

# Some multiplex dynamics that I find interesting

Vincenzo Nicosia

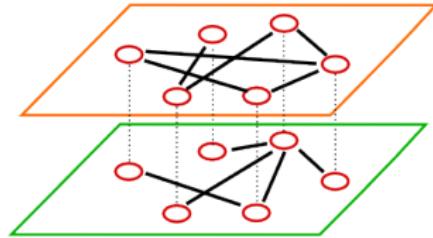
School of Mathematical Sciences, Queen Mary University of London (UK)

Oct. 5<sup>th</sup> 2015

*v.nicosia@qmul.ac.uk*

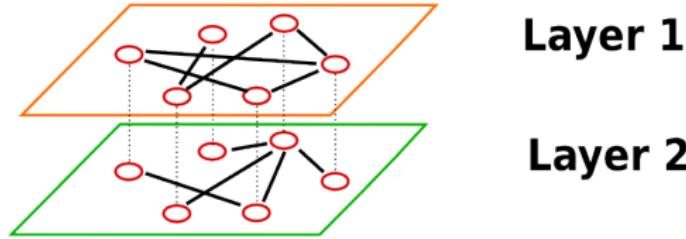
*<http://www.maths.qmul.ac.uk/~vnicosia/>*

# **SUPERDIFFUSION**



**Layer 1**

**Layer 2**

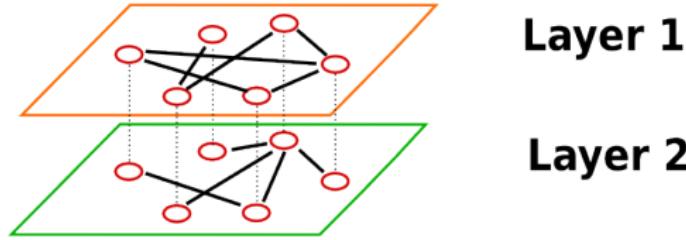


**Layer 1**

**Layer 2**

## DIFFUSION EQUATION

$$\frac{dx_i^{[\alpha]}}{dt} = D^{[\alpha]} \sum_j a_{ij}^{[\alpha]} (x_j^{[\alpha]} - x_i^{[\alpha]}) + D_x (x_i^{[\beta]} - x_i^{[\alpha]})$$



## DIFFUSION EQUATION

$$\frac{dx_i^{[\alpha]}}{dt} = \boxed{D^{[\alpha]} \sum_j a_{ij}^{[\alpha]} (x_j^{[\alpha]} - x_i^{[\alpha]})} + \boxed{D_x (x_i^{[\beta]} - x_i^{[\alpha]})}$$

**INTRA-LAYER**

**INTER-LAYER**

$$\frac{dx_i^{[\alpha]}}{dt} = D^{[\alpha]} \sum_j a_{ij}^{[\alpha]} (x_j^{[\alpha]} - x_i^{[\alpha]}) + D_x (x_i^{[\beta]} - x_i^{[\alpha]})$$

$$\dot{\boldsymbol{x}} = -\mathcal{L}\dot{\boldsymbol{x}}$$

$$\mathcal{L} = \begin{pmatrix} D^{[\alpha]} L^{[\alpha]} + D_x I & -D_x I \\ -D_x I & D^{[\beta]} L^{[\beta]} + D_x I \end{pmatrix}$$

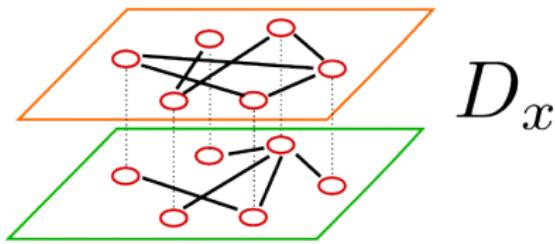
**Where  $L^{[\alpha]}, L^{[\beta]}$  are the Laplacians  
of the two layers**

$$\dot{x} = -\mathcal{L}\dot{x}$$

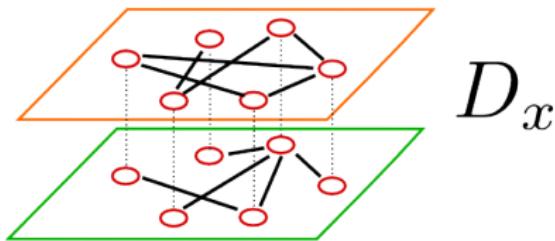
## DIFFUSION TIME-SCALE

$$\tau = \frac{1}{\lambda_{\min}}$$

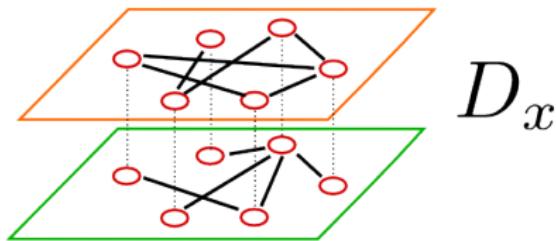
where  $\lambda_{\min}$  is the smallest non-zero eigenvalue of  $\mathcal{L}$



$D_x$



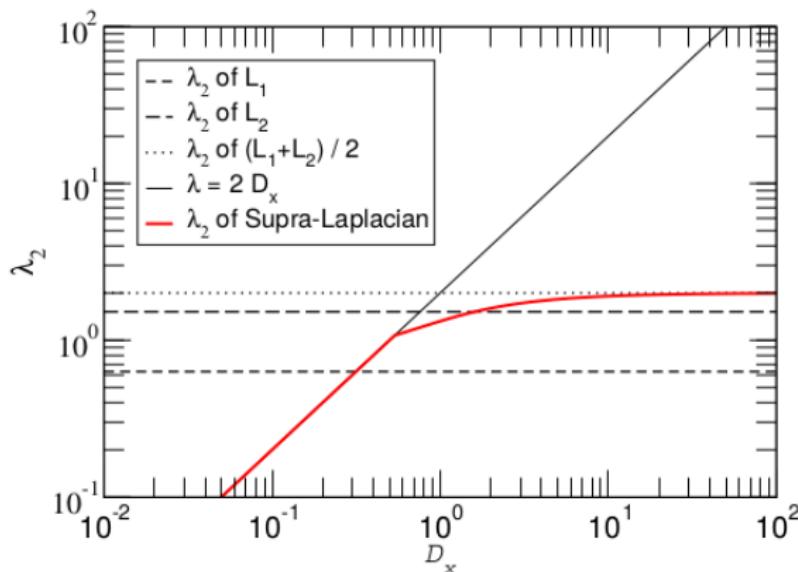
$$D_x \simeq 0 \quad \lambda_{\min} = \min(\lambda_2^\alpha, \lambda_2^\beta)$$



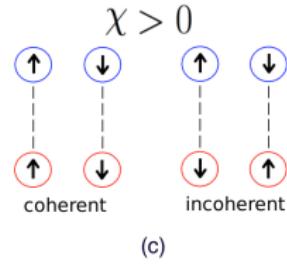
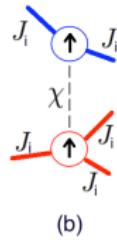
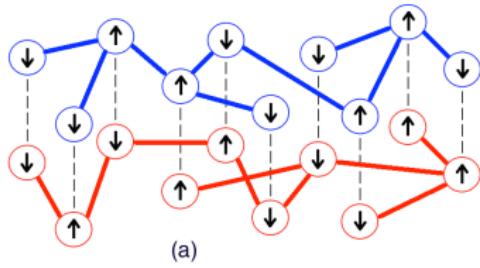
$$D_x \simeq 0 \quad \lambda_{\min} = \min(\lambda_2^\alpha, \lambda_2^\beta)$$

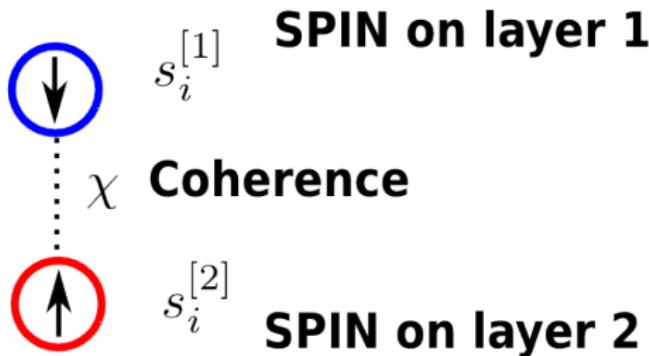
$$D_x \rightarrow \infty$$

$$\lambda_{\min} = \frac{\lambda_s}{2} \geq \frac{\lambda_2^\alpha + \lambda_2^\beta}{2} \geq \min(\lambda_2^\alpha, \lambda_2^\beta)$$



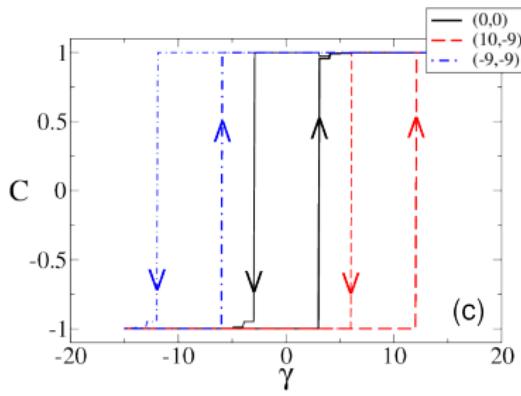
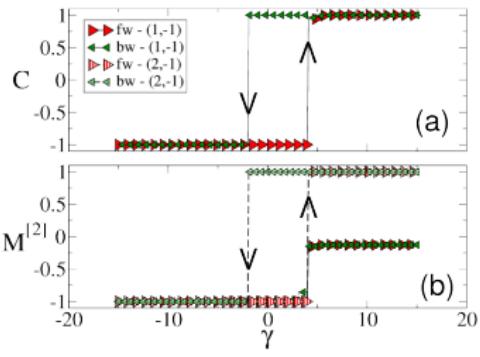
# ISING MODEL

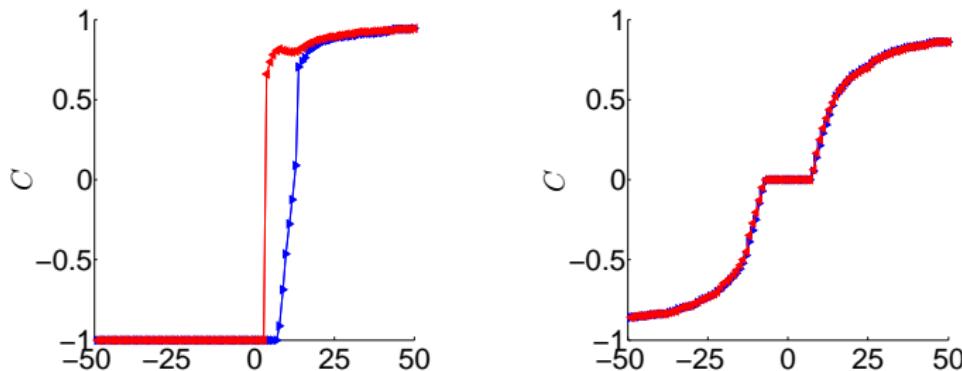
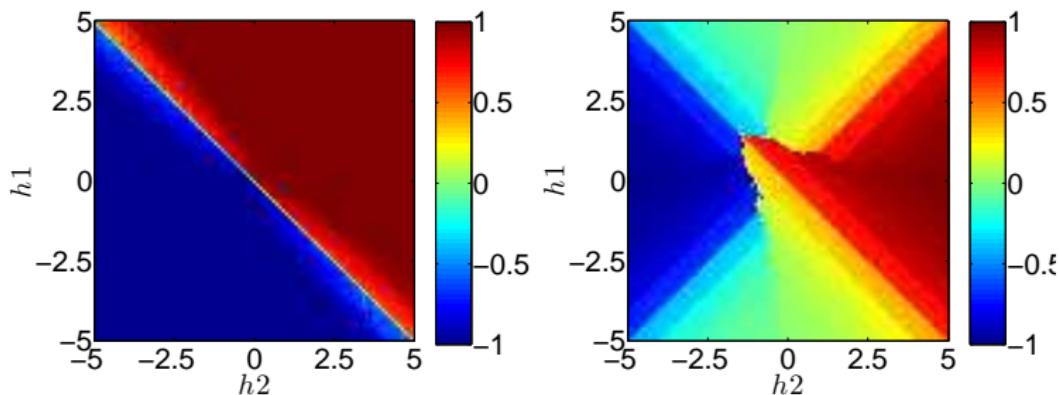




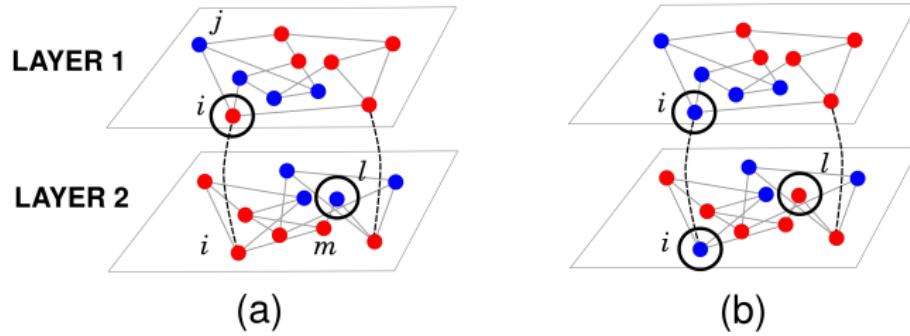
$$F_i^{[\alpha]} = J_i \sum_{j=1}^N a_{ij}^{[\alpha]} s_j^{[\alpha]} + \gamma \sum_{\beta \neq \alpha}^M s_i^{[\beta]} + h^{[\alpha]}$$

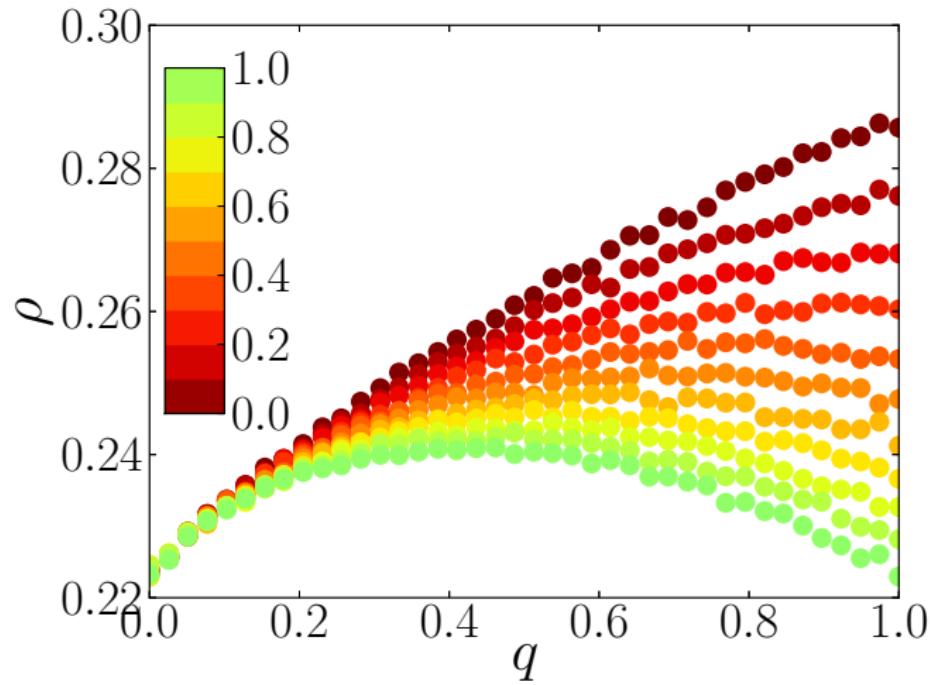
**Relative weight of coherence**

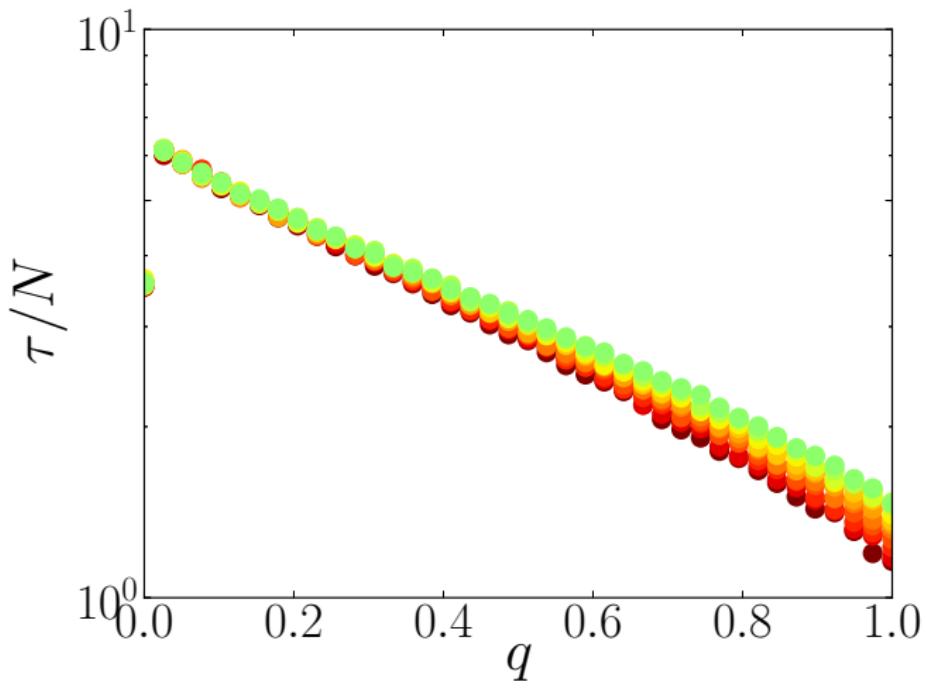


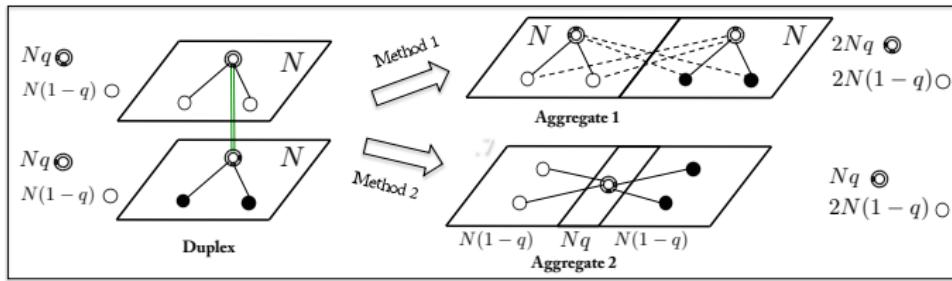


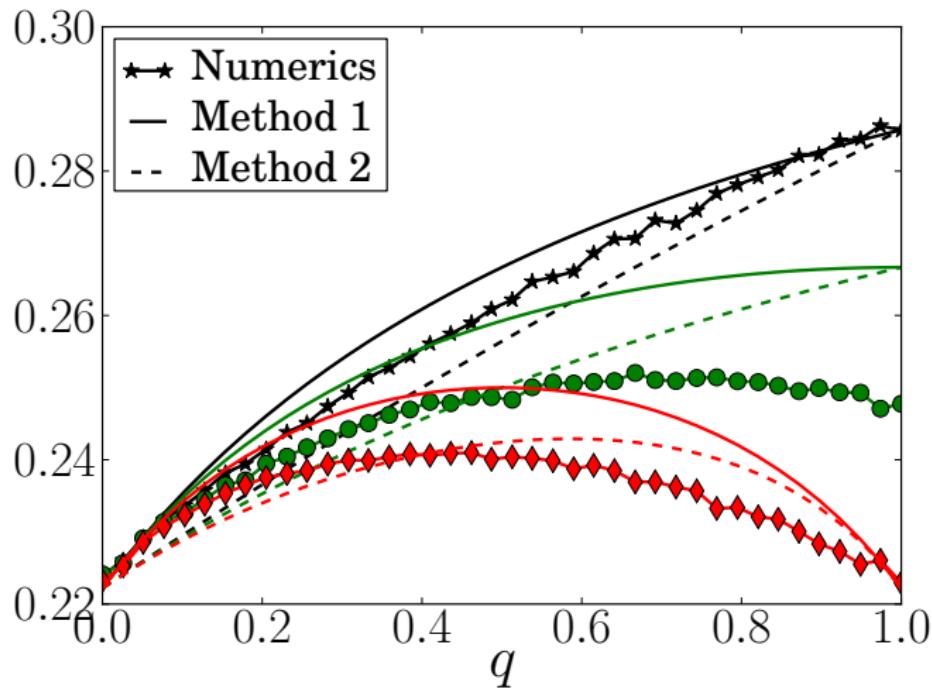
# VOTER MODEL

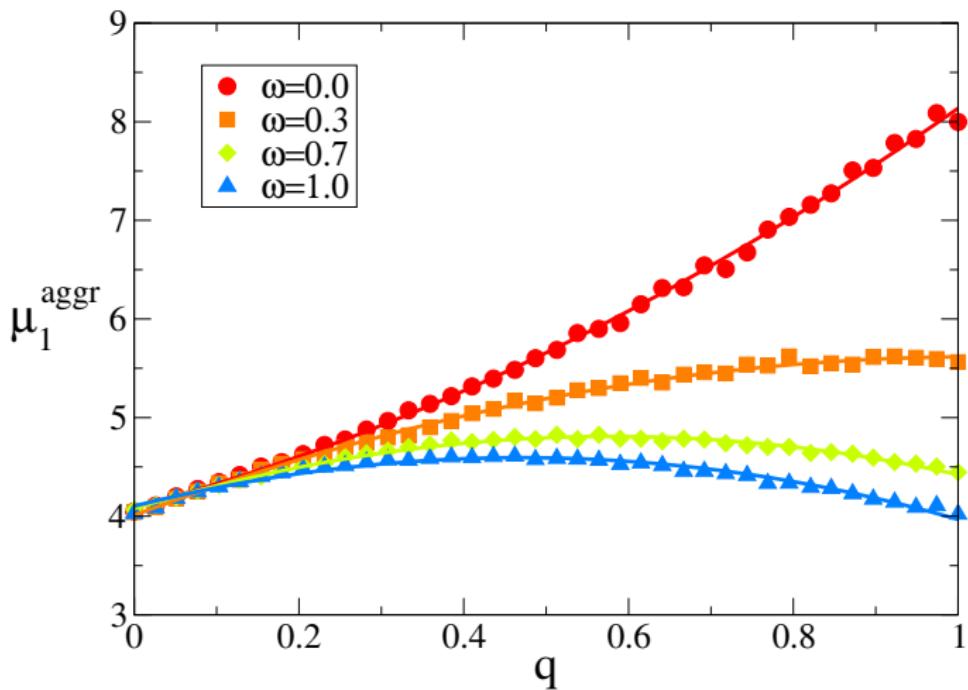


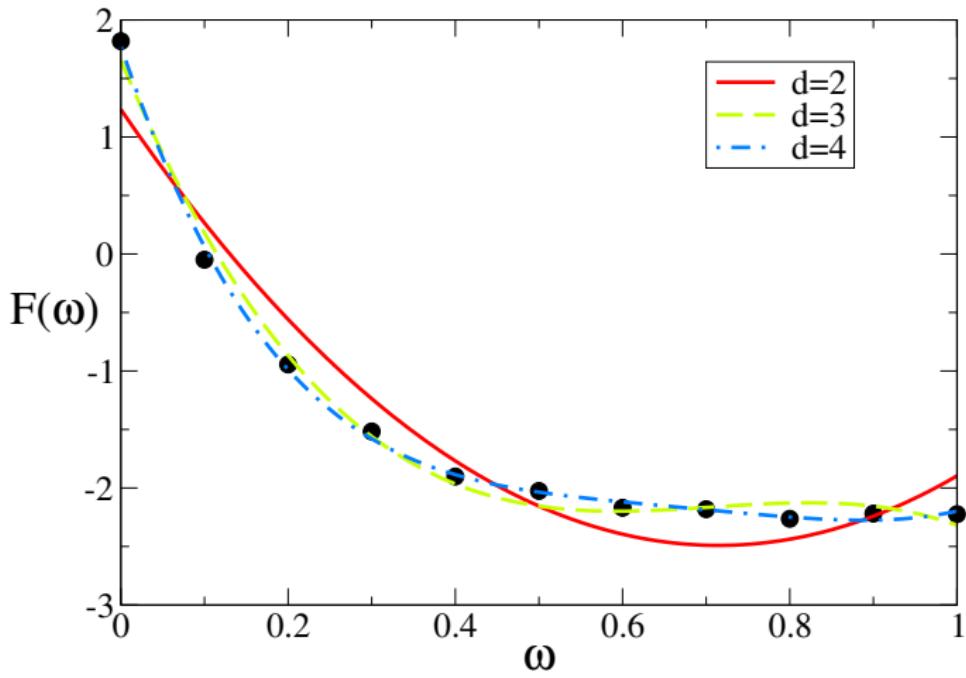


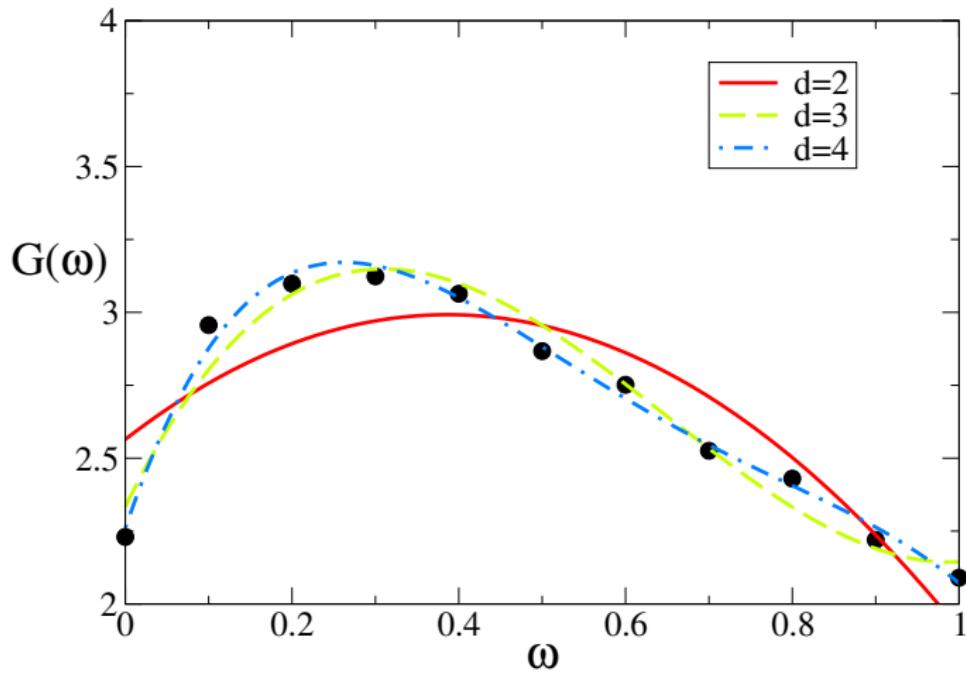




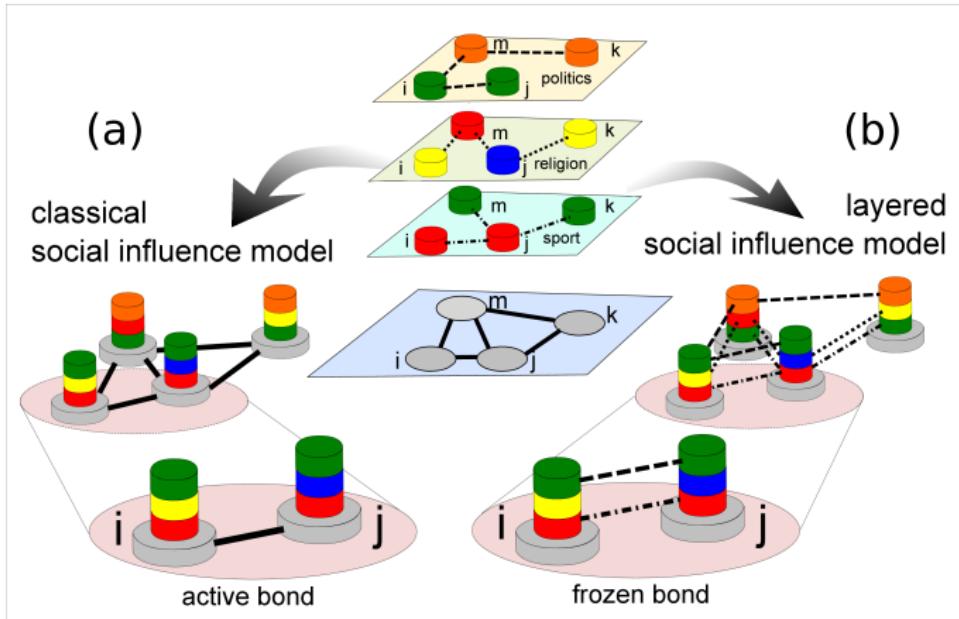




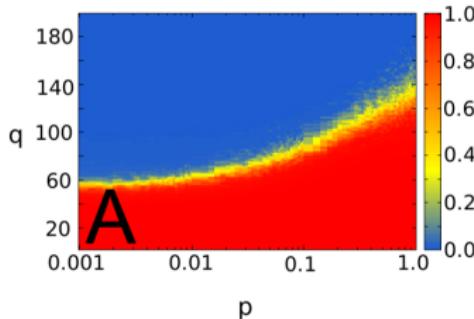




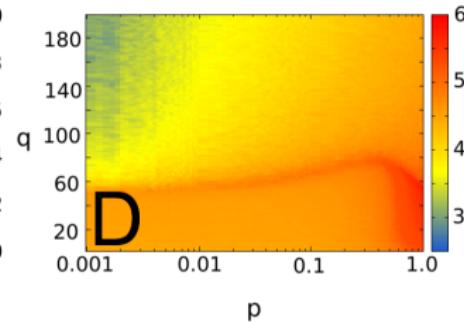
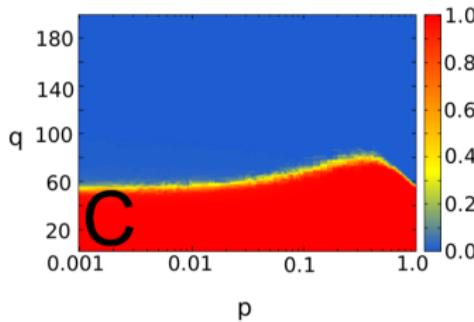
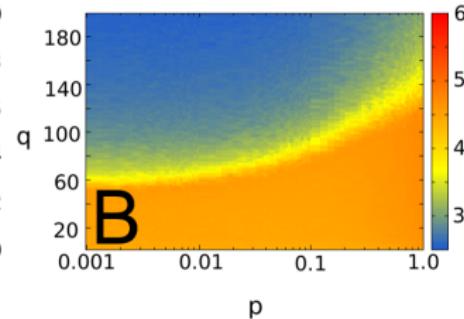
# AXELROD MODEL

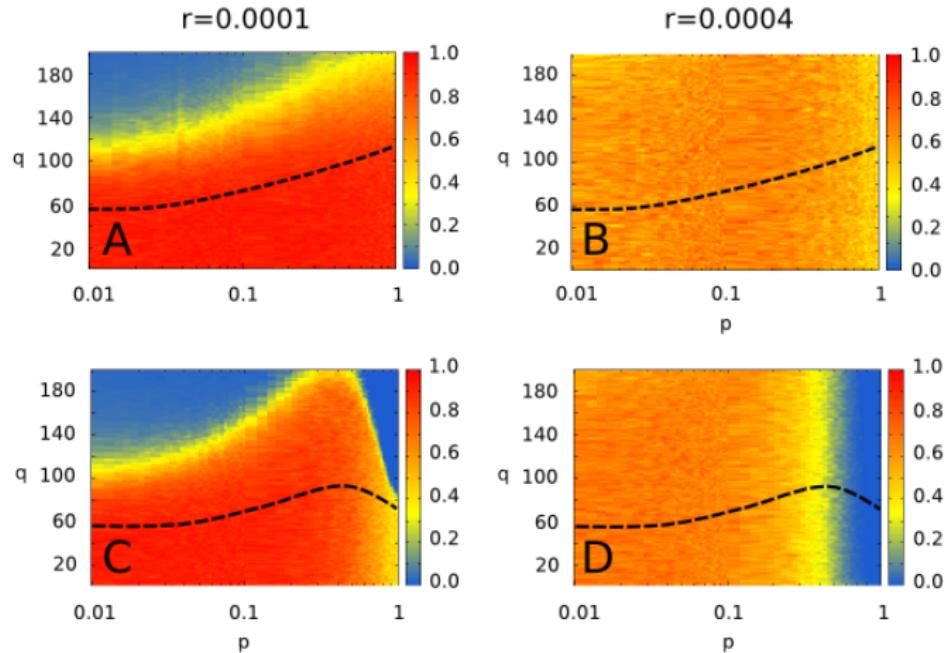


size of  
largest component



log time  
to steady state

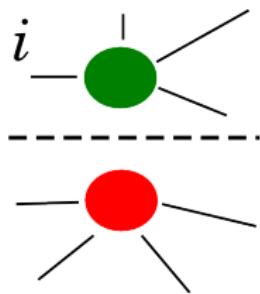


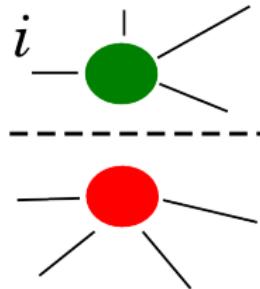


# TURING PATTERNS

You could have had here a nice slide  
with hawks and hares, and another slide  
with some of the **beautiful patterns** formed  
by the skin of fish and other animals  
**BUT I was actually brutally forced** to  
go out for a dessert yesterday night, and  
since **I don't like desserts**, we ended up  
drinking cerveza nacional and talking  
of Yom Kippur, knowledge, atheism,  
Monty Python, and other amenities, while  
a few of us tried to explain to the waiter  
that waffles and bananas cannot stay in  
the same plate.....then I fell asleep...

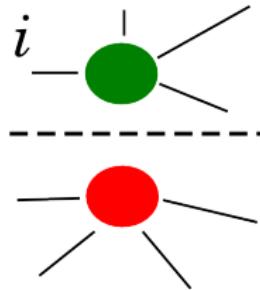






**Activator:**  $u_i(t)$

**Inhibitor:**  $v_i(t)$



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**Inhibitor:**  $v_i(t)$

$$\frac{du(t)}{dt} = F(u(t), v(t)) + \sigma^{[1]} L^{[1]} u(t)$$

$$\frac{dv(t)}{dt} = G(u(t), v(t)) + \sigma^{[2]} L^{[2]} v(t)$$

# Linear Stability:

$$J = \begin{pmatrix} L^{[1]} + f_u I & f_v I \\ g_u I & \sigma(L^{[2]} + g_v I) \end{pmatrix}$$

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$$\lambda_1 < \lambda_2 < \dots < \lambda_N = \lambda_M$$

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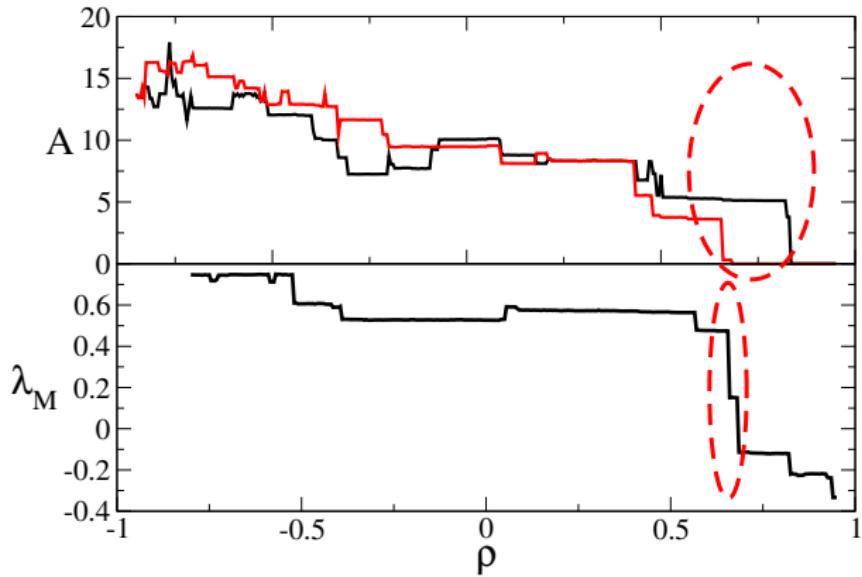
$$\lambda_1 < \lambda_2 < \dots < \lambda_N = \lambda_M$$

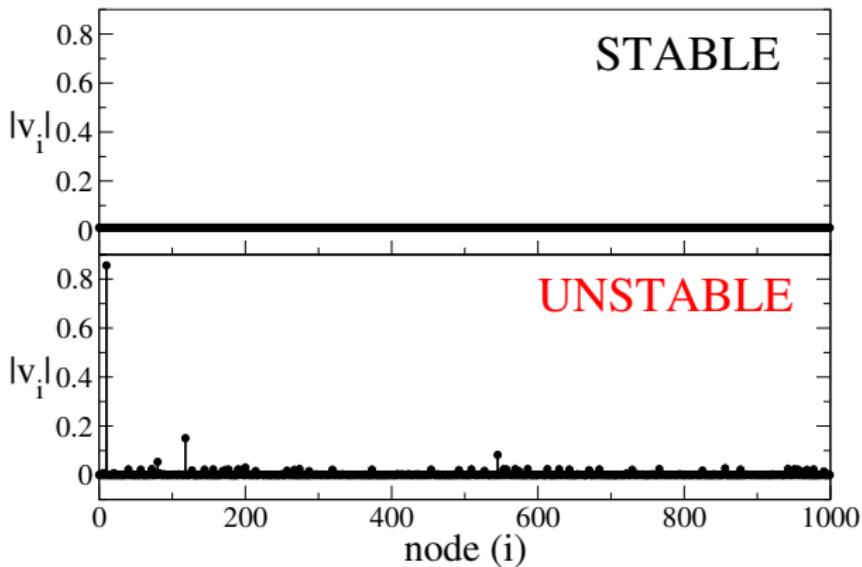
## Amplitude:

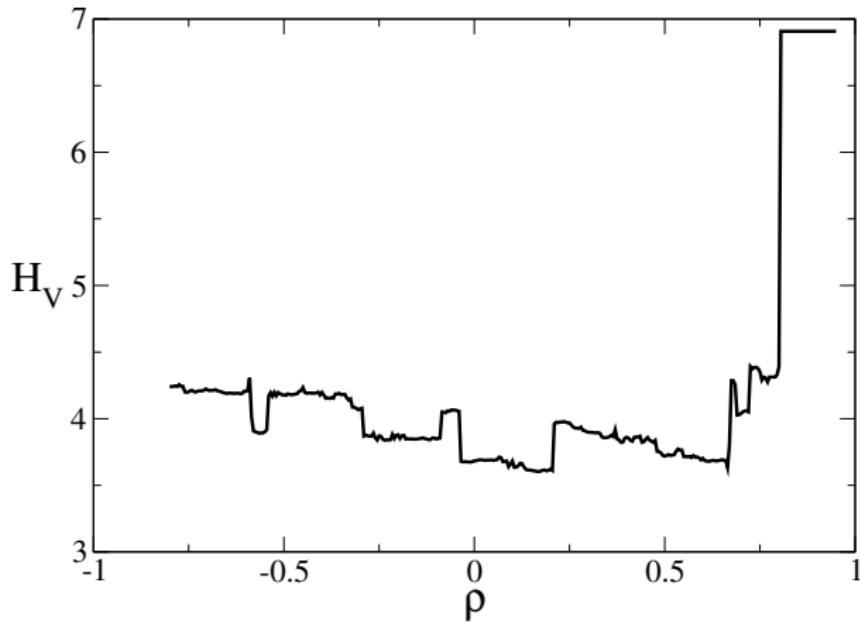
$$A = \sqrt{\sum_i (u_i - \bar{u})^2 + (v_i - \bar{v})^2}$$

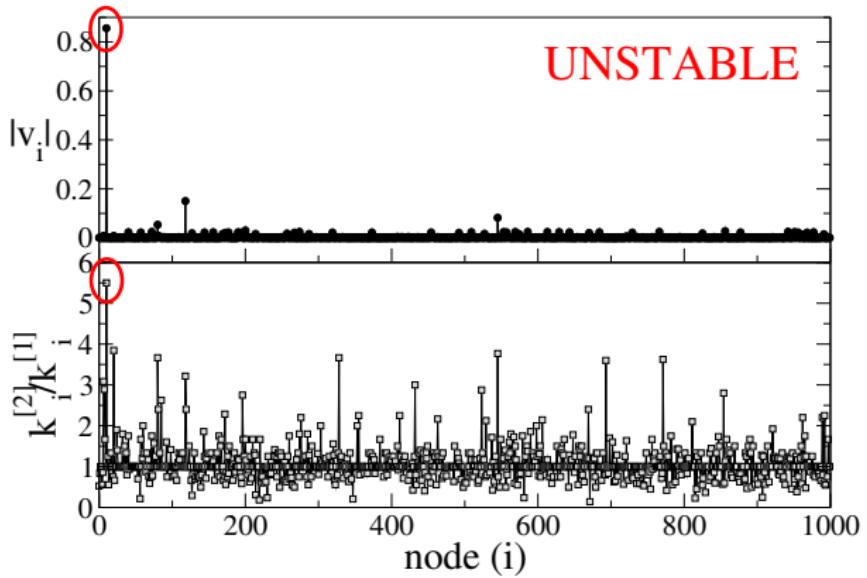
# What if we tune inter-layer correlations?

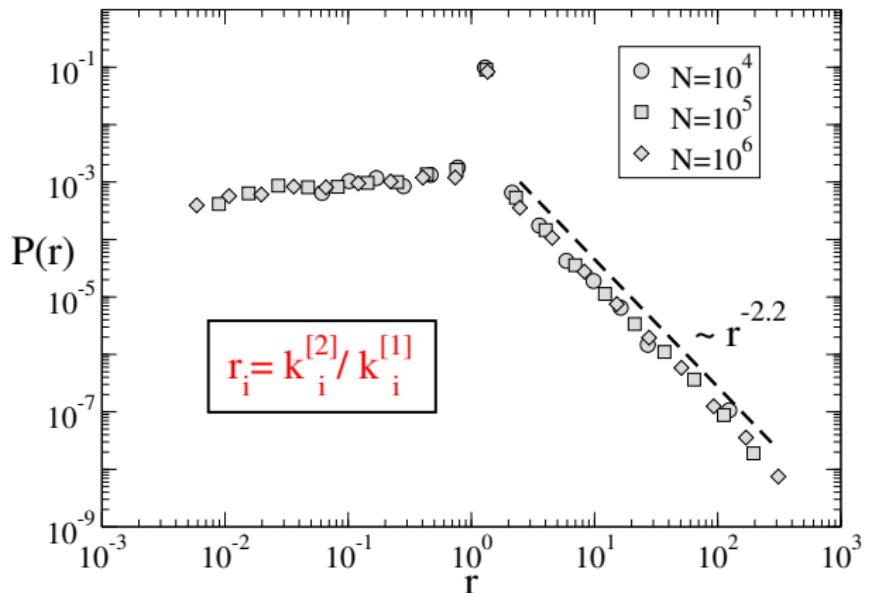
$$\rho_{\alpha,\beta} = \frac{\sum_i \left( R_i^{[\alpha]} - \overline{R^{[\alpha]}} \right) \left( R_i^{[\beta]} - \overline{R^{[\beta]}} \right)}{\sqrt{\sum_i \left( R_i^{[\alpha]} - \overline{R^{[\alpha]}} \right)^2 \sum_j \left( R_j^{[\beta]} - \overline{R^{[\beta]}} \right)^2}}$$







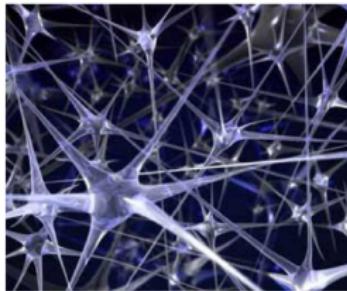




# SYNCHRONISATION

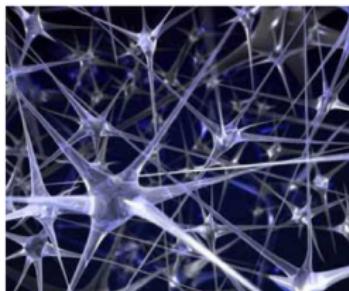
# The "multiplex" brain

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**Neurons  
(Activity)**

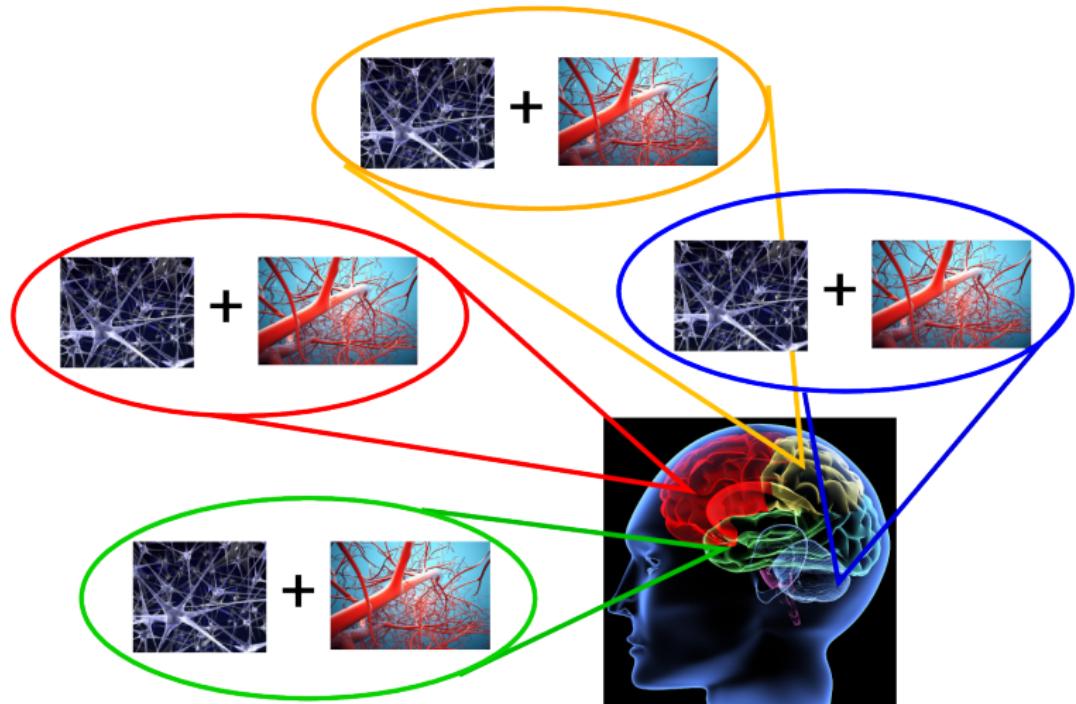
# The "multiplex" brain

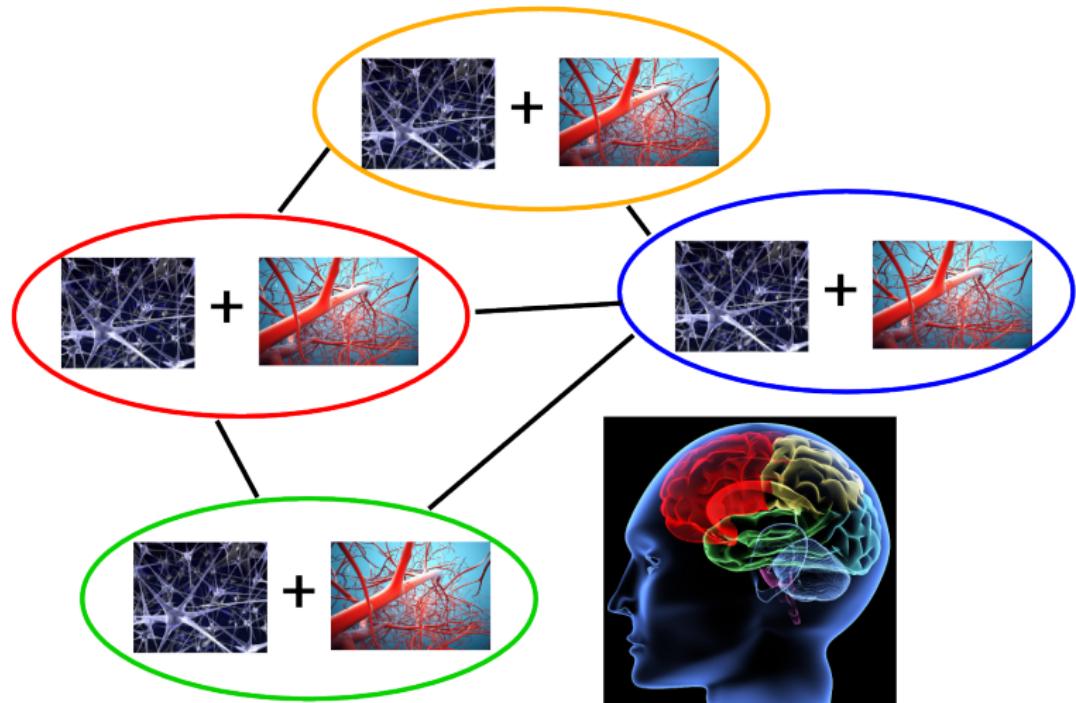


**Neurons**  
**(Activity)**

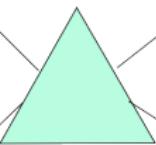
**Blood vessels**  
**(Energy)**



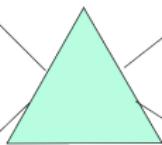






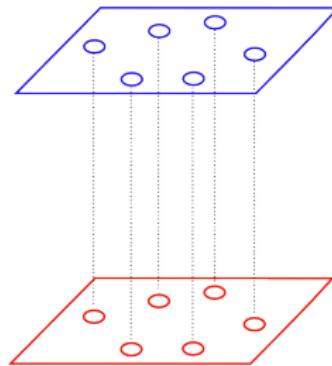


# Multiplex Prism



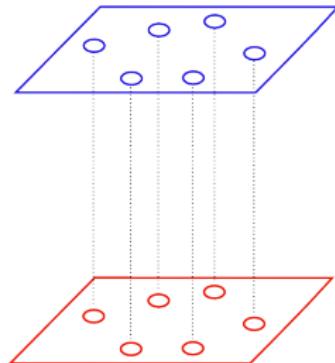
## Multiplex Prism

Activity



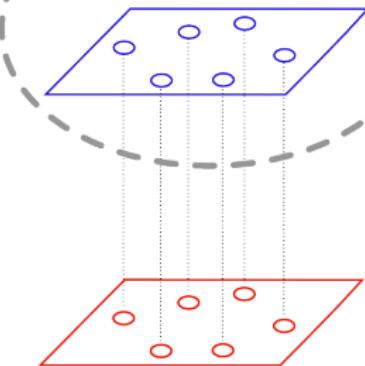
Energy  
transport

# Activity



**Energy  
transport**

**Activity**

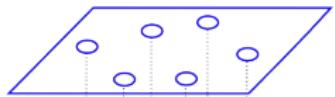


**Kuramoto Dynamics**

$$\dot{\varphi}_i(t) = \omega_i + \lambda \sum_j a_{ij} \sin(\varphi_j - \varphi_i)$$

**Energy  
transport**

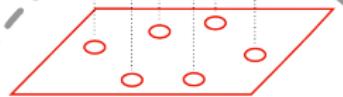
## Activity



## Kuramoto Dynamics

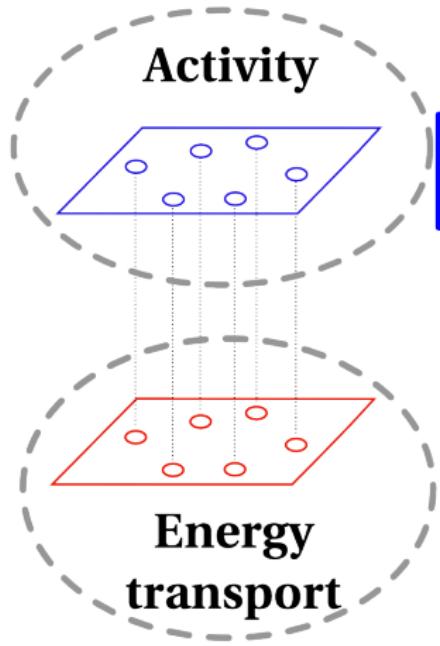
$$\dot{\varphi}_i(t) = \omega_i + \lambda \sum_j a_{ij} \sin(\varphi_j - \varphi_i)$$

## Energy transport



$$p_{i \rightarrow j} \propto e_{ij} f_j$$

## Biased Random Walk



## Kuramoto Dynamics

$$\dot{\varphi}_i(t) = \omega_i + \lambda \sum_j a_{ij} \sin(\varphi_j - \varphi_i)$$



$$p_{i \rightarrow j} \propto e_{ij} f_j$$

## Biased Random Walk

$$\dot{\varphi}_i(t) = \omega_i + \lambda \sum_j a_{ij} \sin(\varphi_j - \varphi_i)$$

(more energy-> higher frequency)

$$\omega_i \propto p_i$$

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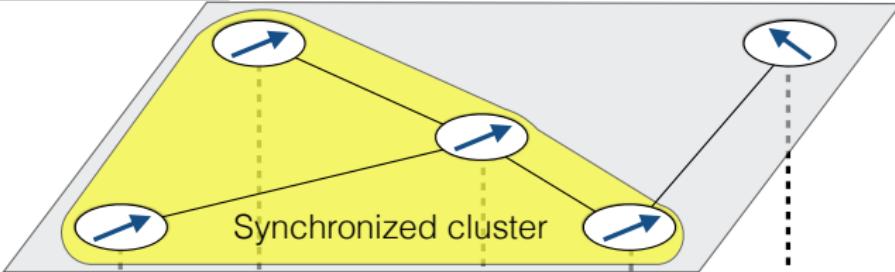
$$\omega_i \propto p_i$$

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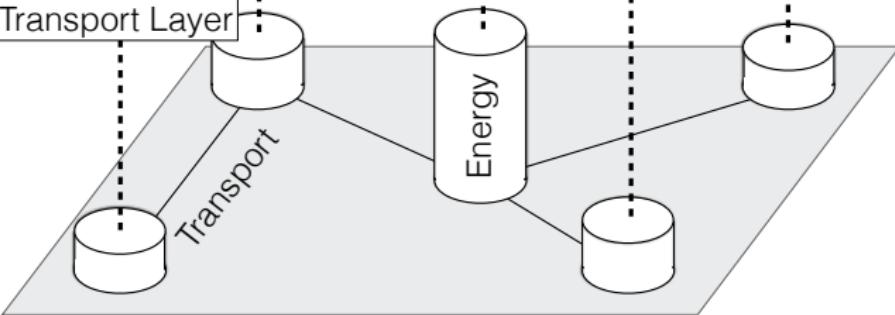
(More synapses -> more blood)

$$f_j = k_j^\alpha$$

## Synchronization Layer



## Energy Transport Layer



## Kuramoto Dynamics

$$\dot{\varphi}_i(t) = \omega_i + \lambda \sum_j a_{ij} \sin(\varphi_j - \varphi_i)$$

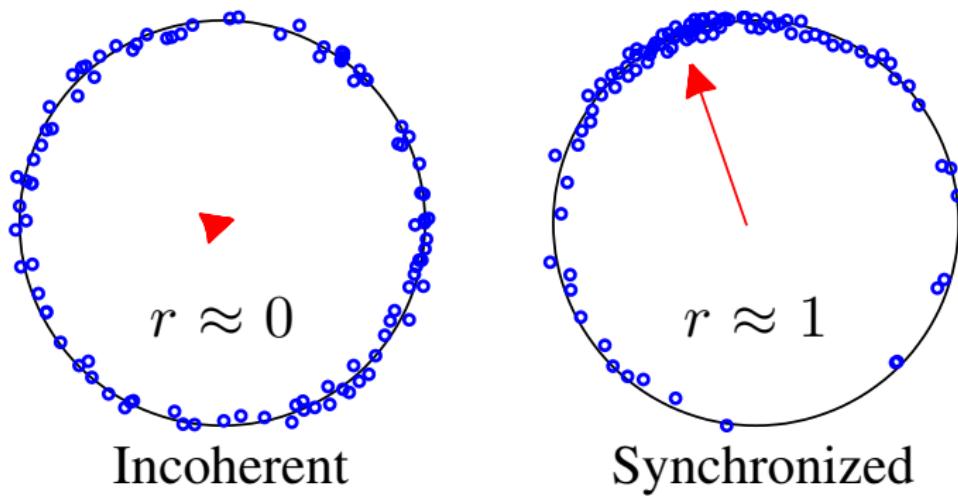
## Biased Random Walk

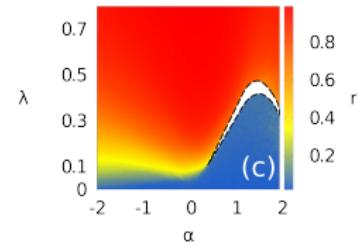
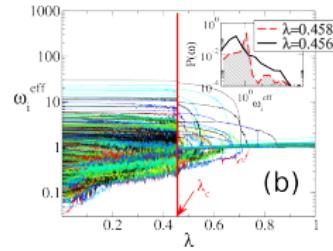
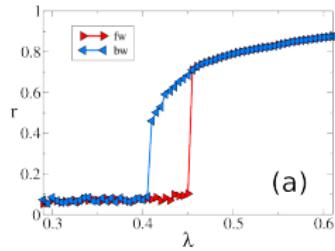
$$p_{i \rightarrow j} \propto e_{ij} f_j$$

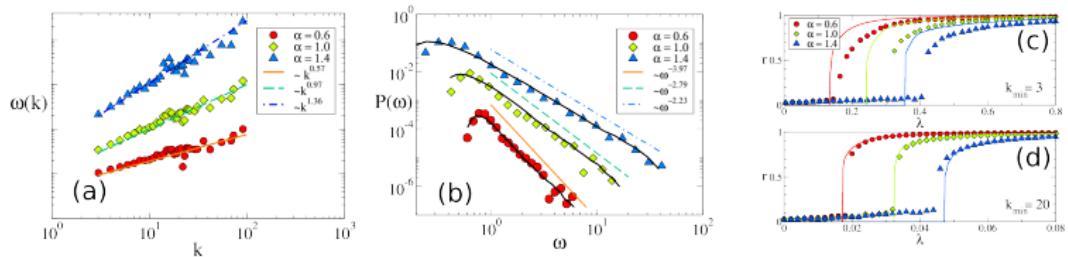
**Node state:**  $(\varphi_i, p_i)$

$\varphi_i$  **phase (activity)**

$p_i$  **fraction of walkers (energy)**







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- **SOMETIMES** multiplex dynamics behave **IN A DIFFERENT WAY** w.r.t. their "monoplex" counterparts
- **SOME** dynamical processes are **BETTER UNDERSTOOD** and studied as multiplex ones
- **IN SOME CASES** multiplex dynamics exhibit original new physics, which is **GENUINELY (due to the) MULTIPLEX**

# References

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