

Causal models of brain dynamics

Unsupervised learning of optogenetic experiments via deep
generative models

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2019-06-17

Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

Appendix

Roadmap

Motivation & Background
Aim 1: Spatial modeling with deep generative models
Aim 2: Optogenetic active learning
Aim 3: Contribution of cell-types and circuit motifs
Appendix

1. I will first talk about why my overall goal is predicting neural activity, and discuss the importance of causal models as opposed to merely descriptive ones. I will further motivate this modeling goal by describing applications that are enabled by this approach.
2. In my first aim, I propose that a reasonable direction is to eschew biological plausibility and leverage state-of-art deep learning networks for predicting neural activity, and show that this approach outperforms current brain-wide modeling.
3. For my second aim, I propose a model-based approach to choosing optogenetic stimulation patterns such that we efficiently learn the best model parameters.
4. Finally, in my third aim, I suggest methods to incorporate biological priors as well as explicitly extract biological hypotheses.

Whole-brain prediction facilitates construction of causal models



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biology
↓
model
↓
observations

biology



model



observations

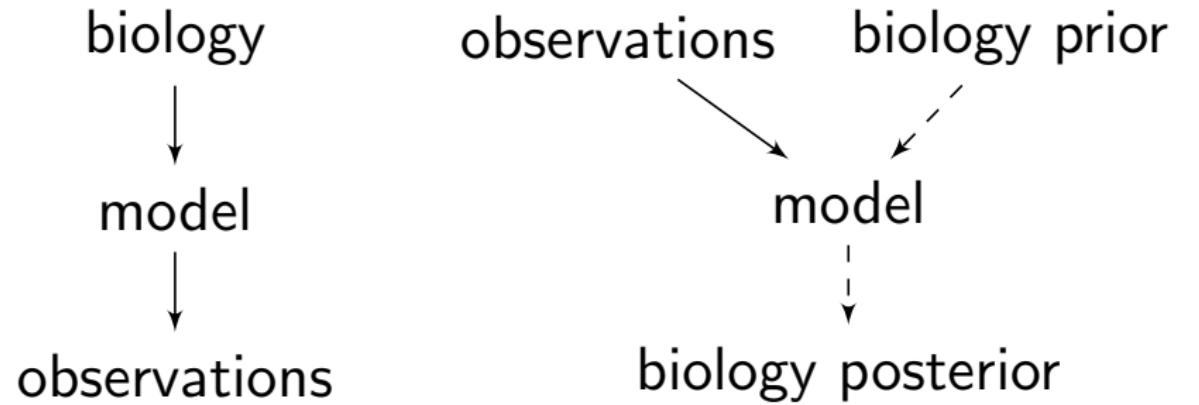
└ Whole-brain prediction facilitates construction of causal models

1. Data-driven approach may result in empirically more accurate model.

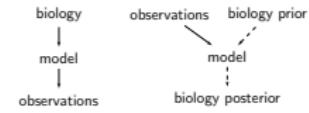
Whole-brain prediction facilitates construction of causal models



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└ Whole-brain prediction facilitates construction of causal models

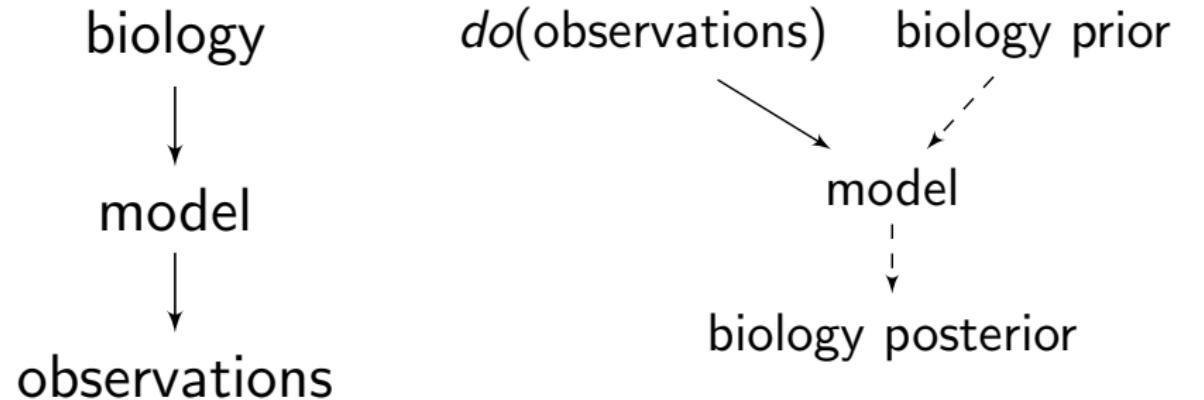


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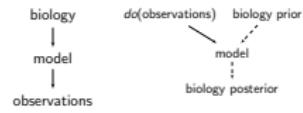
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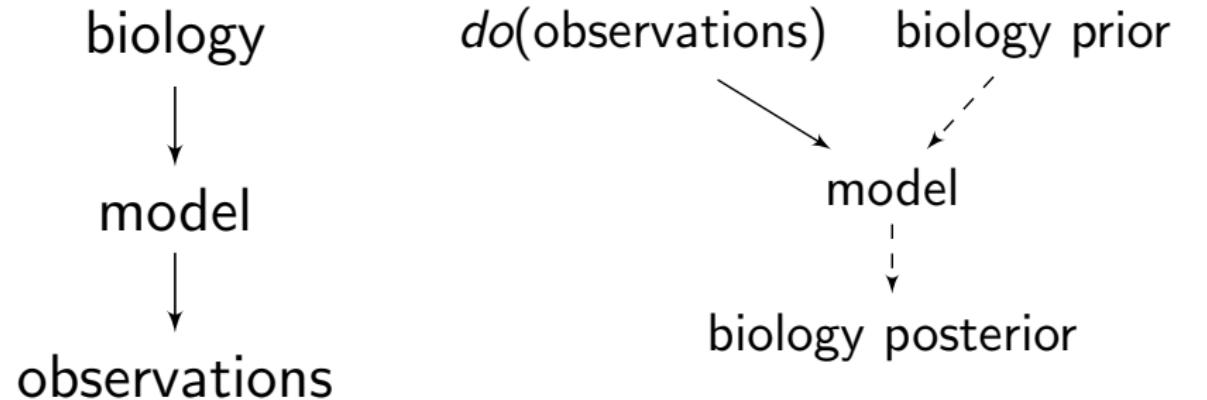


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Whole-brain prediction facilitates construction of causal models

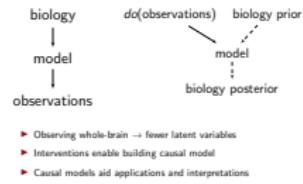


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- ▶ Observing whole-brain → fewer latent variables
- ▶ Interventions enable building causal model
- ▶ Causal models aid applications and interpretations

└ Whole-brain prediction facilitates construction of causal models





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What is the most effective approach to predict whole-brain observations?

- ▶ State-of-art performance in video prediction is achieved by deep generative models
- ▶ Collected preliminary brain-wide calcium data during an optomotor behavior
- ▶ Initial modeling results suggest that spatial modeling out-performs traditional point process models of neurons

└ Aim 1: Spatial modeling with deep generative models

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How do we resolve model underdetermination?

- ▶ For complex models fit to finite observations, multiple choices of parameters may perform equally well
- ▶ We can resolve this by testing if model substructures are causal with optogenetics
- ▶ First experiment failed due to poor optogenetic activation, but a new more-sensitive opsin will make the experiment easier

└ Aim 2: Optogenetic active learning

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Aim 3: Contribution of cell-types and circuit motifs



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Do model substructures map to underlying biology?

- ▶ *in situ* hybridization (ISH) and connectome data contribute to understanding of colored graphs that underlie functional observations
- ▶ First attempt to add excitatory and inhibitory staining as an additional model input modestly hurt performance
- ▶ Training model to predict ISH data will force model to maintain representation of cell type
- ▶ Known circuit motifs can be used as a prior, or we can try to discover structure using structure active learning

Aim 3: Contribution of cell-types and circuit motifs

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Appendix



flickr:zigazou76 CC BY 2.0

Motivation & Background

- Motivation & Background

- Model-based summaries of health vs disease

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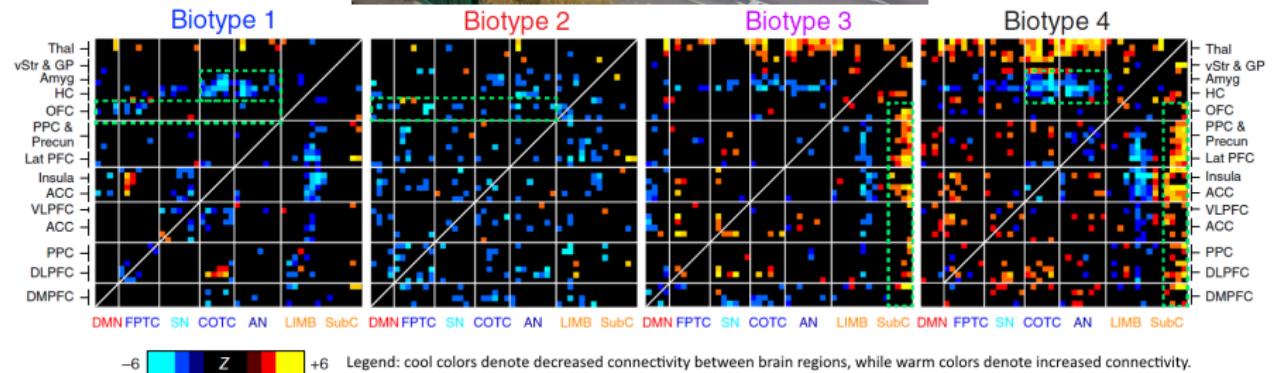


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Let's draw an analogy for healthy vs diseased dynamics: safe vs dangerous driver.

1. static vs temporal: in defensive driving, want to keep staggered position. In static view, minivan driver is dangerous but in temporal view may be healthy as is simply passing the subaru.
2. unit vs population: consider the black sedan following the minivan. If it maintains a consistent following distance by accelerating and braking, then a safe driver, but in a vaccuum with no information of other cars, looks completely erratic.

Model-based summaries of health vs disease



flickr:zigazou76 CC BY 2.0

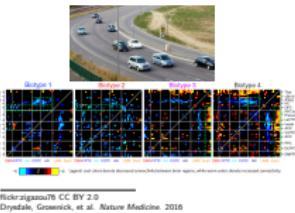
Drysdale, Gosenick, et al. *Nature Medicine*. 2016

Motivation & Background

- Motivation & Background

- Model-based summaries of health vs disease

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Four functional connectivity "biotypes" from fMRI study of depressed patients. Has no notion of time (one true underlying phenotype capturing different snapshots?), and is not a causal model—where should we stim to nudge dynamics back towards health?

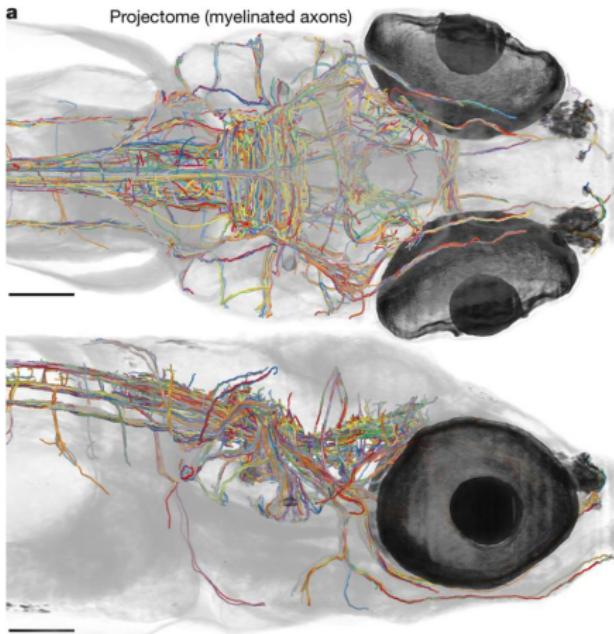
Applications:

- muck with gene, a lot changes → create summary
- “outlierness” of brain dynamics
- model gives reduction of whole data

Bern & Molley 2013 for reliability of resting state fMRI.

transition: lack of spatial resolution motivates jump model organism where we can observe whole-brain at cellular resolution.

Challenge: high underlying complexity as shown by partial zebrafish projectome



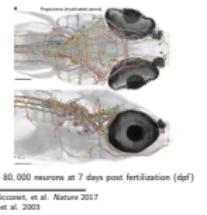
~ 80,000 neurons at 7 days post fertilization (dpf)

Hildebrand, Cicconet, et al. *Nature* 2017
Hill, Howard, et al. 2003

Motivation & Background
└ Motivation & Background

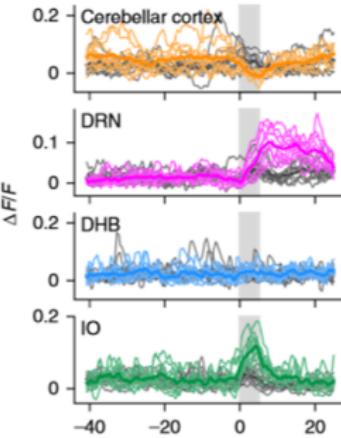
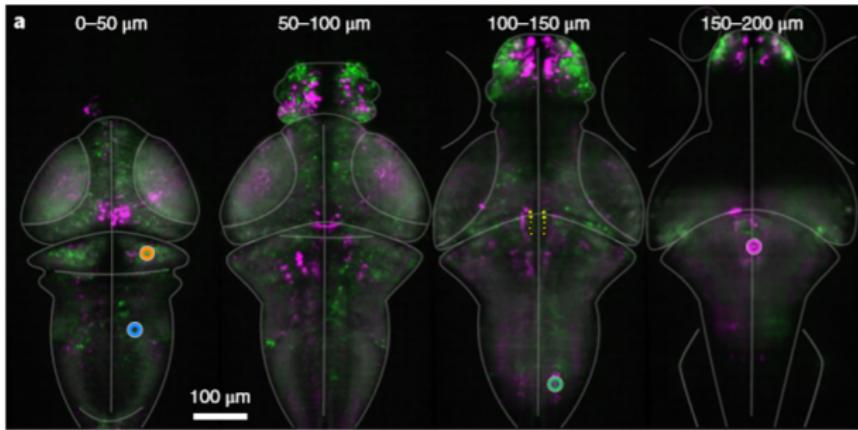
└ Challenge: high underlying complexity

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Opportunity: massive datasets

Whole-brain imaging & stimulation



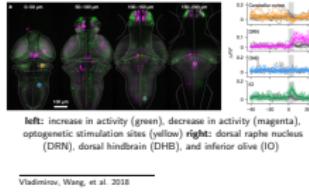
left: increase in activity (green), decrease in activity (magenta),
optogenetic stimulation sites (yellow) **right:** dorsal raphe nucleus
(DRN), dorsal hindbrain (DHB), and inferior olive (IO)

Vladimirov, Wang, et al. 2018

Motivation & Background

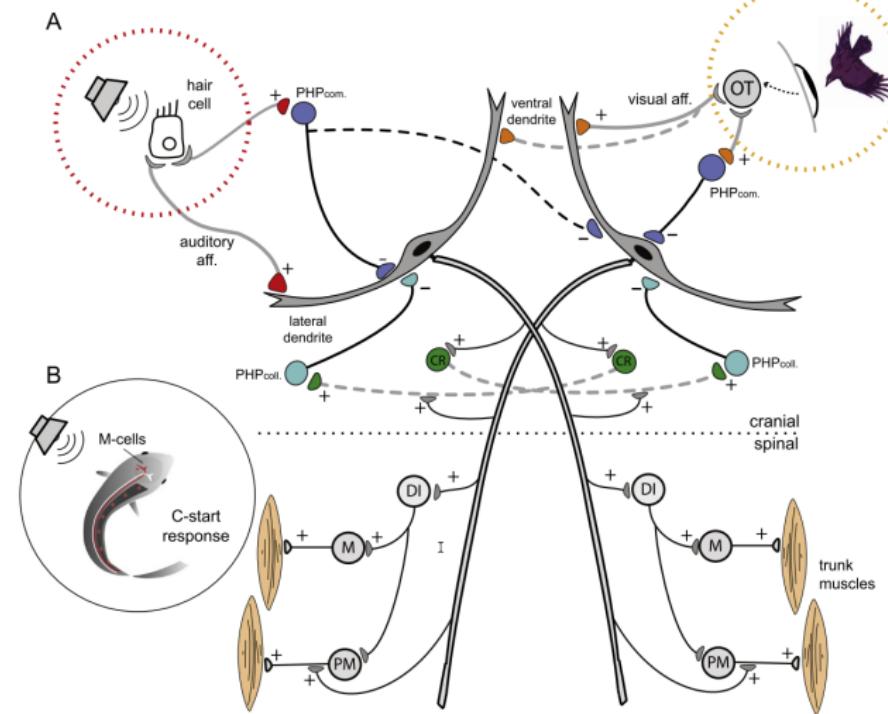
- Motivation & Background

- Opportunity: massive datasets



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Validate modeling results through comparison to well-characterized Mauthner circuit



Medan & Preuss, 2014

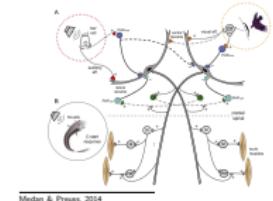
Motivation & Background

Motivation & Background

Validate modeling results through comparison to well-characterized Mauthner circuit

M-cell AP → negative field potential of 20–40 mV close to axon hillock

Schematic shows the paired Mauthner cells (M-cells), their visual and statoacoustic inputs and cranial inhibitory networks. Each M-cell receives bilateral visual inputs and ipsilateral auditory inputs. The schematic shows only the left auditory afferents (red) and the right visual afferents (orange). The auditory pathway is direct, as hair cells activate auditory nerve afferents with synapses on the M-cell's lateral dendrite and also excite bilaterally-projecting feedforward inhibitory interneurons, the commissural PHP cells (blue). The collateral PHP neuron population (coll., light blue) mediates recurrent (feedback) inhibition triggered by firing of either ipsilateral or contralateral M-cells that is conveyed through the cranial relay neurons (CR, green). The polysynaptic visual pathway conveys information from the retina to the optic tectum (OT) which sends afferents that contact both M-cells ventral dendrite. M-cell axons exit the medulla through the spinal cord to make direct contact with primary motoneurons (PM) and indirect contact with other motoneurons (M) through a set of interneurons (DI). Spinal inhibitory networks and cranial motoneurons are omitted to simplify the schematic. A single action potential in one of the M-cell produces contraction of contralateral trunk muscles producing the characteristic C-shape that initiates the startle response or C-start (B).



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Aim 1: Spatial modeling with deep generative models



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What is the most effective approach to predict whole-brain observations?



Hypothesis: deep learning spatial models will outperform point process models

- ▶ Extract neuron fluorescent traces → build RNN
- ▶ Raw fluorescent observations → convolutional deep learning model
- ▶ Compare prediction performance on withheld test data

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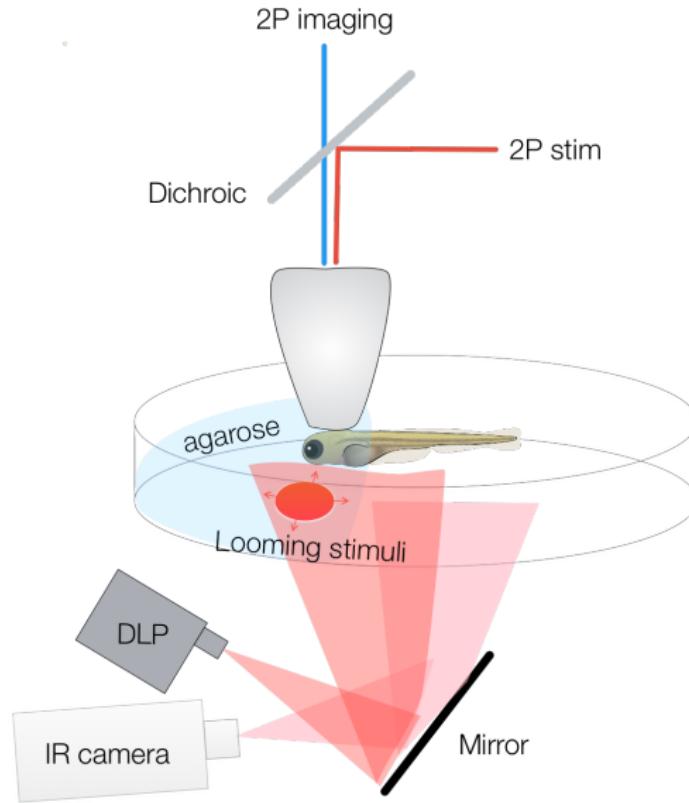
- Aim 1: Spatial modeling with deep generative models
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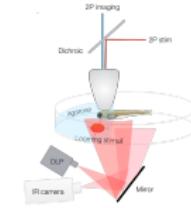
The main buy-in for this talk is that having an accurate model of brain dynamics is useful. Most approaches today for brain-wide modeling use hand-crafted features in a preprocessing pipeline that throws away spatial information. How much better can we do at predicting activity if we do not constrain our modeling by biological plausibility?

2P Experimental setup



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Aim 1: Spatial modeling with deep generative models
└ Aim 1: Spatial modeling with deep generative models
└ 2P Experimental setup



Whole-brain 2P calcium imaging

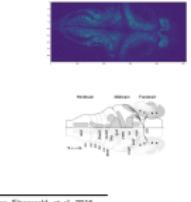
Z-projection of 19 planes, 4x real-time, 2Hz



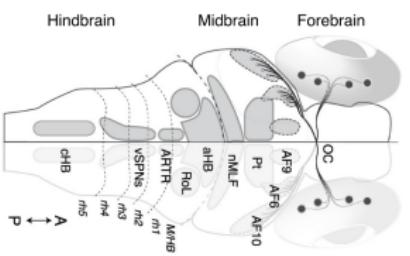
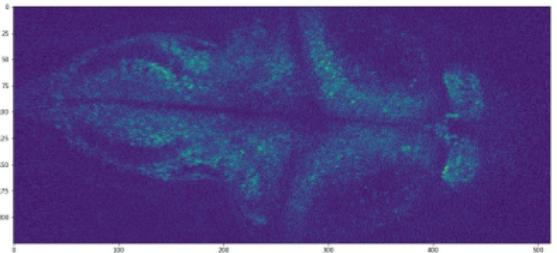
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Aim 1: Spatial modeling with deep generative models

- └ Aim 1: Spatial modeling with deep generative models
 - └ Whole-brain 2P calcium imaging



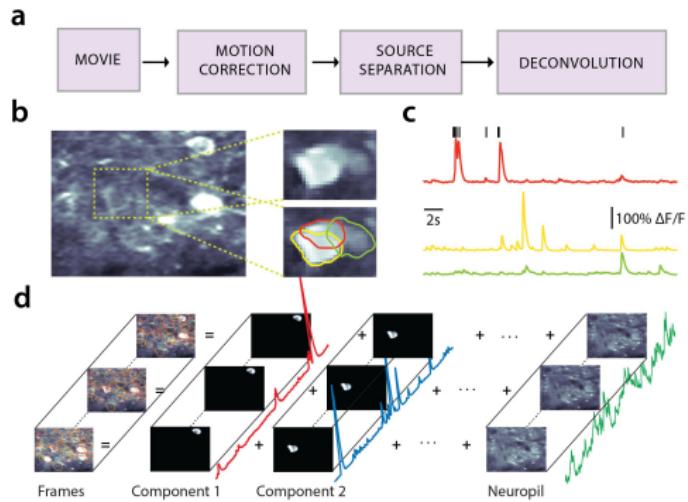
McKeehan, Firestone et al., 2018



need to change 2P offset for bidirectional imaging: 2px jitter line-to-line

1. resting state video, no external stimuli
2. highlight brain deformation during tail movement
3. This is a video. About 2/3 way through, brain goes completely dark (!!), then whole brain lights up.
4. Dorsal overview of zebrafish neuroanatomy. DSRGCs (black dots) project via the optic chiasm (OC) to ten contralateral retinal arborization fields(AFs). Pt,prepectum; nMLF, nucleus of the medial longitudinal fasciculus; aHB, anterior hindbrain; RoL, neurons in rhombomere 1; ARTR, anterior rhombencephalic turningregion; vSPNs, ventromedial spinal projection neurons; cHB, caudal hindbrain; M/HB, midbrain-hindbrain border; rh1–5, rhombomeres 1–5. A, anterior; P,posterior.

Current approaches to brain-wide modeling

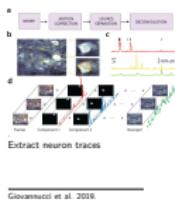


Extract neuron traces

Giovannucci et al. 2019.

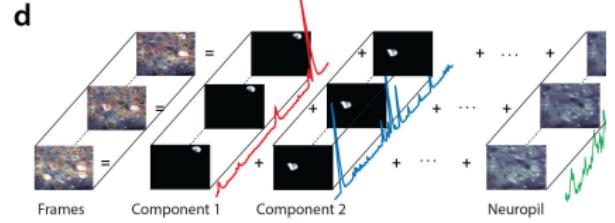
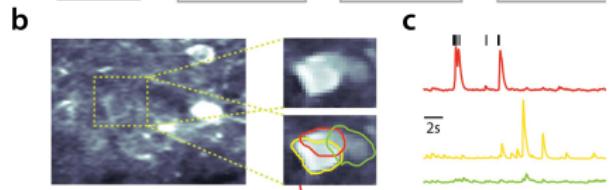
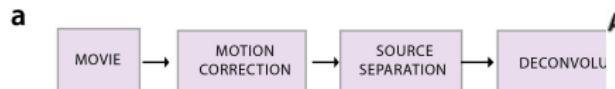
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- Aim 1: Spatial modeling with deep generative models
 - └ Aim 1: Spatial modeling with deep generative models
 - └ Current approaches to brain-wide modeling



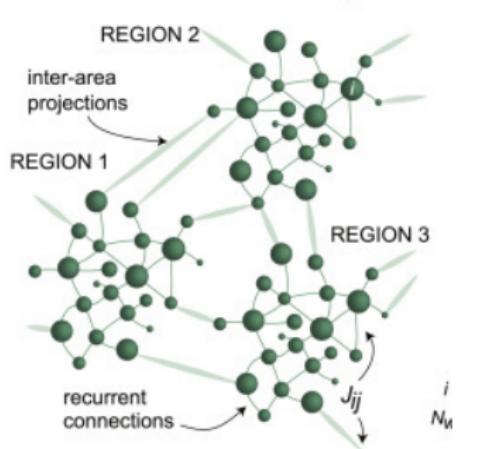
In the early days of machine vision, researchers often used handcrafted feature extractors like edge detection to extract lower dimensional features that are then fed into a model. Today, neuroscience is similar: we motion correct a raw movie, identify independent spatial components, separate the sources, and attempt to whiten the signal based on assumptions of calcium indicator dynamics.

Current approaches to brain-wide modeling



Extract neuron traces

A Neural Network Model Design

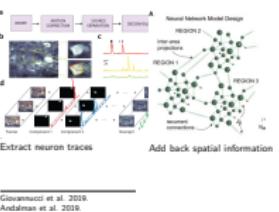


Add back spatial information

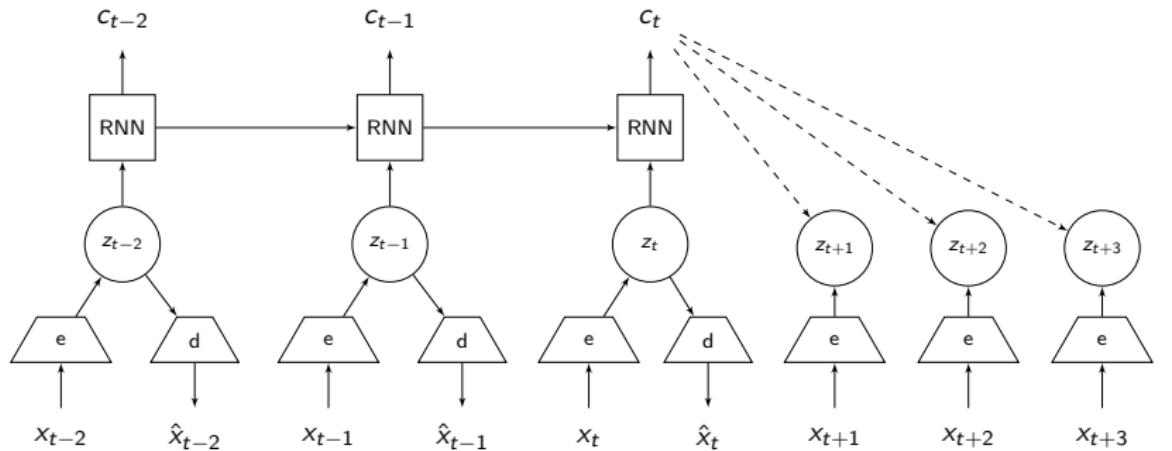
Giovannucci et al. 2019.
Andalman et al. 2019.

- Aim 1: Spatial modeling with deep generative models
└ Aim 1: Spatial modeling with deep generative models
└ Current approaches to brain-wide modeling

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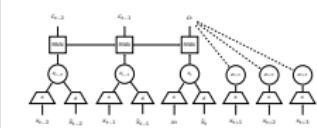


In general, modeling a recurrent neural network is intractable as the number of parameters grows quadratically with a number of neurons. Thus, brain-wide modeling usually involves a sparsity prior based on spatial location. In the neuroscience literature, it is not yet the norm to evaluate performance of modeling on held-out test data so we typically evaluate modeling based on how well it matches previous findings in the literature.



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Aim 1: Spatial modeling with deep generative models
└ Aim 1: Spatial modeling with deep generative models
└ Latent-space volume prediction

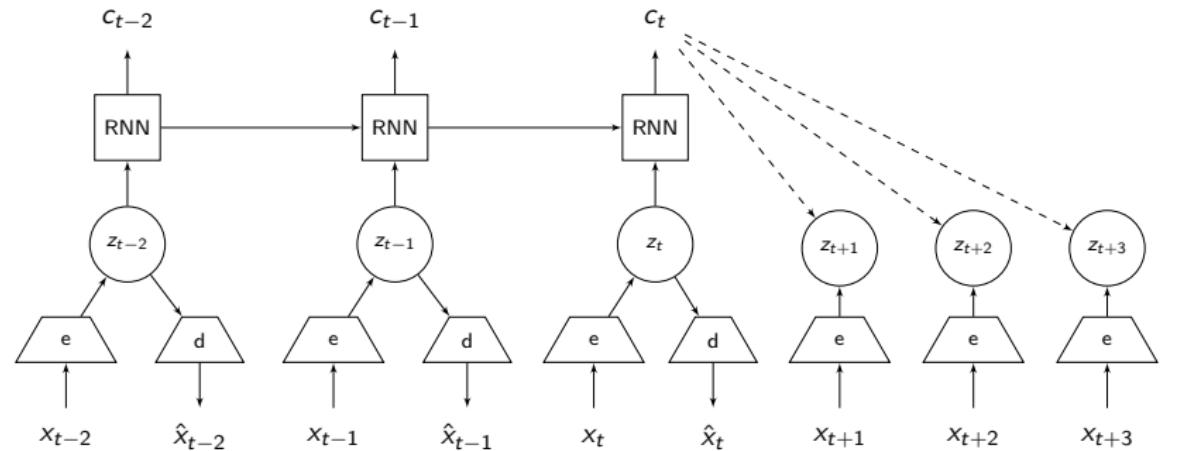
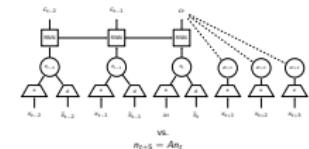


Deep learning approach seems powerful, how well does it work? We're going to do both approaches and compare: CNMF vs raw.feedback: maybe show schematic of what is being compared?



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Aim 1: Spatial modeling with deep generative models
 └─Aim 1: Spatial modeling with deep generative models
 └─Latent-space volume prediction

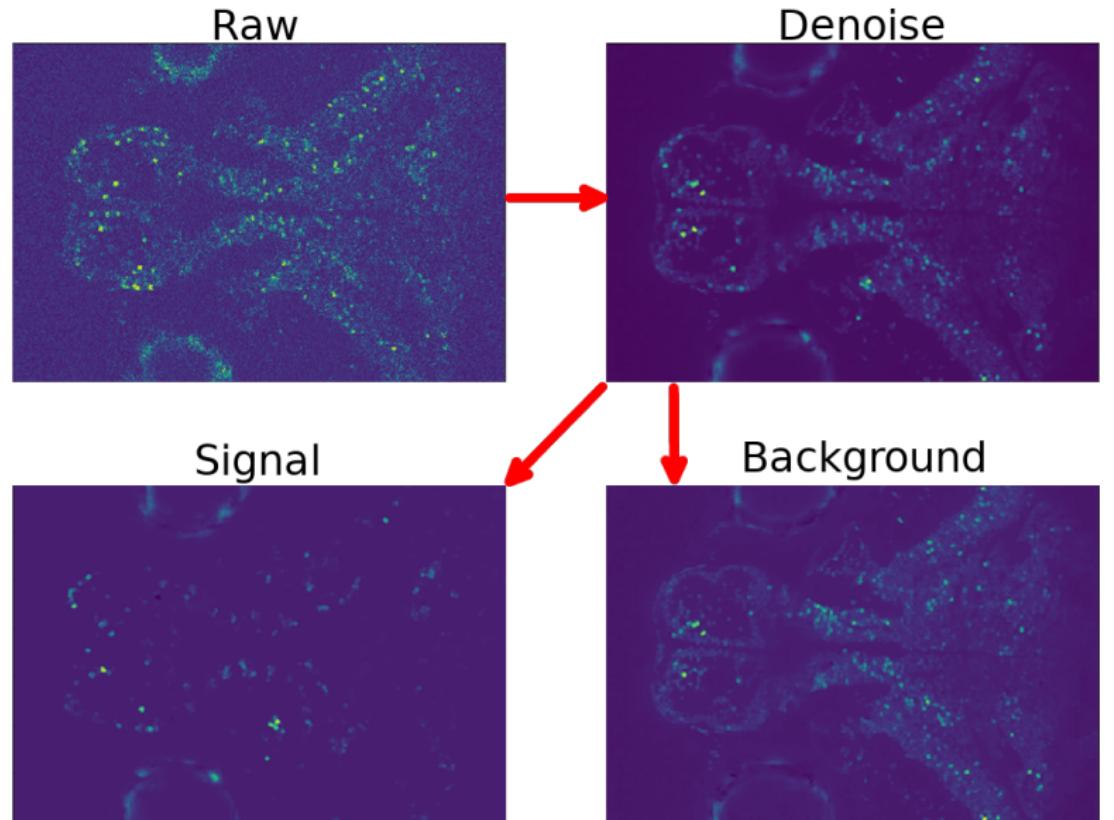


vs.

$$n_{t+5} = An_t$$

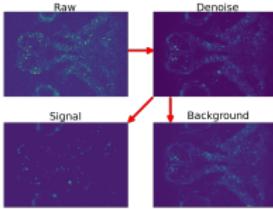
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Mapping CNMF to space

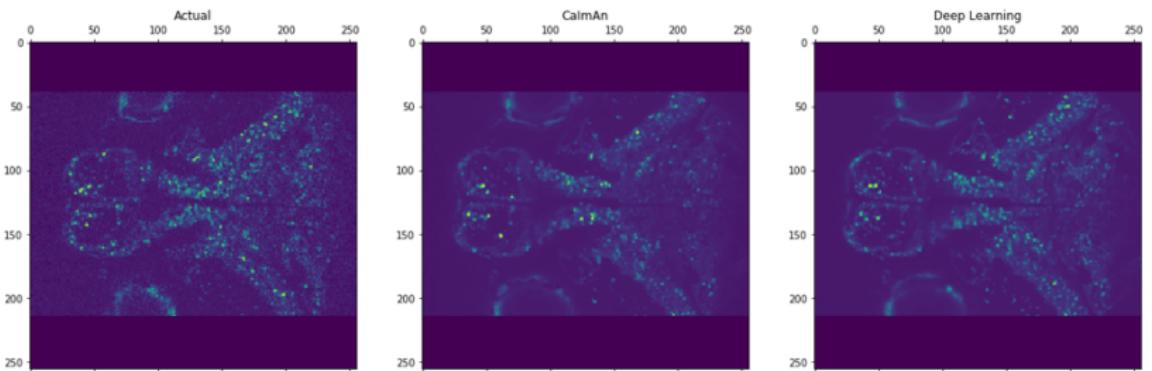


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Aim 1: Spatial modeling with deep generative models
└ Aim 1: Spatial modeling with deep generative models
└ Mapping CNMF to space



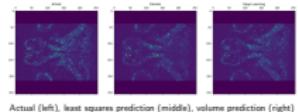
Train data: LS and VP perform equally well
< 5% difference in MSE



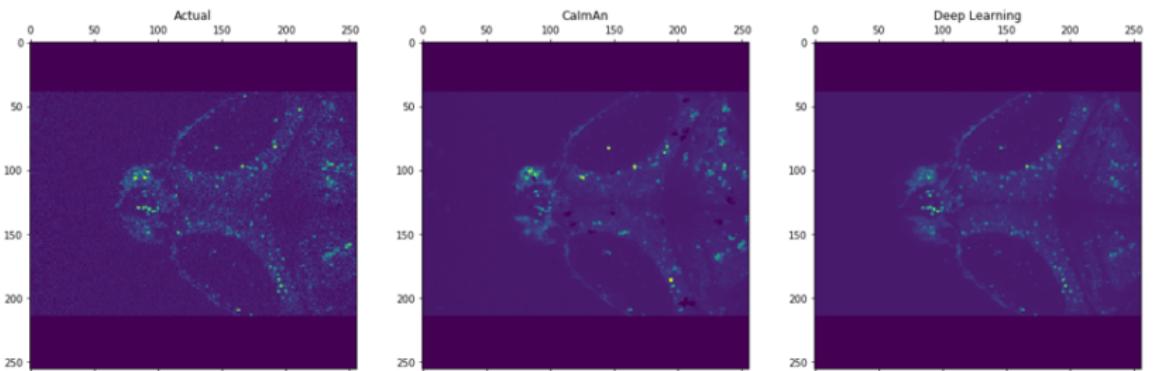
Actual (left), least squares prediction (middle), volume prediction (right)

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Aim 1: Spatial modeling with deep generative models
└ Aim 1: Spatial modeling with deep generative models
└ Train data: LS and VP perform equally well



Test data: VP performs better
LS has 150% greater MSE than VP

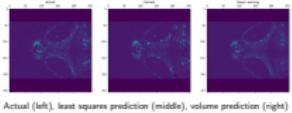


Actual (left), least squares prediction (middle), volume prediction (right)

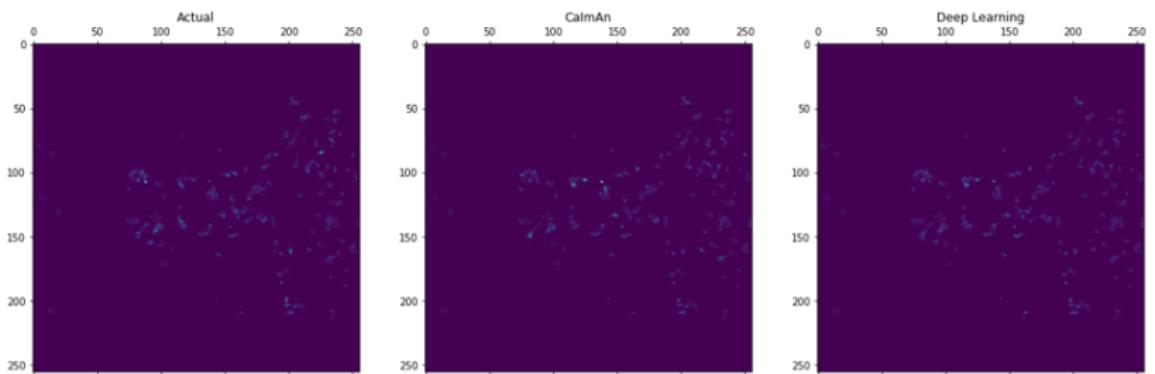
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Aim 1: Spatial modeling with deep generative models

- └ Aim 1: Spatial modeling with deep generative models
- └ Test data: VP performs better



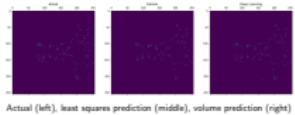
Masked test data: VP performs better LS has 40% greater MSE than VP



Actual (left), least squares prediction (middle), volume prediction (right)

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- Aim 1: Spatial modeling with deep generative models
 - └ Aim 1: Spatial modeling with deep generative models
 - └ Masked test data: VP performs better



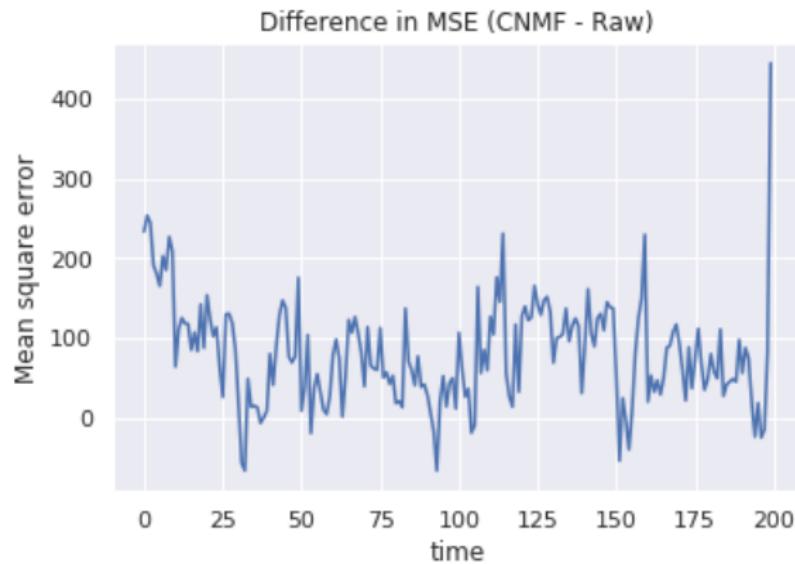
CNMF preprocessing reduces VP performance

Evaluated loss on neuron mask



Aim 1: Spatial modeling with deep generative models
└ Aim 1: Spatial modeling with deep generative models
└ CNMF preprocessing reduces VP performance

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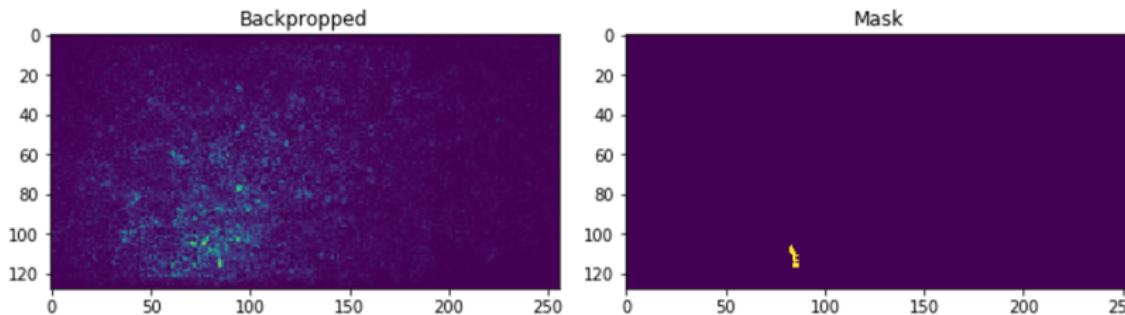
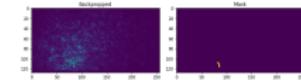
Extracting causal hypotheses

Voxels used for predicted locus coeruleus activation



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- Aim 1: Spatial modeling with deep generative models
 - └ Aim 1: Spatial modeling with deep generative models
 - └ Extracting causal hypotheses



Ask model what is important; here we use backprop

Aim 2: Optogenetic active learning



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Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning

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Appendix

Active learning, also known as optimal experiment design, is a field that concerns itself with estimating statistical models with as few experiments as possible. Existing literature deals mostly with cases where we can choose exactly what to sample; for example, OED has been deployed in the design of guide RNAs for CRISPR gene editing. In our case, we can only choose the stimuli not the entire brain state. Thus, a causal model will be essential for the penultimate application: brain state replay.

How do we resolve model underdetermination?



Hypothesis: Model-based optimal experiment design will reduce underdetermination

- ▶ We can choose optimal optogenetic stimuli to maximally reduce model parameter uncertainty
- ▶ This can be potentially be done online
- ▶ We can evaluate how well we have done by attempting to track a brain trajectory

Aim 2: Optogenetic active learning
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Active learning

Best to ask for category of which image?



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Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning
 └ Active learning



1. For which photo would you ask the oracle for a label?

Active learning

Best to ask for category of which image?



Cat

Mom & Dad. *personal correspondence*. 2016.

Instagram:atchoumthecat

Wikipedia CC BY-SA 3.0

Aim 2: Optogenetic active learning

└ Aim 2: Optogenetic active learning

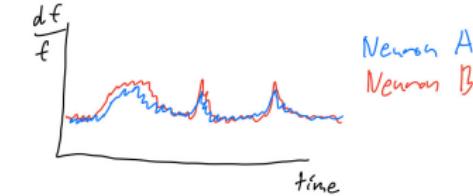
└ Active learning

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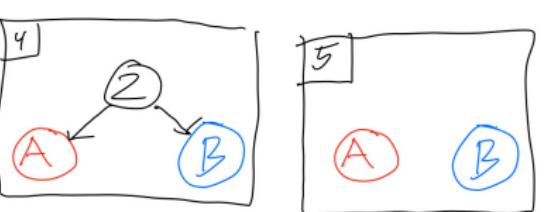
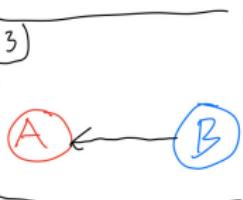
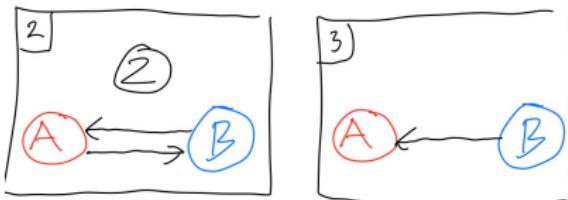
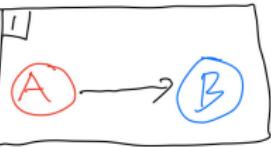


Mom & Dad. *personal correspondence*. 2016.
Instagram:atchoumthecat
Wikipedia CC BY-SA 3.0

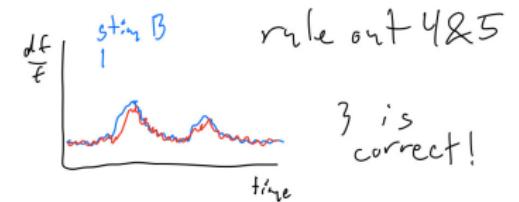
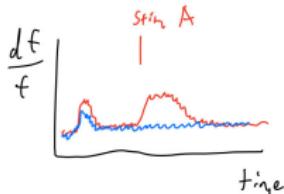
Interventions resolve model underdetermination



Possible models:



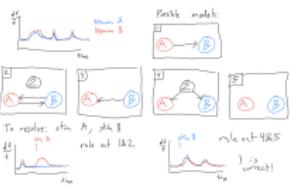
To resolve: stim A, stim B
rule out 1&2



Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning

└ Interventions resolve model underdetermination

We discuss single neuron stim for intuition. For multi-neuron stim, easier to think in terms of latent space.



Bayesian Active Learning by Disagreement



We want to maximize the decrease in expected posterior entropy of model parameters:

$$\underset{s_t}{\operatorname{argmax}} H[\theta|x_{1:t}] - \mathbf{E}_{x_{t+1}}[H[\theta|s_t, x_{t+1}, x_{1:t}]] \quad (1)$$

Entropy of model parameters θ is intractable. So we rearrange to:

$$\underset{s_t}{\operatorname{argmax}} H[x_{t+1}|s_t, x_{1:t}] - \mathbf{E}_\theta[H[x_{t+1}|s_t, x_{1:t}, \theta]] \quad (2)$$

Houlsby, Huszár, et al. 2011

Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning

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└ Bayesian Active Learning by Disagreement

We want to maximize the decrease in expected posterior entropy of model parameters:

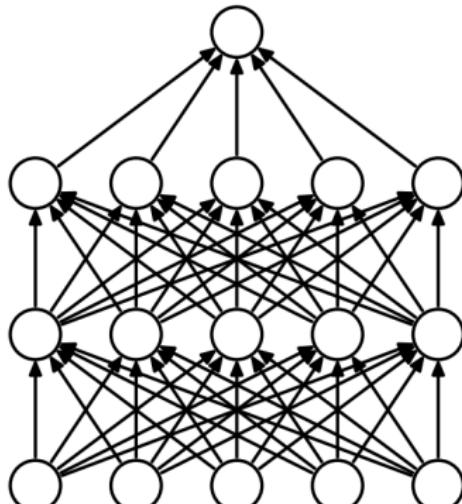
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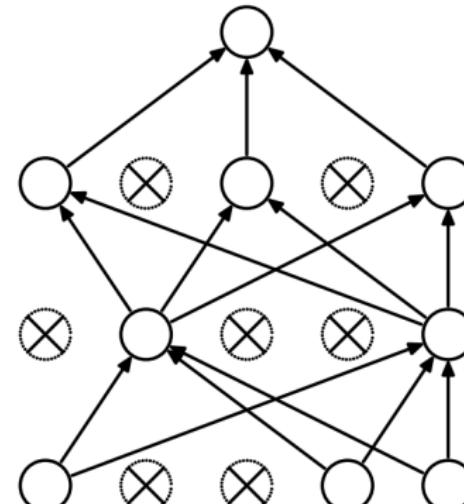
$$\underset{x_{t+1}}{\operatorname{argmax}} H[x_{t+1}|s_t, x_{1:t}] - \mathbf{E}_\theta[H[x_{t+1}|s_t, x_{1:t}, \theta]] \quad (2)$$

Houlsby, Huszár, et al. 2011

Bayesian deep learning via dropout



(a) Standard Neural Net



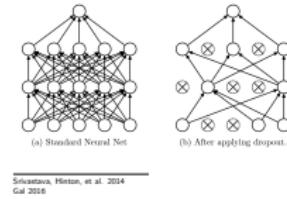
(b) After applying dropout.

Srivastava, Hinton, et al. 2014
Gal 2016

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Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning

└ Bayesian deep learning via dropout



Collect data then iterate the approach offline



Data collection:

- 1 180 trials of looming stimuli (1 hour)
- 2 360 trials of random single-cell perturbation (1 hour)
- 3 180 trials of looming stimuli (1 hour)

Data analysis:

- ▶ train on 80% of trials from [1 & 3]
- ▶ choose 60 trials from [2]
- ▶ Test on withheld trials from [1 & 3]

How much better can we do by choosing trials vs random trials in terms of test performance?

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Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning

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Online optimal experiment design



Data collection:

- 1 225 trials of looming stimuli (1 hour 15 min)
- 2 360 trials, model chooses each single-cell perturbation (1 hour)
- 3 225 trials of looming stimuli (1 hour 15 min)

How well can we predict test data by training on 2 hours of looming stimuli vs 1 hour looming & 1 hour optogenetics?

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Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning

└ Online optimal experiment design

Data collection:

1 225 trials of looming stimuli (1 hour 15 min)

2 360 trials, model chooses each single-cell perturbation (1 hour)

3 225 trials of looming stimuli (1 hour 15 min)

How well can we predict test data by training on 2 hours of looming stimuli vs 1 hour looming & 1 hour optogenetics?

1. Once we've validated offline, can try online. How much can we condense model learning / improve performance?
2. Additional advantage of spatial model is no need for motion correction as convolution is translation invariant. Potential advantage over onACID (online CNMF).

Brain state replay



Aim 2: Optogenetic active learning
└ Aim 2: Optogenetic active learning
 └ Brain state replay

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Data collection:
1 Acquire brain trajectory of interest
2 choose each stimulation pattern sequentially during resting state / experiment of interest
3 Stim brain to keep observations in line with [1]
How well can we track a previously observed trajectory?

Data collection:

- 1 Acquire brain trajectory of interest
- 2 choose each stimulation pattern sequentially during resting state / experiment of interest
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How well can we track a previously observed trajectory?

Aim 3: Contribution of cell-types and circuit motifs



Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

Appendix

Aim 3: Contribution of cell-types and circuit motifs
└ Aim 3: Contribution of cell-types and circuit motifs
└ Aim 3: Contribution of cell-types and circuit motifs

1. Aim 1&2 are about what we can do with best-in-class models; aim 3 is about simplifying the model / making more biologically compatible. Less complexity but simpler. How close in performance can we get to “gold standard” model from Aim 1 & 2?
2. First, we introduce prior work on functional motif discovery via optogenetics.
3. Next, I will discuss possible biological priors and constraints

Motivation & Background
Aim 1: Spatial modeling with deep generative models
Aim 2: Optogenetic active learning
Aim 3: Contribution of cell-types and circuit motifs
Appendix

Do model substructures map to underlying biology?



Hypothesis: Enforcing causal biological constraints will improve model performance while aiding interpretation

1. Requiring model to predict *in situ* hybridization allows for interpretation of cell-type contribution to dynamics
2. Template-based representations allow for unsupervised learning of purported circuit motifs

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Aim 3: Contribution of cell-types and circuit motifs
└ Aim 3: Contribution of cell-types and circuit motifs
└ Do model substructures map to underlying biology?

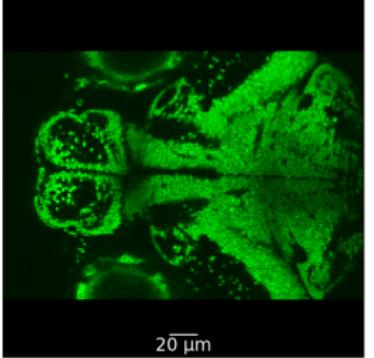
Hypothesis: Enforcing causal biological constraints will improve model performance while aiding interpretation

1. Requiring model to predict *in situ* hybridization allows for interpretation of cell-type contribution to dynamics
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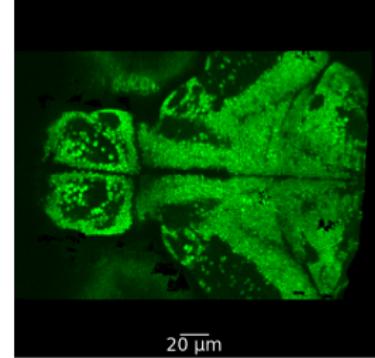
in situ cell type identification



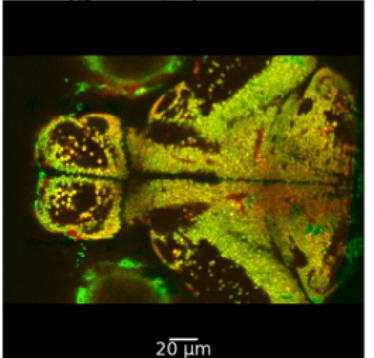
GCamP6s alive (isosbestic)



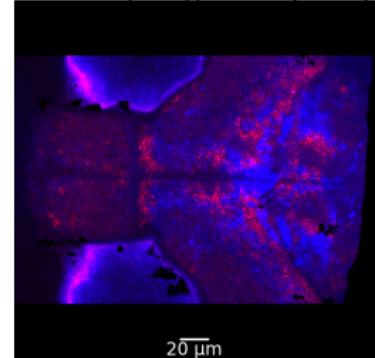
GCamP6s post-fix (isosbestic)



alive (green), post-fix (red)

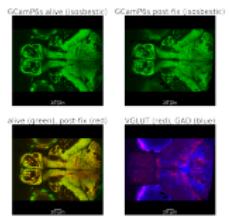


VGLUT (red), GAD (blue)

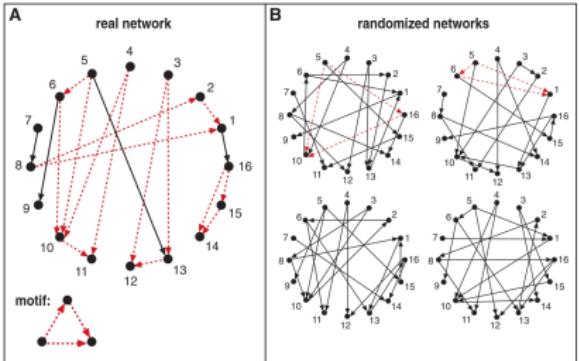


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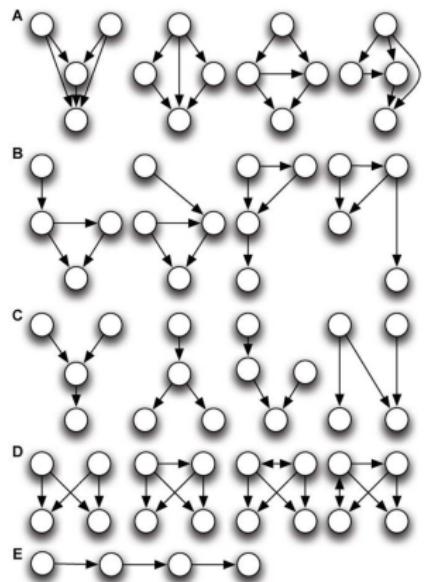
Aim 3: Contribution of cell-types and circuit motifs
└ Aim 3: Contribution of cell-types and circuit motifs
 └ *in situ* cell type identification



Network motifs



Schematic illustrating an over-represented motif



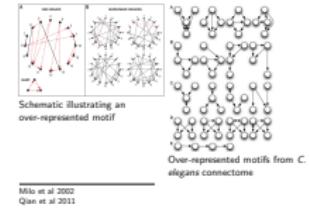
Over-represented motifs from *C. elegans* connectome

Milo et al 2002
Qian et al 2011

Aim 3: Contribution of cell-types and circuit motifs
└ Aim 3: Contribution of cell-types and circuit motifs

└ Network motifs

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For a stringent comparison, we used randomized networks that have the same single-node characteristics as does the real network: Each node in the randomized networks has the same number of incoming and outgoing edges as the corresponding node has in the real network.

A: nested feed-forward motifs, B: feed-forward motifs with entry and exit, C: integrations and bifurcations, D: bi-fan motif with or without coupling of the inputs, and E: linear chains.

Conclusion



- ▶ Aim 1: Spatial modeling with deep generative models
 - ▶ Spatial modeling outperforms point process modeling in prediction accuracy
 - ▶ Next: repeat experiments and analyze tail movement prediction
- ▶ Aim 2: Optogenetic active learning
 - ▶ Established theoretical foundation for selecting optimal optogenetic stimuli to reduce model uncertainty
 - ▶ Next: create transgenic and validate single cell activation
- ▶ Aim 3: Contribution of cell-types and circuit motifs
 - ▶ Acquired preliminary dataset with co-registered functional imaging and excitatory & inhibitory staining
 - ▶ Next: use model to predict cell type and evaluate influence of cell type on dynamics

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Aim 3: Contribution of cell-types and circuit motifs
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└ Conclusion

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Appendix



Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

Appendix

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Appendix
└ Appendix
 └ Appendix

Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

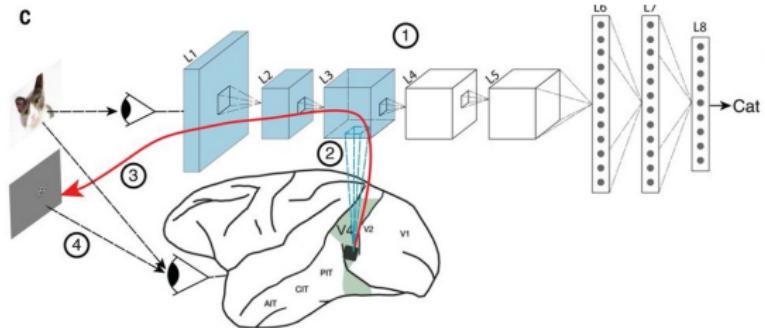
Appendix

Stimulate retina → control v4

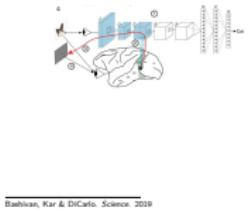
activate only one neuron of population with overlapping receptive fields



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└ Stimulate retina → control v4



Bashivan, Kar & DiCarlo. Science. 2019

Recently, some work has been done that reaches the Counterfactual rung:
Deep Image Synthesis.

train model on imagenet, regress conv layer to macaque V1 neurons. Use
"Deep image synthesis" for one-hot population control. Example of coun-
terfactual model-stim is very different from training! truly "imagined"

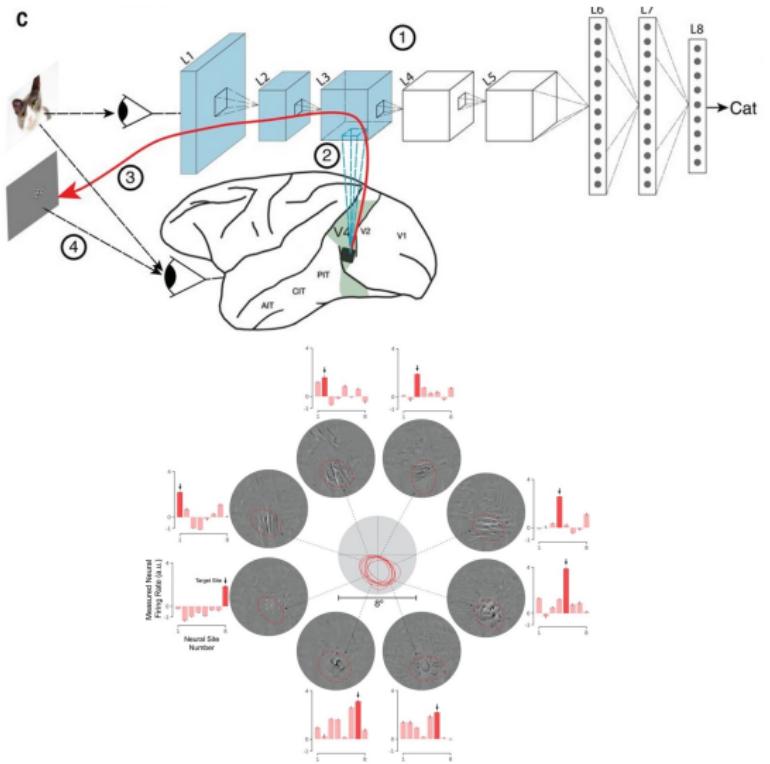
Stimulate retina → control v4

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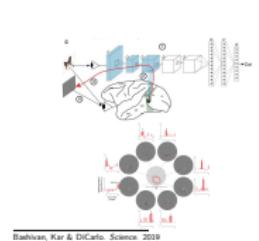
└ Stimulate retina → control v4



Bashivan, Kar & DiCarlo. *Science*. 2019

Tyler Benster, Qualifying Exam

1/10



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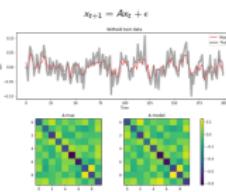
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Linear Dynamical System with noise

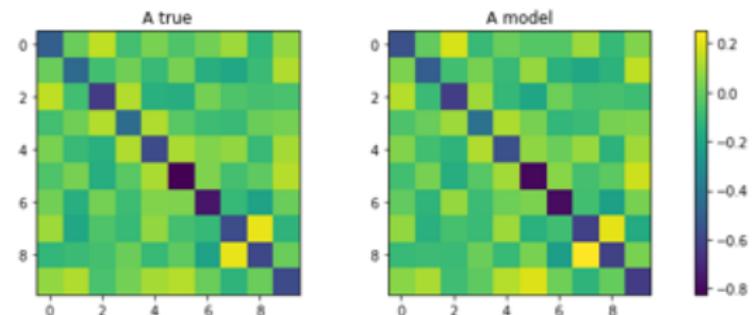
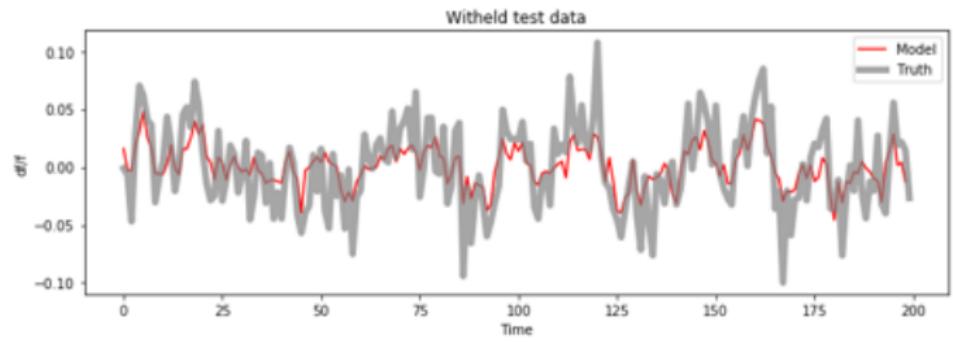


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Linear Dynamical System with noise



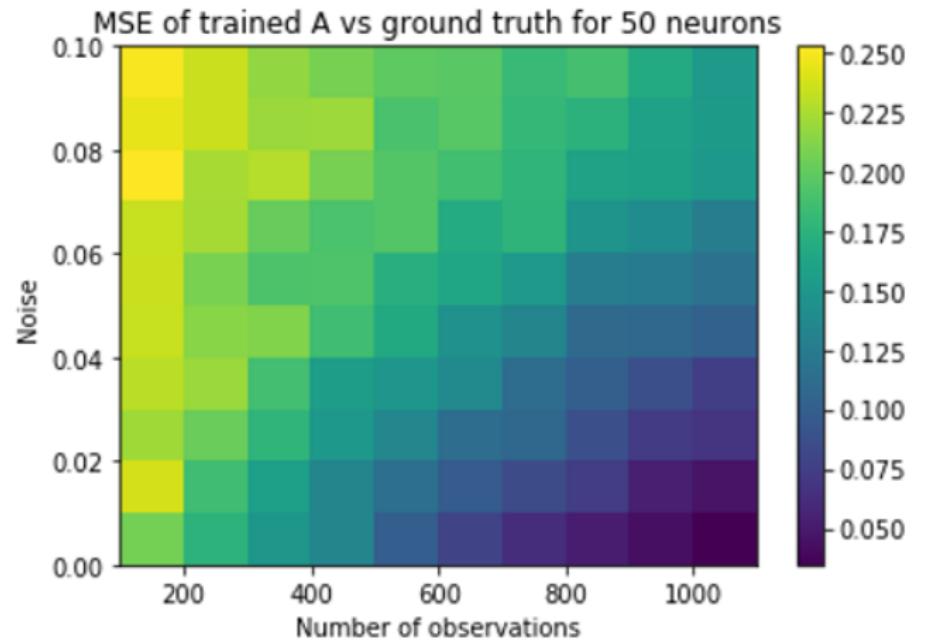
$$x_{t+1} = Ax_t + \epsilon$$



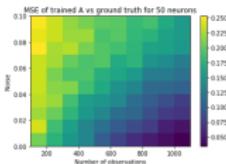
Reconstruction breaks down as noise increases



2019-06-17



└ Reconstruction breaks down as noise increases



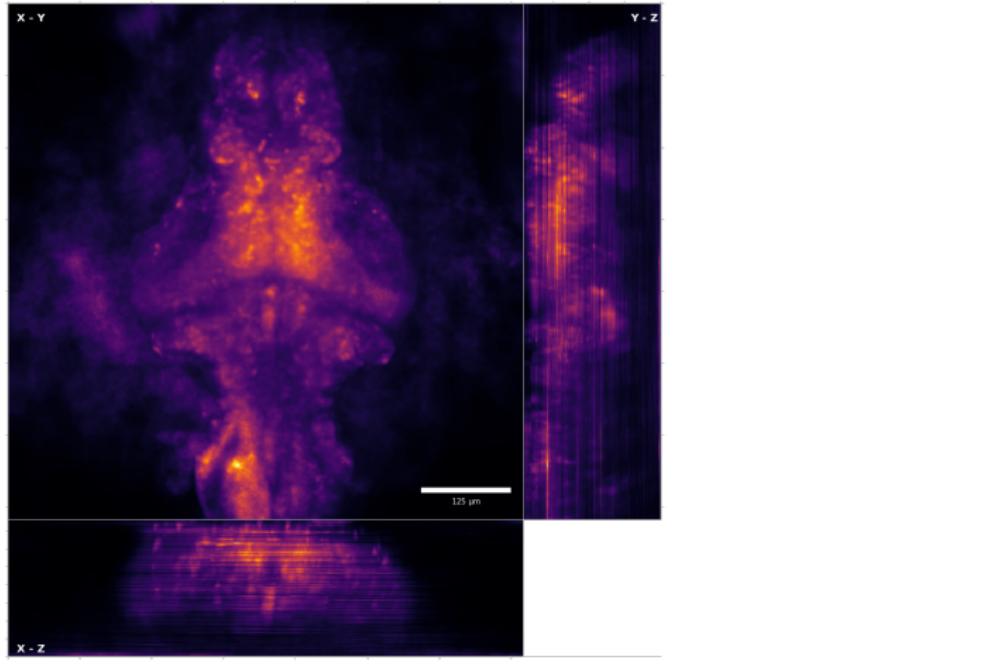
Whole-brain imaging at 200Hz

exemplified by preliminary Extended Light Field Microscopy reconstruction



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└ Whole-brain imaging at 200Hz

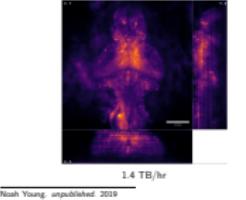


1.4 TB/hr

Noah Young. *unpublished*. 2019

Tyler Benster, Qualifying Exam

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Learning physics from video prediction



2019-06-17



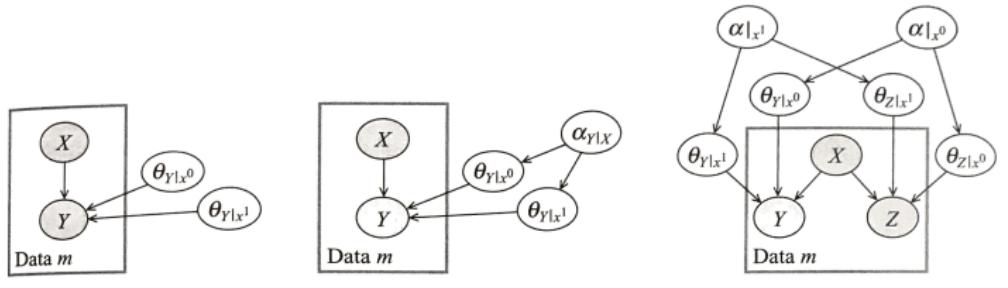
↳ Learning physics from video prediction



Extracting principles from multiple fish



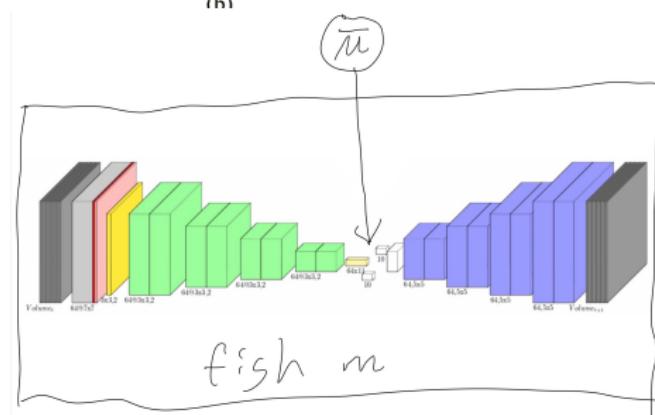
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(a)

40

(c)

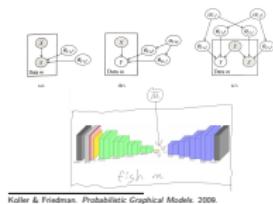


Koller & Friedman. *Probabilistic Graphical Models*. 2009.

Tyler Benster, Qualifying Exam

6/10

Extracting principles from multiple fish

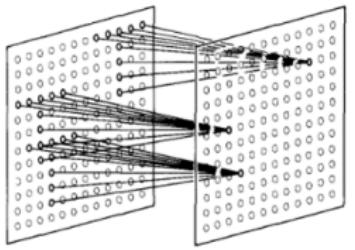


placeholder TODO: Talk about hierarchical bayes / extracting motifs / summarizing across multiple fish

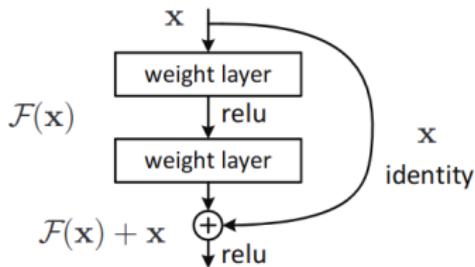
Modern deep learning toolkit



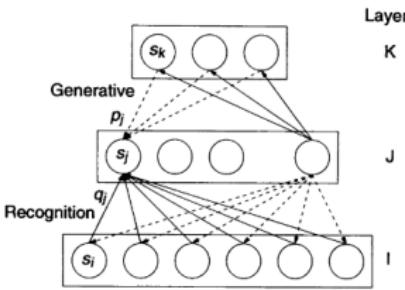
2019-06-17



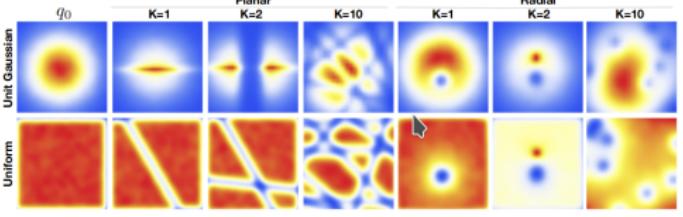
Convolutional neural networks¹



Deep residual structure²

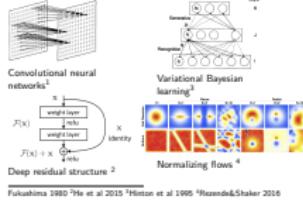


Variational Bayesian learning³



Normalizing flows⁴

Modern deep learning toolkit



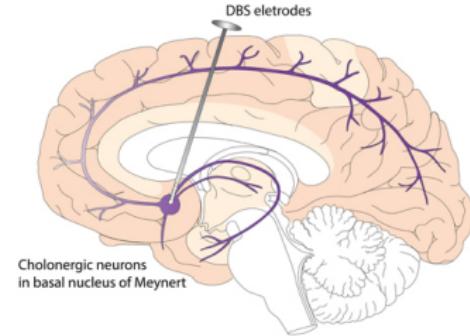


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└ Brain-computer interfaces



Zhang & Kim 2015

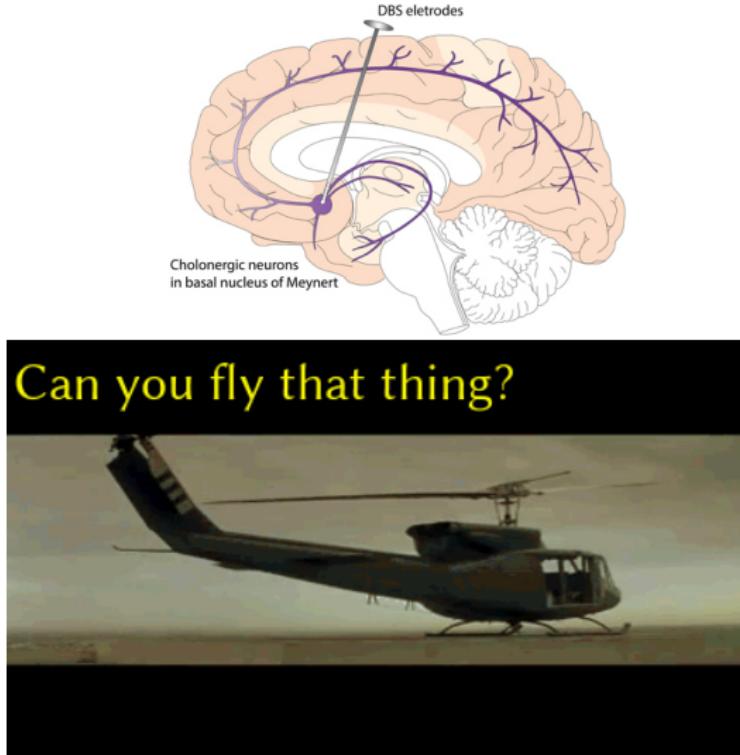
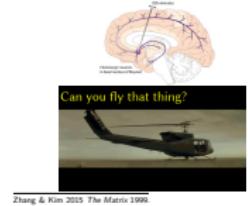


Today's BCI often look like moving a cursor around a screen.



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└ Brain-computer interfaces



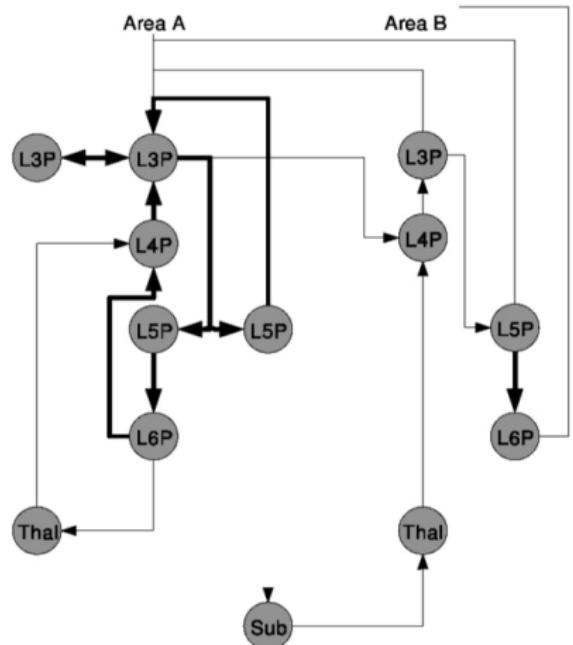
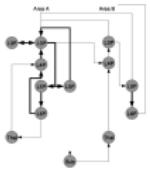
Zhang & Kim 2015 *The Matrix* 1999.

Canonical circuits



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└ Canonical circuits

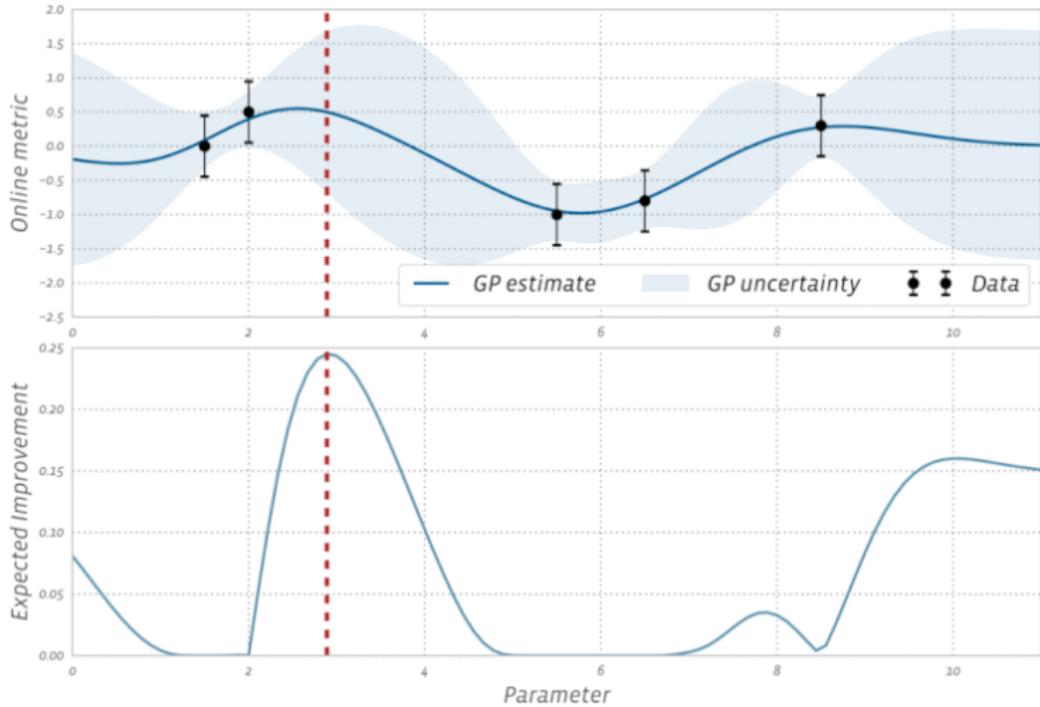


Bayesian optimization of latent space uncertainty

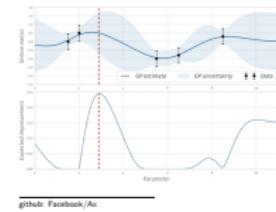
multi-neuron stim



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↳ Bayesian optimization of latent space uncertainty



1. Note: this is a video.
2. Talk about bayesian nerual nets and distribution over network parameters
3. Alternatively, can formulate uncertainty in the latent space only.
4. Finding the best way to do this will be a concerted effort during PhD.
5. Pick stim that generates dynamics that reduce uncertainty.