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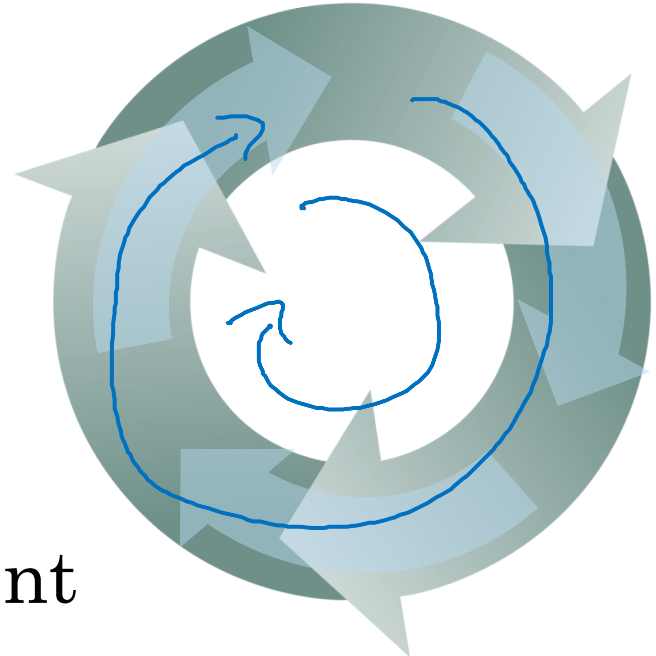
Setting up your ML application

Train/dev/test sets

Applied ML is a highly iterative process

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

Idea



Experiment

Code

NLP, Vision, Speech, Structural data

Ads search Security logistic ....

Train/dev/test sets

training set

- Hold-out cross validation
- Development set "dev"

test

train test

Previous era: 70/30 %

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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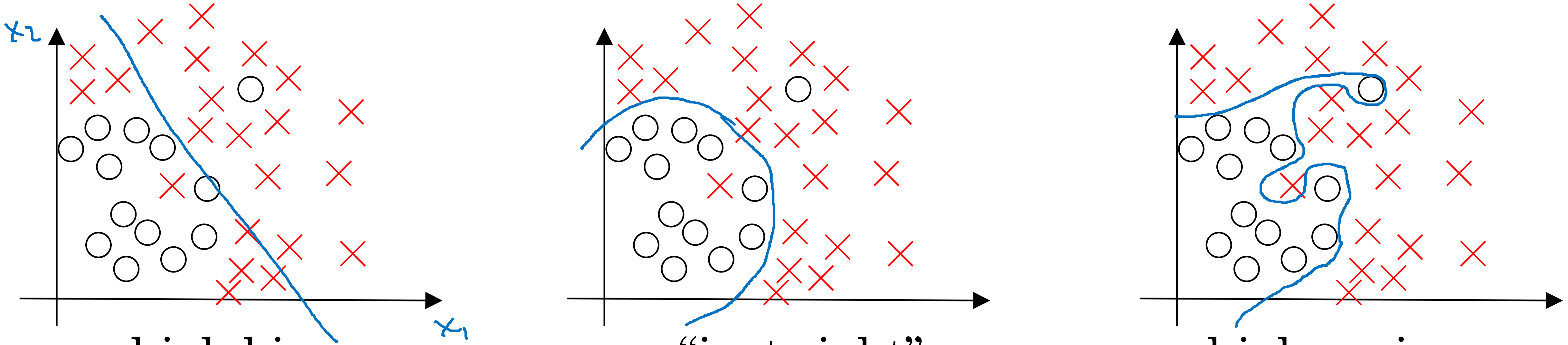
Setting up your ML application

Bias/Variance

Bias and Variance



high bias → "just right" high variance

Underfitting Overfitting

Bias and Variance

Cat classification

y=1

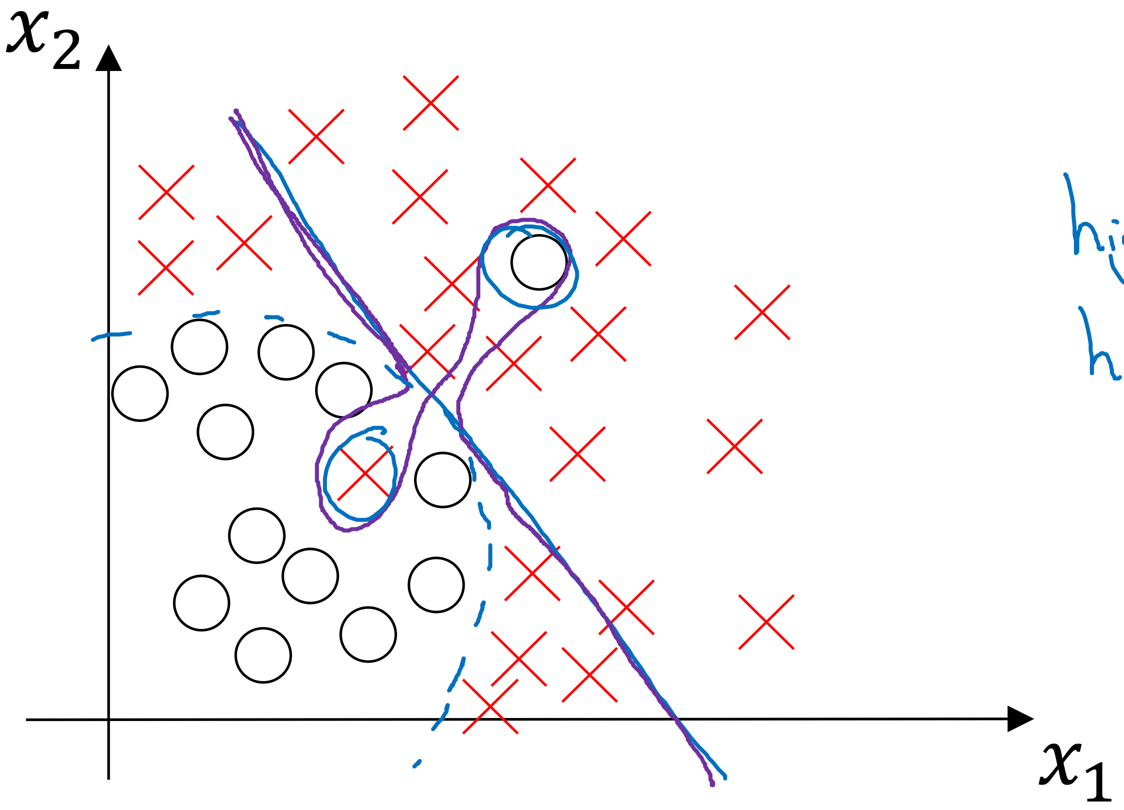
y=0

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

Human: ≈ 0%

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

High bias and high variance



high bias
high varian

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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)

↓ N

High variance?
(dev set performance)

↓ N

Done

→ Y → Bigger network
→ Train longer.
(NN architecture search)

→ Y → More data
→ Regularization
(NN architecture search)

Bias Variance "tradeoff"

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

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

w will be sparse

Neural network

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

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

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

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

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

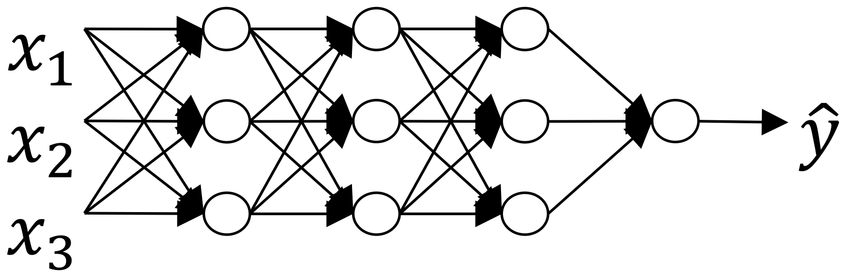
"Weight decay"

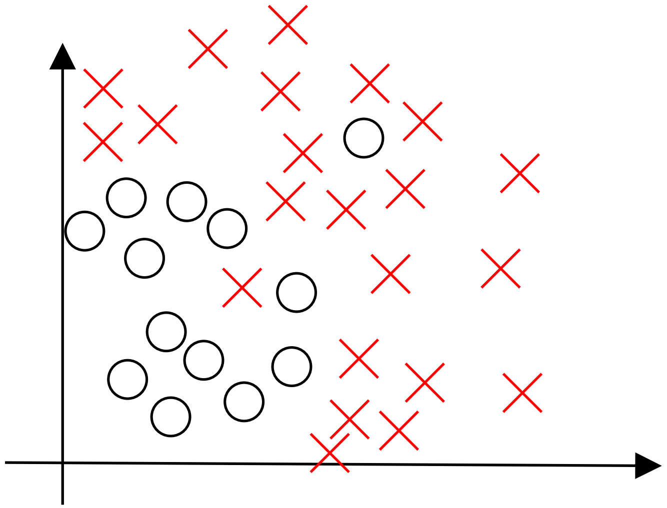
$$w^{[l]} := w^{[l]} - \alpha \left[(\text{from backprop}) + \underline{\frac{\lambda}{m} w^{[l]}} \right]$$

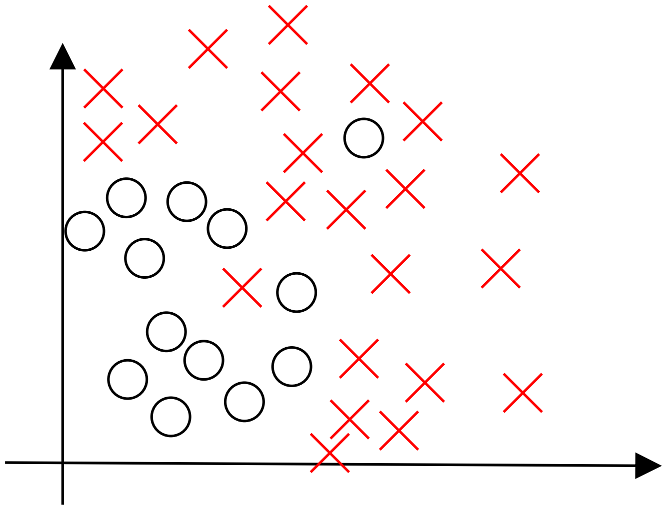
$$= w^{[l]} - \frac{\alpha\lambda}{m} w^{[l]} - \alpha (\text{from backprop})$$

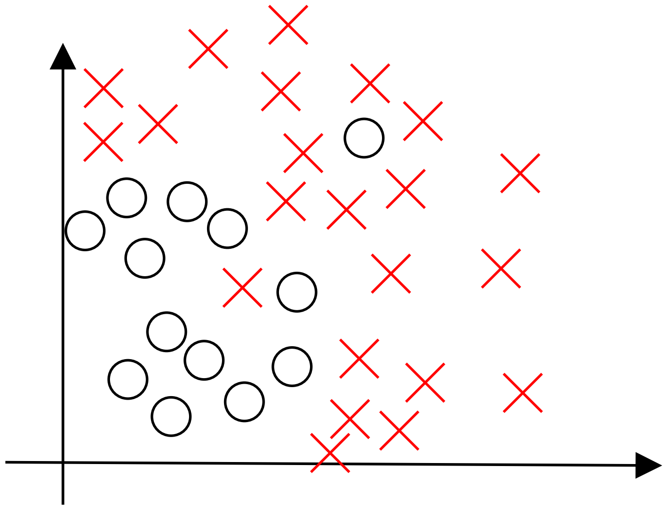
$$= \underbrace{\left(1 - \frac{\alpha\lambda}{m}\right)}_{<1} \underline{w^{[l]}} - \alpha (\text{from backprop})$$

How does regularization prevent overfitting?









How does regularization prevent overfitting?

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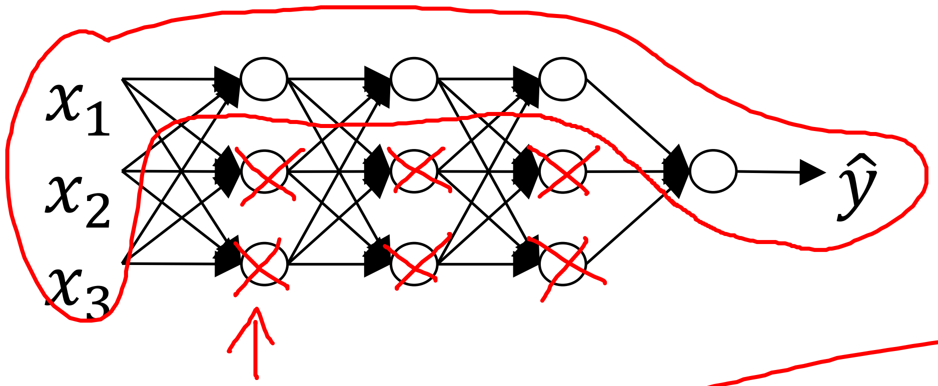
Regularizing your neural network

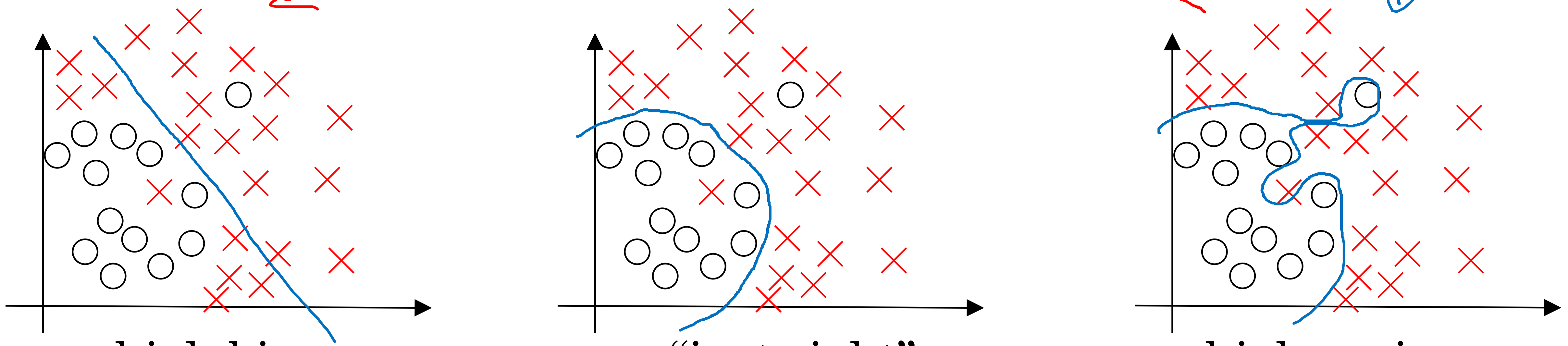
Why regularization reduces overfitting

How does regularization prevent overfitting?



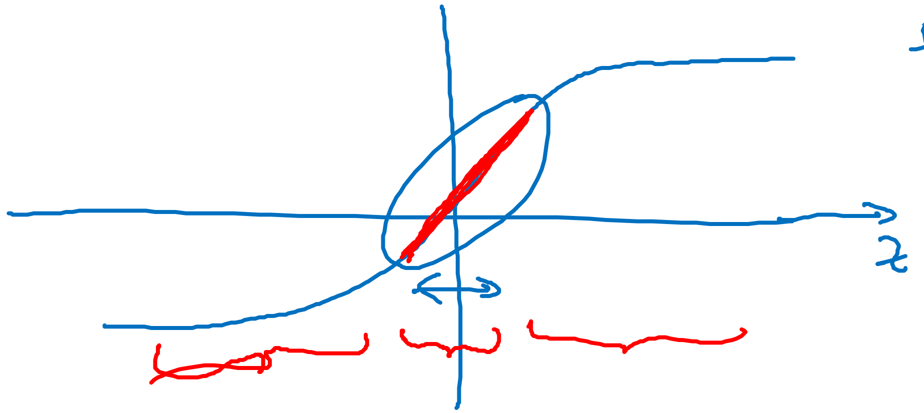
$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2$$

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



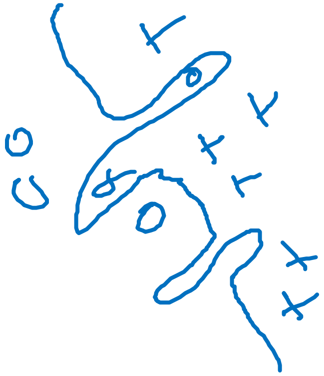
high bias | "just right" | high variance

How does regularization prevent overfitting?



tanh

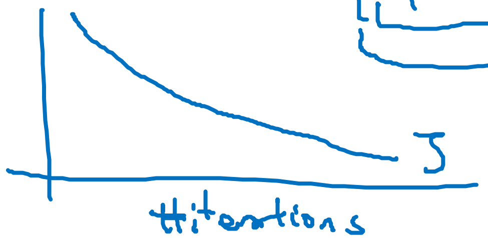
$g(z) = \tanh(z)$



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

Every layer ≈ linear.

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



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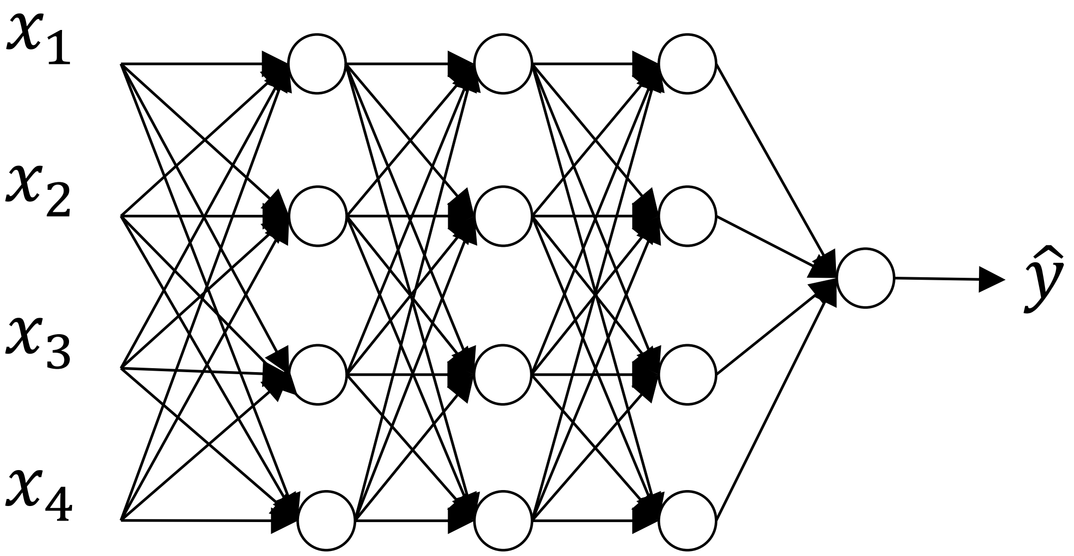
Regularizing your neural network

Dropout regularization

Dropout regularization



0.5 0.5 0.5

Implementing dropout ("Inverted dropout")

Illustrate with layer $l=3$. keep-prob $= 0.8$ $\quad 0.2$

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

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

$\rightarrow \boxed{a3 \mathrel{/}= \cancel{0.8}\ \text{keep-prob}} \leftarrow$

50 units. ⇝ 10 units shut off

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

reduced by 20%. Test

$/= 0.8$

Making predictions at test time

$a^{[0]} = X$

No drop out.

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

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

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

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

$\downarrow$

$\hat{y}$

/= keep-prob

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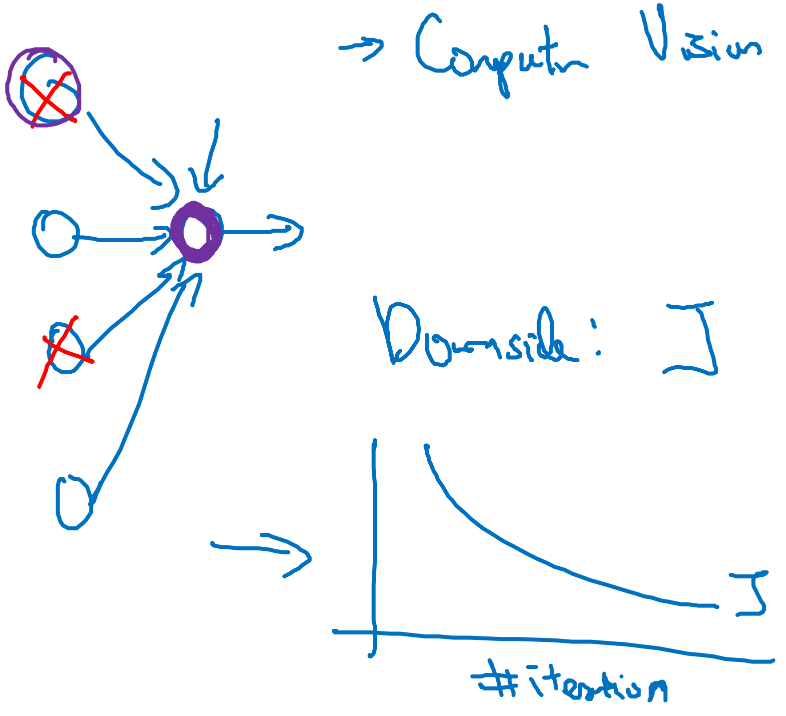
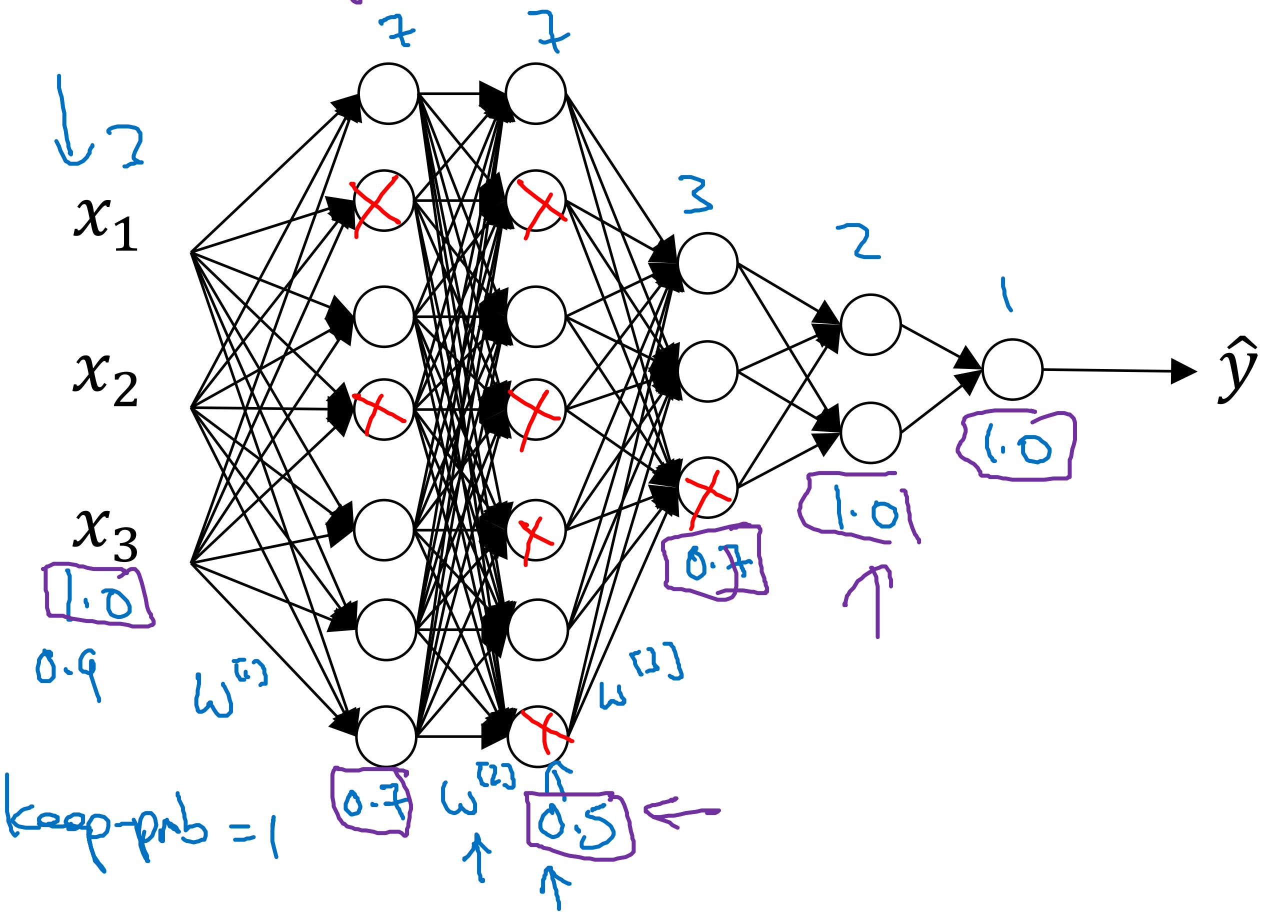
Regularizing your neural network

Understanding dropout

Why does drop-out work?

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





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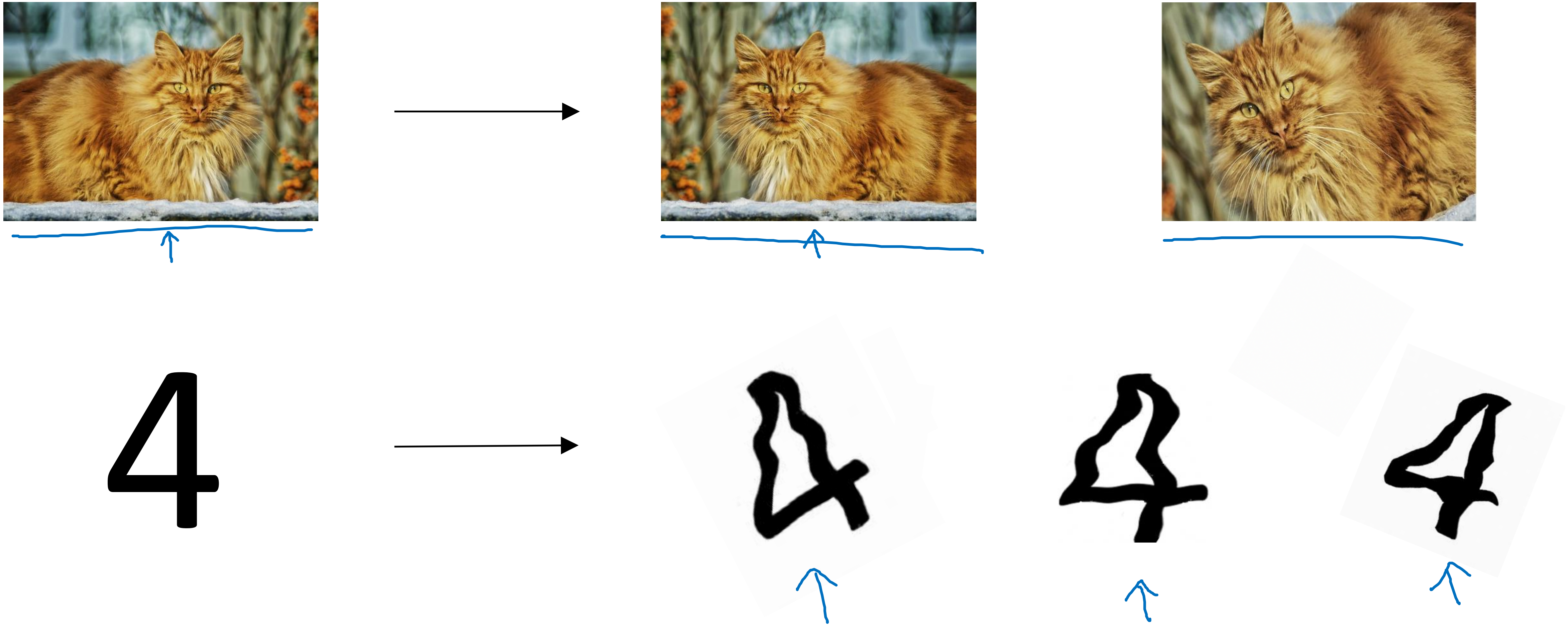
Regularizing your neural network

Other regularization methods

Data augmentation



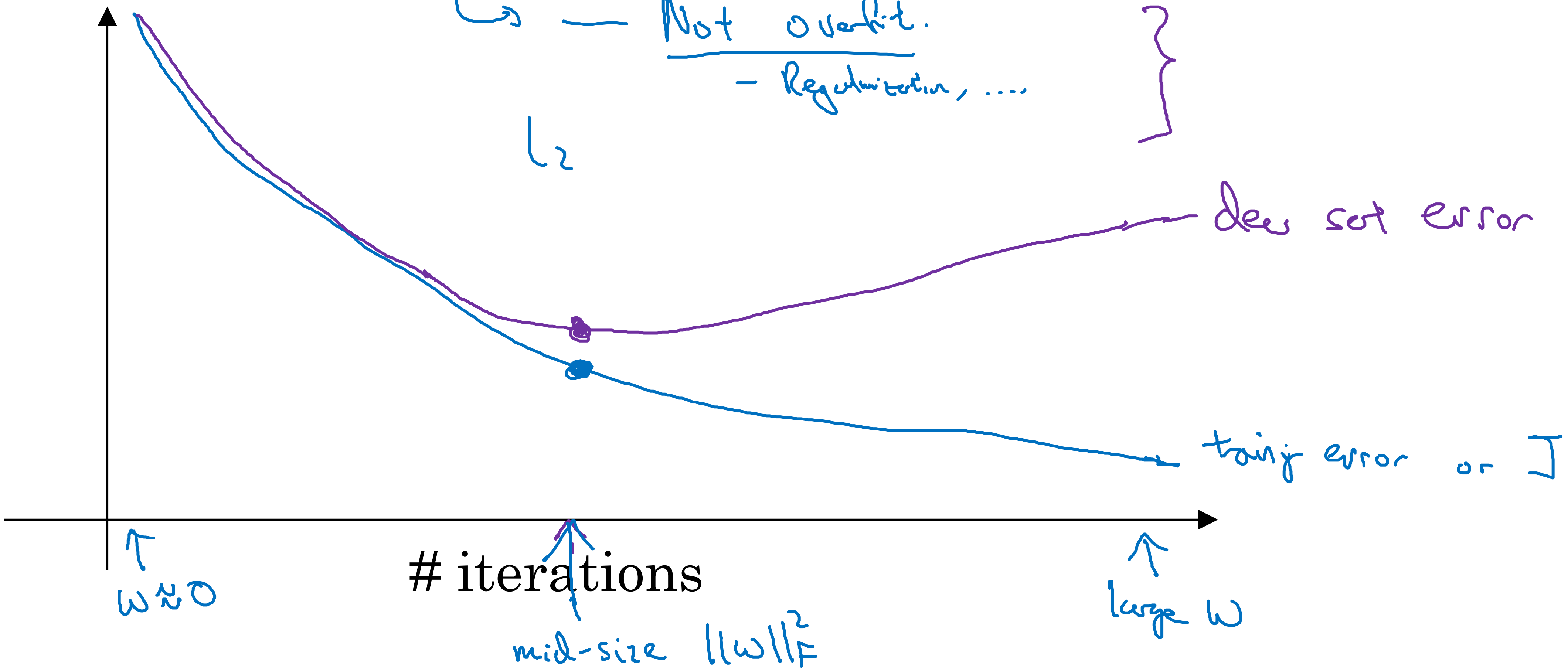
Early stopping

Orthogonalization.

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

L_2

$J(w,b)$



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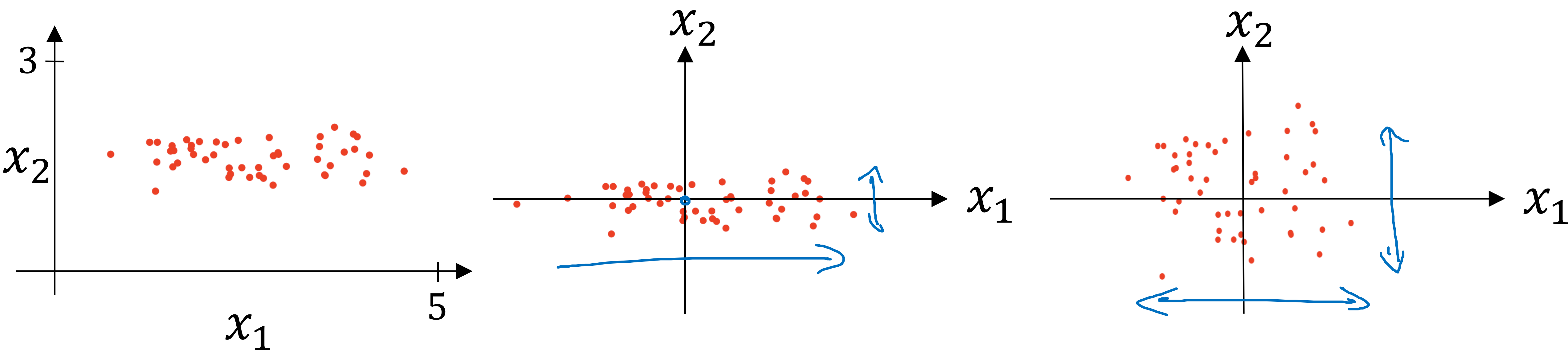
Setting up your optimization problem

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.

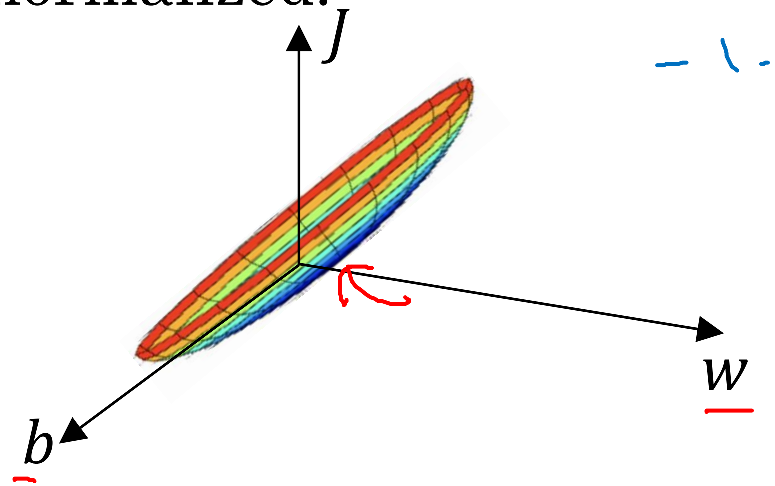
Why normalize inputs?

w_1 x_1: $1 \ldots 1000$ ←

w_2 x_2: $0 \ldots 1$ ←

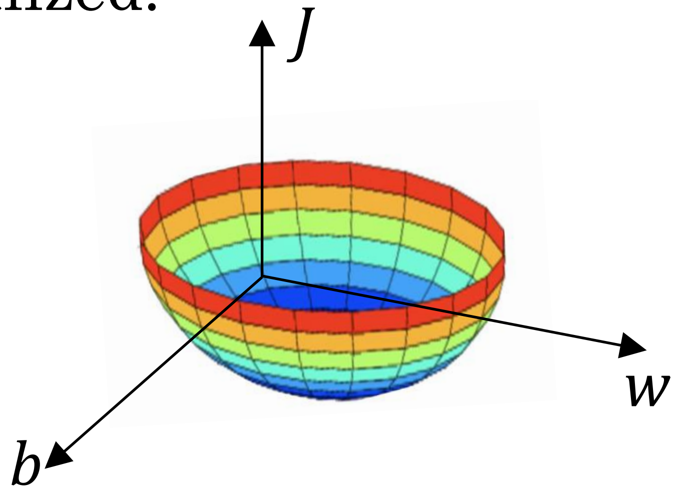
$$J(w,b) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

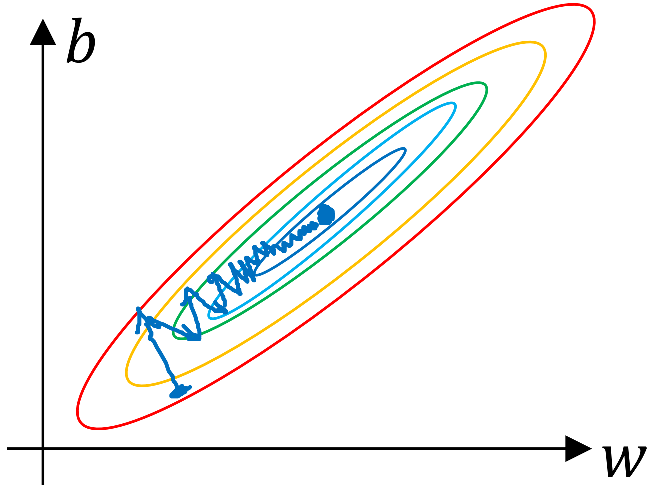
Unnormalized:



$-1 \ldots 1$

Normalized:

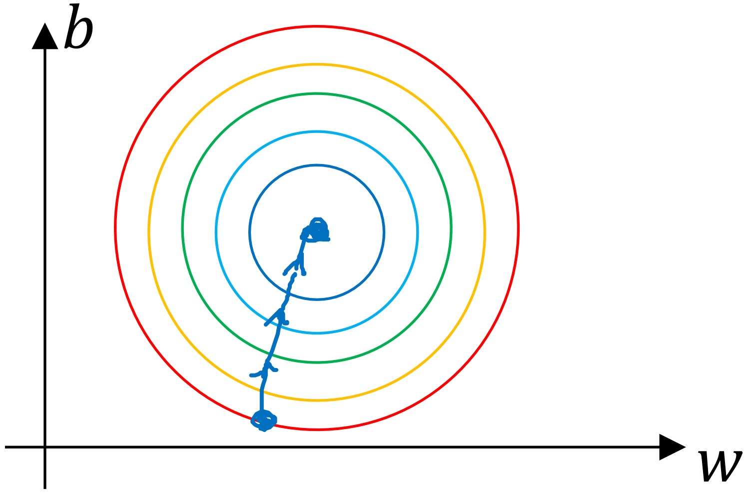




x_1: $0 \ldots 1$

x_2: $-1 \ldots 1$

x_3: $1 \ldots 2$



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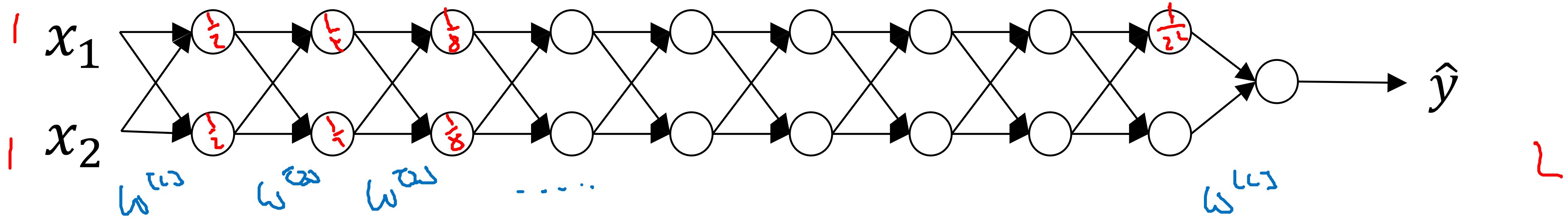
Setting up your optimization problem

Vanishing/exploding gradients

Vanishing/exploding gradients

$L = 150$



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

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

1.5^L

0.5^L

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

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

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

$W^{[l]} > I$

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

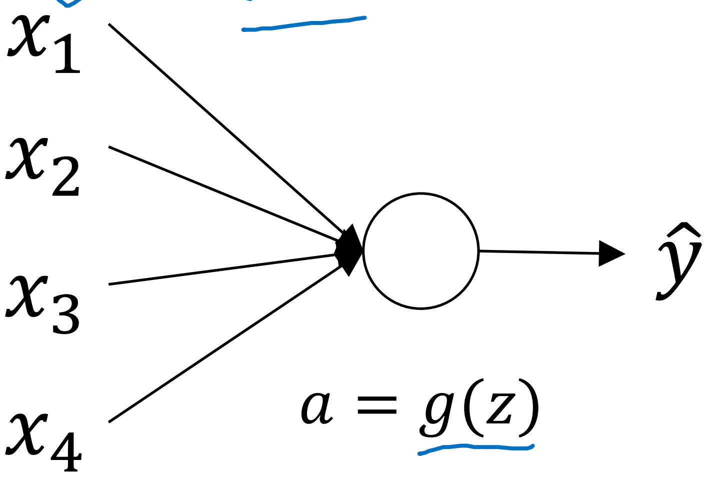
$$W^{[l]} = \begin{bmatrix} \cancel{1.5}\ 0.5 & 0 \\ 0 & \cancel{1.5}\ 0.5 \end{bmatrix}$$

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

$1.5^{L-1} x$

$0.5^{L-1} x$

Single neuron example



$a^{[l]}$

$W^{[l]}$

$a = g(z)$

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

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

Numerical approximation of gradients

Checking your derivative computation

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

$\theta \in \mathbb{R}$

J

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

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

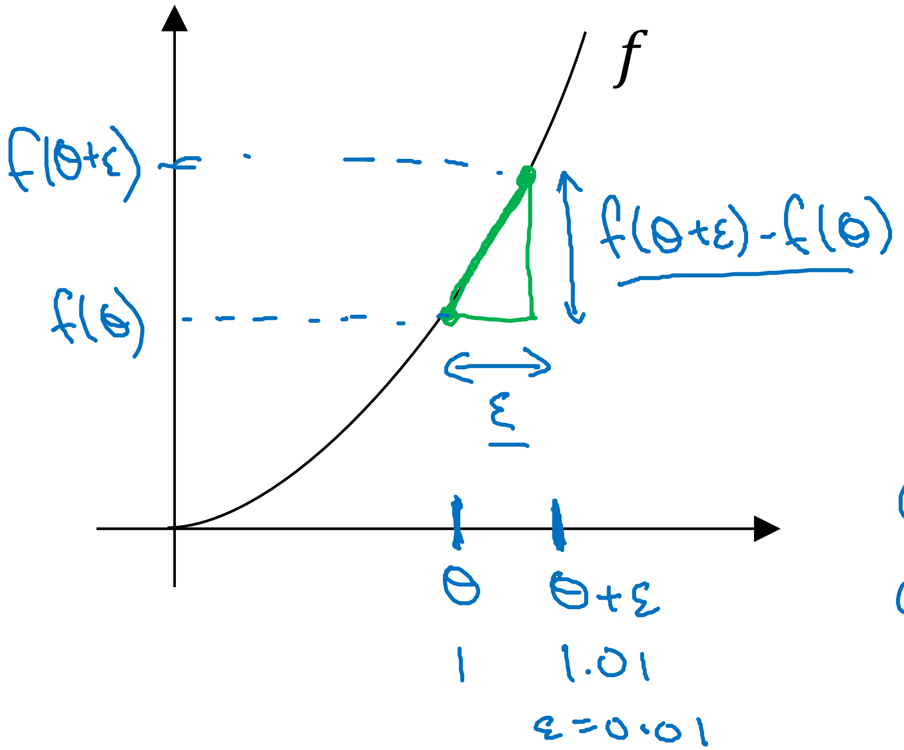
$g(\theta) = 3 \cdot (1)^2 = 3$ when $\theta = 1$

dw

db

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

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



$\theta = 1$

$\theta + \varepsilon = 1.01$

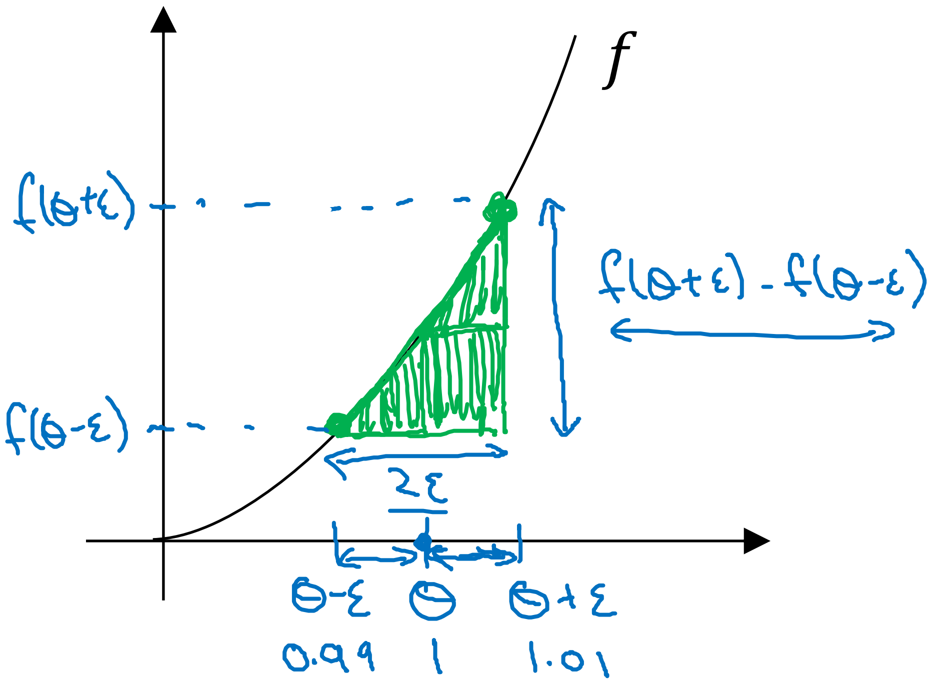
0.0301

3.1

3.2

Checking your derivative computation

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



$\varepsilon = 0.01$

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

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

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

approx error: 0.0001

(prev slide: 3.0301. error: 0.03)

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

0.01

$\underline{0.0001}$

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

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 $J(\theta)$?

Gradient checking (Grad check)

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

for each i :

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

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

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

Check

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

$\underline{\varepsilon = 10^{-7}}$

10^{-5}

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

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

- 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 w.r.t. 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

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

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

$x^{(i)}$

$z^{[l]}$

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

Mini-batch gradient descent

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

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

$\underline{X, Y}$

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)

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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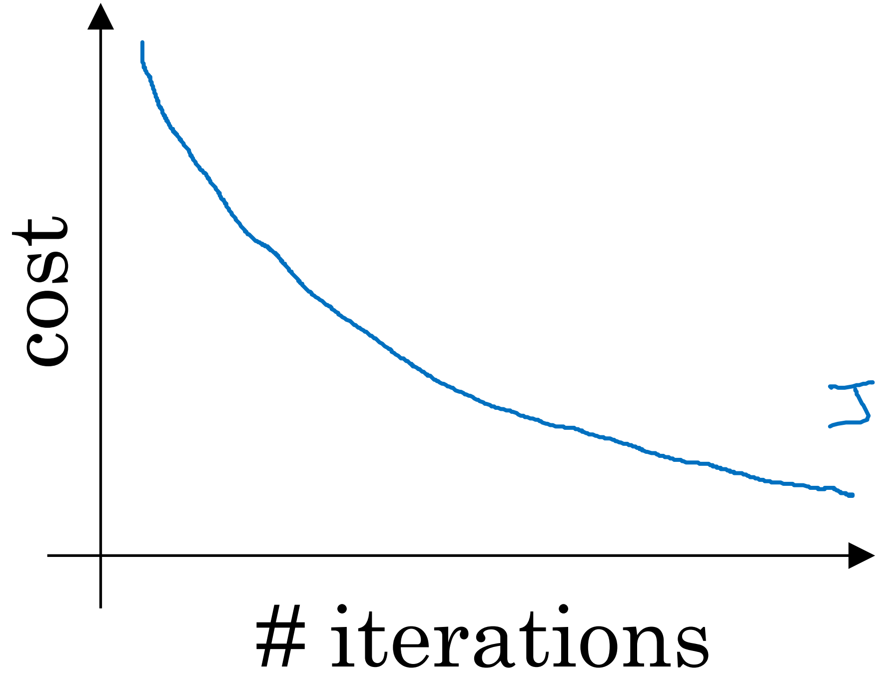
Optimization Algorithms

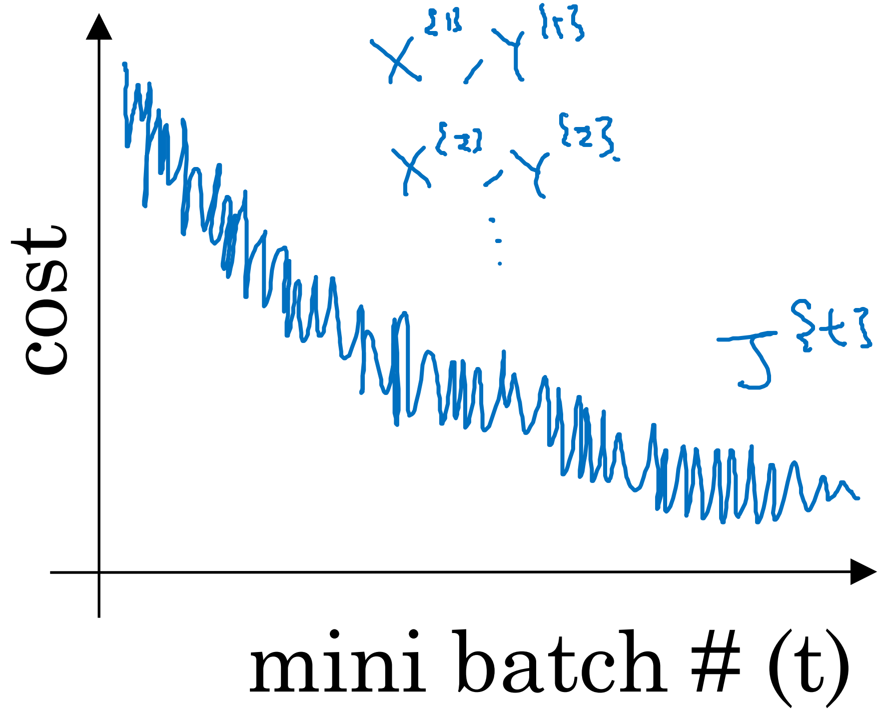
Understanding mini-batch gradient descent

Training with mini batch gradient descent

Batch gradient descent



Mini-batch gradient descent



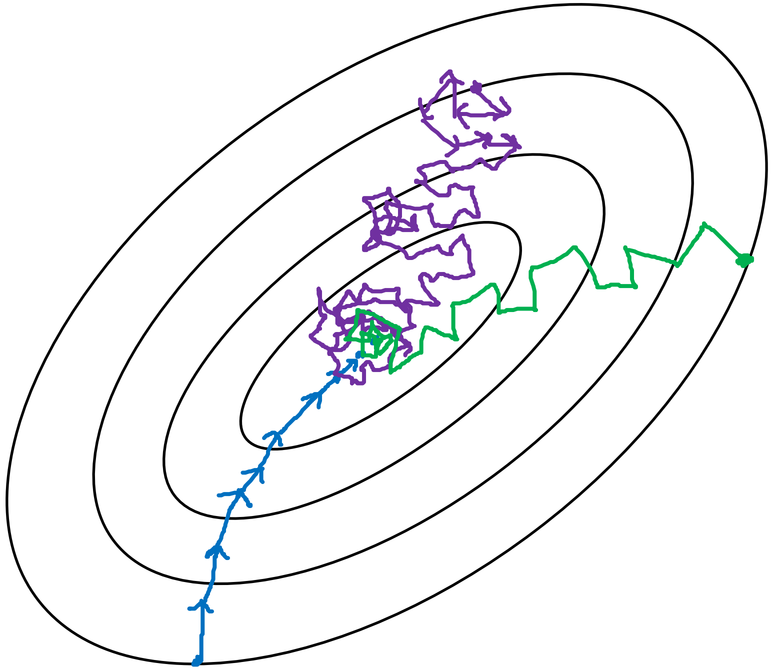
Plot $J^{\{t\}}$ computed using $X^{\{t\}}, Y^{\{t\}}$

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: Somewhere in-between $\underline{1}$ and $\underline{m}$



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

Choosing your mini-batch size

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

Typical mini-batch sizes:

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

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

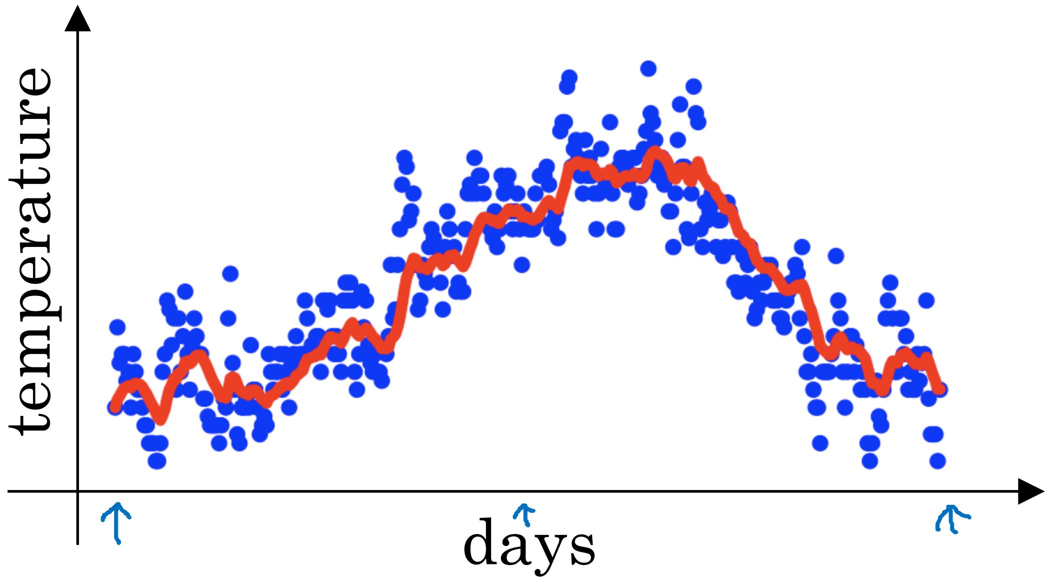
$\theta_3 = 45°F$ ⋮

⋮

$\theta_{180} = 60°F$ 15°C

$\theta_{181} = 56°F$ ⋮

⋮



$V_0 = 0$

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

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

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

⋮

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

Exponentially weighted averages

moving

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

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

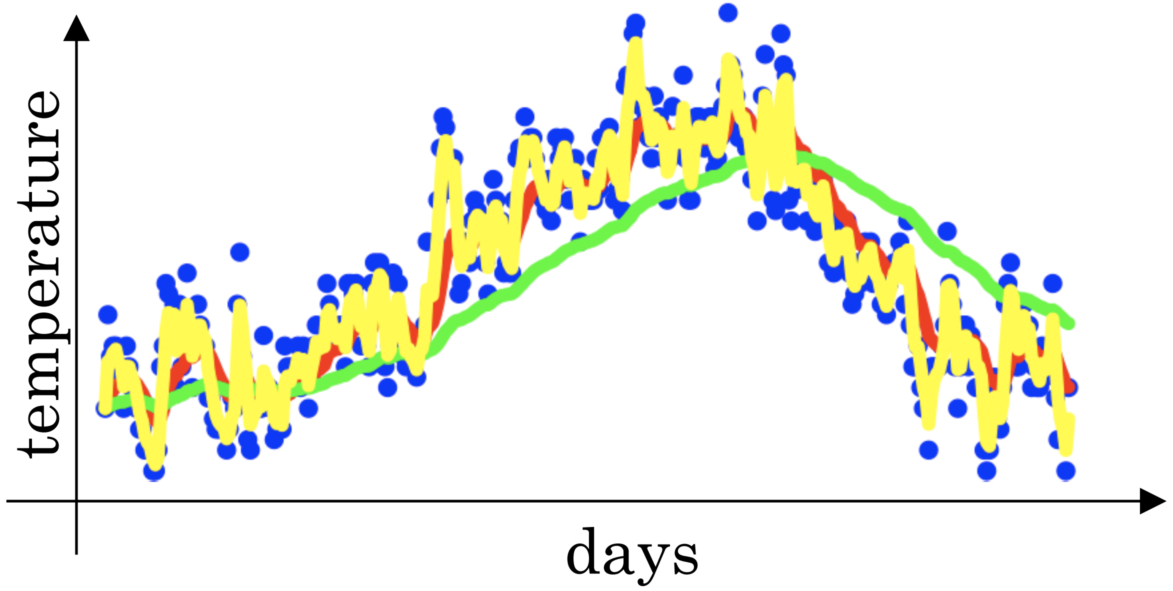
$\beta = 0.98$: ≈ 50 days

$\beta = 0.5$: ≈ 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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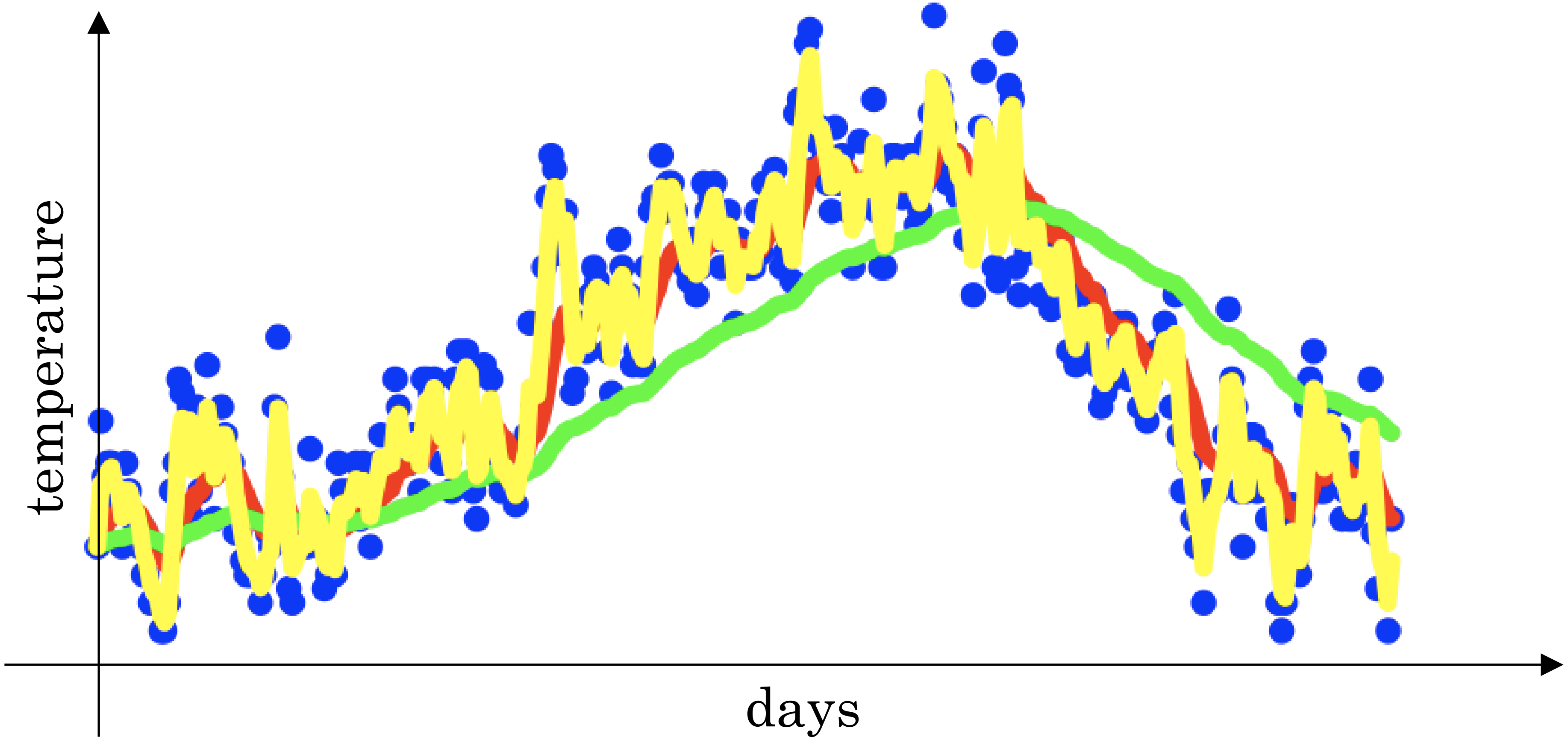
Optimization Algorithms

Understanding exponentially weighted averages

Exponentially weighted averages

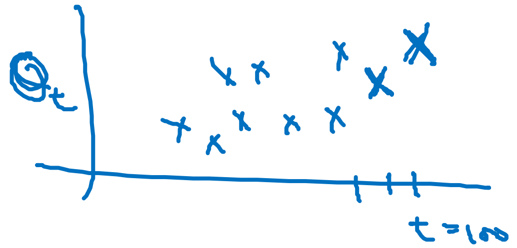
$$\boxed{v_t = \beta v_{t-1} + (1-\beta)\theta_t}$$

$\beta = 0.9$ $\quad 0.98 \quad 0.5$



Exponentially weighted averages

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

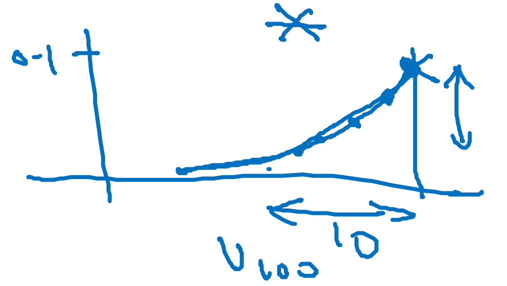


$$v_{100} = 0.9 v_{99} + 0.1\theta_{100}$$

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

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

…



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

$$\varepsilon = 1-\beta$$

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

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

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

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

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

$$0.98^{?}$$

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

Implementing exponentially weighted averages

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

$V_\theta := 0$

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

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

$\vdots$

$\rightarrow V_\theta = 0$

Repeat {

Get next θ_t

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

}

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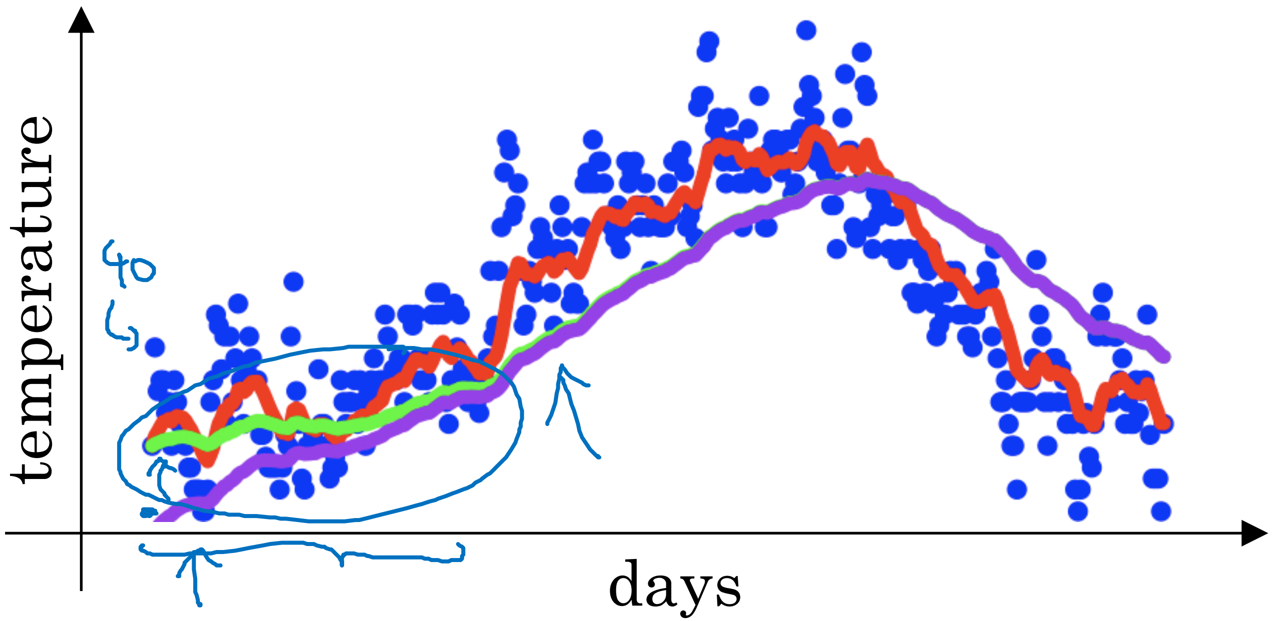
Optimization Algorithms

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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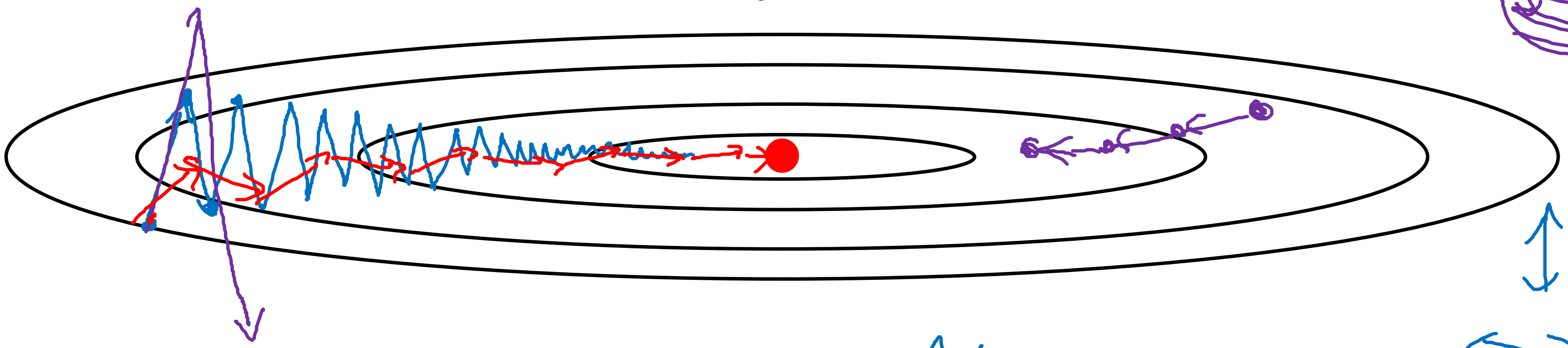
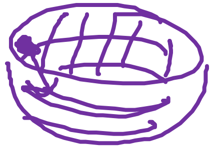
Optimization Algorithms

Gradient descent with momentum

Gradient descent example





↕ 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

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

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

Implementation details

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

On iteration t:

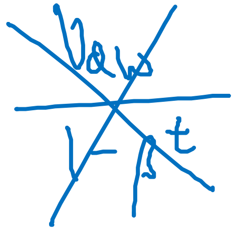
Compute dW, db on the current mini-batch

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

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

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

$$\underbrace{V_{dw} = \beta V_{dw} + \quad dW}$$



Hyperparameters: α, β

$\beta = 0.9$

average over last ≈ 10 gradients

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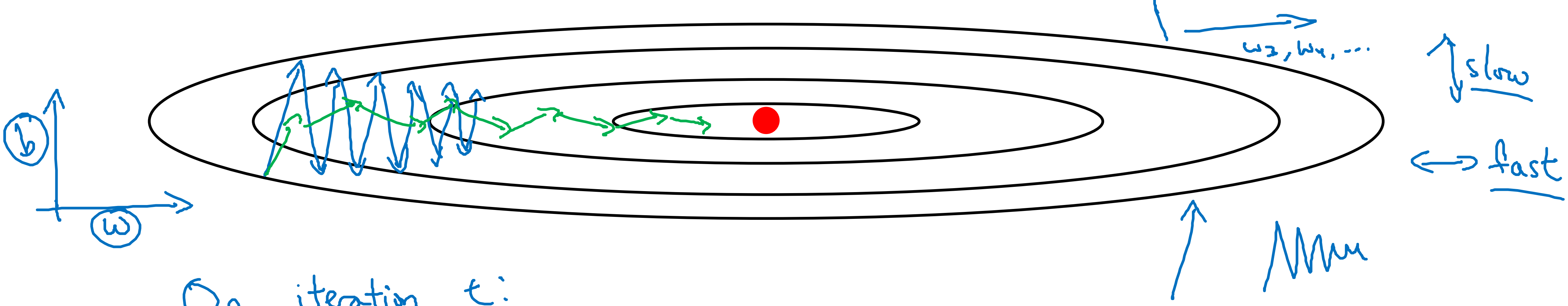
Optimization Algorithms

RMSprop

RMSprop



On iteration t:

Compute dW, db on current mini-batch

element-wise

$$S_{dW} = \beta_2 S_{dW} + (1-\beta_2)\, dW^2 \quad \leftarrow \text{small}$$

$$\rightarrow S_{db} = \beta_2 S_{db} + (1-\beta_2)\, db^2 \quad \leftarrow \text{large}$$

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

$\varepsilon = 10^{-8}$

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Optimization Algorithms

Adam optimization algorithm

Adam optimization algorithm

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

On iteration t:

Compute dW, db using current mini-batch

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

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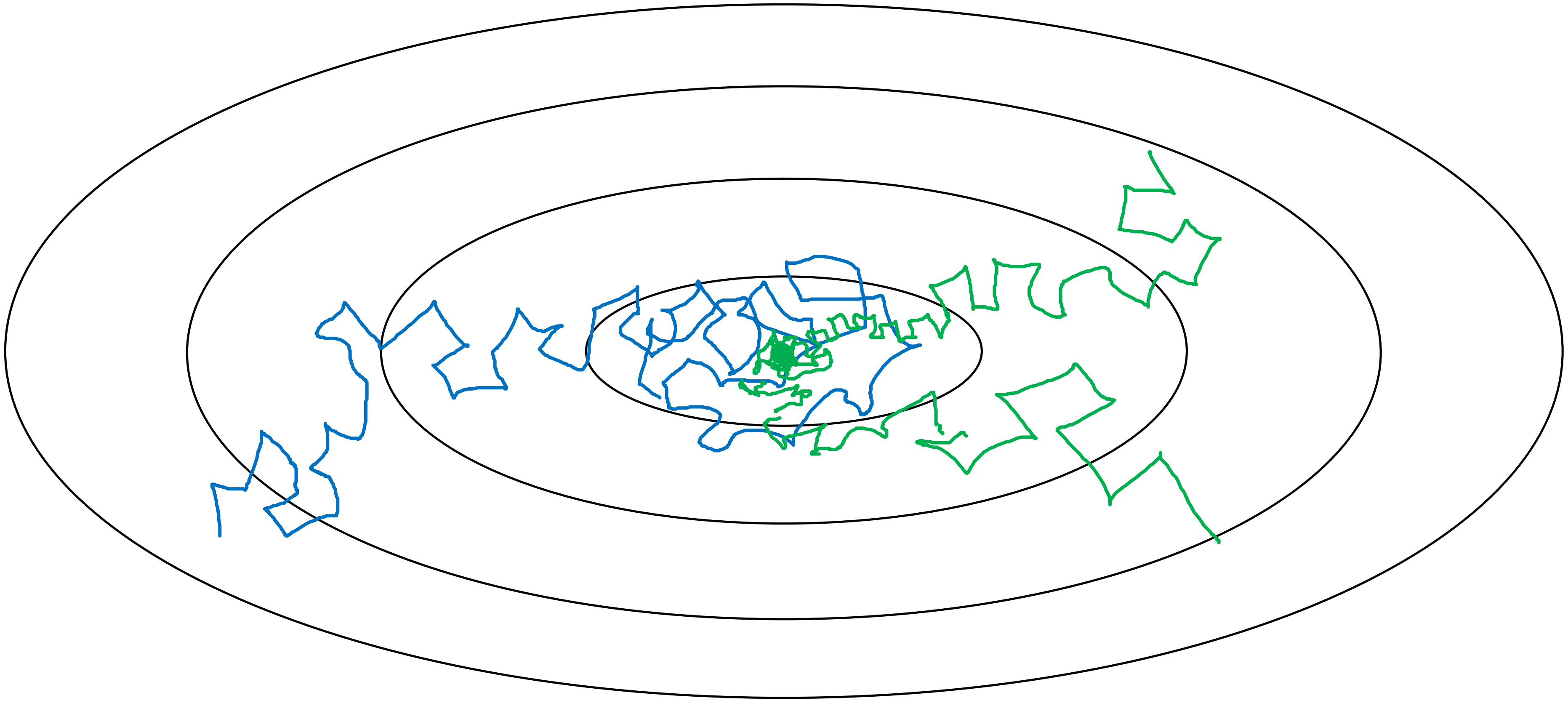
Optimization Algorithms

Learning rate decay

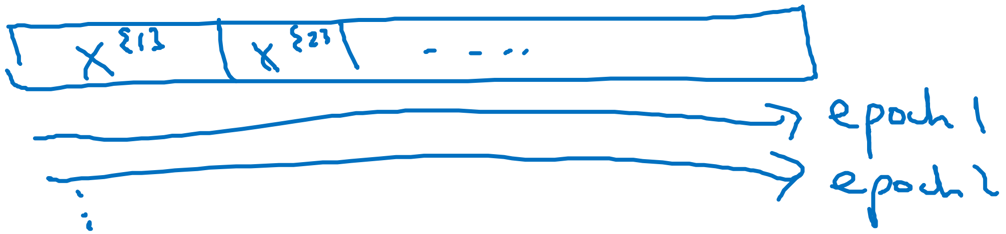
Learning rate decay

Slowly reduce α



Learning rate decay

1 epoch = 1 pass through data.

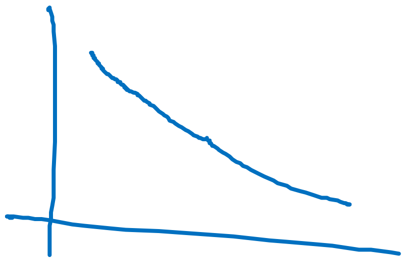


$$\underbrace{\alpha = \frac{1}{1 + \underline{\text{decay-rate}} * \text{epoch-num}}\,\underline{\alpha_0}}$$

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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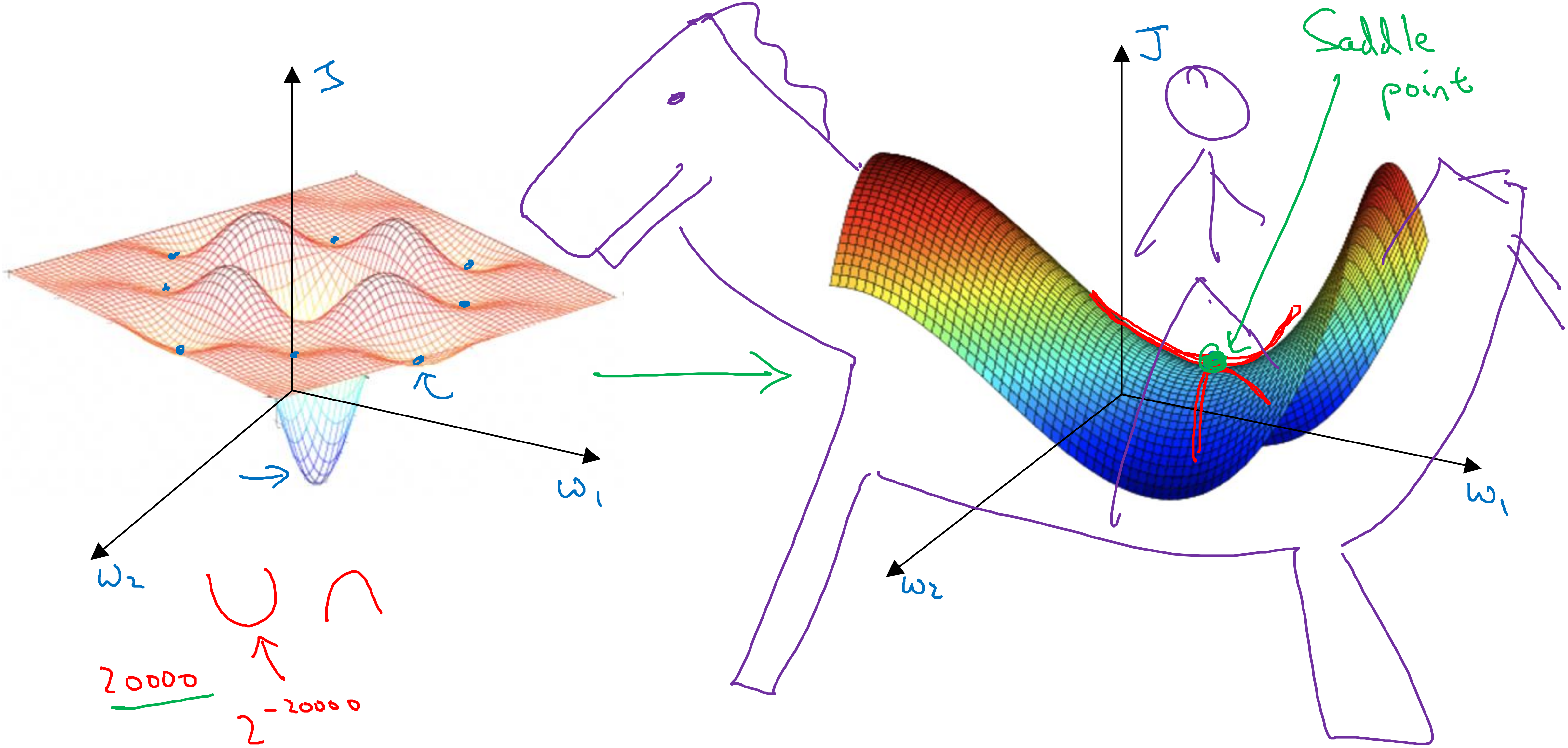
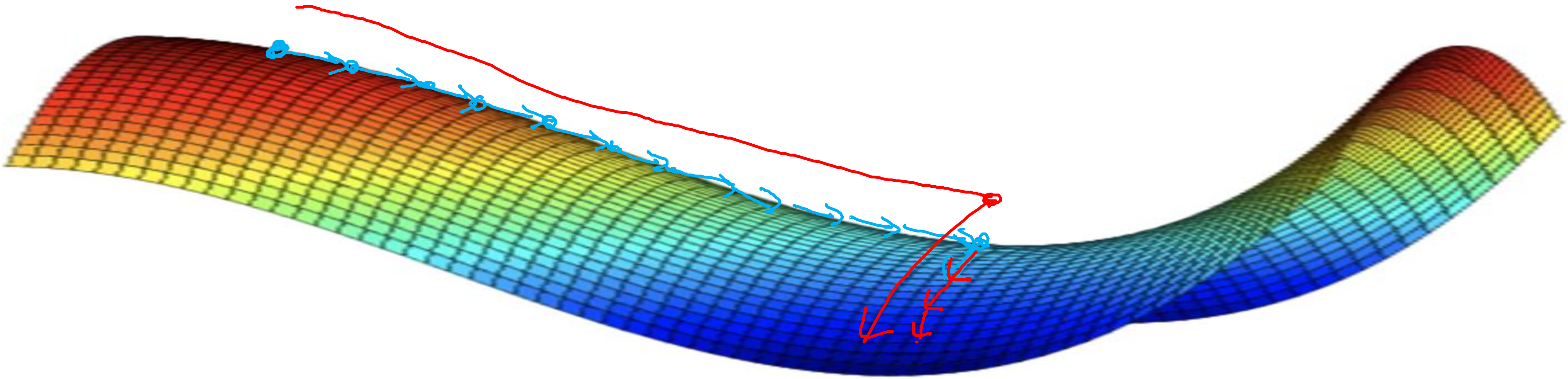
Optimization Algorithms

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

→ $\boxed{\alpha}$

$\boxed{\beta}$ ~0.9

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

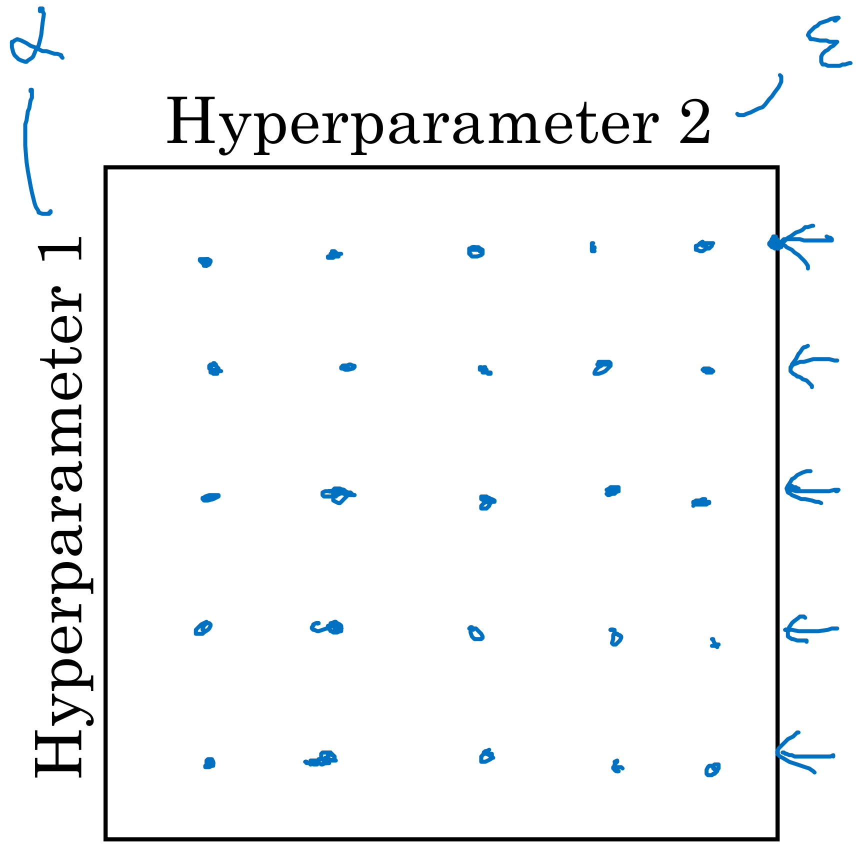
layers

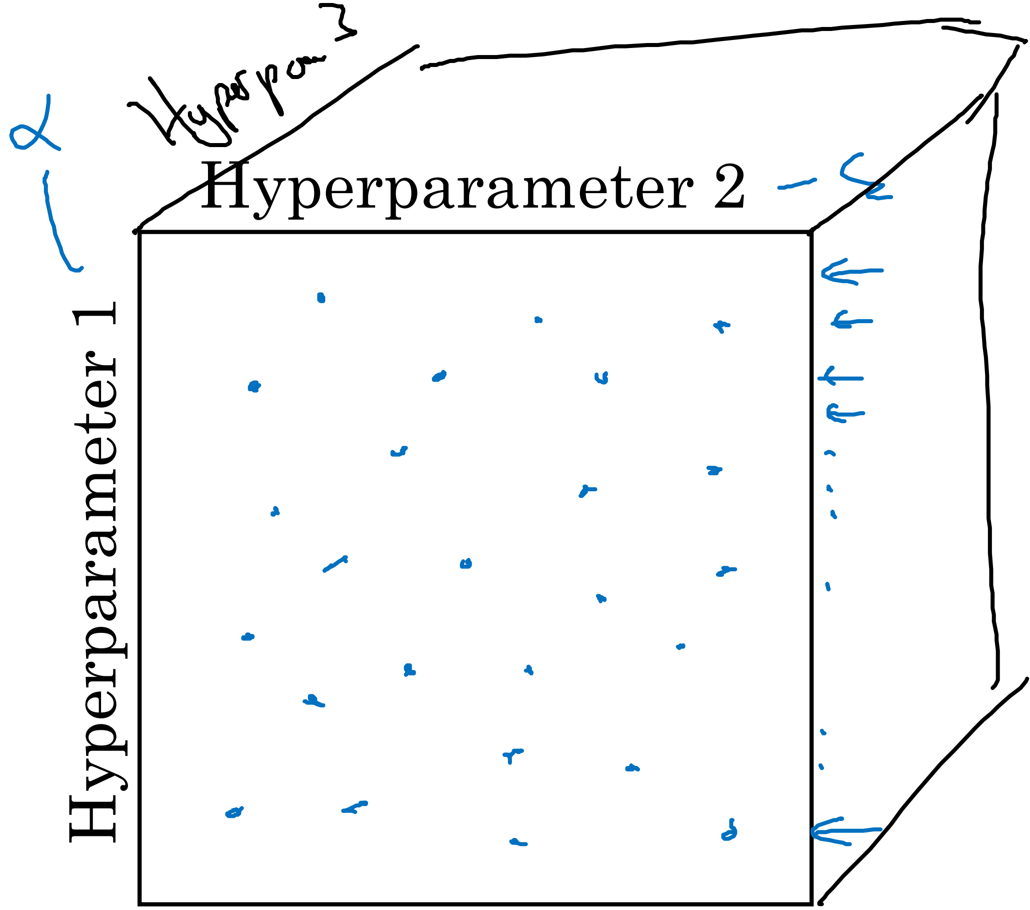
hidden units

learning rate decay

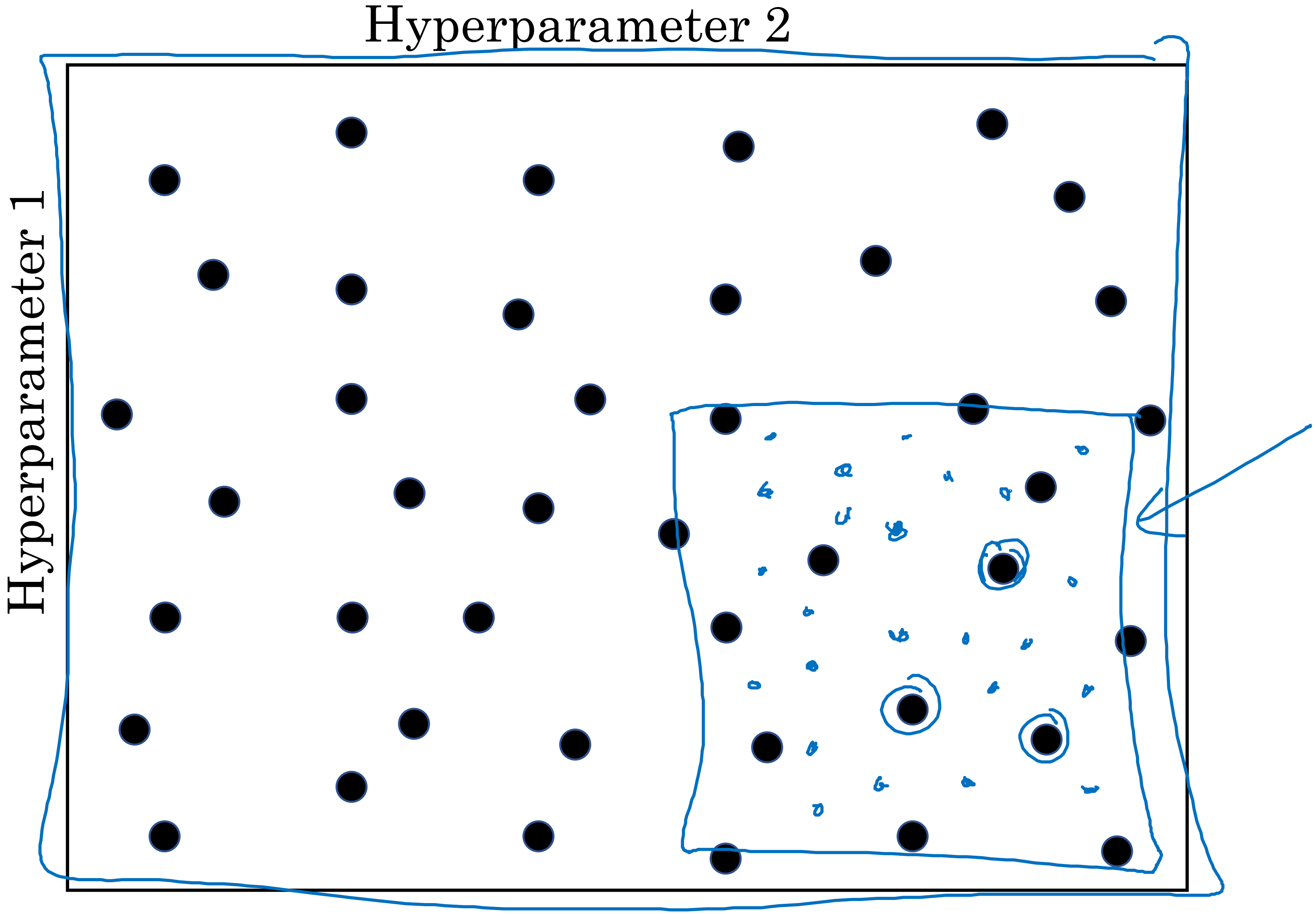
mini-batch size

Try random values: Don’t use a grid





Coarse to fine



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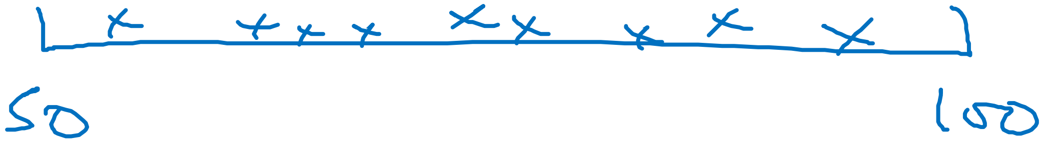
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \ldots, 100$



→ #layers L: 2 – 4

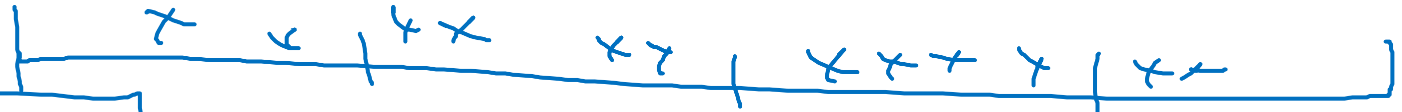
2, 3, 4

Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$

0.0001 $\qquad$ 1

0.1 – – – – – – – 1



$\boxed{0.0001}$ $\quad 0.001 \quad 0.01 \quad 0.1 \quad$ $\boxed{1}$

10^{-4} $\qquad$ 10^{0}

10^{a} $\qquad$ 10^{b}

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

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

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

$10^{a} \ldots 10^{b}$ $\qquad$ $r \in [a, b]$ $\qquad$ $\alpha = 10^{r}$

$[-4, 0]$

Hyperparameters for exponentially weighted averages

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

$10 \qquad\qquad 1000$

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

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

$\beta: 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

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

0.9 0.999

0.9 0.99 0.999

0.1 0.01 0.001

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

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

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

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

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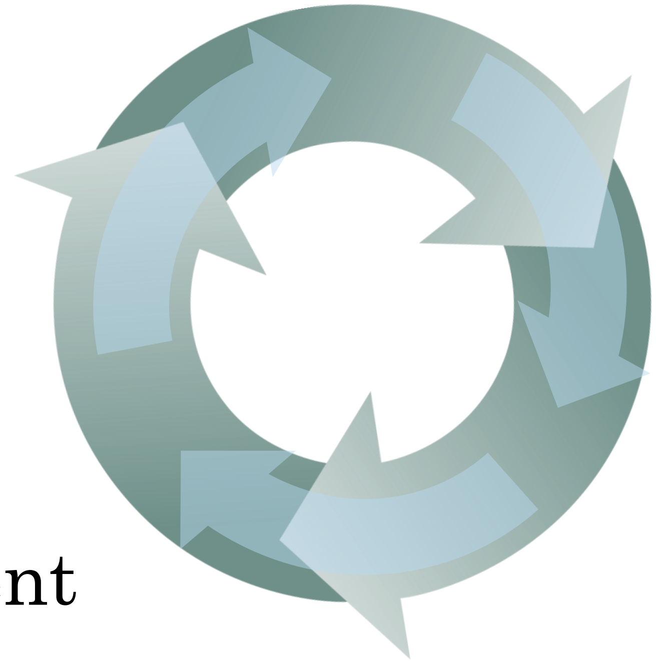
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

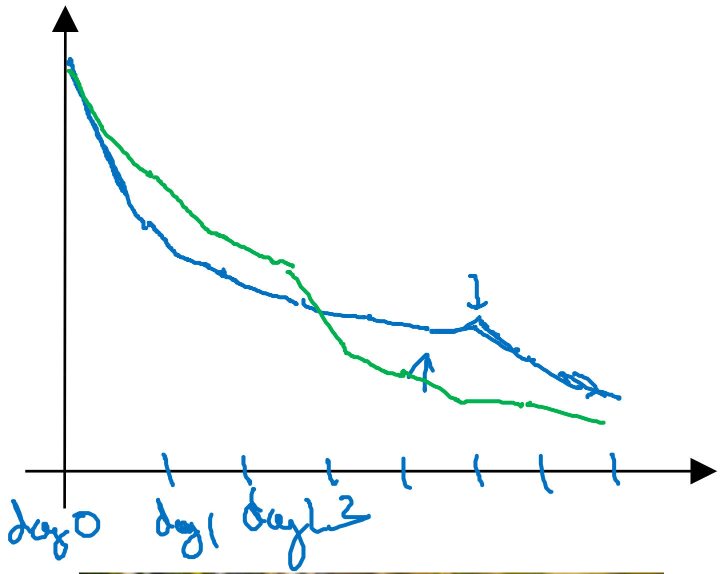
Re-test hyperparameters occasionally

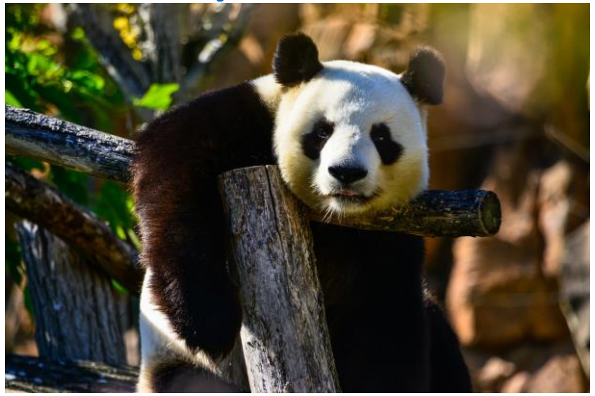


- NLP, Vision, Speech, Ads, logistics, ….

- Intuitions do get stale. Re-evaluate occasionally.

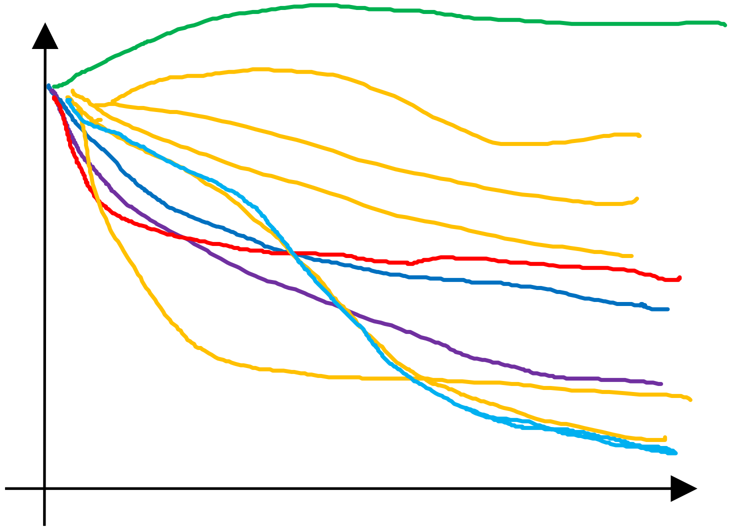
Babysitting one model





Panda

Training many models in parallel



Caviar

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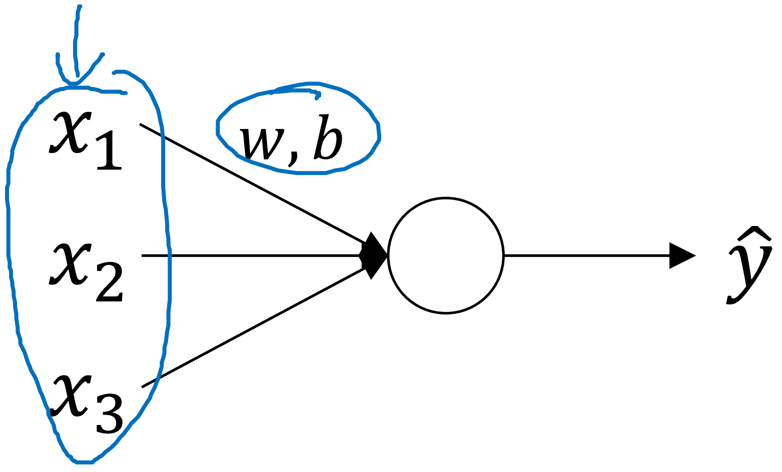
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning

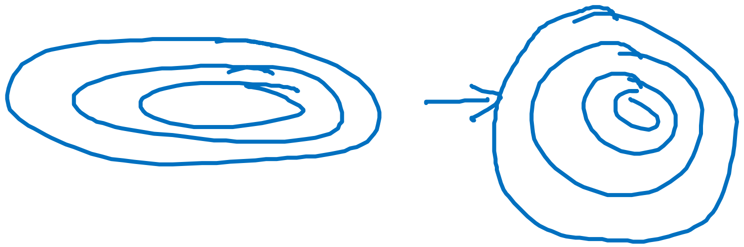


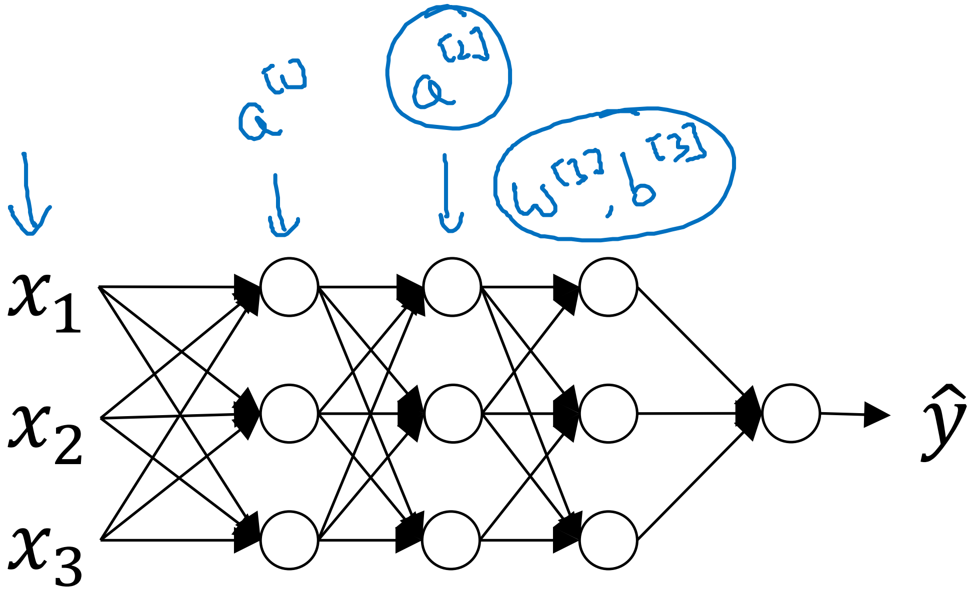
$$\mu = \frac{1}{m} \sum_i x^{(i)}$$

$$X = X - \mu$$ ← 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 $\underbrace{z^{(1)}, \ldots, z^{(m)}}_{z^{[l](i)}}$

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

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

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

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

learnable parameters of model.

If

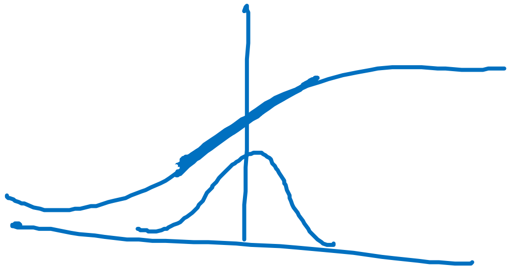
$$\gamma = \boxed{\sqrt{\sigma^2 + \varepsilon}}$$

$$\beta = \boxed{\mu}$$

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

X

$z^{(i)}$



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

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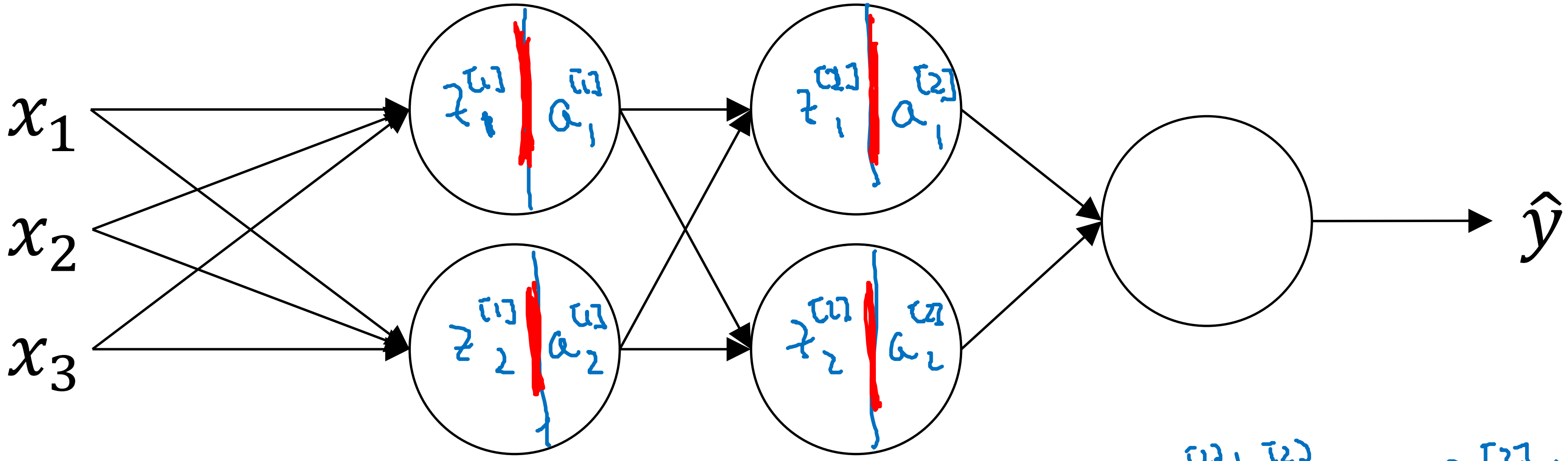
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network



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

Parameters: $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, \ldots, W^{[L]}, b^{[L]},$

$\rightarrow \beta^{[1]}, \gamma^{[1]}, \beta^{[2]}, \gamma^{[2]}, \ldots, \beta^{[L]}, \gamma^{[L]}$

$\rightarrow \beta$

$d\beta^{[l]}$

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

tf.nn.batch_normalization $\Leftarrow$

Working with mini-batches

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

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

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

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

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

$z^{[l]}$

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

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

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

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

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

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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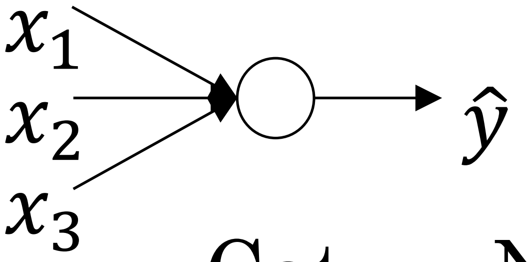
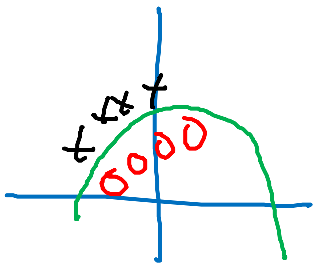
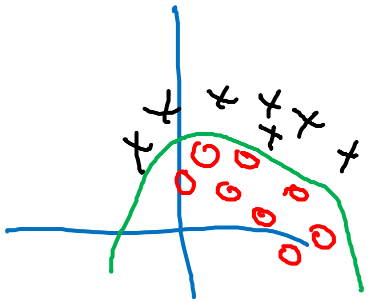
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution

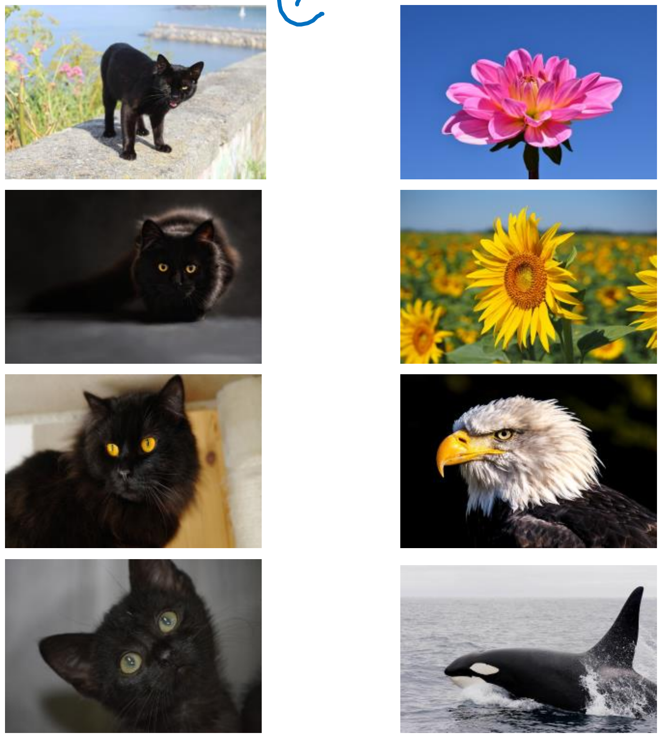




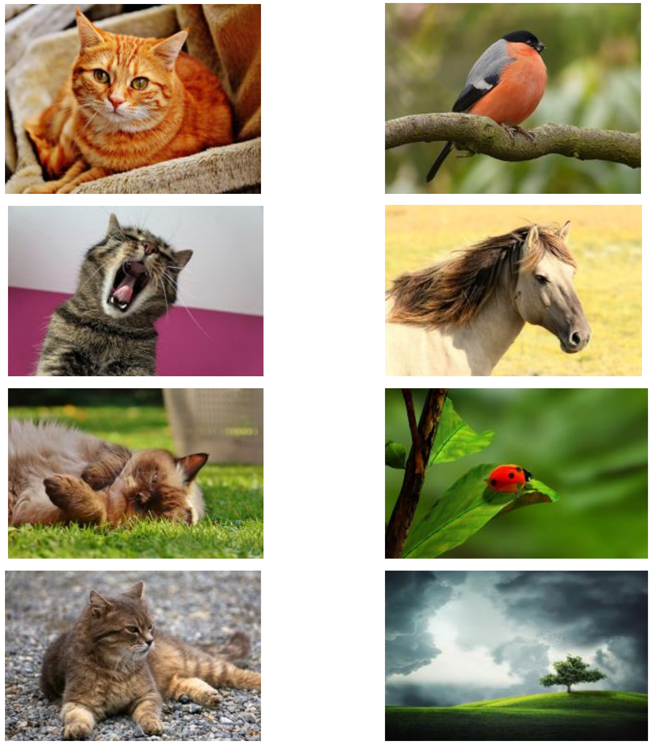


Cat | Non-Cat

$y = 1$ | $y = 0$



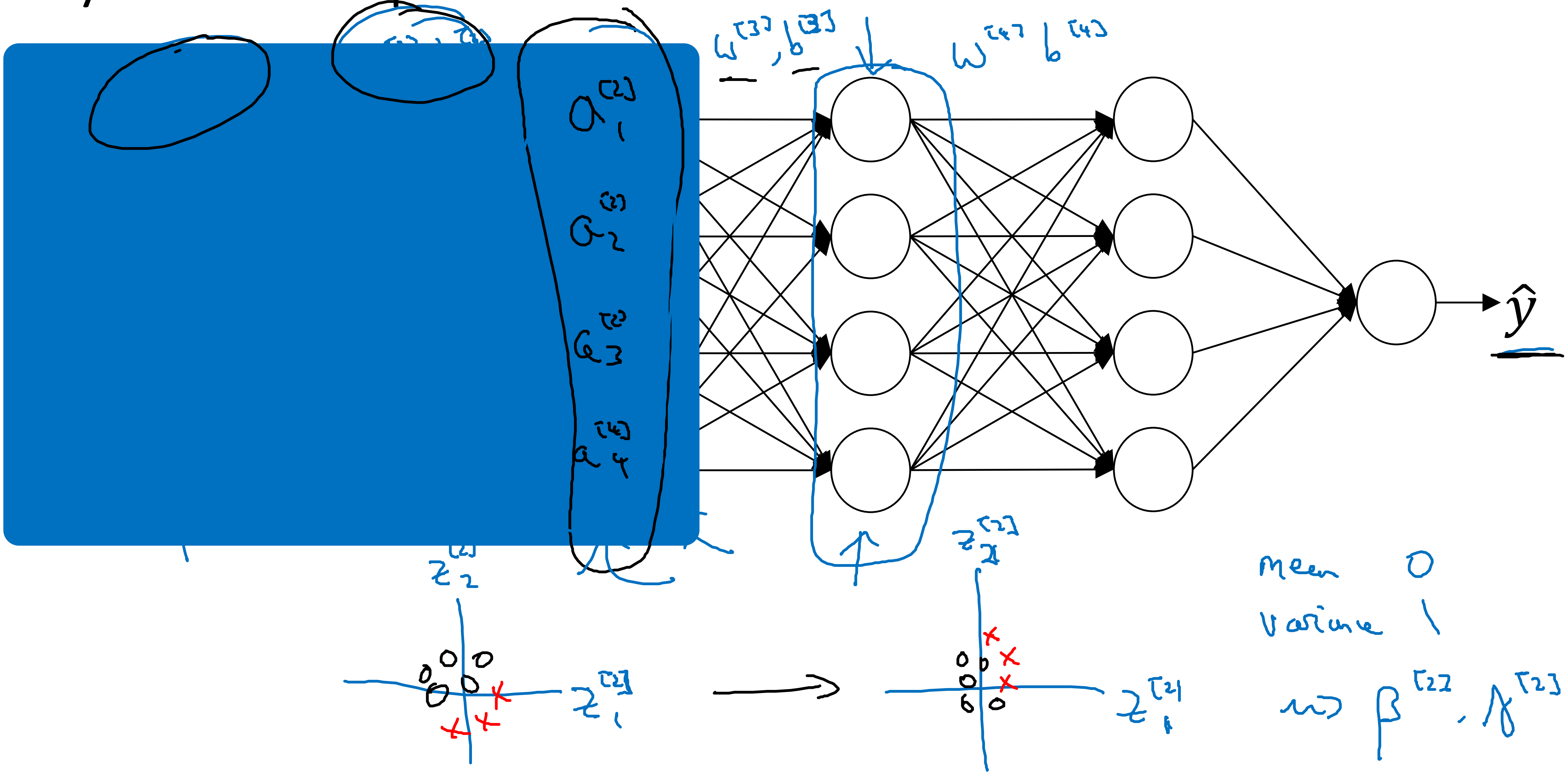
$y = 1$ | $y = 0$



"Covariate shift"

$X \rightarrow y$

Why this is a problem with neural networks?



Batch Norm as regularization

X

- Each mini-batch is scaled by the mean/variance computed on just that mini-batch. $X^{\{t\}}$

$\tilde{z}^{[l]}$ 64, 128 $z^{[l]}$

- 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.

μ, σ^2

- This has a slight regularization effect.

mini-batch : 64 ⟶ 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-batch).

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

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

$\theta_1 \quad \theta_2 \quad \theta_3 \qquad \sigma^2$

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

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

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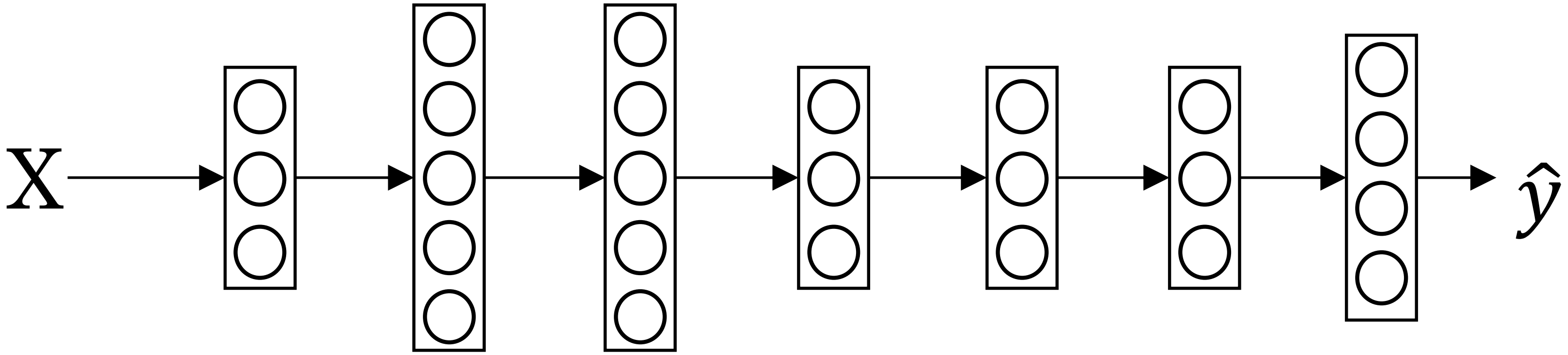
Multi-class classification

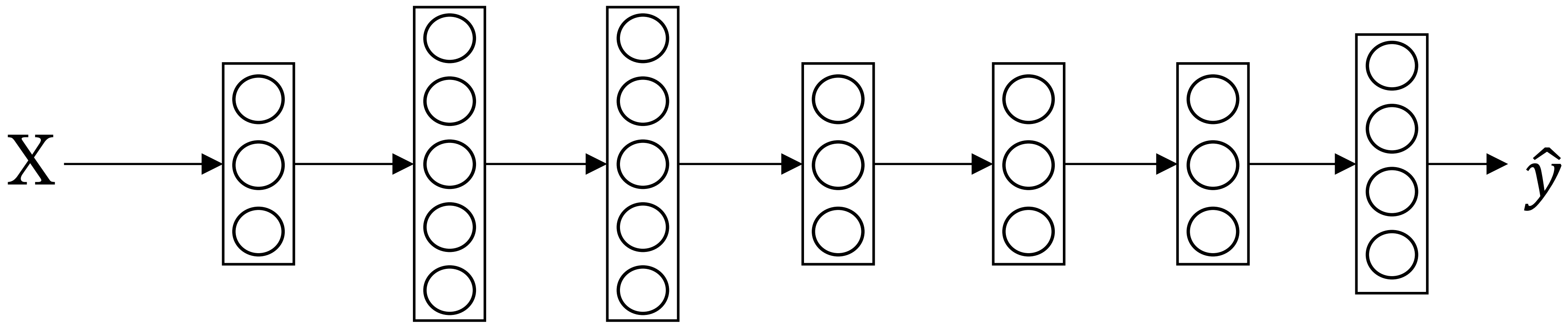
Softmax regression

Recognizing cats, dogs, and baby chicks

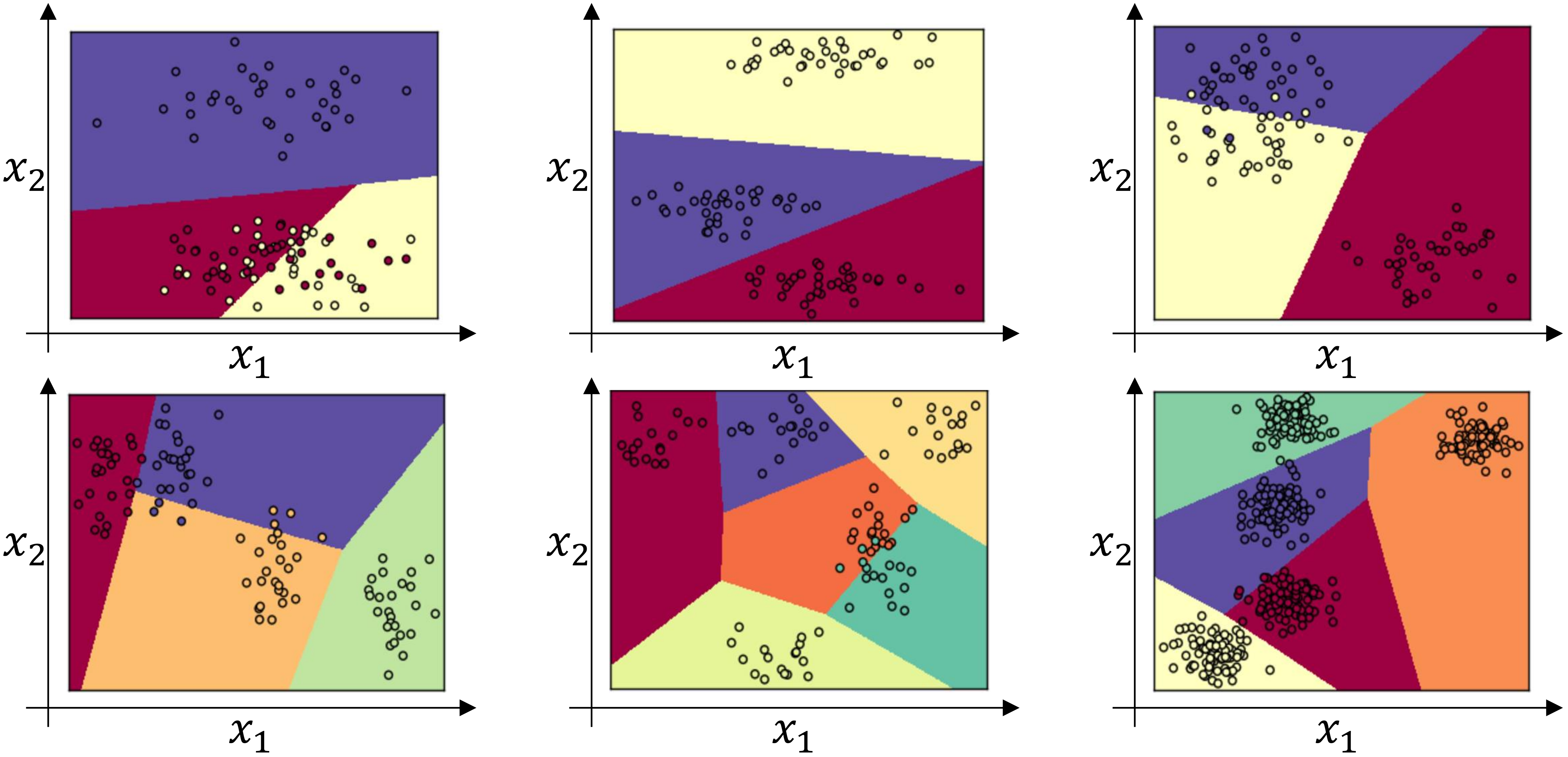
3 1 2 0 3 2 0 1



Softmax layer



Softmax examples



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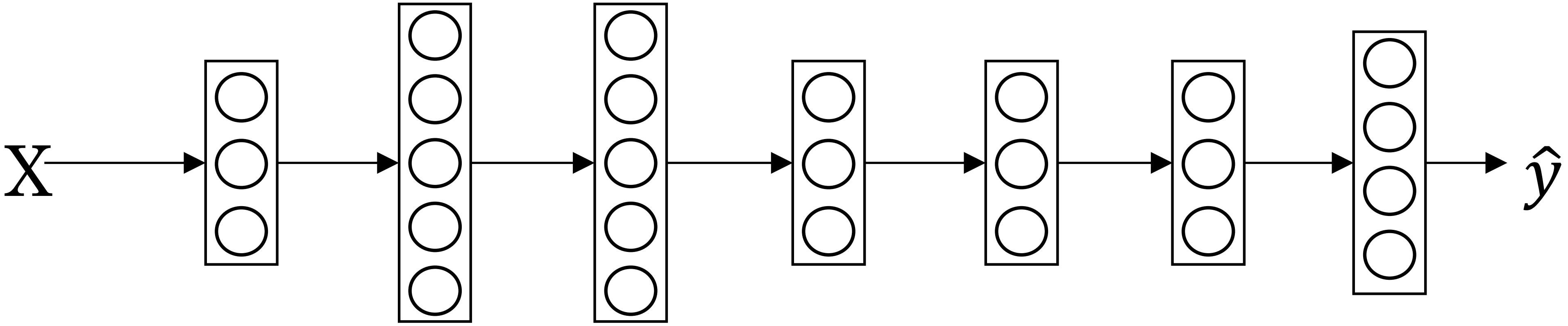
Multi-class classification

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

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

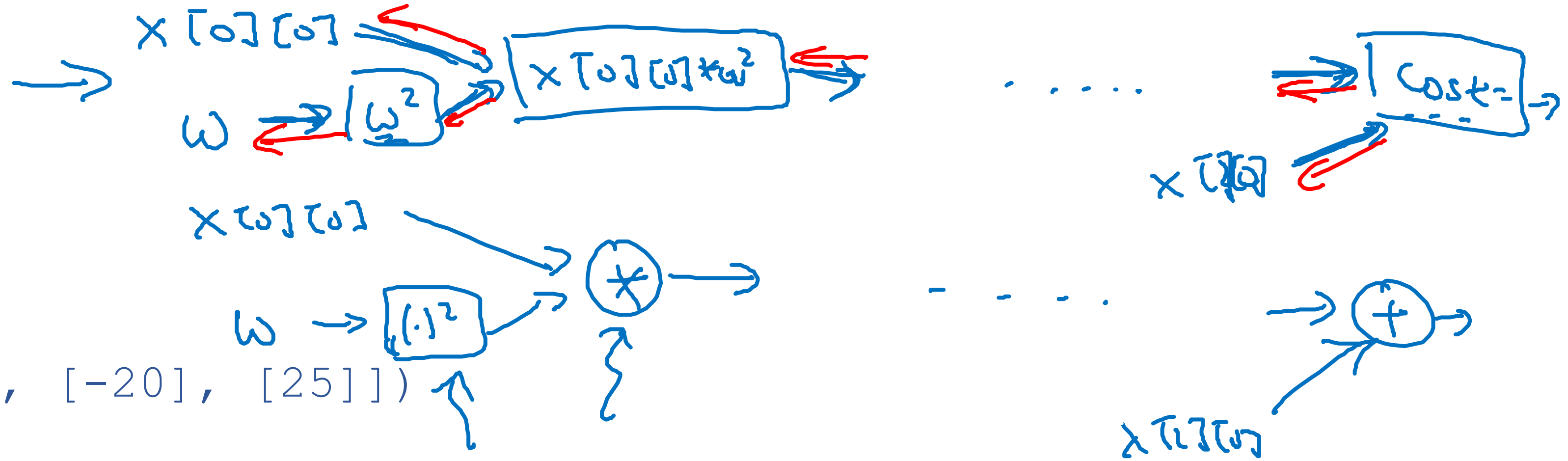
(cost)

$$(w-5)^2$$

$$w = 5$$

$$J(w, b)$$

Code example




```python
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))
```

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

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