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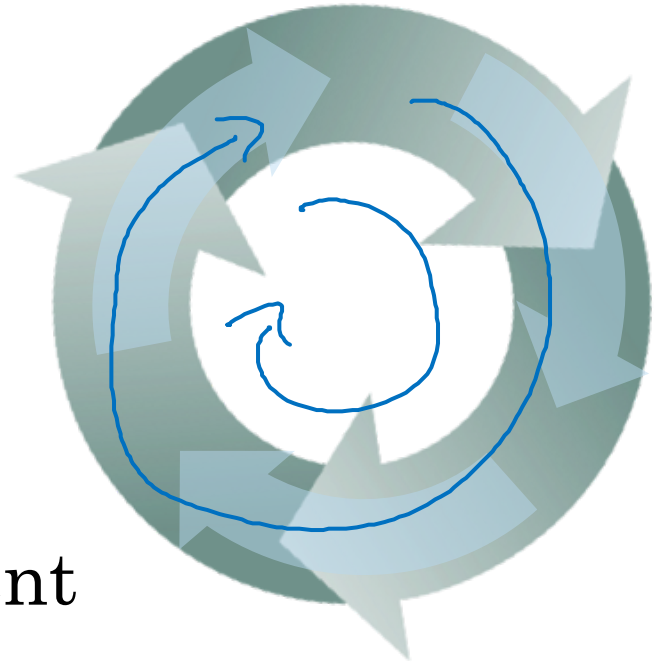
Setting up your ML application

Train/dev/test sets

Applied ML is a highly iterative process

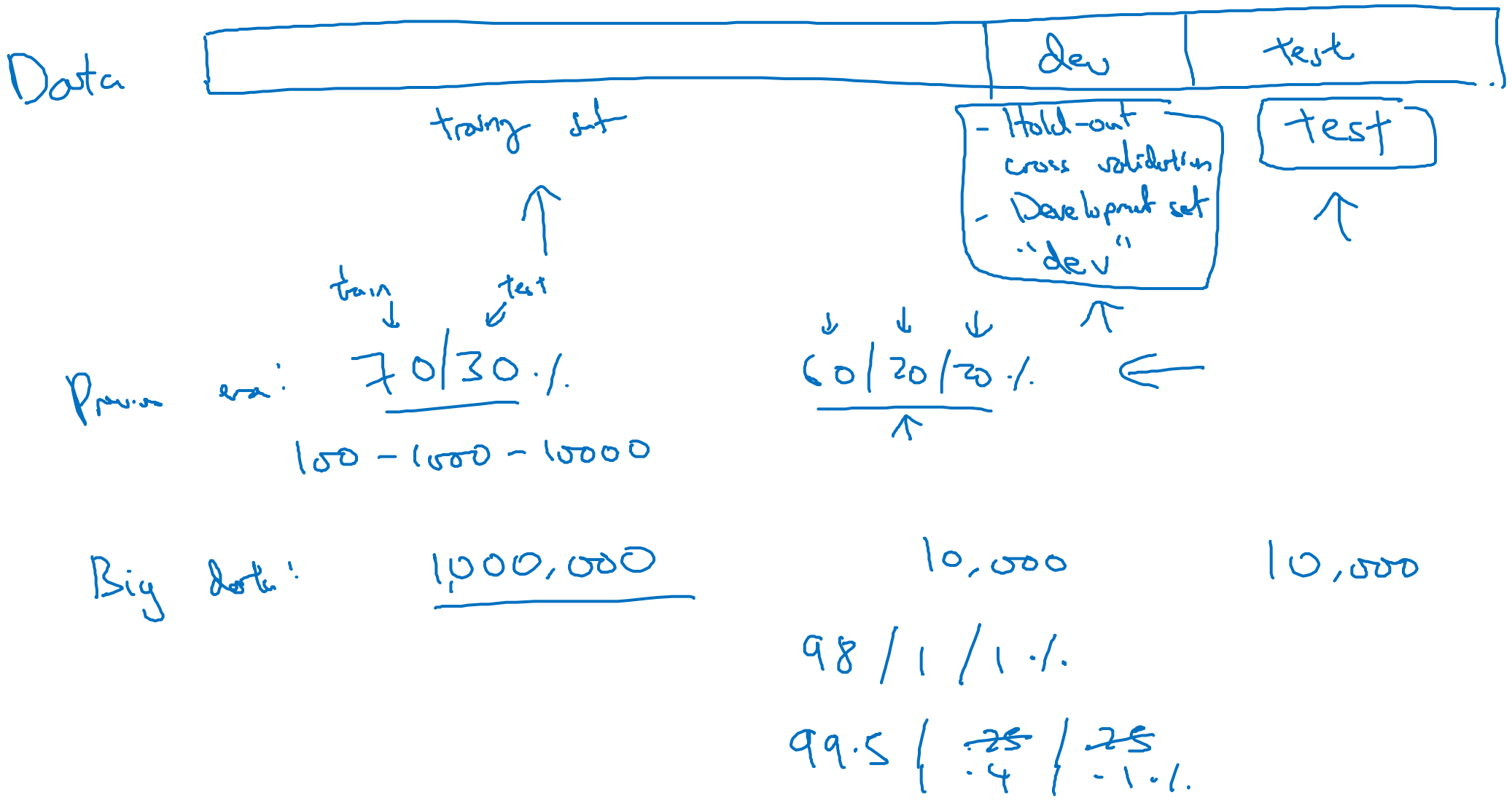
- # layers
- # hidden units
- learning rates
- activation functions
- ...



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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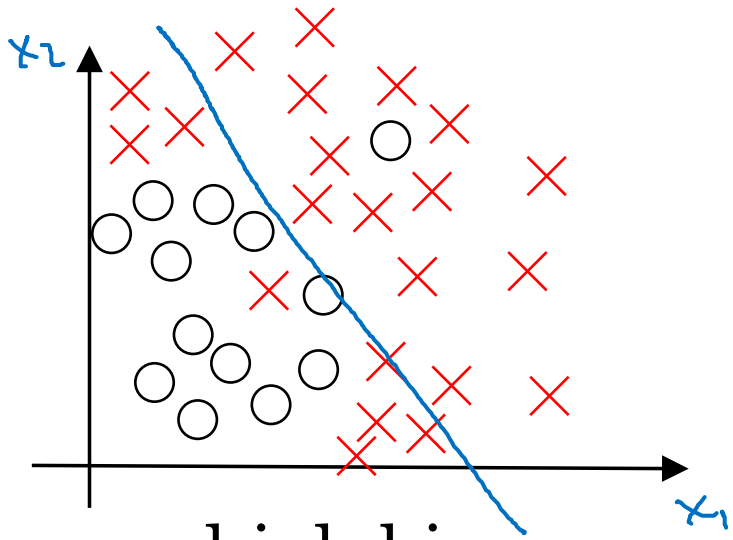
Setting up your ML application

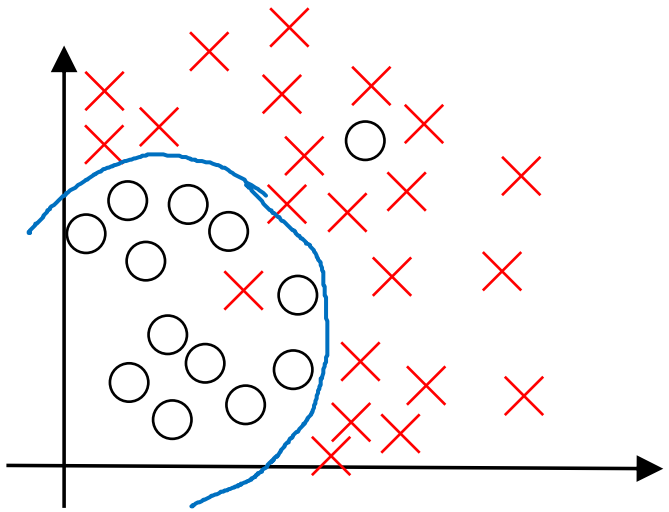
Bias/Variance

Bias and Variance

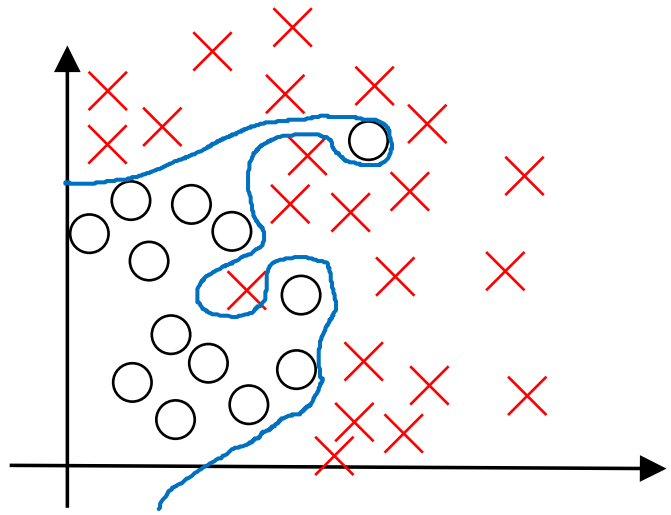


high bias

Underfitting



→ "just right"



high variance

Overfitting

Bias and Variance

Cat classification

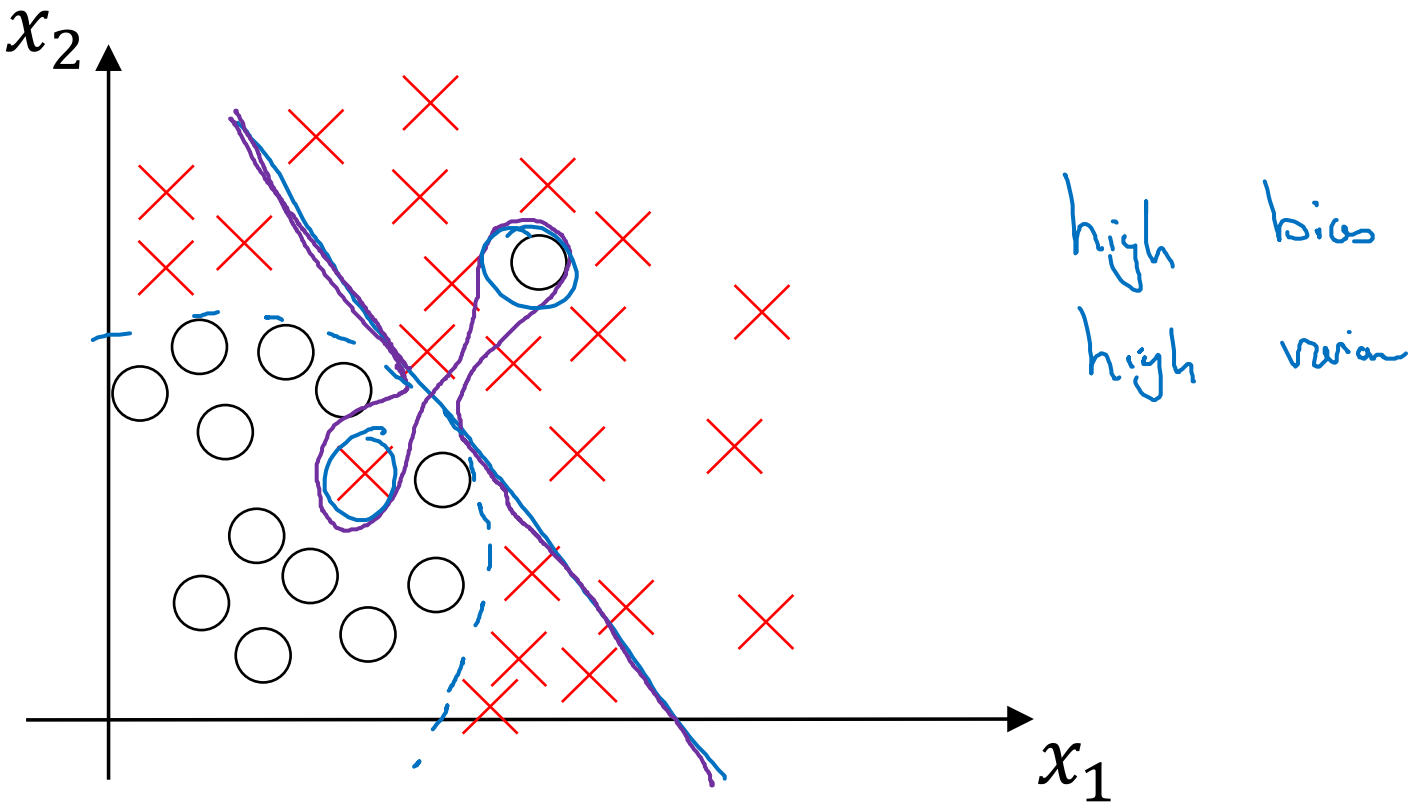
Train set error:	1%	15%	15%	0.5%
Dev set error:	11%	16%	30%	1%
	high variance	high bias	high bias & high variance	low bias low variance

Human: ≈0%

Optimal (Bayes) error: ~~≈0%~~ 15%

Blurry images

High bias and high variance



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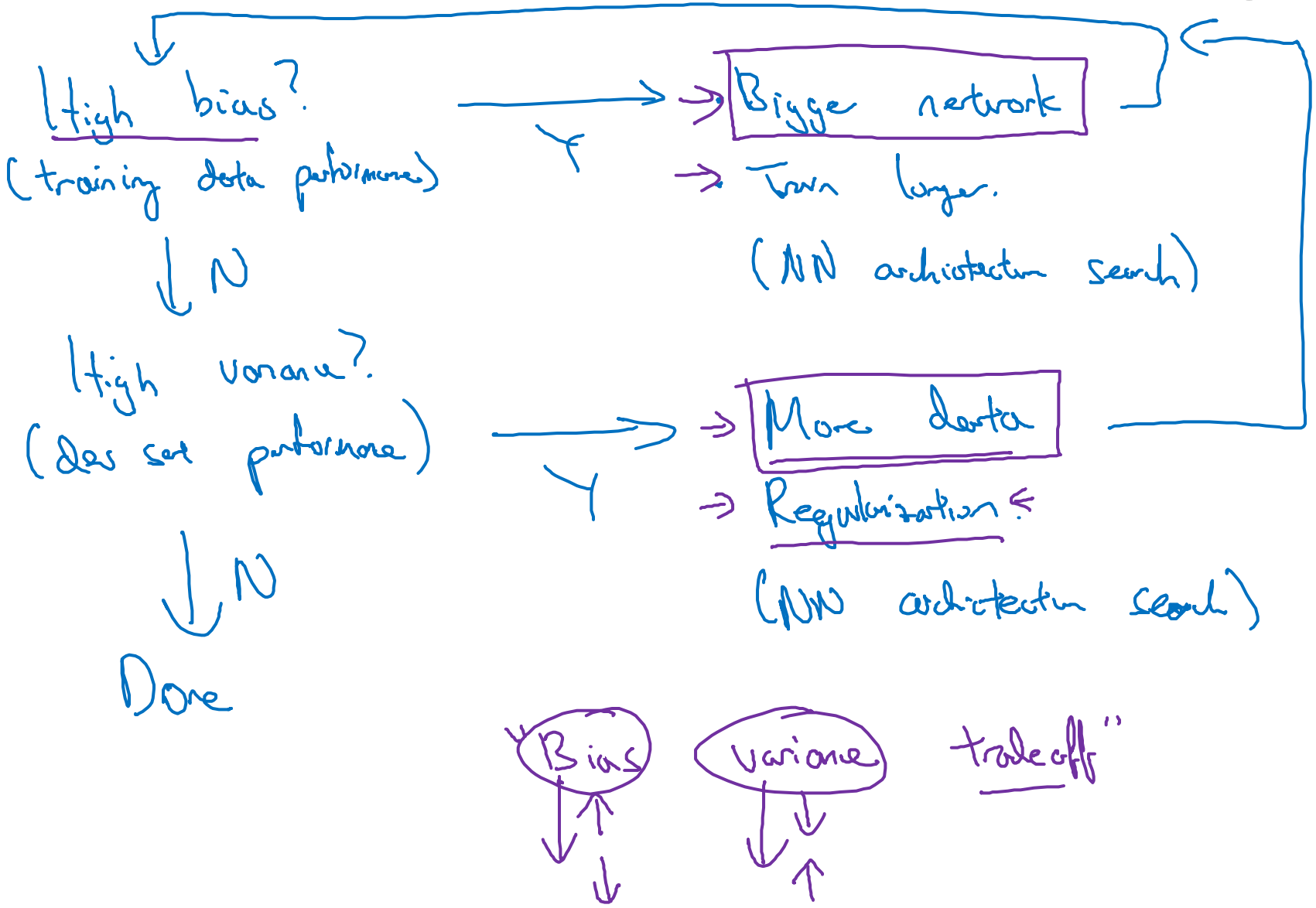
Setting up your ML application

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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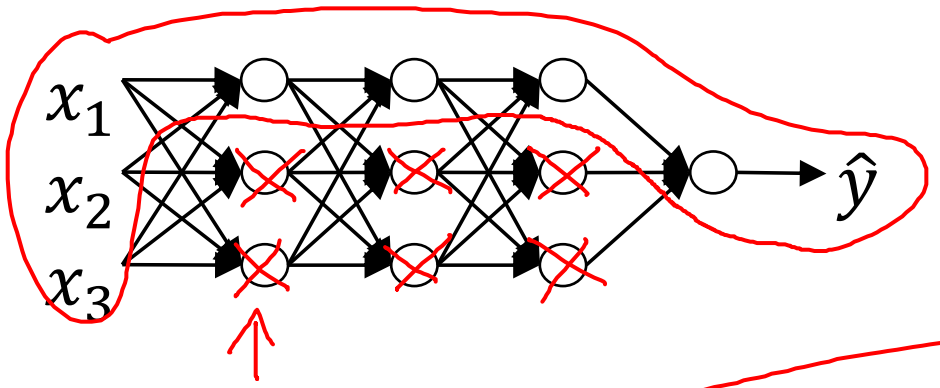
Regularizing your neural network

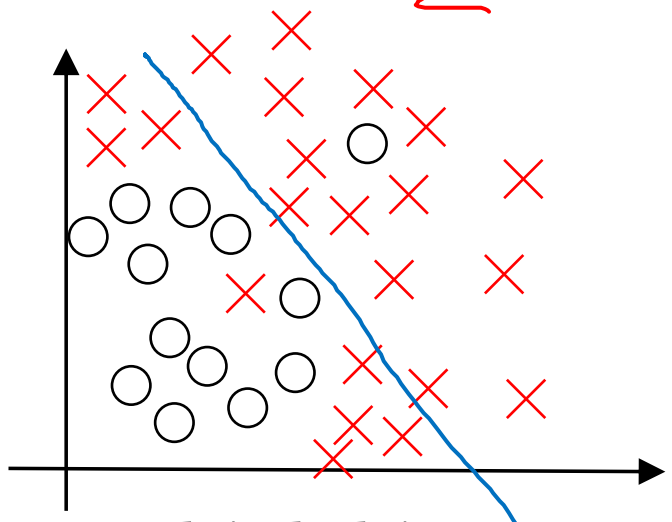
Why regularization reduces overfitting

How does regularization prevent overfitting?

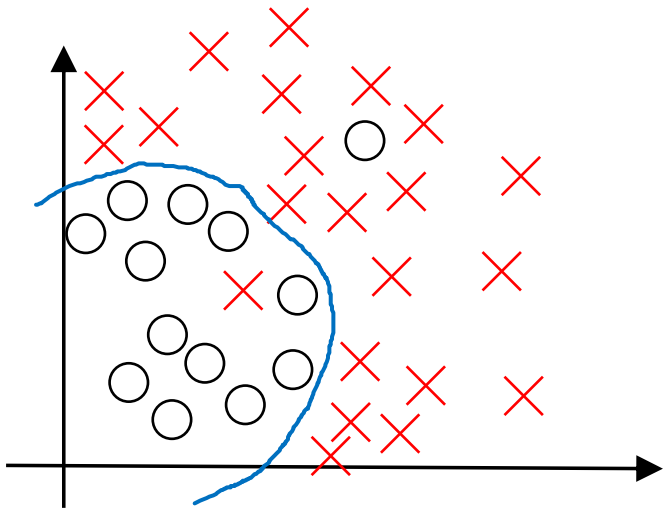


$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2$$

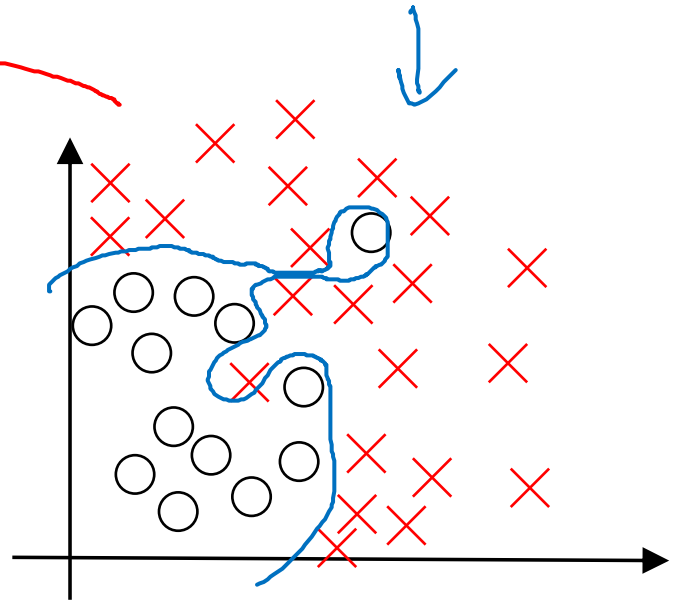
$w^{[l]} \approx 0$



high bias



"just right"



high variance

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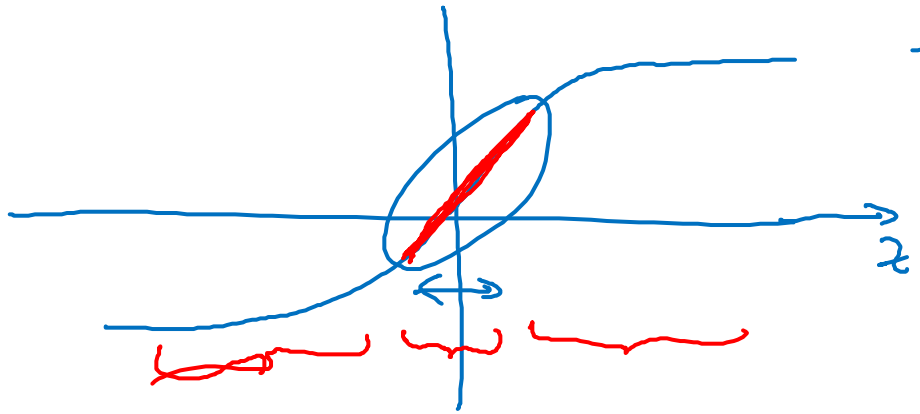
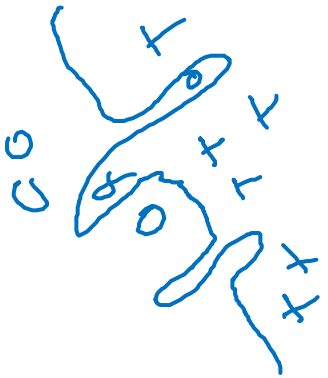
How does regularization prevent overfitting?



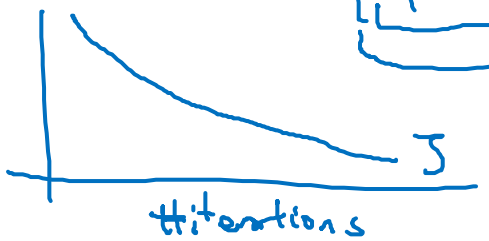
$g(z) = \tanh(z)$

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



Every layer $\approx$ linear.

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



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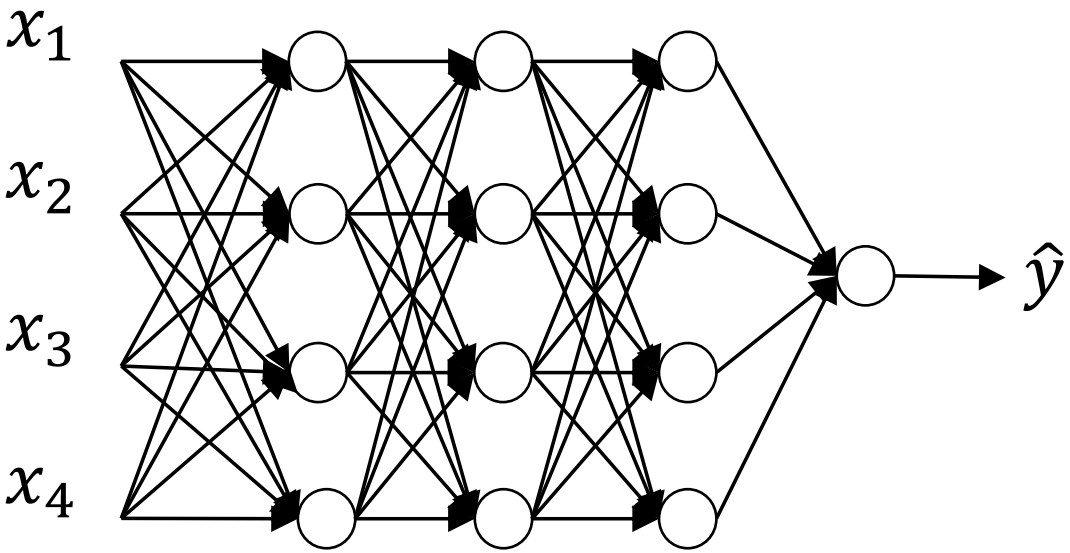
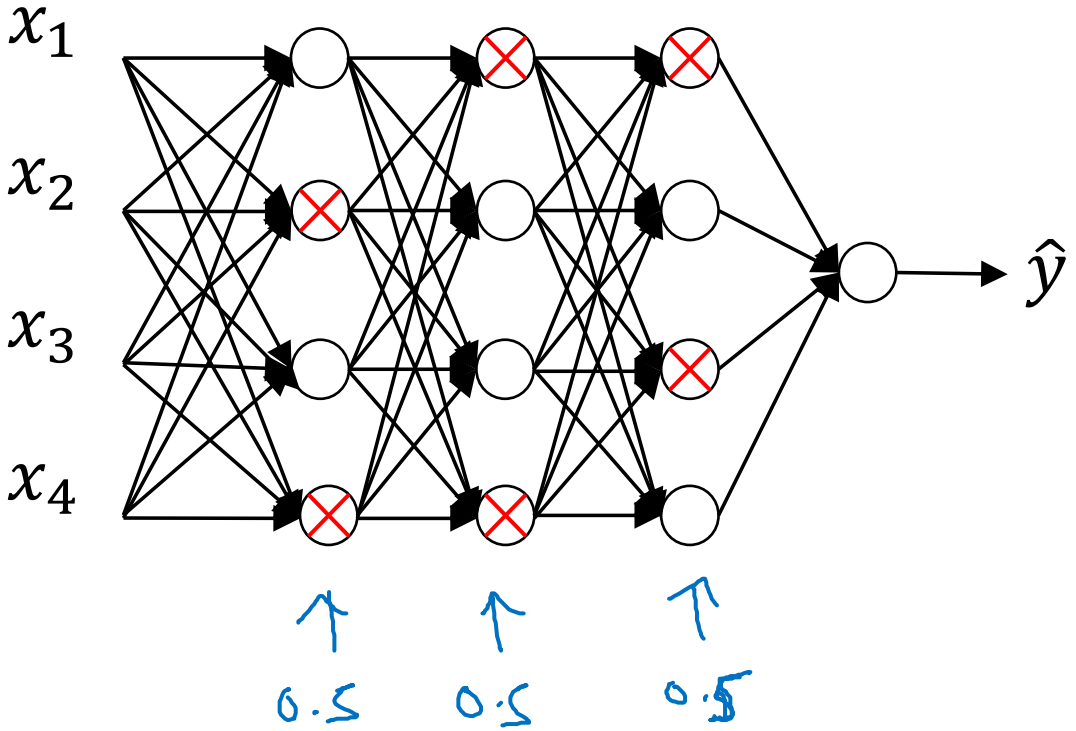
Regularizing your neural network

Dropout regularization

Dropout regularization





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.

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

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

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

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

$\downarrow$

$\hat{y}$

/= keep-prob

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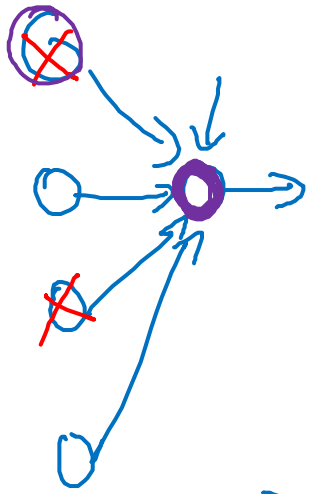
Regularizing your neural network

Understanding dropout

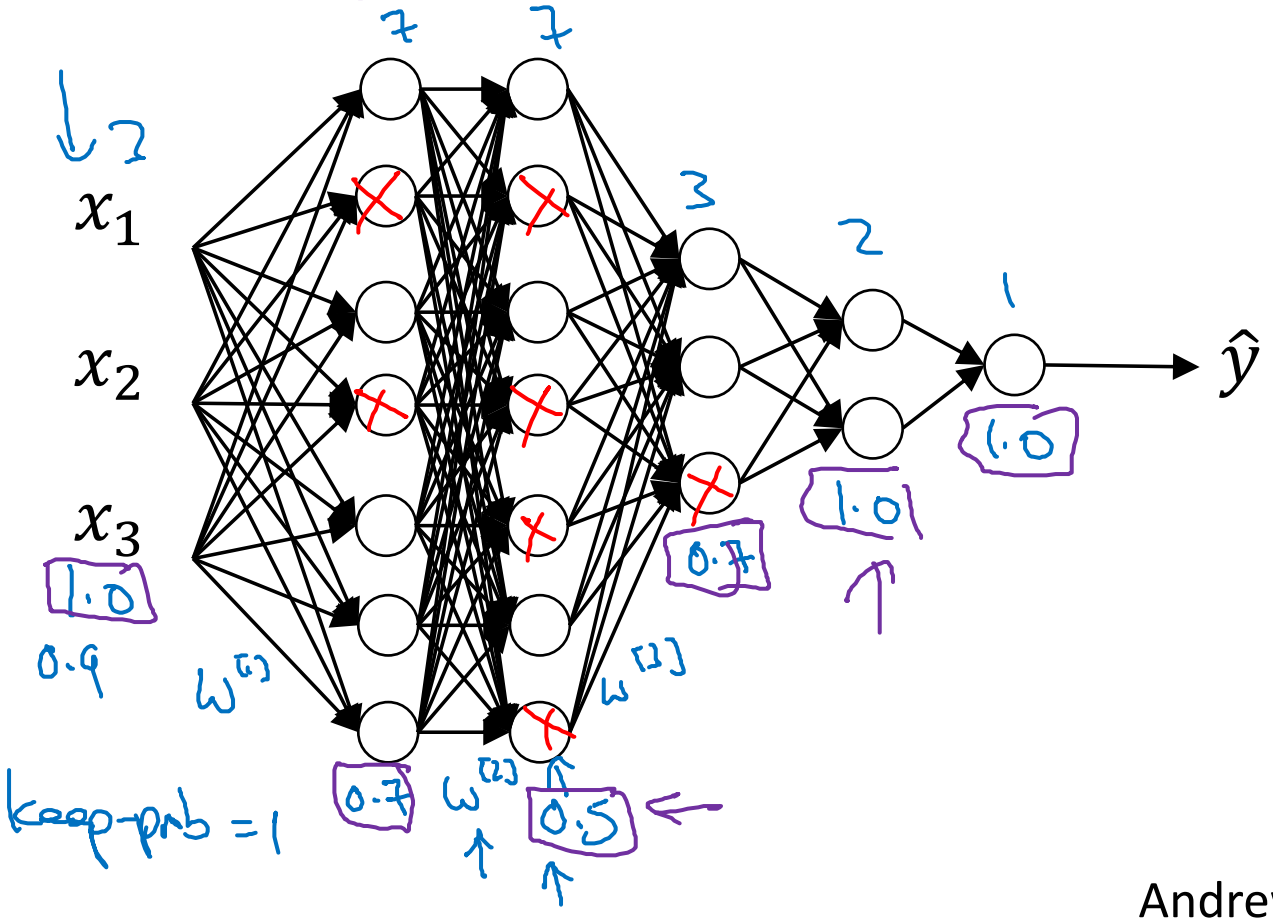
Why does drop-out work?

Intuition: Can't rely on any one feature, so have to spread out weights. ⇝ Shrink weights. b_2



→ Computer Vision

Downside: J



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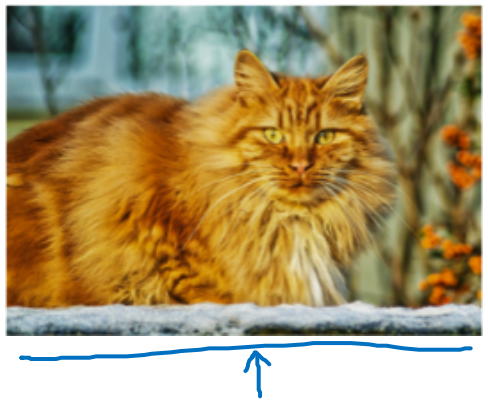
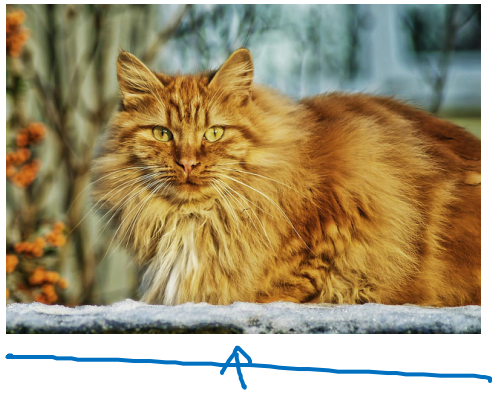
Regularizing your neural network

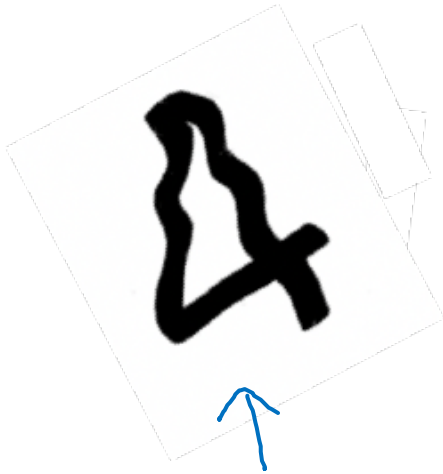
Other regularization methods

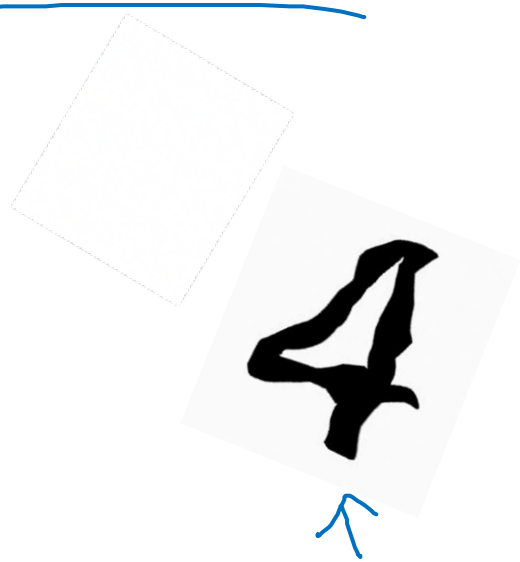
Data augmentation





4





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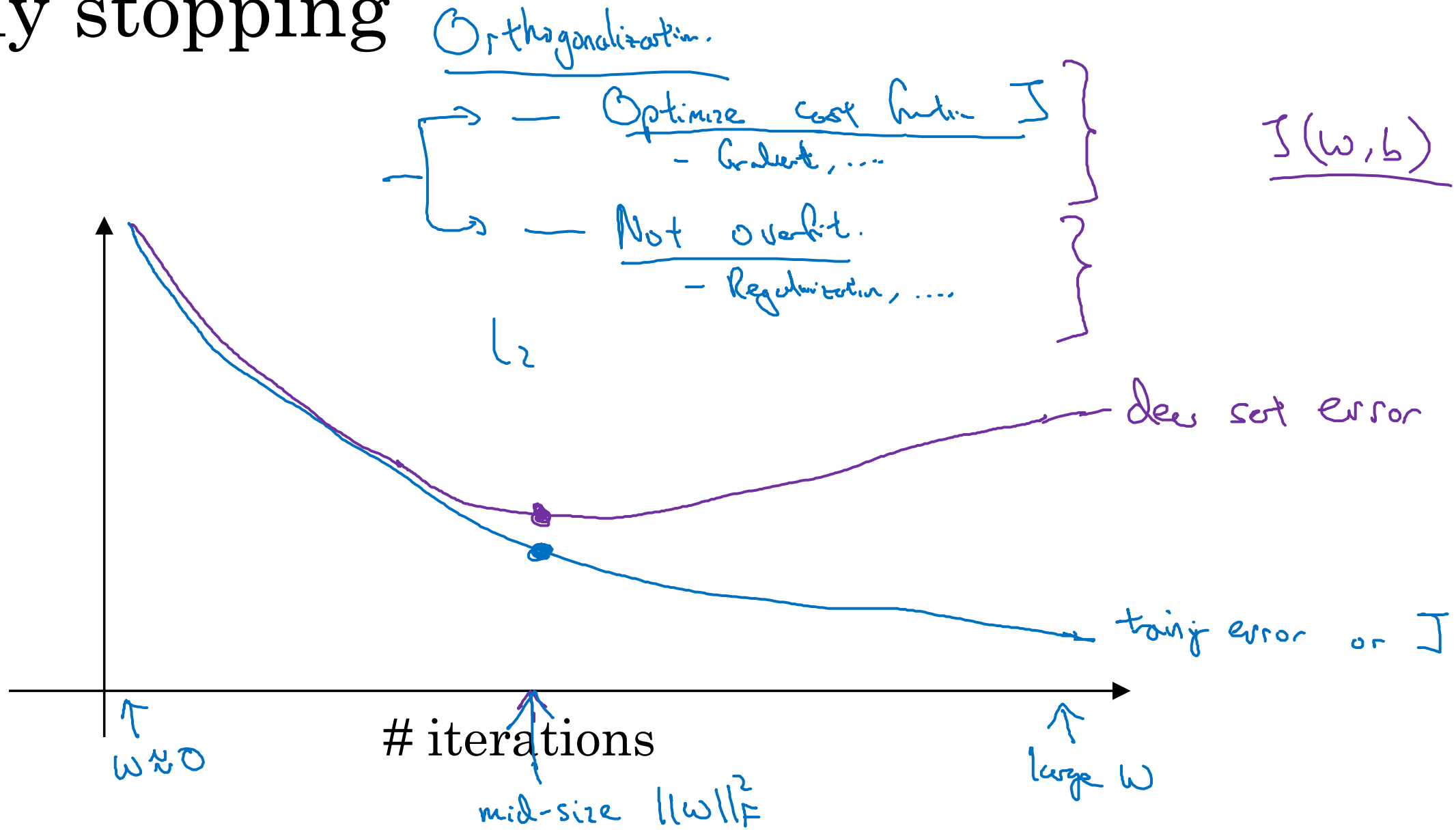
Early stopping



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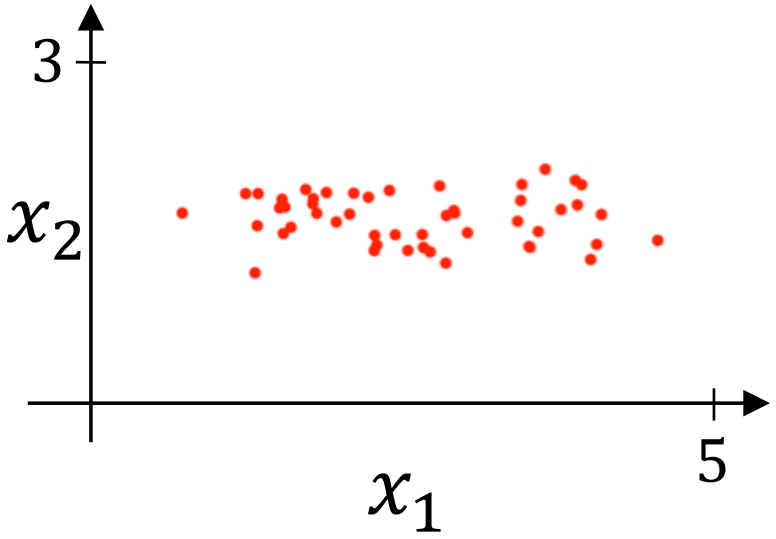
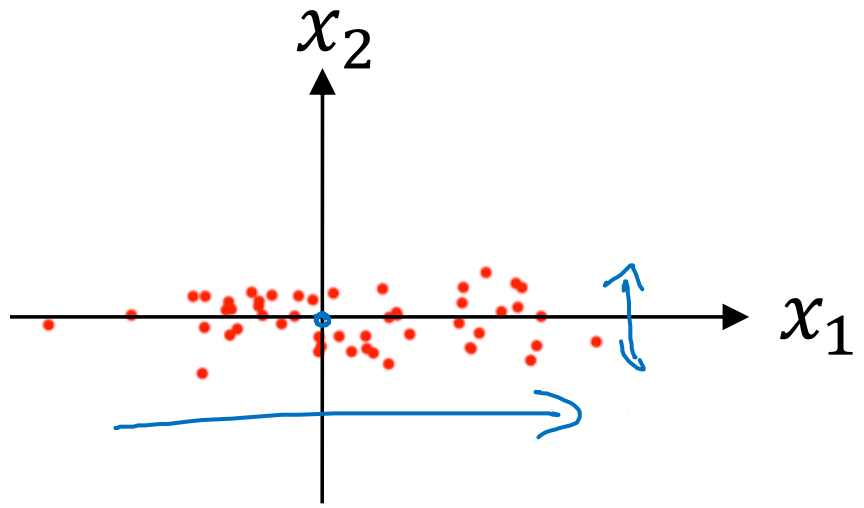
Setting up your optimization problem

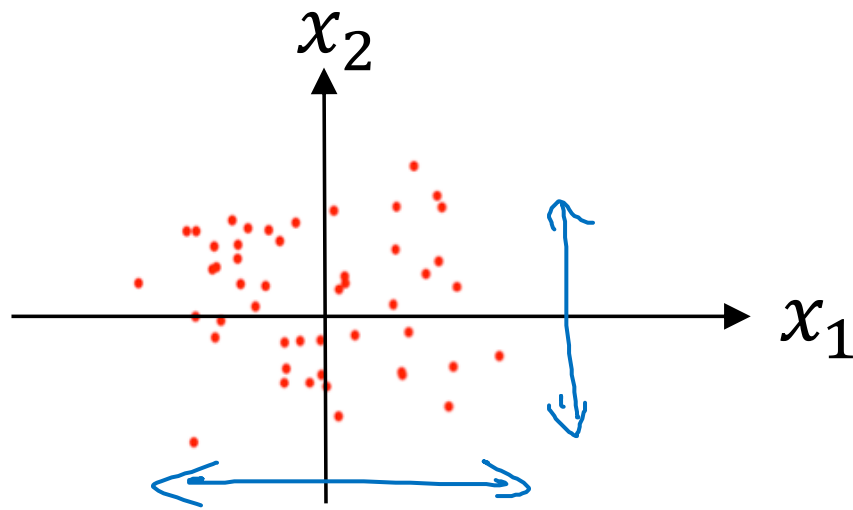
Normalizing inputs

Normalizing training sets

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







Subtract mean:

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

$x := x - \mu$

Normalize variance

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

↑ element-wise

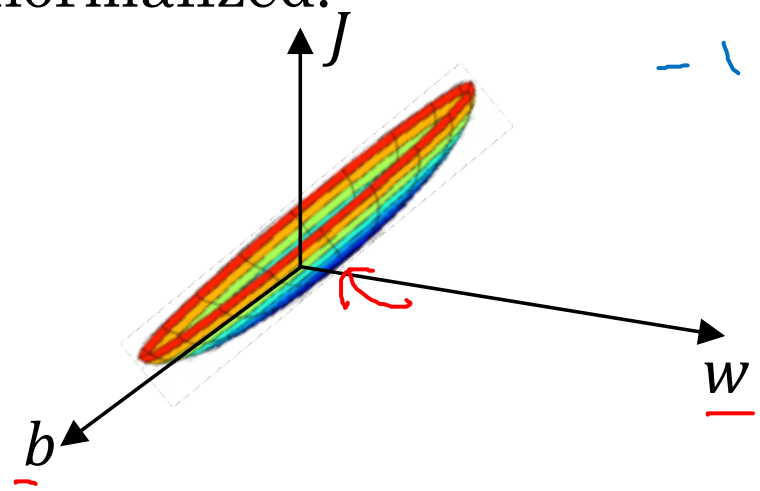
$x /= \sigma^2$

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

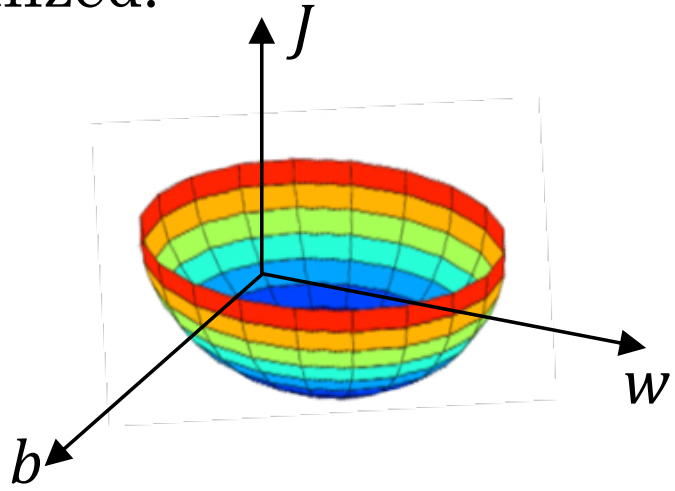
Why normalize inputs?

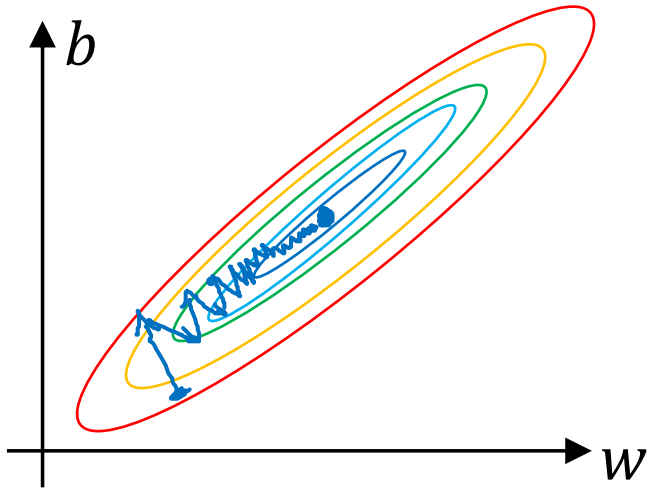
$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

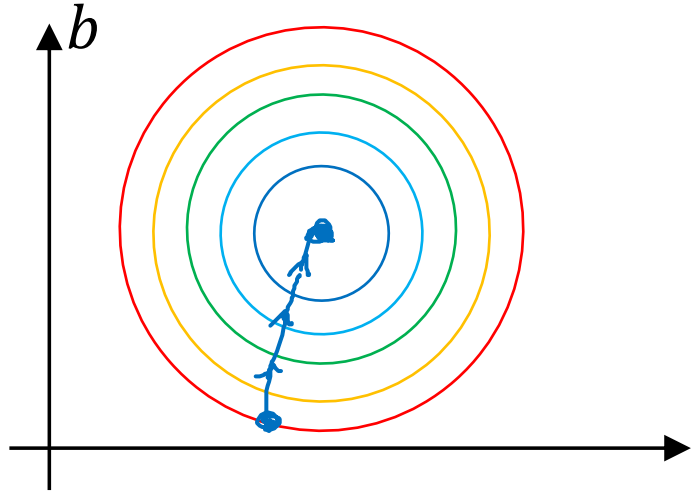
Unnormalized:



Normalized:







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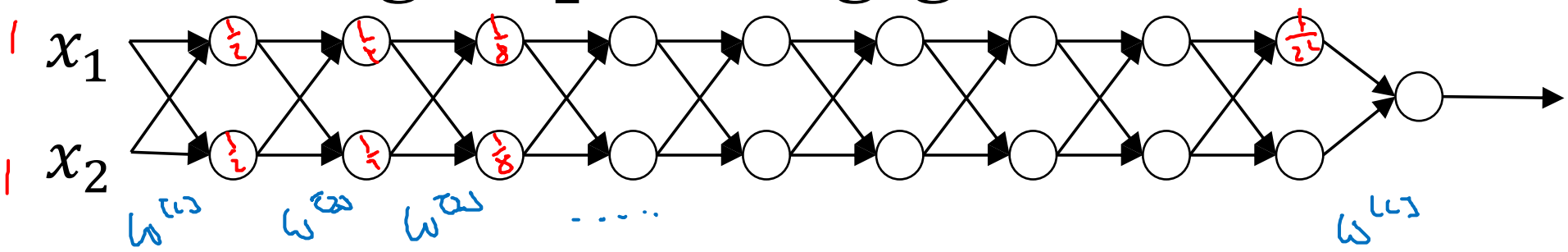
Setting up your optimization problem

Vanishing/exploding gradients

Vanishing/exploding gradients



$L = 150$

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

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

1.5^L

0.5^L

$W^{[l]} > I$

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

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

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

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

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

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

$1.5^{L-1} x$

$0.5^{L-1} x$

Same argument applies for dW, as shown for W here

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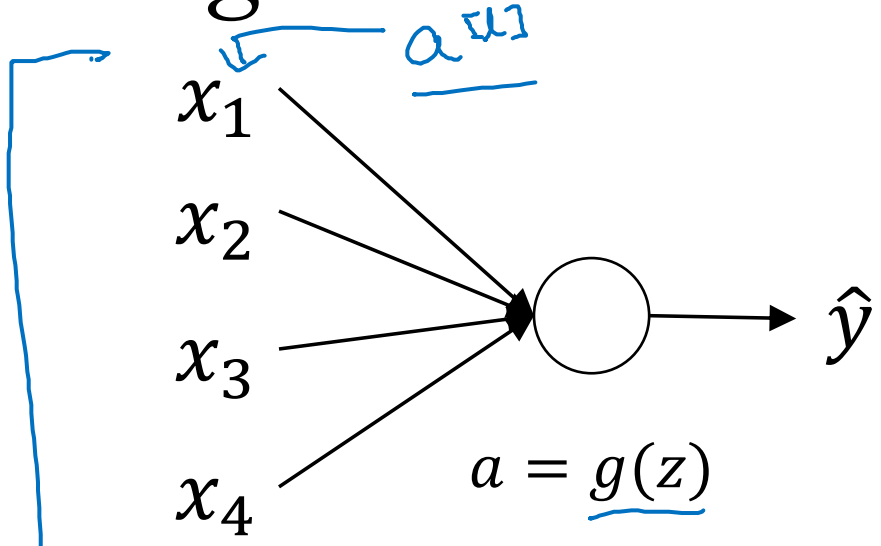
Single neuron example



$w^{[l]}$

Larger the number of nodes 'n', smaller we want 'w' to be to avoid saturation

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

Large n → Smaller w_i

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

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

ReLU

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

Other variants:

tanh

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

Xavier initialization

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

- For ReLU use 2 in numerator
- N[L-1]

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Setting up your optimization problem

Numerical approximation of gradients

Checking your derivative computation

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

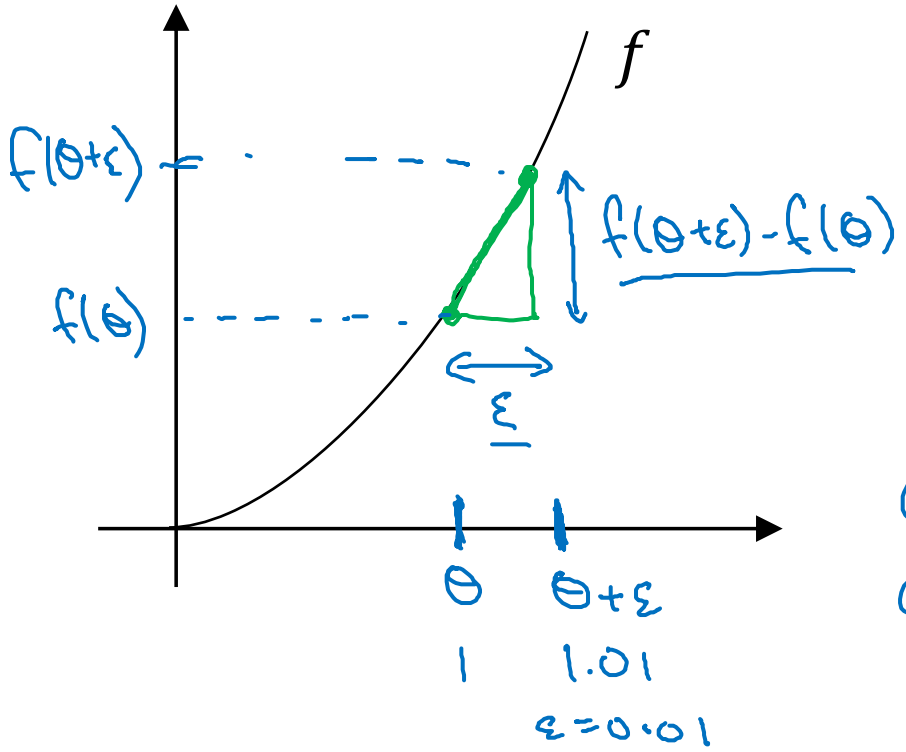
$\theta \in \mathbb{R}$.

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

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

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

$\frac{dw}{db}$



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

$\theta = 1$

$\theta + \varepsilon = 1.01$

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

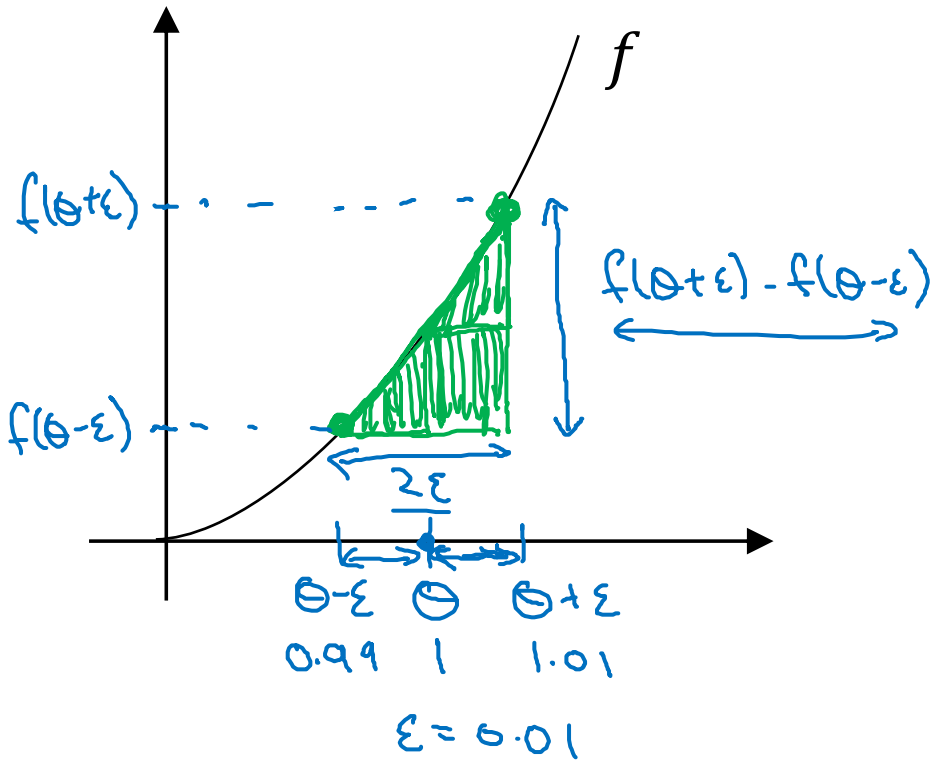
0.0301

3.1

3.2

Checking your derivative computation

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



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

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

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

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

$\varepsilon = 10^{-7}$

$\approx 10^{-7}$ — great! ←

10^{-5}

$\rightarrow 10^{-3}$ — worry. ←

Andrew Ng

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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.

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

$d\theta$ = gradient 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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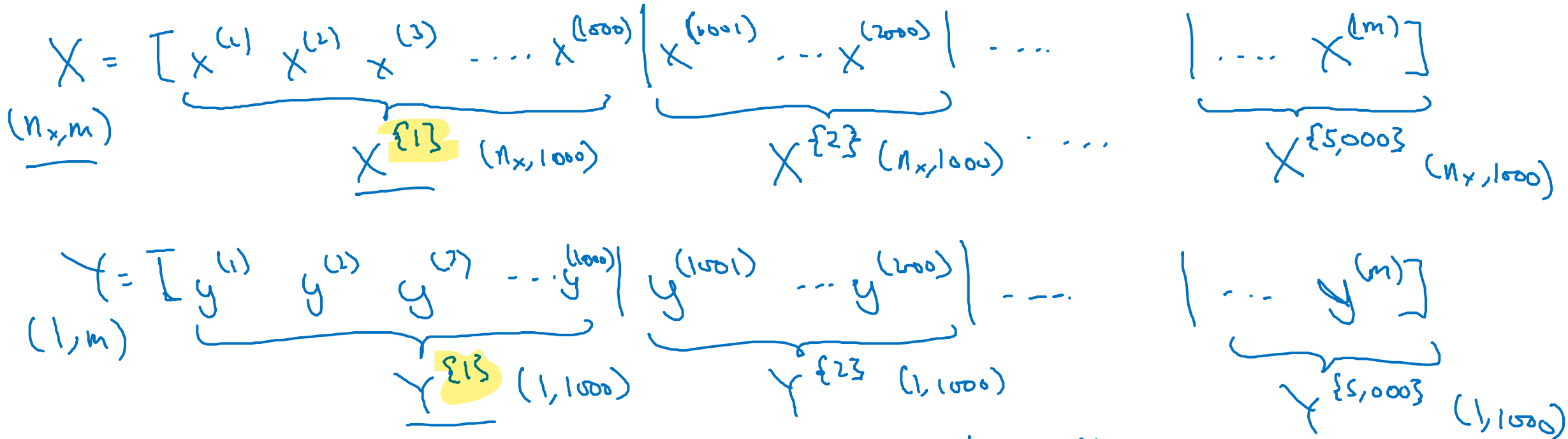
Optimization Algorithms

Mini-batch gradient descent

Batch vs. mini-batch gradient descent

Vectorization allows you to efficiently compute on m examples.



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

5,000 mini-batches of 1,000 each

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

$x^{(i)}$

$z^{[l]}$

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

Andrew Ng

Mini-batch gradient descent

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

X, Y

repeat {

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

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

$$Z^{[1]} = W^{[1]} X^{\{t\}} + b^{[1]}$$
$$A^{[1]} = g^{[1]}(Z^{[1]})$$
$$\vdots$$
$$A^{[L]} = g^{[L]}(Z^{[L]})$$

} Vectorized implementation (1000 examples)

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

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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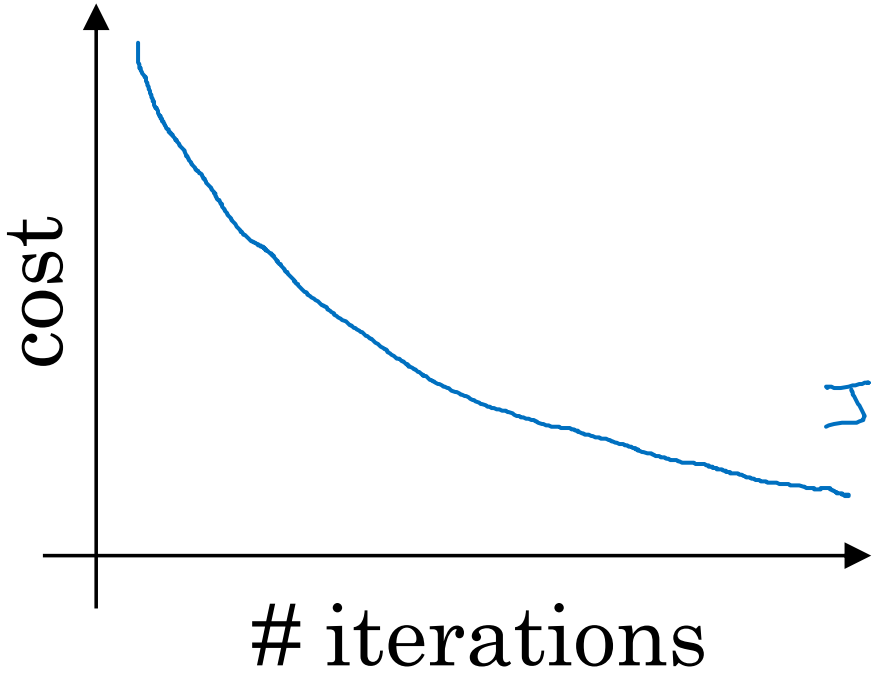
Optimization Algorithms

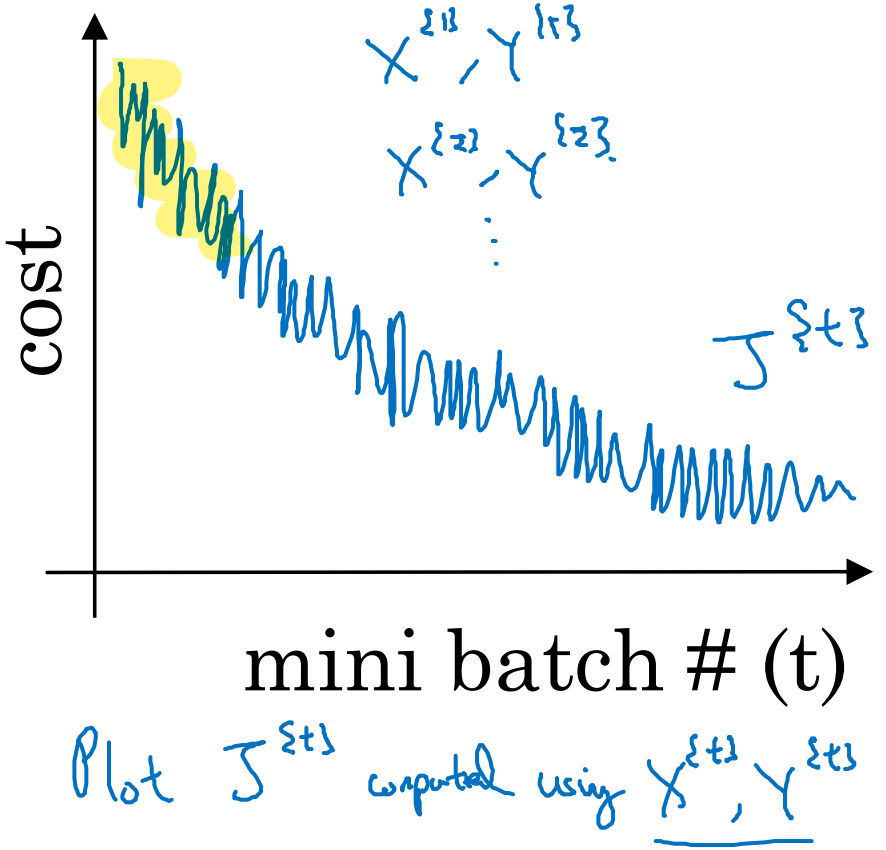
Understanding mini-batch gradient descent

Training with mini batch gradient descent

Batch gradient descent



Mini-batch gradient descent

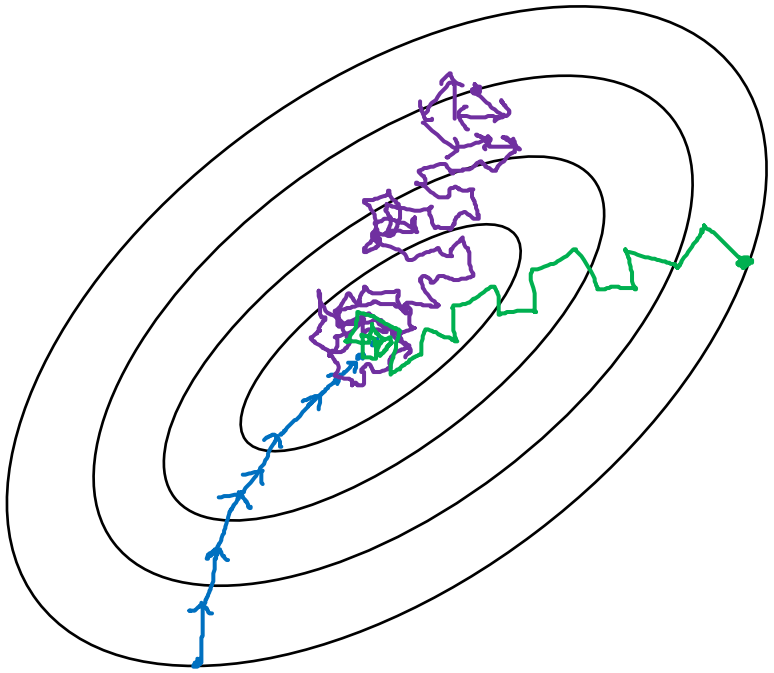


Choosing your mini-batch size

→ 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 mini-batch. $(X^{\{1\}}, Y^{\{1\}}) = (x^{(1)}, y^{(1)})$ ... $(x^{(2)}, y^{(1)})$

In practice: Somewhere in-between 1 and m



Stochastic gradient descent

{

Lose speedup from vectorization

In-between (mini-batch size not too big/small)

Fastest learning.

- Vectorization. (n 1000)
- Make progress without processing entire training set.

Batch gradient descent (mini-batch size = m)

Too long per iteration

Andrew Ng

Choosing your mini-batch size

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

Typical mini-batch sizes:

→ 64, 128, 256, 512 (1024)
2^6, 2^7, 2^8, 2^9 (2^{10})

Make sure mini-batch fit in CPU/GPU memory.

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

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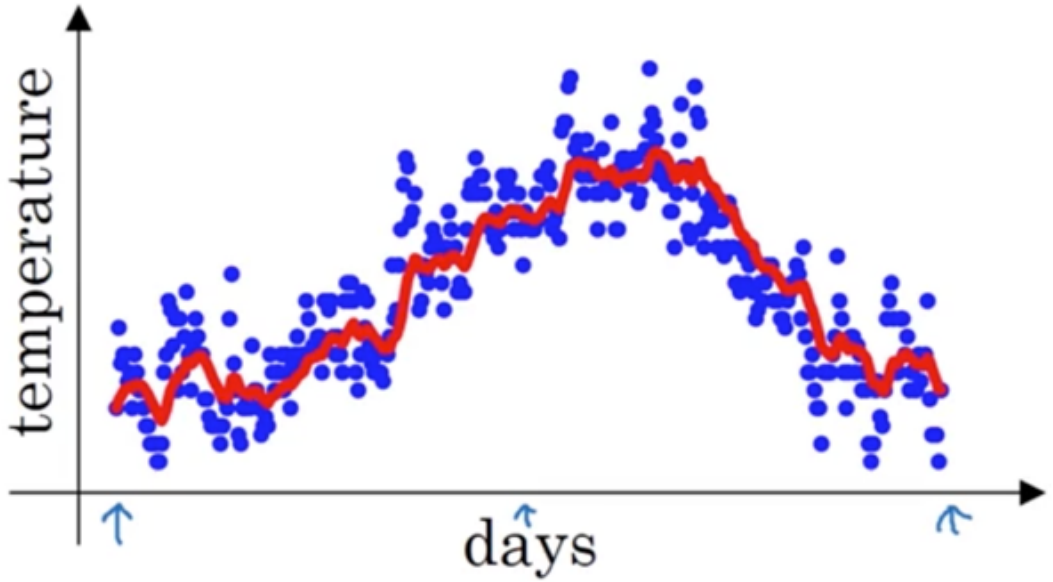
Optimization Algorithms

Exponentially weighted averages

Temperature in London

$\theta_1 = 40°\text{F}$ 4°C ←
$\theta_2 = 49°\text{F}$ 9°C
$\theta_3 = 45°\text{F}$ ⋮
⋮
$\theta_{180} = 60°\text{F}$ 15°C
$\theta_{181} = 56°\text{F}$ ⋮
⋮



$v_0 = 0$
$v_1 = 0.9\, v_0 + 0.1\, \theta_1$
$v_2 = 0.9\, v_1 + 0.1\, \theta_2$
$v_3 = 0.9\, v_2 + 0.1\, \theta_3$
⋮
$v_t = 0.9\, v_{t-1} + 0.1\, \theta_t$

Andrew Ng

Exponentially weighted averages

Moving

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

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

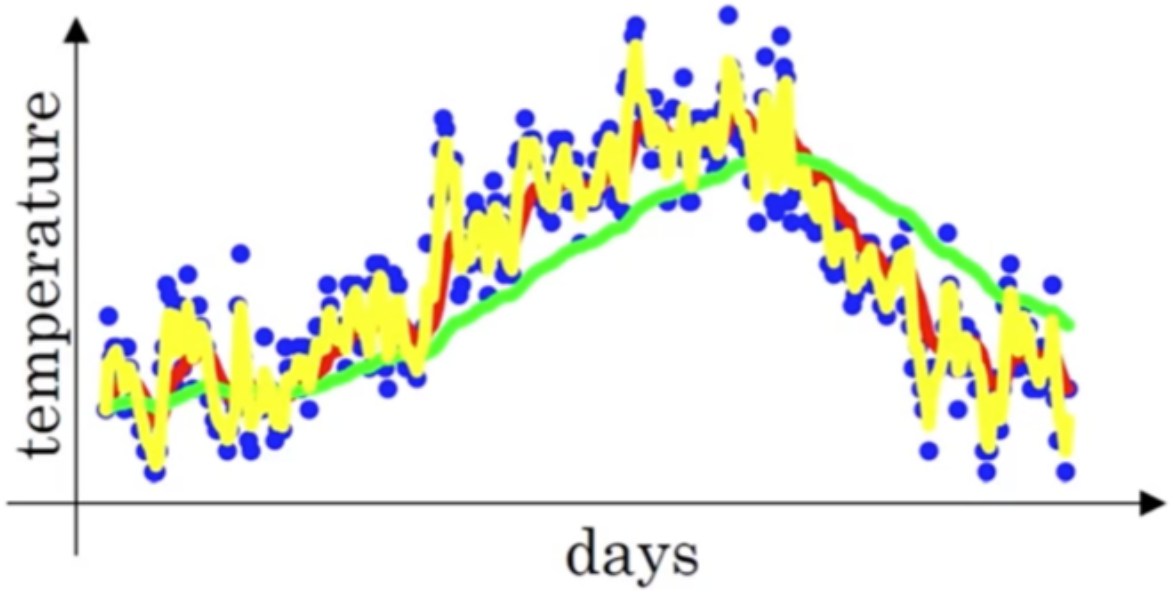
$\beta = 0.98$: $\approx$ 50 days

$\beta = 0.5$: $\approx$ 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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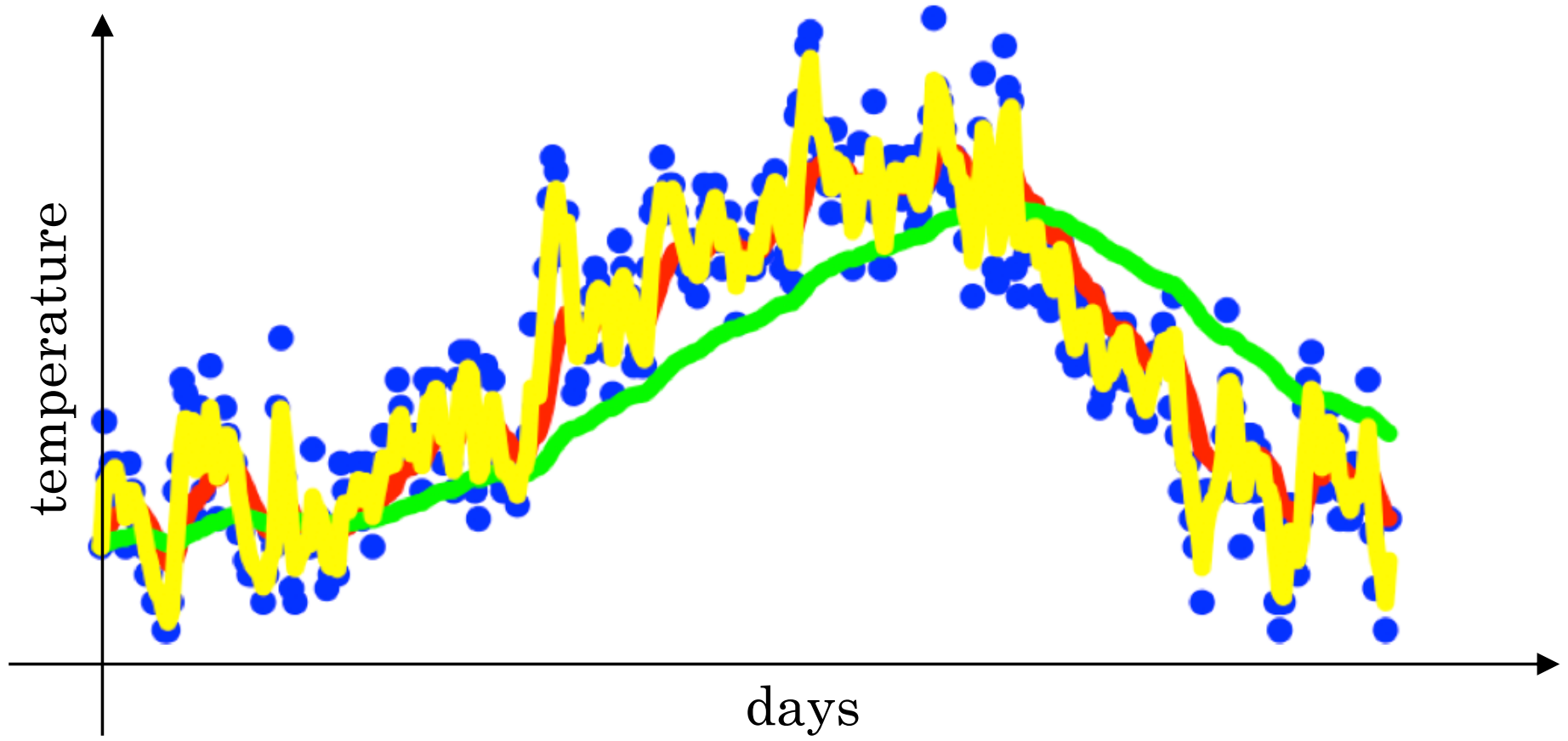
Optimization Algorithms

Understanding exponentially weighted averages

Exponentially weighted averages

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

$\beta = 0.9$ 0.98 0.5



Exponentially weighted averages

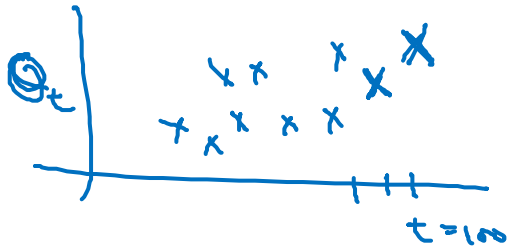
$$v_t = \beta v_{t-1} + (1-\beta)\theta_t$$

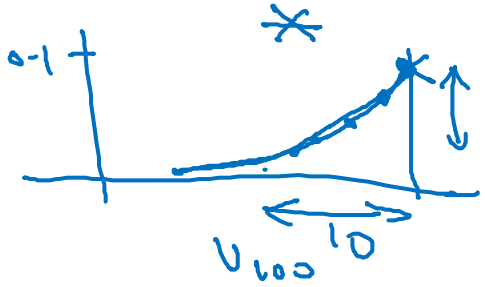
$$v_{100} = 0.9v_{99} + 0.1\theta_{100}$$

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

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

...





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

$\varepsilon = 1-\beta$

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

$v_{100} = 0.1\theta_{100} + 0.9v_{99}(0.1\theta_{99} + 0.9v_{98})$

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

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

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

$0.98^{?}$

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

Andrew Ng

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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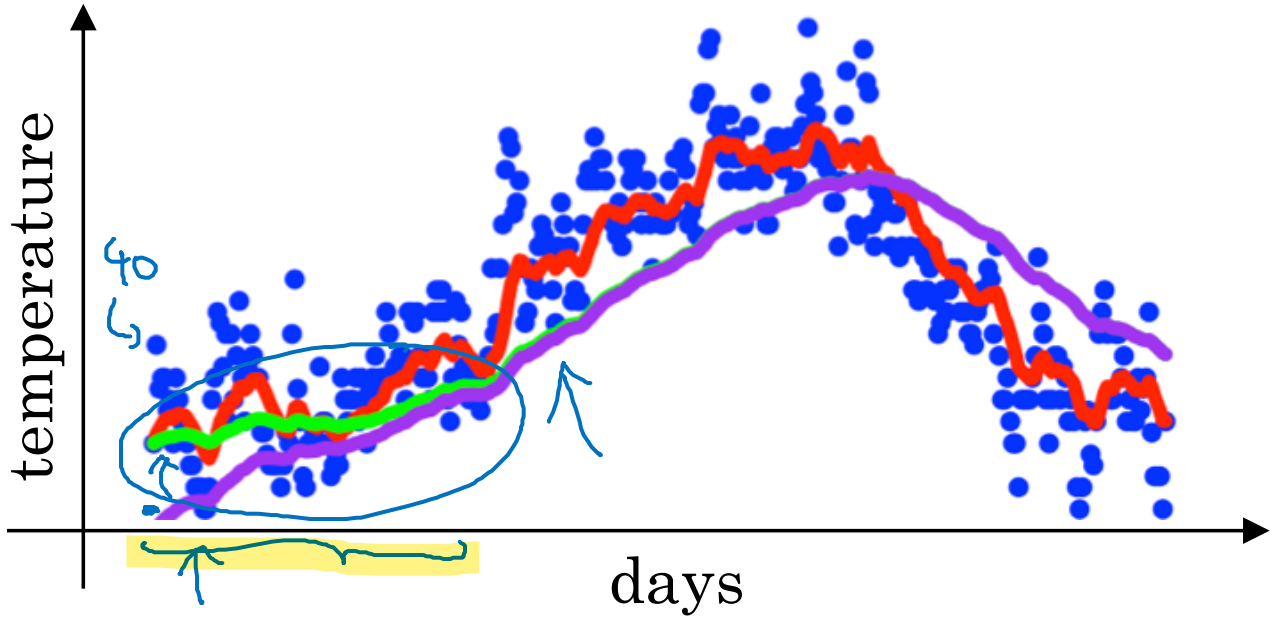
Optimization Algorithms

Bias correction in exponentially weighted average

Bias correction



$\beta = 0.98$

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

$v_0 = 0$

$v_1 = 0.98 v_0 + 0.02 \theta_1$

$v_2 = 0.98 v_1 + 0.02 \theta_2$

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

$= 0.0196 \theta_1 + 0.02 \theta_2$

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

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

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

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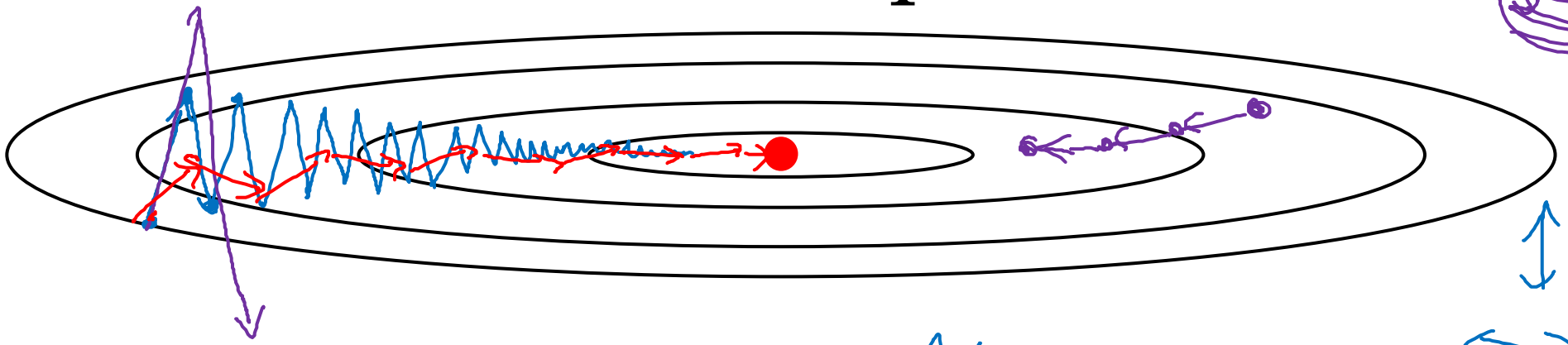
Optimization Algorithms

Gradient descent with momentum

Gradient descent example



slower learning

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

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

"$v_\theta = \beta v_{\theta-1} + (1-\beta)\theta_t$"

Smoothes out the variations in gradient vector / dampens oscillations (in up/down direction in this case)

Implementation details

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

On iteration t:

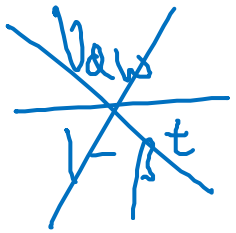
Compute dW, db on the current mini-batch

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

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

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

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



Hyperparameters: α, β

$\beta = 0.9$

average over last ≈ 10 gradients

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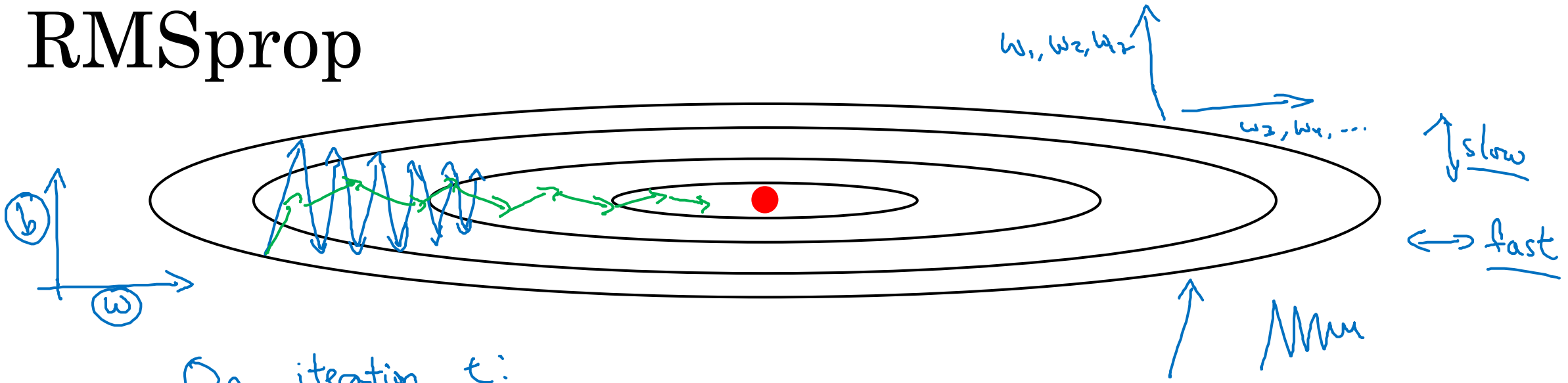
Optimization Algorithms

RMSprop

RMSprop



On iteration t:

Compute dW, db on current mini-batch

$S_{dW} = \beta_2 S_{dW} + (1-\beta_2) \underbrace{dW^2}_{\text{element-wise}}$ ← small

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

$$W := W - \alpha \frac{dW}{\sqrt{S_{dW} + \varepsilon}} \qquad b := b - \alpha \frac{db}{\sqrt{S_{db} + \varepsilon}}$$

$\varepsilon = 10^{-8}$

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Optimization Algorithms

Adam optimization algorithm

Adam optimization algorithm

$V_{dW} = 0, S_{dW} = 0, V_{db} = 0, S_{db} = 0$

On iteration t:

Compute dW, db using current mini-batch

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

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

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

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

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

Bias correction

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

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Hyperparameters choice:

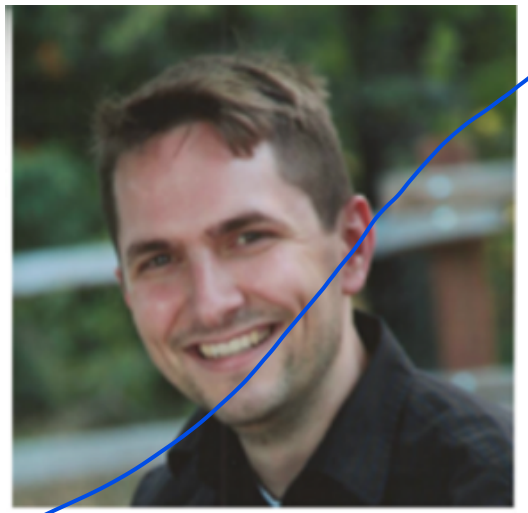
→ α : needs to be tune

→ β_1 : 0.9 → (dw)

→ β_2 : 0.999 → (dw^2)

→ ε : 10^{-8}

Adam : Adaptive moment estimation



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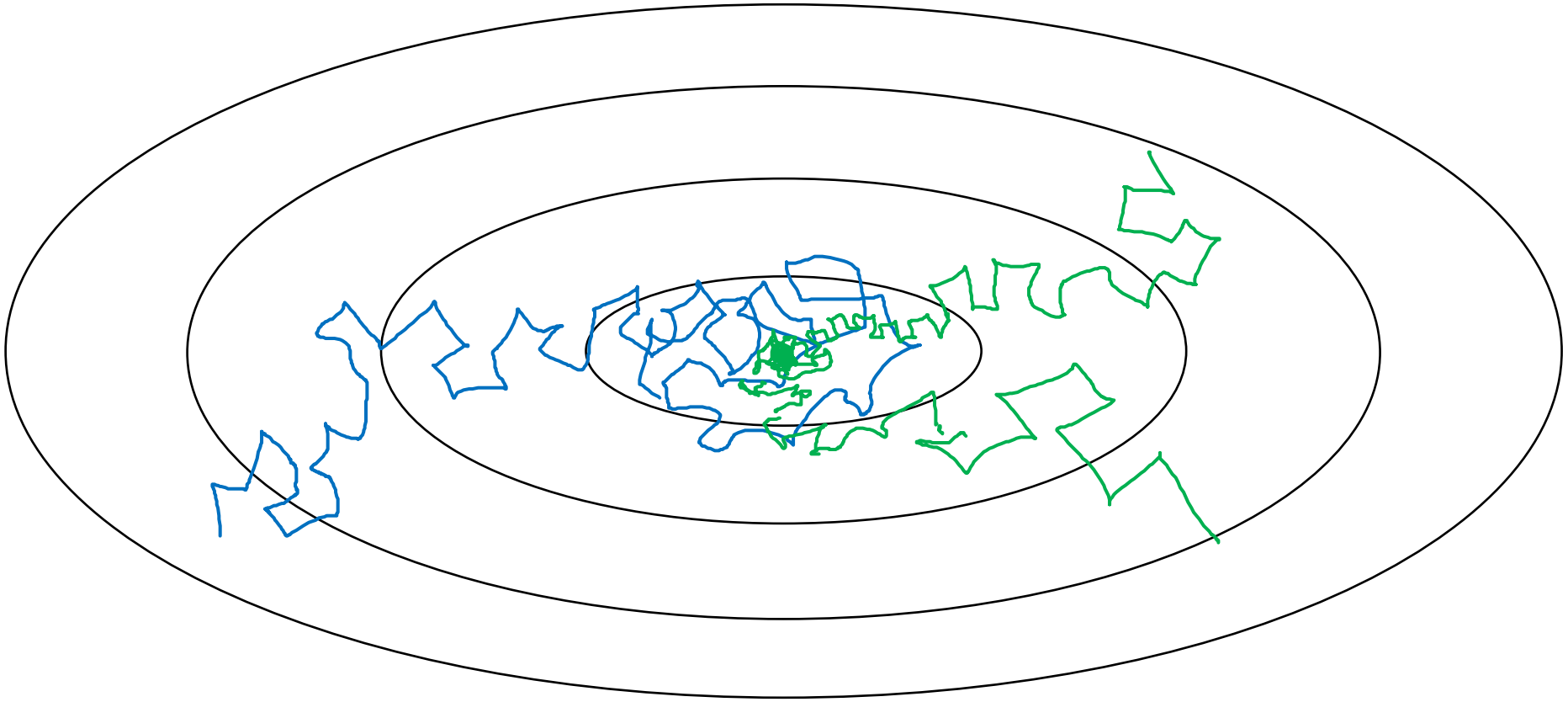
Optimization Algorithms

Learning rate decay

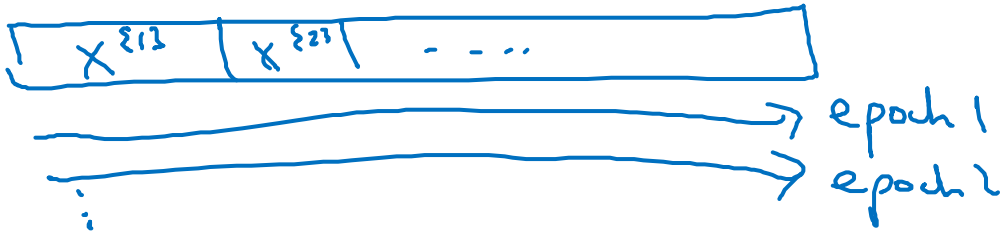
Learning rate decay

Slowly reduce α



Learning rate decay

1 epoch = 1 pass through data.

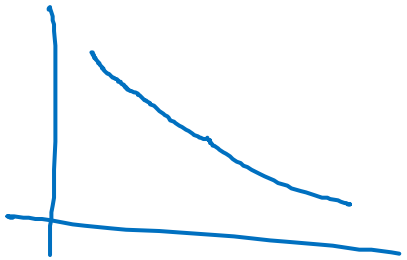


$$\alpha = \frac{1}{1 + \text{decay\_rate} * \text{epoch\_num}} \alpha_0$$

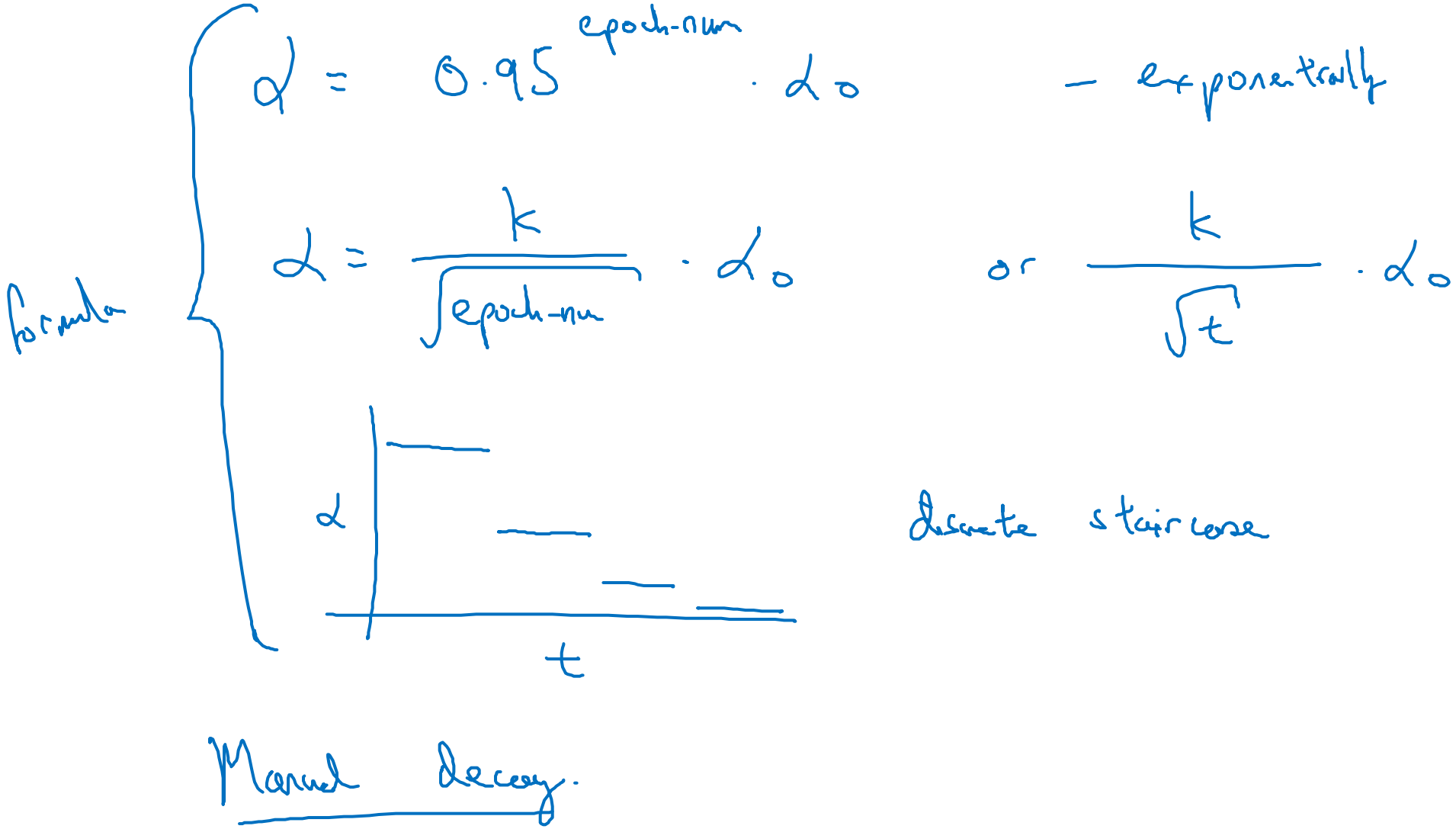
$\alpha_0 = 0.2$

decay_rate = 1

Epoch	α
1	0.1
2	0.67
3	0.5
4	0.4
⋮	⋮



Other learning rate decay methods



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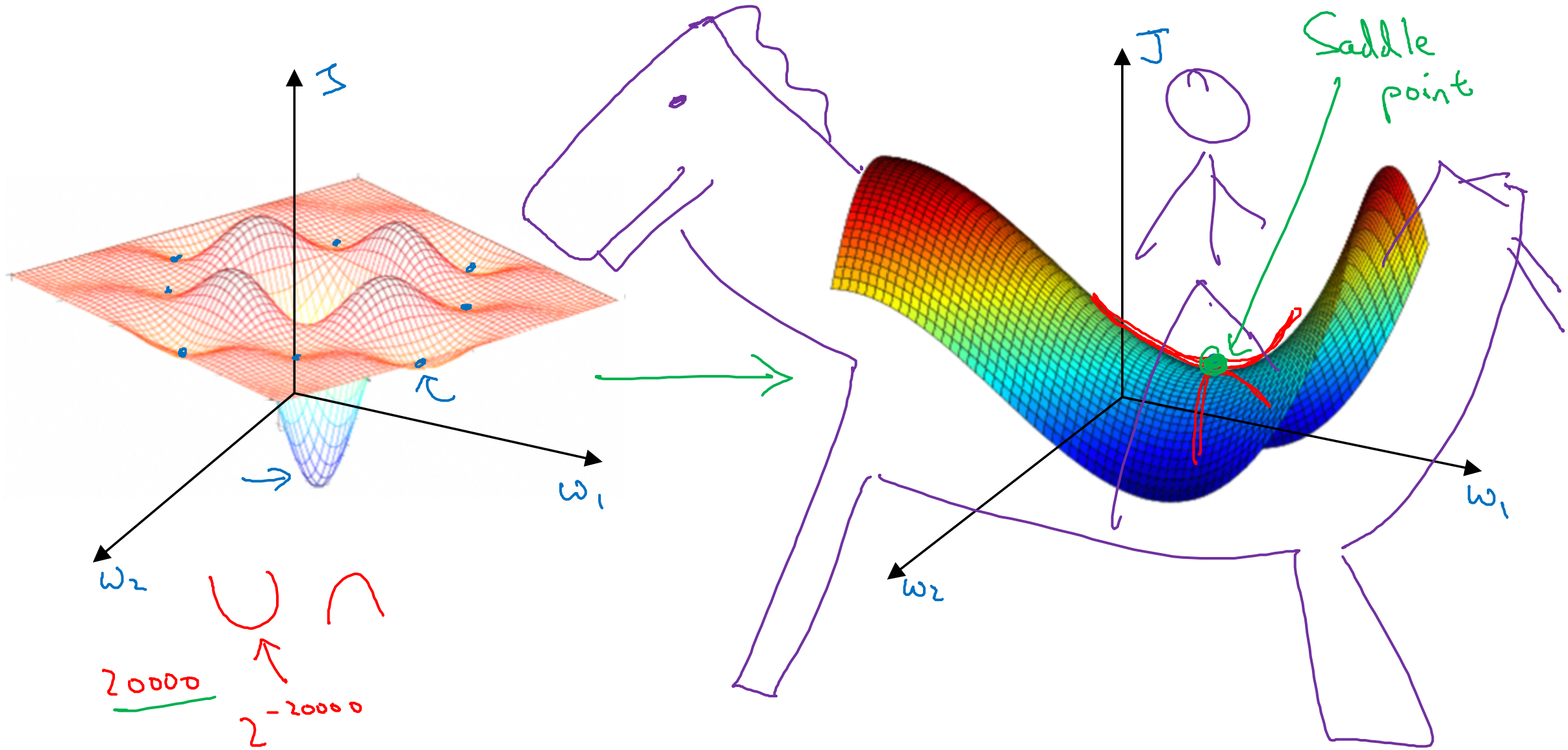
Optimization Algorithms

The problem of local optima

Local optima in neural networks



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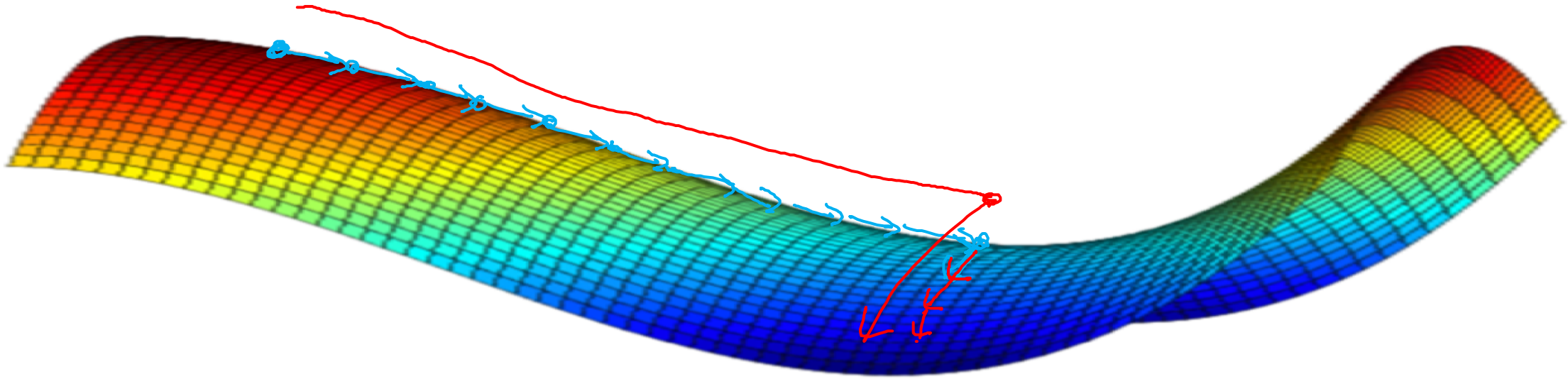
Problem of plateaus



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

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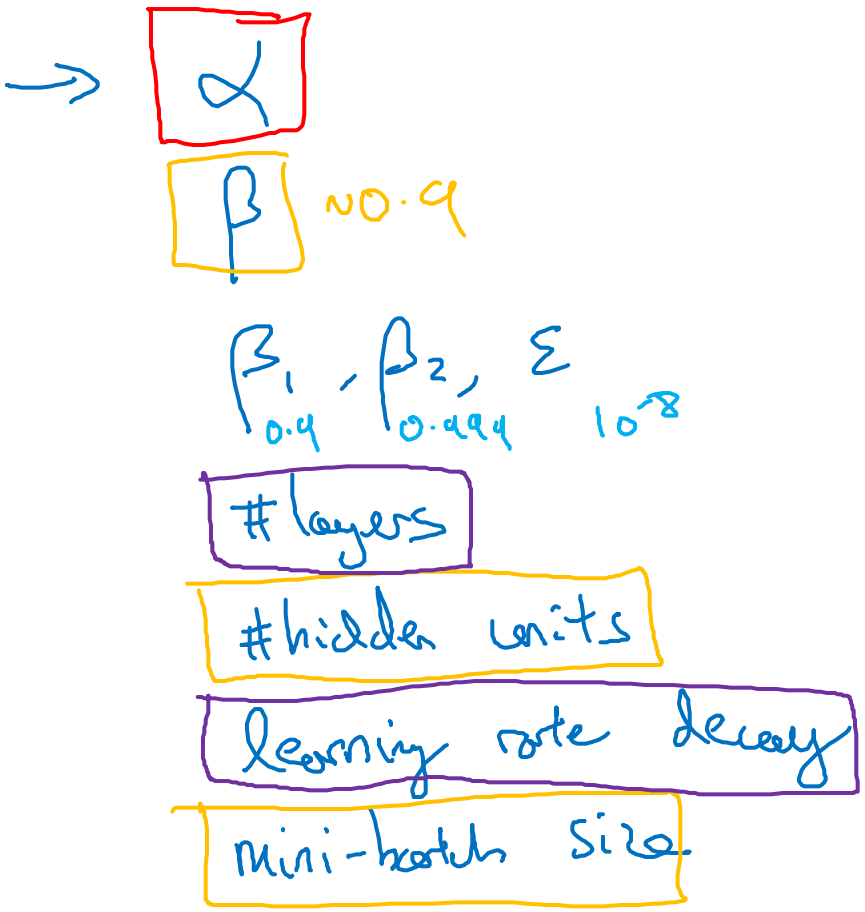
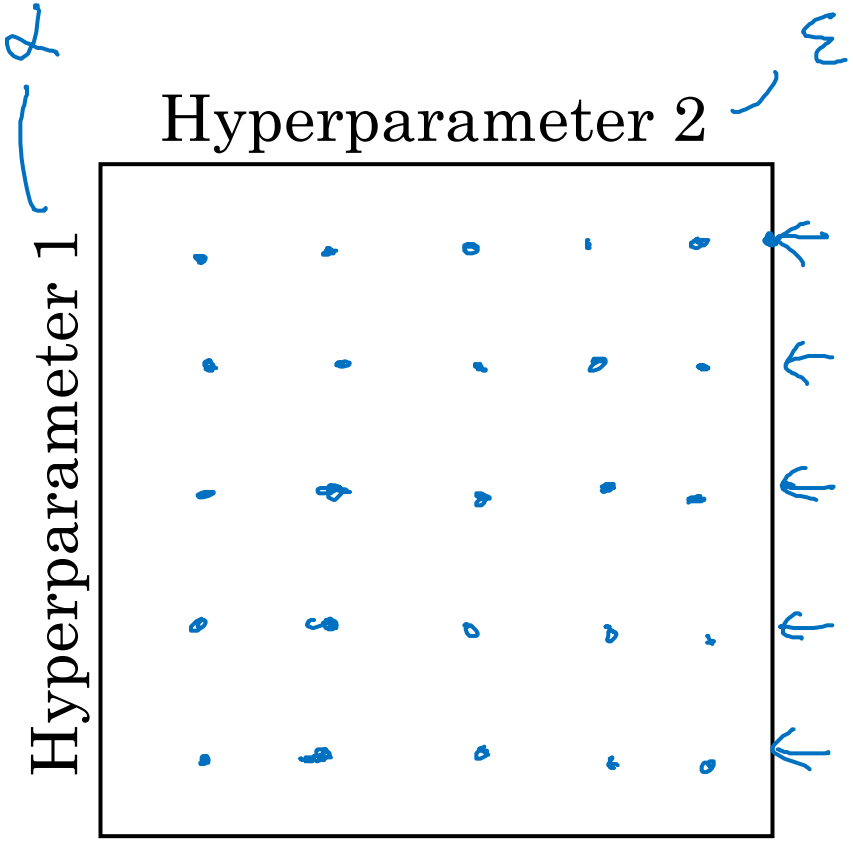
Hyperparameter tuning

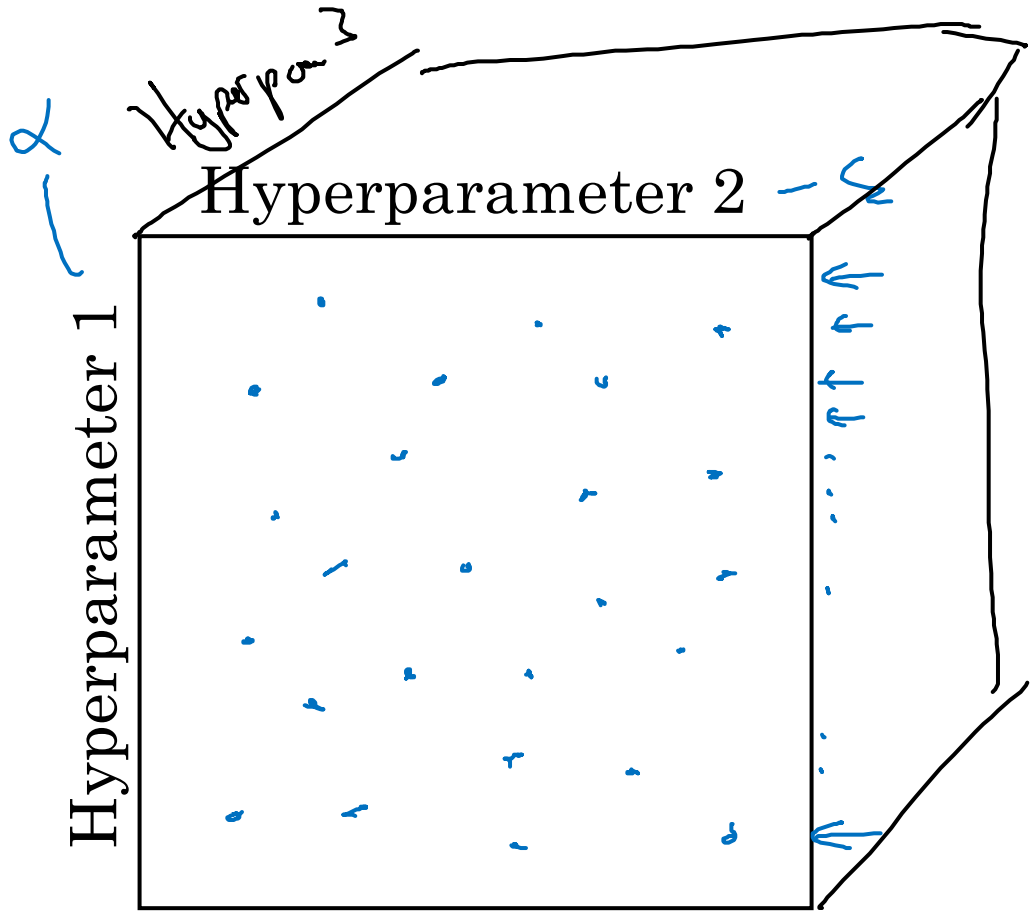
Tuning process

Hyperparameters

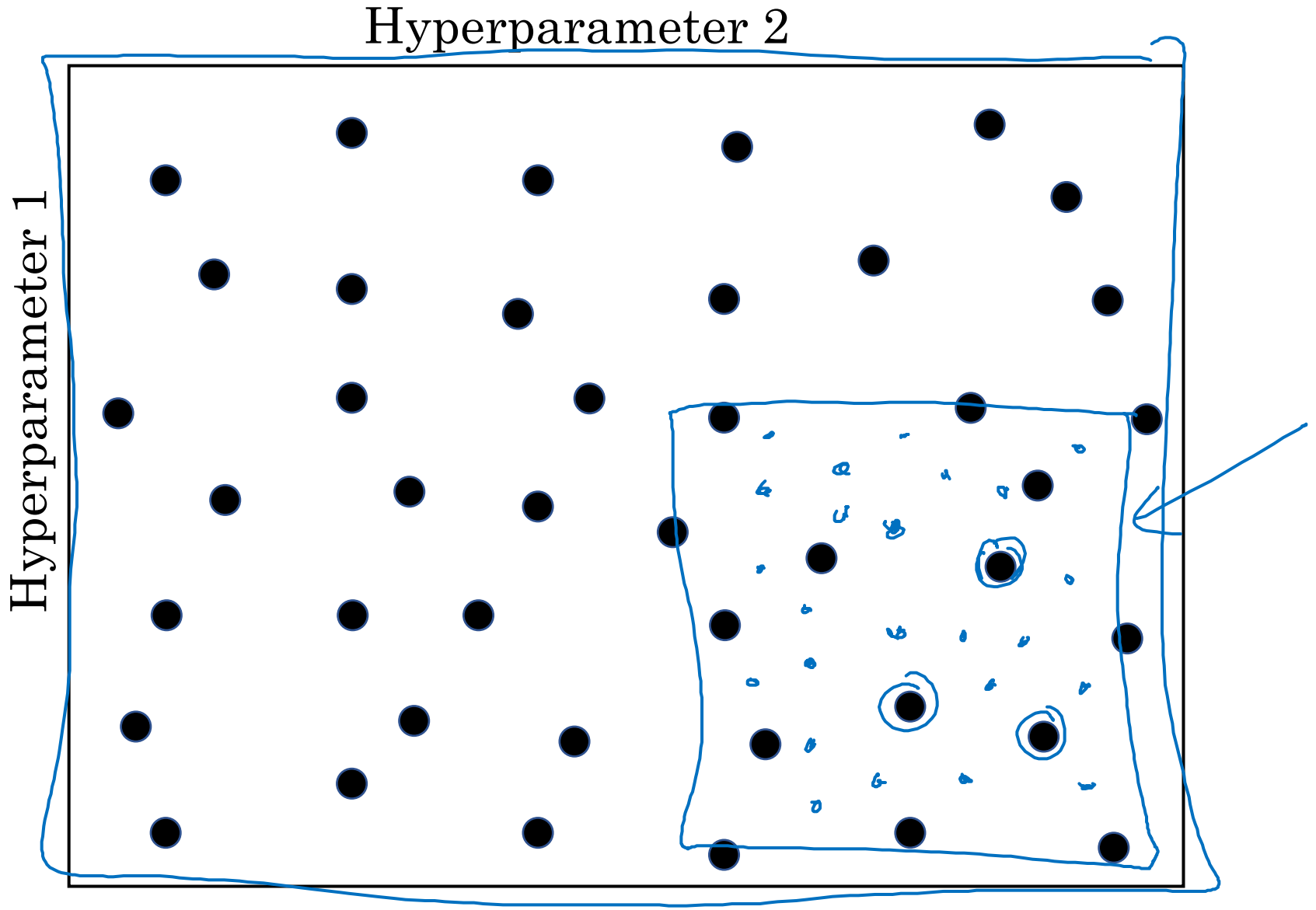


Try random values: Don't use a grid





Coarse to fine



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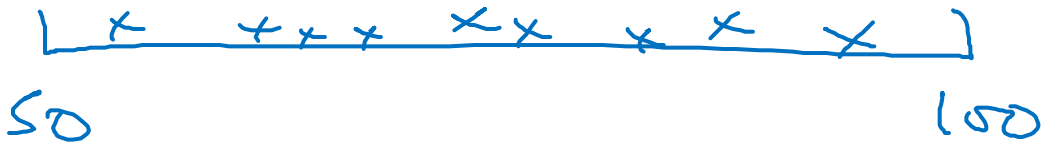
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \ldots, 100$

Sampling over a linear scale doesn't always make sense

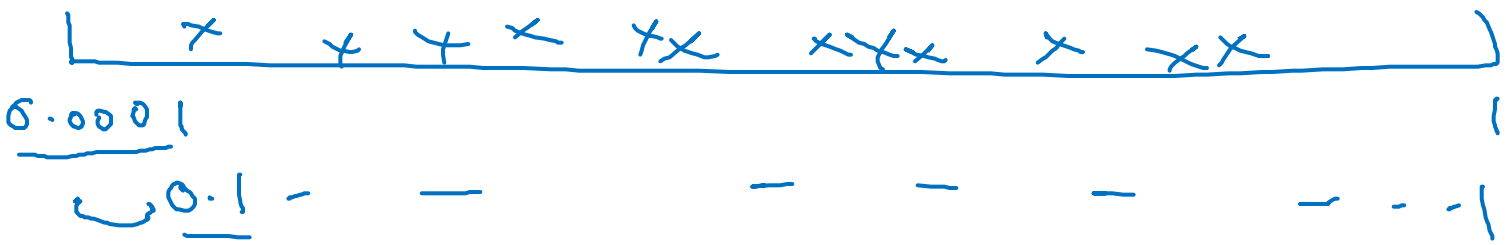


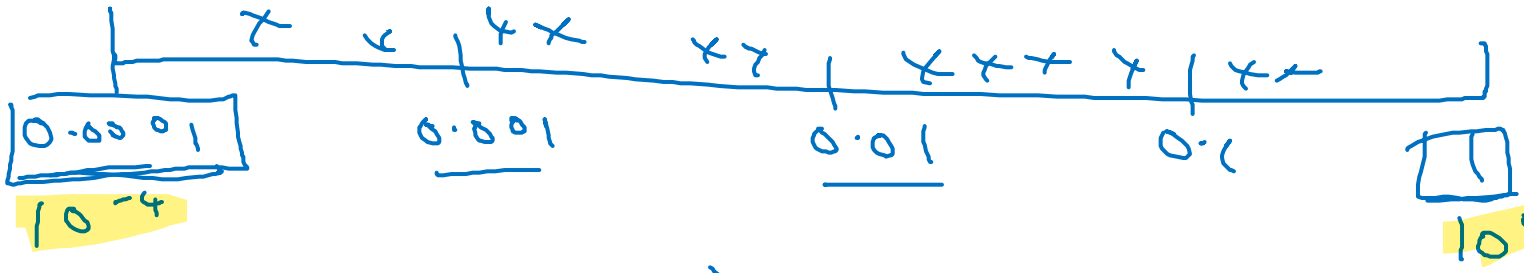
→ #layers L: 2 – 4

2, 3, 4

Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$





10^a 10^b

10^{-4} 10^0

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

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

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

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

Andrew Ng

Hyperparameters for exponentially weighted averages

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

$10 \qquad\qquad 1000$

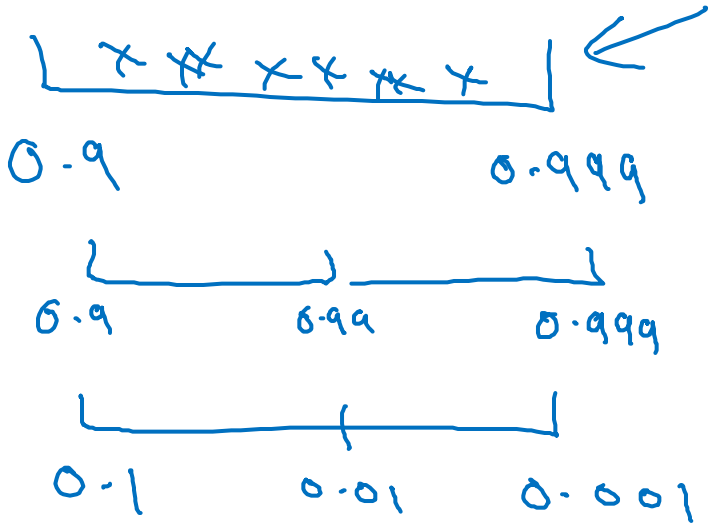
$1-\beta = 0.1 \quad \ldots \quad 0.001$

$\beta: 0.900 \rightarrow 0.9005$ } ~ 10

$\beta: 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

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



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

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

$1-\beta = 10^{r}$

$\beta = 1 - 10^{r}$

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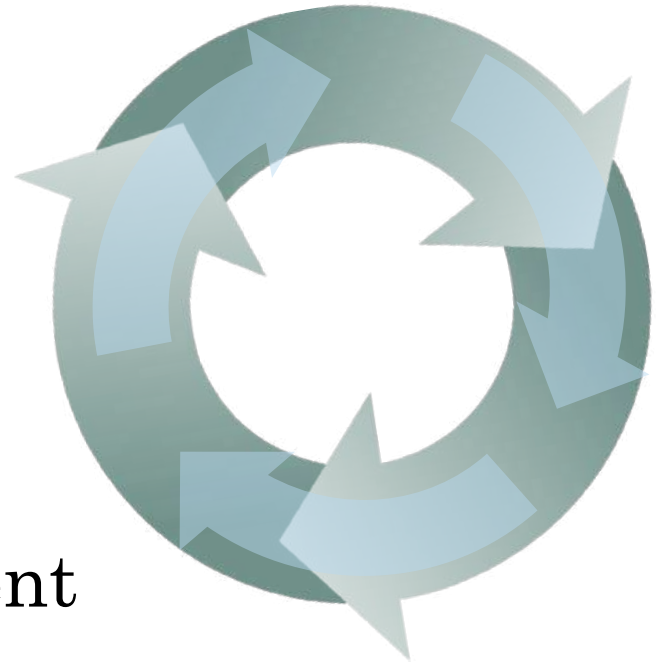
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

Re-test hyperparameters occasionally

Idea



Experiment

Code

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

- Intuitions do get stale. Re-evaluate occasionally.

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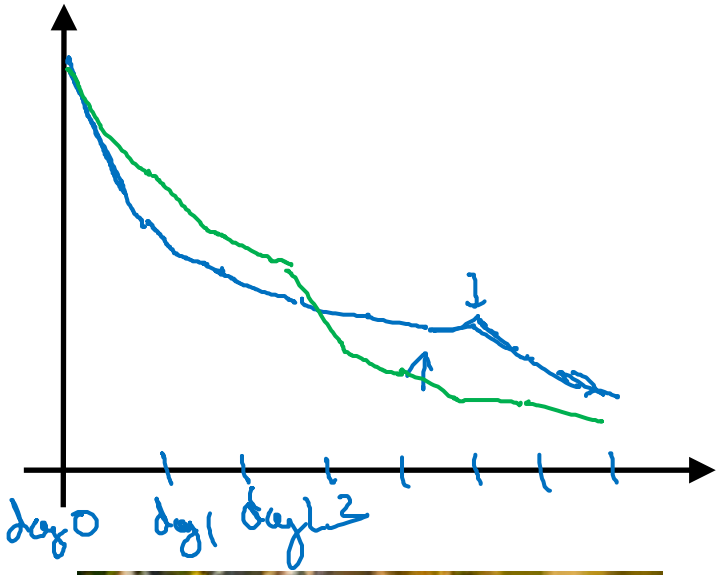
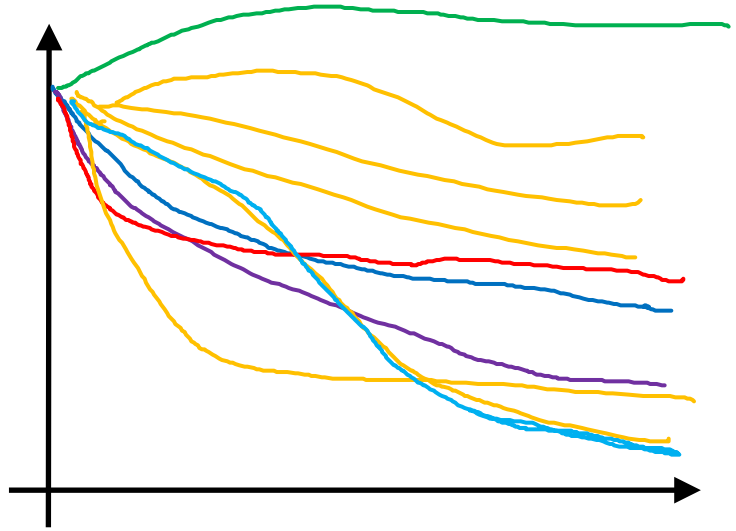
Babysitting one model



Panda

Training many models in parallel



Caviar

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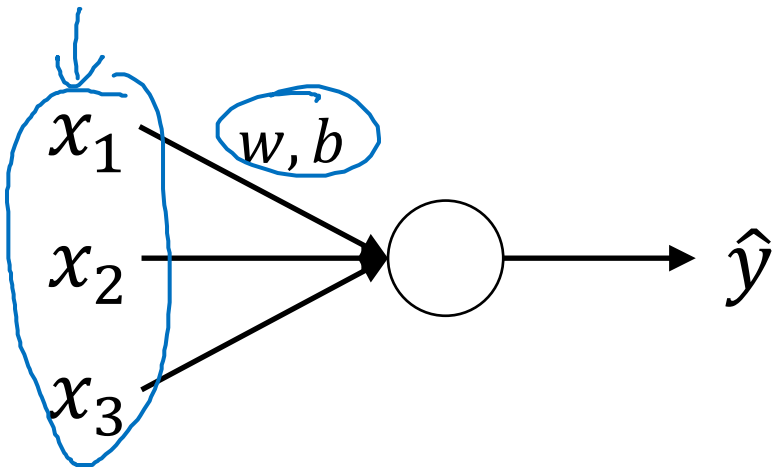
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning

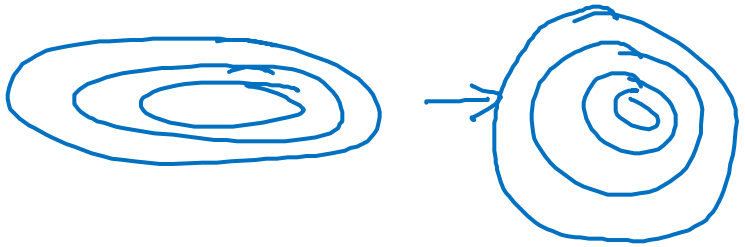


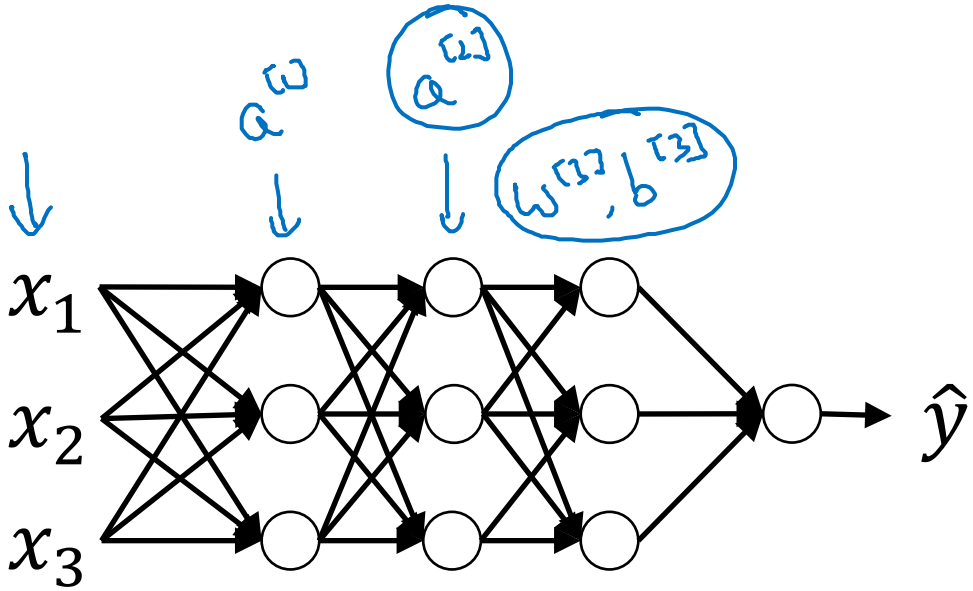
$$\mu = \frac{1}{m} \sum_i x^{(i)}$$

$$X = X - \mu$$ ← element-wise

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

$$X = X / \sigma$$





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

Normalize $z^{[2]}$

Implementing Batch Norm

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

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

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

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

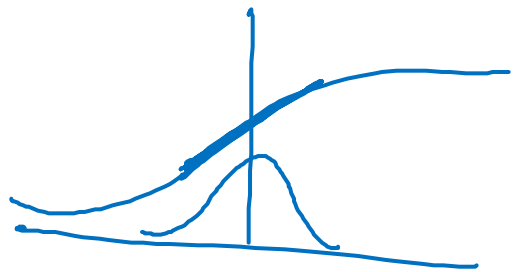
$$\tilde{z}^{(i)} = \gamma z^{(i)}_{norm} + \beta$$

learnable parameters of model.

If $\gamma = \sqrt{\sigma^2 + \varepsilon}$, $\beta = \mu$, then $\tilde{z}^{(i)} = z^{(i)}$

$X \leftarrow$

$z^{(i)} \leftarrow$



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

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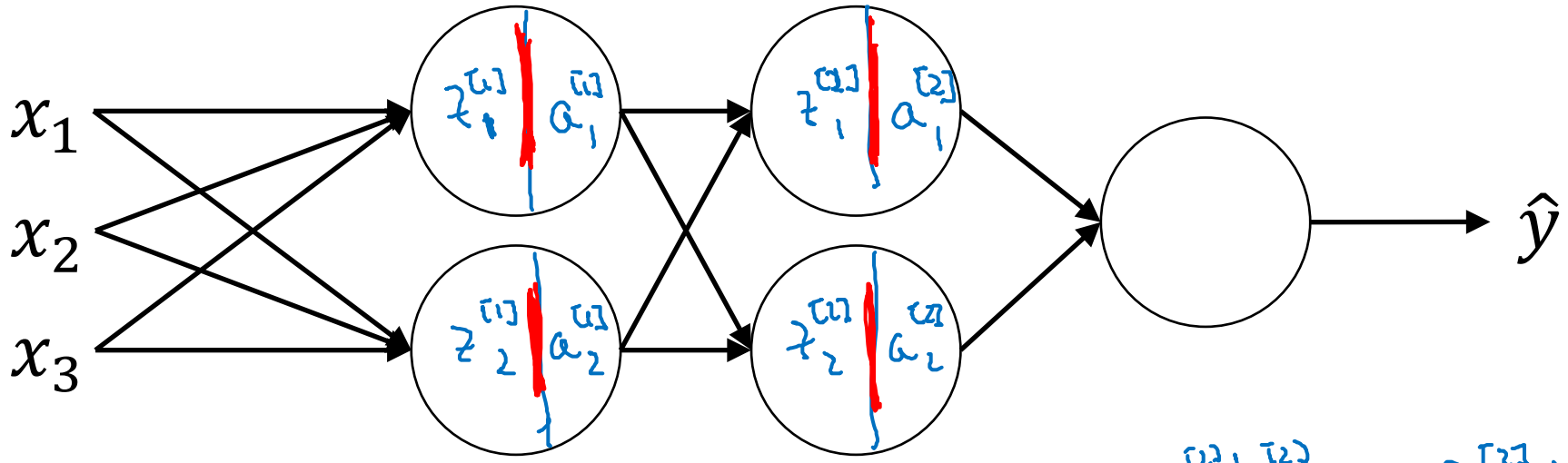
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network



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

Parameters: $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, \dots, W^{[L]}, b^{[L]}, \beta^{[1]}, \gamma^{[1]}, \beta^{[2]}, \gamma^{[2]}, \dots, \beta^{[L]}, \gamma^{[L]}$

$\rightarrow \beta$

$d\beta^{[l]}$

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

tf.nn.batch_normalization

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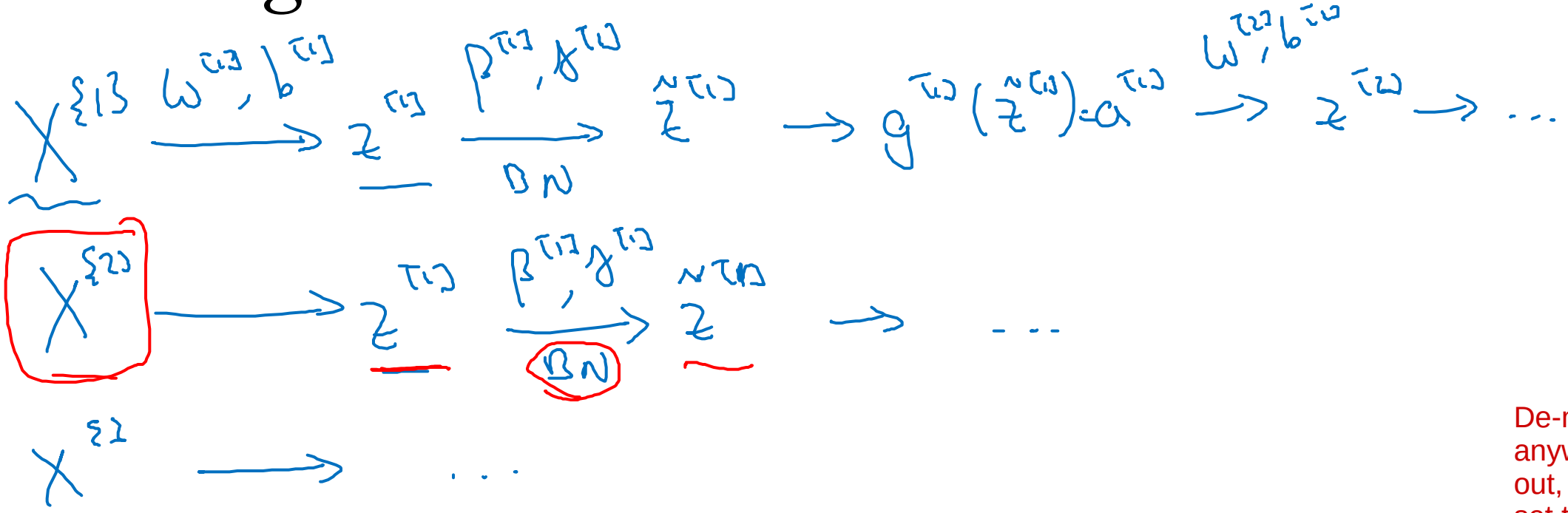
Working with mini-batches



De-meaning will anyway cancel this out, might as well set this to 0

Parameters: $w^{[l]}$, ~~$b^{[l]}$~~, $\beta^{[l]}$, $\gamma^{[l]}$.

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

$(n^{[l]}, 1)$ ↑

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

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

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

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

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

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

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

Update parameters $W^{[l]} := W^{[l]} - \alpha\, dW^{[l]}$

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

$\gamma^{[l]} := \ldots$ ←

Works w/ momentum, RMSprop, Adam.

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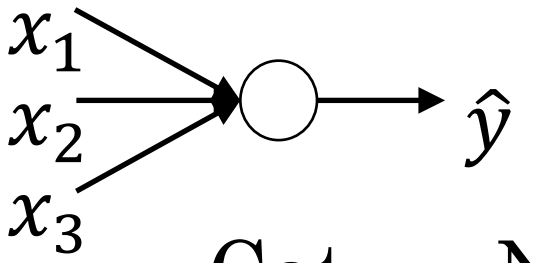
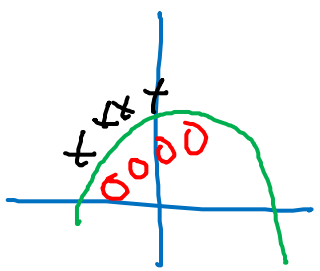
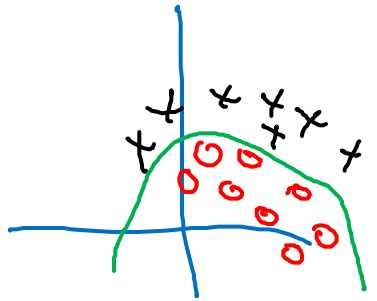
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution







Cat $y = 1$




Non-Cat $y = 0$




"Covariate shift"

$X \rightarrow y$

$y = 1$




$y = 0$

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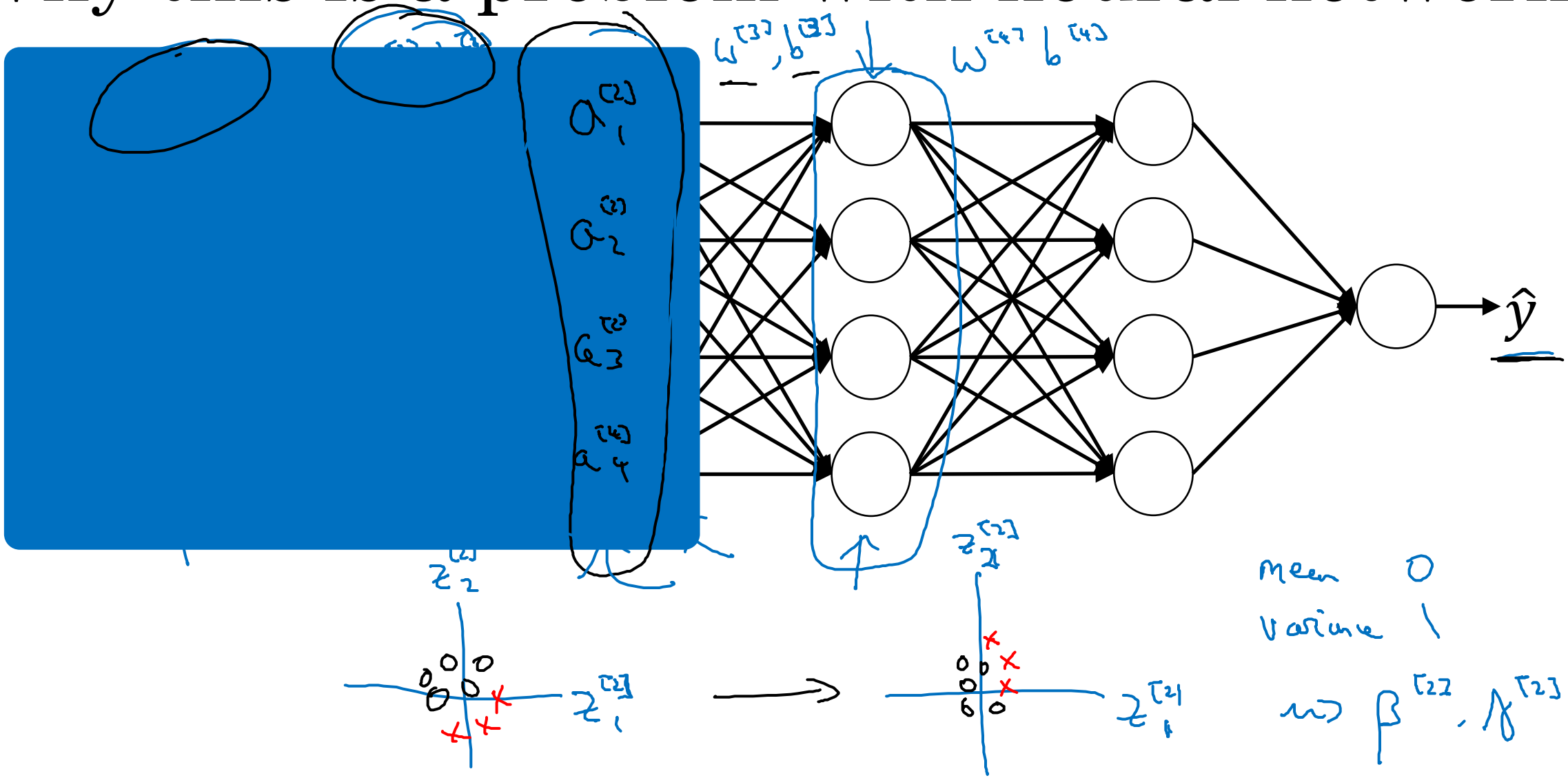
Why this is a problem with neural networks?



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.

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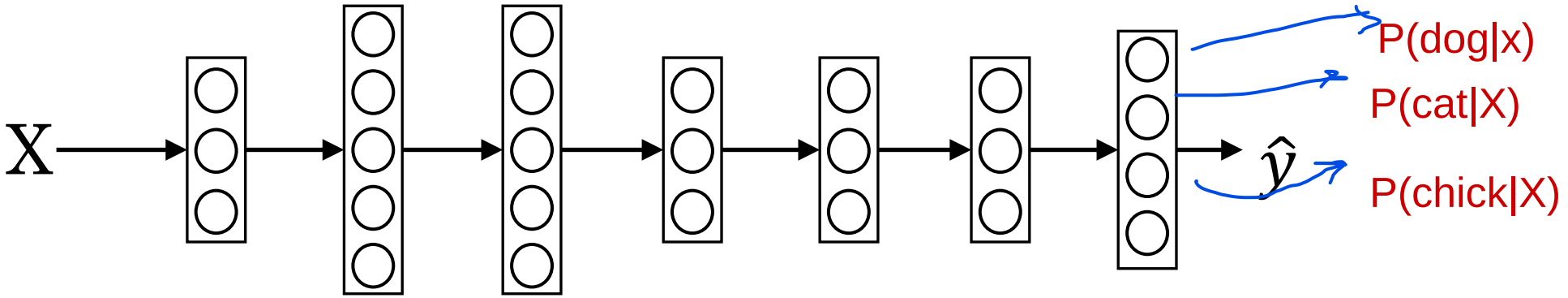
Multi-class classification

Softmax regression

Recognizing cats, dogs, and baby chicks

3 1 2 0 3 2 0 1

Softmax = exp(z1)/ sum(exp(zi))



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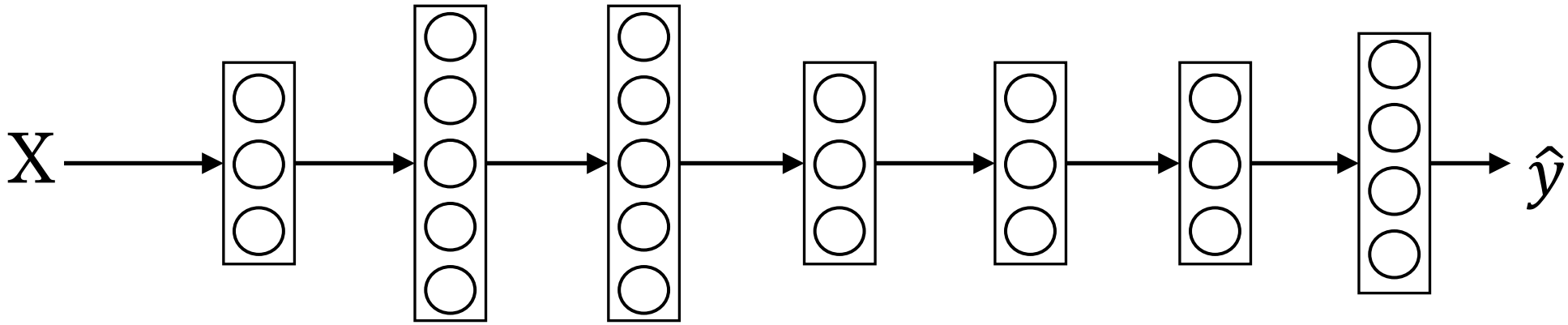
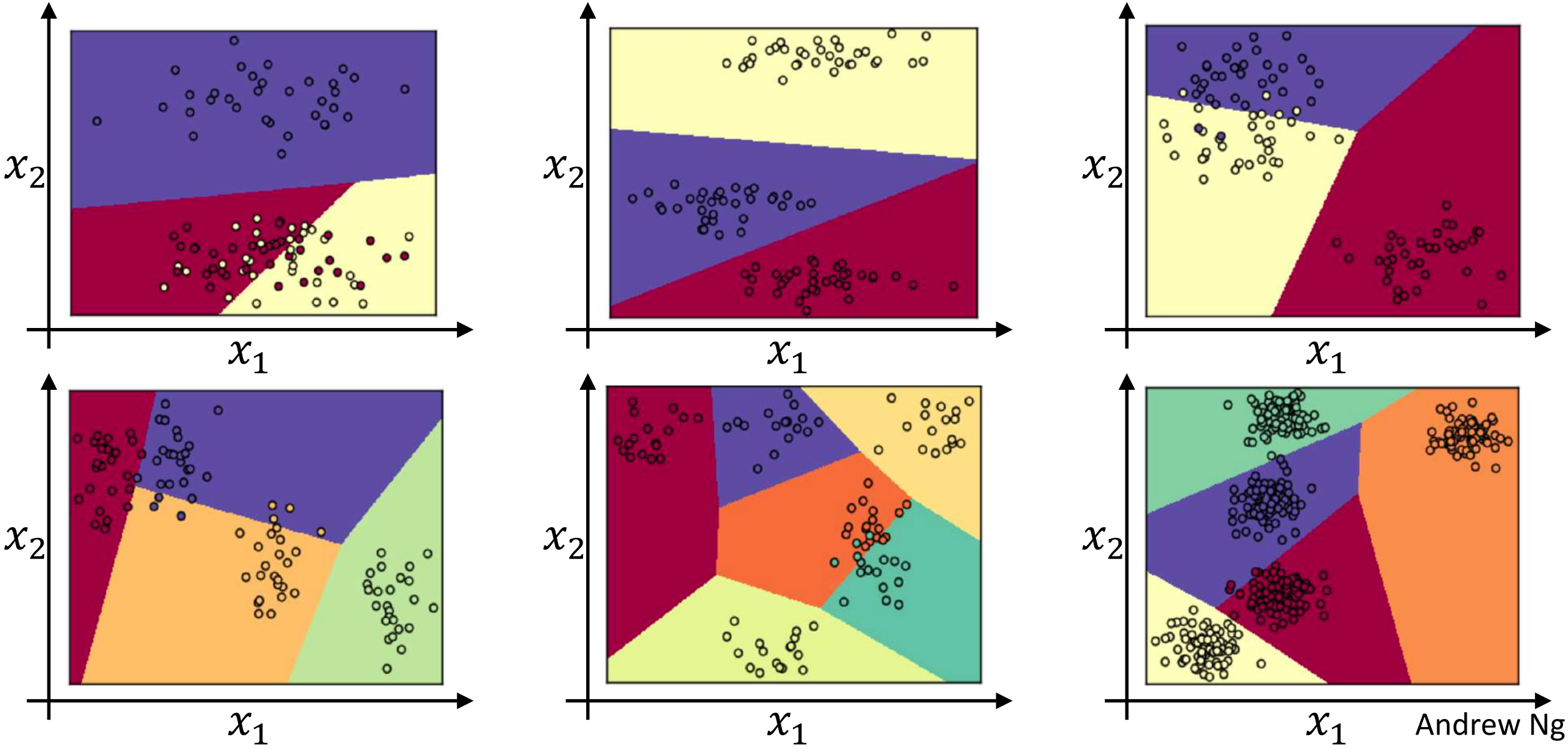
Softmax layer



Softmax examples



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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

$J(w) = w^2 - 10w + 25$

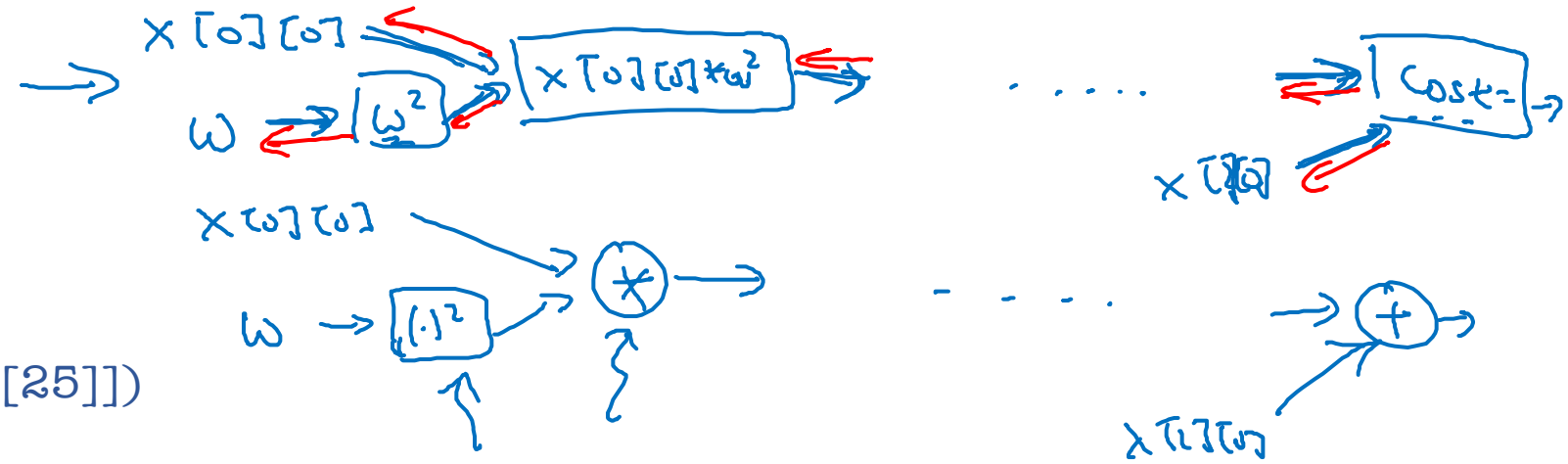
(cost)

$(w-5)^2$

$w = 5$

$J(w, b)$

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))

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

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

Tensorflow creates computation graph on its own; it automatically figures out all the steps for backward propagation.