AUTOMATED ASSESSMENT AND COMPARISON OF CORTICAL NEURON MODELS

Justas Birgiolas, Russell Jarvis, Vergil R. Haynes, Richard C. Gerkin, Sharon M. Crook

Laboratory for Informatics and Computation in Open Neuroscience

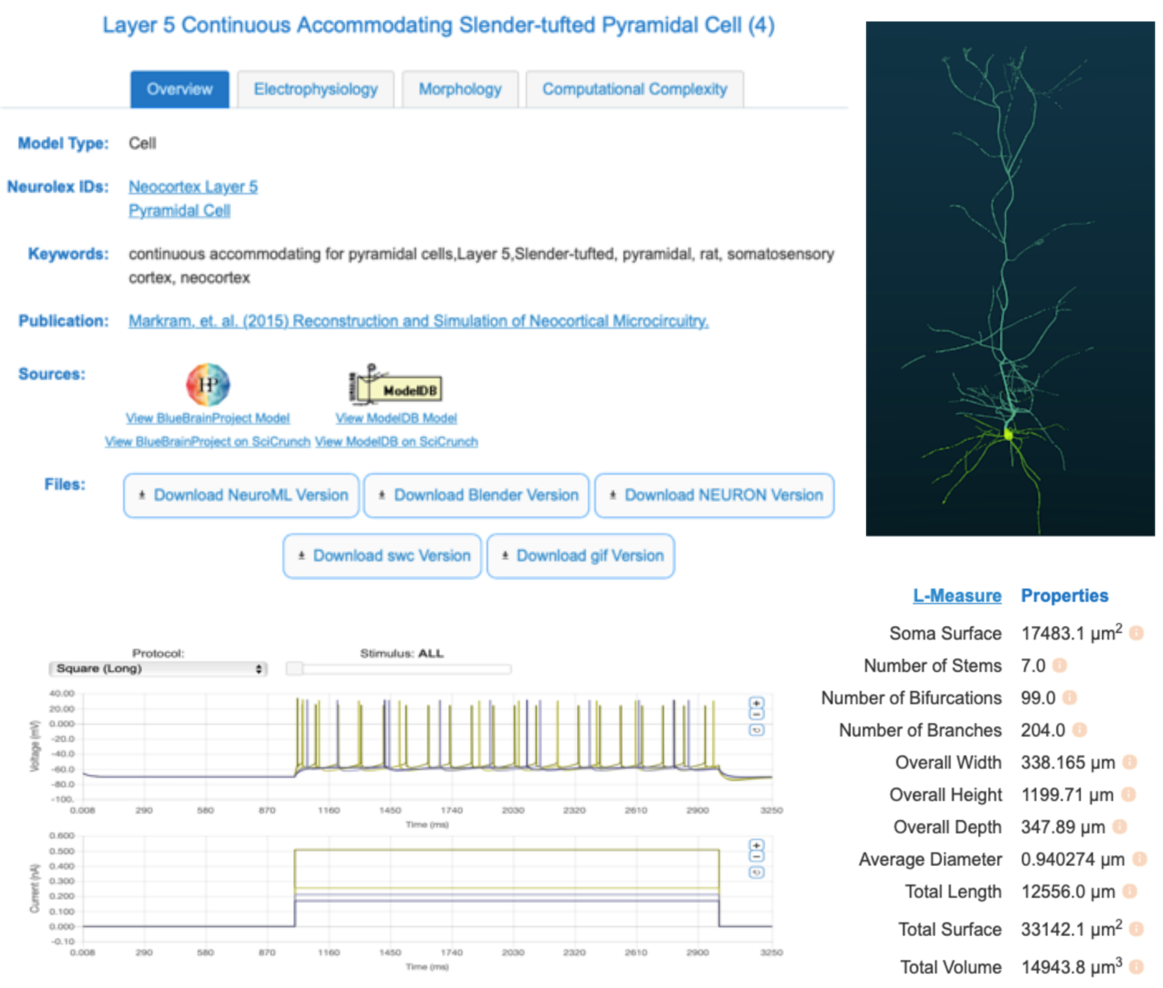
Arizona State University

http://iconlab.asu.edu

WHAT CAN WE LEARN FROM THE LANDSCAPE OF DATA-DRIVEN MODELS OF CORTICAL NEURONS?

MOTIVATION

NeuroML-DB [2] catalogues over 1,500 published models obtained in NeuroML format from Open Source Brain [5]. Complementing OSB, NeuroML-DB provides systematic characterizations of model complexity, electrophysiology, and morphology, making it easy to find, evaluate, and reuse models and their components.



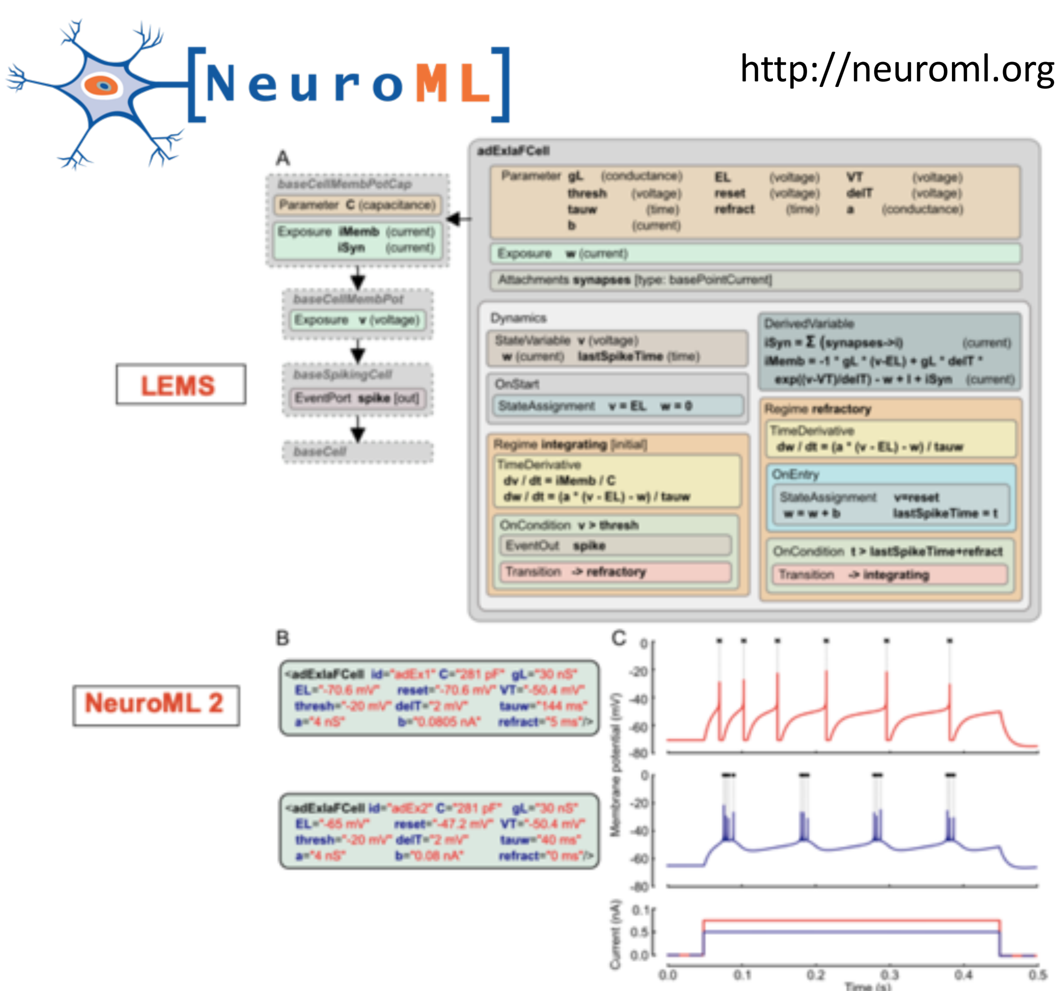
How well do models cover the diversity of experimentally recorded neurons?

Which features maximally differentiate among neuron/model types and their dynamical behaviors?

Are there models of neurons and channels that are outliers when compared to each other and to cortical neuron electrophysiology data?

MODELING METHODS

We focus on models described in ***NeuroML*** – a simulator independent, modular, multiscale model description language [4]. This standardized format allows for automated model analysis.

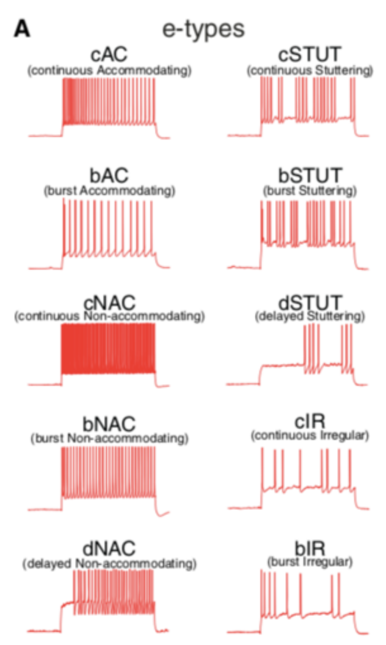


COMPARING TO DATA

Allen Institute for Brain Science, Allen Cell Types Database [7] can be accessed using the SDK. http://celltypes.brain-map.org

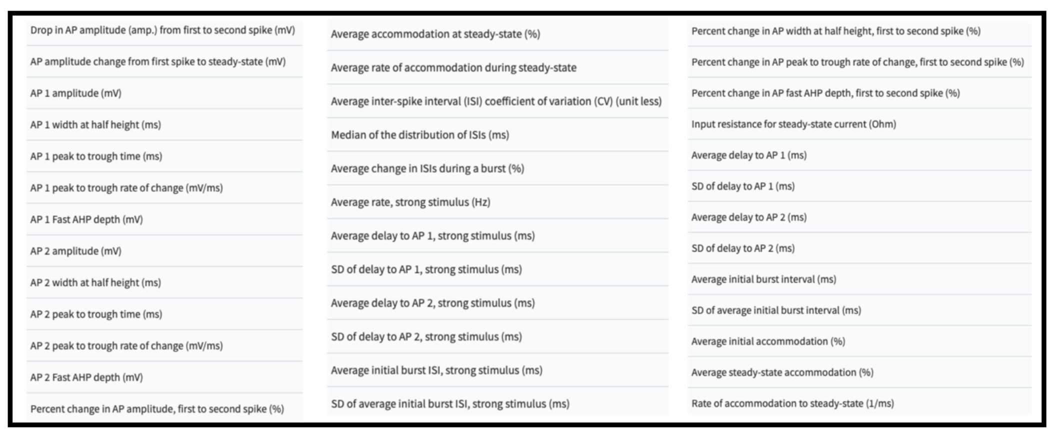
Large-scale Model	Blue Brain Project (1035)	Allen Institute (170)
Publication	Markram et al. (2015) [8]	Gouwens et al. (2018) [6]
Exp. Protocol	Druckmann et al. (2012) [3]	Allen Cell Types Database Protocol
Features	38 Druckmann Features	12 Features

WHICH FEATURES?



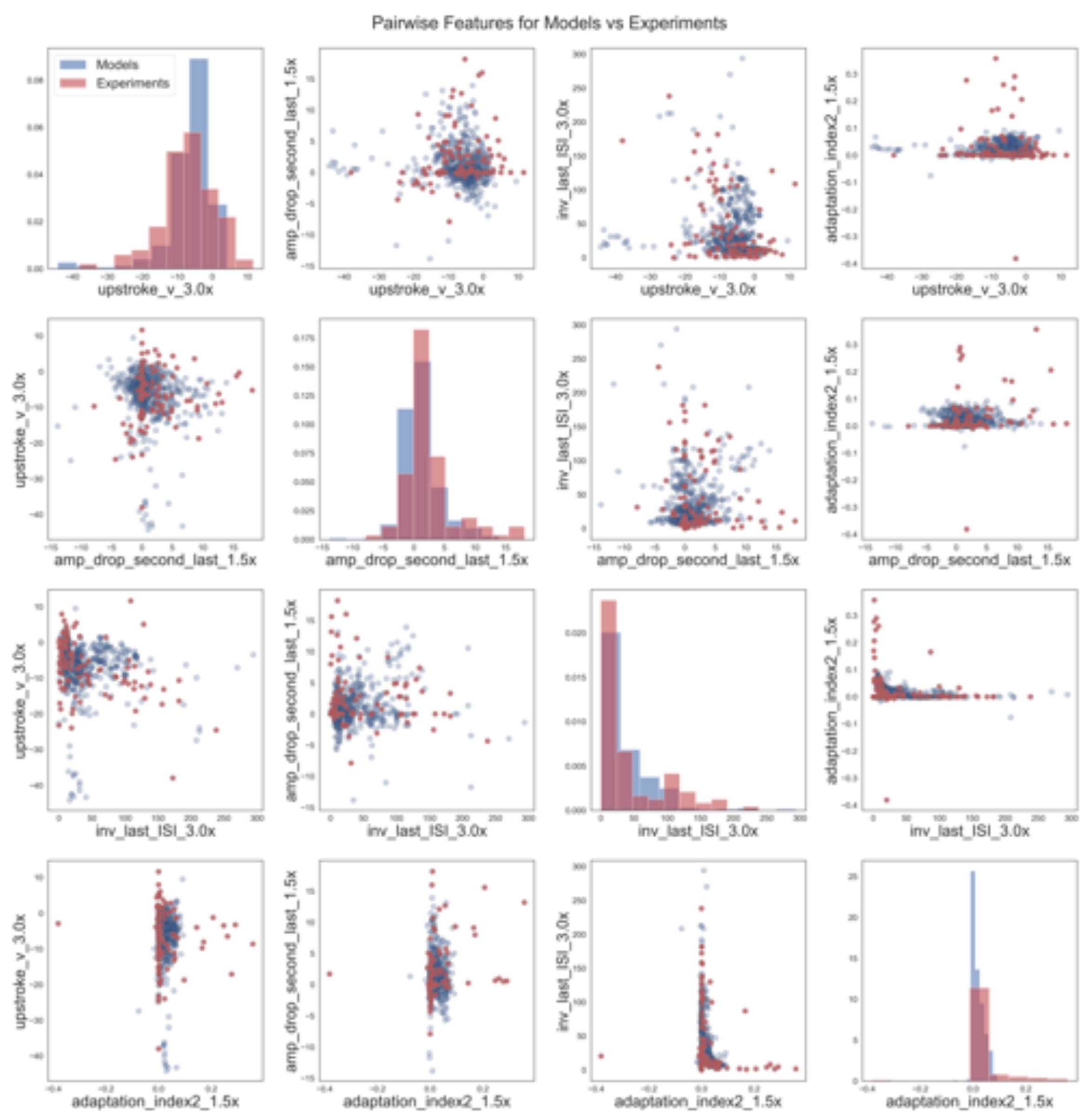
Electrical behavior of neuron types according to the Petilla terminology [1]. (Image from [8].) Druckmann et al. features below [3].

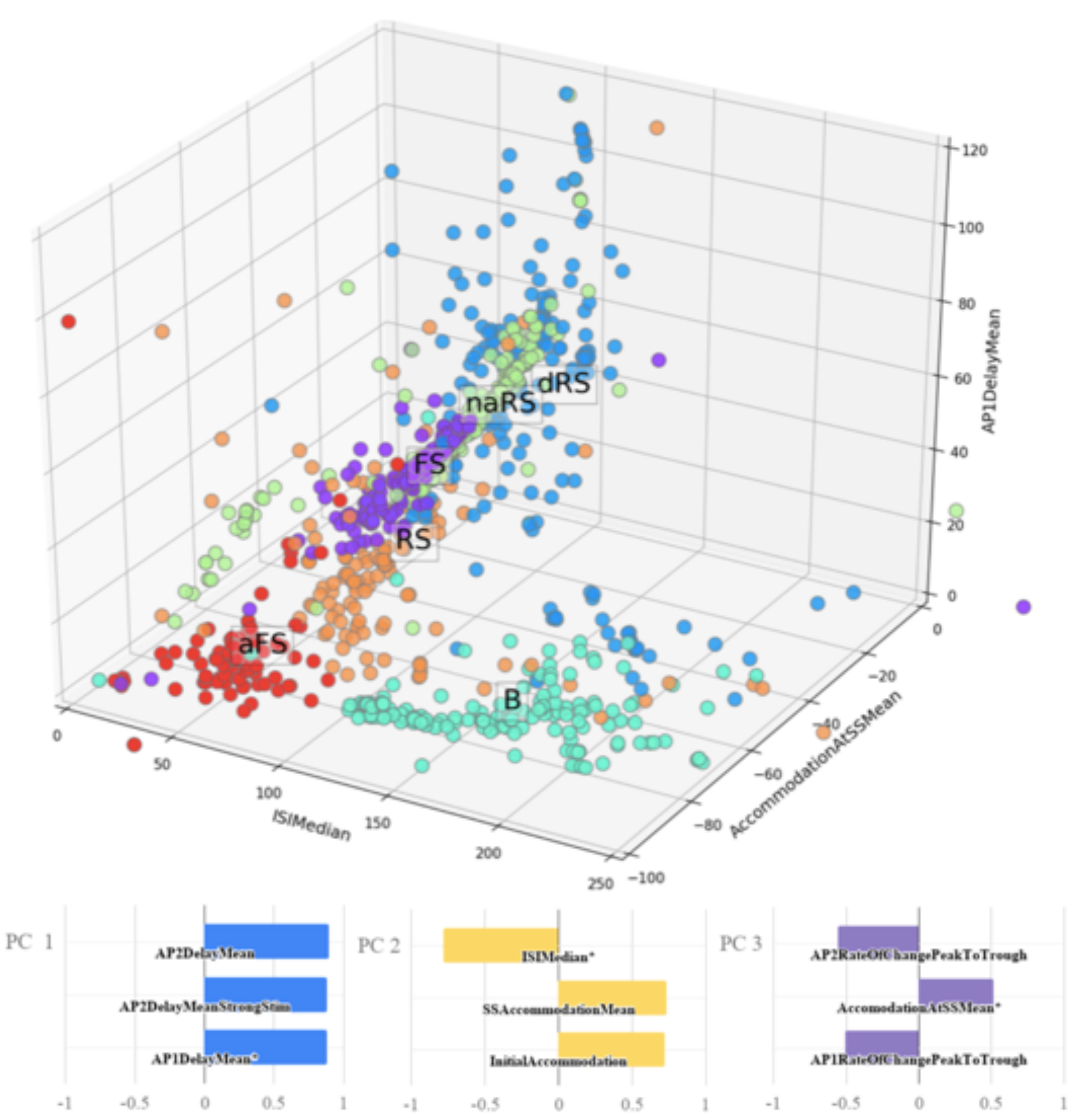
c: continuous
d: delayed
b: bursting
AC: accommodating
NAC: non-accommodating
STUT: stuttering
IR: irregular



WHAT CAN WE LEARN?

Below: Comparisons of open data and cortical neuron model outputs for pairs of features (both from Druckmann et al. [3] and the Allen SDK [7]. There is good agreement between models and data but outliers could reveal specific experimental behaviors that are not captured well by models or models that do not fit data well.

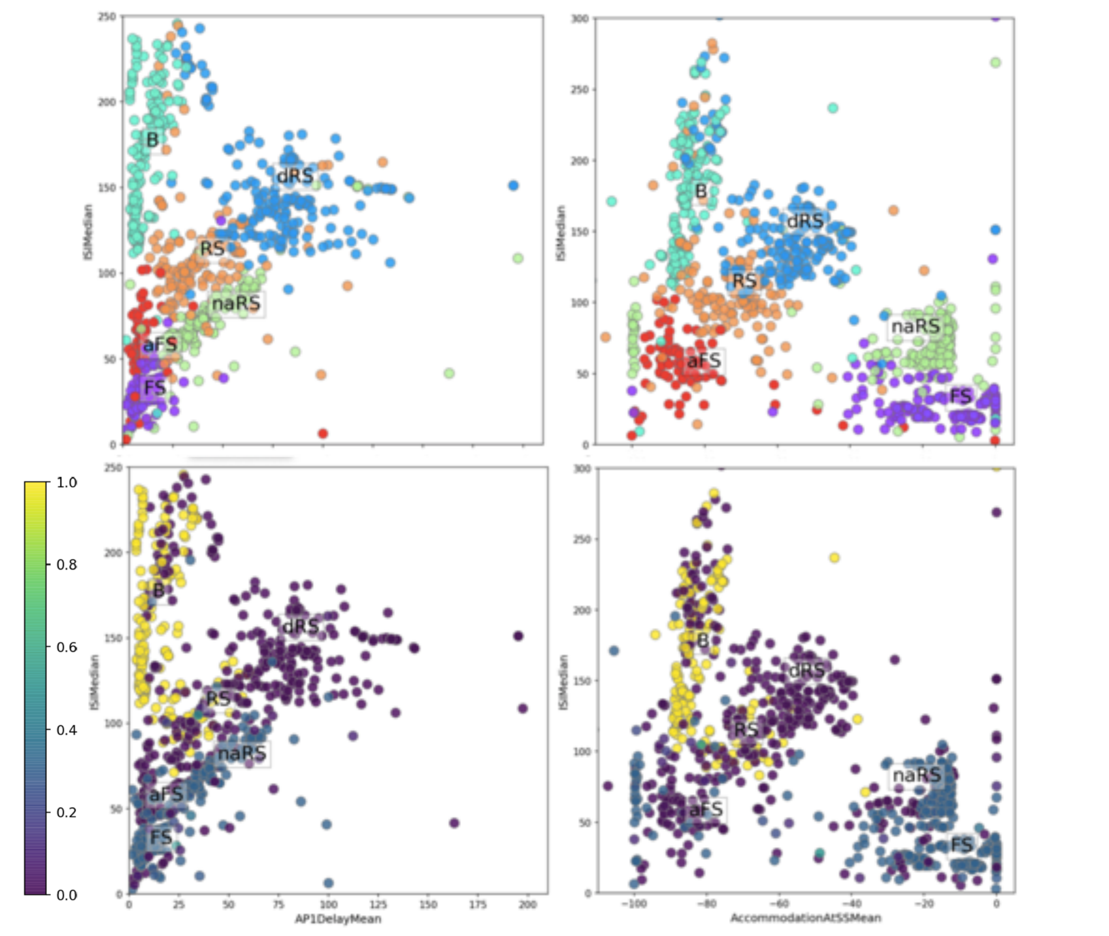




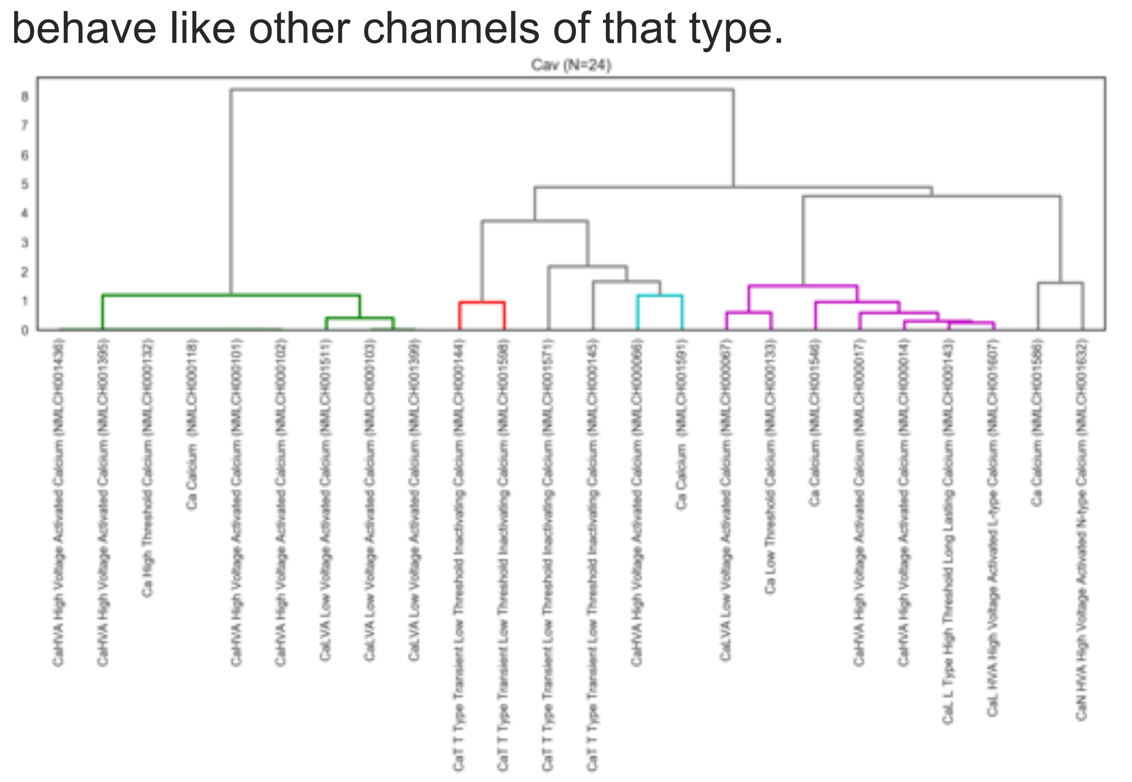
Hierarchical clustering of models with a density-based clustering method (HDBSCAN) on PCA-reduced features. Factor loading reveals features associated with top three components as shown directly above. Clusters correspond well to assigned electrical types, but outliers exist at different levels and will be the subject of further investigation.

CHANNEL MECHANISMS

We investigate different channel types responsible for neuron model behaviors. Top: Projected clusters of cortical neuron models in feature space. Bottom: Normalized maximal conductance for slow inactivating K+ channel in soma for same models.



Agglomerative clustering of model channel dynamics for multiple simulation protocols reveals channels that do not behave like other channels of that type.

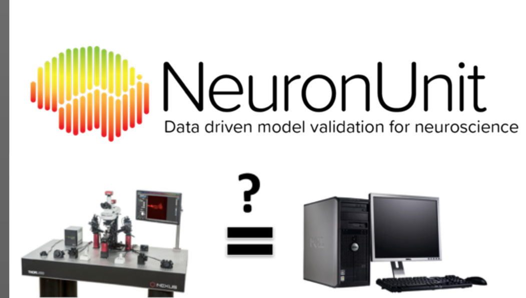


DIY MODEL ANALYSIS!

NeuroML-DB data are available via an ***API***, which returns a JSON object in response to a URL. See documentation at https://neuroml-db.org/api and links to browser add-ons and examples for working with JSON URLs in programming languages like Python, R, and MATLAB.

Code Available at:
https://github.com/vrhaynes/LargeScaleModelAnalysis_2019
Interactive Clustering Visualization Available at:
https://iconlab.asu.edu/barcelona

MODEL/DATA COMPARISONS



http://dash.scidash.org

NeuronUnit [9] provides a way to compare specific models to data using "unit tests". Results are shared at the ***SciDash*** dashboard. Feature extraction routines used here are providing the basis of novel unit tests for further work.

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ACKNOWLEDGEMENTS

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