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Setting up your ML application

Train/dev/test sets

Applied ML is a highly iterative process

layers

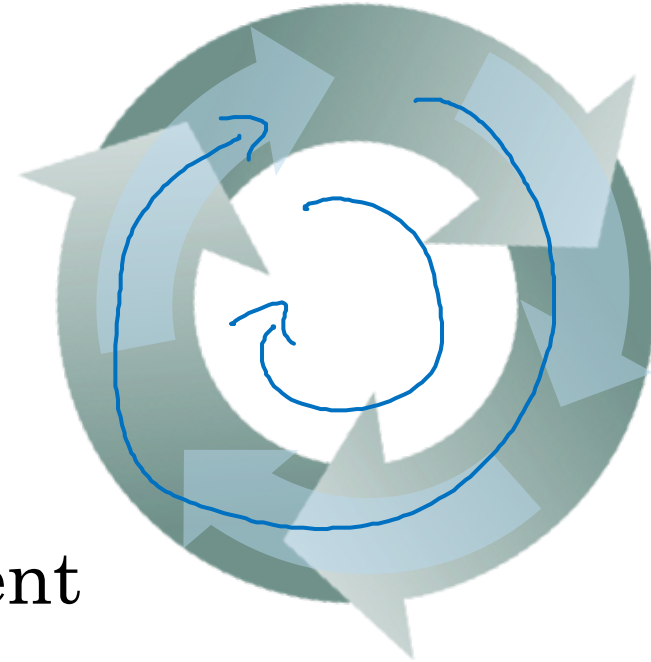
hidden units

learning rates

activation functions

...

Idea



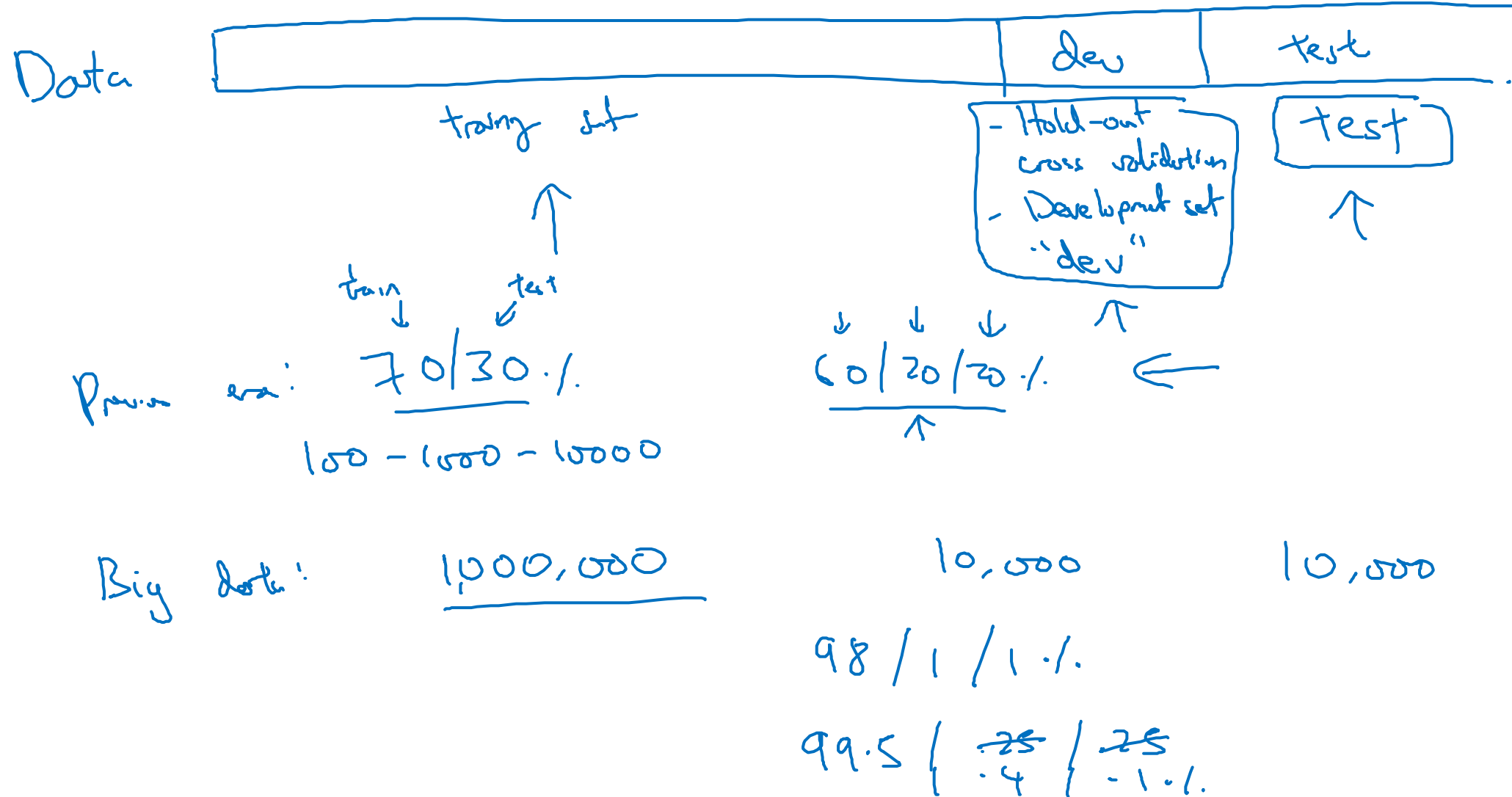
Experiment

Code

NLP, Vision, Speech, Structured data

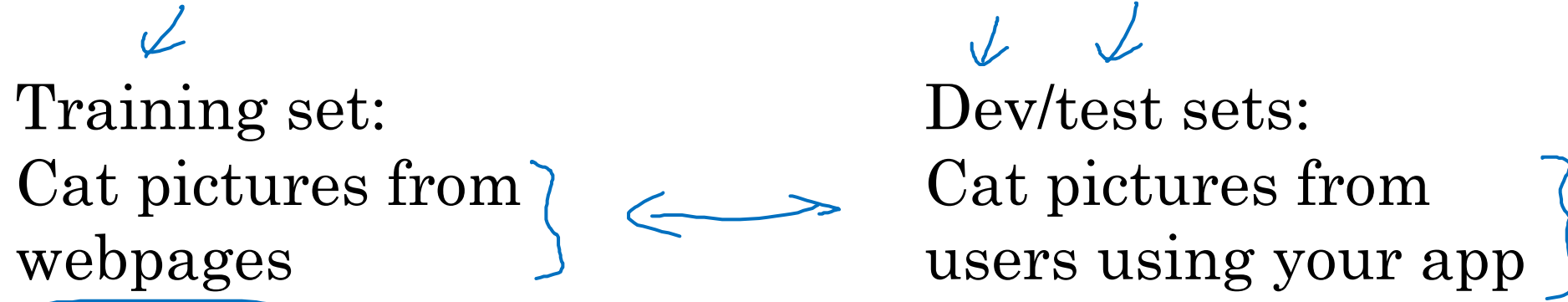
```
graph TD; A["NLP, Vision, Speech"] --> B[Ads]; C[Structured data] --- D[Search]; C --- E[Security]; C --- F["logistic ..."]; E --> F;
```

Train/dev/test sets

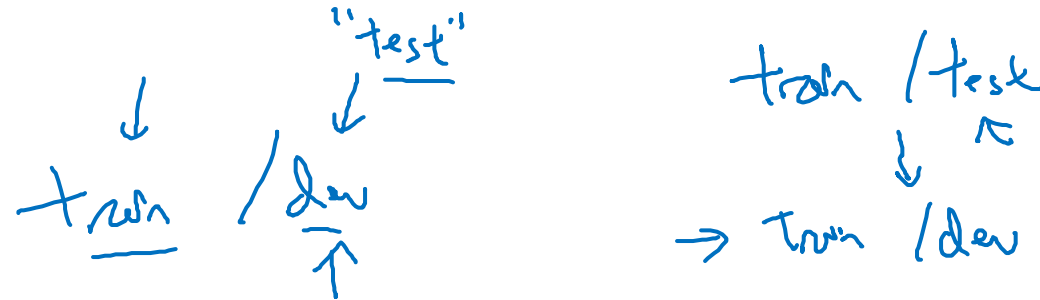


Mismatched train/test distribution

Certs



→ Make sure dev and test come from same distribution.



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

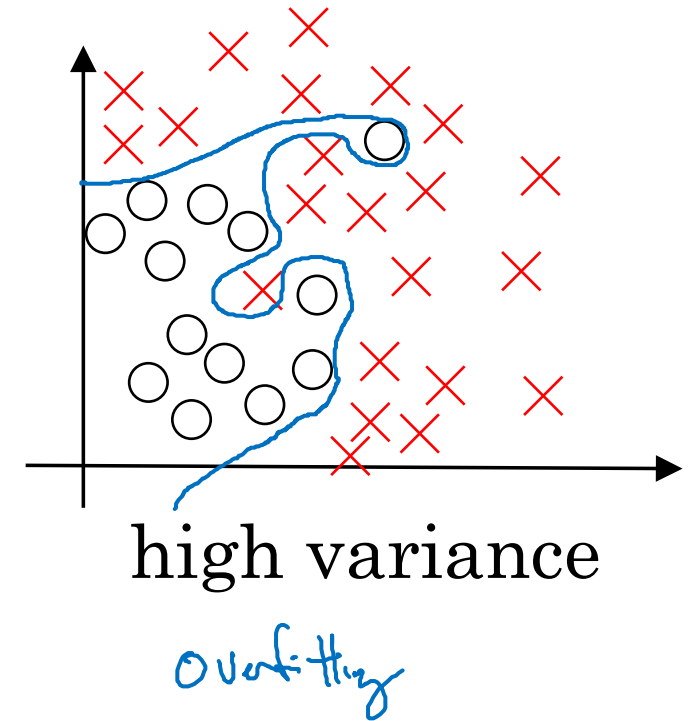
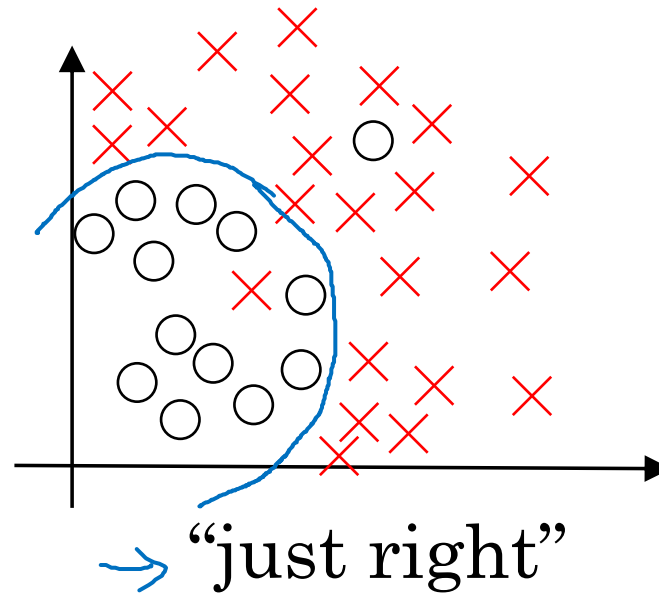
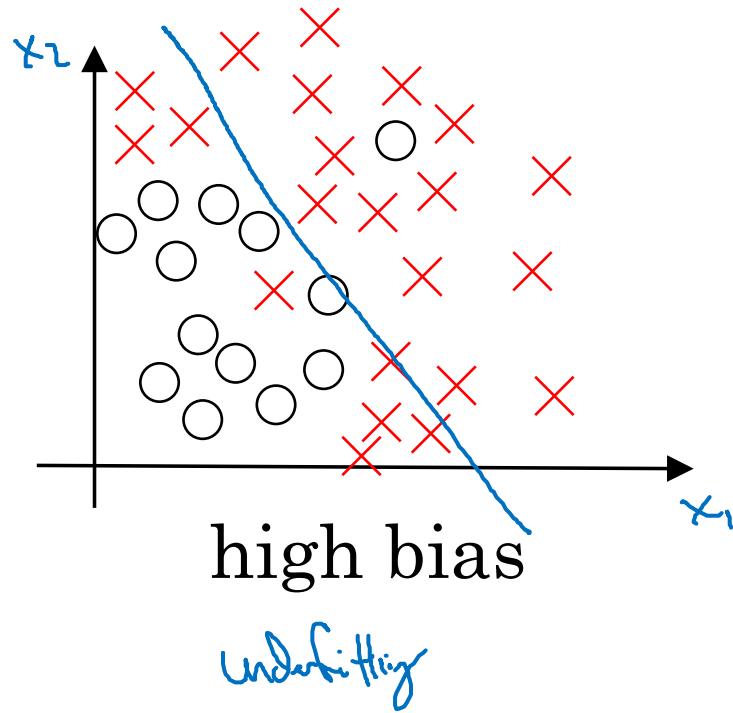


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Setting up your ML application

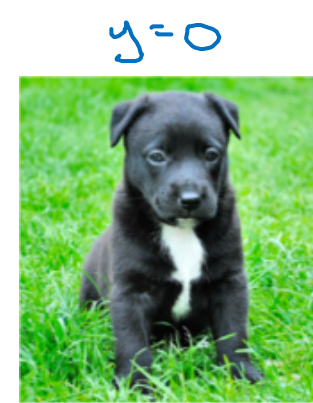
Bias/Variance

Bias and Variance



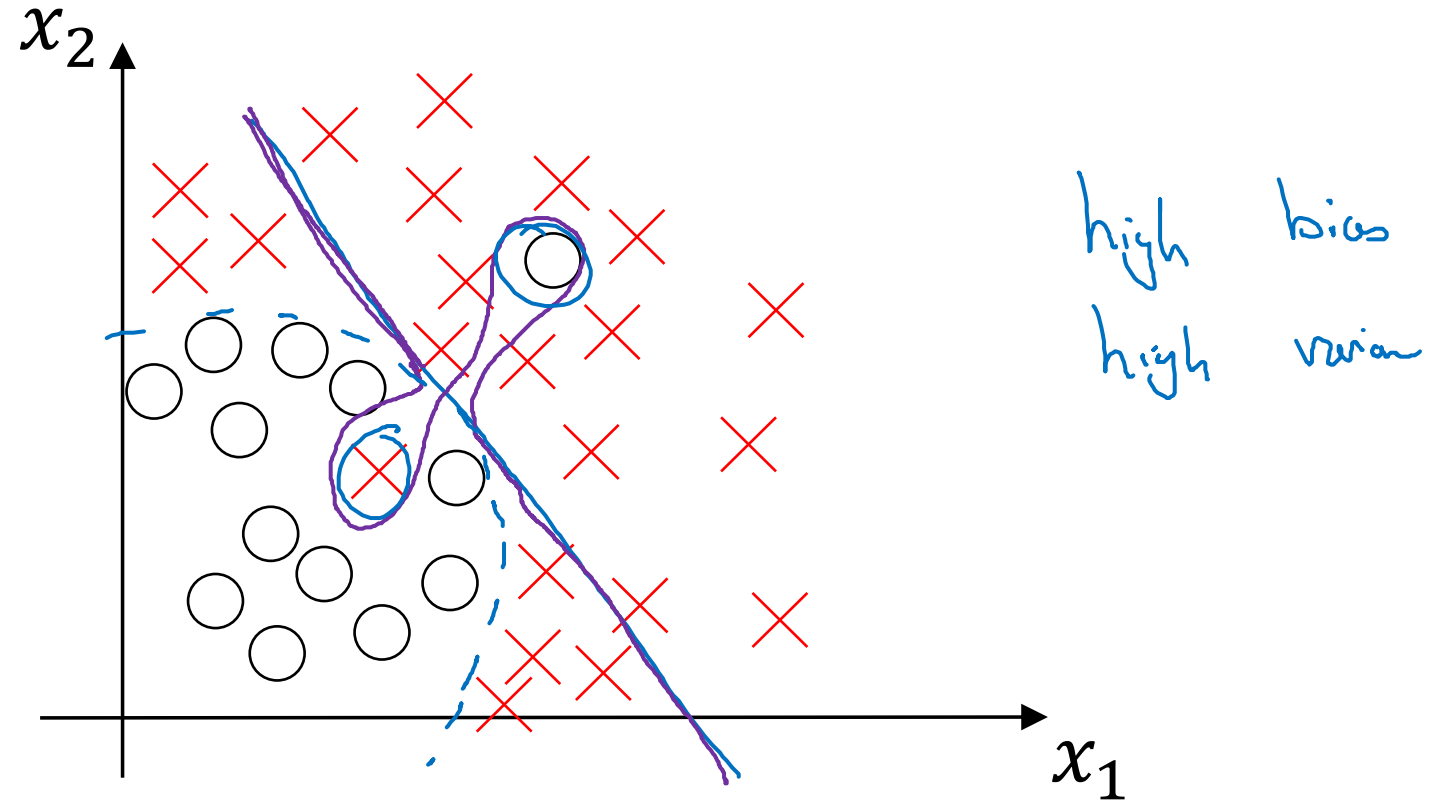
Bias and Variance

Cat classification



	Overfitting	Underfitting		
Train set error:	1%	15%	15%	0.5%
Dev set error:	11%	16%	30%	1%
	high variance ↑	high bias ↑	high bias & high variance	low bias low variance ↑
Human: ~0%				
Optimal (Bayes) error: ~0% <u>15%</u>			Blurry images	

High bias and high variance



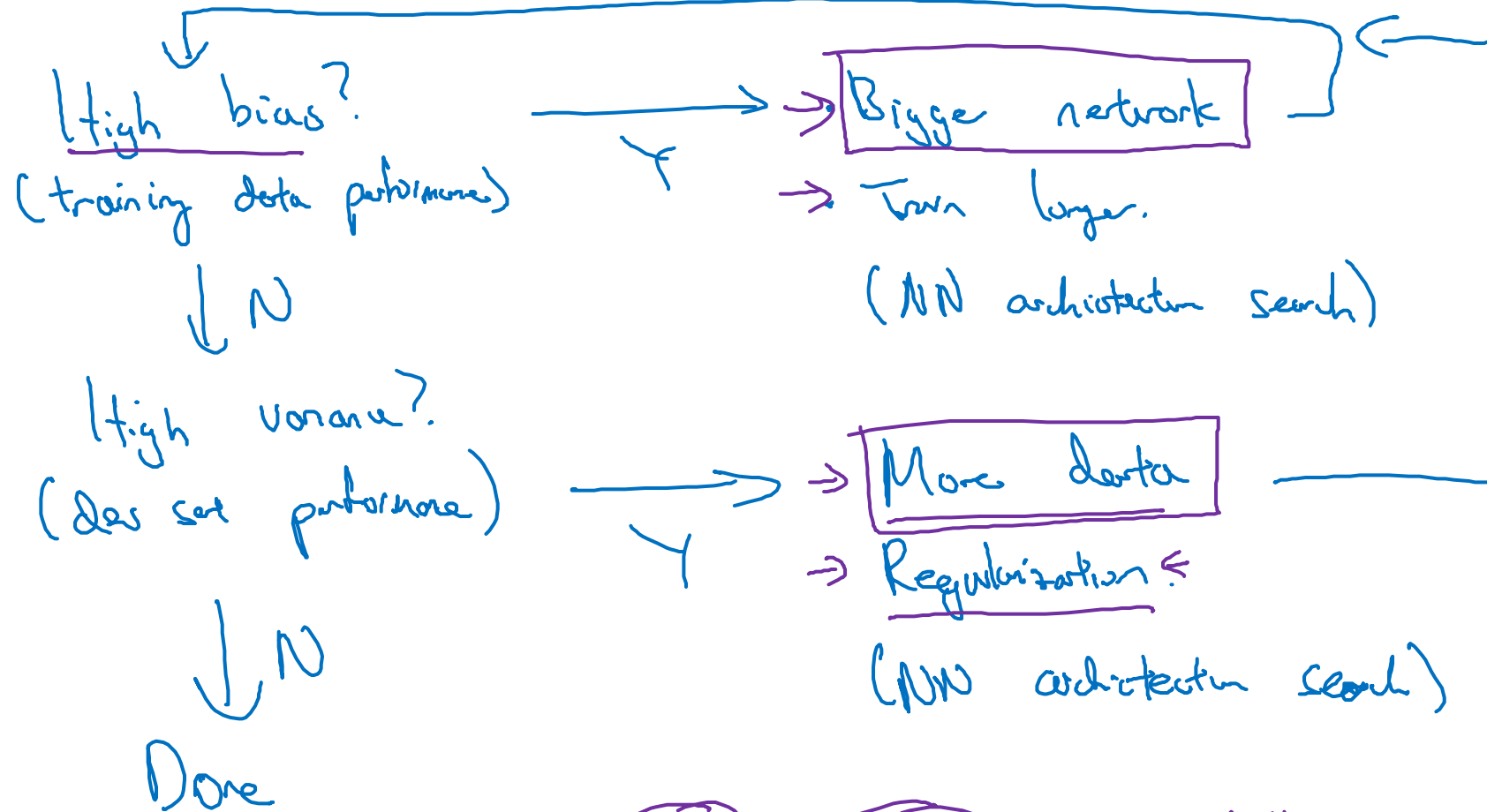


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Setting up your ML application

Basic “recipe” for machine learning

Basic recipe for machine learning





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Regularizing your neural network

Regularization

Logistic regression

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

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

λ = regularization parameter
lambda lambda

$$J(w,b) = \underbrace{\frac{1}{m} \sum_{i=1}^m \ell(y^{(i)}, \hat{y}^{(i)})}_{\text{cost function}} + \frac{\lambda}{2m} \underbrace{\|w\|_2^2}_{\text{L2 regularization}}$$

~~$+\frac{\lambda}{2m} b^2$~~
omit

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

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

w will be sparse

Neural network

$$\rightarrow J(w^{[1]}, b^{[1]}, \dots, w^{[L]}, b^{[L]}) = \underbrace{\frac{1}{n} \sum_{i=1}^n \ell(y^{(i)}, \hat{y}^{(i)})}_{\text{loss}} + \underbrace{\frac{\lambda}{2n} \sum_{l=1}^L \|w^{[l]}\|_F^2}_{\text{weight decay}}$$

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

$w^{[l]}: \begin{matrix} n^{[l]} & n^{[l-1]} \\ \uparrow & \uparrow \end{matrix}$

"Frobenius norm"

$\|\cdot\|_2^2$

$\|\cdot\|_F^2$

$$dw^{[l]} = \left[\text{(from backprop)} + \frac{\lambda}{n} w^{[l]} \right]$$

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

$$\frac{\partial J}{\partial w^{[l]}} = dw^{[l]}$$

"Weight decay"

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

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

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

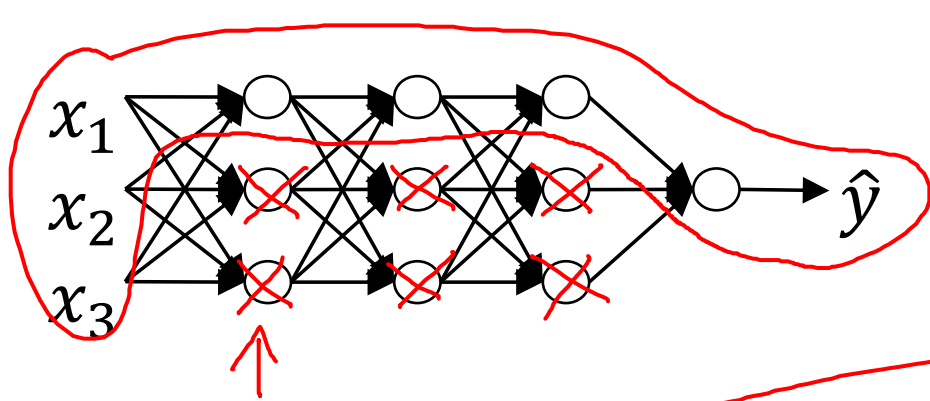


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Regularizing your neural network

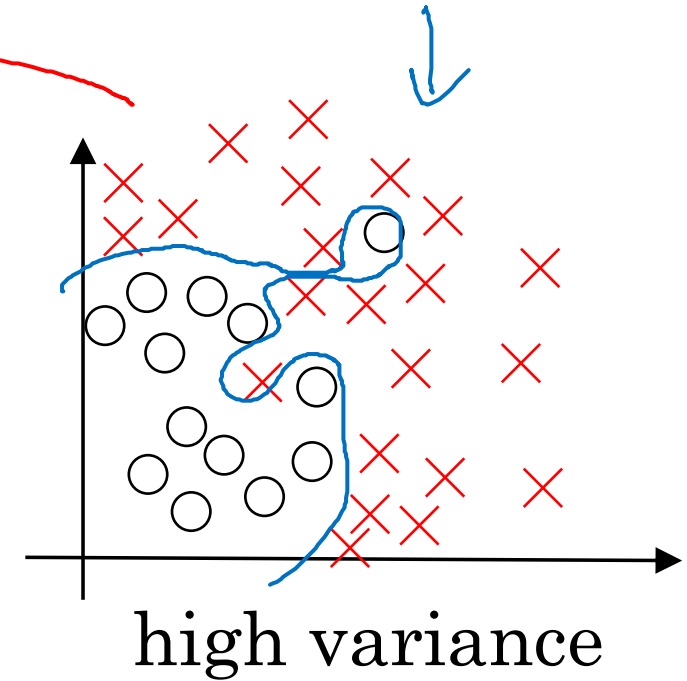
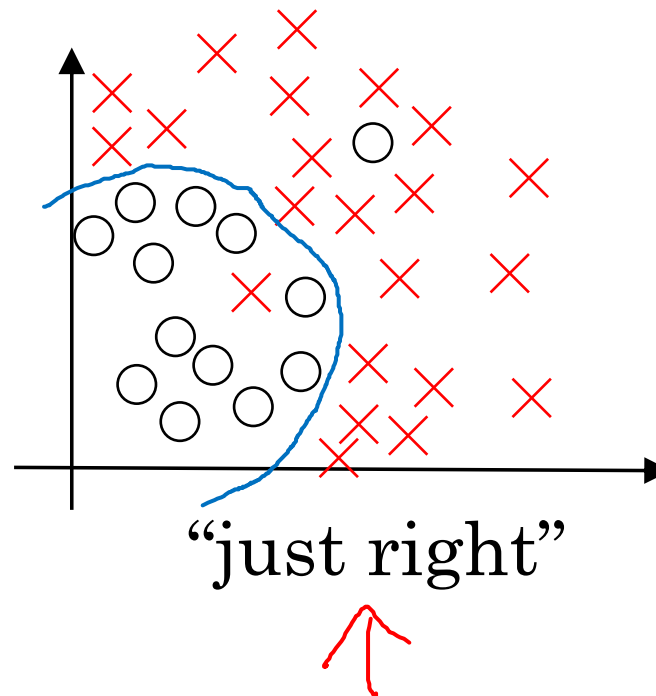
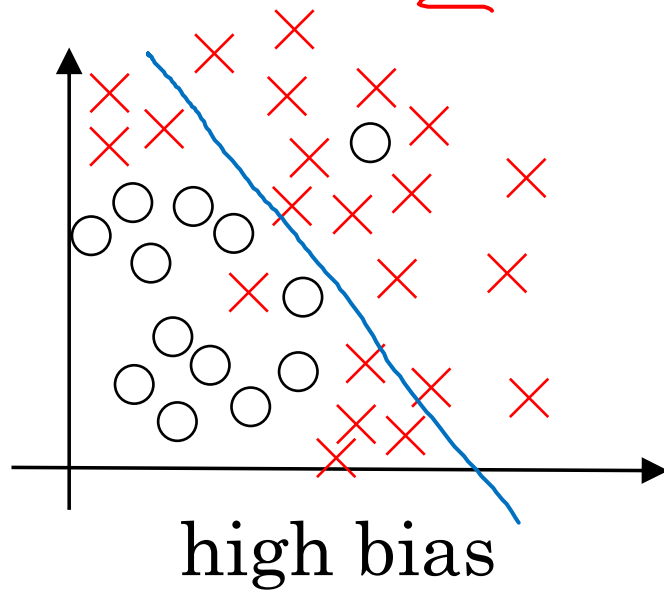
Why regularization reduces overfitting

How does regularization prevent overfitting?

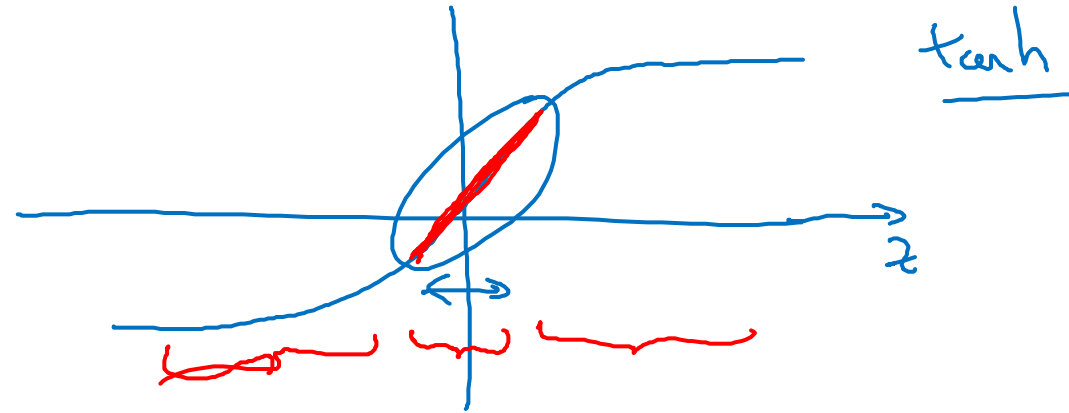


$$J(\mathbf{w}^{(L)}, \mathbf{b}^{(L)}) = \frac{1}{n} \sum_{i=1}^n \ell(y^{(i)}, \hat{y}^{(i)}) + \frac{\lambda}{2n} \sum_{l=1}^L \underbrace{\|\mathbf{w}^{(l)}\|_F^2}_{\text{regularization}}$$

$$\mathbf{w}^{(L)} \approx 0$$



How does regularization prevent overfitting?



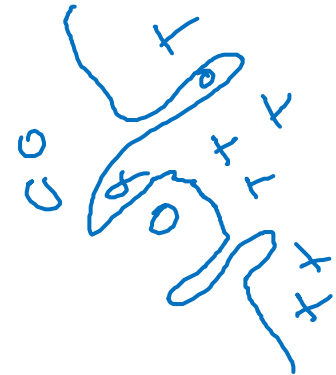
$$g(z) = \tanh(z)$$

$\lambda \uparrow$

$W^{[L]} \downarrow$

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

Every layer \approx linear.



$$J(\dots) = \underbrace{\sum_i \mathcal{L}(\hat{y}^{(i)}, y^{(i)})}_{\text{training loss}} + \underbrace{\frac{\lambda}{2m} \sum_L \|W^{[L]}\|_F^2}_{\text{regularization term}}$$



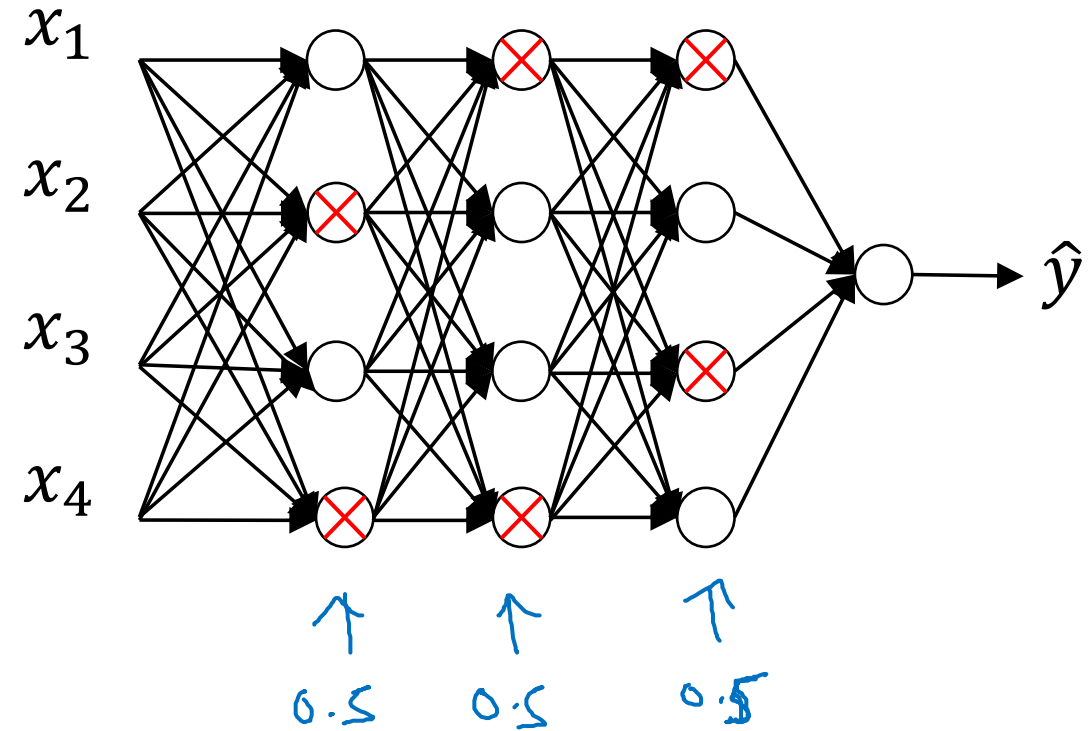
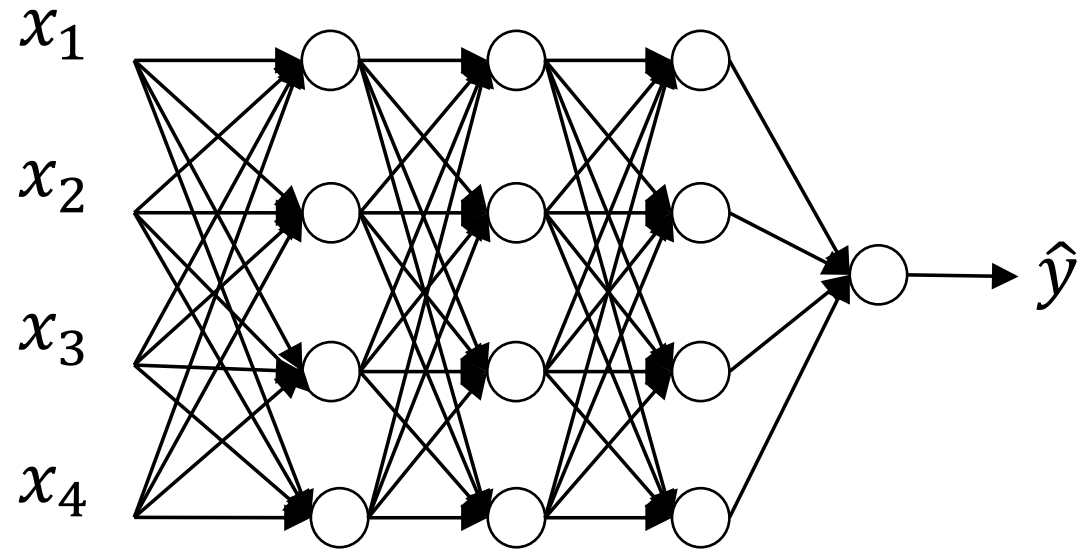


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Regularizing your neural network

Dropout regularization

Dropout regularization



Implementing dropout ("Inverted dropout")

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

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

$a3 = \text{np.multiply}(a3, d3)$ # $a3 \neq d3$.

→ $a3 /= \text{keep-prob}$ ←

50 units. \leadsto 10 units shut off

$$z^{[4]} = w^{[4]} \cdot \underbrace{a^{[3]}}_{\text{reduced by } 20\%} + b^{[4]}$$

\uparrow

reduced by 20%

$$/= \underline{0.8}$$

Test

Making predictions at test time

$$a^{[0]} = X$$

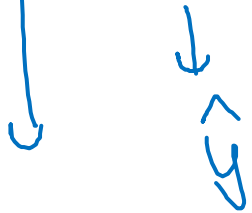
No drop out.

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

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

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

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



\neq keep-prob



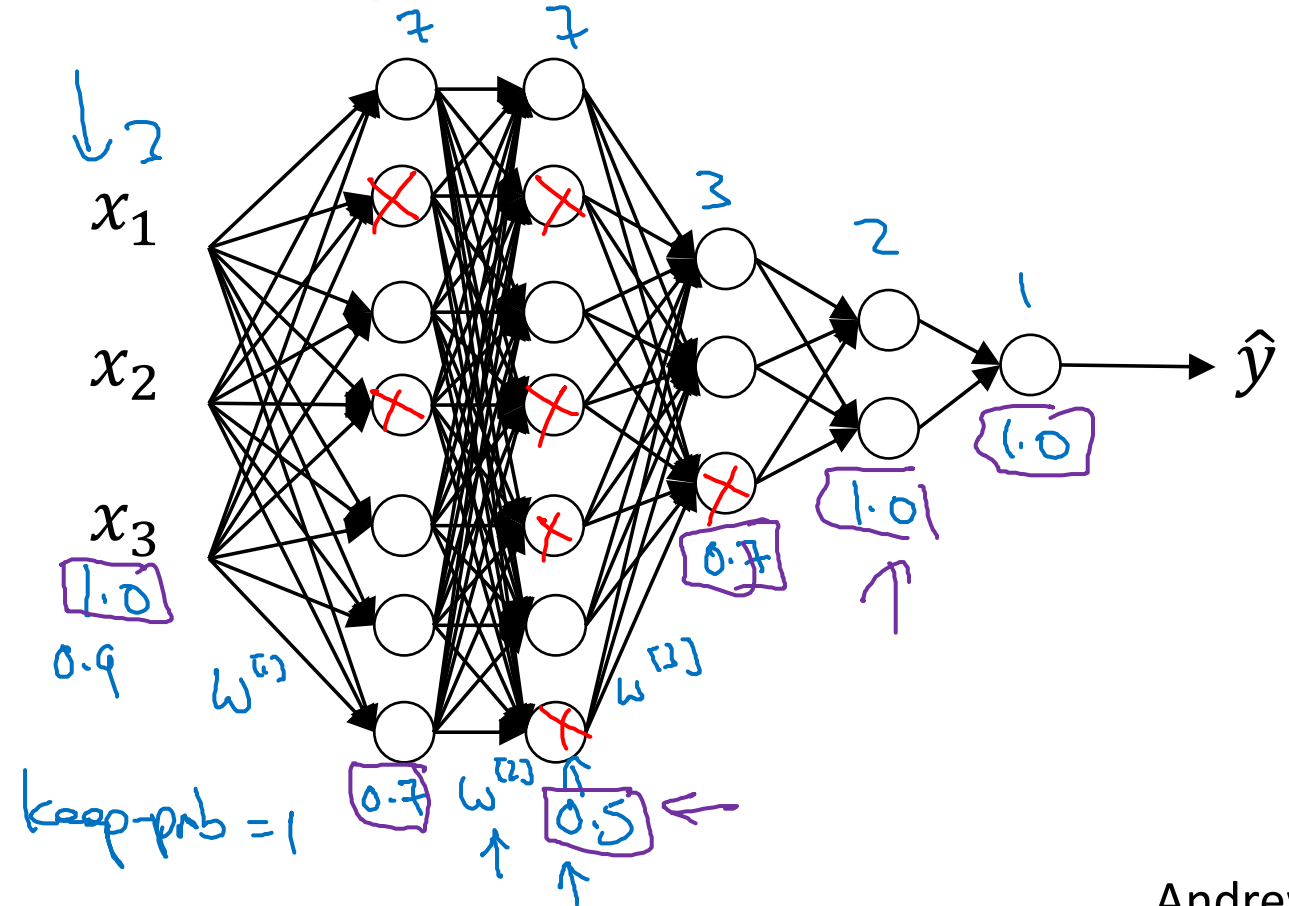
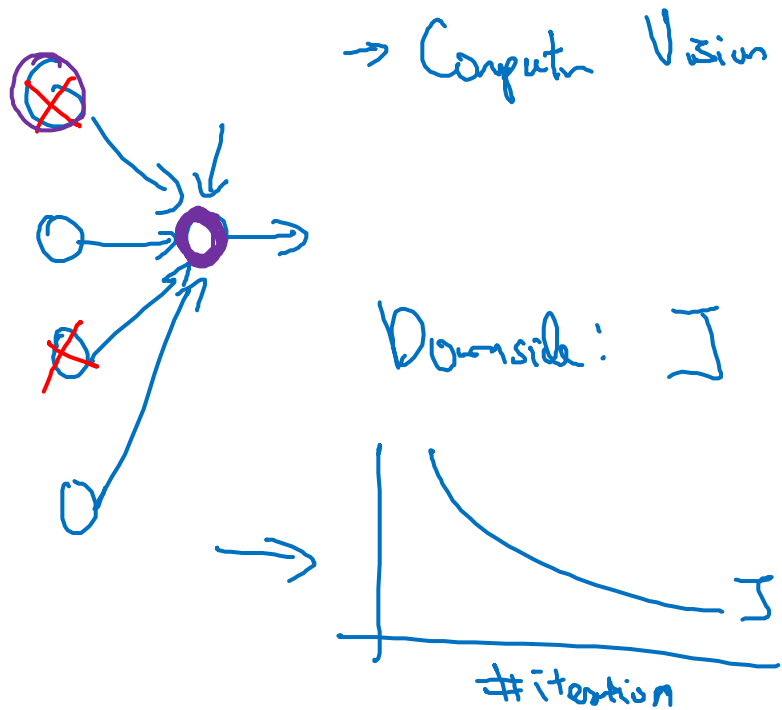
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Regularizing your neural network

Understanding dropout

Why does drop-out work?

Intuition: Can't rely on any one feature, so have to spread out weights. \leadsto Shrink weights. b_2





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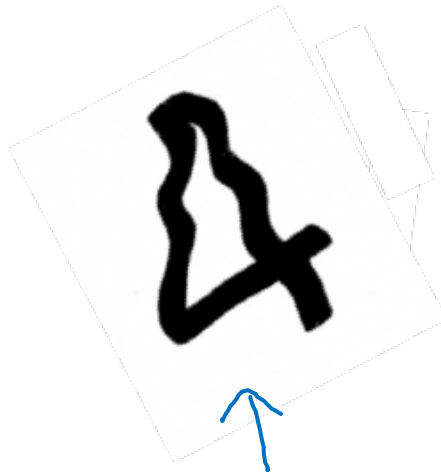
Regularizing your neural network

Other regularization methods

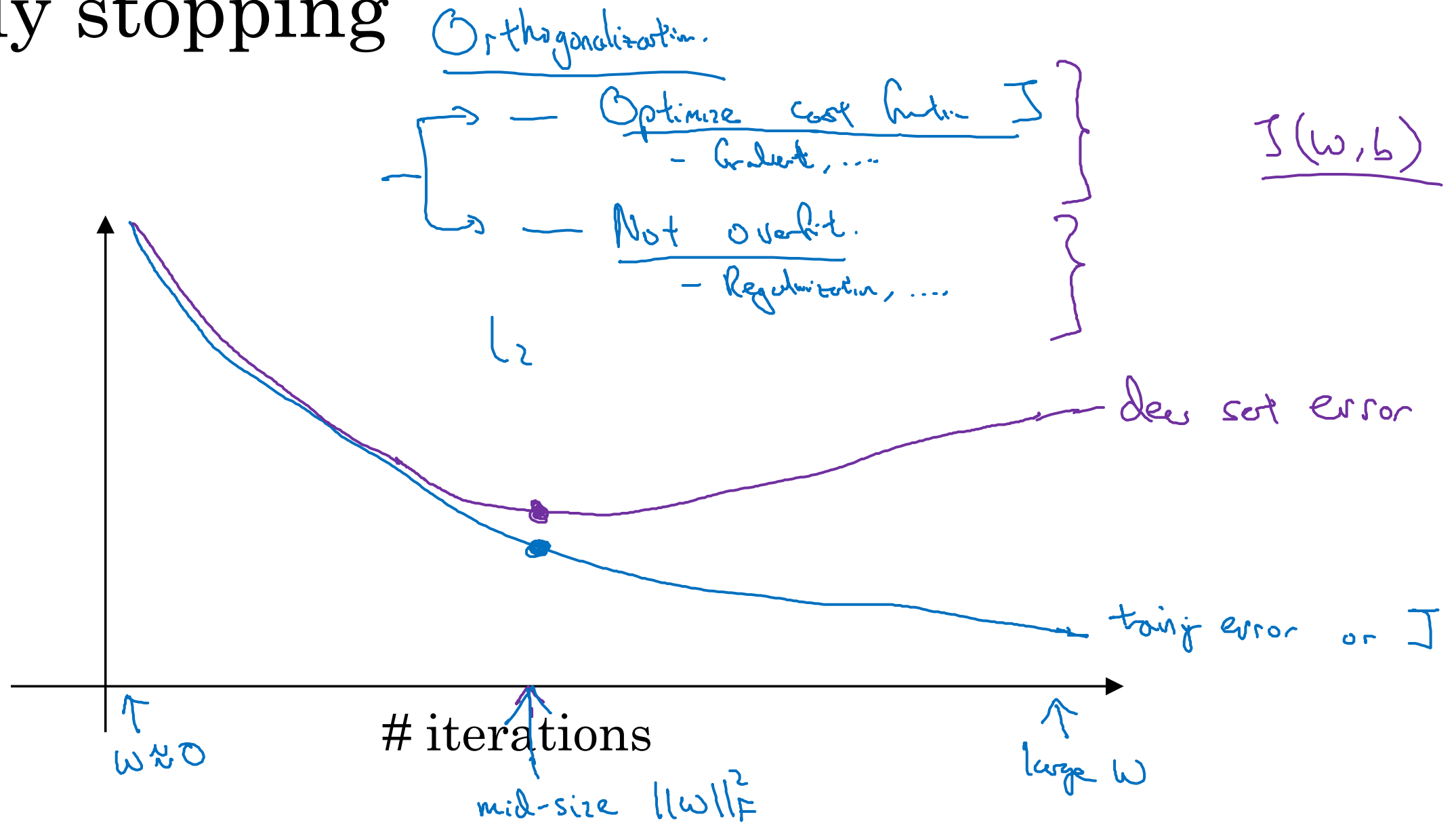
Data augmentation



4



Early stopping





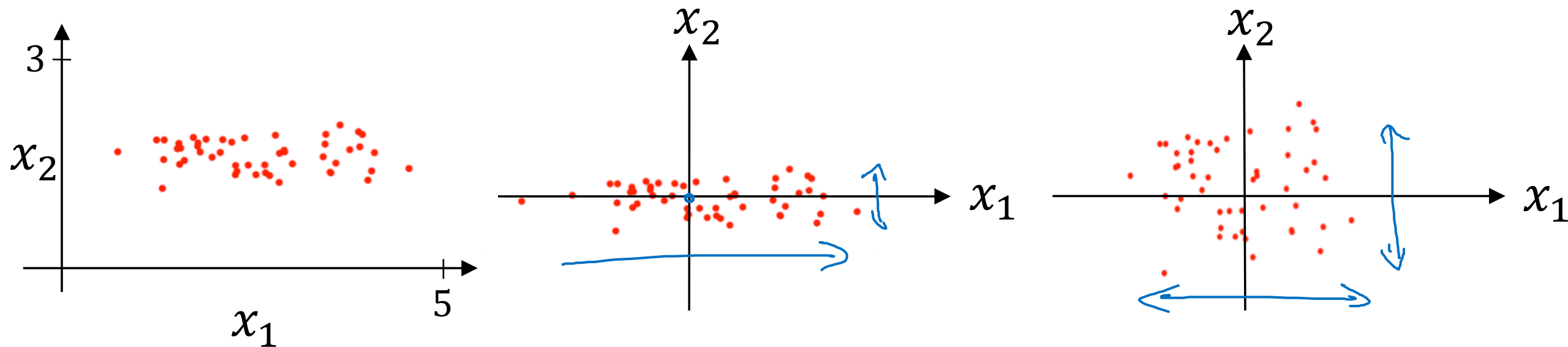
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Setting up your
optimization problem

Normalizing inputs

Normalizing training sets

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



Subtract mean:

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

$$x := x - \mu$$

Normalize variance

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

\hookrightarrow element-wise

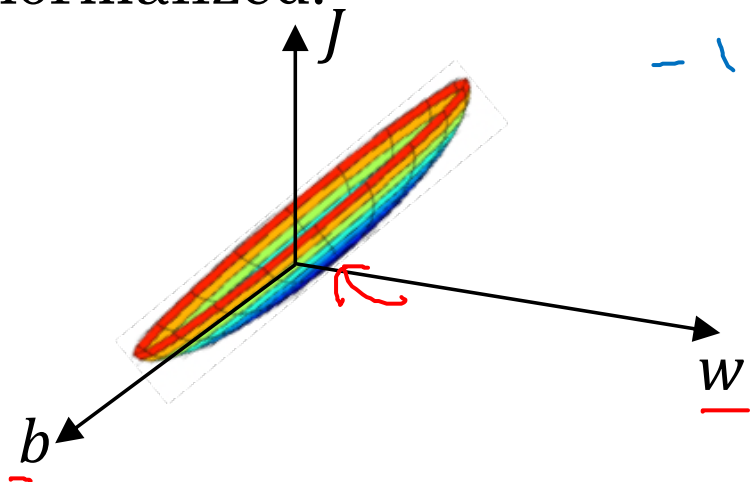
$$x /= \sigma^2$$

Use same μ σ^2 to normalize test set.

Why normalize inputs?

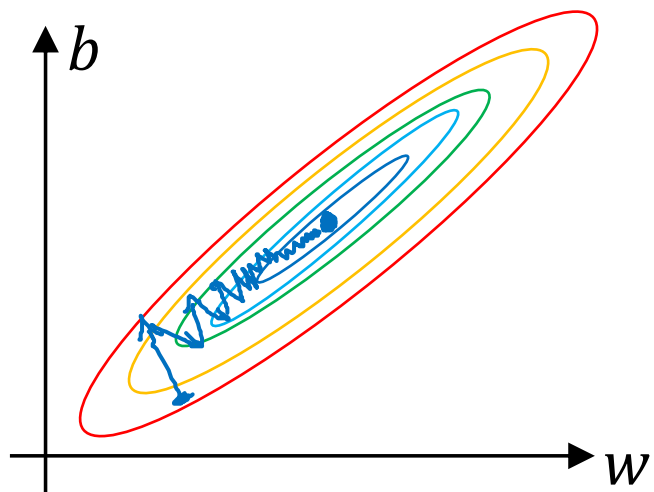
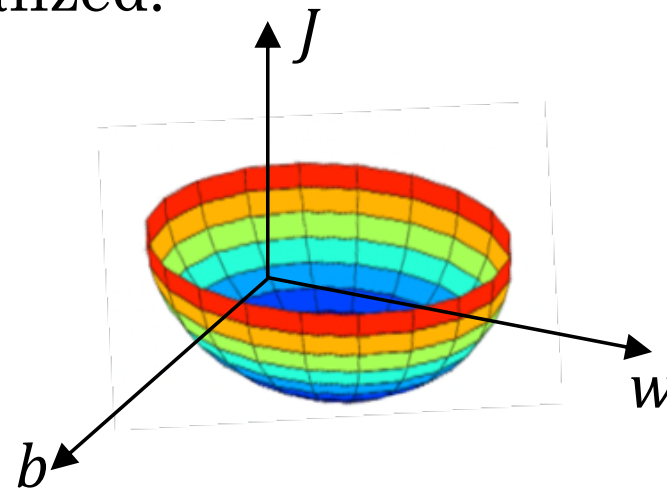
$$J(w, b) = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

Unnormalized:

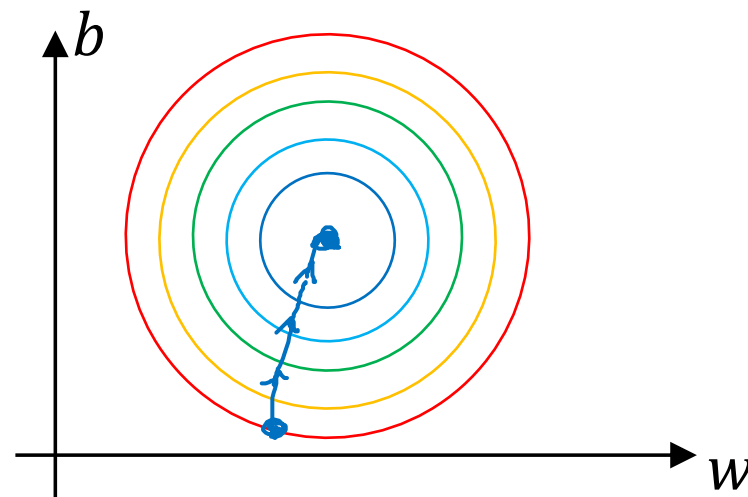


$w_1: x_1: \underline{1 \dots 1000} \leftarrow$
 $w_2: x_2: \underline{0 \dots 1} \leftarrow$
 $\quad \quad \quad -1 \dots 1$

Normalized:



$x_1: 0 \dots 1$
 $x_2: -1 \dots 1$
 $x_3: 1 \dots 2$



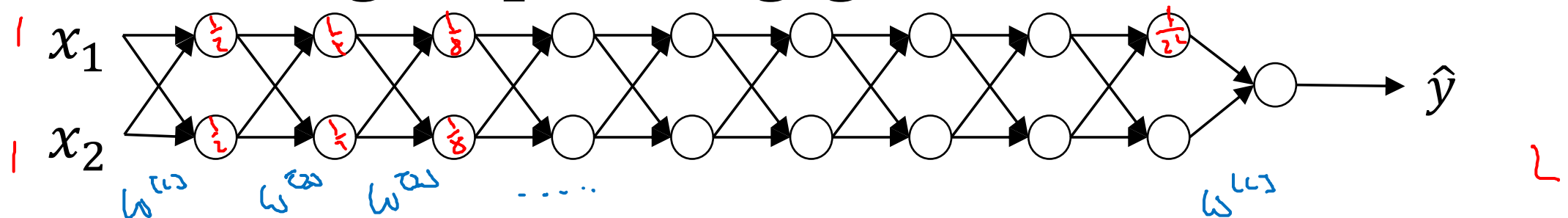


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Setting up your
optimization problem

Vanishing/exploding
gradients

Vanishing/exploding gradients



Handwritten notes: $g(z) = z$, $b^{(L)} = 0$.

Handwritten equation: $\hat{y} = w^{(L)} \left(w^{(L-1)} w^{(L-2)} \dots w^{(2)} w^{(1)} x \right)$

Handwritten note: $w^{(1)} > I$

Handwritten note: $w^{(2)} < I$ with matrix $\begin{bmatrix} 0.9 & 0 \\ 0 & 0.9 \end{bmatrix}$

Handwritten matrix: $w^{(2)} = \begin{bmatrix} 1.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ (Note: 0.5 is written as 0.5 in red, and 1.5 is written as 1.5 in red)

Handwritten equation: $\hat{y} = w^{(L)} \left[\begin{bmatrix} 1.5 & 0 \\ 0 & 0.5 \end{bmatrix}^{L-1} x \right]$

Handwritten equation: $z^{(t)} = w^{(t)} x$

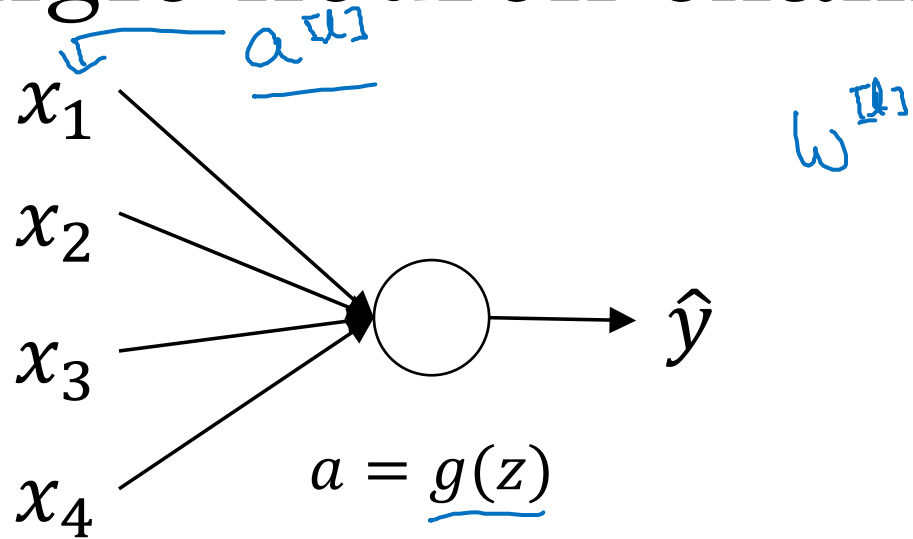
Handwritten equation: $a^{(t)} = g(z^{(t)}) = z^{(t)}$

Handwritten equation: $a^{(t)} = g(z^{(t)}) = g(w^{(t)} a^{(t-1)})$

Handwritten equation: $1.5^{L-1} x$

Handwritten equation: $0.5^{L-1} x$

Single neuron example



$$z = w_1 x_1 + w_2 x_2 + \dots + w_n x_n$$

large $n \rightarrow$ Smaller w_i

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

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

ReLU $g^{[2]}(z) = \text{ReLU}(z)$

Other variants:

tanh

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

Xavier initialization ↑

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

↑



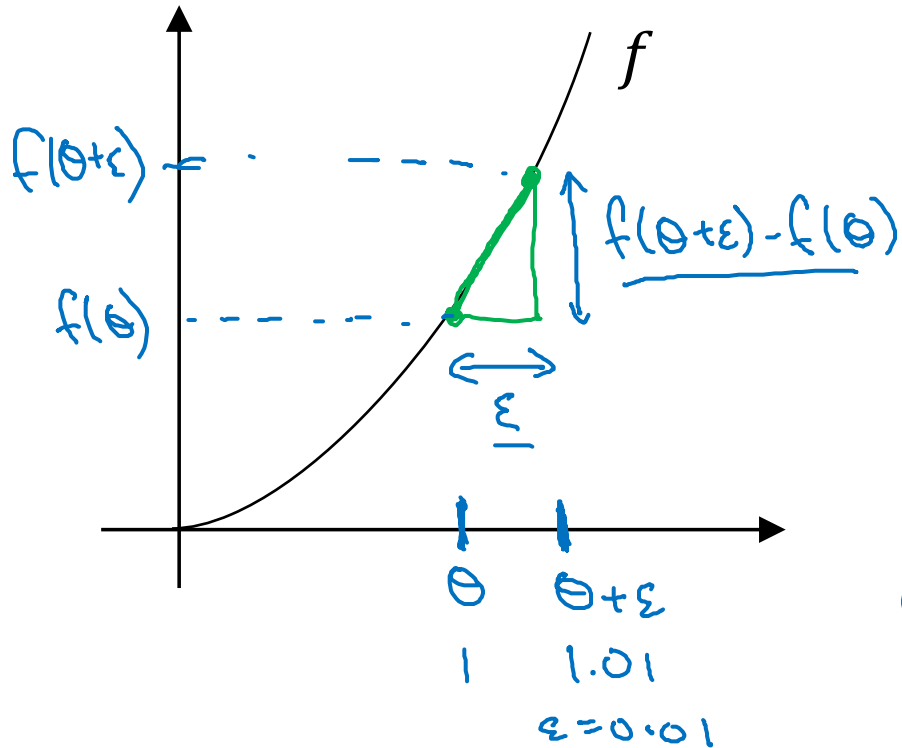
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Setting up your
optimization problem

Numerical approximation
of gradients

Checking your derivative computation

I $f(\theta) = \theta^3$
 $\theta \in \mathbb{R}.$



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

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

$\frac{dw}{db}$

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

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

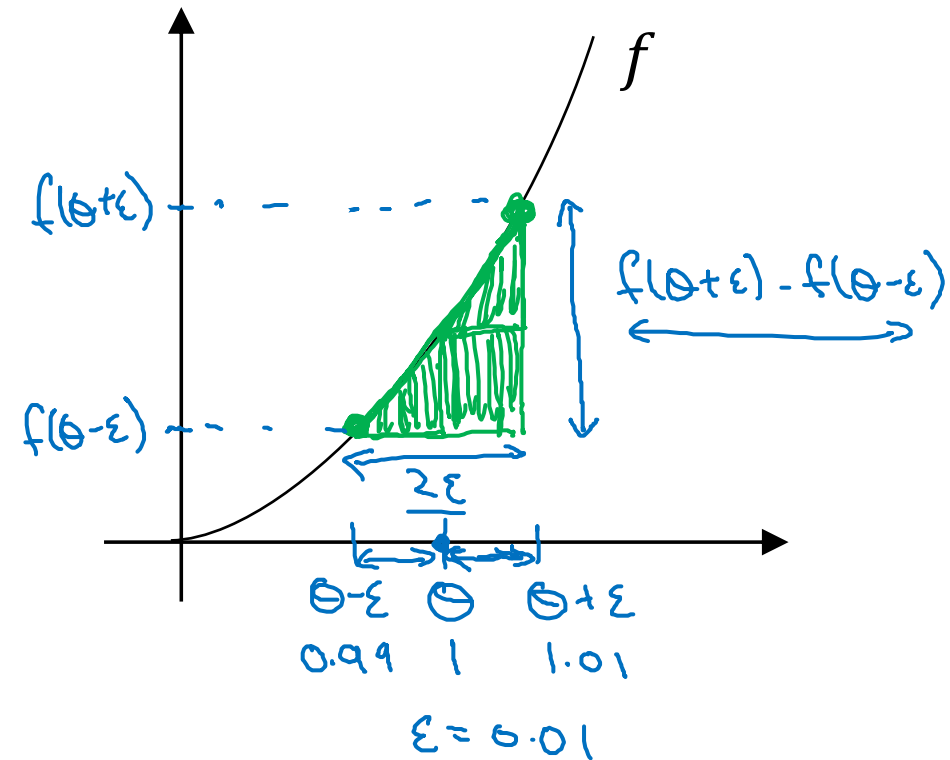
$$\frac{(1.01)^3 - 1^3}{0.01} = \frac{1.030301 - 1}{0.01} = \frac{0.0301}{0.01} = 3.0301 \approx 3$$

Annotations: 0.0301 is the numerator, 3.1 and 3.2 are the integer parts of the division, and 3 is the final result.

$\theta = 1$
 $\theta + \epsilon = 1.01$

Checking your derivative computation

$$\underline{f(\theta) = \theta^3}$$



$$\left[\frac{f(\theta + \epsilon) - f(\theta - \epsilon)}{2\epsilon} \approx \underline{g(\theta)} \right]$$

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

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

approx error: 0.0001

(prev slide: 3.0301. error: 0.03)

$$\left\{ \begin{array}{l} f'(\theta) = \lim_{\epsilon \rightarrow 0} \frac{f(\theta + \epsilon) - f(\theta - \epsilon)}{2\epsilon} \quad \begin{array}{l} O(\epsilon^2) \\ 0.01 \\ \underline{0.0001} \end{array} \quad \left| \quad \begin{array}{l} \frac{f(\theta + \epsilon) - f(\theta)}{\epsilon} \quad \text{error: } O(\epsilon) \\ \quad \quad \quad 0.01 \end{array} \right. \end{array} \right.$$



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Setting up your
optimization problem

Gradient Checking

Gradient check for a neural network

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

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

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

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

Gradient checking (Grad check)

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

for each i :

$$\rightarrow \underline{d\theta_{\text{approx}}[i]} = \frac{J(\theta_1, \theta_2, \dots, \overset{\downarrow}{\theta_i + \epsilon}, \dots) - J(\theta_1, \theta_2, \dots, \overset{\downarrow}{\theta_i - \epsilon}, \dots)}{2\epsilon}$$

$$\approx \underline{d\theta[i]} = \frac{\partial J}{\partial \theta_i} \quad | \quad d\theta_{\text{approx}} \approx d\theta$$

Checks

$$\rightarrow \frac{\|d\theta_{\text{approx}} - d\theta\|_2}{\|d\theta_{\text{approx}}\|_2 + \|d\theta\|_2}$$
$$\underline{\epsilon = 10^{-7}}$$

$$\approx \frac{10^{-7}}{10^{-5}} - \text{great!} \leftarrow$$
$$\rightarrow 10^{-3} - \text{worry.} \leftarrow$$



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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

$$\frac{d\theta_{\text{approx}}[\vec{i}]}{\uparrow \uparrow} \longleftrightarrow \frac{d\theta[\vec{i}]}{\uparrow}$$

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

$$\frac{db^{[L]}}{\uparrow} \quad \frac{dW^{[L]}}{\uparrow}$$

- Remember regularization.

$$\underline{J(\theta)} = \frac{1}{n} \sum_i \ell(y^{(i)}, \hat{y}^{(i)}) + \frac{\lambda}{2n} \sum_l \|W^{[L,l]}\|_F^2$$

$d\theta = \text{gradient of } J \text{ wrt. } \theta$

- Doesn't work with dropout.

J

$$\underline{\text{keep-prob} = 1.0}$$

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

$$\underline{W, b \approx 0}$$