The Institute
for Quantitative Social Science
at Harvard University

Northeastern

FORECASTING SOCIO-TECHNICAL SYSTEMS IN THE DATA SCIENCE AGE

Alessandro Vespignani
@alexvespi

MOBS LAB
LABORATORY FOR THE MODELING OF BIOLOGICAL AND SOCIO-TECHNICAL SYSTEMS

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EPJ Data Science covers a broad range of research areas and applications and particularly encourages contributions from techno-socio-economic systems, where it comprises those research lines that now regard the digital tracks of human beings as first-order objects for scientific investigation. Topics include, but are not limited to, human behavior, social interaction (including animal societies), economic and financial systems, management and business networks, socio-technical infrastructure, health and environmental systems, the science of science, as well as general risk and crisis scenario forecasting up to and including policy advice.

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Prediction= probabilistic on the future based on what is known today (generally mostly influenced by initial conditions).

Forecast = best prediction given the present knowledge on the system.

Projection = attempt to describe what would happen under certain assumptions and hypotheses (what if)

THE SOCIAL COMPONENT

Human science requires a deep understanding of mental processes and reasoning (Psychology and cognitive).

Social science is hard because it involves the infinite psychological and cognitive reactions of individuals. We're too complex and unpredictable.

From "social atom" or "social molecules" (i.e. small social groups) to the quantitative analysis of "social aggregate states" (Lundberg, Moreno).

"social aggregate states"= large-scale social systems consisting of millions of individuals that can be characterized statistically in space (geographic and social) and time.

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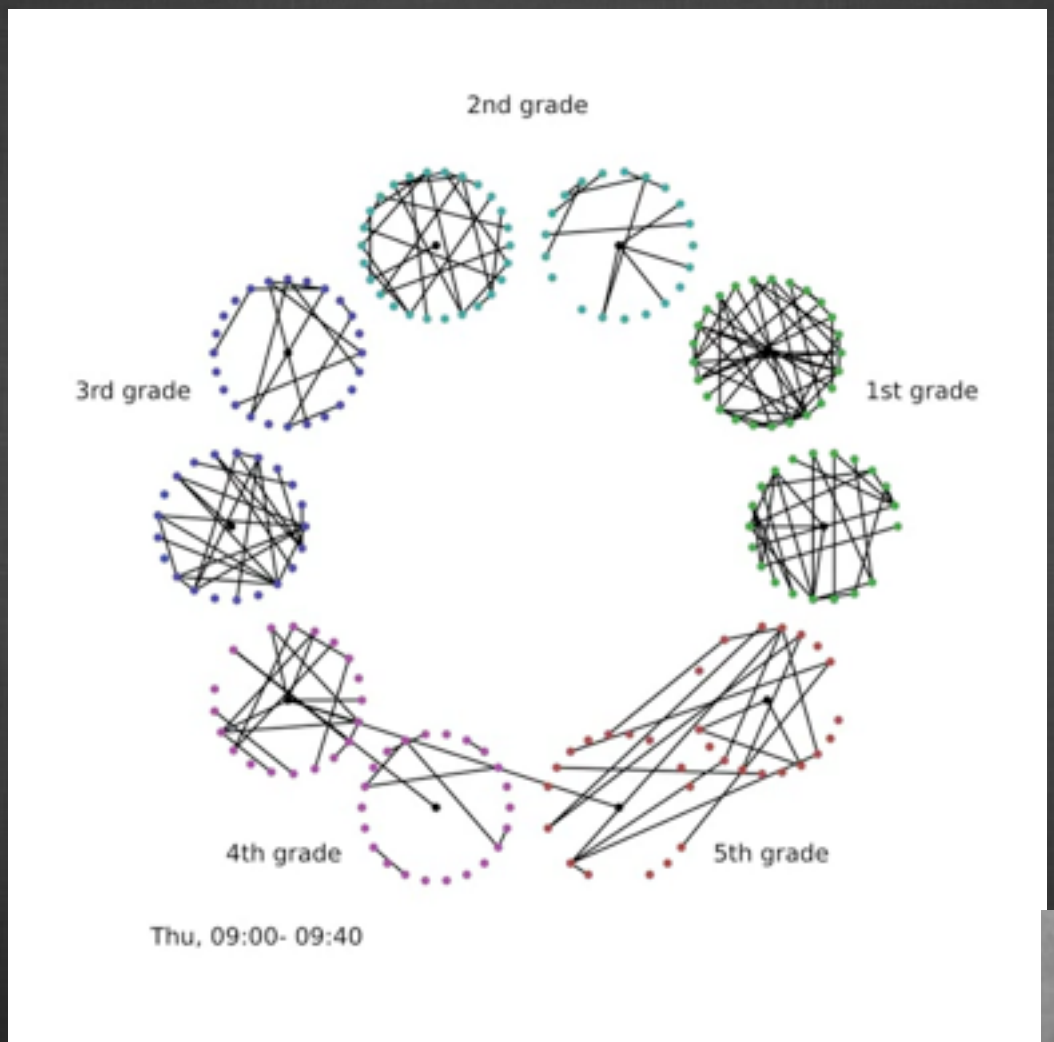
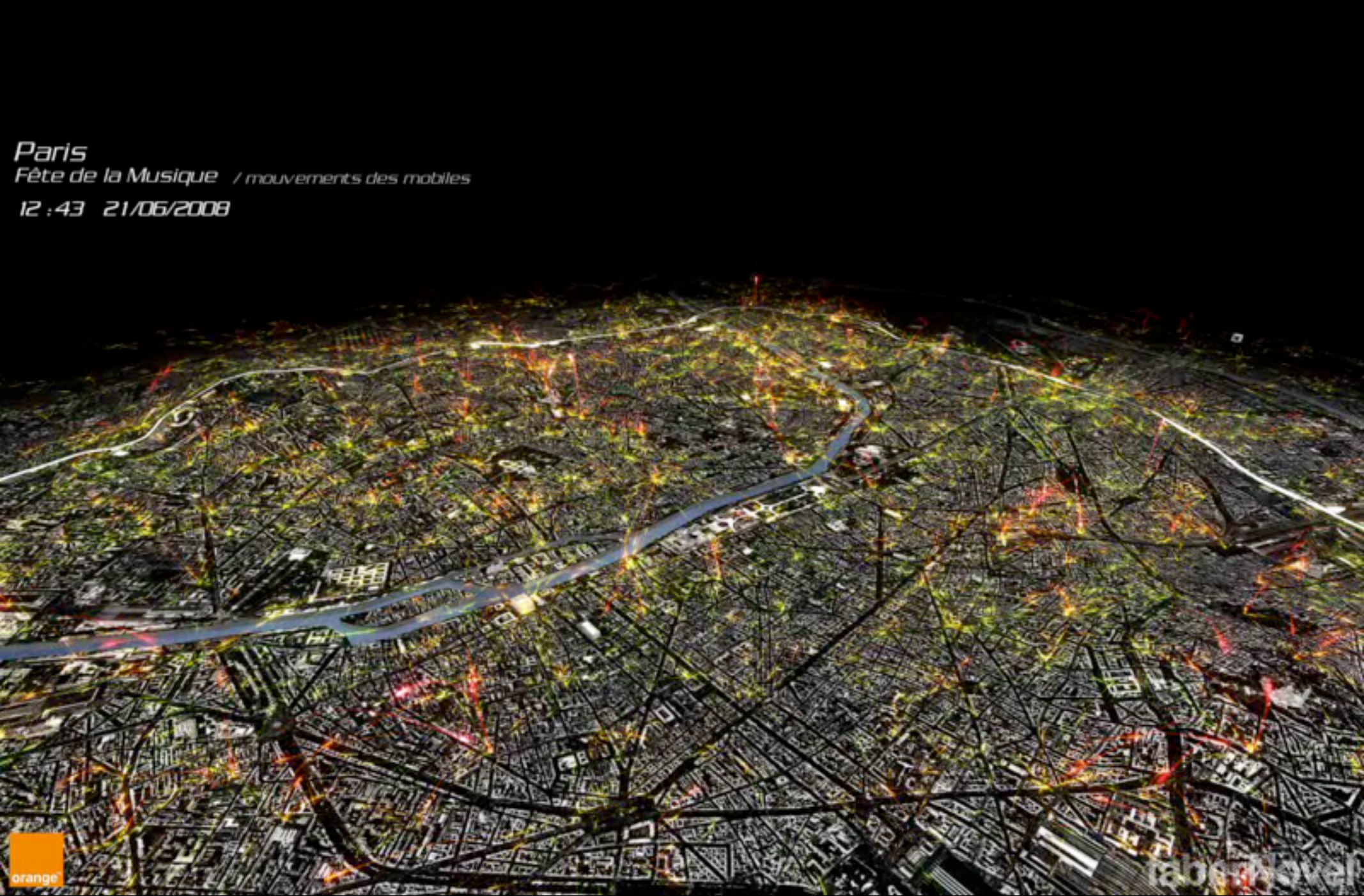
BIG DATA

- Big data has fueled spectacular advances in the natural sciences over the last 100 years.
- So what is different now?
- Every 1.2 years, more human-driven socioeconomic data is produced than during all previous history
- Embedded within the data are the raw ingredients for understanding socio-technical and socio-economic systems
- The focus is on understanding these data sets in a statistical sense and more deeply the real world processes which produced the data

MICRO-SCALE: RFID, BLUETHOOTH, SOCIOBADGE



Sociopatterns experiment in school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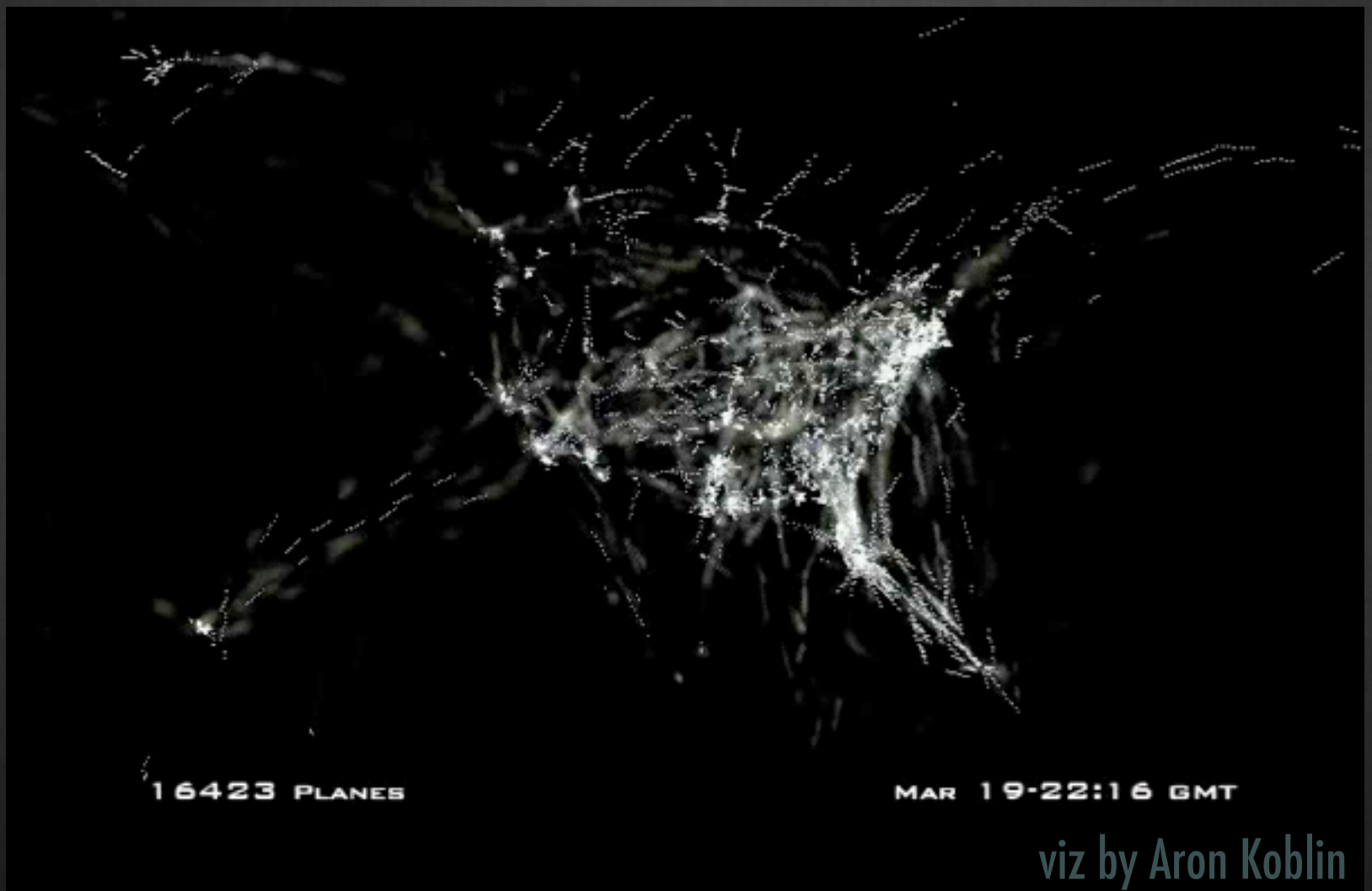
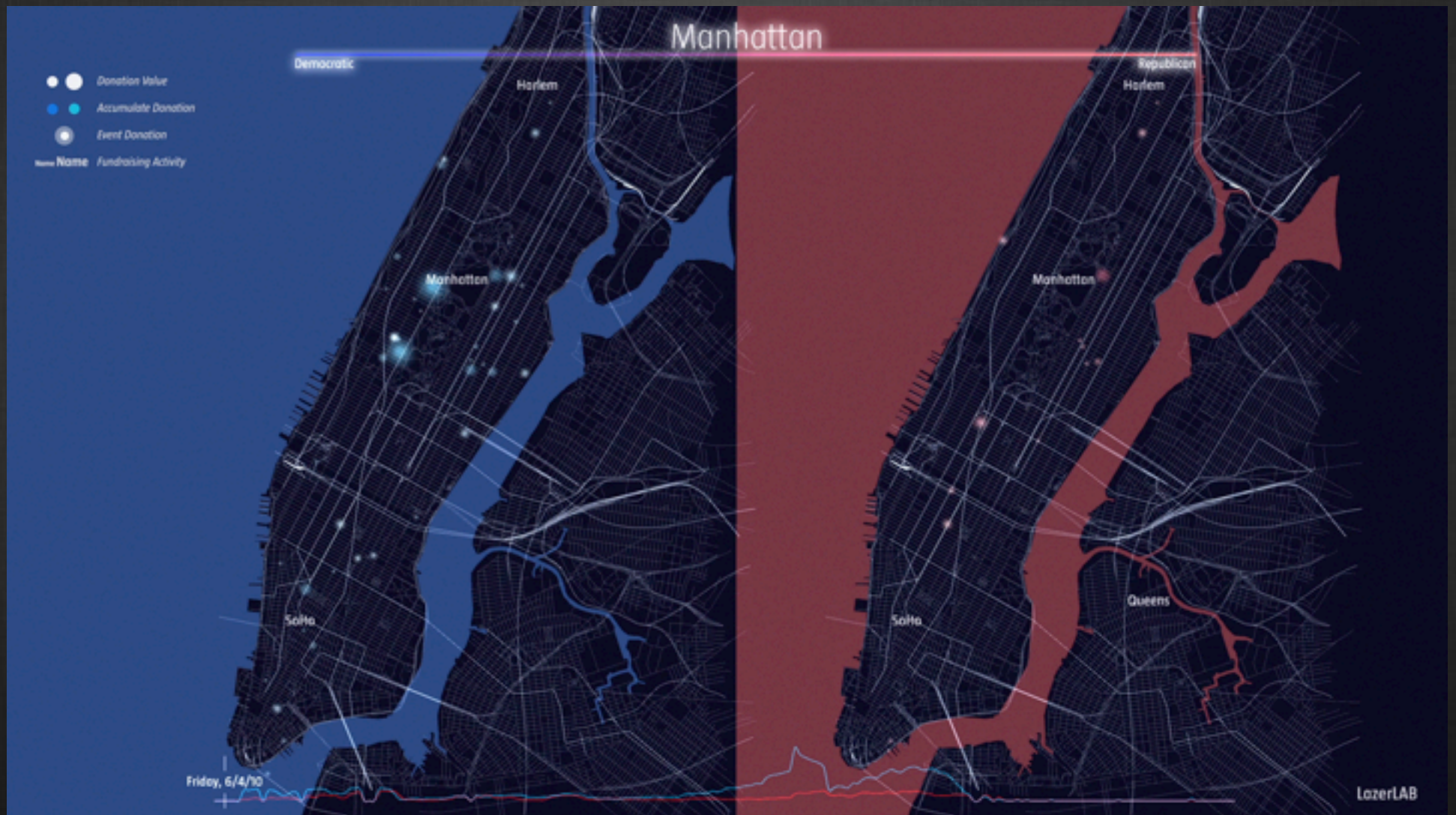
AIRLINE DATA

viz by Aron Koblin

AIRLINE DATA

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Democratic
Republican
Donation Value
Accumulate Donation
Event Donation
Name Fundraising Activity
Harlem
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Manhattan
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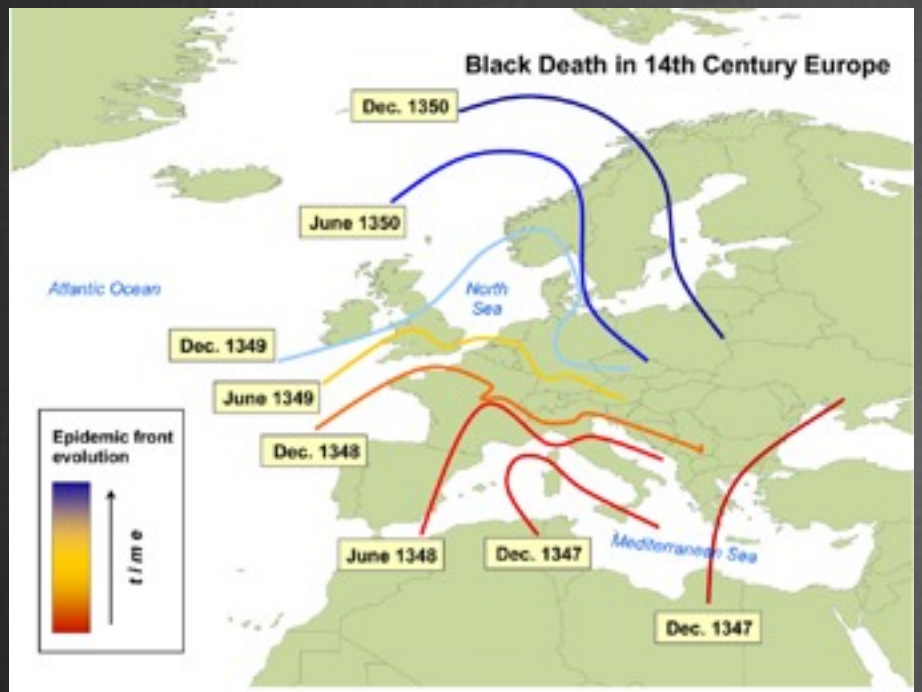
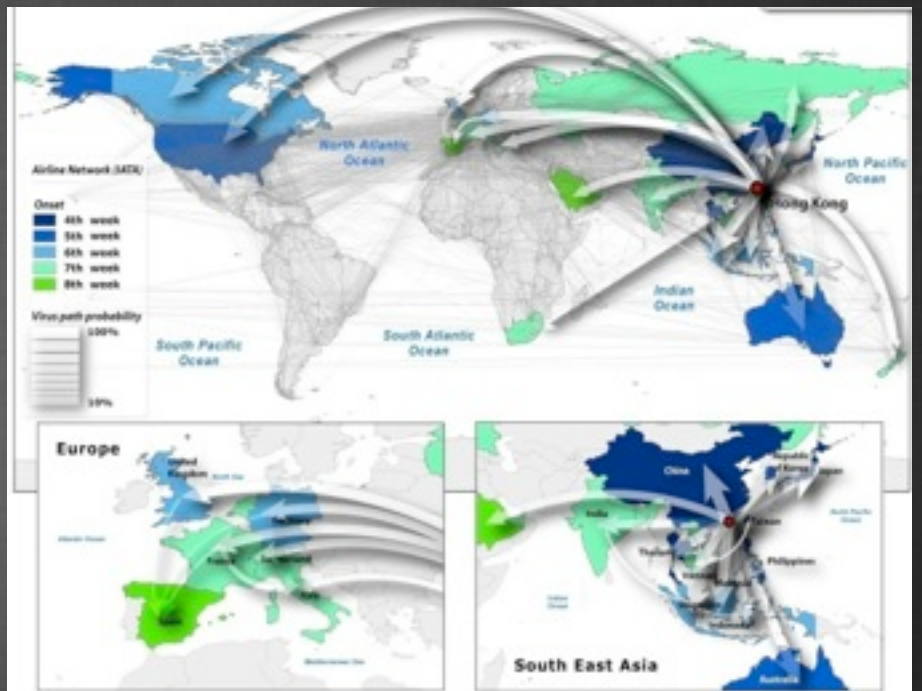
A COMPLEX WORLD

- Large numbers of heterogeneous individuals
- Multiple time and length scales
- Non-linearity, threshold effects, discreteness, cooperation
- Systemic approach/complex systems

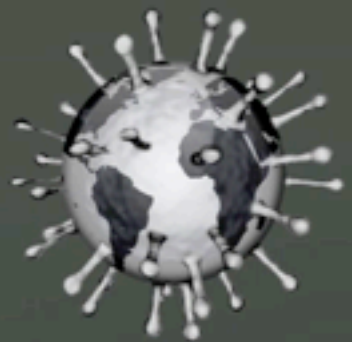
NETWORK THINKING





Black death in1347: a continuous diffusion process

SARS epidemics: a discrete network driven process



GLEAM

GLOBAL EPIDEMIC AND MOBILITY MODEL

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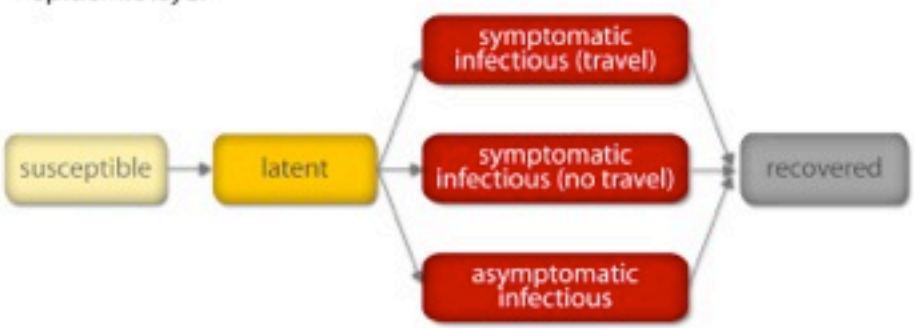
epidemic layer

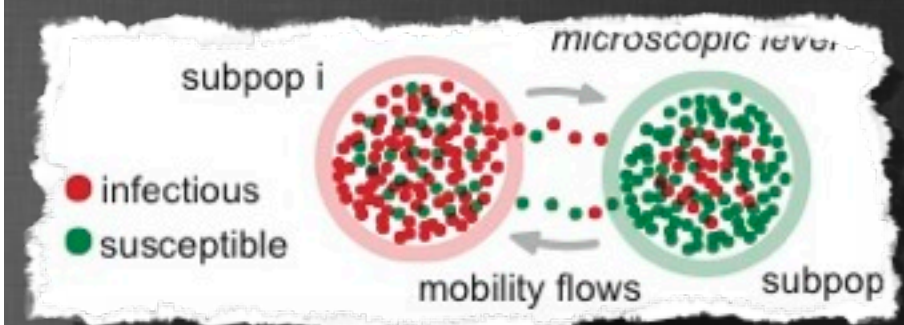


Parameter	Value	Description
β	from R_0	transmission probability
ε^{-1}	1.9 [1.1-2.5] d	average latency period
μ^{-1}	3 [3-5] d	average infectious period
p_t	50%	probability of traveling for infectious individuals
p_a	33%	probability of being asymptomatic
r_β	50%	relative infectiousness of asymptomatic infectious individuals

WHAT IS UNDER THE HOOD

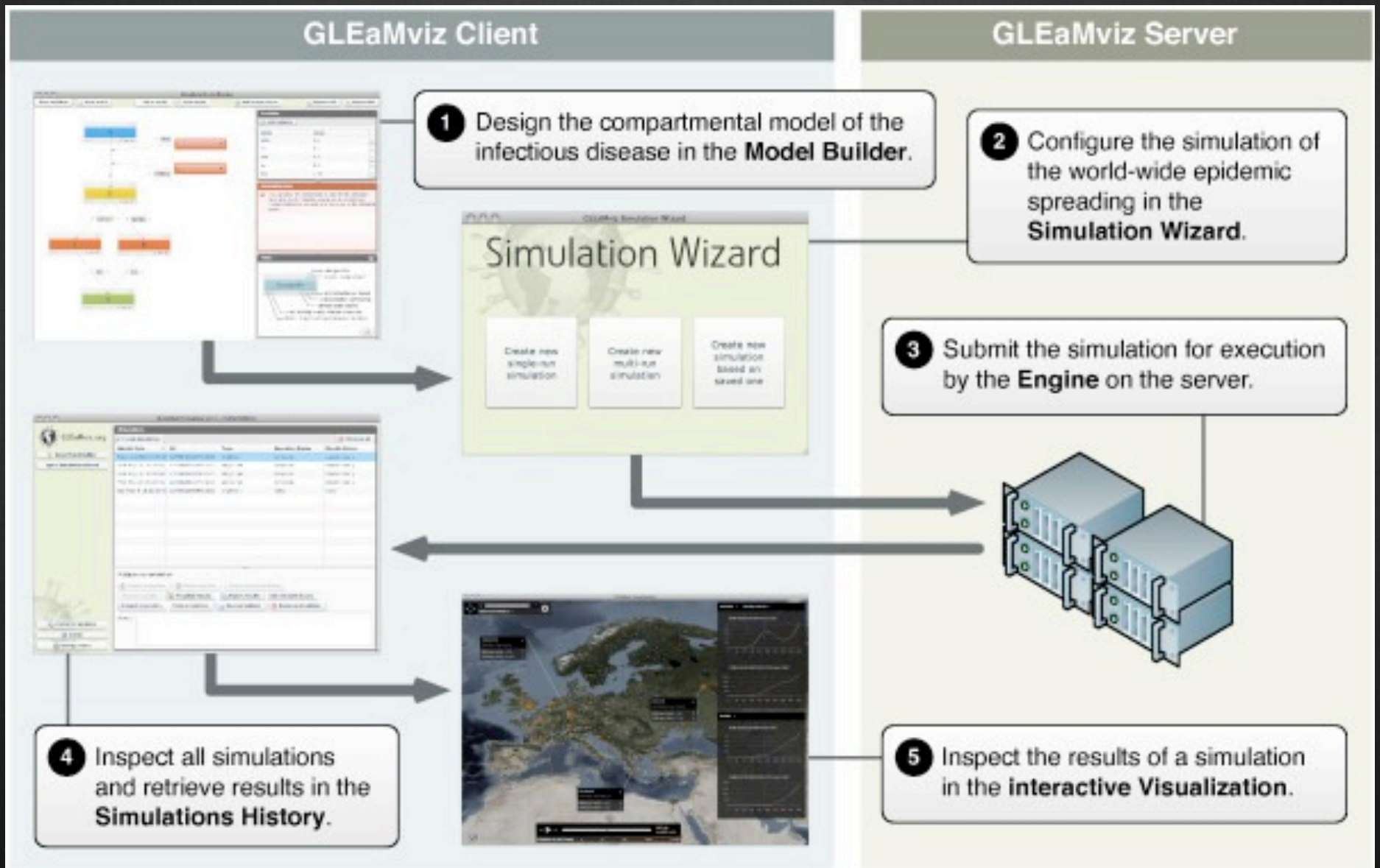
Stochastic Intra population disease evolution: chain binomial process

- REPEAT
  - CALL RANBin$(S, \beta I/N)$ and RANBin(I, μ)
  - S=S-RANBin$(S, \beta I/N)$
  - I=I+RANBin$(S, \beta I/N)$-RANBin(I, μ)
  - R=R+RANBin(I, μ)
  - $t = t + \Delta t$
  - PRINT S, I, R, t
- UNTIL $I = 0$



Stochastic Inter population dynamics:

- data driven Explicit stochastic simulation of slow mode traveling patterns.
- Time-Scale separation through effective force of infection for fast commuting patterns
  - > 3,500 single populations coupled models
  - > 40,000-100,000 stochastic discrete equations


GLEaMviz Client
GLEaMviz Server
1 Design the compartmental model of the infectious disease in the **Model Builder**.
2 Configure the simulation of the world-wide epidemic spreading in the **Simulation Wizard**.
Simulation Wizard
3 Submit the simulation for execution by the **Engine** on the server.
4 Inspect all simulations and retrieve results in the **Simulations History**.
5 Inspect the results of a simulation in the **interactive Visualization**.

REAL TIME FORECAST FOR THE H1N1PDM (2009)

Seasonal transmission potential and activity peaks of the new influenza A(H1N1): a Monte Carlo likelihood analysis based on human mobility

Duygu Balcan[†1,2], Hao Hu[†1,2,3], Bruno Goncalves[†1,2], Paolo Bajardi[†4,5], Chiara Poletto[†4], Jose J Ramasco[4], Daniela Paolotti[4], Nicola Perra[1,6,7], Michele Tizzoni[4,8], Wouter Van den Broeck[4], Vittoria Colizza[4] and Alessandro Vespignani[*1,2,4]

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BMC Medicine 2009, 7:45 doi:10.1186/1741-7015-7-45

Received: 31 July 2009
Accepted: 10 September 2009

Key parameters

- Transmissibility
- Generation time
- Seasonality scaling

Monte-Carlo Likelihood estimate

Structural data

- Transportation/mobility
- Demographic/census

DATA

Plausible parametrization

Parameter	Description	Value	Sensitivity Analysis Range
r_β	Relative infectiousness of asymptomatic individuals	0.5	0.2 – 0.8
p_a	Probability of becoming an asymptomatic individual	0.33	0.33 – 0.5
p_t	Probability of becoming a traveling symptomatic individual	0.5	0.4 – 0.6
β	Transmission rate	$\mu^{-1}R_0/(1 - p_a - r_\beta p_t)$	
α_{max}	Maximal seasonality rescaling	1.1	1.0 – 1.1

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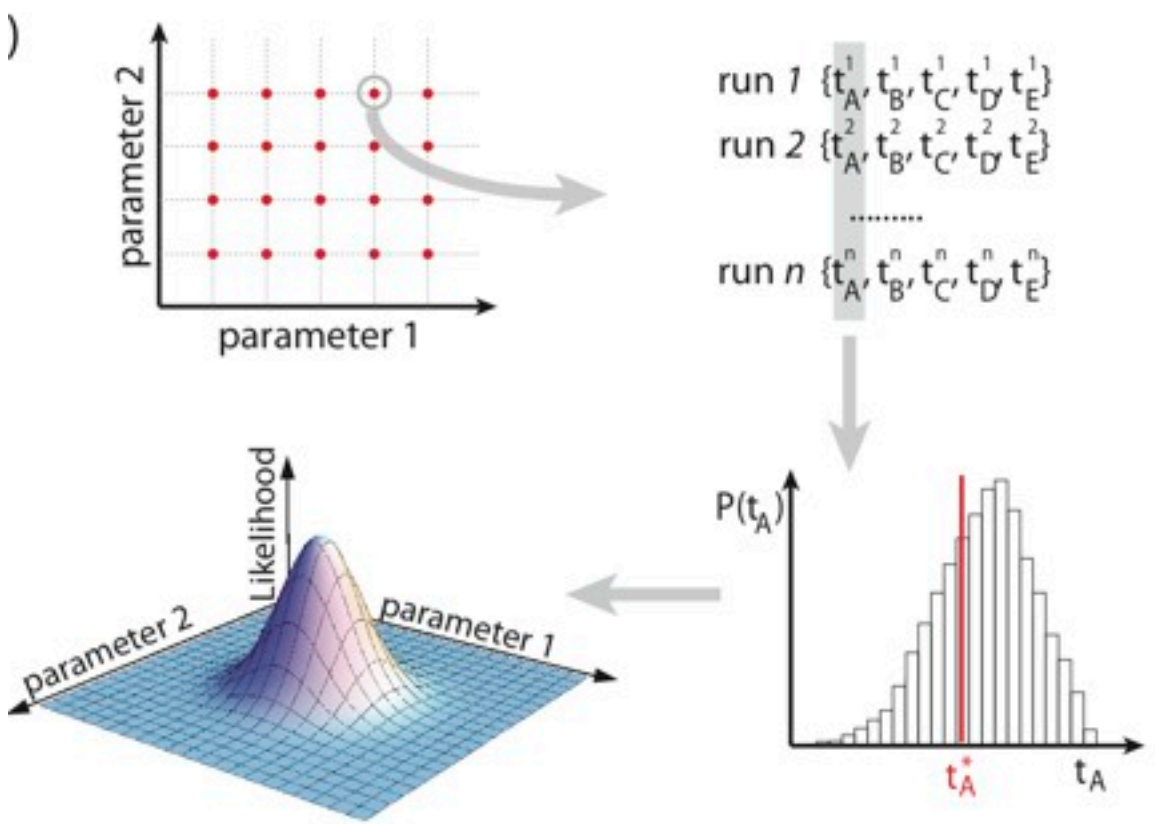
Monte Carlo likelihood parameters' estimate

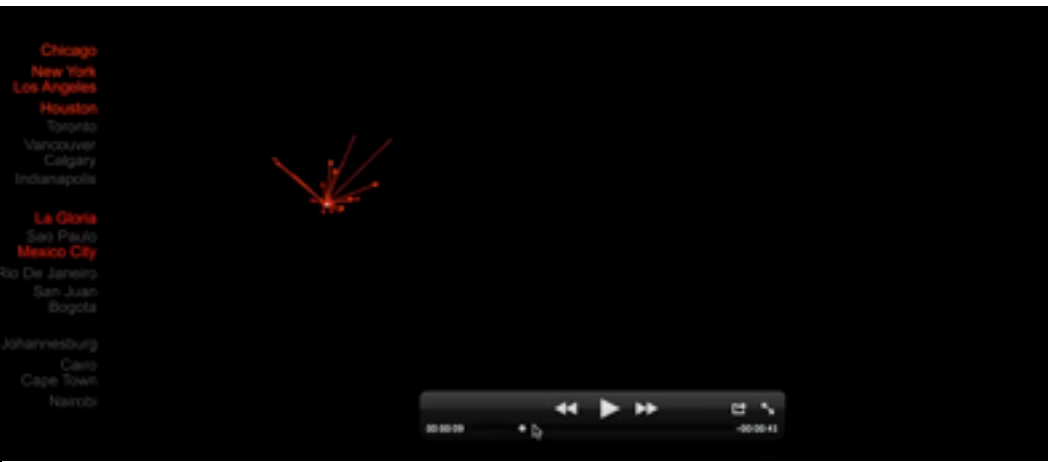
Backtrack of the number of infections in Mexico from case importation and transportation data. (Fraser et al. Science 2009,324,1557)

Numerical generation of thousands of infection trees (Importation/generation of the first symptomatic infectious in a given subpopulation).



Statistical distribution of the seeding time after >10^3-10^4 numerical stochastic realizations for each set of the parameters.

Monte Carlo likelihood parameters' estimate



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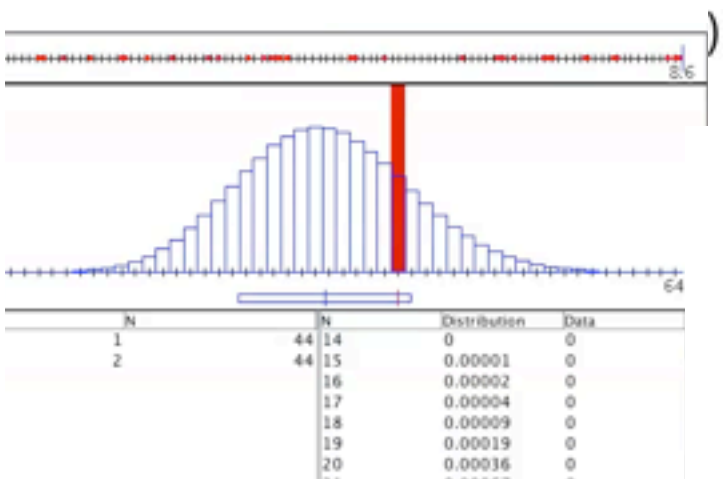
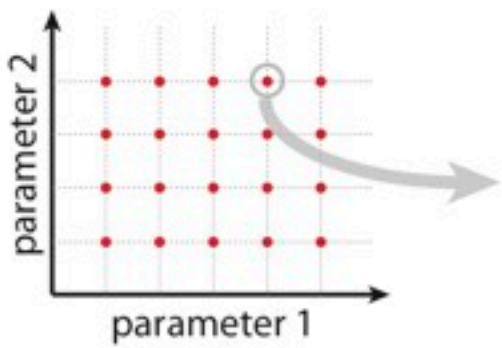
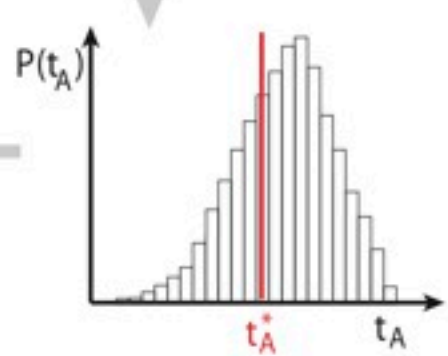
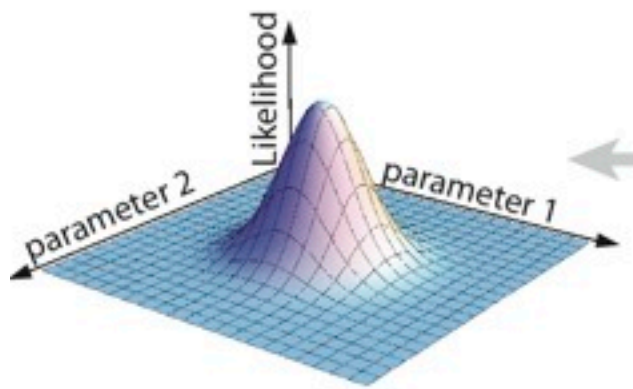


N		N	Distribution	Data
1	44	14	0	0
2	44	15	0.00001	0
		16	0.00002	0
		17	0.00004	0
		18	0.00009	0
		19	0.00019	0
		20	0.00036	0



run *1* $\{t_A^1, t_B^1, t_C^1, t_D^1, t_E^1\}$
run *2* $\{t_A^2, t_B^2, t_C^2, t_D^2, t_E^2\}$
.....
run *n* $\{t_A^n, t_B^n, t_C^n, t_D^n, t_E^n\}$





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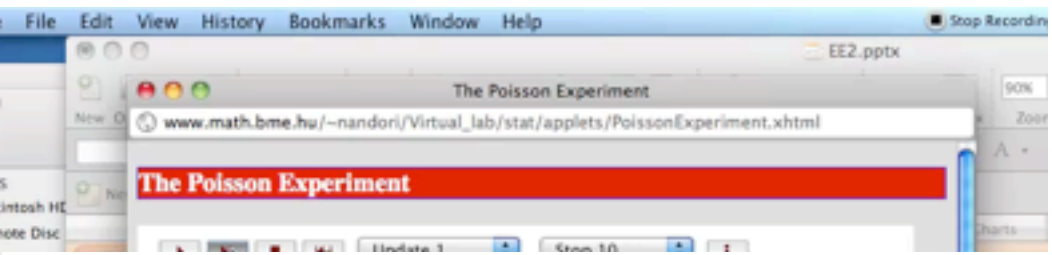

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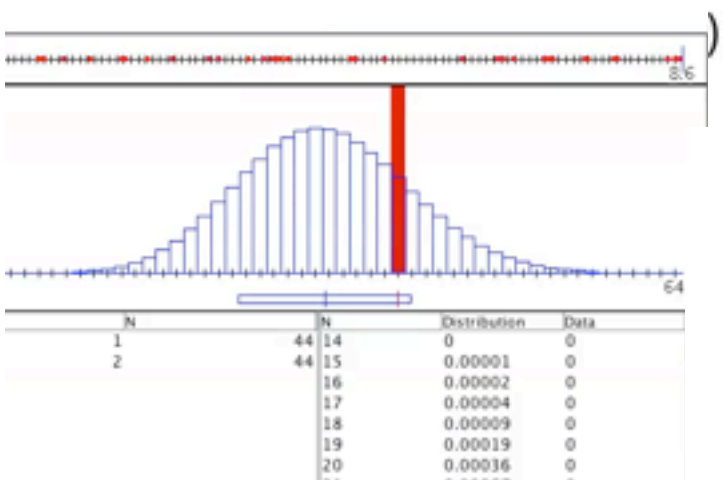
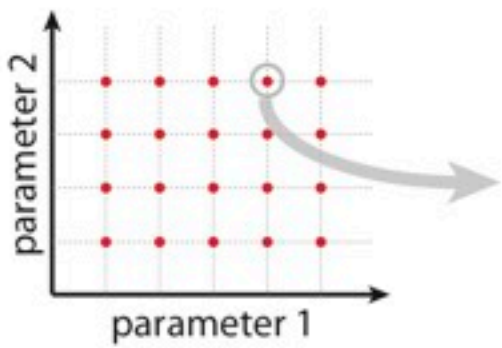
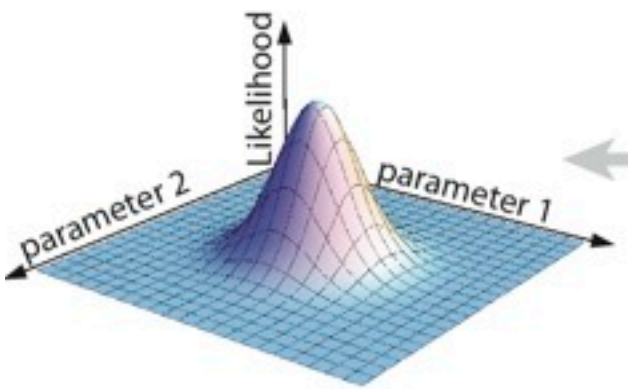
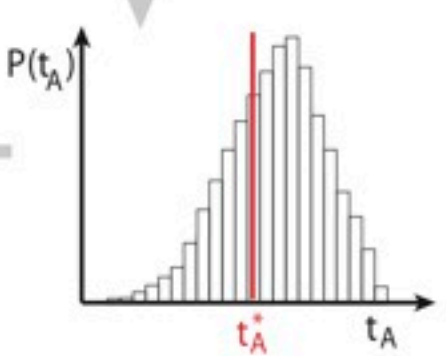




run 1 $\{t_A^1, t_B^1, t_C^1, t_D^1, t_E^1\}$
run 2 $\{t_A^2, t_B^2, t_C^2, t_D^2, t_E^2\}$
.....
run n $\{t_A^n, t_B^n, t_C^n, t_D^n, t_E^n\}$





Statistical distribution of the seeding time after >10^3-10^4 numerical stochastic realizations for each set of the parameters.

STOCHASTIC FORECAST OUTPUT SETS

Ab-initio estimates of the epidemic timeline in each country or urban area without assumptions on case importation.

Model calibration based on case importation and epidemic arrival time in first infected countries

Specific for H1N1

Inclusion of inter-country commuting data

Traffic reduction to and from Mexico

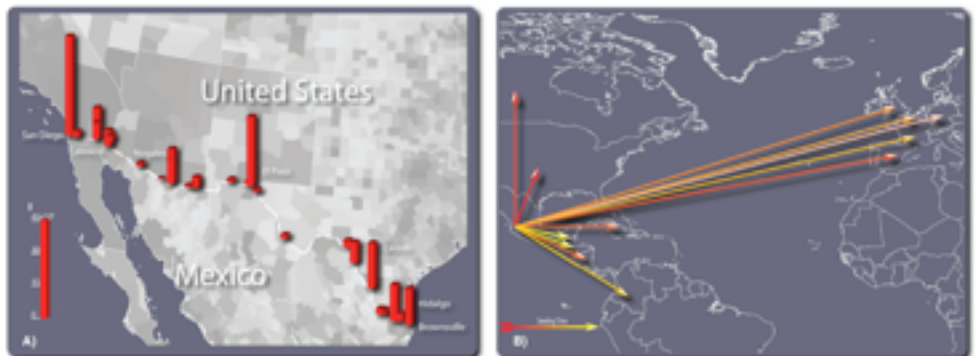
Monte-Carlo likelihood analysis on >6x 106 synthetic epidemic (on supercomputer).

Each realization produces 300-500 MB.

Data from countries reporting the first cases (93 countries by June 18.

Transmissibility determined with the first 12 countries seeded from Mexico.

Seasonality signal by using 60 countries (determine the time window worth of data).



	Baseline	Reference	Pre-exposure immunity
Monte-Carlo likelihood calibration	✔	✔	✔
Worldwide air traffic reduction after April 25th, 2009		✔	✔
Real vaccinations campaigns in the northern hemisphere			✔
Pre-exposure immunity of the elderly			✔
Full mobility database	✔	✔	✔

Infection tree

Real time forecast for the H1N1pdm (2009)

Real time forecast for the H1N1pdm (2009)

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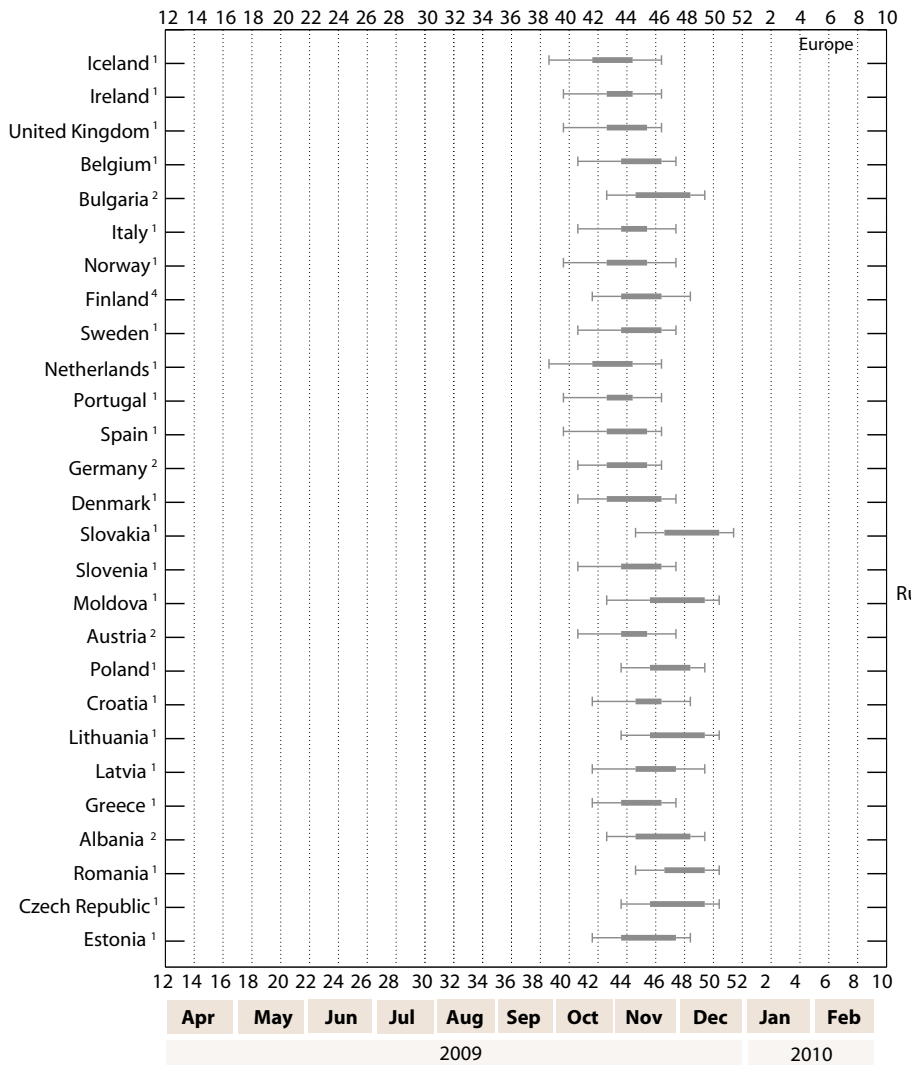

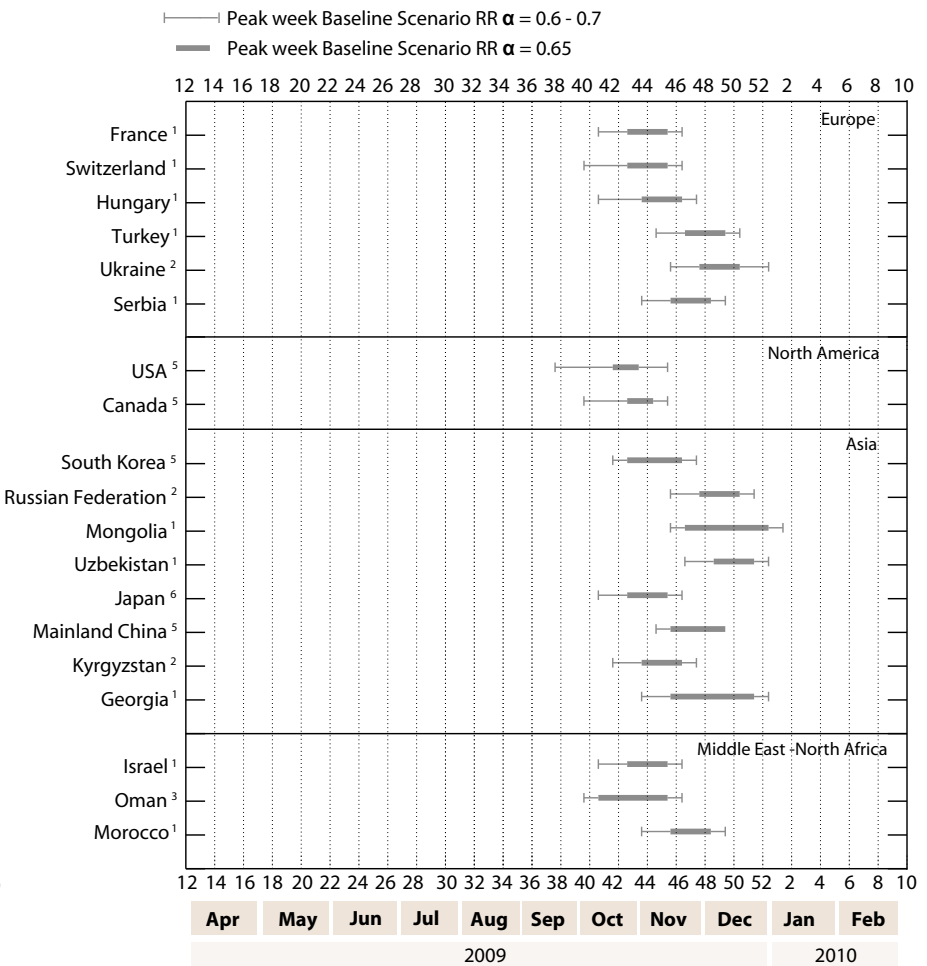

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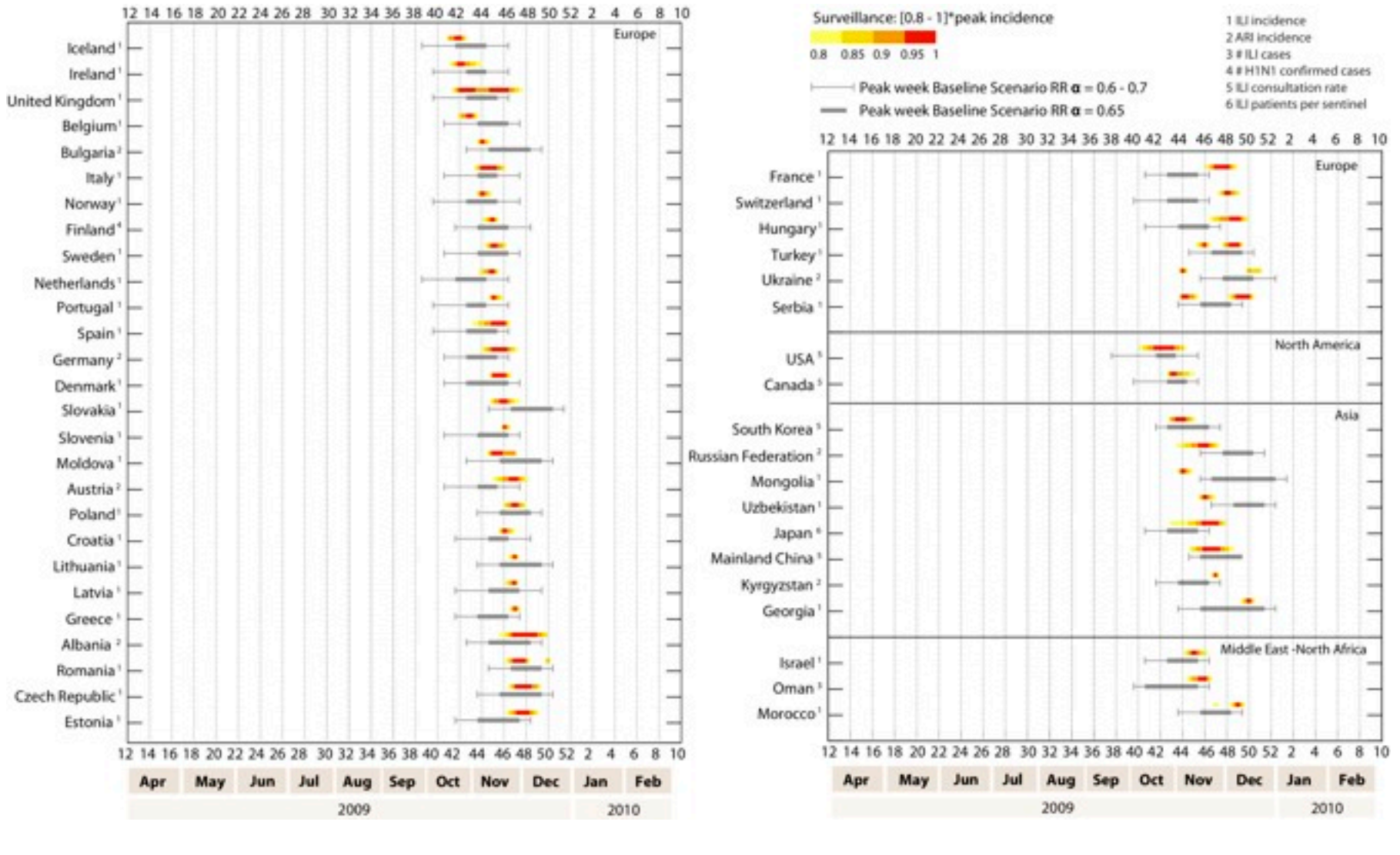


LINEAR-THINKING DOES NOT WORK

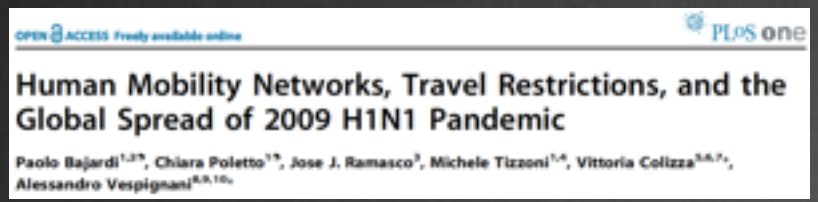
Non-linear Behavior

- an infinitesimal perturbation or change in pattern, sets up macroscopic changes and generate new patterns (and viceversa)
- Surprising phase transitions: one "state" of the system may give way to another, with no precursors or warning
- Counter intuitive change in collective behavior.
- Systemic and interdependent risk
- Global perspective

Computational thinking

- Computational thinking as the "macroscope" for the mind in exploring collective surprises.
- Simulation as an analytical tool for the quantitative understanding

NON-LINEAR THINKING AT WORK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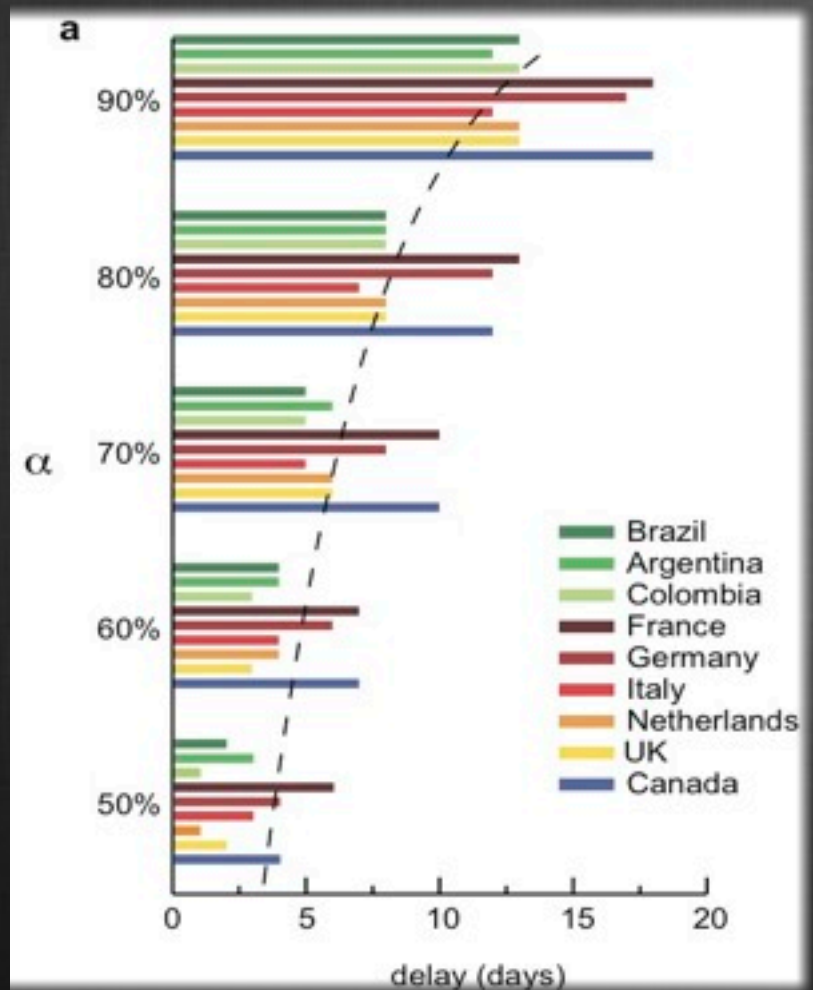
Human Mobility Networks, Travel Restrictions, and the Global Spread of 2009 H1N1 Pandemic

Paolo Bajardi[1,2*], Chiara Poletto[3*], Jose J. Ramasco[3], Michele Tizzoni[1,4], Vittoria Colizza[5,6,7*], Alessandro Vespignani[8,9,10*]



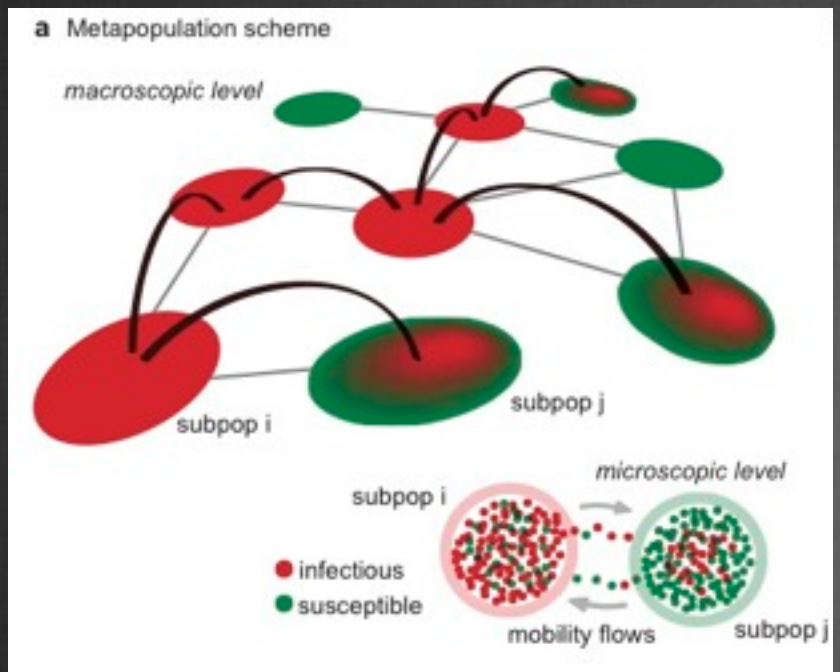
Non-linear features of traffic restriction

Large traffic reduction leads to small delays of the epidemic peak.

- [Hollingsworth et al 2006; Brownstein et al. 2006; Cooper et al. 2006; Scalia Tomba et al. 2008; Gautreau et al. 2008; Colizza et al.2007; Bajardi et al. 2011]

$$\Delta t \sim - \ln (1-\alpha)$$

IS A SUCCESSFUL CONTAGION PROCESS IN A SINGLE SUBPOPULATION ABLE TO SPREAD IN A COLLECTION OF SUBPOPULATIONS?

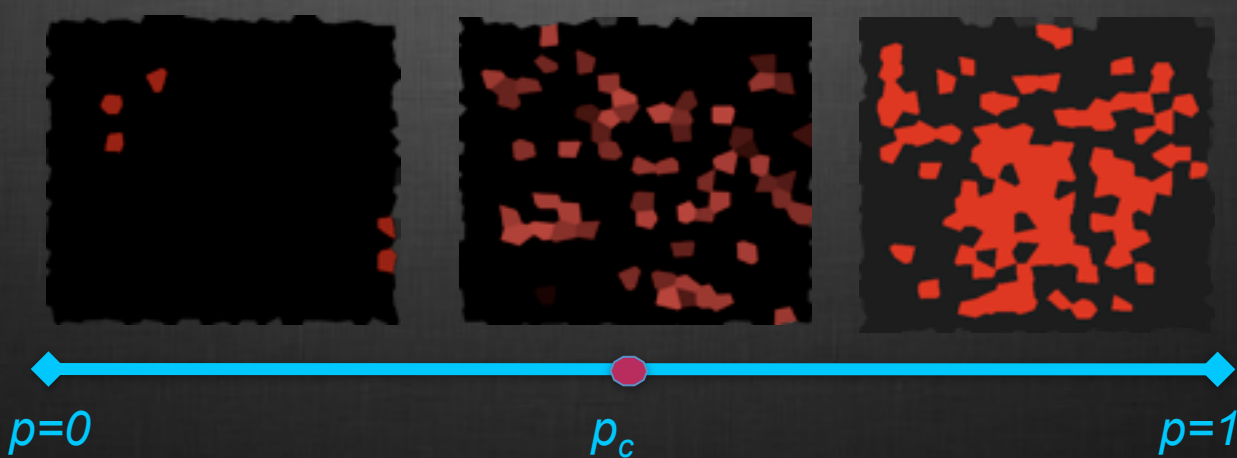


Infection/information is carried by Particles/agents diffusing interacting with rate p
from sub-population to sub-population:

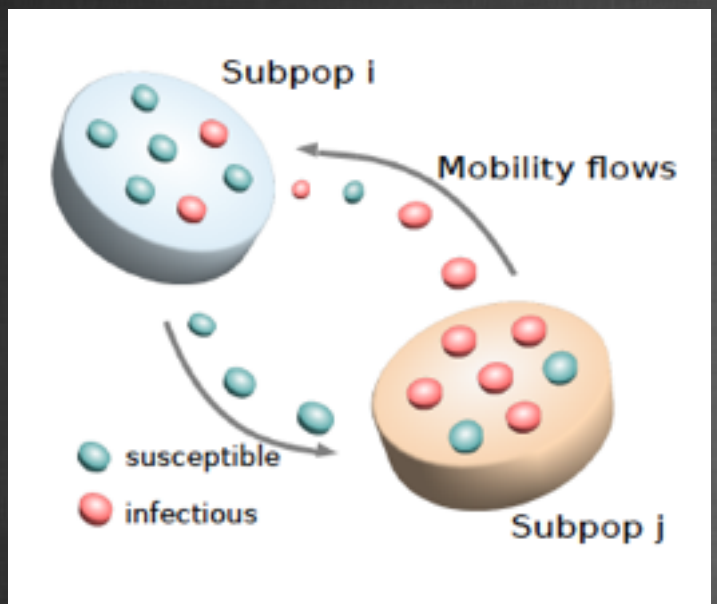
p=0: no spreading

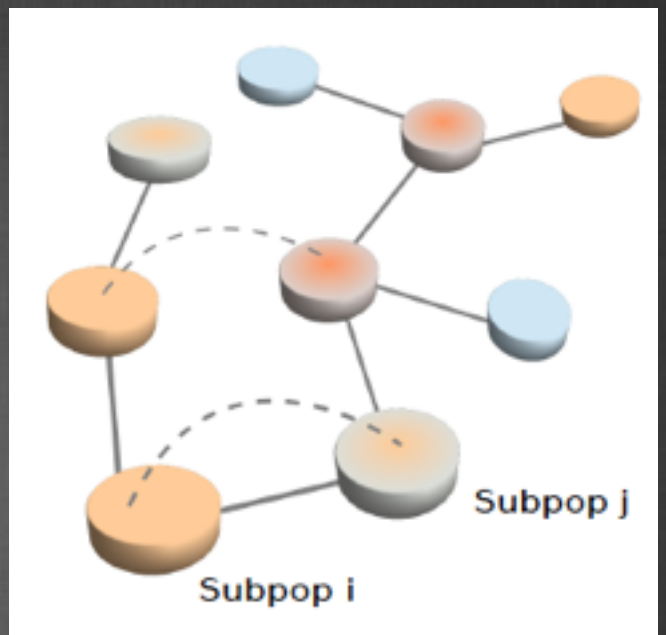
p=1: equivalent to a fully mixed situation

Tipping point/ threshold



MULTI-POPULATION GLOBAL THRESHOLD





Basic equations describing the dynamics

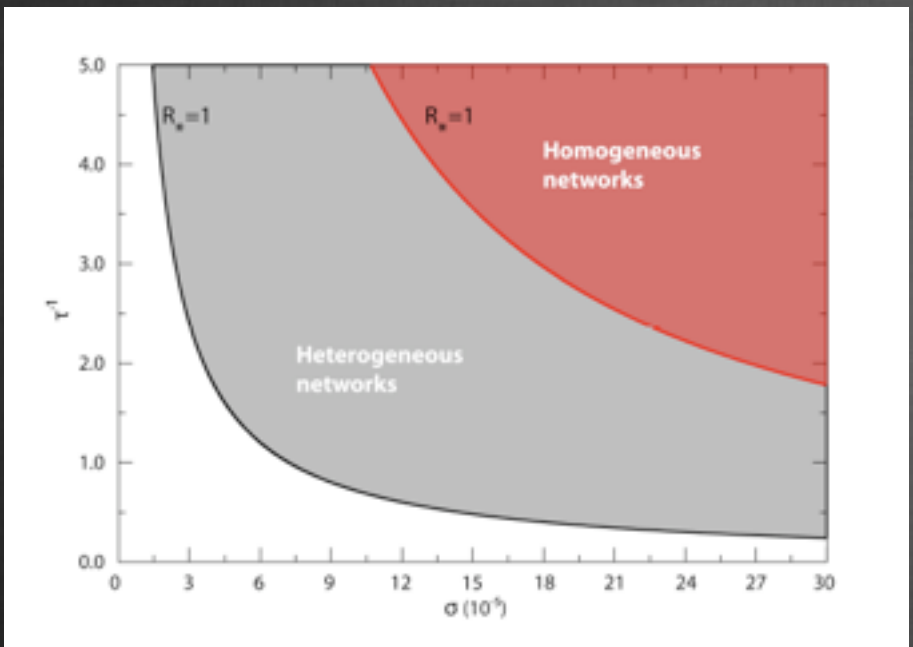
$$\partial_t N_{kk} = -\sigma_k N_{kk} + \tau_k k \sum_{k'} N_{kk'} P(k'|k)$$

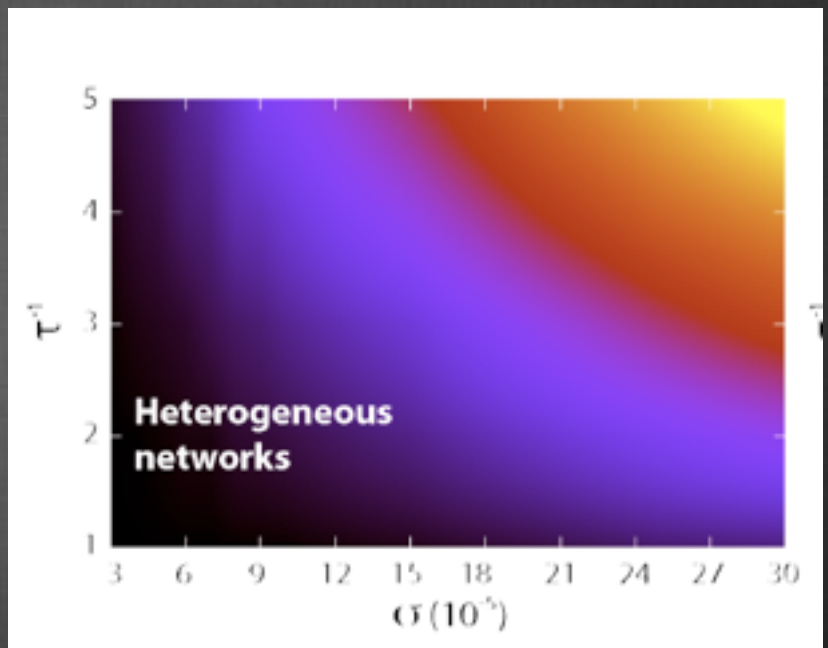
$$\partial_t N_{kk'} = \sigma_{kk'} N_{kk} - \tau_k N_{kk'} \quad ,$$

Basic generation equation for the invasion of new populations

$$D_k^n = \frac{2\overline{N}(R_0-1)^2}{R_0^2\langle k^{1+\theta}\rangle\langle k\rangle} kP(k) \sum_{k'} D_{k'}^{n-1}(k'-1) \times \left[\frac{k'^{1+\theta}\sigma_{k'k}}{(1+\rho_{k'})\tau_{k'}} + \frac{k^{1+\theta}\sigma_{kk'}}{(1+\rho_k)\tau_k}\right]$$

INVASION THRESHOLD AS A FUNCTION OF INTERACTION RATE AND DURATION OF THE INTERACTION.





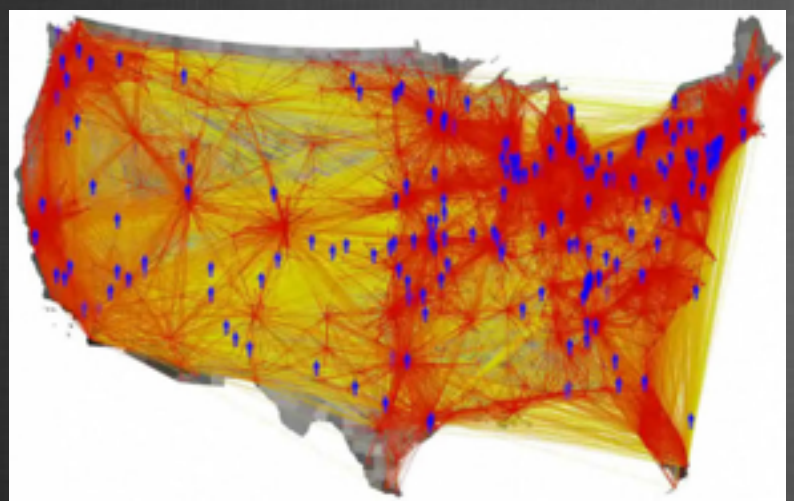
Analytical results

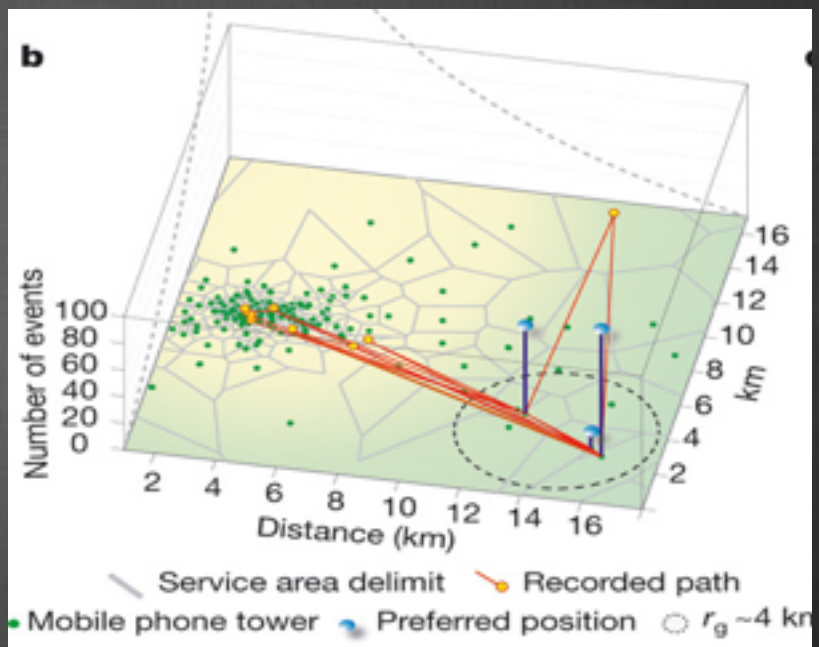
Numerical results

TIPPING POINT AS A FUNCTION OF HUMAN MOBILITY

Tenfold traffic reduction is needed to achieve containment effects

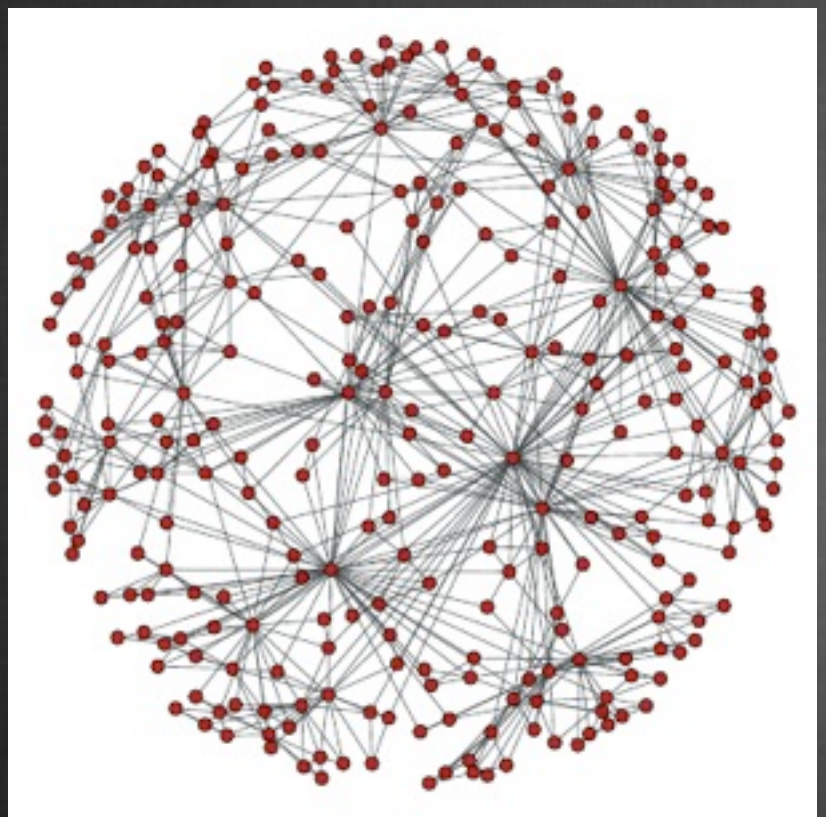
FROM GEOGRAPHY TO SOCIAL SPACE

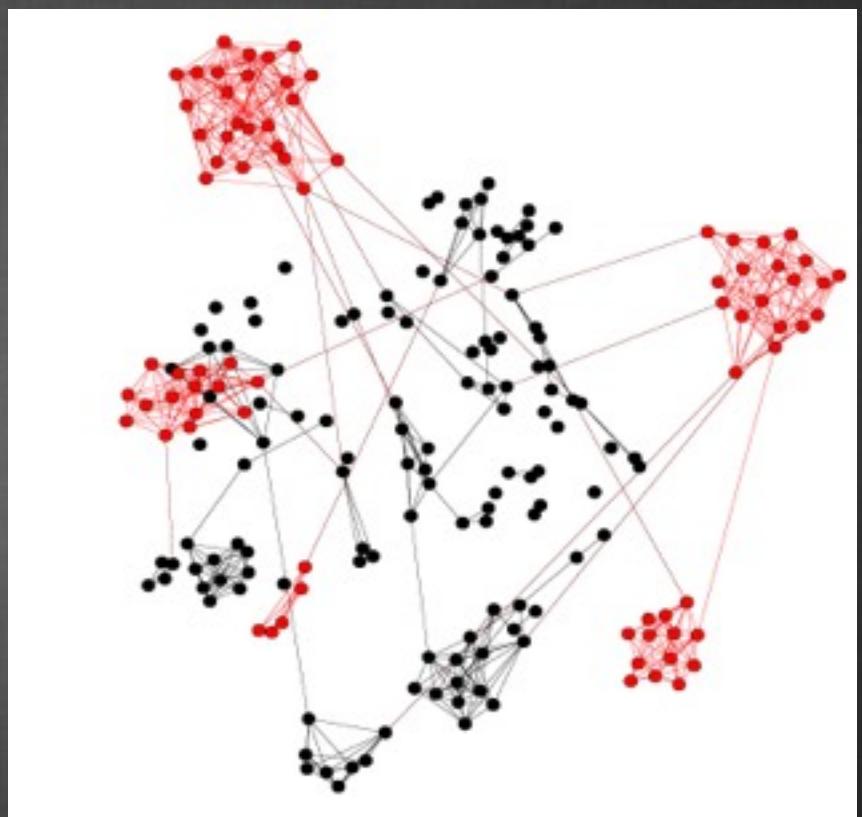




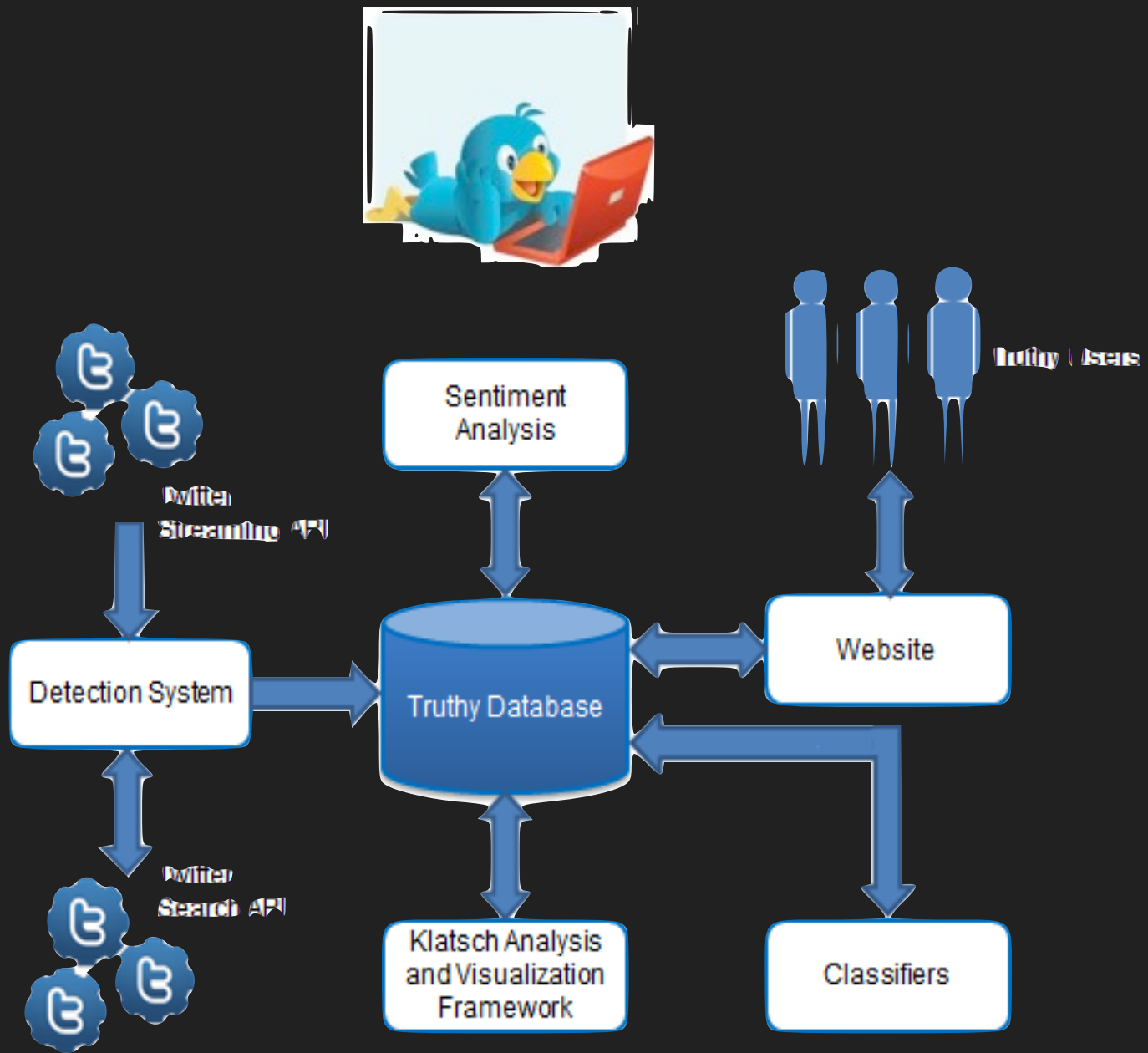
Geographical areas/census
Mobility

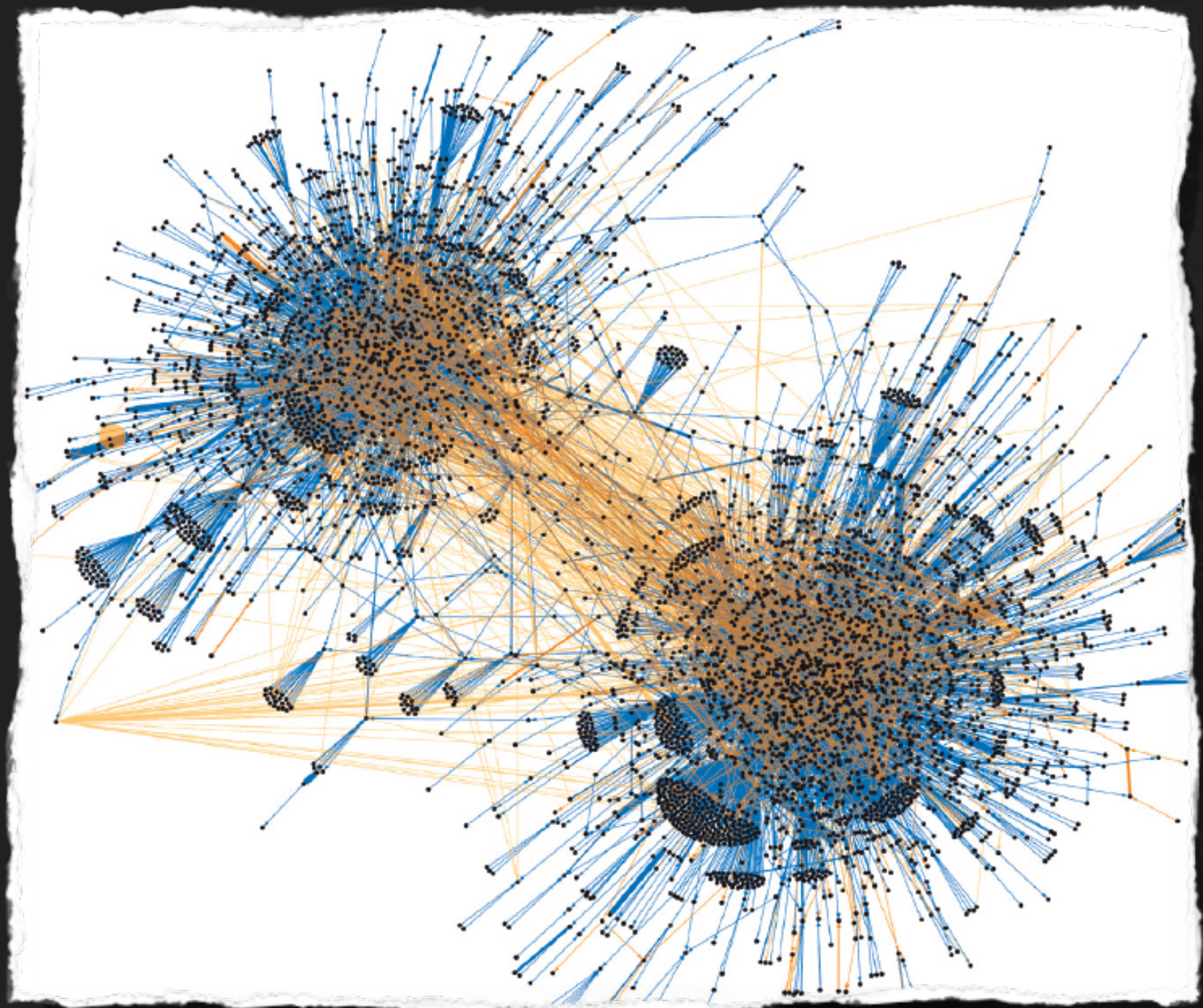
FROM GEOGRAPHY TO SOCIAL SPACE



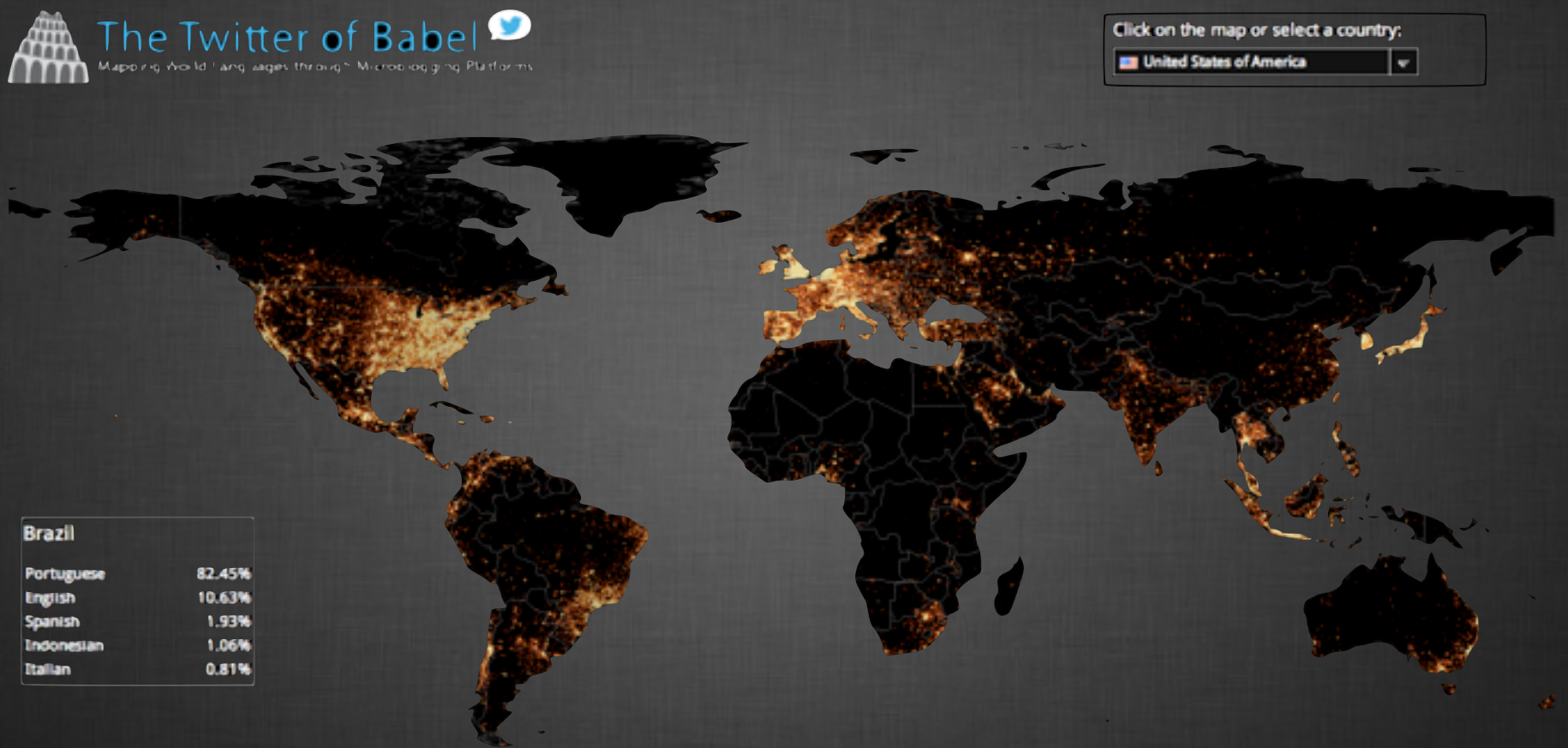


Structured communities in the abstract social space define by knowledge and information


Sentiment Analysis
Truthy Users
Twitter Streaming API
Detection System
Truthy Database
Website
Twitter Search API
Klatsch Analysis and Visualization Framework
Classifiers

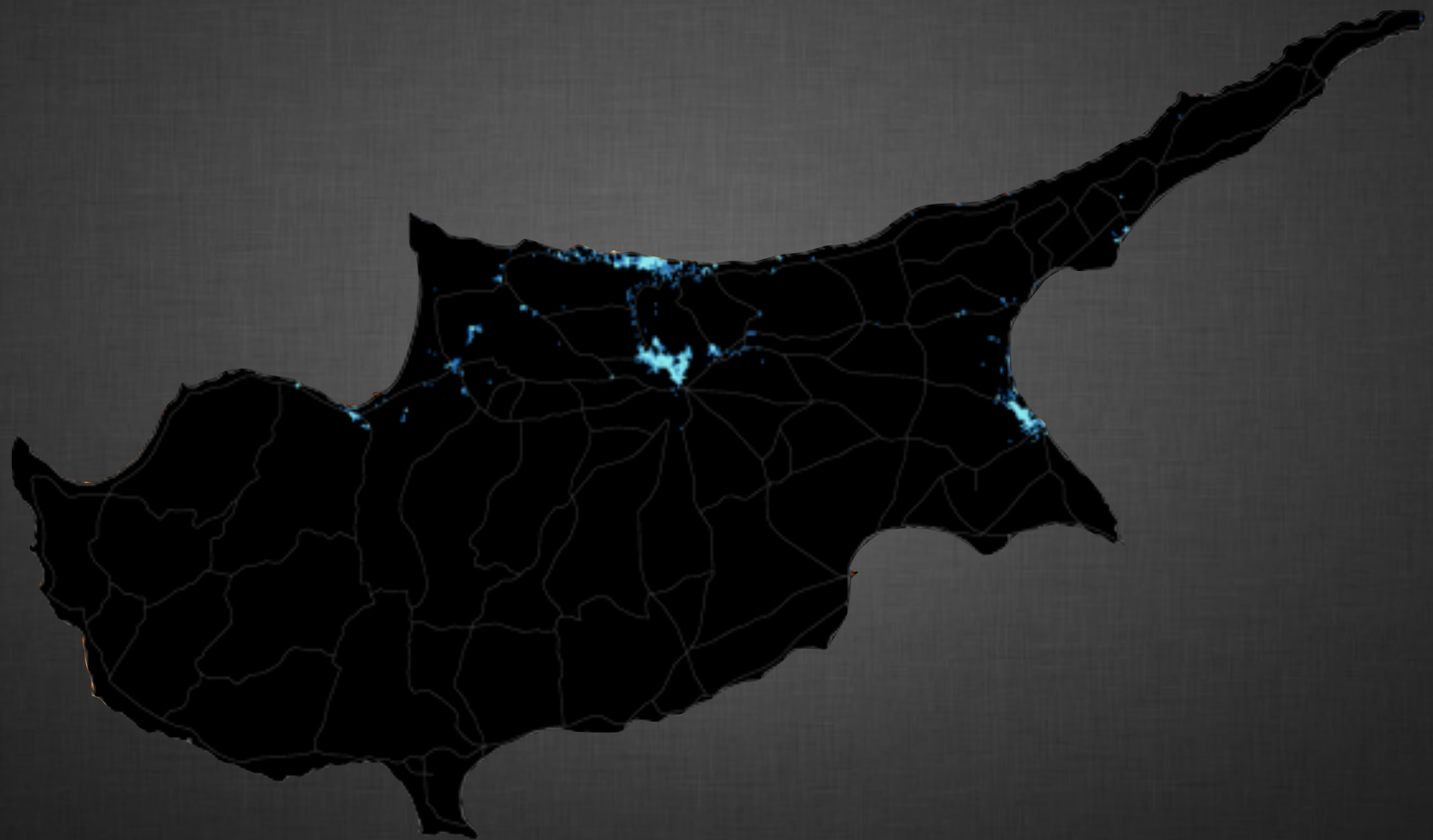


MICROBLOGGING (I.E.TWITTER)



Twitter Signal

MOBS LAB



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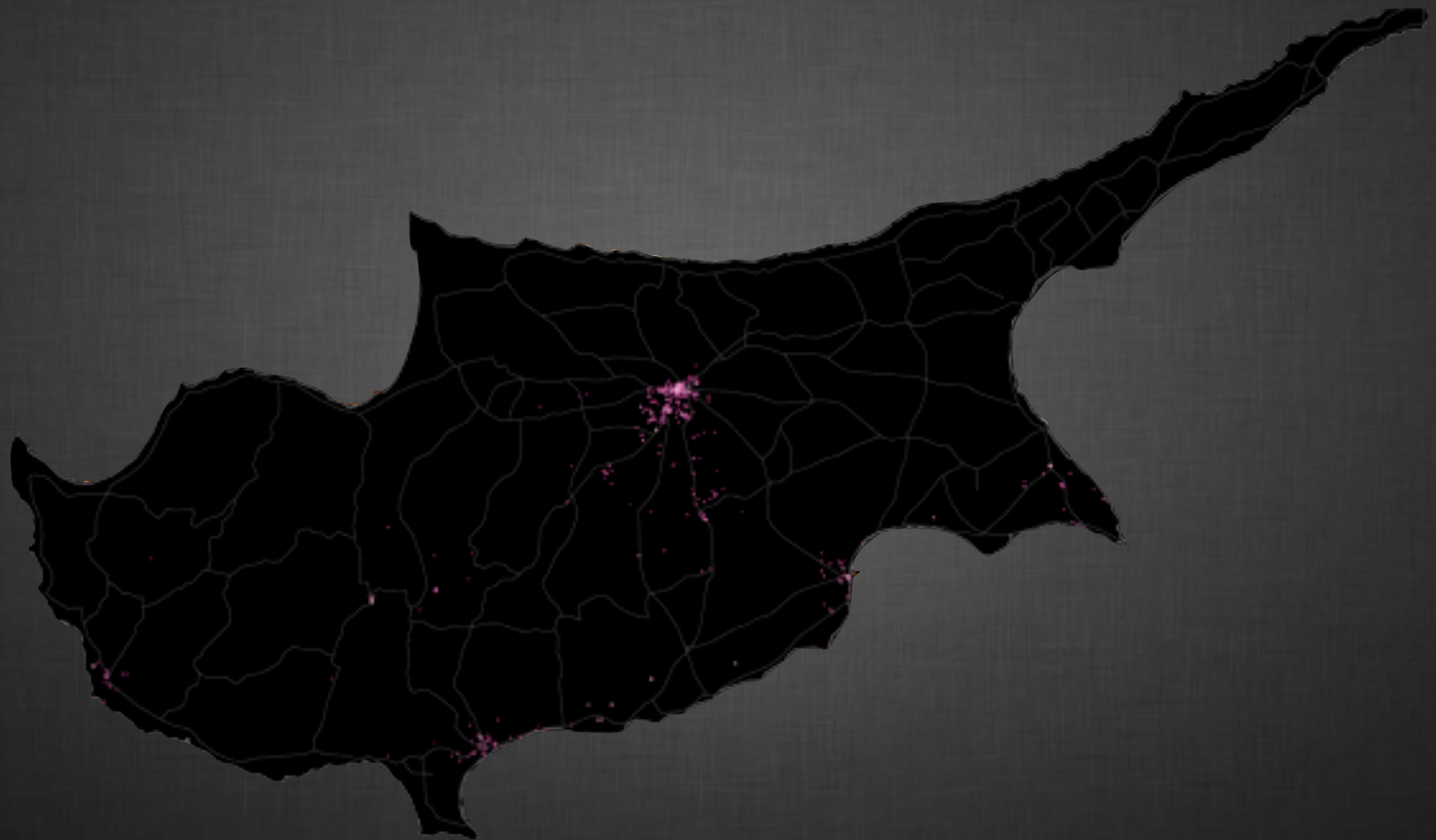

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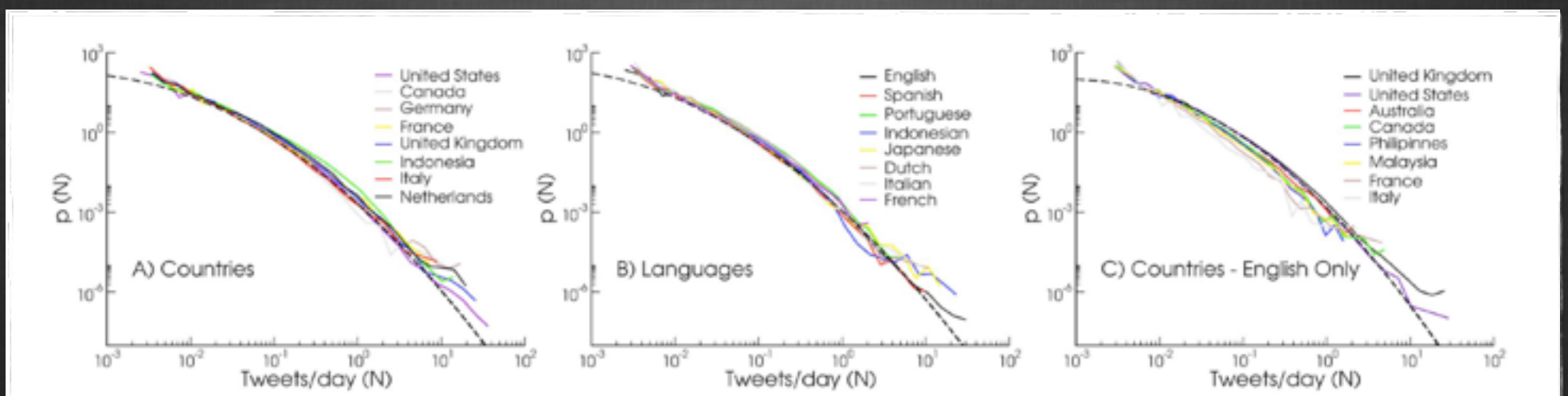
OPEN ACCESS Freely available online

PLOS | ONE

The Twitter of Babel: Mapping World Languages through Microblogging Platforms

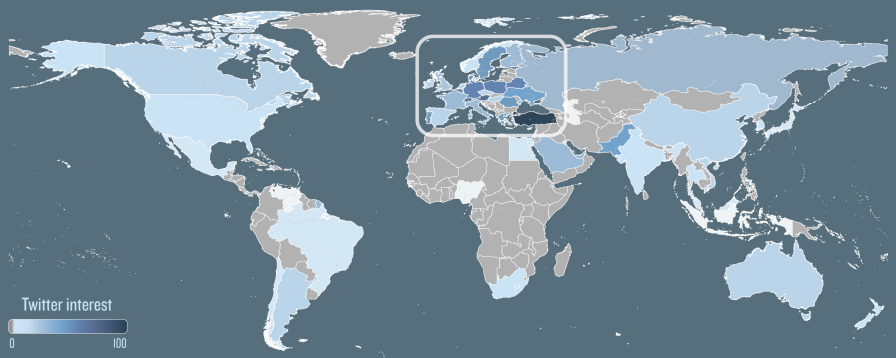


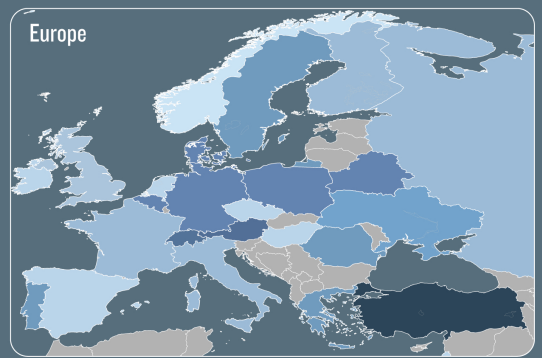
Universal user activity

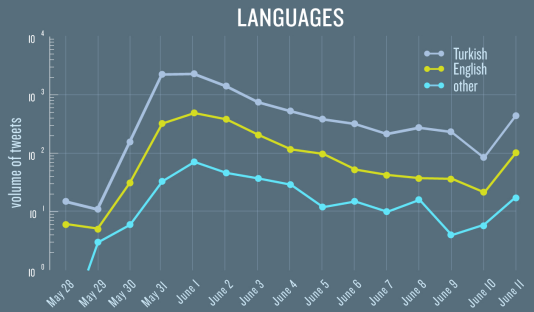
TURKEY PROTESTS

Mapping Events Through Microblogging Platform

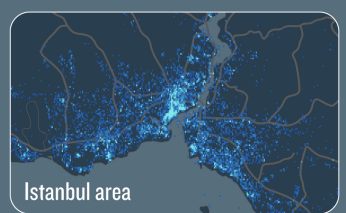
On May 28th 2013, a group of people began protesting against the disruption of Gezi Park in Istanbul, Turkey. The protest spread to the main Turkish cities, generating a massive confrontation with the current Turkish Government. Since the beginning, Twitter has been used as an effective media to coordinate and spread news about the protest. Following Twitter's most popular hashtags related to the protest, it is possible to have a spatiotemporal mapping of the Turkish events.

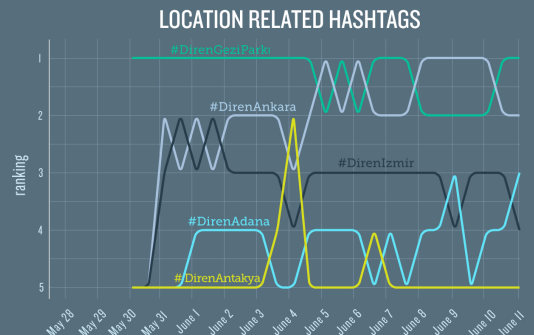


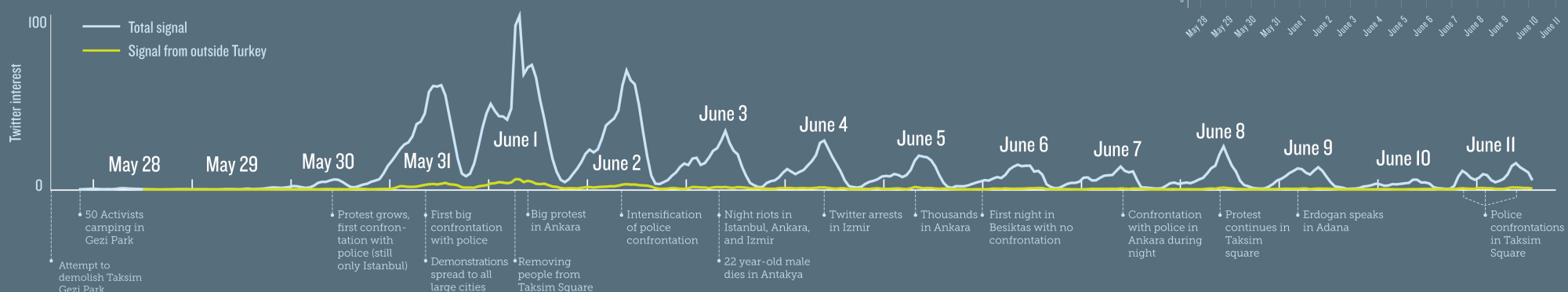




The geolocalized Twitter signal associated with the Turkish protest has been resolved at various geographical resolutions. At the country level we use as a proxy of international concern for the Turkish events the relative volume of tweets signal associated with the protest hashtags. Within Turkey the signal reveals the geographical hot spots for the protest. The language used for tweets reveals the level of international focus on the events. Inspecting the ranking of hashtags related to locations identifies peaks of activity in different cities. Twitter signal also provides a real time monitoring of the ongoing events as shown on the timeline below.







Northeastern University MOBS LAB

TAP THE "GLOBAL CONVERSATION" TO PREDICT THE FUTURE

- Politics (emergence of consensus, election)
- Social collective phenomena (riots, political protests, etc.)
- Economics (stock market)

Many authors have pointed out, there are several challenges:

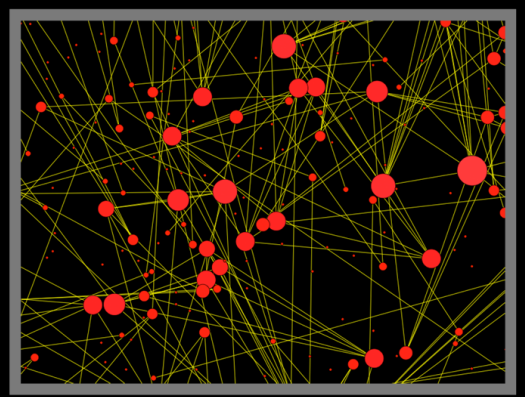
- intrinsic biases,
- uneven sampling across location of interest
- causality assumption

THIS IS NOWCAST !!!

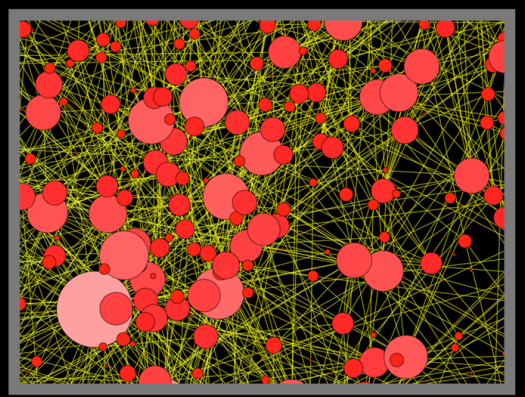
We miss the microscopic generative foundations and models

TWITTER NETWORK ON MAY 15TH PROTEST MOVEMENT IN SPAIN

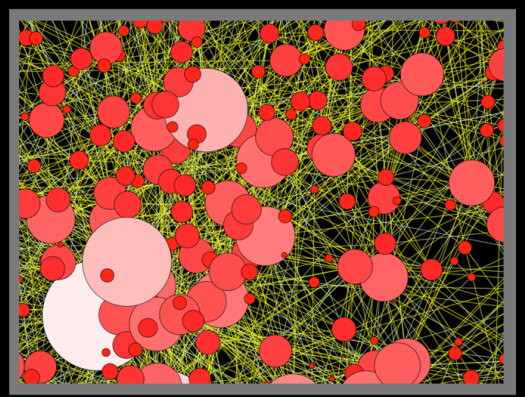
Moreno et al. (BIFI, Universidad de Zaragoza



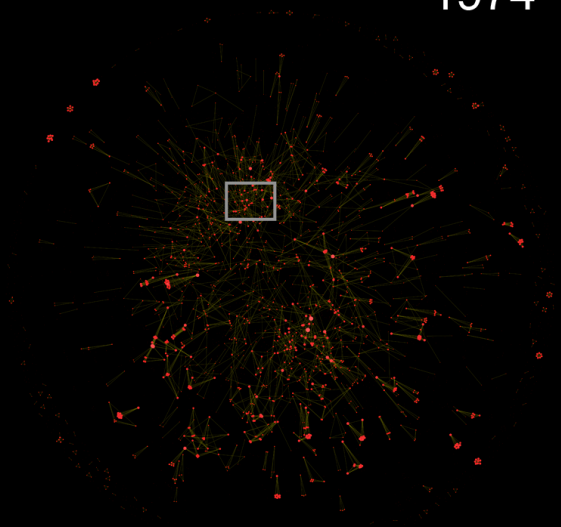
1974

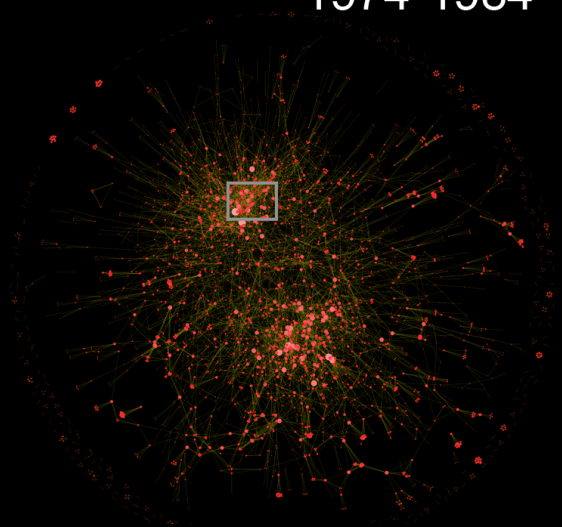


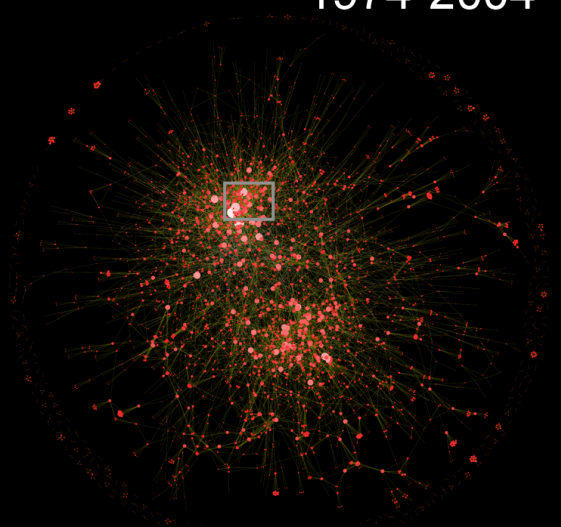
1974-1984

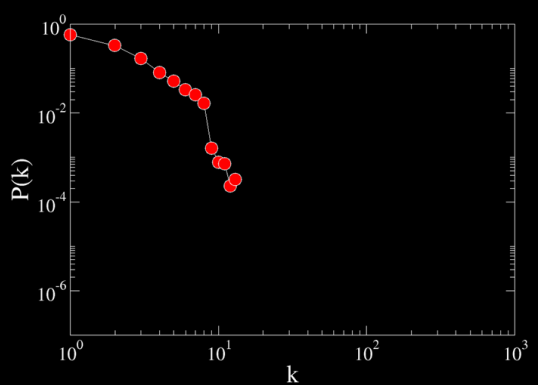


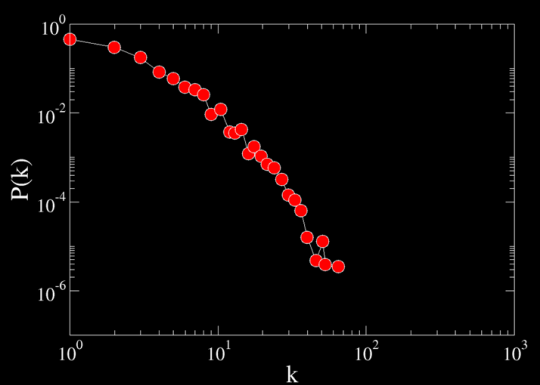
1974-2004

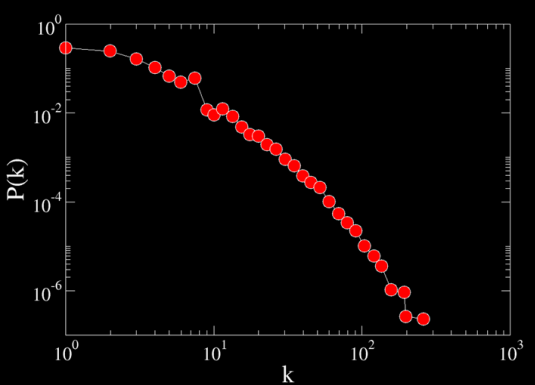












NETWORK MODELING

Connectivity driven models:

- Connectivity patterns as basic ingredient of models generation (Erdös-Rényi model to Logit models, p*-models, Markov random graphs)
- Preferential attachment dynamical models
- [N.B. Topological properties merely represent a time-integrated perspective of the system]

Relational event-based network analyses.

Feedback models

Models generally considered in a time-scale separation regime

- Process dynamics decoupled by network evolution
- Frozen network (process time scale << network evolution time scale)
- Random homogenous mixing (network evolution time scale << process time scale)

DEFINITION OF THE SIMPLEST NON-TRIVIAL NETWORK GENERATIVE MODEL

- Encodes the heterogeneous activity of the nodes in one observable
- Generates fluctuating connectivity patterns
- Amenable of refinement
- Allowing the analytical treatment of dynamical processes

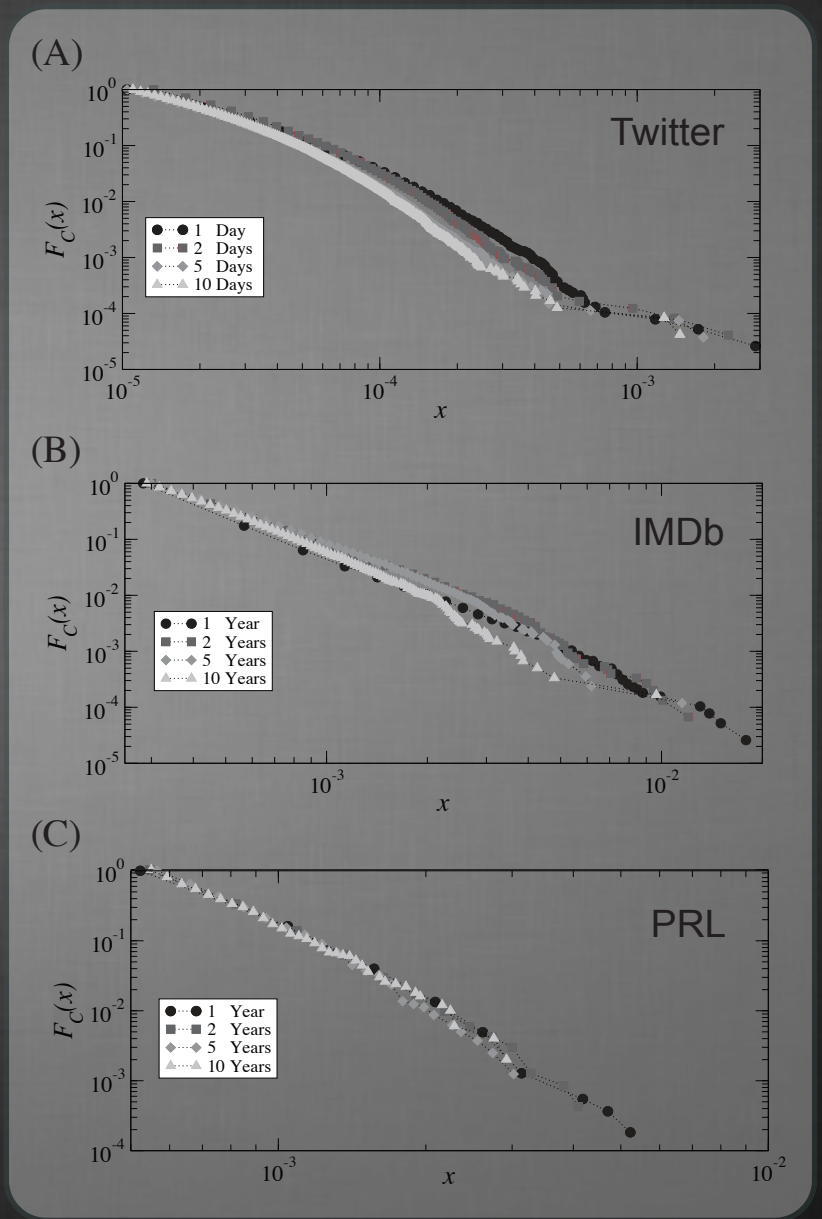
Perra, Goncalves, Pastor-Satorras, Vespignani, Activity driven modeling of time-varying networks, Scientific Reports, 2, 469, (2012).
Perra et al. Random walk and search in time-varying networks, Phys. Rev. Letters, 109, 238701, (2012)

IDENTIFICATION OF A FUNCTION THAT ENCODES THE INSTANTANEOUS DYNAMICS OF THE NETWORK (EVOLUTION RATE)

Activity potential x_i = relative probability of activity of agent i

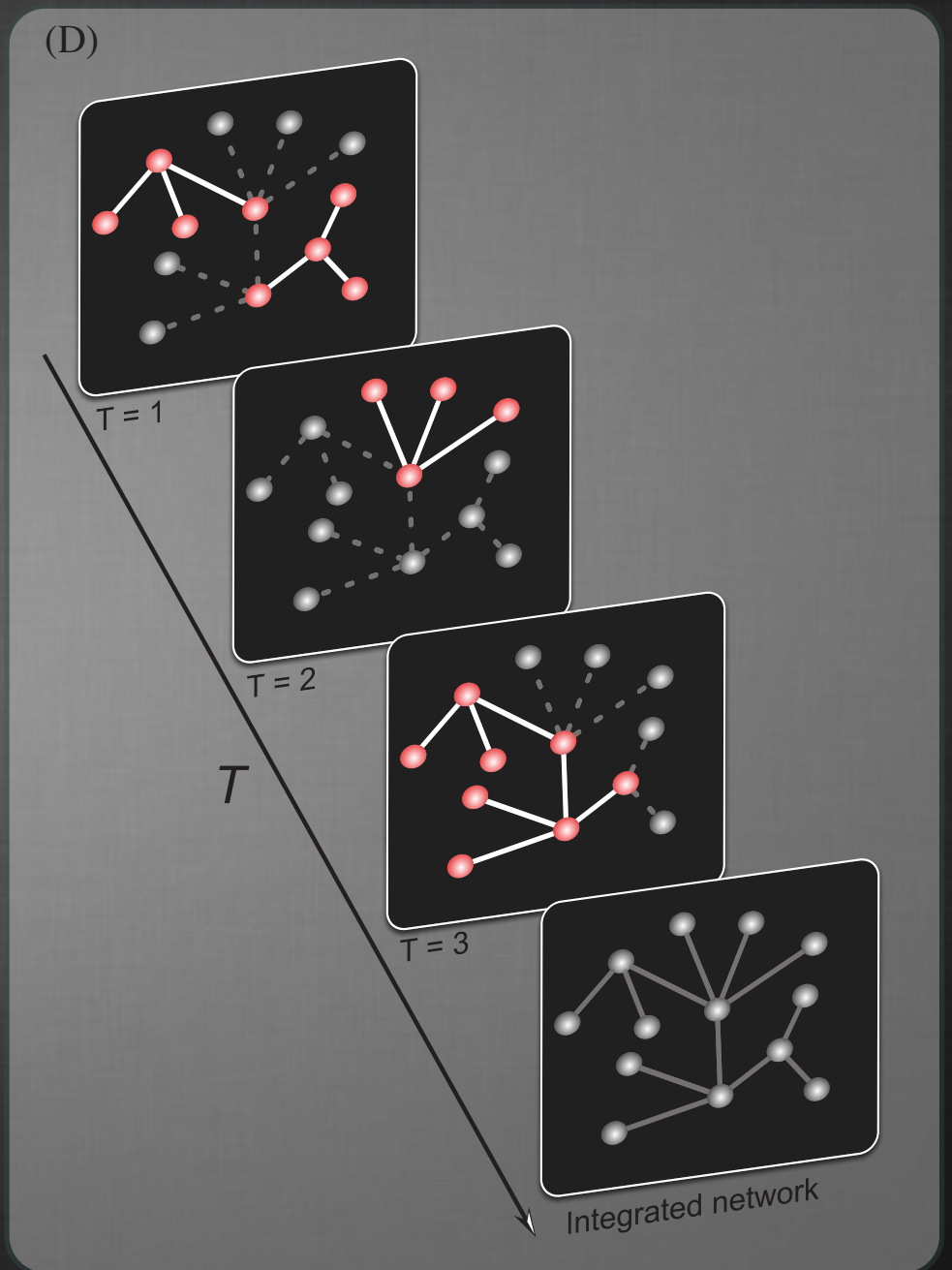
$$x_i = \frac{\#\text{int}_i}{\sum_i \#\text{int}_i}$$

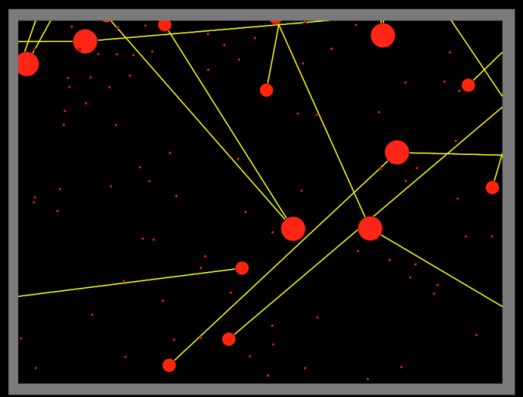
The distribution *Fc(x)* is virtually independent of the time scale over which the activity potential is measured.



A SIMPLE MODEL

- We consider N nodes (agents) .
- Each node i an activity/firing rate ai = η xi, defined as the probability per unit time to create new contacts or interactions with other agents.
- η is a rescaling factor defining the average number of interactions per unit time in the system).
- At each discrete time step t the network Gt starts with N disconnected vertices;
- With probability ai each vertex i becomes active and generates m links that are connected to m other randomly selected vertices. Non-active nodes can still receive connections from other active vertices;
- At the next time step t + 1, all the edges in the network Gt are deleted. From this definition it follows that all interactions have a constant duration τi = 1.





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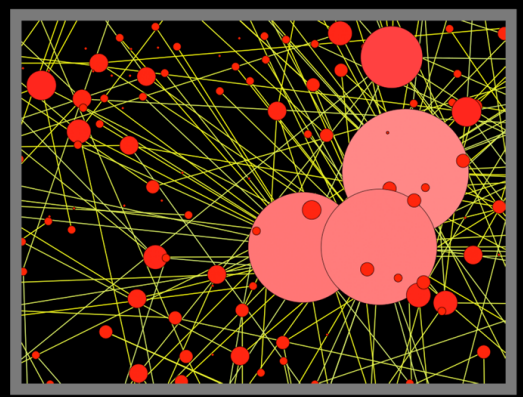
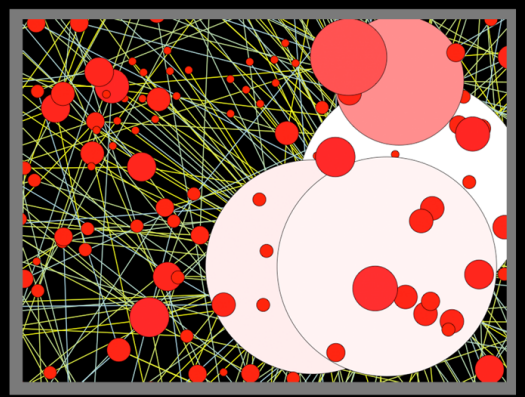


1-10



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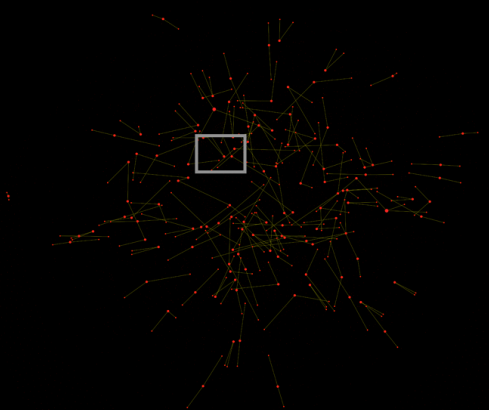
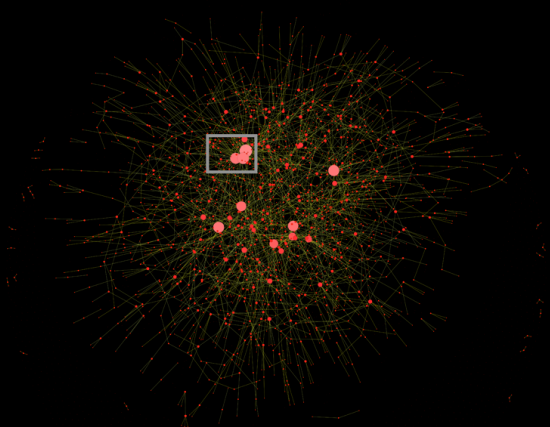
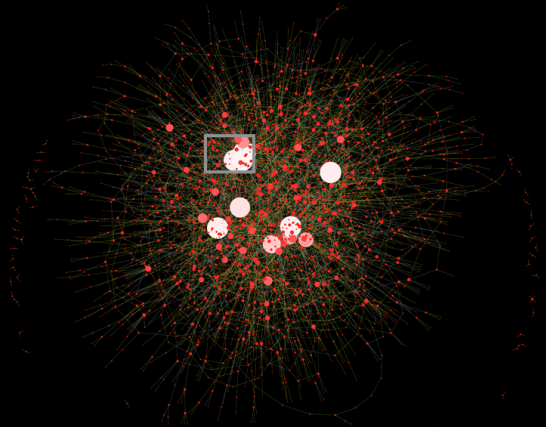
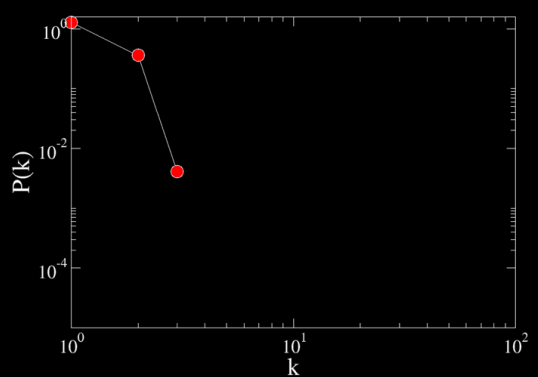
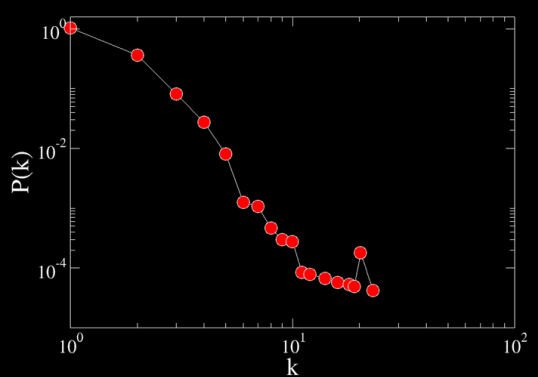
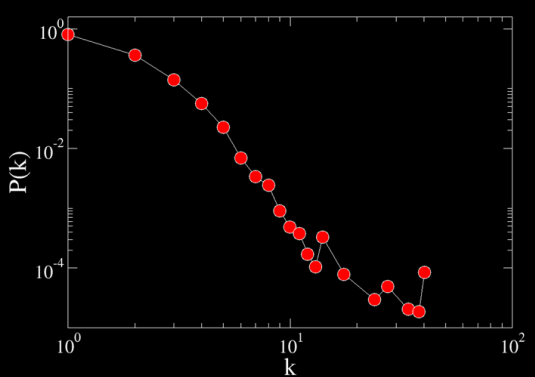












RANDOM WALK PROPERTIES IN TIME-VARYING NETWORKS

Master equation for the number of walkers in nodes of activity a

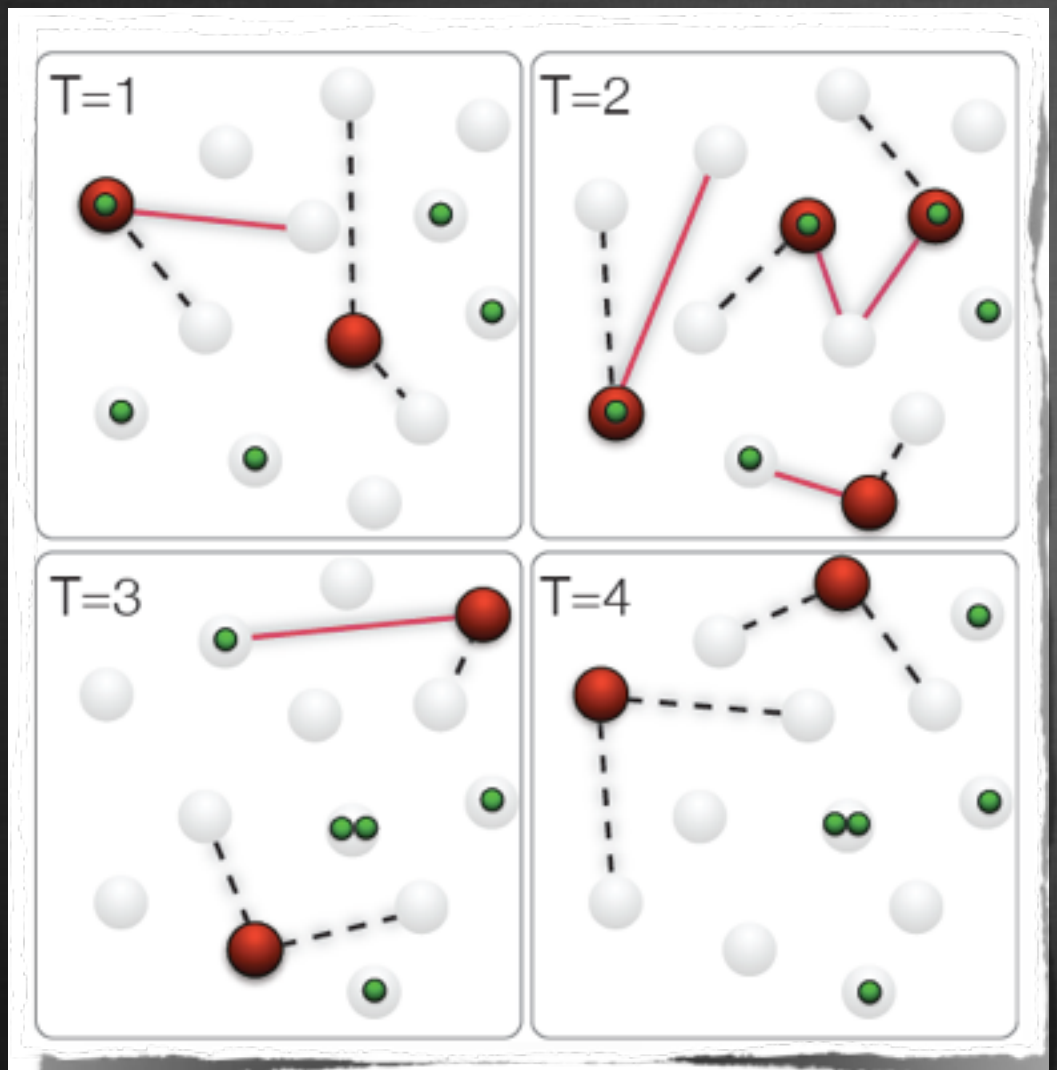
$$\frac{\partial W_a(t)}{\partial t} = -aW_a(t) + amw$$
$$-m\langle a\rangle W_a(t) + \int a' W_{a'}(t) F(a')\,\mathrm{d}a'$$

$$W_a = \frac{amw + \phi}{a + m\langle a\rangle}$$

where

$$\phi = \int aF(a)\frac{amw + \phi}{a + m\langle a\rangle}\mathrm{d}a$$

RANDOM WALK PROPERTIES IN TIME-VARYING NETWORKS



- Walkers diffuse each time a node is active.
- Nodes are active with rate a

- **Trapping of walkers**
- **"Slave mode" with respect to the network dynamic**

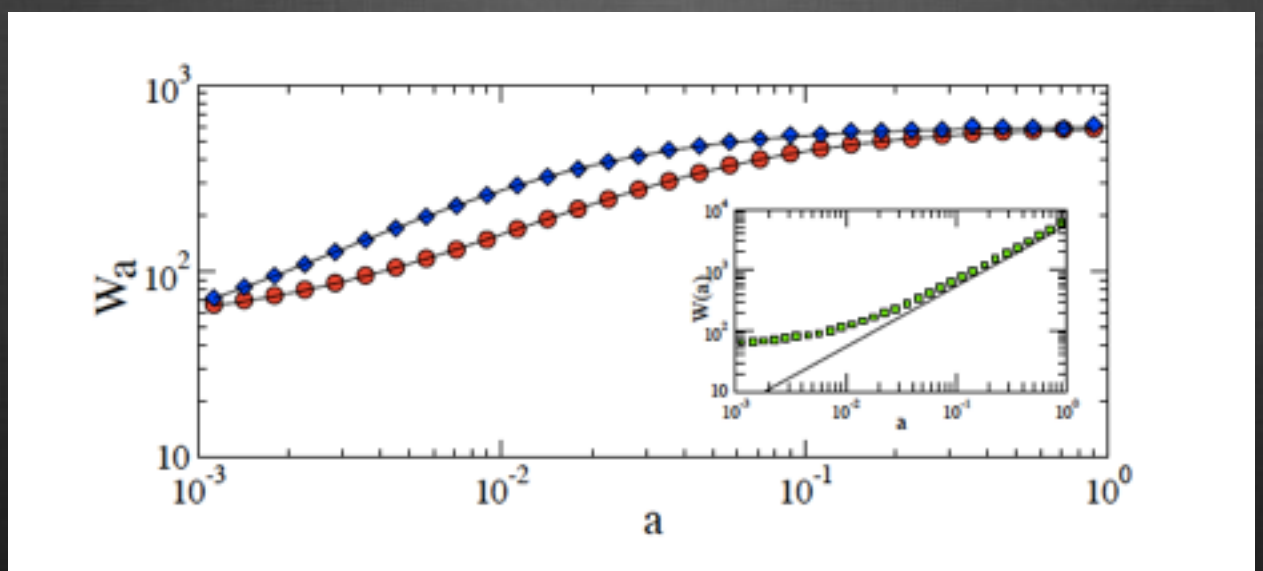
RANDOM WALK PROPERTIES IN TIME-VARYING NETWORKS

Static/time-aggregated networks

$$W_k \sim k \sim a$$

Time-Varying networks

$$W_a = \frac{amw + \phi}{a + m\langle a \rangle}$$



FUTURE QUESTIONS/CHALLENGES

- ➡ Definition of general co-evolving network models (no-time scale separation)
- ➡ Explorations of different dynamical processes in time-varying networks (consensus, game-theoretical,non-linear contagion…)
- ➡ Non-trivial correlations in time and connectivity (assortativity, link persistence, bursts activity…etc.)
- ➡ Response function in co-evolving networks

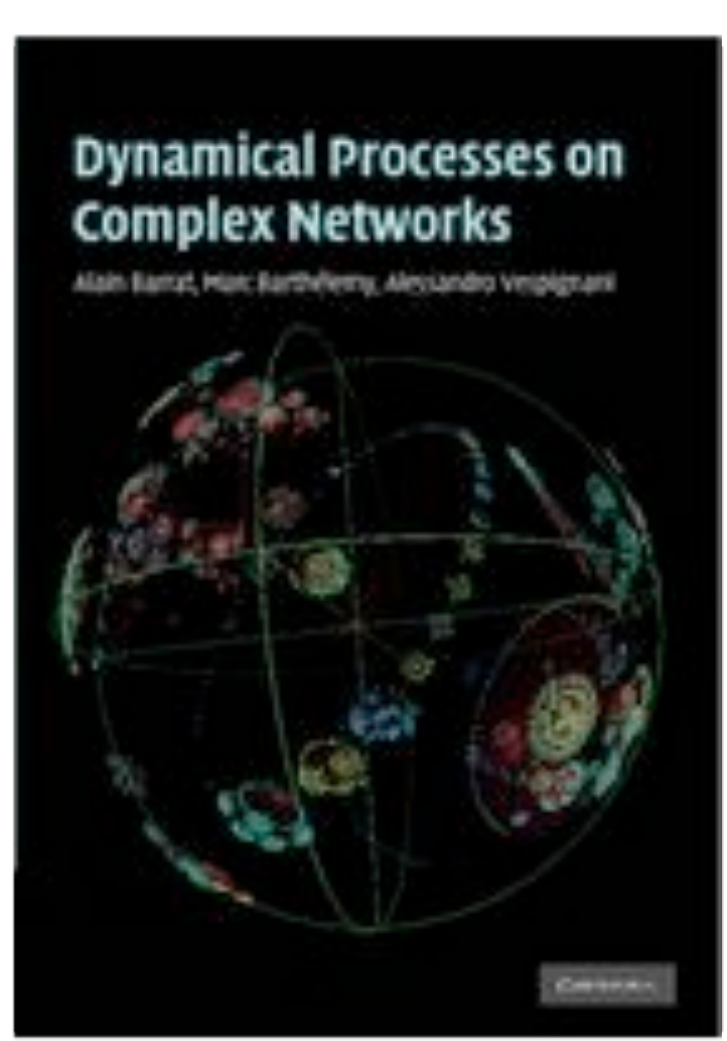
TRANSFORMING THE WAY WE APPROACH SOCIO-TECHNICAL SYSTEMS

- Social computational science
- Computational epidemiology
- Science of Science
- Information systems and data science
  - General classes of tools methods and models generally applicable to complex techno-social systems:
  - New techniques for the generation of models, social analytics, real time empirical data generation.
  - Scenario analysis: systemic risk, economic impact etc.

More Info

http://mobs-lab.org

@alexvespi



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LABORATORY FOR THE MODELING OF BIOLOGICAL
AND SOCIO-TECHNICAL SYSTEMS