

# NETWORKS 2021

## UNIVERSAL NONLINEAR INFECTION KERNEL FROM HETEROGENEOUS EXPOSURE ON HIGHER-ORDER NETWORKS

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## Standard epidemiological models predict exponential growth

For a whole population, with  $I$  the fraction of infectious,

$$\frac{dI}{dt} \approx \lambda I \quad (I \ll 1)$$
$$\implies I \propto e^{\lambda t}$$

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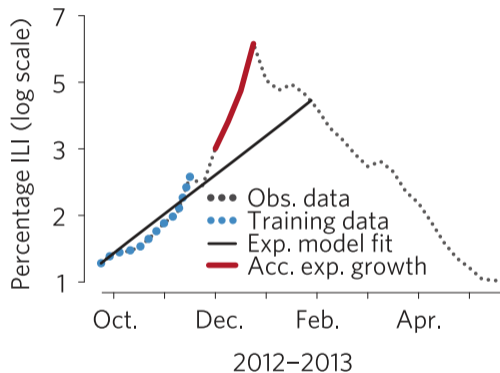
For a whole population, with  $I$  the fraction of infectious,

$$\frac{dI}{dt} \approx \lambda I \quad (I \ll 1)$$
$$\implies I \propto e^{\lambda t}$$

But this is because we assume that the risk of infection is *linear*

$$\theta(I) \propto I$$

## Superexponential spreading of Influenza-Like-Illness

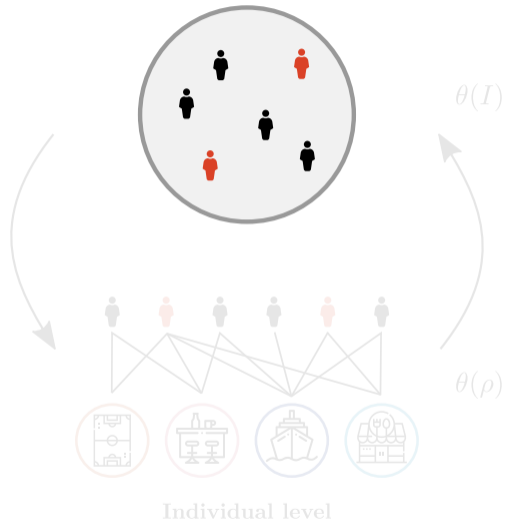


Scarpino, S. V., Allard, A., & Hébert-Dufresne, L. (2016). The effect of a prudent adaptive behaviour on disease transmission. *Nature Physics*, 12(11), 1042-1046.

$$\theta(I) \propto I$$

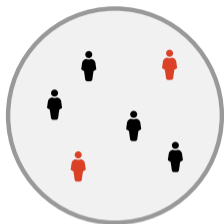
- (i) Why assume linearity?
- (ii) When is linearity valid?
- (iii) What other forms could it take?

## Population level

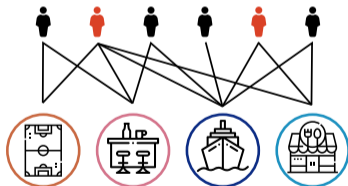


## Individual level

Population level



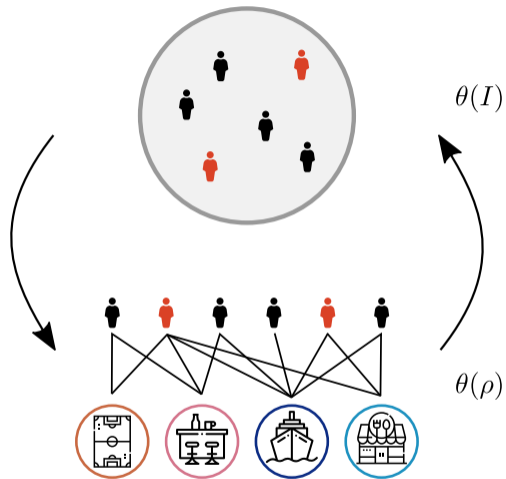
$\theta(I)$



$\theta(\rho)$

Individual level

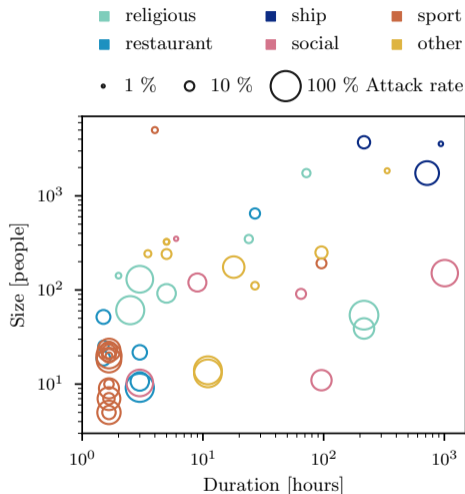
Population level



Individual level



# Motivation for the framework : superspreading events

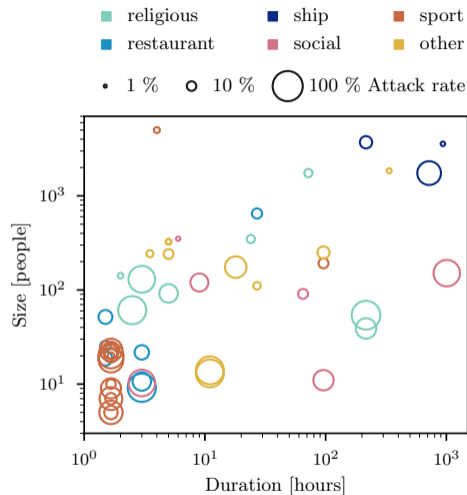


## Model properties

1. Explicit group interactions in *environments*
2. Heterogeneous temporal patterns

St-Onge, G., Sun, H., Allard, A., Hébert-Dufresne, L., & Bianconi, G. (2021). Universal nonlinear infection kernel from heterogeneous exposure on higher-order networks. arXiv :2101.07229.

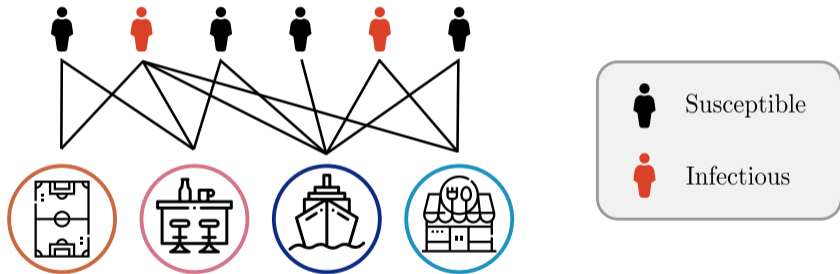
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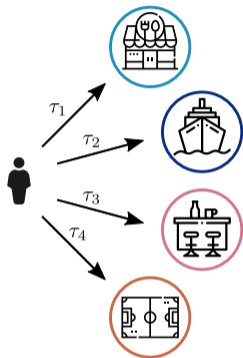
## Model properties

1. Explicit group interactions in *environments*
2. Heterogeneous temporal patterns
3. *Minimal infective dose* (threshold model)

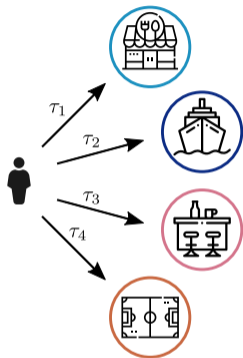
## Property # 1 : Higher-order interactions – bipartite structure



## Property # 2 : heterogeneous temporal patterns

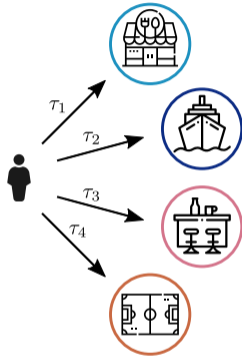


## Property # 2 : heterogeneous temporal patterns



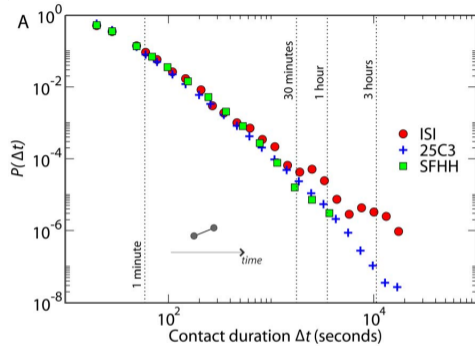
What should be  $p(\tau)$ ?

## Property # 2 : heterogeneous temporal patterns



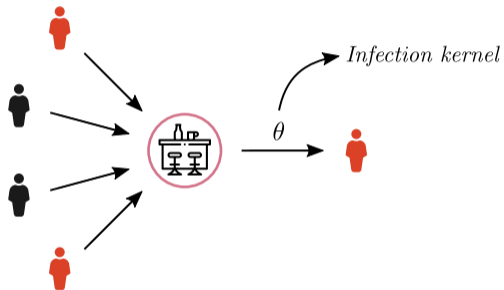
What should be  $p(\tau)$ ?

$$p(\tau) \propto \tau^{-\alpha}$$



Cattuto, C., Van den Broeck, W., Barrat, A., Colizza, V., Pinton, J. F., & Vespignani, A. (2010). Dynamics of person-to-person interactions from distributed RFID sensor networks. PLOS ONE, 5(7), e11596.

## Risk of infection in an environment

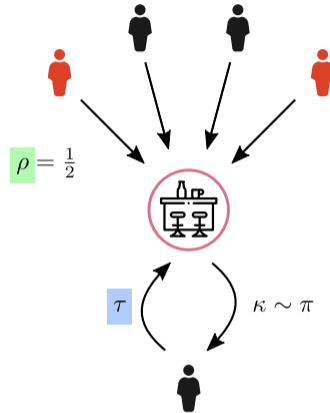


$\theta$  : probability of infection (per environment) during one time step

### Property #3 : threshold model

- Individual receives a dose  $\kappa \sim \pi(\kappa; \rho, \tau)$
- The fraction of infectious participants is  $\rho$
- The mean dose received is

$$\langle \kappa \rangle \propto \rho \tau$$



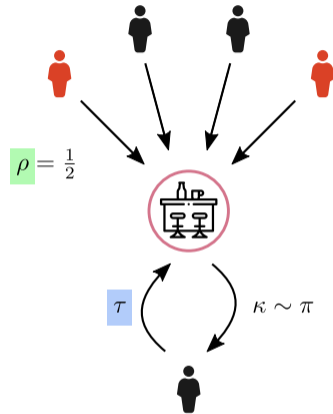


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- Our immune system is able to fight mild challenges
- A minimal infective dose  $K$  is required for infection



The infection kernel is

$$\theta(\rho) = P(\kappa \geq K) = \int_1^T \int_0^K p(\tau) \pi(\kappa; \rho, \tau) \, d\kappa \, d\tau$$

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Assuming :

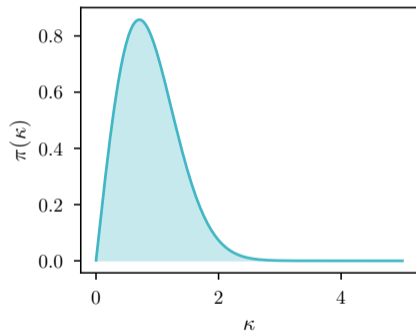
1.  $p(\tau) \propto \tau^{-\alpha-1}$ ;
2. *Some technical conditions for the asymptotic analysis*;

for a large class of dose distribution  $\pi$ , we recover the *universal* infection kernel

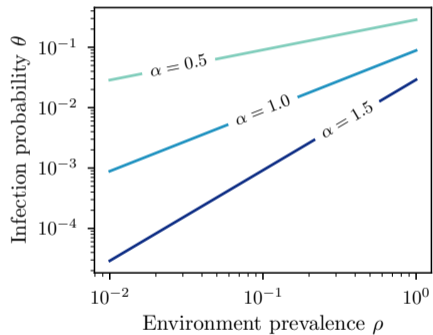
$$\theta(\rho) \propto \rho^{\alpha}$$

## Weibull dose distribution

(a) Dose distribution

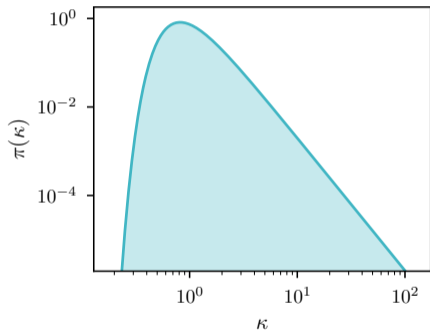


(b) Infection kernel

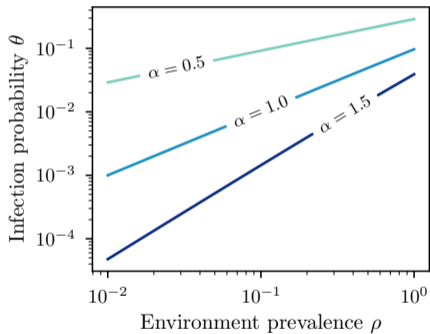


## Fréchet dose distribution

(a) Dose distribution



(b) Infection kernel



**When is linearity valid at the *individual level*?**

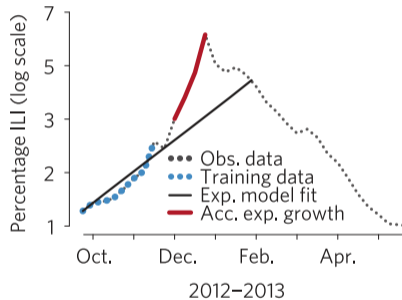
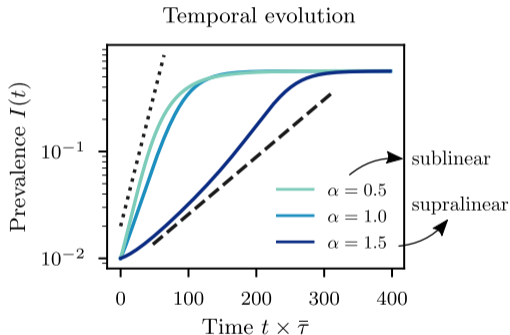
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LINEAR INFECTION KERNELS ARE THE EXCEPTION RATHER THAN THE NORM

## Supralinear infection kernel lead to superexponential spreading





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$$\theta(\rho) \propto \rho^\alpha \quad \text{with } \alpha \in \mathbb{R}^+$$

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At the *individual level*, we found

$$\theta(\rho) \propto \rho^\alpha \quad \text{with } \alpha \in \mathbb{R}^+$$

If we coarse grain at the *population level*,

$$\theta(I) \propto \begin{cases} I & \text{if } I \ll 1 \\ I^\alpha & \text{otherwise} \end{cases}$$

For a standard SIR model, this could look like

$$\frac{dI}{dt} \approx \lambda S \theta(I) - \mu I ,$$

## Thanks to my collaborators

Hanlin Sun, Antoine Allard,  
Laurent Hébert-Dufresne,  
Ginestra Bianconi

## Contact

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🌐 [www.gstonge.ca](http://www.gstonge.ca)

Preprint available!

[arXiv :2101.07229](https://arxiv.org/abs/2101.07229)



*Funding and computational resources*



Sentinel  
North

