1 Probabilistic models of cognition (36)

Cognitive science has seen many approaches to modeling: symbolic/logical systems, connectionist architectures, and most recently, probabilistic models of cognition. Simultaneously, the approach of rational analysis has also gained traction in cognitive science, and is complementary to probabilistic models. Rational analysis emphasizes focusing on the problems that the system is trying to solve, and what possible solutions there are to those problems under certain environmental constraints. Probabilistic modeling is a framework for explicitly writing down solutions to these problems as well as the the desired constraints.

In this topic, I have included papers that start with the foundations of rational analysis, and move on to papers that discuss or reflect the core concepts behind probabilistic models of cognition. I also include several papers that are success stories for probabilistic modeling, both in higher-level cognition as well as perception. One of the core concepts in probabilistic modeling is that of generative models, and thus I also include sections on generative models, analysis-by-synthesis, and theory learning, which span a range of thinking in terms of what generative models are. Finally, I include several papers that challenge the probabilistic approach to cognition, and several papers on rational process models which address some of the "optimality" concerns with the probabilistic/rational analysis approach.

1.1 Rational analysis (3)

Marr, D. (1971). The Philosophy and the Approach. In *Vision* (Chap. 1). Retrieved from http://web.stanford.edu/class/psych209a/ReadingsByDate/01_07/Marr82Philosophy.pdf.

Anderson, J. R. (1990). Introduction. In *The adaptive character of thought* (Chap. 1, pp. 1–40). Lawrence Erlbaum Associates.

Chater, N. & Oaksford, M. (1999). Ten years of the rational analysis of cognition. *Trends in Cognitive Science*, *3*(2), 57–65. doi:10.1016/S1364-6613(98)01273-X.

1.2 Bayesian models of cognition (7)

Tenenbaum, J. B. & Griffiths, T. L. (2001). Generalization, similarity, and Bayesian inference. *The Behavioral and Brain Sciences*, *24*, 629–640, discussion 652–791. doi:10.1017/S0140525X01000061.

Griffiths, T. L. & Tenenbaum, J. B. (2006). Optimal predictions in everyday cognition. *Psychological Science*, *17*(9), 767–773. doi:10.1111/j.1467-9280.2006.01780.x.

Kemp, C. & Tenenbaum, J. B. (2008). The discovery of structural form. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(31), 10687–92. doi:10.1073/pnas.0802631105.

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. doi:10.1016/j.tics.2010.05.004.

Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: statistics, structure, and abstraction. *Science*, *331*(6022), 1279–85. doi:10.1126/science.1192788.

Teglas, E., Vul, E., Girotto, V., Gonzalez, M., Tenenbaum, J. B., & Bonatti, L. L. (2011). Pure reasoning in 12-month-old infants as probabilistic inference. *Science*, *332*(6033), 1054–9. doi:10.1126/science.1196404.

Jacobs, R. A. & Kruschke, J. K. (2011). Bayesian learning theory applied to human cognition. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(1), 8–21. doi:10.1002/wcs.80.

1.3 Probabilistic models of perception (3)

Weiss, Y., Simoncelli, E. P., & Adelson, E. H. (2002). Motion illusions as optimal percepts. *Nature Neuroscience*, *5*(6), 598–604. doi:10.1038/nn858.

Ernst, M. O. & Banks, M. S. (2002). Humans integrate visual and haptic information in a statistically optimal fashion. *Nature*, *415*(6870), 429–433. doi:10.1038/415429a.

Körding, K. P. & Wolpert, D. M. (2004). Bayesian integration in sensorimotor learning. *Nature*, *427*(6971), 244–247. doi:10.1038/nature02169.

1.4 Generative models (6)

Helmholtz, H. (1924). Concerning the perceptions in general. In J. P. C. Southall (Ed.), *Treatise on physiological optics* (Chap. 26, pp. 1–37). New York: Dover Publications.

Craik, K. (1943). Hypothesis on the nature of thought. In *The nature of explanation* (pp. 50–61).

Dayan, P., Hinton, G. E., Neal, R. M., & Zemel, R. S. (1995). The Helmholtz machine. *Neural Computation*, *7*(5), 889–904. doi:10.1162/neco.1995.7.5.889.

Ng, A. Y. & Jordan, M. I. (2002). On Discriminative vs. Generative classifiers: A comparison of logistic regression and naive Bayes. *Advances in Neural Information Processing Systems*, *14*.

Battaglia, P. W., Kersten, D., & Schrater, P. R. (2012). The Role of Generative Knowledge in Object Perception. In J. Trommershauser, K. P. Körding, & M. S. Landy (Eds.), *Sensory cue integration*. Oxford University Press.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *The Behavioral and Brain Sciences*, *36*(3), 181–204. doi:10.1017/S0140525X12000477.

1.5 Analysis by synthesis (3)

Halle, M. & Stevens, K. N. (1962). Speech recognition: a model and a program for research. *IRE Transactions on Information Theory*, *8*(2), 155–159. doi:10.1109/TIT.1962.1057686.

Yuille, A. L. & Kersten, D. (2006). Vision as Bayesian inference: analysis by synthesis? *Trends in Cognitive Sciences*, *10*(7), 301–308. doi:10.1016/j.tics.2006.05.002.

Bever, T. G. & Poeppel, D. (2010). Analysis by Synthesis: A (Re-)Emerging Program of Research for Language and Vision. *Biolinguistics*, *43*(2), 174–200. Retrieved from http://www.psych.nyu.edu/clash/dp_papers/bever.poeppel.pdf.

1.6 Theory learning (4)

Kemp, C., Perfors, A., & Tenenbaum, J. B. (2007). Learning overhypotheses with hierarchical Bayesian models. *Developmental Science*, *10*(3), 307–321. doi:10.1111/j.1467-7687.2007.00585.x.

Griffiths, T. L. & Tenenbaum, J. B. (2009). Theory-based causal induction. *Psychological Review*, *116*(4), 661–716. doi:10.1037/a0017201.

Kemp, C., Tenenbaum, J. B., Niyogi, S., & Griffiths, T. L. (2010). A probabilistic model of theory formation. *Cognition*, *114*(2), 165–196. doi:10.1016/j.cognition.2009.09.003.

Ullman, T. D., Goodman, N. D., & Tenenbaum, J. B. (2012). Theory learning as stochastic search in the language of thought. *Cognitive Development*, *27*(4). doi:10.1016/j.cogdev.2012.07.005.

1.7 Challenges for probabilistic models of cognition (6)

Kahneman, D. & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, *80*(4), 237–251. doi:10.1037/h0034747.

Tversky, A. & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124–1131. doi:10.1126/science.185.4157.1124.

Mozer, M. C., Pashler, H., & Homaei, H. (2008). Optimal predictions in everyday cognition: the wisdom of individuals or crowds? *Cognitive Science*, *32*(7), 1133–1147. Retrieved from http://onlinelibrary.wiley.com/doi/10.1080/03640210802353016/abstract.

Jones, M. & Love, B. C. (2011). Bayesian fundamentalism or enlightenment? On the explanatory status and theoretical contributions of Bayesian models of cognition. *The Behavioral and Brain Sciences*, *34*(4), 169–188. doi:10.1017/S0140525X10003134.

Marcus, G. F. & Davis, E. (2013). How Robust Are Probabilistic Models of Higher-Level Cognition? *Psychological Science*, *24*(12), 2351–2360. doi:10.1177/0956797613495418.

Jones, M. & Dzhafarov, E. N. (2014). Unfalsifiability and Mutual Translatability of Major Modeling Schemes for Choice Reaction Time. *Psychological Review*, *121*(1), 1–32. doi:10.1037/a0034190.

1.8 Rational process models (4)

Hay, N. J., Russell, S. J., Tolpin, D., & Shimony, S. E. (2012). Selecting Computations: Theory and Applications. *arXiv preprint arXiv:1207.5878v1 [cs.AI]*. arXiv: 1207.5879. Retrieved from http://arxiv.org/abs/1207.5879.

Lieder, F., Griffiths, T. L., & Goodman, N. D. (2012). Burn-in, bias, and the rationality of anchoring. *Advances in Neural Information Processing Systems*, *25*. Retrieved from http://papers.nips.cc/paper/4719-burn-in-bias-and-the-rationality-of-anchoring.

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), 599–637. doi:10.1111/cogs.12101.

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 Science*, *7*(2), 217–229. doi:10.1111/tops.12142.

1.9 Questions

1. What are probabilistic models of cognition? In particular, what are probabilistic models in the broad sense, and how does this contrast with how they are used in practice? How are they related to generative models and structured types of representations (such as theories)?

2. Are probabilistic models of cognition formulated at the computational level of analysis useful to the study of the mind? Discuss the ways in which they have been successful, and the ways in which they have not (or, alternately, weaknesses to the approach). How might such failures or weaknesses be resolved?

2 Aspects of simulation in cognitive science (38)

"Simulation" is a bit of a loaded term in cognitive science, as it has been used in many different ways to refer to many different lines of research. To complicate things further, there are areas of research could might be construed as a type of simulation, but which are not referred to as such. Based on the amount of research that touches on simulation, it seems as if there is some important underlying theme that many different cognitive scientists have been picking up on, even if they do not all necessarily use the term in the same way. In this topic, I explore different definitions of simulation which span the following areas of research: perception, language, motor control, theory of mind, and thought experiments.[1]

2.1 Mental imagery (7)

Shepard, R. N. & Metzler, J. (1971). Mental Rotation of Three-Dimensional Objects. *Science*, *171*(3972), 701–703. doi:10.1126/science.171.3972.701.

Just, M. A. & Carpenter, P. A. (1976). Eye fixations and cognitive processes. *Cognitive Psychology*, *8*, 441–480. doi:10.1016/0010-0285(76)90015-3.

Kosslyn, S. M. (1988). Aspect of a Cognitive Neuroscience of Mental Imagery. *Science*, *240*(4859), 1621–1626. Retrieved from http://www.jstor.org/stable/1701012.

Finke, R. A. & Slayton, K. (1988). Explorations of creative visual synthesis in mental imagery. *Memory and Cognition*, *16*(3), 252–257. doi:10.3758/BF03197758.

Grush, R. (2004). The emulation theory of representation: motor control, imagery, and perception. *The Behavioral and Brain Sciences*, *27*(3), 377–96, discussion 396–442. doi:10.1017/S0140525X04000093.

Flusberg, S. J. & Boroditsky, L. (2011). Are things that are hard to physically move also hard to imagine moving? *Psychonomic Bulletin and Review*, *18*(1), 158–164. doi:10.3758/s13423-010-0024-2.

Schacter, D. L., Addis, D. R., Hassabis, D., Martin, V. C., Spreng, R. N., & Szpunar, K. K. (2012). The Future of Memory: Remembering, Imagining, and the Brain. *Neuron*, *76*(4), 677–694. doi:10.1016/j.neuron.2012.11.001.

2.2 Embodied language (3)

Matlock, T. (2004). Fictive motion as cognitive simulation. *Memory and Cognition*, *32*(8), 1389–1400. doi:10.3758/BF03206329.

Bergen, B. K., Lindsay, S., Matlock, T., & Narayanan, S. (2007). Spatial and linguistic aspects of visual imagery in sentence comprehension. *Cognitive Science*, *31*(5), 733–64. doi:10.1080/03640210701530748.

Fischer, M. H. & Zwaan, R. A. (2008). Embodied language: a review of the role of the motor system in language comprehension. *Quarterly Journal of Experimental Psychology*, *61*(6), 825–850. doi:10.1080/17470210701623605.

2.3 Mental models (5)

Gentner, D. & Stevens, A. (Eds.). (1983). *Mental Models*. Lawrence Erlbaum Associates. Retrieved from http://amzn.com/0898592429.

Kuipers, B. (1986). Qualitative Simulation. *Artificial Intelligence*, *29*(3), 289–338. doi:10.1016/0004-3702(86)90073-1.

Forbus, K. D. (2011). Qualitative modeling. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(4), 374–391. doi:10.1002/wcs.115.

Johnson-Laird, P. N. (2012). Inference with Mental Models. In *The oxford handbook of thinking and reasoning* (pp. 134–145). doi:10.1093/oxfordhb/9780199734689.001.0001.

Khemlani, S. S., Mackiewicz, R., Bucciarelli, M., & Johnson-Laird, P. N. (2013). Kinematic mental simulations in abduction and deduction. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(42), 16766–71. doi:10.1073/pnas.1316275110.

[1]Note, however, that this is a very crude breakdown of what is a very complex overarching topic. Even the subtopics here are not necessarily separable: for example, several of the mental models papers could arguably also go under physical reasoning.

2.4 Motor control and action (4)

Parsons, L. M. (1994). Temporal and kinematic properties of motor behavior reflected in mentally simulated action. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(4), 709–730. doi:10.1037/0096-1523.20.4.709.

Kawato, M. (1999). Internal models for motor control and trajectory planning. *Current Opinions in Neurobiology*, *9*(6), 718–727. doi:10.1016/S0959-4388(99)00028-8.

Flanagan, R. R., Vetter, P., Johansson, R. S., & Wolpert, D. M. (2003). Prediction precedes control in motor learning. *Current Biology*, *13*(2), 146–150. doi:10.1016/S0960-9822(03)00007-1.

White, P. A. (2012a). The experience of force: The role of haptic experience of forces in visual perception of object motion and interactions, mental simulation, and motion-related judgments. *Psychological Bulletin*, *138*(4), 589–615. doi:10.1037/a0025587.

2.5 Physical reasoning (5)

Freyd, J. J., Pantzer, T. M., & Cheng, J. L. (1988). Representing Statics as Forces in Equilibrium. *Journal of Experimental Psychology: General*, *117*, 395–407. doi:dx.doi.org/10.1037/0096-3445.117.4.395.

Schwartz, D. L. (1999). Physical imagery: kinematic versus dynamic models. *Cognitive Psychology*, *38*(3), 433–464. doi:10.1006/cogp.1998.0702.

Hegarty, M. (2004). Mechanical reasoning by mental simulation. *Trends in Cognitive Sciences*, *8*(6), 280–285. doi:10.1016/j.tics.2004.04.001.

Zago, M. & Lacquaniti, F. (2005). Visual perception and interception of falling objects: a review of evidence for an internal model of gravity. *Journal of Neural Engineering*, *2*(3), S198–208. doi:10.1088/1741-2560/2/3/S04.

Davis, E. & Marcus, G. F. (2014). The Scope and Limits of Simulation in Cognitive Models. *arXiv:1506.04956 [cs.AI]*. arXiv: 1506.04956. Retrieved from http://arxiv.org/abs/1506.04956.

2.6 Representational momentum (3)

Freyd, J. J. & Finke, R. A. (1984). Representational Momentum. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *10*(1), 126–132. doi:10.1037/0278-7393.10.1.126.

Hubbard, T. L. (2005). Representational momentum and related displacements in spatial memory: A review of the findings. *Psychonomic Bulletin and Review*, *12*(5), 822–851. doi:10.3758/BF03196775.

White, P. A. (2012b). The impetus theory in judgments about object motion: A new perspective. *Psychonomic Bulletin and Review*. doi:10.3758/s13423-012-0302-2.

2.7 Theory of mind (6)

Goldman, A. I. (1992). In Defense of the Simulation Theory. *Mind and Language*, *7*(1-2), 104–119. doi:10.1111/j.1468-0017.1992.tb00200.x.

Stich, S. P. & Nichols, S. (1992). Folk Psychology: Simulation or Tacit Theory? *Mind and Language*, *7*(1-2), 35–71. doi:10.1111/j.1468-0017.1992.tb00196.x.

Gopnik, A. & Wellman, H. M. (1992). Why the Child's Theory of Mind Really Is a Theory. *Mind and Language*, *7*(1-2), 145–171. doi:10.1111/j.1468-0017.1992.tb00202.x.

Gordon, R. M. (1992). The Simulation theory: Objections and misconceptions. *Mind and Language*, *7*(1-2), 11–34. doi:10.1111/j.1468-0017.1992.tb00195.x.

Gallese, V. & Goldman, A. I. (1998). Mirror neurons and the simulation theory of mind-reading. *Trends in Cognitive Sciences*, *2*(12), 493–501. doi:10.1016/S1364-6613(98)01262-5.

Saxe, R. (2005). Against simulation: the argument from error. *Trends in Cognitive Sciences*, *9*(4), 174–179. doi:10.1016/j.tics.2005.01.012.

2.8 Thought experiments (5)

Kahneman, D. & Tversky, A. (1981). *The simulation heuristic*. Retrieved from http://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA099504.

Gendler, T. S. (1998). Galileo and the Indispensability of Scientific Thought Experiment. *The British Journal for the Philosophy of Science*, *49*(3), 397–424.

Trickett, S. B. & Trafton, J. G. (2007). "What if...": The Use of Conceptual Simulations in Scientific Reasoning. *Cognitive Science*, *31*(5), 843–875. doi:10.1080/03640210701530771.

Clement, J. J. (2009). The Role of Imagistic Simulation in Scientific Thought Experiments. *Topics in Cognitive Science*, *1*(4), 686–710. doi:10.1111/j.1756-8765.2009.01031.x.

Brown, J. R. & Fehige, Y. (2014). Thought Experiments. In E. N. Zalta (Ed.), *The stanford encyclopedia of philosophy* (Fall 2014). Retrieved from http://plato.stanford.edu/archives/fall2014/entries/thought-experiment/.

2.9 Questions

1. What is "simulation"? Discuss the various ways that the concept of simulation has been used in explanations or models of the mind. How are these uses of simulation similar or different? Is there any core insight that can be gleaned from the intersection of these topics?

2. What is the relationship between simulation and probabilistic models of cognition? Specifically, one interpretation is that simulations might be thought of as samples from a probability distribution. Does this interpretation work for all the ways in which simulation has been used to explain cognition? Discuss why or why not.

3 Simulation and physical reasoning in computer science and robotics (34)

"Simulation" has also been used extensively in computer science and robotics, in almost as many different ways as it has been in cognitive science. For example, models of physical dynamics have been used in planning algorithms for robotics; approximate physical simulations are computed in computer graphics; and simulations are run to approximate posterior distributions in machine learning. These are, as in cognitive science, quite different interpretations of the term "simulation".

In this topic, I begin with two foundational topics: probabilistic simulation, and planning and decision making in reinforcement learning (with an emphasis on model-based and/or simulation-based planning). Next, I include several papers on planning under uncertain dynamics in order to better understand the challenges (and potential solutions) to using simulation when the dynamics of the world are unknown. The next two subtopics focus more directly on the particular area of physical reasoning, both implicitly (e.g. for motor control) and explicitly (e.g. for predicting what will happen in a scene). In order to understand where simulation is useful, and where it is not, I survey a collection of papers that either do or do not use an explicit dynamics model. Finally, the last topic covers the fundamentals of physically-based animation for computer graphics.

3.1 Probabilistic simulation (4)

Chib, S. & Greenberg, E. (1995). Understanding the Metropolis-Hastings algorithm. *The American Statistician*, *49*, 327–335. doi:10.1080/00031305.1995.10476177.

Van Der Merwe, R., Doucet, A., De Freitas, N., & Wan, E. (2000). The Unscented Particle Filter. *Advances in Neural Information Processing Systems*, *13*. Retrieved from http://papers.nips.cc/paper/1818-the-unscented-particle-filter.pdf.

Neal, R. M. (2003). Slice Sampling. *The Annals of Statistics*, *31*(3), 705–767. Retrieved from http://www.jstor.org/stable/3448413.

Neal, R. M. (2011). MCMC using Hamiltonian dynamics. In S. Brooks, A. Gelman, G. Jones, & X.-L. Meng (Eds.), *Handbook of markov chain monte carlo* (Chap. 5). Chapman and Hall. arXiv: 1206.1901. Retrieved from http://arxiv.org/abs/1206.1901.

3.2 Planning and decision making (6)

Sutton, R. S. & Barto, A. G. (1998). *Reinforcement Learning: An Introduction*. Cambridge, MA: MIT Press. Retrieved from https://mitpress.mit.edu/books/reinforcement-learning.

Dearden, R., Friedman, N., & Andre, D. (1999). Model based Bayesian exploration. *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence*, 150–159. Retrieved from http://dl.acm.org/citation.cfm?id=2073814.

Ross, S. & Pineau, J. (2008). Model-based Bayesian Reinforcement Learning in Large Structured Domains. *Proceedings of the 24th Conference in Uncertainty in Artificial Intelligence*, 476–483. Retrieved from http://arxiv.org/abs/1206.3281.

Browne, C., Powley, E., Whitehouse, D., Lucas, S., Cowling, P. I., Rohlfshagen, P., . . . & Colton, S. (2012). A survey of Monte Carlo tree search methods. *IEEE Transactions on Computational Intelligence and AI in Games*, *4*(1), 1–10. doi:10.1109/TCIAIG.2012.2186810.

Guez, A., Silver, D., & Dayan, P. (2013). Scalable and efficient Bayes-adaptive reinforcement learning based on Monte-Carlo tree search. *Journal of Artificial Intelligence Research*, *48*, 841–883. doi:10.1613/jair.4117.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. a., Veness, J., Bellemare, M. G., . . . & Hassabis, D. (2015). Human-level control through deep reinforcement learning. *Nature*, *518*(7540), 529–533. doi:10.1038/nature14236.

3.3 Planning under uncertain dynamics (3)

Bertuccelli, L. F., Bethke, B., & How, J. P. (2012). Robust adaptive Markov decision processes: Planning with model uncertainty. *IEEE Control Systems Magazine*. doi:10.1109/MCS.2012.2205478.

Aoude, G. S., Luders, B. D., Joseph, J. M., Roy, N., & How, J. P. (2013). Probabilistically safe motion planning to avoid dynamic obstacles with uncertain motion patterns. *Autonomous Robots*, *35*(1), 51–76. doi:10.1007/s10514-013-9334-3.

Han, W., Levine, S., & Abbeel, P. (2015). Learning Compound Multi-Step Controllers under Unknown Dynamics. *Proceedings of the 28th IEEE/RSJ International Conference on Intelligent Robots and Systems*. Retrieved from http://rll.berkeley.edu/reset_controller/reset_controller.pdf.

3.4 Physical reasoning with dynamics models (8)

Brand, M., Cooper, P., & Birnbaum, L. (1995). Seeing Physics, or: Physics is for Prediction. *Proceedings of the Workshop on Physics Based Modelling in Computer Vision*. doi:10.1109/PBMCV.1995.514679.

Mordatch, I., de Lasa, M., & Hertzmann, A. (2010). Robust physics-based locomotion using low-dimensional planning. *ACM Transactions on Graphics*, *29*(4). doi:10.1145/1778765.1778808.

Nguyen-Tuong, D. & Peters, J. (2011). Model Learning for Robot Control: A Survey. *Cognitive Processing*, *12*, 319–340. doi:10.1007/s10339-011-0404-1.

Schulman, J., Lee, A. X., Ho, J., & Abbeel, P. (2013). Tracking deformable objects with point clouds. *Proceedings of the IEEE International Conference on Robotics and Automation*. doi:10.1109/ICRA.2013.6630714.

Zheng, B., Zhao, Y., Yu, J. C., Ikeuchi, K., & Zhu, S.-C. (2014). Detecting Potential Falling Objects by Inferring Human Action and Natural Disturbance. *Proceedings of the IEEE International Conference on Robotics and Automation*. doi:10.1109/ICRA.2014.6907351.

Kitaev, N., Mordatch, I., Patil, S., & Abbeel, P. (2015). Physics-Based Trajectory Optimization for Grasping in Cluttered Environments. *Proceedings of the IEEE International Conference on Robotics and Automation*. Retrieved from http://www.eecs.berkeley.edu/~pabbeel/papers/2015-ICRA-clutter.pdf.

Xie, C., Patil, S., Moldovan, T., Levine, S., & Abbeel, P. (2015). Model-based Reinforcement Learning with Parametrized Physical Models and Optimism-Driven Exploration. *arXiv preprint arXiv:1509.06824v1 [cs.LG]*. arXiv: 1509.06824. Retrieved from http://arxiv.org/abs/1509.06824.

Davis, E. & Marcus, G. F. (n.d.). The Scope and Limits of Simulation in Automated Reasoning. *Artificial Intelligence*. Retrieved from http://www.cs.nyu.edu/faculty/davise/papers/SimulationSubmitAIJ.pdf.

3.5 Physical reasoning without dynamics models (5)

Schulman, J., Ho, J., Lee, C., & Abbeel, P. (2013). Learning from Demonstrations Through the Use of Non-Rigid Registration. *Proceedings of the 16th International Symposium on Robotics Research*. Retrieved from http://www.cs.berkeley.edu/~pabbeel/papers/SchulmanHoLeeAbbeel_ISRR2013.pdf.

Lee, A. X., Lu, H., Gupta, A., Levine, S., & Abbeel, P. (2015). Learning Force-Based Manipulation of Deformable Objects from Multiple Demonstrations. *Proceedings of the IEEE International Conference on Robotics and Automation*. doi:10.1109/ICRA.2015.7138997.

Veiga, F., van Hoof, H., Peters, J., & Hermans, T. (2015). Stabilizing Novel Objects by Learning to Predict Tactile Slip. *Proceedings of the IEEE/RSJ Conference on Intelligent Robots and Systems*. Retrieved from http://www.ausy.tu-darmstadt.de/uploads/Site/EditPublication/IROS2015veiga.pdf.

Paraschos, A., Rueckert, E., Peters, J., & Neumann, G. (2015). Model-Free Probabilistic Movement Primitives for Physical Interaction. *Proceedings of the IEEE/RSJ Conference on Intelligent Robots and Systems*. Retrieved from http://www.ausy.tu-darmstadt.de/uploads/Team/PubAlexParaschos/Paraschos_IROS_2015.pdf.

Levine, S., Wagener, N., & Abbeel, P. (2015). Learning Contact-Rich Manipulation Skills with Guided Policy Search. *Proceedings of the IEEE International Conference on Robotics and Automation*. arXiv: 1501.05611v1. Retrieved from http://arxiv.org/abs/1501.05611v1.

3.6 Physically-based animation (8)

Baraff, D. (1997). Rigid body simulation: unconstrained rigid body dynamics. *ACM SIGGRAPH 1997 Course Notes for "An Introduction to Physically Based Modeling"*. Retrieved from http://www.cs.cmu.edu/~baraff/pbm/rigid1.pdf.

Stam, J. (1999). Stable Fluids. *Proceedings of the 26th Annual Conference on Computer Graphics and Interactive Techniques*. doi:10.1145/311535.311548.

Müller, M., Dorsey, J., & McMillan, L. (2002). Stable Real-time Deformations. *Proceedings of the ACM SIGGRAPH/Eurographics Symposium on Computer Animation*. doi:10.1145/545261.545269.

Guendelman, E., Bridson, R., & Fedkiw, R. (2003). Nonconvex Rigid Bodies with Stacking. *ACM Transactions on Graphics*, *22*(3). doi:10.1145/882262.882358.

Bridson, R., Marino, S., & Fedkiw, R. (2003). Simulation of clothing with folds and wrinkles. *ACM SIGGRAPH 2005 Courses*, *21*, 28–36. doi:10.1145/1198555.1198573.

Müller, M., Charypar, D., & Gross, M. (2003). Particle-Based Fluid Simulation for Interactive Applications. *Proceedings of the ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, (5). Retrieved from http://dl.acm.org/citation.cfm?id=846298.

Nealen, A., Müller, M., Keiser, R., Boxerman, E., & Carlson, M. (2006). Physically based deformable models in computer graphics. *Computer Graphics Forum*, *25*(4), 809–836. doi:10.1111/j.1467-8659.2006.01000.x.

Boeing, A. & Bräunl, T. (2007). Evaluation of real-time physics simulation systems. *Proceedings of the 5th International Conference on Computer Graphics and Interactive Techniques in Australia and Southeast Asia*, *1*(212). doi:10.1145/1321261.1321312.

3.7 Questions

1. How has simulation been used in the context of planning and decision making for robotic systems? In what ways has been successful, and in what ways has it failed? What are challenges for simulation-based algorithms in terms of tractability? What potential improvements over model-free methods do they bring to the table?

2. How does use of simulation in computer science and robotics relate to the use of simulation in cognitive science? Are there ways in which simulation is used in robotics and computer science that could be applicable to cognitive modeling? Be sure to discuss multiple types of simulation, including probabilistic simulation, simulations in planning (e.g. Monte-Carlo Tree Search), physical simulation for computer graphics, and combinations thereof.