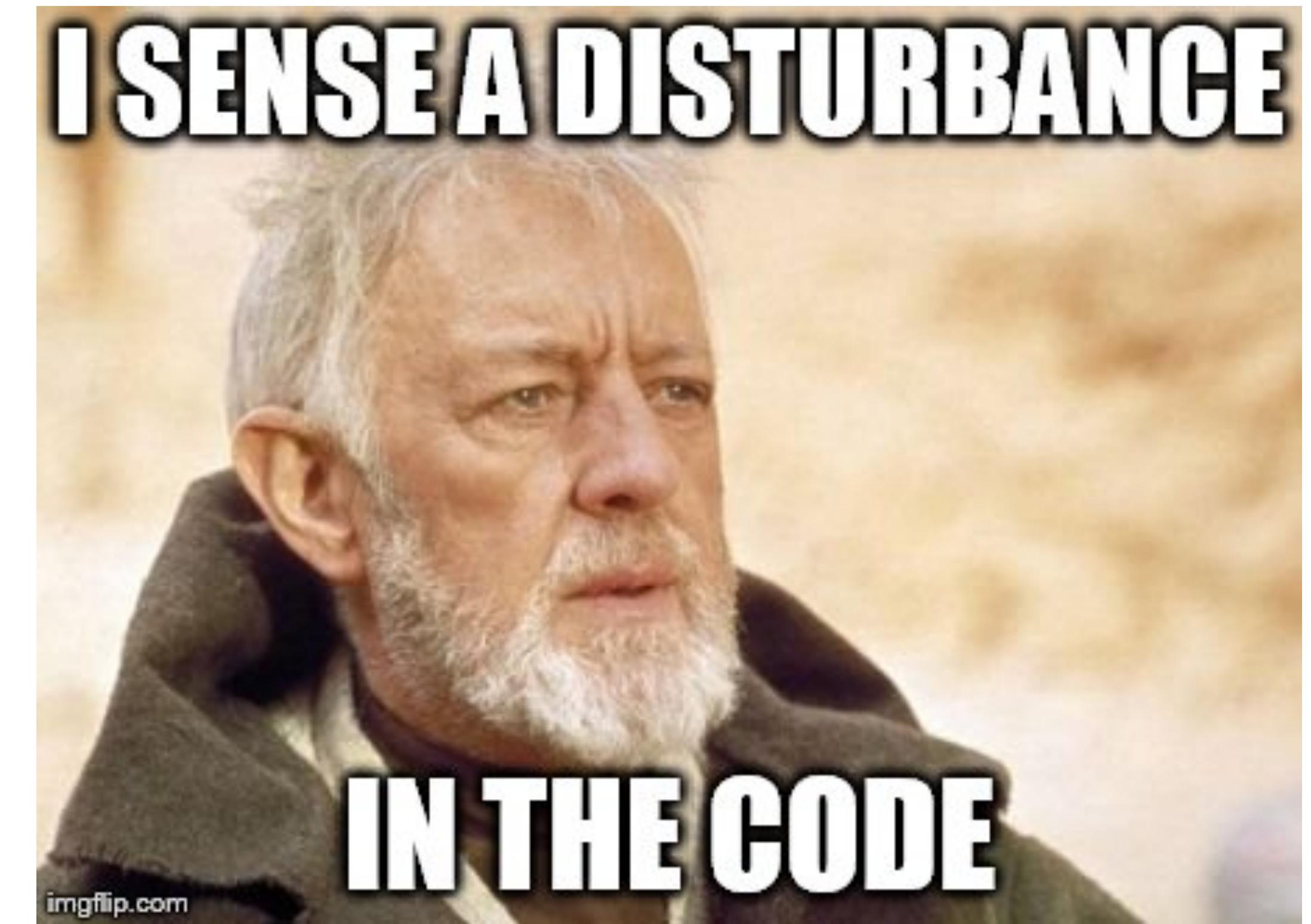
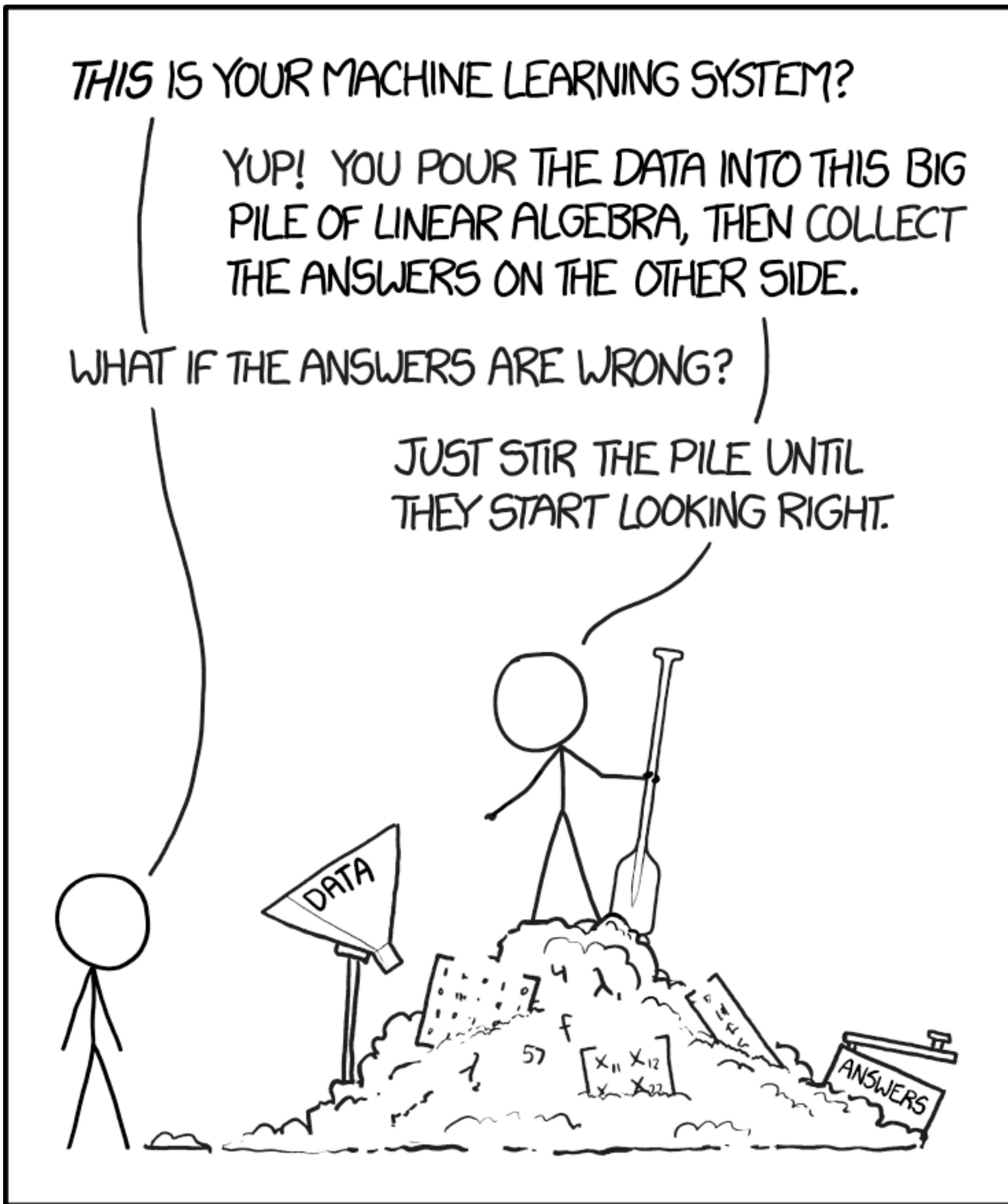


# Introduction to High Performance Machine Learning

DNN Inspection  
Result Interpretation

*Maxwell Cai, PhD*

# Can we trust the results from the DNNs?



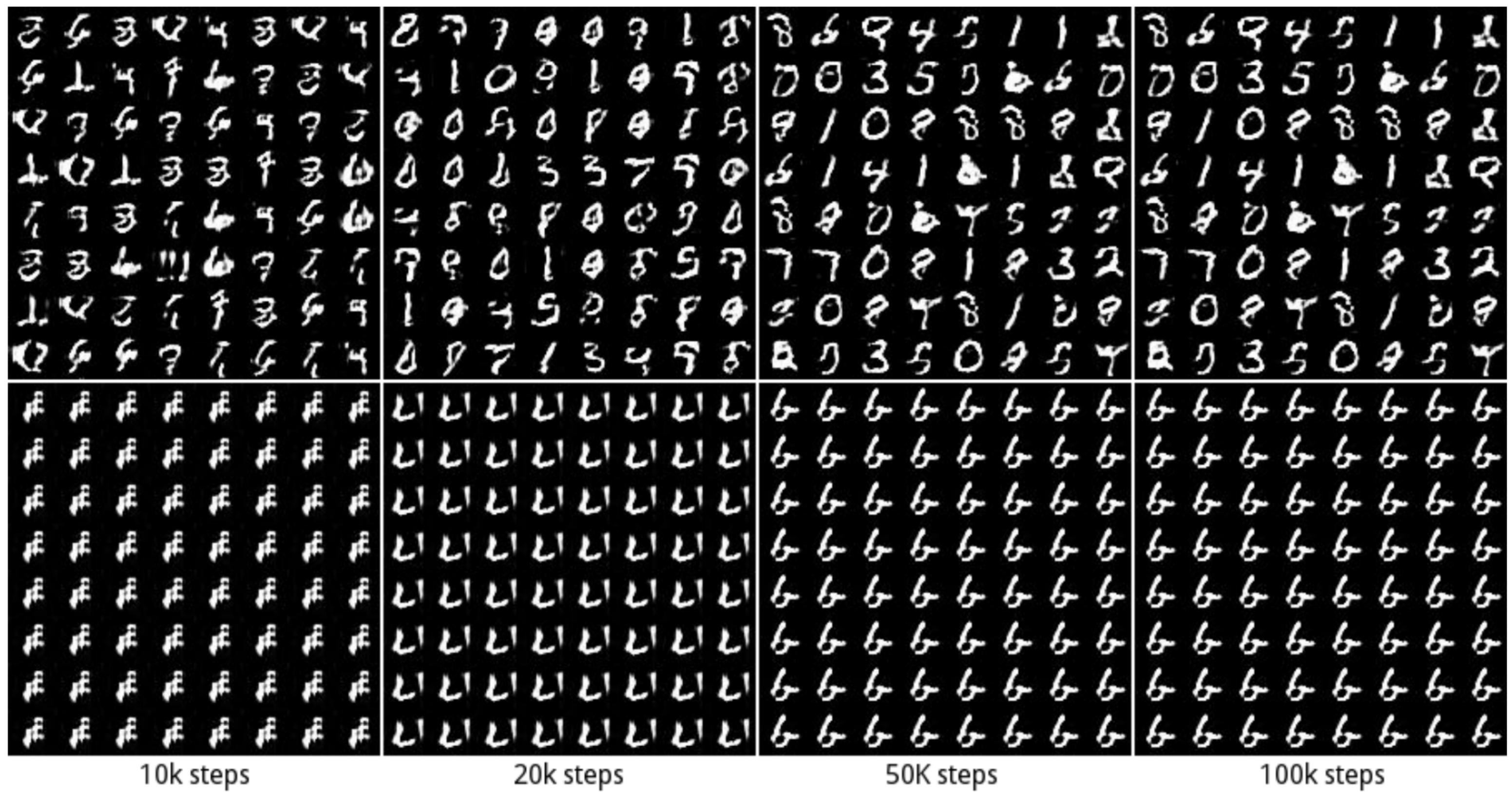
# Challenges of debugging a DNN

Deep learning is a new programming paradigm driven by data. But...

- The code never crashes, raises an exception, or even slows down.
- The network still trains and the loss will still go down.
- The values converge after a few hours, but to really poor results

Metz et al. 2016 ([arXiv:1611.02163](https://arxiv.org/abs/1611.02163))

**Mode collapse of GANs**

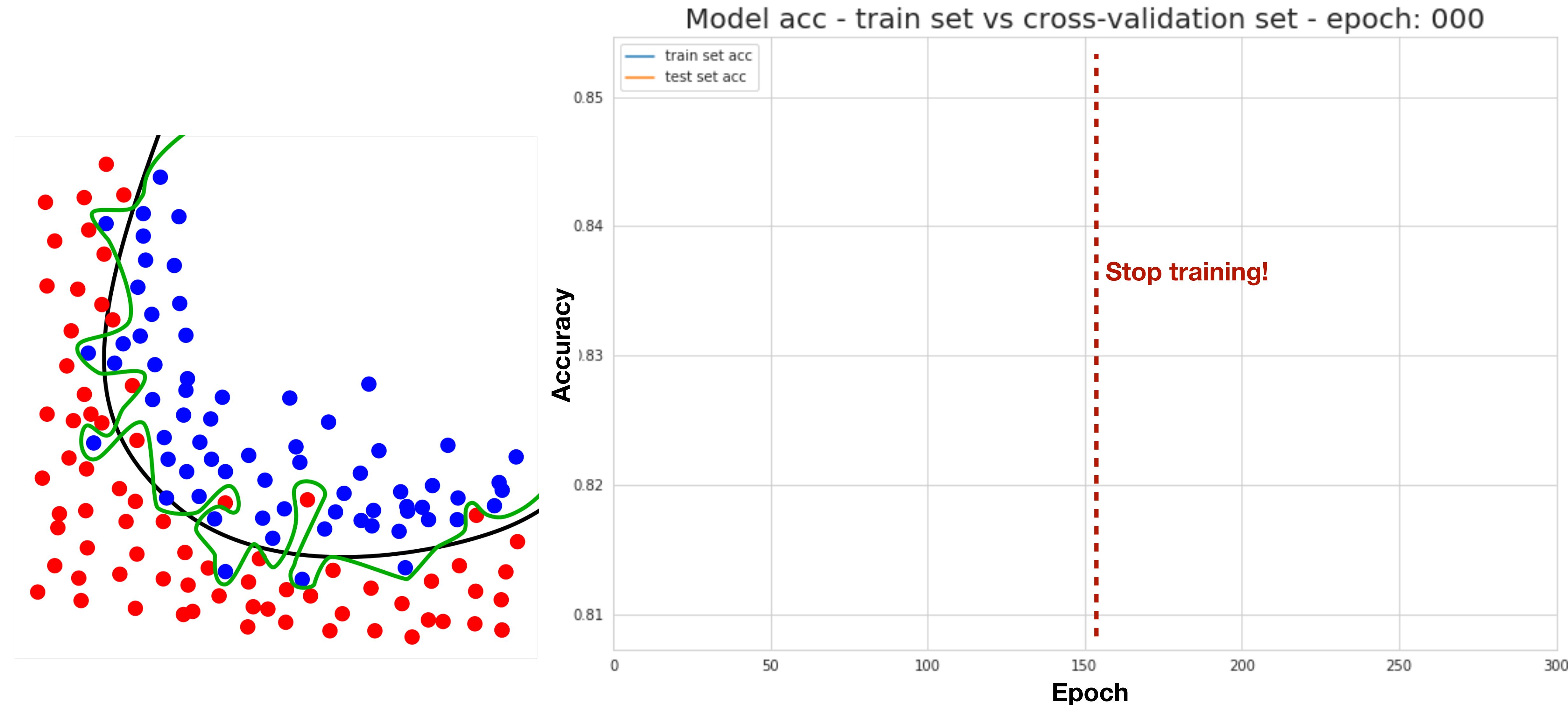


See also: <https://medium.com/@keeper6928/how-to-unit-test-machine-learning-code-57cf6fd81765>

**What can we tell from the training/validation losses?**

# Overfitting

In case of overfitting, train/validation losses are helpful.



# Underfitting

**Train your model with a single data point.**

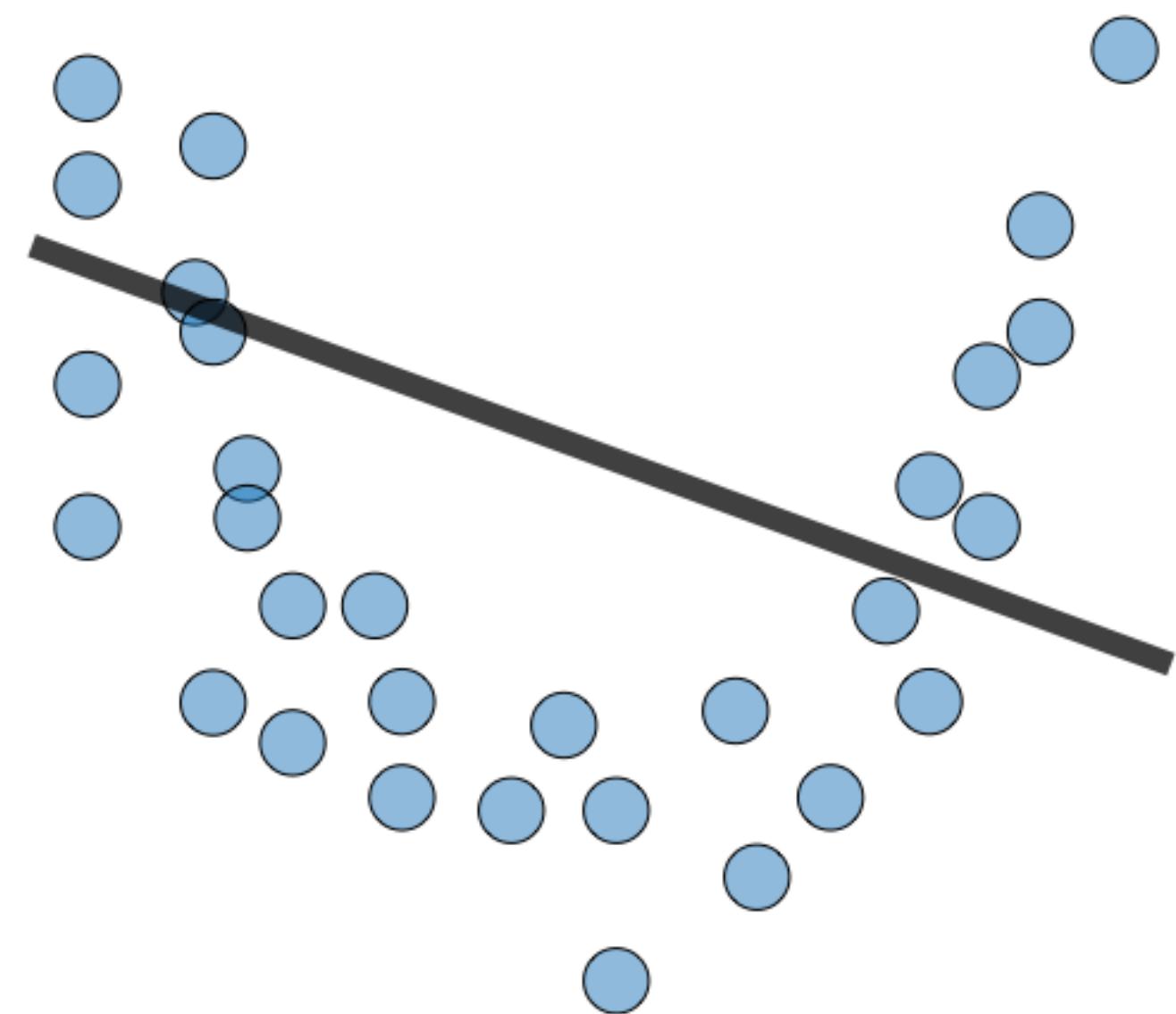
**Expected behaviour:**

Training accuracy = 1

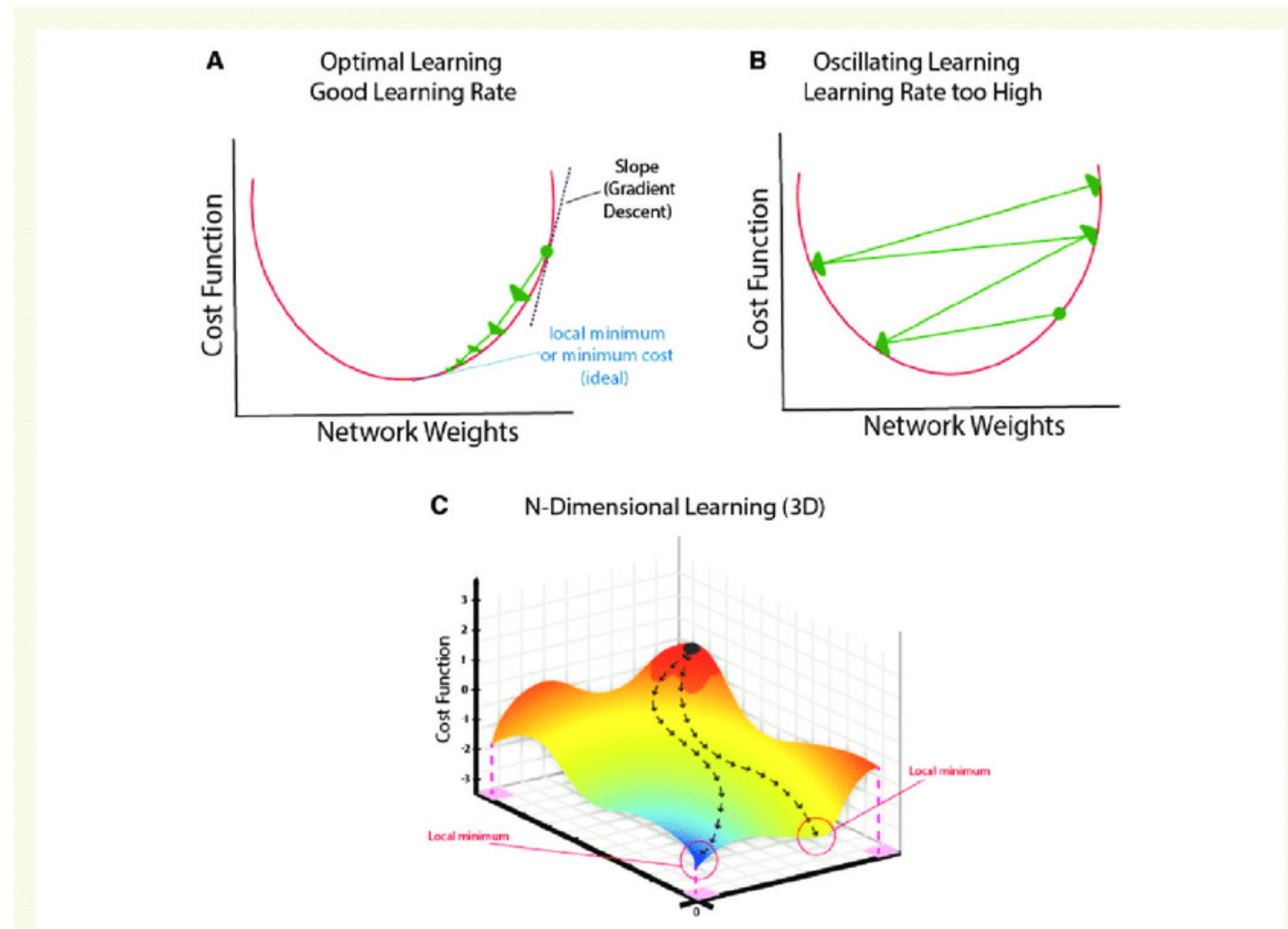
Validation accuracy → Random guess

Otherwise:

DNN too small. Increase its capacity.

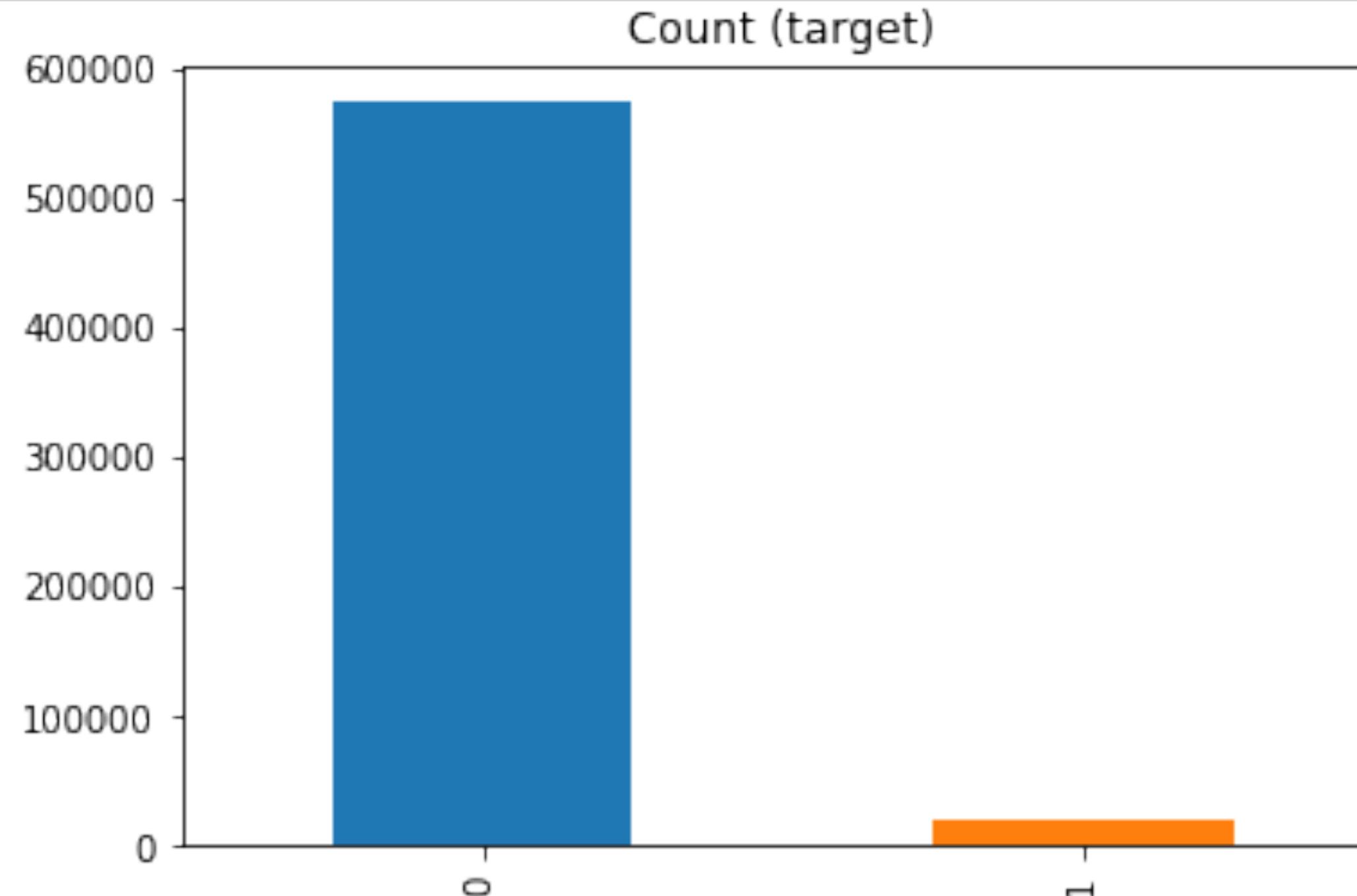


# Learning Rates



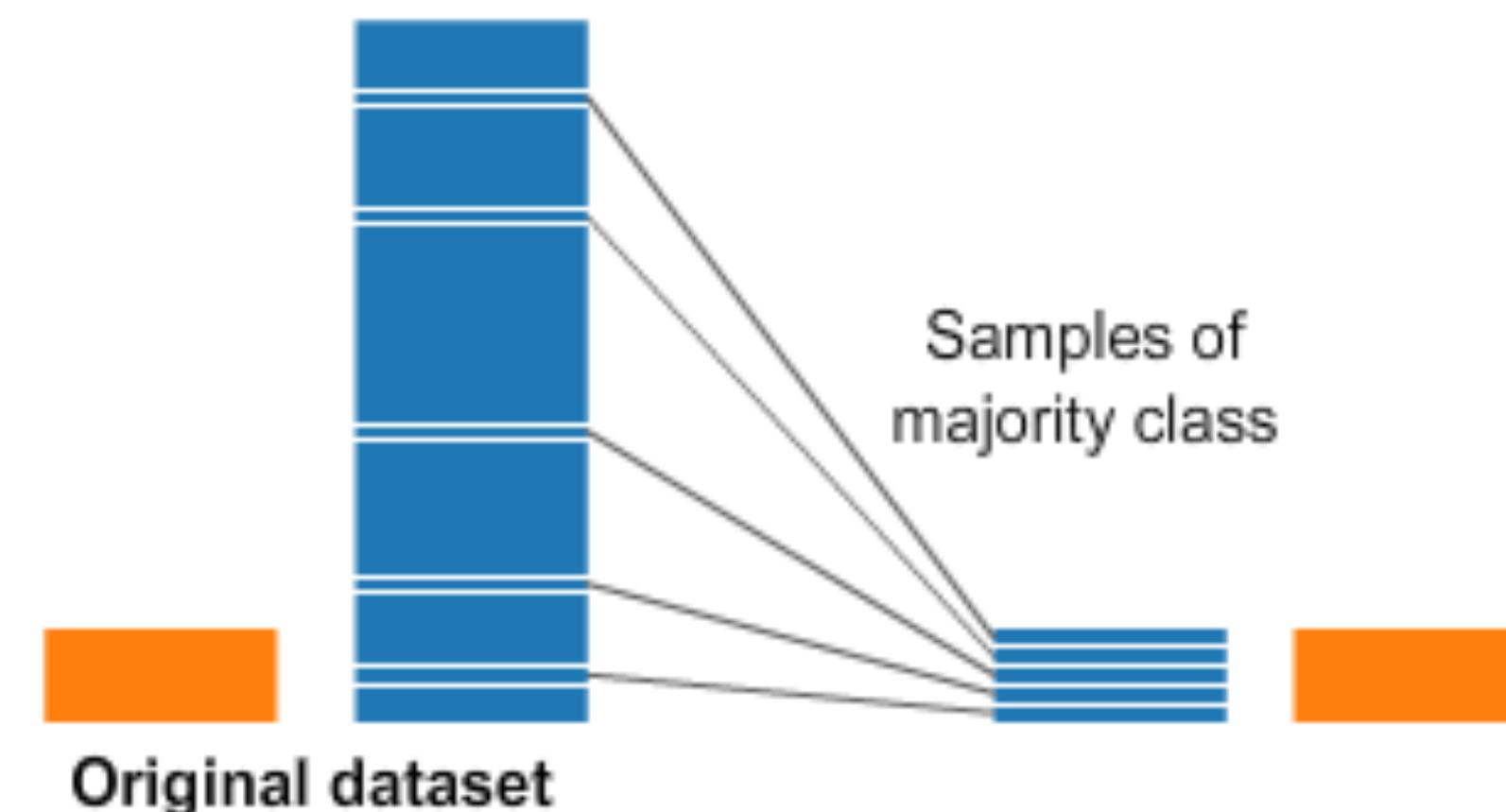
**Don't rely solely on the training/validation loss.**

# Understand Your Data



In case of **imbalanced datasets**, training/validation losses are not helpful indicators of DNN accuracy.

Undersampling

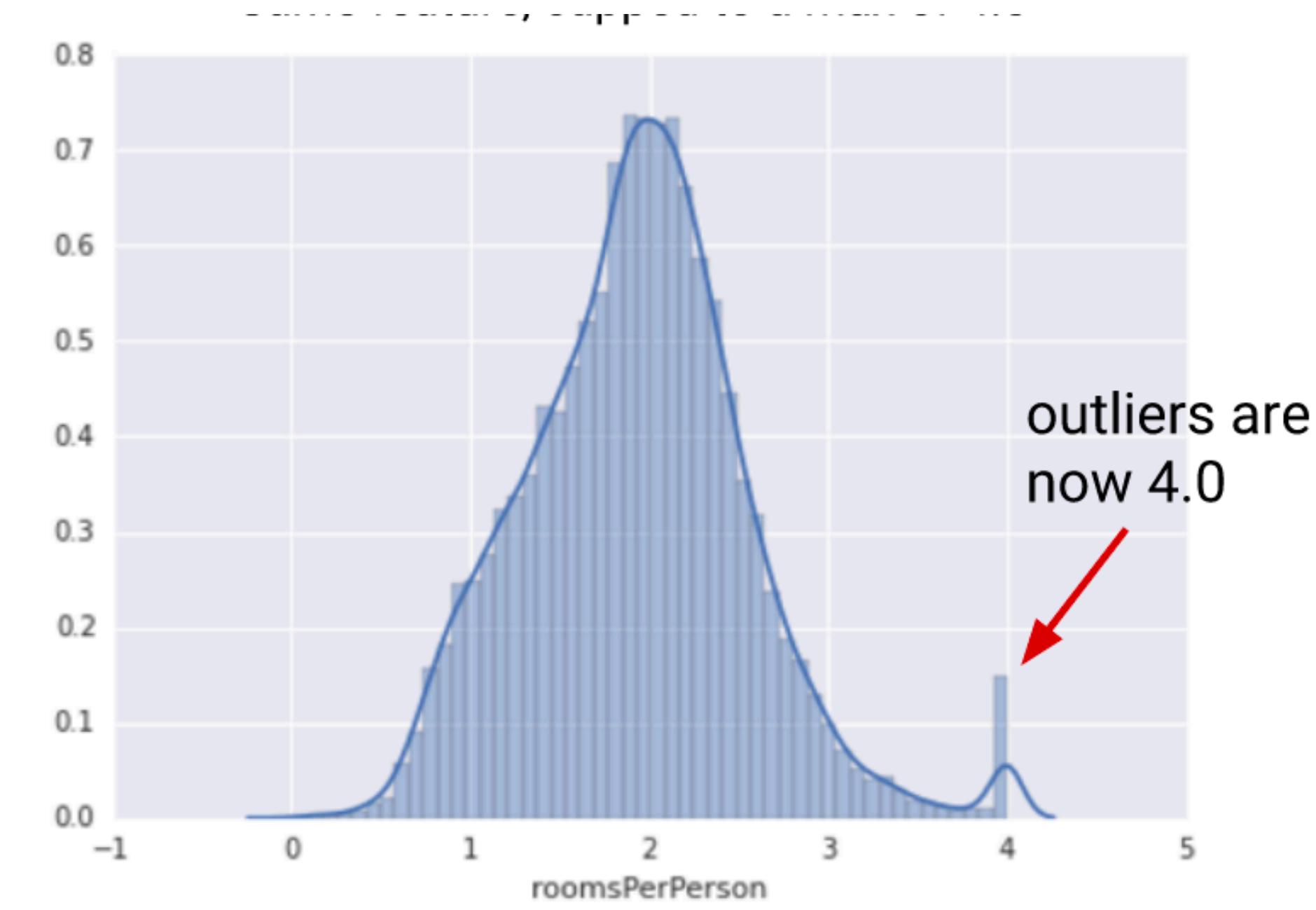
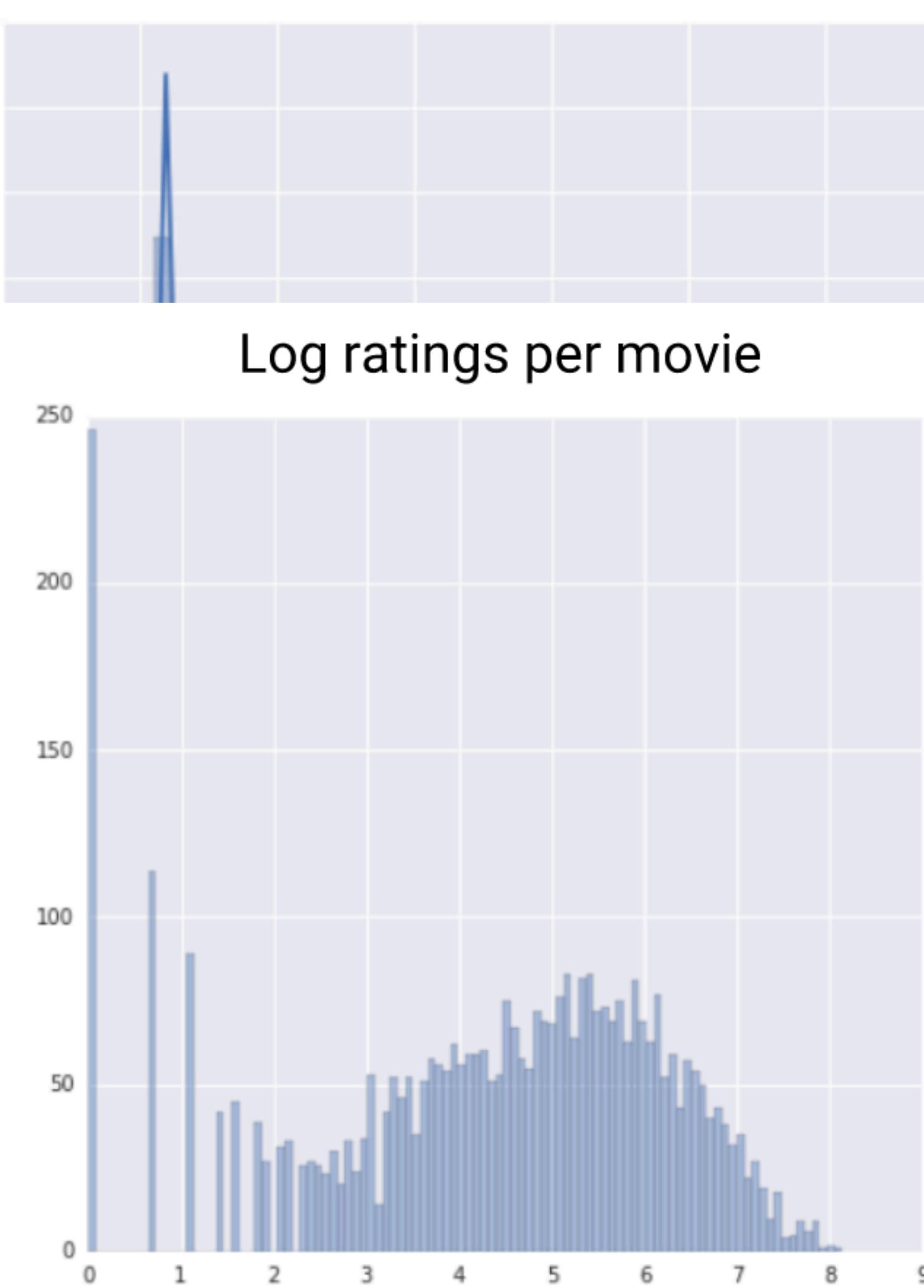
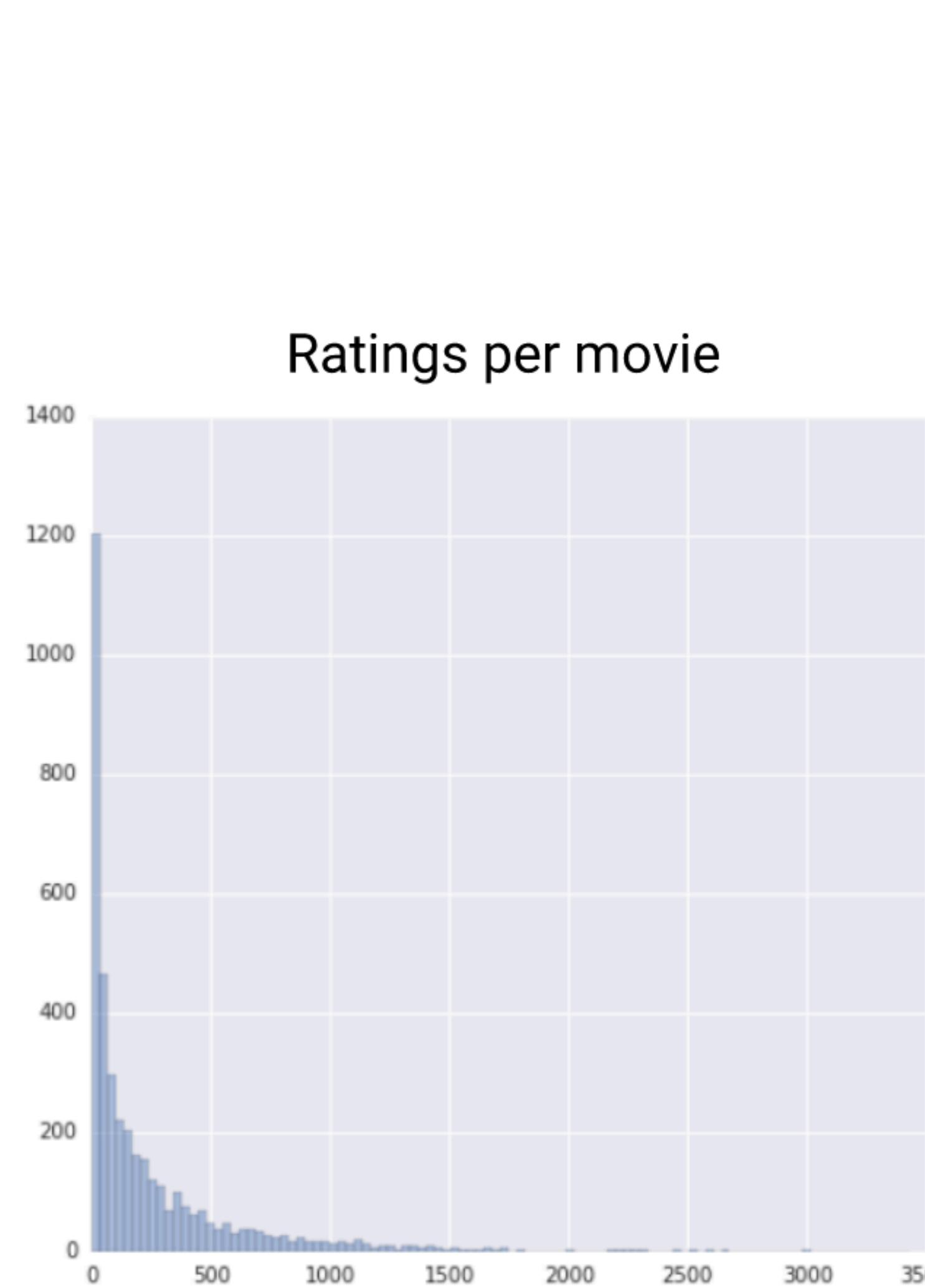


Oversampling



# Understand Your Data

In case of **skewed datasets**, training/validation losses are not helpful indicators of DNN accuracy.



Further reading: [sklearn scalers](#)

# Confusion Matrix

**A confusion matrix can reveal the imbalances in the dataset.**

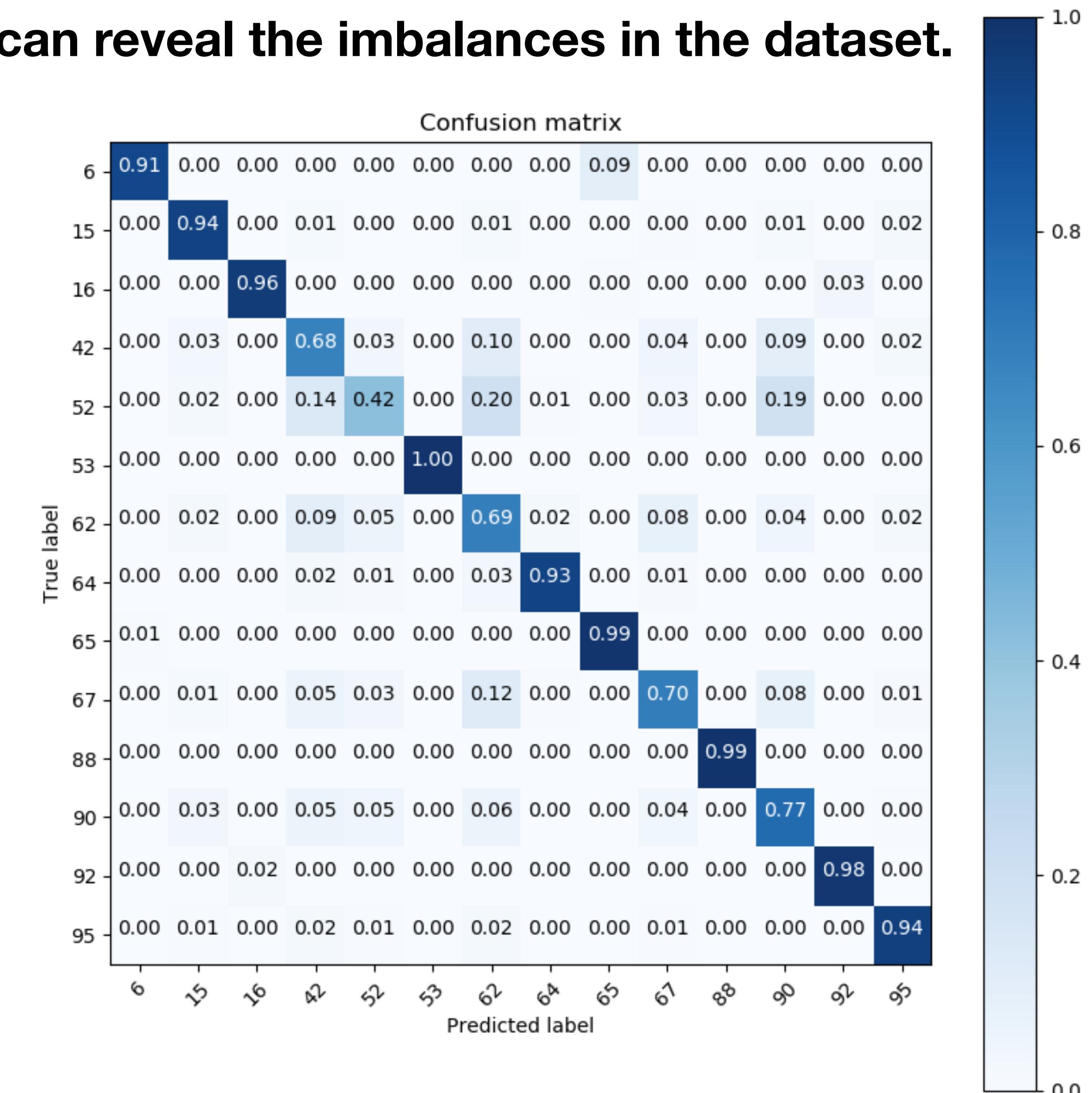
		Prediction outcome		
		p	n	tot
actual value	p'	True Positive	False Negative	P'
	n'	False Positive	True Negative	N'
total		P	N	

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$$

Precision (p) = TP / (TP + FP)

**Recall (r) = TP / (TP + FN)**

$$F_1 = \frac{2}{r^{-1} + p^{-1}}$$



# Understand Your Activation Function

**Use the correct activity function for the correct problem.**

E.g., softmax -> multi-class classification

Sigmoid -> binary classification

Sigmoid


$$y = \frac{1}{1+e^{-x}}$$

Tanh


$$y = \tanh(x)$$

Step Function


$$y = \begin{cases} 0, & x < n \\ 1, & x \geq n \end{cases}$$

Softplus


$$y = \ln(1+e^x)$$

ReLU


$$y = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$

Softsign


$$y = \frac{x}{(1+|x|)}$$

ELU


$$y = \begin{cases} \alpha(e^x-1), & x < 0 \\ x, & x \geq 0 \end{cases}$$

Log of Sigmoid


$$y = \ln\left(\frac{1}{1+e^{-x}}\right)$$

Swish


$$y = \frac{x}{1+e^{-x}}$$

Sinc


$$y = \frac{\sin(x)}{x}$$

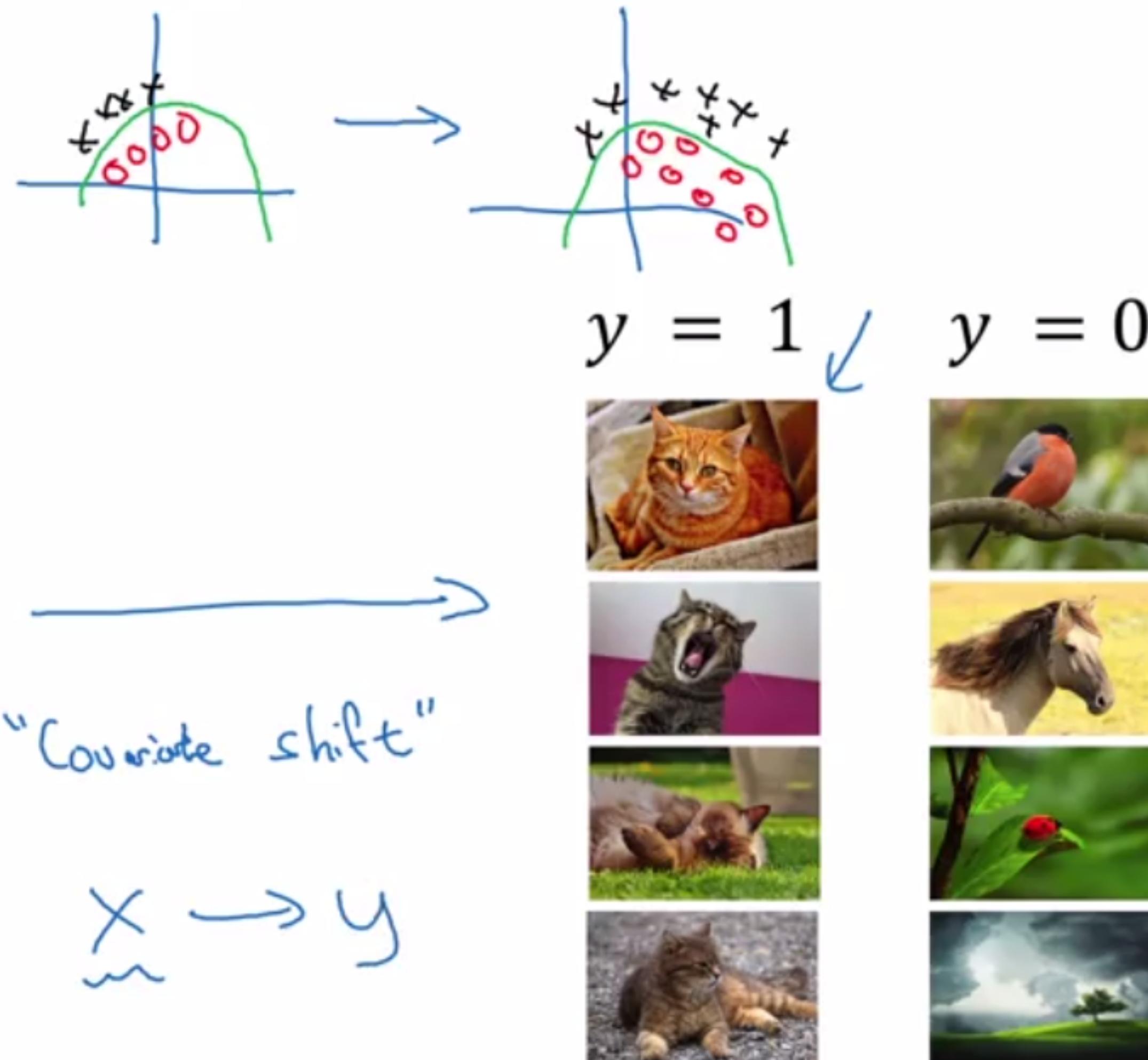
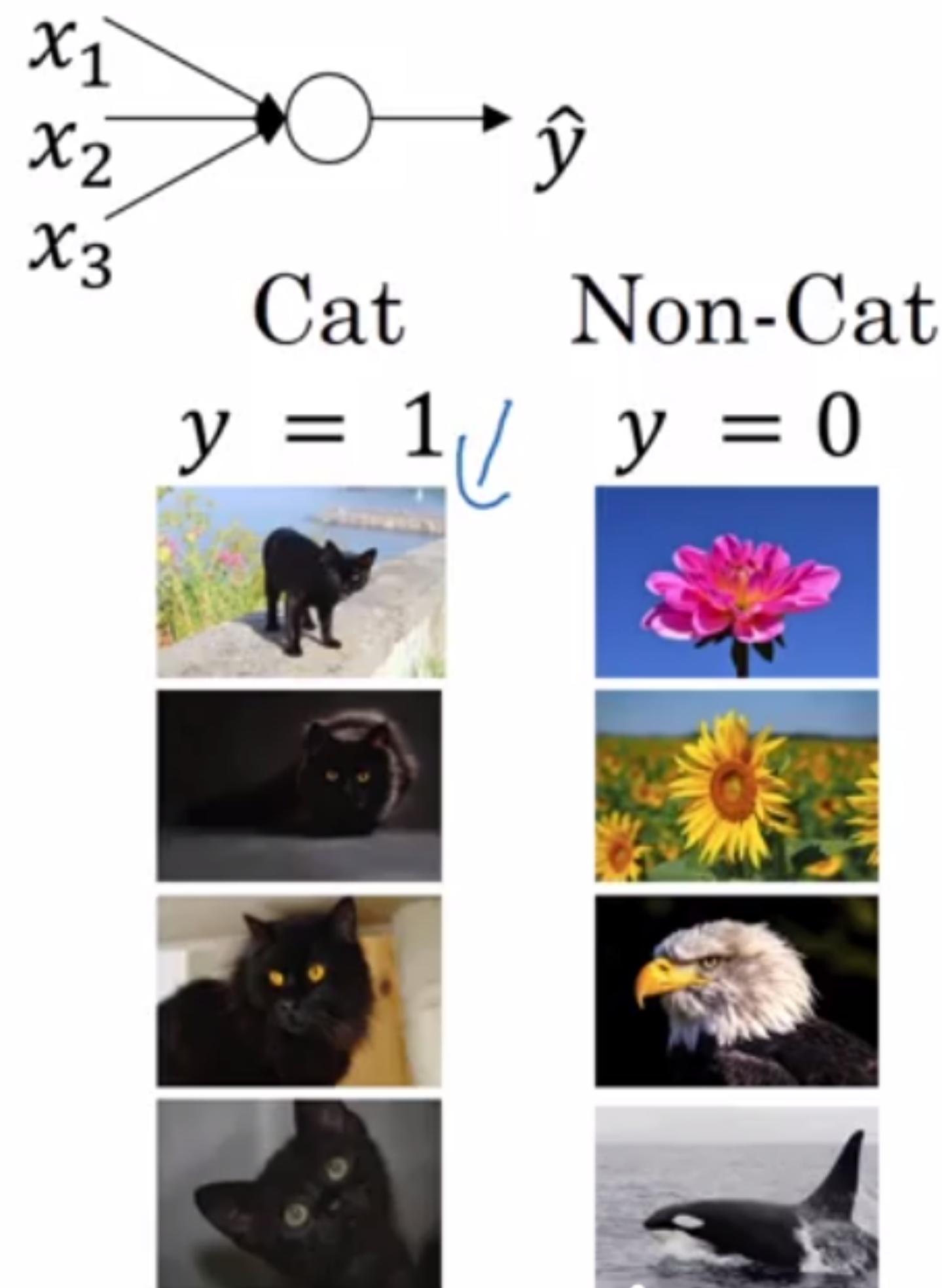
Leaky ReLU


$$y = \max(0.1x, x)$$

Mish


$$y = x(\tanh(\text{softplus}(x)))$$

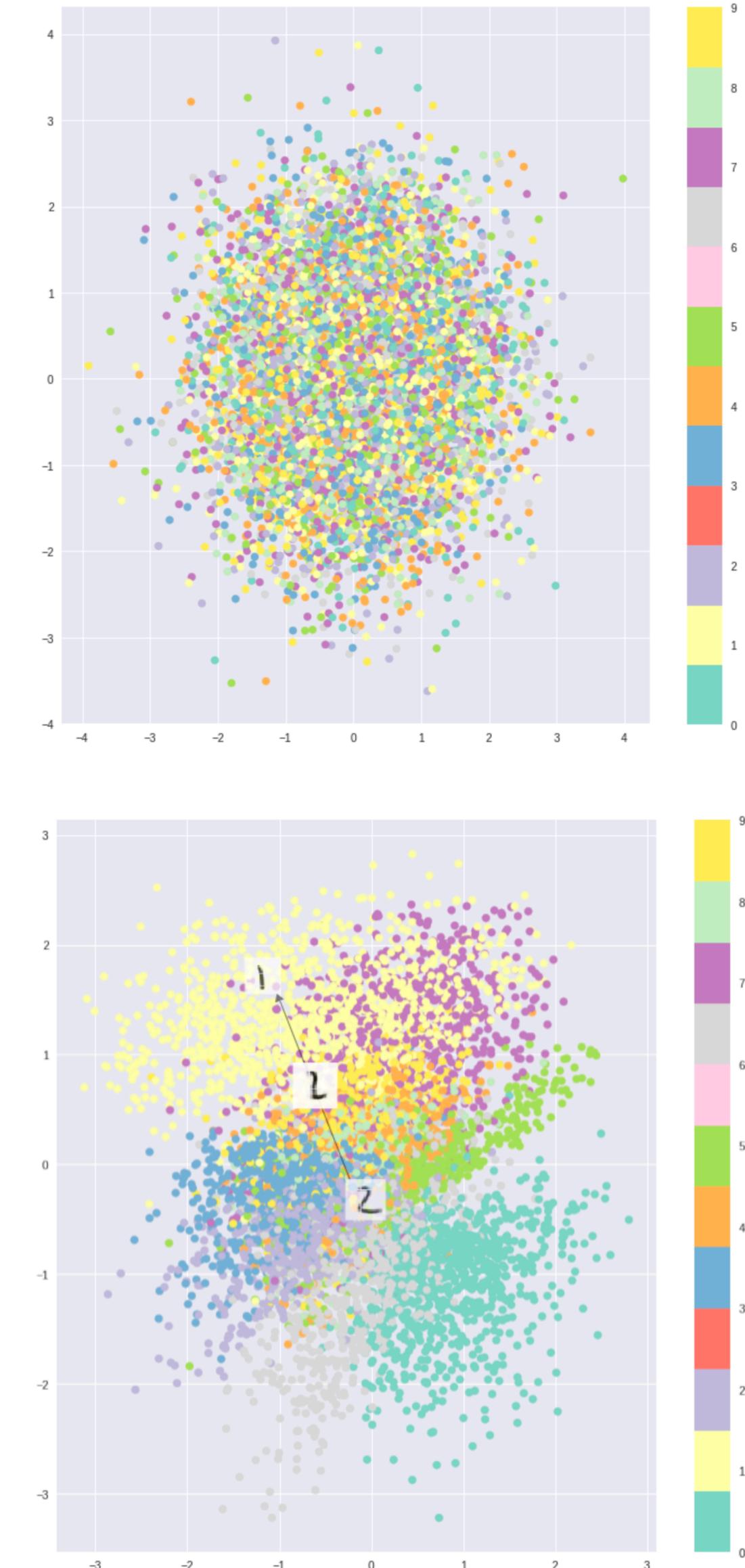
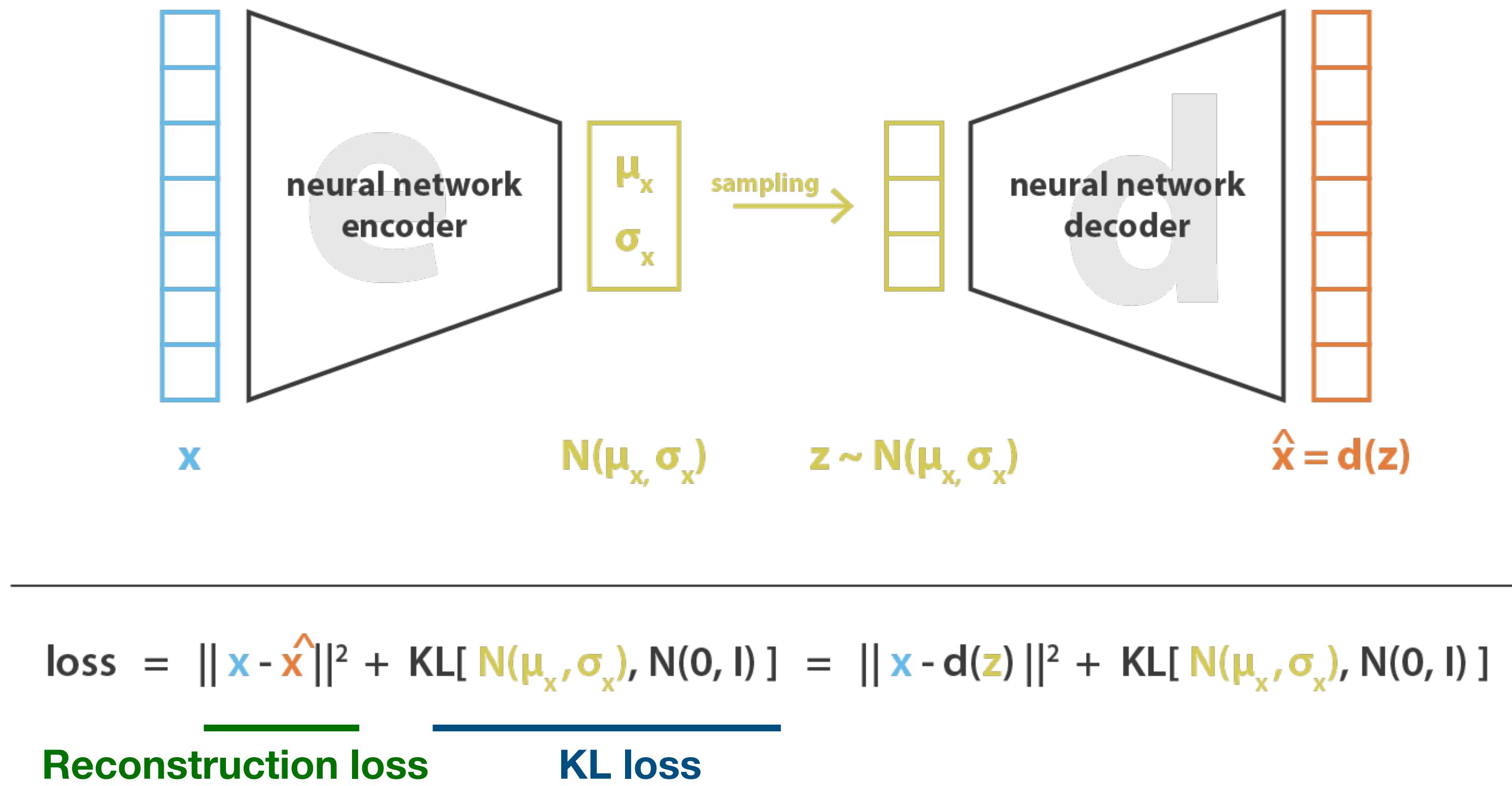
# Batch Size Matters



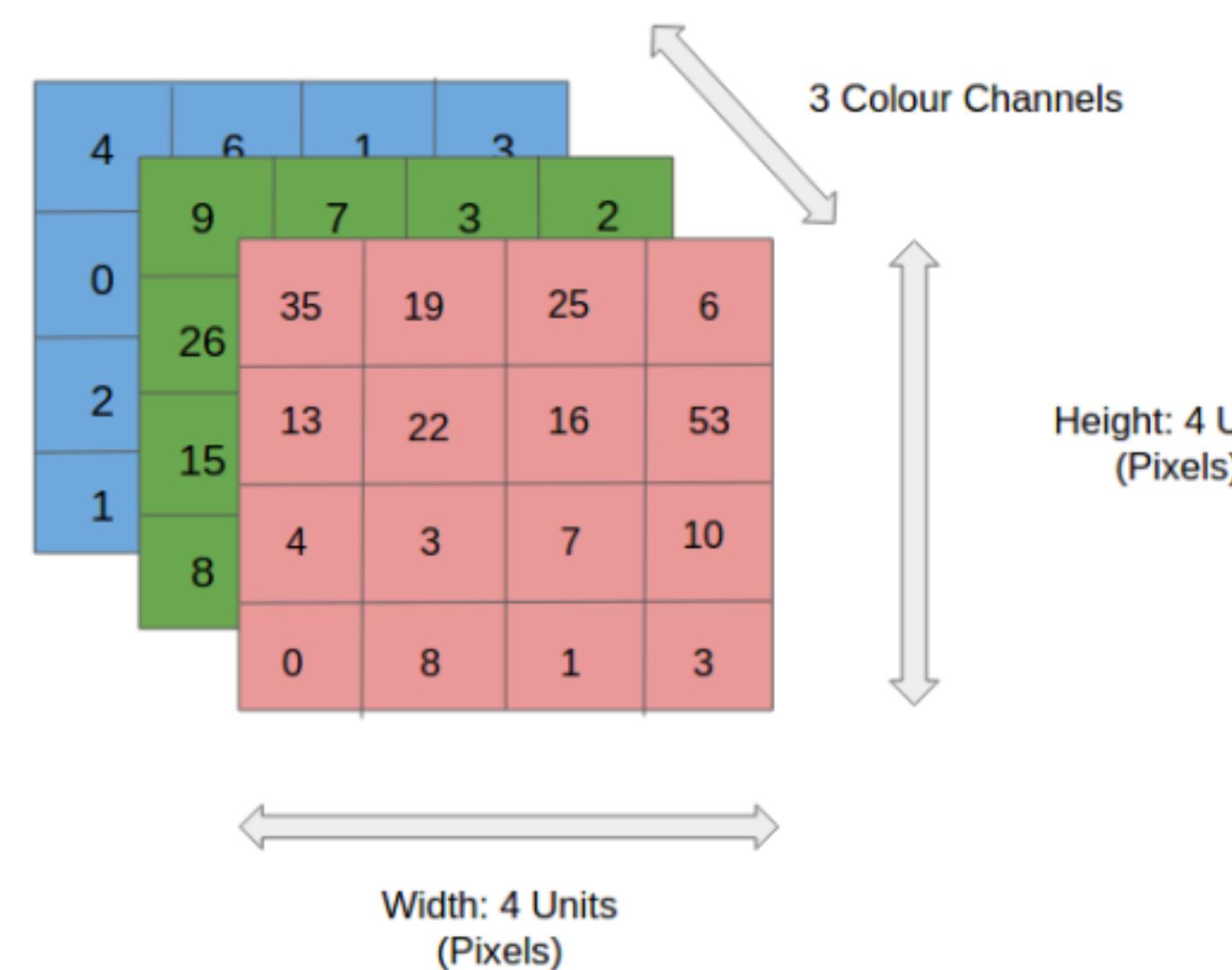
# Understand Your Loss Function

Use an **appropriate** loss function for a given problem.

If **multiple loss functions** are used, make sure that they are of the **same scale**.



# Pay Attention to the Data Format



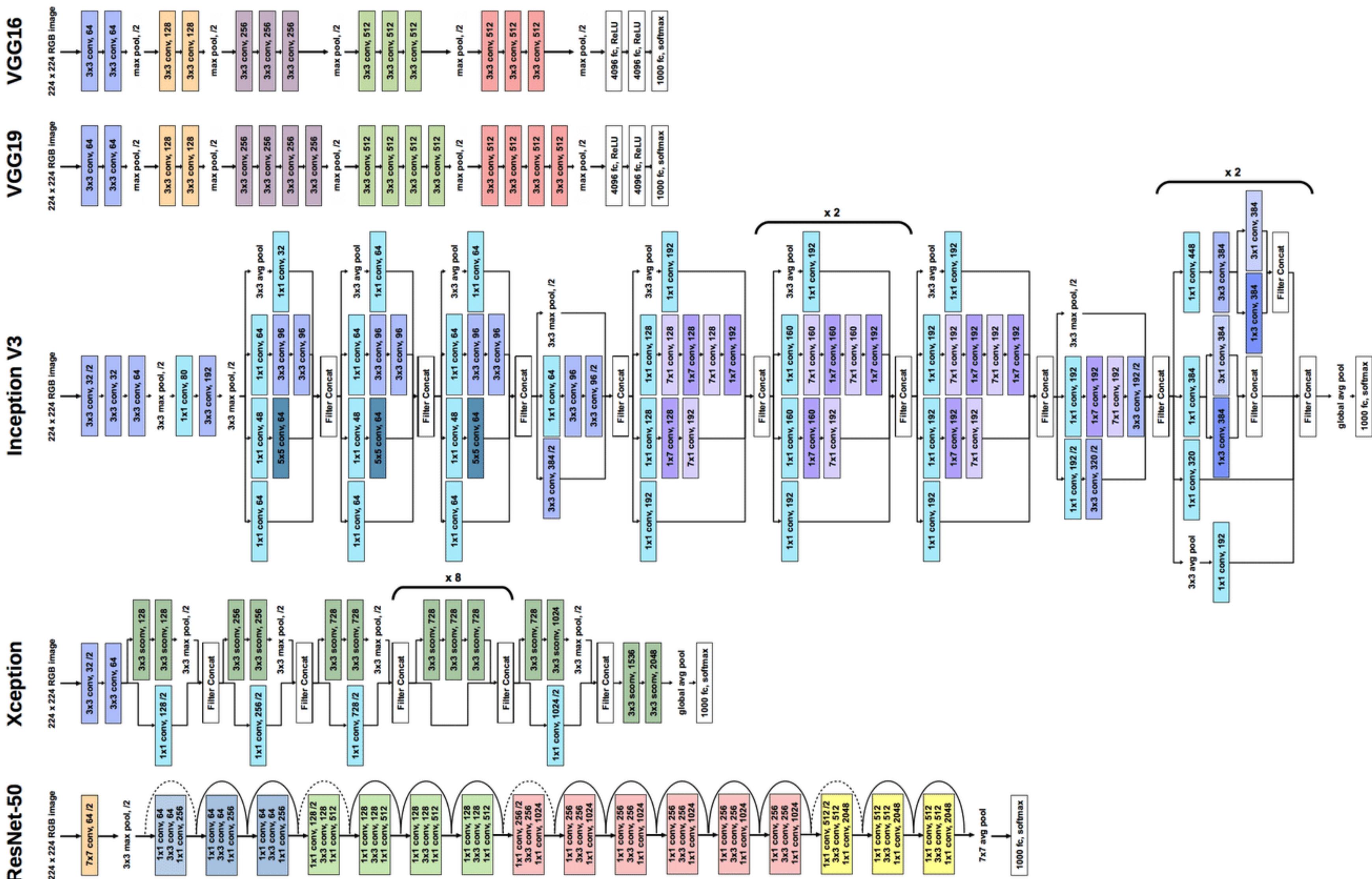
**Channel first:**  
**(W, H, C, N)**

**Channel Last:**  
**N, W, H, C**

**N**

```
model.add(Conv2D(..., data_format='channels_first'))
```

# Compare with baseline models



# Inspect Intermediate Outputs

