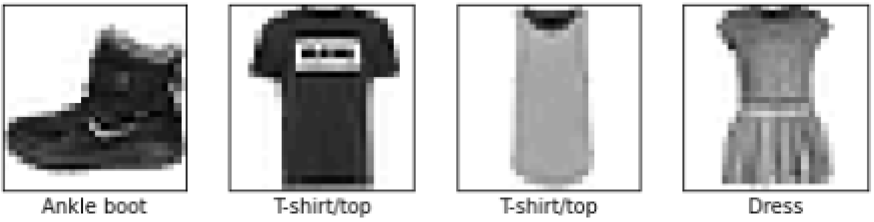
Lecture5 Classification

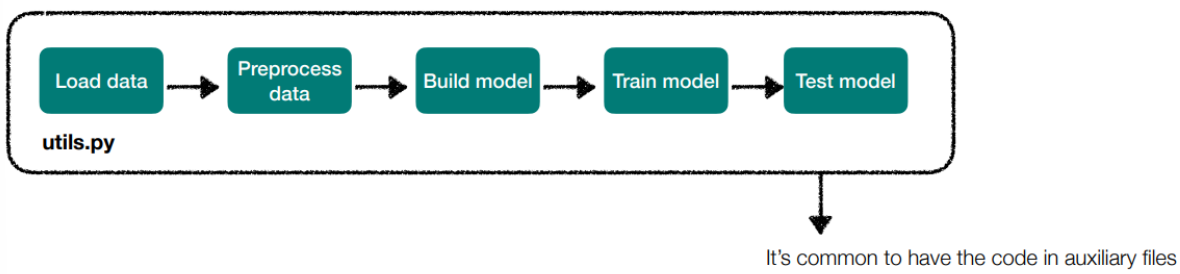
1. Exercise Broken Down

Task

> Fashion-MNIST classification with dense neural network
>
> In this exercise, you will build a deep neural network to classify images from the Fashion-MNIST dataset using only dense layers. The Fashion-MNIST dataset is a collection of images of clothing items, where each image is a 28x28 grayscale image of one of 10 classes.
>
> 
>

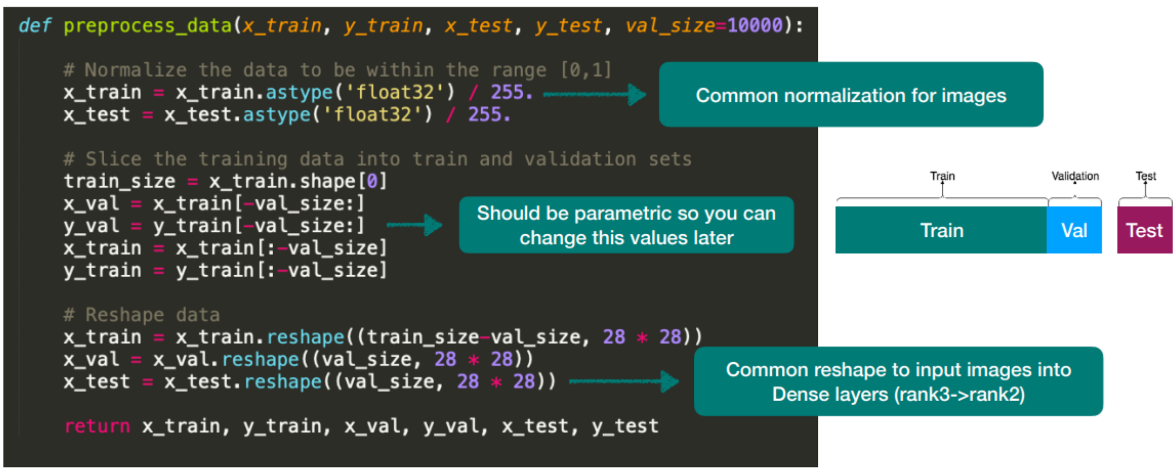
Single-label, multi-class classification problem.

Load Data

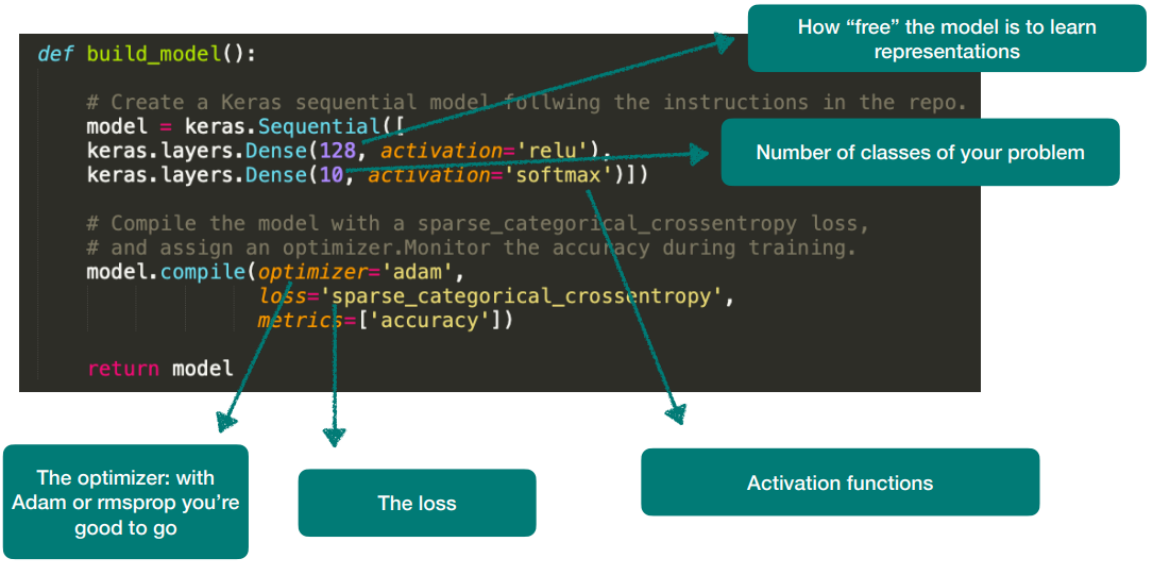


Pre-process Data

A lot of time typically goes into organizing data

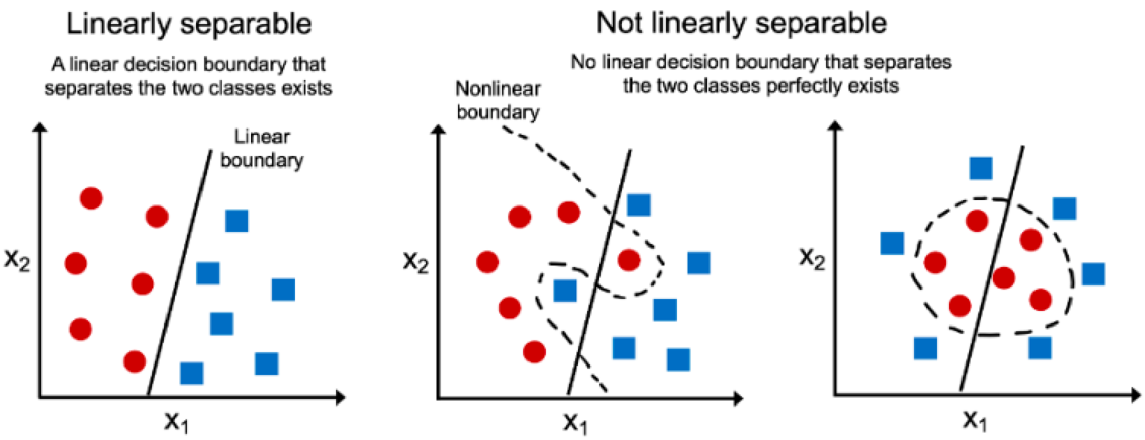


Build Model



Activation function

Dense layer without activation

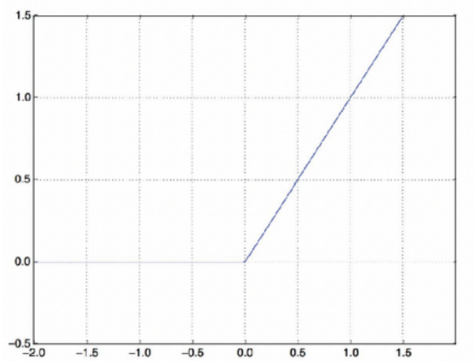


$$\mathrm{output} = \mathrm{dot}(\mathrm{input}, W) + b$$

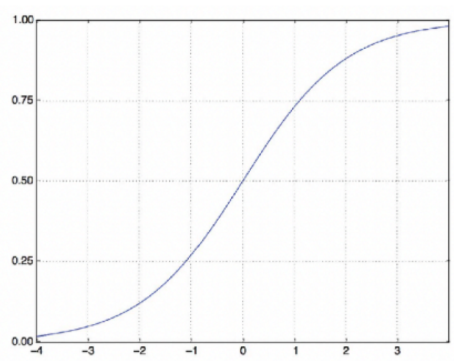
- If you stack many of this, the resulting transformation is still linear. Your model is very restricted on what it can learn.

Activation functions allow the network to learn **non-linear transformations**

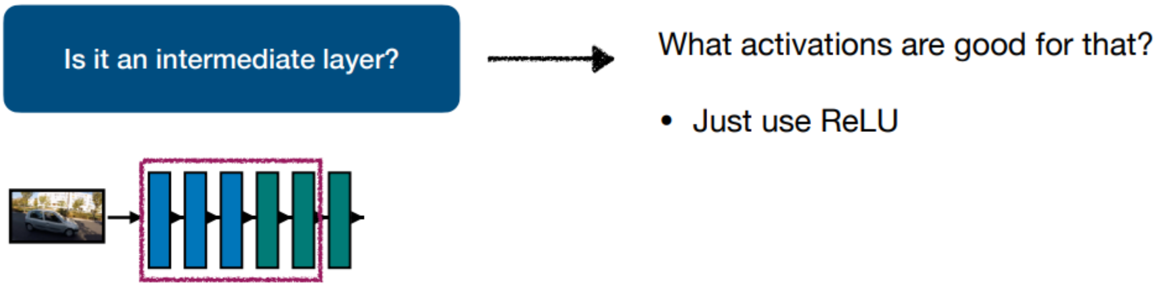
ReLu



Sigmoid

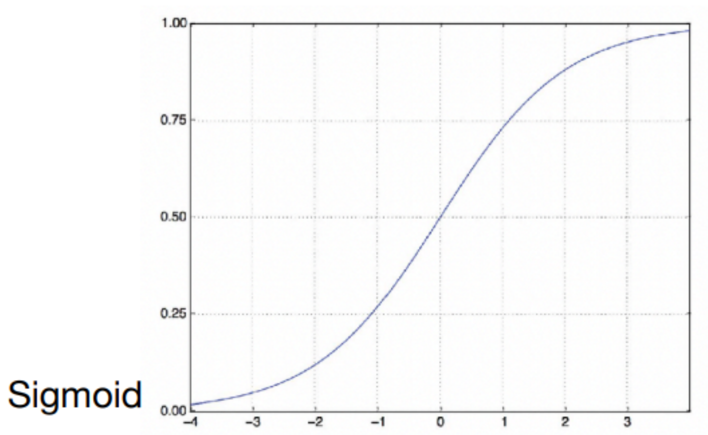


Activation Function in the Intermediate Layer

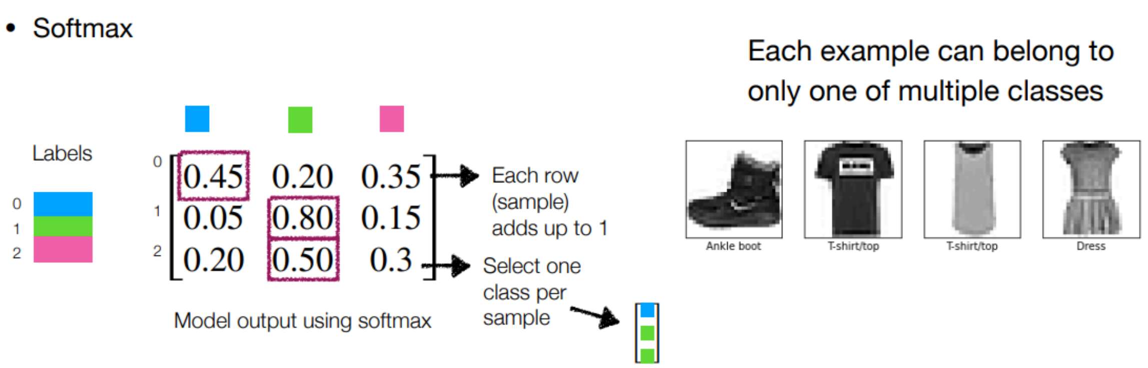


Activation Function in the Last Layer

Binary-class Classification Problem: **Sigmoid**



Multi-class Classification Problem: **Softmax**



Loss function

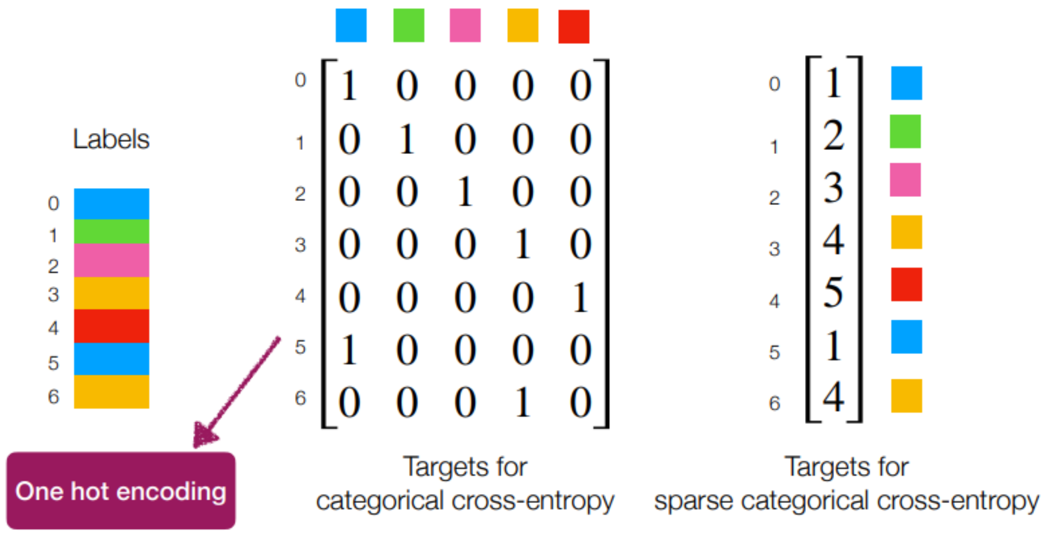
A measure of **how good** your model predictions are. Signal used in training.

The choice of the loss function depends on the problem.

- For our: Single-label, multi-class classification problem
    - Categorical cross-entropy
    - Sparse categorical cross-entropy

Cross-entropy loss

A quantity that measures distances between probability distributions, or ground truth distributions and predictions.



- The cross-entropy loss and sparse categorial cross-entropy loss are mathematically equivalent, is just a different interface

For binary classification

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

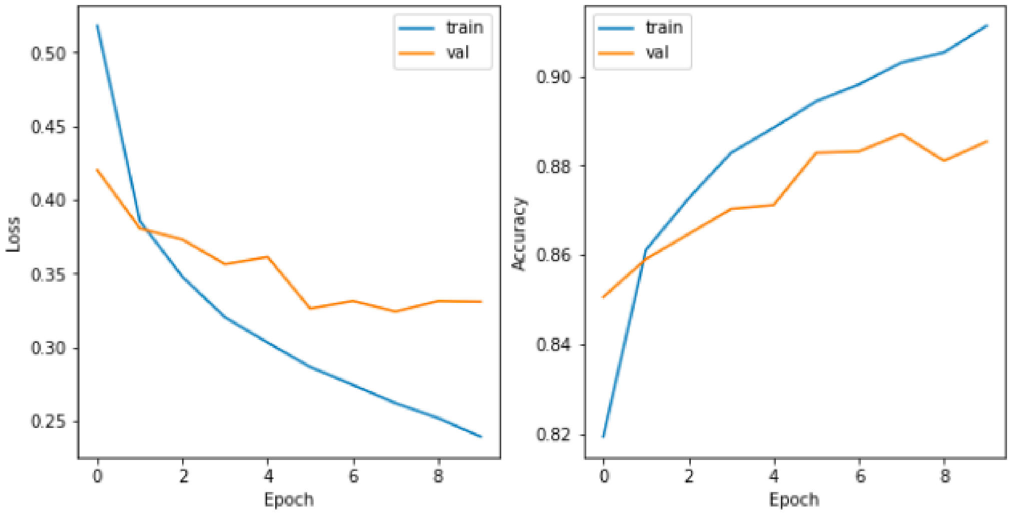
- L is the loss for the entire dataset
- N is the number of samples
- y_i is the actual label (0 or 1)
- p_i is the predicted probability of the class being 1 for the i_{th} sample

For multi-class classification

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{M} y_{ic}\log(p_{ic})$$

- L is the loss for the entire dataset
- N is the number of samples
- M is the number of classes
- y_{ic}: a binary indicator (0 or 1) if class label c is the correct classification for observation i
- p_{ic}: is the predicted probability that observation i is of class c

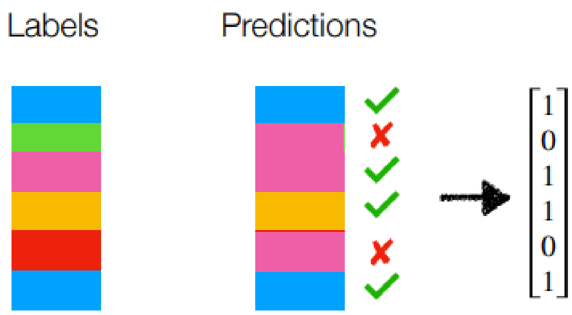
Metrics



We use them to know how training is progressing.

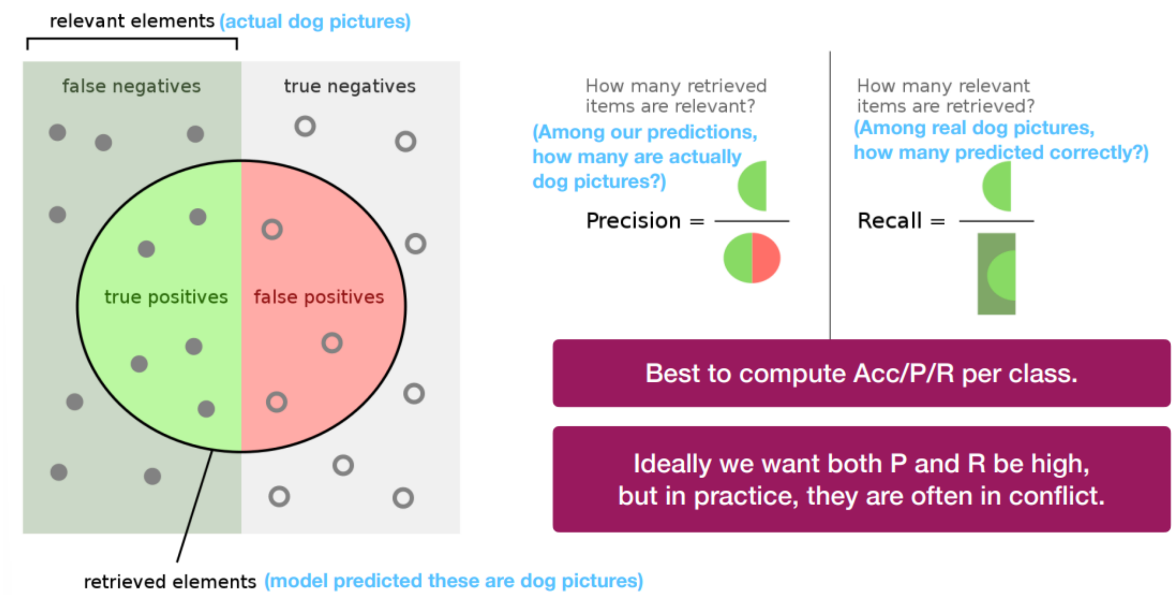
This signal is NOT used by the model during training.

Accuracy

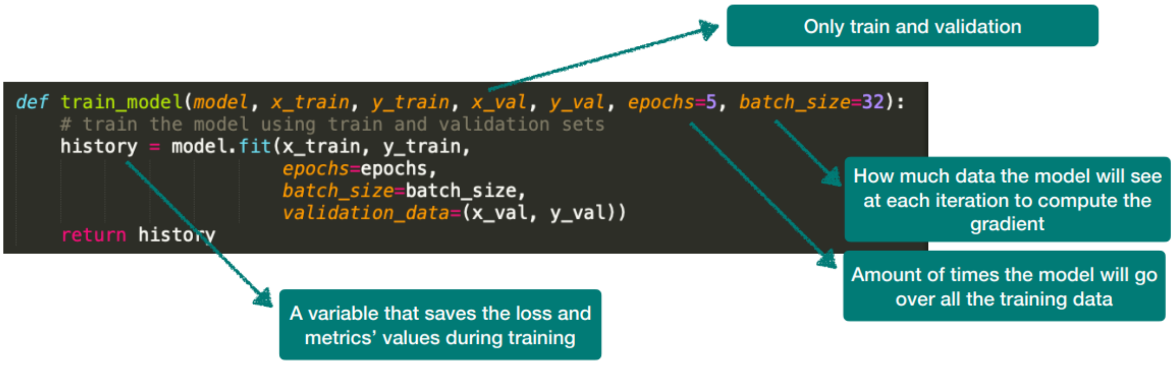


$$acc = \frac{\text{correct predictions}}{\text{total number of predictions}}$$

$$acc = \frac{4}{6} = 0.67$$

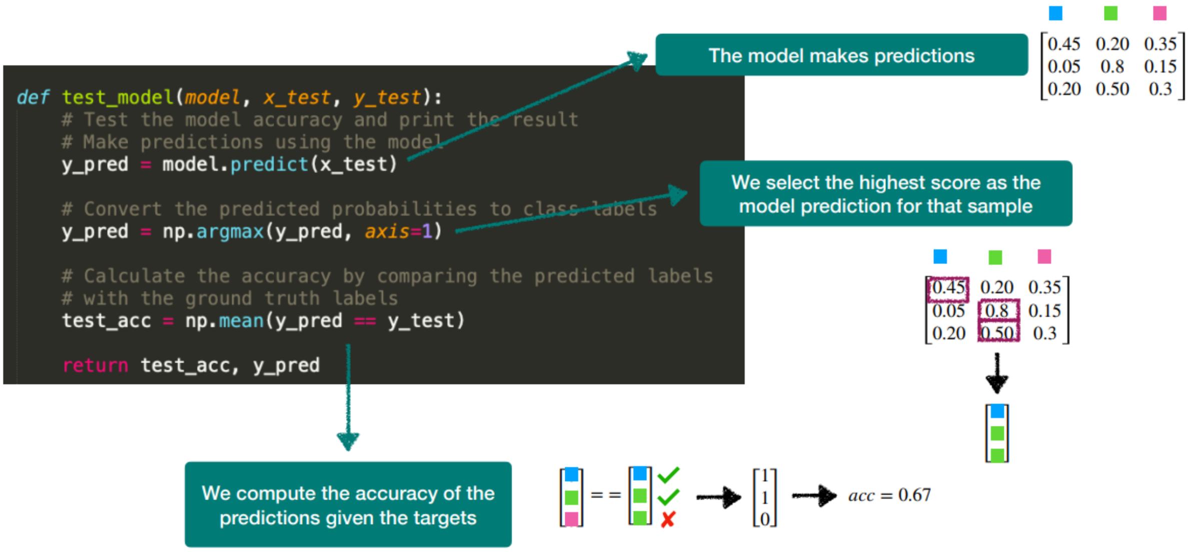


Train Model



- The `fit()` function has other input parameters you can use to tune the training of your model.
- Take a look at the documentation!

Test Model



Classification Problem

Single-label, Binary (=2-class)

Are these mushroom poisonous?

Yes / No

- Binary classification is a special case of classification where `num_class == 2`.
- Treat it as such — use sparse categorical cross entropy, softmax, etc.

Single-label, Multi-class

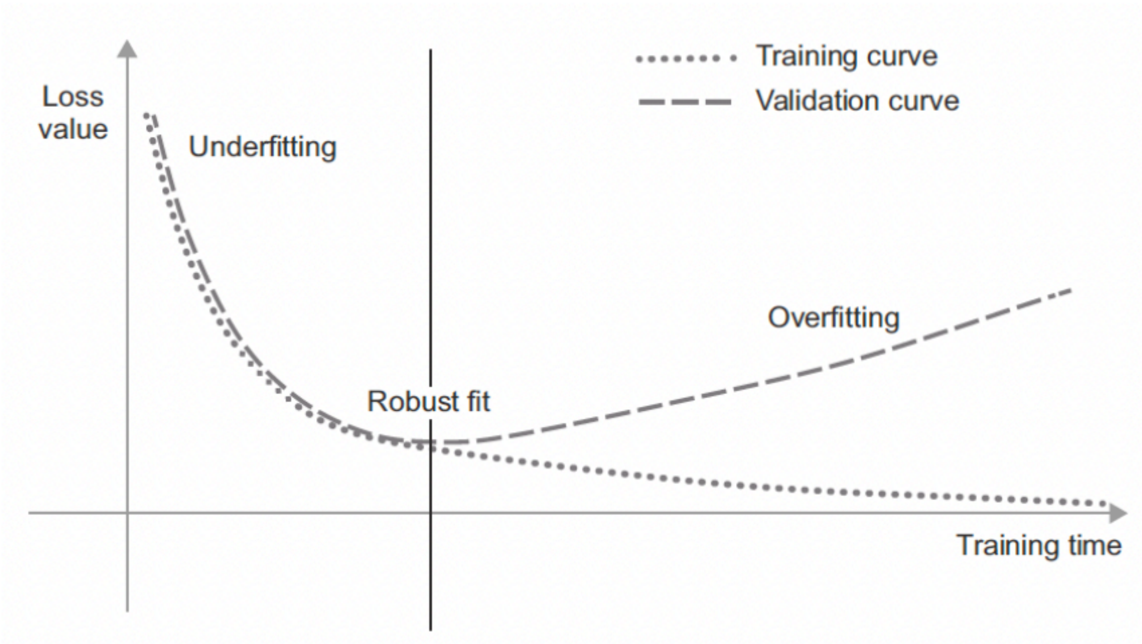
What animal is this?

Input

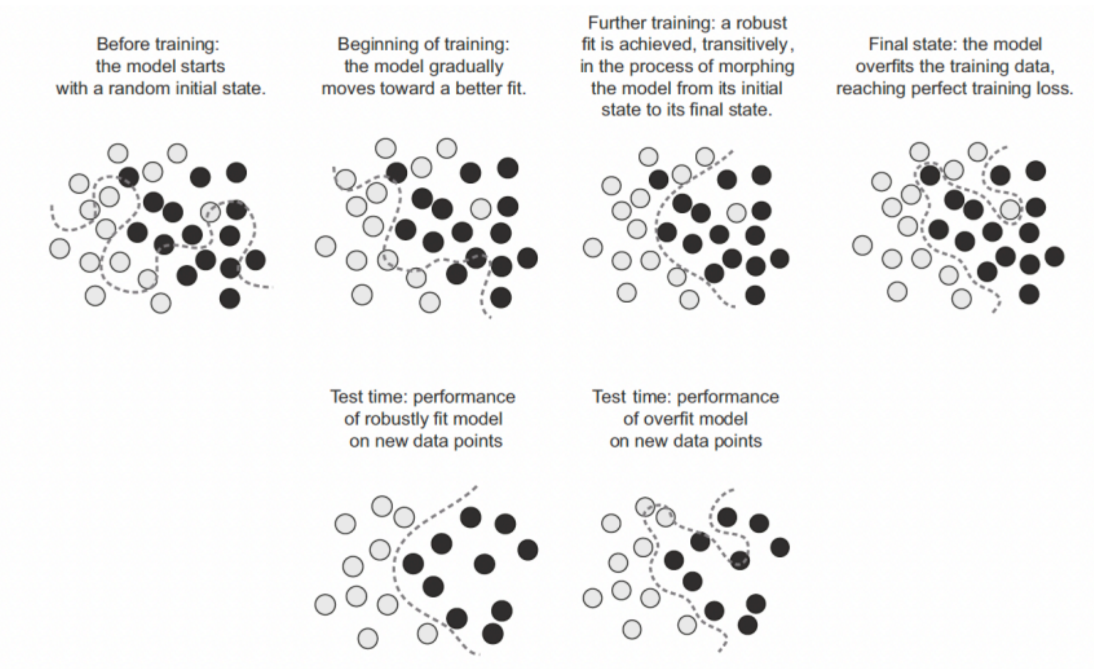
Predicted likelihoods

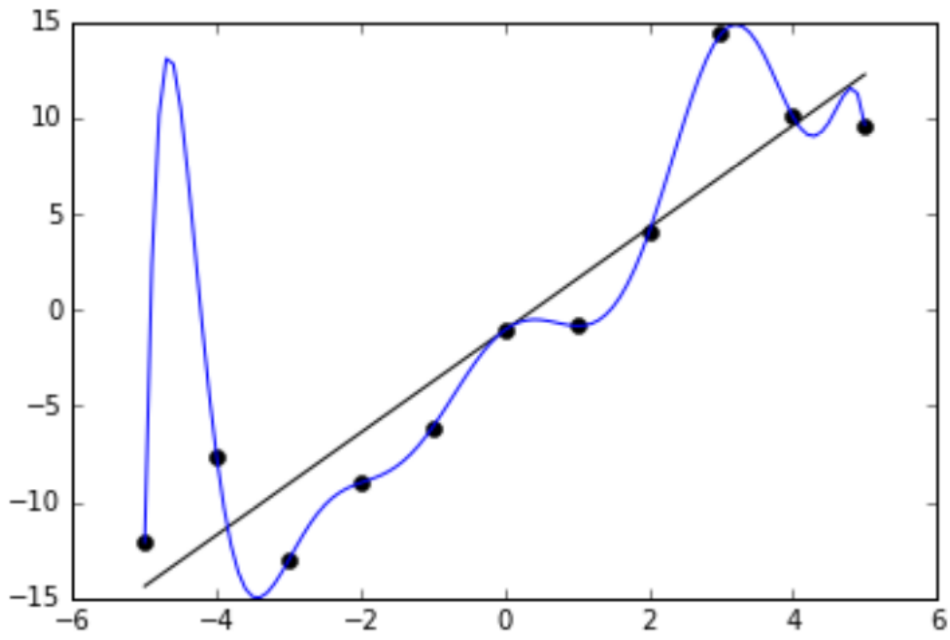
Cat	Dog	Rabbit	Duck
0.2	0.1	**0.7**	0.0

2. The fitting problem



Overfitting

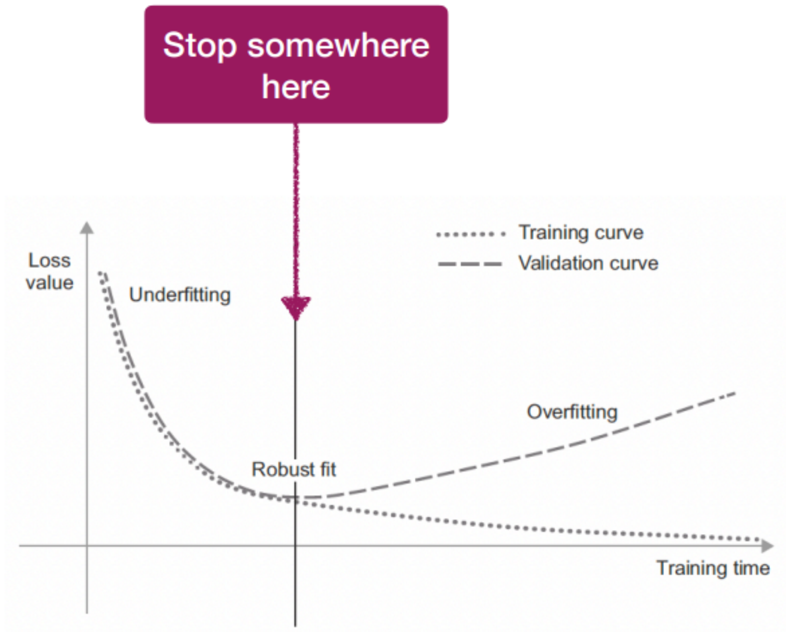




- The model focuses on what it has seen (training examples)
- Too much that it only memorizes the seen examples by focusing on irrelevant details
- Fail at unseen examples

How can you mitigate overfitting?

Early stopping



- Looking at the train and validation losses, you can estimate the number of epochs needed for a robust fit (or use the early stopping callback in `fit()`)

All the things you can find in other resources (web, books, ..) — such as

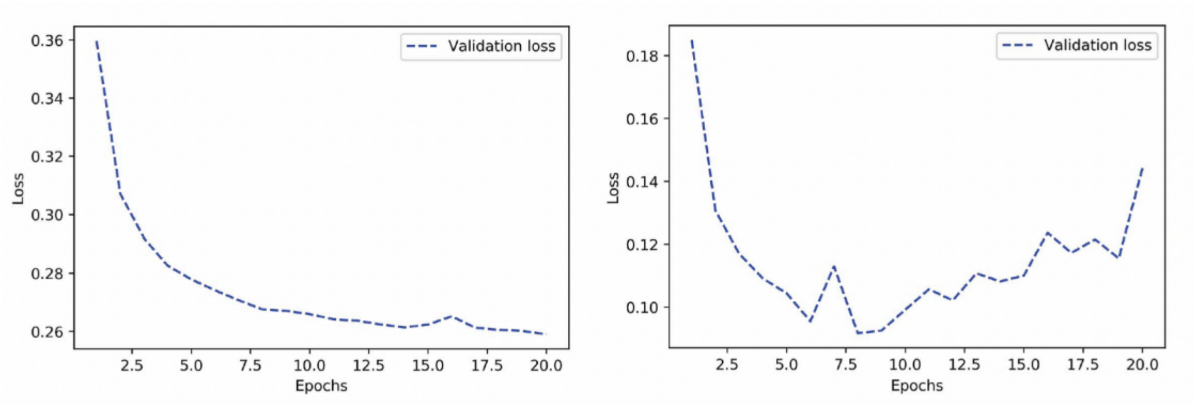
- regularizers
- adding noises
- dropout
- batch norm

- getting more data

are about preventing the model to memorize training examples by their irrelevant aspects

Underfitting

It could also happen that your model doesn't overfit ever. Then it's too small!



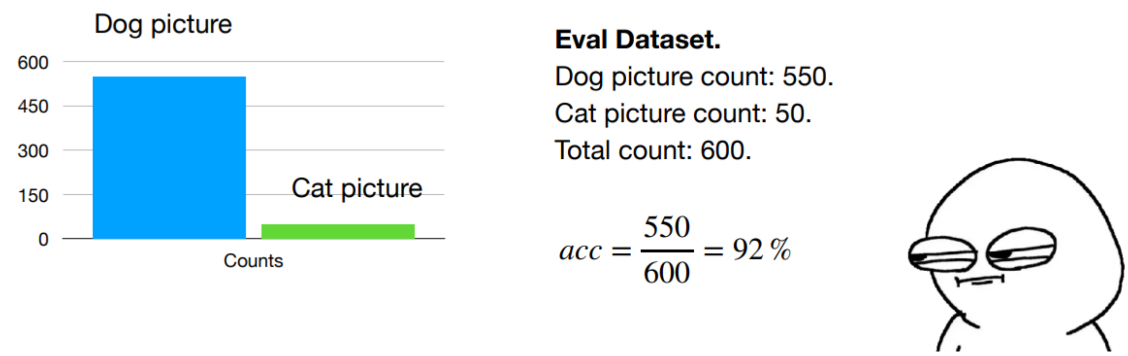
Underfitting Overfitting

How can you mitigate underfitting?

- We need a larger model capacity.
- Increase the model size or stack more layers until the model is able to overfit.

3. The generalization problem

Distribution of training samples

> Given a picture - dog or cat?
>
> 
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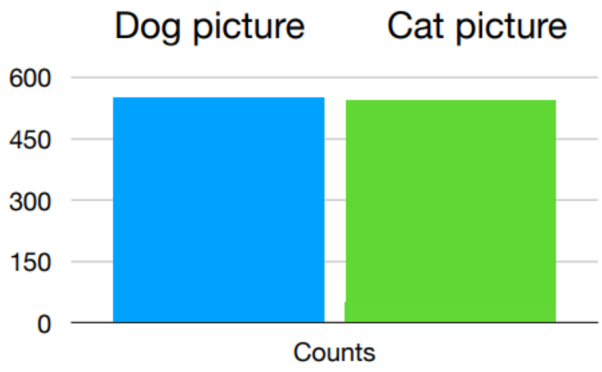
The bias problem

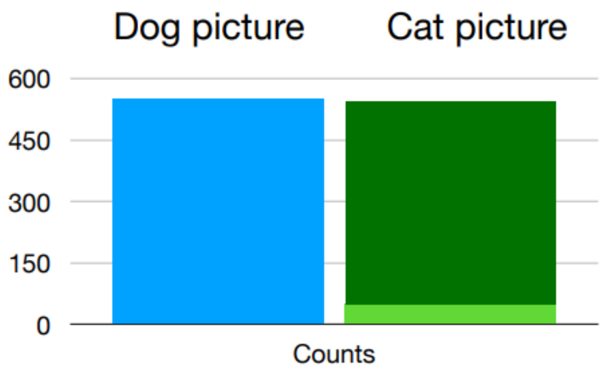
- Our models are not impartial.
- There are always biases we have to take care of.

How can you mitigate biases?

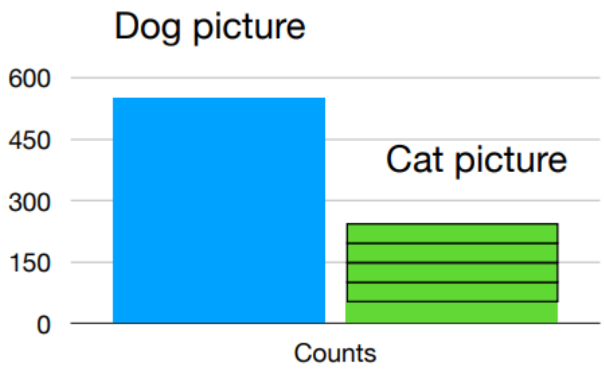
Data: Collect more data to balance the dataset.



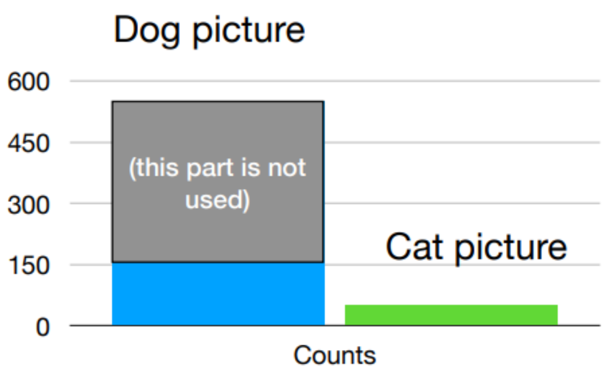
Data: Balance the distribution with synthetic data.



Sampling: Oversample the less represented class.



Sampling: Undersample the majority class.



Loss: Weight the loss to compensate for imbalance.

```
# Train model
class_weights = {0: 1,
                 1: 10}
```

```
history = model.fit(X_train,
                    y_train,
                    validation_data=(X_val, y_val),
                    epochs=epochs,
                    batch_size=batch_size,
                    class_weight=class_weights)
```