Qualifying Examination

Reading Lists (87 papers)

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1 Active Learning (26 papers)

> *Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's?*
> — Alan M. Turing, *Computing Machinery and Intelligence (1950)*

Imagine, to train a human-like machine, how tiresome, if not hopeless, it would be if you have to feed every bit of information it needs. How much easier it can be if this machine can direct it own learning, selecting or generating the right data to learn the right things! Even humans infants are capable of this kind of *active learning*. But how?

As a prerequisite, to sift through the data-rich environment for useful information, an active learner needs a criterion to evaluate information. I open this topic with an overview of the idea of *optimal experiment design* and *sampling norms* that quantify the usefulness of queries. To start active learning, one needs to be motivated and attend to information within her grasp. Here, I include papers on curiosity and selective attention. Then, one needs to actually engage with the environment, generate useful data, and learn from them. Here, I include papers on three case studies: exploratory play, causal interventions, and question-asking. Finally, despite its remarkable potential, active learning does not guarantee that the learner can always figure out the best solution in the most efficient way. Here, I include papers on the limitations and the adaptiveness of active learning..

Questions

1. There are many different ways to understand "active learning". For instance, it could mean being physically active while learning (Hillman et al., 2008). It could mean "doing something besides passively listening" (Bonwell, 1991). Or, it could mean "situations where learners have control of the flow information they experience by way of their ongoing decisions" (Gureckis & Markant, 2012). Also, the active learning literature encompasses a wide range of phenomena, such as visual search, attention, curiosity, exploratory play, question asking, etc.. It seems all learning inevitably has some active components in it.

   What is and isn't active learning? Please describe the central/common characteristics of active learning. Why should we carve up a niche for active learning if all learning can be seen as somewhat active? Elaborate on what you think is the theoretical or practical purchase of studying active learning.

2. The idea of that the child may be an "active learner" has long been popular in developmental psychology (Bruner, 1961; Piaget, 1955), but education research over the past few decades repeatedly demonstrated that children may have limited ability to generate useful evidence and learn from it (Klahr & Nigam, 2004; Kuhn, 1989; Kuhn, Amsel, & O'Laughlin, 1988; Koslowski, 1996; Masnick & Klahr, 2003). However, in recent years, research in

machine learning (e.g., Castro et al., 2008) and human learning (e.g., Markant & Gureckis, 2014; Sim & Xu, 2017) found that under certain conditions, active learning can be superior to passive learning.

How do you reconcile this contradiction? Describe when active learning may have the most benefits and explain where these benefits come from. Also, describe when active learning may not be beneficial and explain how these shortcomings arise. Can you propose 2–4 ways to overcome the limits of active learning in these circumstances?

1.1 Overview (4 papers)

1.1.1 Background & Major Issues (2 papers)

(1) Coenen, A., Nelson, J. D., & Gureckis, T. M. (under review). Asking the right questions about human inquiry.

(2) Gureckis, T. M. & Markant, D. B. (2012) Self-directed learning: A cognitive and computational perspective. *Perspectives on Psychological Science, 7*, 464-481.

1.1.2 Value of Information (2 papers)

(1) Nelson, J. D. (2005). Finding useful questions: On Bayesian diagnosticity, probability, impact, and information gain. *Psychological Review, 112*(4), 979-999.

(2) Nelson, J. D., McKenzie, C. R., Cottrell, G. W., & Sejnowski, T. J. (2010). Experience matters: Information acquisition optimizes probability gain. *Psychological Science, 21*(7), 960-969.

1.2 Case Studies (16 papers)

1.2.1 Attention & Curiosity (2 papers)

(1) Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2012). The Goldilocks effect: Human infants allocate attention to visual sequences that are neither too simple nor too complex. *PloS ONE, 7*(5), e36399.

(2) Gottlieb, J., Oudeyer, P. Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. *Trends in Cognitive Sciences, 17*(11), 585-593.

1.2.2 Exploration & Play (7 papers)

(1) Bruner, J. (1961) The act of discovery. *Harvard Educational Review, 31*, 21-32.

(2) Sim, Z. L., & Xu, F. (2017). Learning higher-order generalizations through free play: Evidence from 2- and 3-year-old children. *Developmental Psychology, 53*(4), 642-651.

(3) Schulz, L. E. (2012). The origins of inquiry: Inductive inference and exploration in early childhood. *Trends in Cognitive Sciences, 16,* 382-389.

(4) Schulz, L. E., & Bonawitz, E. B. (2007). Serious fun: Preschoolers engage in more exploratory play when evidence is confounded. *Developmental Psychology, 43*(4), 1045-1050.

(5) Cook, C., Goodman, N., & Schulz, L. E. (2011). Where science starts: Spontaneous experiments in preschoolers' exploratory play. *Cognition, 120*(3), 341-349.

(6) Bonawitz, E. B., van Schijndel, T. J. P., Friel, D., & Schulz, L. E. (2012). Children balance theories and evidence in exploration, explanation, and learning. *Cognitive Psychology, 64*(4), 215-234.

(7) Kretch, K. S., & Adolph, K. E. (2017). The organization of exploratory behaviors in infant locomotor planning. *Developmental Science, 20*(4), 1-17.

1.2.3 Causal Intervention (4 papers)

(1) Steyvers, M., Tenenbaum, J. B., Wagenmakers, E. J., & Blum, B. (2003). Inferring causal networks from observations and interventions. *Cognitive Science, 27*(3), 453-489.

(2) Schulz, L. E., Gopnik, A., & Glymour, C. (2007). Preschool children learn about causal structure from conditional interventions. *Developmental Science, 10*(3), 322-332.

(3) McCormack, T., Bramley, N. R., Frosch, C., Patrick, F. & Lagnado, D. A. (2016). Children's use of interventions to learn causal structure. *Journal of Experimental Child Psychology. 141,* 1-22.

(4) Coenen, A., Rehder, B., & Gureckis, T. M. (2015). Strategies to intervene on causal systems are adaptively selected. *Cognitive Psychology, 79,* 102-133.

1.2.4 Question Asking (3 papers)

(1) Ruggeri, A., & Lombrozo, T. (2015). Children adapt their questions to achieve efficient search. *Cognition, 143,* 203-216.

(2) Ruggeri, A., Lombrozo, T., Griffiths, T. L., & Xu, F. (2016). Sources of developmental change in the efficiency of information search. *Developmental Psychology, 52*(12), 2159-2173

(3) Mills, C. M., Legare, C. H., Grant, M. G., & Landrum, A. R. (2011). Determining who to question, what to ask, and how much information to ask for: The development of inquiry in young children. *Journal of Experimental Child Psychology, 110*(4), 539-560.

1.3 Adaptiveness & Limitations (6 papers)

1.3.1 Environments & Tasks (4 papers)

(1) Oaksford, M., & Chater, N. (1994). A rational analysis of the selection task as optimal data selection. *Psychological Review, 101*(4), 608-631.

(2) Navarro, D. J., & Perfors, P. F. (2011). Hypothesis generation, sparse categories, and the positive test strategy. *Psychological Review, 118*(1), 120-134.

(3) Markant, D., & Gureckis, T. M. (2012). Does the utility of information influence sampling behavior?. In *Proceedings of the 34th Annual Conference of the Cognitive Science Society*.

(4) Coenen, A., & Gureckis, T. M. (2017). The distorting effect of deciding to stop sampling. In *Proceedings of the 39th Annual Meeting of the Cognitive Science Society*.

1.3.2 Sampling Costs (2 papers)

(1) Denrell, J., & March, J. G. (2001). Adaptation as information restriction: The hot stove effect. *Organization Science, 12*(5), 523-538.

(2) Bramley, N. R., Dayan, P., Griffiths, T. L., & Lagnado, D. A. (2017). Formalizing Neurath's Ship: Approximate algorithms for online causal learning. *Psychological Review, 124*(3), 301-338.

2 Social Learning (31 papers)

If I have seen further, it is by standing on the shoulders of giants.
— Isaac Newton, *Letter to Hook (1676)*

Learning doesn't get far if each learner has to figure out everything on her own; even an extraordinary mind like Newton needed to stand on the "shoulders of giants". Social learning, or *learning from others*, provides quick and cheap information. Moreover, cumulative culture gives learners access to more complex ideas and tools than individuals could create. However, social learning comes with a price. If the source is misinformed, so will the learner be; if the blind continue to lead the blind, nonadaptive behavior may spread and harm a population's fitness. Under what conditions can social learning increase a population's fitness, allowing it to ratchet up in technological complexity and preventing it from slipping back? Most importantly for developmental psychologists, how does the selection pressure on the population level translate to goals of individual learners, including the youngest humans?

I begin with the role culture plays in our species' widespread success. I shift to the uniqueness and the root of our culture before moving on to the analysis of how social learning can contribute to cumulative culture. Like analysis on the computational level sheds light on the goal of a cognitive system, analysis on the population level sheds light on the goal of an individual learner. For instance, one should be selective about when to learn from others, whom to learn from, and in what manner (e.g., faithfully vs. flexibly). Here, I include papers on epistemic trust and cases studies on social learning that follows, including imitation/overimitation, pedagogy, testimony, language, norms and conventions, etc.. I transit to the mechanisms underlying social learning; in particular, whether they differ from those of asocial learning. I conclude this topic with papers on how social learning may differ in different cultures.

Questions

1. "It takes a village to raise a child". Instead of tirelessly figuring everything out by themselves, human children often learn from other people and inherit cultural wisdom accumulated over generations. How do social learning (i.e., learning from others) support individual development and contribute to the success of our species?

   Provide 3–4 examples where social learning facilitates children's learning and explain why. Also, what may be some "pitfalls"? Then, discuss how social learning is related to the human success. To answer this question, you may want to compare 1) different theories (e.g., culture niche vs. cognitive niche, etc.) and 2) consequences of different types of social learning (e.g., high-fidelity imitation vs. flexible imitation, etc.). Finally, how do you think the analysis on the population level can inform empirical research on the individual level?

2. On the one hand, learning socially constructed knowledge (e.g., language, tool use, rituals, etc.) seems no different from learning about physical-causal knowledge: learners observe some data in the world and update their beliefs accordingly. On the other, some (e.g., Legare & Nielsen, 2015) suggest that conventional learning may have fundamentally different mechanisms from instrumental learning: successful learning thus depends on adjudicating between when to engage in what type of learning.

   Both views have support in the literature. Provide 2-4 examples for each and discuss whether you are convinced.

2.1 Culture and Learning (9 papers)

2.1.1 The Role of Culture (3 papers)

(1) Boyd, R., Richerson, P. J., & Henrich, J. (2011). The cultural niche: Why social learning is essential for human adaptation. *Proceedings of the National Academy of Sciences, 108*(26), 10918-10925.

(2) Pinker, S. (2010). The cognitive niche: Coevolution of intelligence, sociality, and language. *Proceedings of the National Academy of Sciences, 107*(Supplement 2), 8993-8999.

(3) Morgan, T. J. (2016). Testing the cognitive and cultural niche theories of human evolution. *Current Anthropology, 57*(3), 370-377.

2.1.2 "Uniqueness" & Roots (4 papers)

(1) Whiten, A., Caldwell, C. A., & Mesoudi, A. (2016). Cultural diffusion in humans and other animals. *Current Opinion in Psychology*, 8, 15-21.

(2) Dean, L. G., Vale, G. L., Laland, K. N., Flynn, E., & Kendal, R. L. (2014). Human cumulative culture: A comparative perspective. *Biological Reviews, 89*(2), 284-301.

(3) Hare, B. (2017). Survival of the friendliest: Homo sapiens evolved via selection for prosociality. *Annual Review of Psychology, 68,* 155-186.

(4) Purzycki, B. G., Apicella, C., Atkinson, Q. D., Cohen, E., McNamara, R. A., Willard, A. K., Xygalatas, D., Norenzayan, A., & Henrich, J. (2016). Moralistic gods, supernatural punishment and the expansion of human sociality. *Nature, 530*(7590), 327-330.

2.1.3 Cultural Evolution (2 papers)

(1) Boyd, R., & Richerson, P. J. (1995). Why does culture increase human adaptability?. *Ethology and Sociobiology, 16*(2), 125-143.

(2) Whiten, A., & Flynn, E. (2010). The transmission and evolution of experimental microcultures in groups of young children. *Developmental Psychology, 46*(6), 1694.

2.2 Learning from & about Others (22 papers)

2.2.1 Epistemic Trust (5 papers)

(1) Landrum, A.R. Eaves Jr, B.S. & Shafto, P. (2015). Learning to trust and trusting to learn: A theoretical framework. *Trends in Cognitive Sciences, 19,* 109-111.

(2) Harris, P. L., Koenig, M. A., Corriveau, K. H., & Jaswal, V. K. (2018). Cognitive foundations of learning from testimony. *Annual Review of Psychology, 69*(1), 253–273.

(3) Kominsky, J. F., Langthorne, P., & Keil, F. C. (2016). The better part of not knowing: Virtuous ignorance. *Developmental Psychology, 52*(1), 31-45.

(4) Whalen, A., Griffiths, T. L., & Buchsbaum, D. (2017). Sensitivity to shared information in social learning. *Cognitive Science, 42*(1), 168-187.

(5) Kinzler, K. D., Corriveau, K. H., & Harris, P. L. (2011). Children's selective trust in native-accented speakers. *Developmental Science, 14*(1), 106-111.

2.2.2 Case Studies (7 papers)

(1) Kalish, C. W., & Sabbagh, M. A. (2007). Conventionality and cognitive development: Learning to think the right way. *New Directions for Child and Adolescent Development, 2007*(115), 1-9.

(2) Clark, E. V. (2010). Learning a language the way it is: Conventionality and semantic domains. In B. C. Malt & P. Wolff (Eds.), *Words and the mind: How words capture human experience*. (pp. 243-265). New York, NY: Oxford University Press.

(3) Schmidt, M. F., Butler, L. P., Heinz, J., & Tomasello, M. (2016). Young children see a single action and infer a social norm: Promiscuous normativity in 3-year-olds. *Psychological Science, 27*(10), 1360-1370.

(4) Legare, C. H., Sobel, D. M., & Callanan, M. (2017). Causal learning is collaborative: Examining explanation and exploration in social contexts. *Psychonomic Bulletin & Review, 24*(5), 1548-1554.

(5) Bridgers, S., Buchsbaum, D., Seiver, E., Griffiths, T. L., & Gopnik, A. (2016). Children's causal inferences from conflicting testimony and observations. *Developmental Psychology, 52*(1), 9-18.

(6) Butler, L. P., & Markman, E. M. (2014). Preschoolers use pedagogical cues to guide radical reorganization of category knowledge. *Cognition, 130*(1), 116-127.

(7) Rhodes, M., Leslie, S. J., & Tworek, C. M. (2012). Cultural transmission of social essentialism. *Proceedings of the National Academy of Sciences, 109*(34), 13526-13531.

2.2.3 Consequences (2 papers)

(1) Bonawitz, E., Shafto, P., Gweon, H., Goodman, N. D., Spelke, E., & Schulz, L. (2011). The double-edged sword of pedagogy: Instruction limits spontaneous exploration and discovery. *Cognition, 120,* 322-330.

(2) Lyons, D. E., Young, A. G., & Keil, F. C. (2007). The hidden structure of overimitation. *Proceedings of the National Academy of Sciences, 104*(50), 19751-19756.

2.2.4 Mechanisms (6 papers)

(1) Csibra, G., & Gergely, G. (2009). Natural pedagogy. *Trends in Cognitive Sciences, 13*(4), 148-153.

(2) Legare, C. H., & Nielsen, M. (2015). Imitation and innovation: The dual engines of cultural learning. *Trends in Cognitive Sciences, 19*(11), 688-699.

(3) Heyes, C. (2016). Who knows? Metacognitive social learning strategies. *Trends in Cognitive Sciences, 20*(3), 204-213.

(4) Schachner, A., & Carey, S. (2013). Reasoning about 'irrational' actions: When intentional movements cannot be explained, the movements themselves are seen as the goal. *Cognition, 129*(2), 309-327.

(5) Hu, J., Buchsbaum, D., Griffiths, T. & Xu, F. (2013) When does the majority rule? Preschoolers' trust in majority informants varies by task domain. In *Proceedings of the 35th Annual Conference of the Cognitive Science Society*.

(6) Jara-Ettinger, J., Gweon, H., Schulz, L. E., & Tenenbaum, J. B. (2016). The naive utility calculus: Computational principles underlying commonsense psychology. *Trends in Cognitive Sciences, 20*(8), 589-604.

2.2.5 Cross-Cultural Comparison (2 papers)

(1) Clegg, J. M., & Legare, C. H. (2016). A cross-cultural comparison of childrenâĂŹs imitative flexibility. *Developmental Psychology, 52*(9), 1435-1444.

(2) Rogoff, B., Moore, L., Najafi, B., Dexter, A., Correa-Chávez, M., & Solís, J. (2007). Children's development of cultural repertoires through participation in everyday routines and practices. In J. E. Grusec & P. D. Hastings (Eds.), *Handbook of socialization: Theory and research* (pp. 490-515). New York, NY, US: Guilford Press.

3 Probabilistic Models of Cognition (30 papers)

In order to understand bird flight, we have to understand aerodynamics; only then does the structure of feathers and the different shapes of bird's wings make sense.

— David Marr, *Vision (1982)*

Lying at the heart of the mystery of human knowledge is the age-old question, how can we learn anything abstract and generalizable at all from concrete, transient, and noisy sensory input, let alone so much and so quickly?

Over the last three decades, probabilistic models of cognition have offered many exiting answers. Traditionally, they address questions at Marr's computational level by elucidating what problem a cognitive system is trying to solve and offering an optimal solution to that problem under certain constraints, which allows us to understand the goal of learning as well as what can in principle be learned. This approach proves highly fruitful and has lent new insights to challenging problems such as the origin of abstract knowledge (e.g., hierarchical Bayesian models), how structured knowledge can be combined with statistical evidence (e.g., theory-based Bayesian models), one-shot learning of rich concepts (e.g., Bayesian program induction), etc.. Recently, probabilistic models such as rational process models also begin to address questions at lower levels, asking what algorithms learners can use to approximate (often intractable) Bayesian inference or what heuristics they should choose for a given task. However, it's worth noting that probabilistic models are not the only modeling framework in cognitive science and they don't go without criticism—we should be aware of the strengths and the weaknesses of different frameworks.

Here, I begin this topic with papers on rational analysis and comparison among different modeling frameworks in cognition. Then I choose to focus on probabilistic models of cognition, shifting to papers on key concepts behind probabilistic models of cognition, cases studies on language and causality, and the recent advancement towards the algorithmic level. I conclude with papers critiquing probabilistic models and papers that responded to these critiques and pointed out alternative approaches forward.

Questions

1. Probabilistic models become increasingly popular and have been applied to studying a wide range of phenomena, ranging from perception, motor control, etc., to higher-level cognition. What are probabilistic models of cognition? What makes them appealing? What kind of questions can they address?

   To answer these questions, you may want to compare probabilistic models with alternatives (e.g., non-probabilistic models, heuristics, etc.). For the last question, you may also want to compare different "flavors" of probabilistic models (rational analysis, ideal observer analysis, descriptive Bayesian models, rational process models, etc.).

2. In recent years, probabilistic models have shed light upon many majors topics in cognitive development, helping researchers 1) rethink familiar findings, 2) generate new empirical research, and 3) resolve age-old debates and puzzles (e.g., the poverty of the stimulus, nativism vs. empiricism, etc.), etc..

   Provide 2–3 examples for each aspect and discuss how probabilistic models generate new insights. In the future, what new cognitive development problems do you wish to address using probabilistic models? Please elaborate.

3. Despite the exiting progress made by probabilistic models, opponents and proponents alike have raised many concerns. List and discuss 4–5 concerns. Which ones do you think resulted from misunderstandings? Can you clarify them? Which ones do you agree with and might potentially help improve probabilistic models? How?

3.1 Overview (7 papers)

3.1.1 Rational Analysis (3 papers)

(1) Marr, D. (1982). The philosophy and the approach. In *Vision* (pp. 8-29). San Francisco, CA: Freeman.

(2) Anderson, J. R. (1990). Introduction. In *The adaptive character of thought* (pp. 1-40). Hillsdale, NJ: Erlbaum.

(3) Chater, N. & Oaksford, M. (1999). Ten years of the rational analysis of cognition. *Trends in Cognitive Science, 3*(2), 57-65.

3.1.2 Frameworks for Cognitive Modeling (4 papers)

(1) McClelland, J. L. (2009). The place of modeling in cognitive science. *Topics in Cognitive Science, 1*(1), 11-38.

(2) Piantadosi, S. T., & Jacobs, R. A. (2016). Four problems solved by the probabilistic language of thought. *Current Directions in Psychological Science, 25*(1), 54-59.

(3) McClelland, J. L., Botvinick, M. M., Noelle, D. C., Plaut, D. C., Rogers, T. T., Seidenberg, M. S., & Smith, L. B. (2010). Letting structure emerge: Connectionist and dynamical systems approaches to cognition. *Trends in Cognitive Sciences, 14*(8), 348-356.

(4) Griffiths, T. L., Chater, N., Kemp, C., Perfors, A., & Tenenbaum, J. B. (2010). Probabilistic models of cognition: Exploring representations and inductive biases. *Trends in Cognitive Sciences, 14*(8), 357-364.

3.2 On the Computational Level (12 papers)

3.2.1 Foundation (4 papers)

(1) Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. *Science, 331*(6022), 1279-1285.

(2) Kemp, C., Perfors, A., & Tenenbaum, J. B. (2007). Learning overhypotheses with hierarchical Bayesian models. *Developmental Science, 10*(3), 307-321.

(3) Lake, B. M., Salakhutdinov, R., & Tenenbaum, J. B. (2015). Human-level concept learning through probabilistic program induction. *Science, 350*(6266), 1332-1338.

(4) Perfors, A. (2012). Bayesian models of cognition: What's built in after all?. *Philosophy Compass, 7*(2), 127-138.

3.2.2 Case Studies: Language (4 papers)

(1) Xu, F., & Tenenbaum, J. B. (2007). Word learning as Bayesian inference. *Psychological Review, 114*(2), 245–272.

(2) Perfors, A., Tenenbaum, J. B., & Regier, T. (2011). The learnability of abstract syntactic principles. *Cognition, 118*(3), 306-338.

(3) Frank, M. C., & Goodman, N. D. (2012). Predicting pragmatic reasoning in language games. *Science, 336*(6084), 998-998.

(4) Meylan, S.C., Frank, M.C., Roy, B.C., & Levy, R. (2017). The emergence of an abstract grammatical category in children's early speech. *Psychological Science, 28*(2), 181-192.

3.2.3 Case Studies: Causality (4 papers)

(1) Griffiths, T. L., & Tenenbaum, J. B. (2007). From mere coincidences to meaningful discoveries. *Cognition, 103*(2), 180-226.

(2) Griffiths, T. L., & Tenenbaum, J. B. (2009). Theory-based causal induction. *Psychological Review, 116*(4), 661-716.

(3) Goodman, N. D., Ullman, T. D., & Tenenbaum, J. B. (2011). Learning a theory of causality. *Psychological Review, 118*(1), 110-119.

(4) Pacer, M. D. & Griffiths, T. L. (2011). A rational model of causal inference with continuous causes. In *Advances in Neural Information Processing Systems 24*.

3.3 Towards the Algorithmic Level (6 papers)

3.3.1 Foundation (2 papers)

(1) Griffiths, T. L., Lieder, F., & Goodman, N. D. (2015). Rational use of cognitive resources: Levels of analysis between the computational and the algorithmic. *Topics in Cognitive Sscience, 7*(2), 217-229.

(2) Gershman, S. J., Horvitz, E. J., & Tenenbaum, J. B. (2015). Computational rationality: A converging paradigm for intelligence in brains, minds, and machines. *Science, 349*(6245), 273-278.

3.3.2 Case Studies (4 papers)

(1) Vul, E., Goodman, N. D., Griffiths, T. L., & Tenenbaum, J. B. (2014). One and done? Optimal decisions from very few samples. *Cognitive Science, 38*(4), 599âĂŞ637.

(2) Sanborn, A. N., Griffiths, T. L., & Navarro, D. J. (2010). Rational approximations to rational models: Alternative algorithms for category learning. *Psychological Review, 117*(4), 1144-1167.

(3) Bonawitz, E., Denison, S., Gopnik, A., & Griffiths, T. L. (2014). Win-stay, lose-sample: A simple sequential algorithm for approximating Bayesian inference. *Cognitive Psychology, 74*, 35-65.

(4) Lieder, F., & Griffiths, T. L. (2017). Strategy selection as rational metareasoning. *Psychological Review, 124*(6), 762-794.

3.4 Critiques & Responses (5 papers)

(1) Marcus, G. F., & Davis, E. (2013). How robust are probabilistic models of higher-level cognition? *Psychological Science, 24*(12), 2351-2360.

(2) Goodman, N. D., Frank, M. C., Griffiths, T. L., Tenenbaum, J. B., Battaglia, P. W., & Hamrick, J. B. (2015). Relevant and robust: A response to Marcus and Davis (2013). *Psychological Science, 26*(4), 539-541.

(3) Griffiths, T. L., Chater, N., Norris, D., & Pouget, A. (2012). How the Bayesians got their beliefs (and what those beliefs actually are): Comment on Bowers and Davis (2012). *Psychological Bulletin, 138*, 415-422.

(4) Frank, M. C. (2013). Throwing out the Bayesian baby with the optimal bathwater: Response to Endress (2013). *Cognition, 128*(3), 417-423.

(5) Tauber, S., Navarro, D. J., Perfors, A., & Steyvers, M. (2017). Bayesian models of cognition revisited: Setting optimality aside and letting data drive psychological theory. *Psychological Review, 124*(4), 410–441.