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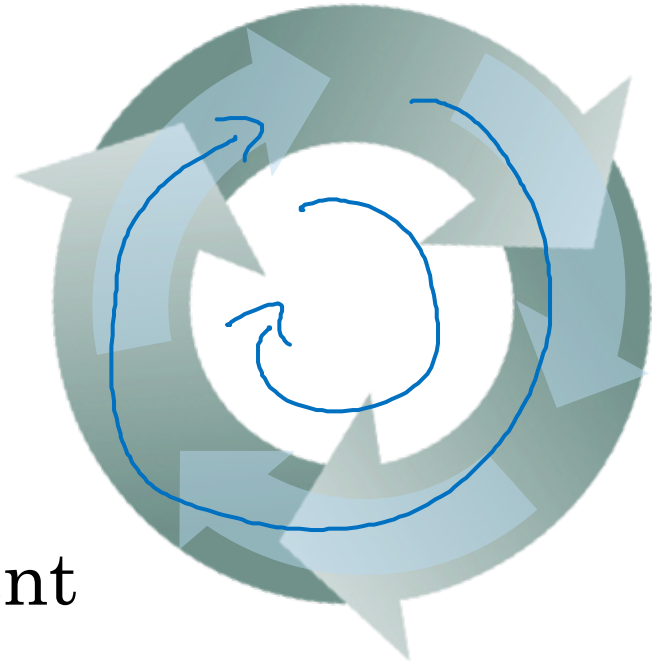
Setting up your ML application

Train/dev/test sets

Applied ML is a highly iterative process

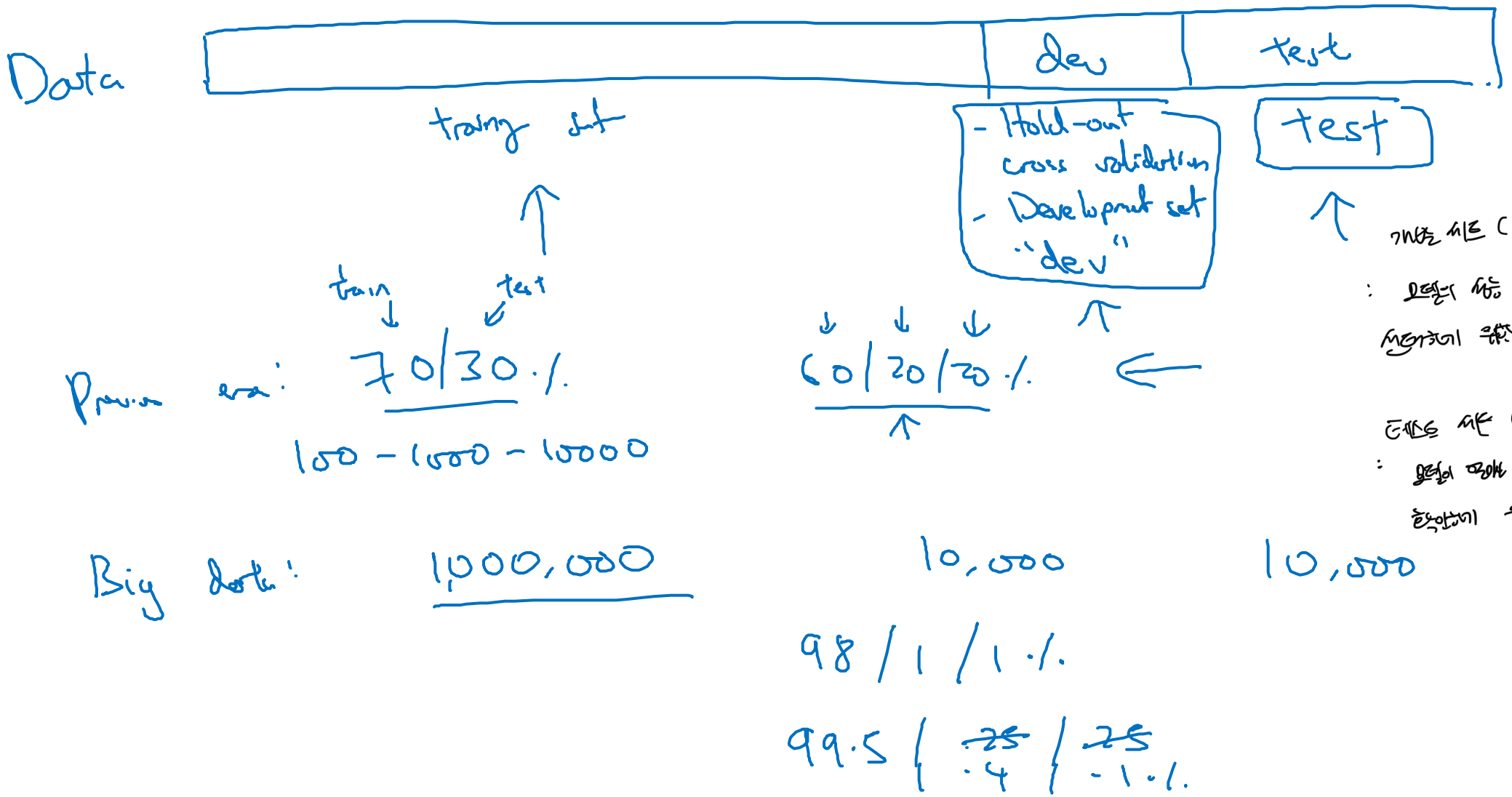
- # layers
- # hidden units
- learning rates
- activation functions
- ...



NLP, Vision, Speech, Structured data

Ads Search Security Logistic ....

Train/dev/test sets



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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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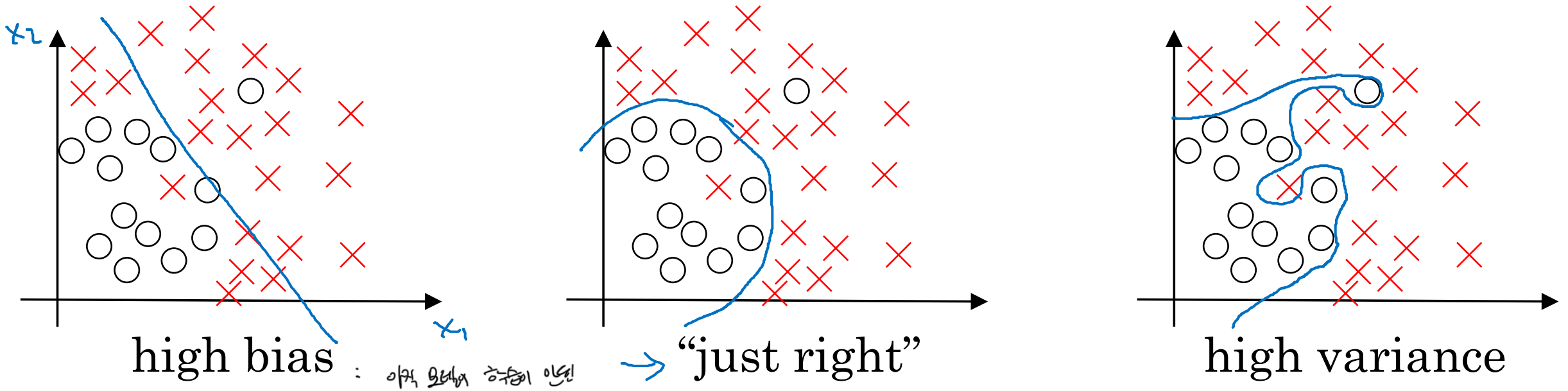
Setting up your ML application

Bias/Variance

Bias and Variance



high bias : 이전 모델에 학습이 안된 과소 적합된 상태

→ "just right"

high variance : 모델이 너무 학습된 과적합 상태

Underfitting

Overfitting

Bias: 예측값과 정답의 차이

Variance: 예측값끼리의 차이

Bias and Variance

Cat classification

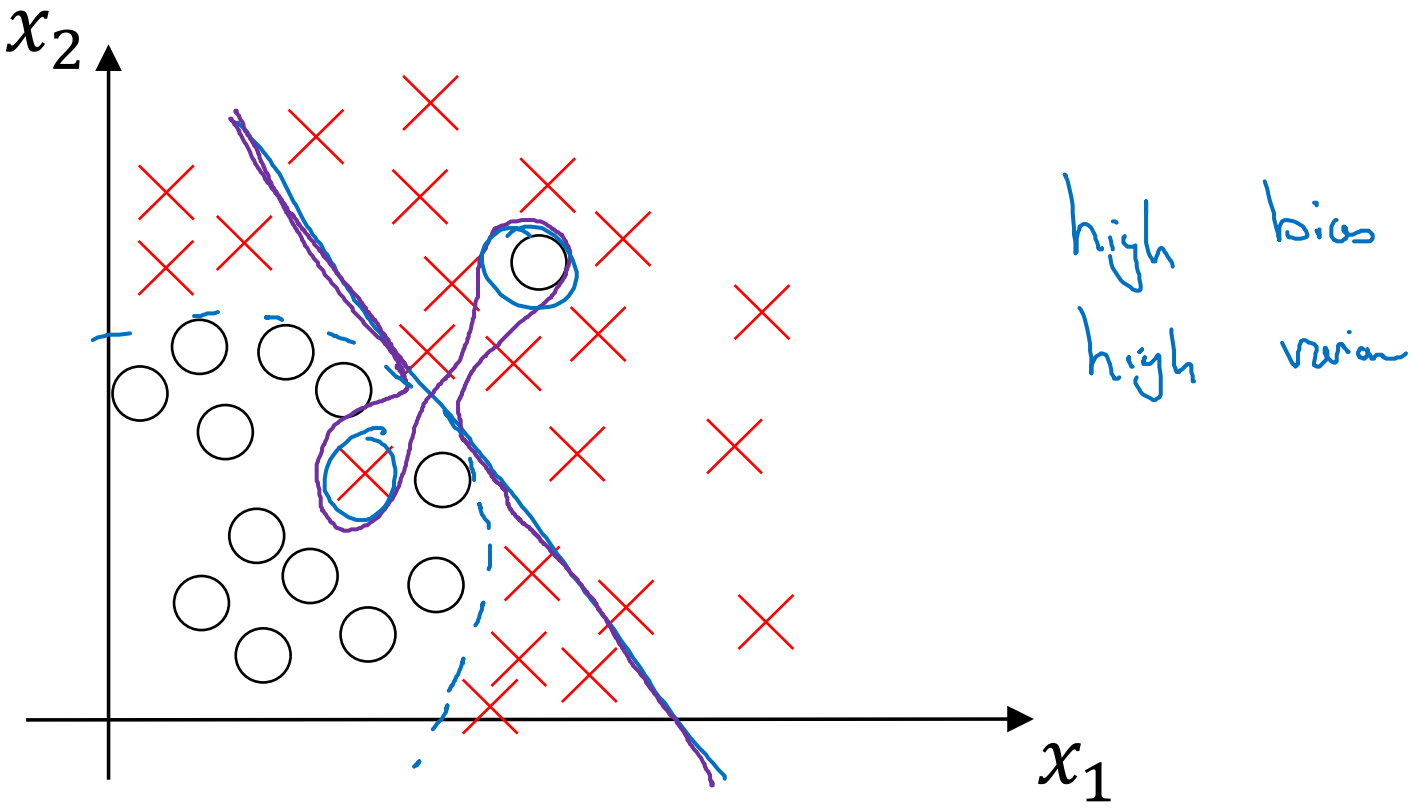
Train set error:	1%	15%	15%	0.5%
Dev set error:	11%	16%	30%	1%
	high variance	high bias	high bias & high variance	low bias low variance

Human: ≈0%

Optimal (Bayes) error: ~~≈0%~~ 15%

Blurry images

High bias and high variance



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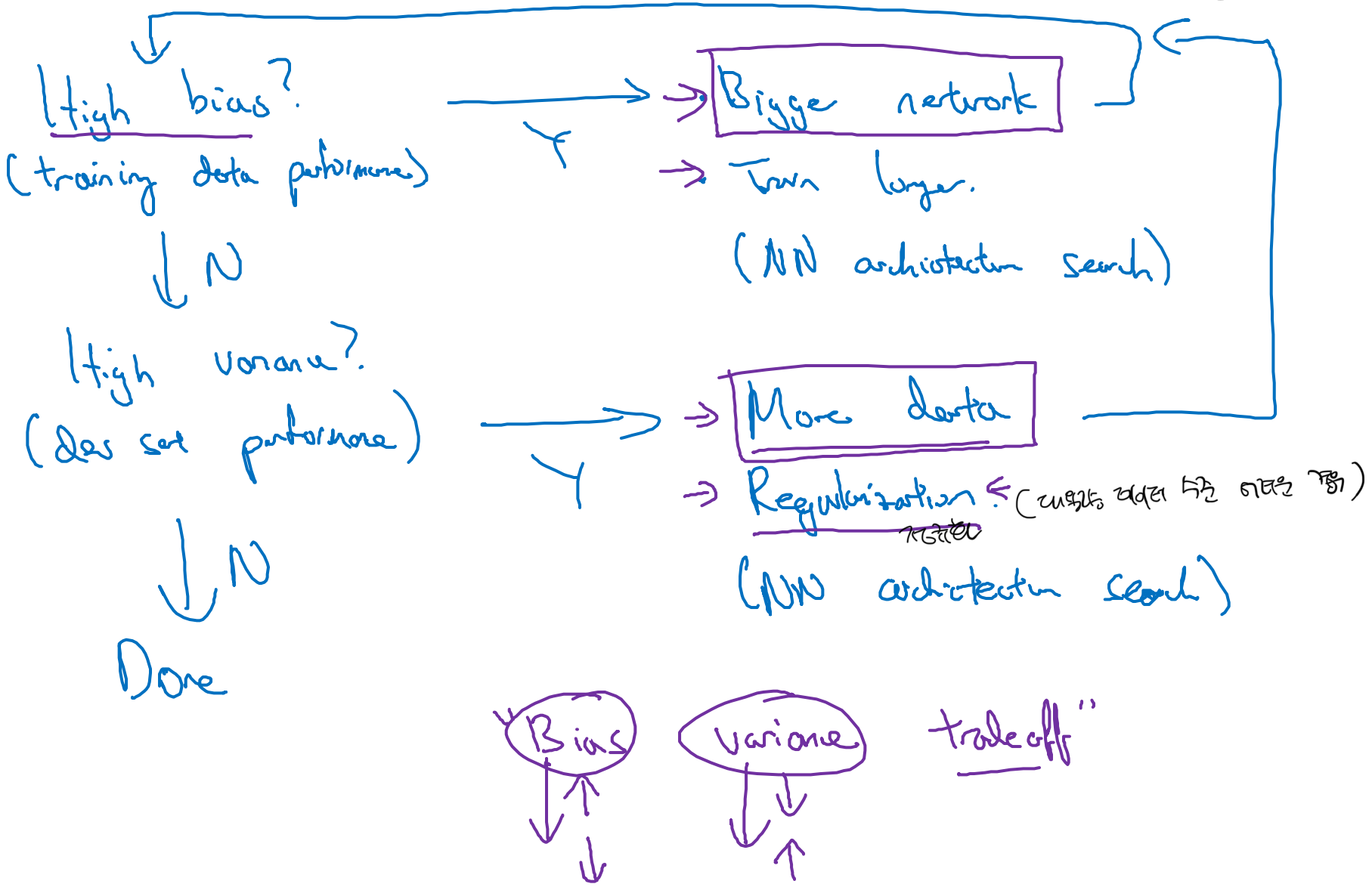
Setting up your ML application

Basic “recipe” for machine learning

Basic recipe for machine learning



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Regularizing your neural network

Regularization

Logistic regression

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

λ = regularization parameter

lambda lambd

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

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

omit

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

: w(가중치)를 활용하고, 절편(b)를 사용하지 않는 이유는 w는 높은 분산을 가지고, b는 상대적으로 큰 영향을 주지 않기 때문

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

w will be sparse

: w벡터 안에 0 값이 많이 존재하게 되어 sparse 상태가 된다. 파라미터 set이 0이면, 모델을 저장하는게 더 적은 메모리를 사용해서, 모델을 압축하는 데 유용하다. 하지만 그렇게 많이 사용되지는 않고, 대신에 L2 regulation이 많이 사용된다.

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Neural network

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

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

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

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

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

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

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

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

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

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

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

L_2 : "Weight decay" 라고 불리는 이유

∴ weight matrix 가 (원래 가지는 값) $\left(1 - \frac{\alpha\lambda}{m}\right)$ 배

줄어들게 되므로

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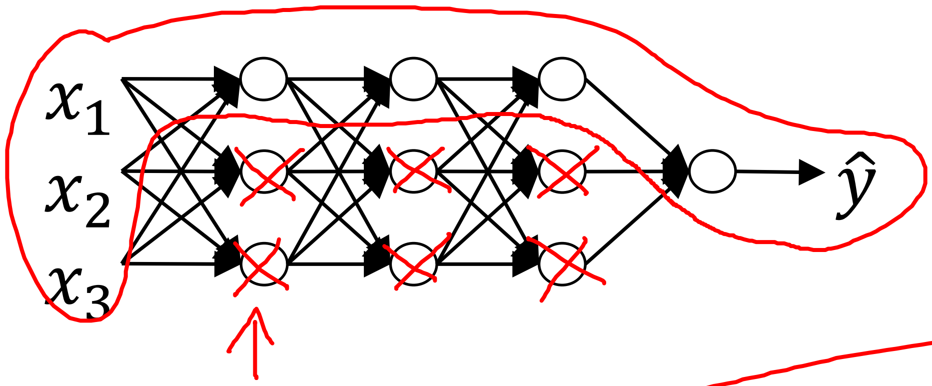
Regularizing your neural network

Why regularization reduces overfitting

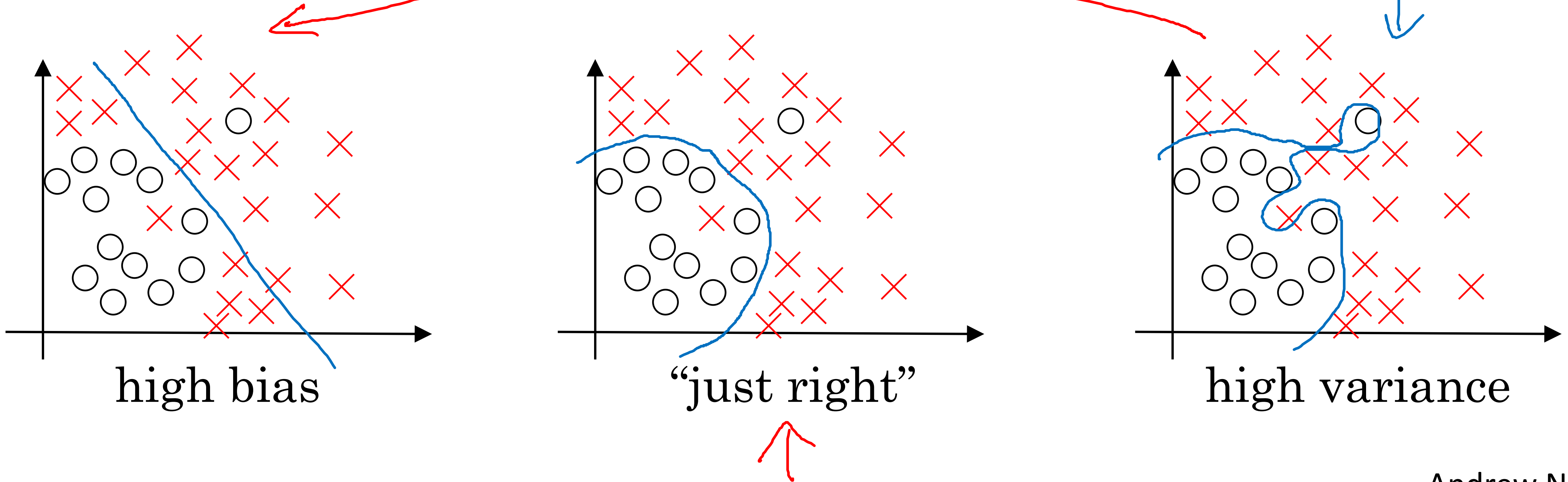
How does regularization prevent overfitting?



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

lambda 값을 크게 만들면, 가중치 행렬 w를 0에 가깝게 설정할 수 있다. (이것에 의해 왼쪽 그림처럼 hidden unit의 영향을 거의 0으로 만듦)
이에 따라 신경망이 간단하고 작은 망으로 이루어져
과대적합이 덜 일어난다.

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

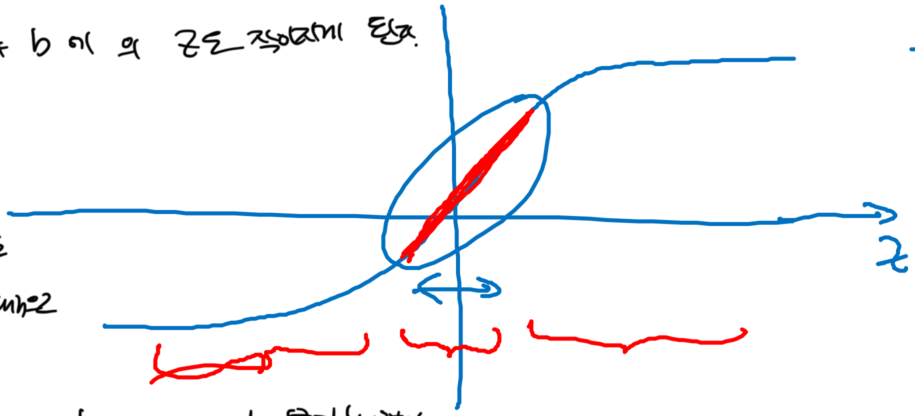


How does regularization prevent overfitting?

tanh 함수를 사용하면 lambda 값이 커지면 비용함수에 의해
가중치 W는 작아지게 되며, $z = w * x + b$ 에 의 z도 작아지게 된다.

결과적으로 일반화 파라미터 λ가 커질
w 매개변수는 작아지고 이에 따라 결과값 z도
작은 범위를 가지게 되며, tanh 함수는 선형
선형관계를 보이게 된다.

=> Activation이 linear 하게 바뀌고 decision 이 단순해져 overfitting 을 할 수 없게 된다.

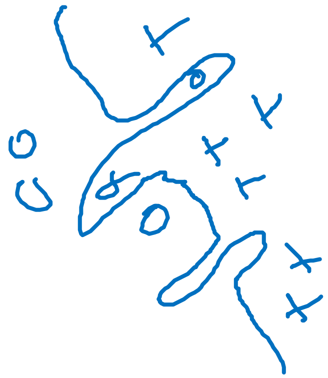


tanh

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

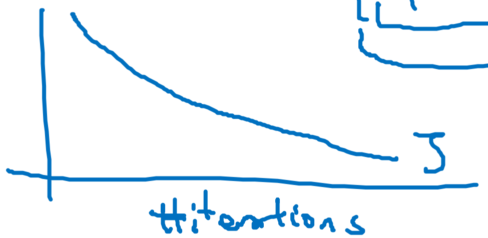
$\lambda \uparrow \quad W^{[l]} \downarrow$

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



Every layer ≈ linear.

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



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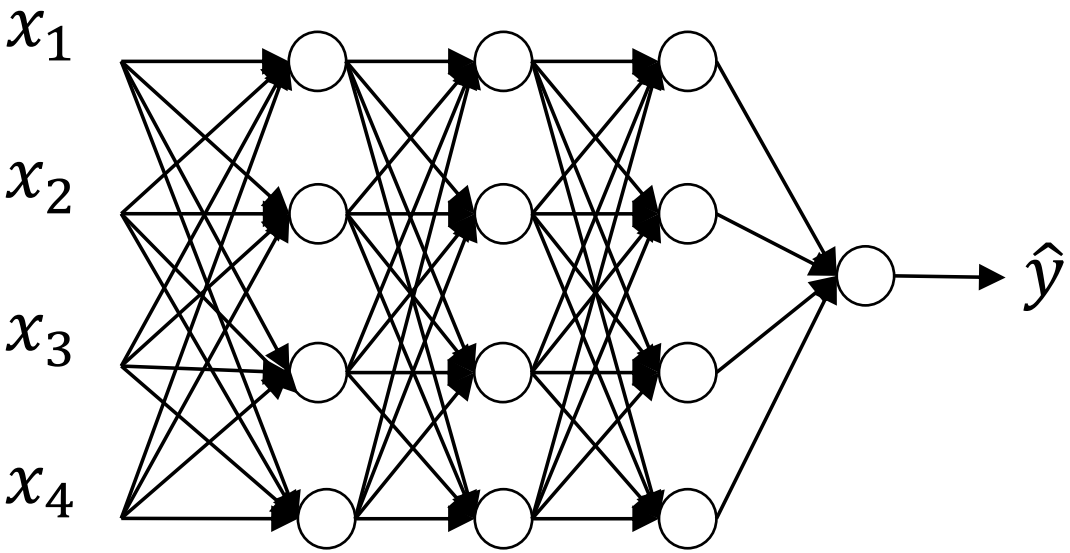
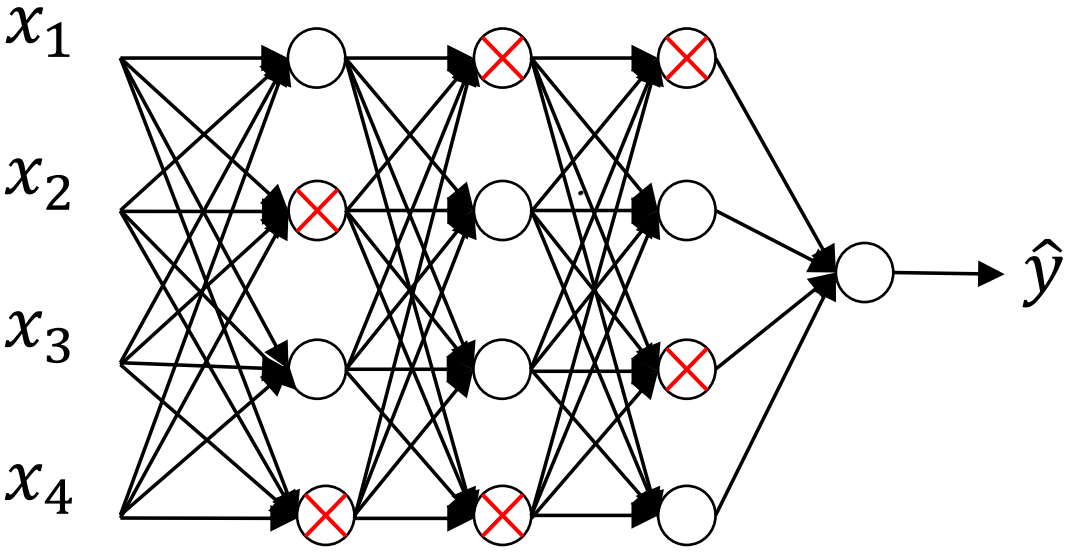
Regularizing your neural network

Dropout regularization

Dropout regularization

: 신경망 각각의 층에 대해 노드를 삭제하는 확률 (1- keep_prob) 을 지정하는 것
이다. 삭제할 노드를 확률에 따라 랜덤으로 선택하여 삭제한 노드의 들어가는
모든 나가는 링크를 모두 삭제한다.
이에 따라 기존 모델에 비해 작고 간단해진 네트워크가 만들어져, 작아진
네트워크로 학습을 진행하게 된다.





각 layer 에 대해 노드에서 확률을 설정

0.5 0.5 0.5

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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%.

$/= 0.8$

Test

역 드롭아웃 (Inverted dropout) 은 드롭아웃 방식에 대해 노드 삭제의 영향을 받는 확률을 줄여 삭제하지 않는 확률 (keep-prob) 을 나누는 것에서 이는 기존의 삭제하여 영향을 준 확률을 기대값으로 맞추기 위함이다.

Andrew Ng

Making predictions at test time

$a^{[0]} = X$

No drop out.

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

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

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

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

$\downarrow$

$\hat{y}$

/= keep-prob

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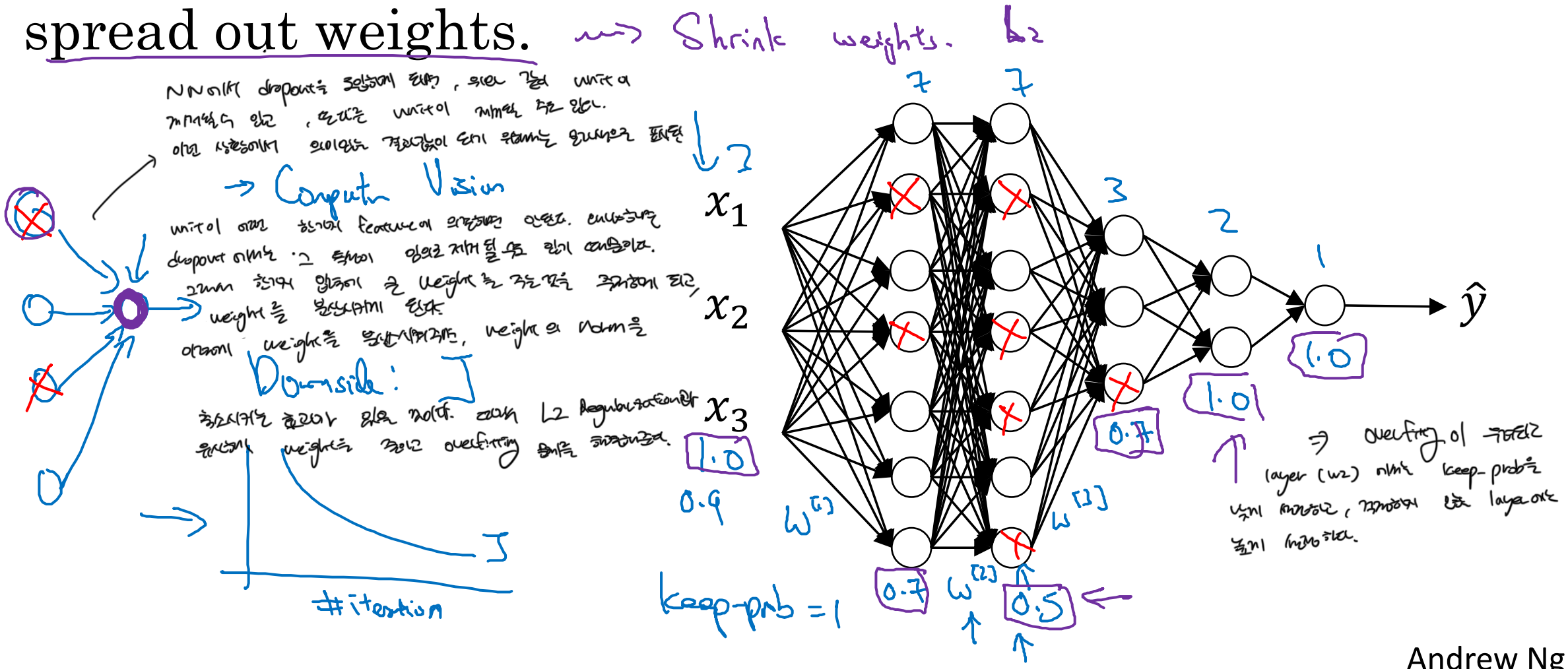
Regularizing your neural network

Understanding dropout

Why does drop-out work?

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



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< Dropout의 단점 >

1. Cross Validation에서 시간낭비해야 함 하이퍼파라미터가 증가했다.
2. Cost Function J가 명확히 계산되지 않았다.
3. 각 반복마다 노드를 확률적으로 제거하기 때문에, Gradient Descent 성능을 최적화하기 어렵다.

Dropout은 Computer Vision에서 도입되었다.
Computer Vision에서 입력값이 너무 커서, 모든 특성들을 알고리즘이 학습 하이퍼파라 부족했다.

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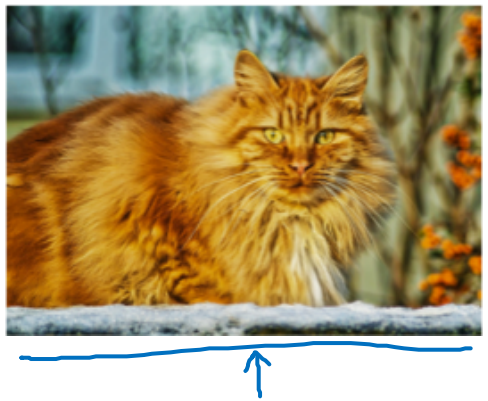
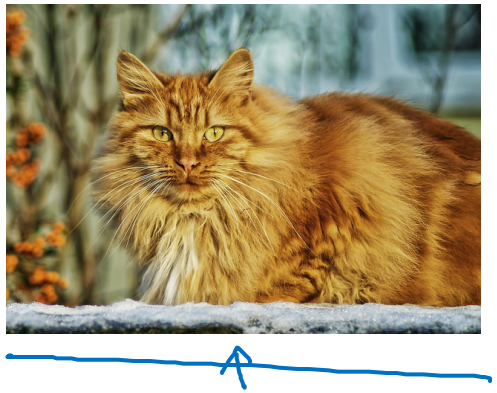
Regularizing your neural network

Other regularization methods

Data augmentation





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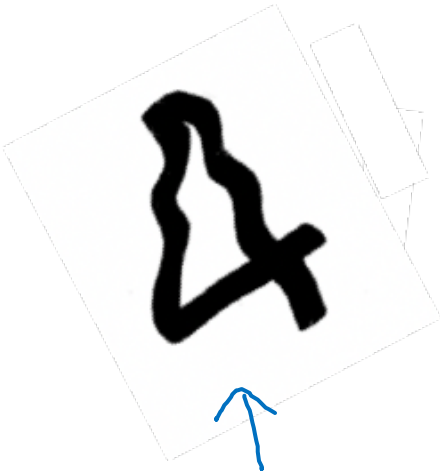

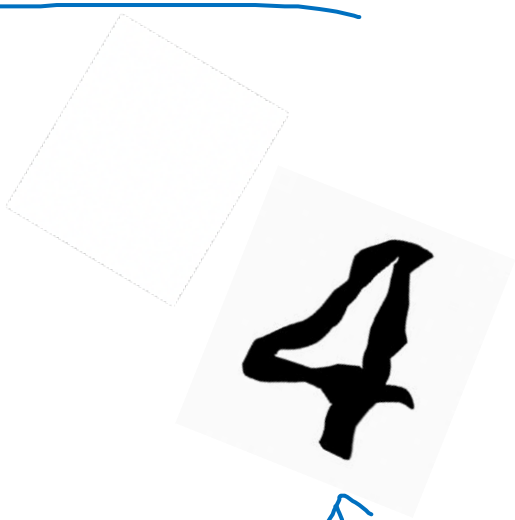

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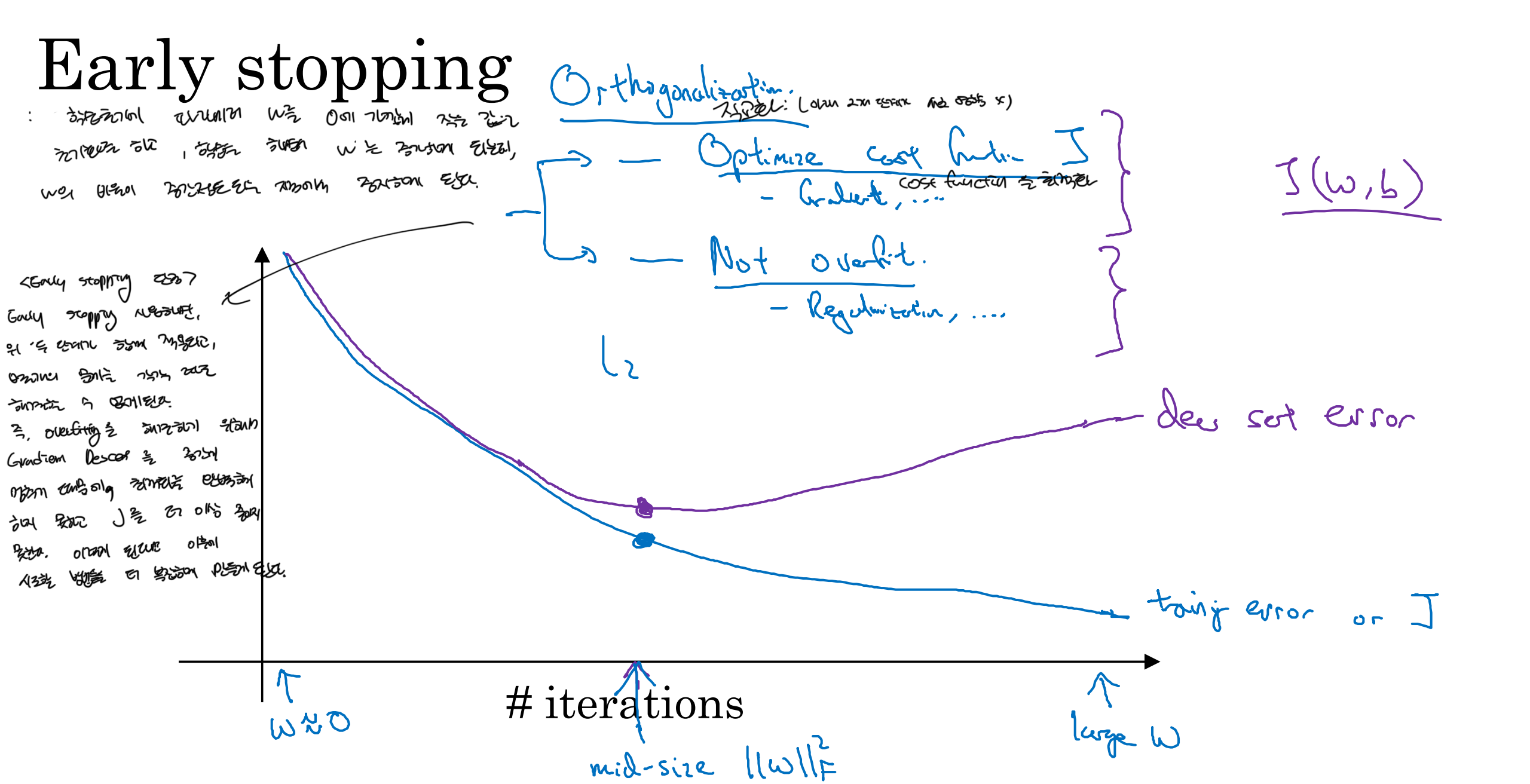
Early stopping



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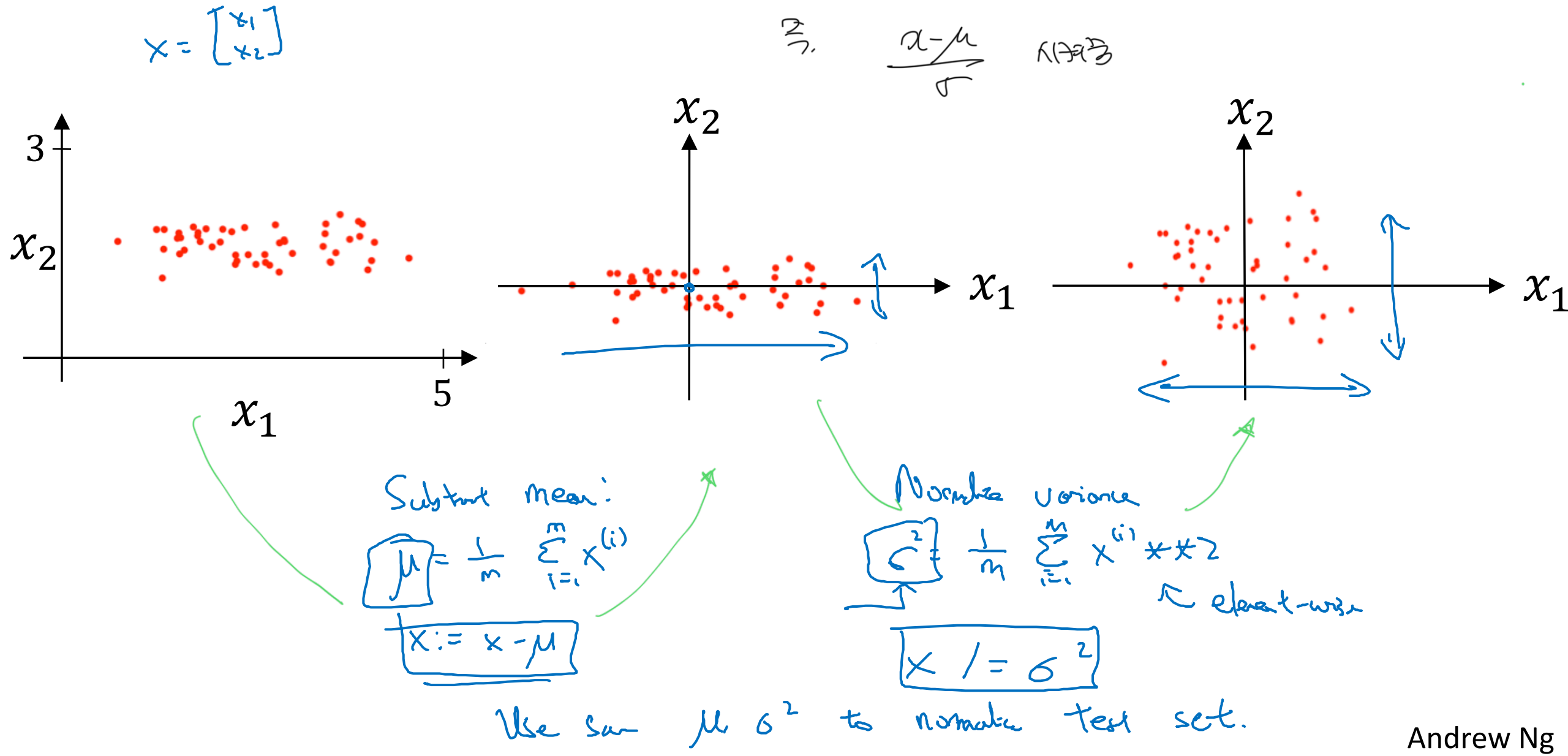
Setting up your optimization problem

Normalizing inputs

Normalizing training sets



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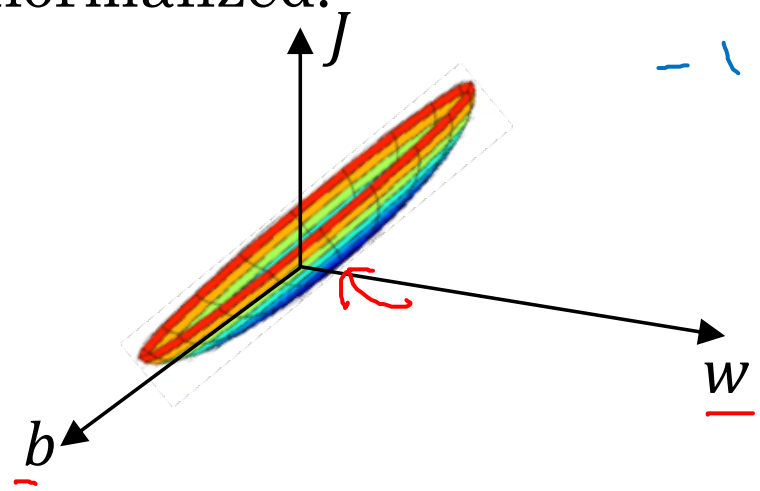
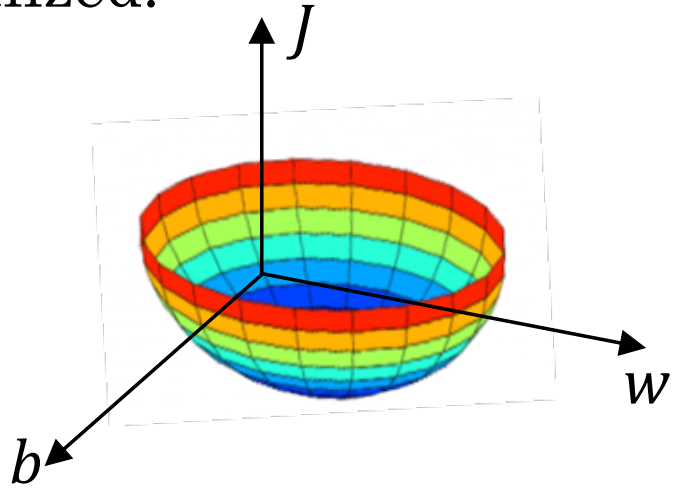
Why normalize inputs?

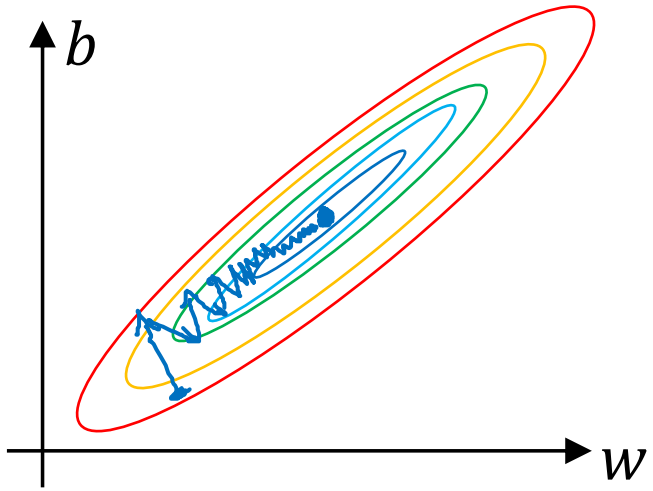
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

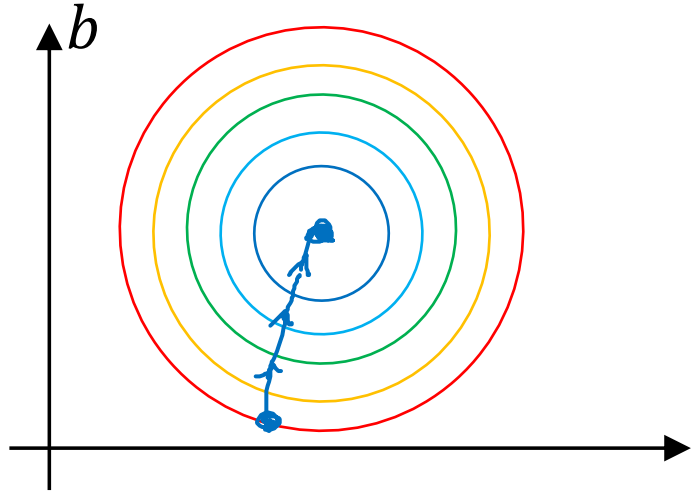
Unnormalized:



Normalized:







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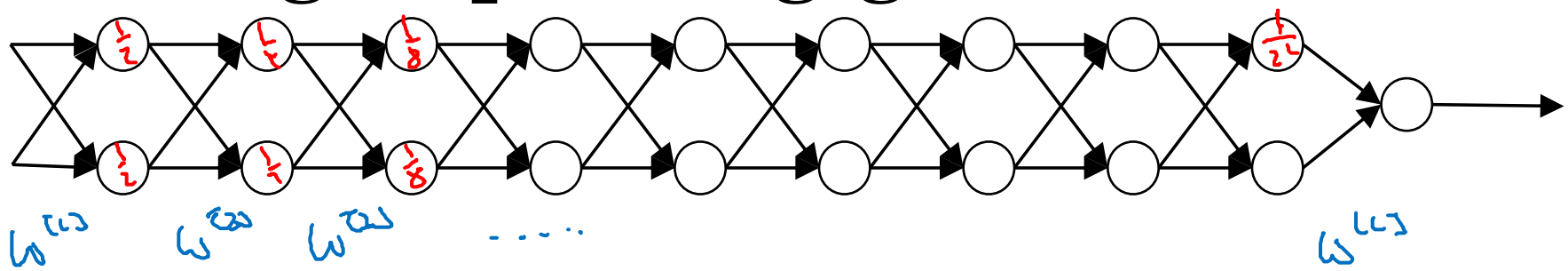
Setting up your optimization problem

Vanishing/exploding gradients

Vanishing/exploding gradients



$L = 150$

$g(z) = z$: linear activation function

$b^{[l]} = 0$

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

$a^{[3]}$

1.5^L

0.5^L

$W^{[l]} > I$

$W^{[l]} < I \quad \begin{bmatrix} 0.9 & 0 \\ 0 & 0.9 \end{bmatrix}$

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

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

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

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

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

$1.5^{L-1} x$

$0.5^{L-1} x$

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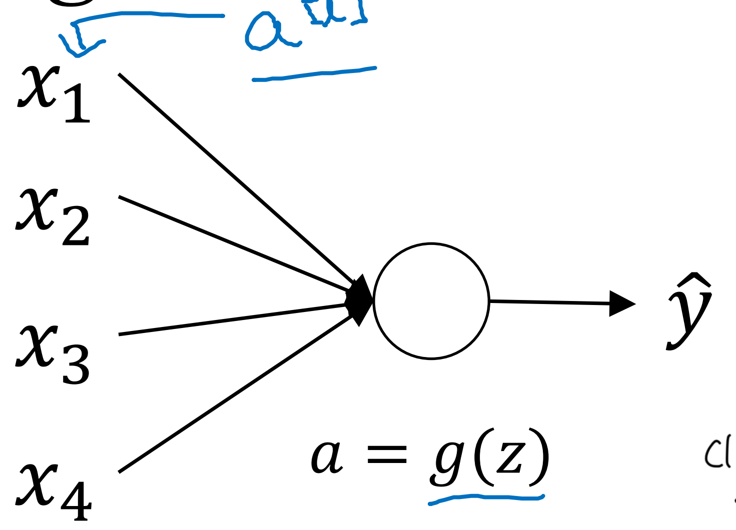
Single neuron example



$w^{[l]}$ < 가중치 초기화 >
: 가중치를 (너무 너무) 큰 수나 너무 작은 수로 하지 않음으로 해서 폭발이나 소실을 막아준다. 즉, 기울기 값이 폭발하거나 너무 작은 값을 가지지 않기 위해서는 좋은 초기화 (large n) 경우에는 작은 가중치 (smaller w)가 필요하다.

$z = w_1x_1 + w_2x_2 + \cdots + w_nx_n$ ~~$+b$~~

large n → smaller w_i

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

(w_i 분산은 $1/n$으로 설정)
n: 입력 특성 개수

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

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

ReLU 사용하는 경우, w_i의 분산: $\frac{2}{n^{[l-1]}}$

Other variants:

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

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

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

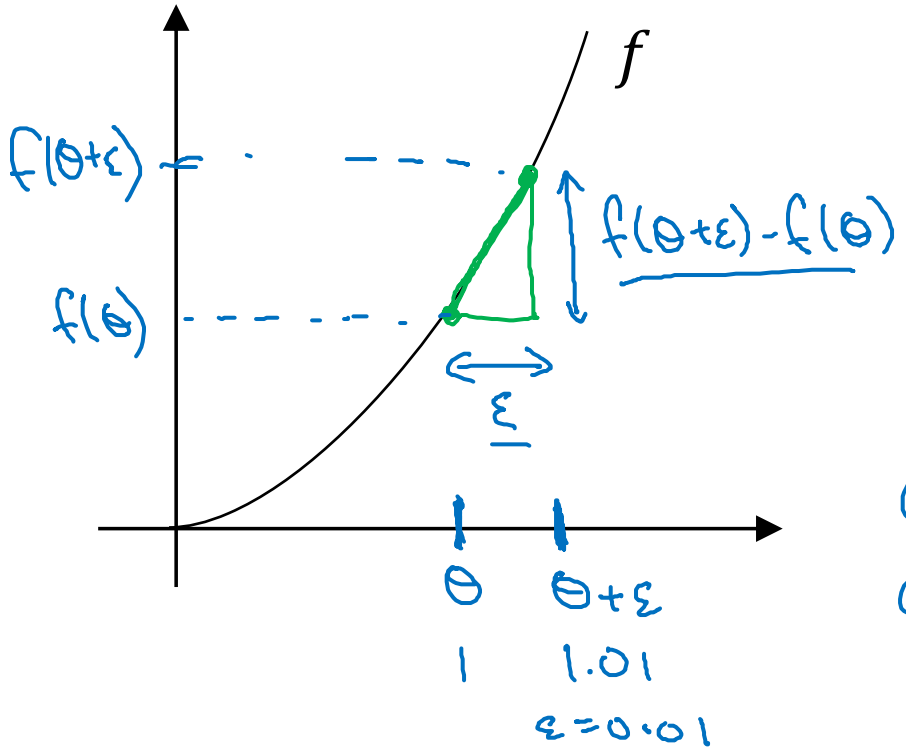
$\theta \in \mathbb{R}$.

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

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

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

$\frac{dw}{db}$



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

$\theta = 1$

$\theta + \varepsilon = 1.01$

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

0.0301

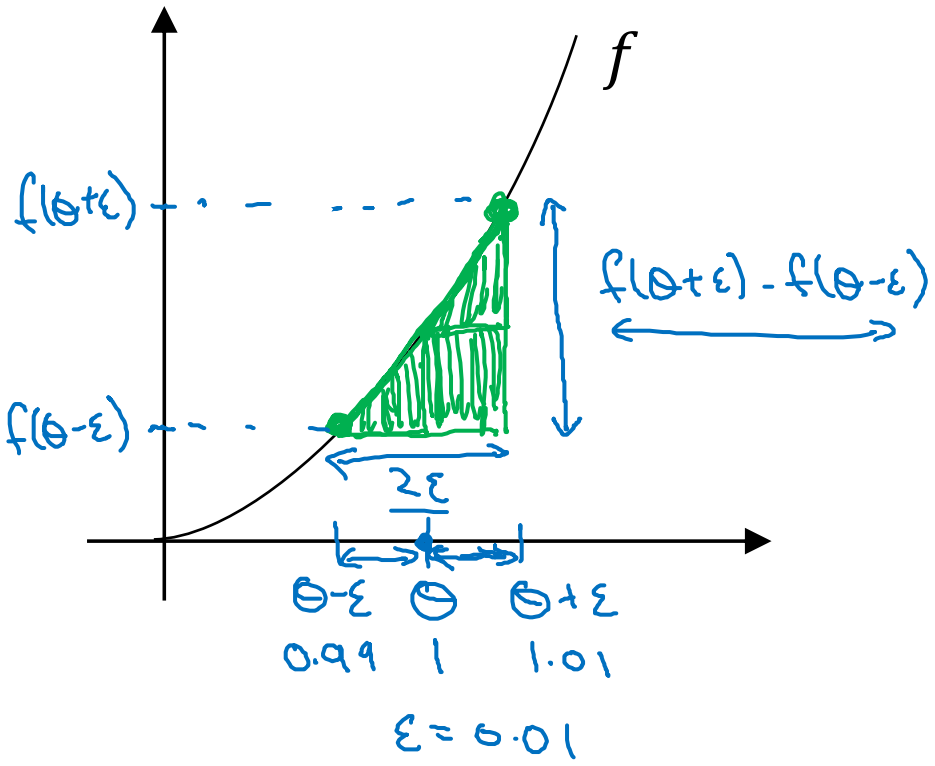
3.1

3.2

Checking your derivative computation

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

Gradient checking in ...



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

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

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

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

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

1. 모든 파라미터를 벡터 형태로 연결시켜 하나의 vector로 만들어줌.

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 $J(\theta)$?

2. dW, db를 $d\theta$로 만들어 $J(\theta)$의 기울기와 비교함.

Gradient checking (Grad check)

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

for each i:

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

$d\theta_{approx}[i]$: 양쪽에서 계산한 값

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

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

Check $\dfrac{\| d\theta_{approx} - d\theta \|_2}{\| d\theta_{approx} \|_2 + \| d\theta \|_2}$ ($d\theta_{approx}$와 $d\theta$의 차이 / 양쪽에서 계산한 값과 그래디언트 값의 차이)

$\varepsilon = 10^{-7}$

$\approx 10^{-7}$ — 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

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

- Remember regularization.

- Doesn't work with dropout.

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

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