Workshop on Applied Deep Learning in Intracranial Neurophysiology

Part 6 – Advanced Recurrent Neural Networks

June 21, 2019

Presented by Chadwick Boulay, MSc, PhD

Sachs Lab

JAX: Autograd and XLA

- https://github.com/google/jax
- No Windows support
- `jit`: just-in-time compilation to GPU
- `grad`: Automatic differentiation of Python/Numpy functions
- `vmap`: Auto-vectorization

Quick demo

LFADS - Latent Factor Analysis via Dynamical Systems

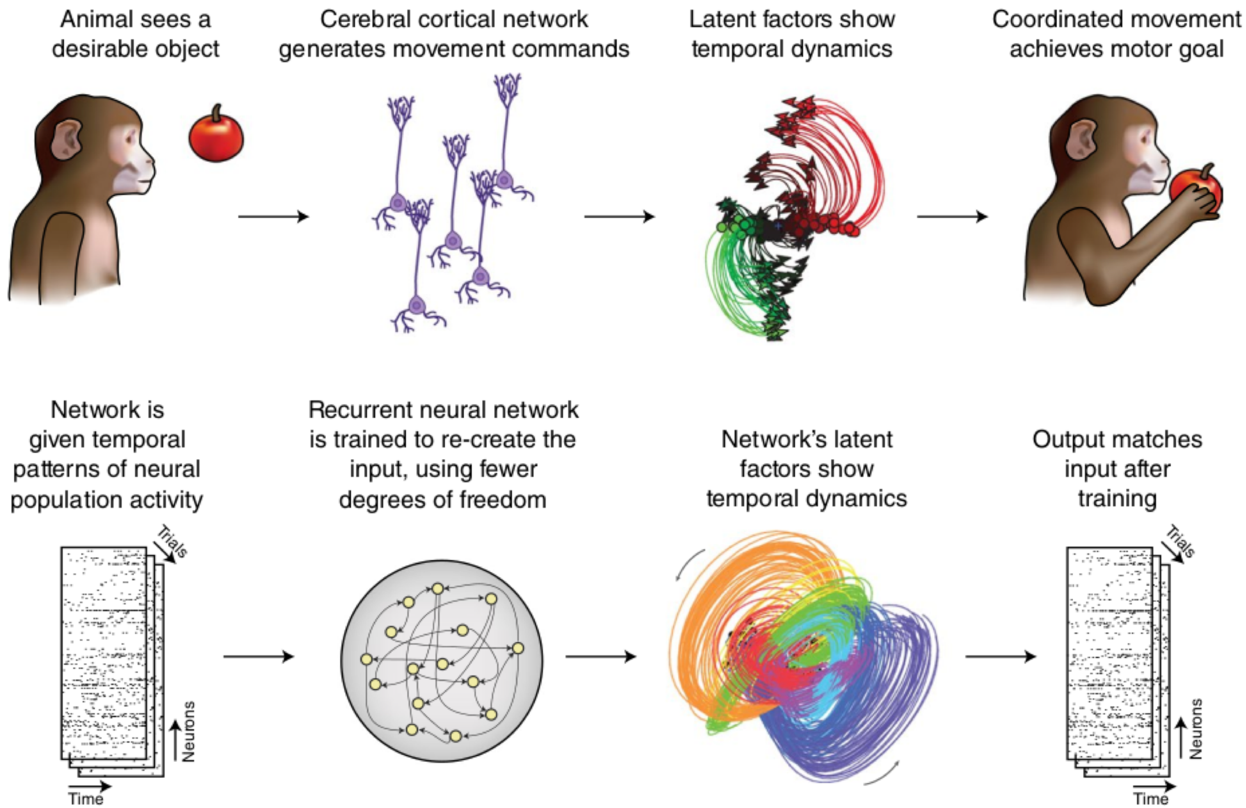


Fig. 1 | An artificial neural network (bottom) can capture the dynamical structure present in neural population activity (top). Credit: Kim Caesar/Springer Nature

nature methods

ysis via

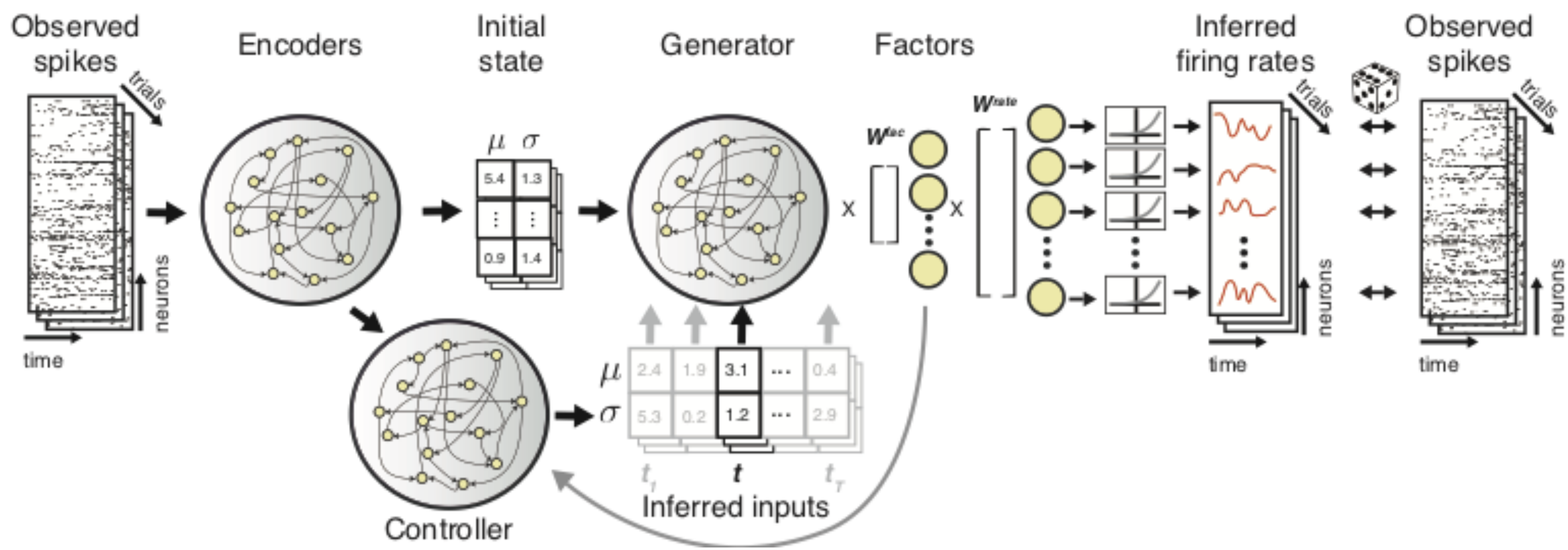
Article | Published: 17 September 2018

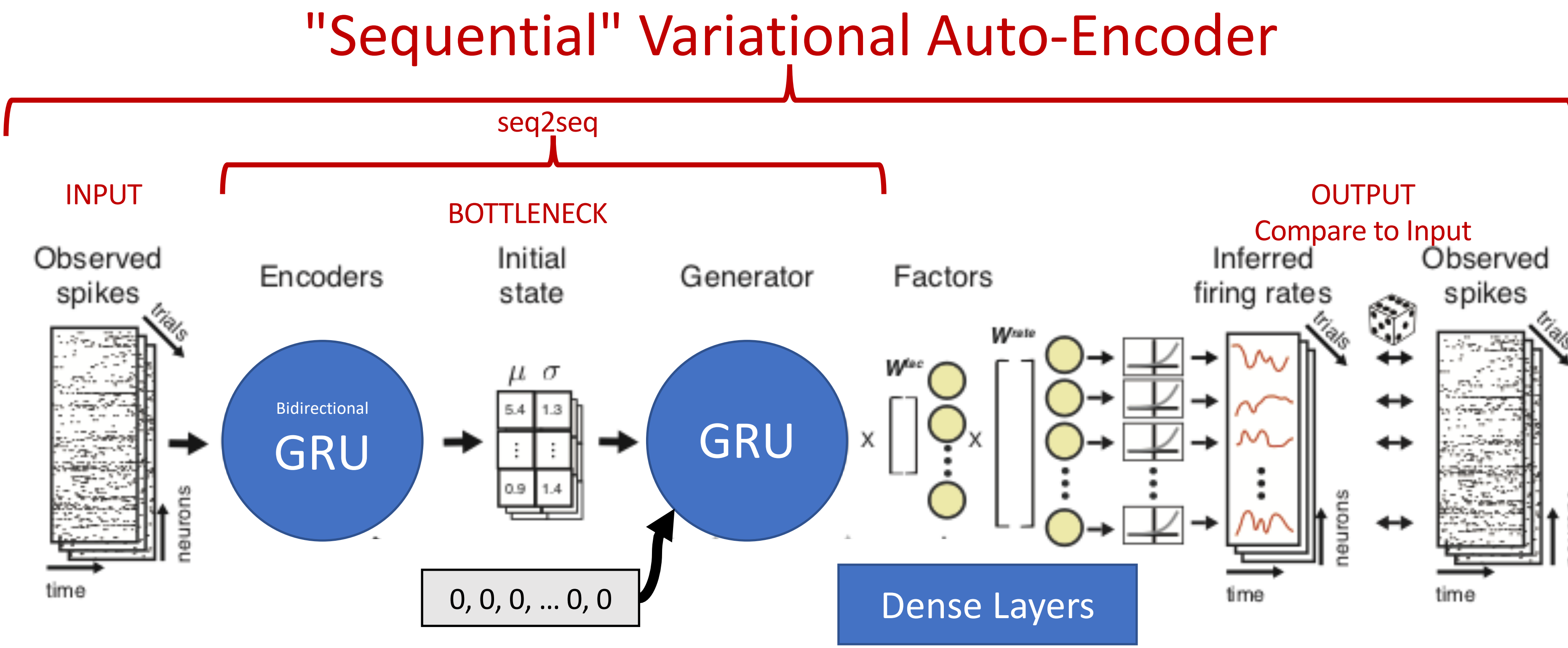
Inferring single-trial neural population dynamics using sequential auto-encoders

Link:
https://rdcu.be/6Wji

Chethan Pandarinath, Daniel J. O'Shea, Jasmine Collins, Rafal Jozefowicz, Sergey D. Stavisky, Jonathan C. Kao, Eric M. Trautmann, Matthew T. Kaufman, Stephen I. Ryu, Leigh R. Hochberg, Jaimie M. Henderson, Krishna V. Shenoy, L. F. Abbott & David Sussillo

Nature Methods **15**, 805–815 (2018) | Download Citation




"Sequential" Variational Auto-Encoder
seq2seq
INPUT
BOTTLENECK
OUTPUT
Compare to Input
Observed spikes
trials
neurons
time
Encoders
Bidirectional
GRU
Initial state
μ σ
5.4 1.3
0.9 1.4
Generator
GRU
0, 0, 0, ... 0, 0
Factors
x
Inferred firing rates
trials
neurons
time
Observed spikes
trials
neurons
time
Dense Layers

FYI: Official LFADS tutorial

- RNN white noise integrator
- LFADS
- Before they work on Colab, change the notebook settings to Python 3, Use GPU, then run the following in a cell at the top.

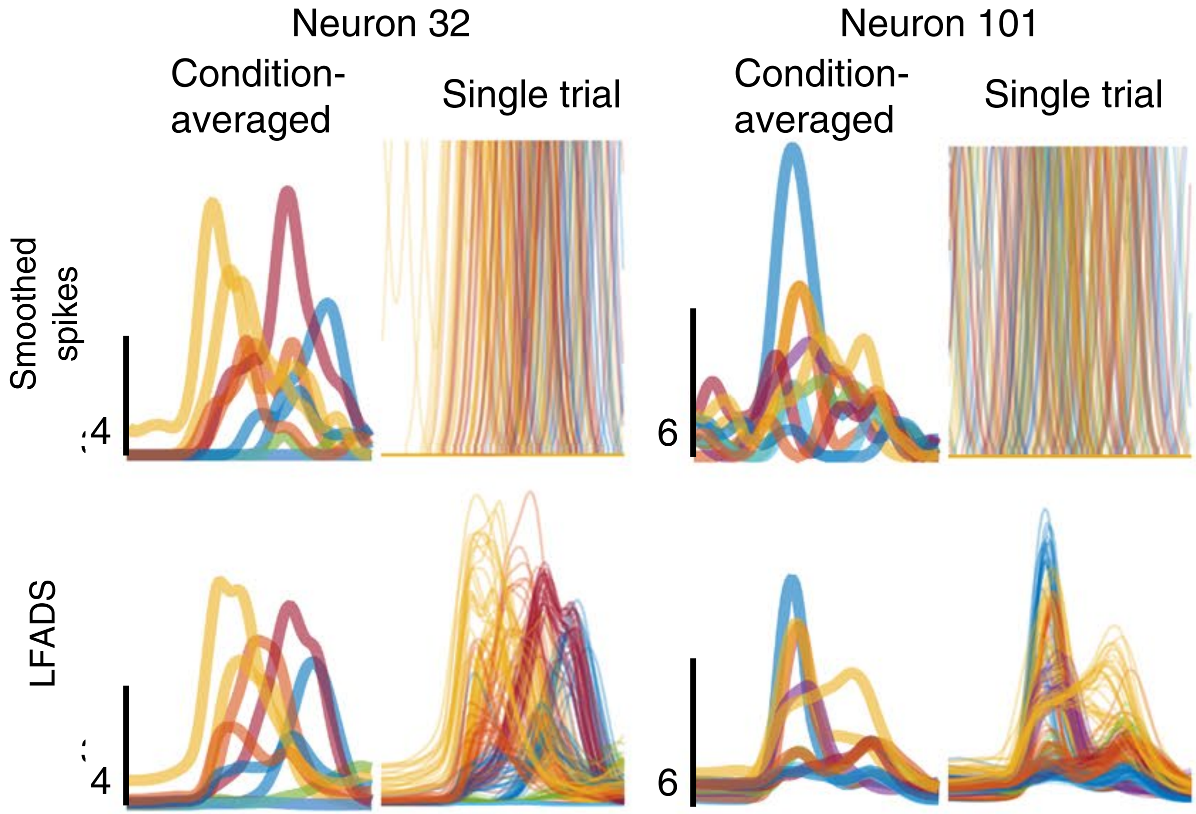
```
import os
import sys
from importlib import reload
!pip install --upgrade -q https://storage.googleapis.com/jax-wheels/cuda$(echo $CUDA_VERSION |
sed -e 's/\.//' -e 's/\..*//')/jaxlib-latest-cp36-none-linux_x86_64.whl
!pip install --upgrade -q git+https://github.com/google/jax.git
!git clone --recursive https://github.com/google-research/computation-thru-dynamics.git
sys.path.append(os.path.join('.', 'computation-thru-dynamics'))
```

- 06_01_LFADS.ipynb
  - Will not work on Windows

LFADS Results

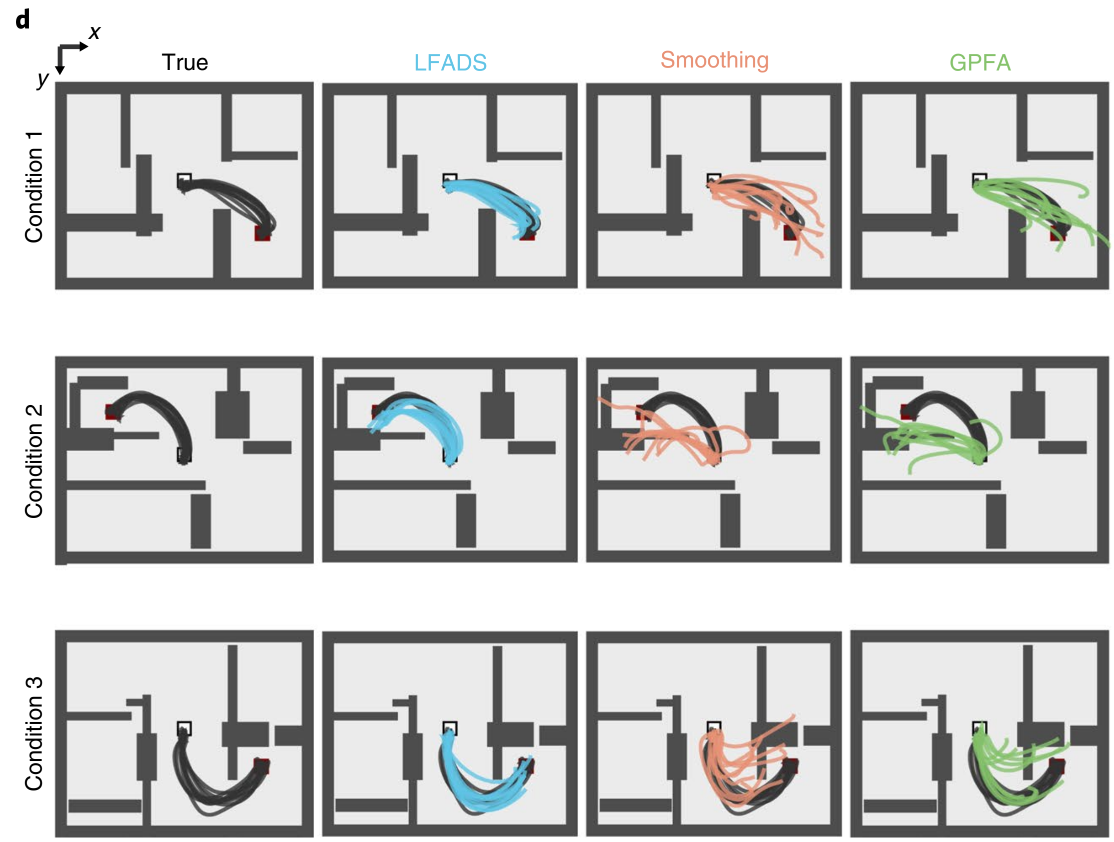
LFADS assumes that rates are predictable.

LFADS-inferred rates are more structured than smoothed spikes.

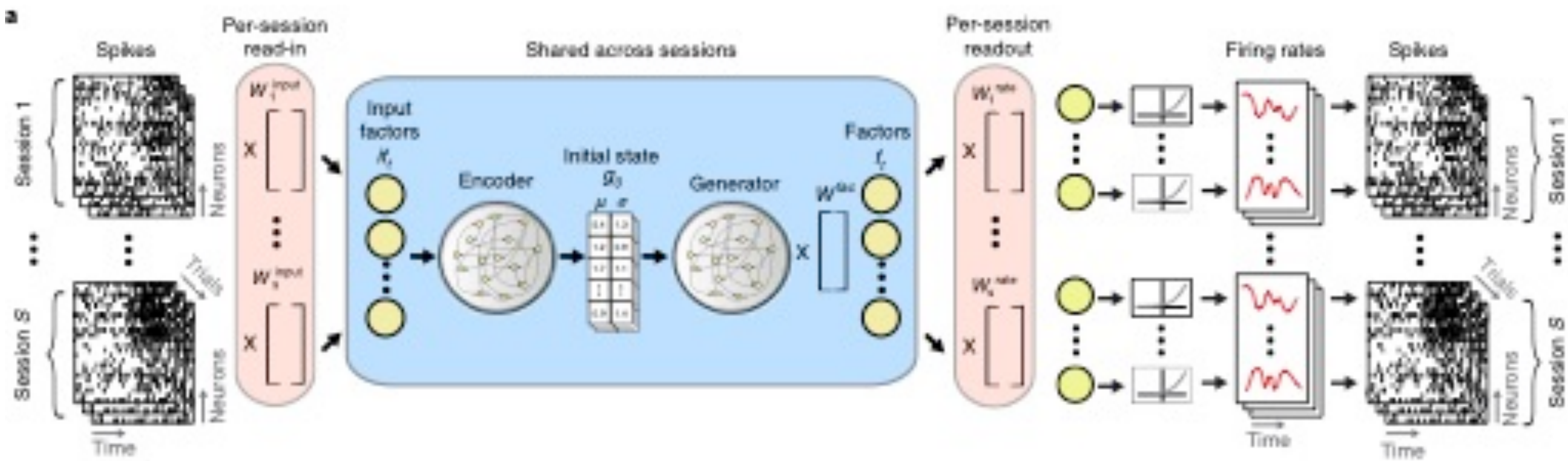


LFADS Results

Reconstructing movement velocities (using OLE), LFADS with lower-dimensional inferred rates outperformed models using more dimensions with different rate-smoothing techniques.



LFADS Results

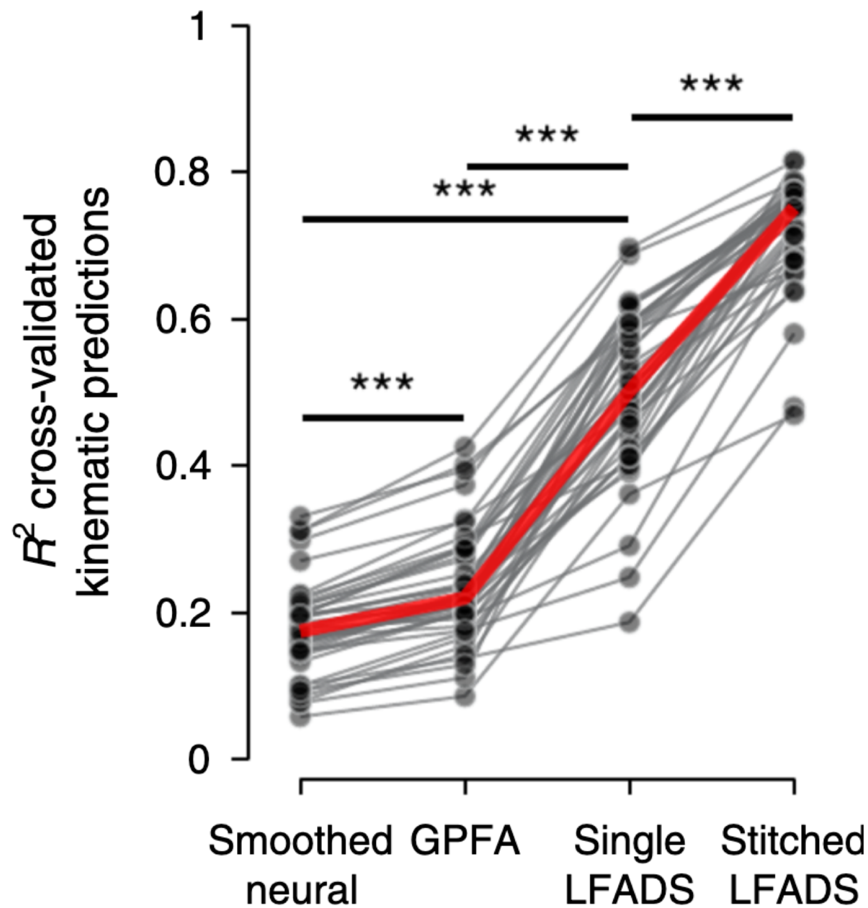


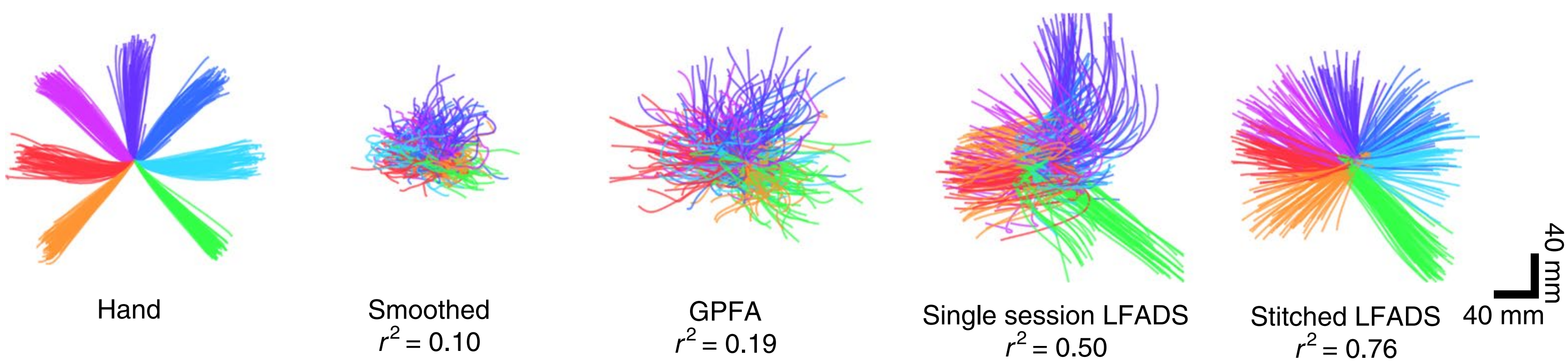
Multiple sessions were used to train the model, using per-session read-in and readout transformations.

- Initialized by principal components regression. Across all sessions, get per-condition average rates, do PCA. Repeat within-session but no PCA. Regress within-session to across-session components.

LFADS Results

- Model trained with multiple sessions (stitched) generates rates that better predict behaviour on a single session.

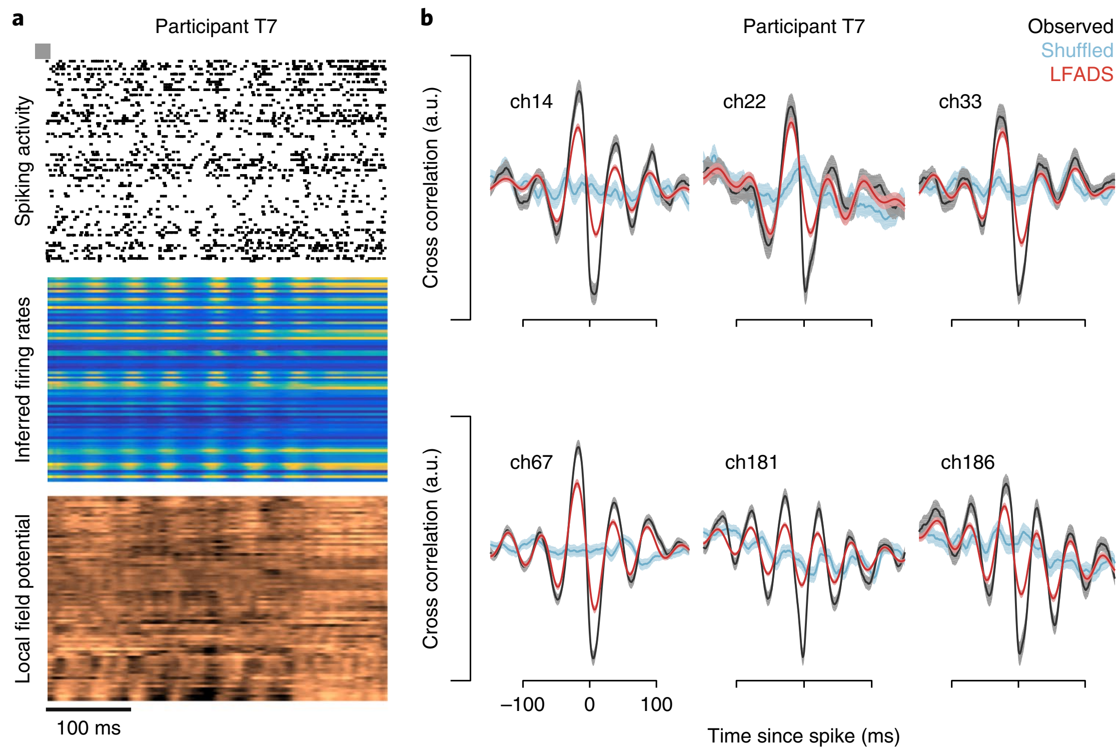




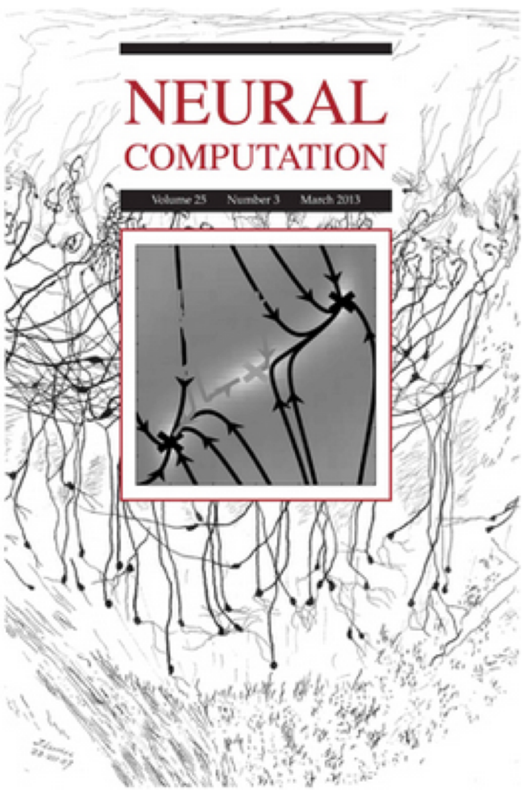
LFADS Results

Cross-correlation with LFPs.

LFADS generates inferred rates that preserve oscillatory structure.



Further inspection of RNN



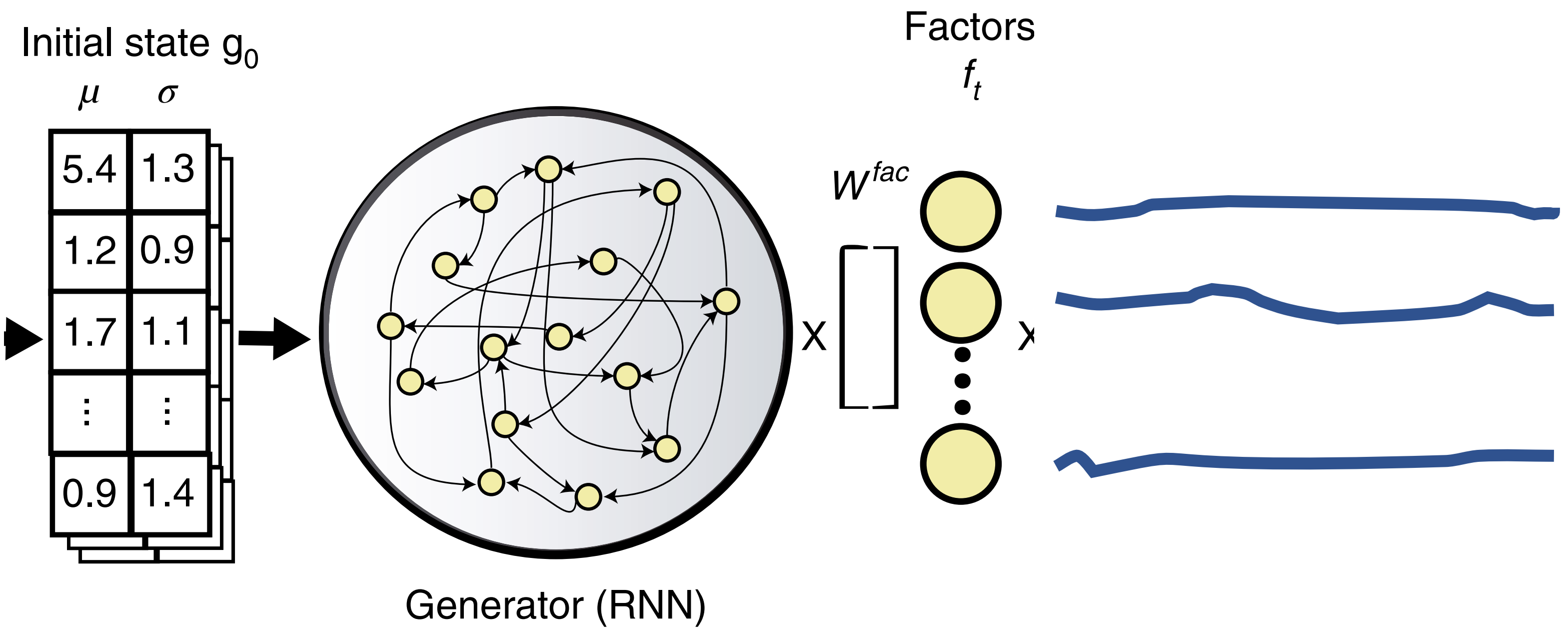
Opening the Black Box: Low-Dimensional Dynamics in High-Dimensional Recurrent Neural Networks

David Sussillo and Omri Barak

Posted Online February 05, 2013
https://doi.org/10.1162/NECO_a_00409

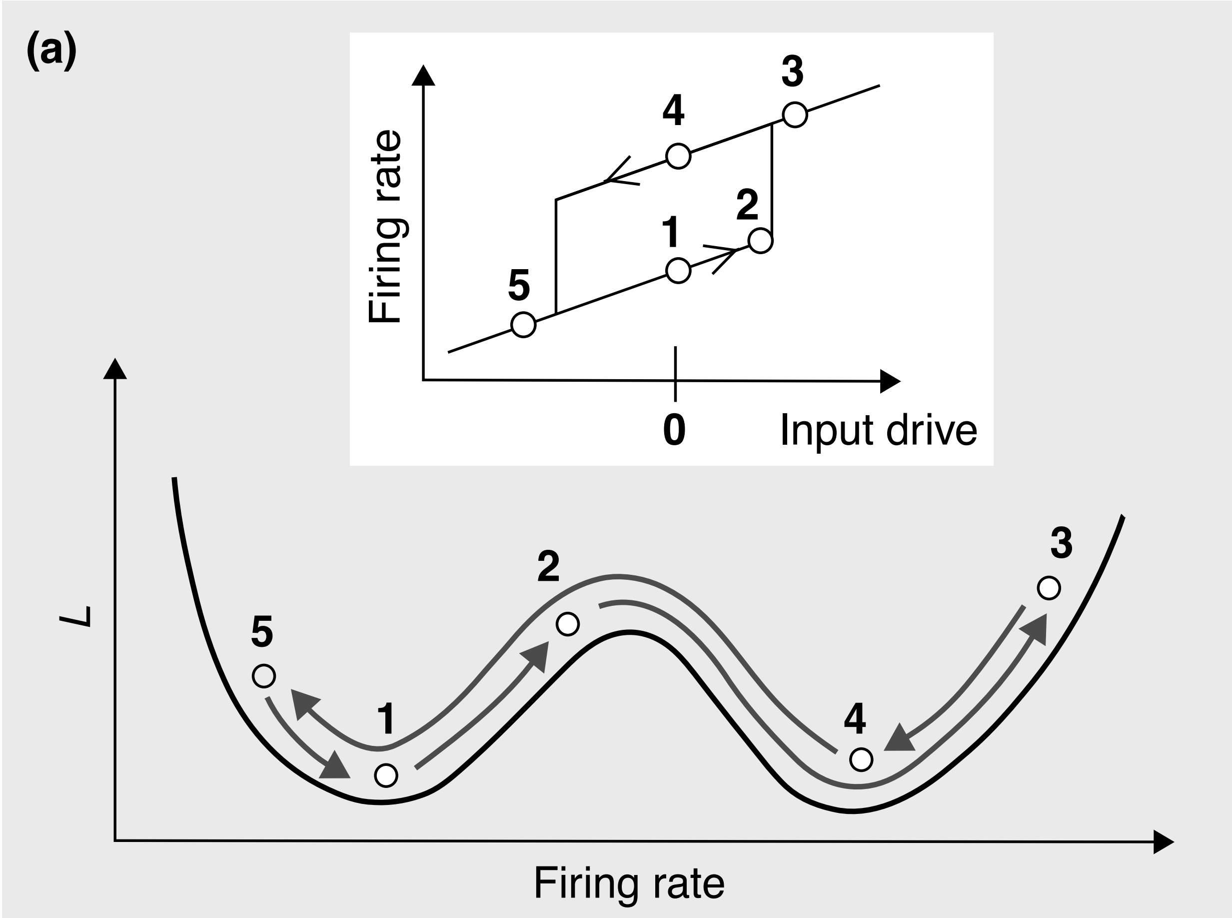
Neural Computation
Volume 25 | Issue 3 | March 2013
p.626-649

Fixed Points



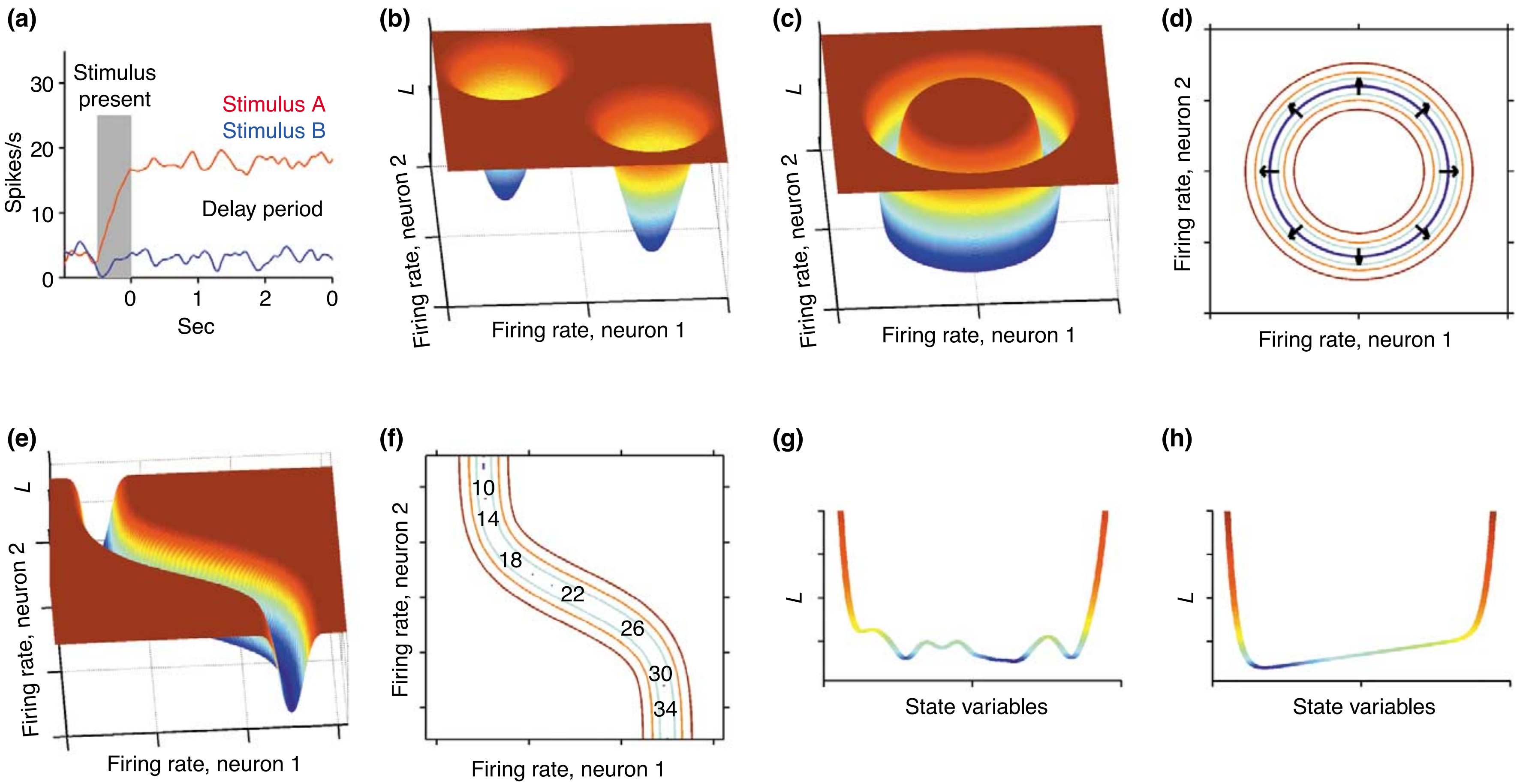
What if we found initial state values that caused the generator to always output (almost) the same value as the input?

Attractor Points



Basic mechanisms for graded persistent activity: discrete attractors, continuous attractors, and dynamic representations

Carlos D Brody*†, Ranulfo Romo‡ and Adam Kepecs*

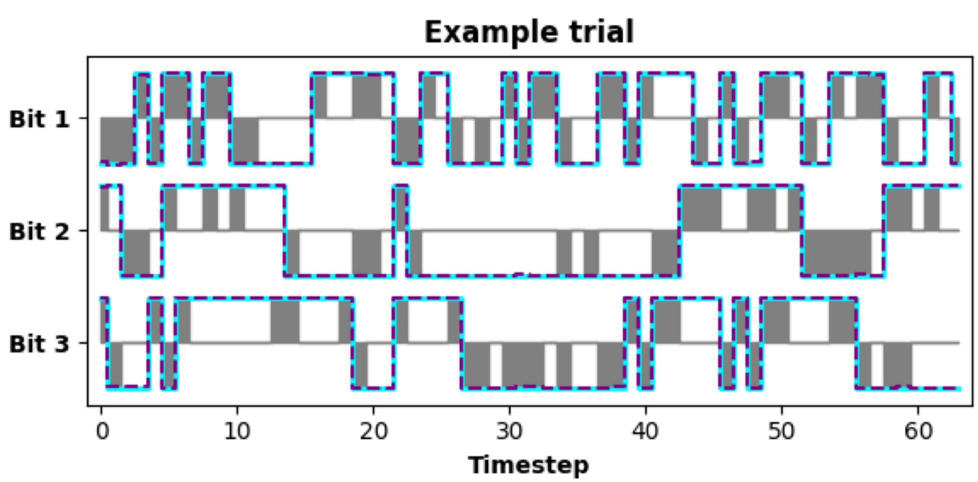


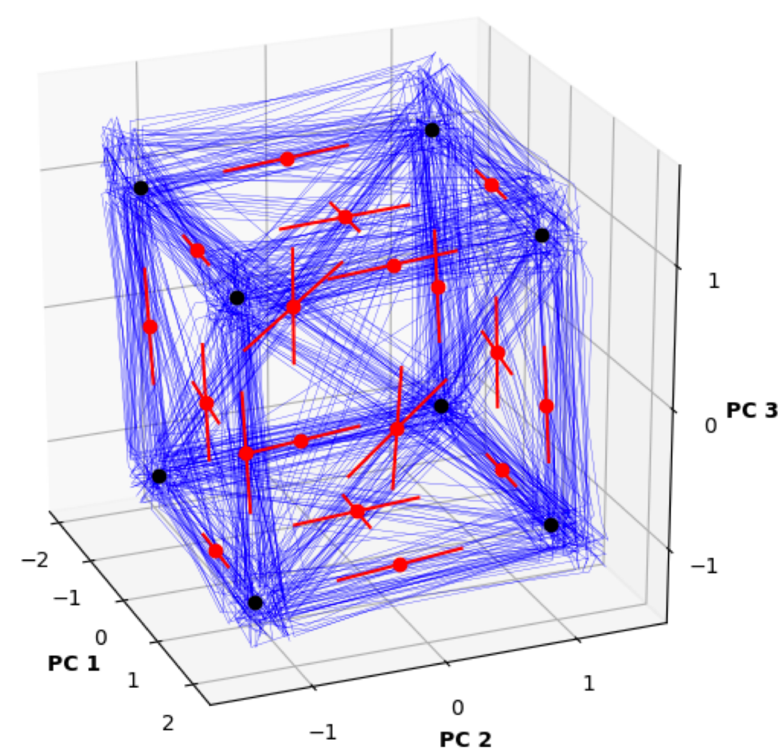
Current Opinion in Neurobiology

FixedPointFinder: A Tensorflow toolbox for identifying and characterizing fixed points in recurrent neural networks

Matthew D. Golub[1,2] **and David Sussillo**[1,2,3,4]

1 Department of Electrical Engineering, Stanford University **2** Stanford Neurosciences Institute, Stanford University **3** Google Brain **4** Work done while at Stanford University





Also JAX-based ipynb tutorial:
https://colab.research.google.com/github/google-research/computation-thru-dynamics/blob/master/notebooks/Fixed%20Point%20Finder%20Tutorial.ipynb

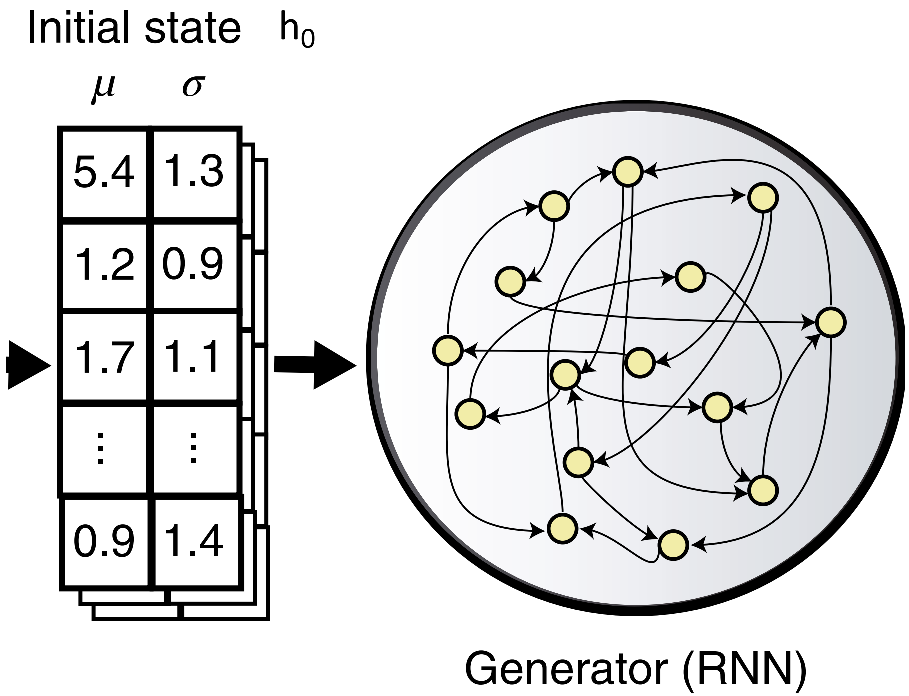
Fixed-point Finder

Start with a set of initial conditions h_0 known to occur in real data.

Loss = $(h - F(h))^2$

Minimize loss w.r.t. initial state h_0. RNN weights do not change!

Sort ‘trained initial conditions’ by loss and take N points with lowest loss.



Context-dependent computation by recurrent dynamics in prefrontal cortex

Valerio Mante[1]†*, David Sussillo[2]*, Krishna V. Shenoy[2,3] & William T. Newsome[1]