



Spreading dynamics: From neural networks to COVID-19

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Selbstorganisation

Göttingen

Overview

- **Subsampling Theory:** Inferring collective properties even under sparse spatial sampling

Levina & VP, Nat Commun, 2017
Wilting & VP, Nat Commun, 2018

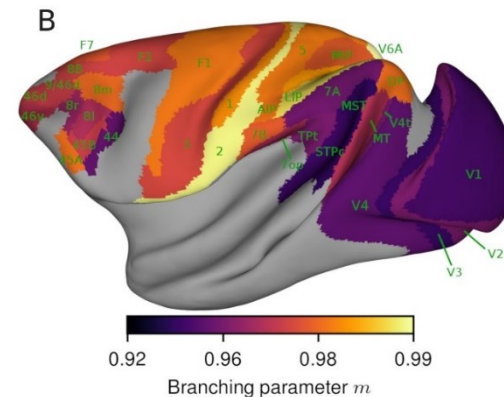
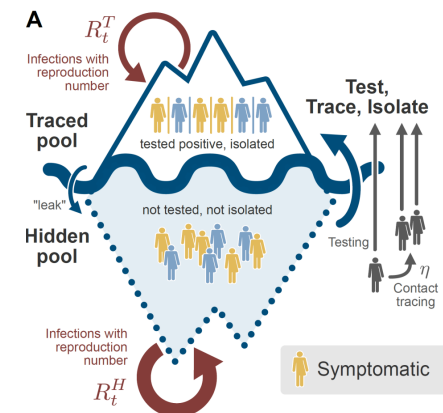
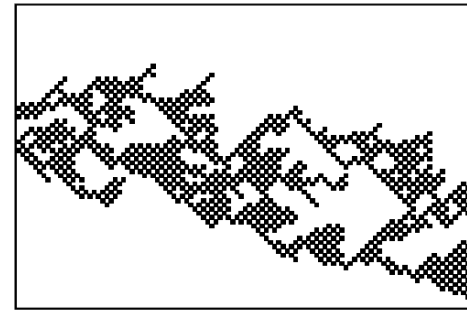
- **COVID-19 Pandemic:** Predicting future scenarios & developing mitigation strategies

Bauer et int., Priesemann, Plos Comp Biol, 2021
Contreras et int., VP, Nat Commun, 2021
Contreras et int., VP, Science Adv, 2021
Dehning et int., VP, Science, 2020
Iftexhar, VP et al., The Lancet Reg. Health Eur., 2021
VP et al., The Lancet, 2021a,b,c

- **Collective Computation in Living Neural Networks:** Critical phenomena, fine-tuning of computation, and clinical implications

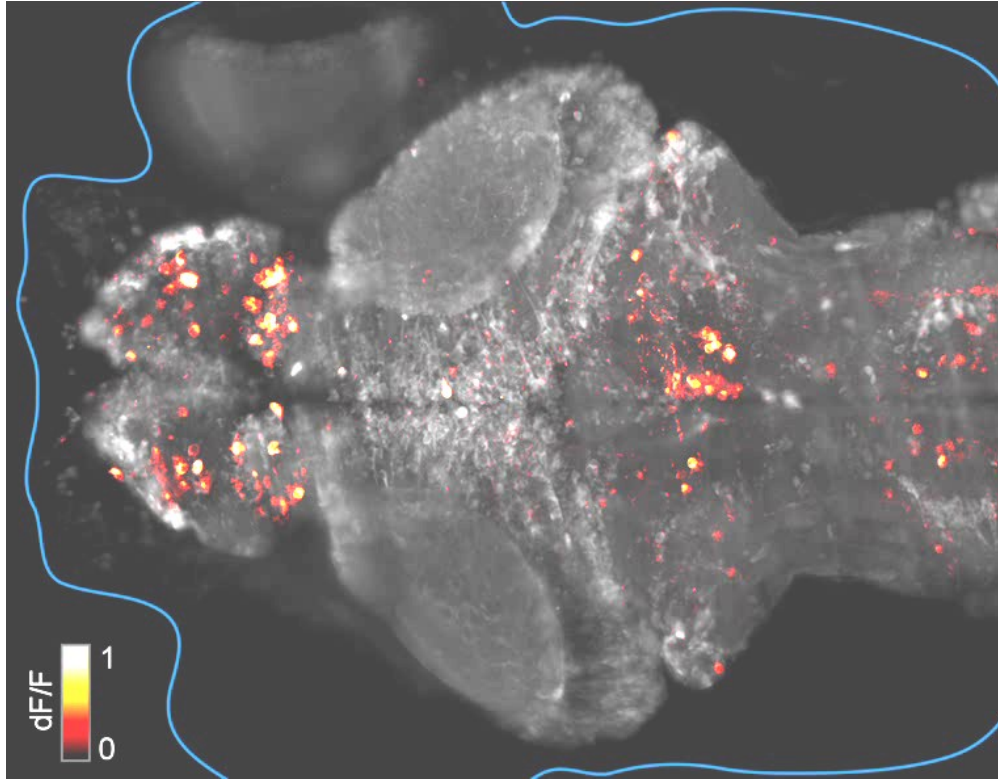
Cramer et int., VP, Nat Commun, 2020
Hagemann et int., VP, Plos Comp Biol., 2021
Zierenberg, Wilting & Priesemann, PRX, 2018

- **Outlook**



Collective Dynamics

Light sheet fluorescence imaging in a zebra fish larva



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

Interactions:

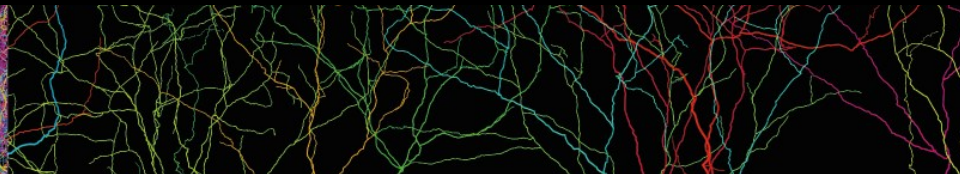
- pulse-like (“spikes“)
- directed
- time-delayed
- plastic (learning!)

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

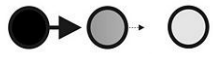


Neto, Spitzner & VP, arxiv
Spitzner et al., Plos One, 2021
Wilting & VP, Cerebral Cortex, 2019
Wilting & VP, Nature Communications, 2018
Levina & VP, Nature Communications, 2017

Propagating Activity as a Branching Process

control parameter R

expected number of “children”



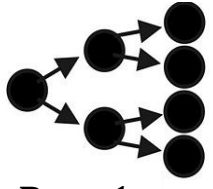
$R < 1$

subcritical



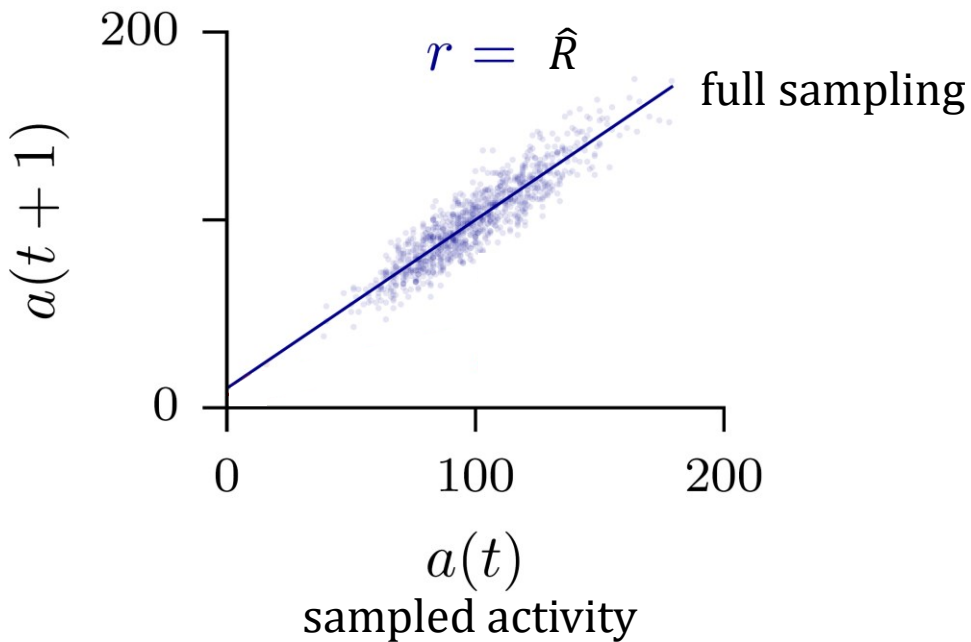
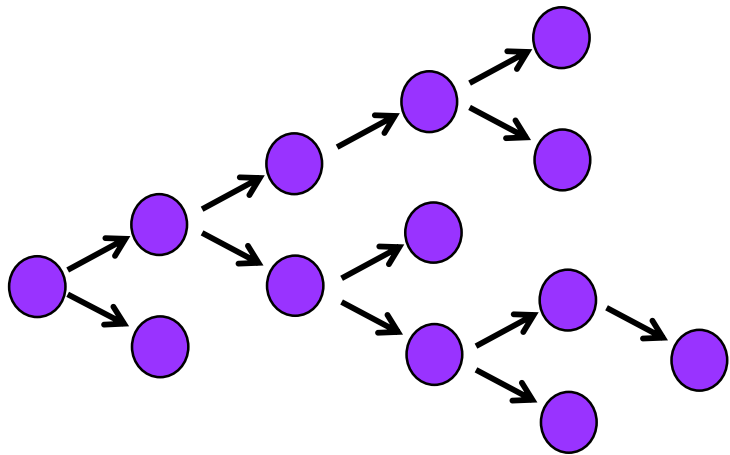
$R = R_c = 1$

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

[Galton & Watson, 1875]

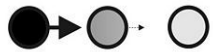
[Wilting & VP, Nature Communications, 2018]

[Levina & VP, Nature Communications, 2017]

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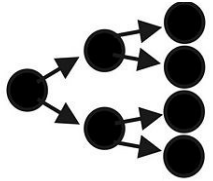
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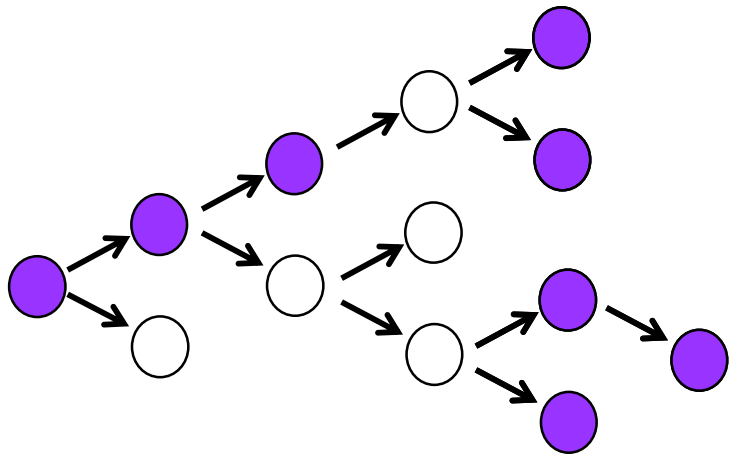
$R = R_c = 1$

critical

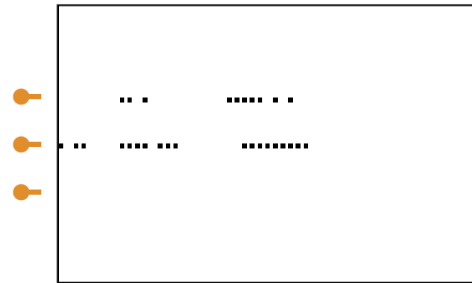


$R > 1$

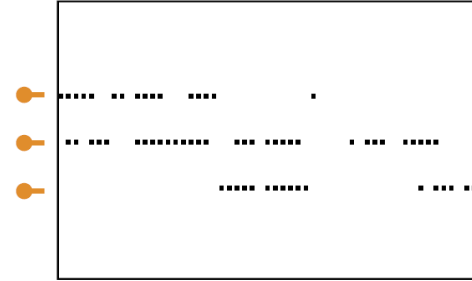
supercritical



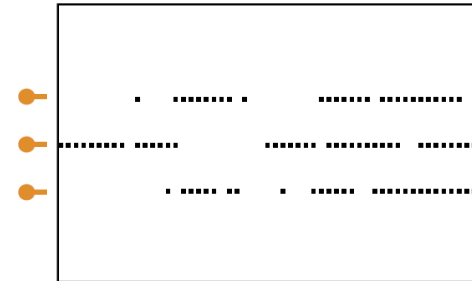
$R < 1$



$R = 1$



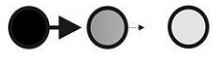
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Propagating Activity as a Branching Process

control parameter R

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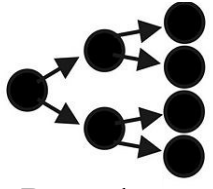
$R < 1$

subcritical



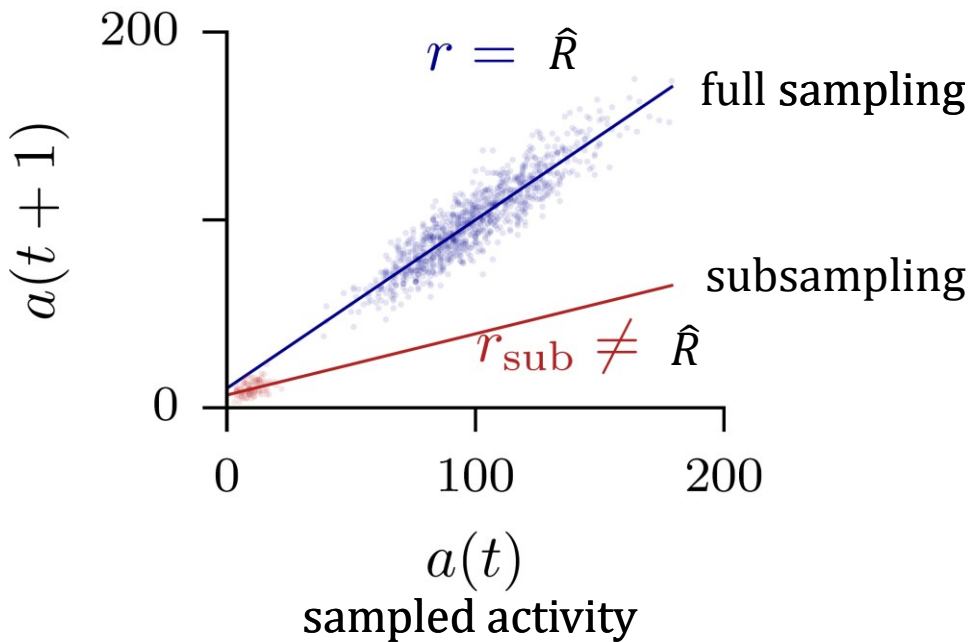
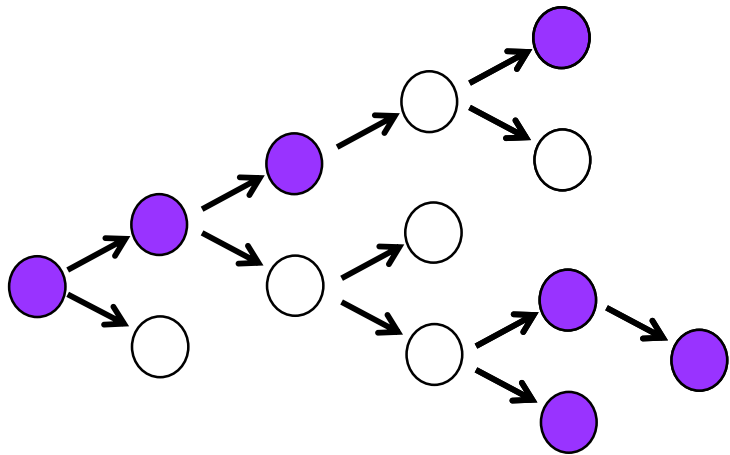
$R = R_c = 1$

critical



supercritical

$R > 1$



→ 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

Inferring Spreading Dynamics

control parameter R

expected number of “children”



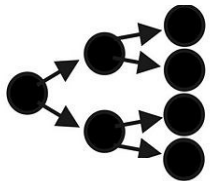
$$R < 1$$

subcritical



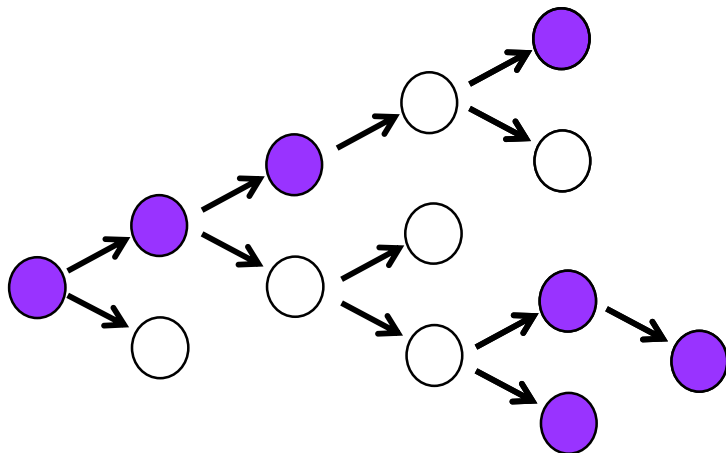
$$R = R_c = 1$$

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.Buttering; e.g. Ma et al., Neuron, 2019

Python Toolbox: github.com/Priesemann-Group

[Spitzner et al., Plos One, 2021]

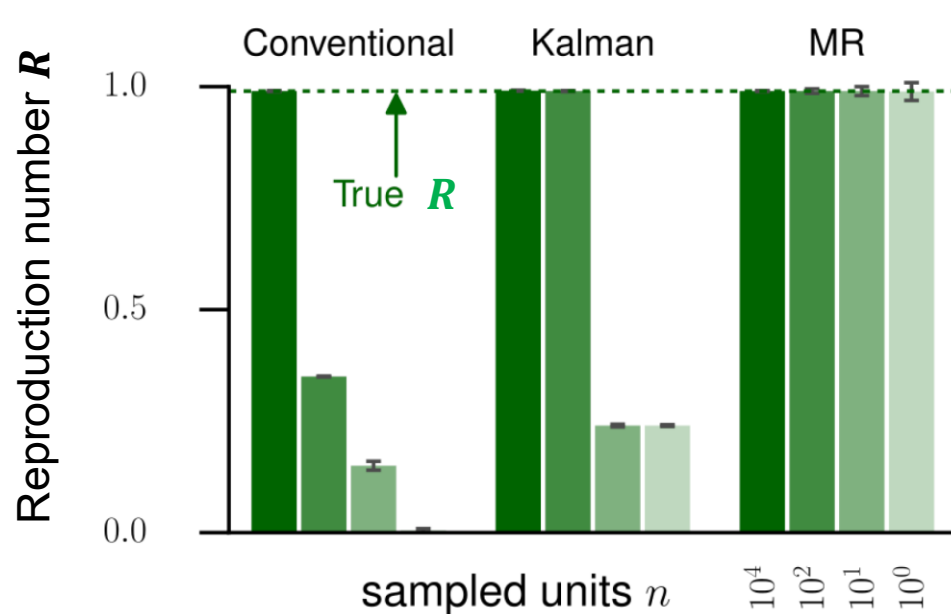
[Dehning et int. VP, Science, 2020]

[Wilting & VP, Nature Communications, 2018]

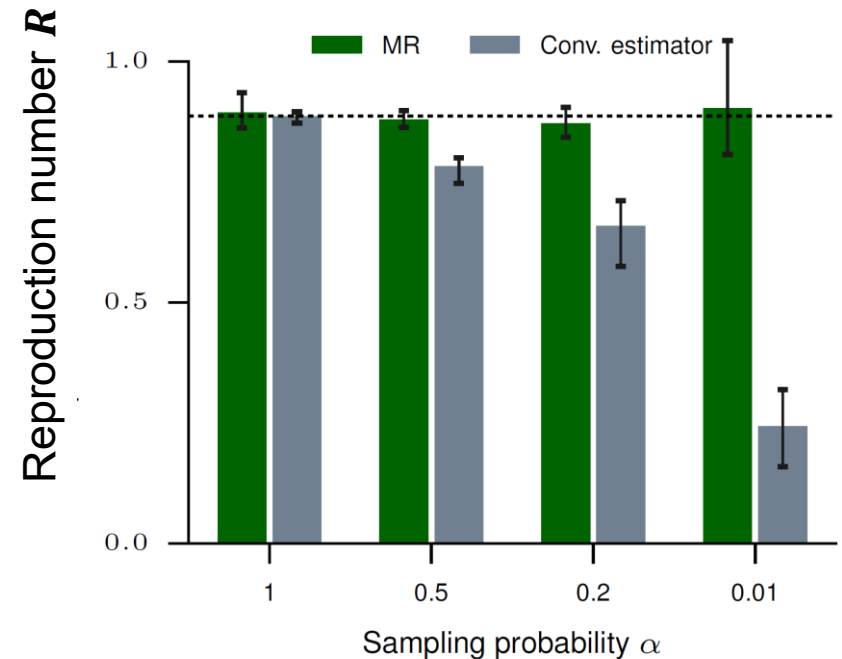
[Levina & VP, Nature Communications, 2017]

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:

[VP et al., The Lancet, 2021a,b,c]

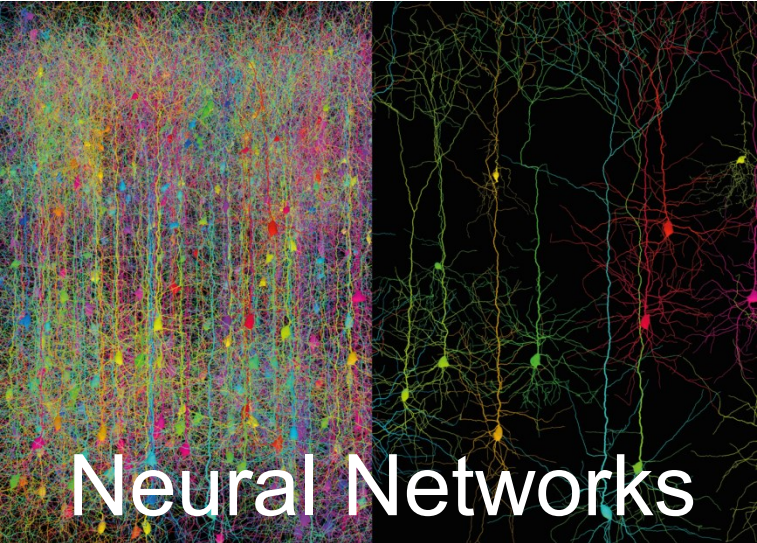
[Bauer et int., VP, Plos CB, 2021]

[Contreras et int., VP, Nat Commun, 2021]

[Linden et int., VP, Dtsch. Arzteblt Int. 2020]

[Wilting & VP, Nature Communications, 2018]

Subsampling is a Ubiquitous Challenge

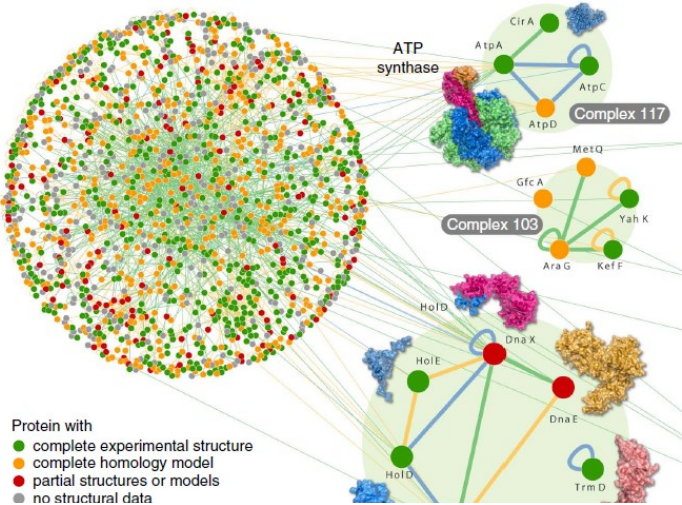


Disease Propagation

"I don't know what these dots are ...
but ya mind if I connect 'em?"



Social or Ecological Systems



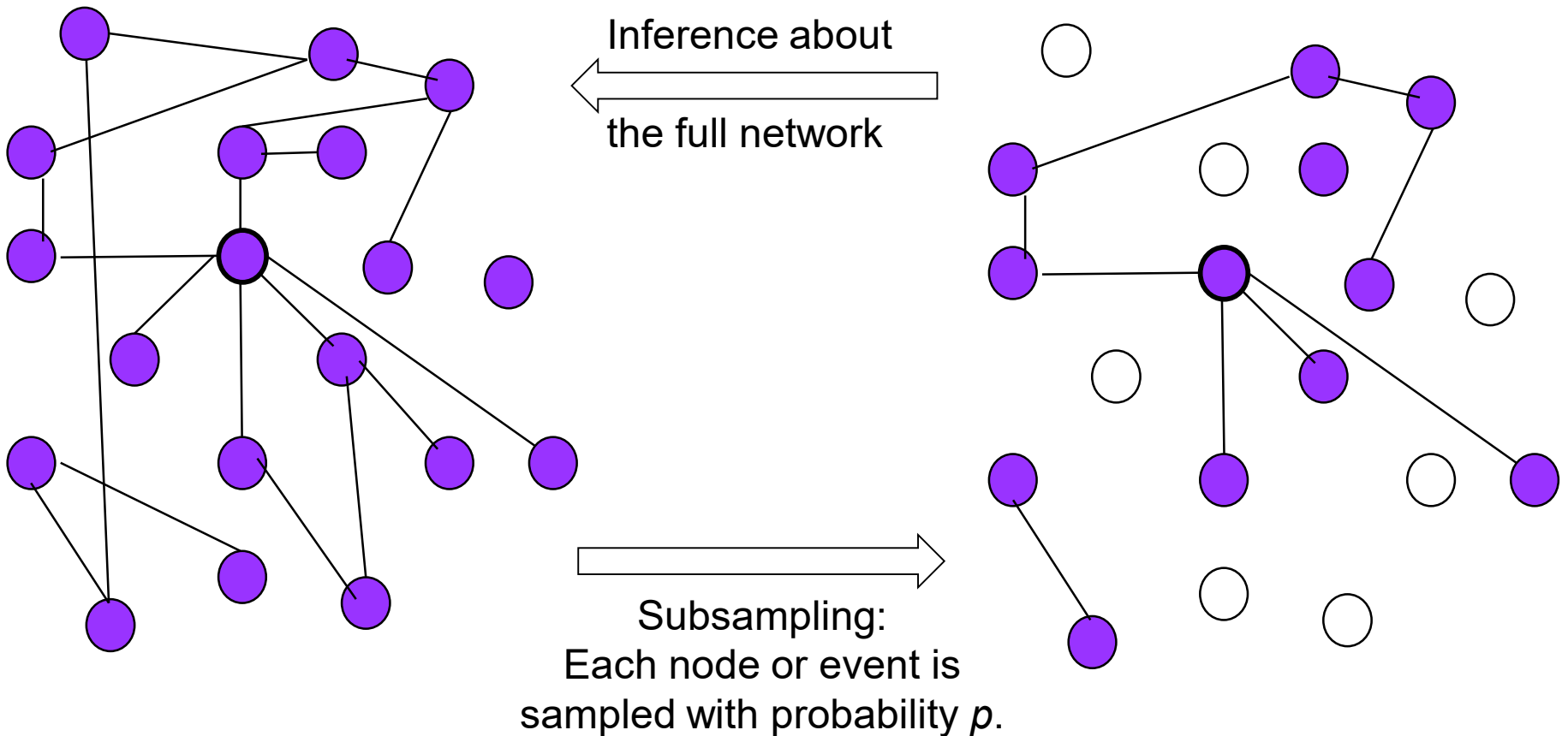
Protein Networks

[Rajagopala et al., 2014]

[Grandjean, 2014]

Subsampling Scaling Theory

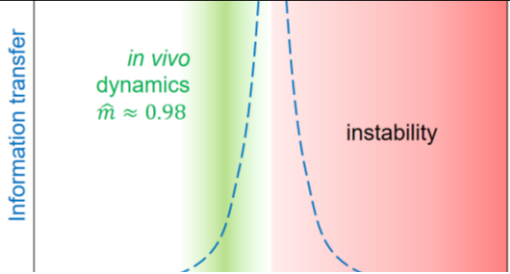
Levina & Prieemann, Nature Communications, 2017



→ Subsampling scaling theory
for graph degree distributions,
clustering, or avalanche size distributions

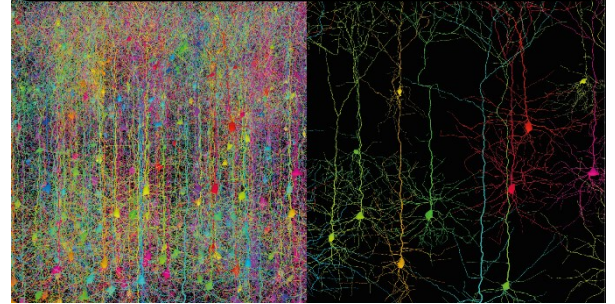
Physics of Neural Systems

Spreading Dynamics and Phase Transitions



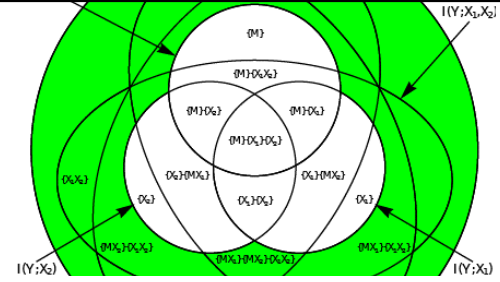
VP et al., Plos Comp Biol., 2013
 Wilting & VP, Cerebr. Ctx, 2019
 Wilting & VP, Curr Op Neurosci, 2019
 Neto, Spitzner & VP, arxiv; Spitzner et al., arxiv

Subsampling Theory



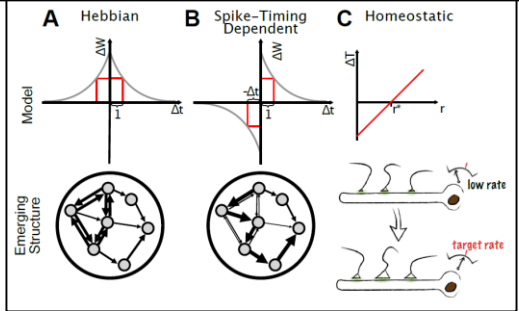
VP et al., 2009, 2013, 2014
 Levina & VP, Nat. Commun., 2017
 Wilting & VP, Nat. Commun., 2018
 Zierenberg et al., PRE & PRR, 2020

Information Theory to Quantify & Design Computation



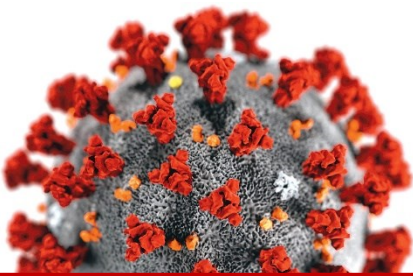
Wibral, Lizier & VP, Matter to Life, 2017
 Wollstadt et al., Plos CB, 2017
 Wibral et al., Entropy, 2017
 Rudelt, ... VP, biorxiv, 2020

Local Learning Rules to Optimize Computation

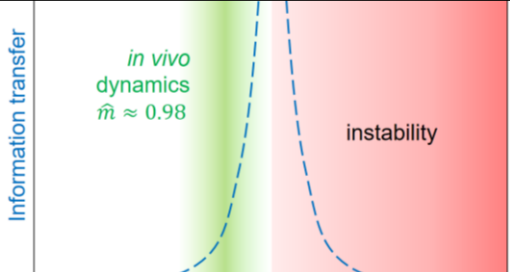


Zierenberg, ... VP, Phys Rev X, 2018
 del Papa, VP & Triesch, 2017, 2019
 Cramer, ... VP, Nat Commun., 2020
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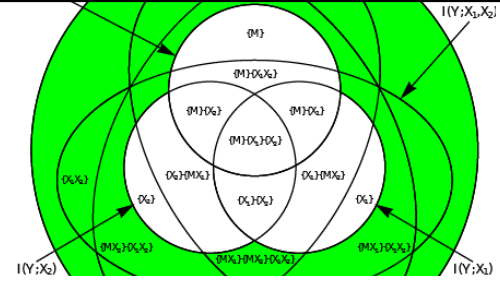


Spreading Dynamics and Phase Transitions



COVID-19
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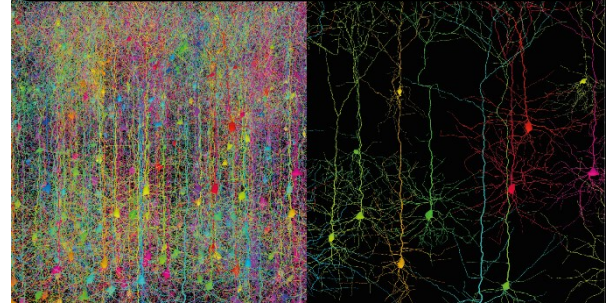
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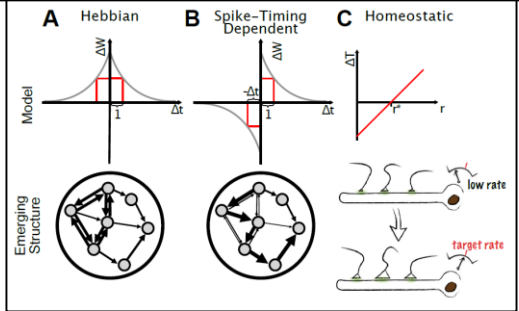
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Subsampling Theory



VP et al., 2009, 2013, 2014
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 Wilting & VP, Nat. Commun., 2018
 Zierenberg et al., PRE & PRR, 2020

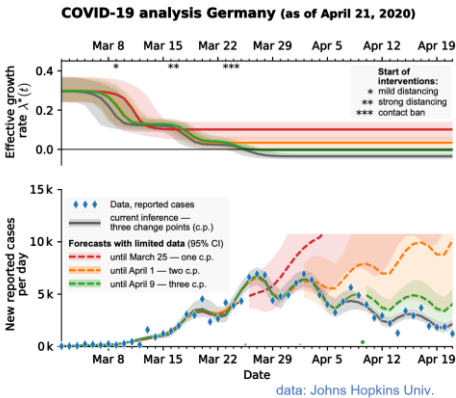
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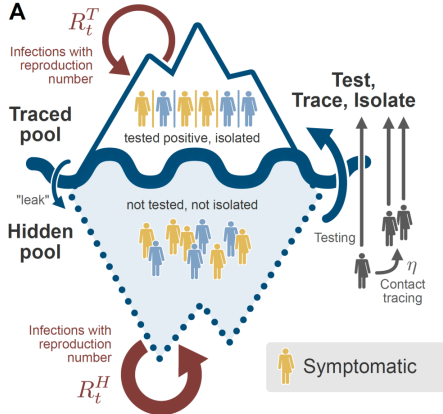
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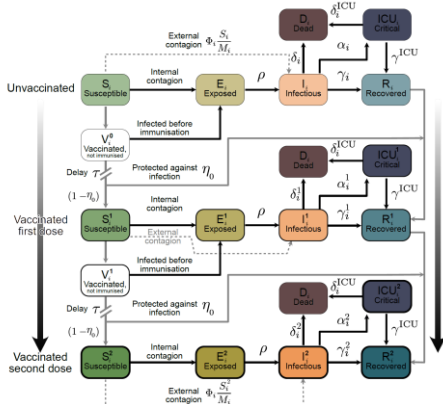
- Quantifying the Effectiveness of COVID-19 Interventions using Bayesian Inference (Dehning et al. Science 2020)



- Mitigating the Spread of COVID-19 via Test-Trace-Isolate (TTI) (Contreras et al. Nat Commun 2021) (Contreras et al. Science Adv., 2021)



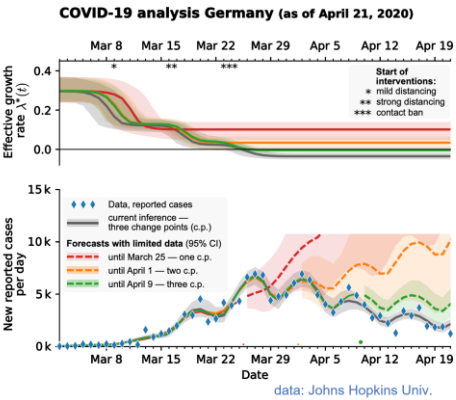
- The Progress of Vaccination Determines the Pace to Lift Restrictions (Bauer, et al. Plos Comp Biol., 2021)



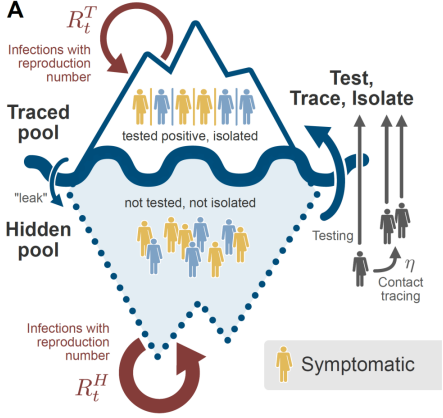
- Estimation of the Underreporting (Linden et al. Dt. Arztebl Int, 2020)

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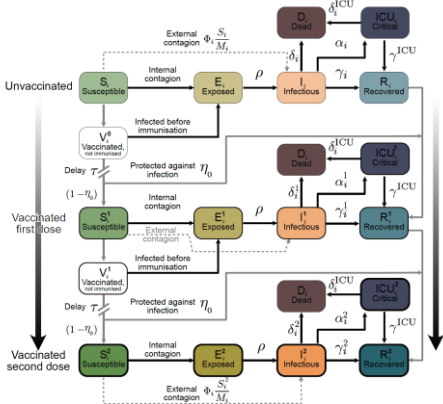
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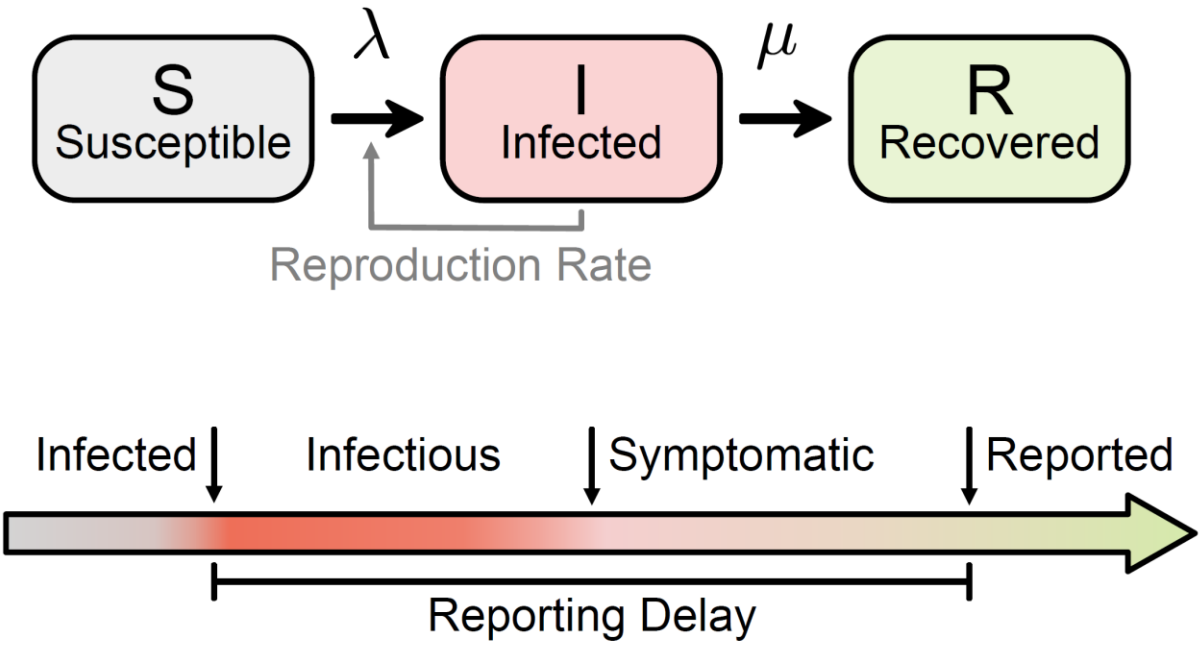
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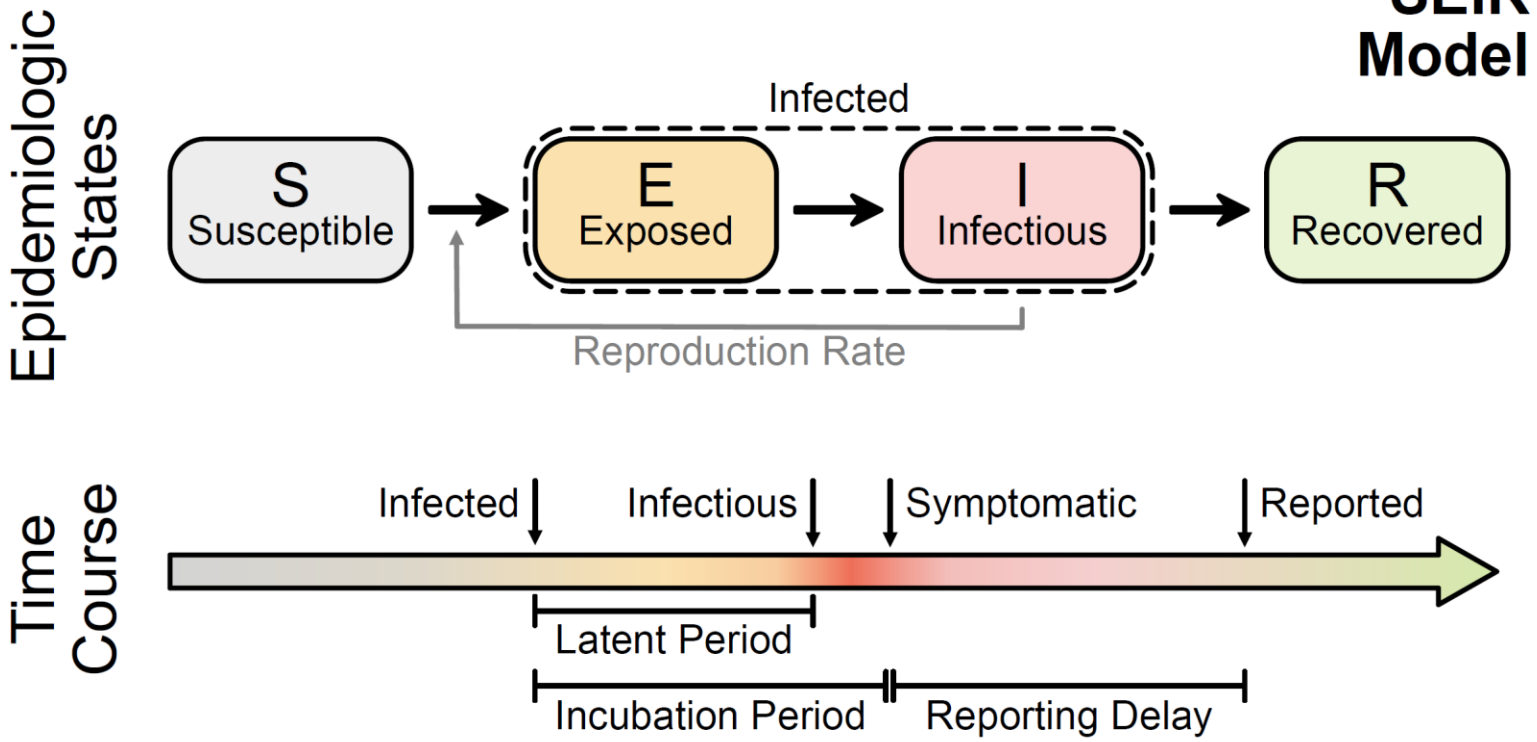
SIR: Susceptible-Infected-Recovered

SIR Model

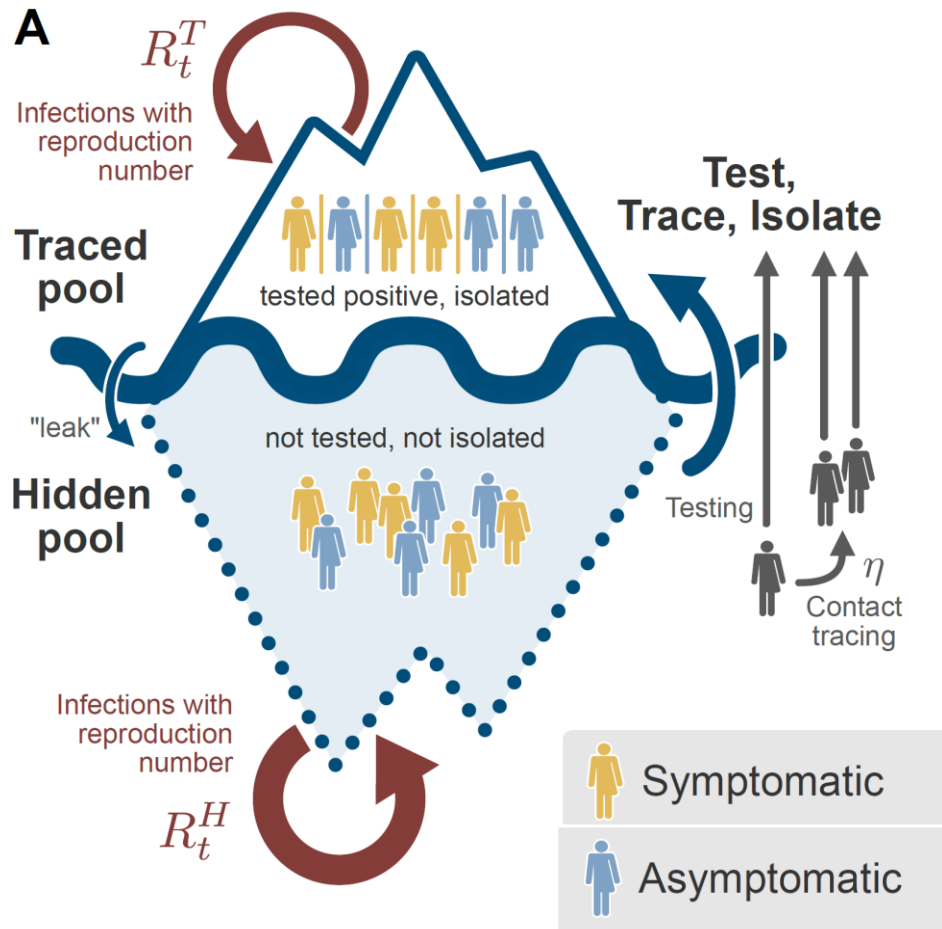


$$\begin{aligned} \frac{dS}{dt} &= -\lambda \frac{SI}{N} \\ \frac{dI}{dt} &= \lambda \frac{SI}{N} - \mu I \\ \frac{dR}{dt} &= \mu I \end{aligned}$$

SEIR: Susceptible-Exposed-Infected-Recovered



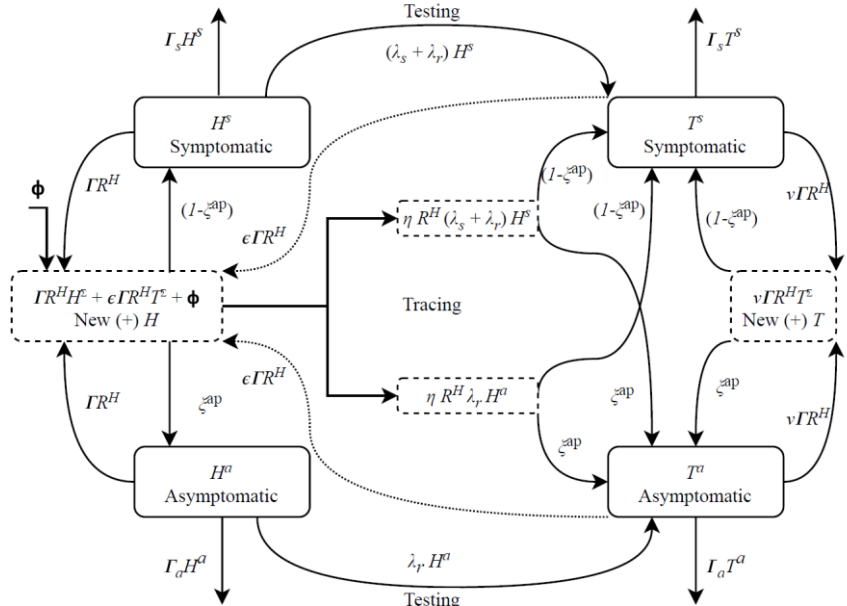
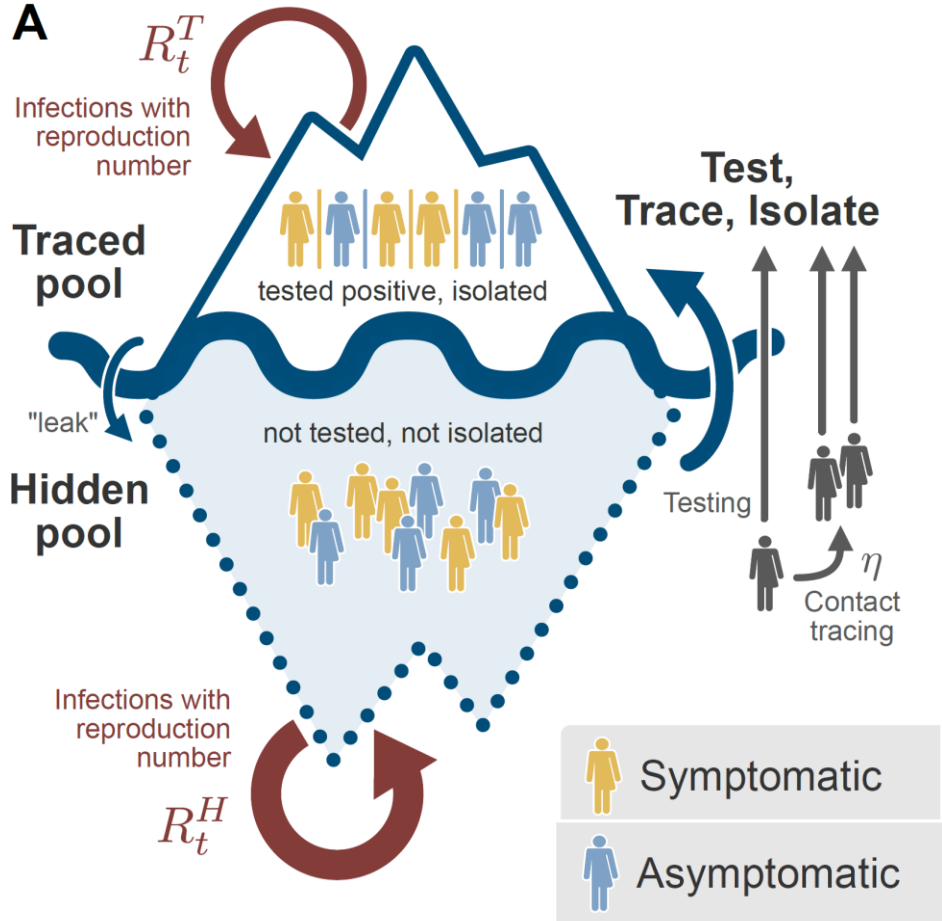
Test-Trace-and-Isolate (TTI) contributes to containment



Test-Trace-Isolate (TTI) is not perfect:

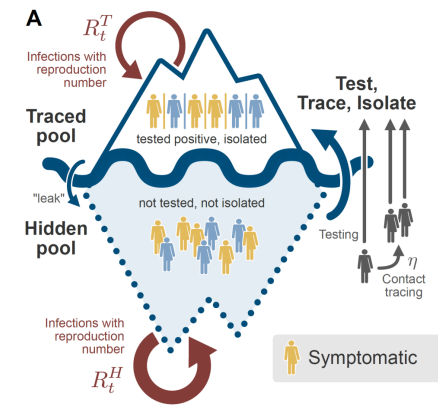
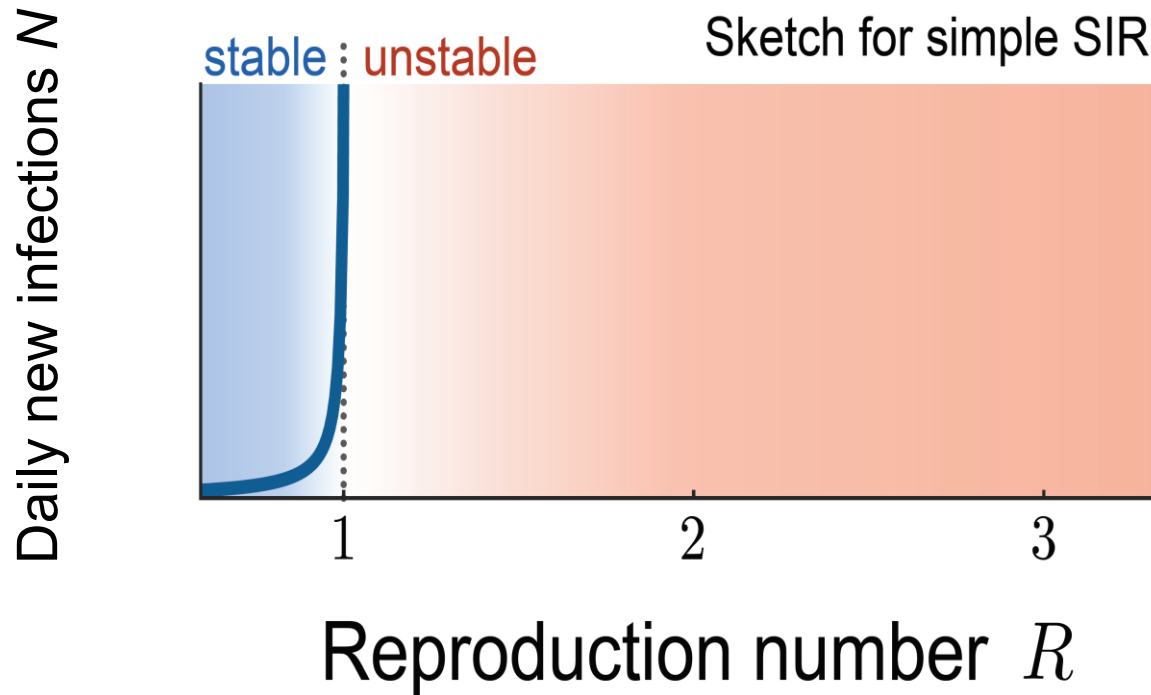
- Pre- and asymptomatic infection are hard to detect
- Contacts are missed (1/3)
- Quarantine is not perfect
- People who do not get tested (20%)
- Introduction of new infectious from abroad
- Limited capacities of health offices for testing and tracing

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

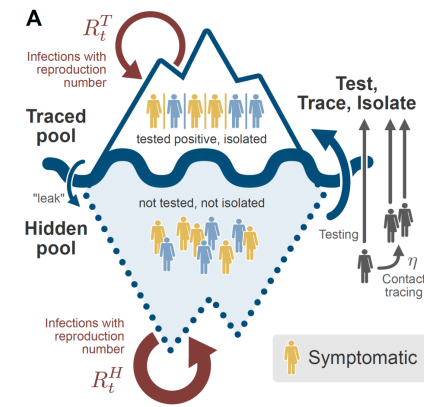
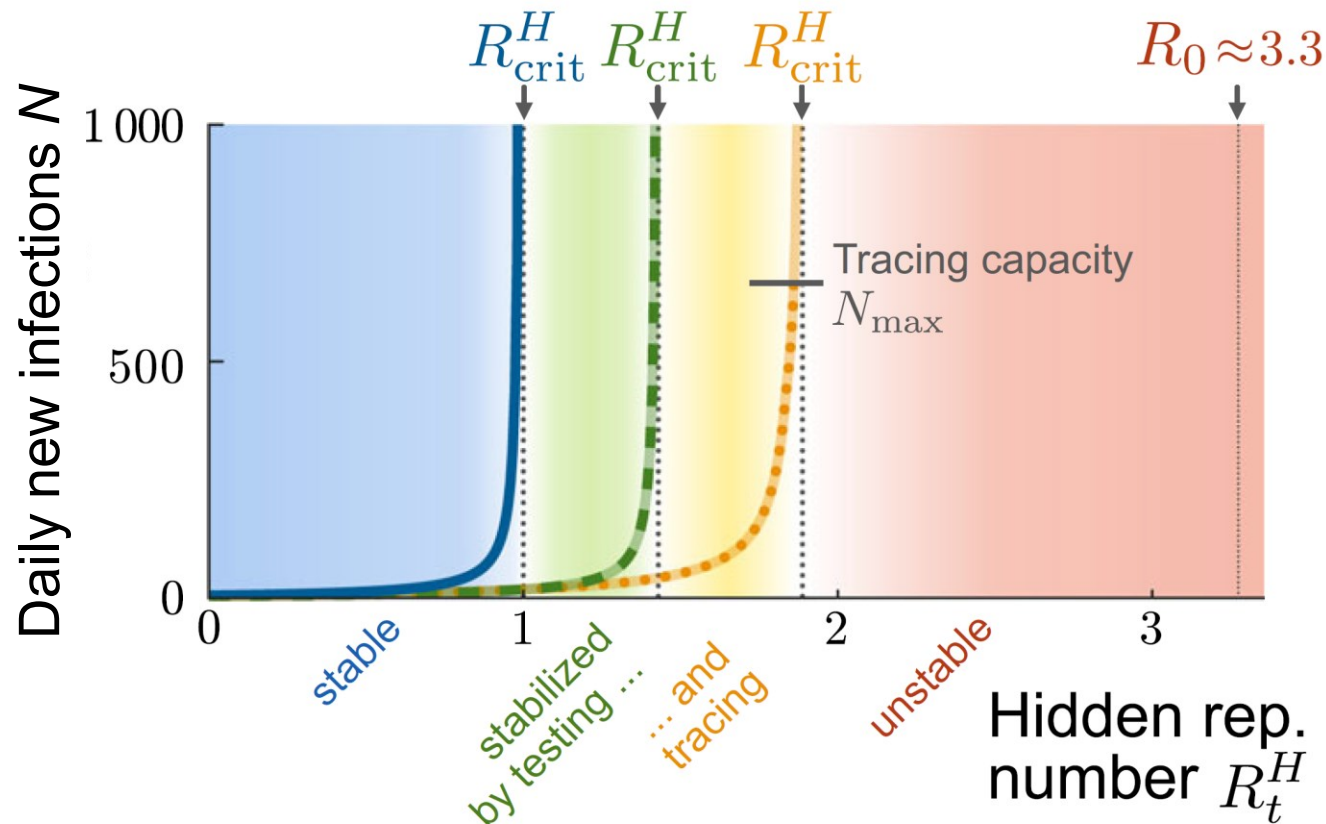
$$N \approx \frac{\Phi}{R_c - R} = \frac{\Phi}{1 - R}, \quad \text{for } R < 1$$



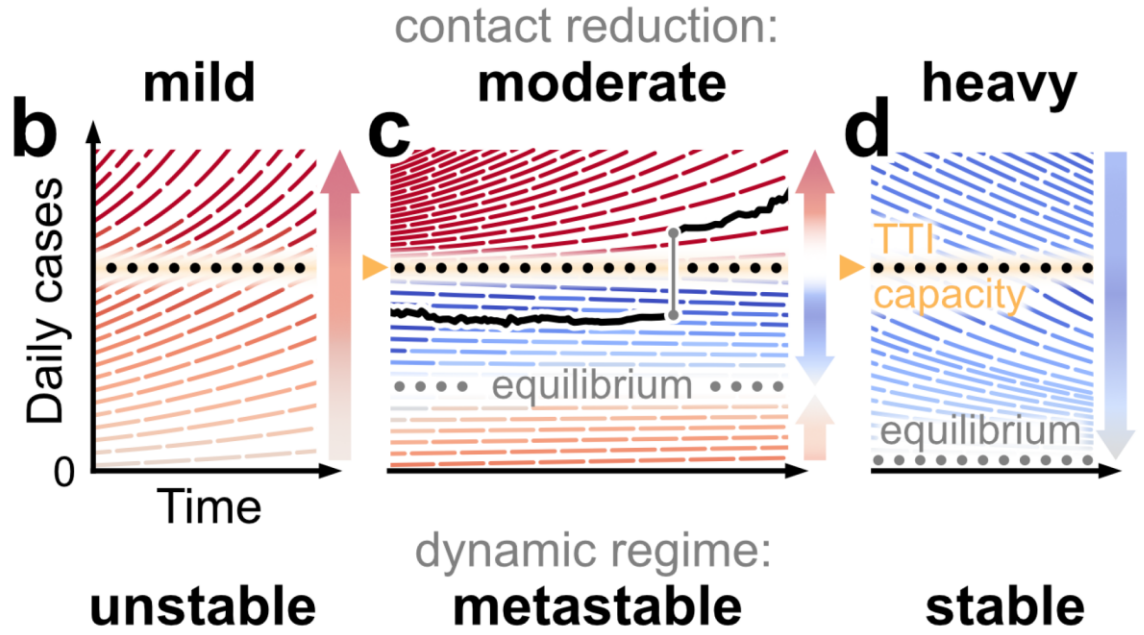
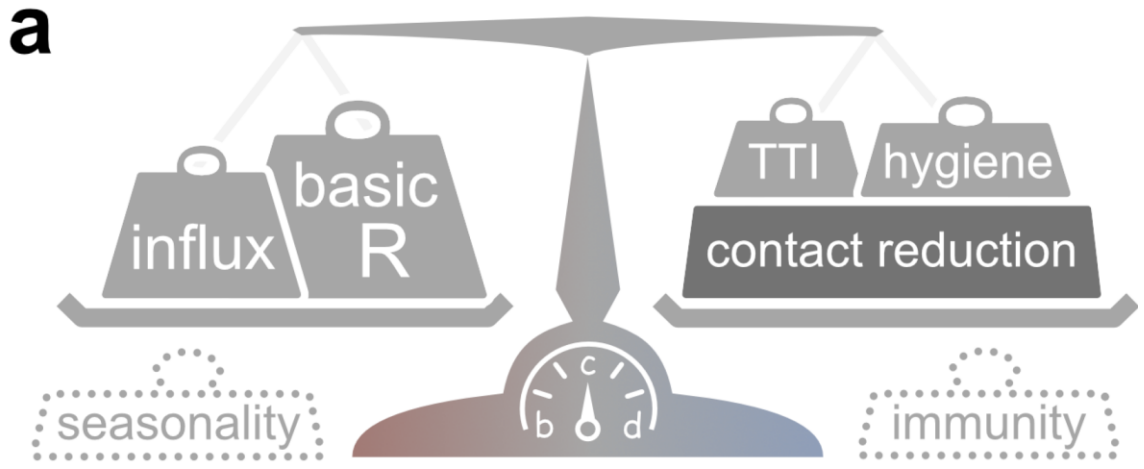
Test-Trace-Isolate (TTI)

pushes the transition to instability R_c to higher contact rates

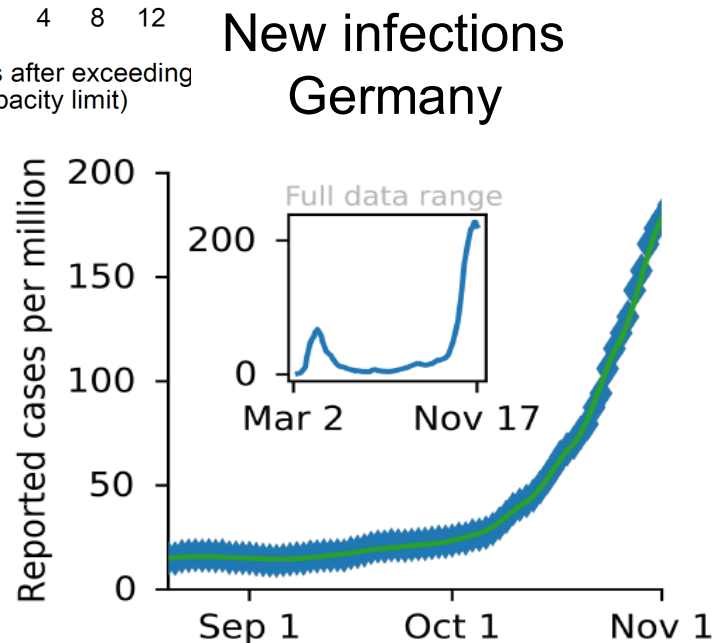
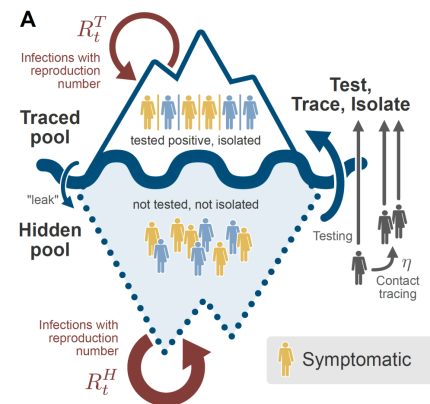
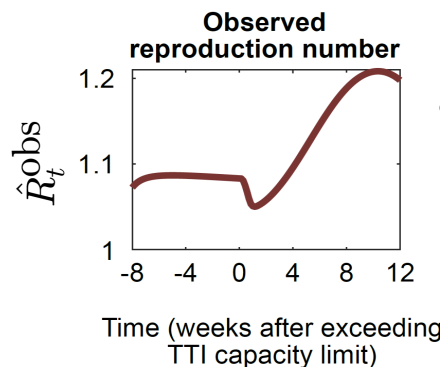
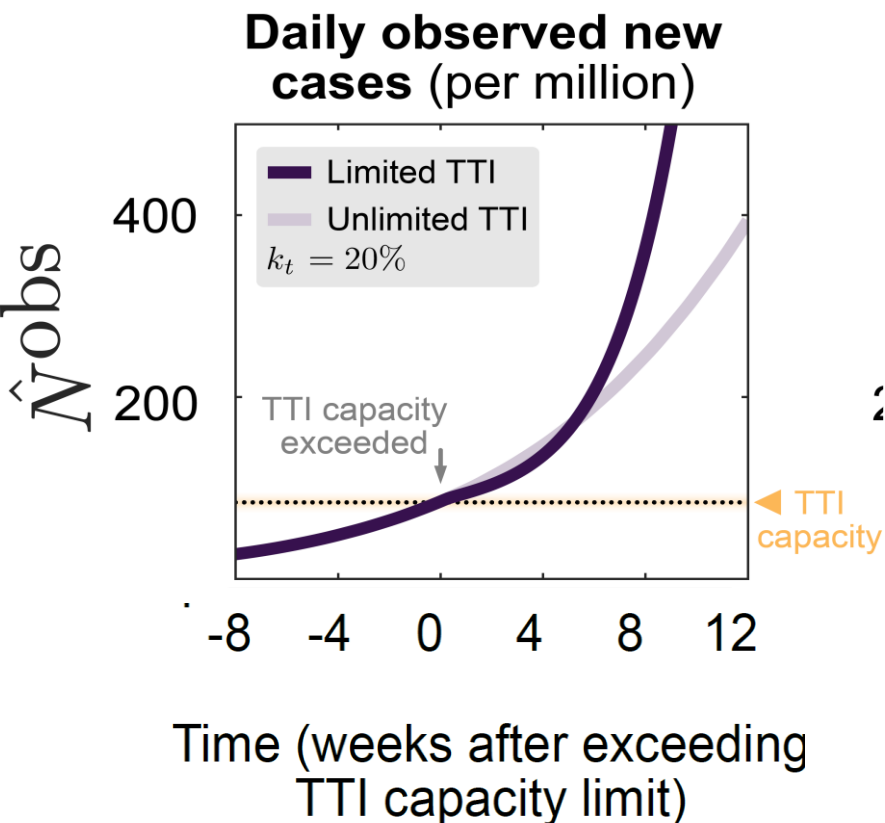
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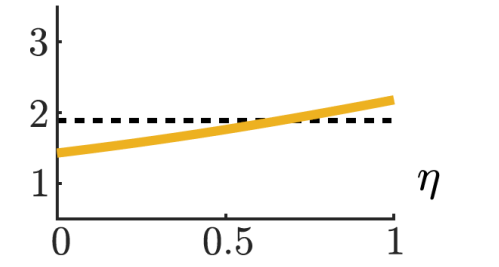
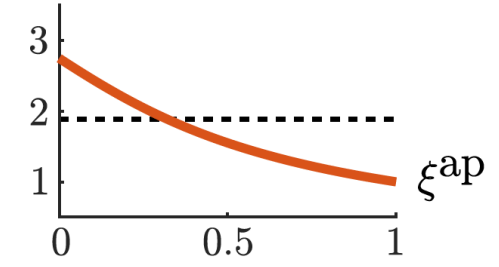
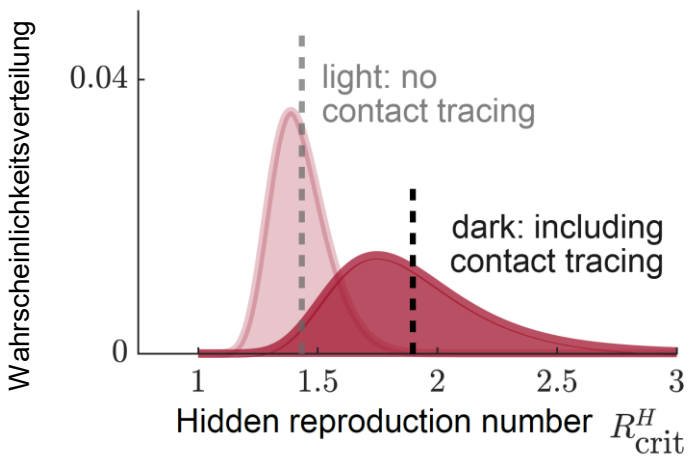
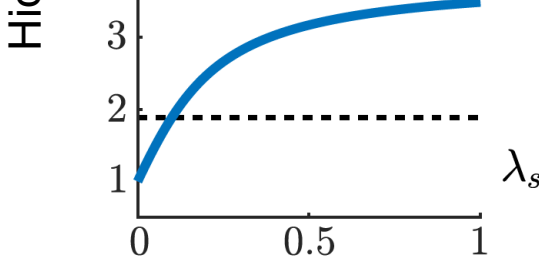
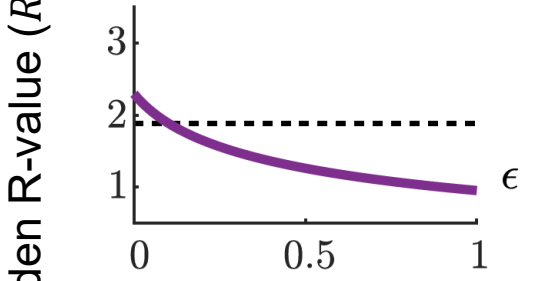
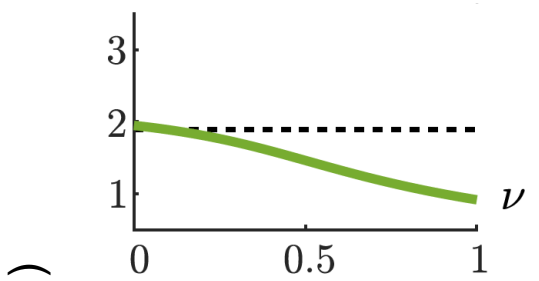
Combined measures to contain COVID-19



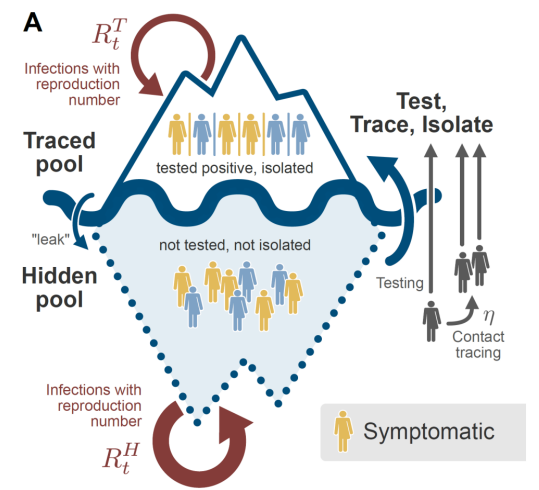
Crossing the TTI Limit: Case numbers grow faster than exponential



Sensitivity Analysis

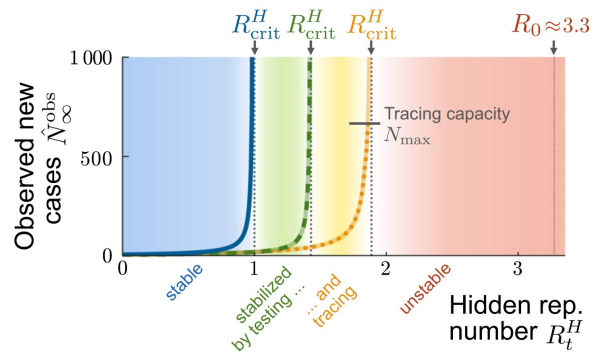
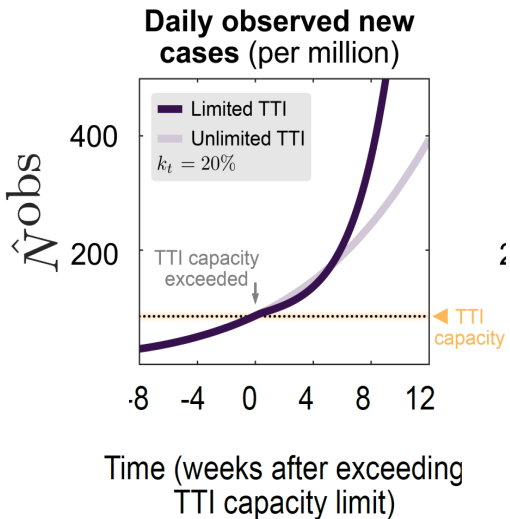
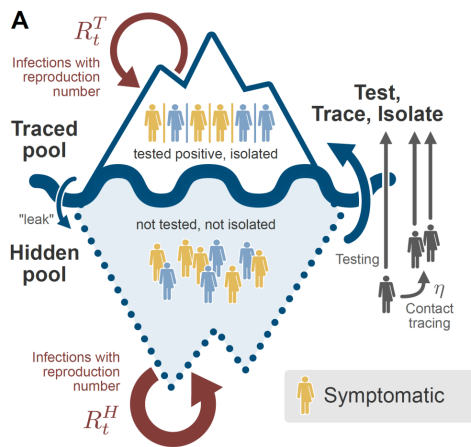


- ν Isolation factor
- ϵ "leak" factor
- λ_s Symptom-driven testing
- ξ^{ap} Apparent asymptomatic fraction
- η Tracing efficiency



Summary of the TTI strategy

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



The undetected cases contribute most strongly to the spread

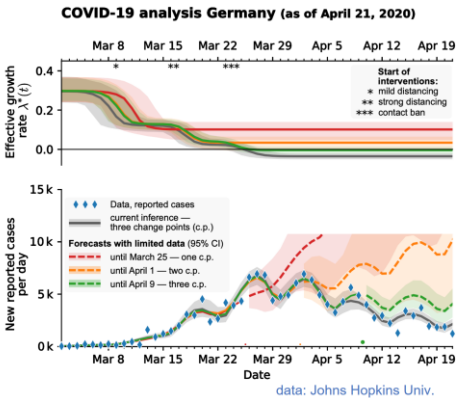
If the TTI capacity is surpassed, a tipping point is crossed, and growth self-accelerates.

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

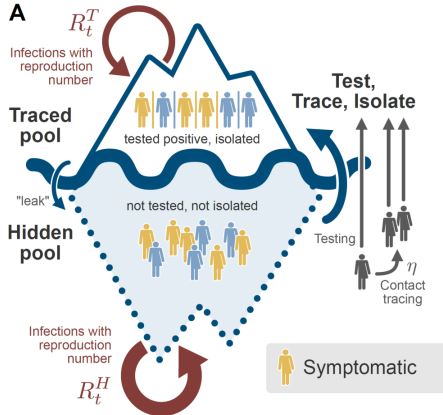
<https://arxiv.org/pdf/2011.11413> [Contreras et int., Priesemann, Science Advances, 2021]
<https://arxiv.org/pdf/2009.05732> [Contreras et int., Priesemann, Nature Communications, 2021]

Overview

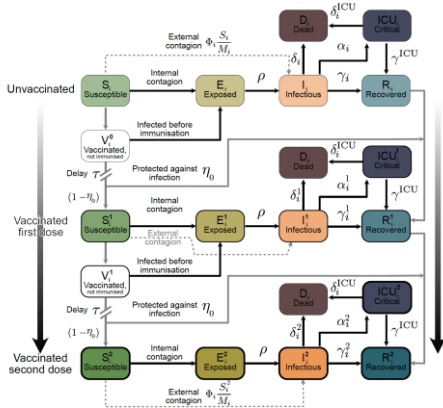
- Quantifying the Effectiveness of COVID-19 Interventions using Bayesian Inference (Dehning et al., Science 2020)



- Mitigating the Spread of COVID-19 via Test-Trace-Isolate (TTI) (Contreras et al., Nat Commun 2021) (Contreras et al., Science Adv., 2021)



- The Progress of Vaccination Determines the Pace to Lift Restrictions (Bauer, et al., Plos Comp Biol., 2021)



- Estimation of the Dark Figure (Linden et al., Dt. Arztebl Int, 2020)

Transdisciplinary Position Papers

- **Initiating discourse and coordinating consensus among dozens of scientists across disciplines**
(Virology, Sociology, Epidemiology, Economy, Public Health...)
- **Timely handling of urgent policy questions**
- **Clear communication** of current state of knowledge *and* of uncertainty
- Public outreach (print, radio, TV, social media)
- Political advising
- Expert papers: The Leopoldina, The Lancet, Zeit, SZ, FAZ, Politico [...]

Expert Paper signed by more than 1000 European scientists.

C. Altmann, K. Becker, M. Brinkmann, S. Ciesek, C. Drosten, C. Fuest, G. Haug, M. Kleiner, H. Kroemer, R. Neugebauer, B. Prainsack, M. Stratmann, H. Streeck, L. Wieler, O. Wiestler [...]

[Priesemann et al., The Lancet, 2021a,b,c]



Published Online
December 18, 2020
[https://doi.org/10.1016/S0140-6736\(20\)32625-8](https://doi.org/10.1016/S0140-6736(20)32625-8)

Calling for pan-European commitment for rapid and sustained reduction in SARS-CoV-2 infections

Across Europe, the COVID-19 pandemic is causing excess deaths, placing a burden on societies and health systems and harming the economy. European governments have yet to develop a common vision to guide the management of the pandemic. Overwhelming evidence shows that not only public health, but also society and the economy benefit greatly from reducing cases of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection. Vaccines will help control the virus, but not until late 2021.

If European governments do not act now, further waves of infection are

to be expected, with consequential damage to health, society, jobs, and businesses. With open borders across Europe, a single country alone cannot keep the number of COVID-19 cases low; joint action and common goals among countries are therefore essential. We therefore call for a strong, coordinated European response and clearly defined goals for the medium and long term. Achieving and maintaining low case numbers should be the common, pan-European goal for the following reasons.

First, low case numbers save lives, and fewer people will die or suffer from long-term effects of COVID-19. In addition, medical resources will not be diverted from other patients in need.

Second, low case numbers save jobs and businesses. The economic impact of COVID-19 is driven by viral

Panel: A joint European strategy for the COVID-19 pandemic

1 Achieve low case numbers

- Aim for a target of no more than ten new COVID-19 cases per million people per day. This target has been reached in many countries, and can be reached again throughout Europe by spring, 2021, at the latest.
- Take firm action to reduce case numbers quickly. Strong interventions have proven efficient and balance the rapid achievement of low case numbers against the strain on mental health and the economy.
- To avoid a ping-pong effect of importing and reimporting severe acute respiratory syndrome coronavirus 2 infections, the reduction should be synchronised across all European countries and start as soon as possible. This synchronisation will allow European borders to stay open.

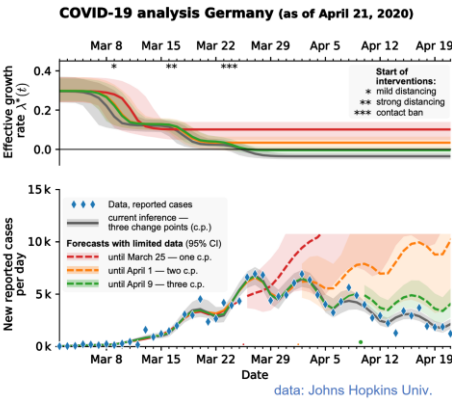
2 Keep case numbers low

- When case numbers are low, easing of restrictions is possible but should be carefully monitored. Continue and improve targeted mitigation measures, such as mask wearing, hygiene, moderate contact reduction, testing, and contact tracing.

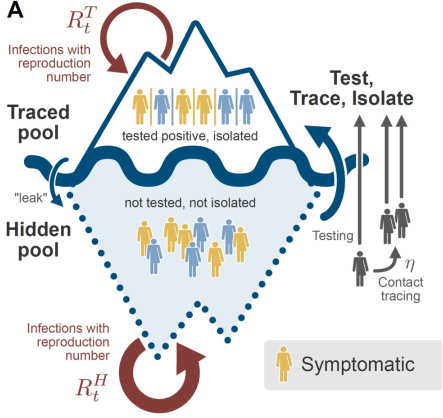
Text and Supporters <https://www.containcovid-pan.eu>

Overview

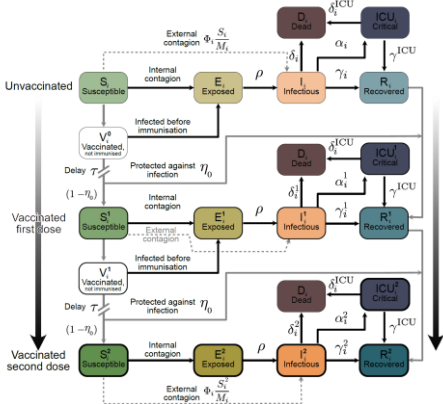
- Inferring the Magnitude of Change Points and Interventions for the Spread of COVID-19**
 (Dehning et al. Science, 2020)



- Mitigating the Spread of COVID-19 via test-trace-isolate (TTI)**
 (Contreras et al. Nat Commun, 2021)
 (Contreras et al. Science Adv., 2021)



- The progress of vaccination determines the pace to lift restrictions**
 (Bauer, et al. Plos Comp Biol., 2021)



- Estimation of the Underreporting**
 (Linden et al. Dt. Arztebl Int, 2020)

Overview

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- **Subsampling Theory:** Inferring collective properties even under sparse spatial sampling

Levina & VP, Nat Commun, 2017
Wilting & VP, Nat Commun, 2018

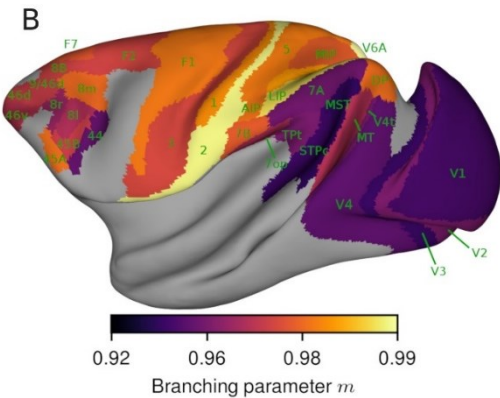
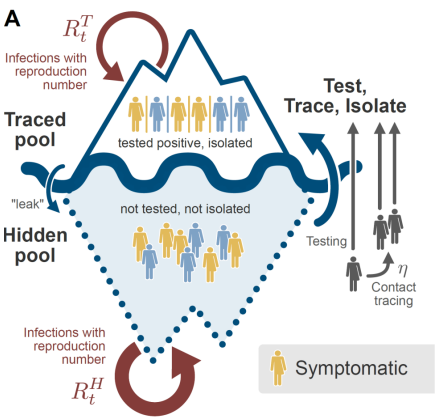
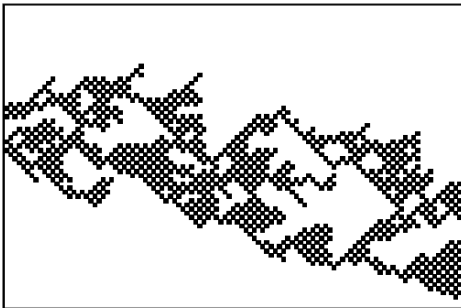
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VP et al., The Lancet, 2021a,b,c

- **Collective Computation in Living Neural Networks:** Critical phenomena, fine-tuning of computation, and clinical implications

Cramer et int., VP. Nat Commun, 2020
Hagemann et int., VP, Plos Comp Biol., 2021
Zierenberg, Wilting & Priesemann, PRX, 2018

- **Research Perspective**



Why are we interested in branching processes?

Inferring Spreading Dynamics

control parameter R

expected number of “children”



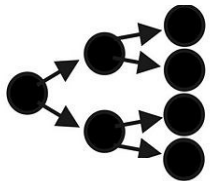
$$R < 1$$

subcritical



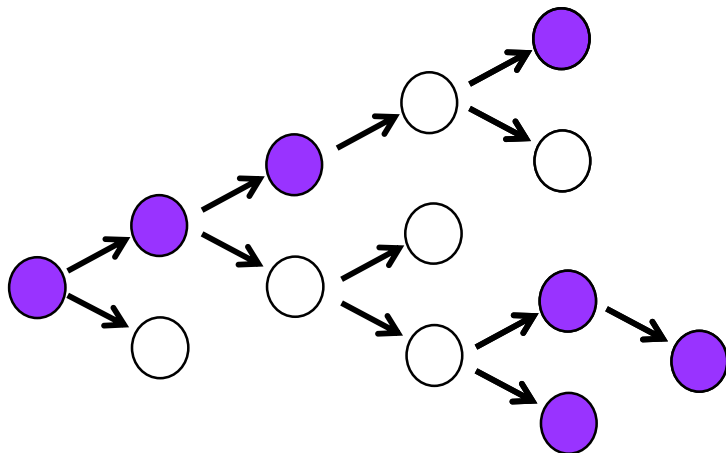
$$R = R_c = 1$$

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!**

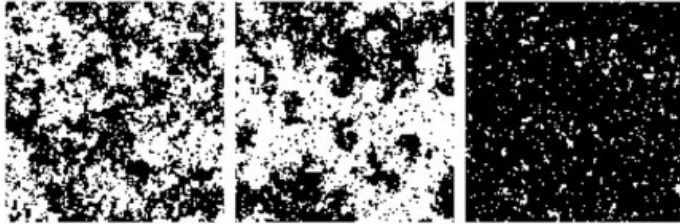
Adopted by: J.Beggs, K.Hengen, C.Buttering; e.g. Ma et al., Neuron, 2019

[Dehning et al., Science, 2020]

[Wilting & VP, Nature Communications, 2018]

[Levina & VP, Nature Communications, 2017]

Critical Phenomena



$T > T_c$

$T = T_c$

$T < T_c$

Ising Model

Divergence at $T = T_c$:

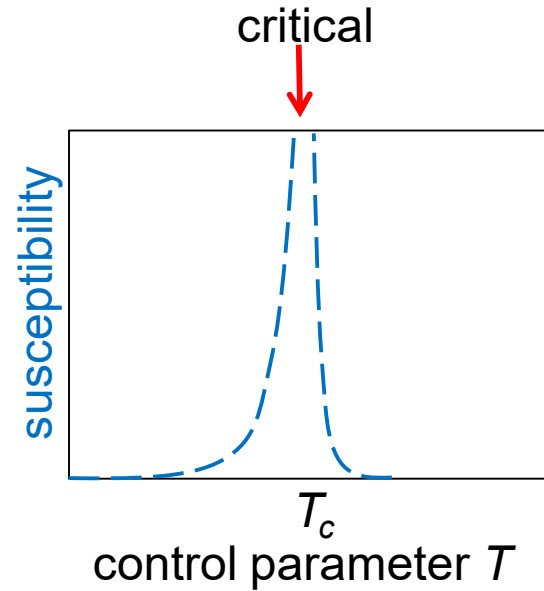
- Susceptibility
- Specific heat
- Correlation length

Neural Network

Control parameter: Effective coupling strength

- Sensitivity to input
- Coding space
- Long-range communication (space)
Active memory (time)

→ Criticality can maximize
information processing properties



Quantifying Information Processing

Chris Langton / Alain Turing

Information processing can be decomposed into:

- Transfer
- Storage
- Modification



Chris Langton

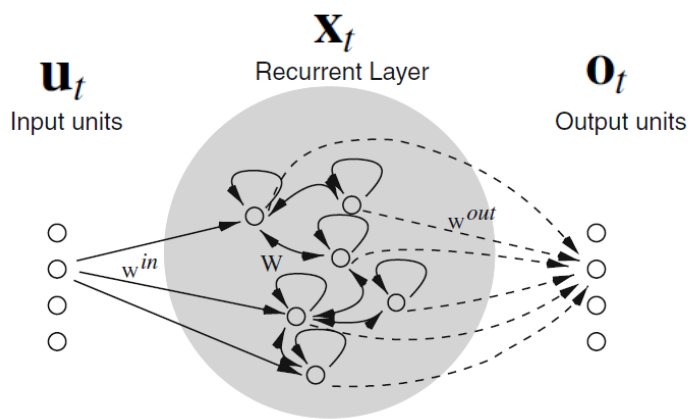
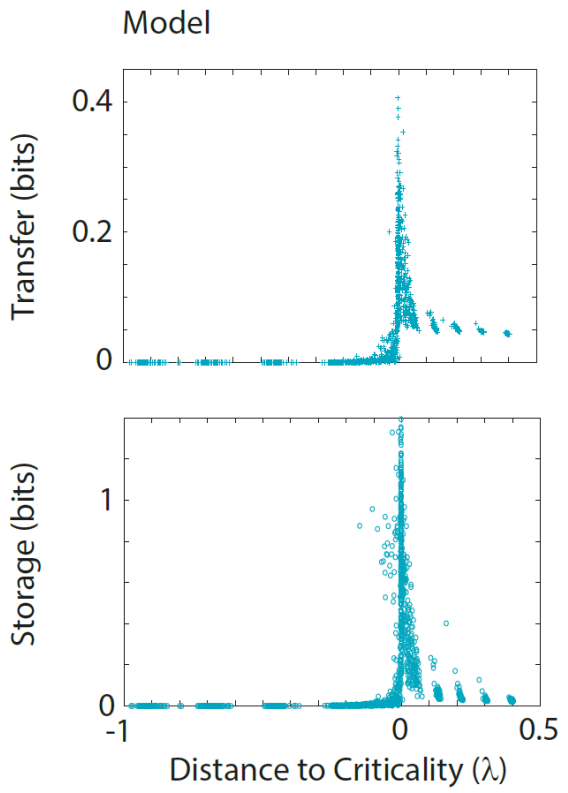
information transfer:

$$TE(\mathbf{X}^- \rightarrow Y^t) = I(Y^t; \mathbf{X}^- | \mathbf{Y}^-)$$

active information storage:

$$AIS(\mathbf{X}^- \rightarrow X^t) = I(X^t; \mathbf{X}^-)$$

Computational Properties at Criticality



Task performance that requires information storage is optimal if the reservoir network is close to a **critical state**

- Crutchfield & Young, 1989, 1990
- Hubermann, 1990
- Langton, 1990
- Li et al., 1990
- Kauffman, 1990
- Arnold, 1996
- Kentridge, 1997
- Greenfield & Lécarr, 2001
- Bertschinger & Natschlaeger, 2004
- Haldemann & Beggs, 2005
- Kinouchi & Kopelli, 2006
- Legenstein & Maass, 2007
- Larremore et al., 2011a,b
- Lizier et al., 2011
- Shew et al., 2011
- Boedecker et al., 2012**
- Barnett et al., 2013
- Beggs & Timme, 2013
- Shew & Plenz, 2013
- Tomen et al., 2014
- [...]

maximal entropy
minimal redundancy

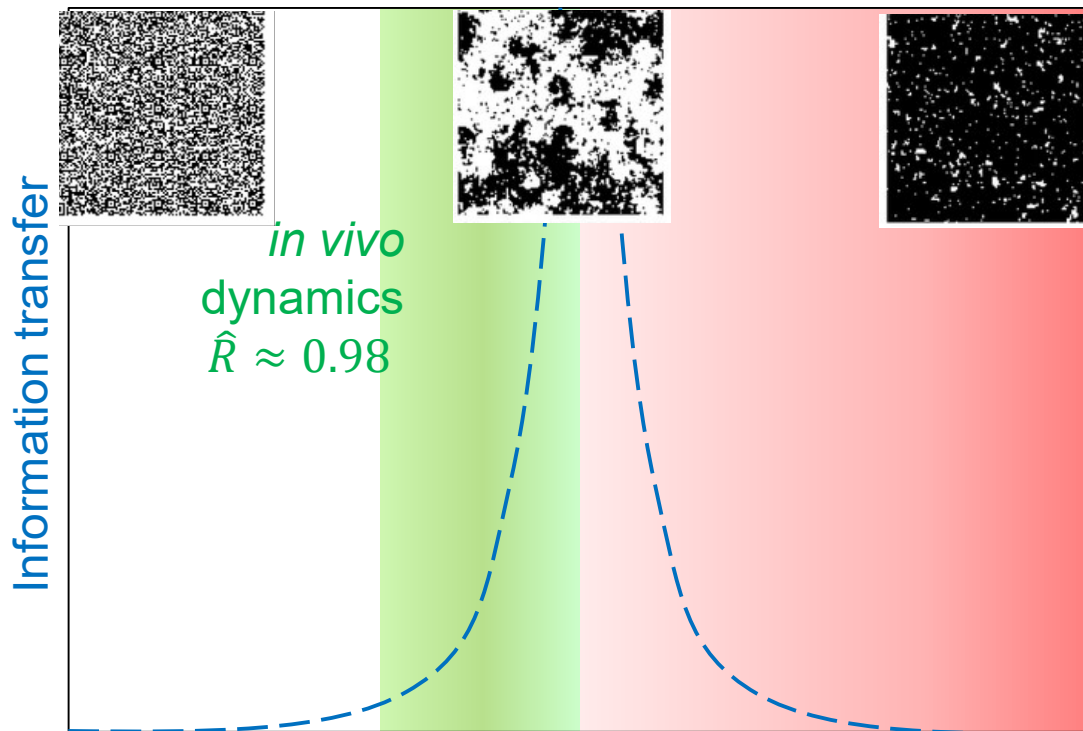
strong amplification
long reverberations

instability
epilepsy

disordered

critical

correlated



in vivo
dynamics
 $\hat{R} \approx 0.98$

Reverberating
regime in rat, cat,
monkey & human:

weak

$R_c = 1$

strong

coupling strength R
(control parameter)

VP et al., 2014

Wilting & VP, 2018

Wilting et al., 2018

Wilting & VP, 2019

Neto, Spitzner & VP, arxiv

Hagemann et al., 2021

maximal entropy
minimal redundancy

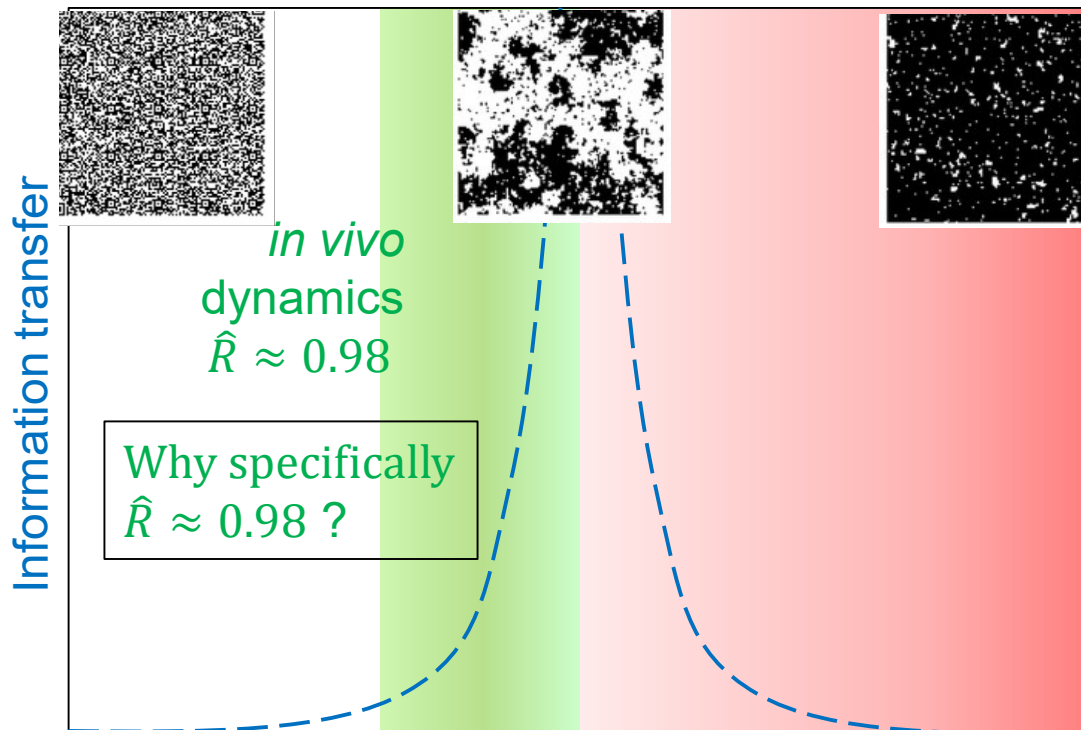
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Hagemann et al., in prep

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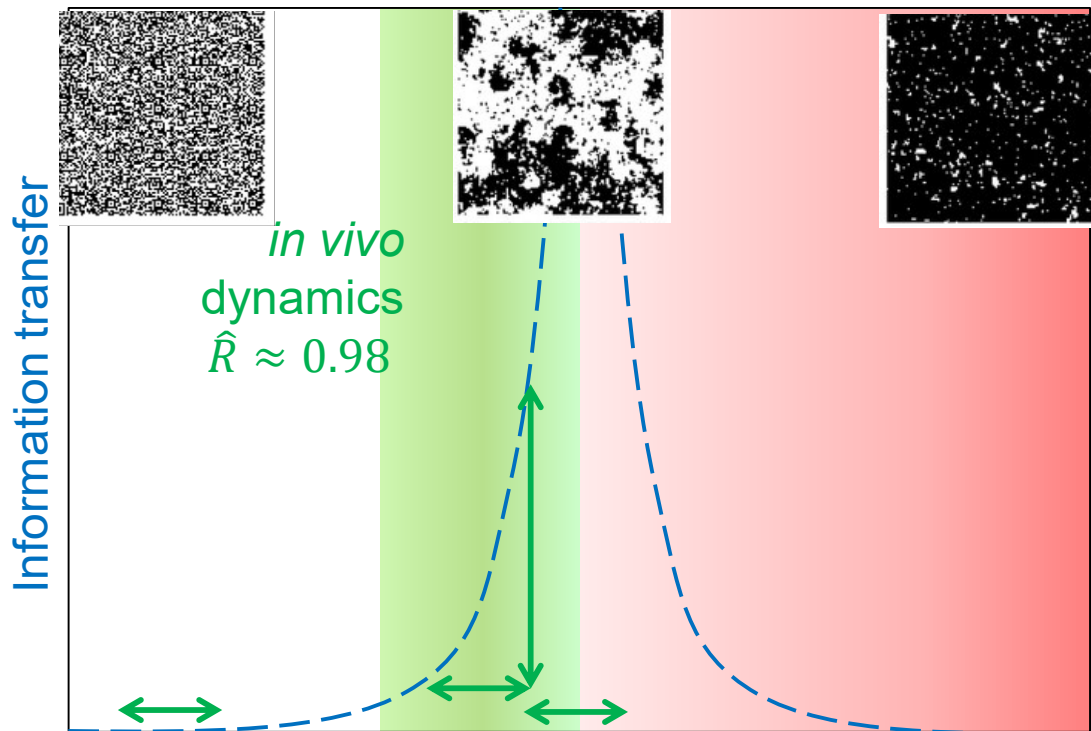
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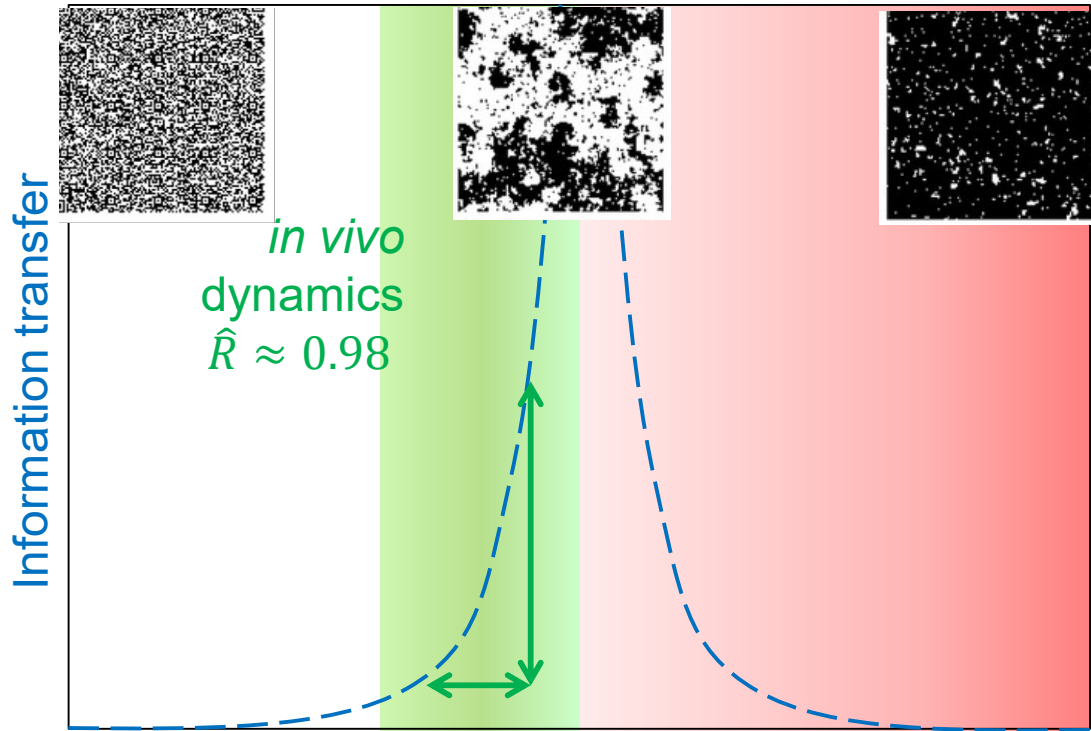
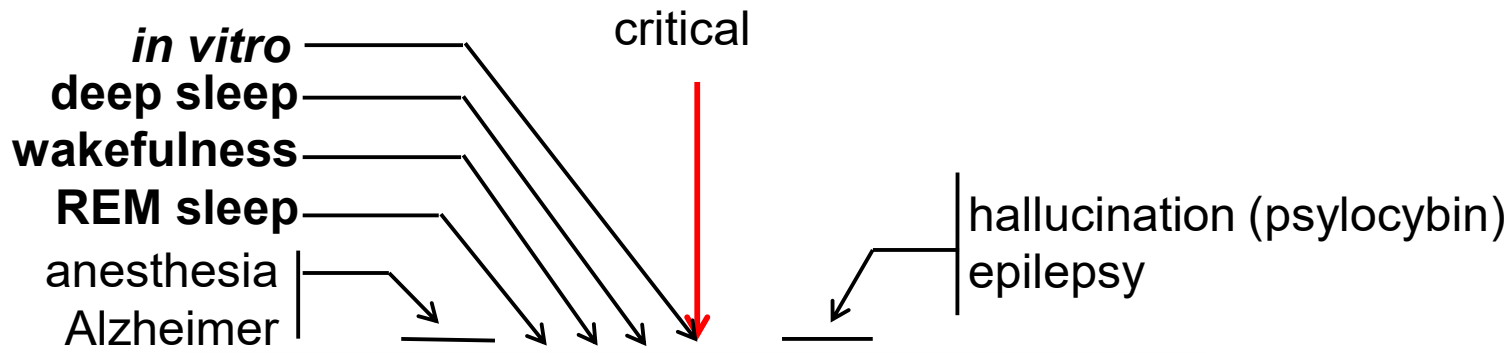
correlated



Reverberating regime in rat, cat, monkey & human:

Dynamic Computation:
Rapid tuning to computational needs

VP et al., 2014
Wilting & VP, 2018
Wilting et al., 2018
Wilting & VP, 2019
Neto, Spitzner & VP, arxiv
Hagemann et al., in prep



Carhart-Harris, et al., 2013
 Dehning, ... VP, in prep
 Hagemann, ... VP, in prep
 Linkenkaer-Hansen, 2001
 Montez et al., 2009
 Tagliacucchi et al., 2014ff
 Tetzlaff et al., 2010
 Tomen et al., 2017
 Levina & VP, 2017
 VP et al., 2013, 2014
 Wilting & VP, 2018, 2019
 Zierenberg, ... VP, 2018

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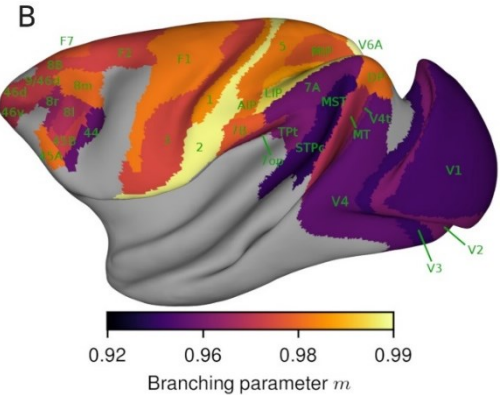
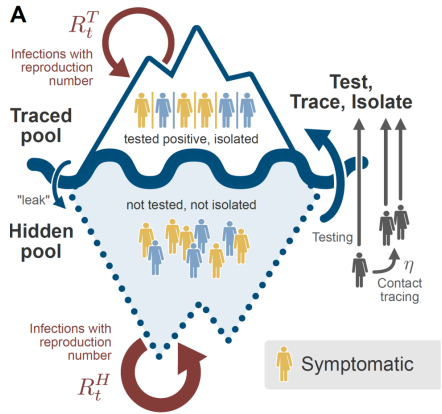
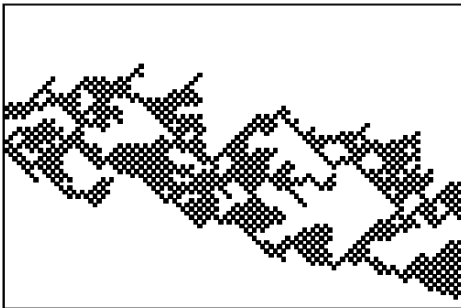
Bauer et int., Priesemann, Plos Comp Biol, 2021
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- **Collective Computation in Living Neural Networks:** Critical phenomena, fine-tuning of computation, and clinical implications

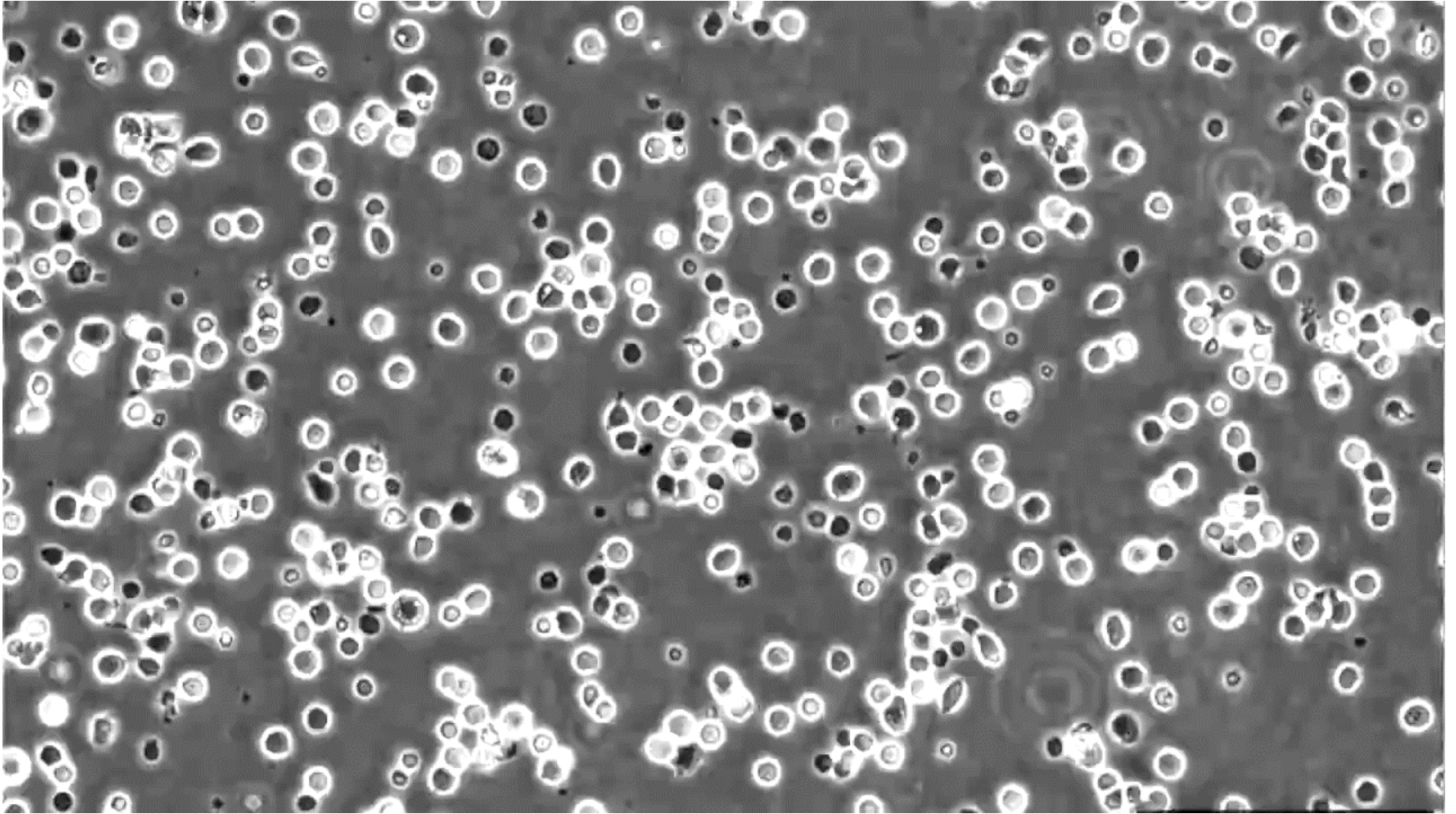
Cramer et int., VP, Nat Commun, 2020
Hagemann et int., VP, Plos Comp Biol., 2021

- **Self-Organization towards Criticality – or Subcriticality**

Zierenberg, Wilting & Priesemann, PRX, 2018



Neurons forming a network *in vitro*



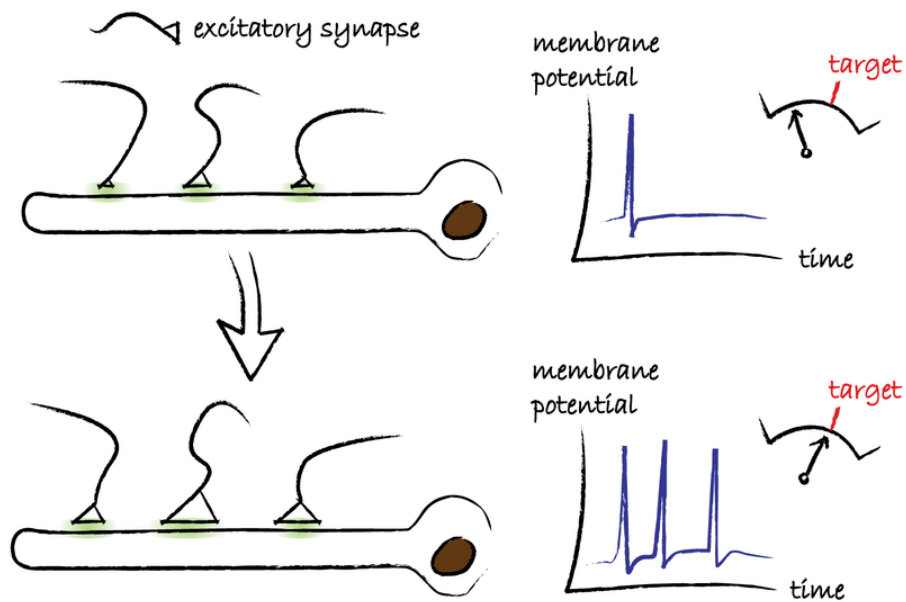
[Cellular Dynamics International]

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

Homeostatic Plasticity

Homeostatic plasticity maintains a *target activity rate* r^* for each neuron by regulating the synaptic strength (or excitability) – i.e. the “coupling” α between neurons.

Synaptic homeostasis



Homeostatic Plasticity

Homeostatic plasticity maintains a *target activity rate* r^* for each neuron by regulating the synaptic strength (or excitability) – i.e. the “coupling” α between neurons.

Small increase if
not spiking

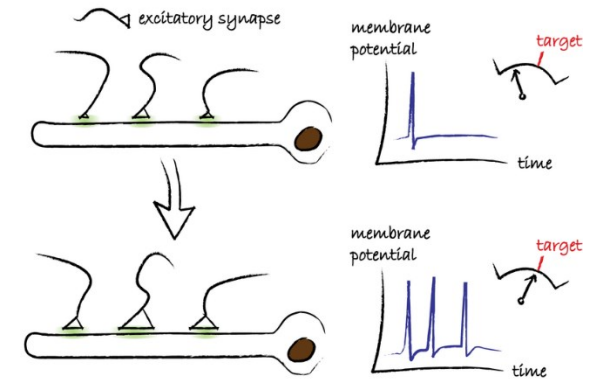
Decrease
upon a spike

$$\Delta\alpha_{j,t} = (\Delta t r_j^* - s_{j,t}) \left(\frac{\Delta t}{\tau_{hp}} \right)$$

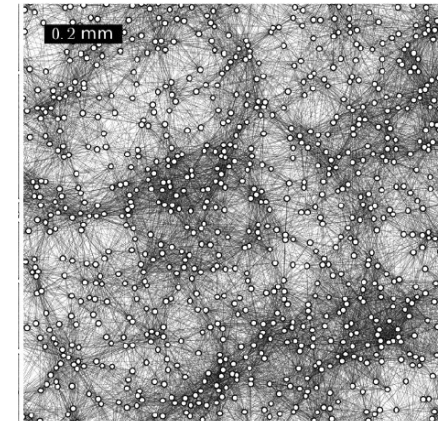
Change in
incoming exc.
synaptic strength

Very slow
timescale

Synaptic homeostasis



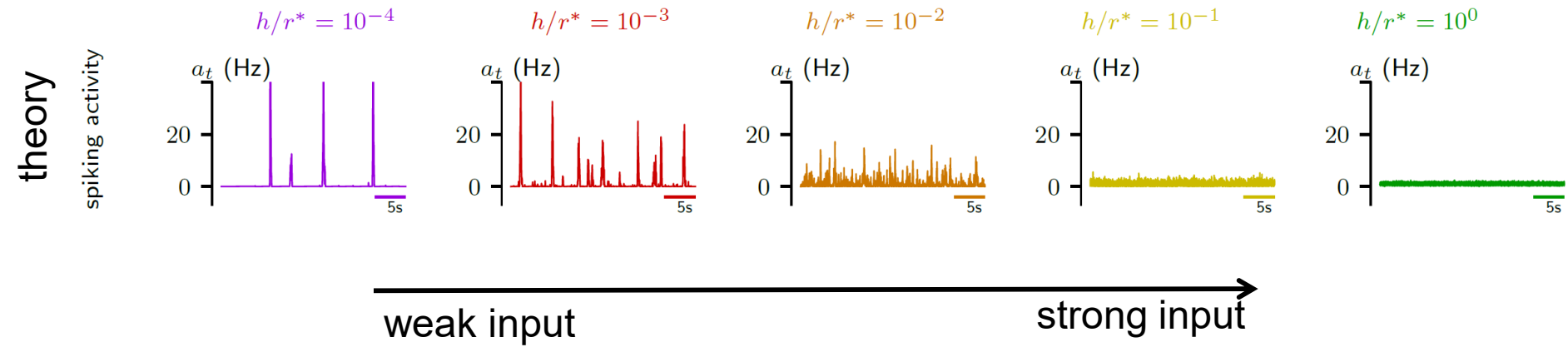
Topology



Advantages:

- Only *local information* required
- No “*memorization*” of past spiking required
- Different target rates r^* for each neuron j can be implemented

From Collective Dynamics to Computation



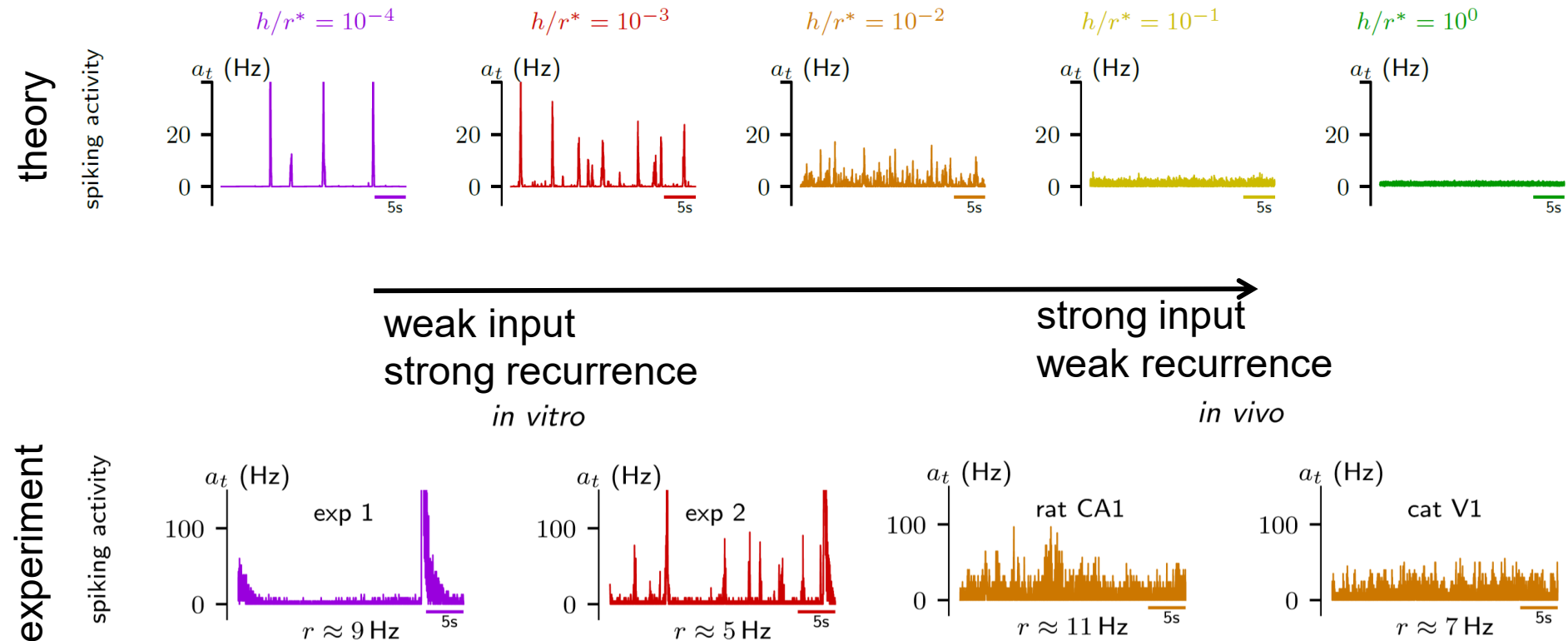
Long intrinsic timescales
Long “active memory”
High variability
Stronger “recurrence”

Short intrinsic timescales
Fast “forgetting”
Less variability
Closely mirroring input

Under homeostatic plasticity, **the input strength** changes collective dynamics, functional recurrence R and hence abstract computational properties.

→ Making use of this in generic tasks!

Increasing input strength abolishes bursts under homeostatic plasticity



Under homeostatic plasticity, **the input strength** becomes the **control parameter**. Differences of input strength can explain the emergence of bursts *in vitro*.

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- **COVID-19 Pandemic:** Predicting future scenarios & developing mitigation strategies

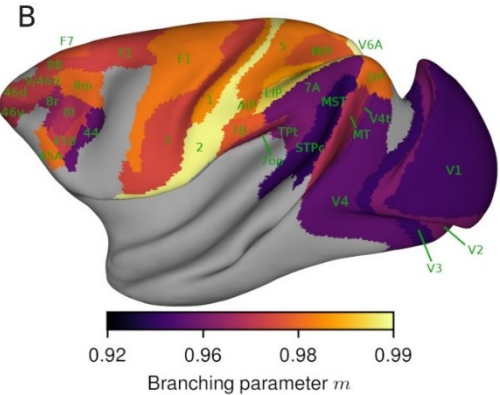
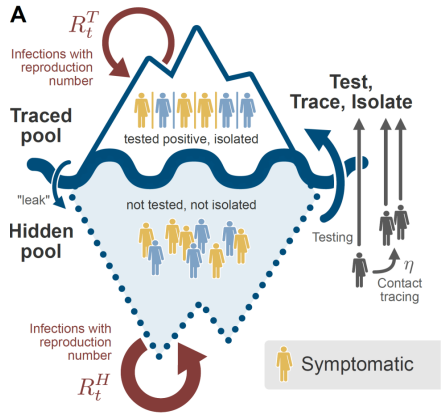
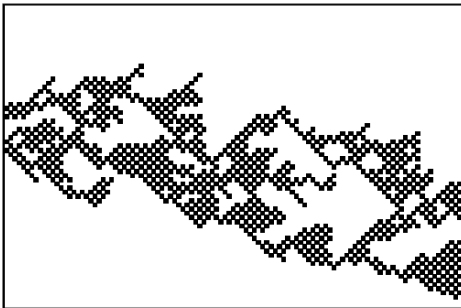
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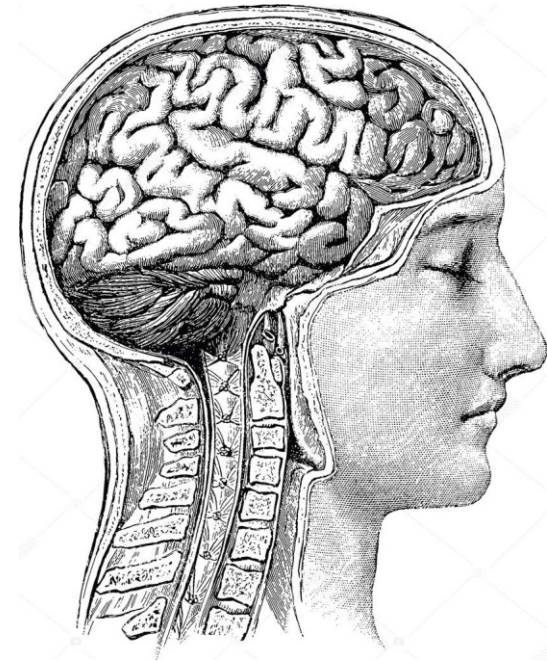
Cramer et int., VP. Nat Commun, 2020
Hagemann et int., VP, Plos Comp Biol., 2021

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Research Perspective



Self-Organization of Living Neural Networks

- “Infogenesis”
- Learning
- Information Flow
- Spreading Dynamics

Pandemic – Infodemic

- Entangled Spread of Information and Disease
- Self-Regulation and Self-Stabilization

Goals

- Energy-efficient, living future AI
- Self-regulation of neural networks and its pathology
- Pandemic and crisis preparedness

→ **PostDoc Position**

Levina & Priesemann, Nature Communications, 2017
Wilting & Priesemann, Nature Communications, 2018
Zierenberg, Wilting & Priesemann, Physical Review X, 2018
Wilting & Priesemann, Cerebral Cortex, 2019
Dehning et int., Priesemann, Science, 2020
Cramer et int., Priesemann, Nature Communications, 2020
Contreras et int., Priesemann, Nature Communications, 2021
Contreras et int., Priesemann, Science Advances, 2021
Jaehne et int., Priesemann, Cell Reports, 2021
Milkulasch, Rudelt, Priesemann, arxiv

Thank you!

Priesemann Group

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Kira Herff
Emil Iftexhar
Matthias Linden
Matthias Loidolt
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Andreas Schneider
Julian Schulz
Paul Spitzner
Patrick Vogt
Johannes Zierenberg



MAX-PLANCK-GESELLSCHAFT

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Madhura Ketkar (ENI Göttingen)
Corentin Nelias (MPI-DS)

Alumni

Bruno del Papa (MERK)
Jan Geisler (Max Planck School)
Bettina Royen (Max Planck School)
Jorge de Heuvel (U Mainz)
Annika Hagemann (Bosch)
Helge Heuer (U Göttingen)

Leonhard Leppin (MPI Garching)
Jens Wilting (Bosch)
Matthias Loidolt (Oxford)
Henrik von der Emde (Cambridge)
Mathias Sogorski (PSI, Berlin)
Moritz Layer (Cambridge)
Victor Brasch (EPFL)

**COVID-19 Expert Consortium
of 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 Wibrál & Michael Wilczek



SPP 2205
Evolutionary optimization
of neuronal processing

