

# NeuroDataReHack Projects

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# Cross-species, cross-modality survey of bursting neurons

## Key Investigators

- Chenggang Chen, Johns Hopkins University

## Project Description

- Comparing the proportion of burst spiking neurons in the sensory cortex of non-human primates (macaque and marmoset) and rodents (gerbil and mouse).
- Comparing the auditory and visual tuning properties of burst spiking neurons (BU), non-burst fast-spiking neurons (FS), and non-burst regular spiking neurons (RS)

## Approach and Plan

- Extract the spike waveform and spike train from raw data, then use that information to classify all the units into three types: BU, FS, and RS. Characterize their tuning properties and running modulations.

## Progress and Next Steps

- Download datasets of various species from different archives
- Change the non-NWB format dataset to NWB format
- Extract the spike train from four NWB datasets using the same code
- Classify the neuronal population into three groups based on firing pattern and spike waveform
- Compute the auditory and visual tuning properties of three types of neurons
- In the future, I will further compare the difference among three types of neurons

## Data

- Change to NWB format; lab data
- Change to NWB format; <https://crcns.org/data-sets/vc/pvc-5/about>
- Change to NWB format; [https://gin.g-node.org/dianamaro/Amaro\\_et\\_al\\_2021\\_CurrBiol](https://gin.g-node.org/dianamaro/Amaro_et_al_2021_CurrBiol)
- Already in NWB format; <https://dandiarchive.org/dandiset/000021>
- Already in NWB format; <https://dandiarchive.org/dandiset/000022>

## Materials

- See below 'Background and References' for details

## Background and References

- Mouse visual cortex, <https://www.nature.com/articles/s41586-020-03171-x>
- Macaque visual cortex, <https://www.sciencedirect.com/science/article/pii/S0042698914000200>
- Gerbil auditory cortex, <https://www.sciencedirect.com/science/article/pii/S0960982221008204>
- Marmoset auditory cortex, <https://journals.plos.org/plosbiology/article?id=10.1371/journal.pbio.3001642>
- Marmoset auditory cortex, <https://academic.oup.com/cercor/article/29/3/1199/4840634>

# Decoding history dependent neural activity in primary and higher visual areas

## Key Investigators

- Lan Luo, Duke University  
Connect with me: <https://www.linkedin.com/in/lan-luo-q42/>


## Project Description

- Investigate how does visual adaptation (history dependency of visual signals in the brain) transform the encoding of stimulus identity using Allen Institute Visual Behavior 2-Photon Imaging & Neuropixels recordings dataset

## Approach and Plan

- Visual Behavior 2-Photon Imaging data viz with dimensionality reduction using different neural subpopulations
- Building linear and nonlinear decoder to decode visual input identity from neural activity
- Explore Visual Behavior Neuropixels data

## Progress and Next Steps

-  Decoding history dependent neural activity in visual areas

## Data

- <https://portal.brain-map.org/explore/circuits/visual-behavior-2p>
- <http://portal.brain-map.org/explore/circuits/visual-behavior-neuropixels>

## Materials

- <https://github.com/lanluo9/inter/blob/4cfd5f89c713439b94803b5e078b1dff518a8834/results/poster/poster%20neurobio%20retreat%202021.pdf>
- <https://github.com/lanluo9/inter>

## Background and References

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# Cross-Lab and Cross-Species co-clustering of cortical intracellular patch-clamp data

## Key Investigators

- Sam Mestern, UWO

## Project Description

With this project, we aim to derive novel insights regarding cortical neuron differences between species and recording conditions. We are also aiming to demonstrate the usefulness of a novel computational method for integrating electrophysiological data

## Approach and Plan

- Extract intracellular single neuron features (using IPFX) from several datasets bridging across labs and species.
- From here, we will apply novel computational methods to integrate the datasets and facilitate co-clustering of similar species

## Progress and Next Steps

- Downloaded several intracellular datasets from dandihub
- Extracted overall features from each dataset using IPFX's run\_feature\_collection
- Co-cluster datasets using extracted features

## Data

- Tolias Patch-seq - <https://dandiarchive.org/dandiset/000008>
- AI Patch-seq - <https://dandiarchive.org/dandiset/000020>
- AI Patch-seq in human - 000023, 000228, 000142, 000209, 000288, 000109

## Materials

- <https://github.com/AllenInstitute/ipfx>

## Background and References

1. <https://www.nature.com/articles/s41586-020-2907-3>
2. [https://www.cell.com/cell/pdf/S0092-8674\(20\)31254-X.pdf](https://www.cell.com/cell/pdf/S0092-8674(20)31254-X.pdf)

# Using DANDI open datasets in transfer learning for decoding proprioception from neuronal calcium image using artificial neural network

## Key Investigators

- Seungbin Park

## Project Description

Decoding proprioception is necessary for proprioceptive feedback to brain-machine interface to improve its movement performance. Artificial neural network is expected to be advantageous in revealing complex encoded proprioception from the two-photon calcium image. However, building massive datasets of the two-photon image and behavior recording is extremely challenging because animal experiments and behavior training require much time, effort, and sophisticated techniques. Moreover, it inevitably accompanies sacrificing numerous animals. Using DANDI open datasets can be a good solution for these problems. Transfer learning refers to the methodology to create high-performance learners using datasets from different domains that can be obtained more easily [1]. DANDI archive has already built various high-quality datasets so they can be exploited for transfer learning. I aim to use the dataset titled as 'A map of anticipatory activity in mouse motor cortex (DANDI ID: 000015). It includes two-photon images of the population activity of neurons related to behavior across a wide range of motor cortex [2]. The dataset is expected to be appropriate for the purpose in that proprioception and anticipatory timing are highly correlated [3]. The main goal is to improve the performance of the neural network trained with my own datasets of mouse limb positions and fluorescence traces extracted from two-photon images through transfer learning using the DANDI open datasets.

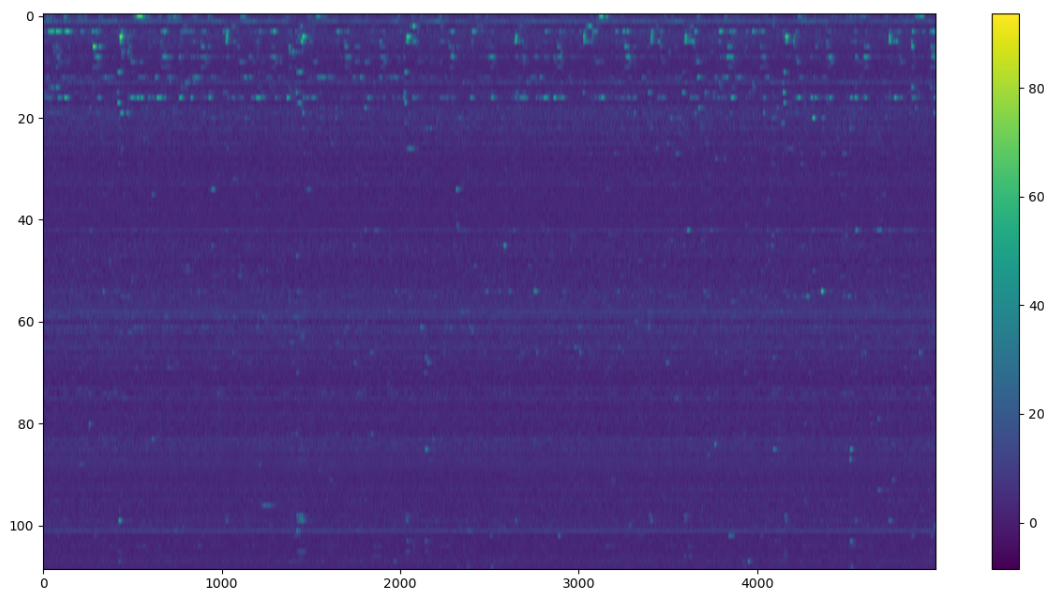
## Approach and Plan

- 1. Load and explore the dataset.
- 2. Preprocess the DANDI dataset for training a neural network.
- 3. Train a neural network with the preprocessed DANDI dataset.
- 4. Train a neural network with my own dataset using pre-trained parameters from step #3.
- 5. Evaluate the performance.

## Progress and Next Steps

- I am in step #1. I plan to follow the following steps in Approach and Plan section.





## Data

- A Map of Anticipatory Activity in Mouse Motor Cortex (DANDI ID: 000015)  
<https://dandiarchive.org/dandiset/000015?search=motor%20anticipatory&pos=1>

## Materials

- DANDI example notebooks: <https://github.com/dandi/example-notebooks>
- PyNWB documentation: <https://pynwb.readthedocs.io/en/stable/>
- Suite2p documentation: <https://suite2p.readthedocs.io/en/latest/>
- Deeplabcut documentation: <http://www.mackenziemathislab.org/deeplabcut>

## Background and References

- [1] Weiss, Karl, Taghi M. Khoshgoftaar, and DingDing Wang. "A survey of transfer learning." *Journal of Big data* 3.1 (2016): 1-40.
- [2] Chen, Tsai-Wen, et al. "A map of anticipatory activity in mouse motor cortex." *Neuron* 94.4 (2017): 866-879.
- [3] Christina, Robert W. "Proprioception as a basis of anticipatory timing behavior." *Motor Control*. Academic Press, 1976. 187-199.

# Validating latent variable models in dandisets with rich behavioral data

## Key Investigators

Ben Lansdell, St Jude

## Project Description

Tracking behavioral data from freely behaving animals, possibly in conjunction with neural recordings, is an exciting and growing direction in neuroscience. These datasets present rich opportunities for discovery, particularly by enabling the study of naturalistic behavior over long time spans. Unsupervised or semi-supervised learning methods that characterize neural activity and/or behavior are useful for summarizing and studying such datasets. I'm interested in understanding these methods, in datasets that have an interesting behavioral component, in addition to neural recordings. The first goal is to understand and implement in my own libraries the ability to read pose-tracking data from NWB datasets. The second goal is to use dandisets to investigate the utility of novel unsupervised/semi-supervised learning methods.

## Approach and Plan

First goal: make NWB datasets, with ndx-pose data, readable in python library Ethome.

Second goal: recently there have been a number of interesting latent variable models, using deep generative models, that characterize neural activity, and that simultaneously model the relation between neural activity and behavior or task variables. One example is pi-VAE [1]. The authors claim this provides a more nuanced, yet still interpretable, characterization of the data, and could serve as an alternative to some of the standard methods in computational neuroscience. Is this true? In their AJILE12 dataset, Peterson et al [2] develops multiple linear regression to characterize the neural activity and its relation to behavioral and task related variables, using it to say which factors are most often encoded by activity in ECoG arrays. I plan to test this latent variable method, to see if the important variables revealed by this latent space analysis are the same as those revealed by the linear model.

## Progress and Next Steps

Read behavior and ecog data from AJILE12. Next steps: format data into format expected by pi-VAE (list of spike data matrices for each trial/behavior), design similar analysis to Fig 6 of AJILE12 paper (Peterson et al 2021 [2]): recompute goodness of fit measures with/without different behavioral variables to judge the degree to which they're encoded in the data.

## Data

Dandisets 55 and 231.

## Materials

Behavior analysis code: <https://github.com/benlansdell/ethome>

## Background and References

- [1] Zhou and Wei 2020. Learning identifiable and interpretable latent models of high-dimensional neural activity using pi-VAE. <https://arxiv.org/pdf/2011.04798.pdf>
- [2] Peterson et al. 2021. Behavioral and Neural Variability of Naturalistic Arm Movements. <https://www.eneuro.org/content/8/3/ENEURO.0007-21.2021.long#sec-18>

# Sub-seconds Neural Emotion-Coding in Amygdala under Diverse Hippocampal Theta-Gamma States

## Key Investigators

- Lu Zhang, Georgia Institute of Technology

## Project Description

Leveraging my methods to capture hippocampal theta-gamma coupling states (Zhang et al., 2019), I found that “non-place” cells, traditionally being ignored, played a role in discriminating goals during spatial navigation (Zhang, et al, 2022). Following the application of my method within hippocampal circuit above, I will further investigate how hippocampal (HPC) theta-gamma states (TG states) affect neural emotion-coding in amygdala (AMY), a brain region highly interacting with hippocampus during emotion memory consolidation.

## Approach and Plan

- Step 1: Categorizing HPC theta oscillations into slow-gamma, medium gamma and fast-gamma states using my previous computational methods integrating Morse wavelet and k means clustering.
- Step 2: Test whether the activities of amygdala cells are different across diverse HPC at both single unit (Firing rate) and population level (Bayesian decoding).
- Step 3: Test whether HPC-AMY interactions differs during different theta-gamma states, at LFP-LFP, unit-LFP, and unit-unit level.
- Step 4: Test whether the results in above steps varies across different behavioral states (learning period, REM sleep, and after memory consolidation)

## Progress and Next Steps

- Downloading the data-set.
- Working on.

## Data

- <https://dandiarchive.org/dandiset/000061/>
- Or <https://crcns.org/data-sets/hc/hc-14>

## Materials

- Video: <https://jrnlclub.org/research-films/sub-second-dynamics-theta-gamma-coupling>
- Code: <https://github.com/singerlabgt/IndividualThetaCluster>

## Background and References

- **Background:** Oscillatory activity is often characterized based only on its frequency content, and interactions or nesting of one faster oscillation in slower such as gamma (30–150 Hz) nested in theta (6–12 Hz) in the hippocampus (HPC) (Buzsáki and Draguhn, 2004). However, current methods to

assess cross-frequency coupling averaging neural signals over long consecutive time periods, which obscure cycle-by-cycle sub-second dynamics that underlie cognitive computations (Kopell et al., 2014). To address that, I developed novel computational approaches combining signal processing and machine learning, to capture moment-to-moment changes in hippocampal theta-gamma coupling in rodents at single theta cycle timescale (Zhang et al., 2019). My methods provide new approaches to investigate the neural code in hippocampus or hippocampal interactions with other regions in spatial navigation, memory, and their alternations in aging and brain diseases (Zhang, et al, 2022). I plan to extend the application of my method to other brain region interacting with hippocampus, such as amygdala in this project.

- **References**

Zhang, L., Prince, S.M., Paulson, A.L., Singer, A.C. (2022). [Goal discrimination in hippocampal non-place cells when place information is ambiguous](#). Proc. Natl. Acad. Sci. 119 (11), e2107337119.

Zhang, L., Lee, J., Rozell, C., and Singer, A.C. (2019). [Sub-second dynamics of theta-gamma coupling in hippocampal CA1](#). Elife 8.

Kopell, N.J., Gritton, H.J., Whittington, M.A., and Kramer, M.A. (2014). [Beyond the connectome: The dynamome](#). Neuron 83, 1319–1328.

Buzsaki, G. and Draguhn, A. (2004). [Neuronal oscillations in cortical networks](#). Science 304, 1926-1929.

# Feature-based embeddings of non-stationary ECoG

## Key Investigators

- Brendan Harris, USyd

## Project Description

Describe the spatio-temporal dynamical structure of an ECoG recording using an existing pipeline for summarizing non-stationary neural data in a low-dimensional space of time-series features.

## Approach and Plan

- Load the dataset into Julia (electrode traces and annotated joint positions) from the NWB file. Begin developing packages that wrap the DANDI and pynwb tools in Julia.
- Feed the dataset into the existing pipeline, then visualize the results (showing per-channel ECoG transitioning between dynamical regimes, and characterize the salient dynamical properties of each regime).

## Progress and Next Steps

- Data are downloaded via the DANDI cli, and loaded into Julia. Automated downloads are not yet implemented.
- Identify a subject and time interval from the full dataset for a pilot analysis.
- Visualize the non-stationary feature-based embedding of the test data (e.g. animate the regions of feature space occupied by each ECoG channel against behavioral data such as the joint position or event labels, over time).

## Data

<https://dandiarchive.org/dandiset/000055>

## Materials

- <https://github.com/brendanjohnharris/Catch22.jl>
- <https://github.com/brendanjohnharris/ParameterInference.jl>

## Background and References

- C. H. Lubba, S. S. Sethi, P. Knaute, S. R. Schultz, B. D. Fulcher, and N. S. Jones, “catch22: CAnonical Time-series CHaracteristics,” *Data Mining and Knowledge Discovery*, vol. 33, Art. no. 6, 2019.
- S. Güttler, H. Kantz, and E. Olbrich, “Reconstruction of the parameter spaces of dynamical systems,” *Physical Review E*, Art. no. 5, 2001.

# Finding neuronal networks based on shared temporal activity across task conditions

## Key Investigators

- Noga Mudrik (JHU)

## Project Description

I propose a framework for finding interpretable functional neuronal networks presented across various non-stationary task conditions, and for assessing neural encoding uncertainty in the networks latent space. I choose to take inspiration from the GraFT algorithm [2] and to develop a multi-dimensional version of it for data from Poisson distribution. This method thus uses neural activity data recorded under different task conditions and finds a low dimensional meaningful representation of the neural activity in each trial, described by matrix factorization where one matrix describe the neuronal networks components and the other refer to their temporal activity. Each of these temporal activities' matrices can be viewed as a trajectory in the networks' space and trajectories associated with different trials of the same condition can jointly form a manifold. These network-space manifolds will then be further analyzed to assess the encoding uncertainty by considering the manifolds' internal structure and separability. In addition to identifying neuronal circuits, testing their activities under varied settings, and using them for uncertainty estimation, this data-driven graph-based framework will also be used to improve understanding of — 1) how different task components are encoded in the brain; 2) the role of inter-regional brain connectivity versus local brain oscillations in driving behavior; 3) abnormal brain activity under pathological or stress conditions; 4) neural variability between and within conditions; and 5) behavior robustness to neural damage.

## Approach and Plan

- Find the most appropriate dandiset for this task
- Data pre-processing and creating the tensors.
- Continue working on the python code for the multidimensional GraFT
- After finding the neuronal networks - study how their composition and activity differ over task condition and study the network level dynamics to assess encoding uncertainty.

## Progress and Next Steps

- Start writing the multi dimensional graft code
- Choosing and downloading the initial dataset
- Data pre-processing
- Next step: apply the data to the multi-dimensional graft

## Data

- <https://dandiarchive.org/dandiset/000127>
- (for future steps: <https://dandiarchive.org/dandiset/000028?search=NEUROPIXELS&pos=1>)

## Materials

- Currently my code is in a private github repository (when I finish I will change it to public). The first version of the code (the python implementation to the graft method) is described and can be downloaded from here -  
<https://pypi.org/project/GraFT-Python/>
- 

## Background and References

1. Raees H Chowdhury, Joshua I Glaser, Lee E Miller (2020) Area 2 of primary somatosensory cortex encodes kinematics of the whole arm eLife 9:e48198. <https://doi.org/10.7554/eLife.48198>
2. A. S. Charles, et al., "GraFT: Graph Filtered Temporal Dictionary Learning for Functional Neural Imaging," bioRxiv, p. 2021.05.24.445514, May 2021, doi: 10.1101/2021.05.24.445514.



# Human iPSC-derived neurons recapitulate phenotypic variation within the Human cortex

## Key Investigators

- Michael Zabolocki, SAHMRI

## Project Description

Human induced pluripotent stem cells (hiPSCs) offer a model which has the capacity to recapitulate the genetic underlying of the human brain across early neurodevelopment. Of these, organoid and monolayer models have repeatedly demonstrated that genetic signatures unique to human pre- and postnatal transitions can be recapitulated in-vitro. However, whether the functionality of these neurons compare to the human brain itself is unknown at the single-cell level. To address this, cortical hiPSC-derived neurons were then patch-clamped at late-stage time points (> 70 days) and compared to Allen Brain Institutes' human cortical brain biopsy acute brain slice patch-clamp database. We reveal that subpopulations of hiPSC derived neurons in organoid or monolayer models emerge to share similar functional properties with the Human cortex, independent of morphological differences. Following on from previous work, integrating additional Human cortical patch-clamp datasets available on Dandi will expand the significance of such findings. Within said subpopulations, patch-seq data available across both Dandi and Allen Brain datasets will be isolated to determine genetic differences in ion channel gene expressions.

## Approach and Plan

- Load raw intracellular EPhys recordings (both voltage and current clamp recordings), collected from all Dandisets containing Human cortical intracellular EPhys.
- Intracellular Ephys feature extraction using a custom Python pipeline for voltage clamp and current clamp recordings.
- Quantify overlapping features between layers and regions with iPSC datasets, and calculate similarity scores
- Visual outputs and quantified metrics between subpopulations
- Extract ion channel expression data using available patch-seq data from 'similar' Human isolated subpopulations

## Materials

[https://github.com/mzabolocki/humanbiopsy\\_ipsc\\_ephys](https://github.com/mzabolocki/humanbiopsy_ipsc_ephys)

<https://github.com/mzabolocki/BrainSpike>

## Progress and Next Steps

- Data is downloaded via the DANDI, raw recordings extracted for all relevant Human cortical datasets. Downloads currently set to local.
- Identify relevant stimulus types (voltage clamp, current clamp long depolarisation, ramp, sag protocols) in the DANDI data.
- Compare features from Dandisets to existing.

## Data

- Dandisets 000293 and 000297

## Background and References

[https://www.cell.com/cell-stem-cell/pdfExtended/S1934-5909\(19\)30337-6](https://www.cell.com/cell-stem-cell/pdfExtended/S1934-5909(19)30337-6)

<https://www.nature.com/articles/s41593-021-00802-y>

<https://www.nature.com/articles/s41467-022-32115-4>

<https://www.nature.com/articles/s41593-021-00906-5>

# Exploring the network of excitatory neurons with regularized GLMs

## Key Investigators

- Tzu-Chi
- Yi-Yun
- Josefina

## Project Description

This project explored statistical methods for extracting network structure from point process observations.

## Approach and Plan

- We analyzed spike trains from excitatory cortical neurons under REM sleep and model each spike train as a linear combination of the past activity of other neurons, up to 1 time bin in the past.

## Progress and Next Steps

- Progress made:
  - Explored methods to infer functional connectivity between neurons based on firing history
  - Built a graphy display of network from the connectivity
- Future plan:
  - Assess goodness of fit
  - Explore non-linear models
  - Compare network structure across different states, awake, non-REM, REM, and across brain regions

Data: Dandiset 000041

Materials:

<https://github.com/junipertcy/NeuroDataReHack>

<https://docs.google.com/presentation/d/1Y6b-s2QMO0UFuWa6hob9OCrirwljyVw-Bg6OqtcGuKI/edit?usp=sharing>

## Background and References

Watson, B.O., Levenstein, D., Greene, J.P., Gelineas, J.N. and Buzsáki, G., 2016. Network homeostasis and state dynamics of neocortical sleep. *Neuron*, 90(4), pp.839-852.

Truccolo, W., Eden, U.T., Fellows, M.R., Donoghue, J.P. and Brown, E.N., 2005. A point process framework for relating neural spiking activity to spiking history, neural ensemble, and extrinsic covariate effects. *Journal of neurophysiology*, 93(2), pp.1074-1089.

# Elucidating Neural Learning Rules from Calcium Imaging Data

## Key Investigators

- Felix Pei
- Alessandro Salatiello

## Project Description

We want to analyze data from a mouse learning a task and see if any insight can be found regarding the learning rules used by the brain

## Approach and Plan

- Download NWB data and gain familiarity with format
- Analyze changes in neural activity during training
- Compare with computational models using different learning rules.

## Progress and Next Steps

- Continue improving computational models to better fit data and cover wider range of learning rules
- Extend calcium imaging analysis to single-trial

## Data

- <https://dandiarchive.org/dandiset/000016/>

## Materials

- <https://github.com/felixp8/neurodatarehack-2022/>

## Background and References

6. Najafi F, Elsayed GF, Cao R, Pnevmatikakis E, Latham PE, Cunningham JP, Churchland AK. Excitatory and Inhibitory Subnetworks Are Equally Selective during Decision-Making and Emerge Simultaneously during Learning. *Neuron*. 2020 Jan 8;105(1):165-179.e8. doi: 10.1016/j.neuron.2019.09.045.
  7. Murray JM. Local online learning in recurrent networks with random feedback. *eLife*. 2019. 8:e43299.
-

# Fitting state space models in SSM repo to NWB datasets

## Key Investigators

- David Zoltowski

## Project Description

My goal is to fit state space models in the SSM code package to NWB datasets. I looked at two different human recording datasets.

## Approach and Plan

I processed the data into trials and fit HMM / LDS / rSLDS models to the trial data.

## Progress and Next Steps

I analyzed recordings from human PPC while a tetraplegic participant generated neural activity corresponded to attempted finger movements. I found some differences in dynamics across the different finger movements.

## Data

- <https://dandiarchive.org/dandiset/000147?pos=8>

## Materials

- <https://github.com/lindermanlab/ssm>

## Background and References

8.

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# Constructing time-probability-matrices from simultaneously recorded visual areas using state space models

## Key Investigators

- Brock Carlson
- Blake Mitchell
- David Zoltowski

## Project Description

We would like to calculate  $\Phi$

## Approach and Plan

- Describe the steps of your planned approach to reach the objectives.

## Progress and Next Steps

- Describe the progress you have made on the project, e.g., which objectives you have achieved and how.
- Describe the next steps you are planning to take to complete the project.

## Data

- Links to the dataset(s) that you are using.

## Materials

- Links to materials relevant to the project, e.g., code, videos.

## Background and References

9. Use this space for information that may help people better understand your project, e.g., links to papers.
-

# Project Title: Identification of theta states in the prefrontal cortex

## Key Investigators

- John Stout

## Project Description

Neural activity, paced at theta frequency (4-12Hz) in the medial prefrontal cortex, is linked to memory-guided decision making. I would like to identify when theta oscillations are present, then use those epochs to build models that predict behavioral/cognitive/neural states.

## Approach and Plan

- First, identify approaches to extract “high” theta power states using extracellular recordings

## Progress and Next Steps

Have spent a lot of time troubleshooting, but some progress has been made. Working on using a linear regression over log-transformed power spectra, then using a metric, like mean squared error, to identify when theta oscillations might deviate from the “typical” cortical oscillations based on the 1/f law

## Data

[DANDI Archive](#) (000041)

## Materials

Not ready yet!

## Background and References

1. O'Neill, P. K., Gordon, J. A., & Sigurdsson, T. (2013). Theta oscillations in the medial prefrontal cortex are modulated by spatial working memory and synchronize with the hippocampus through its ventral subregion. *Journal of Neuroscience*, 33(35), 14211-14224.
2. Jones, M. W., & Wilson, M. A. (2005). Theta rhythms coordinate hippocampal–prefrontal interactions in a spatial memory task. *PLoS biology*, 3(12), e402.
3. Hallock, H. L., Wang, A., & Griffin, A. L. (2016). Ventral midline thalamus is critical for hippocampal–prefrontal synchrony and spatial working memory. *Journal of Neuroscience*, 36(32), 8372-8389.

# Spyglass: data analysis framework for reproducible neuroscience research

## Key Investigators

- Kyu Hyun Lee (Loren Frank lab, UCSF)

## Project Description

Spyglass is a data analysis framework that brings together many open source tools, such as NWB, Datajoint, Spikeinterface, and others. Our lab has built reproducible analysis pipelines using these tools. Our goal is to make it possible to analyze any NWB file from DANDI with Spyglass. More specifically, we want to demonstrate that a neural decoding algorithm based on state-space models can be easily applied to data from other labs and can yield scientific insights.

## Approach and Plan

One difficulty in achieving our goal is the heterogeneity among NWB files. To overcome this issue we plan to add a way to ingest the NWB file by augmenting information with an associated configuration yaml file.

## Progress and Next Steps

- We have made progress toward achieving this goal, though it is not yet complete.
- We have demonstrated that the analysis tools we are using can be applied to data collected from other hippocampal labs by applying neural decoding to Dandiset 59.

## Data

- <https://dandiarchive.org/dandiset/000059>

## Materials

- <https://github.com/LorenFrankLab/spyglass>

## Background and References

10. Use this space for information that may help people better understand your project, e.g., links to papers.



# Contrast sensitivity across layers and cell types within primary visual cortex

## Key Investigators

- Blake Mitchell
- Brock Carlson

## Project Description

To analyze V1 responses ( 2-photon calcium imaging) to full field images with varying image contrast.

## Approach and Plan

Describe the steps of your planned approach to reach the objectives.

## Progress and Next Steps

- Describe the progress you have made on the project, e.g., which objectives you have achieved and how.
- Describe the next steps you are planning to take to complete the project.

## Data

- Links to the dataset(s) that you are using.

## Materials

- Links to materials relevant to the project, e.g., code, videos.

## Background and References

11. Use this space for information that may help people better understand your project, e.g., links to papers.

# Ensemble computational models of neurons individually tuned with multimodal intracellular electrophysiology data

## Key Investigators

- Krishna Pusluluri (Georgia State University)

# Probing excitatory computations underlying probabilistic learning

## Key Investigators

- Nuttida Rungratsameetaweemana (Salk Institute)

## Project Description

It is not well understood how excitatory and inhibitory neurons within each cortical regions (as well as along the cortical hierarchy) work together to allow efficient information processing in dynamic environments.

## Approach and Plan

- Constructing biologically plausible artificial neural network models.
- Developing a training paradigm to have the models perform cognitive tasks (such as probabilistic decision making) used in human and animal experiments.
- Investigating the neural computations that support successful learning and performance of the models on these tasks.
- Analyzing experimental data while the animals performed the same cognitive tasks.

## Progress and Next Steps

- Developed recurrent neural network models to perform probabilistic learning tasks.
- Found that increased excitatory connections within neurons selective for likely sensory stimuli ('expected stimuli') support successful learning of statistical regularities.
- Next step is to look for how/where this dynamics is represented in the cortex.

## Data

- 000037

## Materials

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## Background and References

12. Gillon et al., bioRxiv, 2021. Learning from unexpected events in the neocortical microcircuit