Syllabus for the course «Computational Neuroscience»

Approved

MP Academic Council

Protocol №2.6-06/7 29/08/2019

1. **Course Description**
    a. « Computational Neuroscience»
    b. **Pre-requisites**

    The course is based on the basic knowledge:
    - Calculus;
    - Linear algebra;
    - Introduction to Cognitive Science;
    - Neuroscience.

    c. **elective**
    d. **Abstract**

This course provides an introduction to basic computational methods for understanding what nervous systems do and for determining how they function. We will explore the computational principles governing various aspects of behavior, vision, sensory-motor control, learning, and memory. Specific topics that will be covered include reinforcement learning models, representation of information by spiking neurons, processing of information in neural networks, and models of neuronal dynamics and biophysics. We will make use of Matlab demonstrations and exercises to gain a deeper understanding of concepts and methods introduced in the course. Introduction to mathematical techniques will be given as needed. The course is primarily aimed at masters graduate students interested in learning how the brain processes information and how to use mathematics to model brain processes. The course "Computational Neuroscience" is new and unique discipline within the educational programs of the National Research University Higher School of Economics. The course is based on contemporary scientific research in computational neuroscience and related scientific areas. It is essential in training competent specialist in the areas of cognitive sciences and technologies. The author of the course Boris Gutkin has significant teaching experience, including design and coordination of a similar course in the Cogmaster program at the Ecole Normale Superiuer (Pairs, France),

teaching computational neuroscience lecutres at the University College London, Woods Hole Matine Biology Laboratory and directing and leading several advanced summer schools in the topic.

2. Learning Objectives

Learning objectives of the course "Computational Neuroscience" are to introduce students to the subject of computational neuroscience, its foundation and connections to other branches of knowledge:

- Understand the principles of information processing in brain circuits and networks
- Gain understanding of the mathematical techniques necessary to develop models of brain dynamics
- Gain skills in developing computational models of learning and neuronal plasticity
- Gain skills and knowledge for modeling motivated behavior
- Gains knowledge and skills in applying mathematical models in neuroscience

3. Learning Outcomes

After completing the study of the course "Neuroscience" the student should:

- Know basic notions and definitions in computational neuroscience, its connections with other sciences.
- Know the mathematical methods used for the study of the nervous system
- Know the basic modeling techniques for reinforced behavior.
- Know the basic models of neural encoding, biophysics, network dynamics.
- Be able to relate mathematical models to the functioning of the nervous system.
- Be able to distinguish the capacities and restrictions for models considered
- Possess skills for choosing appropriate computational neuroscience methods for psychological research.
- Possess skills for translation between the various levels of models to describe psychological and physiological levels of interpretation of experimental data

4. Course Plan

№	Topic
1.	Basic concepts of reinforcement learning (models of decision making; classical

	conditioning; operating conditioning, learning by reinforcement; neuroeconomics)
2.	Models of neural coding: (sensory processing; linear filters and receptive fields; estimation of receptive fields; edge detectors; Hubel and Wiesel mode of visual processing; natural image statistics, information theory, independent component analysis, neural decoding, encoding by population)
3.	Models of network dynamics ((biophysics of a neuron, Hudgkin-Huxley formalism, generating action potentials; feedforward and recurrent neural networks; attractors networks; energy functions, Liapunov energy)
4.	Models of Neuro Biophysics and plasticity (learning and synaptic plasticity; associative memories)

5. Reading List

a. Required

1. Naldi G., Nieus T., Mathematical and Theoretical Neuroscience, Springer International Publishing AG, 2017. — Режим доступа: https://link.springer.com/book/10.1007/978-3-319-68297-6
2. Wiering M., van Otterlo M., Reinforcement Learning - State-of-the-Art, Springer-Verlag Berlin Heidelberg, 2012. — Режим доступа: https://link.springer.com/book/10.1007/978-3-642-27645-3

b. Optional

1. Barto A.G., Sutton R.S., Chapter 19 - Reinforcement Learning in Artificial Intelligence, Ad-vances in Psychology, 121:358-386 (1997), — Режим доступа: http://www.sciencedirect.com/science/article/pii/S0166411597801057
2. Schneiderman N., Fuentes I., Gormezano I., Acquisition and extinction of the classically con-ditioned eyelid response in the albino rabbit, Science, 136:650–652(1962). — Режим доступа: http://science.sciencemag.org/content/136/3516/650
3. Pouget A, Dayan P, Zemel R., Information processing with population codes. Nat Rev Neuro -sci. 1(2):125-32(2000). — Режим доступа: https://www.nature.com/articles/35039062

6. Grading System

The grade will be determined by 60% average homework score and 40% Final exam to be completed by the students as a take-home exam.

Table of Grade Correspondence

Ten-point Grading	Scale Five-point Grading Scale	
1 - very bad 2 – bad 3 – no pass	Unsatisfactory – 2	FAIL
4 – pass 5 – highly pass	Satisfactory – 3	PASS
6 – good 7 – very good	Good – 4	
8 – almost excellent 9 – excellent 10 – perfect	Excellent – 5	

The final grade, which is the resultant grade for the course, goes to the certificate of Master's degree.

7. Guidelines for Knowledge Assessment

Type of grading	Type of work	Characteristics
Continuous	Home work assignments	Take home assigments, estimated 5 hours of work per assignment
Final	Exam	Oral exam. Preparation time 30 minutes.

Continuous assessment:

Homework assignments will be given after each lecture and will include written and programming exercises. Assignments are designed to enable grading along correct/incorrect answers to specific questions in each exercise. Total number of questions will be 10. Each correct answer adds one point. The grade is calculated as the proportion of correct answers to the total number of questions.

Ten-point grade	Criteria
0 – not accepted	Less 5%, or the test was not taken
1 – very bad	Not less than 5, but less than 15%
2 – bad	Not less than 15, but less than 25%
3 – no pass	Not less than 25, but less than 35%
4 – pass	Not less than 35, but less than 45%
5 – highly pass	Not less than 45, but less than 55%
6 – good	Not less than 55, but less than 65%
7 – very good	Not less than 65, but less than 75%
8 – almost excellent	Not less than 75, but less than 85%
9 – excellent	Not less than 85, but less than 95%
10 – perfect	Not less than 95% and greater

Sample homework questions:

1. **Temporal-difference learning with discounting.** In many instances, immediate rewards are worth more than those in the future. To take this observation into account, the value $V(s_t)$ of a particular state s_t is not the sum of all future rewards, but rather the sum of all future, *discounted* rewards,

$$V(s_t) = r(s_t) + \gamma r(s_t+1) + \gamma^2 r(s_t+2) + \ldots = \sum_{\tau=0}^{\infty} \gamma^{\tau} r(s_{t} + \tau) \qquad (1)$$

where $0 < \gamma < 1$. Here s_t is the state at time t, i.e., the state in which the agent is right now, s_{t+1} the state that the agent will move to next and so on. Following the derivation in the lecture, show that the temporal-difference-learning rule in this case is given by

$$V(s_t) \rightarrow V(s_t) + (r(s_t) + \gamma V(s_{t+1}) - V(s_t)) \qquad (2)$$

2. **Models for the value function.** In the lecture, we talked about the necessity to introduce models for the value of a state, so that one could properly generalize to new, unseen situations. One very simple model is given by the value function $V(\mathbf{u}) = \mathbf{w} \cdot \mathbf{u}$ where $\mathbf{u}$ is a vector of stimuli that could either be present (1) or absent (0).

a) Take the example of two stimuli, $\mathbf{u} = (u_1, u_2)$. Let us assume that the subject (agent) has already learned the value of a state in which the first stimulus is present, and the value of a state in which the second stimulus is present. The learned values are given by

$$V(\mathbf{u} = (1, 0)) = \alpha \; V(\mathbf{u} = (0, 1)) = \beta$$

What are the values of the parameters $\mathbf{w} = (w_1, w_2)$ that the agent has learnt? Now we assume that the agent, for the very first time, runs into a state in which both stimuli are present. What is the value of this state? What if we now add some uncertainty. What would be the value of a state where the first stimulus has 50% chance of being present and the second stimulus has 10%? In what situation do you think this sort of a more generalized model that you just came up with would not make much sense?

b) Advanced: Derive the temporal-difference learning rule for the parameters $\mathbf{w}$ that need to be learned if the value function is $V(\mathbf{u}) = \mathbf{w} \cdot \mathbf{u}$. Hint: Start from a loss function - what would be a suitable choice? Can you also derive a learning rule if the value function were given by $V(\mathbf{u}) = f(\mathbf{w} \cdot \mathbf{u})$ with $f(\cdot)$ being a known (non-linear) function?

Final exam assessment:

Final assessment is the final exam. Students have to demonstrate the knowledge of theories and facts in computational neuroscience. Students should be able to demonstrate the ability to discuss important topics and problems in the field of computational neuroscience, to understand relations both between course topics and with knowledge of other related fields including psychology, philosophy. Students should demonstrate the ability to appropriately use scientific terms in the field of computational neuroscience and understand the technical aspects of the models.

The final exam grading criteria are:

1. Compliance of the answer to the current question topic;
2. Sufficient volume of knowledge on the current question topic;
3. Ability to understand and discuss other topics within the course scope relevant to the current question topic;

4. Ability to logically organize the answer and to present evidence in adequate order;
5. Ability to correctly use scientific terms within the course scope.

Ten-point grade	Criteria
0 – not accepted	No answer
1 – very bad	No criteria met
2 – bad	Less then 2 criteria met
3 – no pass	Less then 3 criteria met
4 – pass	At least 3 criteria are partially met
5 – highly pass	At least 3 criteria are met
6 – good	At least 4 criteria are partially met
7 – very good	At least 4 criteria are met
8 – almost excellent	All criteria are met.
9 – excellent	All criteria are met, and at least 3 criteria are fully met.
10 – perfect	All criteria are fully met

Final exam questions:

• Explain the Rescorla-Wagner model ["delta-rule"]. Exercise: we give a series of stimulus-reward. How is the answer?
• (+) Explain the "blocking": we now have two types of stimulus
• (+) (Draw a maze). Define and write the value function for a strategy (policy) random. How to learn the right strategy? [Reinforcement learning: TD learning].
• (+) What will happen if the rewards are changing? [Exploitation-exploration]
• Explain the exploration-exploitation dilemma.
• (++) How to learn to play chess? [Dimensionality problem]
• Explains ROC curves (Receiving-operator characteristics)
• What is the "hit rate"? What will happen when we change the threshold?
• Draw the responses of two neurons to two stimuli (2.2), which rule-making?
• What is the selectivity curve of a neuron? (Tuning curve) How to be a linear function of the stimulus (orientation) with linear combinations of neurons preferring some guidance?
• Why is it a neuron polarized at rest? (What are the ion pumps?)
• What is a synapse excitatory / inhibitory? (+)
• Write and explains the equivalent electrical circuit
• Write the membrane equation.

• [Write equation dv / dt = V^3-V] What are the stable and unstable points basins of attraction?

• [Draw autapse] Can you graphically explain the dynamics of this basic network?

• What causes the action potential? What would happen if the Na channel is not inactivated? If there were no potassium channels?

• What is the integrate and fire model?

• What is the linear separability?

• Can a perceptron make or exclusive? And with several layers?

8. Methods of Instruction

The following educational technologies are used in the study process:

- Lectures involving continuous use of multimedia presentations and on-line simulations
- Seminars involving team oral discussions
- Homework assignments
- Self-study of presentation
- Self-study of recommended literature

Course lecturer is advised to use interactive learning methods, which allow participation of the students, such as discussions. It is also expected that multimedia presentations and video materials will be intensively used for the study process.

Students are required to study the presentations, which will be posted on the LMS educational portal, and the recommended reading. Students are required to actively participate in oral discussions during seminars and to take all tests.

9. Special Equipment and Software Support (if required)

The course requires a computer or laptop, projector, and acoustic systems for multimedia presentations and video.