Applied Deep Learning

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Learning objectives of today

Goals:

- Anomaly detection: understand what anomalies are, why we would want to detect them, and how we can do so
- CNNs: Understand how convolution works and how it can be implemented in TensorFlow

How will we do this?

- We will start by discussing anomaly detection and the different techniques used to perform it in different settings
- We will use this to lead over into the student presentations
- We then turn to computer vision, and the fundamental architectural innovation that makes it work: convolutional layers

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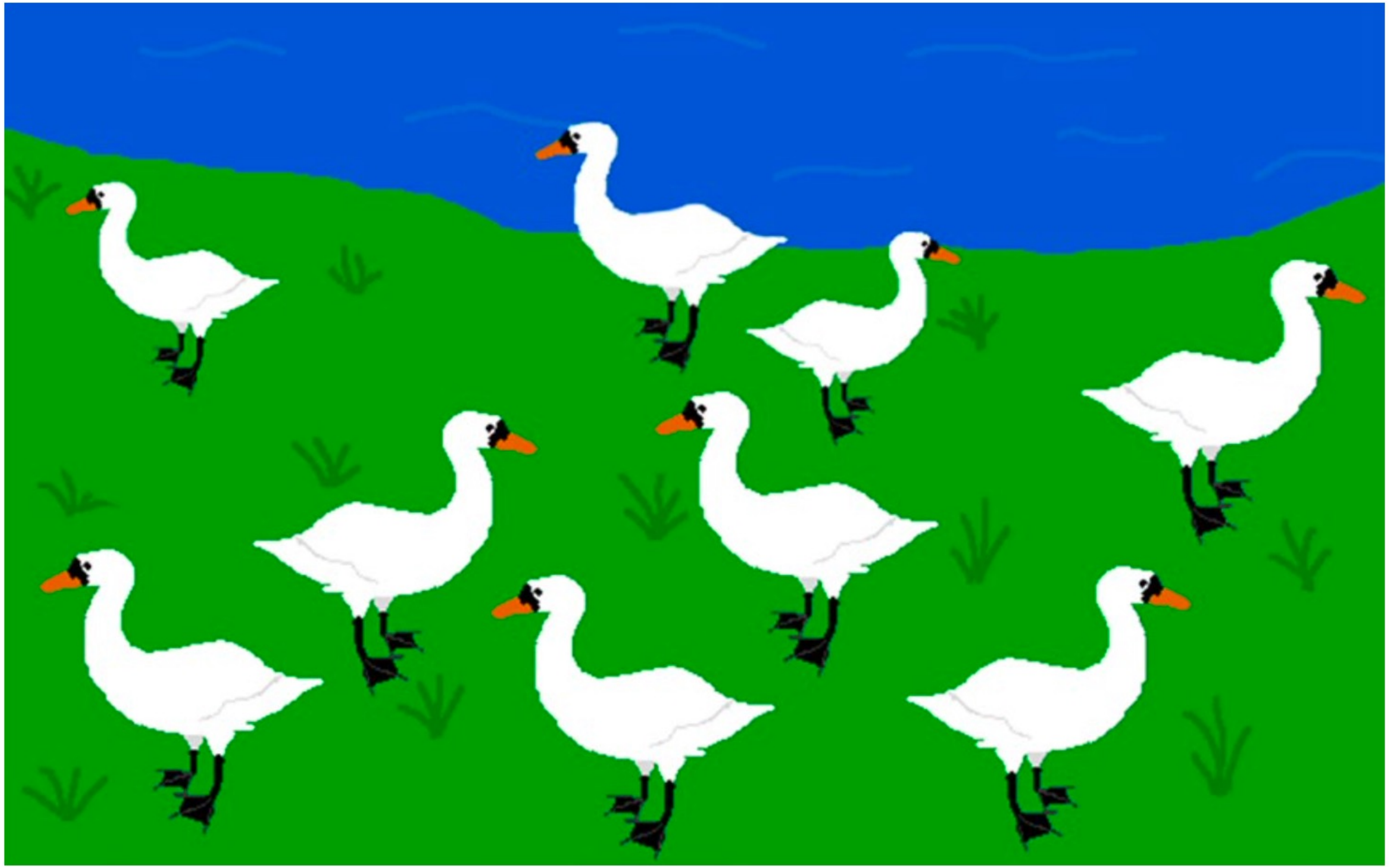
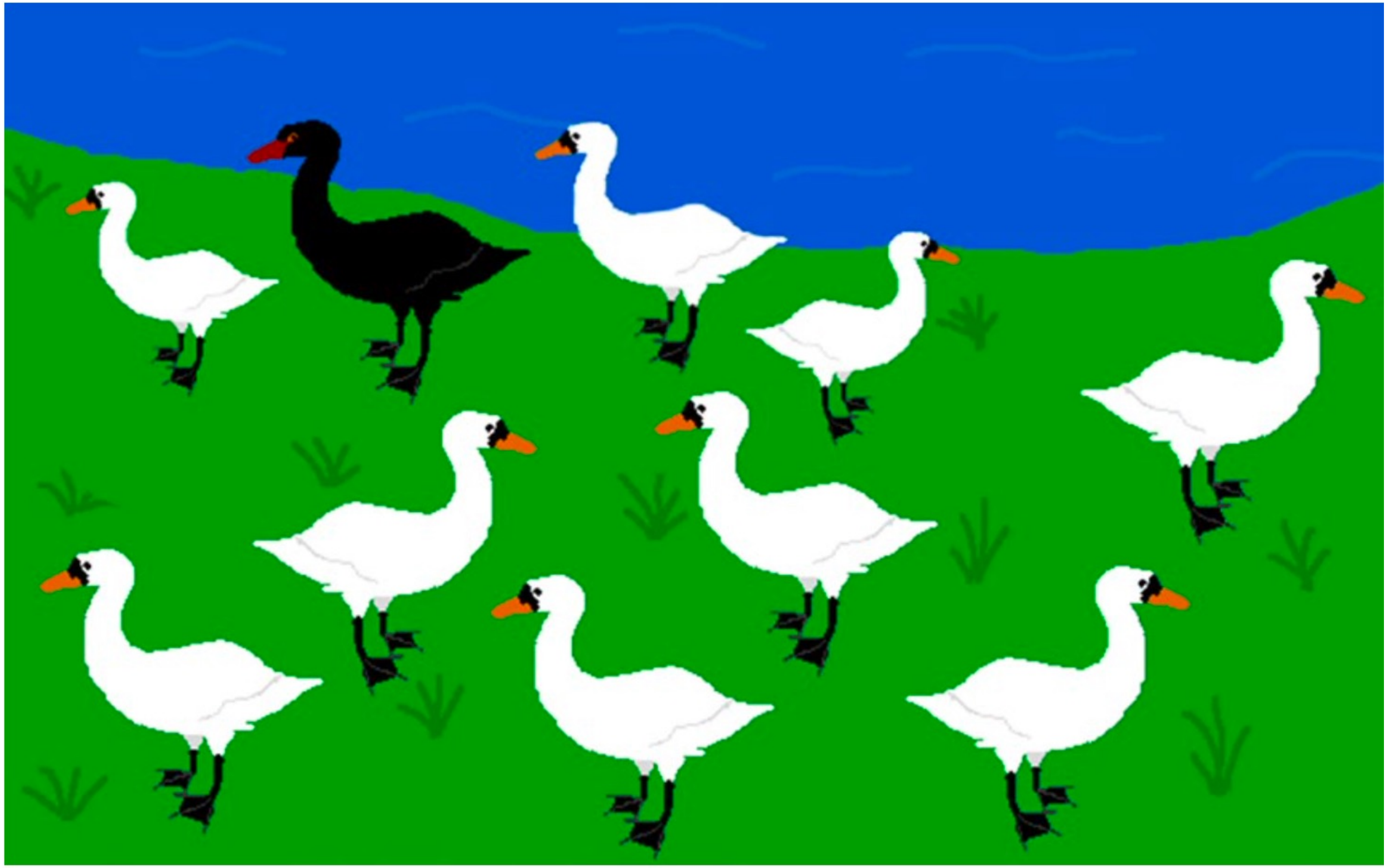
Anomaly detection

What color are swans?



Source: Alla

What color are swans?



Source: Alla

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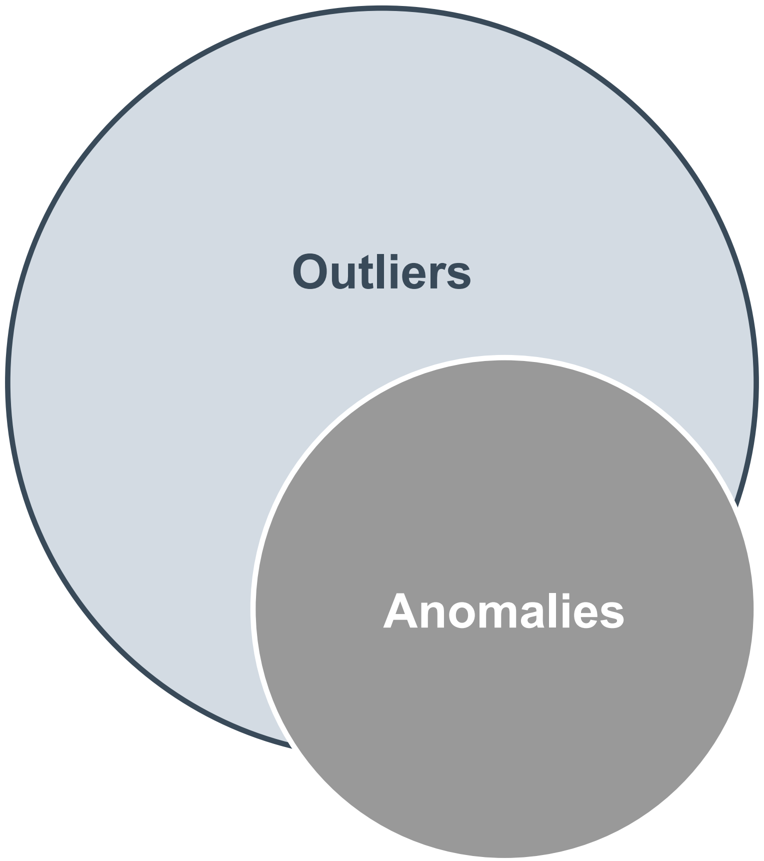
Outliers and anomalies



Outliers:

- Data points that are distinctly different from other data points
- Can be caused by unavoidable random errors or by systematic errors relating to how data was sampled

Anomalies:

- Outliers or other values that are not expected to exist
- Can be context- or pattern-based:
  - Context: exceptionally high credit card spending on Black Friday versus near-simultaneous spending in New York and London
  - Pattern: high credit card spending every Saturday versus high spending on a day where spending is low in other weeks

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What are possible anomalies and how would we detect them?

Consider the following situations:

- A machine produces thousands of screws per minute, every few days the type of screw is changed
- A software developer for a bank downloads a large number of entries from a customer database
- An intermediary supplies fair trade coffee beans

What is the expected outcome in each case?

What is an anomalous outcome?

What data do we observe?

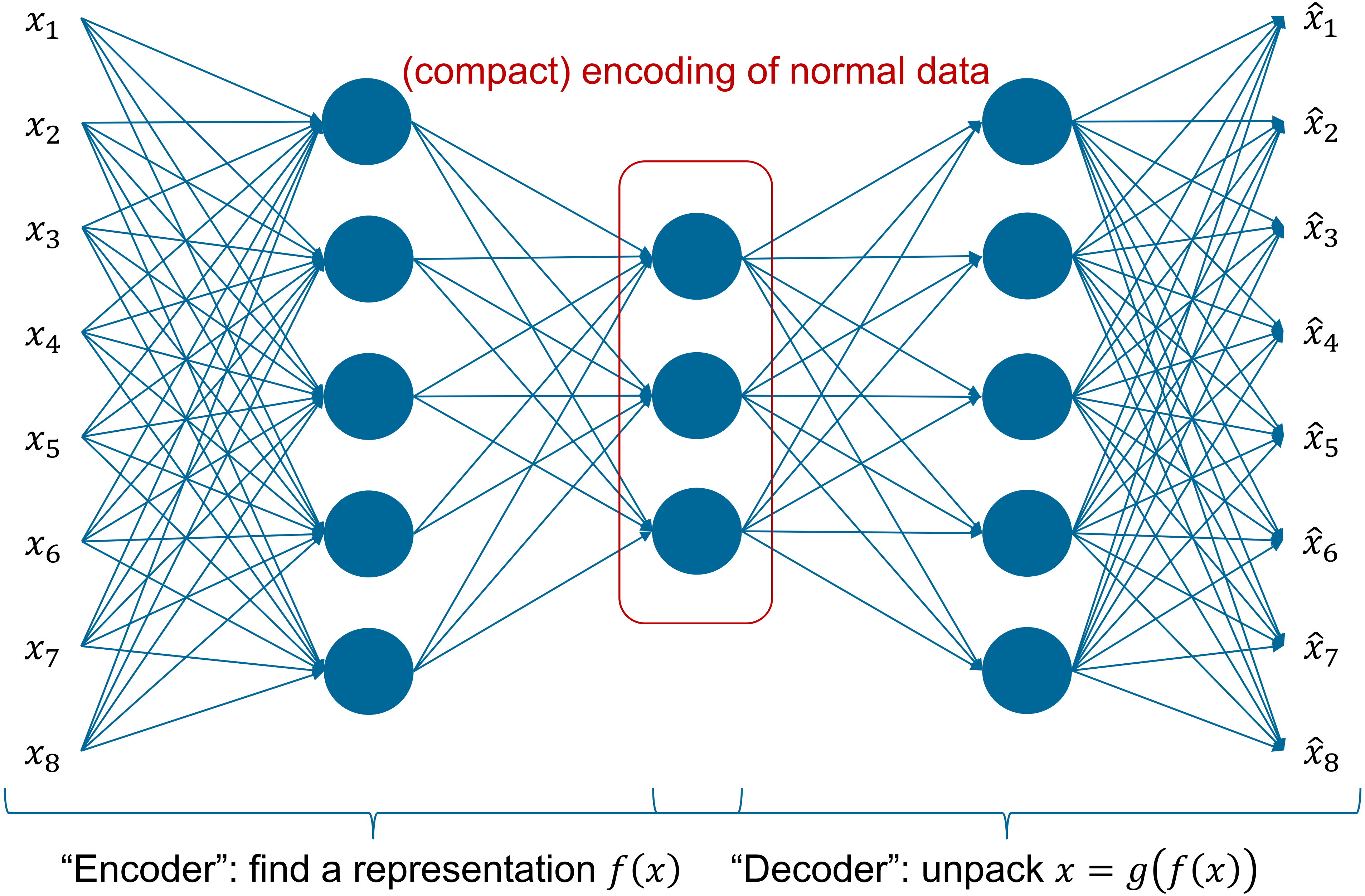
Detecting anomalies

Supervised anomaly detection:
- A fancy way of saying classification – learn to differentiate between two classes
- We can use the standard toolbox
- Upside: When feasible, usually the most failsafe method
- Downside: only works if we know how normal and anormal data looks like

Semi-supervised anomaly detection:
- Learn an efficient representation of normal data and then try to apply this to new data coming in
- We can use autoencoders and other tools
- Upside: we don't need to know how anormal data looks like
- Downside: still need to be sure that our normal data is actually normal

Unsupervised anomaly detection:
- Learn "how far" datapoints are from each other and recognize the ones that are far away from anything else
- We can use isolation forests and other tools
- Upside: we can work with any kind of data
- Downside: we don't have many guarantees

Anomaly detection with an autoencoder



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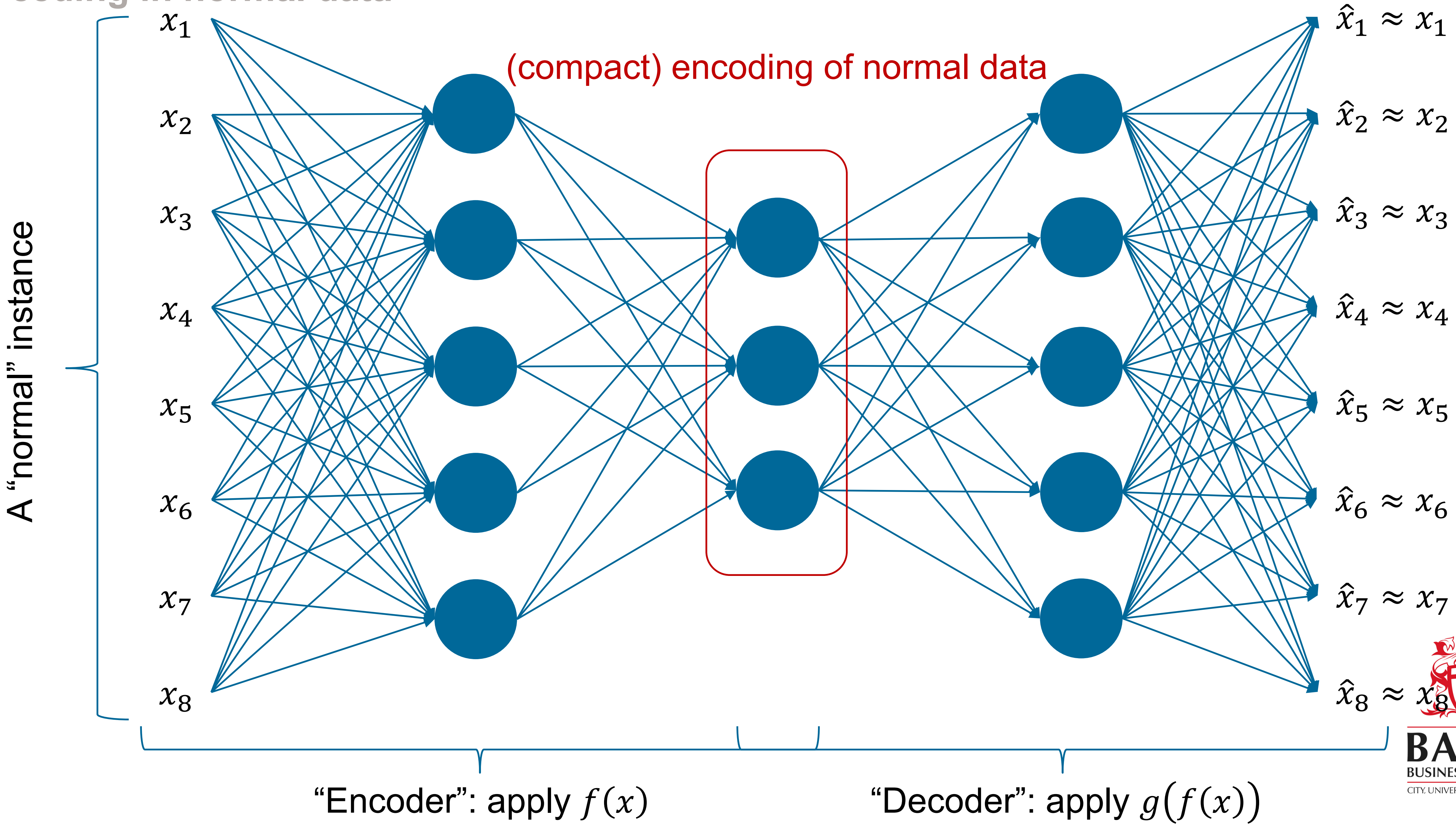
Feeding in normal data



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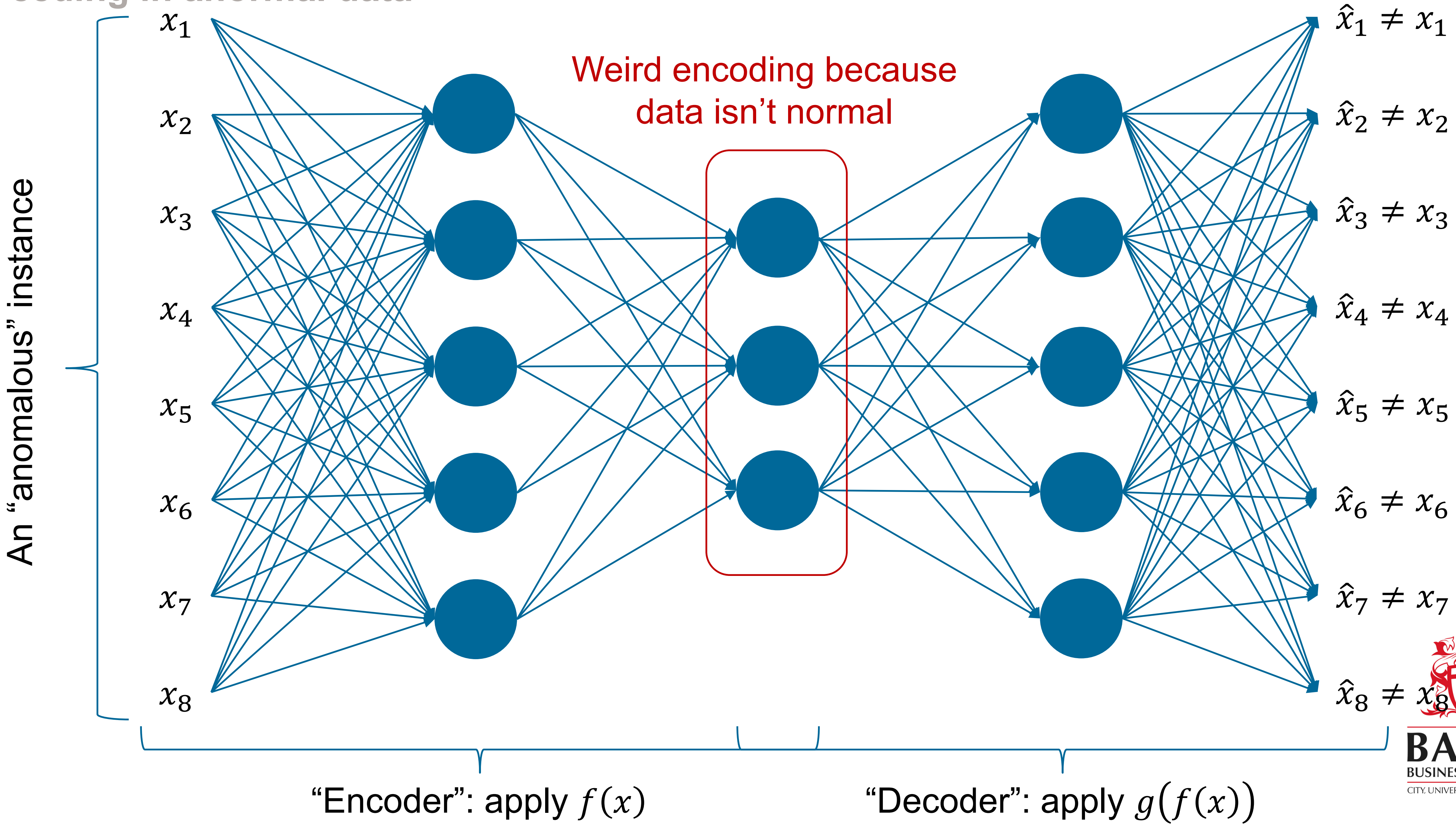
Feeding in anormal data



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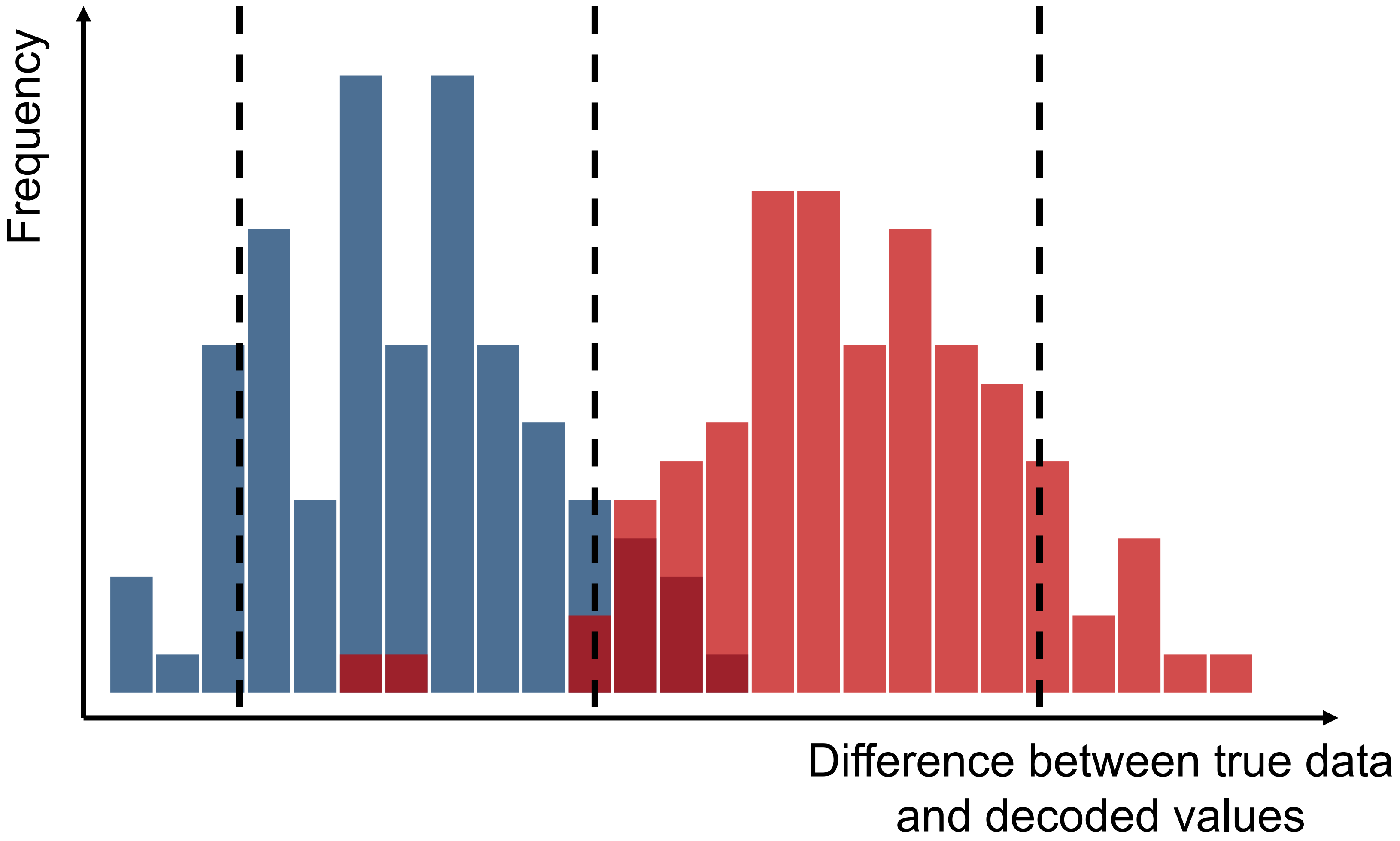
What we should be observing



Your turn – what did you find?

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Computer vision and convolutional layers

Importance of computer vision in business processes

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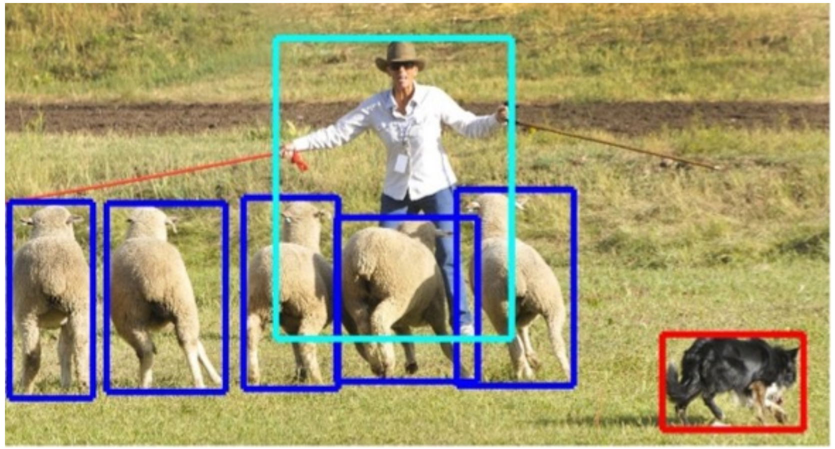
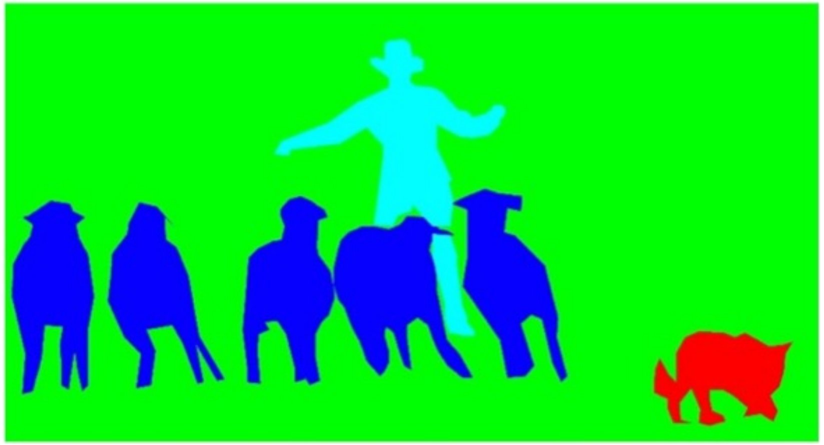
Typical computer vision problems

Image classification

Object detection



Semantic segmentation



Neural style transfer

Source: Lin, reiinakano.com

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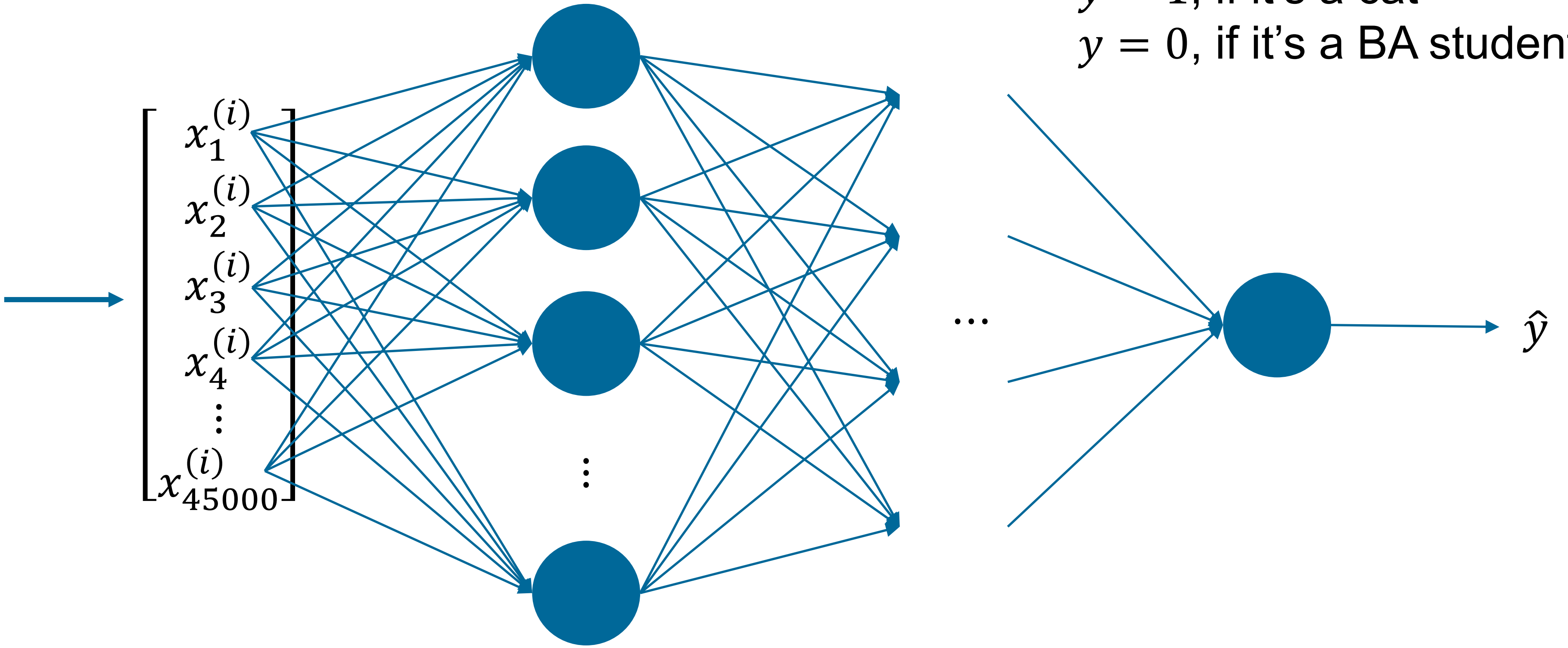
Challenges to deep learning using large images

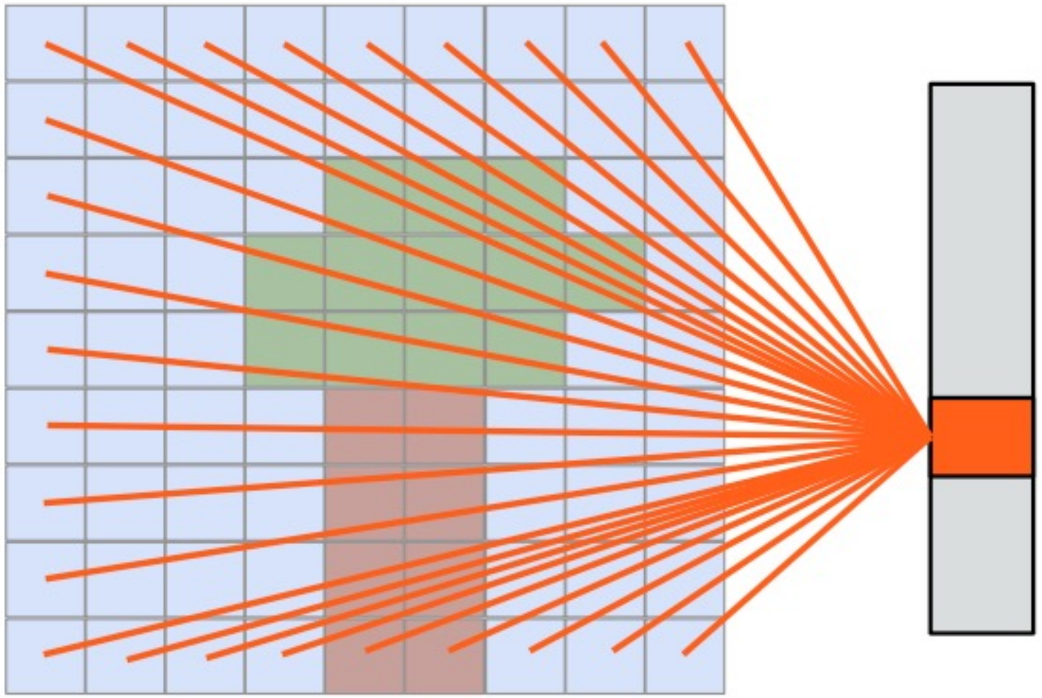
$y = 1$, if it's a cat
$y = 0$, if it's a BA student

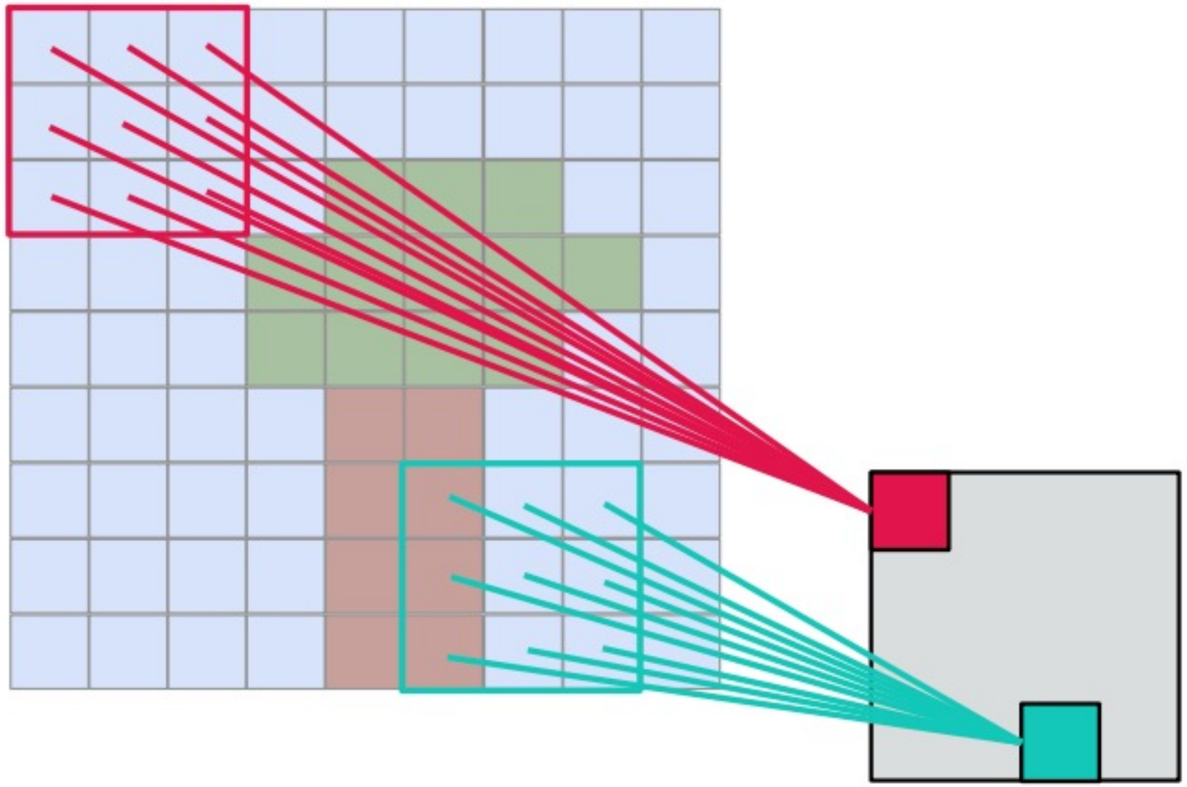
150x100x3



Say we have 100 neurons at the first layer.
Then we need 100*(45000+1)=4.5 mio parameters, just for the first layer!

From fully connected to locally connected





Source: Dieleman

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

=

0			

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An image filter

$$
\begin{bmatrix}
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0
\end{bmatrix}
*
\begin{bmatrix}
1 & 0 & -1 \\
1 & 0 & -1 \\
1 & 0 & -1
\end{bmatrix}
=
\begin{bmatrix}
0 & 30 & & \\
 & & & \\
 & & &
\end{bmatrix}
$$

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An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

$*$

1	0	-1
1	0	-1
1	0	-1

$=$

0	30	30	

An image filter

$$\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 30 & 30 & 0 \\ & & & \\ & & & \end{bmatrix}$$

An image filter

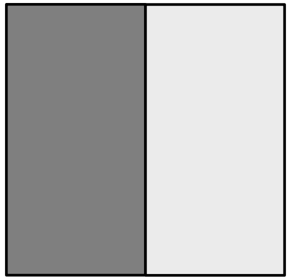
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

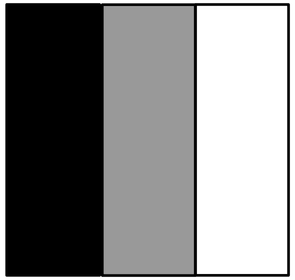
*

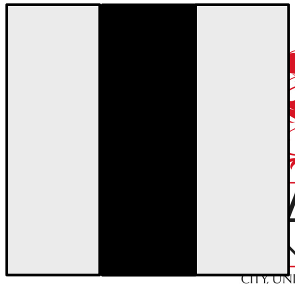
1	0	-1
1	0	-1
1	0	-1

=

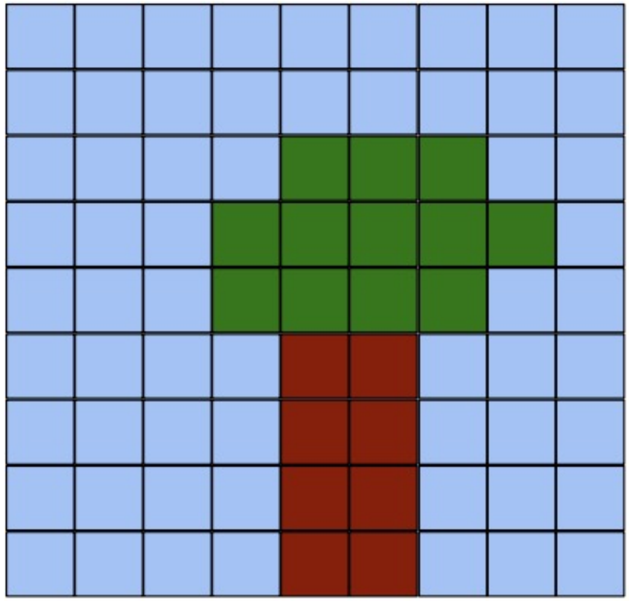
0	30	30	0
0	30	30	0
0	30	30	0



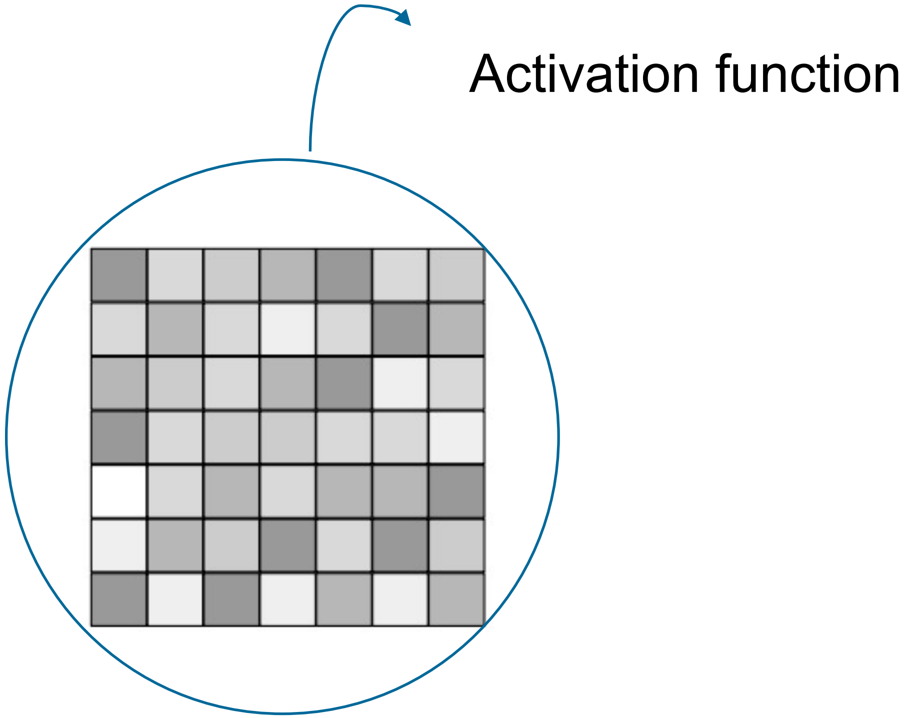




Convolutional layers: learning the filter

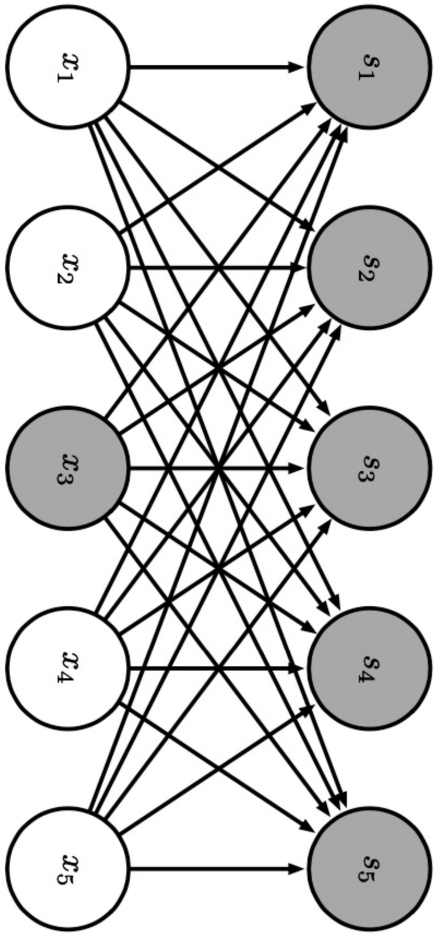


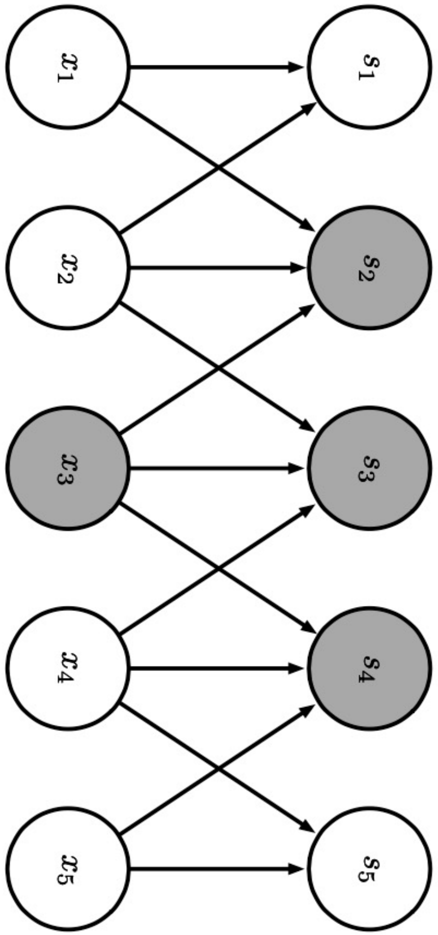
$$* \begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} \\ w_{2,1} & w_{2,2} & w_{2,3} \\ w_{3,1} & w_{3,2} & w_{3,3} \end{bmatrix} + b =$$



Source: Dieleman

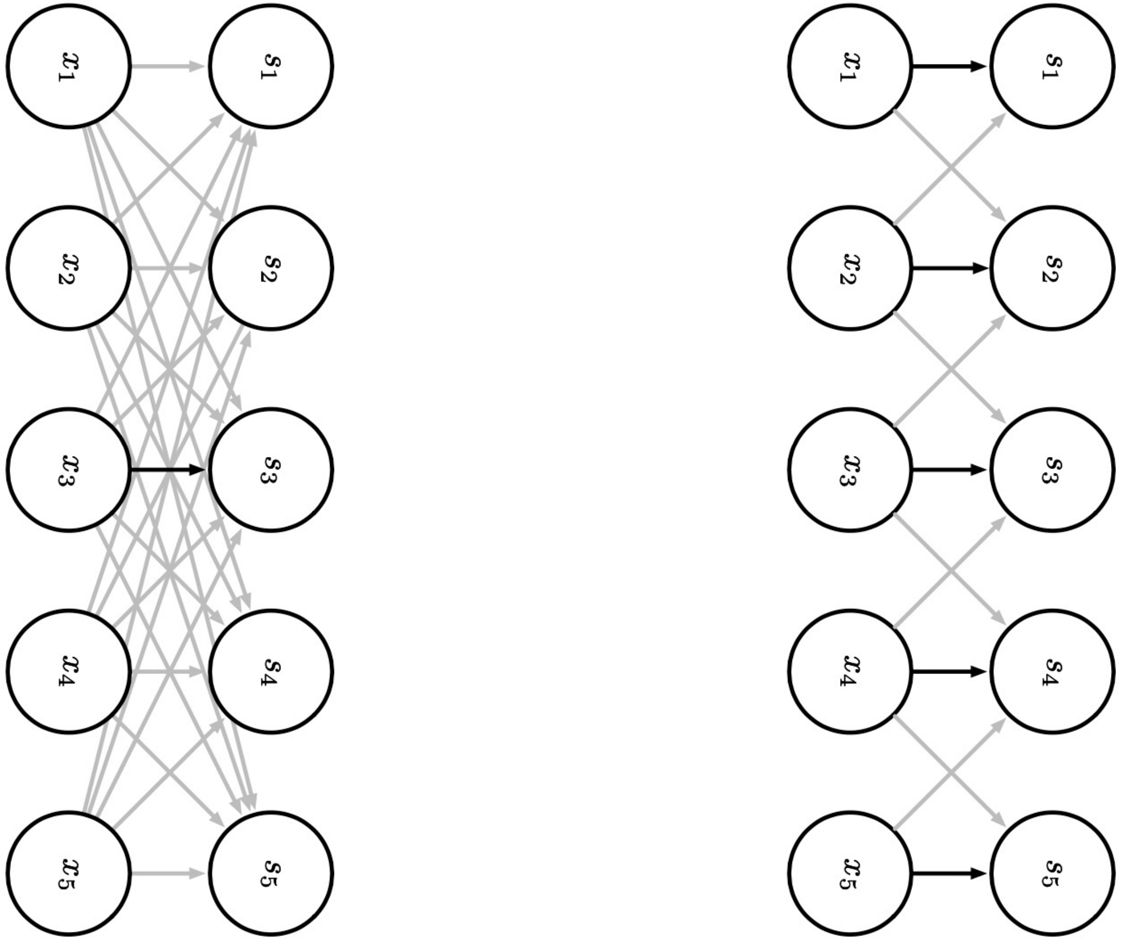
Less parameters required





Source: Goodfellow

Parameters are shared



Source: Goodfellow

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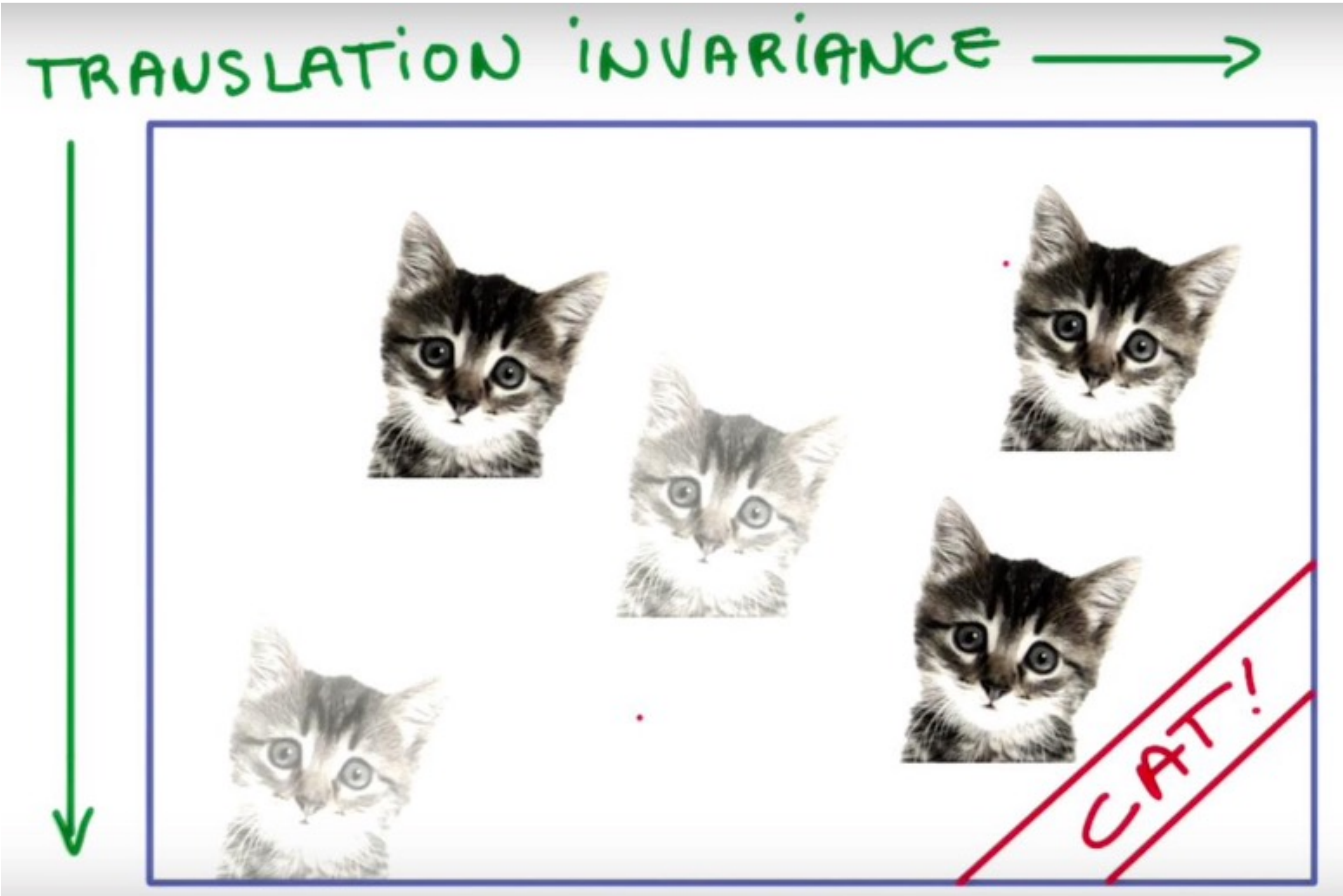
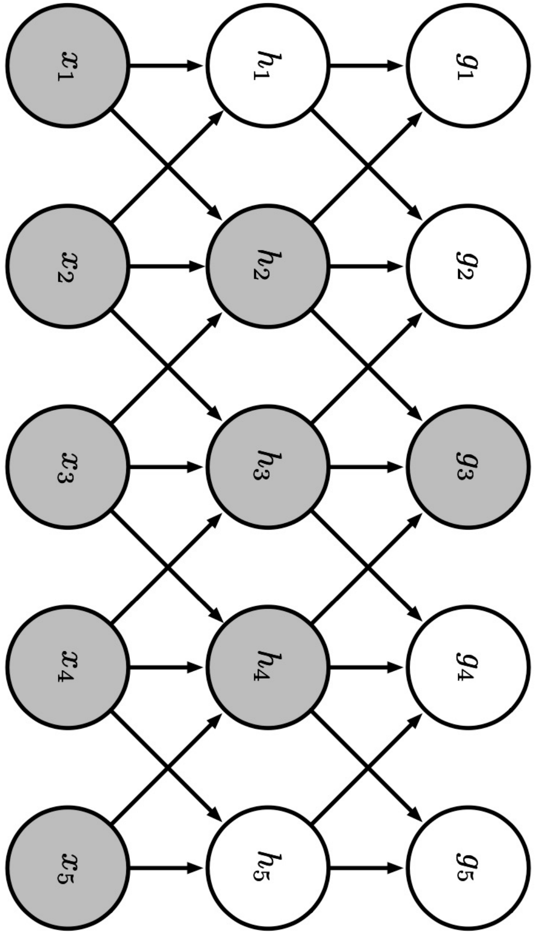
Translation invariance



Source: Bhaskhar

Hierarchical setup



Source: Goodfellow

With convolution, the center matters more

$$\begin{bmatrix} 1 & 3 & 1 & 2 \\ 6 & 1 & 5 & 4 \\ 5 & 4 & 2 & 5 \\ 3 & 3 & 1 & 2 \end{bmatrix} * \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} 20 & 12 & 19 \\ 22 & 21 & 22 \\ 22 & 15 & 16 \end{bmatrix}$$

The convolution operator with padding

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1				

The convolution operator with padding

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1	4			

The convolution operator with padding

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1	4	7		

The convolution operator with padding

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1	4	7	4	4
8	20	12	19	10
17	22	21	22	14
13	22	15	16	9
6	9	5	5	2

The convolution operator with padding and stride

$$
\begin{bmatrix}
 & & & & & \\
 & 1 & 3 & 1 & 2 & \\
 & 6 & 1 & 5 & 4 & \\
 & 5 & 4 & 2 & 5 & \\
 & 3 & 3 & 1 & 2 & \\
 & & & & &
\end{bmatrix}
*
\begin{bmatrix}
1 & 2 \\
2 & 1
\end{bmatrix}
=
\begin{bmatrix}
1 & & \\
 & & \\
 & &
\end{bmatrix}
$$

The convolution operator with padding and stride

$$
\begin{array}{|c|c|c|c|c|c|}
\hline
 & & & & & \\
\hline
 & 1 & 3 & 1 & 2 & \\
\hline
 & 6 & 1 & 5 & 4 & \\
\hline
 & 5 & 4 & 2 & 5 & \\
\hline
 & 3 & 3 & 1 & 2 & \\
\hline
 & & & & & \\
\hline
\end{array}
\;*\;
\begin{array}{|c|c|}
\hline
1 & 2 \\
\hline
2 & 1 \\
\hline
\end{array}
\;=\;
\begin{array}{|c|c|c|}
\hline
1 & 7 & \\
\hline
 & & \\
\hline
 & & \\
\hline
\end{array}
$$

The convolution operator with padding and stride

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1	7	4

The convolution operator with padding and stride

$$
\begin{bmatrix} & & & & & \\ & 1 & 3 & 1 & 2 & \\ & 6 & 1 & 5 & 4 & \\ & 5 & 4 & 2 & 5 & \\ & 3 & 3 & 1 & \boxed{2} & \\ & & & & & \end{bmatrix} * \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 7 & 4 \\ 17 & 21 & 14 \\ 6 & 5 & 2 \end{bmatrix}
$$

4x4
$(n_H^{[0]}, n_W^{[0]})$

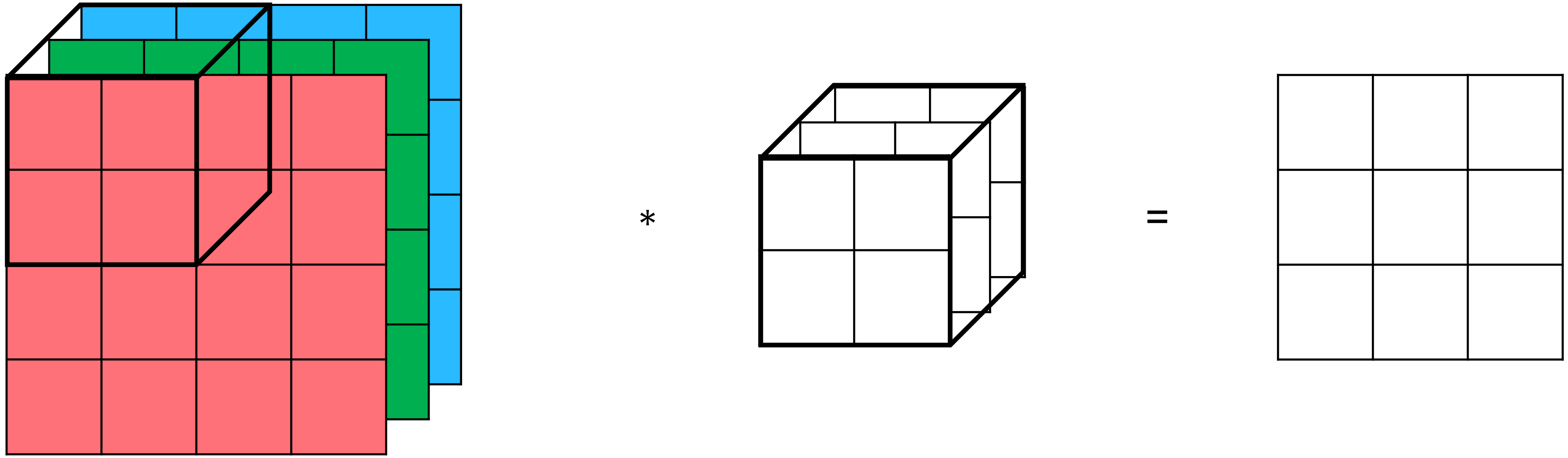
2x2 with padding 1x1 and stride 2x2
(f_H, f_W) with (p_H, p_W) and (s_H, s_W)

3x3
$(n_H^{[1]}, n_W^{[1]})$

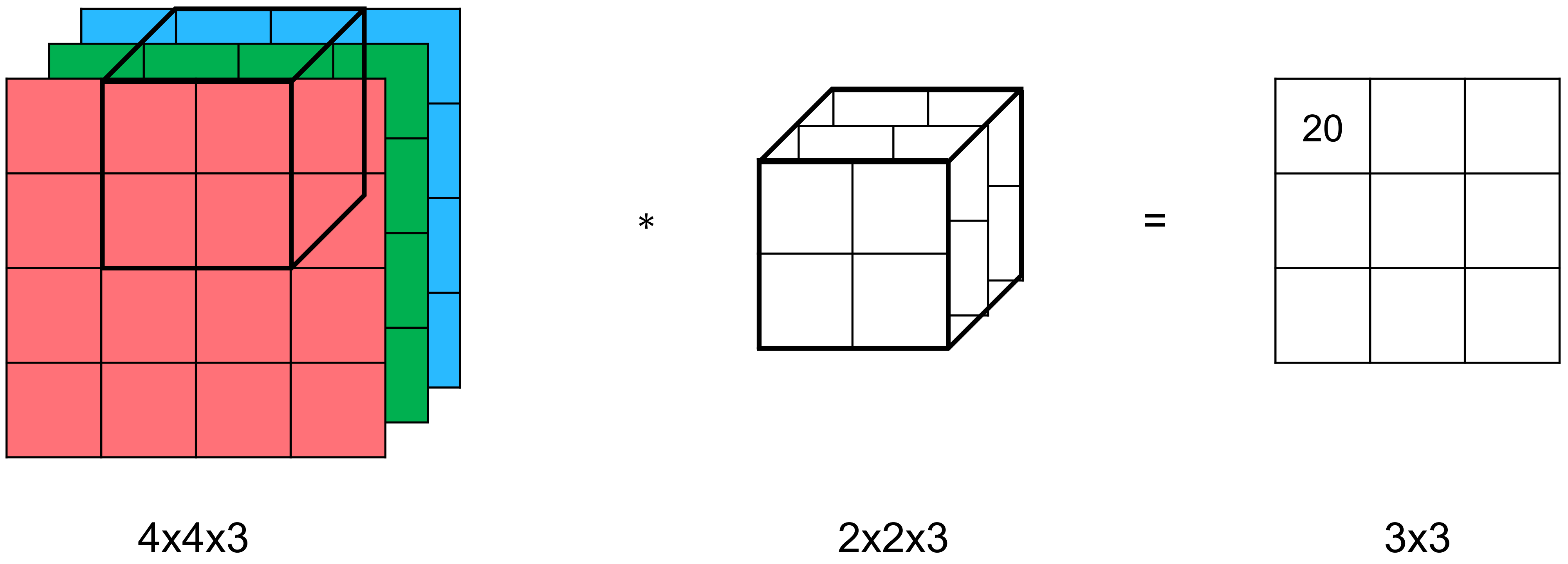
$$n_H^{[1]} = \left\lfloor \frac{n_H^{[0]} + 2p_H - f_H}{s_H} + 1 \right\rfloor \qquad n_W^{[1]} = \left\lfloor \frac{n_W^{[0]} + 2p_W - f_W}{s_W} + 1 \right\rfloor$$

The same, just in 3D

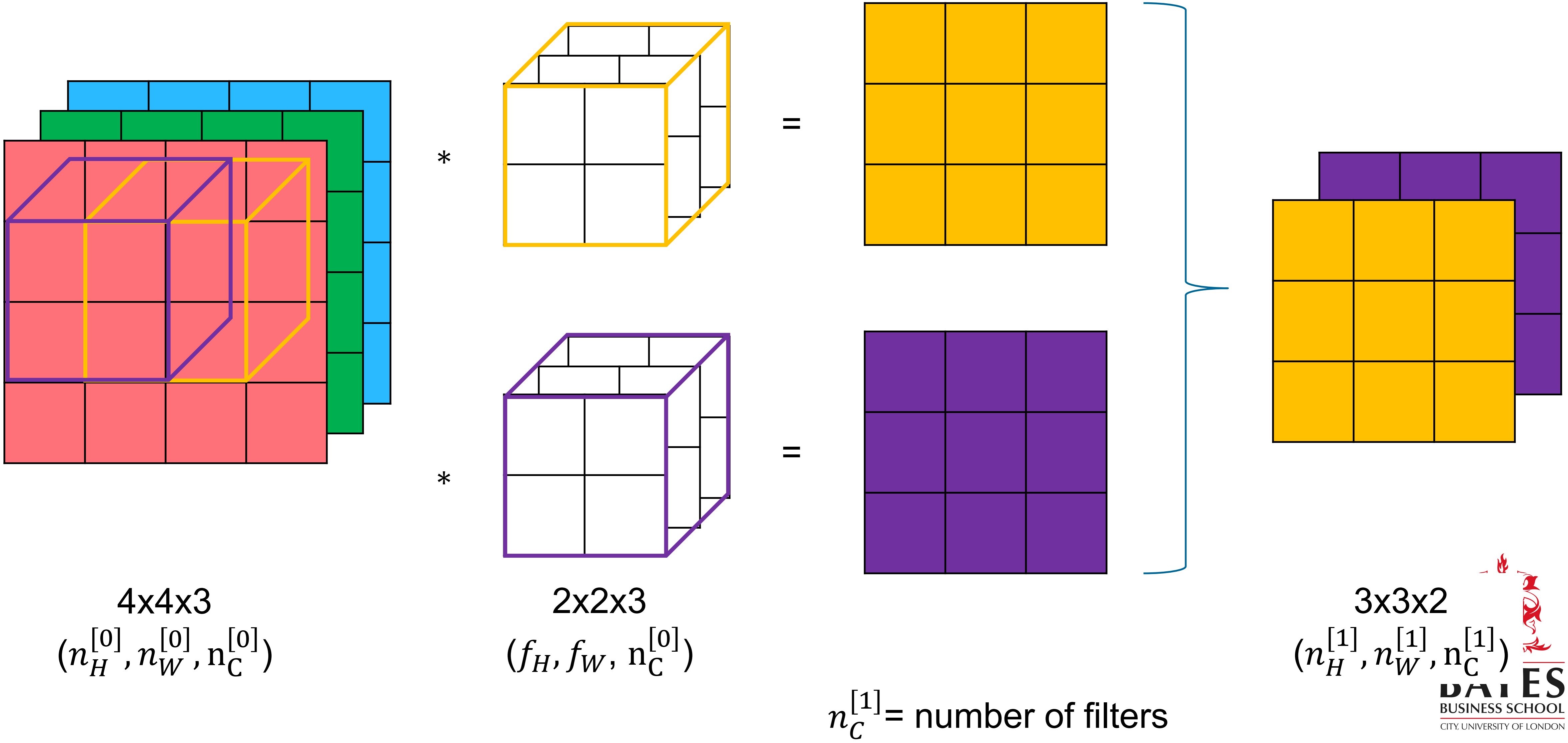
Convolution on a 3D array



Convolution on a 3D array



Multiple 3D convolutions

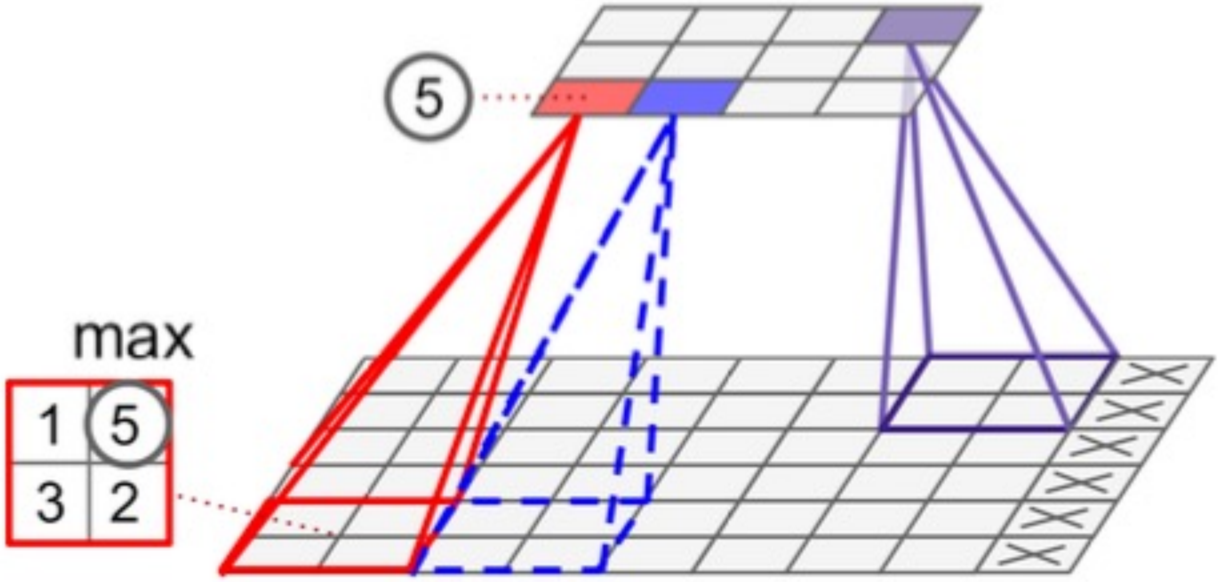


Additional architectural considerations

Objective of pooling layers

- Subsample (i.e., summarize) the input
  - Reduced computational load
  - Reduced memory usage
  - Fewer parameters (and, thus, less overfitting)

Max pooling



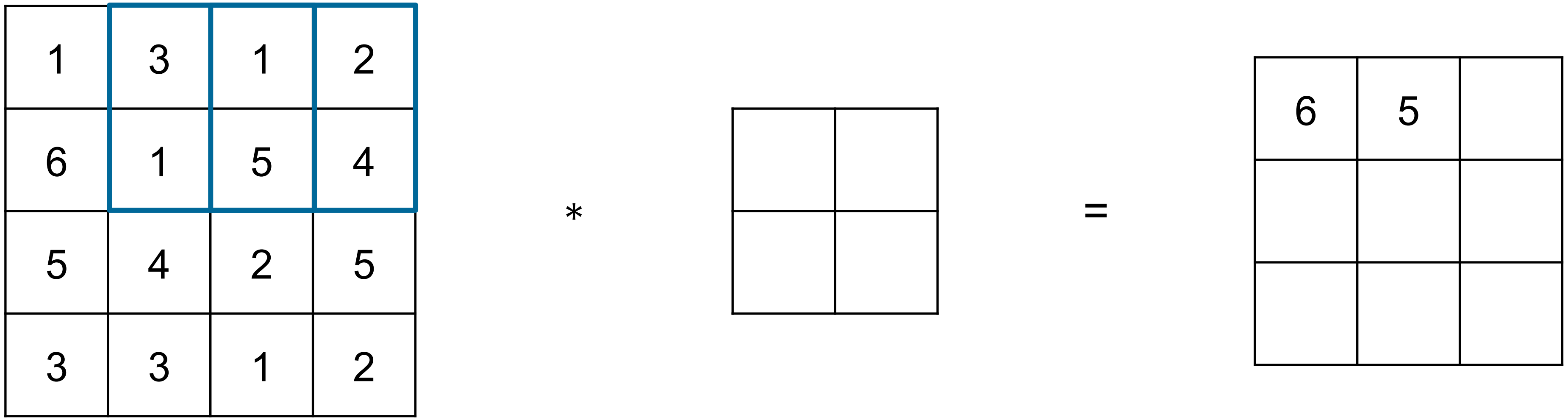
Source: Géron

Max pooling in practice

$$\begin{bmatrix} 1 & 3 & 1 & 2 \\ 6 & 1 & 5 & 4 \\ 5 & 4 & 2 & 5 \\ 3 & 3 & 1 & 2 \end{bmatrix} * \begin{bmatrix} & \\ & \end{bmatrix} = \begin{bmatrix} 6 & & \\ & & \\ & & \end{bmatrix}$$

Source: Géron

Max pooling in practice



Source: Géron

Max pooling in practice

$$\begin{bmatrix}1&3&1&2\\6&1&5&4\\5&4&2&5\\3&3&1&2\end{bmatrix} * \begin{bmatrix} & \\ & \end{bmatrix} = \begin{bmatrix}6&5&5\\ & & \\ & & \end{bmatrix}$$

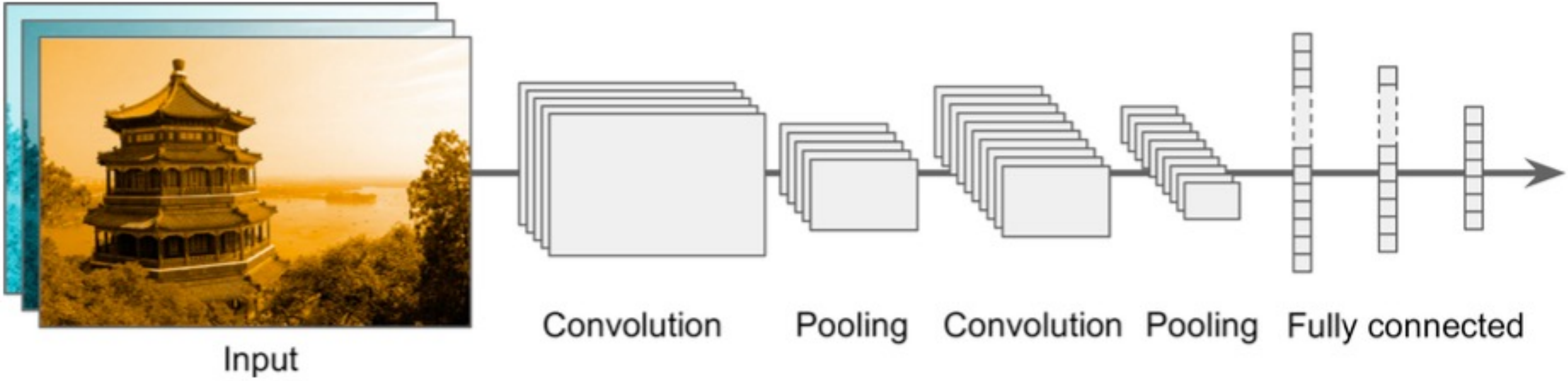
Source: Géron

Max pooling in practice

$$\begin{bmatrix} 1 & 3 & 1 & 2 \\ 6 & 1 & 5 & 4 \\ 5 & 4 & 2 & 5 \\ 3 & 3 & 1 & 2 \end{bmatrix} * \begin{bmatrix} \; & \; \\ \; & \; \end{bmatrix} = \begin{bmatrix} 6 & 5 & 5 \\ 6 & 5 & 5 \\ 5 & 4 & 5 \end{bmatrix}$$

Source: Géron

Typical architecture



Source: Géron

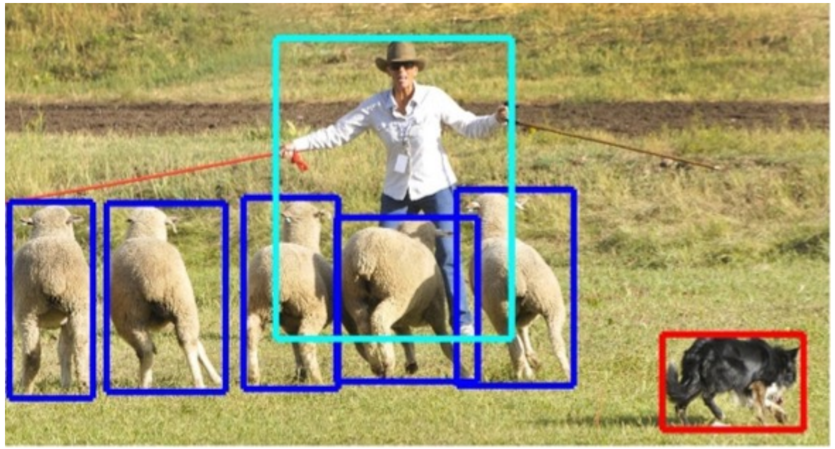
ConvNets in practice

Starting with object detection – non-sequential models

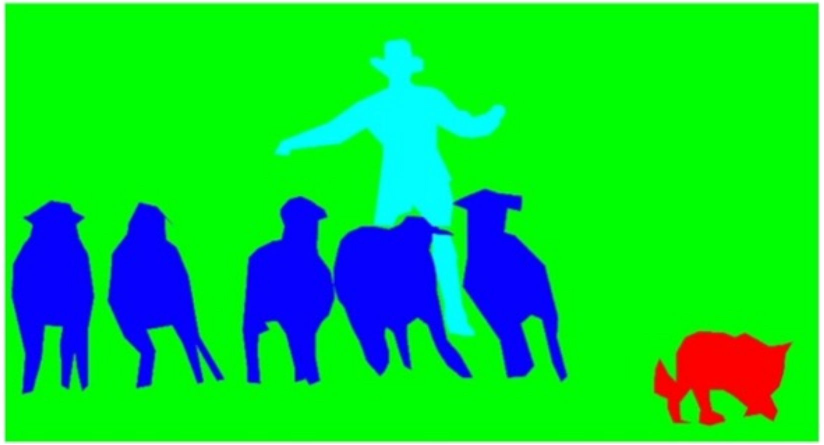
Typical computer vision problems

Image classification

Object detection



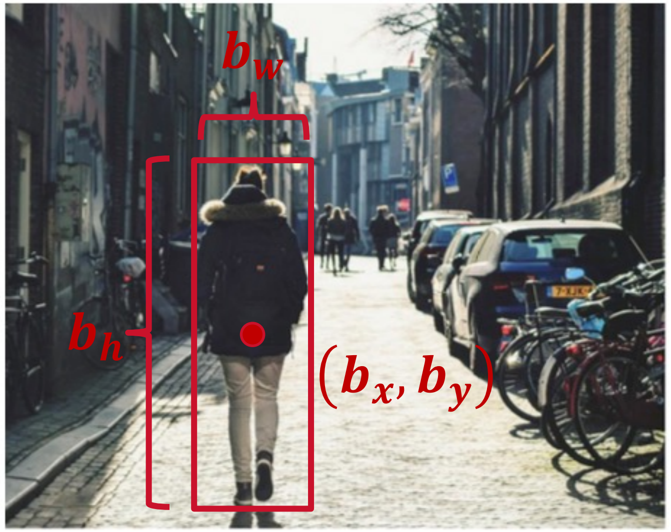
Semantic segmentation



Neural style transfer

Source: Lin, reiinakano.com

Before detection: classification + localization



A CNN

Softmax

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

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

Multi-Regression

Source: Géron

A look at creating non-sequential models

See you next week!

Sources

- Alla & Kalyan Adari, 2019, Beginning Anomaly Detection Using Python-Based Deep Learning, Apress
- Bhaskhar, 2021, Introduction to Deep Learning: https://cs229.stanford.edu/syllabus.html
- DeepLearning.AI, n.d.: deeplearning.ai
- Dieleman, 2020, Lecture 3: Convolutional Neural Networks: https://storage.googleapis.com/deepmind-media/UCLxDeepMind_2020/L3%20-%20UUCLxDeepMind%20DL2020.pdf
- Géron, 2019, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow
- Goodfellow, Bengio, Courville, 2016, The Deep Learning Book: http://www.deeplearningbook.org
- Liang, 2016, Introduction to Deep Learning: https://www.cs.princeton.edu/courses/archive/spring16/cos495/
- Lin et al., 2014, Microsoft COCO: Common Objects in Context: https://arxiv.org/pdf/1405.0312.pdf