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Hyperparameter tuning

Tuning process

Hyperparameters

$\rightarrow \boxed{\alpha}$

$\boxed{\beta}$ ~0.9

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

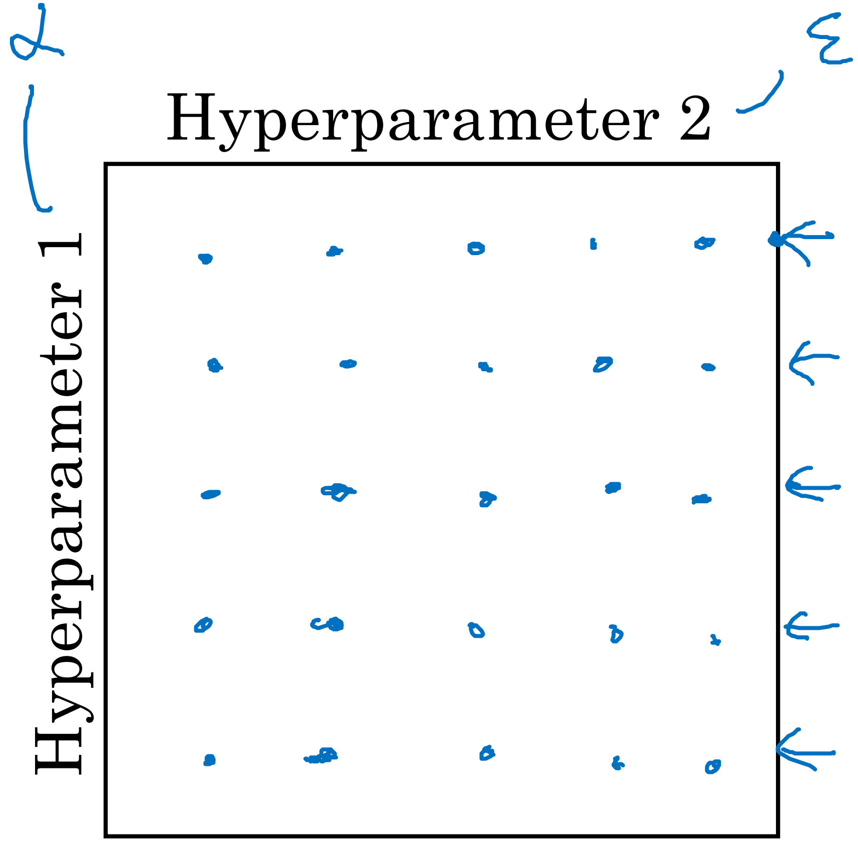
$\boxed{\text{\# layers}}$

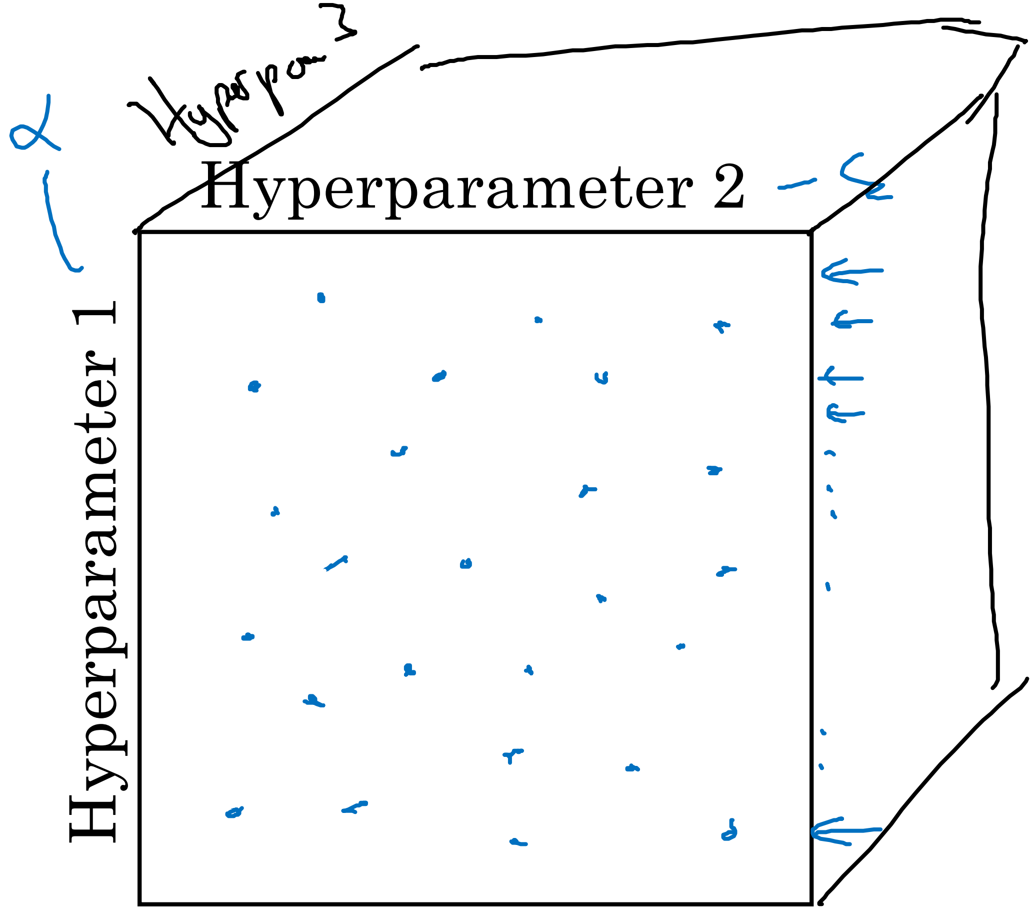
$\boxed{\text{\# hidden units}}$

$\boxed{\text{learning rate decay}}$

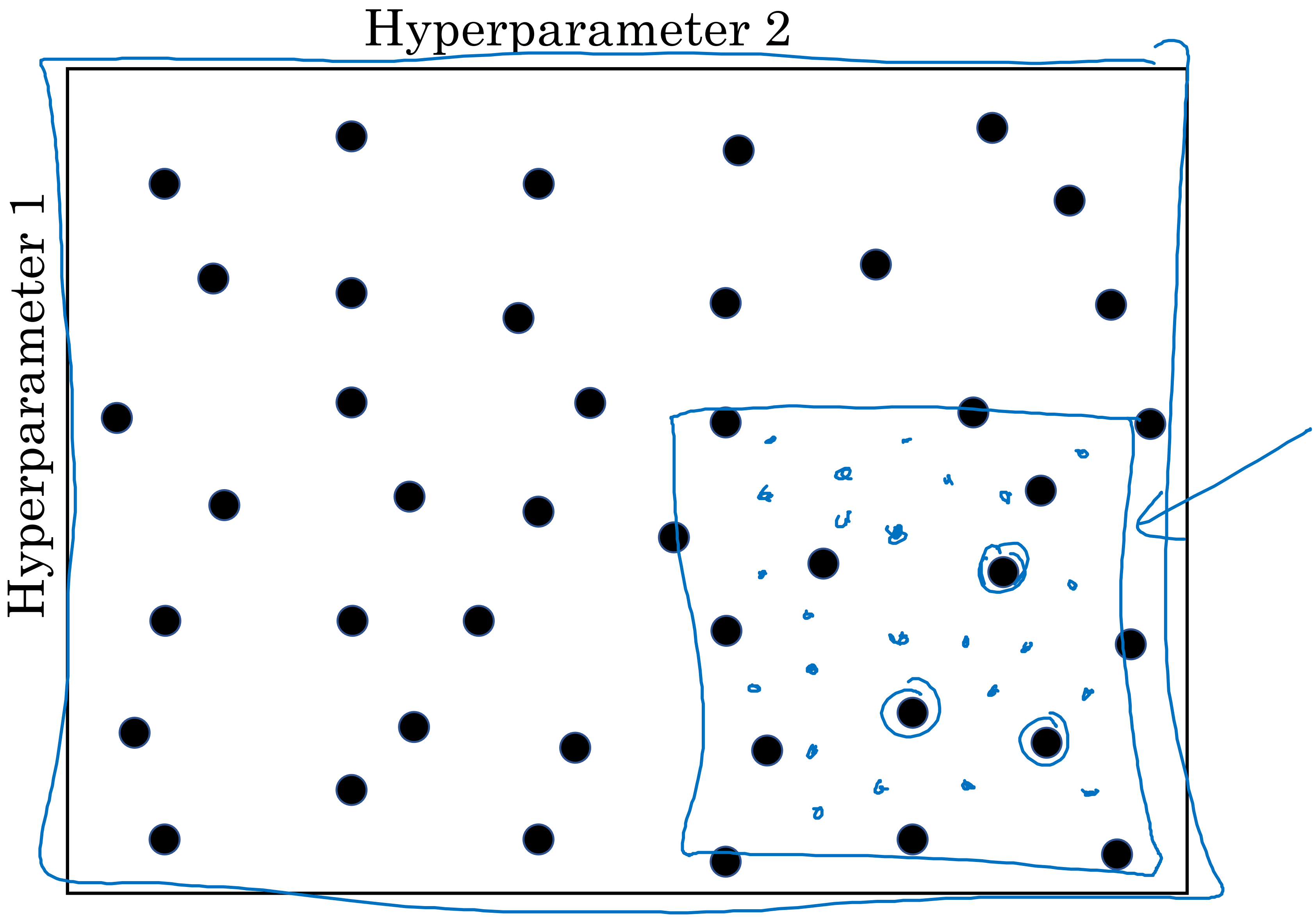
$\boxed{\text{mini-batch size}}$

Try random values: Don't use a grid





Coarse to fine



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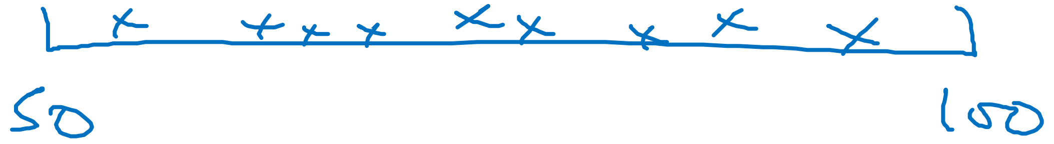
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \ldots, 100$



→ #layers $L: 2 - 4$

$2, 3, 4$

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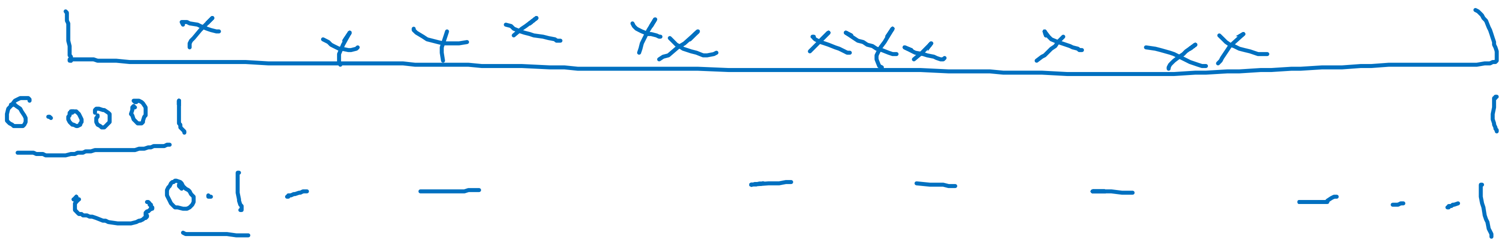
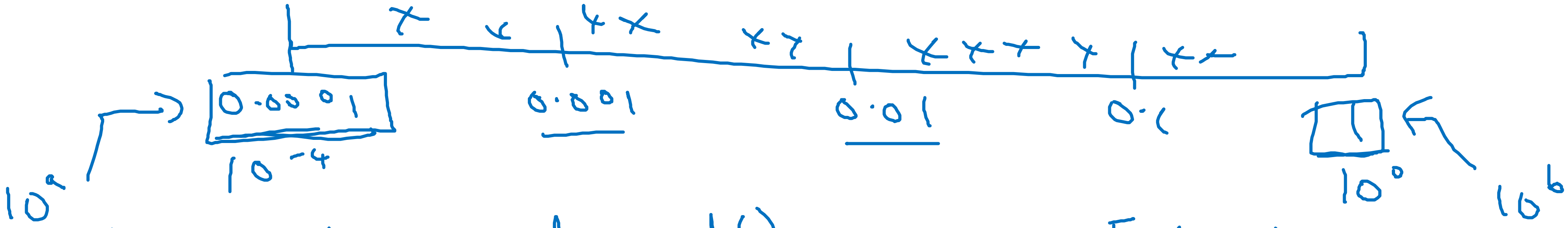
Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$





$a = \log_{10} 0.0001 = -4$

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

$b = \log_{10} 1 = 0$

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

$10^a \ldots 10^b$ $\quad$ $r \in [a, b]$ $\quad$ $\alpha = 10^r$

$[-4, 0]$

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Hyperparameters for exponentially weighted averages

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

$10 \qquad\qquad 1000$

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

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

$\beta: 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

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

$0.9 \qquad 0.999$

$0.9 \qquad 0.99 \qquad 0.999$

$0.1 \qquad 0.01 \qquad 0.001$

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

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

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

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

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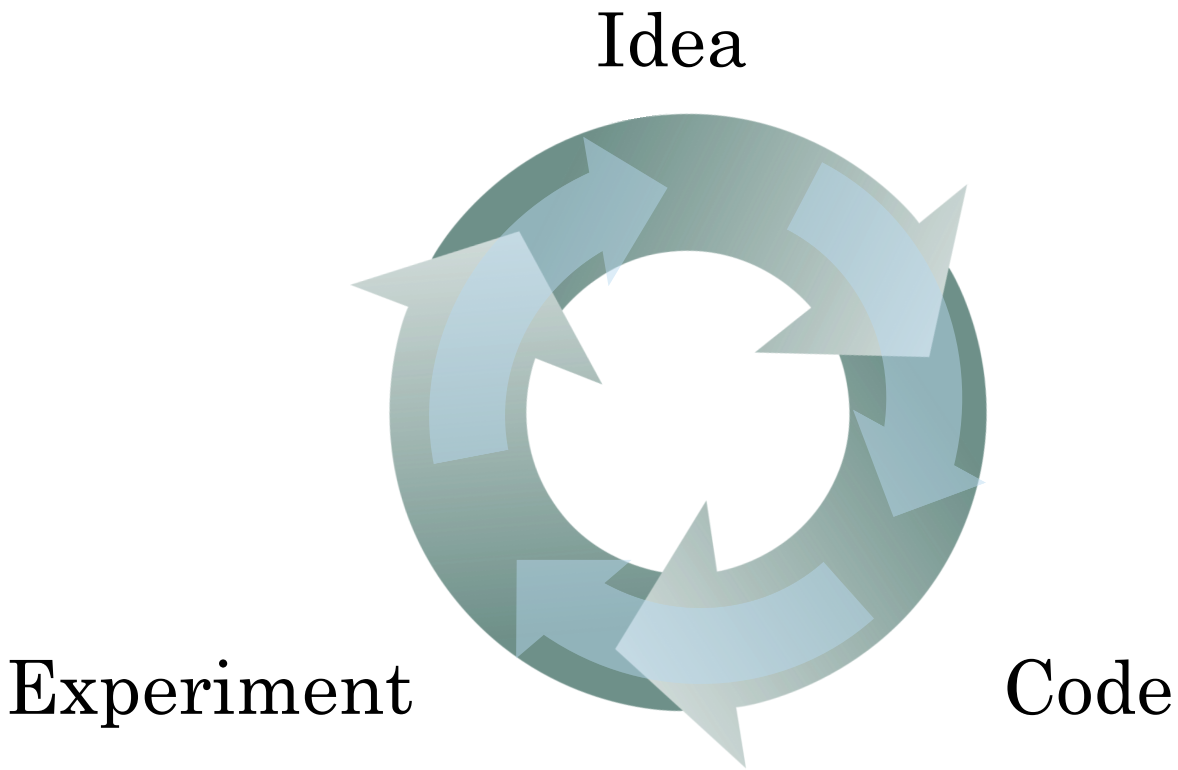
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

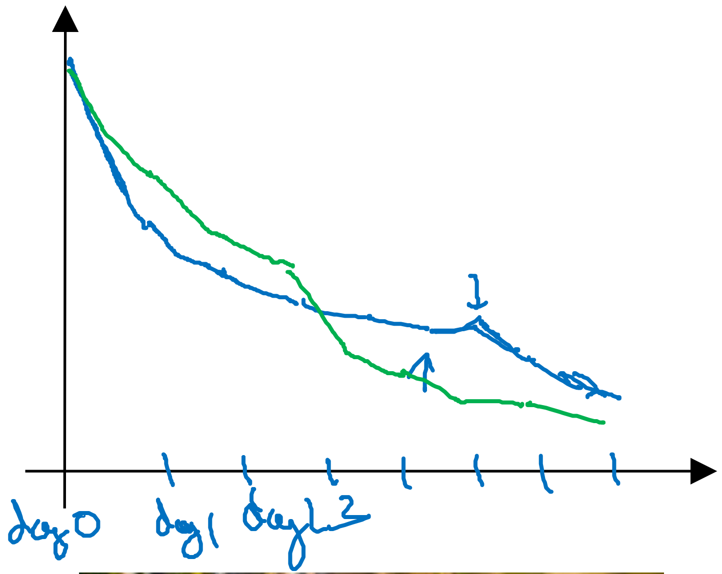
Re-test hyperparameters occasionally

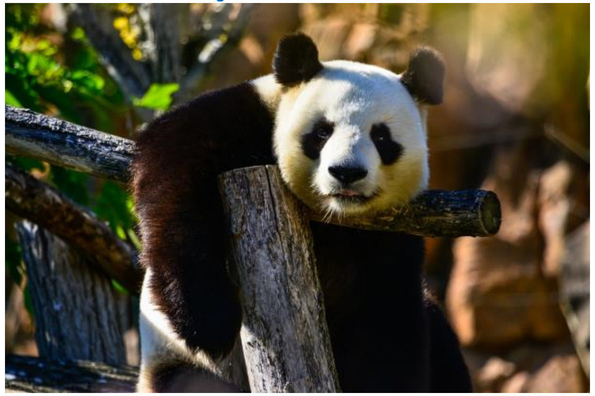


- NLP, Vision, Speech, Ads, logistics, ….

- Intuitions do get stale. Re-evaluate occasionally.

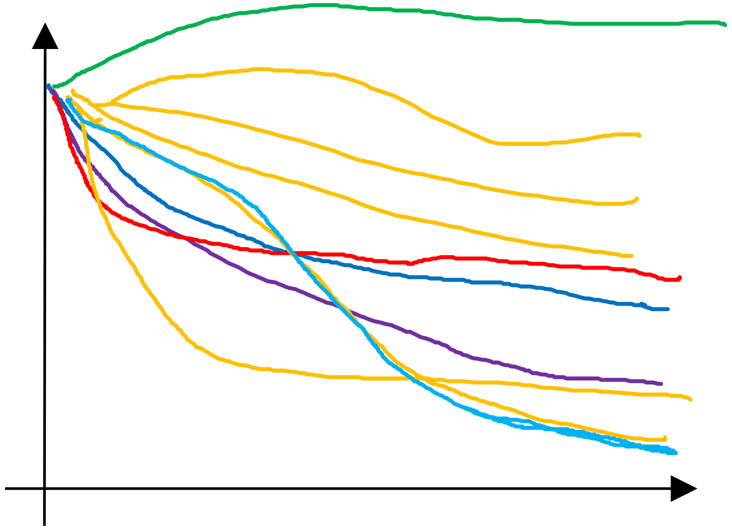
Babysitting one model





Panda

Training many models in parallel



Caviar

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Batch Normalization

Normalizing activations in a network

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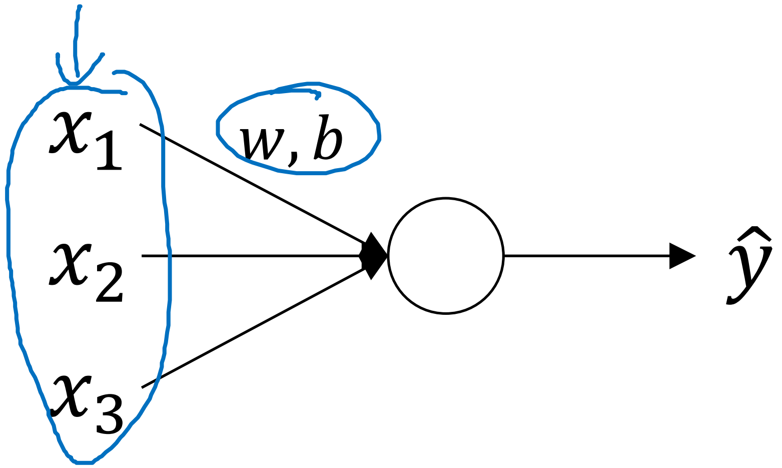
Normalizing inputs to speed up learning

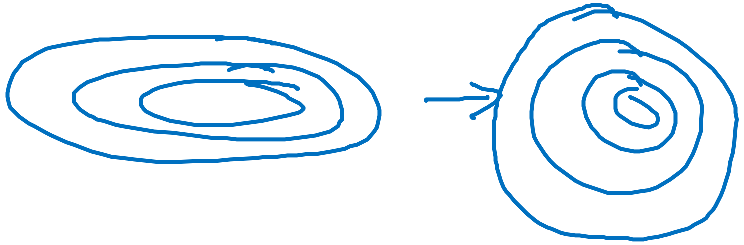


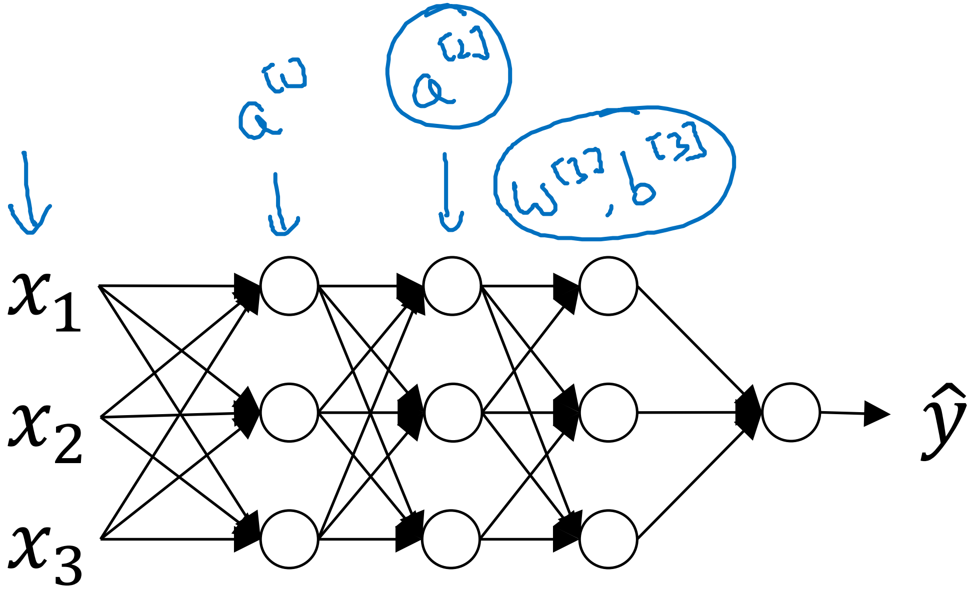
$\mu = \frac{1}{m} \sum_i x^{(i)}$

$X = X - \mu$ ← 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 $\underline{z^{[2]}}$

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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

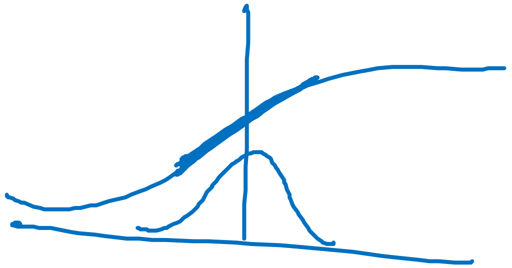
$$\gamma = \boxed{\sqrt{\sigma^2 + \varepsilon}}$$

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

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

X

$z^{(i)}$



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

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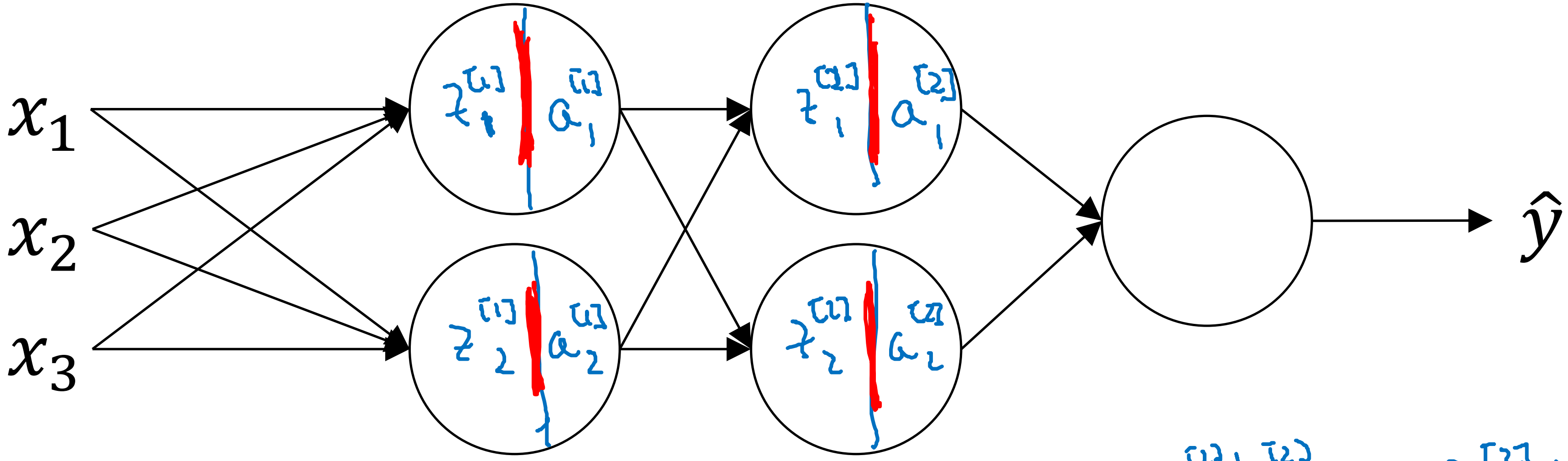
Batch Normalization

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

$d\beta^{[l]}$

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

tf.nn.batch_normalization $\leftarrow$

$\rightarrow \beta$

Working with mini-batches

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

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

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

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

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

$z^{[l]}$

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

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

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

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

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

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Implementing gradient descent

for $t = 1 \ldots$ numMiniBatches

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

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

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

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

Works w/ momentum, RMSprop, Adam.

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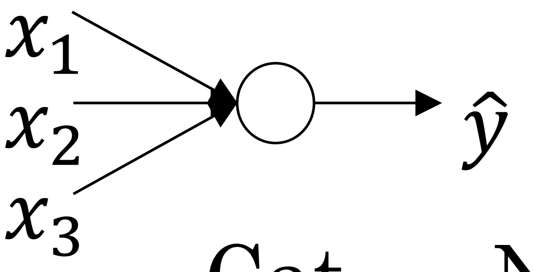
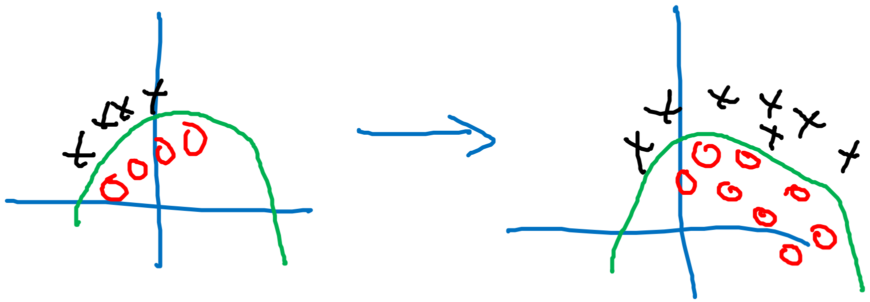
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution



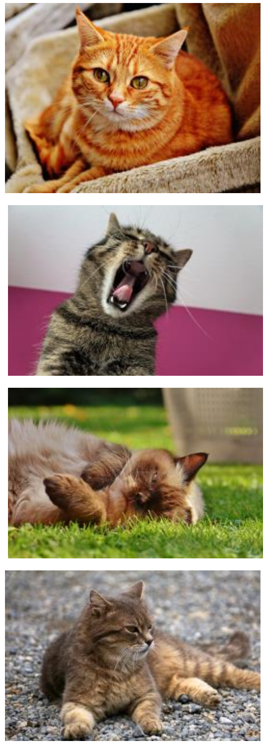


Cat	Non-Cat
$y = 1$	$y = 0$

"Covariate shift"

$X \rightarrow y$

$y = 1$	$y = 0$



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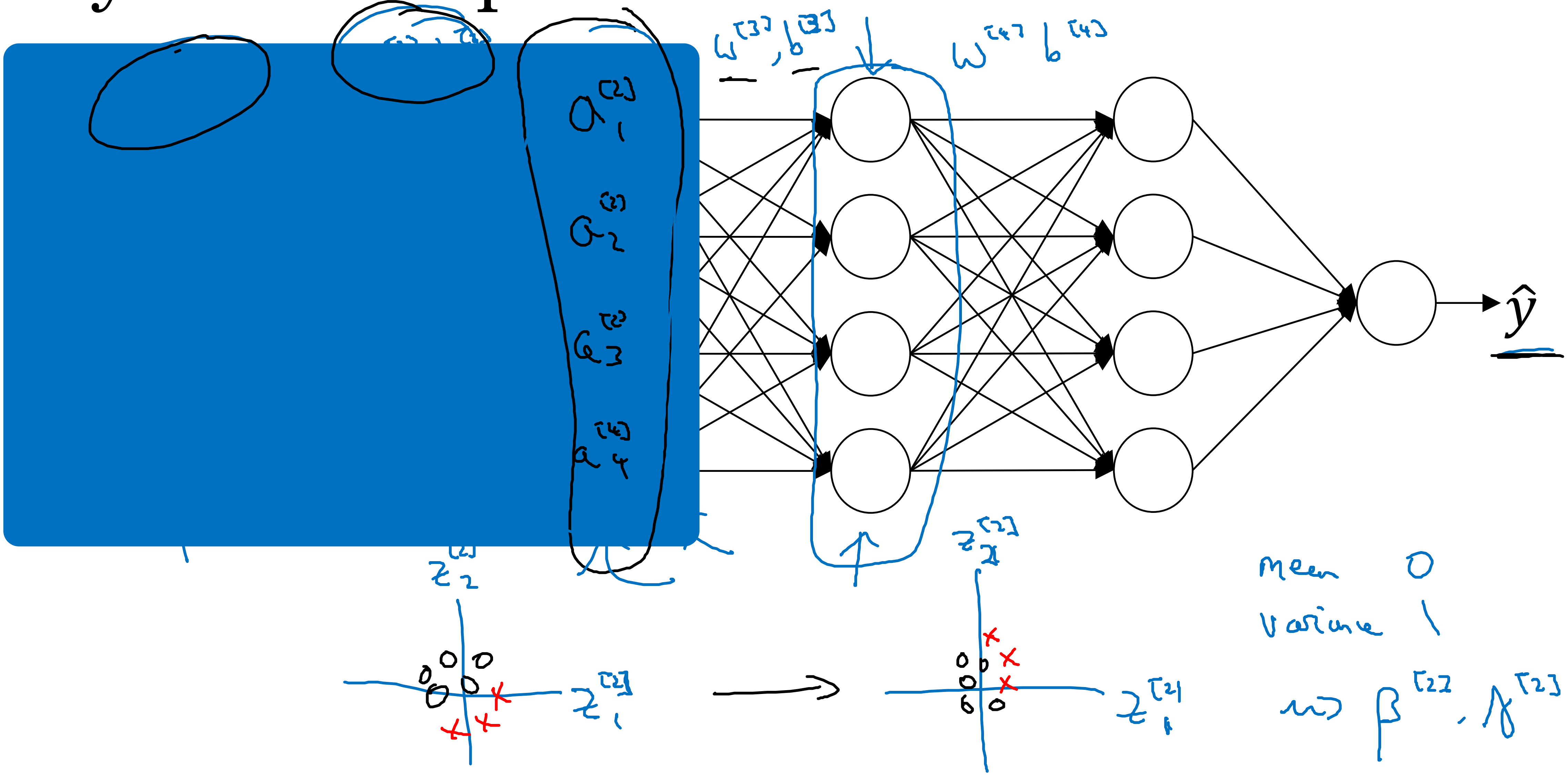
Why this is a problem with neural networks?



Batch Norm as regularization

X

$X^{\{t\}}$

- Each mini-batch is scaled by the mean/variance computed on just that mini-batch.

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

Batch Norm at test time

Batch Norm at test time

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

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

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

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

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

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

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

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

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

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

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

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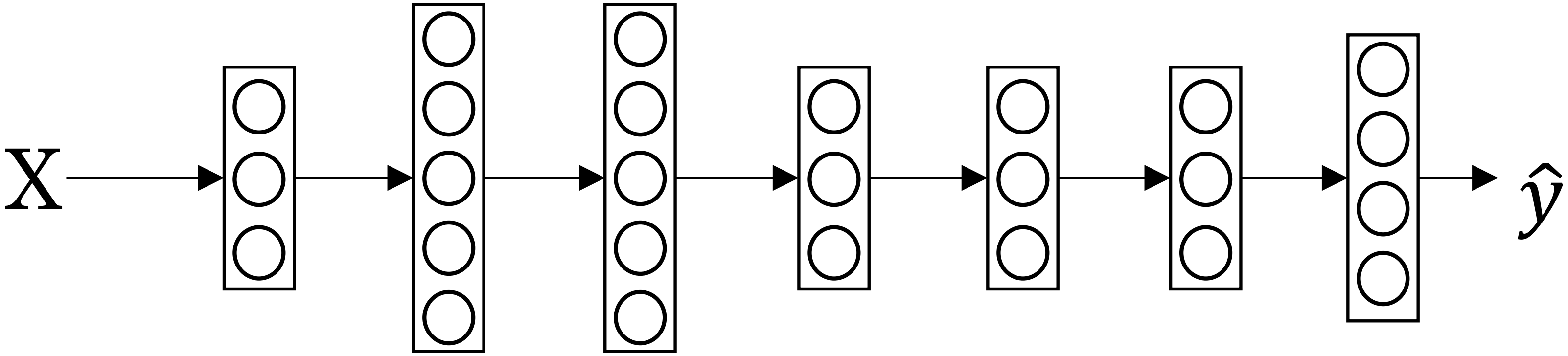
Multi-class classification

Softmax regression

Recognizing cats, dogs, and baby chicks

3 1 2 0 3 2 0 1



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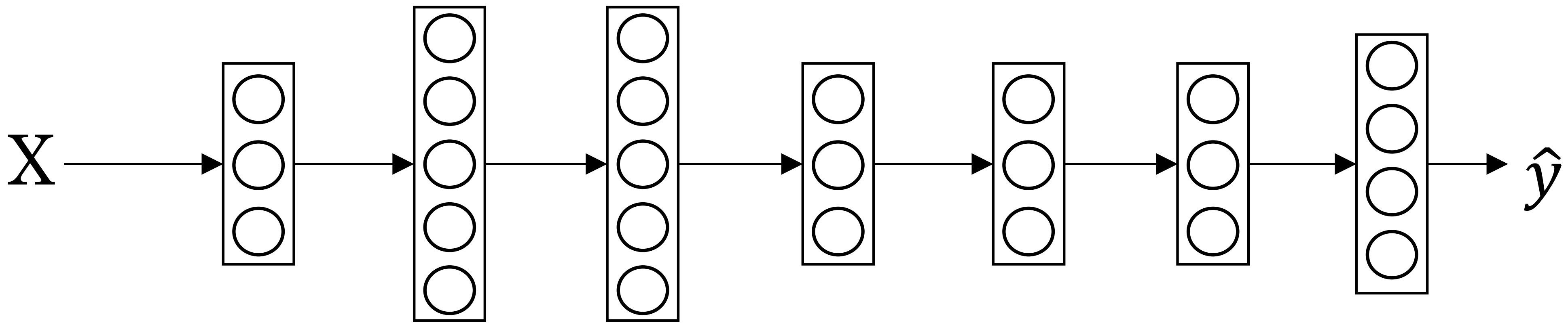
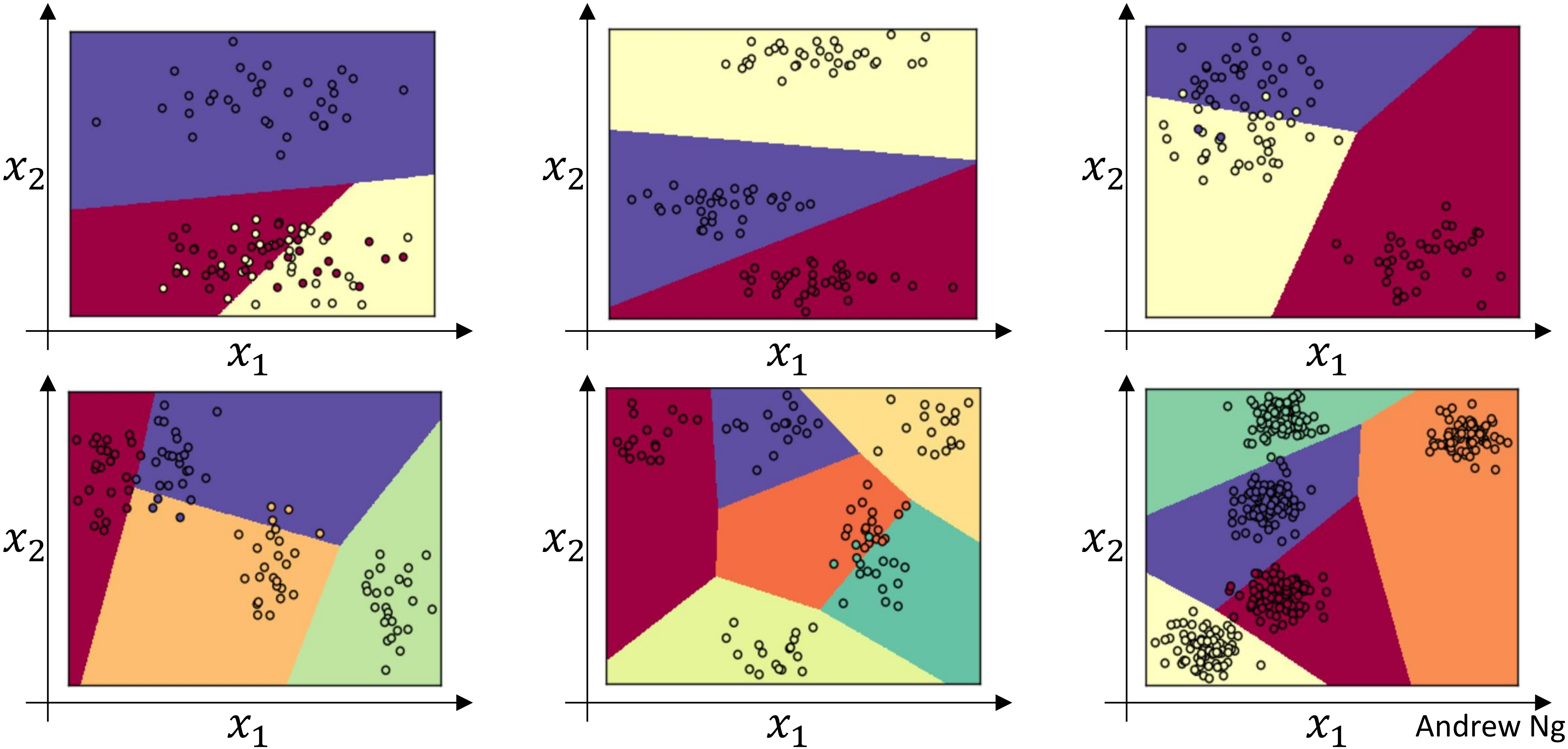
Softmax layer



Softmax examples



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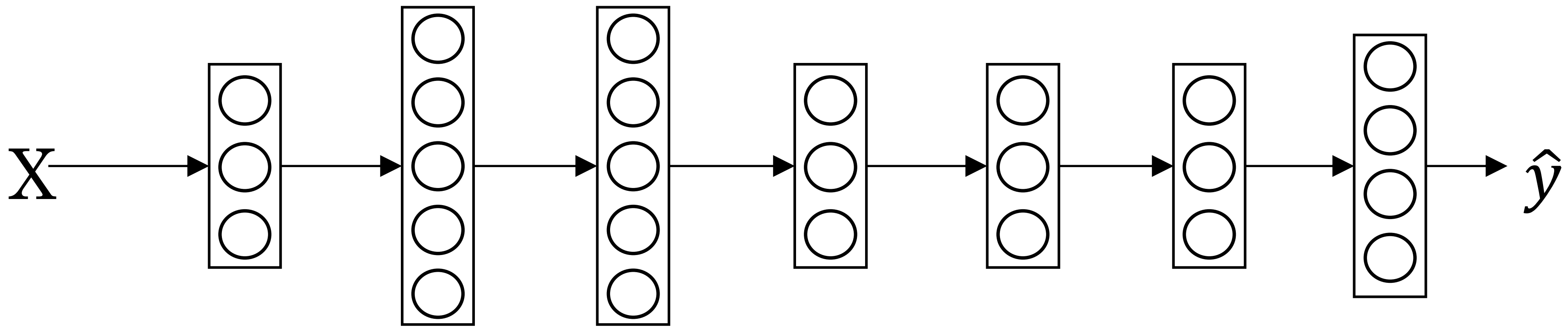
Multi-class classification

Trying a softmax classifier

Understanding softmax

Loss function

Summary of softmax classifier



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Programming Frameworks

Deep Learning frameworks

Deep learning frameworks

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

Choosing deep learning frameworks

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

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Programming Frameworks

TensorFlow

Motivating problem

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

(cost)

$(w-5)^2$

$w = 5$

$J(w, b)$

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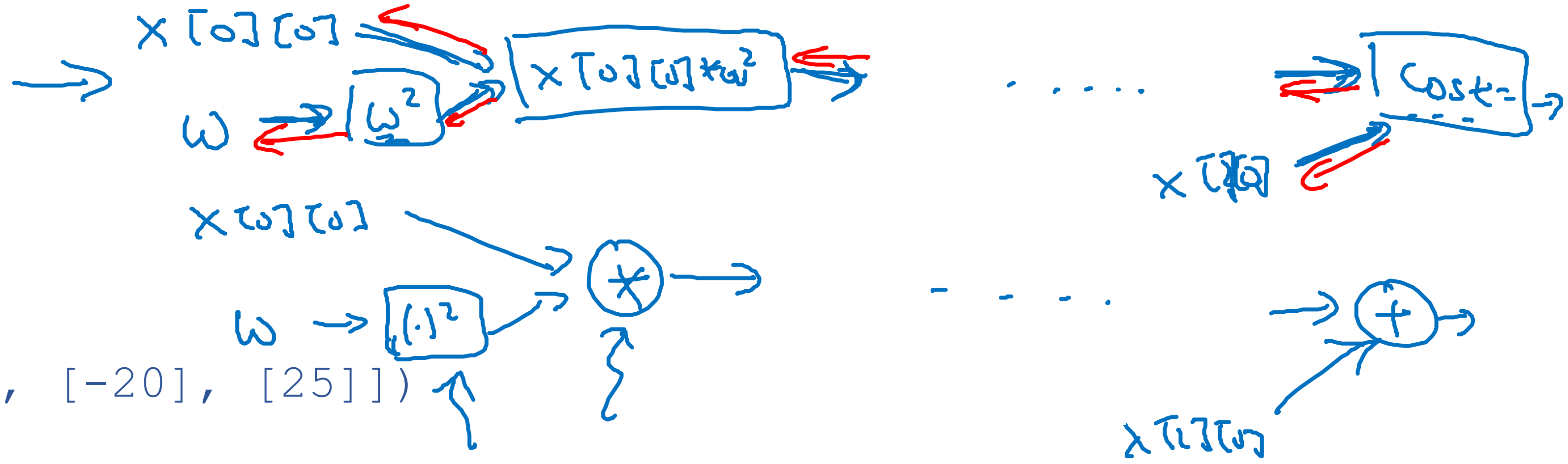
Code example




```
import numpy as np
import tensorflow as tf

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

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

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

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