



The Spreading Dynamics of COVID-19 and its Mitigation

Viola Priesemann

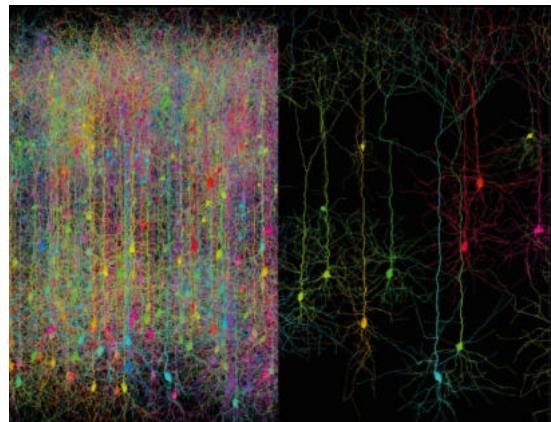
Max-Planck-Institut für
Dynamik und
Selbstorganisation

Göttingen

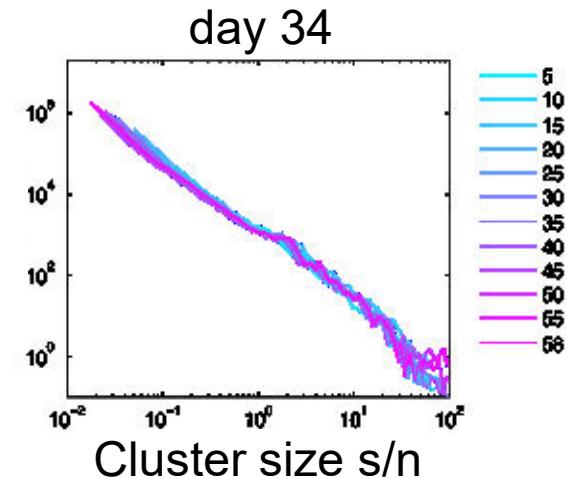
Overview

- **Large Scale Recordings & Subsampling:**

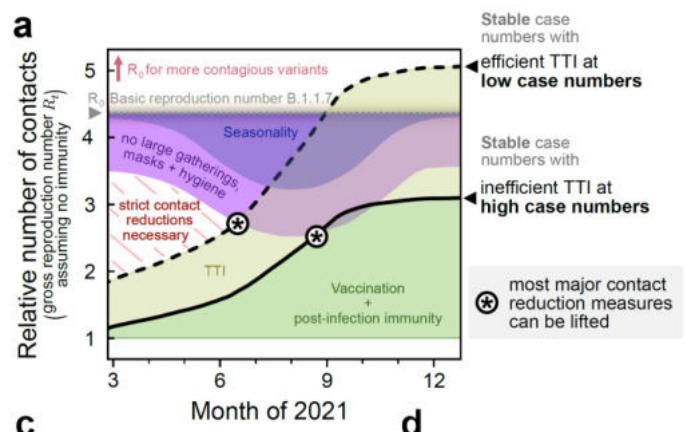
How to infer collective properties and spreading dynamics from vastly under-observed systems



- **Subsampling Scaling:** Inferring avalanche distributions or degree distributions from subsampled networks

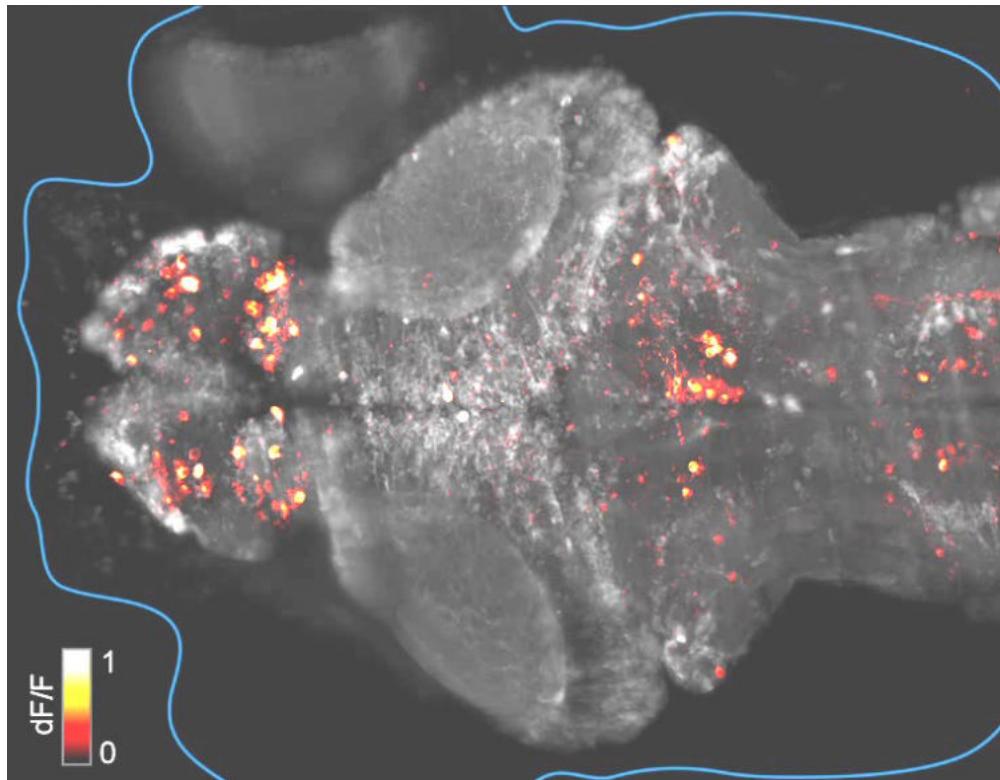


- **Mitigating the Spread of COVID-19:**
 - The effect of test-trace-isolate (TTI)
 - and of the vaccination progress



Collective Dynamics

Light sheet fluorescence imaging in a zebra fish larva



100.000 neurons (80bn in human)
10 – 10.000 connections/neuron

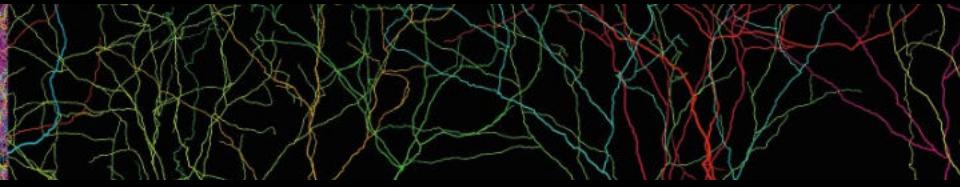
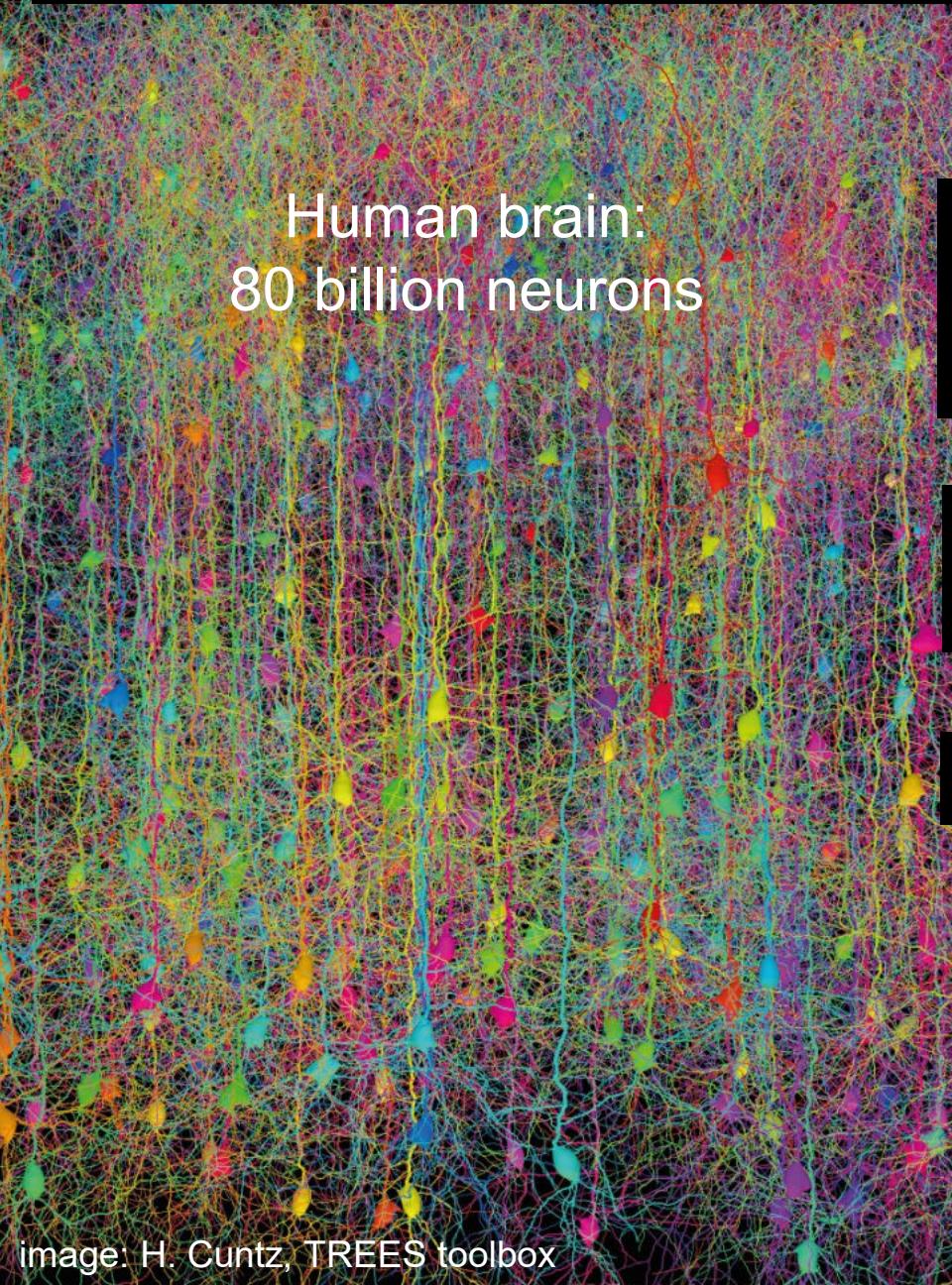
Interactions:

- pulse-like (“spikes”)
- directed
- time-delayed
- plastic (learning!)

High-dimensional topology
→ difficult to characterize
collective properties

Subsampling Can Bias Inference

Human brain:
80 billion neurons



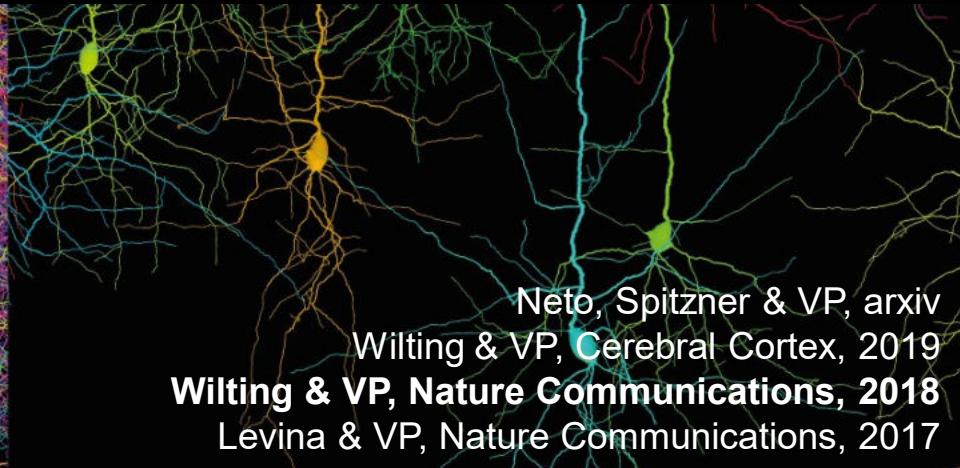
Sampling (experiment):
Only 100-1000 neurons
with sufficient precision



Subsampling bias leads to
misestimations

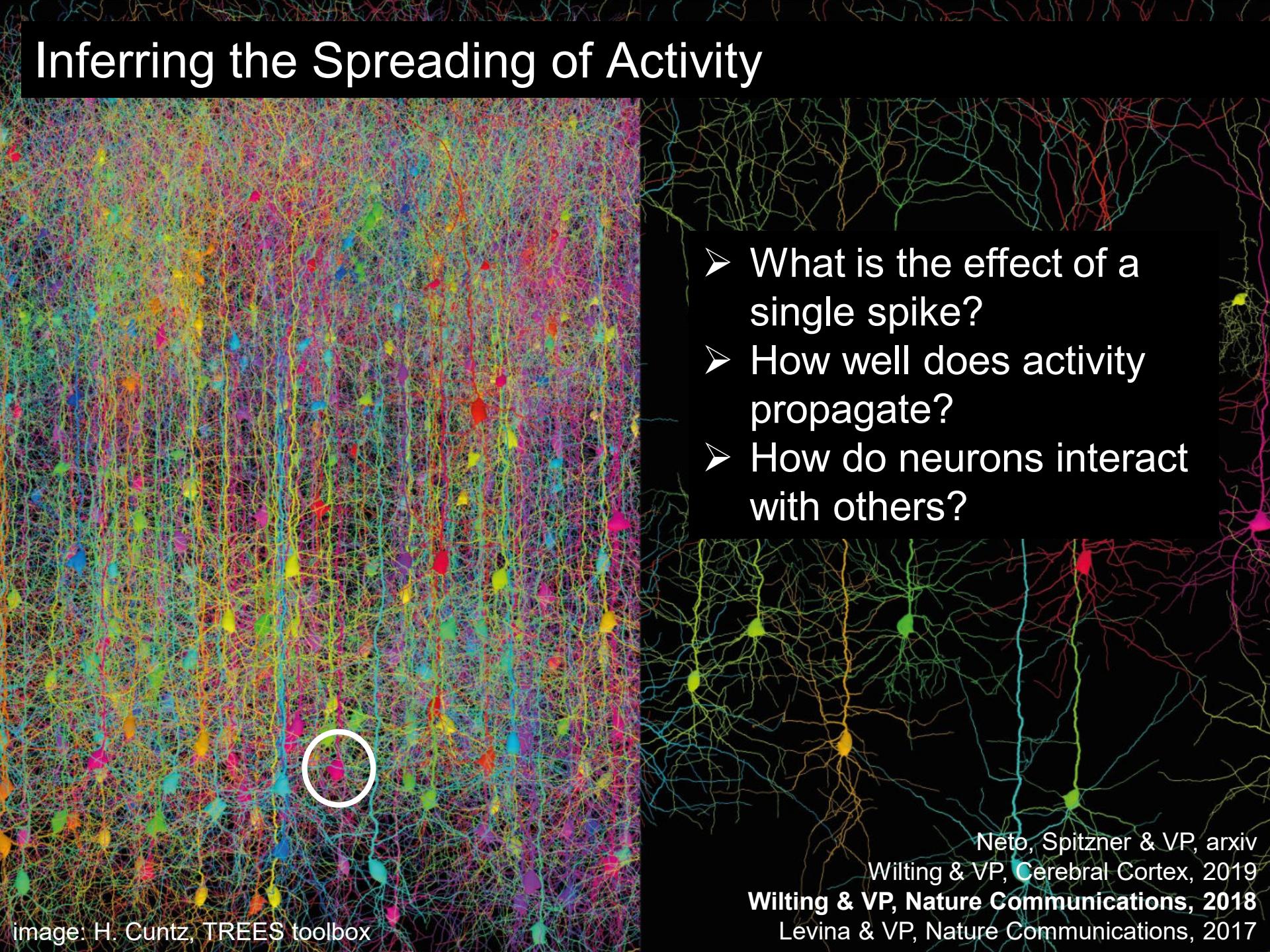


→ Bias-free inference

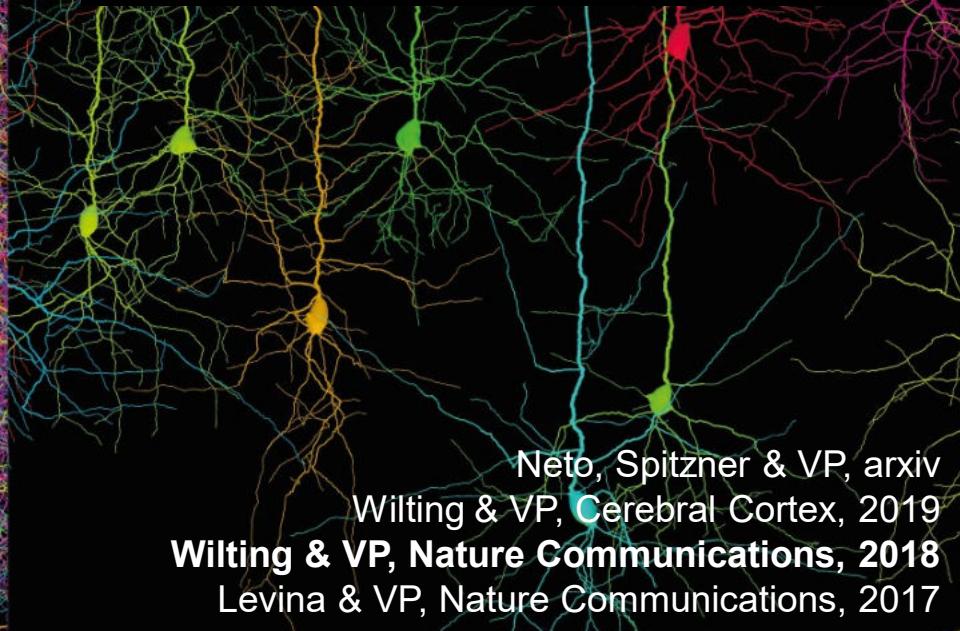


Neto, Spitzner & VP, arxiv
Wilting & VP, Cerebral Cortex, 2019
Wilting & VP, Nature Communications, 2018
Levina & VP, Nature Communications, 2017

Inferring the Spreading of Activity



- What is the effect of a single spike?
- How well does activity propagate?
- How do neurons interact with others?



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Propagating Activity as a Branching Process

control parameter R

expected number of “children”



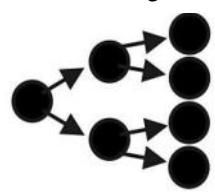
$$R < 1$$

subcritical



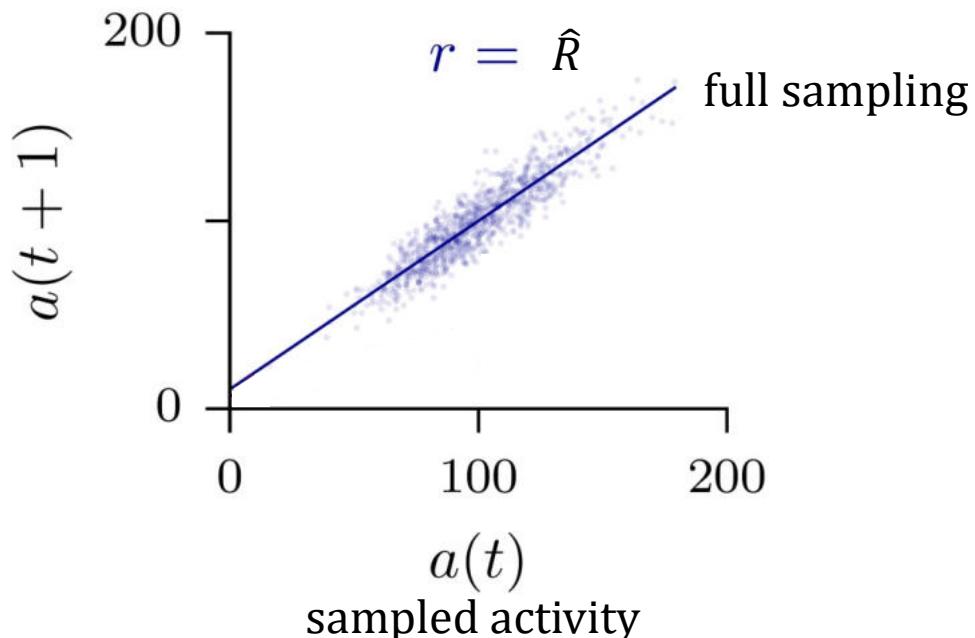
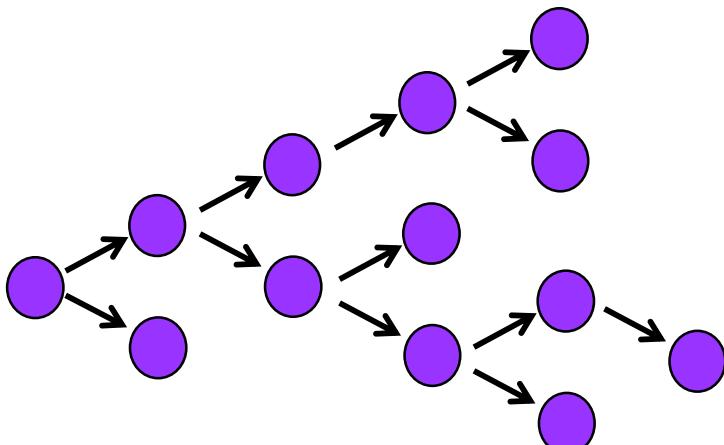
$$R = R_c = 1$$

critical



$$R > 1$$

supercritical



Branching process

activity $A(t)$ in system: $A(t) = \sum_{i=1}^{A(t-1)} Y_{i,t} + h_t$

h_t external input (random variable)

Y # activated units per active unit (r.v.)

$R = E[Y]$ mean # “children” per unit
or eff. coupling strength

[Wilting & VP, Nature Communications, 2018]

[Levina & VP, Nature Communications, 2017]

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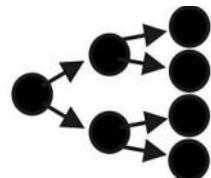


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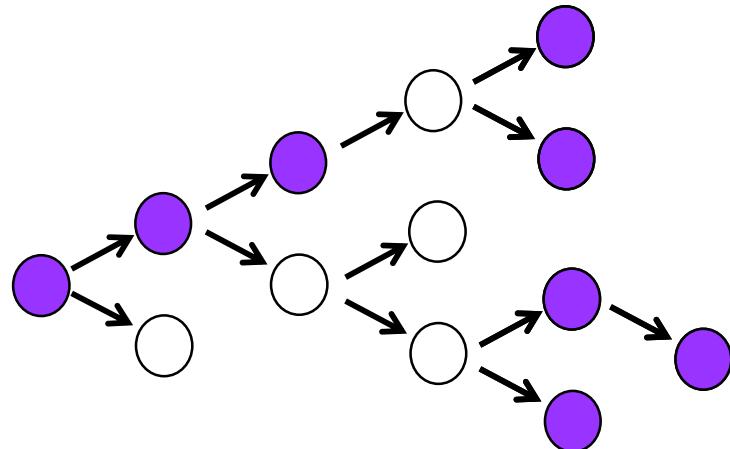
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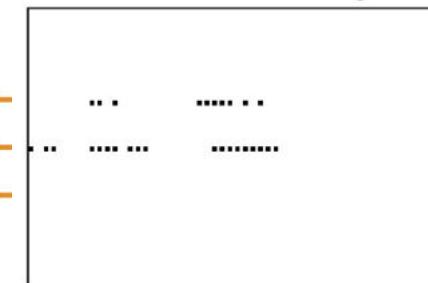
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critical

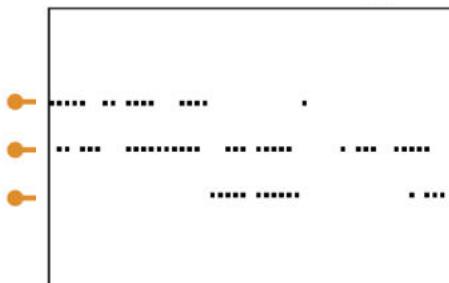
supercritical



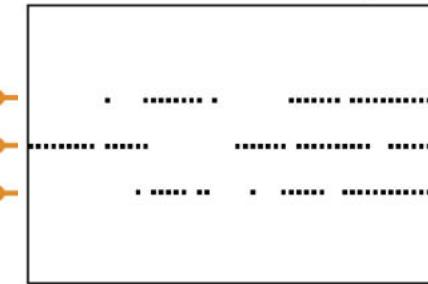
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$$R = 1$$



$$R > 1$$



Propagating Activity as a Branching Process

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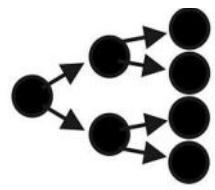
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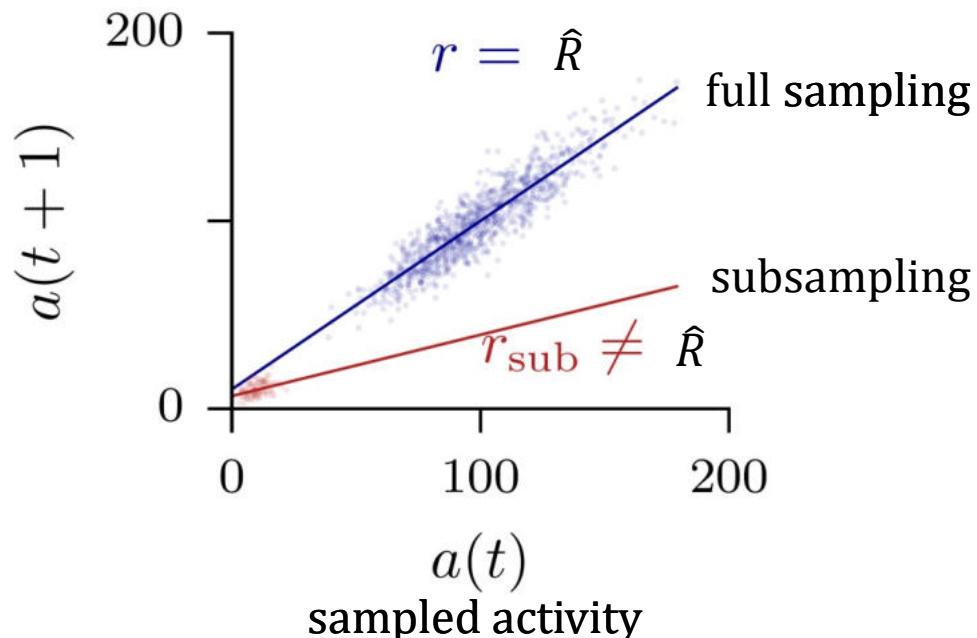
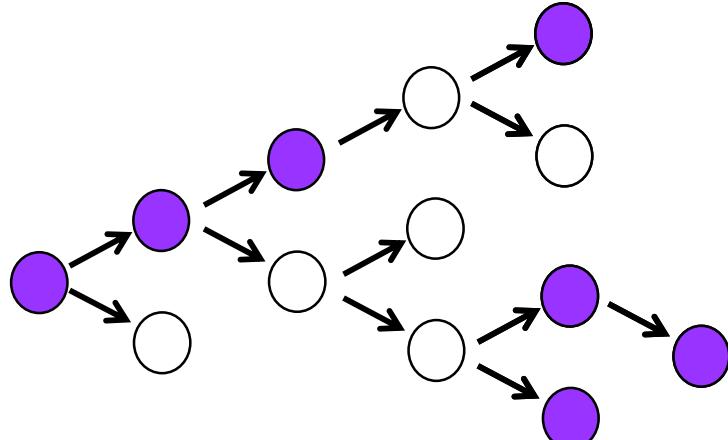
$$R = R_c = 1$$

critical



$$R > 1$$

supercritical



→ Correlation strength r is biased under subsampling!

Ansatz:

- Generalizing estimator to any Δt :
 $r(a(t), a(t + \Delta t))$.
Thereby we can partial out the bias

[Wilting & VP, Nature Communications, 2018]

[Levina & VP, Nature Communications, 2017]

Inferring Spreading Dynamics

control parameter R

expected number of “children”



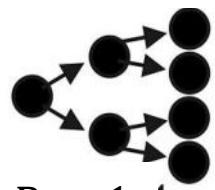
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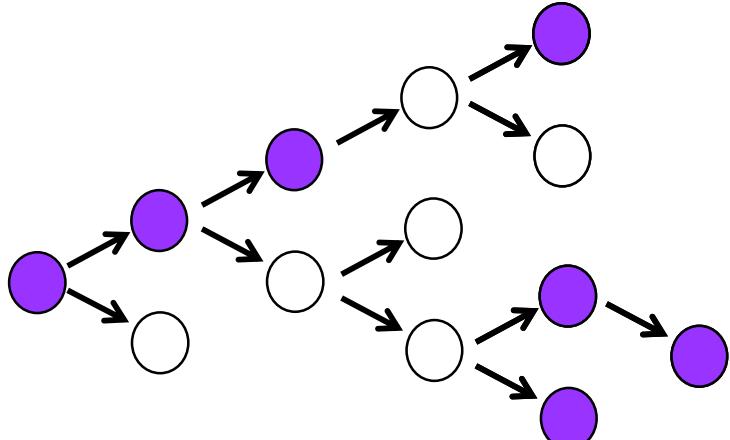
$$R = R_c = 1$$

critical



$$R > 1$$

supercritical



- returns the control parameter R , instead of a binary test for or against criticality

Efficient, precise, easily applicable:

- It only requires knowing $a(t)$, i.e. the *sampled* activity at each time step
- It does not require knowing the system size N , the number of sampled units n , or any of the moments of the process.
- Ideal conditions: Estimation of control parameter from a single unit!

Adopted by: J.Beggs, K.Hengen, C.Butfering;
e.g. Ma et al., Neuron, 2019

Python Toolbox: github.com/Priesemann-Group

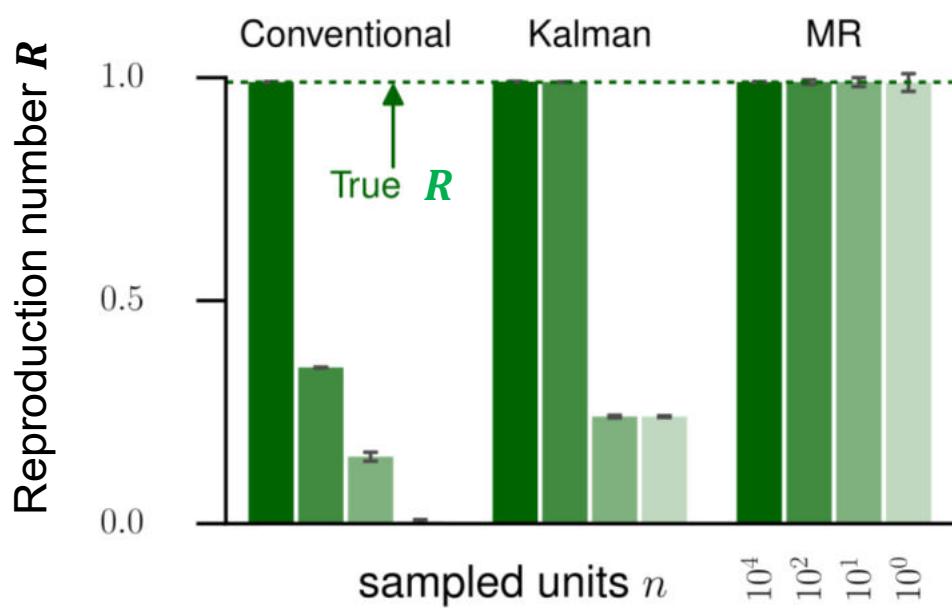
[Dehning et al., Science, 2020]

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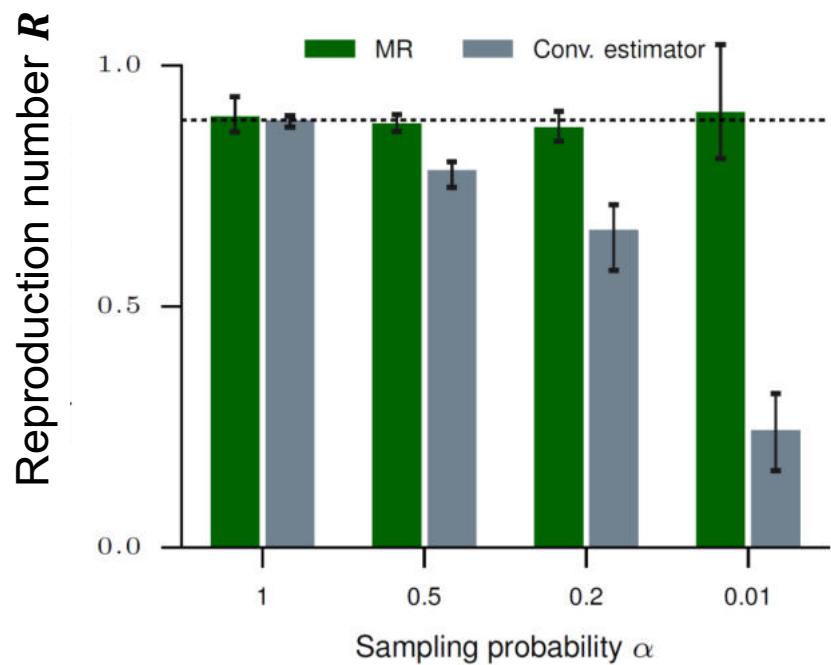
[Levina & VP, Nature Communications, 2017]

Overcoming the Subsampling Problem – to Assess Disease Spreading

Estimation of the reproduction number R in a model of 10.000 neurons



Estimation of the reproduction number R from measles case numbers

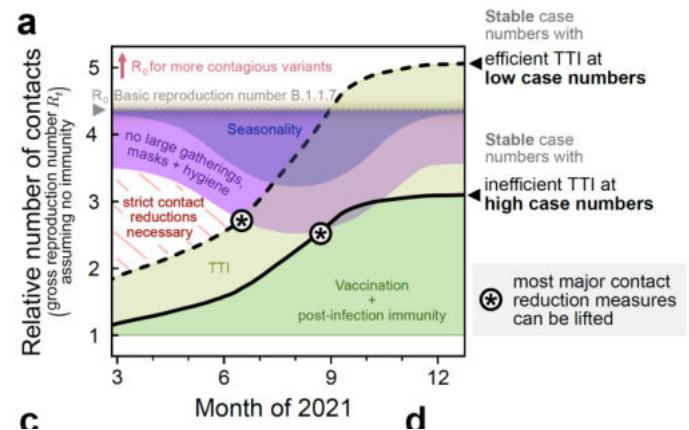
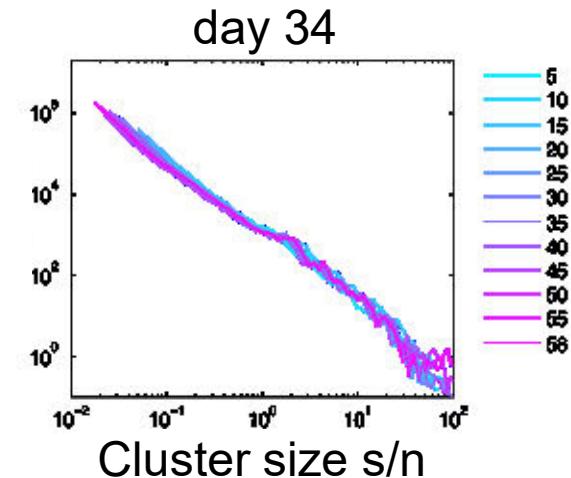
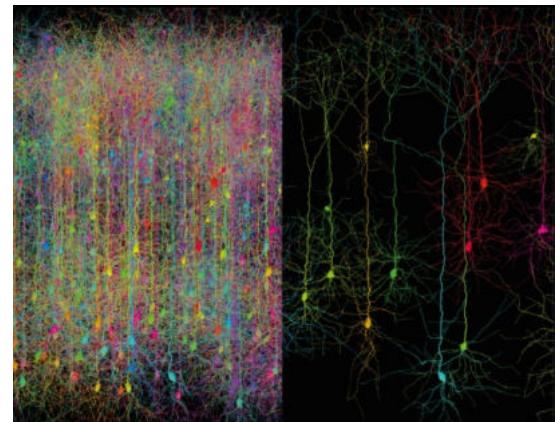


COVID-19:

- [Contreras et al., VP, Nature Communications, 2021]
- [Priesemann et al., The Lancet, 2021a,b]
- [Linden et al., VP, Dtsch. Arztebl. Int. 2020]
- [Bauer et al., VP, arxiv; Contreras et al. VP, arxiv]

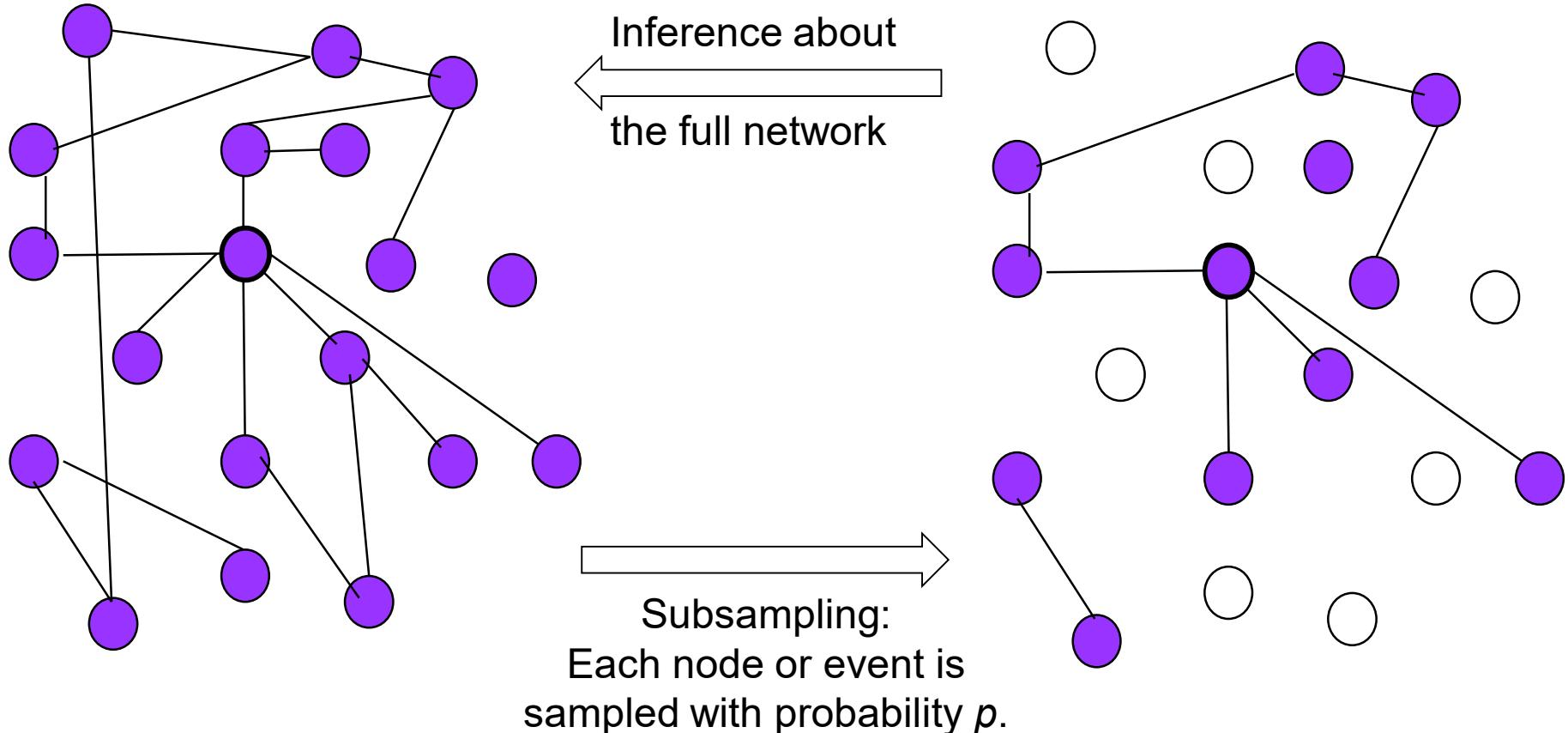
Overview

- **Large Scale Recordings & Subsampling:**
How to infer collective properties and spreading dynamics from vastly under-observed systems
- **Subsampling Scaling:** Inferring avalanche distributions or degree distributions from subsampled networks
- **Mitigating the Spread of COVID-19:**
 - The effect of test-trace-isolate (TTI)
 - and of the vaccination progress



Subsampling Scaling Theory

Levina & Priesemann, Nature Comm, 2017



→ Subsampling Scaling: A theory about inference
of collective properties from partly observed systems

Relation between $P(s)$ under full and under subsampling

$$P_{\text{sub}}(s) = \sum_{k=s}^{\infty} P(k) \underbrace{\binom{k}{s} p^s (1-p)^{k-s}}_{\text{binomial sampling}}$$

probability generating function (PGF)

$$\begin{aligned} G_{\text{sub}}(z; p) &= \sum_{s=0}^{\infty} z^s P_{\text{sub}}(s) \\ &= \sum_{s=0}^{\infty} z^s \sum_{k=s}^{\infty} P(k) \binom{k}{s} p^s (1-p)^{k-s} \\ &= \sum_{k=0}^{\infty} P(k) (zp + (1-p))^k \end{aligned}$$
$$G(z) = \sum_{s=0}^{\infty} z^s P(s)$$
$$P(s=n) = \frac{G^{(n)}(z=0)}{n!}$$

$$G_{\text{sub}}(z; p) = G(\tilde{z}; p) \quad \text{with } \tilde{z} = zp + (1-p)$$

Scaling for Distributions with Cutoff

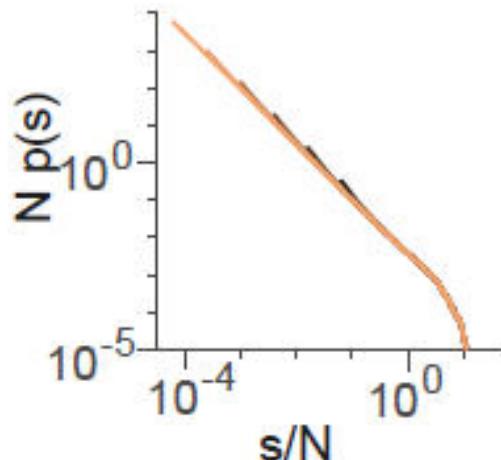
$$P(s) \sim s^{-\gamma}$$

$$P(s) \approx p P_{sub}(p \cdot s)$$

$$P(s) = C_\lambda e^{-\lambda s}$$

$$P(s) = \frac{e^{-\lambda_{sub}} + p - pe^{-\lambda_{sub}}}{p} P_{sub} \left(\frac{\ln(e^{\lambda_{sub}} p - p + 1)}{\lambda_{sub}} s \right)$$

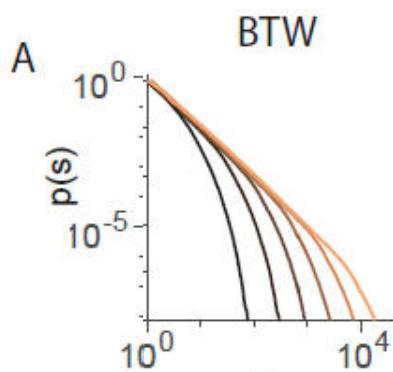
$$P(s) \sim s^{-\gamma} e^{-\lambda s} \quad \text{with } \lambda = 1/s_{max}$$



Subsampling in Models

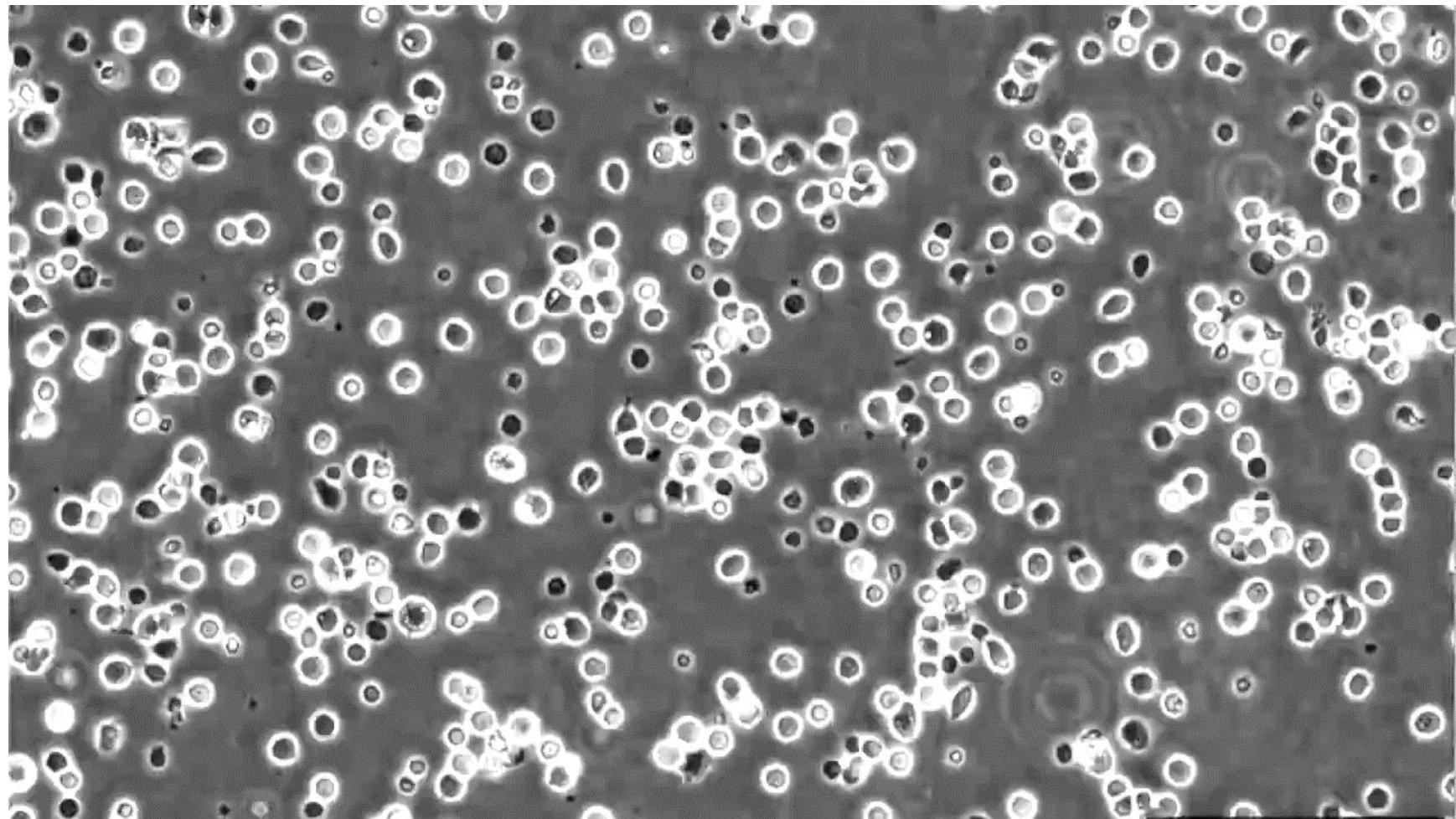
sampled neurons

- 2^4 of 2^{14}
- 2^6 of 2^{14}
- 2^8 of 2^{14}
- 2^{10} of 2^{14}
- 2^{12} of 2^{14}
- 2^{14} of 2^{14}



Scale-free models
from different
universality classes

Developing Neural Network *in vitro*



see e.g. [Levina & VP, Nature Communications, 2017]

Developing Cortical Cultures

- Applying further subsampling to the recordings



Summary

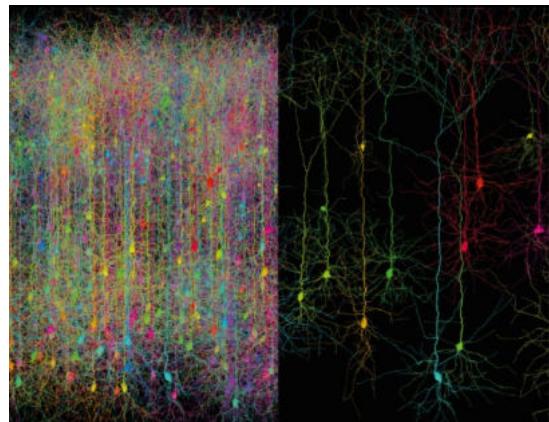
Subsampling Scaling

- reveals the “parent distribution”
- complementary to finite size scaling
- test for scale-free properties

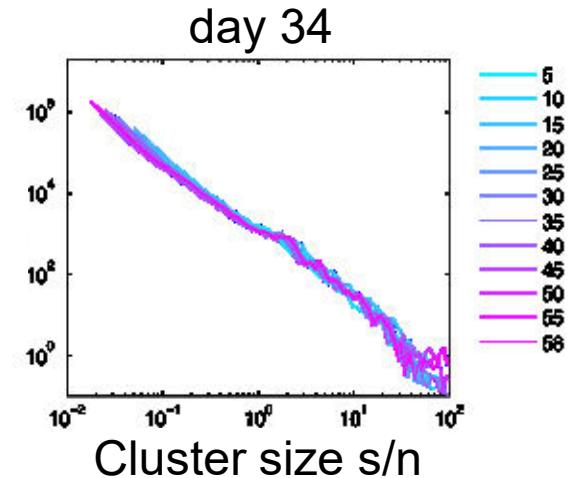
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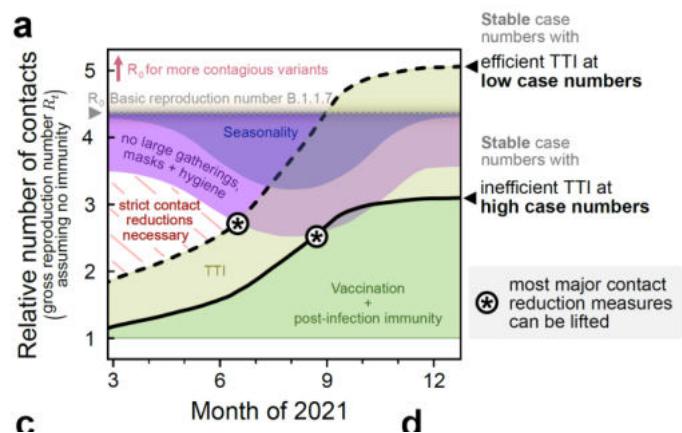
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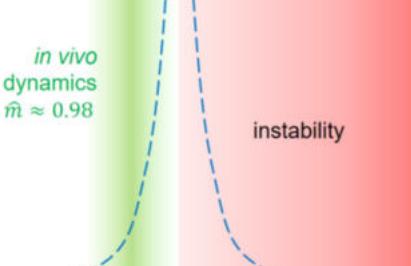
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Physics of Neural Systems

Spreading Dynamics and Phase Transitions

Information transfer



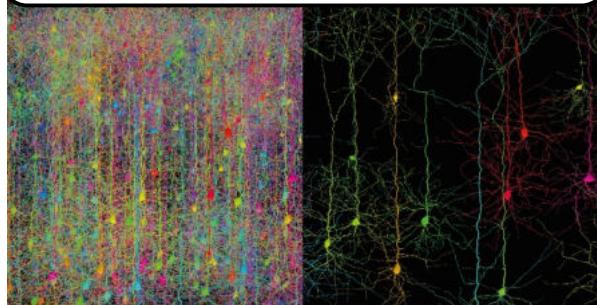
VP et al., Plos Comp Biol., 2013

Wilting & VP, Cerebr. Ctx, 2019

Wilting & VP, Curr Op Neurosci, 2019

Neto, Spitzner & VP, arxiv; Spitzner et al., arxiv

Subsampling Theory



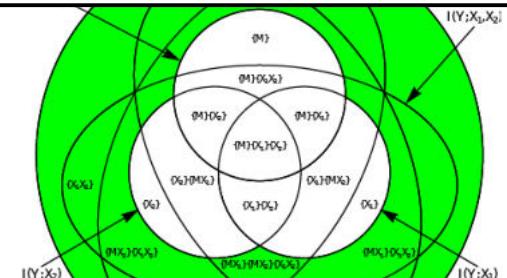
VP et al., 2009, 2013, 2014

Levina & VP, Nat. Commun., 2017

Wilting & VP, Nat. Commun., 2018

de Heuvel et al., PRE & PRR, 2020

Information Theory to Quantify & Design Computation



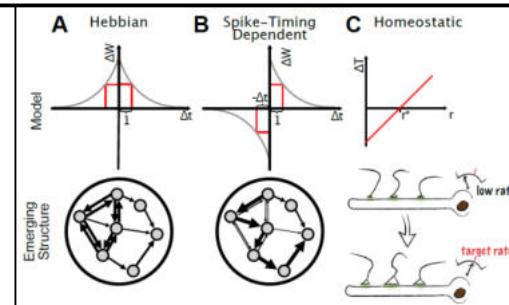
Wibral, Lizier & VP, Matter to Life, 2017

Wollstadt et al., Plos CB, 2017

Wibral et al., Entropy, 2017

Rudelt, ... VP, biorxiv, 2020

Local Learning Rules to Optimize Computation



Zierenberg, ... VP, Phys Rev X, 2018

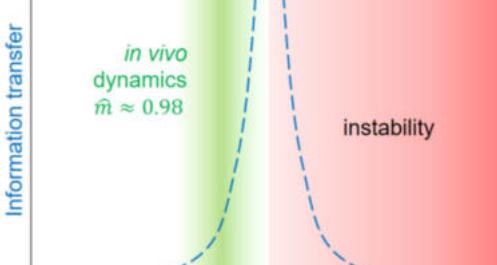
del Papa, VP & Triesch, 2017, 2019

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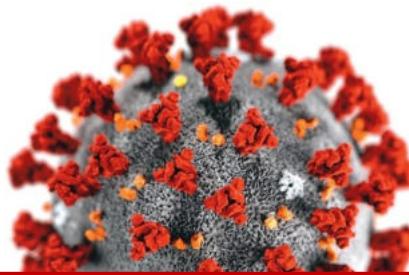
Mikulasch, Rudelt & VP, arxiv; Loidolt et al., arxiv

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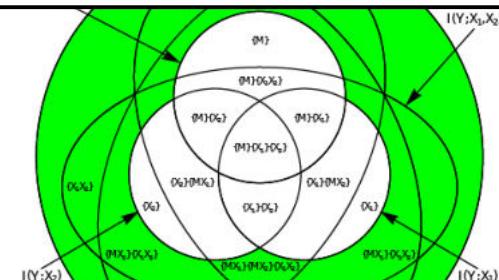
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COVID-19
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Bauer, ... VP, arxiv, 2021

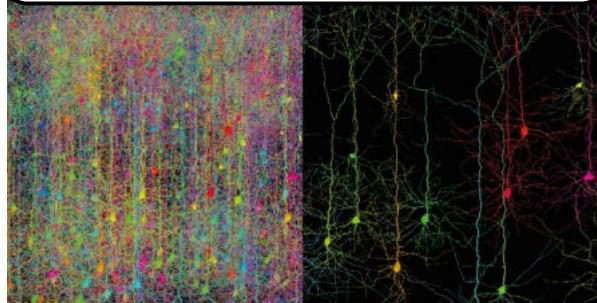


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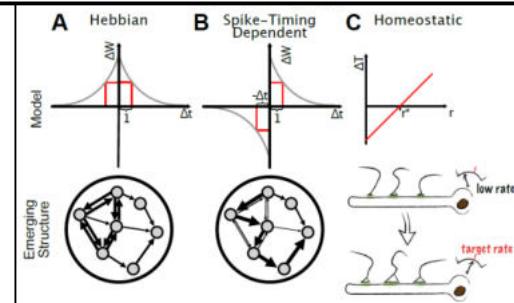
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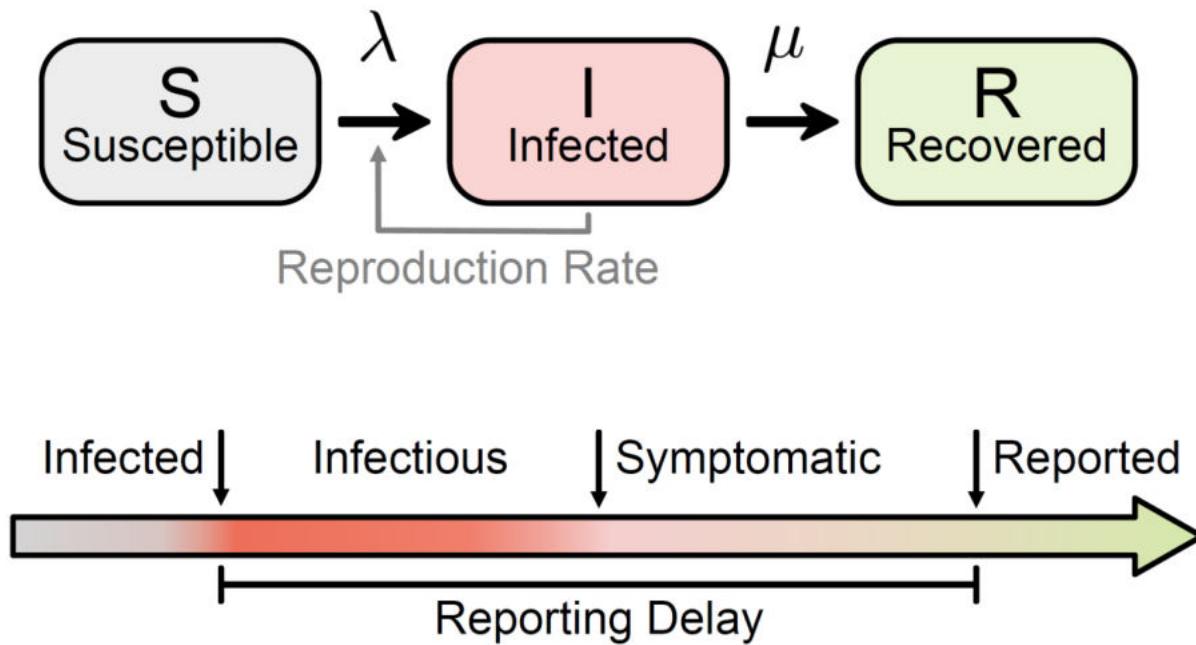
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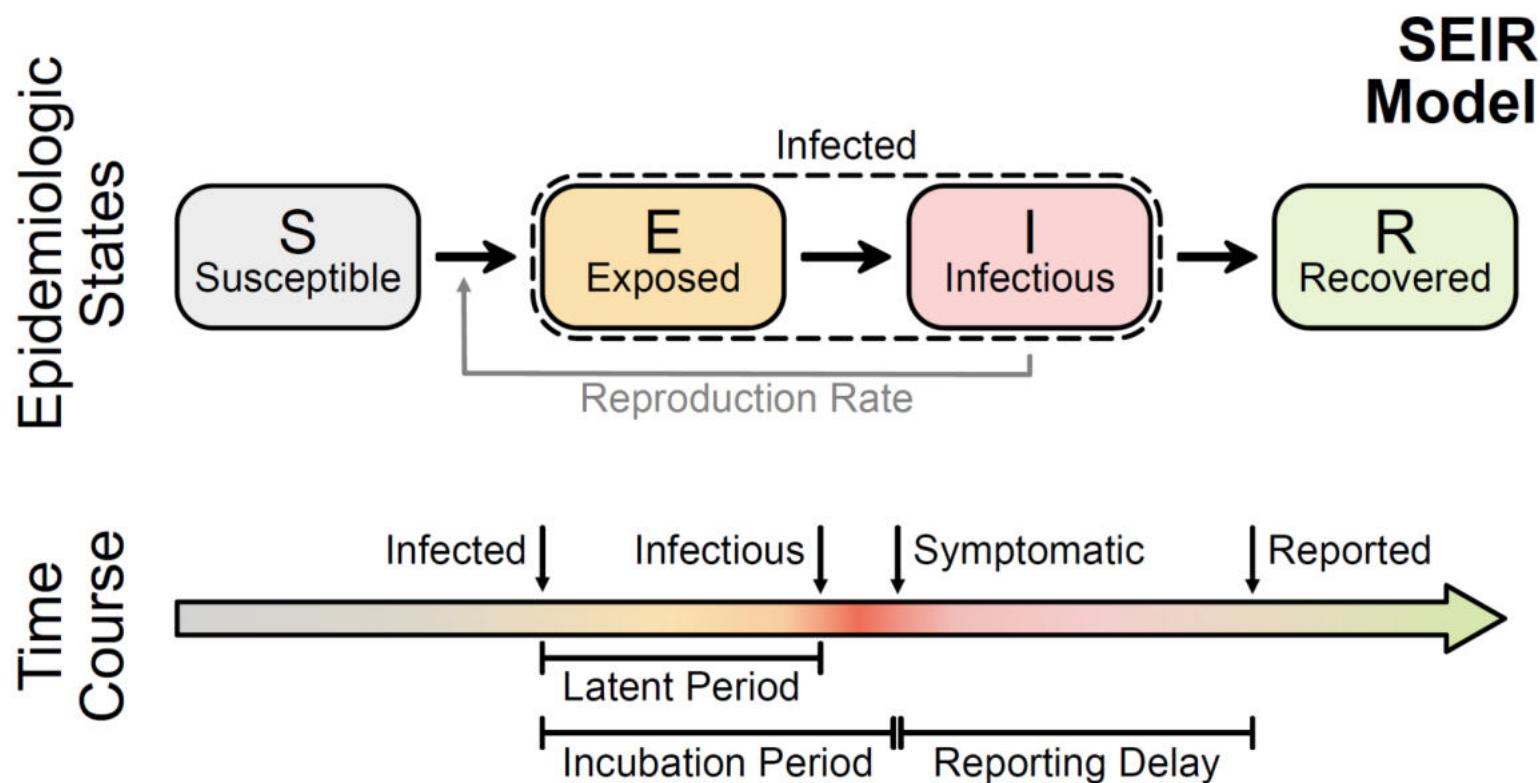
SIR: Susceptible-Infected-Recovered

SIR Model



$$\frac{dS}{dt} = -\lambda \frac{SI}{N}$$
$$\frac{dI}{dt} = \lambda \frac{SI}{N} - \mu I$$
$$\frac{dR}{dt} = \mu I$$

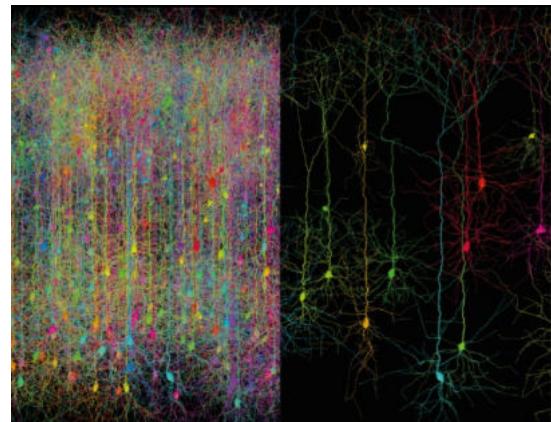
SEIR: Susceptible-Exposed-Infected-Recovered



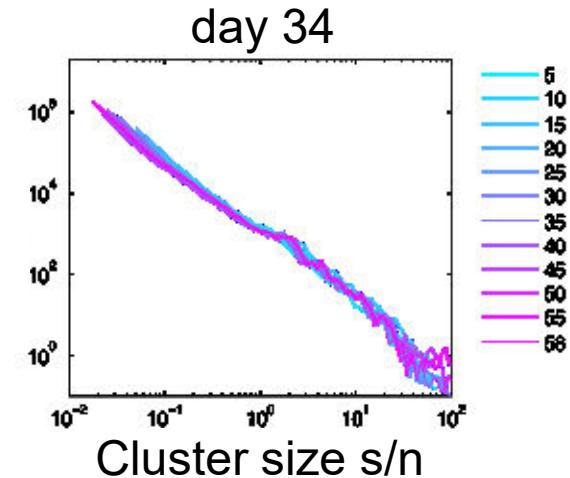
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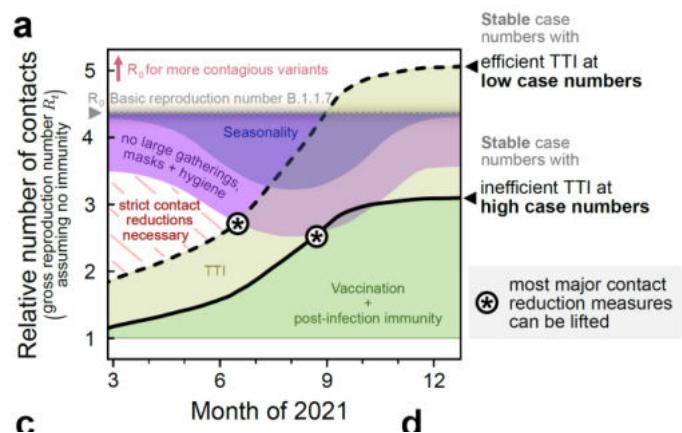
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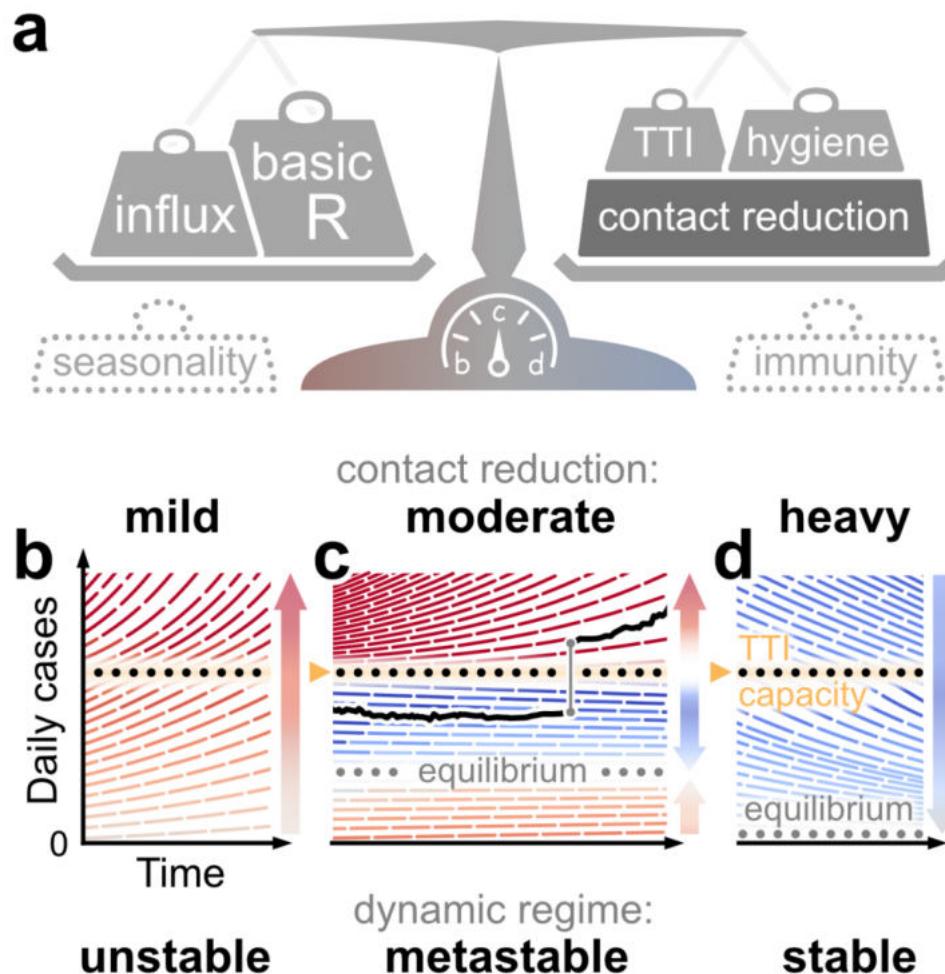
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Combined measures to contain COVID-19



ARTICLE



<https://doi.org/10.1038/s41467-020-20699-8>

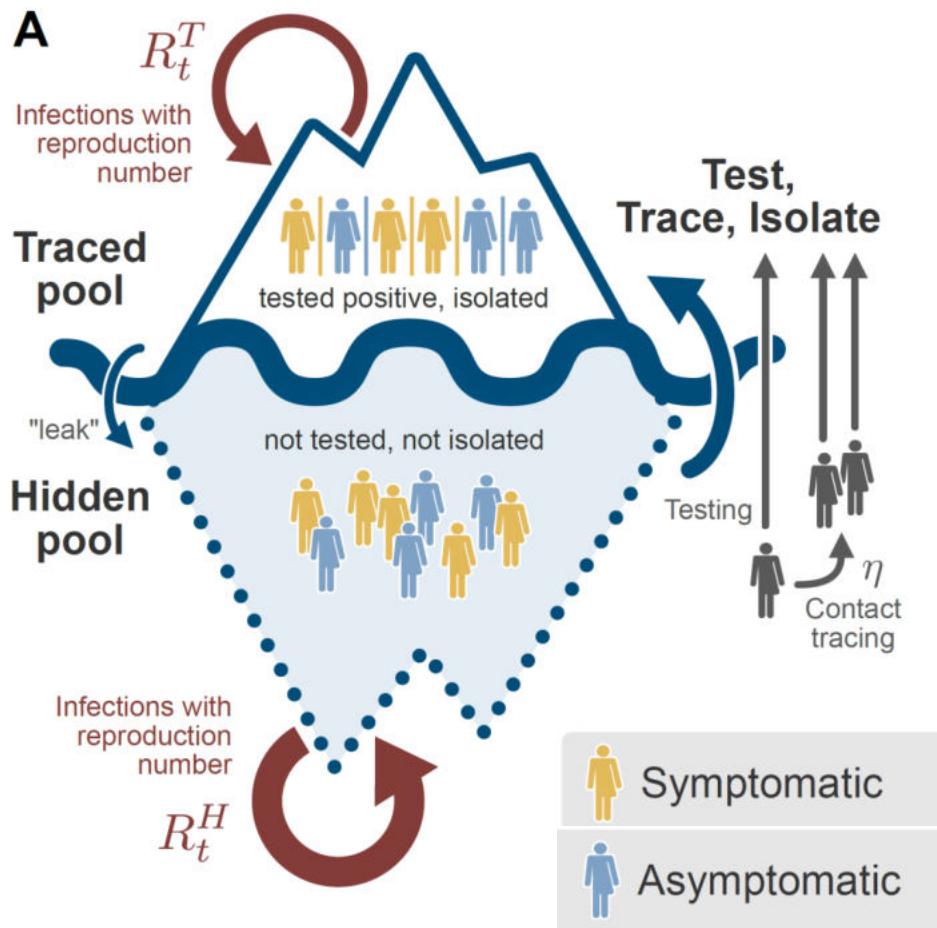
OPEN

The challenges of containing SARS-CoV-2 via test-trace-and-isolate

Sebastian Contreras  ^{1,2,5}, Jonas Dehning  ^{1,5}, Matthias Loidolt  ^{1,5}, Johannes Zierenberg  ¹, F. Paul Spitzner¹, Jorge H. Urrea-Quintero¹, Sebastian B. Mohr  ¹, Michael Wilczek  ^{1,3}, Michael Wibral⁴ & Viola Priesemann  ^{1,3}✉

Without a cure, vaccine, or proven long-term immunity against SARS-CoV-2, test-trace-and-isolate (TTI) strategies present a promising tool to contain its spread. For any TTI strategy, however, mitigation is challenged by pre- and asymptomatic transmission, TTI-avoiders, and undetected spreaders, which strongly contribute to "hidden" infection chains. Here, we study a semi-analytical model and identify two tipping points between controlled and uncontrolled spread: (1) the behavior-driven reproduction number R_t^H of the hidden chains becomes too large to be compensated by the TTI capabilities, and (2) the number of new infections exceeds the tracing capacity. Both trigger a self-accelerating spread. We investigate how these tipping points depend on challenges like limited cooperation, missing contacts, and

Test-Trace-and-Isolate (TTI) contributes to containment



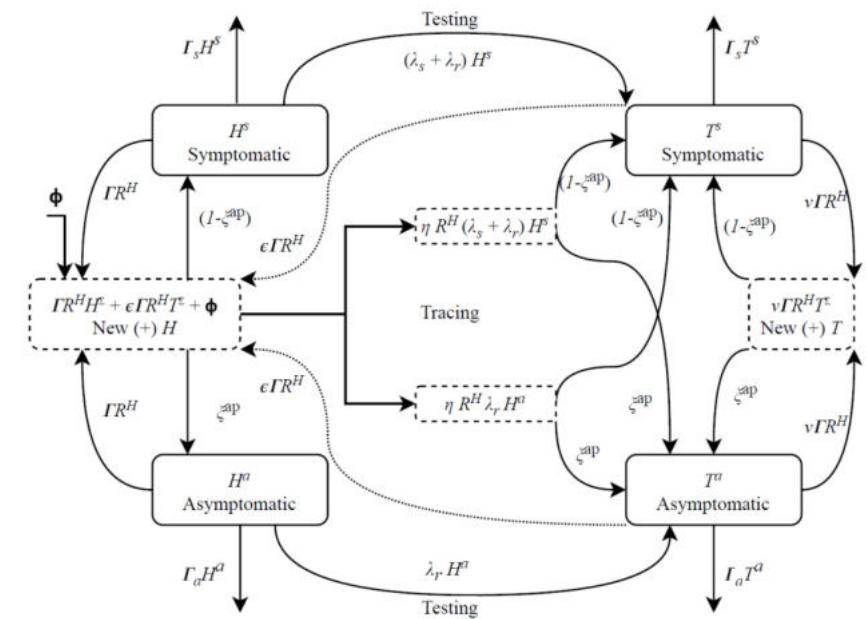
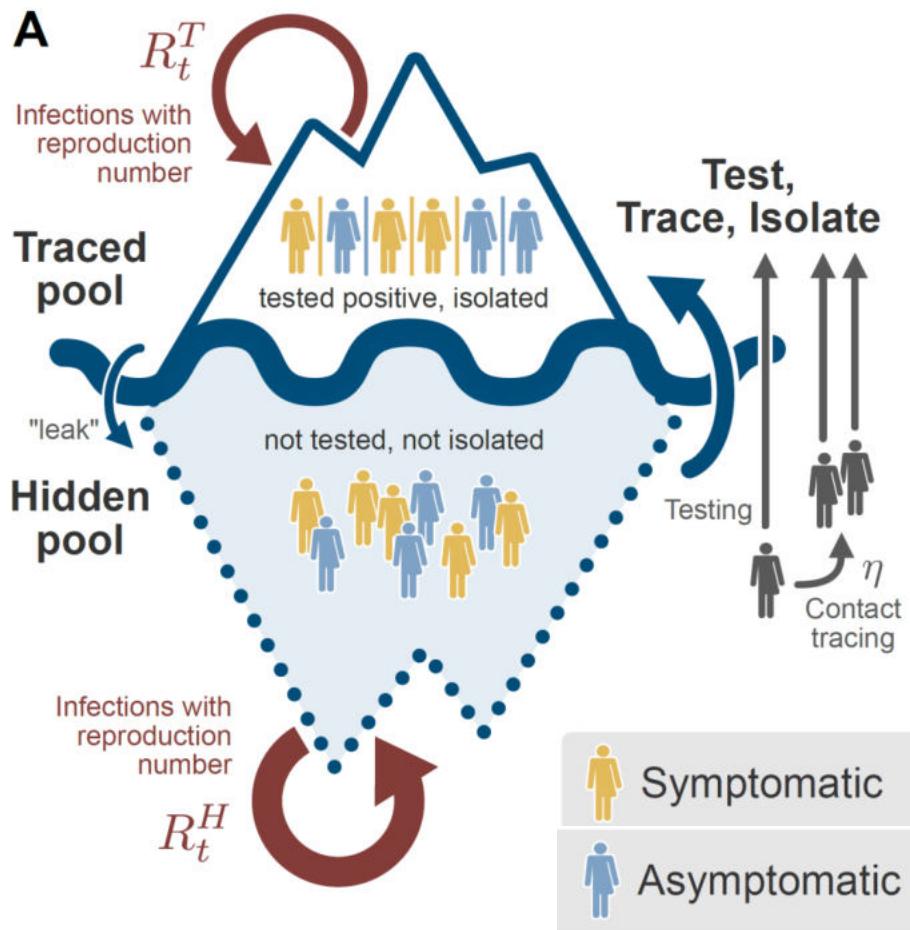
Test & isolated

- Random (0)
- Symptoms (50 % of sympt., on average after 5 days)
- Test contact persons

Contact tracing is difficult:

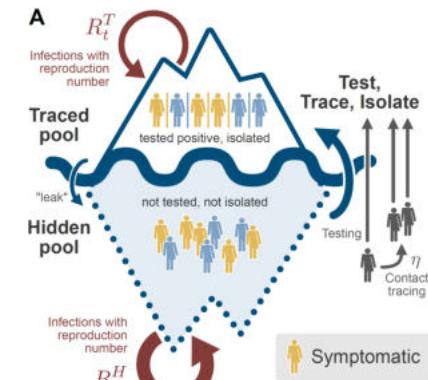
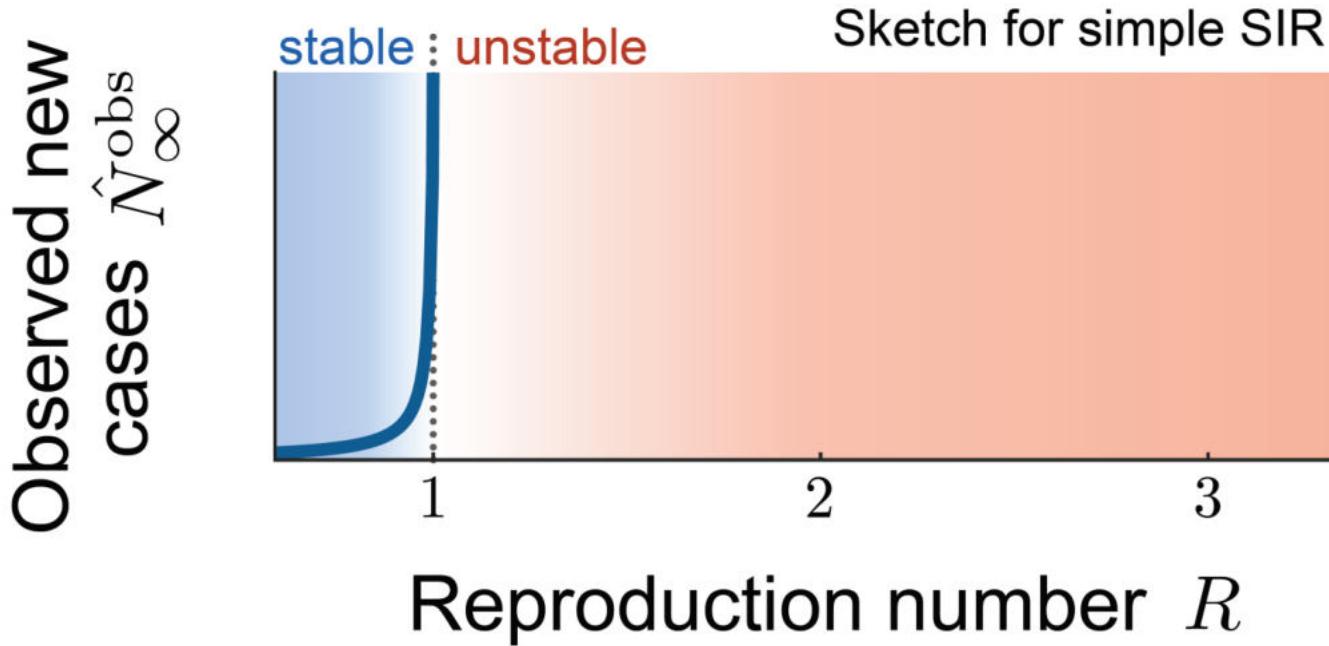
- Pre- und asymptomatic infection
- 1/3 of contacts are overlooked
 - Quarantine is not perfect
- People who do not get tested (20%)
- Introduction of new infectious from abroad
- Limited capacities of health offices for testing and tracing

Test-Trace-and-Isolate (TTI) contributes to containment



The reproduction number R and the external influx of new cases Φ determine the level of new infections N

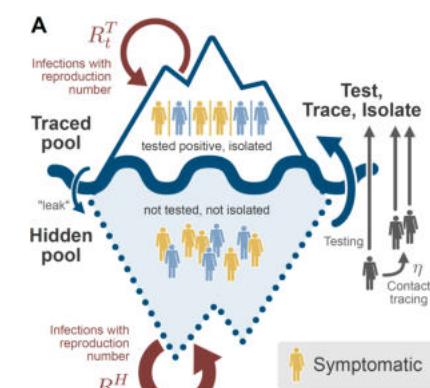
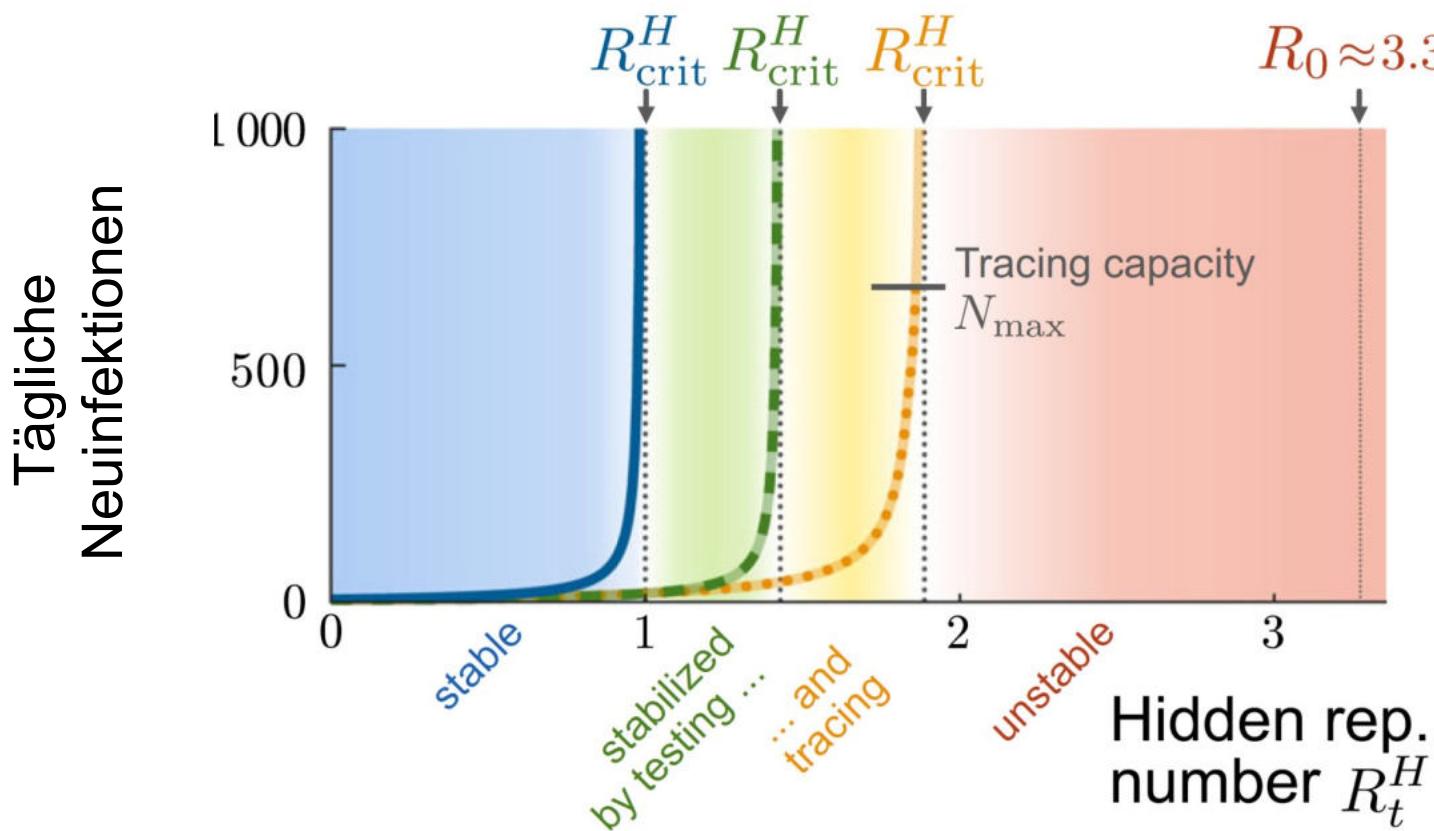
$$N \approx \frac{\Phi}{R_c - R} = \frac{\Phi}{1 - R} , \quad \text{for } R < 1$$



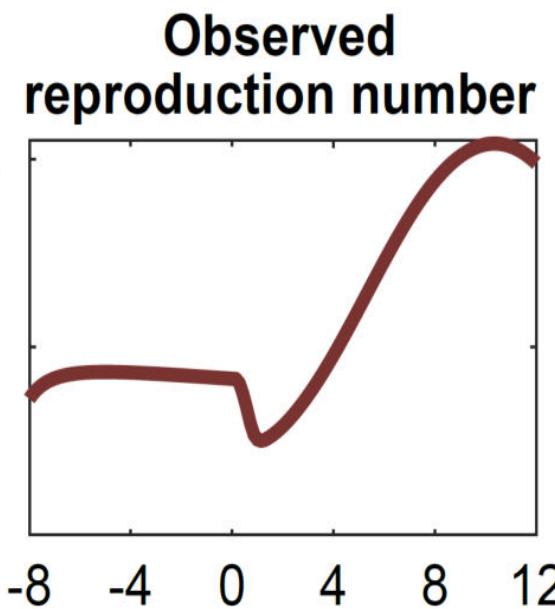
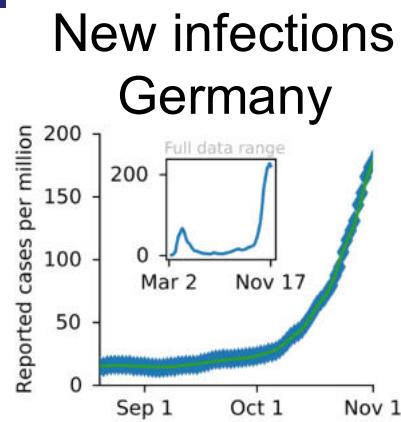
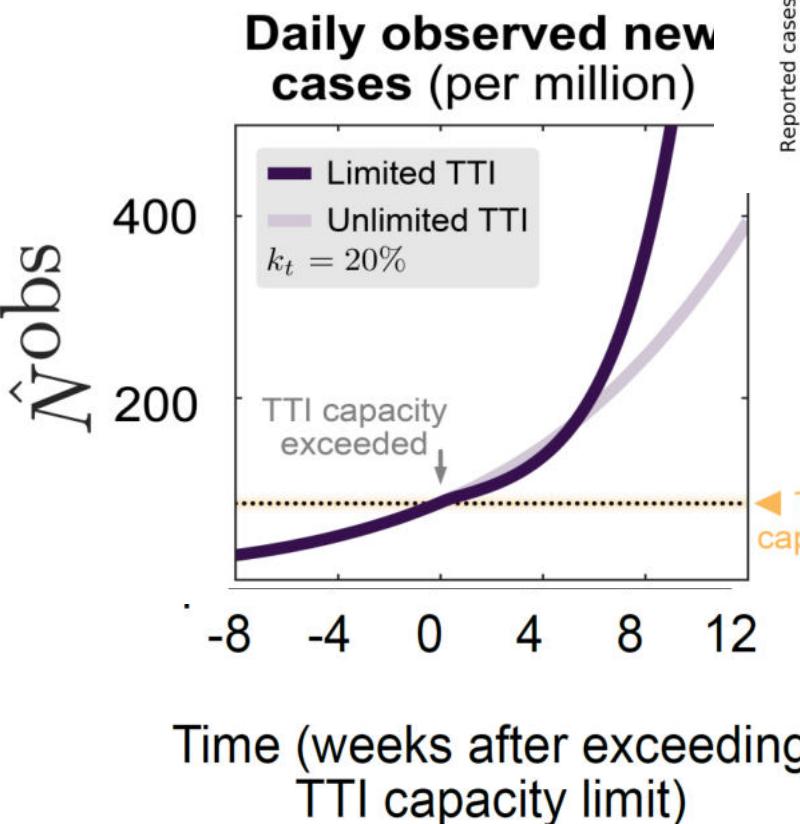
Test-Trace-Isolate (TTI) moves the stability limit:

Without TTI, R must be below 1

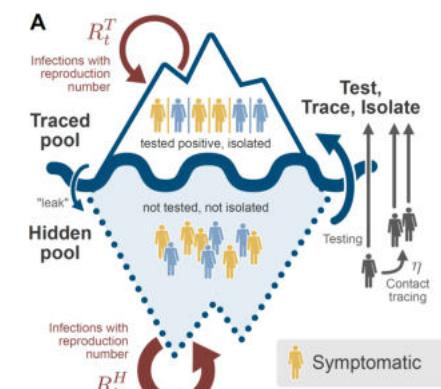
With TTI, R in the day to day life can be up to two



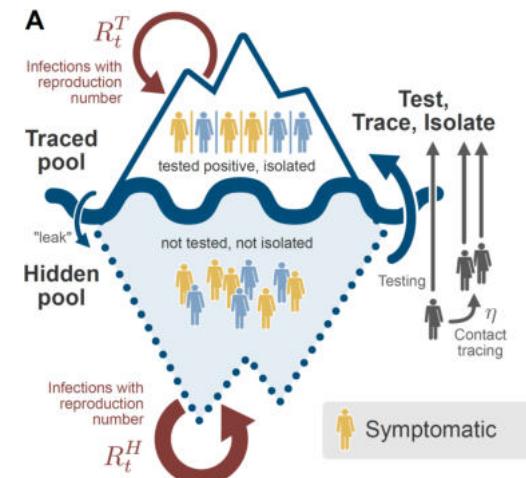
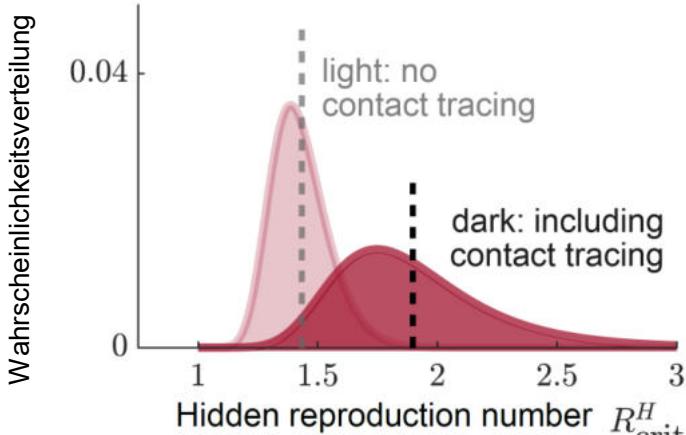
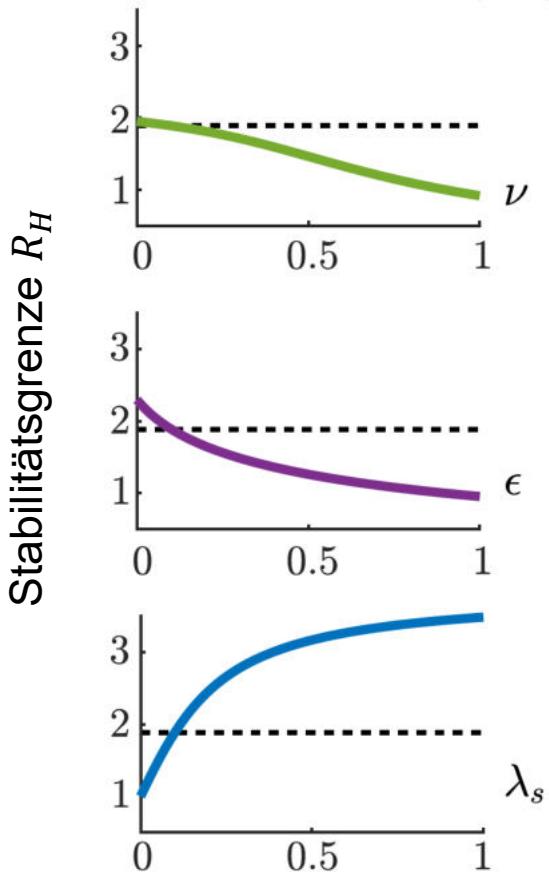
Crossing the TTI Limit: Case numbers grow faster than exponential



Time (weeks after exceeding TTI capacity limit)



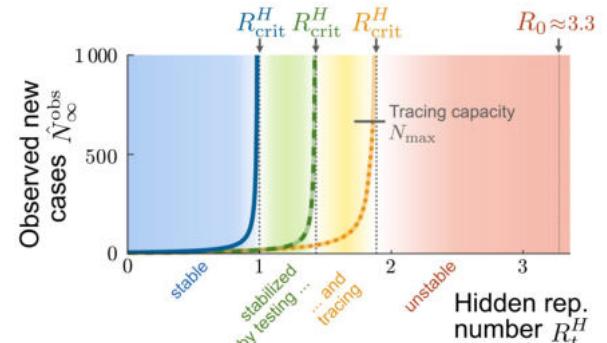
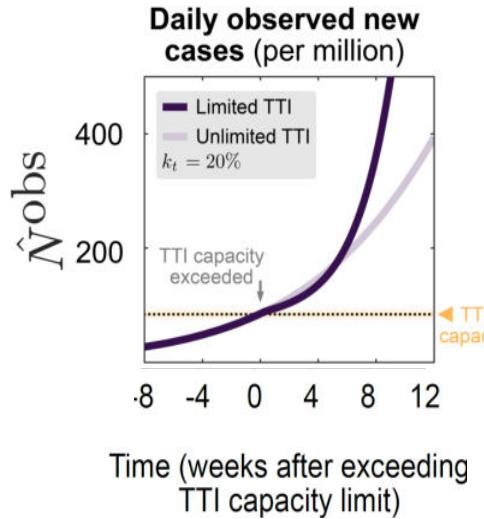
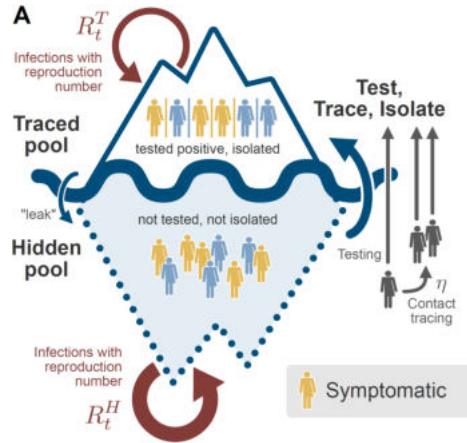
Sensitivity Analysis



- | | |
|-------------------|--------------------------------|
| ν | Isolation factor |
| ϵ | "leak" factor |
| λ_s | Symptom-driven testing |
| ξ^{ap} | Apparent asymptomatic fraction |
| η | Tracing efficiency |

Summary of the TTI strategy

Test-Trace-Isolate (TTI) contributes to containing COVID-19:



The undetected cases contribute most strongly to the spread

If the TTI capacity is surpassed, a tipping point is crossed, and growth self-accelerates.

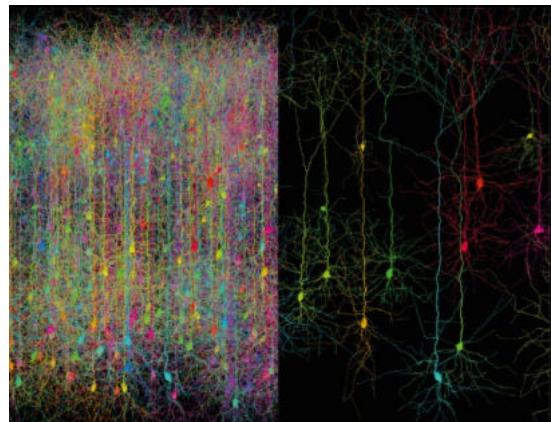
TTI enables every single person to have more contacts: Instead of one, about two persons can be infected
→ Compensation by TTI.

Overview

■ Large Scale Recordings

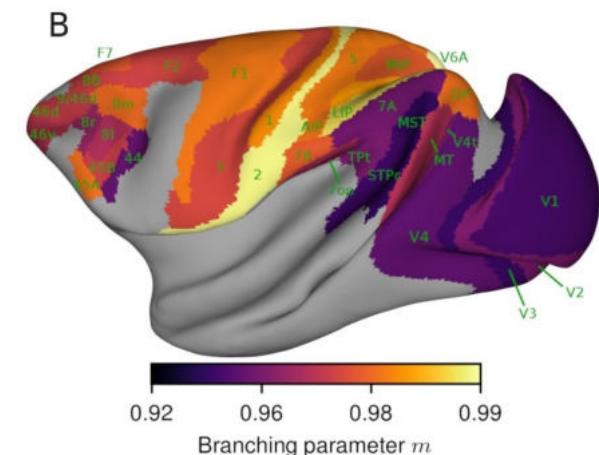
& Subsampling:

How to infer collective properties and spreading dynamics from vastly under-observed systems



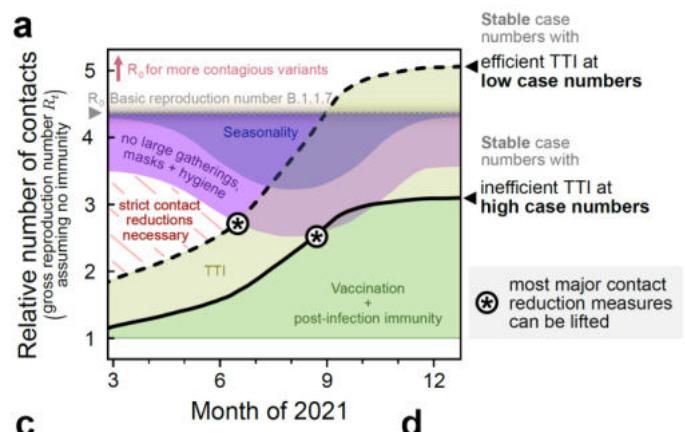
■ Spreading Dynamics & Information Transfer:

Tuning a network close to a second-order phase transition enablese rapid tuning to task requirements

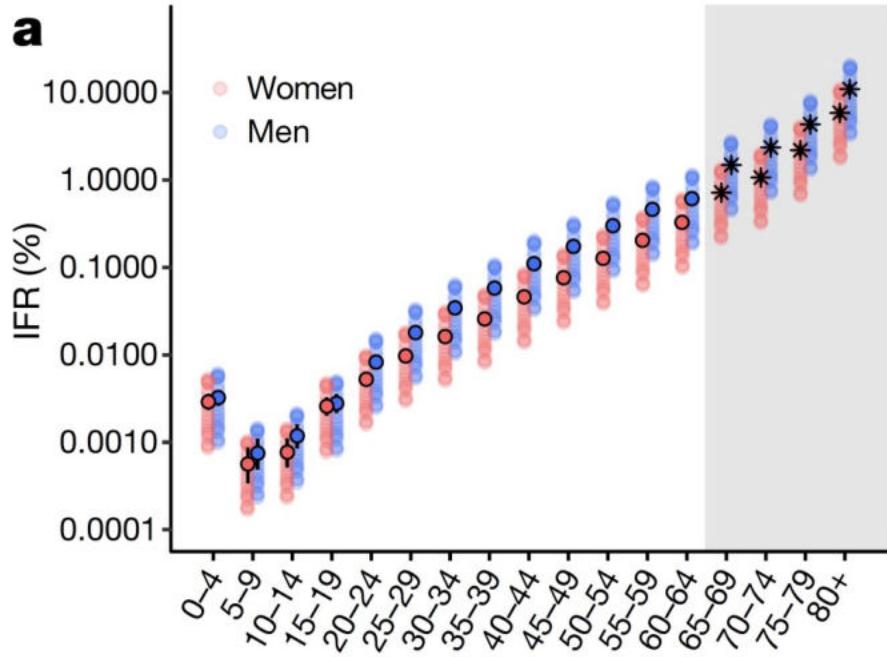


■ Mitigating the Spread of COVID-19:

- The effect of test-trace-isolate (TTI)
- and of the vaccination progress



The age-dependent infection fatality Rate (IFR) of SARS-CoV-2

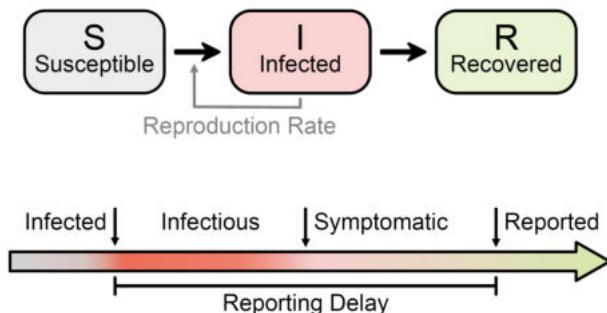


O'Driscoll et al., Nature, 2020; <https://www.nature.com/articles/s41586-020-2918-0>

Levin et al. Eur. J Infect. Disease, 2020; <https://link.springer.com/content/pdf/10007/s10654-020-00698-1.pdf>

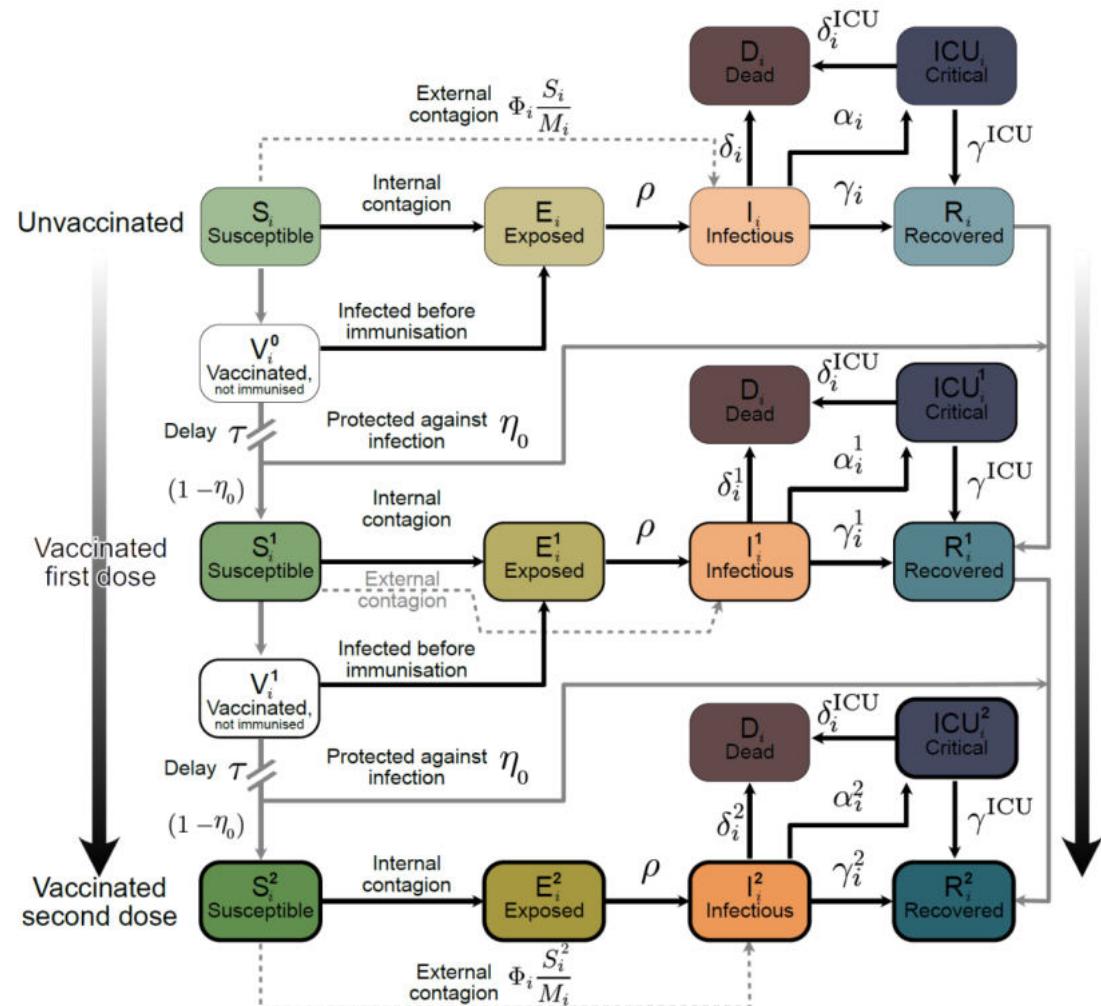
Implementing Vaccination Progress

SIR Model



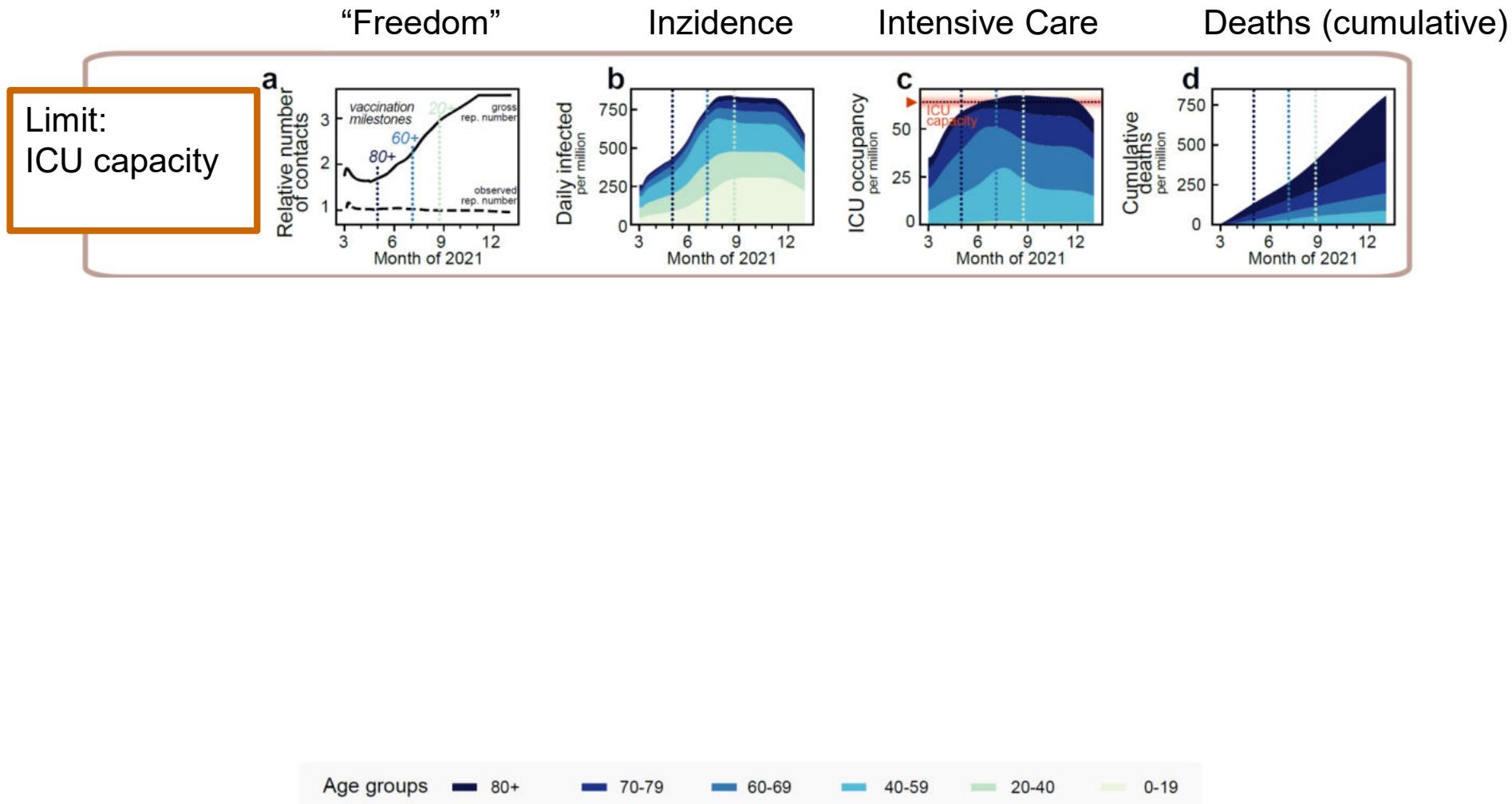
A model with compartments for

- SIRS (naturally infected)
- 1st vaccination dose
- 2nd vaccination dose
- Intensive care units
- Recovered / dead

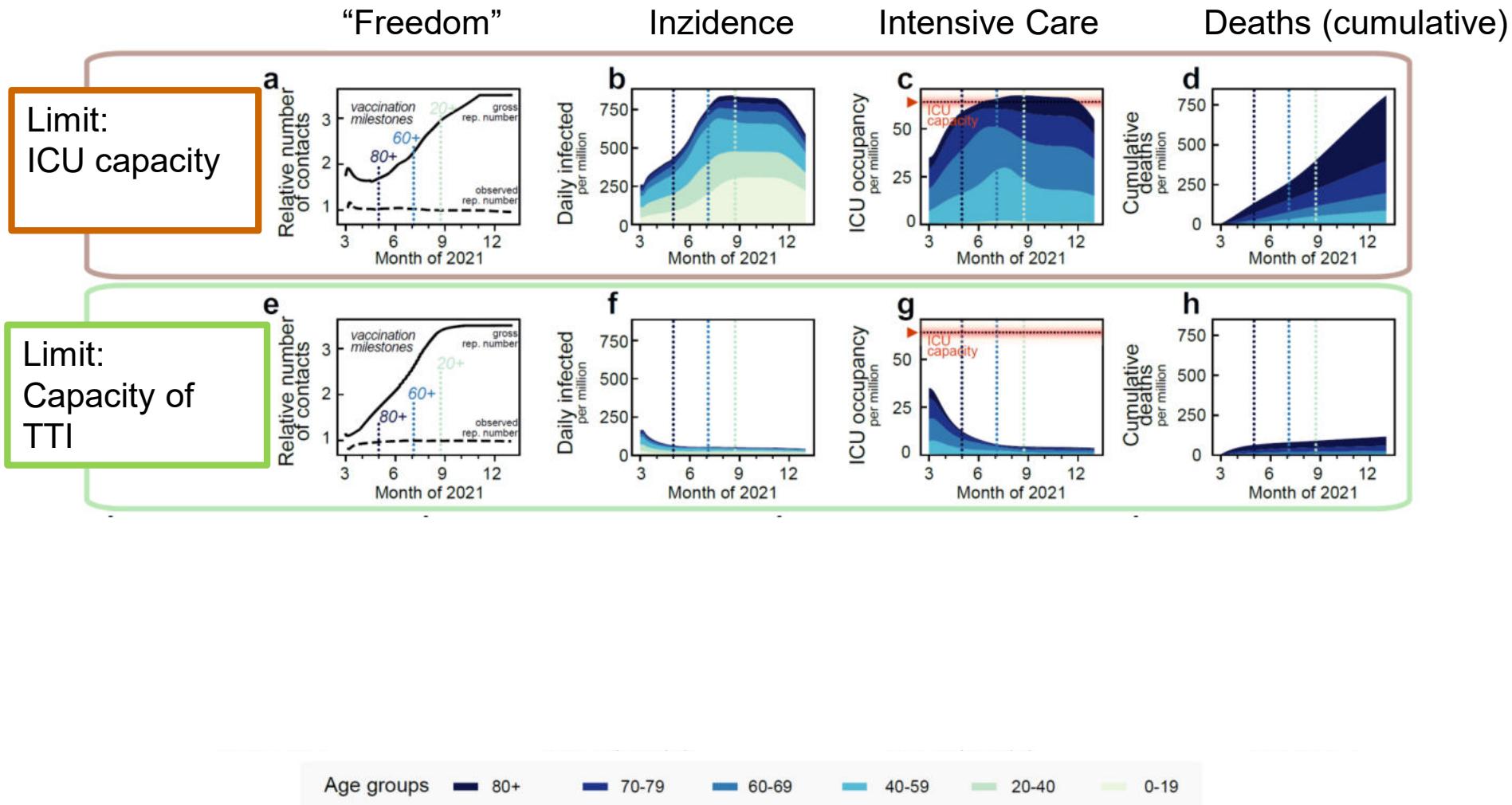


Parameters of the current vaccination delivery plan for Europe

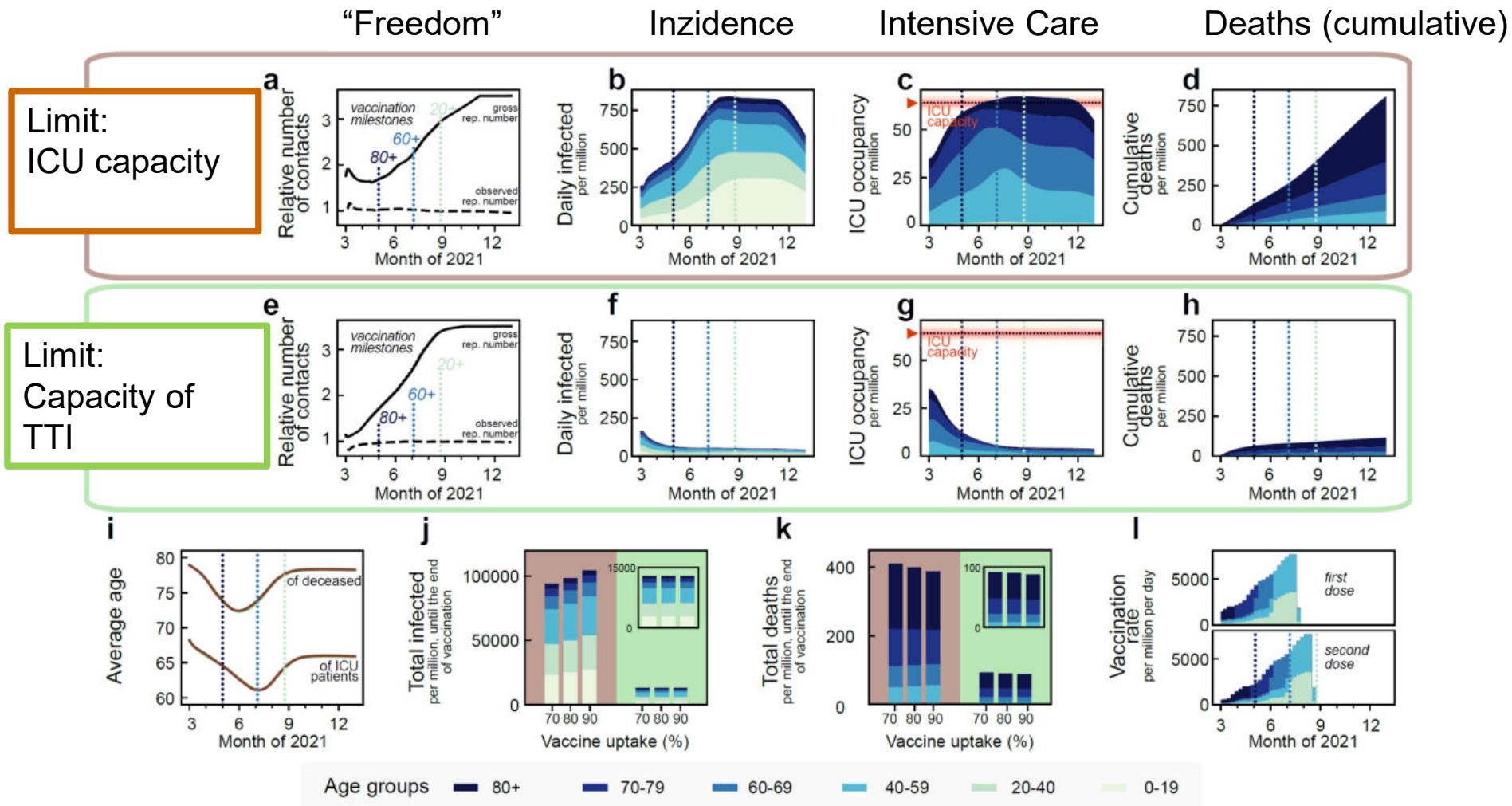
The main determinant of lifting restrictions is the progress in vaccination



The main determinant of lifting restrictions is the progress in vaccination



The main determinant of lifting restrictions is the progress in vaccination



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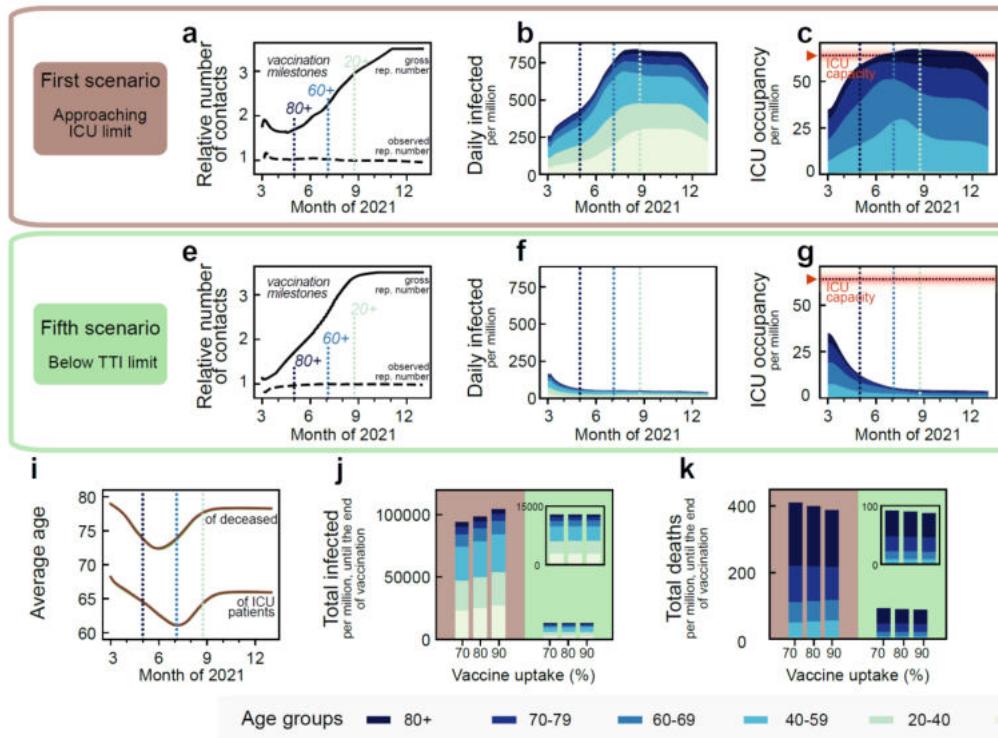
Policy Goals

Not overwhelming the ICU capacity

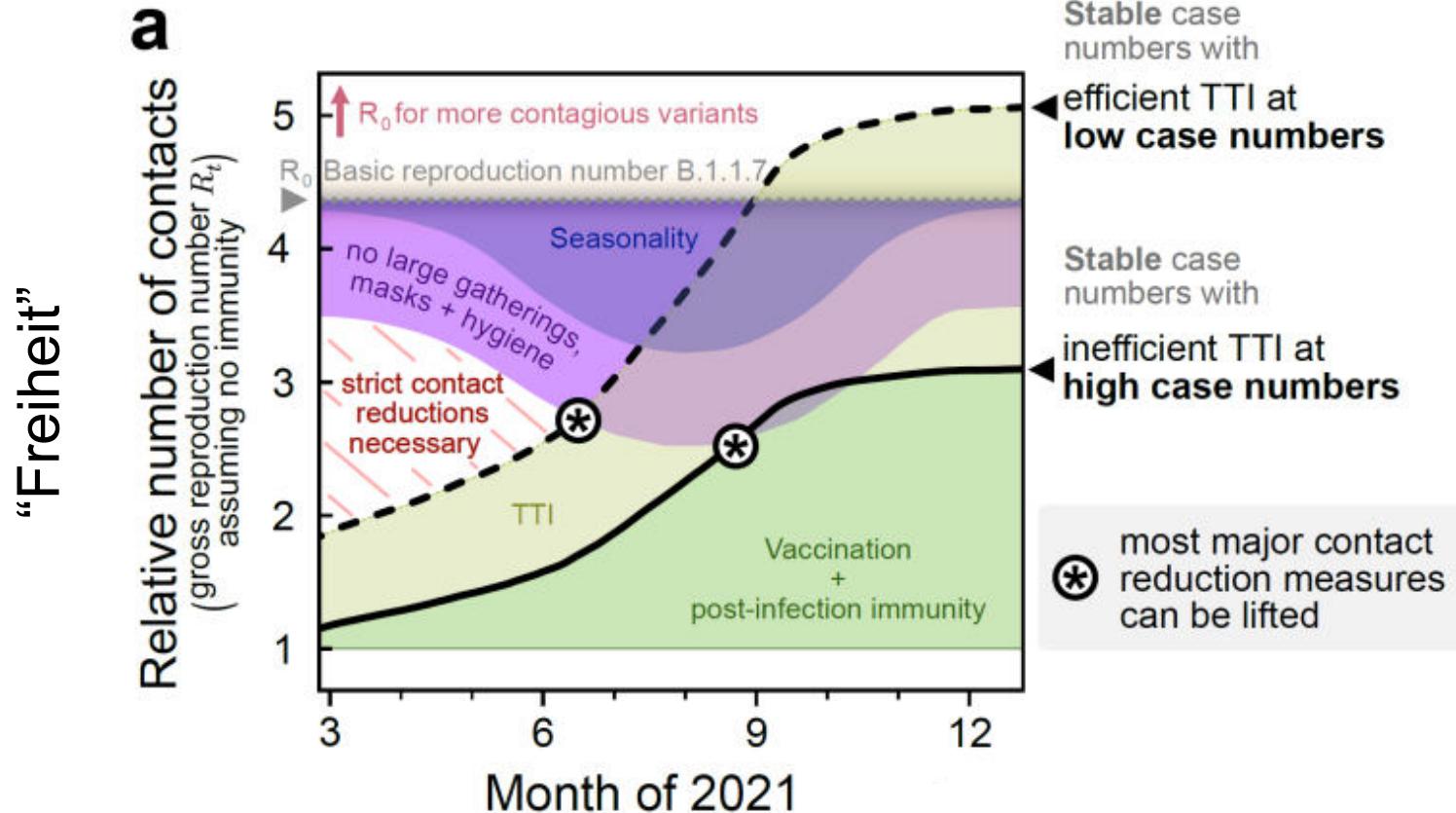
or

Low Incidence and Control

- Intensive care units can still be full for several weeks.
- The number of infections, deaths and long-term consequences (Long-COVID) are very different
- In both cases, the average age of ICU patients and deaths decreases
- The number of contacts ("freedom") increases in a very similar manner for both policy goals



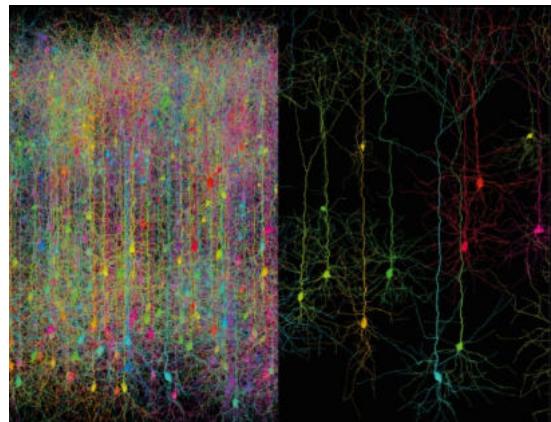
At low case numbers, the lifting of restrictions can be faster, because TTI contributes to containment



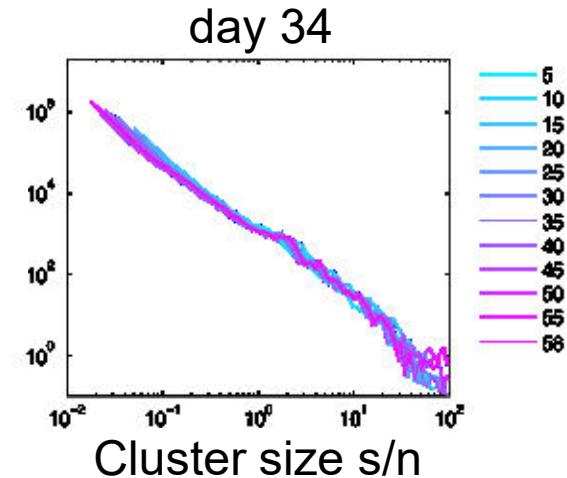
Overview

- **Large Scale Recordings & Subsampling:**

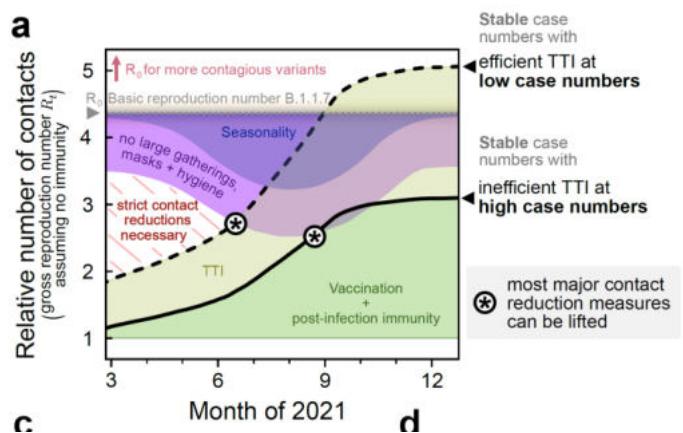
How to infer collective properties and spreading dynamics from vastly under-observed systems



- **Subsampling Scaling:** Inferring avalanche distributions or degree distributions from subsampled networks



- **Mitigating the Spread of COVID-19:**
 - The effect of test-trace-isolate (TTI)
 - and of the vaccination progress



Thank you!

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Discussions on COVID within

the Göttingen Campus and beyond:

Heike Bickeböller, Philip Bittihn, Eberhard Bodenschatz, Wolfgang Brück, Alexander Ecker, Andreas Leha, Theo Geisel, Ramin Golestanian, Helmut Grubmüller, Stephan Herminghaus, Gerald Haug, Reinhard Jahn, Jürgen Jost, Norbert Lossau, Vladimir Zykov, Michael Meyer-Hermann, Iris Pigeot, Simone Scheithauer, Anita Schöbel, Fredi Schüth,
Michael Wibral & Michael Wilczek



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SPP 2205
Evolutionary optimization
of neuronal processing

