Exam:
- written exam Wedn. 21. 06. from 8:15-11:15
- sample exams of previous years online
- miniproject counts 33 percent towards final grade

For written exam:
- bring 1 sheet A5 of own notes/summary
- HANDWRITTEN!
- no calculator, no textbook

LEARNING OUTCOMES
• Solve linear one-dimensional differential equations
• Analyze two-dimensional models in the phase plane
• Develop a simplified model by separation of time scales
• Analyze connected networks in the mean-field limit
• Formulate stochastic models of biological phenomena
• Formalize biological facts into mathematical models
• Prove stability and convergence
• Apply model concepts in simulations
• Predict outcome of dynamics
• Describe neuronal phenomena

Transversal skills
• Plan and carry out activities in a way which makes optimal use of available time and other resources.
• Collect data.
• Write a scientific or technical report.

Biological Modeling of Neural Networks:

9.1 Review: Population dynamics
- competition

9.2 Perceptual decision making
- V5MT
- Decision dynamics: Area LIP

9.3 Theory of decision dynamics
- shared inhibition
- effective 2-dim model

9.4. Decisions in connected pops.
- unbiased case
- biased input

9.5. Decisions, actions, volition
- the problem of free will

Reading for week 9:
NEURONAL DYNAMICS
Ch. 16 (except 16.4.2)
Cambridge Univ. Press
9.1: How do YOU decide?

Decision making

9.1: Decision making

Population activity

Membrane potential caused by input

Attention:
- valid for high noise only, else transients might be wrong
- valid for high noise only, else spontaneous oscillations may arise

9.1: Review of week 8: High-noise activity equation

Noise model A

(escape noise/fast noise)

(high noise)

(slow transient)

\( A(t) = F(h(t)) \)
9.1: Review: microscopic vs. macroscopic

9.1: Competition between two populations

9.1: How do YOU decide?

As selected EPFL student, pick your money at EPFL:

30CHF tomorrow / 100 CHF May first next year

90CHF tomorrow / 100 CHF May first next year

'Neuro-economics'
Biological Modeling of Neural Networks:

Week 9 – Decision models: Competitive dynamics

Wulfram Gerstner
EPFL, Lausanne, Switzerland

9.1 Review: Population dynamics
- competition

9.2 Perceptual decision making
- V5/MT
- Decision dynamics: Area LIP

9.3 Theory of decision dynamics
- shared inhibition
- effective 2-dim model

9.4 Decisions in connected pops.
- unbiased case
- biased input

9.5 Decisions, actions, volition
- the problem of free will

9.2: Perceptual decision making?

Bisection task:
‘Is the middle bar shifted to the left or to the right?’

9.2: Detour: receptive fields in V5/MT

1) Cells in visual cortex MT/V5 respond to motion stimuli
2) Neighboring cells in visual cortex MT/V5 respond to motion in similar direction cortical columns

e.g., Herzog lab, EPFL

1) Albright, Desimone, Gross, J. Neurophysiol, 1985

Detour: receptive fields in V5/MT
9.2: Detour: receptive fields in V5/MT

Recordings from a single neuron in V5/MT

Receptive Fields depend on direction of motion

Random moving dot stimuli:
e.g. Salzman, Britten, Newsome, 1990
Reislman and Shadlen, 2002
Gold and Shadlen 2007

9.2: Detour: receptive fields in V5/MT

Receptive Fields depend on direction of motion: $\beta = \text{preferred direction} = P$

Image: Gerstner et al. (2014), Neuronal Dynamics

9.2: Experiment of Salzman et al. 1990

monkey indicates decision by eye movement
coherence 0.8 = 80%
coherence 0.5 = 50%
coherence 0.0
coherence -1.0

Eye movement
coherence opposite direction

Image: Salzman, Britten, Newsome, 1990
9.2: Experiment of Salzman et al. 1990

Monkey behavior w. or w/o Stimulation of neurons in V5/MT

-1.0 0.5 0.5 1.0

X = coherent motion to bottom right

No bias, each point moves in random direction

Salzman, Britten, Newsome, 1990

Blackboard: Motion detection/stimulation

coherence 0.8 = 80%
coherence 0.5 = 50%
coherence 0.0
cohere -1.0

Excites this group of neurons

Behavior: psychophysics

Image: Gerstner et al. (2014), Neuronal Dynamics; Redrawn after Salzman et al, 1990

With stimulation
Biological Modeling of Neural Networks:

Week 9 – Decision models:

Competitive dynamics

Wulfram Gerstner
EPFL, Lausanne, Switzerland

9.1 Review: Population dynamics
- competition

9.2 Perceptual decision making
- V5MT

9.3 Theory of decision dynamics
- shared inhibition
- effective 2-dim model

9.4 Decisions in connected pops.
- unbiased case
- biased input

9.5 Decisions, actions, volition
- the problem of free will


Neurons in LIP:
- selective to target of saccade
- increases faster if signal is stronger
- activity is noisy

LIP is somewhere between MT (movement detection) and Frontal Eye Field (saccade control)

Roitman and Shadlen 2002

Figure 4: Response of an LIP neuron during the RT-detection.
Quiz 1, now

Receptive field in LIP
[] related to the target of a saccade
[] depends on movement of random dots

Biological Modeling of Neural Networks:

Week 9 – Decision models:

Competitive dynamics

Wulfram Gerstner
EPFL, Lausanne, Switzerland

9.1 Review: Population dynamics
- competition

9.2 Perceptual decision making
- VSTM
- Decision dynamics: Area LIP

9.3 Theory of decision dynamics
- shared inhibition
- effective 2-dim model

9.4. Decisions in connected pops.
- unbiased case
- biased input

9.5. Decisions, actions, volition
- the problem of free will

9.3. Theory of decision dynamics

Activity equations

Membrane potential caused by input

Input indicating left movement

Input indicating right movement

populart activity

Blackboard: reduction from 3 to 2 equations
9.3: Theory of decision dynamics

Population activity
\[ A_i(t) = F(h_i(t)) \]

Activity equations
\[ F(h) = k \text{ for } 0.2 < h < 0.8 \]
\[ F(0) = 0.1 \]
\[ F(1) = 0.9 \]

Inhibitory Population
\[ A_w(t) = F(h_w(t)) = h_w(t) = w_e(A_e(t) + A_i(t)) \]

Blackboard: Linearized inhibition

9.3: Effective 2-dim. model

Membrane potential caused by input
\[ \frac{d}{dt} h_i(t) = -h_i(t) + h''_{ext}(t) + (w_e - \alpha) F(h_i(t)) - \alpha F(h_e(t)) \]
\[ \frac{d}{dt} h_e(t) = -h_e(t) + h''_{ext}(t) + (w_e - \alpha) F(h_e(t)) - \alpha F(h_e(t)) \]

Input indicating left movement
Input indicating right movement

Exercise 1 now: draw nullclines and flow arrows

Next Lecture at 10:38
9.3: Theory of decision dynamics

Phase plane, strong external input

\[ h(t) = g(h(t)) \quad 0.2 < h < 0.8 \]
\[ g(0) = 0.1 \]
\[ g(1) = 0.9 \]

9.3: Theory of decision dynamics: biased input

Population activity

Phase plane – biased input:

\[ K^{ext} < K^{ext} \]

9.3: Theory of decision dynamics: unbiased weak

Phase plane – symmetric but small input

Weak external input:

Stable fixed point
9.3: decision dynamics: unbiased strong to biased

Symmetric, but strong input

\[ \frac{dx}{dt} = h \]

unbiased strong input

= 2 stable fixed points

9.3: Theory of decision dynamics: biased strong

Population activity

Phase plane

Biased input = stable fixed point

\[ \rightarrow \text{decision reflects bias} \]

9.3: Theory of decision dynamics: unbiased strong

Phase plane

\[ \frac{dx}{dt} = k \]

Homogeneous solution

= saddle point

\[ \rightarrow \text{decision must be taken} \]
Biological Modeling of Neural Networks:

Week 9 – Decision models:

Competitive dynamics

Wulfram Gerstner

EPFL, Lausanne, Switzerland

9.1 Review: Population dynamics
- competition

9.2 Perceptual decision making
- V5/MT
- Decision dynamics: Area LIP

9.3 Theory of decision dynamics
- shared inhibition
- effective 2-dim model

9.4. Decisions in connected pops.
- unbiased case
- biased input

9.5. Decisions, actions, volition
- the problem of free will

9.4: Review: unbiased strong

Phase plane

\[ \dot{x}_1 = 0 \]

\[ \dot{x}_2 = 0 \]

Homogeneous solution
- saddle point
- decision must be taken

9.4: Review: unbiased weak

Phase plane – symmetric but small input

\[ \dot{x}_1 = 0 \]

\[ \dot{x}_2 = 0 \]

Weak external input:

Stable fixed point
- no decision

Exercise 2 at home:

stability of symmetric solution
9.4: Decisions in populations of neurons: simulation

Simulation of 3 populations of spiking neurons, unbiased strong input

X.J. Wang, 2002

NEURON

9.3: Review: biased strong

Population activity

Phase plane

\[ \alpha_1 = 0 \]

\[ \alpha_2 = 0 \]

Biased input = stable fixed point

→ decision reflects bias

9.4: Decisions in populations of neurons: LIP data

Stimulus onset

Saccade onset

Roitman and Shadlen 2002

Figure 7. Time course of LIP activity in the 10° direction-discrimination task. A. Average responses from 54 LIP neurons. Responses are grouped by distance correct and choice as in Figure 1. Error bars represent SEM. B. Time course of the 15° direction-discrimination task. The LIP responses were recorded from the same neurons as in A, and they are the average of 60 trials. C. Time course of the 30° direction-discrimination task. The LIP responses were recorded from the same neurons as in A, and they are the average of 60 trials. The X-axis represents the time in seconds from the onset of the stimulus. The Y-axis represents the firing rate of the neurons.
9.5: Decision: risky vs. safe

How would you decide?

- Goal
- Start

Decision: risky vs. safe
What decides? Who decides?

‘Your brain decides what you want or what you prefer …’
‘… but your brain – this is you!!!’
- Your experiences are memorized in your brain
- Your values are memorized in your brain
- Your decisions are reflected in brain activities

‘We don’t do what we want, but we want what we do.’ (W. Prinz)

The problem of Free Will
(see e.g. Wikipedia article)

Decision, Perception and Competition in Connected Populations

Suggested Reading:
- Salzman et al. Nature 1990
- Roitman and Shadlen, J. Neurosci. 2002
- Abbott, Fusi, Miller: Theoretical Approaches to Neurosci.
- Soon et al., Nat. Neurosci., 2008
- free will, Wikipedia

Chapter 16, Neuronal Dynamics, Gerstner et al. Cambridge 2014
Exercise 2.1 now: stability of homogeneous solution

\[ A_h(t) = g(h_h(t)) \]

Membrane potential caused by input

\[ \dot{h}_h(t) = -h_h(t) + b + (w_1 - \alpha)g(h_h(t)) - \alpha g(h_b(t)) \]

\[ \dot{h}_b(t) = -h_b(t) + b + (w_2 - \alpha)g(h_b(t)) - \alpha g(h_h(t)) \]

Assume: \[ h_h^{in} - h_b^{in} = b \]

a) Calculate homogeneous fixed point \( h_1 = h_2 = h'(b) \)

b) Analyze stability of the fixed point \( h(b) \) as a function of \( b \)

Online course evaluation,
still open this week.
1 summary question per class
\( \Rightarrow \) please do it
(for all your classes)