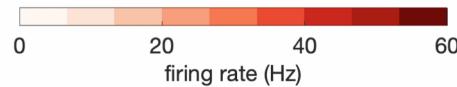


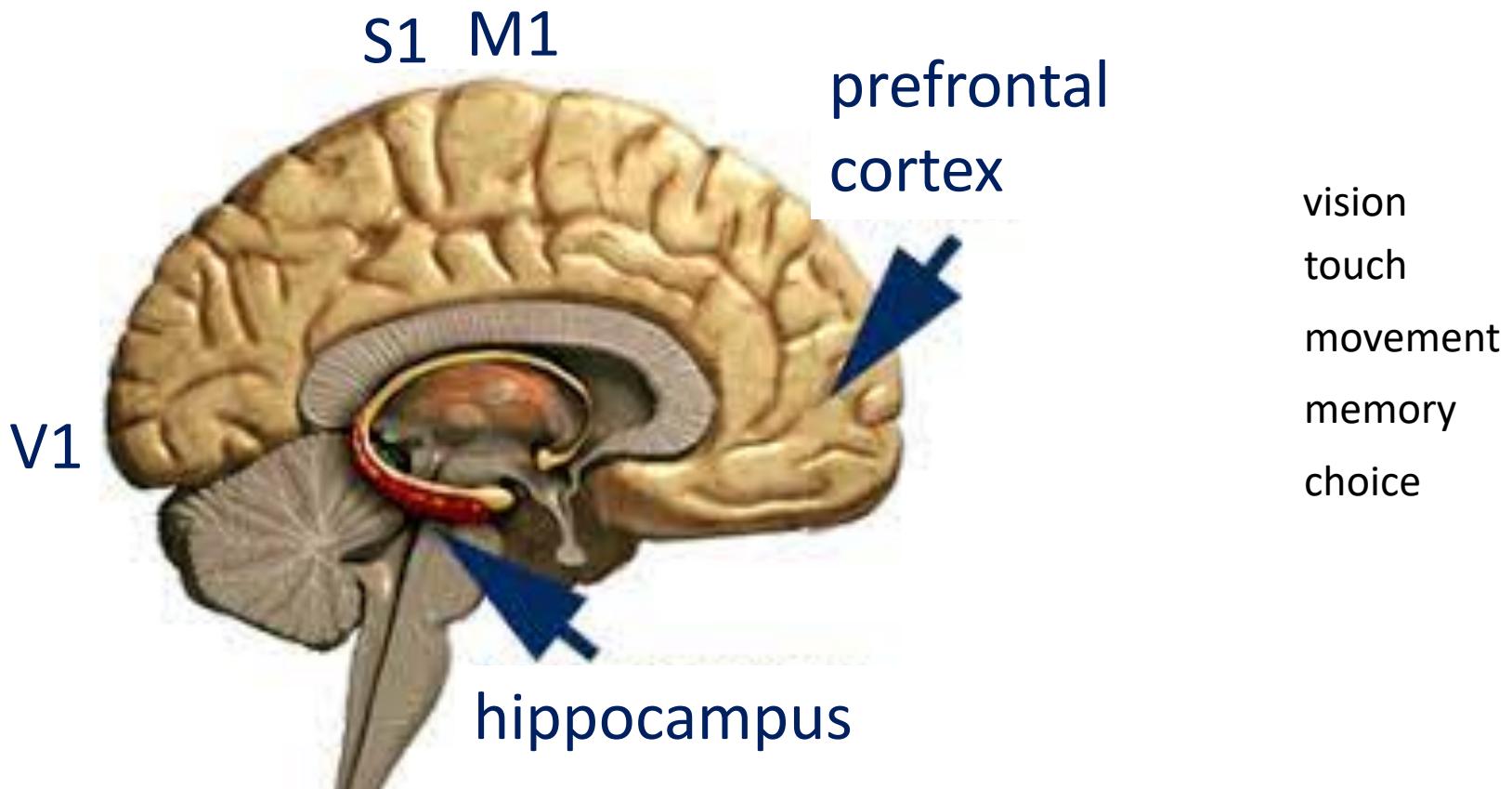
pre-stimulus , time = 0.09 s



Modelling Brain-Wide Activity During Cognitive Tasks

Seán Froudist-Walsh

Lecturer in Computational Neuroscience



Models in computational neuroscience

Chapter 7 - Network Models

- Introduction
- Firing-Rate Models
 - Feedforward and Recurrent Networks
 - Continuously Labelled Networks

- Feedforward Networks
 - Neural Coordinate Transformations

- Recurrent Networks
 - Linear Recurrent Networks
 - Selective Amplification
 - Input Integration
 - Continuous Linear Recurrent Networks
 - Nonlinear Recurrent Networks
 - Nonlinear Amplification
 - A Recurrent Model of Simple Cells in Primary Visual Cortex
 - A Recurrent Model of Complex Cells in Primary Visual Cortex
 - Winner-Take-All Input Selection
 - Gain Modulation
 - Sustained Activity
 - Maximum Likelihood and Network Recoding

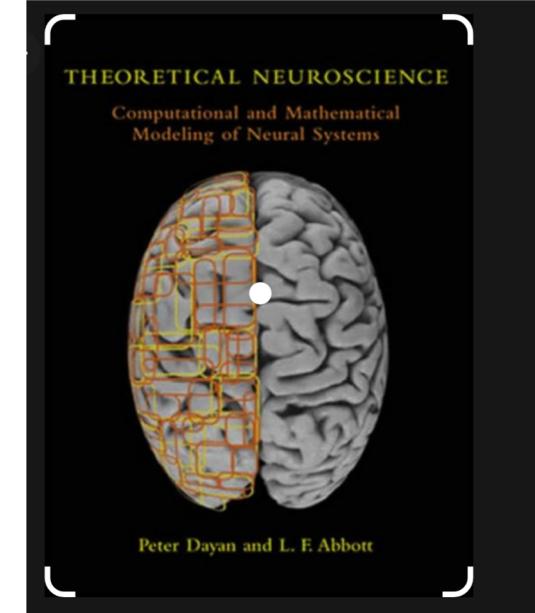
- Network Stability
- Associative Memory
- Excitatory-Inhibitory Networks
 - Homogeneous Excitatory and Inhibitory Populations
 - Phase-Plane Methods and Stability Analysis
 - The Olfactory Bulb
 - Oscillatory Amplification

- Stochastic Networks
- Chapter Summary
- Appendix

IV Dynamics of Cognition

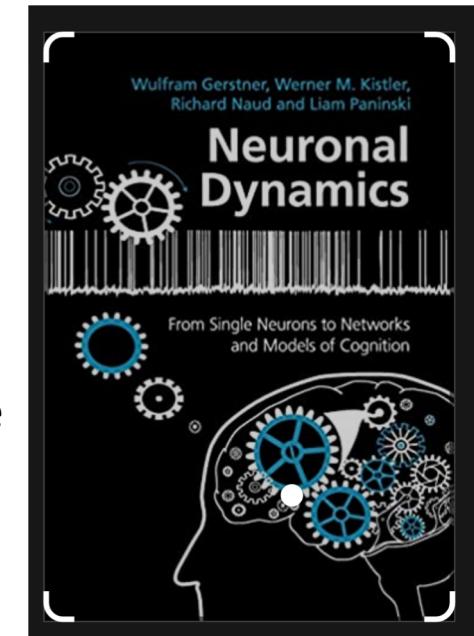
- 16 Competing Populations and Decision Making
- 17 Memory and Attractor Dynamics
- 18 Cortical Field Models for Perception
- 19 Synaptic Plasticity and Learning
- 20 Outlook: Dynamics in Plastic Networks

(pre)motor - reach



V1 - vision

prefrontal – short memory
hippocampus - memory



prefrontal/parietal - choice
hippocampus - memory
V1 - vision

We can now record neurons across many brain areas simultaneously

**Neuropixels
probe**

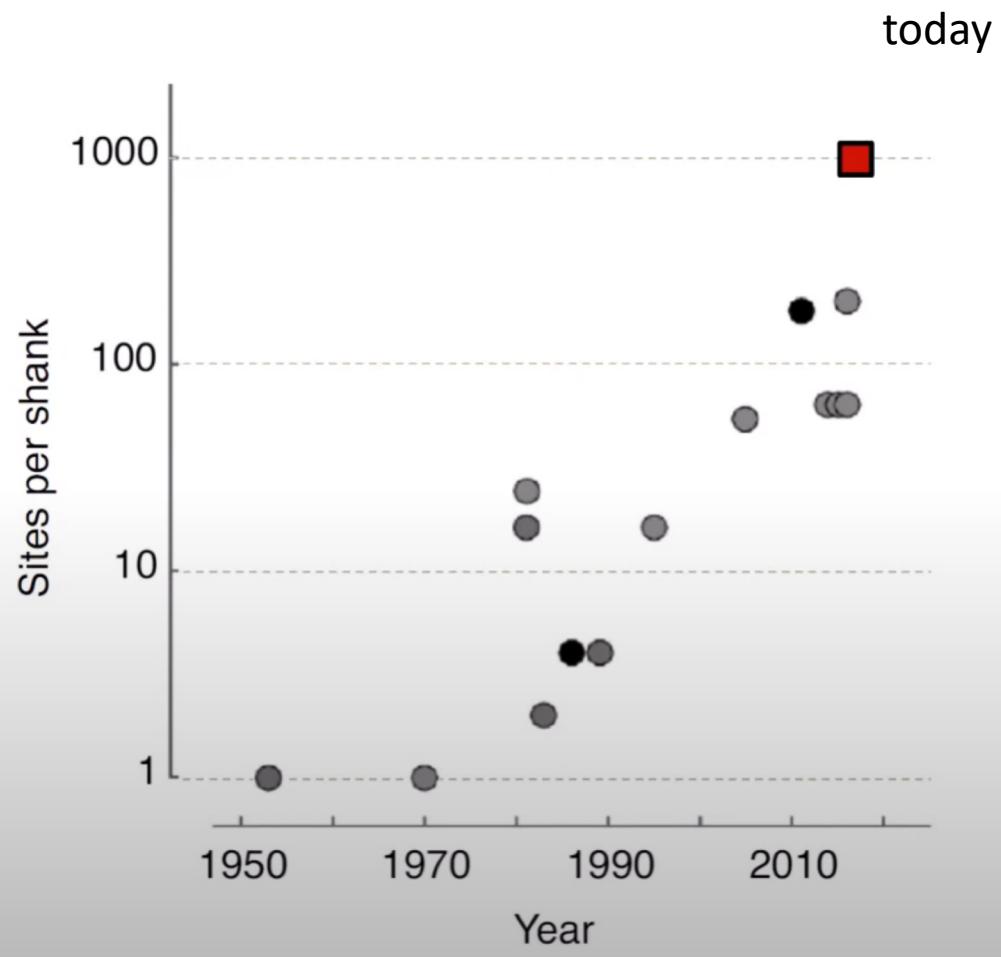
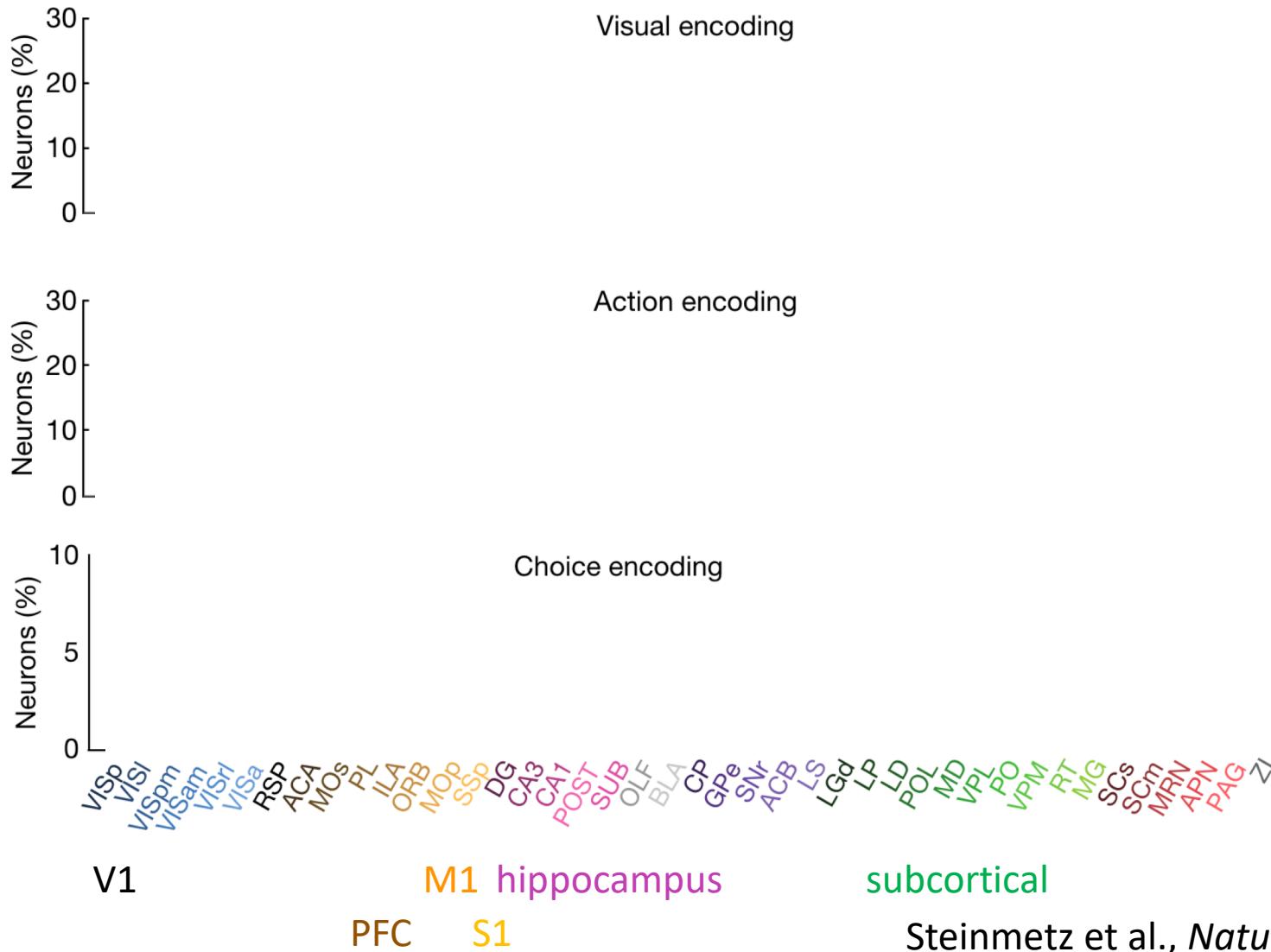


image: Matteo Carandini

Jun et al., *Nature*, 2017
Steinmetz et al., *Nature*, 2019

Sensory, motor and cognitive signals are present across many brain areas



How do dozens of brain areas work together
to produce function?

Models in computational neuroscience

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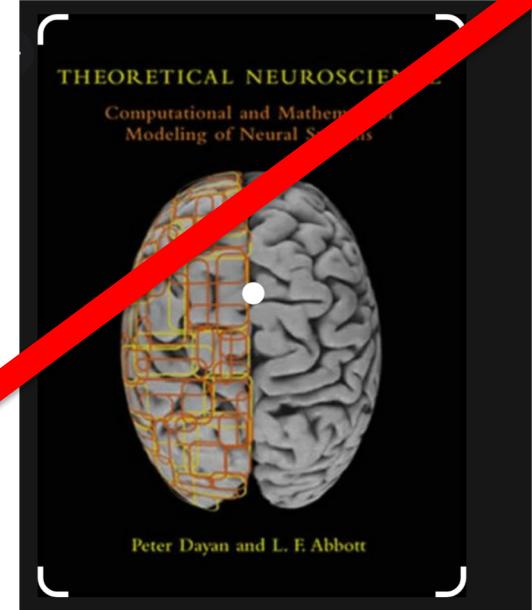
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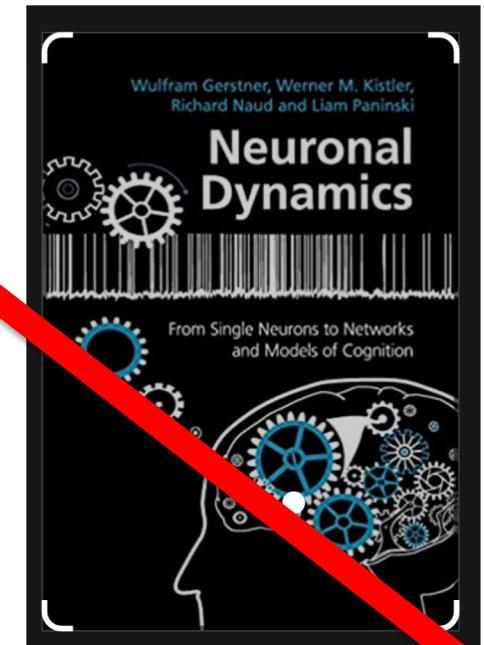
prefrontal – short memory

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V1 - vision



Learning objectives

1. Understand how whole-cortex models are constructed
2. Learn how variation in anatomical properties across the brain may lead to differences in functions across areas
3. Become familiar with some of the latest research on whole-cortex models during cognitive tasks

How do we build a dynamical model of the whole cortex?

Step 1/6: building blocks – local circuit models

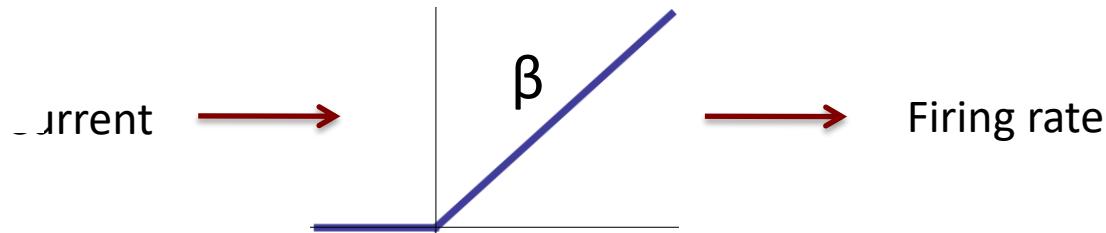
Canonical local cortical circuit

“Our view is that the rapid evolutionary expansion of neocortex has been made possible by building an ‘isocortex’ — a structure that uses **repeats of the same basic local circuits throughout a single [cortical] sheet.**”

RJ Douglas and KA Martin (2012)

A canonical local circuit model

Excitatory and inhibitory populations



$$\tau \frac{dr_{x,E}}{dt} = -r_{x,E} + \beta_E [w_{E,E} r_{x,E} + G \sum_{y \in Y} C_{y \rightarrow x} r_{y,E} - w_{E,I} r_{x,I}]_+$$

At each step in time the firing rate of the Excitatory neurons in area x would drop down towards zero if not for synaptic inputs.

Activity is pushed up by

- positive connections from the Excitatory population to itself
- and long-range inputs from other brain areas y

Activity is pushed down by

- negative inputs from the Inhibitory population

The size of the response to input depends on the slope.

Chaudhuri et al., *Neuron*, 2015

w, β, τ set to match

Binzegger et al (2009)

The time constant determines how quickly the rate can rise and fall in response to input

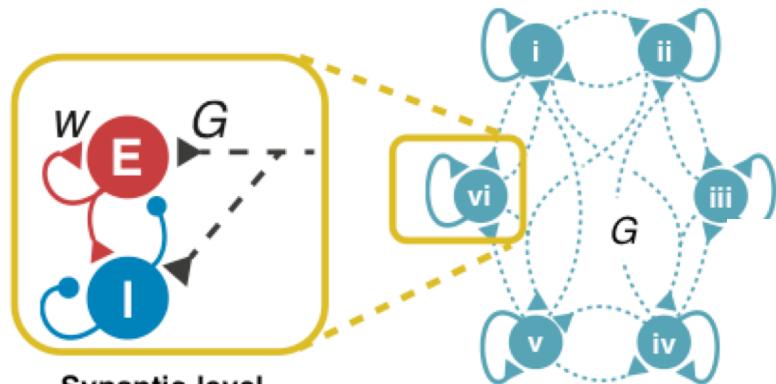
Firing rates cannot be negative.

How do we build a dynamical model of the whole cortex?

Step 1/6: building blocks – local circuit models

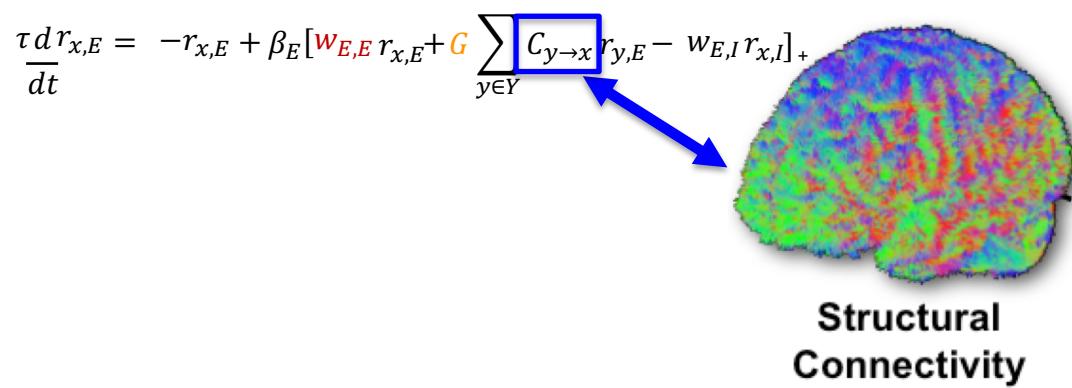
Step 2/6: connect the blocks – anatomical connectivity data

Modeling large-scale resting-state networks



Synaptic-level
model parameters:

w	G
local	global
recurrent	coupling
coupling	across nodes



How do we build a dynamical model of the whole cortex?

Step 1/6: building blocks – local circuit models

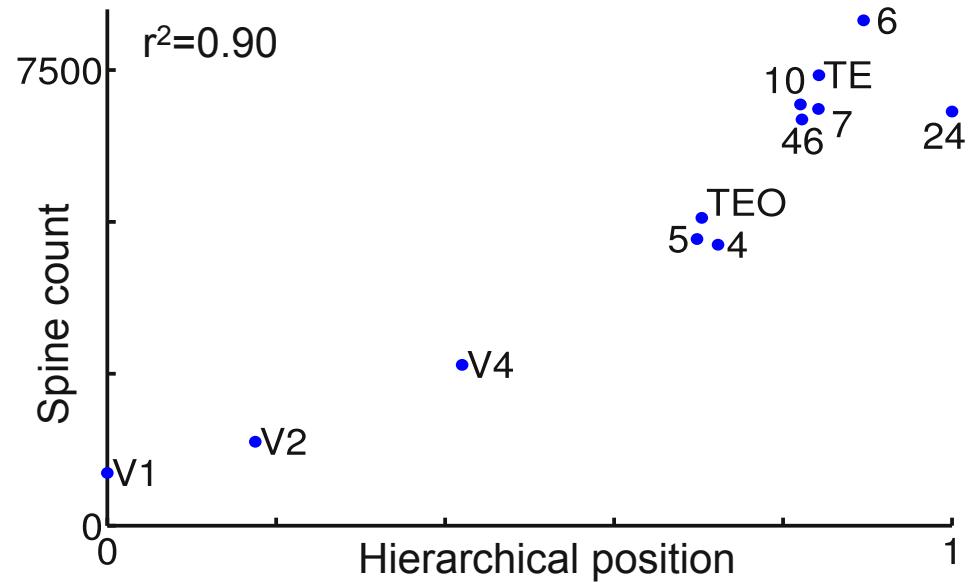
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Step 3/6: (large-scale 2.0) allow local variation of circuit properties, based on data

Brain areas do not have an identical local circuitry

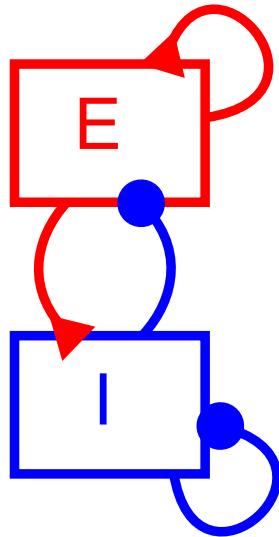


spine=site of
excitatory
synapse

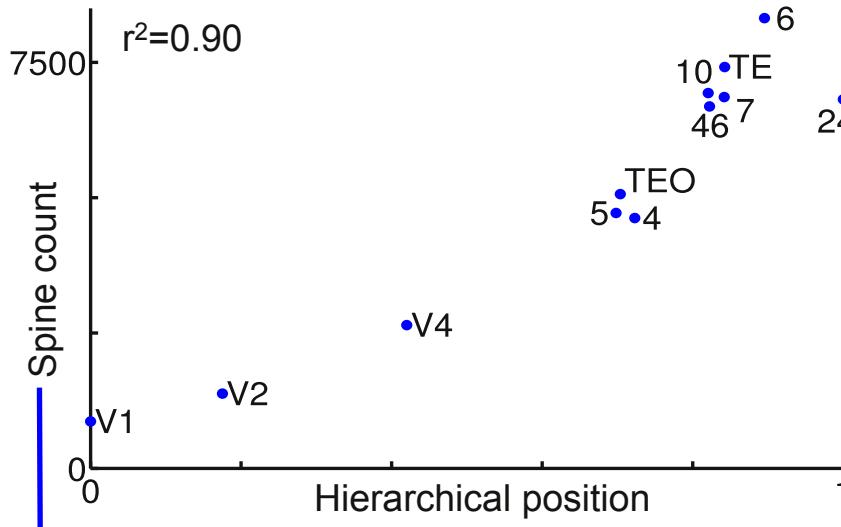


Elston, 2007

A quantitative change to parameters driven by anatomy



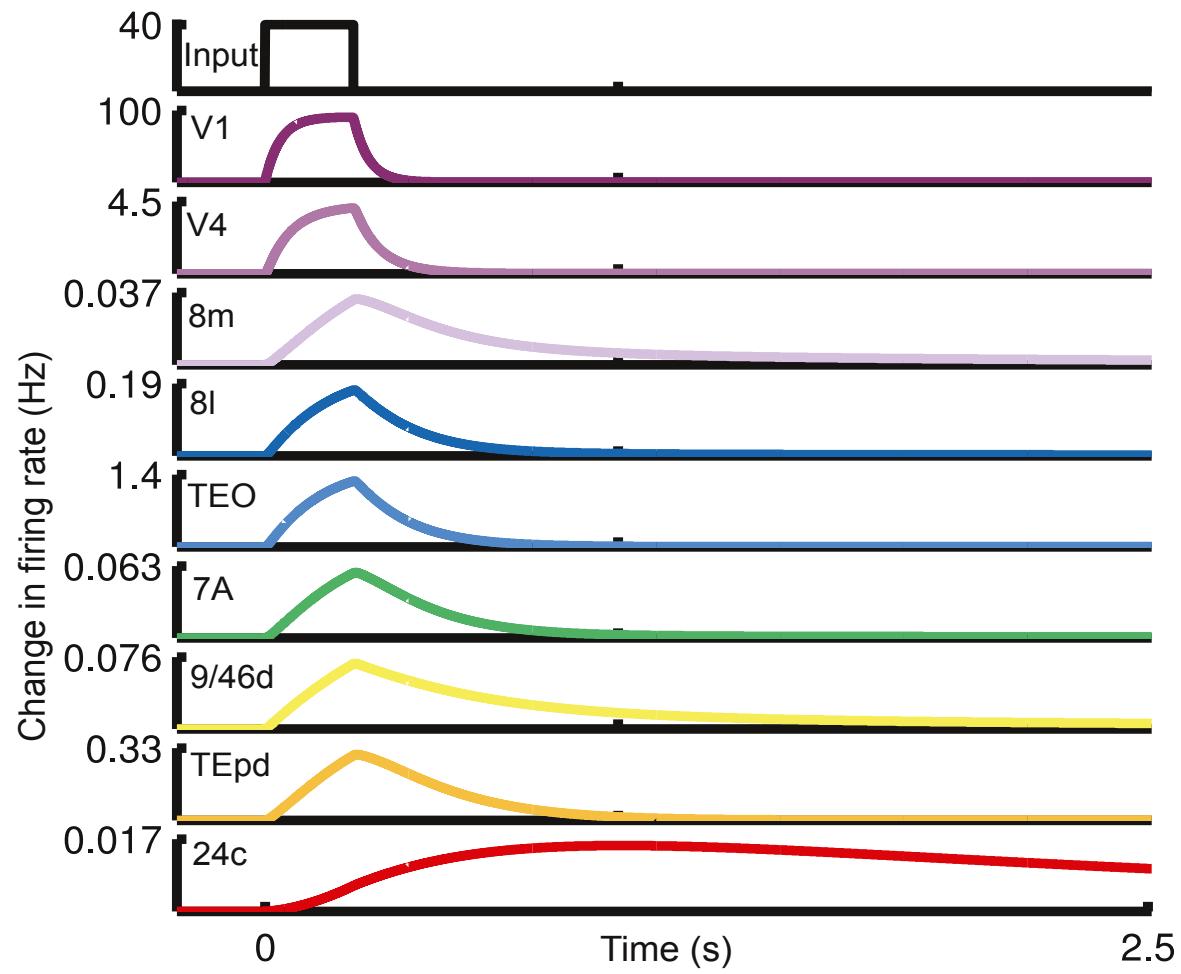
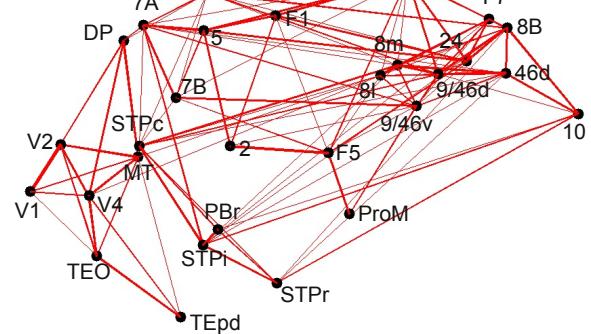
$$\tau \frac{d}{dt} r_{x,E} = -r_{x,E} + \beta x_{,E} [(1 + b S_x) (w_{E,E} r_{x,E} + \sum_{y \in Y} C_{y \rightarrow x} r_{y,E}) - w_{E,I} r_{x,I}]_+$$



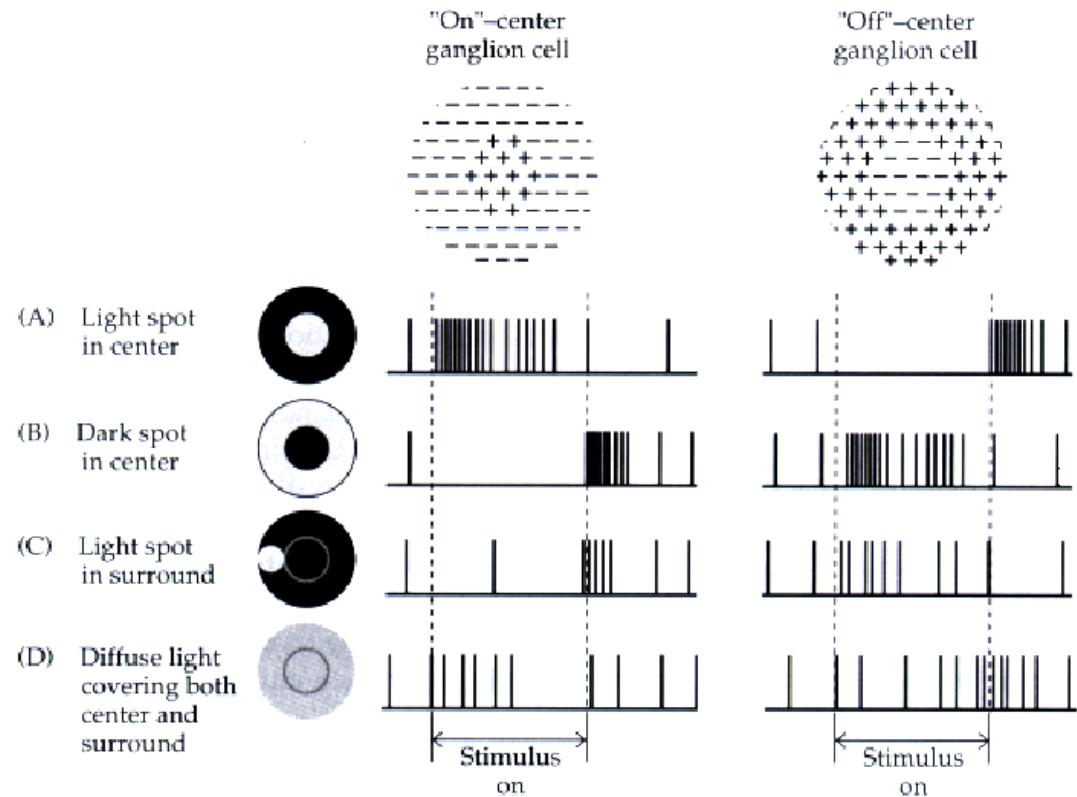
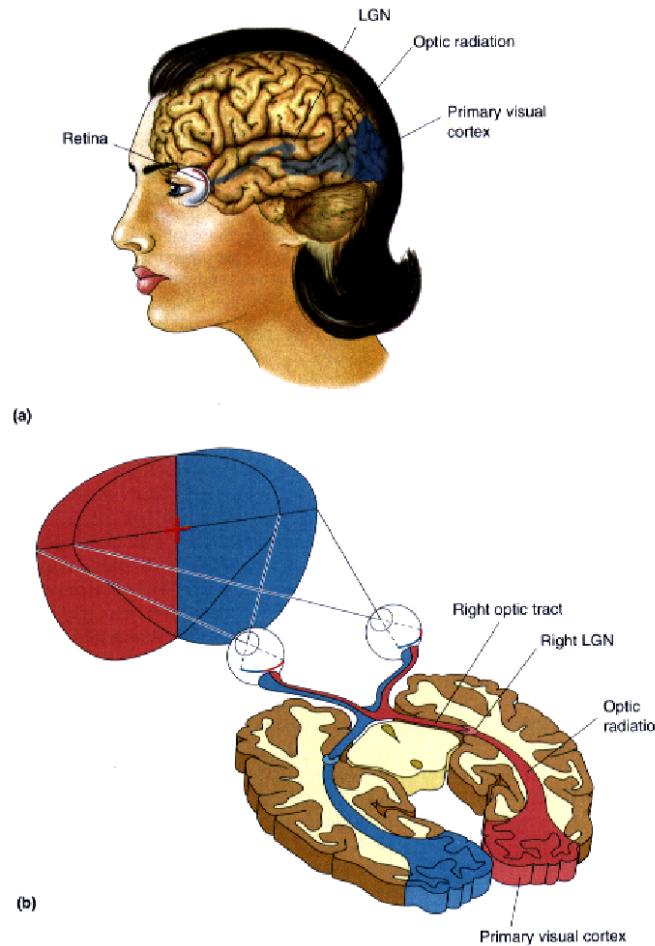
Scale up the strength of excitatory inputs to an area based on the spine count

Only two free parameters

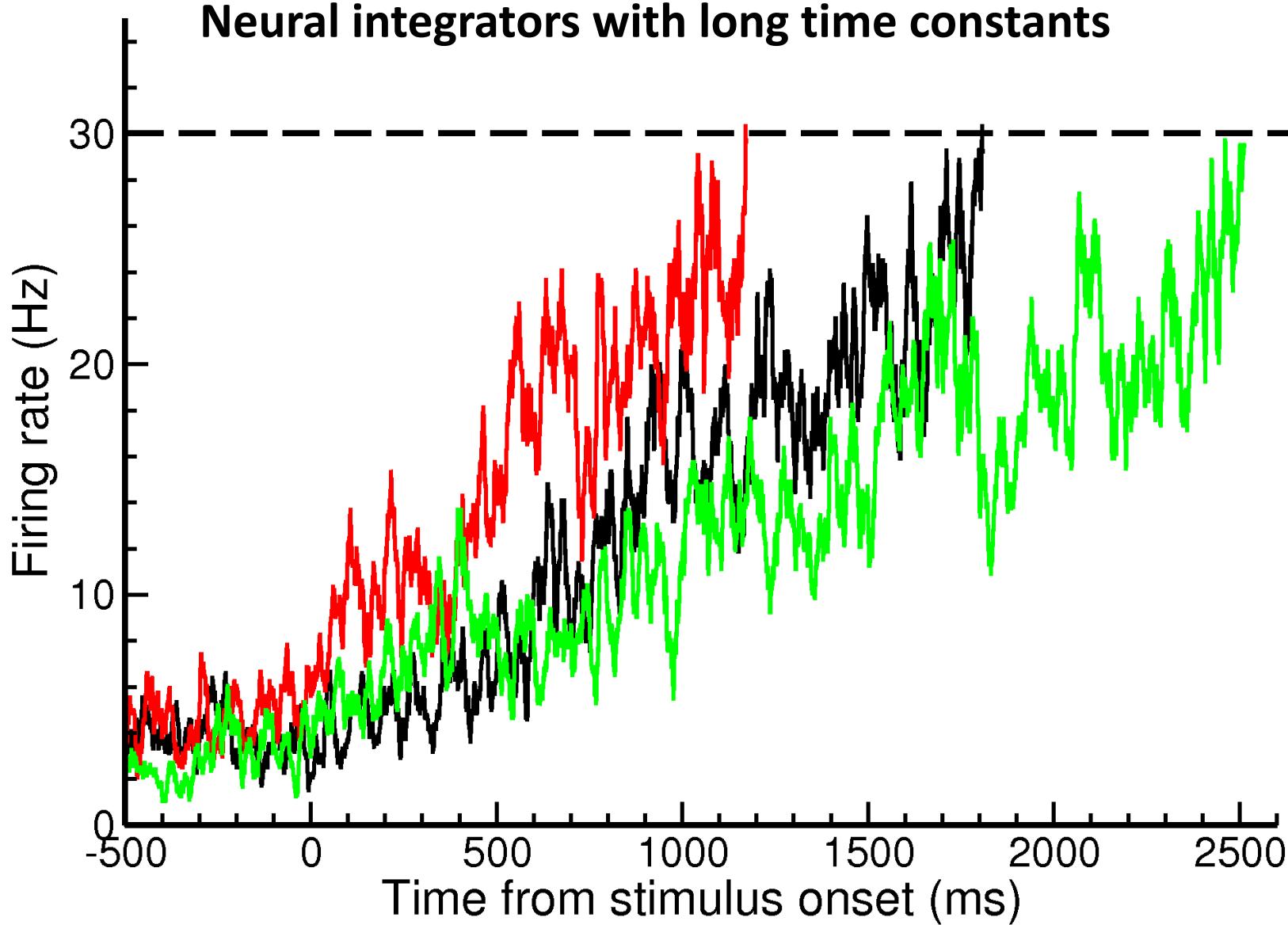
The emergence of a hierarchy of temporal windows



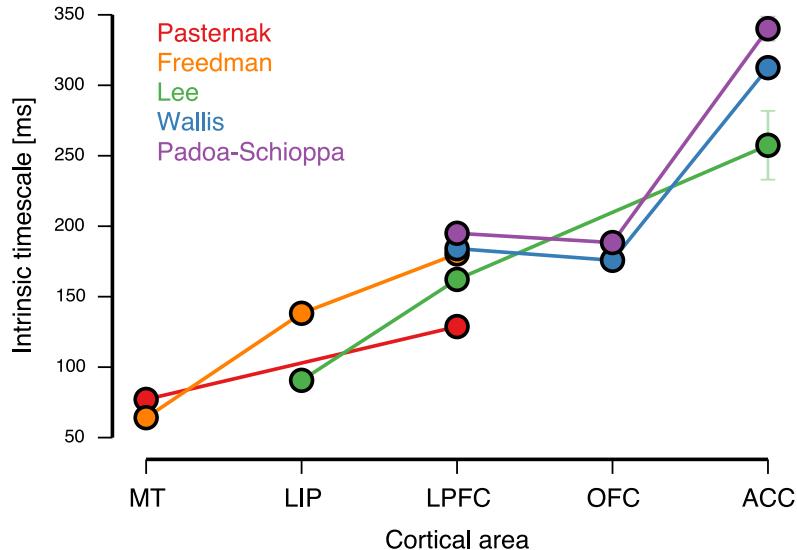
Rapid responses in early visual areas



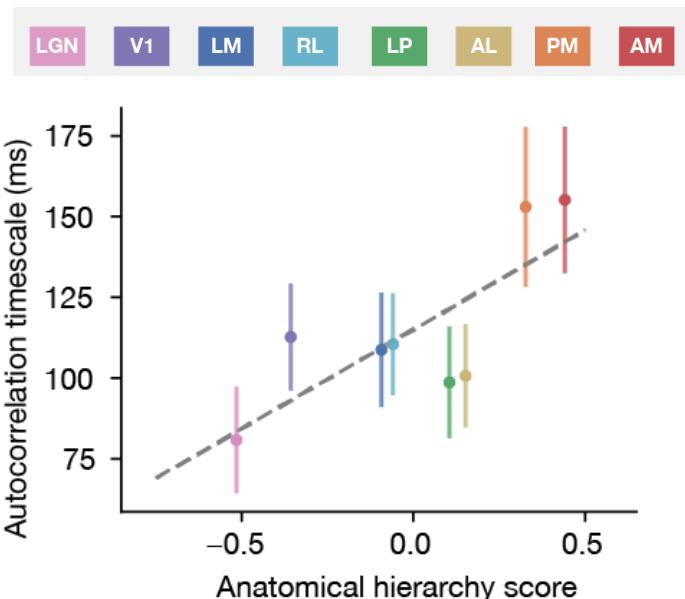
Neural integrators with long time constants



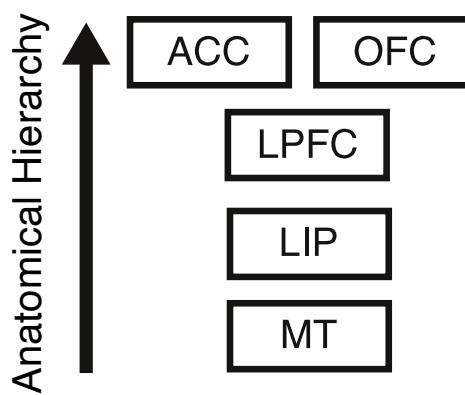
monkey



mice

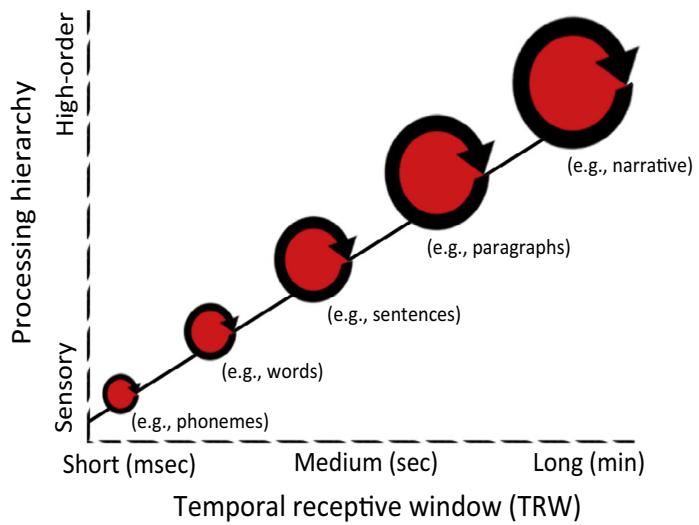


Siegle et al. *Nature* 2021



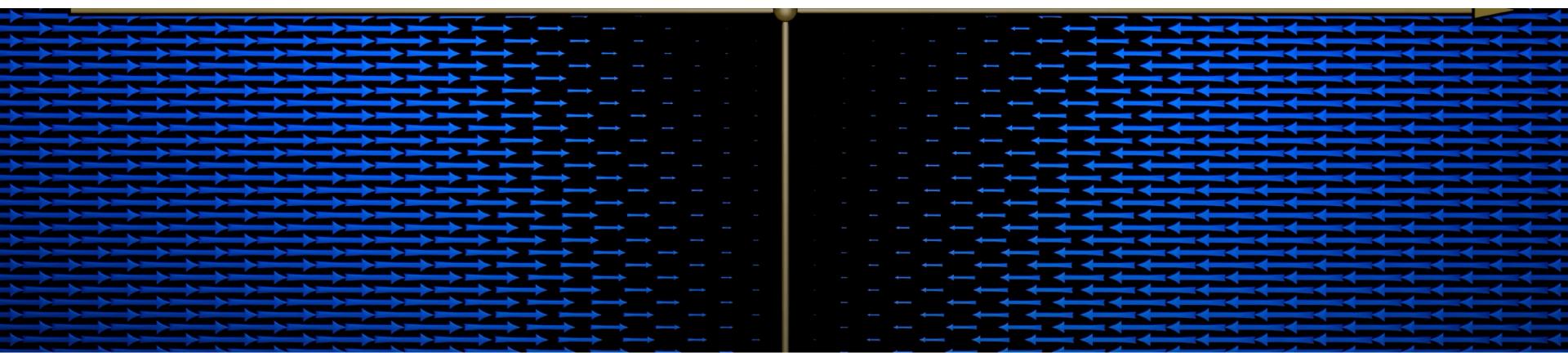
Murray et al.
Nature Neurosci. 2014

human

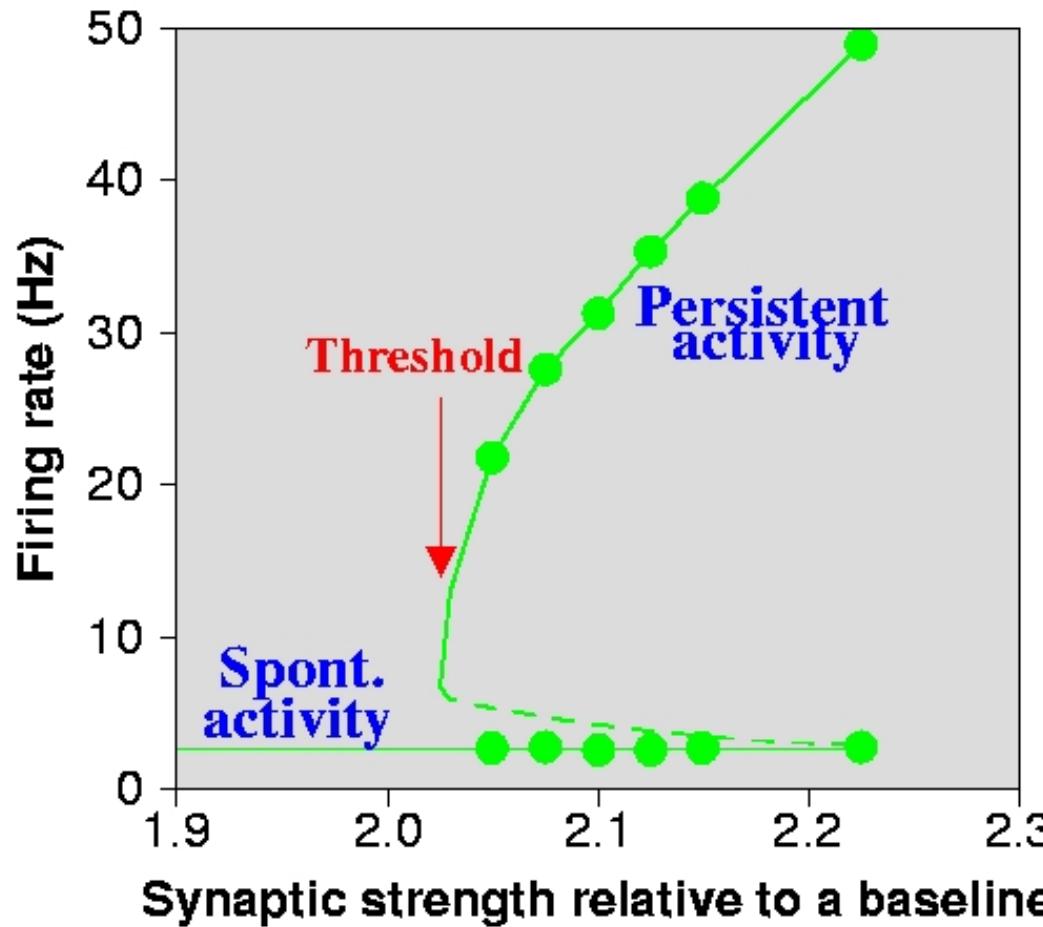


Hasson et al. *Trends in Cogn. Sci.* 2015

How do qualitatively different functions emerge across the cortex?



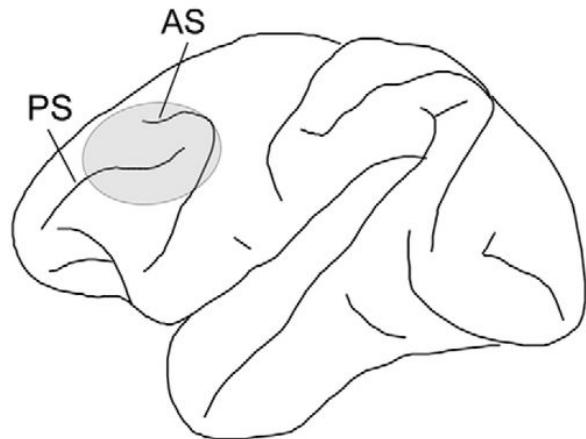
Working memory emerges with sufficiently strong recurrent connections



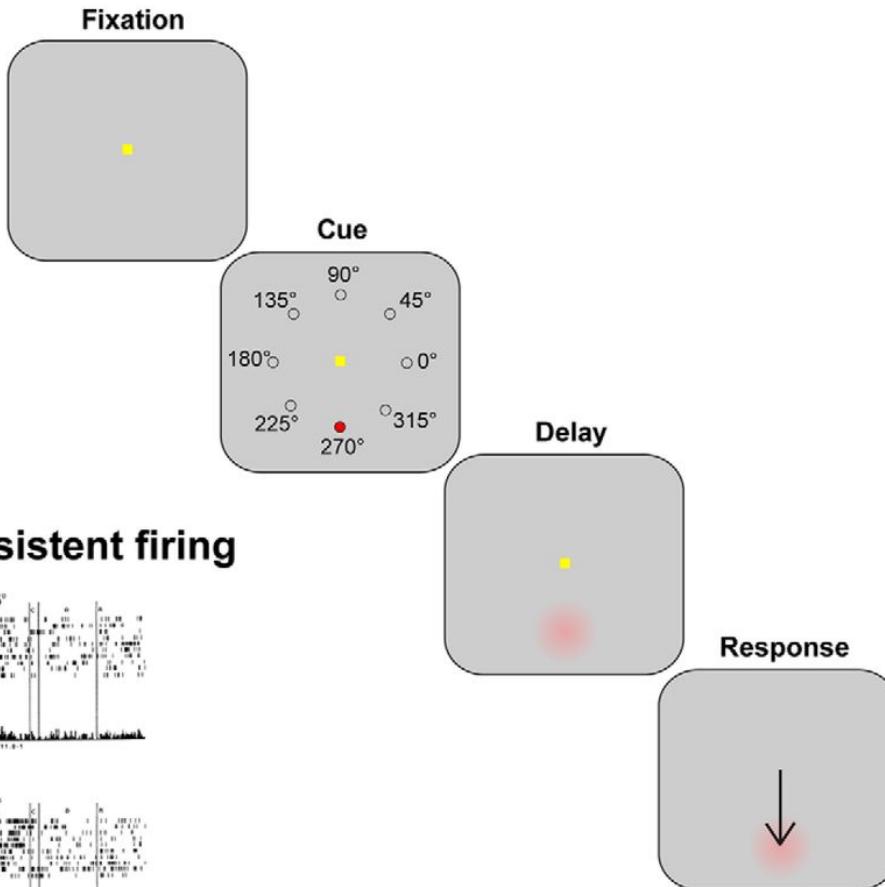
slide: XJ Wang

Bifurcations in nonlinear dynamical systems:
Graded differences give rise to qualitatively novel behavior/functions

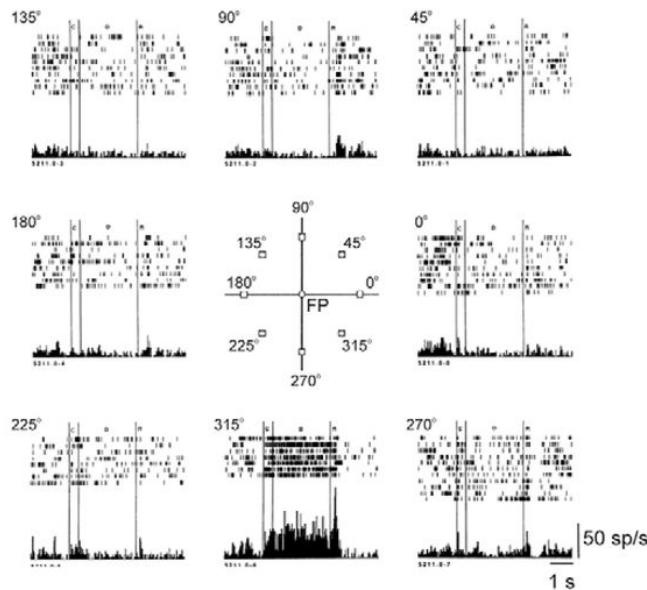
A. Recording area



B. ODR Task



C. Delay cell with persistent firing



Funahashi et al., 1989
Constantinidis et al., 2018

How do we build a dynamical model of the whole cortex?

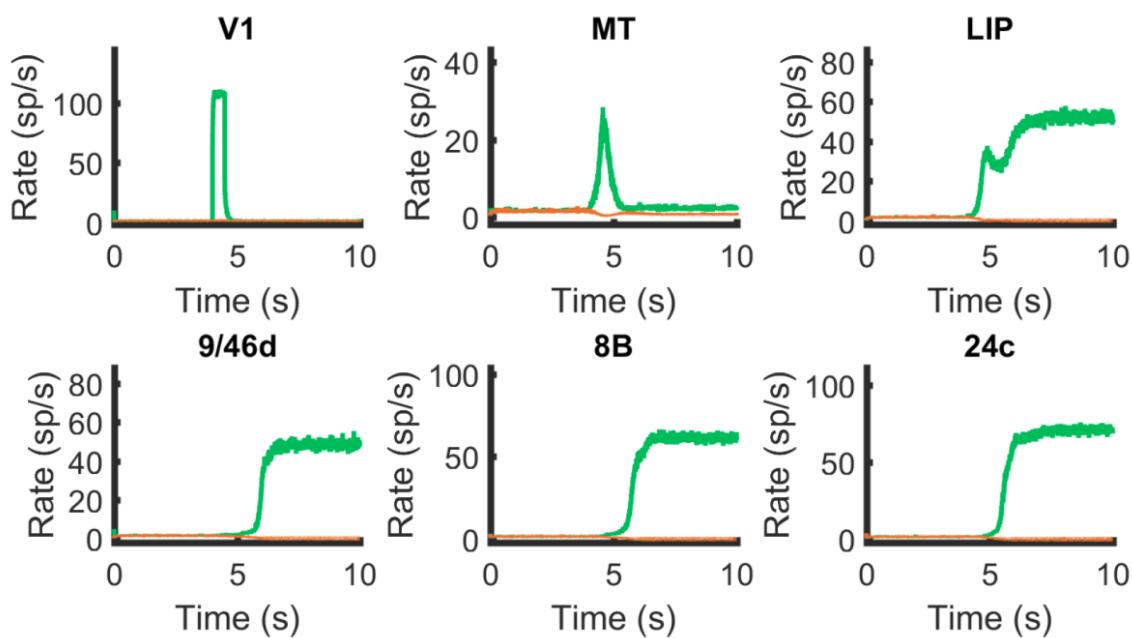
Step 1/6: building blocks – local circuit models

Step 2/6: connect the blocks – anatomical connectivity data

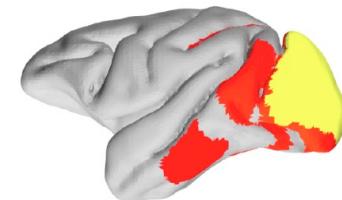
Step 3/6: (large-scale 2.0) allow local variation of circuit properties, based on data

Step 4/6: (large-scale 2.0) simulate task stimuli as input & measure activity

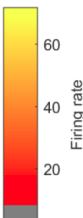
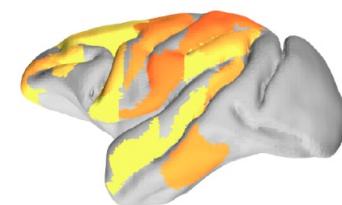
A large-scale working memory model with directed- and weighted- mesoscopic connectivity



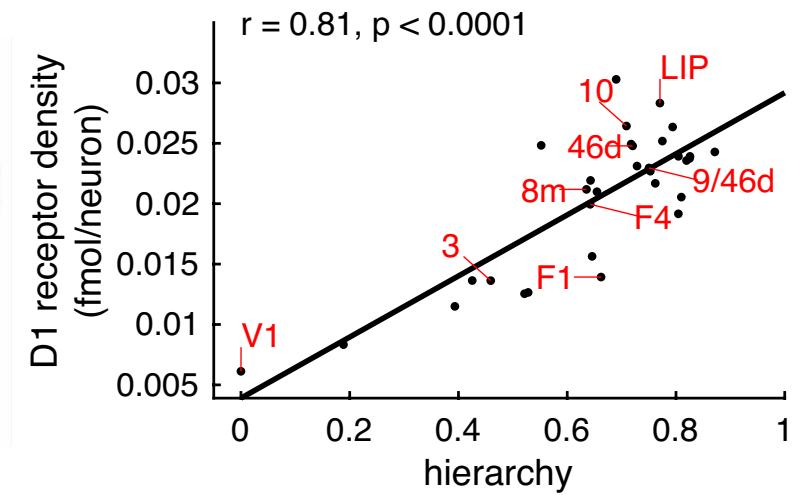
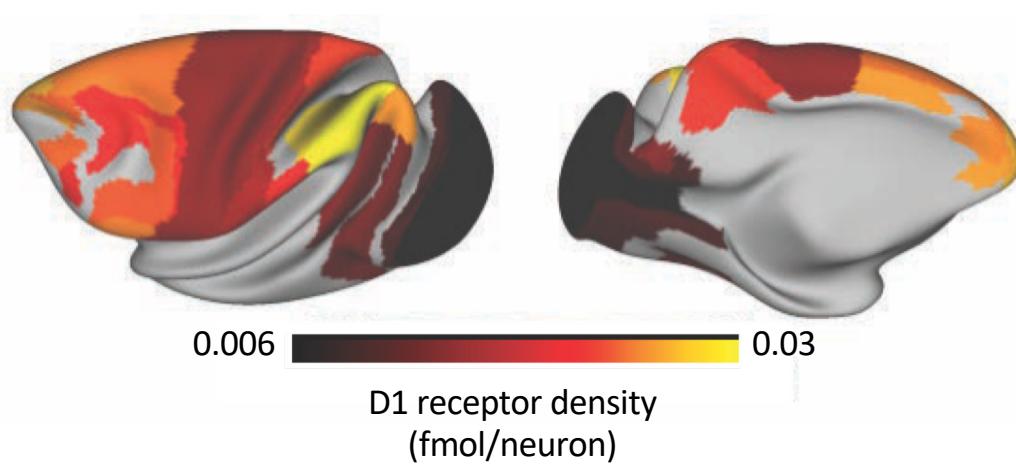
Visual stimulation



Delay period

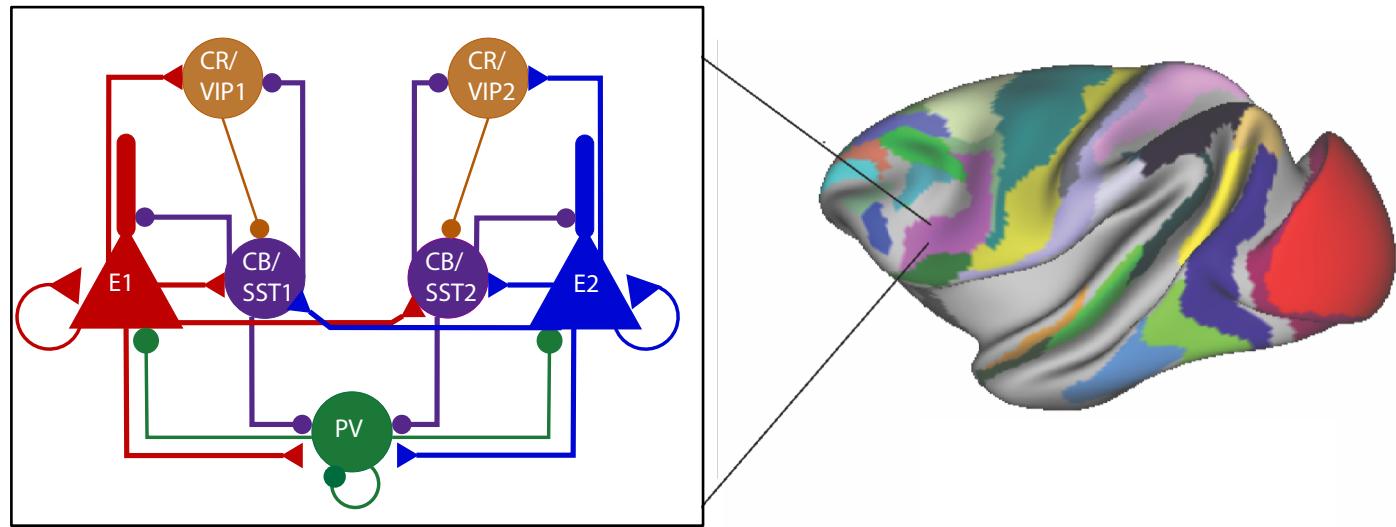


A gradient of dopamine D1 receptors increases along the cortical hierarchy



Froudist-Walsh et al., *Neuron*, 2021

Constructing a large-scale model of dopamine in macaque cortex



How do we build a dynamical model of the whole cortex?

Step 1/6: building blocks – local circuit models

Step 2/6: connect the blocks – anatomical connectivity data

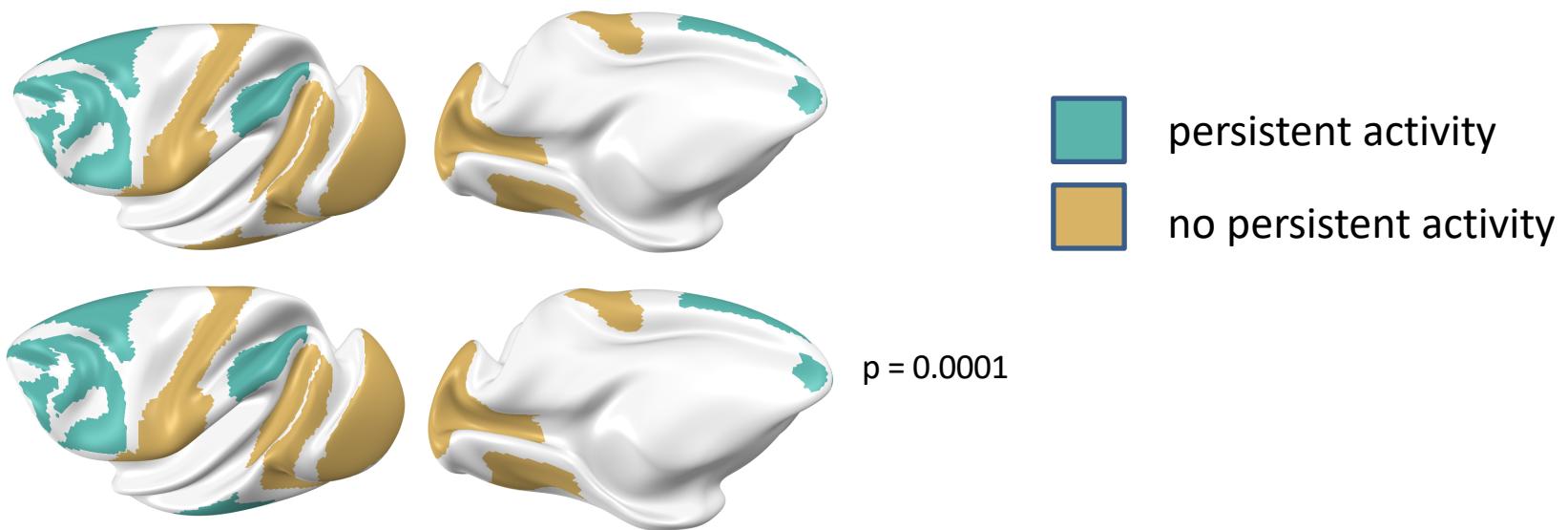
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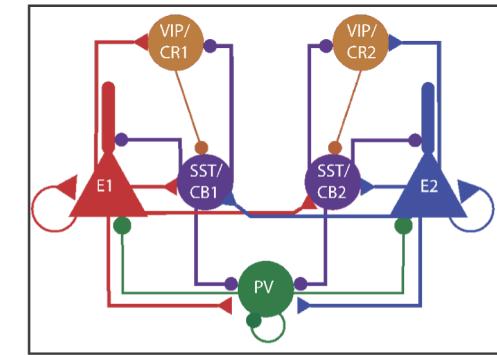
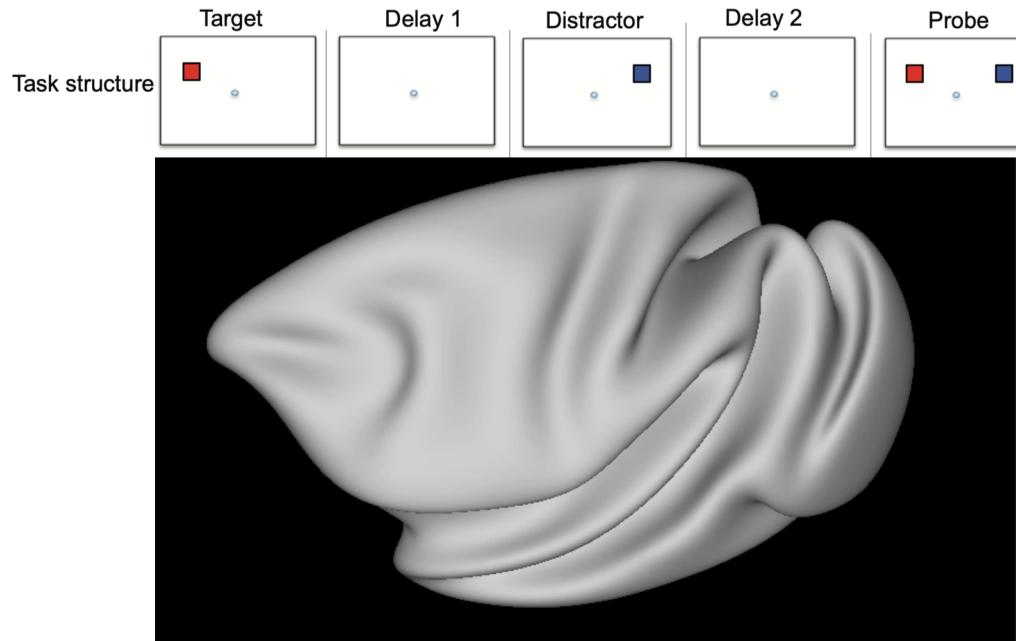
Step 5/6: (large-scale 2.0) validate model against real neural data

The model captures the persistent activity pattern of > 90 experimental studies

mega-analysis of experimental data - Leavitt et al., *TiCS*, 2017



Working memory with the right dopamine level is robust against distraction



Froudist-Walsh et al., *Neuron*, 2021

How do we build a dynamical model of the whole cortex?

Step 1/6: building blocks – local circuit models

Step 2/6: connect the blocks – anatomical connectivity data

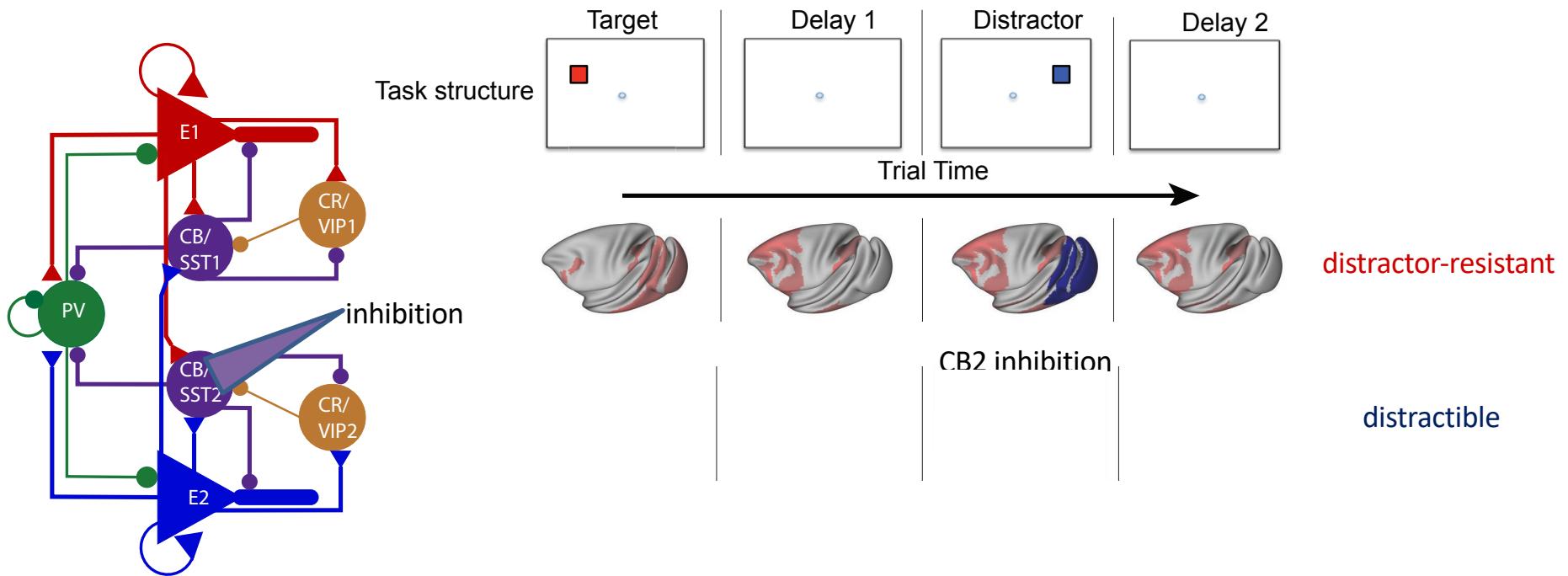
Step 3/6: (large-scale 2.0) allow local variation of circuit properties, based on data

Step 4/6: (large-scale 2.0) simulate task stimuli as input & measure activity

Step 5/6: (large-scale 2.0) validate model against real neural data

Step 6/6: (large-scale 2.0) make predictions for future experiments

“Zoom in” to find the cell-type responsible for distractor-resistance



Froudist-Walsh et al., *Neuron*, 2021

Dopamine & working memory in people with schizophrenia

- Lower cortical dopamine
- Working memory impairments



Anissa Abi-Dargham



Mark Slifstein



Jared van
Snellenberg

Stony Brook, New York

Frontiers of large-scale modelling

- Identifying large-scale mechanisms of distinct cognitive functions
 - e.g. Klatzmann et al., *bioRxiv*, 2022
- Large-scale circuit mechanisms of psychiatric disorders
- Learning in multi-regional models
 - Rui Ponte Costa

Reviewing learning objectives

- Understand how whole-cortex models are constructed
 - local circuit models connected by structural connectivity data
 - Enable anatomical variation of circuit properties across areas
 - Test vs neural data & make predictions
- Learn how variation in anatomical properties across the brain may lead to differences in functions across areas
 - quantitative changes to parameters based on anatomical measurements lead to qualitatively different behavior
- Become familiar with some of the latest research on whole-cortex models during cognitive tasks
 - A hierarchy of timescales
 - Distributed working memory activity
 - Dopamine to reduce distraction
 - Frontiers of large-scale modelling

Contact:

email: sean.froudist-walsh@bristol.ac.uk

Twitter: @seanfw

Thank you!

- Contact me on Teams!