



DYNAMIC CAUSAL MODELING FOR EEG

DARIO SCHÖBI

TRANSLATIONAL NEUROMODELING UNIT (TNU)
UNIVERSITY OF ZURICH & ETH ZURICH

Computational Psychiatry Course 2019

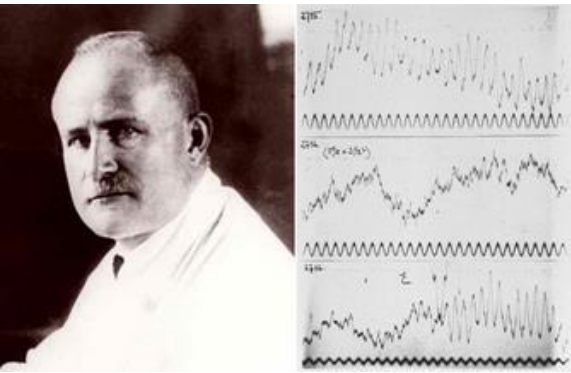
Chapter 1

Story Time



1924

2006



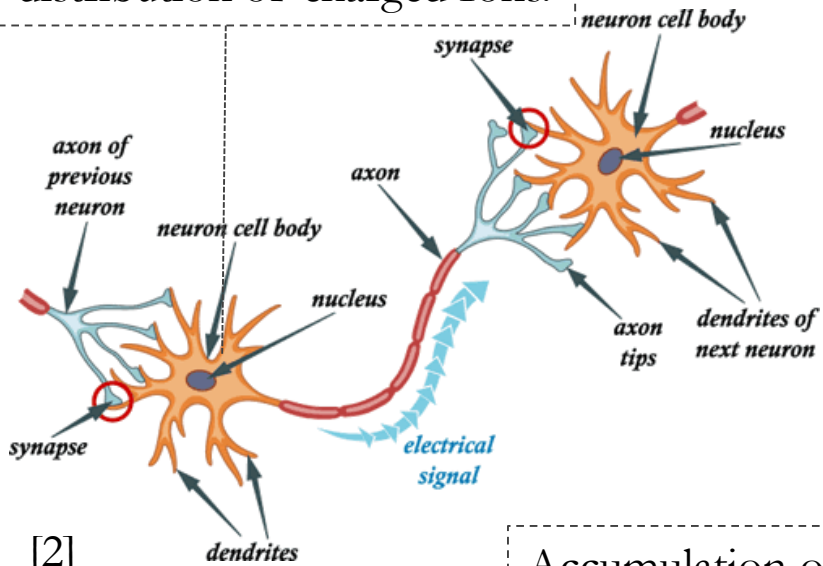
Invention of the EEG
(Hans Berger 1873-1941 [1])

- Non-invasive measure of brain activity
- Electrical signals due to the flow of charged Ions



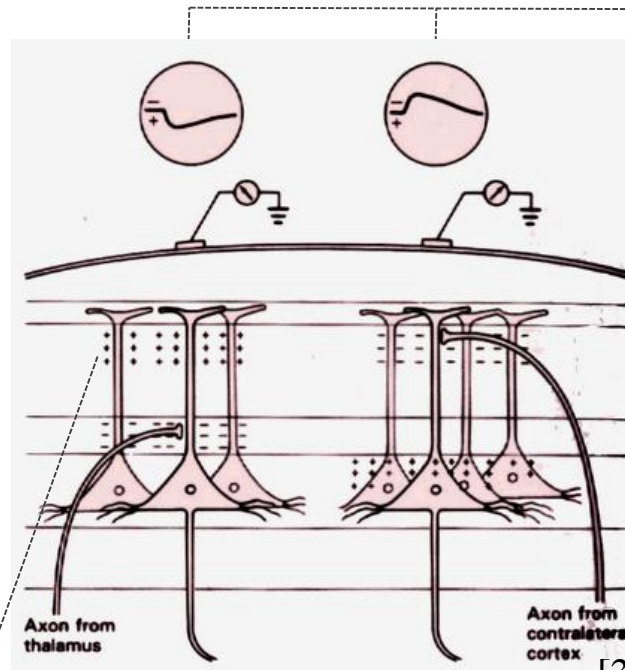
1924

Depolarization of cell membrane due to change in distribution of charged Ions.



[2]

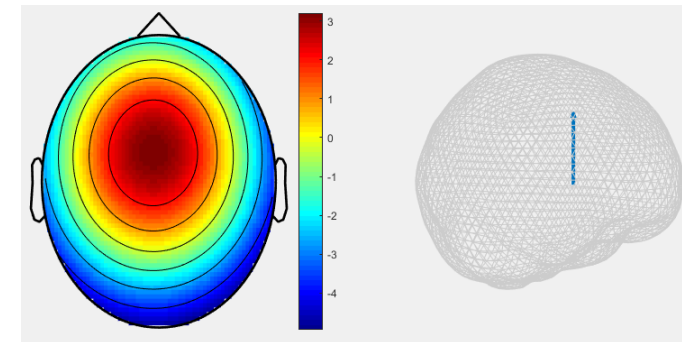
Accumulation of charge leads to dipole field.



[3]

2006

Dipole fields manifest as differences of electrical potentials on the scalp.





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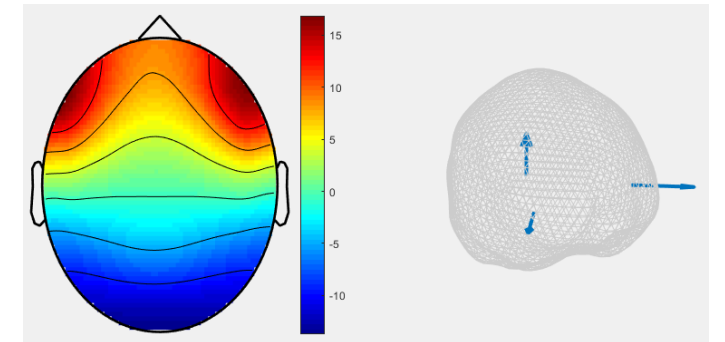
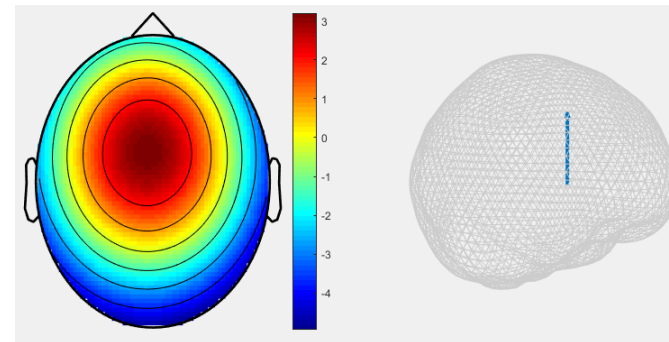
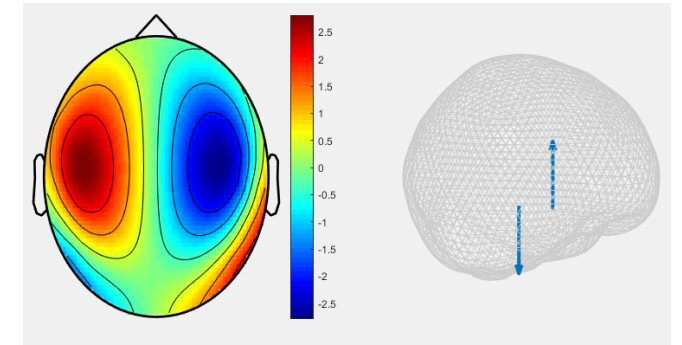
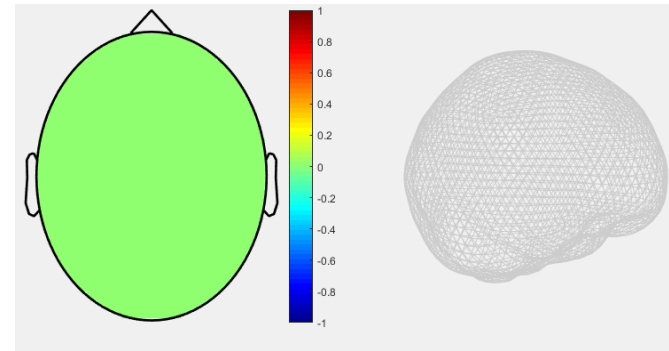
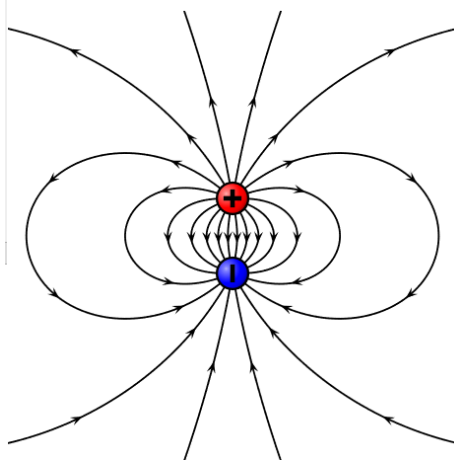


Figure | Electric dipole field [4]

Figure | Different possible dipole configurations that lead to different scalp potentials.



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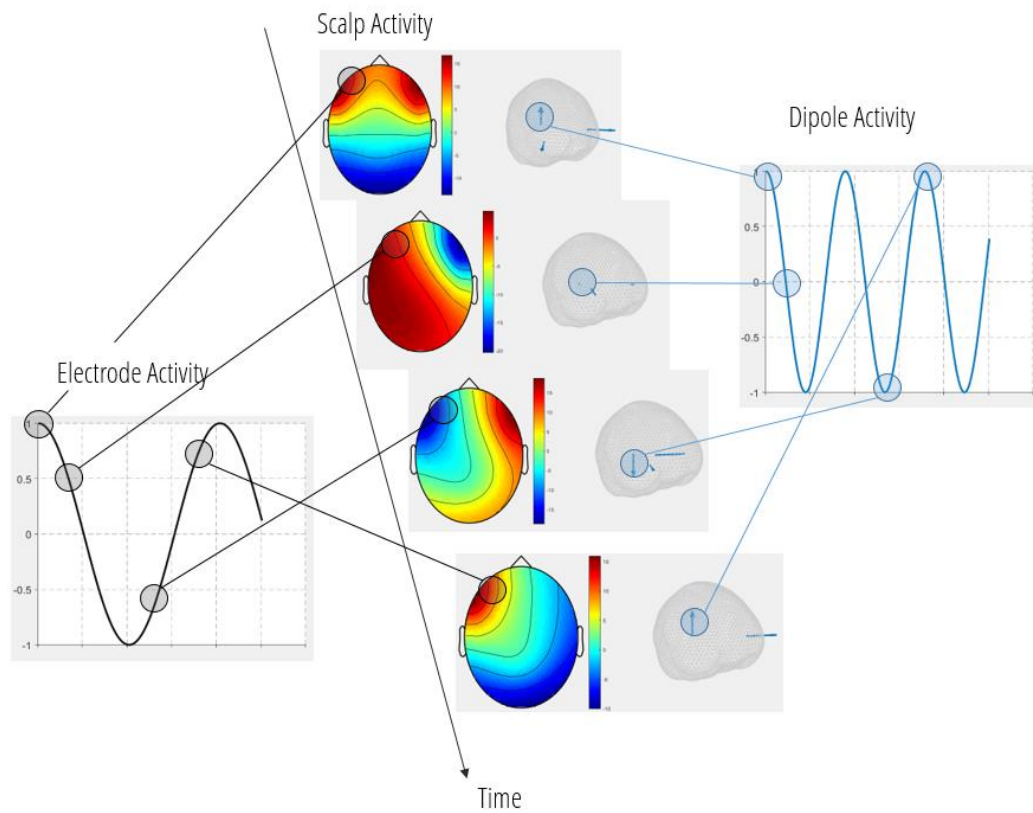
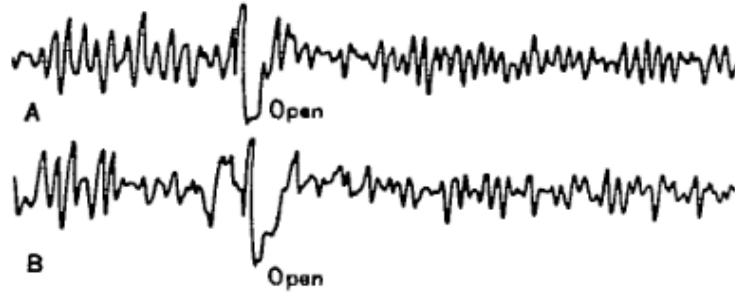


Figure | Changes in the scalp and electrode potential, as the dipole moments change over time.



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Discovery of Evoked Response Potentials
(ERP) across multiple modalities

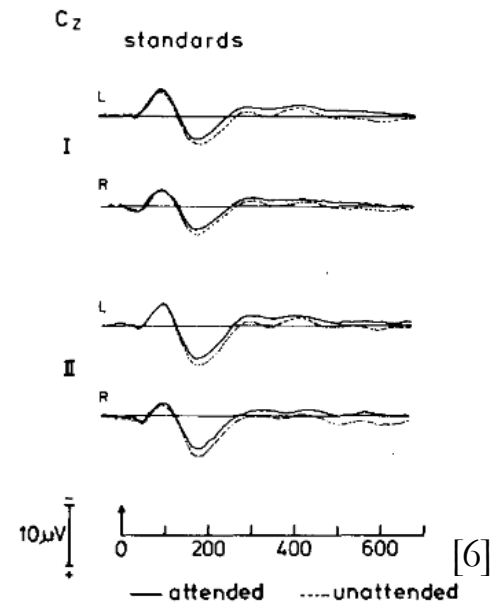
- Somatosensory (SEP) [5]
- Visual
- Auditory



1924

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2006



Change in the average evoked response to attended and unattended stimuli (Mismatch Negativity, MMN)



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Visual Evoked Response in Diagnosis of Multiple Sclerosis

A. M. HALLIDAY, W. I. McDONALD, JOAN MUSHIN

Role of cortical *N*-methyl-D-aspartate receptors in auditory sensory memory and mismatch negativity generation: Implications for schizophrenia

(line/monkey/intracortical/cognitive/event-related potential)

VITT*†, MITCHELL STEINSCHNEIDER†‡, CHARLES E. SCHROEDER†‡, AND JOSEPH C. AREZZO†‡

Acetylcholine modulates averaged sensory evoked responses and perforant path evoked field potentials in the rat dentate gyrus

Tom C. Foster ^a and Sam A. Deadwyler ^b

DIFFERENTIAL EFFECTS OF ASCENDING NEURONS CONTAINING DOPAMINE AND NORADRENALINE IN THE CONTROL OF SPONTANEOUS ACTIVITY AND OF EVOKED RESPONSES IN THE RAT PREFRONTAL CORTEX

J. MANTZ, C. MILLA, J. GLOWINSKI and A. M. THIERRY*

Errors in reward prediction are reflected in the related brain potential

van Nieuwenhuis, Nick Yeung and Jonathan D. Cohen

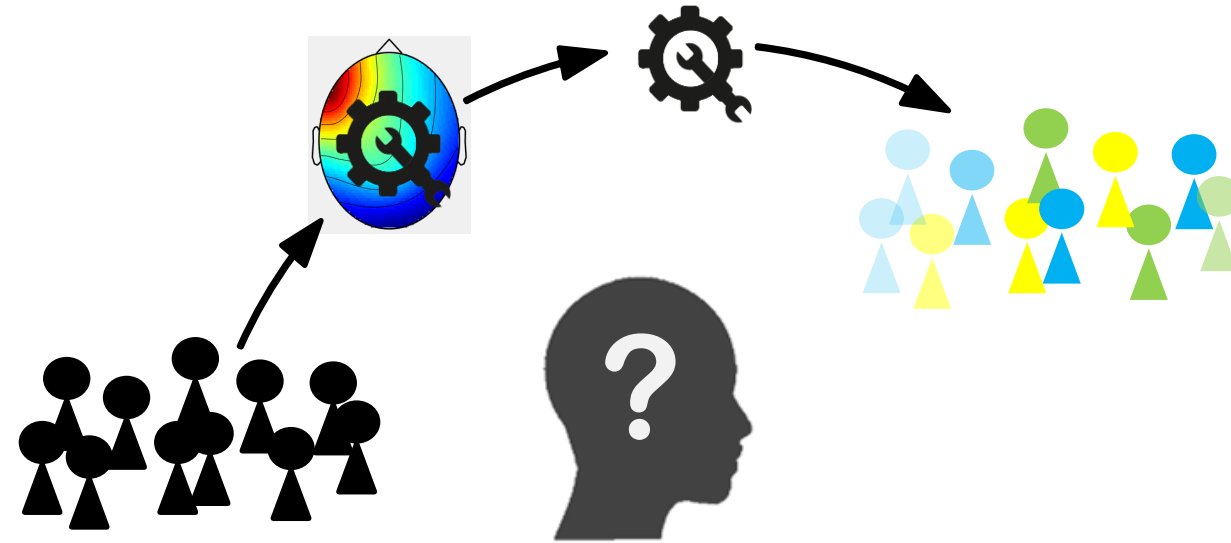


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- Heterogenous, clinical population
- EEG contains information about neuromodulatory processes
- Having a model with the power to estimate these hidden processes from peripheral measures could give a mechanistic understanding ...
- ... And potentially allowing for the identification of clinical subgroups, treatment outcome, disease or relapse risks, etc.





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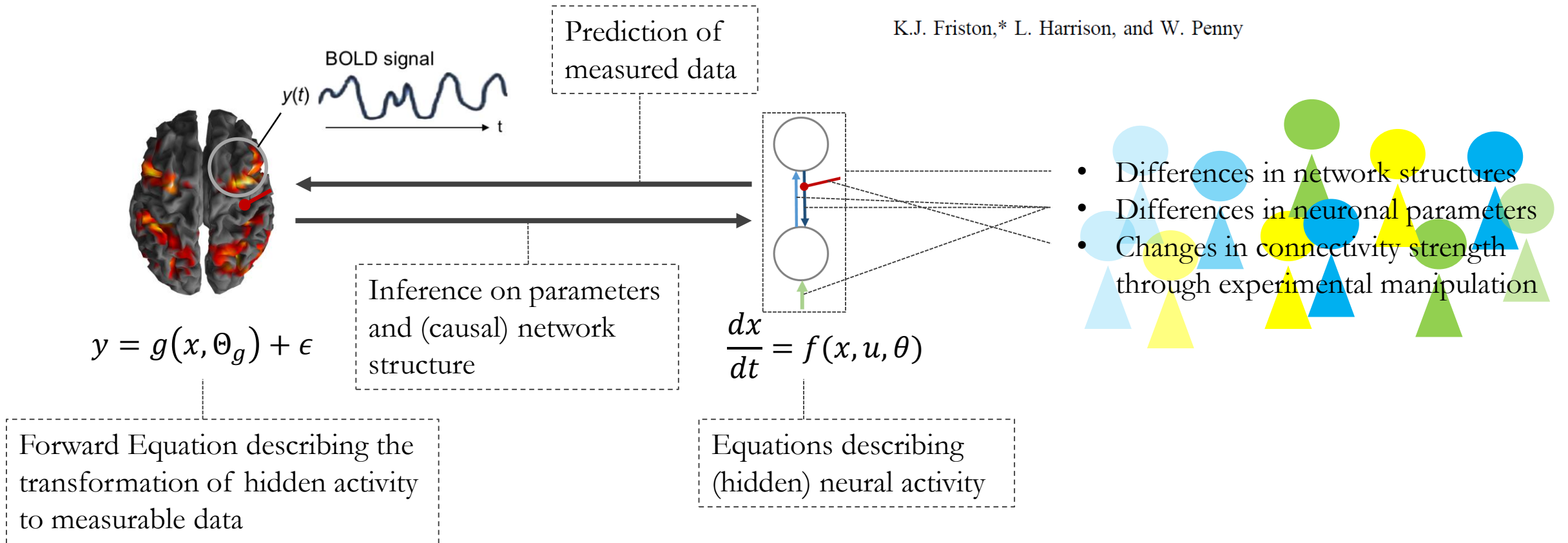
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Dynamic causal modelling

K.J. Friston,* L. Harrison, and W. Penny



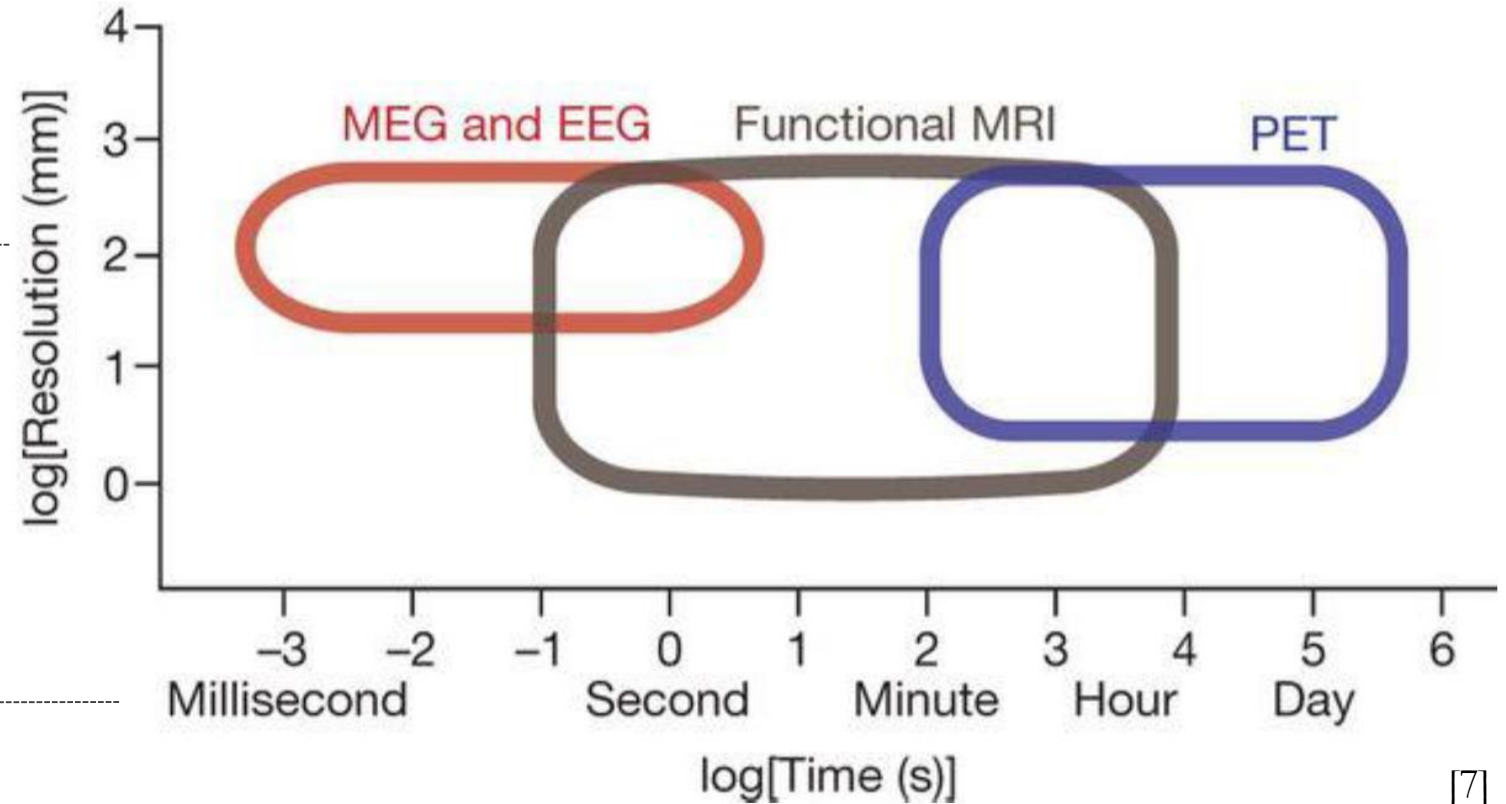


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Much worse spatial resolution than fMRI. Need to know, **where** the signal is coming from!

Much better temporal resolution than fMRI. Modeling of synaptic processes possible.



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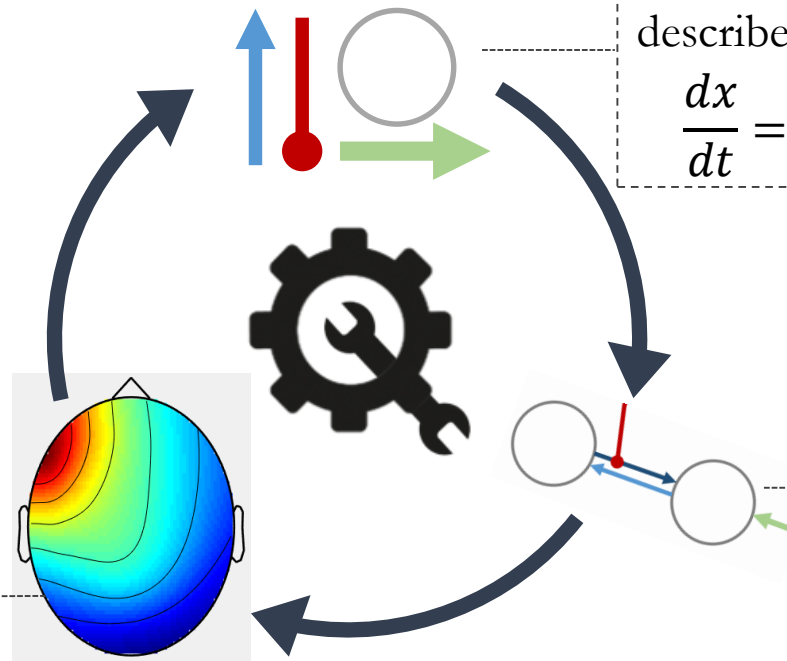
How hidden neural activity transforms into measurable data?

$$y = g(x, \Theta_g) + \epsilon$$

How are the neuronal dynamics described?

$$\frac{dx}{dt} = f(x, u, \theta)$$

How are sources connected?





How are the neuronal dynamics described?

$$\frac{dx}{dt} = f(x, u, \theta)$$

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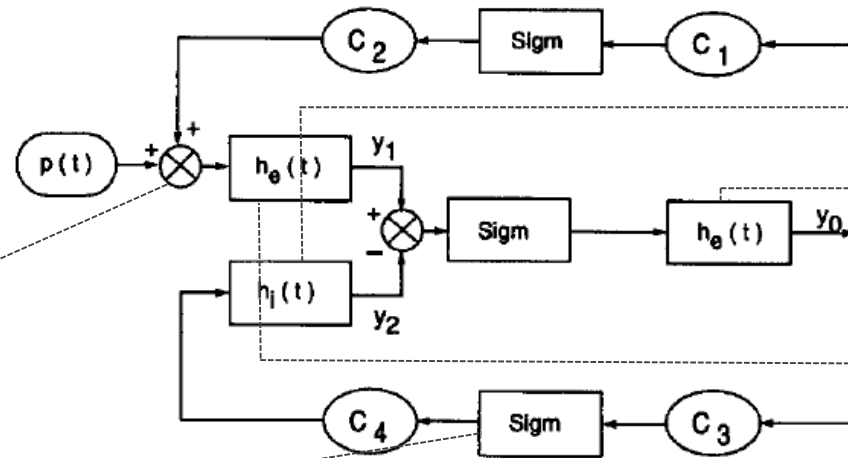
Electroencephalogram and visual evoked potential generation in a mathematical model of coupled cortical columns

Ben H. Jansen, Vincent G. Rit

Presynaptic Firing $\sigma(t)$

Postsynaptic Potential $v(t)$

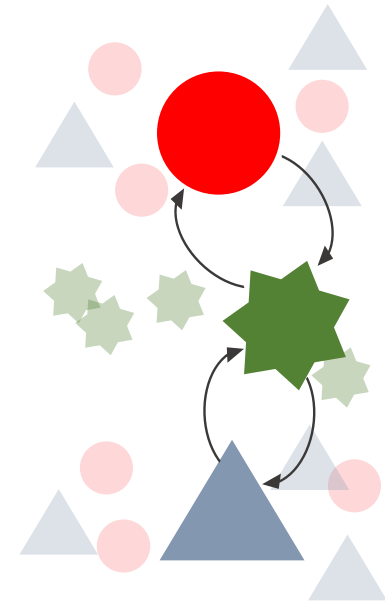
$$v(t) = \int_{-\infty}^t h(t - \tau, H, \kappa) \sigma(\tau) d\tau$$



Inhibitory Cells

Stellate Cells

Pyramidal Cells





How are the
neuronal dynamics
described?
 $\frac{dx}{dt} = f(x, u, \theta)$

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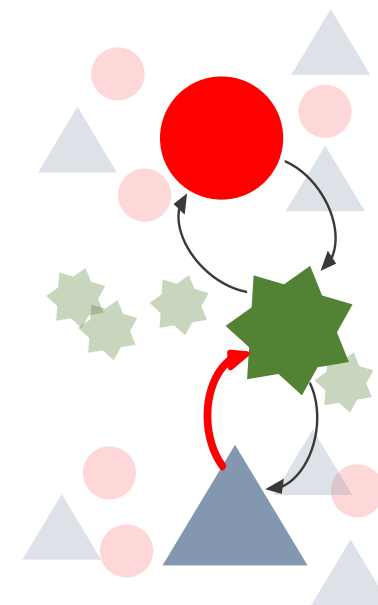
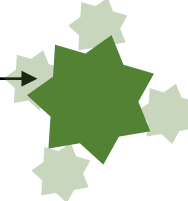
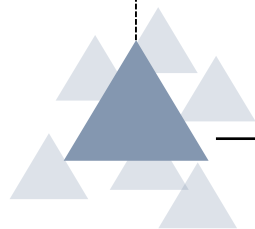
1995

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2006

Pyramidal Cell
population

Stellate Cell
population





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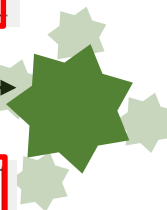
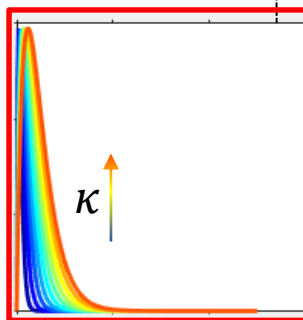
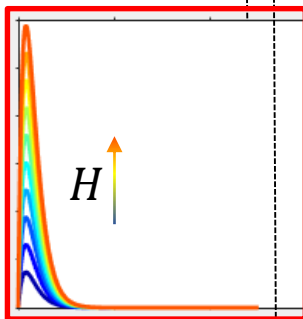
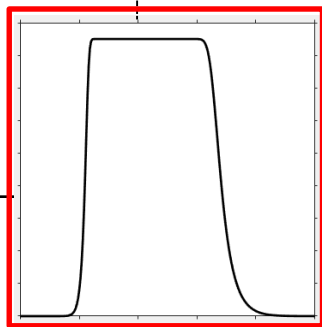
1995

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Different convolution kernels
 $h(H, \kappa)$

Pyramidal Cell Firing (σ)



Equation describing post
synaptic potential, given
some kernel, and input

$$v(t) = \int_{-\infty}^t h(t - \tau, H, \kappa) \sigma(\tau) d\tau$$

Gain

1/Decay



How are the
neuronal dynamics
described?
 $\frac{dx}{dt} = f(x, u, \theta)$

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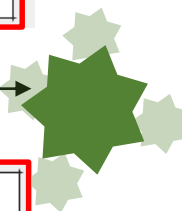
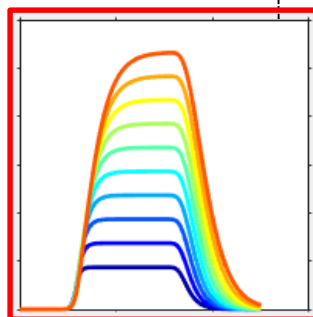
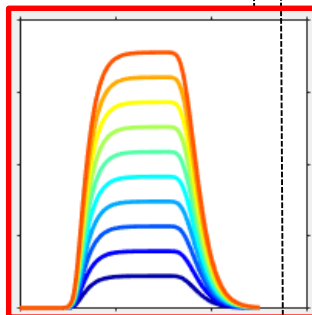
1977

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Postsynaptic potential for
different kernels





How are the
neuronal dynamics
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 $\frac{dx}{dt} = f(x, u, \theta)$

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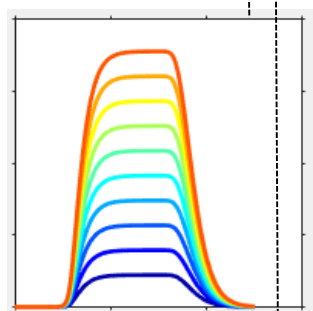
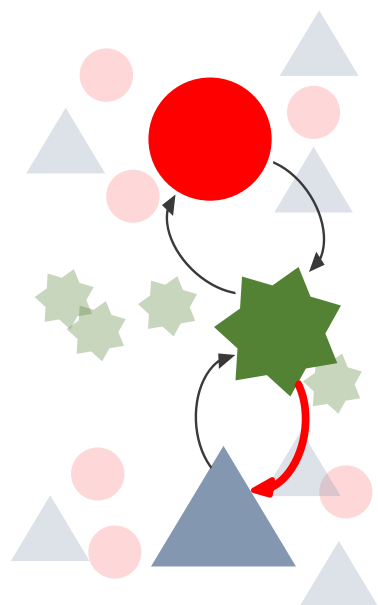
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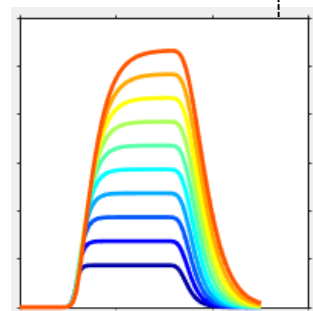
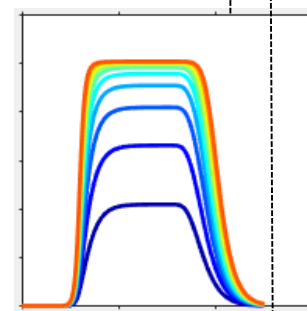
Postsynaptic potential for
different kernels

Stellate Cell Firing

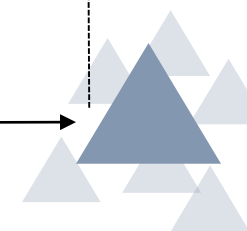
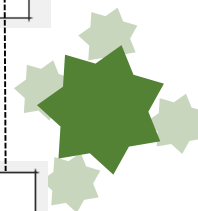
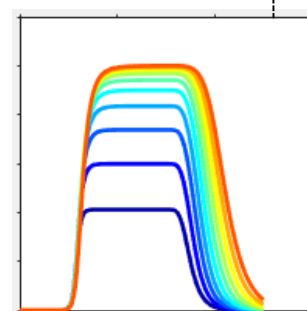
... and here we go
again



σ



σ





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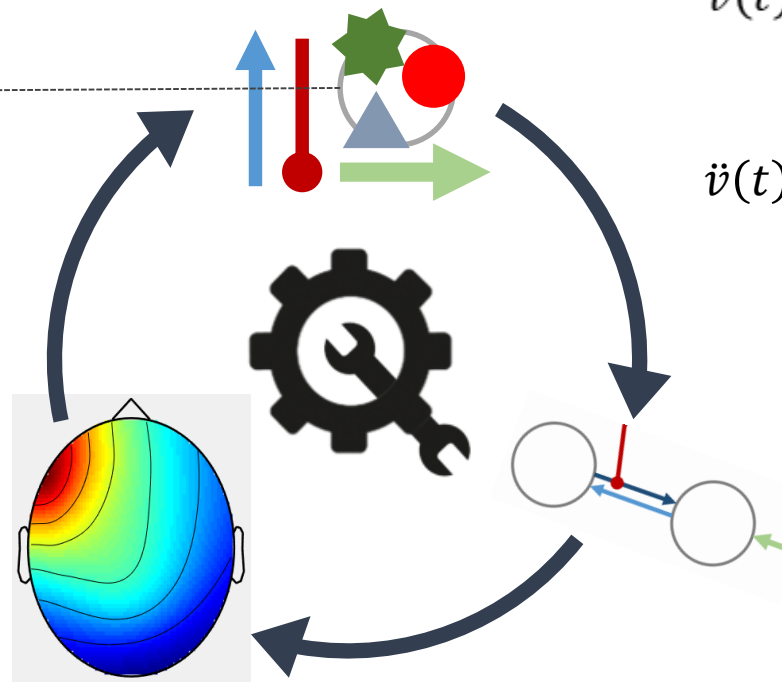
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Each source comprises of a triplet of neuronal populations:

- Stellate Cells
- Inhibitory Interneurons
- Pyramidal Cells



$$v(t) = \int_{-\infty}^t h(t - \tau, H, \kappa) \sigma(\tau) d\tau$$

$$\ddot{v}(t) = \frac{H}{\kappa} \cdot \sigma(t) - \frac{2}{\kappa} \cdot \dot{v}(t) - \frac{1}{\kappa^2} v(t)$$

Second derivative of the post synaptic potential of a population is a function of the current state of depolarization, it's first derivative and the input.



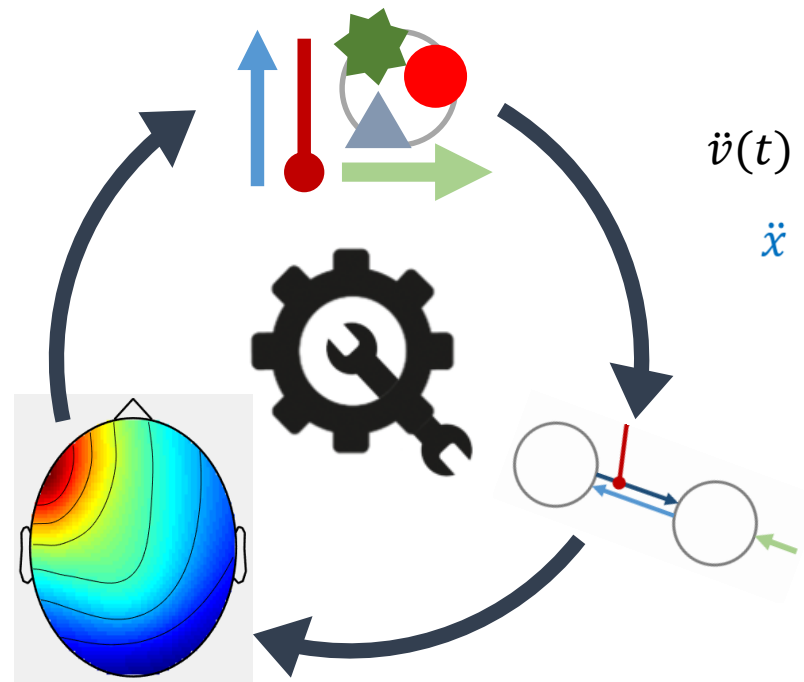
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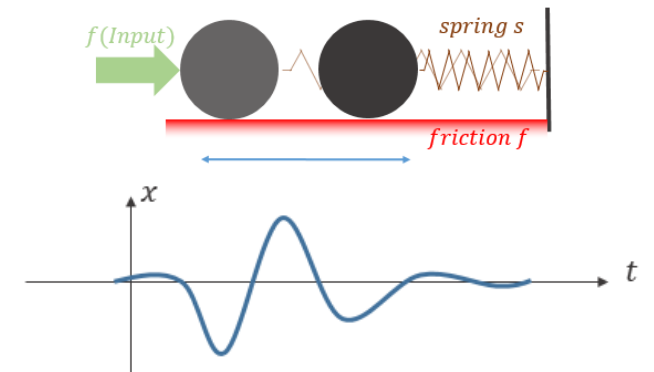
2003

2006



$$\ddot{v}(t) = H \cdot a \cdot \sigma(t) - 2 \cdot a \cdot \dot{v}(t) - a^2 v(t)$$

$\ddot{x} = f(\text{Input}) - f\dot{x} - sx$ Equation describing the behavior of a mass attached to a spring





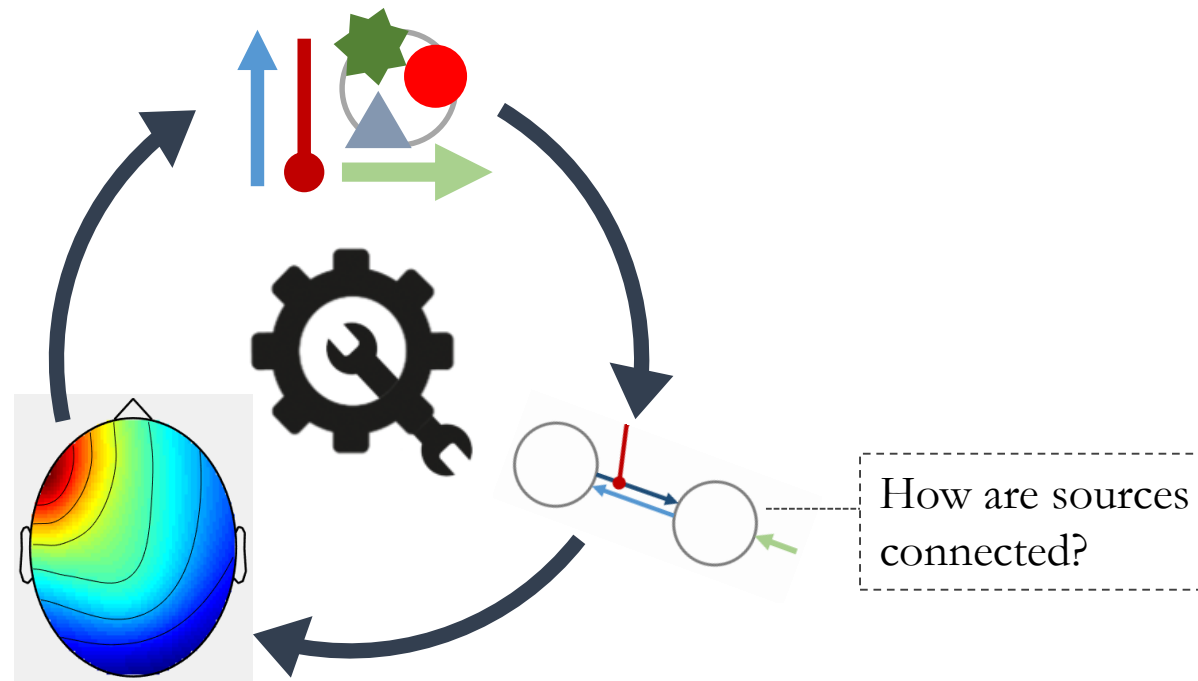
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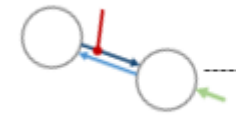
1977

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How are sources connected?

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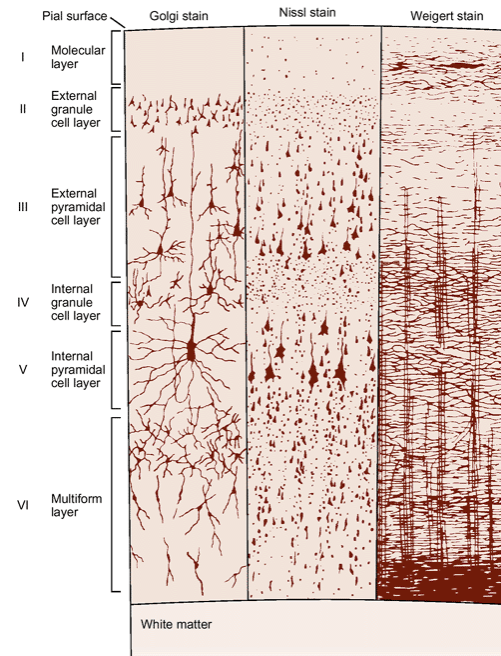
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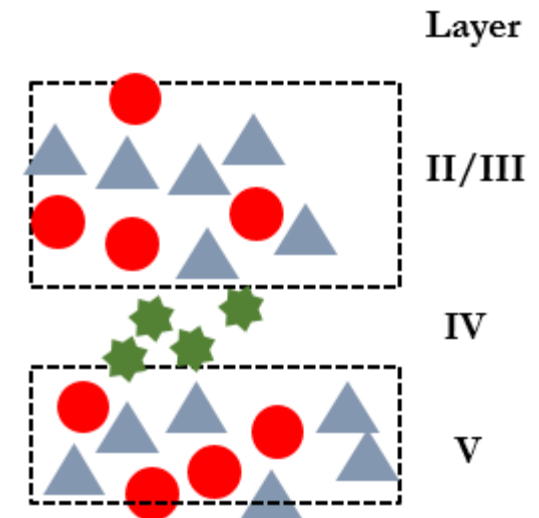
Distributed Hierarchical Processing in the Primate Cerebral Cortex

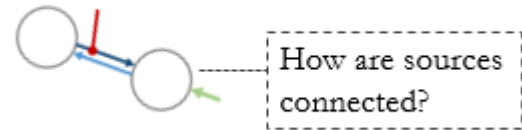
Daniel J. Felleman¹ and David C. Van Essen²

¹ Department of Neurobiology and Anatomy, University of Texas Medical School, Houston, Texas 77030, and ² Division of Biology, California Institute of Technology, Pasadena, California 91125



[8]





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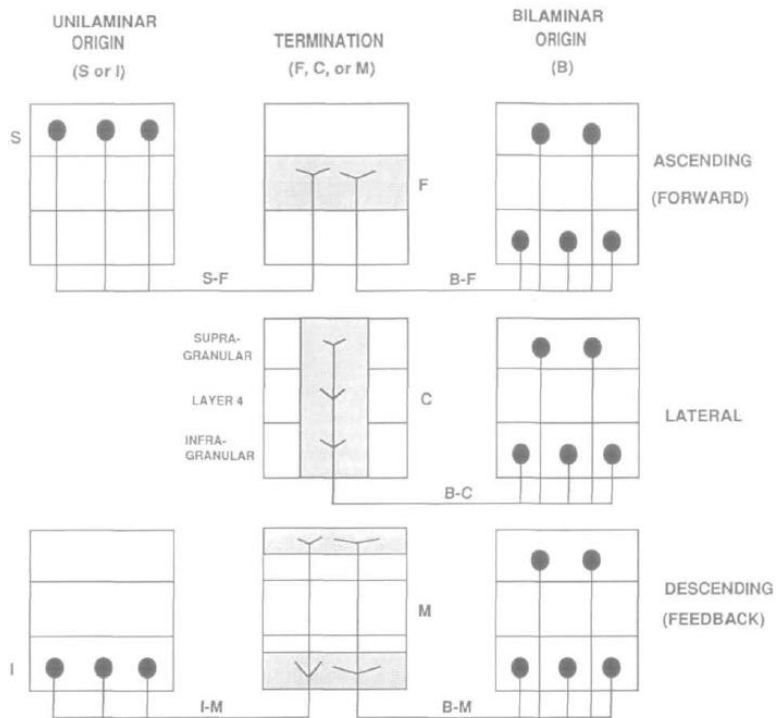
2003

2006

Distributed Hierarchical Processing in the Primate Cerebral Cortex

Daniel J. Felleman¹ and David C. Van Essen²

¹ Department of Neurobiology and Anatomy, University of Texas Medical School, Houston, Texas 77030, and ² Division of Biology, California Institute of Technology, Pasadena, California 91125



Backward Connection

Forward Connection

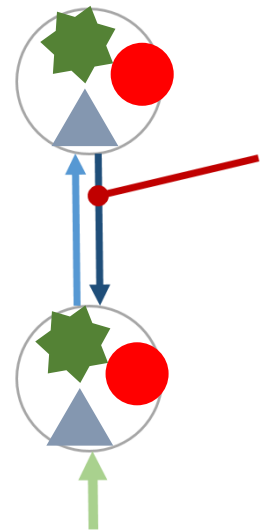
Lateral Connection

Layer

II/III

IV

V





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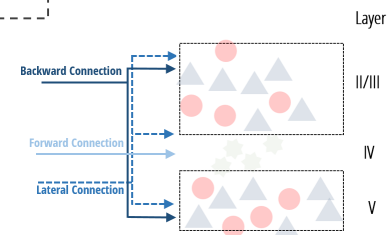
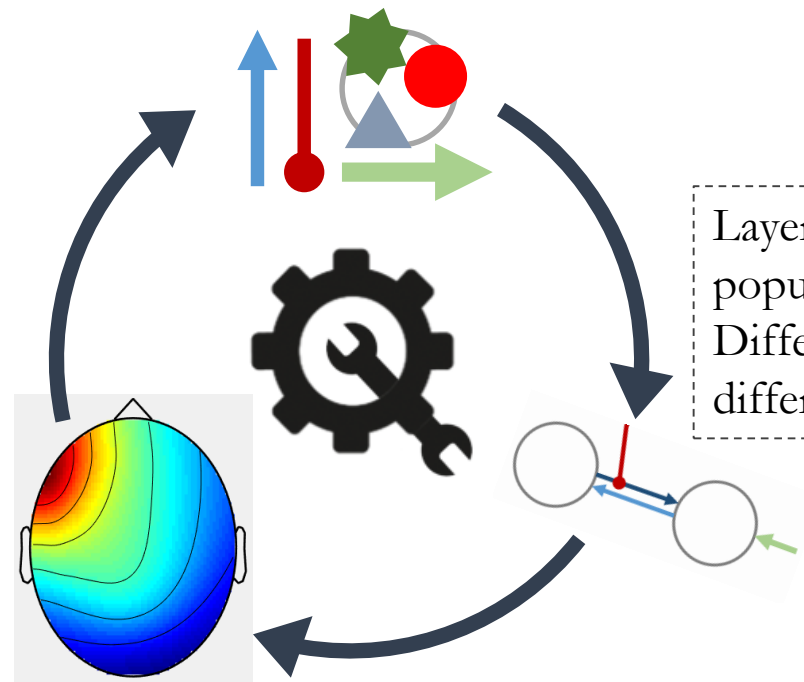
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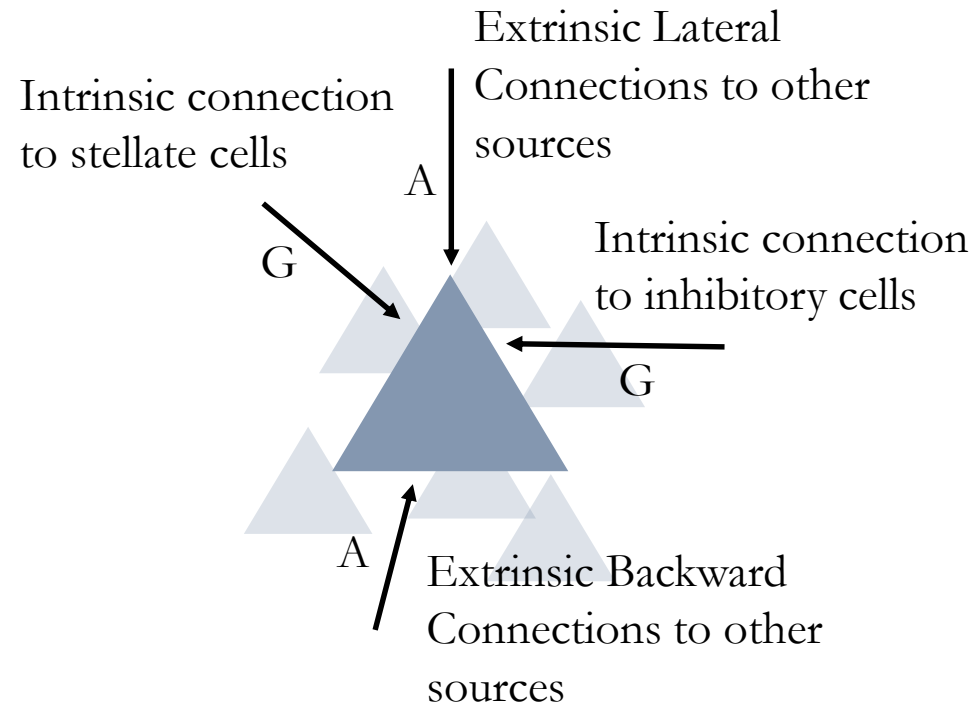
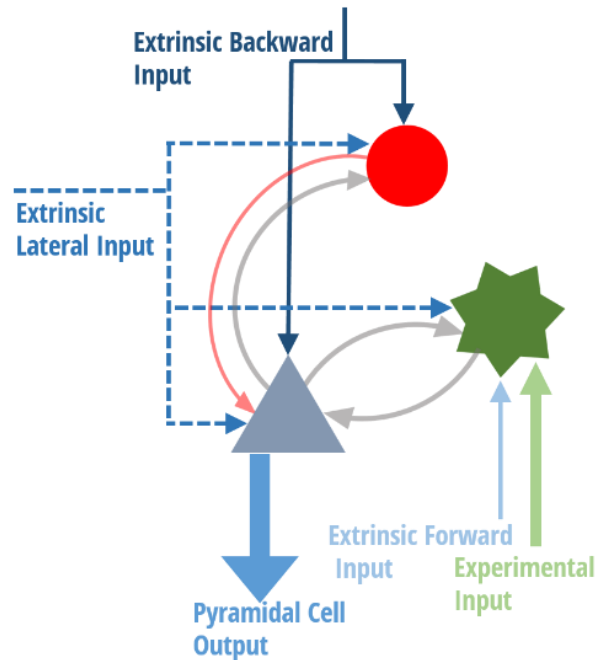
1991

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2006

A slightly different view on the parameters



Current state of the population. How much firing arrives.

$$\frac{dx}{dt} = f(x, A, H, C, \sigma, f_s(\theta_{kernel}))$$

What the cell population is connected to. The size of the kernel.



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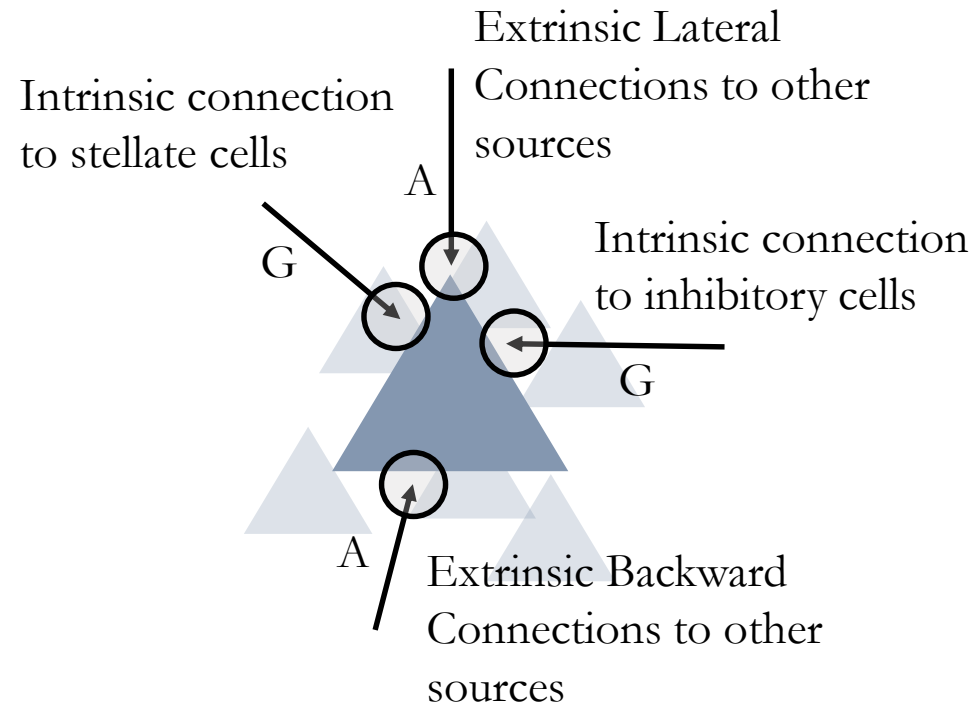
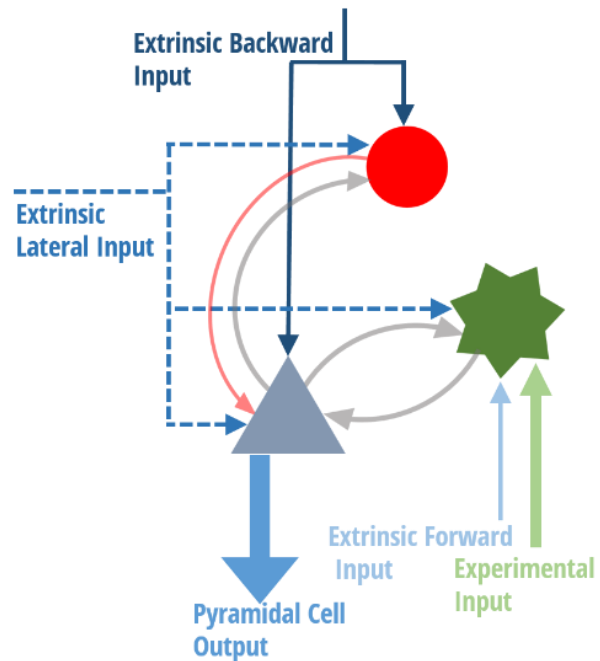
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A slightly different view on the parameters



Current state of the population. How much firing arrives.

$$\frac{dx}{dt} = f(x, A, H, G, C, \sigma, \kappa, \theta_{kernel})$$

What the cell population is connected to. The size of the kernel.



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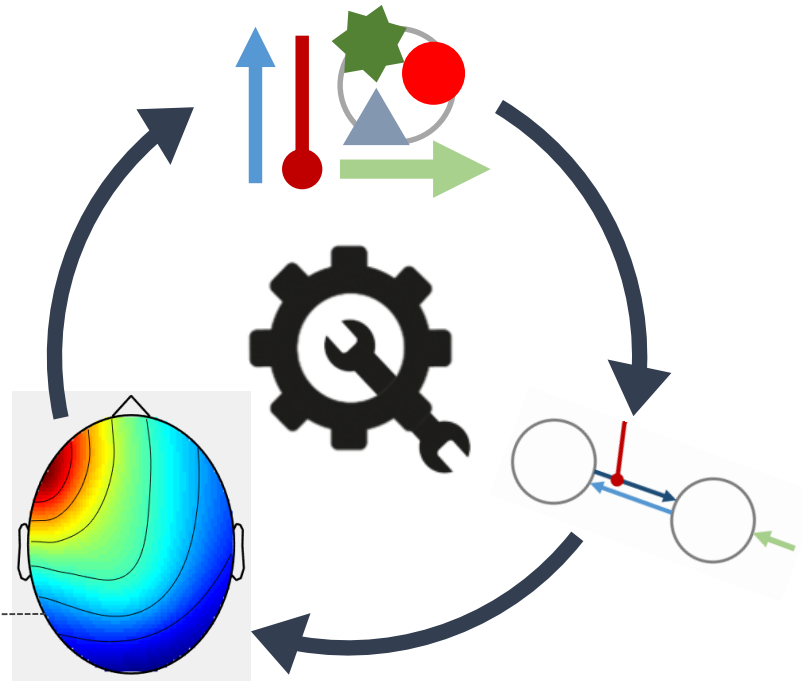
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How hidden neural
activity transforms
into measurable data?

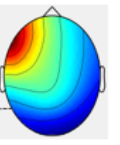
$$y = g(x, \Theta_g) + \epsilon$$





How hidden neural activity transforms into measurable data?

$$y = g(x, \theta_g) + \epsilon$$



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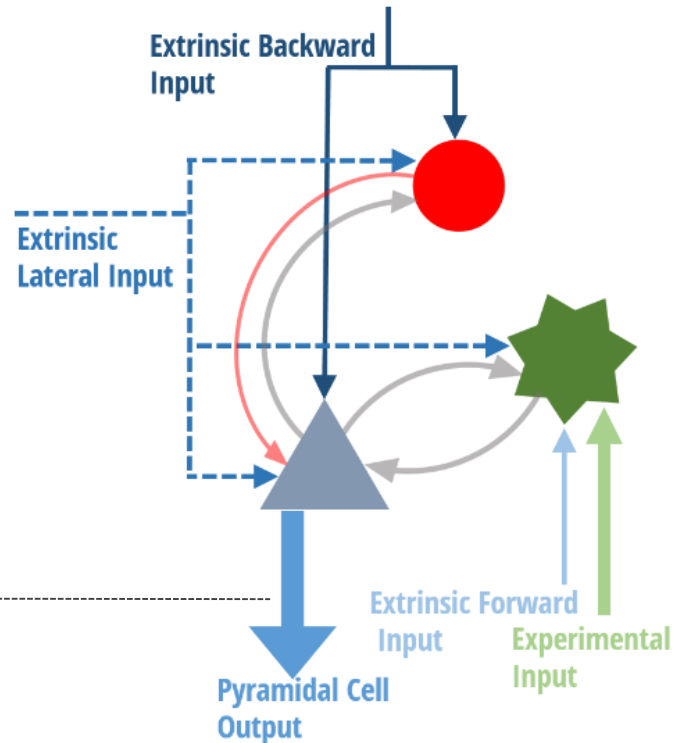
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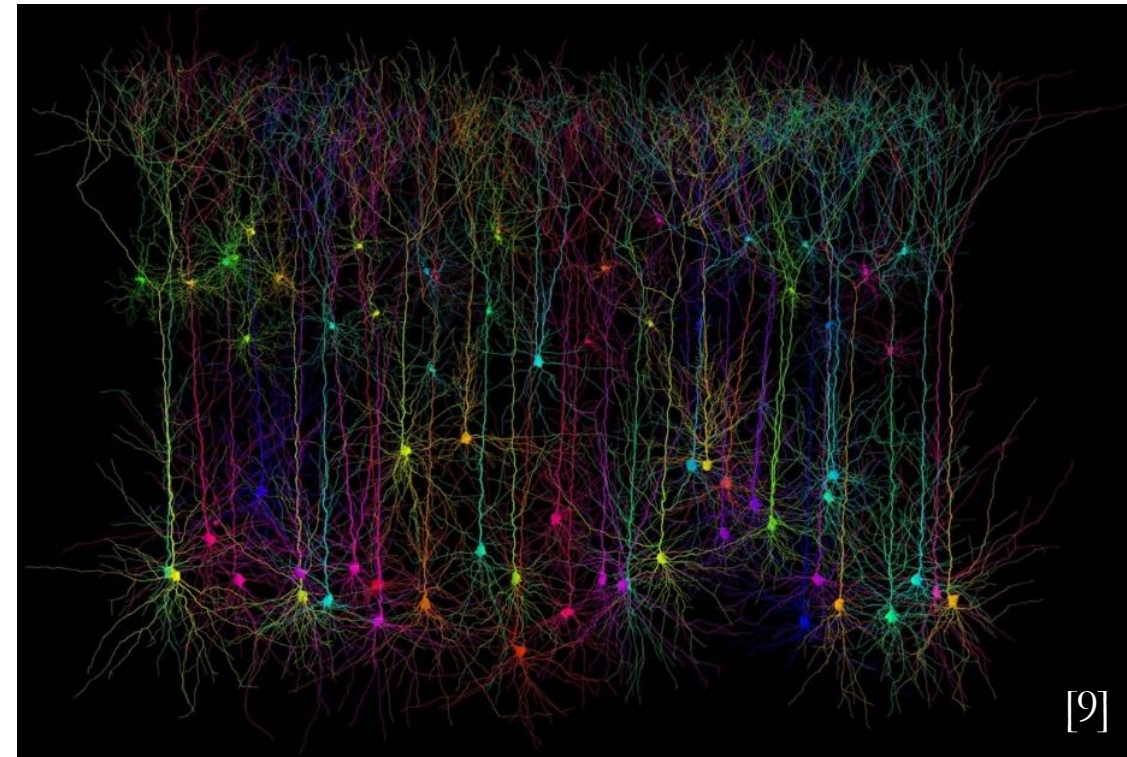
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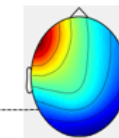


Due to their special alignment, pyramidal cells contribute most to the measured signal.





How hidden neural activity transforms into measurable data?
 $y = g(x, \theta_g) + \epsilon$



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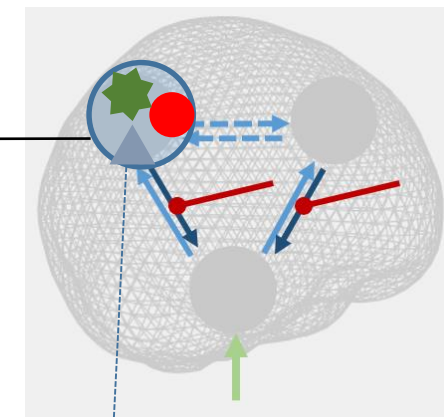
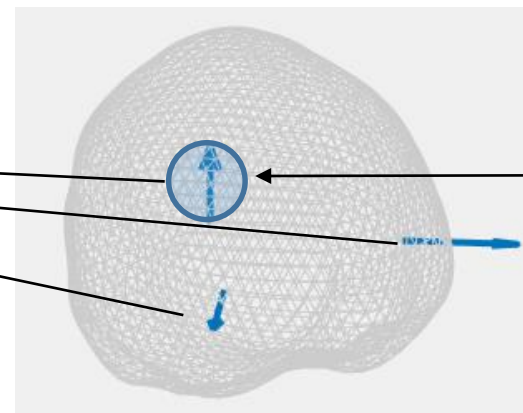
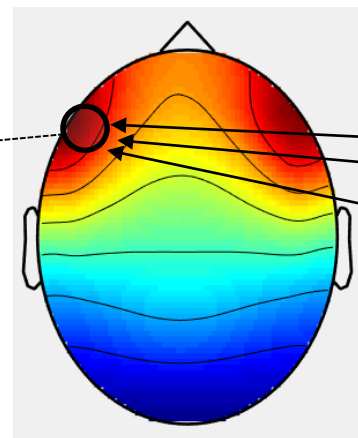
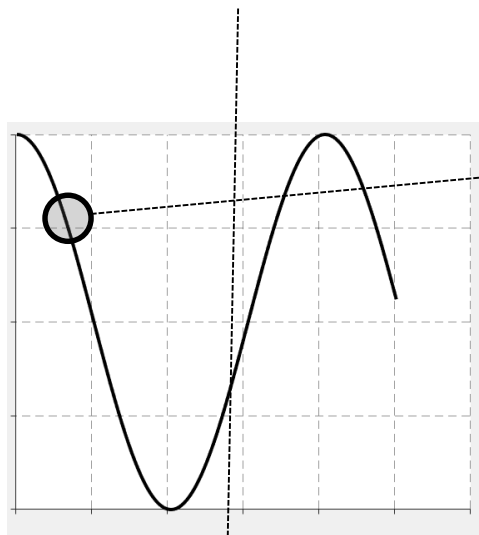
2006

Electrode Activity

Scalp Activity

Dipole Activity

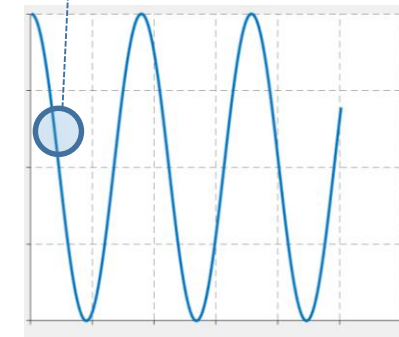
Source Activity



We don't really predict electrode activity, but the first N 'principle components'.

Linear Mapping of all dipoles onto scalp.

Linear Mixture of states onto three dipole moments





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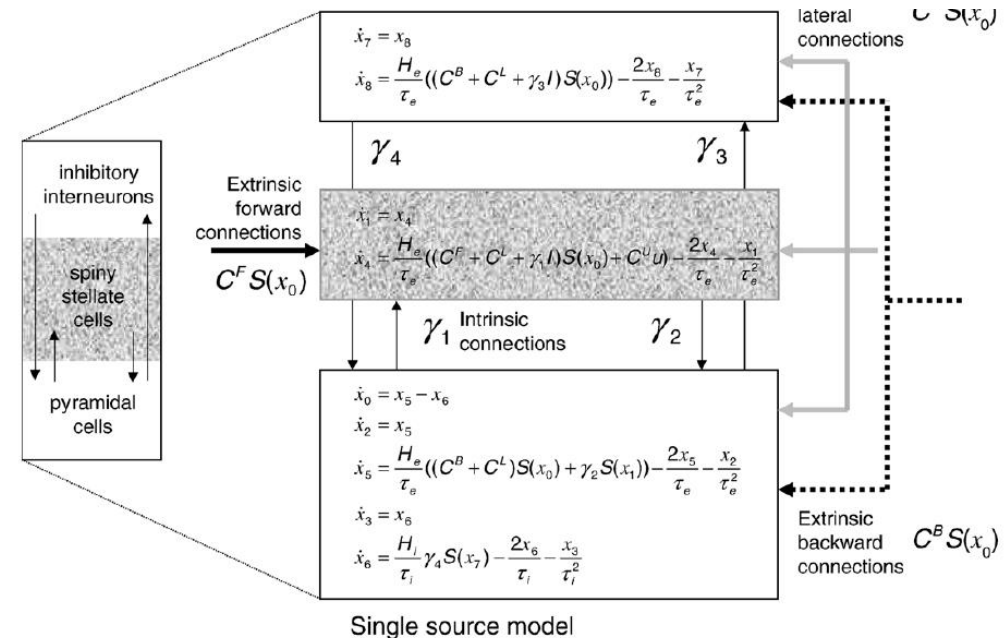
1995

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Dynamic causal modeling of evoked responses in EEG and MEG[☆]

Olivier David,¹ Stefan J. Kiebel,^{*} Lee M. Harrison, Jérémie Mattout,
James M. Kilner, and Karl J. Friston





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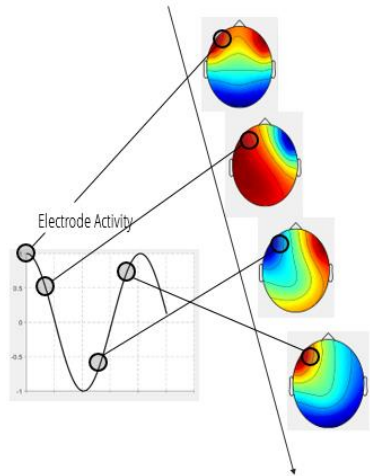
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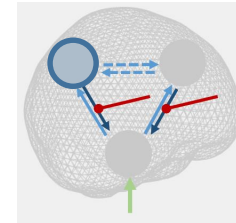


$$y = g(x, \Theta_g) + \epsilon$$

Linear forward mapping
describing the transformation of
hidden source activity to
measurable data

Prediction of
measured data

Inference on parameters
and (causal) network
structure



$$\frac{dx}{dt} = f(x, u, \theta)$$

Equations describing
(hidden) post synaptic
potentials of the
neuronal populations.



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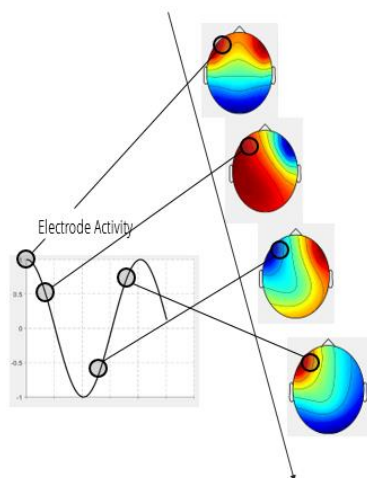
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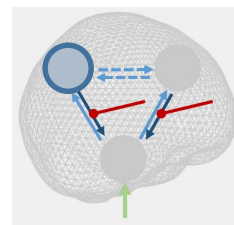
EEG



$$y = g(x, \Theta_g) + \epsilon$$

simple

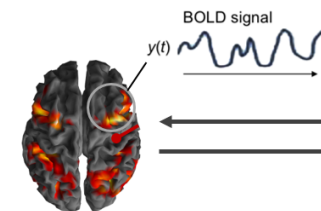
Tough (at least
parameter inference)



$$\frac{dx}{dt} = f(x, u, \theta)$$

complicated

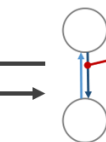
fMRI



$$y = g(x, \Theta_g) + \epsilon$$

complicated

Probably
better
behaved

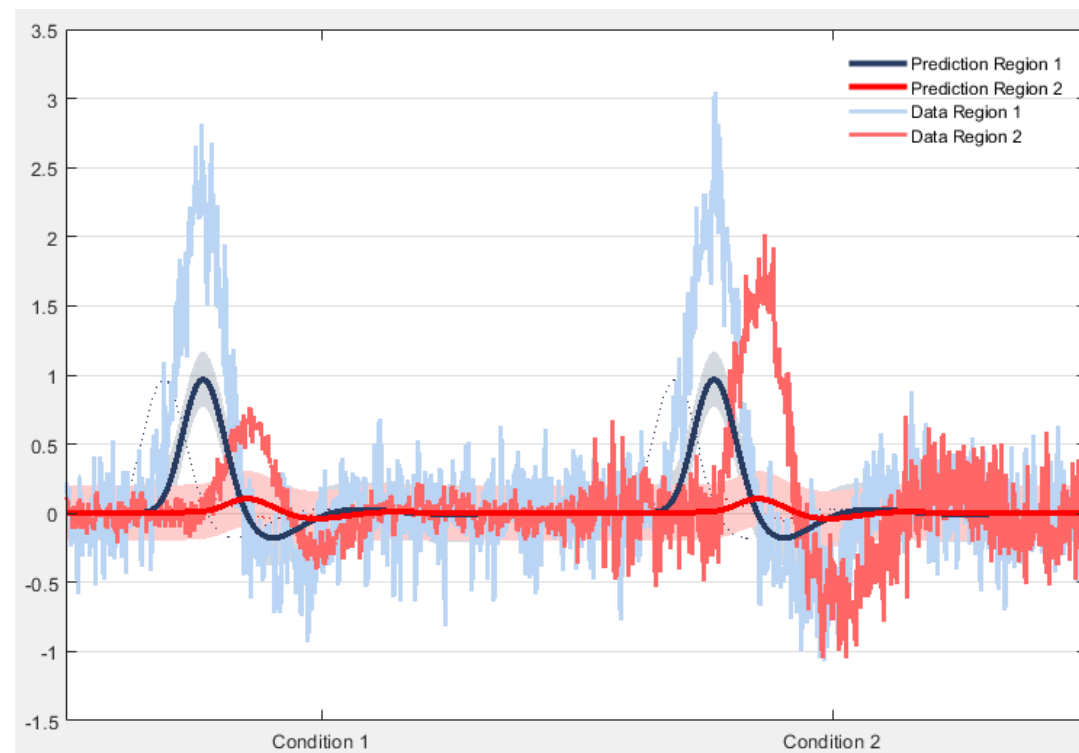
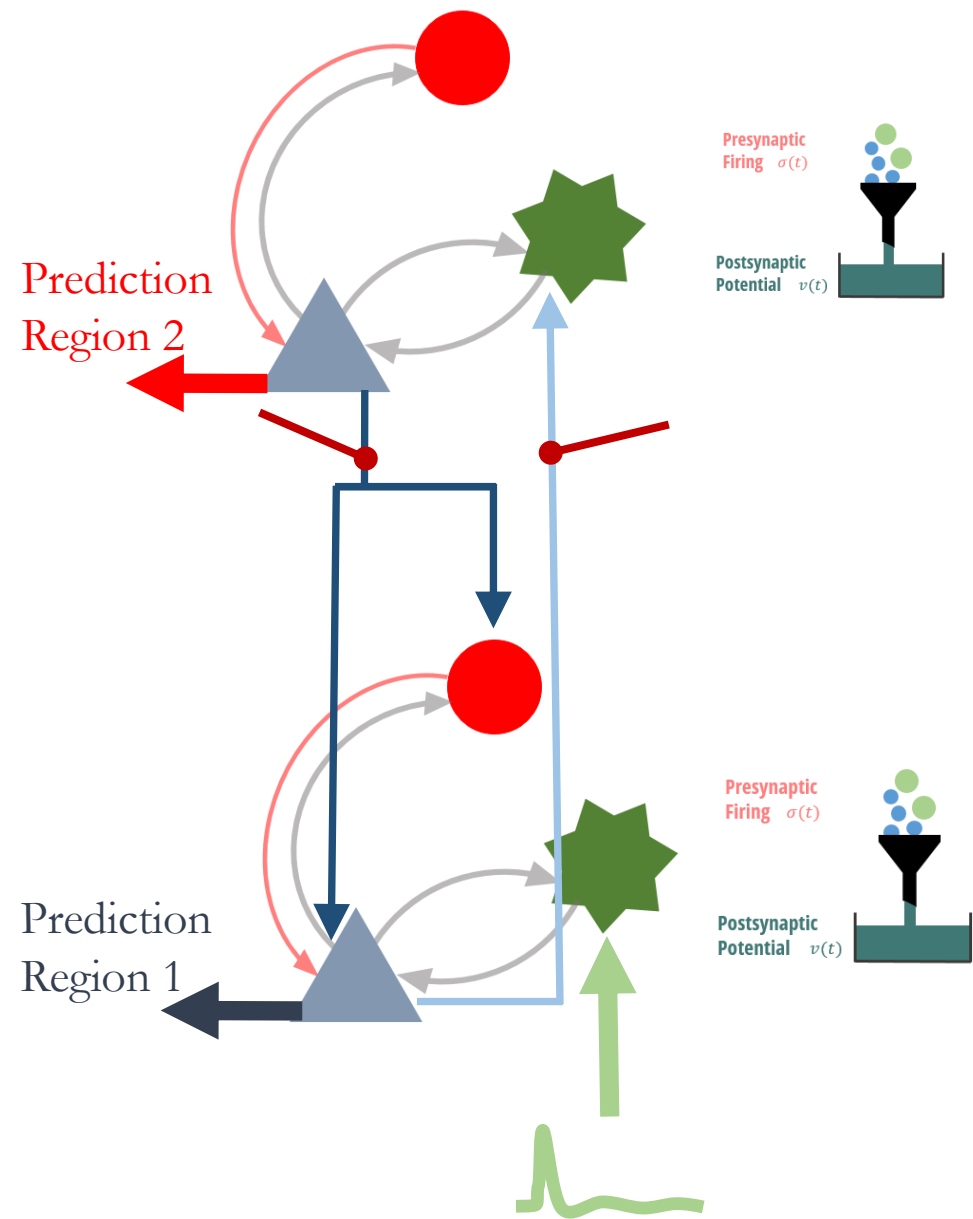


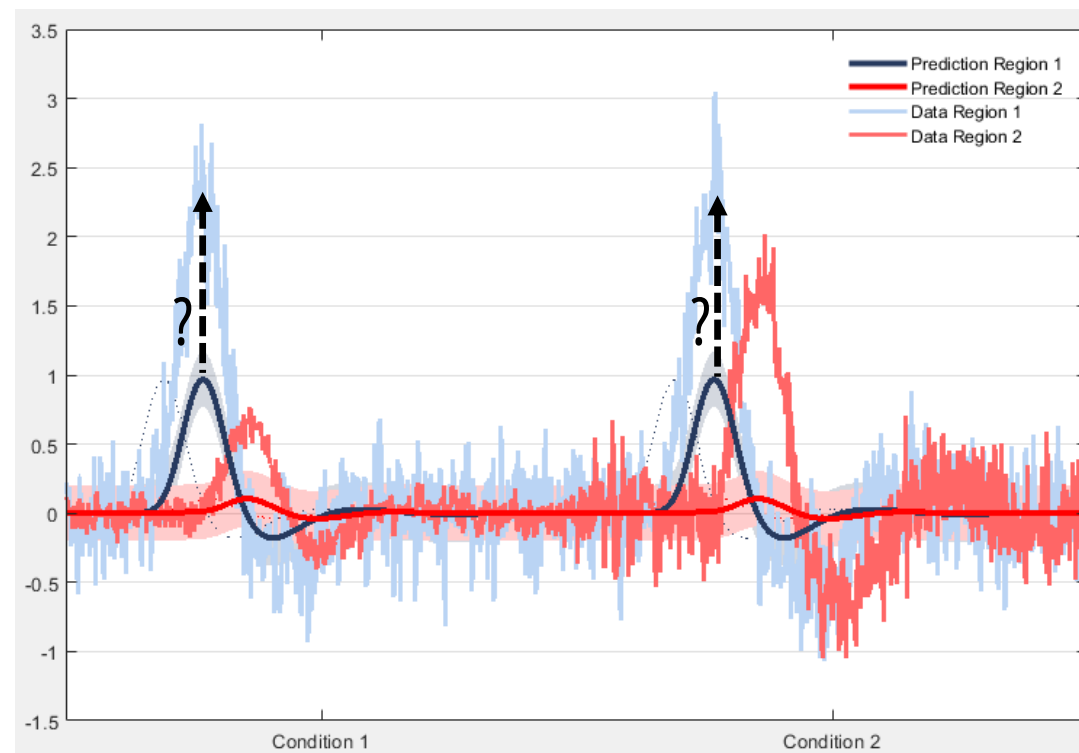
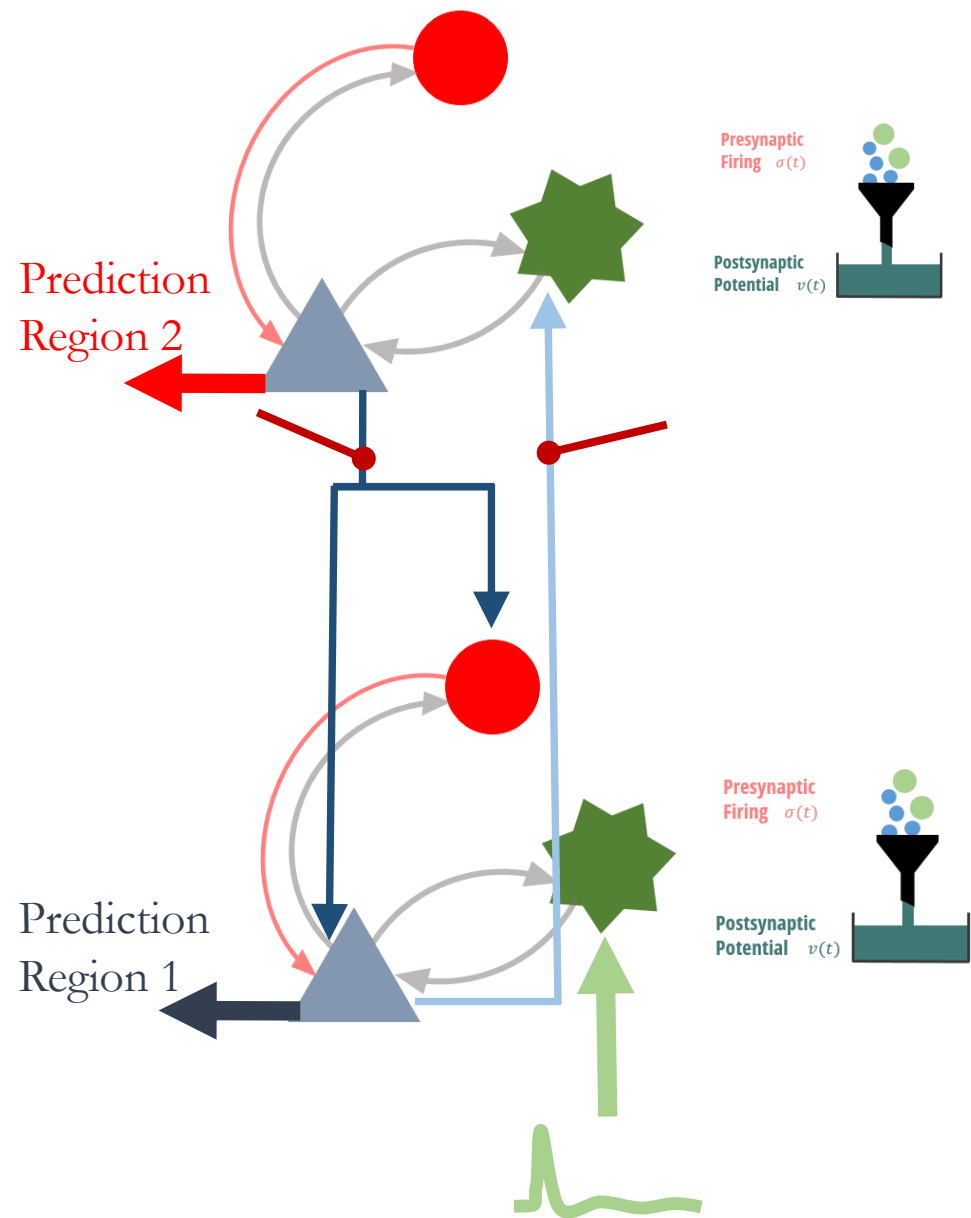
$$\frac{dx}{dt} = f(x, u, \theta)$$

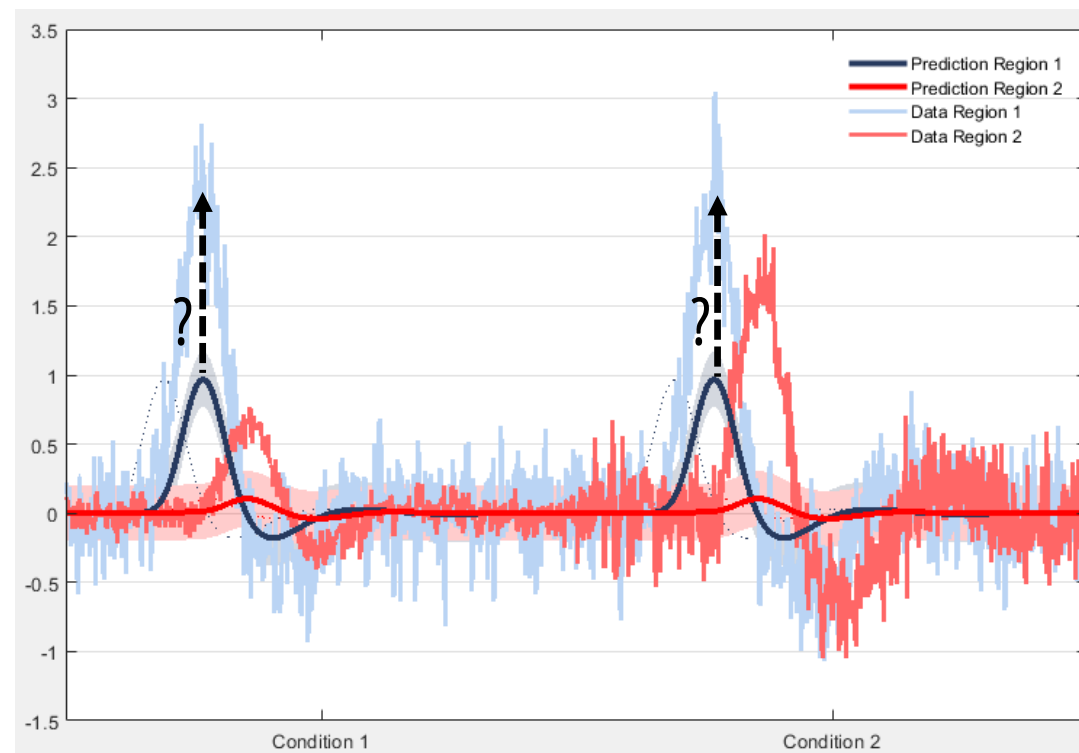
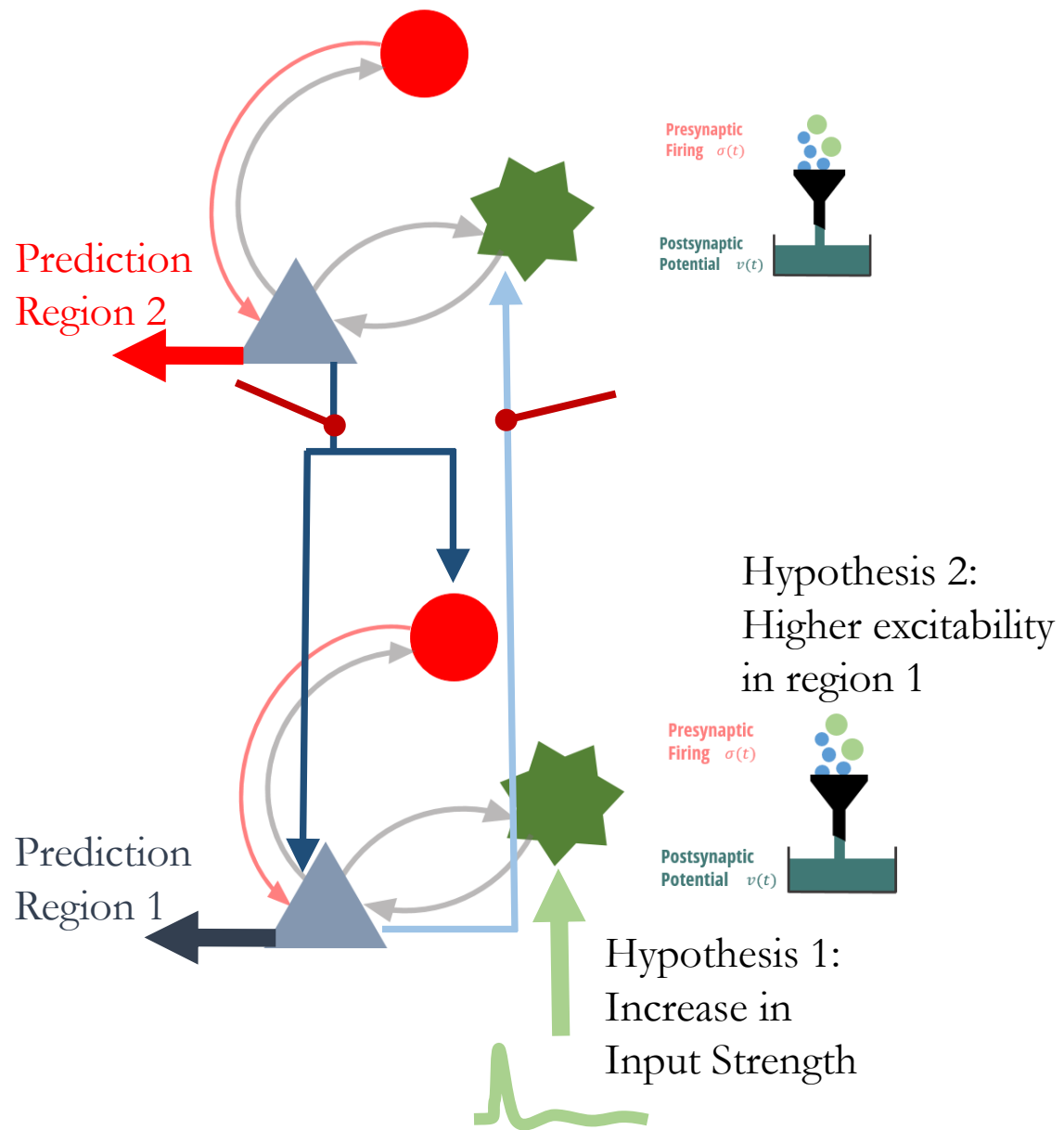
simple

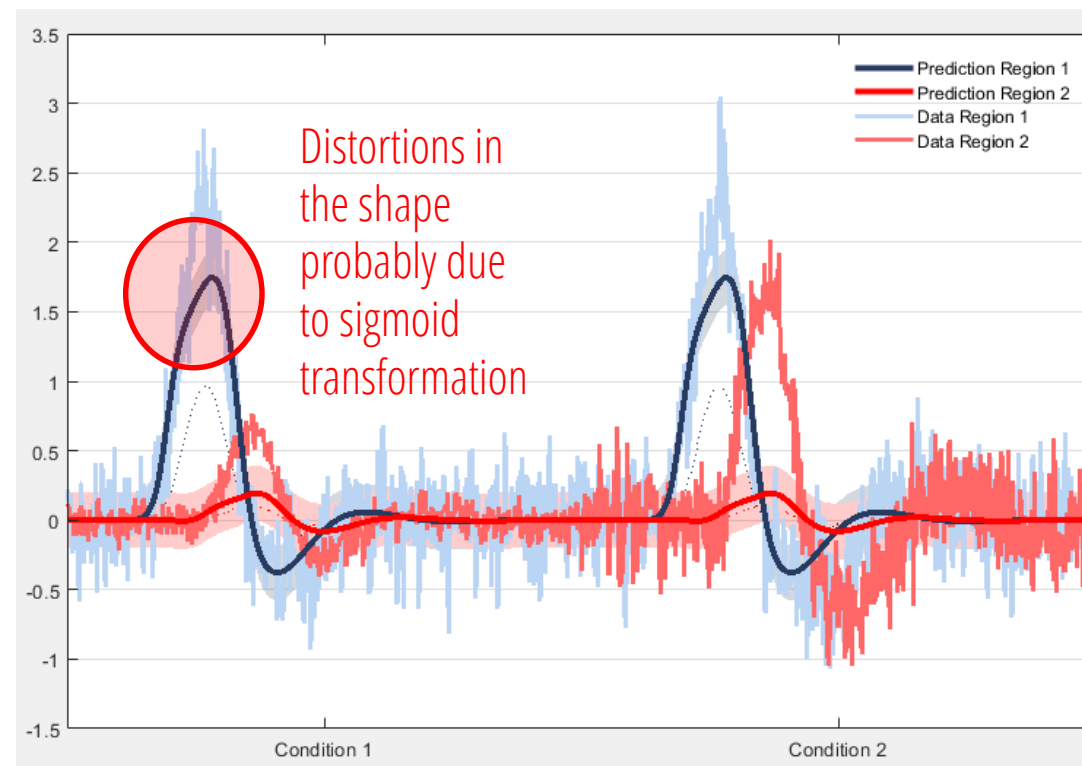
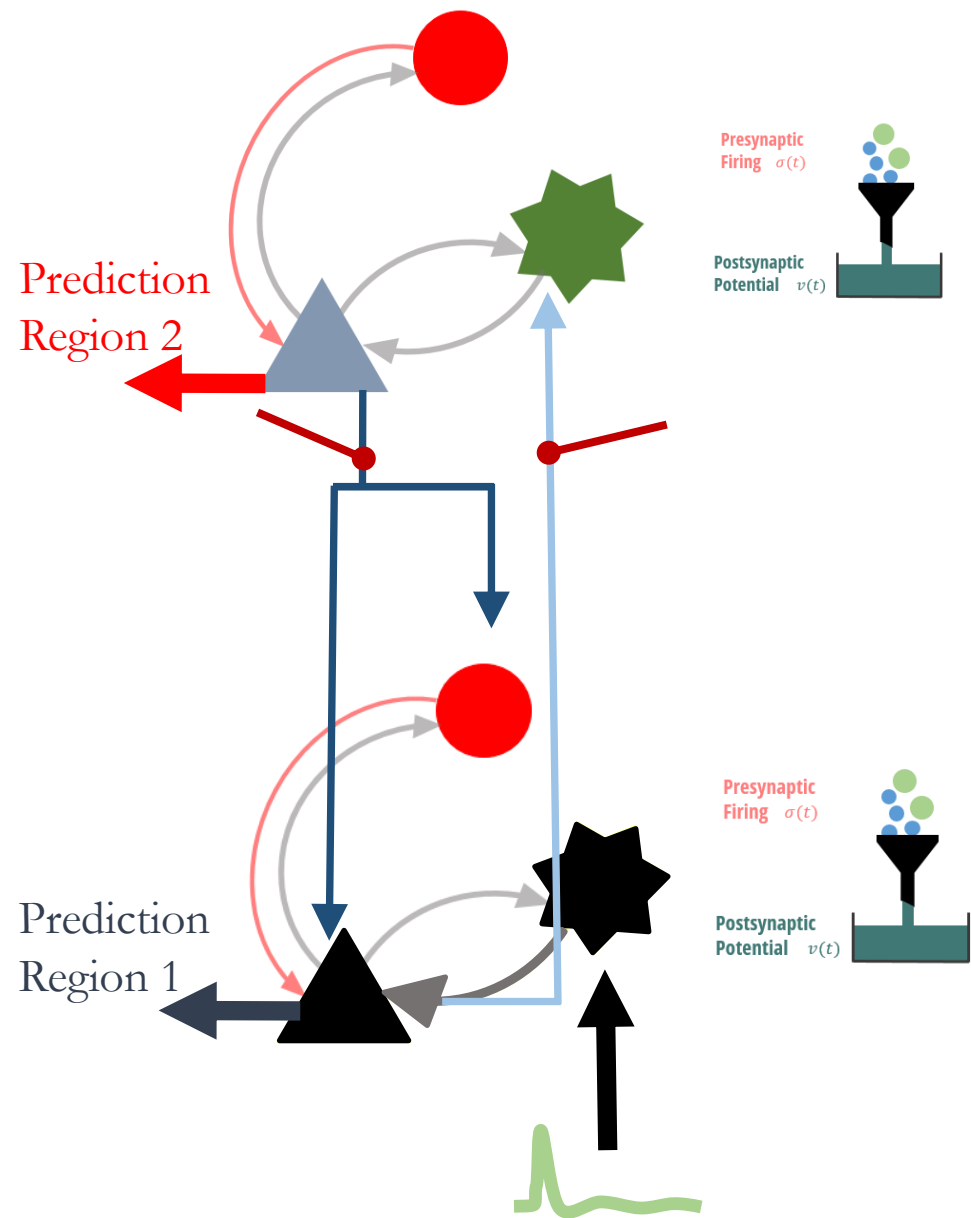
Chapter 2

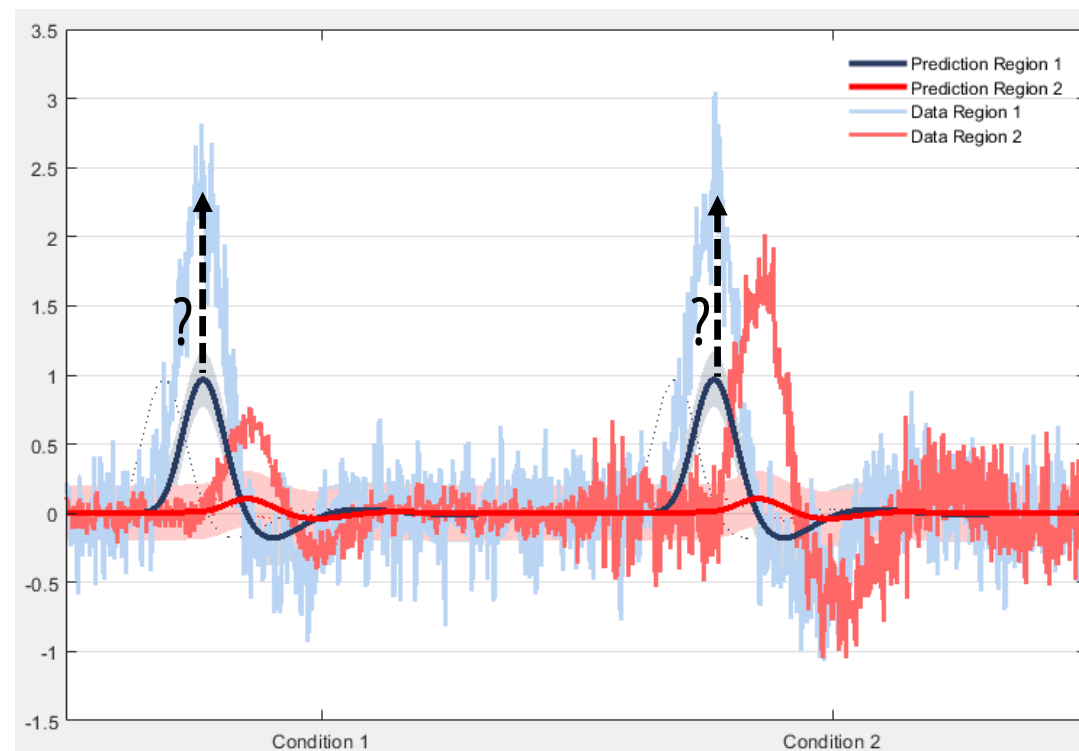
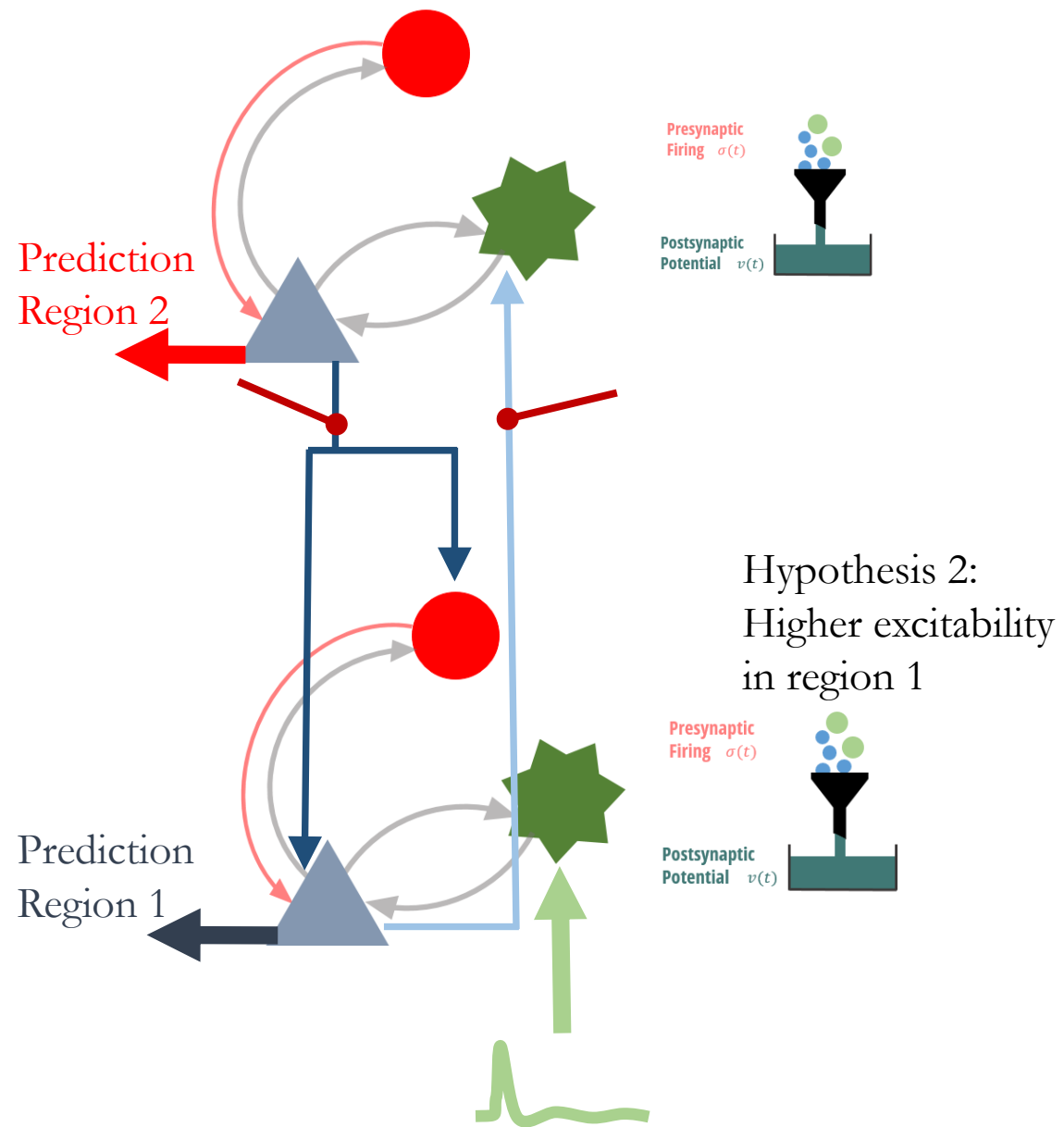
Getting a feel for the equations

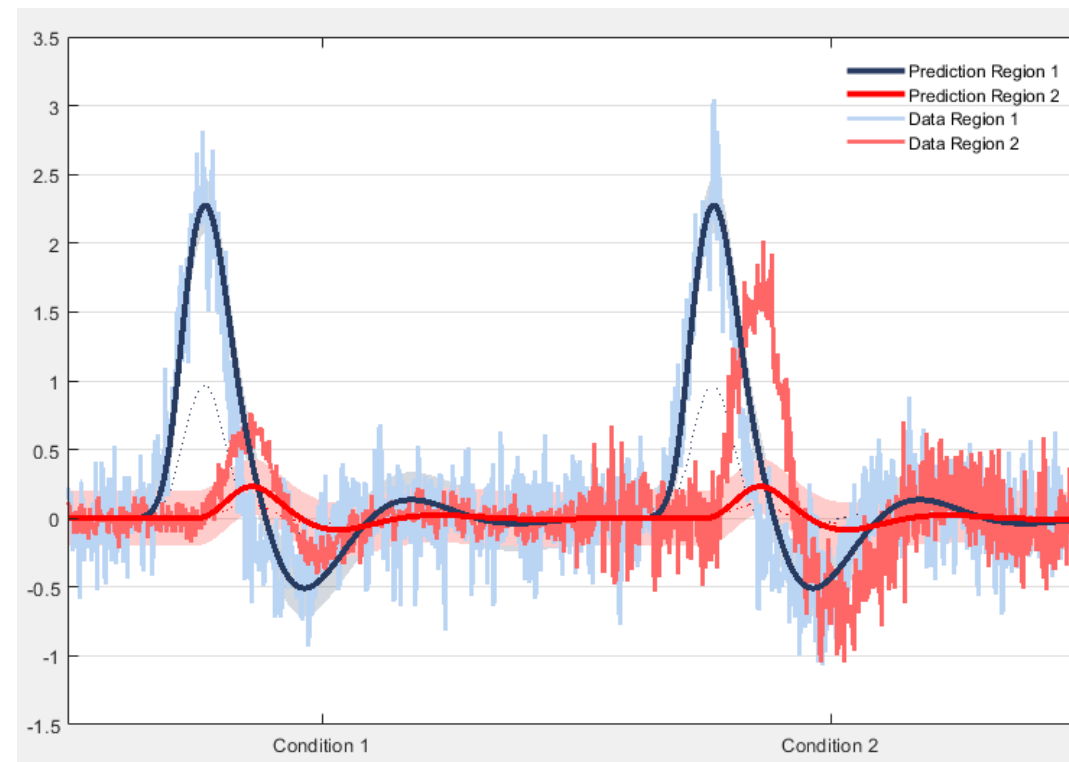
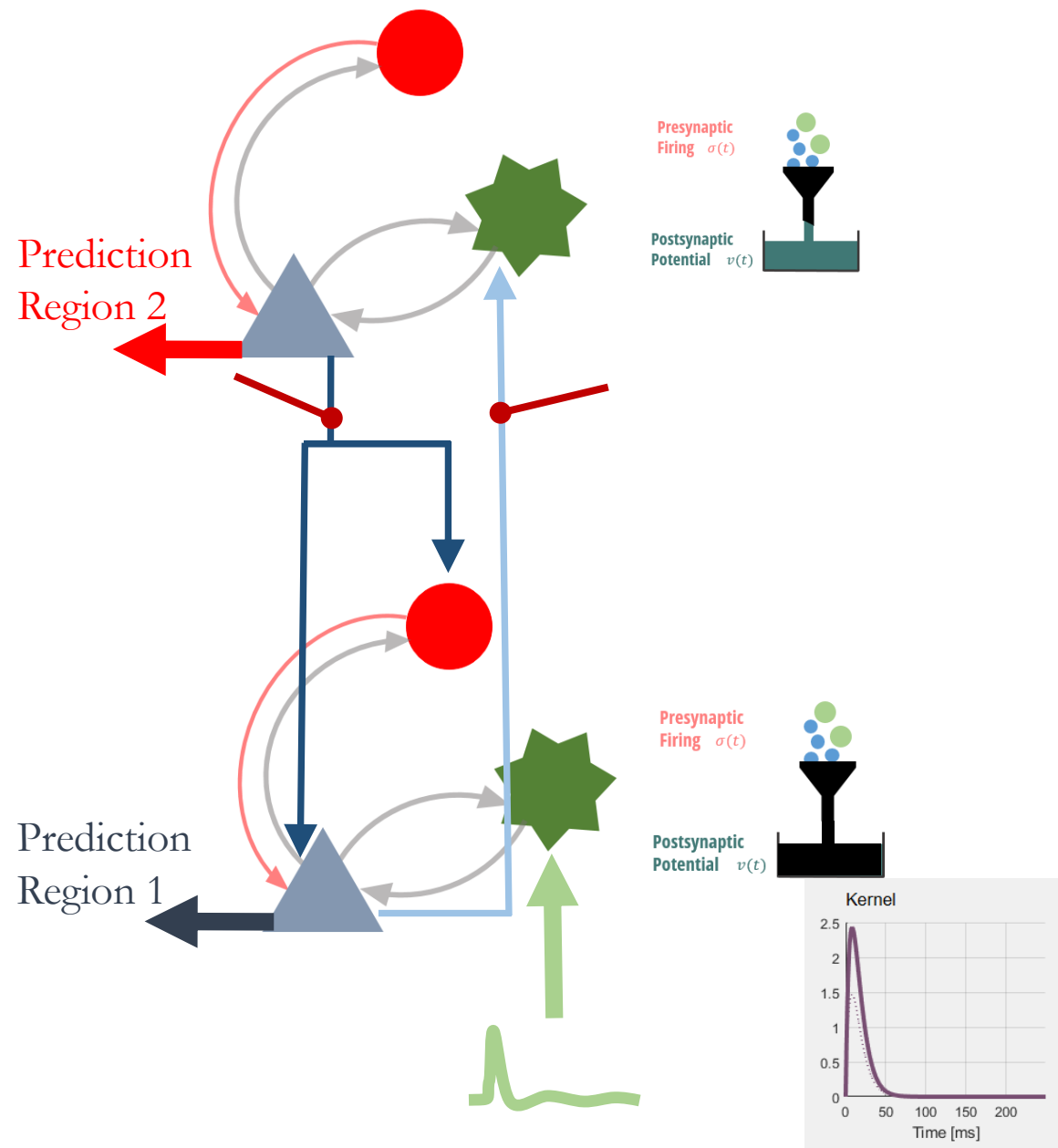


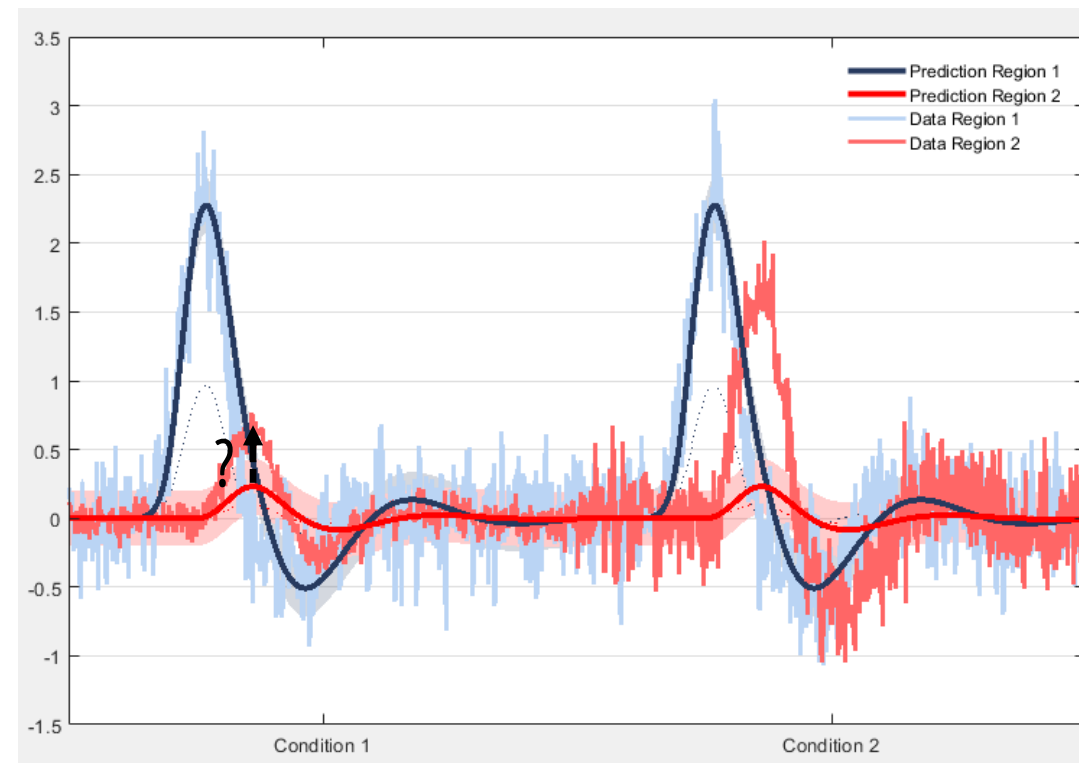
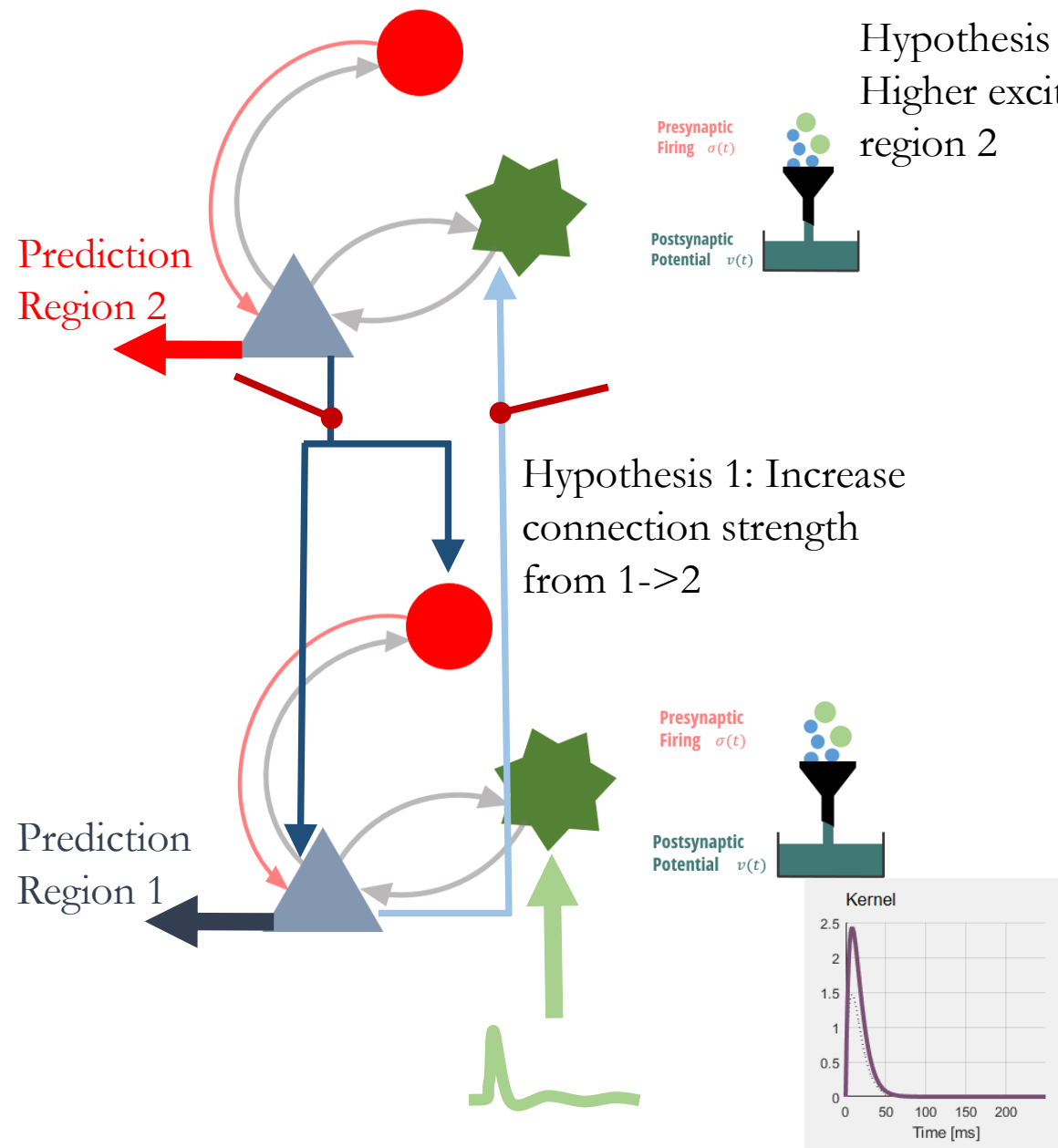


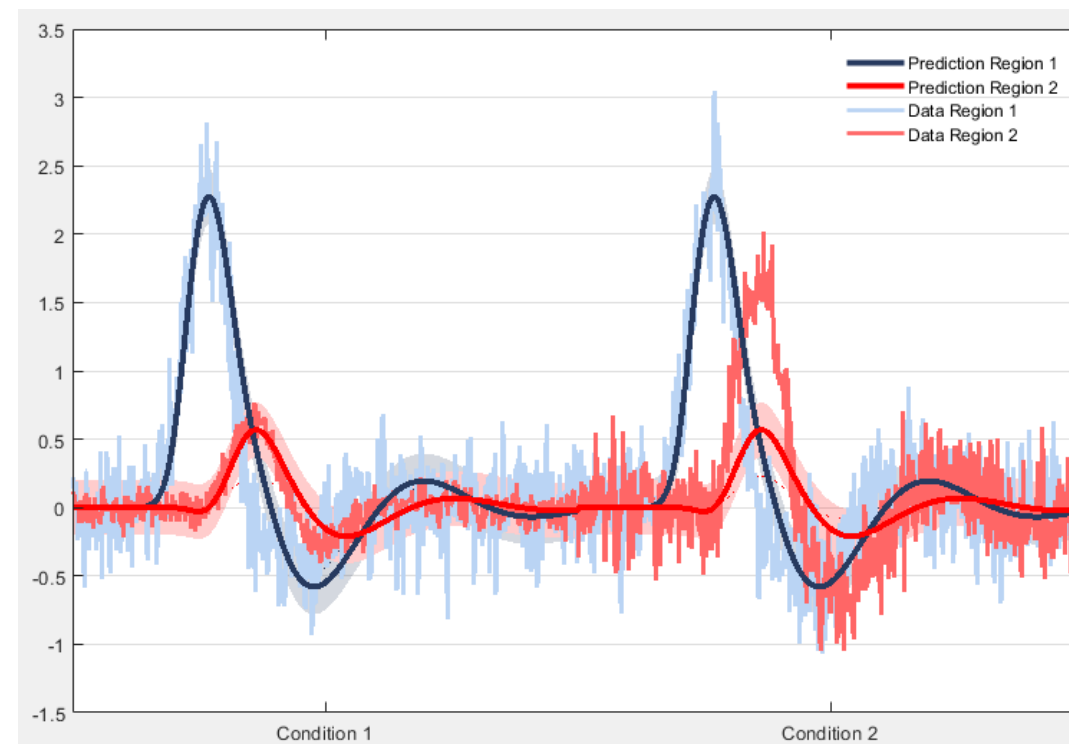
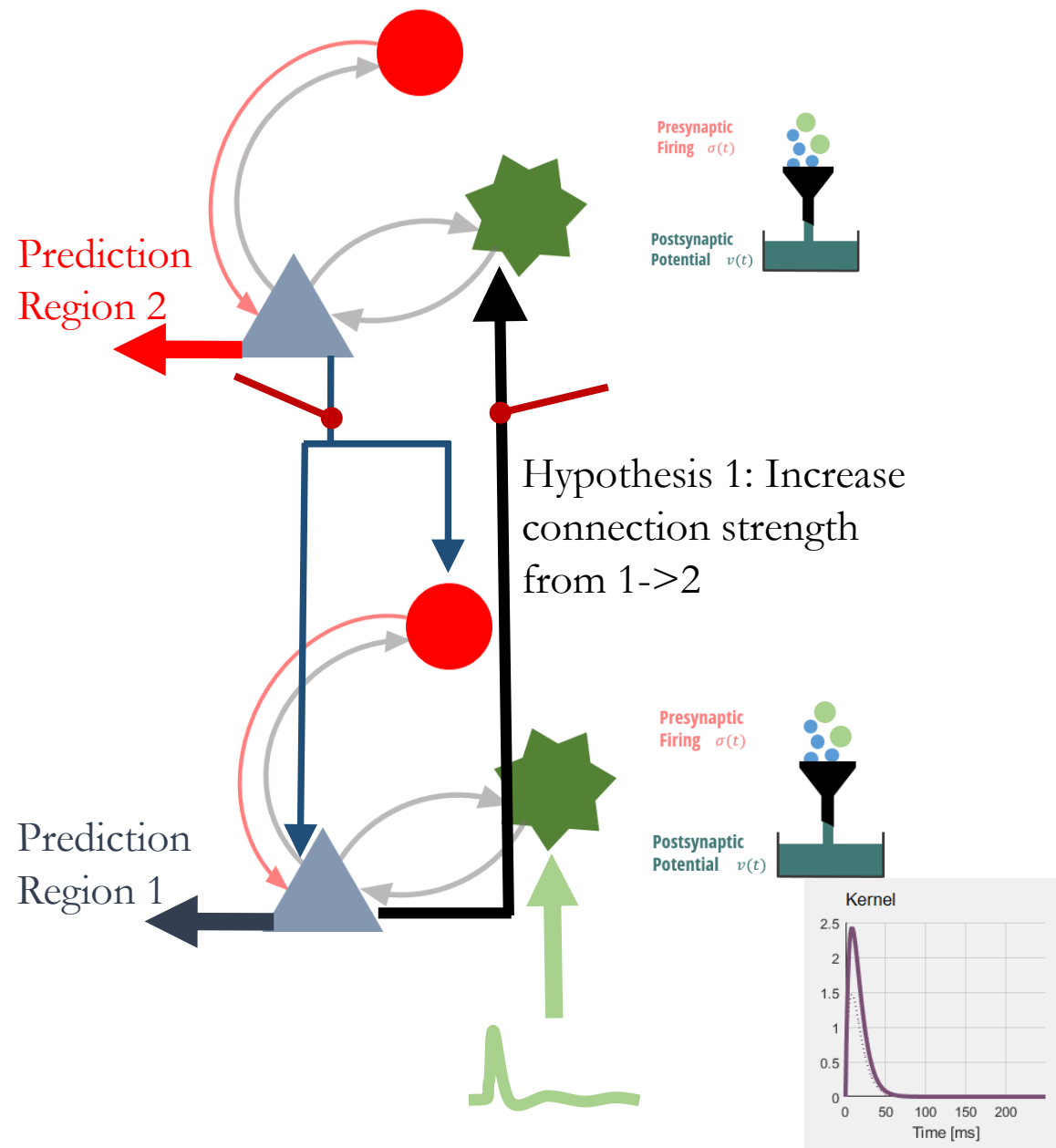


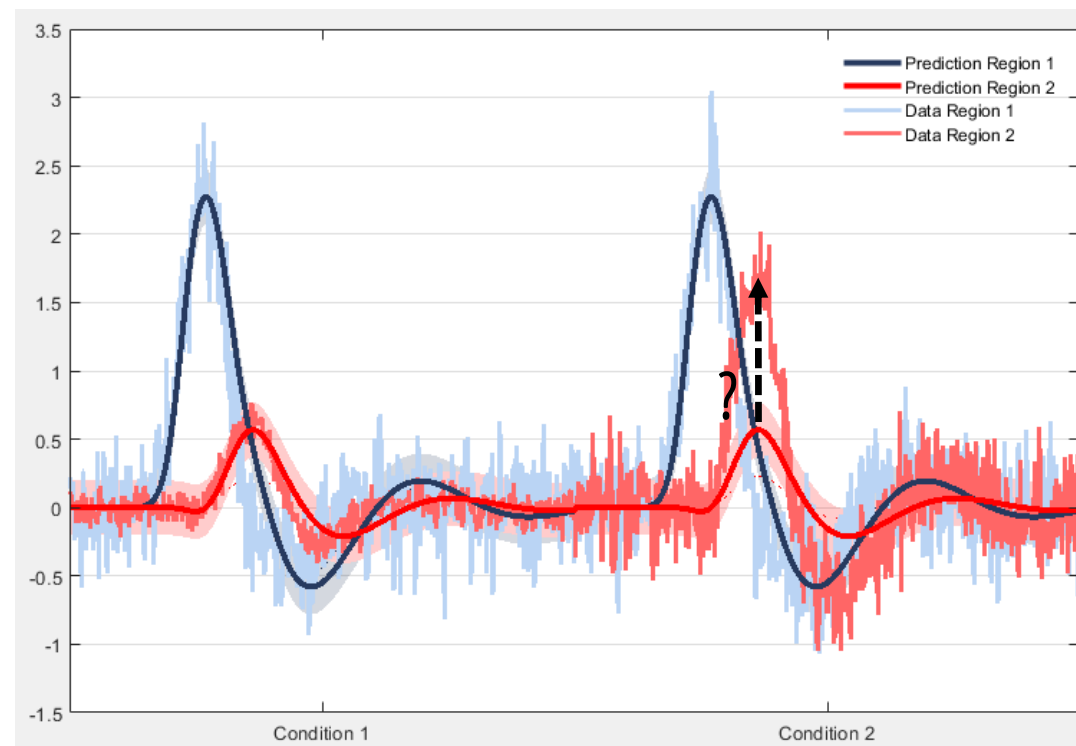
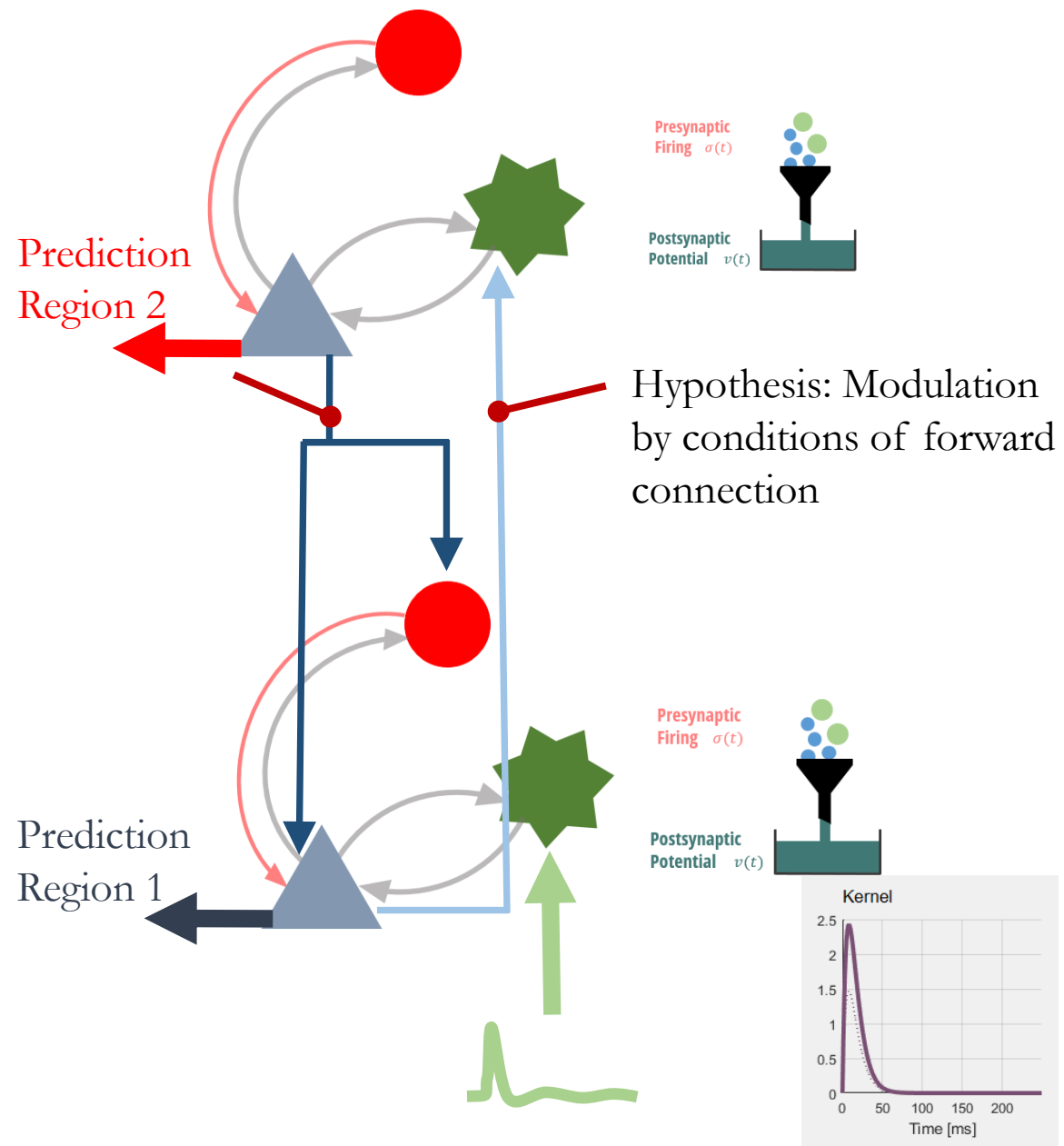














Chapter 3

Application

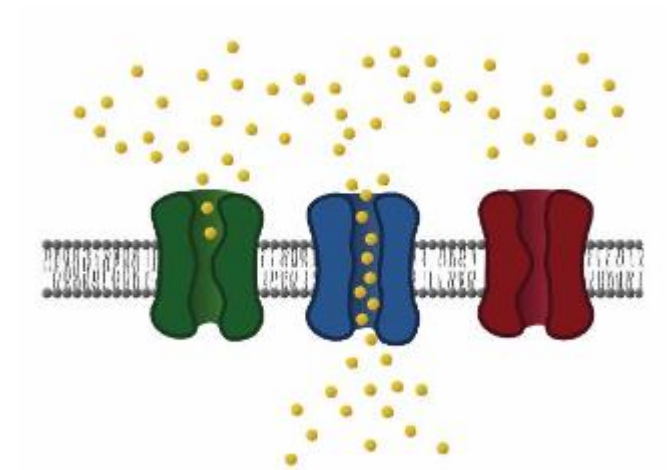
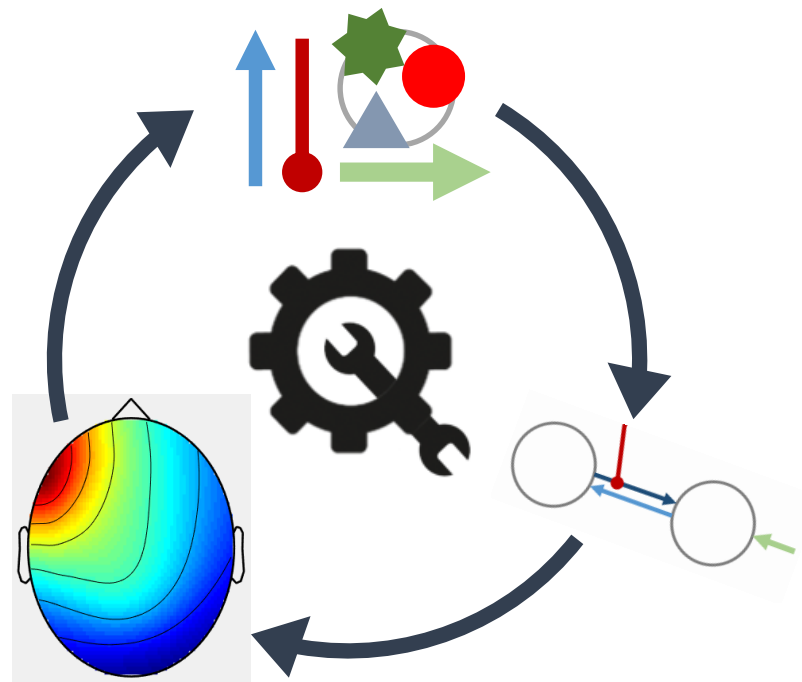


data

macroscale

mesoscale

microscale



Mechanisms governing
generation of average post-
synaptic potentials:

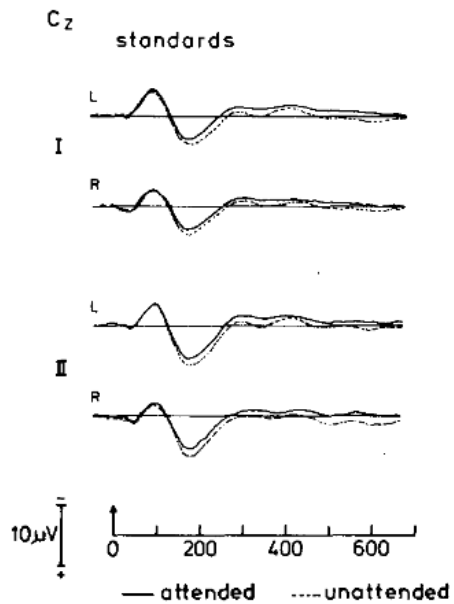


data

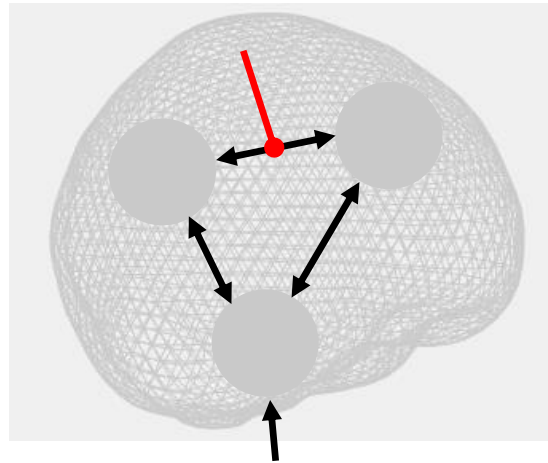
macroscale

mesoscale

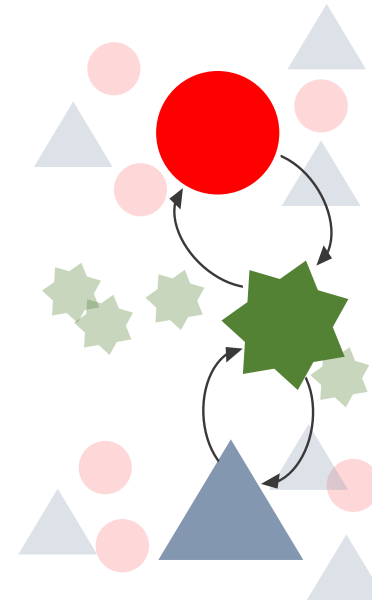
microscale



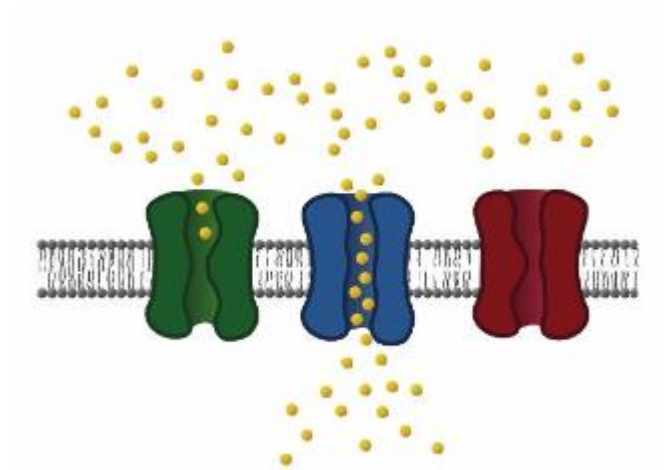
Averaged Evoked Responses



Network and
modulation structure



Layered Structure of
the cortical column

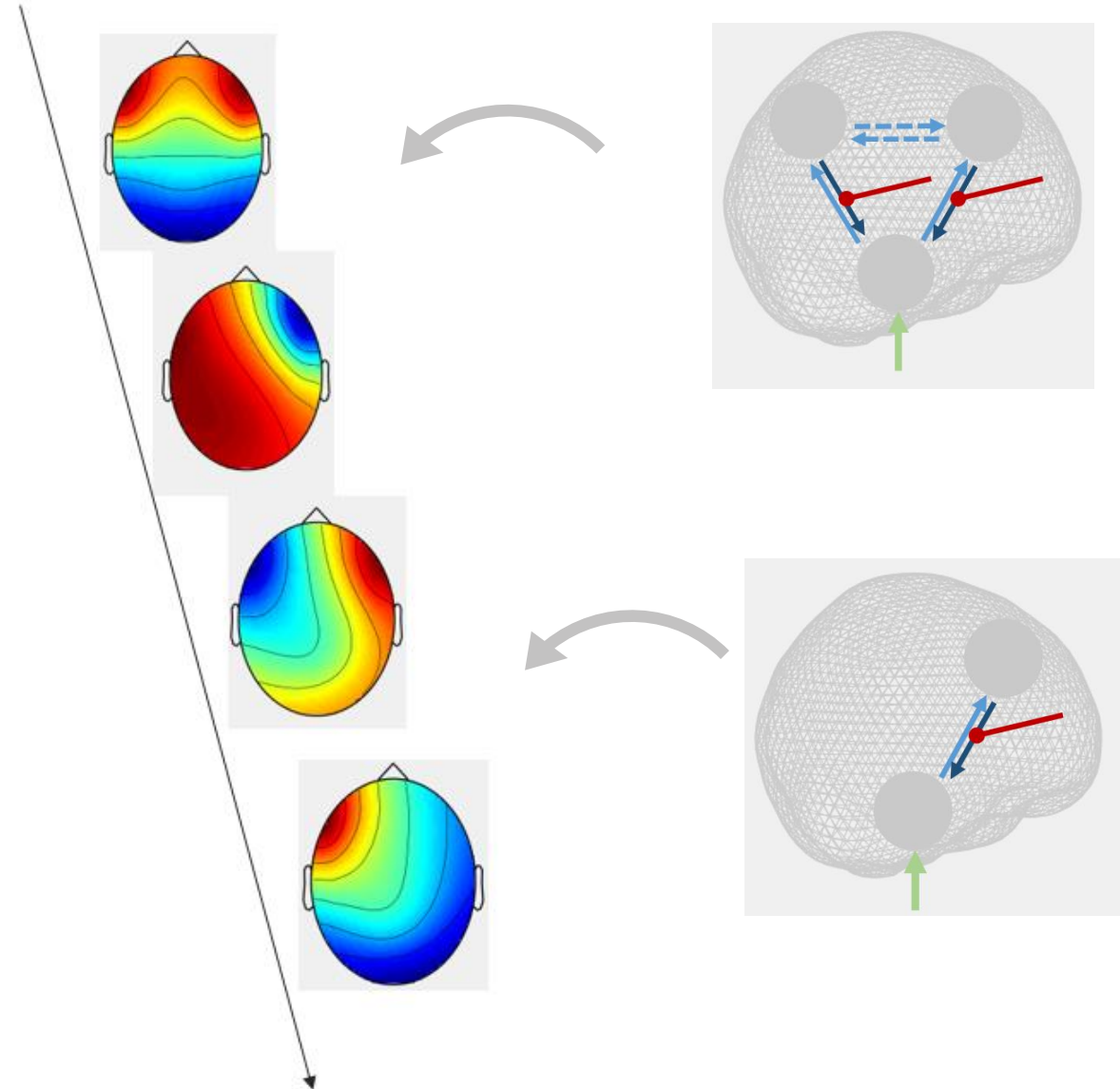


Mechanisms governing
generation of average post-
synaptic potentials



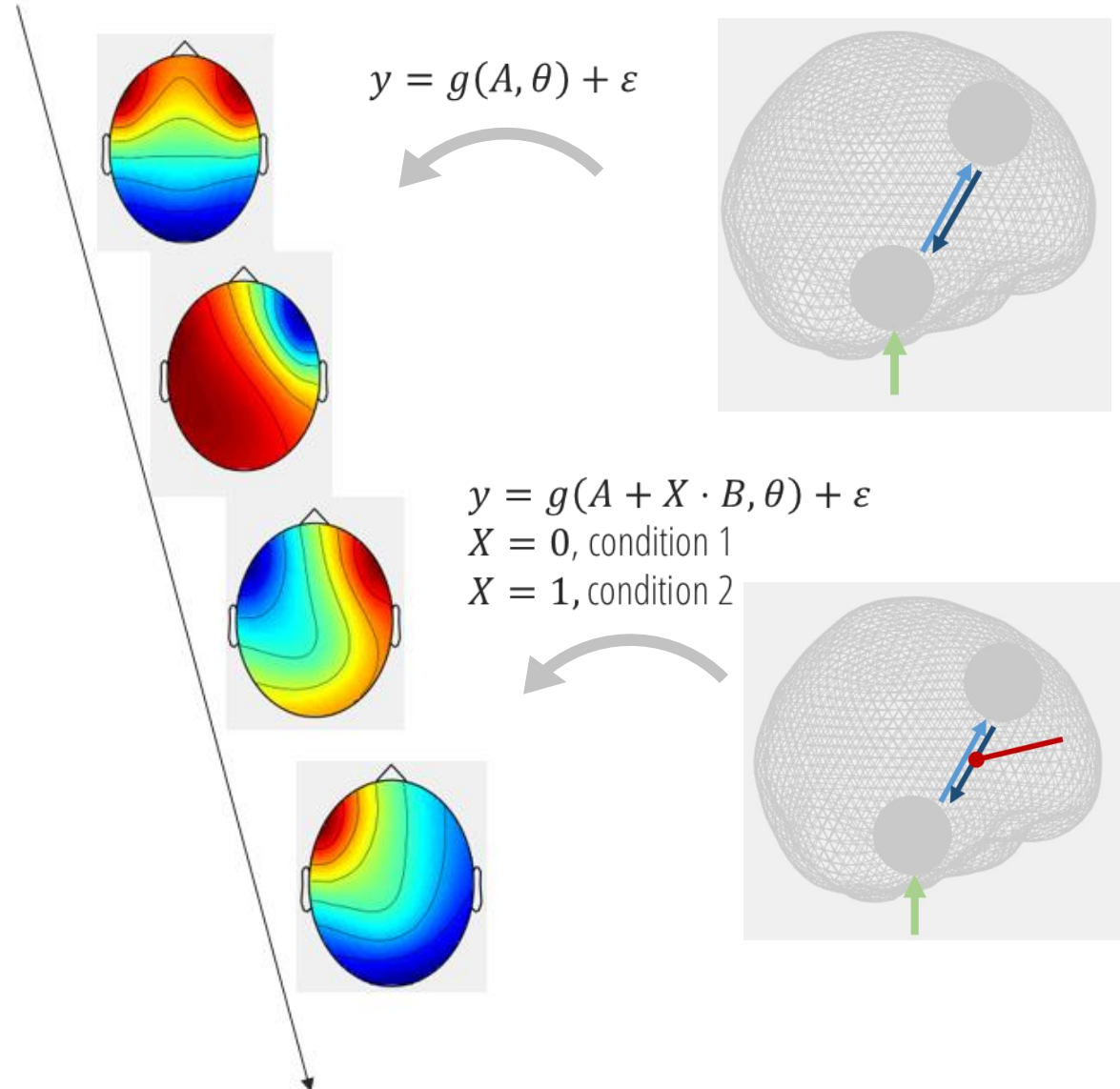
Hypothesis Testing

- Macroscale view (similar to DCM for fMRI)
- Framework to test multiple hypotheses as Bayesian Model Selection (BMS -> Lionel Rigoux) questions:
 - Does a model including regions A, B and C explain the data better than a model including only A and B.
Only possible for scalp data (not LFP or fMRI)

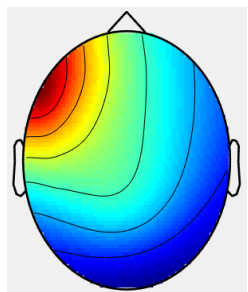


Hypothesis Testing

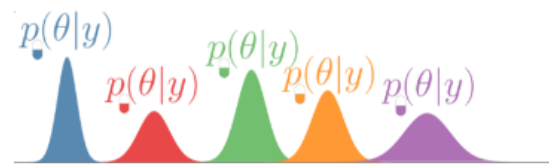
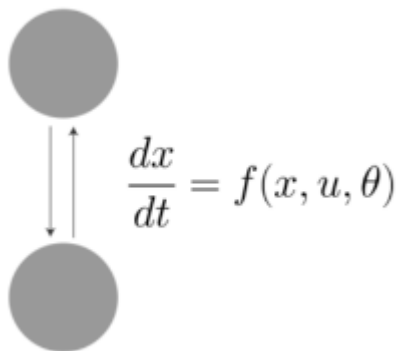
- Macroscale view (similar to DCM for fMRI)
- Framework to test multiple hypotheses as Bayesian Model Selection (BMS -> Lionel Rigoux) questions:
 - Does a model including regions A, B and C explain the data better than a model including only A and B.
Only possible for scalp data (not LFP or fMRI)
 - Can we explain a difference in activation between conditions as a condition specific modulation of one of the connections?



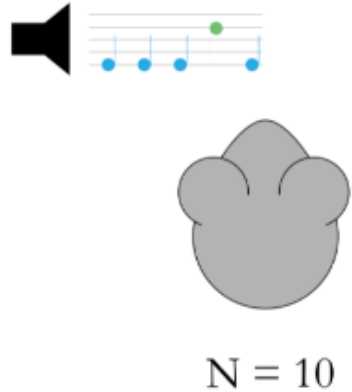
Inferring on parameters



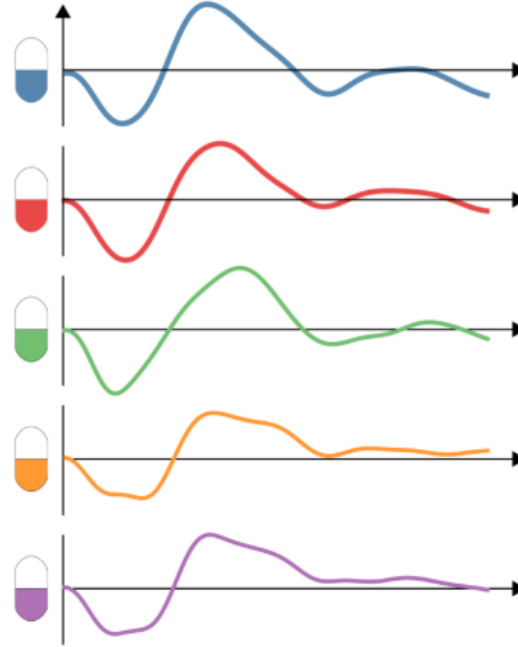
Inference



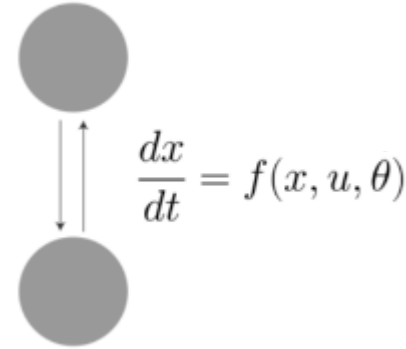
- Differences (across groups, manipulations, interventions, ...)
- Relationships
- Features for classification
- ...



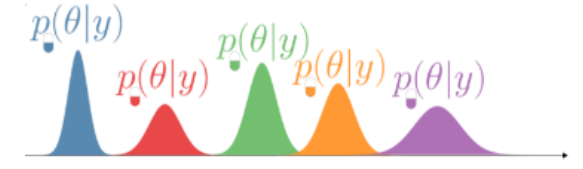
- Auditory MMN
- 10 black hooded rats
- Epidural recordings (bilaterally) from A1 and PAF



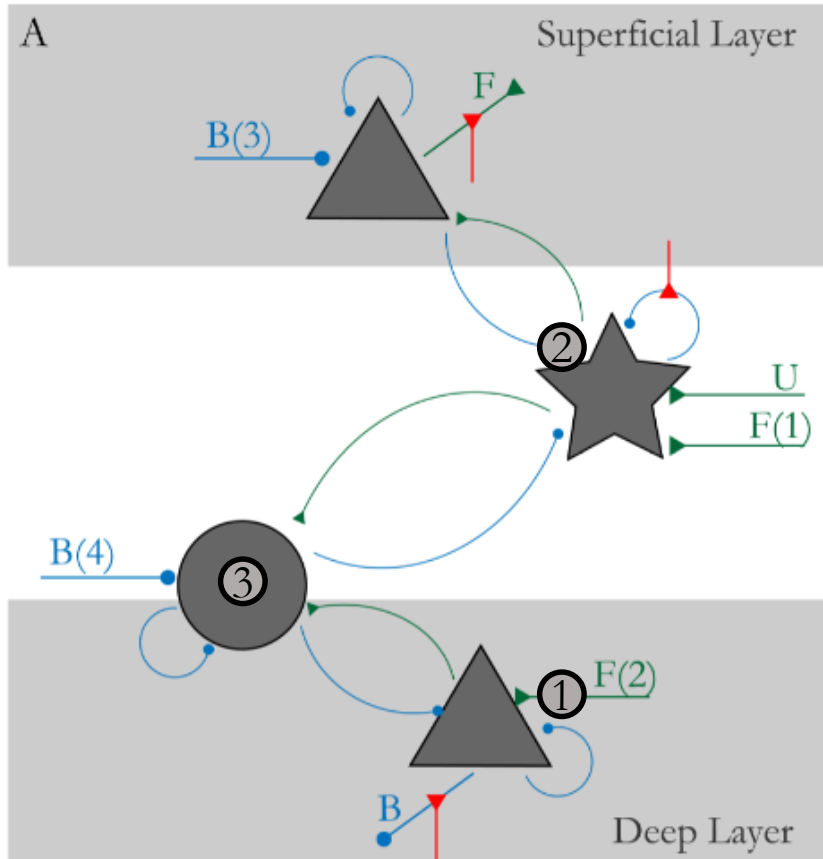
- Five levels of muscarinic manipulations
- Can we detect drug effects in the ERPs?



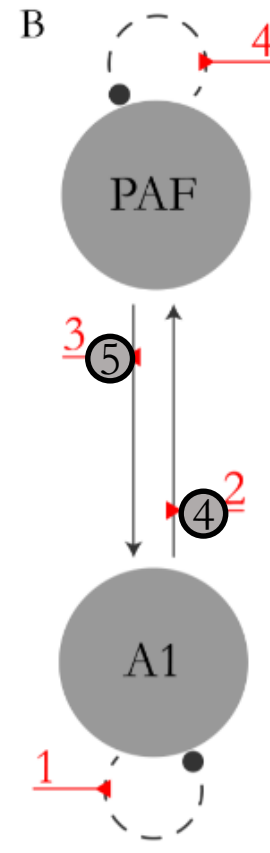
DCM for ERPs
1000 datapoints
reduced to ~20-30
Parameters



- Are there model parameters showing a drug effect?
- What is the dose response relationship?
- Can we predict the drug label of a left out rat in a classification?



Convolution based DCM with CMC



Single hemisphere DCM
with full factorial
modulation structure

○ Linear Effect of drug:

1. Forward connection (decrease)
2. Kernel Gain (increase)
3. Kernel decay (decrease)
4. Forward Modulation (increase)
5. Backward Modulation (increase)

Prediction of left out dataset:

We could significantly* predict the drug label of all classification involving the muscarinic agonist with up to 92.9% (Chance 50%).

* Significance was assessed with a permutation test



1924

1977

1991

1995

2003

2006



Chapter 4

What happened next ...

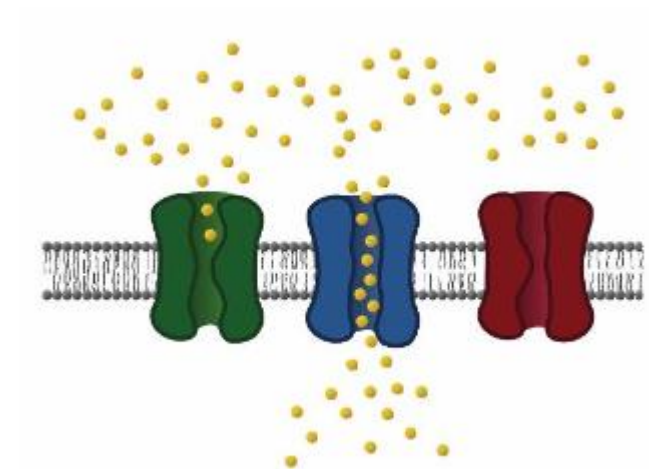
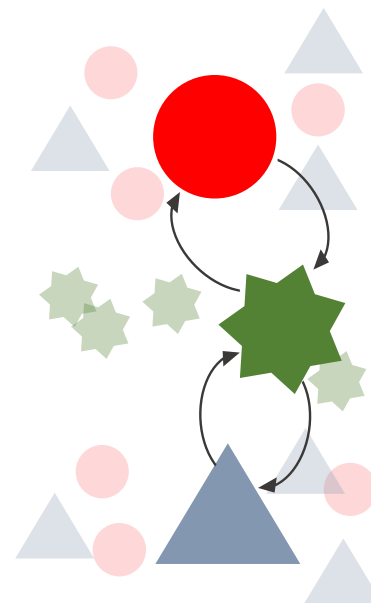
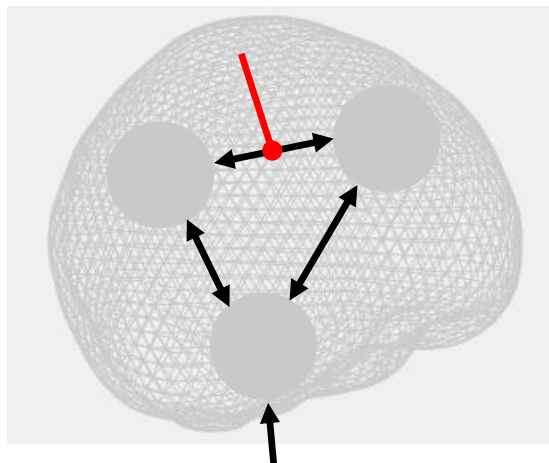
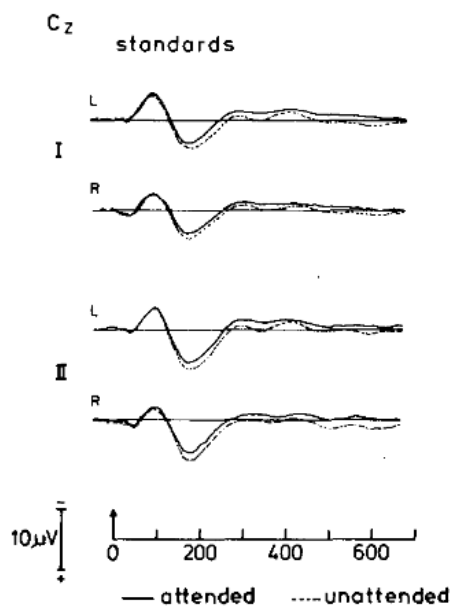


data

macroscale

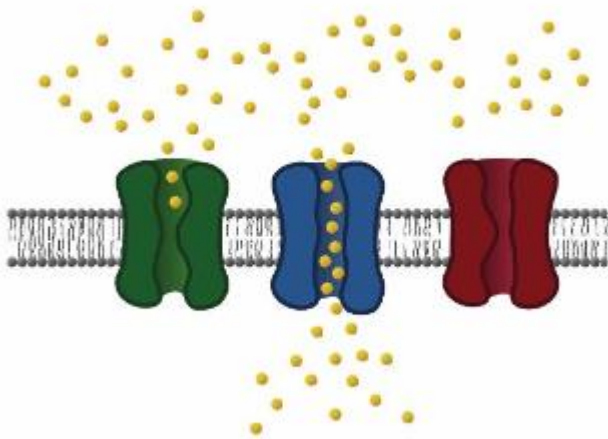
mesoscale

microscale





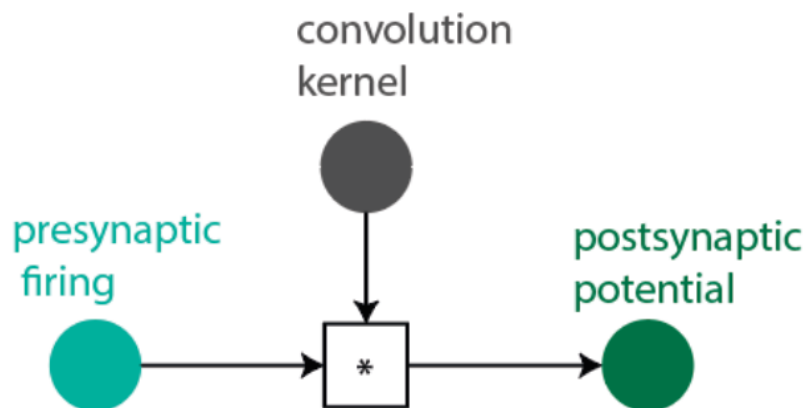
microscale



Transformation of
presynaptic firing
into post synaptic
potential.



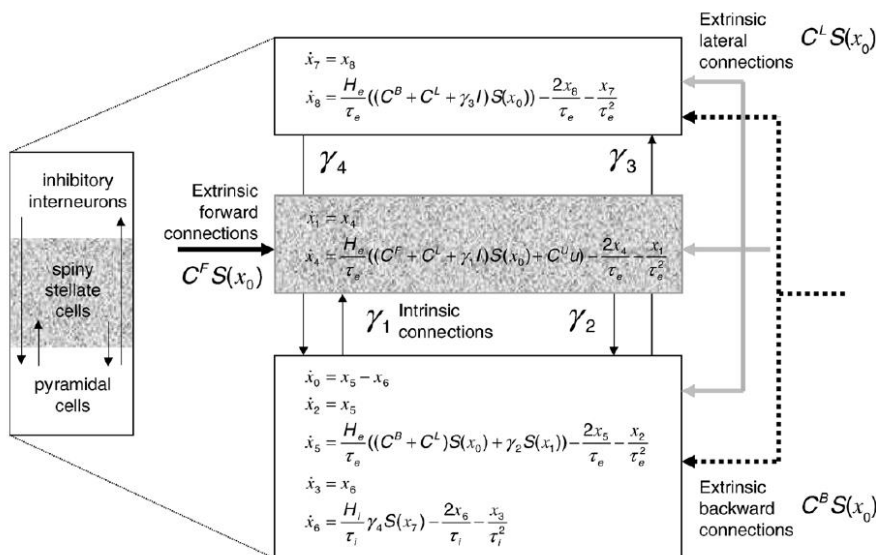
microscale



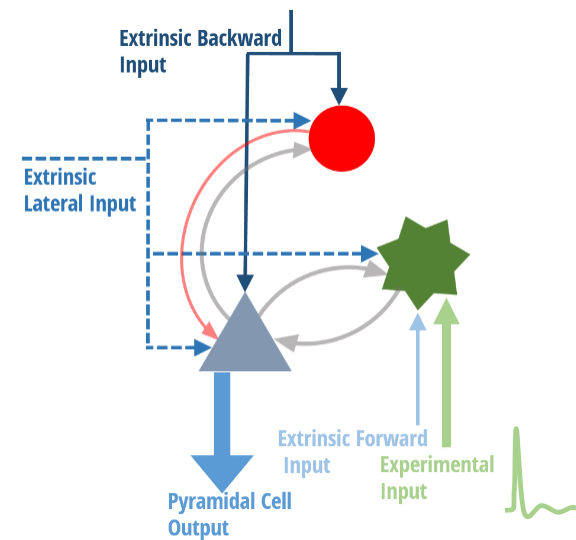
Current state of the population. How much firing arrives.

$$\frac{dx}{dt} = f(x, A, H, C, \sigma, f_s(\theta_{kernel}))$$

What the cell population is connected to. The size of the kernel.



Single source model



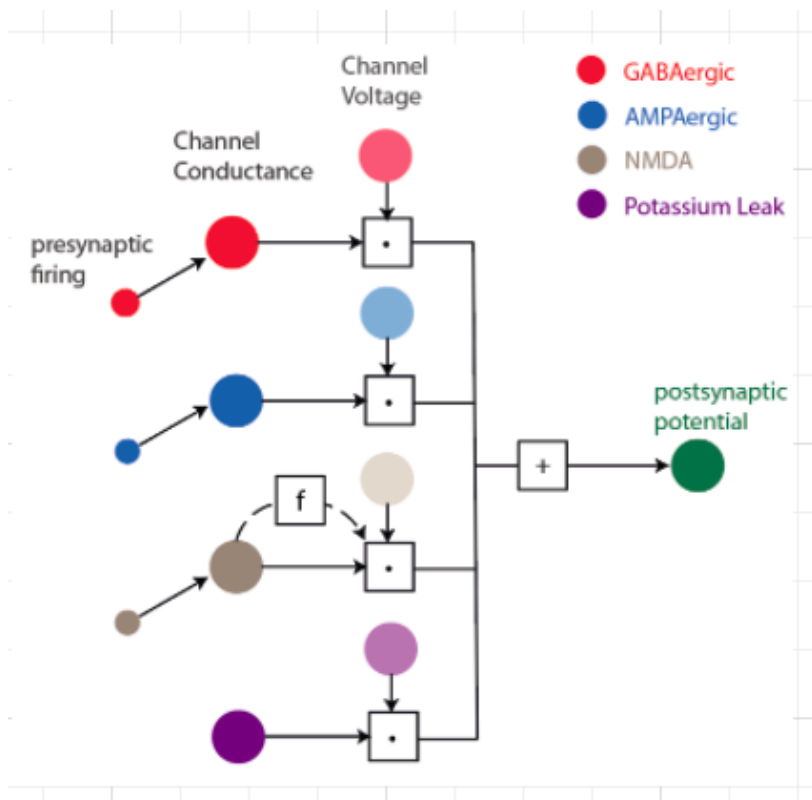
Presynaptic Firing $\sigma(t)$

Postsynaptic Potential $v(t)$





microscale

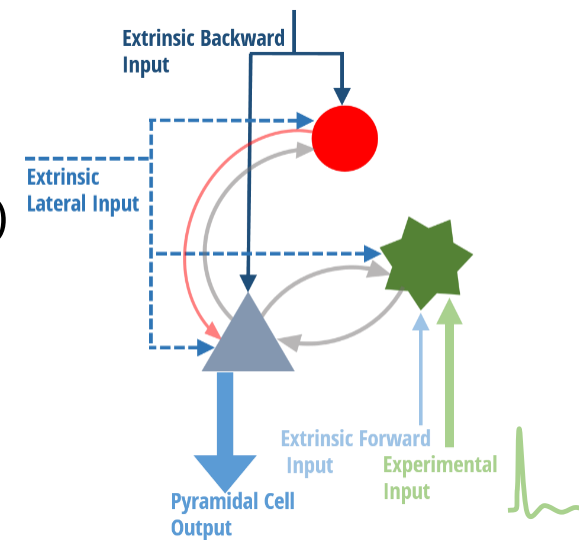


Current state of the population. How much firing arrives.

$$\frac{dx}{dt} = f(x, A, H, C, \sigma, f_s(\theta_{conductance}))$$

Connection strengths

Channel resistance



S1

$$C\dot{V}^{(2)} = g_L(V_L - V^{(2)}) + g_{AMPA}^{(2)}(V_E - V^{(2)}) + g_{NMDA}^{(2)}f_{Mg}(V^{(2)})(V_E - V^{(2)}) + \Gamma_V$$

$$\dot{g}_{AMPA}^{(2)} = \kappa_{AMPA}(\gamma_{2,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)}) - g_{AMPA}^{(2)}) + \Gamma_{AMPA}$$

$$\dot{g}_{NMDA}^{(2)} = \kappa_{NMDA}(\gamma_{2,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)}) - g_{NMDA}^{(2)}) + \Gamma_{NMDA}$$

Extrinsic Cortical Input (μ)

$$C\dot{V}^{(1)} = g_L(V_L - V^{(1)}) + g_{AMPA}^{(1)}(V_E - V^{(1)}) + g_{GABAa}^{(1)}(V_I - V^{(1)}) + u + \Gamma_V$$

$$\dot{g}_{AMPA}^{(1)} = \kappa_{AMPA}(\gamma_{1,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)}) - g_{AMPA}^{(1)}) + \Gamma_{AMPA}$$

$$\dot{g}_{GABAa}^{(1)} = \kappa_{GABAa}(\gamma_{1,2}\sigma(\mu_V^{(2)} - V_R, \Sigma^{(2)}) - g_{GABAa}^{(1)}) + \Gamma_{GABAa}$$

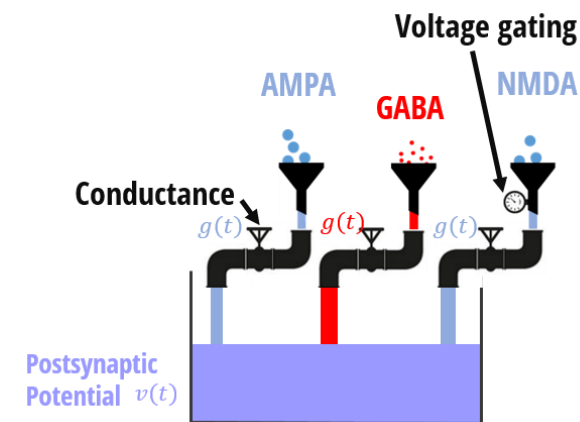
Extrinsic Cortical Input (μ)

$$C\dot{V}^{(3)} = g_L(V_L - V^{(3)}) + g_{AMPA}^{(3)}(V_E - V^{(3)}) + g_{NMDA}^{(3)}f_{Mg}(V^{(3)})(V_E - V^{(3)}) + g_{GABAa}^{(3)}(V_I - V^{(3)}) + \Gamma_V$$

$$\dot{g}_{AMPA}^{(3)} = \kappa_{AMPA}([\gamma_{3,1}\sigma(\mu_V^{(1)} - V_R, \Sigma^{(1)}) + \gamma_{3,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)})] - g_{AMPA}^{(3)}) + \Gamma_{AMPA}$$

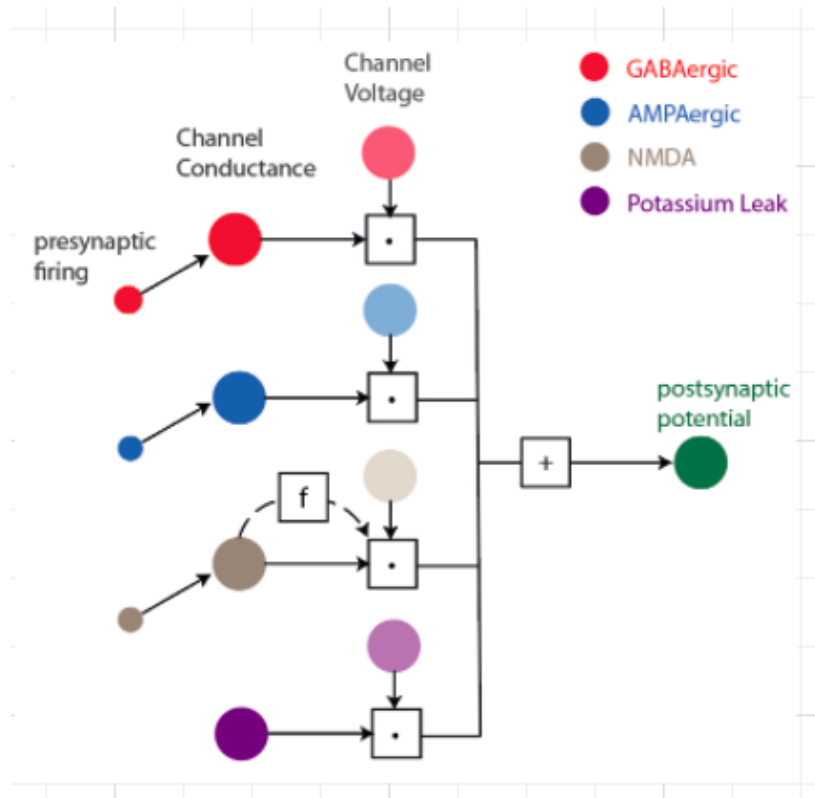
$$\dot{g}_{NMDA}^{(3)} = \kappa_{NMDA}([\gamma_{3,1}\sigma(\mu_V^{(1)} - V_R, \Sigma^{(1)}) + \gamma_{3,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)})] - g_{NMDA}^{(3)}) + \Gamma_{NMDA}$$

$$\dot{g}_{GABAa}^{(3)} = \kappa_{GABAa}(\gamma_{3,2}\sigma(\mu_V^{(2)} - V_R, \Sigma^{(2)}) - g_{GABAa}^{(3)}) + \Gamma_{GABAa}$$





microscale

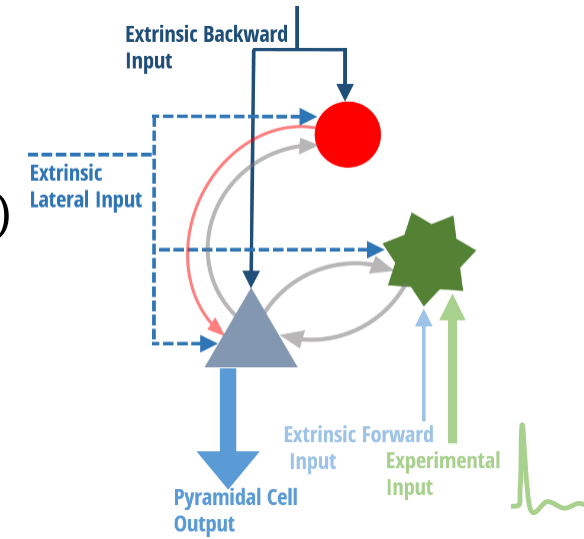


Current state of the population. How much firing arrives.

$$\frac{dx}{dt} = f(x, A, H, C, \sigma, f_s(\theta_{conductance}))$$

Connection strengths

Channel resistance



S1

$$C\dot{V}^{(2)} = g_L(V_L - V^{(2)}) + g_{AMPA}^{(2)}(V_E - V^{(2)}) + g_{NMDA}^{(2)}f_{Mg}(V^{(2)})(V_E - V^{(2)}) + \Gamma_V$$

$$\dot{g}_{AMPA}^{(2)} = \kappa_{AMPA}(\gamma_{2,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)}) - g_{AMPA}^{(2)}) + \Gamma_{AMPA}$$

$$\dot{g}_{NMDA}^{(2)} = \kappa_{NMDA}(\gamma_{2,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)}) - g_{NMDA}^{(2)}) + \Gamma_{NMDA}$$

Extrinsic Cortical Input (μ)

$$C\dot{V}^{(1)} = g_L(V_L - V^{(1)}) + g_{AMPA}^{(1)}(V_E - V^{(1)}) + g_{GABAa}^{(1)}(V_I - V^{(1)}) + u + \Gamma_V$$

$$\dot{g}_{AMPA}^{(1)} = \kappa_{AMPA}(\gamma_{1,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)}) - g_{AMPA}^{(1)}) + \Gamma_{AMPA}$$

$$\dot{g}_{GABAa}^{(1)} = \kappa_{GABAa}(\gamma_{1,2}\sigma(\mu_V^{(2)} - V_R, \Sigma^{(2)}) - g_{GABAa}^{(1)}) + \Gamma_{GABAa}$$

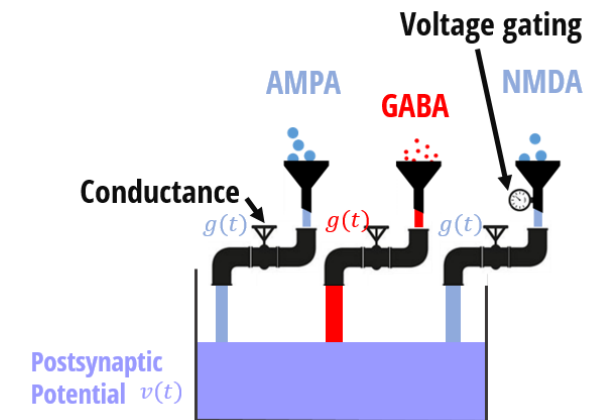
Extrinsic Cortical Input (μ)

$$C\dot{V}^{(3)} = g_L(V_L - V^{(3)}) + g_{AMPA}^{(3)}(V_E - V^{(3)}) + g_{NMDA}^{(3)}f_{Mg}(V^{(3)})(V_E - V^{(3)}) + g_{GABAa}^{(3)}(V_I - V^{(3)}) + \Gamma_V$$

$$\dot{g}_{AMPA}^{(3)} = \kappa_{AMPA}([\gamma_{3,1}\sigma(\mu_V^{(1)} - V_R, \Sigma^{(1)}) + \gamma_{3,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)})] - g_{AMPA}^{(3)}) + \Gamma_{AMPA}$$

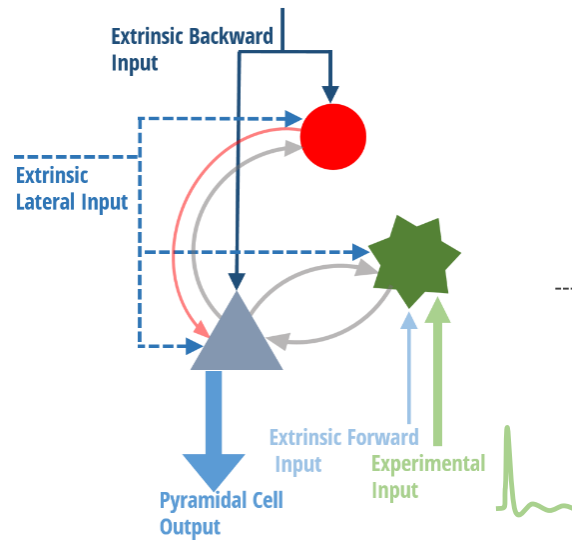
$$\dot{g}_{NMDA}^{(3)} = \kappa_{NMDA}([\gamma_{3,1}\sigma(\mu_V^{(1)} - V_R, \Sigma^{(1)}) + \gamma_{3,3}\sigma(\mu_V^{(3)} - V_R, \Sigma^{(3)})] - g_{NMDA}^{(3)}) + \Gamma_{NMDA}$$

$$\dot{g}_{GABAa}^{(3)} = \kappa_{GABAa}(\gamma_{3,2}\sigma(\mu_V^{(2)} - V_R, \Sigma^{(2)}) - g_{GABAa}^{(3)}) + \Gamma_{GABAa}$$





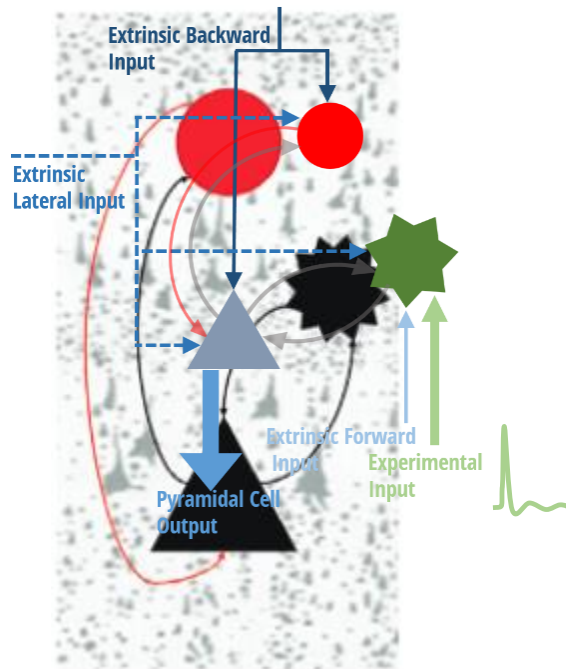
mesoscale



Structure of the
cortical column



mesoscale

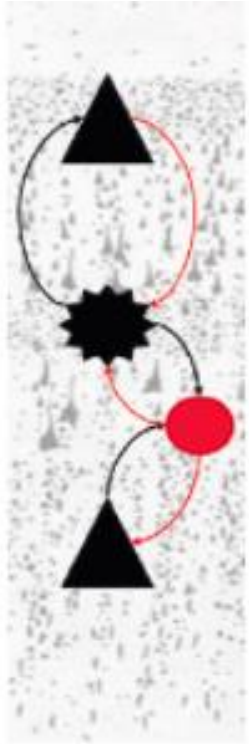


ERP model:

- Inhibitory Population
- Stellate Population
- Pyramidal Population



mesoscale



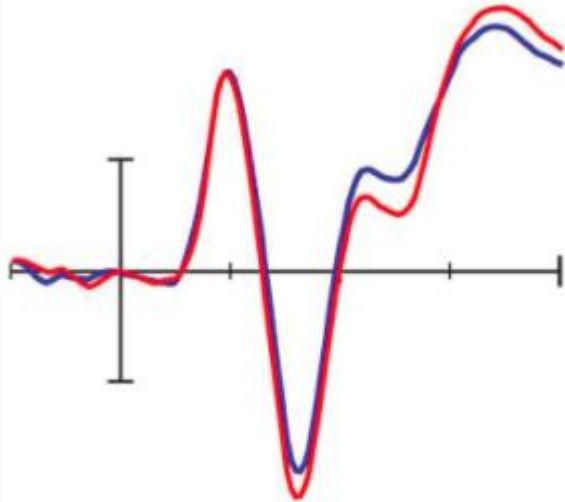
CMC (Canonical Microcircuit Model)

- Inhibitory Population
- Stellate Population
- 2 x Pyramidal Population:
 - Predictive Coding



mech scale

ERP (Evoked Responses)



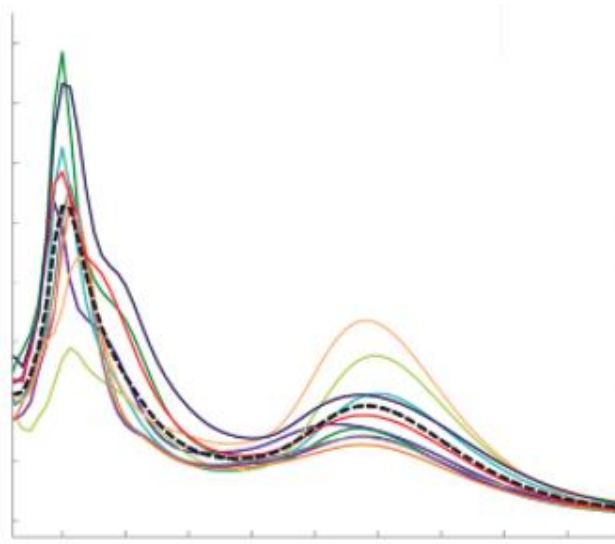
CMC (Canonical Microcircuit Model)

- Inhibitory Population
- Stellate Population
- 2 x Pyramidal Population:
 - Predictive Coding



data

CSD Cross spectral densities

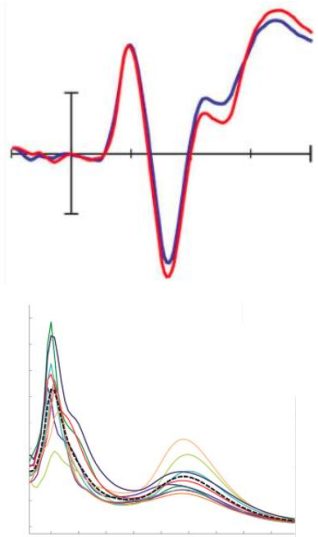


Inverse Problem: Inference

$$p(\theta, \Sigma | y)$$

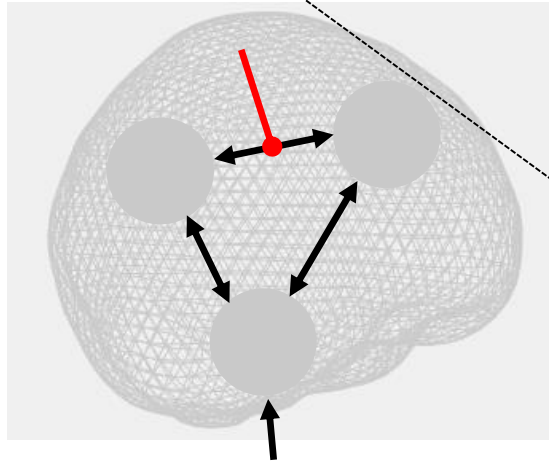
One can only infer on mechanisms,
that have actually been modeled.

data



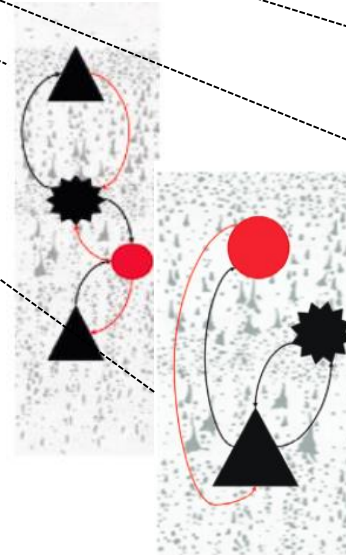
Data features

macroscale



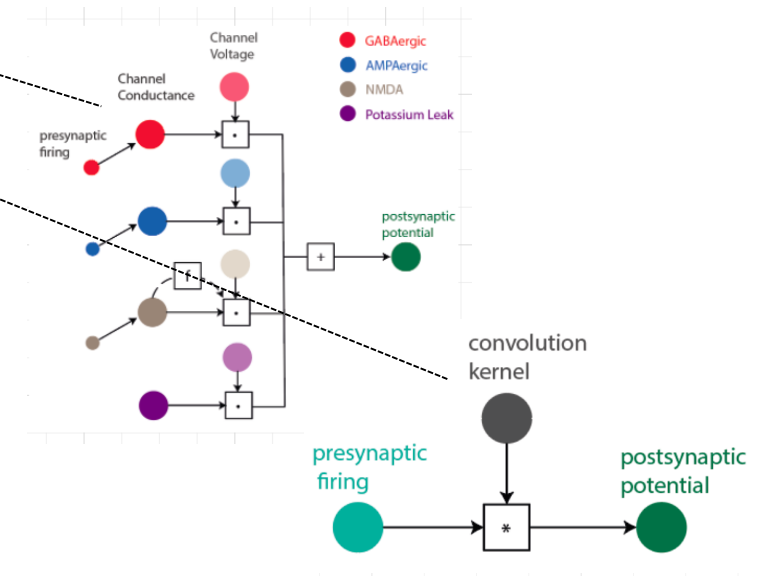
Network and
modulation structure

mesoscale



Layered Structure of
the cortical column

microscale



Mechanisms governing
generation of average post-
synaptic potentials:

MANY THANKS CAO TRI DO FOR
SOME OF THE SLIDES!

Citations

1. <http://the-brain-box.blogspot.com/2015/05/what-does-meg-measure.html>
2. <https://tomofumi.info/and-meet/neurons-axons-and-dendrites-meet.php>
3. Buzsaki et al., 2012, *Nature Reviews*
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5. Adrian, Matthews, 1934, *Brain*
6. Näätänen et al., 1978, *Acta psychologica*
7. https://media.nature.com/full/nature-assets/nature/journal/v468/n7321/images_article/nature09569-f1.2.jpg
8. <https://images.app.goo.gl/S5TwDCXCFk3QL7th7>
9. Häusser, Cuntz, 2016, *Nature*