

# Week 4 – part 1 : Reduction of the Hodgkin-Huxley Model



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail: Two-dimensional neuron models

Wulfram Gerstner

EPFL, Lausanne, Switzerland

#### 4.1 From Hodgkin-Huxley to 2D

- Overview: From 4 to 2 dimensions
- MathDetour 1: Separation of time scales
- MathDetour 2: Exploiting similarities

#### 4.2 Phase Plane Analysis

- Role of nullclines

#### 4.3 Analysis of a 2D Neuron Model

- MathDetour 3: Stability of fixed points

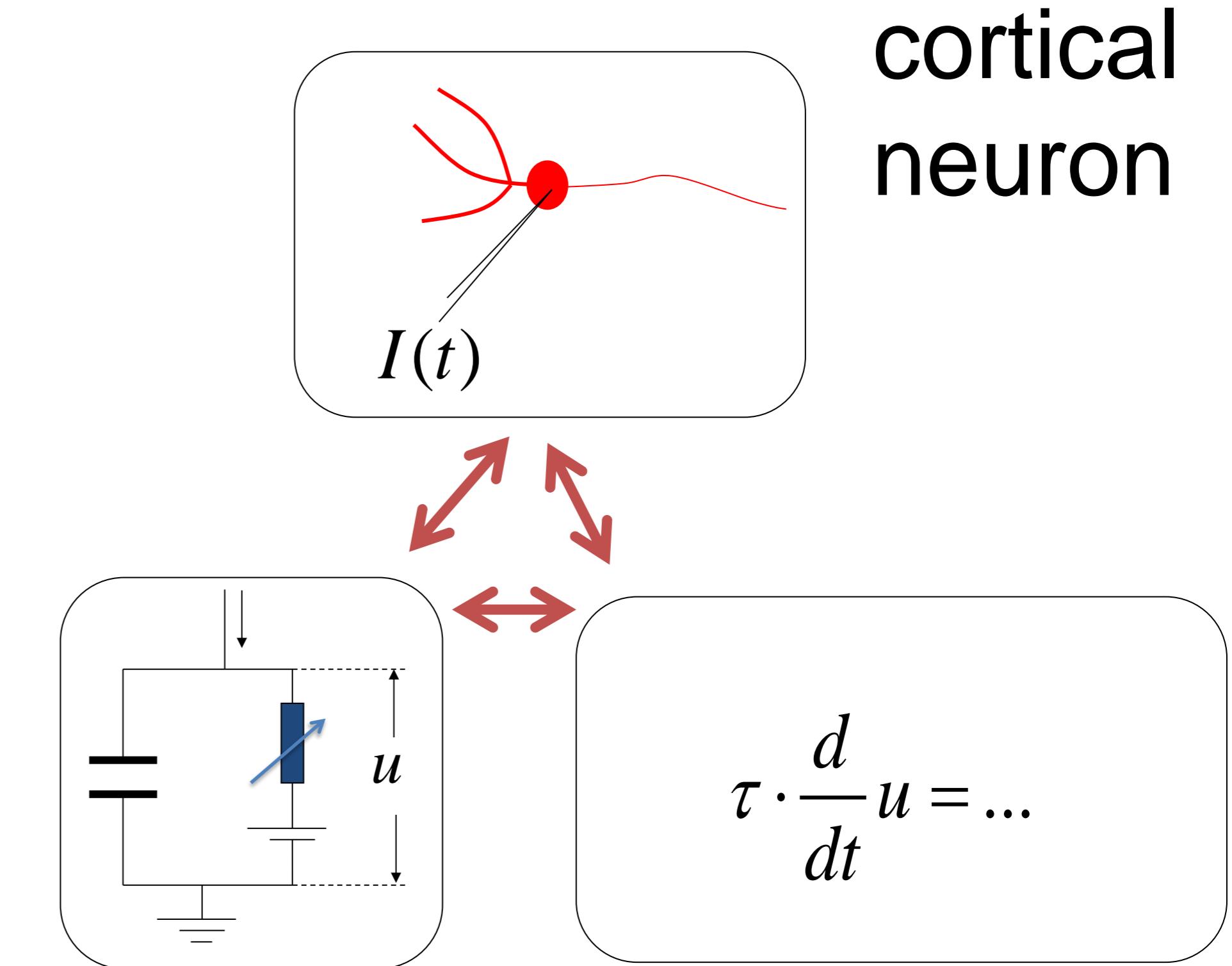
#### 4.4 Type I and II Neuron Models

- where is the firing threshold?
- separation of time scales

#### 4.5 Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – 4.1. Review :Hodgkin-Huxley Model



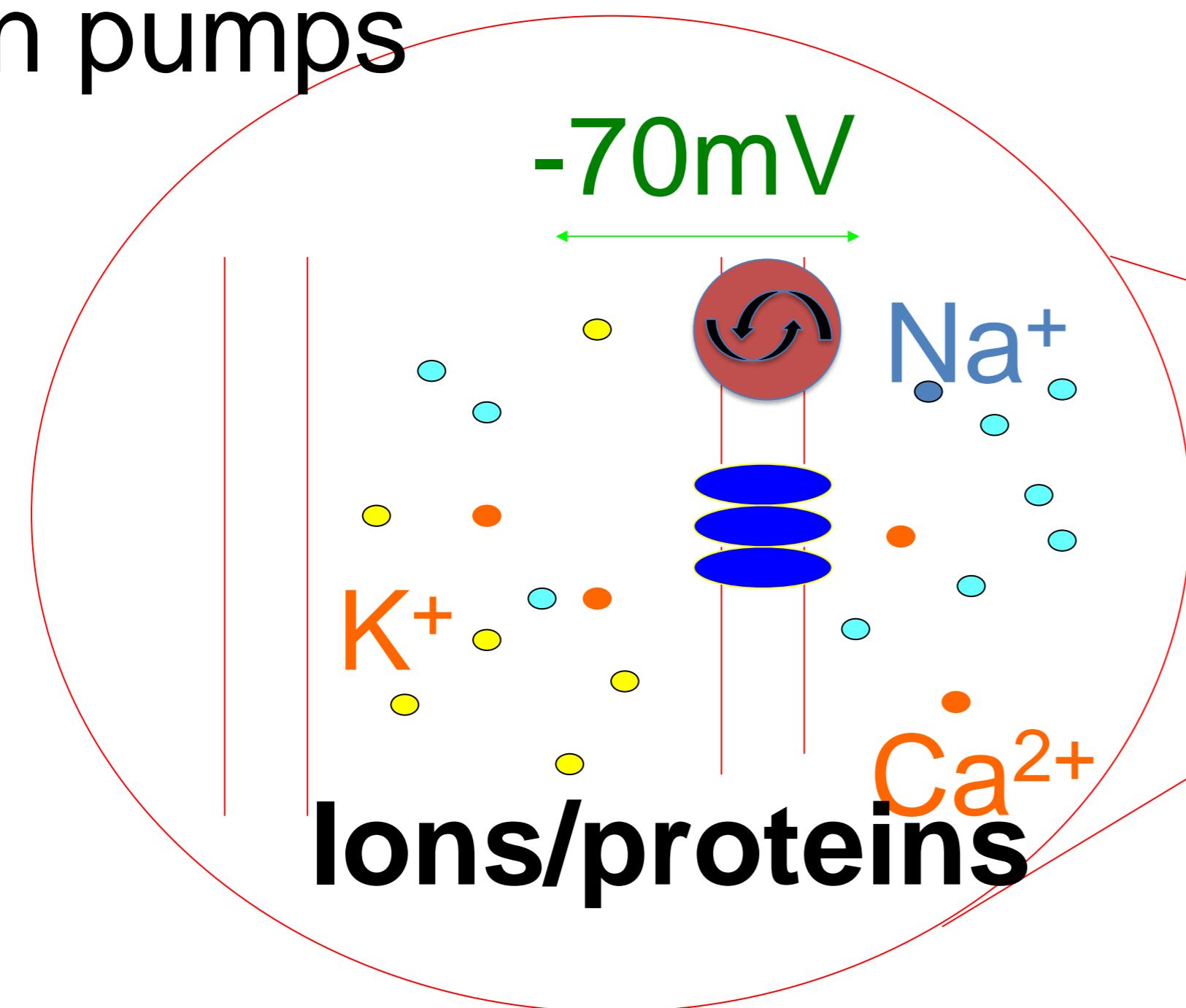
→Hodgkin-Huxley model  
→Compartmental models

# Neuronal Dynamics – 4.1 Review :Hodgkin-Huxley Model

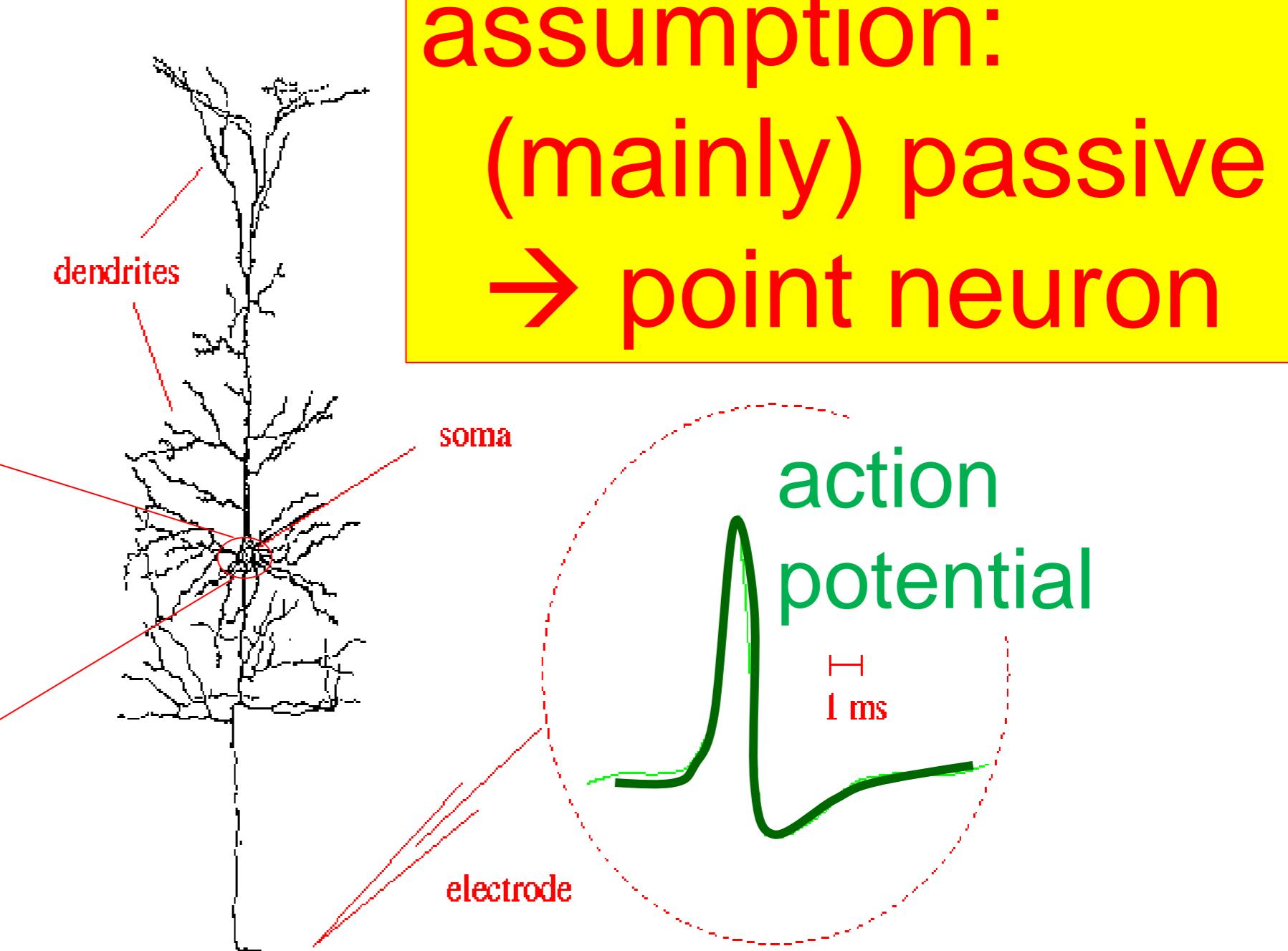
## Week 2:

Cell membrane contains

- ion channels
- ion pumps



Dendrites (week 3):  
Active processes?

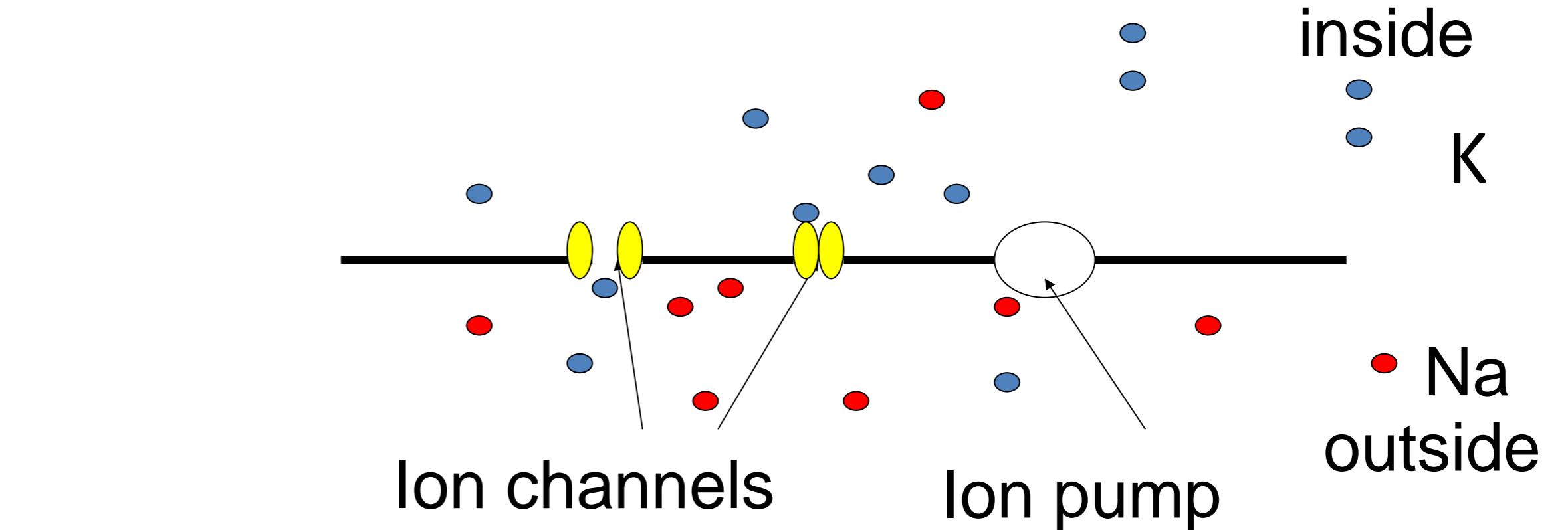


# Neuronal Dynamics – 4.1. Review :Hodgkin-Huxley Model



$n_1$  (inside)

$n_2$  (outside)



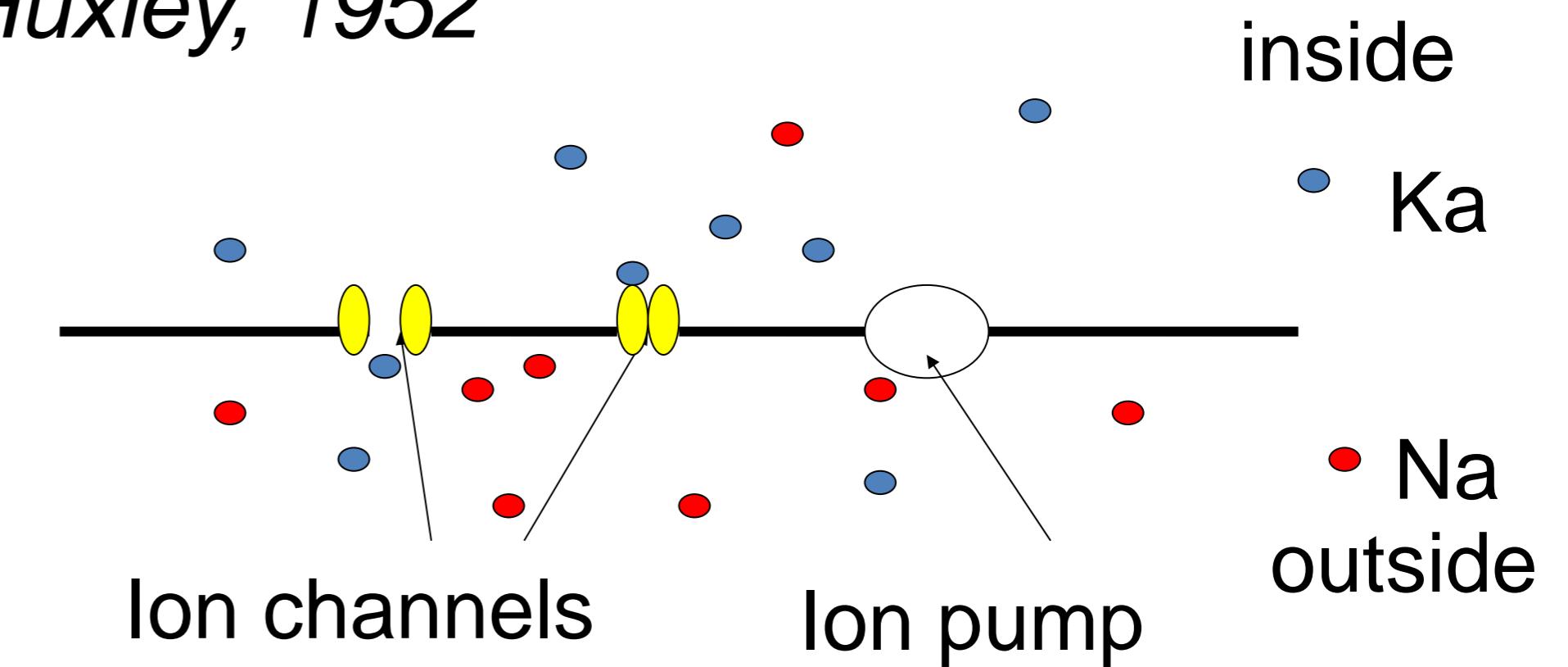
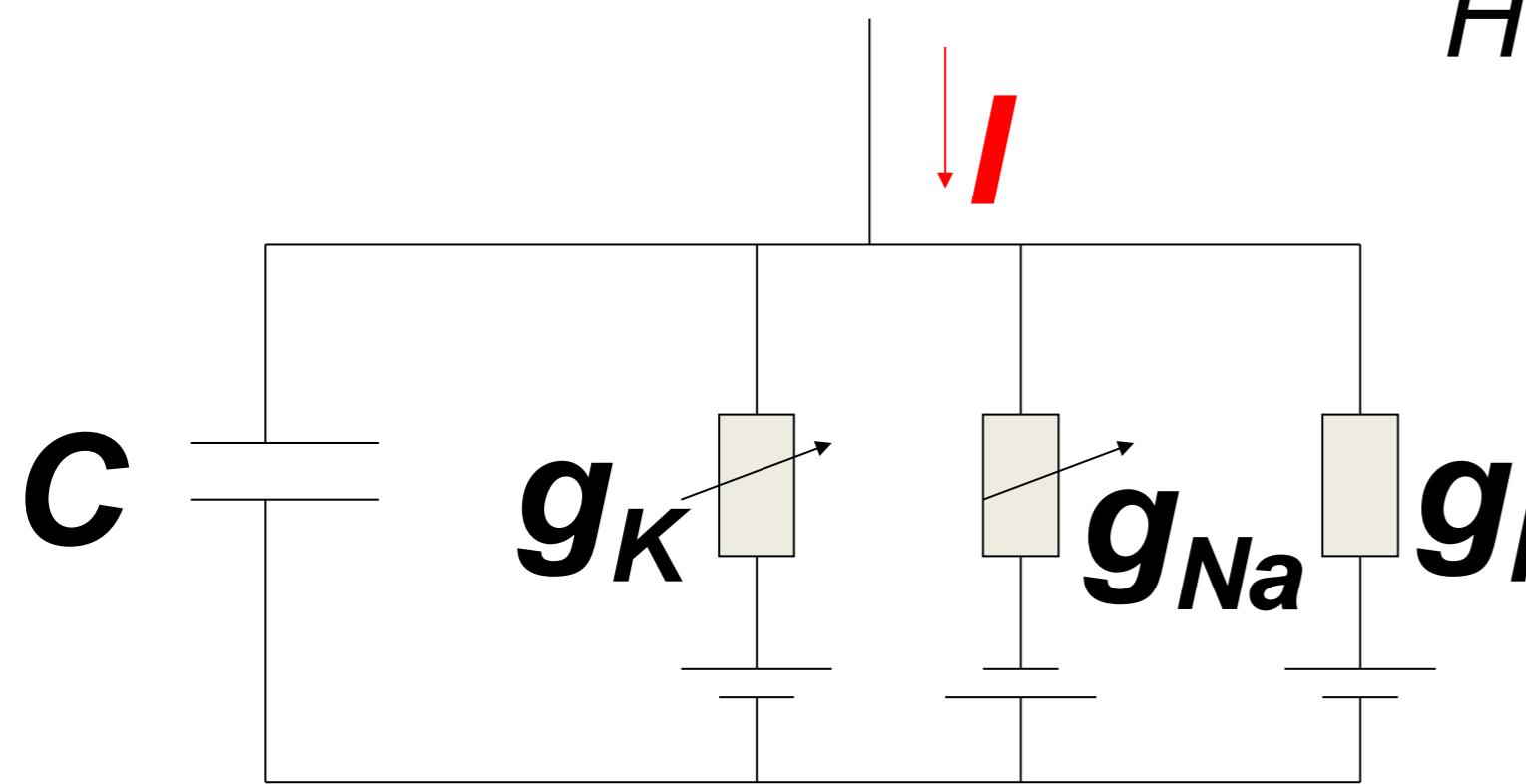
$$\Delta u = u_1 - u_2 = \frac{-kT}{q} \ln \frac{n(u_1)}{n(u_2)}$$

Reversal potential

ion pumps  $\rightarrow$  concentration difference  $\leftrightarrow$  voltage difference

# Neuronal Dynamics – 4.1. Review: Hodgkin-Huxley Model

*Hodgkin and Huxley, 1952*

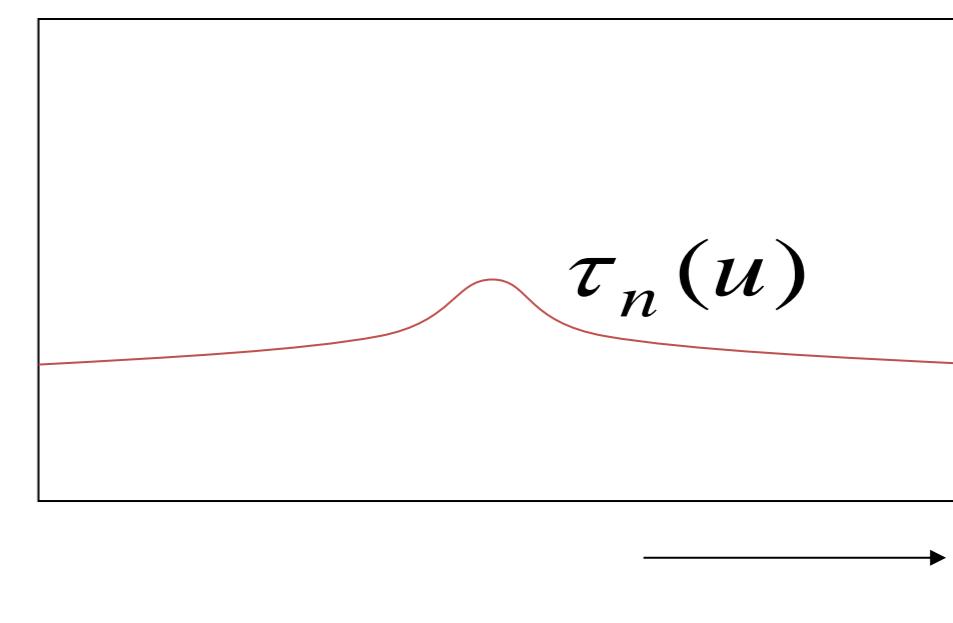
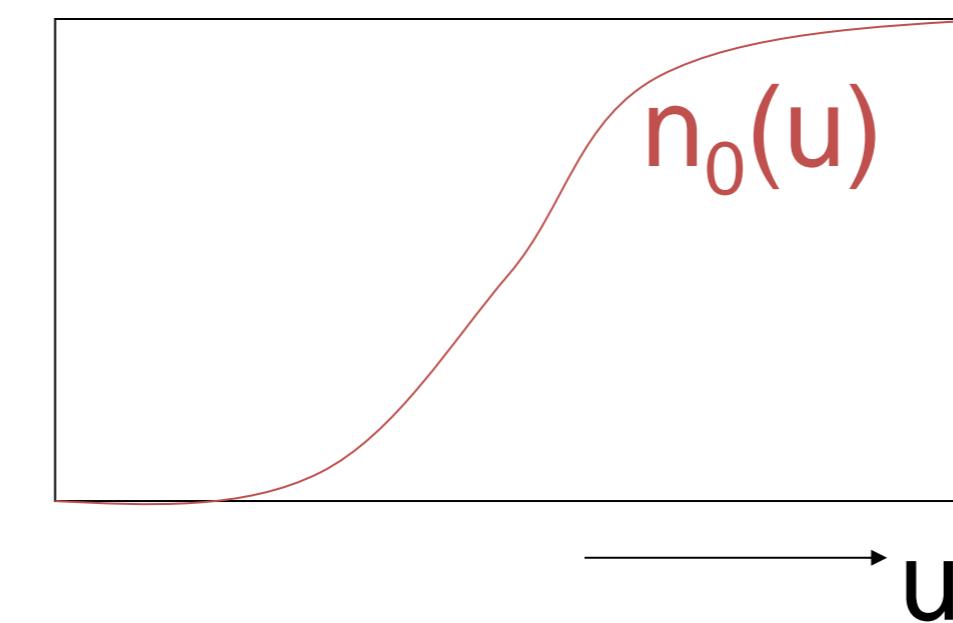


$$C \frac{du}{dt} = -g_{Na}m^3h(u - E_{Na}) - g_Kn^4(u - E_K) - g_l(u - E_l) + I(t)$$

Curved red lines above the equation group  $I_{Na}$ ,  $I_K$ , and  $I_{leak}$  to indicate they are voltage-dependent currents.

4 equations  
= 4D system

$$\frac{dm}{dt} = \frac{h m - h m(u)u}{\tau_m \tau_m(u)u}$$



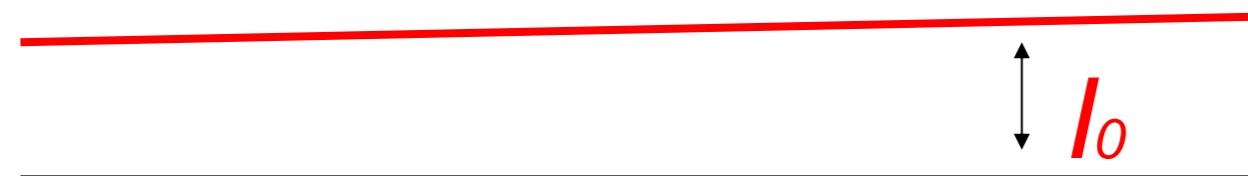
# Neuronal Dynamics – 4.1. Overview and aims

Can we understand the dynamics of the HH model?

- mathematical principle of Action Potential generation?
- Types of neuron model (type I and II)?
- threshold behavior?

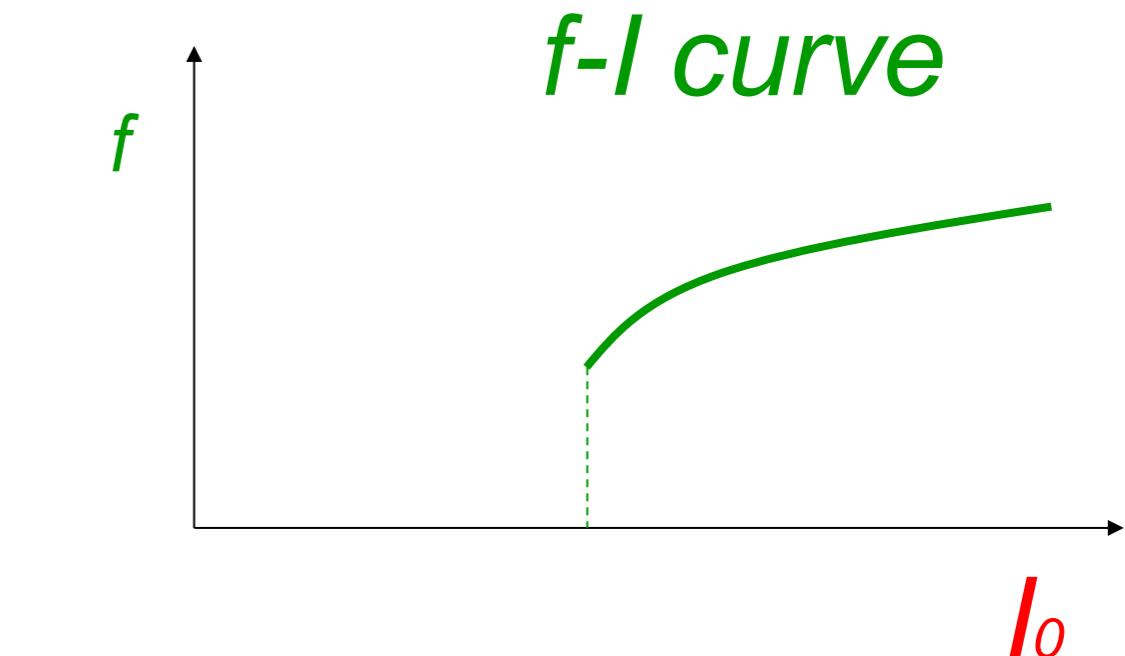
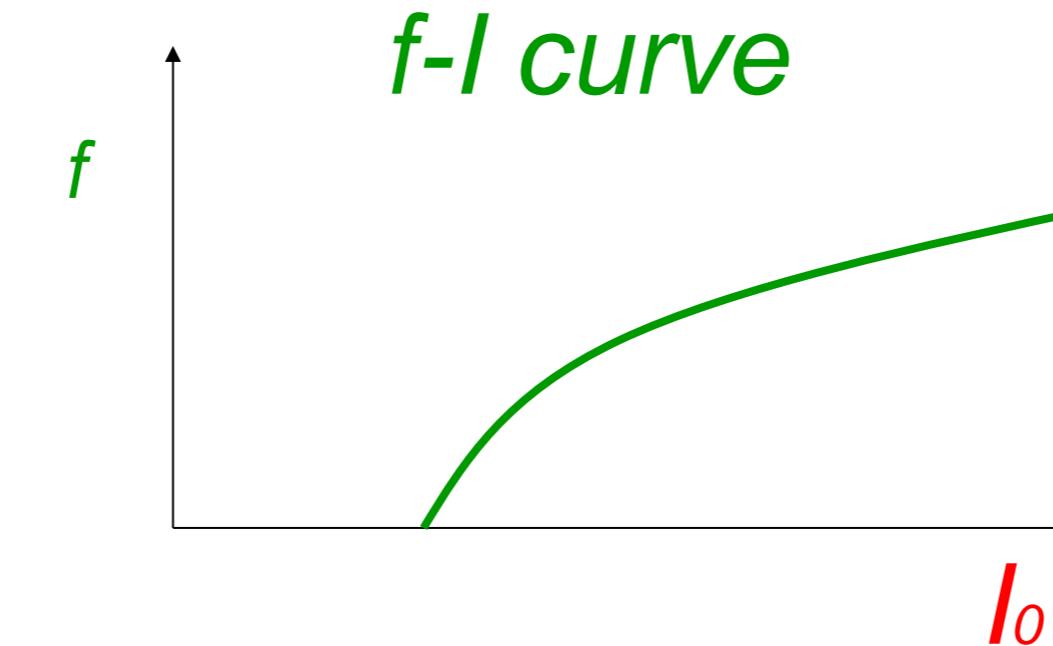
→ Reduce from 4 to 2 equations

ramp input/  
constant input



Type I and

type II models

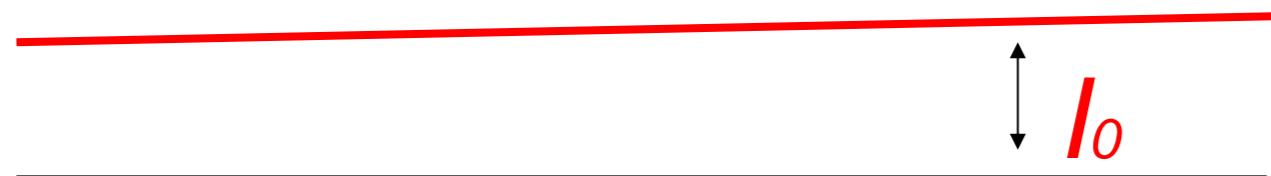


# Neuronal Dynamics – 4.1. Overview and aims

Can we understand the dynamics of the HH model?

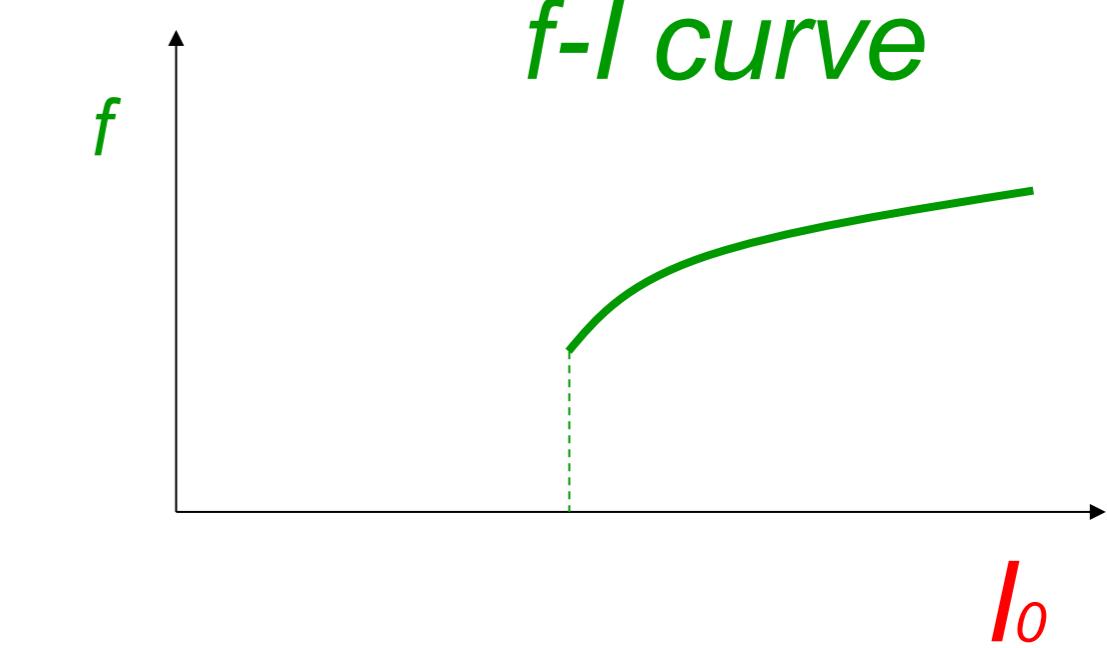
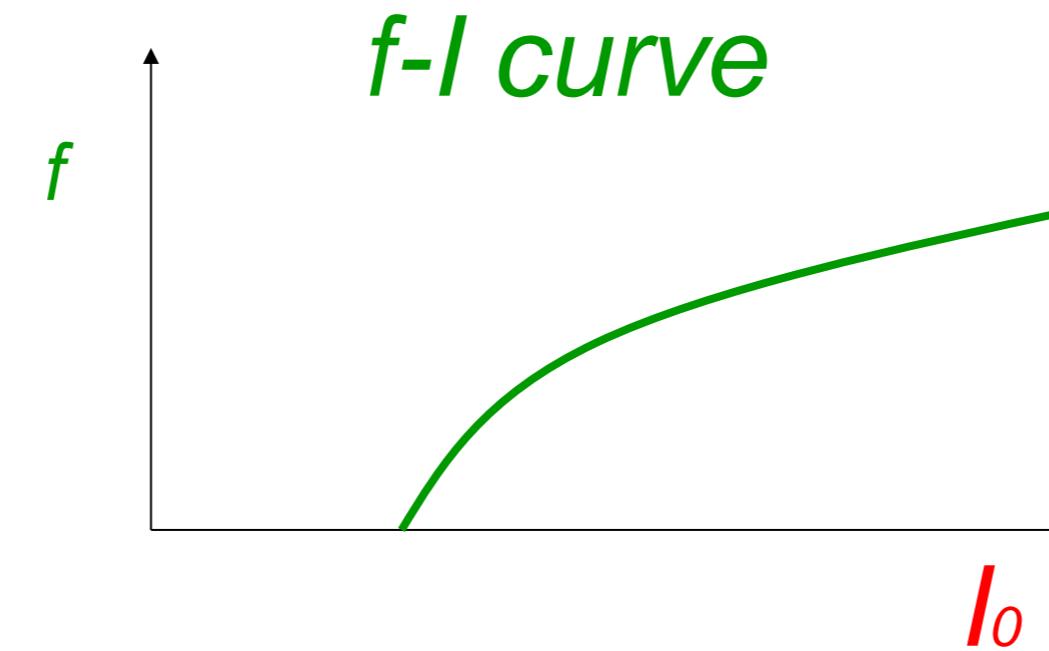
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Type I and

type II models



# Neuronal Dynamics – 4.1. Overview and aims

Toward a  
two-dimensional neuron model

- Reduction of Hodgkin-Huxley to 2 dimension
  - step 1: separation of time scales
  - step 2: exploit similarities/correlations

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

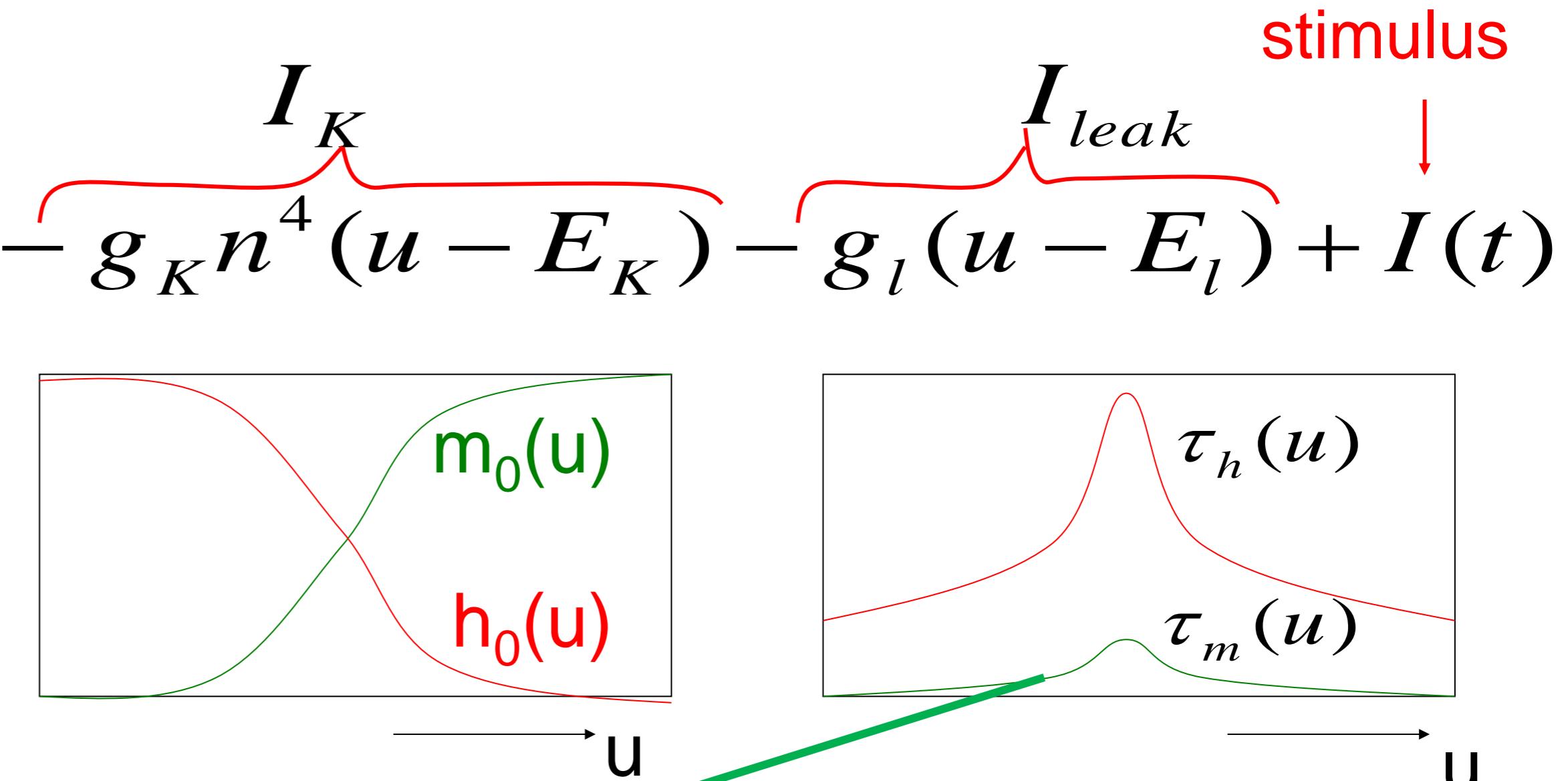
$$C \frac{du}{dt} = -g_{Na} m^3 h (u - E_{Na}) - g_K n^4 (u - E_K) - g_l (u - E_l) + I(t)$$

$$\frac{dm}{dt} = -\frac{m - m_0(u)}{\tau_m(u)}$$

$$\frac{dh}{dt} = -\frac{h - h_0(u)}{\tau_h(u)}$$

$$\frac{dn}{dt} = -\frac{n - n_0(u)}{\tau_n(u)}$$

1) dynamics of  $m$  is fast



*MathDetour 4.1*

$$m(t) = m_0(u(t))$$

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

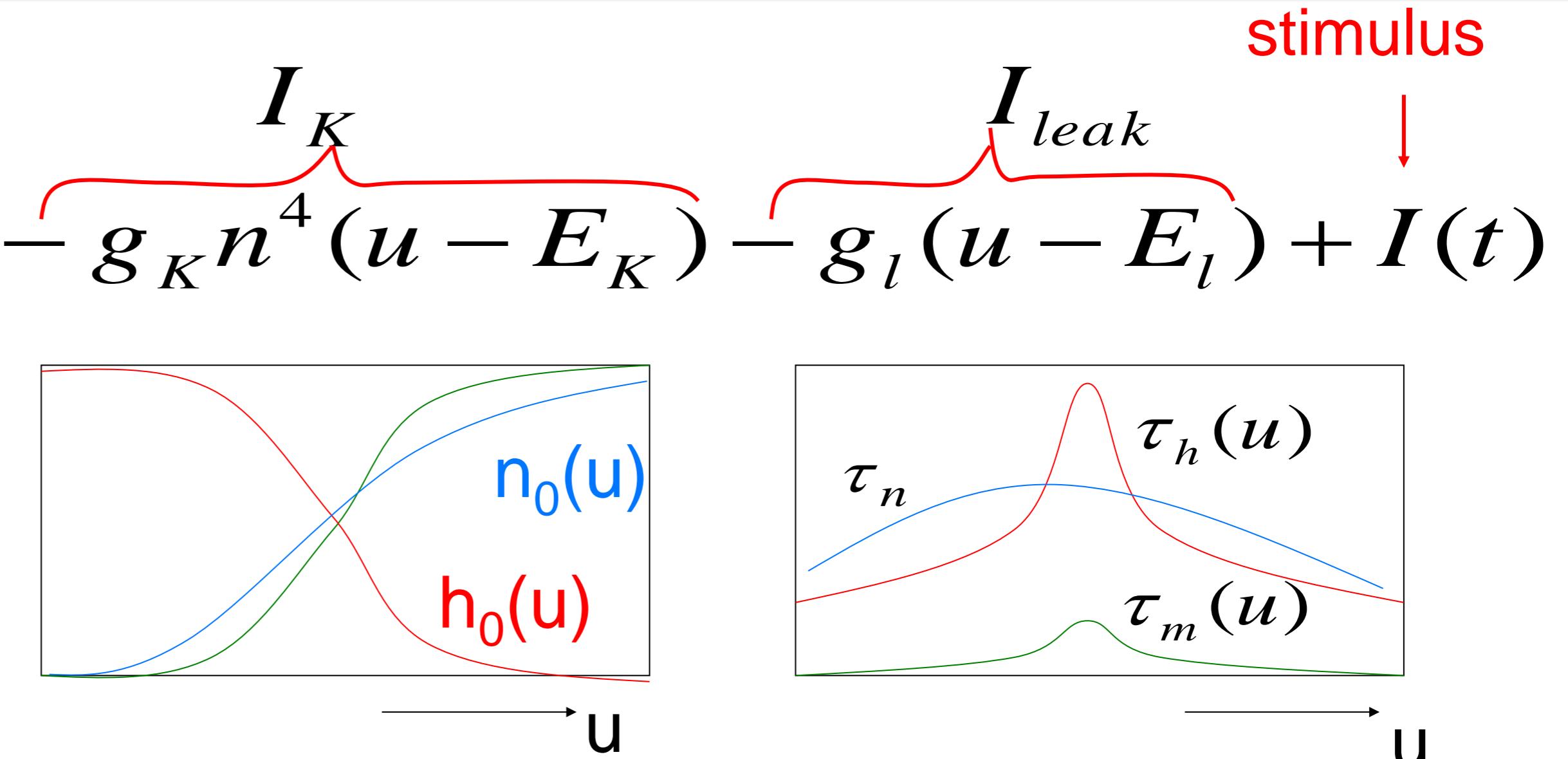
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- 1) dynamics of  $m$  are fast
- 2) dynamics of  $h$  and  $n$  are similar

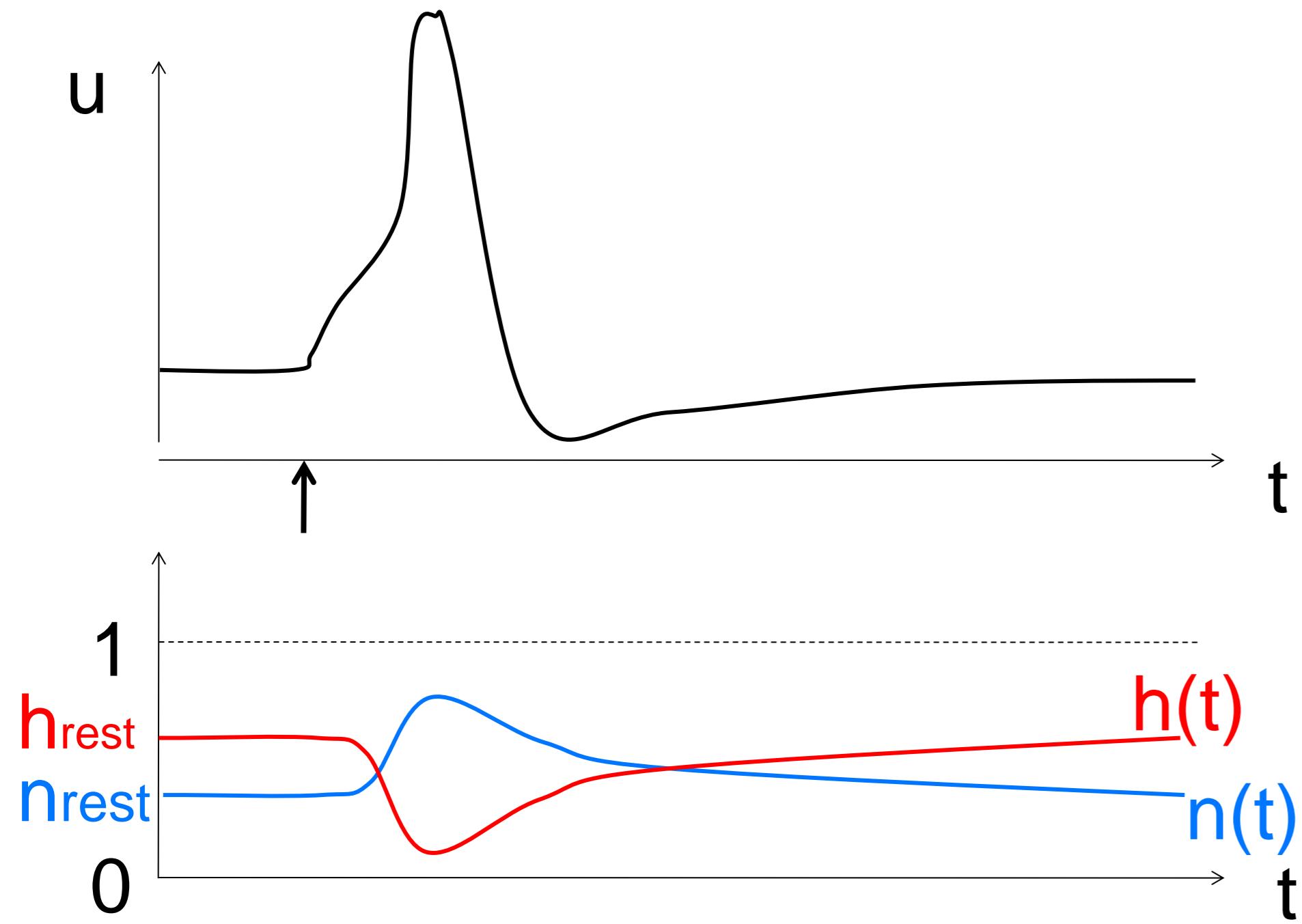


$$\longrightarrow m(t) = m_0(u(t))$$

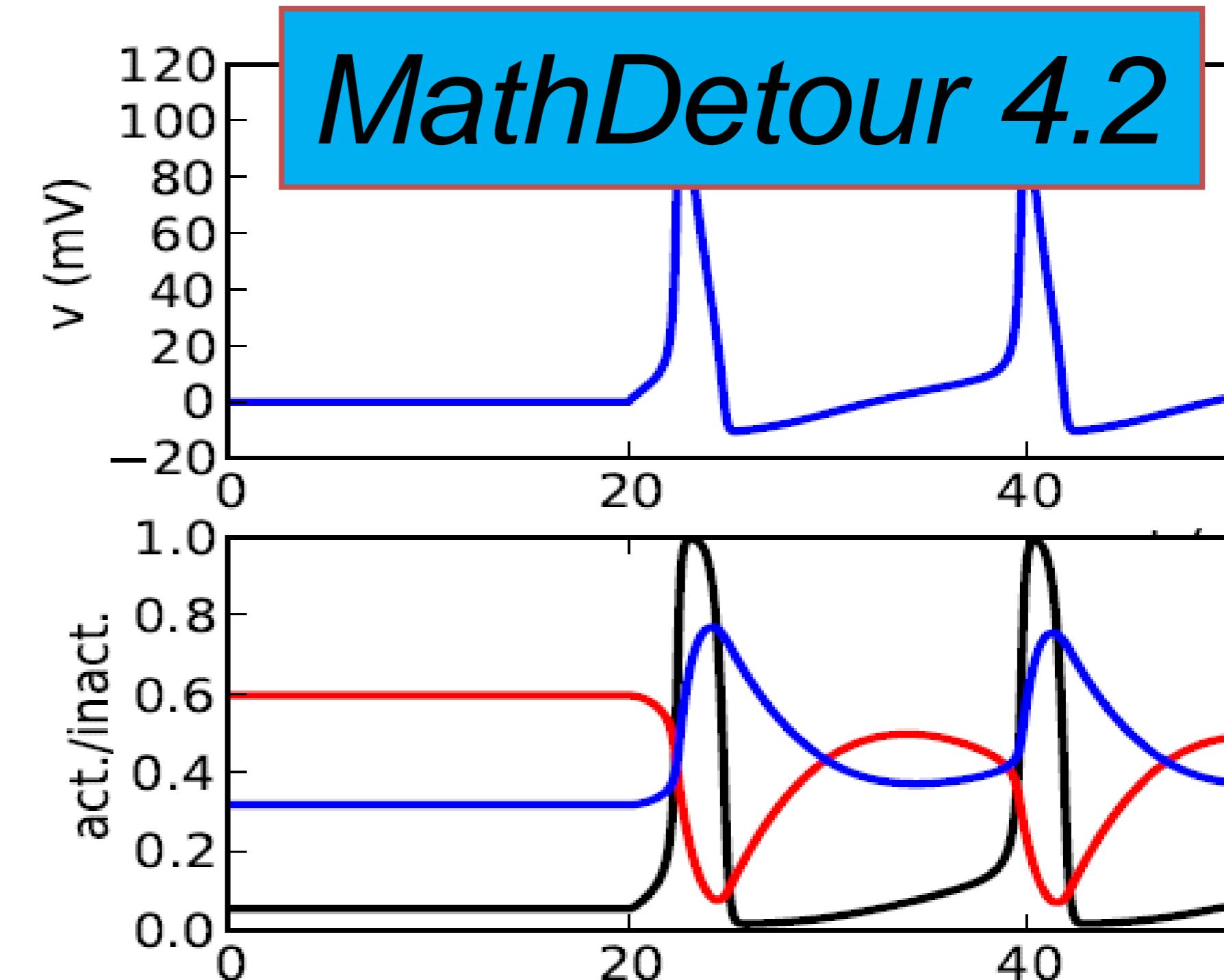
# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -g_{Na}m^3h(u - E_{Na}) - g_Kn^4(u - E_K) - g_l(u - E_l) + I(t)$$

2) dynamics of  $h$  and  $n$  are similar



$$1 - h(t) = a n(t)$$



# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -\underbrace{g_{Na} [m(t)]^3 h(t) (u(t) - E_{Na})}_{I_{Na}} - \underbrace{g_K [n(t)]^4 (u(t) - E_K)}_{I_K} - \underbrace{g_l (u(t) - E_l)}_{I_{leak}} + I(t)$$

$$C \frac{du}{dt} = -g_{Na} m_0 (u)^3 (1-w) (u - E_{Na}) - g_K \left[ \frac{w}{a} \right]^4 (u - E_K) - g_l (u - E_l) + I(t)$$

1) dynamics of  $m$  are fast  $\longrightarrow m(t) = m_0(u(t))$

2) dynamics of  $h$  and  $n$  are similar  $\longrightarrow \underbrace{1-h(t)}_{w(t)} = \underbrace{a n(t)}_{w(t)}$

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -g_{Na} m_0^3 (1-w) (u - E_{Na}) - g_K \left(\frac{w}{a}\right)^4 (u - E_K) - g_l (u - E_l) + I(t)$$

$$\frac{dw}{dt} = -\frac{w - w_0(u)}{\tau_{eff}(u)}$$

$$C \frac{du}{dt} = f(u(t), w(t)) + I(t)$$

$$\frac{dw}{dt} = g(u(t), w(t))$$

# Neuronal Dynamics – 4.1. Reduction to 2 dimensions

2-dimensional equation

$$C \frac{du}{dt} = f(u(t), w(t)) + I(t)$$

$$\frac{dw}{dt} = g(u(t), w(t))$$

Enables graphical analysis!

- Discussion of threshold
- Type I and II
- Repetitive firing

# Neuronal Dynamics – Quiz 4.1.

**A- Assumptions:** In order to reduce a detailed compartmental neuron model to two dimensions we have to assume that

- [ ] dendrites can be approximated as passive
- [ ] the neuron model has no dendrite
- [ ] the neuron model has at most 2 types of ion channels
- [ ] all gating variables are fast
- [ ] no gating variable is fast
- [ ] gating variables fall in two groups: those that are fast and those that are slow

[ ] at least one of the ion channels is inactivating

[ ] the neuron does not generate spikes

**B - A biophysical point model** with 3 ion channels, each with activation and inactivation, has a total number of equations equal to  
 [ ] 3 or  [ ] 4 or  [ ] 6 or  [ ] 7 ;  [ ] 8 or more

**C- Separation of time scales:**

We start with two equations

$$\tau_1 \frac{dx}{dt} = -x + I(t)$$

$$\tau_2 \frac{dy}{dt} = -y + x^2 + A$$

We assume that  $\tau_1 \ll \tau_2$

In this case a reduction of dimensionality

[ ] is not possible

[ ] is possible and the result is

$$\tau_2 \frac{dy}{dt} = -y + [I(t)]^2 + A$$

[ ] is possible and the result is

$$\tau_1 \frac{dx}{dt} = -x + x^2 + A$$

# Week 4 – part 1 : Separation of time scales



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail: Two-dimensional neuron models

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- where is the firing threshold?
- separation of time scales

#### 4.5 Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – MathDetour 4.1: Separation of time scales

Two coupled differential equations

$$\tau_1 \frac{dx}{dt} = -x + c(t)$$

$$\tau_2 \frac{dy}{dt} = f(y) + g(x)$$

Separation of time scales

$$\tau_1 \ll \tau_2$$

Reduced 1-dimensional system

$$\tau_2 \frac{dy}{dt} = f(y) + g(c(t))$$

# Neuronal Dynamics – MathDetour 4.1: Separation of time scales

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$$\tau_2 \frac{dy}{dt} = f(y) + g(c(t))$$

# Neuronal Dynamics – MathDetour 4.1: Separation of time scales

Linear differential equation

$$\tau_1 \frac{dx}{dt} = -x + c(t)$$



step



‘slow drive’

# Neuronal Dynamics – MathDetour 4.1: Separation of time scales

Two differential equations

$$\tau_1 \frac{dx}{dt} = -x + c(t)$$

$$\tau_2 \frac{dc}{dt} = -c + I(t)$$

$$\tau_1 \square \tau_2$$



‘slow drive’



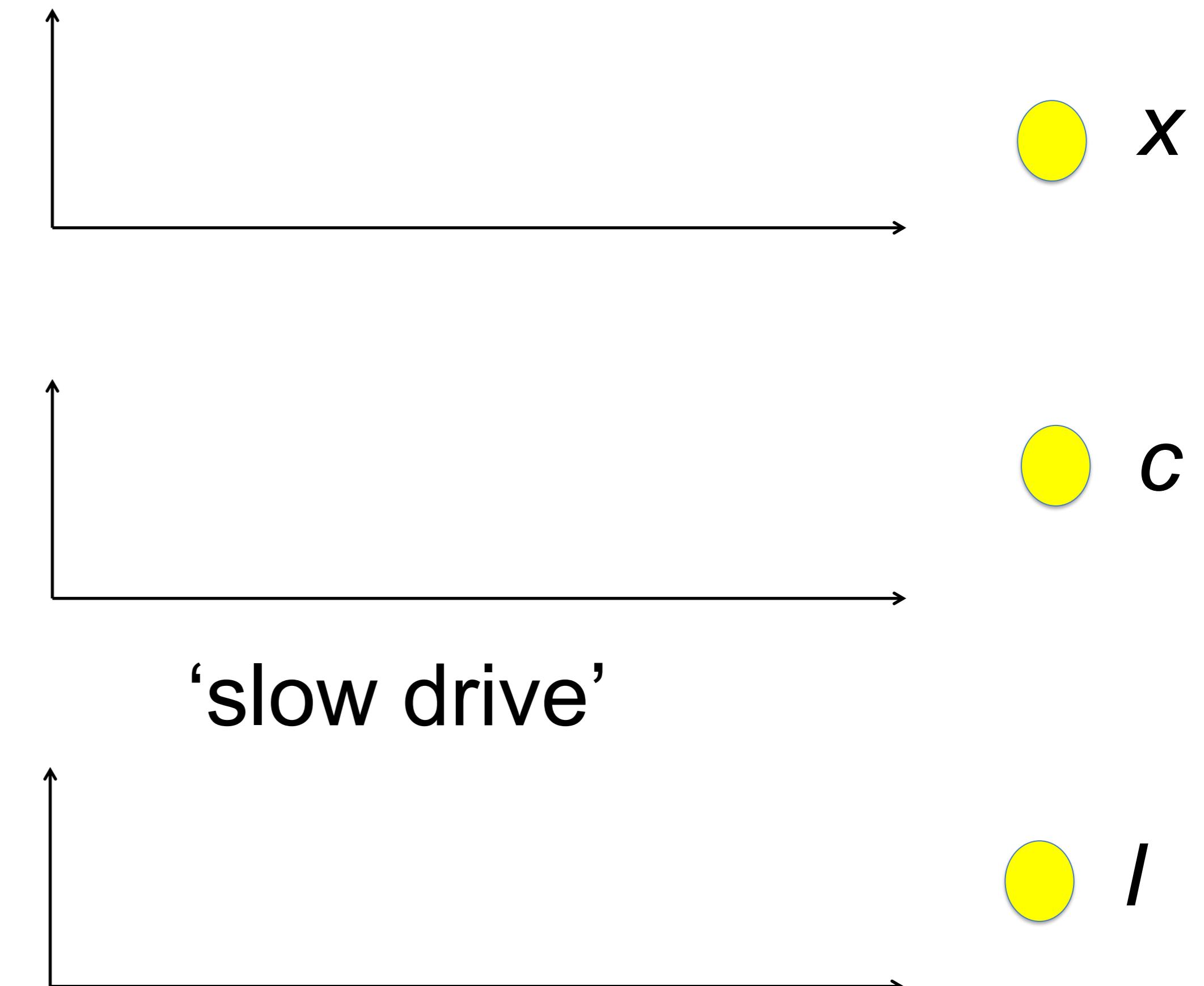
# Neuronal Dynamics – MathDetour 4.1: Separation of time scales

Two coupled differential equations

$$\tau_1 \frac{dx}{dt} = -x + c(t)$$

$$\tau_2 \frac{dc}{dt} = -c + f(x) + I(t)$$

$$\tau_1 \square \tau_2$$



# Neuronal Dynamics – Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -g_{Na} m^3 h (u - E_{Na}) - g_K n^4 (u - E_K) - g_l (u - E_l) + I(t)$$

$$\frac{dm}{dt} = -\frac{m - m_0(u)}{\tau_m(u)}$$

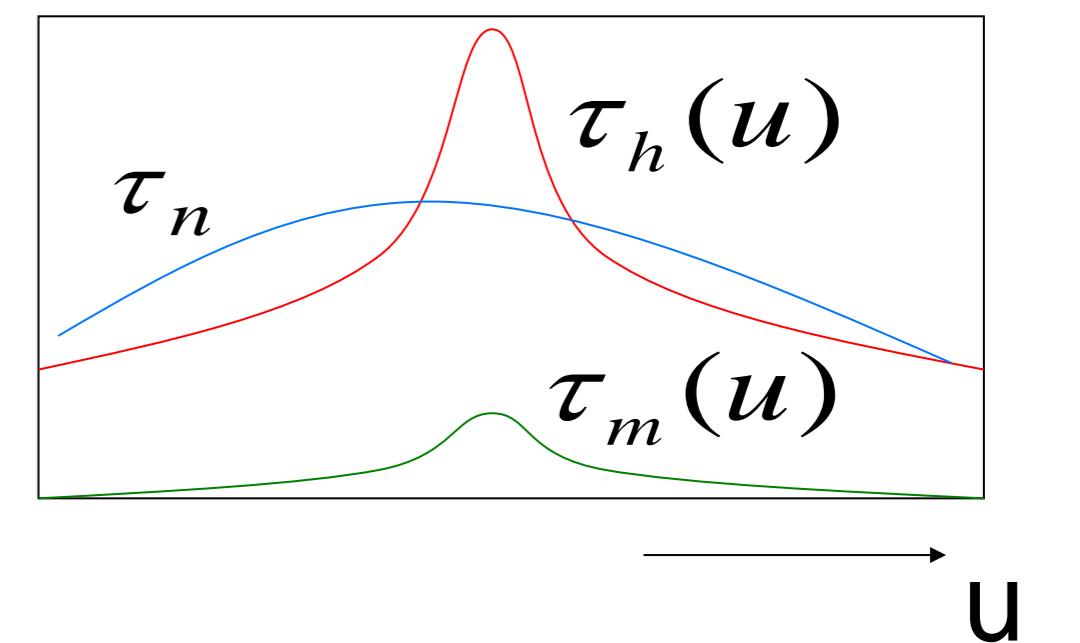
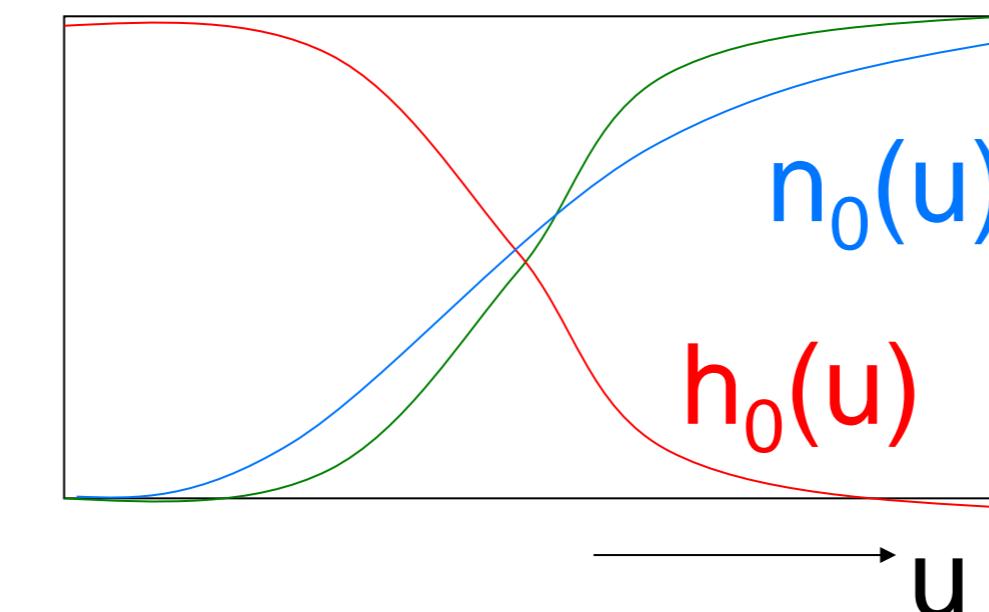
$$\frac{dh}{dt} = -\frac{h - h_0(u)}{\tau_h(u)}$$

$$\frac{dn}{dt} = -\frac{n - n_0(u)}{\tau_n(u)}$$

dynamics of  $m$  is fast

$$\longrightarrow m(t) = m_0(u(t))$$

*Fast compared to what?*



# Neuronal Dynamics – MathDetour 4.1: Separation of time scales

Two coupled differential equations

$$\tau_1 \frac{dx}{dt} = -x + h(y)$$

$$\tau_2 \frac{dy}{dt} = f(y) + g(x)$$

Separation of time scales

$$\tau_1 \ll \tau_2 \rightarrow x = h(y)$$

Reduced 1-dimensional system

$$\tau_2 \frac{dy}{dt} = f(y) + g(h(y))$$

# Neuronal Dynamics – Quiz 4.2.

## A- Separation of time scales:

We start with two equations

$$\tau_1 \frac{dx}{dt} = -x + y + I(t)$$

$$\tau_2 \frac{dy}{dt} = -y + x^2 + A$$

[ ] If  $\tau_1 \ll \tau_2$  then the system can be reduced to

$$\tau_2 \frac{dy}{dt} = -y + [y + I(t)]^2 + A$$

[ ] If  $\tau_2 \ll \tau_1$  then the system can be reduced to

$$\tau_1 \frac{dx}{dt} = -x + x^2 + A + I(t)$$

[ ] None of the above is correct.

## B- Separation of time scales:

A channel with gating variable  $r$ , given by

$$\tau_1 \frac{dr}{dt} = -r + r_0(u)$$

influences the voltage

$$\tau_2 \frac{du}{dt} = -(u - u_0) + r^2 A$$

We assume that  $\tau_1 \ll \tau_2$

In this case a reduction of dimensionality

[ ] is not possible

[ ] is possible and the result is

$$\tau_2 \frac{du}{dt} = -u + u_0 + [r_0(u)]^2 A$$

[ ] is possible and the result is

$$\tau_1 \frac{dr}{dt} = -r + r_0(u_0 + r^2 A)$$

# Week 4 – MathDetour 2: Exploiting similarities



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail: Two-dimensional neuron models

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EPFL, Lausanne, Switzerland

#### 4.1 From Hodgkin-Huxley to 2D

- ✓ - Overview: From 4 to 2 dimensions
- ✓ - MathDetour 1: Separation of time scales
- MathDetour 2: Exploiting similarities

#### 4.2 Phase Plane Analysis

- role of nullclines
- MathDetour 3: Stability of fixed points

#### 4.3 Analysis of a 2D Neuron Model

#### 4.4 Type I and II Neuron Models

- where is the firing threshold?
- separation of time scales

#### 4.5 Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

## Reduction of Hodgkin-Huxley Model to 2 Dimension

-step 1:  
separation of time scales  
(→ 4.1 and 4-Detour1)

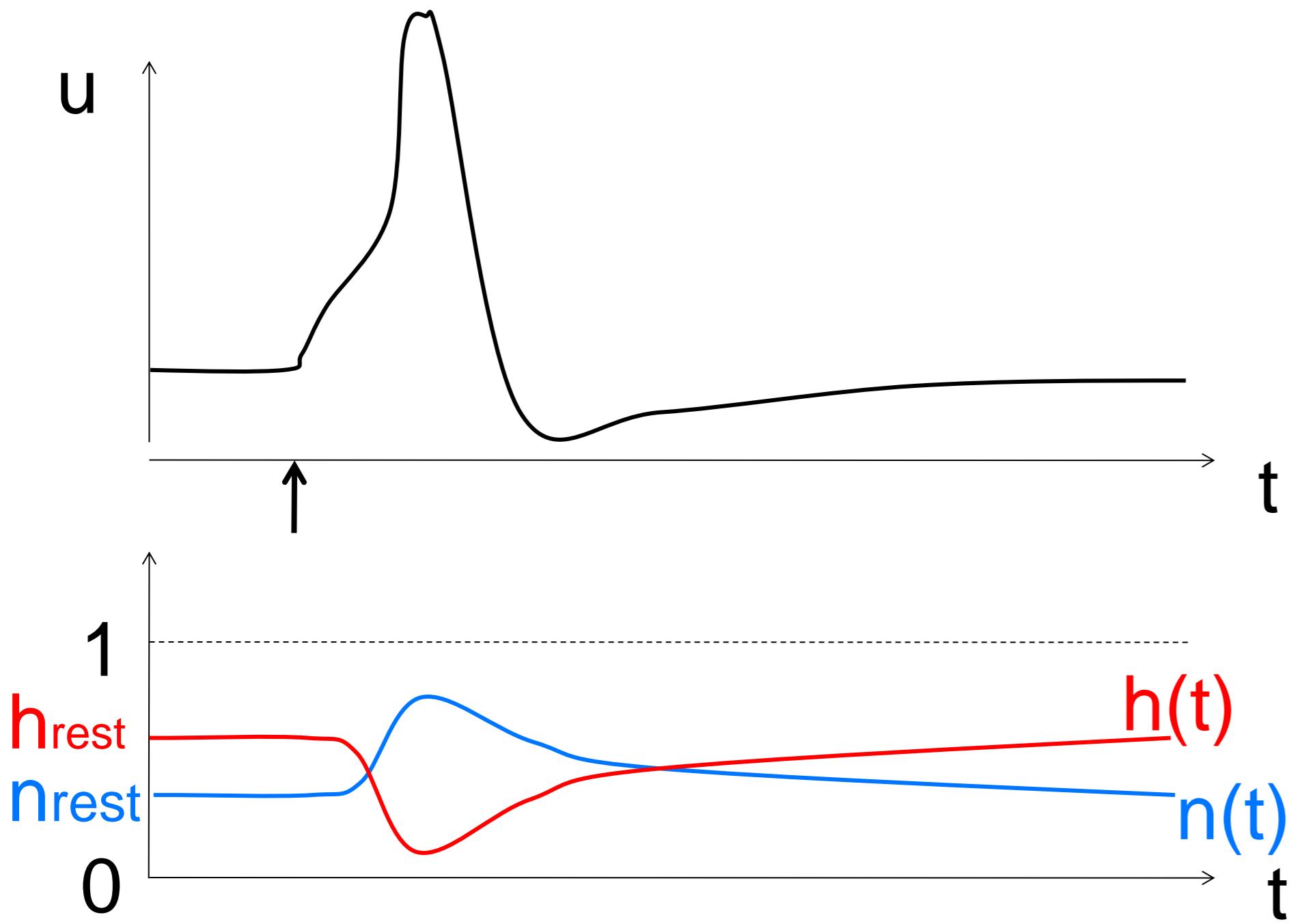
-step 2:  
exploit similarities/correlations

*Now !*

# Neuronal Dynamics – Detour 4.2. Exploit similarities/correlations

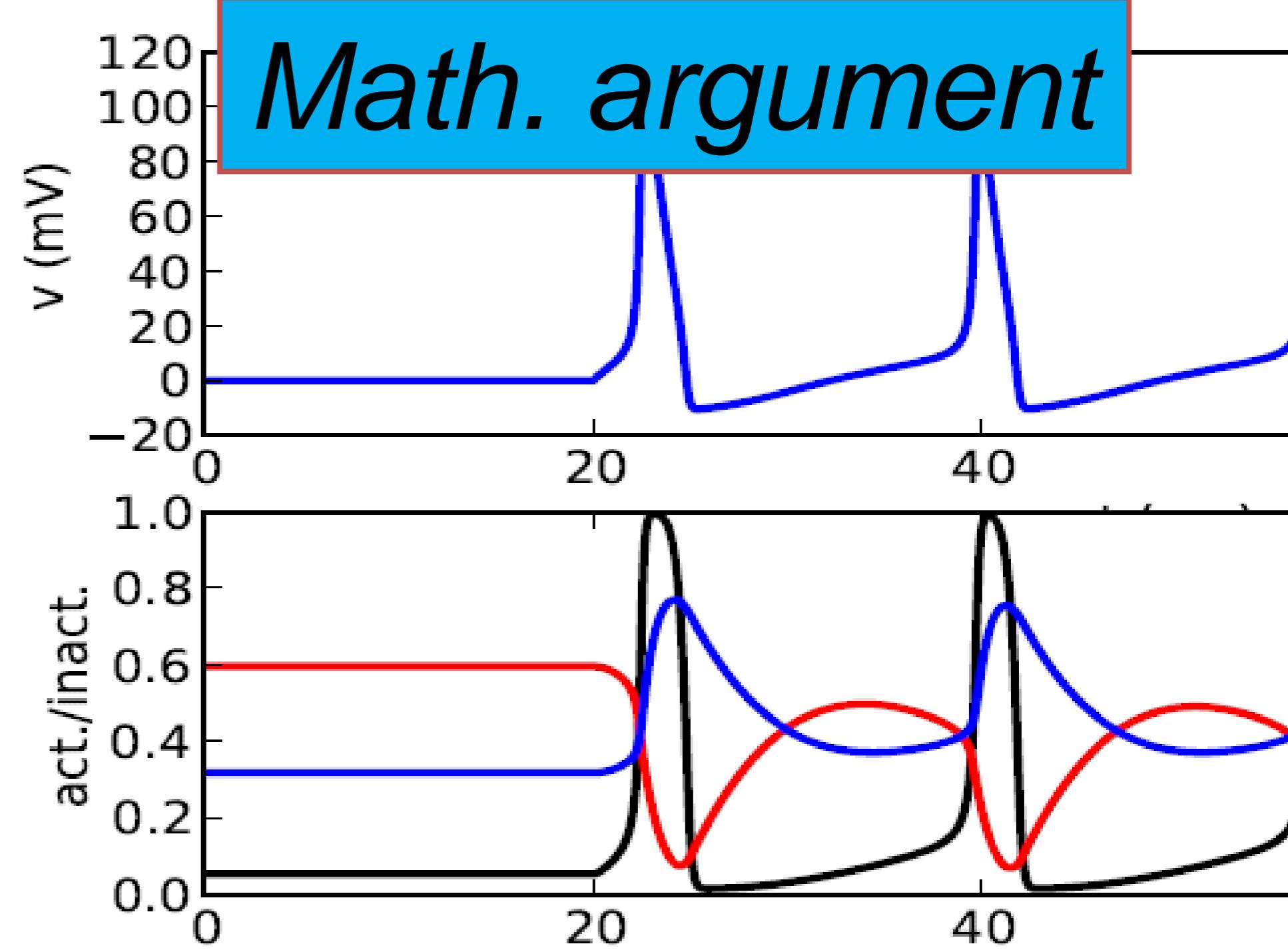
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dynamics of  $h$  and  $n$  is similar



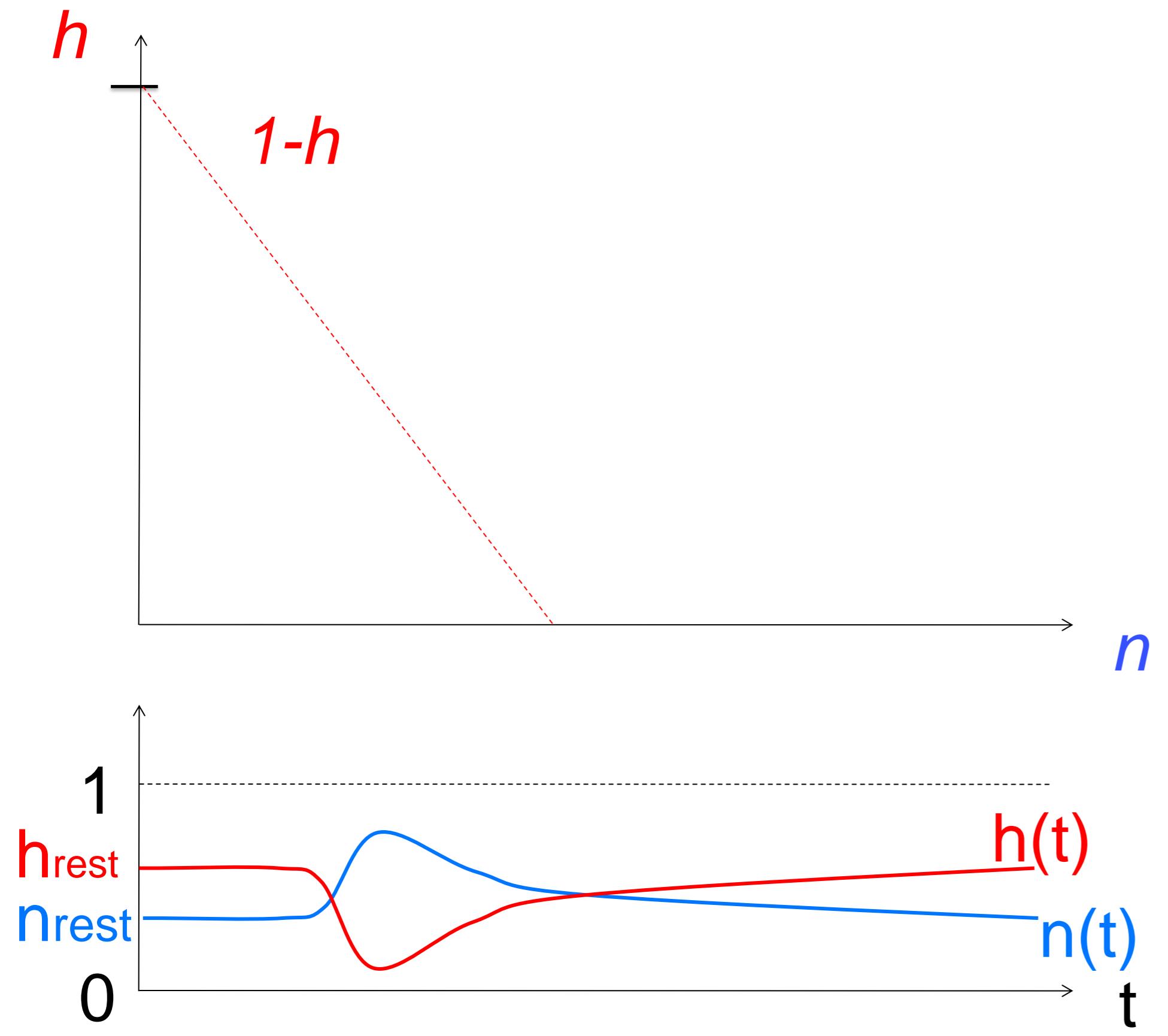
$$1 - h(t) = a n(t)$$

**Math. argument**

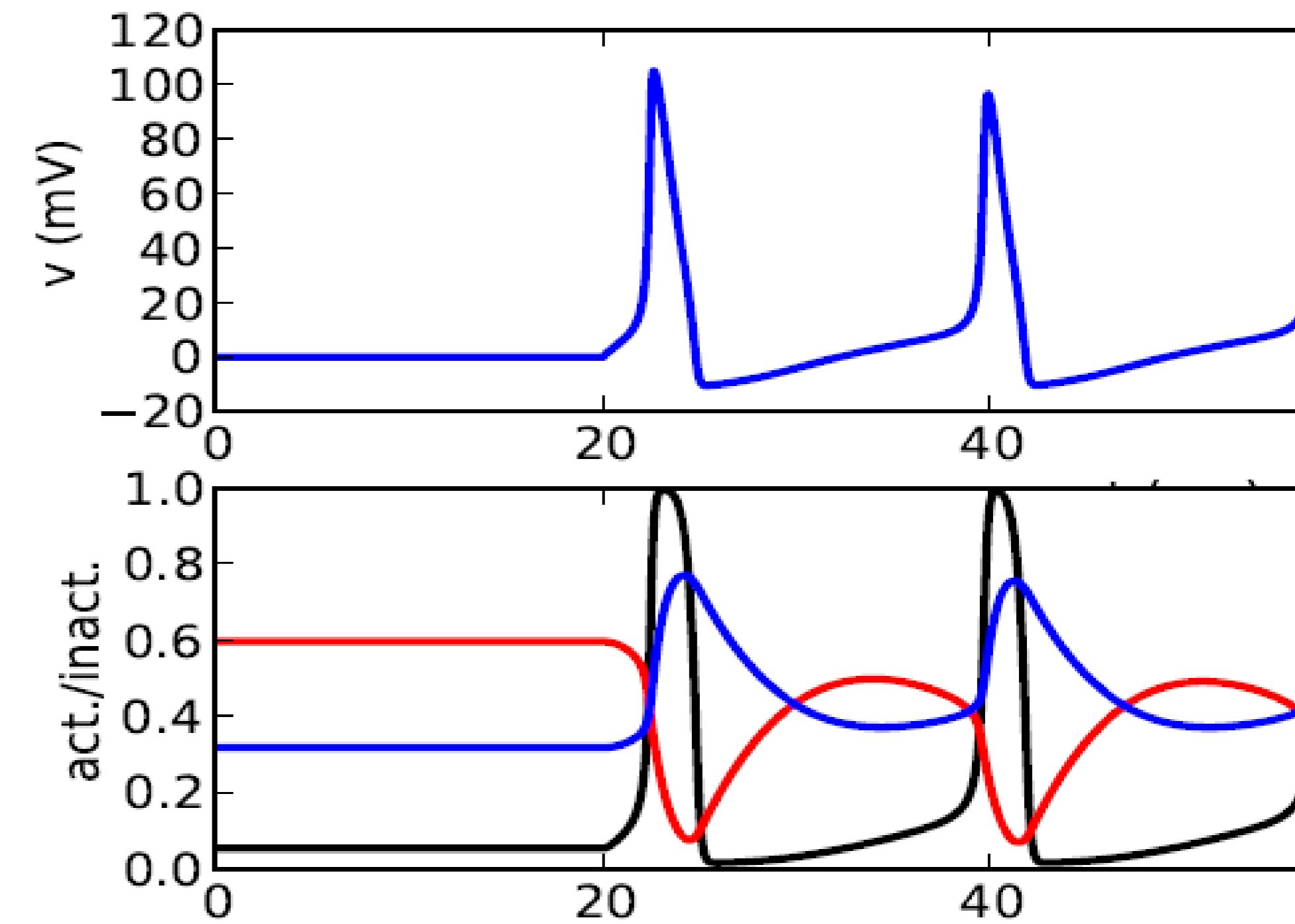


# Neuronal Dynamics – Detour 4.2. Exploit similarities/correlations

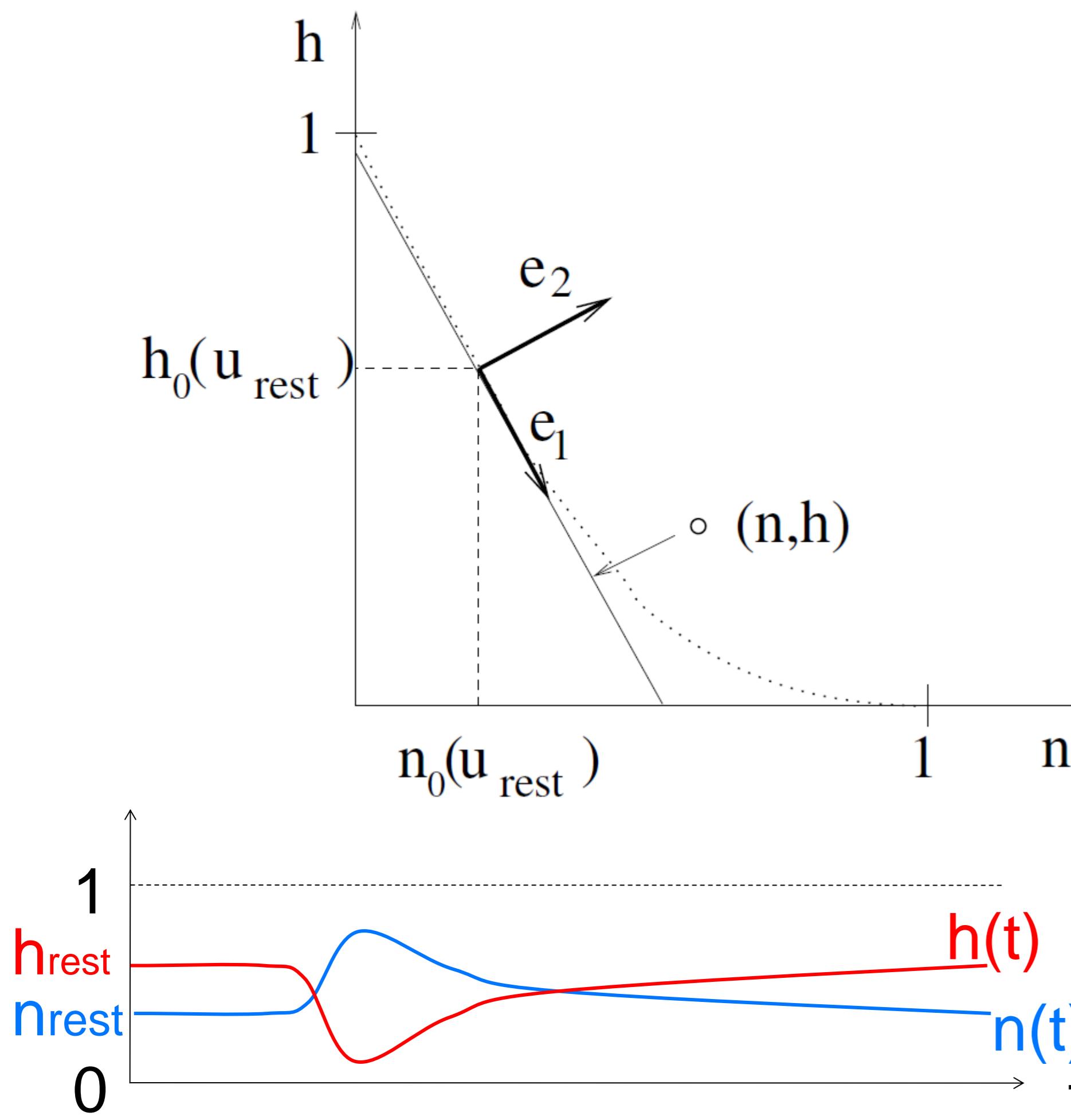
dynamics of  $h$  and  $n$  are similar



$$1 - h(t) = a n(t)$$



# Neuronal Dynamics – Detour 4.2. Exploit similarities/correlations



dynamics of  $h$  and  $n$  are similar

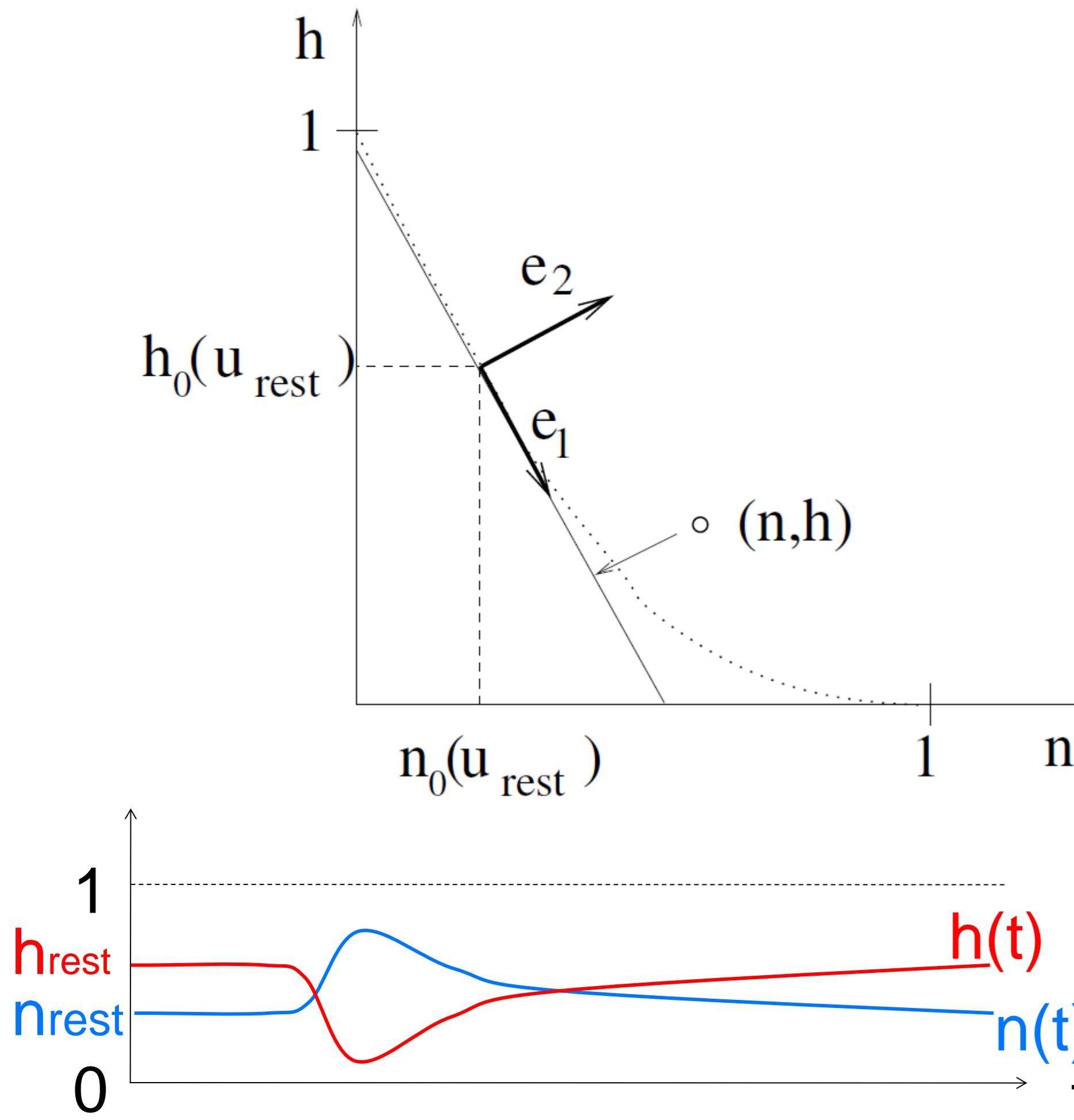
$$1 - h(t) = a n(t)$$

at rest

$$\frac{dh}{dt} = -\frac{h - h_0(u)}{\tau_h(u)}$$

$$\frac{dn}{dt} = -\frac{n - n_0(u)}{\tau_n(u)}$$

# Neuronal Dynamics – Detour 4.2. Exploit similarities/correlations



dynamics of  $h$  and  $n$  are similar

- (i) Rotate coordinate system
- (ii) Suppress one coordinate
- (iii) Express dynamics in new variable

$$1 - h(t) = a n(t) = w(t)$$

$$\frac{dh}{dt} = -\frac{h - h_0(u)}{\tau_h(u)}$$

$$\frac{dn}{dt} = -\frac{n - n_0(u)}{\tau_n(u)}$$

$$\frac{dw}{dt} = -\frac{w - w_0(u)}{\tau_{eff}(u)}$$

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -\underbrace{g_{Na} [m(t)]^3 h(t) (u(t) - E_{Na})}_{I_{Na}} - \underbrace{g_K [n(t)]^4 (u(t) - E_K)}_{I_K} - \underbrace{g_l (u(t) - E_l)}_{I_{leak}} + I(t)$$

$$C \frac{du}{dt} = -g_{Na} m_0 (u)^3 (1 - w) (u - E_{Na}) - g_K \left[ \frac{w}{a} \right]^4 (u - E_K) - g_l (u - E_l) + I(t)$$

1) dynamics of  $m$  are fast  $\longrightarrow m(t) = m_0(u(t))$   
 2) dynamics of  $h$  and  $n$  are similar  $\longrightarrow 1 - h(t) = \underbrace{a n(t)}_{w(t)}$

$$\frac{dh}{dt} = -\frac{h - h_0(u)}{\tau_h(u)} \longrightarrow \frac{dw}{dt} = -\frac{w - w_0(u)}{\tau_{eff}(u)}$$

$$\frac{dn}{dt} = -\frac{n - n_0(u)}{\tau_n(u)}$$

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -g_{Na} m_0^3 (1-w) (u - E_{Na}) - g_K \left(\frac{w}{a}\right)^4 (u - E_K) - g_l (u - E_l) + I(t)$$

$$\frac{dw}{dt} = -\frac{w - w_0(u)}{\tau_{eff}(u)}$$



$$\tau \frac{du}{dt} = F(u(t), w(t)) + R I(t)$$

$$\tau_w \frac{dw}{dt} = G(u(t), w(t))$$

# Neuronal Dynamics – 4.1. Reduction to 2 dimensions

2-dimensional equation

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Enables graphical analysis!

- Discussion of threshold
- Repetitive firing
- Type I and II

# Neuronal Dynamics – Quiz 4.3.

## Exploiting similarities:

A sufficient condition to replace two gating variables  $r, s$  by a single gating variable  $w$  is

- [ ] Both  $r$  and  $s$  have the same time constant (as a function of  $u$ )
- [ ] Both  $r$  and  $s$  have the same activation function
- [ ] Both  $r$  and  $s$  have the same time constant (as a function of  $u$ )  
AND the same activation function
- [ ] Both  $r$  and  $s$  have the same time constant (as a function of  $u$ )  
AND activation functions that are identical after some additive rescaling
- [ ] Both  $r$  and  $s$  have the same time constant (as a function of  $u$ )  
AND activation functions that are identical after some multiplicative  
rescaling

# Week 4 – part 2: Phase Plane Analysis



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail:

#### Two-dimensional neuron models

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- Role of nullcline

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### 4.4 Type I and II Neuron Models

- where is the firing threshold?
- separation of time scales

### 4.5. Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – 4.2. Phase Plane Analysis

2-dimensional equation  
stimulus

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Enables graphical analysis!  
-Discussion of threshold  
-Type I and II

# Neuronal Dynamics – 4.1. Reduction of Hodgkin-Huxley model

$$C \frac{du}{dt} = -g_{Na} m_0(u)^3 (1-w)(u - E_{Na}) - g_K \left(\frac{w}{a}\right)^4 (u - E_K) - g_l (u - E_l) + I(t)$$

$$\frac{dw}{dt} = -\frac{w - w_0(u)}{\tau_w(u)}$$

stimulus

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

# Neuronal Dynamics – 4.2. Nullclines of reduced HH model

$$\tau \frac{du}{dt} = F(u, w) + I(t)$$
$$\tau_w \frac{dw}{dt} = G(u, w)$$

stimulus

there is a factor  $R$  missing here  
( assume  $R=1$ )

u-nullcline

w-nullcline

# Neuronal Dynamics – 4.2. Nullclines of reduced HH model

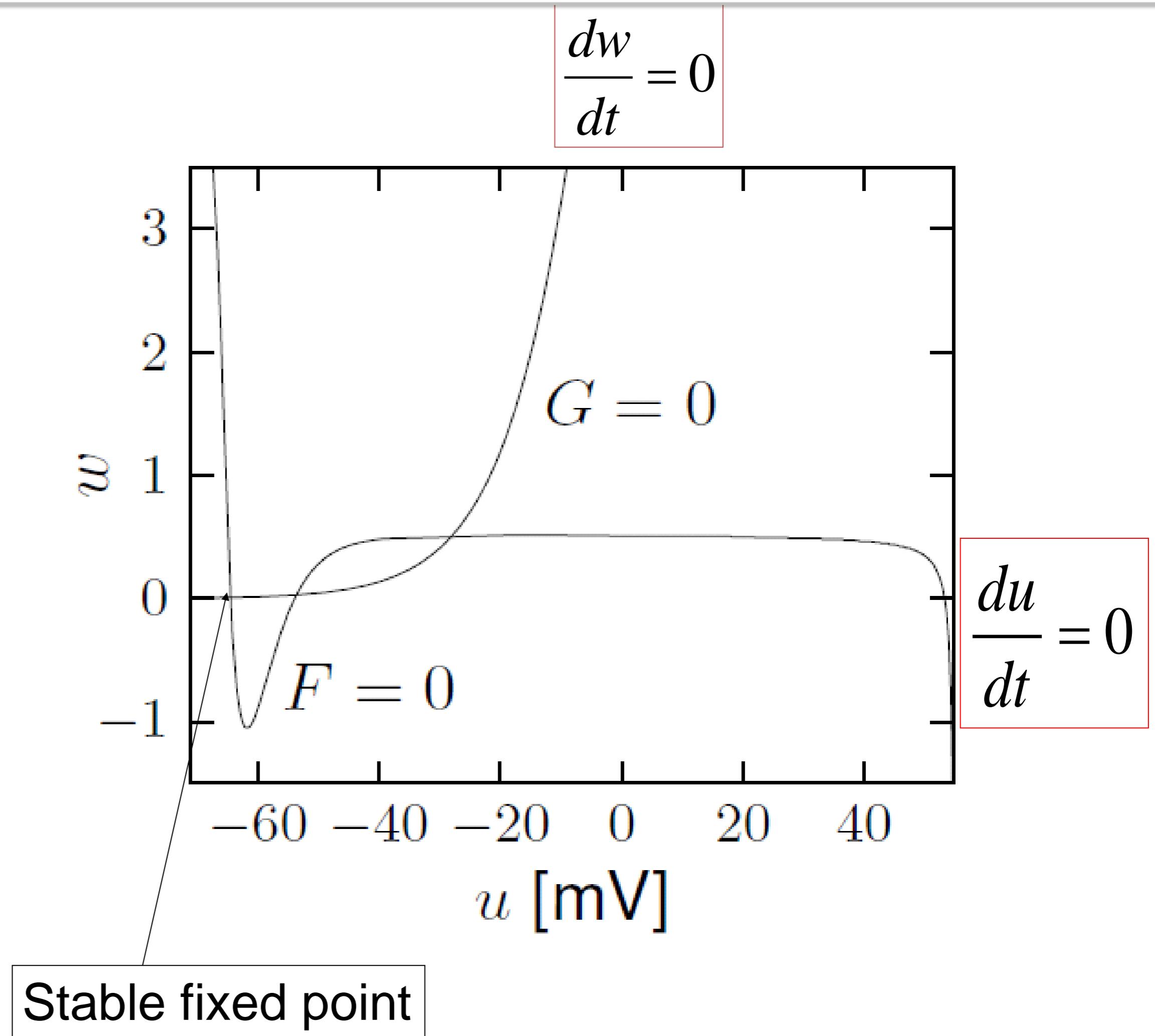
$$\tau \frac{du}{dt} = F(u, w) + I(t)$$

stimulus

$$\tau_w \frac{dw}{dt} = G(u, w)$$

u-nullcline

w-nullcline



# Neuronal Dynamics – 4.2. FitzHugh-Nagumo Model

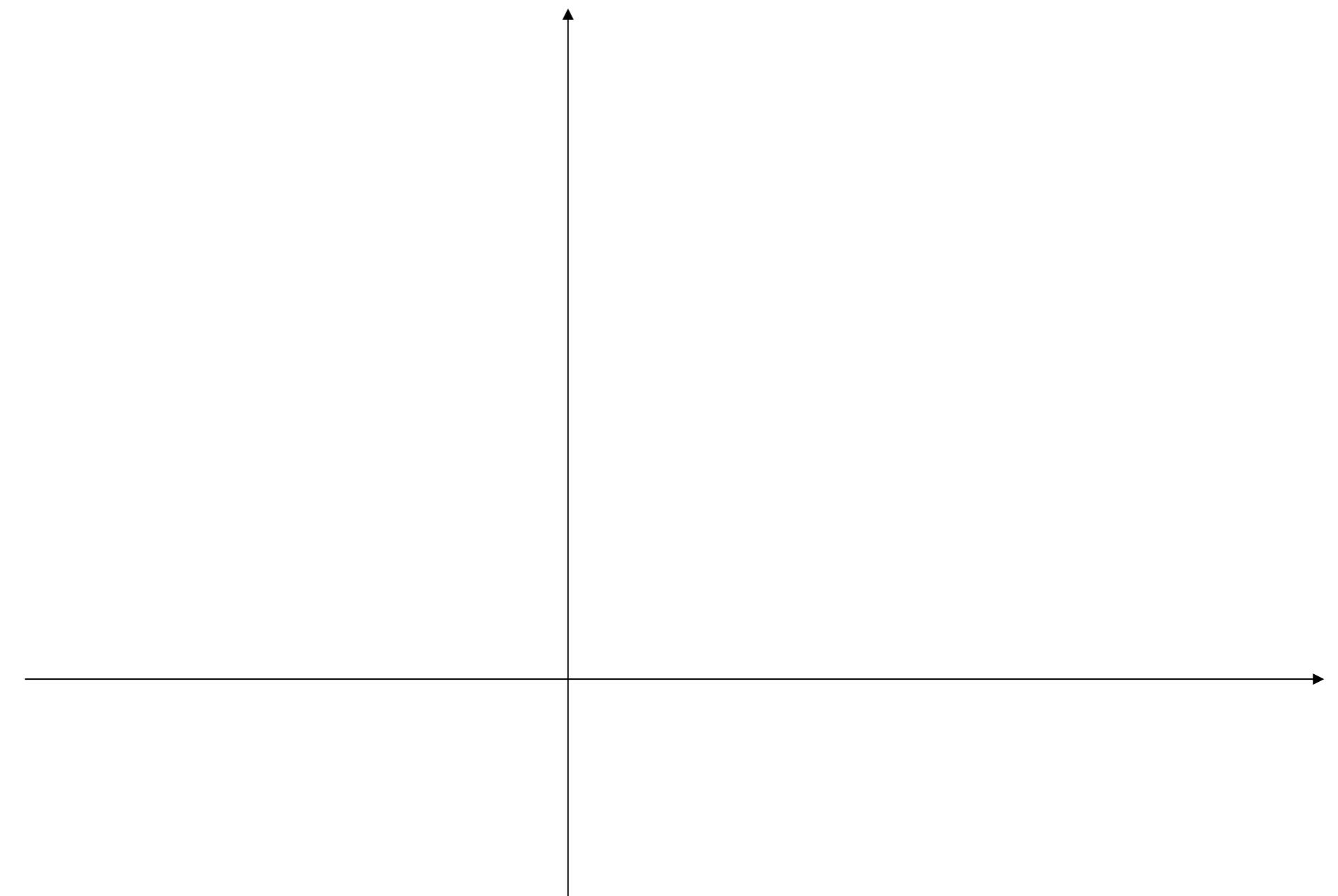
$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$= u - \frac{1}{3}u^3 + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w) = b_0 + b_1 u - w$$

u-nullcline

w-nullcline



# Neuronal Dynamics – 4.2. flow arrows

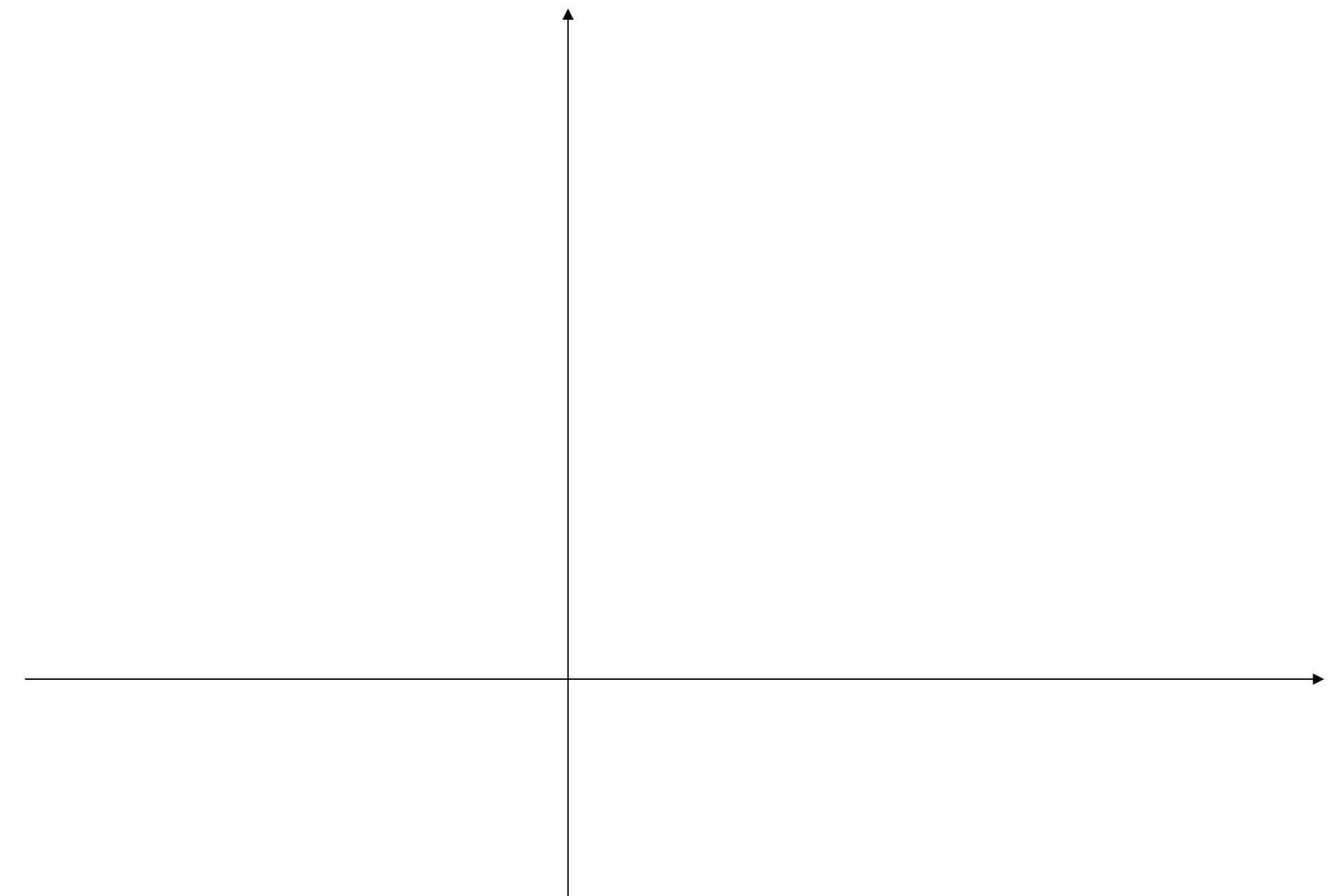
$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$= u - \frac{1}{3}u^3 + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w) = b_0 + b_1 u - w$$

u-nullcline

w-nullcline



# Neuronal Dynamics – 4.2. flow arrows

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

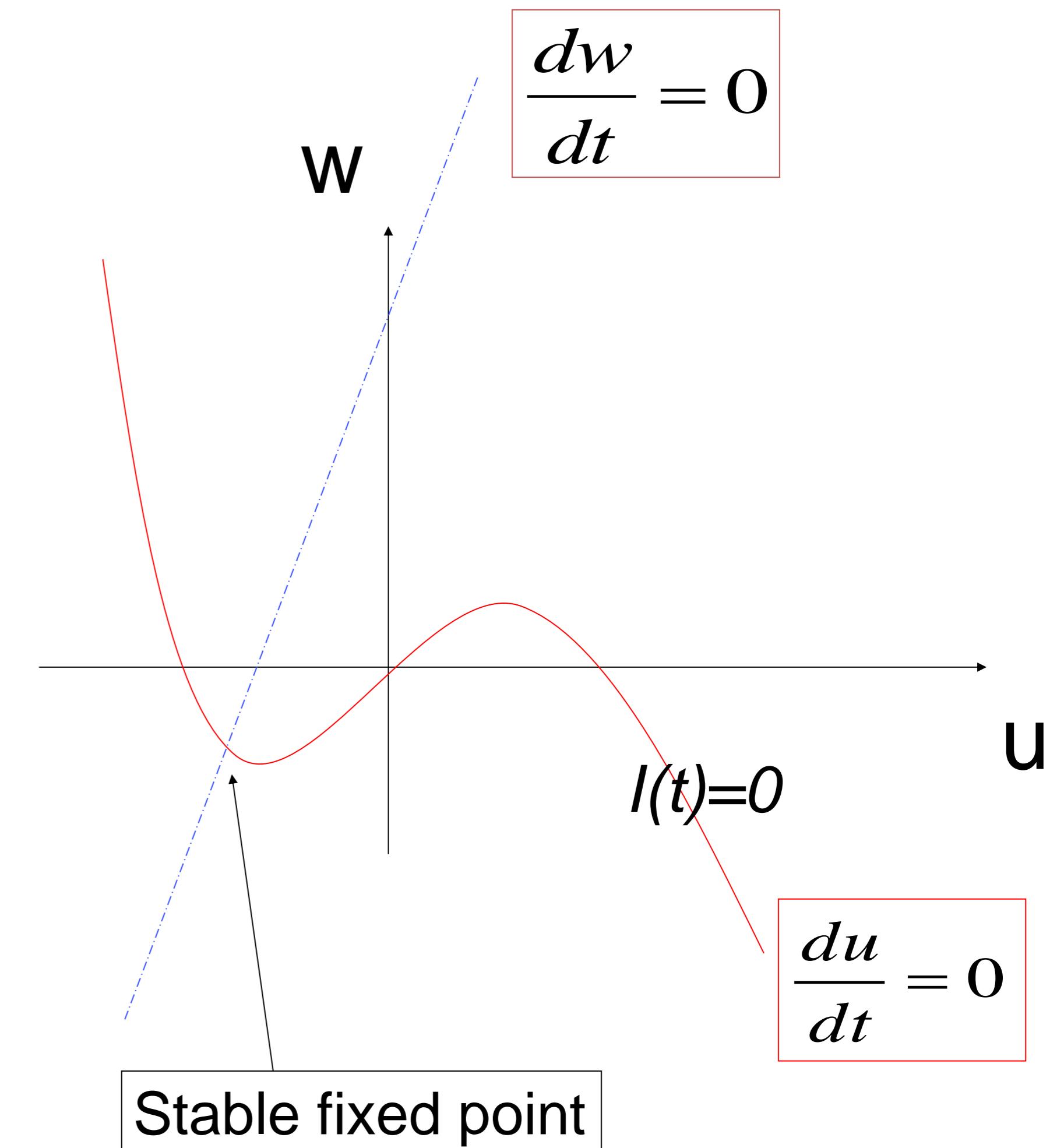
Stimulus  $I=0$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Consider change in small time step

Flow on nullcline

Flow in regions between nullclines

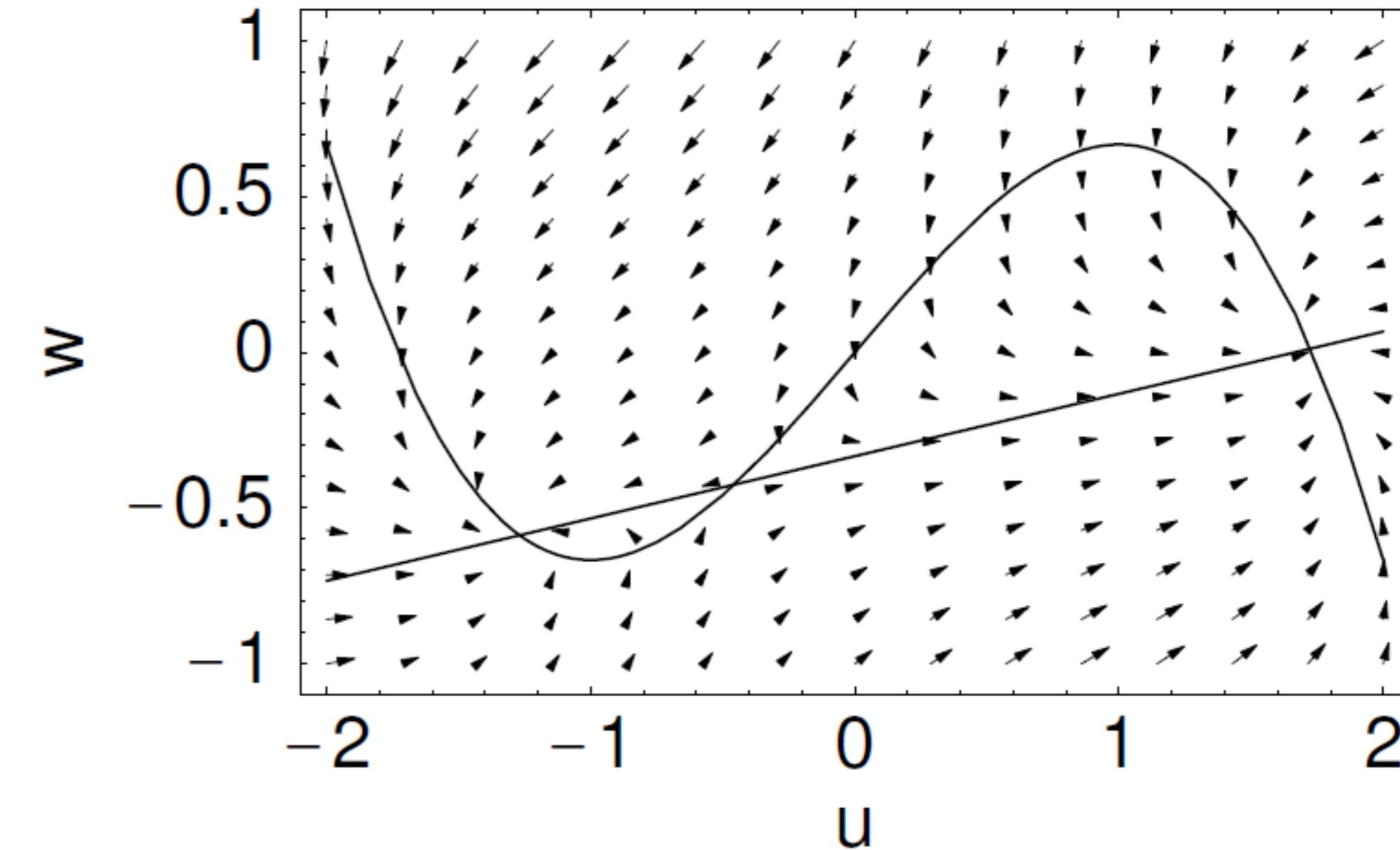


# Neuronal Dynamics – 4.2. FitzHugh-Nagumo Model

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$= u - \frac{1}{3}u^3 + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w) = b_0 + b_1 u - w$$



# Neuronal Dynamics – 4.2. Phase Plane Analysis

2-dimensional equation  
*stimulus*

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Enables graphical analysis!

Important role of

- nullclines
- flow arrows

# Neuronal Dynamics – Quiz 4.4.

## A. u-Nullclines

- On the u-nullcline, arrows are always vertical
- On the u-nullcline, arrows point always vertically upward
- On the u-nullcline, arrows are always horizontal
- On the u-nullcline, arrows point always to the left
- On the u-nullcline, arrows point always to the right

## B. w-Nullclines

- On the w-nullcline, arrows are always vertical
- On the w-nullcline, arrows point always vertically upward
- On the w-nullcline, arrows are always horizontal
- On the w-nullcline, arrows point always to the left
- On the w-nullcline, arrows point always to the right
- On the w-nullcline, arrows can point in an arbitrary direction

# Week 4 – part 3A: Analysis of a 2D neuron model – pulse input



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail: Two-dimensional neuron models

Wulfram Gerstner

EPFL, Lausanne, Switzerland

#### 4.1 From Hodgkin-Huxley to 2D

#### 4.2 Phase Plane Analysis

- Role of nullcline

#### 4.3 Analysis of a 2D Neuron Model

- MathDetour 3: Stability of fixed points

#### 4.4 Type I and II Neuron Models

- where is the firing threshold?
- separation of time scales

#### 4.5 Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – 4.3. Analysis of a 2D neuron model

2-dimensional equation  
stimulus

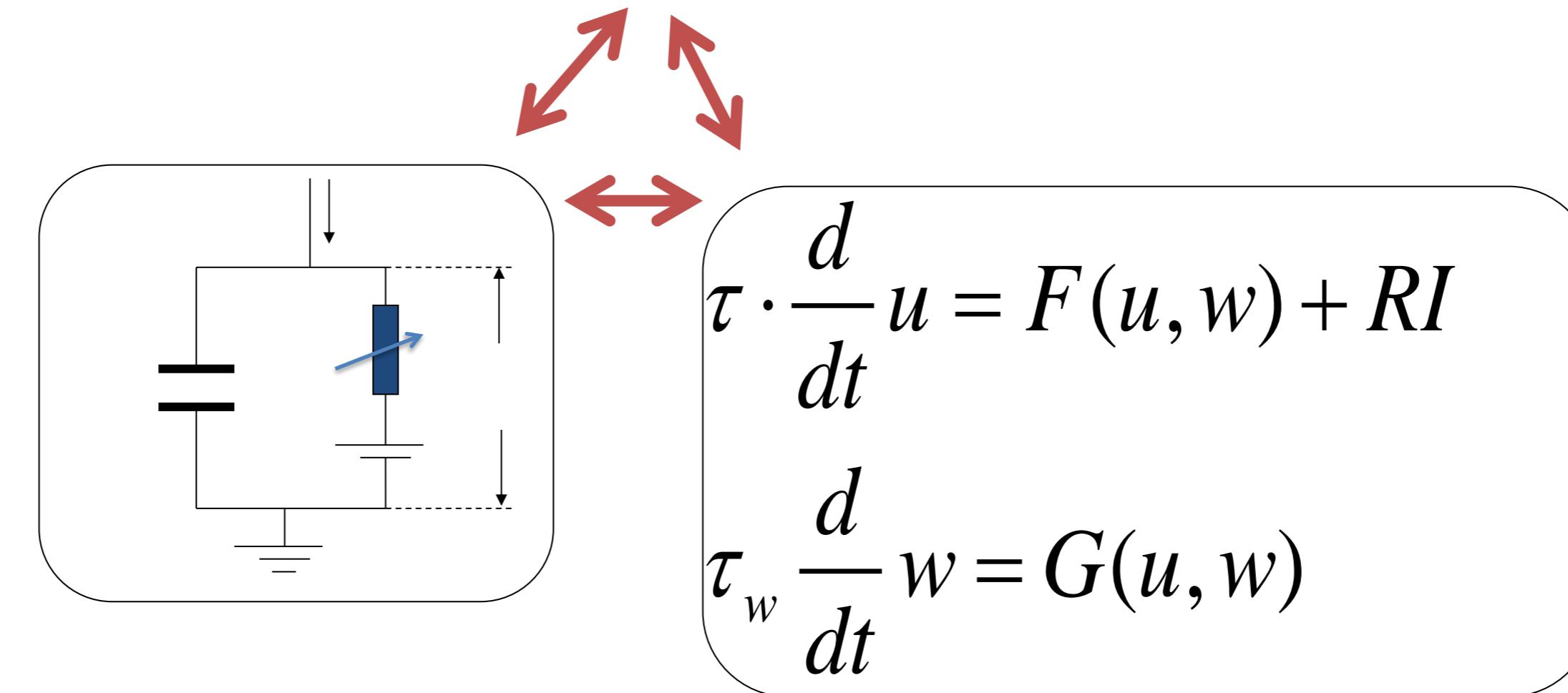
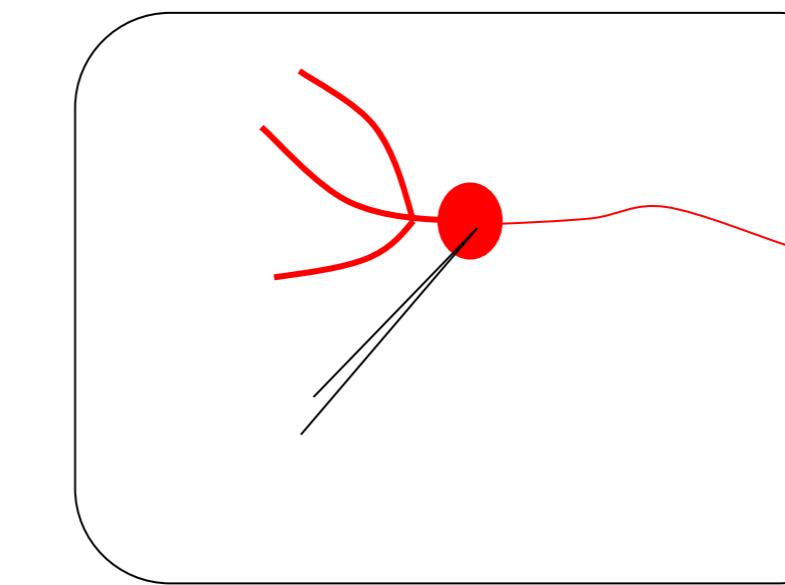
$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Enables graphical analysis!

- Pulse input
- Constant input

# Neuronal Dynamics – 4.3. 2D neuron model : Pulse input



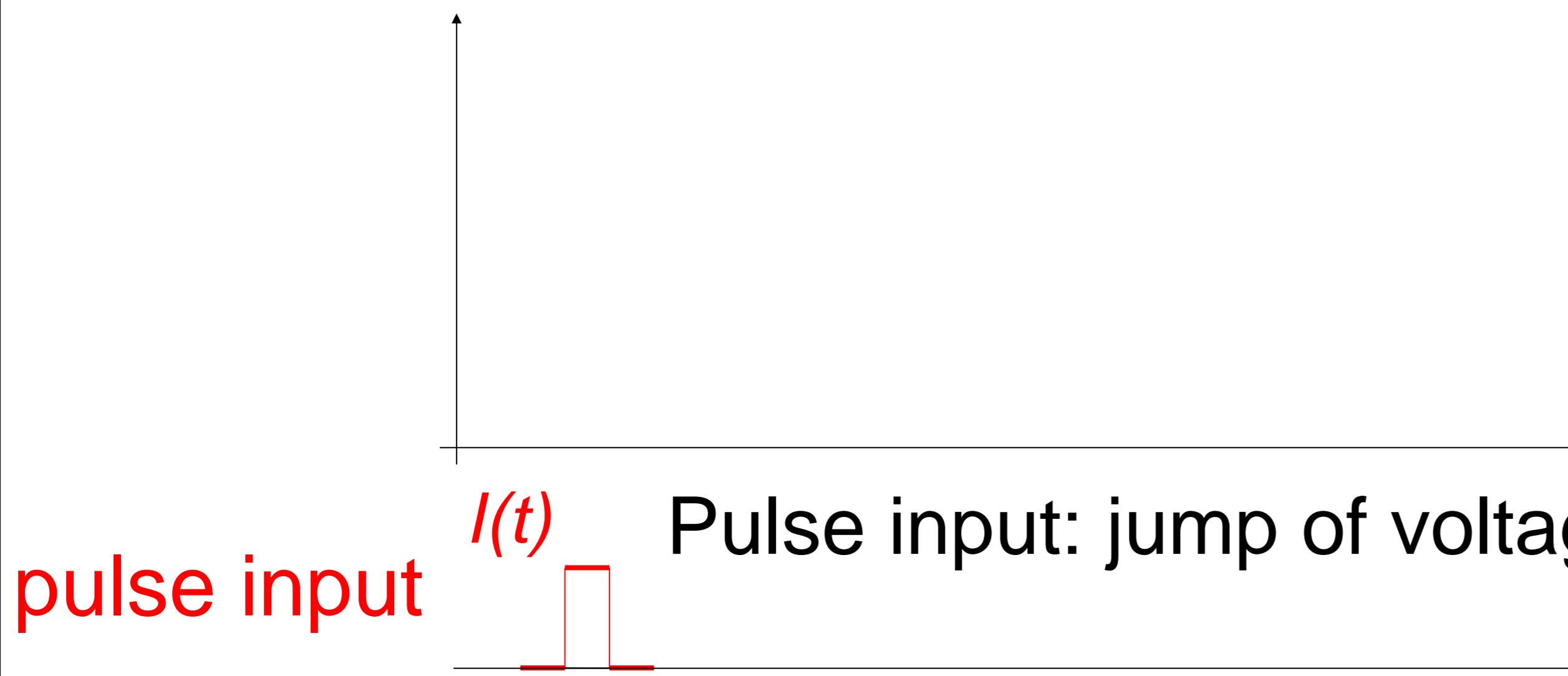
pulse input



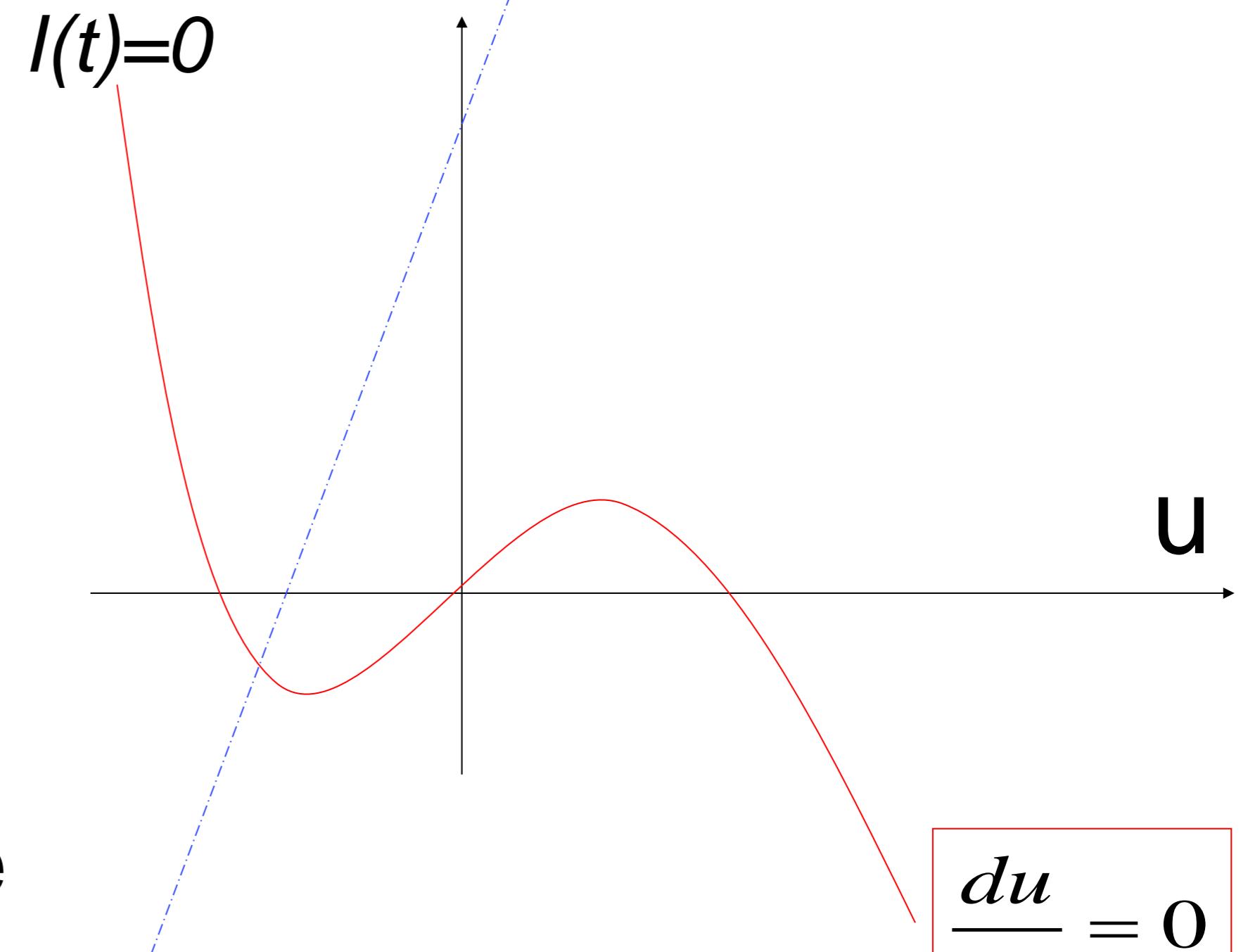
# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model : Pulse input

$$\tau \frac{du}{dt} = F(u, w) + RI(t) = u - \frac{1}{3}u^3 - w + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w) = b_0 + b_1 u - w$$

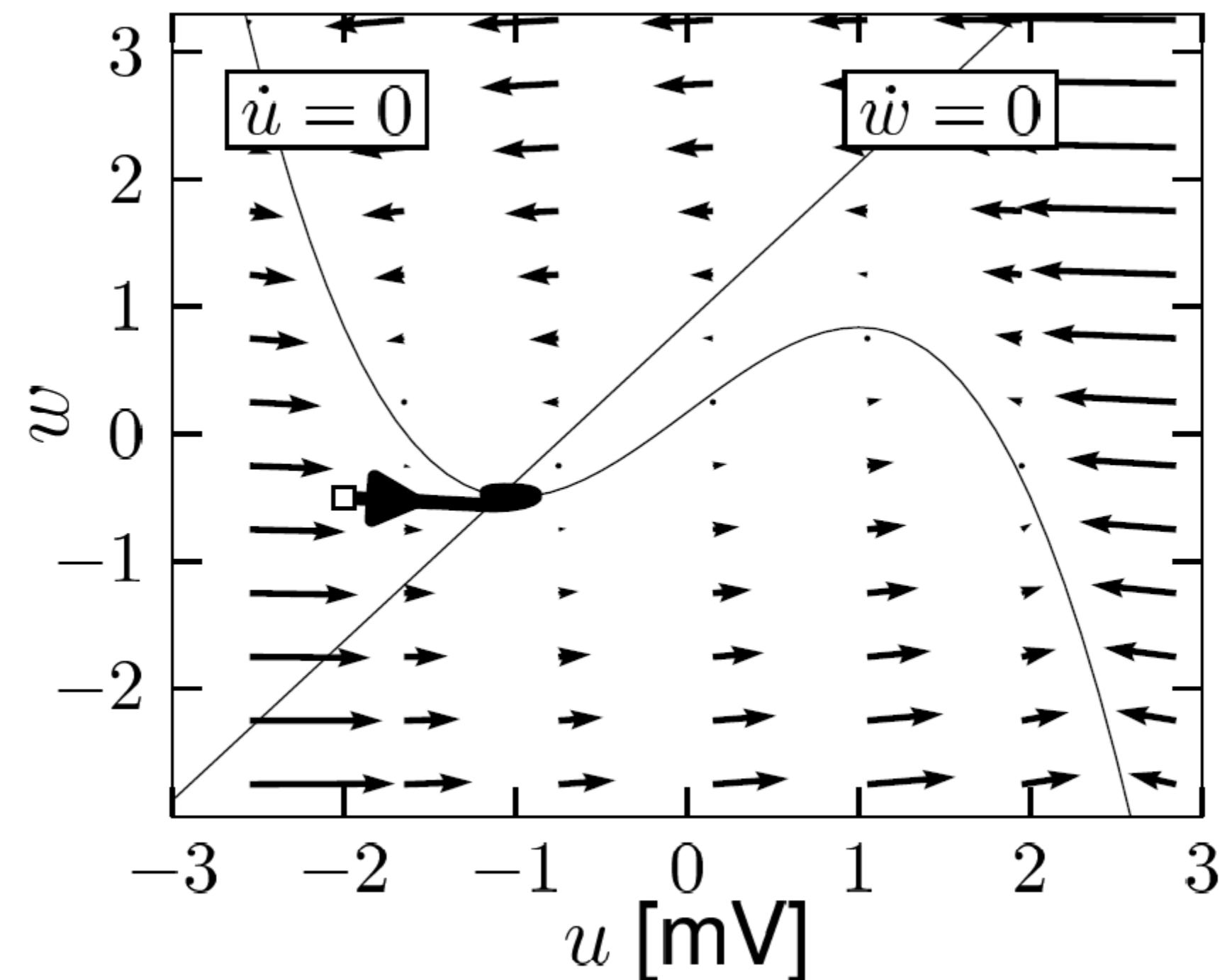


$$\frac{dw}{dt} = 0$$



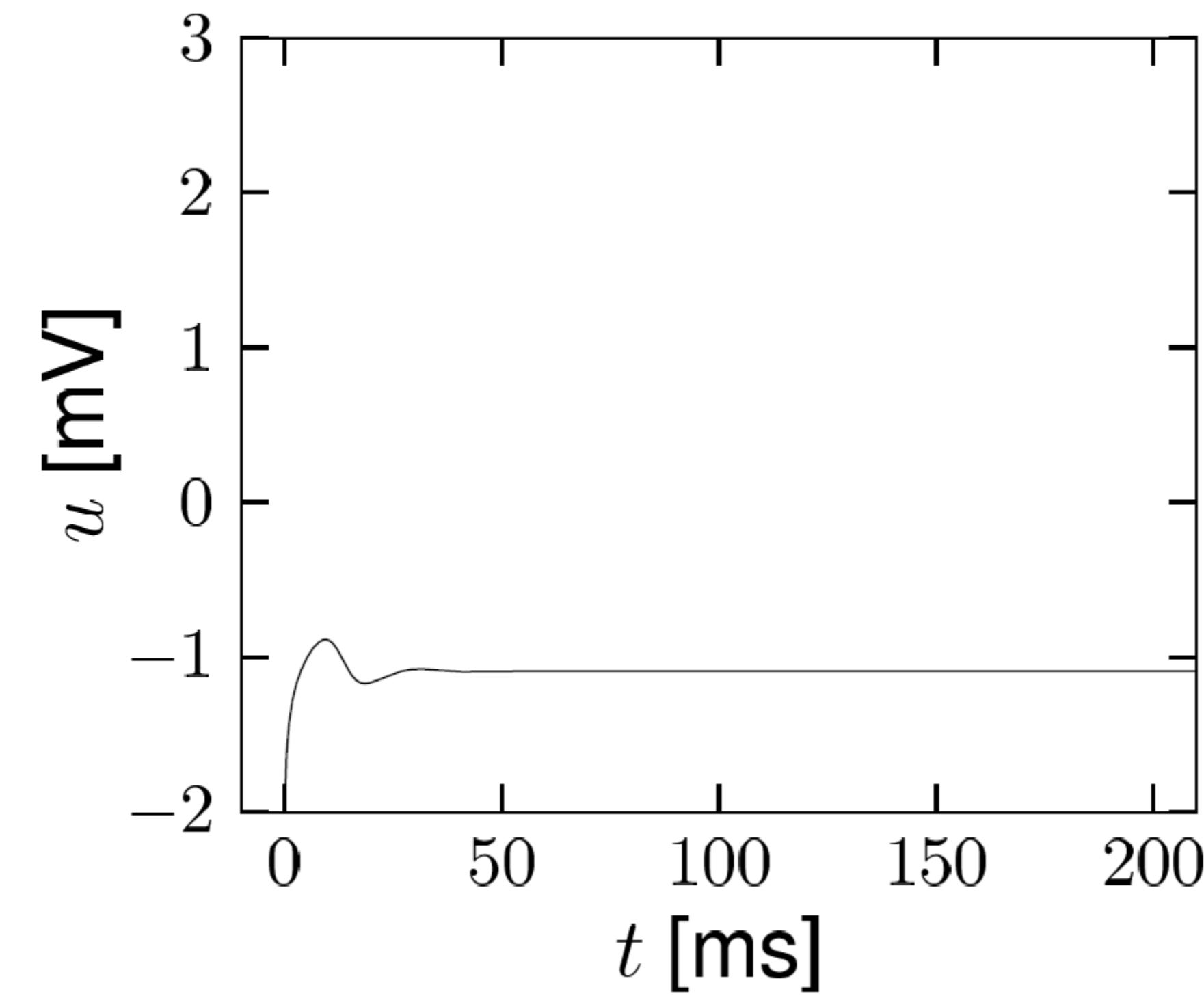
$$\frac{du}{dt} = 0$$

# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model : Pulse input



FN model with  $b_0 = 0.9; b_1 = 1.0$

Pulse input: jump of voltage/initial condition



*Image: Neuronal Dynamics,  
Gerstner et al.,  
Cambridge Univ. Press (2014)*

# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model

**Pulse input:**

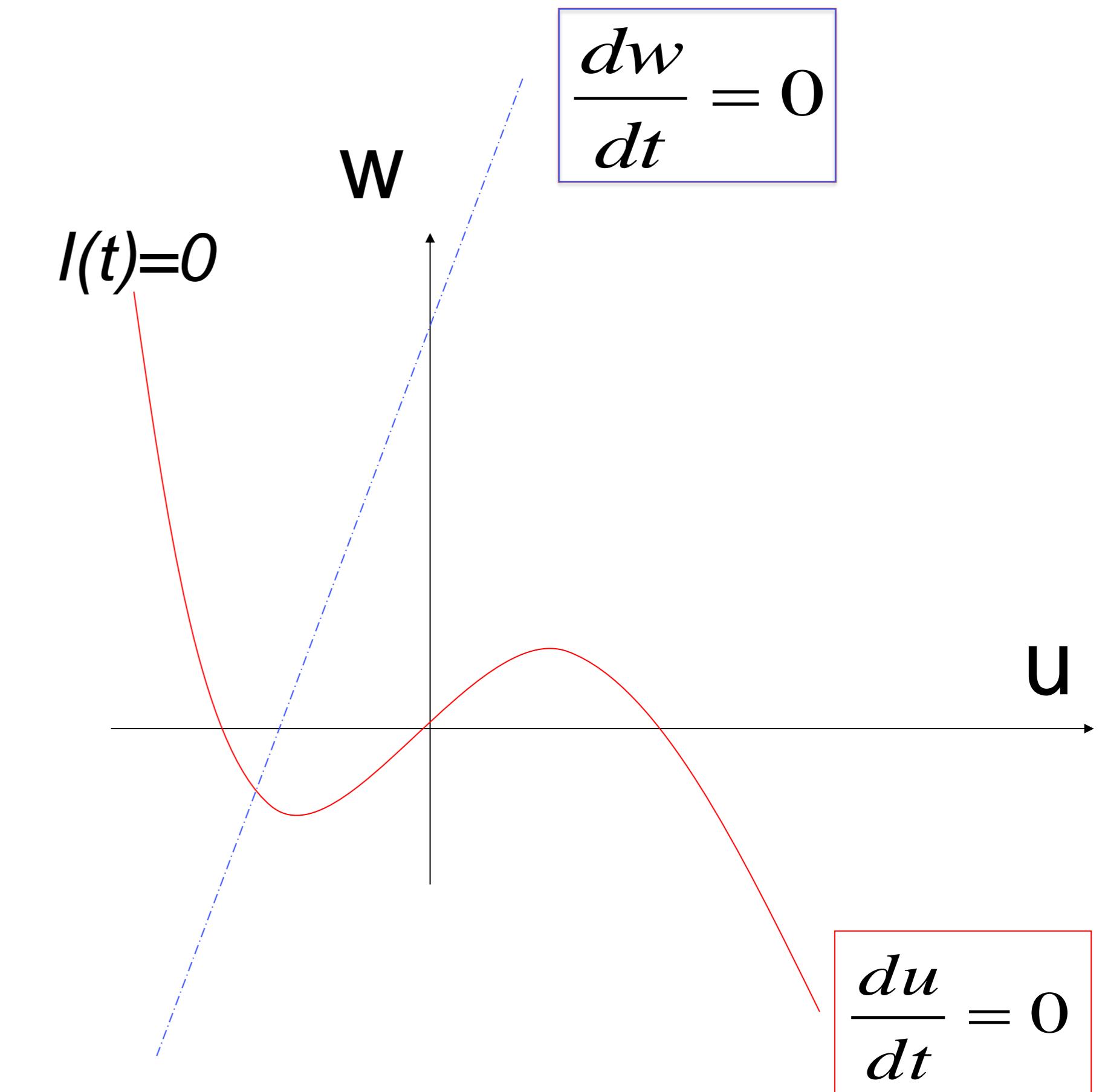
**DONE!**

- jump of voltage
- ‘new initial condition’
- spike generation for large input pulses

**constant input:**

- graphics?
- spikes?
- repetitive firing?

**Lesson 4.3B!**  
...  
Comes next



# Week 4 – part 3B: Analysis of a 2D neuron model – constant input



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail: Two-dimensional neuron models

Wulfram Gerstner

EPFL, Lausanne, Switzerland

#### 4.1 From Hodgkin-Huxley to 2D

#### 4.2 Phase Plane Analysis

- Role of nullcline

#### 4.3 Analysis of a 2D Neuron Model

- MathDetour 3: Stability of fixed points

#### 4.4 Type I and II Neuron Models

- where is the firing threshold?
- separation of time scales

#### 4.5 Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model

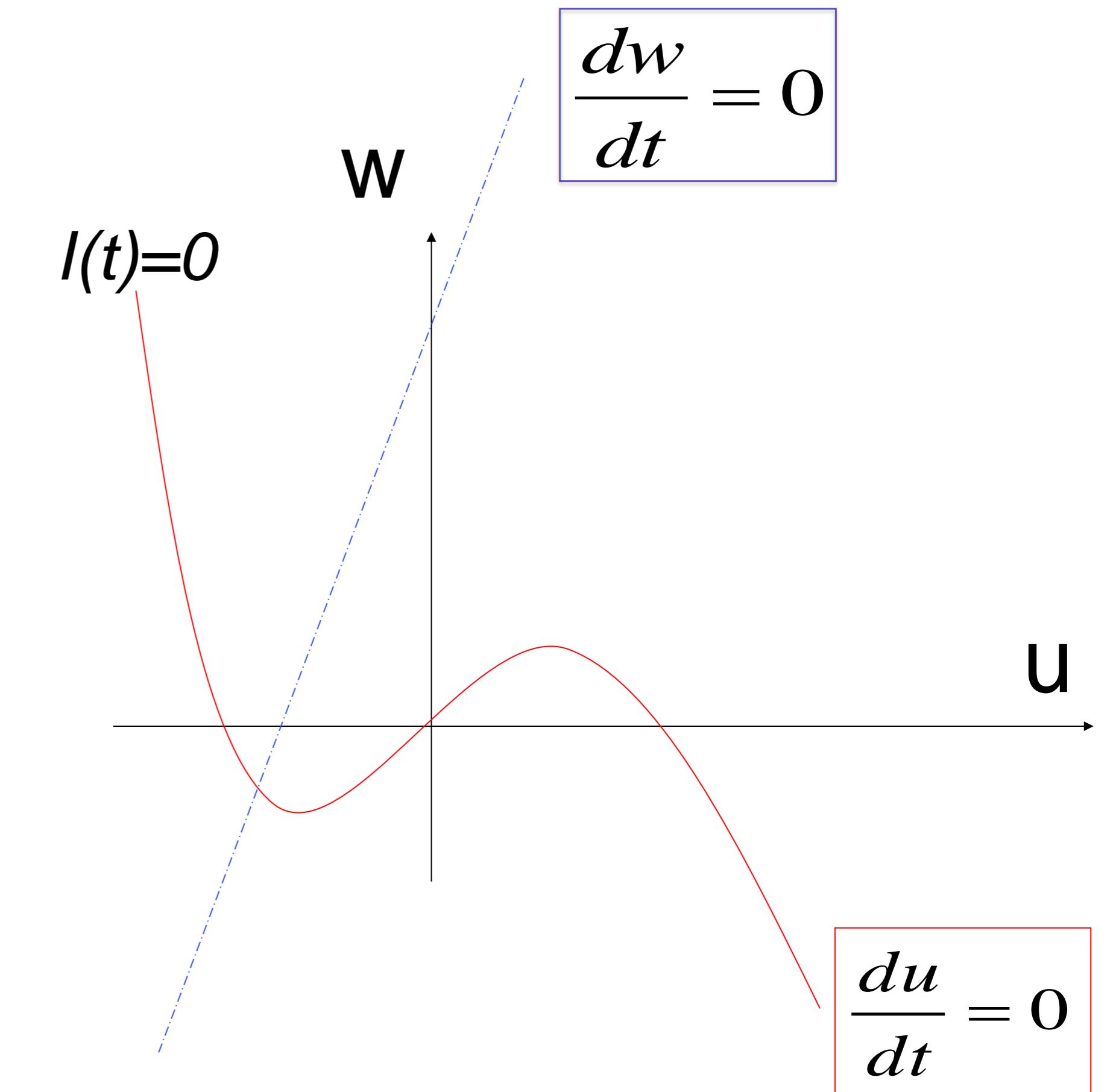
## Pulse input:

- jump of voltage
- ‘new initial condition’
- spike generation for large input pulses

## constant input:

- graphics?
- spikes?
- repetitive firing?

Now!

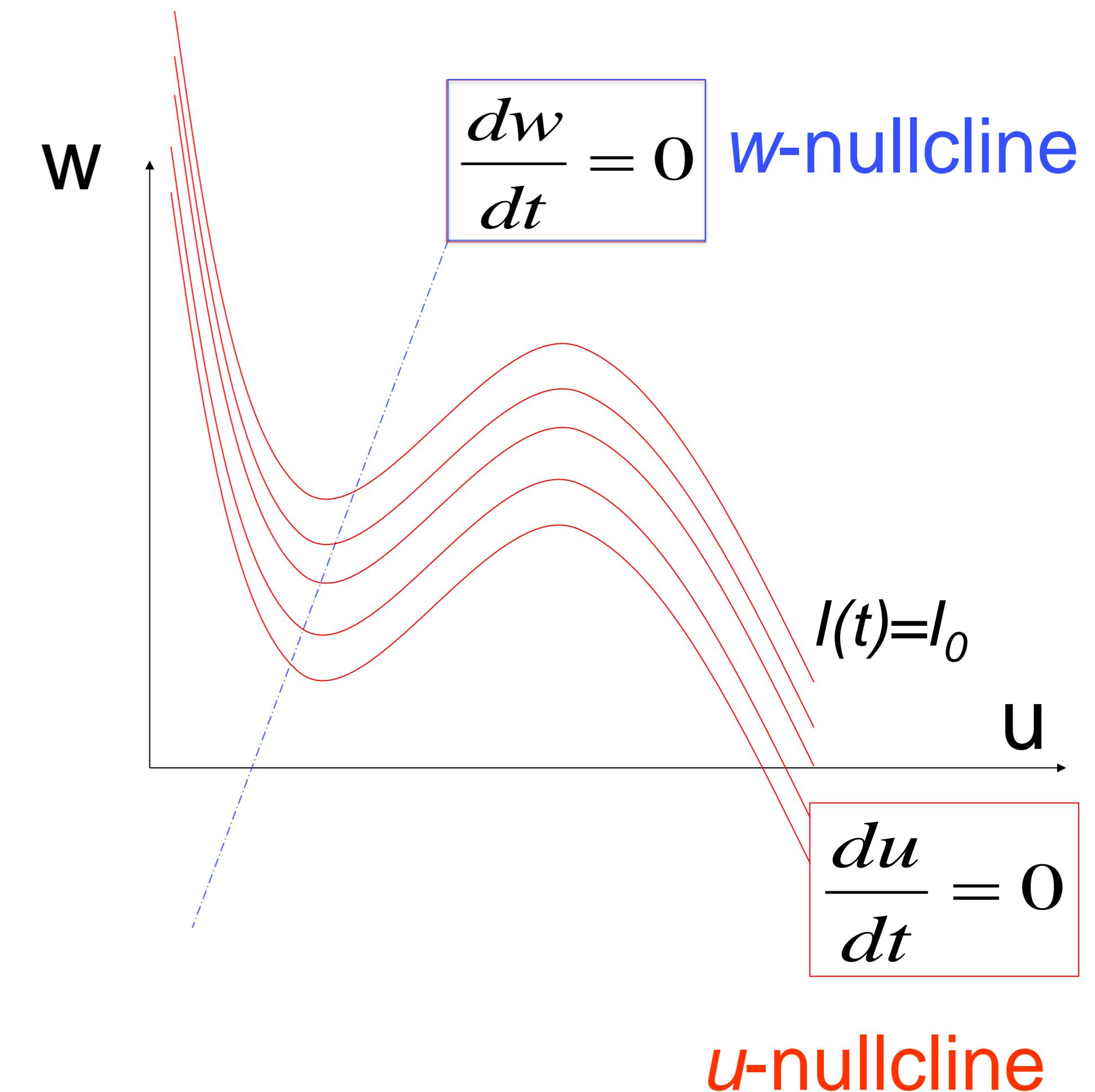


# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model: Constant input

$$\begin{aligned}\tau \frac{du}{dt} &= F(u, w) + RI_0 \\ &= u - \frac{1}{3}u^3 - w + RI_0\end{aligned}$$

$$\tau_w \frac{dw}{dt} = G(u, w) = b_0 + b_1 u - w$$

Intersection point (fixed point)  
-moves  
-changes Stability



# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model: Constant input

$$\tau \frac{du}{dt} = F(u, w) + RI_0$$

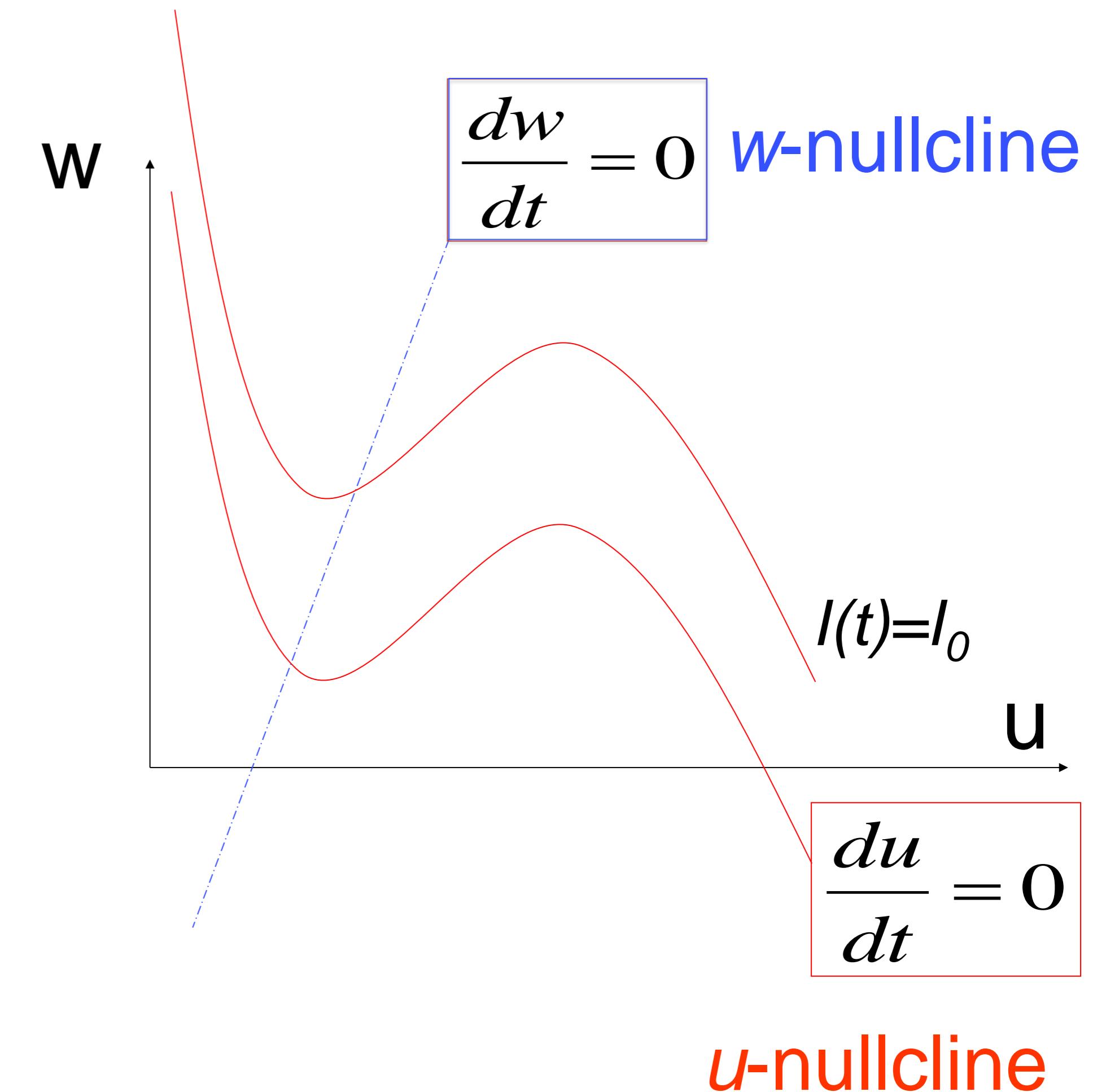
$$= u - \frac{1}{3}u^3 - w + RI_0$$

$$\tau_w \frac{dw}{dt} = G(u, w) = b_0 + b_1 u - w$$

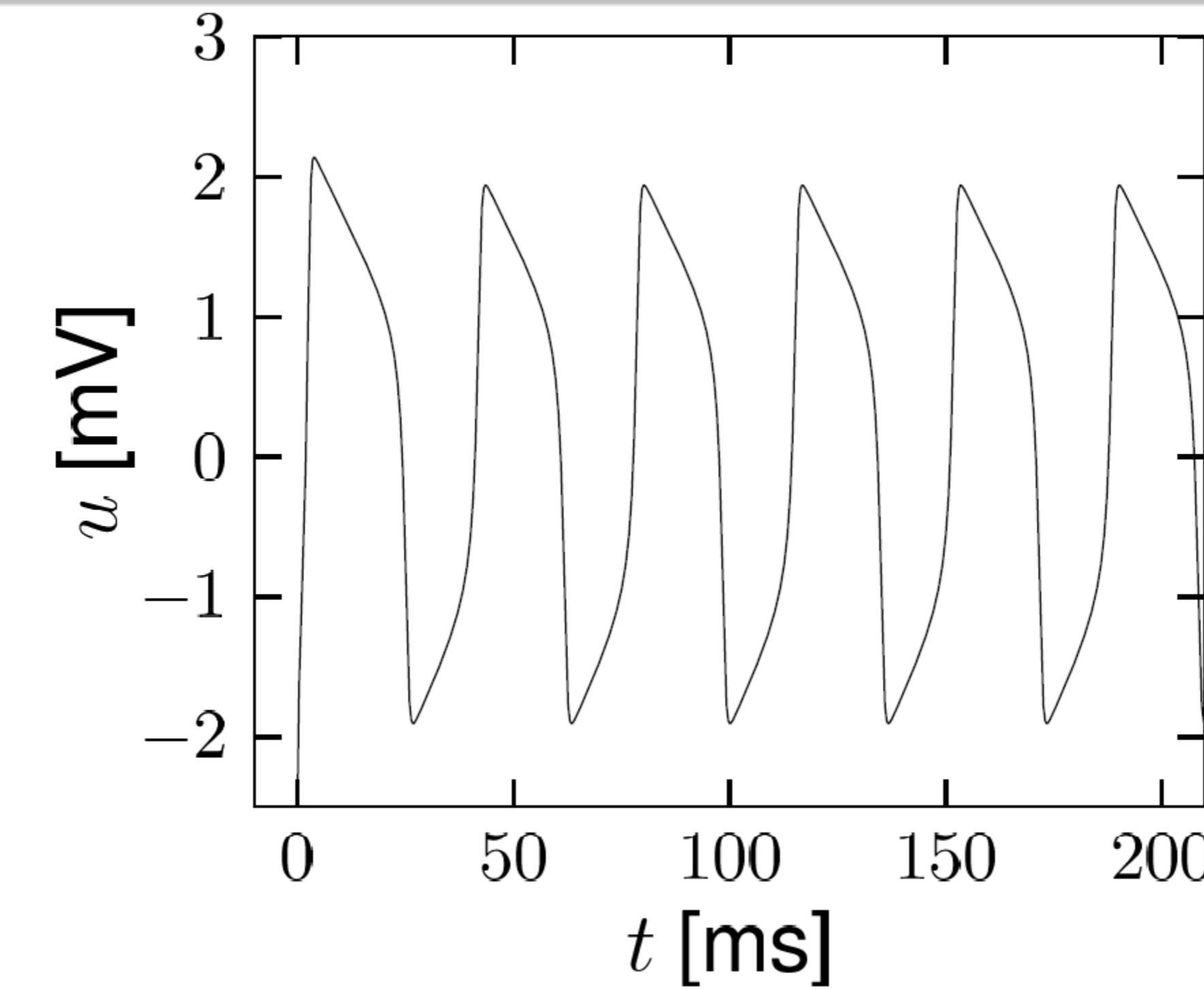
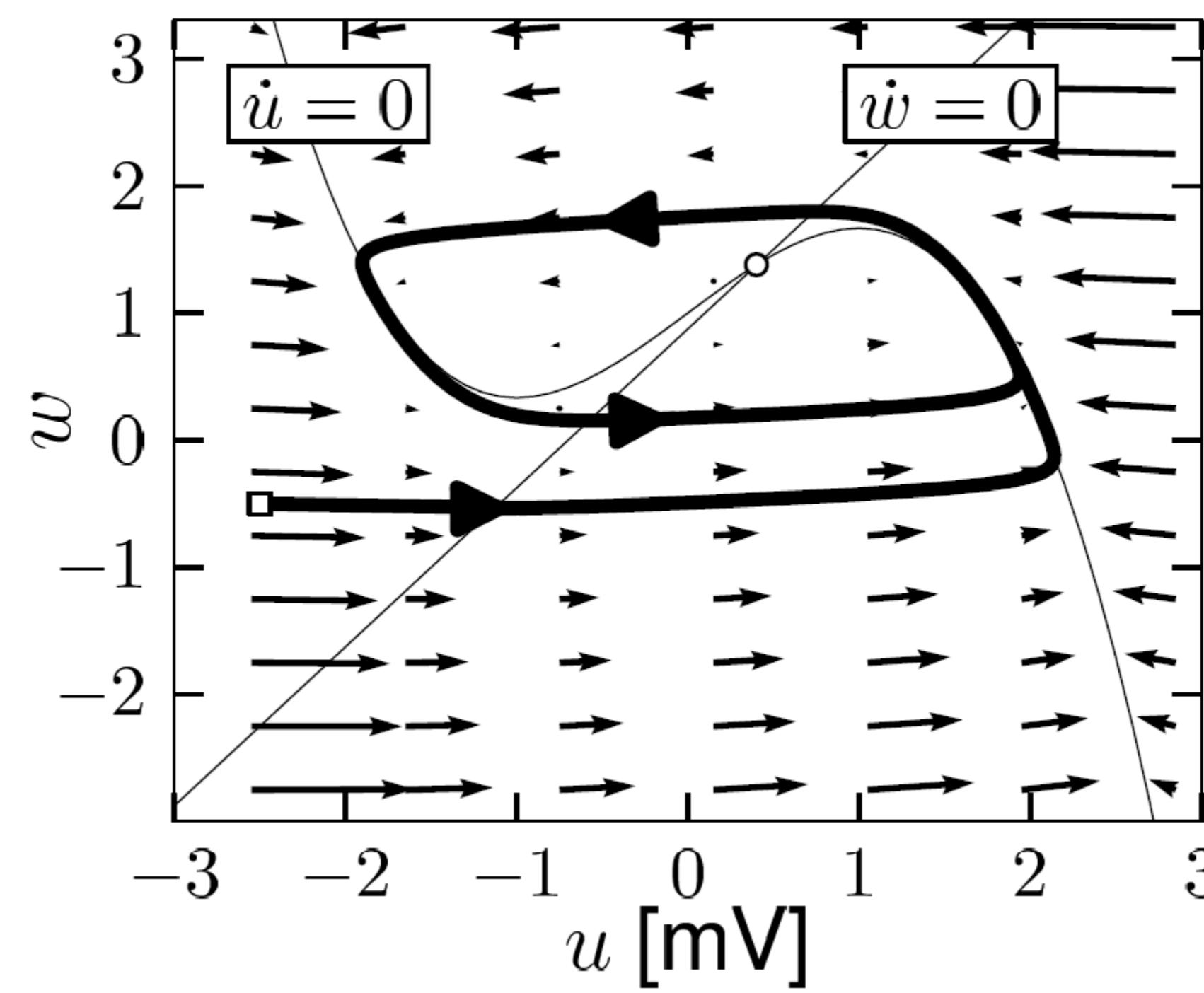
Intersection point (fixed point)

-moves

-changes Stability



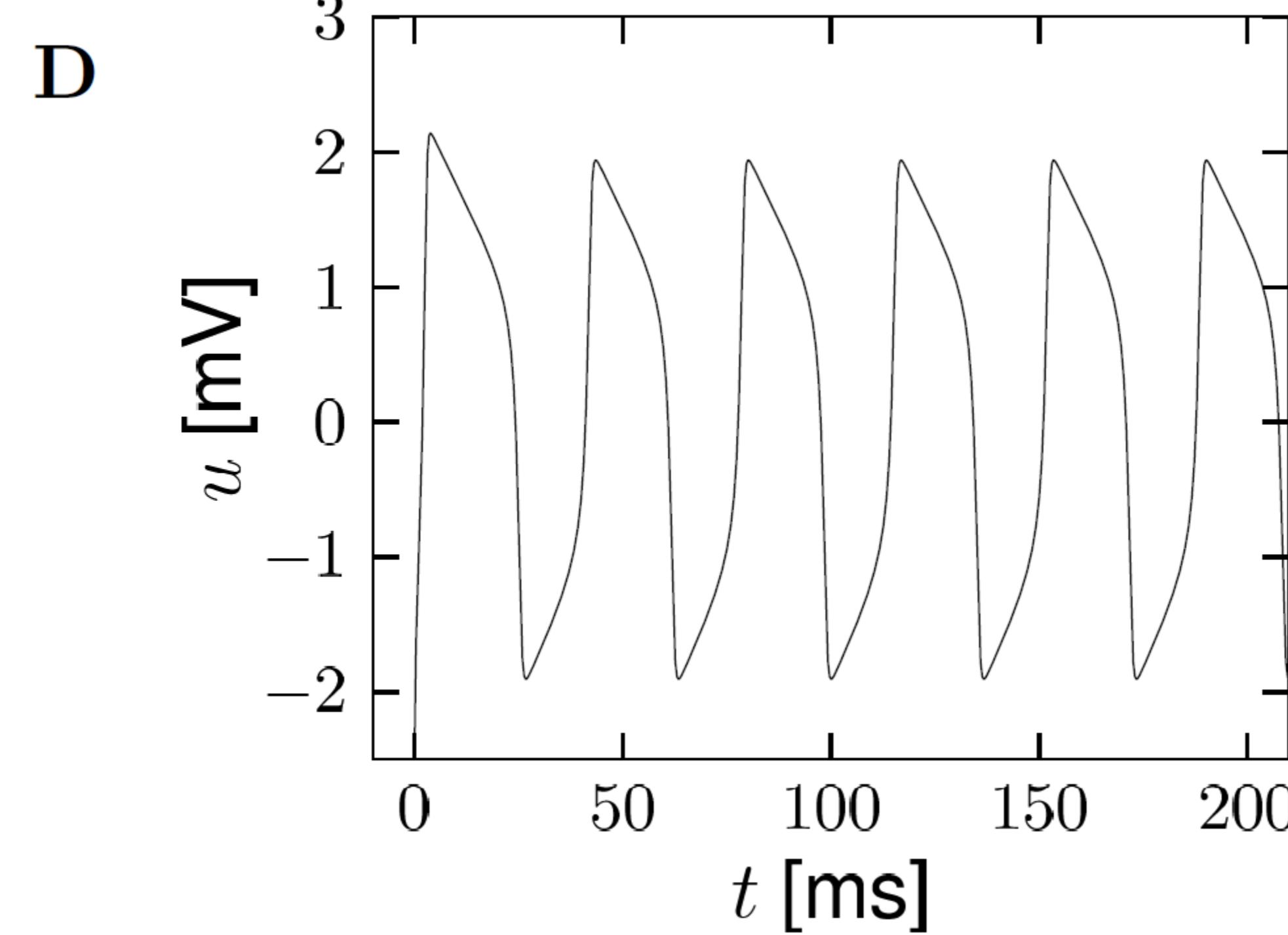
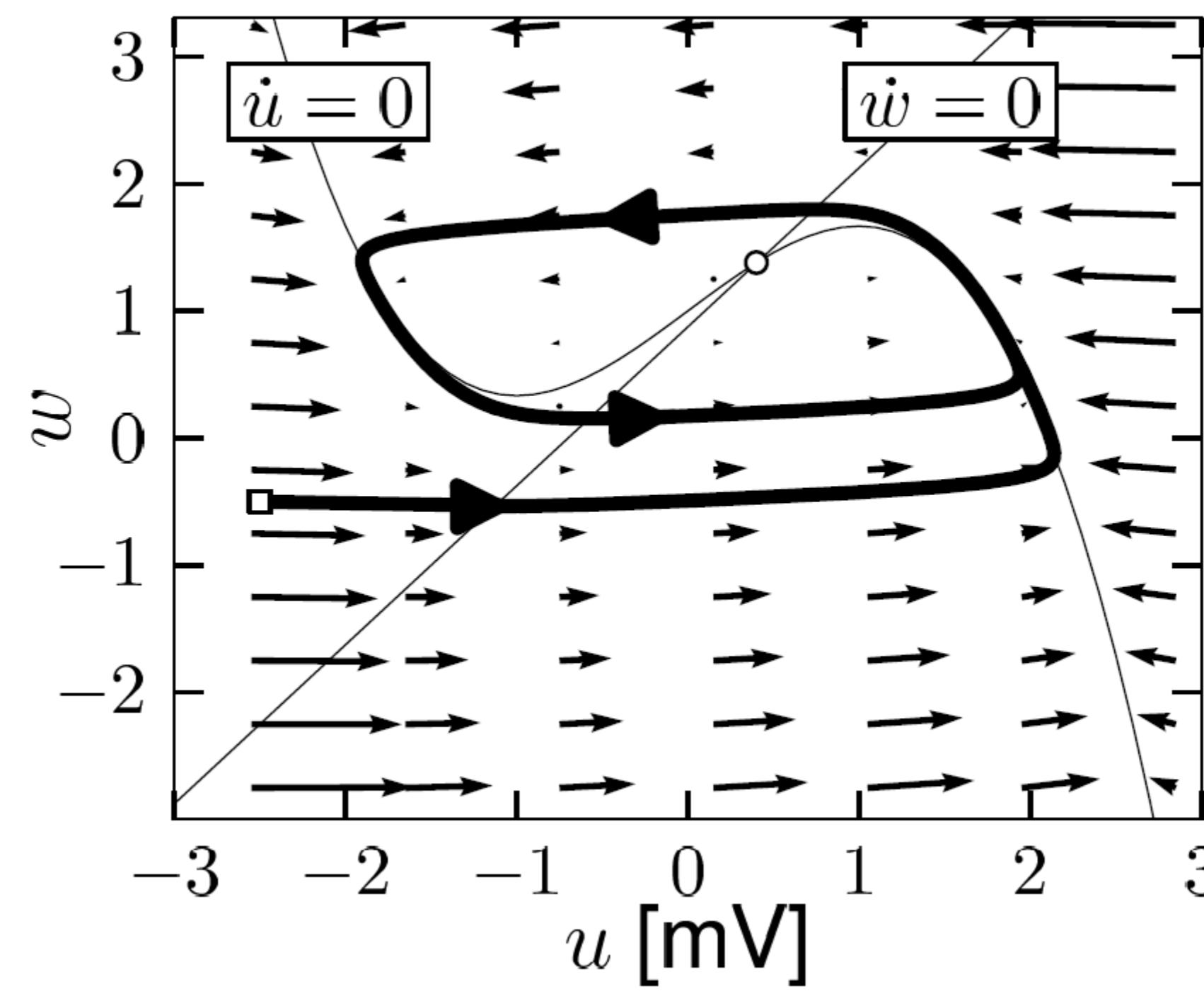
# Neuronal Dynamics – 4.3. FitzHugh-Nagumo Model : Constant input



FN model with  $b_0 = 0.9; b_1 = 1.0; RI_0 = 2$   
constant input:  $u$ -nullcline moves  
limit cycle

*Image: Neuronal Dynamics,  
Gerstner et al.,  
Cambridge Univ. Press (2014)*

# Neuronal Dynamics – 4.3. Limit Cycle



- unstable fixed point in 2D
- bounding box with inward flow
- limit cycle (*Poincare Bendixson*)

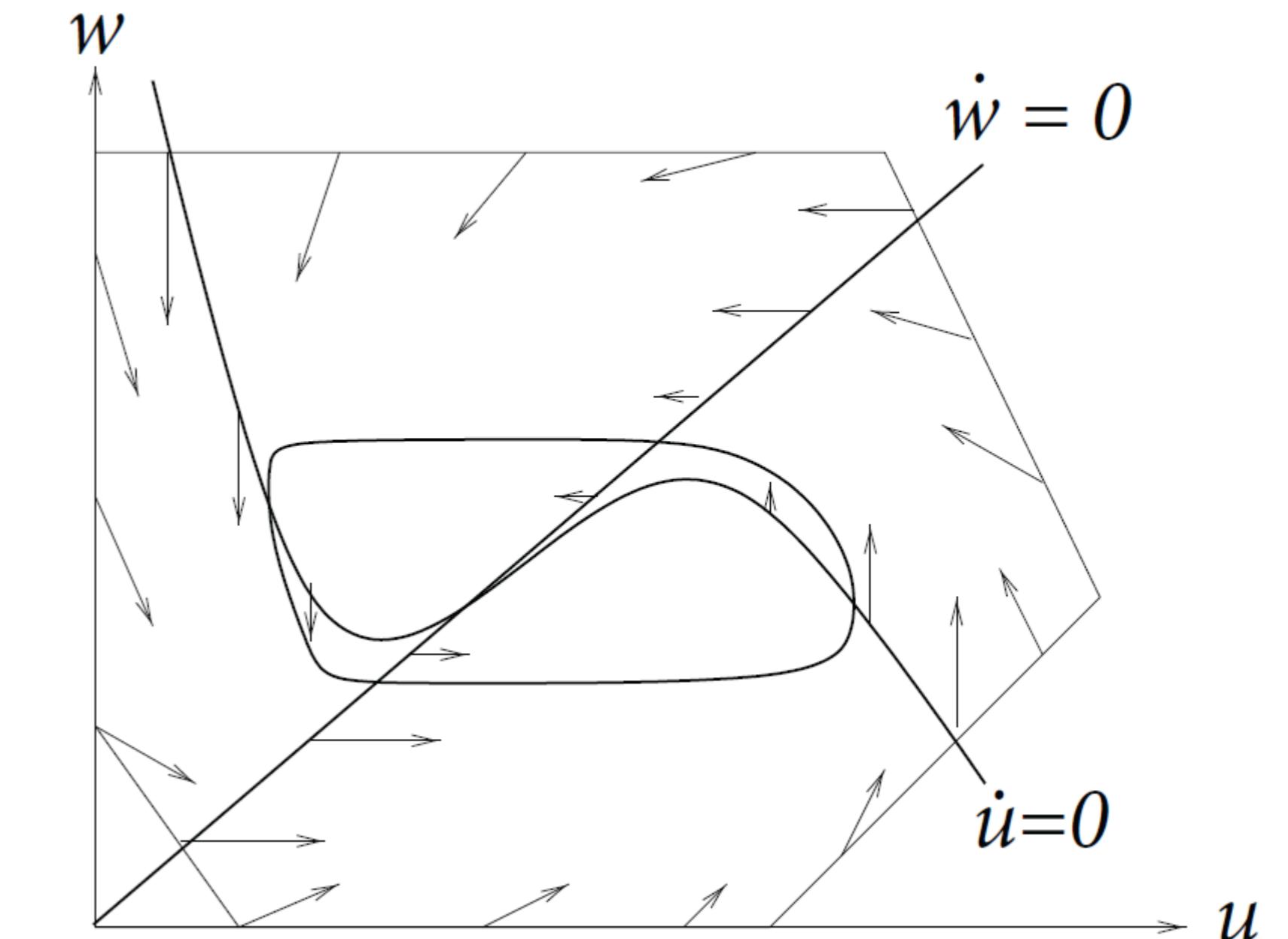
*Image: Neuronal Dynamics,  
Gerstner et al.,  
Cambridge Univ. Press (2014)*

# Neuronal Dynamics – 4.3. Limit Cycle

In 2-dimensional equations, a limit cycle must exist, if we can find a surface

- containing one unstable fixed point
- bounding box with inward flow

→ limit cycle (*Poincare Bendixson*)



*Image: Neuronal Dynamics,  
Gerstner et al.,  
Cambridge Univ. Press (2014)*

# Neuronal Dynamics – 4.3. Analysis of a 2D neuron model

2-dimensional equation  
stimulus

$$\tau \frac{du}{dt} = F(u, w) + RI(t)$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

**Enables graphical analysis!**

- Pulse input
  - AP firing (or not)
- Constant input
  - repetitive firing (or not)

# Neuronal Dynamics – Quiz 4.5.

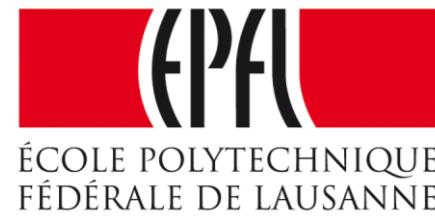
**A. Short current pulses.** In a 2-dimensional neuron model, the effect of a delta current pulse can be analyzed

- By moving the u-nullcline vertically upward
- By moving the w-nullcline vertically upward
- As a potential change in the stability or number of the fixed point(s)
- As a new initial condition
- By following the flow of arrows in the appropriate phase plane diagram

**B. Constant current.** In a 2-dimensional neuron model, the effect of a constant current can be analyzed

- By moving the u-nullcline vertically upward
- By moving the w-nullcline vertically upward
- As a potential change in the stability or number of the fixed point(s)
- As a new initial condition
- By following the flow of arrows in the appropriate phase plane diagram

# Week 4 – MathDetour 3: Stability of fixed points



## Neuronal Dynamics: Computational Neuroscience of Single Neurons

### Week 4 – Reducing detail: Two-dimensional neuron models

Wulfram Gerstner

EPFL, Lausanne, Switzerland

#### 4.1 From Hodgkin-Huxley to 2D

#### 4.2 Phase Plane Analysis

- Role of nullcline

#### 4.3 Analysis of a 2D Neuron Model

- MathDetour 3: Stability of fixed points

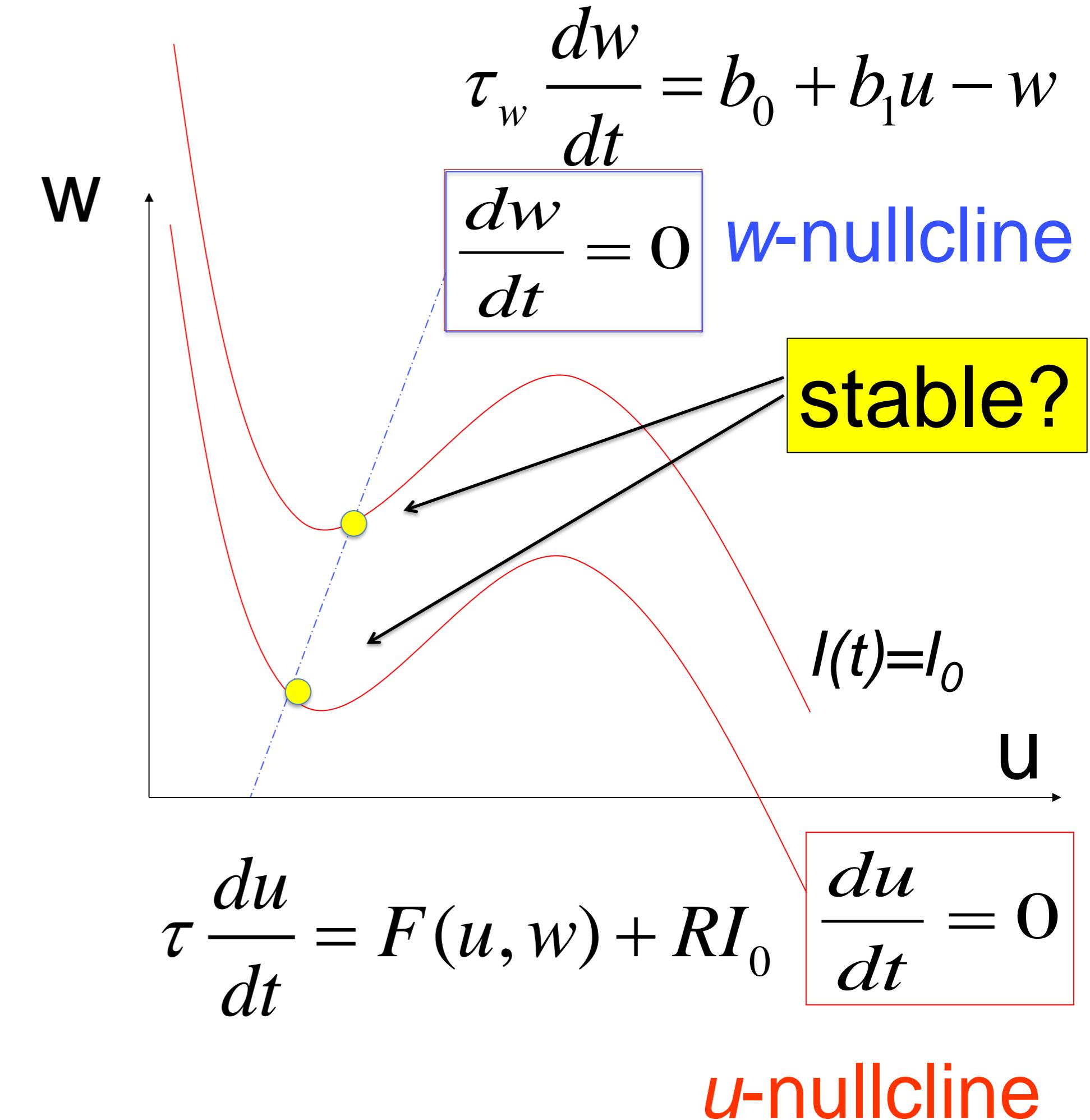
#### 4.4 Type I and II Neuron Models

- where is the firing threshold?
- separation of time scales

#### 4.5 Nonlinear Integrate-and-fire

- from two to one dimension

# Neuronal Dynamics – Detour 4.3 : Stability of fixed points.



# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

2-dimensional equation  
stimulus

$$\tau \frac{du}{dt} = F(u, w) + RI_0$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

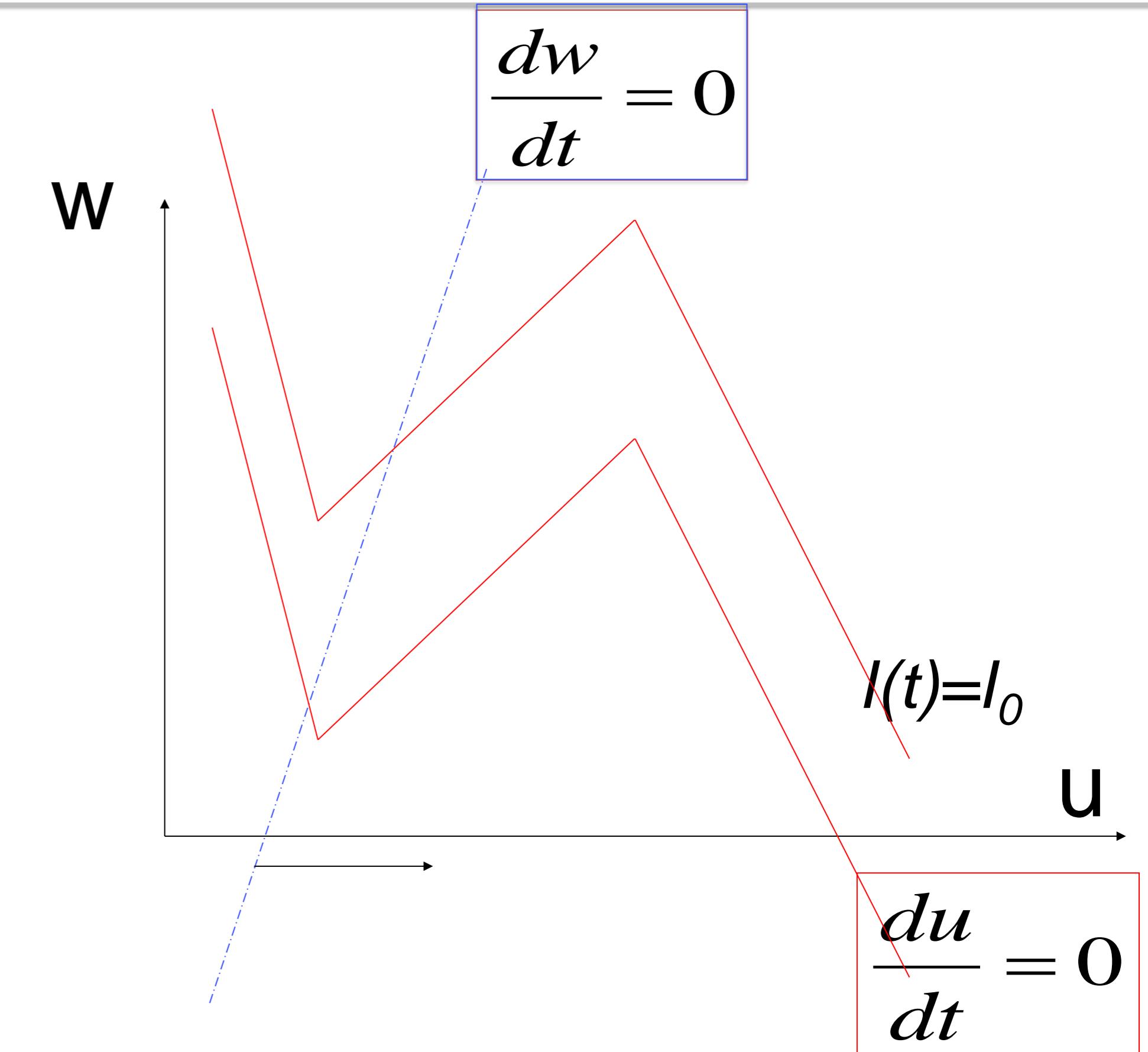
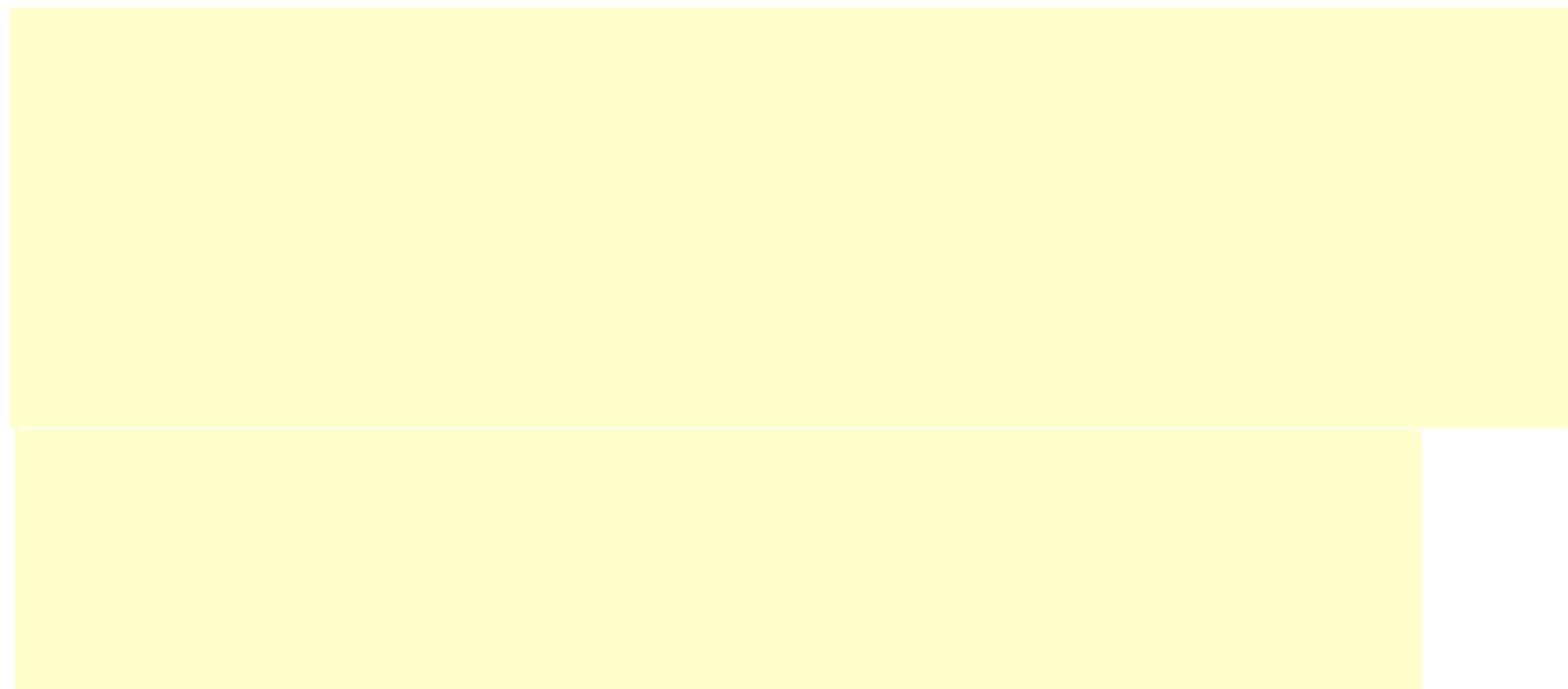
How to determine stability  
of fixed point?

# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

stimulus

$$\tau \frac{du}{dt} = au - w + I_0$$

$$\tau_w \frac{dw}{dt} = c u - w$$

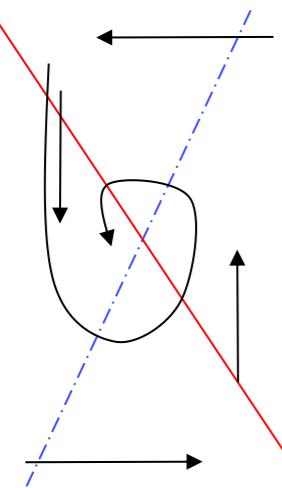


# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

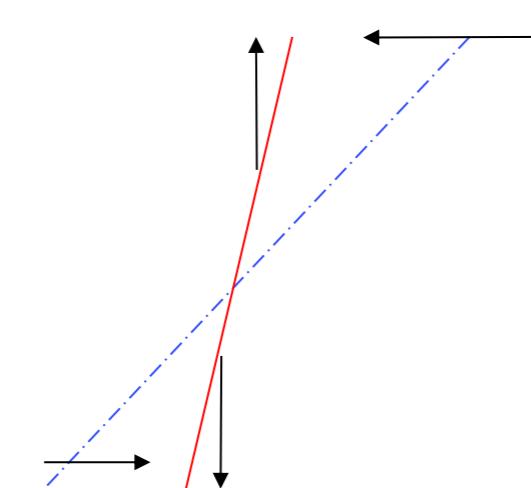
$$\tau \frac{du}{dt} = F(u, w) + RI_0$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

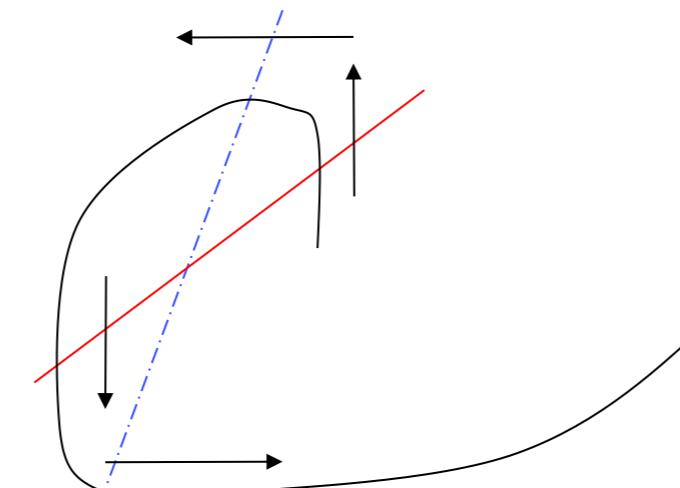
zoom in:



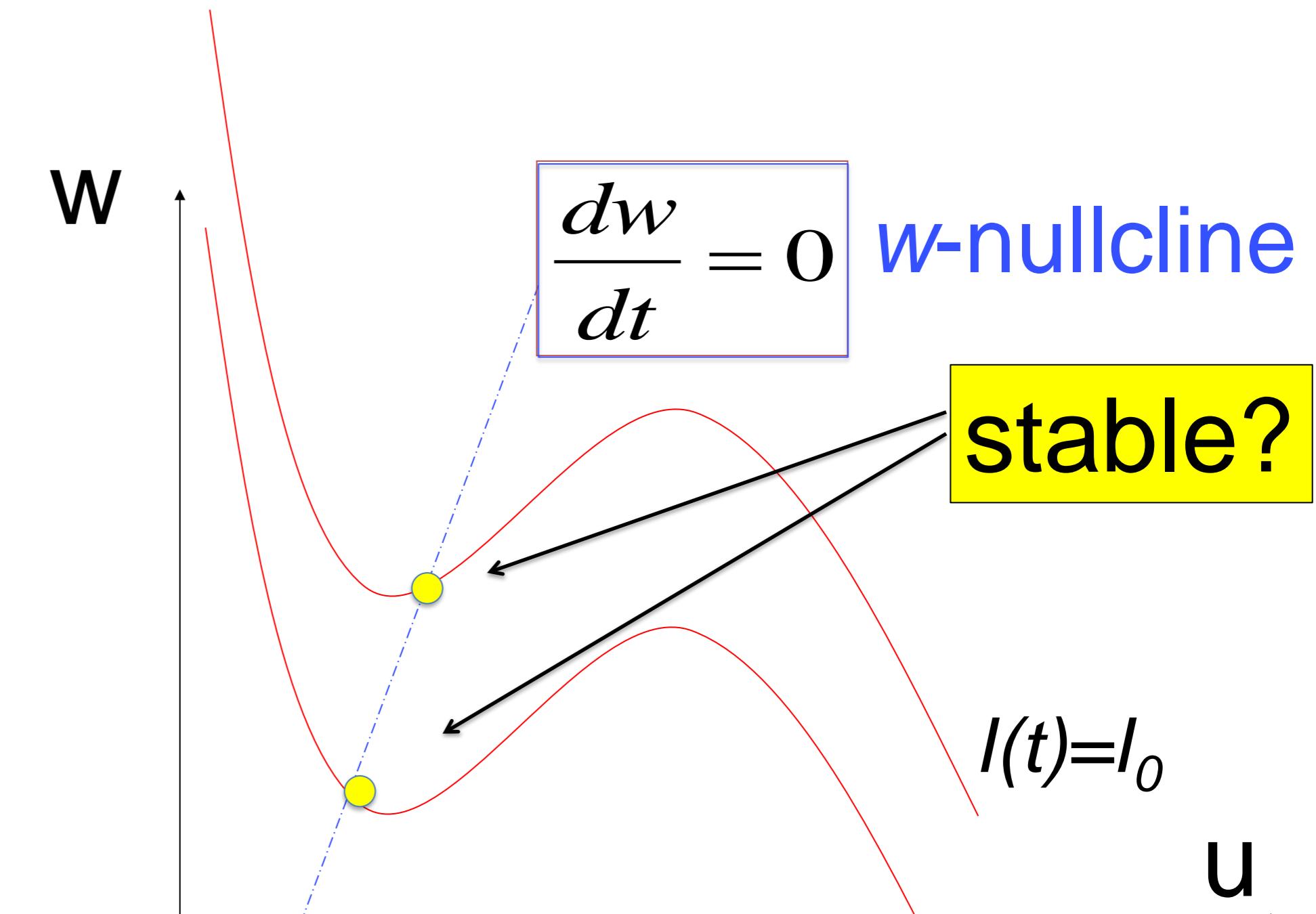
stable



saddle



unstable



Math derivation  
now

u-nullcline

$$I(t) = I_0$$

$$\frac{du}{dt} = 0$$

# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

$$\tau \frac{du}{dt} = F(u, w) + RI_0$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

zoom in:

$$x = u - u_0$$

$$y = w - w_0$$

Fixed point at  $(u_0, w_0)$

At fixed point

$$0 = F(u_0, w_0) + RI_0$$

$$0 = G(u_0, w_0)$$

# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

$$\tau \frac{du}{dt} = F(u, w) + RI_0$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

zoom in:

$$x = u - u_0$$

$$y = w - w_0$$

$$\tau \frac{dx}{dt} = F_u x + F_w y$$

$$\tau_w \frac{dy}{dt} = G_u x + G_w y$$

Fixed point at  $(u_0, w_0)$

At fixed point

$$0 = F(u_0, w_0) + RI_0$$

$$0 = G(u_0, w_0)$$

$$\frac{d}{dt} \mathbf{x} = \begin{pmatrix} F_u & F_w \\ G_u & G_w \end{pmatrix} \mathbf{x},$$

# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

Linear matrix equation

$$\frac{d}{dt} \mathbf{x} = \begin{pmatrix} F_u & F_w \\ G_u & G_w \end{pmatrix} \mathbf{x},$$

Search for solution

$$\mathbf{x}(t) = e^{\lambda t}$$

Two solution with Eigenvalues  $\lambda_+, \lambda_-$

$$\lambda_+ + \lambda_- = F_u + G_w$$

$$\lambda_+ \lambda_- = F_u G_w - F_w G_u$$

# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

Linear matrix equation

$$\frac{d}{dt} \mathbf{x} = \begin{pmatrix} F_u & F_w \\ G_u & G_w \end{pmatrix} \mathbf{x}$$

Search for solution

$$\mathbf{x}(t) = e^{\lambda t}$$

Two solution with Eigenvalues  $\lambda_+, \lambda_-$

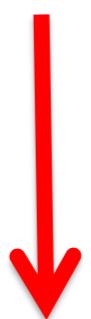
$$\lambda_+ + \lambda_- = F_u + G_w$$

$$\lambda_+ \lambda_- = F_u G_w - F_w G_u$$



Stability requires:

$$\lambda_+ < 0 \text{ and } \lambda_- < 0$$



$$F_u + G_w < 0$$

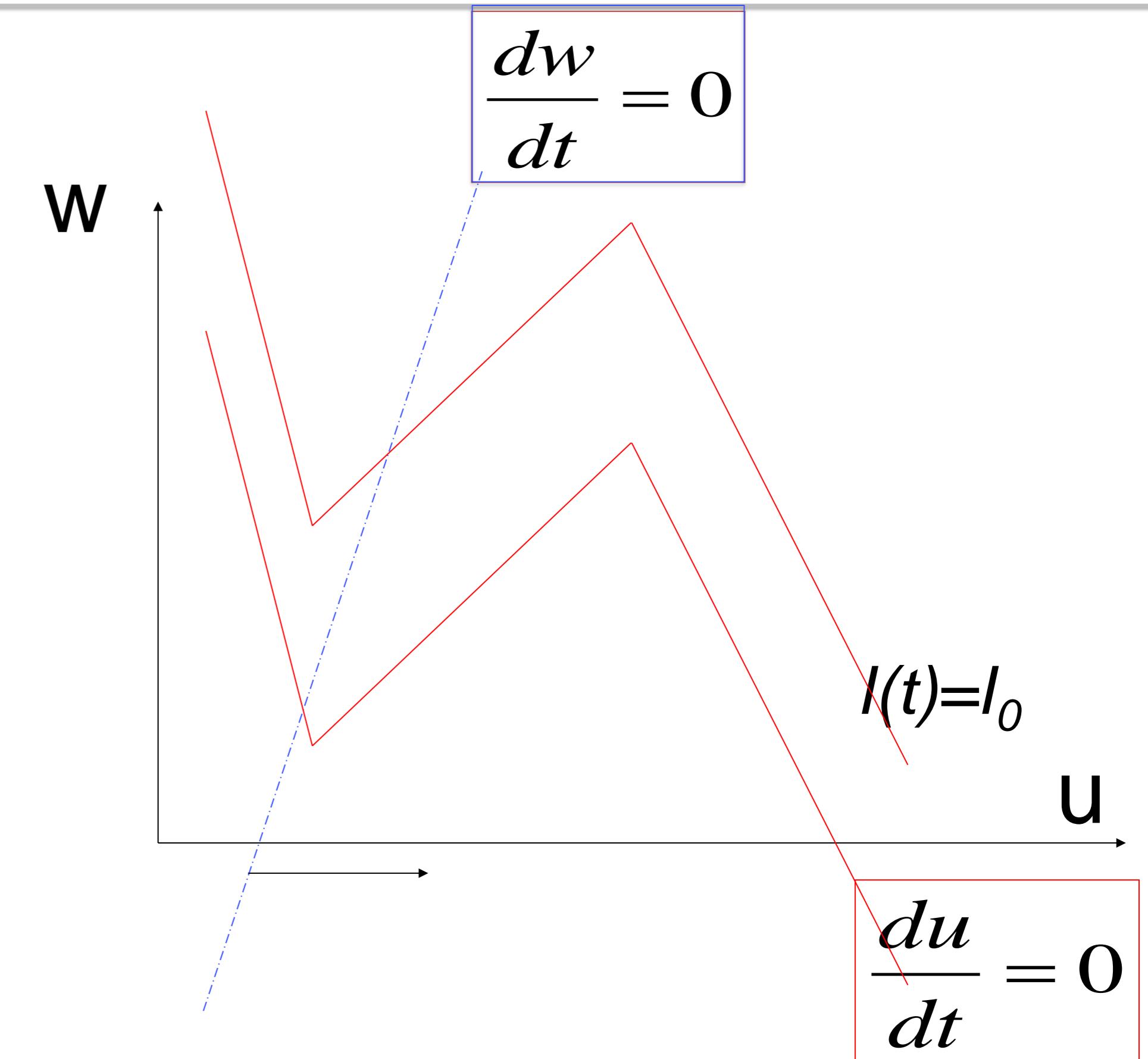
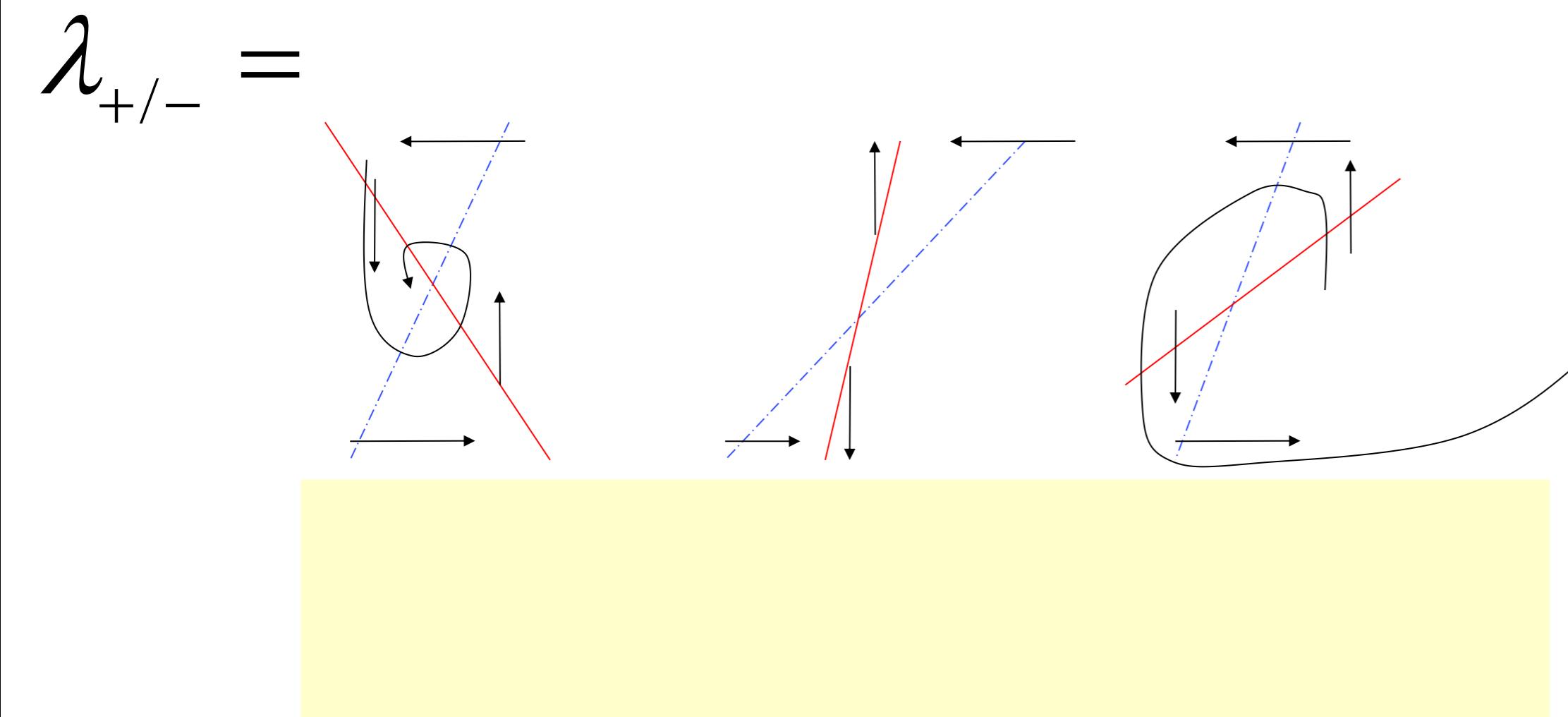
and

$$F_u G_w - F_w G_u > 0$$

# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

$$\tau \frac{du}{dt} = au - w + I_0$$

$$\tau_w \frac{dw}{dt} = cu - w$$



# Neuronal Dynamics – 4.3 Detour. Stability of fixed points

2-dimensional equation

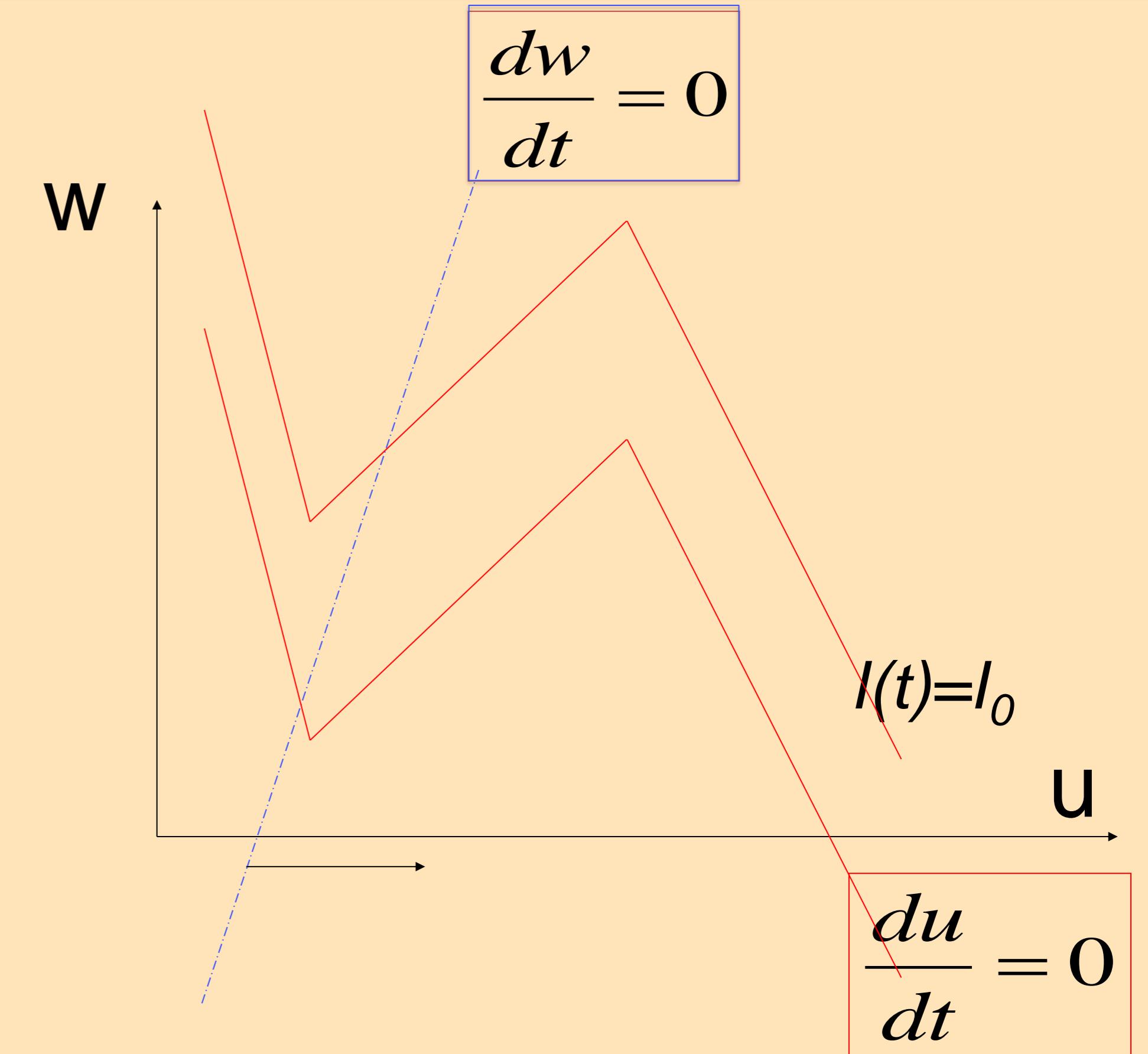
$$\tau \frac{du}{dt} = F(u, w) + RI_0$$

$$\tau_w \frac{dw}{dt} = G(u, w)$$

Stability characterized  
by Eigenvalues of  
linearized equations

$$\frac{d}{dt} \mathbf{x} = \begin{pmatrix} F_u & F_w \\ G_u & G_w \end{pmatrix} \mathbf{x}$$

# Neuronal Dynamics – Assignment.



Stability analysis of 2-dimensional equations is important for the homework assignment of week 4.