Computational Models in Cognition and Programming Skills

M.S. Behavior and Cognition

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Objectives

This course is an introduction into theoretical neuroscience and modeling. The students will furthermore learn how to program and run simulations of mathematical models with Matlab. Modeling is an interdisciplinary research field, which requires skills and knowledge from neuroscience, psychophysics, physics, computer science, and above all mathematics. Dependent on the model under consideration, different combinations of knowledge from these areas will be needed, but fortunately certain mathematical methods and techniques can be found repeatedly in many models. Our aim is that the students learn these techniques by means of typical models. In this way, they should be able to design simple models after the course, evaluating simulation results, and understanding corresponding scientific work.

Methodology

Experiments in neuroscience often deliver highly interesting results, which describe the responses of the brain to specific stimuli. The stimuli are cleverly selected by the scientist, and the results are generated by the neurons of the brain, which interact through complex networks. It is this complexity which leads to a sort of dilemma: If we study single neurons on their own (for example by single cell recording techniques), then we will know only few to nothing about their role in large networks. Conversely, if we study brain networks in action (e.g. by fMRI, MEG, EEG, or TMS), then the overall network activity and thus the response is characterized by just a single quantity (BOLD-constrast, magnetic fields, voltage fluctuations, or behavioral responses, respectively). But again we will not have an answer to the question about how these neurons interact in order to generate the observed responses. This is where theory and modeling comes into play. It serves to provide the answers to these questions. Computers are nowadays so fast that even large networks of neurons can be simulated. The models have to be designed such that they predict the experimental data in which one is interested. And, good models should even take a step ahead, in that they provide new questions for the experimenter. To eventually understand how the brain works, this interplay between theory and experiment is of paramount importance.

For designing a new model, you will need – above all – creativity and the right intuition. Before getting creative, however, you have to dominate mathematical techniques, which may vary from model to model. If your model is amenable to a rigorous mathematical analysis, you certainly have luck, because most models are not. For this reason we need the computer for their analysis. Matlab is an excellent tool to do that, because you get quickly to a working implementation. Matlab provides a lot of mathematical techniques, which can be used without understanding every single detail about their implementation. You can focus on your ideas instead of spending most of your time with programming glitches. For this reason we will learn how to use Matlab.

However, in this course we will not teach lengthy mathematical lessons. First, this approach may be boring for many students, and at the end of the course you probably would not know how to employ all those math things. Instead, you will “learning by doing”. This means that we select some

representative research papers about modeling and simulation, and try to reproduce the results ourselves. The necessary mathematical tools will be introduced "on the fly", in a way that you can apply them readily on a computer. This is more fun than just studying pure theory. In addition, Matlab will greatly help us with mathematics.
Repetition and motivation are essential to pain-free learning. This is also true for mathematics, and for this reason we will invite you to view some nice video lectures (via internet) about applied math as a preparation for our class. These video lectures often go into somewhat more detail than we actually need, and it will not really matter if you cannot understand everything at the first time. In our class we are going to repeat the important things and explain them again, and as you have seen them before, you hopefully will be scared less, and eventually get the idea. We will give you homework for self-evaluation. In this way you will be able to monitor your own progress.

Of course you are encouraged to bring your own laptop with you.

Evaluation

Every two weeks, programming tasks will be assigned to the students which they should solve. The programming tasks can consist of, for example, implementations of a simple model, modification of a model that was discussed in the class, or an additional analysis. Also, some mathematical exercises will be required, typically covering linear algebra and numerical methods. The math exercises could also be assigned as a part of the video lectures which the students should watch in order to prepare a class.
Rather than a written exam, the students will receive a modeling paper, which they have to read. Subsequently, the students will be required to program a corresponding simulation (possibly simplified with respect to the original paper), perform some analysis and answer questions.

Teaching schedule

Each class lasts three hours. Classes will be distributed over 10 weeks.
References to journal articles ("papers") are provided as *"Title",* author(s), Journal #volume(#issue): 1st page – last page (year)
The first paper for each week is the key paper that will be discussed. Other listed papers contain further reading material.

1. Introduction into Programming with Matlab

- defining functions and data types
- loops and plotting
- array indexing
- compiling histograms
- correlation, cross-correlation, and auto-correlation
- a spike generator with Poisson statistics

2. How to Model Neurons: The Basics

- From biophysics to mathematics: Neurons and membrane potential
- The neuron as RC-circuit
- Synaptic input, synaptic weights, reversal potentials, low-pass filtering, threshold, divisive inhibition, shunting inhibition
- steady state solution, divisive inhibition, and normalization
- Simulation of a firing rate model (constant input, temporally varying input)
- Activation functions, neuronal oscillator

Chapter 2 in *"Computational Explorations in Cognitive Neuroscience"*
Randall C. O'Reilly and Yuko Munakata (The MIT Press 2000)

Want to know more?
Chapter 14 in *"Biophysics of Computation – Information Processing in Single Neurons"*
Christof Koch (Oxford University Press 1999)
"Pyramidal Neuron as Two-Layer Neural Network"; P. Poirazi, T. Brannon, and Bartlett W. Mel; Neuron 37:989-999 (2003)
"Shunting inhibition does not have a divisive effect on firing rates"; Holt, GR and Koch, C; Neural Computation 9:1001-1013 (1997)

3. An Example of Modeling a Single Neuron

- The Lobula Giant Movement Detector of the locust
- Collision detection, optical variables, nonlinear inputs, nonlinear operations
- Phenomenological model: The "eta"-function (explicit multiplication; logarithmic encoding)
- Biophysical model: The "psi"-function (emergent multiplication; power law; shunting inhibition)

"Emergence of Multiplication in a Biophysical Model of a Wide-Field Visual Neuron for Computing Object Approaches: Dynamics, Peaks & Fits"; M.S. Keil; Advances in Neural Information Processing Systems 24:469-477 (2011) Available online http://books.nips.cc/nips24.html

Want to know more?
"Collision-avoidance: nature's many solutions"; G. Laurent and F. Gabbiani; Nature Neuroscience 1(4):261-263 (1998)
"Collision Detection as a Model for Sensory-Motor Integration"; H. Fotowat and F. Gabbiani; Annual Review of Neuroscience 34:1-19 (2011)
"Multiplicative computation in a visual neuron sensitive to looming", F. Gabbiani, H.G. Krapp, C. Koch, and G. Laurent Nature 420(6913):320-324 (2002)
"Computation of object approach by a wide-field motion-sensitive neuron", F. Gabbiani, H.G. Krapp, and G. Laurent. Journal of Neuroscience 19(3):1122-1141 (1999)
"Elementary Computation of object approach by a wide-field visual neuron"; N. Hatsopoulos, F. Gabbiani, and G. Laurent; Science 270:1000-1003 (1995)

4. How to Model Receptive Fields with Matlab

- matrices, matrix operations, and matrix indexing
- visualization of matrices
- efficient programming without loops
- convolution and Fourier transforms
- modeling of the receptive fields of the retina and V1
- modeling brightness perception

"A multiscale spatial filtering account of the White effect, simultaneous brightness contrast and grating induction"; Barbara Blakeslee and Mark E. McCourt; Vision Research 39(26):4361-4377 (1999)

Want to know more?
Chapter 8 in *"Computational Explorations in Cognitive Neuroscience";* Randall C. O'Reilly and Yuko Munakata (The MIT Press 2000)

5. Review of Single Neuron Models

- The classical one: Hodgekin-Huxley
- Biophysical details versus computational efficiency
- Spike patterns: tonic, phasic, bursting and such
- Reproducibility of spike patterns and noise
- Coding: population codes, latency codes
- Analysis of spike trains (Fourier, correlation, …)
- The *Blue Brain Project*

"Which Model to Use for Cortical Spiking Neurons?"; E.M. Izhikevhich; IEEE Transactions on Neural Networks 15(5):1063-1070 (2004)

Want to know more?
"A review of the integrate-and-fire neuron model: I. Homogeneous Synaptic Input"; A.N. Burkitt; Biological Cybernetics 95:1-19 (2006)
Blue Brain Project homepage http://bluebrain.epfl.ch/
"Reproducibility and variability in neural spike trains"; R.R. Ruyter van Steveninck, G.D. Lewen, S.P. Strong, R. Koberle, W. and Bialek; Science 275:1805-1808 (1997)
"Rate coding and signal processing"; M.G. Paulin; Biological Cybernetics 66:525-531 (1992)
"A quantitative description of membrane current and its application to conduction and excitation in nerve"; A. L. Hodgkin and A. F. Huxley; Journal of Physiology 117:500-544 (1952)

6. Predictive Coding in the Inner Retina

- structure of the retina and its relation to image statistics
- Classical view: Center-surround receptive fields of retinal ganglion cells
- Predictive coding in amacrine cells and stimulation pattern
- feedforward inhibition, feedback inhibition, Hebbian learning

"Dynamic predictive coding by the retina"; Toshihiko Hosoya, Stephen A. Baccus, and Markus Meister; Nature 436:71-77 (2005)

Want to know more?
"Predictive coding: a fresh view of inhibition in the retina"; Srinivasan, M.V. and Laughlin, S.B. and Dubs, A.; Proceedings of the Royal Society of London B 216:427-459 (1982)
"What Does the Retina Know about Natural Scenes?"; Atick, J.J. and Redlich, A.N.; Neural Computation 4:196-210 (1992)
"Some informational aspects of visual perception"; Attneave, F.; Psychological Review 61(3):184-192 (1954)
"Eye smarter than scientists believed: Neural computations in circuits of the retina"; Gollisch, T., and Meister, M.; Neuron 65:150-164 (2010)
"*How the retina works*"; Helga Kolb; American Scientist 91(1):28 (2003)

7. The Importance of Single Spikes: Latency and Rank order Codes

- rate coding versus temporal coding in rapid scene perception
- the retina as encoder
- the cortex as decoder
- how to compute with inactivity

"Rate coding vs temporal order coding: what the retinal ganglion cells tell the visual cortex"; R. VanRullen & S.J. Thorpe ; Neural Computation 14:(6):1255-1283 (2001)

Want to know more?
"Rapid Neural Coding in the Retina with Relative Spike Latencies"; Tim Gollisch and Markus Meister; Science 319(5866):1108-1111 (2008)
"Animals roll around the clock: The rotation invariance of ultrarapid visual processing"; Rudy Guyonneau, Holle Kirchner, Simon J. Thorpe; Journal of Vision 6(10):1008-1017 (2006)

8. Connecting to each other I: Topology and Network Dynamics

- Connection matrices
- Internet, social networks, traffic networks, neural networks
- Scale free networks versus random networks
- Network activity, oscillations, synchrony
- Fault tolerance; hubs; degree distribution

"*Simple Model of Spiking Neurons";* E.M. Izhikevhich; IEEE Transactions on Neural Networks 14(6):1569-1572 (2003)
"Large-scale model of mammalian thalamocortical systems"; Izhikevich, E and Edelman, GM; PNAS 105(9):3593-3598 (2008)

Want to know more?
Chapter 3 & 7 in *"Computational Explorations in Cognitive Neuroscience";* Randall C. O'Reilly and Yuko Munakata (The MIT Press 2000)
"Complex brain networks: graph theoretical analysis of structural and functional systems"; Ed Bullmore and Olaf Sporns; *Nature Reviews Neuroscience* 10(3):186-198 (2009)
"How to make a fragile network robust and vice versa"; A.A. Moreira, J.S. Andrade, H.J. Herrmann, and J.O. Indekeu; Physical Review Letters 102, 018701 (2009)
"Simple models of human brain functional networks"; Petra E. Vértes, Aaron F. Alexander-Bloch, Nitin Gogtay, Jay N. Giedd, Judith L. Rapoport, and Edward T. Bullmore; PNAS 109(15):5868-5873 (2012)
"Emergence of Scaling in Random Networks"; Albert-Laszlo Barabasi and Roka Albert; Science 286:509-512 (1999)
"Collective dynamics of small-world networks"; Duncan J. Watts, Steven H. Strogatz; Nature 393:440-442 (1998)
"Cortical hubs recvealed by intrinsic functional connectivity: mapping, assessment of stability, and relation to Alzheimer's disease"; Buckner, RL *et al.*; Journal of Neuroscience 29(6):1860-1873 (2009)

9. Connecting to Each Other II: Balanced Networks and Chaos

- what is chaos
- sensory input and gain control by feedforward inhibition
- (bi-)stability of resting and depolarized states
- influence of slow or fast synaptic input
- short term memory

"Chaos in Neuronal Networks with Balanced Excitatory and Inhibitory Activity"; C. van Vreeswijk and H. Sompolinsky; Science 274:1724-1726 (1996)

Want to know more?
"Chaotic Balanced State in a Model of Cortical Circuits"; C. van Vreeswijk, H. Sompolinsky; Neural Computation 10(6):1321–1371 (1998)
"Attractor dynamics of network UP states in the neocortex"; Rosa Cossart, Dmitriy Aronov & Rafael Yuste; Nature 423:283-288 (2003)
"Gain Modulation from Background Synaptic Input"; Chance, F.S., Abbott, L.F. & Reyes, A.D.; Neuron 35:773-782 (2002)
"Inhibitory Modulation of Cortical Up States"; Maria V. Sanchez-Vives, Maurizio Mattia, Albert Compte, Maria Perez-Zabalza, Milena Winograd, Vanessa F. Descalzo, and Ramon Reig; Journal of Neurophysiology 104:1314-1324 (2010)

10. Connecting to each other III: Dynamic Connections

- self-organization of complexity: sandpiles, avalanches and criticality
- the power law signature of criticality
- a dynamic connectivity matrix: depression, facilitation, and STDP
- neuronal avalanches and neuronal delay
- scale-free networks by self-organization and Hebbian learning

"Dynamical synapses causing self-organized criticality in neural networks"; A. Levina, J. M. Herrmann & T. Geisel; Nature Physics 3:857-860 (2007)

Want to know more?
"Spike-timing-dependent plasticity in small-world networks"; Karsten Kube, Andreas Herzog, Bernd Michaelis, Ana D. de Lima and Thomas Voigt; Neurocomputing 71(7-9):1694-1704 (2008)
"Psychophysics: Are our senses critical?"; Dante R. Chialvo; Nature Physics 2:301-302 (2006)
"Optimal dynamical range of excitable networks at criticality"; Kinouchi, O and Copelli, M; Nature Physics 2:348-352 (2006)
"Self-organized criticality in a simple model of neurons based on small-world networks"; M. Lin, M and T.L. Chen; Phys. Rev. E 71:016133 (2005)
Chapter 4 in *"Computational Explorations in Cognitive Neuroscience";* Randall C. O'Reilly and Yuko Munakata (The MIT Press 2000)

Further Reading

"Modeling the Mind" – Special Section about Computational Neuroscience Science 314:75-94 (2006)
Several review articles of computational neuroscience from various authors, published as a special section in Science (https://www.sciencemag.org/site/feature/misc/webfeat/compneuro/)

"Computational Explorations in Cognitive Neuroscience"
Book by Randall C. O'Reilly and Yuko Munakata
(The MIT Press 2000)
Especially interesting are Chapters 2, 3, 4, 7, 8

"Biophysics of Computation – Information Processing in Single Neurons"
A book written by Christof Koch (Oxford University Press 1999)
Especially interesting are Chapter 1, Chapter 4, Chapter 14, and Chapter 15

"Spiking Neuron Models - Single Neurons, Populations, Plasticity"
Book by Wulfram Gerstner and Werner M. Kistler
Cambridge University Press (2002)

"Dynamical Systems in Neuroscience: The Geometry of Excitability and Bursting"
Book by Eugene M. Izhikevich (2007)
(The MIT Press 2007)
avaliable online: www.izhikevich.org/publications/dsn.pdf

"From Computer to Brain: Foundations of Computational Neuroscience"
Book by William W. Lytton
(Springer Verlag New York 2002)