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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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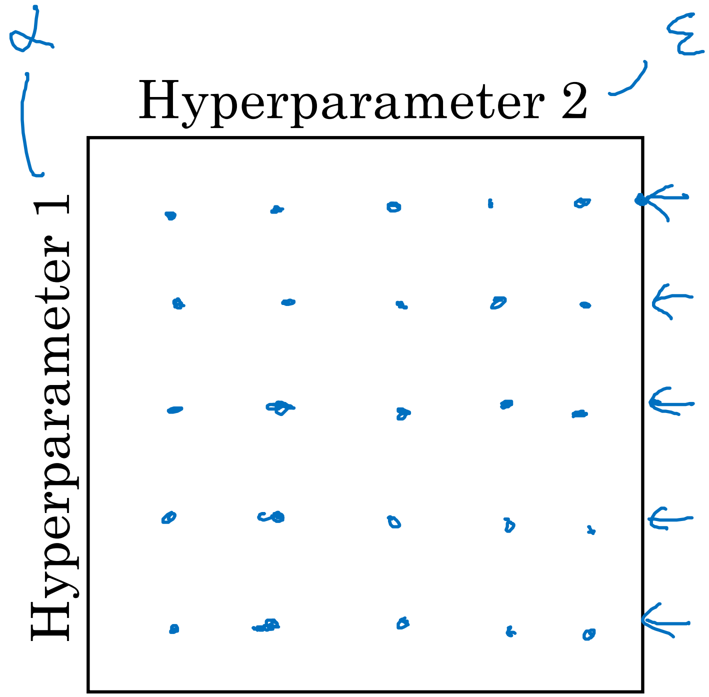
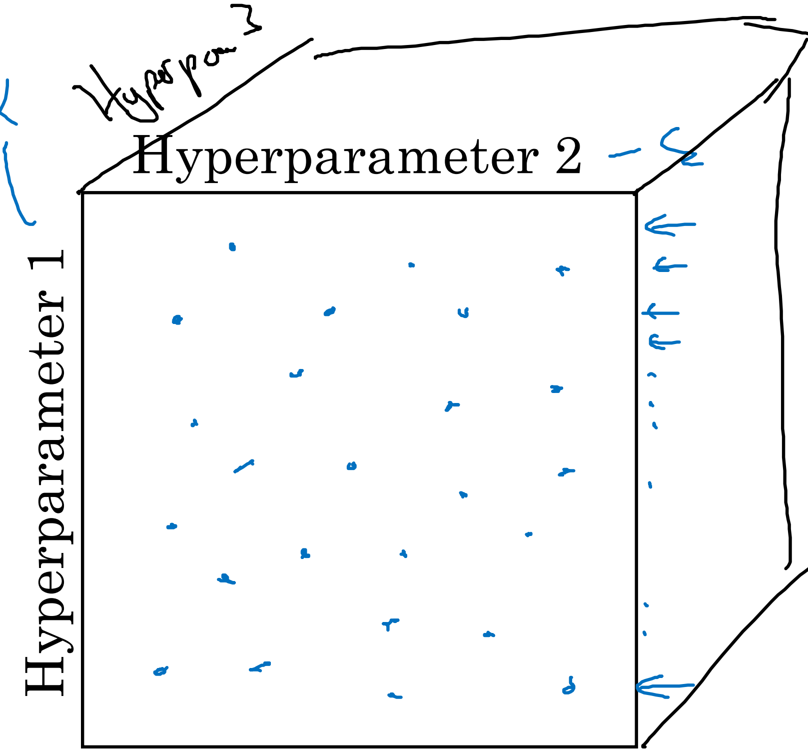
Try random values: Don't use a grid





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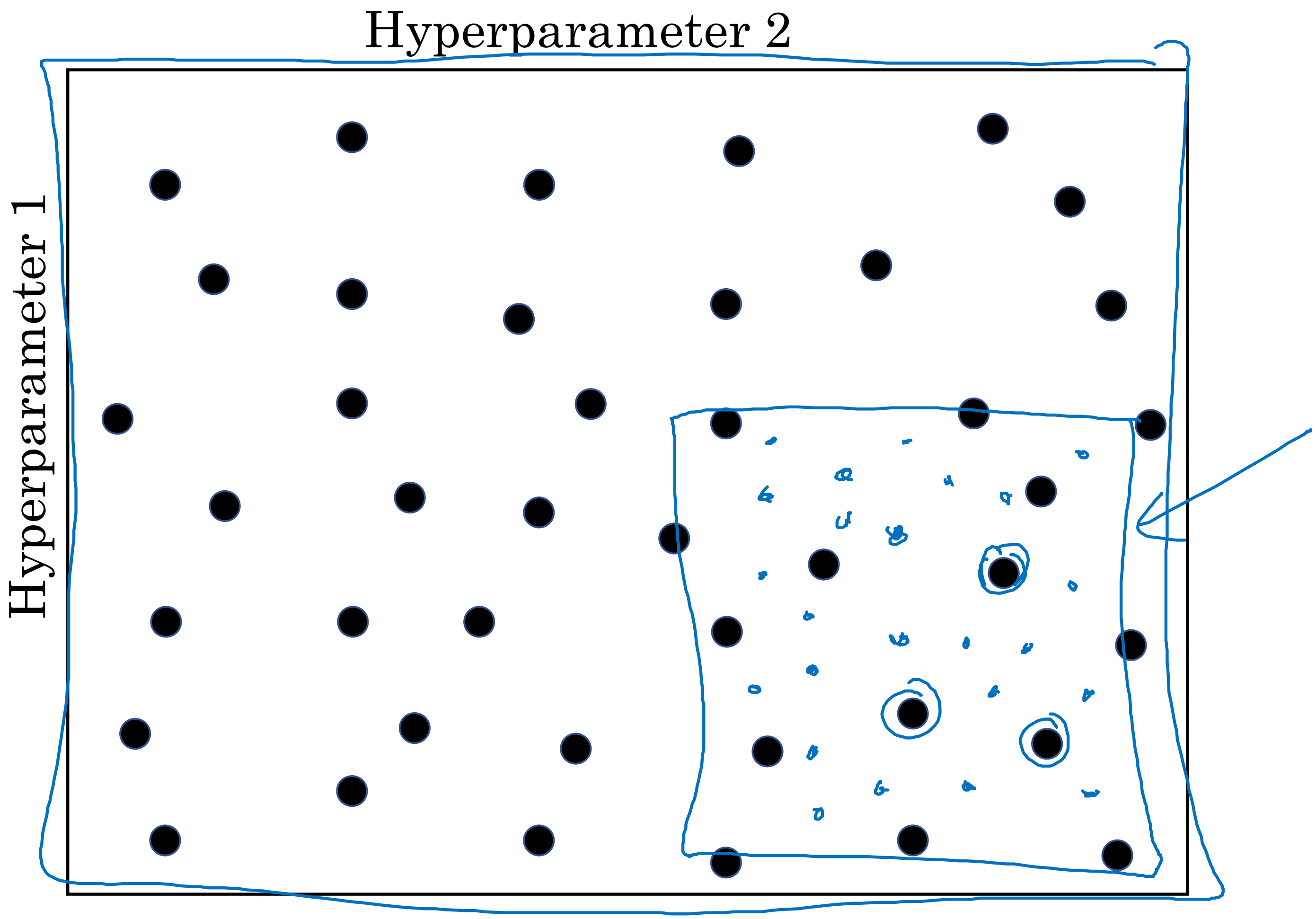
Coarse to fine



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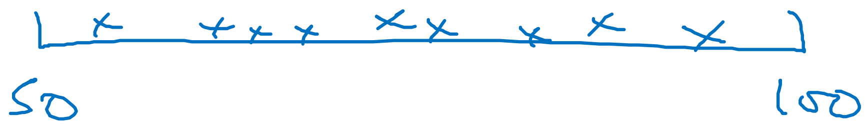
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

$\rightarrow n^{[l]} = 50, \ldots, 100$

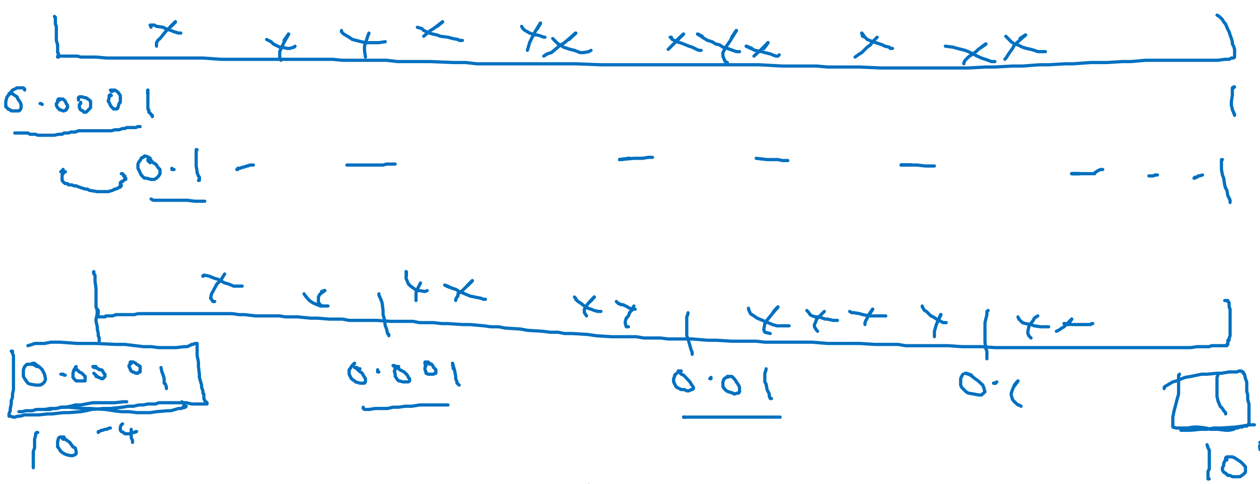


$\rightarrow$ #layers $L: 2 - 4$

$2, 3, 4$

Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$



10^{a} 10^{b}

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

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

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

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

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Hyperparameters for exponentially weighted averages

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

$0.9 \rightarrow 10 \qquad 0.999 \rightarrow 1000$

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

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

$\beta: 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

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

$0.9 \qquad 0.999$

$0.9 \qquad 0.99 \qquad 0.999$

$0.1 \qquad 0.01 \qquad 0.001$

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

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

$1-\beta = 10^r$

$\beta = 1 - 10^r$

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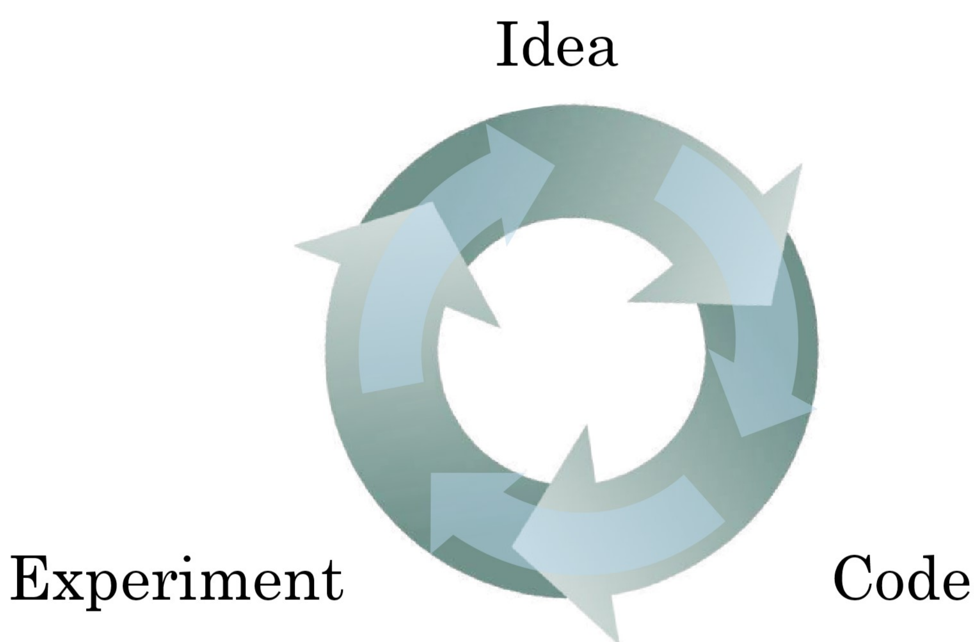
Hyperparameters tuning

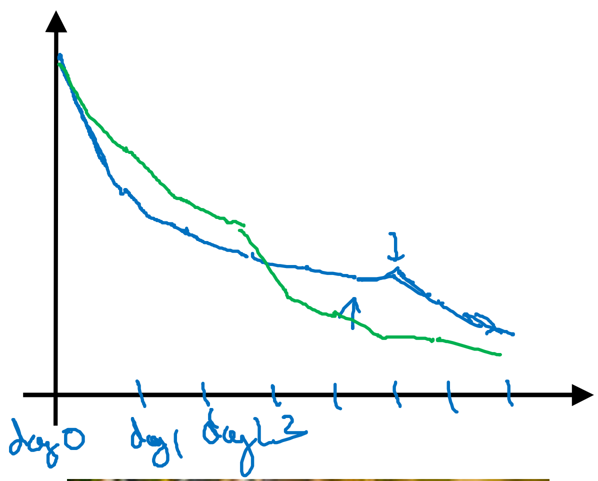
Hyperparameters tuning in practice: Pandas vs. Caviar

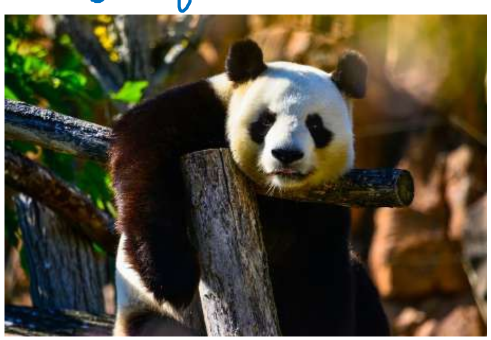
Re-test hyperparameters occasionally



- NLP, Vision, Speech, Ads, logistics, ...
- Intuitions do get stale. Re-evaluate occasionally.

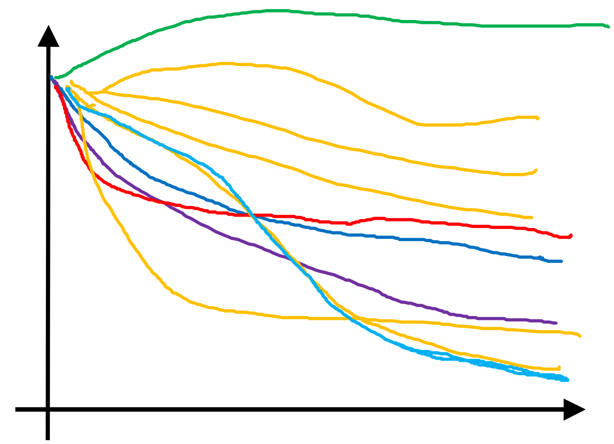
Babysitting one model





Panda

Training many models in parallel



Caviar

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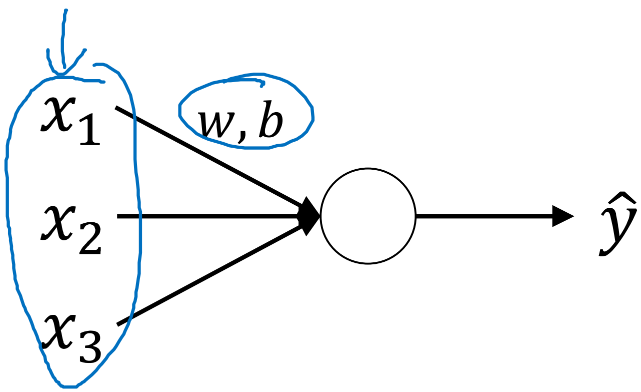
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning

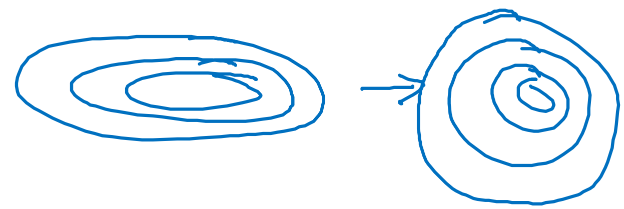


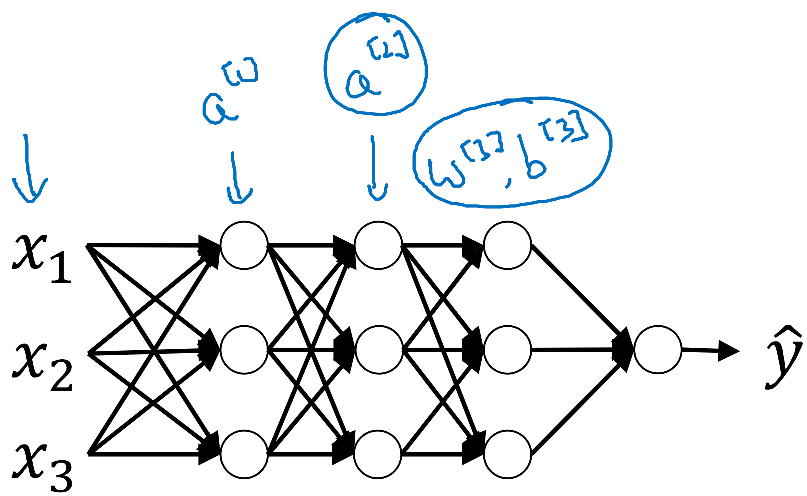
$\mu = \frac{1}{m} \sum_i x^{(i)}$

$X = X - \mu$

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

$X = X / \sigma^2$





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 $\underbrace{z^{(1)}, \ldots, z^{(m)}}_{z^{[l](i)}}$

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

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

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

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

learnable parameters of model.

If

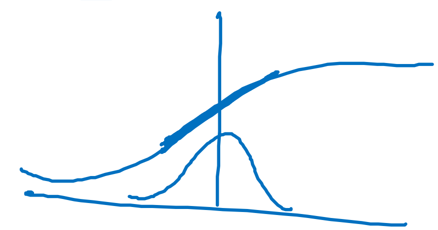
$\gamma = \boxed{\sqrt{\sigma^2 + \varepsilon}}$

$\beta = \boxed{\mu}$

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

X

$z^{(i)}$



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

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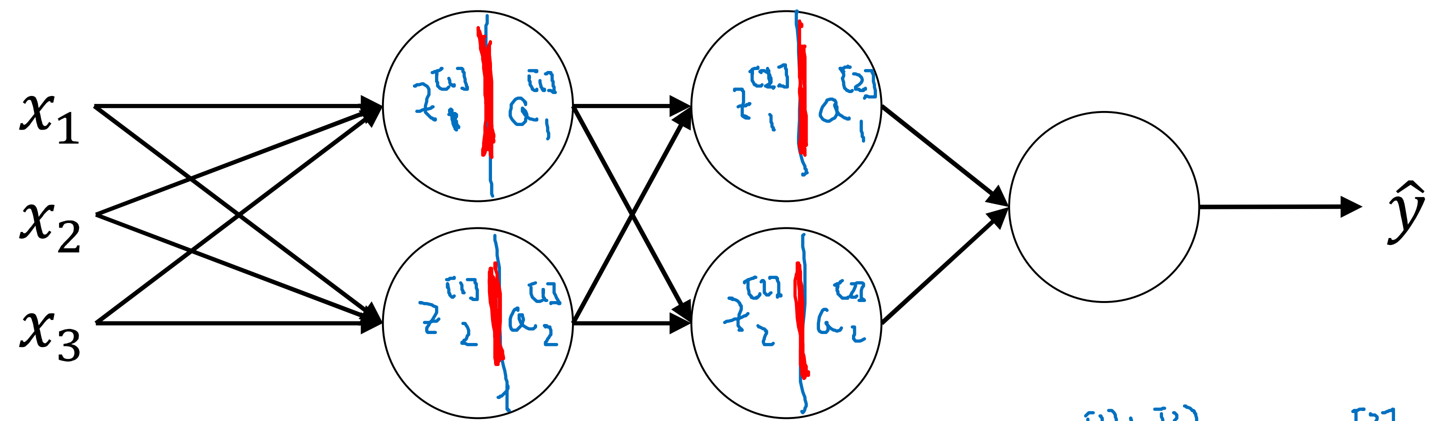
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network



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

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

$\rightarrow \beta$

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

tf.nn.batch_normalization $\Leftarrow$

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Working with mini-batches

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

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

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

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

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

$z^{[l]}$

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

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

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

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

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

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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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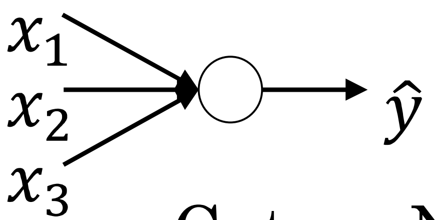
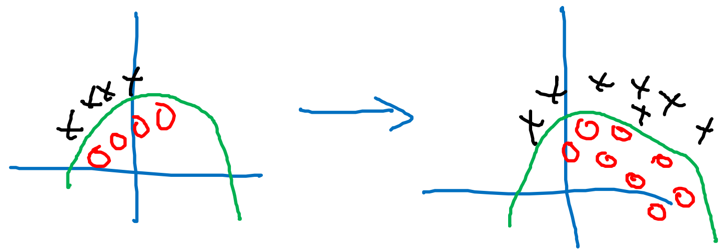
Batch Normalization

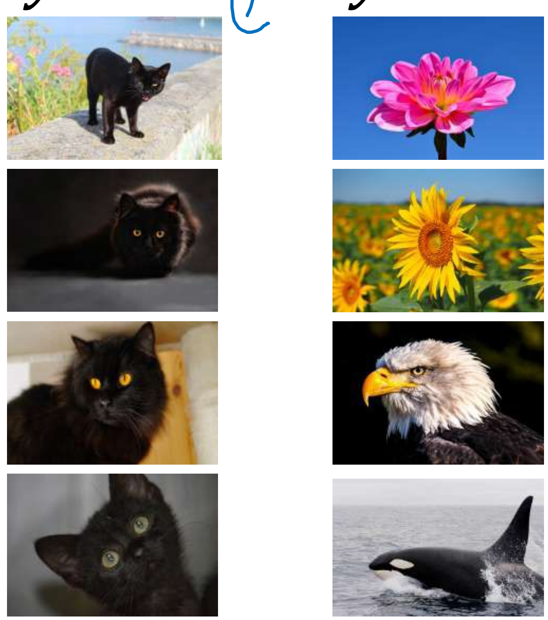
Why does Batch Norm work?

Learning on shifting input distribution





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



"Covariate shift"

$\underset{\sim}{X} \rightarrow y$

$y = 1$ $y = 0$

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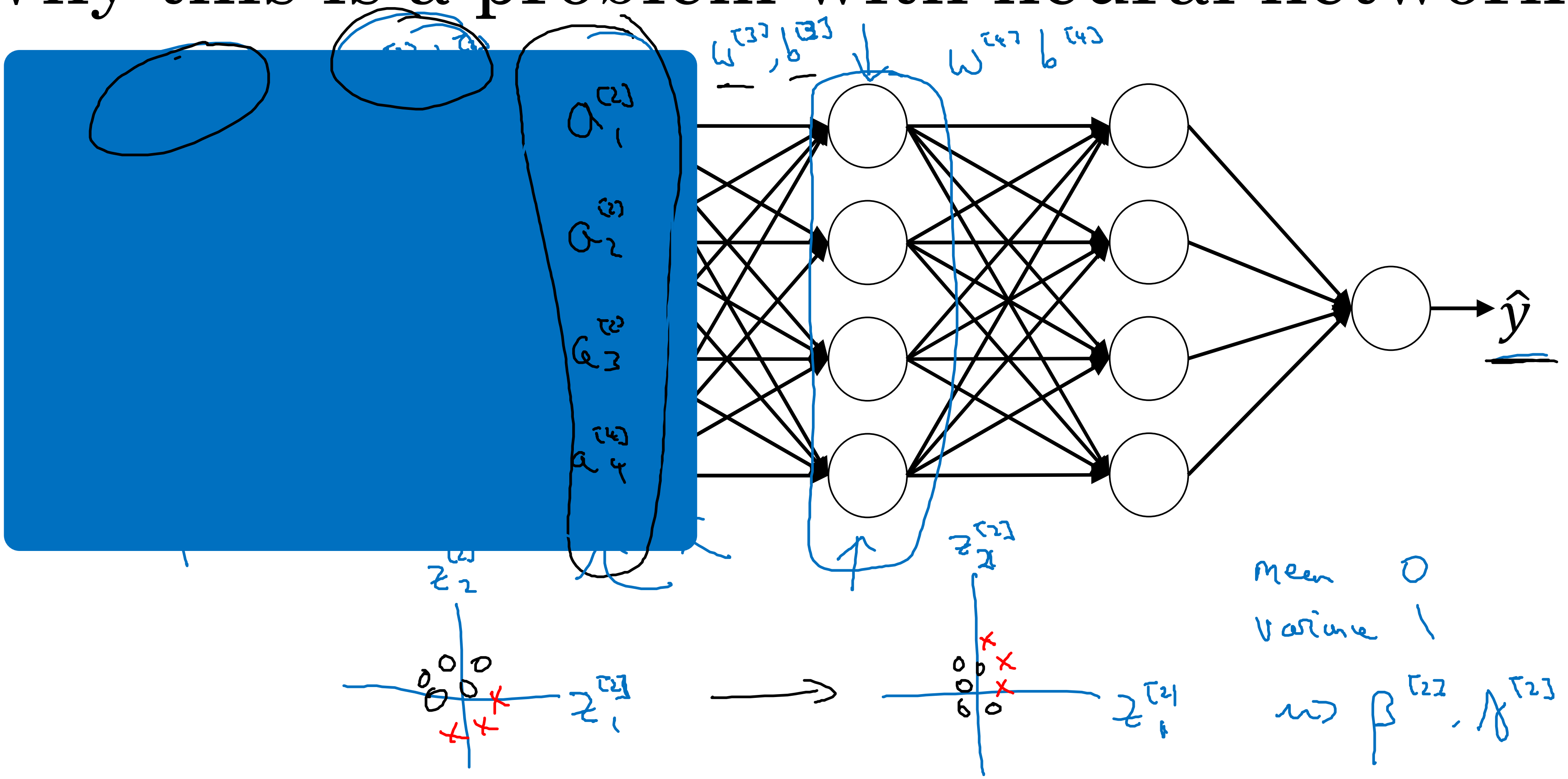
Why this is a problem with neural networks?



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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 $\longrightarrow$ 512

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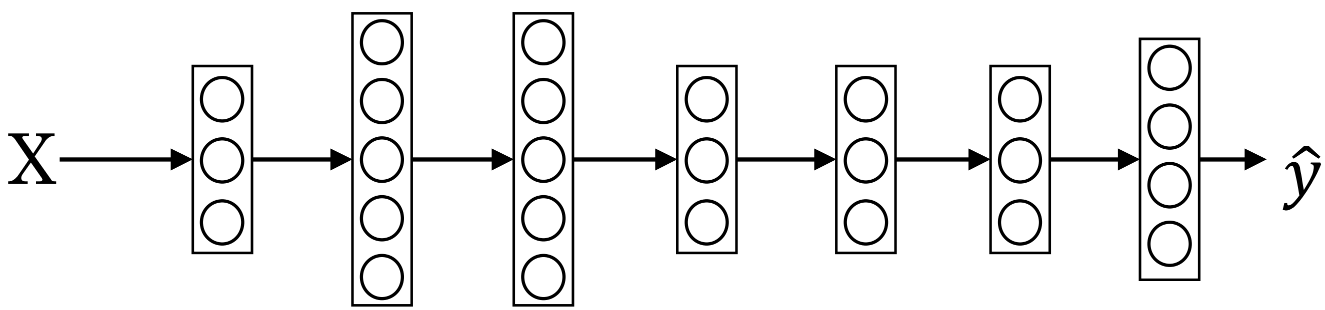
Multi-class classification

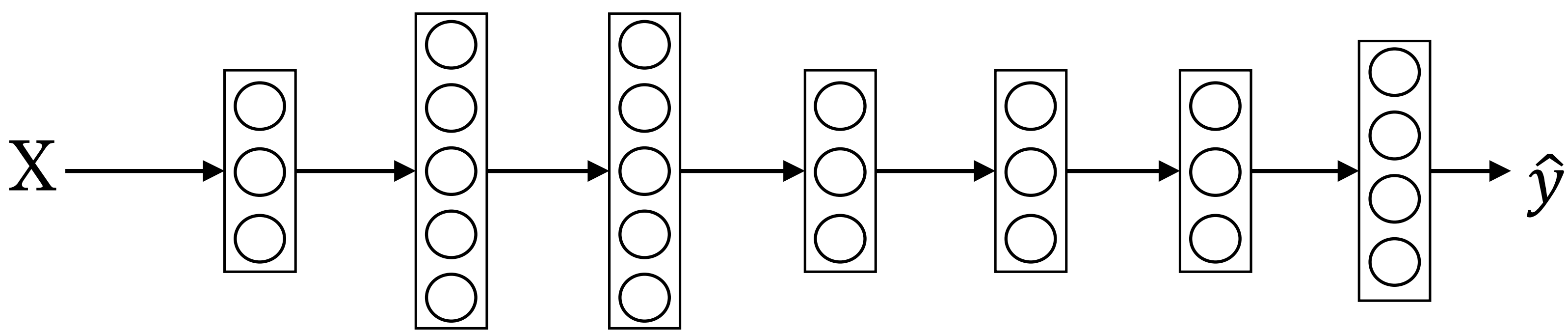
Softmax regression

Recognizing cats, dogs, and baby chicks

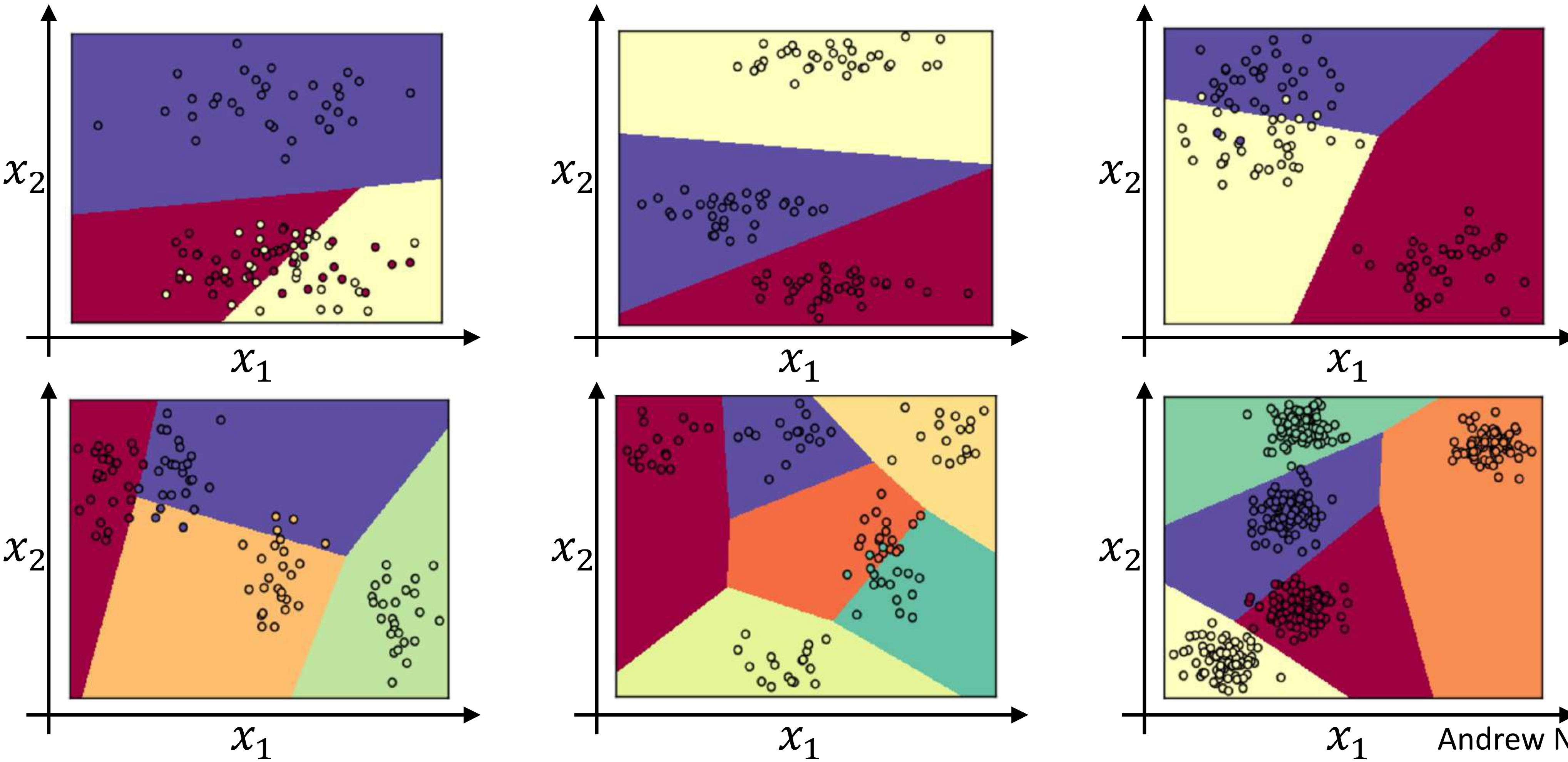
3 1 2 0 3 2 0 1



Softmax layer



Softmax examples



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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

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

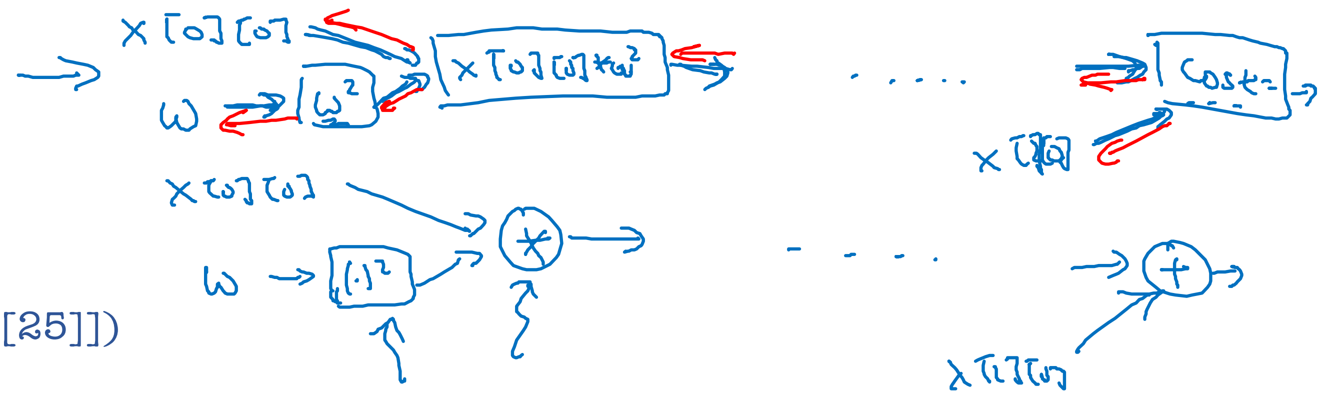
(cost)

$(w-5)^2$

$w = 5$

$J(w, b)$

Code example




```
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))
```

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