

*Computational Neuroscience Group*  
*Department of Physiology*  
*University of Bern*

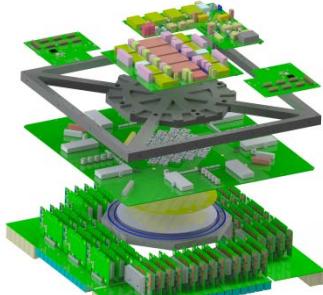
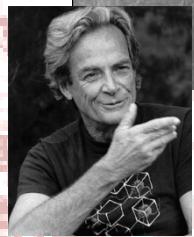
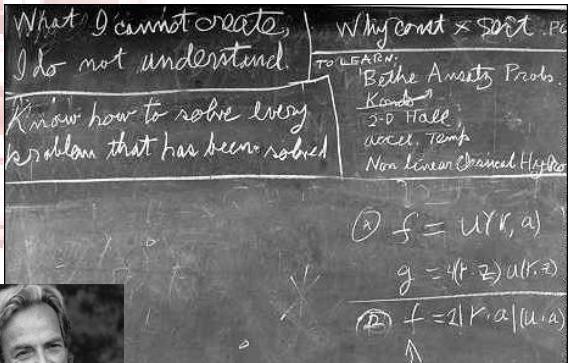
## Computing with physics

# From biological to artificial intelligence and back again

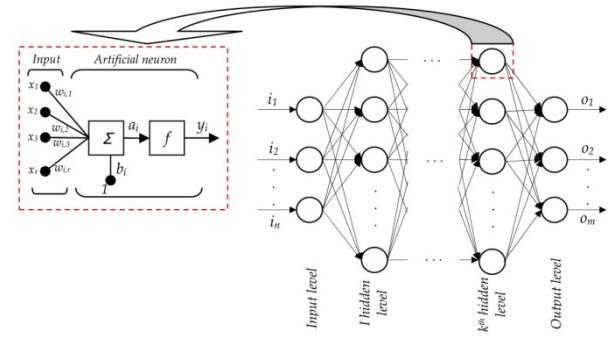
Mihai A. Petrovici

*Electronic Vision(s)*  
*Kirchhoff Institute for Physics*  
*University of Heidelberg*

# Bio-inspired artificial intelligence



messy & hard, but powerful



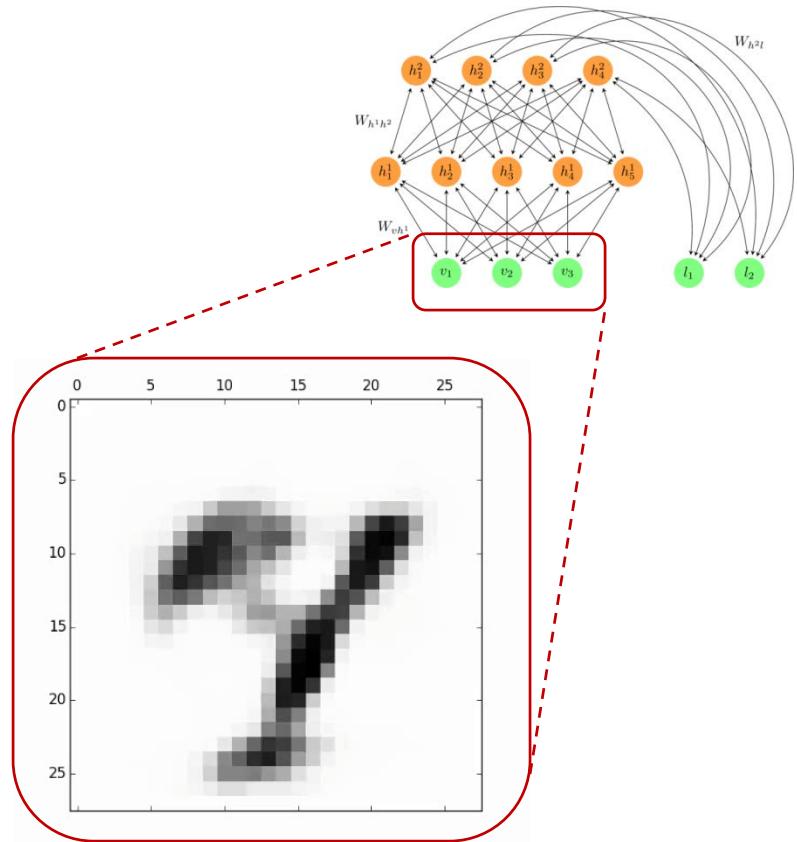
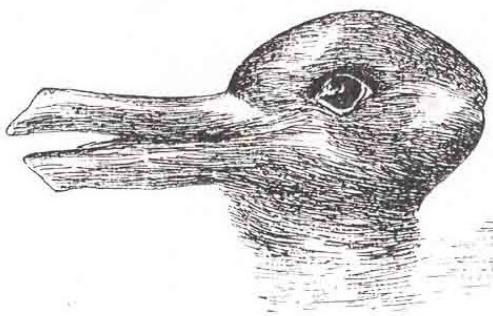
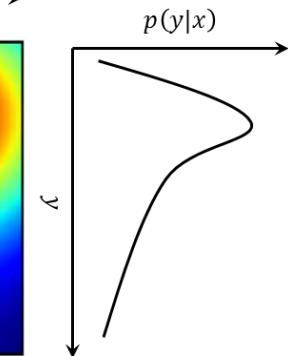
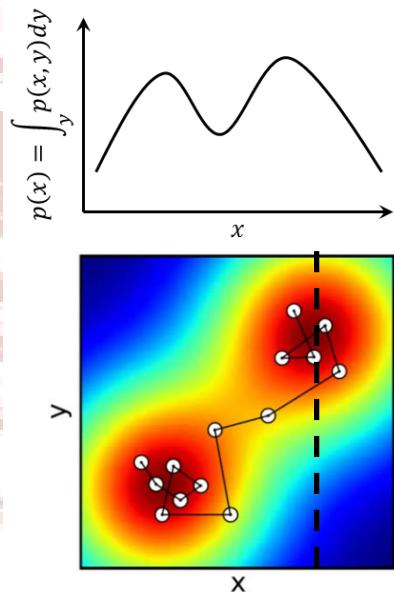
clean & easy, but not as efficient



Why spikes?

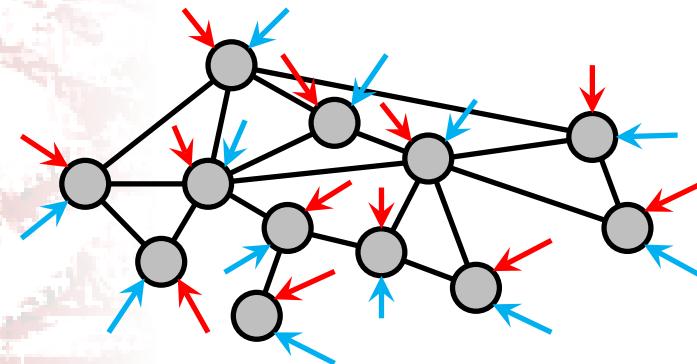


# Sampling-based Bayesian computation



# Whence stochasticity?

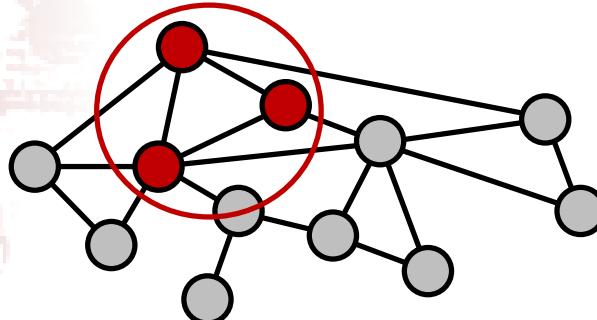
Injection of stochasticity



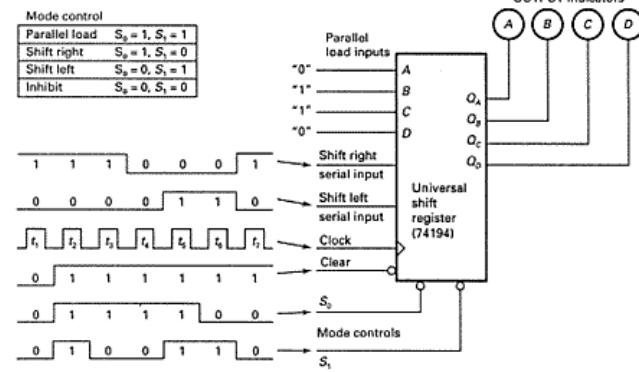
Stochasticity in continuous systems



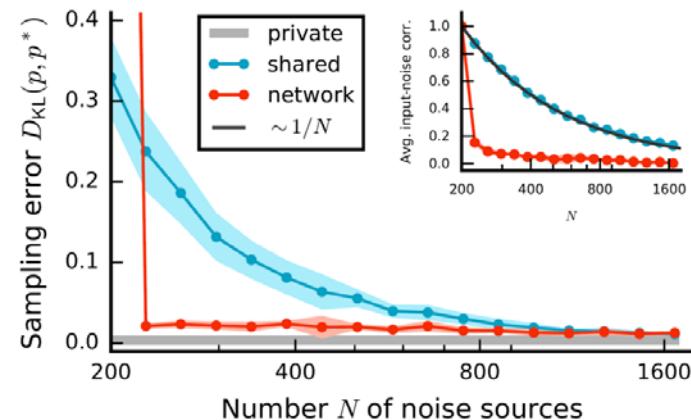
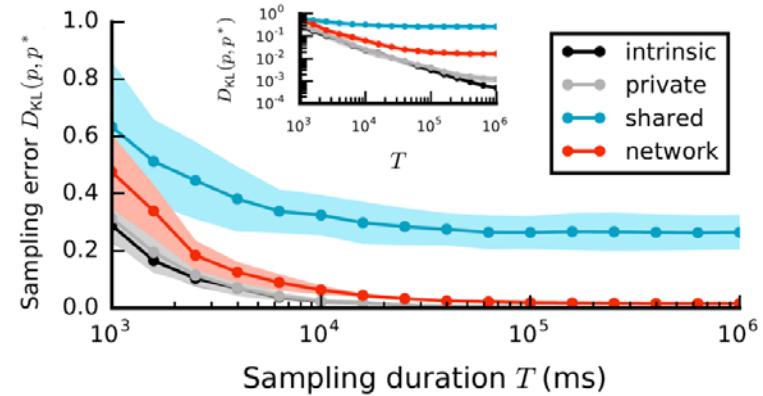
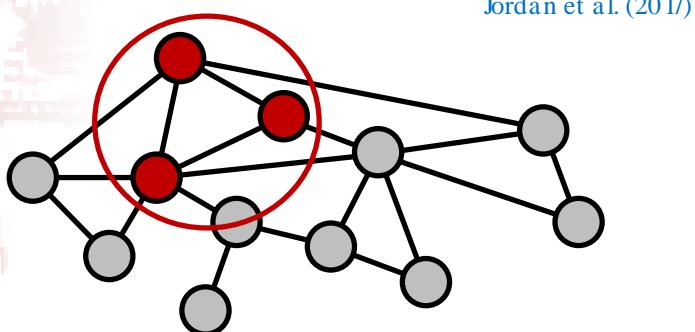
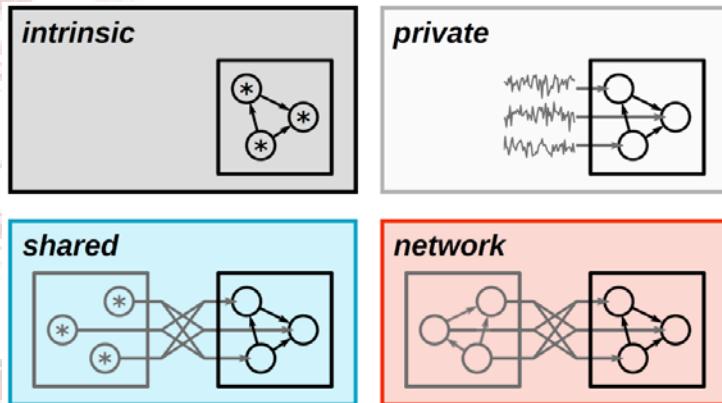
Embedded stochasticity



Stochasticity in (dedicated) discrete systems



## (Pseudo)randomness in deterministic spiking networks

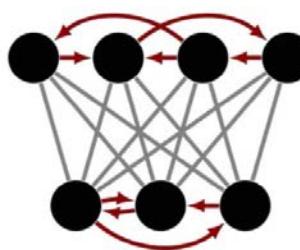
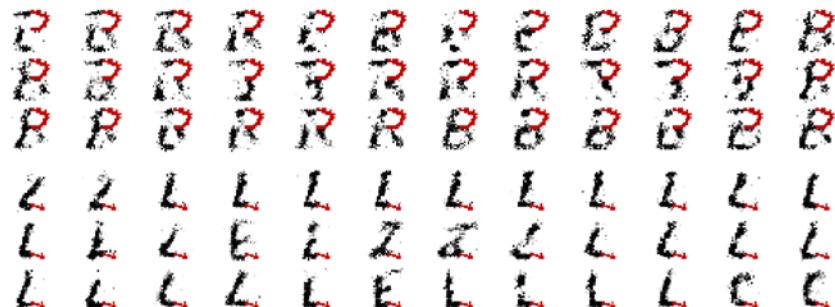
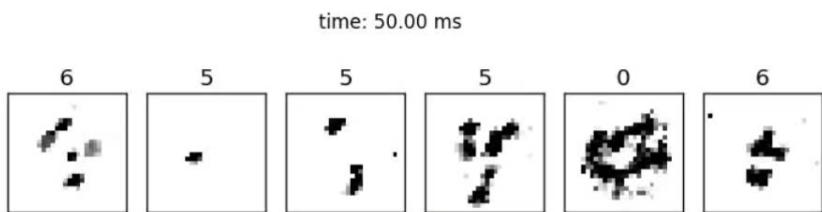


## Stochasticity from function: Bayesian inference & dreaming

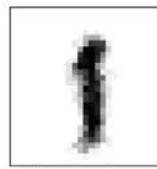
hidden neurons



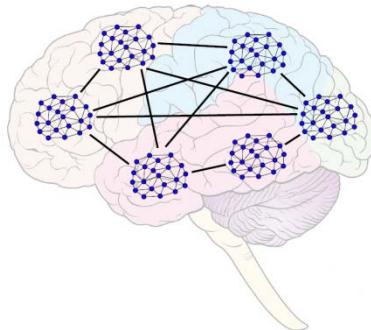
visible neurons



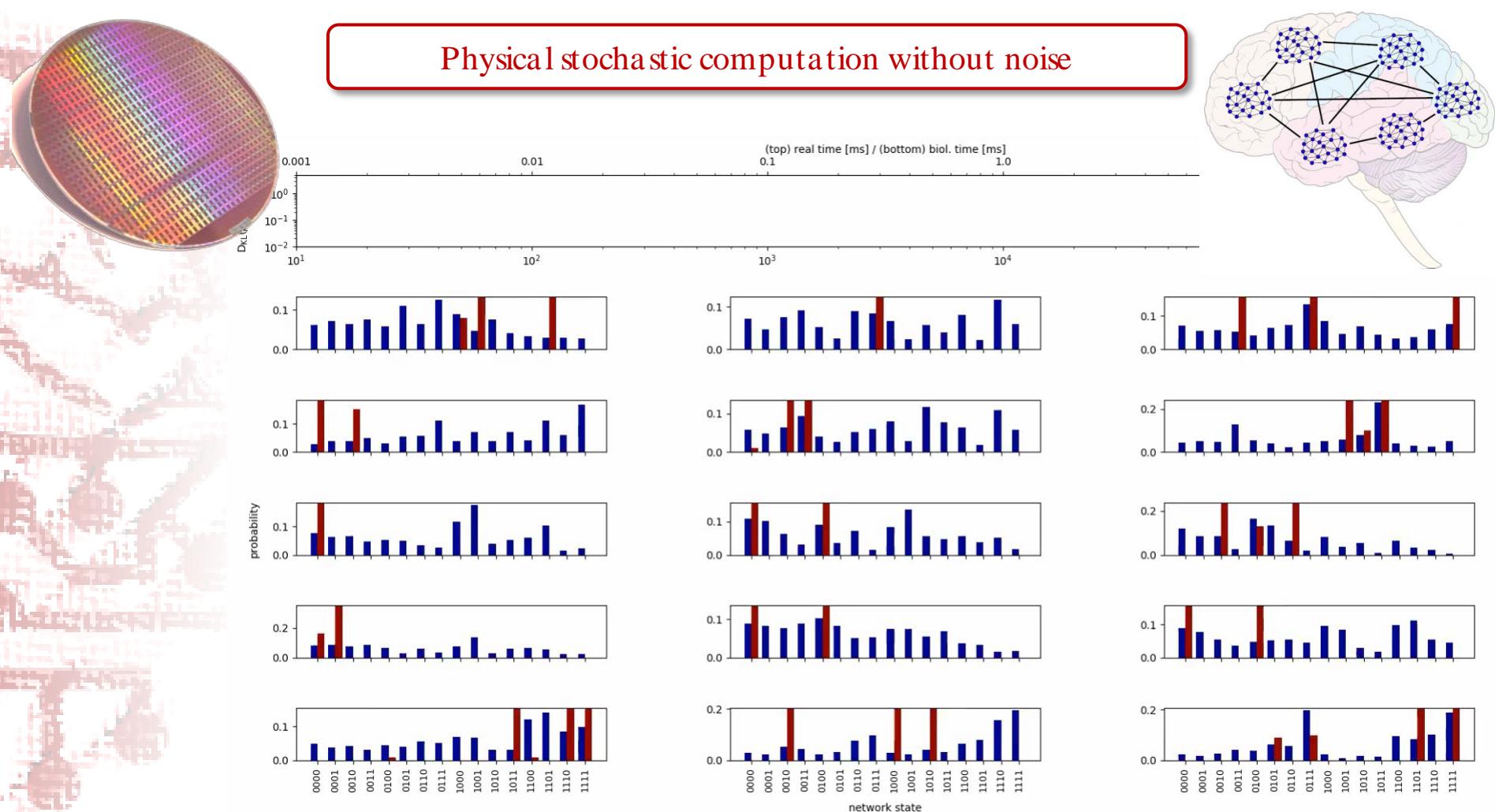
after training  
50ms



Poisson reference



# Physical stochastic computation without noise



## Superior mixing in spiking networks

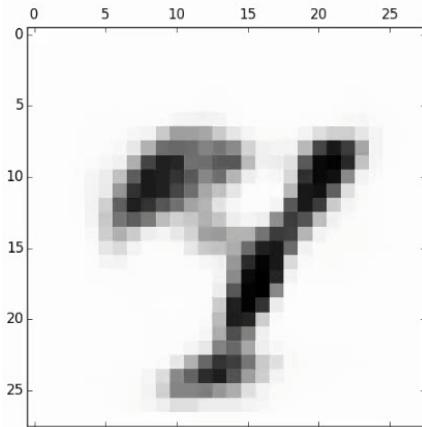
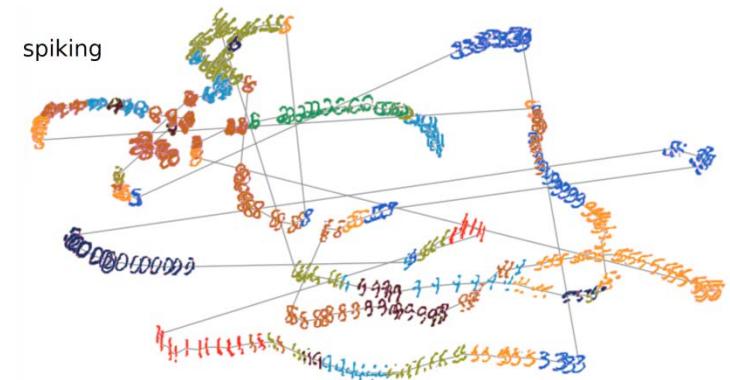
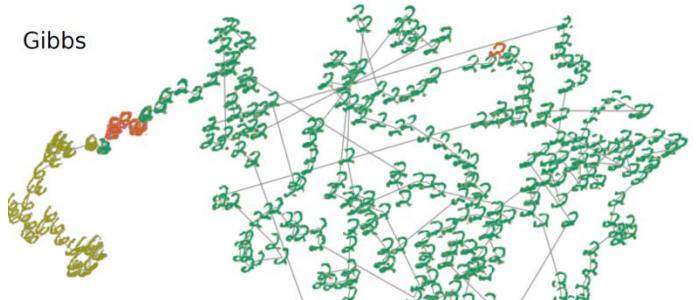
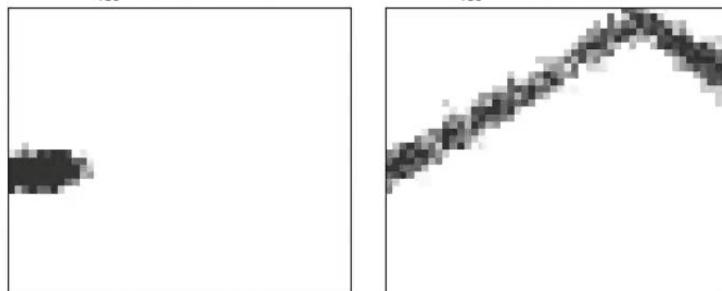
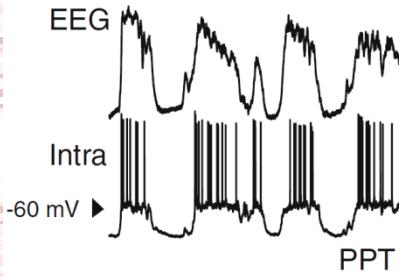


Image 0: 1/980 samples  
 $\tau_{rec} = 10 \text{ ms}, U = 1$        $\tau_{rec} = 50 \text{ ms}, U = 0.22$

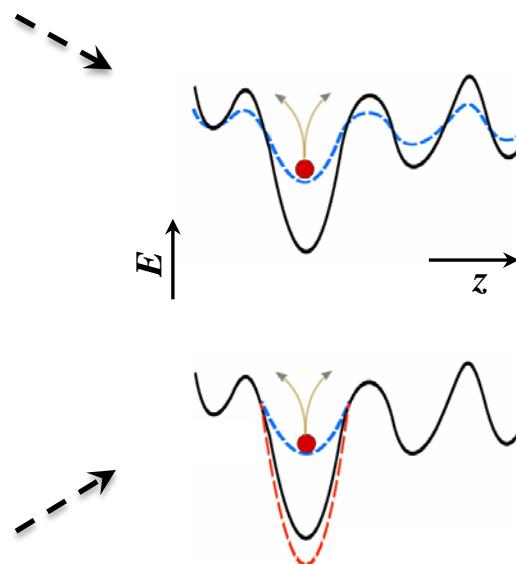
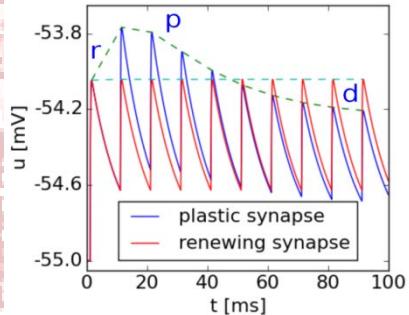


# Biological mechanisms for superior mixing

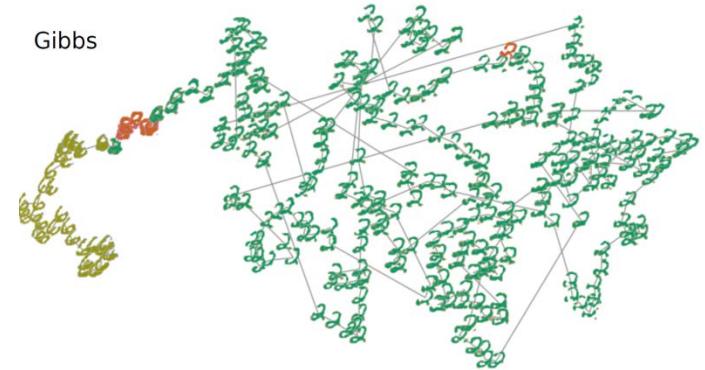
cortical oscillations



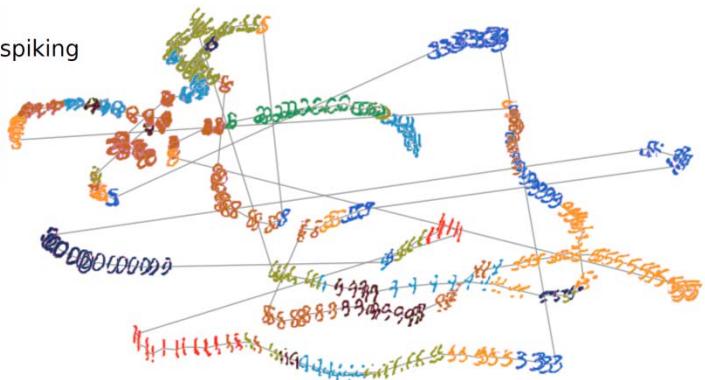
short-term synaptic plasticity

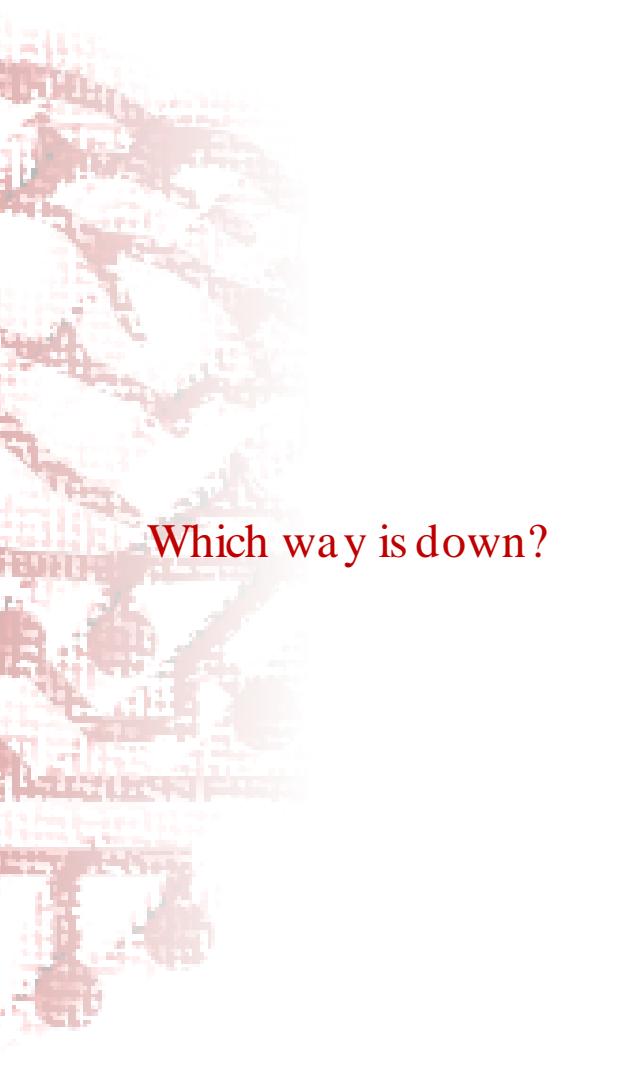


Gibbs



spiking

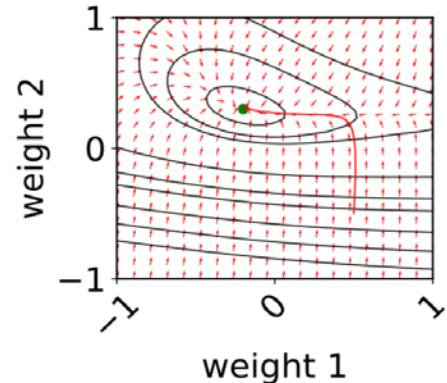
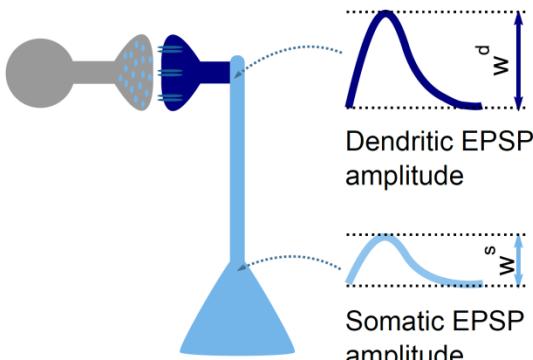




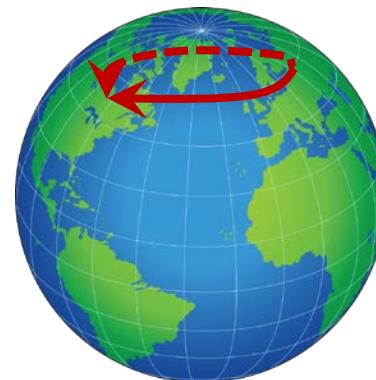
Which way is down?



## What's wrong with Euclidean gradient descent?

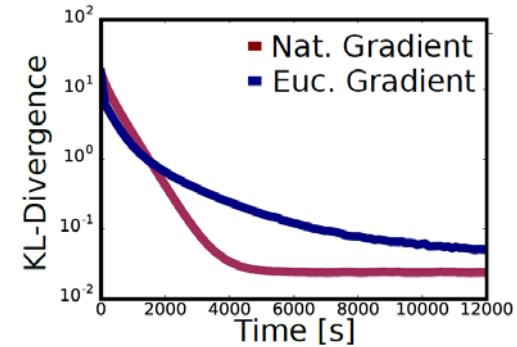
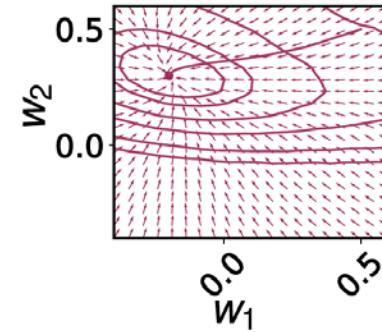
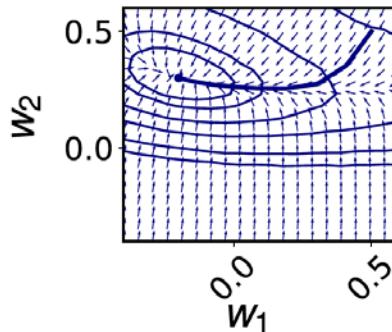
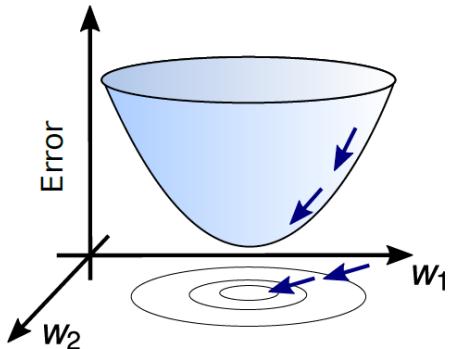


$$\Delta w^{\text{syn}} = -\eta \frac{\partial C(\alpha w^{\text{syn}})}{\partial w^{\text{syn}}} = -\eta \alpha \frac{\partial C(w^{\text{syn}})}{\partial w^{\text{syn}}}$$



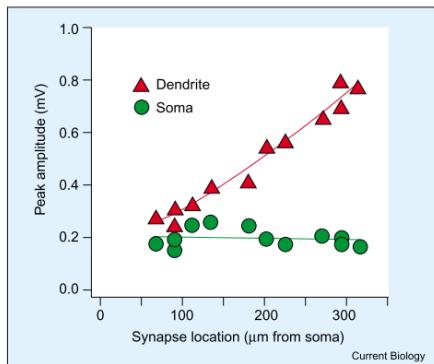
$$\nabla^{\text{n}} = G(\mathbf{w})^{-1} \nabla^{\text{e}}$$

## Synaptic plasticity as natural gradient descent

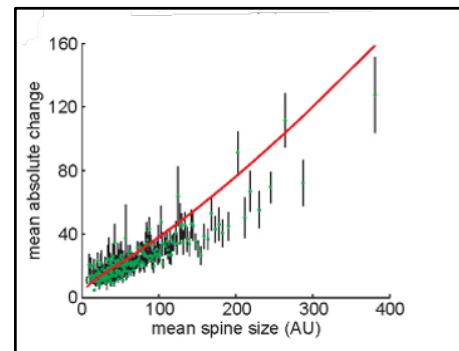


local learning:  $\Delta^n w = \eta \int_0^T \gamma_0 [y^* - \phi(V)] \frac{\phi'(V)}{\phi(V)} \left( \frac{x^\epsilon}{r} - \gamma_1 + \gamma_2 w \right) dt$

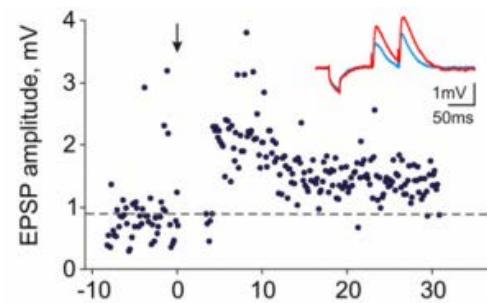
Kreutzer et al., in prep.



Häusser et al. (2001)

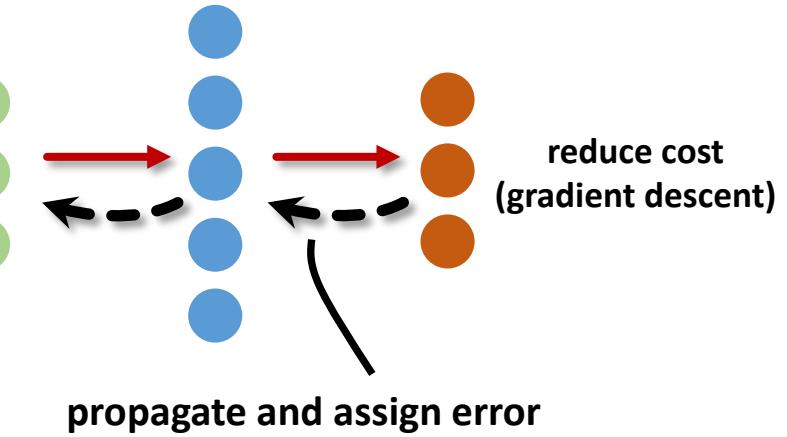
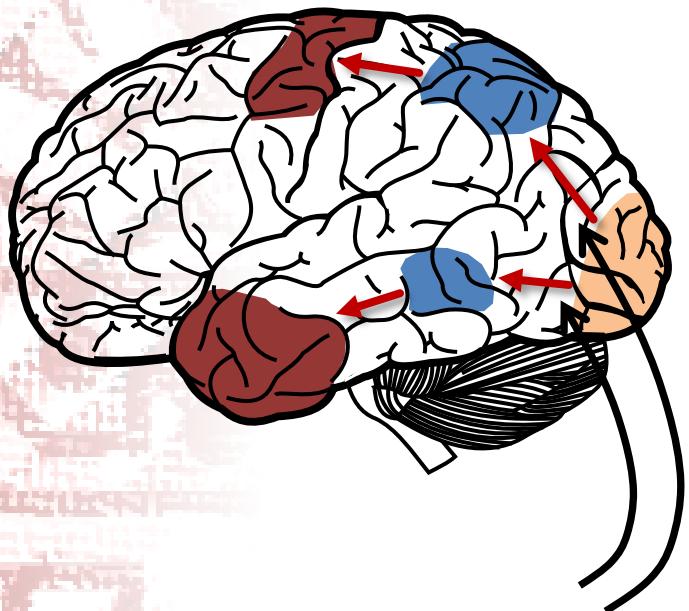


Loewenstein et al. (2011)



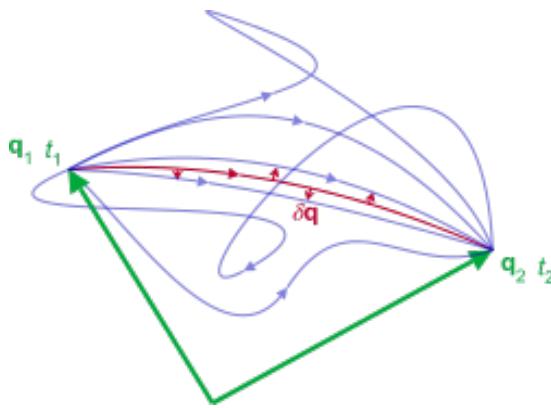
Chen et al. (2013)

## Hierarchical networks and the credit-assignment problem



# Lagrangian mechanics

principle of (least) stationary action



$$\delta \left( \int dt L(\mathbf{q}, \dot{\mathbf{q}}) \right) = 0$$

↓

$$\frac{\partial L}{\partial q_i} - \frac{d}{dt} \frac{\partial L}{\partial \dot{q}_i} = 0$$

- fundamental principle in
- mechanics
  - geometrical optics
  - electrodynamics
  - quantum mechanics
  - ...
  - neurobiology?

Euler-Lagrange equations of motion

## Lagrangian mechanics for neuronal networks

$$E(\mathbf{u}) = \sum_i \frac{1}{2} \|\mathbf{u}_i - \mathbf{W}_i \bar{\mathbf{r}}_{i-1}\|^2 + \beta \frac{1}{2} \|\mathbf{u}_N - \mathbf{u}_N^{\text{tgt}}\|^2 \xrightarrow{\mathbf{u} = \tilde{\mathbf{u}} - \tau \dot{\tilde{\mathbf{u}}}} L(\tilde{\mathbf{u}}, \dot{\tilde{\mathbf{u}}})$$

$$\frac{\partial L}{\partial \tilde{\mathbf{u}}_i} - \frac{d}{dt} \frac{\partial L}{\partial \dot{\tilde{\mathbf{u}}}_i} = 0$$

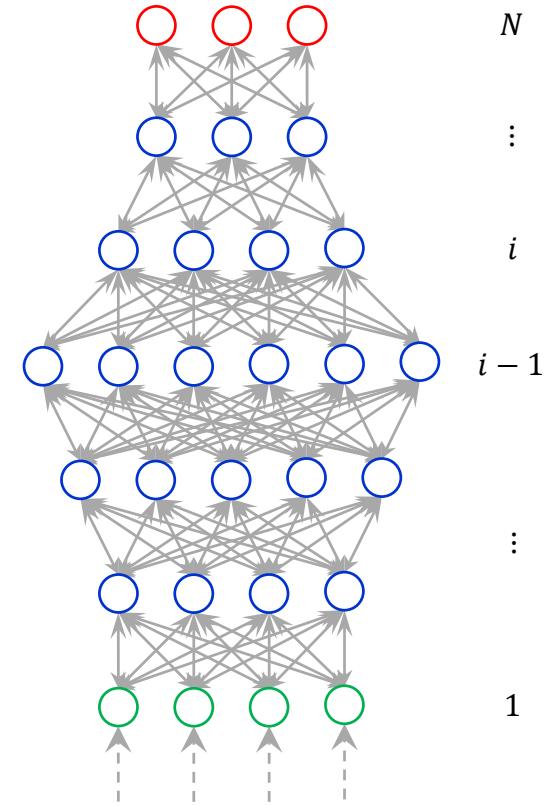
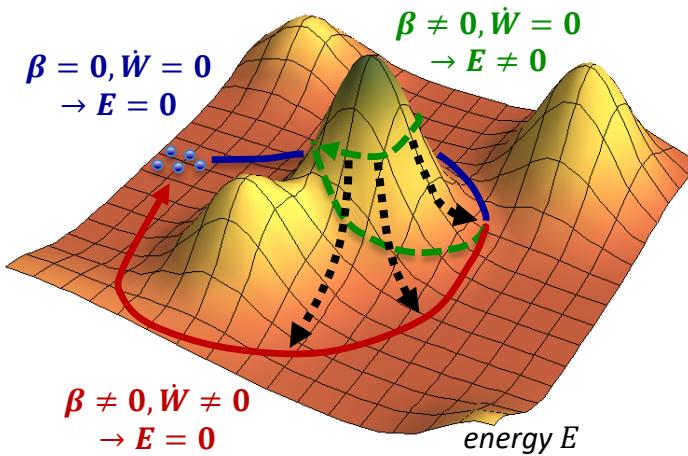
$$\dot{W}_i = -\eta \frac{\partial E}{\partial W_i}$$



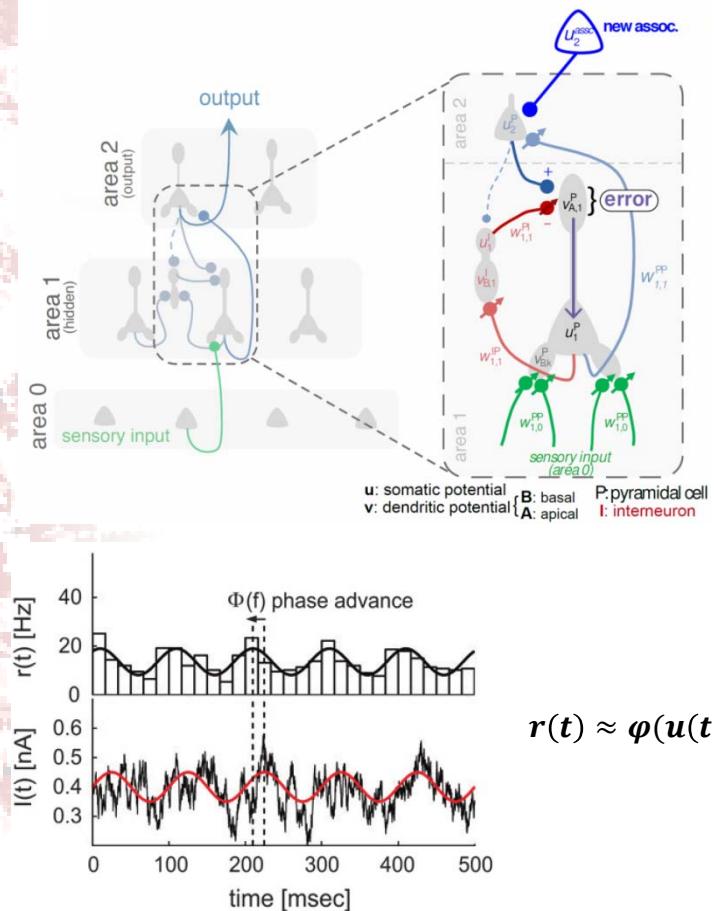
$\tau \dot{\mathbf{u}}_i = \mathbf{W}_i \bar{\mathbf{r}}_{i-1} - \mathbf{u}_i + \mathbf{e}_i \rightarrow$  neuron dynamics!

$\bar{\mathbf{e}}_i = \bar{\mathbf{r}}'_i \odot [\mathbf{W}_{i+1}^T (\mathbf{u}_{i+1} - \mathbf{W}_{i+1} \bar{\mathbf{r}}_i)] \rightarrow$  error backprop!

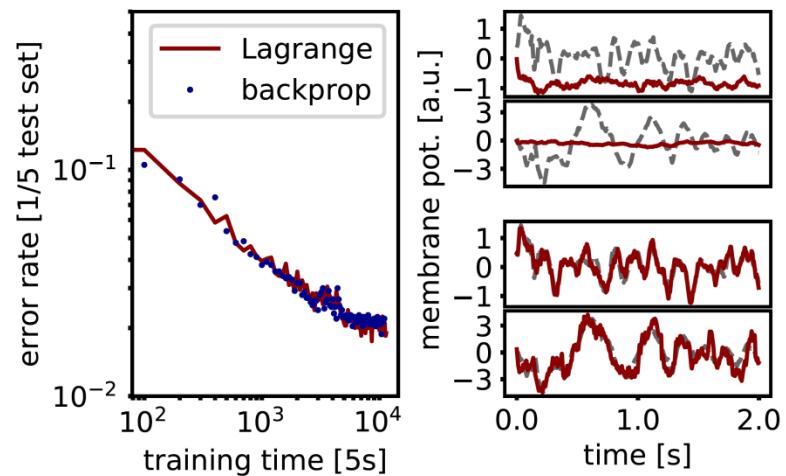
$\dot{W}_i = \eta (\mathbf{u}_i - \mathbf{W}_i \bar{\mathbf{r}}_{i-1}) \bar{\mathbf{r}}_{i-1}^T \rightarrow$  Urbanczik-Senn learning rule!



## Biophysical implementation



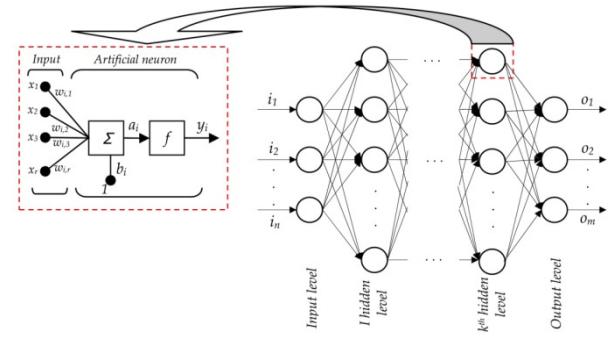
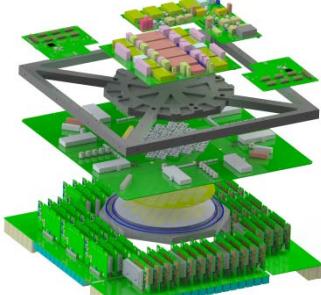
- local representation of errors for plausible synaptic plasticity
- prospective coding for continuous dynamics



# Bio-inspired artificial intelligence



messy & hard, but powerful



clean & easy, but not as efficient

## Some of the neural networks behind our neural networks



Dominik Dold



Akos Kungl



Andi Baumbach



Agnes Korcsak-Gorzo



Luziwei Leng



Elena Kreutzer



Oliver Breitwieser



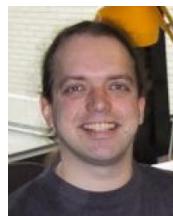
Jakob Jordan



Joao Sacramento



Walter Senn



Johannes Schemmel



Karlheinz Meier