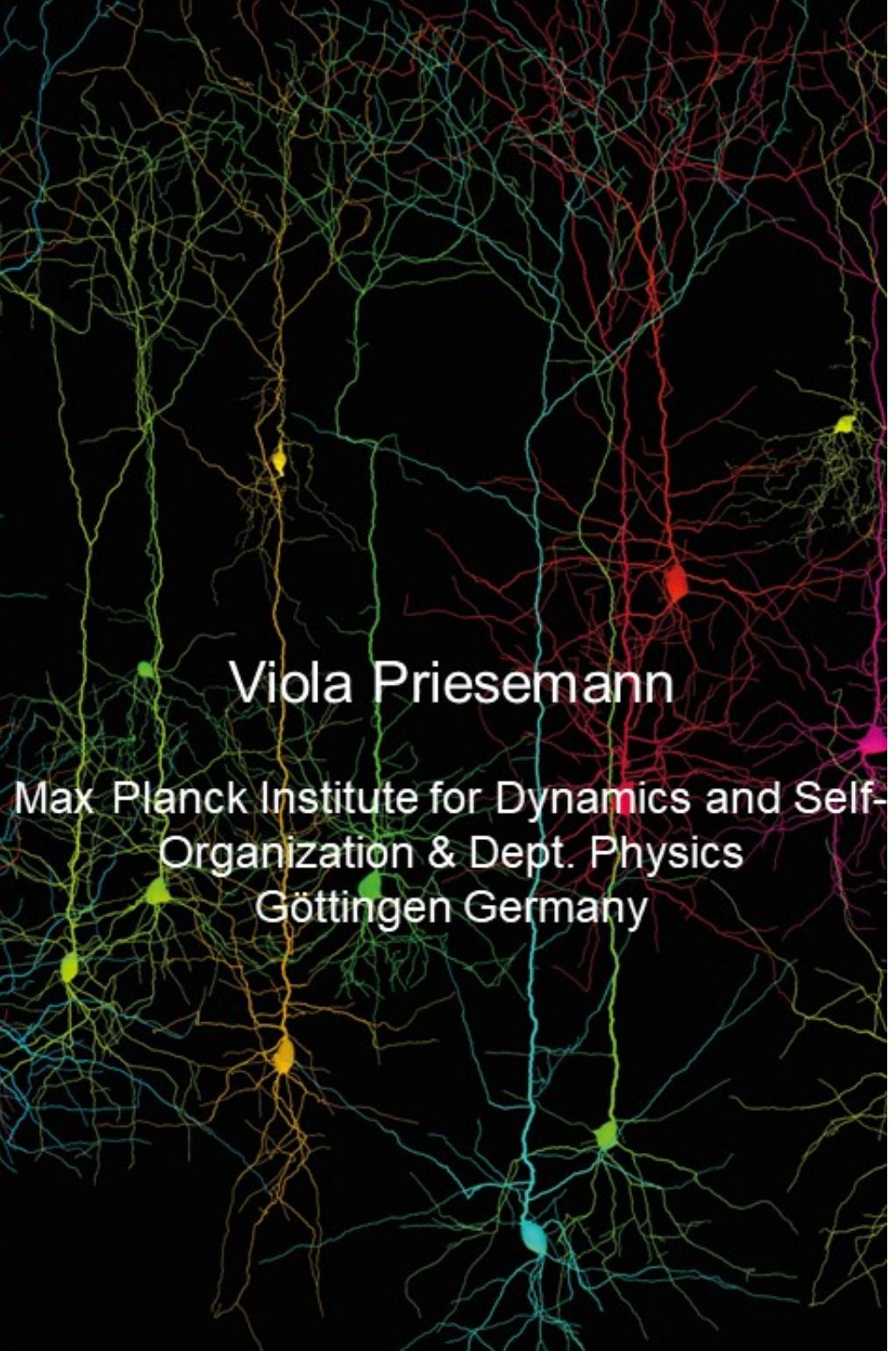
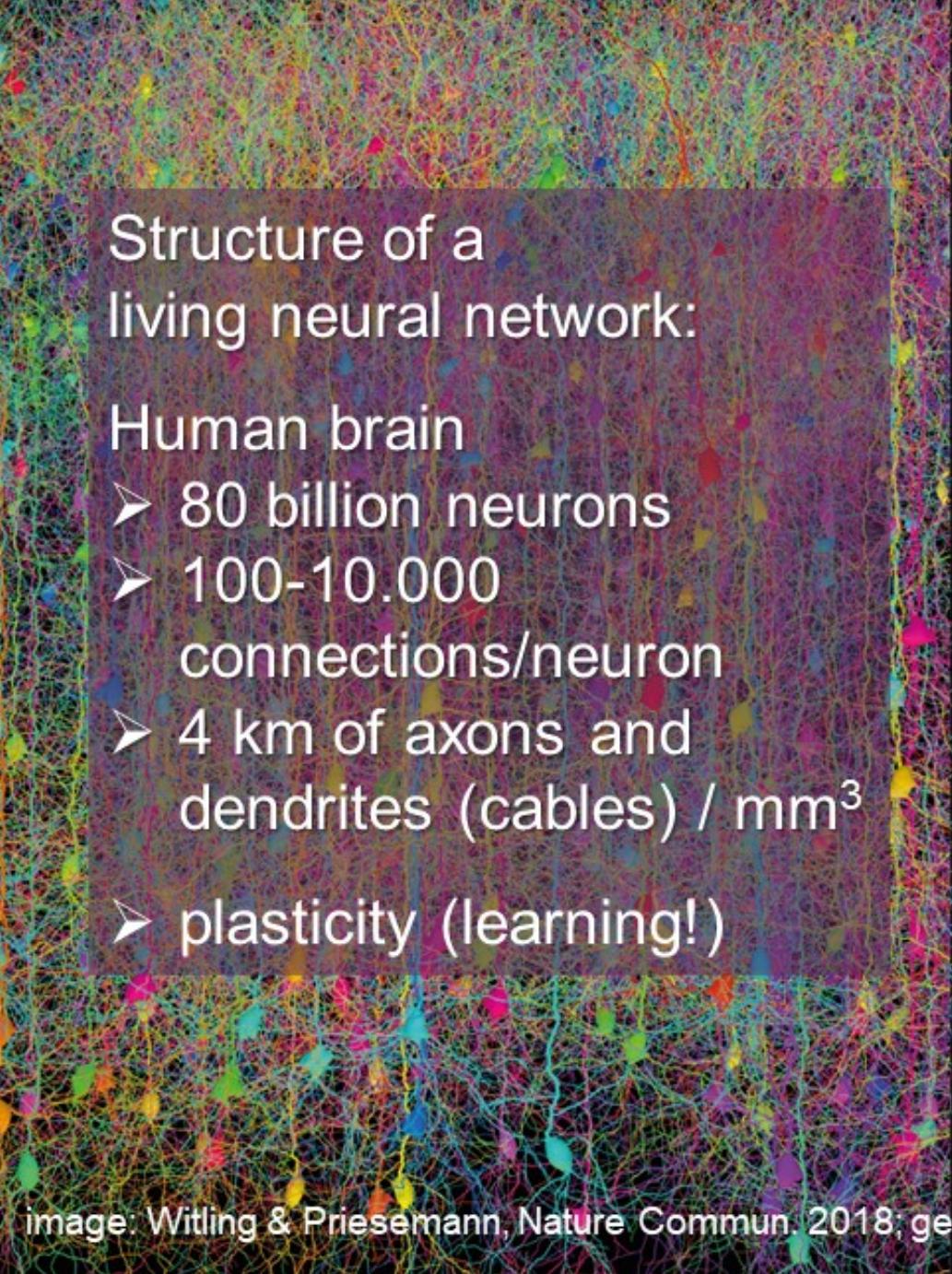


# Phase transitions in complex systems: Shaping information flow in neural networks and changing spreading dynamics of SARS-CoV-2



Viola Priesemann  
Max Planck Institute for Dynamics and Self-Organization & Dept. Physics  
Göttingen Germany

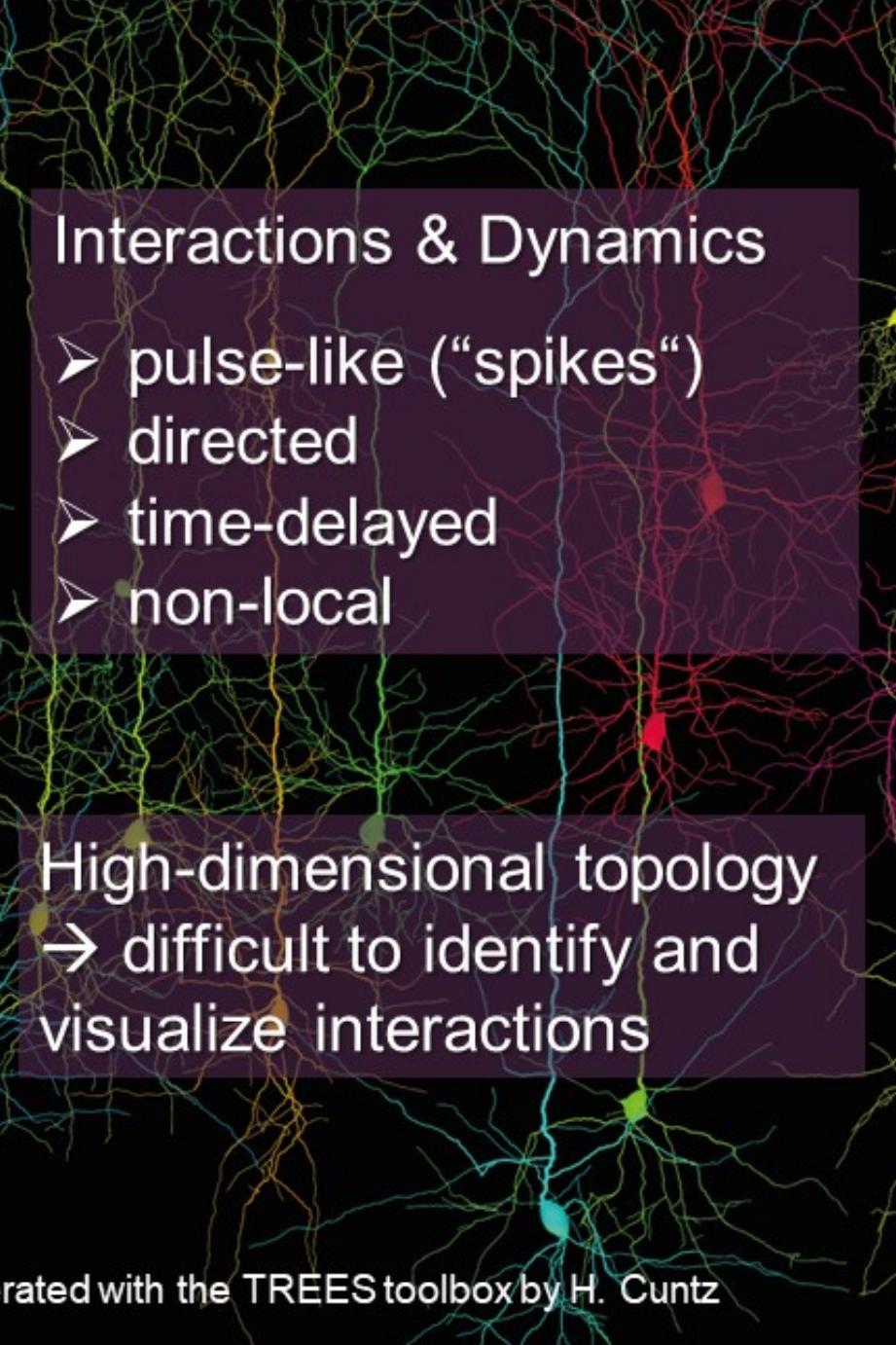
# The physical basis of thought



Structure of a living neural network:

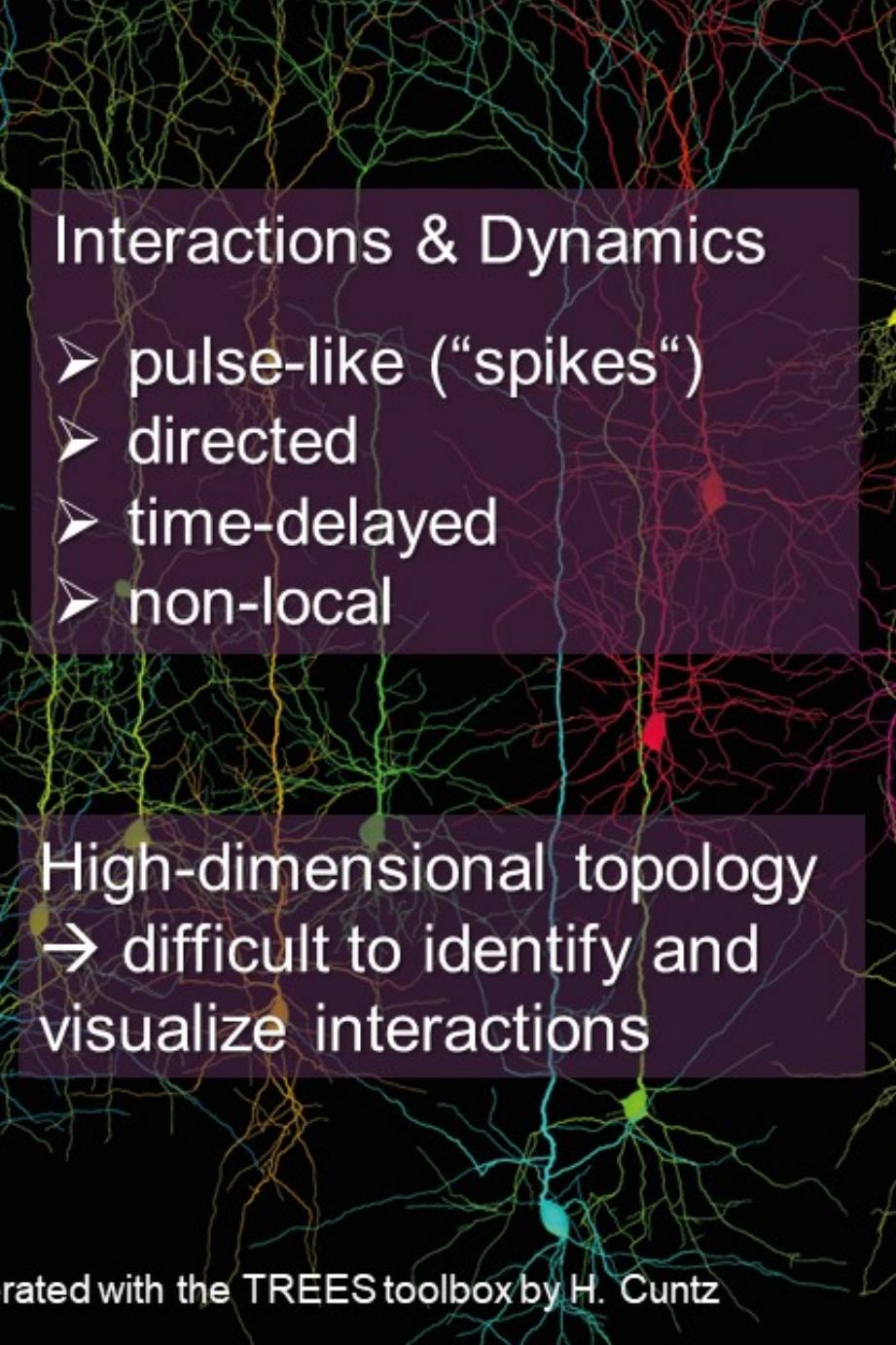
Human brain

- 80 billion neurons
- 100-10.000 connections/neuron
- 4 km of axons and dendrites (cables) / mm<sup>3</sup>
- plasticity (learning!)



Interactions & Dynamics

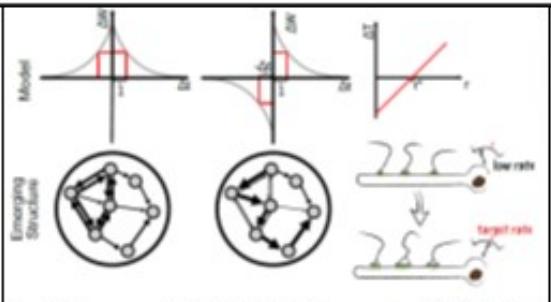
- pulse-like (“spikes”)
- directed
- time-delayed
- non-local



High-dimensional topology  
→ difficult to identify and visualize interactions

# Physics of Computation

## Emergence of Computation and Structure Formation



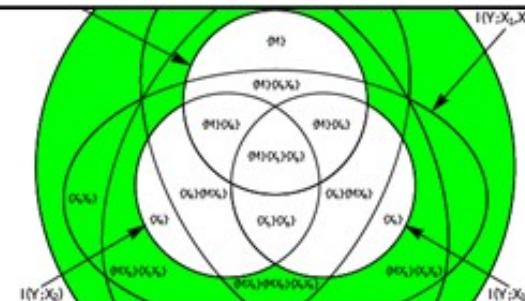
del Papa, VP & Triesch, 2017, 2019

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

Cramer, ... & VP, Nat. Commun., 2020



## Information Theory to Quantify & to Design Computation

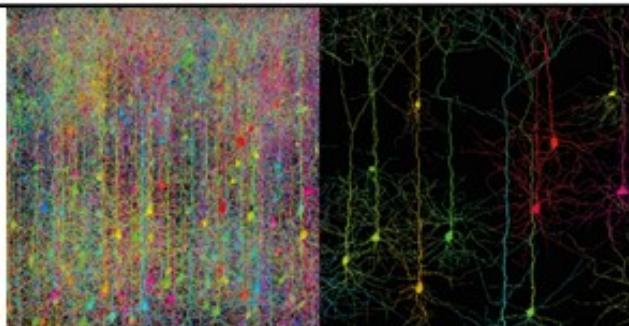


Wibral, Lizier & VP, "Matter to Life", OUP, 2017

Wollstadt et al., Plos CB, 2017

Wibral et al., Entropy, 2017

## Spreading Dynamics and Subsampling Theory



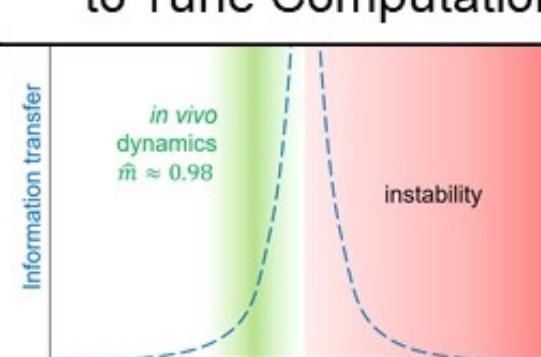
VP et al., 2009, 2014

Levina & VP, Nat. Commun., 2017

Wilting & VP, Nat. Commun., 2018

Dehning et al., ... & VP, Science 2020

## Phase Transitions to Tune Computation



Wilting & VP, Cerebr. Ctx, 2019

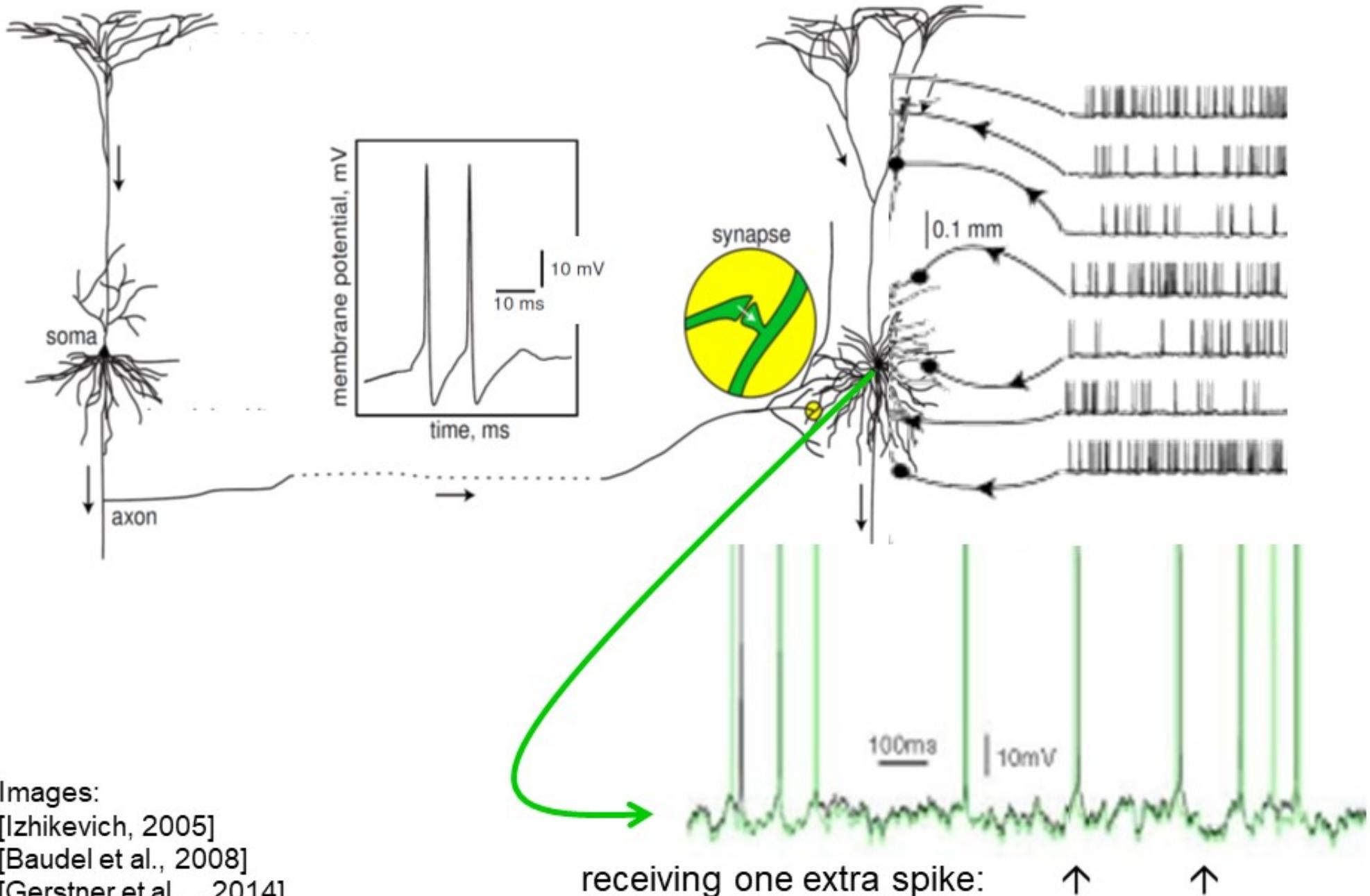
Wilting & VP, Curr Op Neurosci, 2019

Zierenberg, et al., PRR 2020 & PRE 2020

Neto, Spitzner & VP, arxiv

# Spreading Dynamics

# Neurons form a Densely Connected Network



Images:

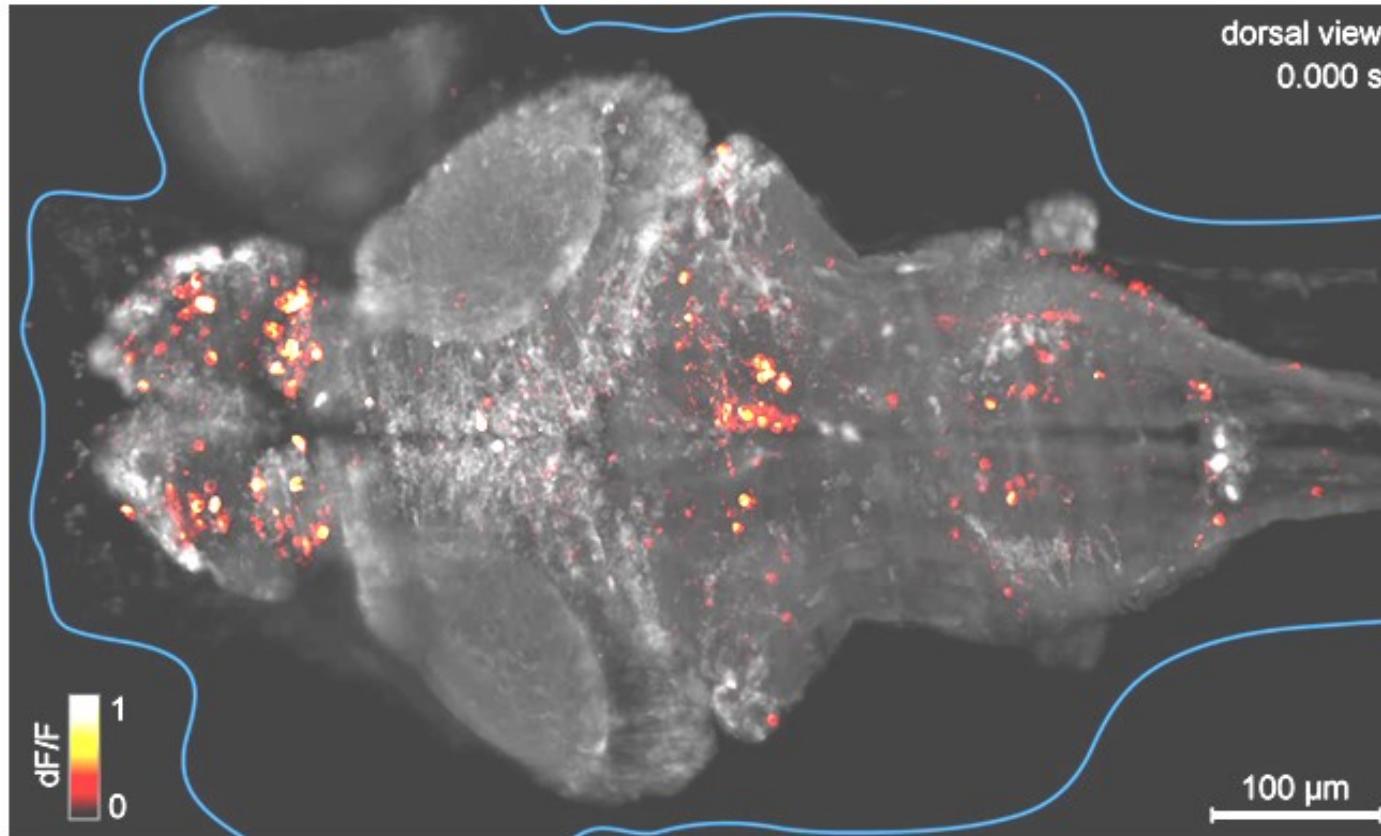
[Izhikevich, 2005]

[Baudel et al., 2008]

[Gerstner et al., , 2014]

# Collective Dynamics

Light sheet fluorescence imaging in a zebra fish larva

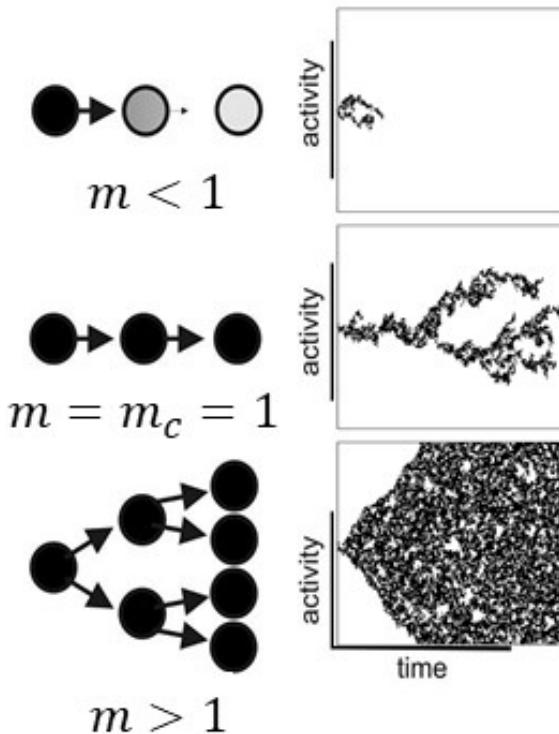


# Branching Processes

Perturbative approach:

Add one single additional spike:

→ One additional spike leads on average to  $m = \langle Y \rangle$  additional spikes in the next step  
( $Y$ : random variable with mean  $m$ )



stationary activity  
with  $\langle A \rangle = \frac{h}{1-m}$

“critical dynamics”

exponential growth  
 $\langle A \rangle \sim m^t$

$$A(t+1) = \sum_{i=1}^{A(t)} Y_{i,t} + h_t$$

$A(t)$  activity (total number of spikes)

$Y$  number of ‘spikes triggered by one spike’ (random var.)

$m = \langle Y \rangle$  average number of spikes triggered by one spike

$h_t$  external input (random variable with mean  $h$ )

Images modified from:

Beggs, 2008

Munoz, 2018

Literature: Galton & Watson, 1875; Harris 1967

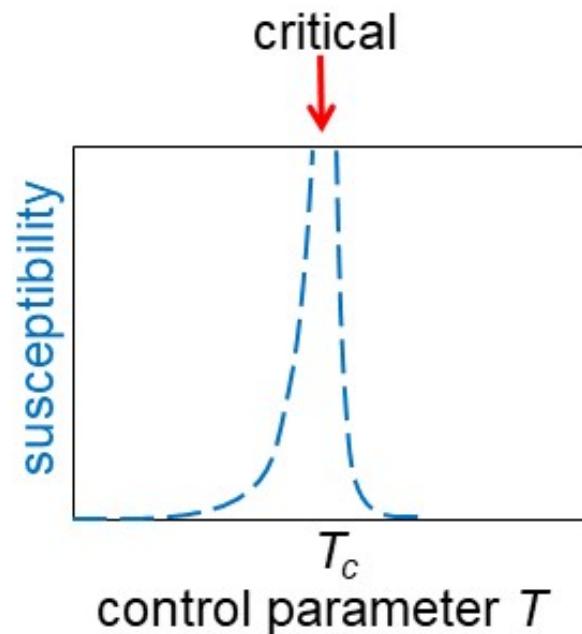
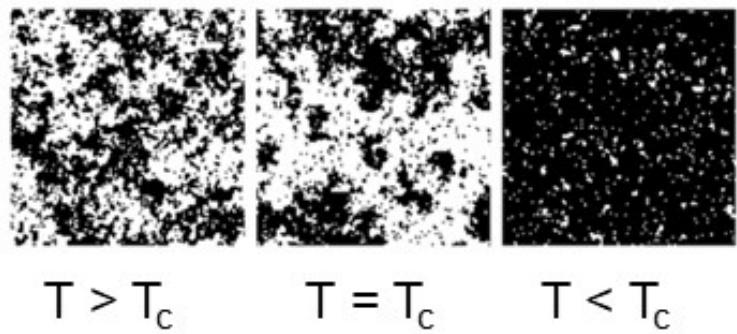
Wilting & VP, Nature Comm., 2018

Wilting & VP, Cerebr. Cortex, 2019

criticality

# Criticality

# Critical Phenomena



## Ising Model

Divergence at  $T = T_c$ :

- Susceptibility
- Specific heat
- Correlation length

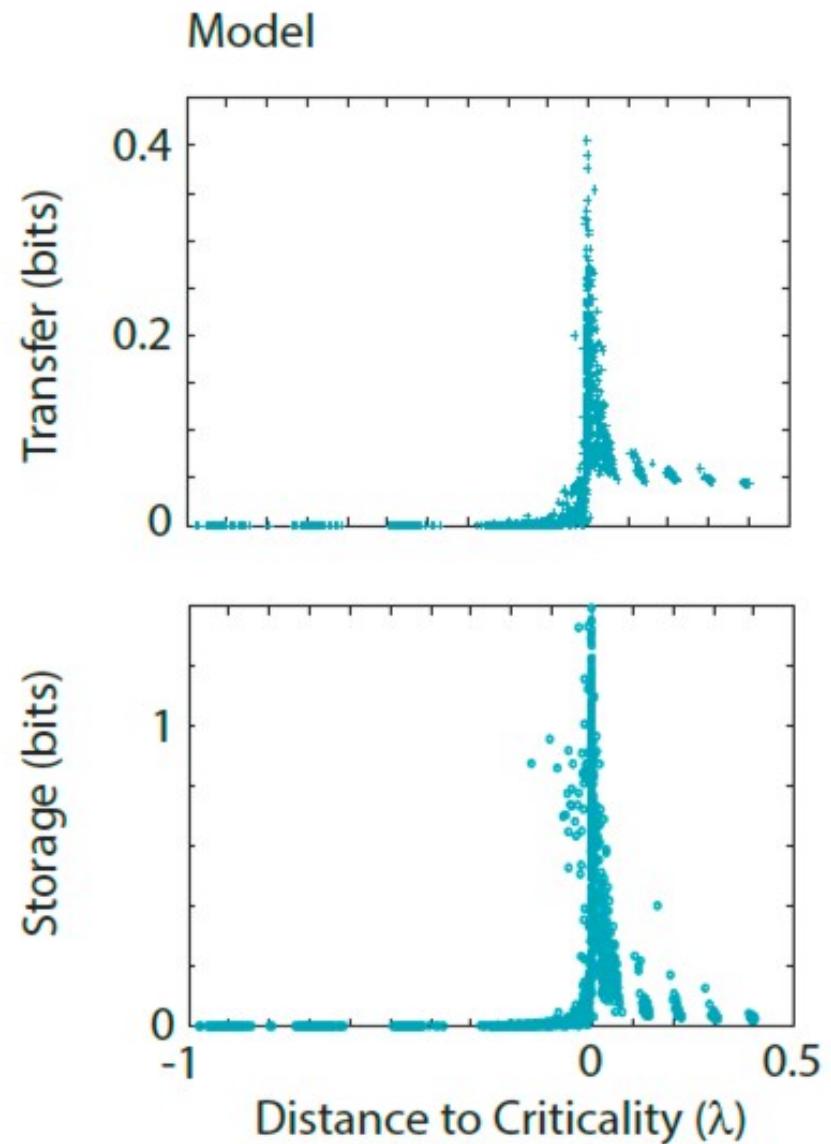
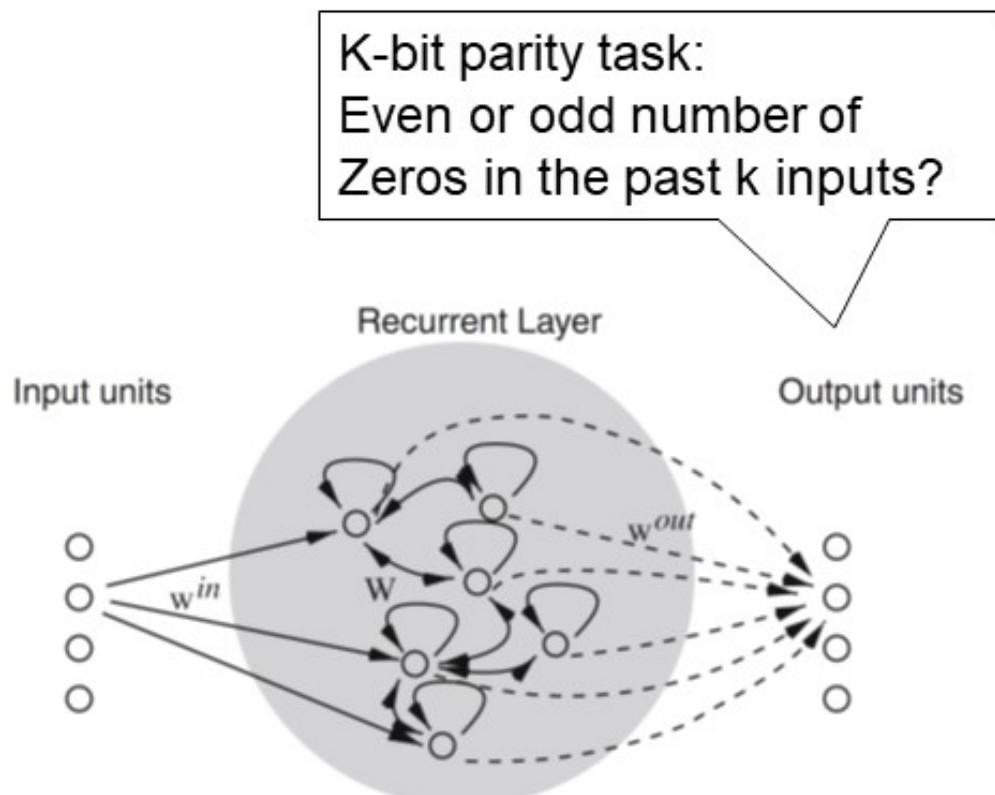
## Neural Network

Control parameter: Effective coupling strength

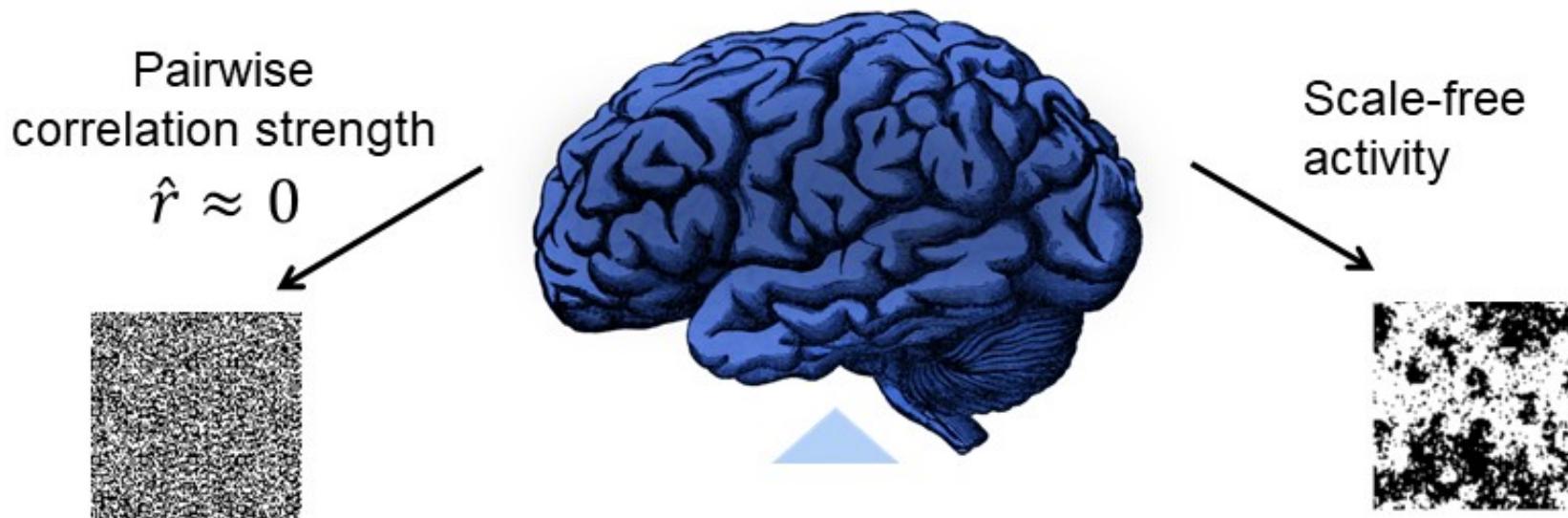
- Sensitivity to input
- Coding space
- Long-range communication (space)  
Active memory (time)

→ Criticality can maximize  
information processing properties

# Reservoir Networks Show Maximal Performance at the Critical State



# Collective Dynamics and Computation



## Disordered [5-6]

("asynchronous-irregular")

- maximum entropy
- minimal redundancy
- efficient code

## Critical [1-4]

- diverging correlation length in space and time
- long "memory"
- high sensitivity

[1] Book: Plenz, Niebur & Schuster (2014),

[2] Book: Tomen, Herrmann, Ernst (2019)

[3] Beggs & Plenz, J Neurosci, 2003

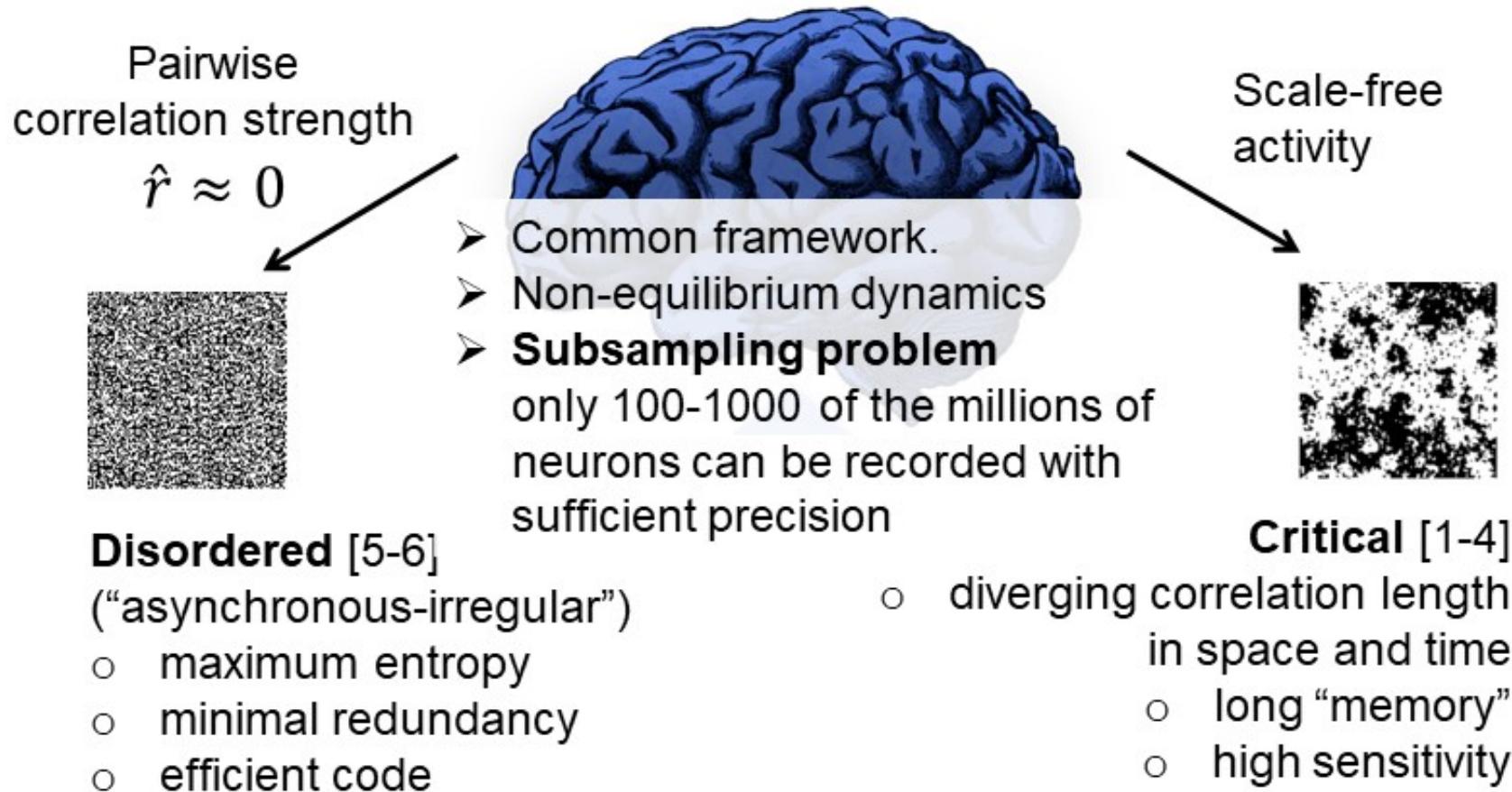
[4] Munoz, Rev Mod Phys, 2018

[5] Vreeswijk & Sompolinsky, Science, 1996

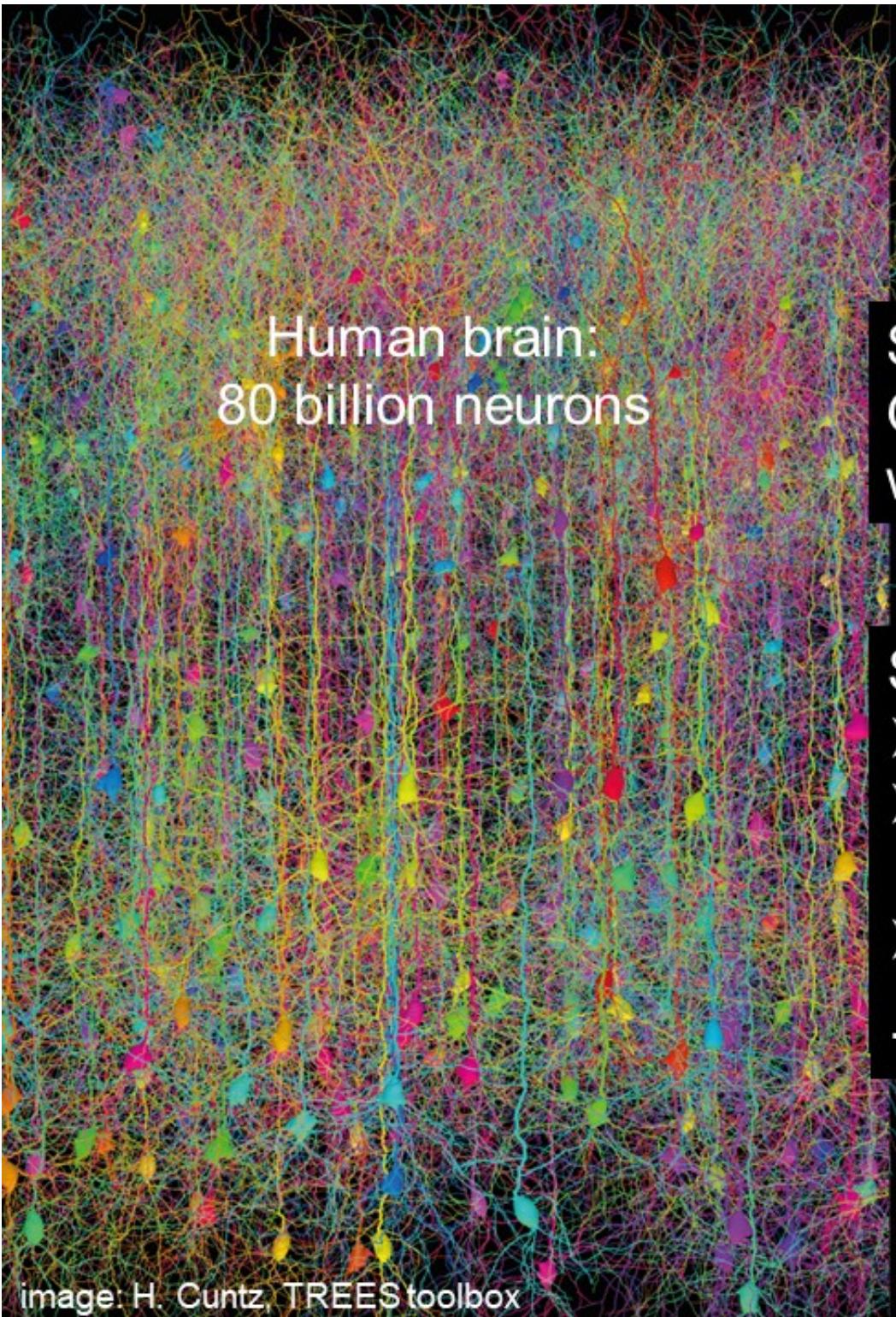
[6] Brunel, J Comp Neurosci, 2000

Neto, Spitzner & VP, arxiv  
Wilting et al., Frontiers Syst Neurosci, 2018  
Wilting & VP, Current Opinion Neurobiol., 2019  
Wilting & VP, Nature Communications, 2018

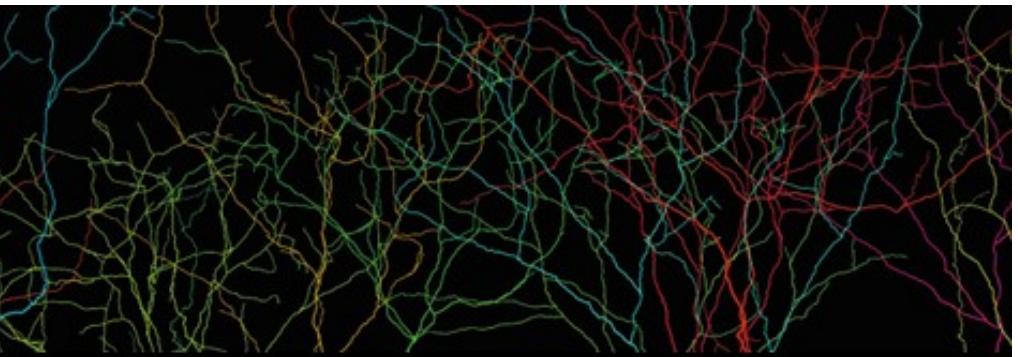
# Collective Dynamics and Computation



- [1] Book: Plenz, Niebur & Schuster (2014)
- [2] Book: Tomen, Herrmann, Ernst (2019)
- [3] Beggs & Plenz, J Neurosci, 2003
- [4] Munoz, Rev Mod Phys, 2018
- [5] Vreeswijk & Sompolinsky, Science, 1996
- [6] Brunel, J Comp Neurosci, 2000



Human brain:  
80 billion neurons



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



Subsampling bias:

- Mis-estimate control parameter
- Scale-free properties are not maintained
- Even correlation strength
- subsampling invariant estimator



# Propagating Activity as a Branching Process

control parameter  $m$

expected number of “children”



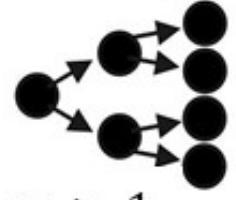
$$m < 1$$

subcritical



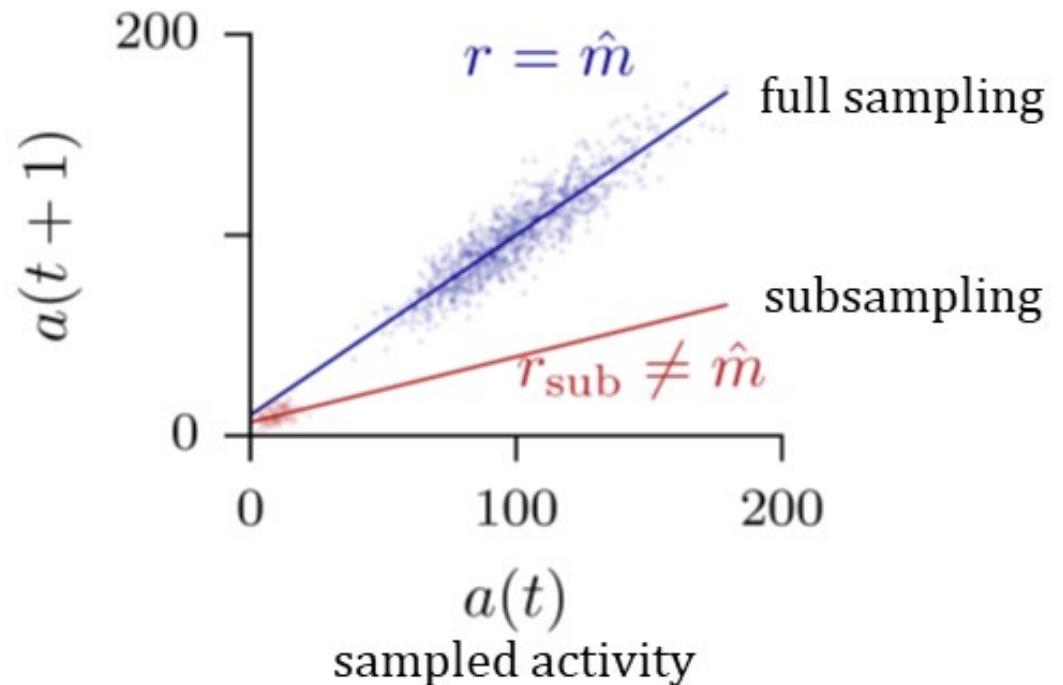
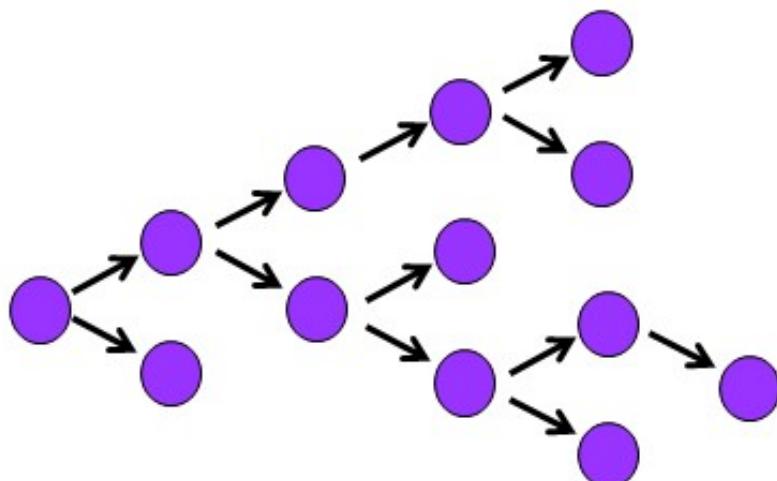
$$m = m_c = 1$$

critical



supercritical

$$m > 1$$



# Propagating Activity as a Branching Process

control parameter  $m$

expected number of “children”



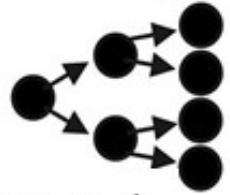
$$m < 1$$

subcritical



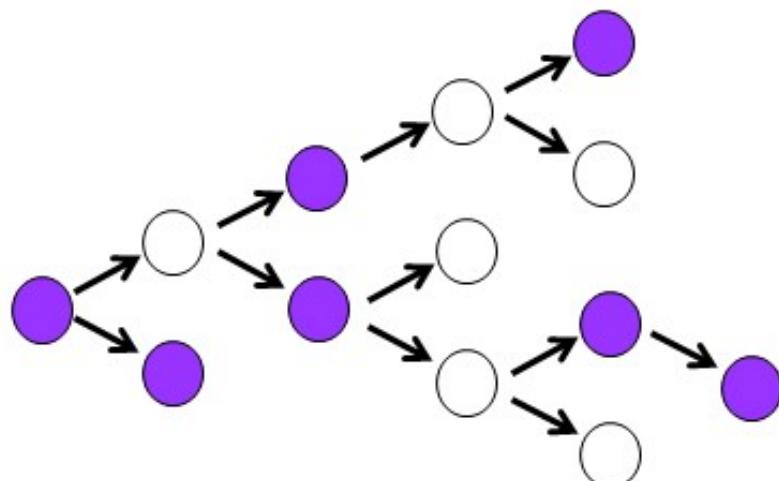
$$m = m_c = 1$$

critical

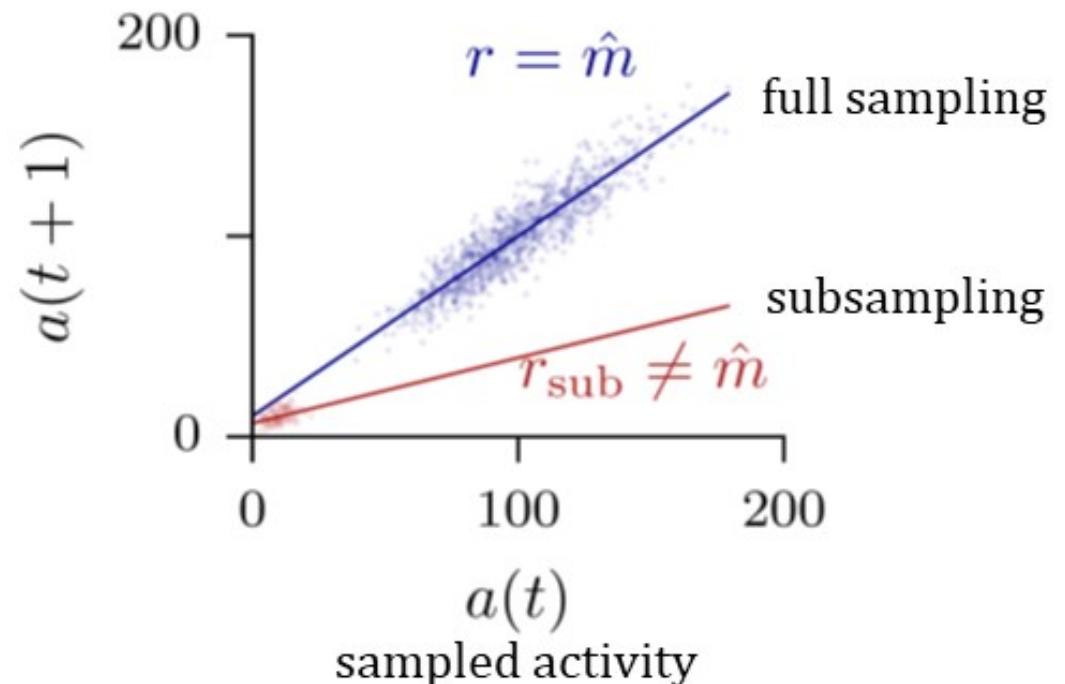


supercritical

$$m > 1$$



→ Correlation strength  $r$   
is biased under subsampling!



Assumption for process and subsampling:  
 $E[A(t)|A(t-1)] = mA(t-1) + h$   
 $E[a(t)|A(t)] = \alpha A(t)$

# Subsampling-Invariant Estimator

**control parameter  $m$**

expected number of “children”



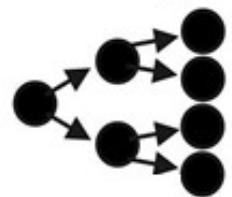
$$m < 1$$

subcritical



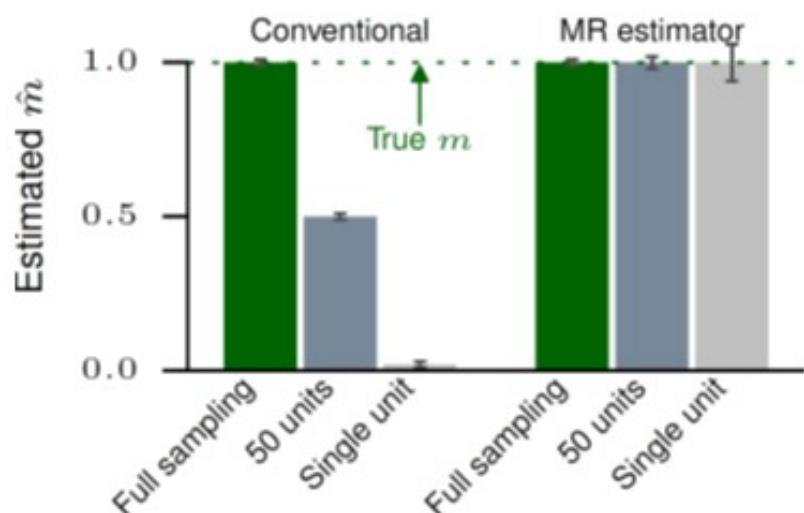
$$m = m_c = 1$$

critical



$$m > 1$$

supercritical



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

Efficient, precise, easily applicable:

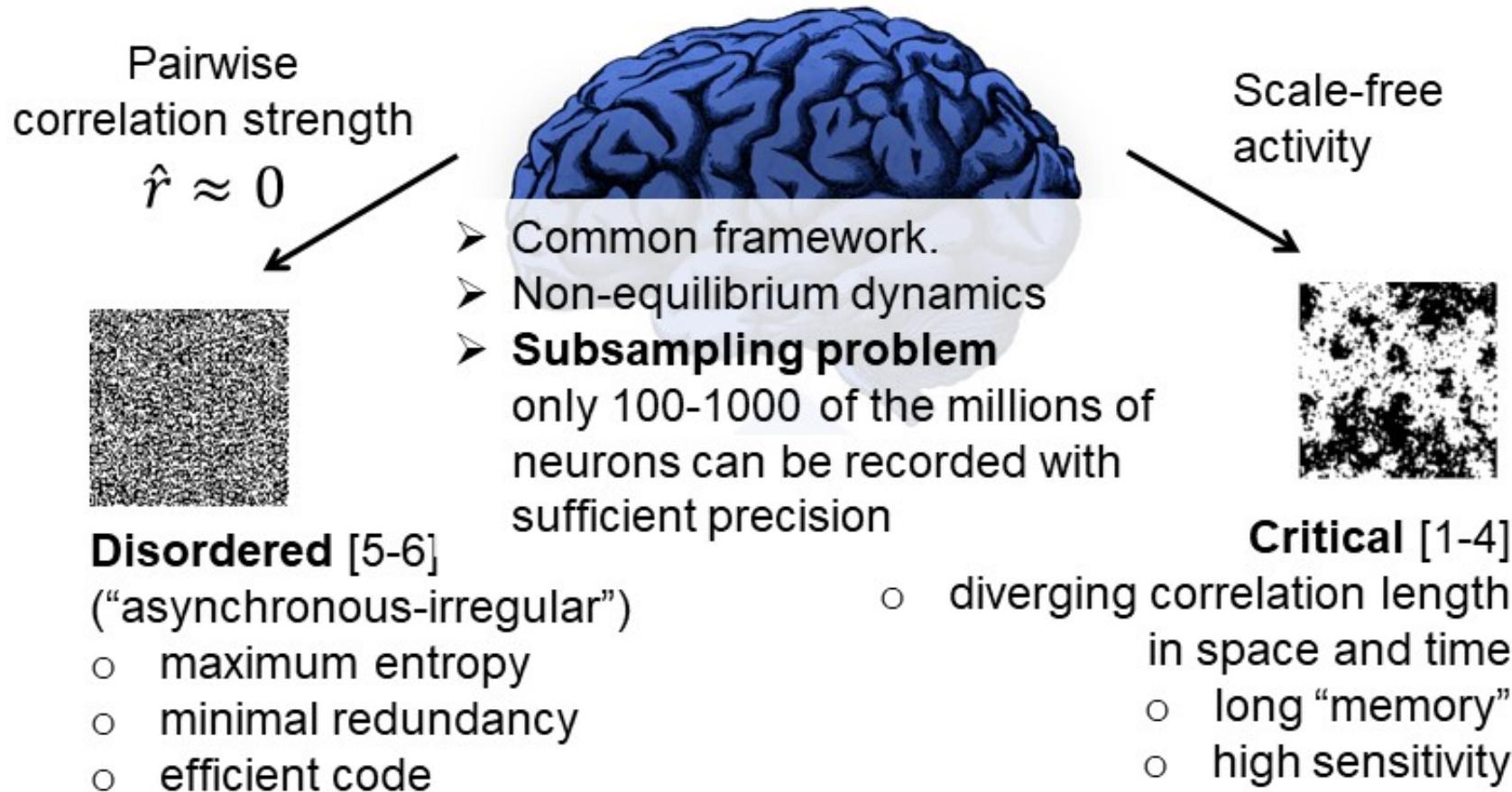
- It only requires knowing  $a(t)$ , i.e. the sampled activity at each time step
- It does not require knowing the system size  $N$ , the number of sampled units  $n$ , or any of the moments of the process.
- Ideal conditions: Estimation of control parameter from a single unit!

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

**Python Toolbox:** [github.com/Priesemann-Group](https://github.com/Priesemann-Group)

For subsampling of graphs: Levina & VP, 2017

# Collective Dynamics and Computation



[1] Book: Plenz, Niebur & Schuster (2014),

[2] Book: Tomen, Herrmann, Ernst (2019)

[3] Beggs & Plenz, J Neurosci, 2003

[4] Munoz, Rev Mod Phys, 2018

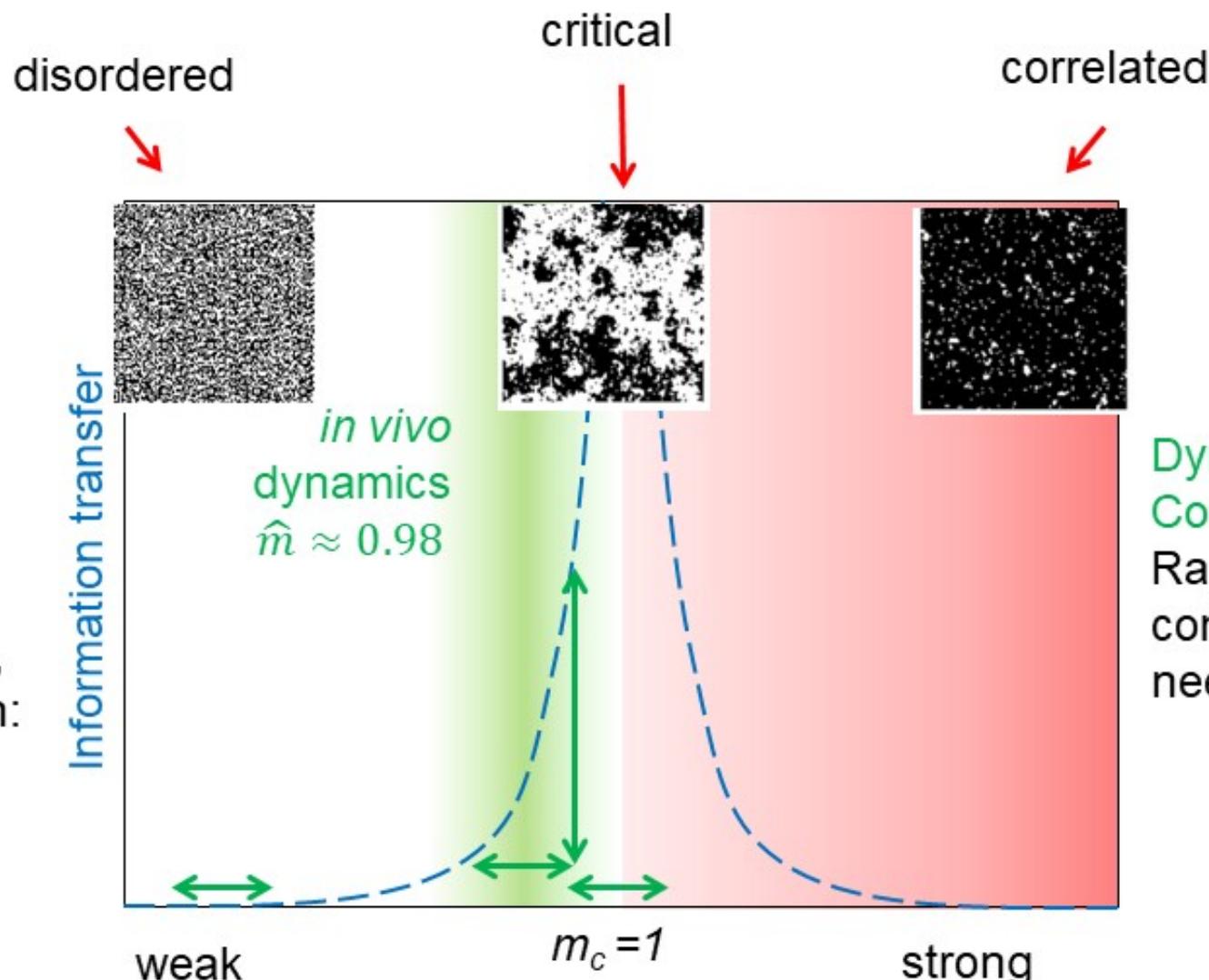
[5] Vreeswijk & Sompolinsky, Science, 1996

[6] Brunel, J Comp Neurosci, 2000

maximal entropy  
minimal redundancy

strong amplification  
long reverberations

instability  
epilepsy



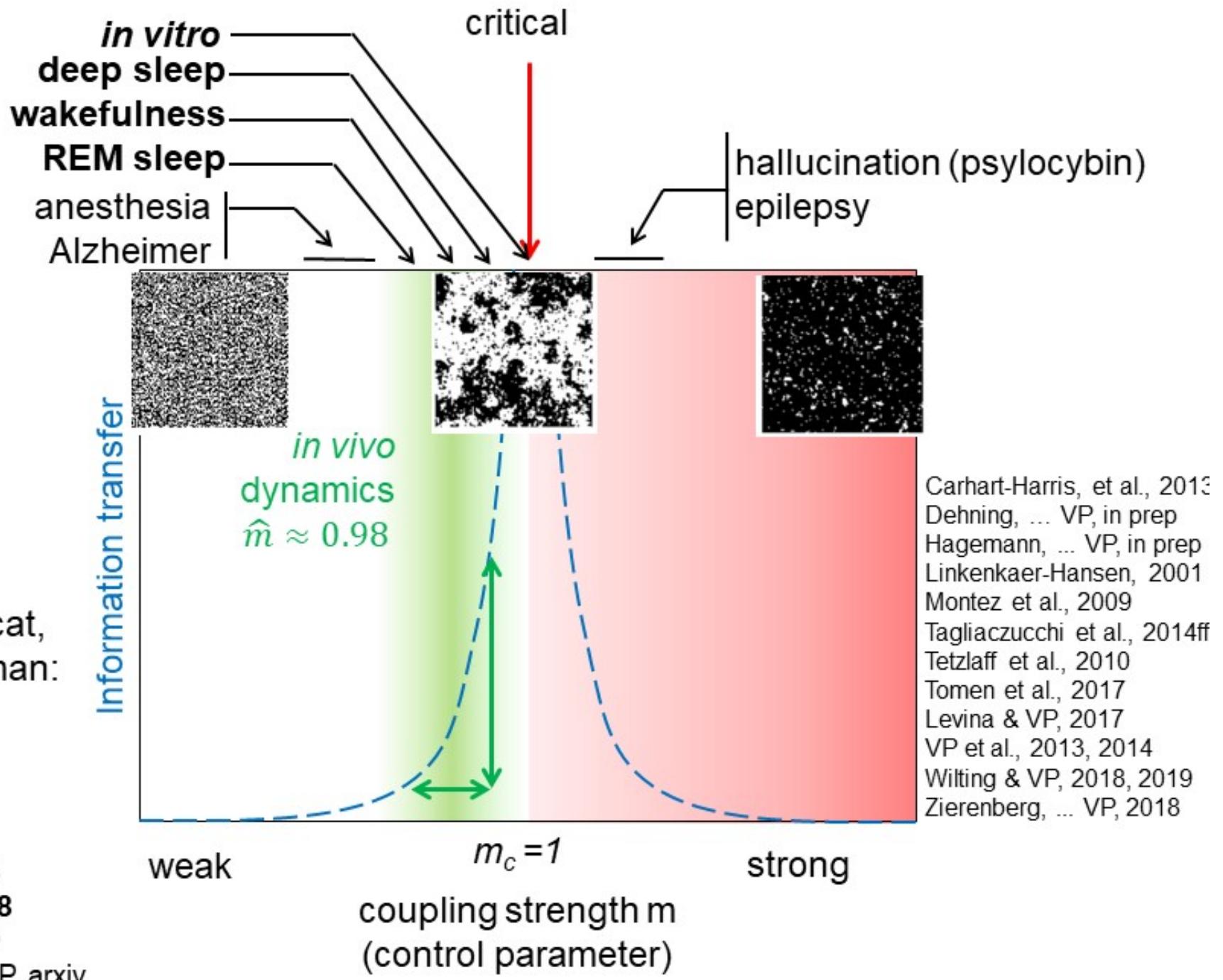
Reverberating  
regime in rat, cat,  
monkey & human:

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

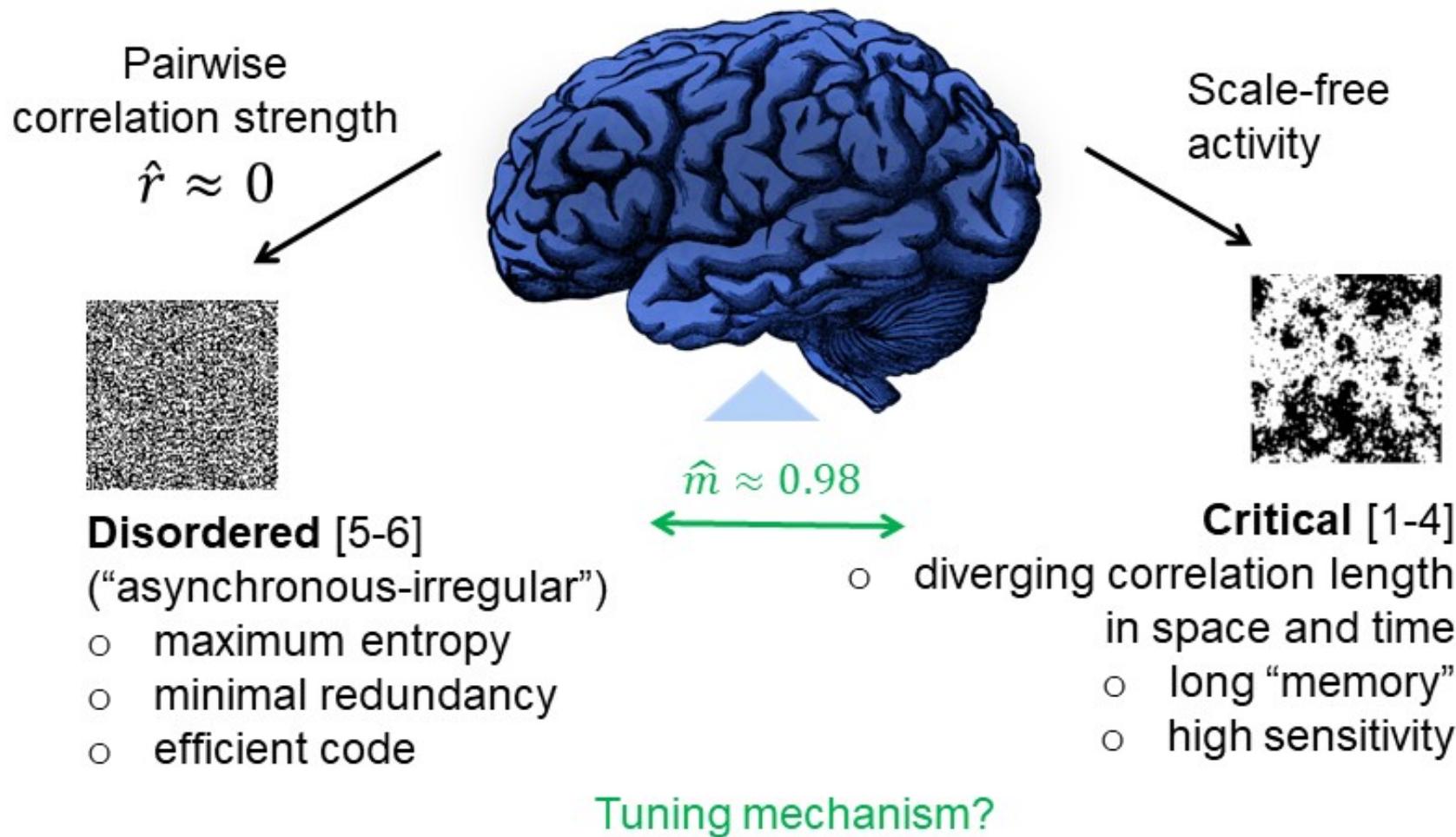
Dynamic  
Computation:  
Rapid tuning to  
computational  
needs

Reverberating  
regime in rat, cat,  
monkey & human:

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



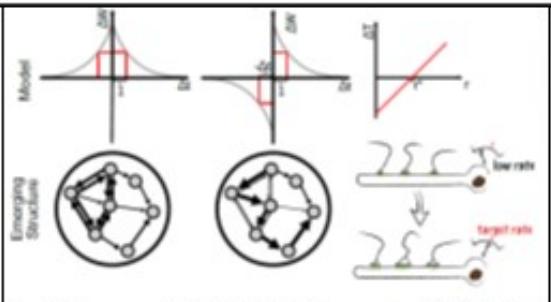
# Collective Dynamics and Computation



- [1] Book: Plenz, Niebur & Schuster (2014),
- [2] Book: Tomen, Herrmann, Ernst (2019)
- [3] Beggs & Plenz, J Neurosci, 2003
- [4] Munoz, Rev Mod Phys, 2018
- [5] Vreeswijk & Sompolinsky, Science, 1996
- [6] Brunel, J Comp Neurosci, 2000

# Physics of Computation

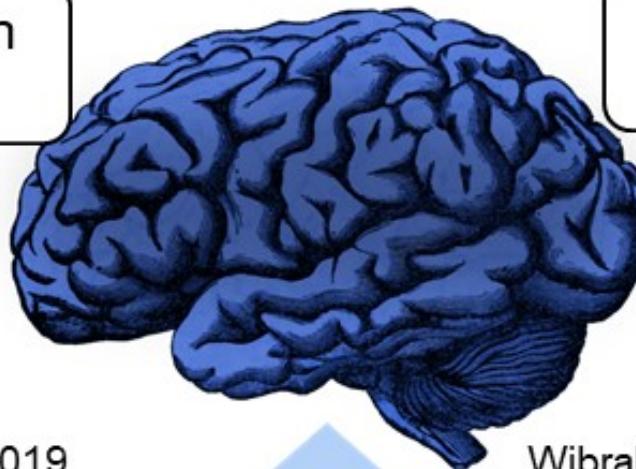
## Emergence of Computation and Structure Formation



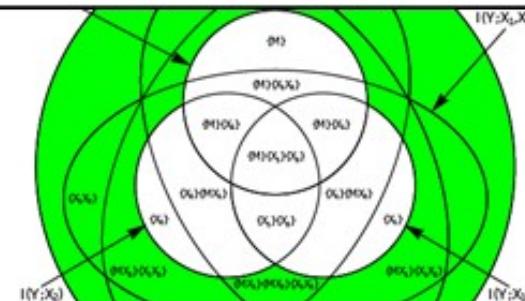
del Papa, VP & Triesch, 2017, 2019

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

Cramer, ... & VP, Nat. Commun., 2020



## Information Theory to Quantify & to Design Computation

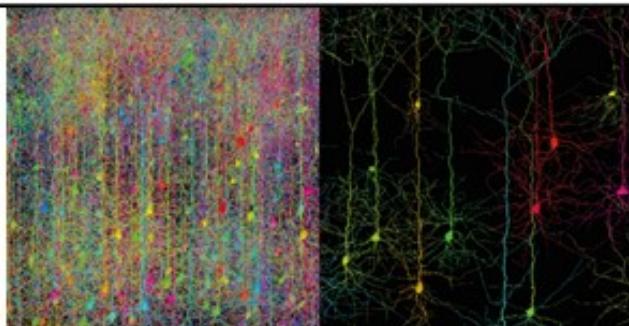


Wibral, Lizier & VP, "Matter to Life", OUP, 2017

Wollstadt et al., Plos CB, 2017

Wibral et al., Entropy, 2017

## Spreading Dynamics and Subsampling Theory



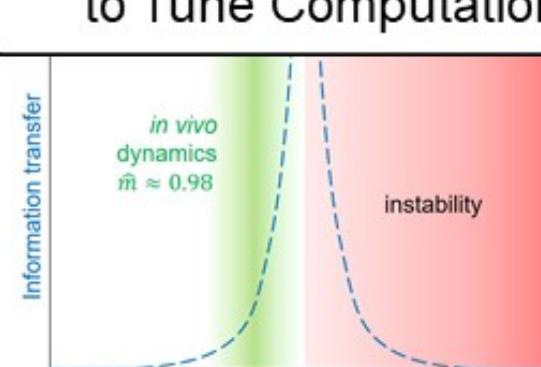
VP et al., 2009, 2014

Levina & VP, Nat. Commun., 2017

Wilting & VP, Nat. Commun., 2018

Dehning et al., ... & VP, Science 2020

## Phase Transitions to Tune Computation



Wilting & VP, Cerebr. Ctx, 2019

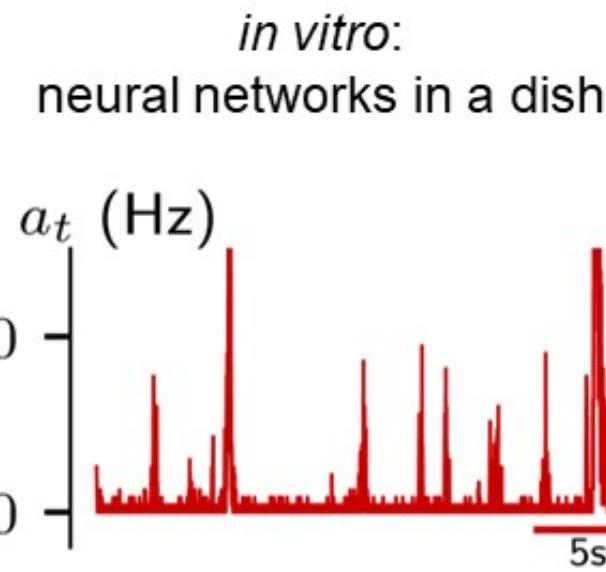
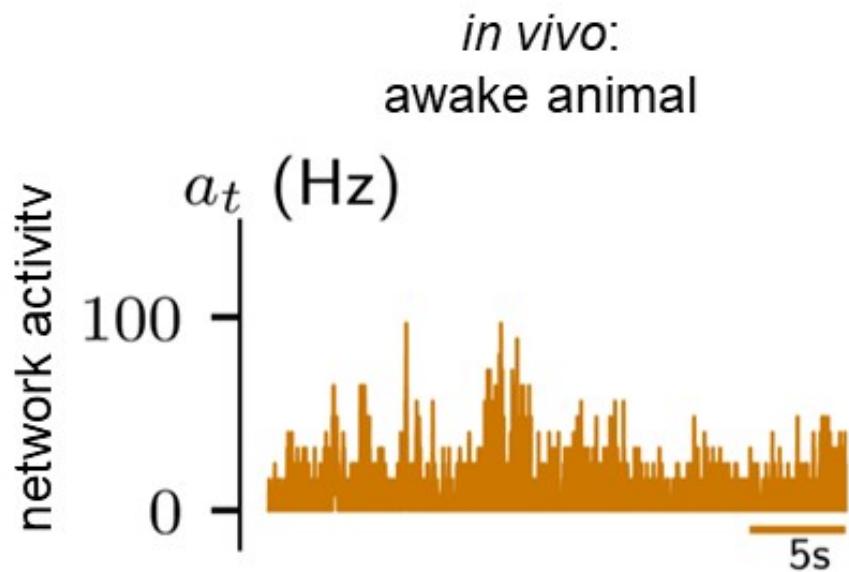
Wilting & VP, Curr Op Neurosci, 2019

Zierenberg, et al., PRR 2020 & PRE 2020

Neto, Spitzner & VP, arxiv

# Homeostasis

# Collective dynamics *in vitro* and *in vivo* clearly differ



Similar single neuron, synaptic and plasticity principles...

... but clearly different dynamics.

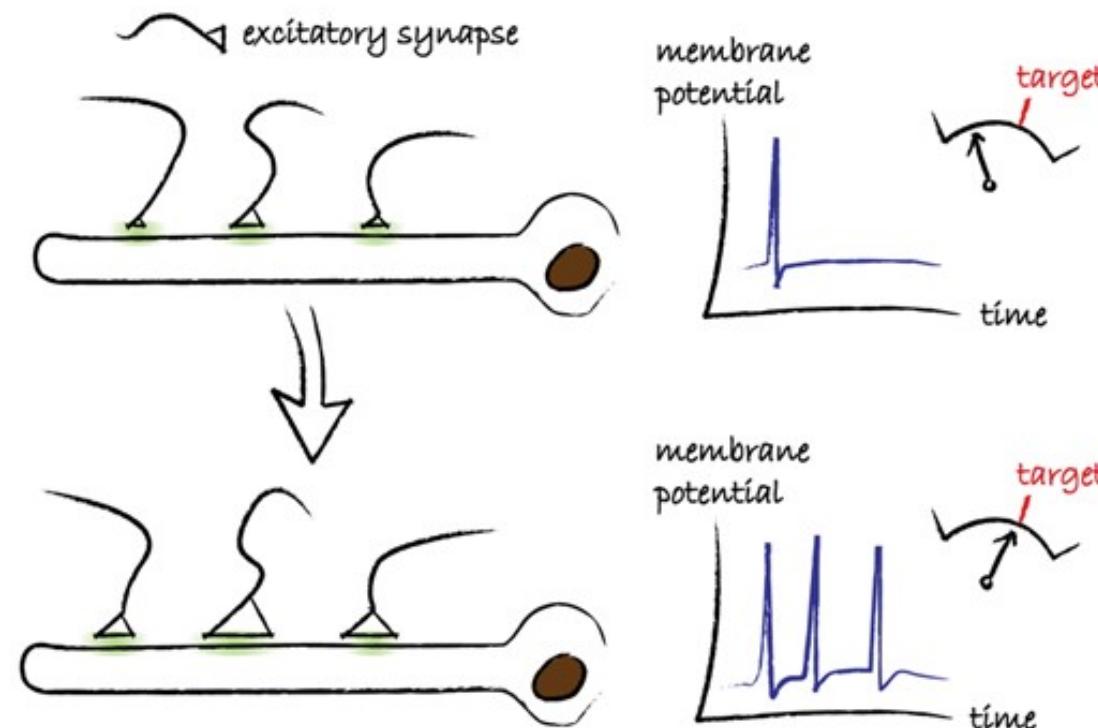
Key difference: Input strength  $h$   
*In vitro*: fully isolated,  $h \rightarrow 0$

Input acts as control parameter under **homeostatic plasticity**.

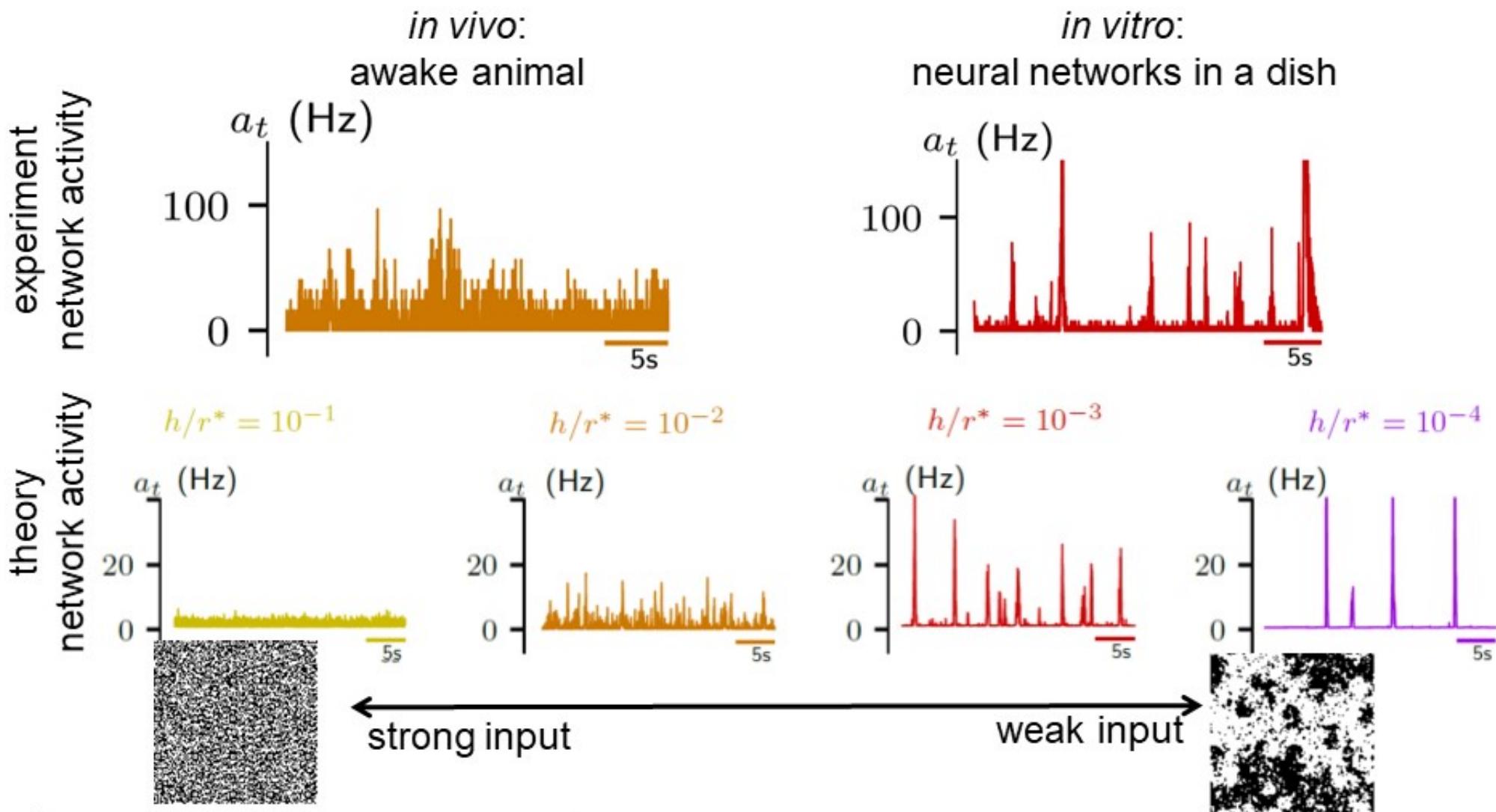
# Homeostatic Plasticity

Homeostatic plasticity maintains a *target activity rate*  $r^*$ . by regulating the synaptic strength (i.e. coupling).

## Synaptic homeostasis



# Collective dynamics *in vivo* and *in vitro* clearly differ



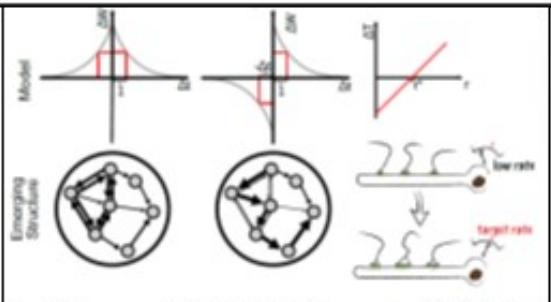
→ **Input strength** becomes control parameter!

1. **Rescue** *in vitro* systems from isolation
  - *in vivo*-like activity for pharmacol. assays
2. **Tune** computation in neuromorphic networks

[Cramer... & VP, Nature Commun. 2020]  
[Zierenberg, Wilting & VP, Phys Rev X, 2018]

# Physics of Computation

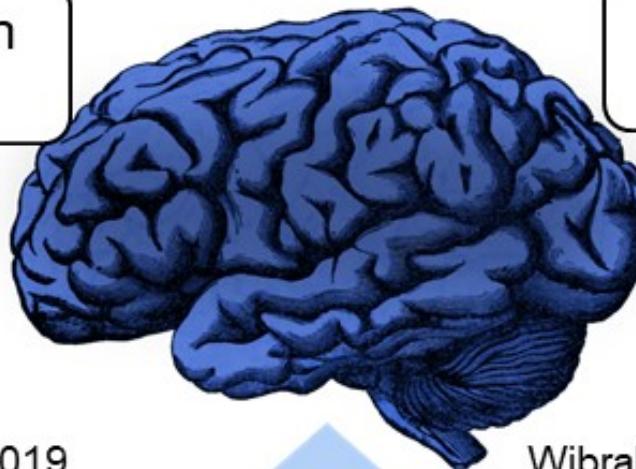
## Emergence of Computation and Structure Formation



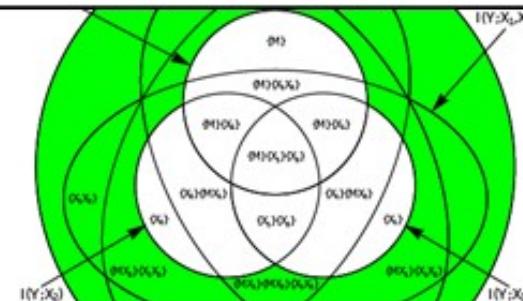
del Papa, VP & Triesch, 2017, 2019

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

Cramer, ... & VP, Nat. Commun., 2020



## Information Theory to Quantify & to Design Computation

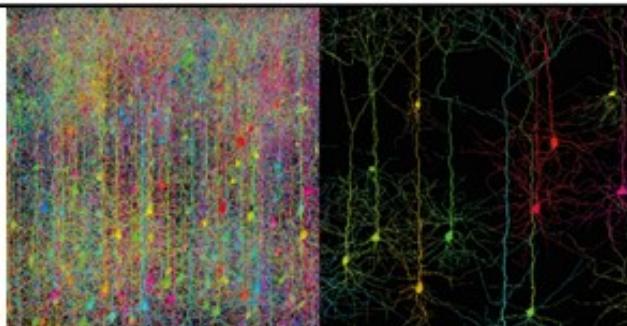


Wibral, Lizier & VP, "Matter to Life", OUP, 2017

Wollstadt et al., Plos CB, 2017

Wibral et al., Entropy, 2017

## Spreading Dynamics and Subsampling Theory



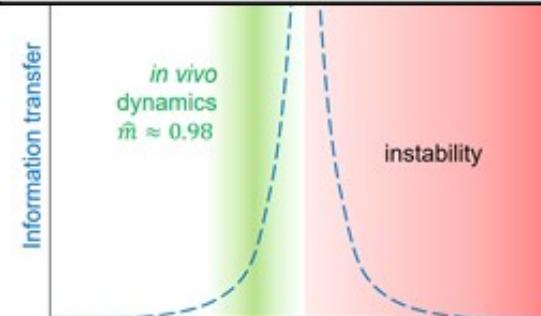
VP et al., 2009, 2014

Levina & VP, Nat. Commun., 2017

Wilting & VP, Nat. Commun., 2018

Dehning et al., ... & VP, Science 2020

## Phase Transitions to Tune Computation



Wilting & VP, Cerebr. Ctx, 2019

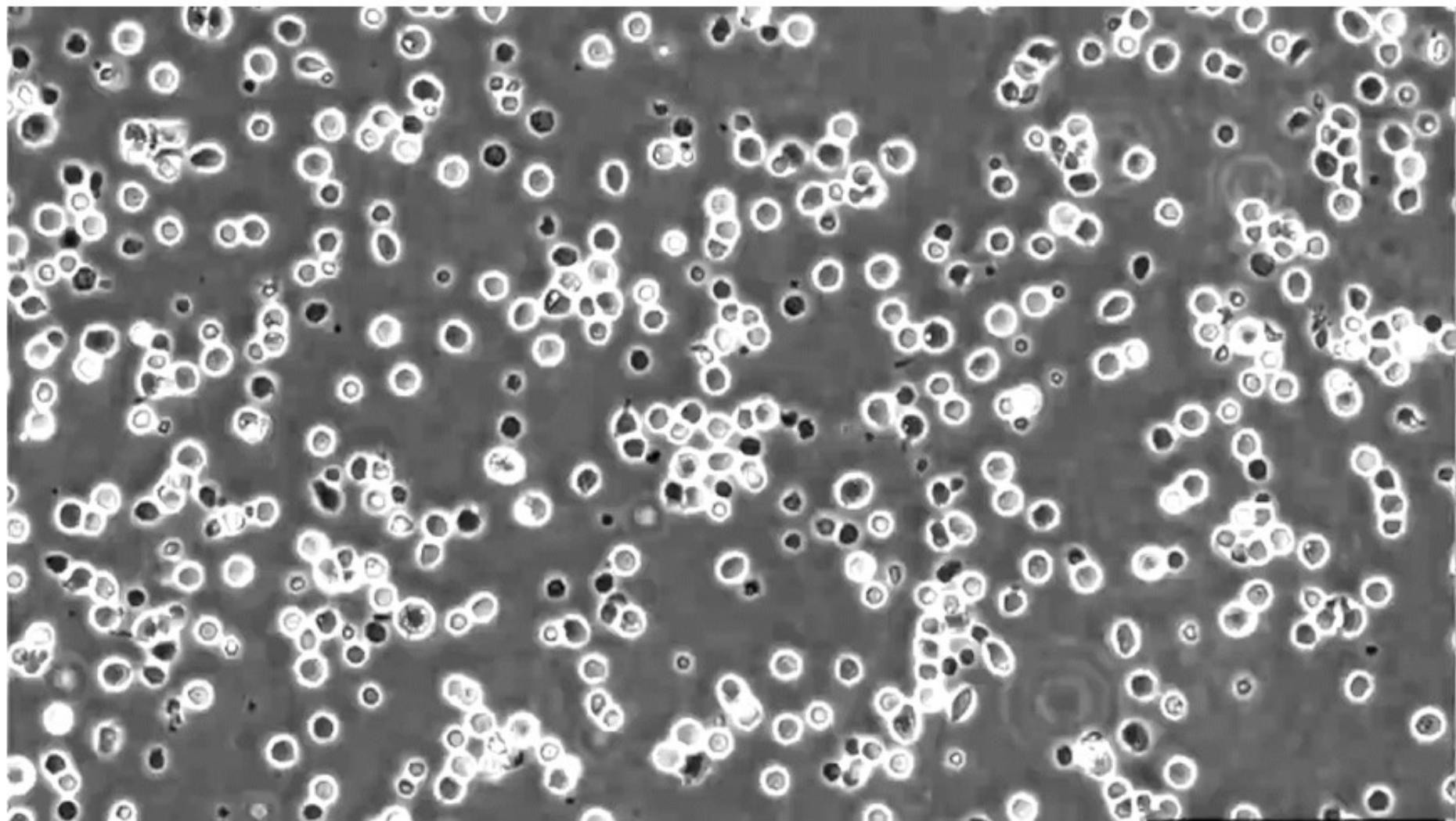
Wilting & VP, Curr Op Neurosci, 2019

Zierenberg, et al., PRR 2020 & PRE 2020

Neto, Spitzner & VP, arxiv

# Information Theory

# Developing Neural Network *in vitro*



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

# Basics of Information Theory

Mutual information  $I(X, Y)$ : statistical dependence between two observables  $X, Y$ .

Independence:

$$p(x, y) = p(x)p(y) \quad \forall x, y \quad \rightarrow I(X, Y) = 0$$

Mutual Information:

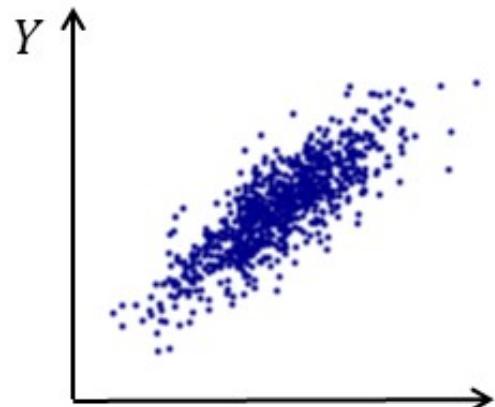
$$I(X, Y) = \left\langle \log \frac{p(x,y)}{p(x)p(y)} \right\rangle_{x,y} = \left\langle \log \frac{p(x|y)}{p(x)} \right\rangle_{x,y}$$

Shannon Entropy:

$$H(X) = I(X, X) = \left\langle \log \frac{p(x|x)}{p(x)} \right\rangle_x = \left\langle \log \frac{1}{p(x)} \right\rangle_x$$

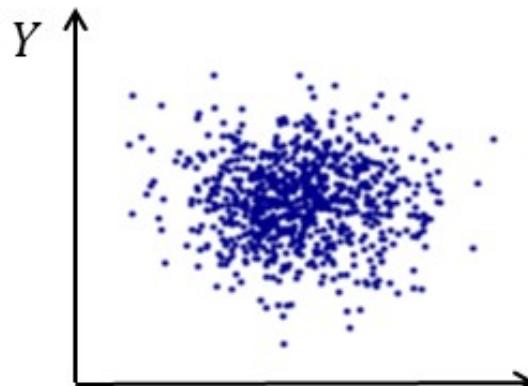
Conditional Mutual Information:

$$I(X, Y|Z) = \left\langle \log \frac{p(x,y|z)}{p(x|z)p(y|z)} \right\rangle_{x,y,z}$$



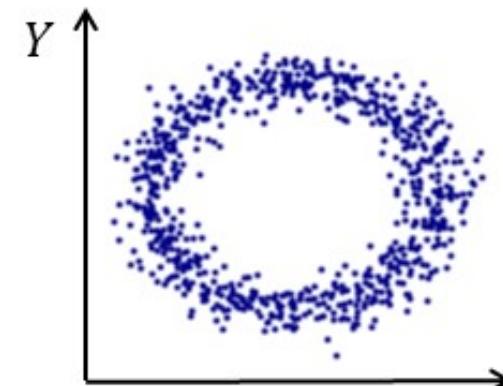
$\text{Correlation}(X, Y) > 0$

$$I(X, Y) > 0$$



$\text{Correlation}(X, Y) = 0$

$$I(X, Y) = 0$$



$\text{Correlation}(X, Y) = 0$

$$I(X, Y) > 0$$

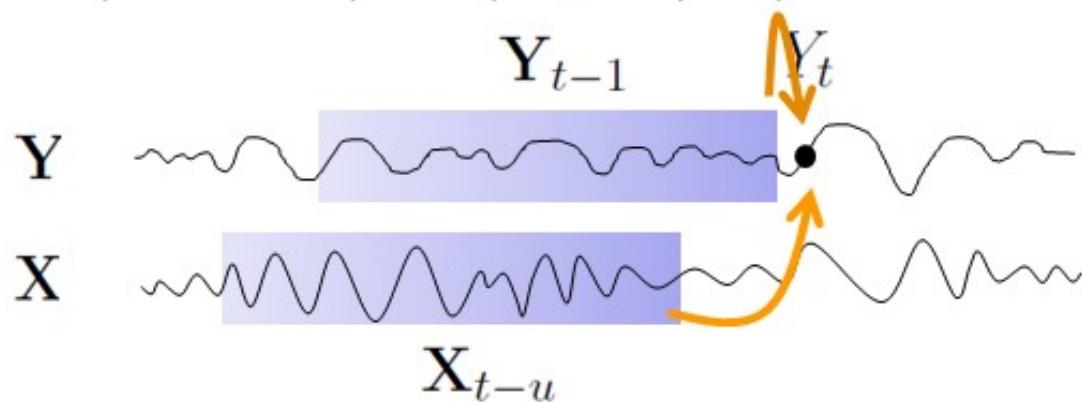
# With Development, Computational Capacity Increase

Alain Turing / Chris Langton  
Components of computation

- Transfer
- Storage
- Modification

information transfer:

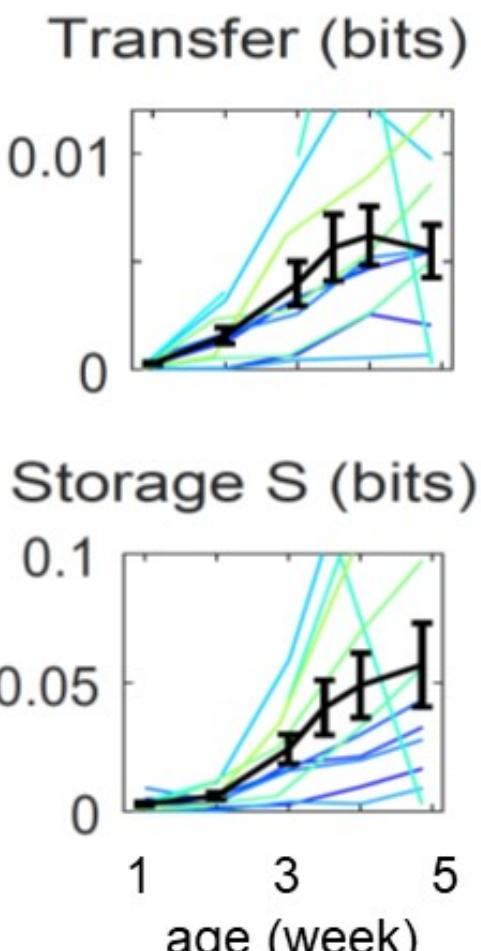
$$TE(\mathbf{X}^- \rightarrow Y^t) = I(Y^t; \mathbf{X}^- | \mathbf{Y}^-)$$



active information storage:

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

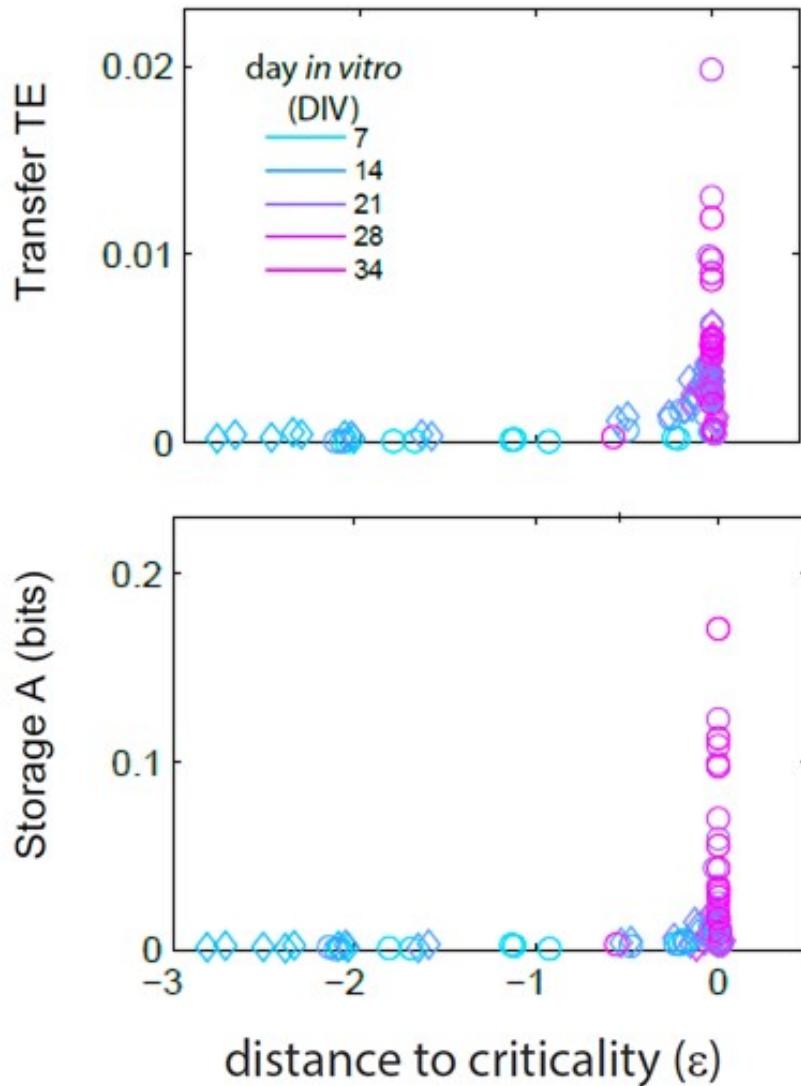
[Langton, 1990; Lindner et al., 2011; Lizier et al., 2014  
[Wibral, Lizier & VP, 2015]



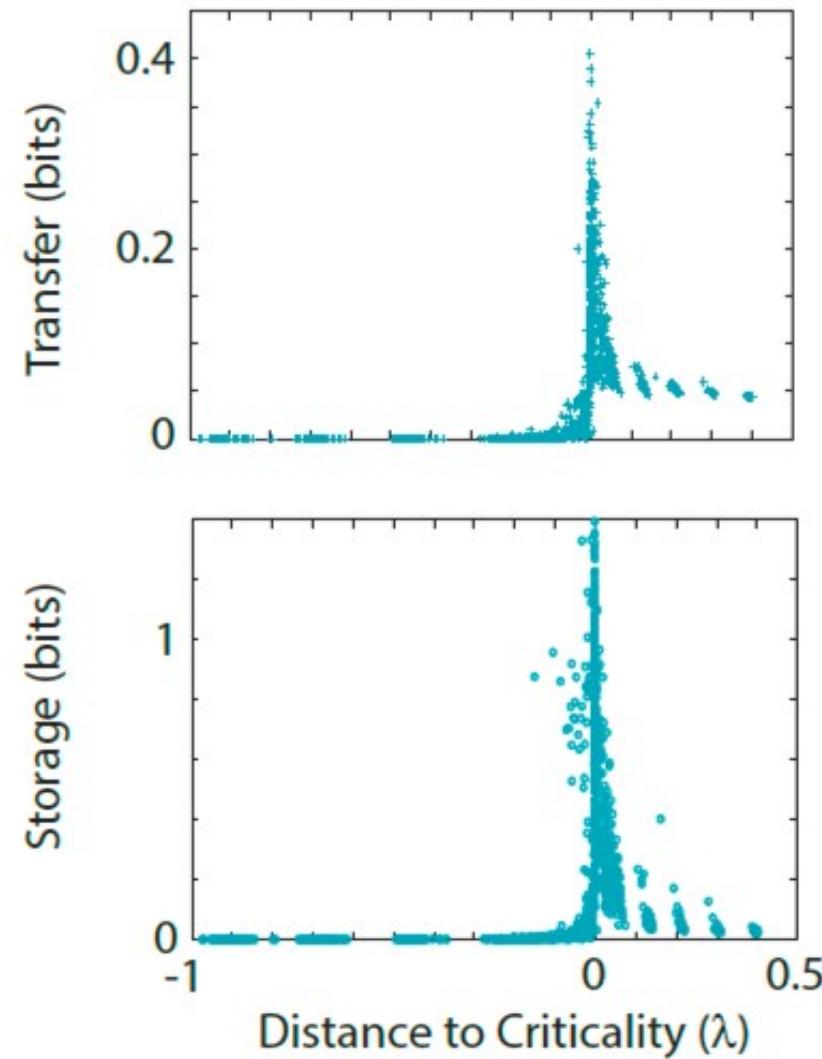
[VP et al., in prep]  
[Wibral, ... & VP, Entropy, 2017]

# Processing Capacity Increases at Criticality

Experiment

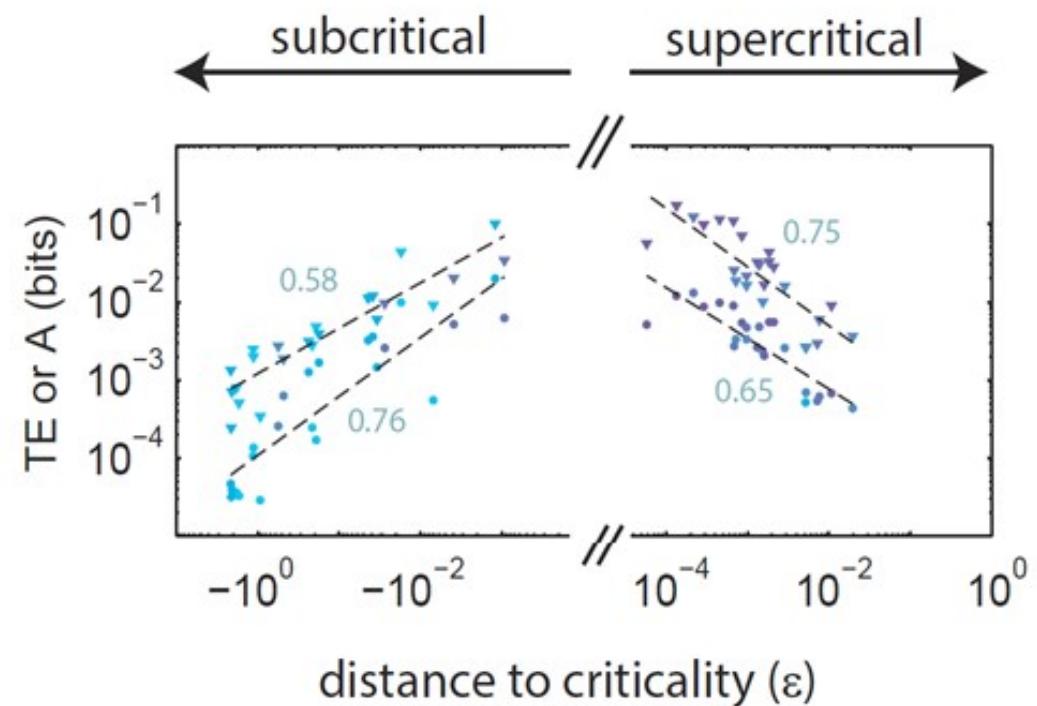
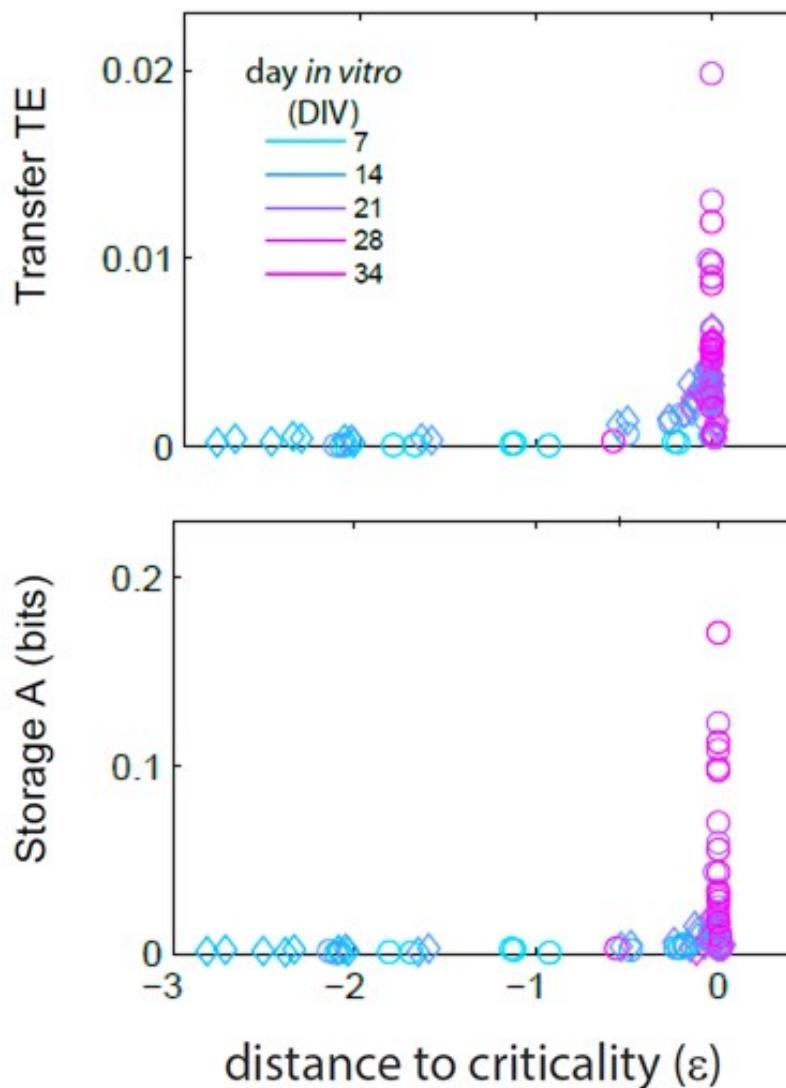


Model

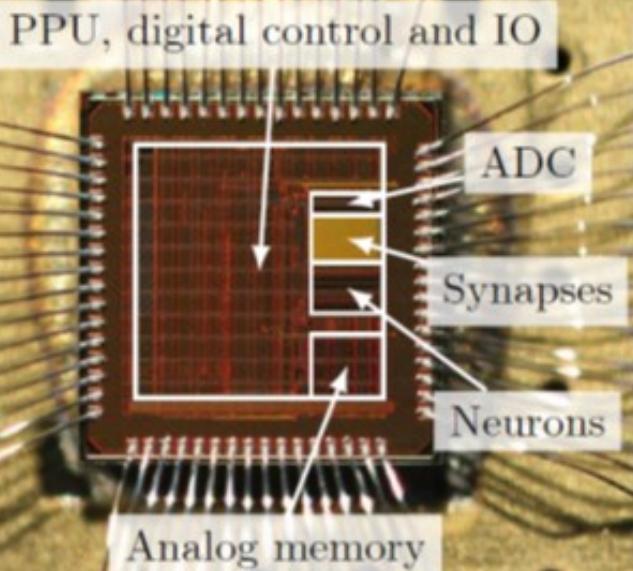


# Processing Capacity Increases at Criticality

Experiment



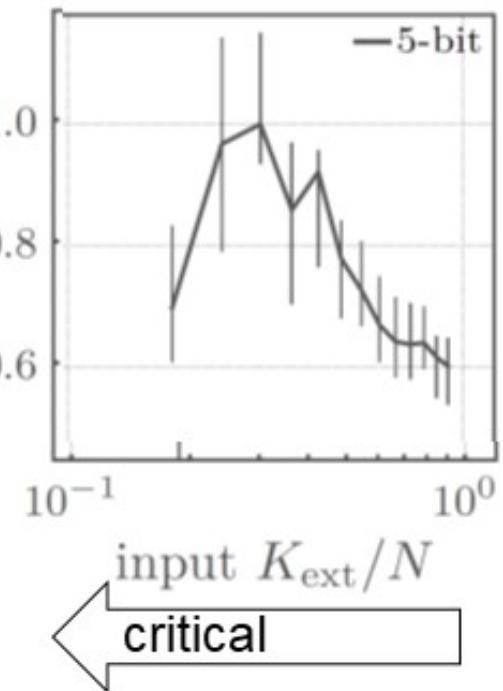
# Neuromorphic Chip



Emulating  
Living Computation

Collaboration with EINC, Heidelberg

Performance

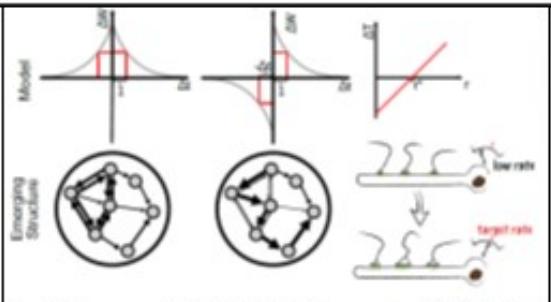


[Cramer et al., & VP, Nature Communications, 2020]

**COVID**

# Physics of Computation

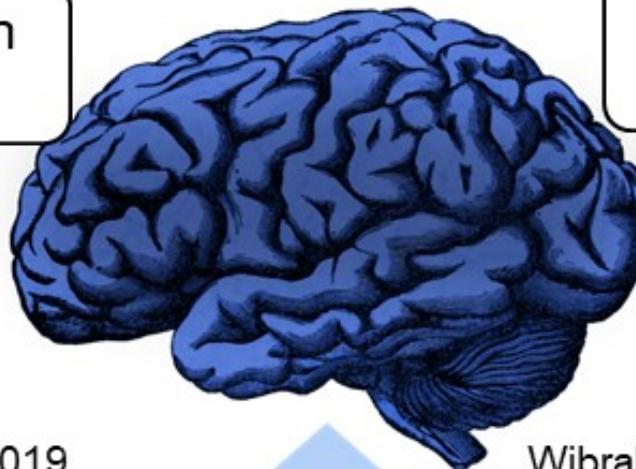
## Emergence of Computation and Structure Formation



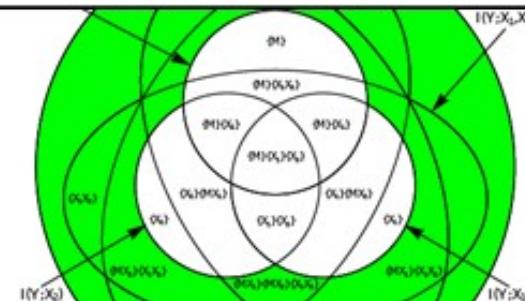
del Papa, VP & Triesch, 2017, 2019

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

Cramer, ... & VP, Nat. Commun., 2020



## Information Theory to Quantify & to Design Computation

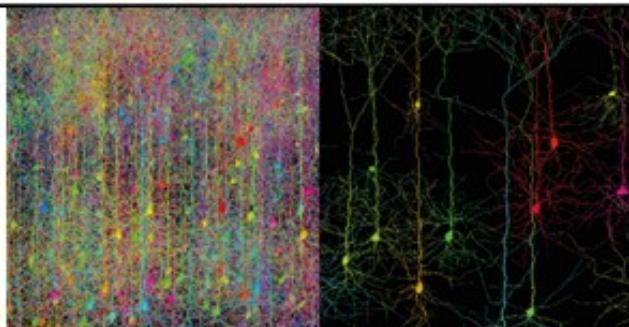


Wibral, Lizier & VP, "Matter to Life", OUP, 2017

Wollstadt et al., Plos CB, 2017

Wibral et al., Entropy, 2017

## Spreading Dynamics and Subsampling Theory



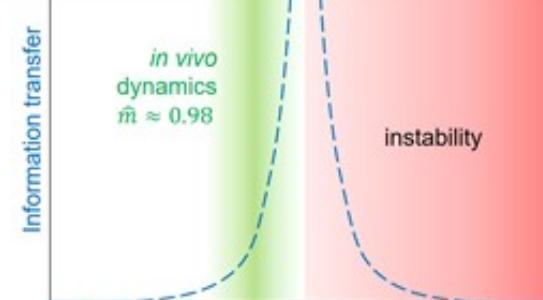
VP et al., 2009, 2014

Levina & VP, Nat. Commun., 2017

Wilting & VP, Nat. Commun., 2018

Dehning et al., ... & VP, Science 2020

## Phase Transitions to Tune Computation



Wilting & VP, Cerebr. Ctx, 2019

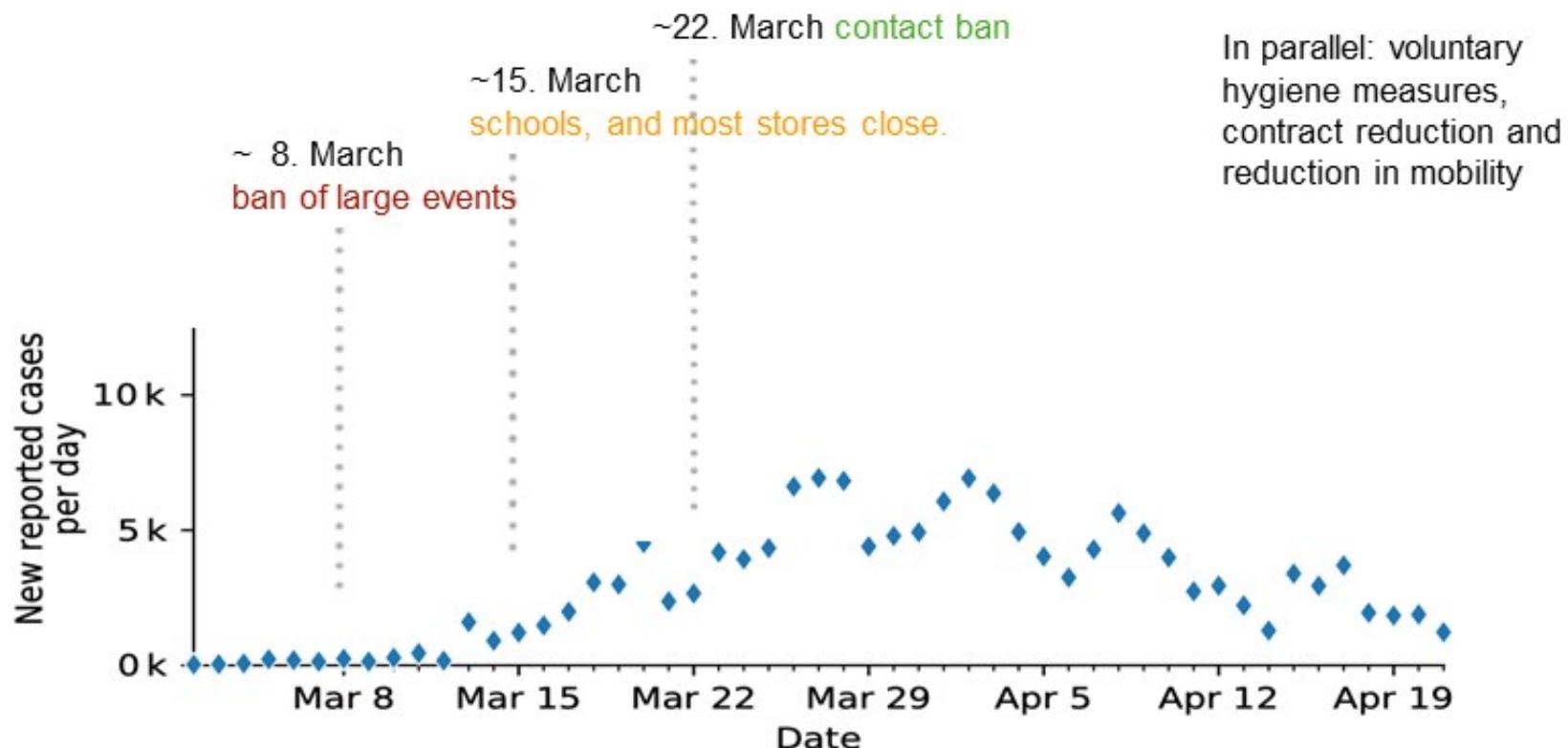
Wilting & VP, Curr Op Neurosci, 2019

Zierenberg, et al., PRR 2020 & PRE 2020

Neto, Spitzner & VP, arxiv

# Spreading of SARS-CoV-2 in Germany and the impact of governmental interventions

# Reported Infections with SARS-CoV-2 in Germany



How does one project the complex system of disease dynamics to a model?

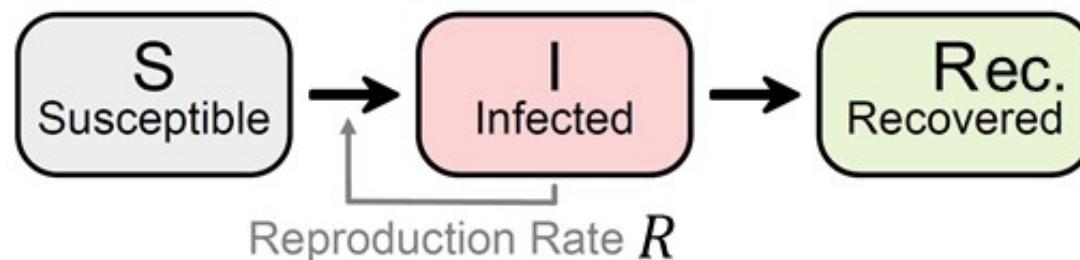
- Epidemiological “SIR” model to estimate R
- Time points of governmental interventions as priors for change points
- Bayes MCMC Sampling

# SIR to Infer the Reproductive Number $R$

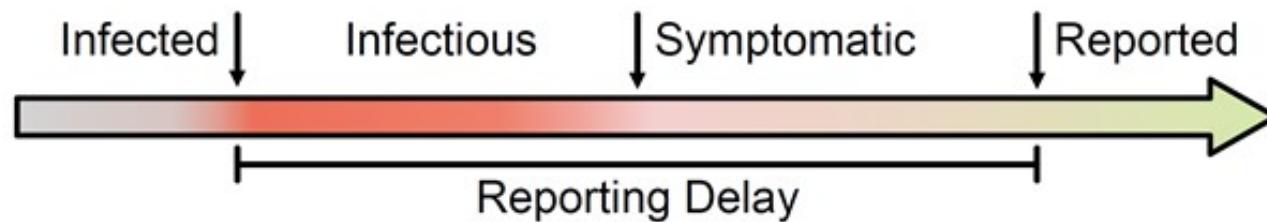
Reproduction number  $R$ :

One person infects on average  $R$  persons in the subsequent generation.

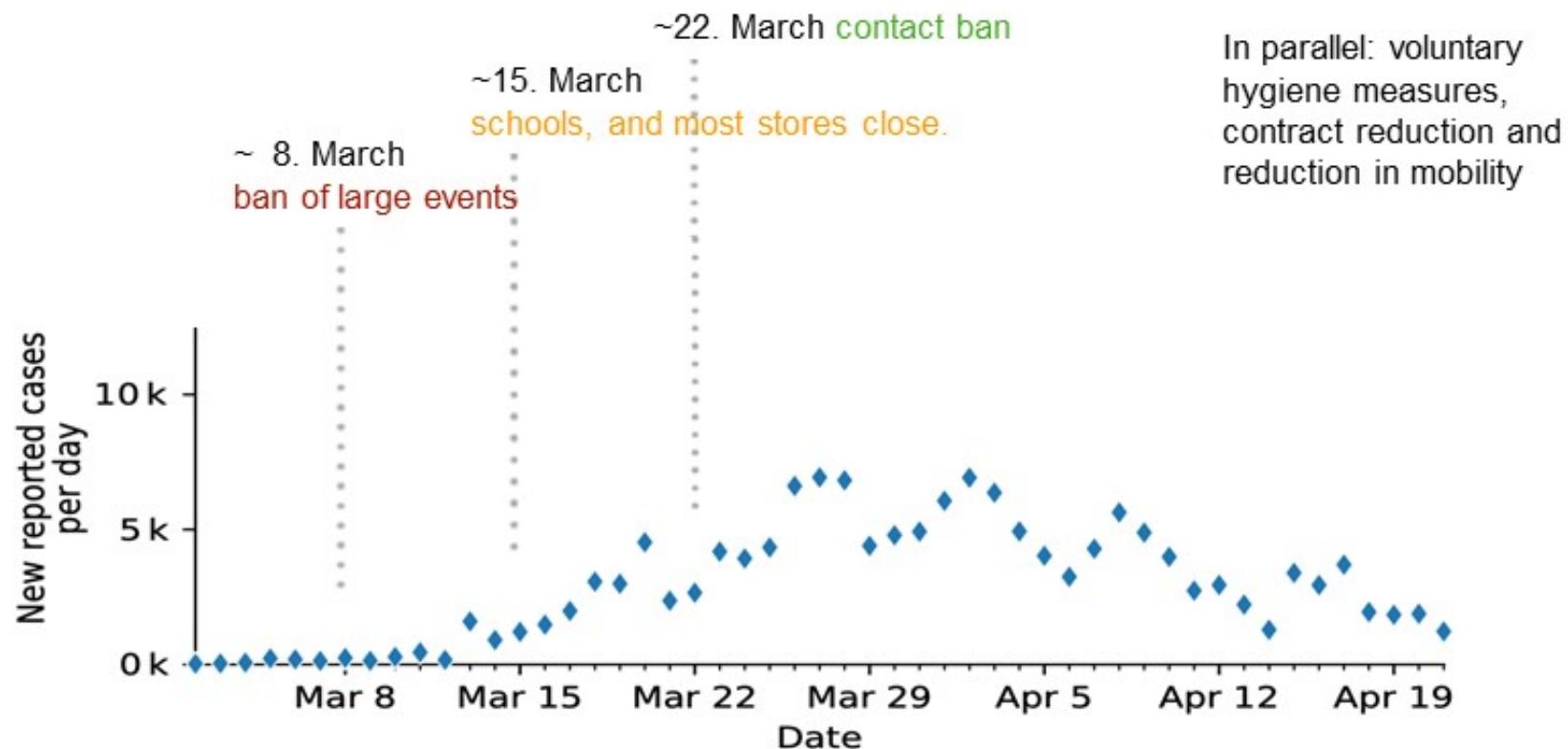
## Epidemiologic States



## Time Course

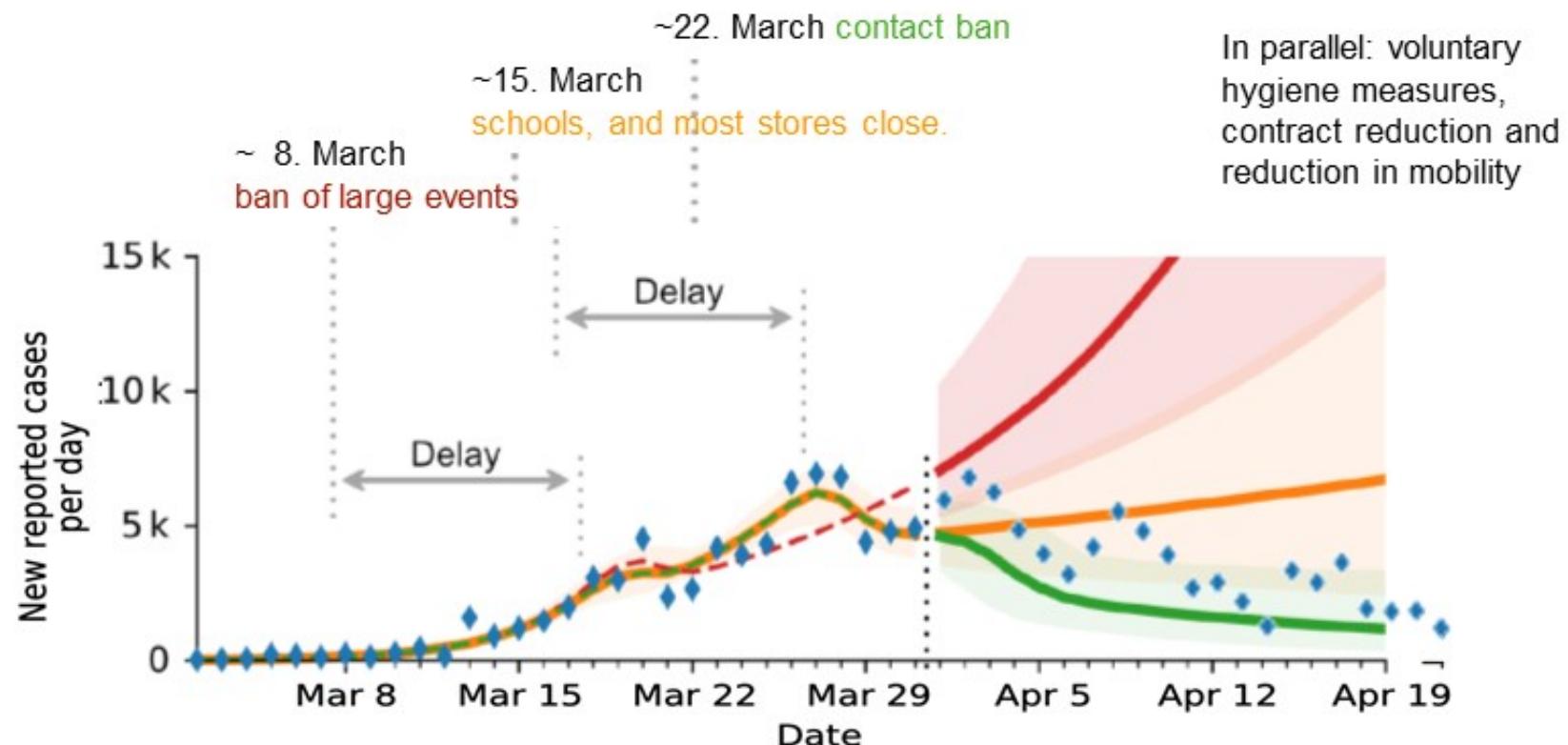


# Reported Infections with SARS-CoV-2 in Germany

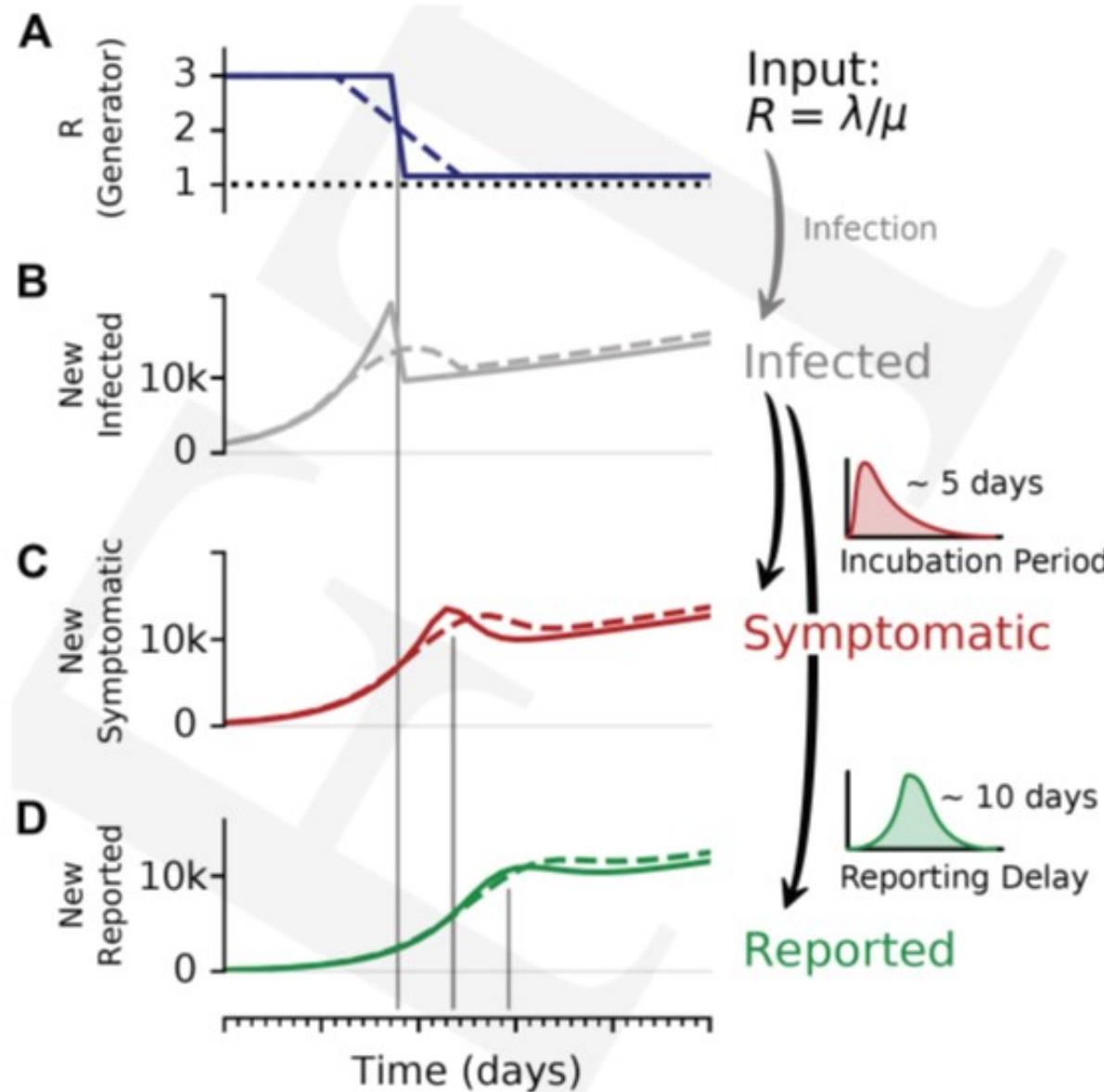


How does one project the complex system of disease dynamics to a model?

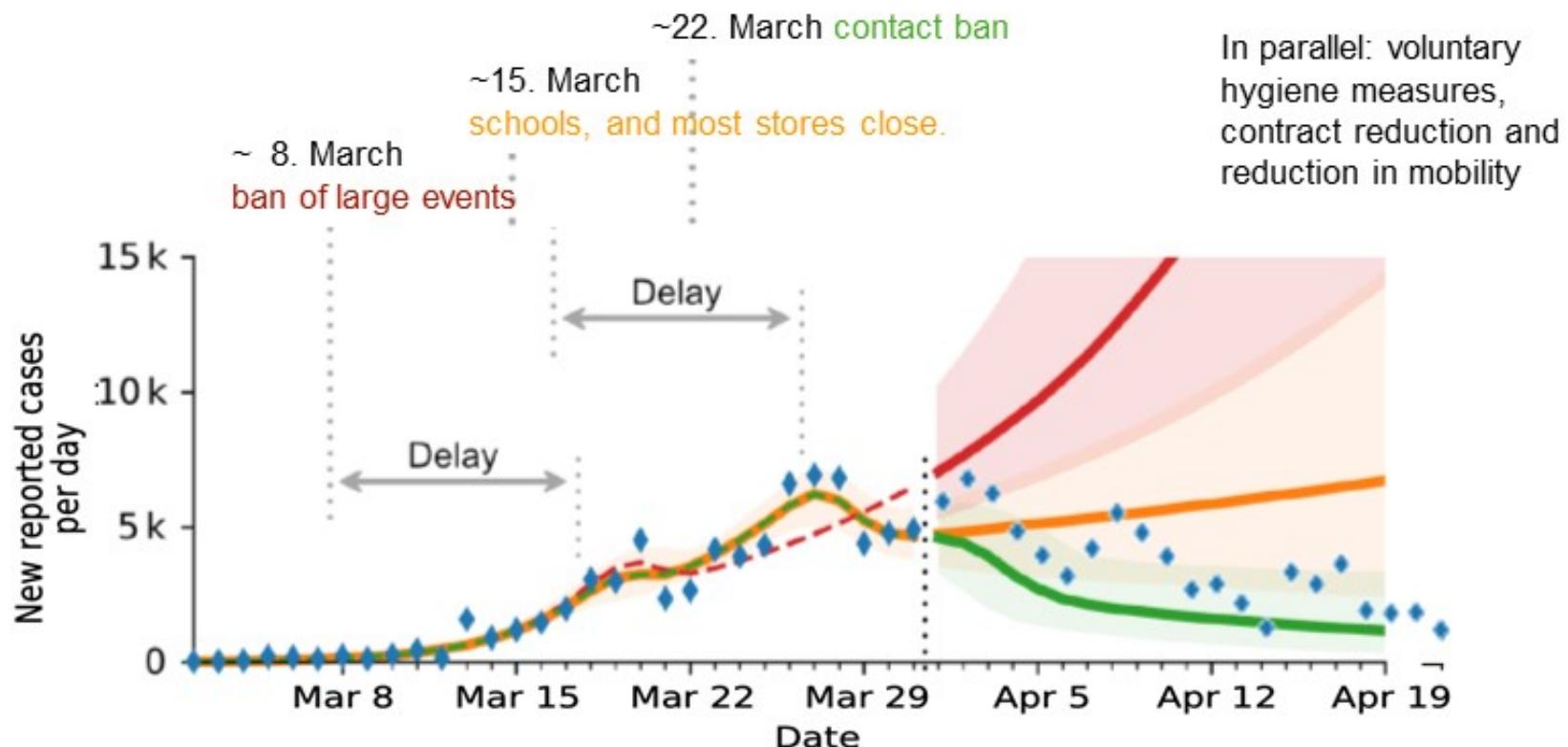
# Reported Infections with SARS-CoV-2 in Germany



# A Transient Reduction in Case Numbers does Not Necessarily Mean that R was below 1.

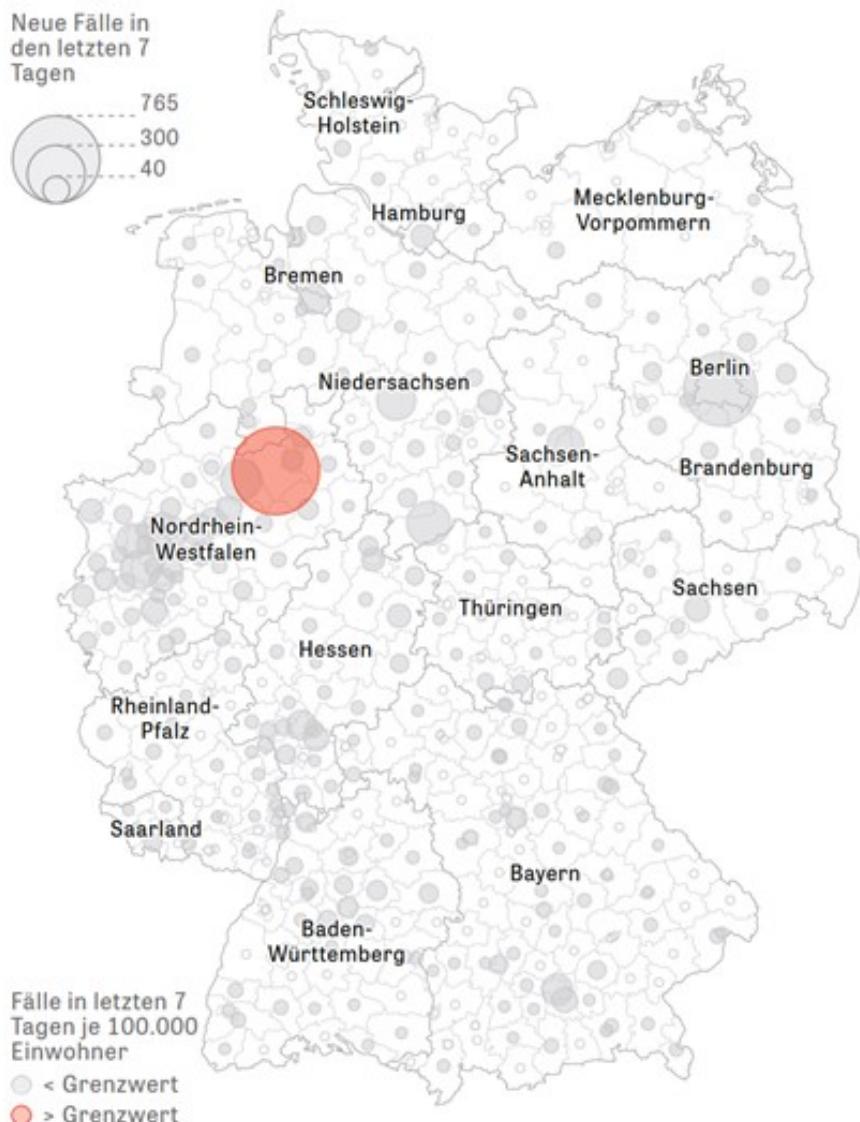


# Reported Infections with SARS-CoV-2 in Germany



- Only after March 22, the reproductive number decreased clearly below 1
- A transient decline in case numbers does not imply that R is smaller than 1.

### 3. Break the Chain!



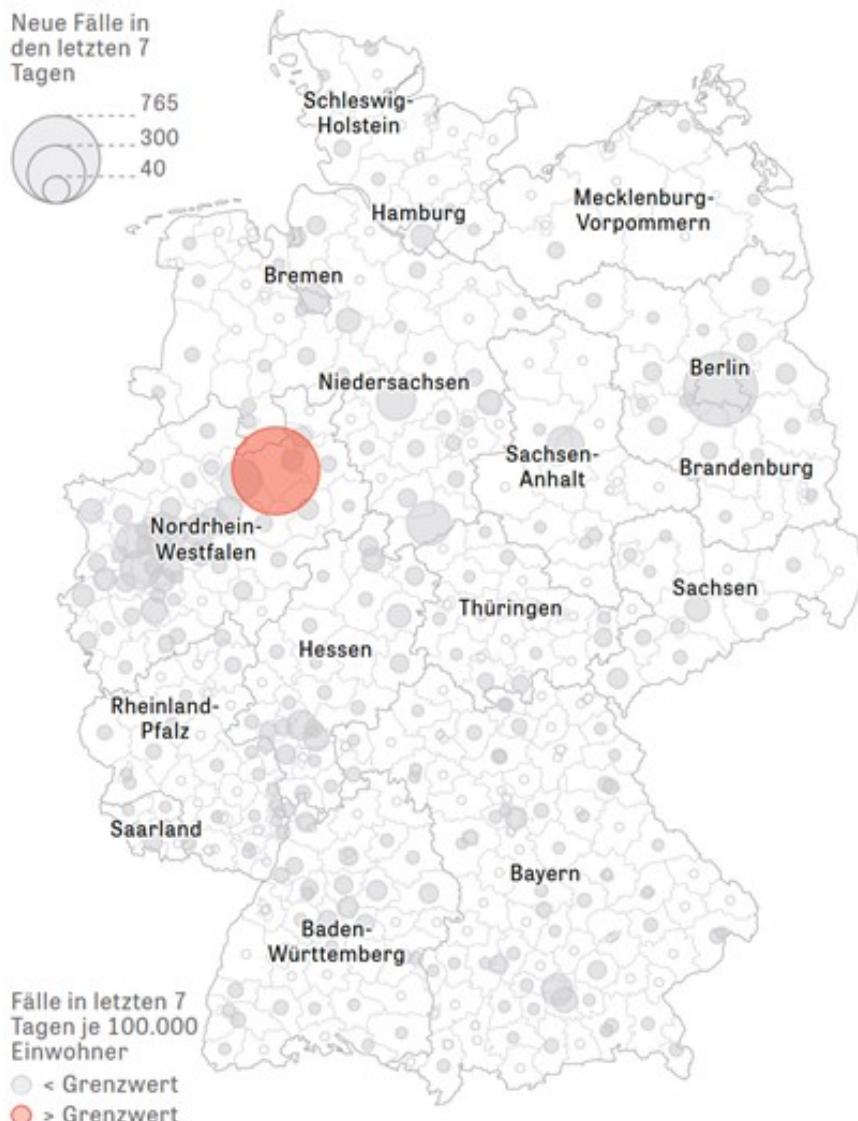
Joint statement of the four large research organizations in Germany [1].

Two Pillars for Disease Containment

- 1. “Break the chain” via test - trace - isolate:
- 2. Detecting new outbreaks as early as possible

Low case numbers have a clear advantage for health – and for the economy.

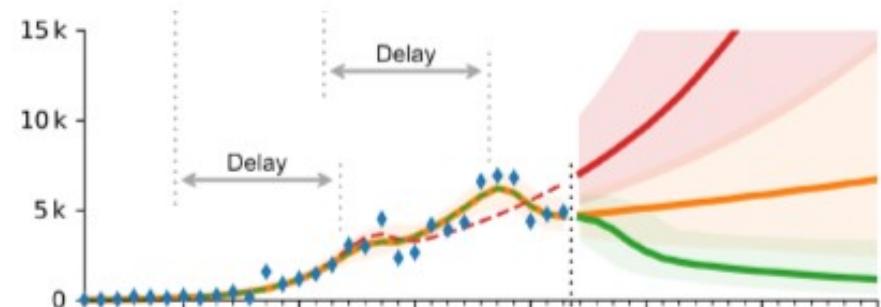
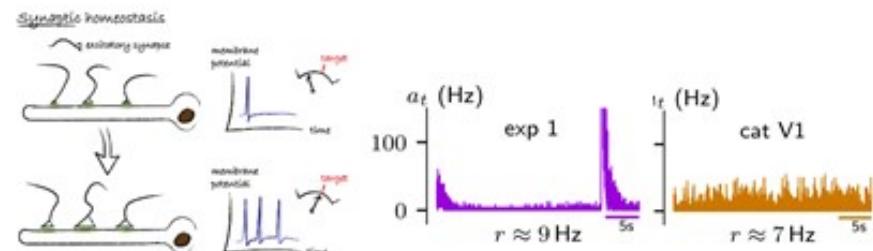
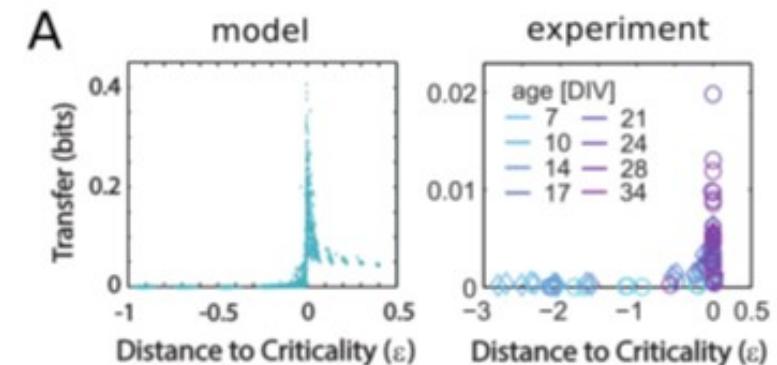
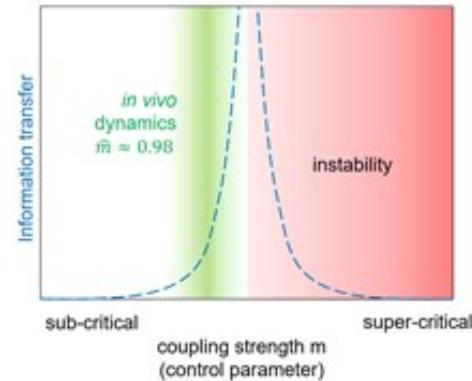
## 4. The coming months



- 1. Local eradication  
European Coordination necessary
- 2. “Chronic” local outbreaks
- 3. “Second wave”, i.e. some large-scale, uncontrolled outbreak
- “Herd immunity” difficult to establish, if Immunity lasts only for a few months or years
- Hopes for improved treatment and development of vaccinations

# Summary

- Criticality maximizes collective computational properties (information transfer, sensitivity, correlation length)
- Harness the vicinity of a critical point for flexible tuning of computational properties  
[Wilting et al., 2018; Cramer et al., 2020]
- Cortical networks show diverse working points  
[Wilting et al., 2018/2019]
- External input strength can account for differences between *in vivo* and *in vitro* dynamics. [Zierenberg, Wilting, VP, 2018]
- Bayesian inference of the spreading dynamics of SARS-CoV-2 in Germany enabled us to quantify the reduction in spreading around the change points.  
[Dehning et al., 2020]



# Thank you!

## Priesemann Group

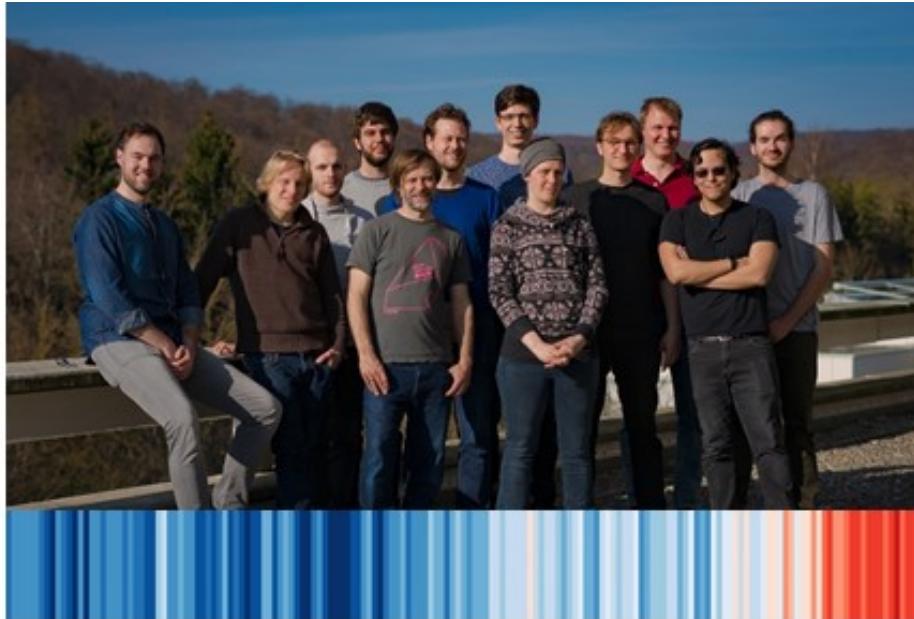
Sebastian Contreras  
Jonas Dehning  
David Ehrlich  
Daniel Gonzalez Marx  
Kira Herff  
Matthias Linden (guest)  
Matthias Loidolt  
Fabian Mikulasch  
Sebastian Mohr  
Joao Neto  
Valentin Neuhaus  
Lucas Rudelt  
Andreas Schneider  
Julian Schulz  
Paul Spitzner  
Patrick Vogt  
Johannes Zierenberg  
+ you?

## External PhD students (co-supervised)

Benjamin Cramer (U Heidelberg)  
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)



**Discussions on COVID within the Göttingen Campus and beyond:**  
Philip Bittihn, Tim Friede, Theo Geisel, Moritz Linkmann, Matthias Loidolt, Vladimir Zykov, Heike Bickeböller, Eberhard Bodenschatz, Wolfgang Brück, Alexander Ecker, Andreas Leha, Ramin Golestanian, Helmut Grubmüller, Stephan Herminghaus, Reinhard Jahn, Norbert Lossau Michael Meyer-Hermann, Iris Pigeot, Simone Scheithauer, Anita Schöbel, Fredi Schüth,  
**Michael Wibral & Michael Wilczek**

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



Gertrud Reemtsma Stiftung