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Hyperparameter tuning

Tuning process

Hyperparameters

→ α

β 0.9

$\beta_1, \beta_2, \epsilon$
0.9 0.999 10^{-8}

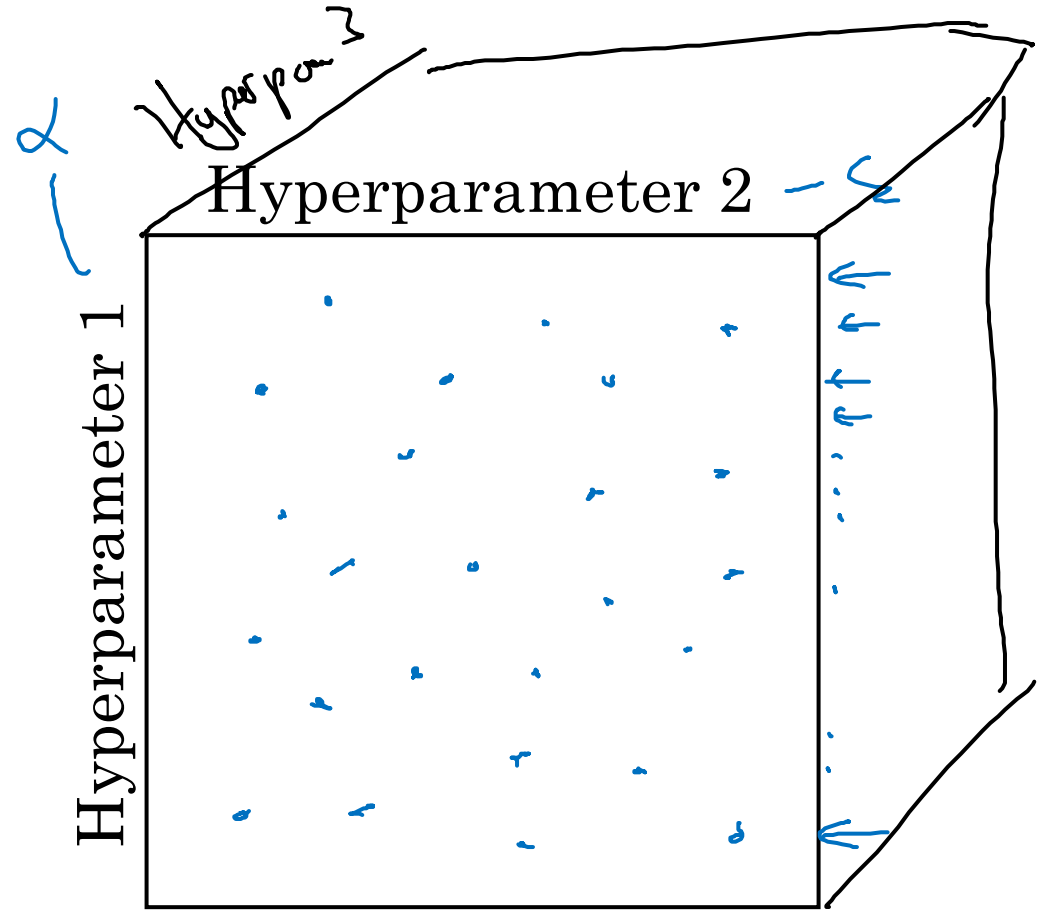
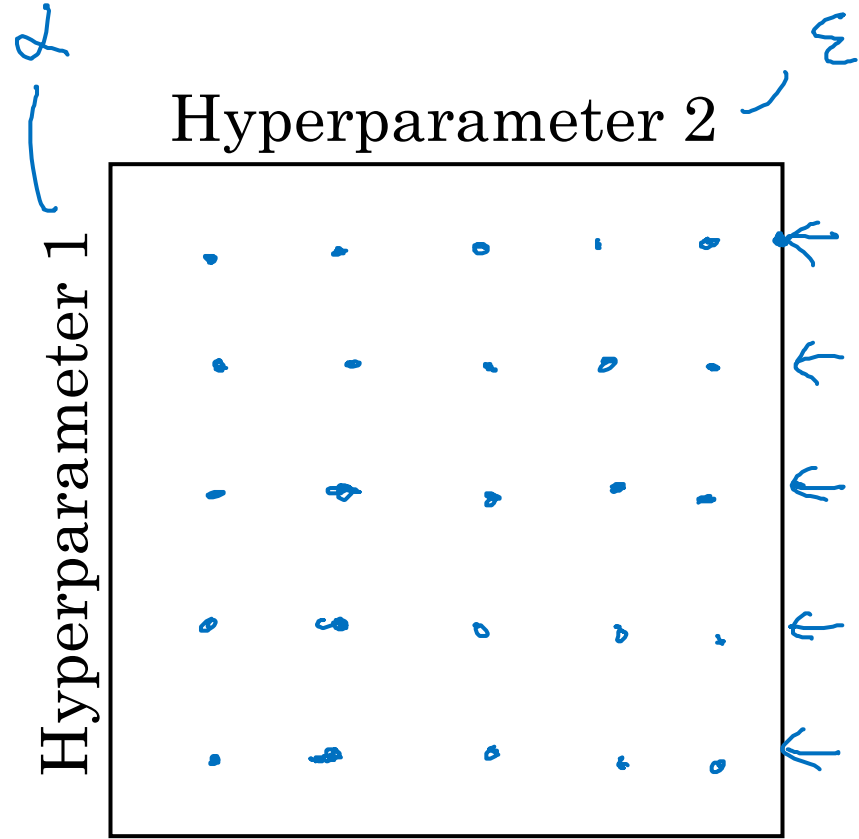
layers

hidden units

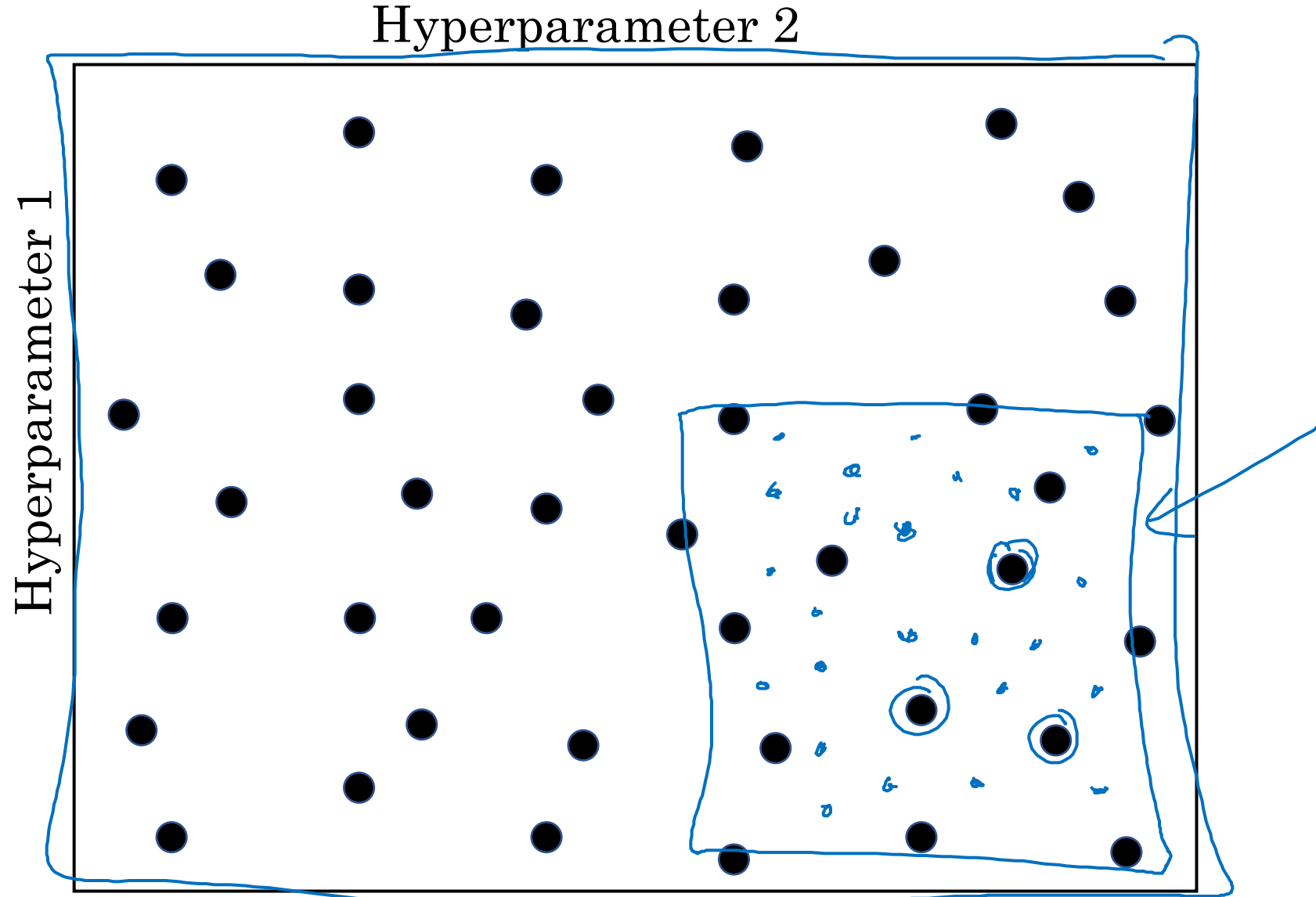
learning rate decay

mini-batch size

Try random values: Don't use a grid



Coarse to fine





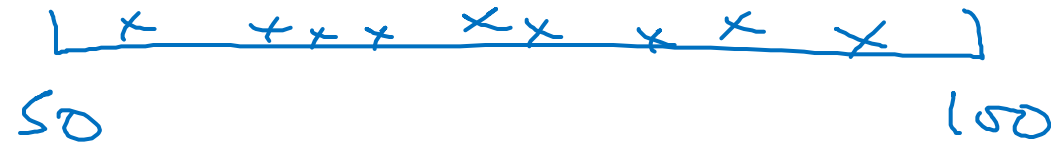
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Hyperparameter tuning

Using an appropriate
scale to pick
hyperparameters

Picking hyperparameters at random

→ $n^{\text{test}} = 50, \dots, 100$

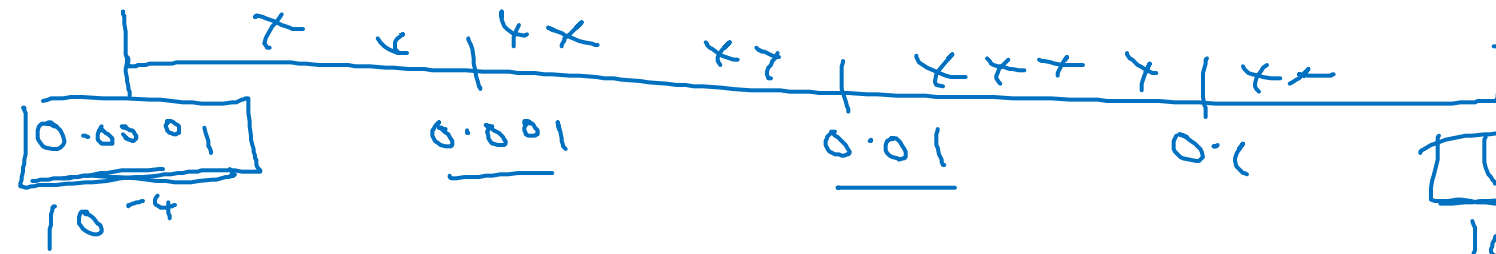
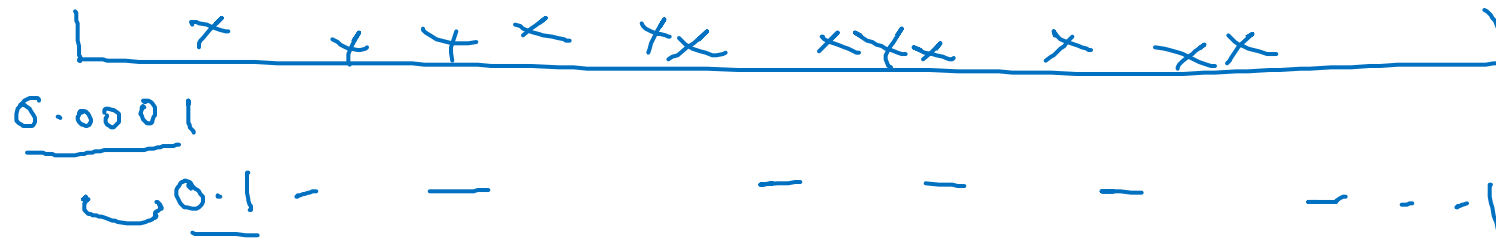


→ #layers L : 2 - 4

2, 3, 4

Appropriate scale for hyperparameters

$$\alpha = 0.0001, \dots, 1$$



$$10^a$$

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

$$= -4$$

$$r = -4 * np.random.rand()$$

$$\alpha = 10^r$$

$$r \in [-4, 0]$$

$$10^{-4} \dots 10^0$$

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

$$= 0$$

$$\frac{10^a \dots 10^b}{}$$

$$\frac{r \in [a, b]}{[-4, 0]}$$

$$\alpha = 10^r$$

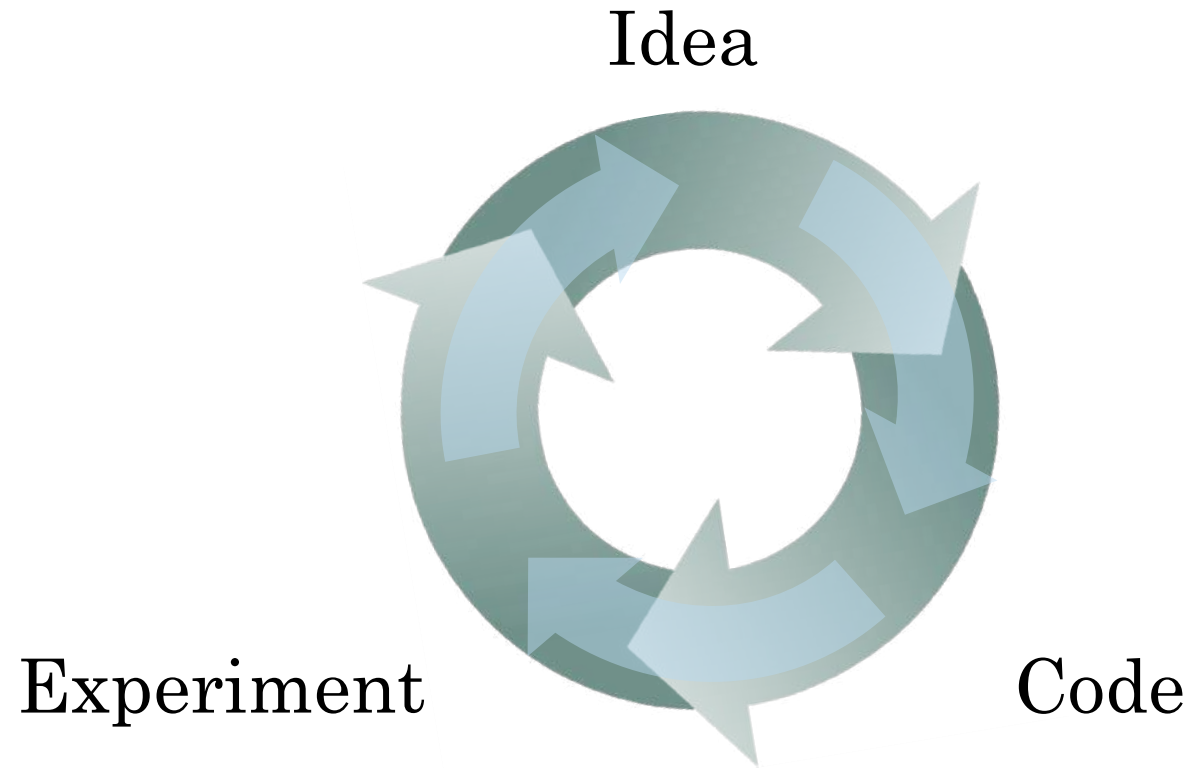


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Hyperparameters tuning

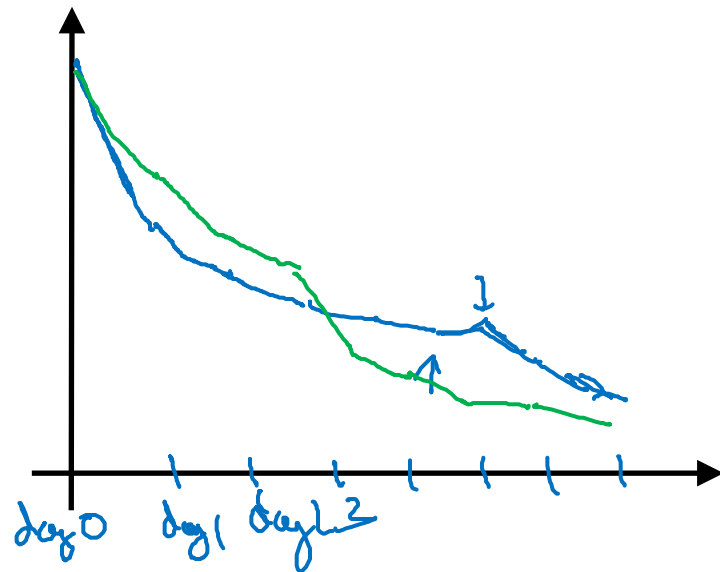
Hyperparameters
tuning in practice:
Pandas vs. Caviar

Re-test hyperparameters occasionally



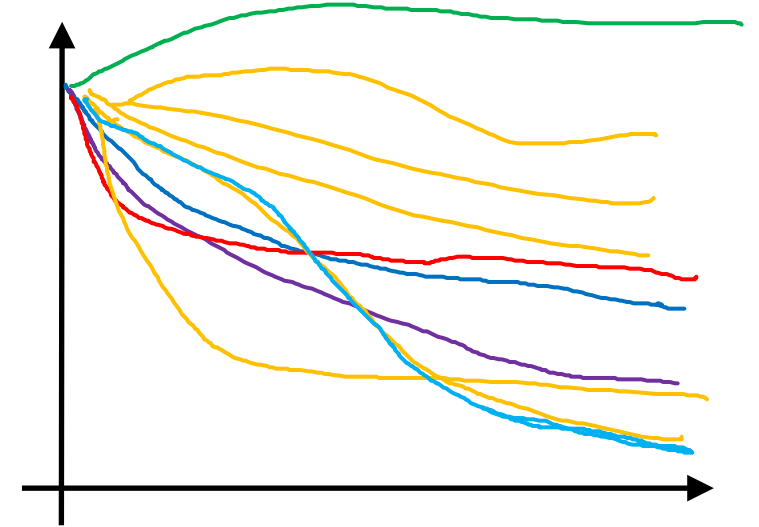
- NLP, Vision, Speech,
Ads, logistics,
- Intuitions do get stale.
Re-evaluate occasionally.

Babysitting one model



Panda ←

Training many models in parallel



Caviar ←

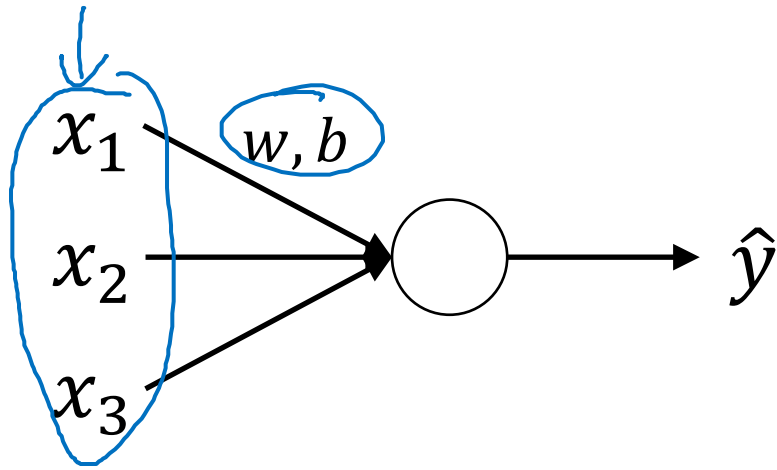


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Batch Normalization

Normalizing activations
in a network

Normalizing inputs to speed up learning



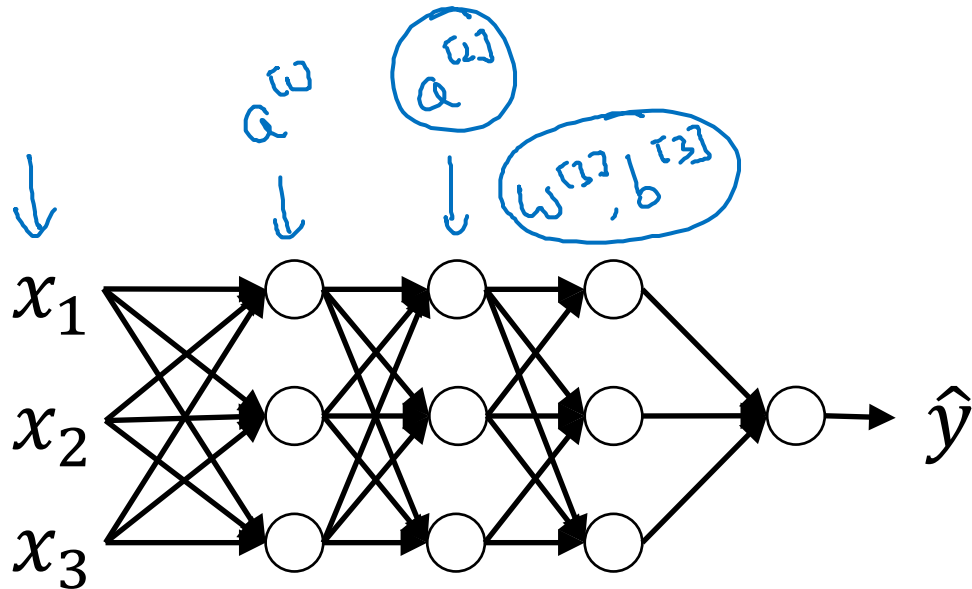
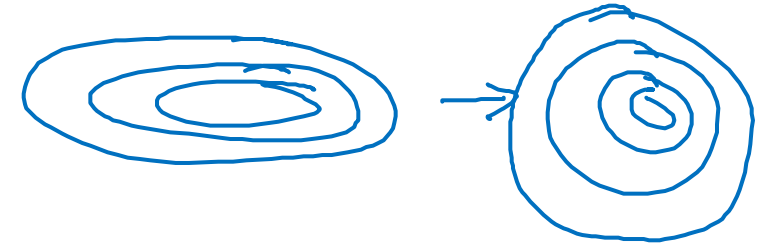
$$\mu = \frac{1}{n} \sum_i x^{(i)}$$

$$X = X - \mu$$

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

$$X = X / \sigma^2$$

← element-wise



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

Normalize $\frac{z^{[2]}}{\uparrow}$

Implementing Batch Norm

Given some intermediate values in NN

$z^{(1)}, \dots, z^{(m)}$

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

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

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

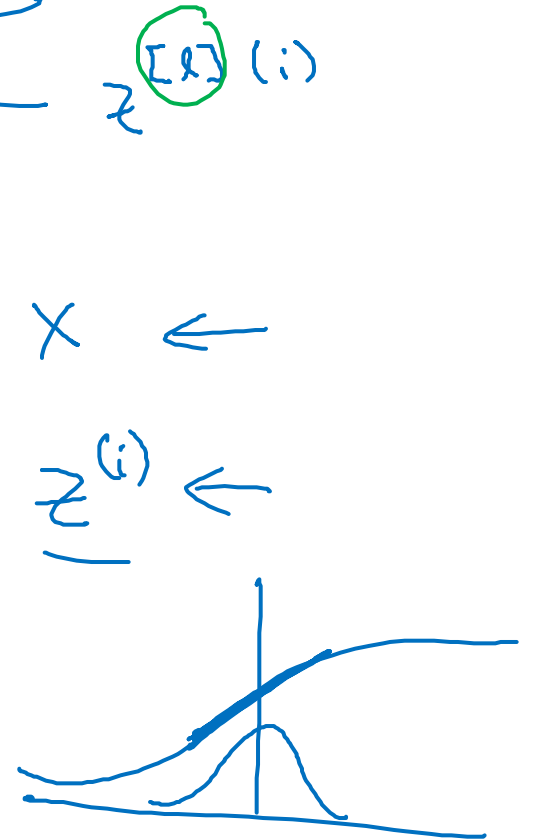
$$\tilde{z}^{(i)} = \gamma z_{\text{norm}}^{(i)} + \beta$$

If $\gamma = \sqrt{\sigma^2 + \epsilon}$

$\beta = \mu$

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

learnable parameters of model.



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

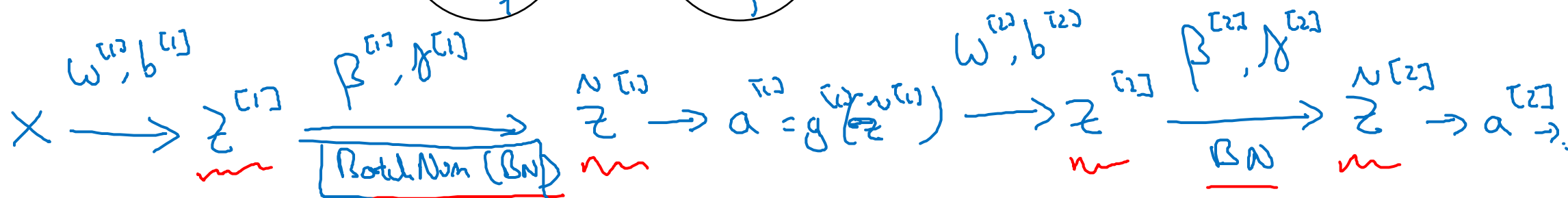
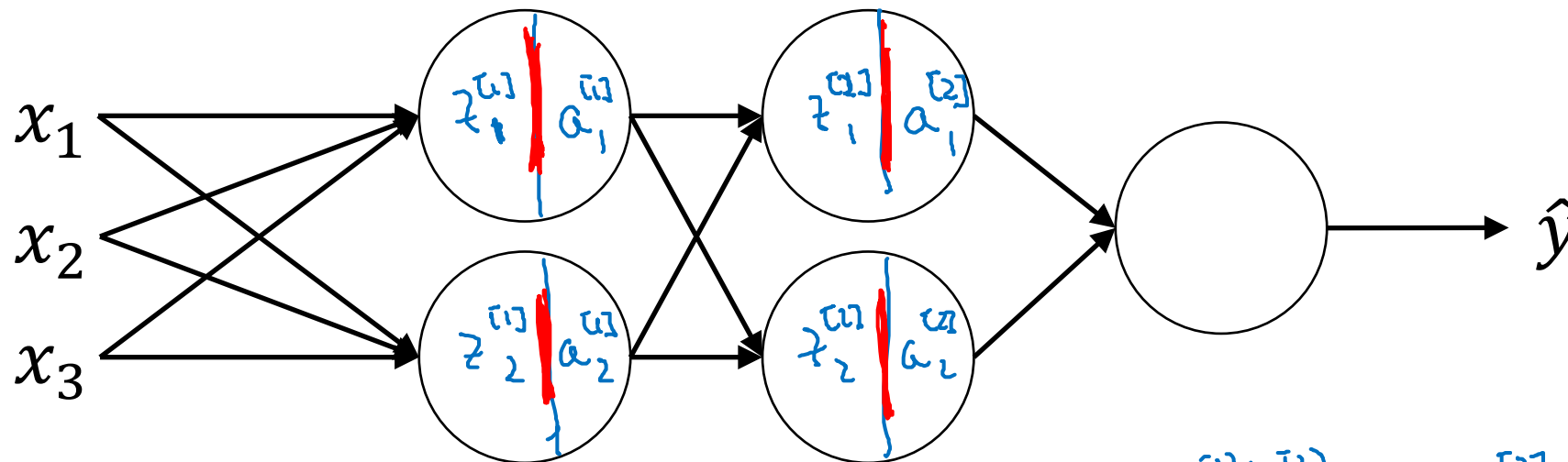


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Batch Normalization

Fitting Batch Norm
into a neural network

Adding Batch Norm to a network



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

$\rightarrow \beta$

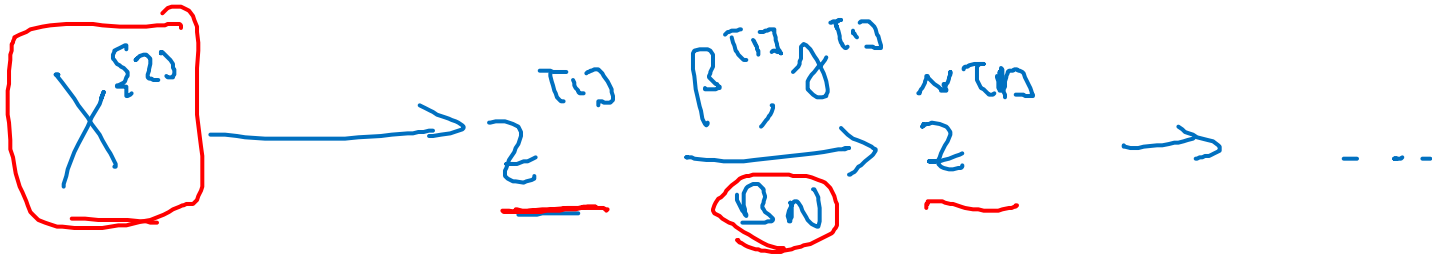
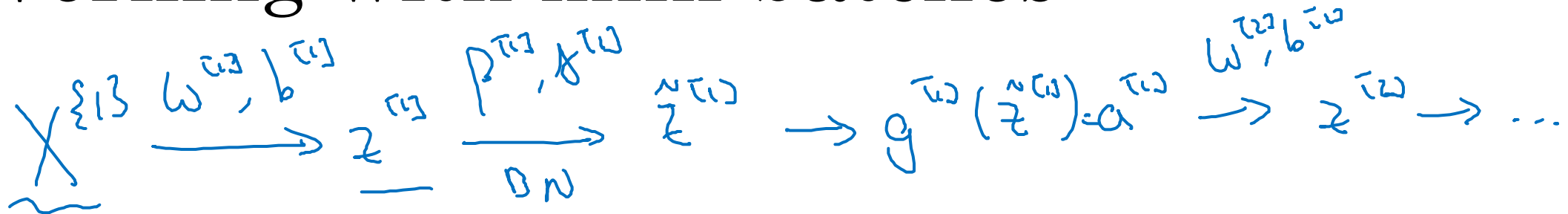
$\rightarrow \beta$

$d\beta^{[l]}$

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

tf.nn.batch-normalization ←

Working with mini-batches



$X^{[l]} \rightarrow \dots$

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

$\tilde{z}^{[l]} \rightarrow (n^{[l]}, 1)$
 $\beta^{[l]} \rightarrow (n^{[l]}, 1)$
 $\gamma^{[l]} \rightarrow (n^{[l]}, 1)$

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

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

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

Implementing gradient descent

for $t = 1 \dots \text{num Mini Batches}$

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

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

Use backprop to compute $\underline{dw}^{\{t\}}$, ~~$\underline{db}^{\{t\}}$~~ , $\underline{d\beta}^{\{t\}}$, $\underline{d\gamma}^{\{t\}}$

Update params
$$\left. \begin{aligned} W^{\{t\}} &:= W^{\{t\}} - \alpha \underline{dw}^{\{t\}} \\ \beta^{\{t\}} &:= \beta^{\{t\}} - \alpha \underline{d\beta}^{\{t\}} \\ \gamma^{\{t\}} &:= \dots \end{aligned} \right\} \leftarrow$$

Works w/ momentum, RMSprop, Adam.

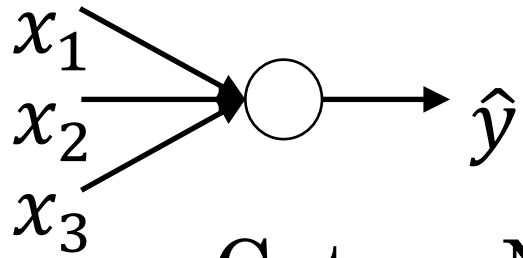


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Batch Normalization

Why does
Batch Norm work?

Learning on shifting input distribution

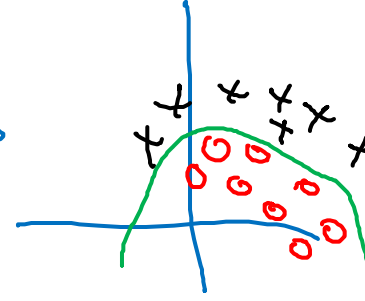
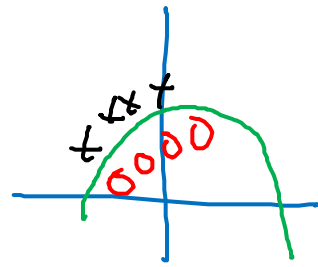


Cat

Non-Cat

$y = 1$

$y = 0$



$y = 1$

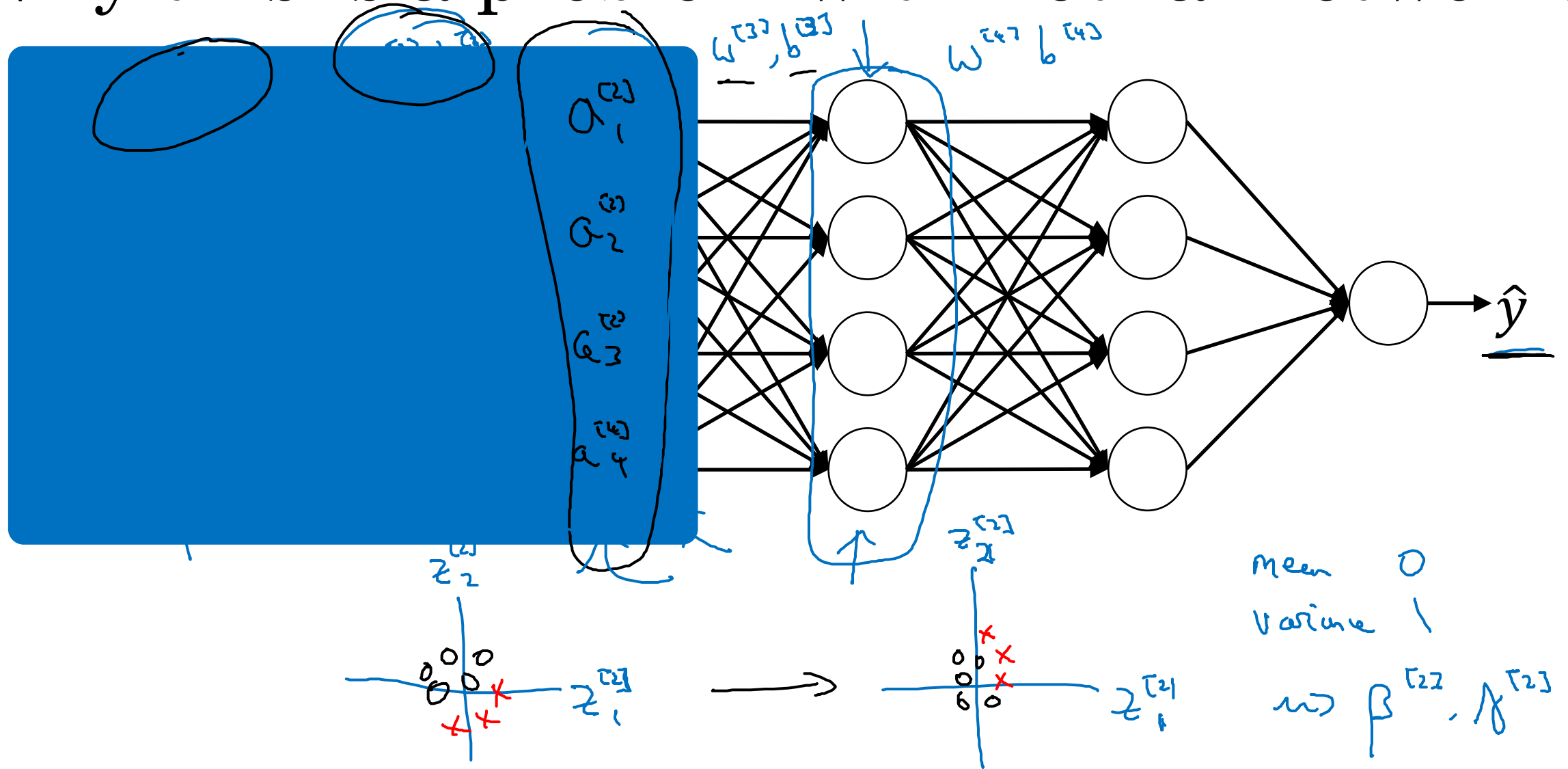
$y = 0$



"Covariate shift"

$x \rightarrow y$

Why this is a problem with neural networks?



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.

mini-batch : 64 \longrightarrow 512

X

X^{t}

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

64, 128

z^{t}

μ, σ^2



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Multi-class
classification

Softmax regression

Recognizing cats, dogs, and baby chicks



3

1

2

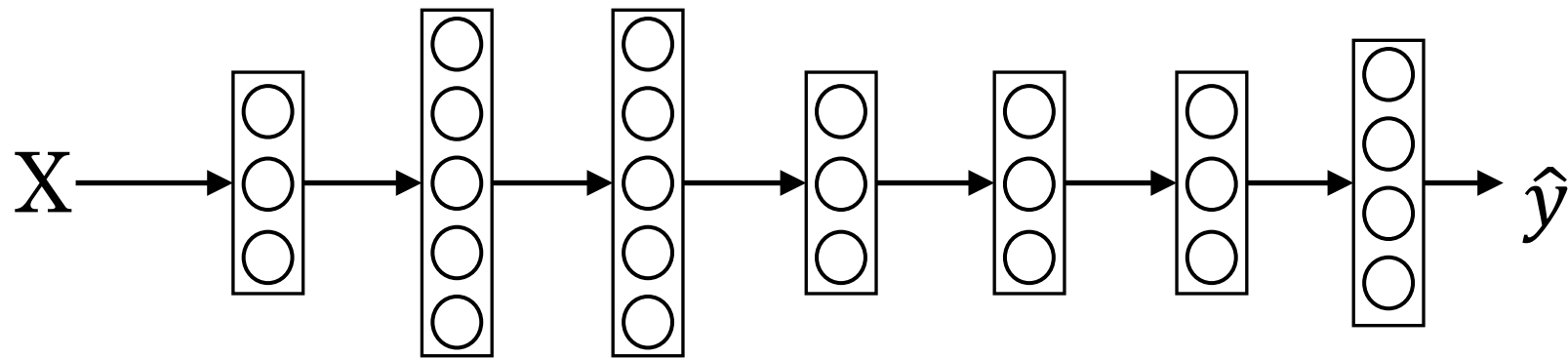
0

3

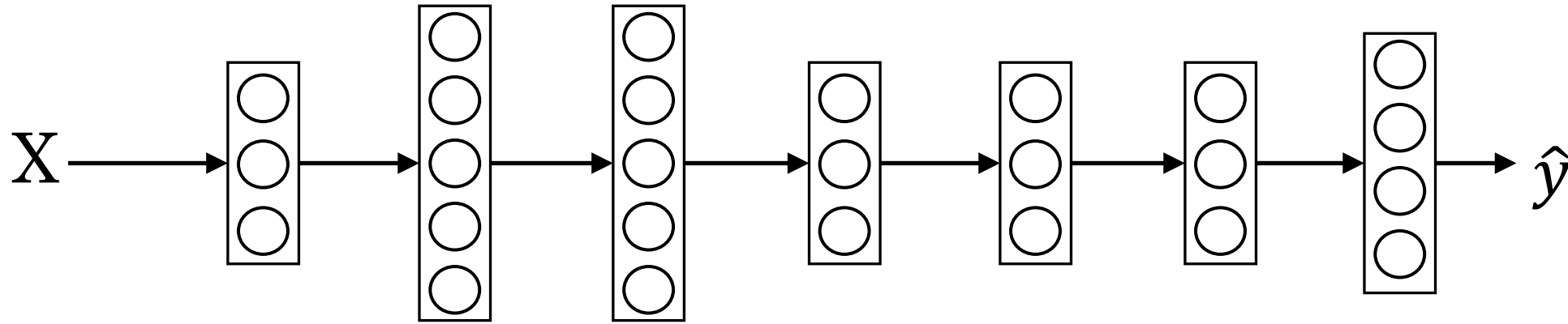
2

0

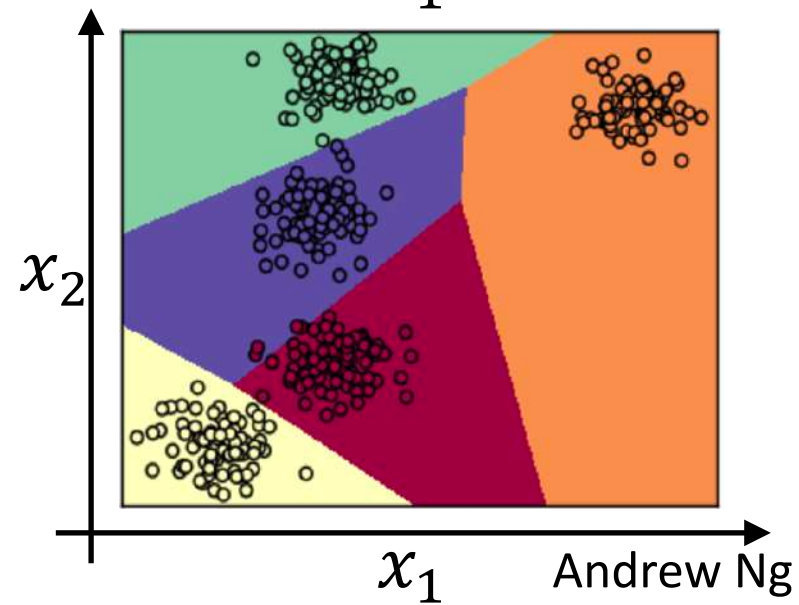
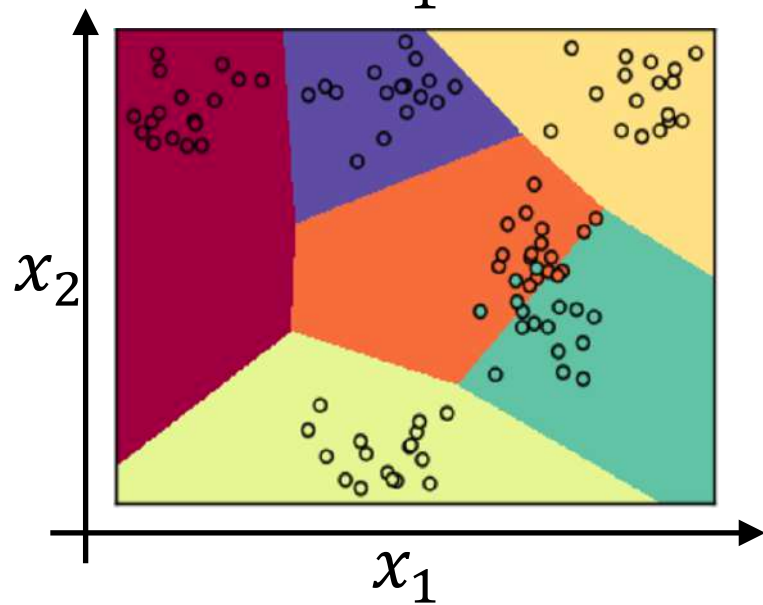
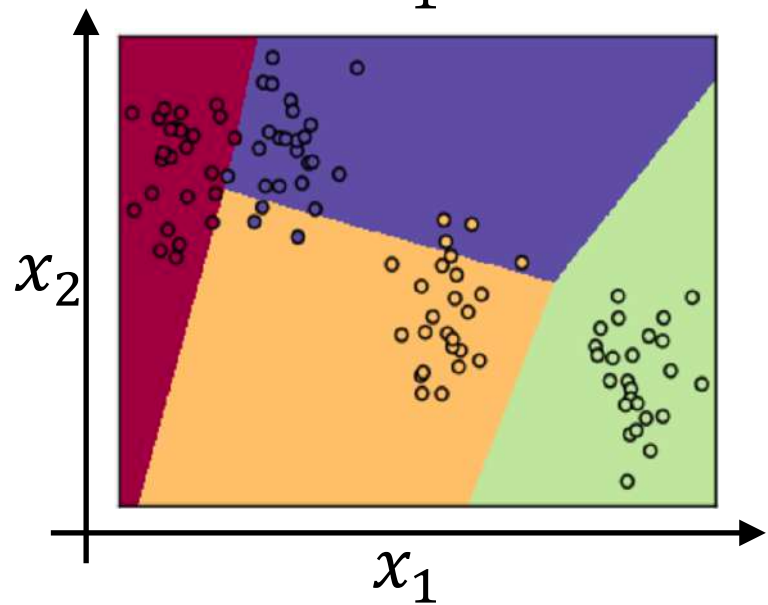
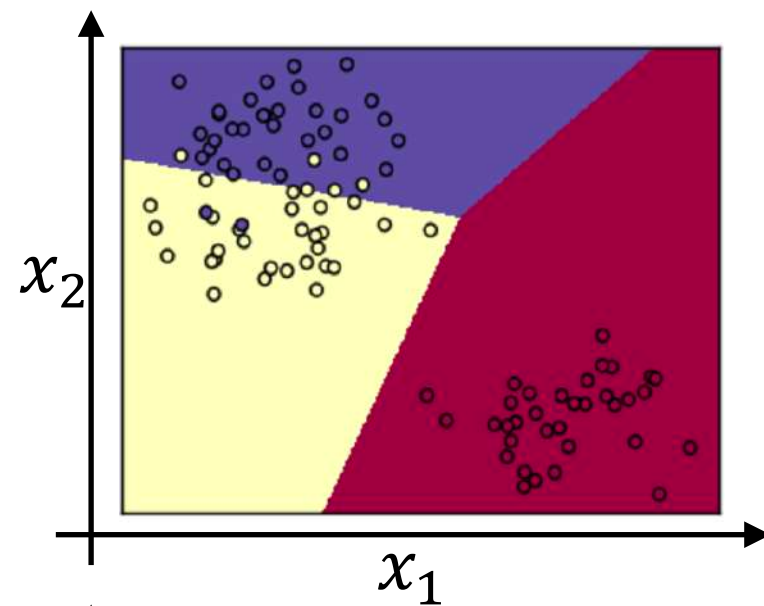
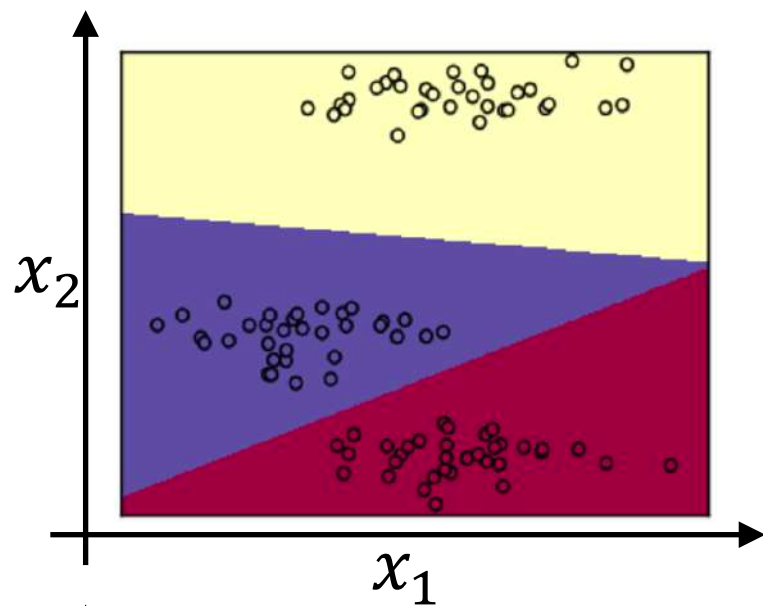
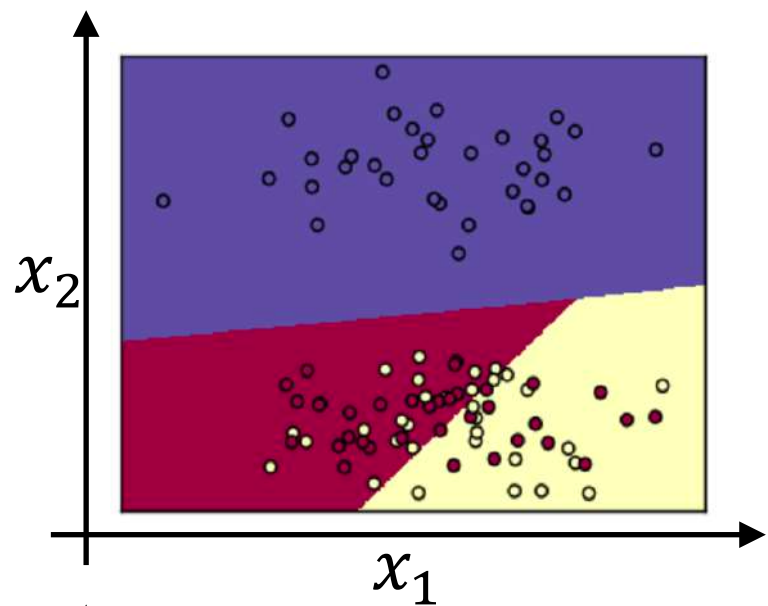
1



Softmax layer



Softmax examples





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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

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

\swarrow
 $(w-5)^2$
 $w=5$

$$J(w, b)$$

$\uparrow \quad \uparrow$