



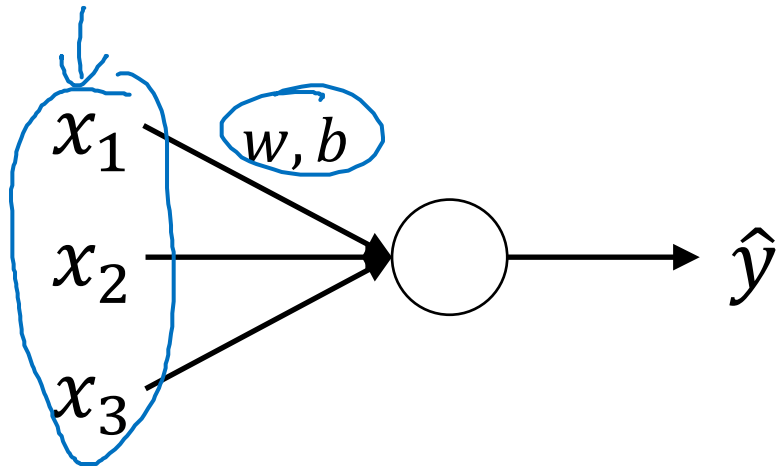
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# Batch Normalization

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Normalizing activations  
in a network

# Normalizing inputs to speed up learning

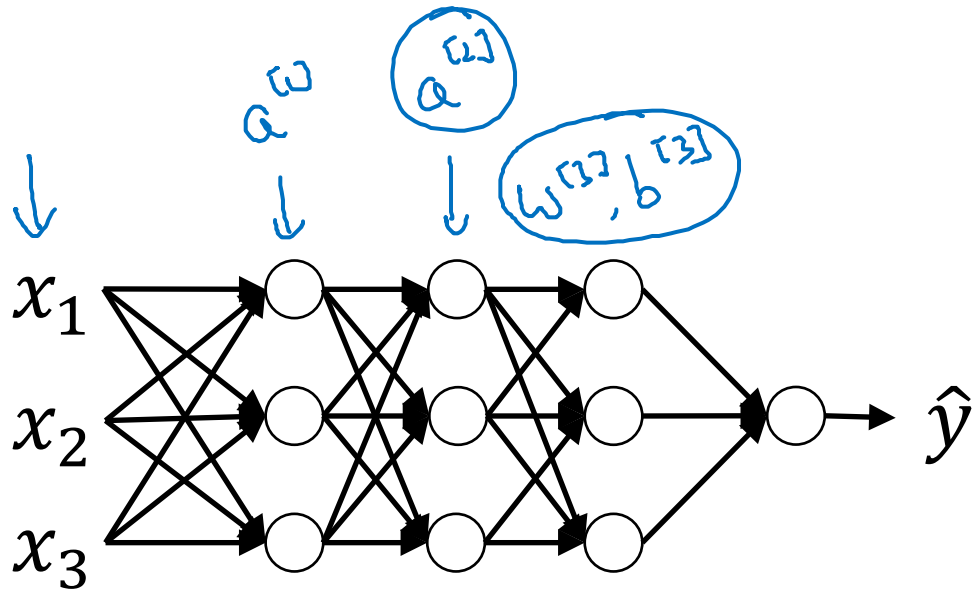
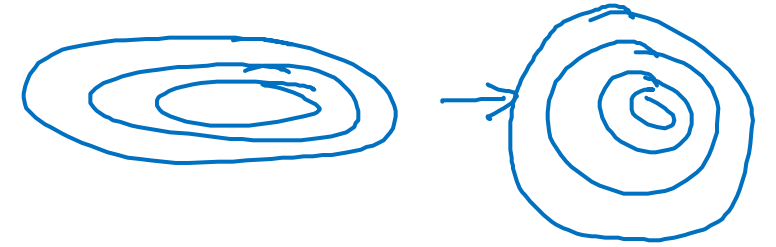


$$\mu = \frac{1}{n} \sum_i x^{(i)}$$

$$X = X - \mu$$

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

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



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

$z^{(1)}, \dots, z^{(m)}$   
 $z^{[l]}(i)$

$$\begin{aligned} \mu &= \frac{1}{m} \sum_i z^{(i)} \\ \sigma^2 &= \frac{1}{m} \sum_i (z^{(i)} - \mu)^2 \\ z_{\text{norm}}^{(i)} &= \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \epsilon}} \\ \hat{z}^{(i)} &= \gamma z_{\text{norm}}^{(i)} + \beta \end{aligned}$$

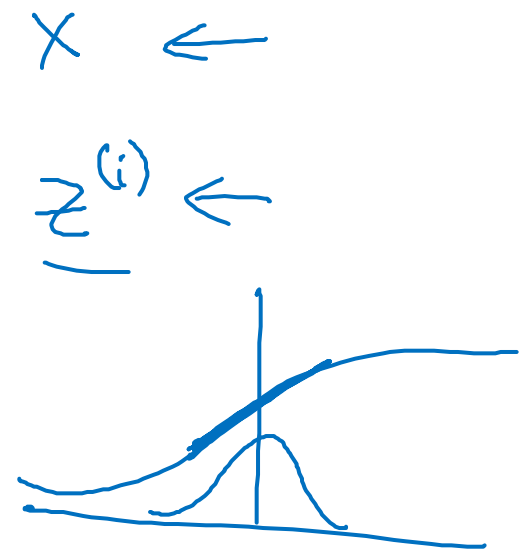
If

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

$$\beta = \mu$$

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

learnable parameters of model.



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



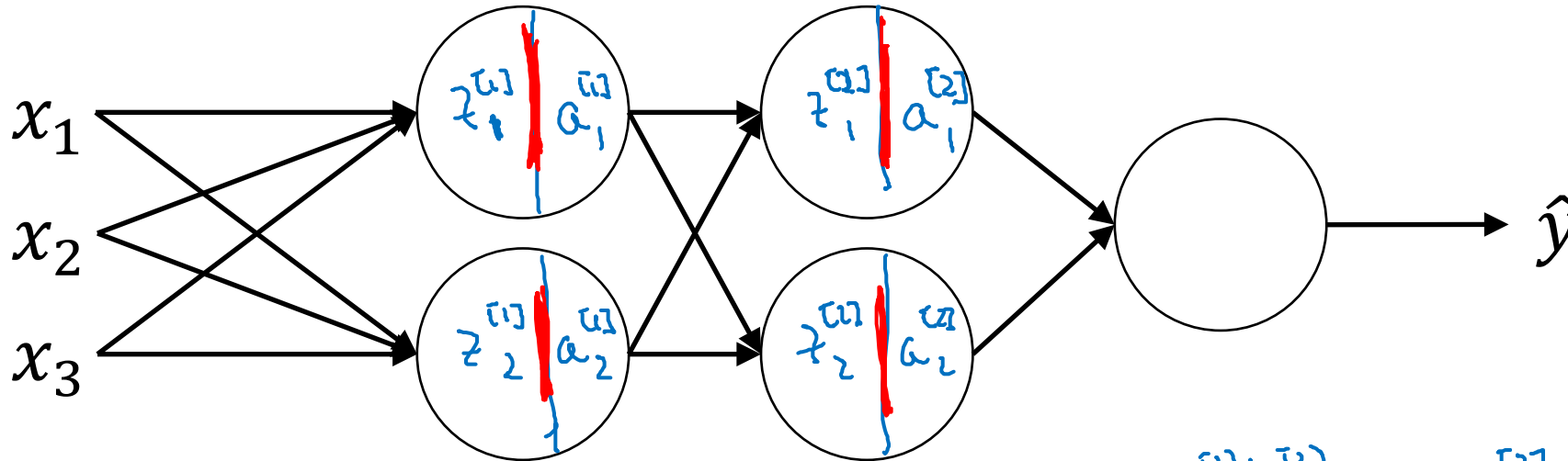
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# Batch Normalization

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Fitting Batch Norm  
into a neural network

# Adding Batch Norm to a network



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

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

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

tf.nn.batch-normalization ←

# Working with mini-batches

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

$$\boxed{X^{[2]}} \rightarrow \underline{z^{[2]}} \xrightarrow[\text{BN}]{\beta^{[2]}, \gamma^{[2]}} \underline{\tilde{z}^{[2]}} \rightarrow \dots$$

$$X^{[3]} \rightarrow \dots$$

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

$\uparrow$   $(n^{[L]}, 1)$      $\uparrow$   $(n^{[L]}, 1)$      $\uparrow$   $(n^{[L]}, 1)$

$\uparrow$   $(n^{[L]}, 1)$

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

$\uparrow$

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

$$z_{\text{norm}}^{[L]}$$

$$\rightarrow \tilde{z}^{[L]} = \gamma^{[L]} z_{\text{norm}}^{[L]} + \boxed{\beta^{[L]}}$$

# 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  $\underline{\hat{z}}^{\{t\}}$ .

Use backprop to compute  $\underline{dw}^{\{t\}}$ ,  ~~$\underline{db}^{\{t\}}$~~ ,  $\underline{dp}^{\{t\}}$ ,  $\underline{df}^{\{t\}}$

Update params 
$$\left. \begin{aligned} w^{\{t\}} &:= w^{\{t-1\}} - \alpha \underline{dw}^{\{t\}} \\ \beta^{\{t\}} &:= \beta^{\{t-1\}} - \alpha \underline{dp}^{\{t\}} \\ \gamma^{\{t\}} &:= \dots \end{aligned} \right\} \leftarrow$$

Works w/ momentum, RMSprop, Adam.



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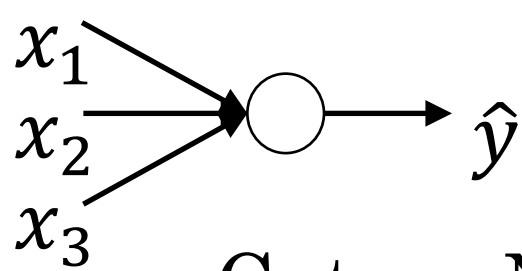
# Batch Normalization

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Why does  
Batch Norm work?



# Learning on shifting input distribution

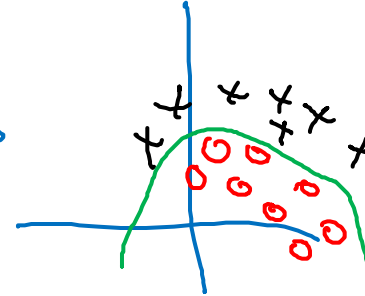
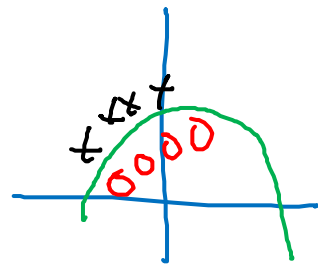


Cat

Non-Cat

$y = 1$  ✓

$y = 0$



$y = 1$  ✓

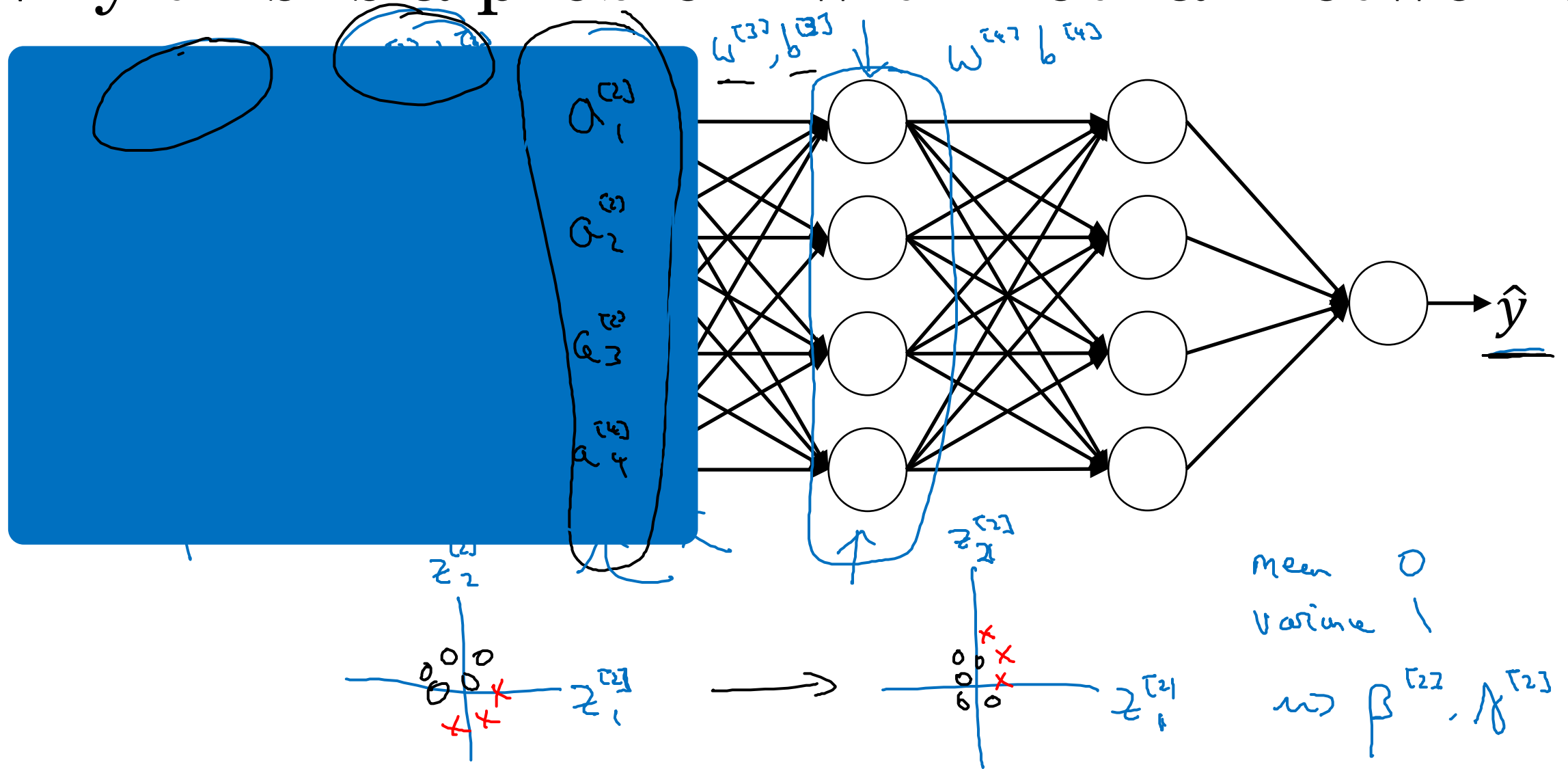
$y = 0$



"Covariate shift"

$\underline{x} \rightarrow y$

# 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