The Ottawa Hospital | L'Hôpital d'Ottawa

RESEARCH INSTITUTE | INSTITUT DE RECHERCHE

uOttawa | Institut de recherche sur le cerveau

Brain and Mind Research Institute

Workshop on Applied Deep Learning in Intracranial Neurophysiology

Part 4 – Advanced Topics in CNNs

September 16, 2019

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Ottawa Hospital Research Institute

University of Ottawa

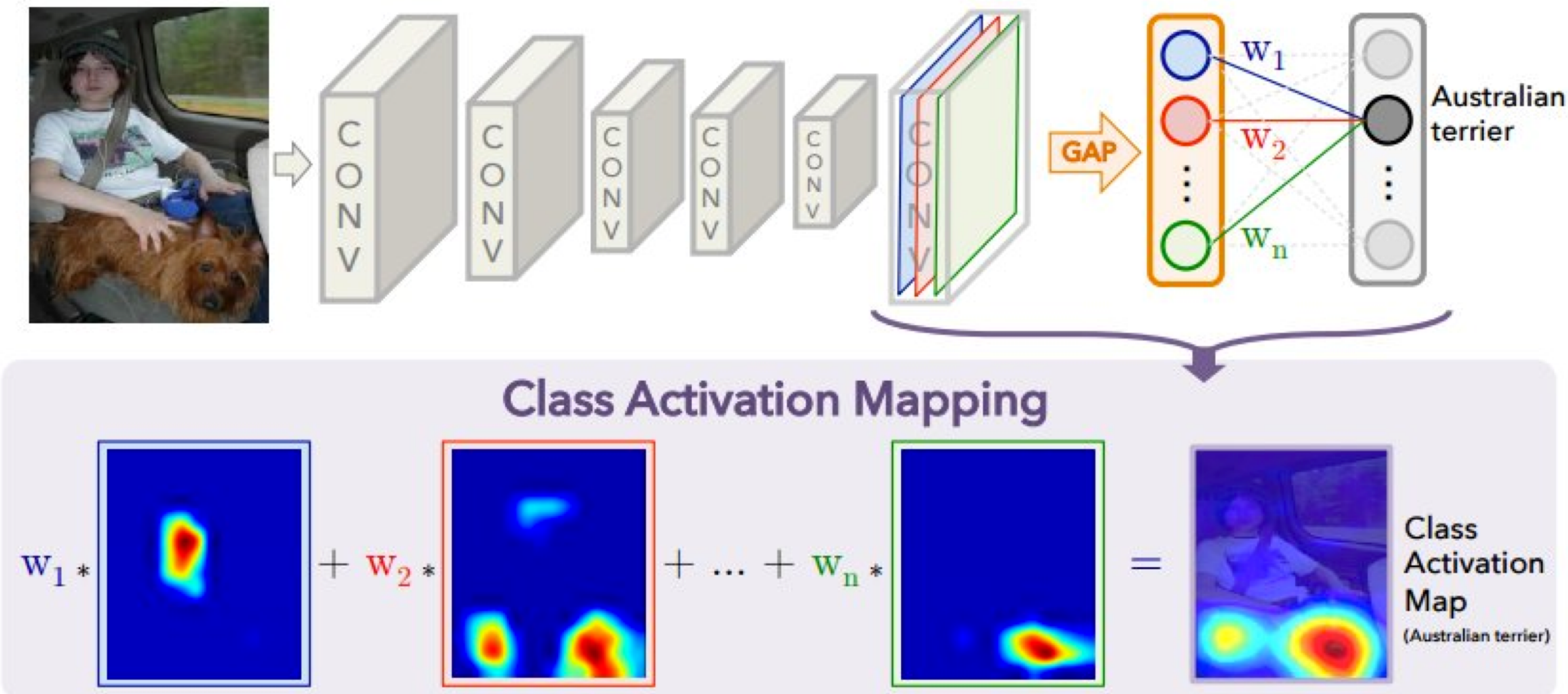
Outline

- Inspecting CNNs (slides + notebook)
- Transfer Learning (notebook)
- CNNs as models of vision processing in the brain
  - DiCarlo paper (slides only)
  - Michaels paper (slides only; first part only)
- CNN Variants: Capsule Networks
- CNN Variants: UNets

Inspecting CNNs

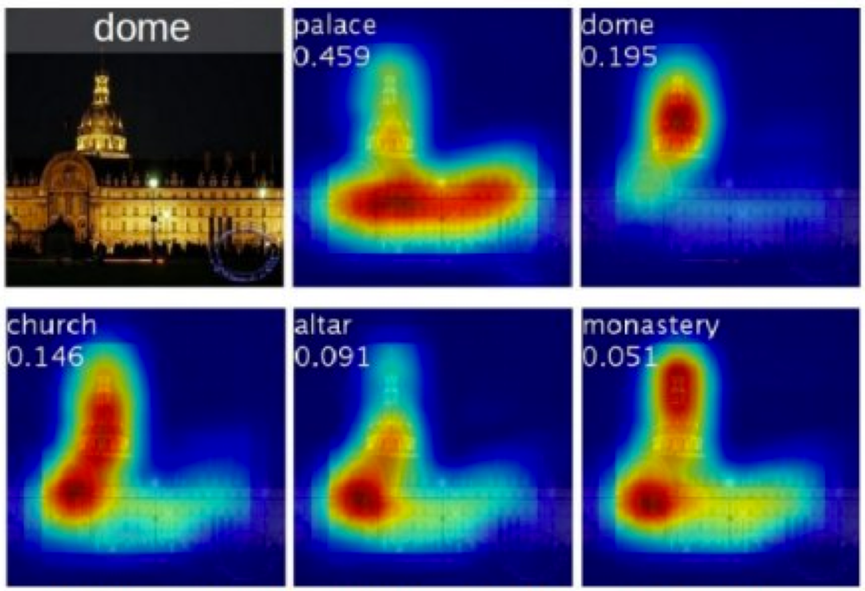
- CAM (slides only)
- Perturbations (slides only)
- Filter-maximizing inputs (notebook)
- Saliency Maps (notebook)

Class Activation Maps



Zhou et al., 2015

Class Activation Maps



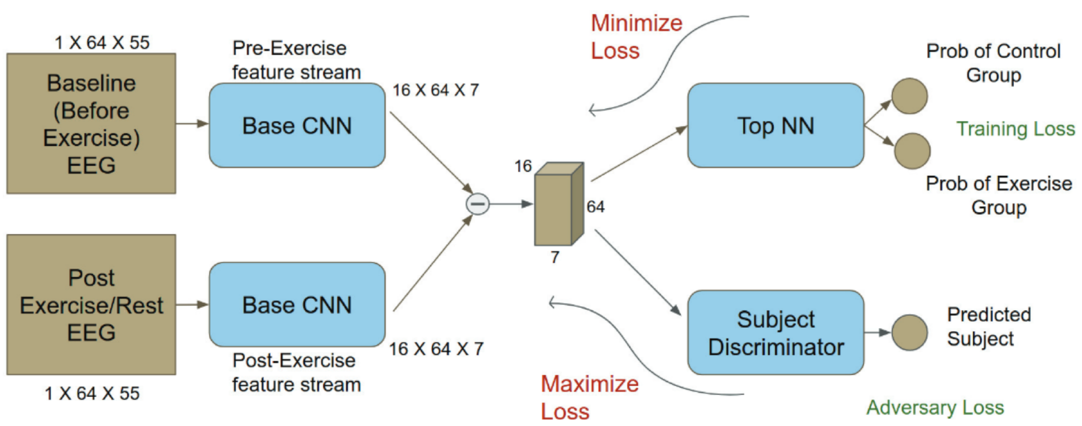
Class activation maps of top 5 predictions

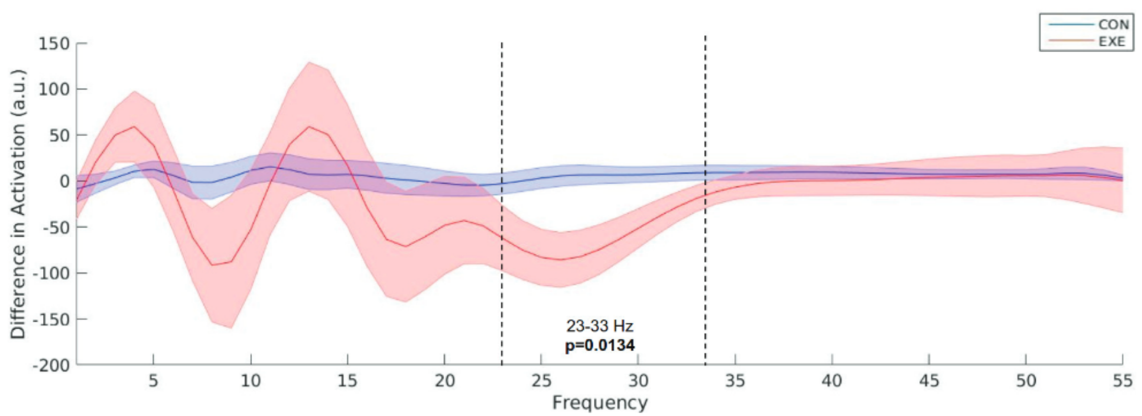
Class activation maps for one object class

Zhou et al., 2015

Cue-combination for Class Activation Map (ccCAM)

- Ghosh et al., 2017



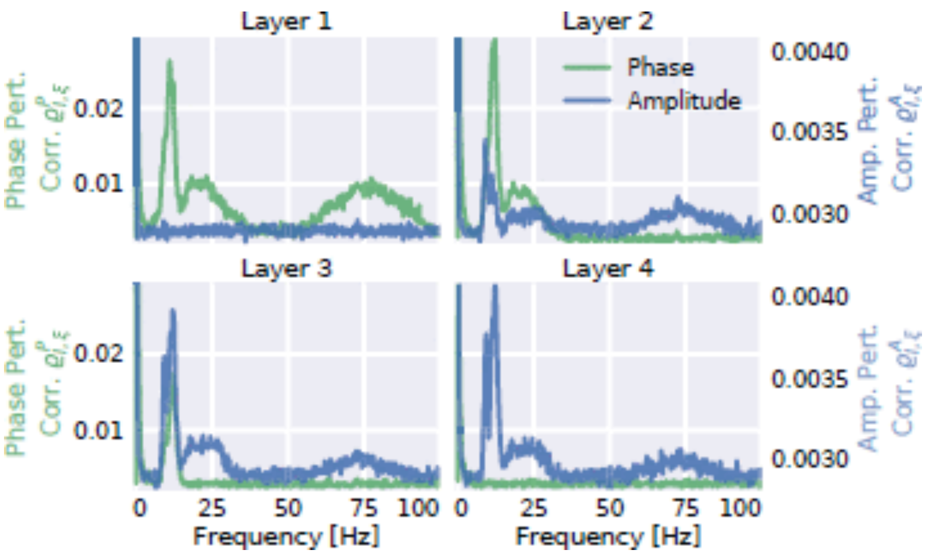


Perturbation Analysis

- "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."

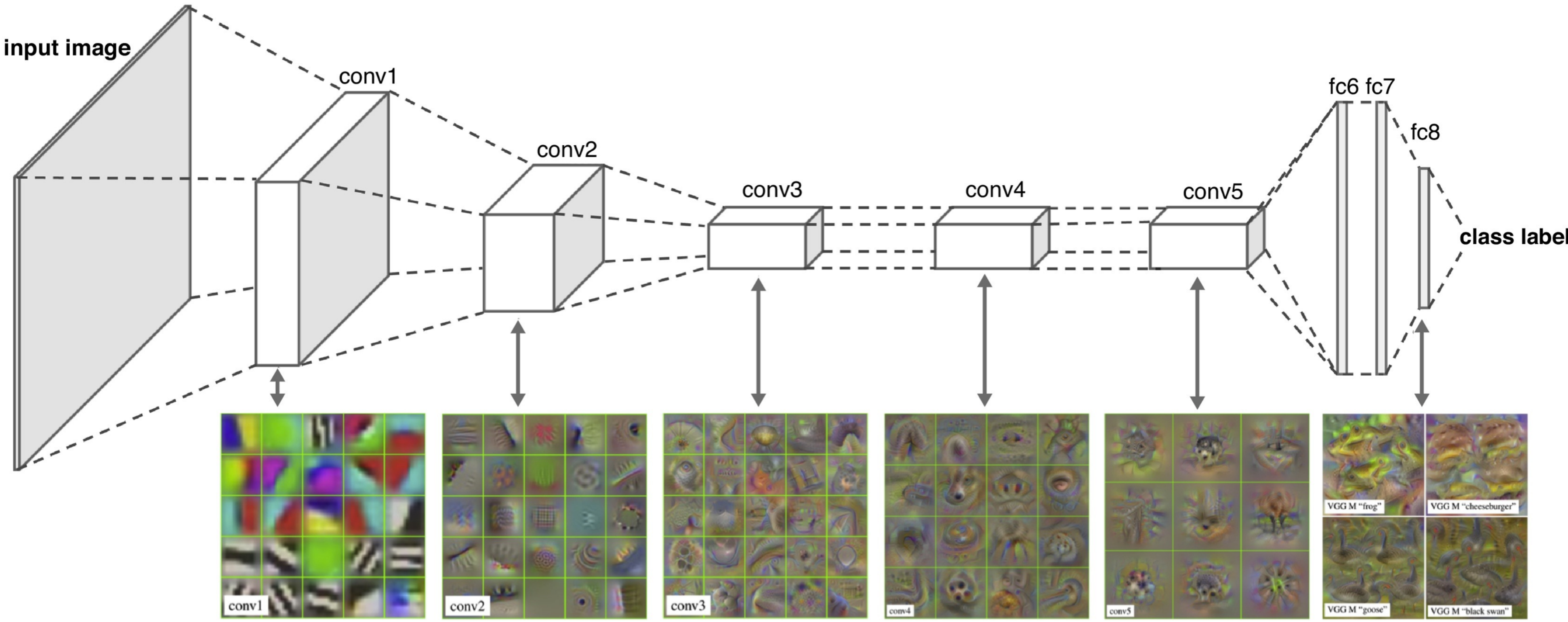
$$\bar{\Delta y}_{f,i} = \frac{1}{N_j}\sum_j (y_{f,i,j} - y^A_{f,i,j})$$

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



- [Hartmann, Schirrmeister, Ball 2018]()

Filter maximizations

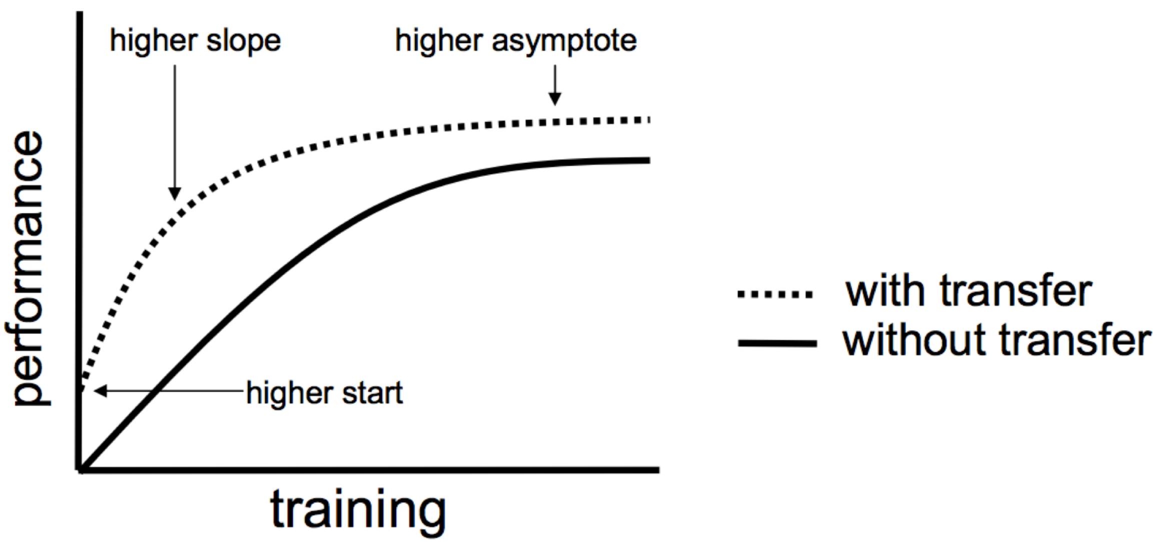


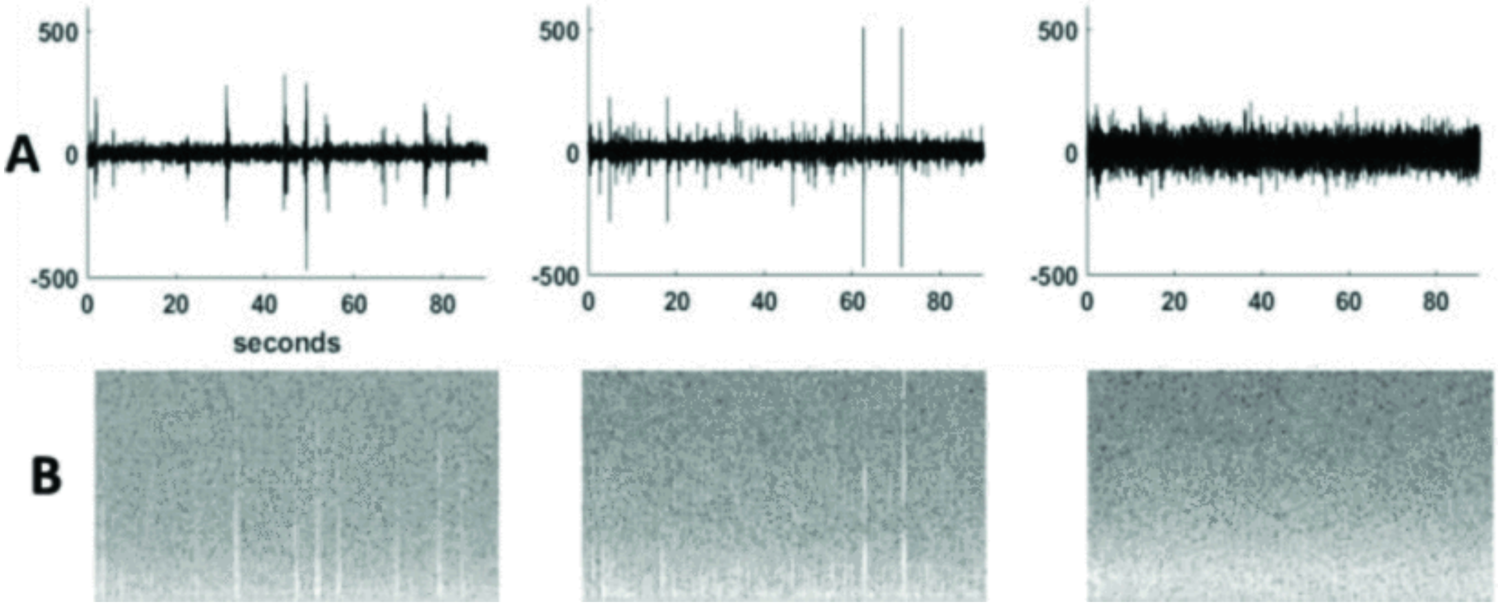
Current Opinion in Neurobiology

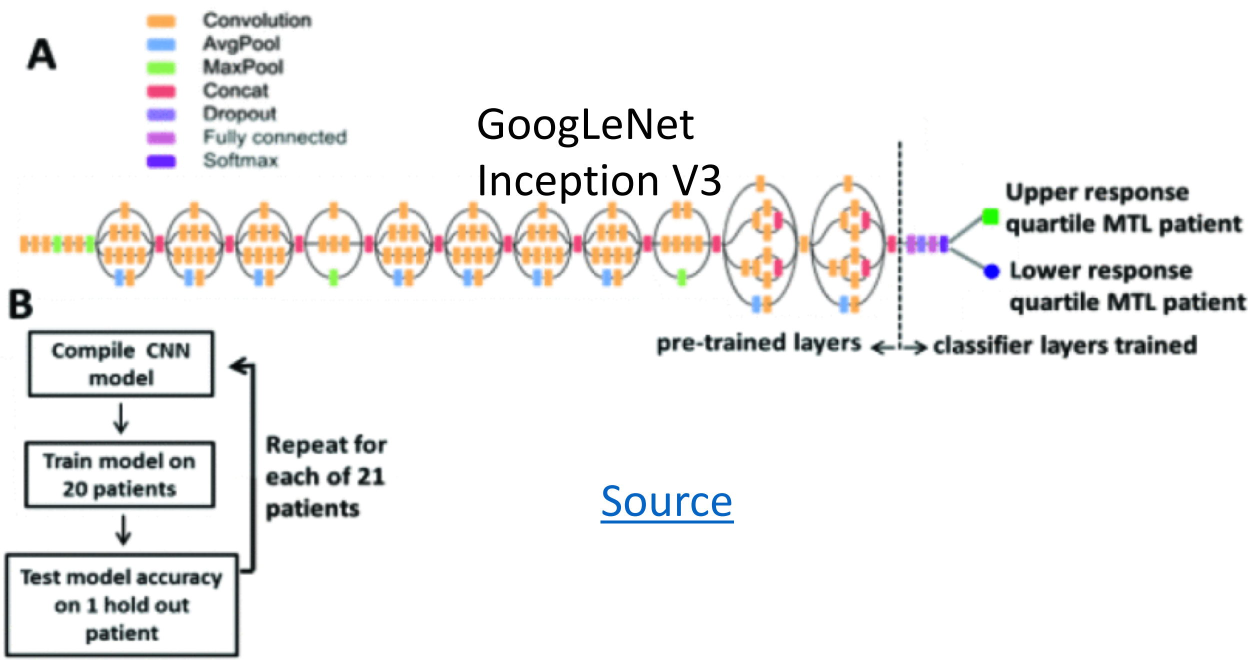
- Go to notebook
- 04_01_CNN_inspect_model.ipynb

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

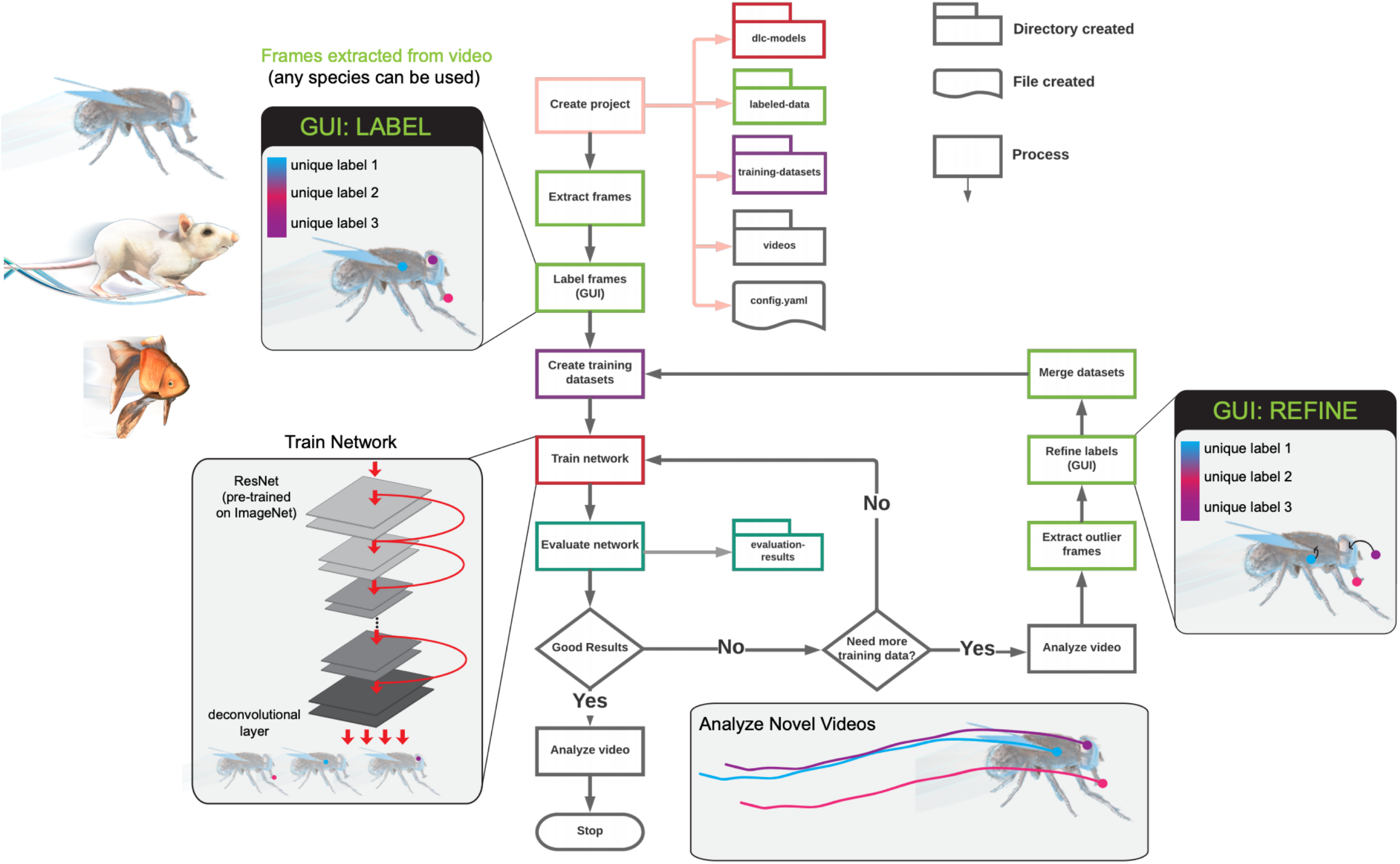






GoogLeNet
Inception V3

Source



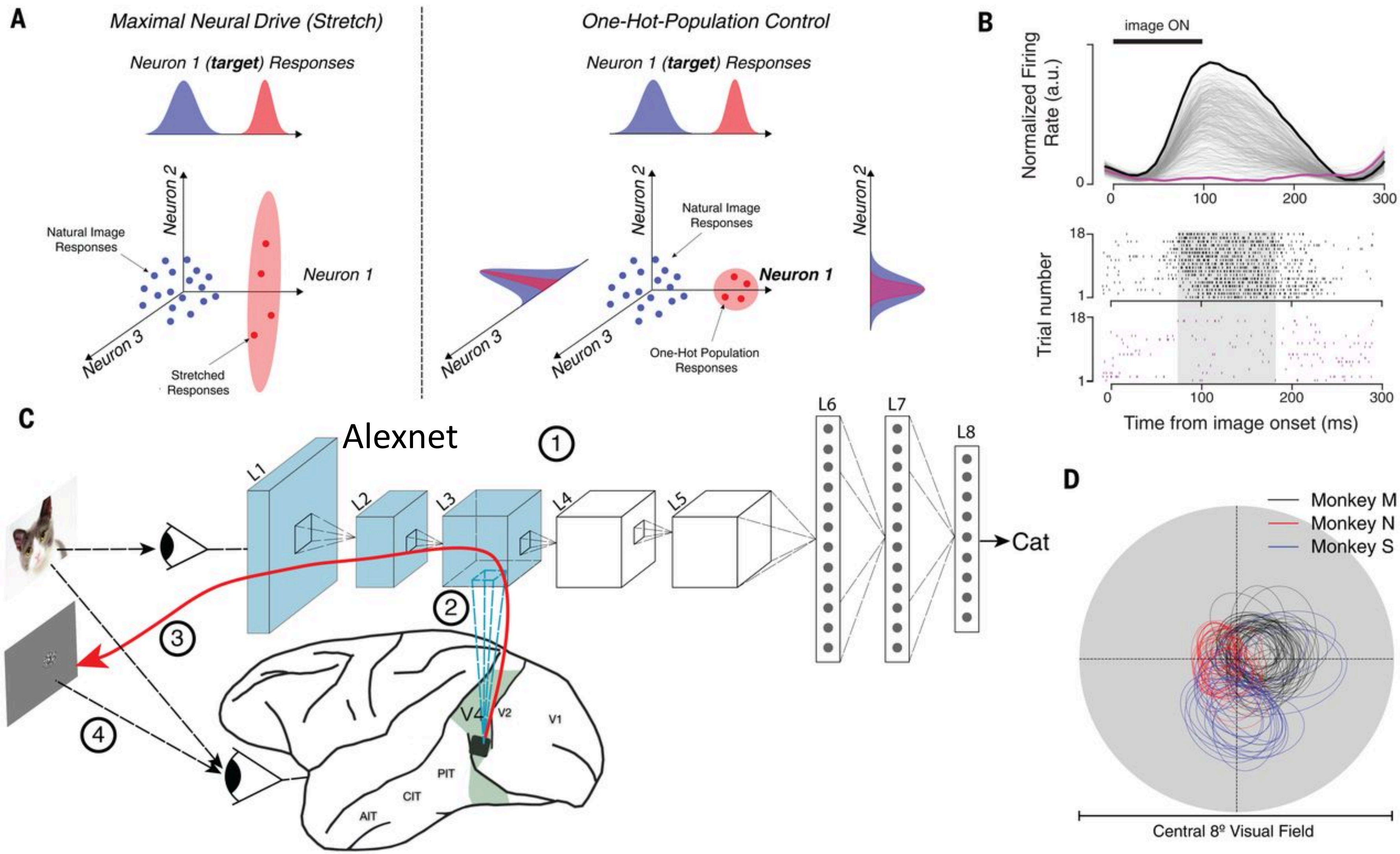
http://www.mousemotorlab.org/deeplabcutdetails

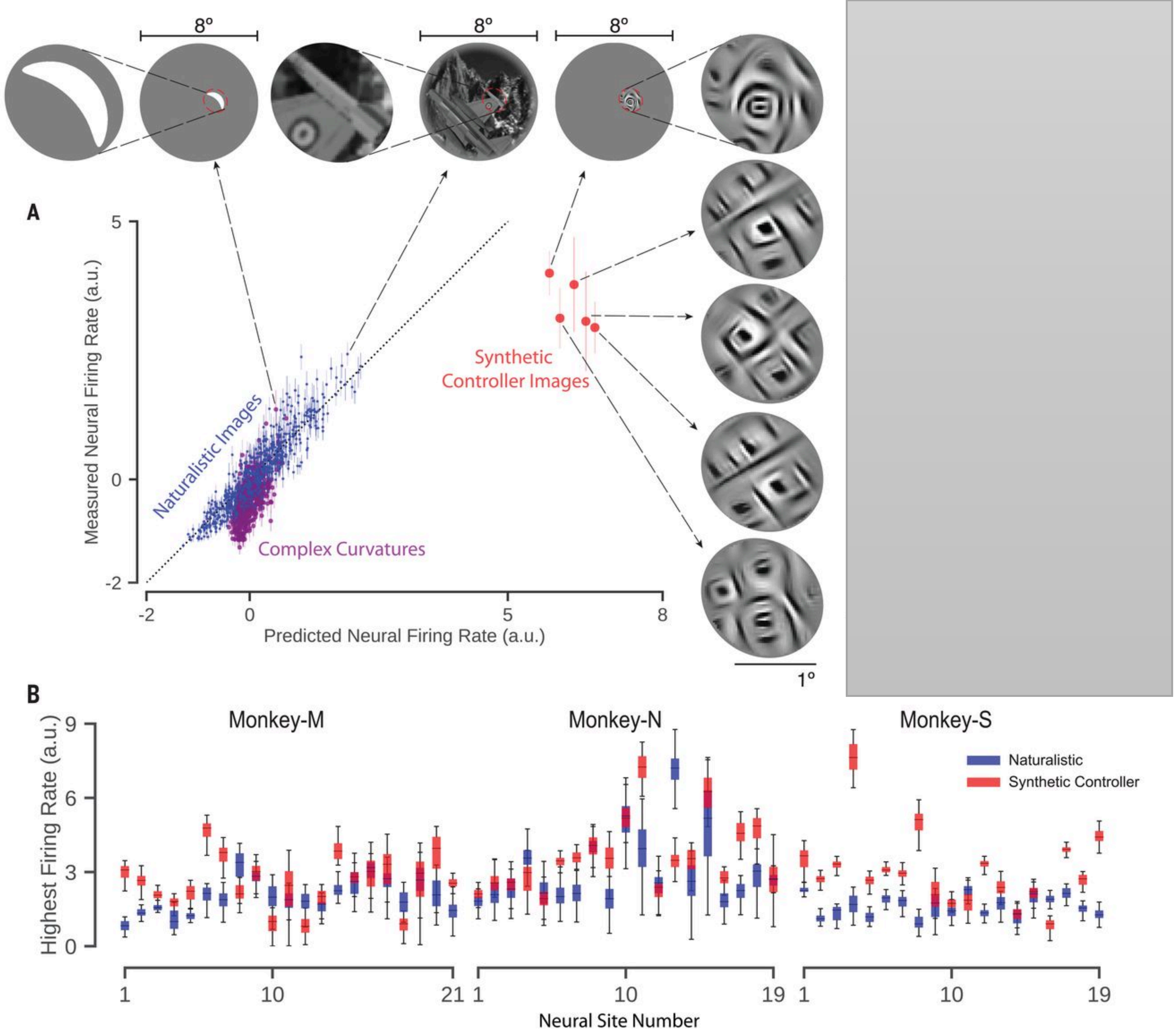
- Go to notebook

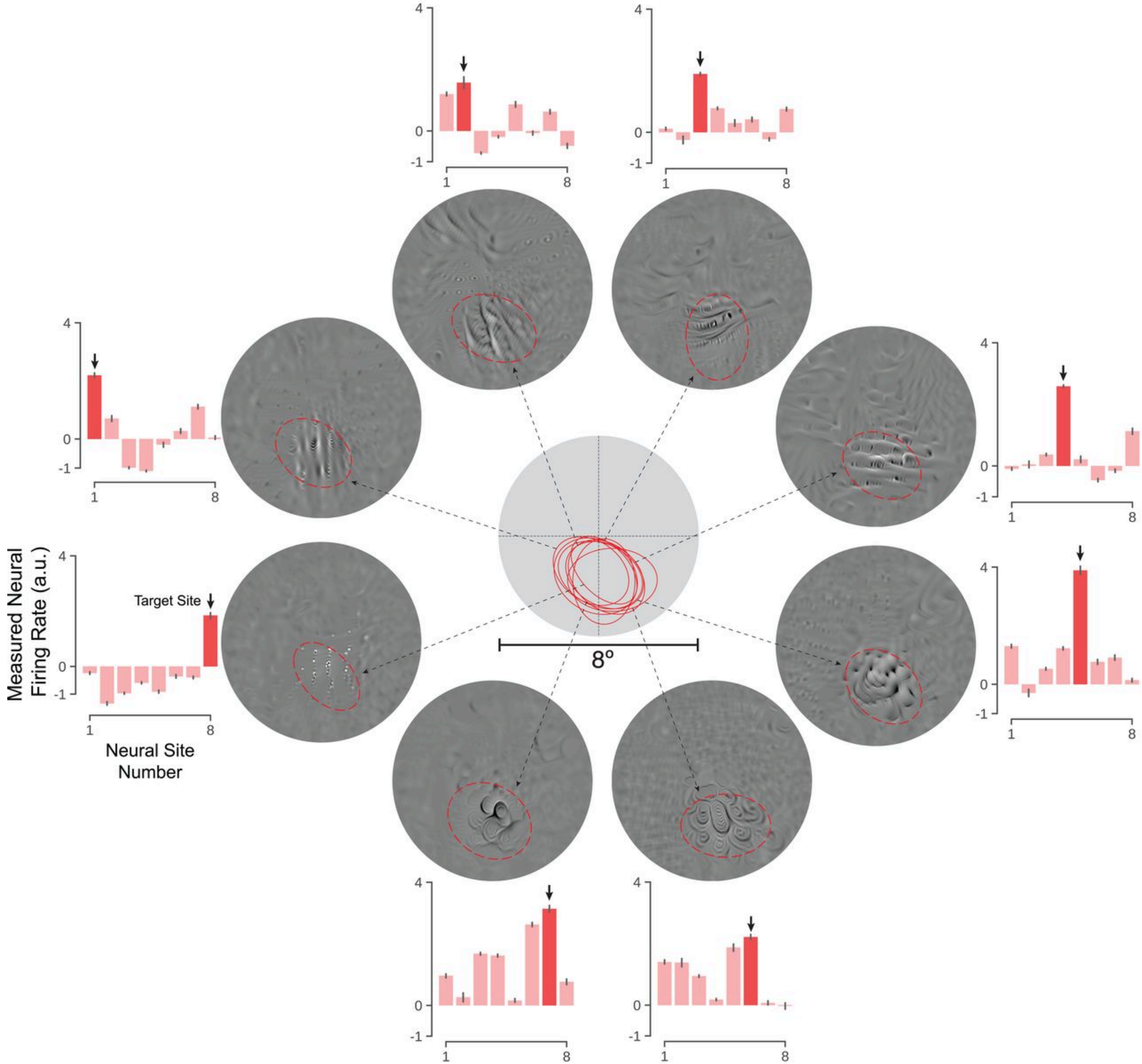
04_02_transfer_learning.ipynb

Neural population control via deep image synthesis

- Bashivan, Kar, DiCarlo – Science 2019

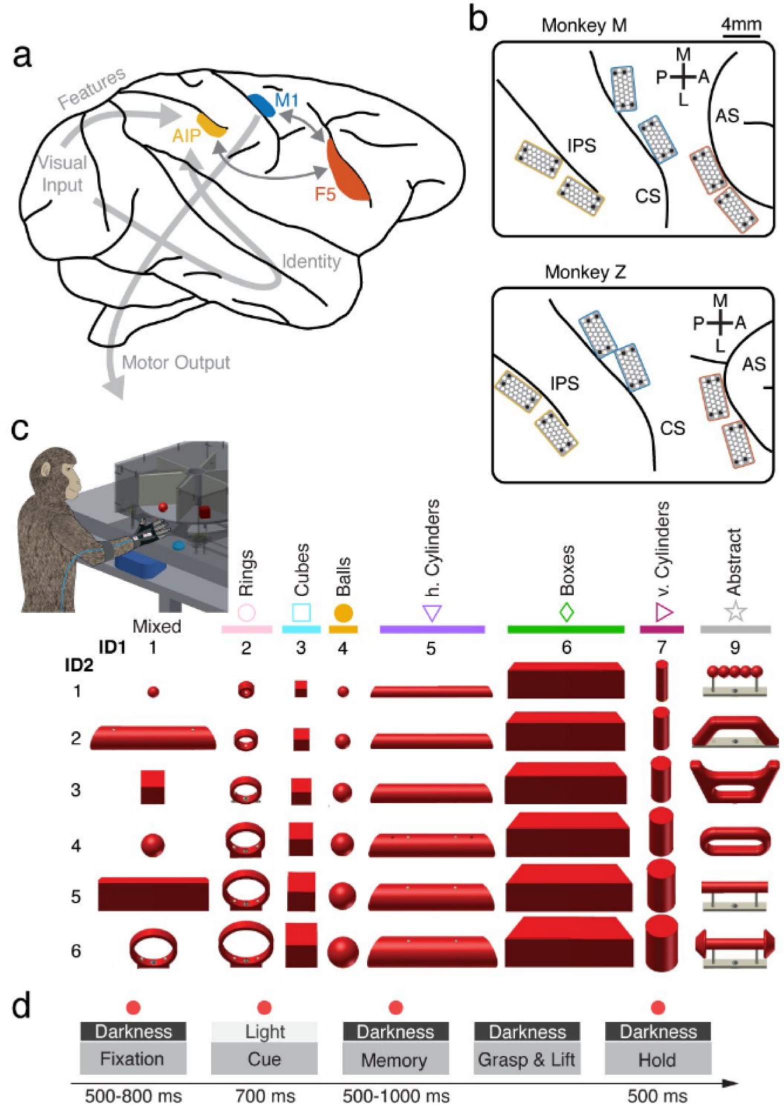



8°
8°
8°
A
5
0
-2
Measured Neural Firing Rate (a.u.)
-2
0
5
8
Predicted Neural Firing Rate (a.u.)
Naturalistic Images
Complex Curvatures
Synthetic
Controller Images
1°
B
Monkey-M
Monkey-N
Monkey-S
Highest Firing Rate (a.u.)
9
6
3
0
Naturalistic
Synthetic Controller
1
10
21
1
10
19
1
10
19
Neural Site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

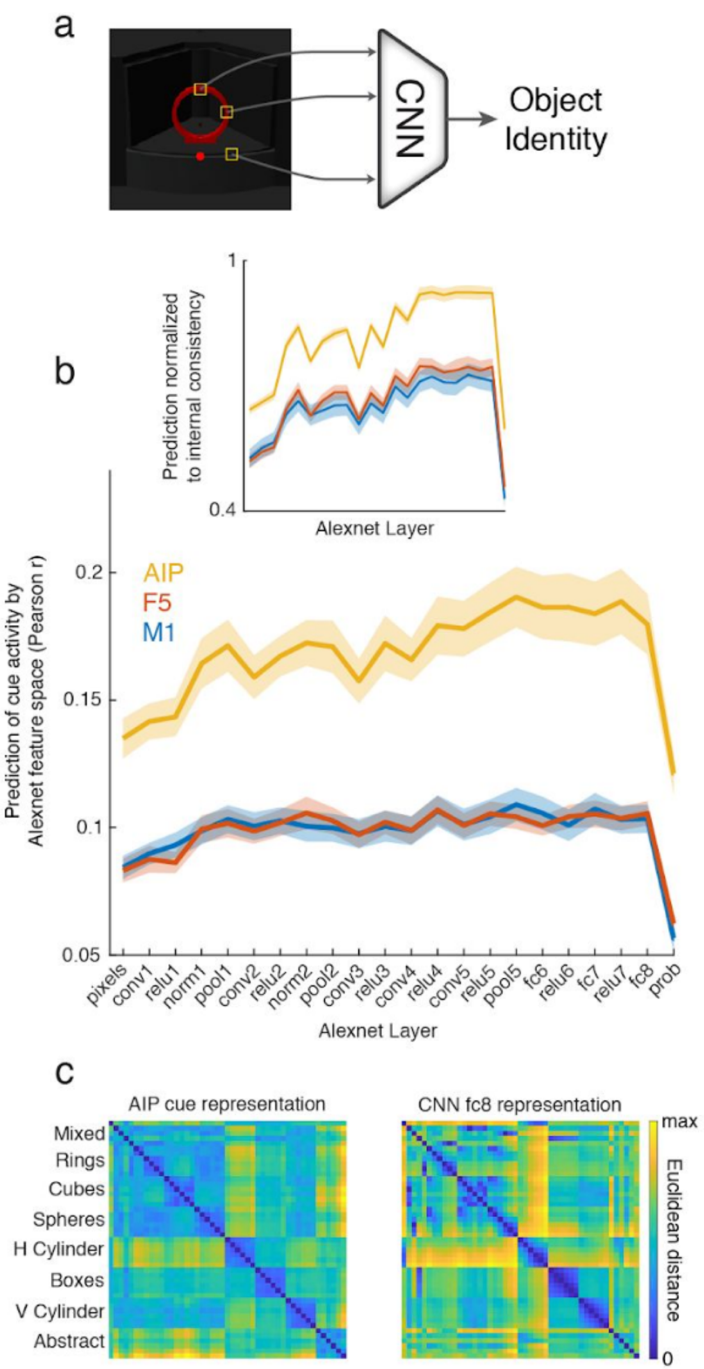


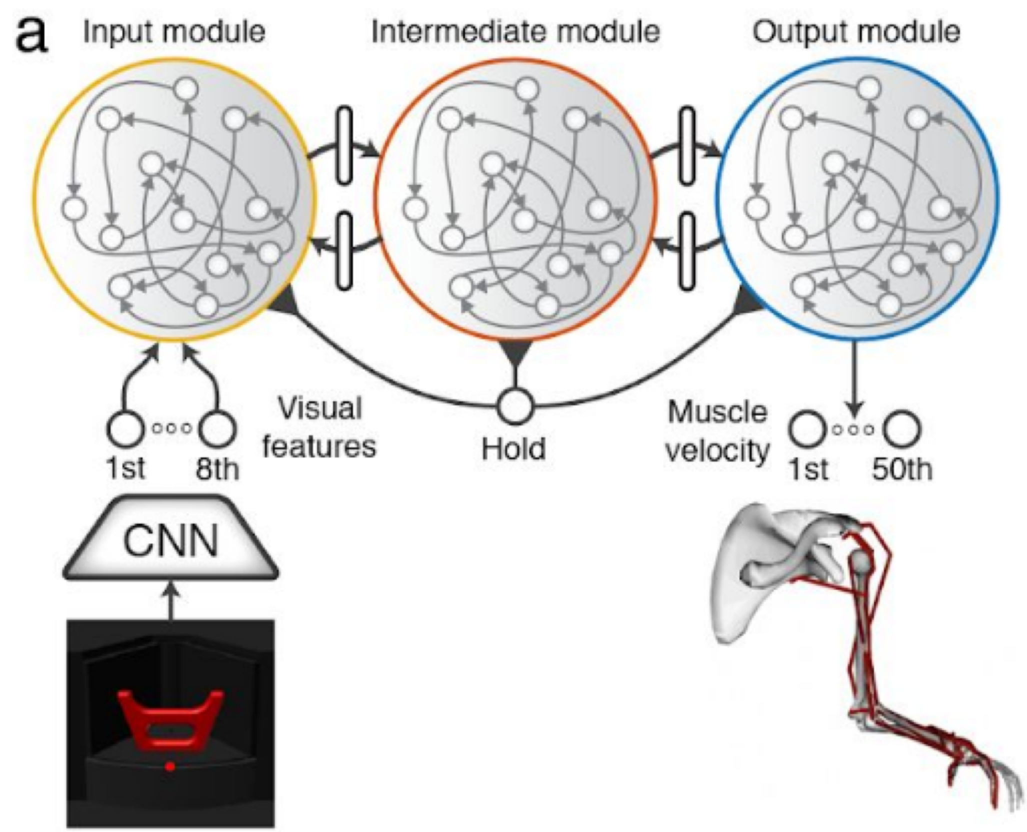
Measured Neural Firing Rate (a.u.)
Neural Site Number
Target Site
8°
4
0
-1
1
8

A neural network model of flexible grasp movementgeneration

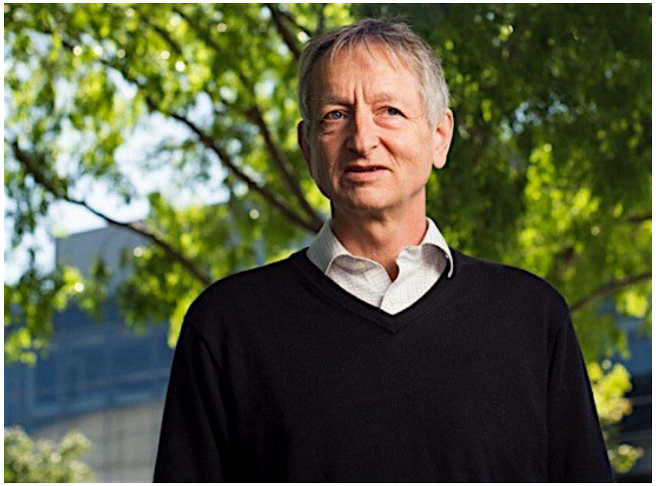


- Michaels et al., 2019


a
CNN
Object
Identity
b
1
0.4
Prediction normalized
to internal consistency
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

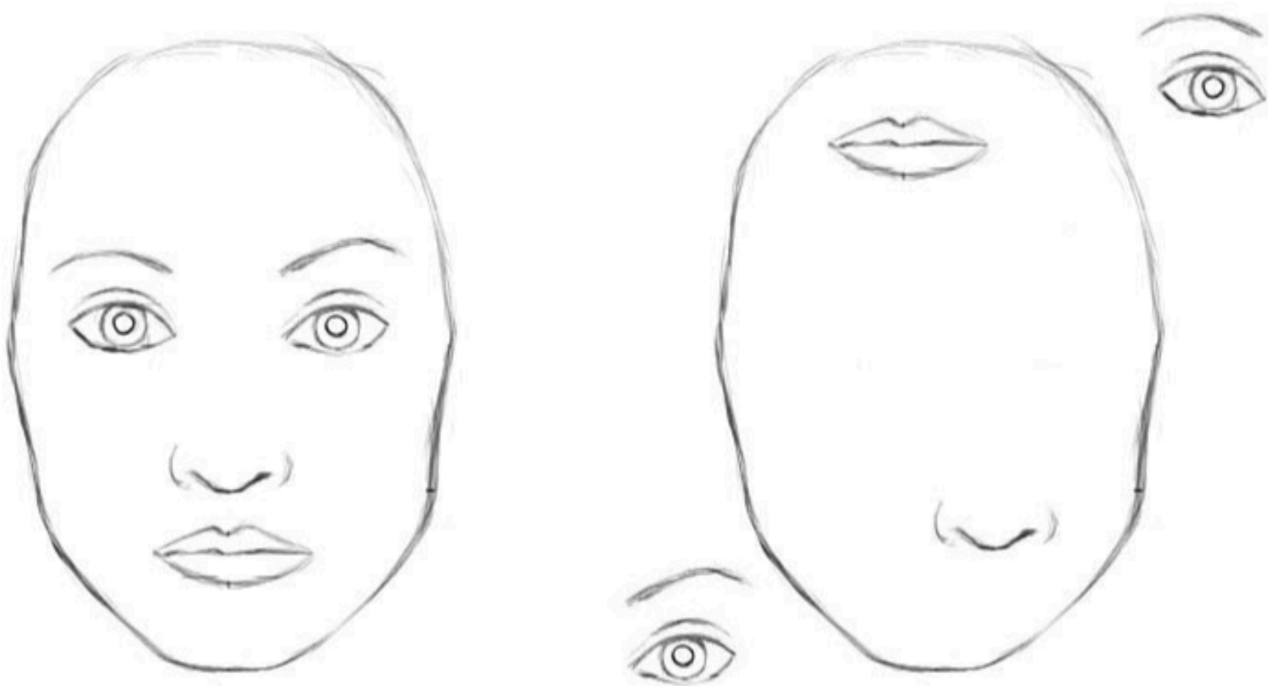

a
Input module
Intermediate module
Output module
Visual
features
1st
8th
Hold
Muscle
velocity
1st
50th
CNN

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*]