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PA-1 : Parameters Initialisation 1-In general, initializing all the weights to zero results in the network failing to break symmetry. This means that every neur

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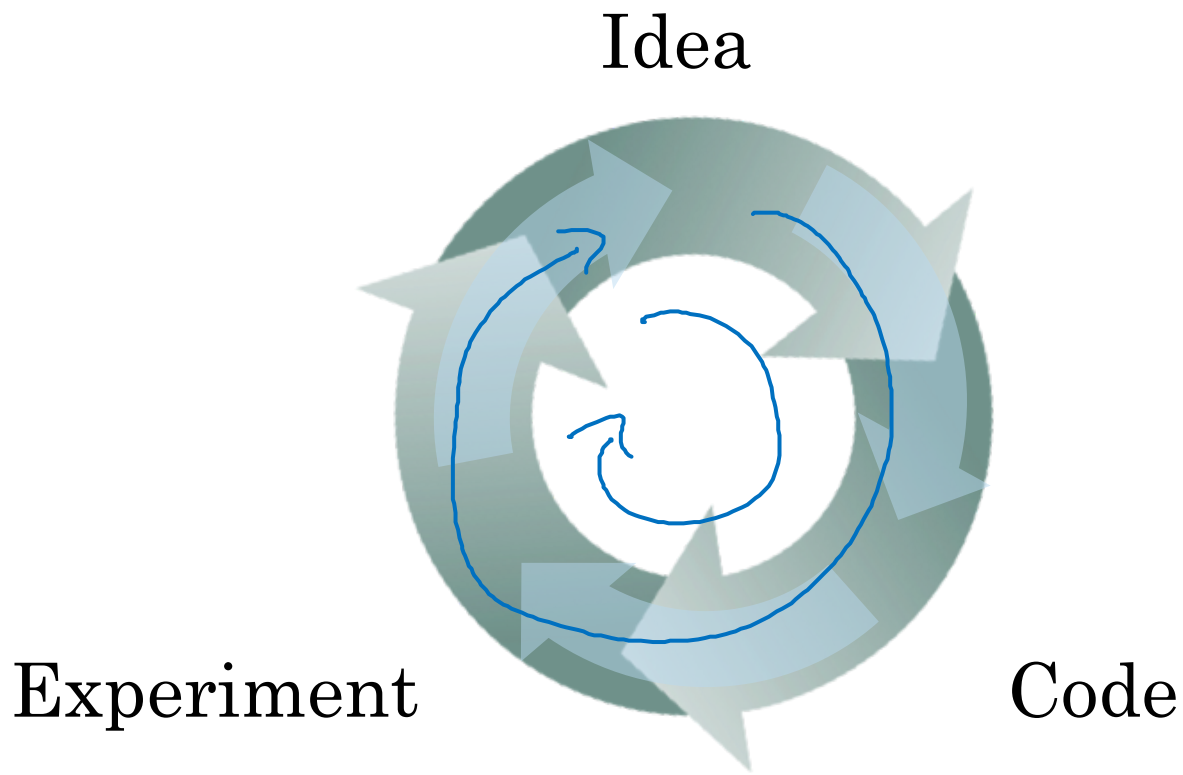
Setting up your ML application

Train/dev/test sets

Applied ML is a highly iterative process

- # layers
- # hidden units
- learning rates
- activation functions
- …



NLP, Vision, Speech, Structured data

Ads search Security logistics ....

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Train/dev/test sets

Data | training set | dev | test

- Hold-out cross validation
- Development set "dev"

test

Previous era: train / test
70/30 %
60/20/20 %
100 - 1000 - 10000

If you have small dataset then it is OK to spililt in the ratio of 60/20/20 and something like

Big data: 1,000,000 | 10,000 | 10,000

98/1/1 %

99.5 / ~~.25~~ .4 / ~~.25~~ .1 %

Mismatched train/test distribution

Cats

Training set:
Cat pictures from webpages

Dev/test sets:
Cat pictures from users using your app

→ Make sure dev and test come from same distribution.

"test"

train / dev

train / test

→ train / dev

Not having a test set might be okay. (Only dev set.)

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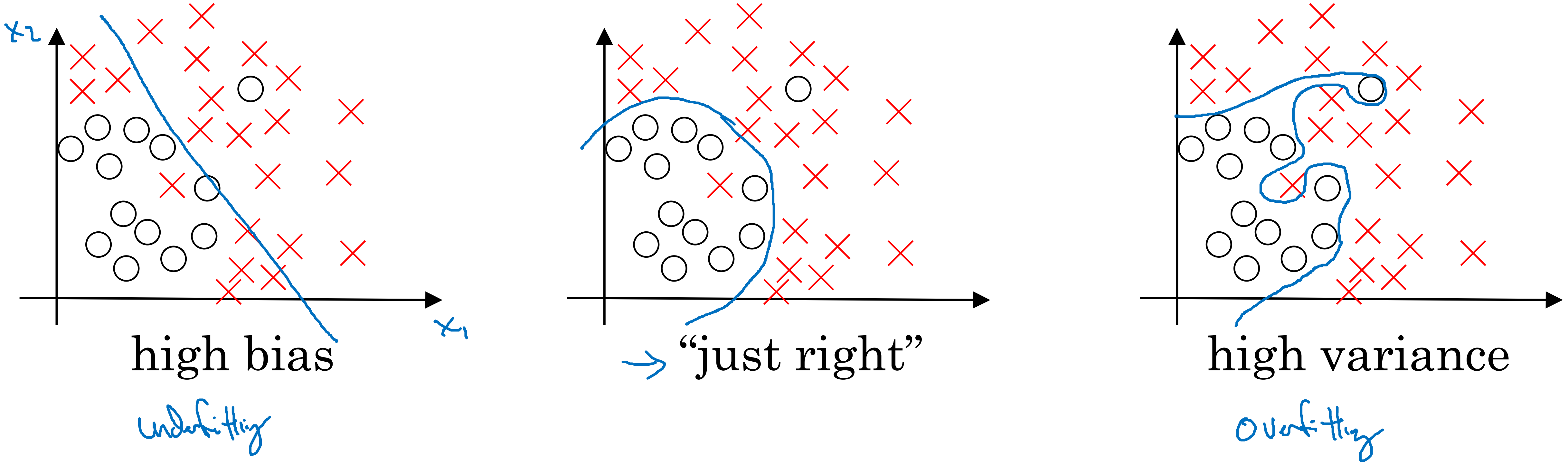
Setting up your ML application

Bias/Variance

Bias and Variance



O and V paas paas hain

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Bias and Variance

Cat classification

$y=1$

$y=0$

Train set error:	1%	15%	15%	0.5%
Dev set error:	11%	16%	30%	1%
	high variance	high bias	high bias & high varian	low bias low variance

Human : ≈ 0%

Optimal (Bayes) error : ~~≈ 0%~~ 15%   Blurry images

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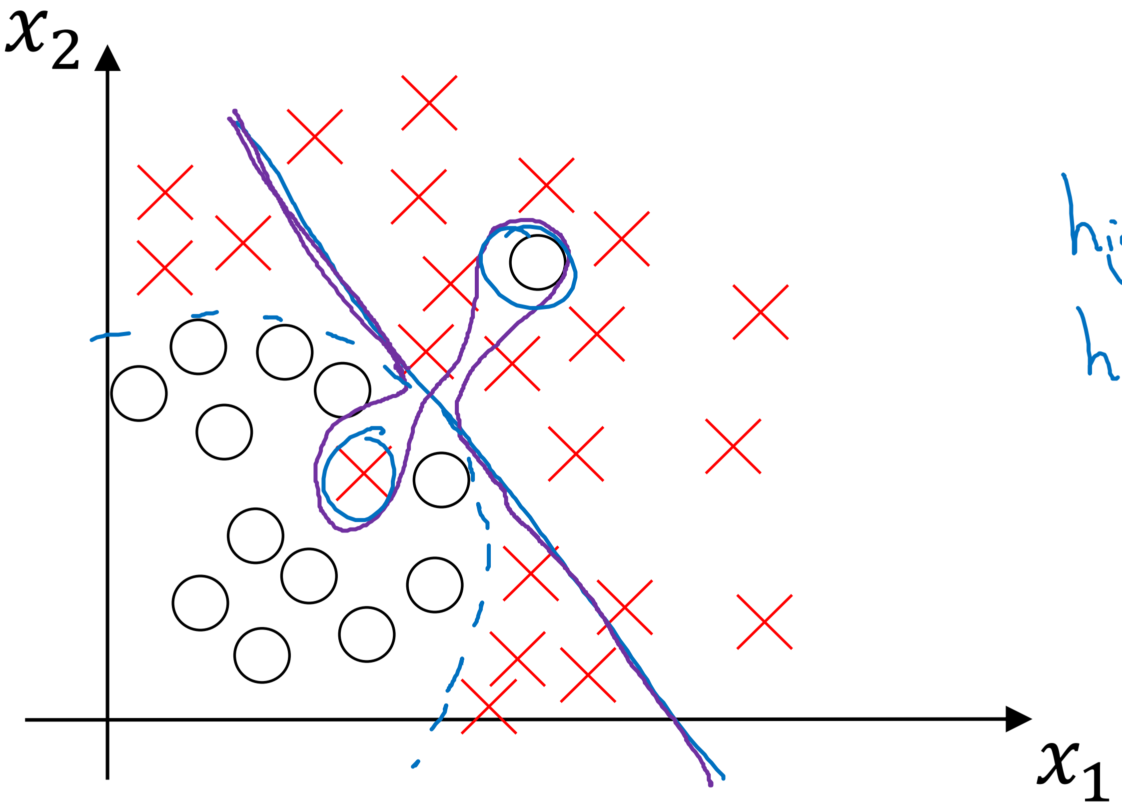
High bias and high variance



high bias
high varian

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Setting up your ML application

Basic “recipe” for machine learning

Basic recipe for machine learning

High bias?
(training data performance)

Y → Bigger network
→ Train longer.
→ (NN architecture search)

↓ N

High variance?
(dev set performance)

Y → More data
→ Regularization
→ (NN architecture search)

↓ N

Done

Bias variance "tradeoff"

In earlier times there used to be trade-off but now w

Regularizing your neural network

Regularization

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Logistic regression

$w \in \mathbb{R}^{n_x}$, $b \in \mathbb{R}$

$\boxed{\lambda = \text{regularization parameter}}$

lambda lambd

$$\min_{w,b} J(w, b)$$

$$J(w,b) = \underbrace{\frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})} + \frac{\lambda}{2m} \underbrace{\|w\|_2^2}$$

$$\cancel{+ \frac{\lambda}{2m} b^2}$$

omit

L_2 regularization $\quad \|w\|_2^2 = \sum_{j=1}^{n_x} w_j^2 = w^T w \longleftarrow$

L_1 regularization $\quad \frac{\lambda}{2m} \sum_{j=1}^{n_x} |w_j| = \frac{\lambda}{2m} \|w\|_1$

w will be sparse

Neural network

$$J(w^{[1]}, b^{[1]}, \ldots, w^{[L]}, b^{[L]}) = \underbrace{\frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})} + \underbrace{\frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2}$$

$$\|w^{[l]}\|_F^2 = \sum_{i=1}^{n^{[l]}} \sum_{j=1}^{n^{[l-1]}} \left(w_{ij}^{[l]}\right)^2 \qquad w^{[l]} : (n^{[l]}, n^{[l-1]})$$

"Frobenius norm" $\qquad \|\cdot\|_2^2 \qquad \|\cdot\|_F^2$

$$dw^{[l]} = (\text{from backprop}) + \frac{\lambda}{m} w^{[l]} \qquad \underbrace{\frac{\partial J}{\partial w^{[l]}}} = dw^{[l]}$$

$$\rightarrow w^{[l]} := w^{[l]} - \alpha \, dw^{[l]}$$

"Weight decay"

$$w^{[l]} := w^{[l]} - \alpha\left[(\text{from backprop}) + \frac{\lambda}{m} w^{[l]}\right]$$

$$= w^{[l]} - \frac{\alpha\lambda}{m} w^{[l]} - \alpha(\text{from backprop})$$

$$= \underbrace{\left(1 - \frac{\alpha\lambda}{m}\right)}_{<1} w^{[l]} - \alpha(\text{from backprop})$$

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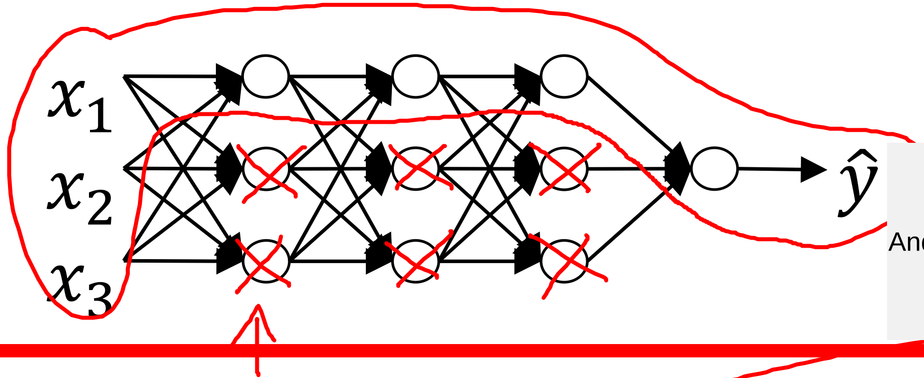
Regularizing your neural network

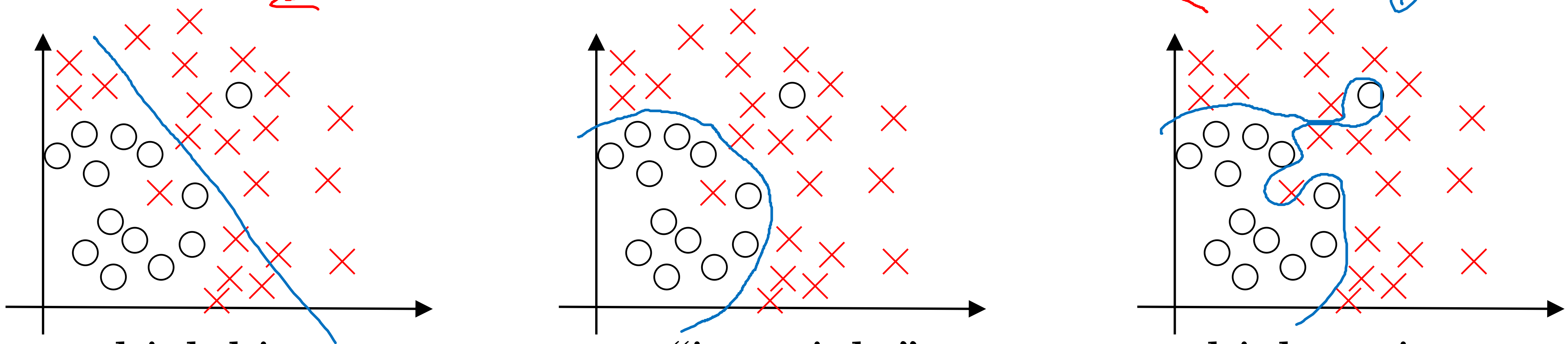
Why regularization reduces overfitting

How does regularization prevent overfitting?



$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \underbrace{\|w^{[l]}\|_F^2}$$

And so what we did for regularization was add this extra term thatpenalizes the weight matrices from being too large.And we said that v



high bias "just right" high variance

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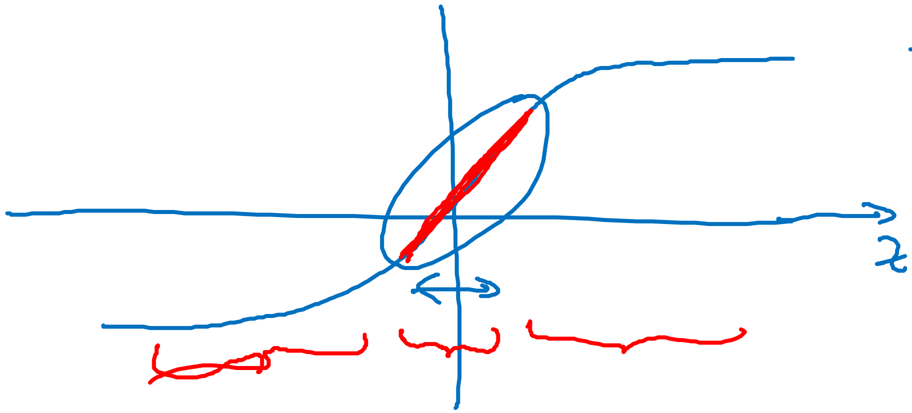
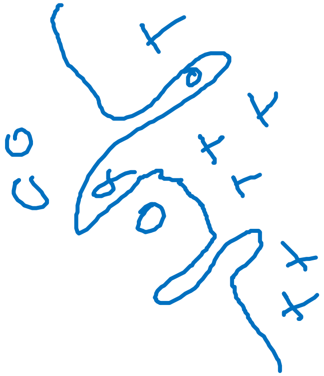
How does regularization prevent overfitting?



tanh

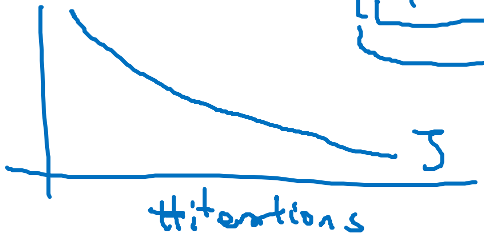
$g(z) = \tanh(z)$



$\lambda \uparrow$ $\quad W^{[l]} \downarrow$ $\quad z^{[l]} = W^{[l]} a^{[l-1]} + b^{[l]}$

Every layer $\approx$ linear.

$$J(\dots) = \underbrace{\boxed{\sum_i \mathcal{L}(\hat{y}^{(i)}, y^{(i)})} + \frac{\lambda}{2m} \sum_l \|W^{[l]}\|_F^2}$$



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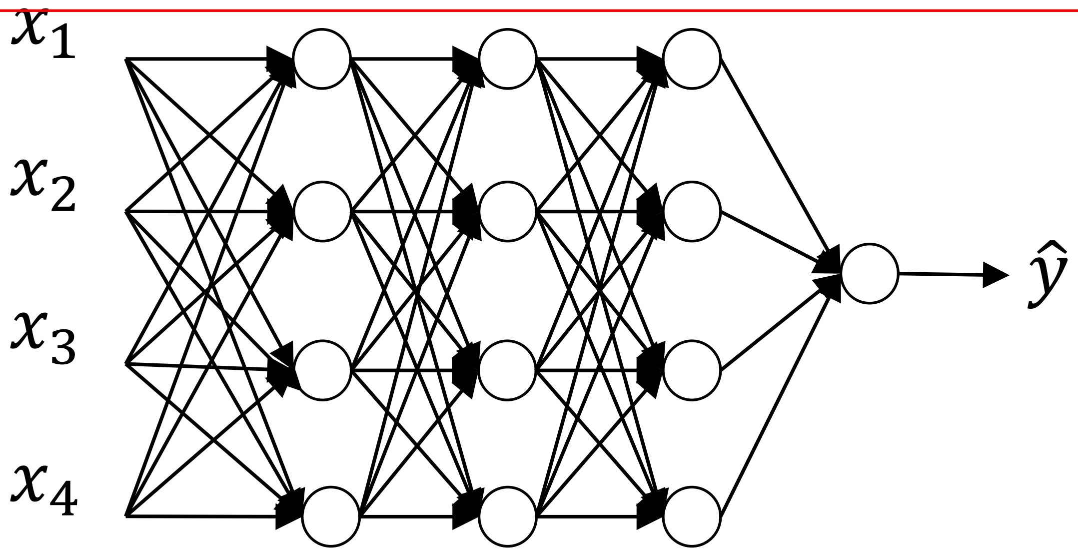
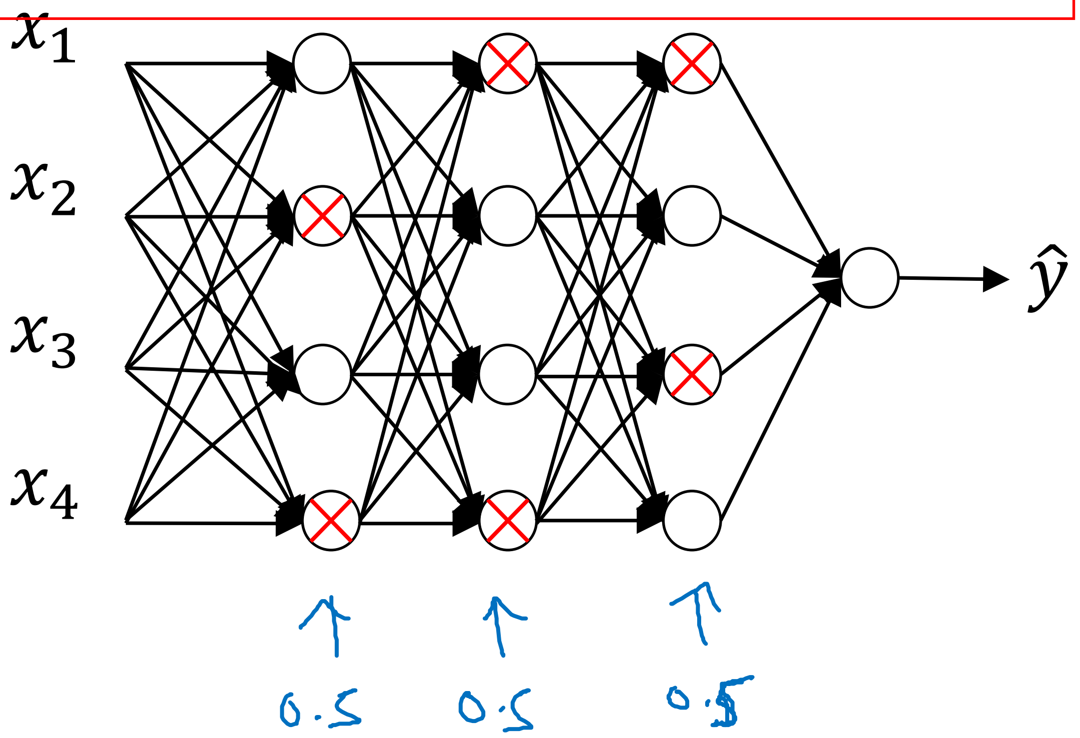
Regularizing your neural network

Dropout regularization

Dropout regularization

what we do we assoctiate a probability with each node denoting its probability of being dropped out. then we actiallly drop those nodes and do our traini





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Implementing dropout ("Inverted dropout")

Illustrate with layer $l=3$. keep-prob $= 0.8$ 0.2

→ $\boxed{d3}$ = np.random.rand(a3.shape[0], a3.shape[1]) < keep-prob

a3 = np.multiply(a3, d3) # a3 *= d3.

→ $\boxed{\text{a3 /= }\cancel{0.8}\text{ keep-prob}}$ ←

50 units. ⇝ 10 units shut off

$z^{[4]} = W^{[4]} \cdot a^{[3]} + b^{[4]}$

reduced by 20%. Test

/= 0.8

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Making predictions at test time

$a^{[0]} = X$

$\boxed{\text{No drop out.}}$

No drop out at the testong time.

$z^{[1]} = W^{[1]} a^{[0]} + b^{[1]}$

$a^{[1]} = g^{[1]}(z^{[1]})$

$z^{[2]} = W^{[2]} a^{[1]} + b^{[2]}$

$a^{[2]} = \ldots$

$\downarrow$

$\hat{y}$

$/= \text{keep-prob}$

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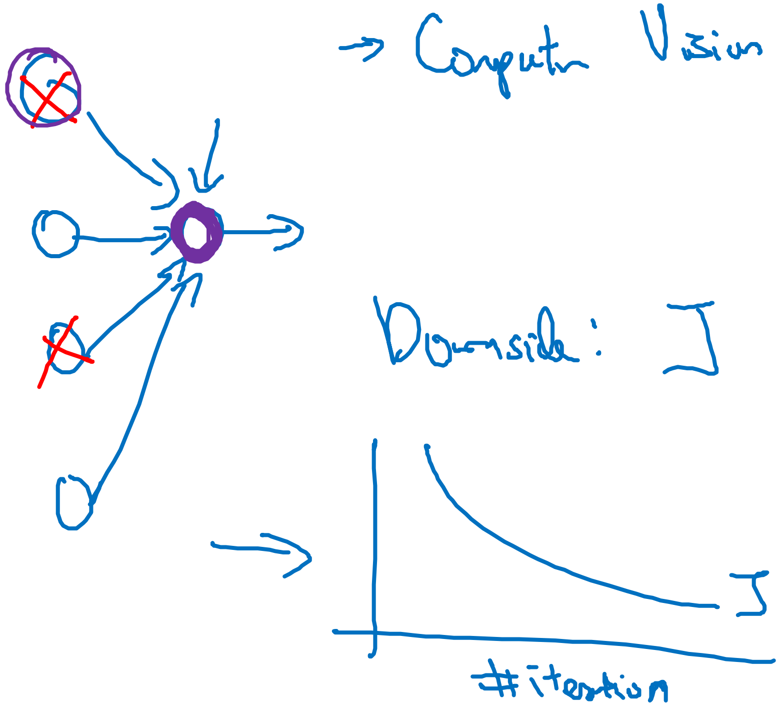
Regularizing your neural network

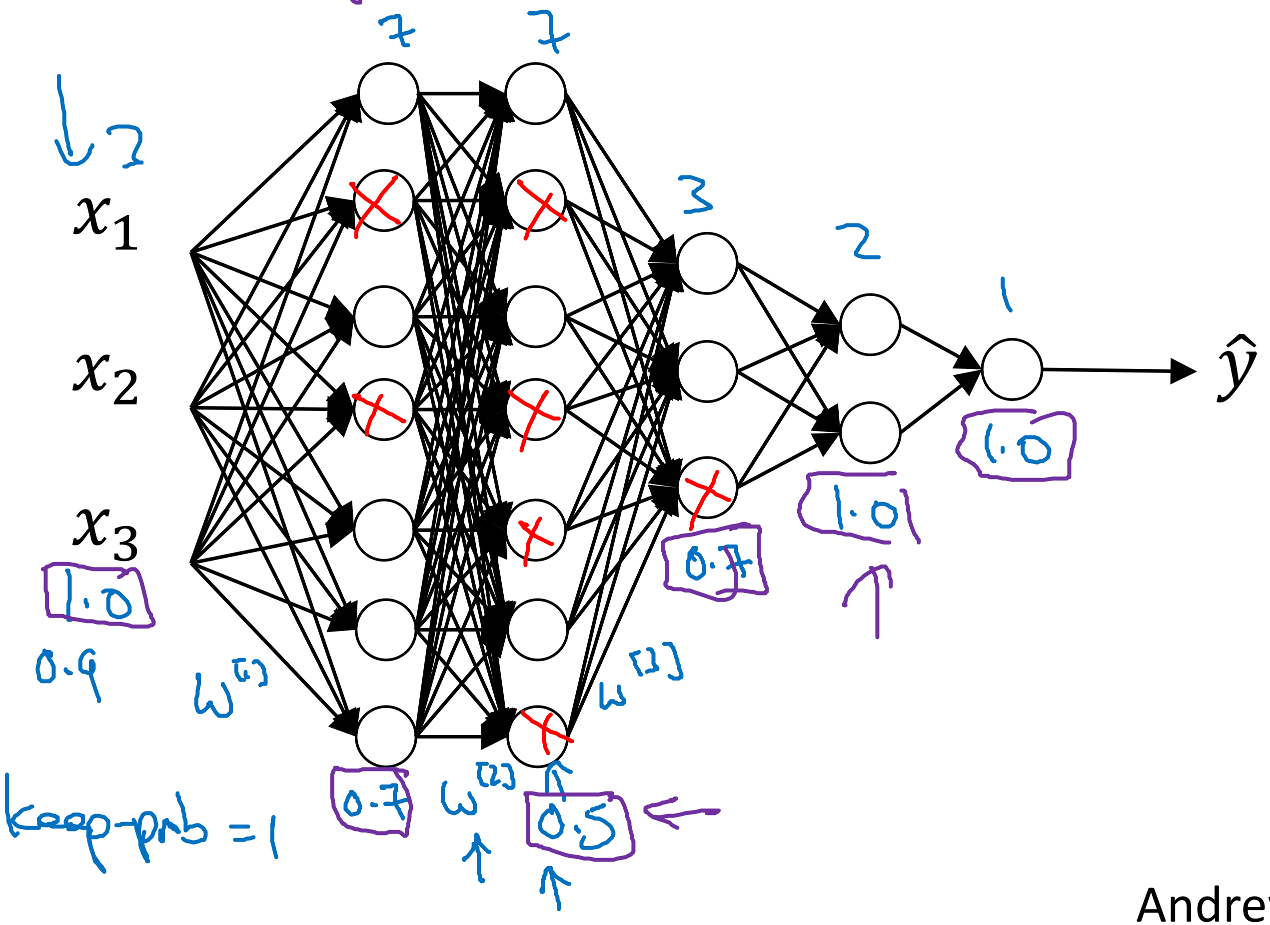
Understanding dropout

Why does drop-out work?

Jahan par overfitting ka dar lage, ya parameters jyada hon waha

Intuition: Can't rely on any one feature, so have to spread out weights. ⇝ Shrink weights.





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Regularizing your neural network

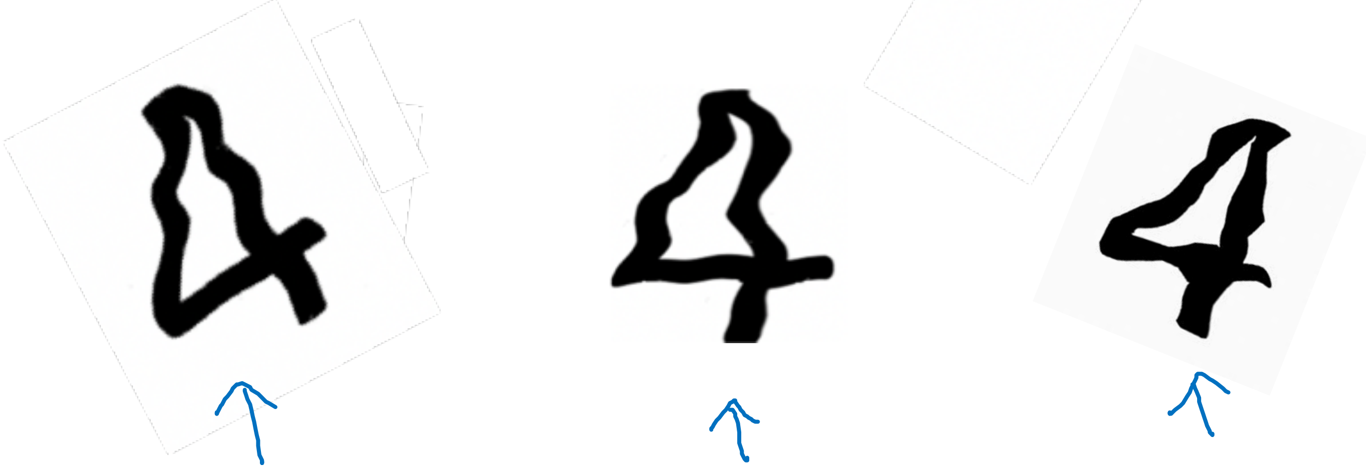
Other regularization methods

Data augmentation

Jo data hai usi ko ghuma phira ke naya data bana do. Kahin se aur dataa mil jaay

4

Augument karo



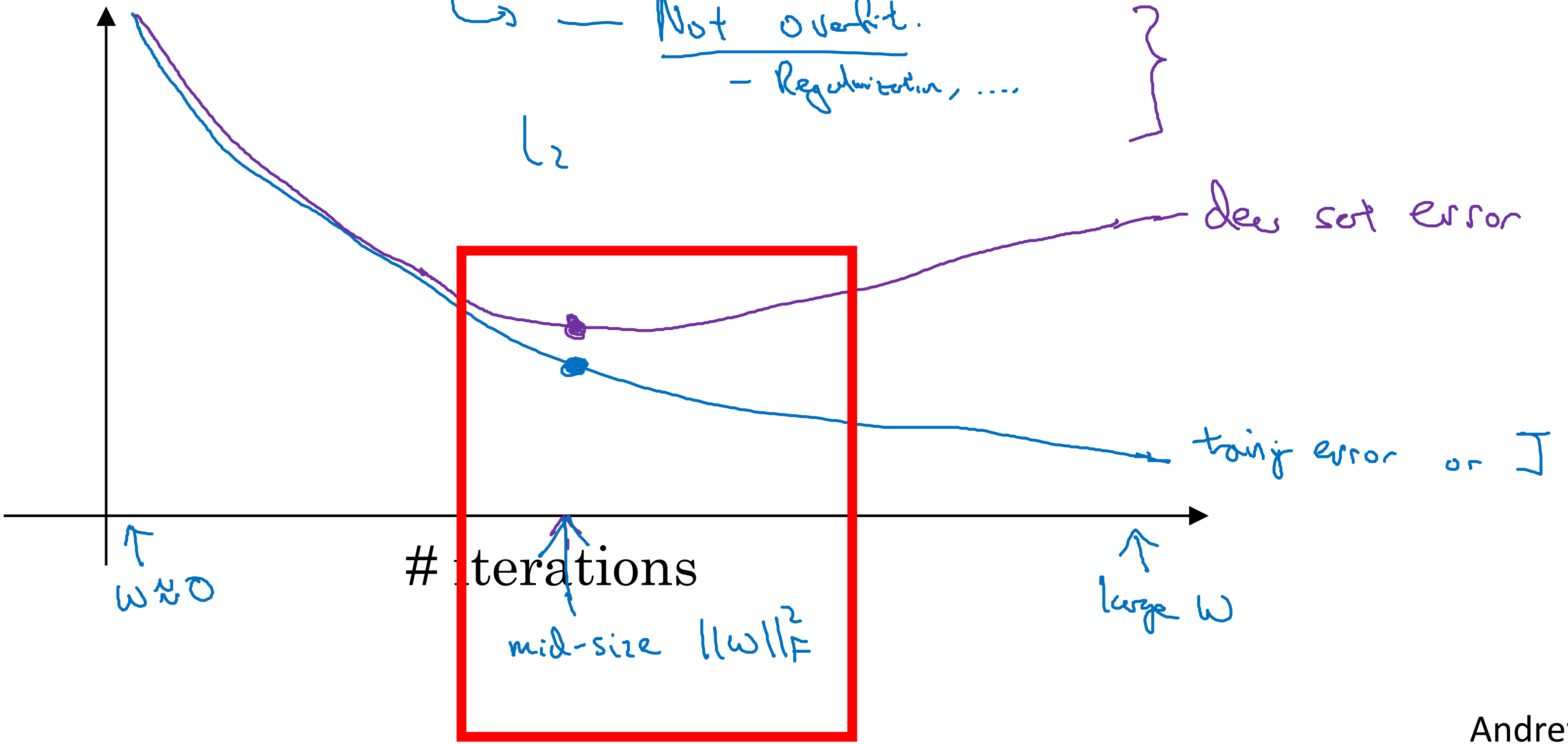
Early stopping

Orthogonalization.

- Optimize cost function J
  - Gradient, ...
- Not overfit.
  - Regularization, ...

$J(w,b)$

L_2



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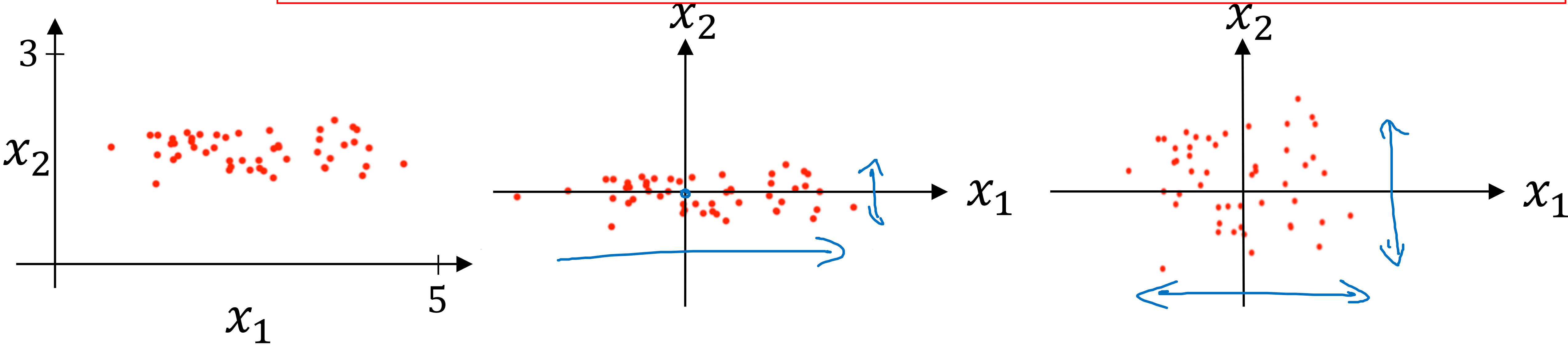
Setting up your optimization problem

Normalizing inputs

Normalizing training sets

$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

Normalizing involves two steps. The first is two is subtract out means from every training set and then to normalize the variance



Subtract mean:

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

$$\boxed{x := x - \mu}$$

Normalize variance

$$\boxed{\sigma^2} = \frac{1}{m} \sum_{i=1}^{m} x^{(i)} {**} 2$$

← element-wise

$$\boxed{x \mathbin{/}= \sigma^2}$$

Use same μ, σ^2 to normalize test set.

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Why normalize inputs?

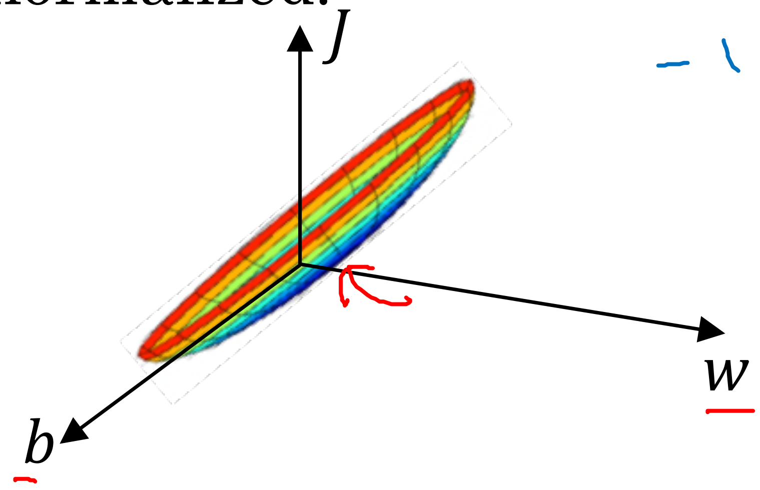
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

w_1 x_1 : 1 . . . . 1000 ←

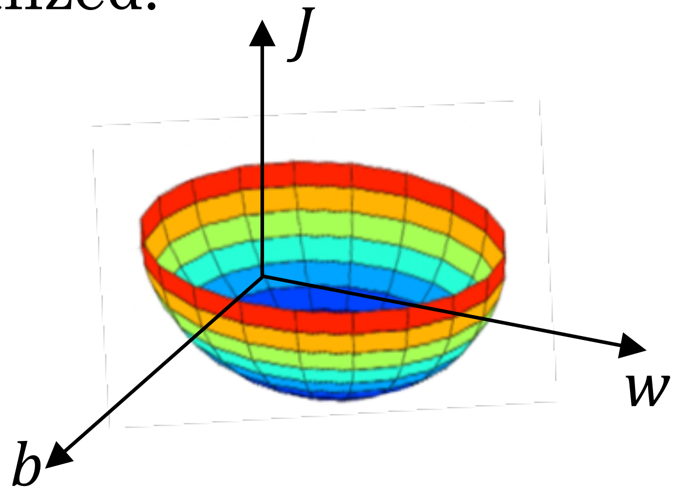
w_2 x_2 : 0 . . . 1 ←

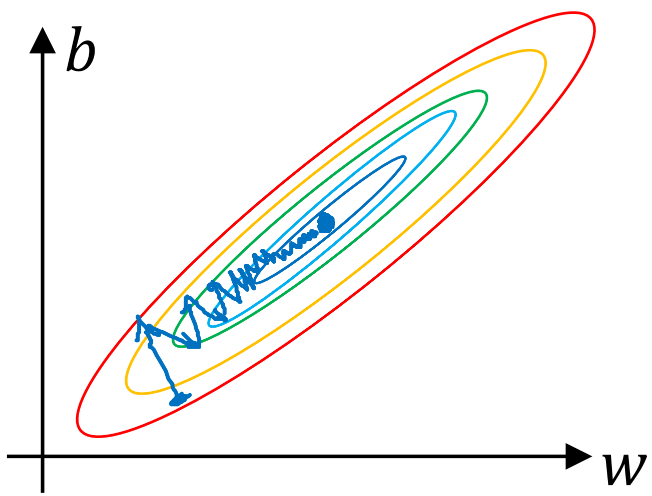
−1 . . . 1

Unnormalized:



Normalized:

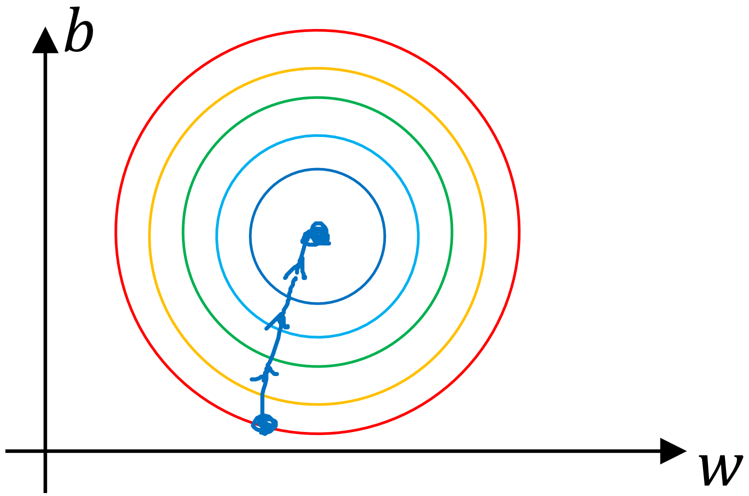




x_1 : 0 . . . 1

x_2 : −1 . . 1

x_3 : 1 . . 2



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What that means is that when you're training a very deep network your derivatives or your slopes can sometimes get either very, very big or very, very sm

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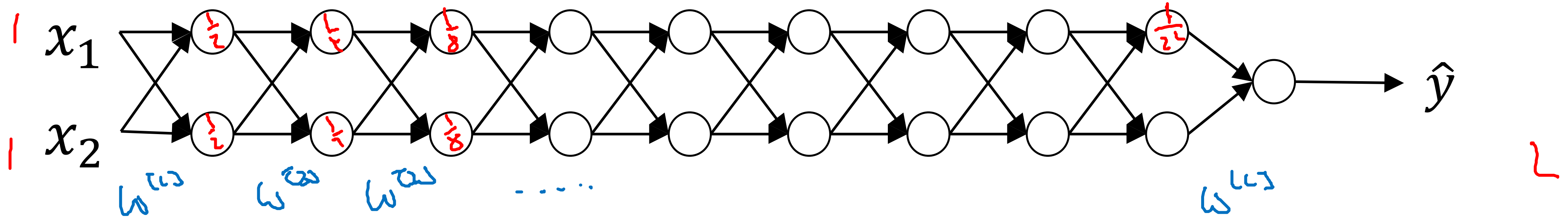
Setting up your optimization problem

Vanishing/exploding gradients

Vanishing/exploding gradients

$L = 150$



$g(z) = z$. $\quad b^{[l]} = 0$.

$\hat{y} = W^{[L]} W^{[L-1]} W^{[L-2]} \cdots \boxed{W^{[3]} \boxed{W^{[2]} W^{[1]} x}}$ $\quad a^{[3]}$

1.5^L

0.5^L

$z^{[1]} = W^{[1]} x$

$a^{[1]} = g(z^{[1]}) = z^{[1]}$

$a^{[2]} = g(z^{[2]}) = g(W^{[2]} a^{[1]})$

$W^{[l]} > I$

$W^{[l]} < I \quad \begin{bmatrix} 0.9 & \\ & 0.9 \end{bmatrix}$

$W^{[l]} = \begin{bmatrix} \cancel{1.5} \; 0.5 & 0 \\ 0 & \cancel{1.5} \; 0.5 \end{bmatrix}$

$\hat{y} = W^{[L]} \begin{bmatrix} \cancel{1.5} \; 0.5 & 0 \\ 0 & \cancel{1.5} \; 0.5 \end{bmatrix}^{L-1} x$

$1.5^{L-1} x$

$0.5^{L-1} x$

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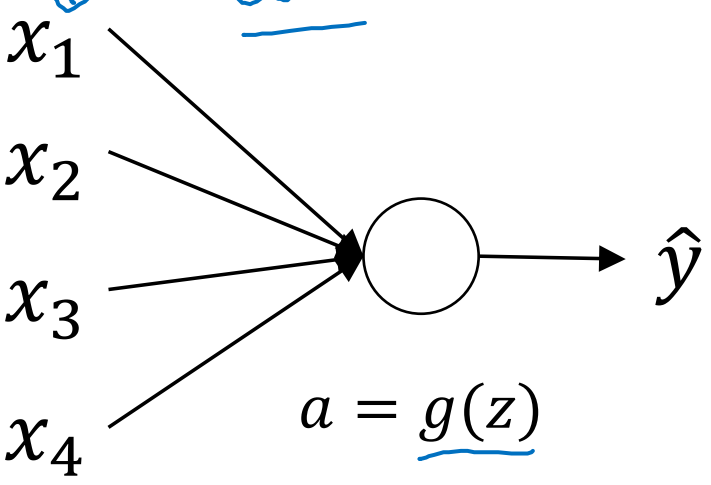
Single neuron example

$a^{[l]}$



$w^{[l]}$

$z = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n \cancel{+b}$

Large n → Smaller w_i

$Var(w_i) = \cancel{\frac{1}{n}}\ \frac{2}{n}$

$W^{[l]} =$ np.random.randn(shape) $*$ $\boxed{\text{np.sqrt}\left(\frac{2}{n^{[l-1]}}\right)}$

ReLU $\qquad g^{[l]}(z) = \text{ReLU}(z)$

Other variants:

tanh $\quad \sqrt{\frac{1}{n^{[l-1]}}}$

$\boxed{\text{Xavier initialization}}$

$\sqrt{\frac{2}{n^{[l-1]} + n^{[l]}}}$

for other than relu, numerator is 1

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Setting up your optimization problem

Numerical approximation of gradients

Checking your derivative computation

$$f(\theta) = \theta^3$$

J

$\theta \in \mathbb{R}$.

$$g(\theta) = \frac{d}{d\theta} f(\theta) = f'(\theta)$$

$$g(\theta) = 3\theta^2.$$

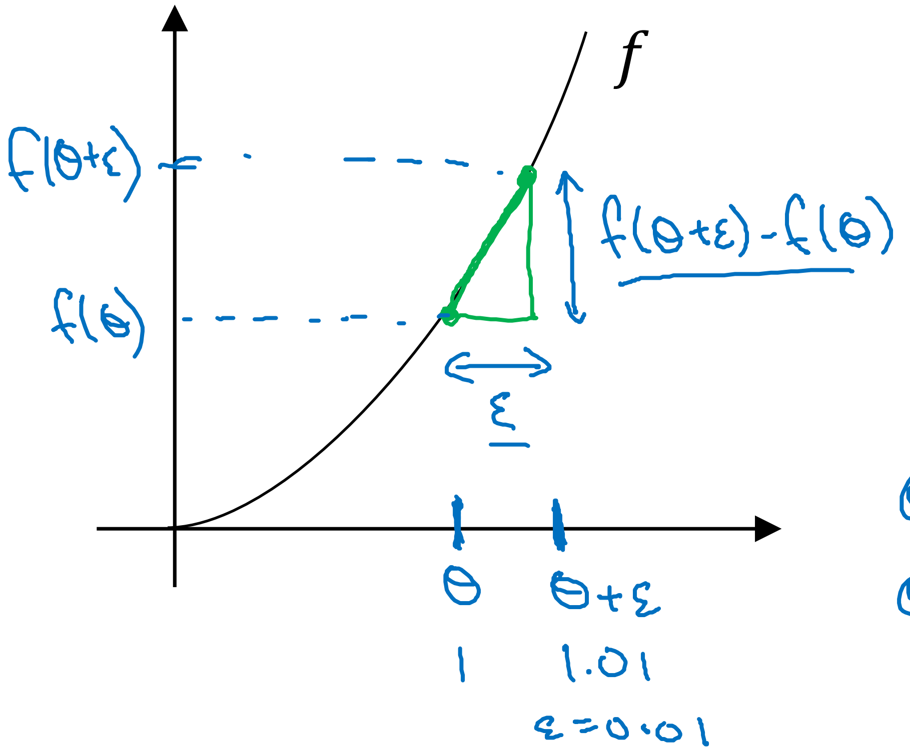
dw

db

$g(\theta) = 3 \cdot (1)^2 = 3$

when $\theta = 1$

$$\boxed{\frac{f(\theta+\varepsilon) - f(\theta)}{\varepsilon} \approx g(\theta)}$$



$$\frac{(1.01)^3 - 1^3}{0.01} = 3.0301 \approx 3$$

$\theta = 1$

$\theta + \varepsilon = 1.01$

0.0301

3.1

3.2

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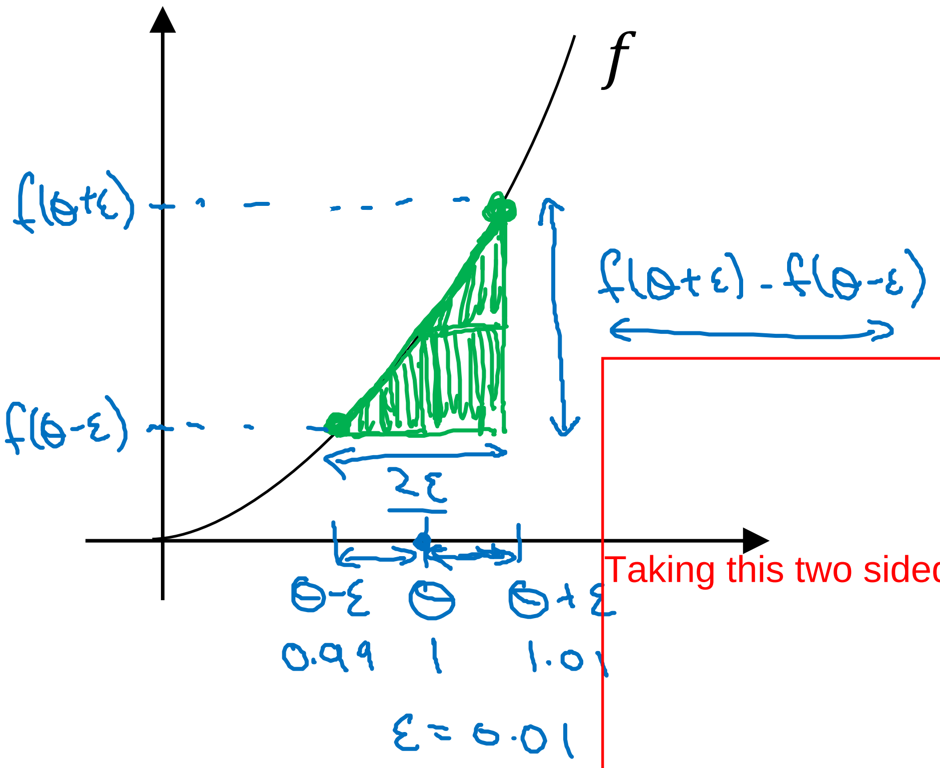
Checking your derivative computation

$f(\theta) = \theta^3$



Taking this two sided approx arou

$$\frac{f(\theta+\varepsilon) - f(\theta-\varepsilon)}{2\varepsilon} \approx g(\theta)$$

$$\frac{(1.01)^3 - (0.99)^3}{2(0.01)} = 3.0001 \approx 3$$

$$g(\theta) = 3\theta^2 = 3$$

approx error: 0.0001

(prev slide: 3.0301. error: 0.03)

$$f'(\theta) = \lim_{\varepsilon \to 0} \frac{f(\theta+\varepsilon) - f(\theta-\varepsilon)}{2\varepsilon} \qquad O(\varepsilon^2)$$

0.01

0.0001

$$\frac{f(\theta+\varepsilon) - f(\theta)}{\varepsilon} \qquad \text{error}: O(\varepsilon)$$

0.01

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Setting up your optimization problem

Gradient Checking

To check correctness of gradient descent and to find bug in back propo case it is useful.

Gradient check for a neural network

Take $W^{[1]}, b^{[1]}, \ldots, W^{[L]}, b^{[L]}$ and reshape into a big vector θ.

concatenate

$J(W^{[1]}, b^{[1]}, \ldots, W^{[L]}, b^{[L]}) = J(\theta)$

Take $dW^{[1]}, db^{[1]}, \ldots, dW^{[L]}, db^{[L]}$ and reshape into a big vector $d\theta$.

concatenate

Is $d\theta$ the gradient of $J(\theta)$?

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Gradient checking (Grad check)

$J(\theta) = J(\theta_1, \theta_2, \theta_3, \ldots)$

for each i :

$\rightarrow d\theta_{approx}[i] = \dfrac{J(\theta_1, \theta_2, \ldots, \theta_i + \varepsilon, \ldots) - J(\theta_1, \theta_2, \ldots, \theta_i - \varepsilon, \ldots)}{2\varepsilon}$

Only change theta_i

$\approx d\theta[i] = \dfrac{\partial J}{\partial \theta_i}$

$d\theta_{approx} \overset{?}{\approx} d\theta$

Check $\dfrac{\| d\theta_{approx} - d\theta \|_2}{\| d\theta_{approx} \|_2 + \| d\theta \|_2}$ $\approx$ $\boxed{10^{-7} - \text{great!}}$ $\leftarrow$

10^{-5}

$\rightarrow 10^{-3}$ – worry. $\leftarrow$

$\boxed{\varepsilon = 10^{-7}}$

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Setting up your optimization problem

Gradient Checking implementation notes

Gradient checking implementation notes

- Don't use in training – only to debug

$d\theta_{approx}[i] \longleftrightarrow d\theta[i]$

- If algorithm fails grad check, look at components to try to identify bug.

$db^{[l]}$ $dw^{[l]}$

- Remember regularization.

$J(\theta) = \frac{1}{m} \sum_i \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m} \sum_l \|w^{[l]}\|_F^2$

$d\theta$ = gradient of J w.r.t. θ

- Doesn't work with dropout.

J keep-prob = 1.0

- Run at random initialization; perhaps again after some training.

$w, b \approx 0$

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