



MATHEMATICAL FRONTIERS

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**Board on
Mathematical Sciences & Analytics**

MATHEMATICAL FRONTIERS

2018 Monthly Webinar Series, 2-3pm ET

February 13: *Recording posted*
Mathematics of the Electric Grid

March 13: *Recording posted*
Probability for People and Places

April 10:
Social and Biological Networks

May 8:
Mathematics of Redistricting

June 12:
Number Theory: The Riemann Hypothesis

July 10: *Topology*

August 14:
Algorithms for Threat Detection

September 11:
Mathematical Analysis

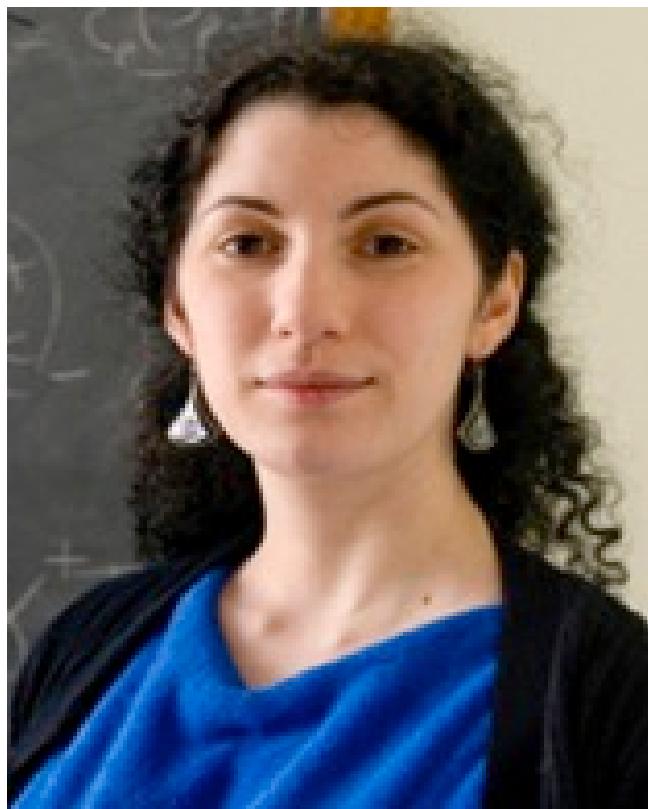
October 9: *Combinatorics*

November 13:
Why Machine Learning Works

December 11:
Mathematics of Epidemics

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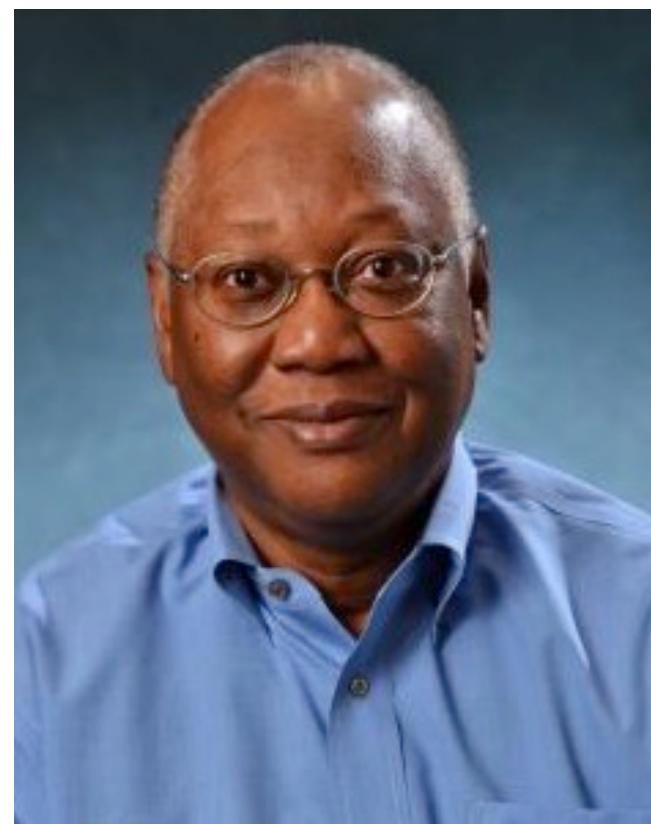
Social and Biological Networks



Nina H. Fefferman,
University of Tennessee, Knoxville



Alessandro Vespignani,
Northeastern University



James H. Curry,
University of Colorado, Boulder

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Social and Biological Networks



*Associate Professor
in the departments of
Ecology and Evolutionary Biology
& Mathematics*

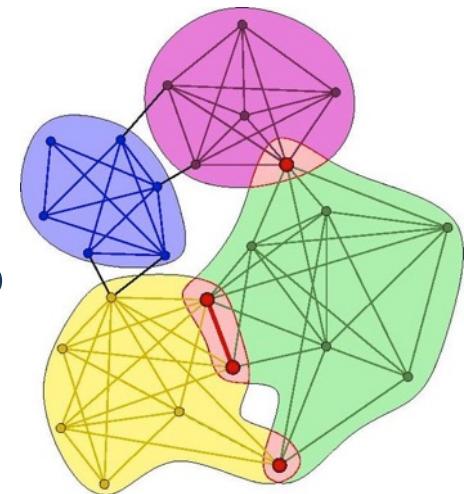
The Evolution of Social Systems

Nina H. Fefferman,
University of Tennessee, Knoxville

View webinar videos and learn more about BMSA at www.nas.edu/MathFrontiers

Animal Social Networks Questions

- How do groups form?
- Who is important/in charge?
- Are there distinct communities?
- How does the social network affect ongoing biological processes?
 - Mating
 - Disease spread*
- How do groups change over time?
- How did group behaviors evolve?



How Groups of Animals Organize

Solitary



Gregarious



Social



Eusocial

There are different costs and benefits to each strategy

Who Benefits and How?

- Benefits of Group Success

- Diffusion of risk from predators
- Increased foraging success
- Better engineering



From telegraph.co.uk

- Costs of Group Participation

- Attract predators
- Competition for food/mates
- Disease transmission



© Fran Veale

Biology Question, Math Answer

How do you Evolve these different strategies?

- Main idea of evolution:

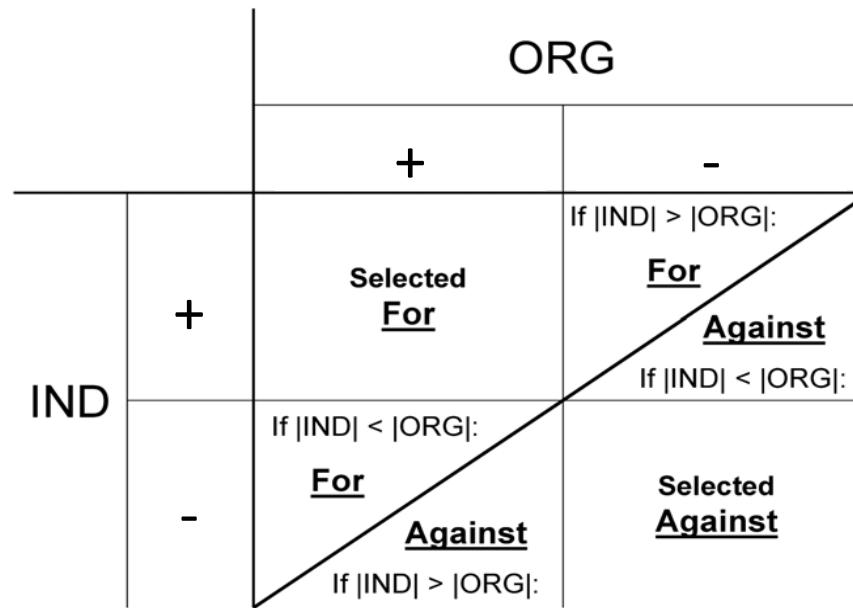
Traits survive and spread if they improve survival and/or reproduction of individuals that carry them

Social systems = many individuals, many roles

- How to study them?

But Genes are Carried by Individuals

- We need Multilevel Selection:



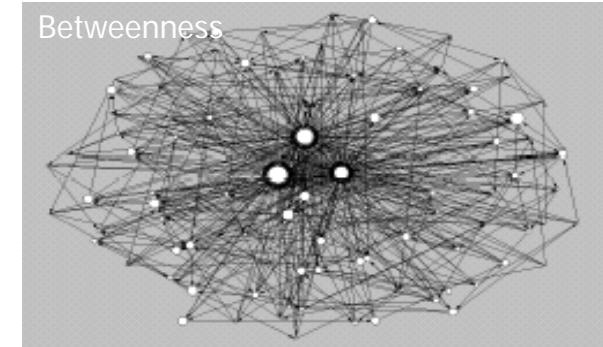
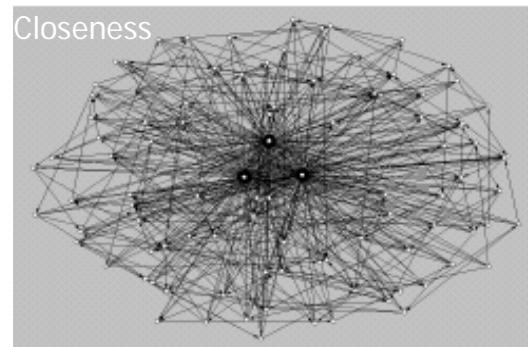
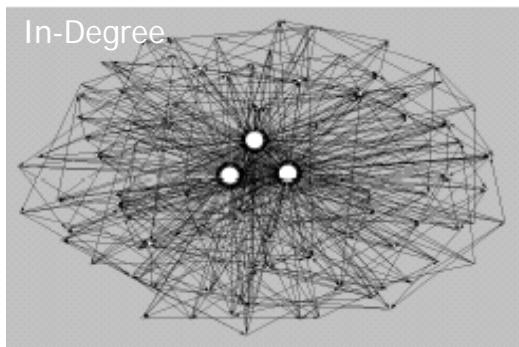
Reproduced from Hock, Ng and Fefferman, 2010

- For social systems, this means NETWORKS!

We build a mathematical abstraction and use it for computational experiments

Assumption: Individuals make genetically determined “selfish” social affiliation choices (with no regard for group-level effects)

We can compare networks that emerge from different beliefs about what is selfishly best



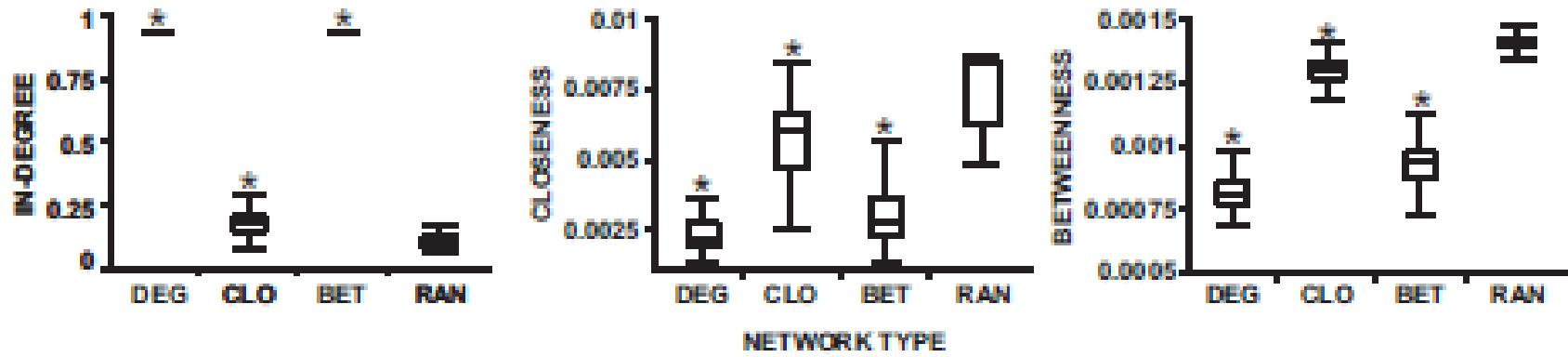
Reproduced from Fefferman and Ng, 2007a

Result: Different Individual Strategies Work to Accomplish Different Tasks

$D \approx B > C > R$

$R > C > B > D$

$R > C > B > D$

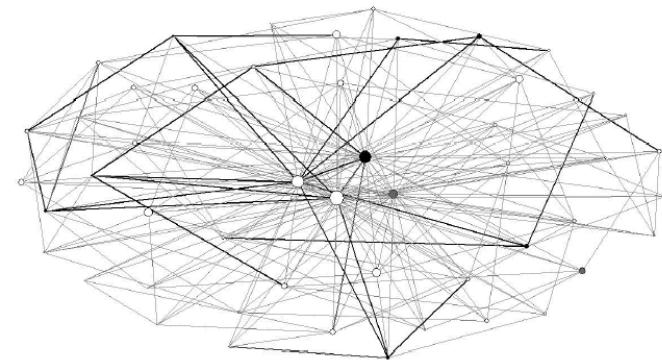


*Discussed in Fefferman and Ng, 2007a
and Hock and Fefferman 2011, and 2012*

Already gives us some insight into evolutionary pressures on self-organizing social behaviors

Those are just the benefits, what about the costs?

- What happens if there is disease on these networks?



	3-Way Test	B-population		C-population		D-population	
		Dynamic	Static	Dynamic	Static	Dynamic	Static
B	Dynamic [†]	B static > B dynamic [†]		< [*]	< [*]	>	> [*]
C				C static > C dynamic [†]		> [*]	> [*]
D	Static [†]					D static > D dynamic [†]	
		Overall: Dynamic C>B>D; Static C>B>D					

Reproduced from Fefferman and Ng, 2007b

Now we can ask about costs and benefits!

Social Benefits:	D-Preference	C-Preference	D-Preference
	$D \approx B > C > R$	$R > C > B > D$	$R > C > B > D$

Disease Risks:

Overall: Dynamic $C > B > D$; Static $C > B > D$

*Reproduced from Fefferman and Ng, 2007b
and from Hock and Fefferman 2012*

Sometimes more organizational efficiency also means more disease, but not always – it depends on what type of organizational task the population needs!

Only the beginning...

These are just scratching the surface of the questions we've already asked with networks and the evolution of social systems

- ✓ Populations with mixed social preferences
- ✓ Learned social preferences
- ✓ Friends vs. Family
- ✓ More about diseases and how to prevent them

More to come!

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Social and Biological Networks



*Sternberg Family Distinguished Professor
and Director of Physics,
Bouve College of Health Sciences, College of
Computer and Information Science*

Contagion processes in social networks

Alessandro Vespignani,
Northeastern University @alexvespi



CENTER FOR
INFERENCE &
DYNAMICS
OF INFECTIOUS DISEASES

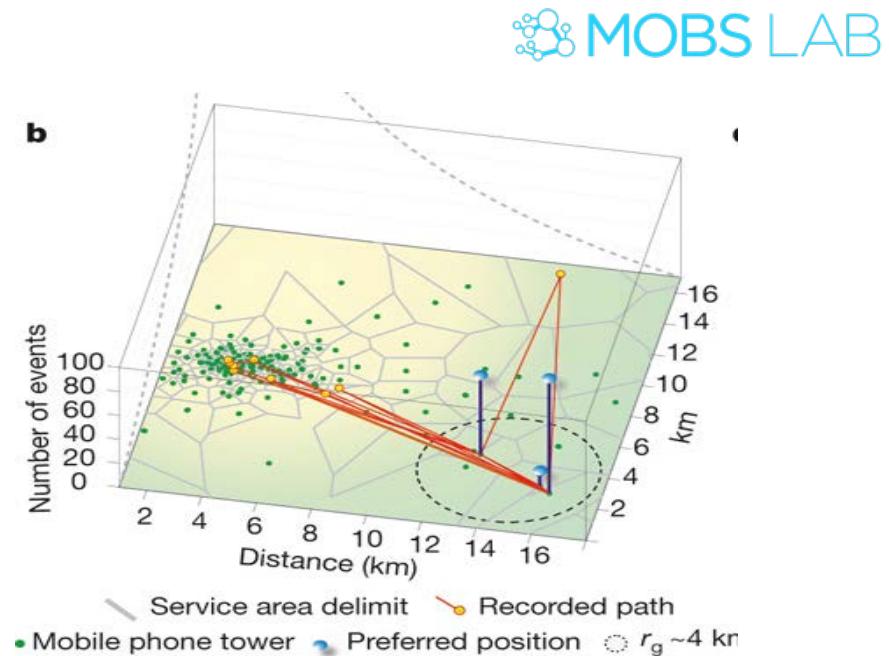
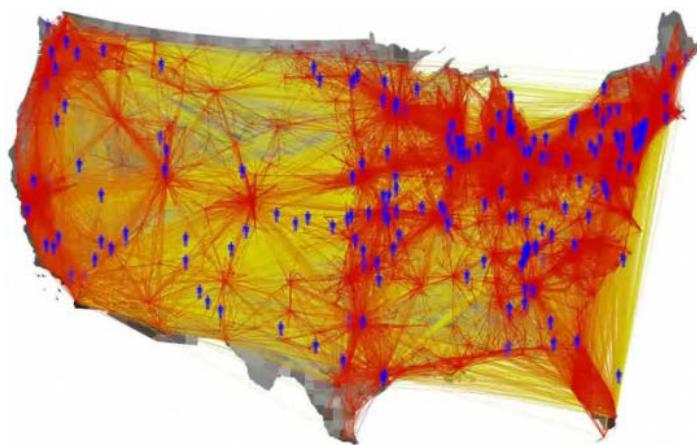


Northeastern

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LABORATORY FOR THE MODELING OF BIOLOGICAL
AND SOCIO-TECHNICAL SYSTEMS

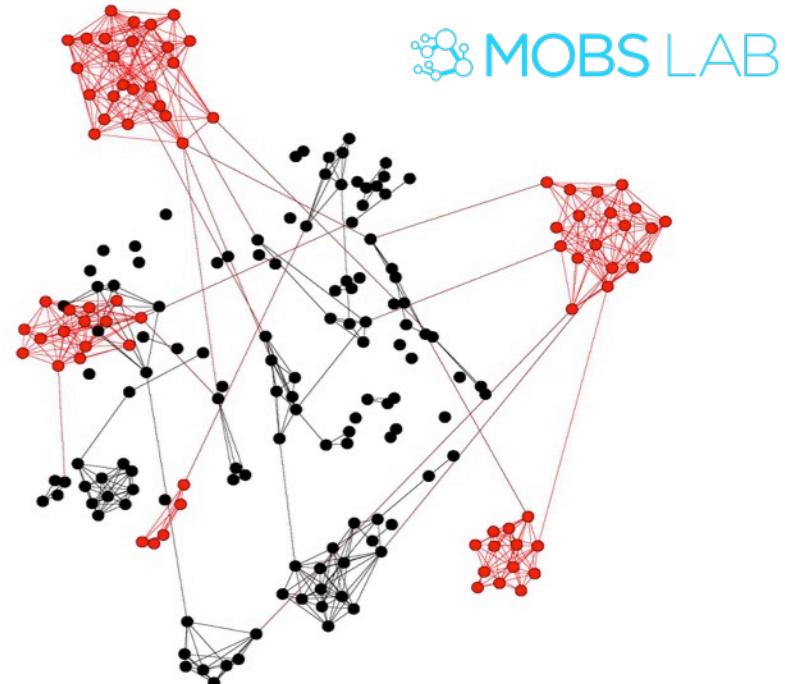
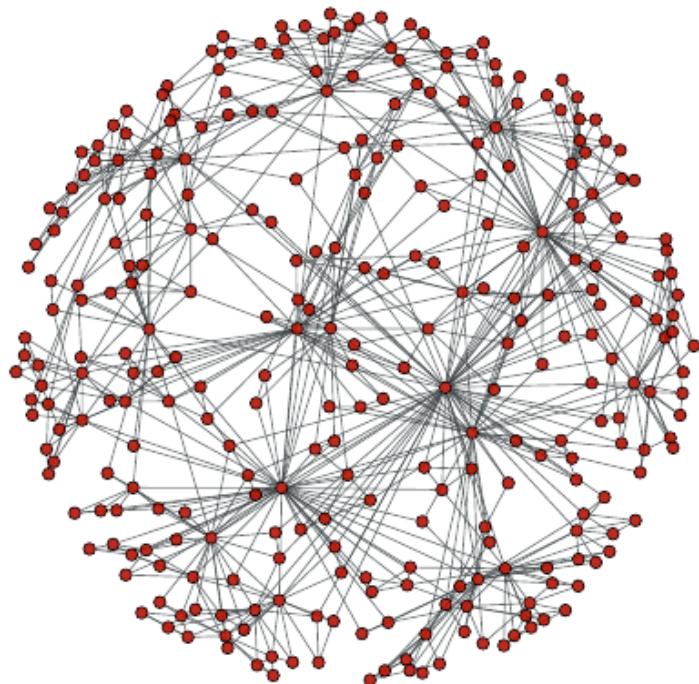
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Contagion: From geography to social space



**Graphical areas/census
Mobility**

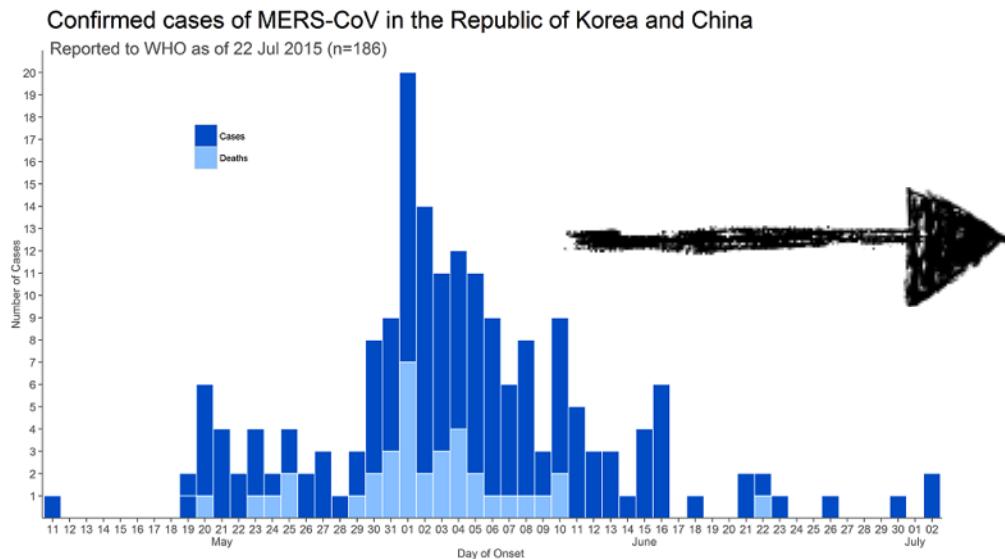
Contagion: From geography to social space



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

Epidemic/contagion modeling

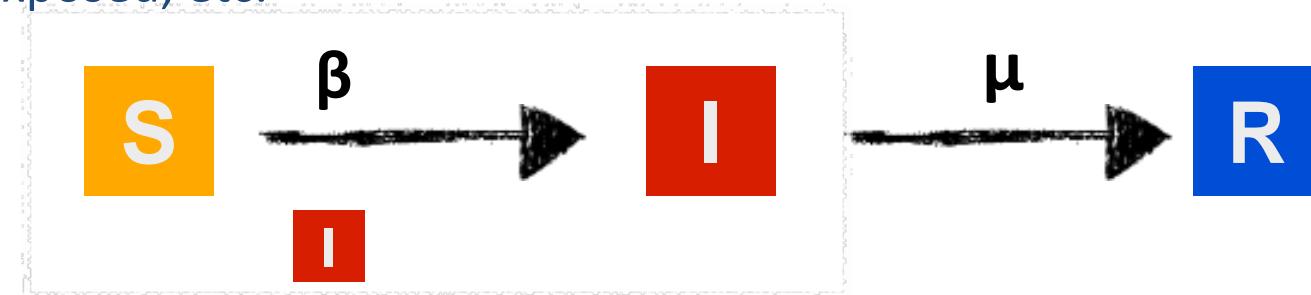
“I simply wish that, in a matter which so closely concerns the wellbeing of the human race, no decision shall be made without all the knowledge which a little analysis and calculation can provide”
Daniel Bernoulli ~1760



Mathematics of contagion processes

~1766

- Based on the disease compartmental structure: Individuals are characterized by the disease stage: susceptible, infectious, recovered, exposed, etc.



- The mathematical description is based on the so called homogenous assumption

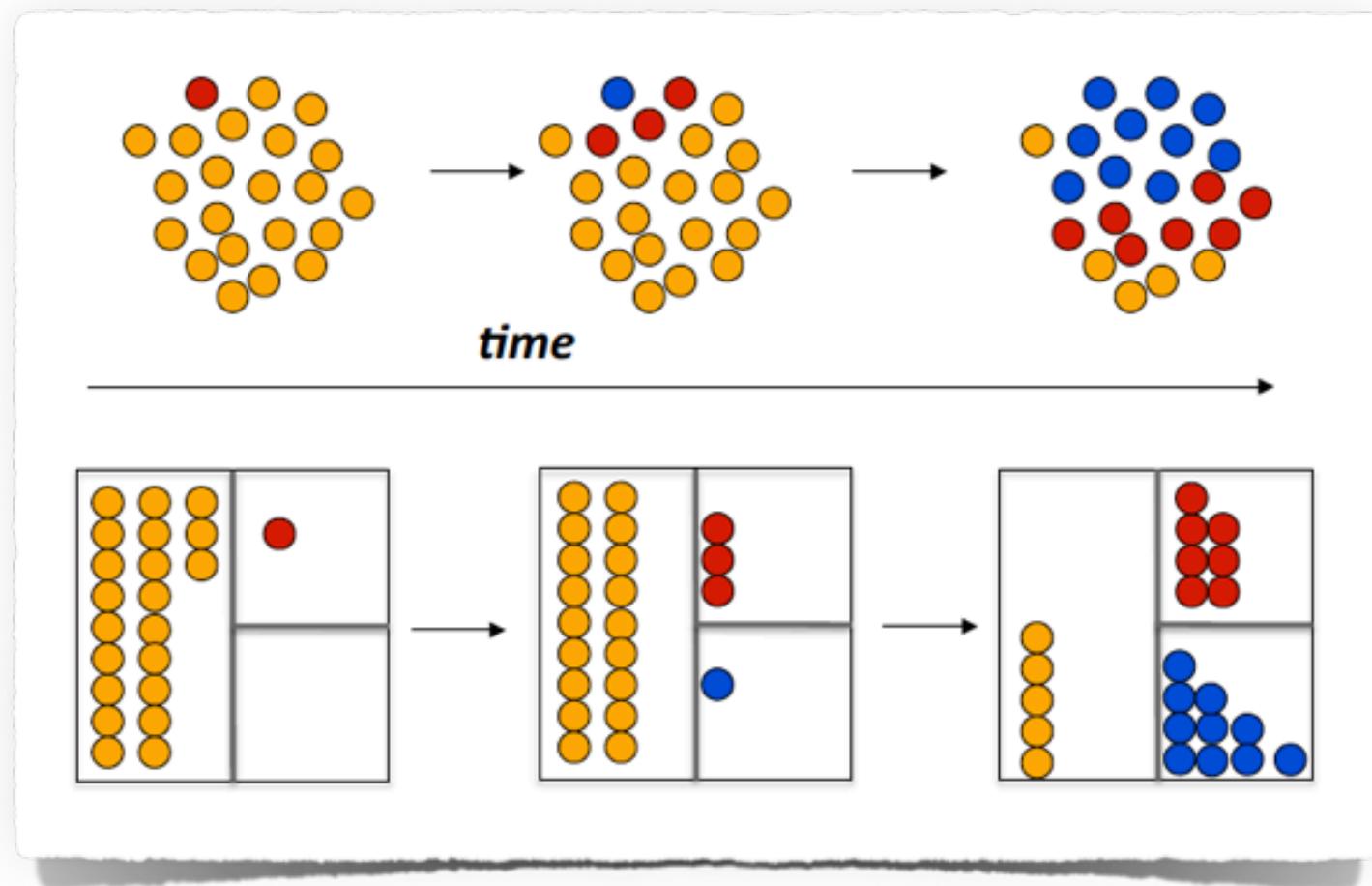
$$\partial_t S(t) = -\beta \frac{I(t)S(t)}{N}$$

$$\partial_t I(t) = \beta \frac{I(t)S(t)}{N} - \mu I(t)$$

$$\partial_t R(t) = \mu I(t)$$

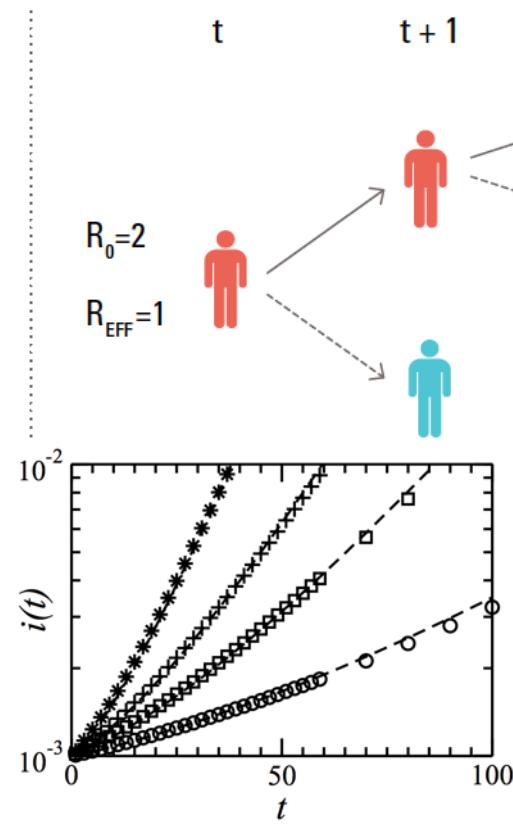
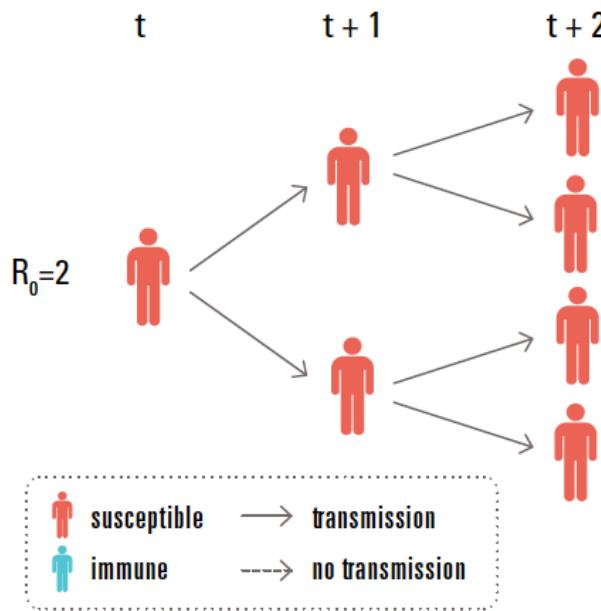
Reaction rate equations

Indistinguishable + homogeneity



Basic reproductive number R_0

R_0 is the average number of individuals infected directly by an infected individuals during his infectious period in a fully susceptible population.



Exponential growth

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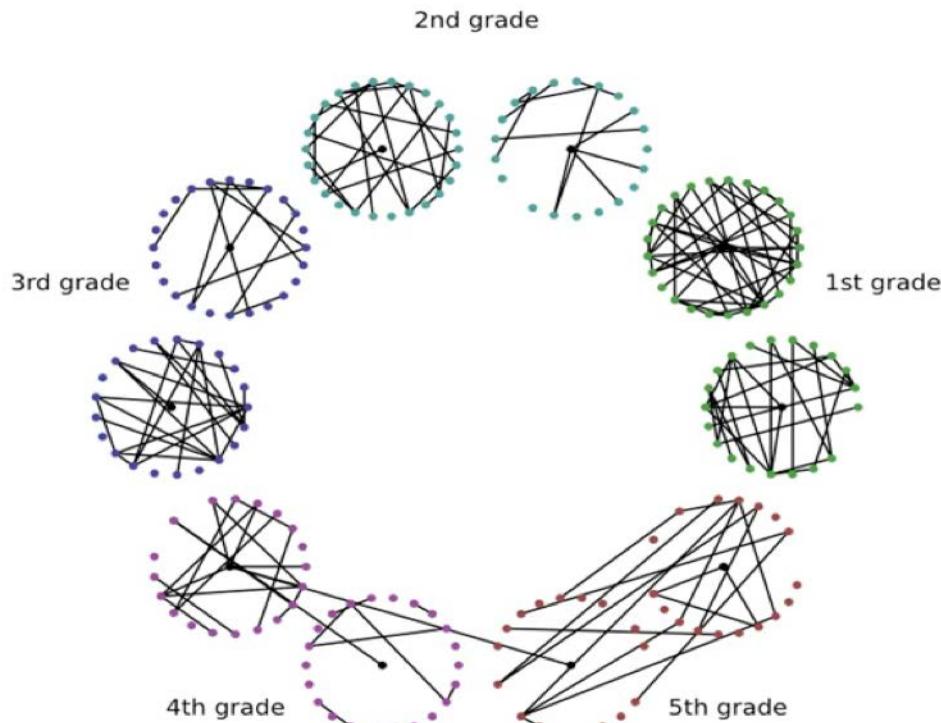
Homogenous assumption limits



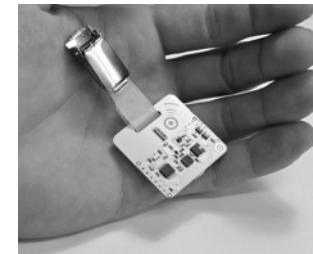
Random mixing

Networks

Micro-scale: proximity interactions in confined environments

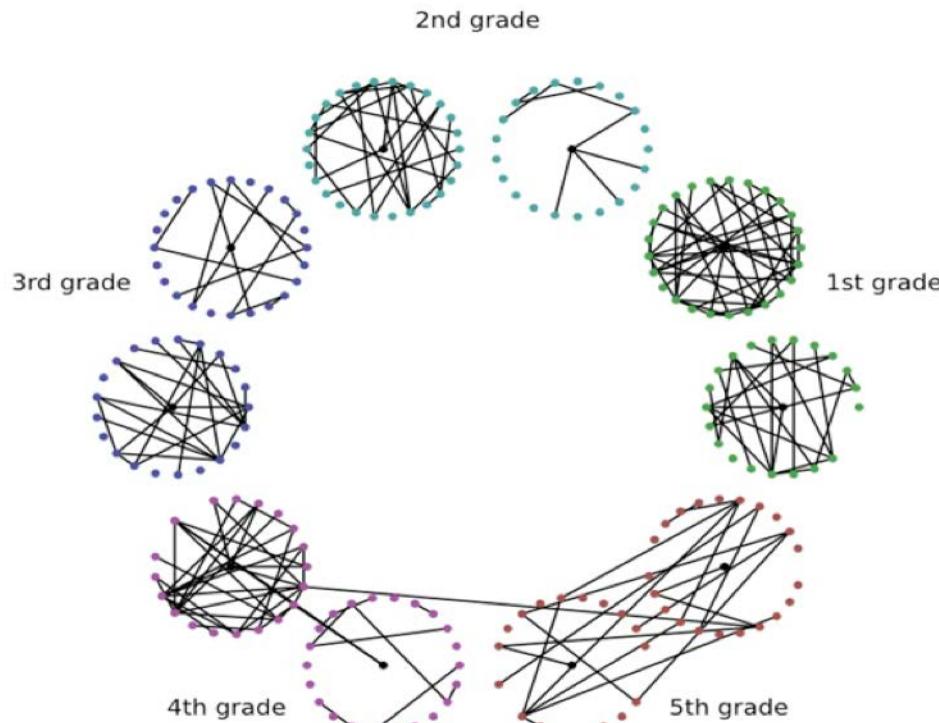


Thu, 09:00- 09:40

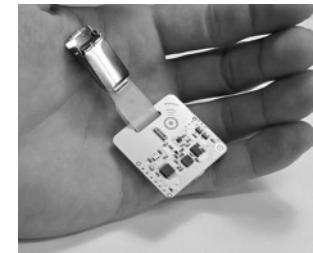


Sociopatterns experiment
in school
(Cattuto, PLoS ONE 5(7):
e11596 (2010))

Micro-scale: proximity interactions in confined environments



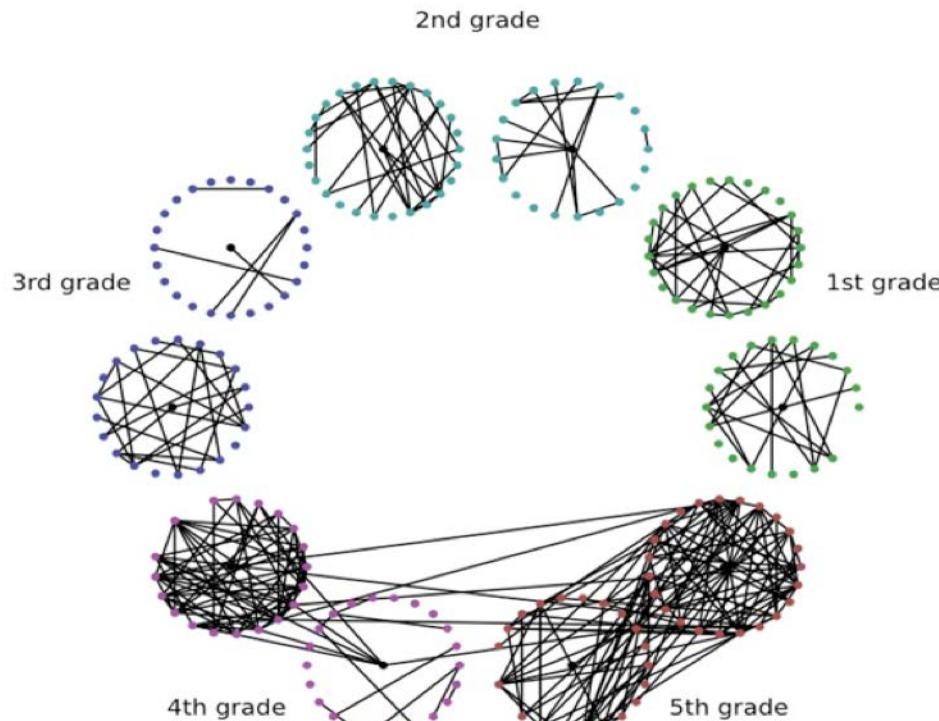
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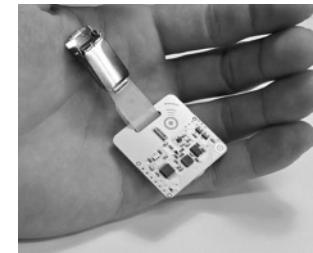
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Micro-scale: proximity interactions in confined environments

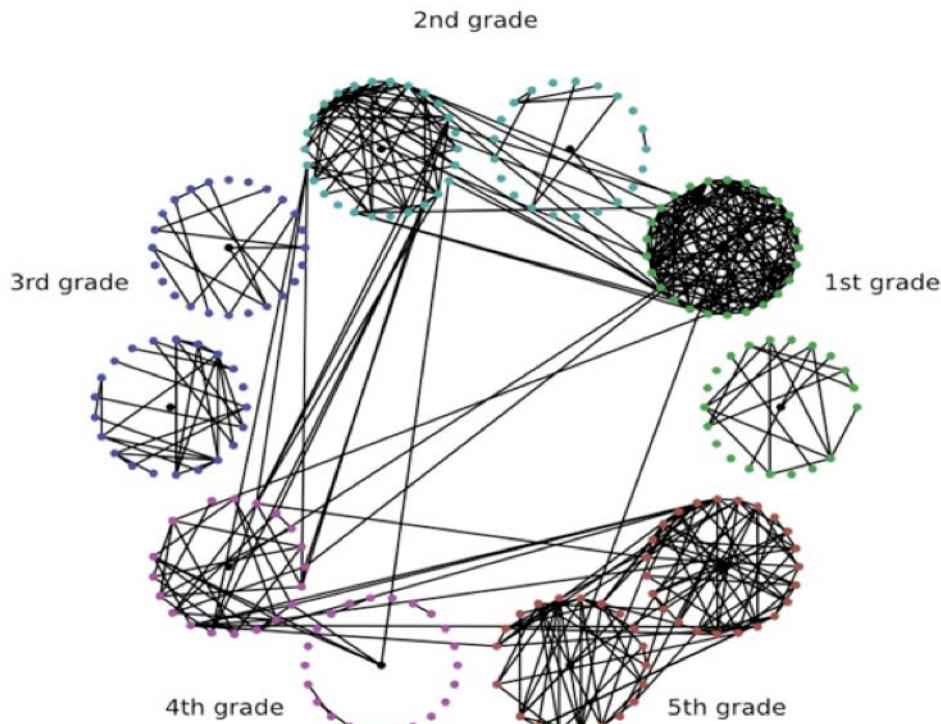


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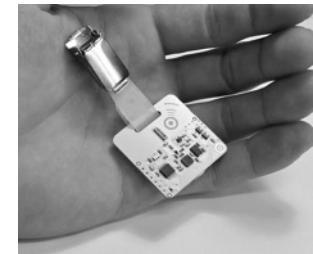


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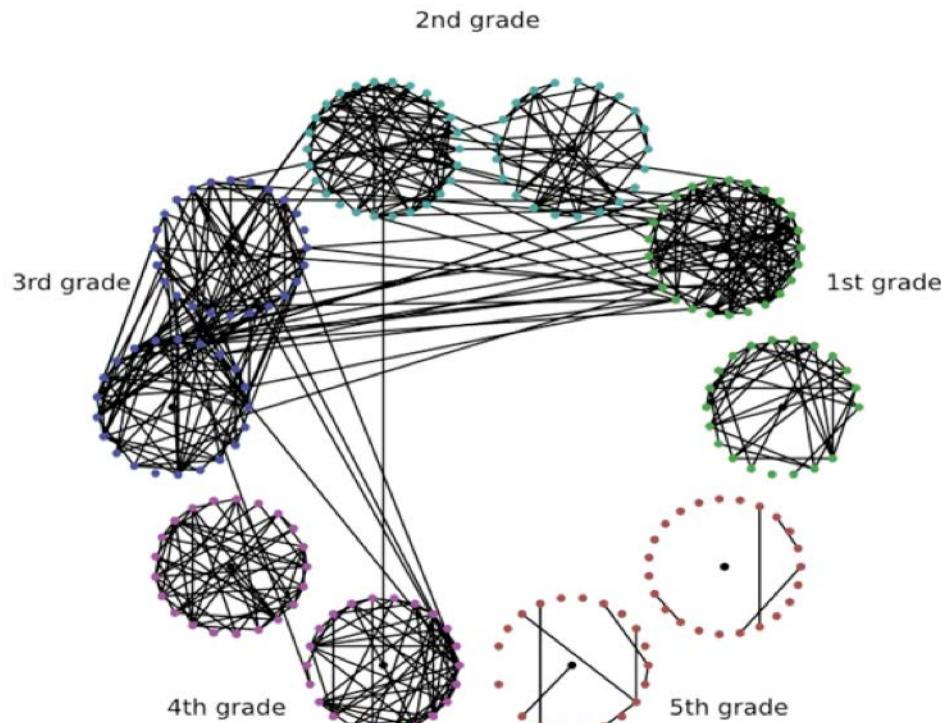
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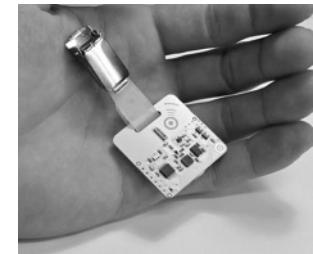
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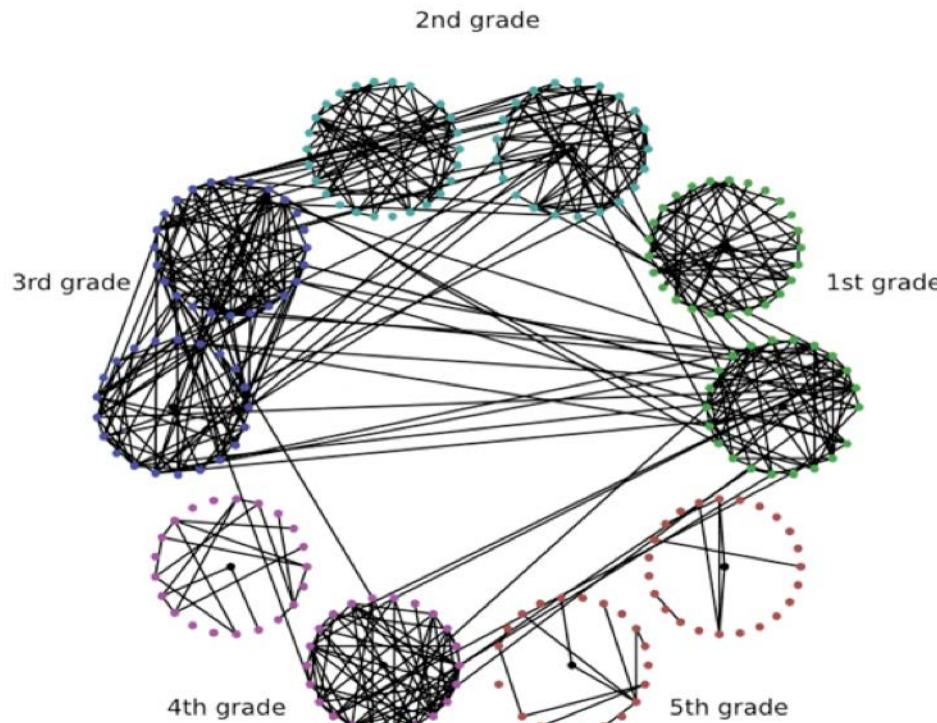


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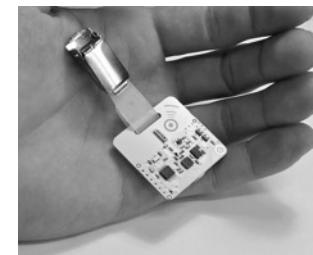


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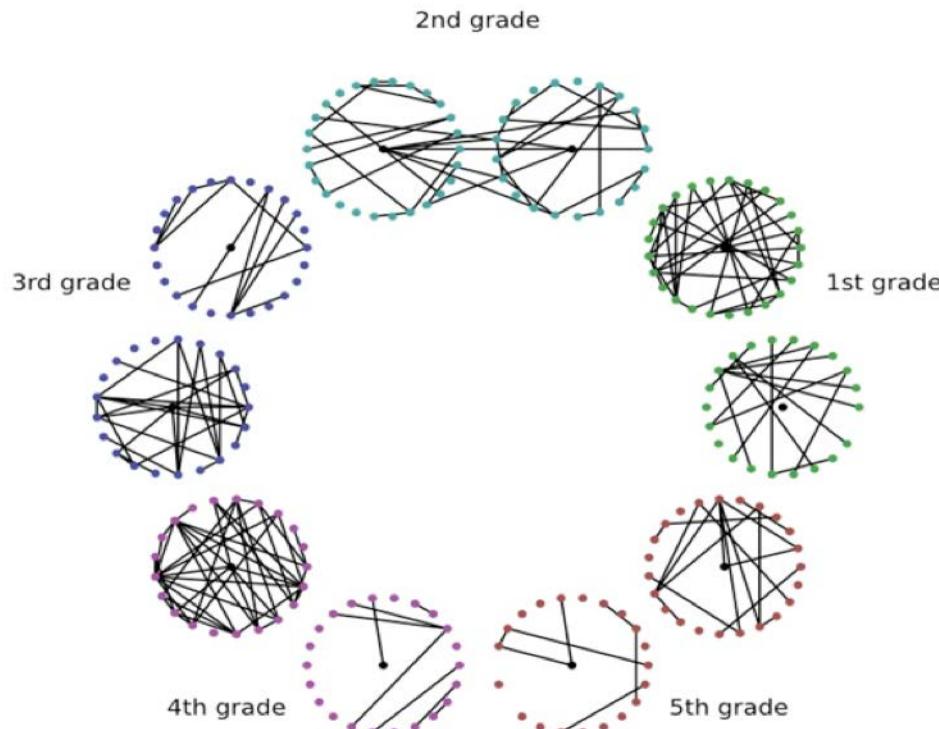
Thu, 10:40- 11:20



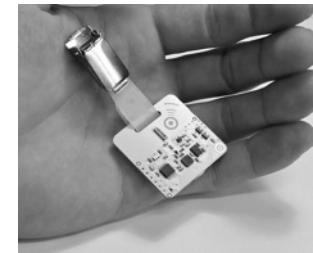
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Micro-scale: proximity interactions in confined environments



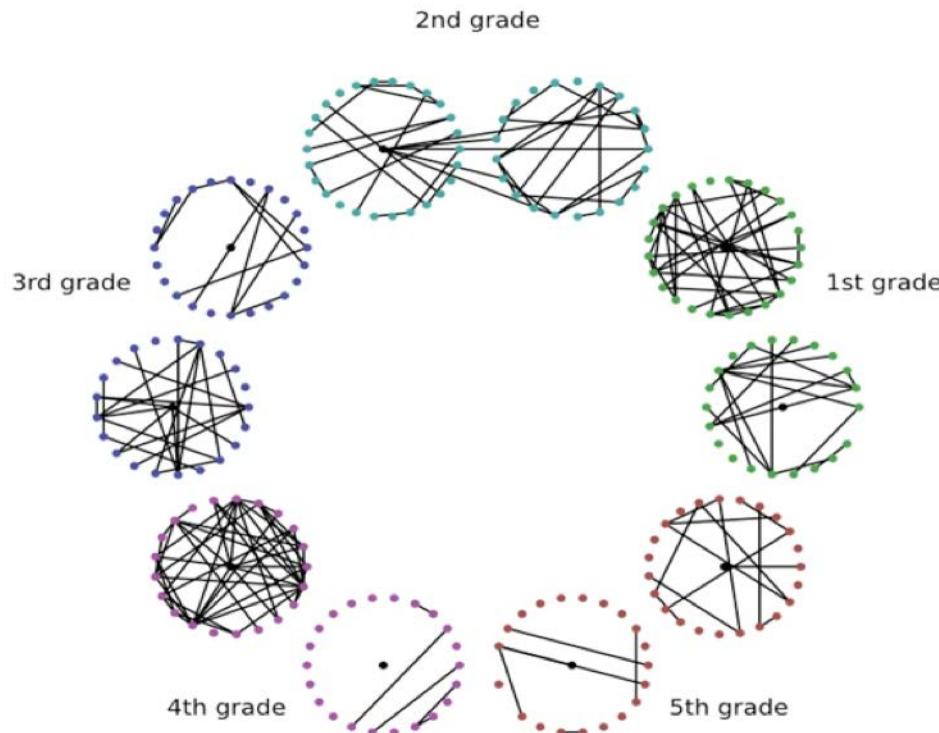
Thu, 11:00- 11:40



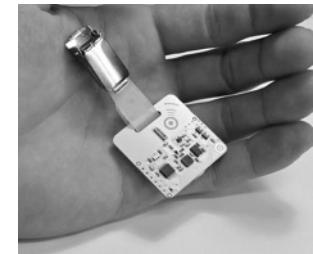
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Micro-scale: proximity interactions in confined environments



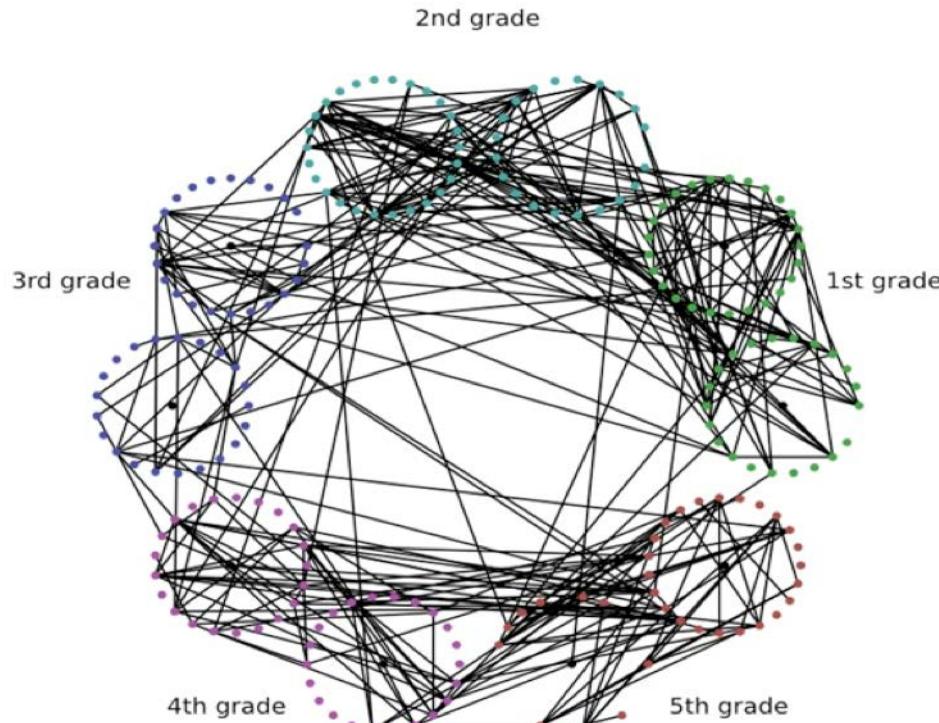
Thu, 11:20- 12:00



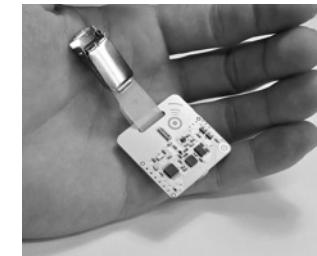
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Micro-scale: proximity interactions in confined environments

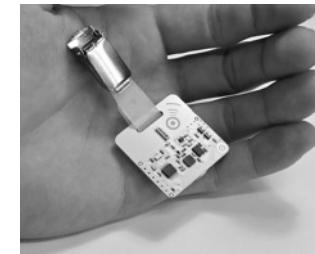
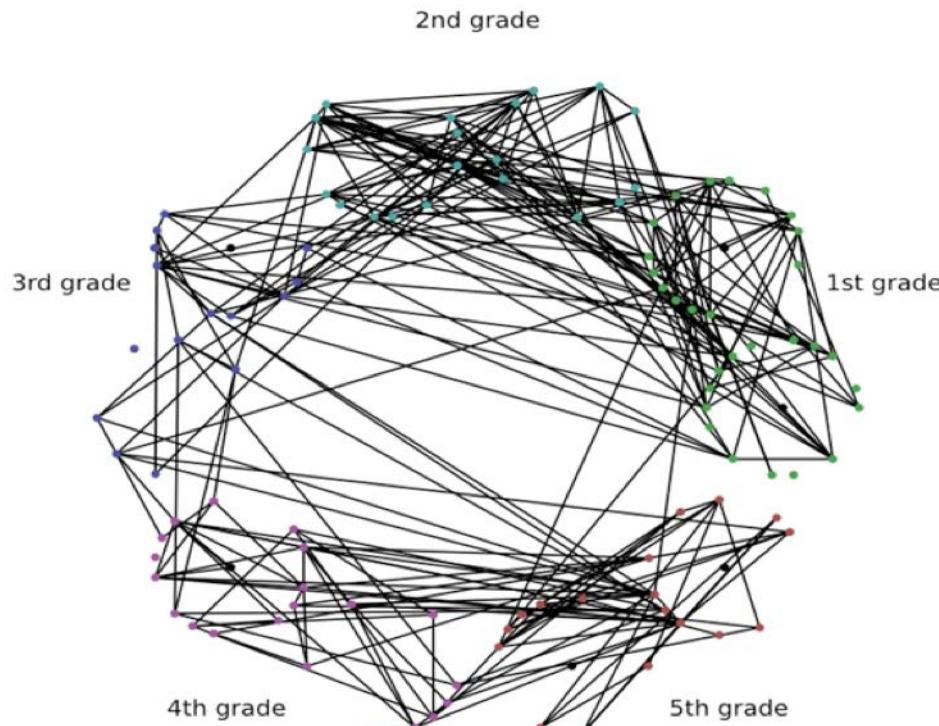


Thu, 11:40- 12:20



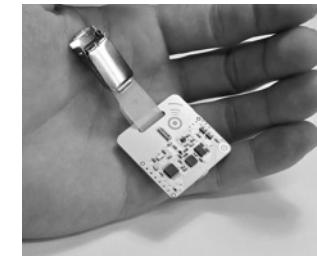
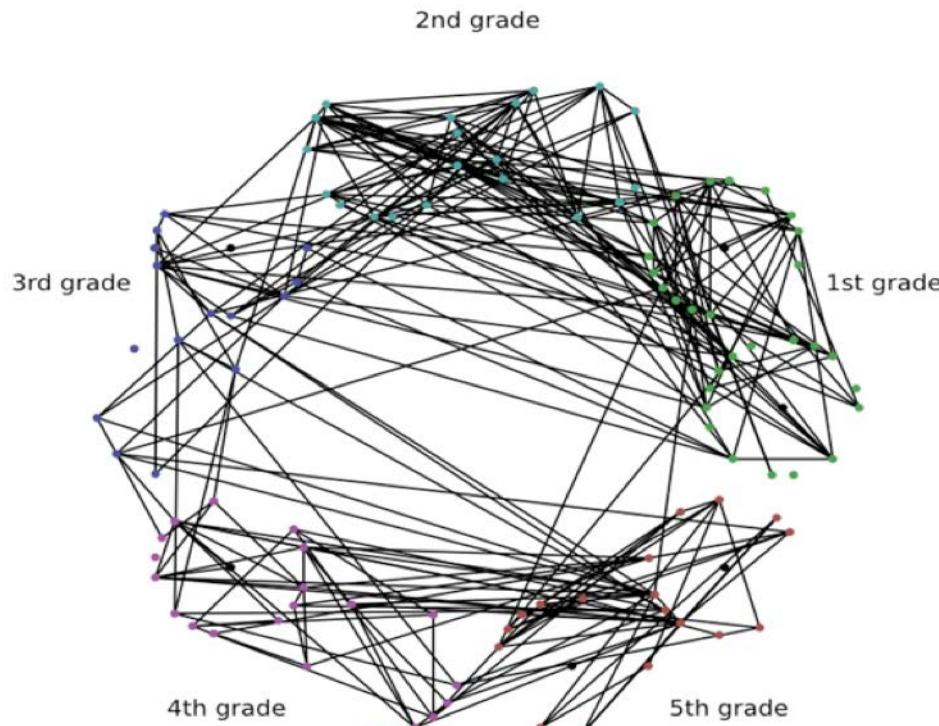
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Micro-scale: proximity interactions in confined environments



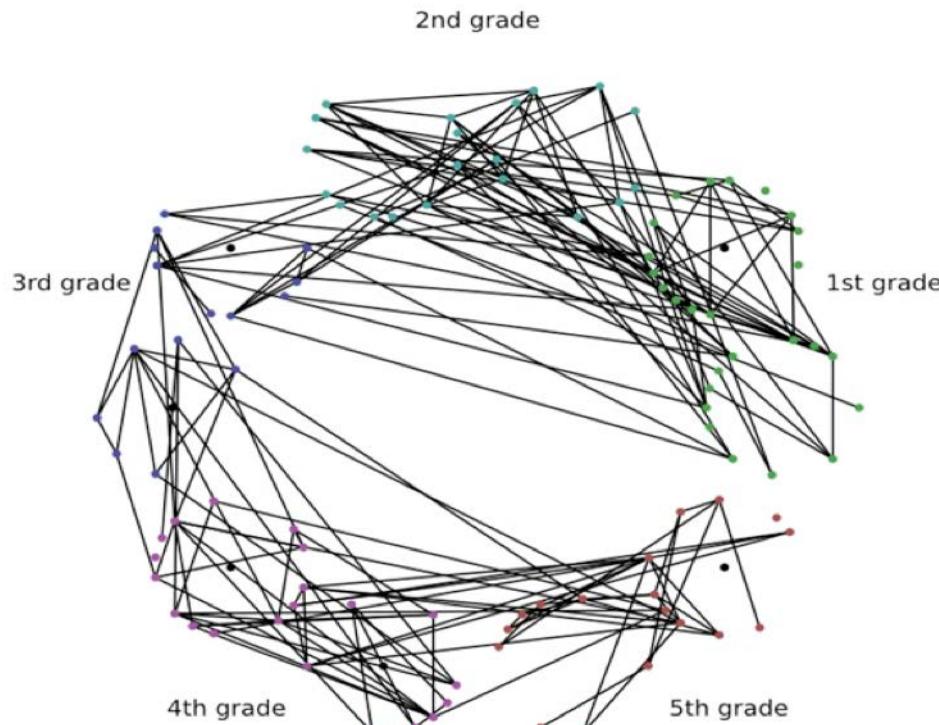
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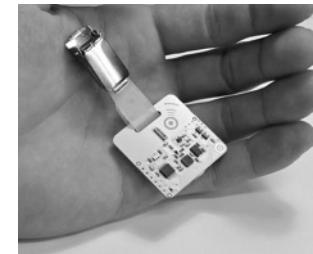


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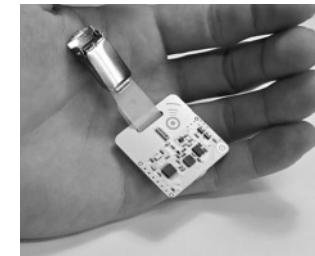
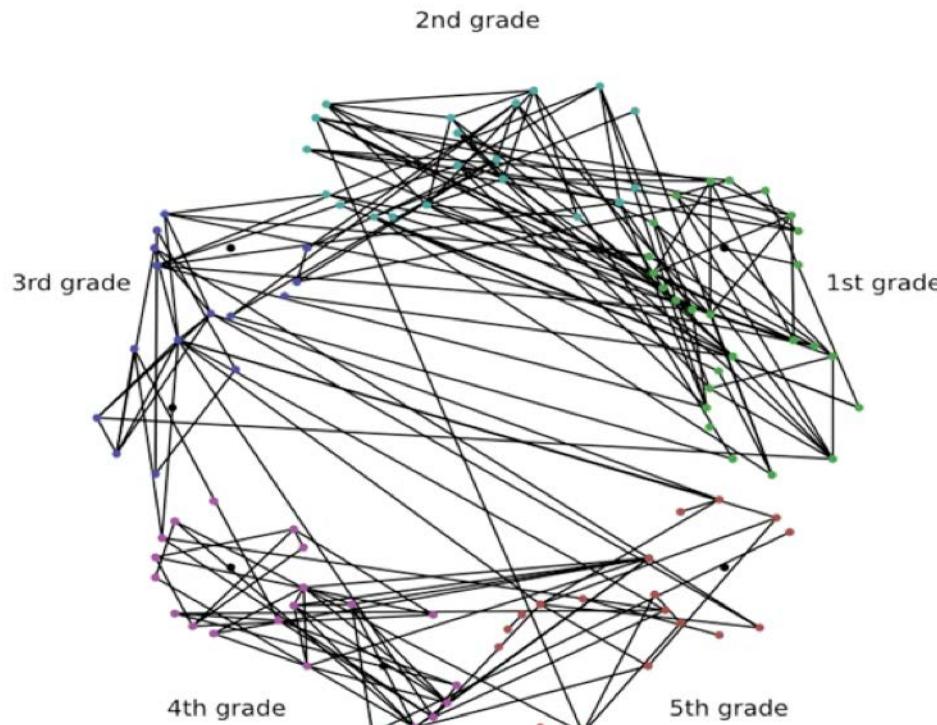


Thu, 12:20- 13:00



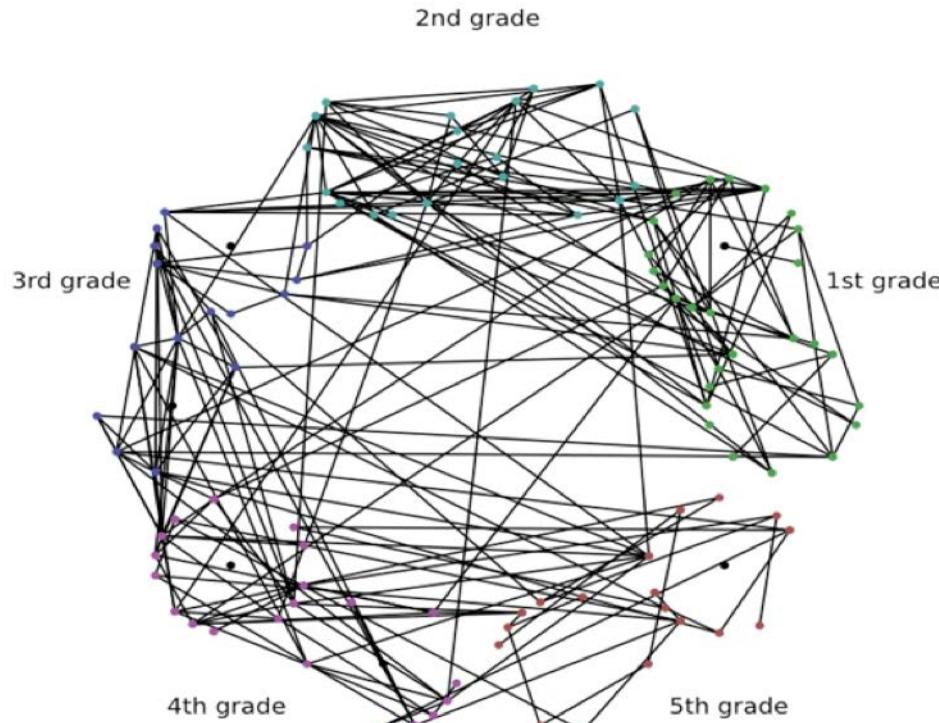
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Micro-scale: proximity interactions in confined environments

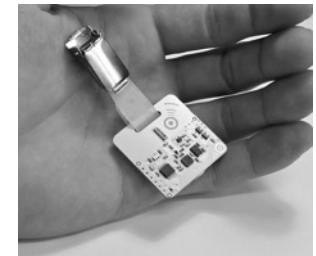


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Micro-scale: proximity interactions in confined environments

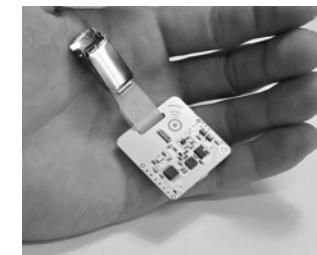
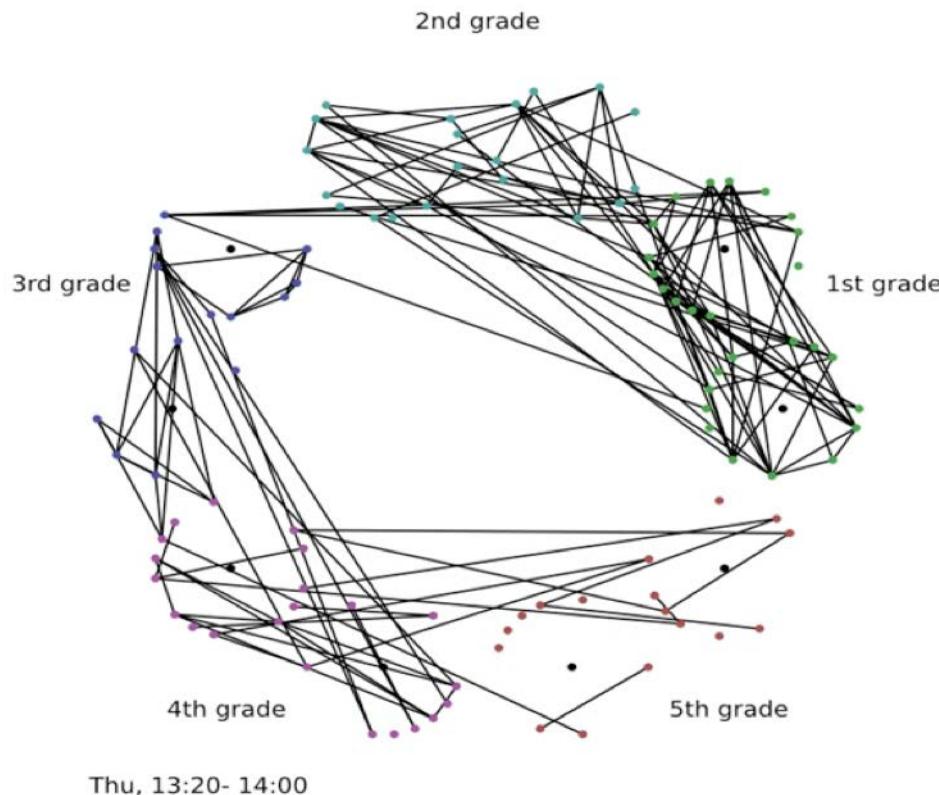


Thu, 13:00- 13:40



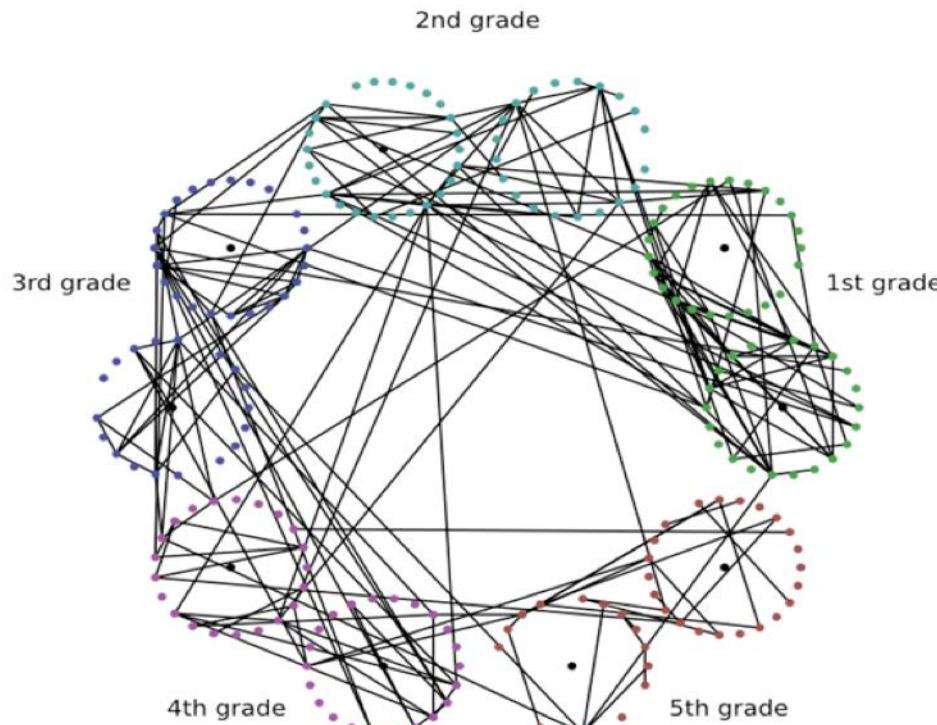
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Micro-scale: proximity interactions in confined environments

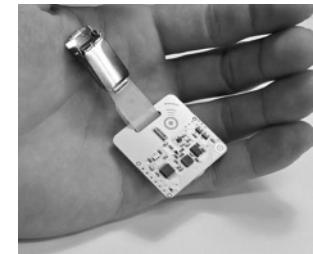


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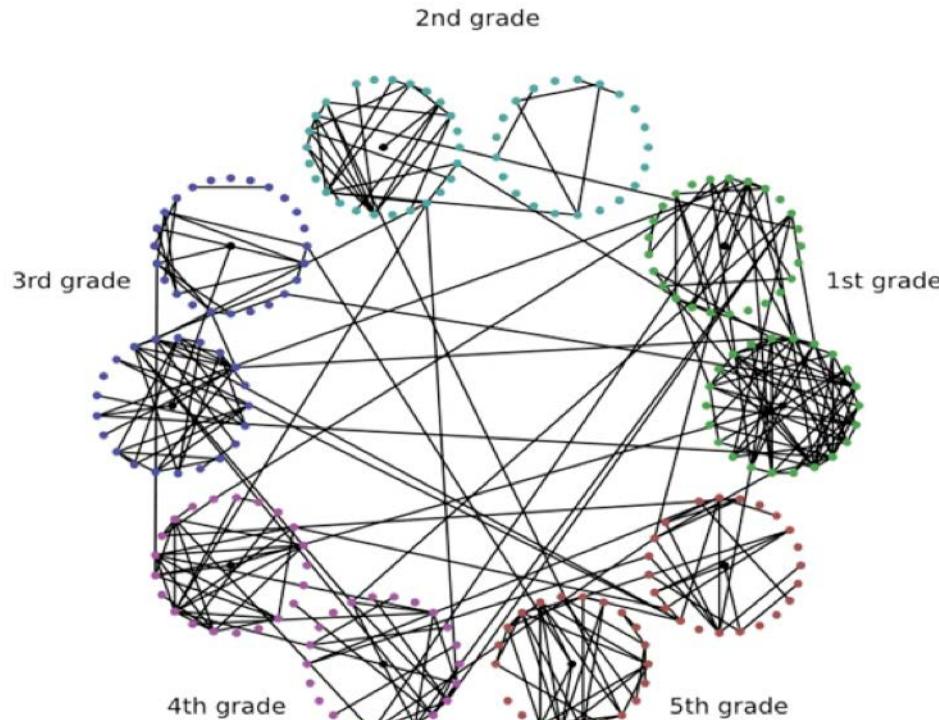


Thu, 13:40- 14:20

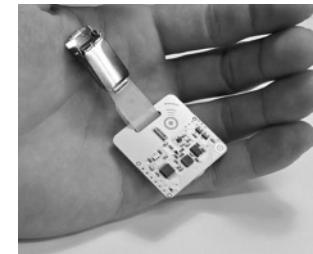


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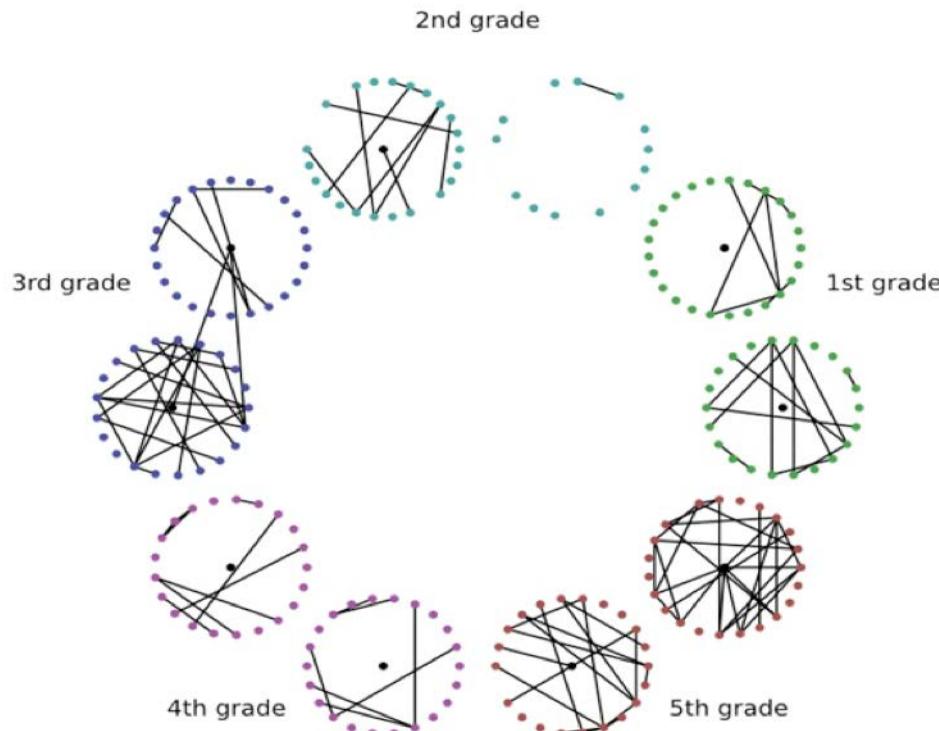


Thu, 14:00- 14:40

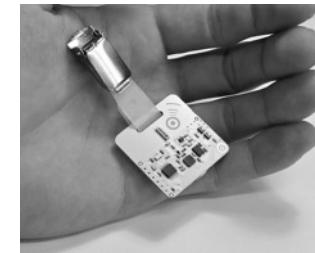


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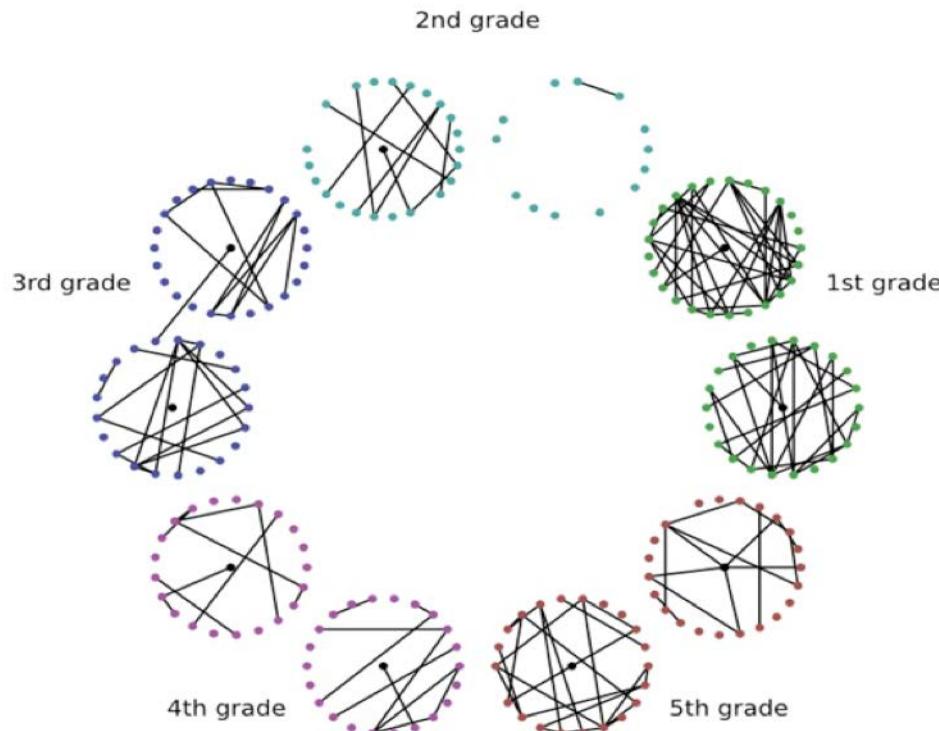


Thu, 14:20- 15:00

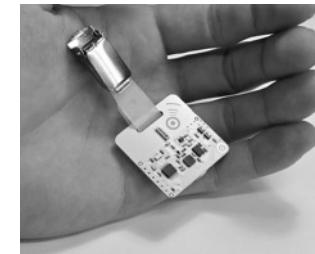


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Micro-scale: proximity interactions in confined environments



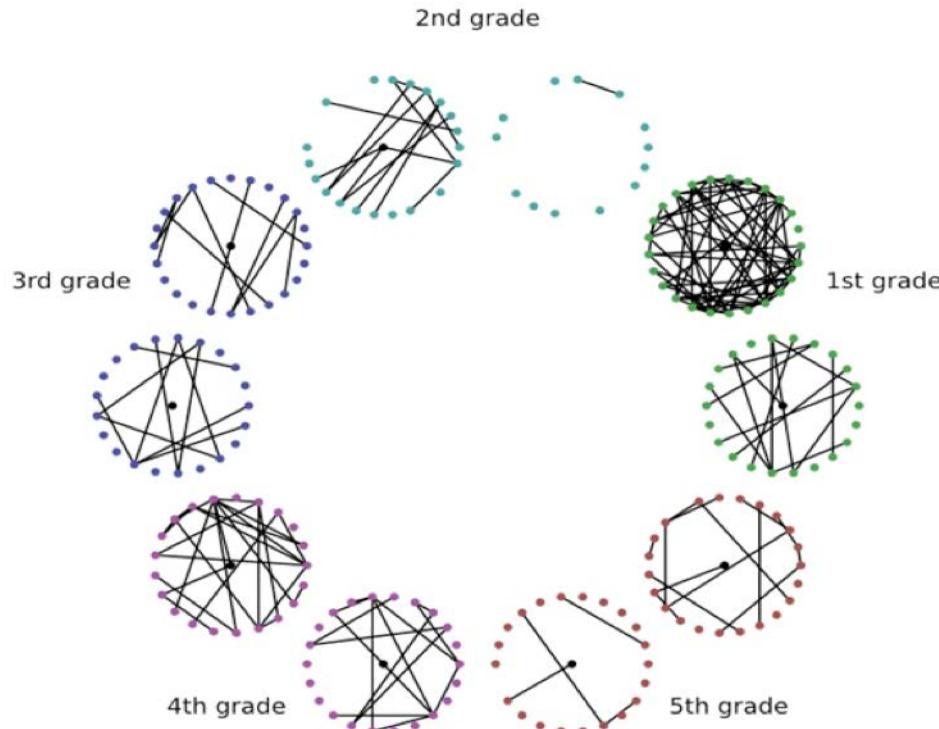
Thu, 14:40- 15:20



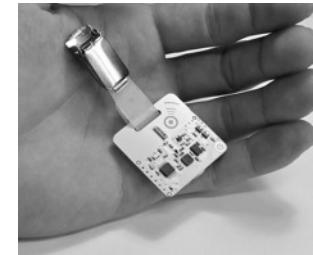
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Micro-scale: proximity interactions in confined environments

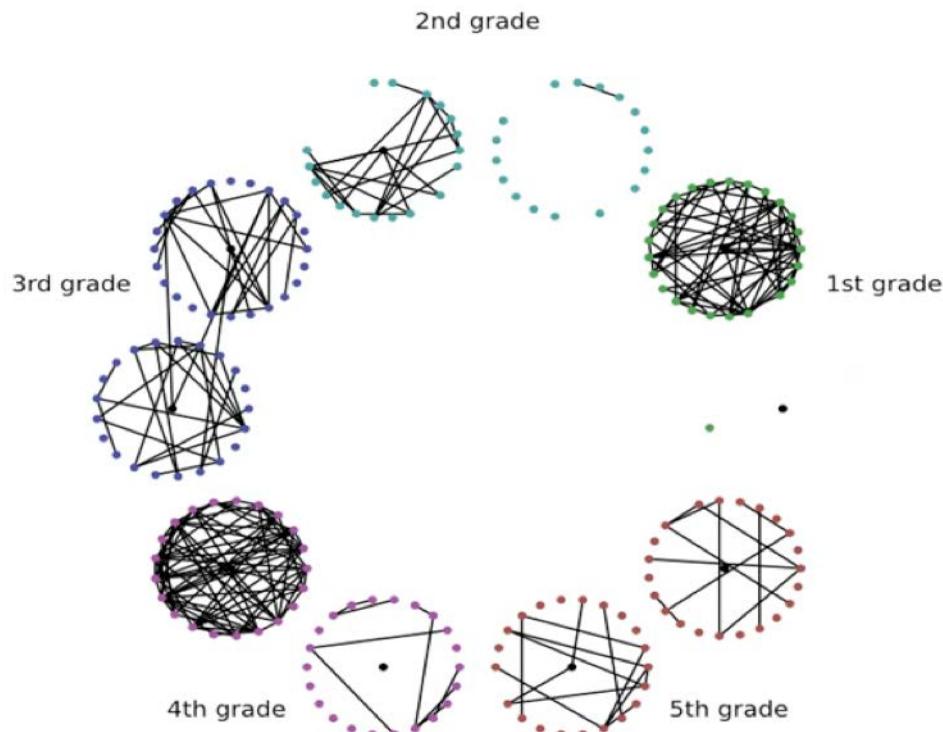


Thu, 15:00- 15:40

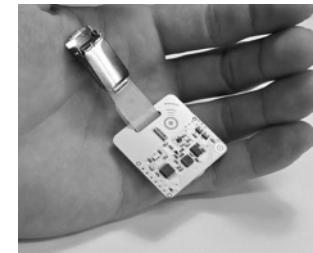


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Micro-scale: proximity interactions in confined environments



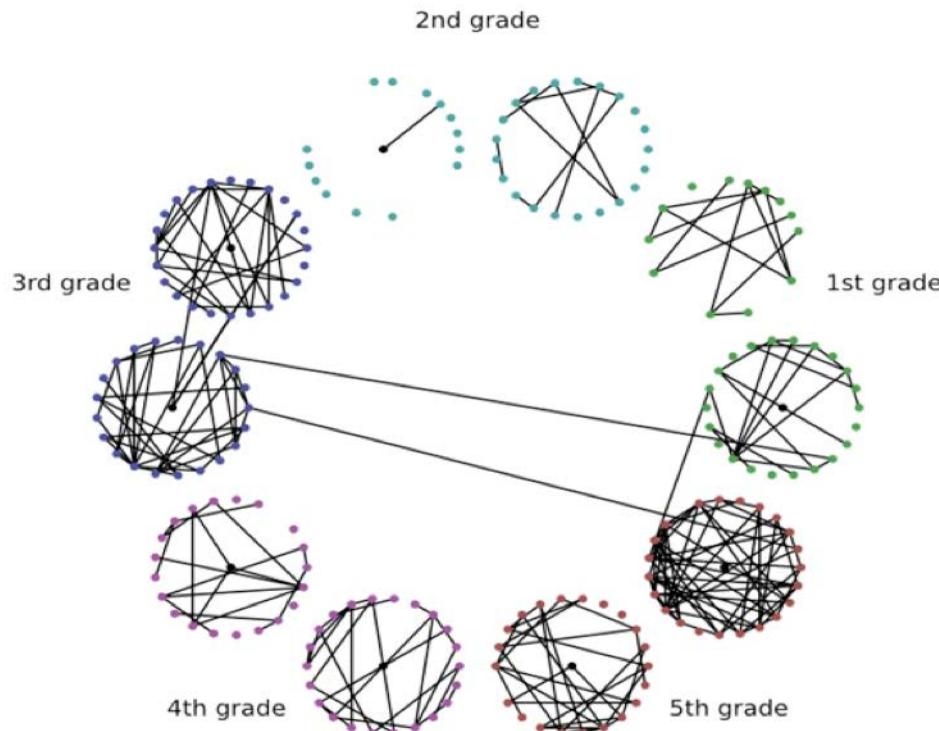
Thu, 15:20- 16:00



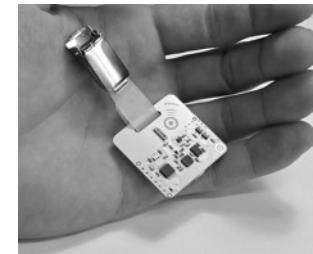
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 MOBS LAB

Micro-scale: proximity interactions in confined environments

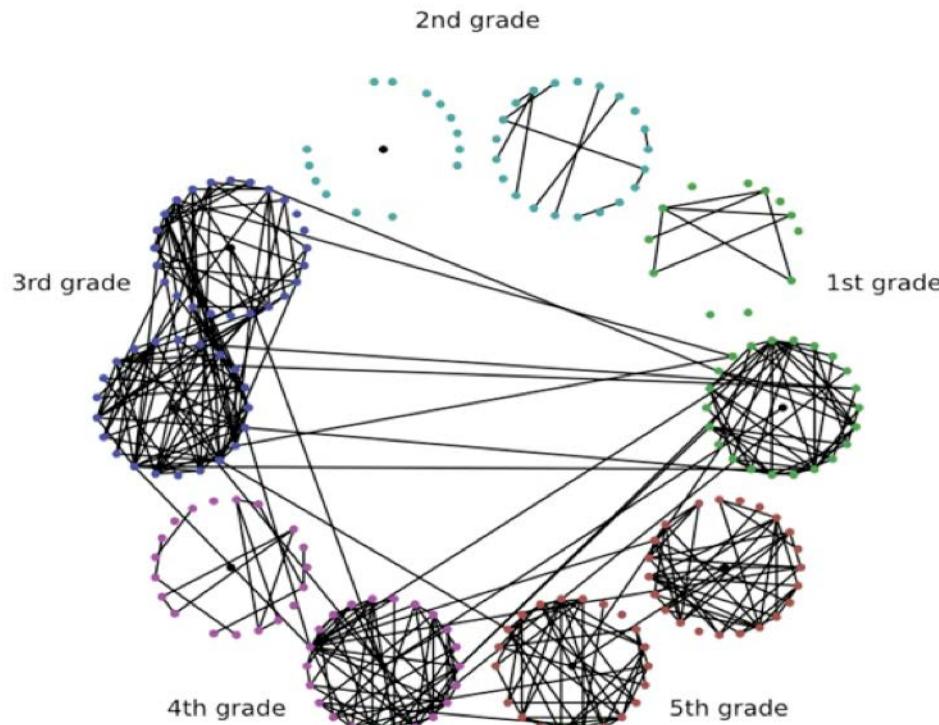


Thu, 15:40- 16:20

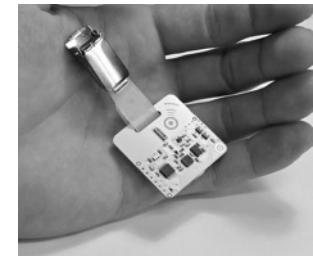


Sociopatterns experiment
in school
(Cattuto, PLoS ONE 5(7):
e11596 (2010))

Micro-scale: proximity interactions in confined environments



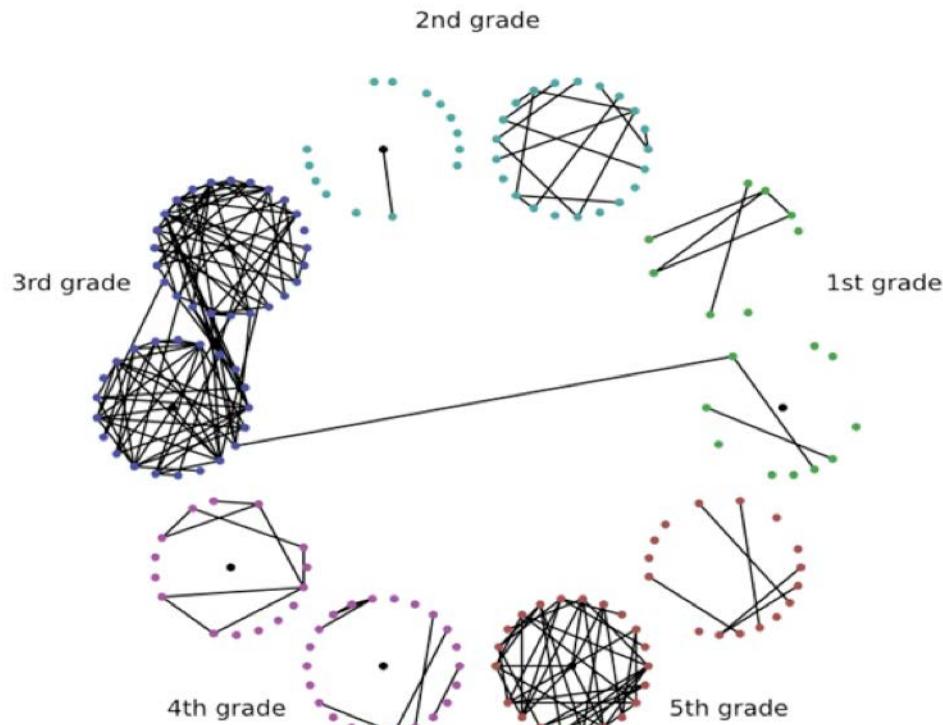
Thu, 16:00- 16:40



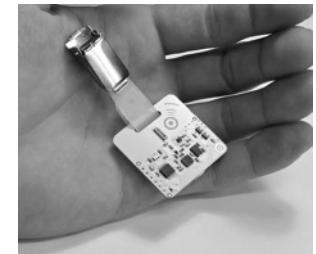
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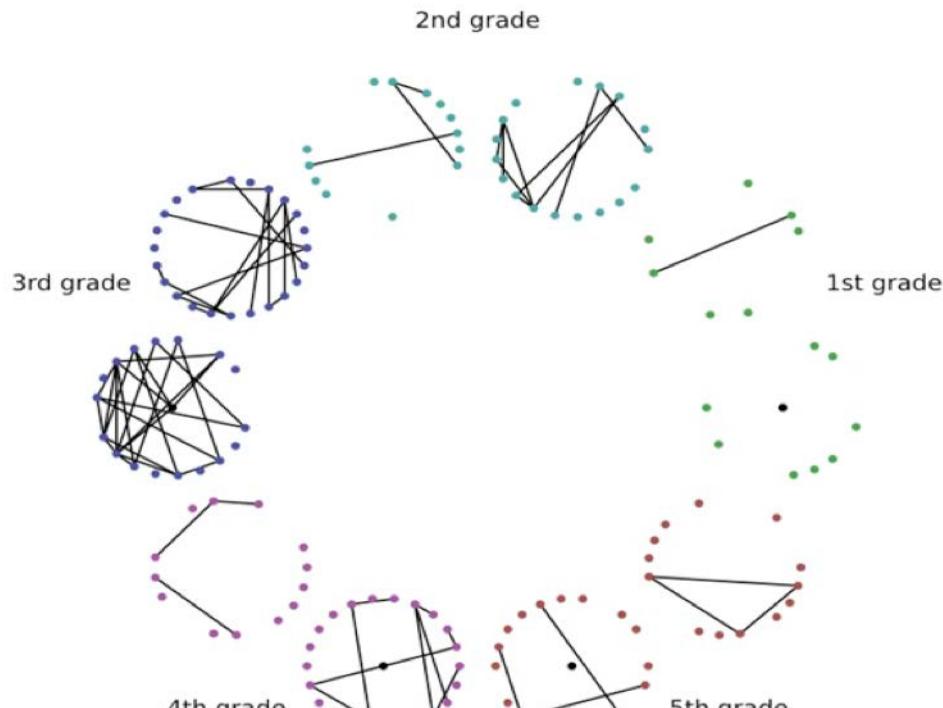
Thu, 16:20- 17:00



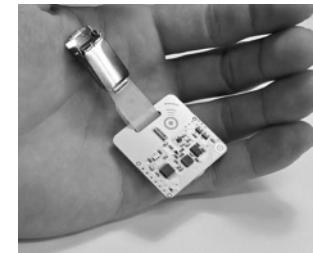
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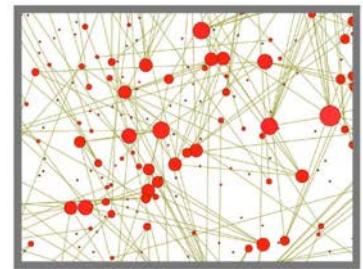
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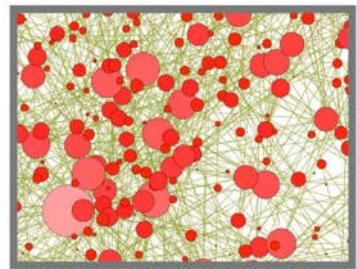
Sociopatterns experiment
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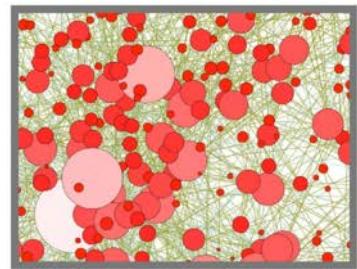
Scientific collaboration network



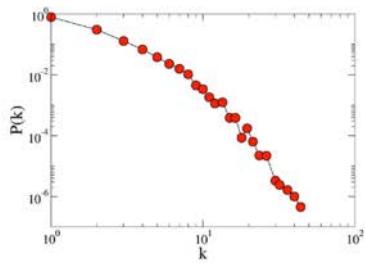
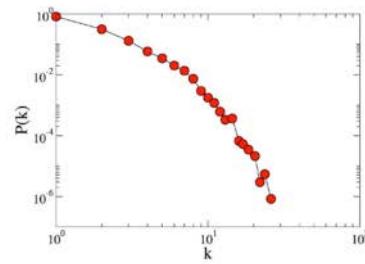
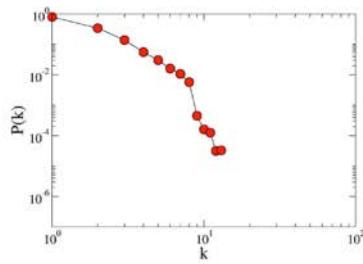
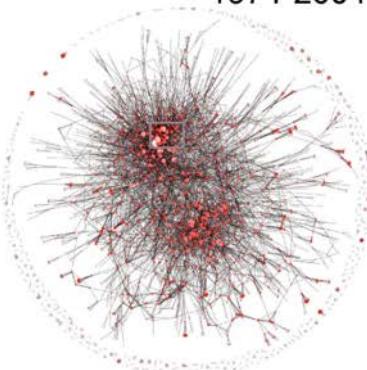
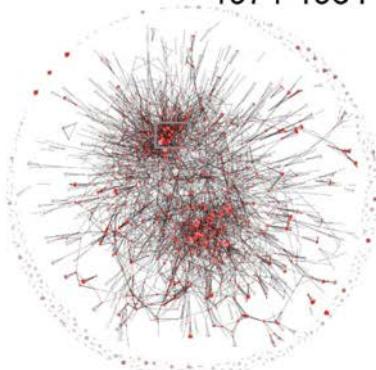
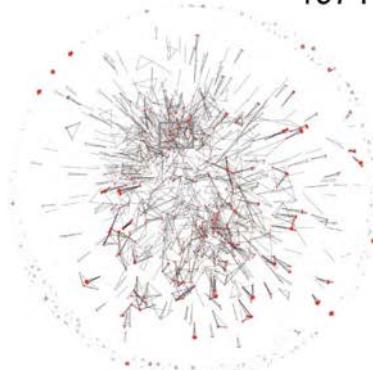
1974



1974-1984

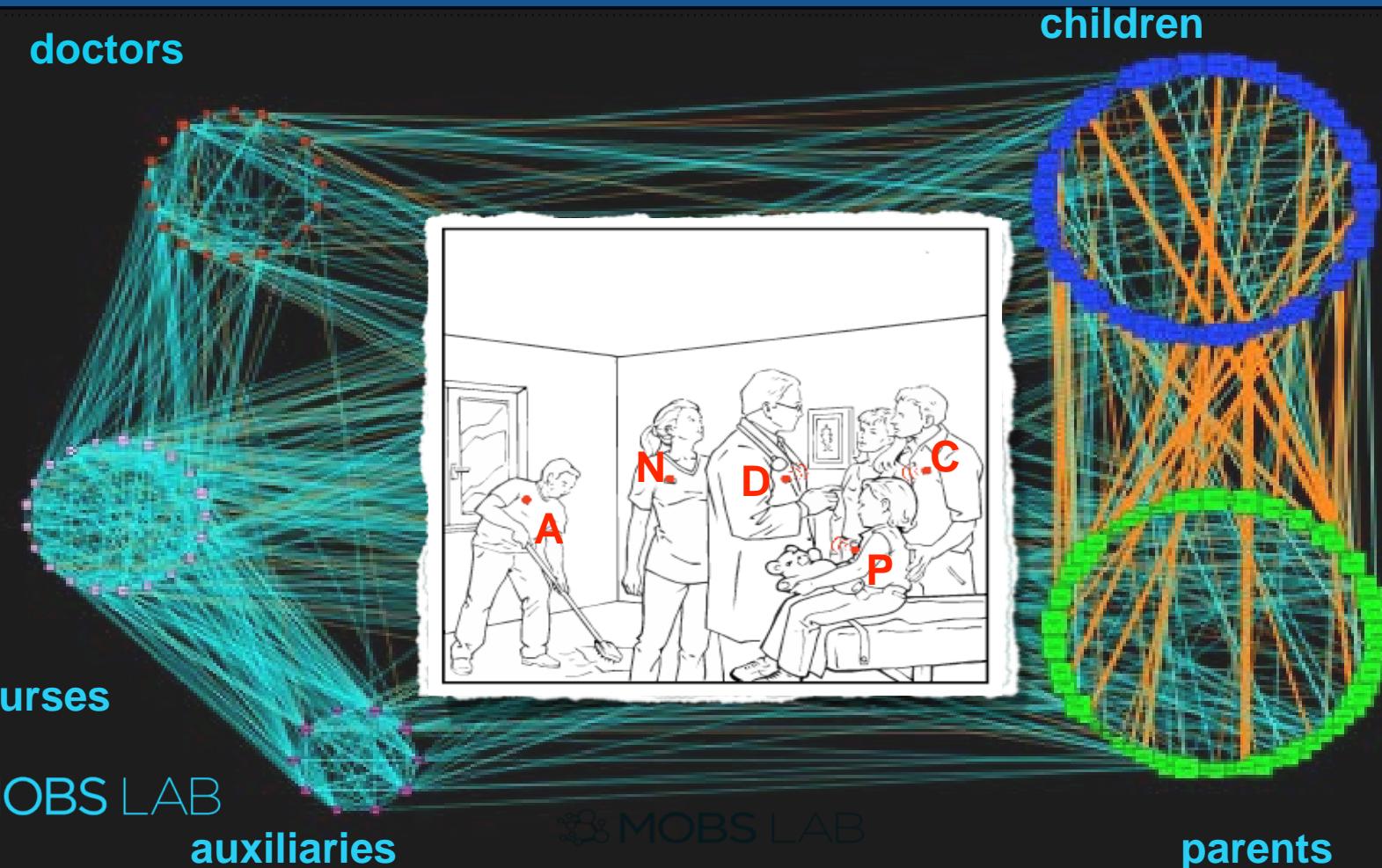


1974-2004



Interaction in hospital wards

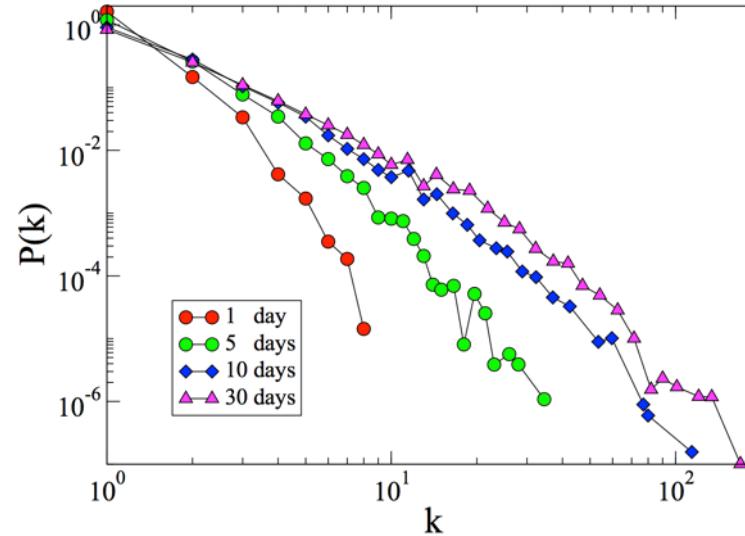
Vanhems PLoS ONE 8(9), e73970 (2013)



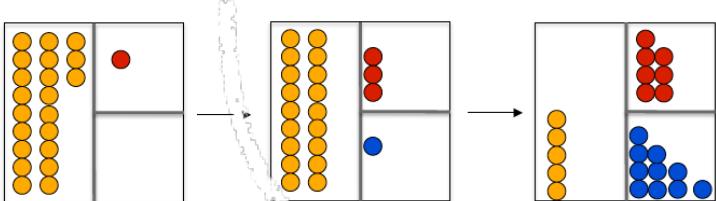
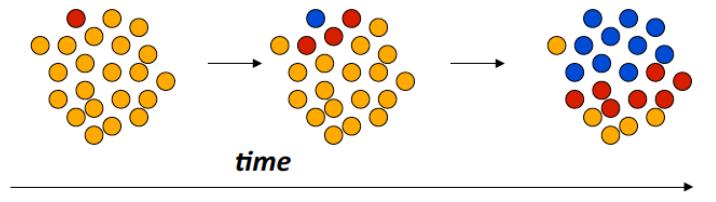
Heterogeneity and structure

Statistical distribution for the # of contacts (degree k)

- Skewed
- Heterogeneity and high variability
- Very large fluctuations (variance>>average)
- Small World
- Clustering
- Assortativity



Individual based Models



State vector
 $X = (x_1, x_2, \dots, x_N)$

Random process for
each specific variable

Discrete individuals tracked
one by one

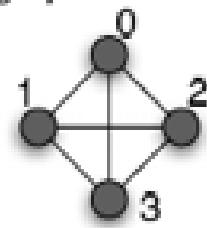
Three tables showing the tracked states of individual IDs over time. The first table shows a sequence of states for 22 individuals, starting with S (Susceptible) and transitioning through I (Infected) and R (Recovered). The second table shows a sequence of states for 22 individuals, starting with I (Infected) and transitioning through S (Susceptible) and R (Recovered). The third table shows a sequence of states for 22 individuals, starting with R (Recovered) and transitioning through S (Susceptible) and I (Infected). A horizontal arrow labeled "time" indicates the progression of the states.

ID	State	ID	State	ID	State
1	S	1	S	1	I
2	S	2	I	2	R
3	S	3	I	3	I
4	S	4	I	4	R
5	S	5	R	5	R
6	S	6	S	6	R
7	S	7	S	7	I
8	S	8	I	8	R
9	S	9	I	9	R
10	S	10	I	10	S
11	S	11	I	11	S
12	S	12	I	12	R
13	S	13	I	13	I
14	S	14	I	14	R
15	S	15	I	15	S
16	S	16	I	16	R
17	S	17	I	17	I
18	S	18	I	18	S
19	S	19	I	19	R
20	S	20	I	20	I
21	S	21	I	21	R
22	S	22	I	22	R

Contact Networks

Undirected
graphs

	0	1	2	3
0	0	1	1	1
1	1	0	1	1
2	1	1	0	1
3	1	1	1	0

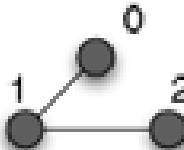


Subgraph of original graph

	0	1	2
0	0	1	1
1	1	0	1
2	1	1	0

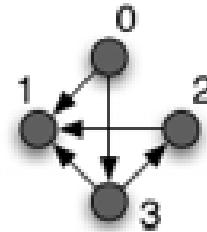


	0	1	2
0	0	1	0
1	1	0	1
2	0	1	0

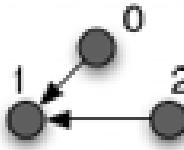


Directed
graphs

	0	1	2	3
0	0	1	0	1
1	0	0	0	0
2	0	1	0	0
3	0	1	1	0



	0	1	2
0	0	1	0
1	0	0	0
2	0	1	0

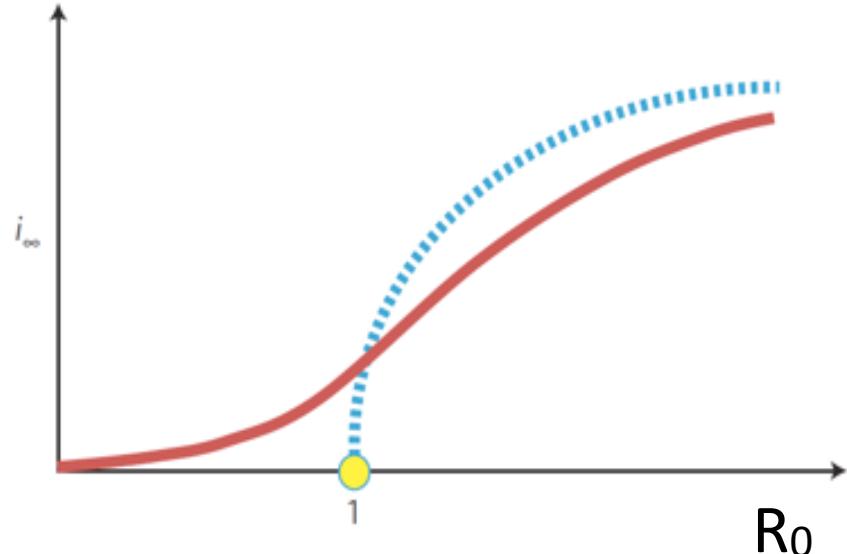


Network topology affects epidemic threshold and dynamical behavior of epidemics

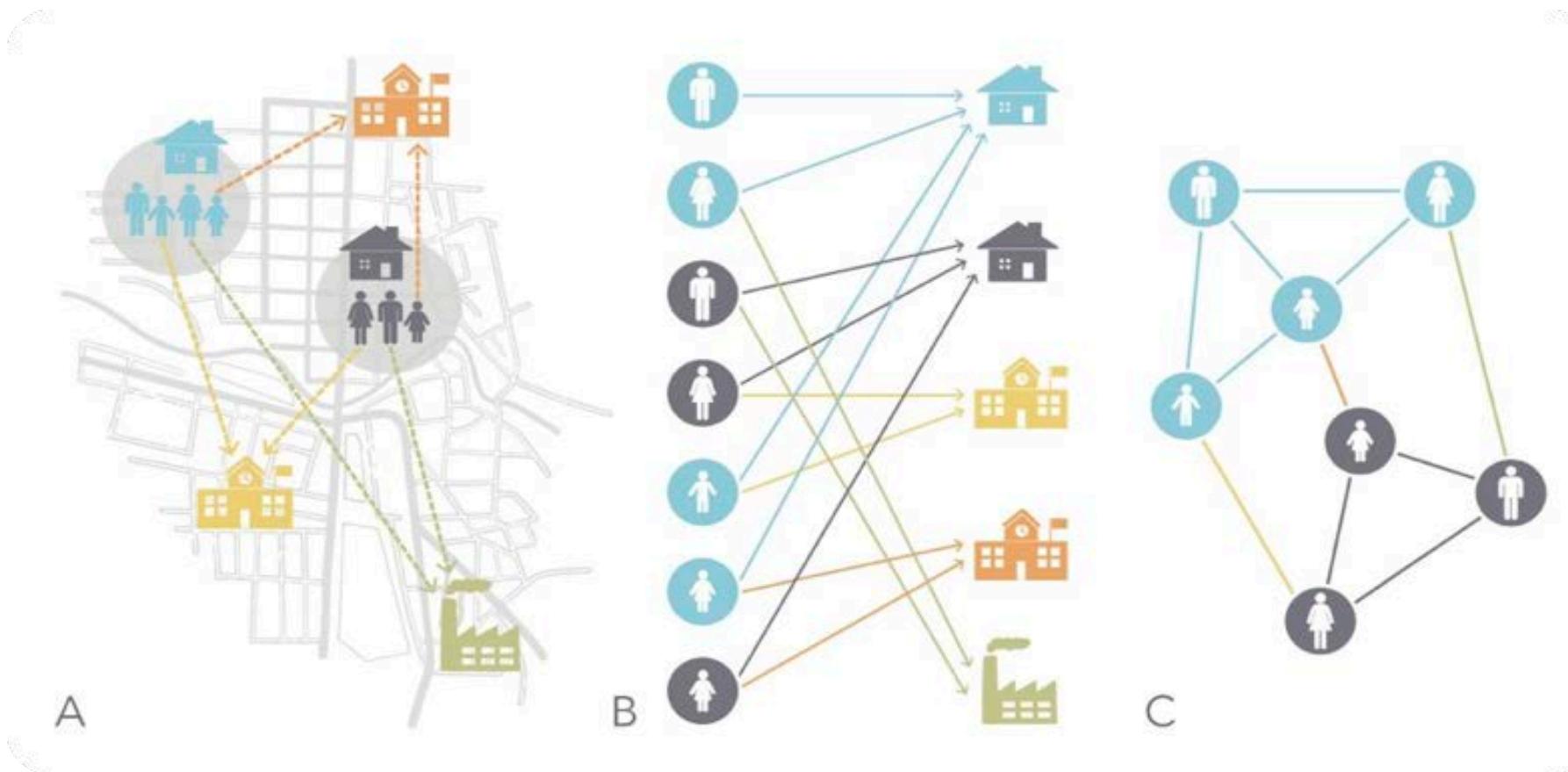
- Network heterogeneity tend to suppress the spreading threshold
- **Random-annealed network patterns have a vanishing epidemic threshold**

$$R_0 \rightarrow R_0 \langle k^2 \rangle / \langle k \rangle^2$$

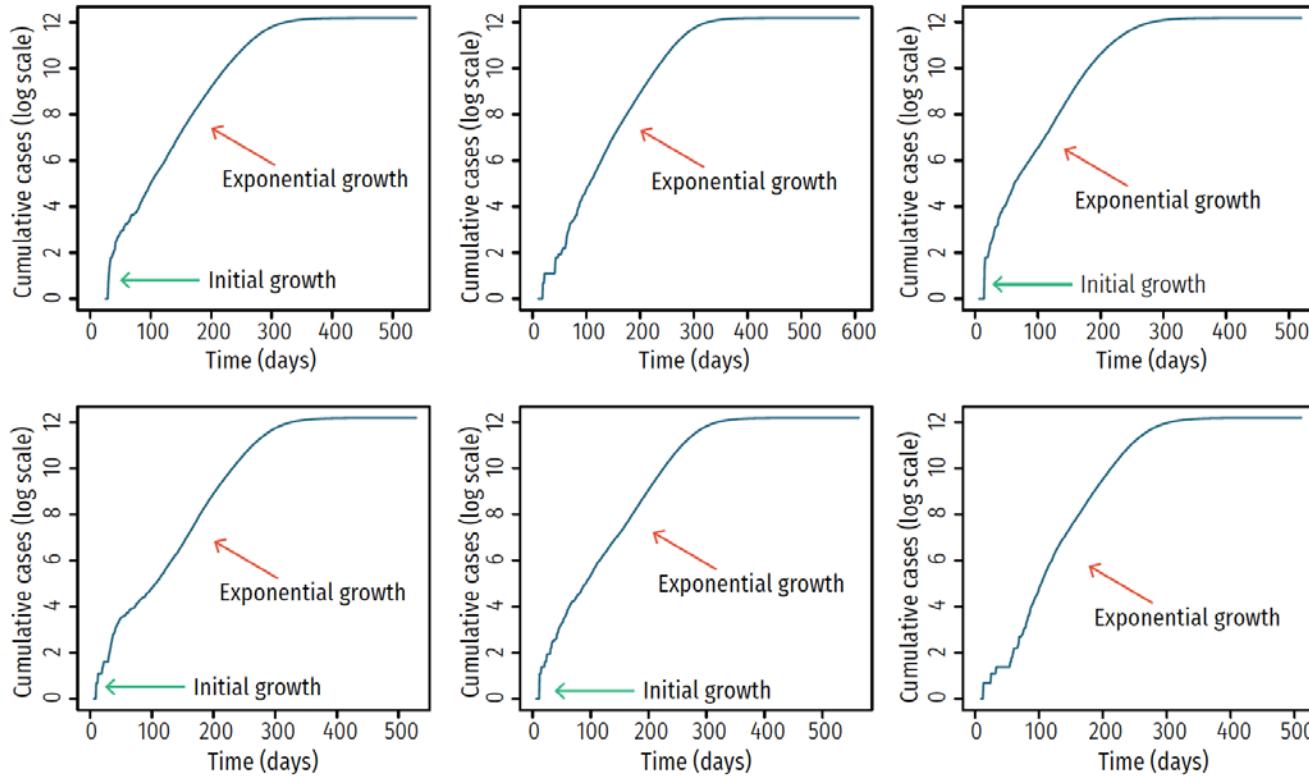
- Quenched networks have an epidemic threshold vanishing as the inverse of the largest eigenvalue of the connectivity matrix.
- Structure may change the results, however, assortativity/disassortativity do not impact the qualitative behavior concerning threshold.



Large scale population mapping and Networks



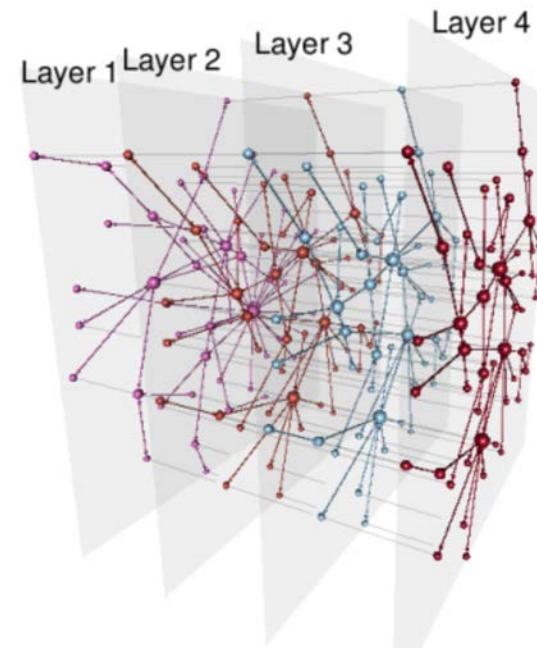
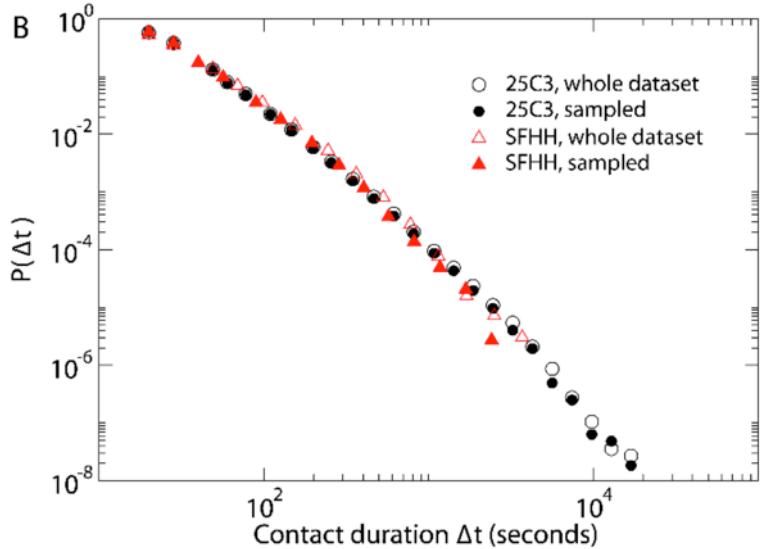
Reproduction number... what?



- Clustering effects and heterogeneous transmission interplay to create a complicate picture for which we do not yet have analytic understanding.
- Major barrier in modeling alignment and forecasts.

The frontier

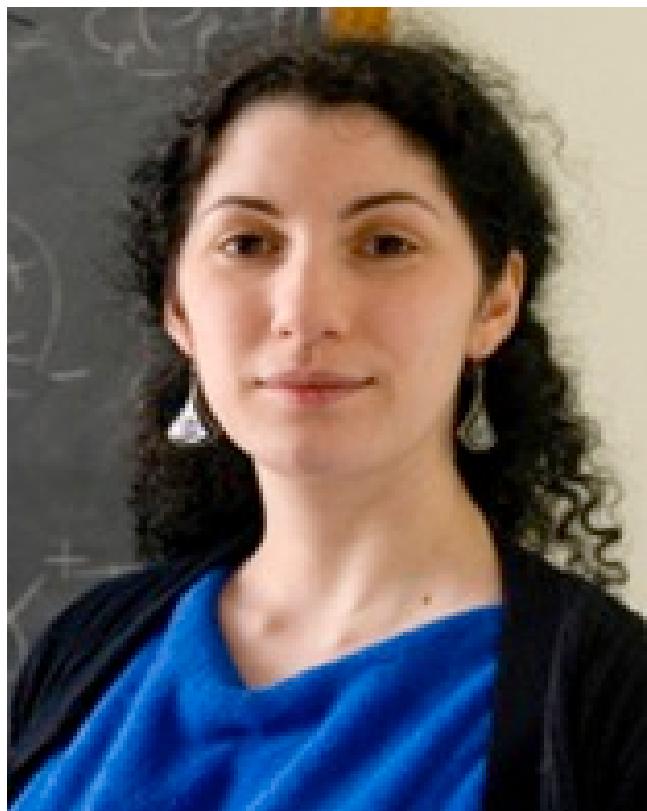
Multiplexity



Time scale: From
minutes to years.

MATHEMATICAL FRONTIERS

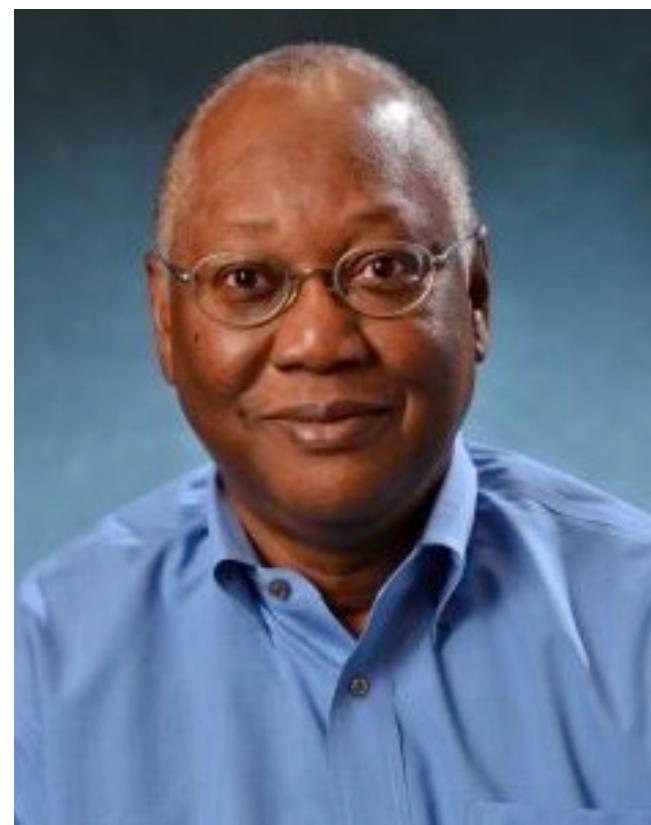
Social and Biological Networks – Q&A



Nina H. Fefferman,
University of Tennessee, Knoxville



Alessandro Vespignani,
Northeastern University



James H. Curry,
University of Colorado, Boulder

MATHEMATICAL FRONTIERS

2018 Monthly Webinar Series, 2-3pm ET

February 13: *Recording posted*
Mathematics of the Electric Grid

March 13: *Recording posted*
Probability for People and Places

April 10:
Social and Biological Networks

May 8:
Mathematics of Redistricting

June 12:
Number Theory: The Riemann Hypothesis

July 10: *Topology*

August 14:
Algorithms for Threat Detection

September 11:
Mathematical Analysis

October 9: *Combinatorics*

November 13:
Why Machine Learning Works

December 11:
Mathematics of Epidemics