

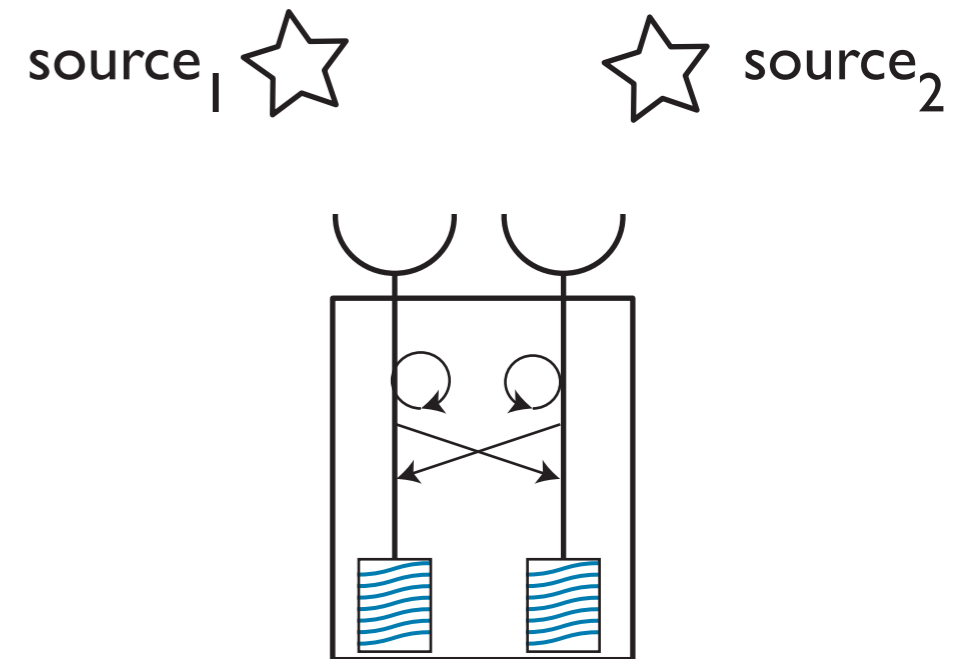
Neural Dynamics

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Activation

- how to represent the inner state of the Central Nervous System?
- => activation concept

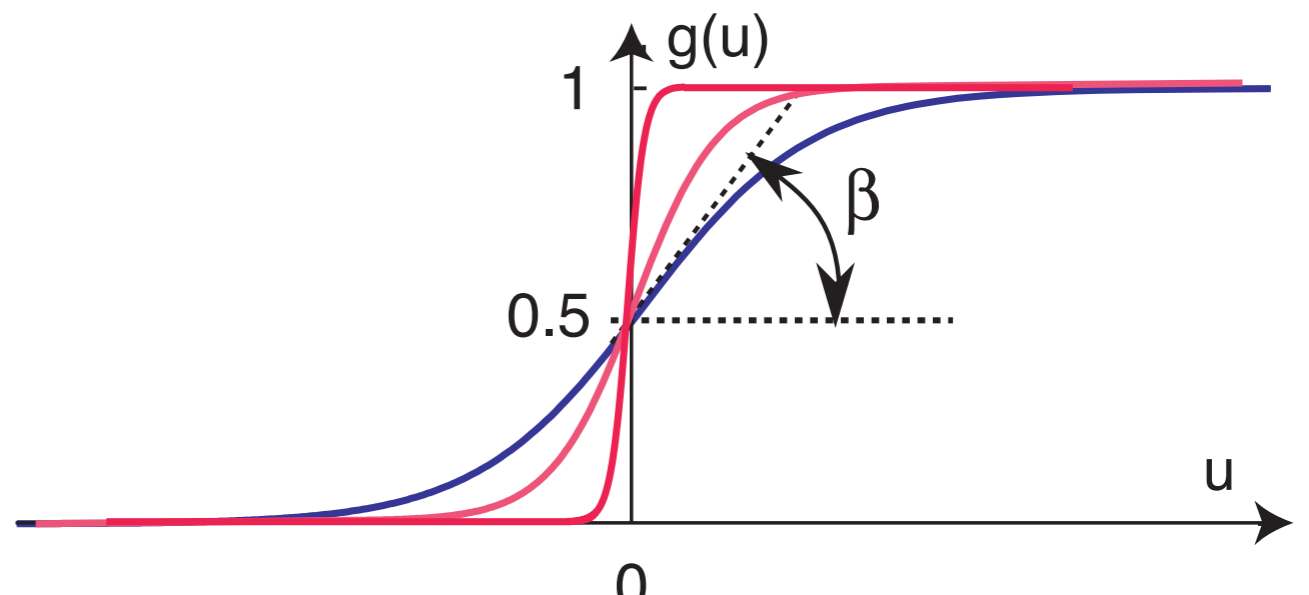


Activation

- neural state variables
 - membrane potential of neurons?
 - spiking rate?
 - ... population activation...

Activation

- activation as a real number, abstracting from biophysical details
- low levels of activation: not transmitted to other systems (e.g., to motor systems)
- high levels of activation: transmitted to other systems
- as described by sigmoidal threshold function
- zero activation defined as threshold of that function

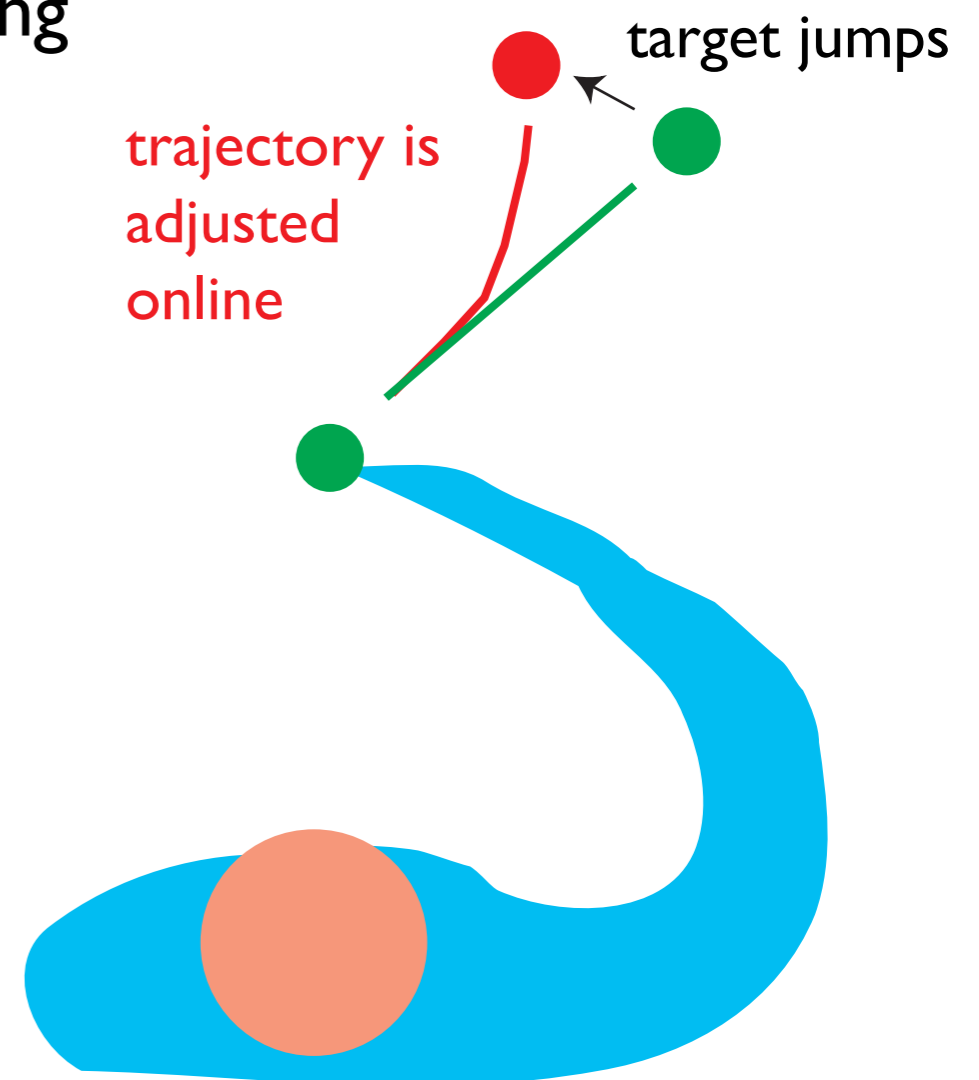


Activation

- compare to connectionist notion of activation:
 - same idea, but tied to individual neurons
- compare to abstract activation of production systems (ACT-R, SOAR)
 - quite different... really a function that measures how far a module is from emitting its output...

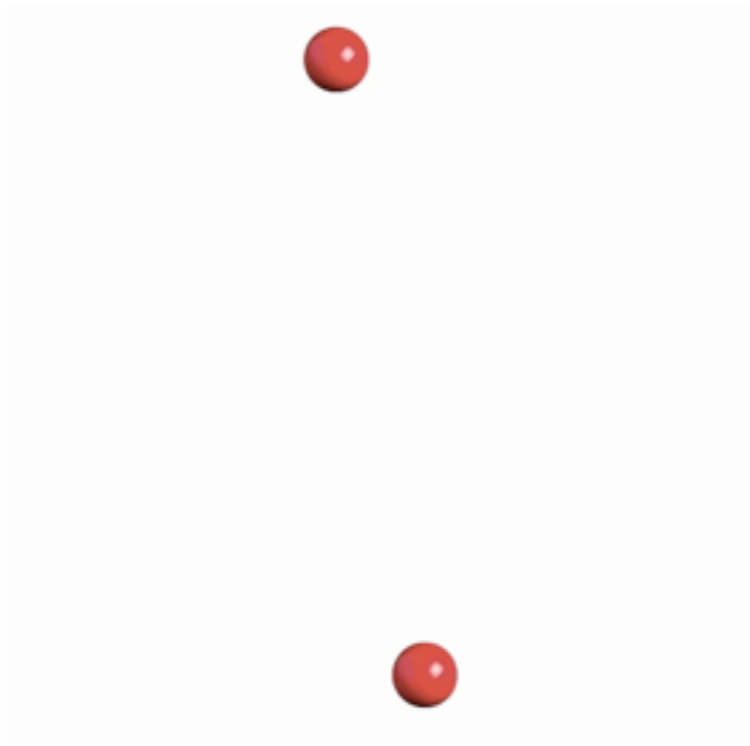
Activation dynamics

- activation evolves in continuous time
 - no evidence for a discretization of time, for spike timing to matter for behavior
 - evidence for continuous online updating



Activation dynamics

- activation evolves continuously in continuous time
- no evidence for a discrete events mattering...
- evidence for continuity: visual inertia



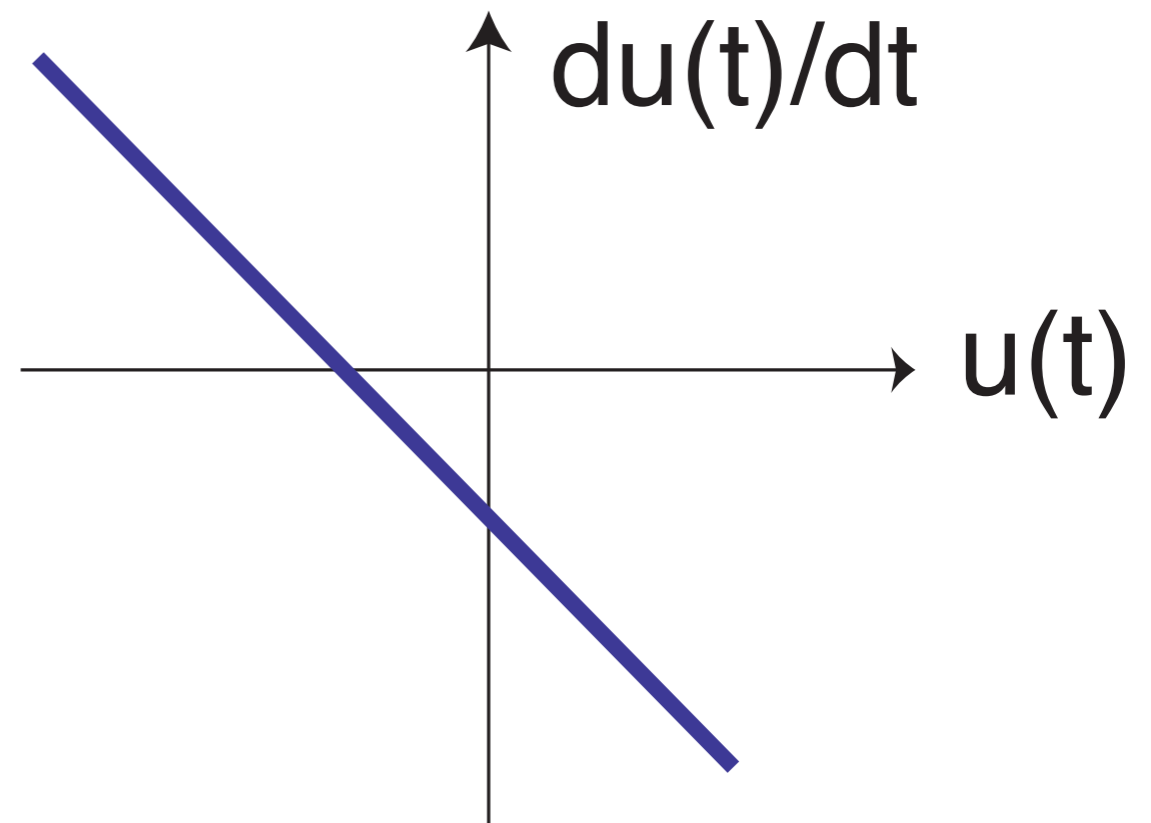
+

Activation dynamics

- activation variables $u(t)$ as time continuous functions...

$$\tau \dot{u}(t) = f(u)$$

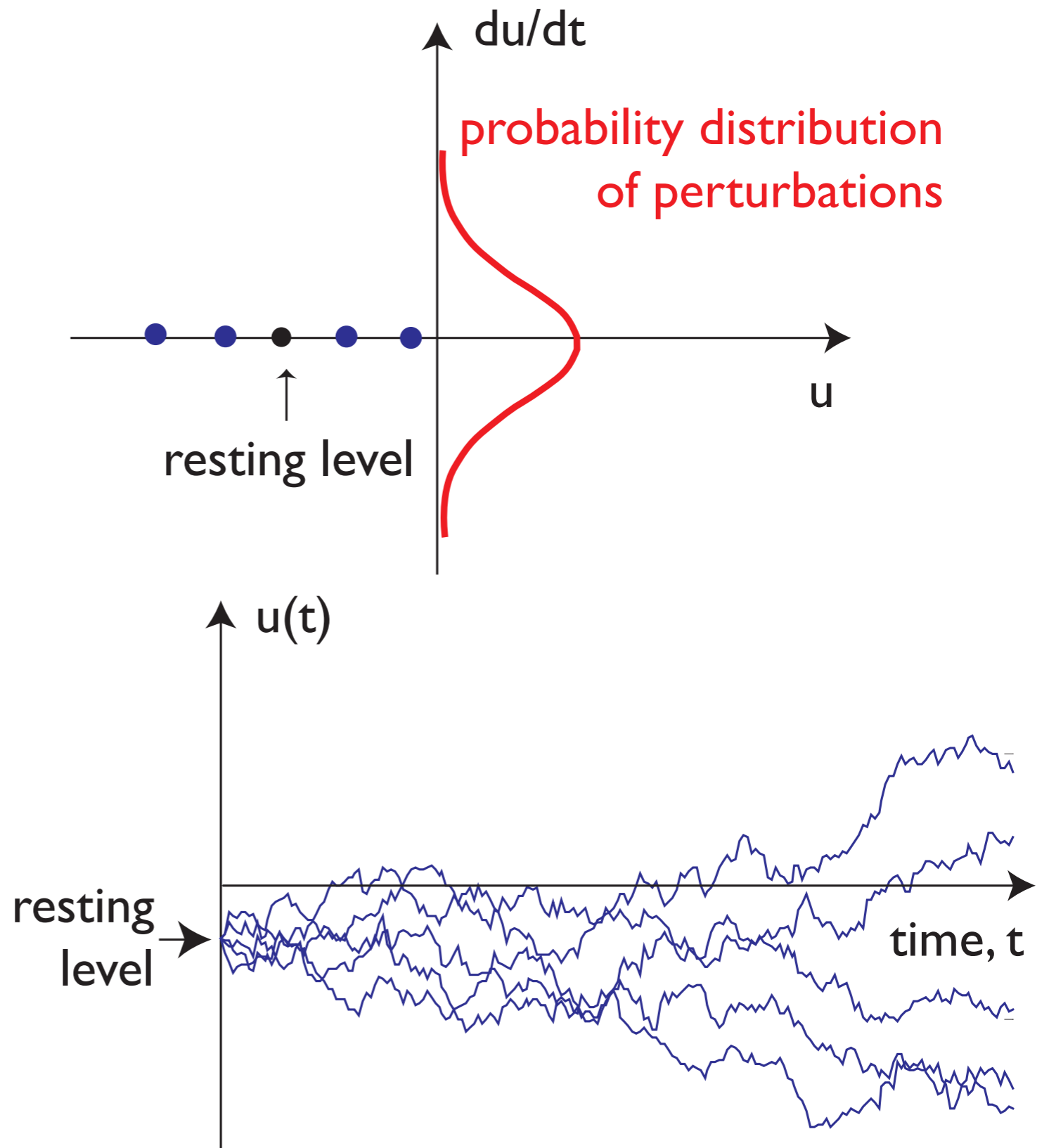
- what function f ?



Activation dynamics

■ start with $f=0$

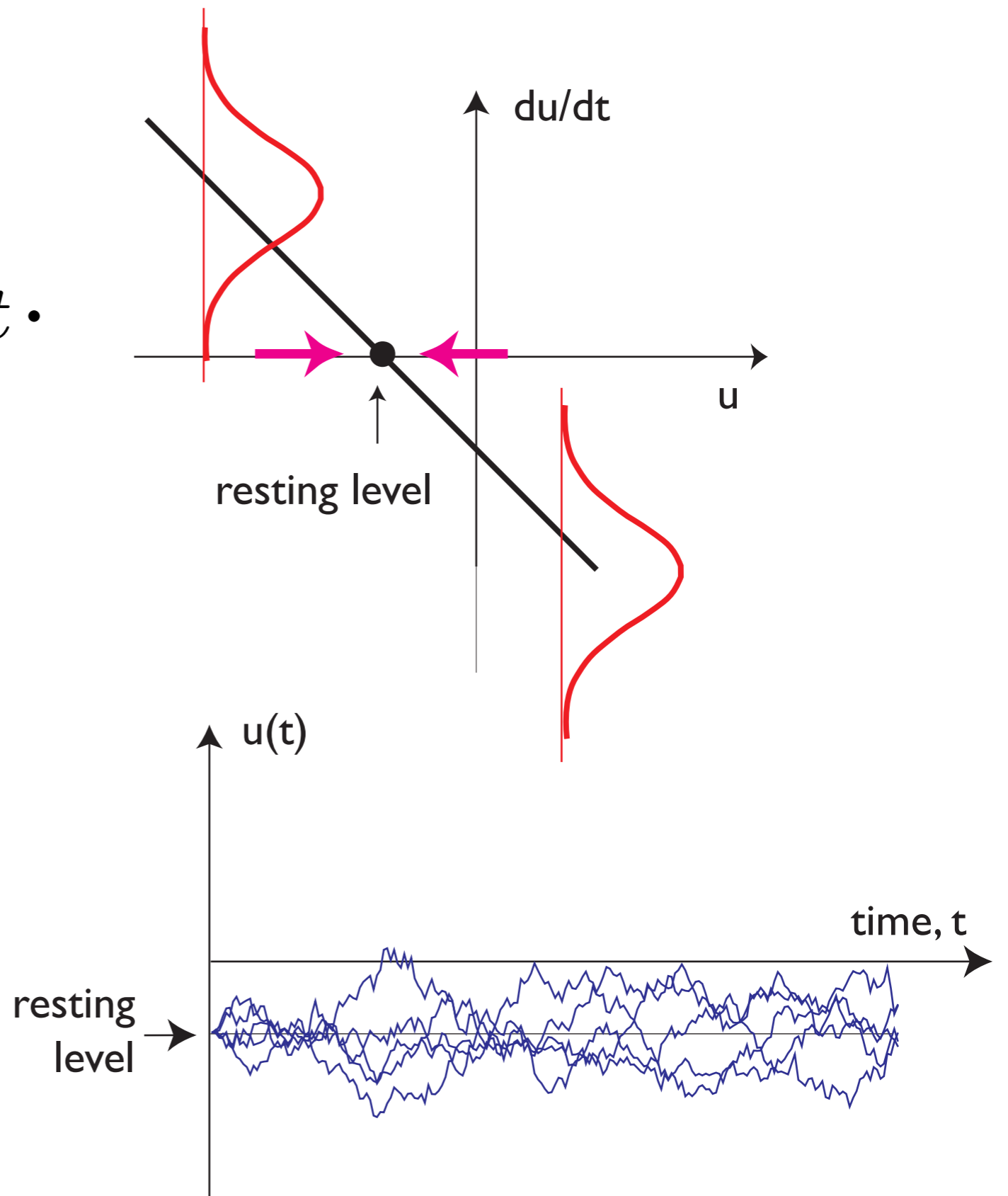
$$\tau \dot{u} = \xi_t$$



Activation dynamics

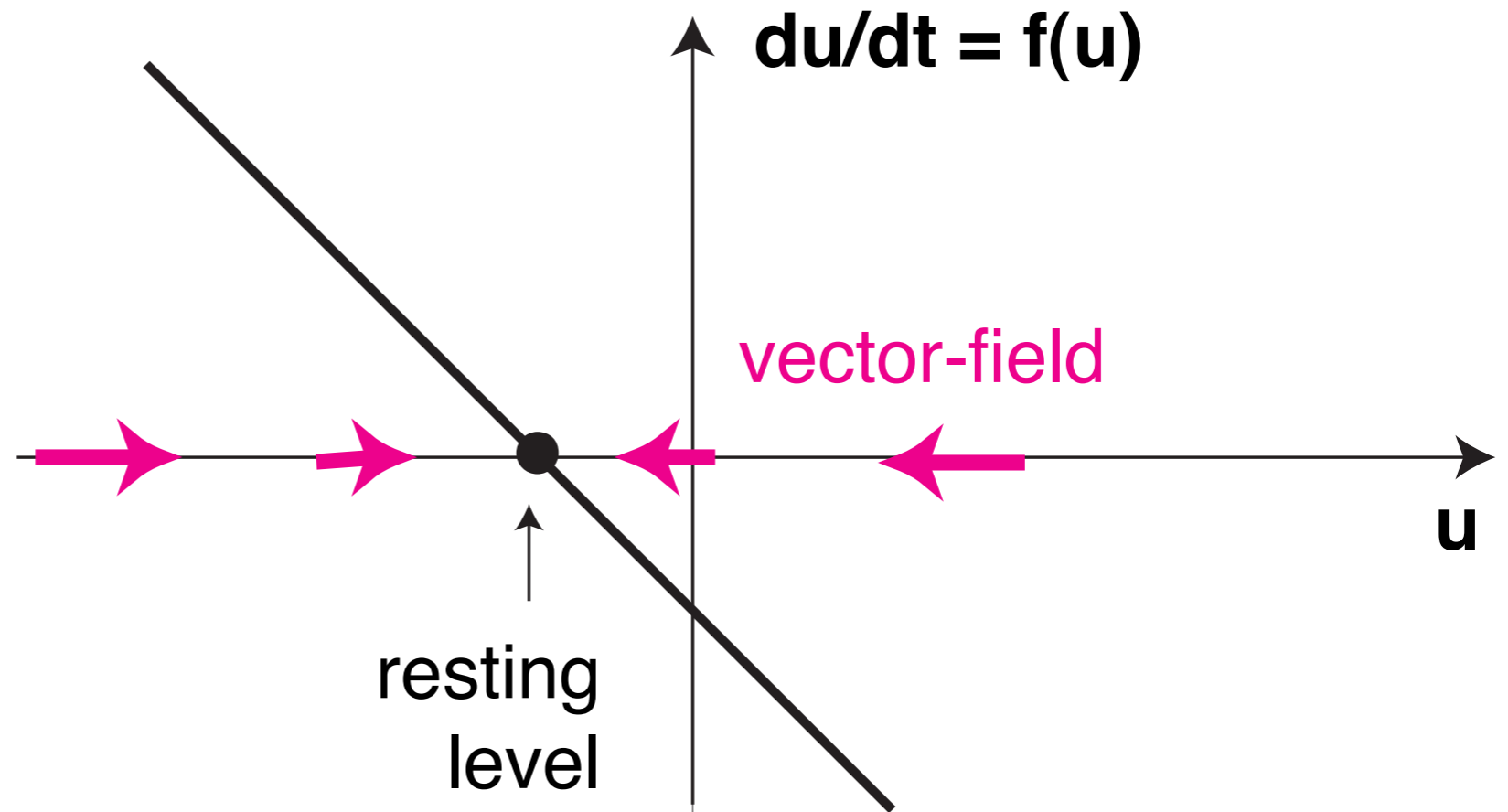
■ need stabilization

$$\tau \dot{u} = -u + h + \xi_t.$$



Neural dynamics

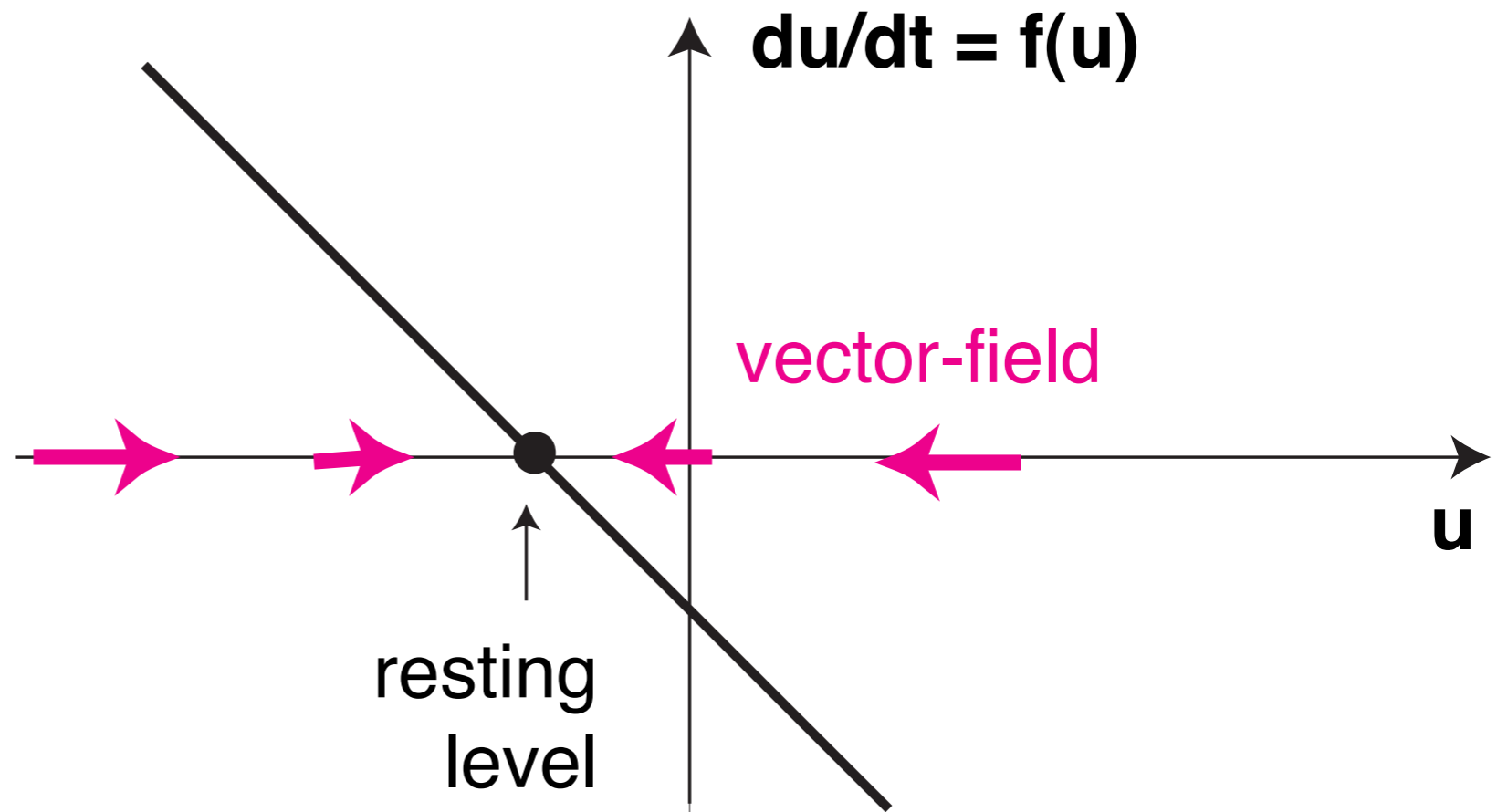
- In a dynamical system, the present predicts the future: given the initial level of activation $u(0)$, the activation at time t : $u(t)$ is uniquely determined



$$\frac{du(t)}{dt} = \dot{u}(t) = -u(t) + h \quad (h < 0)$$

Neural dynamics

- stationary state=**fixed point**= constant solution
- stable fixed point: nearby solutions converge to the fixed point=**attractor**

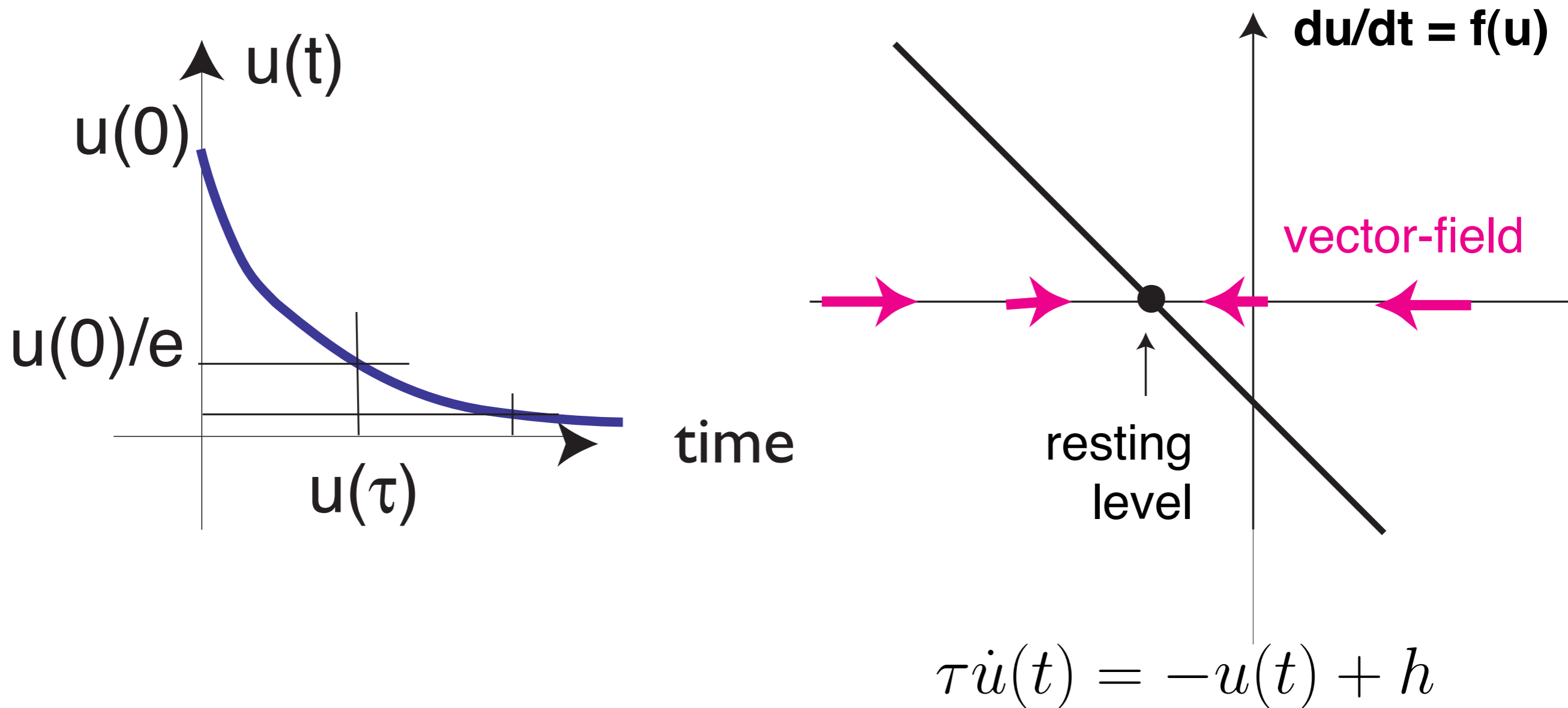


$$\frac{du(t)}{dt} = \dot{u}(t) = -u(t) + h \quad (h < 0)$$

Neural dynamics

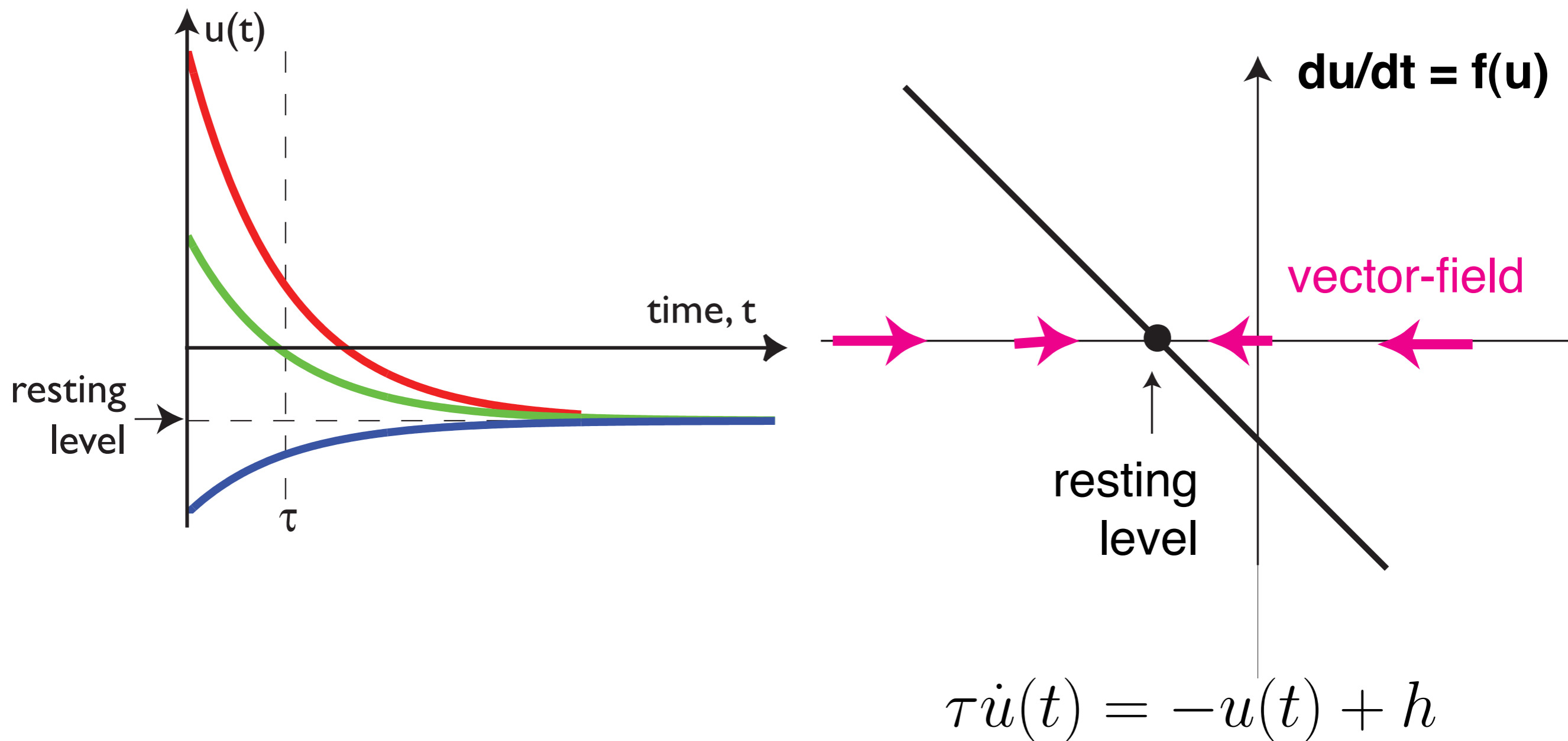
■ exponential relaxation to fixed-point attractors

■ => time scale



Neural dynamics

- attractor structures ensemble of solutions=flow



Neuronal dynamics

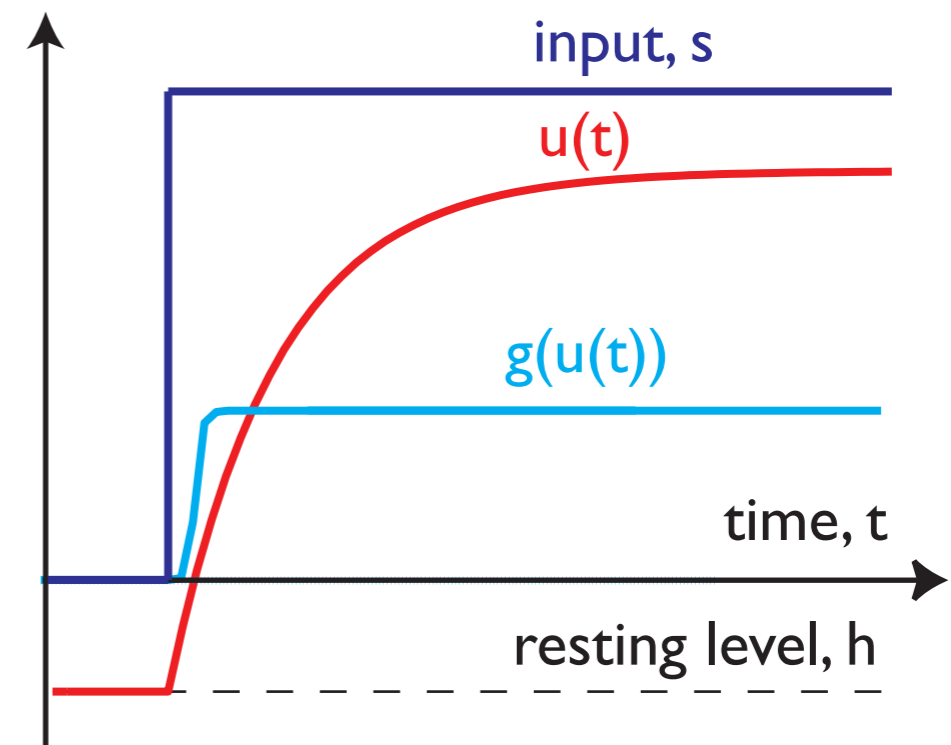
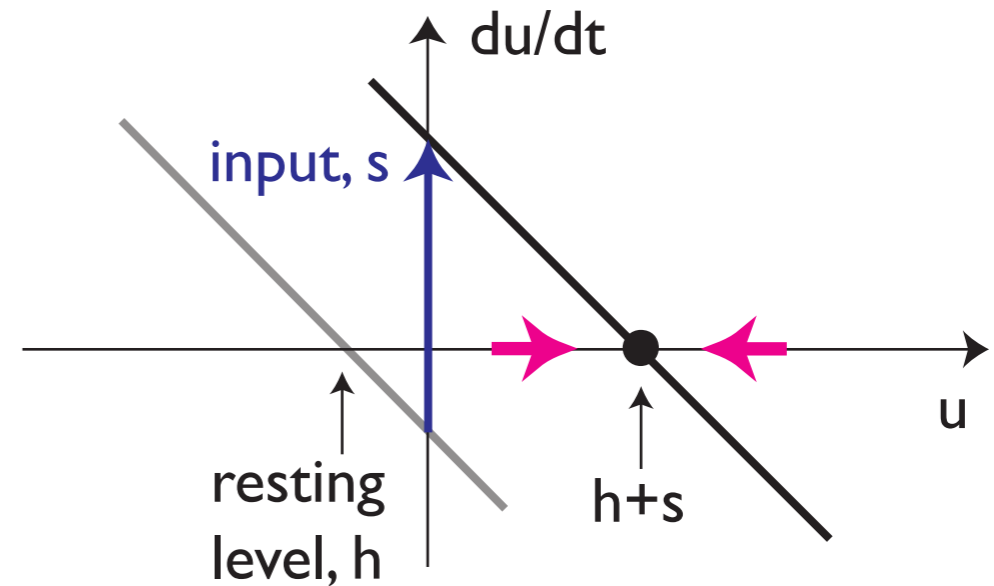
■ inputs=contributions to the rate of change

■ positive: excitatory

■ negative: inhibitory

■ => shifts the attractor

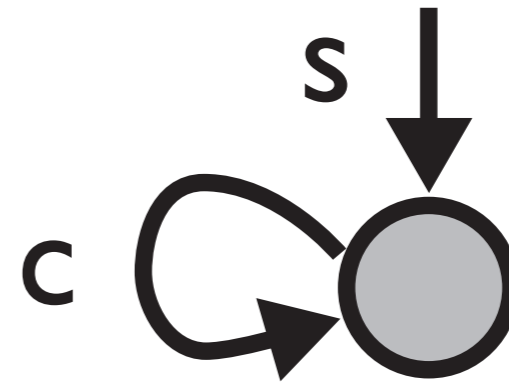
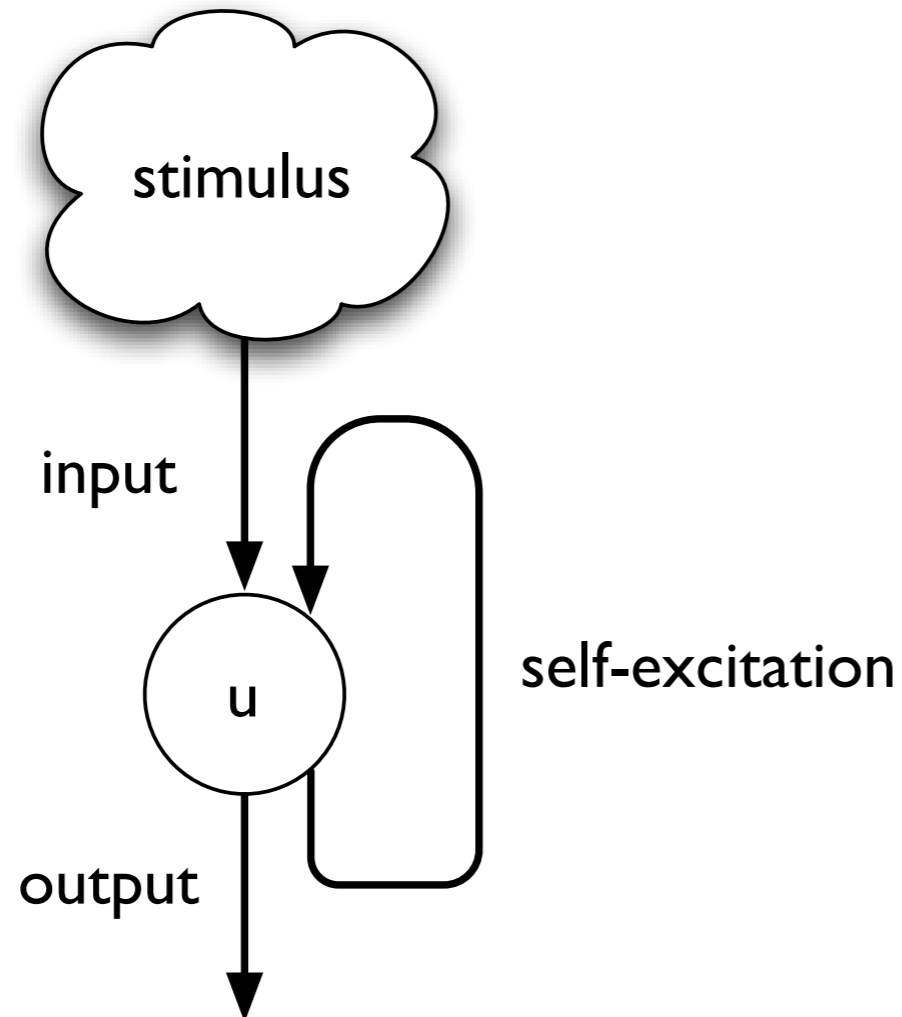
■ activation tracks this shift (stability)



$$\tau \dot{u}(t) = -u(t) + h + \text{inputs}(t)$$

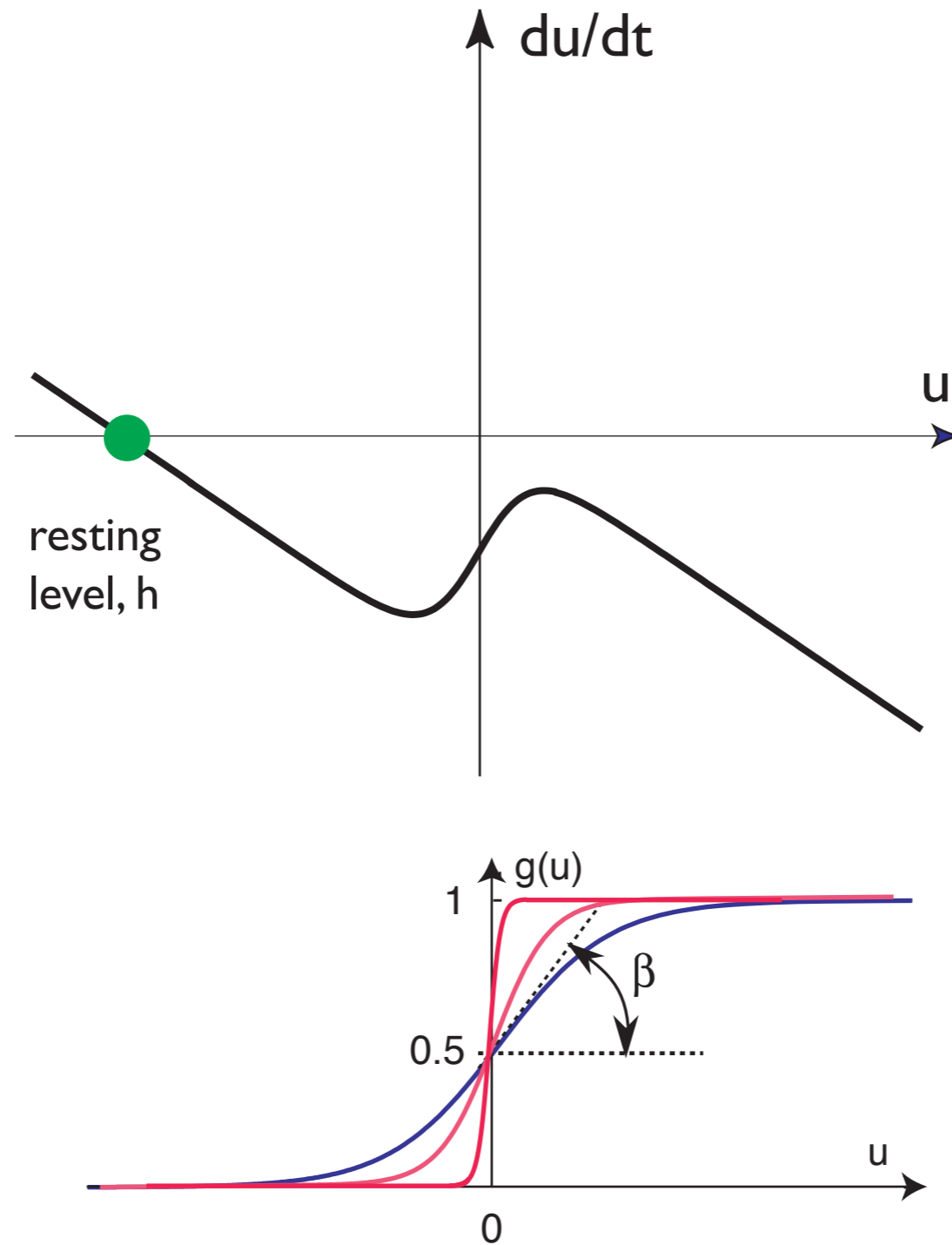
\Rightarrow simulation

Neuronal dynamics with self-excitation



$$\tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

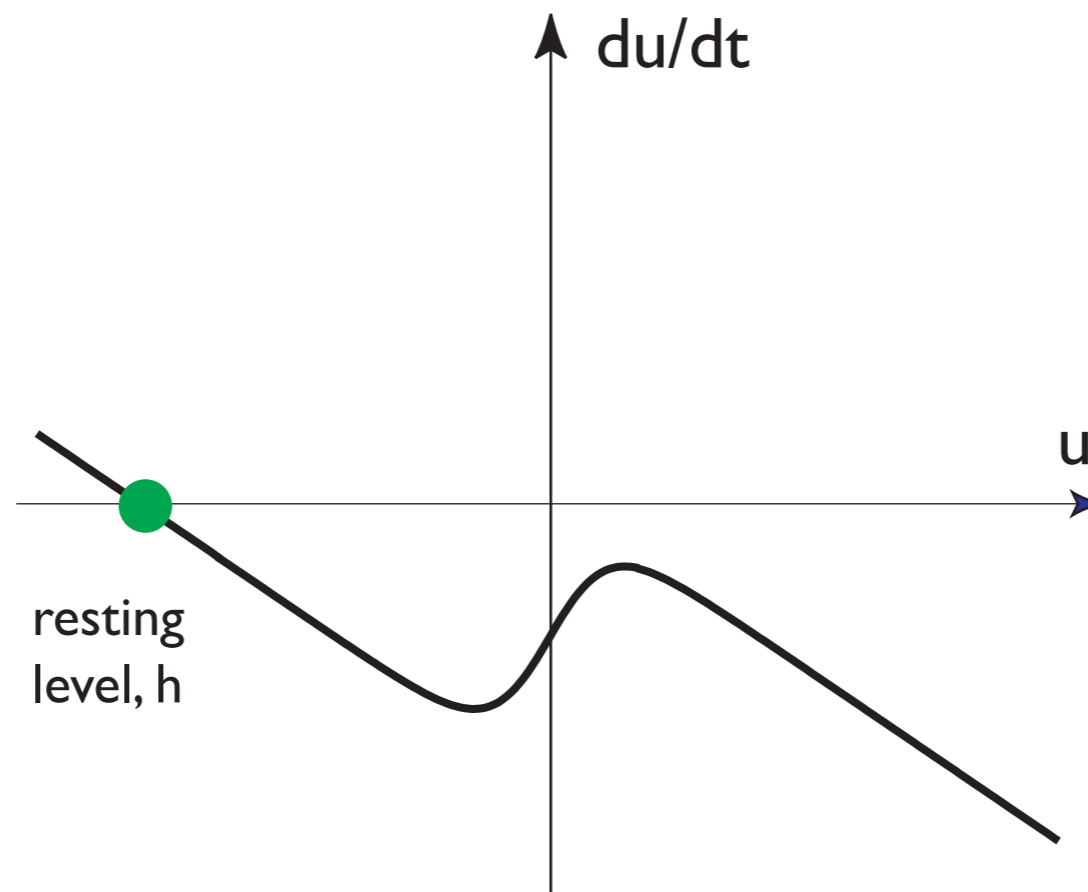
Neuronal dynamics with self-excitation



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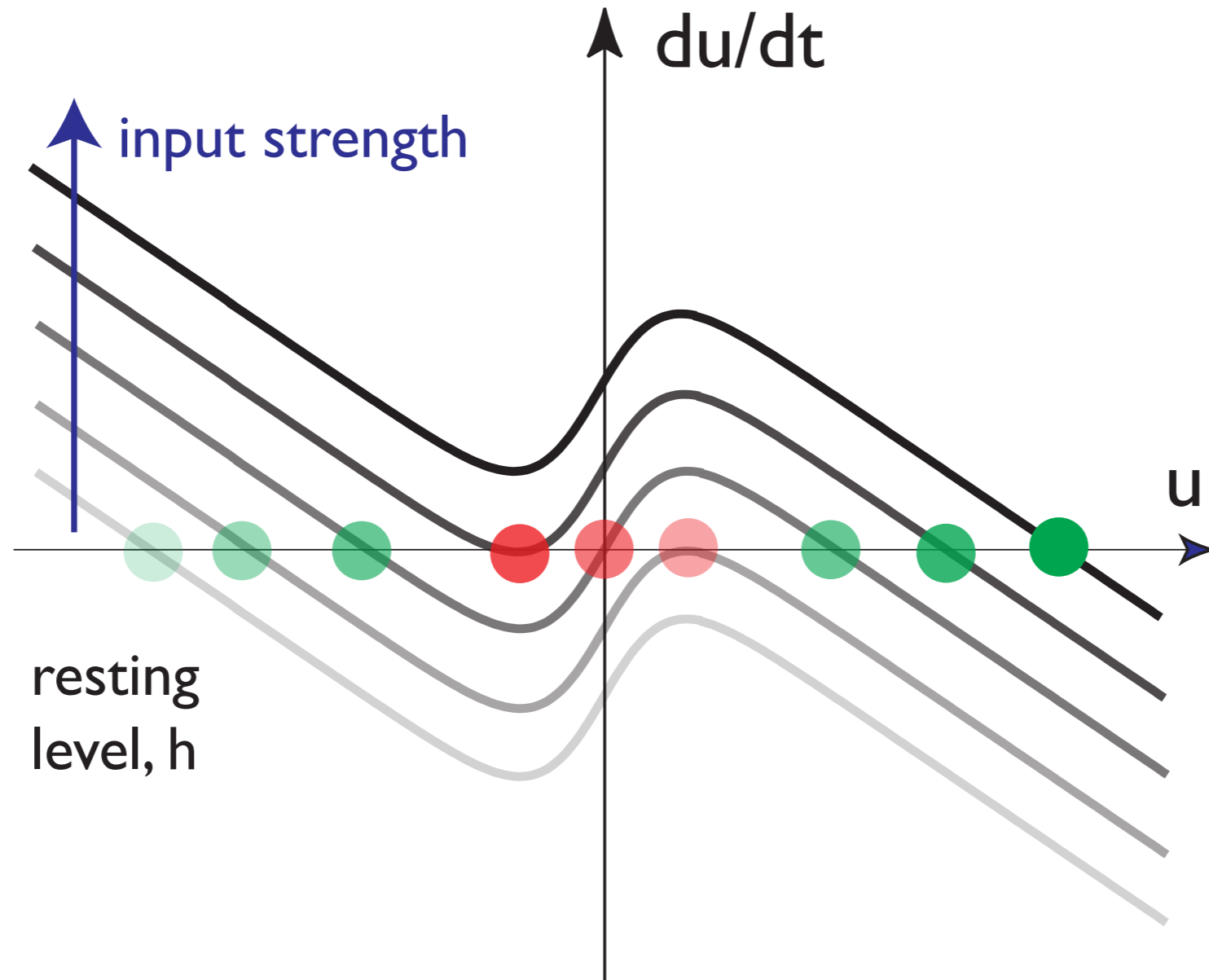
Neuronal dynamics with self-excitation

■ => this is nonlinear dynamics!



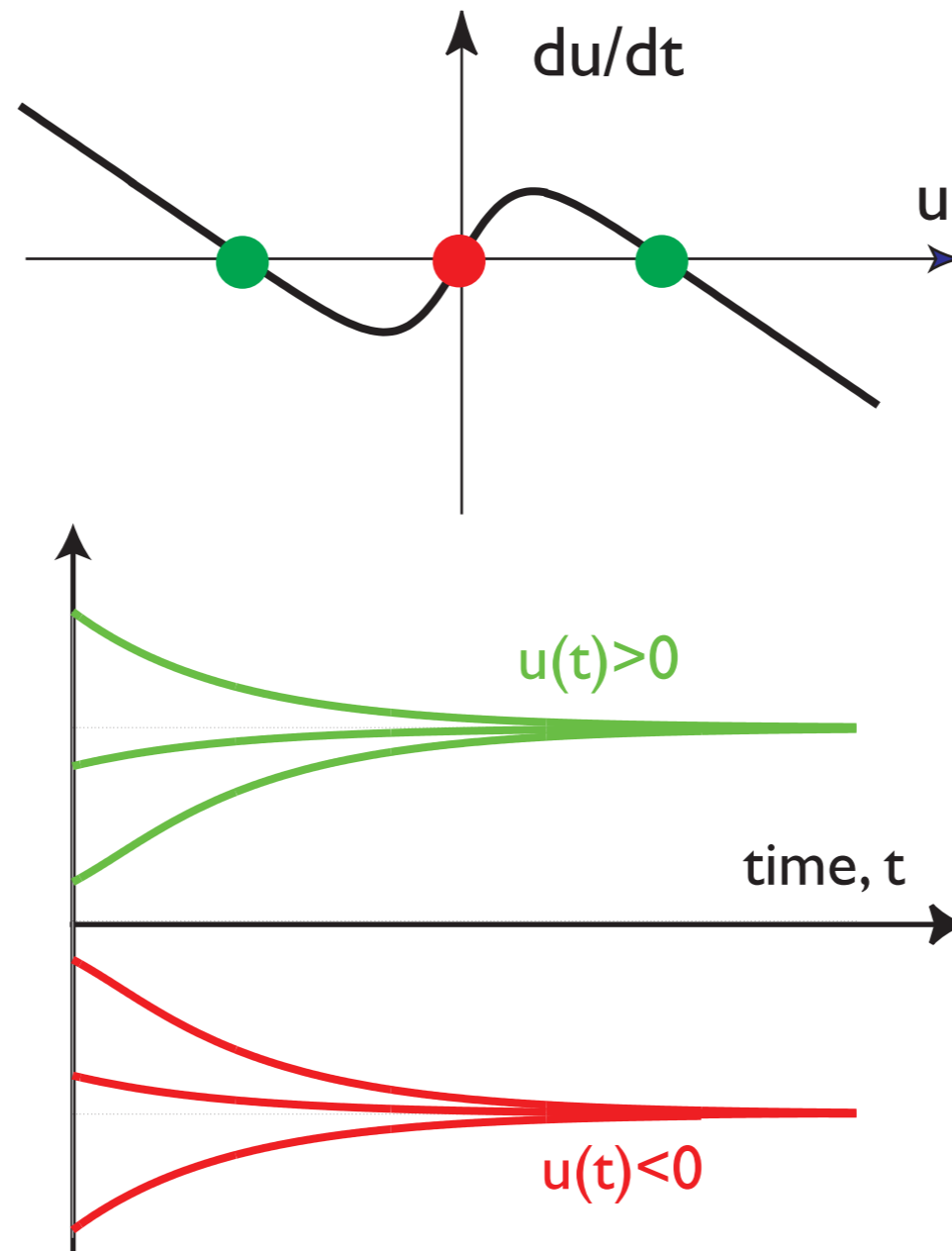
Neuronal dynamics with self-excitation

■ stimulus input



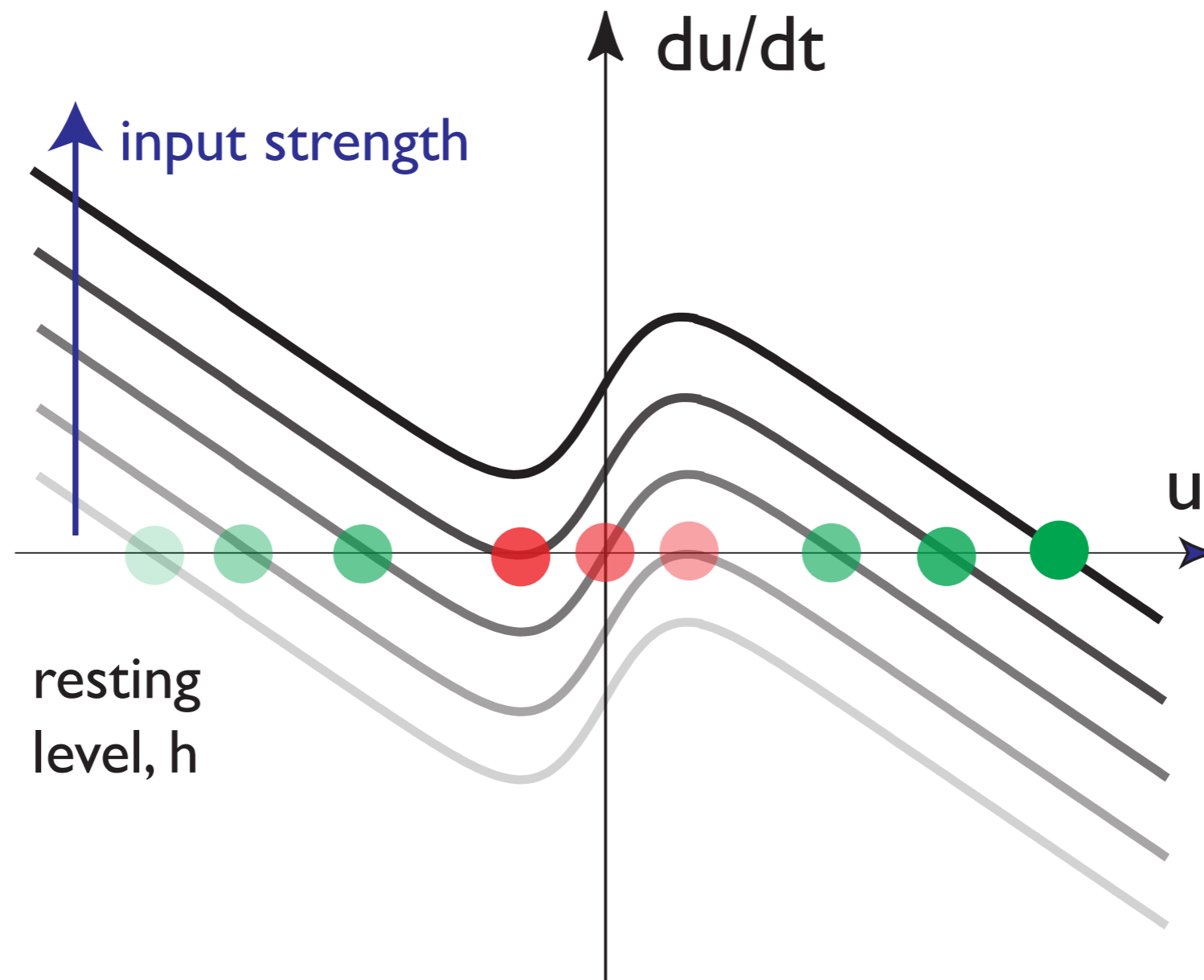
Neuronal dynamics with self-excitation

- bistable regime at intermediate stimulus strength
- => essentially nonlinear!



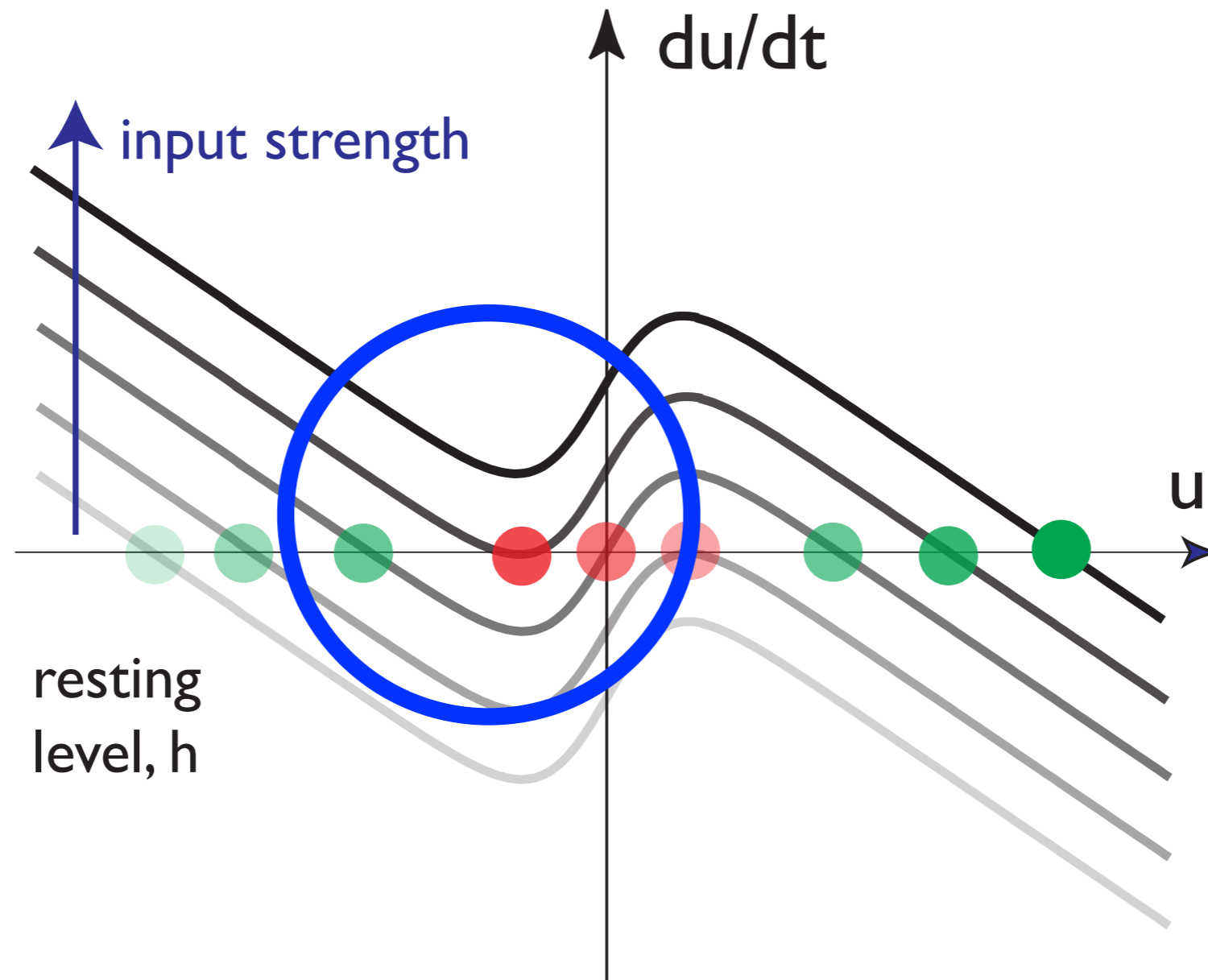
Neuronal dynamics with self-excitation

- with varying input strength system goes through two instabilities: the **detection** and the **reverse detection** instability



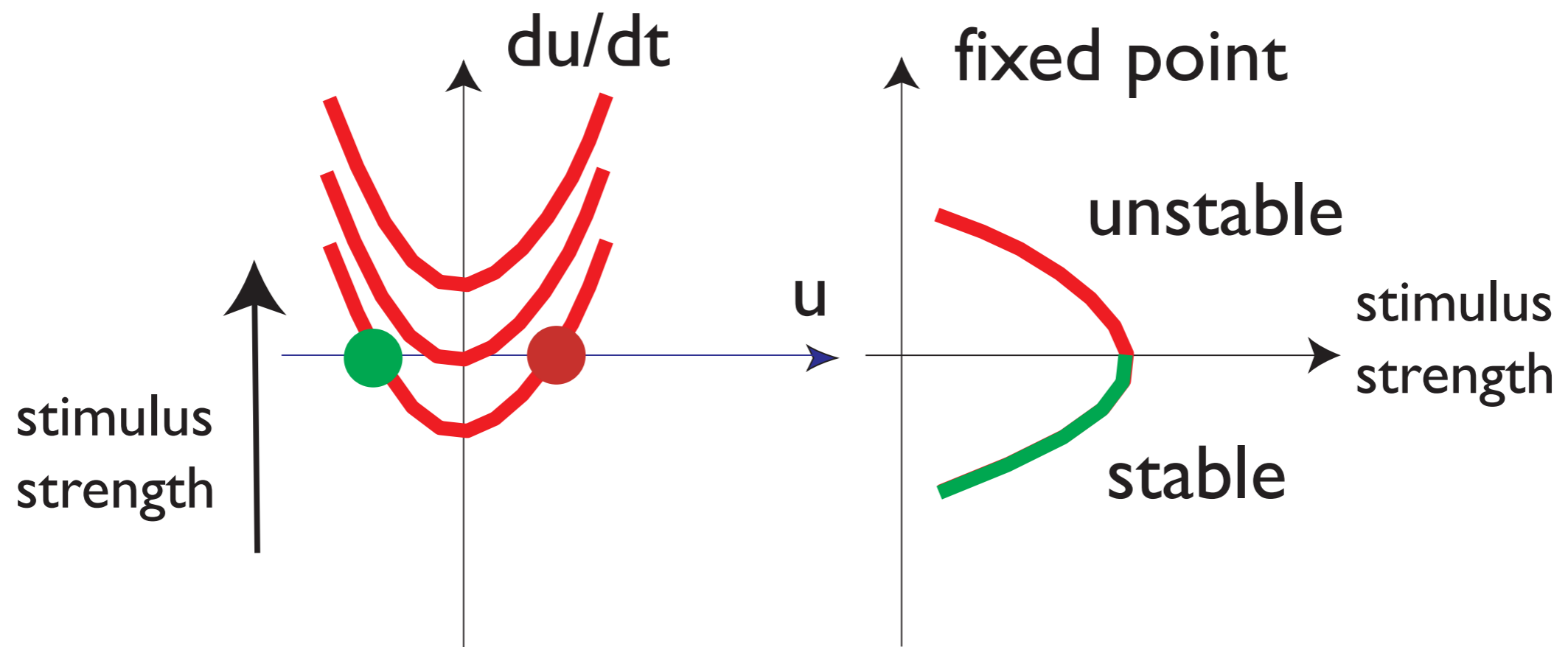
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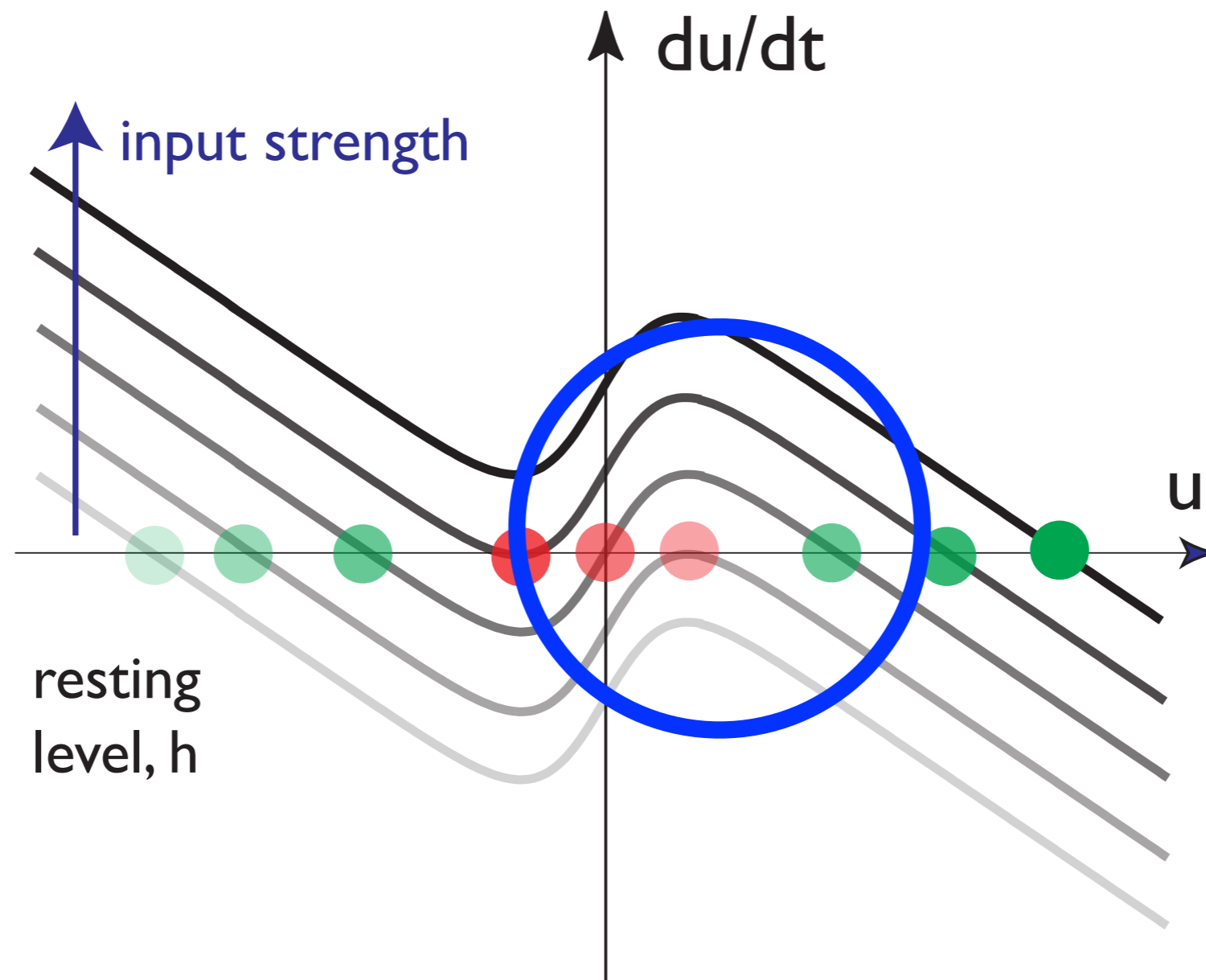
Neuronal dynamics with self-excitation

- detection instability



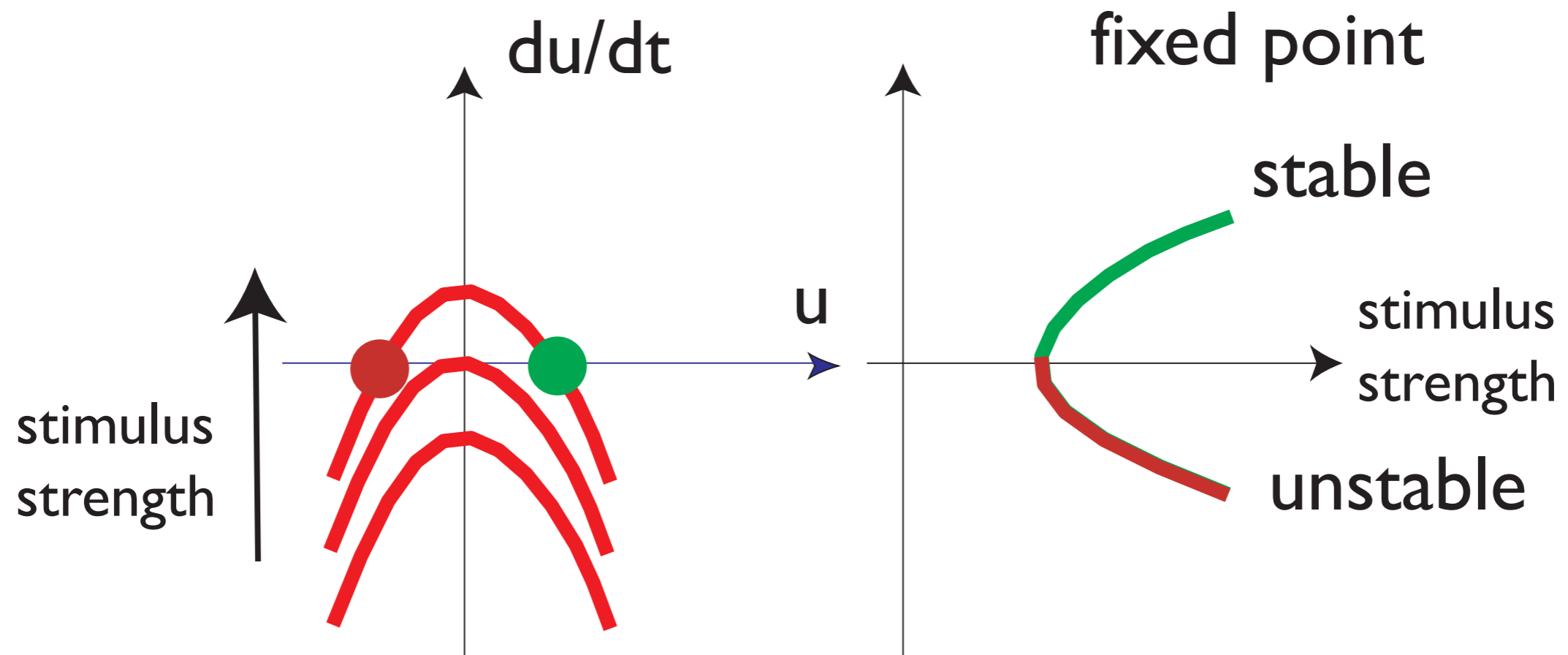
Neuronal dynamics with self-excitation

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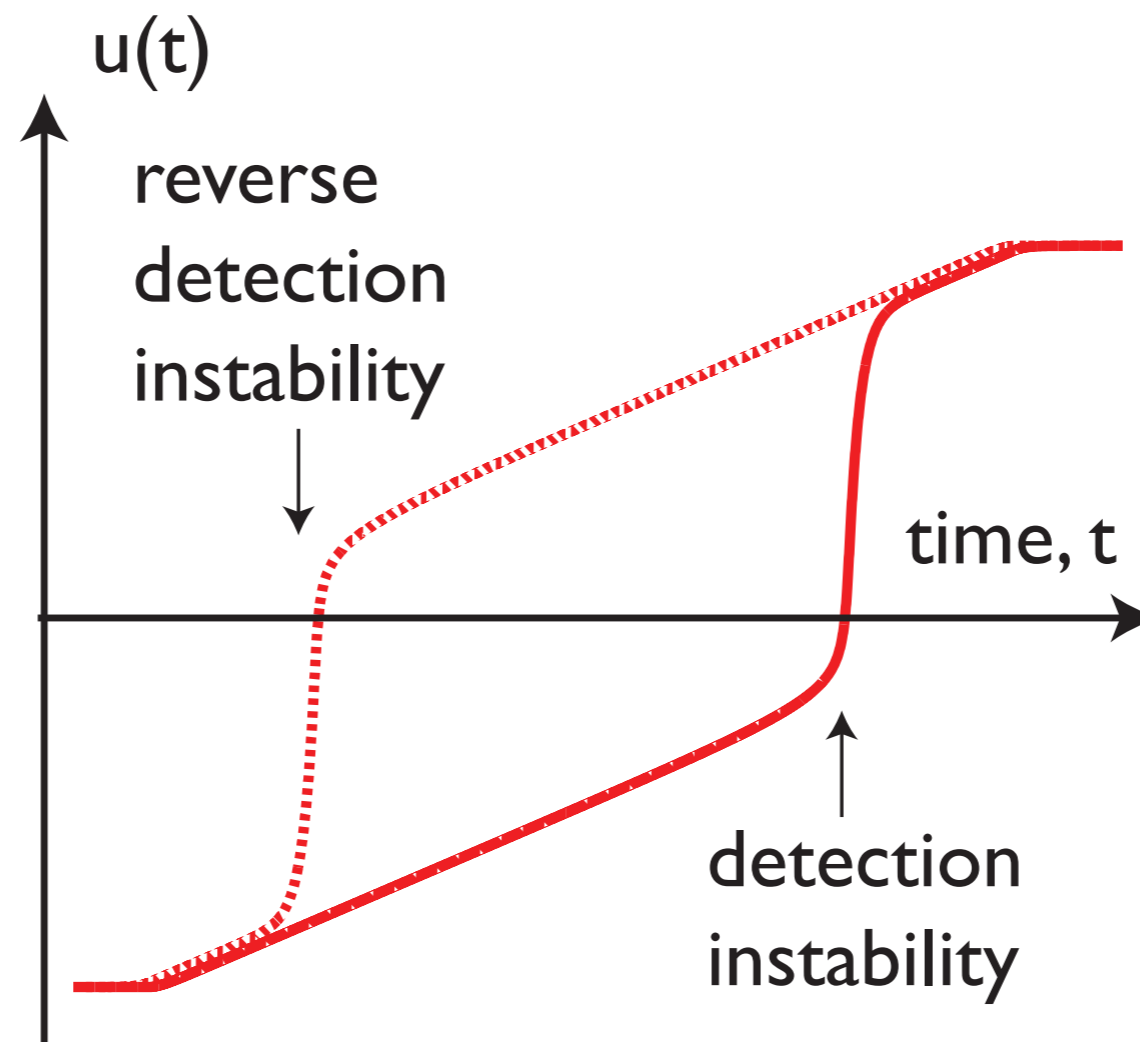
Neuronal dynamics with self-excitation

■ reverse detection instability



Neuronal dynamics with self-excitation

- signature of instabilities: hysteresis



 => simulation