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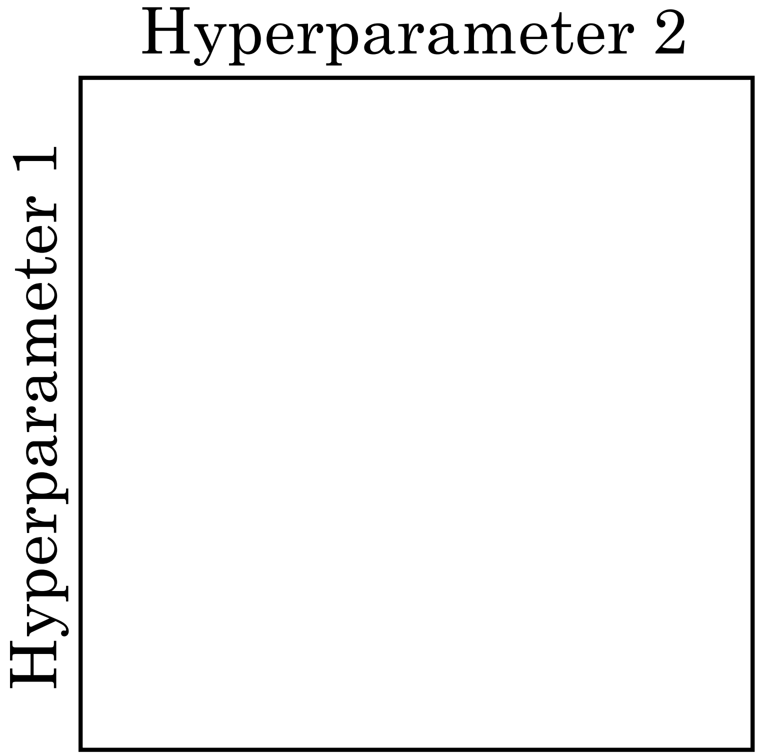
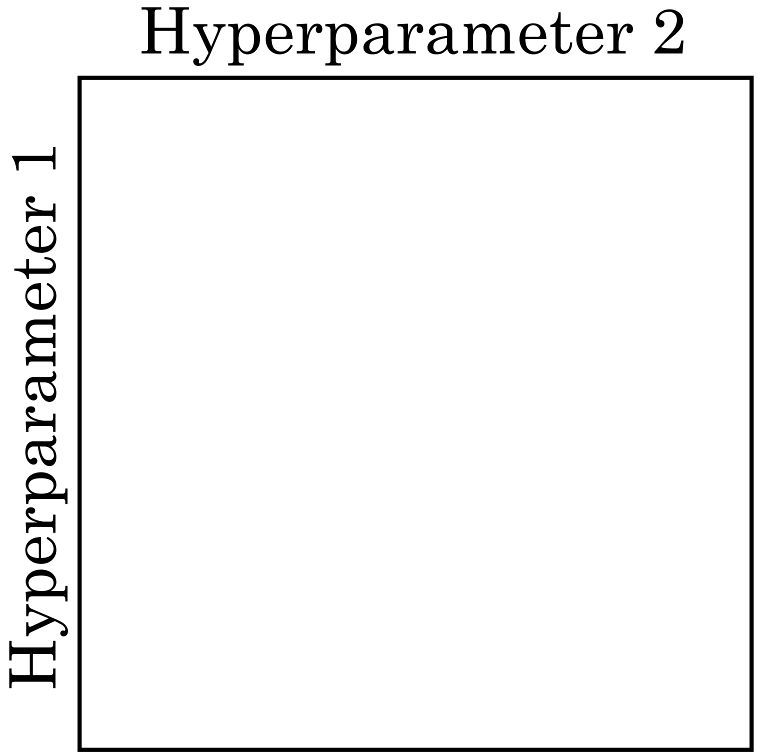
Hyperparameter tuning

Tuning process

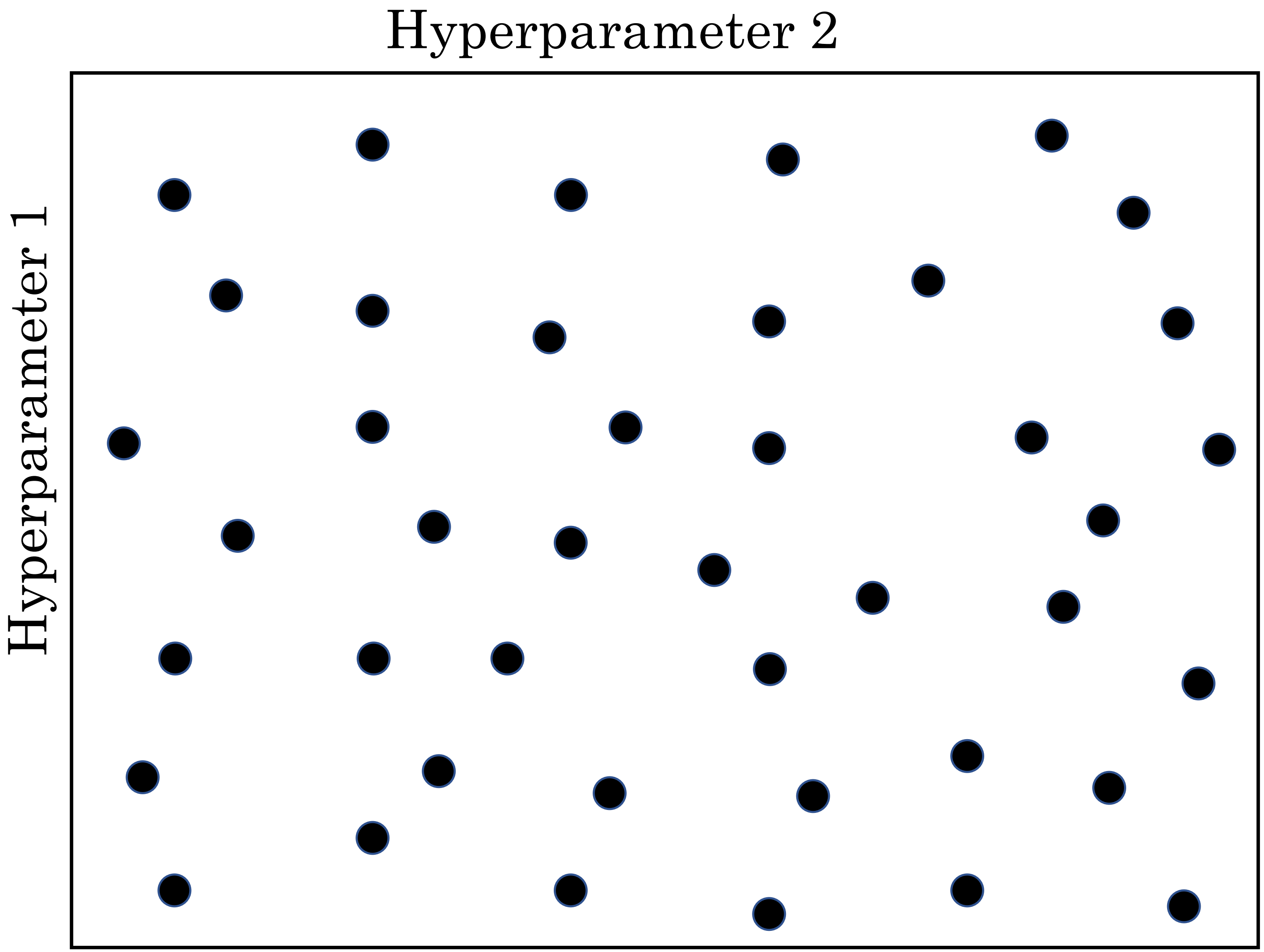
Hyperparameters

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

Appropriate scale for hyperparameters

Hyperparameters for exponentially weighted averages

Hyperparameters tuning

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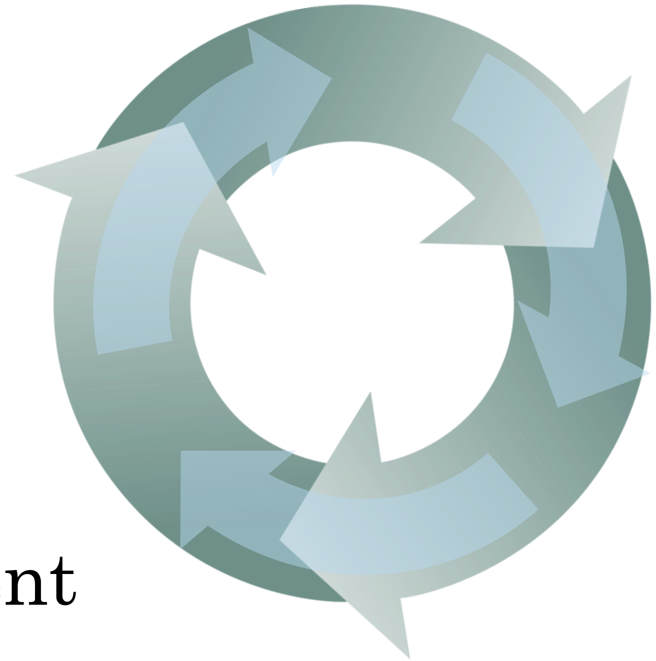
Hyperparameters tuning in practice: Pandas vs. Caviar

Re-test hyperparameters occasionally



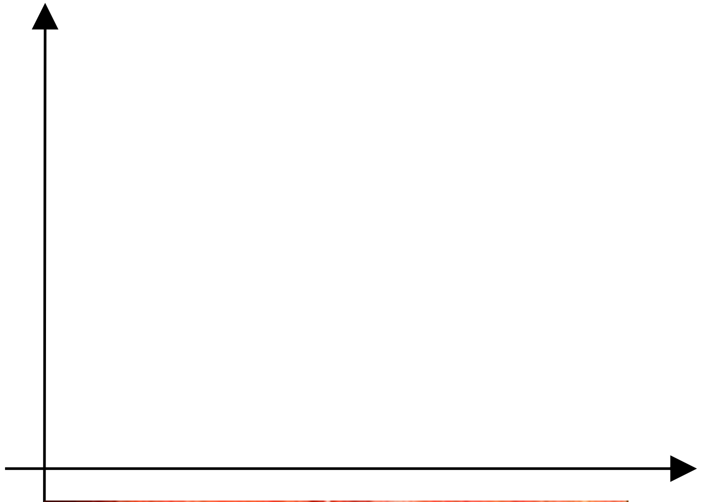
- NLP, Vision, Speech, Ads, logistics, ….

- Intuitions do get stale. Re-evaluate occasionally.

Babysitting one model

Panda

Training many models in parallel



Caviar

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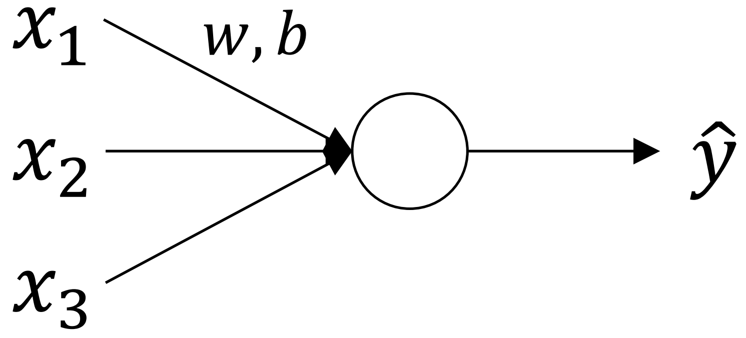
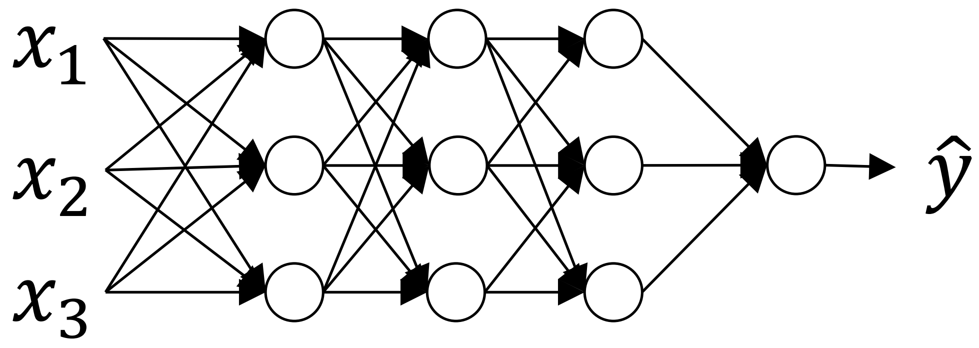
Batch Normalization

Normalizing activations in a network

Normalizing inputs to speed up learning





Implementing Batch Norm

Batch Normalization

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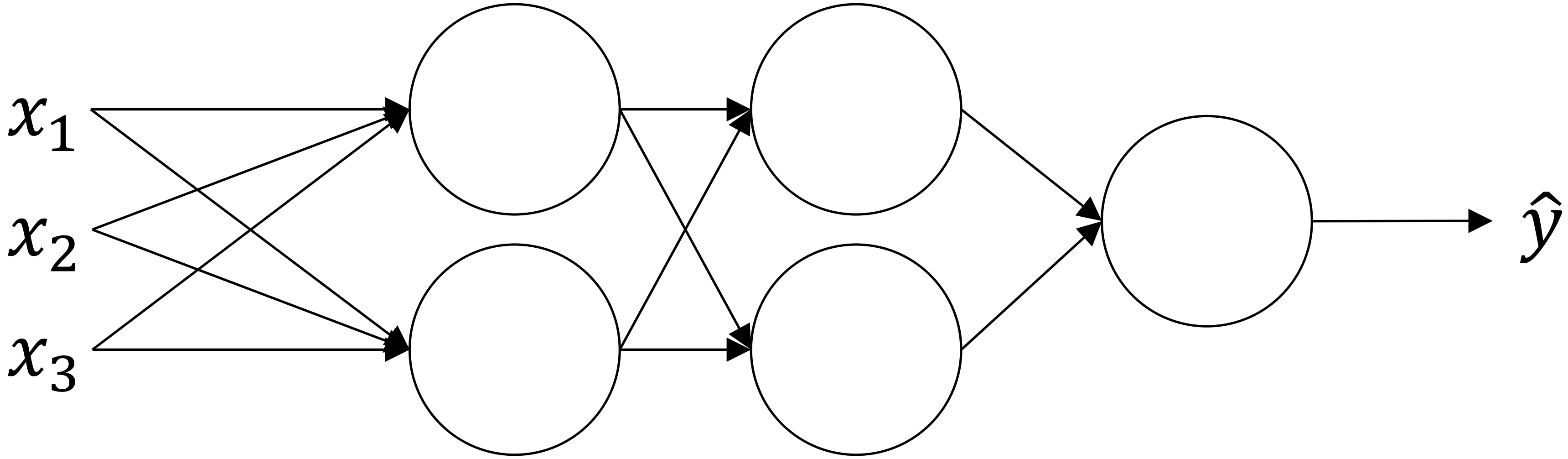
Fitting Batch Norm into a neural network

Adding Batch Norm to a network



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Working with mini-batches

Implementing gradient descent

Batch Normalization

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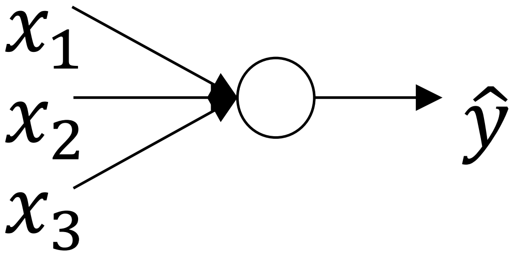
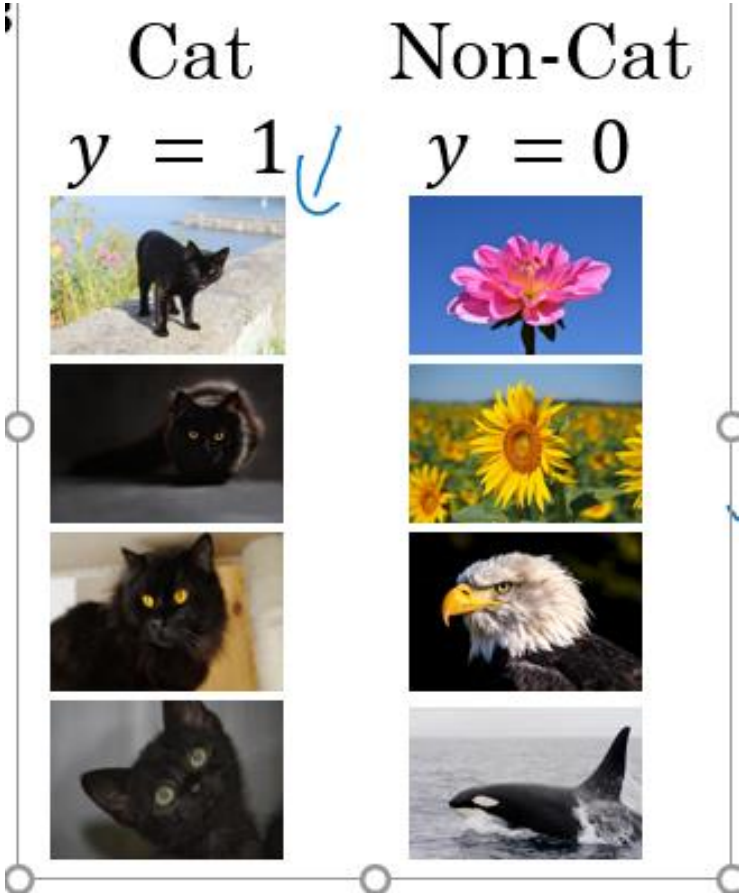
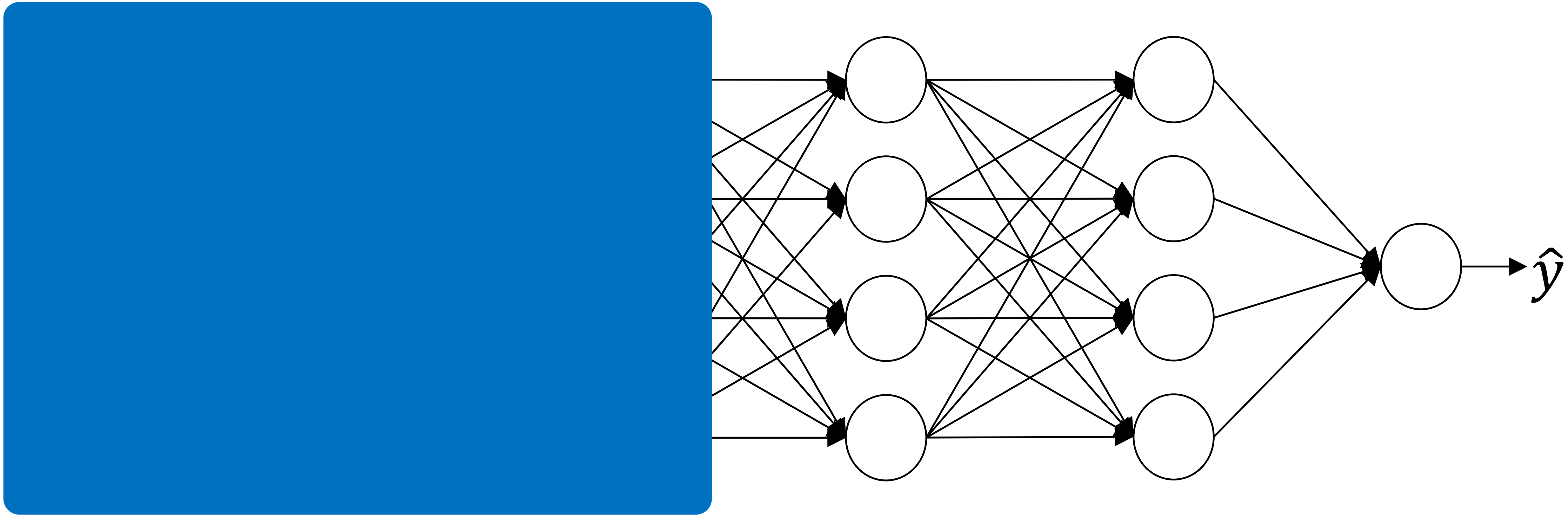
Why does Batch Norm work?

Learning on shifting input distribution





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.

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Batch Normalization

Batch Norm at test time

Batch Norm at test time

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

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

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

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

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Batch Normalization

Batch Norm at test time

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Multi-class classification

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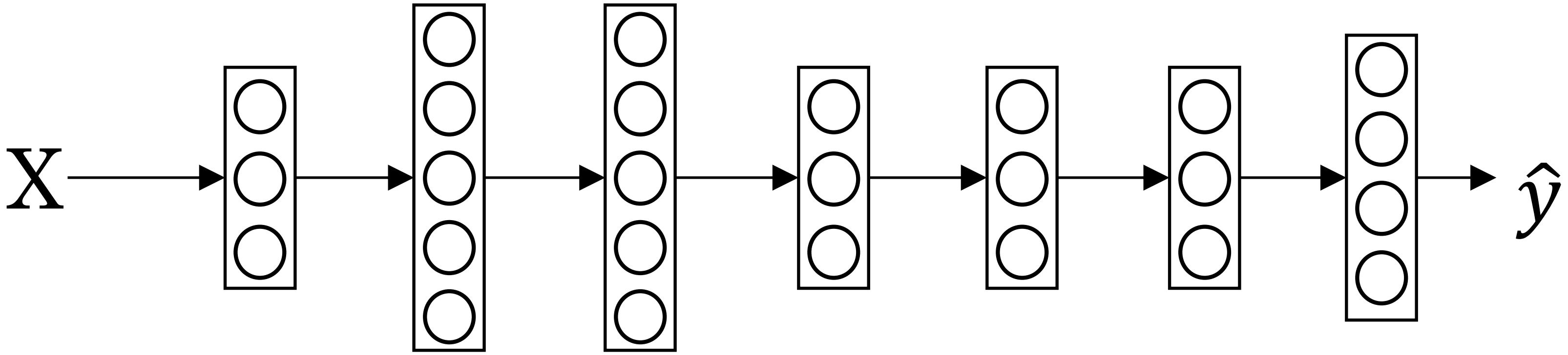
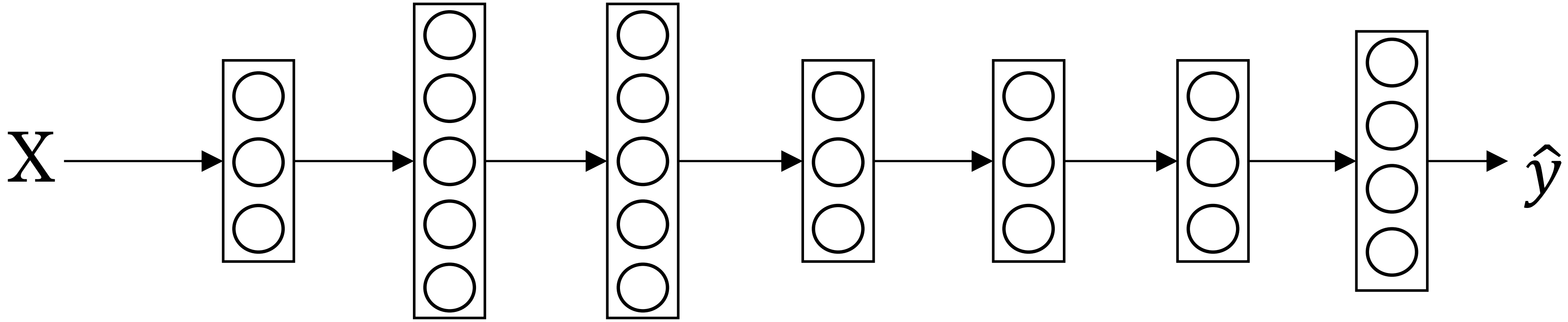
Softmax regression

Recognizing cats, dogs, and baby chicks

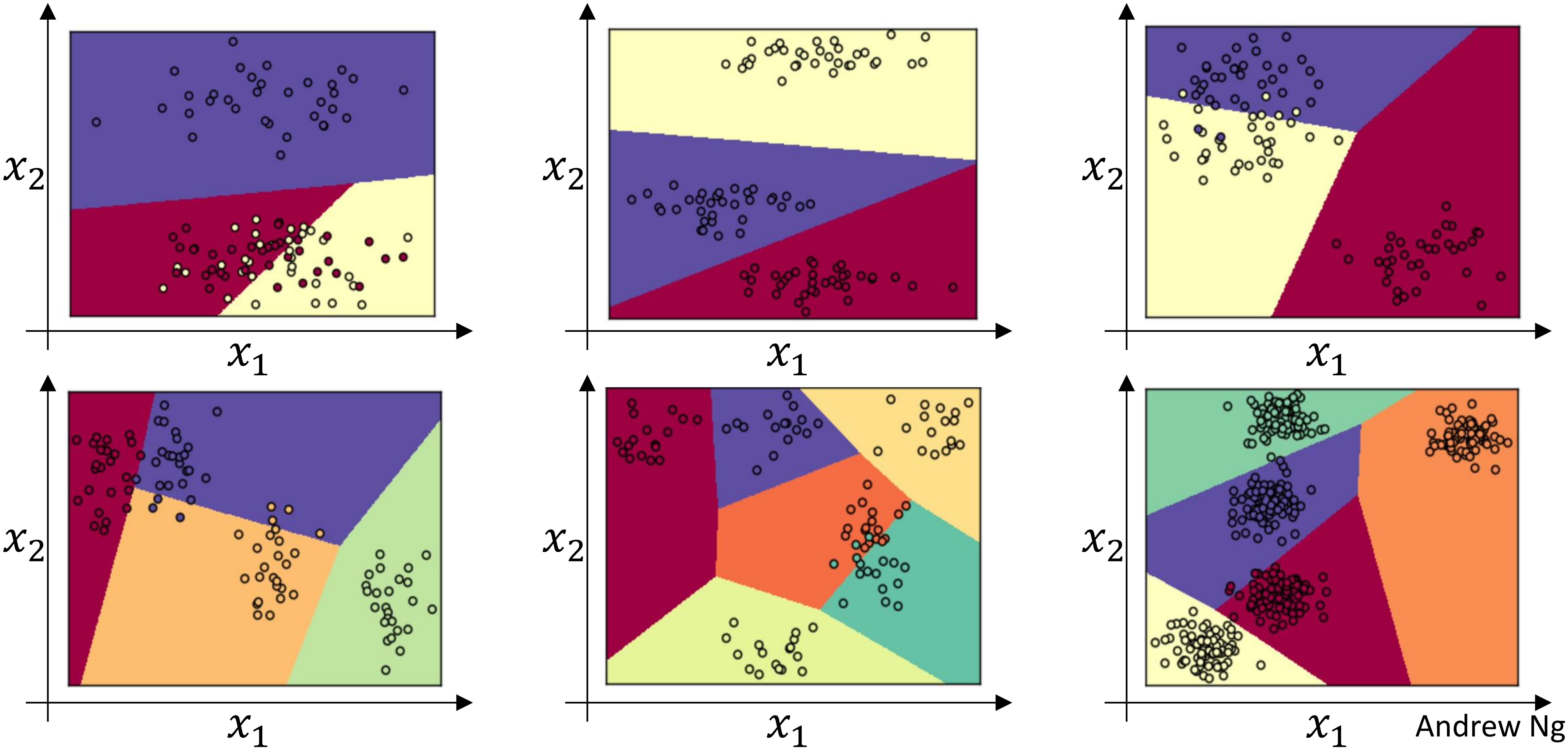
3 1 2 0 3 2 0 1



Softmax layer



Softmax examples



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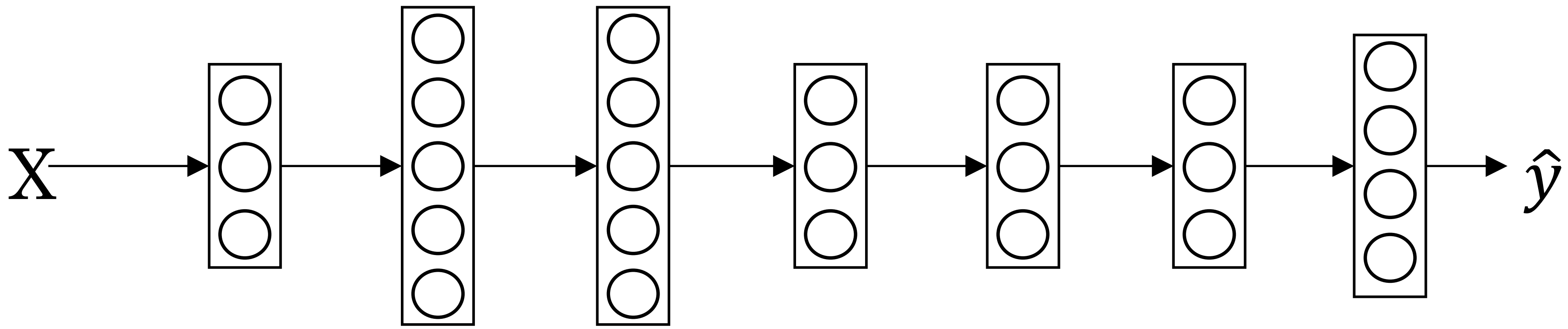
Multi-class classification

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

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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