Mathematical Psychology satellite meeting

The meeting is scheduled in Room 516A of the Montreal Convention Centre on November 14, 2019.

The Lexical Context Model: A continuous bag of words model of semantic and episodic memory

Dr. Cassandra Jacobs, University of Wisconsin

Tulving (1972) proposed that semantic memory is fundamentally different than episodic memory, using different representations and processes. In support of this proposal, most episodic memory models assume conjunctive representations that are unique to episodic memory, even if they build upon semantic memory. Hintzman's MINERVA model (1984) is a notable exception, assuming that semantic memory reflects the combination of episodic traces during retrieval. Like Hintzman, we propose a single form of memory, capturing episodic memory phenomena within a model of word meaning. However, unlike Hintzman, we propose that episodic memory reflects small changes to distributed semantic memory. We propose the Lexical Context Model of episodic list learning, which builds on the continuous bag-of-words (CBOW) model (Mikolov et al., 2013), a model of distributional semantics that explicitly formulates learning word meaning as the process of predicting a word by the words that surround it in a text. Previous work with CBOW has explained semantic memory phenomena, including brain activity, lexical processing, and spontaneous naming data. In this initial investigation, LCM accounts for a range of memory phenomena, including effects of serial order (primacy and recency), list length, item strength, and pure/mixed list composition effects. The LCM demonstrates that a single learning mechanism and distributed representation can parsimoniously account for many behaviors from both episodic and semantic memory tasks.

Are you an exception to Cumulative Prospect Theory?

Dr. Michel Regenwetter, University of Illinois at Urbana-Champaign

I discuss internal inconsistencies and oversimplifications surrounding Tversky and Kahneman's (1992) seminal paper on Cumulative Prospect Theory. Their test of loss aversion provides evidence that half of the population violates their theory. Among those who satisfy Cumulative Prospect Theory, everyone may nonetheless systematically violate at least some of the stylized characteristics that permeate both popular science and scholarly treatises about how 'people' make decisions.

Bayesian hierarchical modeling of cognitive processes: Benefits and pitfalls

Dr. Julia Haaf, University of Amsterdam

Cognitive process models are a popular tool to examine the underlying processing structure of cognitive phenomena. These models can be applied to data in three different ways: 1. To data from each individual participants independently; 2. to data aggregated across all participants; and 3. to the data on the trial-level and for all participants combined. The latter implies the use of hierarchical modeling where participant-level random effects are introduced, and the approach has many frequently discussed benefits. Here, I highlight one such benefit of hierarchical cognitive models that is commonly overlooked: the possibility to properly assess individual differences based on the distribution of individual-level parameters. I discuss that individual differences may affect the empirical validity of cognitive process models, and how validity can be assessed using a strict selective influence test. I also highlight a potential pitfall of Bayesian hierarchical modeling in this context, the specification of inappropriate prior distributions.

Science, statistics and the problem of pretty good inference

Dr. Danielle Navarro, University of New South Wales

A central problem facing scientists is choosing the most appropriate explanation of some observed phenomenon. In statistics, we face an analogous problem of selecting the model that provides the "best" account of a data set. The two problems have much in common, but in this talk I'll argue that in practice they are not the same. Part of the scientific problem we face—particularly in psychology—is that all of our theories (both formal and informal) are wrong, and usually quite badly wrong, yet we still need to make decisions about which of these (bad) theories is the most useful one to guide our future work. In statistics, the analogous problem is one of model misspecification – we cannot select the "true" model because in all likelihood no such thing exists, and even if it did it most certainly does not exist among the models under consideration. This leaves us facing the problem of "pretty good inference" – of trying to make inferences that will guide us toward sensible actions despite our ignorance of the world. In this talk I do not propose any strong "solutions" to this problem, but will aim to highlight how this perspective creates a certain tension between what we hope to achieve (learning about the world) and the tools we usually rely on—as open scientists—to do so.