COURSE SYLLABUS

VISUAL PERCEPTION AND LEARNING IN THE BRAIN

Instructor: József Fiser, Professor
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Term: Fall, 2023/24
Course level: PhD (2 credits Graded)
Pre-requisites: -
E-learning site: **http://ceulearning.ceu.hu/**
Time and place: Wednesday 10:50 – 12:30 Dept. CogSci QS, Room C-503

Course Description

This course will be built around the contemporary research on vision to give an overview of researching cognitive processes in general. First, we will briefly cover the classical approaches of low and high-level vision, visual learning, the neural implementation of perception and learning in the brain, and their computational models. Alongside, we will critically evaluate the state-of-the-art in these domains and explore alternative approaches to the same issues. Next, we will learn the probabilistic view on vision, and how it changes the research questions in focus. We will investigate how interpreting sensory perception, cue-combination, statistical learning, and rule learning in the framework of probabilistic inference can expand the range of interpretable phenomena in vision and cognition. We will also cover theories of possible neural embodiment of such computations in the brain, and review evidence that supports such an implementation. Completion of this course will provide a self-contained theory of cognitive processes and their implementation in the brain.

Learning Outcomes

- Getting acquainted with vision research and its links to higher cognition
- Understanding the link between perception and learning
- Exploring the probabilistic interpretation of vision and cognitive functions
- Tying abstract computational and behavioral results to neural implementation of visual coding
- Gaining experience in how to read and present various scientific materials

Course Requirements

The course grading is based on the following three components.

- Each student will have to make a number of presentations based on the assigned readings during the semester. Making a presentation involves reading the assigned papers, if necessary reading additional material, preparing a brief summary slide presentation of the topic, and leading the discussion during class. Performance will be evaluated based on how well the student understood and presented the essence (!) of the topic rather than getting lost in details, how well s/he could keep the presentation conscience and within proper time frame instead of repeating back the entire content of the paper, and how well s/he integrates the given topic with the previous topics discussed in class. The slide presentations will be collected and used in the final evaluation.

- In addition, each student needs to read each assigned paper for each class (before the class!). While this does not have to be a deep thorough reading (although that is the best), it must be sufficient to be familiar with the topic covered in the paper. Having said that, reading of the course material is essential component of the course, and keeping up with the readings will be expected. To facilitate this, each student has to submit (before the class by E-learning Dropbox) and also bring to class a copy of a one-page summary sheet. On this sheet, for each paper, 4 items should be presented in an itemized manner: a) one-two sentences about the gist of the paper, b) a single idea/result/methodological trick that was the most interesting, c) the list of topics, notions, equations that the student did not understand or did not agree with, d) at least one question that s/he wants to clarify based on the study that defines the next step in the research. During the class the student will present his/her summary and the question, which will be discussed in class. Students will be required to reach and present an answer to the question by the end of the class. When the student is one of the presenters in the class, s/he is still required to present a summary sheet of the other papers, but s/he does not need to come up with a presentable question.
- Participation in class sessions. This is a small, seminar-style course with the goal of integrating several topics. It is essential that the class formed a coherent view on the covered topics by the end of the semester. To achieve this, I expect a highly interactive and critical discussing during classes.

Required Materials:

- PDFs of the reading will be provided.

COURSE SCHEDULE

Date	Topic
Sept. 13	0 Introduction: Why studying visual perception and learning in the brain?
Sept. 20	1 Classical neural results visual perception and learning
Sept. 27	2 Classical behavioral results of visual perception and learning
Oct. 4	3 Classical computational models of visual perception and cognitive learning
Oct. 11	4 The role of statistics
Oct. 18	5 Statistical learning
Oct. 25	6 Rule learning
Nov. 1	7 The probabilistic framework
Nov. 8	8 Applying the probabilistic framework to perception and learning
Nov. 15	9 Probabilistic interpretation of illusions and cue combination
Nov. 22	10 Evidence for probabilistic processes in infants
Nov. 29	11 Spontaneous activity in the cortex
Dec. 6	12 Probabilistic theory of perception and learning and its neural evidence

TOPICS:

0) Intro: Why learning visual perception and learning in the brain?

1) Classical neural results of visual perception and learning

Frisby, J.P. & Stone. J. V. (2010). Chapter 3: Seeing with receptive fields 55-74

Frisby, J.P. & Stone. J. V. (2010). Chapter 10: Seeing with brain maps 229-254

DiCarlo, J.J., Zoccolan, D., and Rust, N.C. (2012). How Does the Brain Solve Visual Object Recognition? Neuron 73, 415-434.

Miller, K. D., Erwin, E., & Kayser, A. (1999). Is the development of orientation selectivity instructed by activity? Journal of Neurobiology, 41(1), 44-57

2) Classical behavioral results of visual perception and learning

Frisby, J.P. & Stone. J. V. (2010). Chapter 4: Seeing aftereffects: the psychologist's microelectrode 75-110

Frisby, J.P. & Stone. J. V. (2010). Chapter 8: Seeing objects 173-204

Fine, I., and Jacobs, R.A. (2002). Comparing perceptual learning across tasks: A review. Journal of Vision 2, 190-203.

3) Classical computational models of visual perception and cognitive learning

Frisby, J.P. & Stone. J. V. (2010). Chapter 11: Seeing and complexity theory 255-280

Frisby, J.P. & Stone. J. V. (2010). Chapter 12: Seeing and psychophysics 280-306

Serre, T., Oliva, A., & Poggio, T. (2007). A feedforward architecture accounts for rapid categorization. Proceedings of the National Academy of Science, 104(15), 6424-6429

McClelland, J. L., & Rogers, T. T. (2003). The parallel distributed processing approach to semantic cognition. Nature Reviews Neuroscience, 4(4), 310-322

4) The role of statistics

Barlow, H. B. (2001). Redundancy reduction revisited. Network: Computation in Neural Systems, 12, 241-253.

Simoncelli, E. P., & Olshausen, B. A. (2001). Natural image statistics and neural representation. Annual Review of Neuroscience, 24, 1193-1216

Olshausen, B. A., & Field, D. J. (1996). Emergence of simple-cell receptive field properties by learning a sparse code for natural images. Nature, 381, 607-609.

Brady, T. F., Konkle, T., & Alvarez, G. A. (2009). Compression in Visual Working Memory: Using Statistical Regularities to Form More Efficient Memory Representations. Journal of Experimental Psychology-General, 138(4), 487-502

5) Statistical learning

Nicolas Turk-Brown. (2012). Statistical learning and its consequences. *in* M. D. Dodds, J. H. Flowers (eds.) *The influence of attentions, learning and motivation on vision research* Nebraska Symposium on Motivation Springer, NY 117-146.

Fiser, J., and Aslin, R.N. (2002). Statistical learning of new visual feature combinations by infants. Proceedings of the National Academy of Sciences of the United States of America 99, 15822-15826.

Fiser, J., and Aslin, R.N. (2005). Encoding multielement scenes: Statistical learning of visual feature hierarchies. Journal of Experimental Psychology-General 134, 521-537

6) Rule learning

Marcus, G.F., Vijayan, S., Bandi Rao, S., and Vishton, P.M. (1999). Rule-learning by seven-month-old infants. Science 283, 77-80.

Pena, M., Bonatti, L.L., Nespor, M., and Mehler, J. (2002). Signal-driven computations in speech processing. Science 298, 604-607.

Saffran, J.R., Pollak, S.D., Seibel, R.L., and Shkolnik, A. (2007). Dog is a dog is a dog: Infant rule learning is not specific to language. Cognition 105, 669-680

MacKenzie, K. J. and Fiser, J. (2012). The relationship between statistical learning and rule learning in vision Cognition (under revision)

7) The probabilistic framework

Jacobs R. A., and Kruschke, J.K. (2011). Bayesian learning theory applied to human cognition Wiley Interdisciplinary Reviews in Cognitive Science, 8-21

Knill, D. C., Kersten, D., & Yuille, A., (1996) A Bayesian formulation of visual perception, in (Knill, D. C. and Richards, W., eds.) Perception as Bayesian Inference, Cambridge University Press. Cambridge, England. 1-21

Tenenbaum, J.B., Kemp, C., Griffiths, T.L., and Goodman, N.D. (2011). How to Grow a Mind: Statistics, Structure, and Abstraction. Science 331, 1279-1285

8) Applying the probabilistic framework to perception and learning

Kording, K.P., and Wolpert, D.M. (2004). Bayesian integration in sensorimotor learning. Nature 427, 244-247

Orbán, G., Fiser, J., Aslin, R.A., and Lengyel, M. (2008). Bayesian learning of visual chunks by human observers. Proceedings of the National Academy of Science 105, 2745-2750

Kemp, C., and Tenenbaum, J.B. (2008). The discovery of structural form. Proceedings of the National Academy of Sciences of the United States of America 105, 10687-10692.

9) Probabilistic interpretation of illusions and cue combination

Weiss, Y., Simoncelli, E.P., and Adelson, E.H. (2002). Motion illusions as optimal percepts. Nature Neuroscience 5, 598-604.

Atkins, J.E., Fiser, J., and Jacobs, R.A. (2001). Experience-dependent visual cue integration based on consistencies between visual and haptic percepts. Vision Research 41, 449-461

Series, P. and Seitz, A. R. (2013). Learning what to expect (in visual perception) Frontiers in Human Neuroscience 7, 1-14 doi: 10.3389/fnhum.2013.00668

10) Evidence for probabilistic processes in infants

Gopnik, A., Glymour, C., Sobel, D.M., Schulz, L.E., Kushnir, T., and Danks, D. (2004). A theory of causal learning in children: Causal maps and Bayes nets. Psychological Review 111, 3-32

Xu, F., and Garcia, V. (2008). Intuitive statistics by 8-month-old infants. Proceedings of the National Academy of Sciences of the United States of America 105, 5012-5015.

Teglas, E., Vul, E., Girotto, V., Gonzalez, M., Tenenbaum, J.B., and Bonatti, L.L. (2011). Pure Reasoning in 12-Month-Old Infants as Probabilistic Inference. Science 332, 1054-1059.

11) Spontaneous activity in the cortex

Kenet, T., Bibitchkov, D., Tsodyks, M., Grinvald, A., and Arieli, A. (2003). Spontaneously emerging cortical representations of visual attributes. Nature 425, 954-956

Fiser, J., Chiu, C.Y., and Weliky, M. (2004). Small modulation of ongoing cortical dynamics by sensory input during natural vision. Nature 431, 573-578.

Buckner, R.L., Andrews-Hanna, J.R., and Schacter, D.L. (2008). The brain's default network - Anatomy, function, and relevance to disease. In Year in Cognitive Neuroscience 2008, Volume 1124. pp. 1-38

12) Probabilistic theory of perception and learning and its neural evidence

Fiser, J., Berkes, P., Orban, G., and Lengyel, M. (2010). Statistically optimal perception and learning: from behavior to neural representations. Trends in Cognitive Sciences 14, 119-130.

Fiser, J. and Lengyel, G. (2022) Statistical learning in vision. Annual Review of Vision Science 8

Berkes, P., Orban, G., Lengyel, M., and Fiser, J. (2011). Spontaneous cortical activity reveals hallmarks of an optimal internal model of the environment. Science 331.