Student discovered papers Week 3
Categorization, Anderson and Tenenbaum et al

- Sanborn, A., T. Griffiths, and D. Navarro. "A more rational model of categorization." (2006).
- Lee, Michael D. "How Cognitive Modeling Can Benefit from Hierarchical Bayesian Models." Journal of Mathematical Psychology, vol. 55, no. 1, 2011, pp. 1–7., doi:10.1016/j.jmp.2010.08.013.
- Petkov, G. et al. "Discovering the Dimension of Abstractness: Structure-Based Model that Learns New Categories and Categorizes on Different Levels of Abstraction." World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering 12 (2018): 554-559.
- "A Bayesian Computational Cognitive Model", NeSy'07: Proceedings of the 3rd International Conference on Neural-Symbolic Learning and Reasoning - Volume 230 (???)
- Lake, Brenden M., Ruslan Salakhutdinov, and Joshua B. Tenenbaum. "Human-level concept learning through probabilistic program induction." Science 350.6266 (2015): 1332-1338.
- Garcia, Victor, and Joan Bruna. "Few-shot learning with graph neural networks." arXiv preprint arXiv:1711.04043 (2017).
- Salakhutdinov, R., Tenenbaum, J., & Torralba, A. (2012, June). One-shot learning with a hierarchical nonparametric Bayesian model. In Proceedings of ICML Workshop on Unsupervised and Transfer Learning (pp. 195-206).
- Harnad, Stevan. "To cognize is to categorize: Cognition is categorization." In Handbook of categorization in cognitive science, pp. 21-54. Elsevier, 2017.
- Gopnik, Alison, et al. "A theory of causal learning in children: causal maps and Bayes nets." Psychological review 111.1 (2004): 3.
- Lapidow, Elizabeth, and Caren M. Walker. "Informative experimentation in intuitive science: Children select and learn from their own causal interventions." Cognition 201 (2020): 104315.
- Price, T. F., & Harmon-Jones, E. (2010). The effect of embodied emotive states on cognitive categorization. Emotion, 10(6), 934–938. https://doi.org/10.1037/a0019809

Student discovered papers Week 3 (from 2019)
Categorization, Anderson

- Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. Psychological Review, 99(1), 22-44. (EM, HM)
- Anderson, J. R., & Betz, J. (2001). A hybrid model of categorization. Psychonomic Bulletin & Review, 8(4), 629–647. doi: 10.3758/bf03196200 (NH)
- Love, B. C., Medin, D. L., & Gureckis, T. M. (2004). SUSTAIN: A Network Model of Category Learning. Psychological Review, 111(2), 309–332. (BJ)
- Shafto, Patrick, et al. "A probabilistic model of cross-categorization." Cognition 120.1 (2011): 1-25. (JR)
- Konovalova, Elizaveta and Gaël Le Mens. "Predictions with Uncertain Categorization: A Rational Model." CogSci (2016). (DS)
- Ashby, F. G., & Maddox, W. T. (1993). Relations between prototype, exemplar, and decision bound models of categorization. Journal of Mathematical Psychology, 37, 372-400.
- Farrell, S., Ratcliff, R., Cherian, A. et al. Learning & Behavior (2006) 34: 86. https://doi.org/10.3758/BF03192874
- Summerfield, C., Behrens, T. E., & Koechlin, E. (2011). Perceptual classification in a rapidly changing environment. Neuron, 71(4), 725-736. (KM
- Hierarchical Learning of Dimensional Biases in Human Categorization (Heller, Sanborn, Chater) (KL)
- Hoffman, Aaron B. & Rehder, Bob (2009). Attentional and representational flexibility of feature inference learning. In N. A. Taatgen & H. van Rijn (eds.), Proceedings of the 31st Annual Conference of the Cognitive Science Society pp. 1864—1869. (MB)
- Nosofsky, R. M. (1991). Tests of an exemplar model for relating perceptual classification and recognition memory. Journal of Experimental Psychology: Human Perception & Performance, 17, 3-27. (HM)
- Nosofsky, R. M. (1987). Attention and learning processes in the identification and categorization of integral stimuli. Journal of Experimental Psychology: Learning, Memory, and Cognition, 13, 87-108.
- Nosofsky, R. M., Little, D. R., & James, T. W. (2012). Activation in the neural network responsible for categorization and recognition reflects parameter changes. Proceedings of the National Academy of Sciences, 109(1), 333-338.
- Nosofsky RM, Sanders CA, Zhu X, McDaniel MA. Model-guided search for optimal natural-science-category training exemplars: A work in progress. Psychon Bull Rev. 2019;26: 48–76. (KK
- Nosofsky RM, Sanders CA, Meagher BJ, Douglas BJ. Search for the Missing Dimensions: Building a Feature-Space Representation for a Natural-Science Category Domain. Comput Brain Behav. 2019; (KK
- Shen, Jianhong, and Thomas J. Palmeri. "Modelling individual difference in visual categorization." Visual cognition 24, no. 3 (2016): 260-283. (CK
- Emmanuel M. Pothos, Amotz Perlman, Todd M. Bailey, Ken Kurtz, Darren J. Edwards, Peter Hines, John V. McDonnell, Measuring category intuitiveness in unconstrained categorization tasks, Cognition, Volume 121, Issue 1, 2011, Pages 83-100 (MS

Themes (2019)

Models
- Rational/Bayesian Model (DS, KM)
- ANNs
  - Alcove (EM, HM)
- Rule based (decision boundary)
  - RuleX (NH)
  - Generalized Recognition Model (GRM) (DL
- Exemplar (KL)
  - Alcove (EM, HM)
  - EBRW (NH)
- Hybrid (NH, DL)
- Generalized Context Model (GCM) (DL
- Sustain (BJ)
- CrossCat (JR)

Unidimensional bias
(BJ, KL, MS)

Attention
(EM, HM, MB)

Feature correlation
(JR, DS)

Recognition/categorization
- FMRI (SJ)

Brain activity
- FMRI (SJ, KM)

Clustering strategies
- Clumping (JR)
- Sorting (MS)
- Treating exceptions (BJ)
- Intuitiveness (MS)

Data representation
- Missing features (training) (KK)
- Continuous features (DS)
- Changing environment (KM, MB?)

Experimental Methodology
- FMRI (SJ, KM)
- Individual behavior and group behavior (CK)

A More Rational Model of Categorization

Bikram De

"Another algorithm discussed in the paper is the particle filtering algorithm. It is a sequential Monte Carlo that provides a discrete approximation to a posterior distribution that can be updated with new data. Unlike previous MAP (maximum a posteriori) algorithm of Anderson[3], in which the posterior distribution is approximated with a single partition, the particle filter uses a set number of partitions."

[1] Sanborn, A., T. Griffiths, and D. Navarro. "A more rational model of categorization." (2006).

[2] Anderson, John R. "The adaptive nature of human categorization." Psychological review 98.3 (1991): 409.

[3] Anderson, J. R. (1990). The adaptive character of thought. Erlbaum, Hillsdale, NJ

Hierarchical Bayesian Models Can Extend Our Ability to Model Cognition

Gabriela Gresenz

"Tenenbaum et al. propose Hierarchical Bayesian models (HBMs) as a method of uncovering the underlying structures used in modeling cognitive processes [1]. I have chosen a related paper titled "How cognitive modeling can benefit from hierarchical Bayesian models" [2]. In this paper, Lee discusses four ways that HBMs can "broaden the scope of current cognitive models" [2, pg. 6], two of which are of particular relevance to the course content."

[1] Tenenbaum, J. B., et al. "How to Grow a Mind: Statistics, Structure, and Abstraction." Science, vol. 331, no. 6022, 2011, pp. 1279–1285., doi:10.1126/science.1192788.

[2] Lee, Michael D. "How Cognitive Modeling Can Benefit from Hierarchical Bayesian Models." Journal of Mathematical Psychology, vol. 55, no. 1, 2011, pp. 1–7., doi:10.1016/j.jmp.2010.08.013.

[3] Palmeri, Thomas J., and Garrison W. Cottrell. "Modeling Perceptual Expertise." 2009, pp. 197–244., doi:10.1093/acprof:oso/9780195309607.003.0008.

Hierarchical Structure-based Model for Categorization and Learning
James Raubenheimer
"Whereas Tenenbaum utilizes a feature-based model founded on neural networks which represents the properties of a category, Petkov champions a model that not only utilizes these features but also how the objects are defined with the relation to other categories. These structural descriptions can include hunts, breathes, and hatches when abstracting a model based on animals."

- **Petkov, G. et al. "Discovering the Dimension of Abstractness: Structure-Based Model that Learns New Categories and Categorizes on Different Levels of Abstraction." World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering 12 (2018): 554-559.**

Modeling Cognition with Connected Bayesian Networks
Evan Segaul
"From our discussion in class on Tannenbaum's paper, the probabilistic nature of Bayesian models can be thought of as analogous to the inherent randomness of chemical concentrations activating neural action potentials. I found a paper, **"A Bayesian Computational Cognitive Model",** which describes graph architecture where each node is a Bayesian network. Their Globally Connected and Locally Autonomic Network (GCLABN), when "employed as a cognitive model, all of its nodes, each of which can be viewed as a neuron"."

Graph Neural Networks for Few-Shot Categorical Learning
Derek Gloudemans
"I chose the paper "Few-Shot learning with Graph Neural Networks" [Garcia and Bruna, 2018]. The paper attempts to address a shortcoming in most highly accurate machine learning models; these models take hundreds of examples of a class of objects to be able to accurately categorize them; by comparison humans require just one or a few examples to do the same. Closing this gap in machine learning terms broadly defines the categories of one-shot, few-shot and semi-supervised learning."

- **Lake, Brenden M., Ruslan Salakhutdinov, and Joshua B. Tenenbaum. "Human-level concept learning through probabilistic program induction." Science 350.6266 (2015): 1332-1338.**
- **Garcia, Victor, and Joan Bruna. "Few-shot learning with graph neural networks." arXiv preprint arXiv:1711.04043 (2017). (Later in ICLR**

One-shot learning with a hierarchical nonparametric Bayesian model - Salakhutdinov et al.
Soumyajit Chakraborty
"Tenenbaum et al. showed how we can classify objects using Hierarchical Bayesian models whereas Salakhutdinov et al. has extended this idea further and they have developed a hierarchical nonparametric Bayesian model, where the computers do not need to learn from several trainings. They can learn from a single training example and categorize objects into novel categories. Their experimental results demonstrate that their model is able to effectively transfer appropriate similarity metric from the previously learned categories to a novel category based on observing a single example."

[1] Salakhutdinov, R., Tenenbaum, J., & Torralba, A. (2012, June). One-shot learning with a hierarchical nonparametric Bayesian model. In Proceedings of ICML Workshop on Unsupervised and Transfer Learning (pp. 195-206).

To cognize is to categorize: Cognition is categorization

Ali Ozdagli

"To explain the importance of recognition and abstraction, as a thought experiment, Harnad asks the following question: What would happen we could not abstract? Let's say we have a perfect memory, we can keep all the experience in our memory. But because we cannot conceptualize the experience, we think that each of those memories is a unique experience. In other words, without abstraction skills, we simply cannot extract abstract knowledge out of the experience. Furthermore, we fail to categorize since we cannot perceive invariant when there is a lack of abstraction. With the abstraction, we selectively forget some unimportant details regarding the experience (THIS IS MINDBLOWING OBSERVATION FOR ME). This leads us generalization of many experiences into one category. The important details (or the generalizations) are is the invariant we use for recurrence/remembering/synthesis."

- **Harnad, Stevan. "To cognize is to categorize: Cognition is categorization." In Handbook of categorization in cognitive science, pp. 21-54. Elsevier, 2017.**
- Searle, John. 1980a. "Minds, Brains, and Programs." Behavioral and Brain Sciences 3, 417-424.
- Watanabe, S., (1985) "Theorem of the Ugly Duckling", Pattern Recognition: Human and Mechanical. Wiley http://www.kamalnigam.com/papers/thesis-nigam.pdf
- Pevtzow, R. & Harnad, S. (1997) Warping Similarity Space in Category Learning by Human Subjects: The Role of Task Difficulty. In: Ramscar, M., Hahn, U., Cambouropolos, E. & Pain, H. (Eds.) Proceedings of SimCat 1997: Interdisciplinary Workshop on Similarity and Categorization. Department of Artificial Intelligence, Edinburgh University: 189 - 195. http://cogprints.soton.ac.uk/documents/disk0/00/00/16/07/index.htm

Causal Learning in Children - Gopnik et al.

Neel Kurupassery

"To connect the article to the present--the learning of these causal maps could be based on innate abstract abilities, which could be modelled using the bayesian network schemes in Tenenbaum. In a more recent article (2020), it was found that children prefer to choose informative actions that help them understand causal relationships [3]. This seems to suggest that causal relationship inferences in children are an extension of their natural biological instinct to interpret the information given by the senses. One topic I am curious about is the regions of the brain that are active in children making inferences."

[1] Tenenbaum, Joshua B., et al. "How to grow a mind: Statistics, structure, and abstraction." science 331.6022 (2011): 1279-1285.

[2] Gopnik, Alison, et al. "A theory of causal learning in children: causal maps and Bayes nets." Psychological review 111.1 (2004): 3.

[3] Lapidow, Elizabeth, and Caren M. Walker. "Informative experimentation in intuitive science: Children select and learn from their own causal interventions." Cognition 201 (2020): 104315.

Beyond Simply Induction: Effects of Affect and Motivational Intensity on Categorization

Caleb Vatral

"Several studies have previously confirmed that a positive emotion affect (i.e. happiness or joy) broadens categorization. However, Price et al hypothesized that the effects on categorization were caused by a combination of affect and approach motivational intensity. Approach motivation can be generally thought of as the urge to move."

[1] Price, T. F., & Harmon-Jones, E. (2010). The effect of embodied emotive states on cognitive categorization. Emotion, 10(6), 934–938. https://doi.org/10.1037/a0019809