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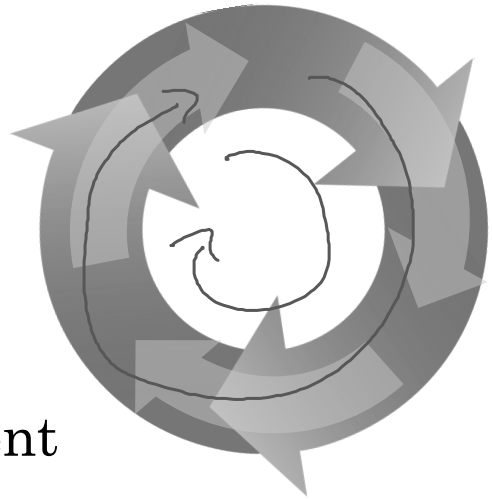
Setting up your ML application

Train/dev/test sets

structured data
- advertising
- search
- security
- logistics

Applied ML is a highly iterative process

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



NLP, Vision, Speech, Structured data

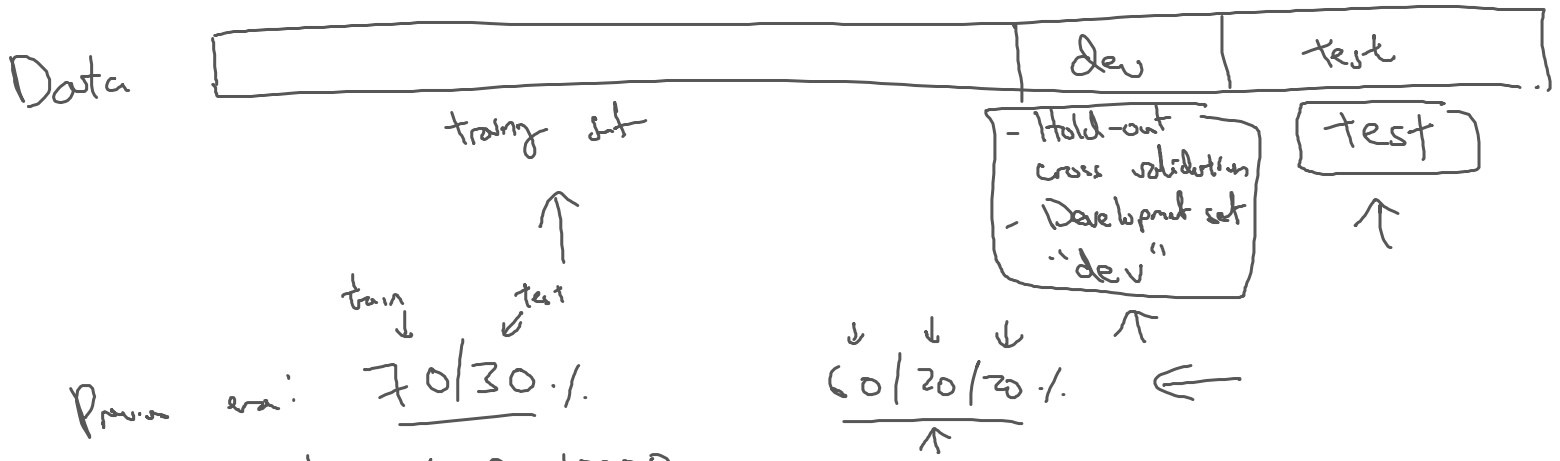
Ads Search Security logistic ....

Data : ① Training ② Development ③ Testing

Dev set = Hold-out = Cross validation = development

برای تطابیس عملکرد چندین الگوریتم جامعه است.

Train/dev/test sets



Mismatched Distributions اگر منبع Train متفاوت از dev/Test باشد ⇐ Solution: حداقل dev/test منبع مشابه باشند.

Mismatched train/test distribution

Carts

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

→ Make sure dev and test come from same distribution.

train / dev ("test")

train / test → train / dev

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

خصوصاً اگر unbiased estimate مهم نباشد (چون ماشین قبلاً dev set را دیده است، Test کردن با dev دقیق نیست)

← وقتی می‌گویند Train/Test منظور Train/dev است.

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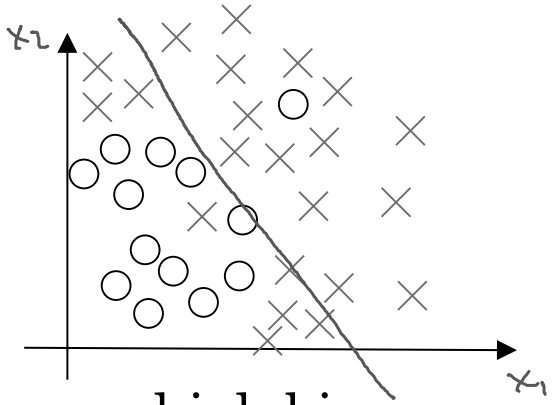
Setting up your ML application

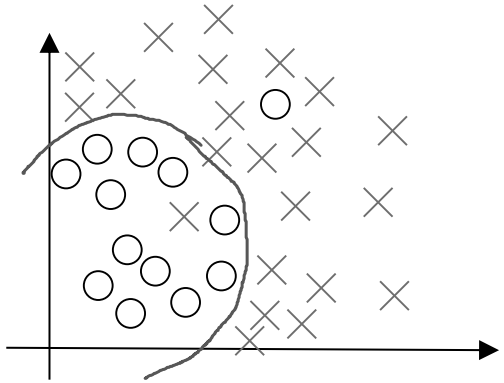
Bias/Variance

Bias and Variance

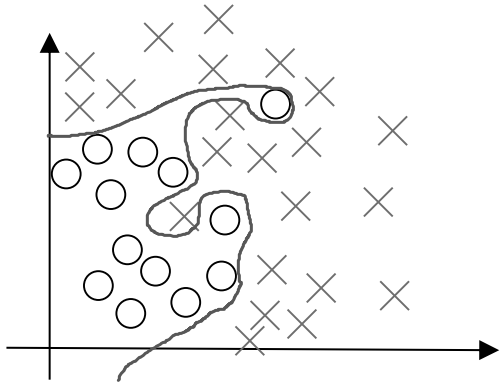


high bias

underfitting



→ "just right"



high variance

overfitting

آدم یک انسان بخواهد بین سگ/گربه classification کند شاید با خطای 5% بکند ← این عدد معیاری برای عملکرد بالا یا پایین optimal (Bayes) Error

تا بین خطای Train, Dev است. مثلا Train خطای 6% بد نیست.

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

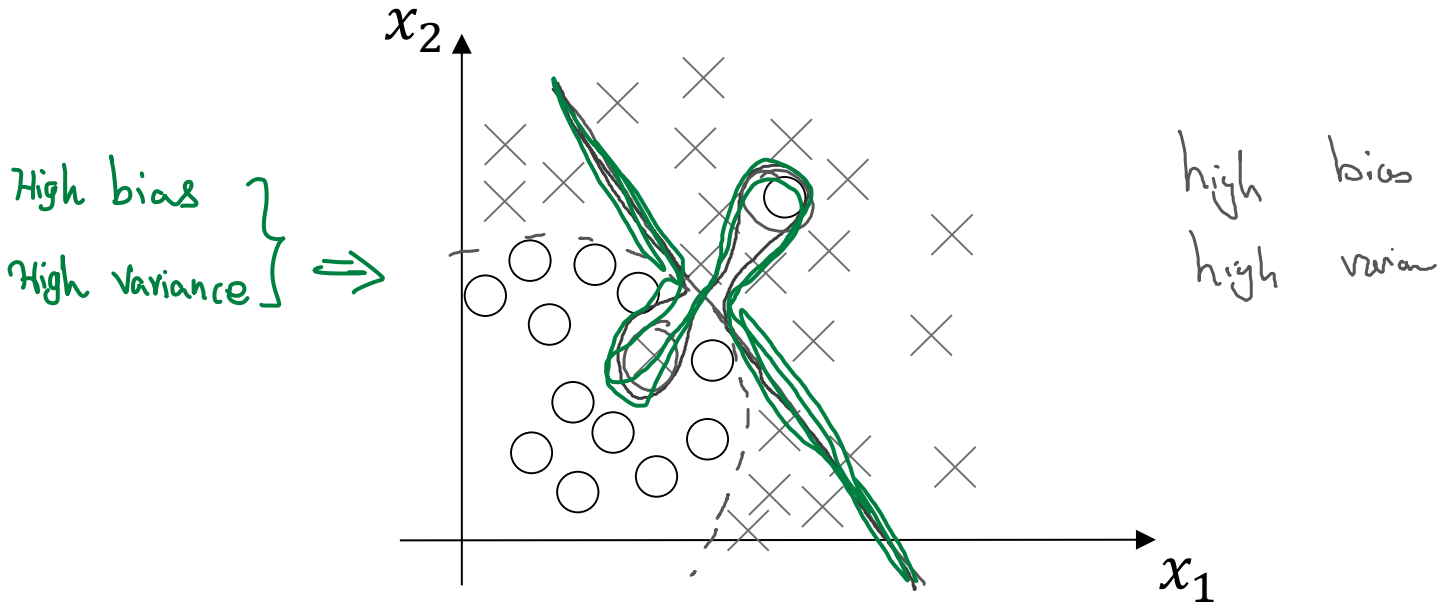
بهترین حالت زمانی است که Bias, Variance هر دو minimal باشند و بدترین وقتی هر دو maximal باشند.

High Bias: Training error ≫ Bayes error ⇒ underfitting

High Variance: Dev error ≫ Training error ⇒ overfitting

Can we have under/over fitting simultaneously?

High bias and high variance



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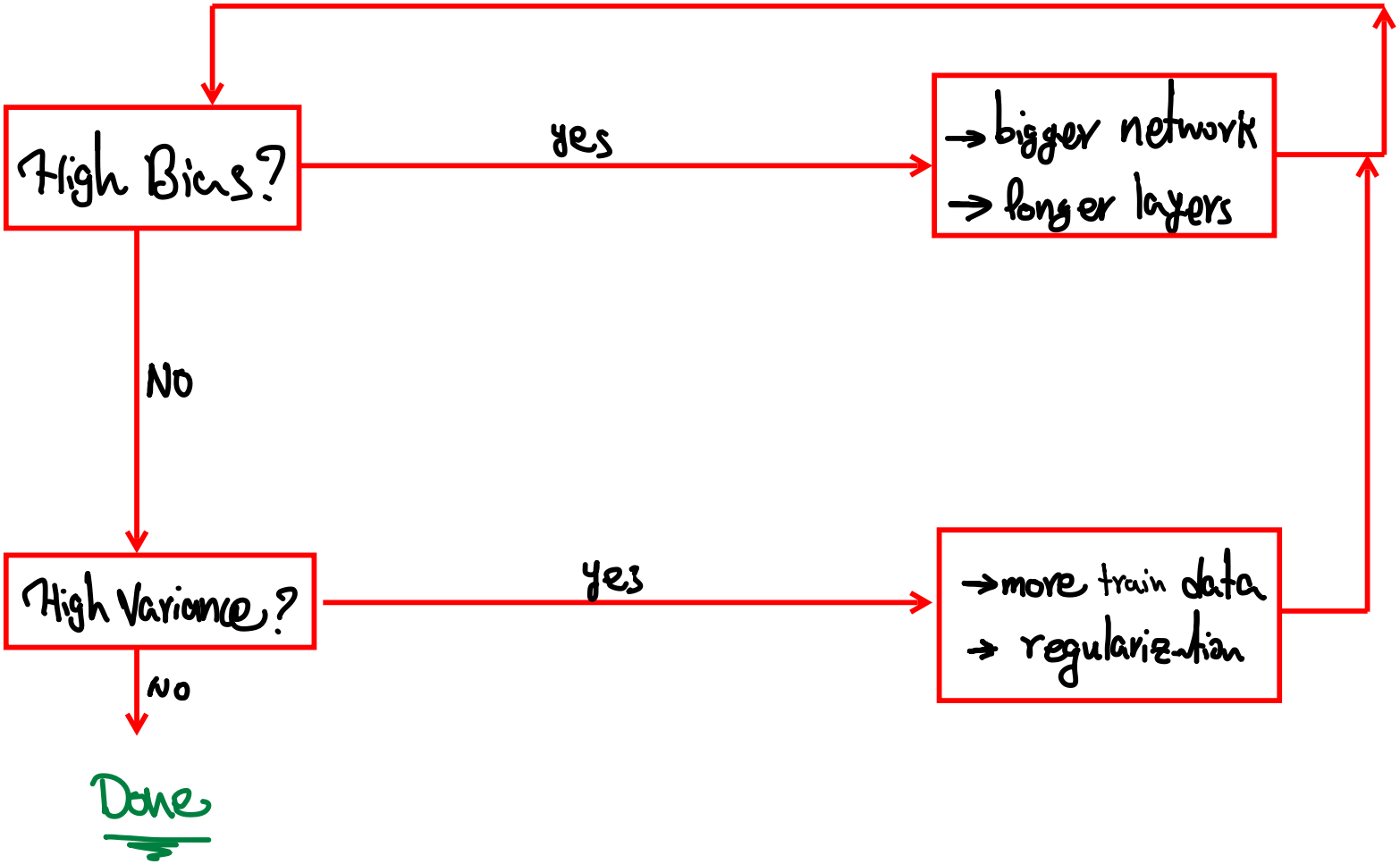
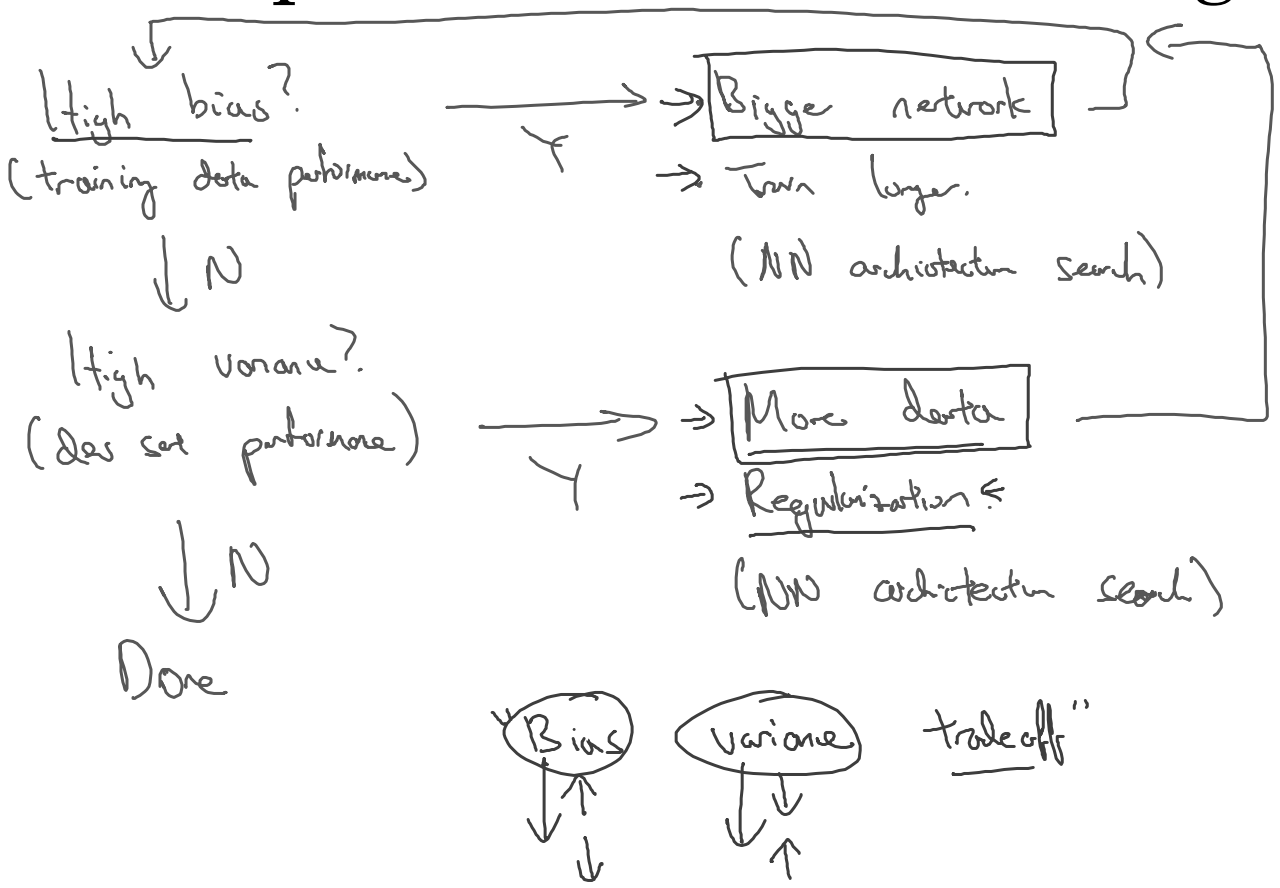
Setting up your ML application

Basic “recipe” for machine learning

Basic "recipe" for machine learning



Basic recipe for machine learning



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Regularizing your neural network

Regularization

Logistic regression

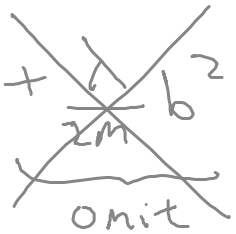
$\min_{w,b} J(w,b)$

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

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

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

w will be sparse

L_2 Regularization $\frac{\lambda}{2m}\|w\|_2^2$ (weight decay)

L_1 Regularization $\frac{\lambda}{2m}\|w\|_1 \Rightarrow$ Sparse w (more zero components)

For vectors

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

Frobenius norm (matrix) $\|W^{[l]}\|_F^2 = \sum_{i=1}^{n^{[l]}}\sum_{j=1}^{n^{[l-1]}}(W_{ij}^{[l]})^2$ where $W^{[l]} : (n^{[l]}, n^{[l-1]})$

Neural network

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

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

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

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

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

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

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

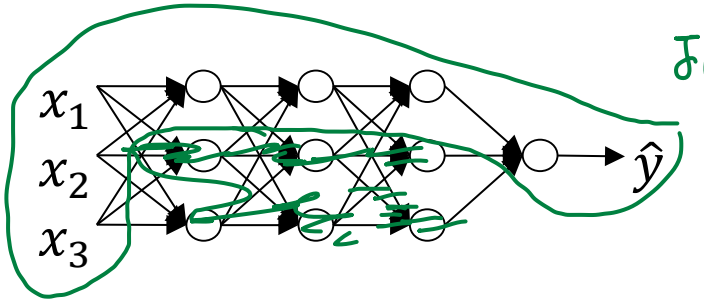
$$= \underbrace{\left(1 - \frac{\alpha\lambda}{m}\right)}_{<1} w^{[l]} - \alpha(\text{from backprop})$$

L_2 Regularization $\equiv$ "Weight decay"

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

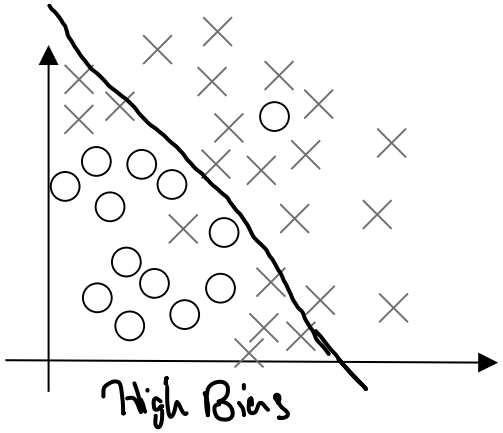
$w^{[l]} = w^{[l]} - \alpha(\text{from backprop})$ $\rightsquigarrow$ without regularization

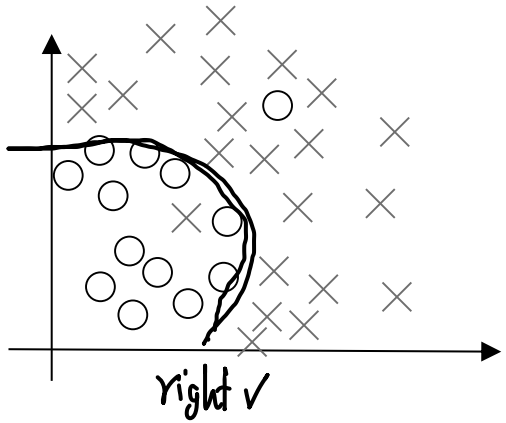
How does regularization prevent overfitting?

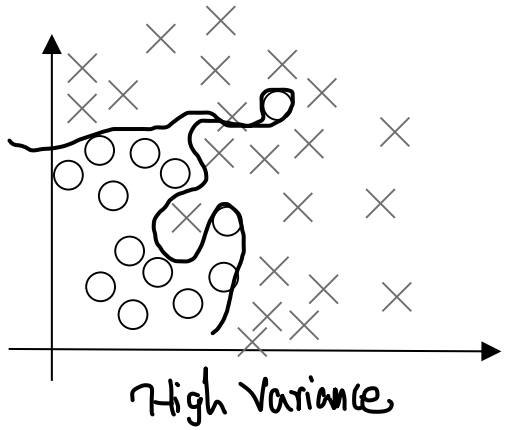


$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum \mathcal{L}(\hat{y}_i, y_i) + \frac{\lambda}{2m}\sum_{l=0}^{L} \|w^{[l]}\|_F^2$$

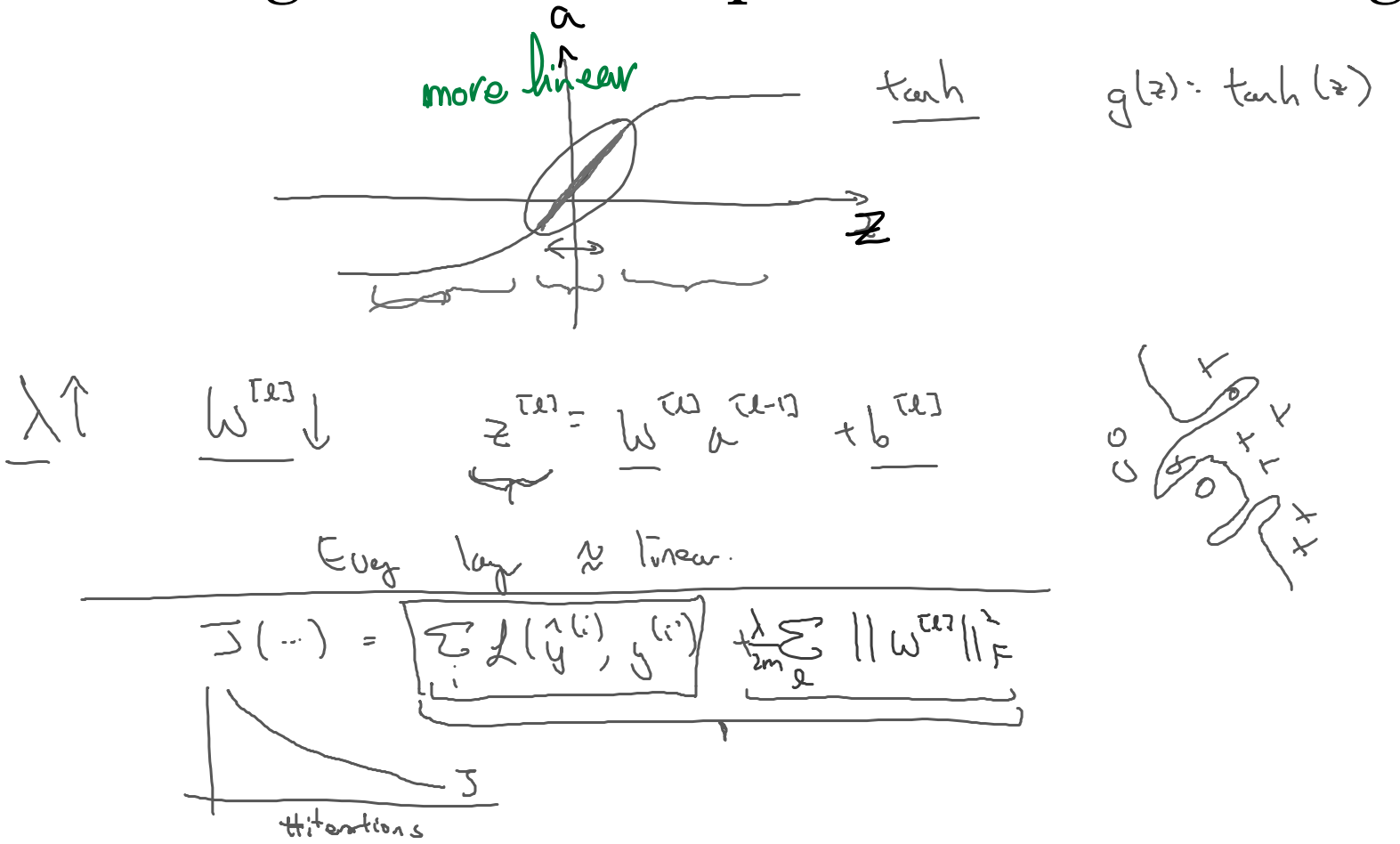
If $\lambda \uparrow \Rightarrow J_{min}$ leads to $w^{[l]} \simeq 0 \Rightarrow$ simpler model $\Rightarrow$ overfitting $\downarrow$







How does regularization prevent overfitting?



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Regularizing your neural network

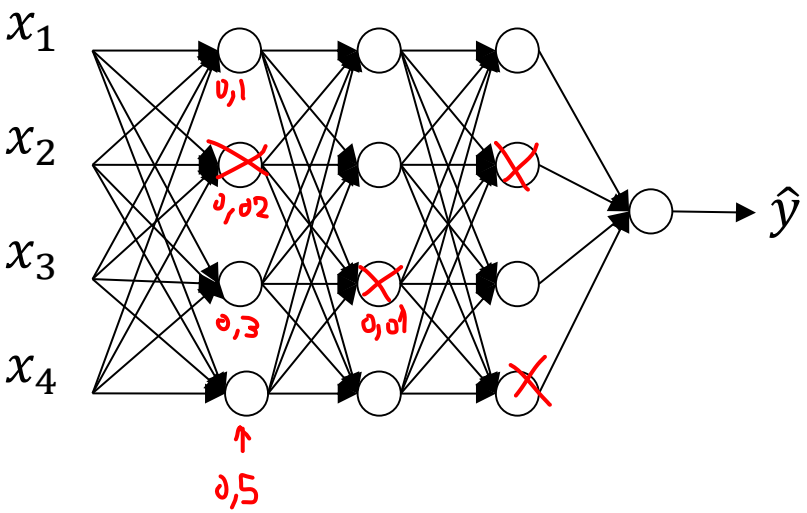
Dropout regularization

Dropout regularization

برای جلوگیری از overfitting

keep_prob ← احتمال صفر شدن یک hidden node به صورت تصادفی به هر

← هر بار در هر iteration این نوع zero-assignment را انجام می‌دهیم



0.5 0.5 0.5

معروف‌ترین نوع از regularization technique، dropout است.

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

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

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

$/= 0.8$

1. $d3 = np.random.rand(a3.shape[0], a3.shape[1]) < keep\_Prob$ ⇒ d3 برداری از T و F با احتمال 0,8 و 0,2 می‌شود.
2. $a3 = np.multiply(a3, d3)$
3. $a3 = a3 / keep\_prob$

در مرحله Test set دیگر انجام نمیدهیم dropout .

Making predictions at test time

$a^{[0]} = X$

No drop out.

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

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

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

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

$\hat{y}$

/= keep-prob

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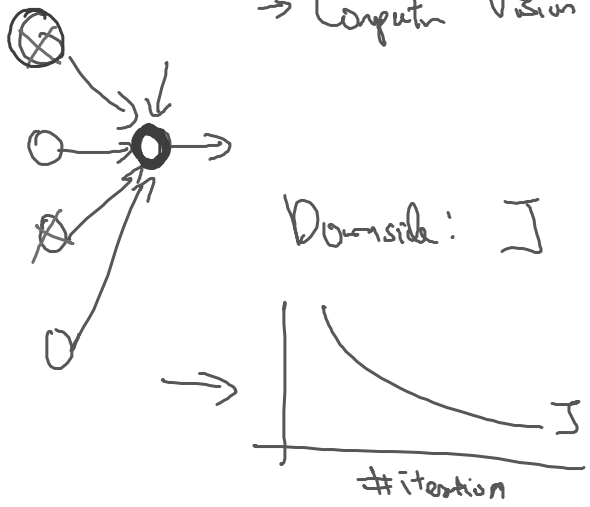
Regularizing your neural network

Understanding dropout

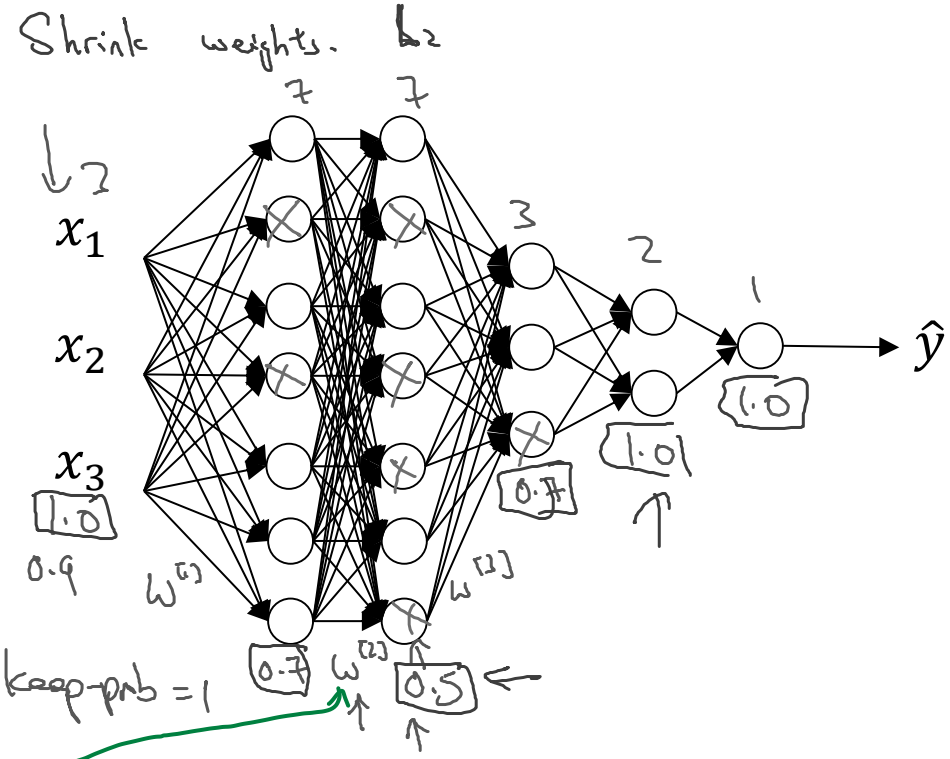
Why does drop-out work? ⇒ Similar to L_2 & shrinking the weights!

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



→ Computer Vision

Downside: J



برای هر لایه می‌توان keep-prob خاص خودش را تعریف کرد ⇐ مخصوصاً برای لایه‌هایی که بزرگ‌ترند. حتی می‌توان برای Input features این کار کرد.

البته مشکل این است که cost function را دیگر نمی‌توان Consistantly تعریف کرد.

Regularization: ① L_2 ② dropout ③ data augmentation ④ early stopping

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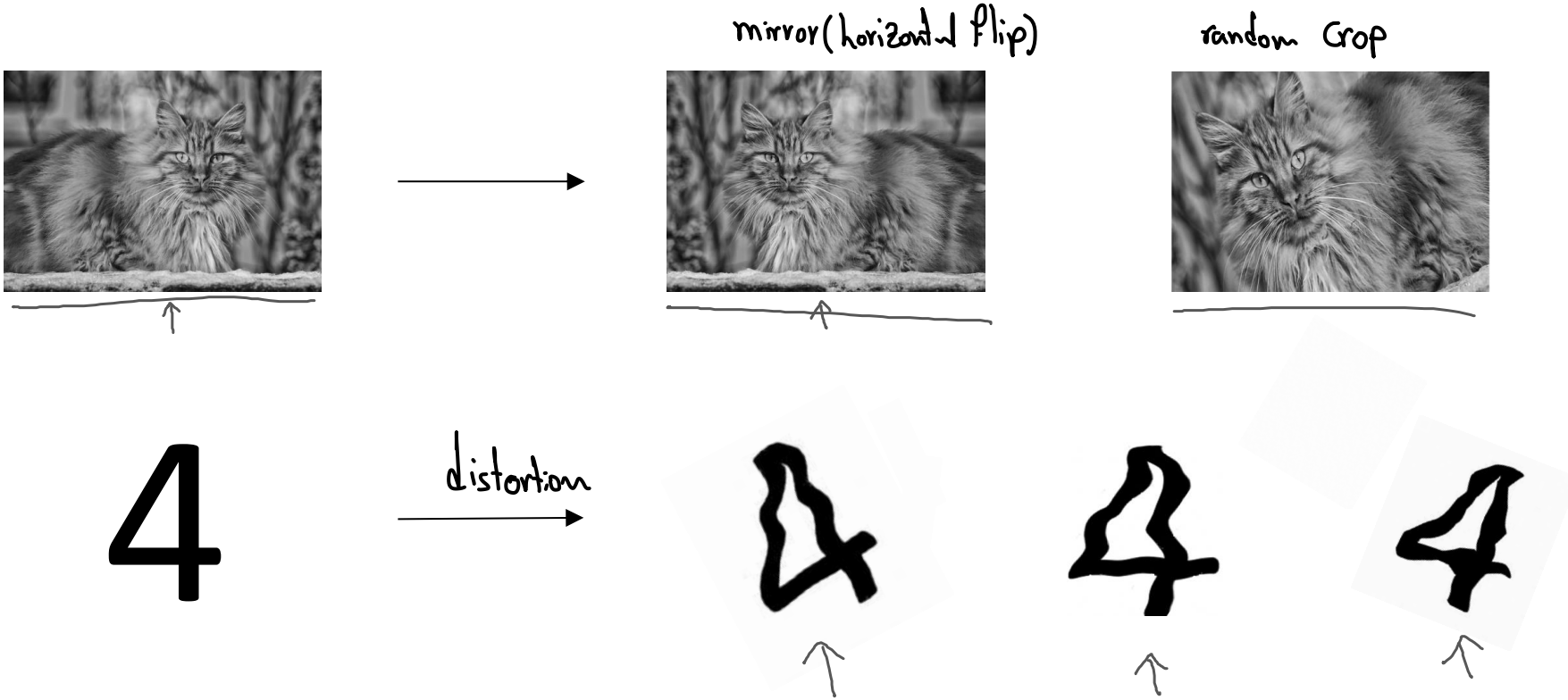
Regularizing your neural network

Other regularization methods

بجای اینکه more training data جمع کنیم ← یک حیله augmentation میکنیم که regularization است.

Data augmentation



orthogonalization ⇐ to independently do the two tasks.

⇐ عیب early stopping: orthogonalization را رعایت نمی‌کند.

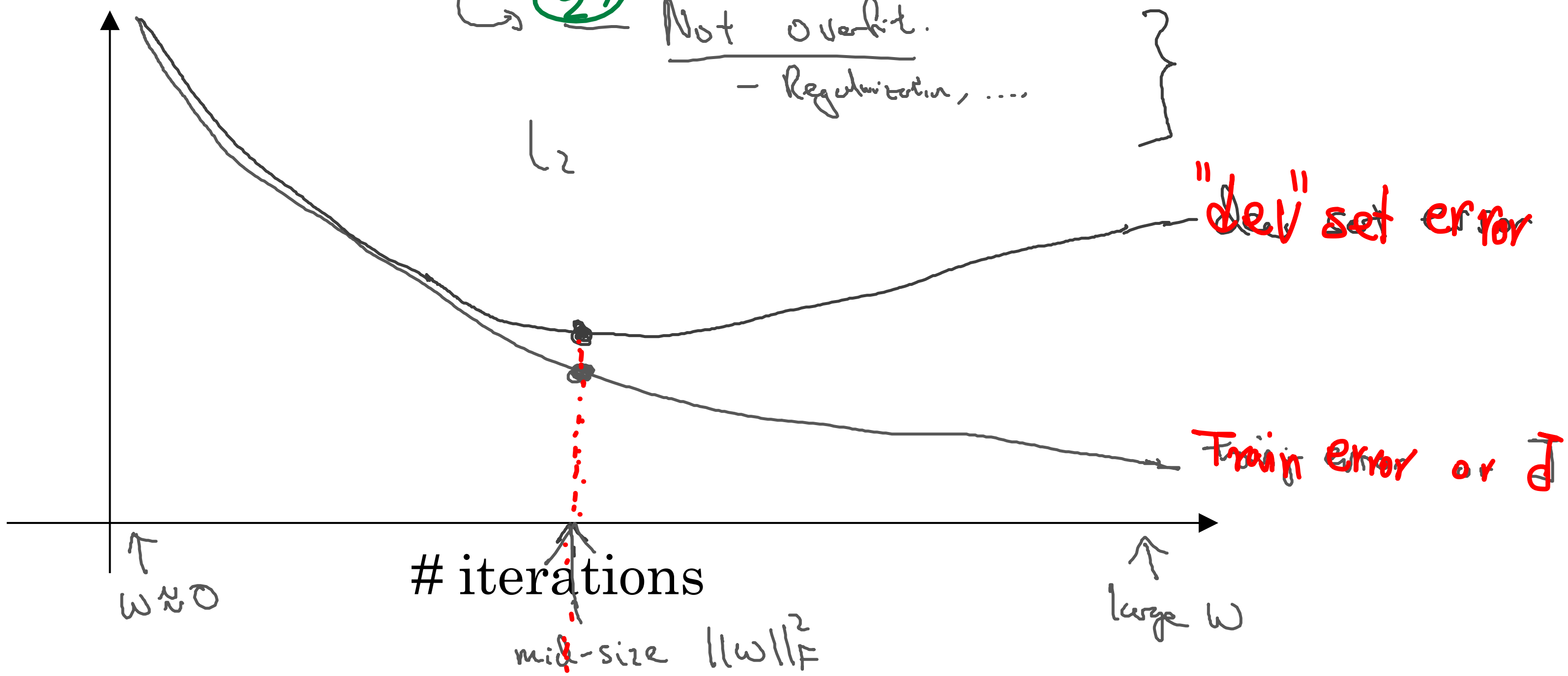
Early stopping

Orthogonalization.

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

L_2

$J(w, b)$



early-stop (زود train می‌کنه)

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Setting up your optimization problem

Normalizing inputs

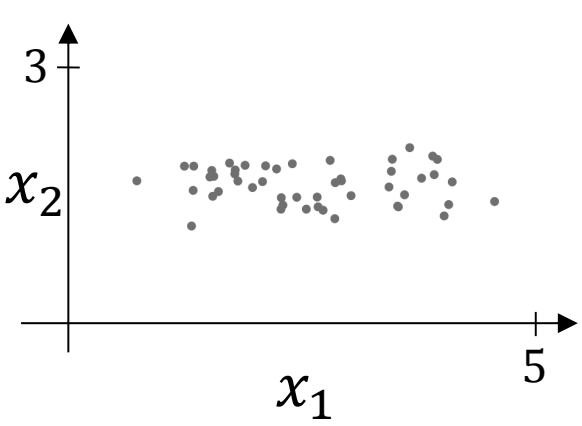
میانگین و واریانس داده‌ها صفر نمی‌شود.

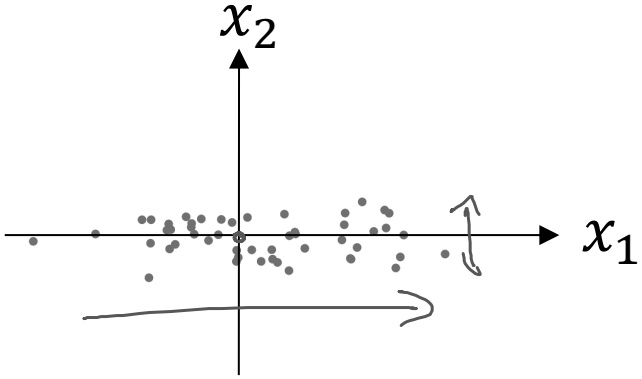
برای داده‌های normalization باید Train و dev مثل هم باشد و جداگانه نباشد

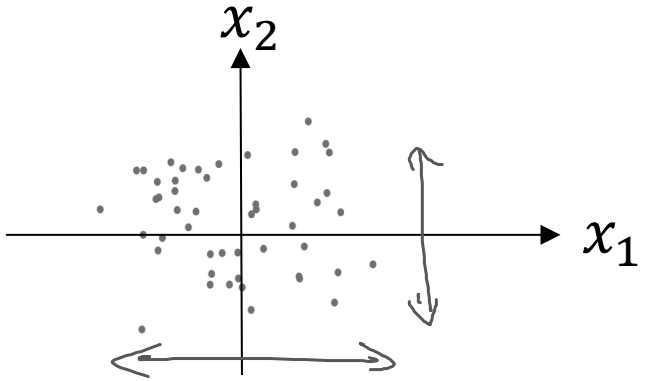
Normalizing training sets

$$X = \frac{X - \mu}{\sigma}$$

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







Subtract mean:

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

$x := x - \mu$

Normalize variance

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

↖ element-wise

$x /= \sigma$

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

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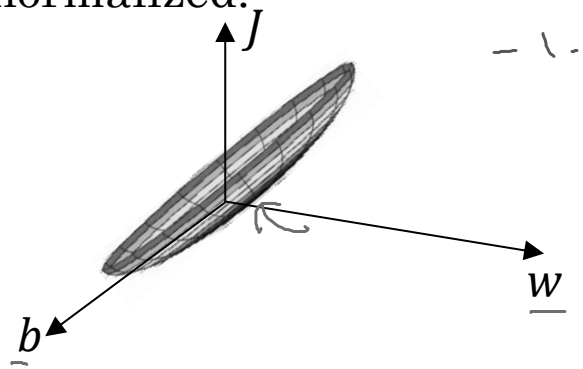
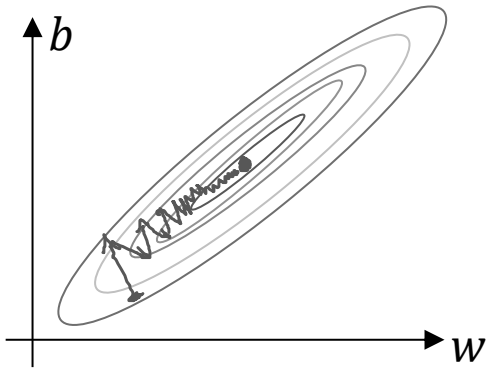
Why normalize inputs?

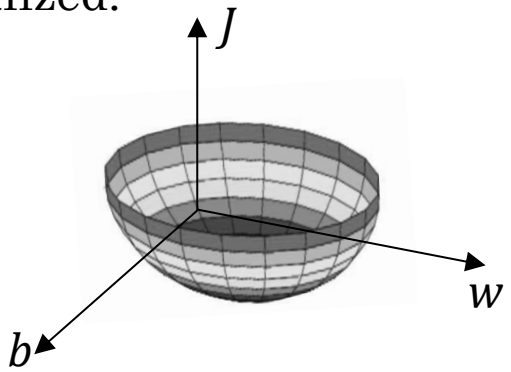
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

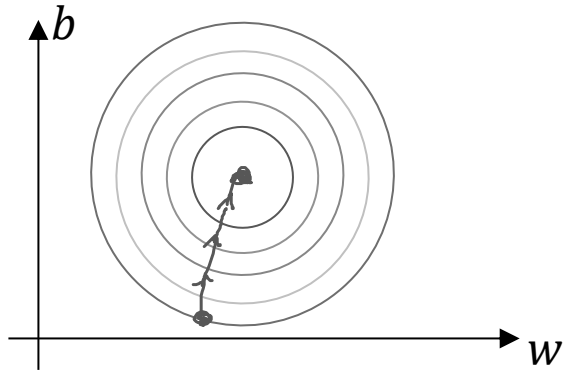
Unnormalized:





Normalized:





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Setting up your optimization problem

Vanishing/exploding gradients

$\frac{\partial J}{\partial w} \to 0$ or $\to \infty$ ، deep های خیلی NN در ⇐ $(w^{[l]} < 1$ or $> 1)$ اگر مقادیر اولیه $w^{[l]}$ ها کمتر یا بیشتر از یک باشد

می‌رود ⇐ باید initial values را هوشمند انتخاب کرد.

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

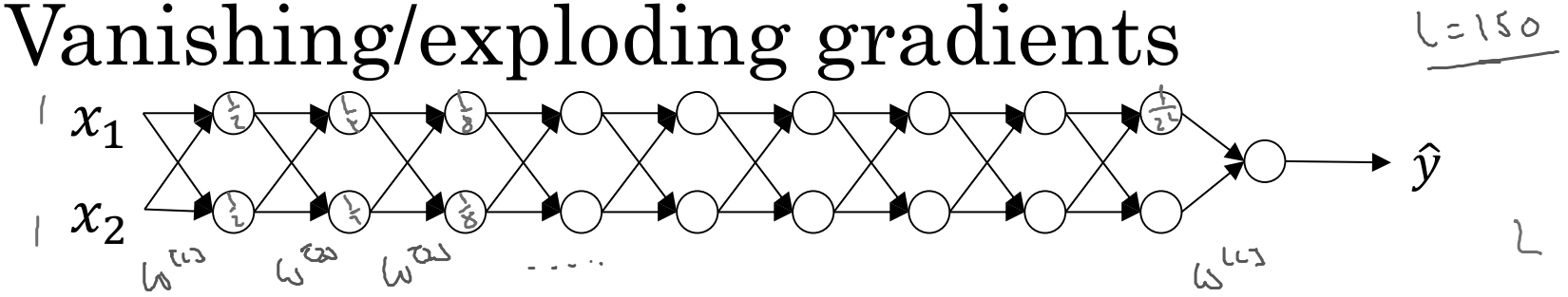
Tanh: $\frac{1}{\sqrt{n^{[l-1]}}}$

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

این جا گفته می‌شود که $Var(w^{[l]})$ بصورت $\frac{2}{n}$ شود ⇐ $w^{[l]}$ خیلی کمتر یا بیشتر از یک نیست.

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

Vanishing/exploding gradients



$L = 150$

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

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

$a^{[3]} = w^{[3]} w^{[2]} w^{[1]} x$

1.5^{L}

0.5^{L}

$w^{[l]} > I$

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

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

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

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

$w^{[l]} = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$

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

$1.5^{L-1} x$

$0.5^{L-1} x$

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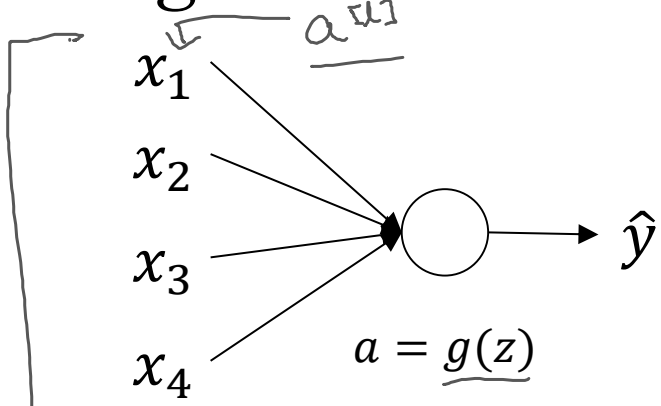
Single neuron example



$w^{[l]}$

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

large n → smaller w_i

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

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

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

Other variants:

tanh

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

Xavier initialization

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

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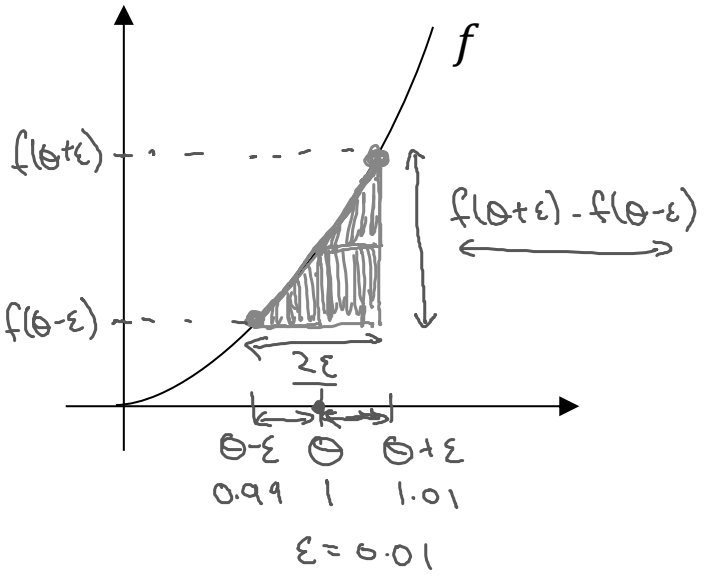
Setting up your optimization problem

Numerical approximation of gradients

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

Gradcheck

Gradient check for a neural network

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

concatenate

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

② 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)

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

(3) for each i:

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

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

(4) Check

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

$\varepsilon = 10^{-7}$

$\approx$ 10^{-7} — 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

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

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

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

- Remember regularization.

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

$d\theta$ = grad of J wrt. 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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