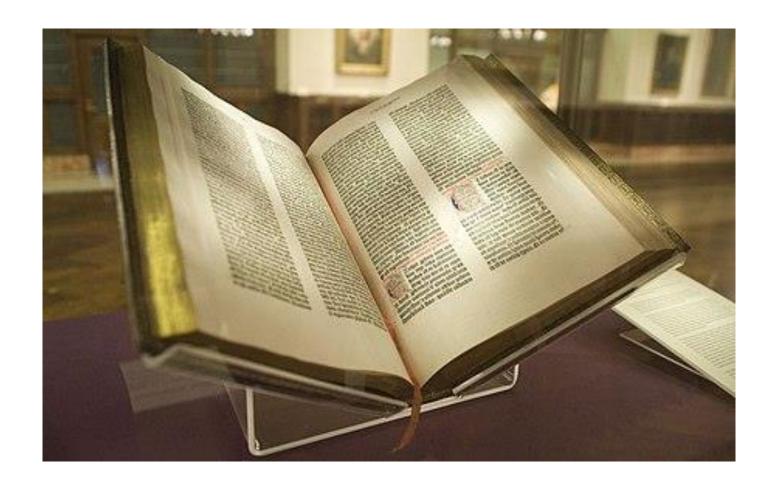
# Dynamics for working memory and time encoding

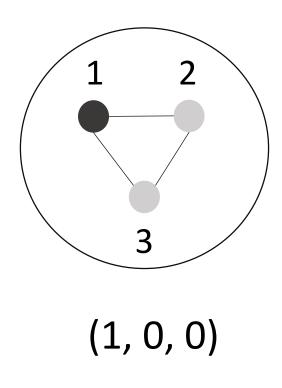
Zeyuan Ye



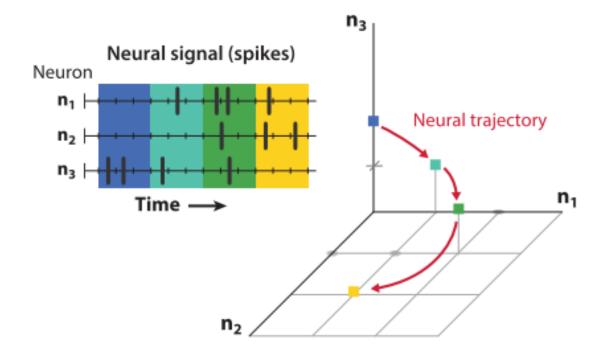
The mechanism of working memory?

2. Three hypotheses of the working memory

3. Experiments



**b** Neural trajectory



x(t): N dimensional vector, N = # of neurons

$$\frac{dx_i}{dt} = -x_i + \sum_{j=1}^N J_{ij}\phi(x_j)$$

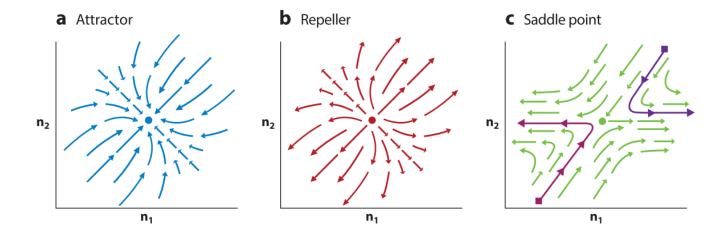
$$\frac{\mathbf{dx}}{\mathbf{dt}} = f\left(\mathbf{x}\left(t\right), \mathbf{u}\left(t\right)\right),\,$$

$$\frac{\mathbf{dx}}{\mathbf{dt}} = f(\mathbf{x}(t), \mathbf{u}(t)) \neq \mathbf{0}$$



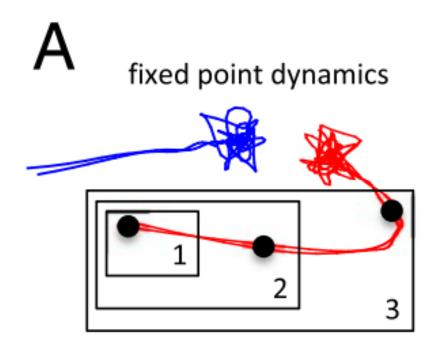
$$\frac{\mathbf{d}\left(\delta\mathbf{x}\right)}{\mathbf{dt}}=\mathbf{A}\left(\mathbf{x}^{*}\right)\delta\mathbf{x}\left(t\right),$$

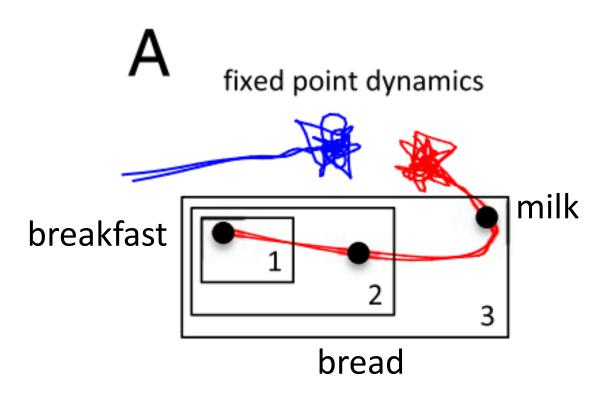
#### Fix Point



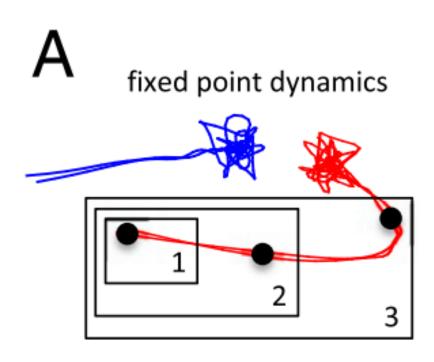
2. Three hypotheses of the working memory

3. Experiments





**Associated Memory** 



Trial Average

How the brain realize the attractor system?

# Hopfield networks

We started with this dynamical equation

$$\tau_n \frac{d\vec{v}}{dt} = -\vec{v} + F \left[ \vec{h} + M \vec{v} \right]$$

We are going to simplify this as follows:

$$\vec{v}(t+1) = F\left[M \vec{v}(t)\right] \qquad v_i(t+1) = F\left[\sum_{j=1}^N M_{ij} v_j(t)\right]$$

where the neuronal activation function is

$$F(I)$$

$$F(x) = \operatorname{sgn}(x) = \begin{cases} 1 & \text{if } x > 0 \\ -1 & \text{if } x \le 0 \end{cases}$$

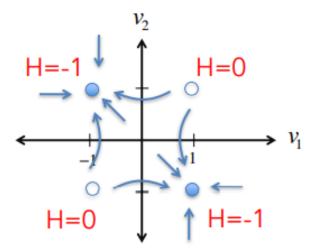
binary threshold neuron

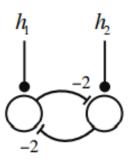
# The Energy Function

• Each possible state of the network has an energy given by:

$$H = -\frac{1}{2} \ \vec{v}^T M \vec{v}$$

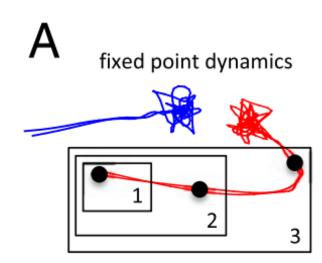
$$M = \left(\begin{array}{cc} 0 & -2 \\ -2 & 0 \end{array}\right)$$





Conclusion:

1. Properties of attractor system

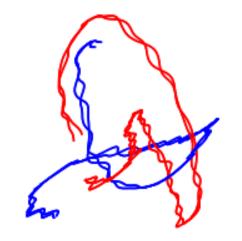


2. One realization of attractor system

Hopfield networks

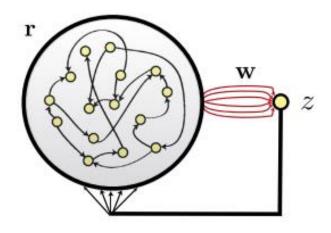
$$\vec{v}(t+1) = F[M \, \vec{v}(t)]$$

Neural trajectory stabilized random RNN



Time encoding

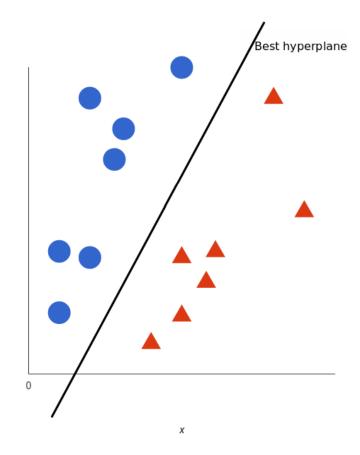
How the brain realize trajectory hypothesis?



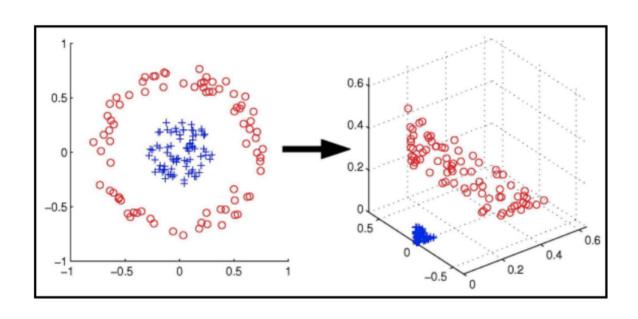
Echo state network

How this network works?

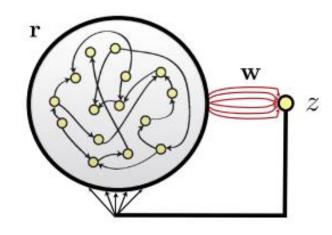
#### SVM linear kernel



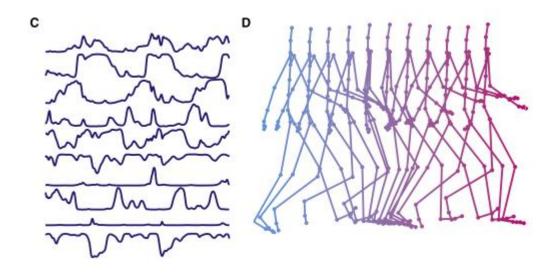
$$u = ax + by$$



$$u = ax + by + cz$$



High dimensional mapping

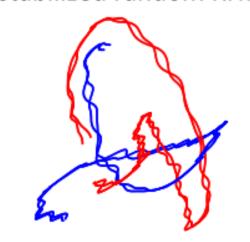


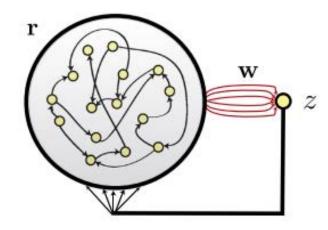
#### Conclusion:

1. Neural Trajectory is easy for time encoding

2. One realization of trajectory hypothesis

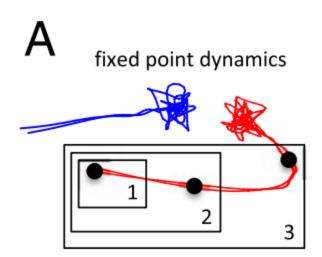
# Neural trajectory stabilized random RNN

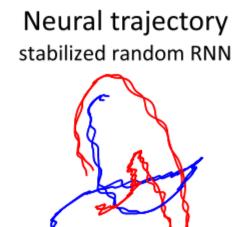


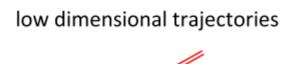


# 3. Low dimensional trajectory

low dimensional trajectories









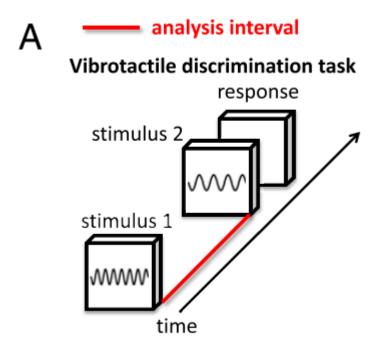
Experiment?

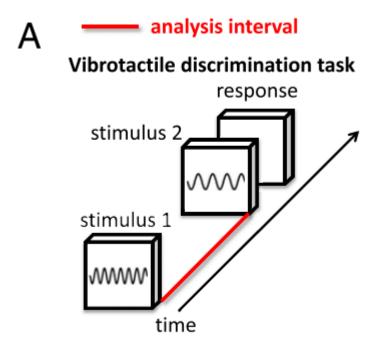
2. Two hypotheses of the working memory

3. Experiments

# Low-dimensional dynamics for working memory and time encoding

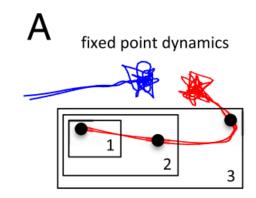
Christopher J. Cueva<sup>a,b,c,1</sup>, Alex Saez<sup>a</sup>, Encarni Marcos<sup>d,e</sup>, Aldo Genovesio<sup>e</sup>, Mehrdad Jazayeri<sup>f,g</sup>, Ranulfo Romo<sup>h,i,1</sup>, C. Daniel Salzman<sup>a,c,j,k,l</sup>, Michael N. Shadlen<sup>a,c,j,m</sup>, Stefano Fusi<sup>a,b,c,j,1</sup>





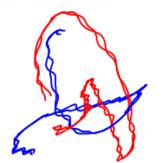
#### Prediction from two hypothesis

#### 1. Neural state will not changed

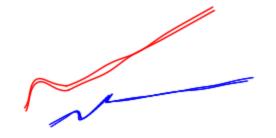


#### 2. Neural state will change

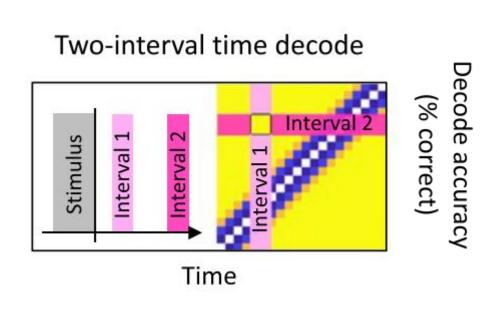
Neural trajectory stabilized random RNN

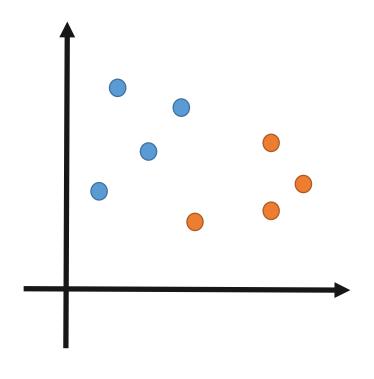


low dimensional trajectories

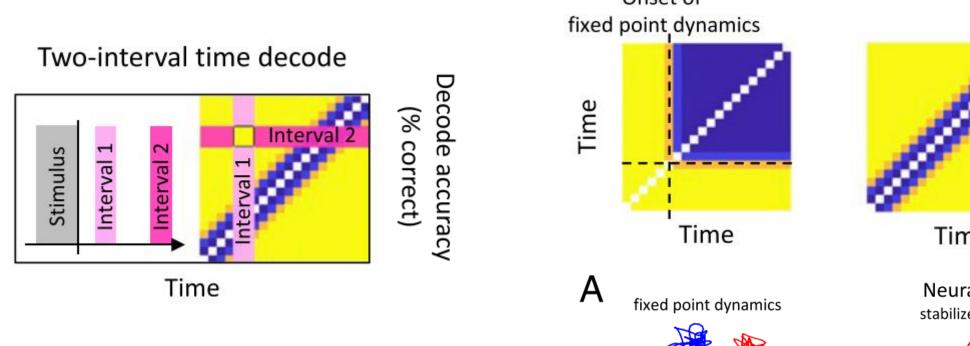


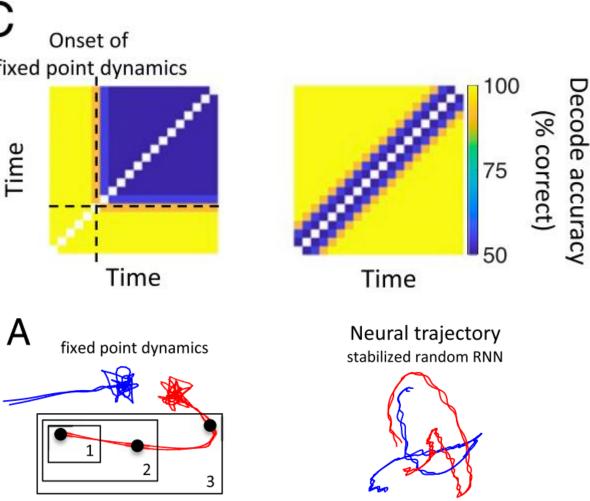
How to tell if the neural state change over time or not?

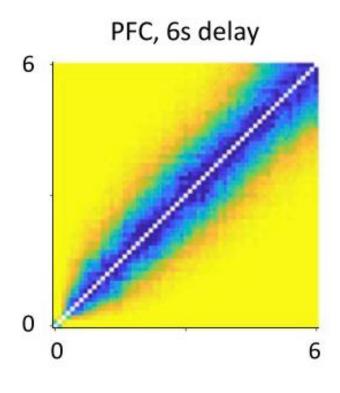




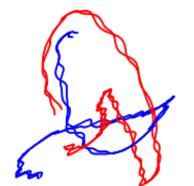
How to tell if the neural state change over time or not?



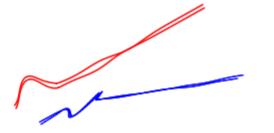




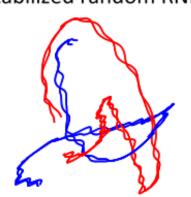
Neural trajectory stabilized random RNN



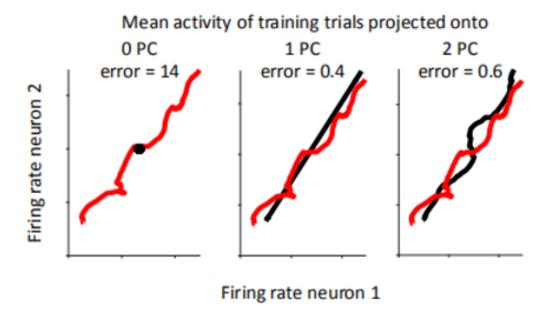
low dimensional trajectories



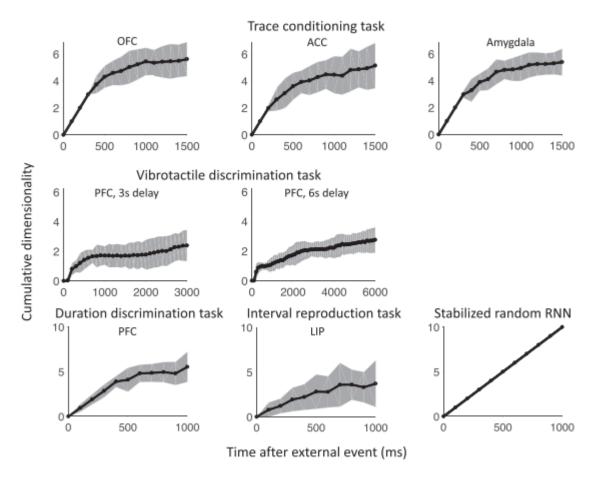
Neural trajectory stabilized random RNN



low dimensional trajectories



#### Experiment



#### **RNN**

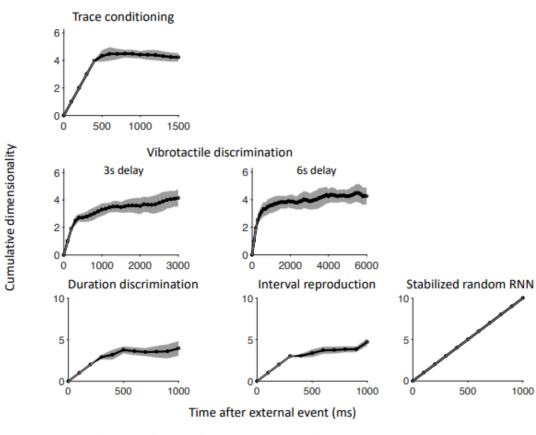
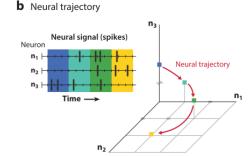


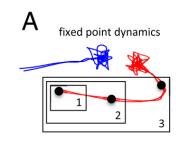
Fig. S14. Cumulative dimensionality for the RNN models. Error bars show one standard deviation.

4. Conclusion

1. Concepts of dynamics



2. Three hypotheses of the working memory



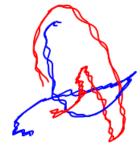
Neural trajectory stabilized random RNN



low dimensional trajectories

3. Experiments

Neural trajectory stabilized random RNN



low dimensional trajectories

