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Applied Deep Learning

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Learning objectives of today

Goals:

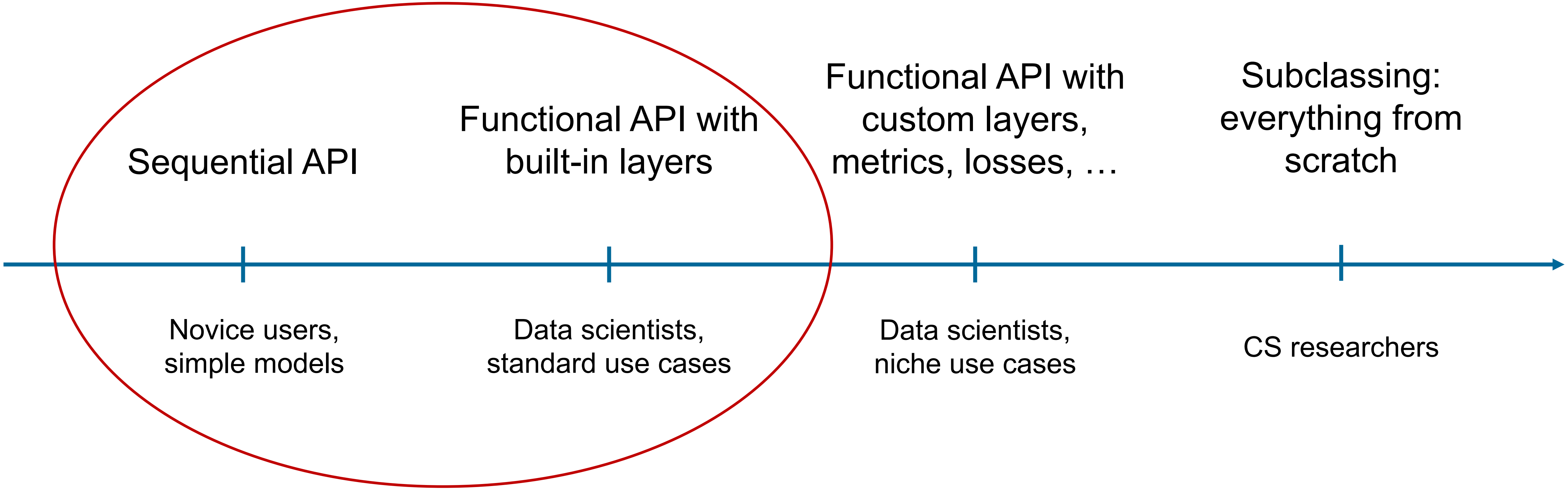
- Understand some of the key tools to run computer vision algorithms in practice

How will we do this?

- We start with discussing the Functional API and the added flexibility it enables use
- We then take a look at architectural typical for CNNs and specific tips and tricks of modifying them
- Finally, we introduce transfer learning, a key tool to create powerful algorithms from little data

From Sequential to Functional

TensorFlow: the right complexity for everyone



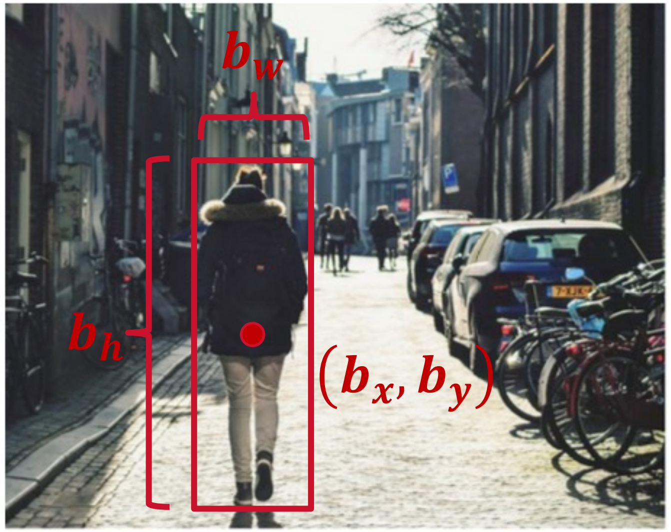
Source: Chollet

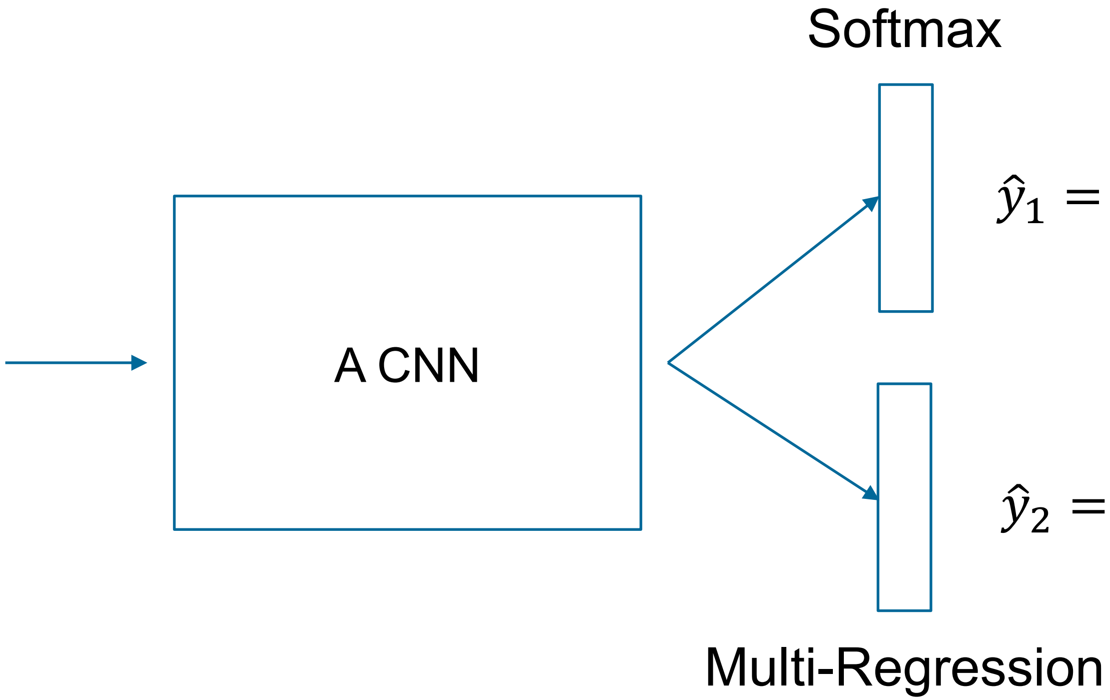
Try it out – Code Parts 1.1-1.3!

- What key differences do you observe between the Sequential API and the Functional API?

- For which types of applications is the Sequential API insufficient?

A typical application: object localization and detection





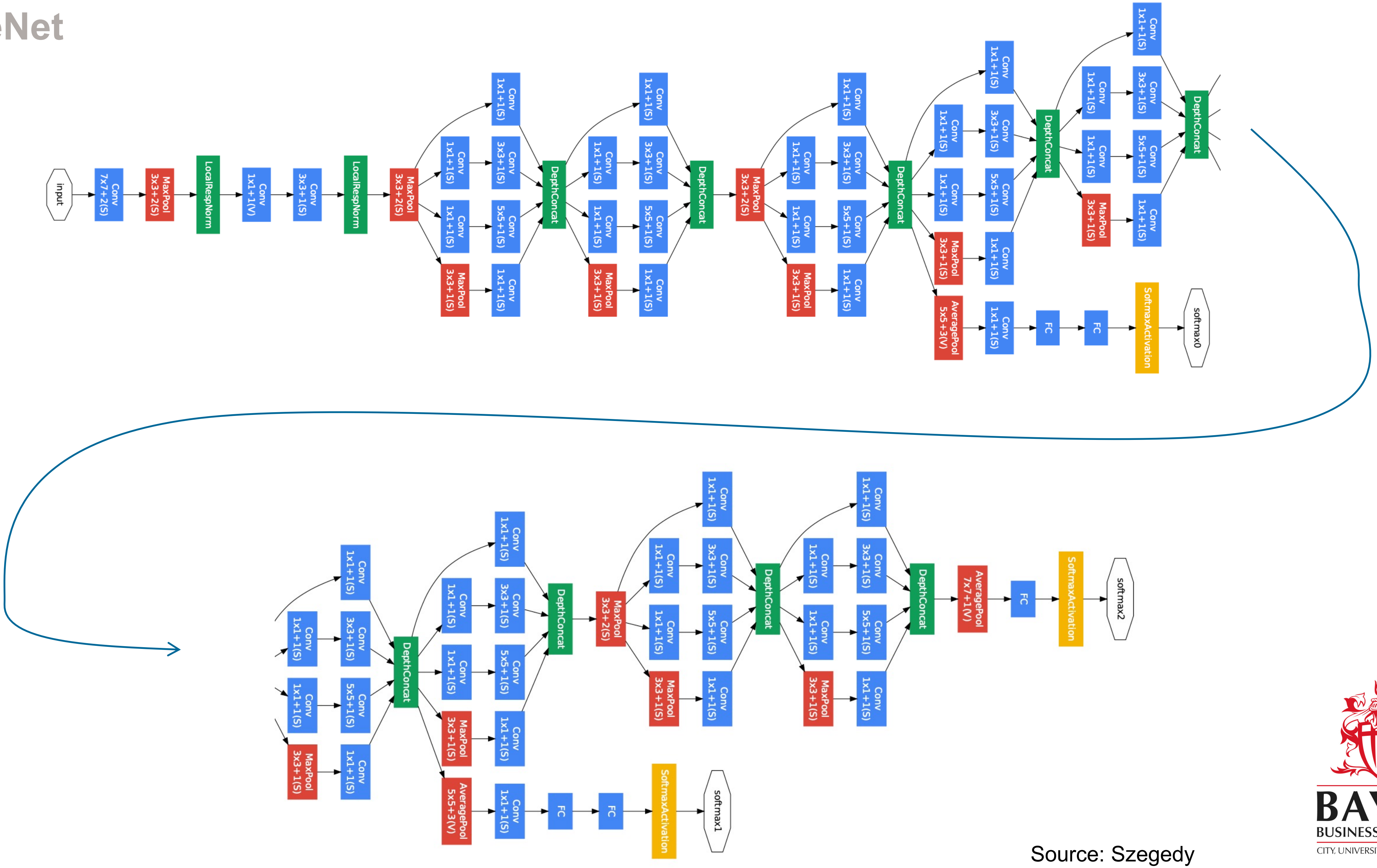
$$\hat{y}_1 = \begin{cases} 1 \ - person \\ 2 - car \\ 3 \ - background \end{cases}$$

$$\hat{y}_2 = \begin{pmatrix} b_x \\ b_y \\ b_w \\ b_h \end{pmatrix}$$

Source: Géron

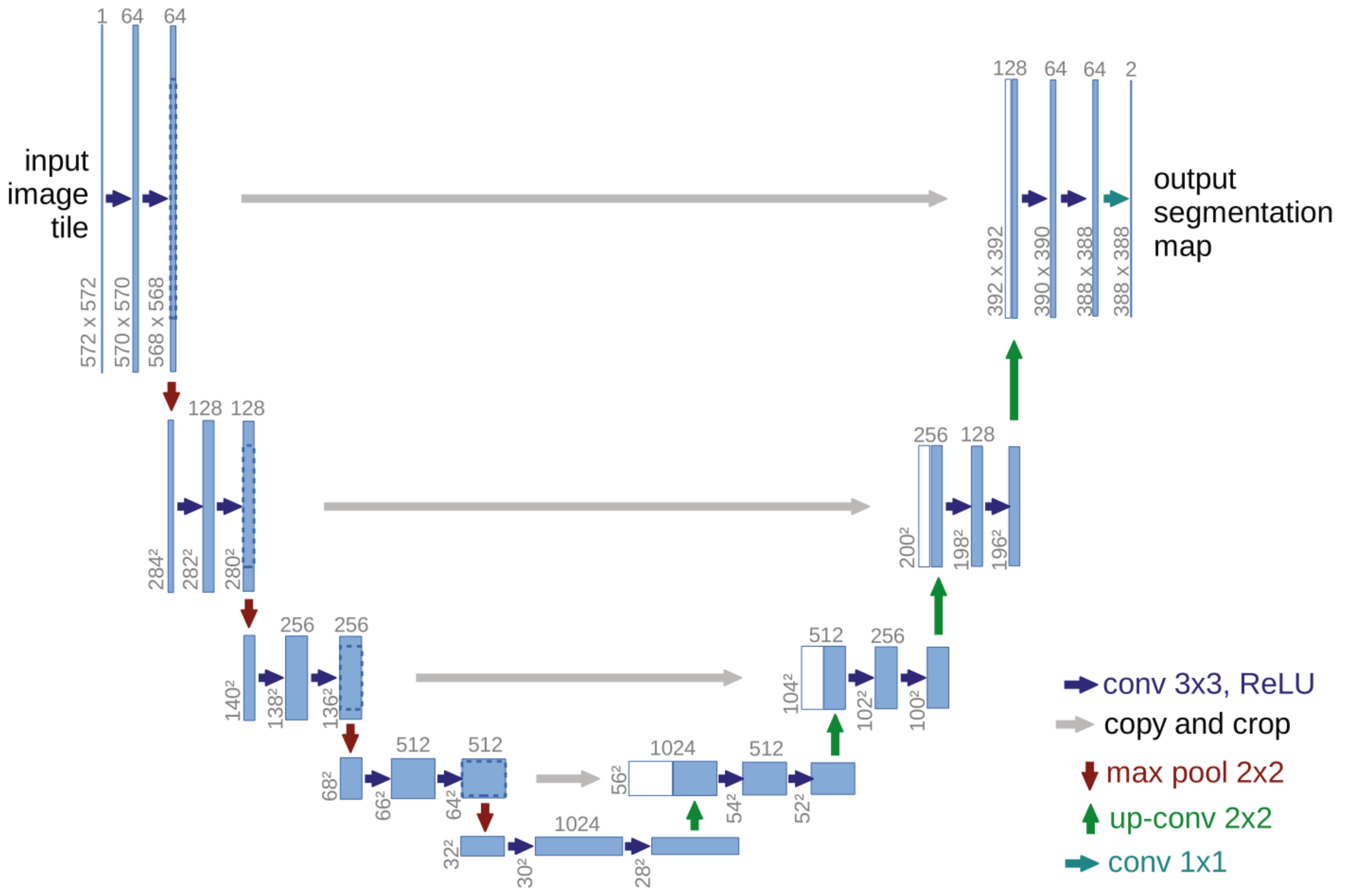
Some architectural ideas specific to CNNs

GoogLeNet



Source: Szegedy

U-Net



Source: Ronneberge

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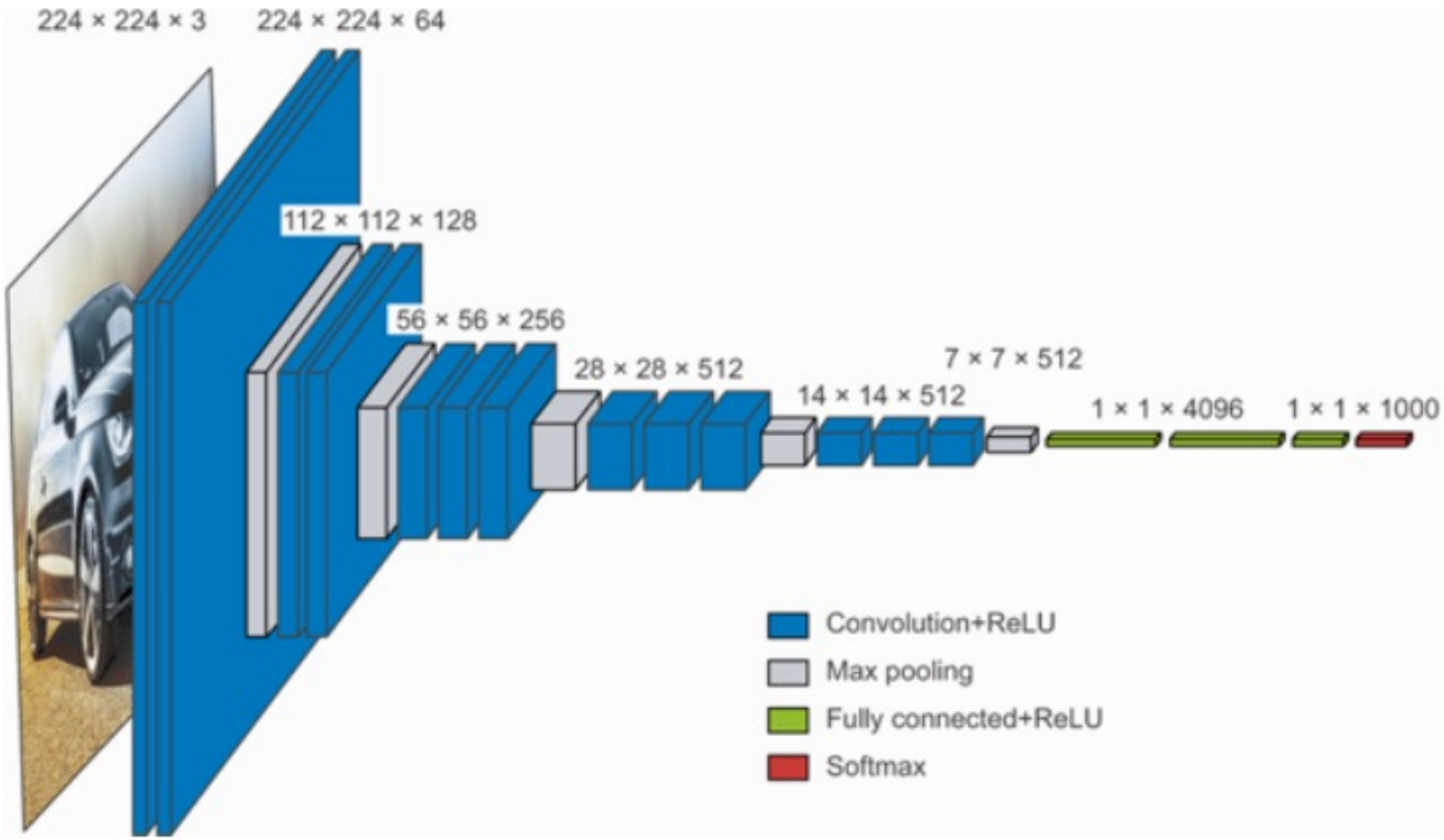
VGG16



Source: Chollet

Architectural tips and tricks around CNNs

- Create modules, organize them into hierarchies, and reuse the same modules
- Create deep stacks of narrow layers (rather than shallow stacks of large layers)

The problem with deep stacks

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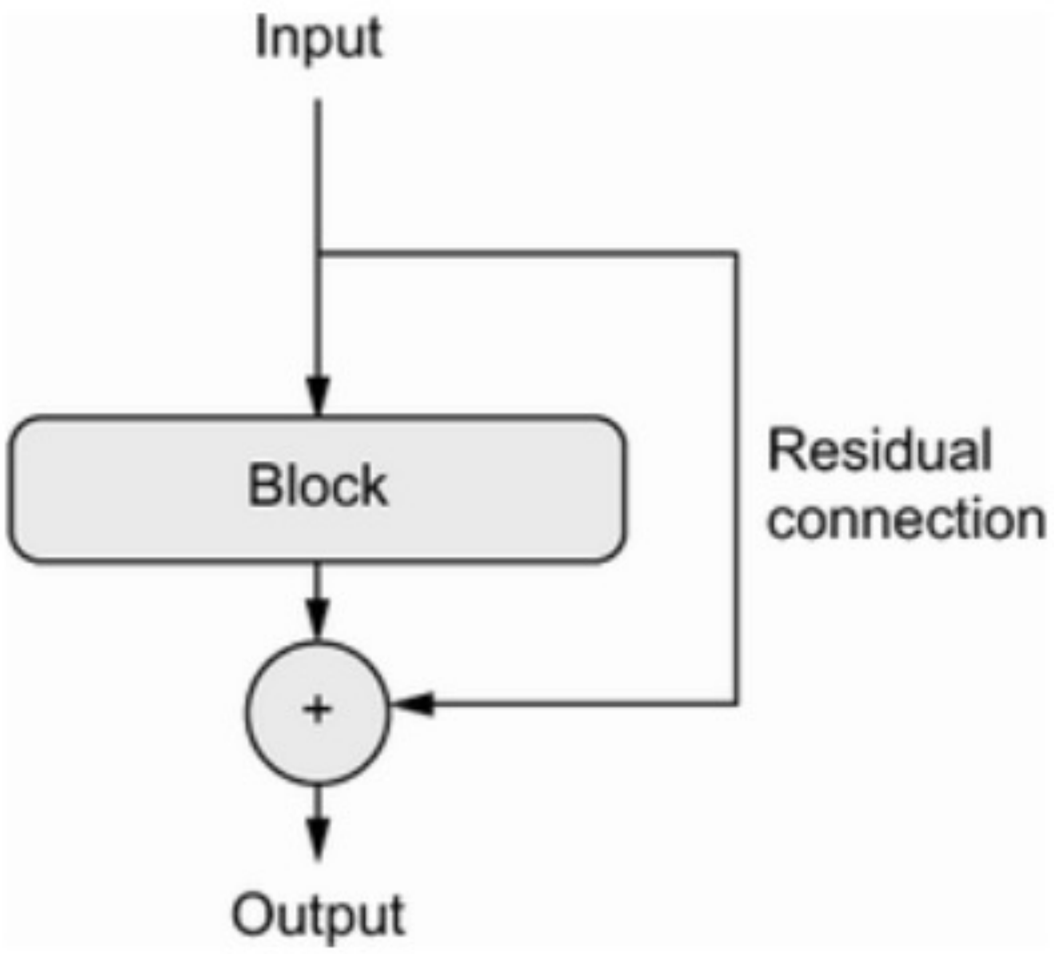
Architectural tips and tricks around CNNs

- Create modules, organize them into hierarchies, and reuse the same modules
- Create deep stacks of narrow layers (rather than shallow stacks of large layers)
- To avoid vanishing gradients in deep networks, retain noiseless versions of information from previous input (“residual connections”)

A residual connection



→ Watch out for dimensions!

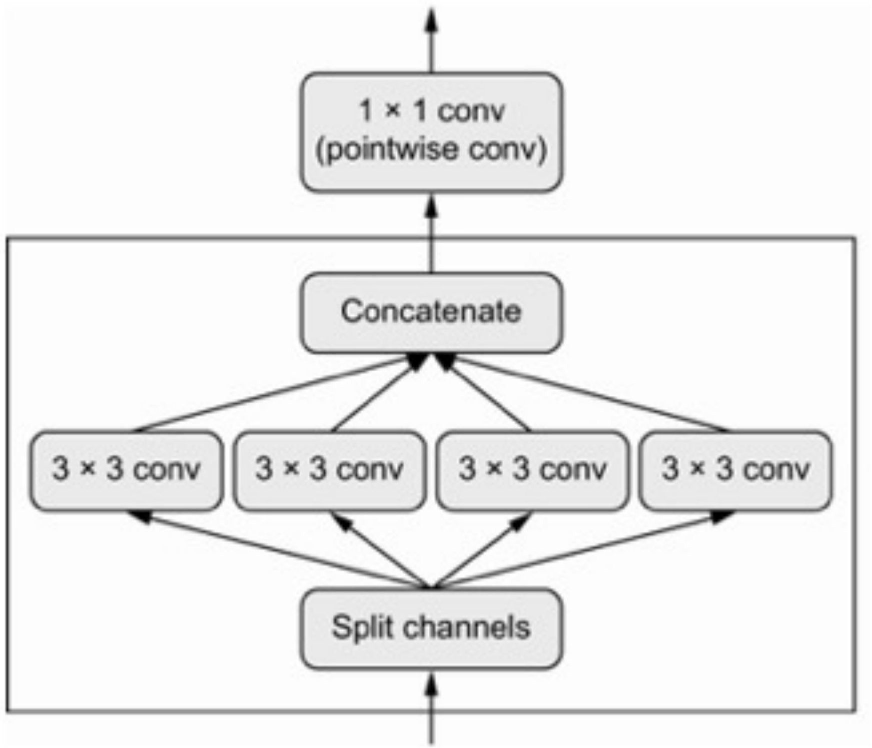
Source: Chollet

Architectural tips and tricks around CNNs

- Create modules, organize them into hierarchies, and reuse the same modules
- Create deep stacks of narrow layers (rather than shallow stacks of large layers)
- To avoid vanishing gradients in deep networks, retain noiseless versions of information from previous input (“residual connections”)
- Use data augmentation
- Use batch normalization (even more so than in other types of networks)
- Use advanced layers that make efficient use of the information structure of your data

Depthwise separable convolutions

- Convolute channels independently
- Assumes information is spatially highly correlated but largely independent across channels → this is usually the case for representations of images
- Key benefit: much fewer parameters and computations



Source: Chollet

Try it out – Code Part 2!

- Which architectural features do you notice? Do they make sense to you?
- What do we have to do to make the residual dimensions stack up?

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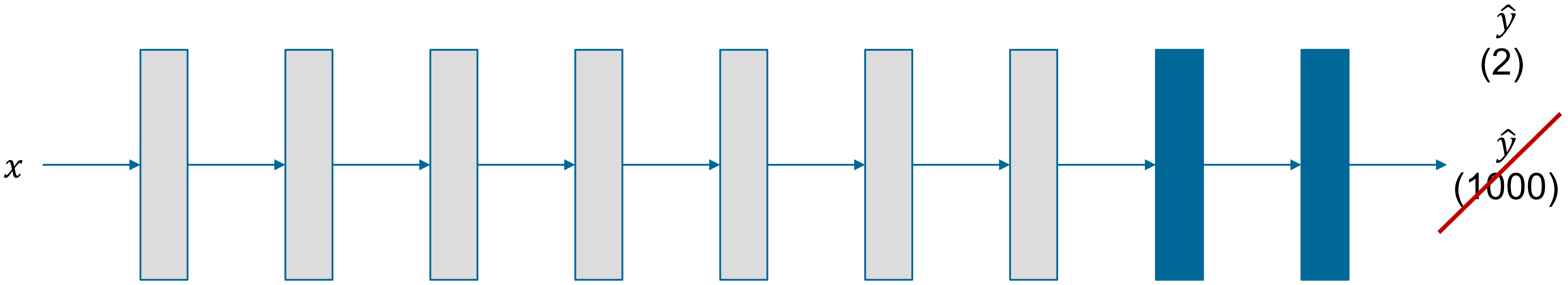
Transfer learning: creating powerful computer vision algorithms with little data

Transfer learning: using pre-trained models

- If a CNN is trained on a large number of images, the spatial feature hierarchy can act as a generic model of the visual world
- For example, take a model trained on the ImageNet dataset (1.4 million labeled images of 1,000 different classes, such as animals and everyday objects)
    - What type of classification tasks might this be useful for?

Repurposing a neural network

- Naïve approach: take the existing (trained) neural network
- Adjust the output layer
- Train some more with your data set



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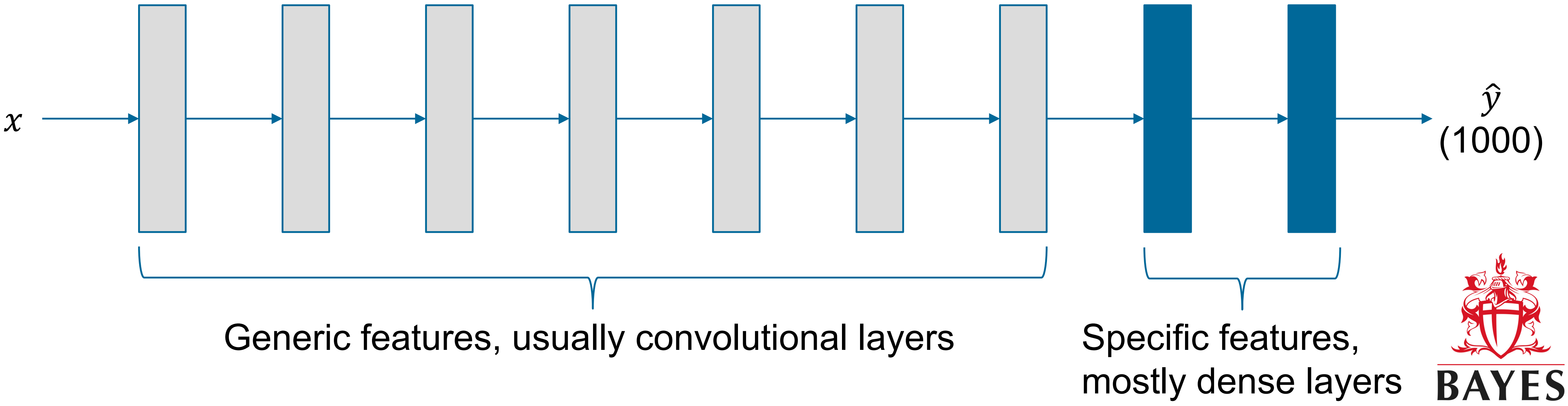
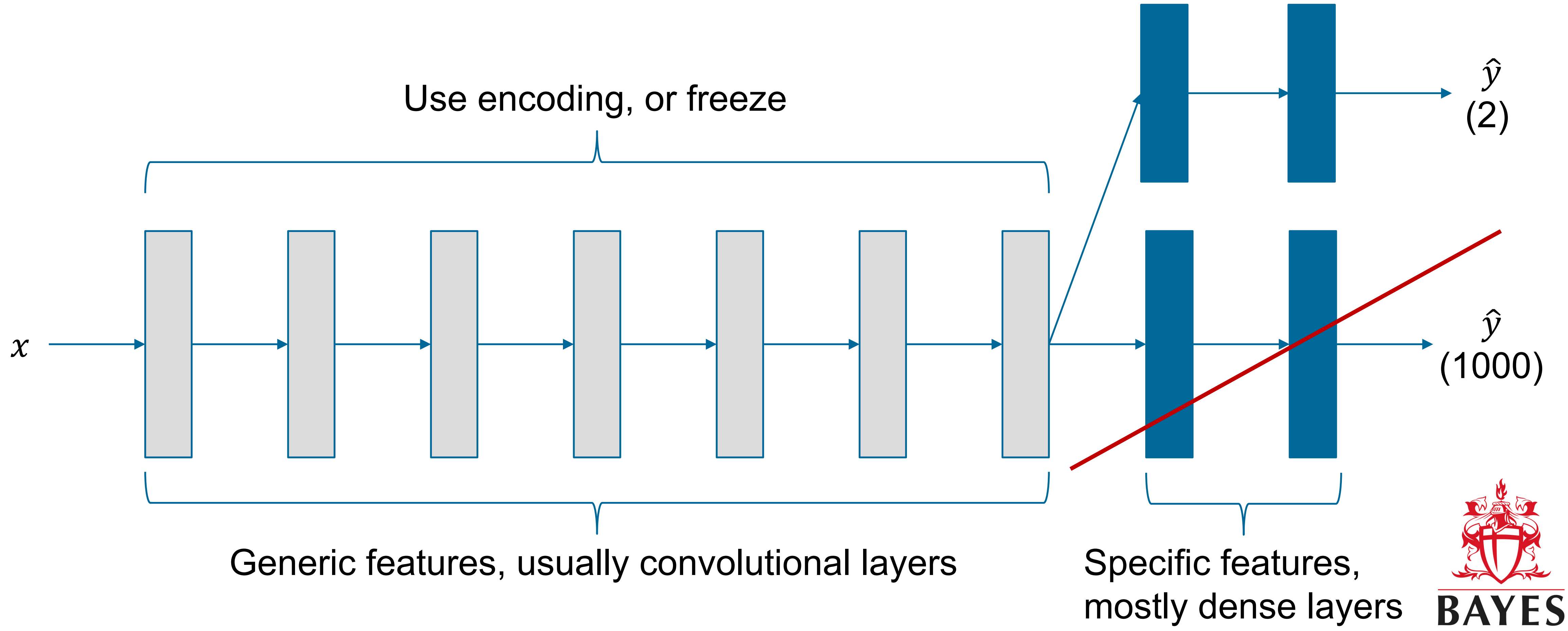
Difference between low-level and high-level features

- Problem with the previous approach: training may be very slow. Because the added training is on less data (usually), we might also be adding overfitting issues
- But: early layers capture low-level features that are unlikely to be different
- Deeper layers capture high-level features that are likely to be different



Option 1: Feature extraction



Try it out – Code Part 3!

- In 3.1, you use the outputs from a pre-trained model
- In 3.2, you build a model including the pre-trained layers, but freeze training for these

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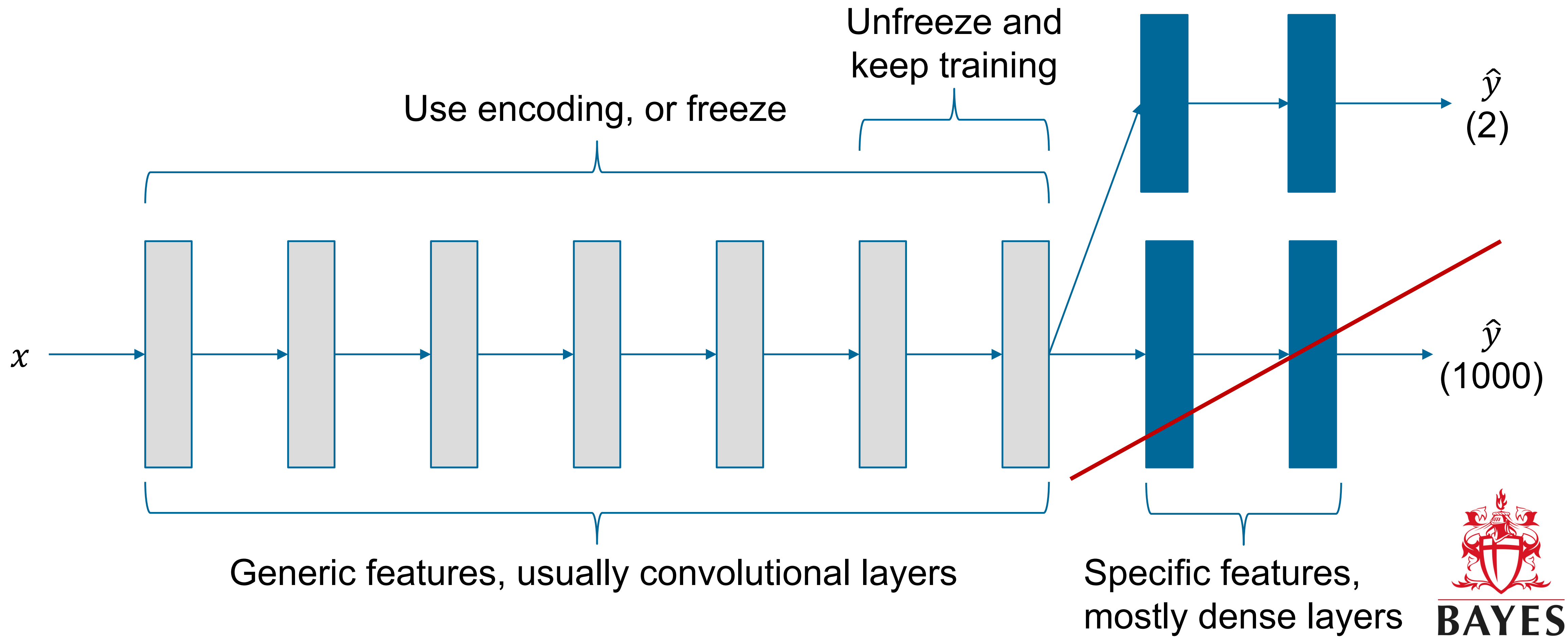
Option 2: Fine-tuning



Transfer learning for computer vision

- In deep learning for computer vision, the visual input is broken down into generic patterns, which are then combined in a hierarchy to derive the ultimate prediction

- The deeper we go in the network, the more we move from representing the visual content to representing its meaning

- If we are not too deep, the representations are quite independent of the specific task but are (good) representations of a visual input

Time permitting – Apply what you learned in Code Part 4

Please fill out the module evaluation

https://city.surveys.evasysplus.co.uk/

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See you next week!

Sources

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