Ideal Bayesian Observer and Statistical Decisión Theory for Cognition, Perception and Cognitive Neuroscience

Synopsis: Statistical decision theory (SDT) consists of an important set of tools used to study decisions under uncertainty. Because of the variability in the environment and the stochastic nature of neural processing, SDT has become an important tool to study the brain. The main applications are: 1) to assess how well human/animals perform in perceptual and decision tasks relative to an optimal machine system, 2) to model human cognitive and perceptual mechanisms, 3) to analyze human/animal behavioral results, and 4) to analyze neurophysiology and cognitive neuroscience data in order to relate neural activity to behavior. The goal of the seminar is to allow you to have an understanding of these tools for modeling and data analysis in perception, cognition and cognitive neuroscience.

Expectations at the end of this seminar: In particular, the goal is that by the end of the course you will able to: 1) think of a theoretical question of interest in perception and cognition, and cognitive neuroscience, 2) create an experimental task that allows for the ideal observer framework or statistical decision theory analysis, 3) derive the ideal observer decision rule for the task or if unavailable choose an approximation, 4) determine how to obtain ideal observer predictions, 5) successfully implement the ideal observer on a computer, 6) compare ideal observer performance to that of human/animal/neuronal performance, 7) explain to other investigators what you've gained by using the ideal observer framework.

Reference textbooks:

Perception as a Bayesian Inference, Edited by David C. Knill and W. Richards, Cambridge University Press (1996)

Probabilistic models of the brain – Perception and neural function, Edited by Rao, Olshausen, Lewicki, MIT Press (2002)

Foundations of image science, Barrett and Myers, Wiley (2004)

Schedule

Lecture 1: Basics: Single variable ideal observer and multivariate ideal observer
Class handouts

Readings: Introductory papers

A Bayesian formulation of visual perception, David C. Knill, Kersten, Mammasian (Chapter 0, Perception as a Bayesian Inference)

Illusions, percepts and Bayes, Geisler WS, Kersten D., Nat Neurosci. 2002 Jun;5(6):508-10.

Knill, D. C. and Pouget, A. (2004) The Bayesian brain: The role of uncertainty in neural coding and computation for perception and action, *Trends in Neuroscience*, 27(12), 712-719

Mamassian, P., Landy, M. S., & Maloney, L. T. (2002), Bayesian modeling of visual perception. In Rao, R., Lewicki, M., & Olshausen, B. [Eds], Probabilistic Models of the Brain; Perception and Neural Function. Cambridge, MA: MIT Press, 13-36.

Maloney, L. T. (2002), Statistical decision theory and biological vision. In Heyer, D. & Mausfeld, R. [Eds], Perception and the Physical World: Psychological and Philosophical Issues in Perception.. New York: Wiley, pp. 145-189.

Lecture 2: Uncertainty and ideal observers
Class handouts.

Readings: Low and mid-level vision

<u>Spatial vision</u>:

Geisler, W.S. (2003). Ideal Observer Analysis. In L. M. Chalupa & J. S. Werner (Eds). Visual Neurosciences. Cambridge, MA: MIT Press.

<u>Color vision:</u>

Brainard DH, Freeman WT. (1997) Bayesian color constancy. J Opt Soc Am A. 14(7):1393-411.

Lotto RB, Purves D. (1999) The effects of color on brightness. Nat Neurosci. 2(11):1010-4

Purves D, Lotto RB, Williams SM, Nundy S, Yang Z. (2001) Why we see things the way we do: evidence for a wholly empirical strategy of vision. Philos Trans R Soc Lond B Biol Sci. 356(1407):285-97.

<u>Visual and haptic intergration:</u>

Ernst, M.O. & Banks, M.S. (2002). Humans integrate visual and haptic information in a statistically optimal fashion. Nature, 415, 429-433.

Trommershäuser, J., Landy, M. S. & Maloney, L. T. (2006), Humans rapidly estimate expected gain in movement planning. Psychological Science, 11, 981-988.

Motion perception:

Y. Weiss, E.P. Simoncelli and E.H. Adelson, Motion illusions as optimal percepts, Nature Neuroscience 5 (2002), pp. 598–604

Heading judgments:

Crowell JA, Banks MS. (1996). Ideal observer for heading judgments. Vision Research 36 (3): 471-490 FEB 1996

Lecture 3: Assessing human and model performance (ROC analysis)

Animal physiology and ideal observers

Cell Neurophysiology:

Parker, A.J. & Newsome, W.T. (1998). Sense and the single neuron: Probing the physiology of perception. Annual Review of Neuroscience, 21, 227-277.

Gold JI, Shadlen, MN, Neural computations that underlie decision about sensory stimuli, Trends Cogn, Sci, (2001), 5, 10-16

Hung C*, Kreiman G*, Poggio T, DiCarlo J. (2005) Fast read-out of object information in inferior temporal cortex. *Science,* **310**:863-866

M. Jazayeri and J. A. Movshon (2006). Optimal representation of sensory information by neural populations. Nature Neuroscience 9: 690-696.

Gnadt JW, Breznen B., Statistical analysis of the information content in the activity of cortical neurons. Vision Res. 1996 Nov;36(21):3525-37.

Optical imaging:

Chen Y., Geisler W.S., & Seidemann, E., Optimal decoding of correlated neural population responses in the primate visual cortex, Nature Neuroscience, 9, 1412-1420, (2006)

Lecture 4: High level perception, action, and ideal observers

Object perception & recognition:

Tjan B.S., & Legge G.E. (1998). The viewpoint complexity of an object recognition task. Vision Research 38 (15/16), 2335-50.

Kersten, D. K. & Yuille, A. (2003), Bayesian models of object perception. Current Opinion in Neurobiology, 13, 1-9

Liu Z, Knill DC, & Kersten D. 1995. Object Classification for Human and Ideal Observers. Vision Research 35: 549-68.

Tjan B.S., Braje W.L., Legge G.E., & Kersten D. (1995). Human efficiency for recognizing 3-D objects in luminance noise. Vision Research 35 (21), 3053-69

Motor planning:

Trommershäuser, J., Landy, M. S. & Maloney, L. T. (2006), Humans rapidly estimate expected gain in movement planning. Psychological Science, 11, 981-988.

Visual attention:

Eckstein, MP, Drescher BA, Shimozaki,SS. "Attentional cues in real scenes, saccadic targeting and Bayesian priors," *Psychological Science*, v.17, 2006, p. 973-980.

Eckstein, M.P. (1998). The lower visual search efficiency for conjunctions is due to noise and not serial attentional processes. Psychological Science, 9(2), 111–118.

Shimozaki, S.S., Eckstein, M.P., Abbey C.K., Comparison of two weighted integration models for the cueing task: linear and likelihood. J Vis. 2003;3(3):209-29.

Perceptual learning:

Eckstein, M. P., Abbey, C. K., Pham, B. T., & Shimozaki, S. S. (2004). Perceptual learning through optimization of attentional weighting: Human versus optimal Bayesian learner. *Journal of Vision*, *4*(12):3, 1006-1019

Lecture 5: Cognitive Neuroscience, statistical decision theory,

Functional Magnetic Resonance Imaging:

Haxby, J. V, Hoffman, EA, & Gobbini, MI (2000). The distributed human neural system for face perception. Trends in Cognitive Sciences, 4, 223-233

Kamitani, Y., Tong, F. (2005). Decoding the visual and subjective contents of the human brain. Nature Neuroscience, 8, 679-85.

Haynes J-D & Rees G. (2005) Predicting the orientation of invisible stimuli from activity in. human visual cortex. Nature Neuroscience 8, 686-91

Kamitani, Y. & Tong, F. (2006). Decoding seen and attended motion directions from activity in the human visual cortex. Current Biology, 16, 1096-1102.

Li S, Ostwald D, Giese M, Kourtzi Z. (2007) Flexible coding for categorical decisions in the human brain. *J Neurosci.* 27(45):12321-12330

Event Related Potentials:

M.G. Philiastides, R. Ratcliff and P. Sajda (2006) Neural representation of task difficulty and decision making during perceptual categorization: a timing diagram, Journal of Neuroscience, 26 (35): 8965-8975, Aug. 30, 2006.

Hung C*, Kreiman G*, Poggio T, DiCarlo J. (2005) Fast read-out of object information in inferior temporal cortex. *Science,* **310**:863-866

M.G. Philiastides and P. Sajda (2005) Temporal Characterization of the Neural Correlates of Perceptual Decision Making in the Human Brain, Cerebral Cortex, 16 (4): 509-518, Apr. 2006.

EEG & FMRI:

Marios G. Philiastides and Paul Sajda (2007) EEG-Informed fMRI Reveals Spatiotemporal Characteristics of Perceptual Decision Making. J. Neurosci., Nov 2007; 27: 13082 - 13091 ; doi:10.1523/JNEUROSCI.3540-07.2007

Lecture 7. Cognition and ideal observers

Concept learning and memory:

Bayesian modeling of human concept learning. J. B. Tenenbaum (1999), Advances in Neural Information Processing Systems 11. Kearns, M., Solla, S., and Cohn, D. (eds). Cambridge, MIT Press, 1999, 59-68.

Griffiths, T. L., Kemp, C., & Tenenbaum, J. B. (in press). Bayesian models of cognition. In Ron Sun (ed.), *Cambridge handbook of computational cognitive modeling*. Cambridge University Press.

Group decisions:

Sorkin, R. D., Hayes, C. J. and West, R., Signal detection analysis of group decision making, Psych. Rev., v108, pp. 183-203, 2001.

Bayesian modeling of human concept learning. J. B. Tenenbaum (1999), Advances in Neural Information Processing Systems 11. Kearns, M., Solla, S., and Cohn, D. (eds). Cambridge, MIT Press, 1999, 59-68

Decision making**:**

Maloney, L. T., Trommershäuser, J. & Landy, M. S. (2007), Questions without words: A comparison between decision making under risk and movement planning under risk. In Gray, W. (Ed), Integrated Models of Cognitive Systems. New York , NY : Oxford University Press, pp. 297-313