COURSE SYLLABUS

COMPUTATIONAL COGNITIVE SCIENCE

Instructor
Gergo Orban
Department of Cognitive Science, Central European University
Department of Computational Sciences, MTA Wigner RCP

Term: Fall 2018/19
Course level: PhD
Time and place: Thursday 1100 — 1240, room 103 Okt.6/7

Description
The course introduces rational analysis and its application to a range of domains in cognitive science. The main goal of the course is to introduce principles which are central to current computational theories in a format that requires only minimal mathematical background. Introduction of novel principles is followed by a demonstration of the ways these principles can be used to address problems in cognitive science. The course is supported by programming exercises which provides a tool to test the ideas in practice. These exercises are designed to be accessible to students with limited programming experience.

Learning outcomes
By the end of the course, students should
- understand mathematical concepts used in computational cognitive science
- have an overview of have these mathematical tools can be applied in cognitive science

- have experience with applying these tools to construct computational models

Evaluation
Students will have to
- attend classes and participate in discussions
- submit assignments
- final project

Lecture 1, 13 September
Functional models, rational analysis, probability calculus

- Marr D, Vision, MIT Press, Chapter 1
- Chater N, Oaksford M (1999) Ten years of the rational analysis of cognition. Trends

Cogn Sci 3(2):57–65.
- Jaynes ET, Probability Theory, Cambrdige University Press, Chapter 1

Optional:
- Russel S & Norvig P, Artificial intelligence, A moder Approach, Chapters 1.1 & 1.2

Lecture 2, 20 September
Introduction to probabilistic models, graphical models, Bayes rule, generative models

- Jaynes ET, Probability Theory, Cambrdige University Press, Chapter 2
- Battaglia PW, Hamrick JB, Tenenbaum JB (2013) Simulation as an engine of physical scene understanding. Proceedings of the National Academy of Sciences 110(45):18327–18332.
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Lecture 3, 27 September
Bayesian behavior, inference and priors

- Körding KP, Wolpert DM (2004) Bayesian integration in sensorimotor learning. Nature 427(6971):244–247.

Lecture 4, 4 October
Approximate inference, sampling

- Bishop CM, Pattern Recognition and Machine Learning, Springer, Chapter 11

Lecture 5, 11 October
Perceptual bistability and sampling in cognition

- Moreno-Bote R, Knill DC, Pouget A (2011) Bayesian sampling in visual perception. Proc Natl Acad Sci U S A 108(30):12491–12496.
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- Vul E, Goodman ND, Griffiths TL (2009) One and done? Optimal decisions from very few samples. Proceedings of the 31st Annual Conference of the Cognitive Science Society, pp 66–72.
- Sanborn AN, Griffiths TL, Navarro DJ (2010) Rational approximations to rational models: Alternative algorithms for category learning. Psych Rev 117(4):1144–1167.

Lecture 6, 11 October
Subjective beliefs, internal models, priors

- Weiss Y, Simoncelli EP, Adelson EH (2002) Motion illusions as optimal percepts. 5(6):598–604.
- Sanborn A, Griffiths T (2008) Markov chain Monte Carlo with people. Advances in neural information processing systems
- Houlsby NMT, et al. (2013) Cognitive Tomography Reveals Complex, Task-Independent Mental Representations. Curr Biol:1–7.

Lecture 7, 18 October
Source coding theorem, compression, rate distortion theory, information bottleneck

- Brady TF, Störmer VS, Alvarez GA (2016) Working memory is not fixed-capacity: More active storage capacity for real-world objects than for simple stimuli. Proceedings of the National Academy of Sciences 113(27):7459–7464.
- Sims CR (2016) Rate–distortion theory and human perception. Cognition 152:181–198.

Lecture 8, 25 October
Parametric and nonparametric probabilistic models

- Gershman SJ, Monfils MH, Norman KA, Niv Y (2017) The computational nature of memory modification. Elife. doi:10.7554/eLife.23763.001.

Lecture 9, 8 November
Occam's razor, marginal likelihood, structure learning, parametric and nonparametric approaches

- Tenenbaum JB, Kemp C, Griffiths TL, Goodman ND (2011) How to grow a mind: statistics, structure, and abstraction. Science 331(6022):1279–1285.

Lecture 10, 15 November
Structure learning in conditioning, causal learning and high-level vision, hierarchical models

- Courville AC, Daw ND, Touretzky DS (2006) Bayesian theories of conditioning in a changing world. Trends Cogn Sci 10(7):294–300.
- A. Gopnik, C. Glymour, D. Sobel, L. Schulz, T. Kushnir, & D. Danks (2004). A theory of causal learning in children: Causal maps and Bayes nets. Psychological Review 111(1):1-31
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- Kemp C, Tenenbaum JB (2008) The discovery of structural form. Proc Natl Acad Sci U S A 105(31):10687–10692.
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Lecture 11, 8 November
Particle filters

- Daw ND, Courville AC (2008) The pigeon as particle filter. Advances in Neural Information Processing Systems 20 (MIT Press, Cambridge, MA), pp 369–376.
- Bramley NR, Dayan P, Psychological TG, 2017 Formalizing Neurath's ship: Approximate algorithms for online causal learning. psycnetapaorg. doi:10.1037/rev0000061.supp.
- Gebhart AL, Aslin RN, Newport EL (2009) Changing Structures in Midstream:

Learning Along the Statistical Garden Path. Cognitive Science 33(6):1087–1116.

Lecture 12, 29 November
Probablistic programs

- Goodman, Mansinghka, et al., 2008
- Lake Science
- Goodman?

Lecture 13, 6 December
Project presentations