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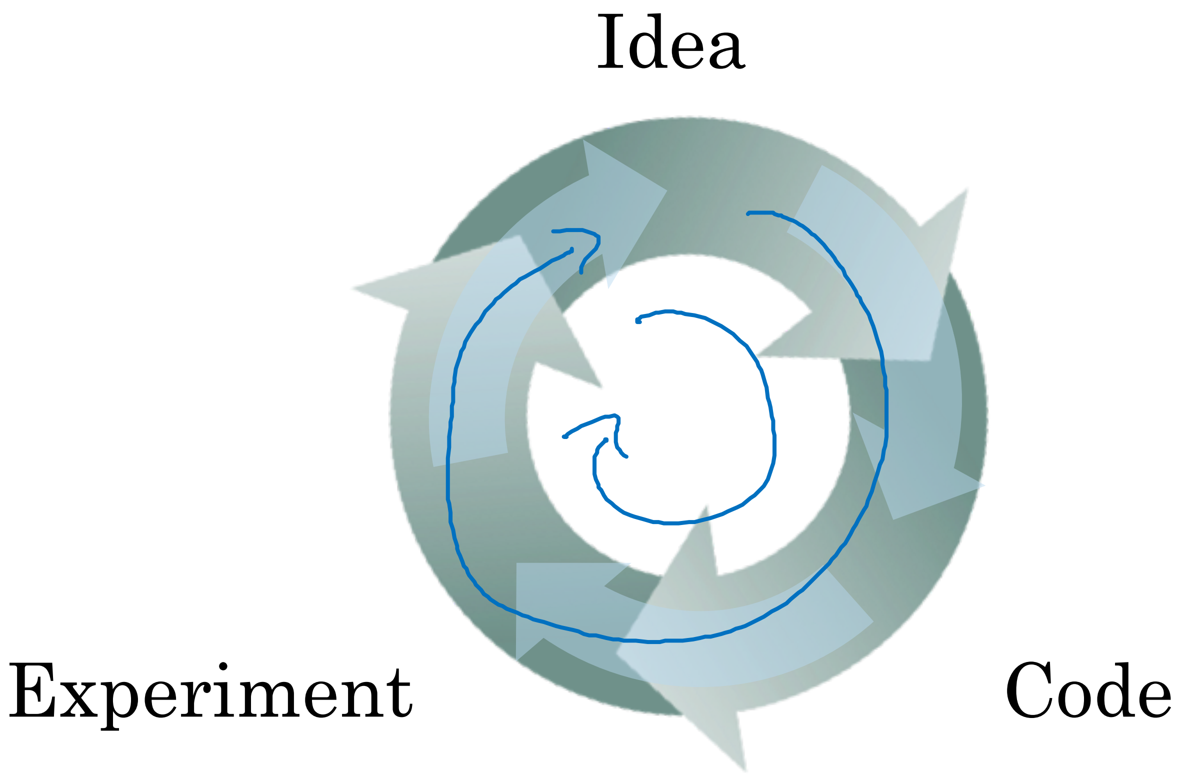
# Setting up your ML application

# Train/dev/test sets

# Applied ML is a highly iterative process

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




NLP, Vision, Speech, Structural data

Ads search Security logistic ....

# Train/dev/test sets

Data | | dev | test
training set

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

test

train → test →

Previous era: 70/30 %   60/20/20 %

100 – 1000 – 10000

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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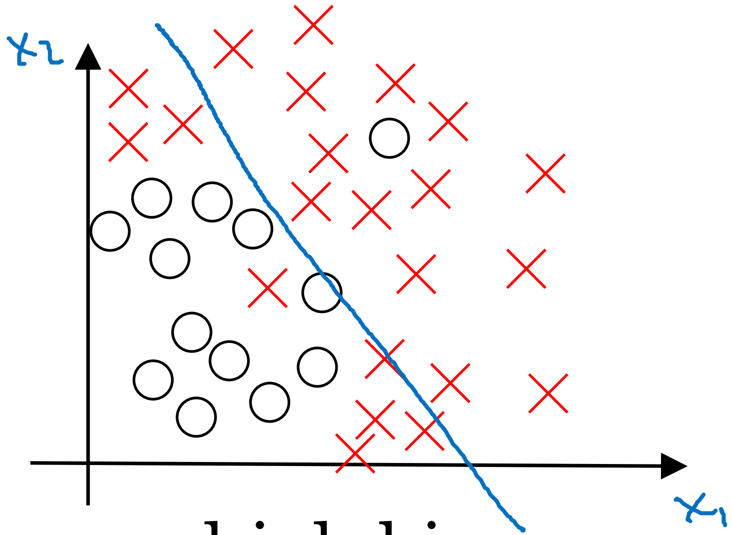
# Setting up your ML application

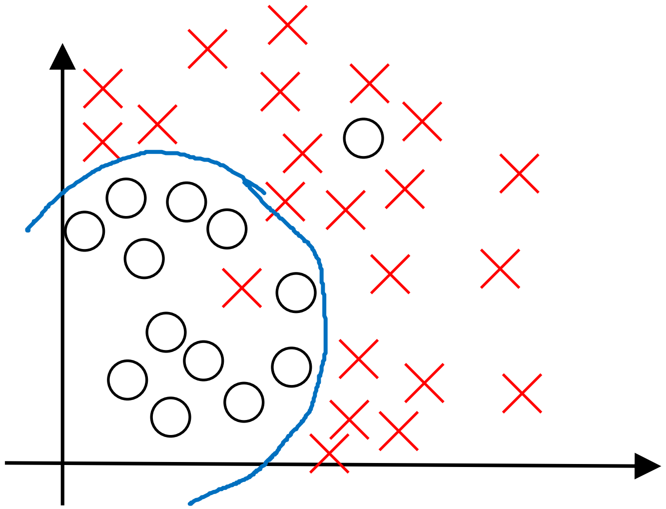
## Bias/Variance

# Bias and Variance

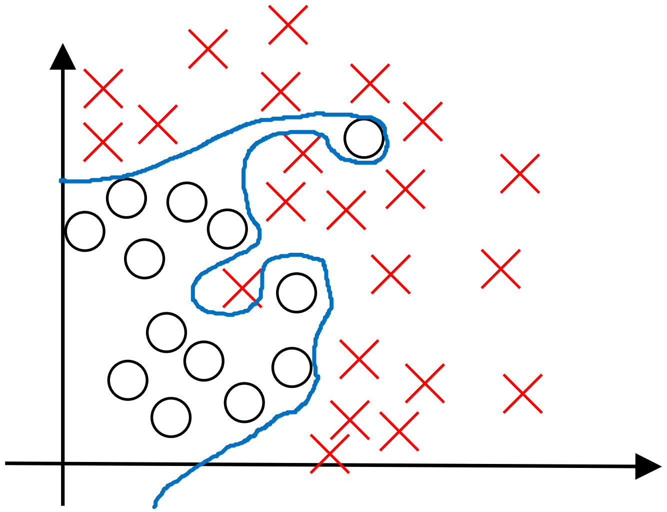



high bias

underfitting



→ "just right"



high variance

overfitting

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# Bias and Variance

## Cat classification

y=1

y=0

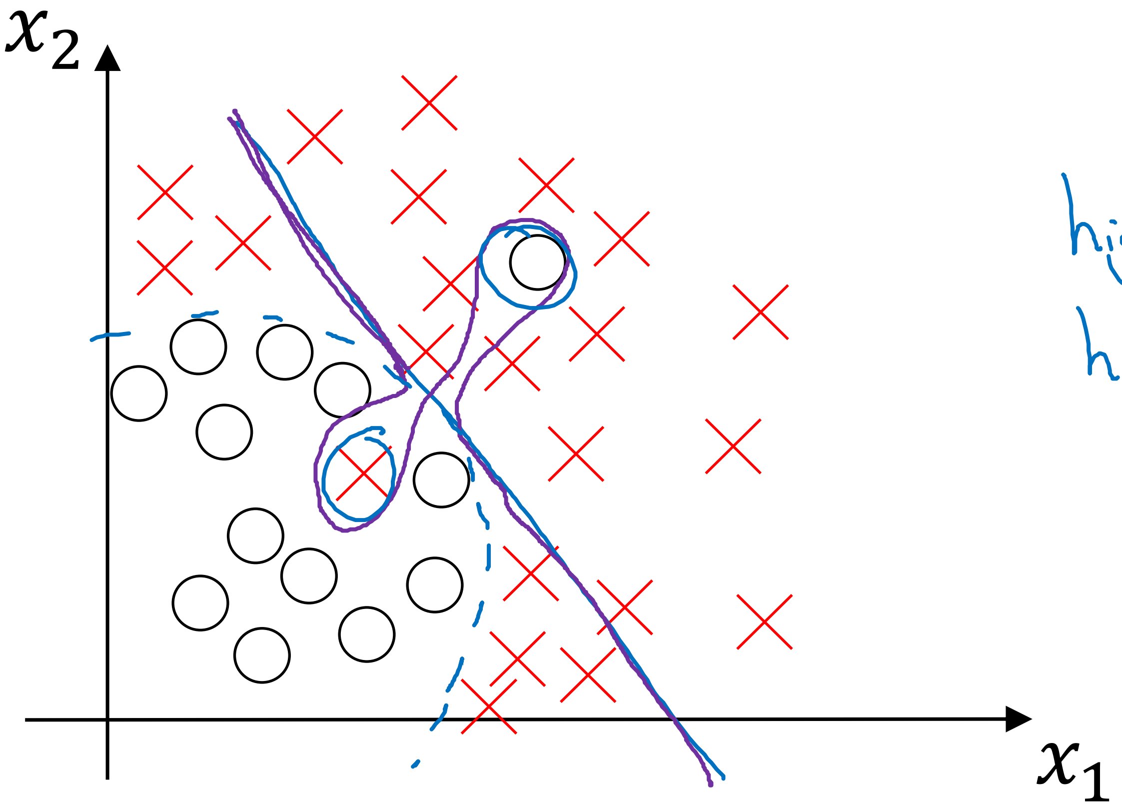
| | | | | |
|---|---|---|---|---|
| Train set error: | 1% | 15% | 15% | 0.5% |
| Dev set error: | 11% | 16% | 30% | 1% |
| | high variance | high bias | high bias & high varian | low bias low variance |

Human: ≈0%

Optimal (Bayes) error: ≈ ~~0%~~ 15%

Blurry images

# 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 → $\boxed{\text{Bigger network}}$

→ Train longer.

(NN architecture search)

↓ N

High variance?
(dev set performance)

→ Y → $\boxed{\text{More data}}$

→ Regularization ←

(NN architecture search)

↓ N

Done

It means, adding more hidden layers or hidden units in each layer making the network deeper !!

Bias ↓↑ ↓   variance ↓↓ ↑   "tradeoff"

# Regularizing your neural network

## Regularization

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# Logistic regression

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

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

$\lambda$ = regularization parameter

lambda lambd

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

omit

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

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

w will be sparse

Being Sparse means that W vector will have a lot of zeros in it. Many people believe that this will help in compressing the model as it will make our calculations more quicker due to presence of 0's in W vector, but in practice it doesn't have very huge difference so L2 regularization is preferred over this one !!

# Neural network

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

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

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

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

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

"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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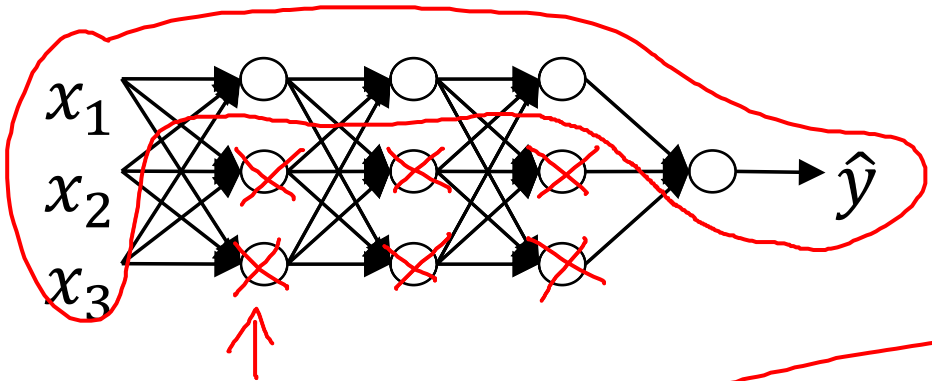
# Regularizing your neural network

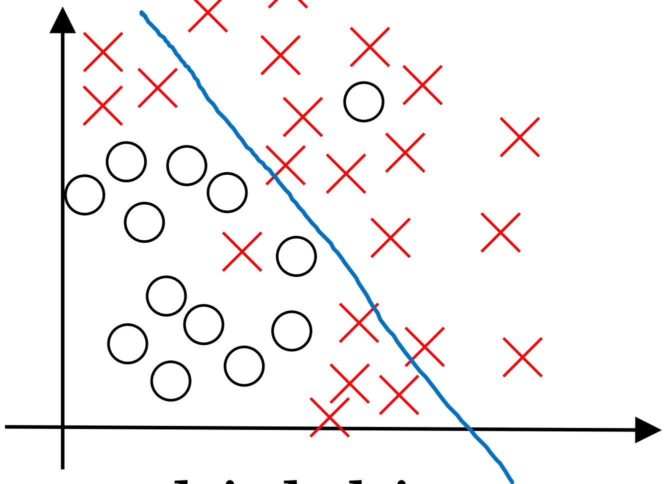
# Why regularization reduces overfitting

# How does regularization prevent overfitting?

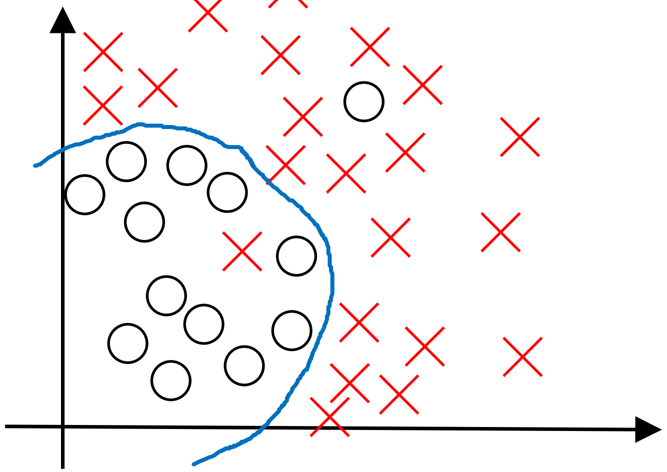



$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2$$

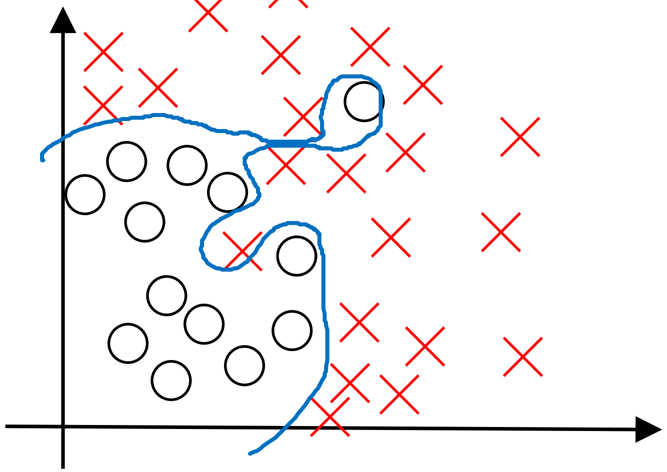
$$w^{[l]} \approx 0$$



high bias



"just right"



high variance

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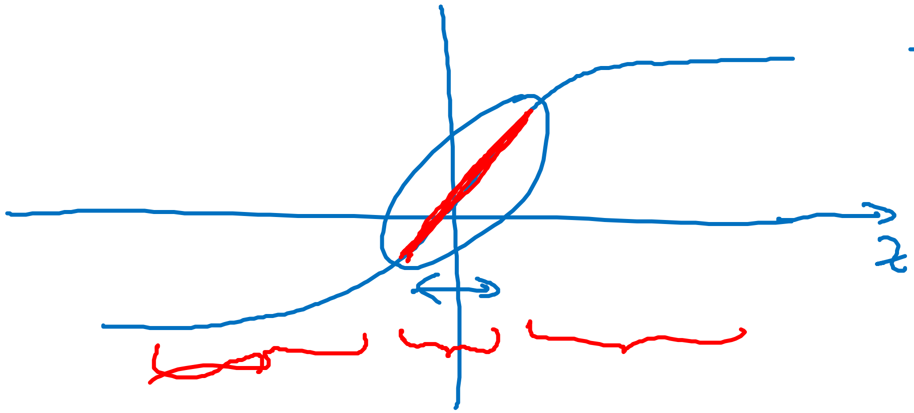
# How does regularization prevent overfitting?

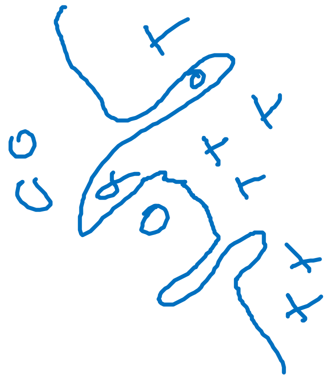



tanh

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

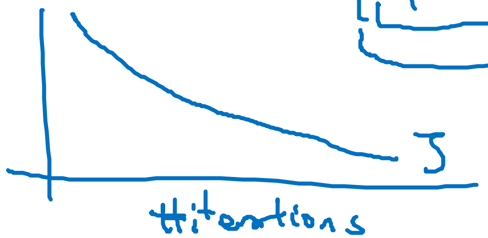
$\lambda \uparrow$ $\quad W^{[l]} \downarrow$

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



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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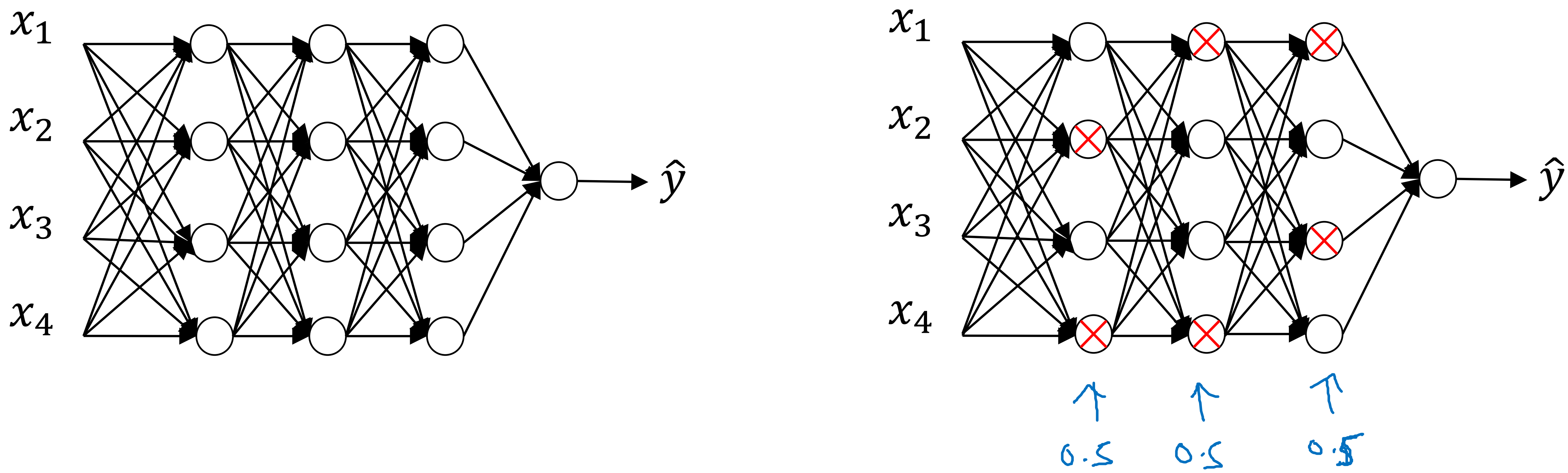
# Regularizing your neural network

## Dropout regularization

# Dropout regularization

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# Implementing dropout ("Inverted dropout")

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

→ $\boxed{d3}$ = 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

$a^{[0]} = X$

No drop out.

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

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

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

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

$$\downarrow$$

$$\hat{y}$$

/= keep-prob

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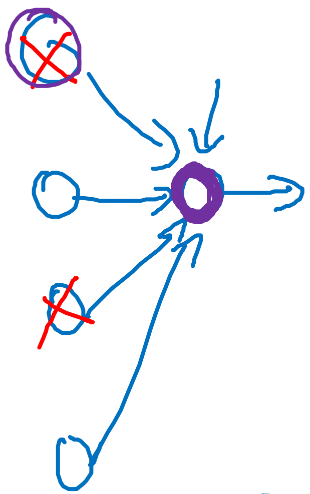
# Regularizing your neural network

## Understanding dropout

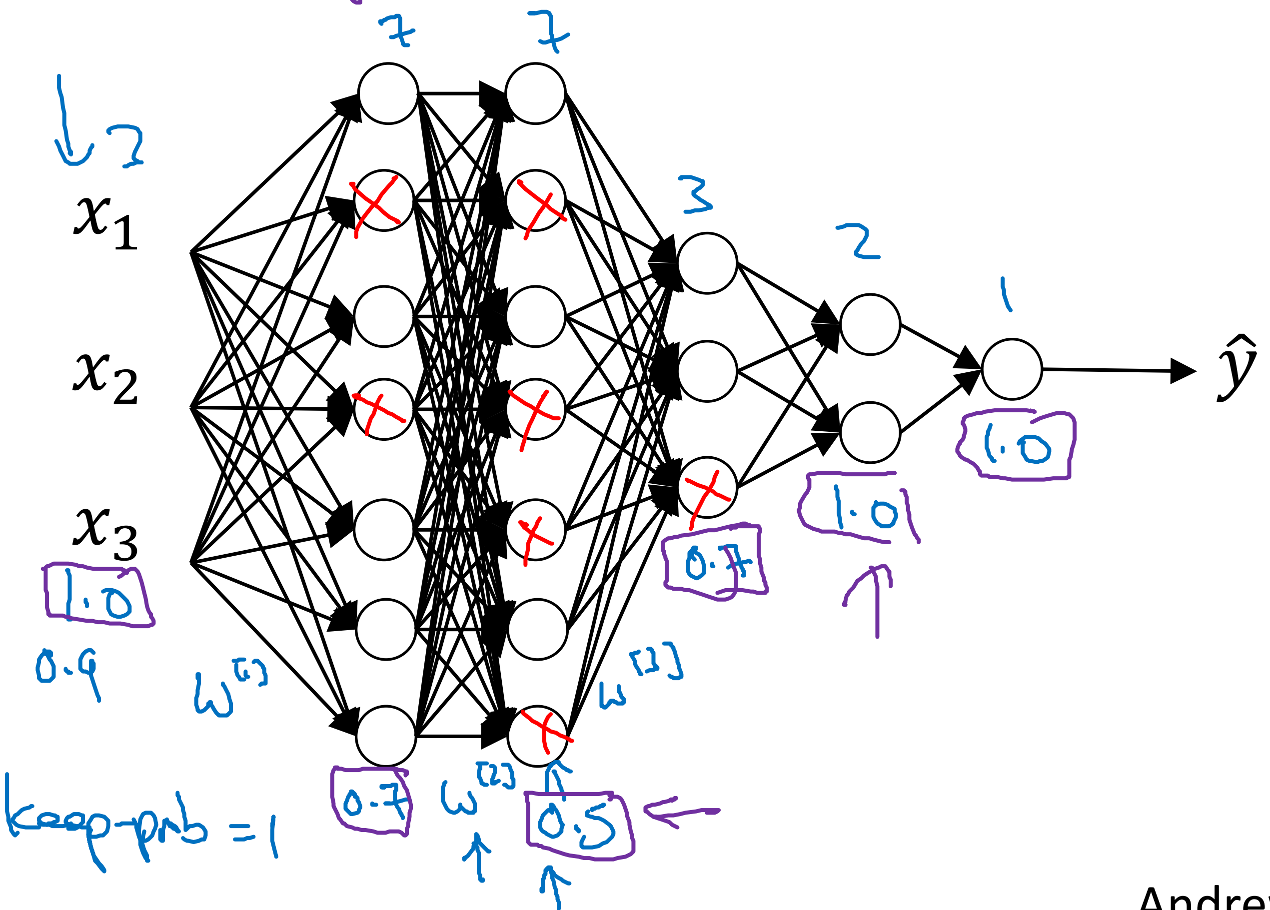
# Why does drop-out work?

Intuition: Can't rely on any one feature, so have to spread out weights. ⇝ Shrink weights. L2



→ Computer Vision

Downside: J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# Regularizing your neural network

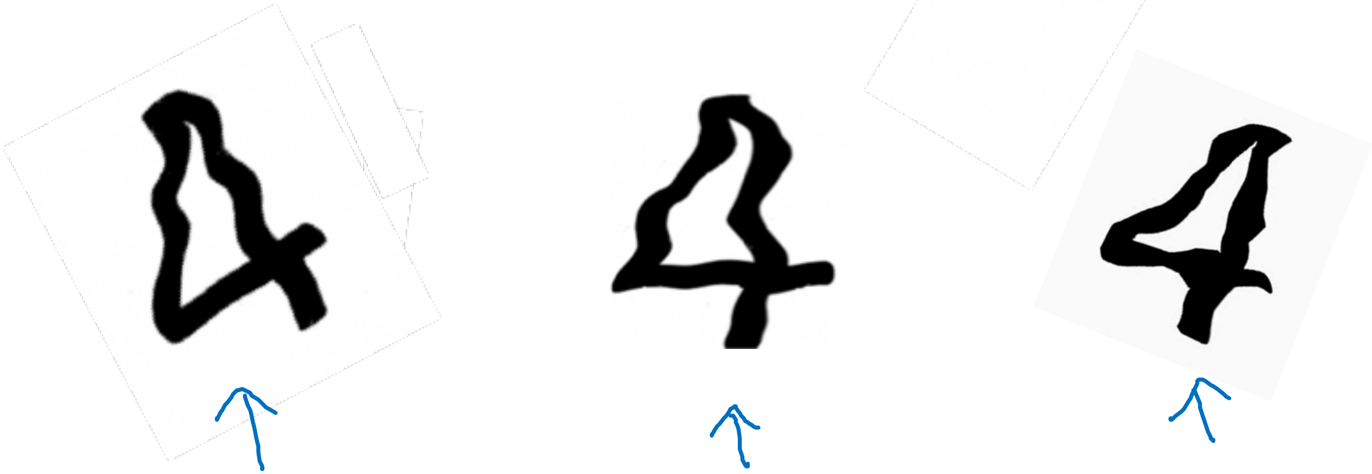
# Other regularization methods

# Data augmentation

If you are over fitting getting more training data can help, but getting more training data can be expensive and sometimes you just can't get more data. But what you can do is augment your training set by taking image like this. And for example, flipping it horizontally and adding that also with your training set. So now instead of just this one example in your training set, you can add this to your training example. So by flipping the images horizontally, you could double the size of your training set.

you can also take random crops of the image. So here we're rotated and sort of randomly zoom into the image and this still looks like a cat. So by taking random distortions and translations of the image you could augment your data set and make additional fake training examples

4



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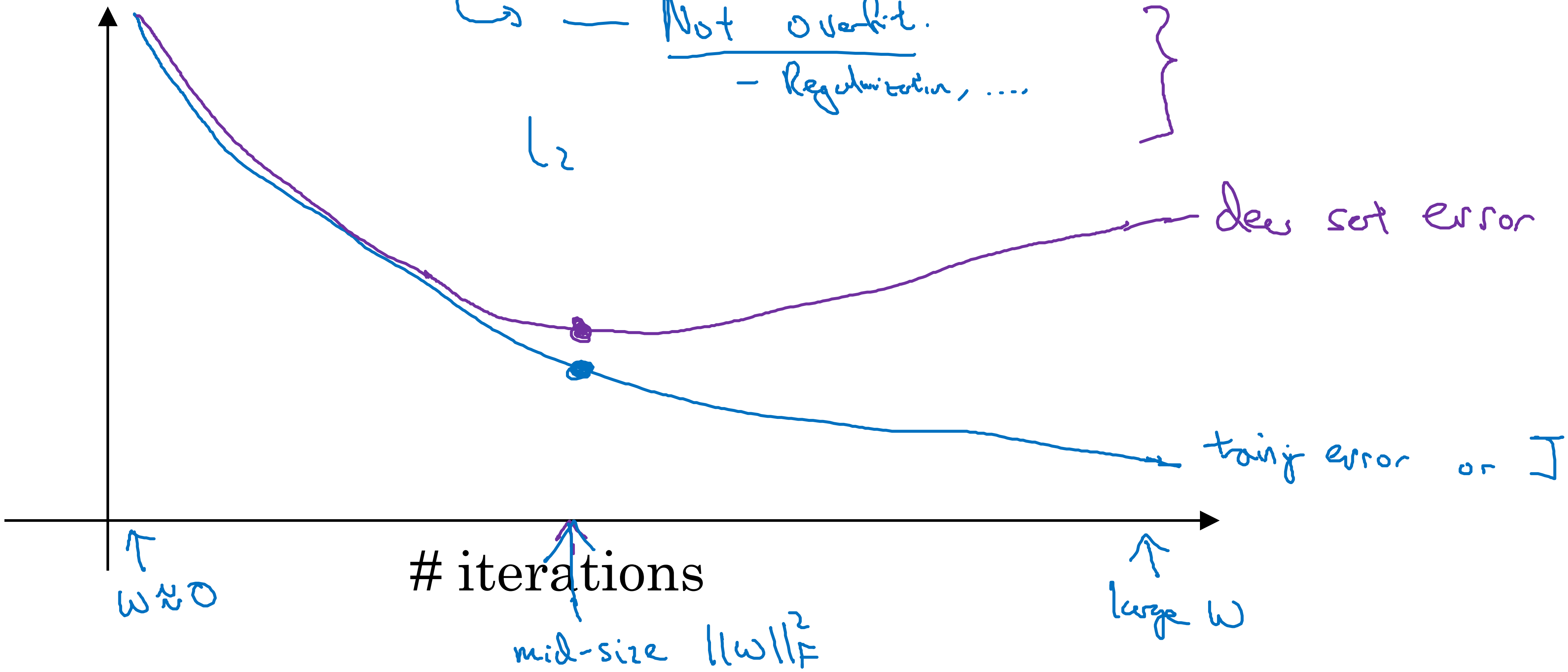
# Early stopping

Orthogonalization.

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

$J(w,b)$

$L_2$



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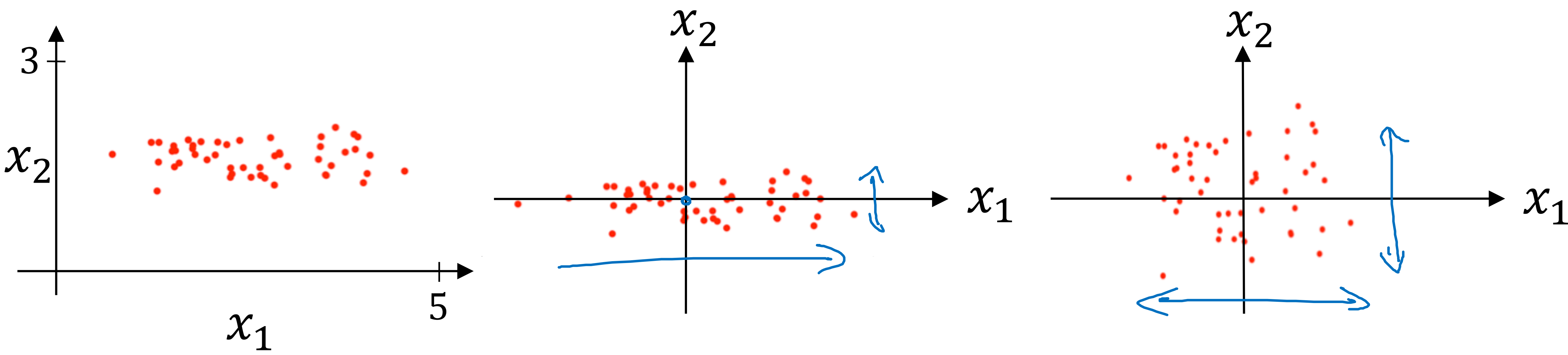
# Setting up your optimization problem

## Normalizing inputs

# Normalizing training sets

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




Subtract mean:

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

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

Normalize variance

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

element-wise

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

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

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# Why normalize inputs?

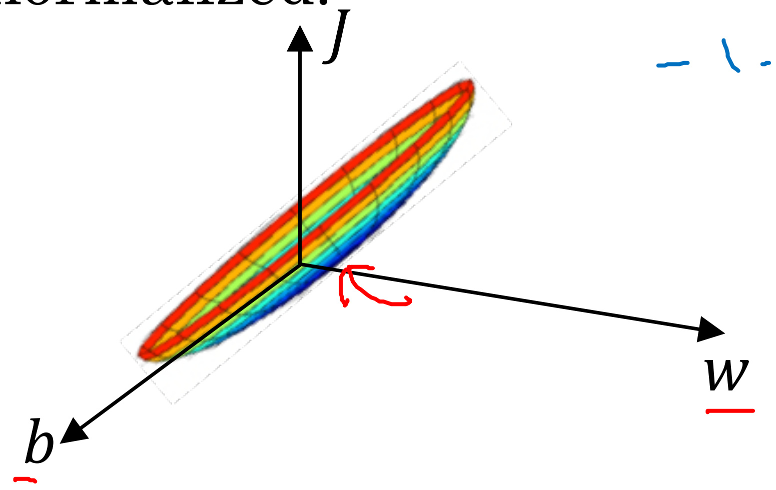
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m}\mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

$w_1$ $x_1$: $1 \ldots 1000$ ←

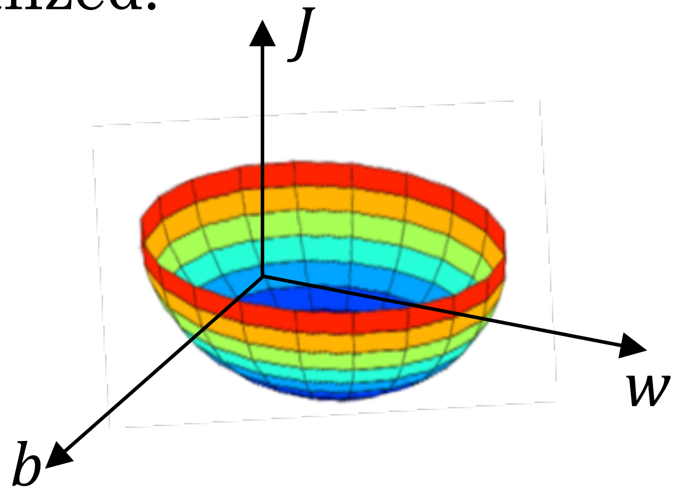
$w_2$ $x_2$: $0 \ldots 1$ ←

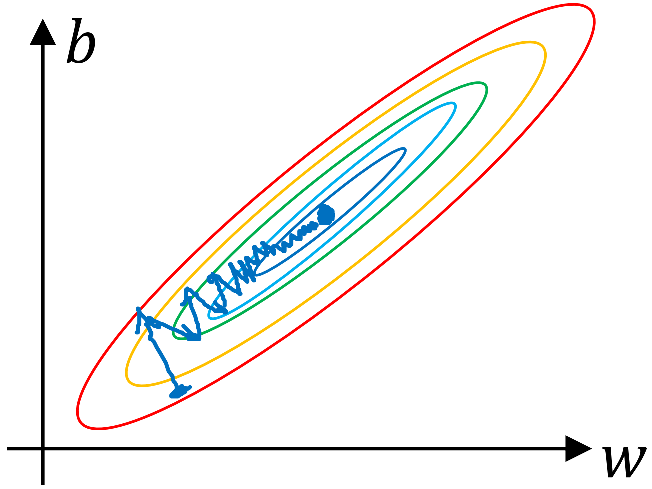
$-1 \ldots 1$

Unnormalized:




Normalized:

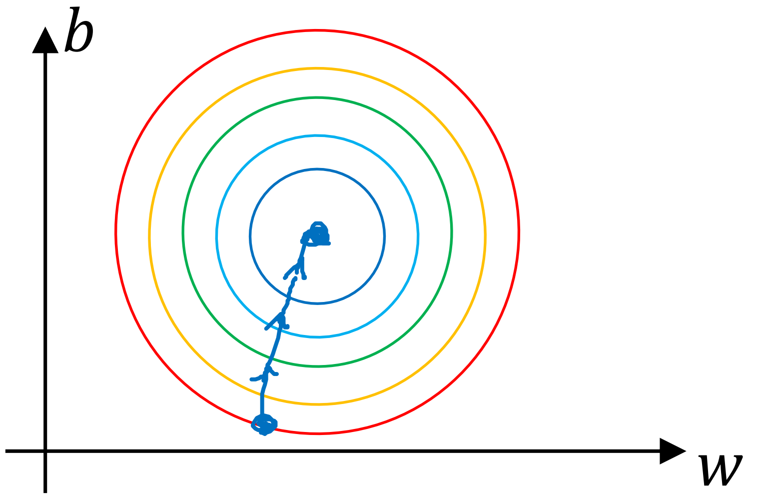



$x_1$: $0 \ldots 1$

$x_2$: $-1 \ldots 1$

$x_3$: $1 \ldots 2$

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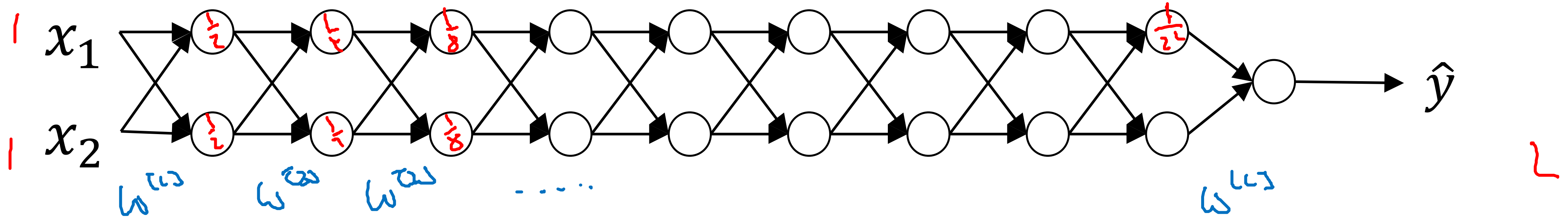
# Setting up your optimization problem

# Vanishing/exploding gradients

# Vanishing/exploding gradients

$L = 150$




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

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

$a^{[3]}$

$1.5^L$

$0.5^L$

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

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

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

$W^{[l]} > I$

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

If W[small L] > I (identity matrix) then y_hat will become W[L] * W[small L] **(L-1) * X because all the W's will act as input for the next layer and the gradients will explode due to very large values of W. Similarly, the trend goes downhill when W[small L] < I (identity matrix), the gradients will Vanish or get close to 0

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

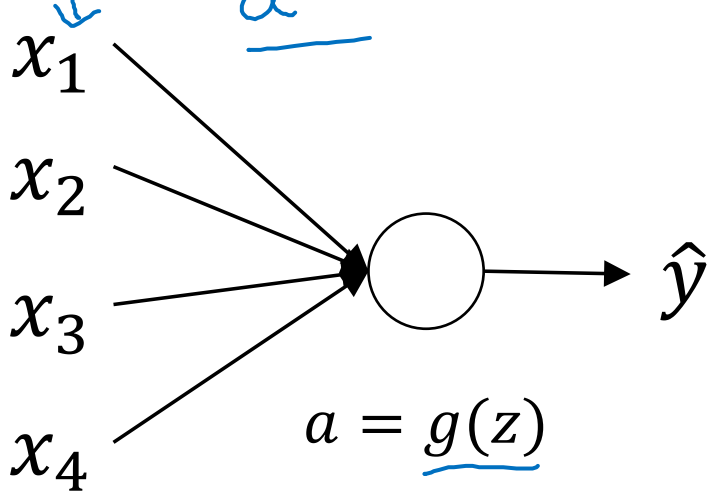
$$\hat{y} = W^{[L]} \begin{bmatrix} \cancel{1.5}\ 0.5 & 0 \\ 0 & \cancel{1.5}\ 0.5 \end{bmatrix}^{L-1} x$$

$1.5^{L-1} x$

$0.5^{L-1} x$

# 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 $w_i$

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

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

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

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

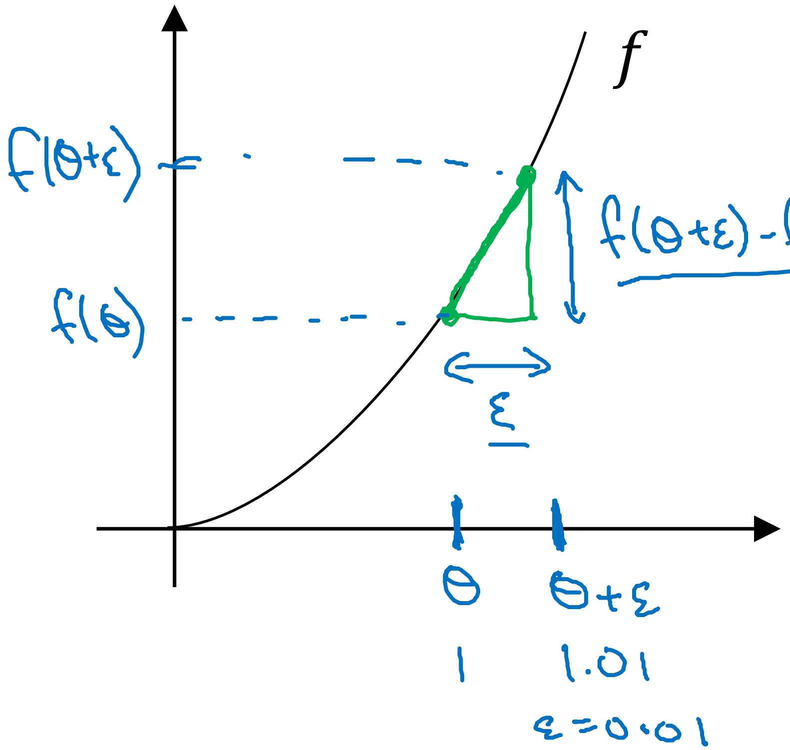
$\theta \in \mathbb{R}.$

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

$dw \quad db \rightarrow g(\theta) = 3\theta^2.$

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

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




$\theta = 1$

$\theta + \varepsilon = 1.01$

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

0.0301

3.1

3.2

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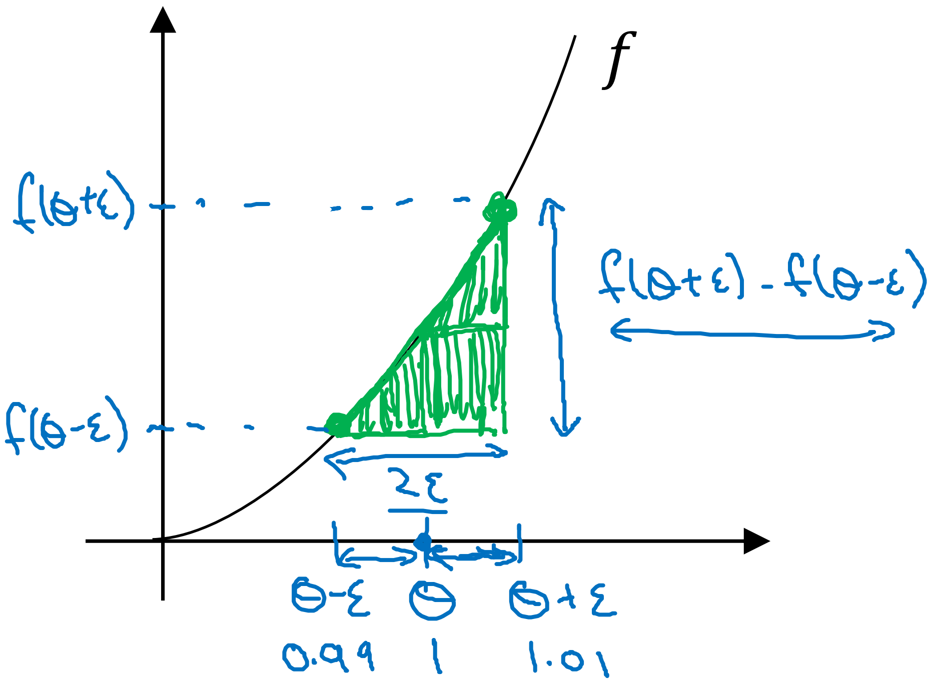
# Checking your derivative computation

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




$\varepsilon = 0.01$

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

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

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

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 $J(\theta)$?

# Gradient checking (Grad check)

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

for each $i$:

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

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

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

Check $\dfrac{\|d\theta_{approx} - d\theta\|_2}{\|d\theta_{approx}\|_2 + \|d\theta\|_2}$

$\varepsilon = 10^{-7}$

$\approx \boxed{10^{-7} \text{ - great!}}$

$10^{-5}$

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

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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. $\theta$

- 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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