Using Convolutional Neural Networks to Classify Brain States

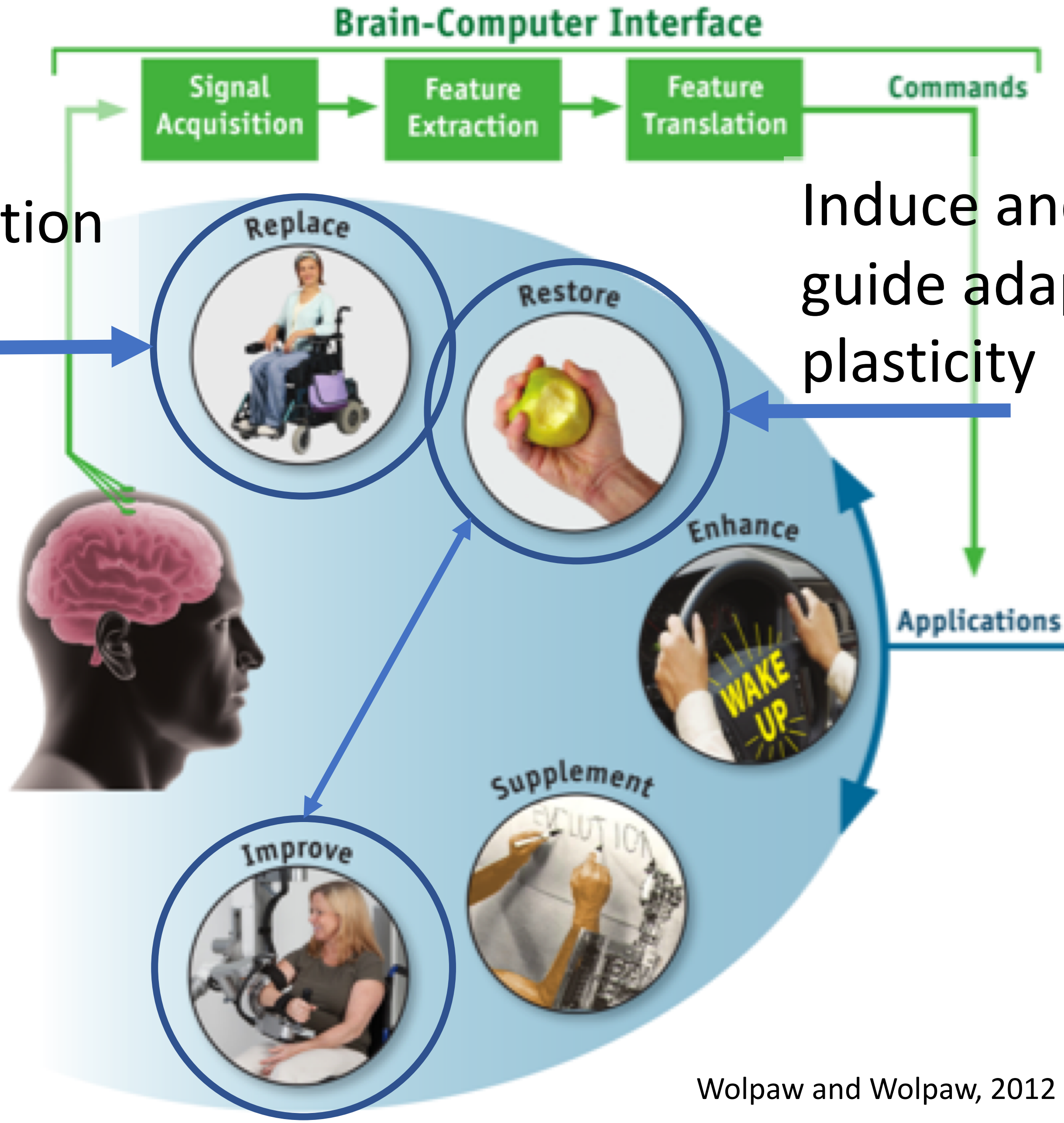
Ottawa AI Alliance
Second Annual Workshop
November 28, 2019

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

Resources

- Wi-Fi
  - SSID: S77-3001-AP
  - Password: NRCwifiK1A0R6
- Need Kaggle API token (Kaggle.com)
- github.com/SachsLab/IntracranialNeurophysDL
  - Slides
  - notebooks

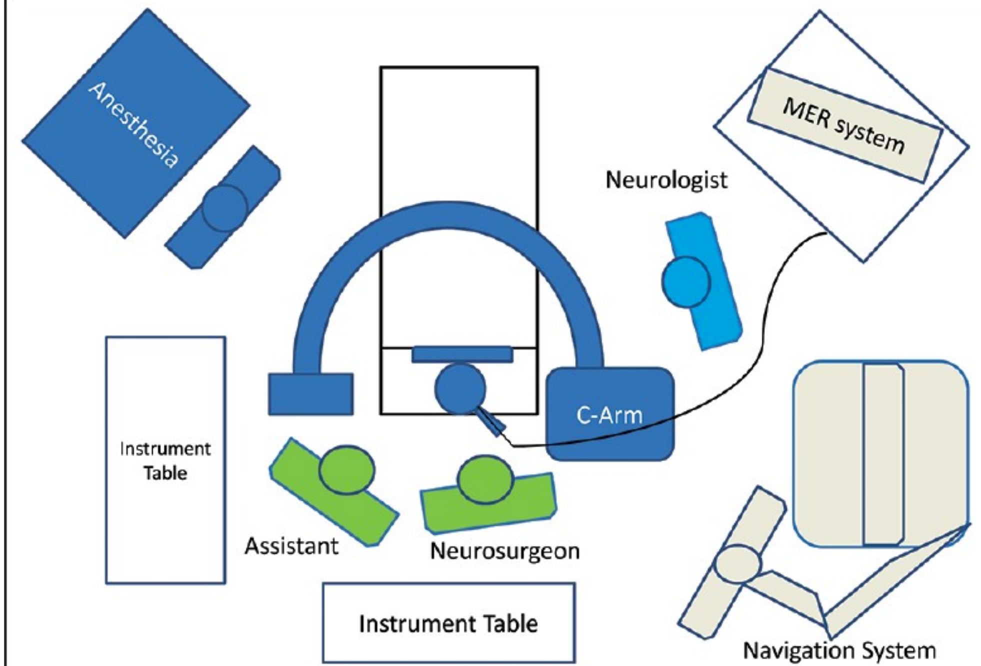
Assistive communication device



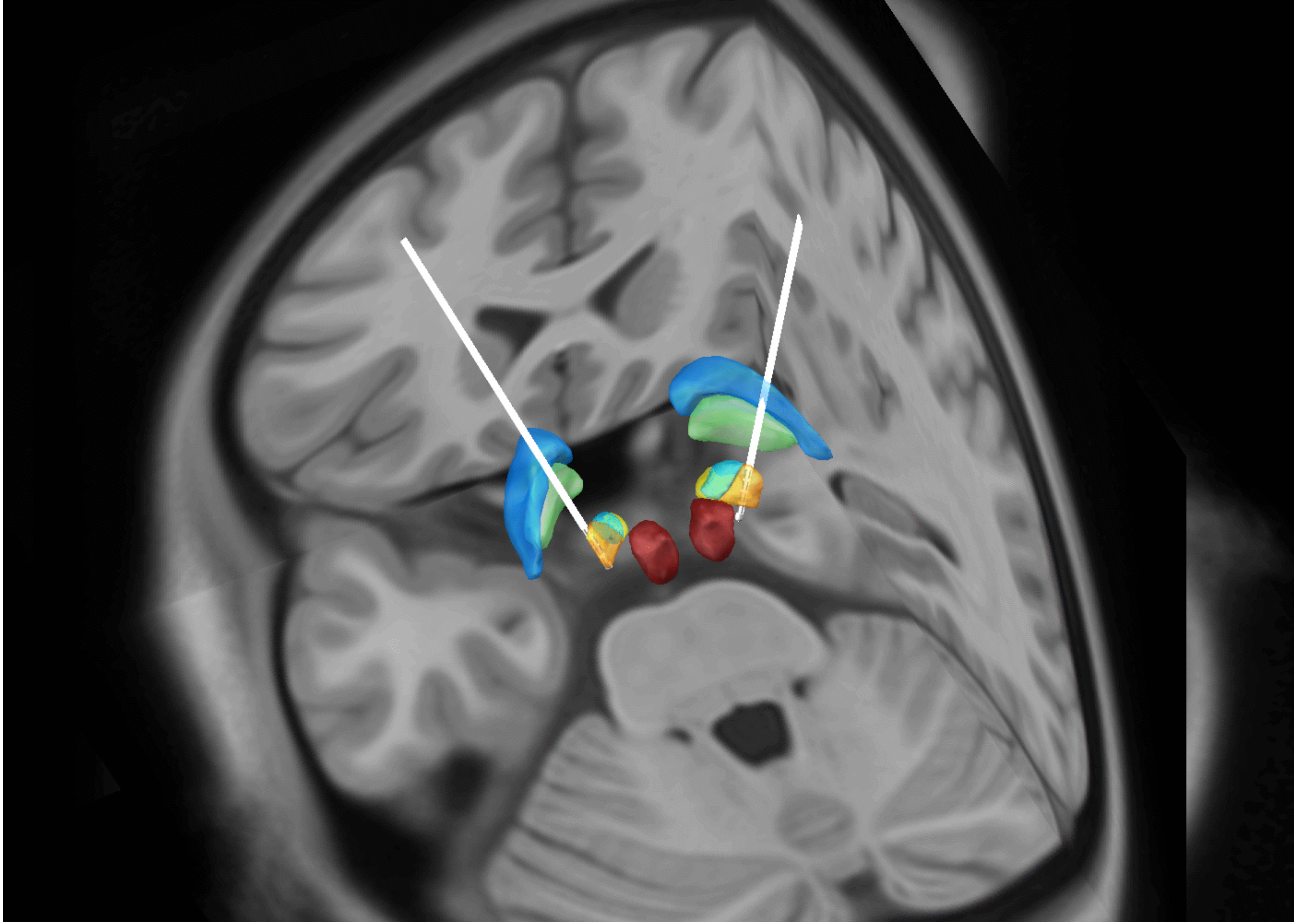
Induce and guide adaptive plasticity

Wolpaw and Wolpaw, 2012

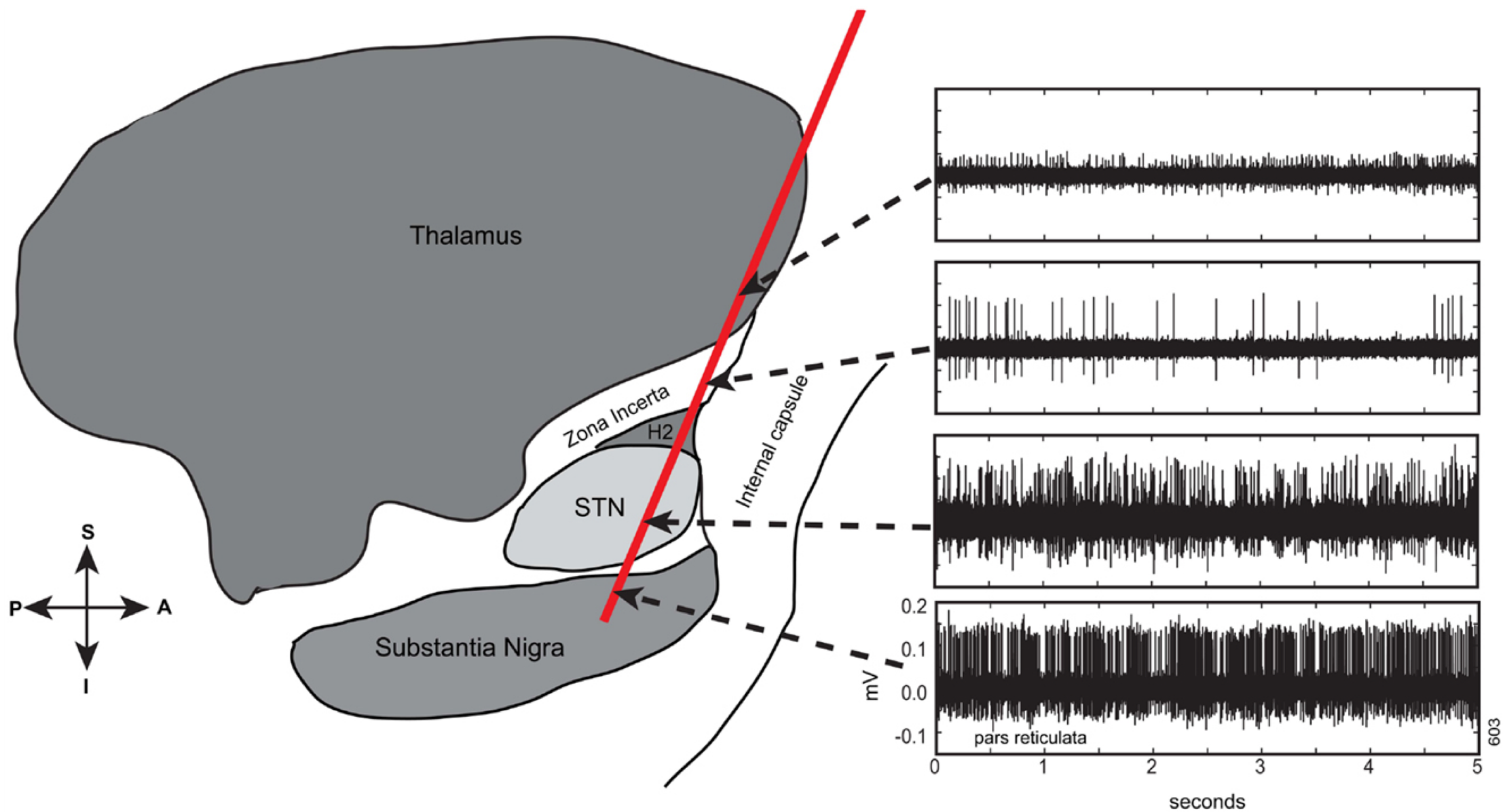
Clinical & Research Setting 1



Lin et al., Journal of Medical Sciences, 2014



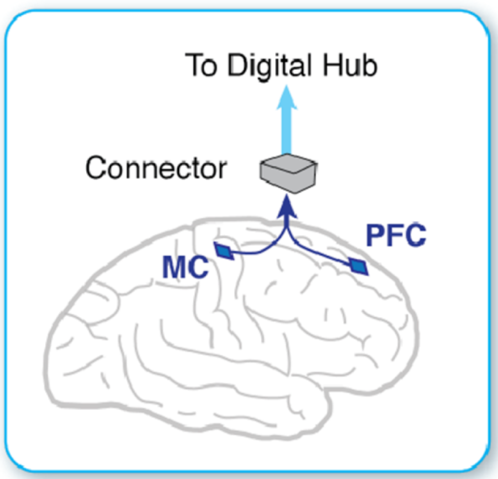
Microelectrode Mapping

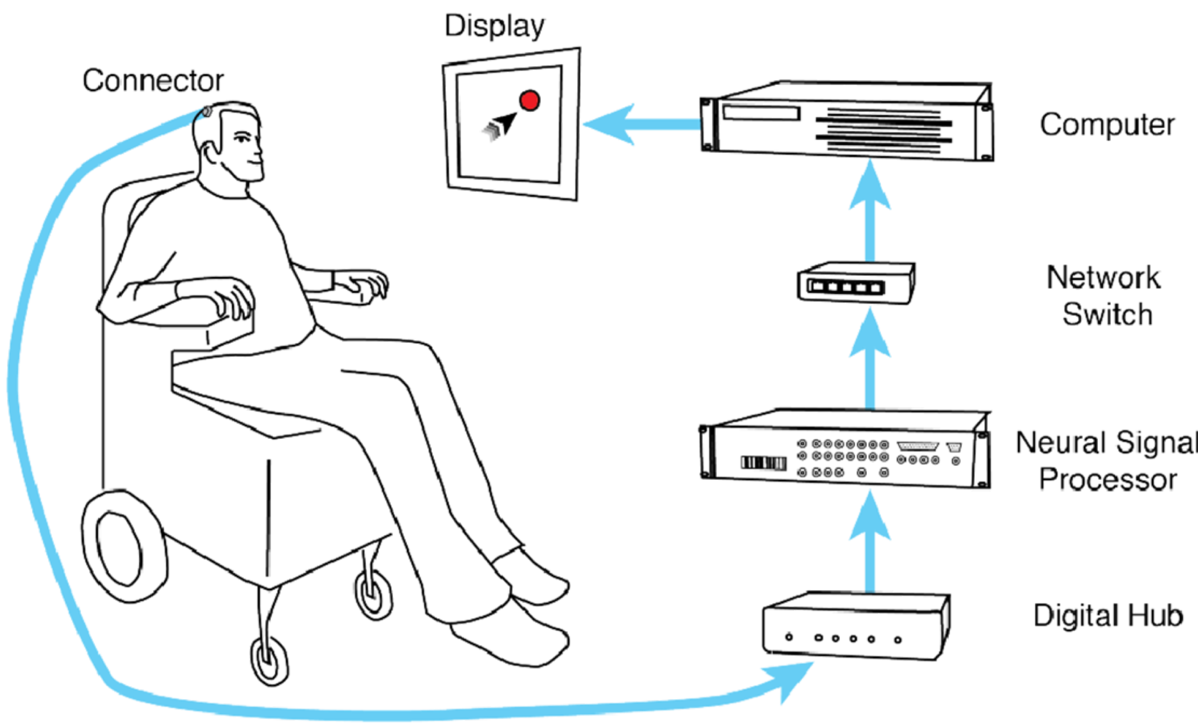


Camalier et al., Front. Neurol. 2014

Clinical & Research Setting 2

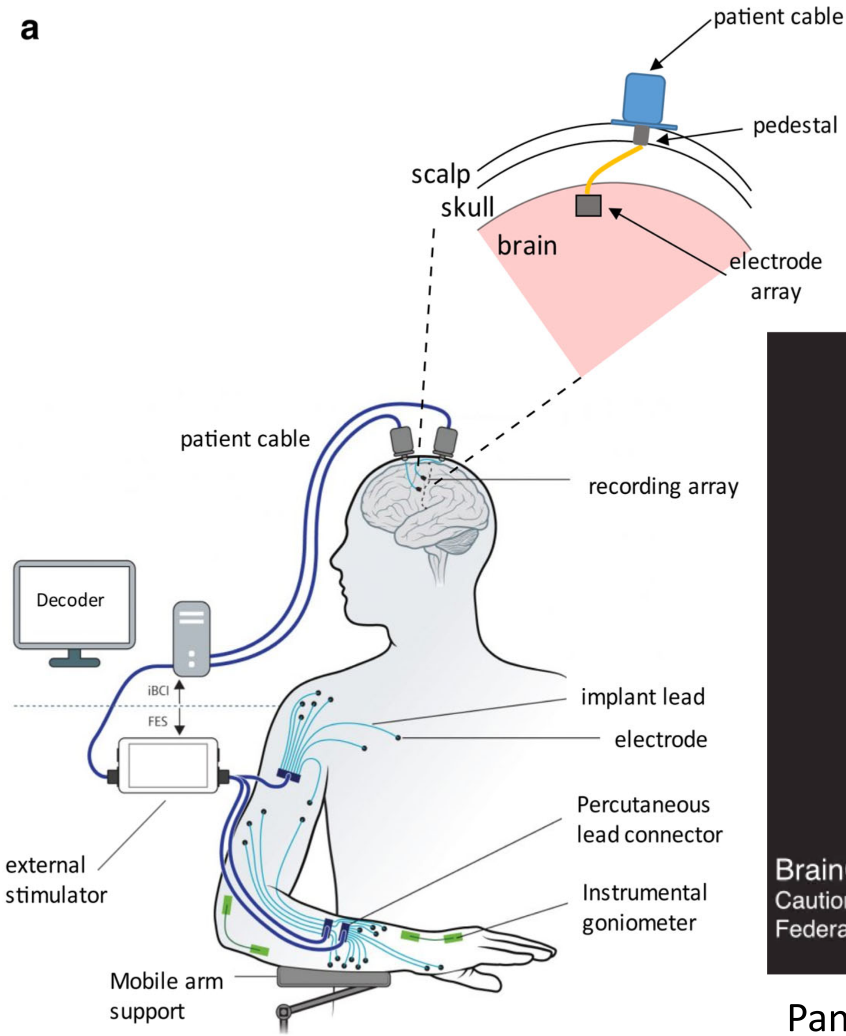
Neuro Cognitive Communicator (NCC-1701)





ClinicalTrials.gov: NCT03100110

In active recruitment!

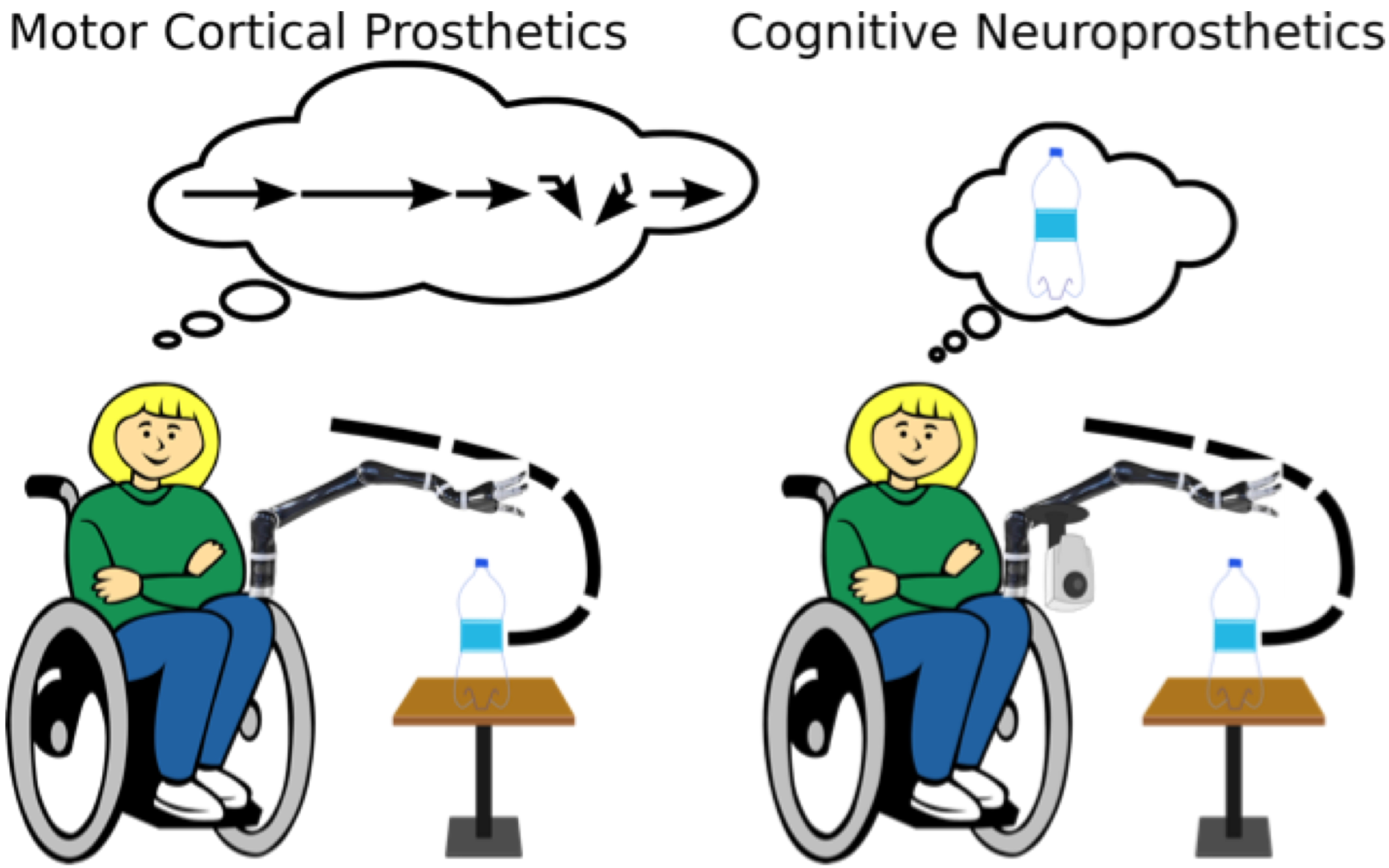


Bullard et al., Neuromodulation 2019

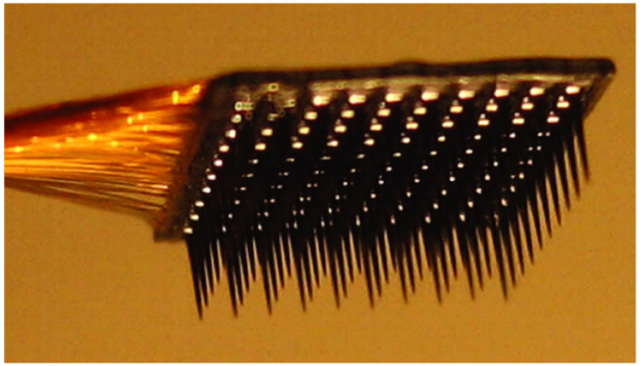
Pandarinath et al., Elife 2017

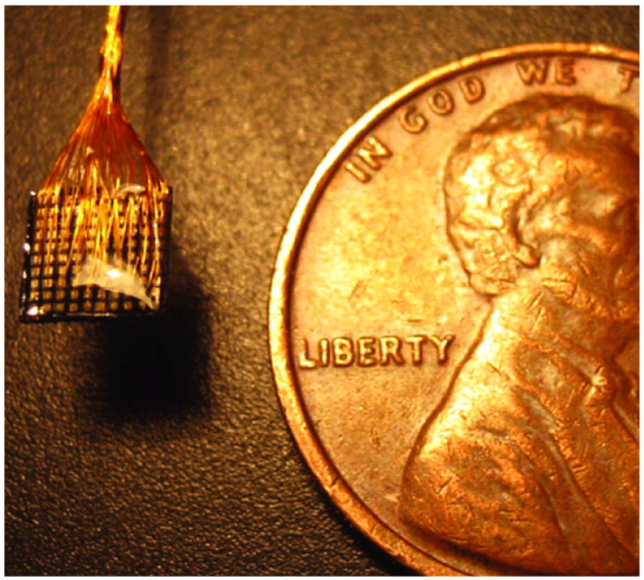
Clinical & Research Setting 2

Neuro Cognitive Communicator (NCC-1701)

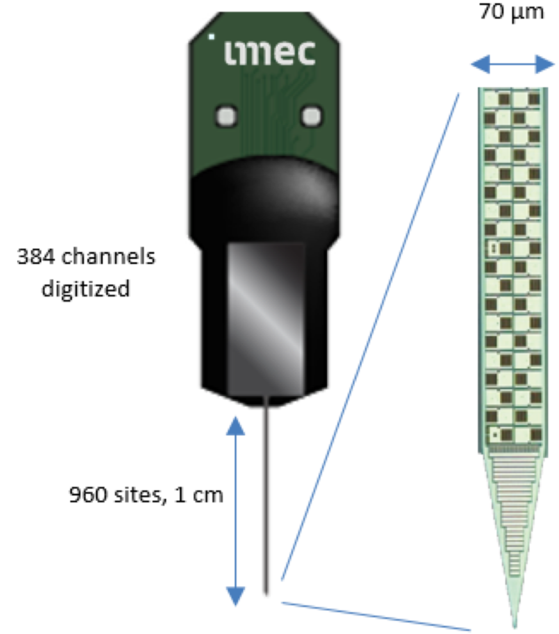


Utah Array

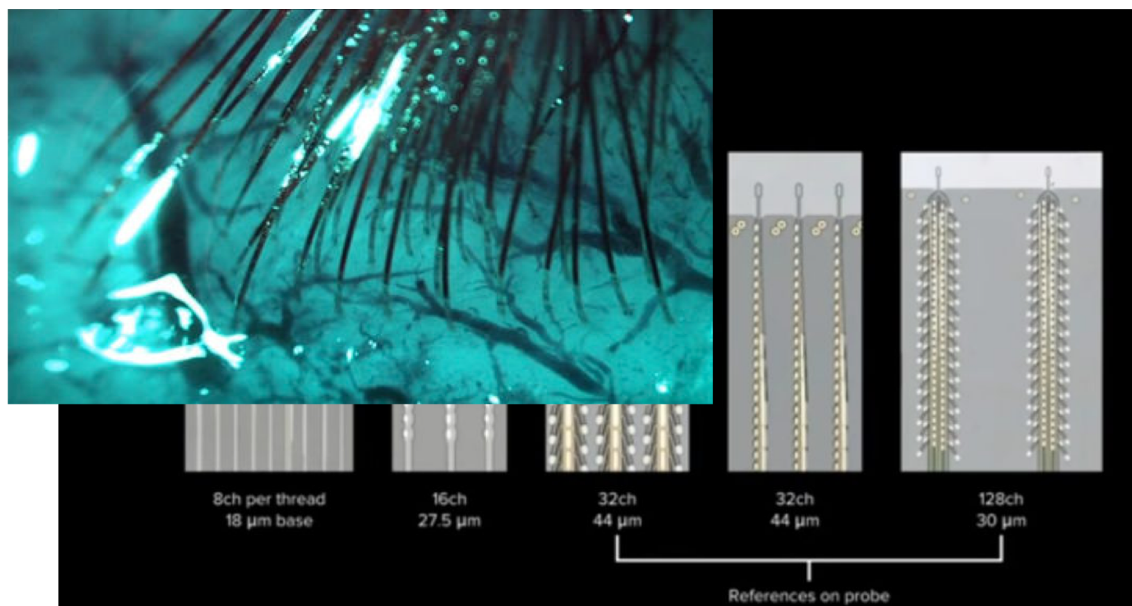




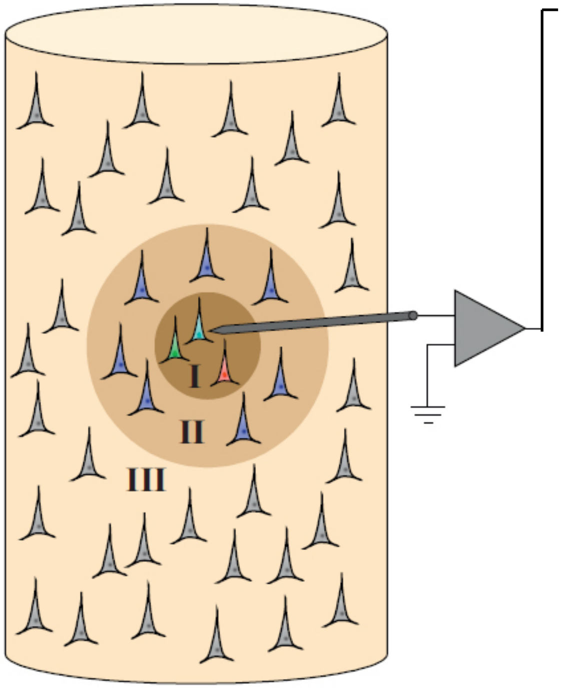
NeuroPixel

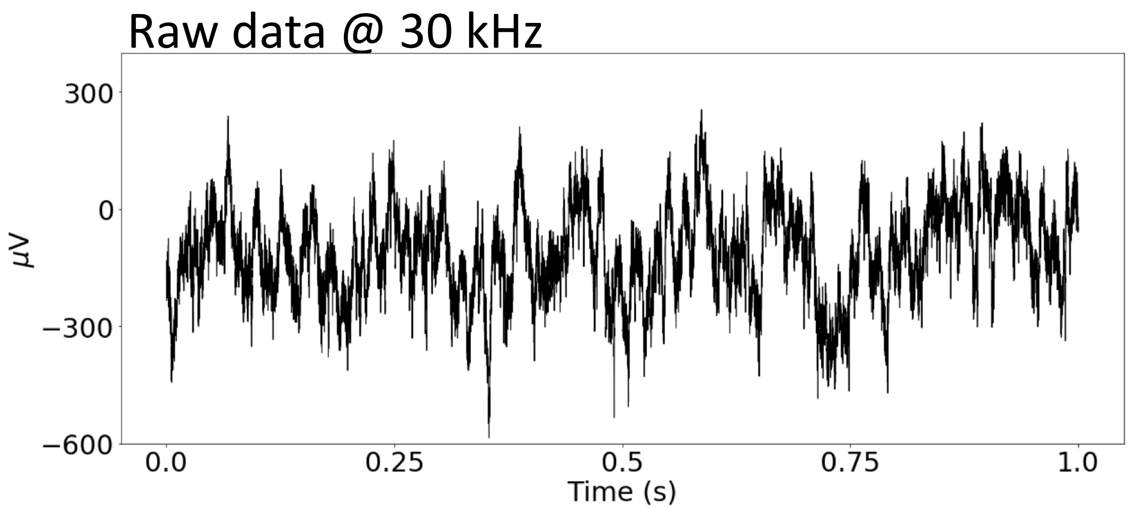


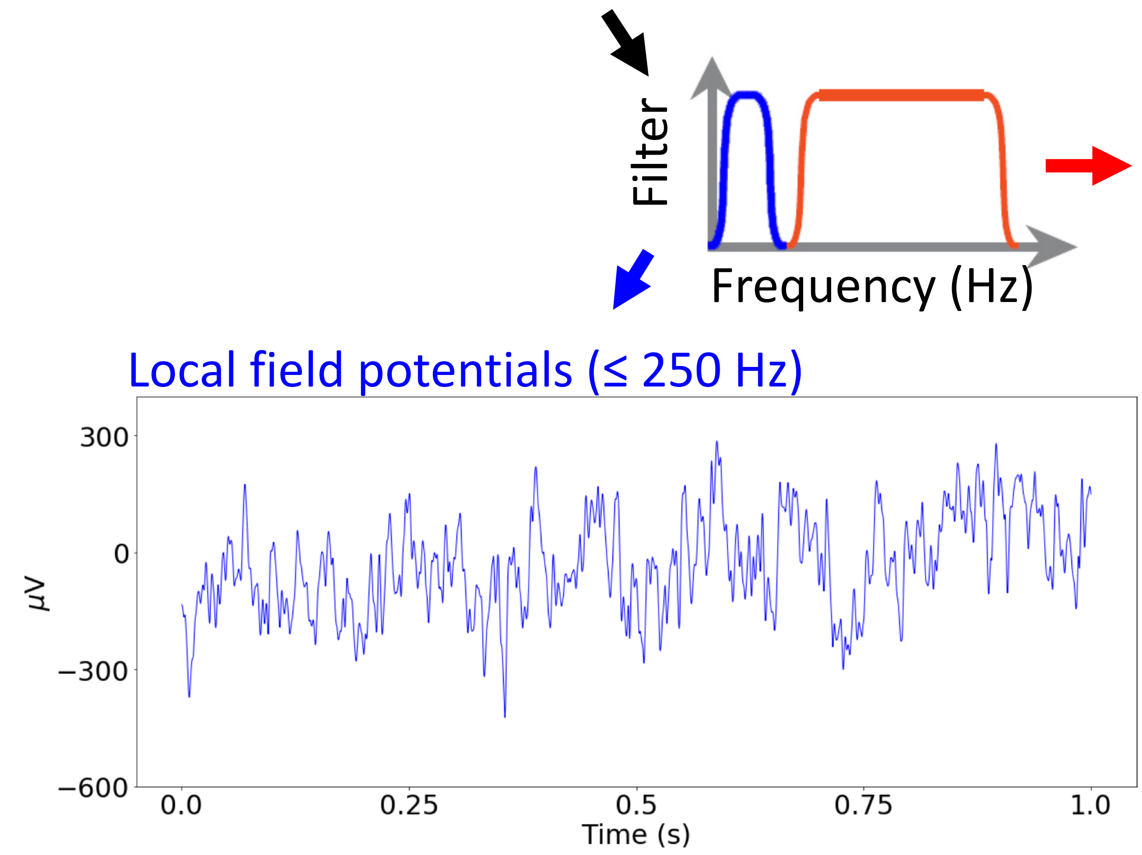
Neuralink



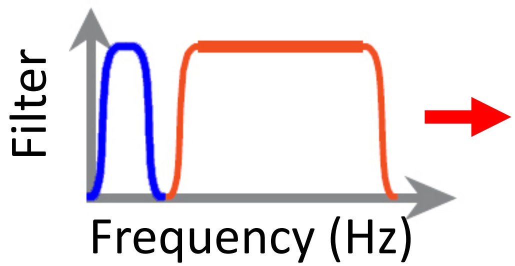
Microelectrode Signal Processing

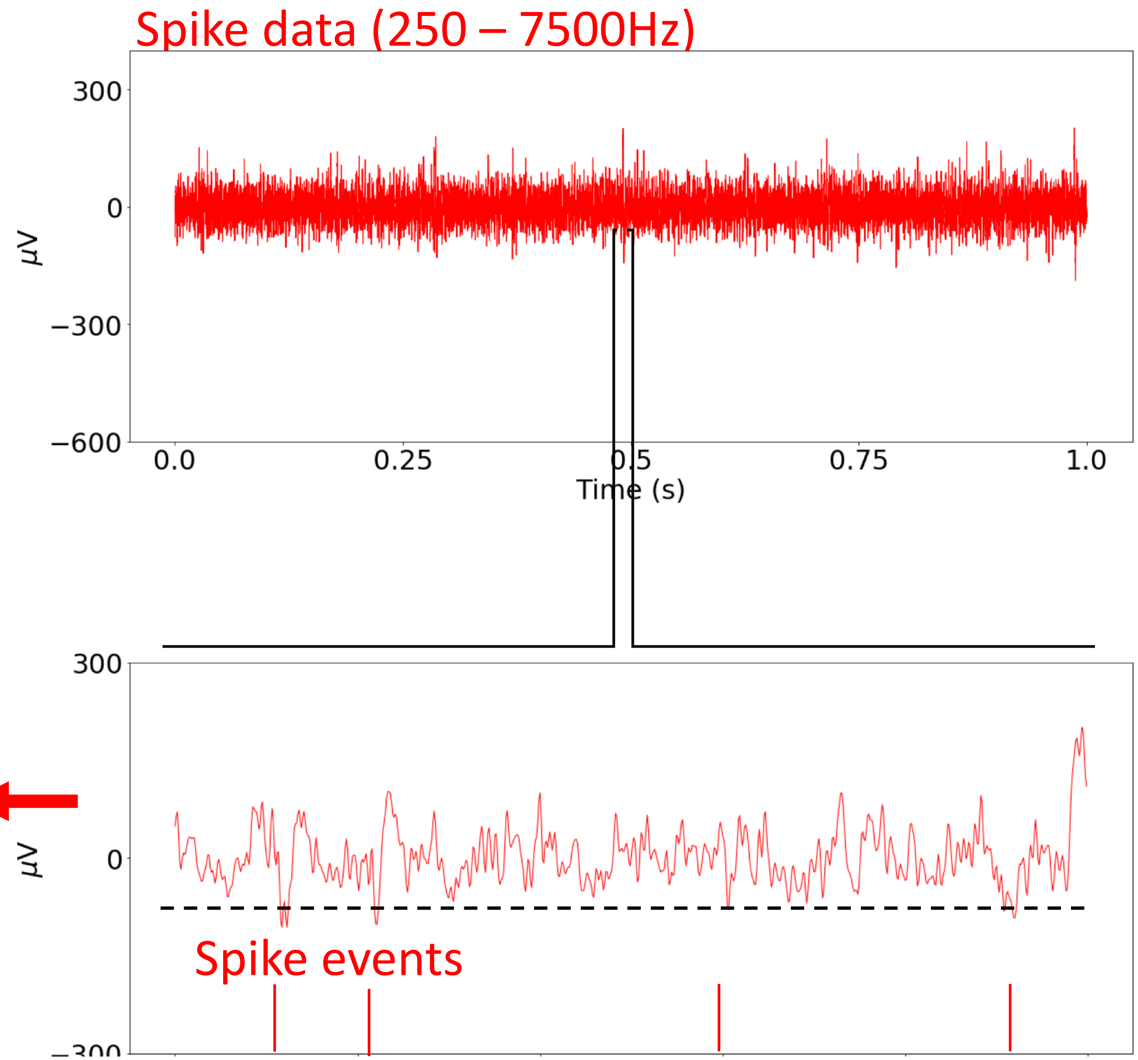


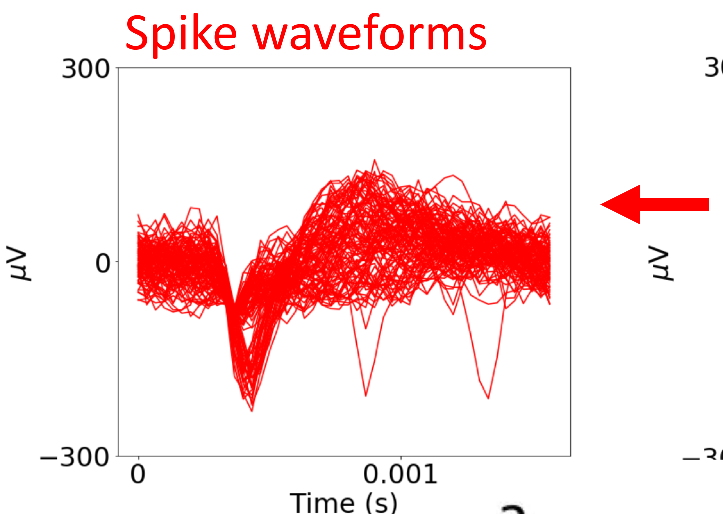


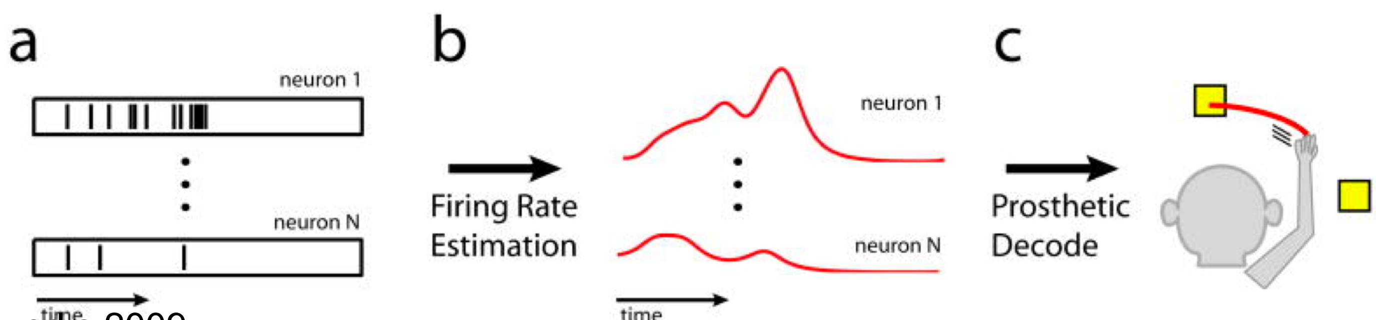


Convolutions!



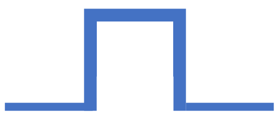
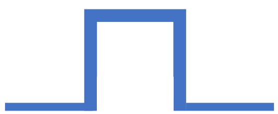
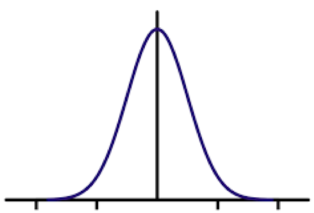




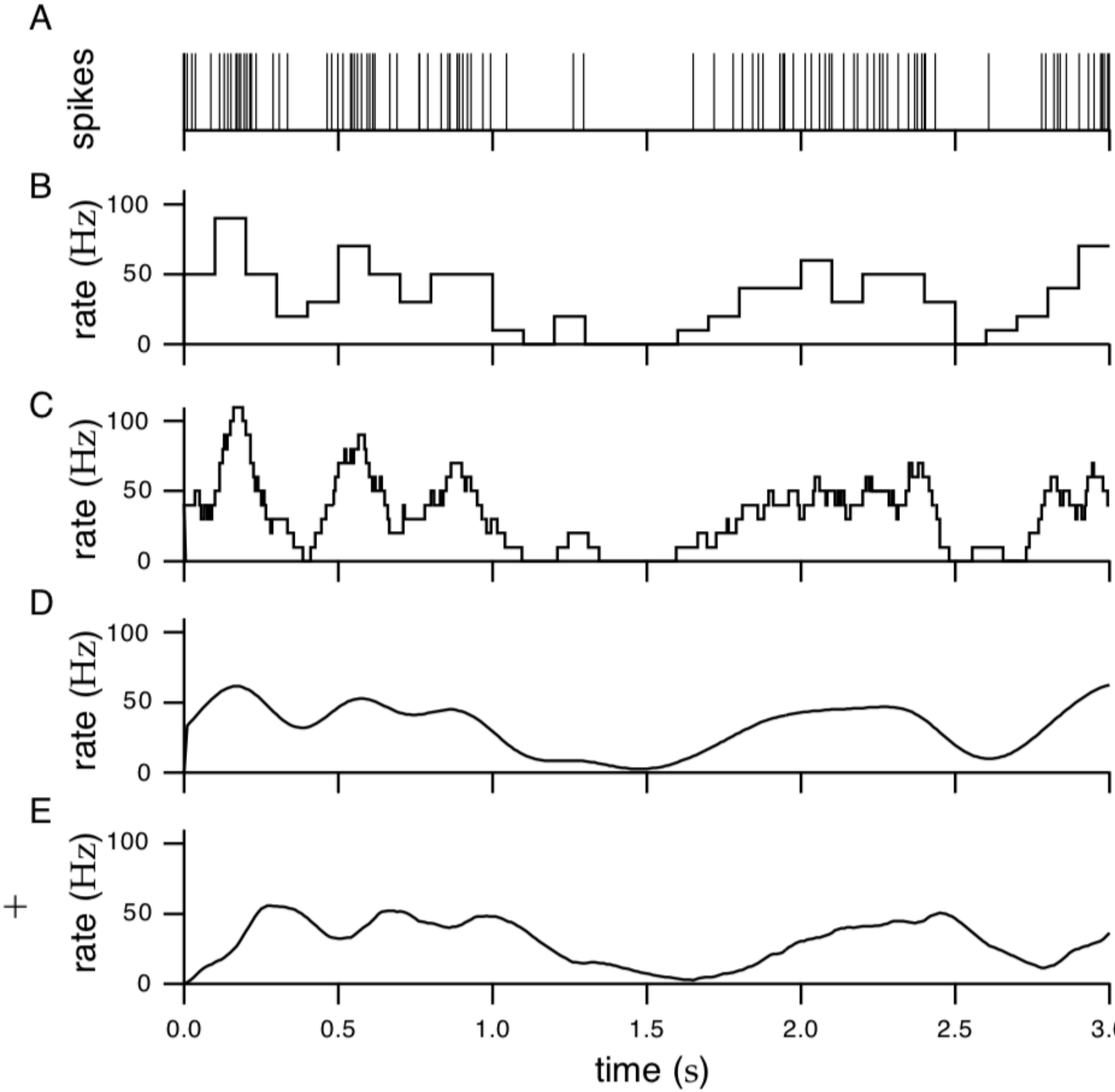


Cunningham et al., Neural Networks 2009

Convolutions!

Kernel	Step Size (Stride)
	100 msec
	1 samp
	1 samp

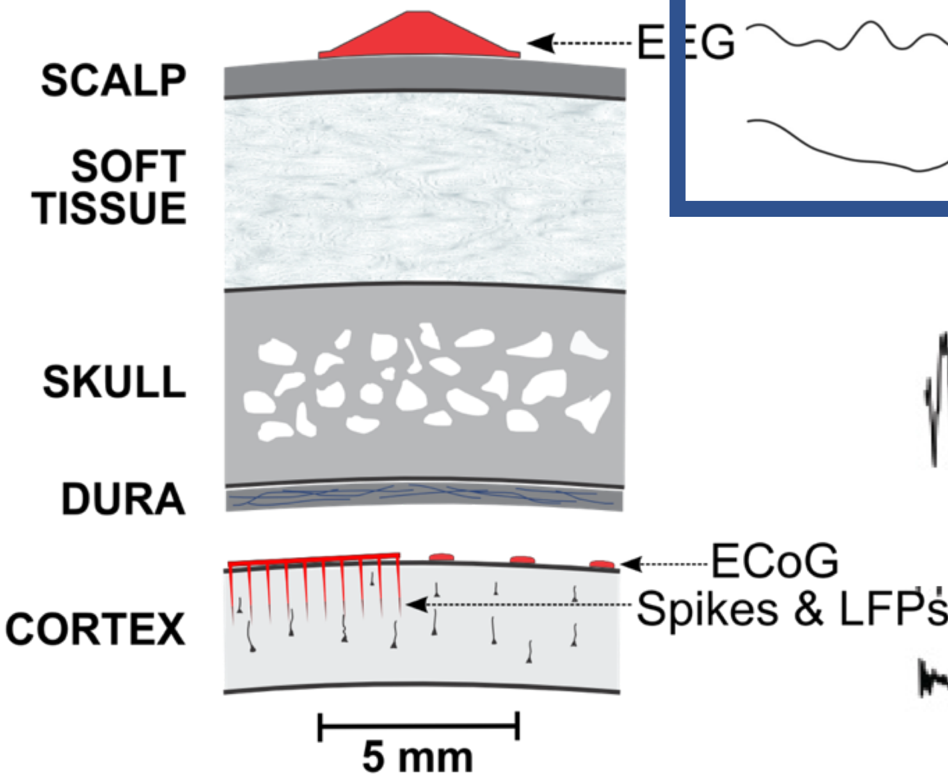
$$w(\tau) = [\alpha^2 \tau \exp(-\alpha \tau)]_+$$

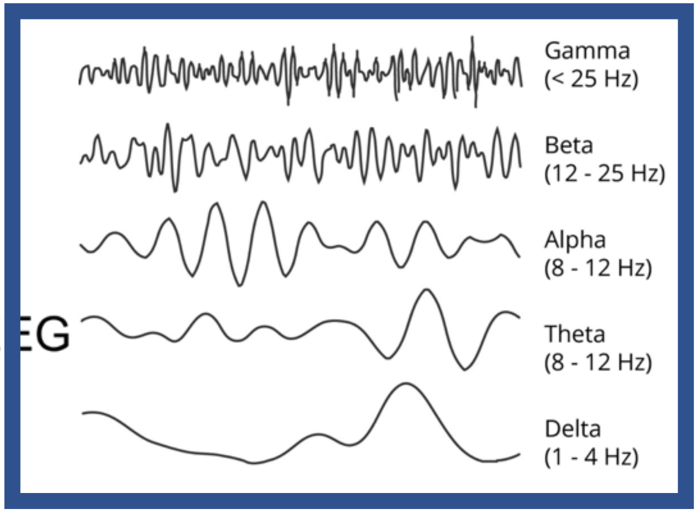


Dayan and Abbott, Theoretical Neuroscience

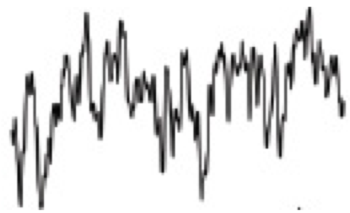
Filter Bank

Convolutions!



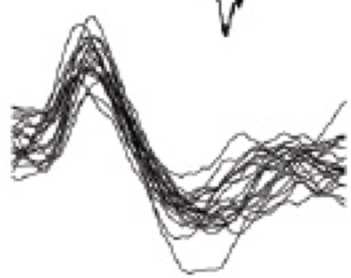


- EEG
  - 1 – 300 µV
  - 10^6 neurons
  - Synchronized synaptic activity
  - < 50 Hz



- ECoG
  - 1 – 5000 µV
  - 10^2 – 10^4 neurons
  - < 250 Hz

- LFP
  - 1 – 1000 µV
  - 10^2 synapses
  - < 250 Hz

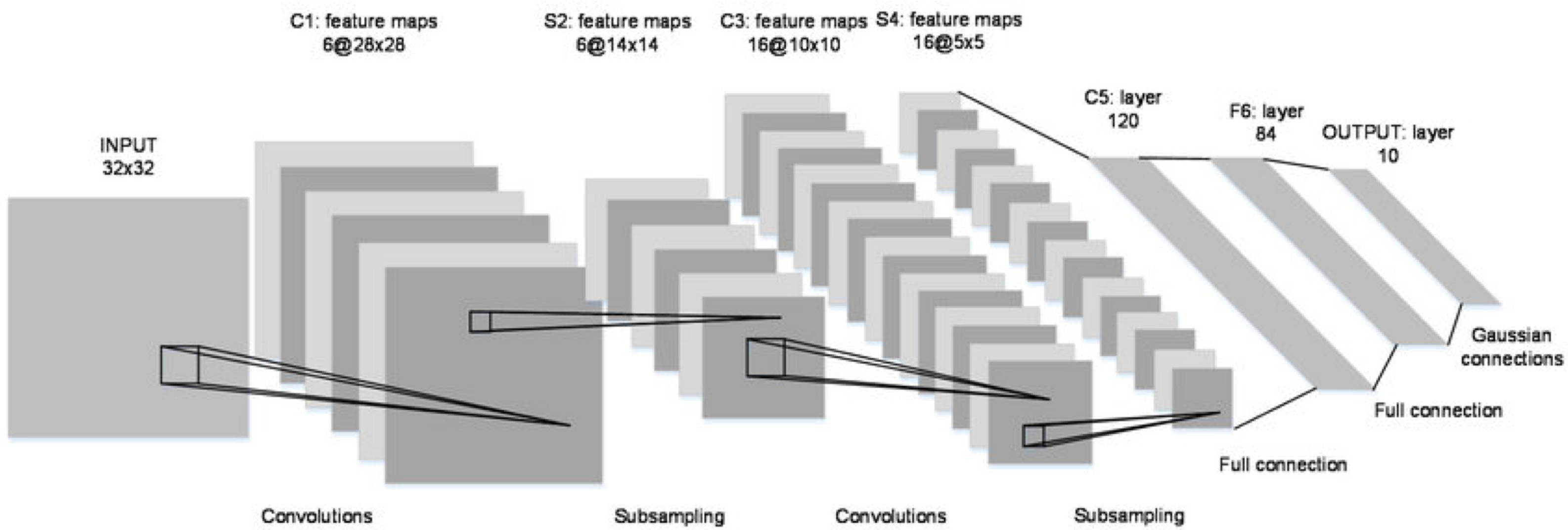


- Spikes
  - 200 – 500 µV
  - 1-4 neurons
  - 0.1 – 7 kHz

Convolutions in Deep Learning

ConvNets, CNNs

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

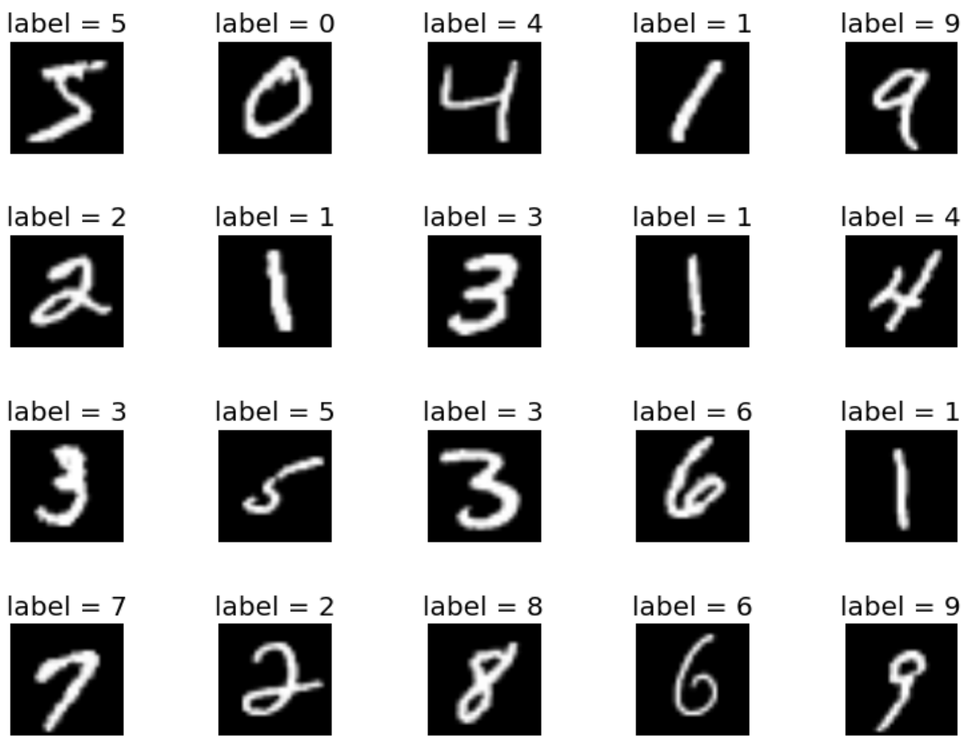


"LeNet" – Yann LeCun

[1-NIPS 1990]

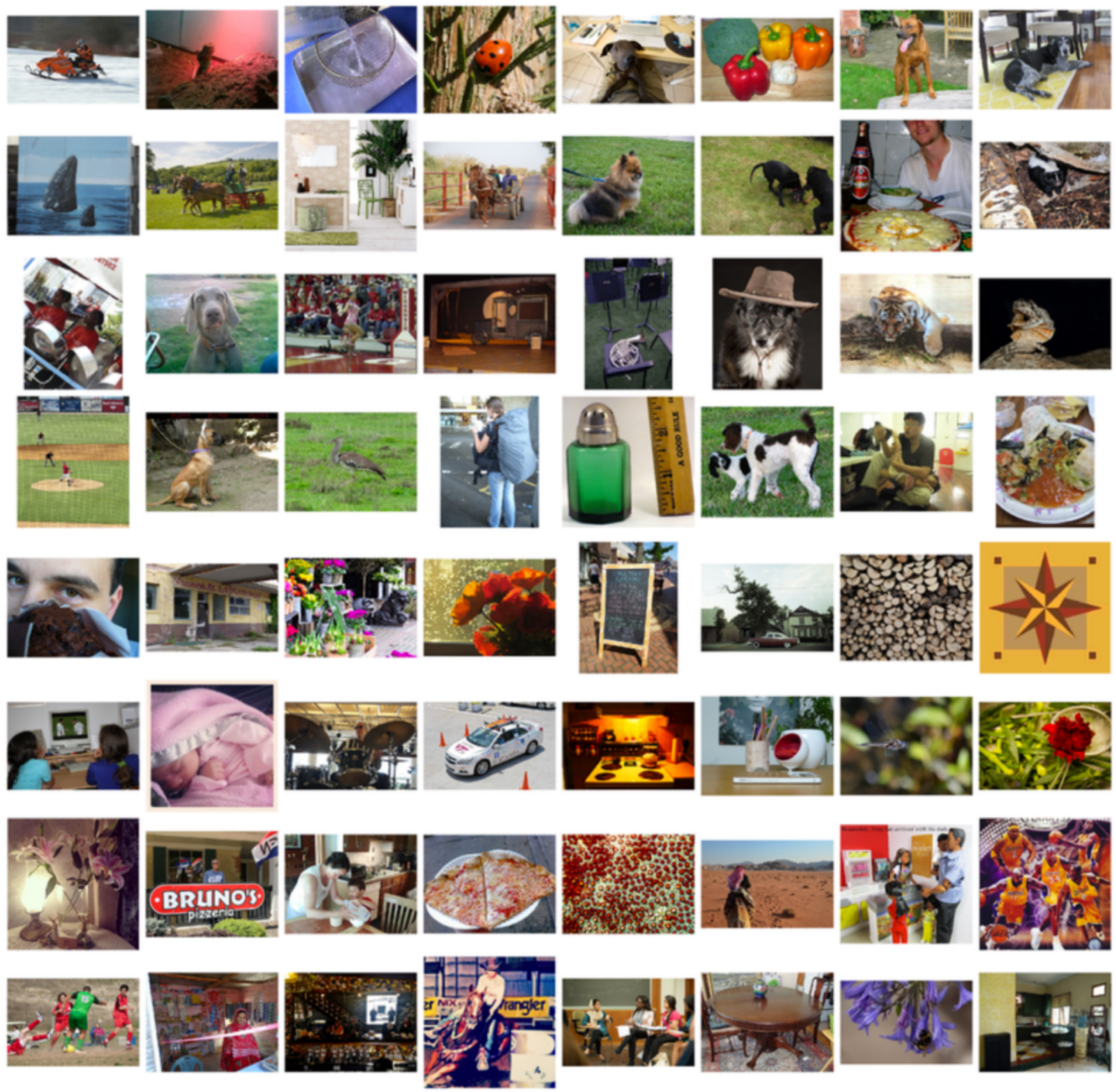
MNIST = “Hello World”

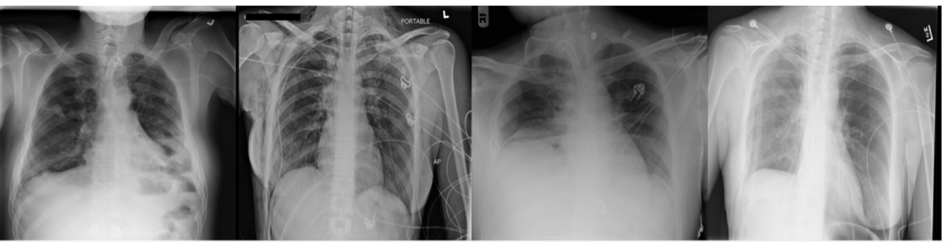
- And due to the availability of great image datasets.



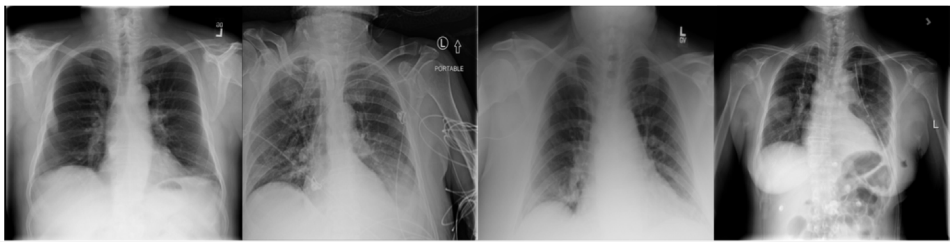
ImageNet 14M labeled images

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

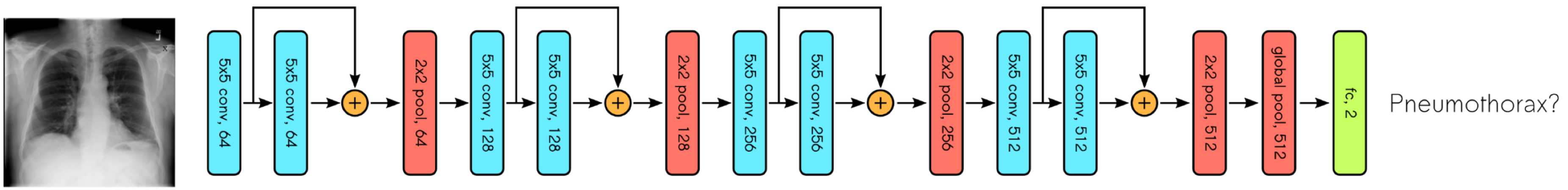


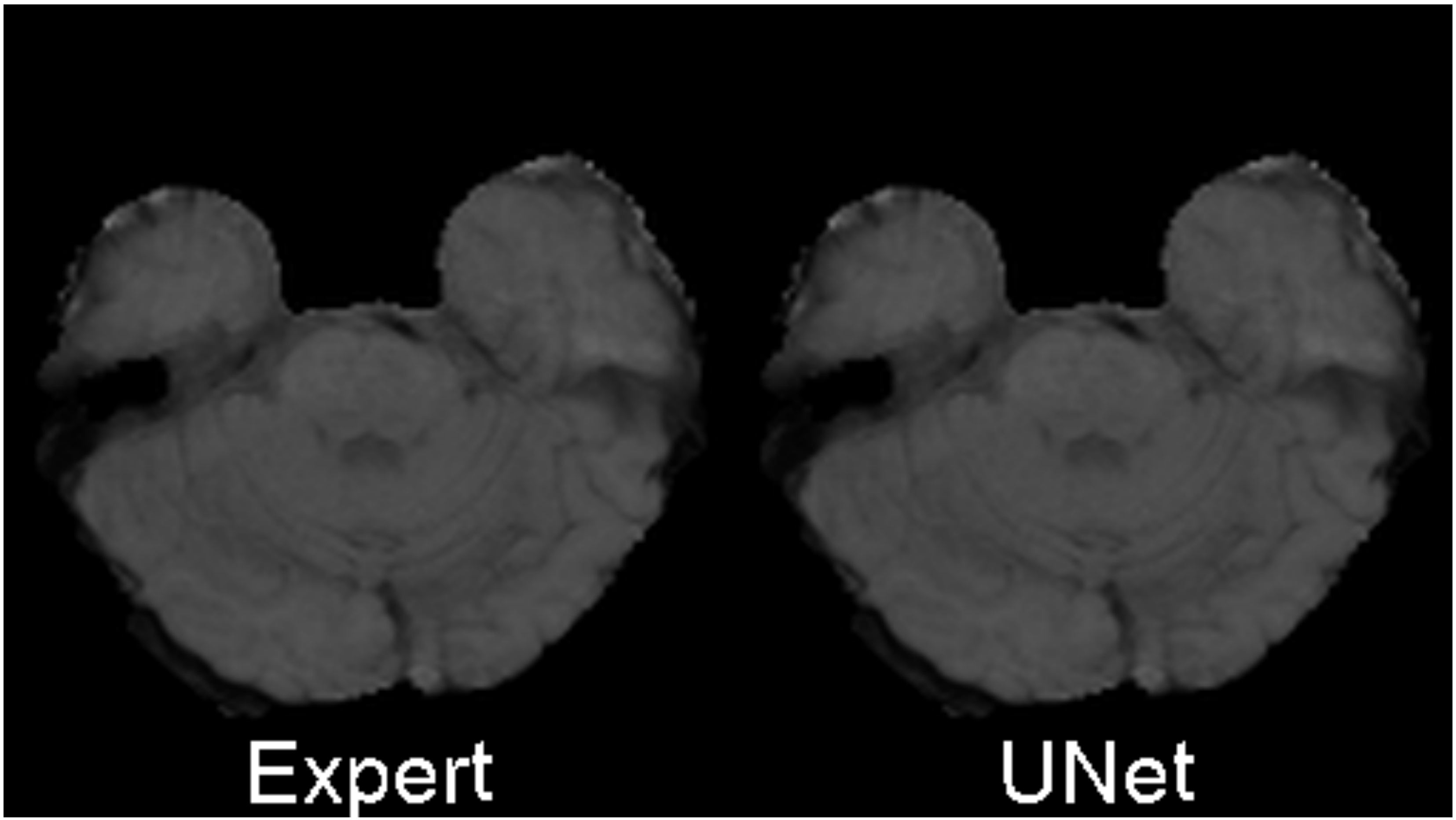


Dataset images without pneumothorax

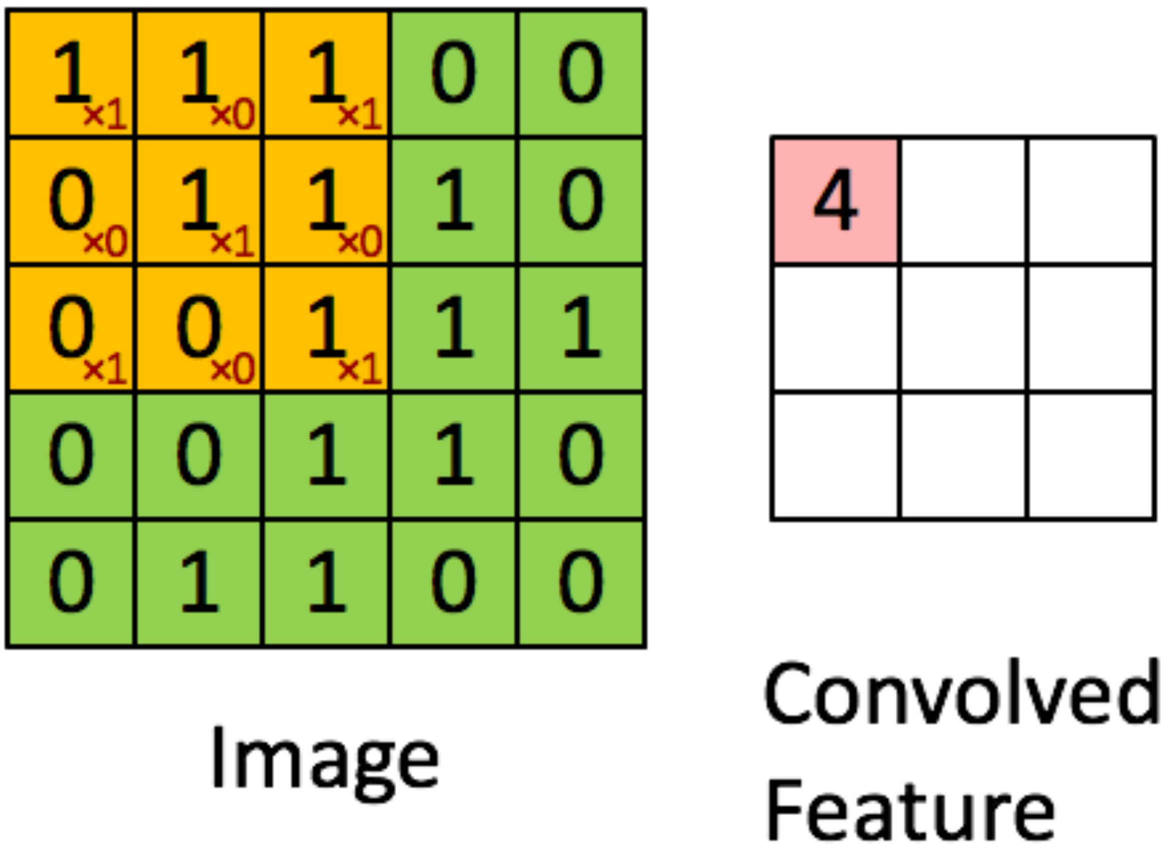


Dataset images with pneumothorax

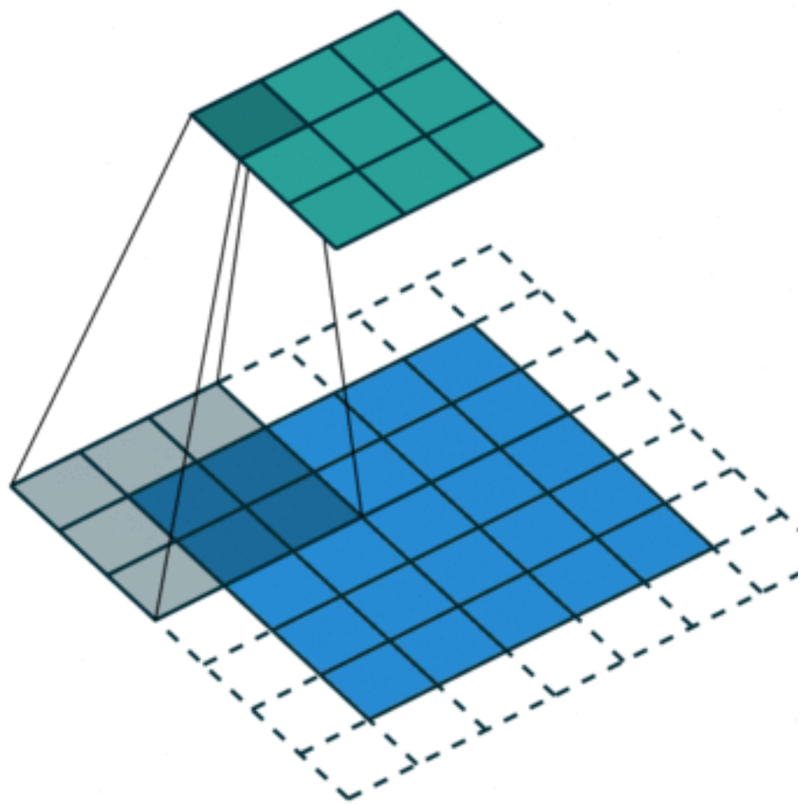



Expert
UNet

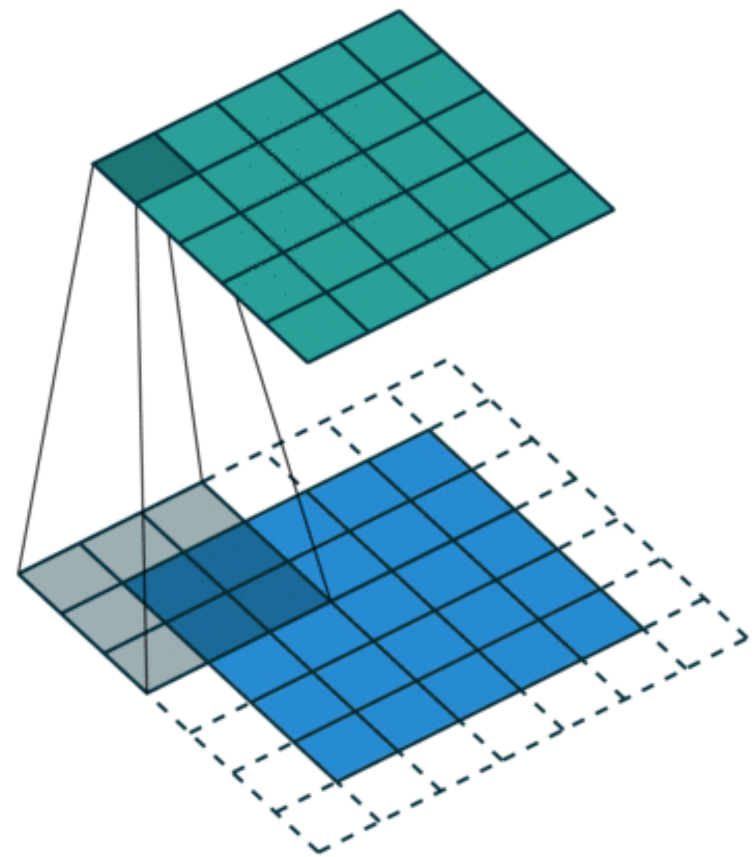
Convolution Operation



[Comprehensive Guide to CNN – ELI5]()

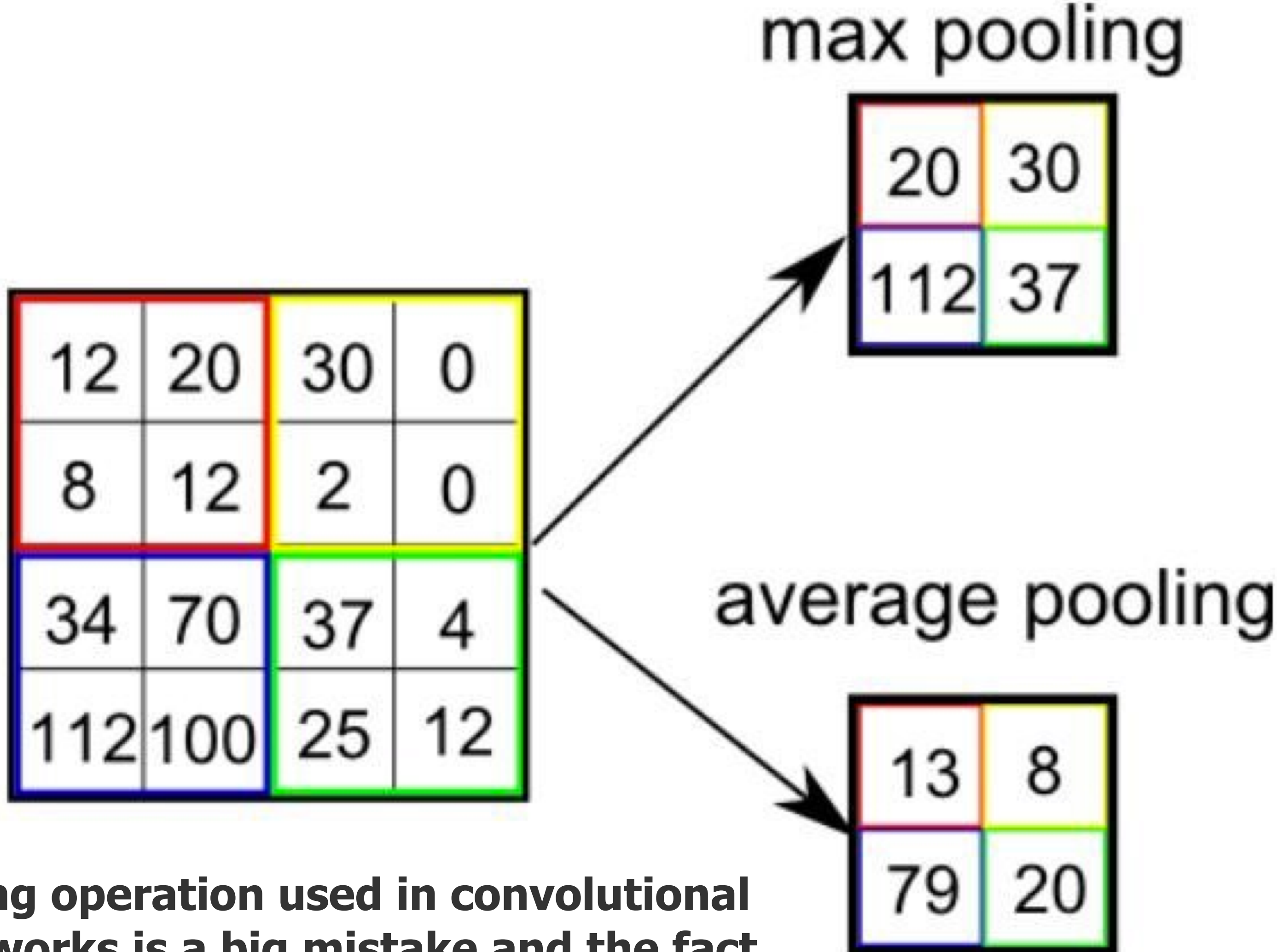


Strides = 2



Strides=1, Padding=1

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



“The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster.”
-Geoff Hinton

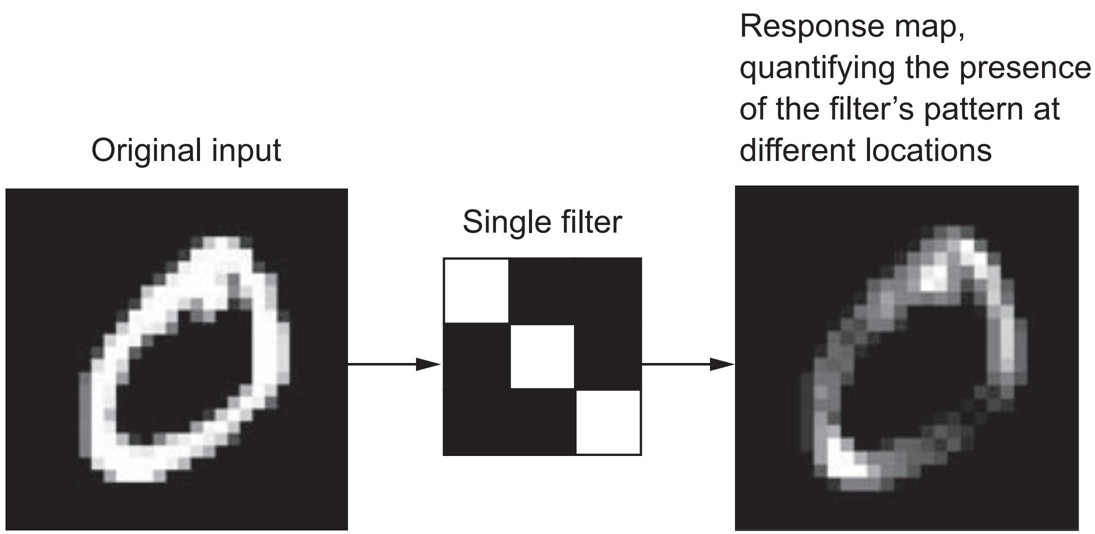


Figure 5.3 The concept of a *response map*: a 2D map of the presence of a pattern at different locations in an input

Deep Learning with Python by Chollet

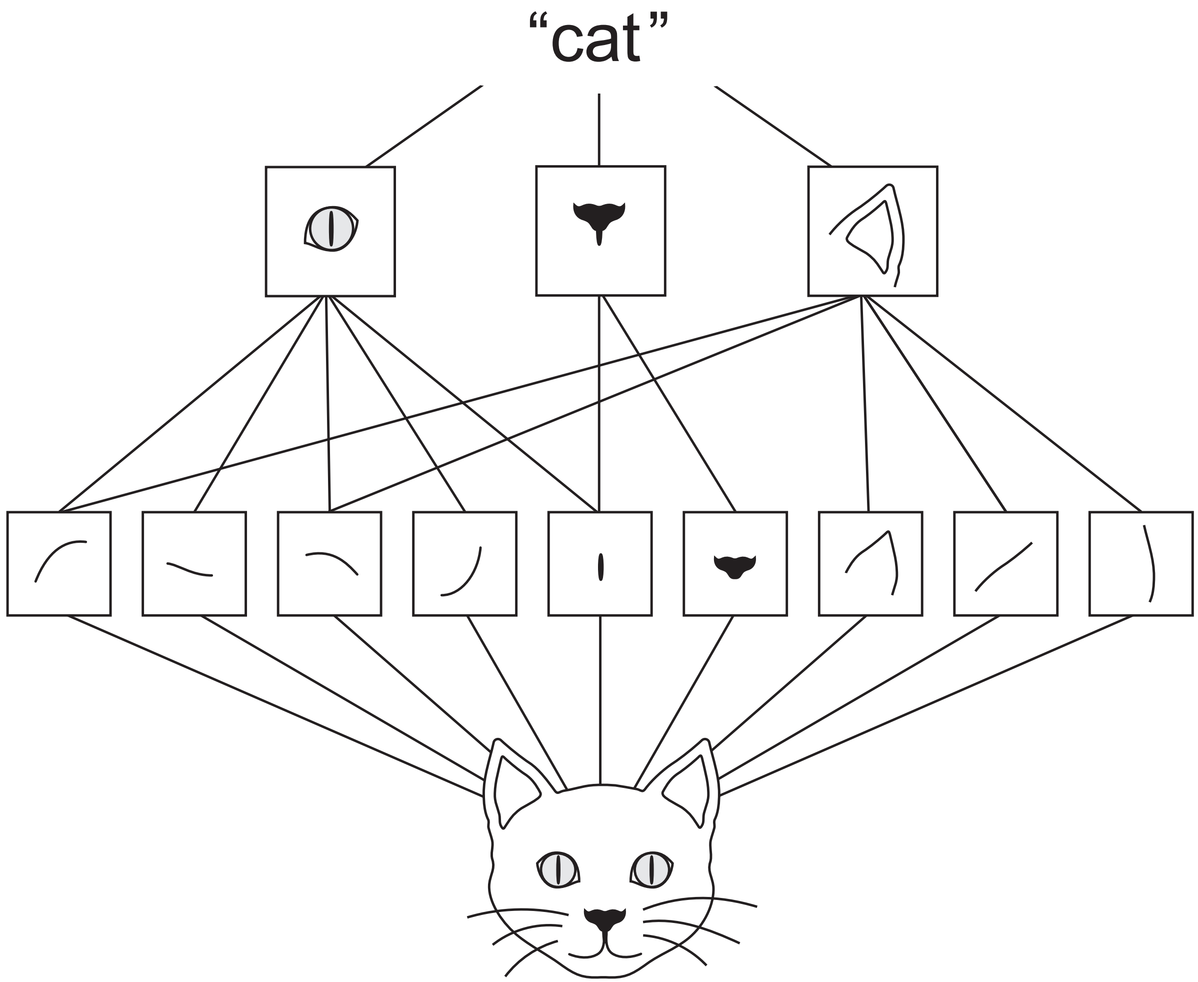


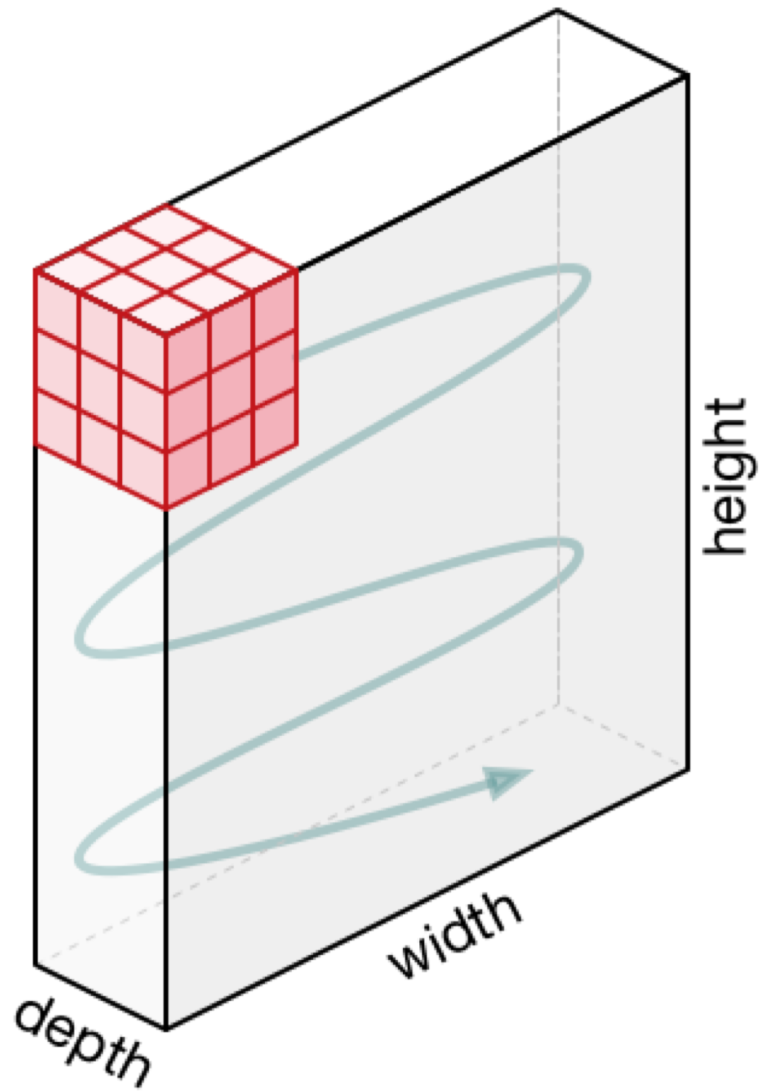
Figure 5.2 The visual world forms a spatial hierarchy of visual modules: hyperlocal edges combine into local objects such as eyes or ears, which combine into high-level concepts such as "cat."

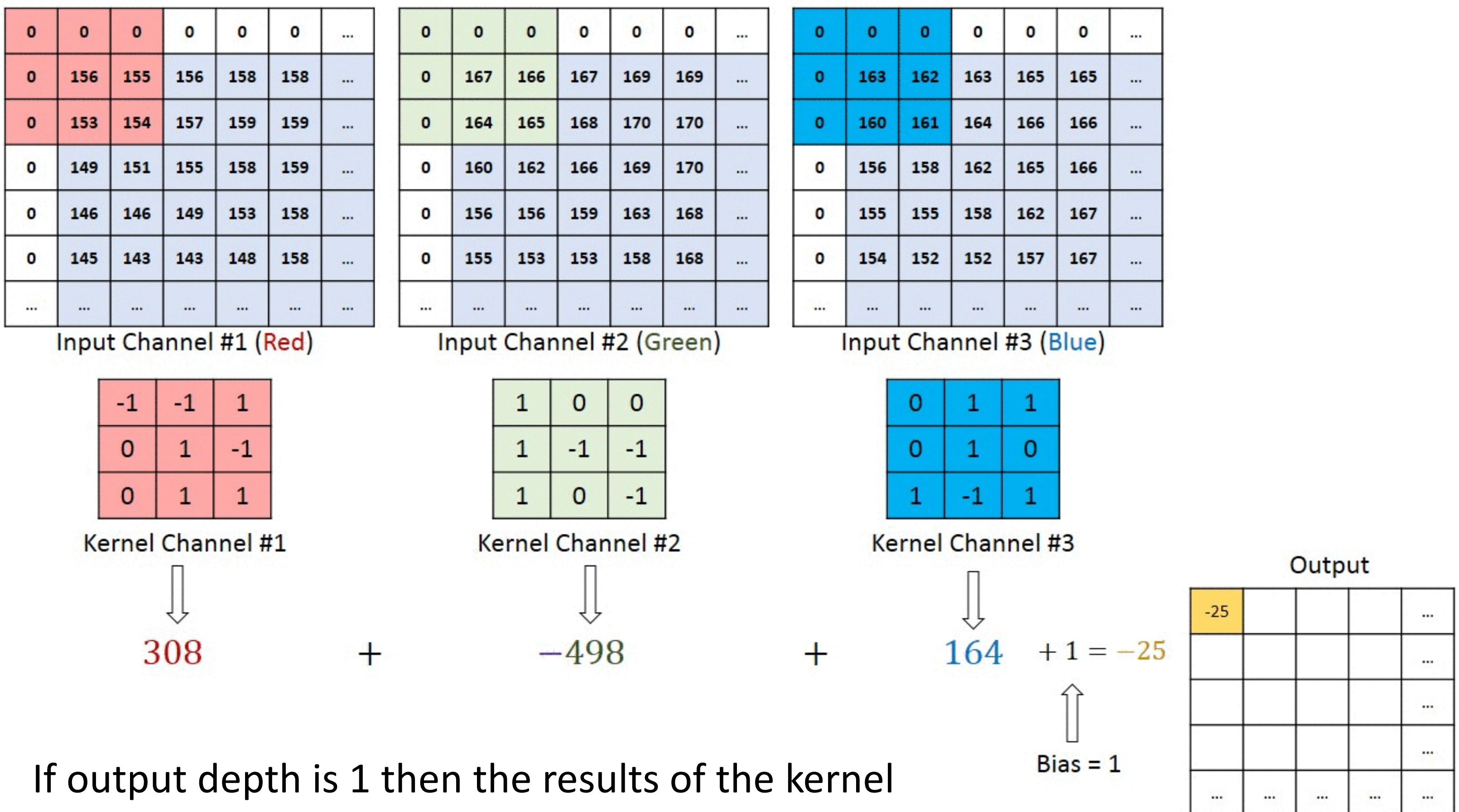
Deep Learning with Python by Chollet

Kernel has depth

In images, depth is number of channels (RGB)

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





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 3x3x2

Kernel is 3x3x2, x3

Output is 1x1x3

Note the change in depth

2 input channels → 3 kernels

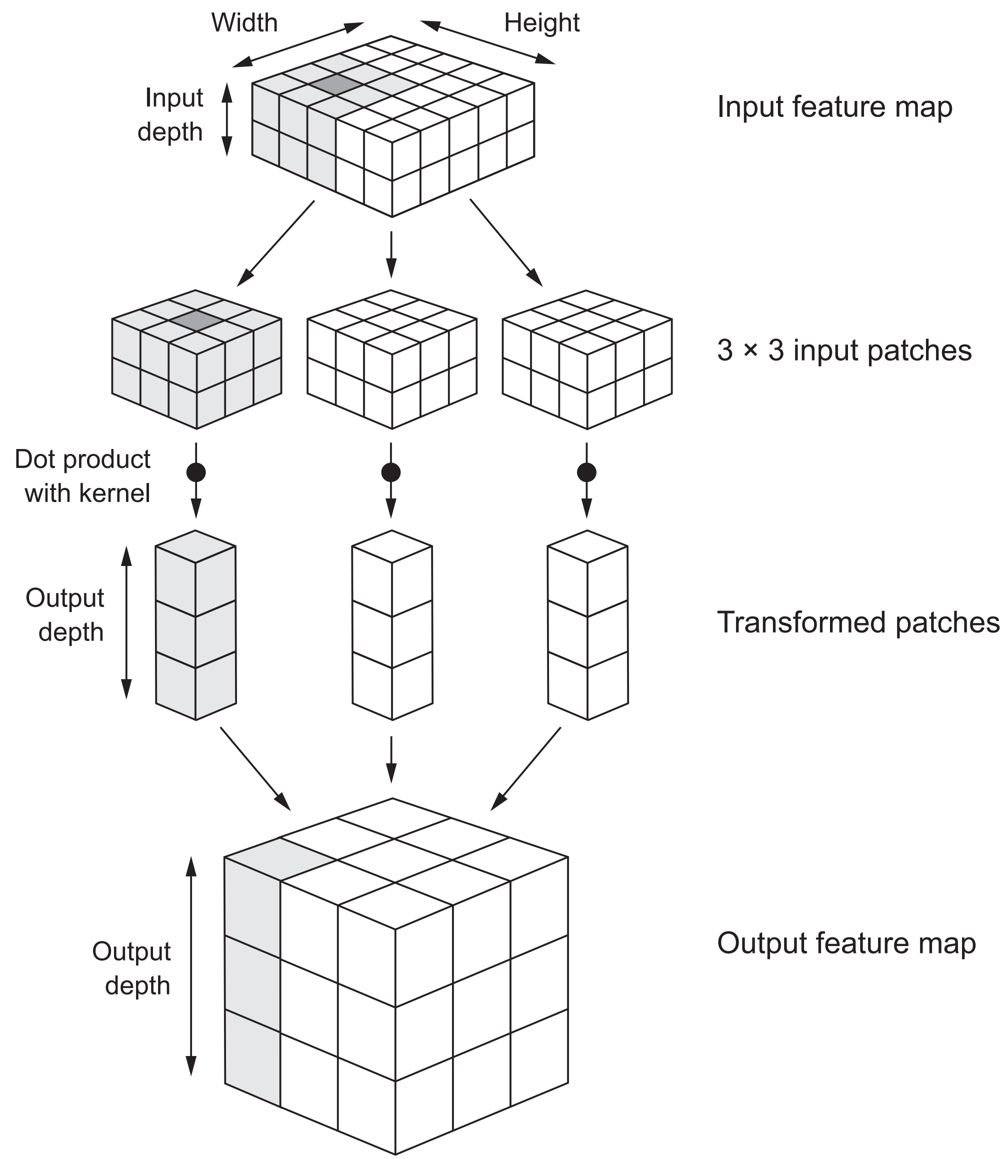


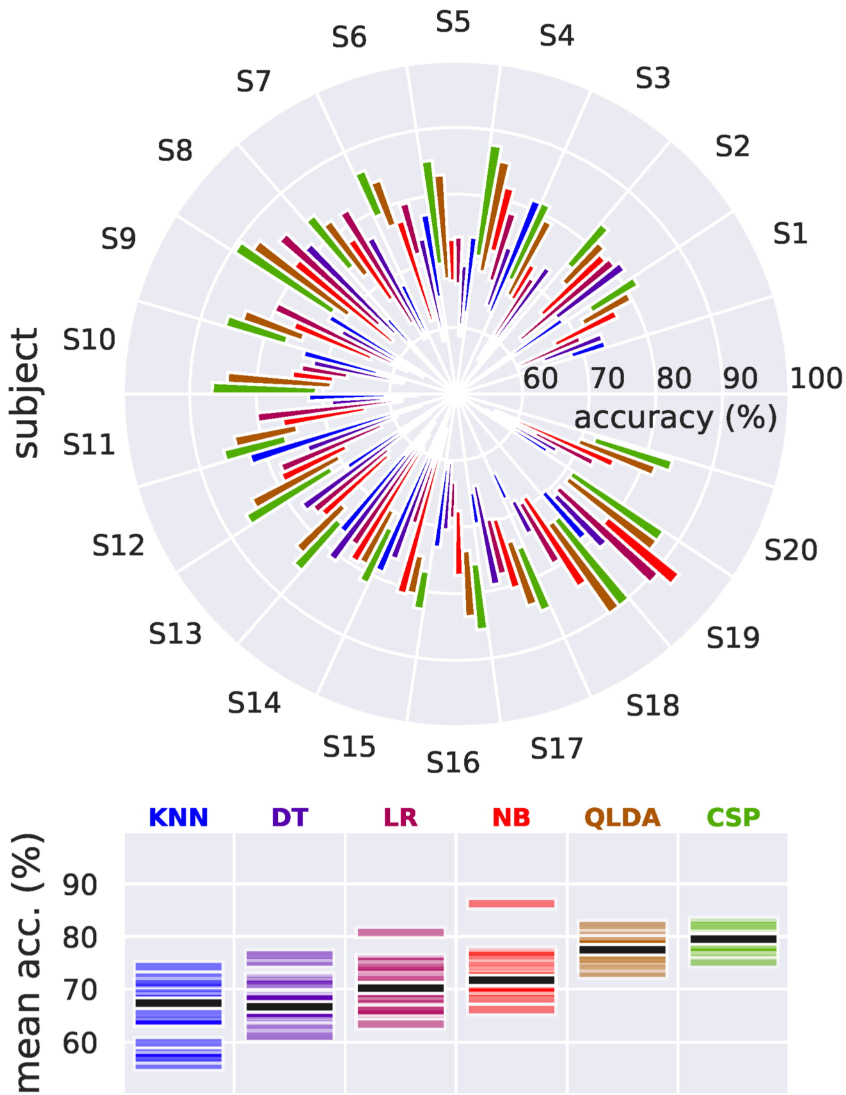
Figure 5.4 How convolution works

Deep Learning with Python by Chollet

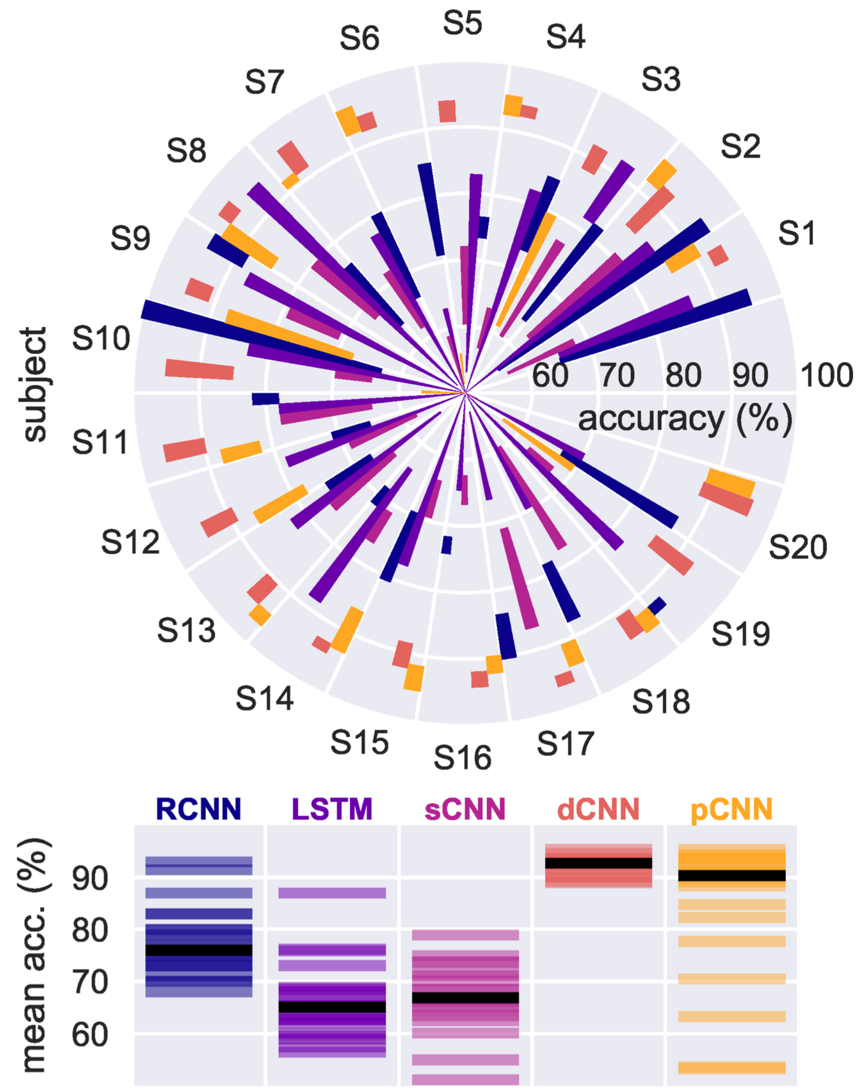
Convolutions in 1D on timeseries

- Proceed to notebook

03_01_Intro_to_CNNs.ipynb



(**a**) classical

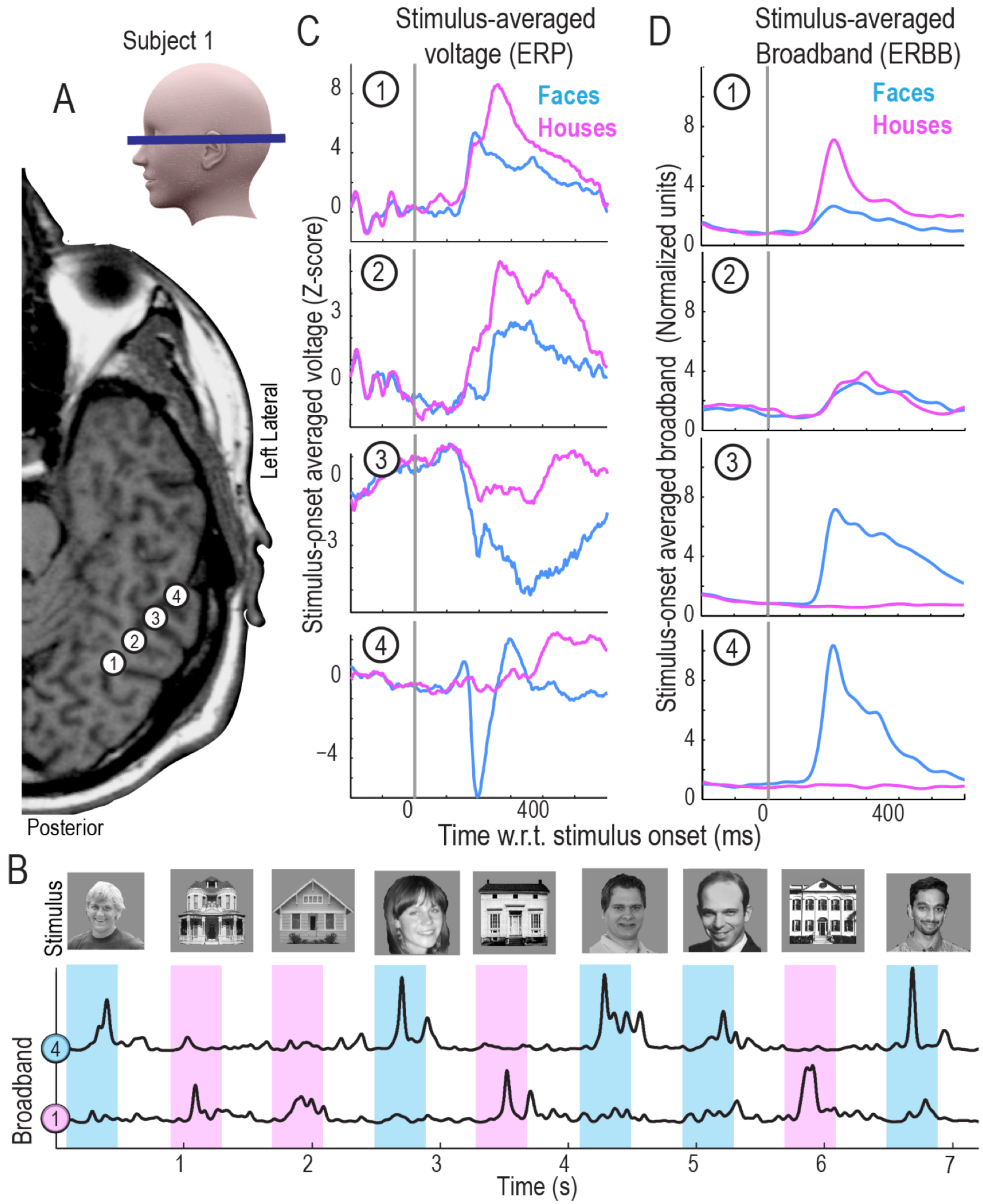


(**b**) neural

Tayeb et al., Sensors 2019

ECoG Data Library

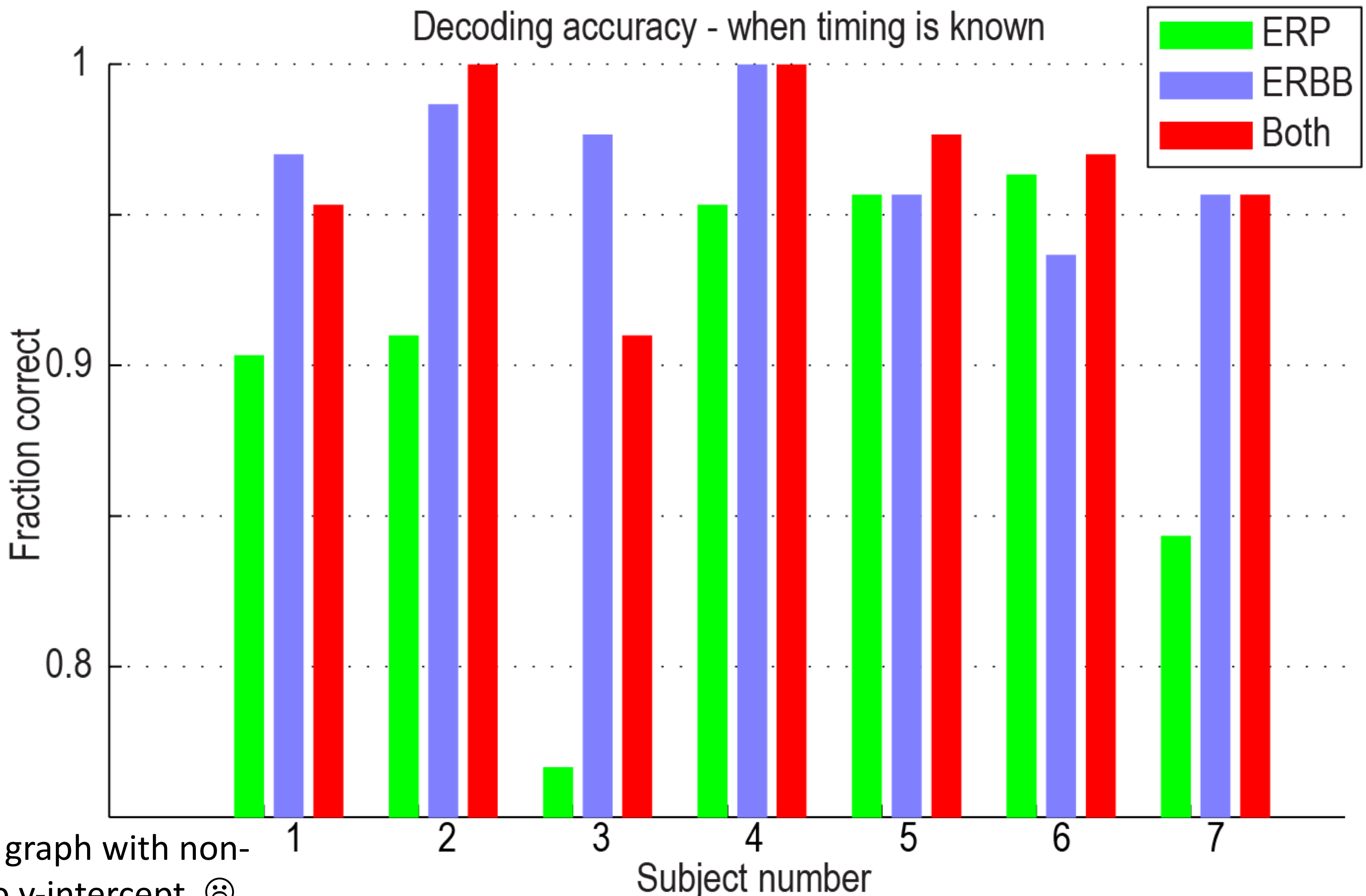
- Kai J Miller has made available a library of ECoG data he collected. Link.
- Today we will use one of the datasets from that library, found in the "faces_basic" folder.
  - Miller, Kai J., Gerwin Schalk, Dora Hermes, Jeffrey G. Ojemann, and Rajesh PN Rao. "Spontaneous decoding of the timing and content of human object perception from cortical surface recordings reveals complementary information in the event-related potential and broadband spectral change." PLoS computational biology 12, no. 1 (2016): e1004660.
  - **Ethics statement**: All patients participated in a purely voluntary manner, after providing informed written consent, under experimental protocols approved by the Institutional Review Board of the University of Washington (#12193). All patient data was anonymized according to IRB protocol, in accordance with HIPAA mandate. These data originally appeared in the manuscript “Spontaneous Decoding of the Timing and Content of Human Object Perception from Cortical Surface Recordings Reveals Complementary Information in the Event-Related Potential and Broadband Spectral Change” published in PLoS Computational Biology in 2016



Broadband: Power in 50-300 Hz

Event-Related Potential: Stimulus-locked time-domain signal

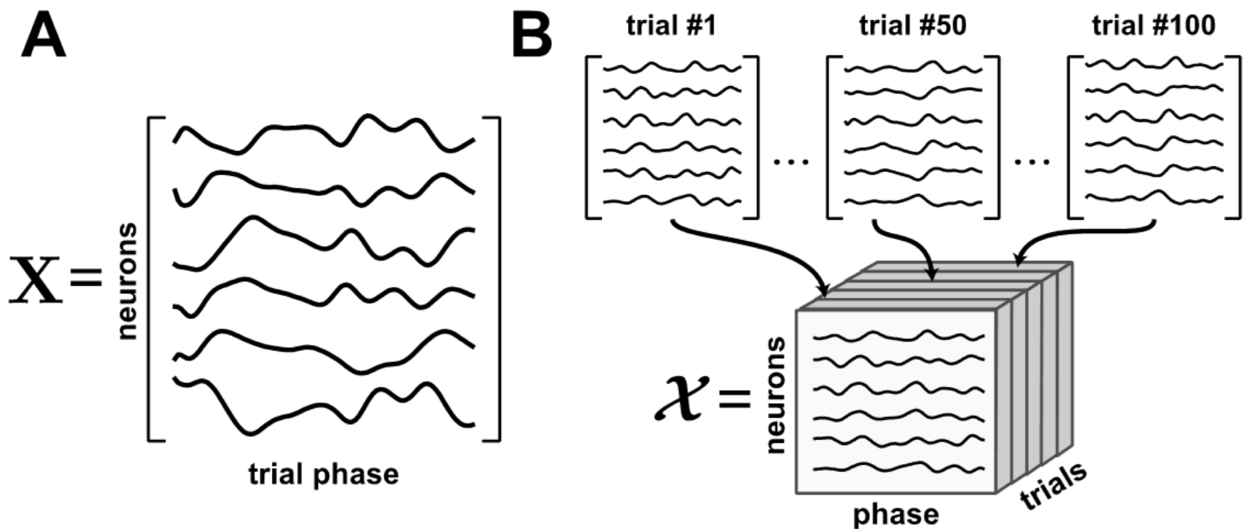
3 Conditions:
* Inter-Stimulus Interval
* face
* house



Bar graph with non-zero y-intercept. ☹

Data Structure

- `The 'signals' chunk has data with shape (603, 17, 31).`
  - `(trials, samples, channels)`



"matrix" "tensor"

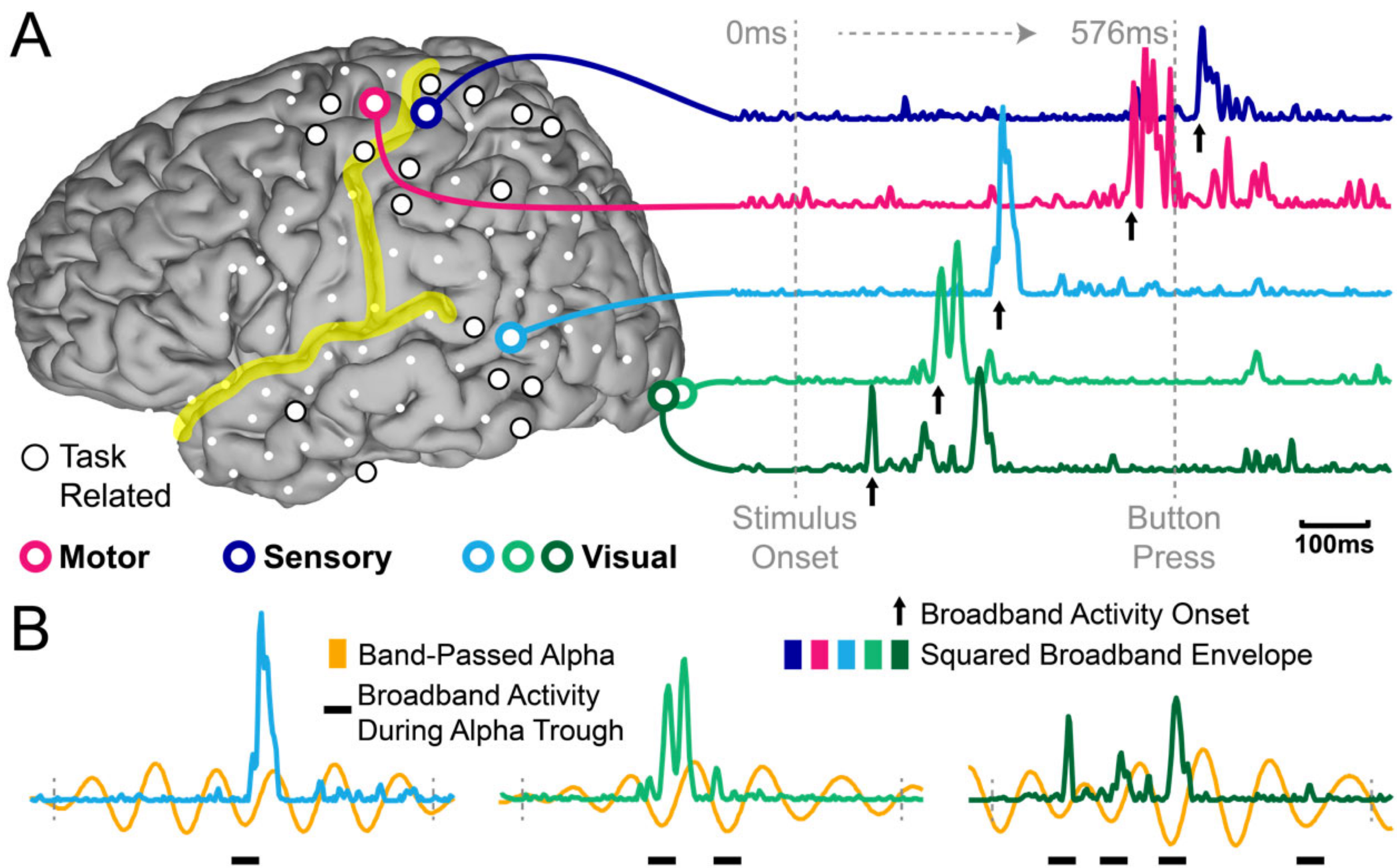
Convolutions in 1D on ECoG data

- Mac Users:
    - (Cmd + Up Arrow) to go up a folder in finder
    - (Cmd + Shift + .) to show hidden files/folders.

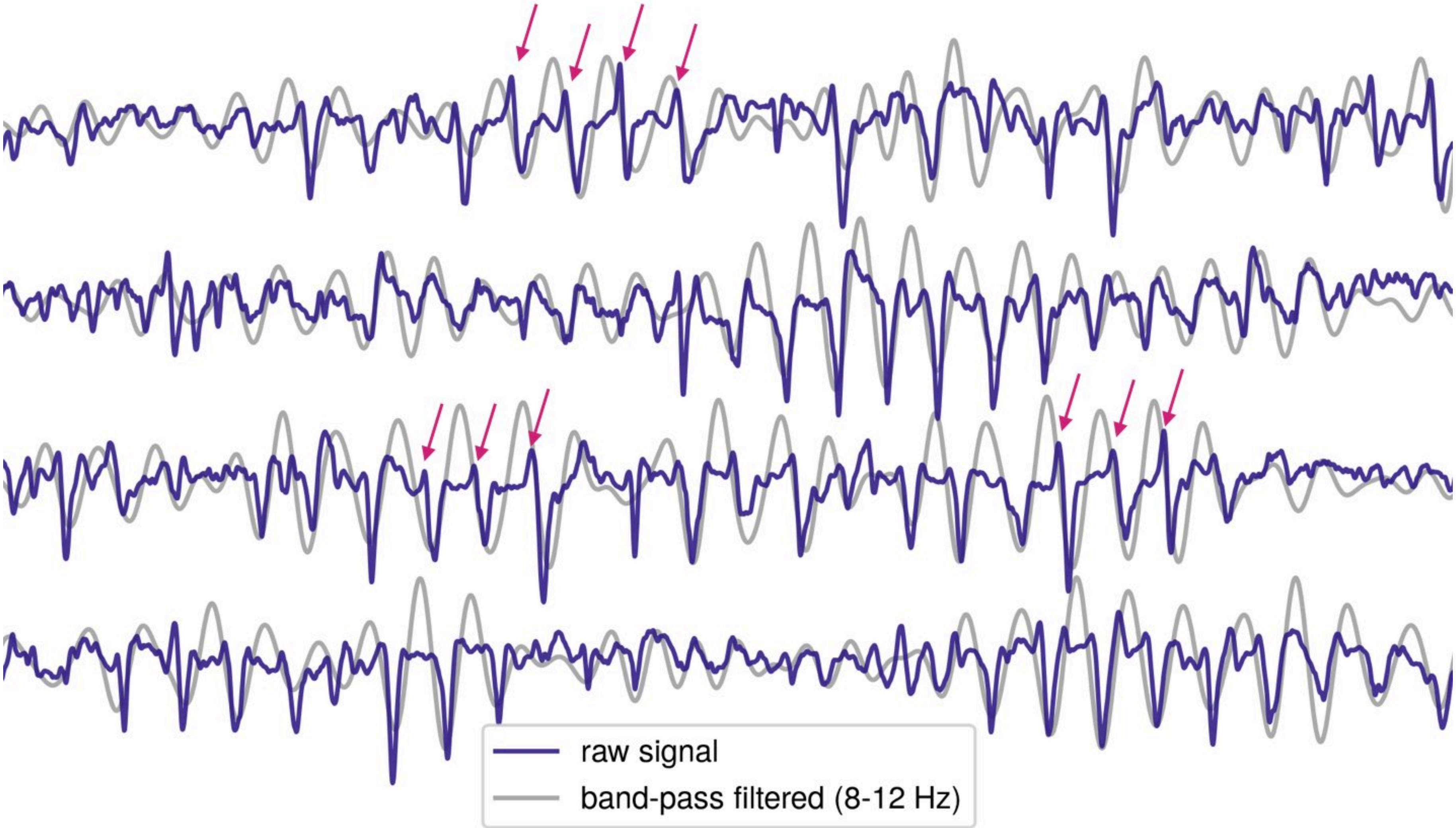
- Proceed to notebook

03_02_CNN_faces_houses.ipynb

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



Why train filter kernels?

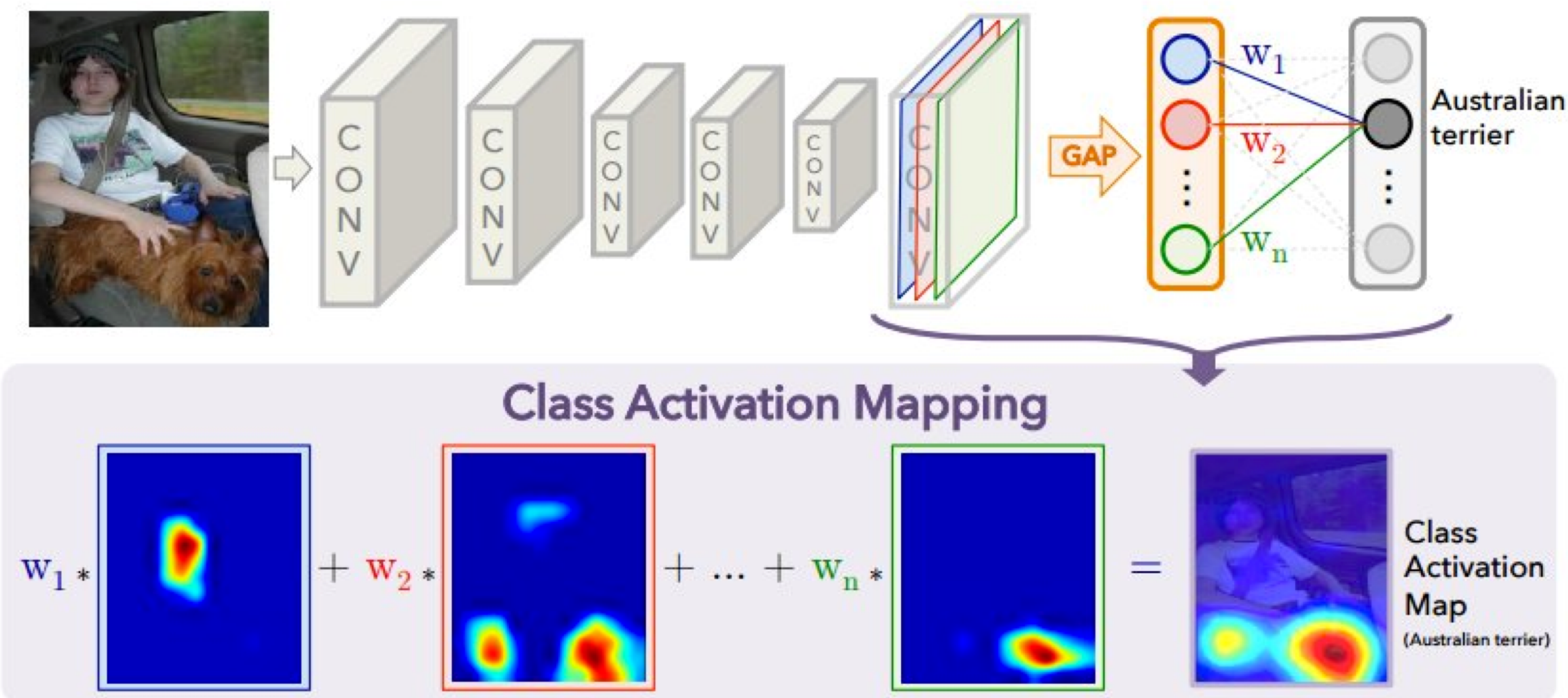


Natalie Schaworonkow - @nschawor

Inspecting CNNs

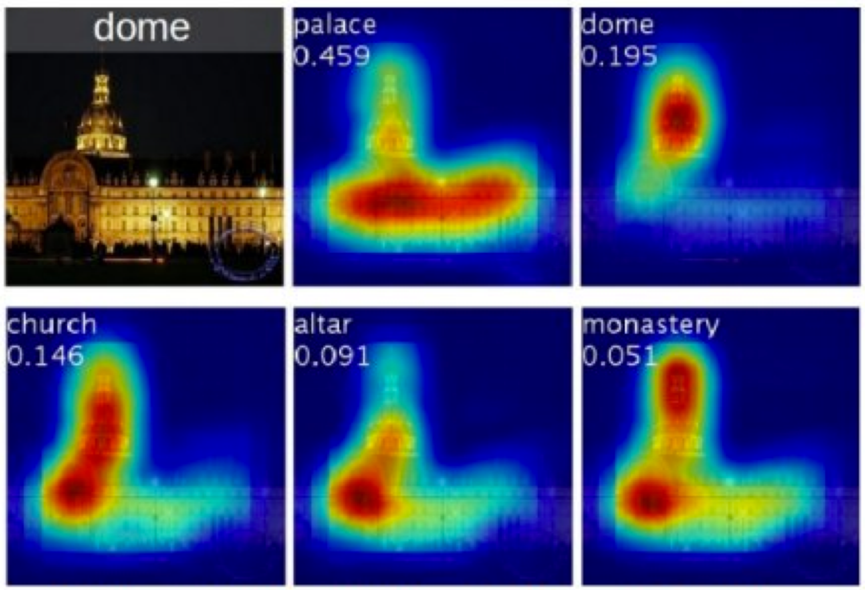
- CAM (slides only)
- Perturbations (slides only)
- Filter-maximizing inputs (notebook)
- Saliency Maps (notebook)

Class Activation Maps



[Zhou et al., 2015]

Class Activation Maps



Class activation maps of top 5 predictions

Class activation maps for one object class

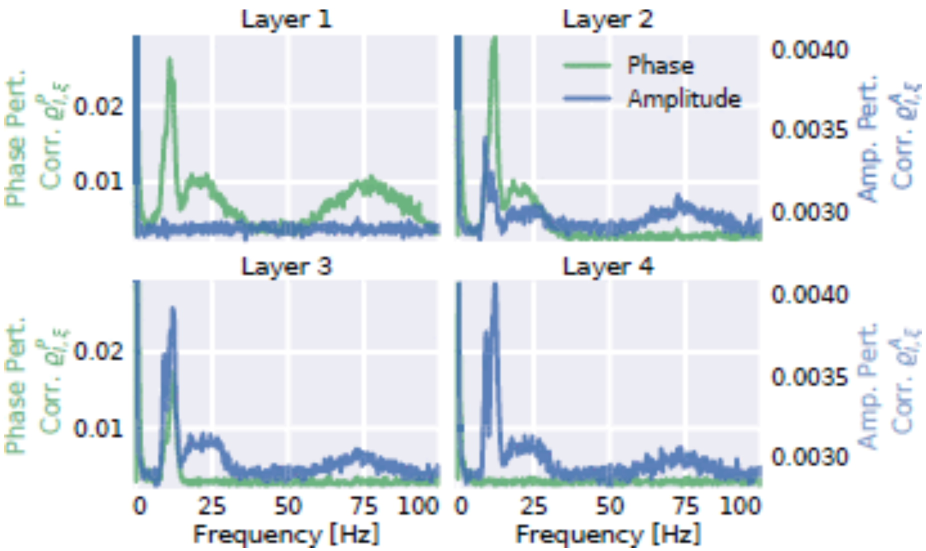
Zhou et al., 2015

Perturbation Analysis

- "In case a filter extracts the amplitude of a certain frequency, a perturbation of the amplitude of that frequency should evoke a consistent change of activity in all units of that filter. An amplitude increase should evoke either an activation increase or an activation decrease in all units. The opposite should happen for an amplitude decrease."

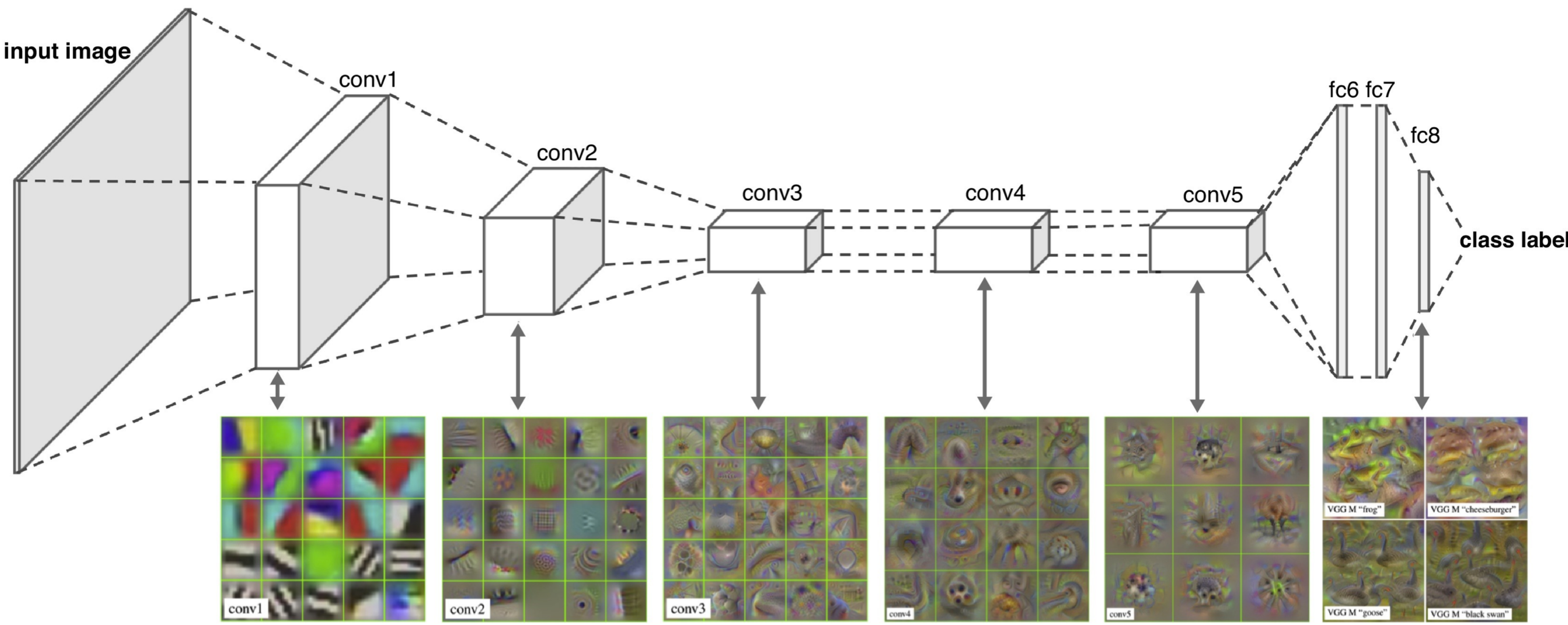
$$\bar{\Delta y}_{f,i} = \frac{1}{N_j} \sum_j (y_{f,i,j} - y^A_{f,i,j})$$

$$\rho_{p^A_{\xi,c}, \bar{\Delta y}_f} = corr(p^A_{\xi,c}, \bar{\Delta y}_f)$$



- [Hartmann, Schirrmeister, Ball 2018]()

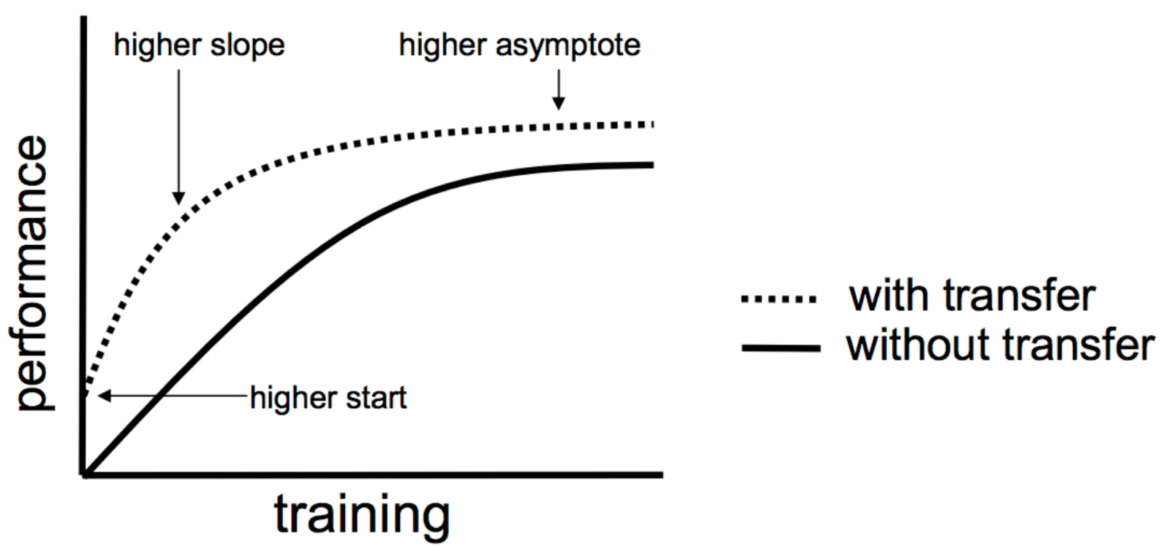
Filter maximizations

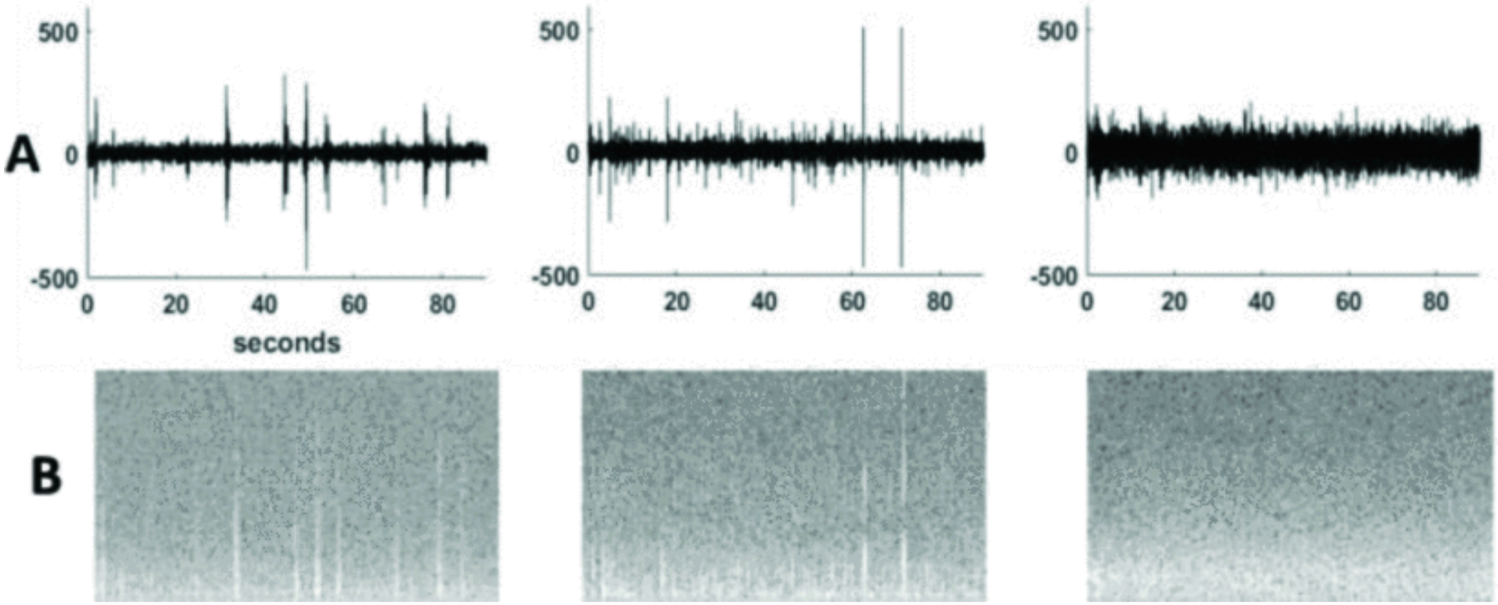


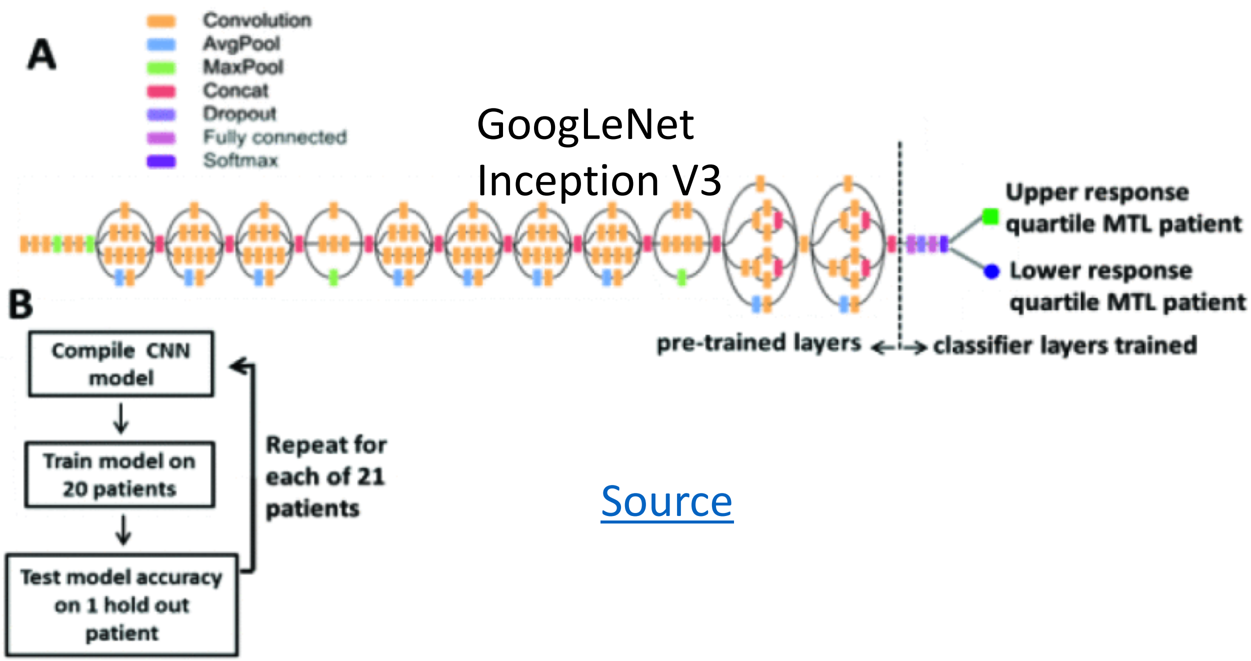
Current Opinion in Neurobiology

Transfer Learning

- CNNs are often trained in 1 domain then used in another.
  - Train on ImageNet for object classification
  - Bottom layers are general feature extractors and can be reused.
  - Change top layers for task at hand: dogs vs cats; cancer vs not-cancer; spectrogram for task A vs spectrogram for task B

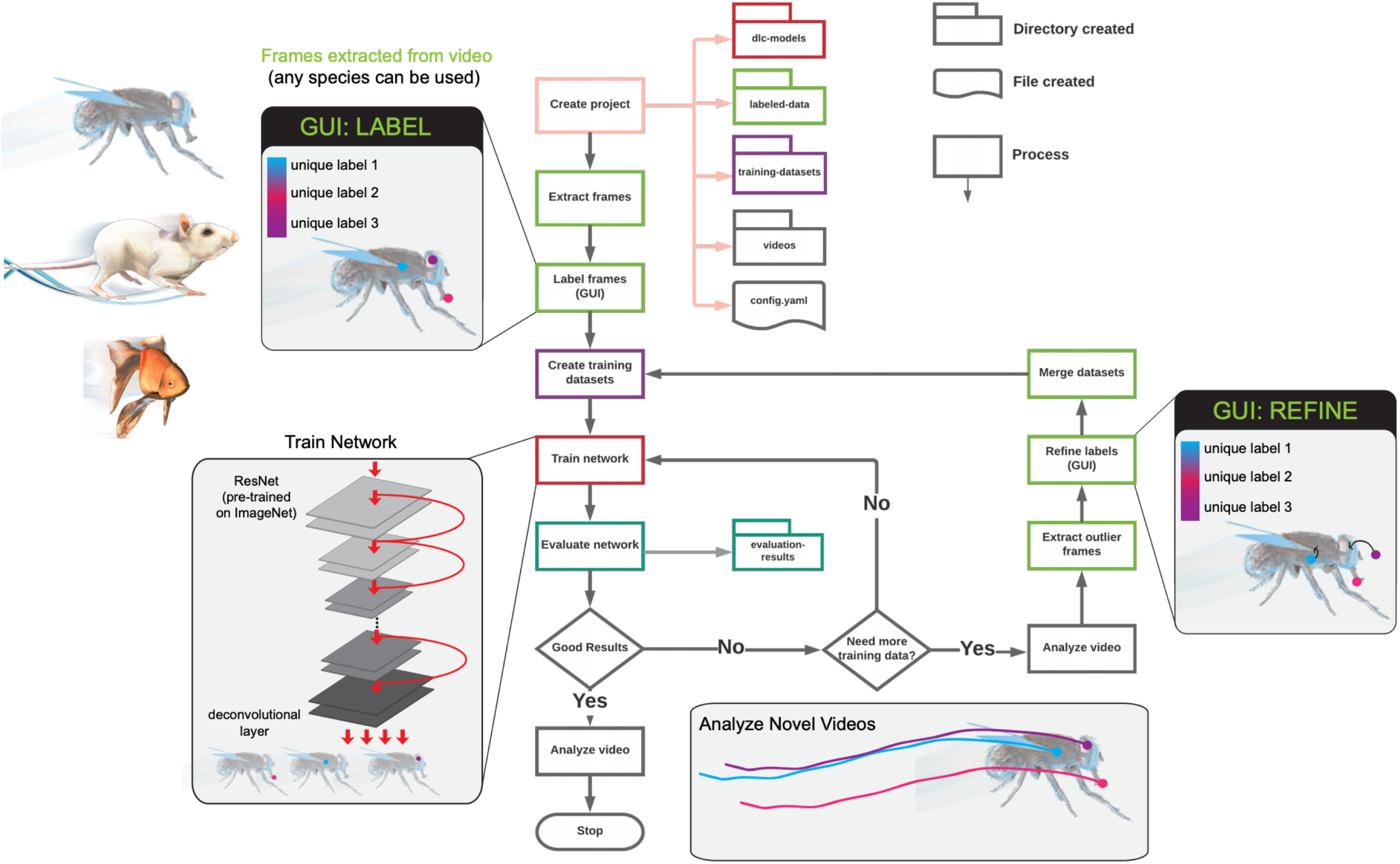






GoogLeNet
Inception V3

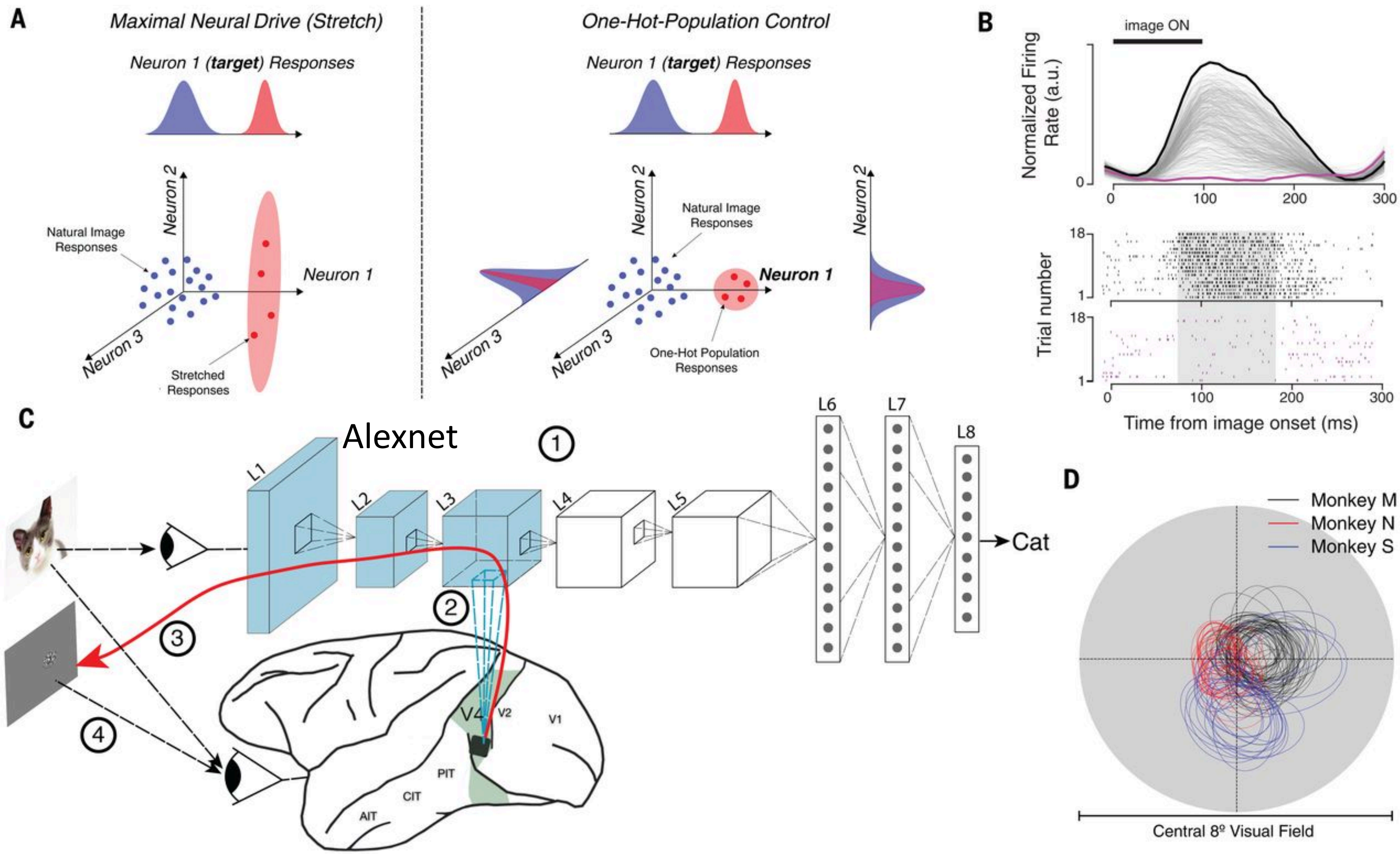
[Source]

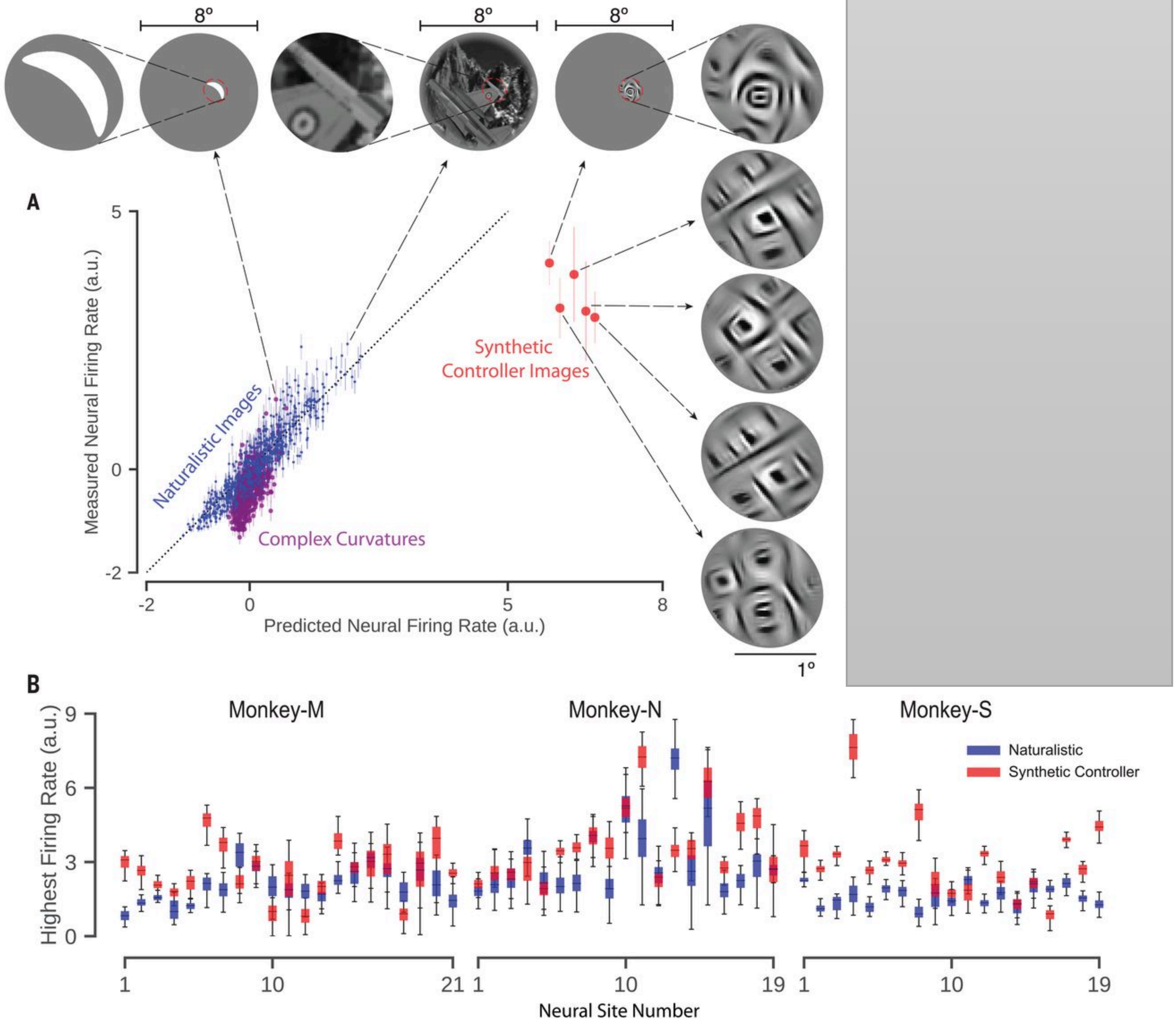


http://www.mousemotorlab.org/deeplabcutdetails

Neural population control via deep image synthesis

- Bashivan, Kar, DiCarlo – Science 2019





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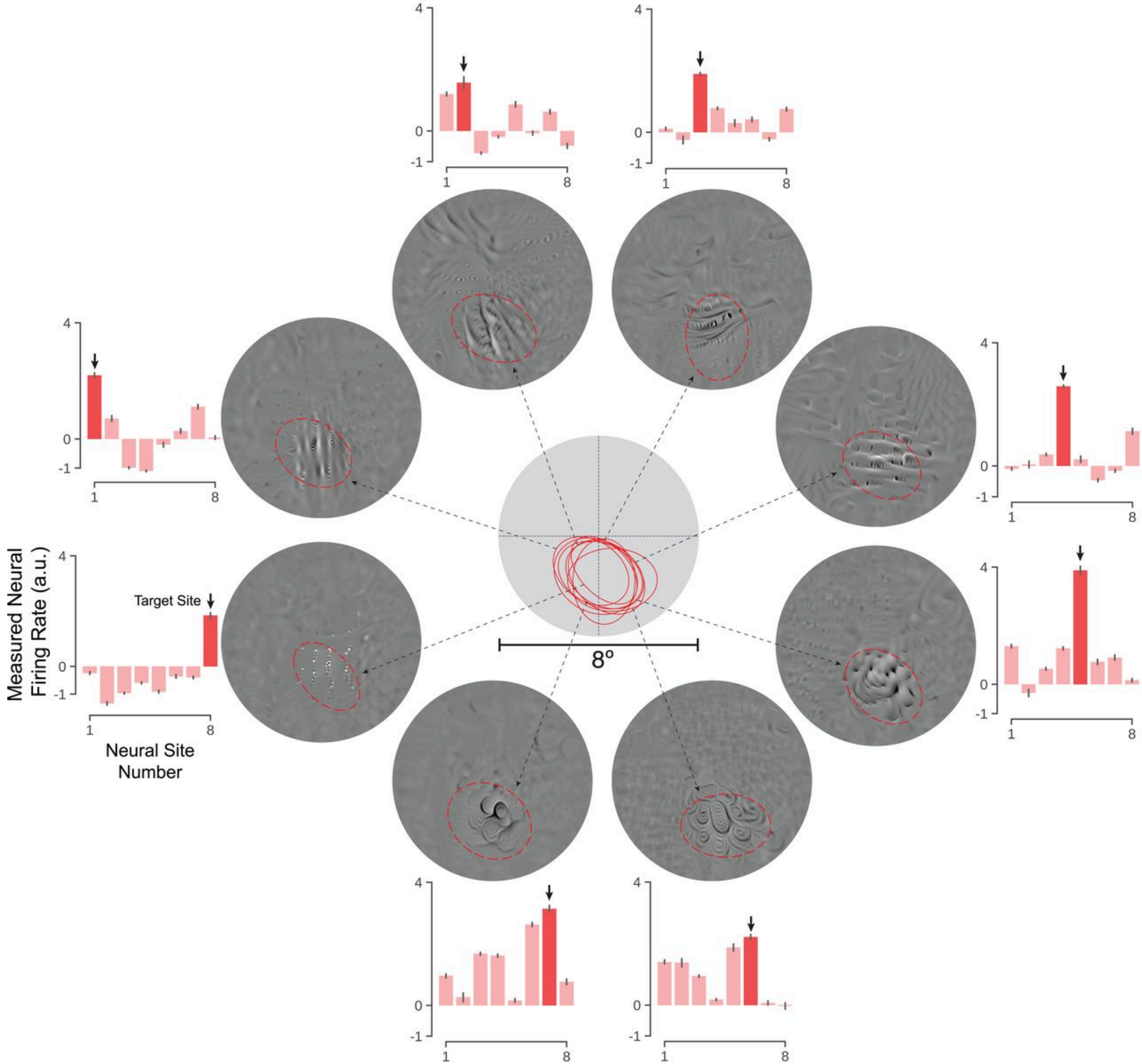
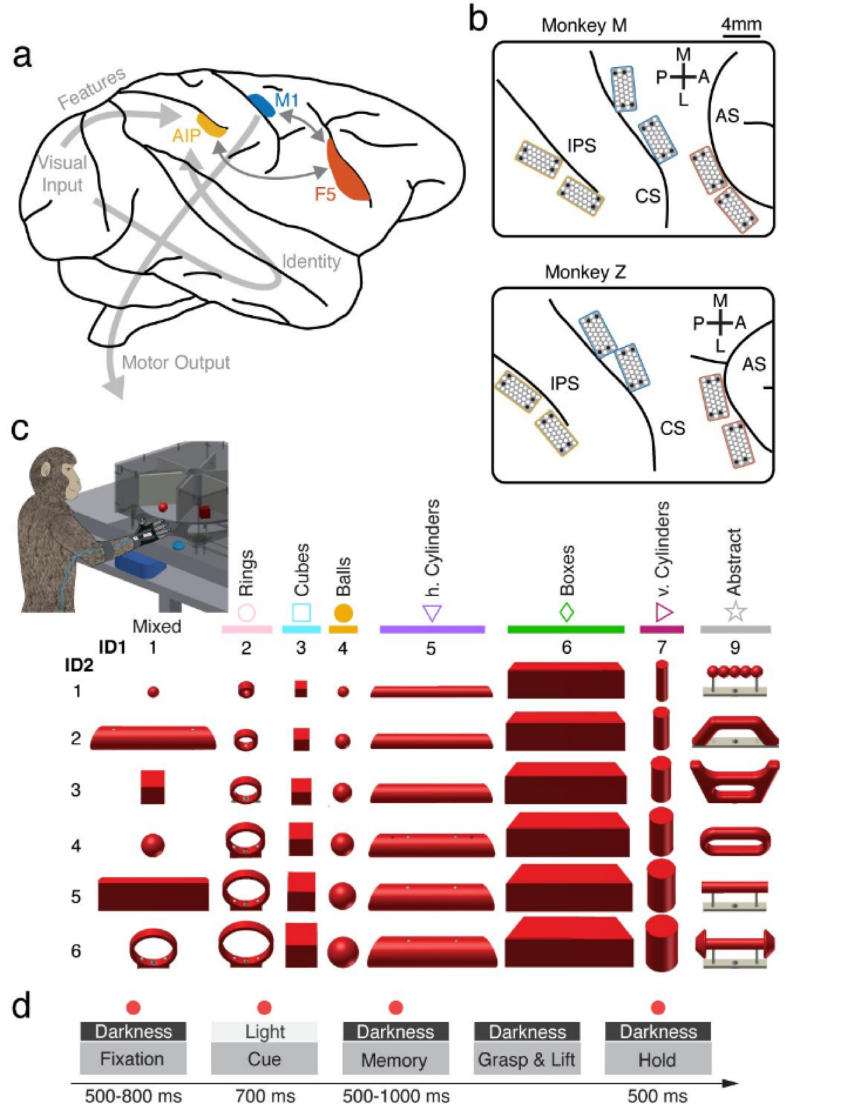
8°
A
Measured Neural Firing Rate (a.u.)
Predicted Neural Firing Rate (a.u.)
5
0
-2
-2
0
5
8
Naturalistic Images
Complex Curvatures
Synthetic Controller Images
1°
B
Monkey-M
Monkey-N
Monkey-S
Highest Firing Rate (a.u.)
9
6
3
0
Naturalistic
Synthetic Controller
1
10
21
1
10
19
1
10
19
Neural Site Number

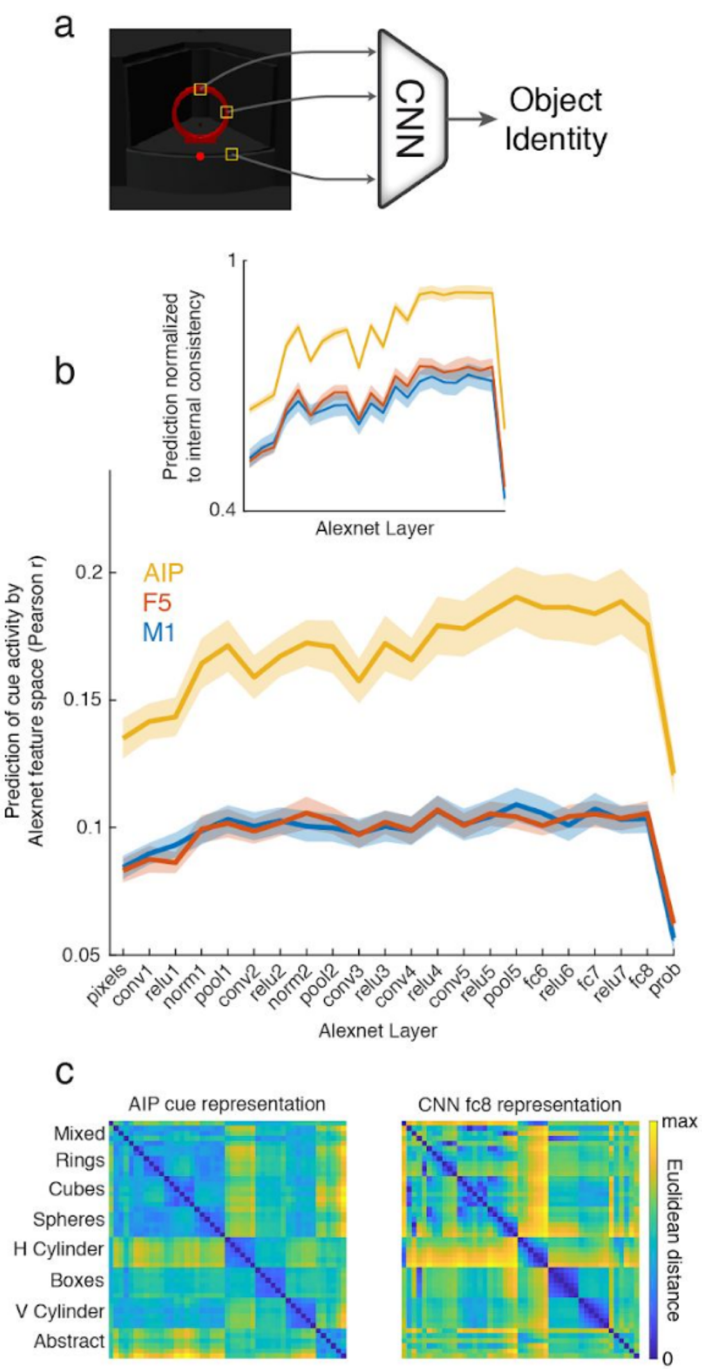


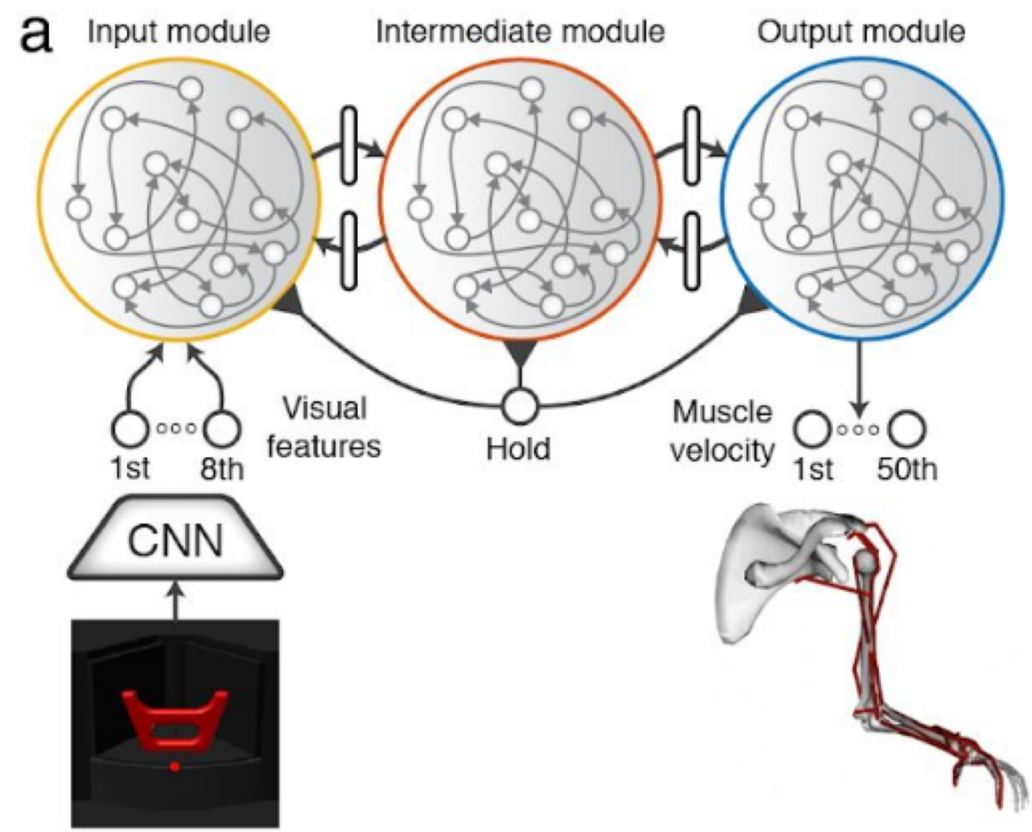
Measured Neural Firing Rate (a.u.)
Neural Site Number
Target Site
8°
4
0
-1
1
8

A neural network model of flexible grasp movementgeneration

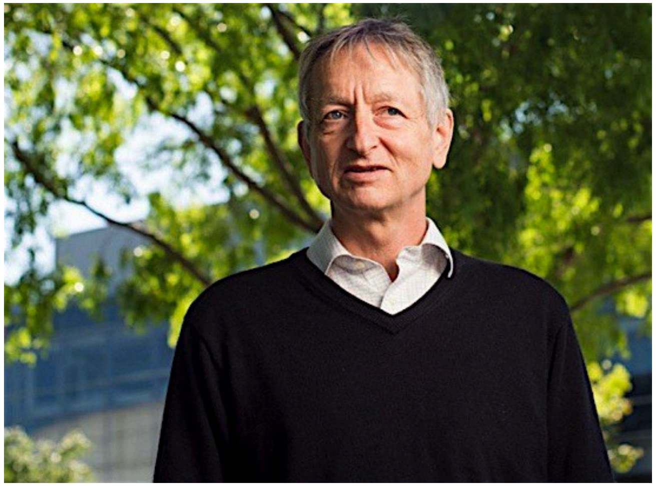


- [Michaels et al., 2019]


a
CNN
Object Identity
b
Prediction normalized to internal consistency
1
0.4
Alexnet Layer
AIP
F5
M1
Prediction of cue activity by Alexnet feature space (Pearson r)
0.2
0.15
0.1
0.05
pixels
conv1
relu1
norm1
pool1
conv2
relu2
norm2
pool2
conv3
relu3
conv4
relu4
conv5
relu5
pool5
fc6
relu6
fc7
relu7
fc8
prob
Alexnet Layer
c
AIP cue representation
CNN fc8 representation
Mixed
Rings
Cubes
Spheres
H Cylinder
Boxes
V Cylinder
Abstract
max
Euclidean distance
0

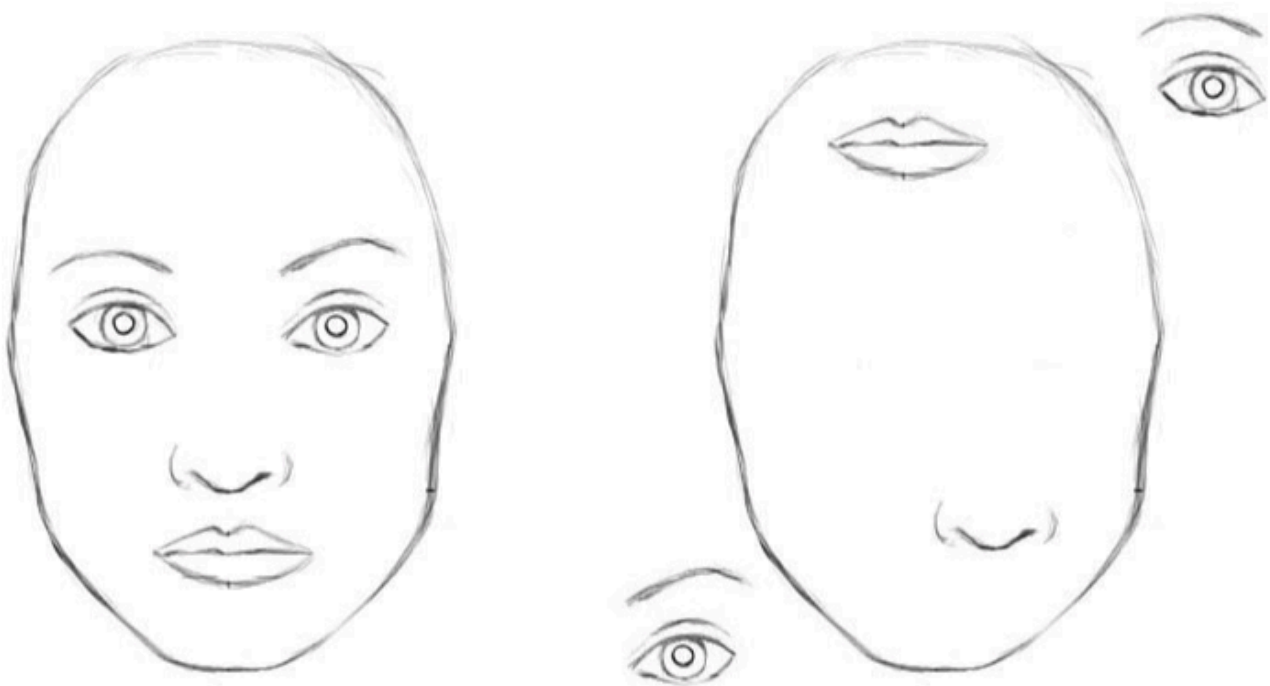

a
Input module
Intermediate module
Output module
Visual features
1st
8th
Hold
Muscle velocity
1st
50th
CNN

Capsule Networks



Hinton: "**The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster.**"

CNNs don't care about poses (position + orientation), only whether or not the objects are present.



Capsule Networks

- Computer graphics: From state of objects to render image
- Brain inverse graphics: From image to state of objects

A capsule is a group of neurons whose activity vector represents the instantiation parameters of a specific type of entity such as an object or an object part. We use the length of the activity vector to represent the probability that the entity exists and its orientation to represent the instantiation parameters. [*- Source*]