**Syllabus – Advanced Cognitive Modeling – Spring 2020**

Cognitive models are explicit formalizations of cognitive theories. But they are much more than that. When applied to data, cognitive models can afford deep insights about how people learn, choose, perceive, and co-operate in experimental and real world settings. Cognitive modeling is thus remarkably integrative. It allows us to combine many of the strengths of theory, data, measurement, and experimentation in the same logical system. The purpose of this course is to provide you with knowledge and skills in building cognitive models from existing theory, in evaluating the strengths and weaknesses of existing models, and in applying models you have built to novel data sets. At the end of the course, you should be able to start thinking about how to use your own theoretical knowledge in cognitive science to build your own models.

The theoretical focus of the course is on learning, decision making, and social interaction, but the methods learned in the course can be applied within any theoretical domain. The course is divided into five modules. These modules are focused on 1) the basic mechanics of Bayesian modeling, and the modeling language JAGS; 2) a priori evaluation and comparison of models of learning and choice; 3) applying and extending reinforcement learning models of decision making, with applications to empirical data; 4) modeling social co-operation, and 5) using cognitive modeling to make inferences about group and individual differences.

The course will be very hands on. The main goal of the course is not just for you to understand how cognitive modeling works, but to build and use your own models. Most modules will start with theoretical lecturing of 2-4 hours. The remainder of each module will focus on live/collaborative coding, led by me, with selected exercises for you to complete in class and for homework. Each module will end with a portfolio writing workshop. All of these activities will be focused on building, using, and explaining models, and class time will be devoted to going from a blank page to functional model code; complete with simulations, a priori tests, and inference. We will take the time to do this together, and there will be time for lots of questions. The schedule for the course will therefore be somewhat flexible, and adaptive to your collective learning speed.

There will not be many readings for this class. But the readings you have will be difficult and you will need to read some of them multiple times. There will be equations in the papers, and you will need to understand the equations and how they formalize cognitive processes. And you will need to learn how to translate the equations into working code. You will get help with this, and this is the purpose of the class work. You should read the papers before the starting lectures for each module. There may be some additional papers assigned later, depending on the empirical cases we use in later modules.

There is a portfolio examination associated with each module. The exam is pass or fail. The focus of the portfolio is not on coding. It is on understanding the models you are working with, on understanding the processes we use to evaluate and compare models, and on understanding how to make appropriate inferences from models and data. Portfolios will therefore be more focused on equations, figures, numbers, and prose text. You should support your answers in module portfolios with reference to the readings. After you’ve completed the classes and exams, you’ll know how to develop your own model code, and to effectively communicate your models and the inferences you want to draw from them.

**Module 1: Building models to infer the cognitive causes of behavior: Approx. Class 1 – 4**

The aim of this module is for you to get up and running with the software, and start thinking about how to construct models as systems of interacting probability distributions. We will cover the main concepts from graphical modeling and probability that we’ll be using in the course, and you’ll start using the JAGS software. We’ll build a couple of very simple models together, and start to think about some important a priori conditions of good cognitive models. There will be more reading in this module than the others.

***Readings:***

***For Class 1:***

Busemeyer, J. R., & Diederich, A. (2009). *Cognitive Modeling.* Sage.

Chapter 1: Introduction to Cognitive Modeling. Available as free excerpt from book website. <https://uk.sagepub.com/en-gb/eur/cognitive-modeling/book226030#preview>

***For Class 2-3:***

Pearl. J. (2018). The Book of Why. New York: Basic Books.

Chapter 1: The Ladder of Causation. Available as free excerpt from author’s website. <http://bayes.cs.ucla.edu/WHY/>

Lee, M. D., & Wagenmakers, E. J. (2014). *Bayesian Cognitive Modeling: A Practical Course.* Cambridge University Press.

Chapter 3: Inferences From Binomials. Available as download from book website <https://bayesmodels.com/>

Robinson, D. (2014). Understanding the Beta Distribution. Blog available. <http://varianceexplained.org/statistics/beta_distribution_and_baseball/>

Toboga, M. (online). Beta Distribution on StatLect Blog available <https://www.statlect.com/probability-distributions/beta-distribution>

***For Class 3-4***

Heathcote, A., Brown, S. D., & Wagenmakers, E.-J. (2015). An introduction to good practices in cognitive modeling. In B. U. Forstmann, & E.-J. Wagenmakers (Eds.), *An Introduction to Model-Based Cognitive Neuroscience*, pp. 25-48. Springer: New York.

Available as download on the author’s homepage <http://ejwagenmakers.com/inpress/HeathcoteModelingIntro.pdf>

Wilson & Collins (2019). Ten simple rules for the computational modeling of behavioural data *PsyarXiv Preprint.* <https://psyarxiv.com/46mbn/>

Anglim, J. (2012) Getting started with JAGS, rjags, and Bayesian Modelling. *R-bloggers blog.* <https://www.r-bloggers.com/getting-started-with-jags-rjags-and-bayesian-modelling/>

**Module 2: Modeling learning and choice: Approx. Class 5 – 9**

The aim of this module is for you to start thinking theoretically about the relationships between models and data. We’ll take a closer look at some classic – and very important – models of learning and choice. These models will form the theoretical basis of much of the rest of the course. We’ll delve deeper into a priori methods for evaluating models, and look closely at the kinds of scientific decisions that need to be made when constructing cognitive models.

***Readings***

Rescorla, R.A., & Wagner, A.R. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In A.H. Black & W.F. Prokasy (Eds.) *Classical Conditioning II*. pp. 64–99. Appleton-Century-Crofts.

Pleskac, T. J. (2015). Decision and Choice: Luce’s Choice Axiom. In J. D. Wright (Ed). *International Encyclopedia of the Social & Behavioral Sciences* (Second Edition).

Re-Read Wilson and Collins (2019).

**Module 3: Applying and extending decision models: Approx. Class 10 – 15**

The aim of this module is for you to start thinking about modeling in terms of competition between theories, and to start applying theory to data. Here we’ll focus on model comparison and start to apply a posteriori methods for evaluating and comparing models as explanations of empirical phenomena. We will do this in the context of the classic decision making paradigm, the Iowa Gambling Task. We will assess competing theoretical explanations of performance on the task, and apply our models to explaining meaningful empirical phenomena.

***Readings***

Steingroever, H., Wetzels, R., & Wagenmakers, E.-J. (2013). Validating the PVL-Delta model for the Iowa gambling task. Frontiers in Psychology, 4.

Haines, N., Vassileva, J., & Ahn, W.-Y. (2018). The Outcome-Representation Learning Model: A Novel Reinforcement Learning Model of the Iowa Gambling Task. Cognitive Science, 42(8), 2534–2561.

Ligneul, R. (2019). Sequential exploration in the Iowa gambling task: Validation of a new computational model in a large dataset of young and old healthy participants. PLOS Computational Biology, 15(6), e1006989.

**Module 4: Modeling interaction – combing cognitive and agent based models: Approx. Class 16 – 21**

The aim of this module is generalize your learning to contexts involving social interaction, and to begin modeling more complex behaviours. We will focus on the tragedy of the commons and the public goods game, and investigate competing theories of group behavior in this context. We will draw some connections between cognitive modeling and agent-based methods for understanding social behavior.

***Readings***

Camerer, C., & Ho, T. H. (2003). Experience-weighted attraction learning in normal form games. *Econometrica, 67*(4), 827-874

Fischbacher, U., & Gachter, S. (2010). Social preferences, beliefs, and the dynamics of free riding in public goods experiments. *American Economic Review, 100*(1), 541-556.

**Module 5: Inferring group and individual differences: Approx. Class 22 – 24**

The aim of this module is for to start making inferences from hierarchically structured data. The focus of the module will be on simple differences between groups, and on individual differences within groups. You will learn how to embed your models in hierarchical Bayesian tests. You will also learn how to use latent mixture models to make inferences about individual differences. We will start to think about how some competing cognitive models may be better understood as alternative cognitive strategies for solving the same task, rather than competing theories of underlying processes.

***Readings***

Lee, M. D., & Wagenmakers, E. J. (2014). *Bayesian Cognitive Modeling: A Practical Course.* Cambridge University Press.

Chapter 6: Latent Mixture Models. Available as download from book website <https://bayesmodels.com/>

Wetzels, R., Raaijmakers, J. G. W., Jakab, E., & Wagenmakers, E.-J. (2009). How to quantify support for and against the null hypothesis: A ﬂexible WinBUGS implementation of a default Bayesian t test. *Psychonomic Bulletin & Review, 16*, 752–760