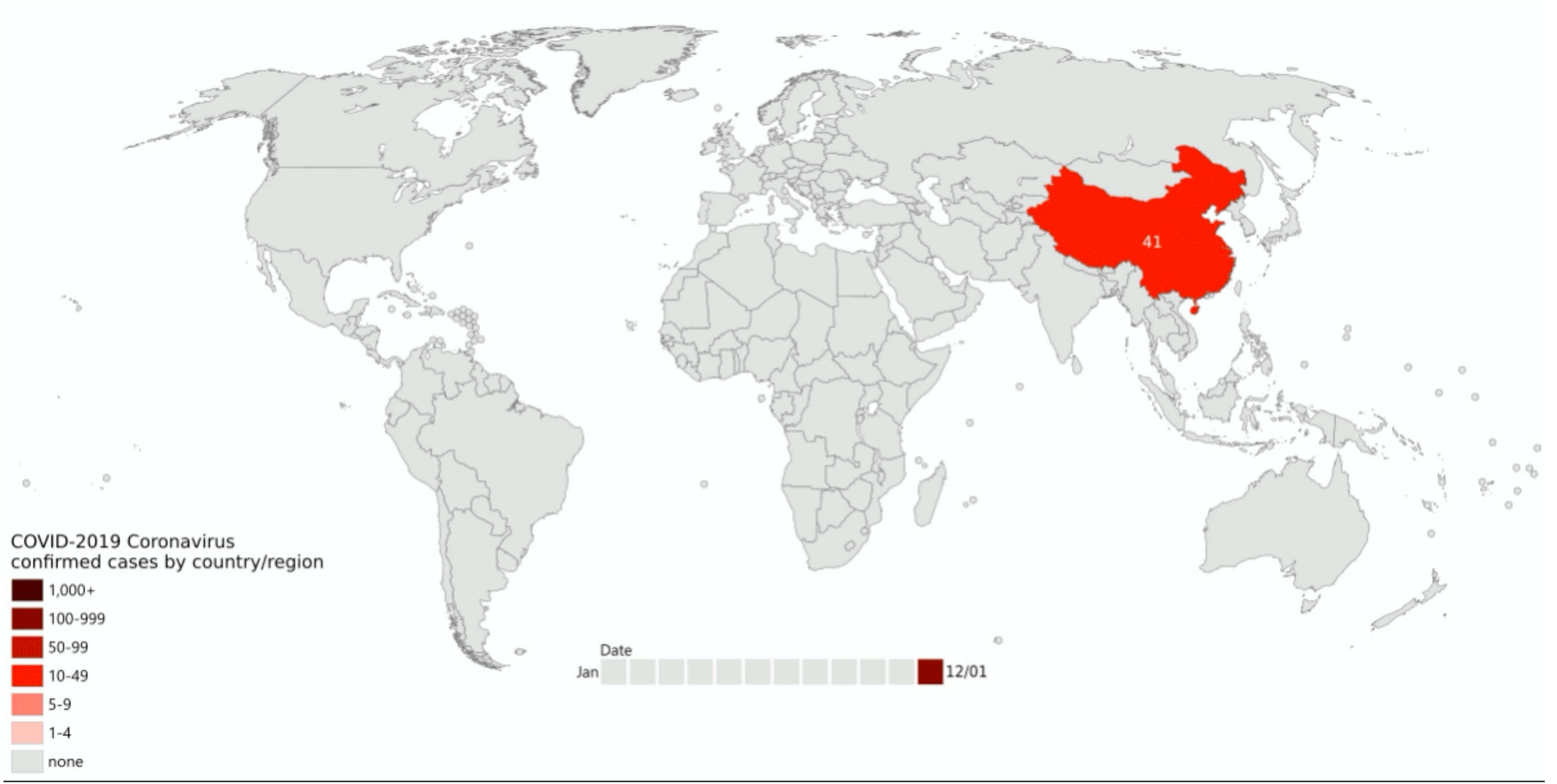
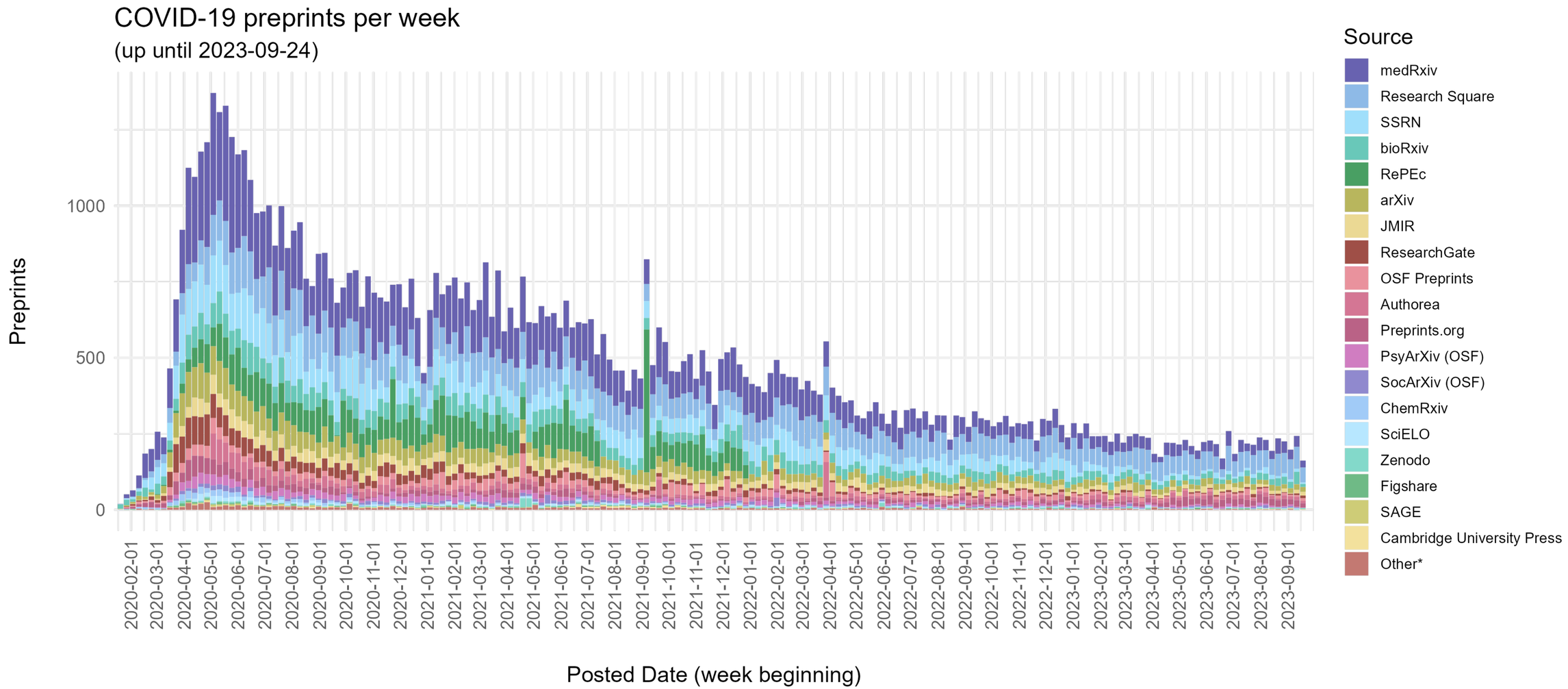
How contact patterns affect the non-equilibrium physics of epidemic outbreaks

Johannes Zierenberg
Max Planck Institute
for Dynamics and Self-Organization

Theorie Kolloquium
Oldenburg, 04/2024



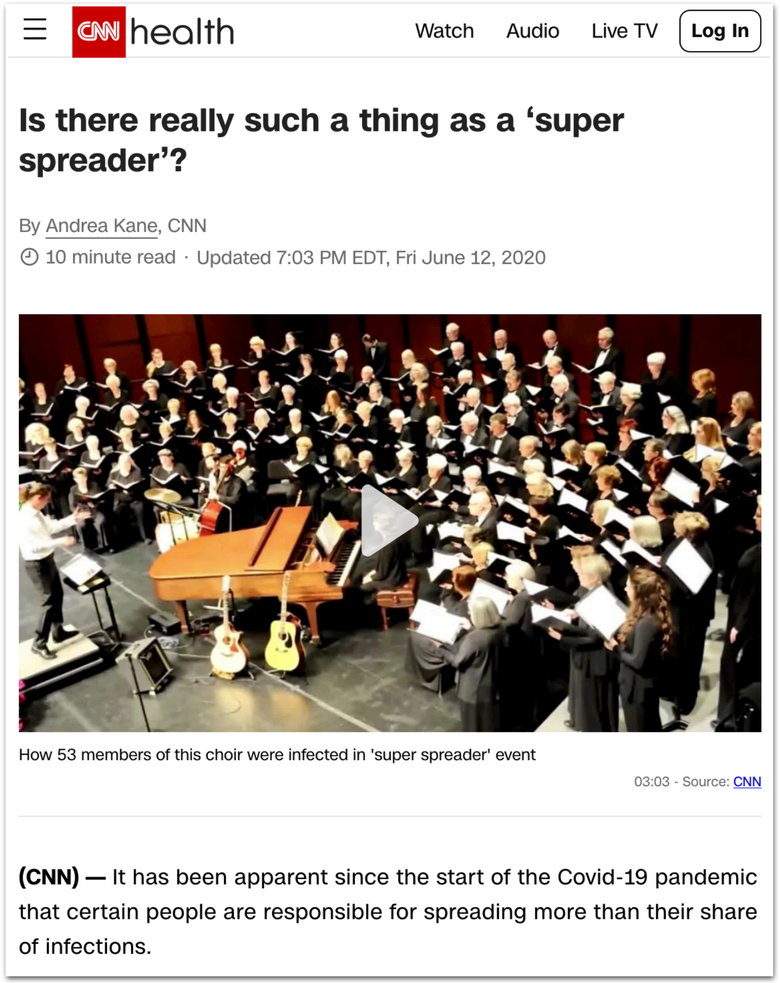
Source: Wikipedia



* 'Other' refers to preprint repositories containing <175 total relevant preprints. These include: AfricArXiv (OSF), AgriXiv (OSF), BioHackrXiv (OSF), Copernicus GmbH, ESSOAR, EcoEvoRxiv (OSF), EdArXiv (OSF), Frenxiv (OSF), INA-Rxiv (OSF), IndiaRxiv (OSF), LawArXiv (OSF), MediArXiv (OSF), MetaArXiV (OSF), NutriXiv (OSF), ScienceOpen, SportRxiv (OSF), Techrxiv (IEEE), WHO, engrXiv (OSF).

Source: https://github.com/nicholasmfraser/covid19_preprints

The role of superspreading in epidemics



CNN health Watch Audio Live TV Log In

Is there really such a thing as a 'super spreader'?

By Andrea Kane, CNN

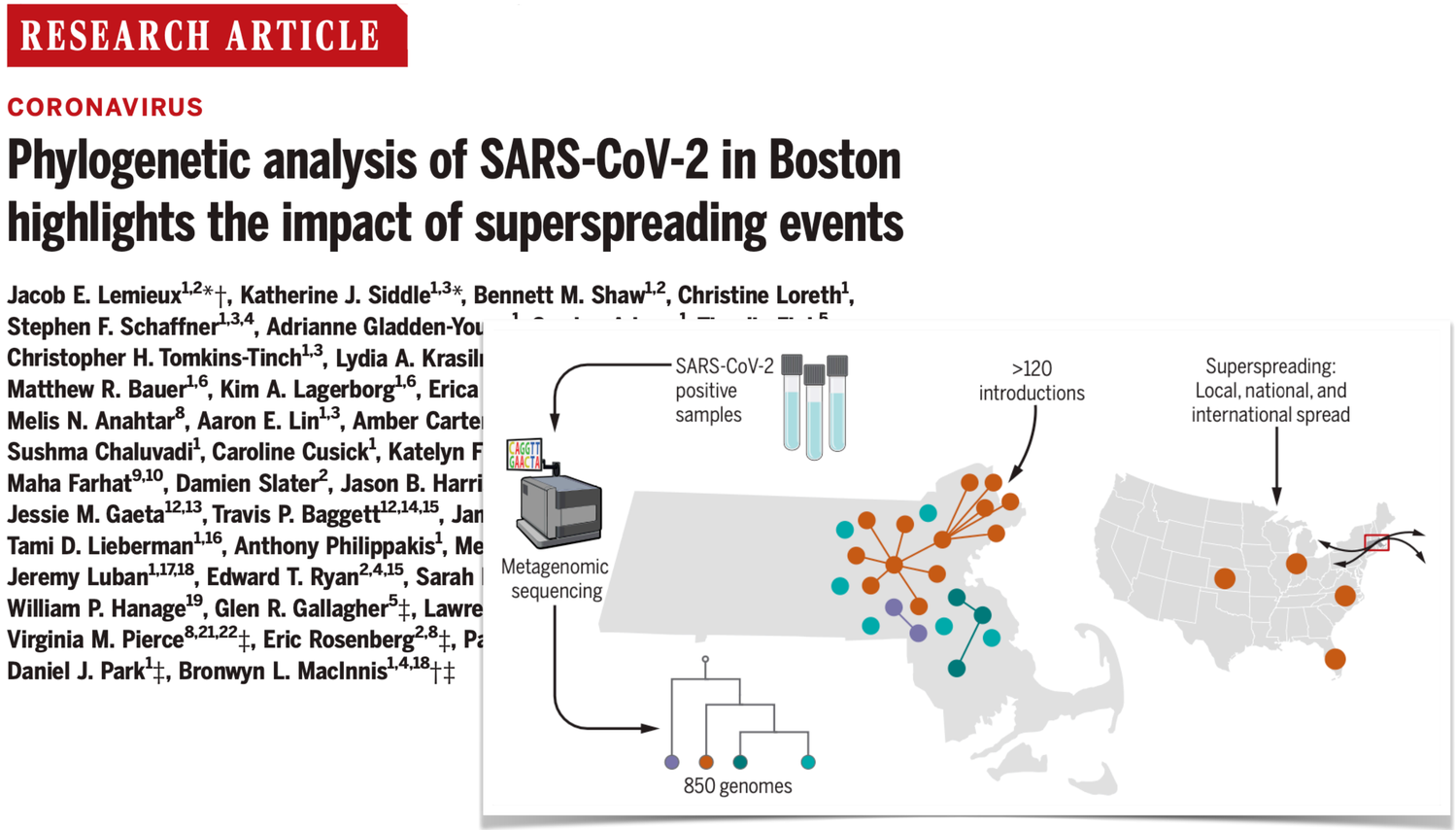
10 minute read · Updated 7:03 PM EDT, Fri June 12, 2020

How 53 members of this choir were infected in 'super spreader' event

03:03 - Source: CNN

(CNN) — It has been apparent since the start of the Covid-19 pandemic that certain people are responsible for spreading more than their share of infections.

- Clear evidence that most virus introductions spread little and few cases amplify considerably.



RESEARCH ARTICLE

CORONAVIRUS

Phylogenetic analysis of SARS-CoV-2 in Boston highlights the impact of superspreading events

Jacob E. Lemieux[1,2]*†, Katherine J. Siddle[1,3]*, Bennett M. Shaw[1,2], Christine Loreth[1], Stephen F. Schaffner[1,3,4], Adrianne Gladden-You… Christopher H. Tomkins-Tinch[1,3], Lydia A. Krasil… Matthew R. Bauer[1,6], Kim A. Lagerborg[1,6], Erica … Melis N. Anahtar[8], Aaron E. Lin[1,3], Amber Carte… Sushma Chaluvadi[1], Caroline Cusick[1], Katelyn F… Maha Farhat[9,10], Damien Slater[2], Jason B. Harri… Jessie M. Gaeta[12,13], Travis P. Baggett[12,14,15], Jan… Tami D. Lieberman[1,16], Anthony Philippakis[1], Me… Jeremy Luban[1,17,18], Edward T. Ryan[2,4,15], Sarah … William P. Hanage[19], Glen R. Gallagher[5]‡, Lawre… Virginia M. Pierce[8,21,22]‡, Eric Rosenberg[2,8]‡, Pa… Daniel J. Park[1]‡, Bronwyn L. MacInnis[1,4,18]†‡

Lemieux et al. Science (2021)

The role of superspreading in epidemics

- Clear evidence that most virus introductions spread little and few cases amplify considerably.
- Many mechanisms underlying superspreading!

Exhaled aerosol increases with COVID-19 infection, age, and obesity

David A. Edwards[a,b,1], Dennis Ausiello[c], Jonathan Salzman[b], Tom Devlin[b], Robert Langer[d,1], Brandon J. Beddingfield[e], Alyssa C. Fears[e], Lara A. Doyle-Meyers[e], Rachel K. Redmann[e], Stephanie Z. Killeen[e], Nicholas J. Maness[e], and Chad J. Roy[e,f,1]

[a]John A. Paulson School of Engineer
Assessment Technology and Continu
Chemical & Biological Engineering, N
Research Center, Covington, LA 7011

variability in exhaled bioaerosol

Contributed by Robert Langer, January 12, 2021 (sent for review October 26, 2020; reviewed by Justin Hanes and Melanie Ott)

The role of superspreading in epidemics

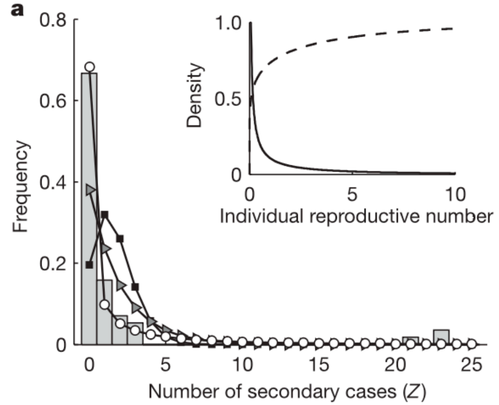
- Clear evidence that most virus introductions spread little and few cases amplify considerably.
- Many mechanisms underlying superspreading!
- From a statistical perspective super-spreading can be considered a `rare` event.

Vol 438|17 November 2005|doi:10.1038/nature04153 nature

LETTERS

Superspreading and the effect of individual variation on disease emergence

J. O. Lloyd-Smith[1,2], S. J. Schreiber[3], P. E. Kopp[4] & W. M. Getz[1]



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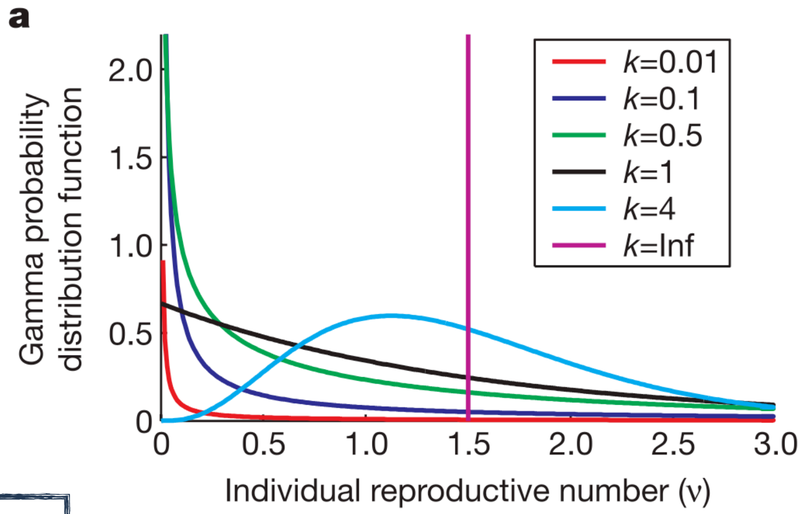
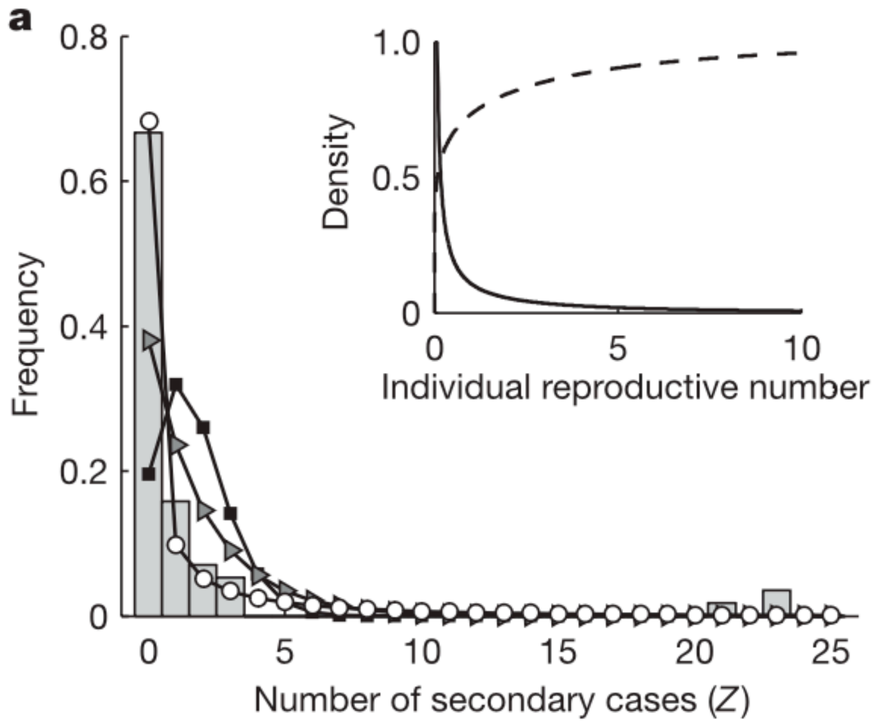


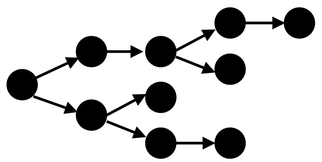
Overdispersion: $\sigma_Z^2 = R_0 + R_0^2/k$



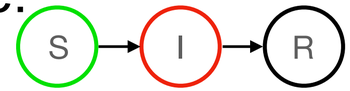
Individual 'reproductive number' $\nu \sim P(R_0)$ with mean R_0

Secondary cases stochastic $Z \sim \text{Poisson}(\nu)$

- Branching Process:
  $P(R_0) = \delta(\nu - R_0)$ then $Z \sim \text{Poisson}(R_0)$



- Homogeneous transmission and recovery rate:
  $P(R_0) = \text{Exp}(R_0)$ then $Z \sim \text{Geometric}(R_0)$



- More general:
  $P(R_0) = \text{Gamma}(R_0, k)$ then $Z \sim \text{Neg.Binomial}(R_0, k)$

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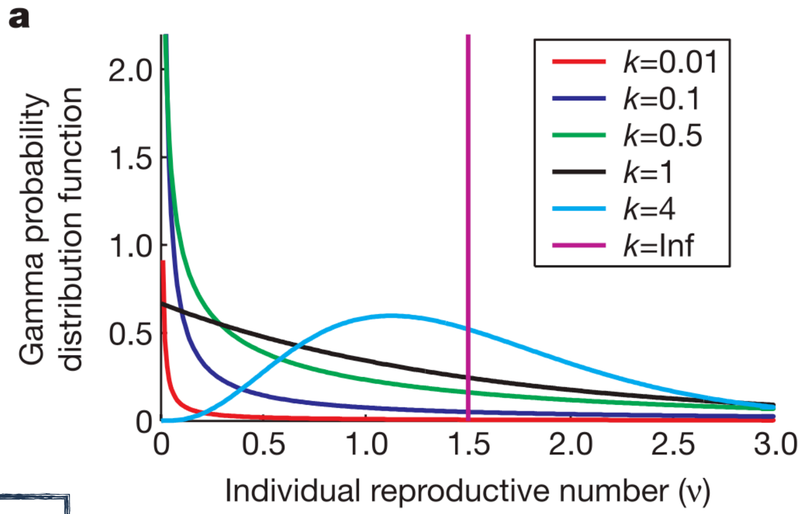

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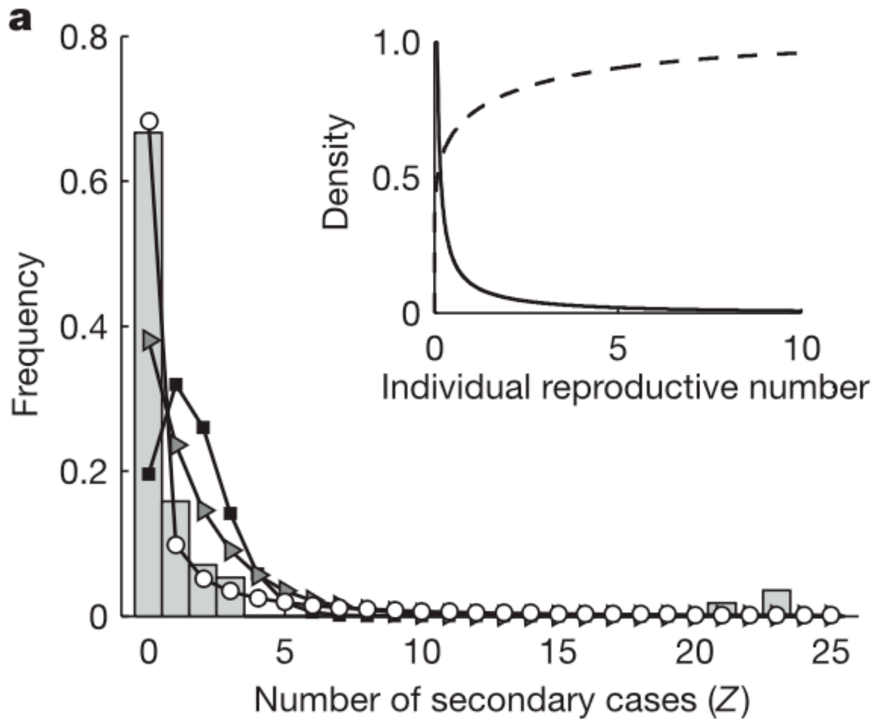

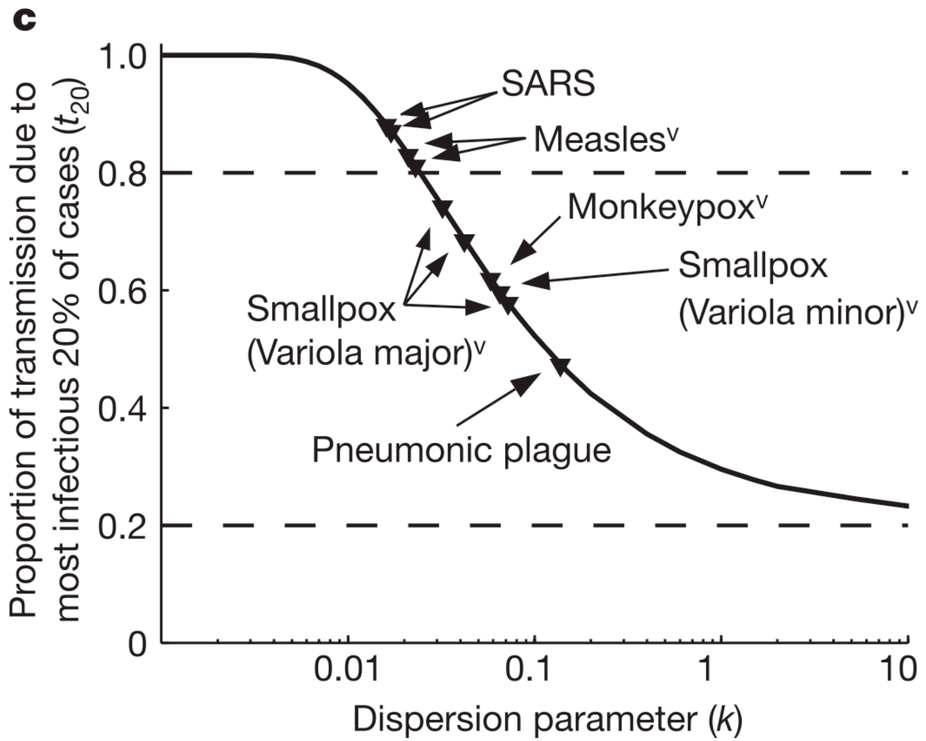

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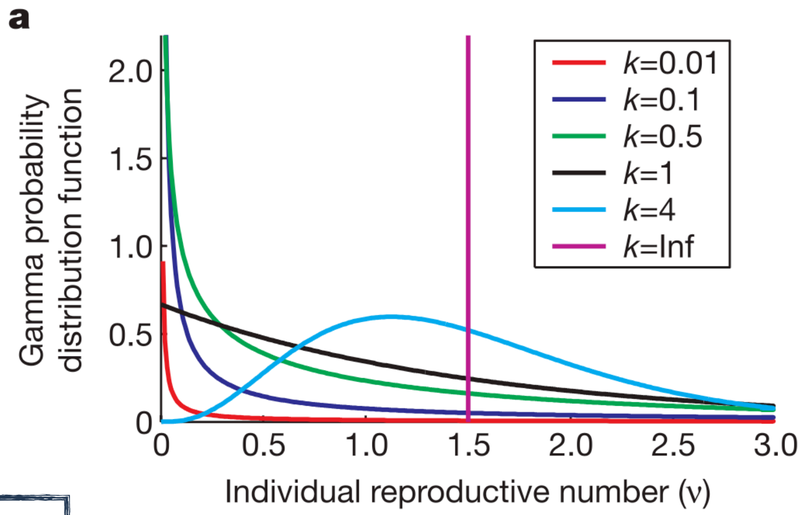

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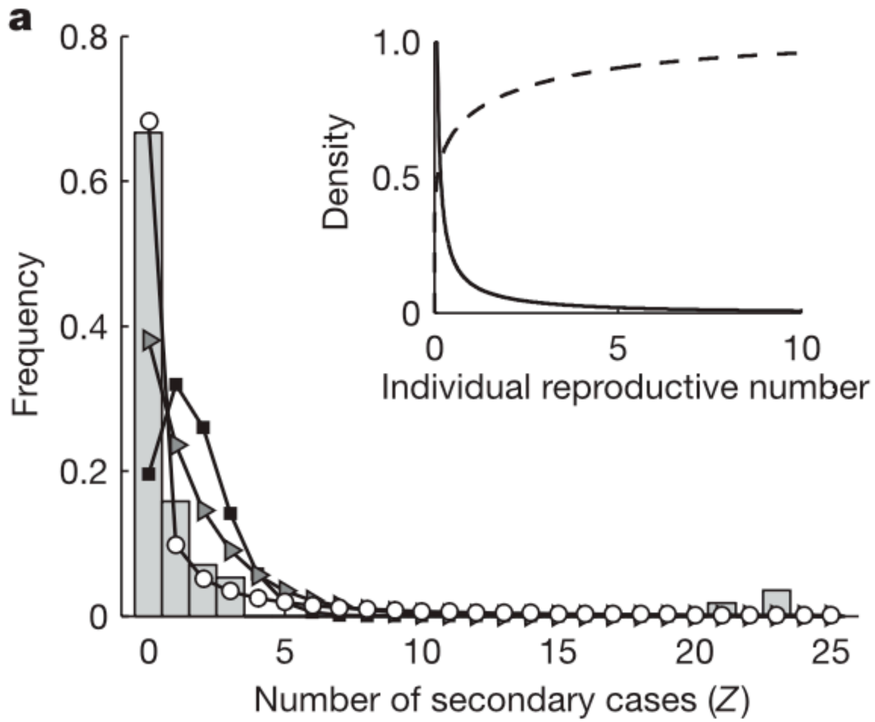
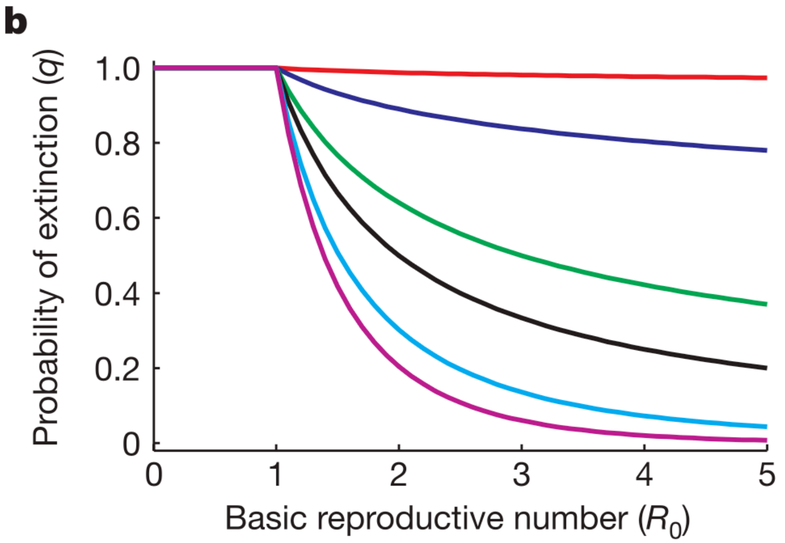


Strong effect on statistics of epidemic outbreaks:



The role of superspreading in epidemics

- Clear evidence that most virus introductions spread little and few cases amplify considerably.
- Many mechanisms underlying superspreading!
- From a statistical perspective super-spreading can be considered a `rare` event.

> Cumulatively, these observations suggest that behavioural, interventional, general demographic, seasonal, and other environmental factors might affect transmissibility but are not the key determinants of overdispersion for directly transmitted viruses. They suggest instead that *k*, at least in part, is an intrinsic characteristic of these viruses and, as obligate intracellular parasites, their host interactions. That is, poorly ventilated, crowded spaces with susceptible individuals facilitate superspreading, but whether a virus tends to transmit via large clusters in the first place seems to be intrinsic to that viral infection. Thus, the previous question can be reframed: which virological factors mediate *k*?

Chen et al. Lancet Infect. Dis. (2021)

The role of superspreading in epidemics

How much do human contact patterns contribute to overdispersion?

> Cumulatively, these observations suggest that behavioural, interventional, general demographic, seasonal, and other environmental factors might affect transmissibility but are not the key determinants of overdispersion for directly transmitted viruses. They suggest instead that *k*, at least in part, is an intrinsic characteristic of these viruses and, as obligate intracellular parasites, their host interactions. That is, poorly ventilated, crowded spaces with susceptible individuals facilitate superspreading, but whether a virus tends to transmit via large clusters in the first place seems to be intrinsic to that viral infection. Thus, the previous question can be reframed: which virological factors mediate *k*?

Chen et al. Lancet Infect. Dis. (2021)

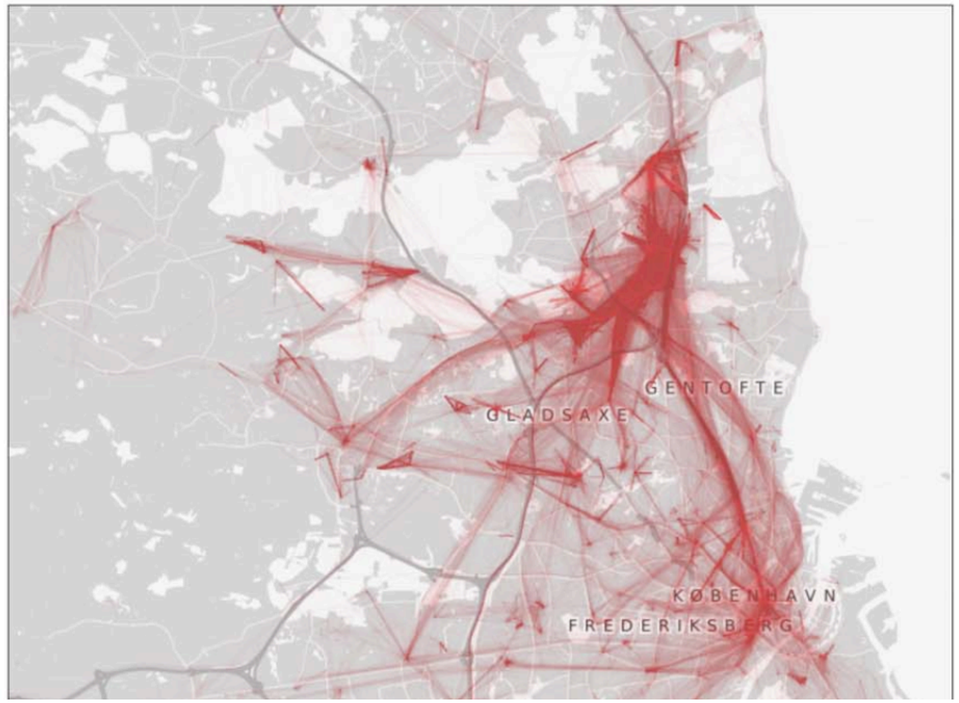
Contact patterns and epidemic outbreaks

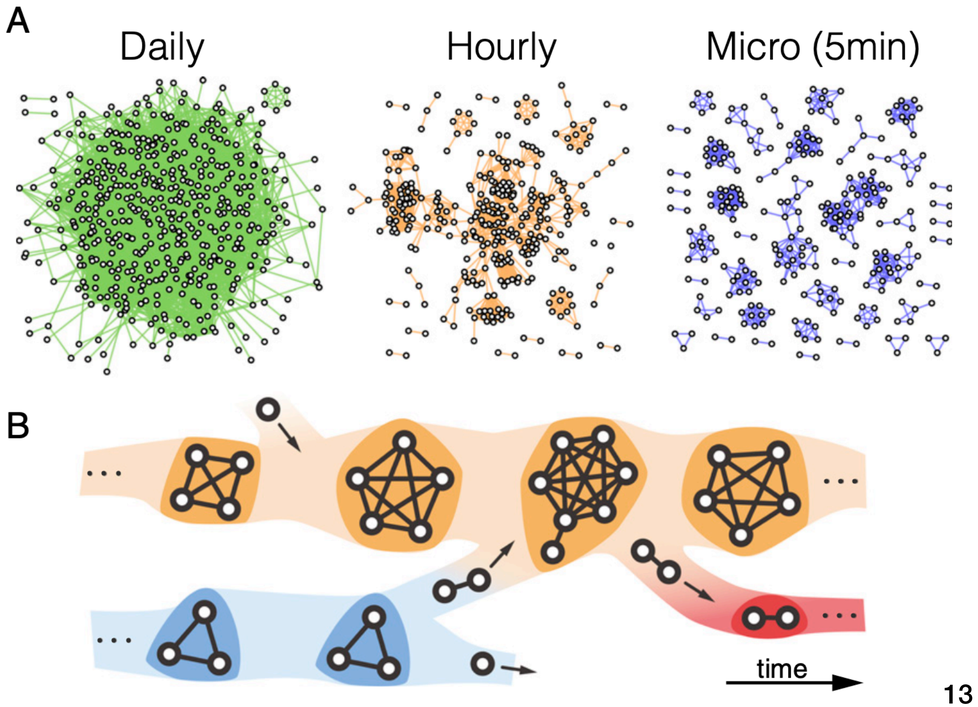
Statistical analysis of disease spread from human contact patterns

Epidemic phase transition in a toy model of spatiotemporal contacts

Copenhagen Networks Study

- 1000 participants from DTU with smartphones as social sensors
- Face-to-face interactions, telecommunication, social networks, location, and background information





SCIENTIFIC DATA

OPEN

DATA DESCRIPTOR

Interaction data from the Copenhagen Networks Study

Piotr Sapiezynski[1], Arkadiusz Stopczynski[1], David Dreyer Lassen[2] & Sune Lehmann[1,2*]

Sapiezynski et int Lehmann, Sci. Data (2019)
Sekara Stopczynski, Lehmann, PNAS (2016).
Stopczynski et int. Lehmann, PLOS ONE (2014)

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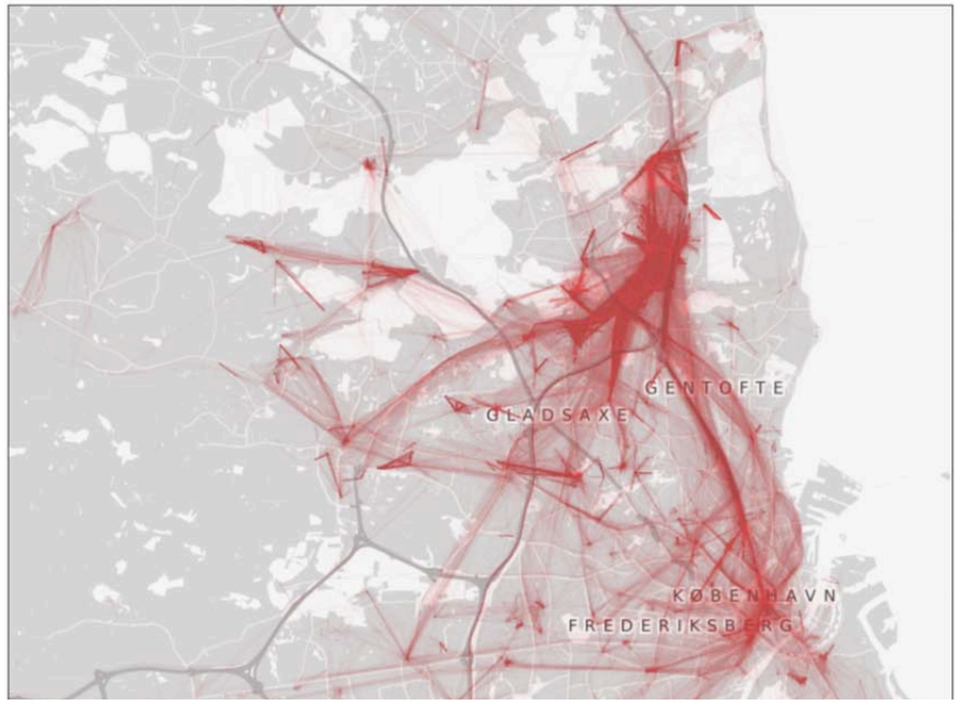

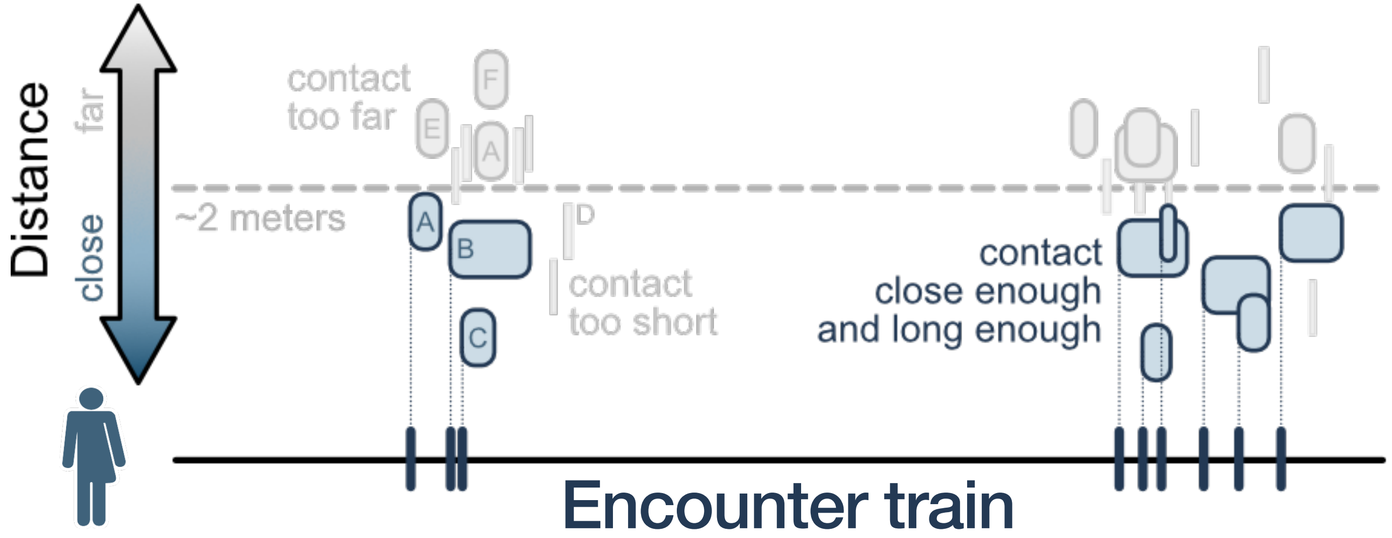

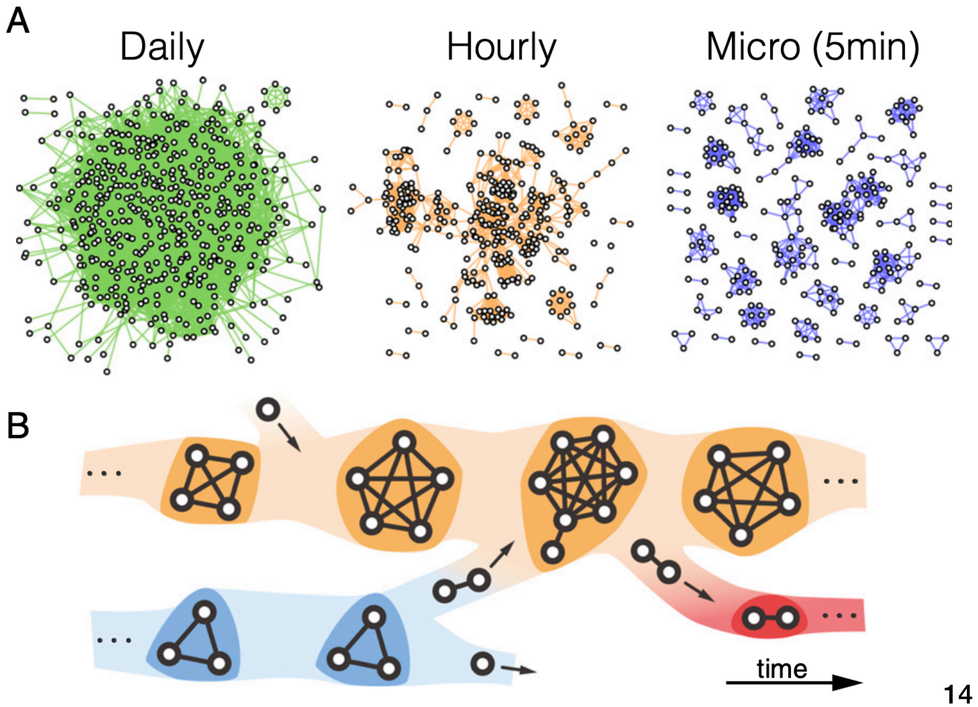

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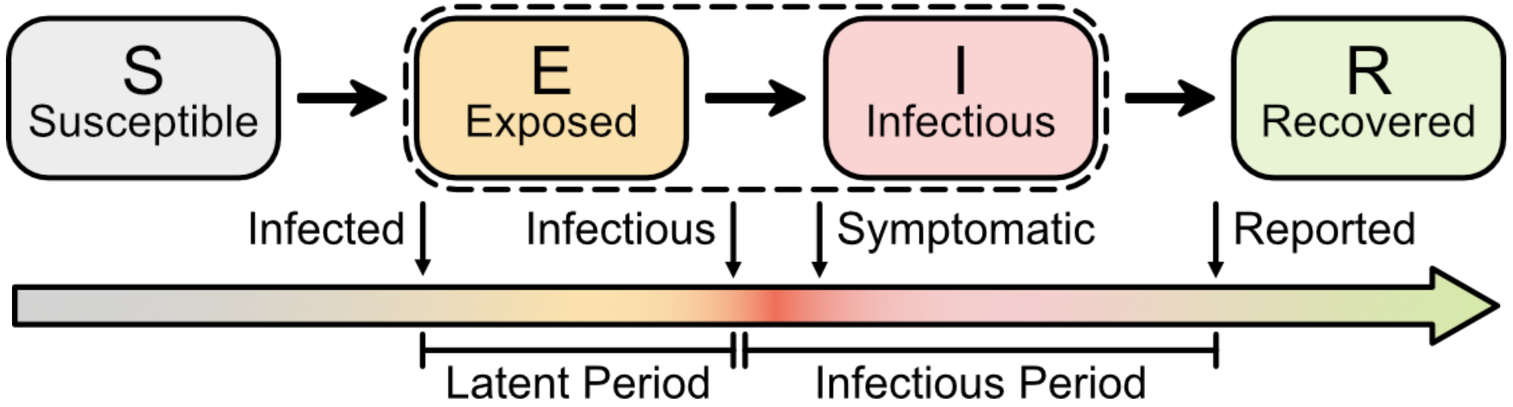
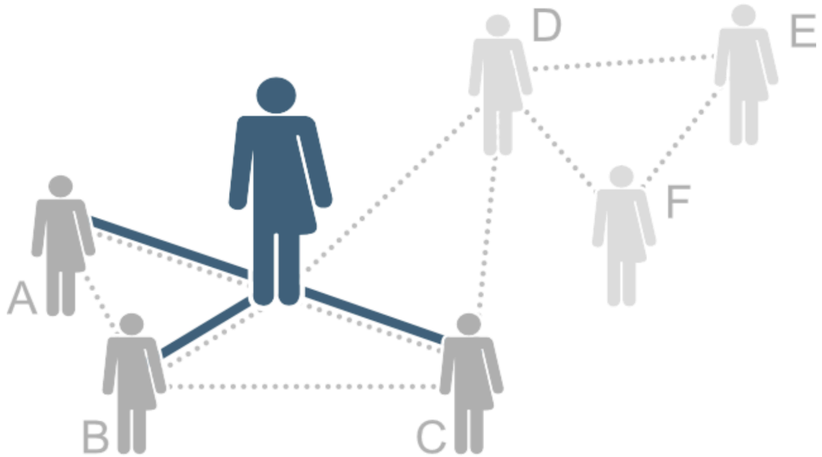
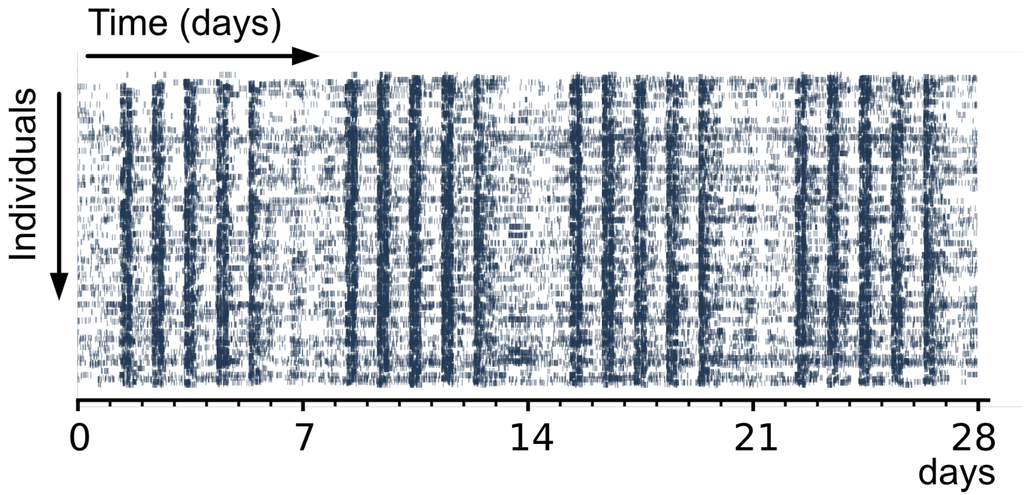
Dispersion from human contact patterns







Zierenberg, Spitzner et al., New. J. Phys. (2023)

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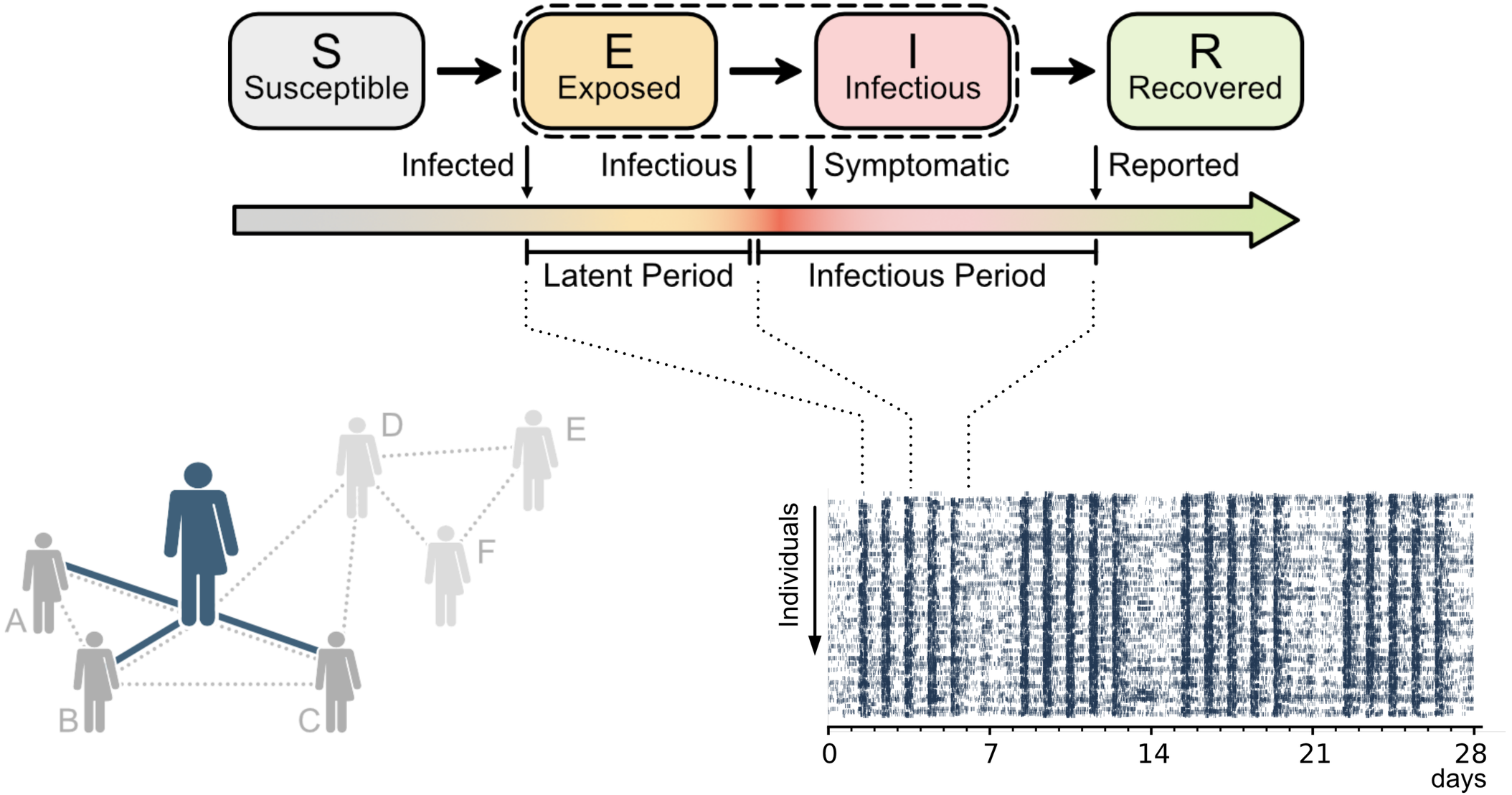

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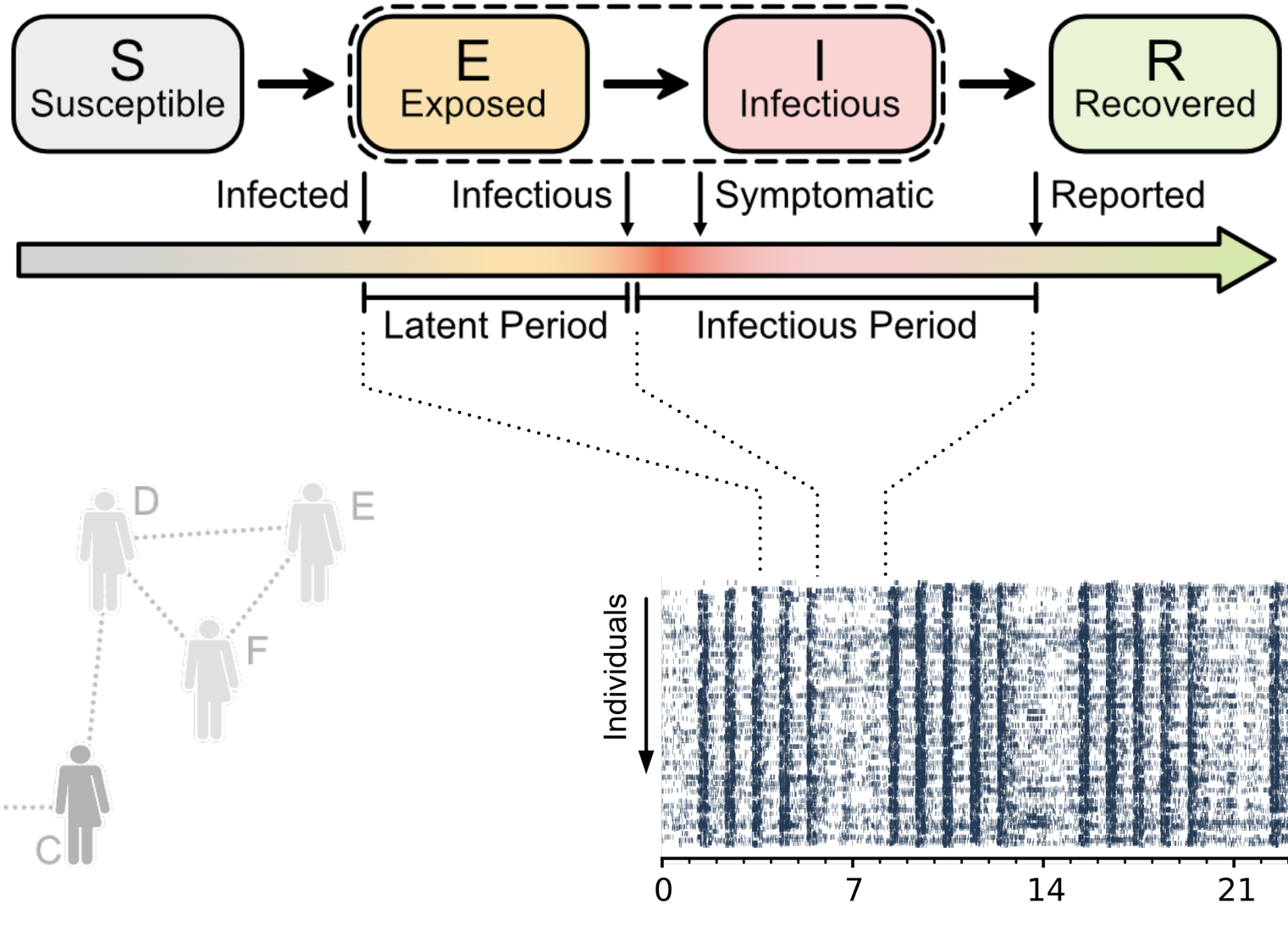

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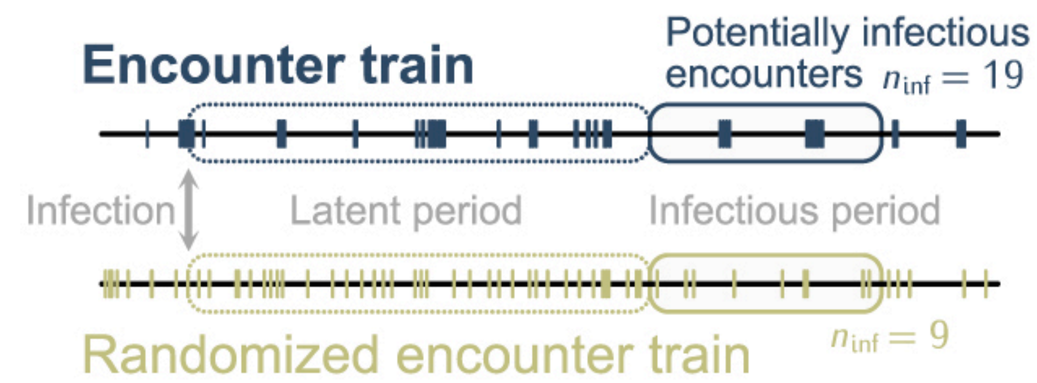

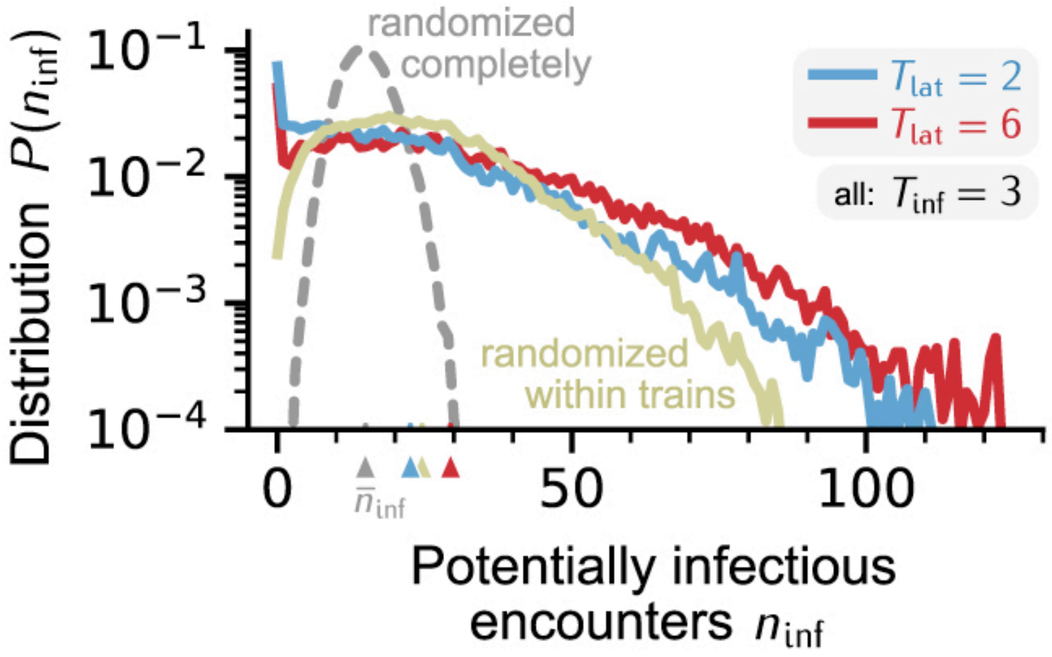

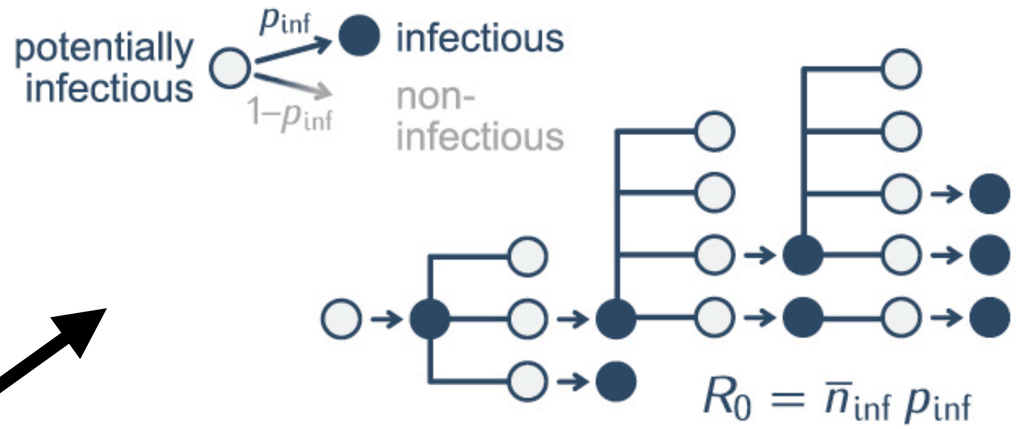

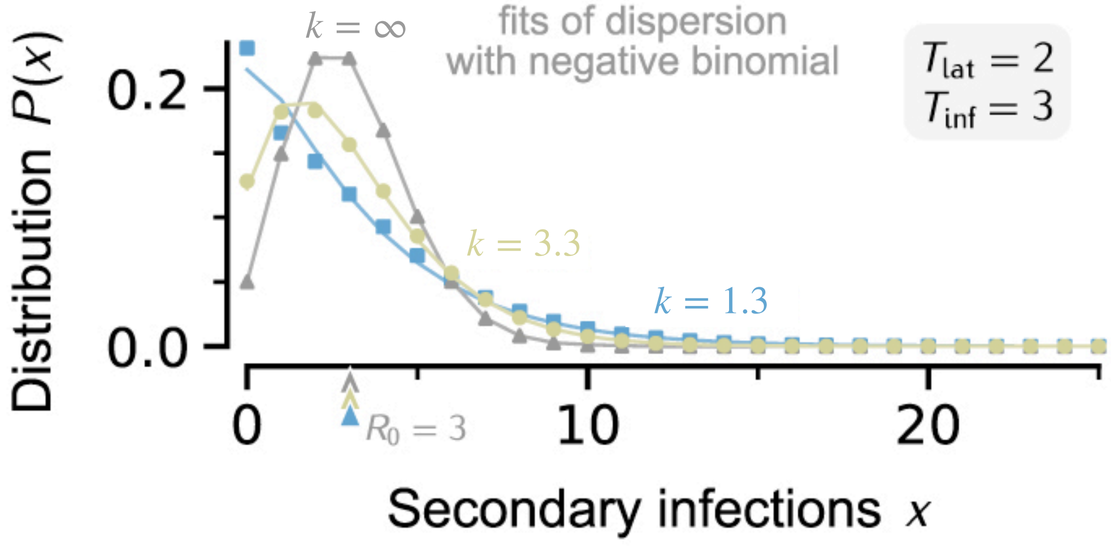

Zierenberg, Spitzner et al., New. J. Phys. (2023)

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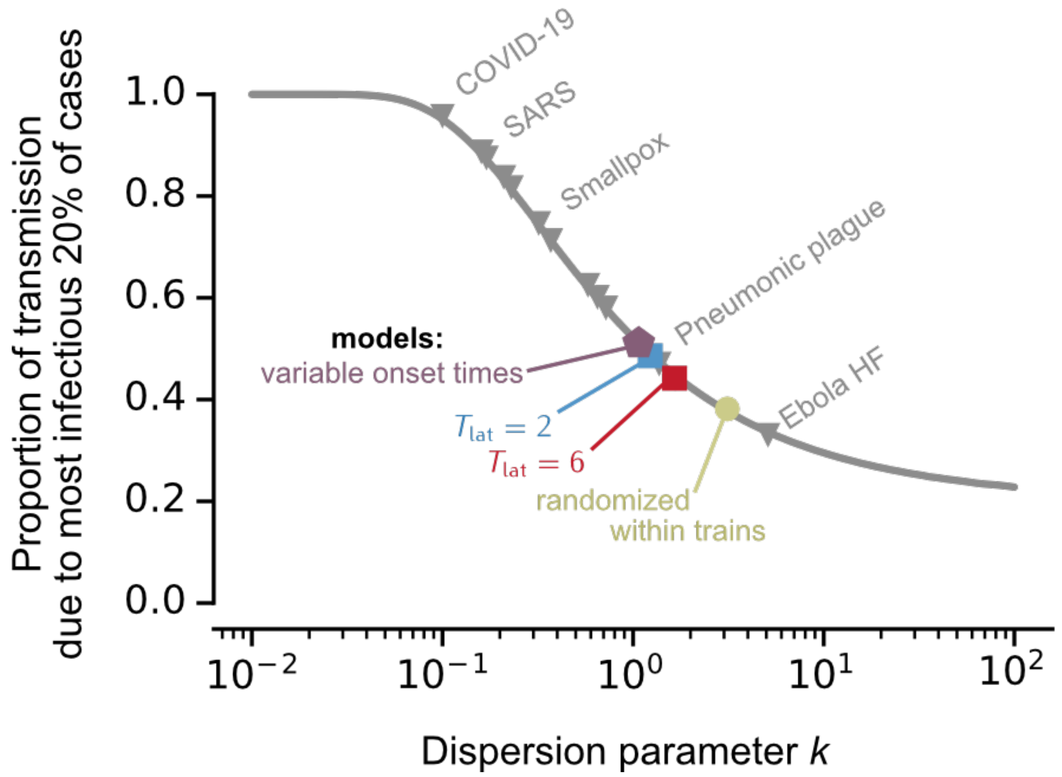

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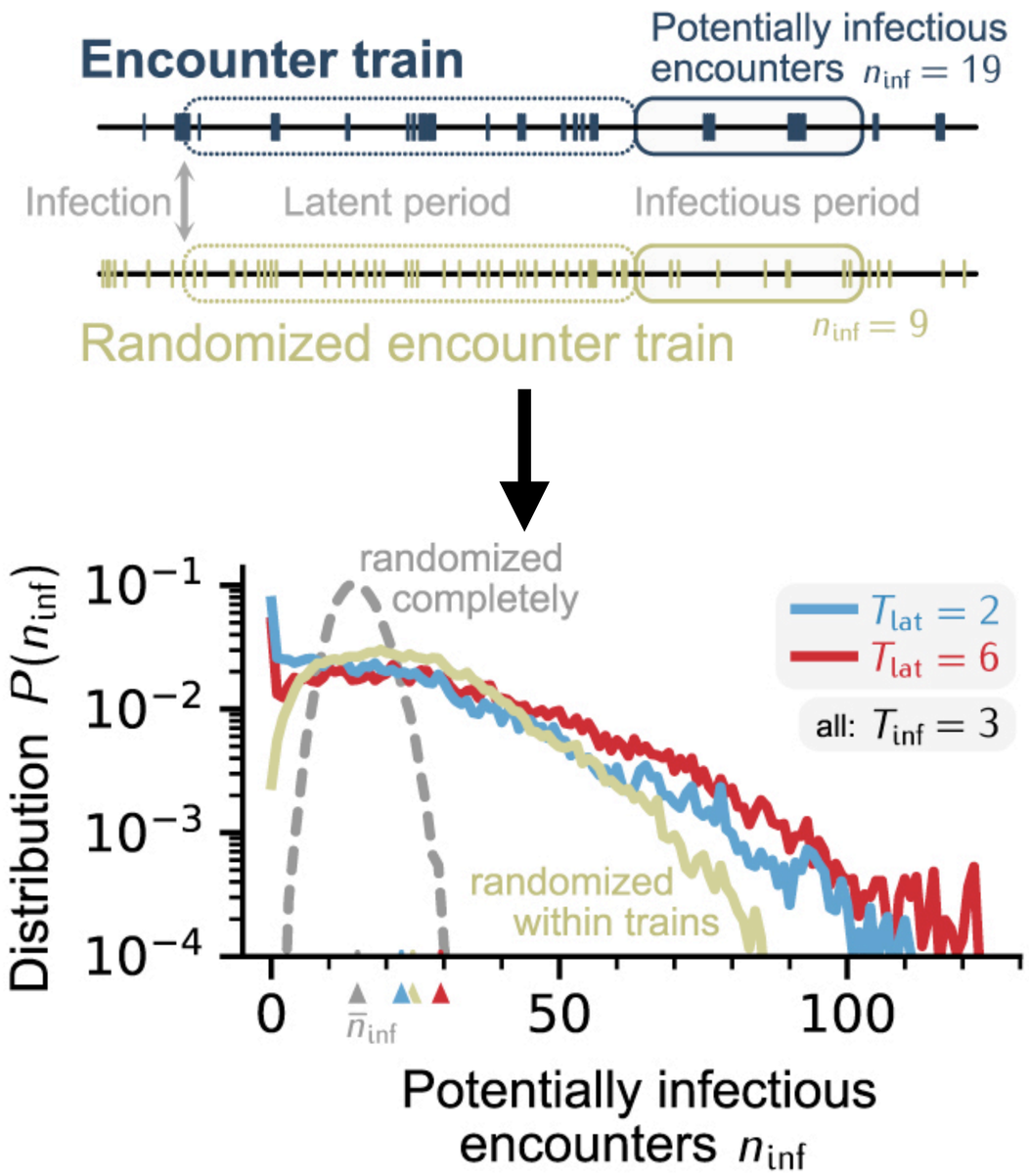
cf. Chen et al. Lancet Infect. Dis. (2021)

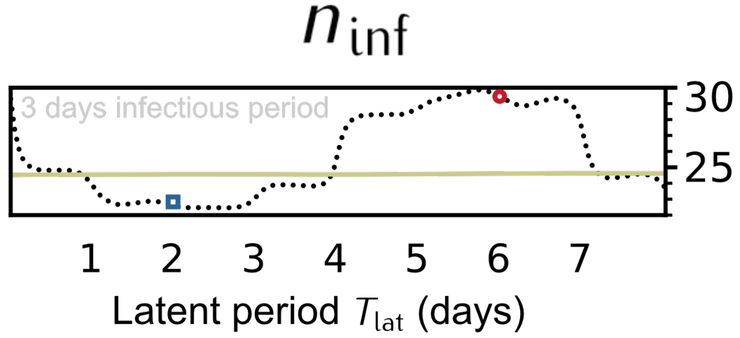
We used a very simple disease model, yet dispersion from contact patterns is in the right regime

Our perspective:
Contact patterns form baseline;
Physiological disease details are higher order

Lloyd-Smith et al., Nature (2005)
Zierenberg, Spitzner et al., New. J. Phys. (2023)

Modulation from human contact patterns





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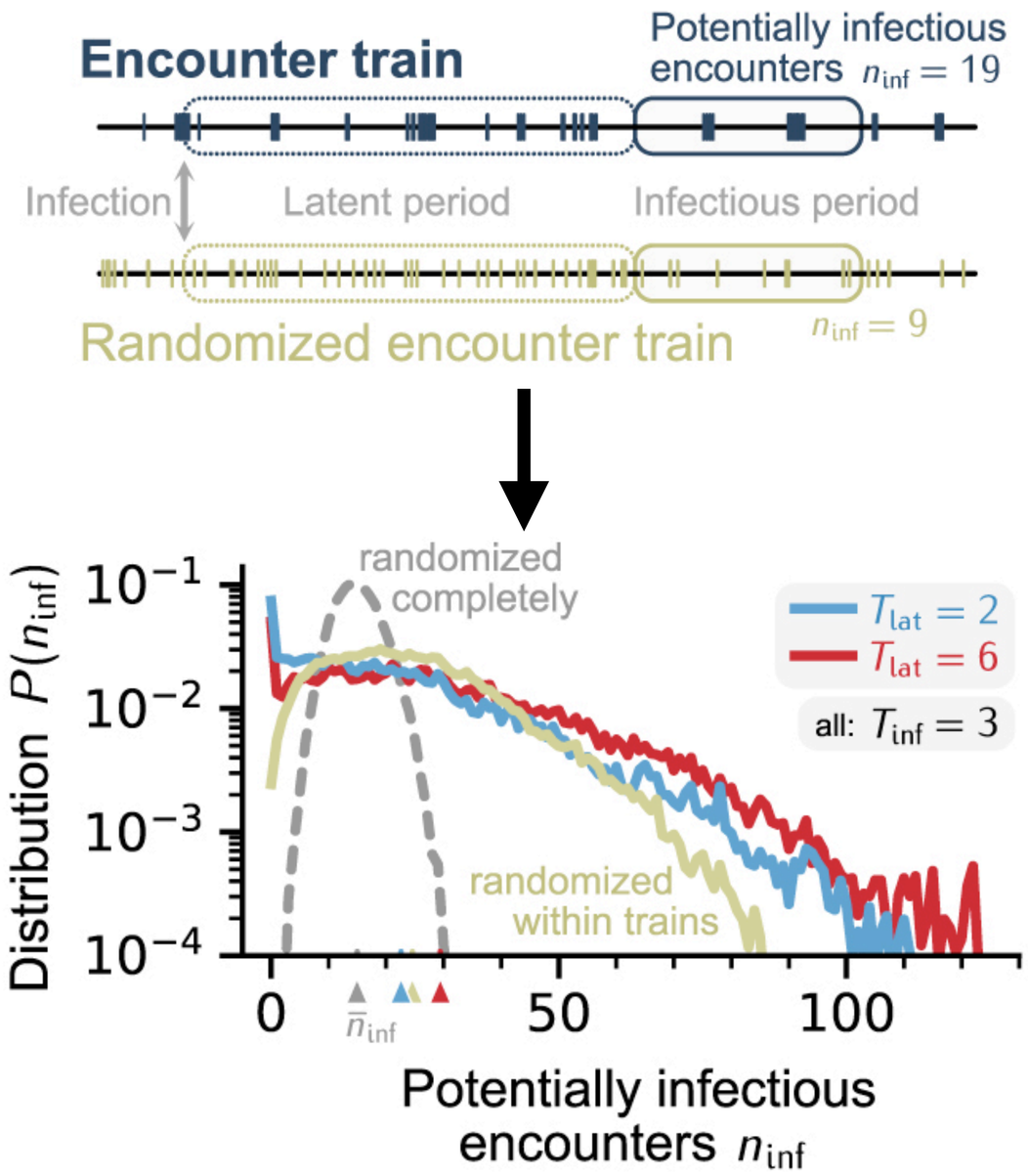

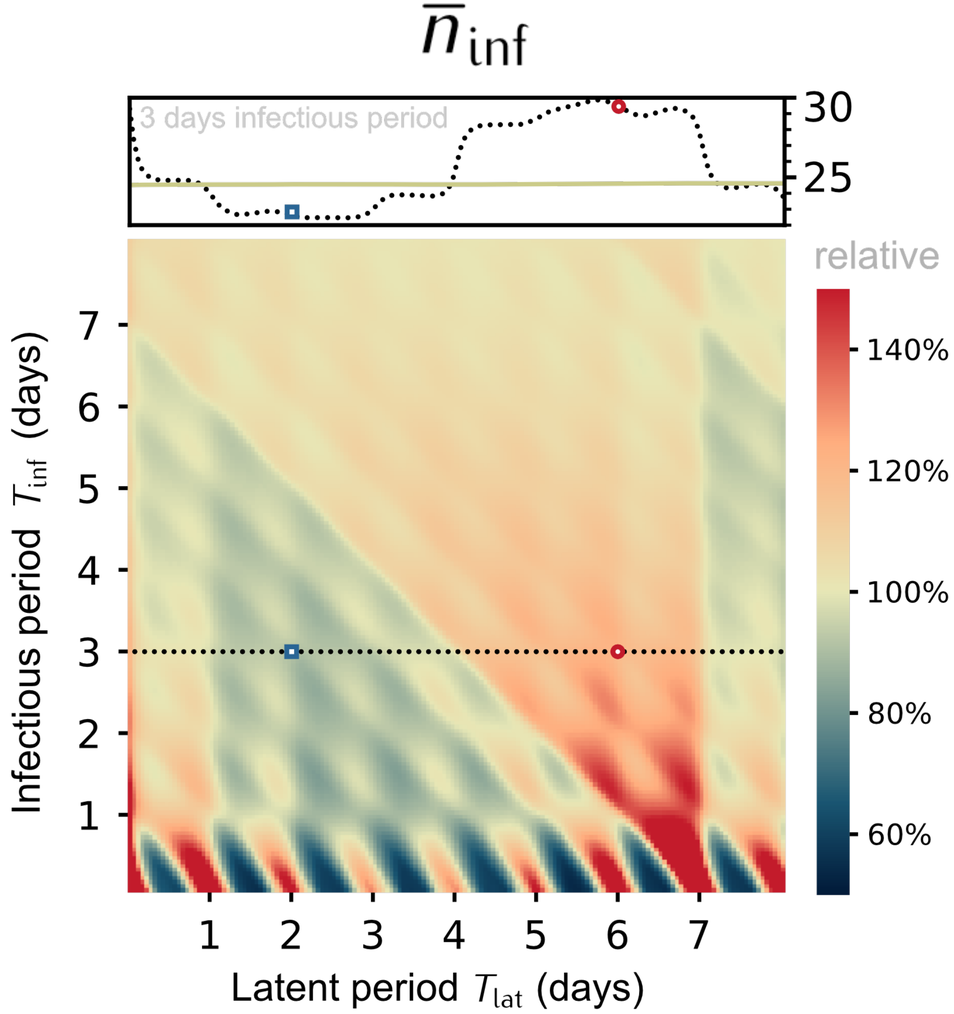

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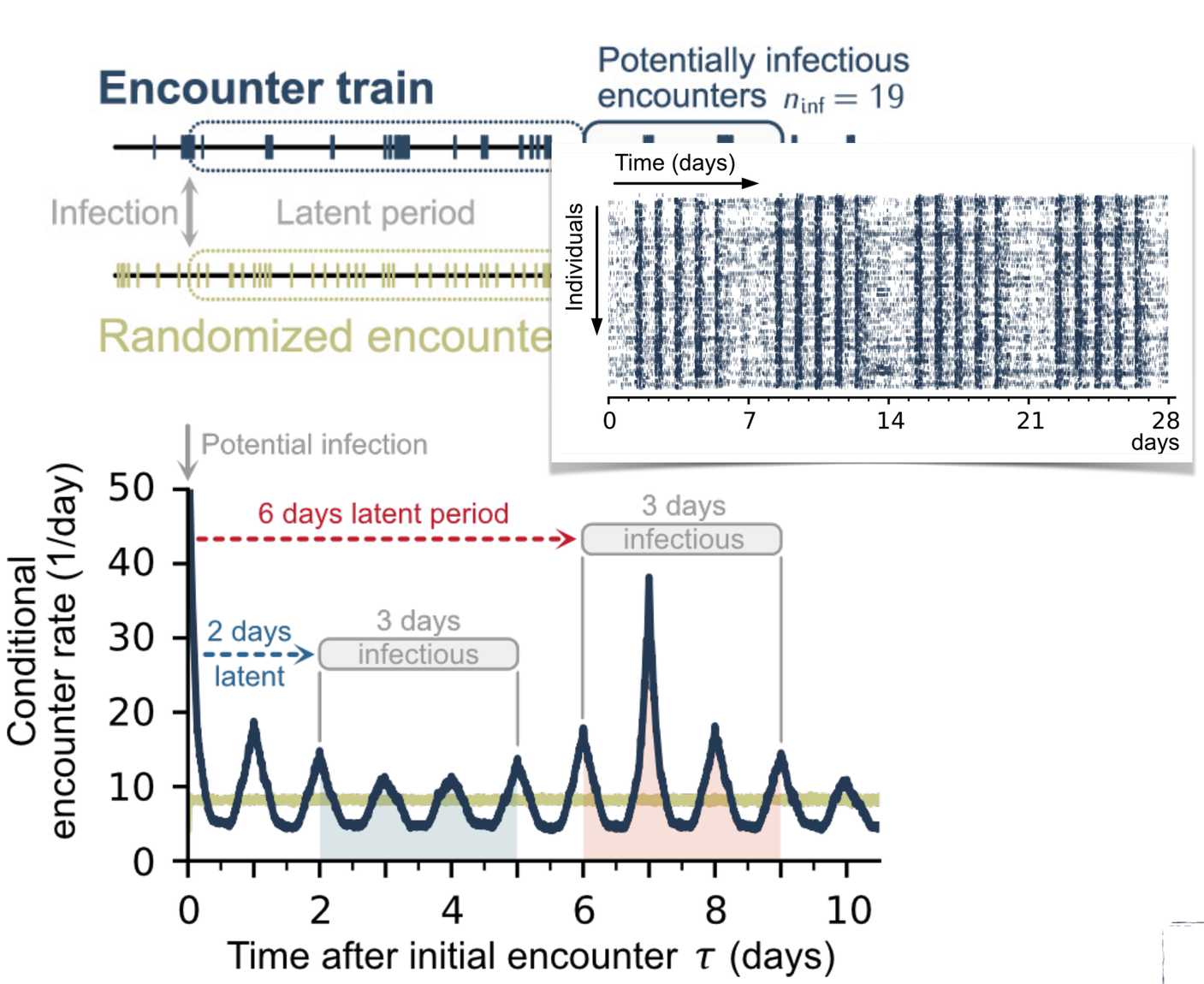
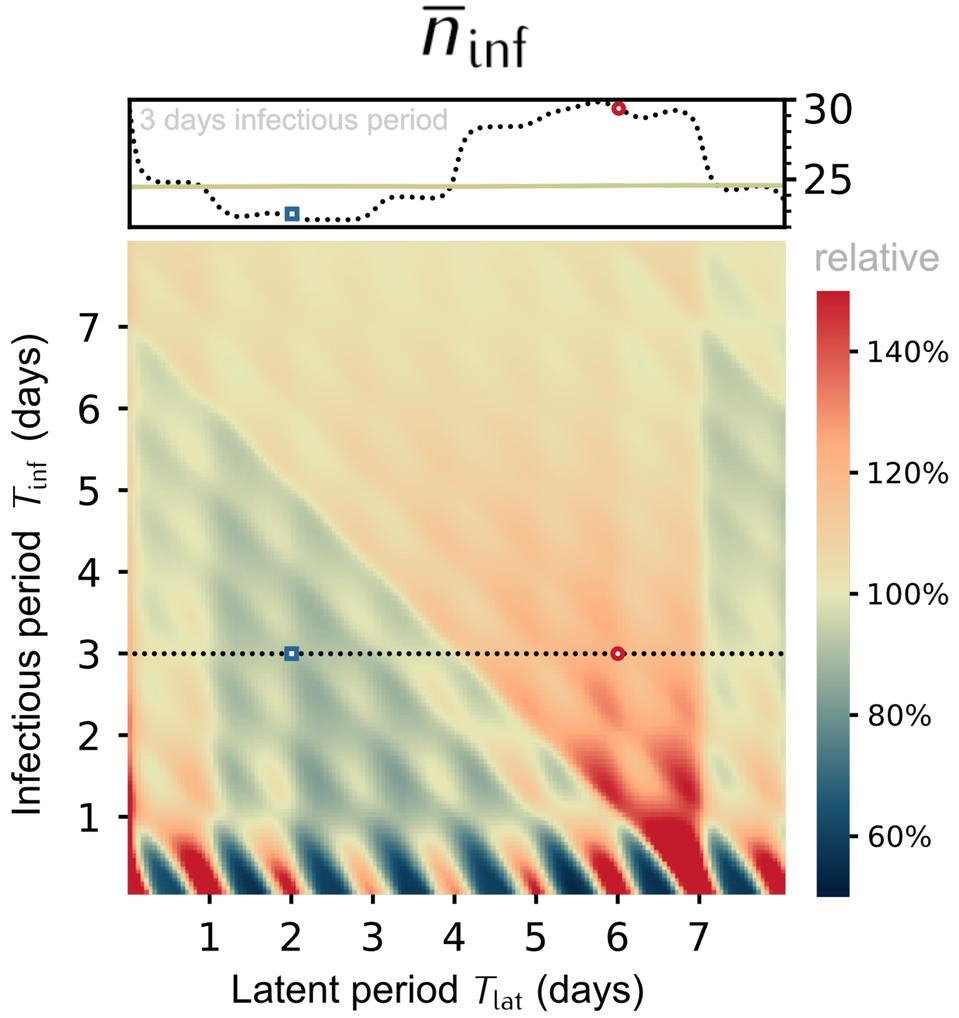
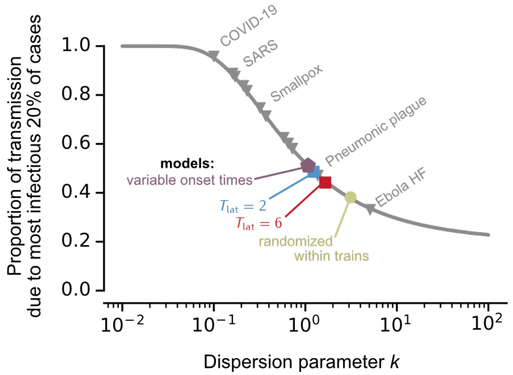


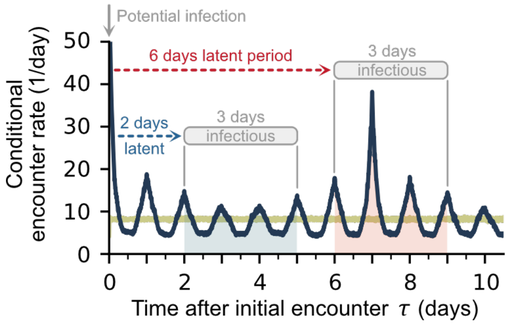


Memory effects in contact patterns can modulate the disease spread (R_0)

Zierenberg, Spitzner et al., New. J. Phys. (2023)

Contact patterns and epidemic outbreaks



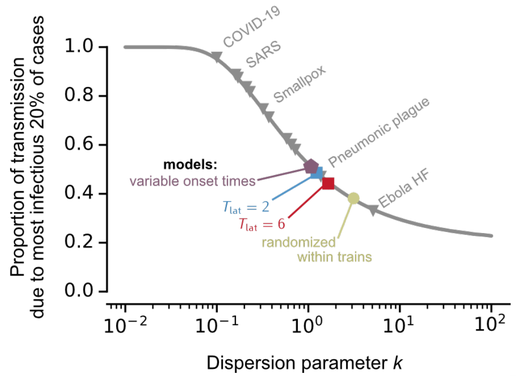


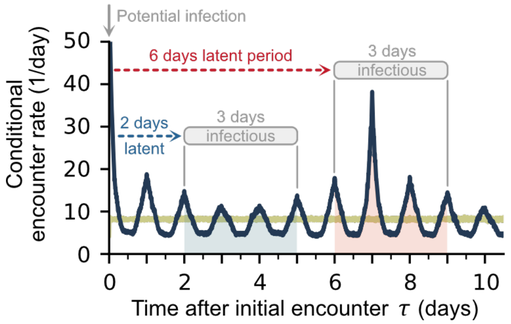
Statistical analysis of disease spread from human contact patterns

Contact patterns affect the dispersion k and disease spread R_0

Epidemic phase transition in a toy model of spatiotemporal contacts

Contact patterns and epidemic outbreaks





Statistical analysis of disease spread from human contact patterns

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Epidemic phase transition in a toy model of spatiotemporal contacts

Random walkers with stochastic resetting

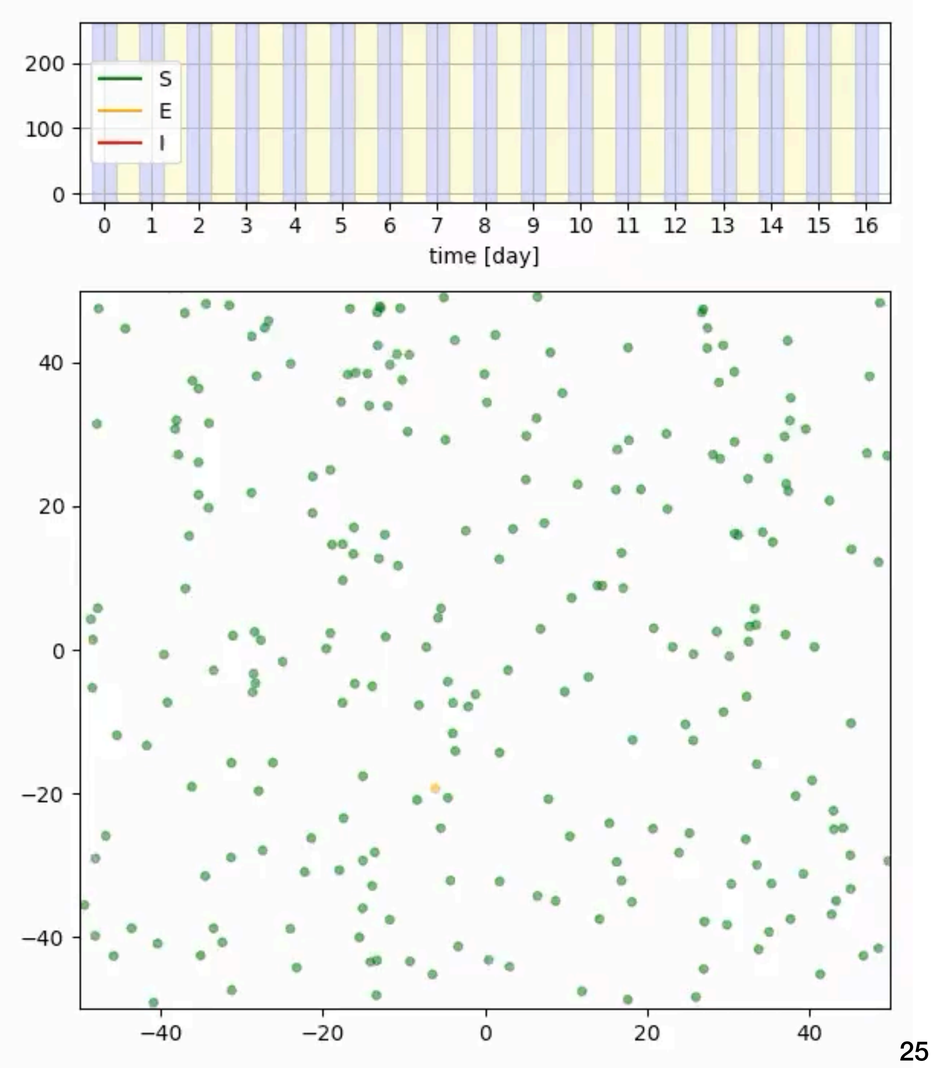
Dario Barone

During day: Diffusive motion
During night: reset to individual home location

Overdamped Langevin dynamics:

$$\dot{\mathbf{r}}_i = -F(t)\nabla V\left(\mathbf{r}_i - \mathbf{r}_i^0\right) + \sqrt{2D}\boldsymbol{\eta}_i$$

Non-Markovian Infection dynamics:
Upon infection agent is exposed for τ_{lat} and infectious for τ_{inf} , where they infect only upon close contact.

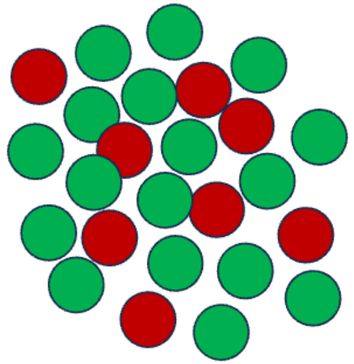


Barone et al. (in preparation)

Random walkers with stochastic resetting - growth

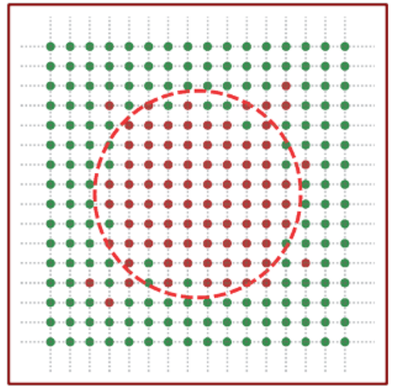
Dario Barone

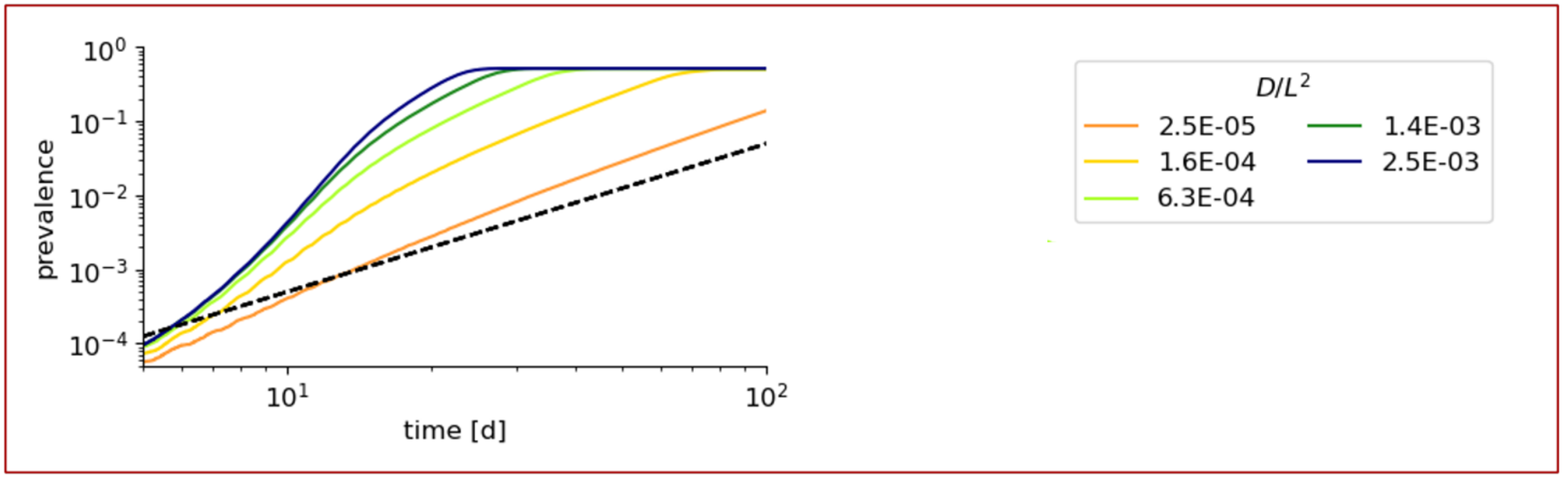
Mean-field model



$$\dot{\mathbf{r}}_i = -F(t)\nabla V\left(\mathbf{r}_i - \mathbf{r}_i^0\right) + \sqrt{2D}\boldsymbol{\eta}_i$$

2D lattice





Instantaneous log slope:

$$\alpha = \frac{d\log I}{d\log t} = \frac{t}{I}\frac{dI}{dt}$$

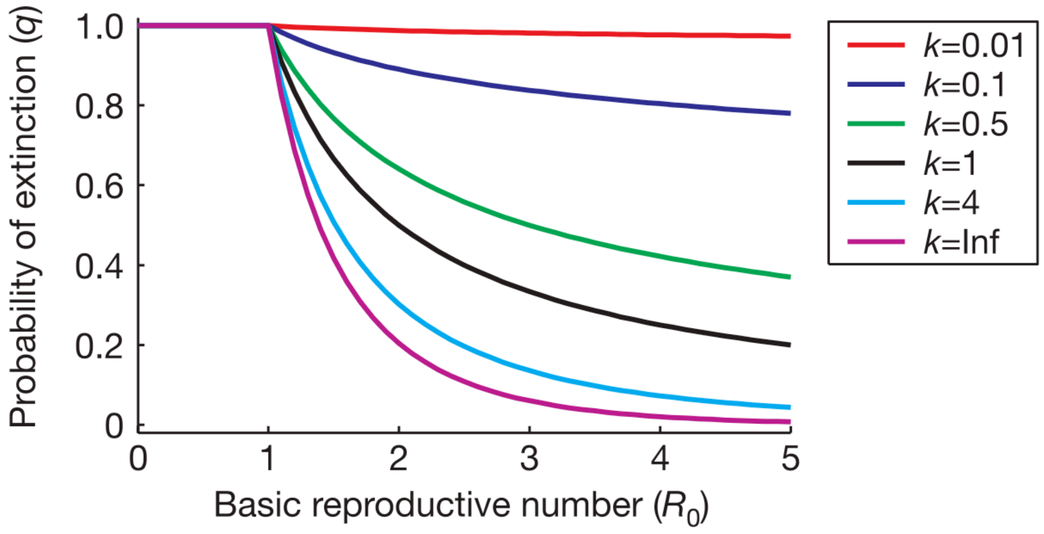
$$\alpha(t) = kt \rightarrow I(t) \propto e^{kt}$$

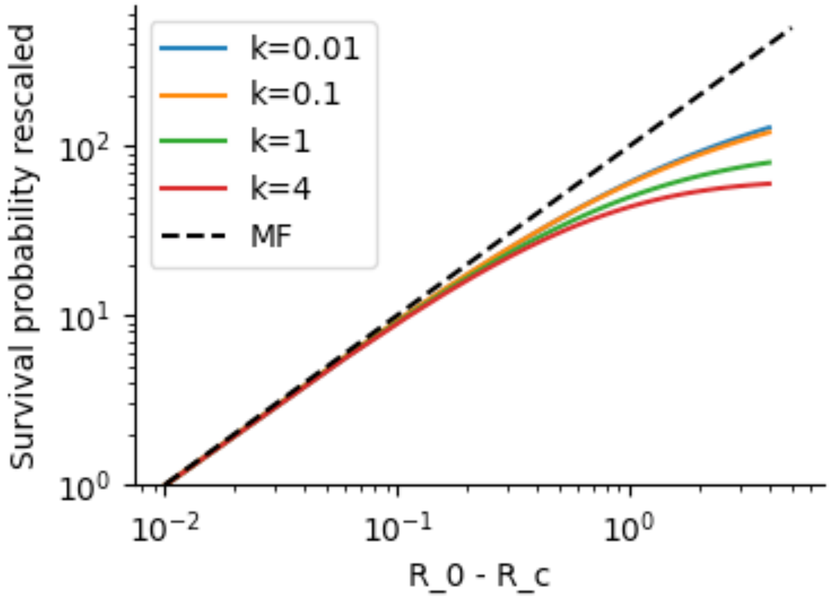
$$\alpha(t) = k \rightarrow I(t) \propto t^k$$

Cycloactive walkers interpolate between mean-field and spatial dynamics with super-quadratic growth

Barone et al. (in preparation)

Random walkers with stochastic resetting - scaling



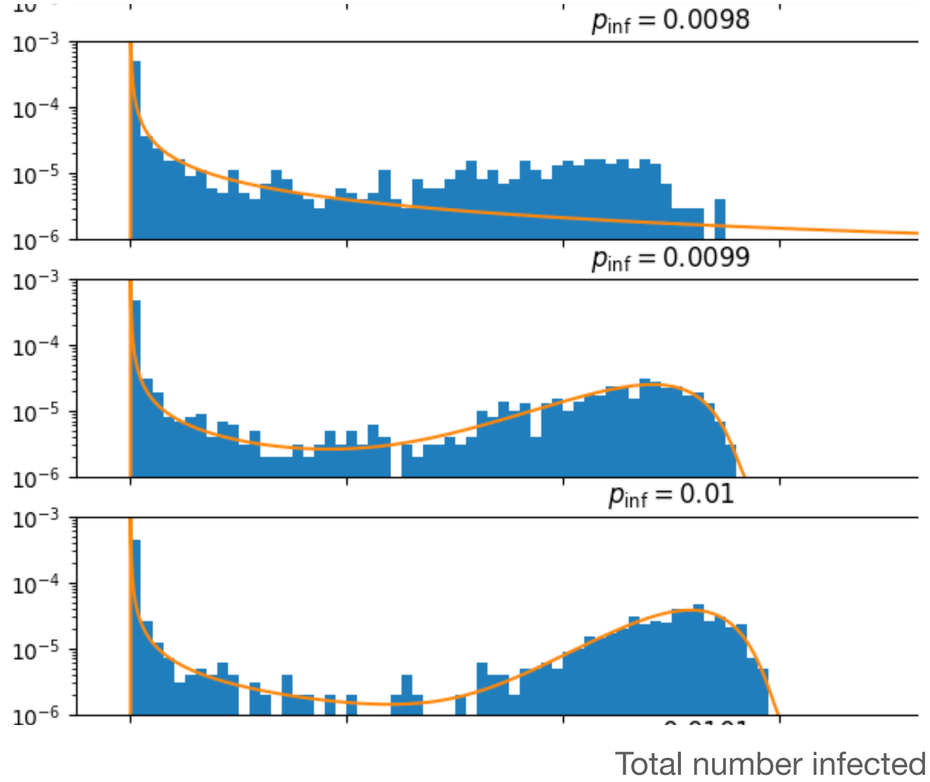


Lloyd-Smith et al., Nature (2005)
Barone et al. (in preparation)

Expected scaling of the survival probability:

$$1 - p_{\text{ext}} = p_{\text{surv}} \sim (p_{\text{inf}} - p_c)^{\beta'}$$

Focus on SEIR and distinguish which runs survive



Henkel et al., Non-equilibrium Phase Transitions (2008) $\beta'_{\text{MF}} = 1$ $\beta'_{\text{DP,2D}} = 0.5834(30)$

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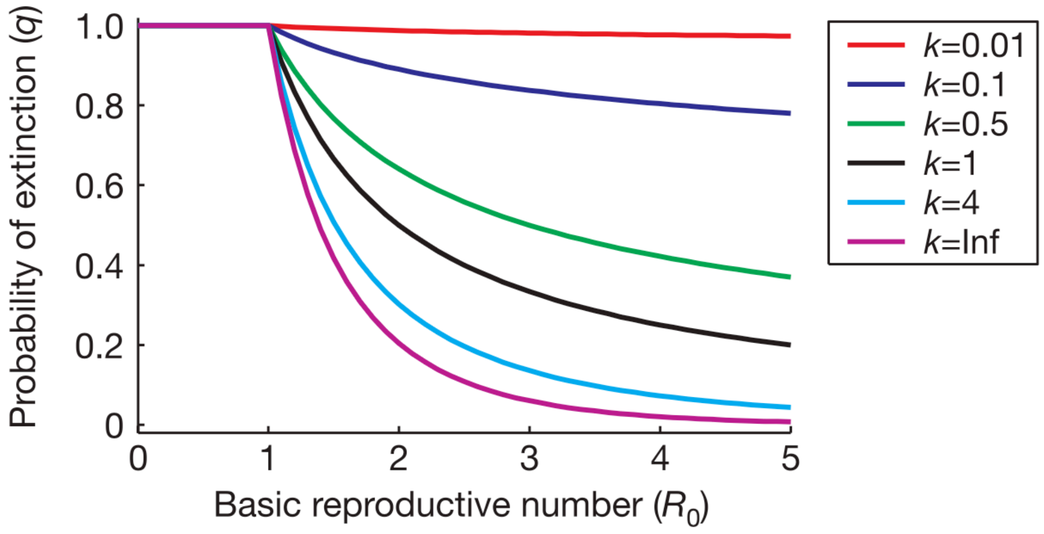
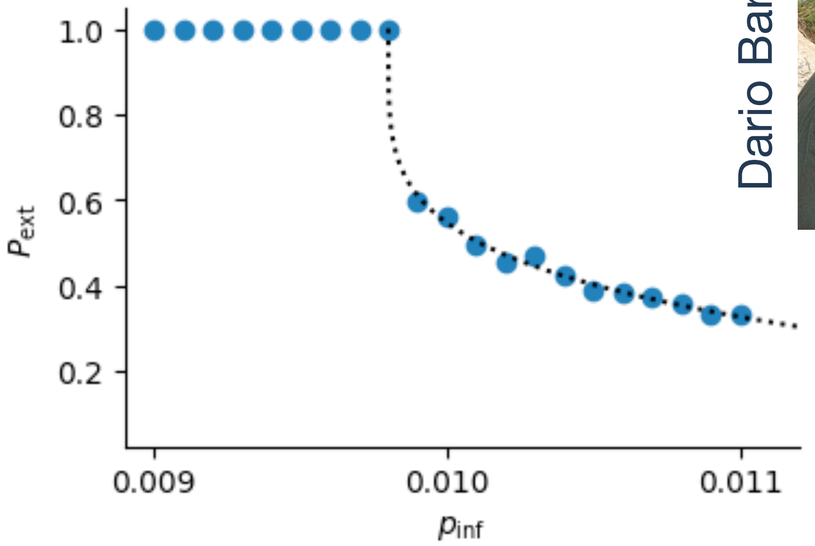
Random walkers with stochastic resetting - scaling





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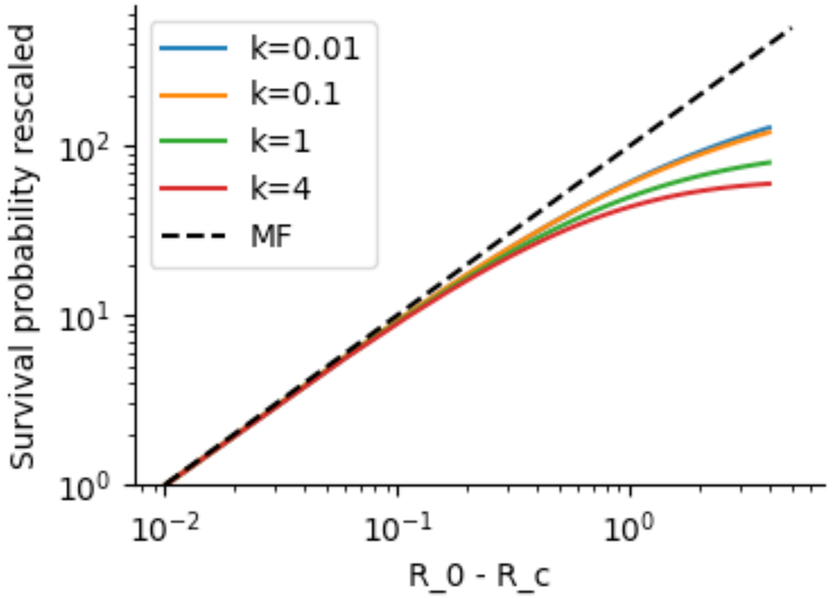
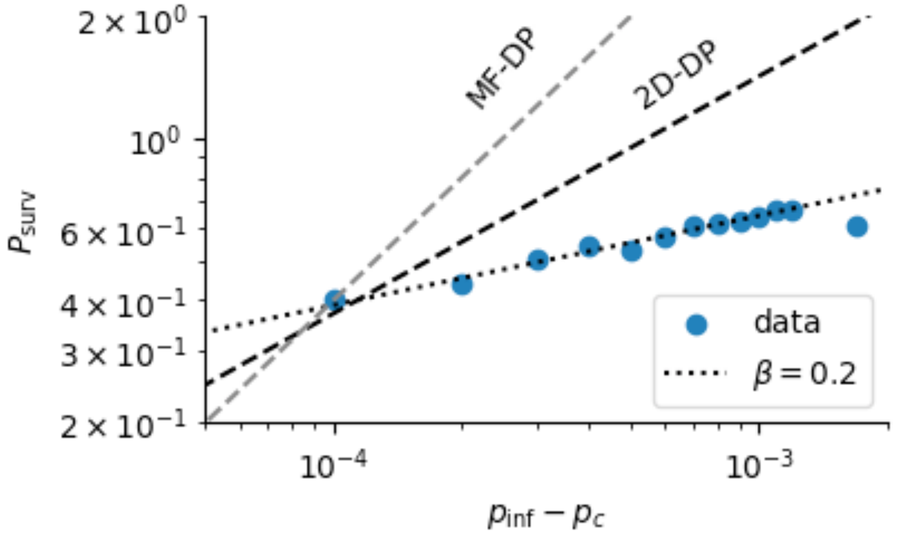
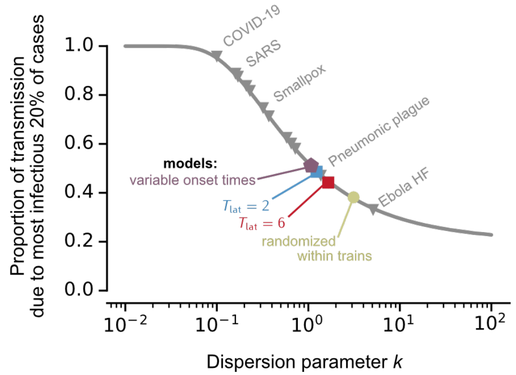




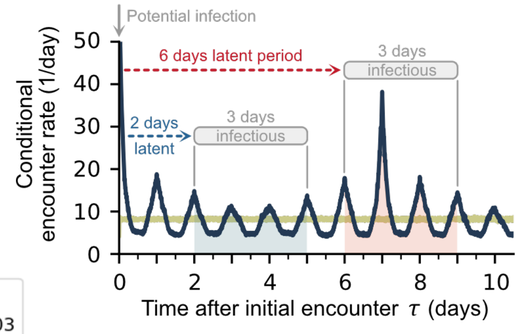
Lloyd-Smith et al., Nature (2005)
Barone et al. (in preparation)

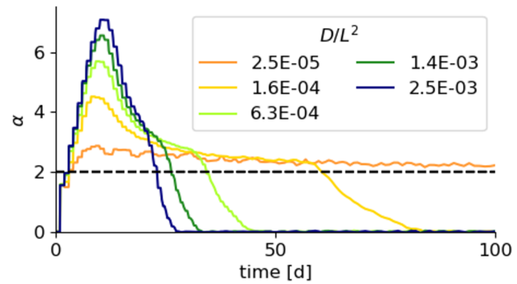
Contact patterns and epidemic outbreaks



Statistical analysis of disease spread from human contact patterns

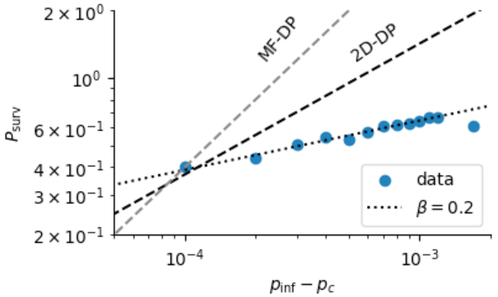
Contact patterns affect the dispersion k and disease spread R_0.



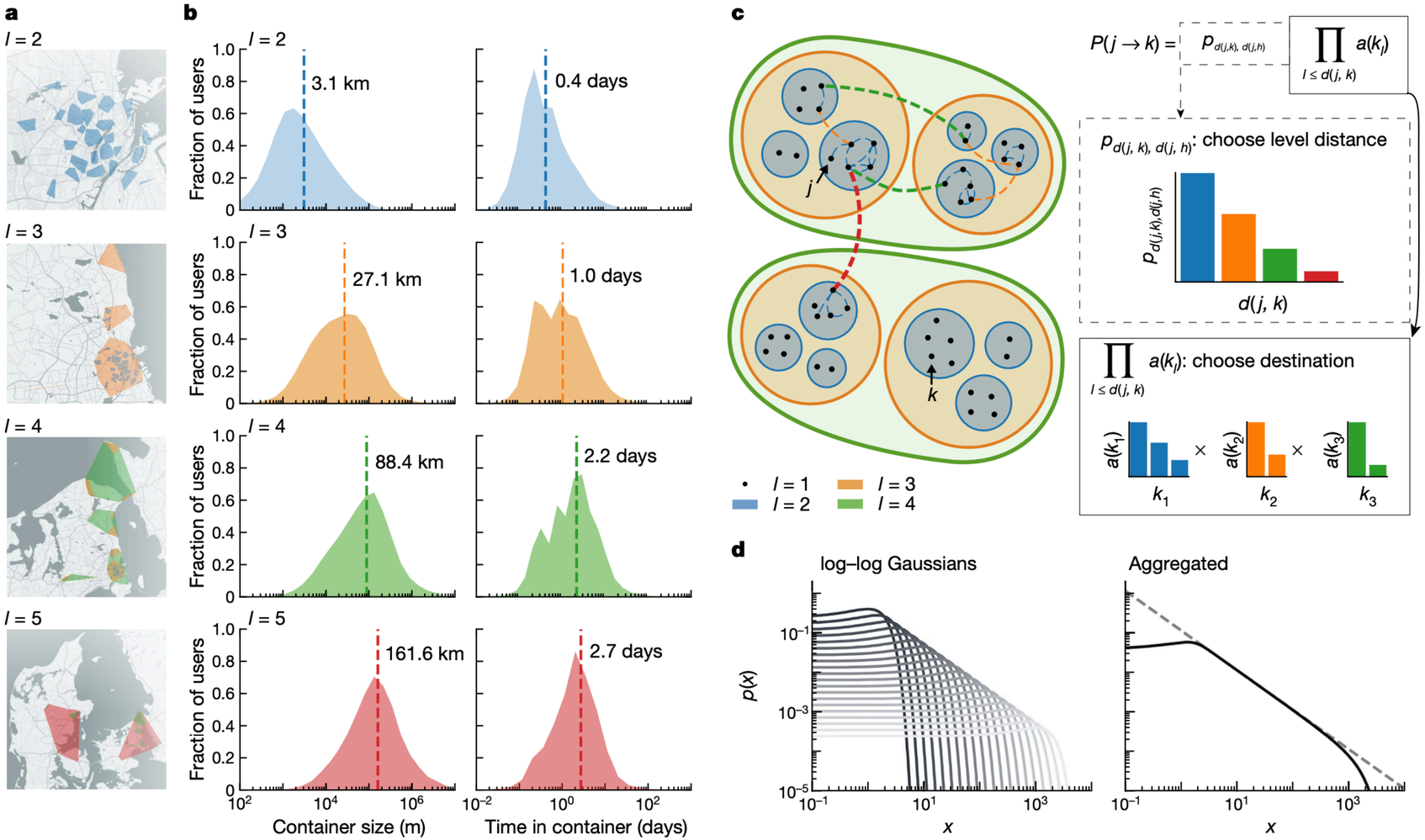


Epidemic phase transition in a toy model of spatiotemporal contacts

Toy model interpolates between mean-field and spatial dynamics with non-trivial critical exponents.



Outlook: Hierarchical Mobility



Alessandretti et al., Nature (2020)

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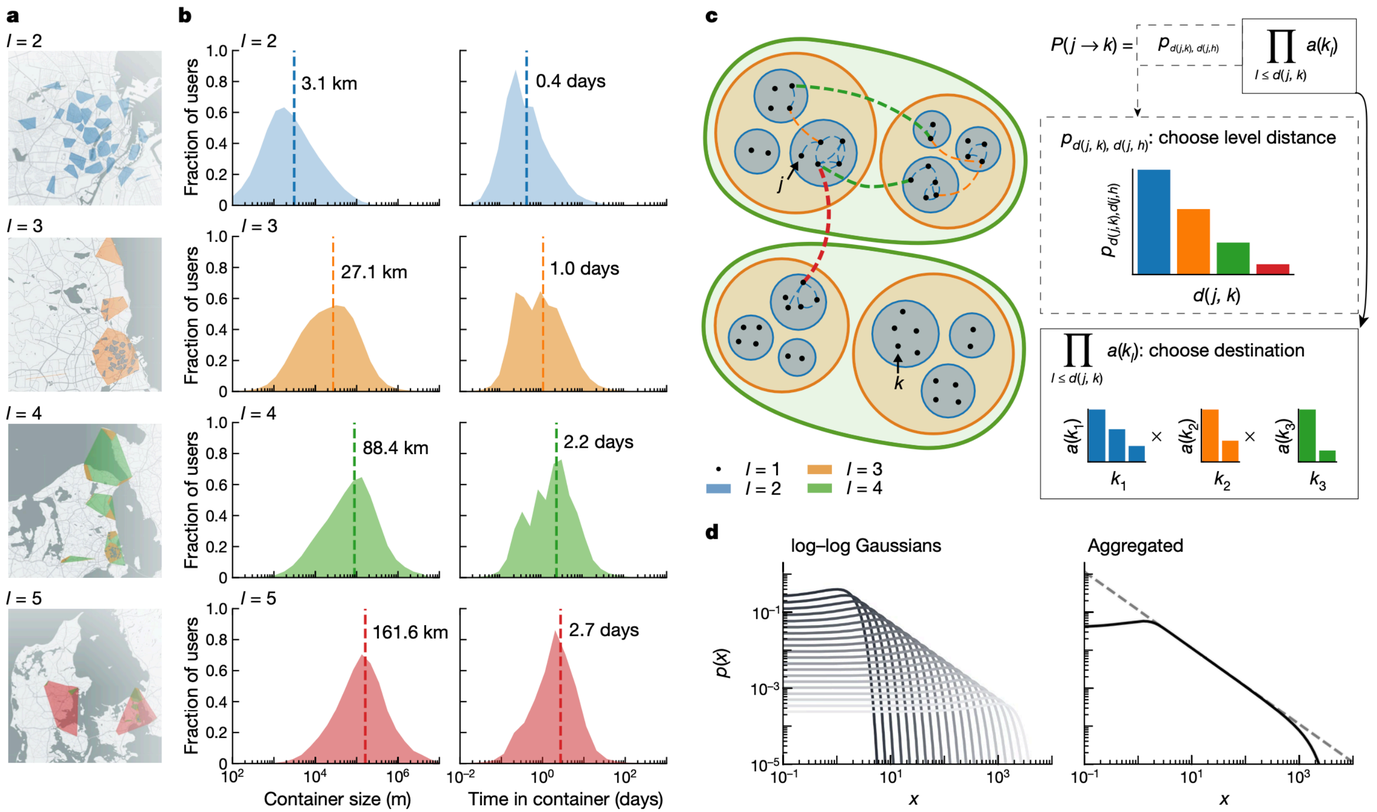

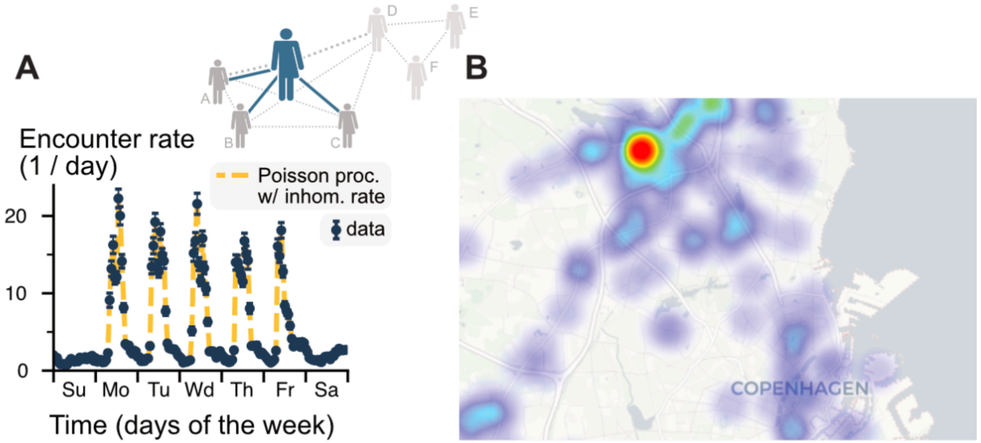

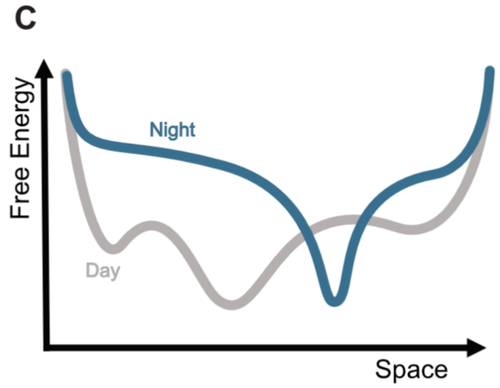

My Future: Cycloactive agents with individual, hierarchical, discrete interaction sites inspired by data

Alessandretti et al., Nature (2020)

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Summary

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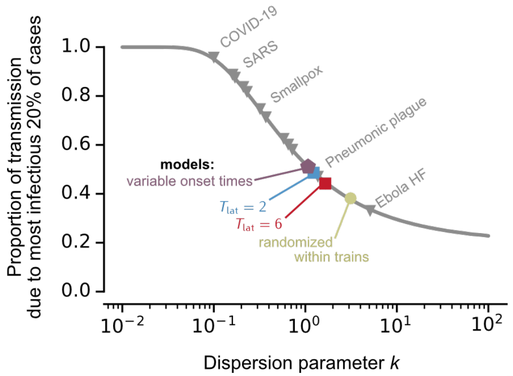

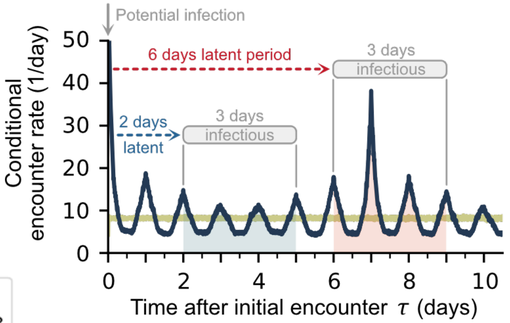

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