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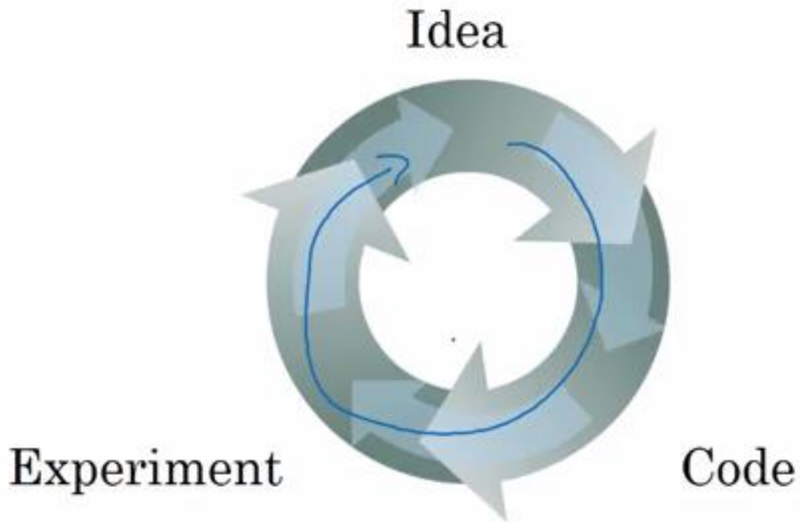
# Setting up your ML application

# 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 logistic ....

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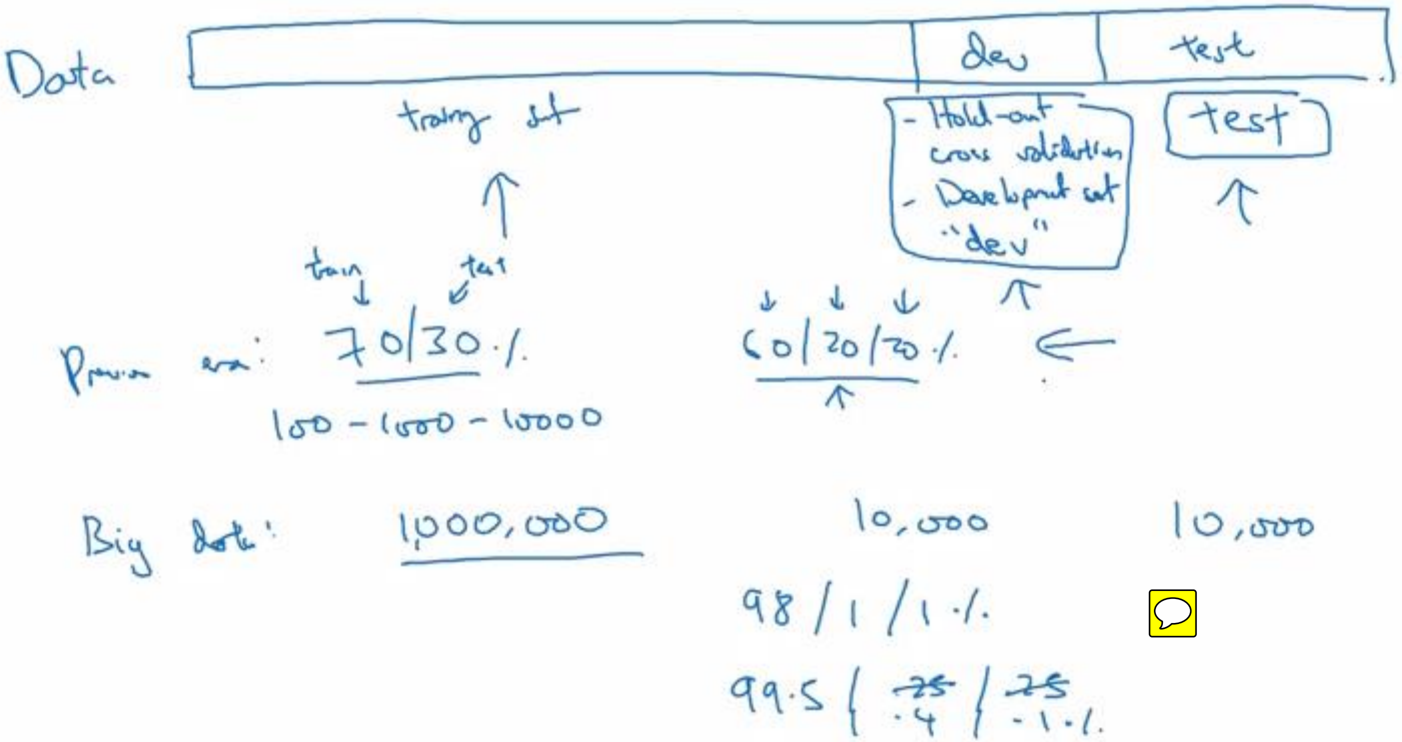
# Train/dev/test sets

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# 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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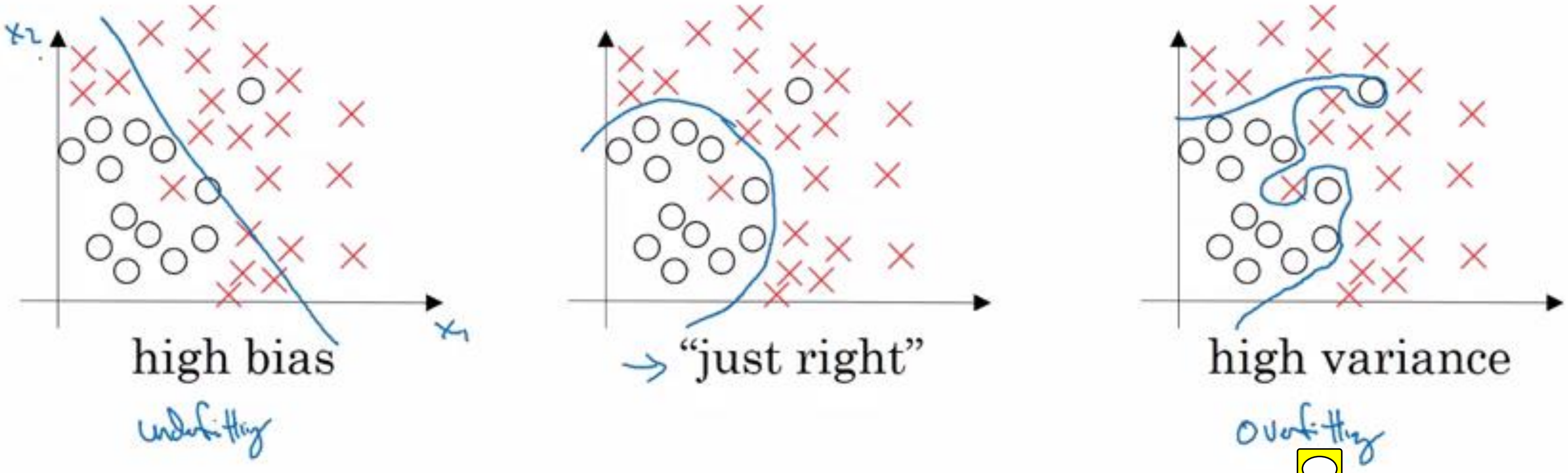
# Setting up your ML application

## Bias/Variance

# Bias and Variance

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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 variance | low bias low variance |

Human: ≈ 0%

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

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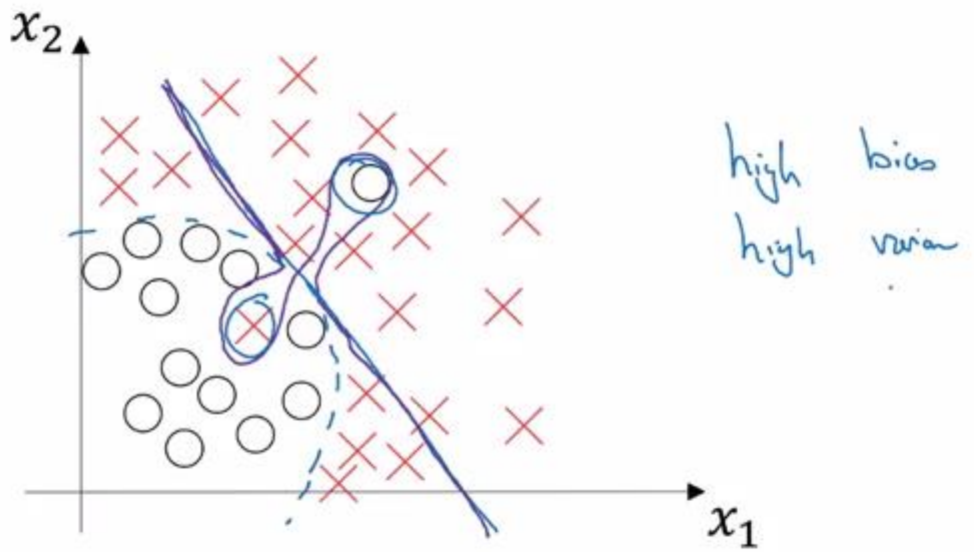
# High bias and high variance

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# Setting up your ML application

## Basic "recipe" for machine learning

0:21 / 6:21

# 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"

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# Regularizing your neural network

## Regularization

# Logistic regression

$w \in \mathbb{R}^{n_x}$, $b \in \mathbb{R}$ $\qquad \lambda$ = regularization parameter

lambda $\qquad$ lambd

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

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

omit

L2 regularization $\quad \|w\|_2^2 = \sum_{j=1}^{n_x} w_j^2 = w^T w \leftarrow$

L1 regularization $\quad \frac{\lambda}{2m}\sum_{j=1}^{n_x} |w_j| = \frac{\lambda}{2m}\|w\|_1$

$w$ will be sparse

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# Neural network

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

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

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

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

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

"Weight decay"

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

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

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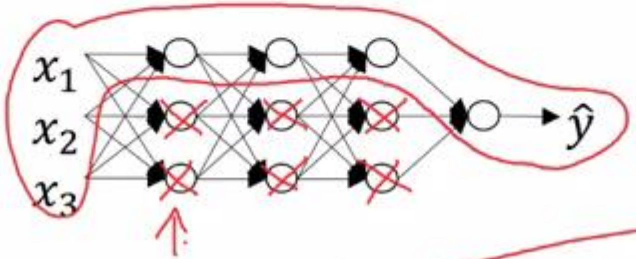
# Regularizing your neural network

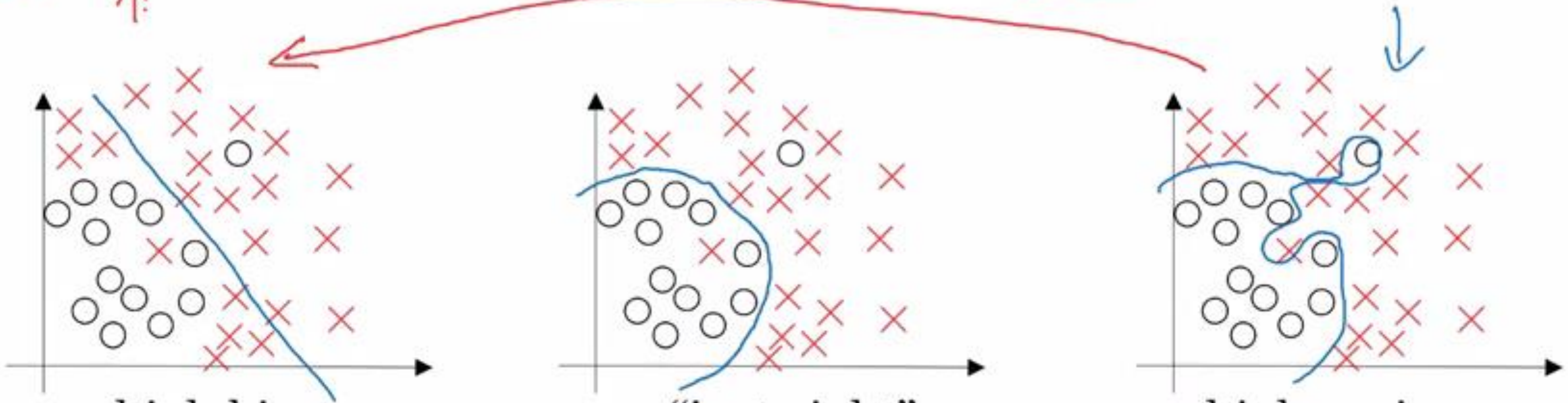
## Why regularization reduces overfitting

# How does regularization prevent overfitting?




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

$$\underbrace{w^{[l]} \approx 0}$$



high bias | "just right" | high variance

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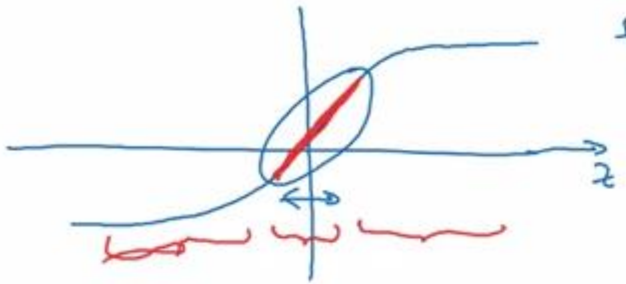
# How does regularization prevent overfitting?




tanh

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

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

Every layer ≈ linear.

$$J(\ldots) = \boxed{\sum_i \mathcal{L}(\hat{y}^{(i)}, y^{(i)})} + \frac{\lambda}{2m} \sum_l \|W^{[l]}\|_F^2$$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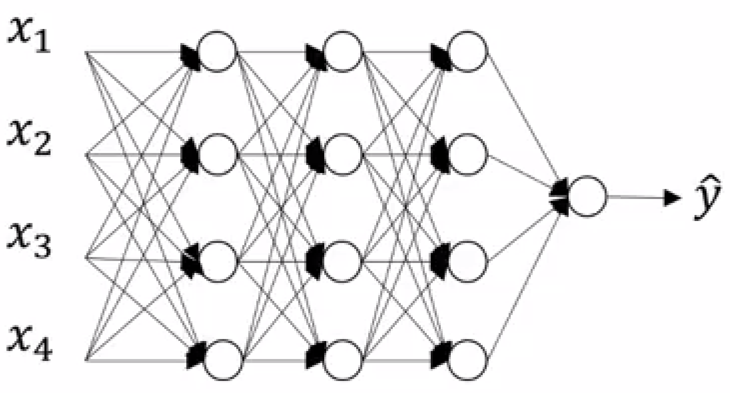
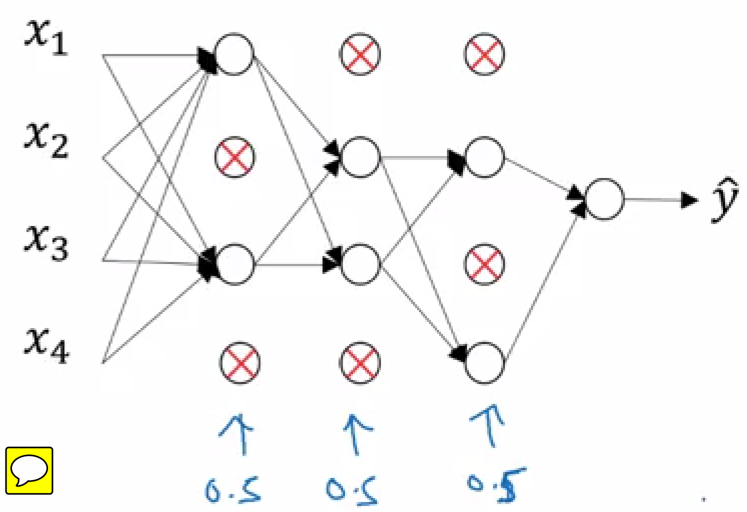
# Regularizing your neural network

## Dropout regularization

# Dropout regularization



# Implementing dropout ("Inverted dropout")

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

```
d3 = np.random.rand(a3.shape[0], a3.shape[1]) < keep-prob
a3 = np.multiply(a3, d3)        # a3 *= d3.
a3 /= keep-prob
```

50 units. ⇝ 10 units shut off

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

reduced by 20%. Test

$/= 0.8$

# Making predictions at test time

$a^{[0]} = X$

No drop out.

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

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

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

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

$\downarrow$

$\hat{y}$

$/=$ keep-prob

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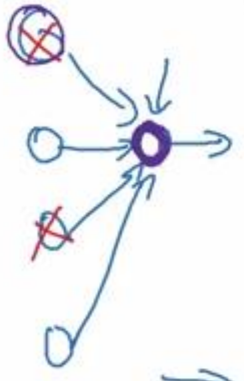
# Regularizing your neural network

## Understanding dropout

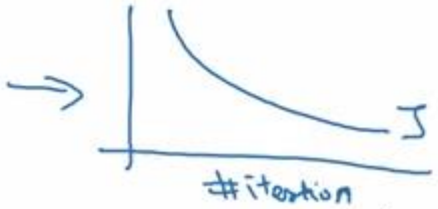
# Why does drop-out work?

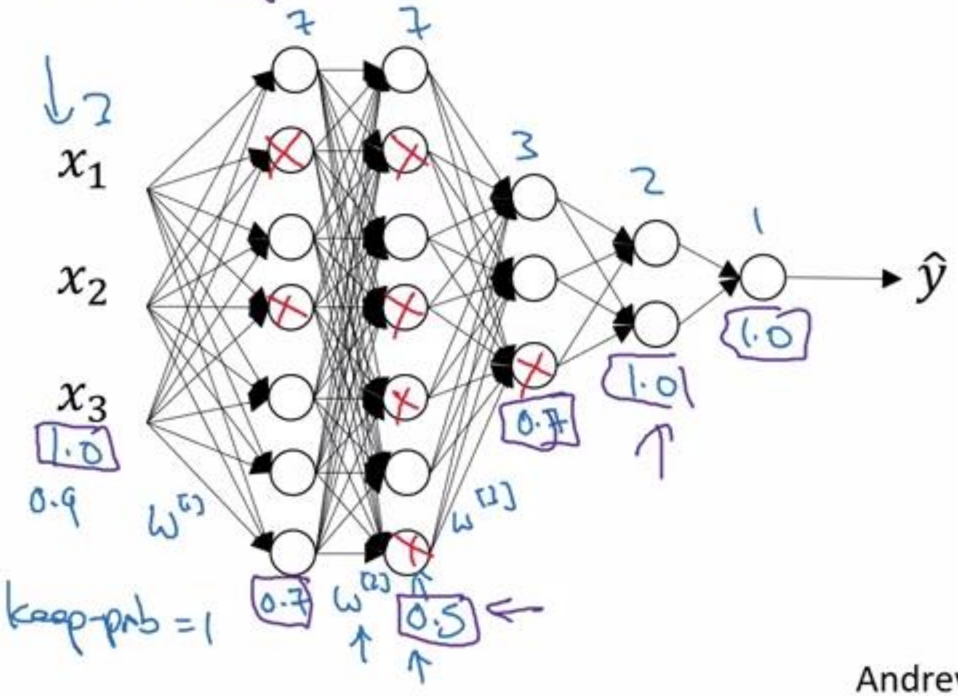
Intuition: Can't rely on any one feature, so have to spread out weights. ⇝ Shrink weights. $L_2$



→ Computer Vision

Downside: J

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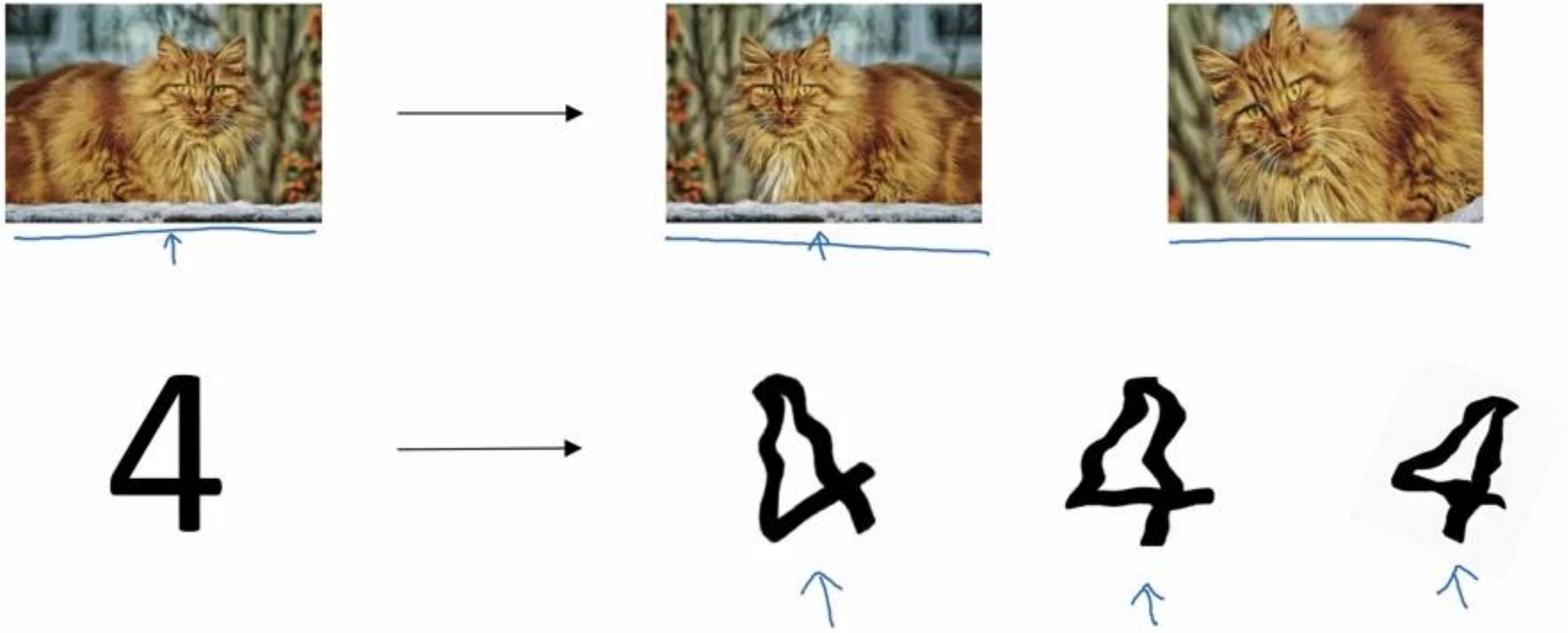
# Regularizing your neural network

## Other regularization methods

# Data augmentation



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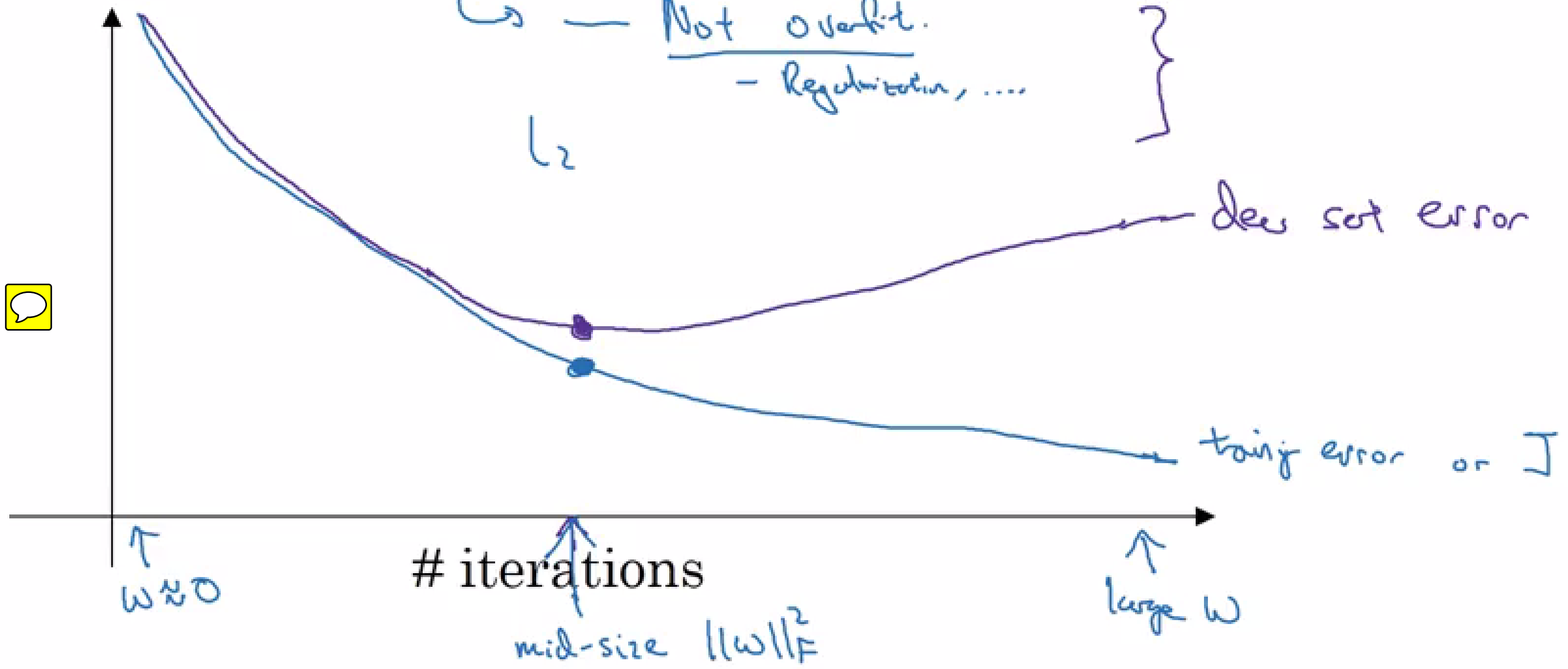
# Early stopping

Orthogonalization.

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

$J(w,b)$



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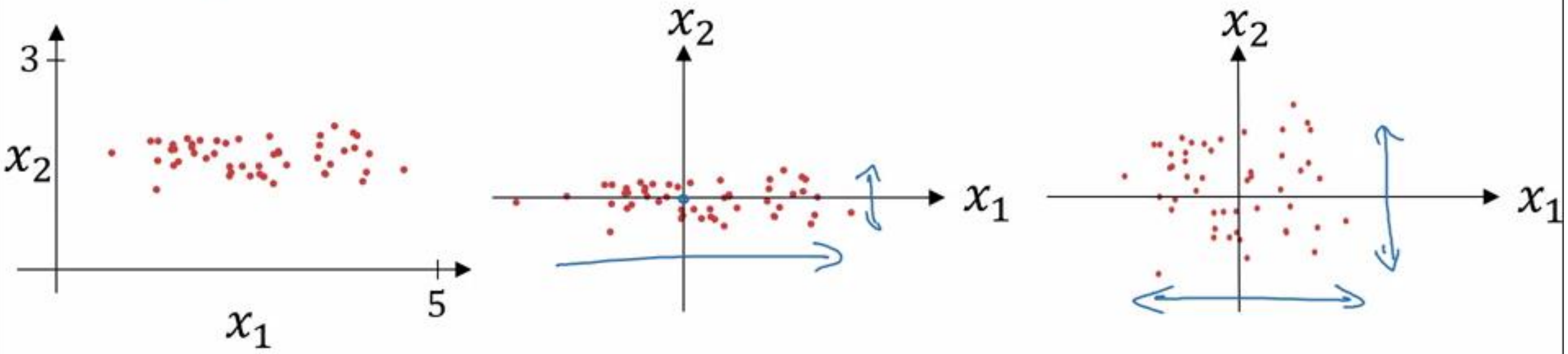
# Setting up your optimization problem

## Normalizing inputs

# Normalizing training sets

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




Subtract mean:

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

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

Normalize variance

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

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

Use same $\mu, \sigma^2$ to normalize test set.

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# Why normalize inputs?

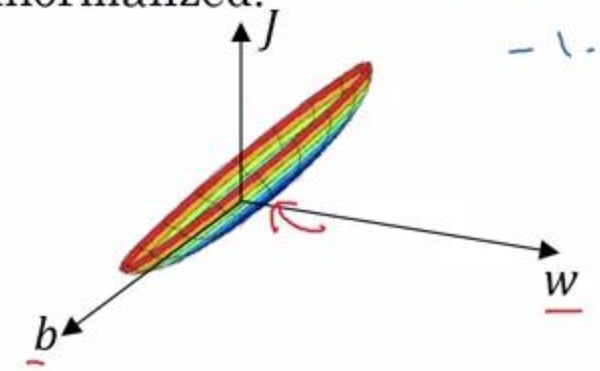
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m}\mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

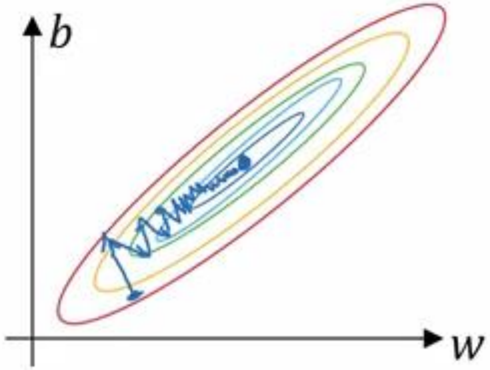
$w_1$ $x_1$: 1 ... 1000 ←

$w_2$ $x_2$: 0 ... 1 ←

−1 ... 1

Unnormalized:



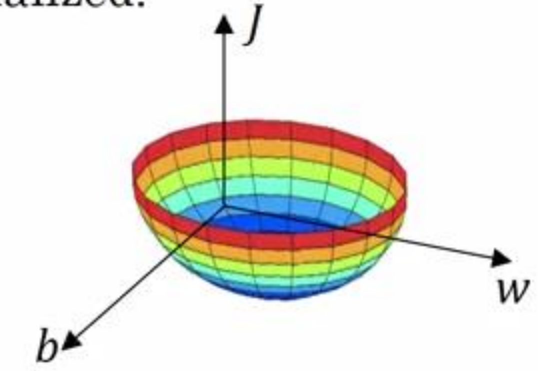



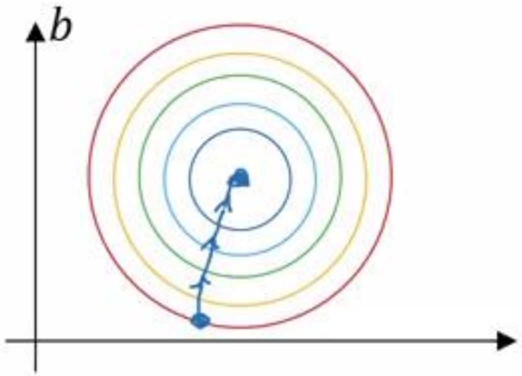

$x_1$: 0 ... 1

$x_2$: −1 ... 1

$x_3$: 1 ... 2

Normalized:

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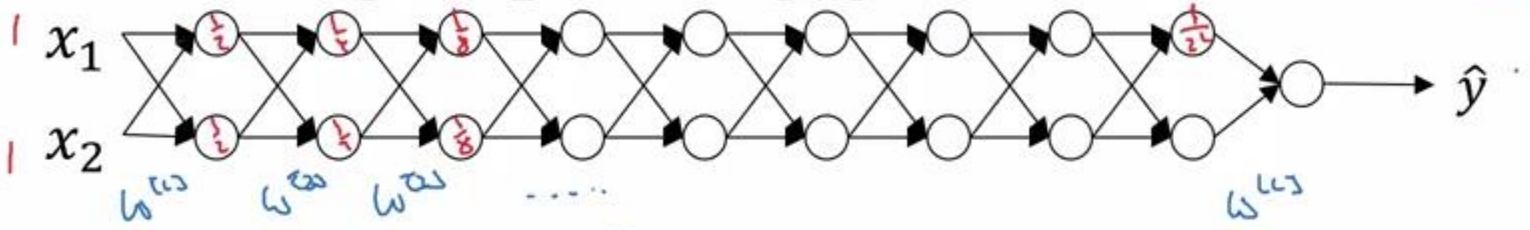
Setting up your optimization problem

# Vanishing/exploding gradients

# Vanishing/exploding gradients

$L = 150$




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

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

$1.5^L$

$0.5^L$

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

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

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

$W^{[l]} > I$

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

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

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

$1.5^{L-1} x$

$0.5^{L-1} x$

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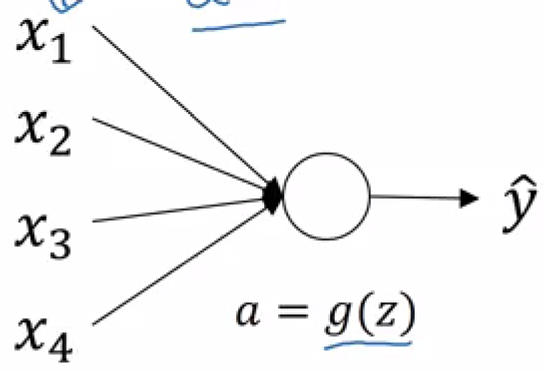
# Setting up your optimization problem

## Weight initialization for deep networks

# 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 $w_i$

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

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

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

Other variants:

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

Xavier initialization

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

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# Setting up your optimization problem

## Numerical approximation of gradients

# Checking your derivative computation

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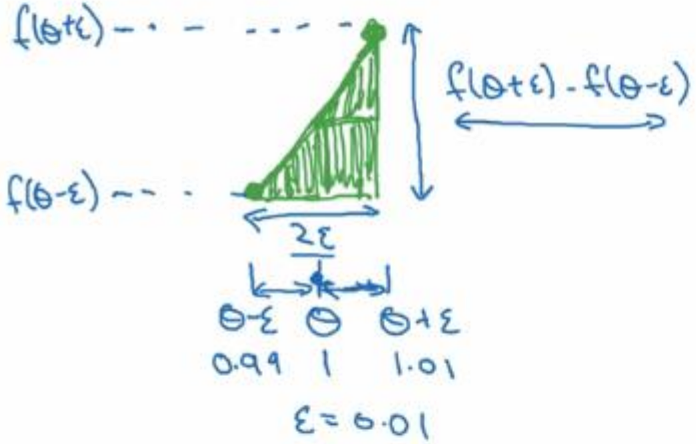
$f(\theta)=\theta^3$

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




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

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

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

# Gradient check for a neural network

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

concatenate

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

Take $\boxed{dW^{[1]}}, \boxed{db^{[1]}}, \ldots, dW^{[L]}, db^{[L]}$ 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)

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

for each $i$:

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

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

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

Check

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

$10^{-5}$

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

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

6:18 / 6:34

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

- If algorithm fails grad check, look at components to try to identify bug.
  $db^{[l]} \quad dw^{[l]}$

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

- Remember regularization. $\quad d\theta$ = gradt of $J$ wrt. $\theta$

- Doesn't work with dropout. $\quad J \quad$ keep-prob = 1.0

- Run at random initialization; perhaps again after some training.
  $w, b \approx 0$

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