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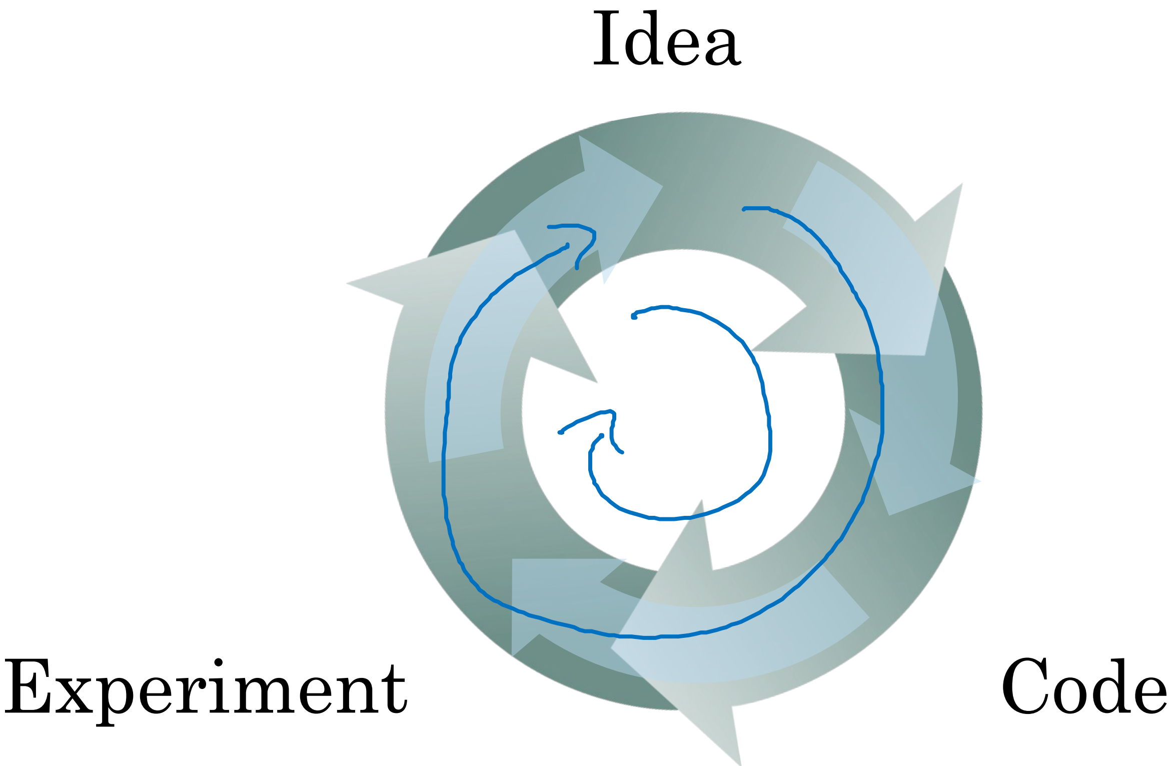
Setting up your ML application

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 logistics ....

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Train/dev/test sets

Data | | dev | test
--- | --- | ---
training set | - Hold-out cross validation
- Development set "dev" | test

Previous era: 70/30 % (train / test)

100 - 1000 - 10000

60/20/20 %

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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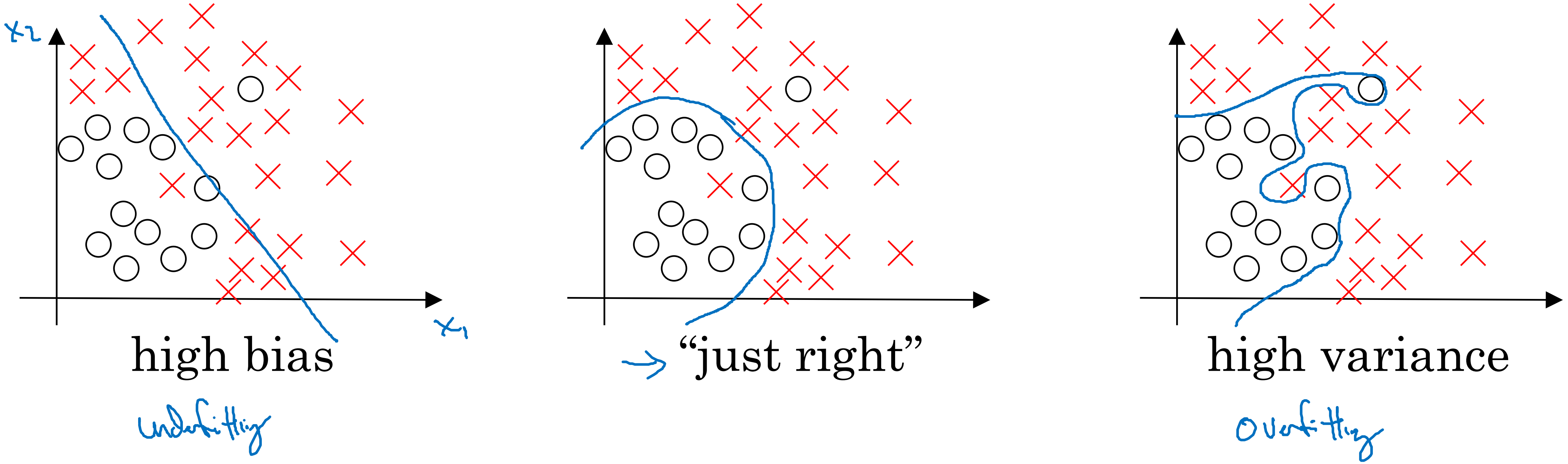
Setting up your ML application

Bias/Variance

Bias and Variance



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Bias and Variance

Cat classification

y=1

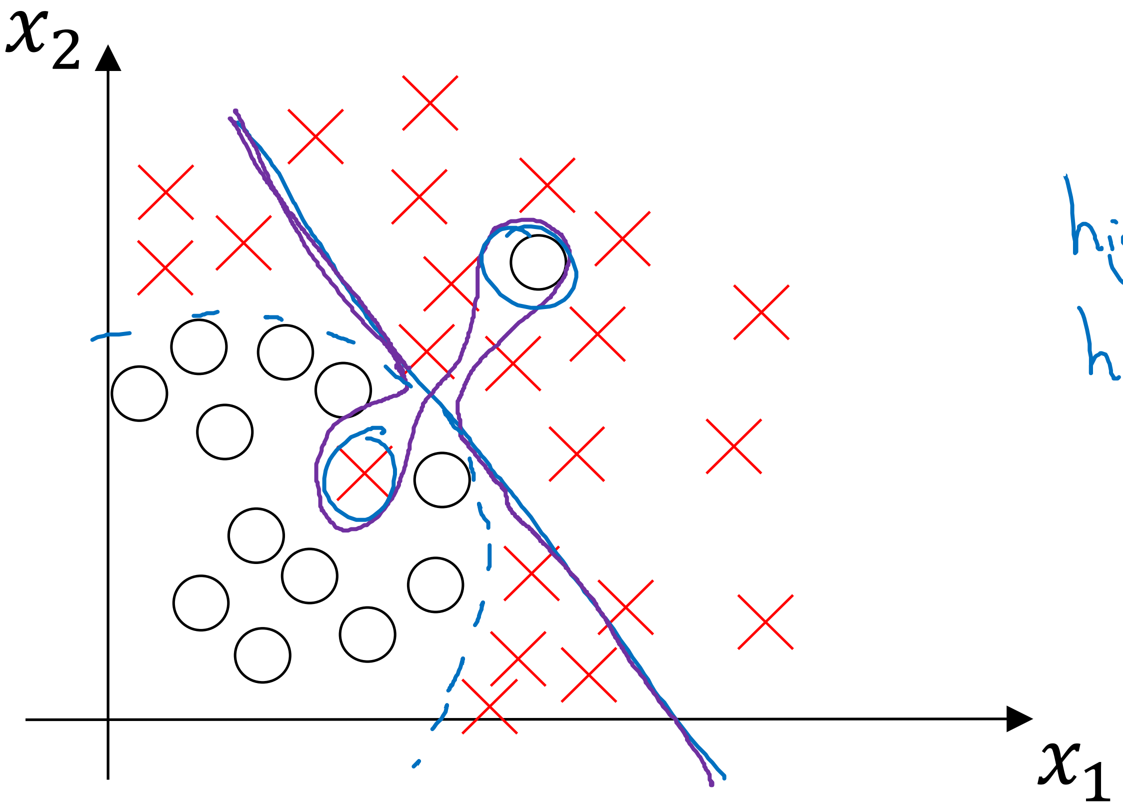
y=0

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%

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

High bias and high variance



high bias
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

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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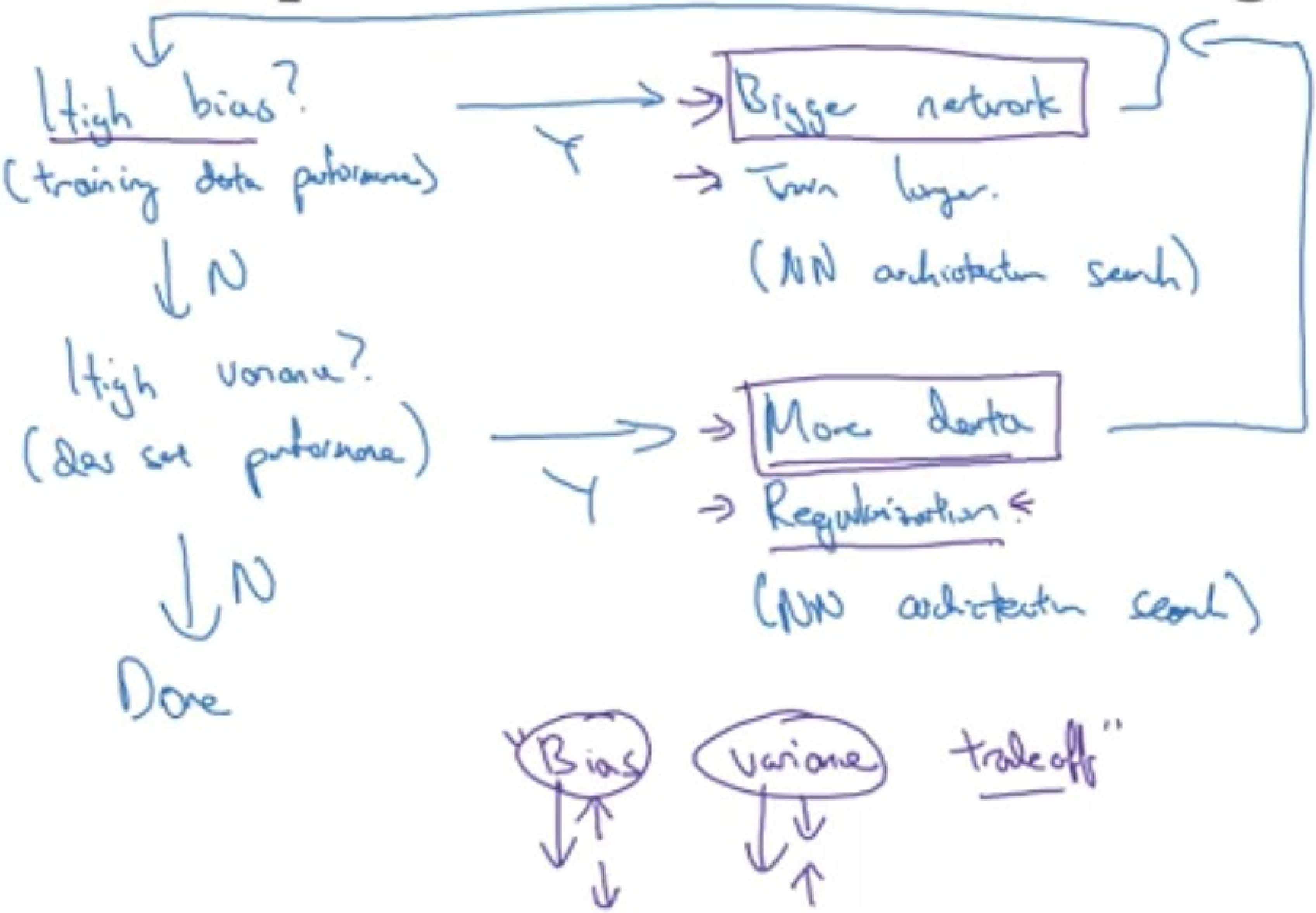
Setting up your ML application

Basic "recipe" for machine learning

Basic recipe for machine learning



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Regularizing your neural network

Regularization

Logistic regression

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

λ = regularization parameter

lambda lambd

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

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

omit

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

L$_1$ 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

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

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

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

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

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

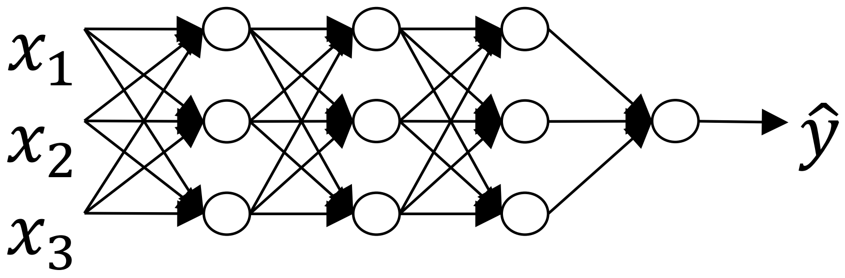
"Weight decay"

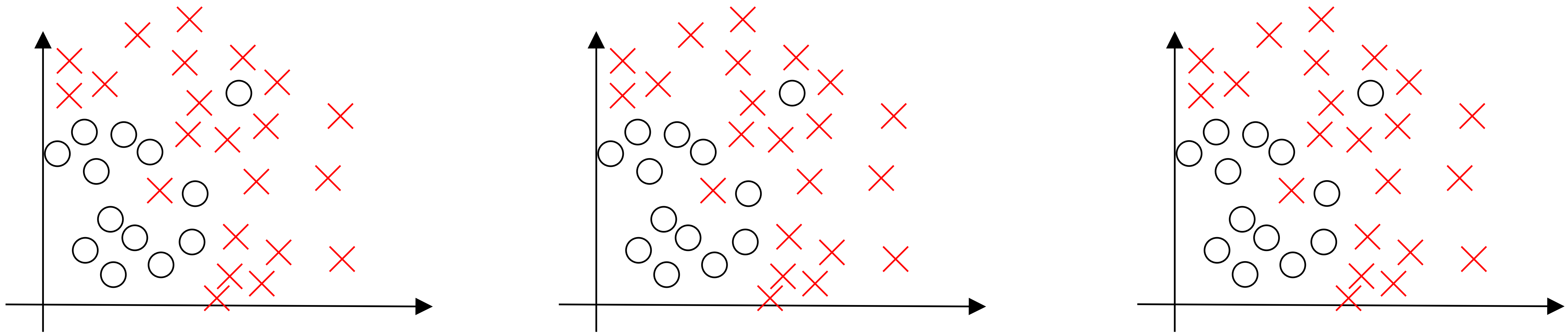
$$w^{[l]} := w^{[l]} - \alpha\left[(\text{from backprop}) + \frac{\lambda}{m} w^{[l]}\right]$$

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

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

How does regularization prevent overfitting?





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How does regularization prevent overfitting?

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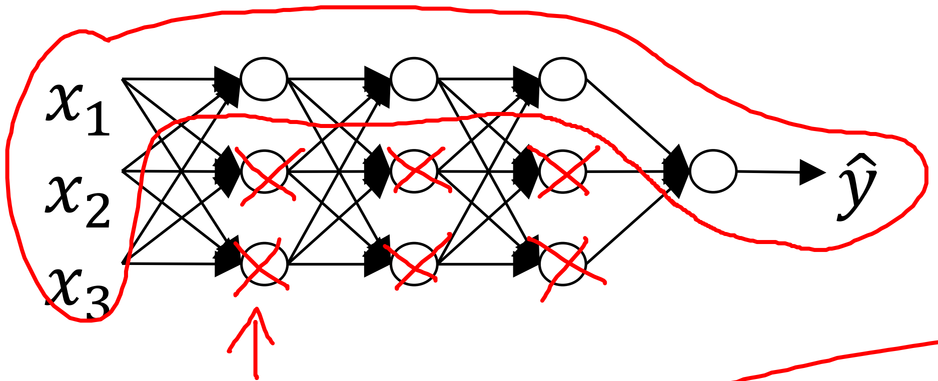
Regularizing your neural network

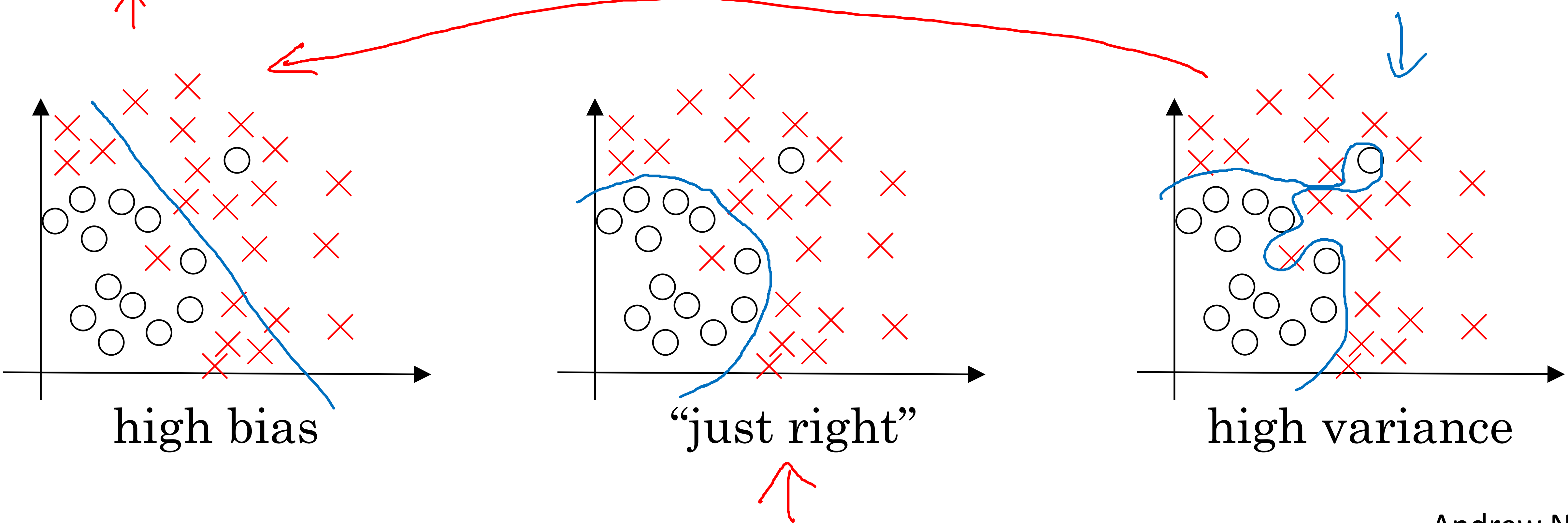
Why regularization reduces overfitting

How does regularization prevent overfitting?

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

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





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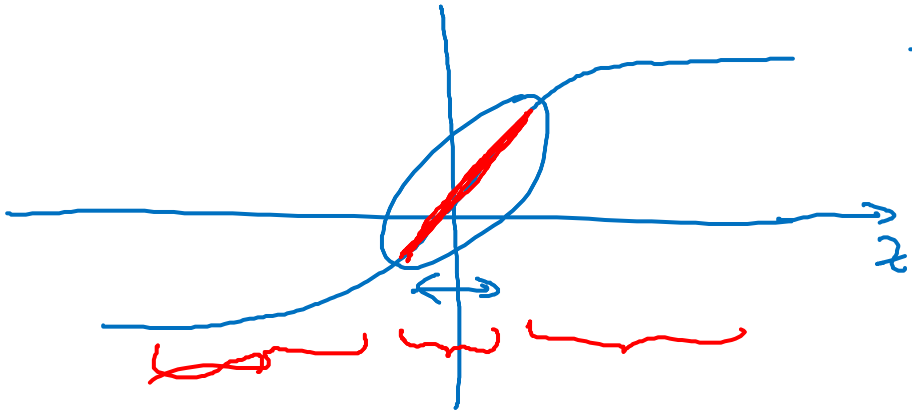
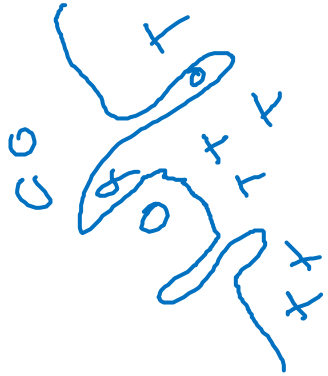


tanh

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

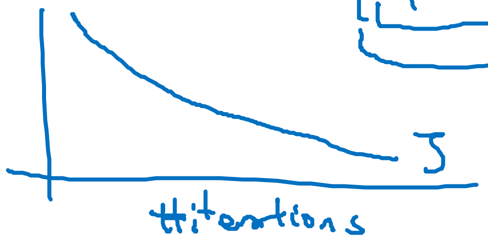


$\lambda \uparrow \qquad W^{[l]} \downarrow$

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

Every layer $\approx$ 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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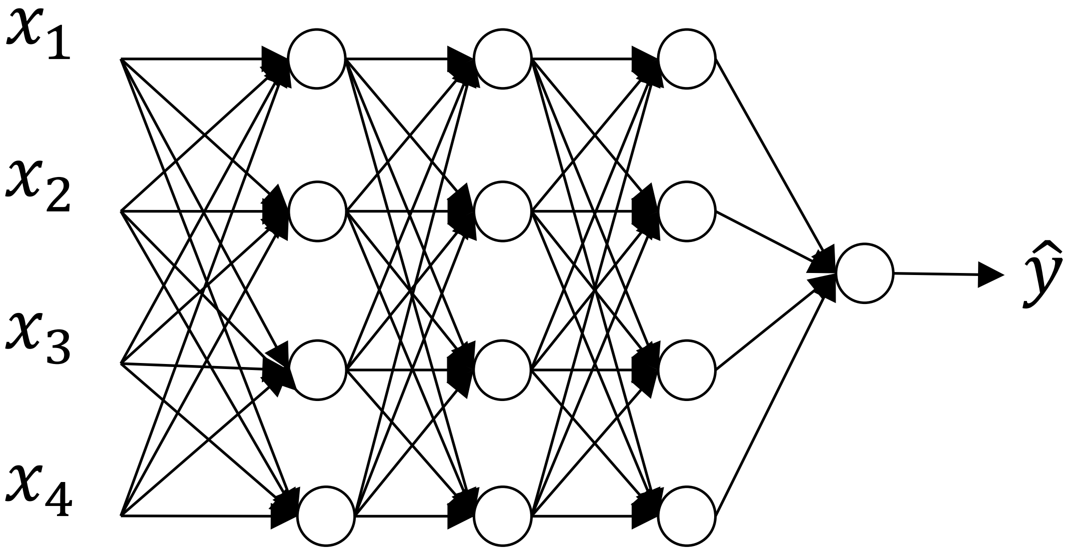
Regularizing your neural network

Dropout regularization

Dropout regularization



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

→ $\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.

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

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

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

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

$\downarrow$

$\hat{y}$

$/= \text{keep-prob}$

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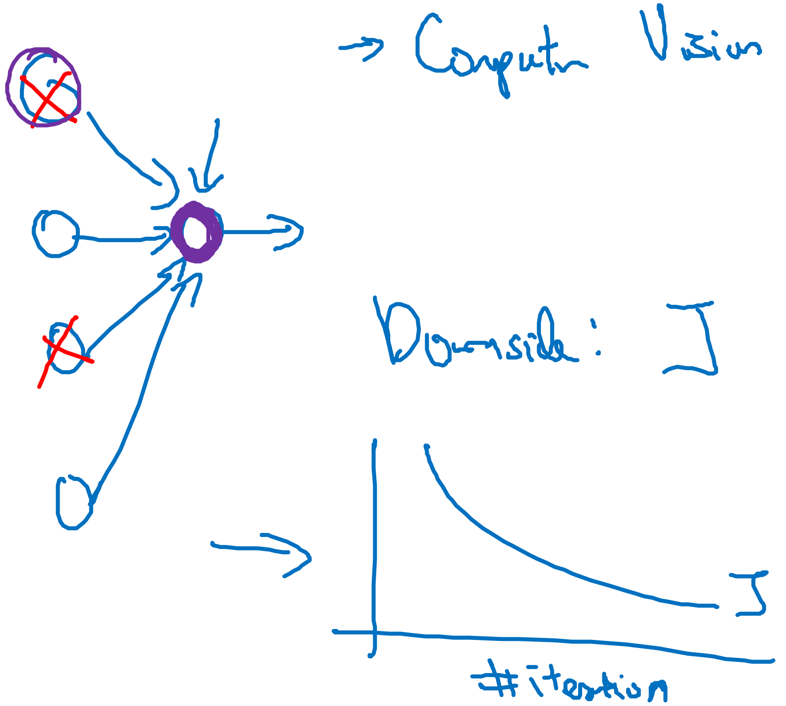
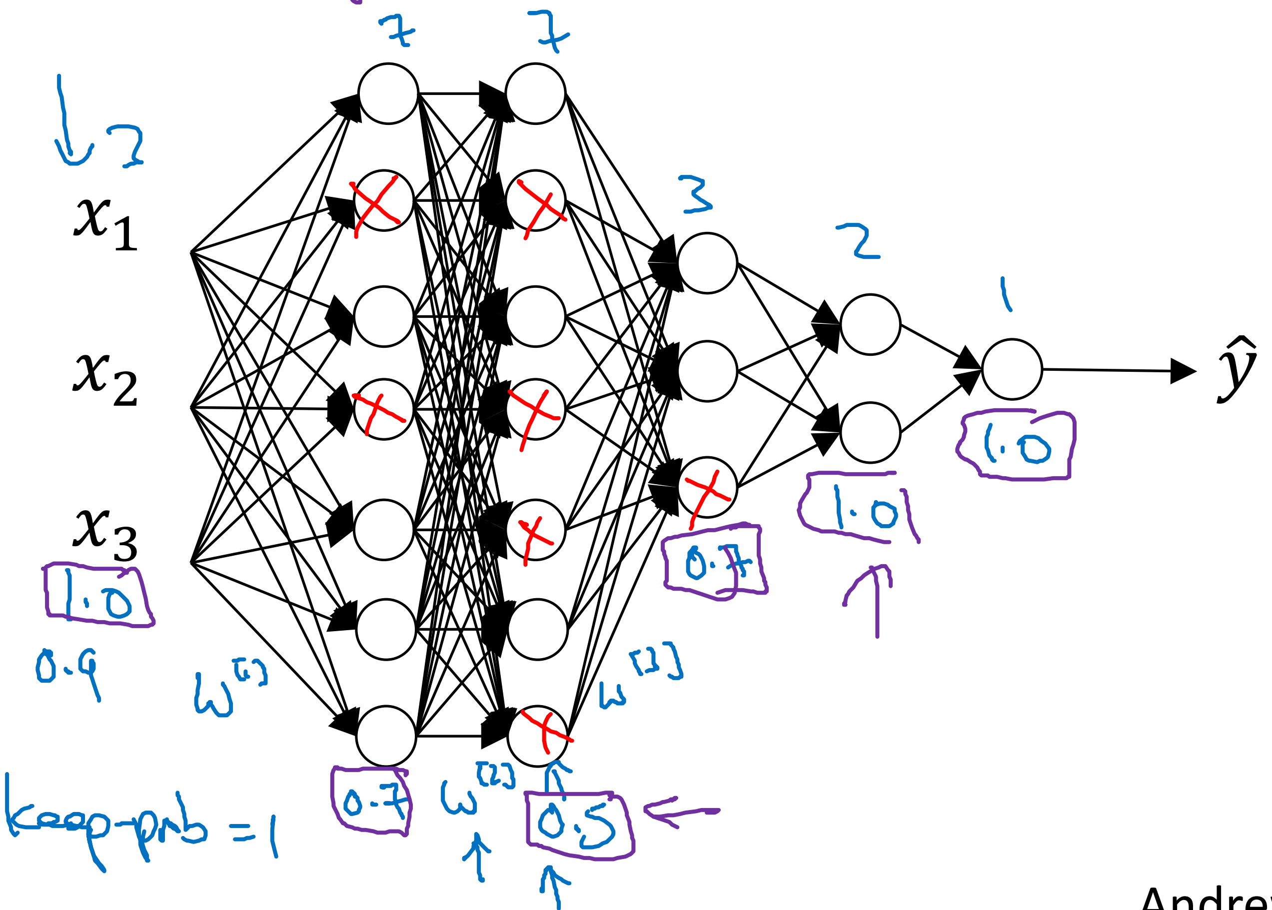
Regularizing your neural network

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





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Regularizing your neural network

Understanding dropout

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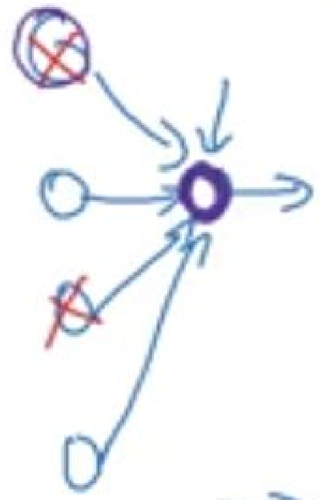
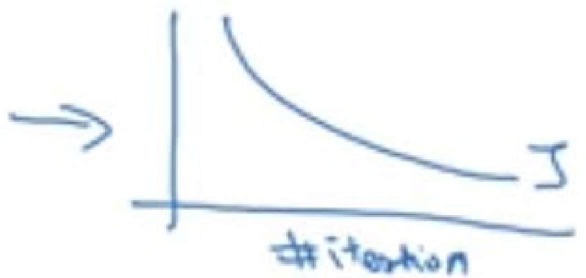
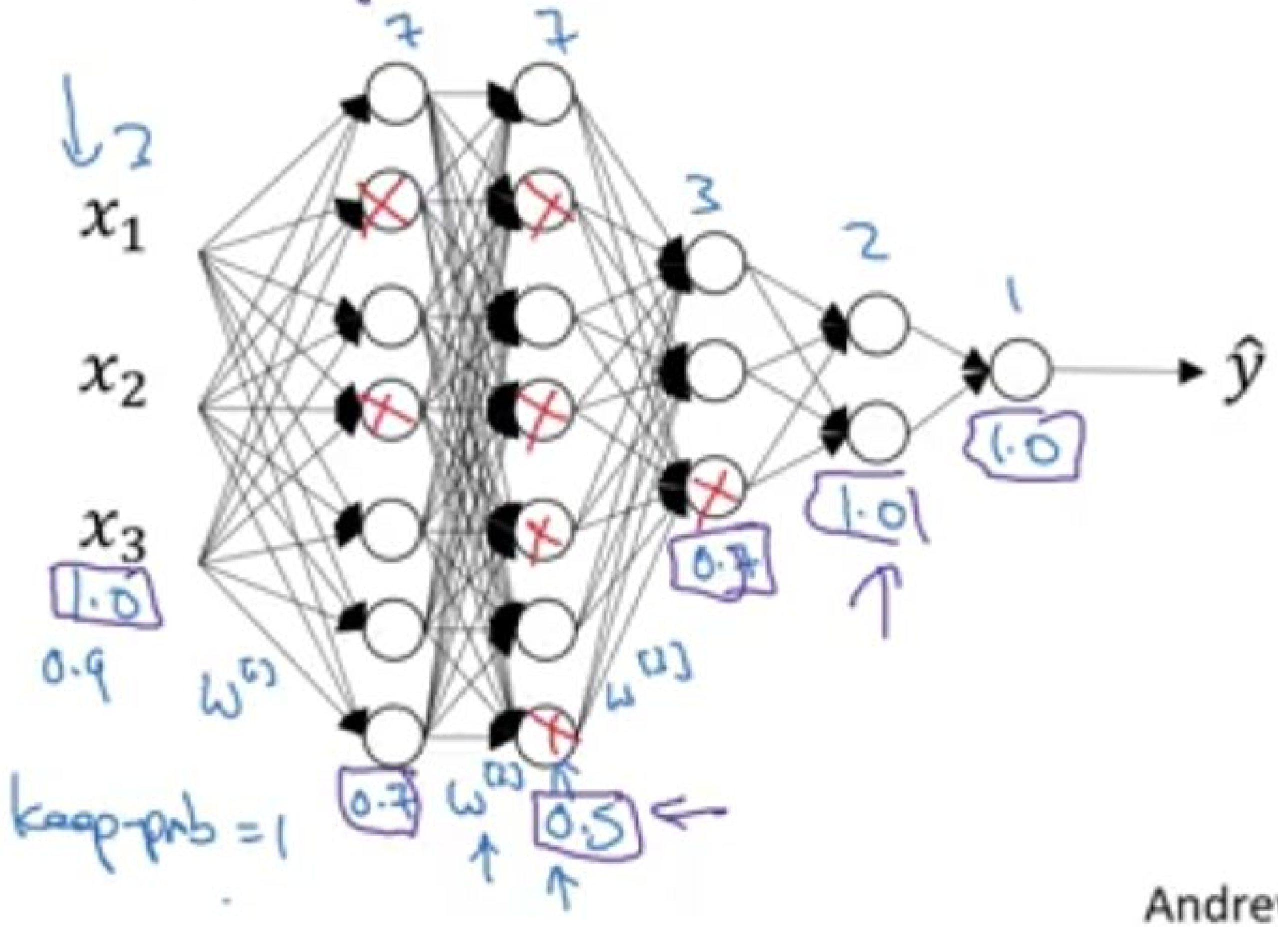
→ Computer Vision



Downside: J





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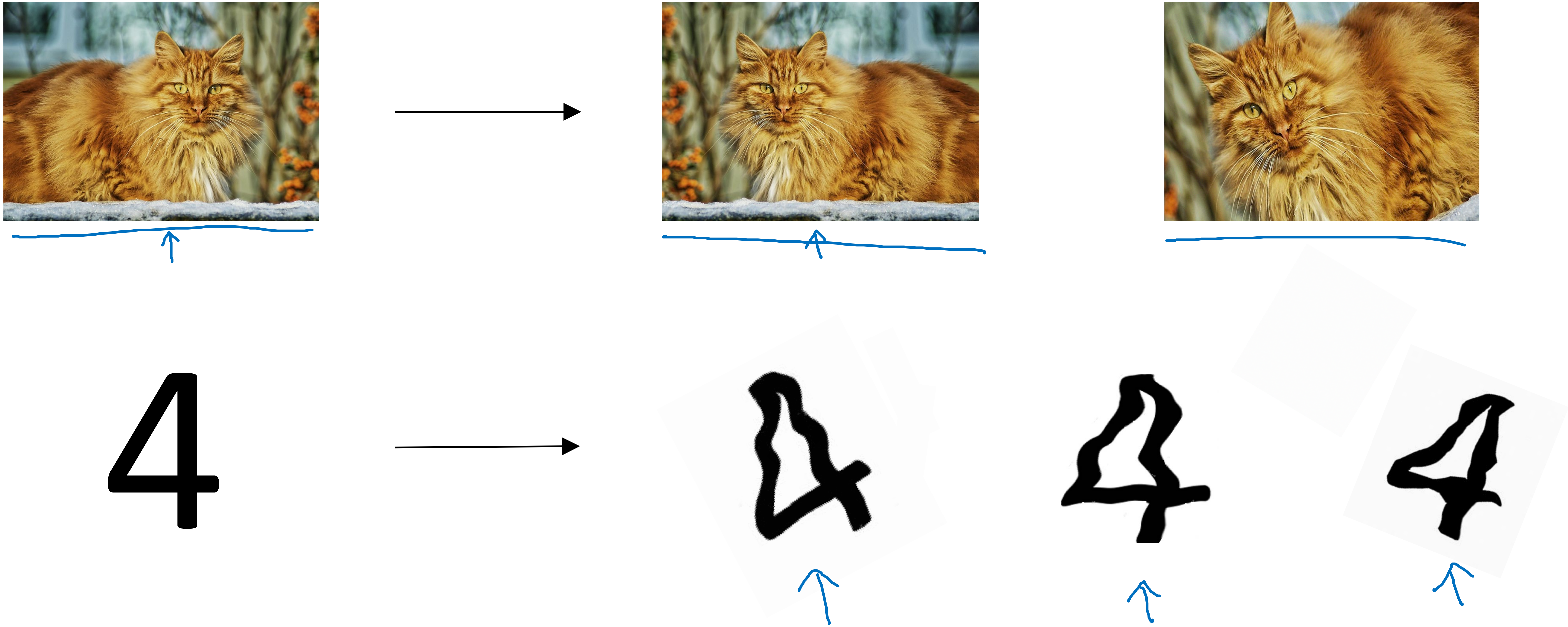
Regularizing your neural network

Other regularization methods

Data augmentation



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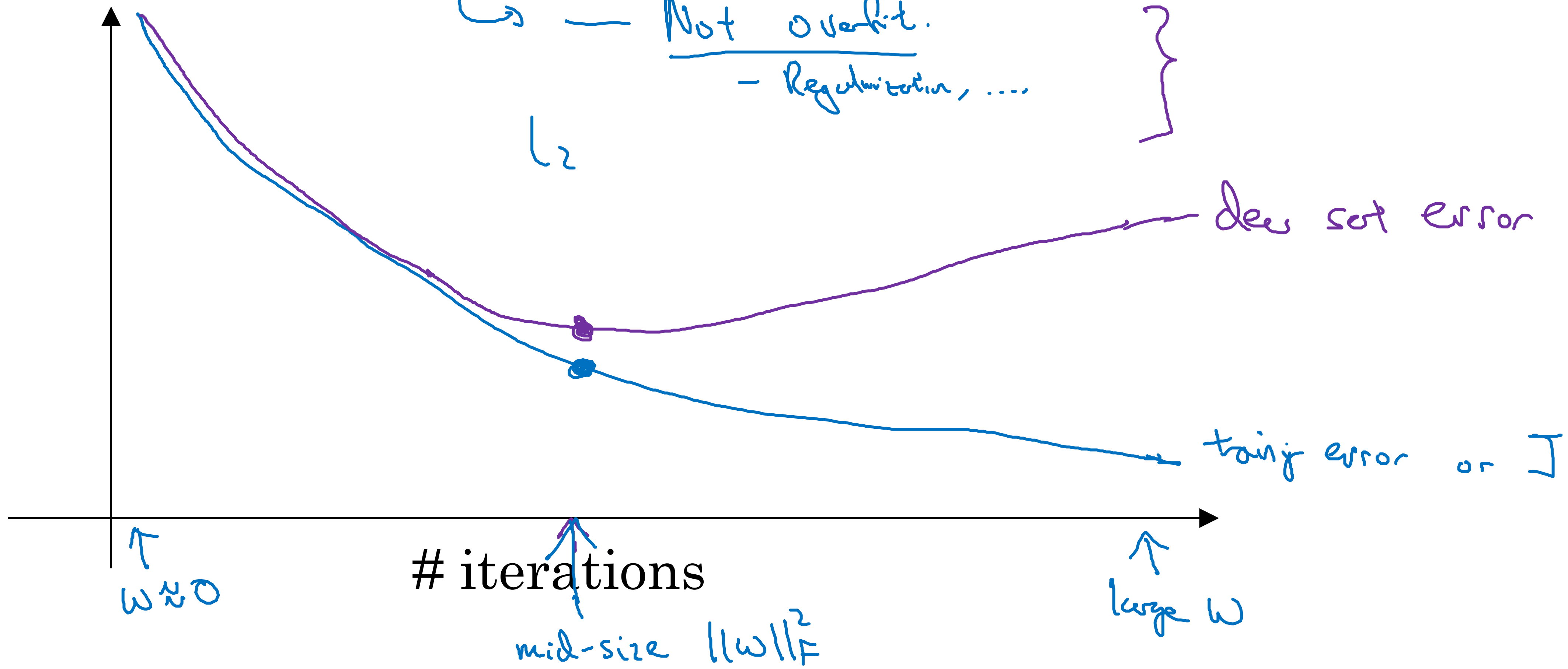
Early stopping

Orthogonalization.

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

$J(w,b)$

L_2



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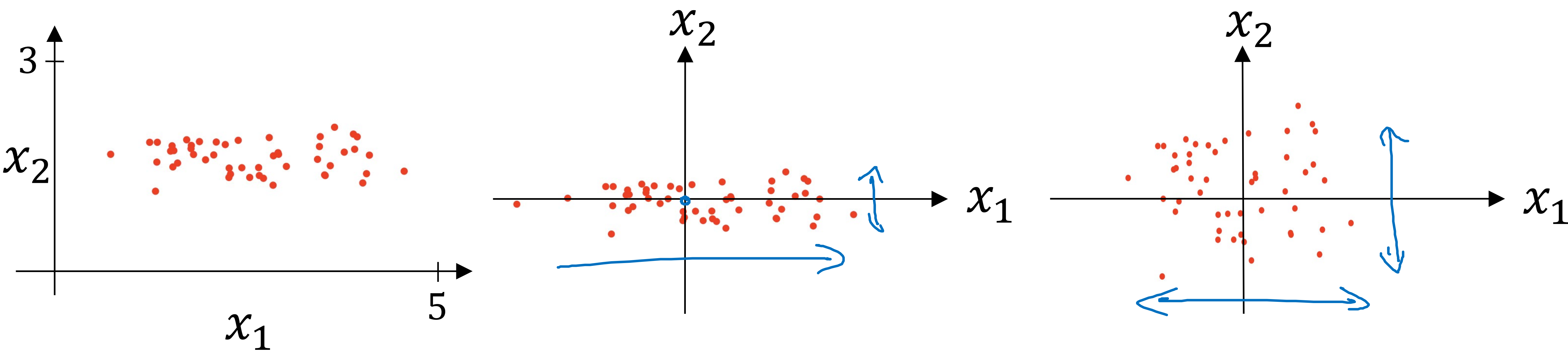
Setting up your optimization problem

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

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

← element-wise

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

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

Why normalize inputs?

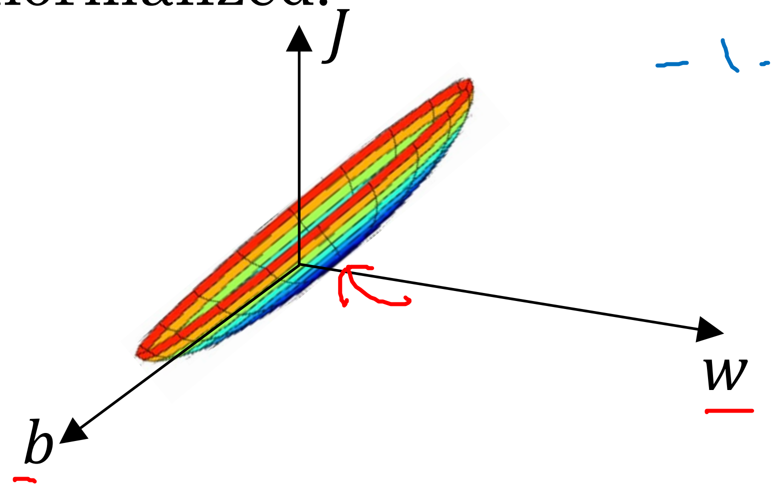
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m}\mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

w_1 x_1: $1 \ldots 1000$ ←

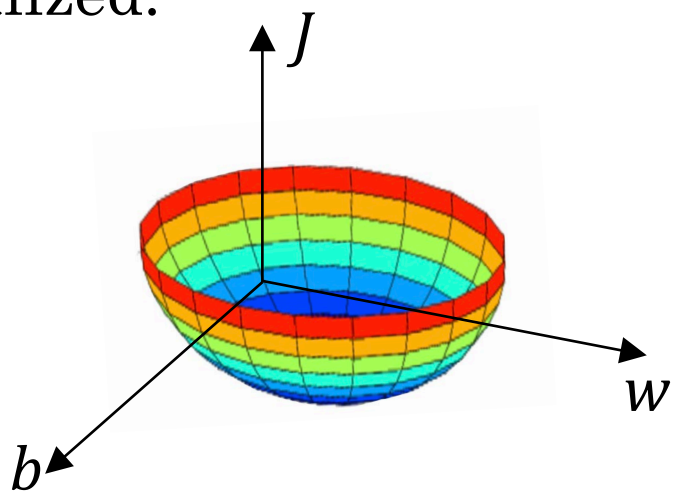
w_2 x_2: $0 \ldots 1$ ←

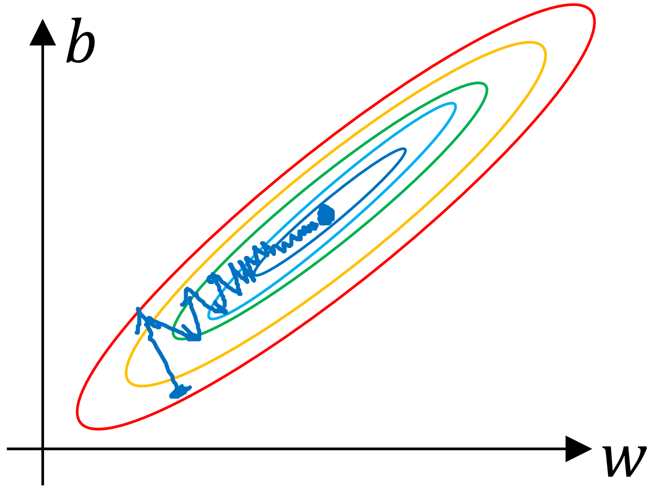
$-1 \ldots 1$

Unnormalized:



Normalized:

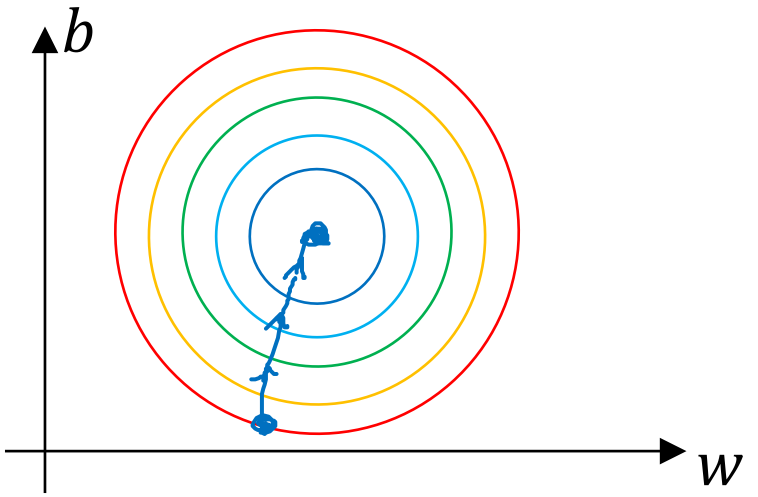




x_1: $0 \ldots 1$

x_2: $-1 \ldots 1$

x_3: $1 \ldots 2$



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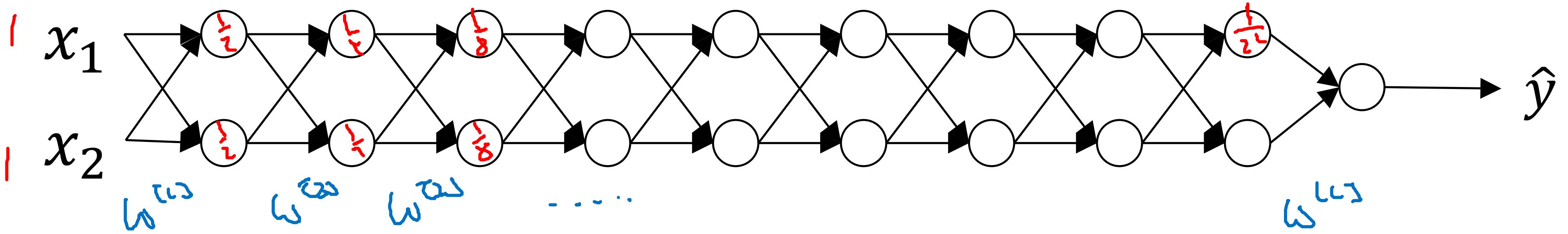
Setting up your optimization problem

Vanishing/exploding gradients

Vanishing/exploding gradients

$L=150$



L

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

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

$a^{[3]}$

1.5^L

0.5^L

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

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

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

$W^{[l]} > I$

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

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

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

$1.5^{L-1}x$

$0.5^{L-1}x$

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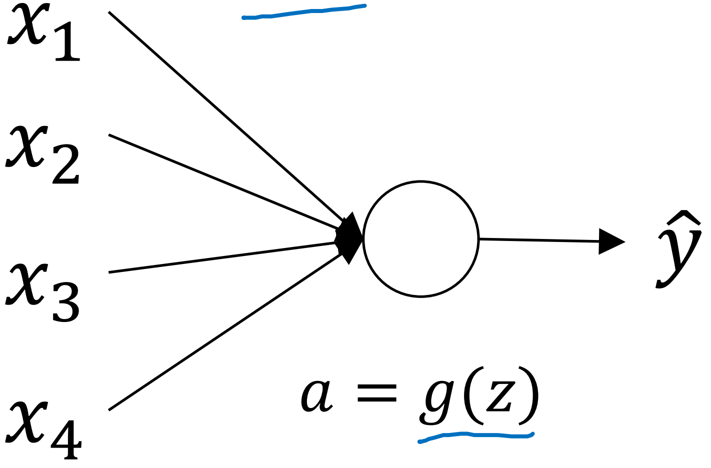
Single neuron example

$a^{[l]}$



$a = g(z)$

$W^{[l]}$

$z = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + \cancel{b}$

Large n → smaller w_i

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

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

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

Other variants:

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

Xavier initialization

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

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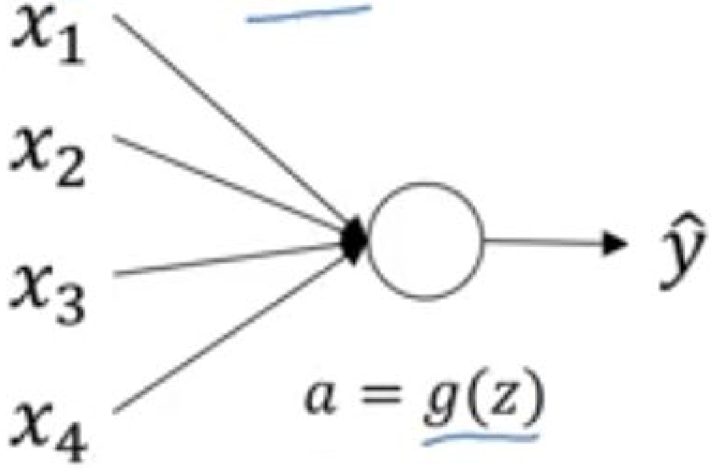
Setting up your optimization problem

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

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

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

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

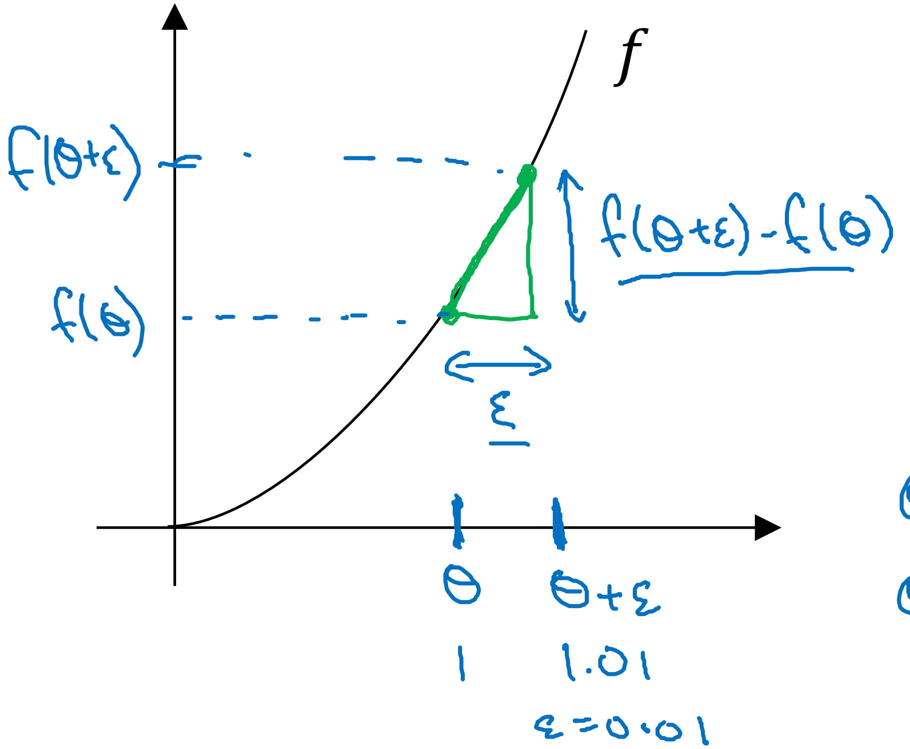
Numerical approximation of gradients

Checking your derivative computation

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

J

$\theta \in \mathbb{R}$



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

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

dw

db

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

when $\theta = 1$

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

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

$\theta = 1$

$\theta + \varepsilon = 1.01$

0.0301

3.1

3.2

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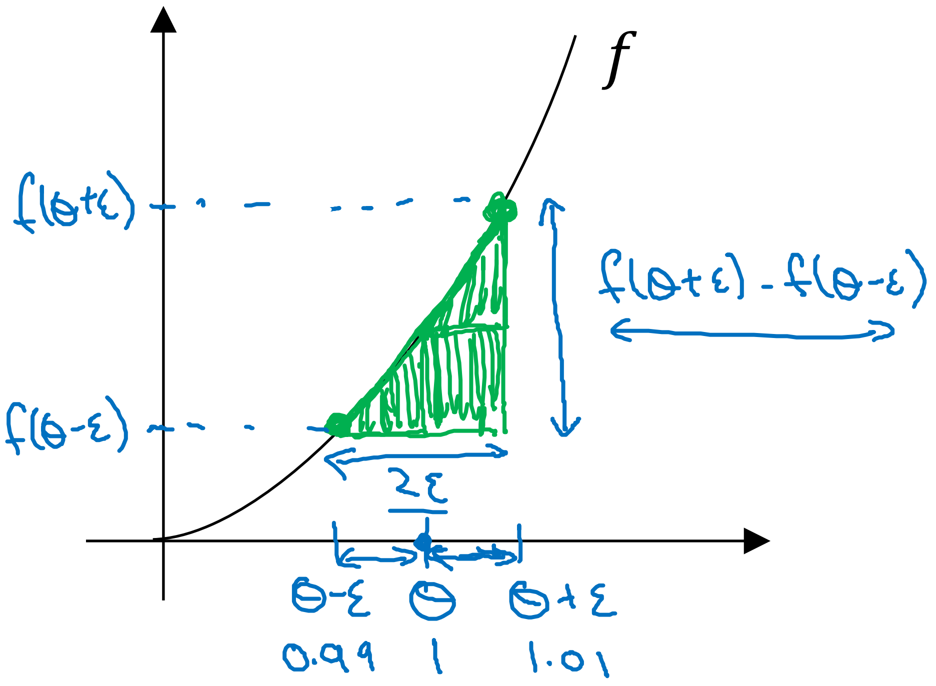
Checking your derivative computation

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



$\varepsilon = 0.01$

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

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

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

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 θ.

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)

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

for each i:

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

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

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

Check

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

10^{-5}

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

$\varepsilon = 10^{-7}$

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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

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

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

$\underline{db^{[l]}} \qquad \underline{dW^{[l]}}$

- Remember regularization.

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

$d\theta$ = gradient of J w.r.t. θ

- Doesn't work with dropout. $\quad J \qquad$ $\underline{\text{keep-prob} = 1.0}$

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

$\underline{W, b \approx 0}$

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Setting up your optimization problem

Gradient Checking implementation notes

Gradient checking implementation notes

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

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- Doesn't work with dropout.

J keep-prob = 1.0

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$W, b \approx 0$

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Optimization Algorithms

Mini-batch gradient descent

Batch vs. mini-batch gradient descent

X, Y $\quad X^{\{t\}}, Y^{\{t\}}$

Vectorization allows you to efficiently compute on m examples.

$$X = [\underbrace{x^{(1)}\ x^{(2)}\ x^{(3)} \dots x^{(1000)}}_{X^{\{1\}}\ (n_x,1000)} \mid \underbrace{x^{(1001)} \dots x^{(2000)}}_{X^{\{2\}}\ (n_x,1000)} \mid \dots \mid \underbrace{\dots x^{(m)}}_{X^{\{5,000\}}\ (n_x,1000)}]$$

(n_x, m)

$$Y = [\underbrace{y^{(1)}\ y^{(2)}\ y^{(3)} \dots y^{(1000)}}_{Y^{\{1\}}\ (1,1000)} \mid \underbrace{y^{(1001)} \dots y^{(2000)}}_{Y^{\{2\}}\ (1,1000)} \mid \dots \mid \underbrace{\dots y^{(m)}}_{Y^{\{5,000\}}\ (1,1000)}]$$

$(1, m)$

What if $m = 5{,}000{,}000$?

5,000 mini-batches of 1,000 each

Mini-batch t: $X^{\{t\}}, Y^{\{t\}}$

$x^{(i)}$

$z^{[l]}$

$X^{\{t\}}, Y^{\{t\}}$.

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Mini-batch gradient descent

1 step of grad descent using $X^{\{t\}}, Y^{\{t\}}$ (as if $m = 1000$)

X, Y

repeat {

for $t = 1, \ldots, 5000$ {

Forward prop on $X^{\{t\}}$.

$$\left.\begin{aligned} Z^{[1]} &= W^{[1]} X^{\{t\}} + b^{[1]} \\ A^{[1]} &= g^{[1]}(Z^{[1]}) \\ &\vdots \\ A^{[L]} &= g^{[L]}(Z^{[L]}) \end{aligned}\right\}$$ Vectorized implementation (1000 examples)

from $X^{\{t\}}, Y^{\{t\}}$.

Compute cost $J^{\{t\}} = \frac{1}{1000} \sum_{i=1}^{l} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2 \cdot 1000} \sum_{l} \|W^{[l]}\|_F^2$.

Backprop to compute gradients wrt $J^{\{t\}}$ (using $(X^{\{t\}}, Y^{\{t\}})$)

$W^{[l]} := W^{[l]} - \alpha dW^{[l]}$, $b^{[l]} := b^{[l]} - \alpha db^{[l]}$

}

}

"1 epoch" — pass through training set.

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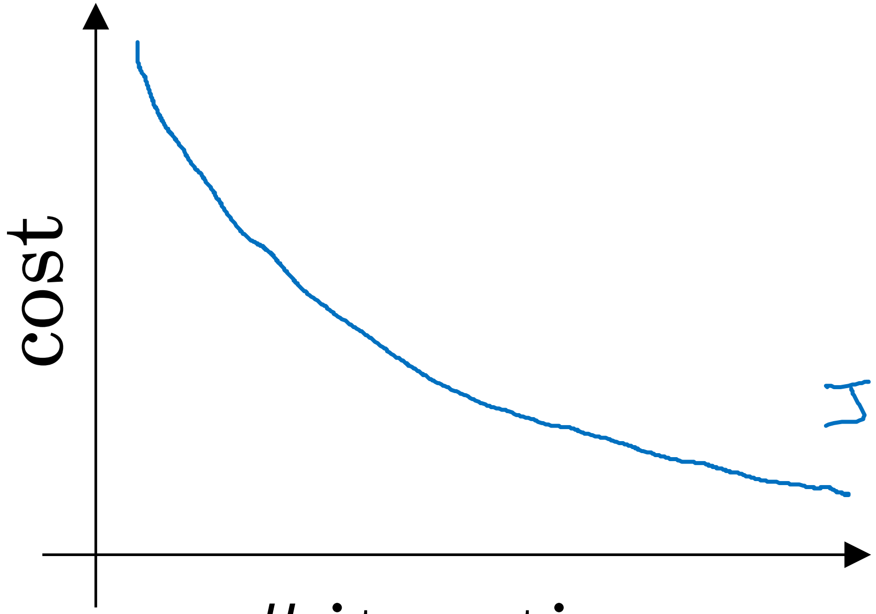
Optimization Algorithms

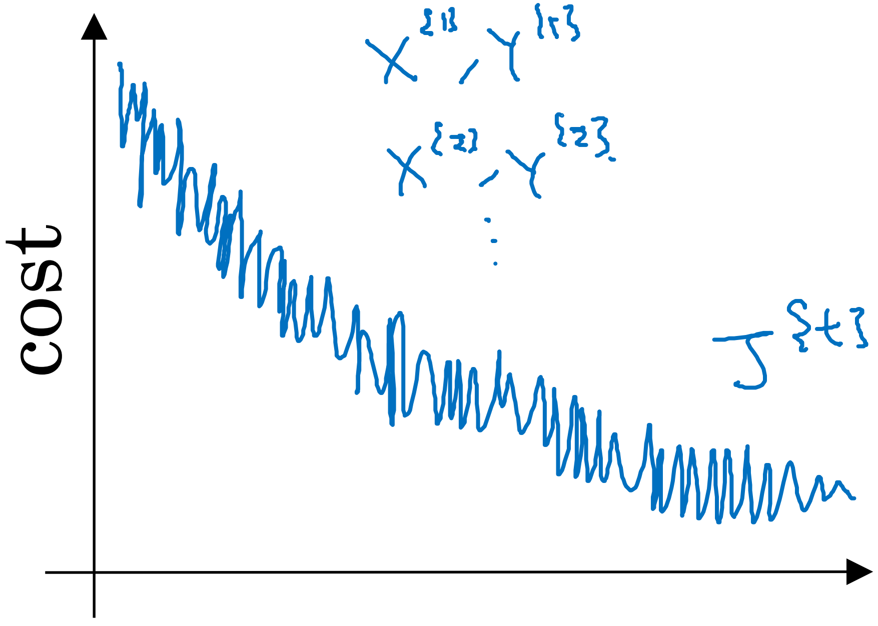
Understanding mini-batch gradient descent

Training with mini batch gradient descent

Batch gradient descent



Mini-batch gradient descent



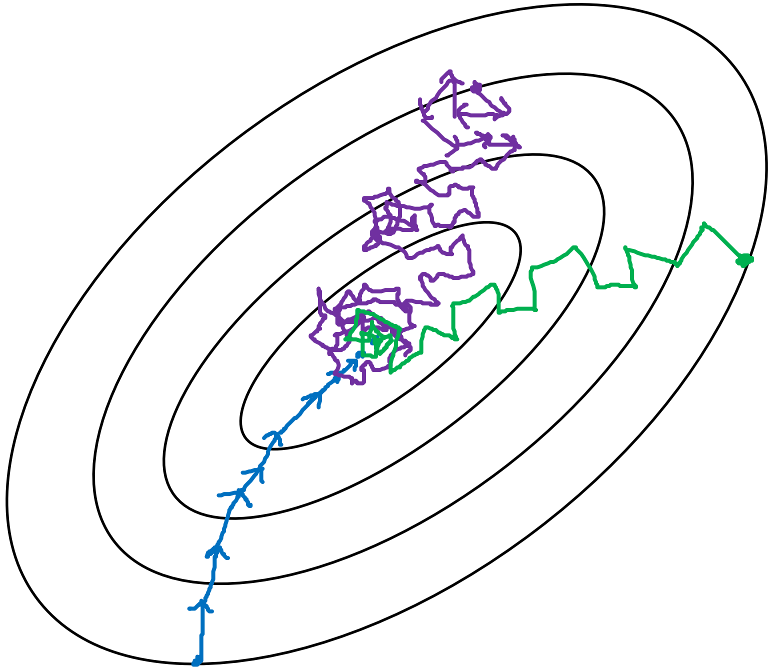
Plot $J^{\{t\}}$ computed using $\underline{X^{\{t\}}, Y^{\{t\}}}$

Choosing your mini-batch size

→ If mini-batch size = m : Batch gradient descent. $(X^{\{1\}}, Y^{\{1\}}) = (X, Y)$.

→ If mini-batch size = 1 : Stochastic gradient descent. Every example is it own
$(X^{\{1\}}, Y^{\{1\}}) = (x^{(1)}, y^{(1)})$ ... $(x^{(2)}, y^{(2)})$ mini-batch.

In practice: Somewh in-between 1 and m



Stochastic gradient descent
↓
Lose speedup from vectorization

In-between (mini-batch size not too big/small)
↓
Fastest learning.
- Vectorization. (~1000)
- Make progress without processing entire training set.

Batch gradient descent (mini-batch size = m)
↓
Too long per iteration

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Choosing your mini-batch size

If small training set: Use batch gradient descent.
($m \leq 2000$)

Typical mini-batch sizes:

$\rightarrow$ $\underbrace{\underset{2^6}{64}, \underset{2^7}{128}, \underset{2^8}{256}, \underset{2^9}{512}}$ $\qquad \underline{1024}$
$\qquad 2^{10}$

Make sure mini-batch fit in CPU/GPU memory.
$X^{\{t\}}, Y^{\{t\}}$

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Optimization Algorithms

Exponentially weighted averages

Temperature in London

$\theta_1 = 40°F$ 4°C ←

$\theta_2 = 49°F$ 9°C

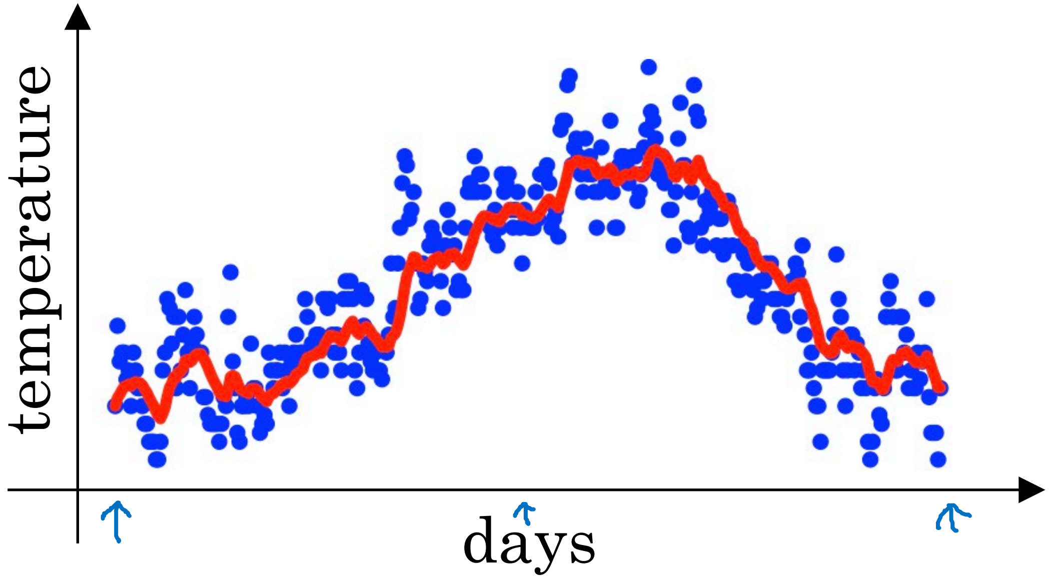
$\theta_3 = 45°F$ ⋮

⋮

$\theta_{180} = 60°F$ 15°C

$\theta_{181} = 56°F$ ⋮

⋮



$V_0 = 0$

$V_1 = 0.9\, V_0 + 0.1\, \theta_1$

$V_2 = 0.9\, V_1 + 0.1\, \theta_2$

$V_3 = 0.9\, V_2 + 0.1\, \theta_3$

⋮

$$\boxed{V_t = 0.9\, V_{t-1} + 0.1\, \theta_t}$$

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Exponentially weighted (moving) averages

$$V_t = \beta V_{t-1} + (1-\beta)\theta_t \leftarrow$$

$\beta = 0.9$: ≈ 10 days' temperature.

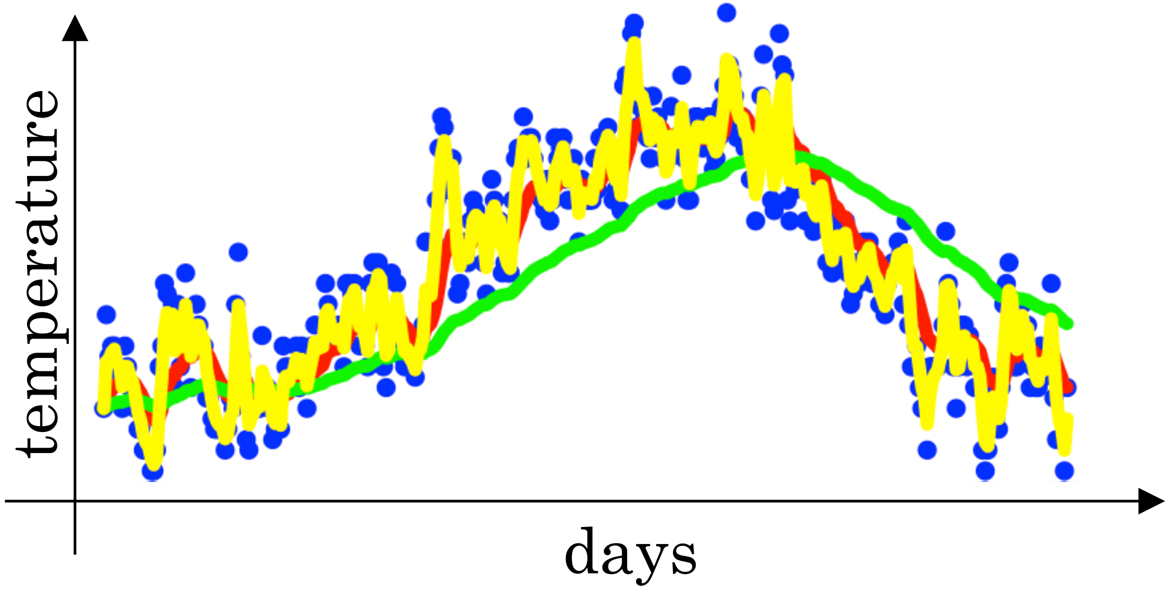
$\beta = 0.98$: ≈ 50 days

$\beta = 0.5$: ≈ 2 days

V_t as approximately average over

$\rightarrow \approx \frac{1}{1-\beta}$ days' temperature.

$$\frac{1}{1-0.98} = 50$$



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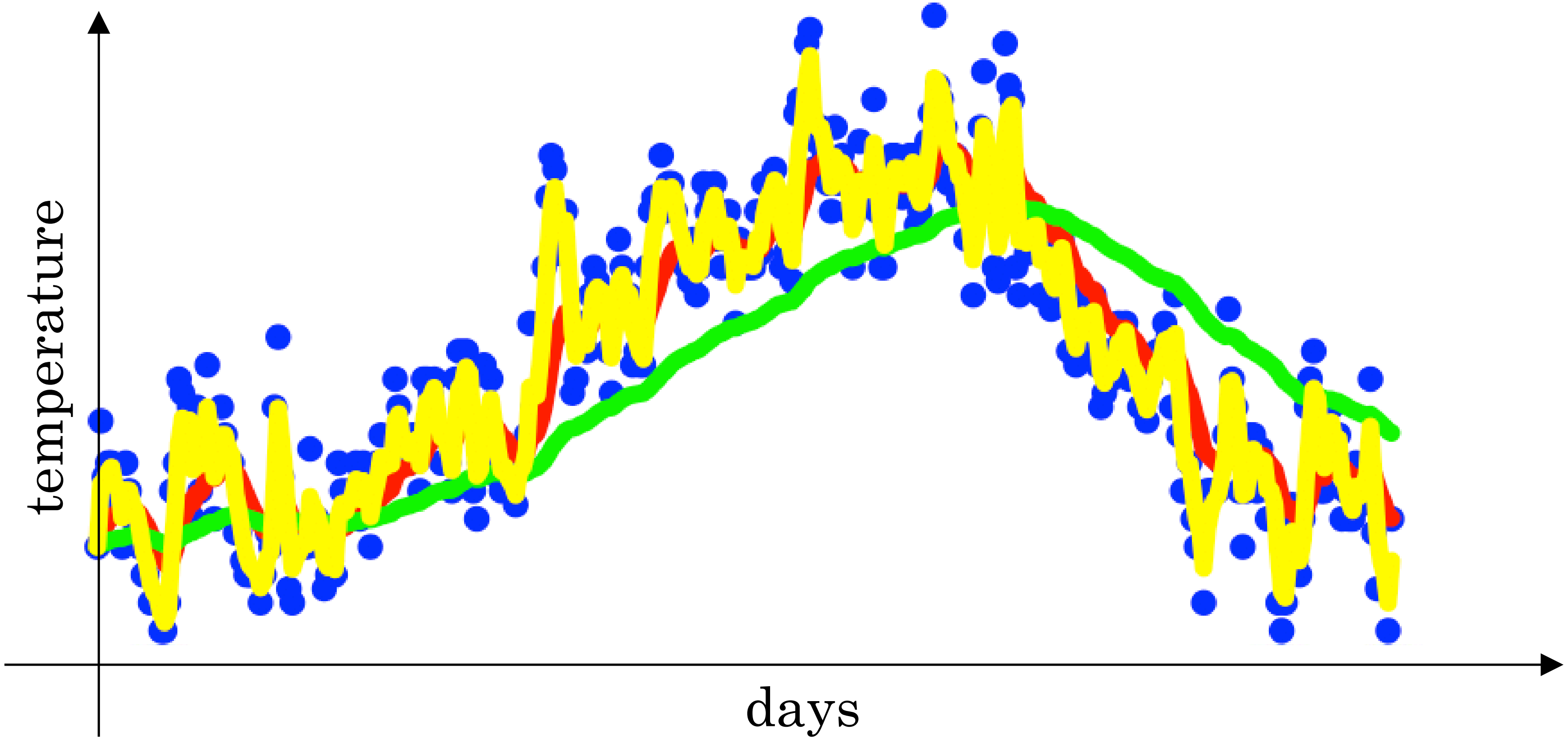
Optimization Algorithms

Understanding exponentially weighted averages

Exponentially weighted averages

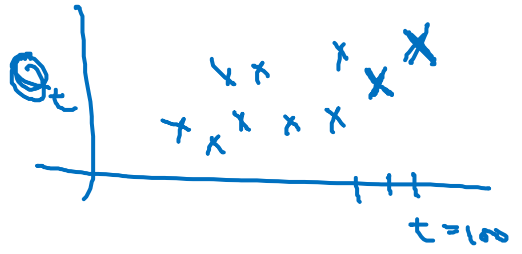
$$\boxed{v_t = \beta v_{t-1} + (1-\beta)\theta_t}$$

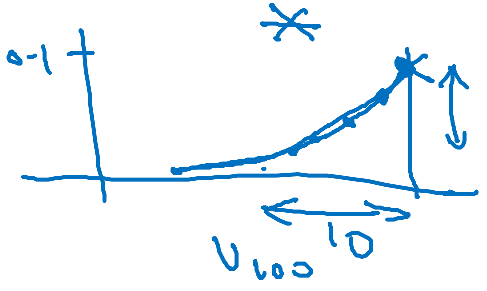
$\beta = 0.9$ 0.98 0.5



Exponentially weighted averages

$$v_t = \beta v_{t-1} + (1-\beta)\theta_t$$





$\approx \frac{1}{1-\beta}$

$\varepsilon = 1-\beta$

$$v_{100} = 0.9 v_{99} + 0.1\theta_{100}$$

$$\boxed{v_{99} = 0.9 v_{98} + 0.1\theta_{99}}$$

$$\boxed{v_{98} = 0.9 v_{97} + 0.1\theta_{98}}$$

...

$0.1\,\theta_{98} + 0.9\, v_{97}$

$$V_{100} = 0.1\,\theta_{100} + 0.9\,\cancel{V_{99}}\,(0.1\,\theta_{99} + 0.9\,\cancel{V_{98}})$$

$$= 0.1\,\theta_{100} + 0.1\times 0.9\cdot\theta_{99} + 0.1\,(0.9)^2\,\theta_{98} + 0.1\,(0.9)^3\,\theta_{97} + 0.1\,(0.9)^4\,\theta_{96} + \dots$$

$0.9^{10} \approx 0.35 \approx \frac{1}{e}$

$\underbrace{(1-\varepsilon)}_{0.9}{}^{1/\varepsilon} = \frac{1}{e}$

0.98 ?

$\varepsilon = 0.02 \to 0.98^{50} \approx \frac{1}{e}$

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Implementing exponentially weighted averages

$$v_0 = 0$$
$$v_1 = \beta v_0 + (1-\beta)\,\theta_1$$
$$v_2 = \beta v_1 + (1-\beta)\,\theta_2$$
$$v_3 = \beta v_2 + (1-\beta)\,\theta_3$$
$$\ldots$$

$V_\theta := 0$

$V_\theta := \beta V + (1-\beta)\,\theta_1$

$V_\theta := \beta V + (1-\beta)\,\theta_2$

$\vdots$

$V_\theta = 0$

Repeat {

Get next θ_t

$V_\theta := \beta V_\theta + (1-\beta)\,\theta_t$

}

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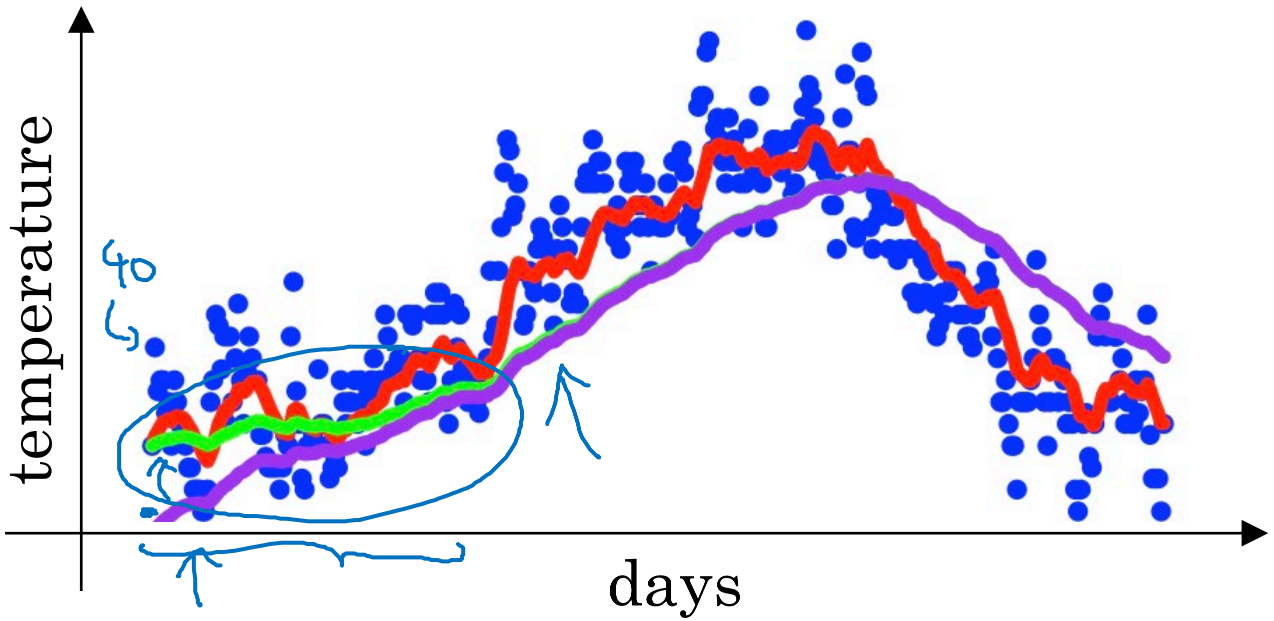
Optimization Algorithms

Bias correction in exponentially weighted average

Bias correction



$\beta = 0.98$

$$\rightarrow v_t = \beta v_{t-1} + (1-\beta)\theta_t$$

$v_0 = 0$

$v_1 = \cancel{0.98 v_0 +} \; 0.02\,\theta_1$

$v_2 = 0.98\, v_1 + 0.02\,\theta_2$

$= 0.98 \times 0.02 \times \theta_1 + 0.02\,\theta_2$

$= 0.0196\,\theta_1 + 0.02\,\theta_2$

$$\frac{v_t}{1-\beta^t}$$

$t=2: \quad 1-\beta^t = 1-(0.98)^2 = 0.0396$

$$\frac{v_2}{0.0396} = \frac{0.0196\,\theta_1 + 0.02\,\theta_2}{0.0396}$$

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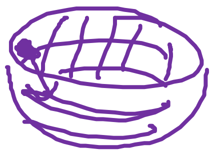
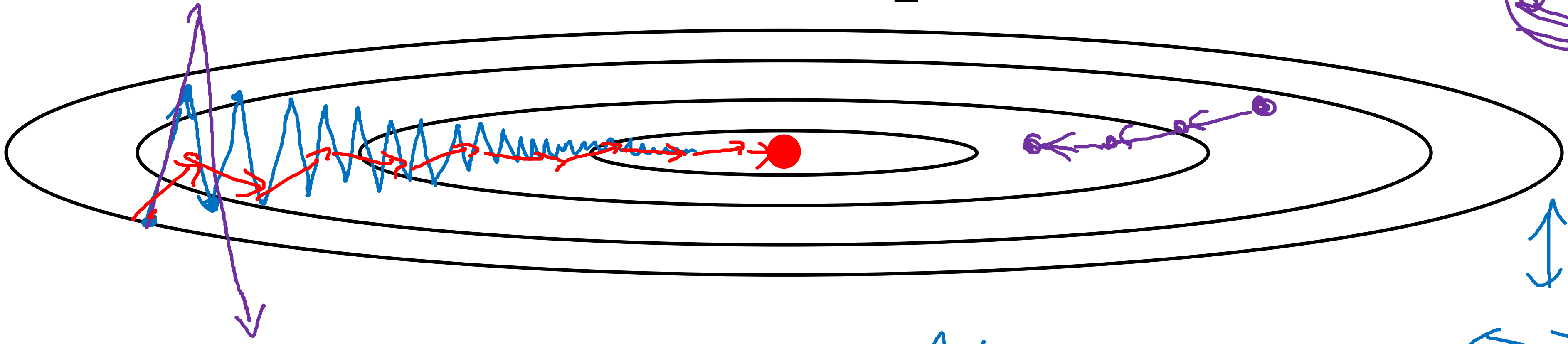
Optimization Algorithms

Gradient descent with momentum

Gradient descent example





$\updownarrow$ slower learning

$\leftrightarrow$ faster learning.

Momentum:

On iteration t:

Compute dW, db on current mini-batch.

$$V_{dW} = \beta V_{dW} + (1-\beta) dW$$

$$V_{db} = \beta V_{db} + (1-\beta) db$$

friction, velocity, acceleration

"$V_\theta = \beta V_\theta + (1-\beta)\theta_t$"

$$W := W - \alpha V_{dW}, \quad b := b - \alpha V_{db}$$

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Implementation details

$V_{dw} = 0$, $V_{db} = 0$

On iteration t:

Compute dW, db on the current mini-batch

$$\rightarrow v_{dW} = \beta v_{dW} + \cancel{(1-\beta)}\, dW$$

$$\rightarrow v_{db} = \beta v_{db} + \cancel{(1-\beta)}\, db$$

$$W = W - \alpha v_{dW}, \quad b = b - \alpha v_{db}$$

$V_{dw} = \beta V_{dw} + dW \leftarrow$

$\cancel{\dfrac{V_{dw}}{1-\beta^t}}$

Hyperparameters: α, β

$\beta = 0.9$

average over last ≈ 10 gradients

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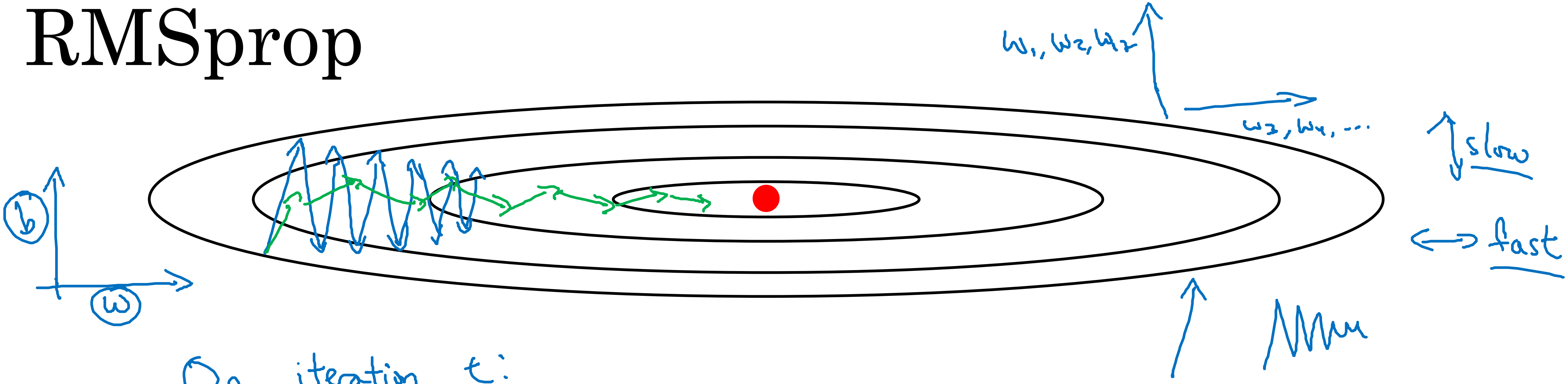
Optimization Algorithms

RMSprop

RMSprop



On iteration t:

Compute dW, db on current mini-batch

element-wise

$S_{dW} = \beta_2 S_{dW} + (1-\beta_2) dW^2$ ← small

→ $S_{db} = \beta_2 S_{db} + (1-\beta_2) db^2$ ← large

$W := W - \alpha \frac{dW}{\sqrt{S_{dW}+\varepsilon}}$ ← ←

$b := b - \alpha \frac{db}{\sqrt{S_{db}+\varepsilon}}$ ← ←

$\varepsilon = 10^{-8}$

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Optimization Algorithms

Adam optimization algorithm

Adam optimization algorithm

$V_{dw} = 0,\ S_{dw} = 0.\quad V_{db} = 0,\ S_{db} = 0$

On iteration t:

Compute dW, db using current mini-batch

$V_{dw} = \beta_1 V_{dw} + (1-\beta_1) dW, \quad V_{db} = \beta_1 V_{db} + (1-\beta_1) db \leftarrow$ "momentum" β_1

$S_{dw} = \beta_2 S_{dw} + (1-\beta_2) dW^2, \quad S_{db} = \beta_2 S_{db} + (1-\beta_2) db \leftarrow$ "RMSprop" β_2

yhat = np.array([.9, 0.2, 0.1, .4, .9])

$V_{dw}^{corrected} = V_{dw} / (1-\beta_1^t), \quad V_{db}^{corrected} = V_{db} / (1-\beta_1^t)$

$S_{dw}^{corrected} = S_{dw} / (1-\beta_2^t), \quad S_{db}^{corrected} = S_{db} / (1-\beta_2^t)$

$$W := W - \alpha \frac{V_{dw}^{corrected}}{\sqrt{S_{dw}^{corrected}} + \varepsilon} \qquad b := b - \alpha \frac{V_{db}^{corrected}}{\sqrt{S_{db}^{corrected}} + \varepsilon}$$

Hyperparameters choice:

→ α : needs to be tune

→ β_1 : 0.9 → $(\underline{dw})$

→ β_2 : 0.999 → $(\underline{dw^2})$

→ ε : 10^{-8}

Adam: Adaptive moment estimation

Adam Coates

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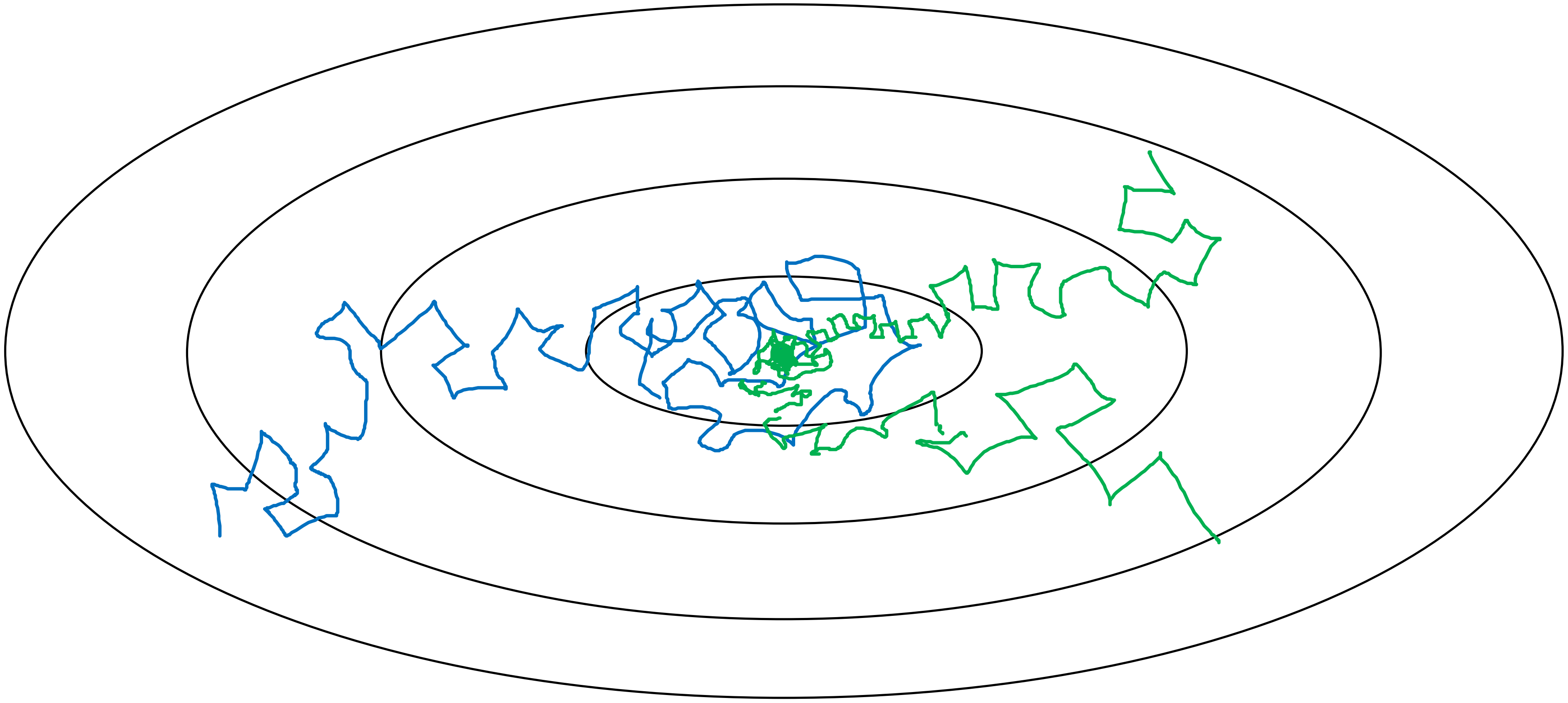
Optimization Algorithms

Learning rate decay

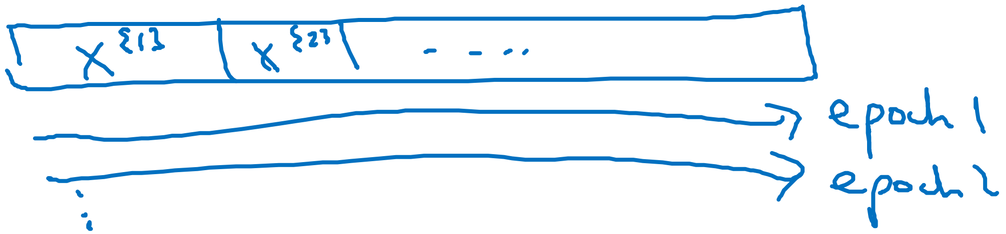
Learning rate decay

Slowly reduce α



Learning rate decay

1 epoch = 1 pass through data.

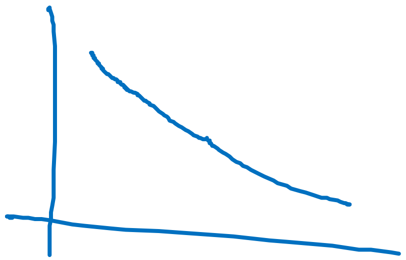


$$\alpha = \frac{1}{1 + \text{decay-rate} * \text{epoch-num}} \alpha_0$$

Epoch	α
1	0.1
2	0.67
3	0.5
4	0.4
⋮	⋮

$\alpha_0 = 0.2$

decay.rate = 1



Other learning rate decay methods

formula

$$\alpha = 0.95^{\text{epoch-num}} \cdot \alpha_0$$ — exponentially decay.

$$\alpha = \frac{k}{\sqrt{\text{epoch-num}}} \cdot \alpha_0 \quad \text{or} \quad \frac{k}{\sqrt{t}} \cdot \alpha_0$$

discrete staircase

Manual decay.

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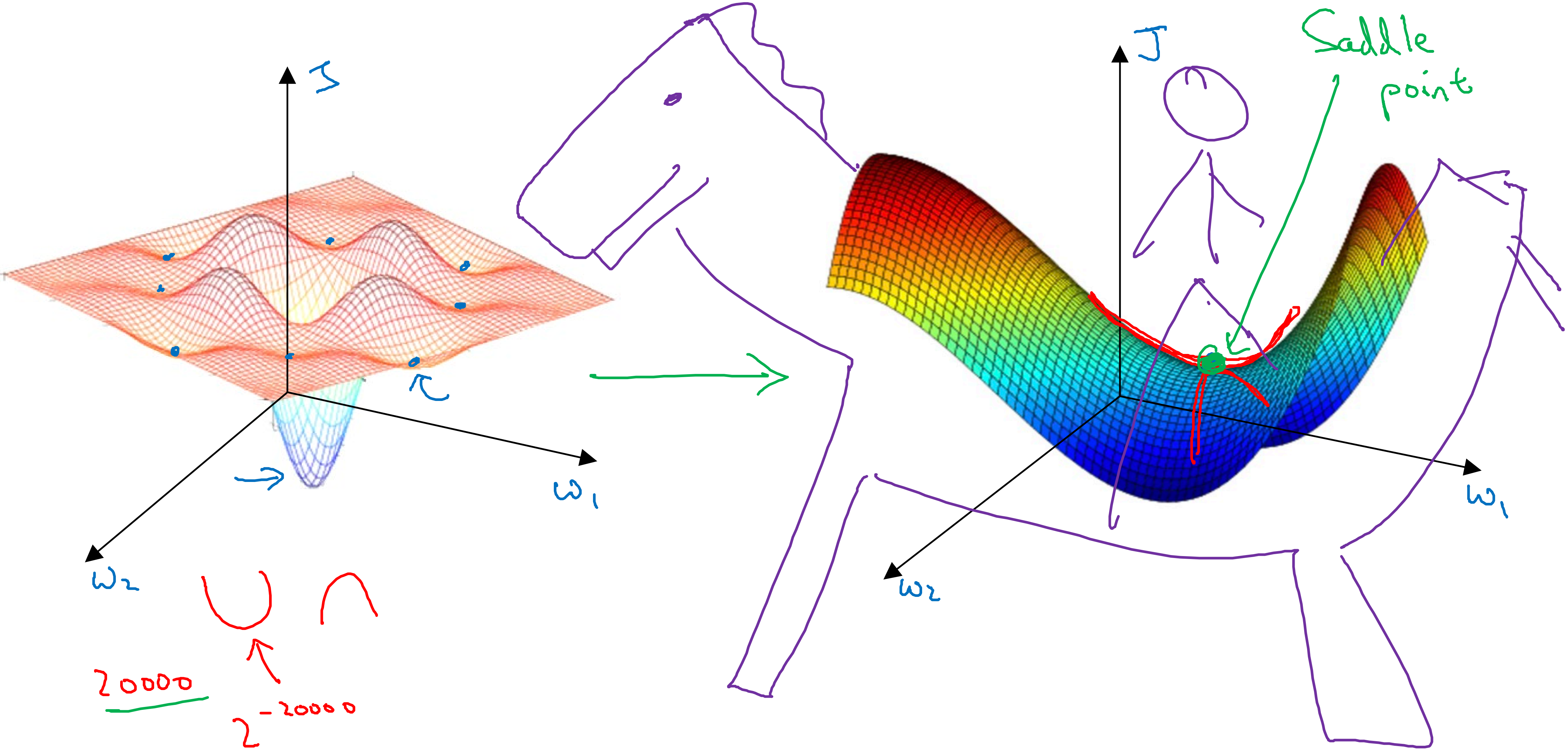
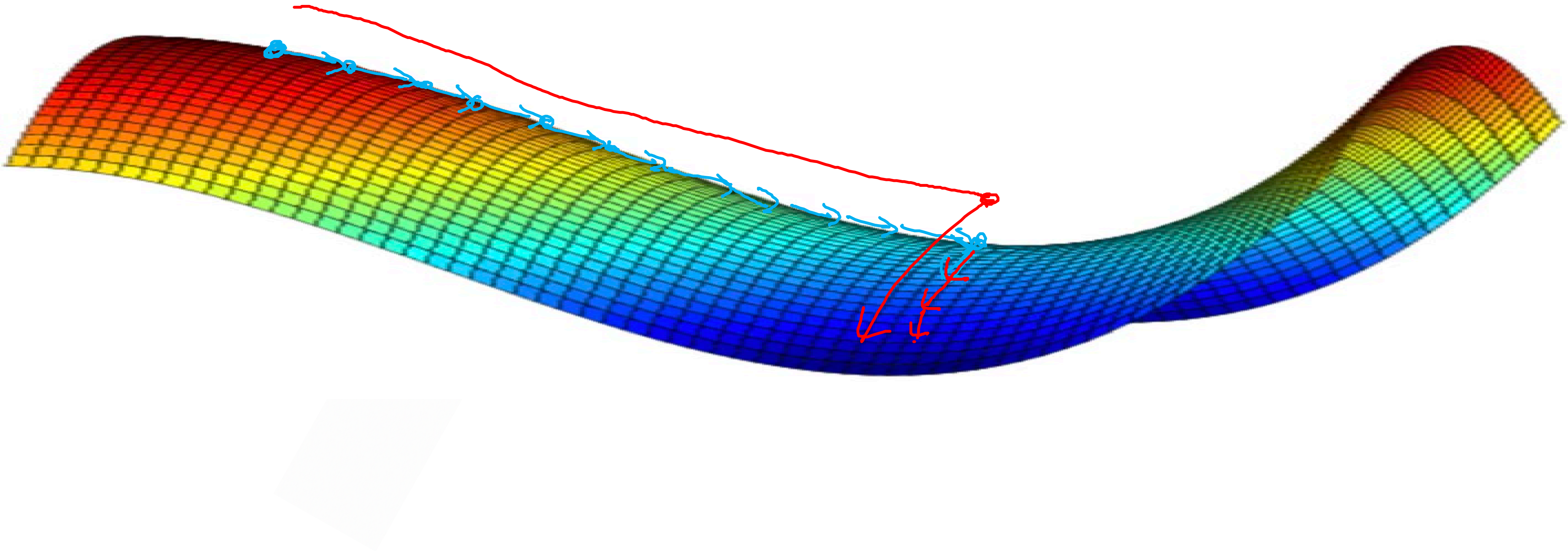
Optimization Algorithms

The problem of local optima

Local optima in neural networks



Problem of plateaus



- Unlikely to get stuck in a bad local optima
- Plateaus can make learning slow

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Hyperparameter tuning

Tuning process

Hyperparameters

$\rightarrow \boxed{\alpha}$

$\boxed{\beta}$ ~0.9

$\underset{0.9}{\beta_1}$, $\underset{0.999}{\beta_2}$, $\underset{10^{-8}}{\varepsilon}$

layers

hidden units

learning rate decay

mini-batch size

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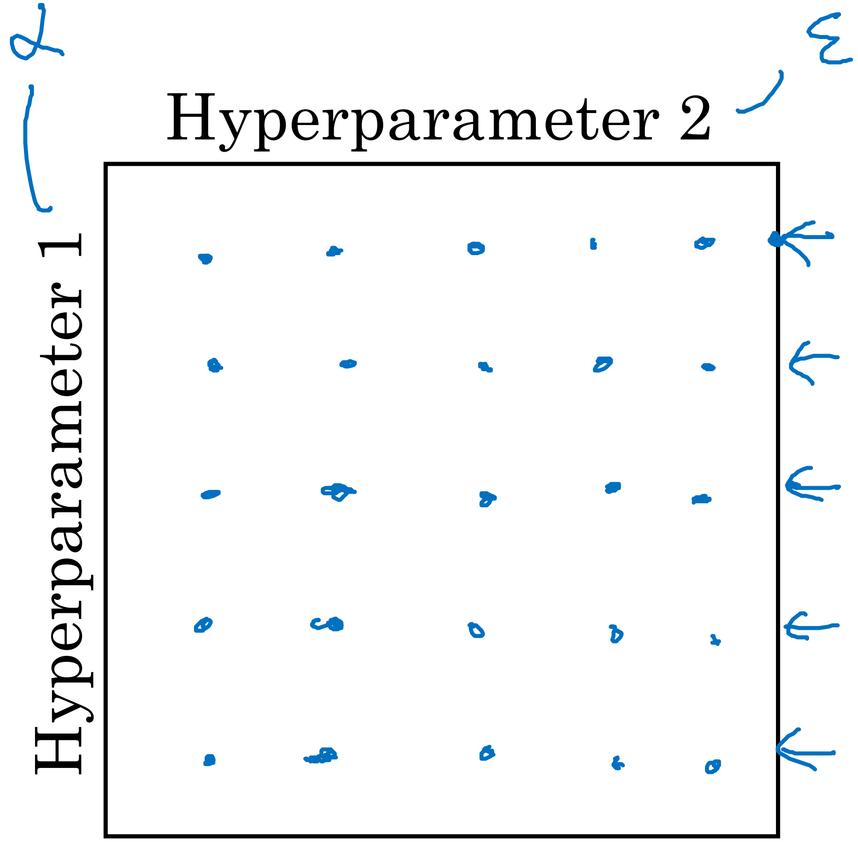
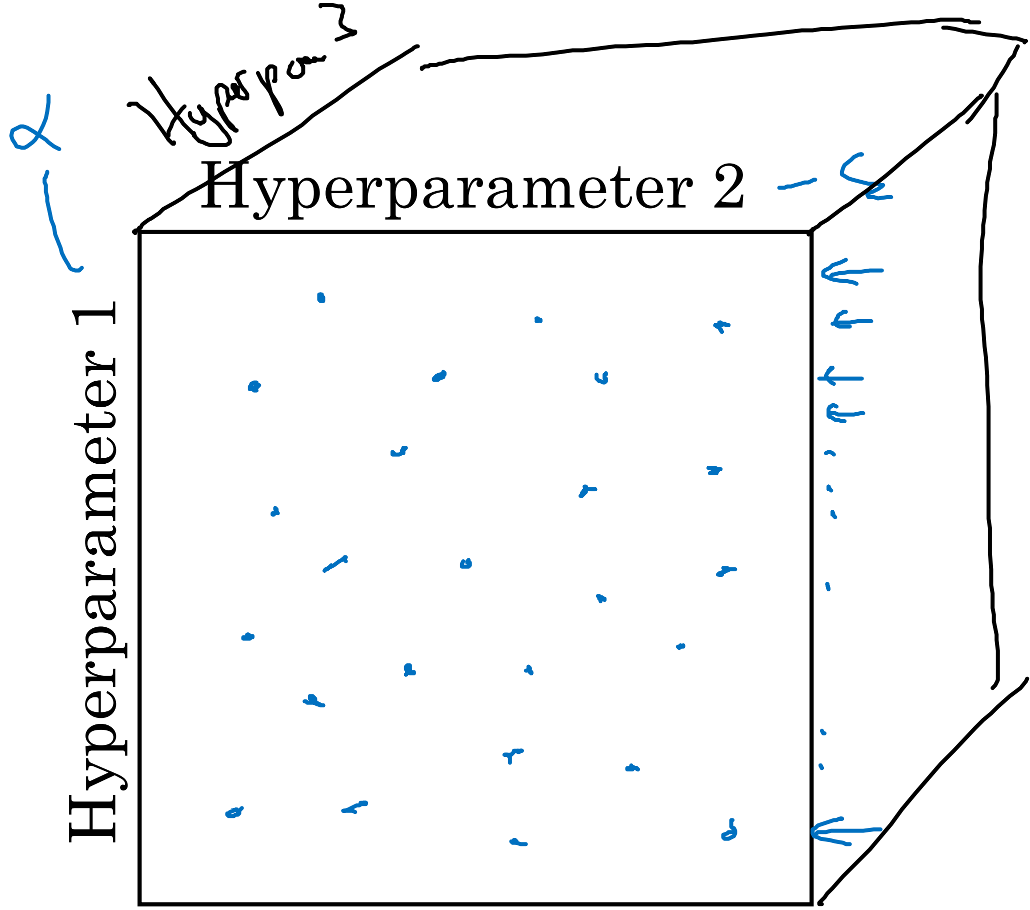
Try random values: Don't use a grid





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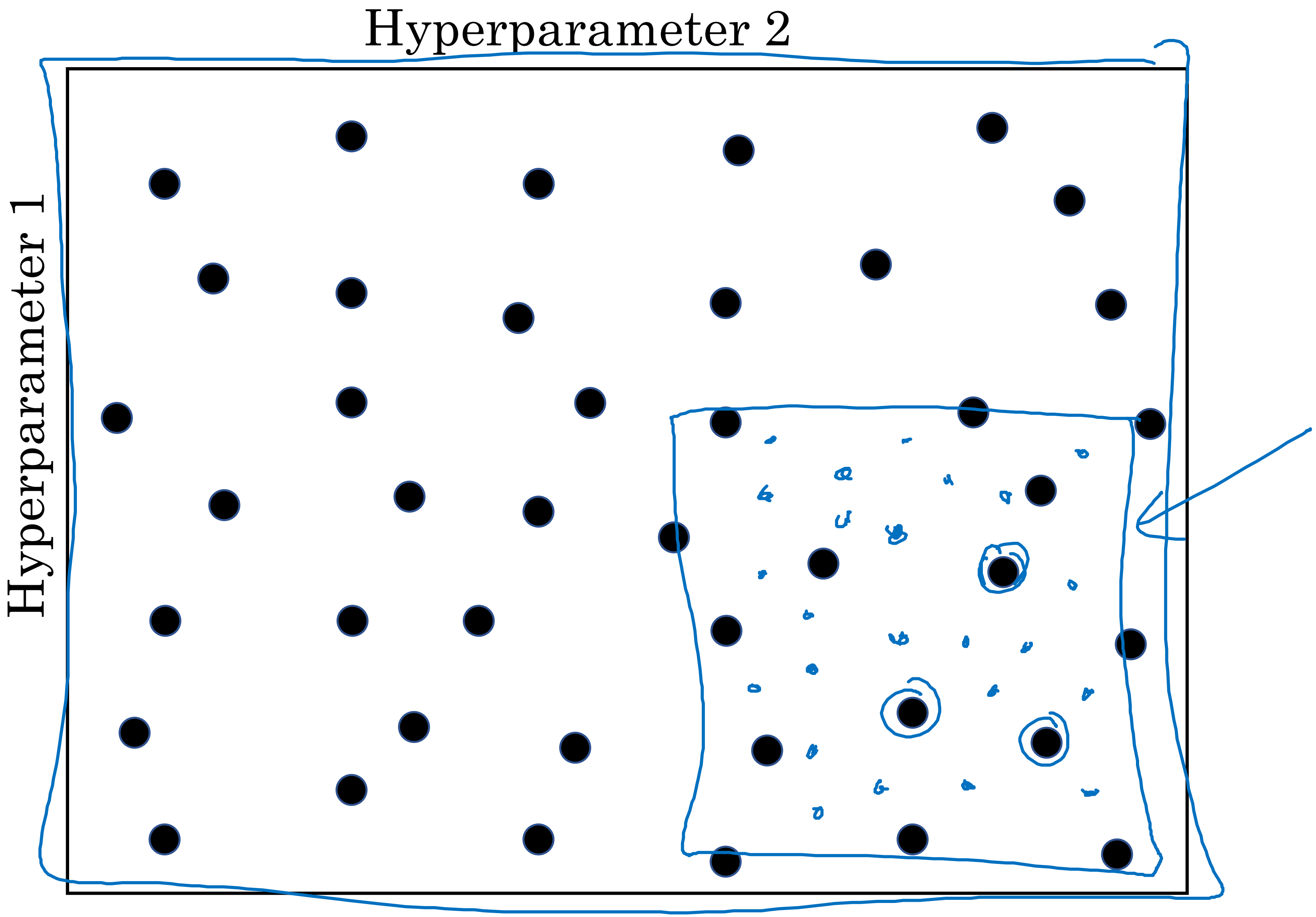
Coarse to fine



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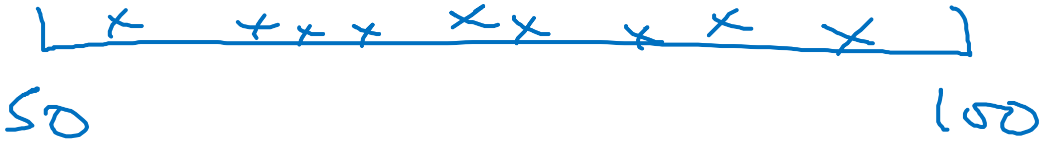
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \ldots, 100$



→ #layers L: 2 – 4

2, 3, 4

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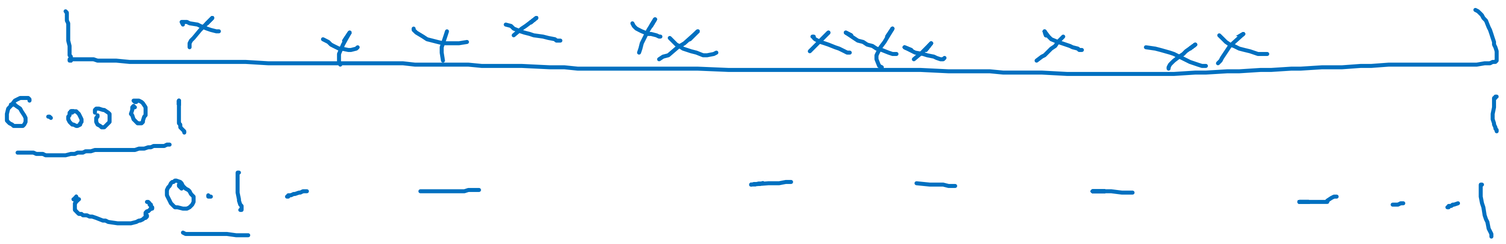
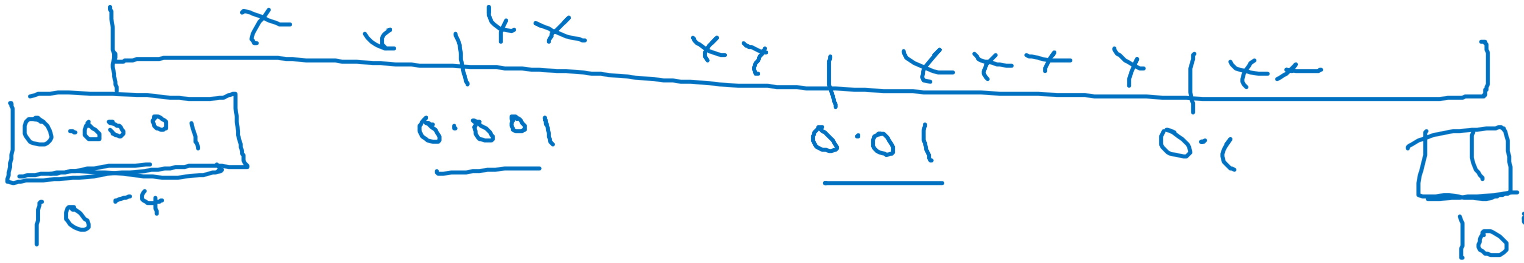
Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$





10^a $\quad$ 10^b

$a = \log_{10} 0.0001 = -4$ $\qquad$ $b = \log_{10} 1 = 0$

$r = -4 * np.random.rand()$ $\leftarrow$ $r \in [-4, 0]$

$\alpha = 10^r$ $\leftarrow$ $10^{-4} \ldots 10^{0}$

$10^a \ldots 10^b$ $\qquad$ $r \in [a, b]$ $\quad$ $[-4, 0]$ $\qquad$ $\alpha = 10^r$

Andrew Ng

Hyperparameters for exponentially weighted averages

$\beta = 0.9 \quad \ldots \quad 0.999$

$\downarrow \qquad\qquad \downarrow$

$10 \qquad\qquad 1000$

$1-\beta = 0.1 \quad \ldots \quad 0.001$

$\beta: 0.9000 \rightarrow 0.9005 \Big\} \sim 10$

$\beta: 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

$\frac{1}{1-\beta}$

$0.9 \qquad\qquad 0.999$

$0.9 \qquad 0.99 \qquad 0.999$

$0.1 \qquad 0.01 \qquad 0.001$

$10^{-1} \qquad\qquad 10^{-3}$

$r \in [-3, -1]$

$1-\beta = 10^r$

$\beta = 1-10^r$

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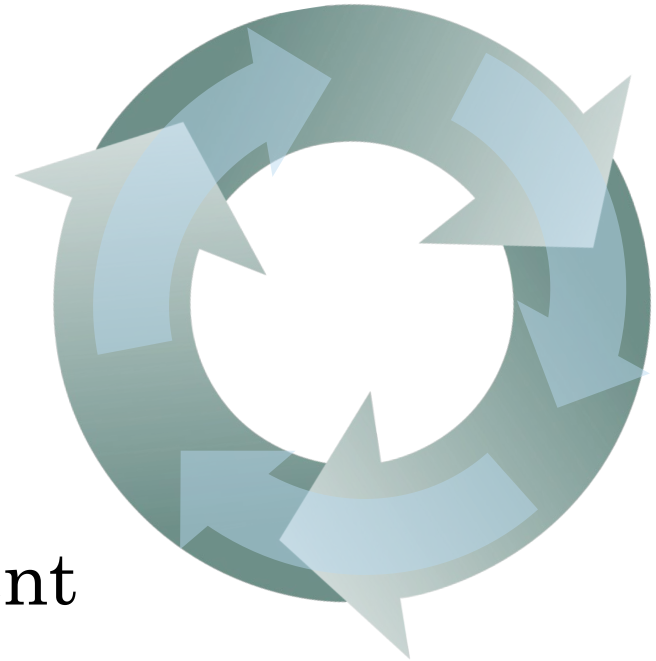
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

Re-test hyperparameters occasionally



- NLP, Vision, Speech, Ads, logistics, ...

- Intuitions do get stale. Re-evaluate occasionally.

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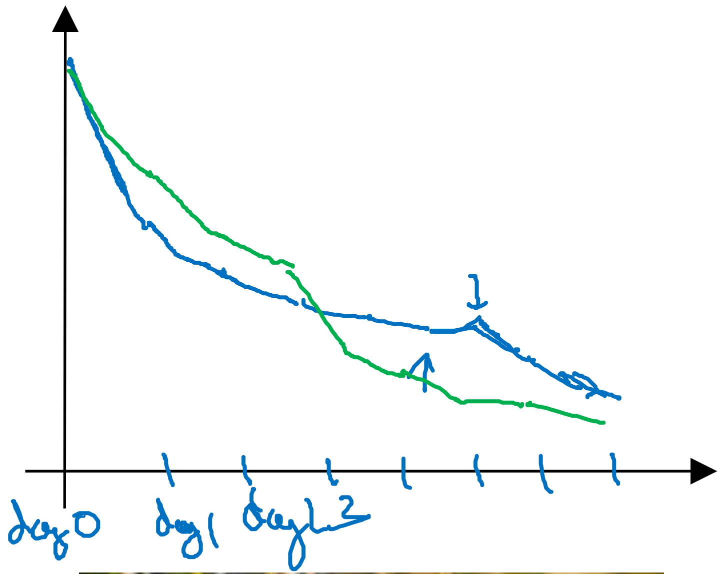
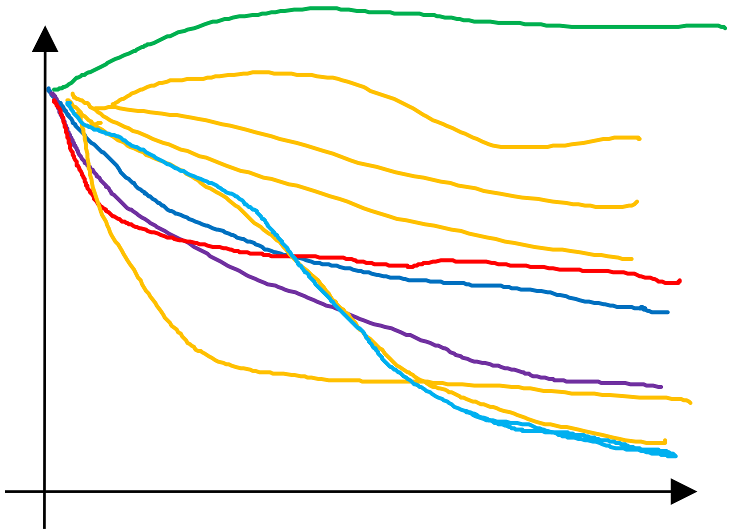
Babysitting one model



Panda

Training many models in parallel



Caviar

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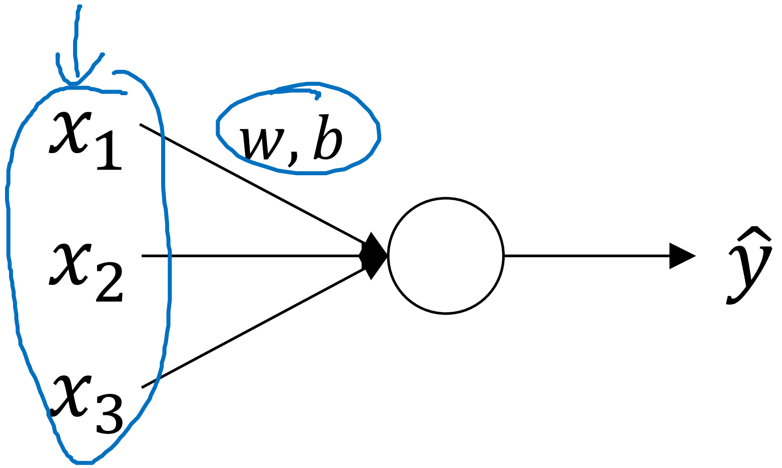
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning

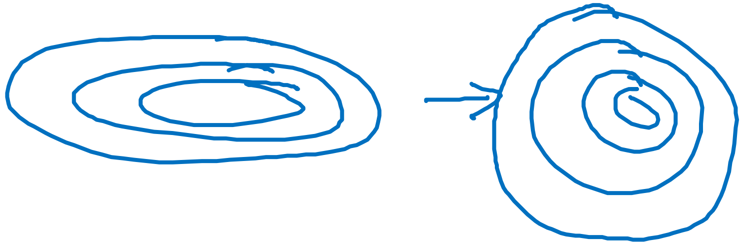


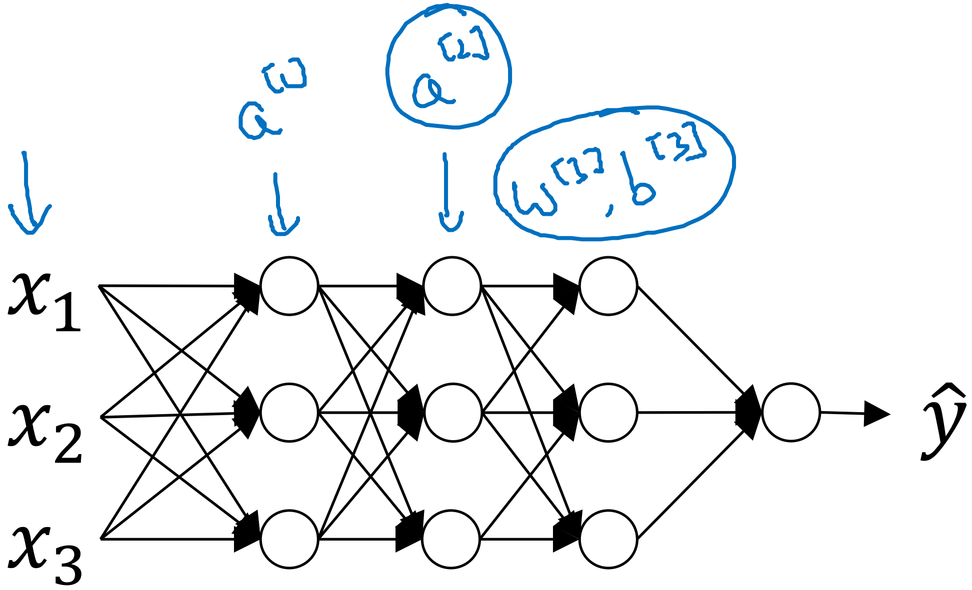
$\mu = \frac{1}{m} \sum_i x^{(i)}$

$X = X - \mu$ ← element-wise

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

$X = X / \sigma^2$





Can we normalize $\underline{a^{[2]}}$ so as to train $W^{[3]}, b^{[3]}$ faster

Normalize $\underline{z^{[2]}}$

Implementing Batch Norm

Given some intermediate values in NN $\underbrace{z^{(1)}, \ldots, z^{(m)}}_{z^{[l](i)}}$

$$\mu = \frac{1}{m} \sum_i z^{(i)}$$

$$\sigma^2 = \frac{1}{m} \sum_i (z_i - \mu)^2$$

$$z^{(i)}_{norm} = \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \varepsilon}}$$

$$\tilde{z}^{(i)} = \gamma z^{(i)}_{norm} + \beta$$

learnable parameters of model.

Use $\tilde{z}^{[l](i)}$ instead of $z^{[l](i)}$.

If

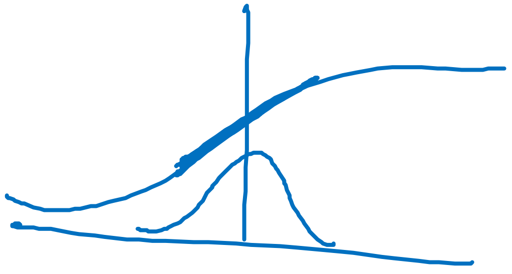
$$\gamma = \sqrt{\sigma^2 + \varepsilon}$$

$$\beta = \mu$$

then $\tilde{z}^{(i)} = z^{(i)}$

X

$z^{(i)}$



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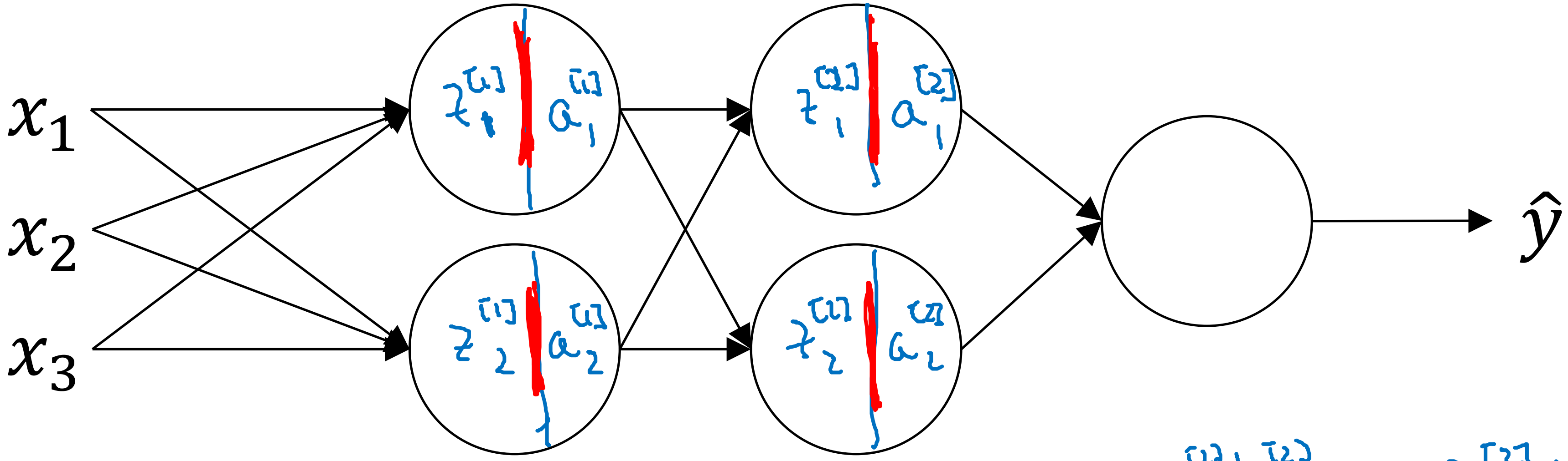
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network



$$X \xrightarrow{W^{[1]}, b^{[1]}} z^{[1]} \xrightarrow[\text{Batch Norm (BN)}]{\beta^{[1]}, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow a^{[1]} = g^{[1]}(\tilde{z}^{[1]}) \xrightarrow{W^{[2]}, b^{[2]}} z^{[2]} \xrightarrow[\text{BN}]{\beta^{[2]}, \gamma^{[2]}} \tilde{z}^{[2]} \rightarrow a^{[2]} \rightarrow \cdots$$

Parameters: $\left.\begin{array}{l} W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, \ldots, W^{[L]}, b^{[L]}, \\ \rightarrow \beta^{[1]}, \gamma^{[1]}, \beta^{[2]}, \gamma^{[2]}, \ldots, \beta^{[L]}, \gamma^{[L]} \end{array}\right]$

$d\beta^{[l]}$ $\quad \beta^{[l]} = \beta^{[l]} - \alpha\, d\beta^{[l]}$

tf.nn.batch_normalization $\Leftarrow$

$\rightarrow \beta$

Andrew Ng

Working with mini-batches

$$X^{\{1\}} \xrightarrow{W^{[1]},\, b^{[1]}} z^{[1]} \xrightarrow[BN]{\beta^{[1]},\, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow g^{[1]}(\tilde{z}^{[1]}) = a^{[1]} \xrightarrow{W^{[2]},\, b^{[2]}} z^{[2]} \rightarrow \cdots$$

$$\boxed{X^{\{2\}}} \rightarrow z^{[1]} \xrightarrow[BN]{\beta^{[1]},\, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow \cdots$$

$$X^{\{3\}} \rightarrow \cdots$$

Parameters: $W^{[l]}, \cancel{b^{[l]}}, \beta^{[l]}, \gamma^{[l]}$.

$\cancel{b^{[l]}}$: $(n^{[l]}, 1)$, $\beta^{[l]}$: $(n^{[l]}, 1)$, $\gamma^{[l]}$: $(n^{[l]}, 1)$

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

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

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

$$z^{[l]}_{norm}$$

$$\tilde{z}^{[l]} = \gamma^{[l]} z^{[l]}_{norm} + \boxed{\beta^{[l]}}$$

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Implementing gradient descent

for $t = 1 \ldots$ numMiniBatches

Compute forward prop on $X^{\{t\}}$.

In each hidden layer, use BN to replace $\underline{z^{[l]}}$ with $\underline{\tilde{z}^{[l]}}$.

Use backprop to compute $\underline{dW^{[l]}}$, $\cancel{db^{[l]}}$, $\underline{d\beta^{[l]}}$, $\underline{d\gamma^{[l]}}$

Update params

$$\left.\begin{aligned} W^{[l]} &:= W^{[l]} - \alpha\, dW^{[l]} \\ \beta^{[l]} &:= \beta^{[l]} - \alpha\, d\beta^{[l]} \\ \gamma^{[l]} &:= \ldots \end{aligned}\right\} \leftarrow$$

Works w/ momentum, RMSprop, Adam.

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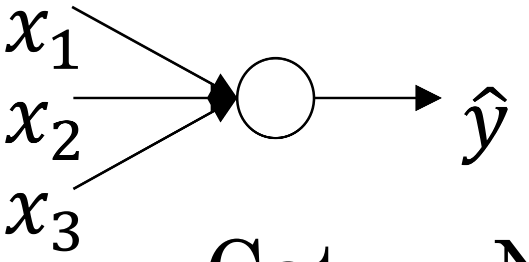
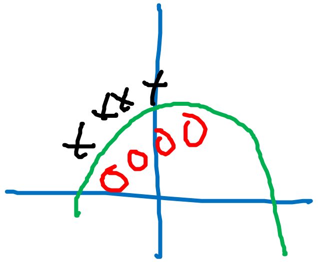
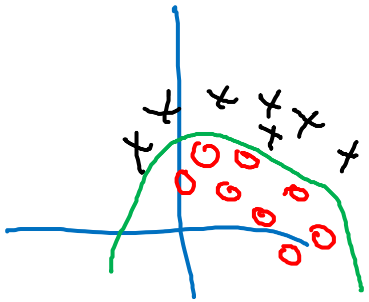
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution





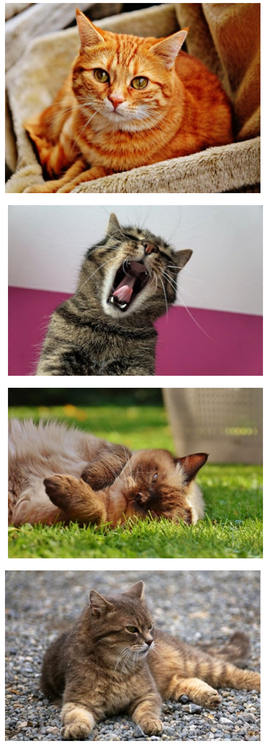


Cat	Non-Cat
$y = 1$	$y = 0$

"Covariate shift"

$X \rightarrow y$

$y = 1$ $\quad$ $y = 0$



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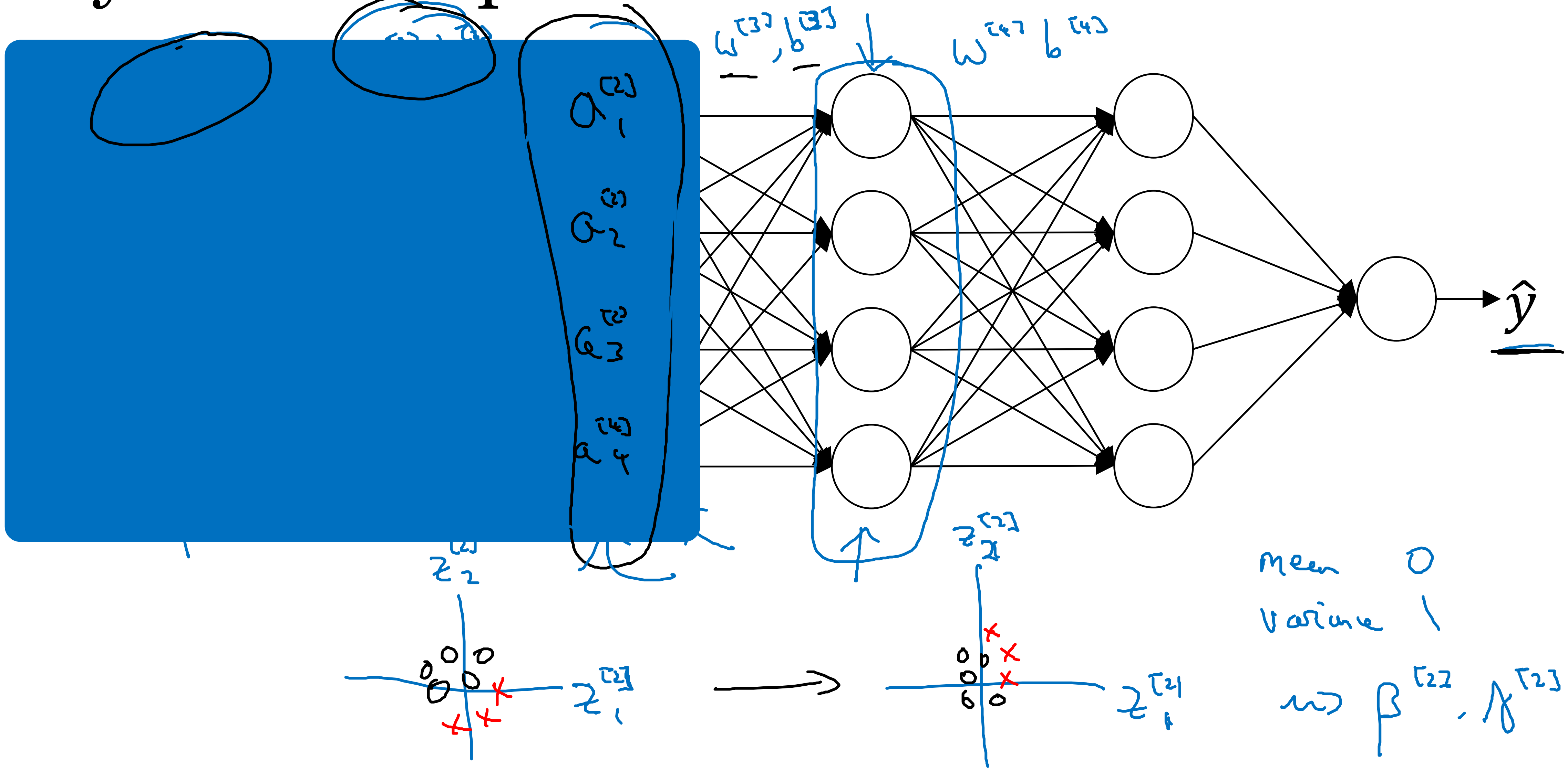
Why this is a problem with neural networks?



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Batch Norm as regularization

- Each mini-batch is scaled by the mean/variance computed on just that mini-batch.
- This adds some noise to the values $z^{[l]}$ within that minibatch. So similar to dropout, it adds some noise to each hidden layer's activations.
- This has a slight regularization effect.

X

$X^{\{t\}}$

$\tilde{z}^{[l]}$

64, 128

$z^{[l]}$

μ, σ^2

mini-batch : 64 $\longrightarrow$ 512

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Batch Normalization

Batch Norm at test time

Batch Norm at test time

$$\mu = \frac{1}{m}\sum_i z^{(i)}$$

$$\sigma^2 = \frac{1}{m}\sum_i (z^{(i)} - \mu)^2$$

$$z_{\text{norm}}^{(i)} = \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \varepsilon}}$$

$$\tilde{z}^{(i)} = \gamma z_{\text{norm}}^{(i)} + \beta$$

μ, σ^2: estimate using exponentially weighted average (across mini-batches).

$X^{\{1\}}, X^{\{2\}}, X^{\{3\}}, \ldots$

$\cancel{\mu^{[l]}}$

$\mu^{\{1\}[l]}$ $\quad \mu^{\{2\}[l]}$ $\quad \mu^{\{3\}[l]}$ $\longrightarrow \mu$

θ_1 $\quad \theta_2$ $\quad \theta_3$ $\qquad \sigma^2$

$\sigma^{2\{1\}[l]}$ $\quad \sigma^{2\{2\}[l]}$ $\quad \ldots$

$z_{\text{norm}} = \dfrac{z - \mu}{\sqrt{\sigma^2 + \varepsilon}}$ $\qquad \tilde{z} = \gamma z_{\text{norm}} + \beta$

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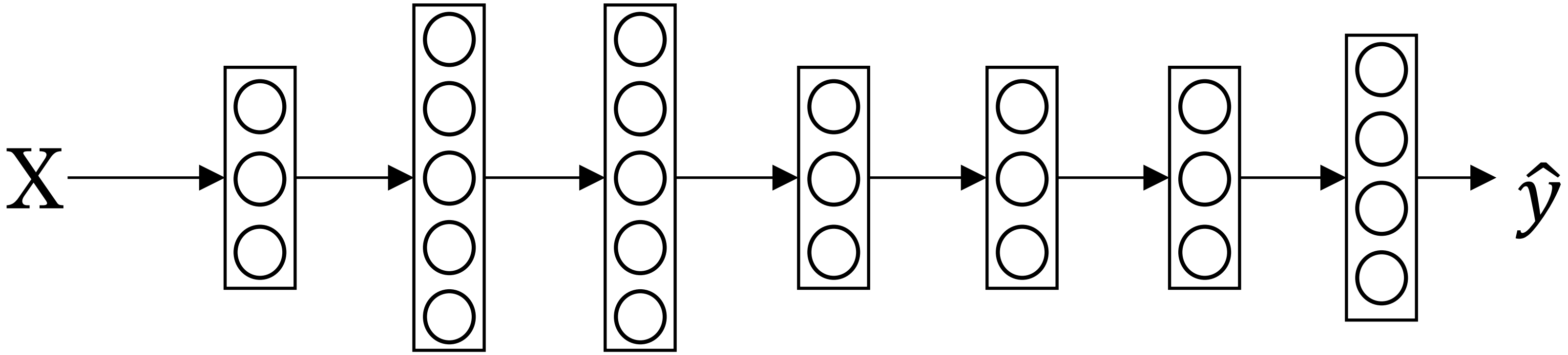
Multi-class classification

Softmax regression

Recognizing cats, dogs, and baby chicks

3 1 2 0 3 2 0 1



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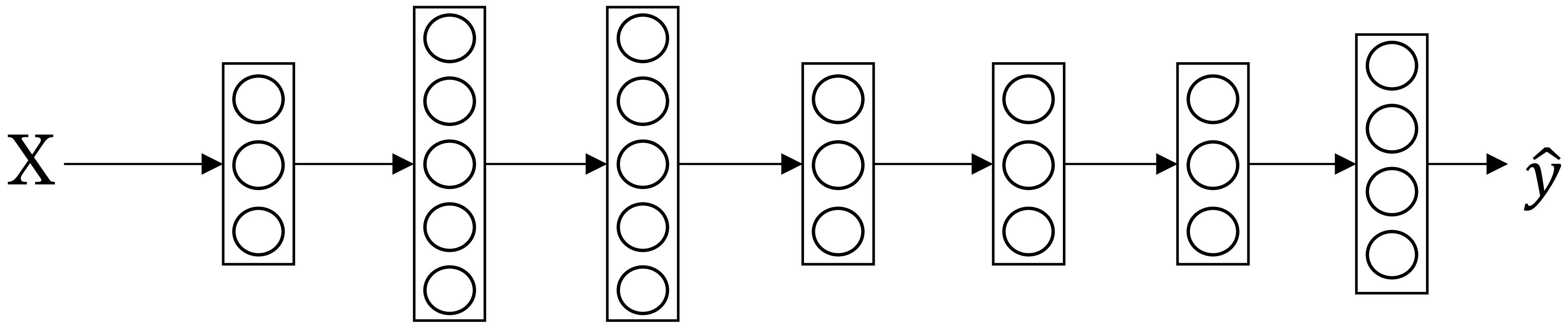
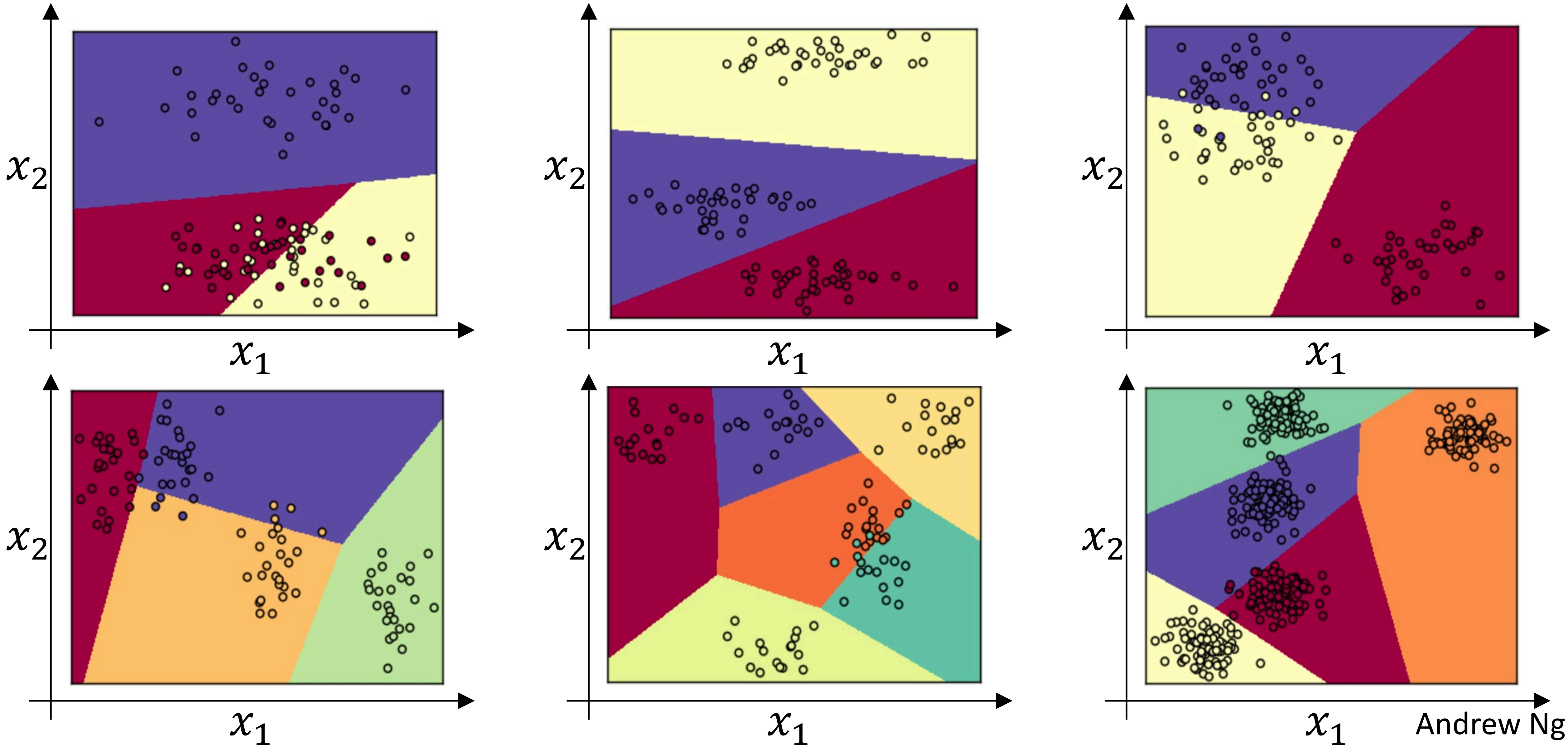
Softmax layer



Softmax examples



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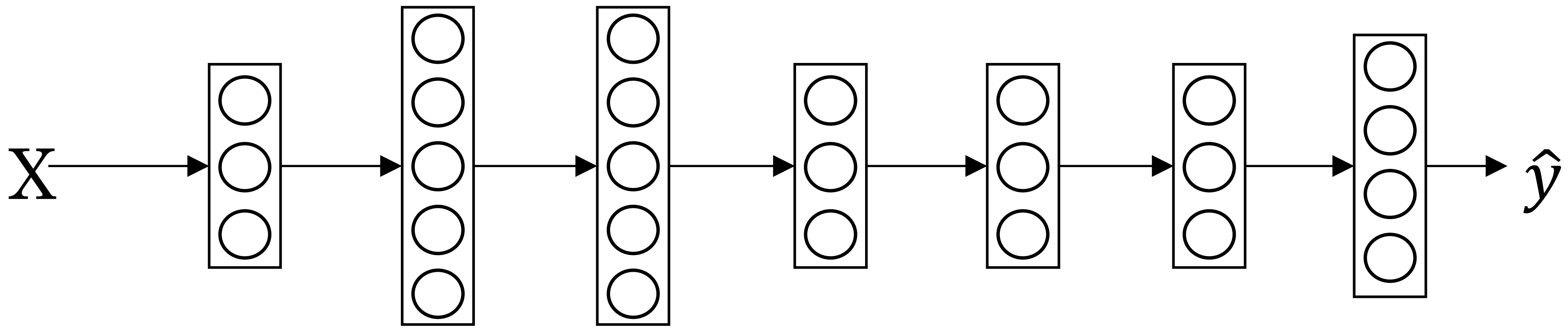
Multi-class classification

Trying a softmax classifier

Understanding softmax

Loss function

Summary of softmax classifier



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Programming Frameworks

Deep Learning frameworks

Deep learning frameworks

- Caffe/Caffe2
- CNTK
- DL4J
- Keras
- Lasagne
- mxnet
- PaddlePaddle
- TensorFlow
- Theano
- Torch

Choosing deep learning frameworks

- Ease of programming (development and deployment)
- Running speed
- Truly open (open source with good governance)

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Programming Frameworks

TensorFlow

Motivating problem

$J(w) = \boxed{w^2 - 10w + 25}$
(cost)

$(w-5)^2$

$w = 5$

$J(w, b)$
$\uparrow \quad \uparrow$

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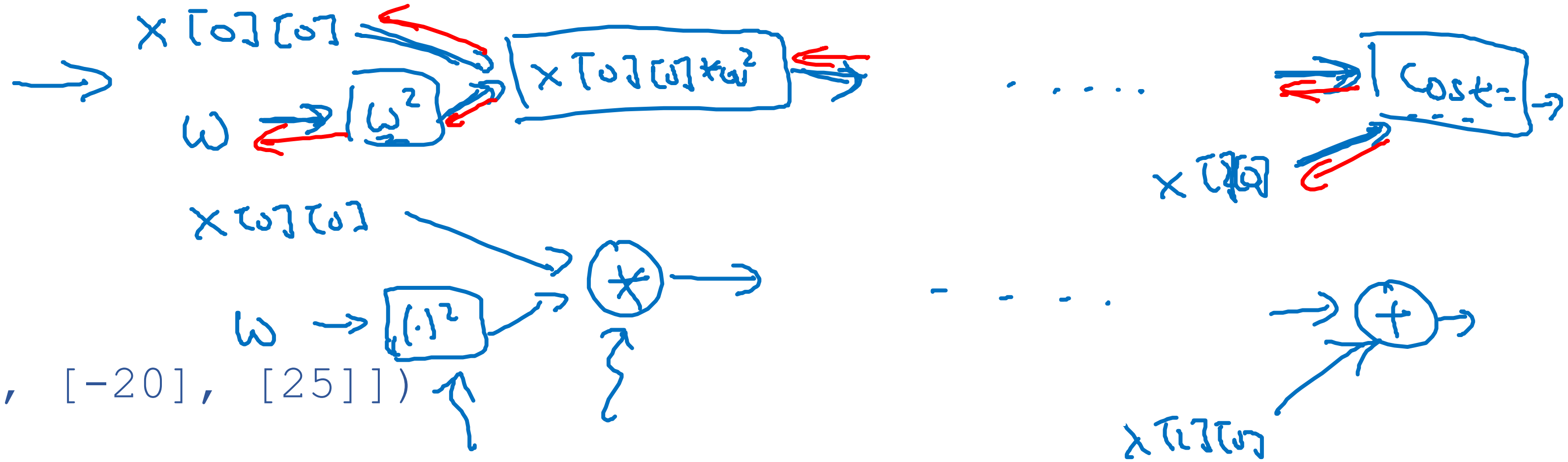
Code example




```
import numpy as np
import tensorflow as tf

coefficients = np.array([[1], [-20], [25]])

w = tf.Variable([0],dtype=tf.float32)
x = tf.placeholder(tf.float32, [3,1])
cost = x[0][0]*w**2 + x[1][0]*w + x[2][0]     # (w-5)**2
train = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
init = tf.global_variables_initializer()
session = tf.Session()
session.run(init)
print(session.run(w))
```

```
with tf.Session() as session:
    session.run(init)
    print(session.run(w))
```

```
for i in range(1000):
    session.run(train, feed_dict={x:coefficients})
print(session.run(w))
```

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