Neuro 140:
Biological & Artificial Intelligence

Feb 9th, 2021: Using AI in the laboratory
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Outline
3 – 5 PM

(1) Animal behavior in the laboratory: what problems could use “better” quantification of behavior?

(2) What are the challenges for video based analysis?

(3) How can deep neural networks help automate the process

(4) Transfer learning & pose estimation

~4 – 4:15 PM BREAK!

(5) Using transfer learning for robustness in o.o.d. data

(6) Google Colab intro / model zoo (if you have a dog/cat video, you can have it handy!)
Animal behavior in the lab: how to quantify the behavior?

Natural behaviors
- Robust & “simple” trial-based behaviors
- Classical conditioning

Complex & more variable (trial-based) behaviors
- Multi-directional reaching (and neural reconstruction with DL)

Diverse species, natural environments, many animals
- Looming stimulus

No trial structure
- Video: http://open.lib.umn.edu/intropsyc/

Diverse species, natural environments, many animals
Measuring behavior

observation → pose estimation → kinematics

- Image of a robot
- Image of a rat in a device
- Graph showing neuron activity and licking
- Graph showing joystick activity
- Graph showing time [s] vs. X, Y, and velocity with a reward line
Pose estimation in the laboratory

- Detailed pose
- Center of mass tracking

Time commitment & Inflexibility of tracking system

- Azim et al. 2014
- Wilschko et al. 2015
- Dell et al. 2014
- Berman 2018
- Vargas-Irwin et al. 2010
- Pereira et al. 2018
- Human motion capture systems

Manual annotation
Deep learning in the lab

DeepPose
DeeperCut
OpenPose
Conv. PoseMachines
...

DATA hungry algorithms... how to bring this to the lab?

Transfer Learning: take a trained network and ask it to learn a new task

ResNet-50 (or 101)
CNNs

VGG-19

3x3 conv, 64
3x3 conv, 64
3x3 conv, 128
3x3 conv, 128
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
fc 4096
fc 4096
fc 6

ResNet-152

7x7 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 128
3x3 conv, 128
152 layers

Image

Convolved Feature
ResNet-50 (or 101)

Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]
Do Better ImageNet Models Transfer Better?

Simon Kornblith, Jonathon Shlens, and Quoc V. Le
Google Brain
{skornblith, shlens, qvl}@google.com

![Graphs showing performance of different models](image)
Do Better ImageNet Models Transfer Better?

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Figure 1. Transfer learning performance is highly correlated with ImageNet top-1 accuracy for fixed ImageNet features (left) and fine-tuning from ImageNet initialization (right). The 16 points in each plot represent transfer accuracy for 16 distinct CNN architectures, averaged across 12 datasets after logit transformation (see Section 3). Error bars measure variation in transfer accuracy across datasets. These plots are replicated in Figure 2 (right).

Output:
Steel drum

Output:
Scale
T-shirt
Steel drum
Drumstick
Mud turtle

✓

✗
DeepGaze II: Reading fixations from deep features trained on object recognition

Matthias Kümmerer  Thomas S. A. Wallis  Matthias Bethge

Figure 1: The architecture of DeepGaze II. The activations of a subset of the VGG feature maps for a given image are passed to a second neural network (the readout network) consisting of four layers of \(1 \times 1\) convolutions. The parameters of VGG are held fixed through training (only the readout network learns about saliency prediction). This results in a final saliency map, which is then blurred, combined with a centre bias and converted into a probability distribution by means of a softmax.
Challenges for animal pose estimation in the laboratory

• animals have highly different bodies
• not practical to label >10,000 frames for training
• 3D postures
• fast video analysis for many experiments (such as closed-loop optogenetics)
• Multi-animal tracking
• Generalization & Robustness
DeepLabCut: animal pose estimation w/transfer learning

A. Mathis .... M.W. Mathis* and Bethge*
Nature Neurosci, 2018
DeepLabCut: a toolbox for markerless pose estimation
Benchmarking: testing accuracy
End-to-end training with more labels improves performance
Generalization: multi-mice

Mathis …. M.W. Mathis* and Bethge*
Nature Neurosci, 2018
Score-maps provide network confidence readout

A. Mathis et al, Nature Neuroscience 2018
DeepLabCut Horse Network

A. Erskine (Hires Lab)

J. Saunders

11 frames added....

Frame-by-frame predictions (no filtering)
Transfer learning enables deep learning in the lab

Pre-trained! (i.e. on ImageNet)

Only a few examples (10-200) for most applications

Deep learning + transfer learning
“Software 2.0” – integration of annotation, training and inference


Create a project, extract frames, + GUIs to label your data

Select + Train your deep neural network

Evaluate network performance
(active learning + GUIs if improvement needed)

Run inference on new videos, create labeled videos, + plot your results!

refine?

Mathis et al. Nature Neurosci, 2018
Nath* & Mathis* et al. Nature Protocols 2019
DeepLabCut: training one network for 3D tracking of a hunting cheetah
DeepLabCut: training one network for 3D tracking of a hunting cheetah

3D pose estimation

Courtesy Amir Patel (U of Cape Town)
Nath et al. Nat. Protocols, 2019
How does markerless pose estimation work?

Key Features:
- Data augmentation
- Model architecture
- Optimization

Mathis, Schneider, Lauer & Mathis, 2020
Neuron
Data Augmentation: how to get the most out of your data!

Mathis, Schneider, Lauer & Mathis
2020 Neuron
Create a project, extract frames, + GUIs to label your data

Select + Train your deep neural network

Evaluate network performance (active learning + GUIs if improvement needed)

Run inference on new videos, create labeled videos, + plot your results!

refine?

Mathis et al 2020 Neuron

refine:

28 frames added from another camera
Built on the open source python stack:

- Python
- TensorFlow
- NumPy
- Pandas

Insights from Computer Vision:

User testing/dev & deployment:

- Docker
- Amazon Web Services
- DataJoint

Neuroscience-specific tools:

- Bonsai
- Visual Reactive Programming
- AutoPilot

Post-pose estimation tools:

- Classifiers: SVMs, Random Forrest, ANNs, B-SOID, ETH-DLC Analyzer, simba
- Models: HMMs, decision-trees, ANNs
- Ethograms: BORIS, BASIN, BENTO
- Clustering: MoSeq, MotionMapper, JAABA
- Motor analysis: KINEMATIK

Larger scale pipeline computing:
How AI can influence new behavioral paradigms (and model systems...)

- Robust tracking can allow for more natural behaviors, and better analysis of classical paradigms ...

- Opens new research avenues in behavioral phenotyping, new tools for relating neural circuits to behavior ...

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- Complex & more variable (trial-based) behaviors

- Natural behaviors

- Diverse species, natural environments, many animals

http://open.lib.umn.edu/intropsych

C. Everett Bendesky lab

M. Meister/Cal Tech

C. Meister Bendesky lab

Looming stimulus

Classical conditioning

Robust & “simple” trial-based behaviors

No trial structure

Diverse species, natural environments, many animals
BREAK ....
ACROSS ALL MAMMALS …

ONE LABORATORY EXPERIMENT

EXPERIMENTS WITHIN A LAB

EXPERIMENTS ACROSS LABS?

ACROSS AN ANIMAL GROUP? (quadrupeds)

The larger the scale, the greater the diversity ….
How do we create generalizable pose estimation networks?
An animal pose benchmark (horses) for robustness
ImageNet performance correlates with pose estimation robustness and generalization on out-of-domain data.

More powerful architectures generalize better.
Transfer learning (using pretrained ImageNet models), gives a 2X boost on out-of-domain data vs. from scratch training.

Mathis*, Biasi* et al. 2021 WACV
Using transfer learning boosts out of domain robustness 
(bonus: 6× shorter training times, and less data required)
we present Horse-C to contrast the domain shift inherent in the Horse-10 dataset with domain shift induced by common image corruptions
Animal Pose Estimation Benchmarks for Robustness

Horse-10:
an animal pose estimation benchmark for out-of-domain robustness

Horse-C
an animal pose estimation corruption benchmark for robustness

Paper, data, etc. at: http://horse10.deeplabcut.org/

Robustness and Generalizability - How do we achieve them?

~2 min talk by first author, Tom Biasi:
https://www.youtube.com/watch?v=pM6Z-ASii2Y
Continual learning; adding small amounts of data from a new source to bring it “within domain”
Transfer learning: a more robust & generalizable network, plus less data needed
Google Colab demo!

https://colab.research.google.com/
DeepLabCut Model Zoo

Here we provide model weights that are already trained on specific animals & scenarios. You can use these models for video analysis (inference) without the need to train it yourself. Simply click on the blue icon to try it out on your videos now (and watch our tutorial):

model options:

full_cat
A pre-trained cat network. More details will be released soon. (video courtesy of Dr. Eric Died)

full_dog
A pre-trained dog network. More details will be released soon.

model contributed by Jim McIlwain at University of California, Riverside, USA!

mouse_pupil_vclose
A pre-trained mouse pupil detector. Video must be cropped around the eye (as shown). Trained on 637/36 mice eyes in 12 to 24 weeks (both sexes). Read more here!

http://modelzoo.deeplabcut.org