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Hyperparameter tuning

Tuning process

Hyperparameters

$\rightarrow \boxed{\alpha}$

$\boxed{\beta}$ ~0.9

$\beta_1, \beta_2, \varepsilon$

$0.9 \quad 0.999 \quad 10^{-8}$

layers

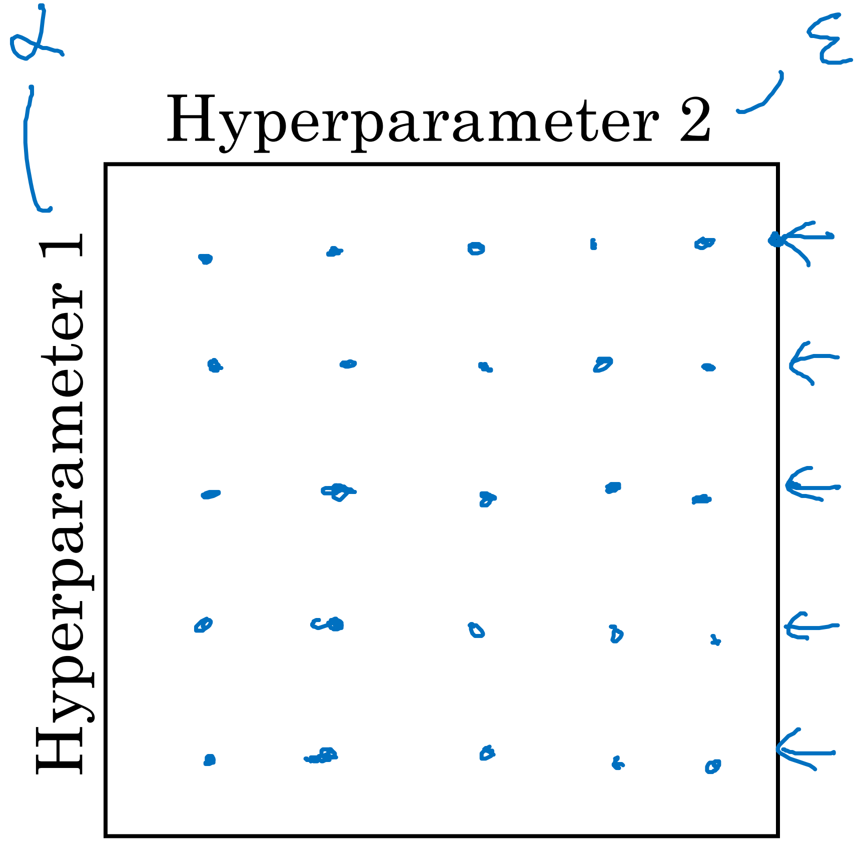
hidden units

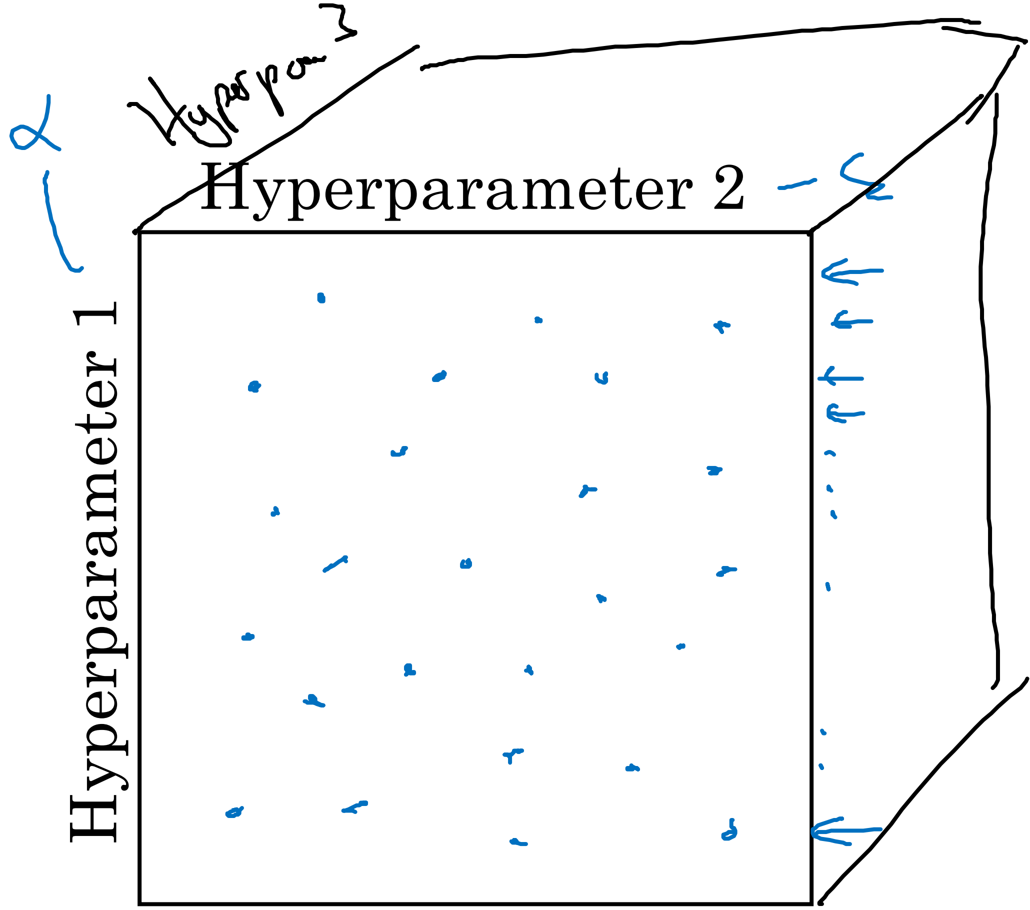
learning rate decay

mini-batch size

Red is most important, ornage is little less while the purple ones are the ones yo

Try random values: Don't use a grid





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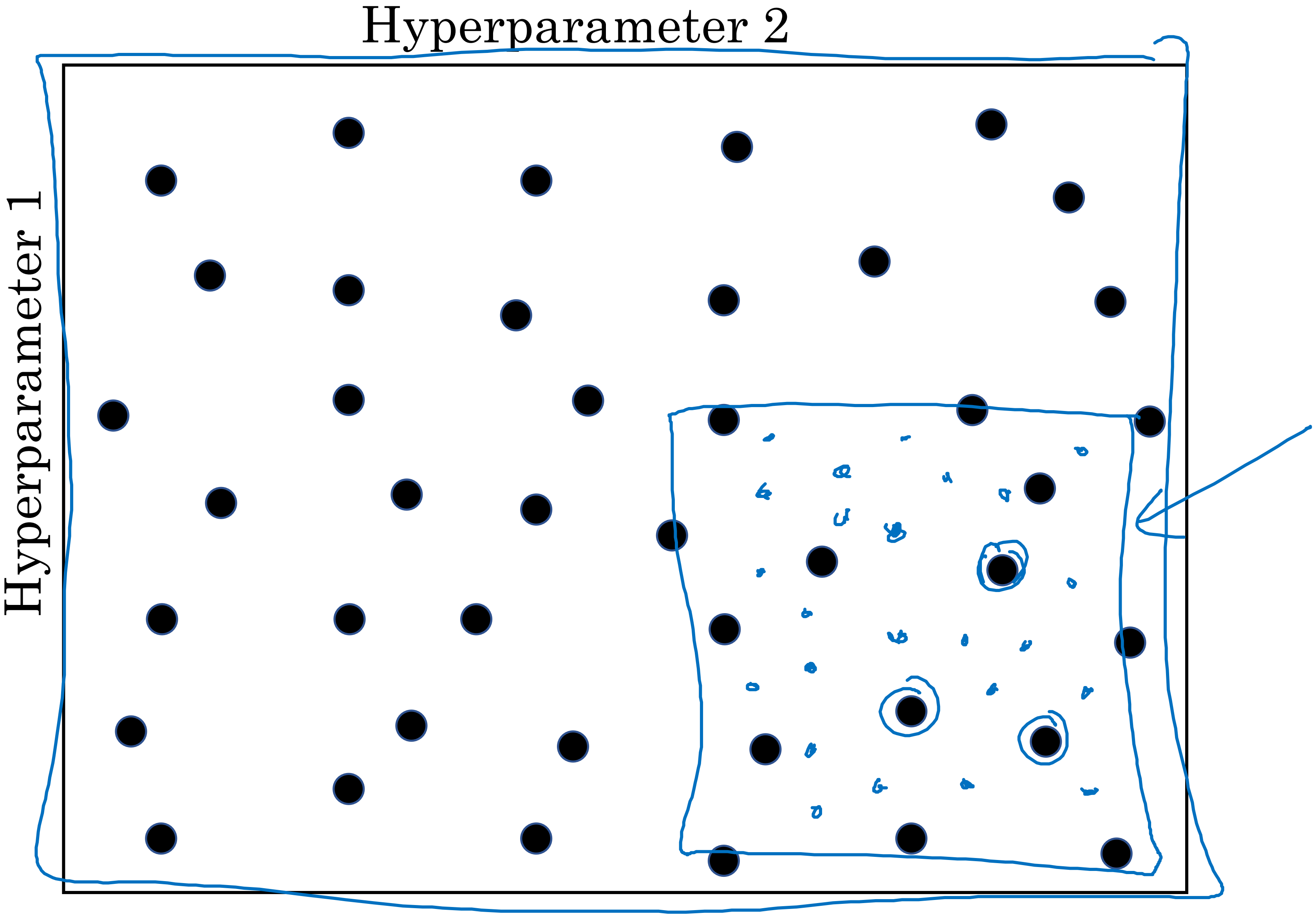
Coarse to fine

First go fine coarse, then if y



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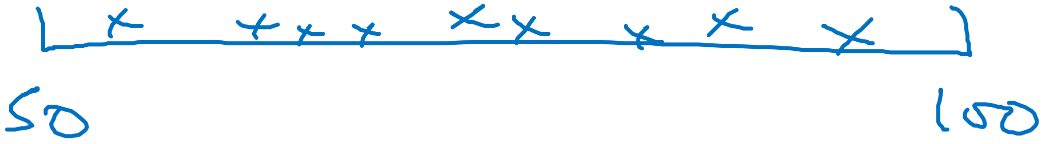
Hyperparameter tuning

Using an appropriate scale to pick hyperparameters

Picking hyperparameters at random

→ $n^{[l]} = 50, \ldots, 100$

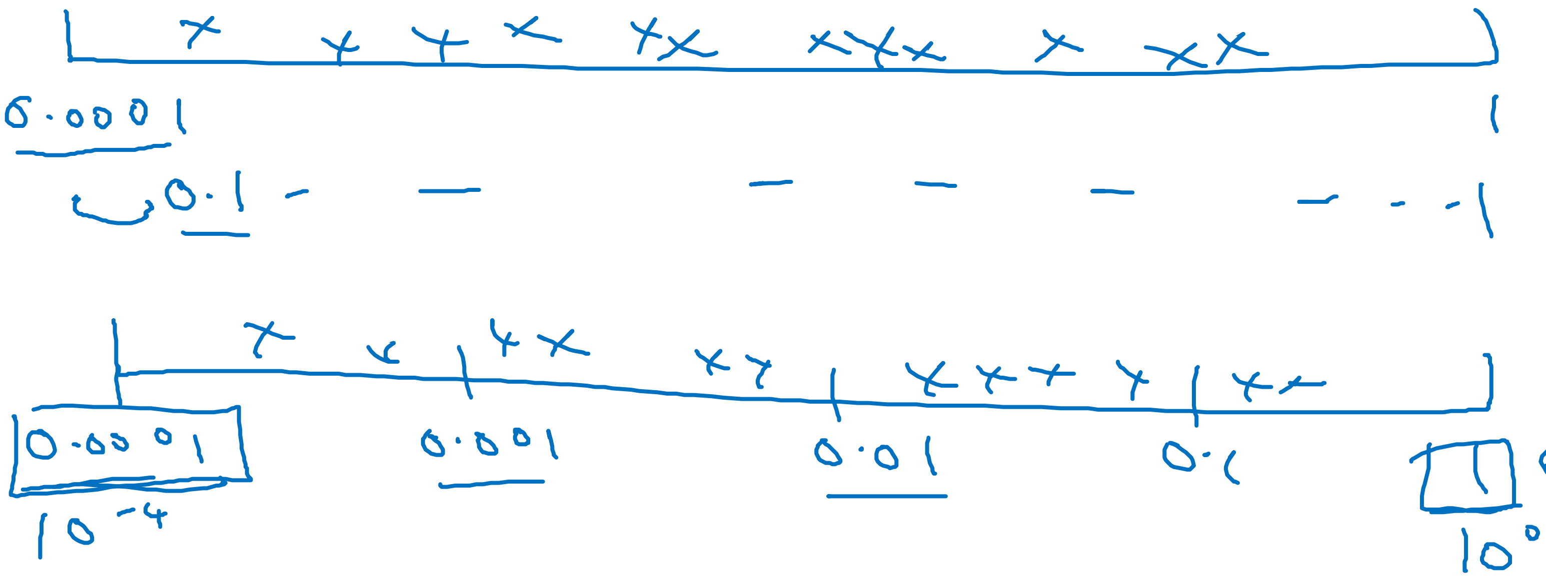


→ #layers $L: 2 - 4$

$2, 3, 4$

Appropriate scale for hyperparameters

$\alpha = 0.0001, \ldots, 1$



10^{a} $\qquad$ 10^{b} $\qquad$ $b = \log_{10} 1 = 0$

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

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

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

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

Hyperparameters for exponentially weighted averages

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

$10 \qquad\qquad 1000$

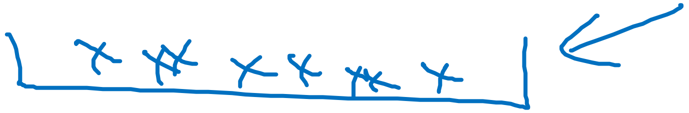
$1-\beta = 0.1 \quad \ldots \quad 0.001$

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

$\beta: 0.999 \rightarrow 0.9995$

$\sim 1000 \qquad \sim 2000$

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



0.9 0.999

0.9 0.99 0.999

0.1 0.01 0.001

10^{-1} 10^{-3}

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

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

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

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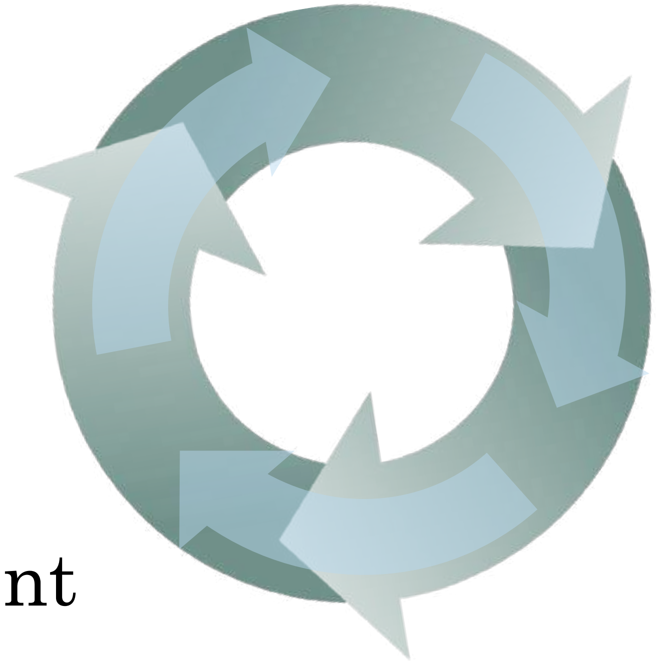
Hyperparameters tuning

Hyperparameters tuning in practice: Pandas vs. Caviar

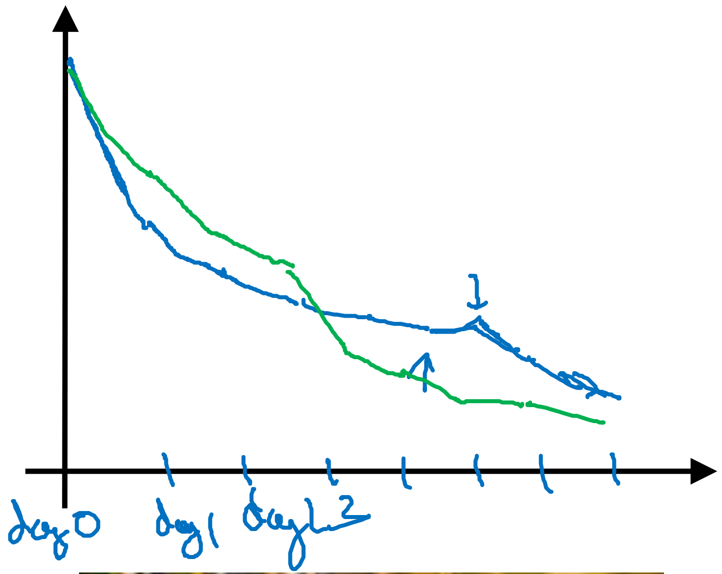
Re-test hyperparameters occasionally



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

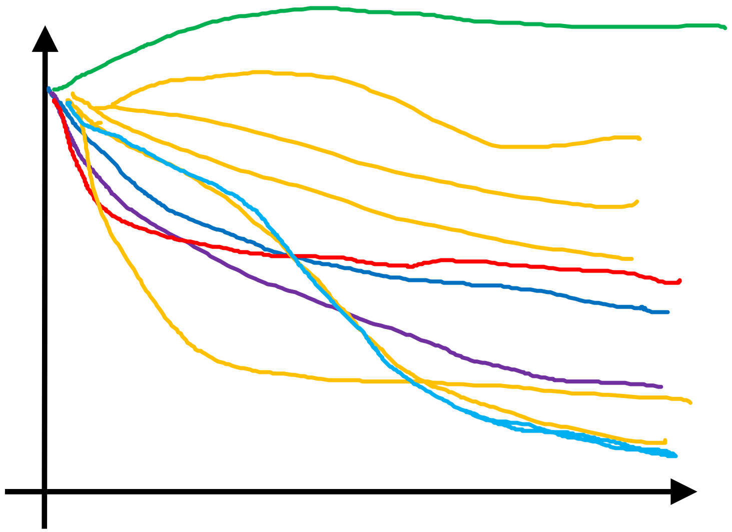
- Intuitions do get stale. Re-evaluate occasionally.

Babysitting one model



Panda

Training many models in parallel



Caviar

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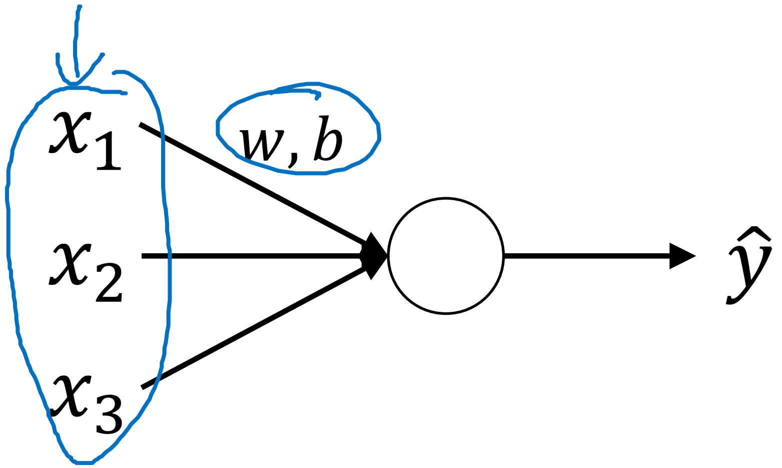
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning

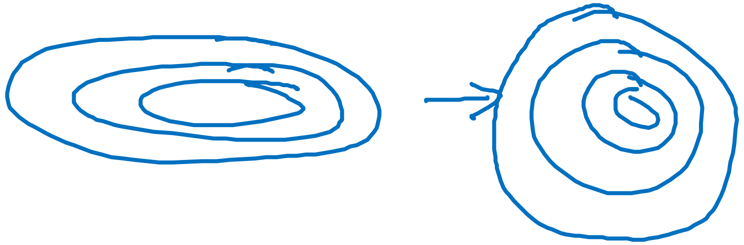


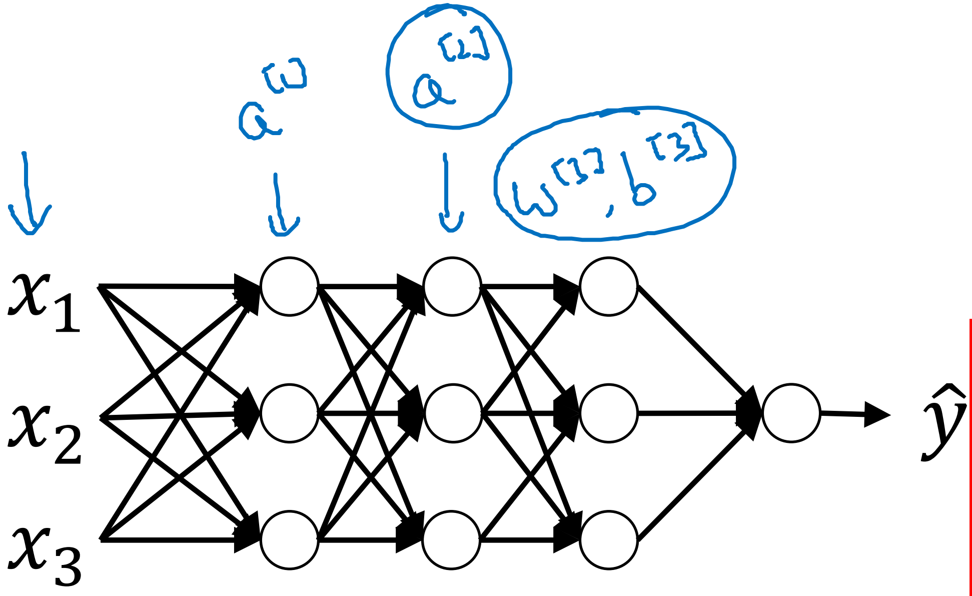
$\mu = \frac{1}{m} \sum_i x^{(i)}$

$X = X - \mu$ ← element-wise

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

$X = X / \sigma$ [1]





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

Normalize $z^{[2]}$

The result would be that ki a[2] which acts as i

Implementing Batch Norm

Given some intermediate values in NN $z^{(1)}, \ldots, z^{(m)}$

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

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

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

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

learnable parameters of model.

If

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

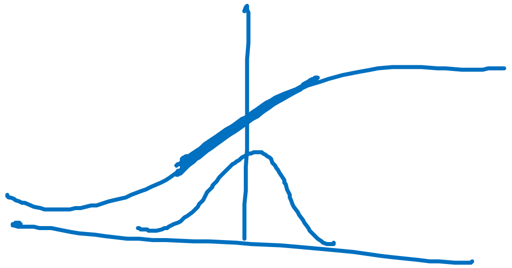
$$\beta = \boxed{\mu}$$

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

$z^{[l](i)}$

X

$z^{(i)}$



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

Using gamma and beta so that in case the z isn't follwing standard

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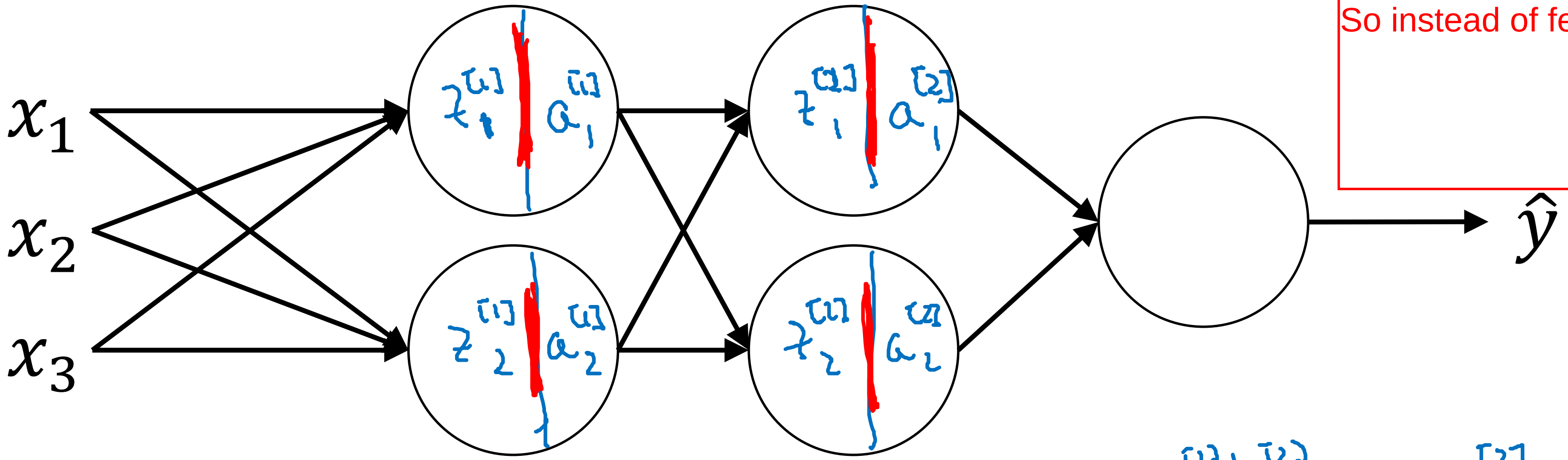
Batch Normalization

Fitting Batch Norm into a neural network

Adding Batch Norm to a network

So instead of feeding a = g(z) we will use



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

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

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

tf.nn.batch_normalization $\Leftarrow$

$\rightarrow \beta$

Working with mini-batches

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

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

Batch norm is applied genrally with mini batch . Take different batches

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

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

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

$z^{[l]}$

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

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

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

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

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

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Implementing gradient descent

for $t = 1 \ldots$ numMiniBatches

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

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

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

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

Works w/ momentum, RMSprop, Adam.

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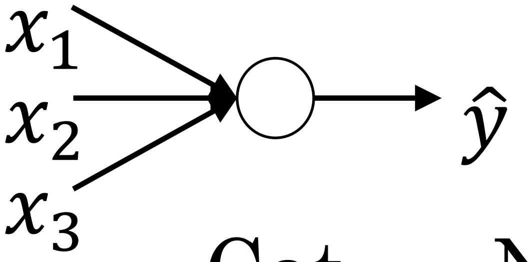
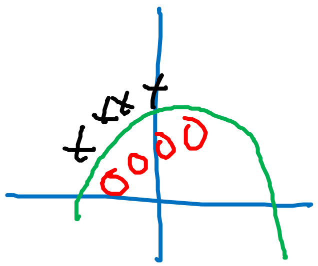
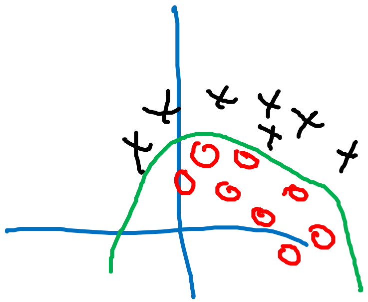
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution

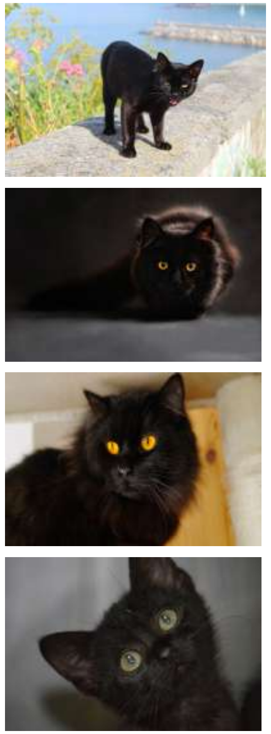






Cat

$y = 1$



Non-Cat

$y = 0$

"Covariate shift"

$X \rightarrow y$

$y = 1$

$y = 0$

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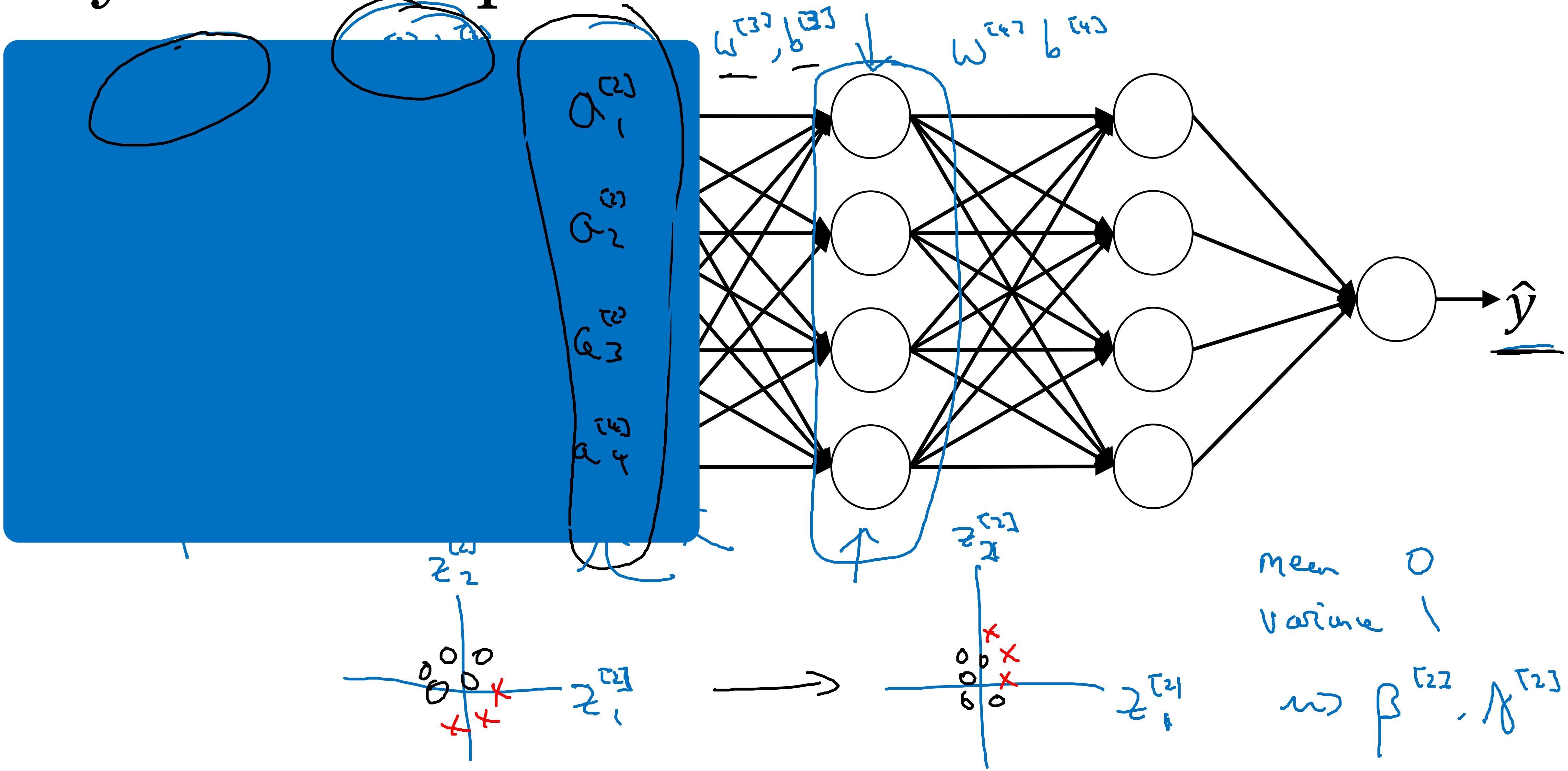
Why this is a problem with neural networks?



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Batch Norm as regularization

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

X

$X^{\{t\}}$

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

64, 128

$z^{[l]}$

μ, σ^2

mini-batch : 64 $\longrightarrow$ 512

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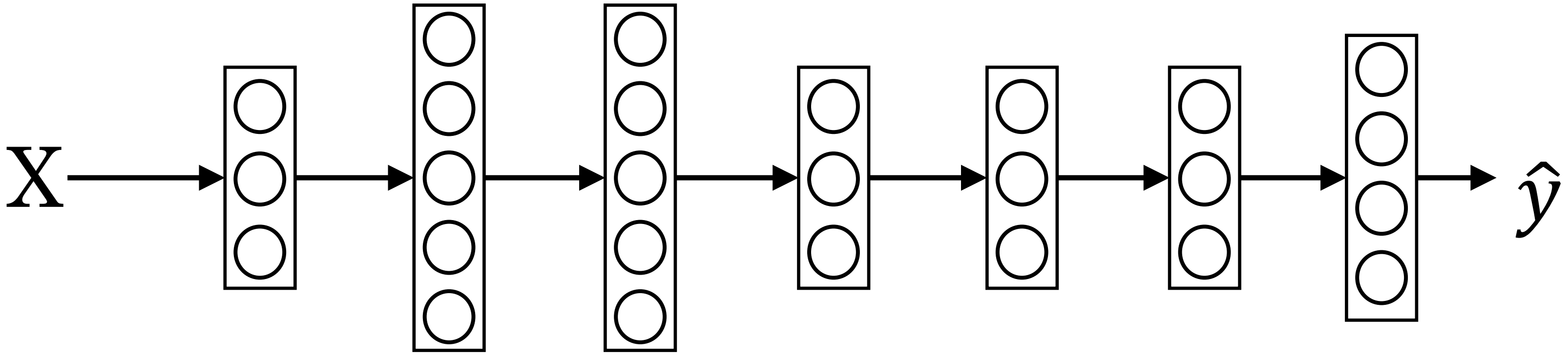
Multi-class classification

Softmax regression

Recognizing cats, dogs, and baby chicks

3 1 2 0 3 2 0 1



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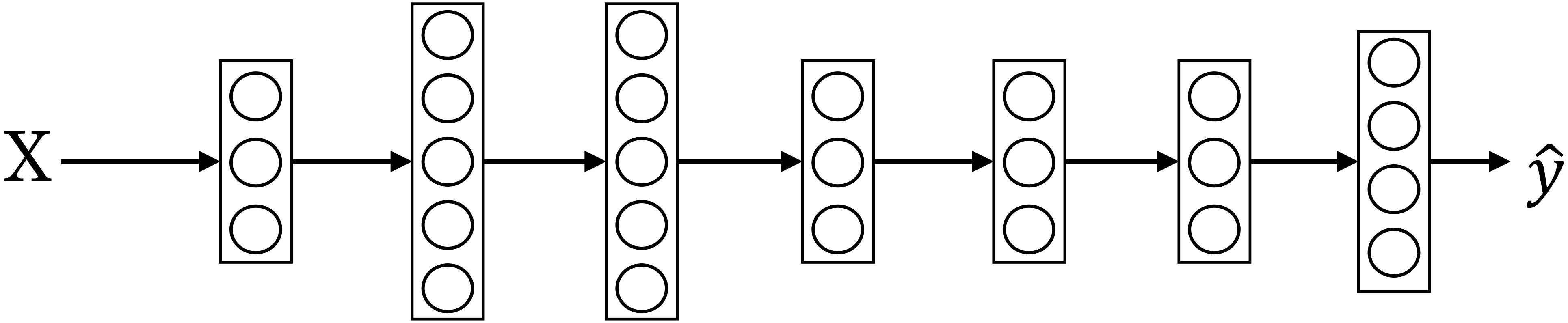
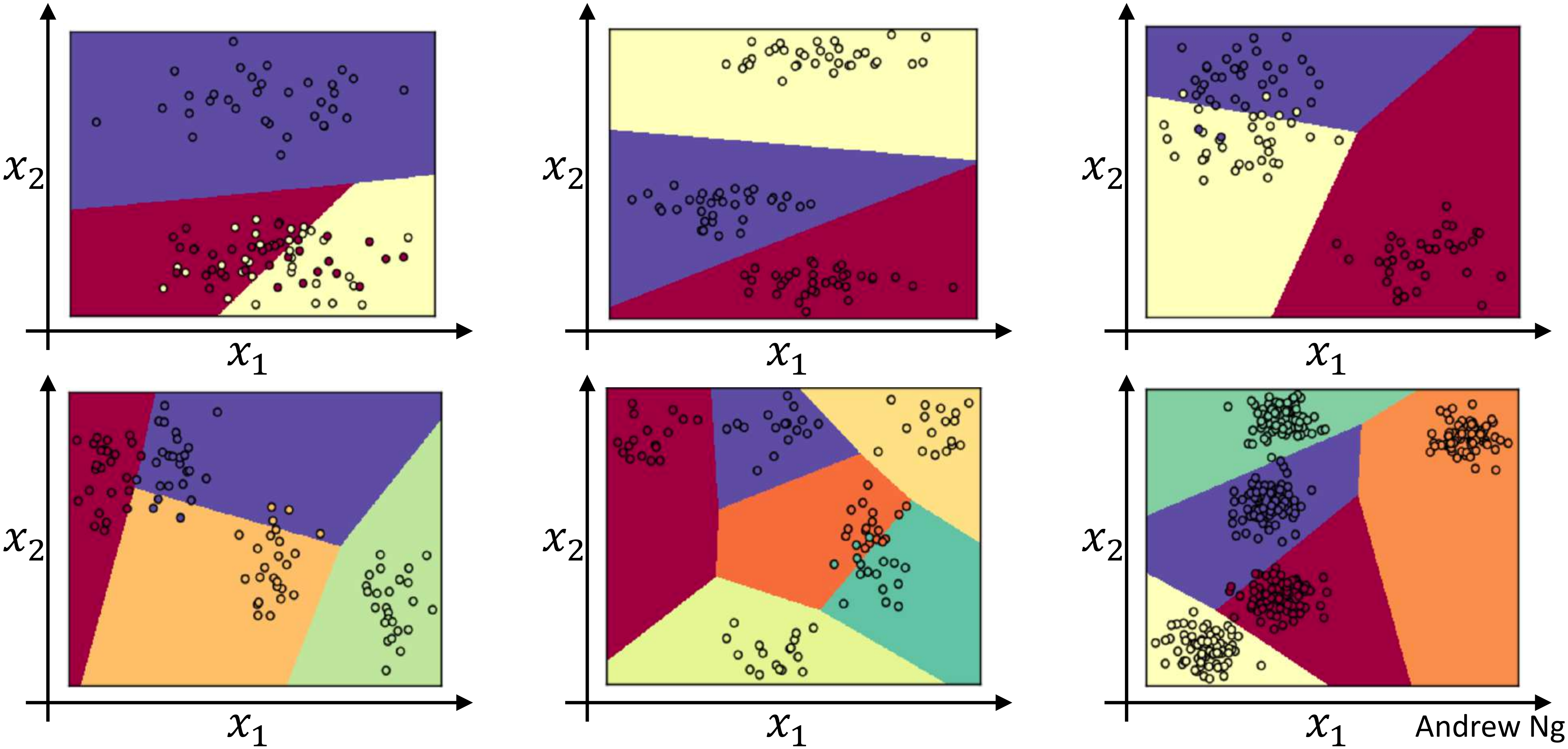
Softmax layer



We calculate z as normal for the last layer but apply activation fn to be softmax activation function. let C be the number of classes. STEPS : t = e^(z[L]

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)

$(w-5)^2$

$w = 5$

$J(w, b)$

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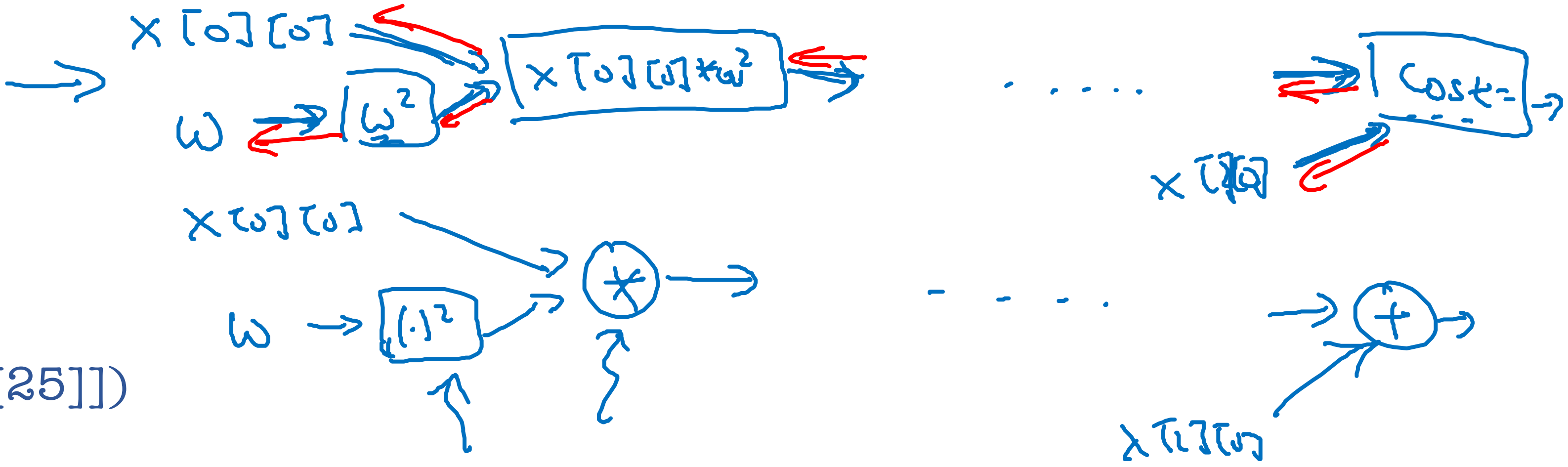
Code example




```
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))

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))
```