

# Voter model, opinion diffusion and mobility networks

***MAXI SAN MIGUEL***



**JUAN  
FERNANDEZ-  
GRACIA**



**KRZYSZTOF  
SUCHECKI**

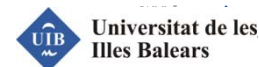


**JOSE J.  
RAMASCO**

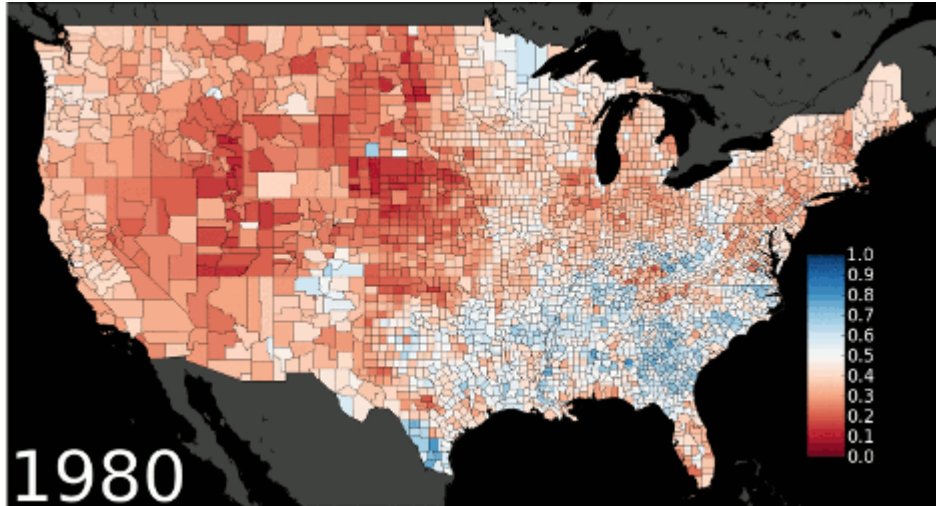


**VICTOR  
M. EGUILUZ**

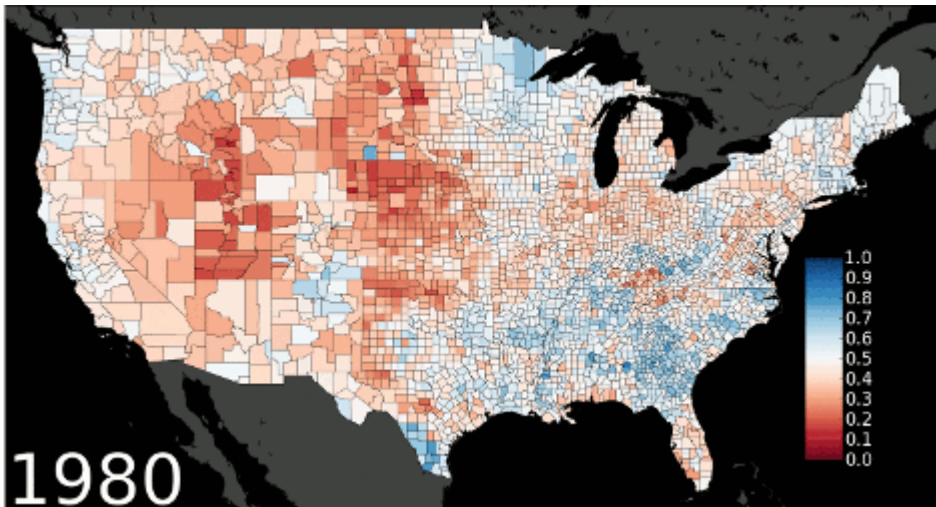
 **IFISC**



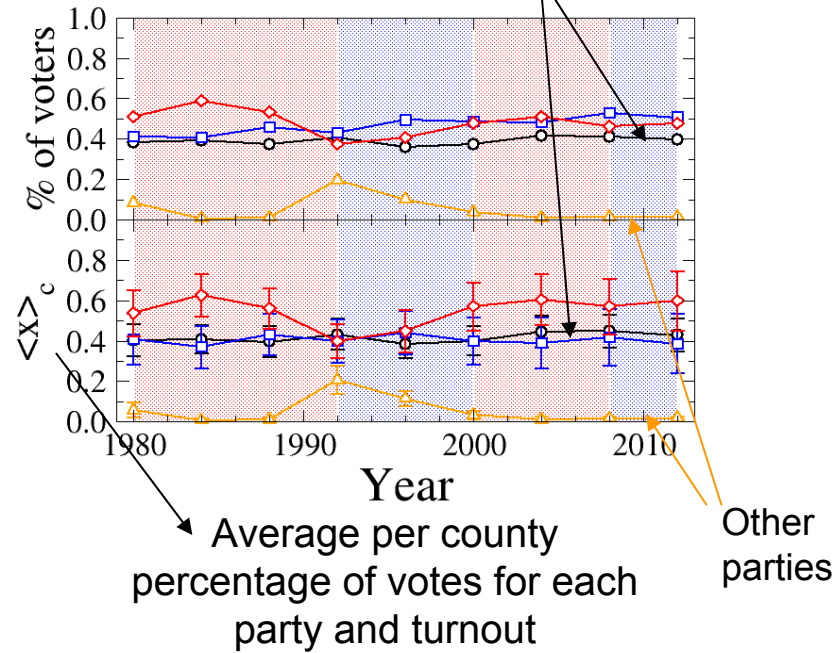
Evolution of democrat shares



Evolution of republican shares



Global percentage of votes for each party and turnout

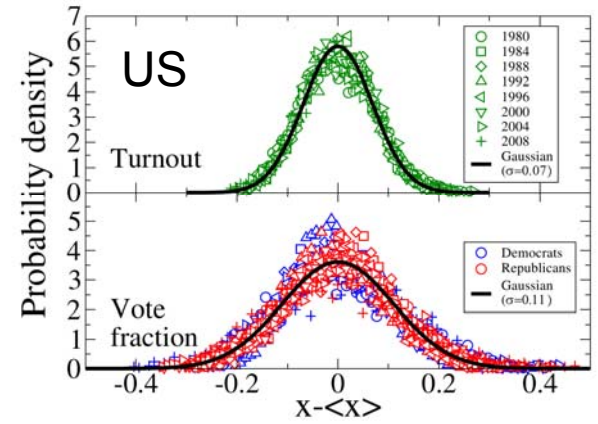
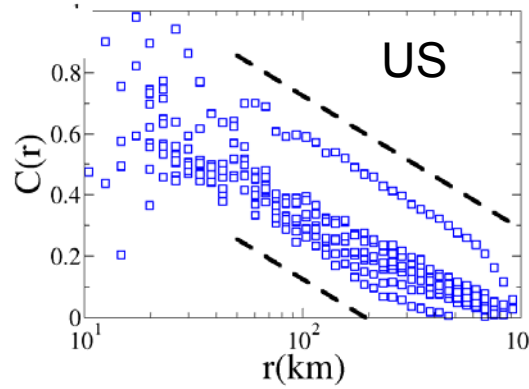
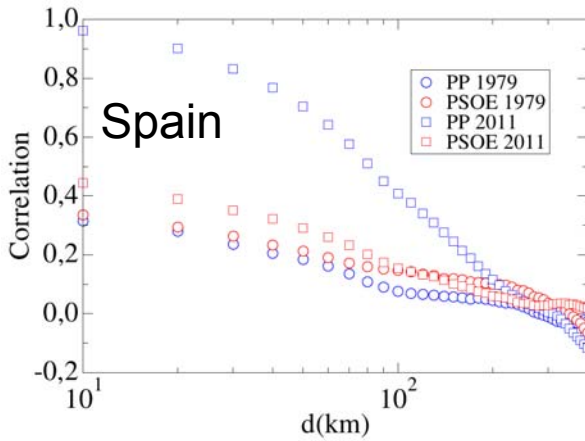


Basically two option system

Blue: Democrat

Red: Republican

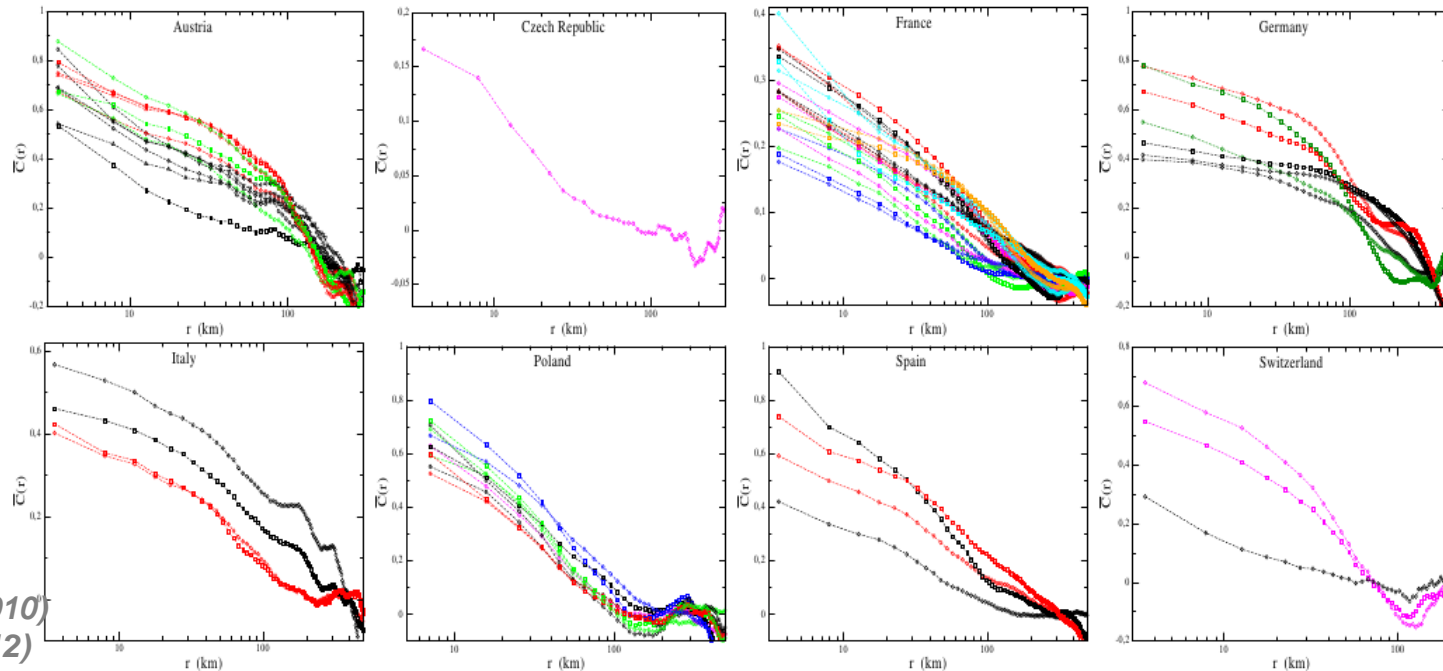
## Irrespective of the winner!



**IBM**  
**Diffusive model?**

**SPATIAL**  
**CORRELATIONS**

$\sim \log$  decay



*C. Borghesi et al.*  
*Eur. Phys. J. B 75, 395-404 (2010)*  
*PLoS ONE 7(5):e36289,05 (2012)*

Ingredients of a social influence model:

a) **Interaction mechanism:** Imitation as basic manifestation of social influence.

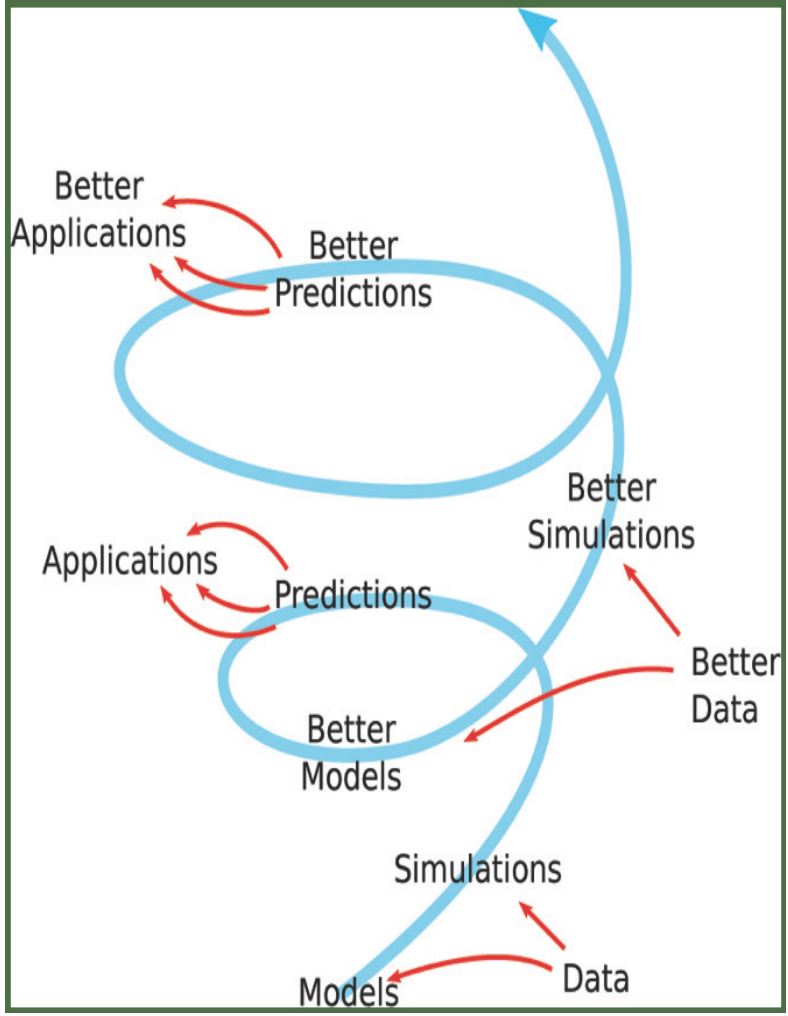


THEORY

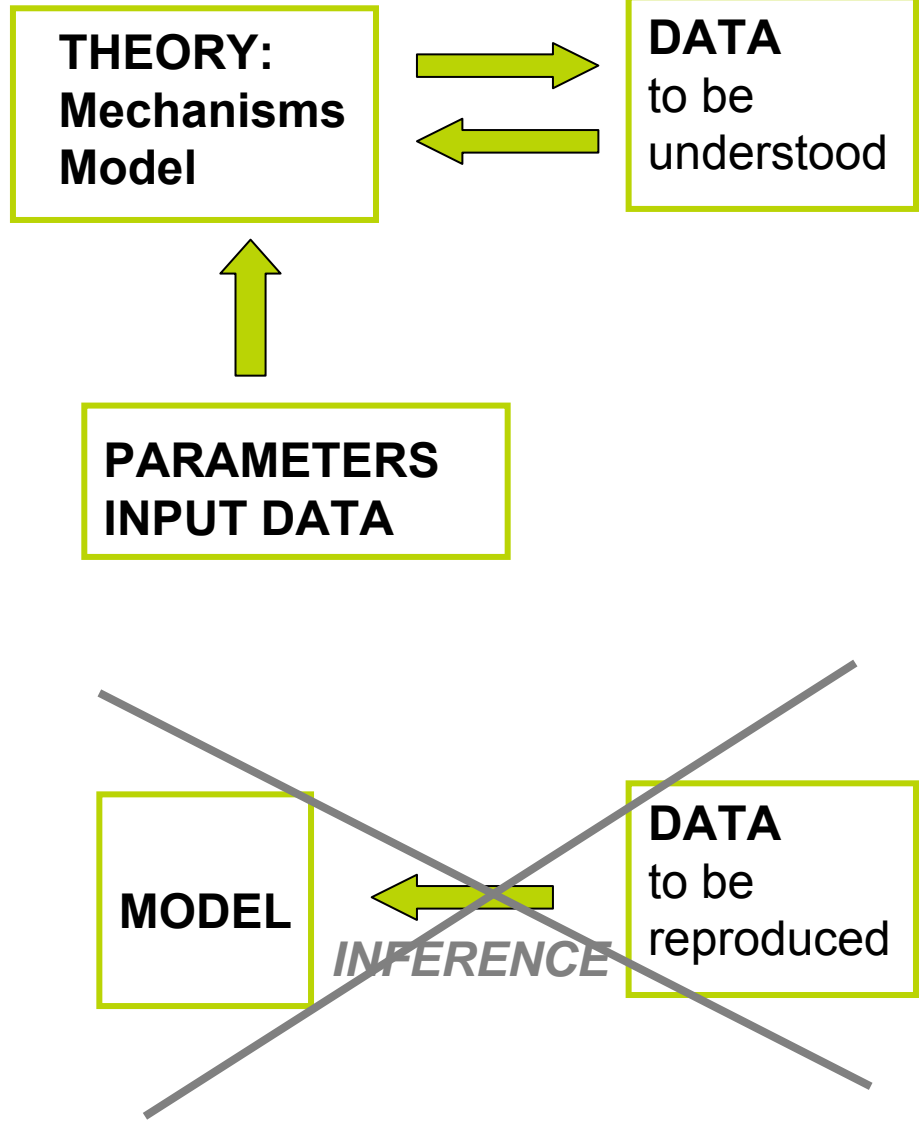
MODELLING

b) **Social context:** Set of all possible interactions of an individual with any other peer. We model it as a network of interactions from census data for population and mobility.

INPUT DATA



## MODELS and DATA



Ingredients of a social influence model:

a) Interaction mechanism: Imitation as basic manifestation of social influence.



**THEORY**

**MODELLING**

*What can we learn from models of simple social behavior?*

*Reaching agreement by imitation?*

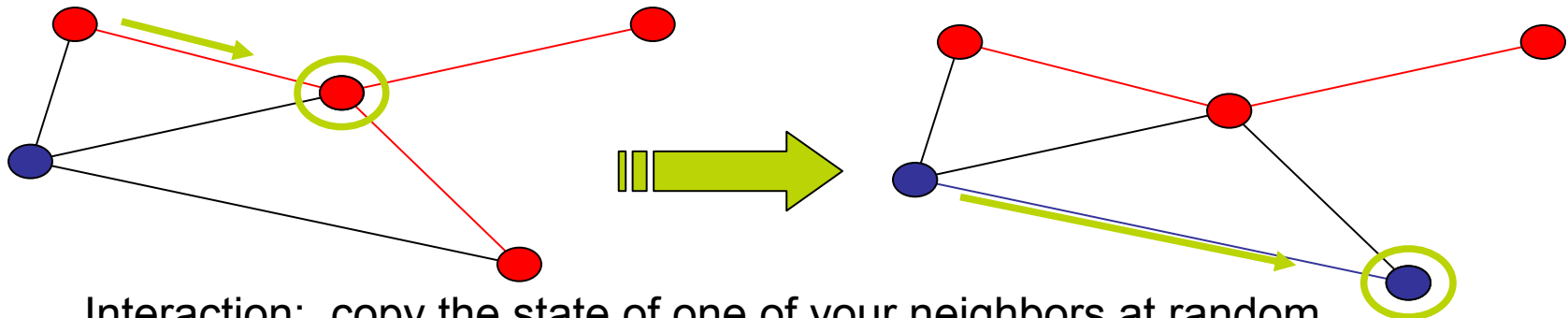




Herding Behavior

## Voter model (Ann Prob. 1975)

Two options: ● ●



Interaction: copy the state of one of your neighbors at random

$\sigma_i = \pm 1$   $\longrightarrow$  Value of the state at site  $i$ .

$k_i$  degree

$$\langle \dot{\sigma}_i \rangle = \frac{1}{k_i} \sum_j L_{ij} \langle \sigma_j \rangle$$

$$\sum_j L_{ij} = 0$$

Laplacian matrix

$a_{ij}$  adjacency

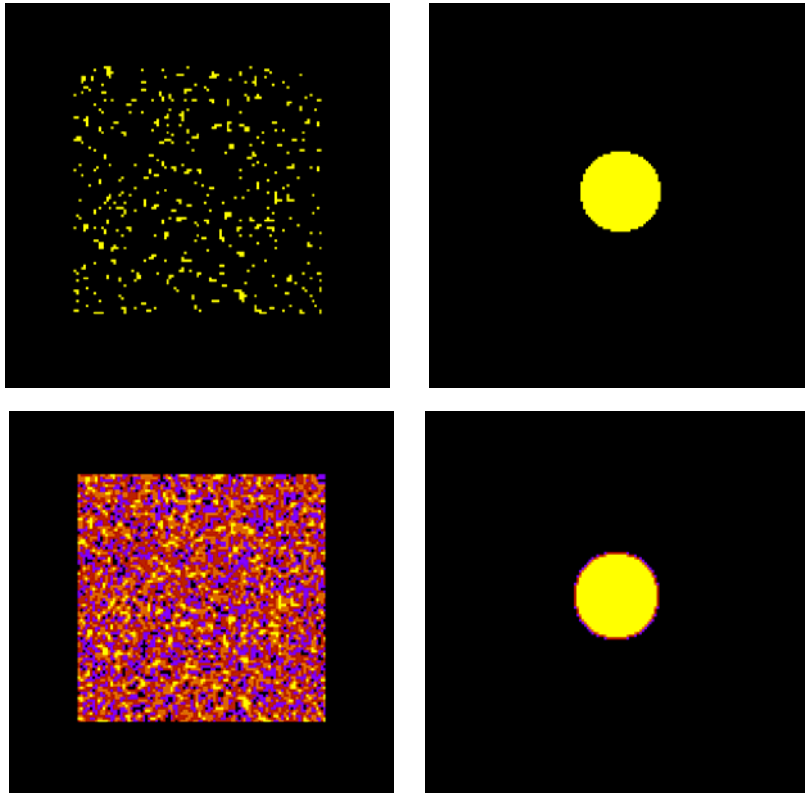
$$L_{ij} = a_{ij} - k_i \delta_{ij}$$

$$\frac{d}{dt} \frac{\sum_i k_i \langle \sigma_i \rangle}{\sum_i k_i} = 0$$

Conserved quantity:

Ensemble average weighted magnetization

*Klemm et al, Sci. Rep. 2, 292 (2012)*



For a noisy diffusive model, spatial correlations decay logarithmically in 2d.

$$\dot{\psi} = \nabla^2 \psi + \eta$$

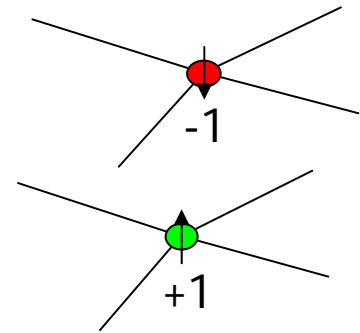
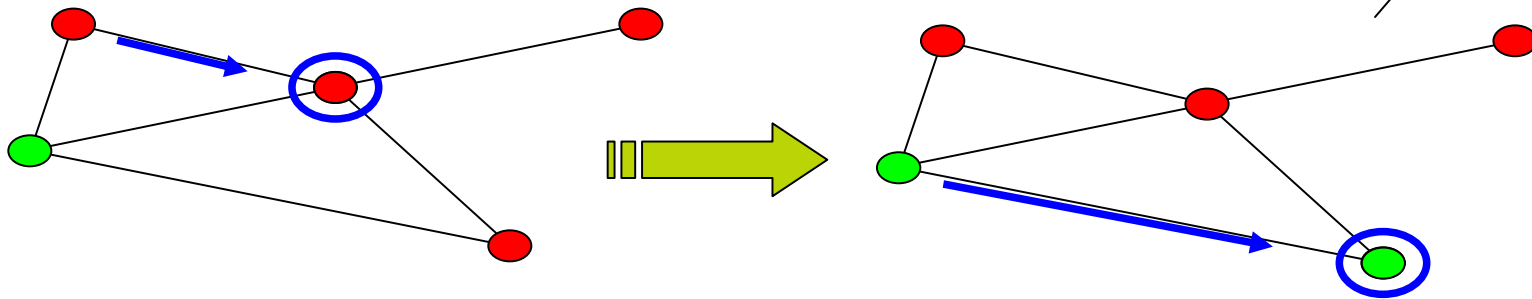
$$\Rightarrow \langle \psi(\vec{r}) \psi(\vec{r}') \rangle \xrightarrow{d=2} a - b \ln(|\vec{r} - \vec{r}'|)$$

$\eta$   $\longrightarrow$  Uncorrelated gaussian white noise.

Spatial correlation and average over realizations do not commute

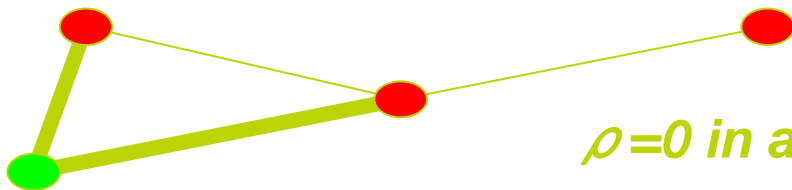


- “Voters” located in the nodes of a network have “opinions”  $\sigma_i=1$  or  $\sigma_i=-1$ .
- **A randomly chosen voter takes the opinion of one of its neighbors chosen at random**



*Question: When and how one of the two absorbing states (**agreement or consensus**) is reached by imitation dynamics?*

Order Parameter: Average interface density



$\rho=0$  in absorbing state

Interface: a link connecting nodes with different states.

$$\rho = \frac{1}{2N \langle k \rangle} \left( \sum_{i=1}^N \sum_j (1 - \sigma_i \sigma_j) \right)$$

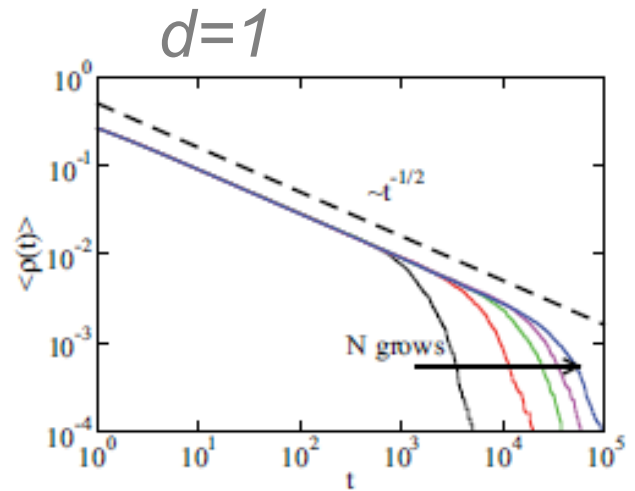


# Voter Model in regular networks

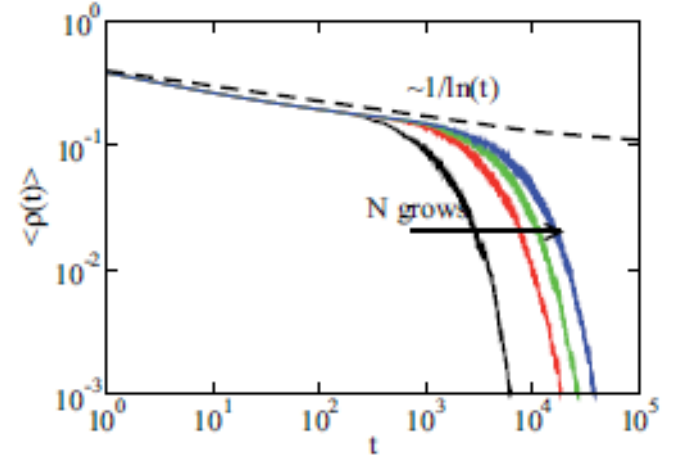
$$\langle \rho \rangle \sim \begin{cases} t^{-1/2}, & d = 1 \\ (\ln t)^{-1}, & d = 2 \\ \xi - bt^{-d/2}, & d > 2 \end{cases} \quad \tau \sim \begin{cases} N^2, & d = 1, \text{ time to reach absorbing state} \\ N \ln N, & d = 2, \text{ time to reach absorbing state} \\ N, & d > 2, \text{ survival time of metastable state} \end{cases}$$

## d=1,2: Coarsening/Ordering

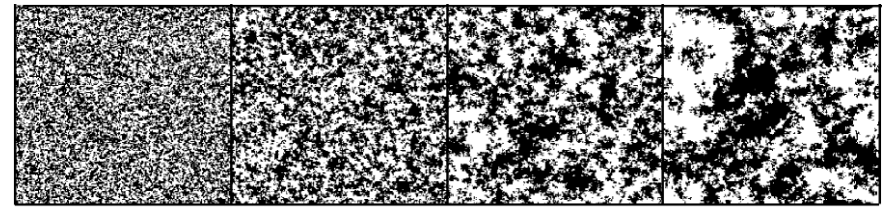
Unbounded growth of domains of absorbing states



d=2



Coarsening driven by interfacial noise



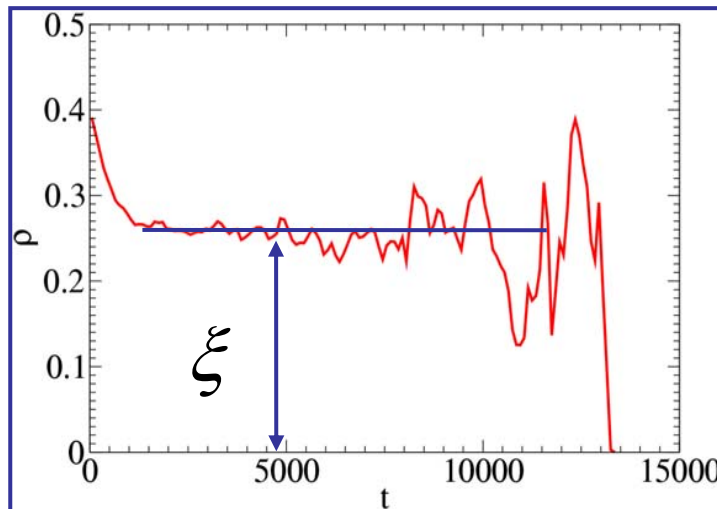
## d>2 regular and complex networks

$$\langle \rho \rangle \sim \xi$$

$\tau(N) \approx N$ , survival time of metastable state

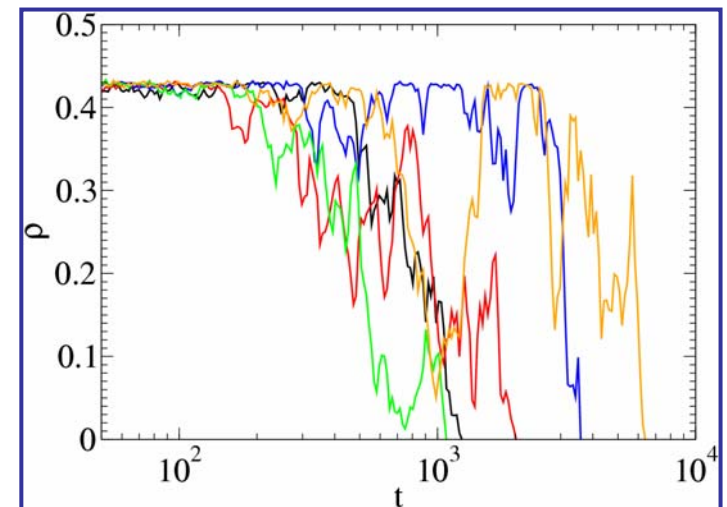
### *d>2: No Coarsening : Dynamical Metastability*

Disordered states.



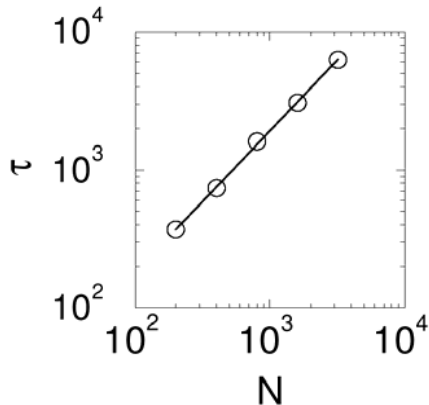
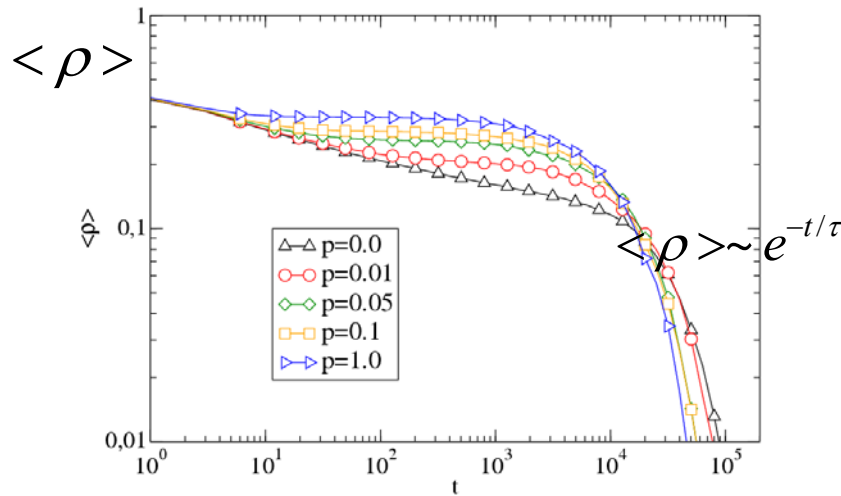
$l = \xi^{-1}$  Characteristic size of ordered domain

Finite size fluctuations take the system to an absorbing state



$$\langle \rho \rangle \sim e^{-t/\tau}$$

## Small World Networks

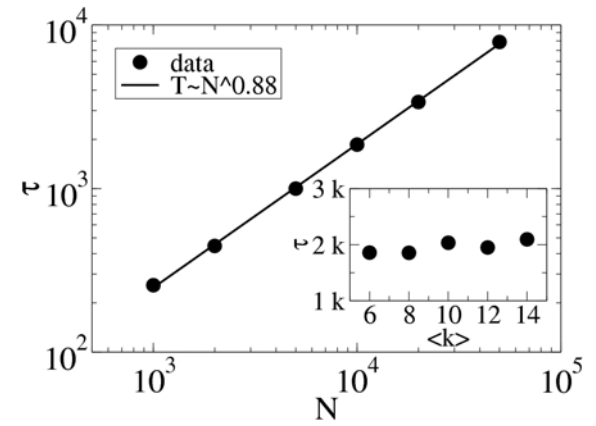
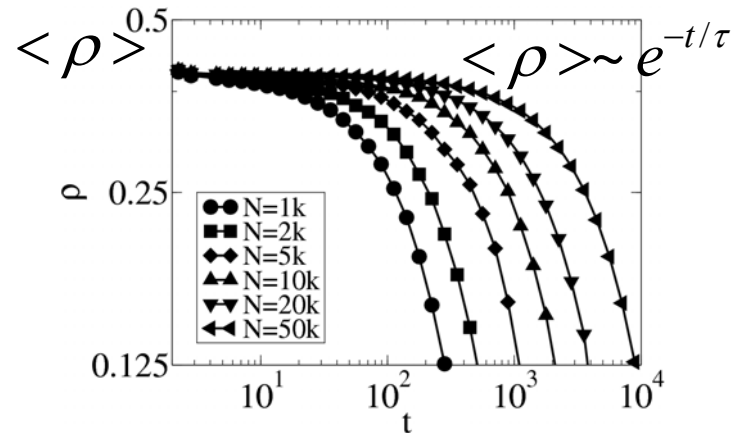


Survival time scales as in regular  $d > 2$ :

$$\tau \sim N$$

Castellano et al, Eur. Phys. Lett. 63,153(2003)

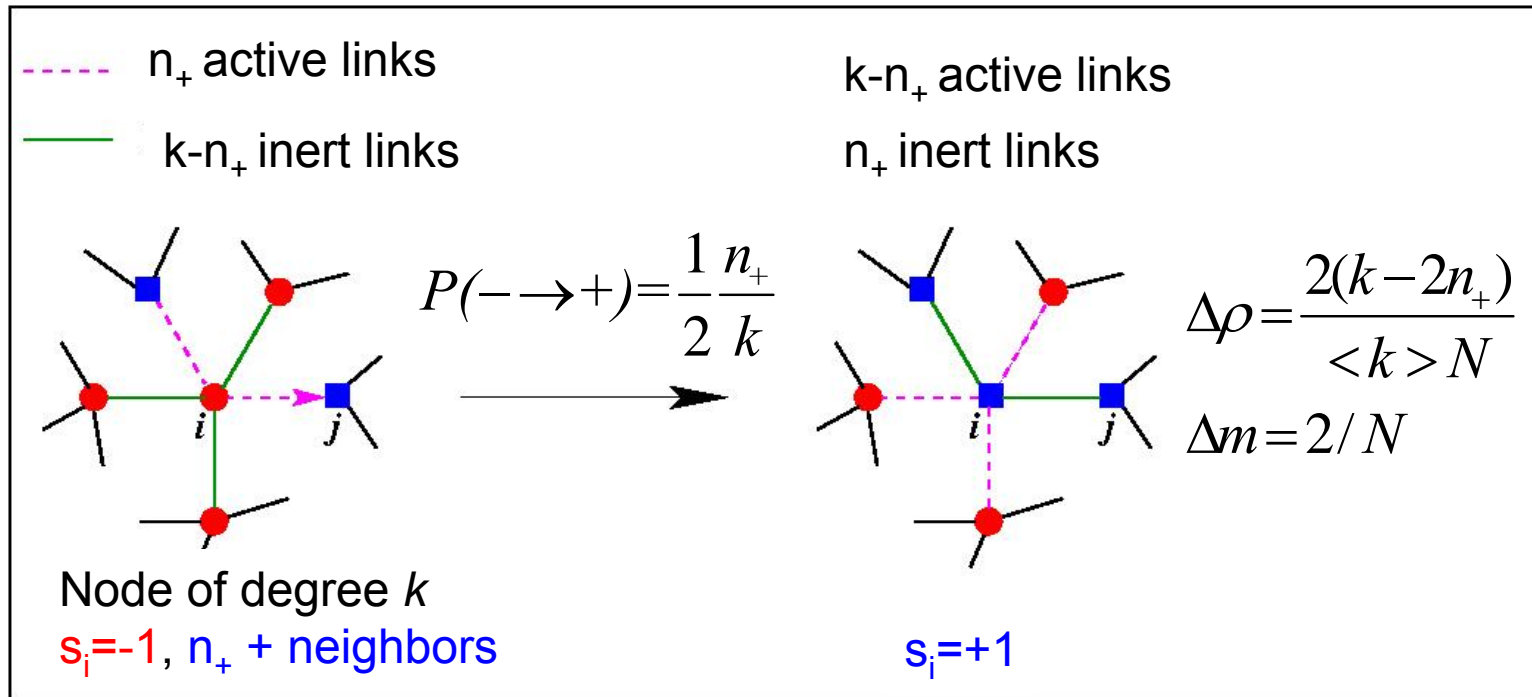
## Scale Free Barabasi-Albert Nets



$$\tau \sim N/\ln N$$

SucHECKI et al, Eur. Phys. Lett. 69,228(2005)

## UNCORRELATED NETWORKS



Coupled eqs. for  $\langle m \rangle$  and  $\langle \rho \rangle$

Mean field link approx. for  $Prob(k, -, n_+)$ :

Neglect 2nd nearest-neighbor correlations

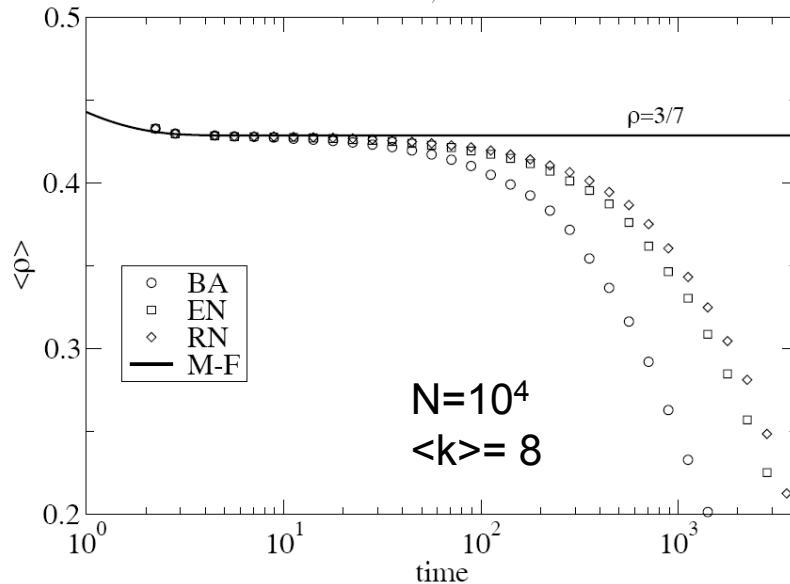


## Mean Field Link Dynamics:

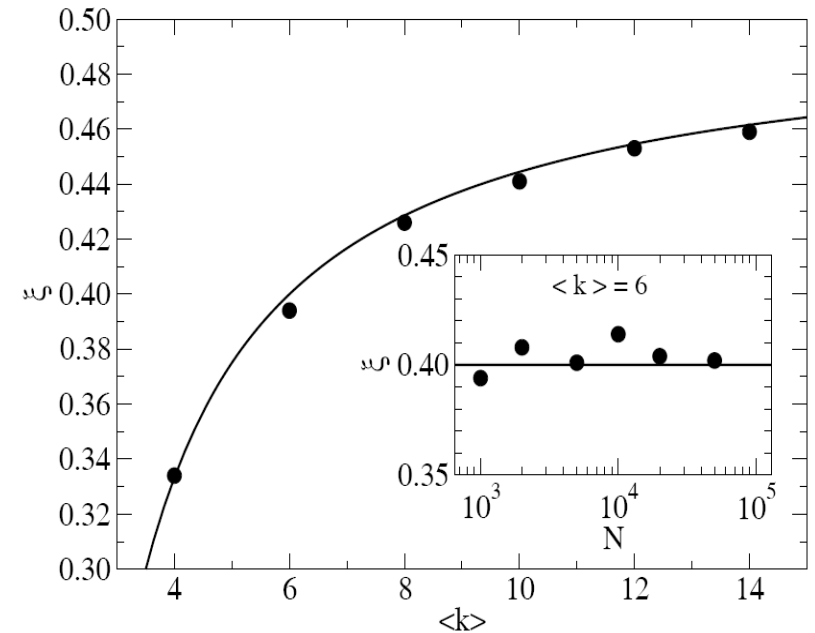
$$\rho^s = \xi = \frac{\langle k \rangle - 2}{2(\langle k \rangle - 1)}$$

Single parameter theory

### Network topology independence



### Barabasi-Albert Scale Free Networks

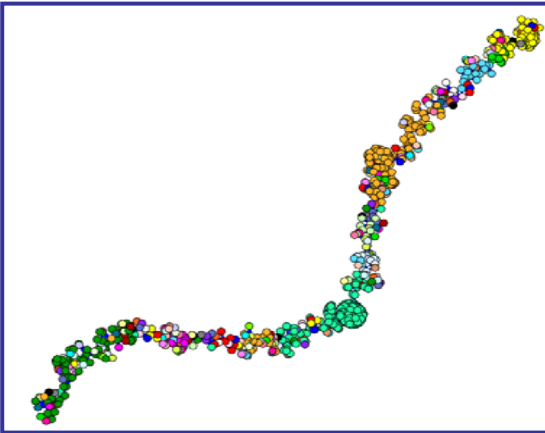


## Role of dimensionality

1D Scale free net?

Structured SF: **SSF**

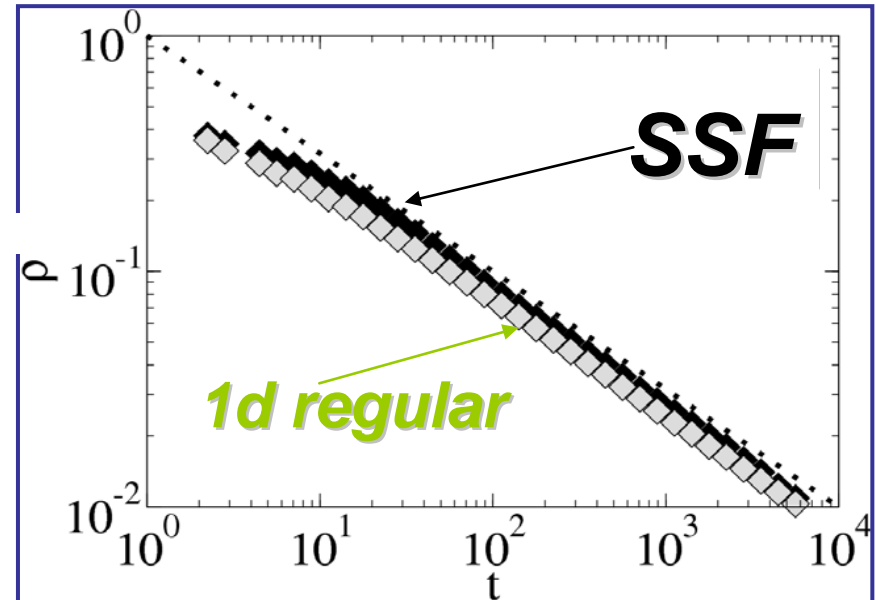
*Klemm and Eguíluz,*  
*Phys. Rev. E 65,036123 (2002)*



Scale free but  
high clustering and 1d

$$P(k) \sim k^{-3}$$

$$L \sim N \quad C \sim N^0$$



$$\text{SSF} \quad \rho \gtrsim t^{-1/2}$$

$$\tau_1 \approx N^2$$

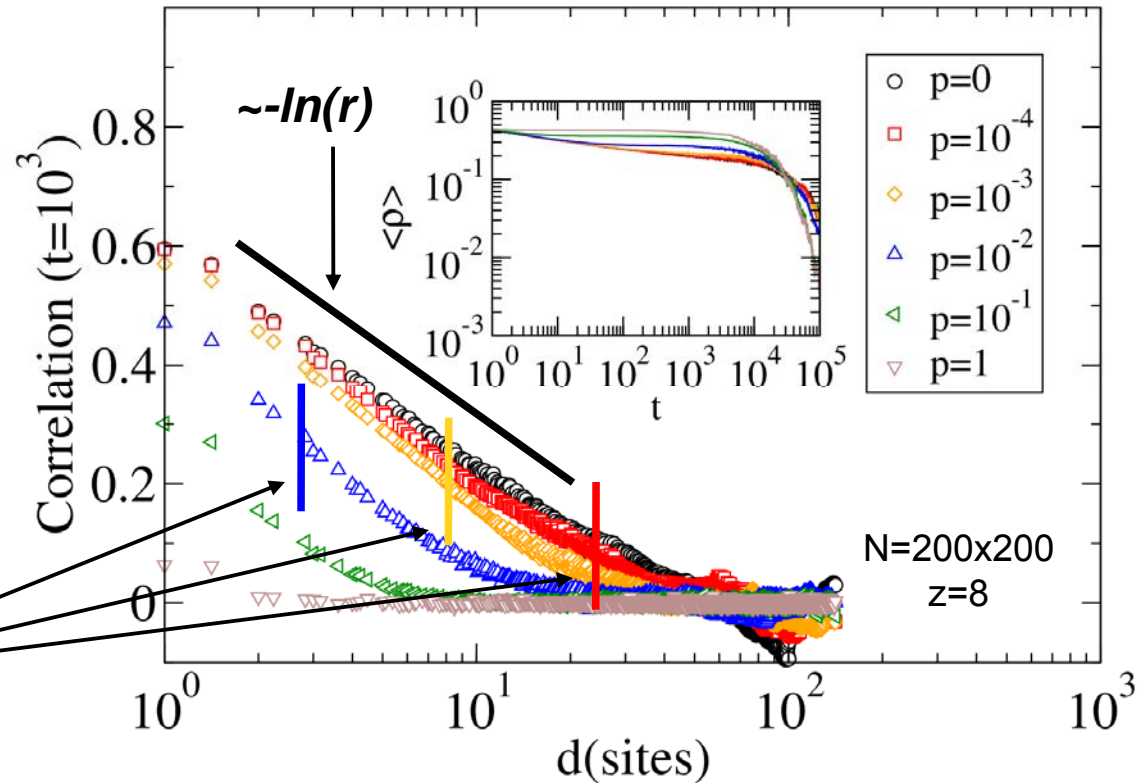
**Dimensionality** determines when voter  
dynamics orders the system

**Degree distribution or network disorder**  
are not relevant

## 2d Small World Network

A small world network in 2d is locally a 2d network.

$$r_{max}(p) = \frac{1}{\sqrt{\frac{z}{2}\pi p}}$$



**Small-world topology destroys correlations.**

**Logarithmic scaling observed only locally .**

## REACHING AGREEMENT BY IMITATION?



\* Role of topology of interactions (tie heterogeneity)

\* Coevolution (non persistent ties):

Imitating neighbors vs Choosing neighbors

*F. Vazquez, et. al, Phys. Rev. Lett. 100, 108702 (2008)*

\* Heterogeneity in the timing of interactions

*J. Fernández-Gracia, et al. Phys. Rev. E 84, 015103 (2011)*

\* Imitation vs Rational Behavior

*D. Vilone, et al. Sci. Rep. 2, 686 (2012)*

Ingredients of a social influence model:

a) Interaction mechanism: Imitation as basic manifestation of social influence.



**THEORY**

**MODELLING**

b) Social context: Set of all possible interactions of an individual with any other peer. We model it as a network of interactions from census data for population and mobility.

**INPUT DATA**



## US: geographical adjacency of populations

Undirected,  
unweighted  
network.

$$N=3114$$

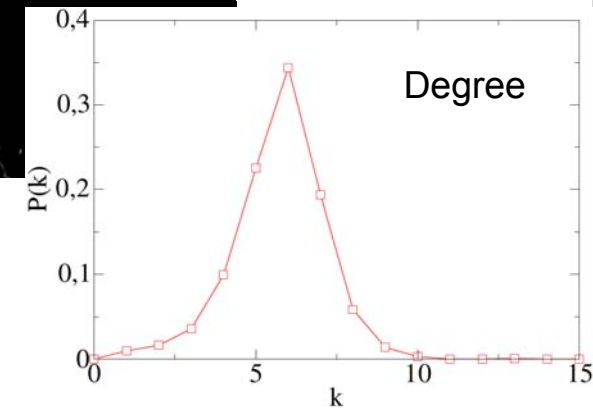
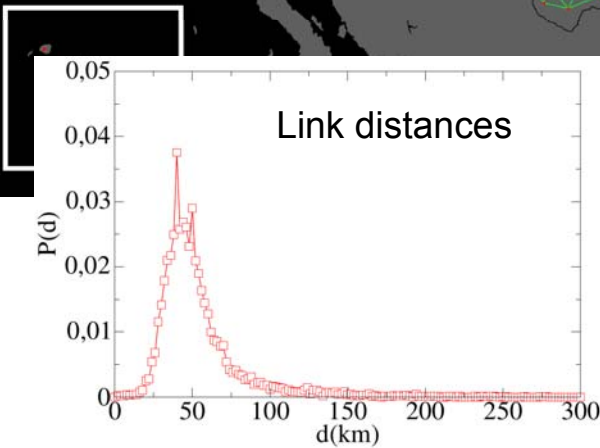
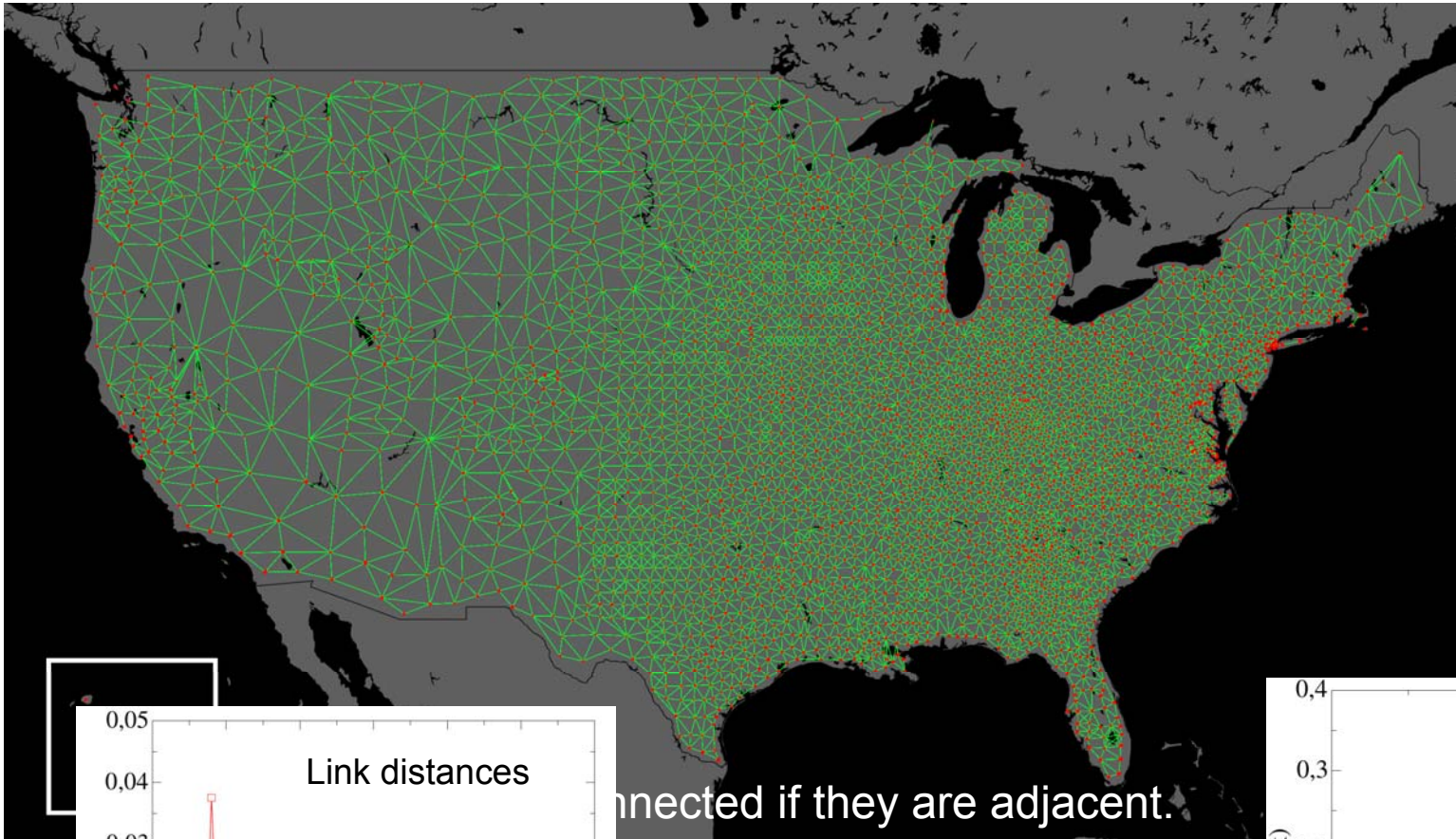
$$\langle k \rangle \sim 6$$

$$\langle C \rangle = 0.431$$

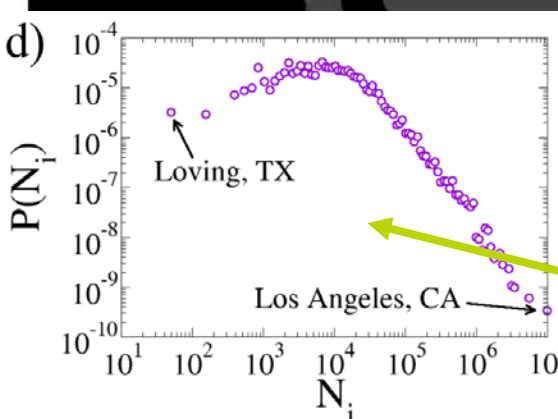
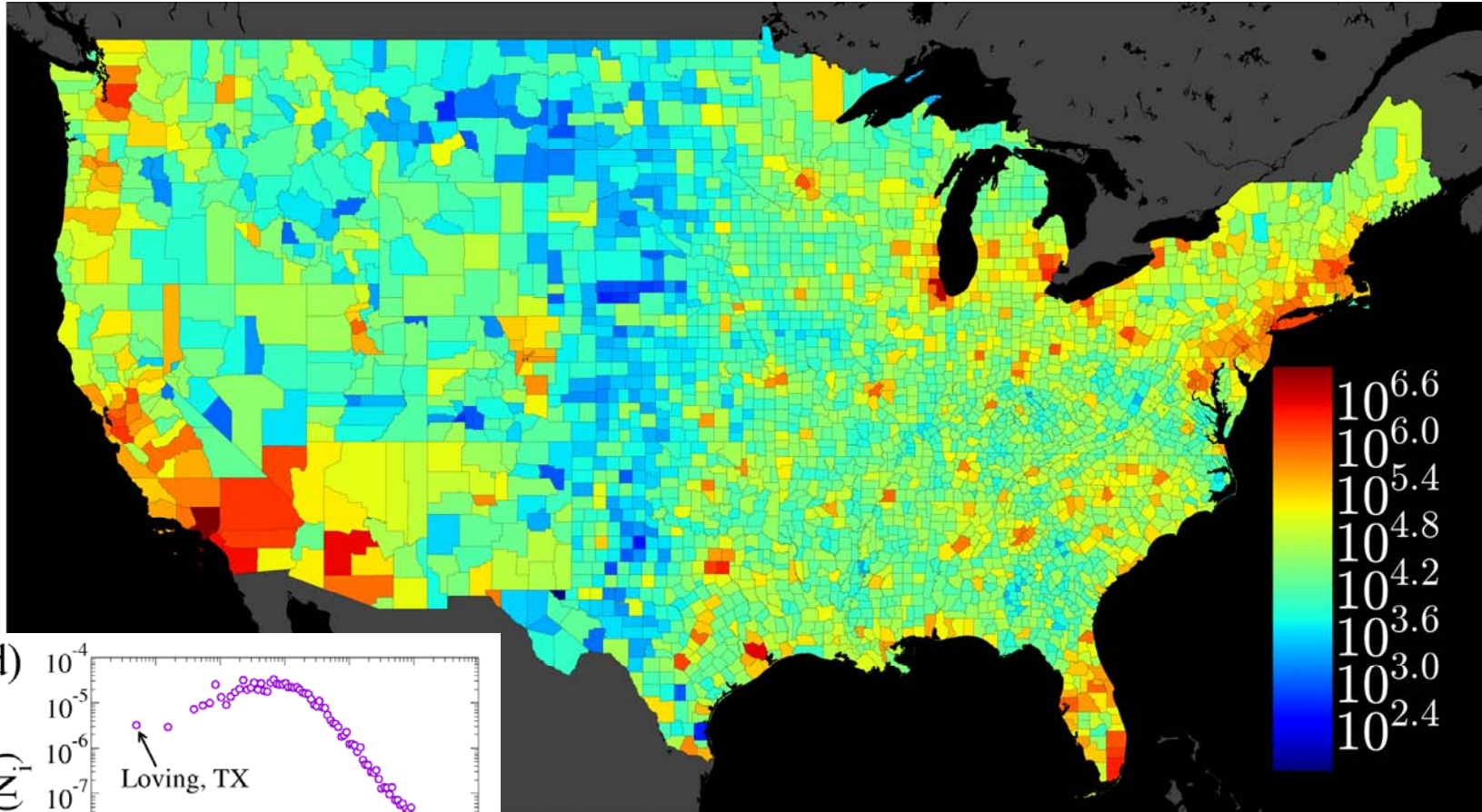
$$\langle L \rangle = 26.86$$

$$\langle C \rangle_{\text{Hex}} = 0.4$$

$$\langle L \rangle_{\text{Hex}} = 22.15$$



## US: Heterogeneous population distribution

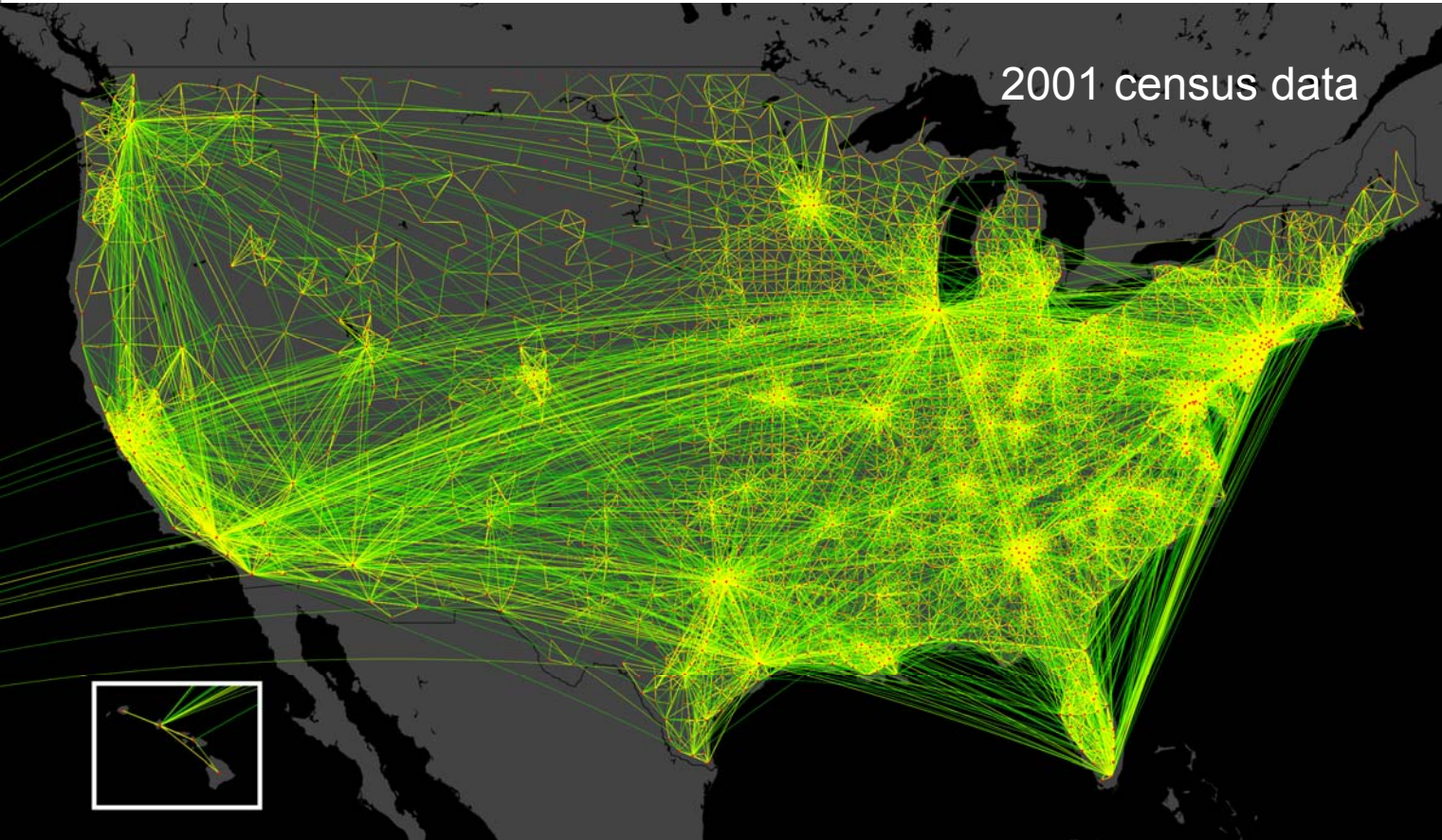


Populations



## US: commuter network for human mobility

Directed, weighted network.



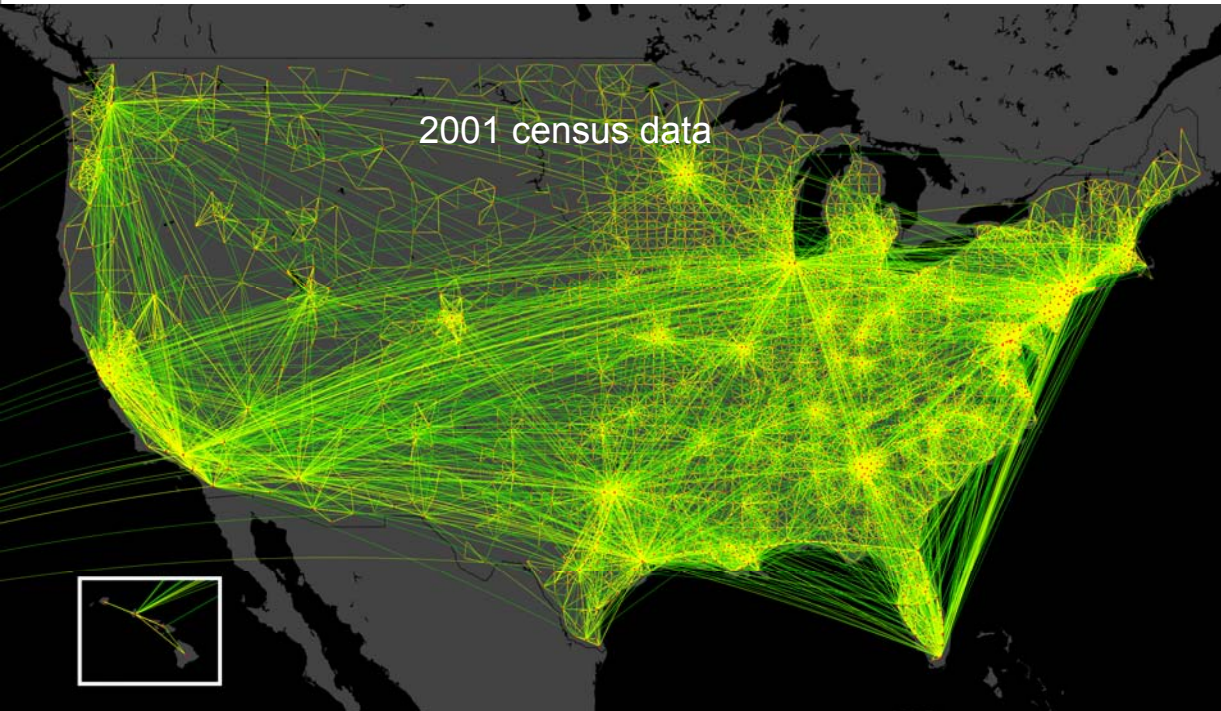
$N=3114$   
 $\langle k \rangle \sim 50$

$\langle C \rangle = 0.36$   
 $\langle L \rangle = 2.31$

For 10 independent randomizations of degree sequence:

$\langle C \rangle = 0.088$   
 $\langle L \rangle = 2.15$

Counties linked by fluxes of commuters. Color indicates number of commuters. 20% of all connections shown.



**US: commuter network for human mobility**

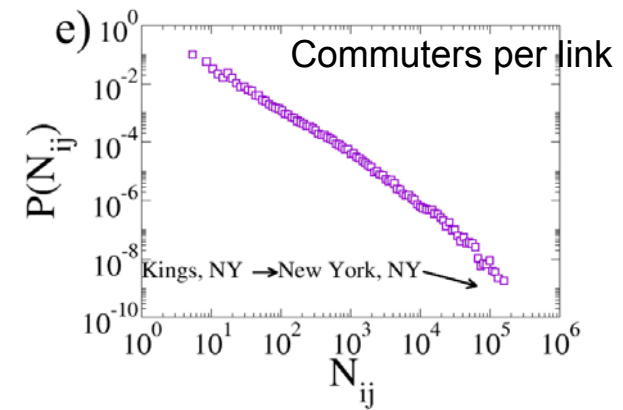
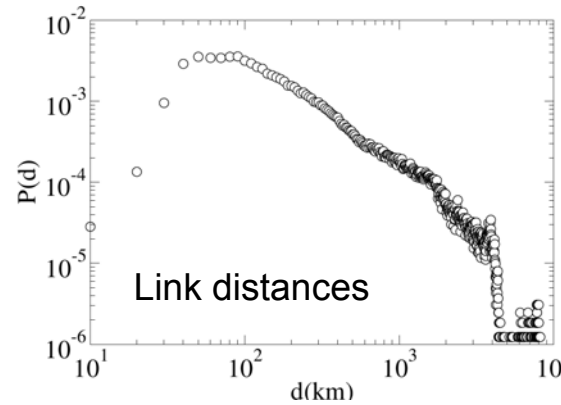
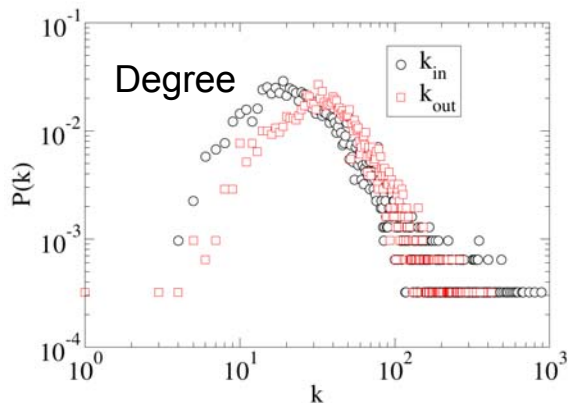
Directed, weighted network.

$N=3114$

$\langle k \rangle \sim 50$

Not a 2d network

**Heterogeneous network in many characteristics**

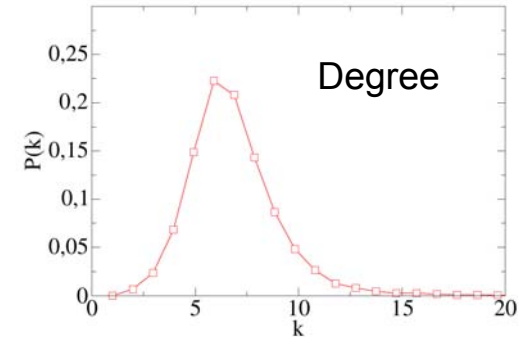




## Spain: geographical adjacency of populations

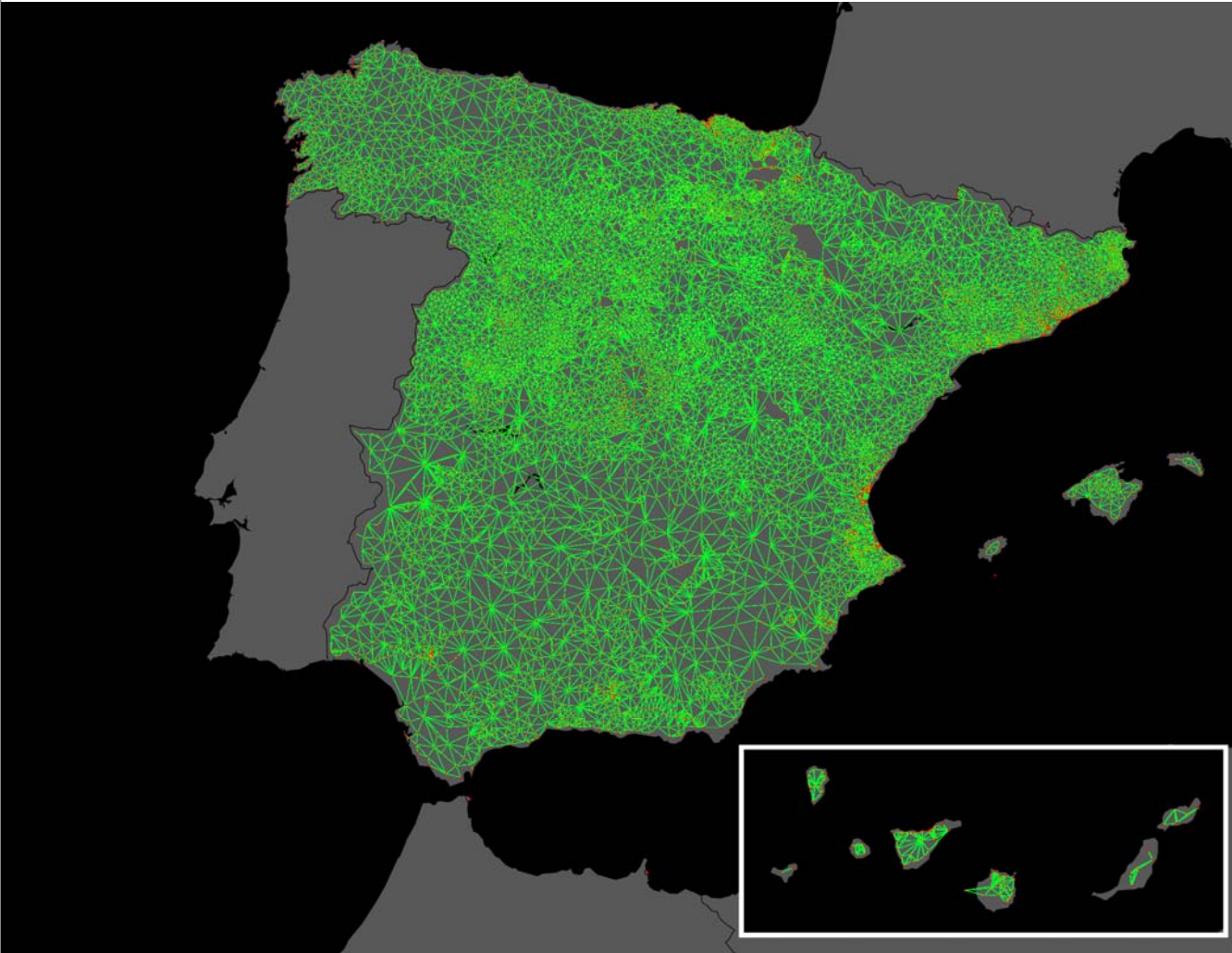
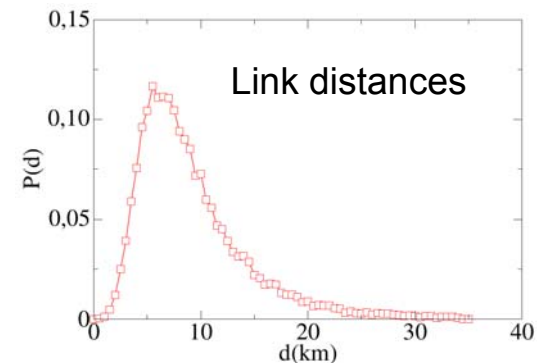
Undirected,  
unweighted network.

$N=8104$   $\langle k \rangle \sim 6$



$\langle C \rangle = 0.49$ ;  $\langle C \rangle_{Hex} = 0.4$

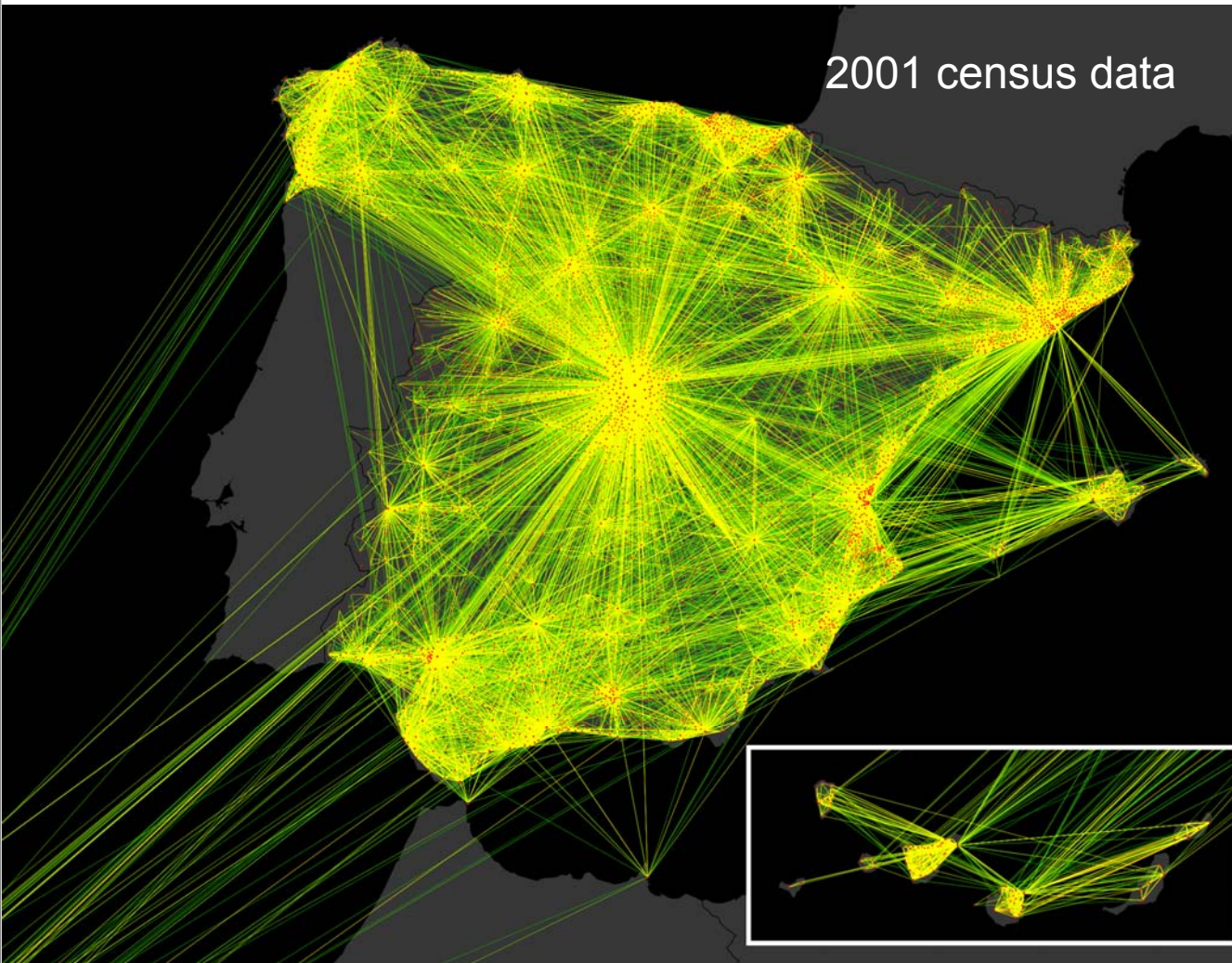
$\langle L \rangle = 25.79$ ;  $\langle L \rangle_{Hex} = 35.32$



Municipalities in Spain connected if they are adjacent.



## Spain: commuter network for human mobility



Directed, weighted network.

$N=8104$

$\langle k \rangle \sim 34$

$\langle C \rangle = 0.54$

$\langle L \rangle = 2.34$

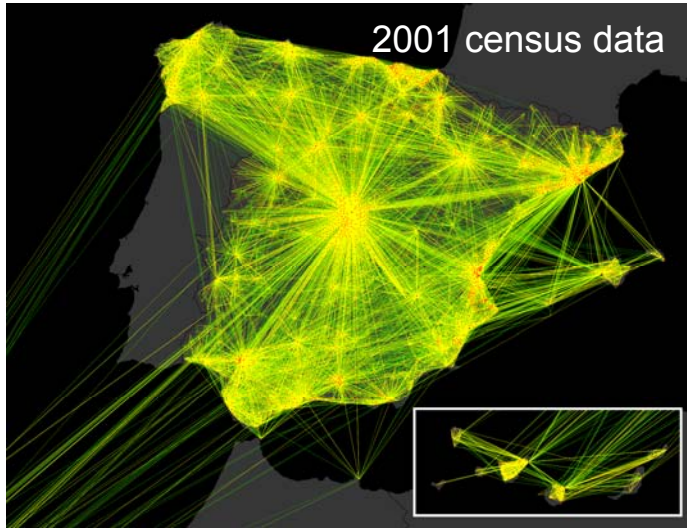
For 10 independent randomizations of degree sequence:

$\langle C \rangle = 0.096$

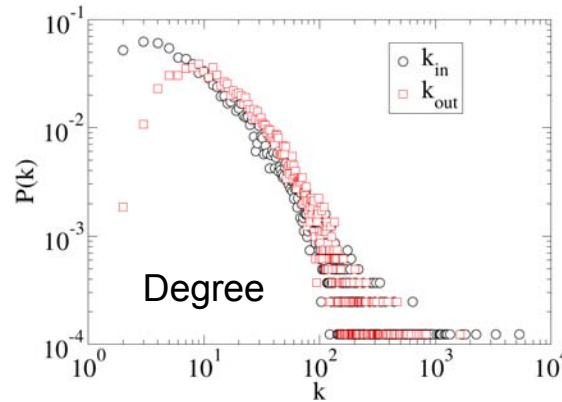
$\langle L \rangle = 2.53$

Municipalities linked by fluxes of commuters. Color indicates number of commuters. 20% of all connections shown.

## Spain: commuter network for human mobility

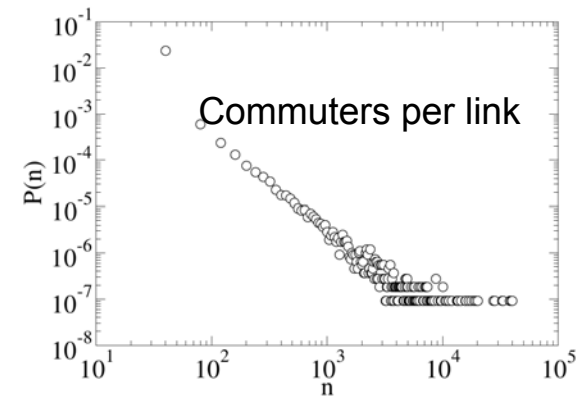
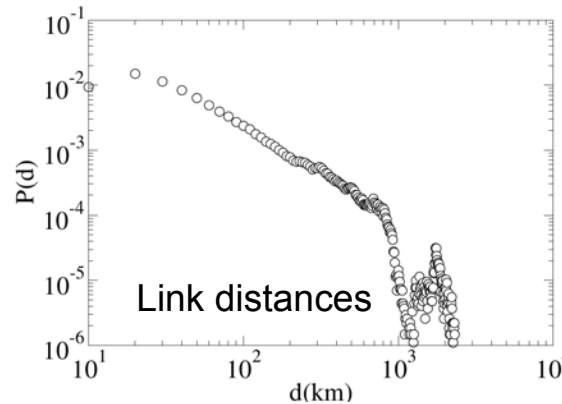
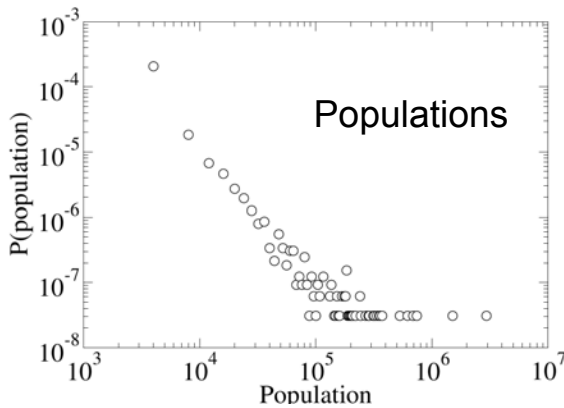


Directed, weighted network.



$N=8104$   
 $\langle k \rangle \sim 34$

**Not a 2d network**



Heterogeneous network in many characteristics

Ingredients of a social influence model:

a) **Interaction mechanism:** Imitation as basic manifestation of social influence.



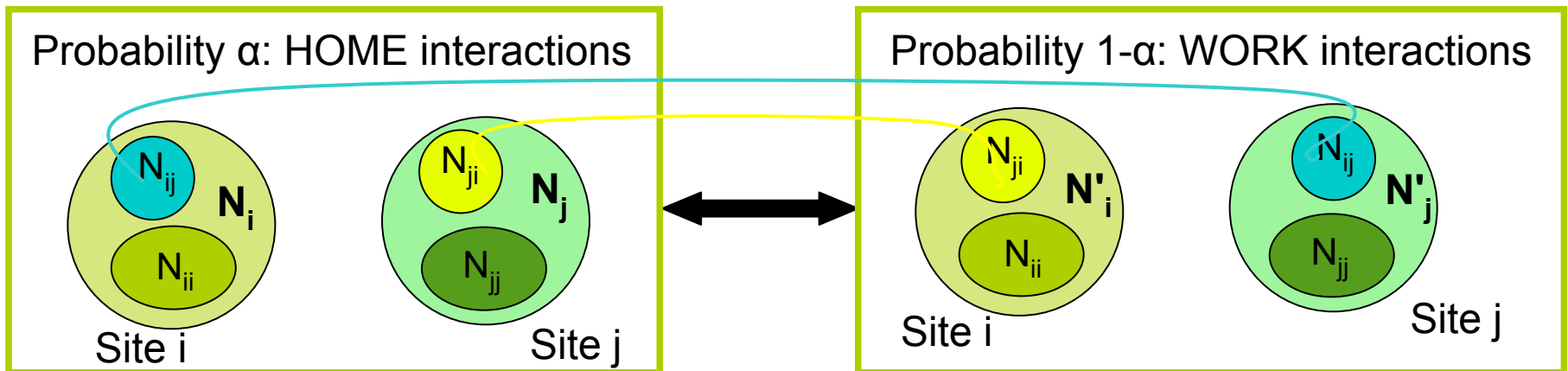
THEORY

MODELLING

b) **Social context:** Set of all possible interactions of an individual with any other peer. We model it as a network of interactions from census data for population and mobility.

INPUT DATA

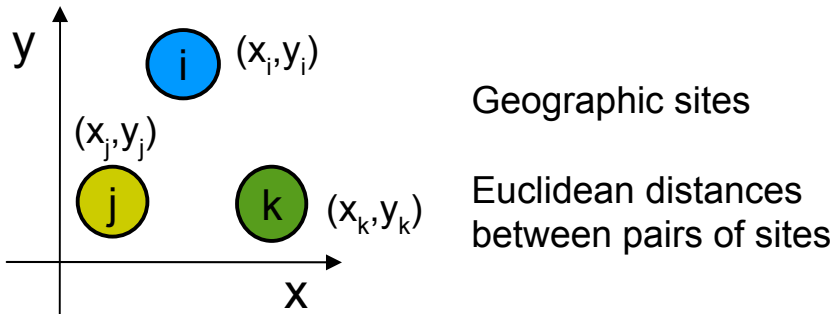
- $N$  agents with a binary variable (state, opinion,...) with voter-like interaction
- There are  $N_{\text{sites}}$  (counties).
- Each agent is considered in two sites: where she lives and where she works.



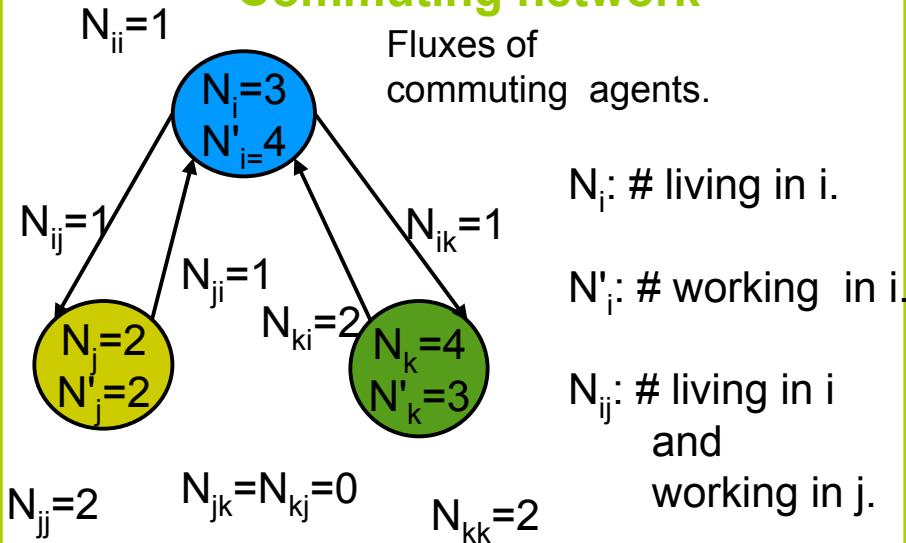
- $N_{ij}$  = # of agents living in  $i$  and working in  $j$ .
- $N_i$  = # number of agents living in  $i$  =  $N_{ij} + N_{ii}$
- $N'_i$  = # number of agents working in  $i$ .

**An agent interacts with probability  $\alpha$  with anyone in  $N_i$ : lives where she lives.  
With probability  $1-\alpha$  interacts with anyone in  $N'_i$ : works where she works.**

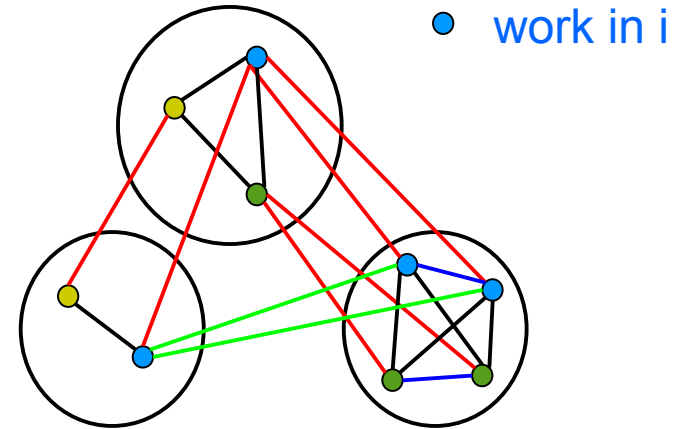
## Geography: adjacency network



## Commuting network



## Interaction network



Link	P	Meaning
—	$\alpha$	Live in same place, work in different.
—	$1-\alpha$	One works where the other works and lives.
—	$1-\alpha$	Live in different places, work in same place.
—	1	Live in same place, work in same place.

## Parameters (census)

$N_{ij}$ : number of agents living in  $i$  and working in  $j$ .  $N_i = \sum_j N_{ij}$

$X_i, Y_i$ : location of city  $i$ .  $N'_i = \sum_j N_{ji}$

## Variables

$V_{ij}$ : number of agents living in  $i$  and working in  $j$  holding opinion  $+1$ .

Correlations  $\langle v_i v_j \rangle$  of densities

$$v_{ij} = \frac{V_{ij}}{N_{ij}}$$

$$v_i = \frac{\sum_j V_{ij}}{N_i}$$

## Transition rates

$$r_{ij}^+(V_{ij} \rightarrow V_{ij} + 1) = (N_{ij} - V_{ij}) \left[ \alpha \frac{V_i}{N_i} + (1 - \alpha) \frac{V'_j}{N'_j} \right]$$

$$r_{ij}^-(V_{ij} \rightarrow V_{ij} - 1) = V_{ij} \left[ \alpha \frac{N_i - V_i}{N_i} + (1 - \alpha) \frac{N'_j - V'_j}{N'_j} \right]$$

**Simulation step:** Update in random order each of the  $V_{ij}$



## Master equation

$$\begin{aligned} \frac{\partial P(\{V_{ij}\}; t)}{\partial t} = & \sum_{i,j} \left[ r_{ij}^+(\{\dots, V_{ij} - 1, \dots\} \rightarrow \{V_{ij}\}) P(\{\dots, V_{ij} - 1, \dots\}; t) \right. \\ & + r_{ij}^-(\{\dots, V_{ij} + 1, \dots\} \rightarrow \{V_{ij}\}) P(\{\dots, V_{ij} + 1, \dots\}; t) \\ & \left. - (r_{ij}^+(\{V_{ij}\} \rightarrow \{\dots, V_{ij} + 1, \dots\}) + r_{ij}^-(\{V_{ij}\} \rightarrow \{\dots, V_{ij} - 1, \dots\})) P(\{V_{ij}\}; t) \right] \end{aligned}$$

## Langevin equation

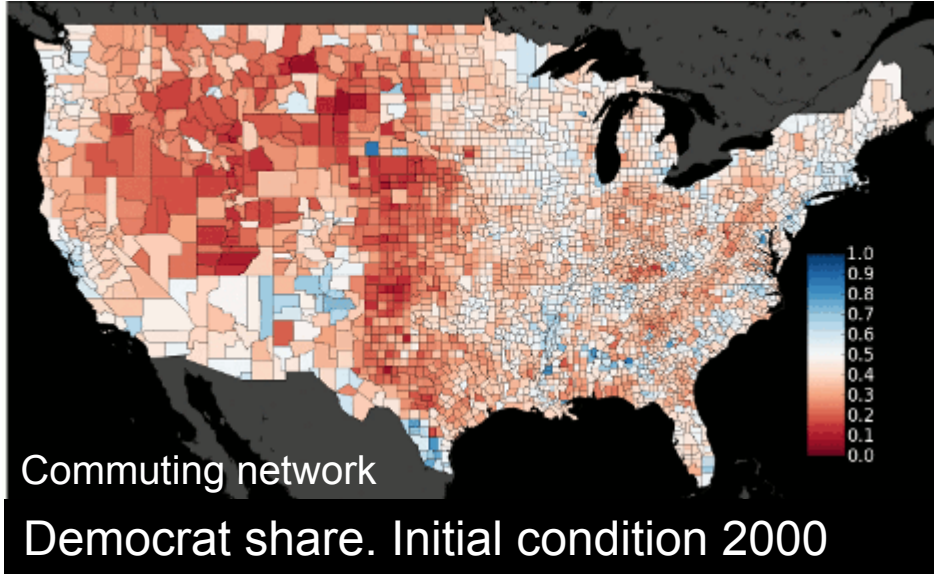
$$\begin{aligned} \frac{dv_{ij}}{dt} = & \alpha \sum_l \left( \frac{N_{il}}{N_i} - \delta_{jl} \right) v_{il} + (1 - \alpha) \sum_l \left( \frac{N_{lj}}{N'_j} - \delta_{li} \right) v_{lj} \\ & + \frac{1}{\sqrt{N_{ij}}} \sqrt{(1 - 2v_{ij}) \left( \alpha \frac{\sum_l N_{il} v_{il}}{N_i} + (1 - \alpha) \frac{\sum_l N_{lj} v_{lj}}{N'_j} \right)} + v_{ij} \eta_{ij}^*(t). \end{aligned}$$

$$v_{ij} = \frac{V_{ij}}{N_{ij}}$$

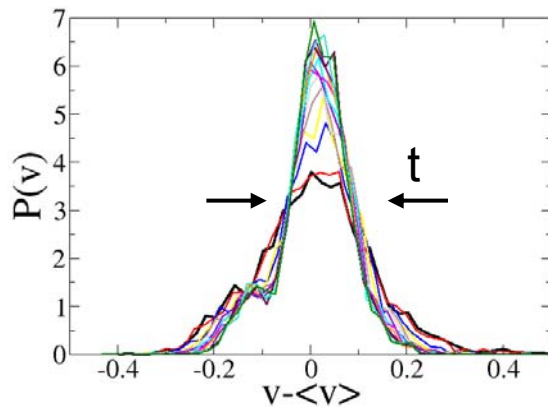
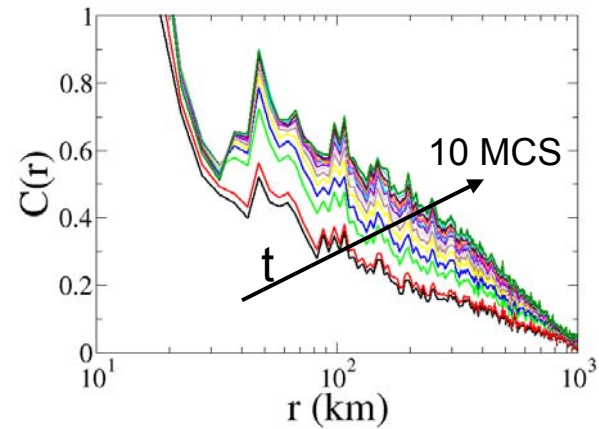
**Laplacian model:** Conserved quantity:  $\sum_{ij} \langle V_{ij} \rangle$  <Number of + voters>



$$\alpha = 1/2$$



Diffusion process:  
→ correlations grow, share distribution narrows.



**Extra ingredient needed for stationarity:  
Imperfect imitation or External noise**

## Parameters (census)

$N_{ij}$ : number of agents living in  $i$  and working in  $j$ .  $N_i = \sum_j N_{ij}$   
 $X_i, Y_i$ : location of county  $i$ .  $N'_i = \sum_j N_{ji}$

## Variables

$V_{ij}$ : number of agents living in  $i$  and working in  $j$  holding opinion +1.  $v_{ij} = \frac{V_{ij}}{N_{ij}}$   
 Correlations  $\langle v_i v_j \rangle$  of densities  $v_i = \frac{\sum_j V_{ij}}{N_{ij}}$

## Transition rates

$$r_{ij}^+(V_{ij} \rightarrow V_{ij} + 1) = (N_{ij} - V_{ij}) \left[ \alpha \frac{V_i}{N_i} + (1 - \alpha) \frac{V'_j}{N'_j} \right] + N_{ij} \frac{D}{2} \eta_{ij}^+(t),$$

$$r_{ij}^-(V_{ij} \rightarrow V_{ij} - 1) = V_{ij} \left[ \alpha \frac{N_i - V_i}{N_i} + (1 - \alpha) \frac{N'_j - V'_j}{N'_j} \right] + N_{ij} \frac{D}{2} \eta_{ij}^-(t)$$

Imperfect imitation

## Langevin equation

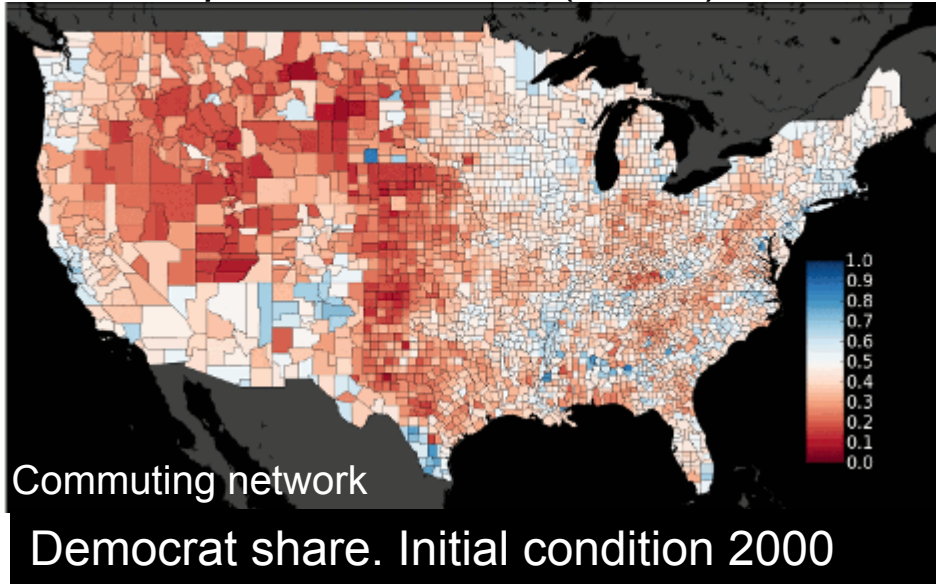
$$\frac{dv_i}{dt} = \alpha \sum_l \left( \frac{N_{il}}{N_i} - \delta_{jl} \right) v_{il} + (1 - \alpha) \sum_l \left( \frac{N_{lj}}{N'_j} - \delta_{li} \right) v_{lj} + D \eta_{ij}(t) \quad (7) \langle v_{ij} \rangle$$

Laplacian model for  $\langle v_{ij} \rangle$

$$+ \frac{1}{\sqrt{N_{ij}}} \sqrt{(1 - 2v_{ij}) \left( \alpha \frac{\sum_l N_{il} v_{il}}{N_i} + (1 - \alpha) \frac{\sum_l N_{lj} v_{lj}}{N'_j} \right) + v_{ij} + \frac{D}{2} \eta'_{ij}(t) \eta_{ij}(t)}$$

Conserved quantity

Imperfect imitation ( $D=0.2$ )

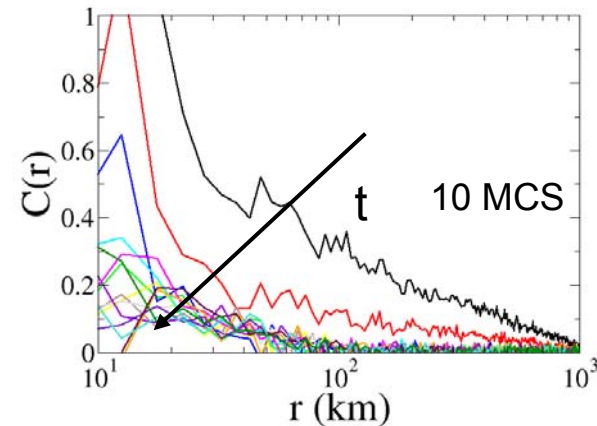
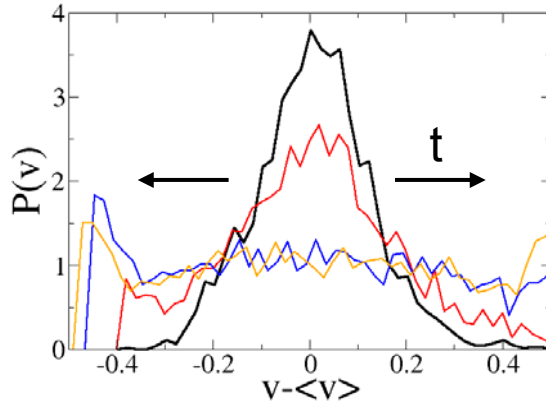


$$\frac{dv_{ij}}{dt} = \alpha \sum_l \left( \frac{N_{il}}{N_i} - \delta_{jl} \right) v_{il} + (1 - \alpha) \sum_l \left( \frac{N_{lj}}{N'_j} - \delta_{li} \right) v_{lj} + D \eta_{ij}(t)$$

$$+ \frac{1}{\sqrt{N_{ij}}} \sqrt{(1 - 2v_{ij}) \left( \alpha \frac{\sum_l N_{il} v_{il}}{N_i} + (1 - \alpha) \frac{\sum_l N_{lj} v_{lj}}{N'_j} \right) + v_{ij} + \frac{D}{2} \eta'_{ij}(t) \eta_{ij}(t)}$$

$$\alpha = 1/2$$

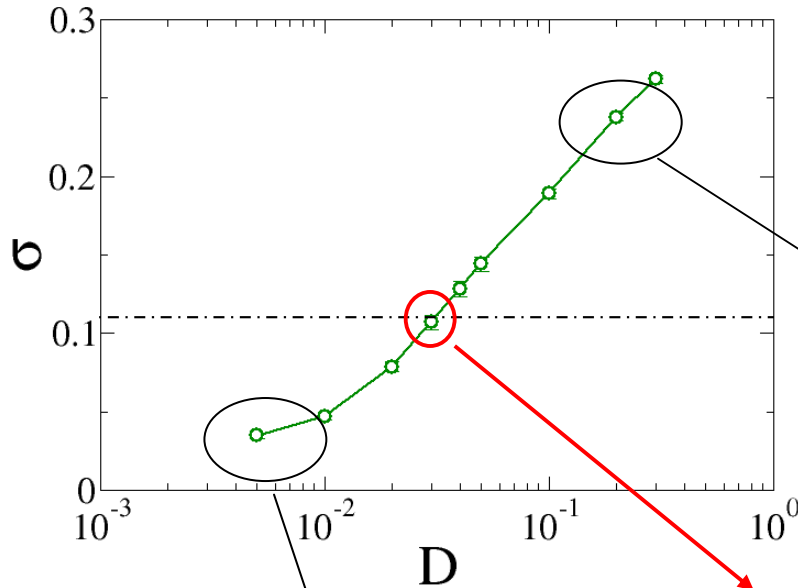
Large noise intensity  $D$   
produces a random field  
→ correlations disappear, share  
distribution grows wider.



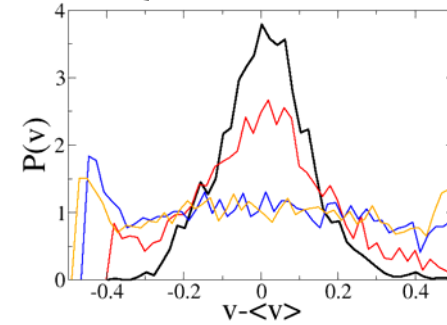
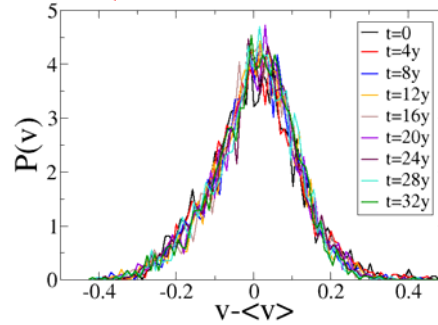
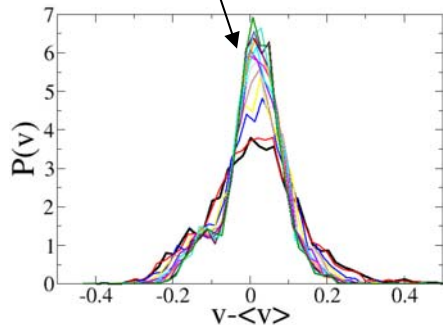
**Question:** *Is there a value of  $D$  for which the process reproduces the noisy diffusive data between a diffusive variable a random field?*

## Noise calibration

$\alpha=1/2$



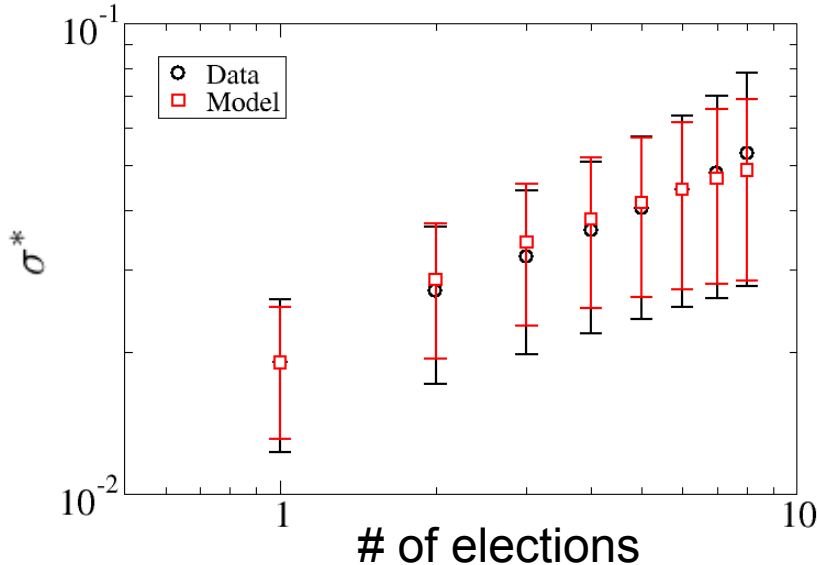
We compute the standard deviation  $\sigma$  of the vote share distribution after 1000 MC steps.



**For  $D=0.03$  the st. dev. of the vote share distribution remains stationary and fits the empirical value (data)**

## Time calibration

For each time series of a county share we compute the standard deviation  $\sigma^*$  as a function of the number of election points. Black symbols in the figure represent the average of this quantity over all counties.



Both data and model show a growth

$$\sigma^* \simeq t^{1/2}$$

To make the curves overlapping we have to calibrate how many MC steps correspond to the time between two consecutive elections

**10 MC steps = 4 years = 1 election period**  
**St. dev. of county share grows in time equally for model and data.**

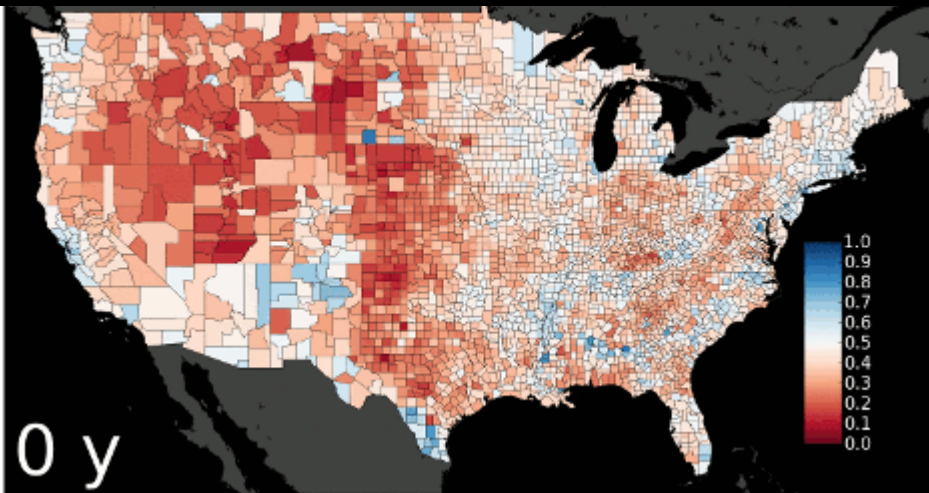


## Calibrated Model

Reproduces the statistical regularities found in election data

*(Single fitted parameter:  $D$ )*

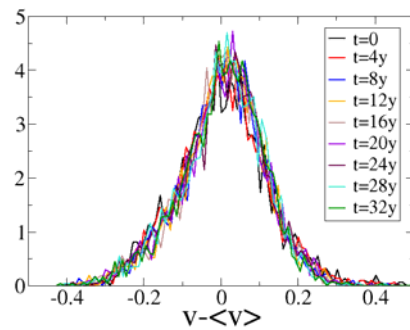
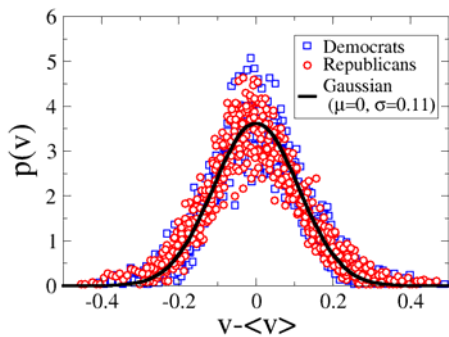
Democrat share. Initial condition 2000



### Vote share distribution

Data

Model

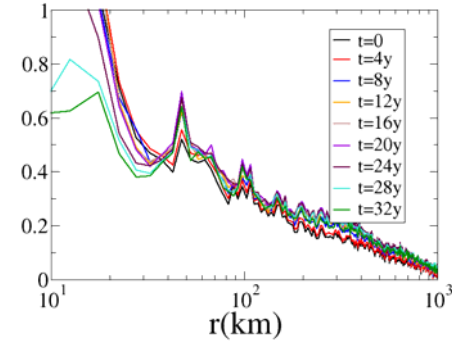
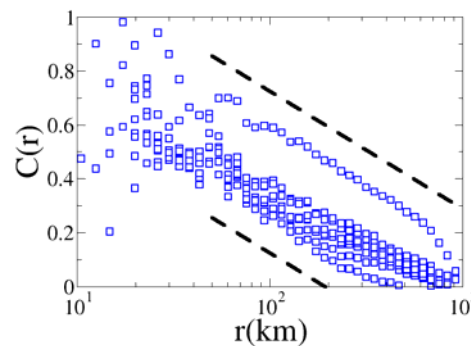


St. dev. remains constant.

### Spatial correlations

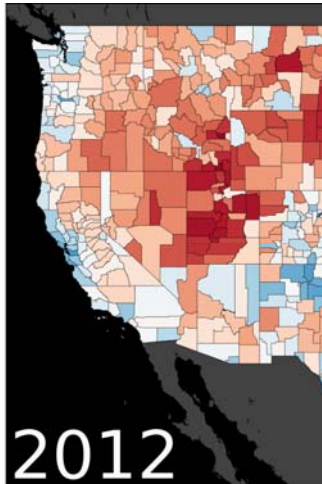
Data

Model

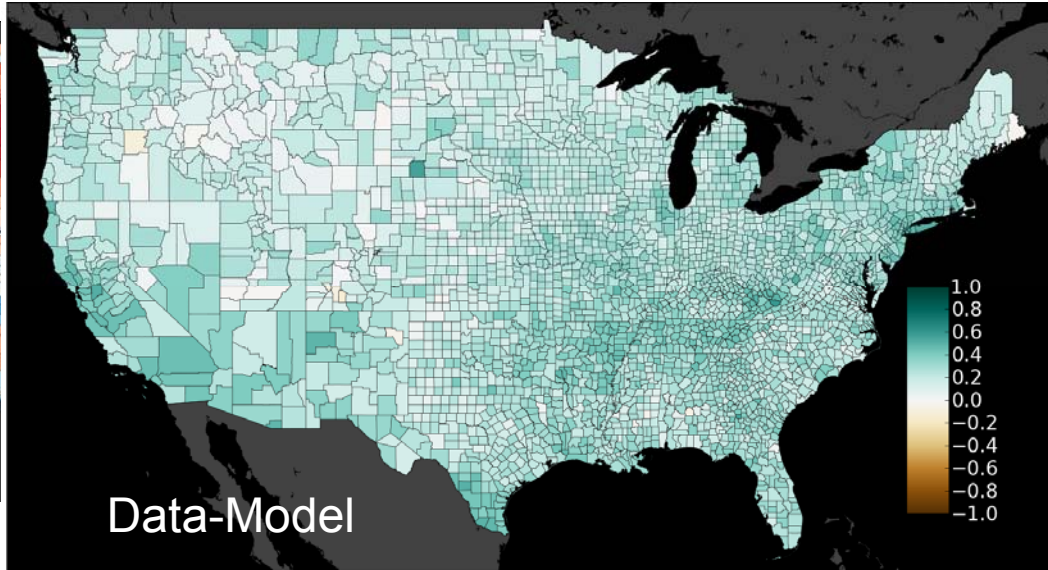


Logarithmic decay remains.

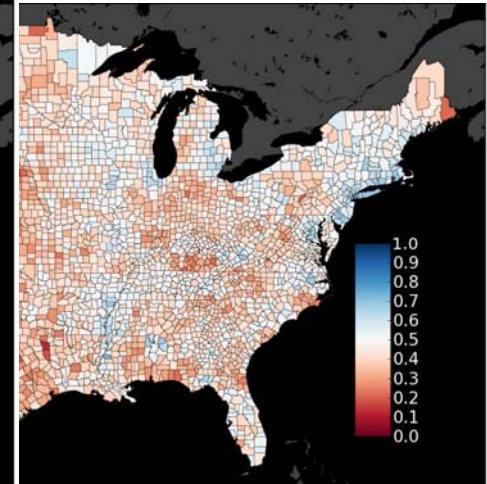
## Results for democrat party



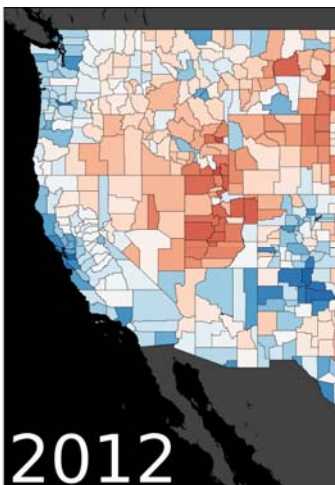
2012  
Data



Data-Model

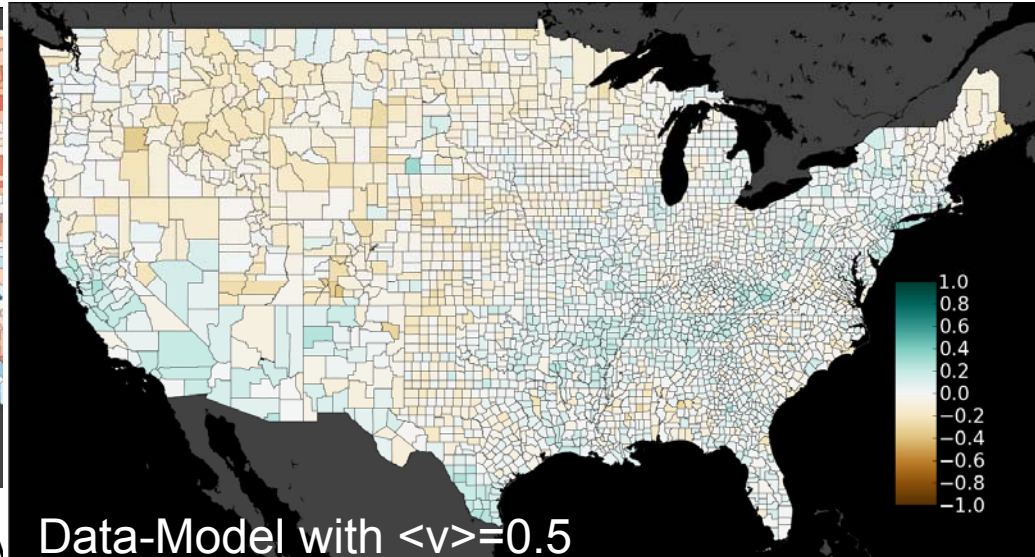


Model (i.c. 2000)

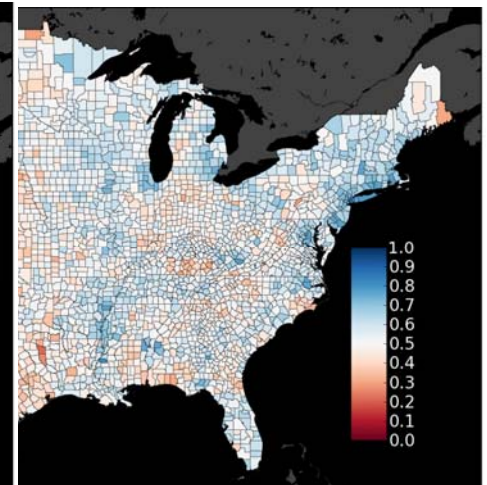


2012

Data with  $\langle v \rangle$

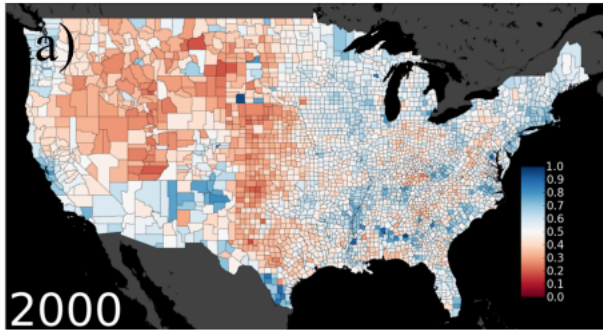


Data-Model with  $\langle v \rangle = 0.5$

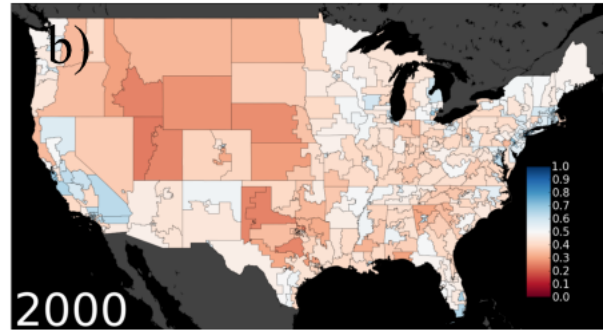


Model with  $\langle v \rangle = 0.5$

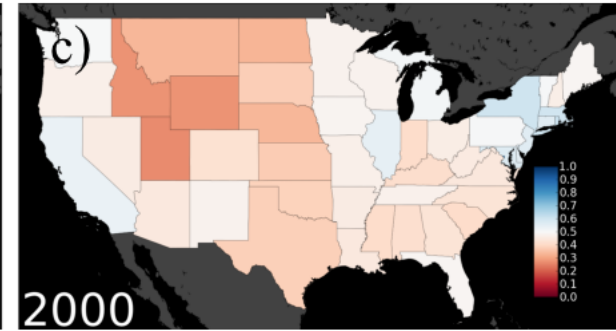




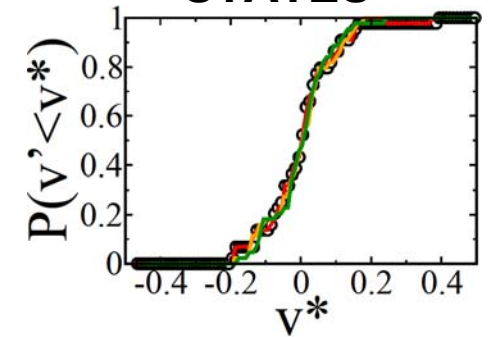
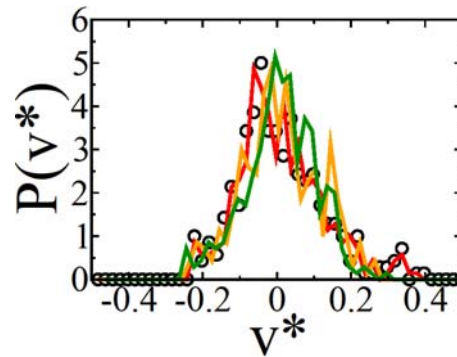
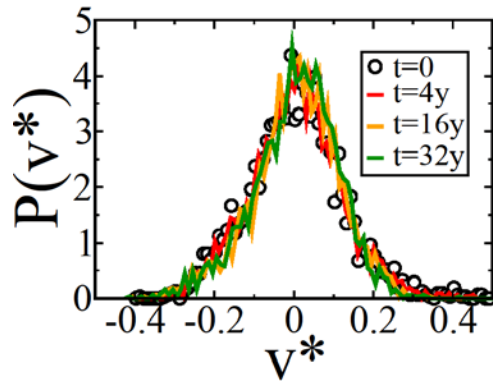
COUNTIES



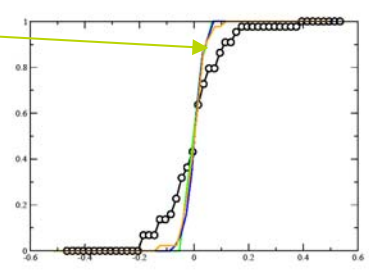
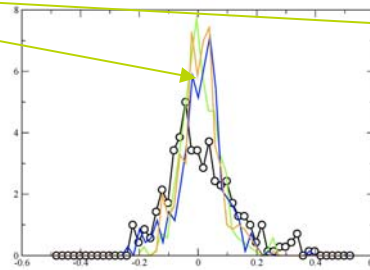
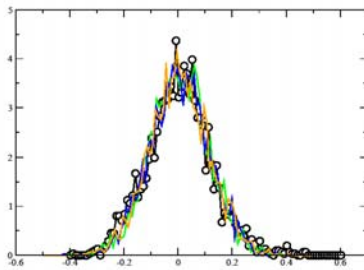
CONGRESSIONAL DISTRICTS

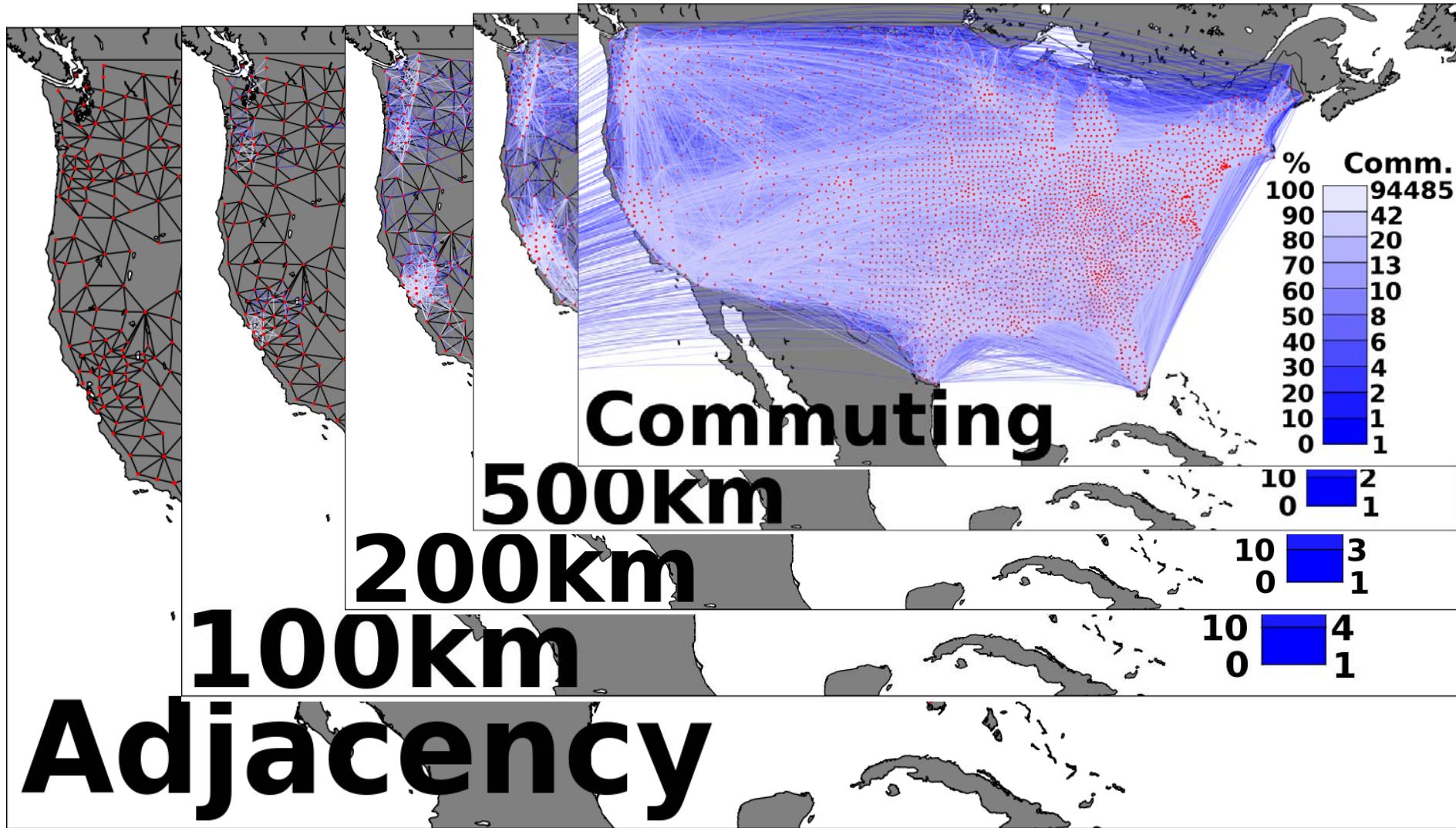


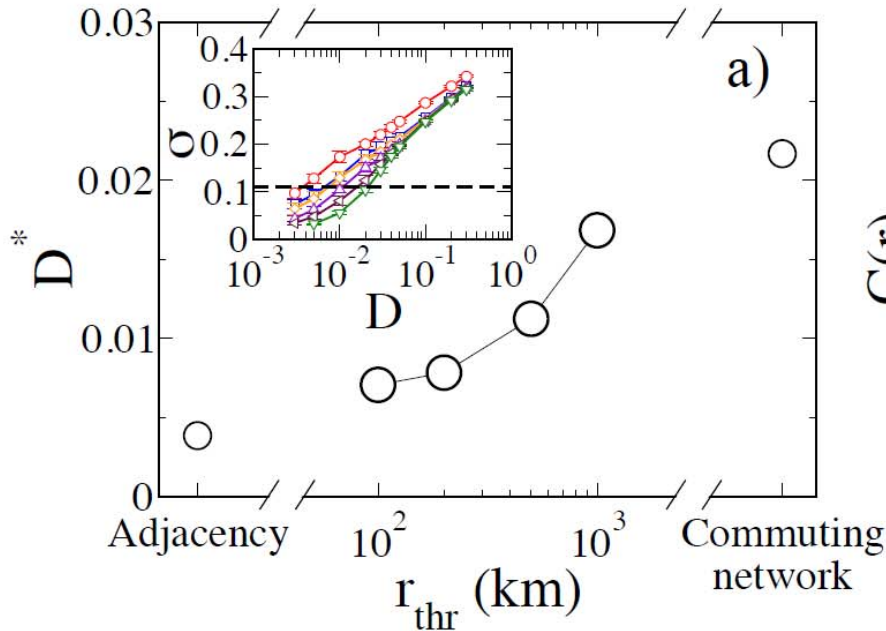
STATES



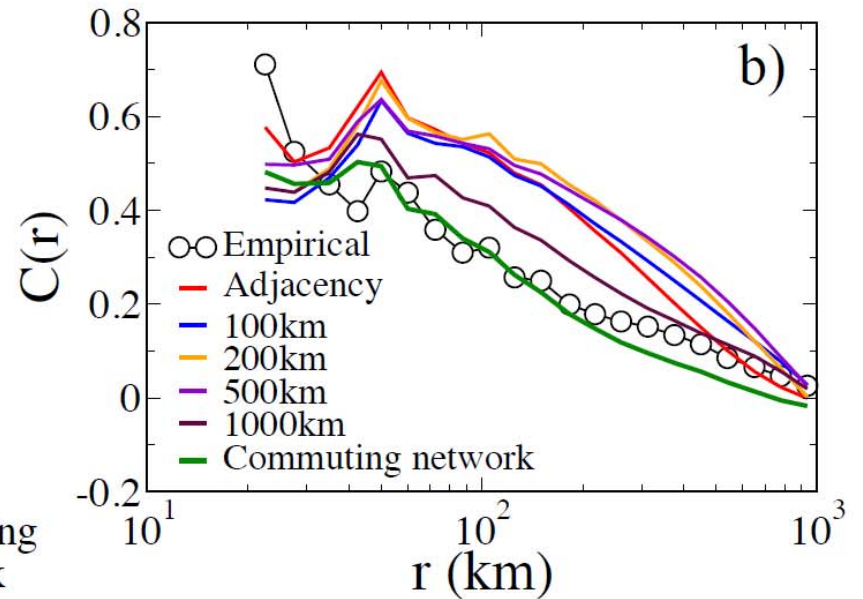
**RANDOMIZED DATA**







**Noise calibration for different mobility ranges**



**Spatial correlations in different networks:**

**LONG RANGE CORRELATIONS NEEDED TO REPRODUCE DATA**



- \* IBM implementation of a microscopic mechanism leading to ***diffusive mesoscopic stochastic*** dynamics reproducing statistical regularities of election data.
- \* Data Based Modeling: Input parameters from census data for populations and commuting fluxes.
- \* Single calibrated model parameter:  $D$ , the noise intensity. Also calibration of time scale.
- \* **What do we explain?**
  - Two generic features in the background of election results:  
i) Stationarity of the dispersion of vote shares and ii) the time persistent logarithmic decay of spatial correlations.
  - Spatiotemporal fluctuations in electoral results at **different length scales**
  - No attempt to predict electoral results***
- \* **Open question:** Role of network (dimensionality, range and weights of links), vs noise (imperfect imitation) in spatial log correlations.