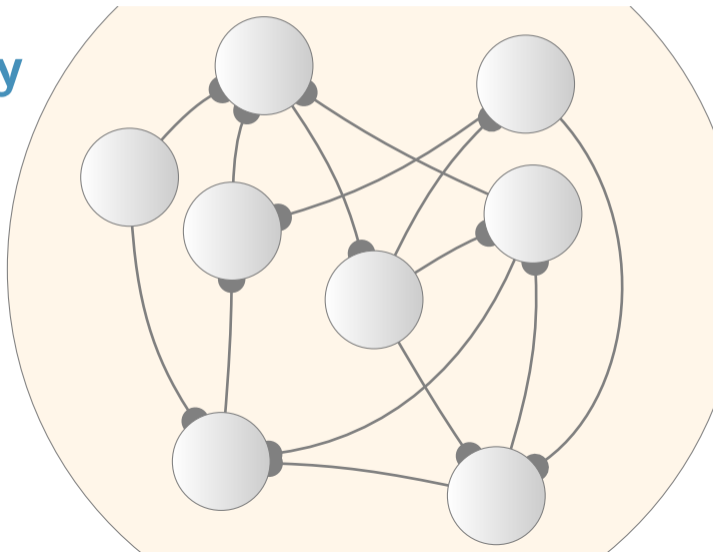


**Failing to prepare is preparing to fail:**

**A network theory  
of movement  
preparation and  
execution**

Guillaume Hennequin  
University of Cambridge, UK



# Failing to prepare is preparing to fail:

## A network theory of movement preparation and execution

Guillaume Hennequin  
University of Cambridge, UK



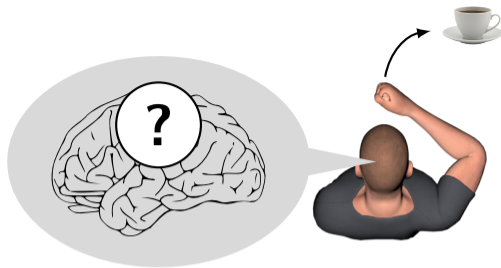
# Failing to prepare is preparing to fail:

## A network theory of movement preparation and execution

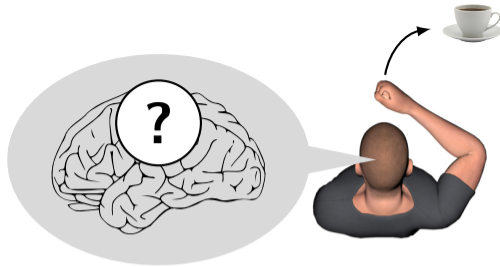
Guillaume Hennequin  
University of Cambridge, UK



**How do brains  
control  
movement?**



# How do brains control movement?

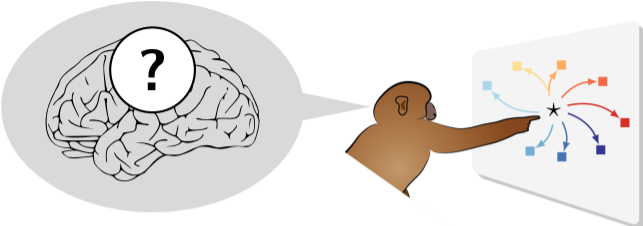


computational  
principles

phenomenology of  
neural activity

circuit  
mechanisms

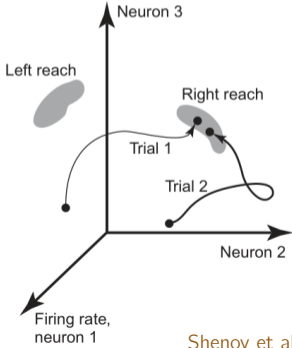
# How do brains control movement?



computational principles

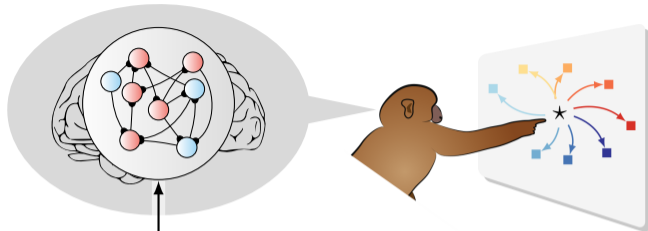
phenomenology of neural activity

circuit mechanisms



# How do brains control movement?

Illustration: Y.T. Kimura

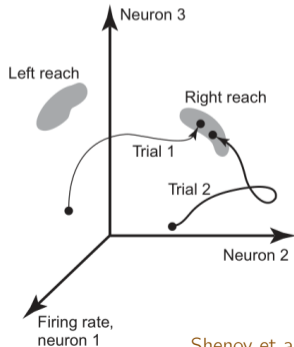


computational principles

phenomenology of neural activity

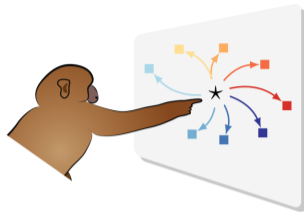
circuit mechanisms

**network-level theories**



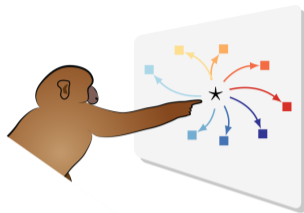
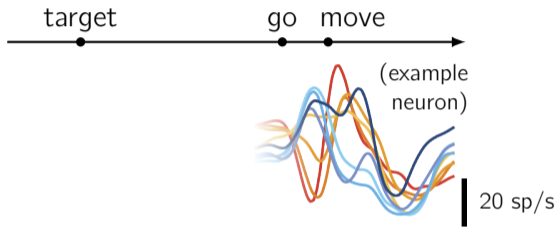
Shenoy et al. (2013)

## delayed reaching task

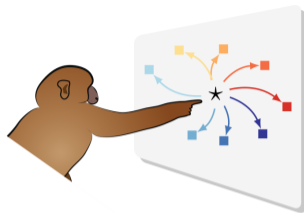
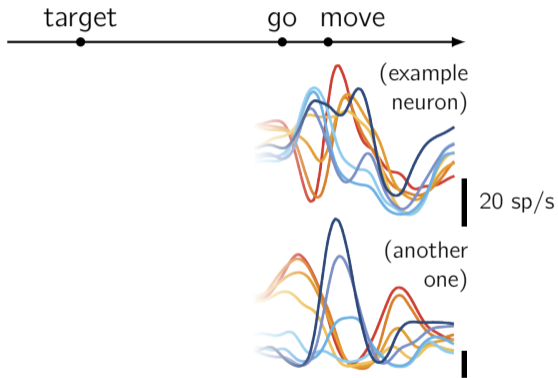




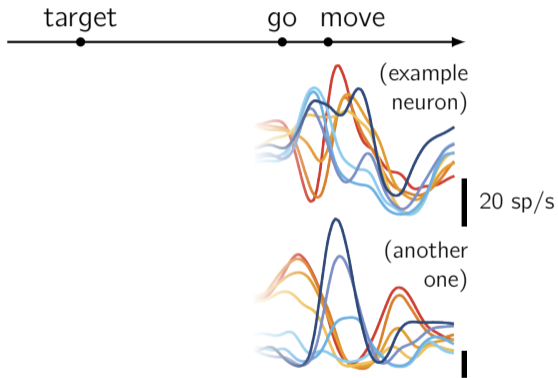
## delayed reaching task



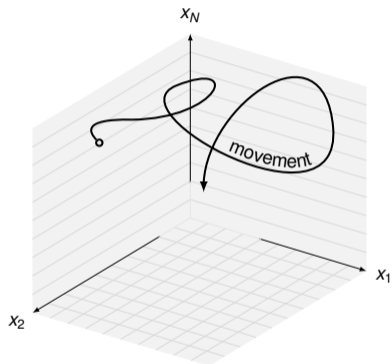
## delayed reaching task



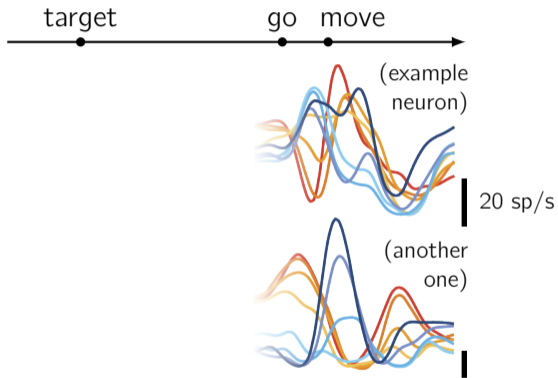
## delayed reaching task



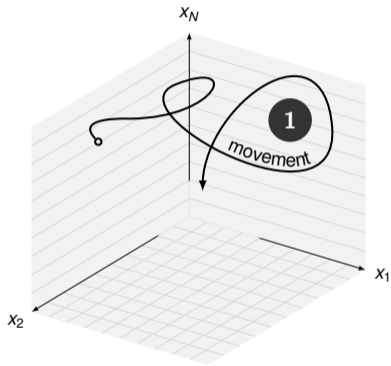
$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x})$$



## delayed reaching task



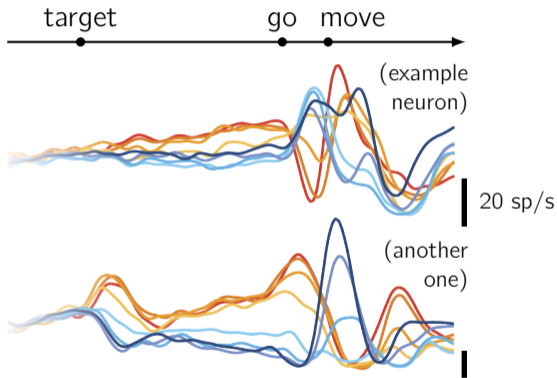
$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x})$$



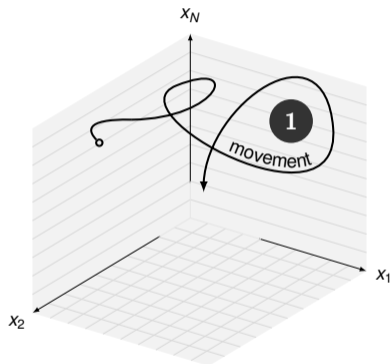
1

network principles underlying:  
movement-related activity?

## delayed reaching task

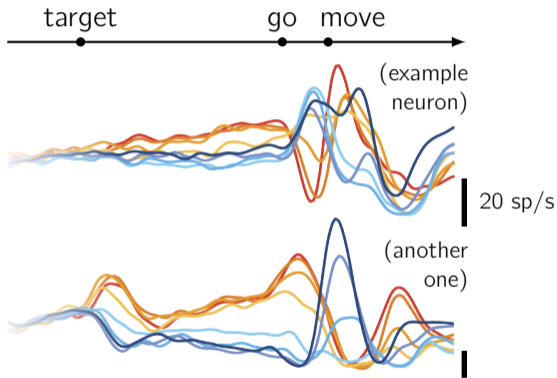


$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x})$$

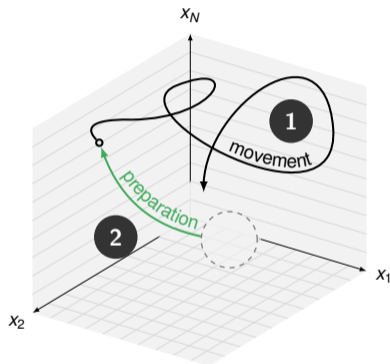


network principles underlying:  
1 movement-related activity?

## delayed reaching task



$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{u})$$



network principles underlying:

1

movement-related activity?

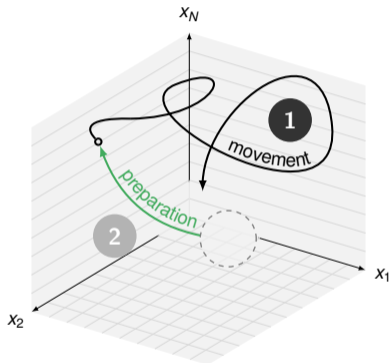
2

preparatory activity?

# 1

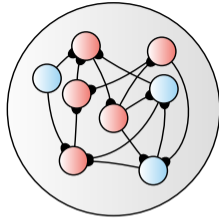
network dynamics  
for movement generation

- ▶ off-the-shelf models of cortical dynamics struggle to produce M1-like activity
- ▶ new model class with **detailed E/I balance** generate M1-like activity transients
- ▶ **simple learning rules** can construct such networks



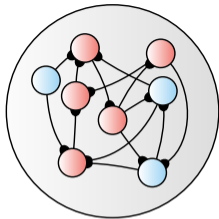
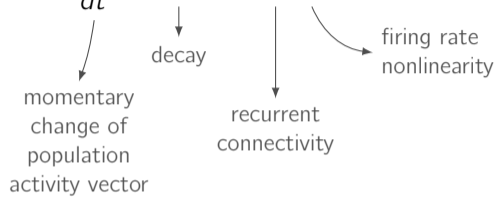
Hennequin et al., *Neuron* (2014)  
Li et al., *in prep*

$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + \text{input}$$



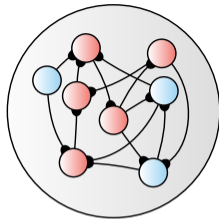
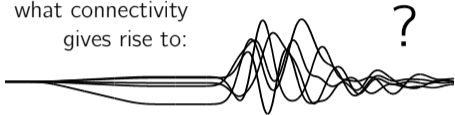


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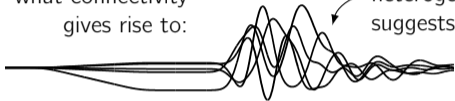
$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + \text{input}$$

what connectivity  
gives rise to:

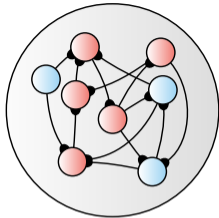


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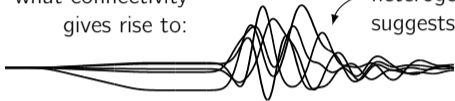


complexity /  
heterogeneity  
suggests disorder

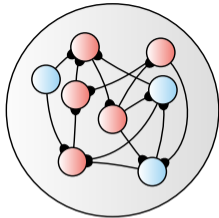


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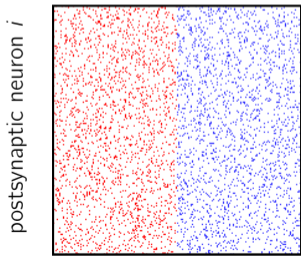


complexity /  
heterogeneity  
suggests disorder



Rajan and Abbott (2006)

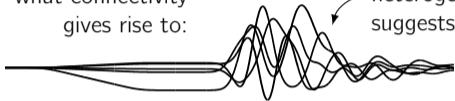
connectivity matrix  $\mathbf{W}$



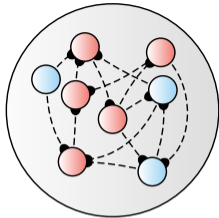
presynaptic neuron  $j$

$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + \text{input}$$

what connectivity  
gives rise to:

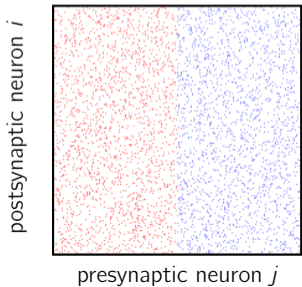


complexity /  
heterogeneity  
suggests disorder



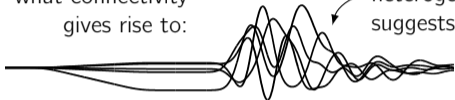
Rajan and Abbott (2006)

connectivity matrix  $\mathbf{W}$

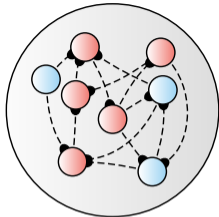


$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + \text{input}$$

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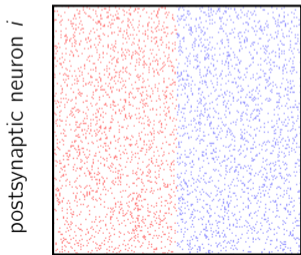


complexity /  
heterogeneity  
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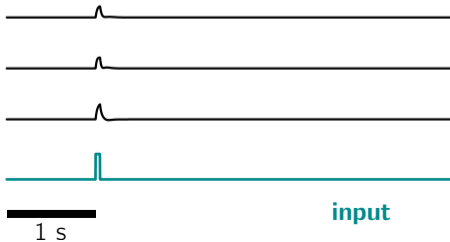


Rajan and Abbott (2006)

connectivity matrix  $\mathbf{W}$

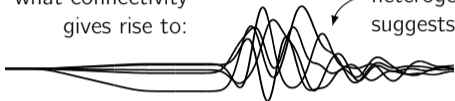


weak connectivity: stable but simple dynamics

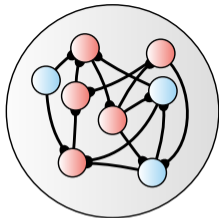


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what connectivity  
gives rise to:

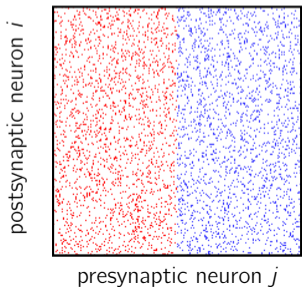


complexity /  
heterogeneity  
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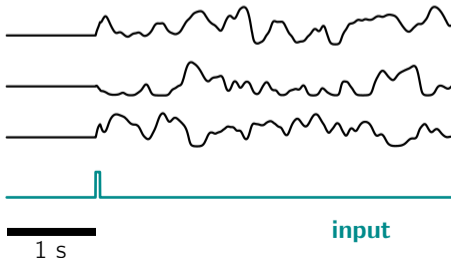


Rajan and Abbott (2006)  
Sompolinsky et al. (1988)  
Kadmon and Sompolinsky (2015)  
Mastrogiuseppe and Ostojic (2017)

connectivity matrix  $\mathbf{W}$

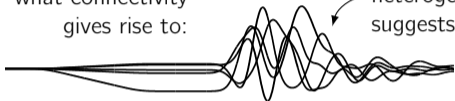


strong connectivity: complex but chaotic dynamics

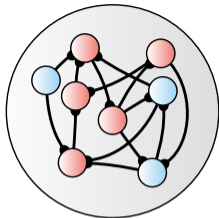


$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + \text{input}$$

what connectivity  
gives rise to:

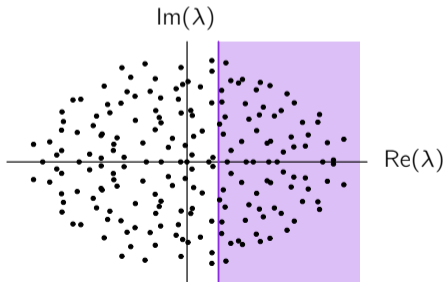
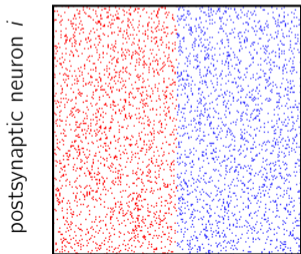


complexity /  
heterogeneity  
suggests disorder



- Rajan and Abbott (2006)
- Sompolinsky et al. (1988)
- Kadmon and Sompolinsky (2015)
- Mastrogiuseppe and Ostojic (2017)
- Ahmadian et al. (2015)
- Aljadeff et al. (2015)

connectivity matrix  $\mathbf{W}$



postsynaptic neuron  $i$

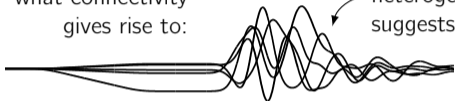
presynaptic neuron  $j$

stable unstable

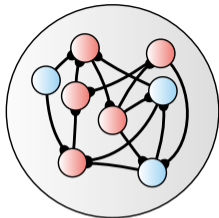


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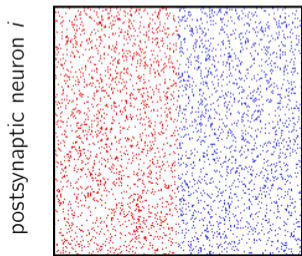


complexity /  
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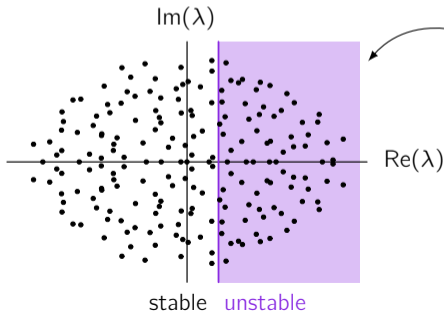


Rajan and Abbott (2006)  
Sompolinsky et al. (1988)  
Kadmon and Sompolinsky (2015)  
Mastrogiuseppe and Ostojic (2017)  
Ahmadian et al. (2015)  
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Vanbiervliet et al. (2009)  
Hennequin et al. (2014)

connectivity matrix  $\mathbf{W}$



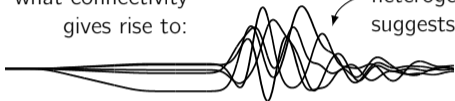
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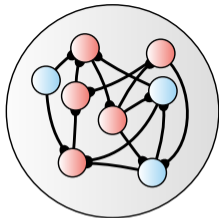
minimisation of the  
“smoothed spectral abscissa”  
w.r.t. inhibitory weights

$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + \text{input}$$

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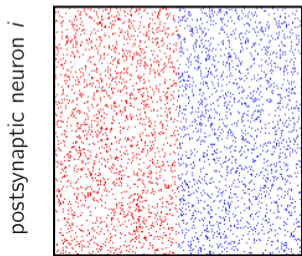


complexity /  
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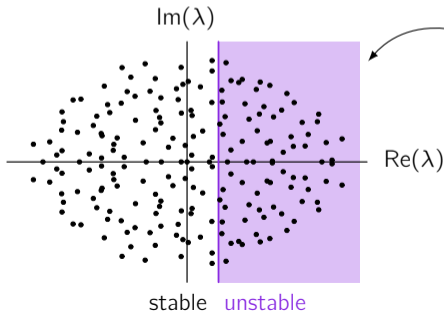


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connectivity matrix  $\mathbf{W}$



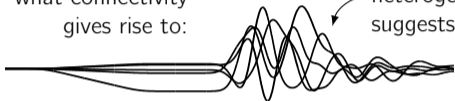
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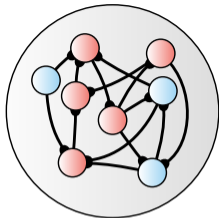
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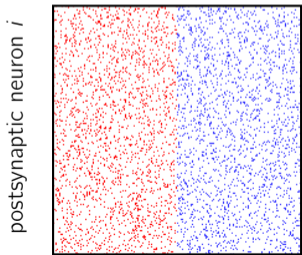


complexity /  
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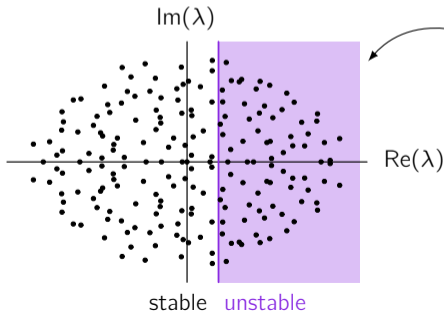


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connectivity matrix  $\mathbf{W}$



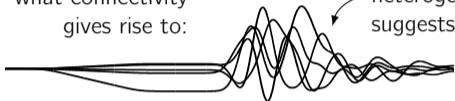
presynaptic neuron  $j$



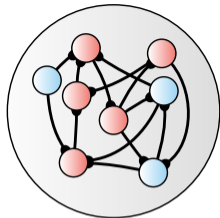
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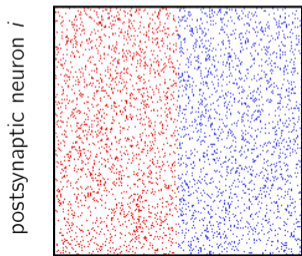


complexity /  
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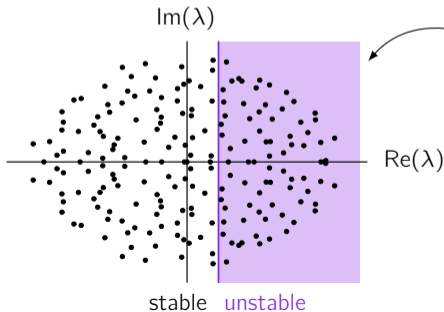


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Sompolinsky et al. (1988)  
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connectivity matrix  $\mathbf{W}$



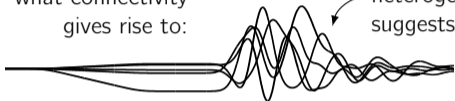
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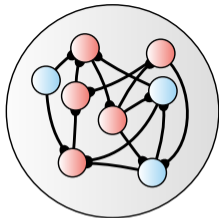
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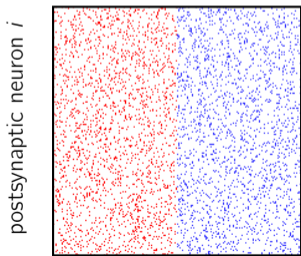


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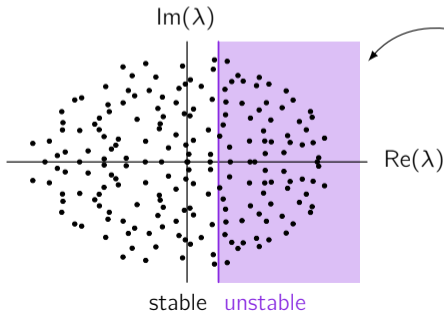


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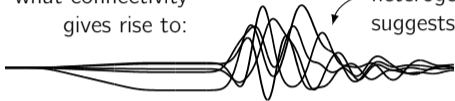
presynaptic neuron  $j$



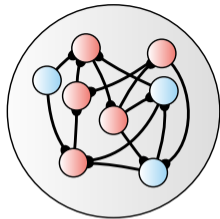
minimisation of the  
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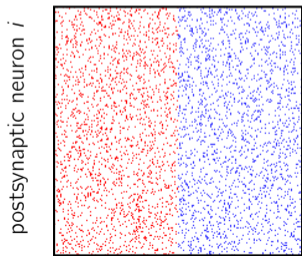


complexity /  
heterogeneity  
suggests disorder

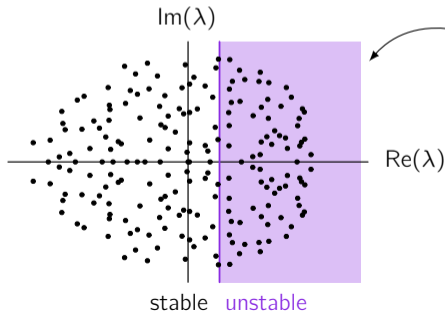


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connectivity matrix  $\mathbf{W}$



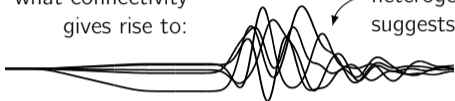
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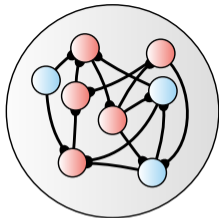
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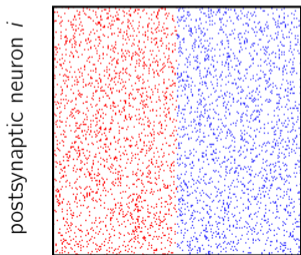


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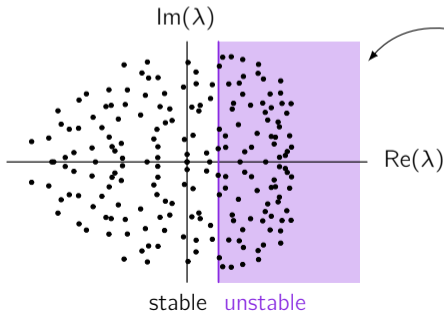


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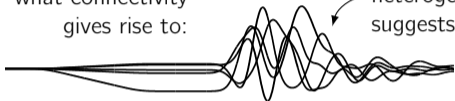
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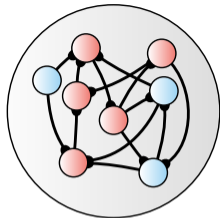
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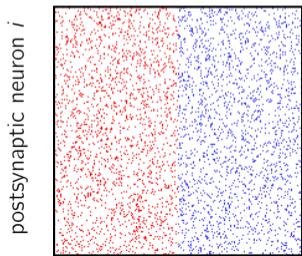


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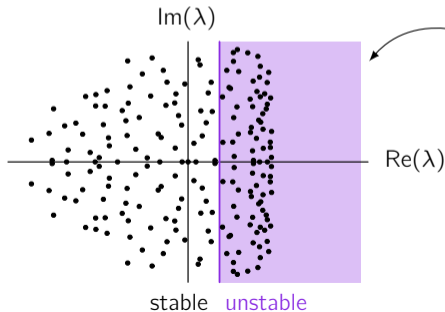


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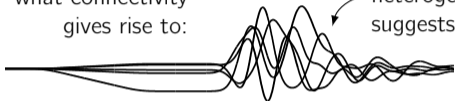


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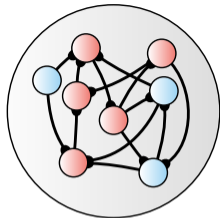


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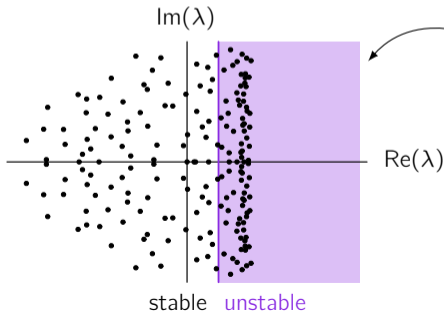
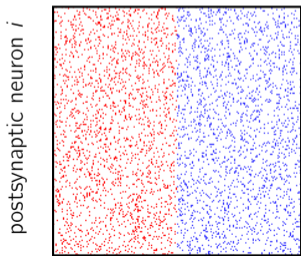


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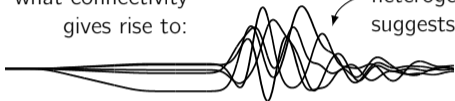
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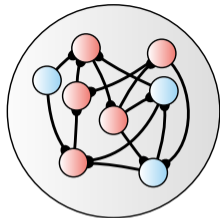
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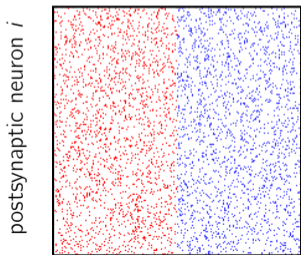


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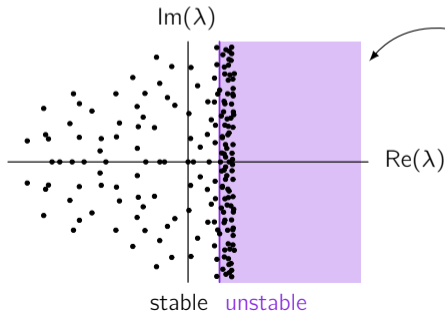


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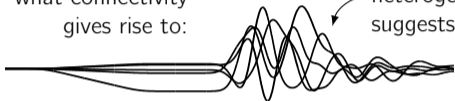
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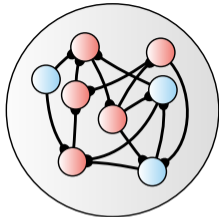
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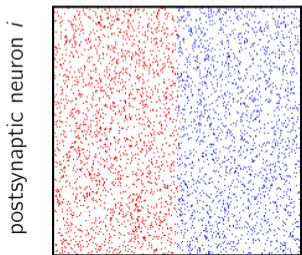


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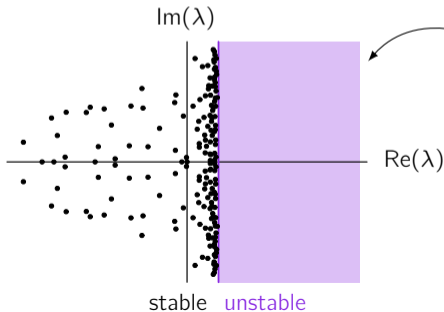


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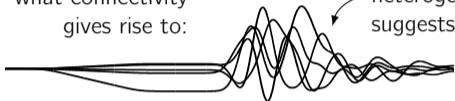
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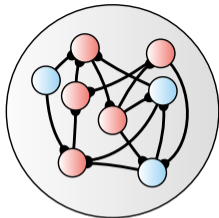
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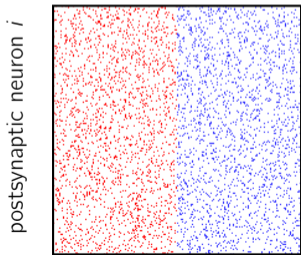


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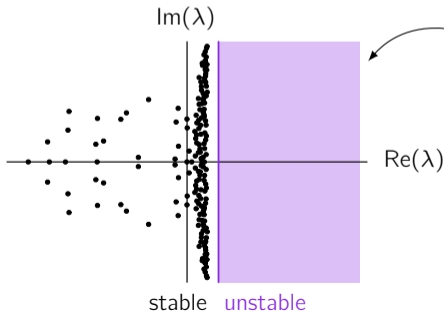


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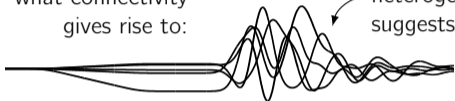
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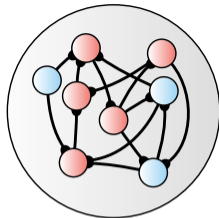
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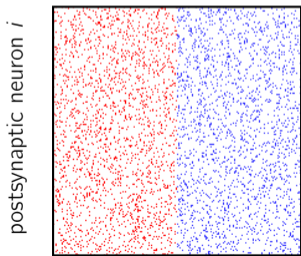


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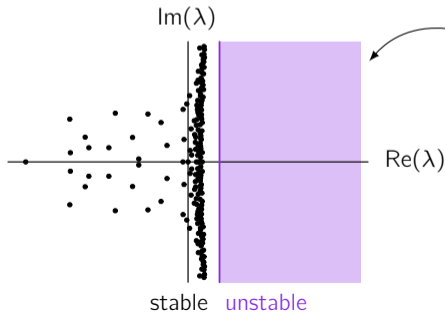


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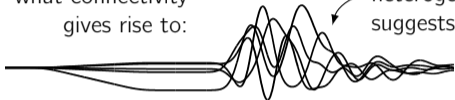
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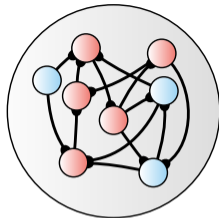
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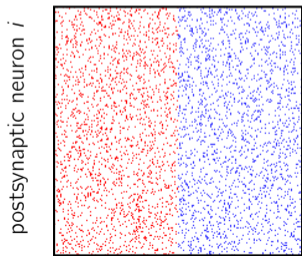


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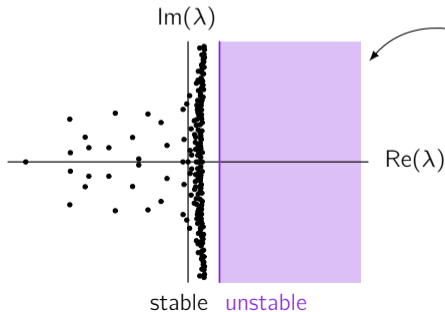


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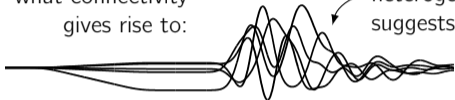
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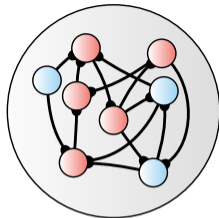
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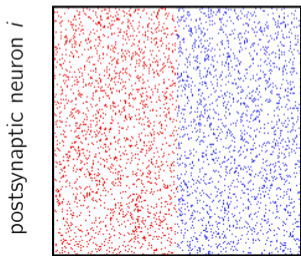


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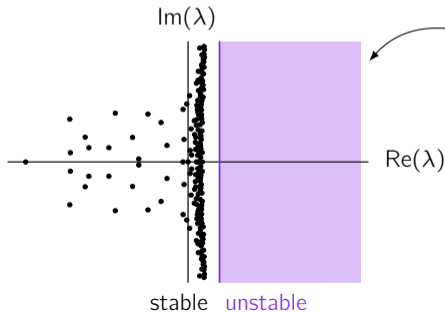


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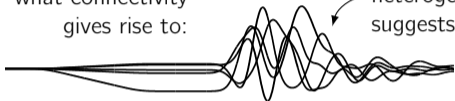
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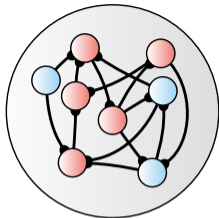
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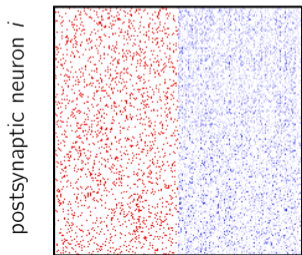


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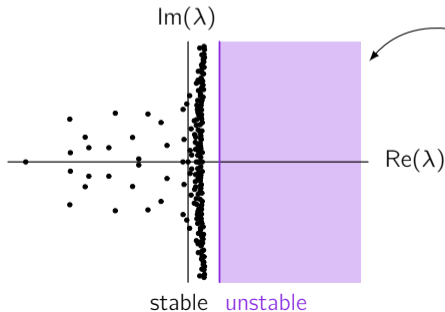


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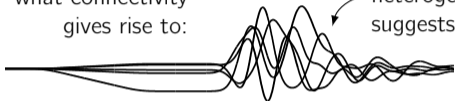


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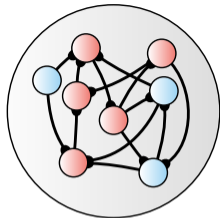


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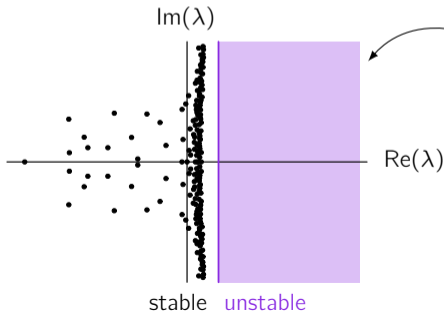
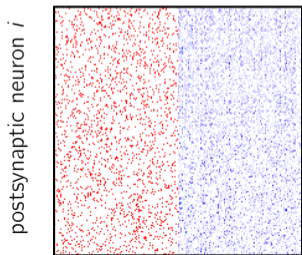


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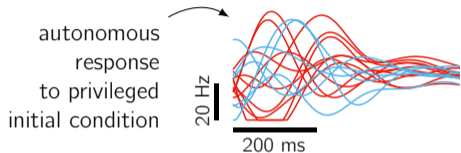
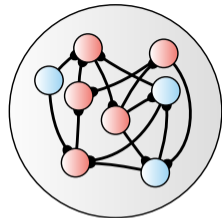


minimisation of the  
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⇒ precisely balanced  
‘nonnormal’ network with  
rich transient behaviour

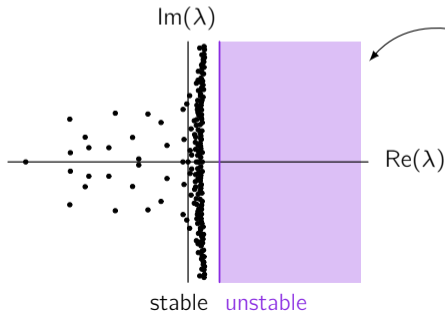
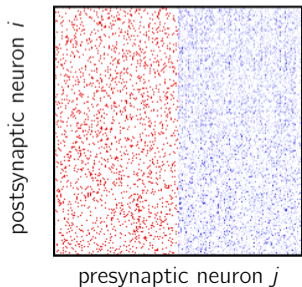
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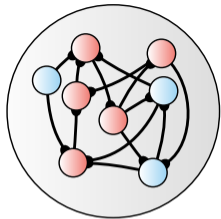
connectivity matrix  $\mathbf{W}$

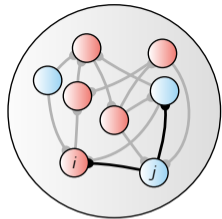


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Hebbian ISP

$$\Delta|W_{ij}| \propto \phi(x_j)(x_i - \alpha)$$



Xizi Li

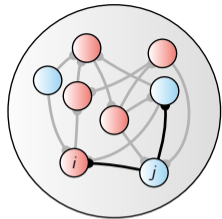
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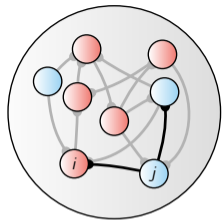
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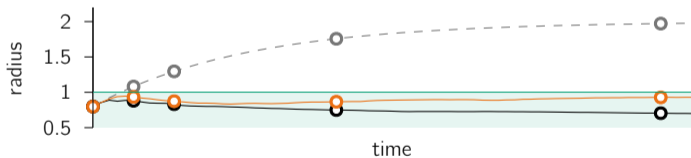
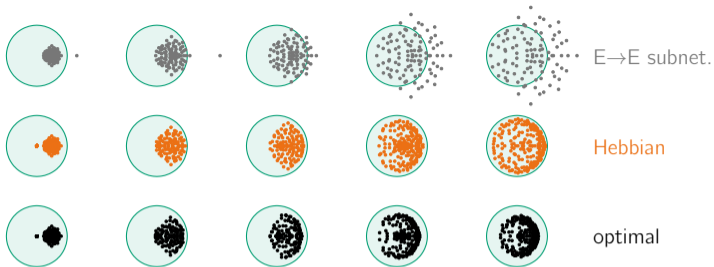
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Xizi Li

Vogels\*, Sprekeler\*, et al. (2011)

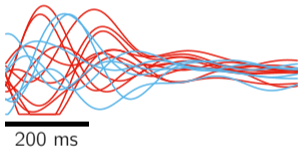
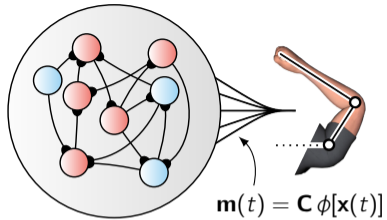
Luz and Shamir (2012)

Vogels et al. (2013)

Hennequin et al. (2017)

Li et al. (in prep)

Hebbian ISP enables unsupervised construction of high-dimensional inhibition-stabilised networks

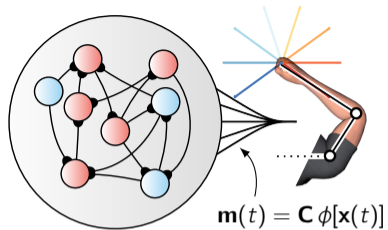


Li & Todorov (2004)

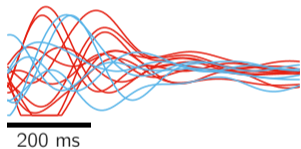
Kao et al., *Neuron* (2021)



Calvin Kao



fix the ISN; optimise readout and initial conditions

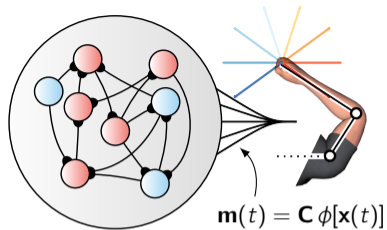


Li & Todorov (2004)  
Kao et al., *Neuron* (2021)

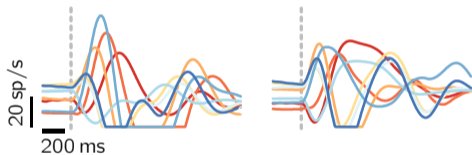


Calvin Kao





fix the ISN; optimise readout and initial conditions

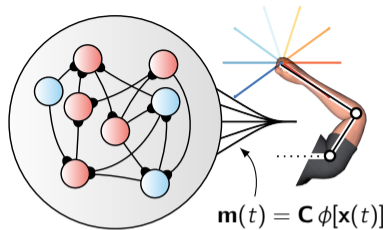


Li & Todorov (2004)

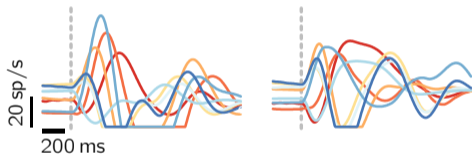
Kao et al., *Neuron* (2021)



Calvin Kao



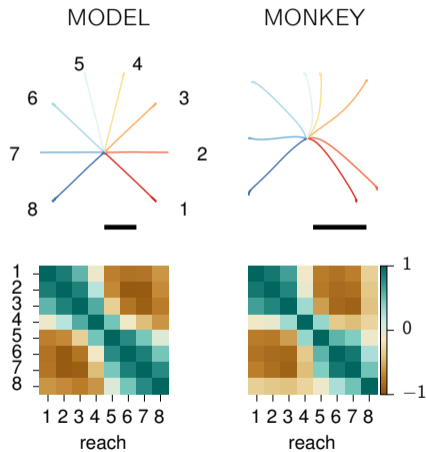
fix the ISN; optimise readout and initial conditions



Li & Todorov (2004)  
Kao et al., *Neuron* (2021)

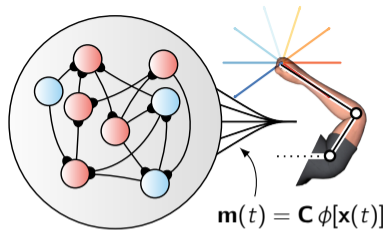


Calvin Kao

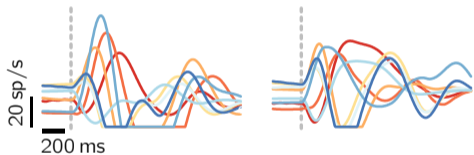


data from  
Churchland,  
Kaufman,  
et al.

similar structure in initial conditions



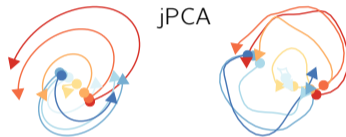
fix the ISN; optimise readout and initial conditions



Li & Todorov (2004)  
Kao et al., *Neuron* (2021)

MODEL

MONKEY



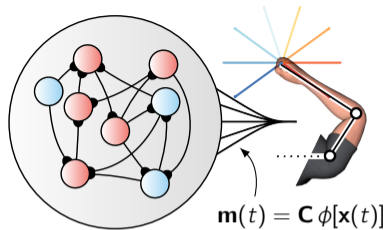
data from  
Churchland,  
Kaufman,  
et al.

activity rotates  
at the population level

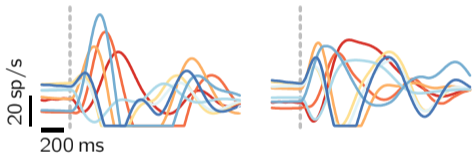
Churchland\*, Cunningham\*, et al. (2012)



Calvin Kao



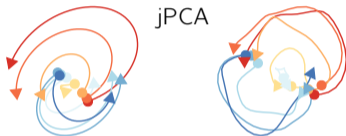
fix the ISN; optimise readout and initial conditions



MODEL

MONKEY

jPCA



data from  
Churchland,  
Kaufman,  
et al.

activity rotates  
at the population level

Li & Todorov (2004)  
Kao et al., *Neuron* (2021)

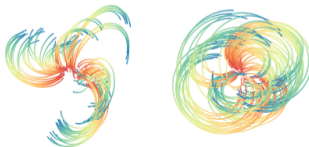
Churchland\*, Cunningham\*, et al. (2012)



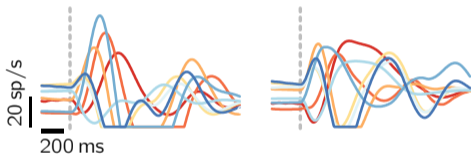
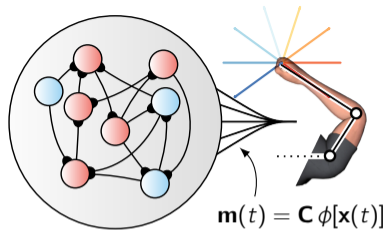
Calvin Kao



Virginia Rutten



see also:  
Rutten et al.,  
*Neurips* (2020)

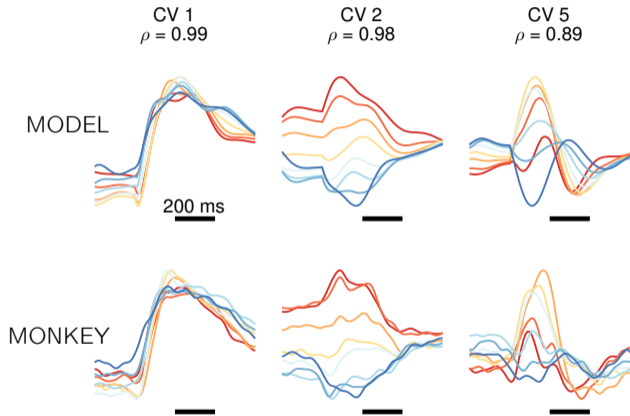


Li & Todorov (2004)  
Kao et al., *Neuron* (2021)



Calvin Kao

fix the ISN; optimise readout and initial conditions



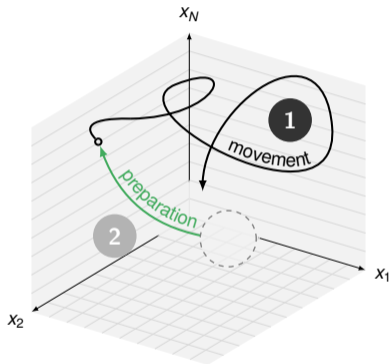
monkey and model embed similar signals

see also Sussillo et al. (2015)

# 1

network dynamics  
for movement generation

- ▶ off-the-shelf models of cortical dynamics struggle to produce M1-like activity
- ▶ new model class with **detailed E/I balance** generate M1-like activity transients
- ▶ **simple learning rules** can construct such networks



Hennequin et al., *Neuron* (2014)  
Li et al., *in prep*  
Stroud et al., *Nat Neurosci* (2018)

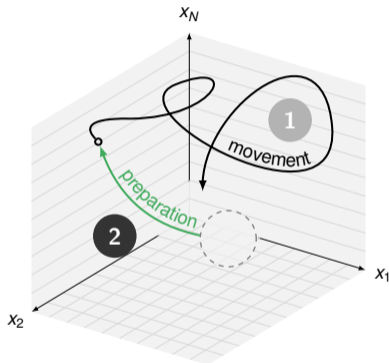


Jake Stroud

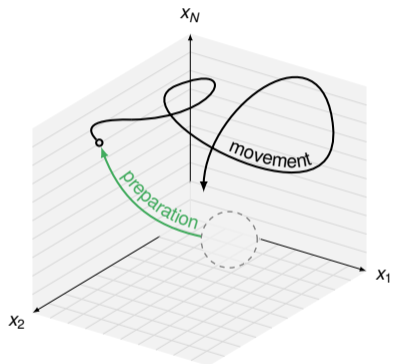
# 2

a network theory of  
motor preparation

- ▶ preparation is important  
(failing to prepare...)
- ▶ formalised as **optimal anticipatory control**
- ▶ realised in gated **thalamo-cortical loops**



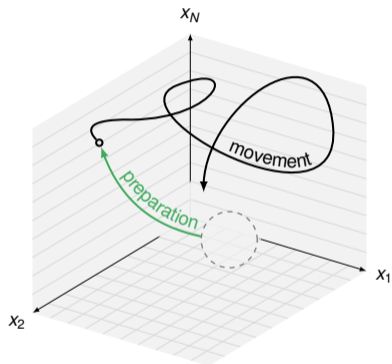
Kao et al., *Neuron* (2021)





Empirically:

- ▶ neural perturbations during the delay period increases reaction time (RT)



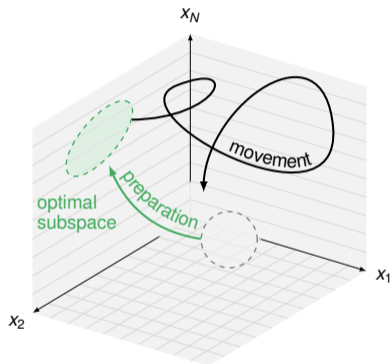
Empirically:

Churchland et al. (2007)

Churchland et al. (2006)

Lara et al. (2018)

- ▶ neural perturbations during the delay period increases reaction time (RT)
- ▶ activity converges to an “optimal subspace” in each trial



Empirically:

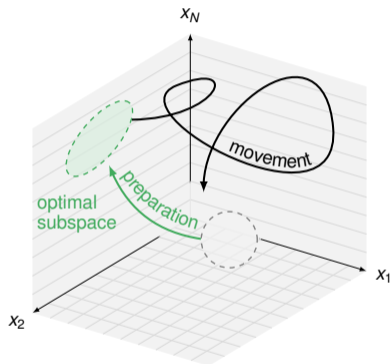
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Churchland et al. (2006)

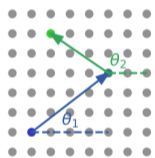
Lara et al. (2018)

Afshar et al. (2011)



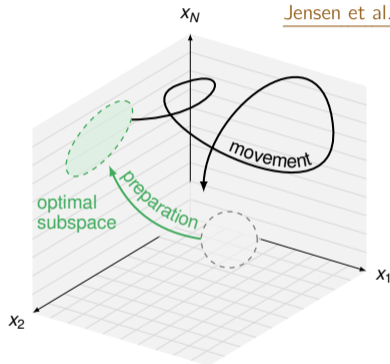
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- ▶ activity converges to an “optimal subspace” in each trial
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- ▶ preparation also predictive of RT in self-paced reaching:



continuous reaching for 30+ min

Churchland et al. (2007)  
Churchland et al. (2006)  
Lara et al. (2018)  
Afshar et al. (2011)  
O'Doherty et al. (2017)  
Jensen et al. (2021)



Kris Jensen



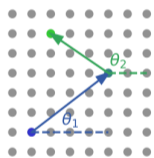
Calvin Kao



Jasmine Stone

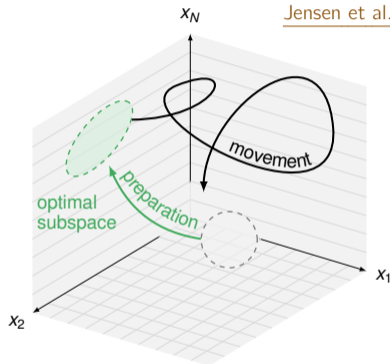
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continuous reaching for 30+ min  
scalable, fully-Bayesian GPFA  
(here: 10M+ datapoints)

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Jensen et al. (2021)



Kris Jensen



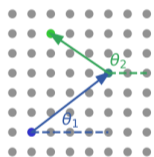
Calvin Kao



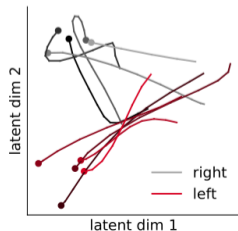
Jasmine Stone

Empirically:

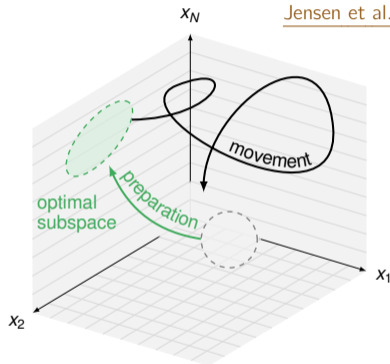
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Kris Jensen



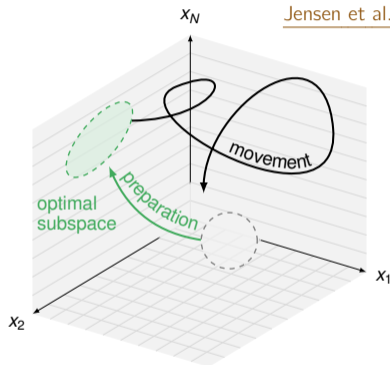
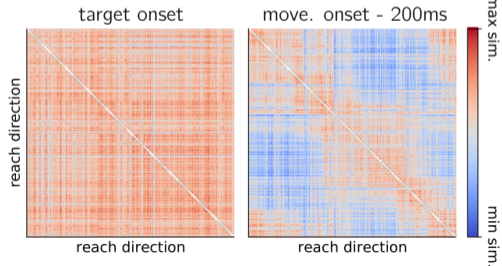
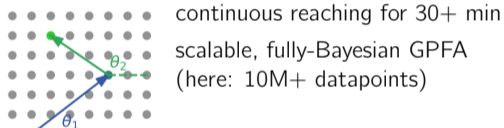
Calvin Kao



Jasmine Stone

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Kris Jensen



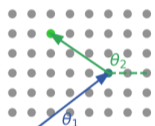
Calvin Kao



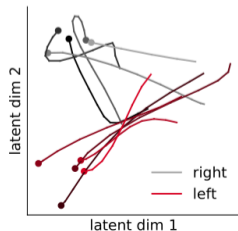
Jasmine Stone

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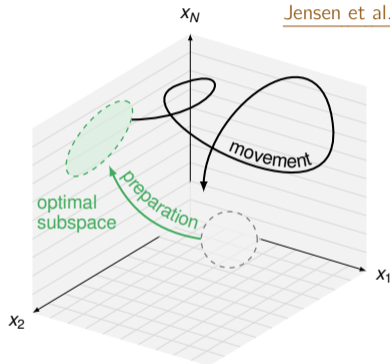
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Kris Jensen



Calvin Kao

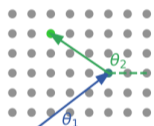


Jasmine Stone

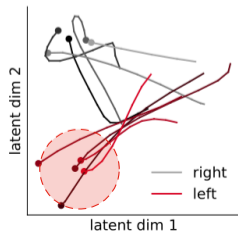


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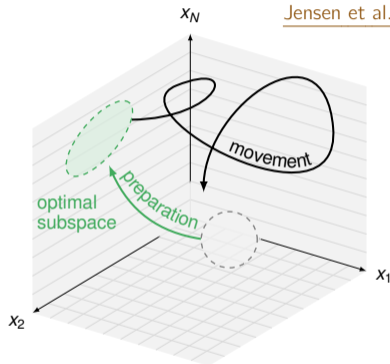
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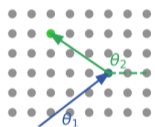
Calvin Kao



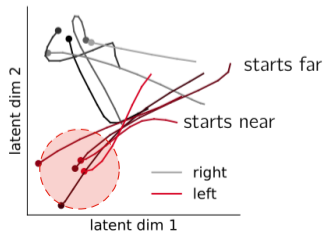
Jasmine Stone

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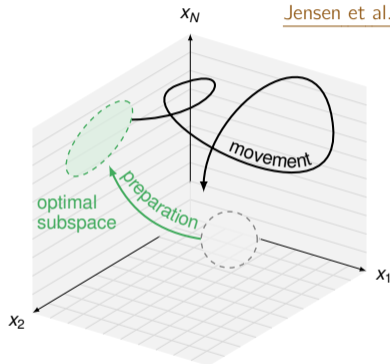
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Kris Jensen



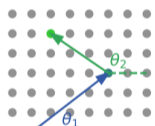
Calvin Kao



Jasmine Stone

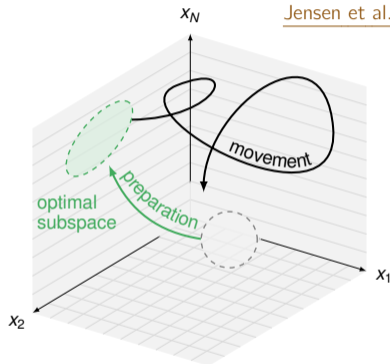
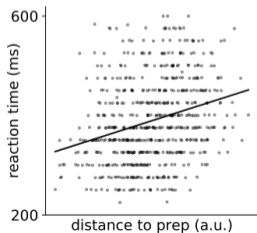
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continuous reaching for 30+ min  
scalable, fully-Bayesian GPFA  
(here: 10M+ datapoints)

$r = 0.28$



Kris Jensen

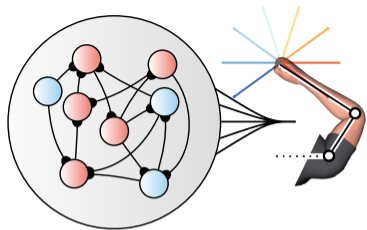


Calvin Kao



Jasmine Stone

Churchland et al. (2007)  
Churchland et al. (2006)  
Lara et al. (2018)  
Afshar et al. (2011)  
O'Doherty et al. (2017)  
Jensen et al. (2021)



how do  
we get  
there?

$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + h$$

M1 activity

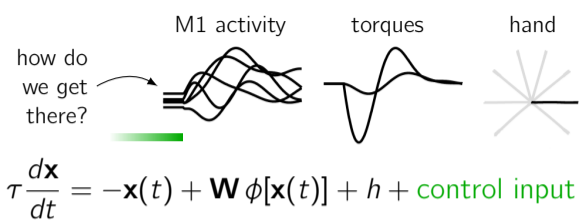
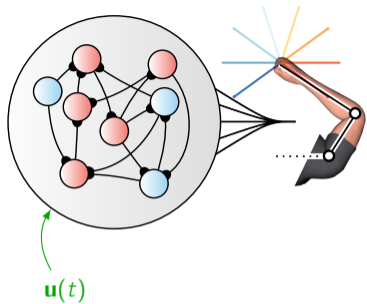


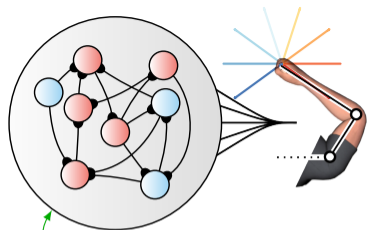
torques



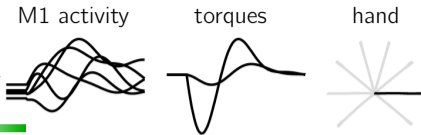
hand







how do we get there?



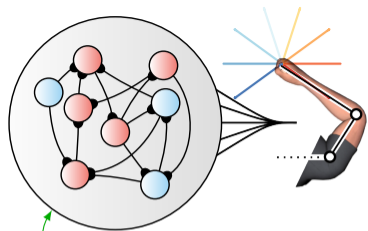
$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + h + \text{control input}$$

$\mathbf{u}(t)$

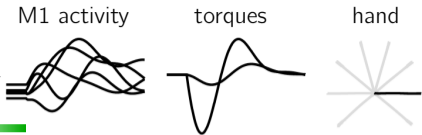
simplest "naive" strategy:  
constant  $\mathbf{u}$  to  
establish right fixed point

200 ms





how do we get there?



$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x}(t) + \mathbf{W} \phi[\mathbf{x}(t)] + h + \text{control input}$$

$\mathbf{u}(t)$

simplest "naive" strategy:  
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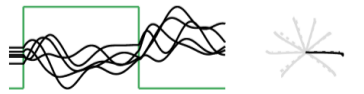
200 ms

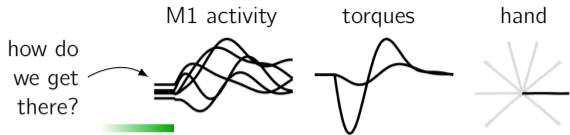
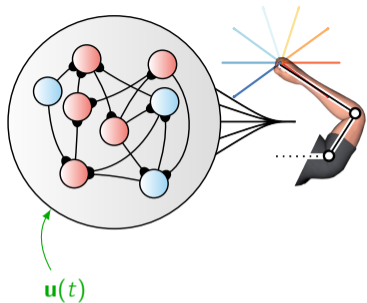


400 ms



800 ms

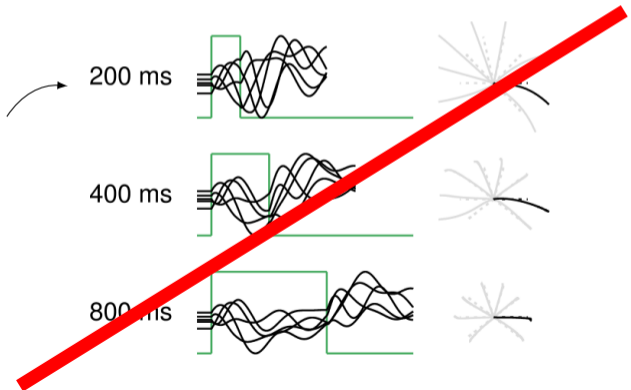




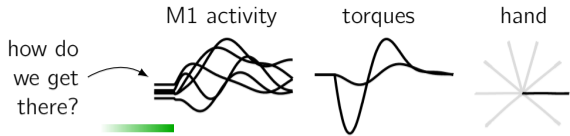
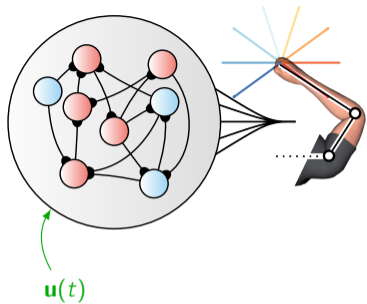
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simplest "naive" strategy:  
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 establish right fixed point

also conflicts with:  
 Kaufman et al. (2014)  
 Elsayed et al. (2016)

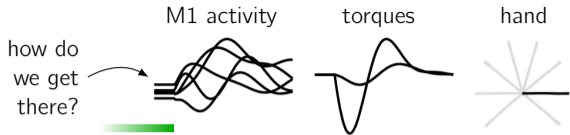
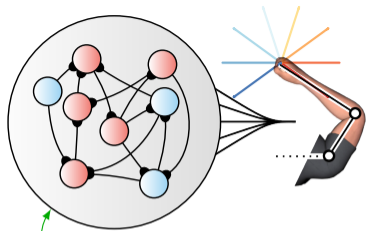






how do we get there?

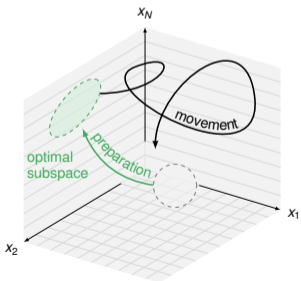
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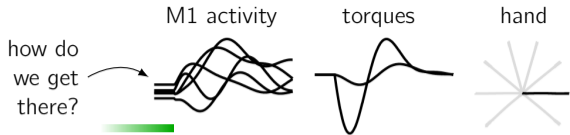
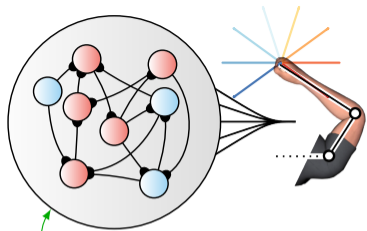


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motor preparation as optimal anticipatory control:

choose  $\mathbf{u}(t)$  so as to “be ready for movement, rapidly”

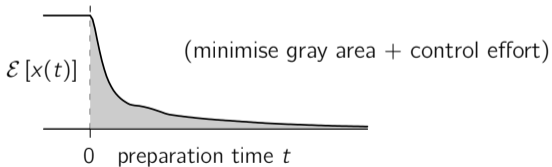
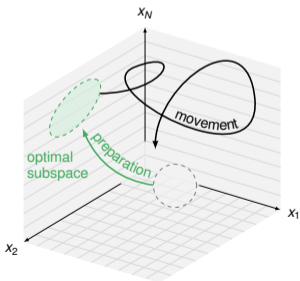


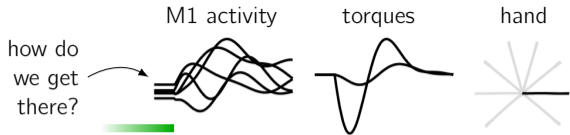
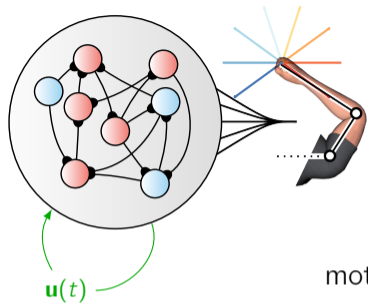


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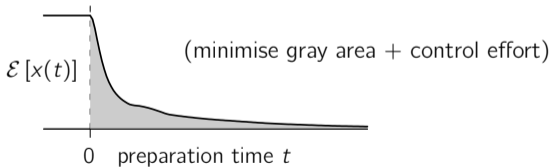
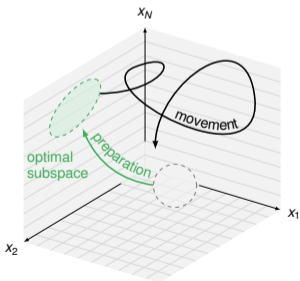




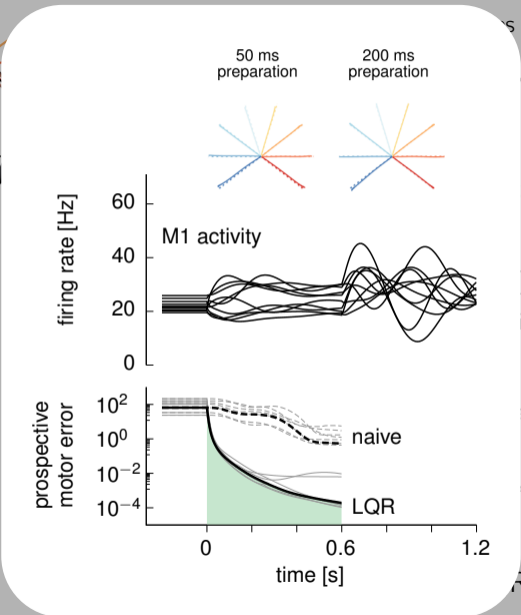
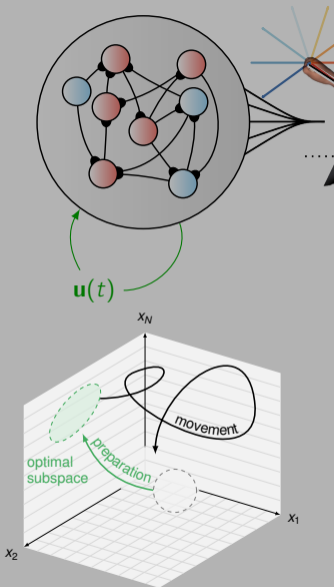
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motor preparation as optimal anticipatory control:

choose  $u(t)$  so as to "be ready for movement, rapidly"



optimal solution = state feedback ('LQR')



Kao et al., *Neuron* (2021)

hand

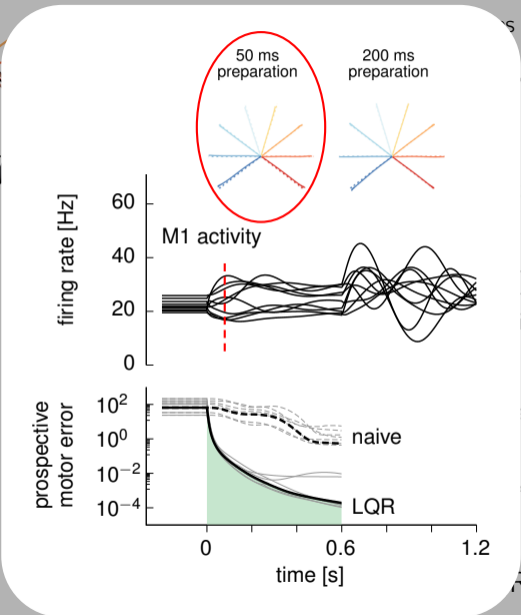
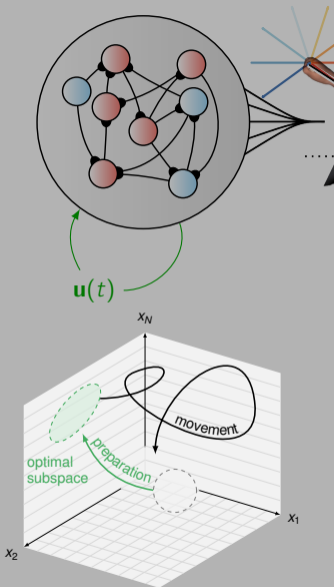
control input

control:

ably

ably area + control effort)

R')



Kao et al., *Neuron* (2021)

hand

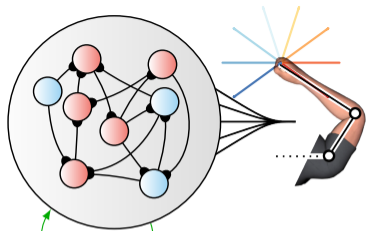
control input

y control:

idly"

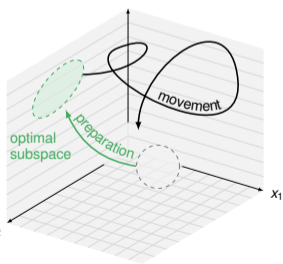
y area + control effort)

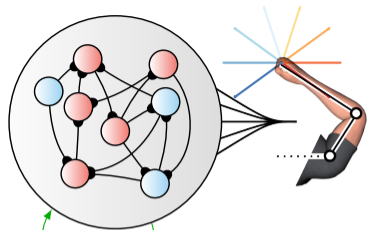
R')



$\mathbf{u}(t)$

$x_N$





$\mathbf{u}(t)$

$x_N$

movement

optimal subspace

preparation

$x_1$

$x_2$

Kao et al., *Neuron* (2021)

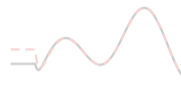
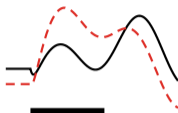
prospectively potent

prospectively null

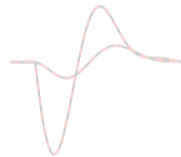
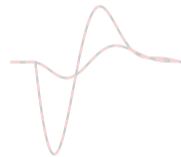
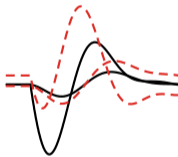
readout-null

dynamic-null

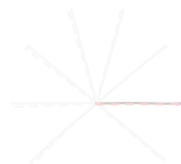
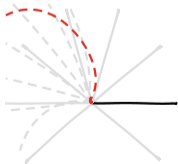
M1 activity



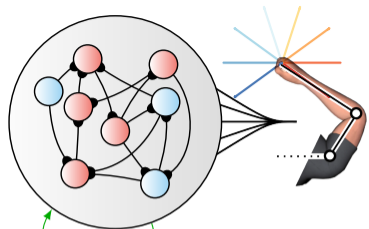
torques



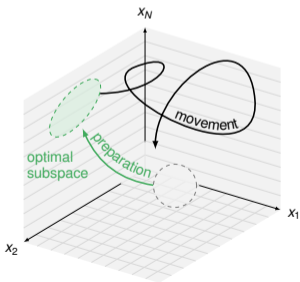
hand







$\mathbf{u}(t)$



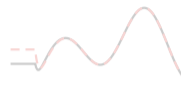
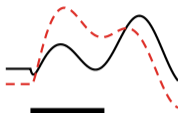
prospectively potent

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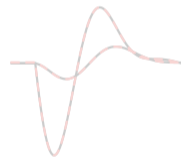
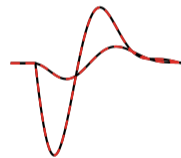
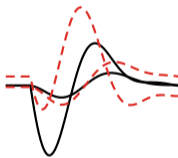
readout-null

dynamic-null

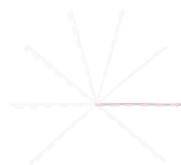
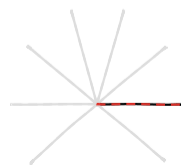
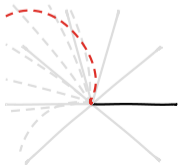
M1 activity

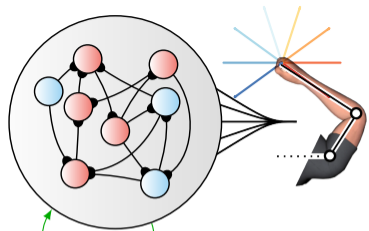


torques

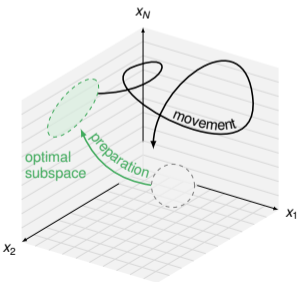


hand





$\mathbf{u}(t)$



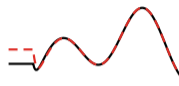
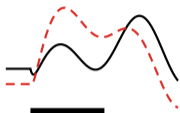
prospectively potent

prospectively null

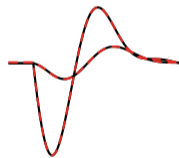
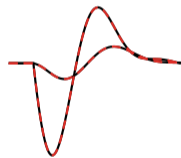
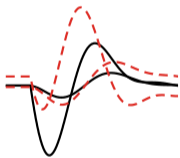
readout-null

dynamic-null

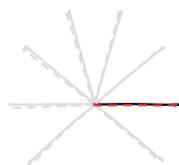
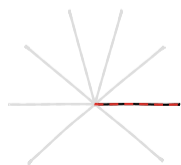
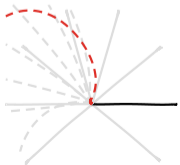
M1 activity

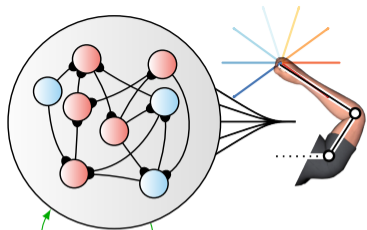


torques



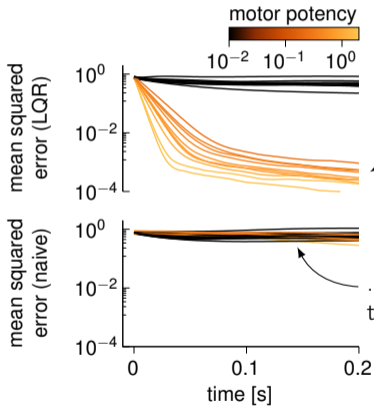
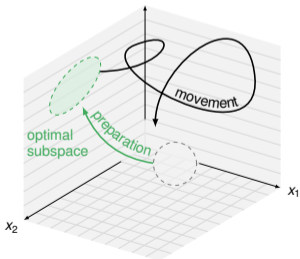
hand





$\mathbf{u}(t)$

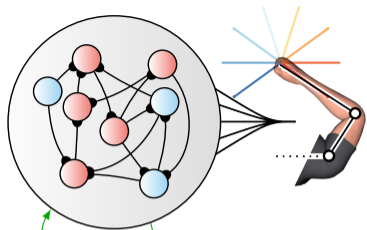
$x_N$



optimal, selective  
elimination of errors  
in potent dimensions . . .

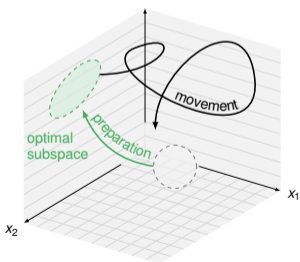
c.f. also Li, Daie, et al. (2016)

. . . not observed in  
the naive strategy

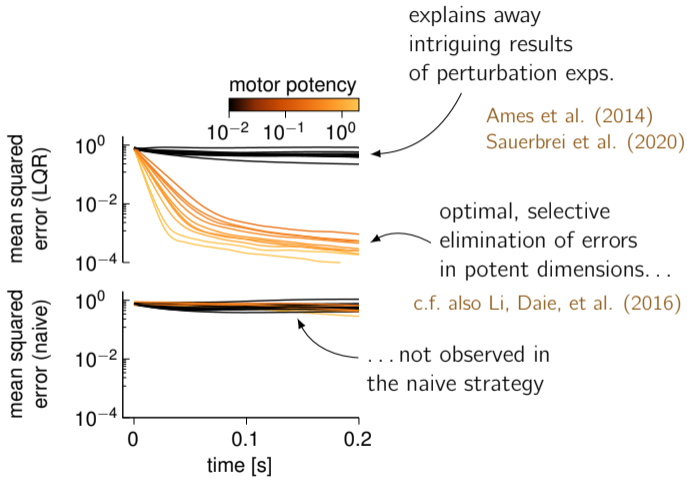


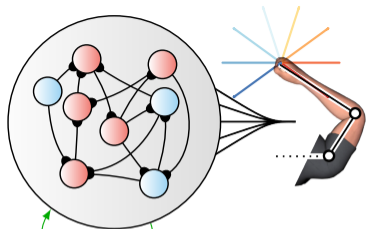
$\mathbf{u}(t)$

$x_N$

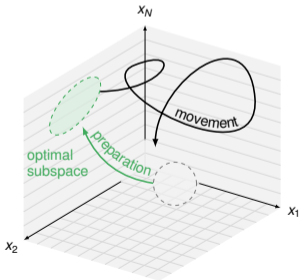


Kao et al., *Neuron* (2021)

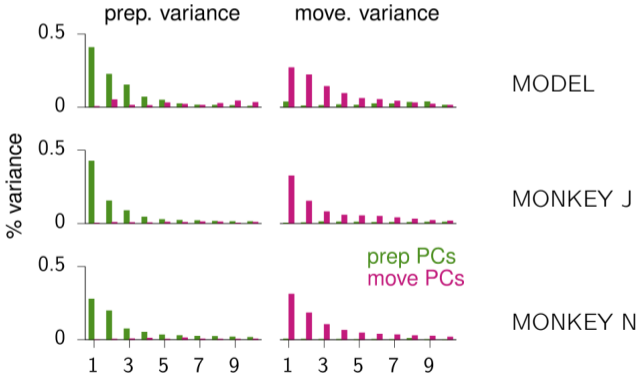


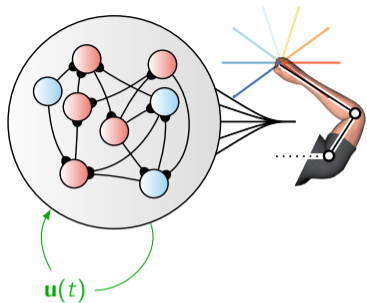


$u(t)$

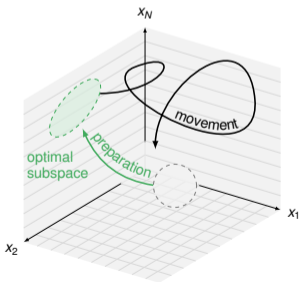


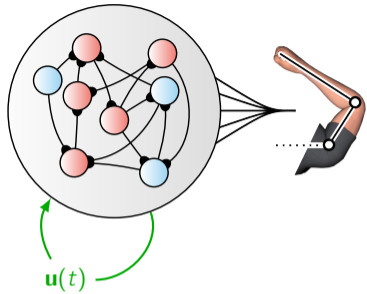
optimal preparation also explains orthogonality between preparatory and movement subspaces:

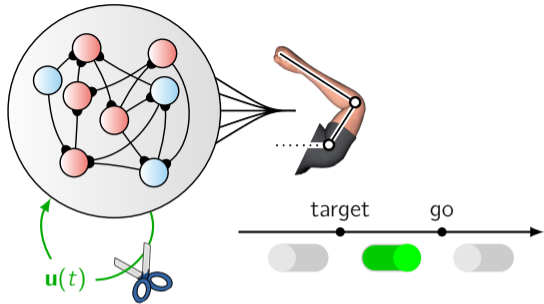




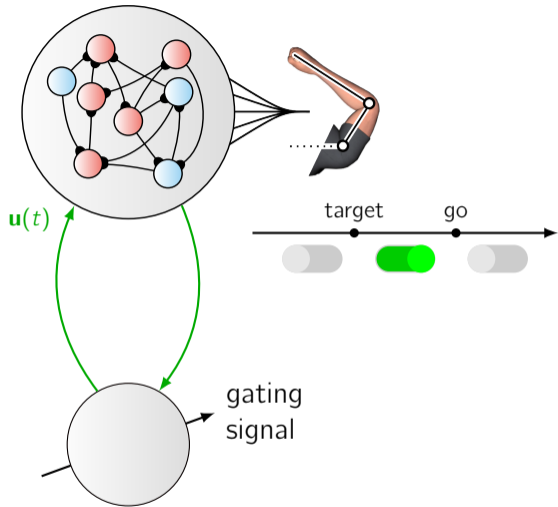
algorithm  $\longrightarrow$  circuit implementation?







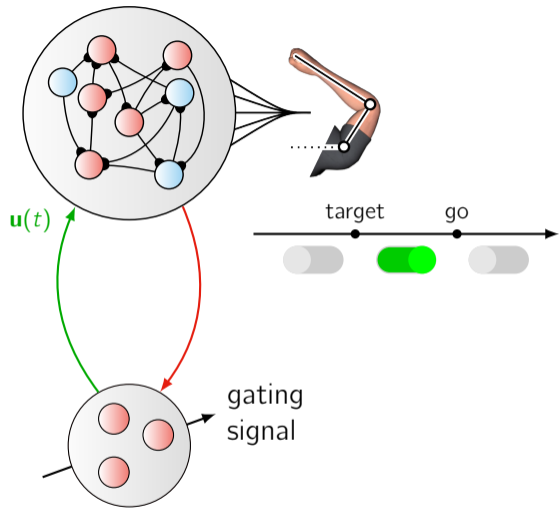




Guo et al. (2017)

see also: Logiaco et al., *Cell Reports* (2021)

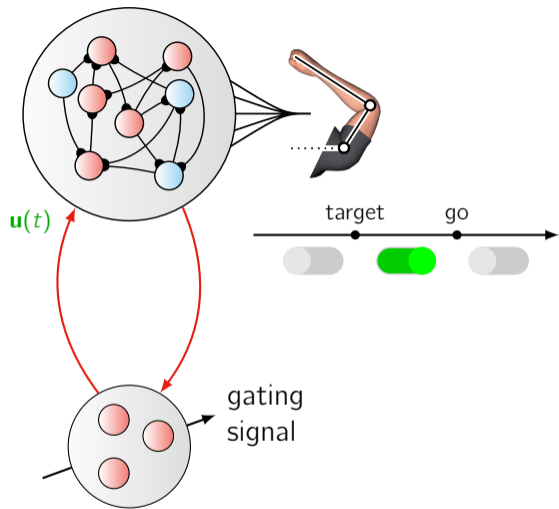
Kao et al., *Neuron* (2021)



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Guo et al. (2017)

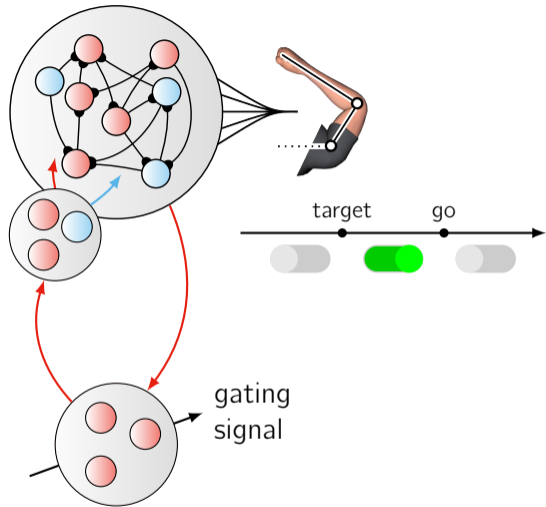
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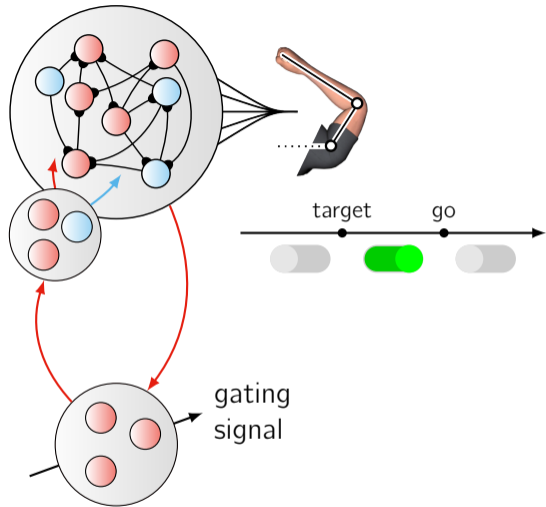
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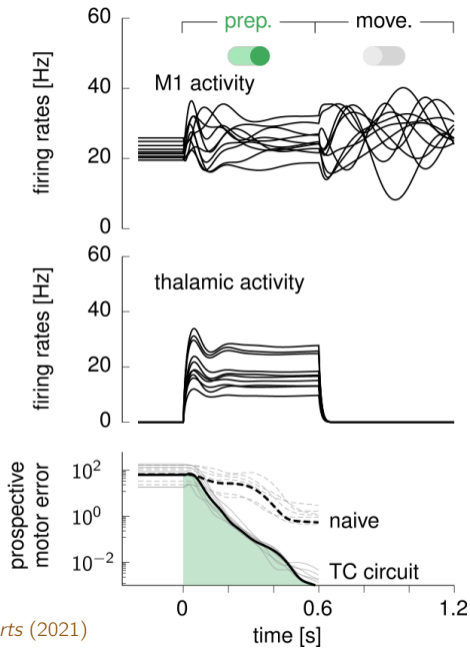
Kao et al., *Neuron* (2021)



Kao et al., *Neuron* (2021)

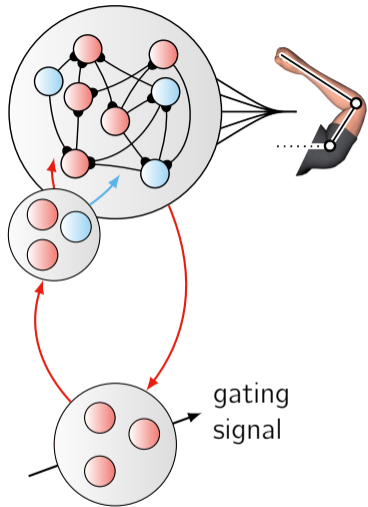
Guo et al. (2017)

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## Take home:

- ▶ precise E/I balance enables generation of motor commands in M1
  - ▶ stabilisation of high-D recurrent pathways via Hebbian ISP
  - ▶ ISN dynamics account for salient dynamical structure in M1 activity during movement

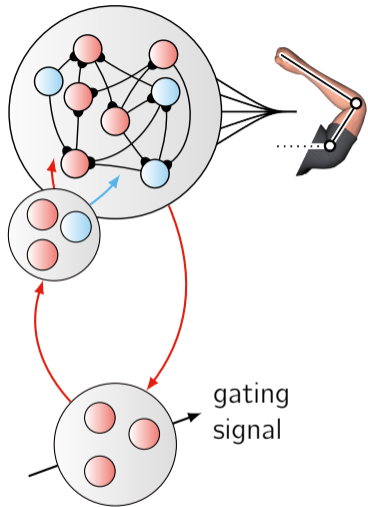


Hennequin et al., *Neuron* (2014)

Kao et al., *Neuron* (2021)

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- ▶ strong dynamics in M1 is both a blessing and a curse

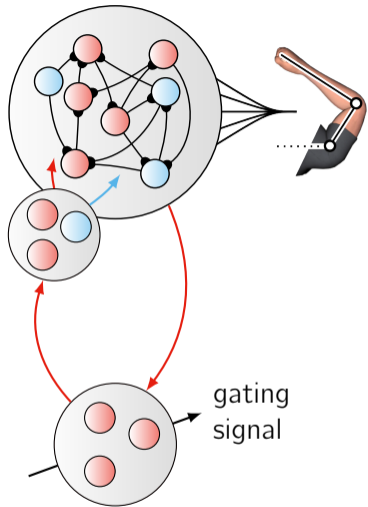


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- ▶ strong dynamics in M1 is both a blessing and a curse
- ▶ there is a cure for the curse: flexible thalamo-cortical loops
  - ▶ enables (optimal) anticipatory control of movement
  - ▶ reconciles ISN dynamics with key features of M1 prep. activity
  - ▶ much to be tested, as more quantitative models of M1 emerge...



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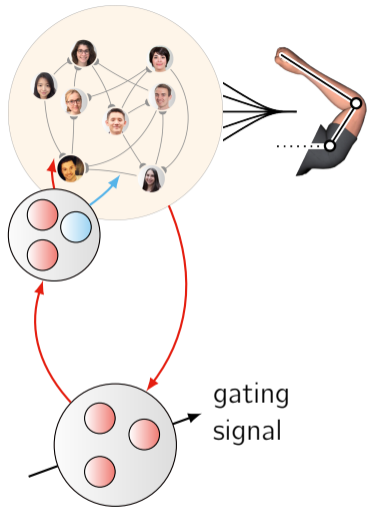


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Kristopher Jensen  
Ta-Chu (Calvin) Kao  
Xizi Li  
Virginia Rutten  
Mahdieh Sadabadi  
Marine Schimel  
Jasmine Stone  
Jake Stroud

Swiss National Science Foundation  
Wellcome Trust



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