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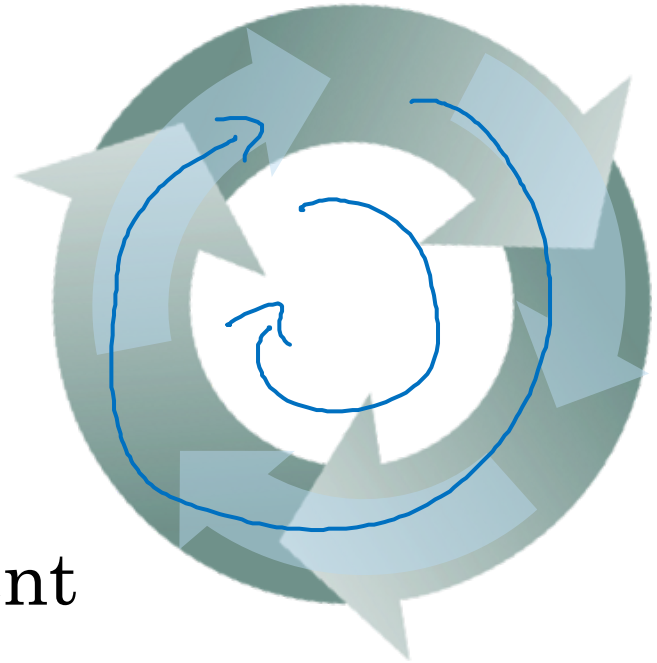
Setting up your ML application

Train/dev/test sets

Applied ML is a highly iterative process

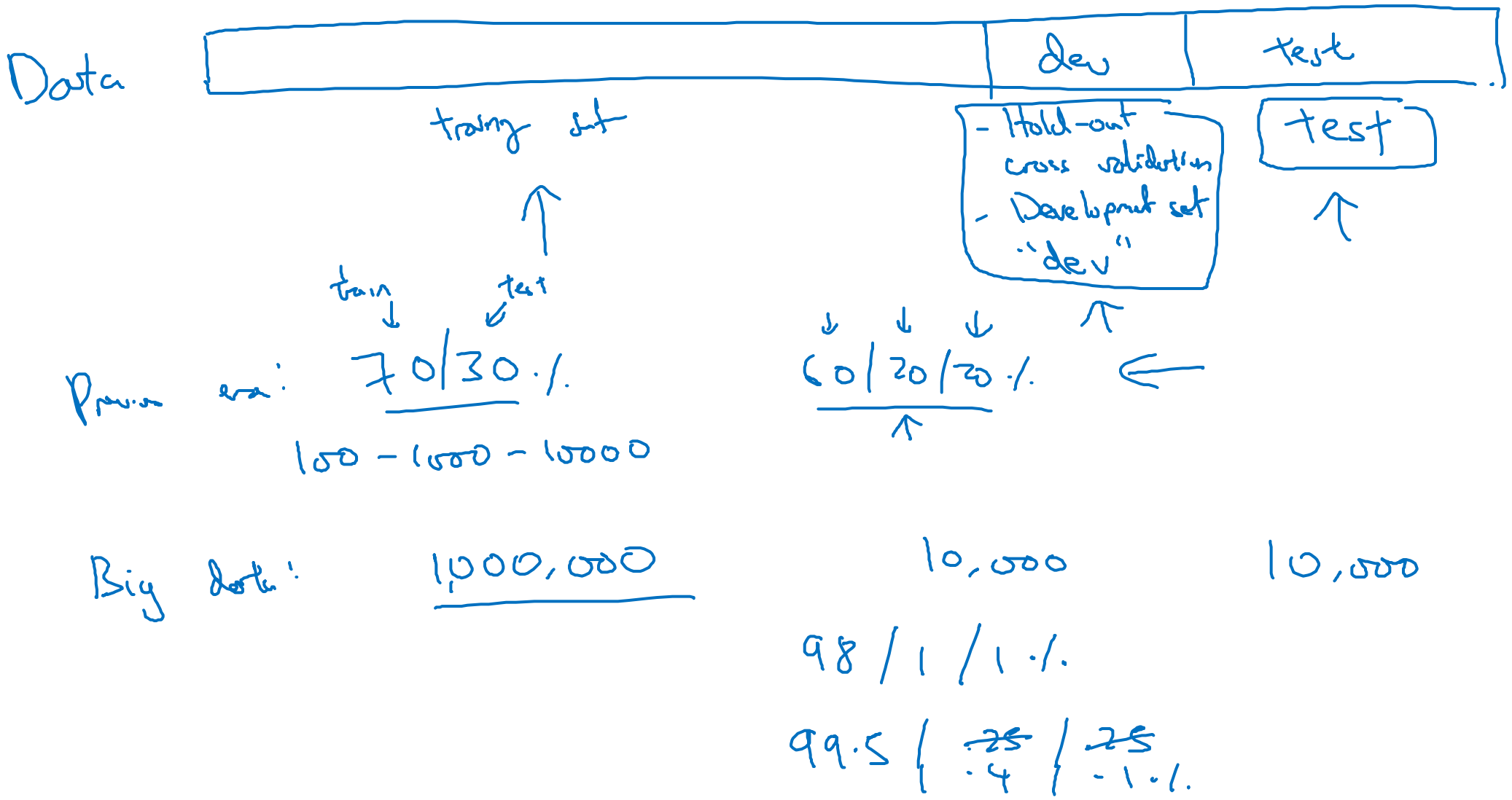
- # layers
- # hidden units
- learning rates
- activation functions
- ...



NLP, Vision, Speech, Structured data

Ads Search Security Logistic ....

Train/dev/test sets



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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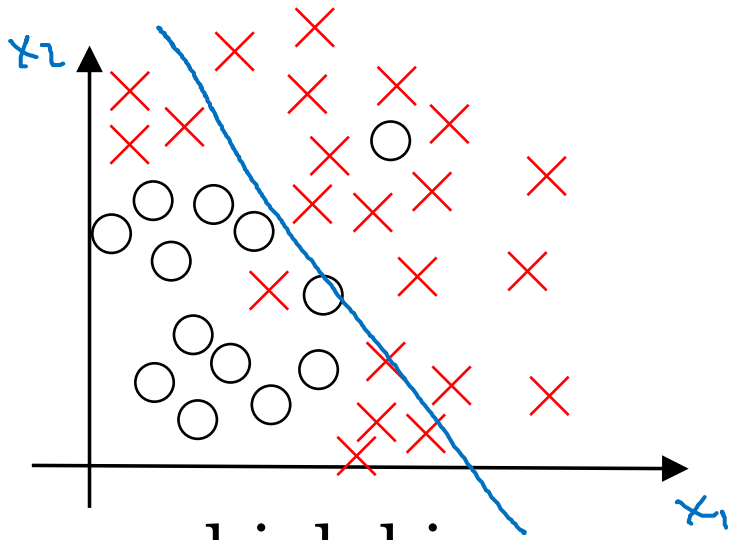
Setting up your ML application

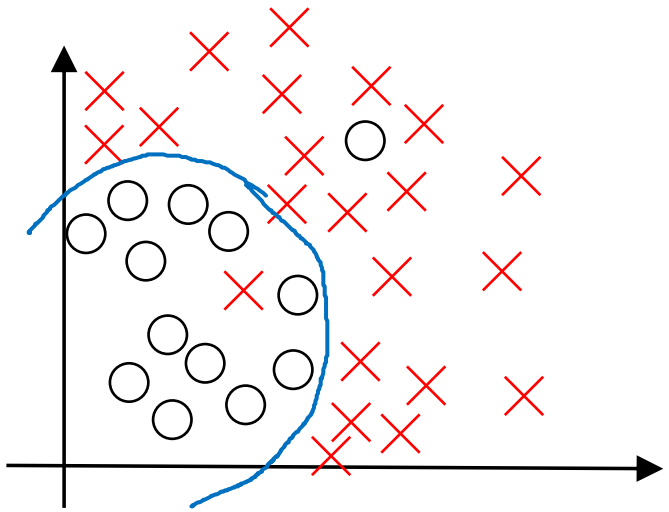
Bias/Variance

Bias and Variance

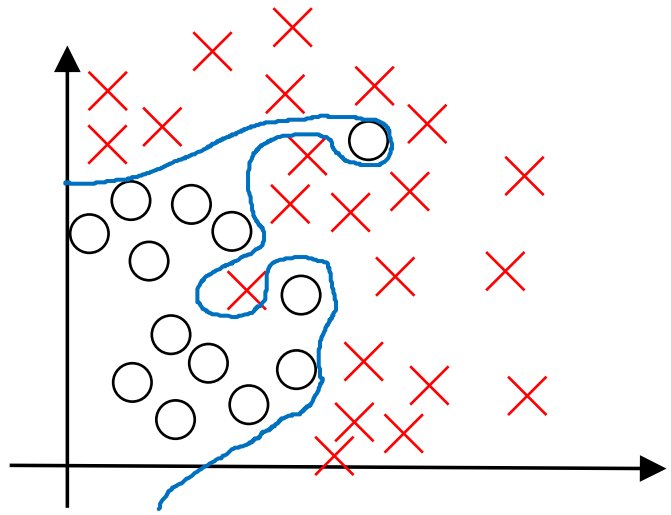


high bias

Underfitting



→ "just right"



high variance

Overfitting

Bias and Variance

Cat classification

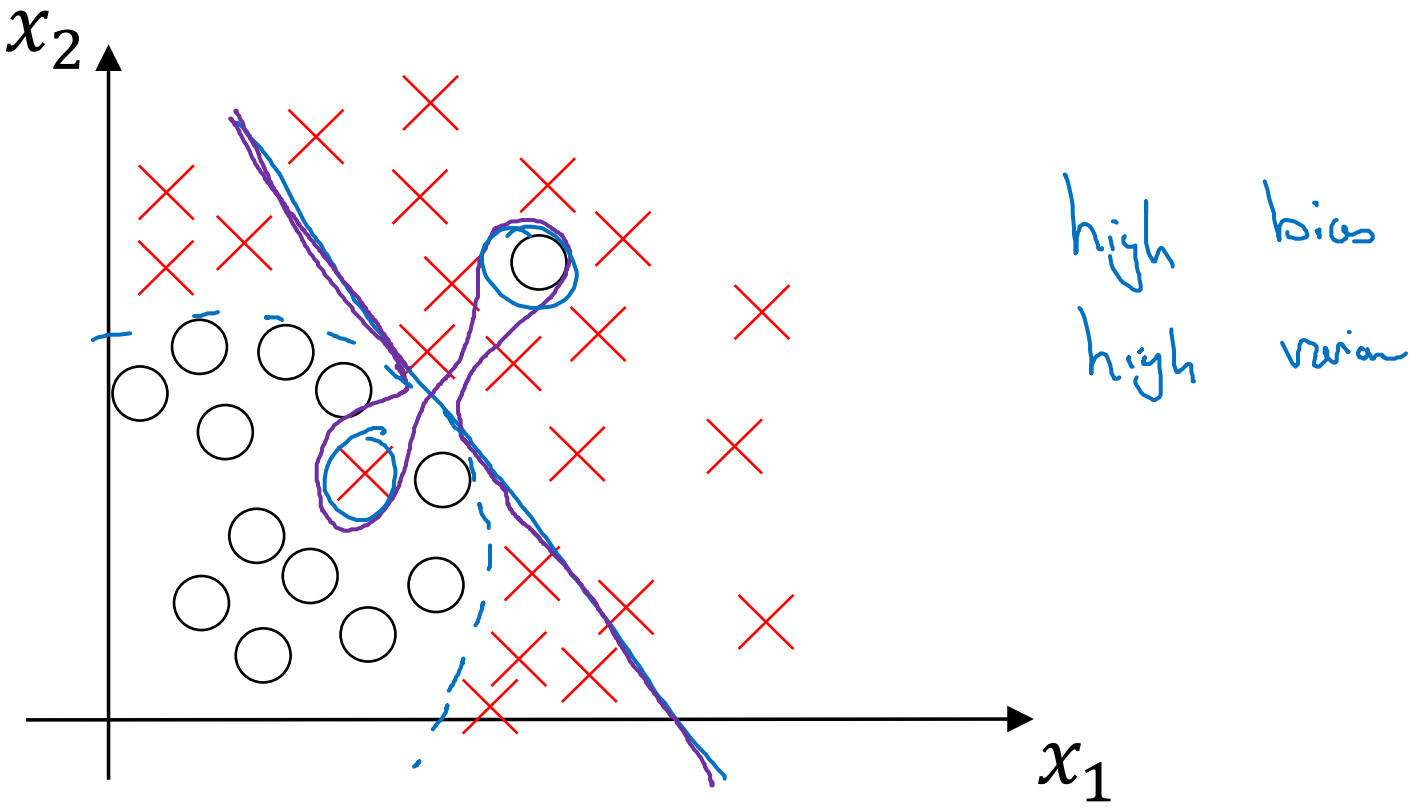
Train set error:	1%	15%	15%	0.5%
Dev set error:	11%	16%	30%	1%
	high variance	high bias	high bias & high variance	low bias low variance

Human: ≈0%

Optimal (Bayes) error: ~~≈0%~~ 15%

Blurry images

High bias and high variance



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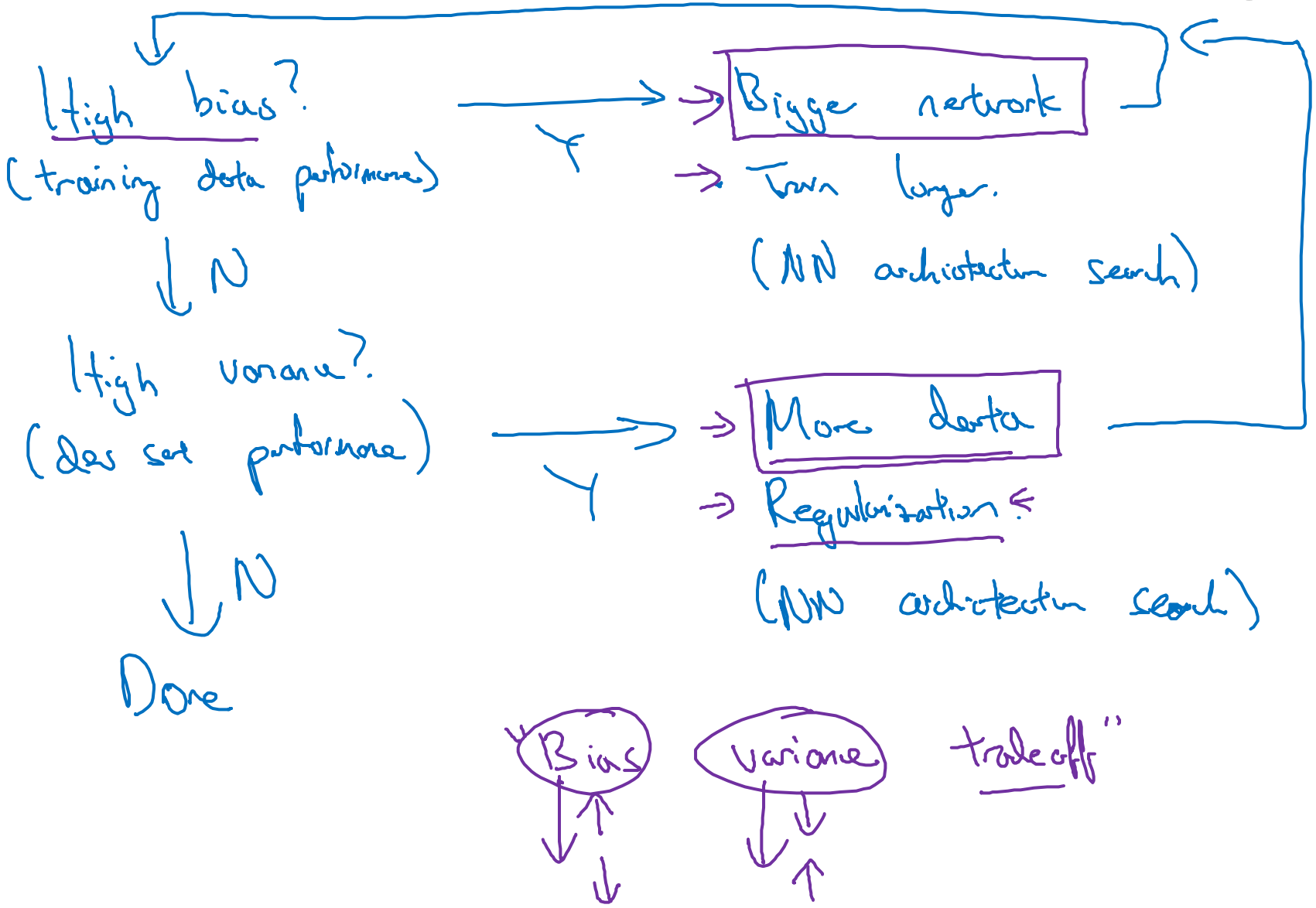
Setting up your ML application

Basic “recipe” for machine learning

Basic recipe for machine learning



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Regularizing your neural network

Regularization

Logistic regression

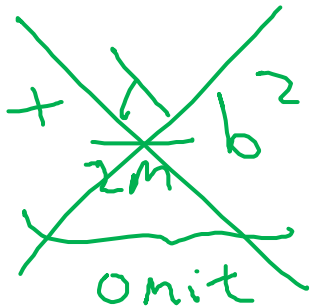
$\min_{w,b} J(w,b)$

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

λ = regularization parameter

lambda lambd

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



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

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

w will be sparse

Neural network

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

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

$w^{[l]}: (n^{[l]}, n^{[l-1]})$

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

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

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

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

"Weight decay"

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

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

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

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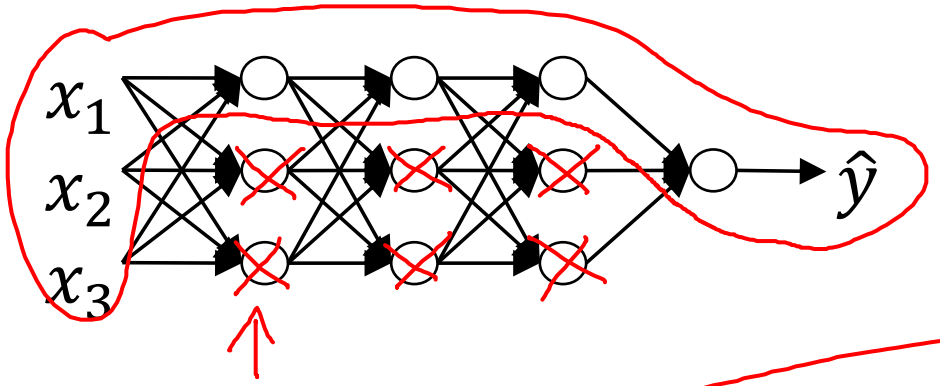
Regularizing your neural network

Why regularization reduces overfitting

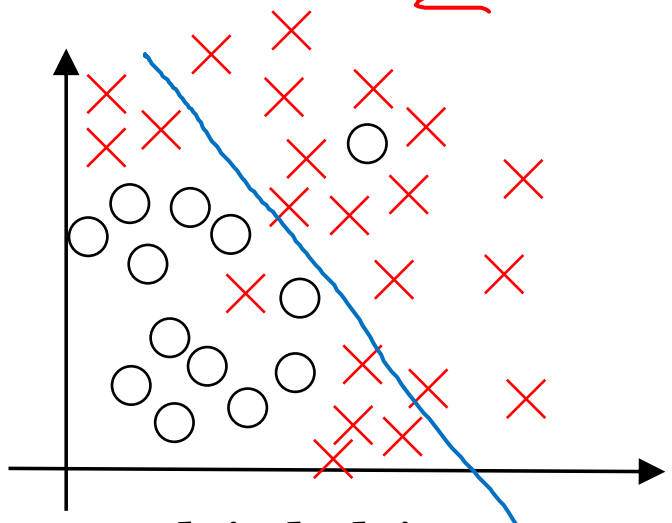
How does regularization prevent overfitting?



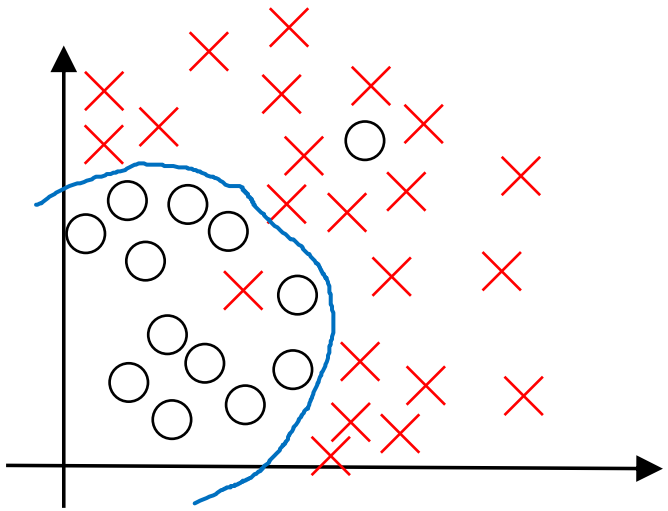
$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2$$

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

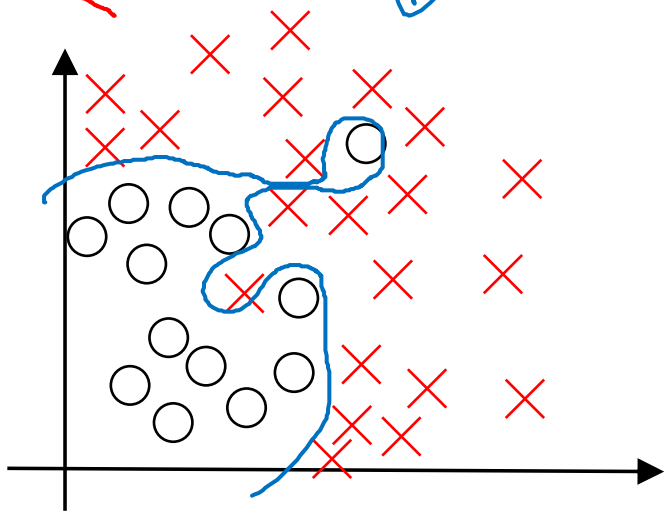
lambda 1 e yaklaşınca w 0 a yaklaşır



high bias



"just right"



high variance

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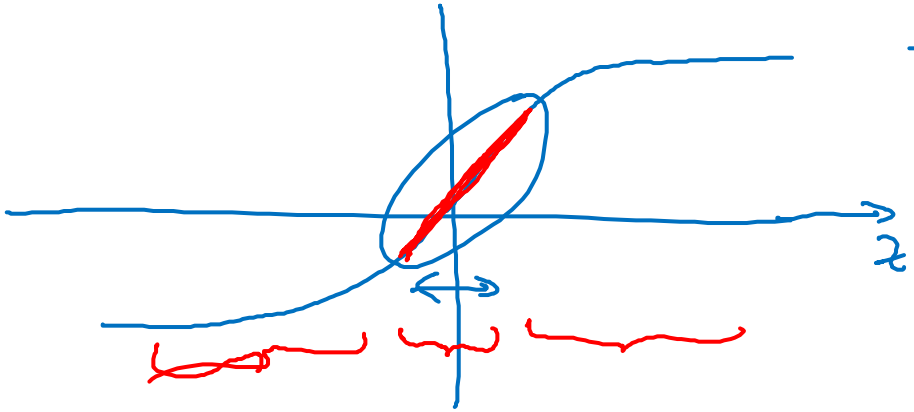
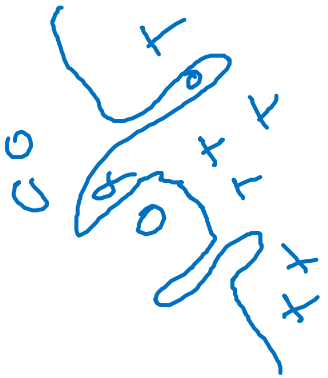
How does regularization prevent overfitting?

w nun küçük değerler alması linear bir problem çözmemizi sağlar



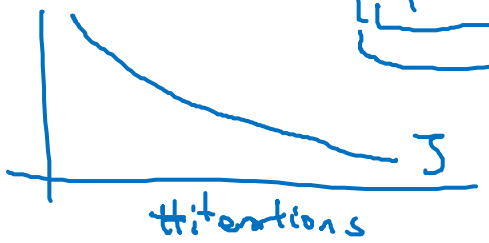
$g(z) = \tanh(z)$

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



Every layer ≈ linear.

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



weight decay olduğu için cost sürekli azalıyor olmasa bir yerden sonra düz devam ederdi

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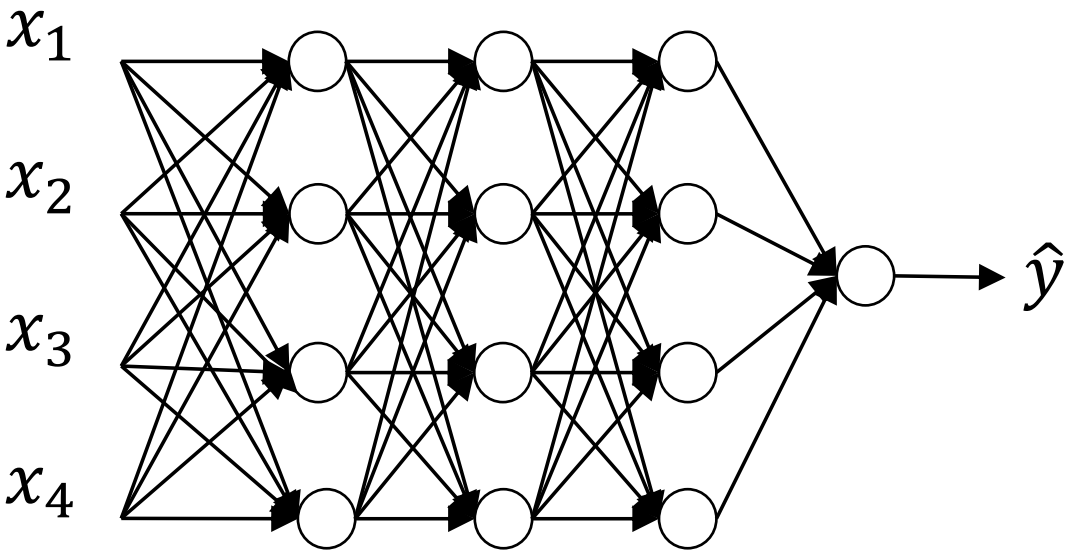
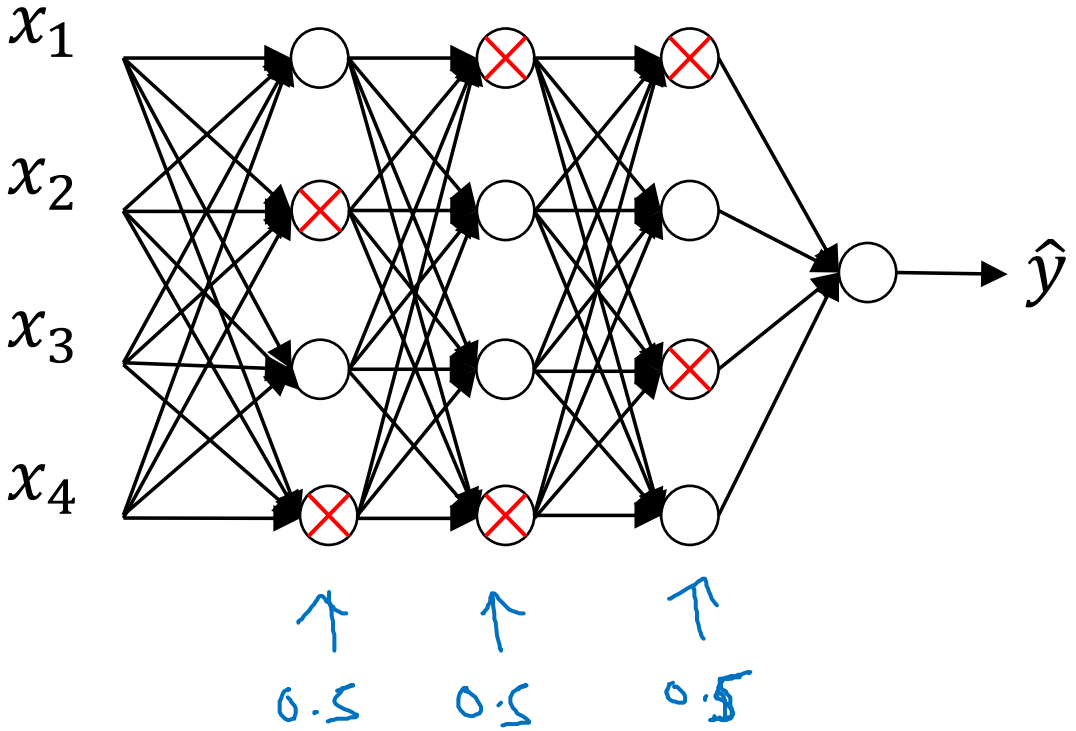
Regularizing your neural network

Dropout regularization

Dropout regularization





Implementing dropout ("Inverted dropout")

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

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

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

$a3 /= keep\text{-}prob$ (was ~~0.8~~)

50 units. ⇝ 10 units shut off

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

$a^{[3]}$ reduced by 20%.

$/= 0.8$

Test

Making predictions at test time

$a^{[0]} = X$

No drop out.

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

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

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

$a^{[3]} = \ldots$

$\hat{y}$

we dont want randomness in test time that would just add noise to our output

/= keep-prob

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Regularizing your neural network

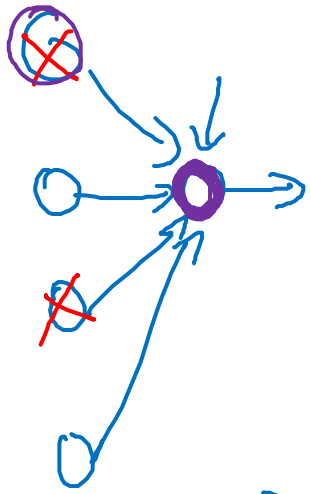
Understanding dropout

Why does drop-out work?

mantık şöyle: modelimizdeki weighlerimizin tek bir featureye bağlı olmasını istemiyoruz dağınık olmaları daha mantıklı

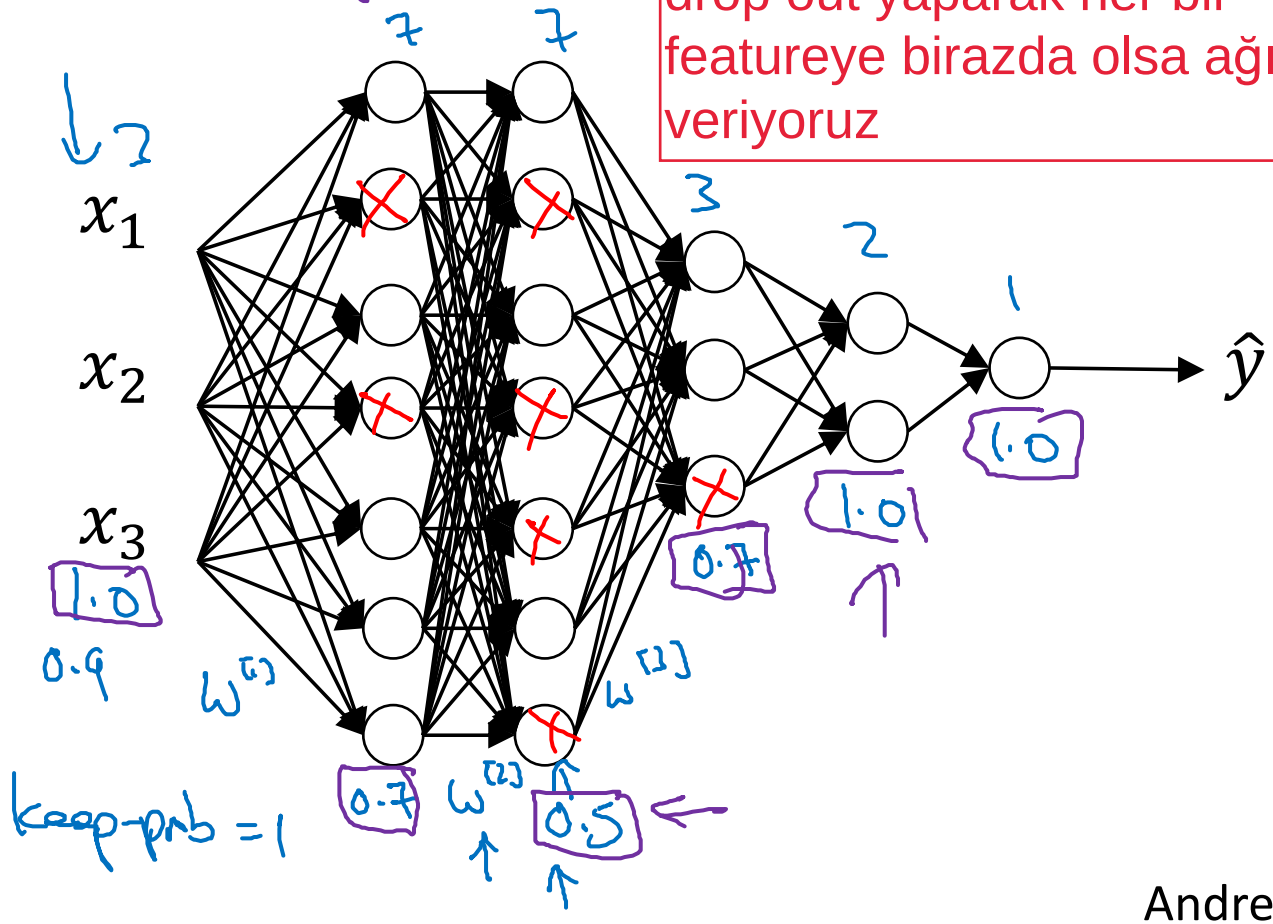
Intuition: Can't rely on any one feature, so have to spread out weights.

bu yüzden random şekilde drop out yaparak her bir featureye birazda olsa ağırlık veriyoruz



→ Computer Vision

Downside: J



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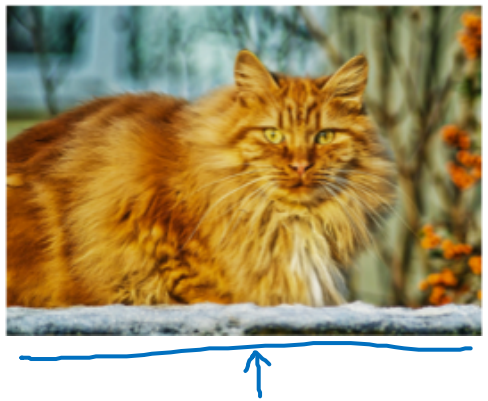
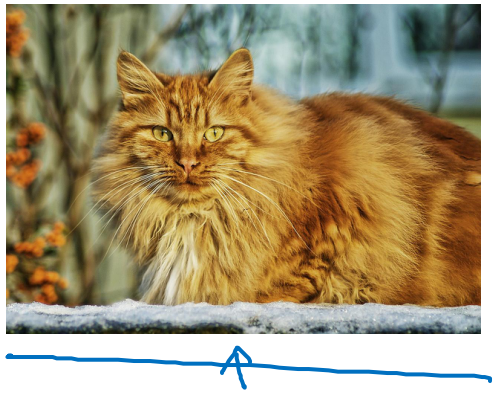
Regularizing your neural network

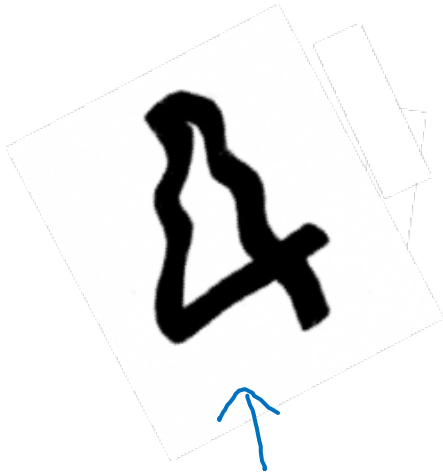
Other regularization methods

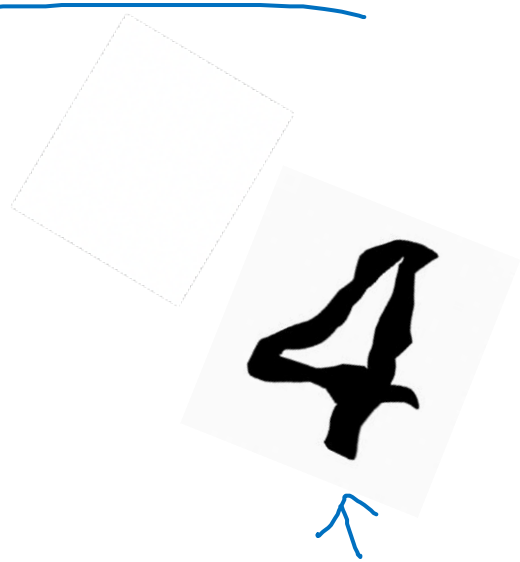
Data augmentation





4





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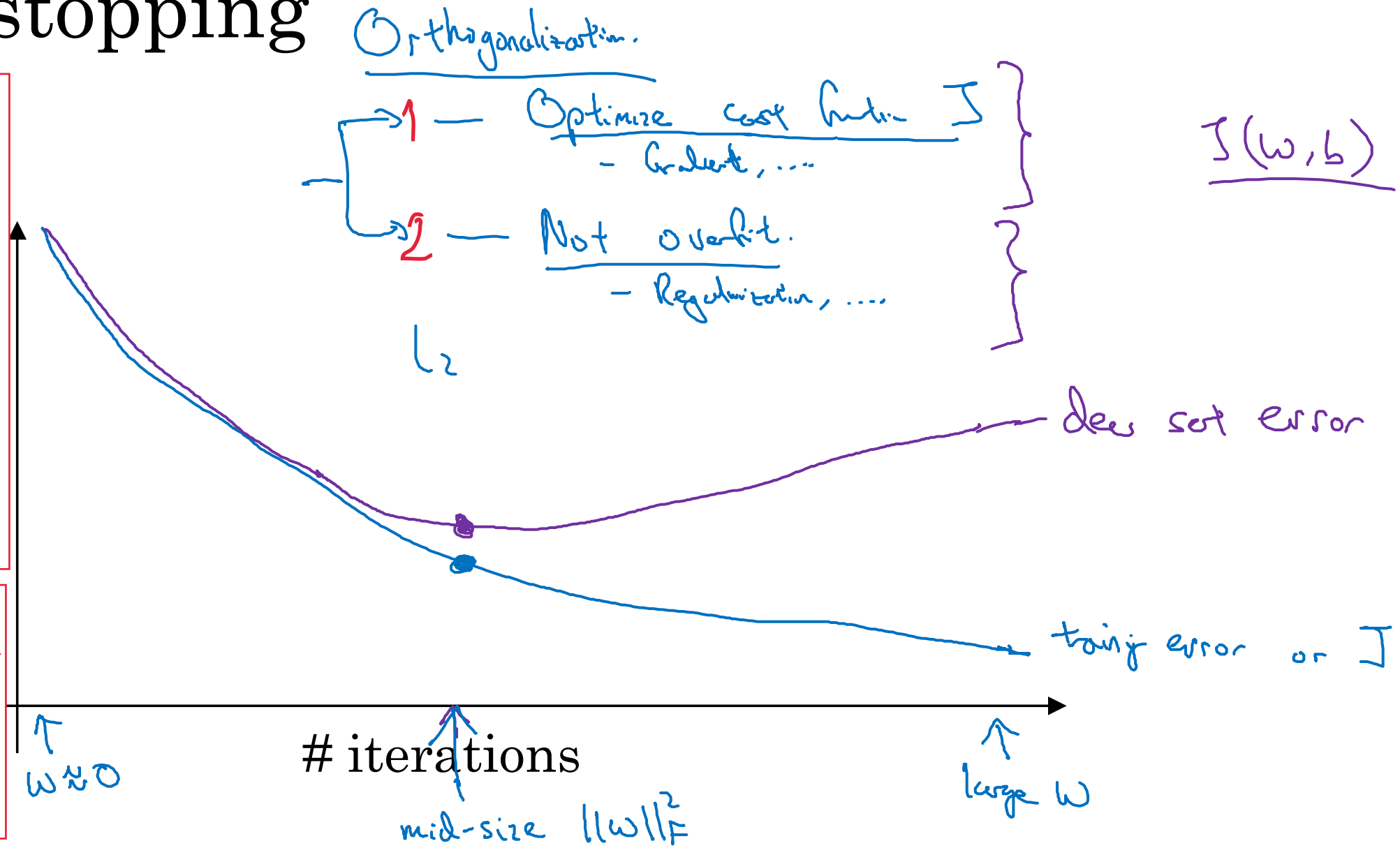
Early stopping

1 ve 2 işlerini aynı anda yapamayız bu sebeble en optimal yerde gradient descendi durdukmak early stopping oluyor ama bu cost functionumu daha fazla optimize etmemizi engelliyor.

L2 regularizationunda bu dezavantaj yok ama onunda lambda değerini bulmak maliyetli



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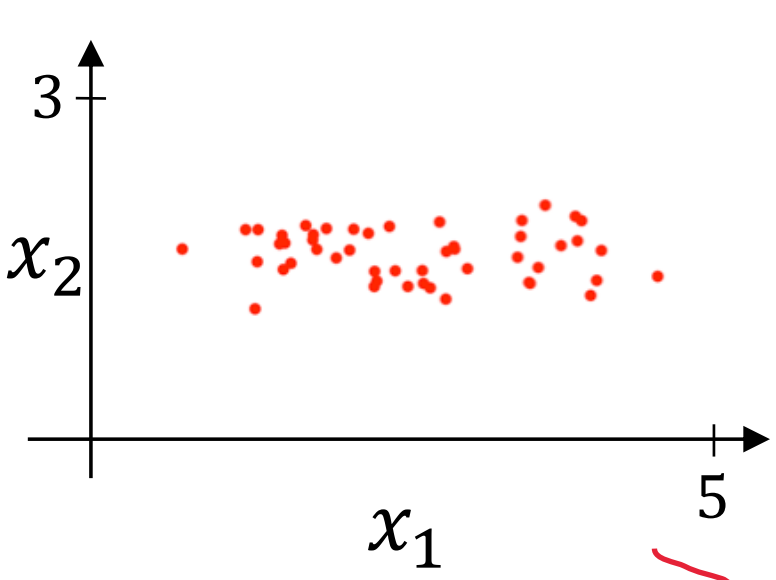
Setting up your optimization problem

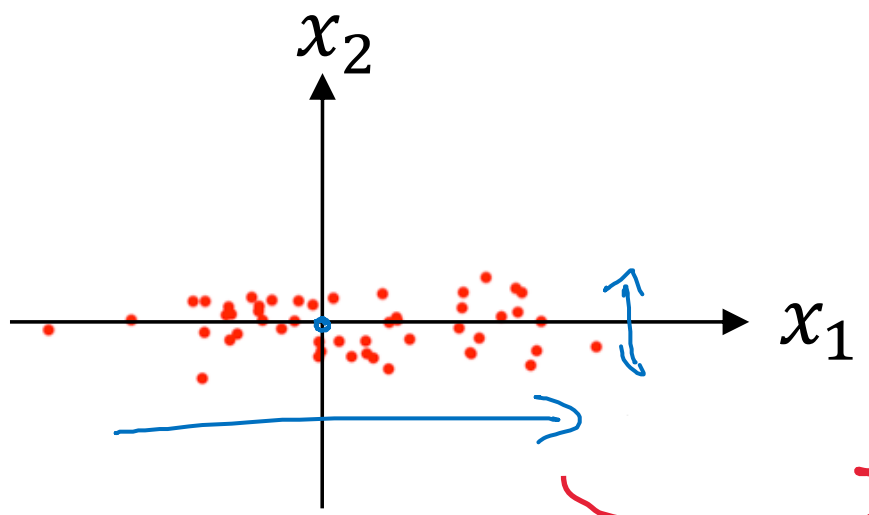
Normalizing inputs

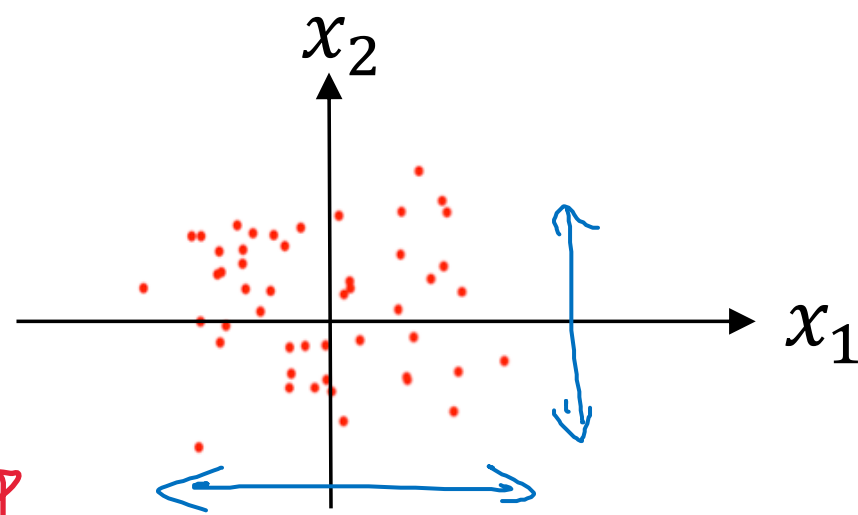
Normalizing training sets

normalize derken aynı m ve var değerlerini kullan train ve test için ve bunları train datası üzerinden hesapla

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







ortalamasını 0 yaptık

1) Subtract mean:

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

$x := x - \mu$

dağılımdaki variance eşitsizliğini düzelttik

2) Normalize variance

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

← element-wise

$x /= \sigma^2$

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

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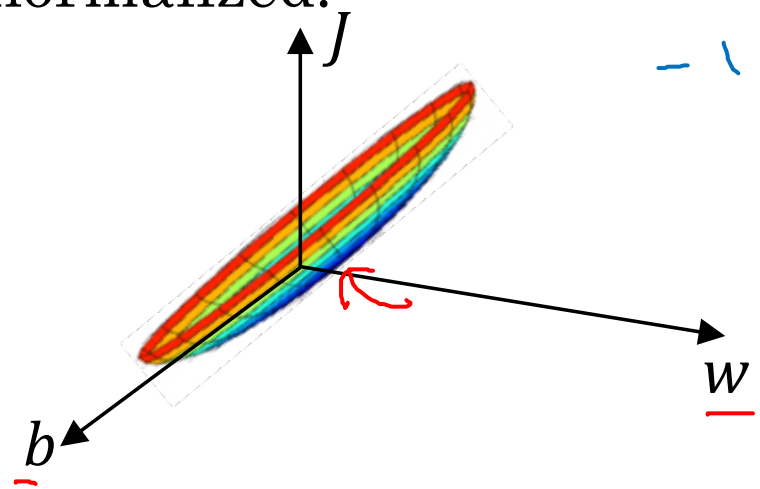
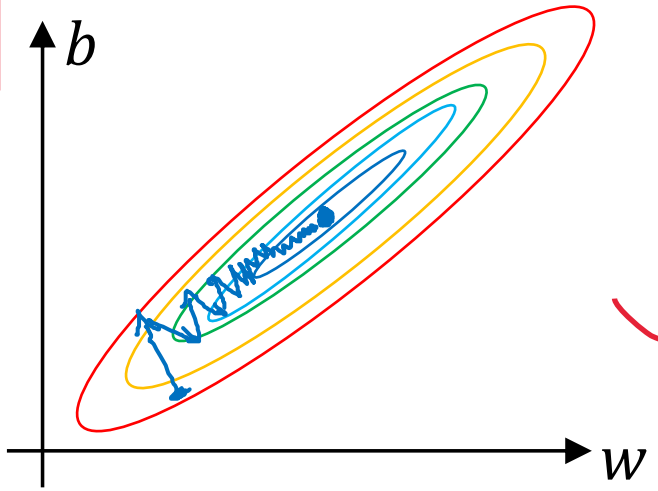
Why normalize inputs?

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

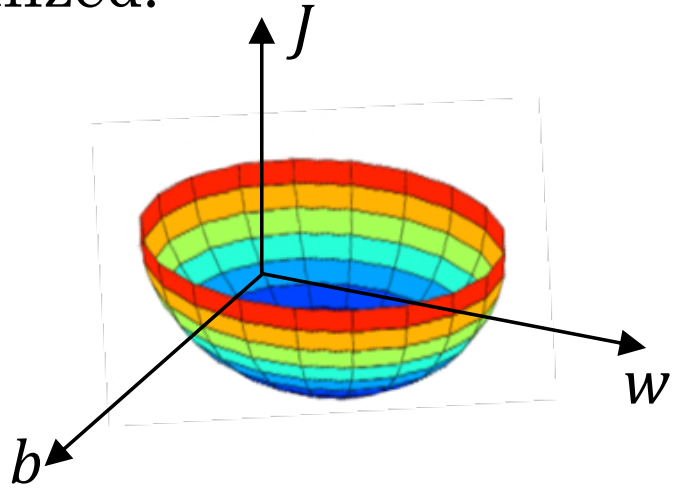
Unnormalized:



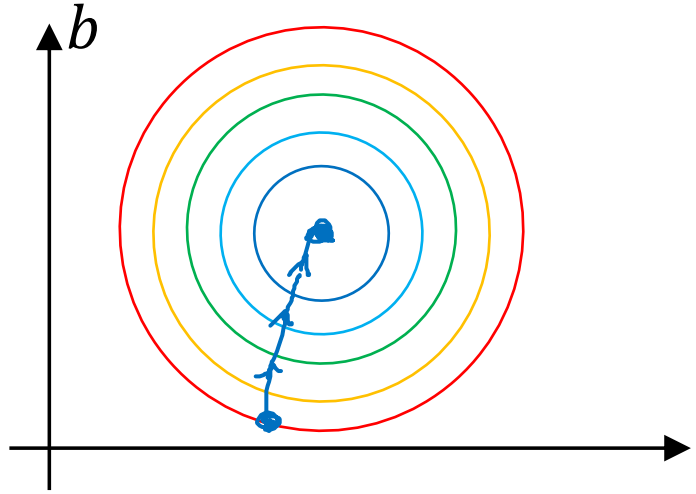
weightlerimizin aralıkları birbirinden çok farklı olması optimization algoritmaları için büyük bir sorun



Normalized:



benzer aralıklara normalize ettiğimizde GD daha hızlı şekilde converge olucaktır



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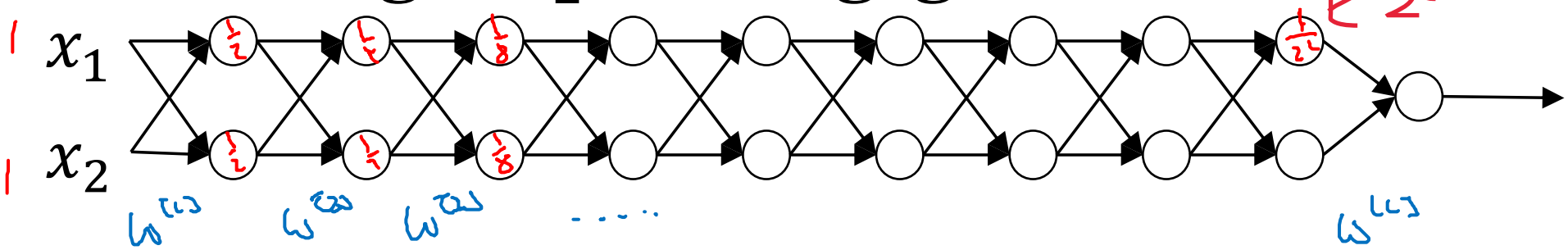
Setting up your optimization problem

Vanishing/exploding gradients

Vanishing/exploding gradients



eğer w muz identity matrixten birazcık büyük veya küçük olursa layerlarımızın çok fazla olduğu durumlarda bu katlanarak arttığı için gradient explode veya gradient vanishing durumlarıyla karşılaşırız.

w lerimiz her layerde aynı

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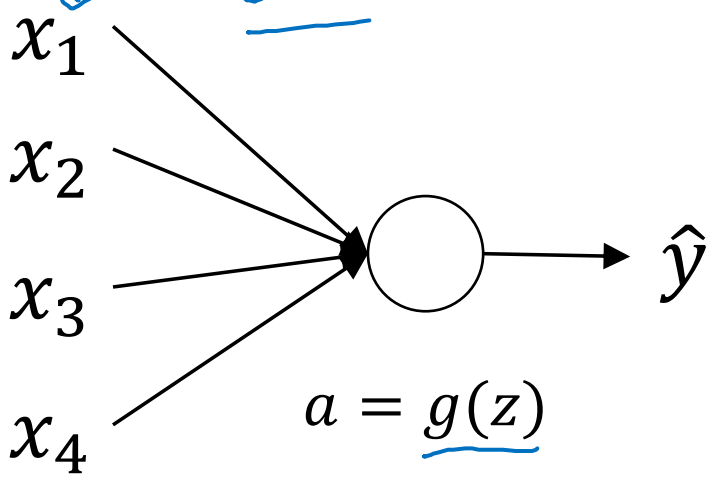
Single neuron example



$a^{[l]}$

$w^{[l]}$

x lerimizin sayısı artıkça w larımınz değerlerinin azalmasını istiyoruz ki exploding/ vanishing problemi ortadan tam olmasada kalksın

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

Large n → Smaller w_i

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

random initilialize yaptığımız dist nın variancesini bu formullerle scallememiz sorunu partially çözüyor

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

ReLU

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

Other variants:

tanh

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

Xavier initialization

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

relu

- So lets say when we initialize `W`'s like this (better to use with `tanh` activation):

```
np.random.rand(shape) * np.sqrt(1/n[l-1])
```

or variation of this (Bengio et al.):

```
np.random.rand(shape) * np.sqrt(2/(n[l-1] + n[l]))
```

- Setting initialization part inside sqrt to `2/n[l-1]` for `ReLU` is better:

```
np.random.rand(shape) * np.sqrt(2/n[l-1])
```

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Setting up your optimization problem

Numerical approximation of gradients

Checking your derivative computation

gradient checking which tells you if your implementation of backpropagation is correct.

but it's slower than gradient descent (so use only for debugging).

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

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

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

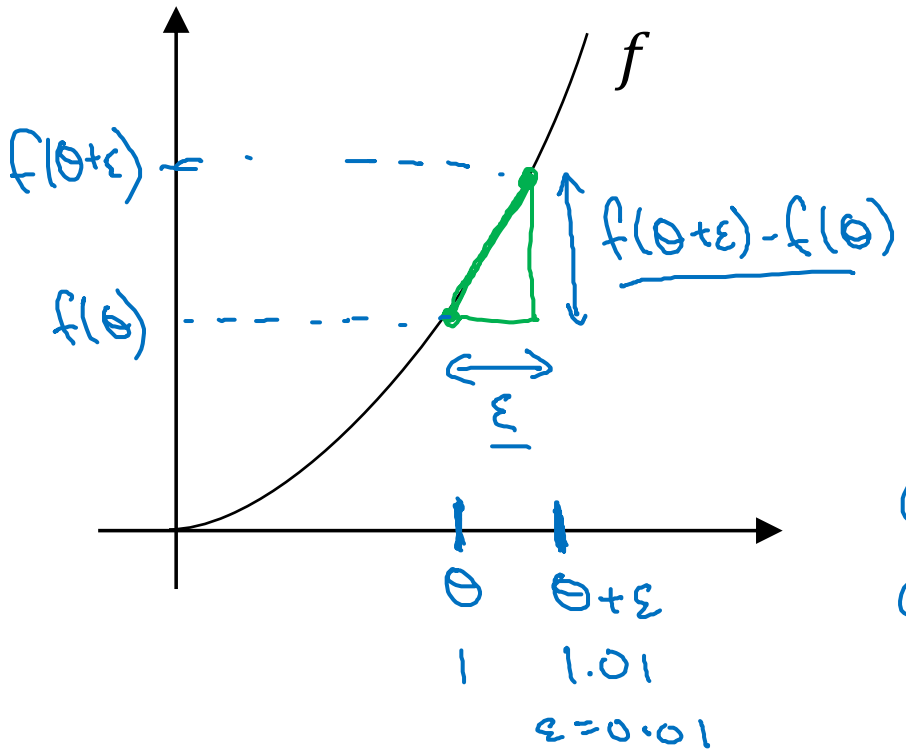
$g(\theta) = 3\theta^2$.

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

dw

db

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



$\theta = 1$

$\theta + \varepsilon = 1.01$

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

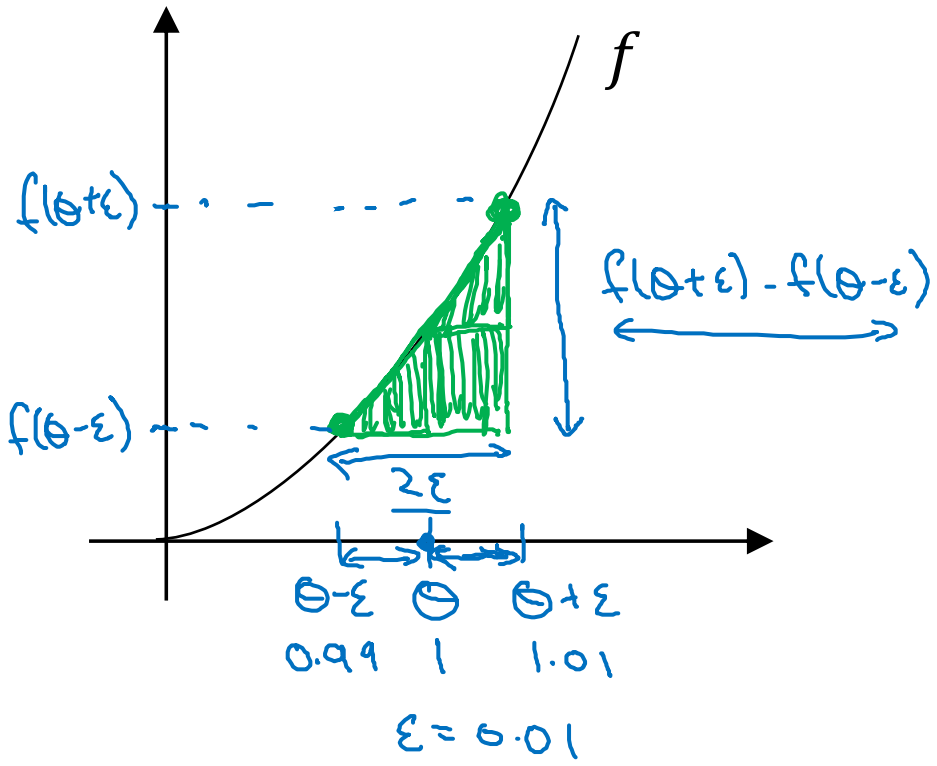
0.0301

3.1

3.2

Checking your derivative computation

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



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

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

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

approx error: 0.0001

(prev slide: 3.0301. error: 0.03)

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

$O(\varepsilon^2)$

0.01

0.0001

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

0.01

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Setting up your optimization problem

Gradient Checking

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 $J(\theta)$?

Gradient checking (Grad check)

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

for each i:

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

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

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

Check

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

öklid

$\varepsilon = 10^{-7}$

$\approx 10^{-7}$ — great!

10^{-5}

$\rightarrow 10^{-3}$ — worry.

debug

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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

debug için kullan değerler birbirine çok yakınsa kapatıp devam et değilse hata ara

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

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

hatayı birbirinden çok farklı olan değerlerde aramamız lazım bunlarıda Q yı veren W ve B lere bakarak yapacağız

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

- 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 wrt. θ

- Doesn't work with dropout.

J keep-prob = 1.0

drop out için kullanıcaksak keep_prob = 1.0 olarak kontrol et sonra drop out uygula

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

$W, b \approx 0$

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