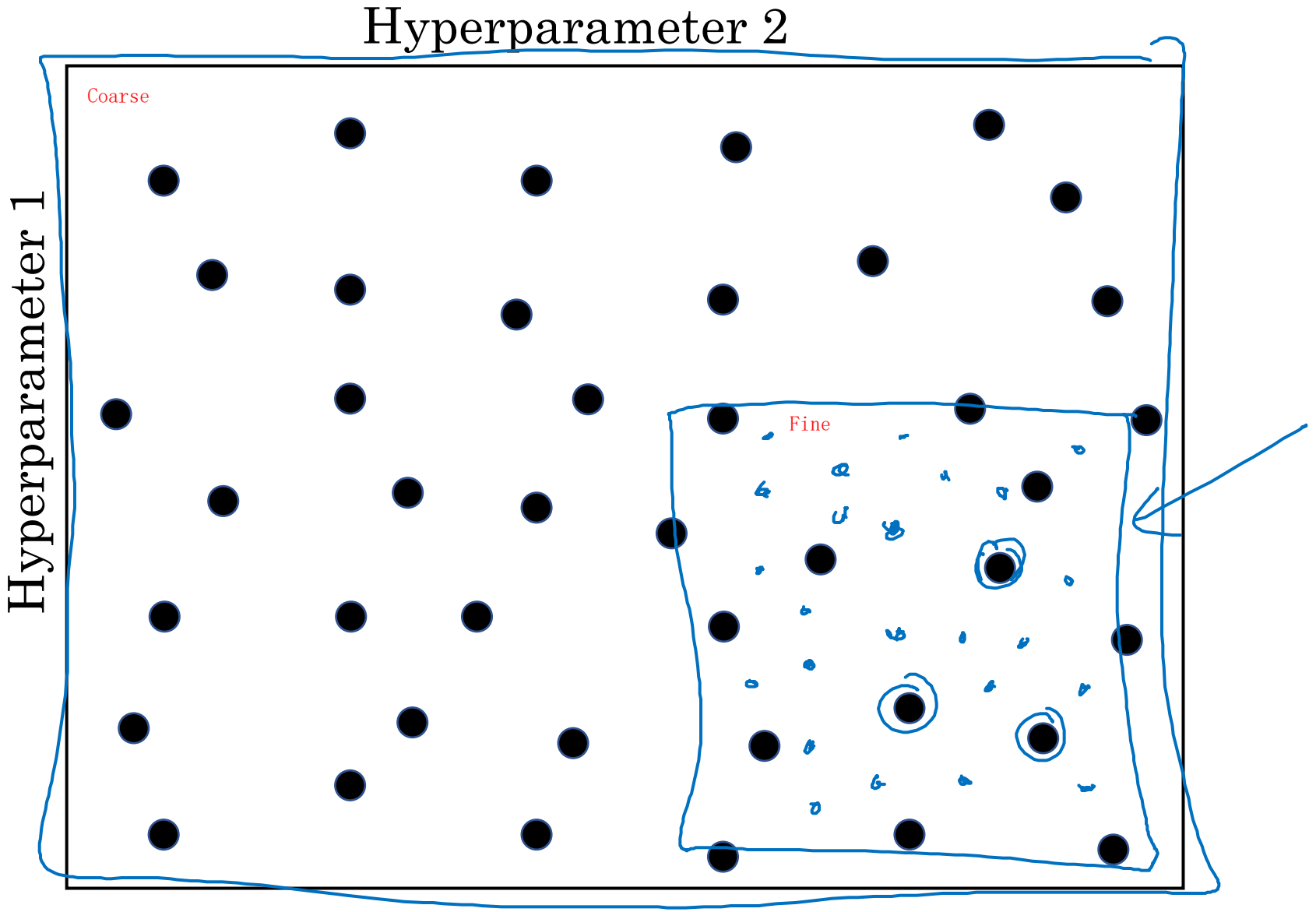


Try random values: Don't use a grid





Coarse to fine



Andrew Ng

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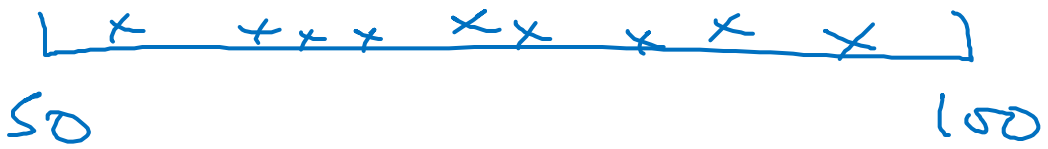
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \ldots, 100$



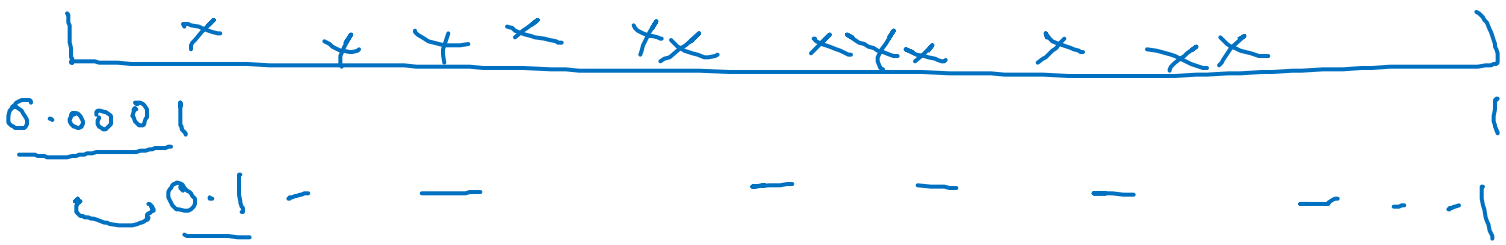
→ #layers L: 2 — 4

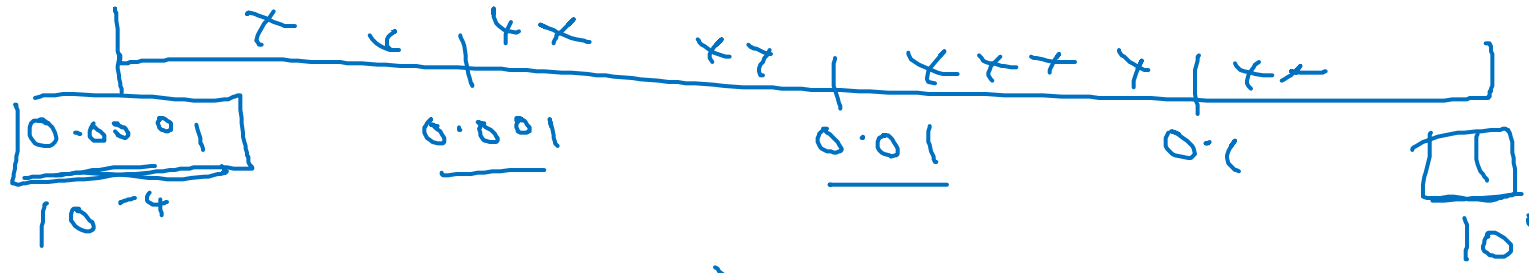
sometimes sampling uniformly at random might be reasonable

2, 3, 4

Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$





10^{a} 10^{b}

$a = \log_{10} 0.0001 = -4$

$r = -4 * np.random.rand()$ ← $r \in [-4, 0]$

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

$b = \log_{10} 1 = 0$

$10^{a} \ldots 10^{b}$

$r \in [a, b]$

$[-4, 0]$

$\alpha = 10^{r}$

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Hyperparameters for exponentially weighted averages

$\beta = 0.9 \quad \ldots \quad 0.999$

average over last $10 \quad 1000$

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

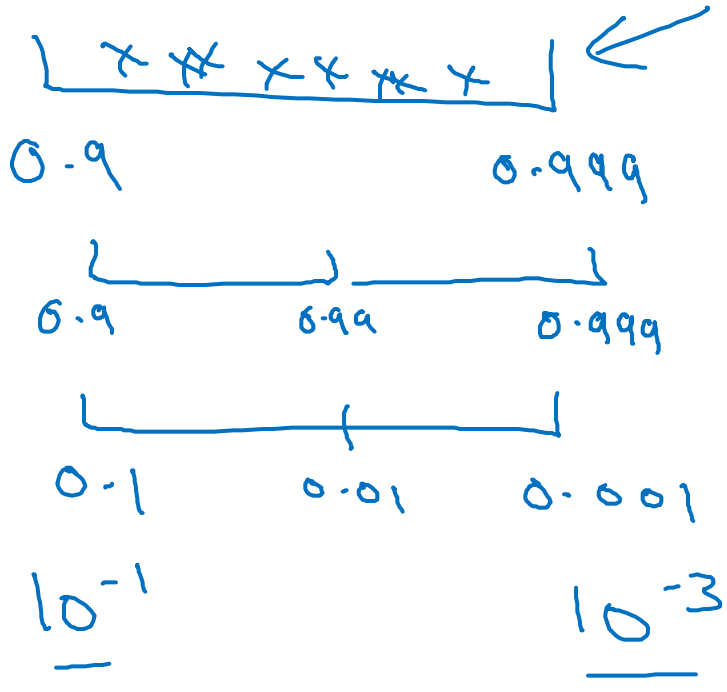
$\beta: \ 0.900 \rightarrow 0.9005$ } ~ 10

$\beta: \ 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

become away
more sensitive

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



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

$1-\beta = 10^{r}$

$\beta = 1 - 10^{r}$

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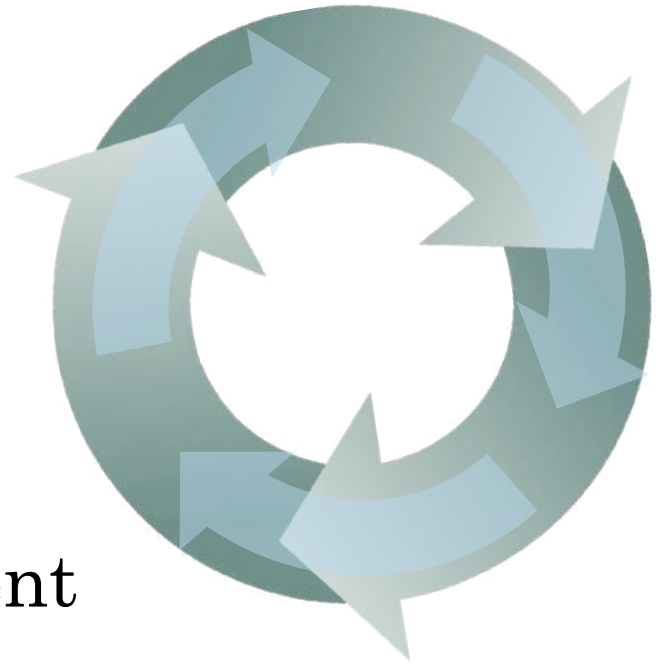
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

Re-test hyperparameters occasionally

Idea



Experiment

Code

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

- Intuitions do get stale. Re-evaluate occasionally.

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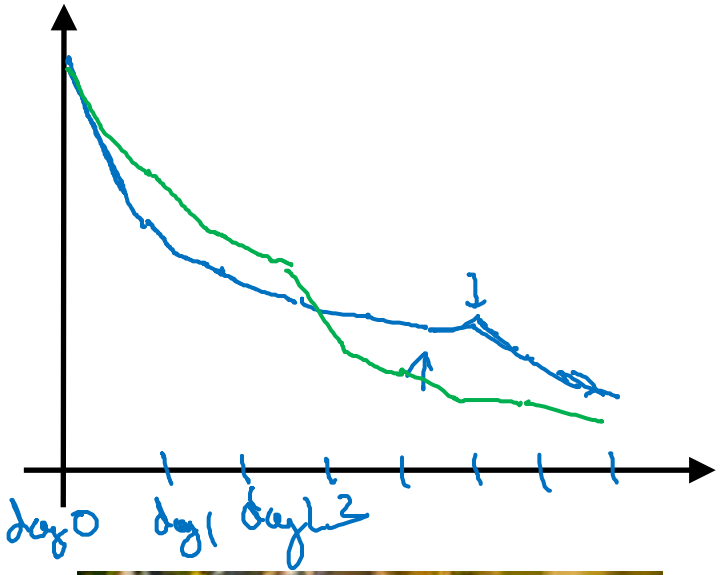
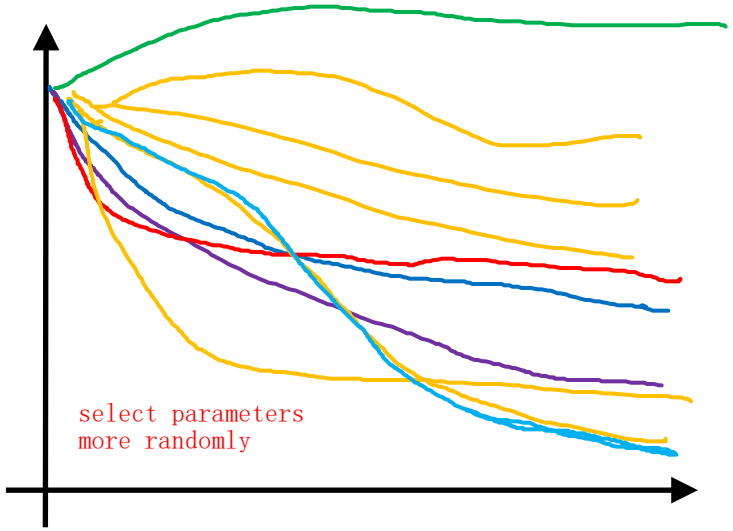
Babysitting one model



Panda

Training many models in parallel



Caviar

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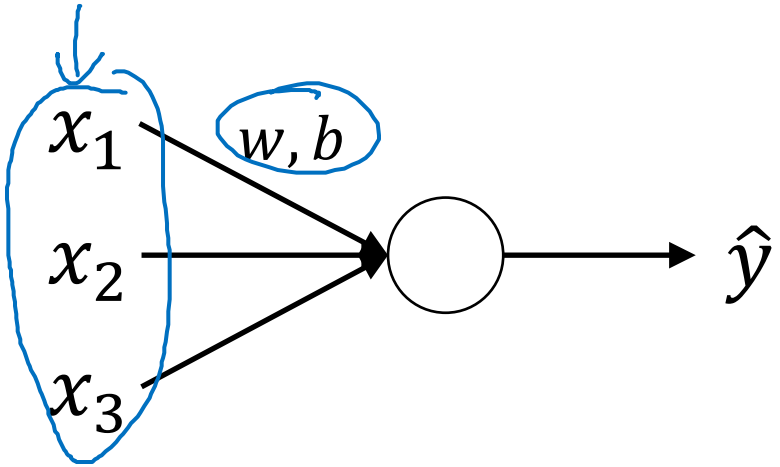
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning

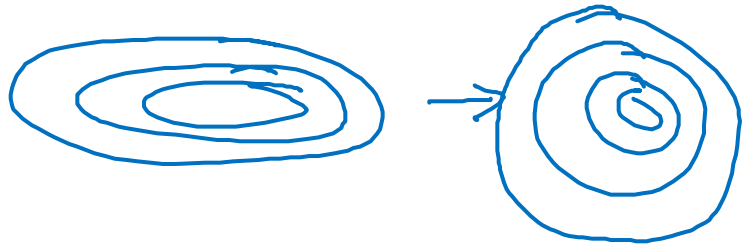


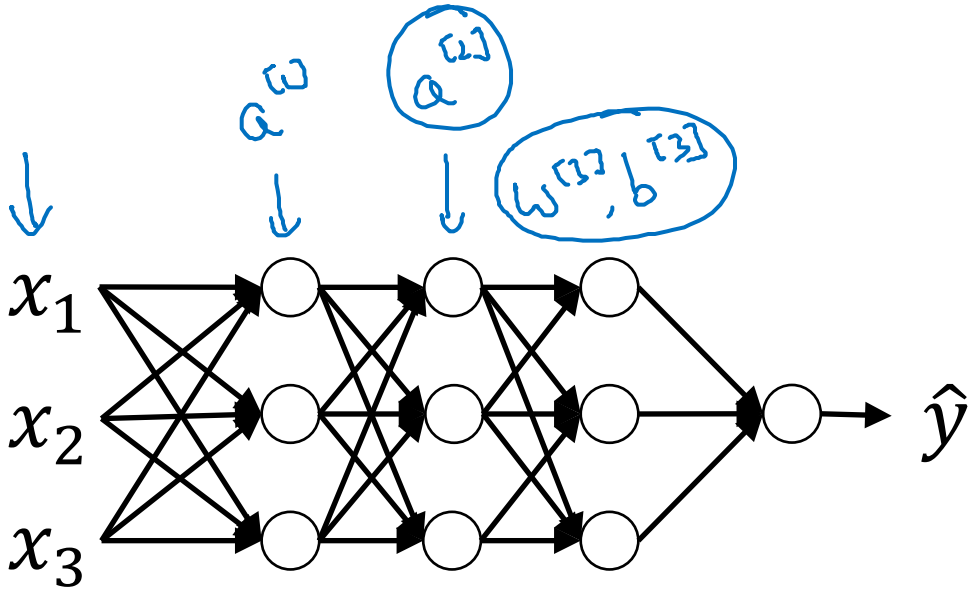
$$\mu = \frac{1}{m}\sum_i x^{(i)}$$

$$X = X - \mu \quad \text{← element-wise}$$

$$\sigma^2 = \frac{1}{m}\sum_i x^{(i)2}$$

$$X = X / \sigma$$





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

Normalize $z^{[2]}$

Andrew Ng

Implementing Batch Norm

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

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

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

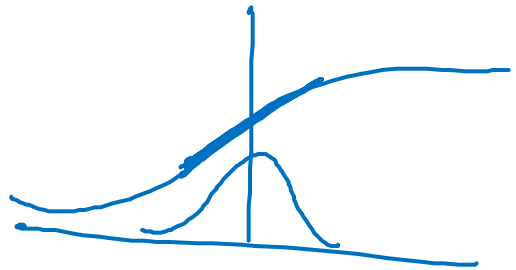
$$z^{(i)}_{norm} = \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \varepsilon}}$$

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

learnable parameters of model.

If $\gamma = \sqrt{\sigma^2 + \varepsilon}$, $\beta = \mu$, then $\tilde{z}^{(i)} = z^{(i)}$

$X \rightarrow z^{(i)}$



not necessarly mean 0, variance 1

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

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

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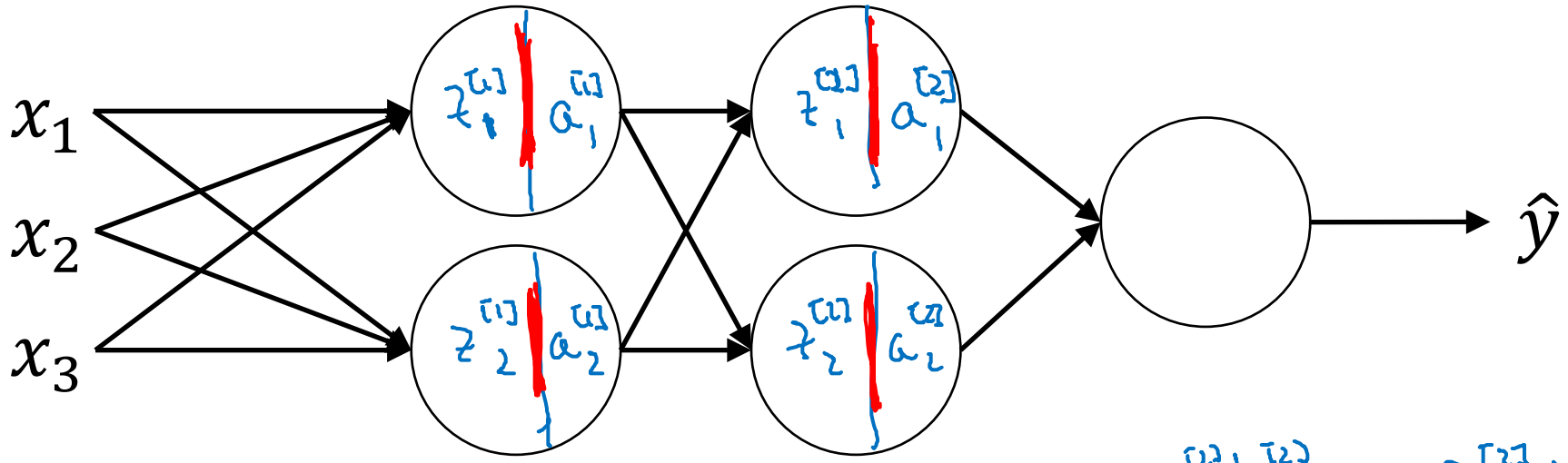
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network



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

Parameters: $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, \dots, W^{[L]}, b^{[L]}, \beta^{[1]}, \gamma^{[1]}, \beta^{[2]}, \gamma^{[2]}, \dots, \beta^{[L]}, \gamma^{[L]}$

$\rightarrow \beta$

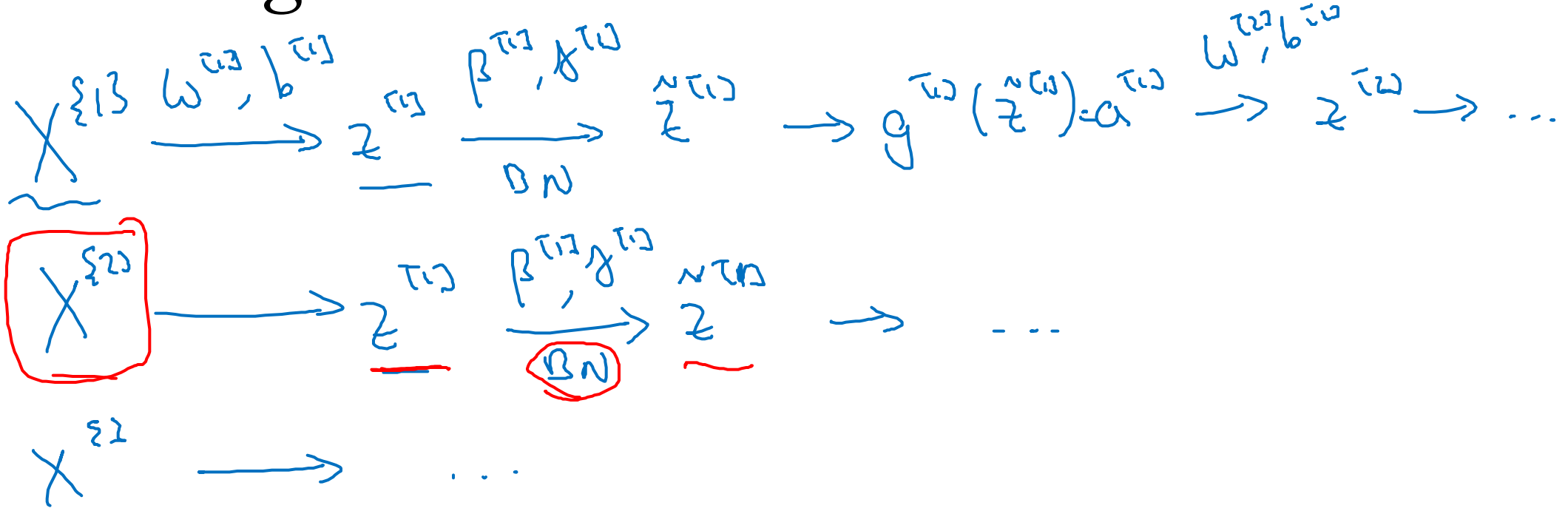
$d\beta^{[l]}$

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

tf.nn.batch_normalization

Andrew Ng

Working with mini-batches



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

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

$Z^{[l]}$

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

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

subtracted out

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

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

$$Z^{[l]} = \gamma^{[l]} Z^{[l]}_{norm} + \beta^{[l]}$$

Andrew Ng

Implementing gradient descent

for $t = 1 \ldots$ numMiniBatches

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

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

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

Update parameters $W^{[l]} := W^{[l]} - \alpha\, dW^{[l]}$

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

$\gamma^{[l]} := \ldots$ ←

Works w/ momentum, RMSprop, Adam.

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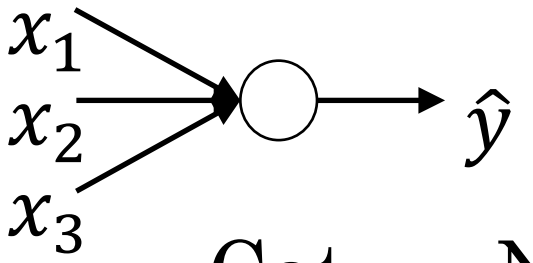
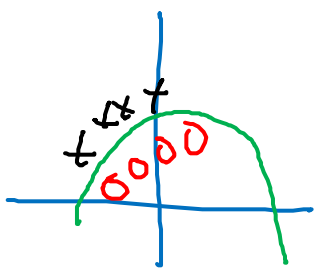
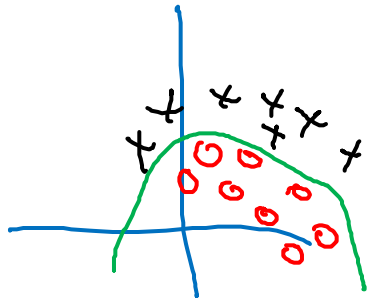
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution







Cat $y = 1$




Non-Cat $y = 0$




"Covariate shift"

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

$X \rightarrow y$

$y = 1$




$y = 0$

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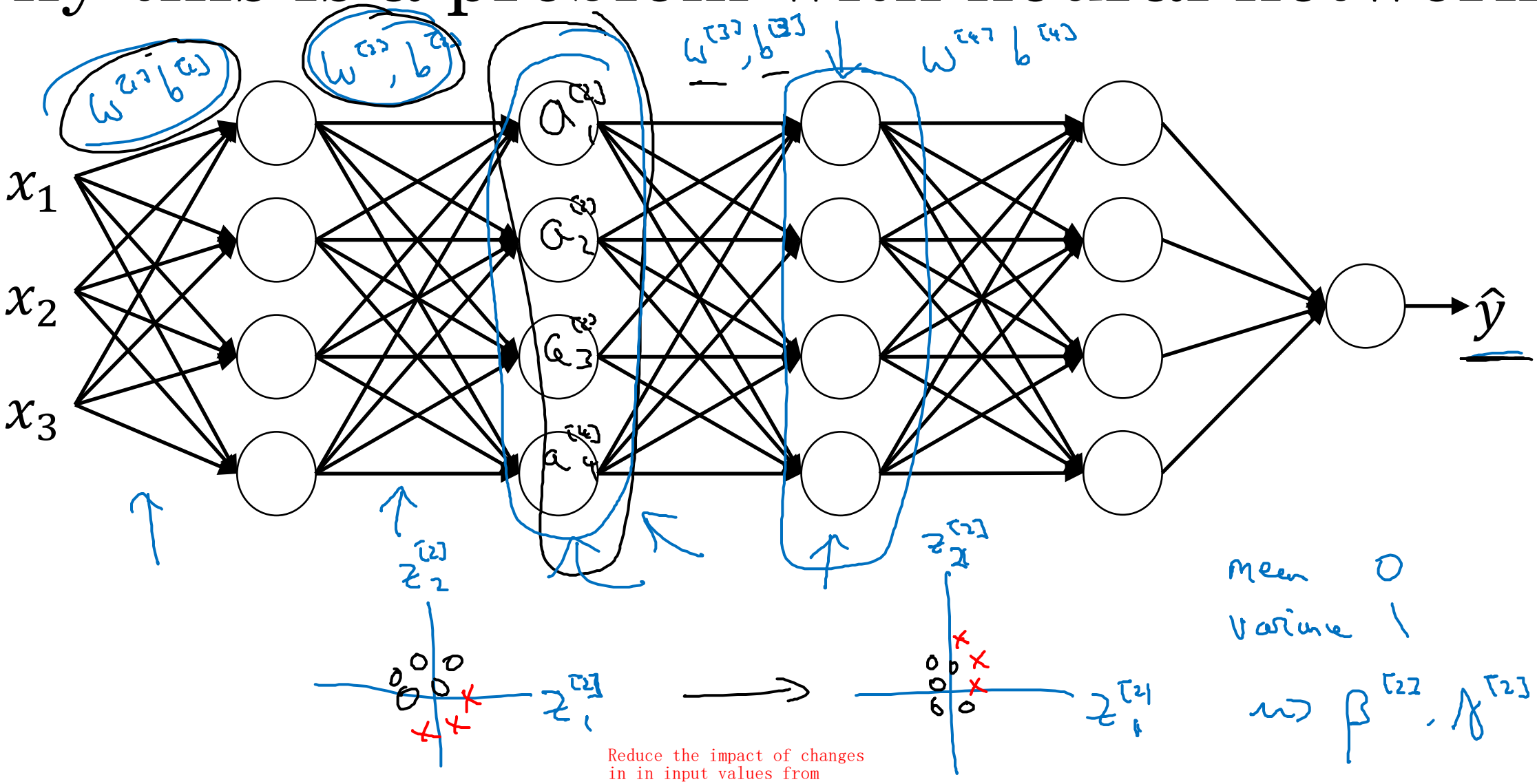
Why this is a problem with neural networks?



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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.

Batch Norm at test time

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

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

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

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

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

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

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

θ_1 θ_2 θ_3 σ^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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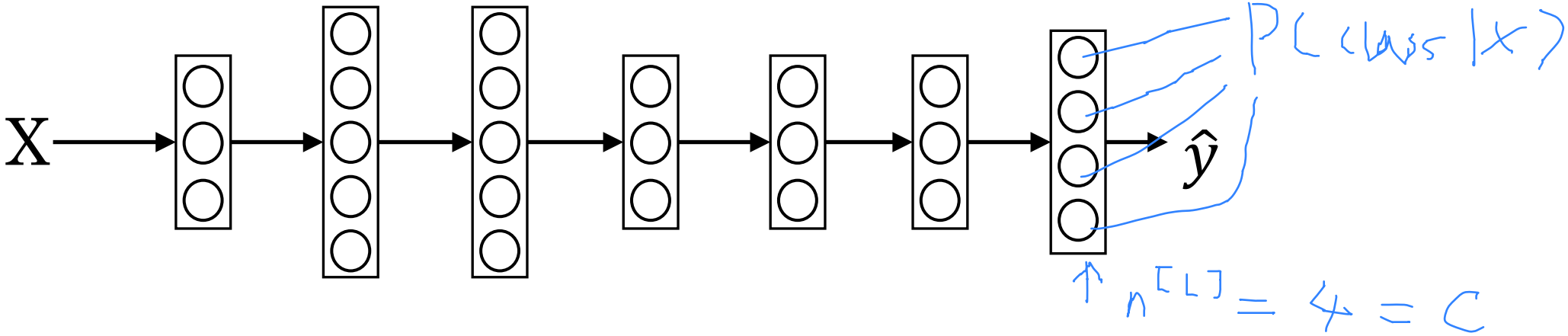
Multi-class classification

Softmax regression

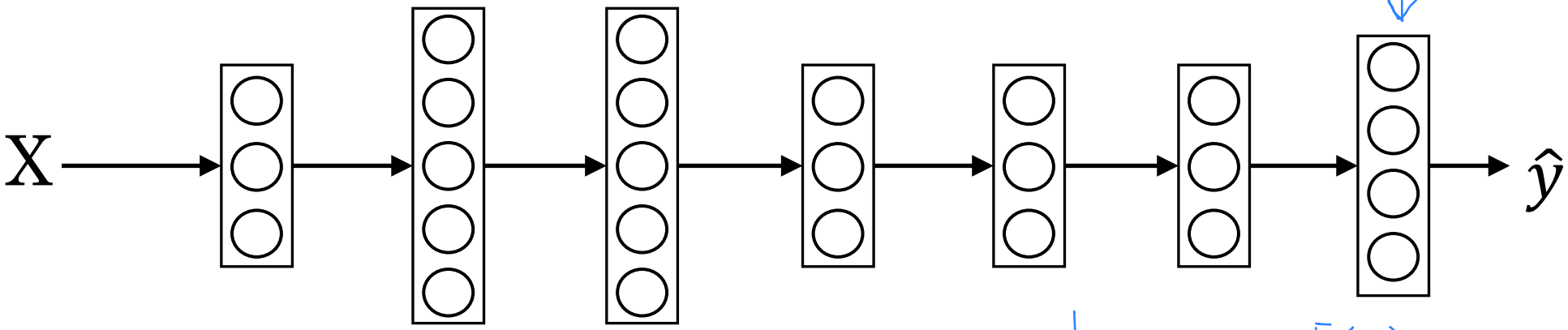
Recognizing cats, dogs, and baby chicks

3 1 2 0 3 2 0 1

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



Softmax layer



$a^{[L]}$

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

$(4,1)$

Activation Function:

$t = e^{(z^{[L]})}$ $(4,1)$

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

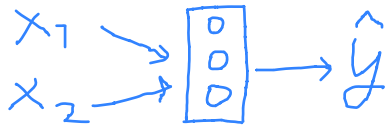
$(4,1)$

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

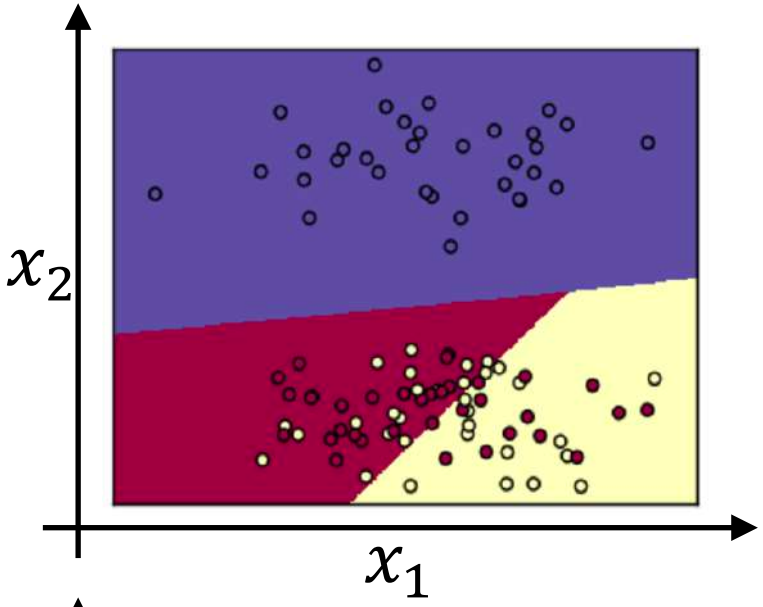
$t = \begin{bmatrix} e^5 \\ e^2 \\ e^{-1} \\ e^3 \end{bmatrix} = \begin{bmatrix} 148.4 \\ 7.4 \\ 0.4 \\ 20.1 \end{bmatrix}$ $\sum_{j=1}^{4} t_j = 176.3$

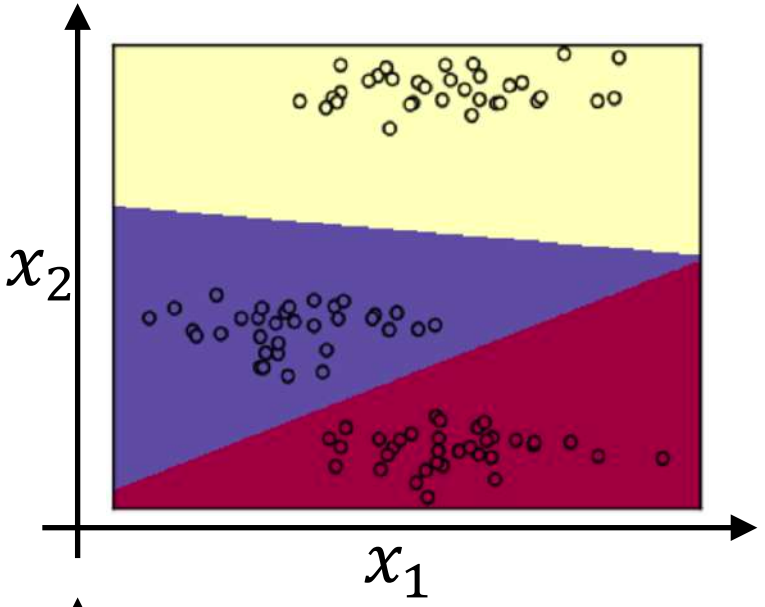
$a^{[L]} = t / 176.3$

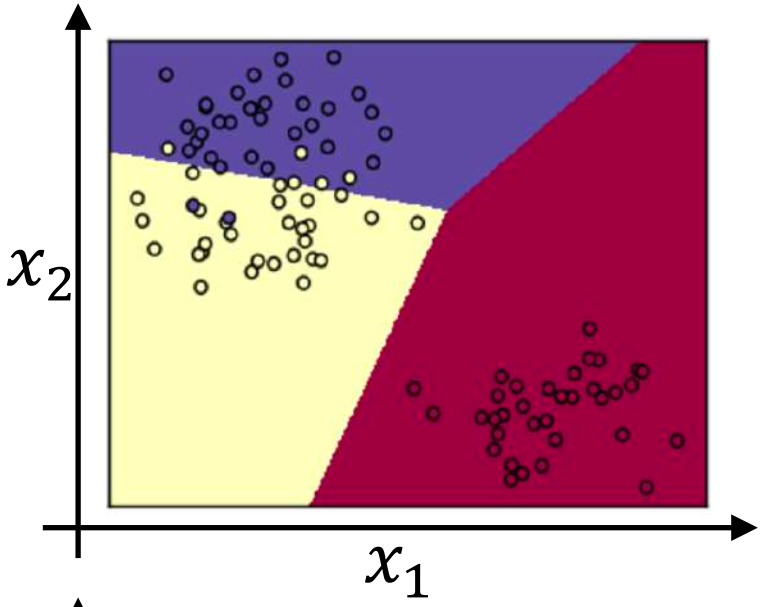
Softmax examples

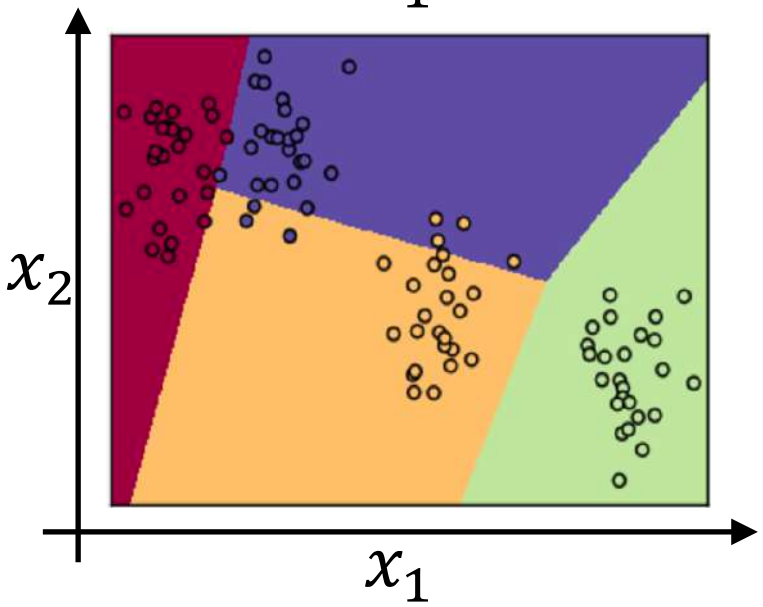


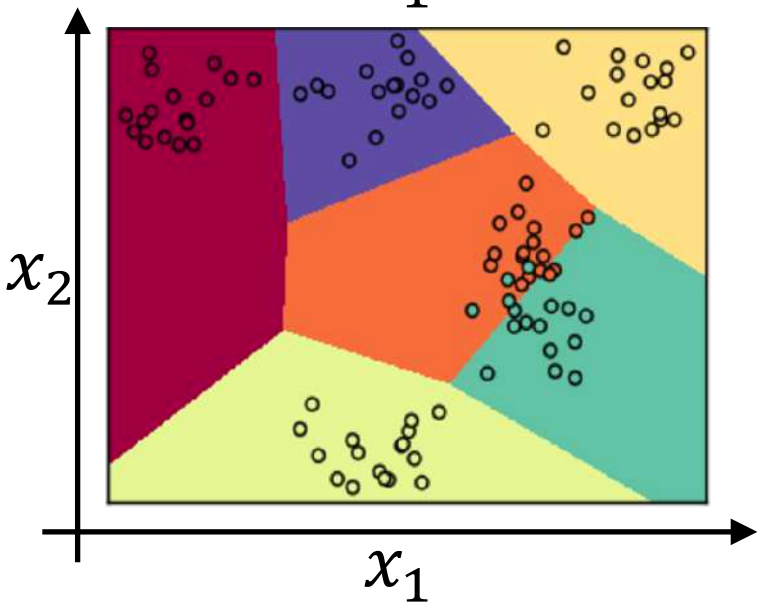
$$z^{[l]} = w^{[l]}x + b^{[l]}$$
$$a^{[l]} = \hat{y} = g(z^{[l]})$$

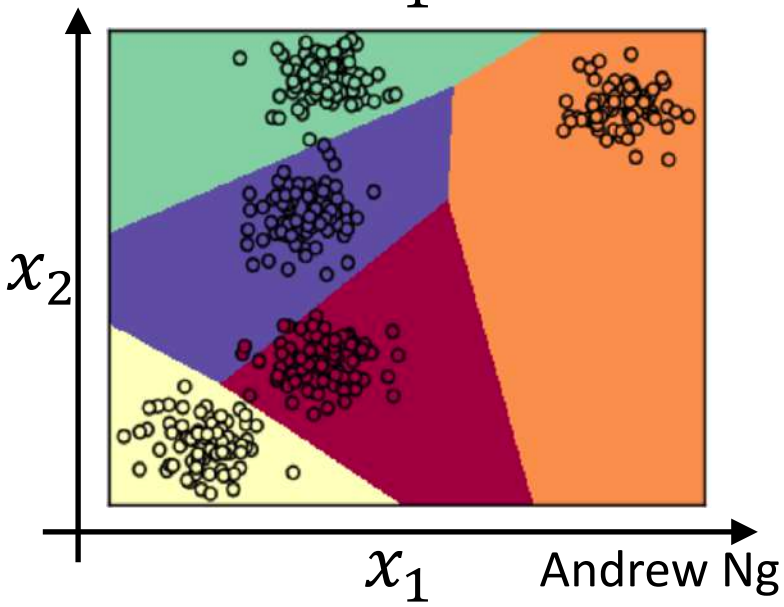












Understanding softmax

(4,1)

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

"Soft max"

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

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

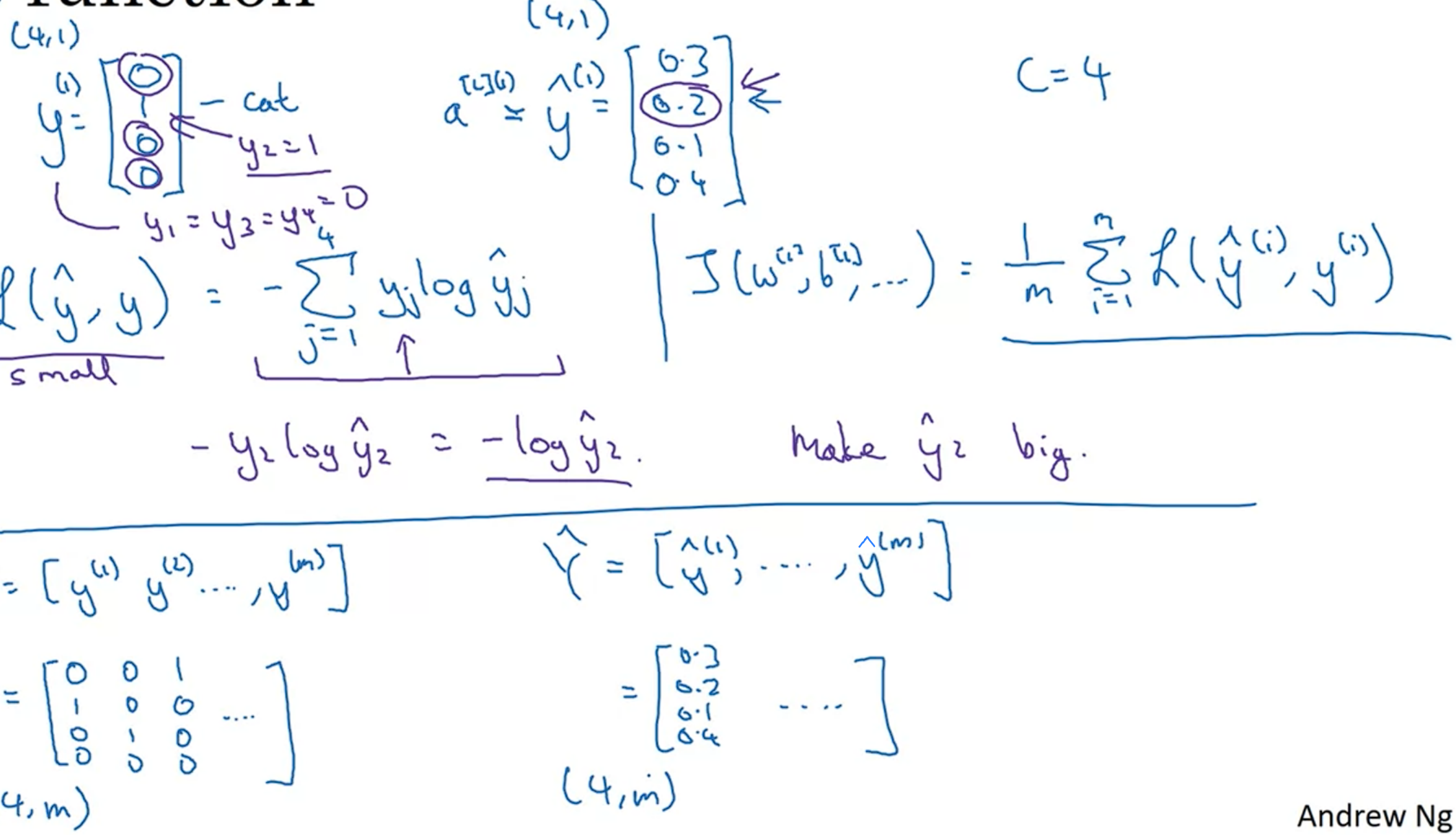
"hard max"

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

Softmax regression generalizes logistic regression to C classes.

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

Loss function



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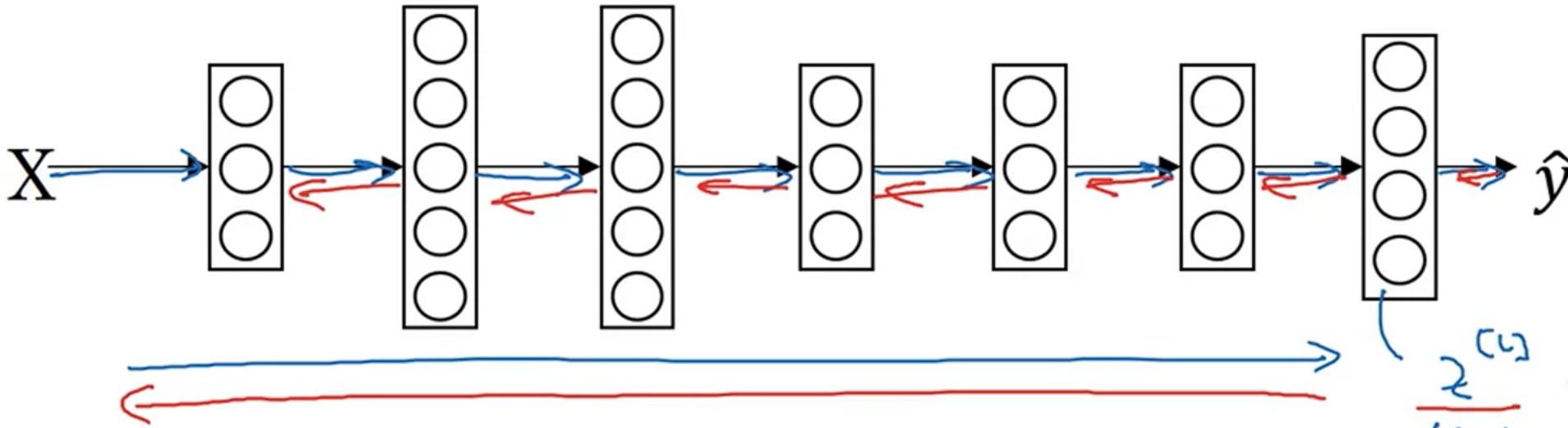
Gradient descent with softmax



$z^{[L]}$
$(4,1)$

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

Backprop:

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

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

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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

$J(w) = w^2 - 10w + 25$

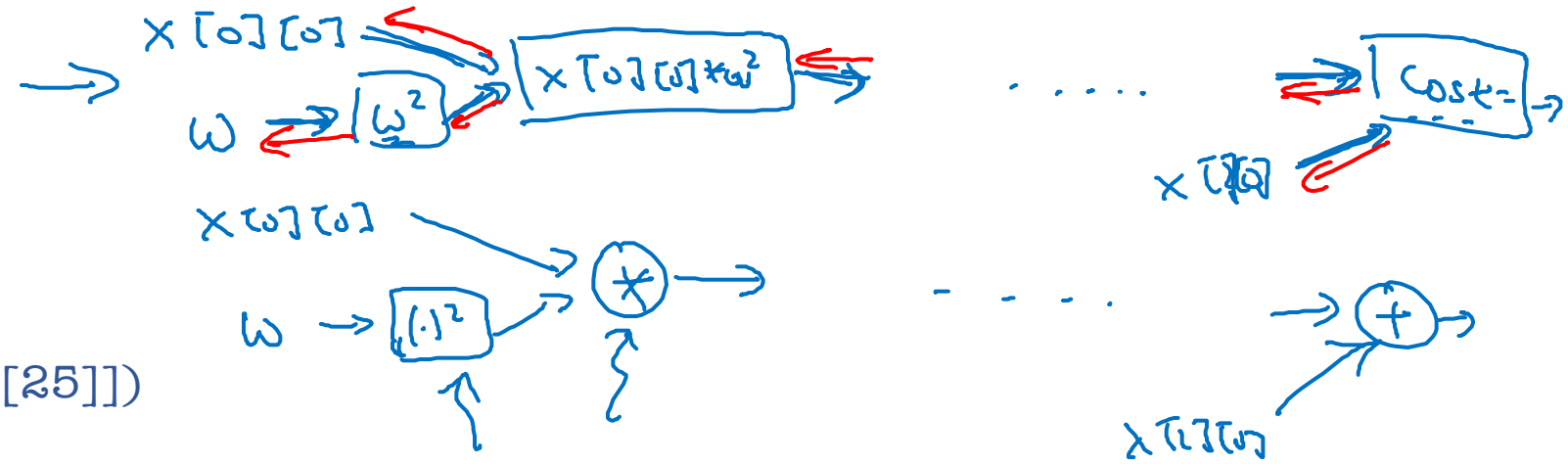
(cost)

$(w-5)^2$

$w = 5$

$J(w, b)$

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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