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Workshop on Applied Deep Learning in Intracranial Neurophysiology

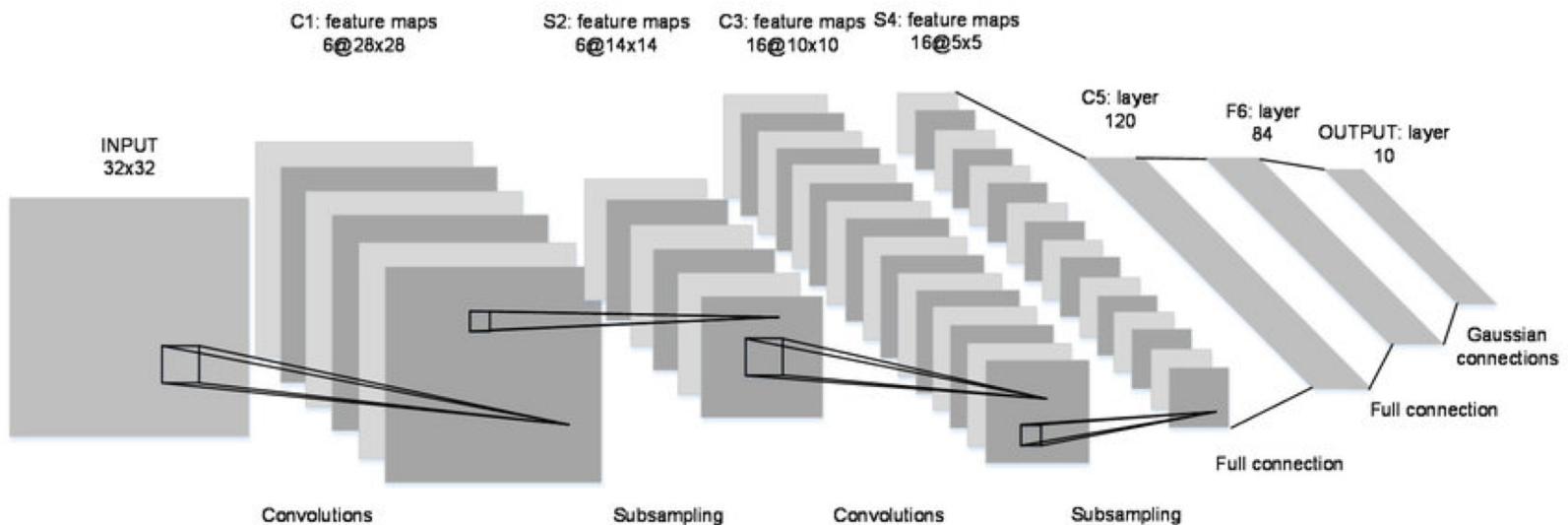
Part 3 – Using Convolutional Neural Networks to Analyze Brain Signals

September 16, 2019

Presented by Chadwick Boulay, MSc, PhD
Ottawa Hospital Research Institute
University of Ottawa

ConvNets, CNNs

- Convolutional Neural Networks have exploded in popularity due to their utility in classifying images.



“LeNet” – Yann LeCun

[1-NIPS 1990](#)

MNIST = “Hello World”

- And due to the availability of great image datasets.

label = 5



label = 0



label = 4



label = 1



label = 9



label = 2



label = 1



label = 3



label = 1



label = 4



label = 3



label = 5



label = 3



label = 6



label = 1



label = 7



label = 2



label = 8



label = 6

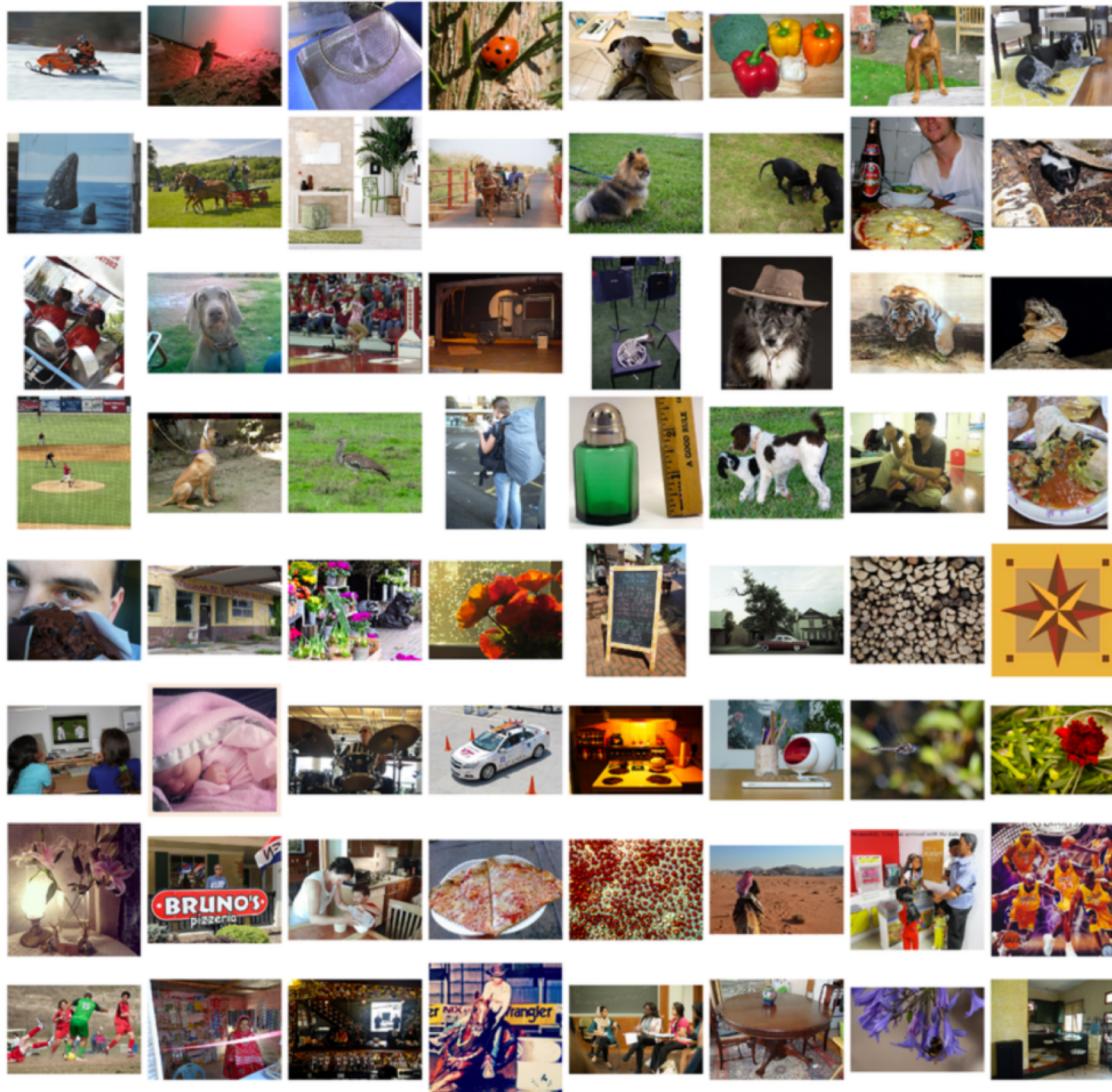


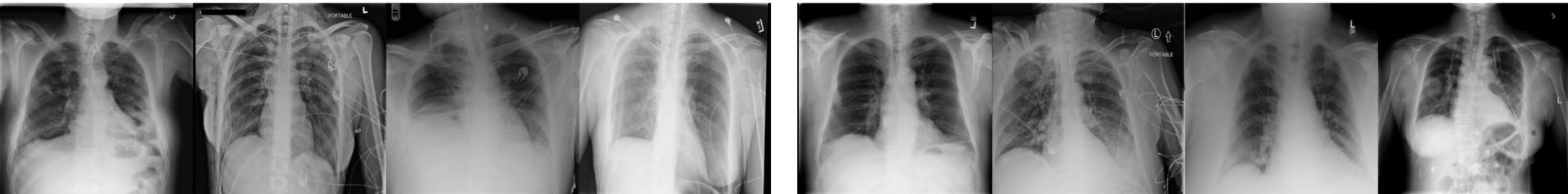
label = 9



ImageNet 14M labeled images

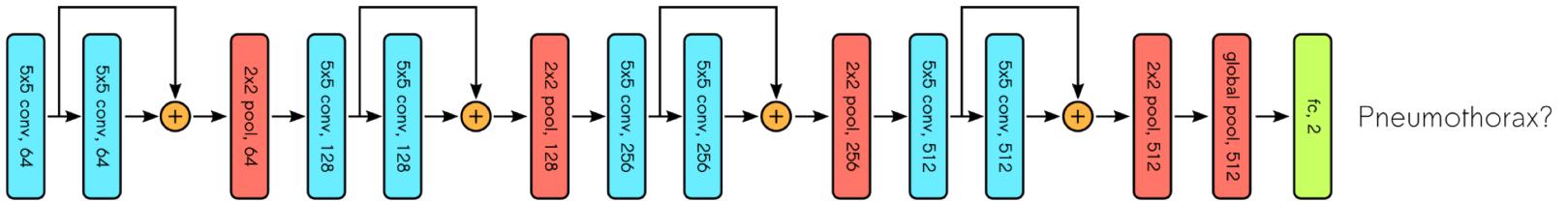
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

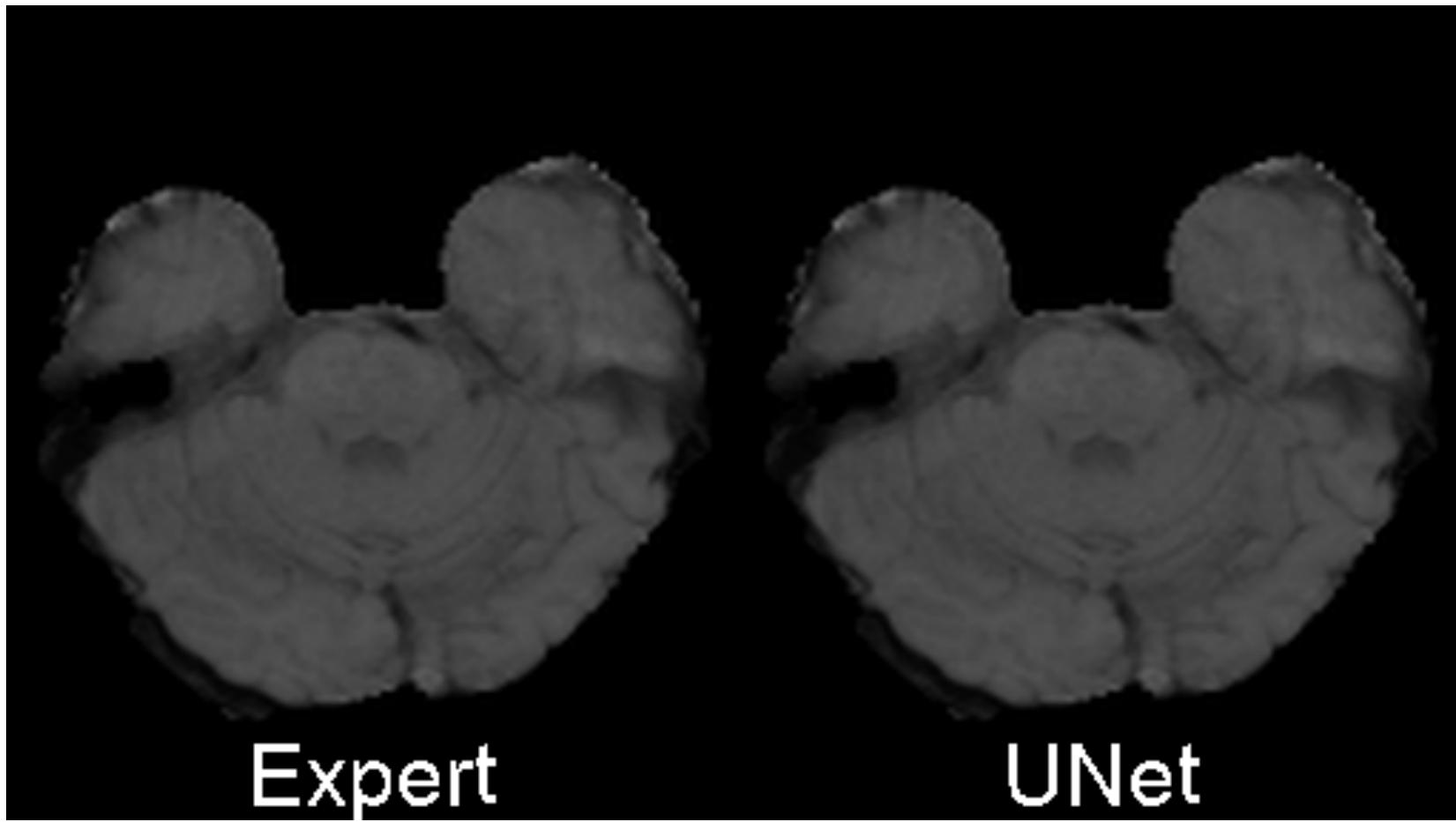




Dataset images without pneumothorax

Dataset images with pneumothorax





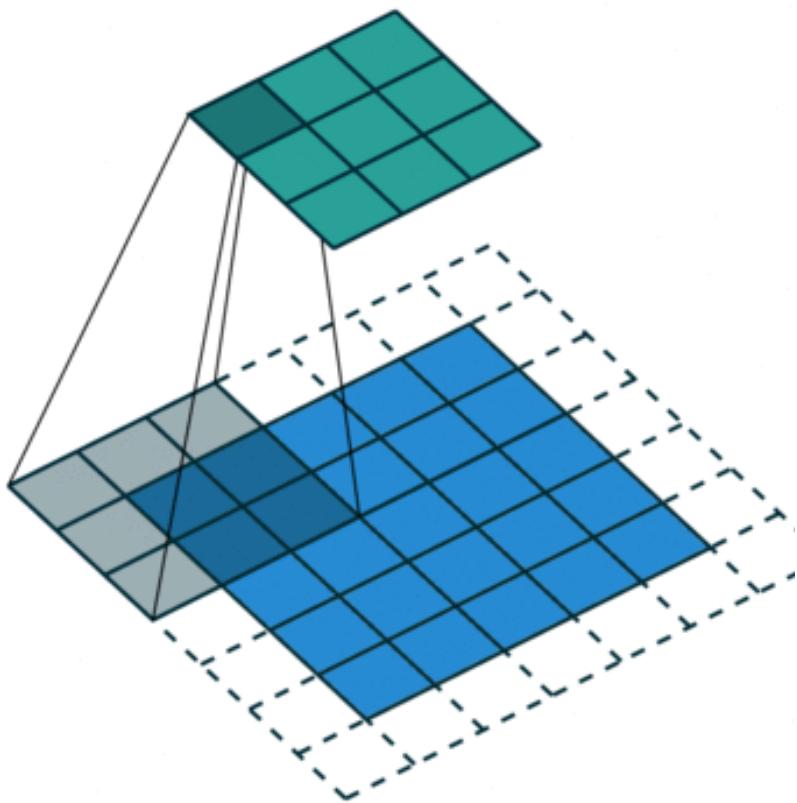
Convolution Operation

1 <small>×1</small>	1 <small>×0</small>	1 <small>×1</small>	0	0
0 <small>×0</small>	1 <small>×1</small>	1 <small>×0</small>	1	0
0 <small>×1</small>	0 <small>×0</small>	1 <small>×1</small>	1	1
0	0	1	1	0
0	1	1	0	0

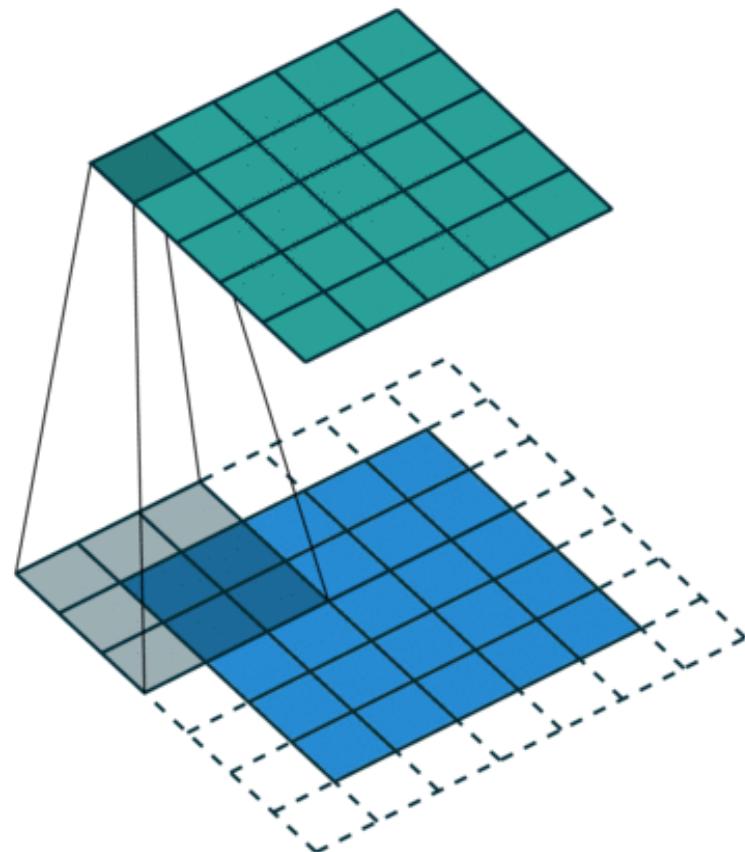
Image

4		

Convolved
Feature

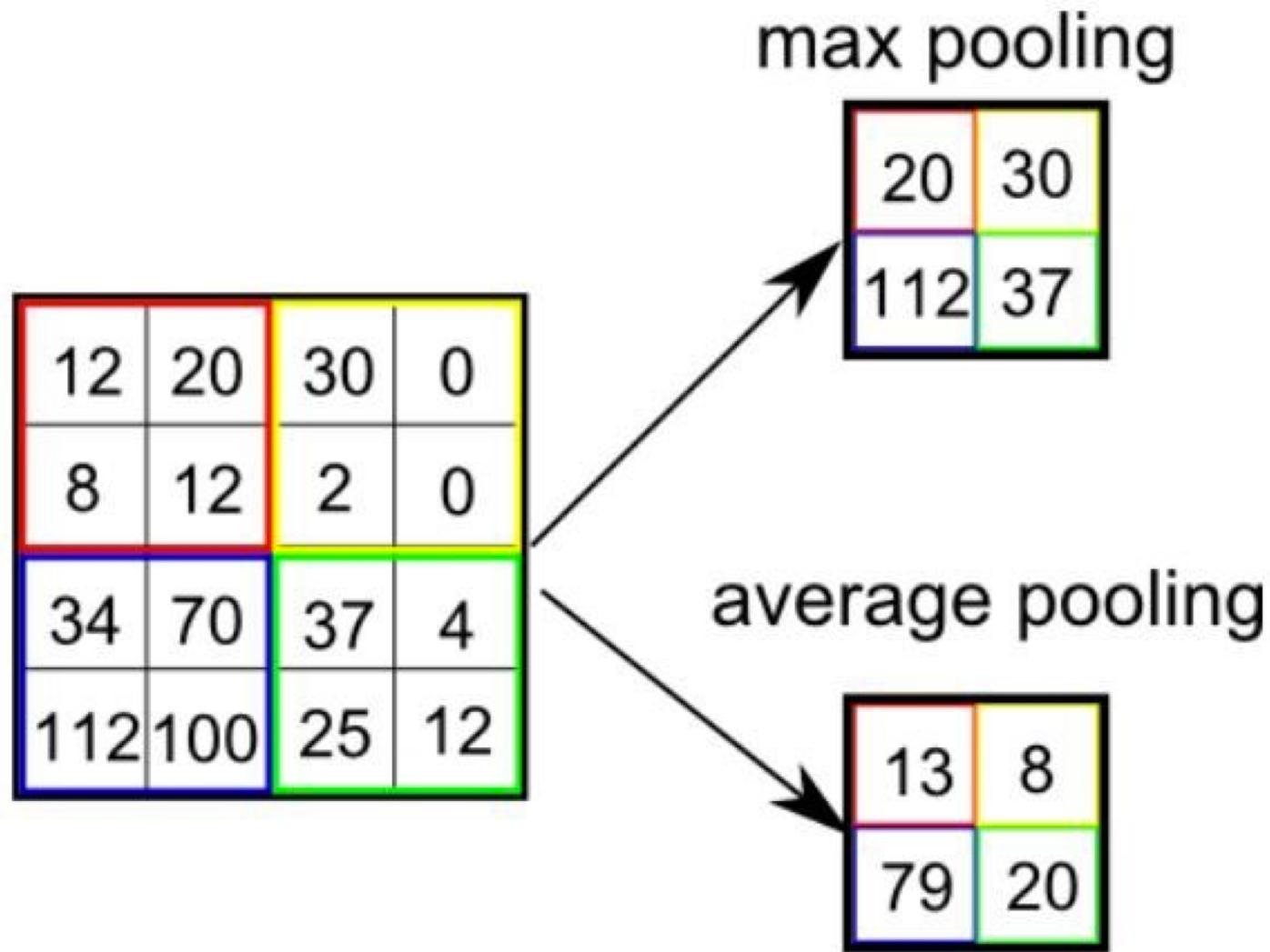


Strides = 2



Strides=1, Padding=1

Pooling: Dimensionality reduction, noise suppression, translation/rotation invariance



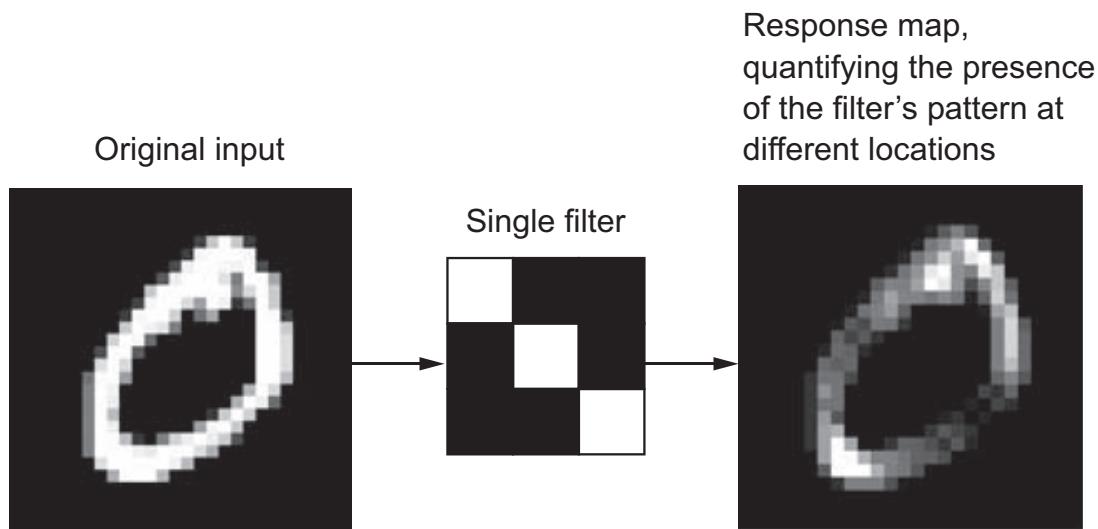


Figure 5.3 The concept of a *response map*: a 2D map of the presence of a pattern at different locations in an input

Deep Learning with Python by Chollet

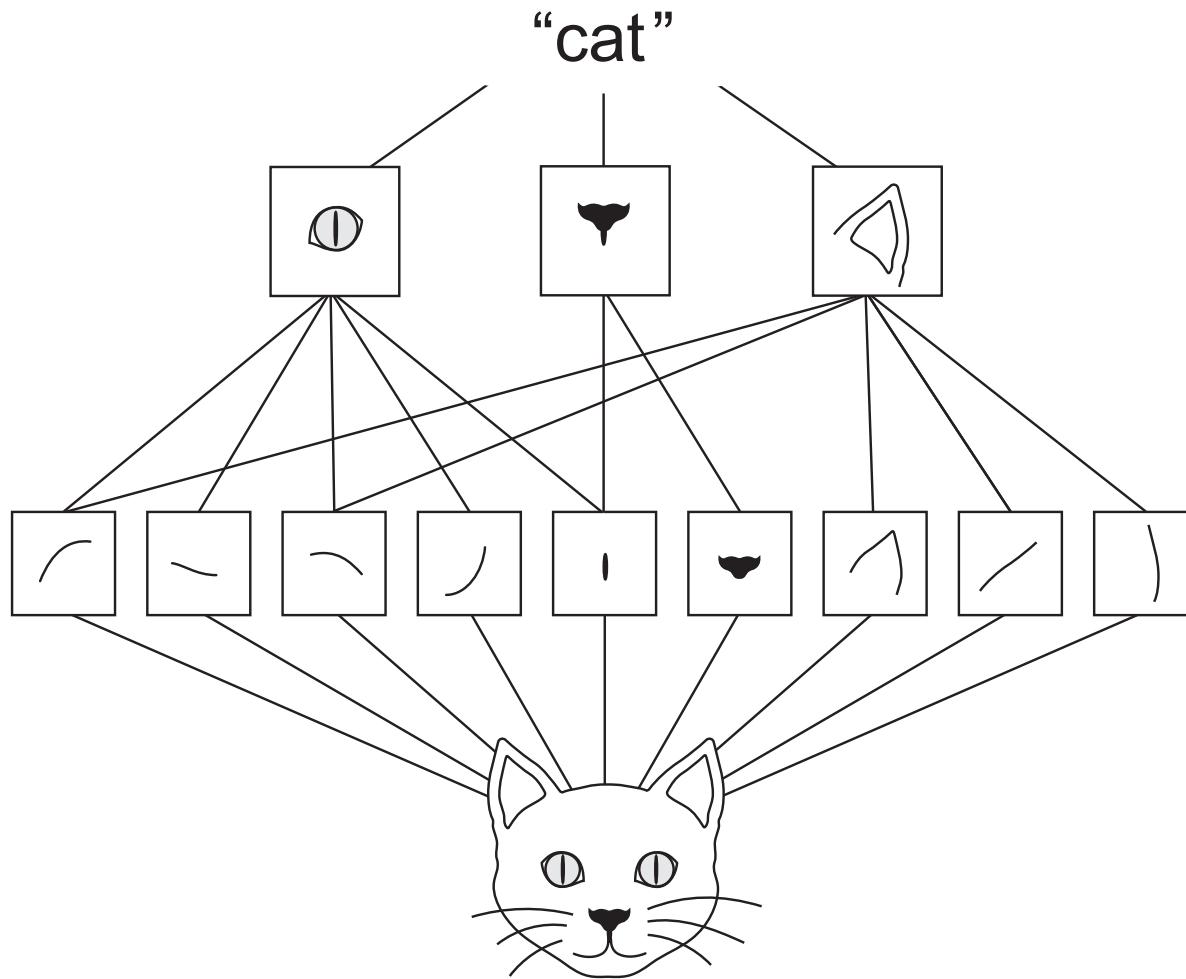
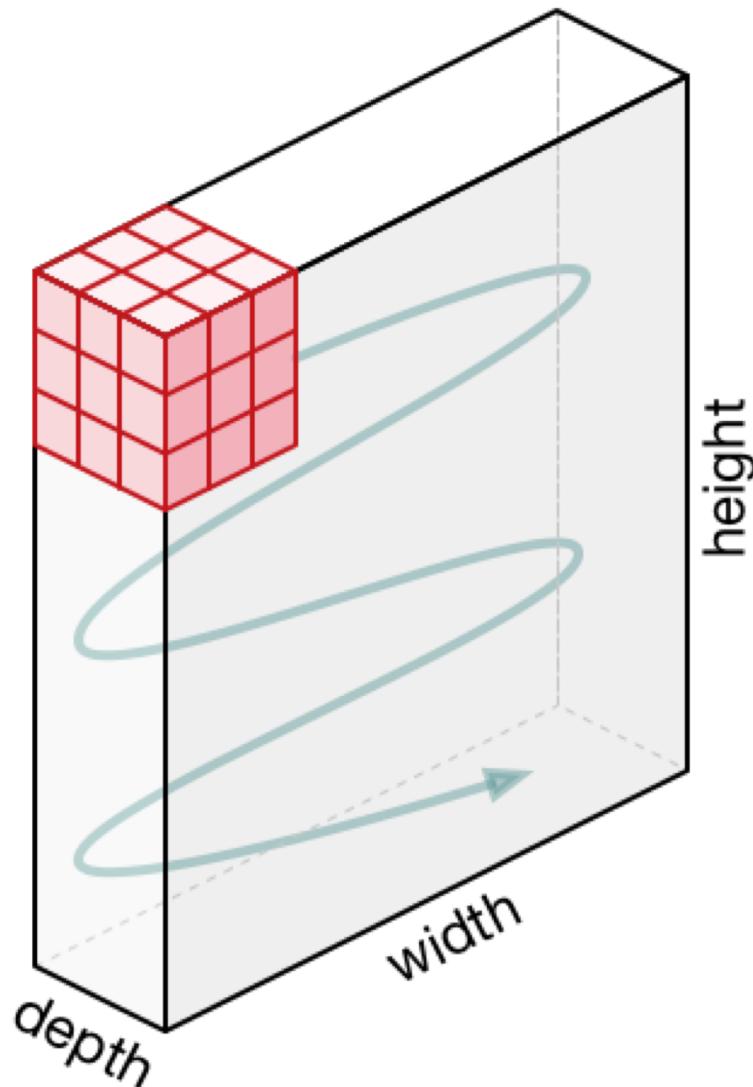


Figure 5.2 The visual world forms a spatial hierarchy of visual modules: hyperlocal edges combine into local objects such as eyes or ears, which combine into high-level concepts such as “cat.”

Kernel has depth

In images, depth is number of channels (RGB)

In neural data, depth could be number of channels (electrodes)



0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...

Input Channel #3 (Blue)

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

Kernel Channel #1



308

+

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

Kernel Channel #2



-498

0	1	1
0	1	0
1	-1	1

Kernel Channel #3



164

+

-25				...
				...
				...
				...
...

Output

Bias = 1

If output depth is 1 then the results of the kernel multiplications are summed into a flat image.
This is rarely the case.

For each step...

Input is $3 \times 3 \times 2$

Kernel is $3 \times 3 \times 3$

Output is $1 \times 1 \times 3$

Note the change in depth

$2 \rightarrow 3$

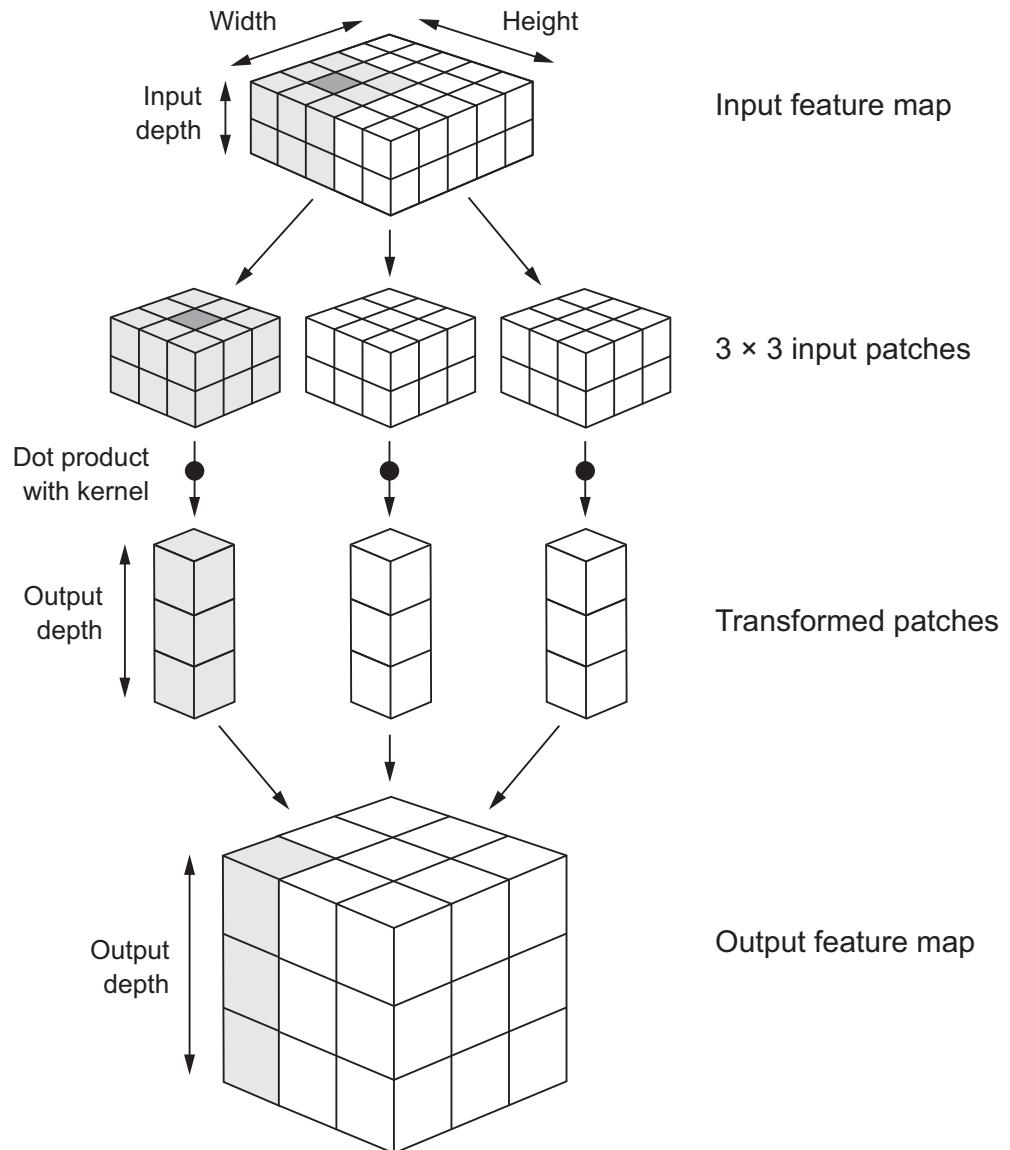


Figure 5.4 How convolution works

Convolutions in 1D on timeseries

- Proceed to notebook

[03_01 Intro to CNNs.ipynb](#)

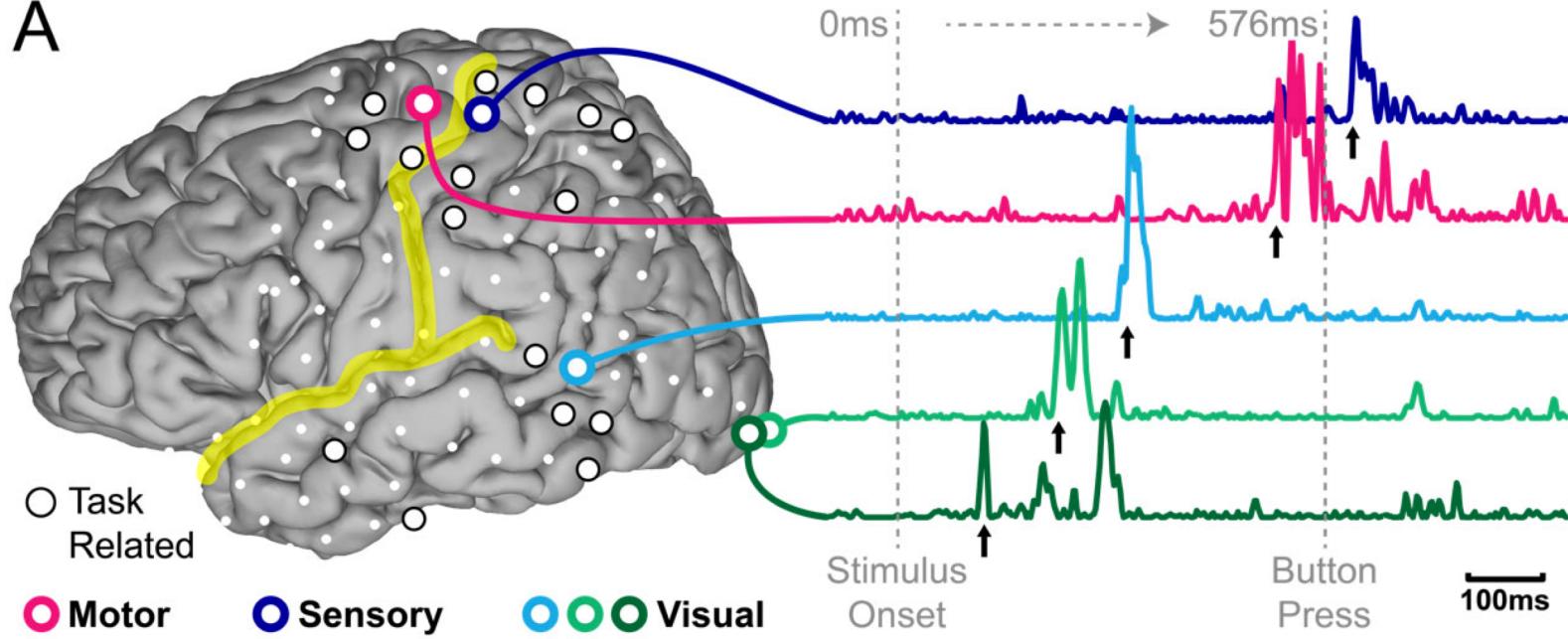
Convolutions in 1D on ECoG data

- Proceed to notebook

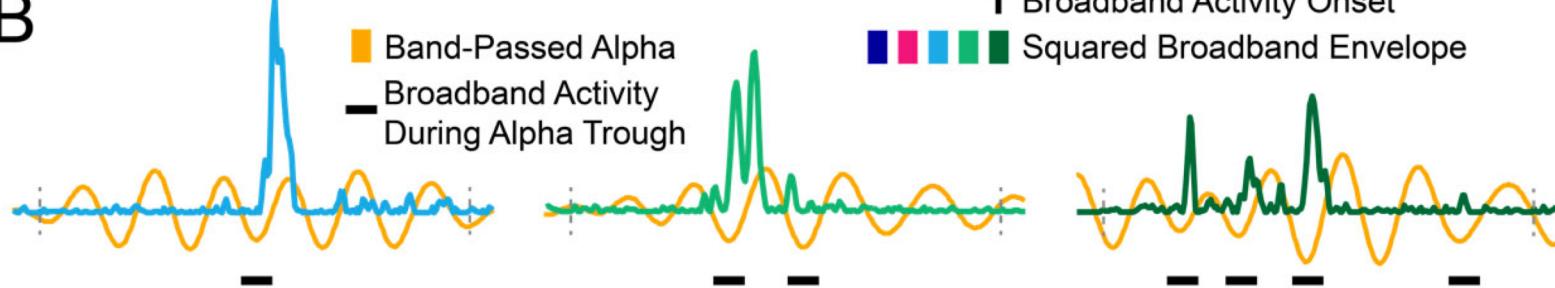
[03_02_CNN_faces_houses.ipynb](#)

Translation Invariance – Isn't that a bad thing? Maybe not.

A



B



Why train filter kernels?

