

data.0

Tyler Benster

Deisseroth and Druckmann Labs



d-lab meeting

Sept 24, 2019

2019-09-24



2019-09-24

Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

Experiment planning

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
Experiment planning

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.

New kids: PhD Orientation Weekend Retreat



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└ New kids: PhD Orientation Weekend Retreat



Whole-brain prediction facilitates construction of causal models



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biology
↓
model
↓
observations

biology



model



observations

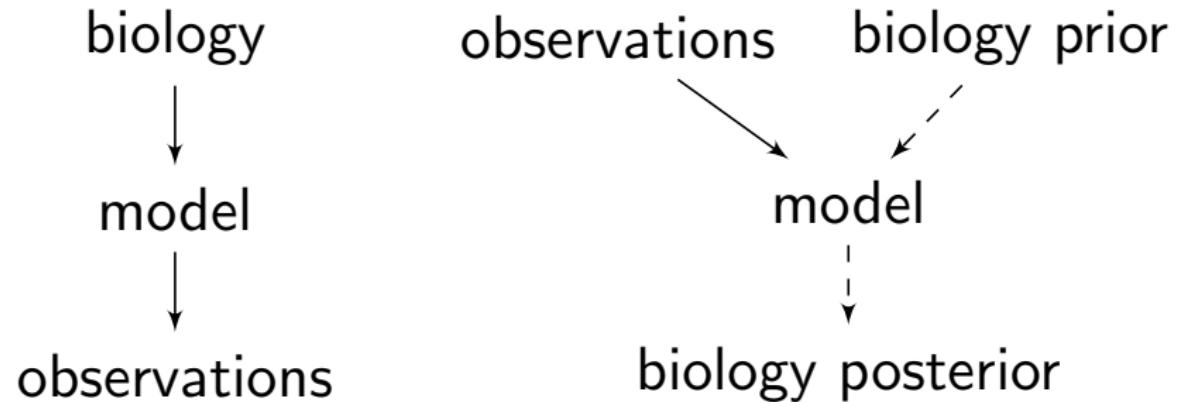
└ Whole-brain prediction facilitates construction of causal models

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

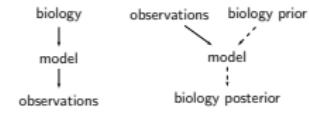
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└ Whole-brain prediction facilitates construction of causal models

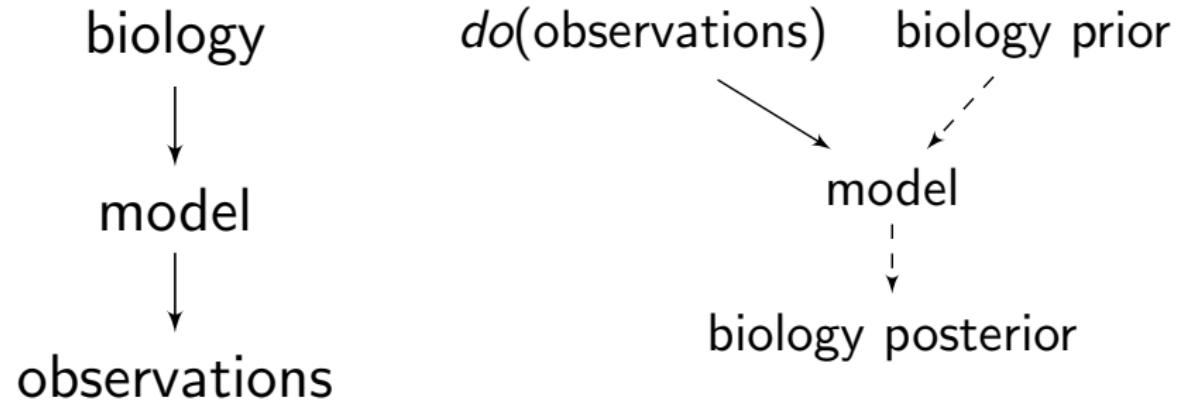


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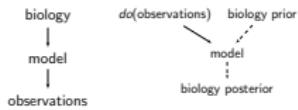
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└ Whole-brain prediction facilitates construction of causal models

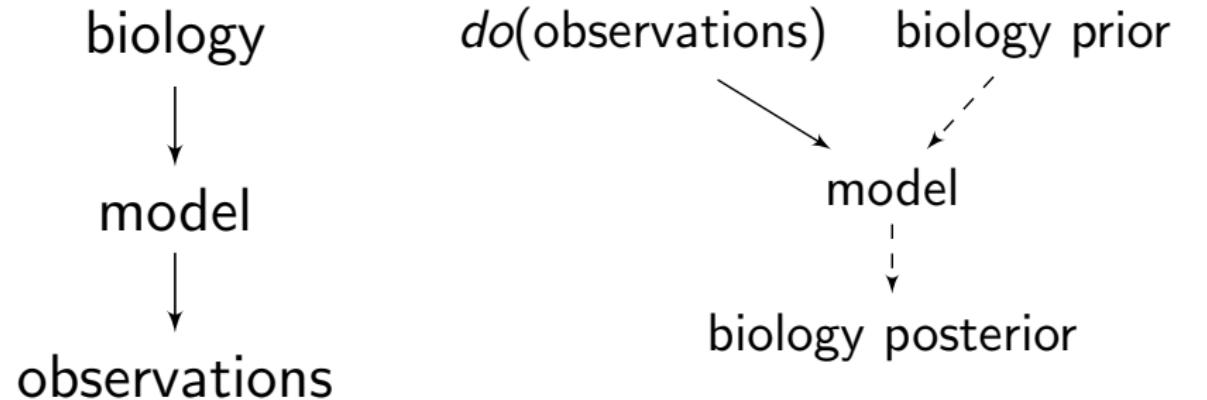


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Whole-brain prediction facilitates construction of causal models

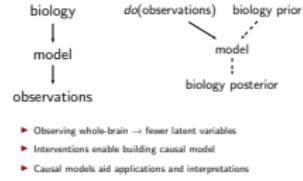


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- ▶ Observing whole-brain → fewer latent variables
- ▶ Interventions enable building causal model
- ▶ Causal models aid applications and interpretations

└ Whole-brain prediction facilitates construction of causal models



1. Data-driven approach may result in empirically more accurate model.
2. Behavior is encoded by populations of neurons distributed across whole-brain.



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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
- ▶ Initial modeling results suggest that spatial modeling out-performs traditional point process models of neurons on Calcium data
- ▶ Performed prototype analysis on voltage indicator data

└ Aim 1: Spatial modeling with deep generative models

- What is the most effective approach to predict whole-brain observations?
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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
- ▶ ChRmine Tol2 injections show sparse expression, but behavioral signs of efficacy

└ 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
- ▶ Experimented with training model to predict ISH data, with no success yet
- ▶ 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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Motivation & Background



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Aim 2: Optogenetic active learning

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Experiment planning

Motivation & Background

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Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

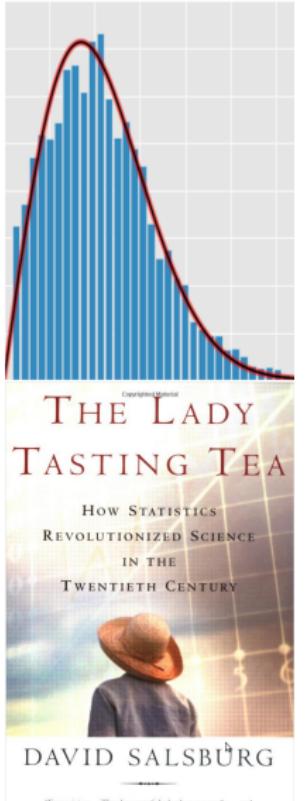
Aim 3: Contribution of cell-types and circuit motifs

Experiment planning

The probability distribution revolution



- ▶ Karl Pearson (1857-1936) came with the idea that scientific measurements should be conceived as coming from probability distributions.
- ▶ Scientific measurements are just random reflections of the underlying truth that is the distribution.
- ▶ “A great book on the history of statistics” → Aaron



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Motivation & Background

- └ Motivation & Background

- └ The probability distribution revolution

Lets start with a bit of history. The idea that scientific measurements are best understood as reflecting underlying probabilities distributions is a relatively new idea.

It was a now famous thinker and scientist, Karl Pearson (of the Pearson correlation coefficient) who conceived the idea in late 18 hundreds.

He realized randomness was inherent part of nature and of scientific measure, and he formulated the idea that all measurements should be conceived of as coming from an underlying probability distributions.

In other words, the underlying truth is the distributions, and the measurements are just random reflections of this truth. At the time, this was a revolutionary idea.

▶ Karl Pearson (1857-1936) came with the idea that scientific measurements should be conceived as coming from probability distributions.

▶ Scientific measurements are just random reflections of the underlying truth that is the distribution.

▶ “A great book on the history of statistics” → Aaron



The power of probability distributions



Distributions allow scientists to:

- ▶ Understand scientific measurement
- ▶ Predict the probability of specific data
- ▶ Test specific hypothesis (p-values)
- ▶ Produce generative models
- ▶ Better conceptual understanding data.

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Motivation & Background

- └ Motivation & Background

- └ The power of probability distributions

And it was an idea that revolutionized science.
It allowed scientists to:

- Better understand their measurements.
- To make predictions about what data they should expect to observe.
- To test scientific hypotheses in a mathematically rigorous way.
- To build generative models of their data, and to test how well those models explain the observed measurements.
- And in general to have a better conceptual understanding of the data they generated.

Distributions allow scientists to:
▶ Understand scientific measurement
▶ Predict the probability of specific data
▶ Test specific hypothesis (p-values)
▶ Produce generative models
▶ Better conceptual understanding data.



Low-Dimensional:

- ▶ Great tools to fit and understand the underlying probability distribution of data.

High-Dimensional:

- ▶ In some cases, classical statistical tools are insufficient.
- ▶ Problematic for modern neuroscience:
 - ▶ Thousands of electrodes.
 - ▶ Millions of voxels.

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Motivation & Background

- └ Motivation & Background

- └ Estimating distributions from data

Low-Dimensional:

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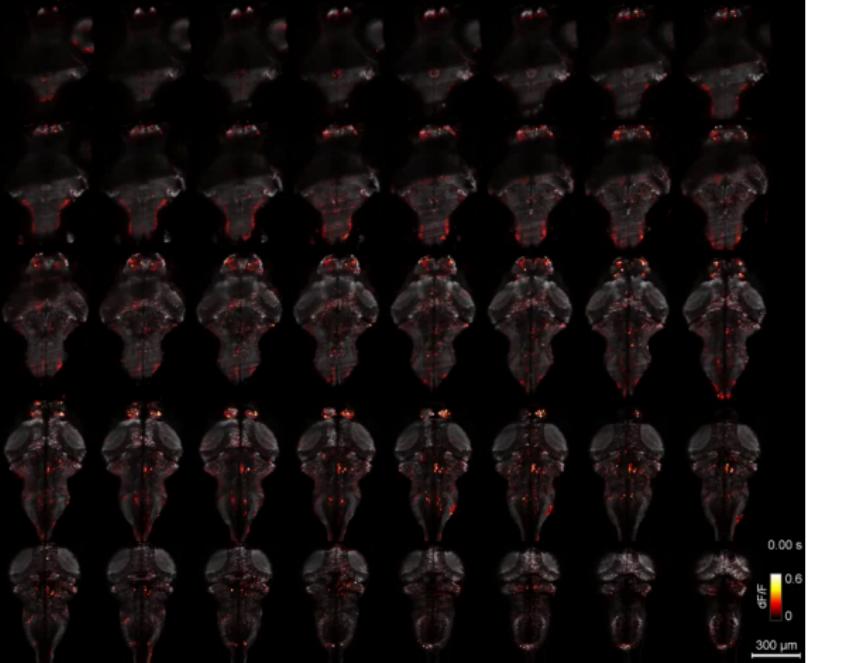
Since Pearson's early work, scientists and statisticians have devised an enormous number of related tools.

For example they've defined many many distributions, and they've created tools for working with those distributions (calculating likelihoods and fitting them).

One class of tools aim to estimate the underlying distribution that generated an observed empirical measurement.

These tools are highly effective when data is low dimensional, but they are sometimes insufficient when data is high dimensional.

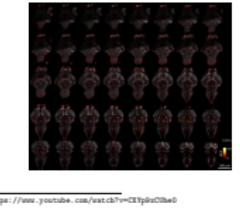
How can we build statistical distributions for neuroscience datasets?



<https://www.youtube.com/watch?v=CXYp9xCUhe0>

Motivation & Background
└ Motivation & Background

└ How can we build statistical distributions for neuroscience datasets?



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Aim 1: Spatial modeling with deep generative models



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- └ Aim 1: Spatial modeling with deep generative models
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Motivation & Background

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Experiment planning

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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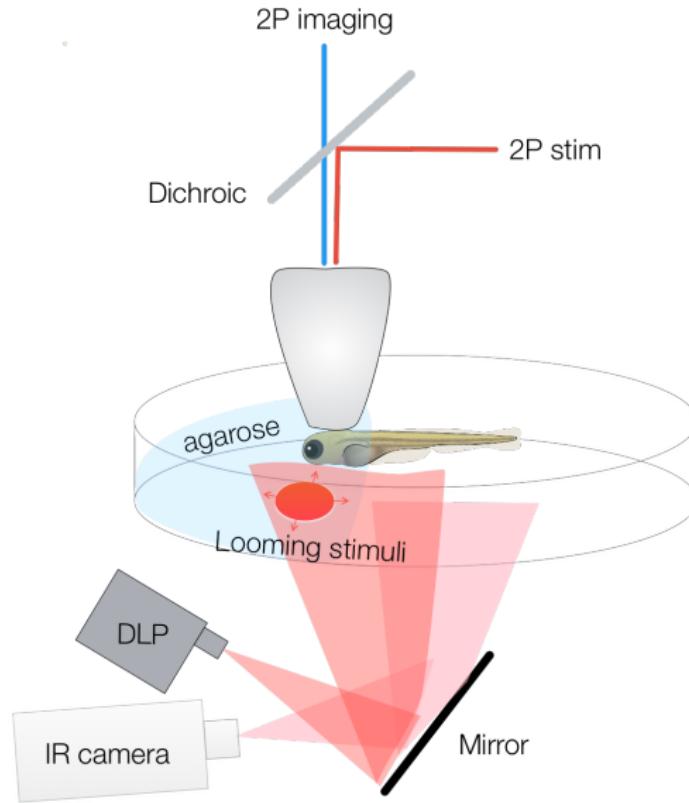
- Aim 1: Spatial modeling with deep generative models
 - └ Aim 1: Spatial modeling with deep generative models
 - └ What is the most effective approach to predict whole-brain observations?

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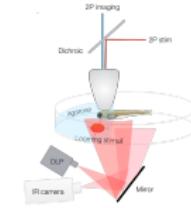
The main buy-in for this talk is that having an accurate model of brain dynamics is useful. Most approaches today for brain-wide modeling use hand-crafted features in a preprocessing pipeline that throws away spatial information. How much better can we do at predicting activity if we do not constrain 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

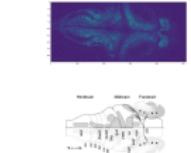
Z-projection of 19 planes, 4x real-time, 2Hz



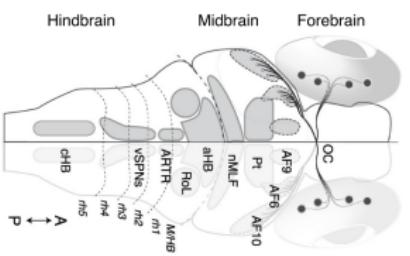
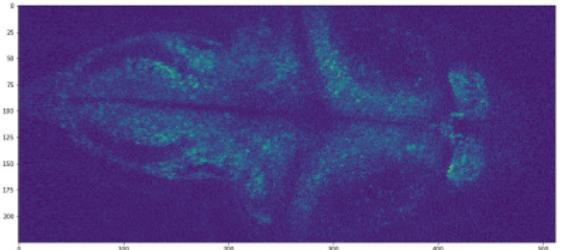
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Aim 1: Spatial modeling with deep generative models

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



Buccino et al., 2018



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

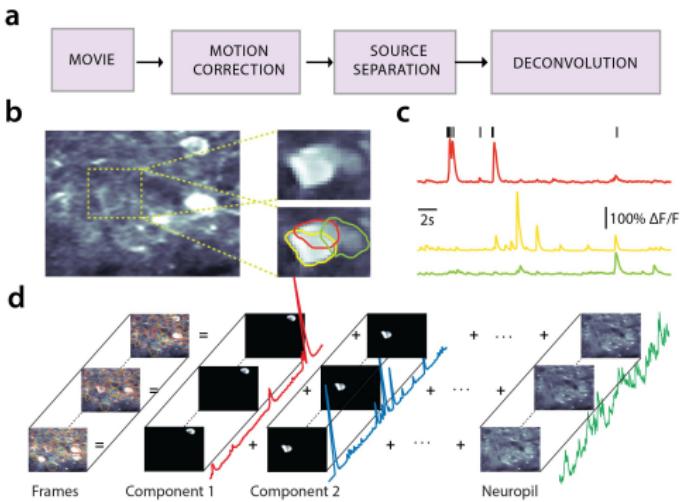
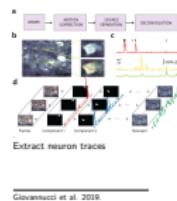
1. resting state video, no external stimuli
2. highlight brain deformation during tail movement
3. This is a video. About 2/3 way through, brain goes completely dark (!!), then whole brain lights up.
4. Dorsal overview of zebrafish neuroanatomy. DSRGCs (black dots) project via the optic chiasm (OC) to ten contralateral retinal arborization fields(AFs). Pt,prectectum; 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



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

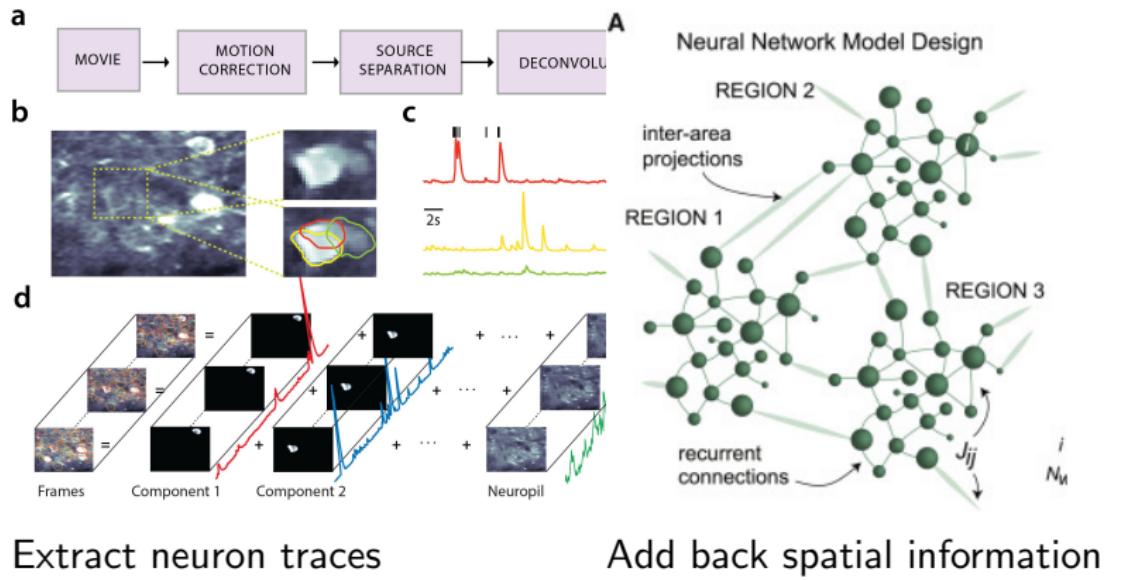
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Extract neuron traces

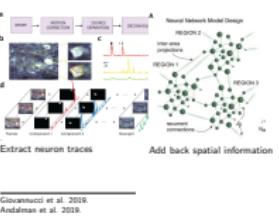
Giovannucci et al. 2019.

Current approaches to brain-wide modeling

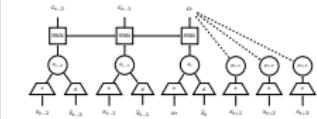


Giovannucci et al. 2019.
Andalman et al. 2019.

- 2019-09-24
- Aim 1: Spatial modeling with deep generative models
- └ Aim 1: Spatial modeling with deep generative models
 - └ Current approaches to brain-wide modeling

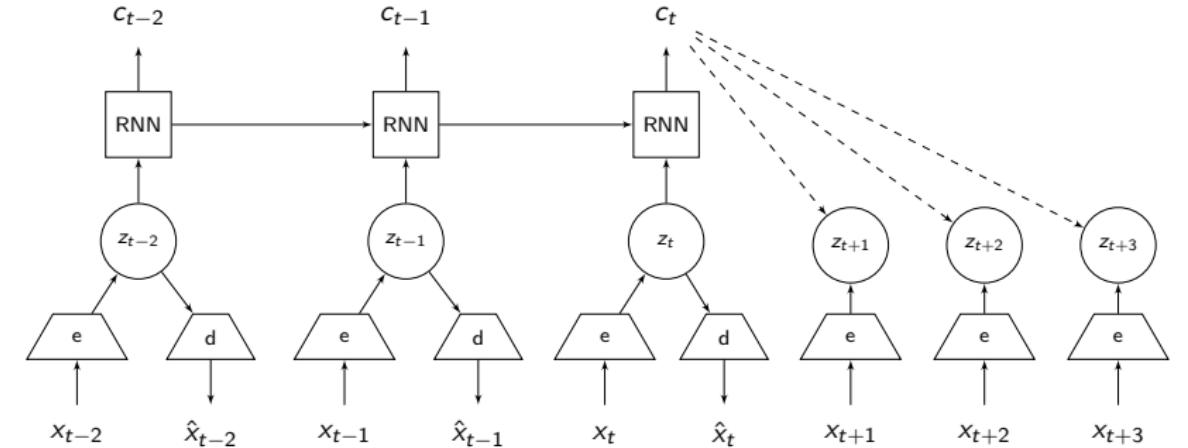


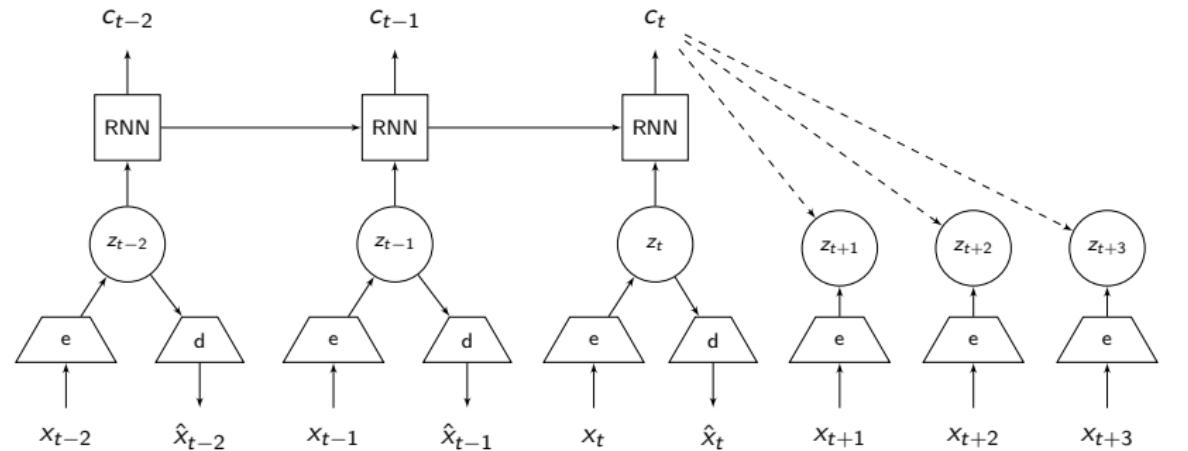
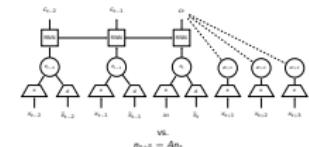
In general, modeling a recurrent neural network is intractable as the number of parameters grows quadratically with a number of neurons. Thus, brain-wide modeling usually involves a sparsity prior based on spatial location. In the neuroscience literature, it is not yet the norm to evaluate performance 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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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?



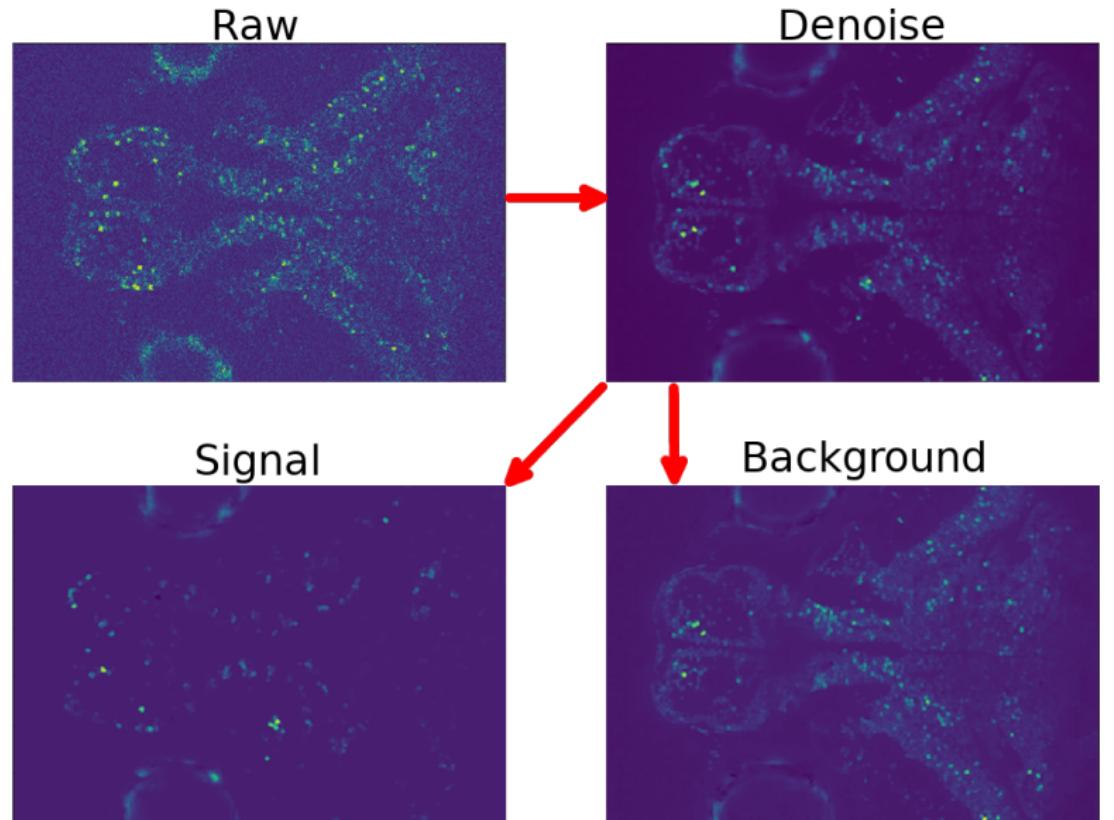


vs.

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

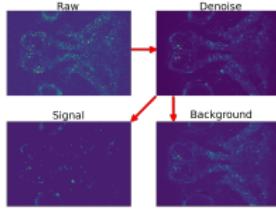
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Mapping CNMF to space

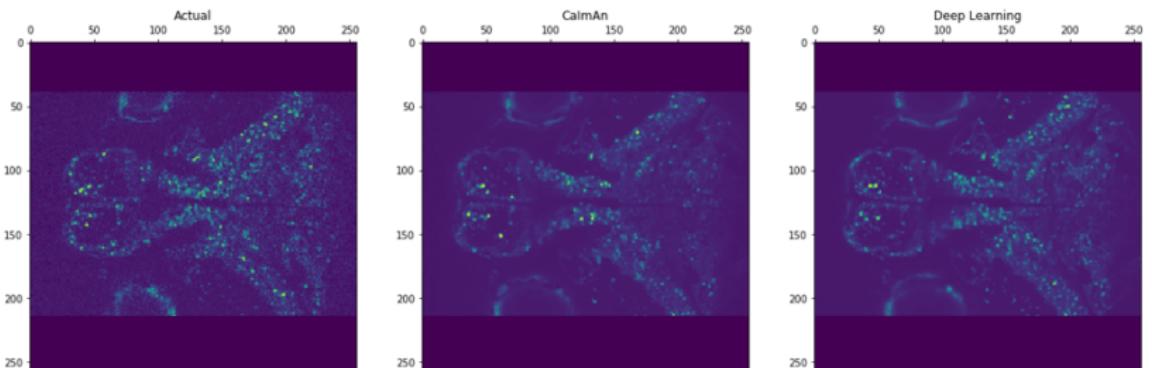


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- Aim 1: Spatial modeling with deep generative models
 - └ Aim 1: Spatial modeling with deep generative models
 - └ Mapping CNMF to space



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

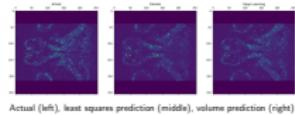


Actual (left), least squares prediction (middle), volume prediction (right)

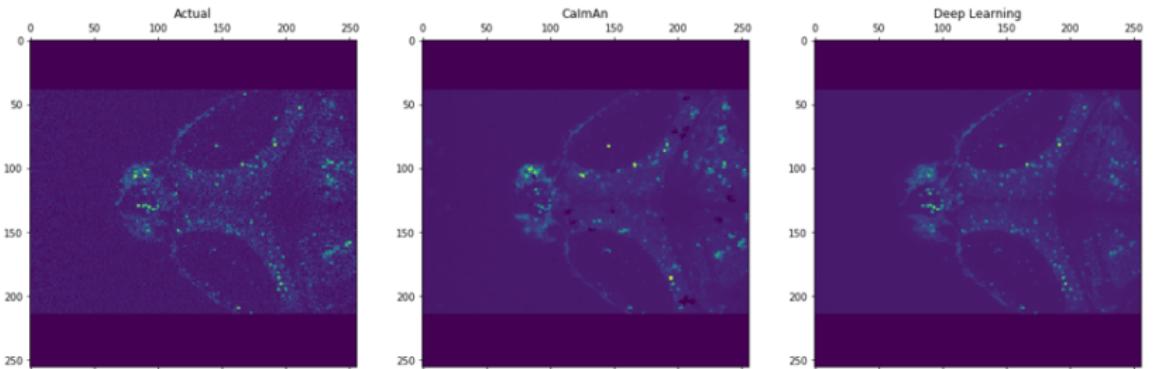
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Aim 1: Spatial modeling with deep generative models

- └ 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

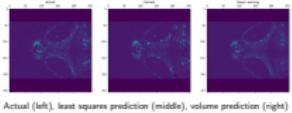


Actual (left), least squares prediction (middle), volume prediction (right)

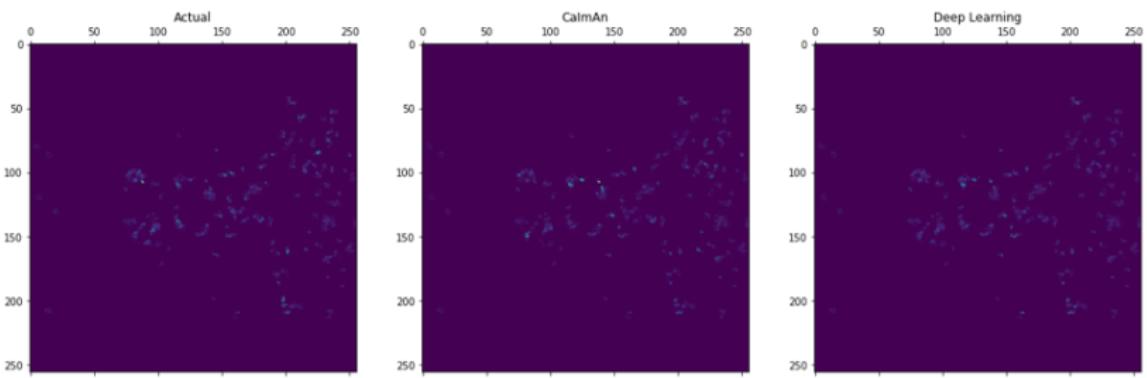
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Aim 1: Spatial modeling with deep generative models

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

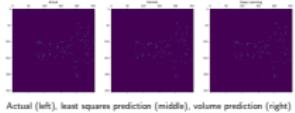


Masked test data: VP performs better LS has 40% greater MSE than VP



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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



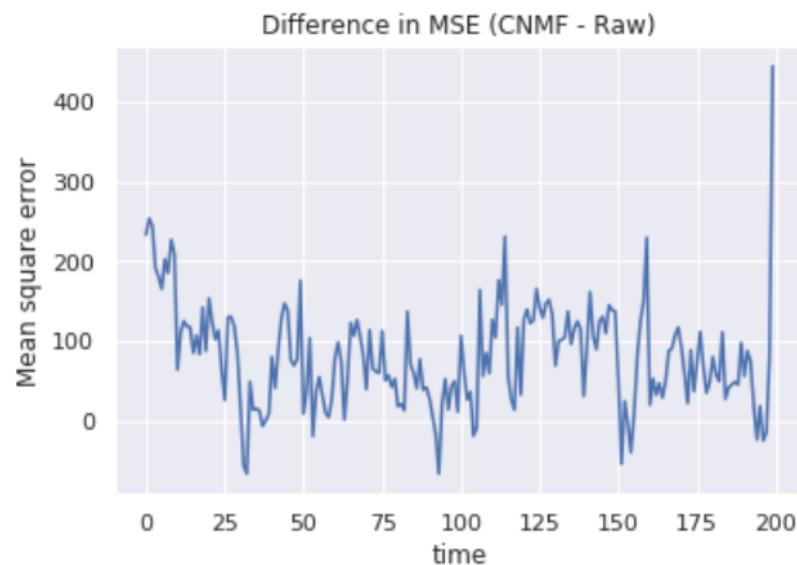
CNMF preprocessing reduces VP performance

Evaluated loss on neuron mask



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



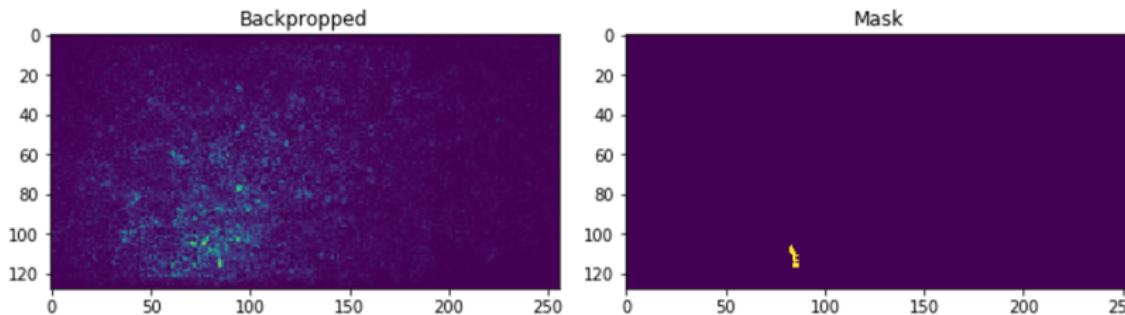
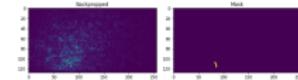
Extracting causal hypotheses

Voxels used for predicted locus coeruleus activation



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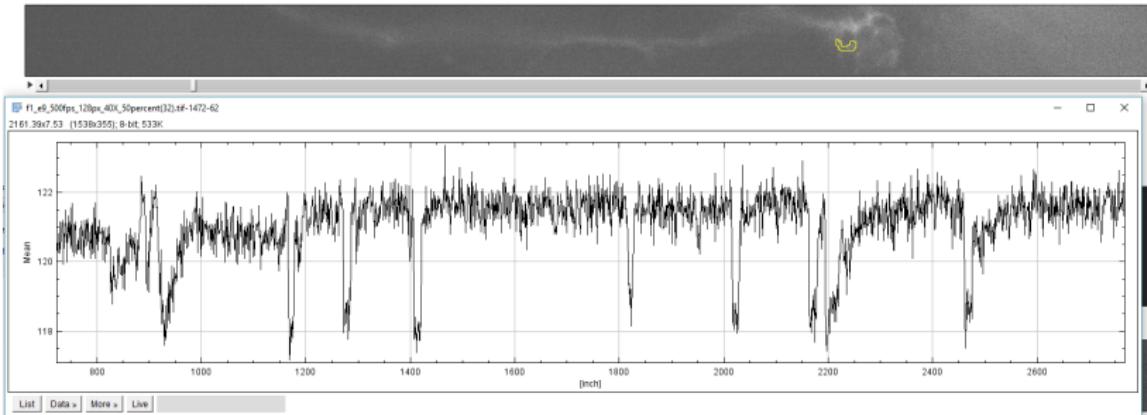
- Aim 1: Spatial modeling with deep generative models
 - └ Aim 1: Spatial modeling with deep generative models
 - └ Extracting causal hypotheses



Ask model what is important; here we use backprop

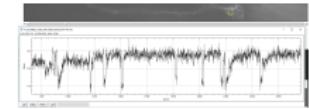
Voltron 549 imaging

Widefield @ 500Hz with Orca Flash 4.0 V2+

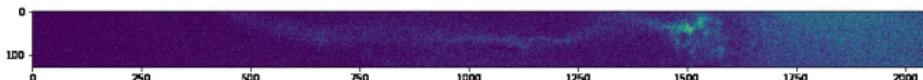


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 └ Voltron 549 imaging

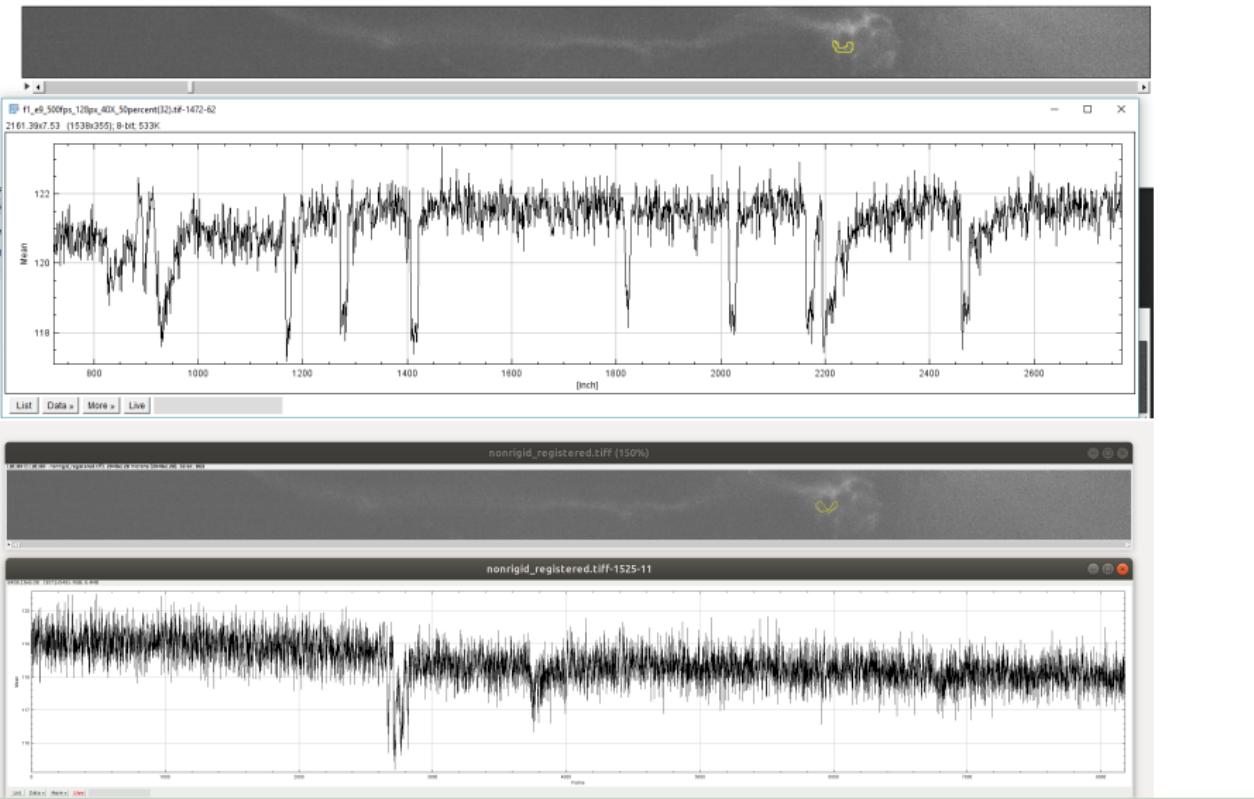


at first excited, then noticed video had major motion artifacts



Voltron pre vs post motion correction

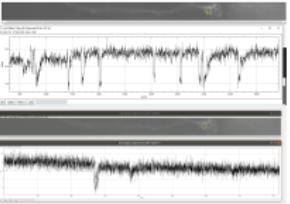
After non-rigid motion correction, no APs are visible



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- └ Aim 1: Spatial modeling with deep generative models
- └ Voltron pre vs post motion correction



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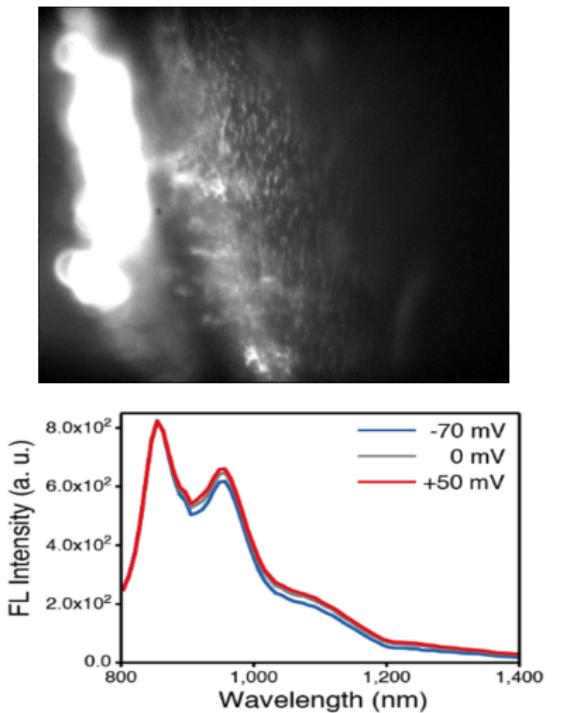
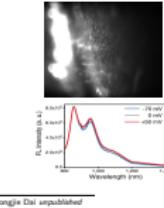
Voltage dye in the near-infrared II window (1000nm-1700nm)



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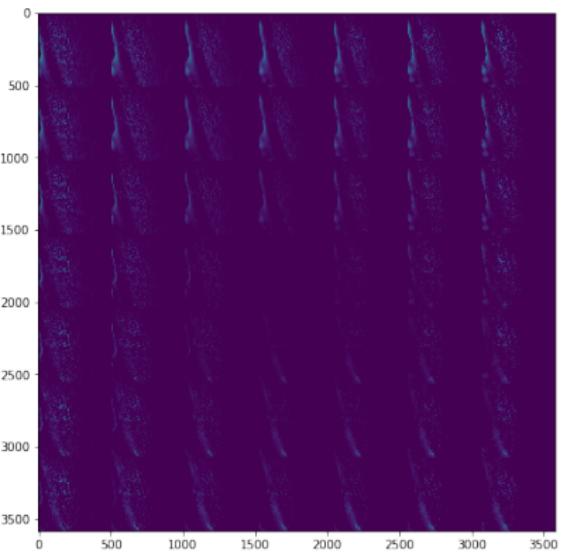
Aim 1: Spatial modeling with deep generative models

- └ Aim 1: Spatial modeling with deep generative models
- └ Voltage dye in the near-infrared II window
(1000nm-1700nm)

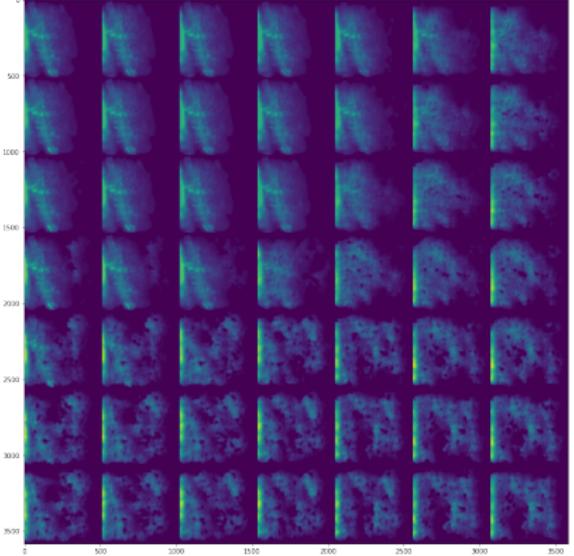


Ye Tian, Hongjie Dai *unpublished*

Latent space interpretation



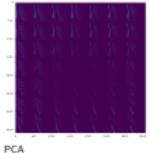
PCA



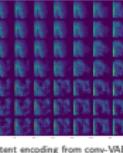
Latent encoding from conv-VAE

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



PCA



Latent encoding from conv-VAE

Aim 2: Optogenetic active learning



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

Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

Experiment planning

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.

Motivation & Background
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Aim 2: Optogenetic active learning
Aim 3: Contribution of cell-types and circuit motifs
Experiment planning

How do we resolve model underdetermination?



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

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└ 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

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

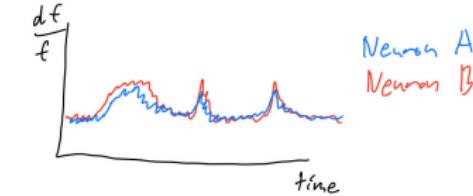
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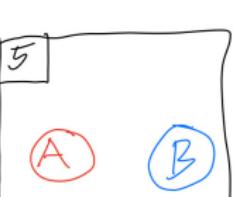
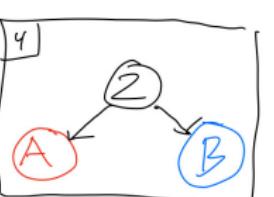
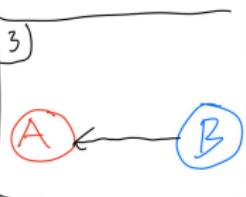
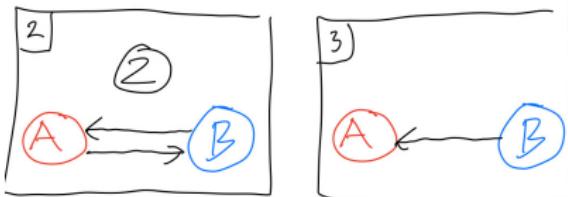
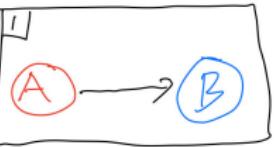
Mom & Dad. personal correspondence. 2016.
Instagram:atchoumthecat
Wikipedia CC BY-SA 3.0

1. For which photo would you ask the oracle for a label?
2. Might learn to better use the eyes as a feature

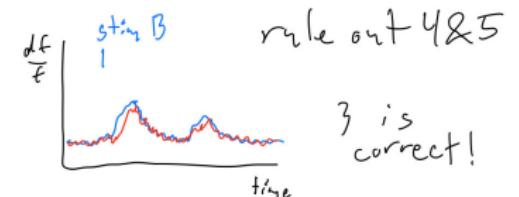
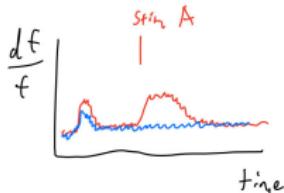
Interventions resolve model underdetermination



Possible models:



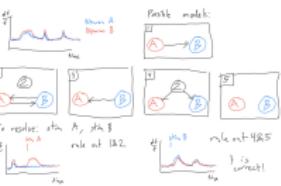
To resolve: stim A, stim B
rule out 1&2



rule out 4&5
3 is correct!

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



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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

└ Bayesian Active Learning by Disagreement

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

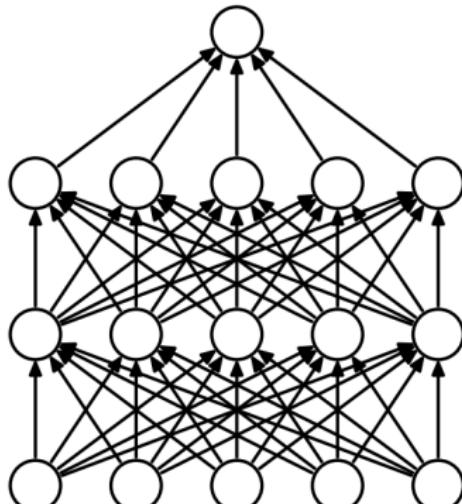
$$\underset{\theta}{\operatorname{argmax}} H[\theta|x_{1:t}] - \mathbf{E}_{x_{t+1}}[H[\theta|x_t, x_{t+1}, x_{1:t}]] \quad (1)$$

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

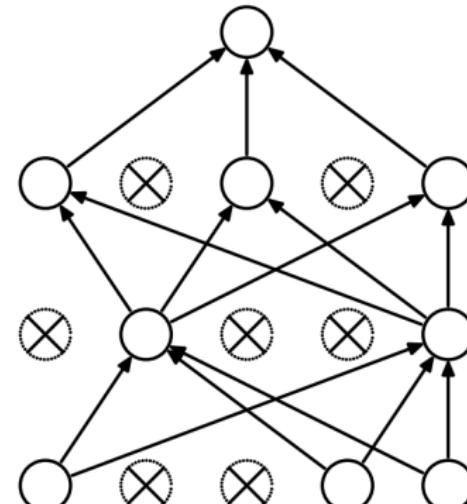
$$\underset{x_{t+1}}{\operatorname{argmax}} H[x_{t+1}|s_t, x_{1:t}] - \mathbf{E}_\theta[H[x_{t+1}|s_t, x_{1:t}, \theta]] \quad (2)$$

Houlsby, Huszár, et al. 2011

Bayesian deep learning via dropout



(a) Standard Neural Net



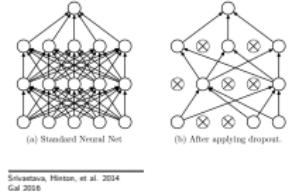
(b) After applying dropout.

Srivastava, Hinton, et al. 2014
Gal 2016

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

└ Bayesian deep learning via dropout

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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?

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

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└ Collect data then iterate the approach offline

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1 180 trials of looming stimuli (1 hour)
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How much better can we do by choosing trials vs random trials in terms of test performance?

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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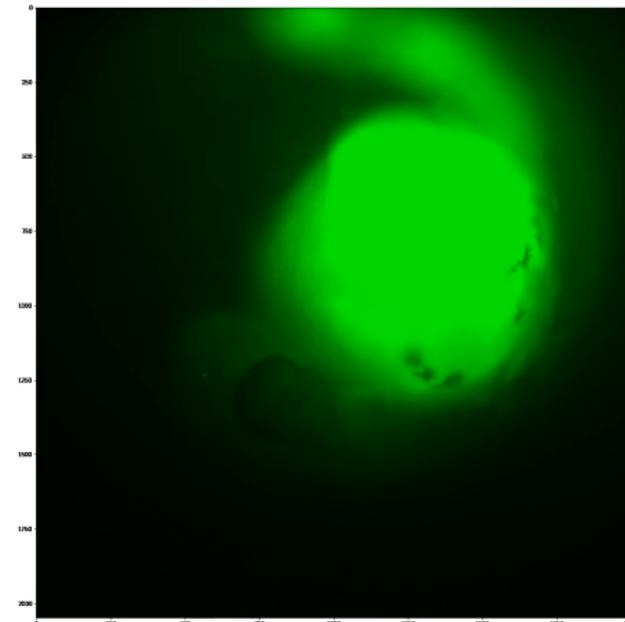
Data collection:

- 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?

Tol2 injections of HuC:GCaMP6f-p2a-ChRmine-oScarlet

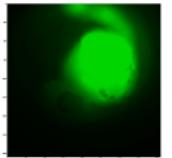


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Aim 2: Optogenetic active learning

└ Aim 2: Optogenetic active learning

└ Tol2 injections of
HuC:GCaMP6f-p2a-ChRmine-oScarlet



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

Experiment planning

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- 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
Experiment planning

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?

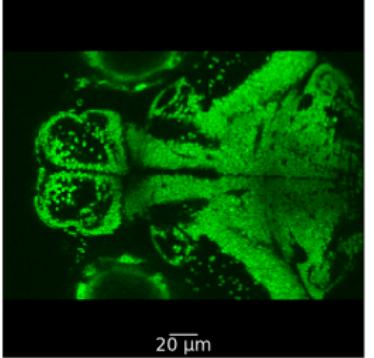
Hypothesis: Enforcing causal biological constraints will improve model performance while aiding interpretation

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

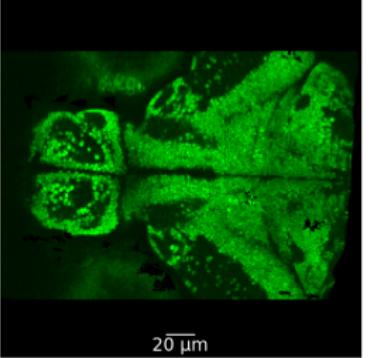
in situ cell type identification



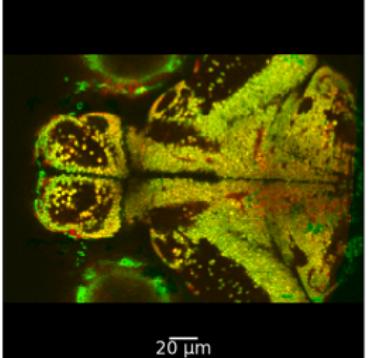
GCamP6s alive (isosbestic)



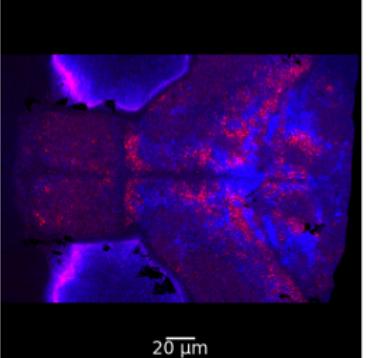
GCamP6s post-fix (isosbestic)



alive (green), post-fix (red)



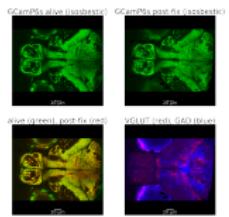
VGLUT (red), GAD (blue)



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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



Talk about colored graphs, predicting cell type,

in situ cell type identification: attempts to date

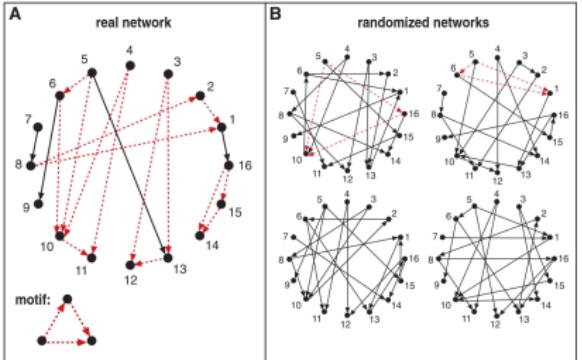


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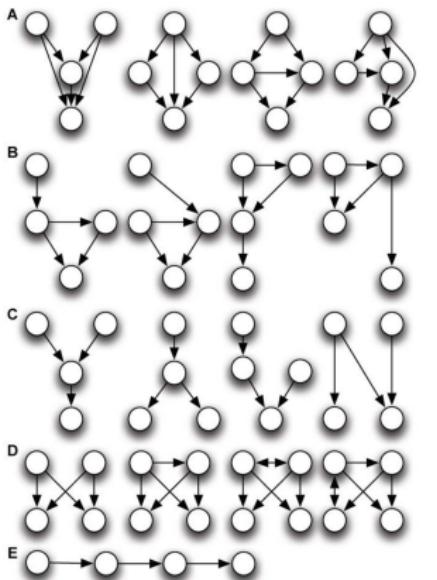
- Aim 3: Contribution of cell-types and circuit motifs
 - └ Aim 3: Contribution of cell-types and circuit motifs
 - └ *in situ* cell type identification: attempts to date

- Thus far, including *in situ* data has not helped with functional prediction
- Thus far, including *in situ* data has not succeeded in predicting cell type (attempted conv-GRU and conv-LSTM)
- Additional architectures should be explored / debugged

Network motifs



Schematic illustrating an over-represented motif



Over-represented motifs from *C. elegans* connectome

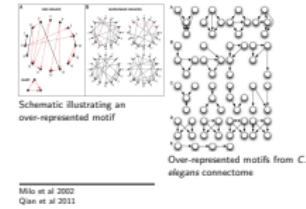
Milo et al 2002
Qian et al 2011

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

└ Network motifs

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

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Experiment planning



Experiment planning
└ Experiment planning

2019-09-24

└ Experiment planning

Motivation & Background

Aim 1: Spatial modeling with deep generative models

Aim 2: Optogenetic active learning

Aim 3: Contribution of cell-types and circuit motifs

Experiment planning

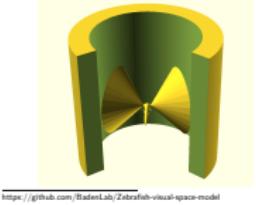
Motivation & Background
Aim 1: Spatial modeling with deep generative models
Aim 2: Optogenetic active learning
Aim 3: Contribution of cell-types and circuit motifs
[Experiment planning](#)



Experiment planning
└ Experiment planning

└ fishVR V2 Concept

2019-09-24





└ fishVR V2 Reality

2019-09-24

Unlike LCD and projector, can completely turn off green light



Next steps (feedback welcome!)



Experiment planning

- Experiment planning

2019-09-24

↳ Next steps (feedback welcome!)

- ▶ Focus on calcium imaging for immediate future & analyze behavior from optomotor response data
- ▶ Contextualized passive coping: Aaron's regime with colored queue to indicate if shock is escapable
- ▶ Pursue initial optogenetic experiments with predicting dynamics recovery after region-wide NpHR inhibition
- ▶ Outcross F0s in 1-2 weeks to see if stable F1 emerges

Acknowledgements



- ▶ Aaron
 - ▶ Matt LB
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- ▶ Karl
 - ▶ Shaul
 - ▶ Charu
 - ▶ Sally
 - ▶ Cynthia

2019-09-24

Experiment planning

- └ Experiment planning

- └ Acknowledgements

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